

(THE DEEP BLUE) NILE:
Neuronal Influences on Language Evolution

Connectionist models for the
simulation of the evolution of language

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Abstract

A simulation of language evolution as described in [BATALI 98] is replicated, in which a population of communicative agents implemented as simple recurrent networks develops, from no explicit initial knowledge, effective linguistic representations for a small set of predefined meanings. The author of the original paper claims to have found a language emerging from his simulation which was compositional, in that it reflected regularities in the structure of the meanings. Such results could not be fully reproduced. A detailed analysis of the results of the replication, and additional experiments, suggest that the training regime used seeks to maximise the information content of the linguistic expressions with respect to meaning space, which fails to support compositionality. It is shown that while languages which emerge naturally from the simulations can be transmitted successfully over hundreds of cycles, ideally compositional languages, which were artificially generated, can not be learned properly.

Acknowledgements

Because I find it very difficult to decide on the order in which to mention the people I want to thank for their help with this project, I decided to mention them in alphabetical order. I hope that nobody will be offended or feel insufficiently appreciated by this possibly unusual way.

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Preface

Language is fascinating. Everybody is a language expert and yet nobody really knows how and why it works. We find it amazingly simple to use (our native) language, but to consciously adopt a foreign language can be terribly difficult. Theoretical language models for the most part still fail to capture even simple facts. Language seems absolutely logical and simple, but a closer look often reveals chaotic and highly complex dependencies and structures. Language is organic.

I think it is important to admit that as yet there exists no generally valid theory of the origin of language. Formalisms which have been developed during the last decades may be able to capture many facets of natural language, may help people to learn foreign languages, and may provide useful and valuable explanations of certain phenomena. But still there is no one fundamentally correct answer to the questions of the how and the why. Why did humans develop complex languages? Why did not the apes? Or did they, and we did not realise? How does it all really work?

I did very much enjoy learning about different aspects of current linguistic theory ([RADFORD 97], [AARTS 97] and especially [STEEDMAN *in press*]) and their relevance for automated processing of natural language (e.g. [RITCHIE & MELLISH 97]). But the most interesting question for me is whether there are any simple, well understood principles which inevitably lead to the development of languages as we know them. Does our brain need a highly specialised, highly sophisticated, genetically determined and inherited “language faculty” to enable us to use language naturally ([PINKER 94])? Is the process of language adoption really a process of fixing certain free parameters of the “language faculty” ?

Or is there an alternative route ? Can we take a test tube full of language ingredients and watch it evolve as we can watch DNA evolve structure in

watery solution ? There is no way I would want to attempt to answer these questions — but at least I believe it is fair to have doubts about predominant paradigms.

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Chapter 1

Introduction

This thesis describes a replication of a simulation of language evolution originally presented in [BATALI 98], which is concerned with the question of which features of natural language can be explained as a consequence of non-biological evolution of language through continued social transmission. The principal aim of the project described herein is to investigate to what extent the results of the original paper are reproducible and to analyse them in detail.

A population of simple recurrent neural network agents is simulated, which send each other “linguistic representations” for a small set of predefined “meanings”. The agents are trained to interpret each other’s “words”, and as a consequence develop a code for the meaning set without having been given any explicit initial linguistic knowledge. The population converges to a state where all agents possess similar knowledge about the code, such that any word produced by any agent for a meaning has a high probability of being interpreted correctly by all the others. Thus a working communicative system has evolved in the artificial.

The code emerging from the system is shown to be a nearly optimal representation of the predefined meanings. These being constructed from two components, the author of the original paper also claims that the emerging

code was compositional in that it reflected this regularity. His claim can only be verified to a limited extent. A detailed analysis of the results, as well as additional experiments, lead to the conclusion that the phenomena of BATALI's simulation are caused by the agents seeking to maximise the information content of the "words" with respect to the meaning set, while minimising their length, which does not support optimal compositionality. Variations of the simulation's parameters are investigated and some of these can be shown to be irrelevant.

The networks' capacity is shown to be relevant to their ability to process long sequences, but no clear connection with compositionality can be established. Ideally compositional (but "random") languages are shown to be not adequately reproducible by the networks, while those which emerge naturally from continued transmission are stable for up to hundreds of transmission cycles.

For these experiments, a set of packages has been implemented in *ANSI Common Lisp* which provides all necessary functionality for general purpose neural network simulations. The speed of this software is considered competitive with programs written in languages closer to machine level. It outperforms at least one neural network simulator written in C.

1.1 Outline

This document is structured according to a top-down approach. First I will give a general introduction to the field of language evolution (chapter 2), and then in chapter 3 review in detail the paper which has been replicated. Necessary background in connectionist methods will be given in chapter 4, and the main aspects of the software implementation will be presented in chapter 5. In chapter 6 the results of the replication and the additional experiments will be discussed, and conclusions will be drawn in chapter 7.

More detailed discussions of Elman network training and the derivation of a measure of information content can be found in the appendices together with raw data from the experiments.

All software developed for this project and a documentation will be made available at <http://www.cityline.net/~slink/nile/>.

Chapter 2

Language Evolution

Of all known natural communication systems, human language occupies a unique position. Linguistic research has revealed complex but highly regular structures in languages and has developed theoretical models to (approximately) describe them. The ultimate goal of many linguists in recent decades has been to discover a Universal Grammar which underlies all human languages.

Many cross-linguistic phenomena and phenomena of children's progress in language acquisition are so striking that indeed it seems reasonable to postulate that different human languages are manifestations of a single general, innate device common to all humans. Consequently, the task of language acquisition is reduced to the configuration of this *language faculty*. It may directly implement versatile grammatical production and parsing mechanisms, which have a few free parameters such as general word order or Wh movement rules. In order to learn a language, a child's *language acquisition device* has only to acquire a lexicon and derive from language samples the set of language parameters which is being used in its social environment.

This *innateness hypothesis* attributes most of the features of language to biological evolution. The language faculty is assumed to be genetically inherited. *Language genes* would predetermine the development of an indi-

vidual’s language faculty and thus any defects in these genes would lead to flaws in linguistic ability. Although the hypothetical language facility must be extremely complex, its genotype must have spread virtually unchanged, because all humans possess nearly identical language abilities.

On the other hand, concepts of innateness can not fully explain all of the features of language, for example why it is not a static system, or why the hypothetical “language parameters” should not have an optimal configuration on which they would inevitably converge. Human languages are manifold and in permanent flux. Different languages strongly influence each other where societies with different languages overlap, and social and cultural changes clearly cause changes in human language. An innate language facility should lead to fairly regular languages, but an important property of language is systematic irregularity¹. Even without any detailed investigation this seems to suggest that language evolves to some extent independently of the human body.

2.0.1 Two aspects of language evolution

The biological and non-biological aspects of language evolution are likely to be confused, as both influence what we observe as language. HURFORD pointed out that these two lines of language evolution do not have to be contradictory, mainly because they occur on different time scales: *Phylogenetic* language evolution [HURFORD 92] shapes the language faculty in the long term through genetic transmission and in accordance with the principles of Darwinian evolution. Universal mechanisms may evolve which influence the general types of languages which are available to us.

In the short term, *glossogenetic* processes [HURFORD 90] shape language

¹such as irregular verbs or lexemes. I do not mean here irregularities which can be attributed to imperfections in the speakers’ language production systems (competence/performance distinction)

specific features (or grammars) through cultural transmission over several generations. Though Phylogeny may strongly influence Glossogeny, the two processes should be separated. Which features of (a particular) language to attribute to which mechanism should be carefully investigated.

2.1 Language as a dynamical system

In this thesis I will concentrate on the glossogenetic domain, so let us first recapitulate some basic and commonly accepted properties of language:

1. Languages live only through populations of speakers. Properties of languages are constantly being formed and reformed by all members of their user groups. New expressions are invented permanently while others die out. Even complex grammatical rules change over time.
2. Every language user acts independently, but is influenced by others.
3. The goals which are to be achieved by language and the concepts it describes are continually changing.
4. On the other hand, communication is only possible when language users have agreed upon certain linguistic conventions.

These qualities make language an *adaptive complex dynamical system* [STEELS 97]: It consists of independent elements (1) which interact in some non-linear way (2), this interaction being strictly local² (within the social environment of each language user). The system is open, in that new elements (language users) enter while others leave. Changing environmental conditions (3) make the system adaptive, as it has to react to permanent, externally caused change.

²which by no means needs to be geographically local, though in former times this was certainly the case as well

While these properties (1, 2 and 3) press the system towards diversity, its overall goal, communication between its elements (4), pulls it towards a steady state (equilibrium). As long as neither of these forces takes over, the system as a whole, though not being completely regular, should develop regular structures through *self-organisation*.

2.2 The framework for simulations of the evolution of language

These insights are helpful in developing a framework for computational simulations of the complex language system we observe in reality. Of course, any such model can only approximate natural processes and for the sake of computational feasibility further simplifications may have to be made. But still this approach could provide us with useful insight into which requirements are necessary, or possibly sufficient, for certain features of natural language to evolve through glossogenetic processes.

The framework which is common to much research in simulations of the evolution of language is characterised by the following aspects (see also figure 2.1, [HURFORD *in press*] and [STEELS 97]):

1. The language system as a whole is represented as a population of independent agents, each of which possesses an internal representation of language. Often, the population is made open in that new, “fresh” agents regularly enter it while others “die”.
2. The agent’s language representation is usually realised as memory, private to each agent, which is processed by a set of predefined functions common to all agents.
3. The information available to each agent is restricted to its own memory and well defined data exchange procedures with other agents in a

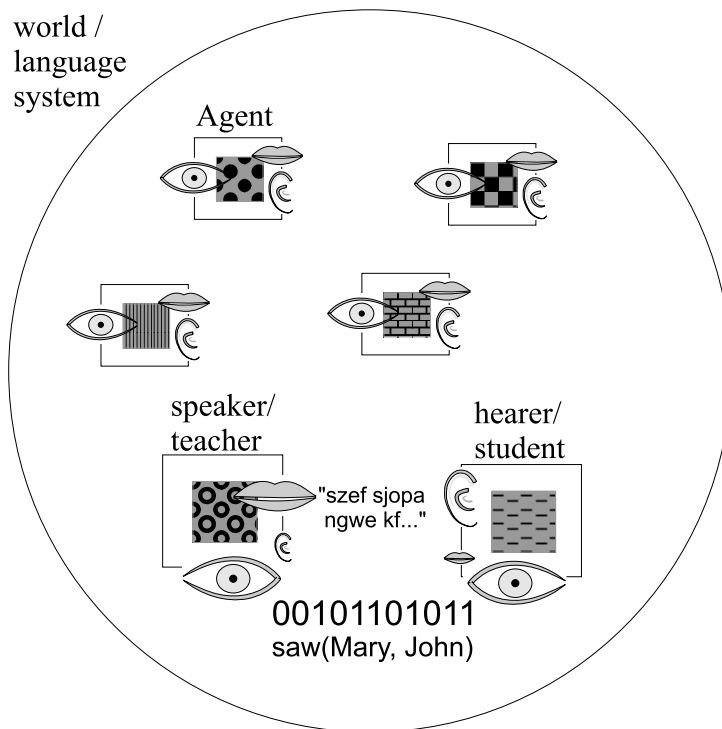


Figure 2.1: An illustration of the typical setup of simulations of language evolution: A population of independent agents, each possessing their own independent memory, is used to model processes within a language system. Agents are able to produce utterances, interpret those of others and associate them with meanings. Communicative processes are usually modelled by having one agent produce an utterance which it associates with a given meaning and having another agent interpret it.

strictly local environment. No agent has a full view of the whole population, nor is any agent's behaviour directed by some central controller³.

4. A set of meanings is defined by the experimenter for which agents are to develop linguistic representations. A common simplification is

³This condition can never be fulfilled completely using simulations, as certainly the instance within which the simulation is run does and has to have a complete view of what is being simulated. This general dilemma affects most research trying to recreate things in the artificial, but one should always be aware of the fact that the environment in which a simulation is conducted *always* influences the simulation itself.

not to change over time the distribution from which meanings to be communicated are drawn, which means that the system does not have to adapt to a changing environment.

5. The overall communicative goal is usually implemented as “communication episodes” whereby one agent is made to communicate to another a linguistic representation for one or many given meaning(s). The speaker/teacher is used to produce a “surface form” for each presented meaning which is to be interpreted by the “hearer/student”. As the descriptions suggest, this process usually involves some kind of training where the student’s internal representation is altered to associate the sequence produced by the teacher with the given meaning.

It should be emphasised that the meaning is imposed externally onto both the speaker and the hearer, contrary to models where the speaker would provide both an own representation of a meaning and a surface form.

Though communication episodes are often designed to take place between two agents, events involving several agents are also possible as long as locality with respect to the size of the whole population is preserved.

A particular condition as a consequence of (3) is that agents participating in a communication episode should be chosen at random. For any other strategy it could be very hard to guarantee that an external selection pressure is not imposed onto the system which would lead to some languages being preferred over others⁴. This also means that no selection as in biological evolution is included.

⁴Strictly generational models in which teachers are always chosen as “knowledgeable” agents while students are always “unknowing” are problematic according to this condition. Though such models can easily be justified by intuitive reasons, more formal arguments should be found. I cannot provide any such argument

It is understood that in order to investigate how language could have evolved within a dynamical system, no explicit initial linguistic knowledge must be given to agents entering the population. In particular, the initial population of a simulation has to be “unknowing”. This condition is not easy to fulfil as the agents are given initial biases through the representation of their linguistic knowledge and the functions for production and interpretation. I will return to this point later on.

2.3 Agents

As a consequence of the previously described setup, the agents used for such simulations have to fulfil some basic requirements as illustrated in figure 2.2:

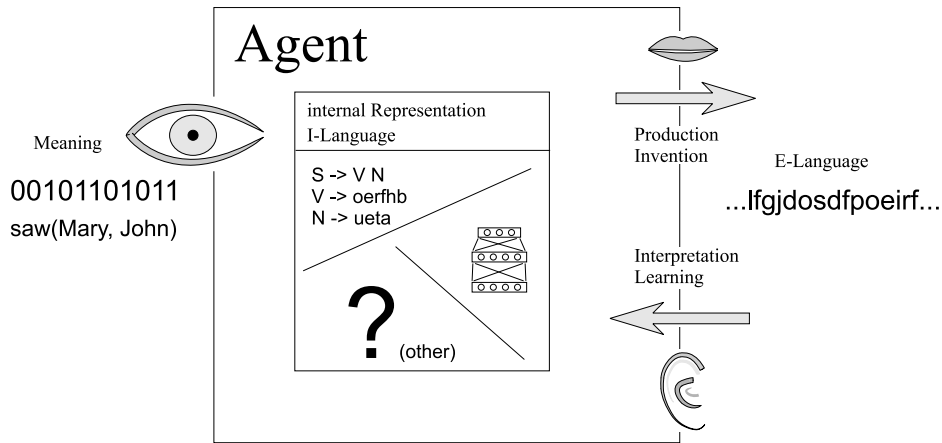


Figure 2.2: An illustration of the prototype for agents used in simulations of language evolution

- Every agent has to have internal memory in which to store its linguistic knowledge, using a (usually predefined) representation. Theoretically agents should also be enabled to develop their own functions to operate on their internal data, but presumably because this would significantly increase the complexity of the simulation, there are no known attempts to follow this path explicitly⁵.

A basic criterion for internal representations is whether they are of symbolic or non symbolic nature. While both representations could theoretically be equivalent (see 4.2.1, page 38), they are not in practice

⁵Because data may also represent instructions to some possibly Turing complete mechanism defined outside the agent, no explicit notion of agents' internal methods is necessary per se (*universal turing machine*, e.g. [HOPCROFT & ULLMAN 79], pages 181–182)

and thus do impose strong biases onto the agents and thereby onto the system as a whole.

- The agents need mechanisms to interpret and represent some kind of externally imposed (presented) meaning.
- To produce a mapping⁶ from meanings to some pseudo-lingual surface form (labelled *E-Language*, see below) using its internal representation (*I-Language*), an agent needs some *production mechanism*. Especially for symbolic internal representations, *invention capability* is often needed in order to produce utterances for meanings for which no or only partial linguistic knowledge has been internalised.
- In the other direction, some *interpretation mechanism* must be available to the agents to produce mappings from the E-Language to meanings, given their internal knowledge. In order to enable the population to at least partially converge onto common meaning-form mappings (property 4 in section 2.1, page 7), agents must be able to change their internal representation to associate with a given meaning the surface form produced by a teacher agent. Such a learning mechanism should provide generalisation capabilities such that agents can develop more sophisticated internal representations than just 1:1 *idiosyncratic* memorisation of meaning-form pairs.

⁶Please note that throughout this thesis I am using the term *mapping* in a slightly sloppy way, along the lines of association, correspondence or relation. In the strict mathematical sense, a mapping from a set \mathcal{S} to a set \mathcal{T} is a correspondence from \mathcal{S} to \mathcal{T} such that for each $x \in \mathcal{S}$ there corresponds exactly one $y \in \mathcal{T}$. This condition is not always fulfilled where I use the term. Thanks to BRUCE EDDY for having pointed this out to me.

2.4 Glossogenetic transmission of language

The notion of *I/E-Language* (introduced in [CHOMSKY 86], pages 19–24) is used here in the broader sense to distinguish between the agents’ internal linguistic representation and its effect, the surface forms conveyed to other agents. KIRBY and HURFORD ([KIRBY *in press*] and [HURFORD *in press*]) used this notation to describe the process of continued production from I– to E–Language and acquisition from E– to I–Language (figure 2.3): In a language system as described here, the only way a language can manifest itself is through continued transformation between both media (internal representation and “surface forms”). Even in non generational systems, the language evolved has to undergo this transformation in order to spread within a population of agents.

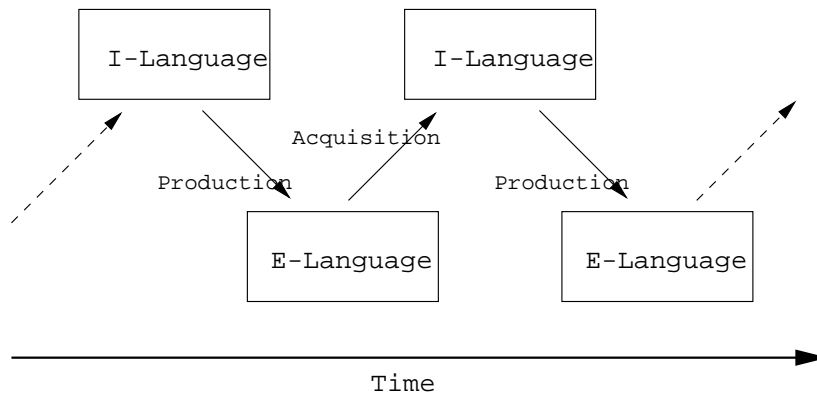


Figure 2.3: Transmission of language over time through repeated production and acquisition (from [KIRBY *in press*], page 4)

2.4.1 Production and acquisition mechanisms

It is clear that whatever the model of a glossogenetic language system, the production and acquisition mechanisms as well as the representations used for the I– and E–Language are what shape the characteristics of language —

be they biologically determined or not. They impose biases onto the whole system.

The question of how sophisticated the inherited language faculty has to be thus may be divided into the questions of how complex our internal language representation (I–Language), our production mechanism and our language acquisition device have to be in order to yield features of the E–Language which we observe.

Under the assumption that biologically determined influence is minimal, the goal of research by means of computational simulations should be to find a minimal set of prerequisites which make certain features of language evolve in the glossogenetic domain. These basic mechanisms have to be attributed to phylogenetic evolution, but in any case they could constitute very general principles which are fundamental to human nature or languages per se.

2.4.2 Bottlenecks

Another aspect identified by HURFORD and KIRBY is that during the continued transmission of language under realistic conditions the set of meaning–form pairs communicated between agents always has to be partial with respect to the full set of predefined meanings:

- For an infinite meaning space, a student agent can never be presented all possible meaning–form pairs, though there may exist a finite set of recursive rules in an agent’s internal representation (I–Language) to describe a mapping for all possible meanings. This has been called the *semantic bottleneck*. It can also be modelled for finite meaning spaces by artificially limiting the number of meanings to be uttered by any agent in a transmission process. As a consequence, a language can only surface if it can be adequately inferred from a comparably small set of examples from the E–Language domain, given the biases

described above.

- If agents' I-Languages and their representations allow several different forms for a single meaning, then the production mechanism may be designed as to only ever produce a subset of these forms when queried for a meaning. This *production bottleneck* should always be extant for natural systems.

2.4.3 Identification in the limit

GOLD has proven in [GOLD 67] that even with an infinite number of examples, in the general case a language of any class including the class of super-finite⁷ languages cannot be learned from positive textual examples alone.

From this it follows that a semantic bottleneck is always extant because not only the number of language samples which can be transmitted within finite time is limited under realistic circumstances, but according to GOLD it is not even guaranteed that a language of significant complexity⁸ can be learned within *infinite* time.

Another consequence of GOLD's work is that if an infinite meaning set is to be expressed by a language which *can* be transmitted within a language system, then the system **must** have prior biases, including the bias caused by necessarily imperfect learning.

⁷"A *super-finite* class of languages denotes any class which contains all languages of finite cardinality and at least one of infinite cardinality." ([GOLD 67], page 452). In the current context these are any languages able to express infinite meaning sets.

⁸at least super-finite

2.5 Relevant syntactic features

The research to be presented here is mainly centred around two fundamental syntactic features of language, which I would like to introduce briefly:

2.5.1 Compositionality

“The meaning of an expression is a monotonic function of the meaning of its parts and the way they are put together”

[CANN 93], page 4

Given that any natural meaning space is regularly structured, in that certain of its elements can be identified as being made of coherent, integral parts, any language system should naturally reflect such regularity at least in part in surface forms of the E-Language.

“Michael likes cows” shows compositionality in that the sentence is made of two quite clearly identifiable entities, a person called “Michael” and the class of animals called “cows”, connected by the proposition of liking.

2.5.2 Recursion

“**Recursion** /n./ See recursion. [...]”

[THE JARGON FILE 99]

“**Recursive** [lat] is the term given to a function whose values are related such that they can be calculated from a given initial value by continued application of the same formula [...]”

Translation from [DTV BROCKHAUS 88]⁹, pages 15:125–126

⁹The original entry is: **rekursiv** [lat] heißt eine Funktion, deren Werte derart zusammenhängen, daß sie sich aus einem gegebenen Anfangswert nacheinander durch jeweils die gleiche Formel (Rekursionsformel) berechnen lassen.

“**Recursive** A recursive operation is one which can be repeated any number of times. For example, the process by which an adjective comes to modify a noun might be said to be recursive in that we can position any number of adjectives in front of a noun (e.g. *a (tall, dark, handsome) stranger*).

[RADFORD 97], page 270

These definitions should make clear that recursive properties of language¹⁰ may best be defined in terms of recursive properties of the representation used for the I–Language. The example by RADFORD could have been generated by the following context free rules of which N' is defined recursively.

$$NP \rightarrow Det N'$$

$$N' \rightarrow Adj N'$$

$$N' \rightarrow N$$

¹⁰Note that the set of *recursive languages* is defined as “those languages accepted by at least one Turing machine that halts on all inputs” ([HOPCROFT & ULLMAN 79], page 151), which is much larger than the linguistically relevant classes of context free and indexed languages.

2.6 A short overview of current research

The field of research into language evolution by means of computational simulations as outlined here is still quite young, thus there is only a small number of research results available so far, of which I will briefly present two.

2.6.1 Learning and morphological change

In [HARE & ELMAN 95] two experiments are described which make use of some of the basic ideas set out above, though the authors obviously had more specific goals. The aim of their work is to simulate the historical change of the morphology of the verb system of Old English into that of the language as known today, where more regular inflections persisted over time.

A simple, strictly generational model is used whereby for every generation one agent (the teacher) generates input data for another (the student). For every subsequent generation, the student from the previous generation is taken to be the teacher of the current, the student agent of the first generation being trained on historical linguistic data. Thus the simulation implements a very simple E/I-Model (see 2.4, page 14).

The agents are realised as feed forward neural networks (see 4.2, page 36) which are set up in order to predict morphological features given a verb and an “inflection request”. Two different experiments are conducted, one to show a general tendency towards regular inflections and another to investigate how still certain forms of “strong verbs” can be immune to such regularisation. Basically, the results of both experiments are reported to be consistent with the historic reality.

The paper may be interesting in that it gives an account as to why a real language system should have changed in the way it did, and in that the research reported does describe a typical example of glossogenetic change. On the other hand it does not fit very well into the framework introduced

here:

- The initial agent is trained on real linguistic data, thus the simulation does not evolve regular structure itself.
- The encoding for “surface forms” is very abstract and in particular the networks used are not able to produce strings of symbols corresponding to surface forms.

In general, some aspects of the methodology used seem unclear. There are no details and no clear justification given for the encoding of the networks’ input and output. The training of networks of the first simulation is stopped before convergence is reached in order to reach generalisation, as the authors argue. This method seems quite dubious because networks of appropriate layout (especially of proper hidden layer size) should generalise even if trained until the error does not decrease any more. And finally, the observed regularisation effect may be primarily due to frequency effects of the training data, which makes the results less interesting¹¹.

Overall, I would not consider this paper to be typical of current research in language evolution, but in retrospect it may be one of the first which implemented some of its basic principles.

2.6.2 Learning, Bottlenecks and the Evolution of Recursive Syntax

KIRBY was the first who could show that within the general framework outlined in this chapter even recursive internal grammars can evolve

¹¹When used as described in the paper, feed forward neural networks are trained to maximise the probability $P(\mathbf{t}|\mathbf{i})$ of their output being correct (being the target \mathbf{t}) given a particular input \mathbf{i} . If the distribution of the random variable \mathbf{I} of inputs \mathbf{i} is not uniform, $P(\mathbf{t}|\mathbf{i})$ can be increased without any sophisticated training by preferably predicting the more likely events of \mathbf{I} . This is also known as the *block of wood* base case.

[KIRBY *in press*]. He also uses a strictly generational model with just two agents where the student of one generation is taken to be the teacher of the next.

The author chose purely symbolic representations. The meanings to be expressed consist of predicates over symbols and, for the second simulation, also predicates over predicates. This regularity can be exploited in full by the agents, because their internal grammar is implemented as definite clause grammars, which allows agents to find directly representations for individual symbols and predicates.

The learning algorithm is based on subsumption: First, every meaning-form pair to be learned is internalised, then any pair of rules which could be expressed by a single rule subsuming both of them is replaced by the subsuming rule. For the case of an agent being queried to produce a form for a meaning for which it has no internalised rules, KIRBY designed an invention method: To produce a meaning, the algorithm tries to find a “similar” rule of the internal grammar of an agent, in which those parts of the form which correspond to differing parts of the meaning to be expressed are replaced by random strings. This mechanism could also be seen to be based on subsumption, as it should be equal to generation of a rule which would subsume a previously internalised rule and the new, yet unknown rule for the meaning to be expressed.

Two experiments are described in this paper. The first was set up with a finite meaning space, using only symbols within predicates. It was shown that from this setup very regular, compositional internal grammars would evolve, surfacing in equally regular E-Languages. A second experiment was run using an infinite meaning space where also predicates within predicates were allowed. This simulation could even evolve recursive internal grammars.

Though these results are new and exciting, the representation used for the I-Language, the learning and induction algorithms and the highly regular

meaning space impose strong biases onto the system as a whole. Thus if these results are to provide insight into the natural glossogenetic evolution of language, it has to be asked how the production and acquisition mechanisms could be explained to be existing in nature without some kind of strong biological determinism. But still the requirements of this model seem to be weaker than what has often been claimed to be necessary for language to evolve.

2.7 Conclusion

For this thesis I have concentrated on simulations of language evolution from no initial language by replicating work originally reported in [BATALI 98]. This experiment, which I will describe in detail in chapter 3, is similar to [HARE & ELMAN 95] in modelling continued transmission of language using connectionist methods. It is, however, fundamentally different in directly implementing the generation of surface forms as sequences of characters. The initial agent is not given any knowledge and the simulation does not rely on frequency effects as all meanings are equally probable to be uttered¹². This makes BATALI's experiment a simulation of real language evolution from no initial language. Like [KIRBY *in press*] it is concerned with compositionality, but, being of non symbolic nature, it uses relatively simple production and acquisition methods.

BATALI's paper is widely considered to be the precursor to much research in the area of language evolution. Quite surprisingly, the author claims that within a population of simple recurrent network agents a language emerges which is compositional in that it reflects regularities of the meaning set which is used.

As far as I know, the results of this paper have never been replicated and

¹²in the original version of the experiment

although it has influenced much work in the field of language evolution, so far it has not been analysed independently. In the following chapters I will describe this paper, its motivation and the techniques it uses before finally presenting the results from my replication and some additional work based on the same methods. I will attempt a different perspective on BATALI's work, trying to contribute to a more thorough understanding of what he achieved and why.

Chapter 3

JOHN BATALI's Computational simulations of the emergence of grammar

The principal goal of this thesis is the replication of *Computational simulations of the emergence of grammar* as conducted by JOHN BATALI. This chapter is dedicated to a description of his work and will naturally recapitulate much of [BATALI 98], though I will try to give a different perspective. I will only introduce briefly here the neural networks which are used for the simulation — more background is given in chapter 4 from page 35 onwards.

BATALI's work does fit quite well into the general framework described in 2.2¹: A population of agents is simulated whose members communicate to each other linguistic representations for a small set of predefined meanings. The agents are set up as simple recurrent networks (Elman networks) which are not provided with any explicit representation for I-Language. The population is made static in that agents neither leave nor enter, and the

¹In fact what I tried to abstract to a general framework was very much influenced by BATALI.

initial population is not given any explicit linguistic knowledge (i.e. unlike [HARE & ELMAN 95], see 2.6.1, page 19). The language which evolves within the population reflects regularities of the meaning space used, in that it shows *compositionality*.

3.1 Why connectionist models ?

For his simulation, BATALI decided to implement the agents using artificial neural networks (ANNs), which was probably motivated by the relevance of connectionist techniques as simple models of the brain. Though ANNs can only provide very simple approximations of the functionality of the natural organ, and despite the fact that many ANN models and methods can hardly be motivated neurobiologically, they are attractive for simulations of language evolution for a number of reasons.

- Like the brain, artificial neural networks perform *Parallel Distributed Processing (PDP)*: As opposed to serial computers where a central processing unit implements a number of potentially sophisticated operations on large amounts of data, natural and artificial neural networks consist of many massively interconnected units which each perform a simple calculation and constitute a small amount of memory².
- Most formal neuron models are inspired by some aspects of neural cells from the cerebral cortex: Each neuron's incoming activation is determined by those of others through excitatory or inhibitory connections (axons, dendrites, synapses), with some variation in strength. A cell's soma is assumed then to integrate over incoming activations for a certain period of time to finally pass on to other cells an activation

²Still, in most cases, *simulations of PDP systems* are implemented on serial machines where sophisticated and specialised hardware is not available to directly implement artificial neural networks.

calculated by some non-linear function. Activations are passed on as series of spikes of different frequencies (roughly 1–1000 Hz).

The *perceptron* is a simple formal neuron model (see section 4.2) which to some extent reflects the observations summarised above: For each neuron, the activations of other units received through weighted connections are summed and passed through an *activation function* to calculate its activation (potential), which is subsequently passed on to other units.

Though other ANN models may be much more adequate given what is known to date about the neurophysiological reality, most or all of them are similar to the perceptron in some way. *Multi layer perceptron* networks (MLP, see section 4.2) are often preferred for their clear mathematical basis and their comparably simple and fast implementation.

- Though the dynamics of (artificial) neural networks can be complex, they can always be reduced to the simple and well understood units of which they are made.
- Many of the different ANN models which are available can each be used for very different purposes. For simulations of language evolution no special internal representation has to be designed because the networks will evolve it themselves.

Again, it should be emphasised that despite their potential explanatory value, *artificial* neural networks are only very simple models of natural systems, and the latter are not yet understood properly:

“Many uncertainties surround the questions of how [...] changes in synaptic effectiveness embed a memory in the distributed systems of the brain, how memories are maintained, sometimes for a lifetime, in the face of recurrent molecular turnover, and how

they can be recalled almost instantaneously to conscious experience”

[MOUNTCASTLE 98], page 137

3.2 Agents

Agents used in simulations of language evolution need some kind of internal memory, a mechanism to associate a meaning with a surface form from the E-Language, and the inverse process to produce a surface form for a given meaning (see 2.3, page 12).

BATALI chose to represent the E-Language quite naturally as sequences of characters from a small alphabet such that each utterance is just a “word”. In analogy to natural languages, the characters can be thought of as phonemes, the fundamental constituents of spoken language. A very simple kind of artificial neural network which on first sight seems suitable for processing sequences of inputs (in this case characters) is the *Elman network* (see section 4.3 pages 46–50).

This is a recurrent network, such that when activated several times, it can at every step not only calculate a function of its inputs, but one which also depends on all its previous internal states. Practically the Elman network is realised as a *multi layer perceptron network* (see section 4.2 from page 36 onwards) of which after each activation the values of the hidden layer are copied to *context units* which form part of the input layer. For the first activation where no context is available, the context units are set to 0.0³.

In more detail, the networks used for this simulation have four input units to each represent one possible “input character”, a hidden layer of 30 units and an output layer of size ten (see figure 3.1). The input values are

³Which is different to an initial value of 0.5 as proposed by ELMAN in [ELMAN 90].

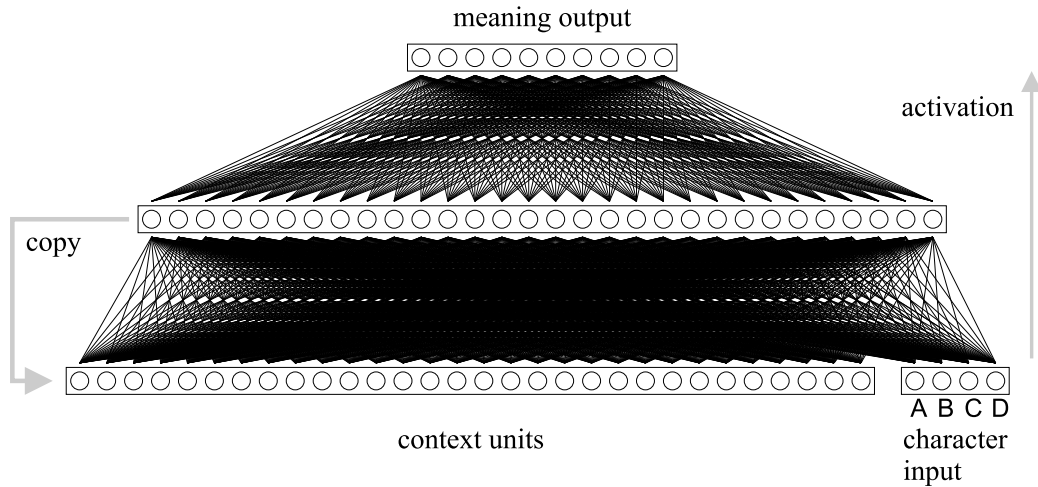


Figure 3.1: The Elman network used for BATALI’s simulation. It is activated from bottom to top, copying after each activation the values of the hidden layer units to context units which form part of the input layer. For reasons of simplicity and clarity I will use for all other figures in this thesis simplified representations with fully connected layers being implied by a small number of connections, but I believe that it helps one to imagine how the net really looks to have at least one complete figure.

coded as 1-of- n : Each input unit corresponds to exactly one character of the alphabet that the E-Language sequences are made of. When the net is activated, exactly the one input unit representing the current character is set to 1.0, all others being 0.0. The sigmoid activation function with gain one ($\frac{1}{1+e^{-x}}$) is used for all units.

3.2.1 “Hearing”: Association of meanings with character sequences

When activated, networks of this layout map any input sequence of the four possible characters to a ten dimensional real valued vector: The first character of the sequence is presented at the input units with all context units being set to 0.0. Then the network is activated like an ordinary multi layer perceptron network, the hidden layer activations are copied to the context

units and the process is repeated for all characters of a sequence. The output layer represents at each step an “association” of the network with the sequence processed so far, as the context units provide the network with memory over arbitrary time spans.

Being used as agents in a simulation of language evolution, the networks can thus naturally “hear” sequences of characters from the E–Language domain (Section 2.4, page 2.4) and associate with them a simple meaning. Production is not so straightforward and I will return to this aspect shortly.

3.3 Meaning set

Using networks as agents, the representation for the meaning set is determined by their output layer, which in this case is a ten dimensional vector of real values. As \mathcal{R}^{10} could theoretically represent an infinite number of meanings⁴, it makes sense to choose a simple, canonic encoding. BATALI decided to define 100 meanings over $\{0, 1\}^{10}$.

3.3.1 “Correctness”

An output layer activation is considered “correct” with respect to a given meaning, if each of its dimensions is within 0.5 of the meaning. Though being injective, this is only a partial mapping from the space of output layer activations to the set of meanings.

3.3.2 Structure

As this simulation is concerned with compositionality (see section 2.5.1, page 17), the meaning vectors are set up to be structured in two ways (see table 3.1):

⁴It cannot for practical implementations using finite precision floating point numbers.

referent	sp	hr	ot	pl	predicate	value	meaning	value
<i>me</i>	1	0	0	0	<i>happy</i>	011001	<i>(one angry)</i>	0010101001
<i>we</i>	1	0	0	1	<i>sad</i>	011100	<i>(yumi silly)</i>	1101010101
<i>mip</i>	1	0	1	1	<i>angry</i>	101001	<i>(all sick)</i>	1111100101
<i>you</i>	0	1	0	0	<i>tired</i>	100011	<i>(yup hungry)</i>	0111100110
<i>yall</i>	0	1	0	1	<i>excited</i>	110001	<i>(mip silly)</i>	1011010101
<i>yup</i>	0	1	1	1	<i>sick</i>	100101	<i>(yup sick)</i>	0111100101
<i>yumi</i>	1	1	0	1	<i>hungry</i>	100110	<i>(you tired)</i>	0100100011
<i>one</i>	0	0	1	0	<i>thirsty</i>	000111	<i>(they thirsty)</i>	0011000111
<i>they</i>	0	0	1	1	<i>silly</i>	010101	<i>(we sad)</i>	1001011100
<i>all</i>	1	1	1	1	<i>scared</i>	010011	<i>(me excited)</i>	1000110001

Table 3.1: Referents and predicates used to build the meaning space of BATALI’s simulation: A total of 100 meanings is made up by all possible concatenations of ten referents and ten predicates, in that order. Some example meaning vectors are given on the right (from [BATALI 98], page 413)

- The meaning set is constructed of all possible concatenations of a four bit “referent encoding” and a six bit “predicate encoding”. The labels used do not make any difference to the simulation, they are just defined to simplify the identification of particular meanings. What is of importance to the simulation is that the meaning set is componential, in that it is constructed from two “chunks” in a very regular way. So the agents could develop pseudo-linguistic representations which in some way reflect this regularity.
- While the particular “predicate” vectors were chosen at random, the “referent” vectors are constructed in a regular way to reflect human intuition about which persons involved in communication are addressed by a referent (left table of 3.1): One bit each represents whether the speaker (sp), the hearer (hr) or another person (ot) are involved and whether or not a group is addressed (pl for plural).

Thus the “referent” encoding constitutes more regularity of the meaning space which could possibly surface in regularity of the E-Language

of the population⁵.

3.4 The Communication Episode

The meanings from the set defined above are used in *communication episodes* between a speaker/teacher and a hearer/student agent: For a given meaning, the teacher produces a sequence, which the student is trained to associate with the meaning.

3.4.1 Production

Because the Elman networks used for this simulation can only directly produce a mapping from character strings (“surface forms”) to meanings as described in 3.2.1, an ad hoc method was developed by BATALI for production of strings⁶: To generate a character of a sequence to be communicated by a speaker/teacher network for a given meaning, the network is activated for all possible characters given as input, recording for each the error of the network’s output layer given the meaning to be communicated. Of all possible characters, the one with the lowest error is chosen⁷, the network is activated again with this character as input and the hidden layer activations are copied to the context units⁸. This process is repeated until either a cut-off length of 20 characters is reached, or the speaker’s output is “correct” (see 3.3.1).

⁵There is also unintended structure in the encoding of the “predicates” which could be exploited.

⁶The limitation of Elman networks to produce unidirectional mappings suggests that possibly they are not a very good choice for the purpose at hand. I will propose an alternative model in section 7.1, page 97.

⁷BATALI implemented this by first calculating for each character the “correctness” value (see 3.3.1). It is compared with the currently best correctness value for any previously tried characters and only if they are equal, the sum of squares error is calculated to find the character with the lowest error. This is equivalent to choosing in the first place the character for which the error is lowest. For the (highly unlikely) case of equal errors, my implementation implicitly chooses the character which comes first in the alphabet.

⁸For the first activation, the context units are set to 0.0 as in the hearing procedure.

Thus the production method conducts a local search, choosing for each position of the string to be uttered the character which, had it been “heard”, would bring the network closest to the chosen meaning. In particular, this method does not necessarily generate the one sequence for which the final error was lowest. Instead it chooses for every position in the output string the character for which the error is minimised locally. This also means that the error may increase while characters are produced.

3.4.2 Acquisition

Compared with the production mechanism, the acquisition/training method is relatively straightforward. To train a student agent to associate a given meaning with the sequence produced by the speaker, the network is activated as if “hearing” the sequence (see 3.2.1), but after each activation (presentation of a character) its weights are adjusted in order to decrease the error given the meaning to be learned. The weight update is chosen as standard steepest-descent using back propagation with a learning rate η of 0.01 (see 4.2.2 on page 38)⁹.

This acquisition method does by no means guarantee that a student network would generate the same sequence it was trained on for the given meaning. It just brings the network’s output a little bit closer to the given meaning for each of the characters of the sequence it is trained on, which should finally increase the likelihood of parts of this sequence being generated when the network is used as a speaker on that meaning.

⁹This method is only approximately correct, see 4.3.1 on page 47 and appendix A for more detailed discussions.

3.5 The simulation as a whole

The simulation is started by creating 30 agent networks with randomly initialised weights from a uniform distribution of $[-0.5 \dots 0.5]$, and is then run in subsequent “negotiation rounds”: For each round, a student agent is selected randomly from the population. Ten teachers (different from the student) are selected (with replacement) and communication episodes, as defined above, are held for all meanings, thus training the student on the sequences generated by each teacher for every meaning.

Because the population is static in that neither agents enter or leave, this simulation emphasises aspects of agreement on “linguistic conventions” within language evolution. There is no semantic bottleneck in the original version of the simulation, but BATALI also reported on a run where ten of the 100 meanings are never used by any agent. A production bottleneck is implicit to the production method. The E/I model as introduced in 2.4 (page 14) does apply as in order to spread within the population, a language has to undergo a number of transmissions between the E- and I-Language domains.

The results BATALI reports in his paper are consistent with intuitive expectations that the surface forms which evolve do show some regularity, though not being completely regular. I will present a comparison between his results and those of my replication in section 6.1 from page 57 onwards. I will also investigate into the influence of the various parameters of the simulation, which BATALI seems to have set intuitively or after unreported evaluation.

Chapter 4

A very short journey into connectionism

The field of research into neural networks is so broad and manifold that it would be foolish to attempt any kind of comprehensive review within this thesis. Neither shall I descend to the mathematical foundations on which connectionist techniques are built, but instead attempt to illustrate those methods which are important for the implementation of the simulation described in chapter 3. I will also try to give some context in order to evaluate the methodology used.

4.1 Artificial Neural Networks

Artificial Neural Networks (ANNs) are simple models which are inspired by the way (human) brains are made up (see also 3.1 on page 26). Even though they might yield some insight into how brains possibly *could* work in parts, *artificial* neural network *simulations* should never be confused with real, biological neural networks.

All kinds of ANN models have in common that they consist of nodes (neurons), which are connected with each other in some way. Like real neur-

ons, artificial neurons activate each other through connections between them, and every neuron may perform some simple calculation, depending on the activation it “sees” from other neurons to which it is connected. What calculation a neuron performs depends on the model which is being used and some variable parameters which can be used to “train” it. Naturally, some neurons also have to communicate with the “outside world”, so neurons can also be inputs and outputs. As a whole, such a network can process data which is fed into it through the input nodes and “display” the result through the output nodes.

Usually ANNs are set up according to some specific model which seems suitable for the problem at hand, but in most cases they are not given any initial “knowledge” about the problem by initialising their free parameters with random values. In a subsequent phase the networks are trained on some data before finally being used to perform the calculation which they have learned.

All different ANN models have in common that they are inspired by some aspects of natural neurons, but their mathematical bases, how and if training is done and their practical applications vary a great deal.

4.2 Multi–Layer Perceptron Networks

One of the simplest and most commonly used types of ANNs is the Multi Layer–Perceptron (MLP), which consists of several layers of simple neurons called *perceptrons*. The function which each of the perceptrons calculates is fixed, but the strength of connections between them can be adjusted. The inputs to each perceptron are scaled by flexible weights, which are modified when the network is trained (see figure 4.1). One of the weights, the bias weight w_0 , is always connected to a potential of -1 . These scaled input activations are summed and used as input to the neuron’s activation function.

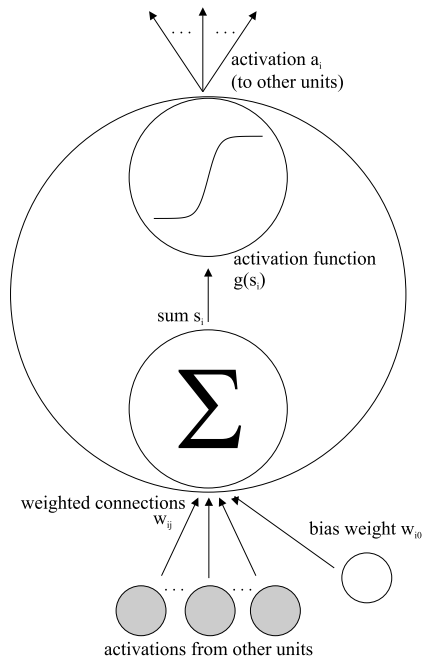


Figure 4.1: The perceptron. Its inputs are the weighted activations of the neurons it is connected to, which are added up and fed into the neuron’s activation function (here: sigmoid).

Which activation function to choose is very important, and I will come back to this point shortly.

In principle, any kind of network can be constructed from perceptrons, but for many purposes a very simple layout is sufficient. The layered feed forward network (figure 4.2) consists of one layer of input units, one or many hidden layers and one output layer. Usually the neurons between succeeding layers are fully interconnected.

4.2.1 Activation

The activation of MLPs is straightforward. Usually an input pattern is presented at the input layer and then the activation values for all subsequent layers are computed, each of the layer’s units depending upon the activations

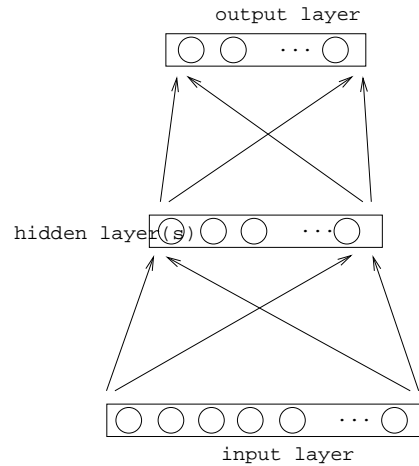


Figure 4.2: Structure of a simple feed forward network

of all nodes in the previous layer.

Feed-forward networks simply associate outputs with inputs. How complex this mapping can be, depends on the structure of the network (how many layers, sizes of the layers) and the activation functions. It has been proven that a three layer neural network could theoretically represent any mapping which is continuous (Kolmogorov’s theorem, see for example [BISHOP 95], page 137ff). The drawback which makes this insight practically useless is that the activation functions of such a net are generally arbitrarily complex and as such there is no construction method for them.

4.2.2 Training

As any neural network represents a well-defined function, networks can in principle be tailor-made to at least approximate a known mapping. The problem is that it may be arbitrarily complicated to find such a network and, worst of all, in most cases the exact function which one wants a net to approximate is simply not known. Thus one needs a way to train neural

networks “by example”.

In neural network terms the examples are called *patterns*, which are pairs of desired input and output combinations. Usually training patterns represent only scarce (but hopefully typical) samples from a complex, unknown mapping, and one would like the net to learn more about the structure of these samples than just memorise them. In other words, one would like the network to generalise from some training patterns to the whole set of possible input/output pairs.

4.2.3 The sum of squares error

In order to quantify how well a network is doing on such a mapping task, we need a measure, which is often called the *objective function*. There are many possible choices, and which objective function to use very much depends on the problem and the encoding used. One “generic” objective function for many problems is the sum of squares error

$$E = \frac{1}{2} \sum_{k=1}^c (d_k - a_k)^2 \quad (4.1)$$

with a being the activations of nodes in the output layer of size c , and d being a pattern’s target¹.

It is helpful to imagine the error as a surface with hills and valleys in the multi-dimensional space of the network’s weights. The optimum we are looking for is the combination of weights which yields the smallest possible error. On the error surface, this is the lowest point.

To actually train a net to minimise an objective function and thus to find the lowest point of the error surface, the number of methods is not limited in principle. For example, it has been reported that genetic algorithms can

¹assuming a to be the output values after activation of the net for a pattern’s input. Error functions are discussed in detail for example in [BISHOP 95], chapter 6.

be used to evolve neural networks (see [YAMAUCHI & BEER 94] for one of many examples). But a natural method which can be derived directly from the sum of squares error is what is known as back propagation.

4.2.4 Calculating the derivatives of the error: Back propagation

The task of training a net may be seen as a search in the space of possible weight values of a network. One very simple method of tackling any search problem is the principle of *hill climbing* — trying to find a good solution by making many small steps, each in a direction for which the error decreases².

As opposed to many other search problems, where we have to take samples of a local neighbourhood of the current state, we can for neural nets, under certain circumstances, calculate the direction of steepest descent of the objective function. If the activation functions of all nodes are continuous and differentiable everywhere, we can calculate the partial derivatives of the error by every weight $\frac{\partial E}{\partial w_{ij}}$ for any activation of the net.

The algorithmic procedure to calculate these derivatives, back propagation, got its name from the fact that certain derivatives ($\delta = \frac{\partial E}{\partial s_m}$) are being propagated backwards through the network. In principle, it is not much more than continued application of the chain rule on the error function.

4.2.5 Activation functions

The fundamental requirement for back propagation to work is that the activation functions used for every neuron of a net are continuous and differentiable everywhere. They also have to be non-linear if networks are to approximate

²Usually, connectionist people seem not to like hill walking — all common error functions have their optimum at zero and thus on an error surface we are looking for minima instead of maxima

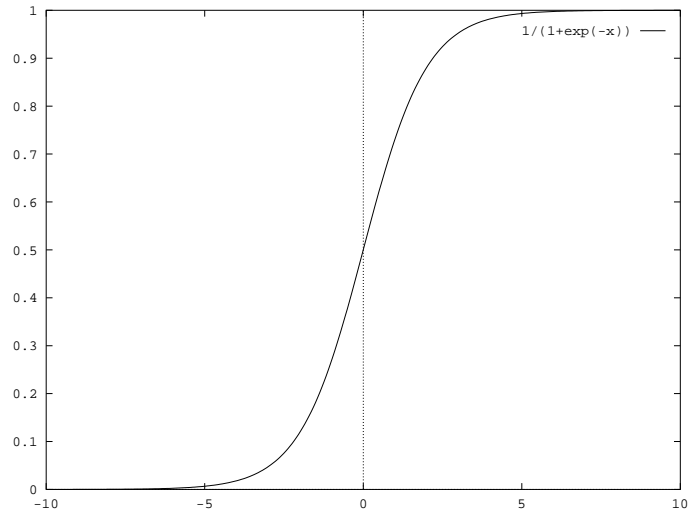


Figure 4.3: The sigmoid activation function with gain one ($D = 1$).

complex mappings. Other desirable properties for activation functions are (from [ROSS & WILLIAMS 98], pages 1–2):

- Their values should be bounded for two reasons. Biological neurons can only emit spike frequencies within a bounded range, and in ANN simulations infinite values would cause a *gain problem* in practice. If activation values were not bounded, the range over which weights have to be adjusted would be increased even more, as weights would at times have to counteract high activation values.
- They should be monotonic to reduce symmetries of the error surface.
- It is advantageous if they and their derivative are easy to compute.

One function which fulfils all of these is the *sigmoid function* (see also figure 4.3):

$$g(x) = \frac{1}{1 + e^{-Dx}} \quad (4.2)$$

For large gain D , the sigmoid becomes similar to a step-function which is 0 for all values lower than a certain threshold and 1 for values above it. This is why it is sometimes also called a “smooth step function”.

Where unbounded output values are needed, for example for regression problems, the simple linear $l(x) = x$ is often used for the output layer of MLPs.

4.2.6 Steepest descent updates

For any function $f(\mathbf{x})$, its gradient $f'(\mathbf{x}) = \frac{df}{dx}$ by definition points in the direction for which the function’s value increases, so if we want to minimise the error of a network, we can just update all weights a small amount in the direction opposite the derivatives we calculated using back propagation:

$$w_{ij} \leftarrow w_{ij} - \eta \frac{\partial E}{\partial w_{ij}} \quad (4.3)$$

$$\begin{aligned} &\equiv \\ \mathbf{w} &\leftarrow \mathbf{w} - \eta \frac{dE}{d\mathbf{w}} \quad (4.4) \end{aligned}$$

By using just the gradient information, we implicitly model the local neighbourhood of the current point \mathbf{x} on the error surface as a plane — an approximation which is in general only valid for a tiny neighbourhood. Thus we have to choose η small and repeat the process very often.

This is an important disadvantage of steepest descent updates. Training can take very long indeed, even though at certain times during training large steps could be possible because some regions of the error surface may be level. If we stick to the idea of an error surface with hills and valleys, we can imagine that a ball rolling on this surface would eventually fall into holes and thus find optima of the error. If the ball has mass, then it would not react to changes of the surface immediately and, especially rolling down long steep

valleys, it will gain speed. It is this idea which leads to momentum terms for steepest descent updates:

$$\Delta \mathbf{w}^0 = -\eta \left. \frac{dE}{d\mathbf{w}} \right|_{\mathbf{w}^0} \quad (4.5)$$

$$\Delta \mathbf{w}^{t+1} = \alpha \Delta \mathbf{w}^t - \eta \left. \frac{dE}{d\mathbf{w}} \right|_{\mathbf{w}^{t+1}} \quad (4.6)$$

The first update we make is only a small step in the direction of steepest descent as before, but for all subsequent updates we add a portion of the previous update. α is usually chosen between 0.1 and 0.9.

The use of momentum terms can significantly increase learning speed, but they may also prevent training from finally settling down at some point if α and η are set at too high a value.

4.2.7 Line searches

Another very simple idea to improve training is to adjust the learning rate while training. The error gradient vector $\left. \frac{dE}{d\mathbf{w}} \right|_{\mathbf{w}^t}$ describes a line starting at the current point on the error surface. We may now go downhill along this line until the error increases again after a distance λ and so find a minimum in this direction. The weight update is then $\Delta \mathbf{w}^t = \lambda \left. \frac{dE}{d\mathbf{w}} \right|_{\mathbf{w}^t}$.

Naturally, to search along a line on the error surface, we need to evaluate the error several times, which means that we have to calculate all of the net's activation functions and the objective function. These calculations are time intensive, which is why line searches are not usually the best choice for steepest descent updates.

4.2.8 More sophisticated update methods

The idea behind many other advanced update methods is to model the local neighbourhood of a point on the error surface not as a plane but as a “quadratic bowl”. The principal drawback of this idea is that it needs second order information and straightforward calculation of the second derivatives of the error ($\frac{\partial^2 E}{\partial w_{ij} \partial w_{kl}}$) takes $\mathcal{O}(W^3)$ time steps (W being the number of weights of the net), which means a massive increase in effort compared to $\mathcal{O}(W^2)$ time steps needed for back propagation (calculation of the gradients).

It turns out, however, that we never need to calculate the second derivatives to exploit second order information. If we conduct a line search in the direction of steepest descent and find the minimum, then this means that the gradient in this direction becomes zero at the new point:

$$\mathbf{w}^{t+1} = \mathbf{w}^t + \Delta \mathbf{w}^t \quad (4.7)$$

$$= \mathbf{w}^t + \lambda \left. \frac{dE}{d\mathbf{w}} \right|_{\mathbf{w}^t} \quad (4.8)$$

$$(\Delta \mathbf{w}^t)^T \left. \frac{dE}{d\mathbf{w}} \right|_{\mathbf{w}^{t+1}} = 0 \quad (4.9)$$

If we now make sure that the gradient in this direction remains zero also for the next update such that

$$(\Delta \mathbf{w}^t)^T \left. \frac{dE}{d\mathbf{w}} \right|_{\mathbf{w}^{t+1} + \Delta \mathbf{w}^{t+1}} = 0 \quad (4.10)$$

then this can be shown to be equal to

$$(\Delta \mathbf{w}^t)^T \frac{d^2 E}{d\mathbf{w}^2} \Delta \mathbf{w}^t = 0 \quad (4.11)$$

for quadratic error functions. The method to calculate updates with respect to condition 4.10 is called the *conjugate gradient algorithm*. Though

in principle this does rely on a precise (and thus labour intensive) line search, there are methods of approximating the λ value under the assumption of a locally quadratic surface (*scaled conjugate gradients*).

4.2.9 Batch techniques: Training multiple patterns

If multiple patterns are to be learned, they can be trained consecutively one at a time³. But such *on-line* methods have the disadvantage that the most useful update to decrease the error of one pattern may cause a drastic increase in the error of other patterns. Watching on-line training often looks as if the patterns are “fighting against each other”, in that naturally the error for a pattern decreases when it is trained, but when the pattern is presented the next time, updates for other patterns may have adjusted the weights in such a way that the error for this pattern is much higher than it was when last trained. As this effect increases with the learning rate η , methods trying to optimise η (and here especially conjugate gradients using line searches) work very badly if updates are done on line.

The way out here is to use batch methods, where many patterns are trained simultaneously. The error for a whole set of patterns is usually taken as $E = \sum_p E^{(p)}$ which for methods using gradient information leads to the gradients being summed up as well $\frac{dE}{d\mathbf{w}} = \sum_p \frac{dE^{(p)}}{d\mathbf{w}}$.

Batch methods generally are much faster than on-line methods, their performance is easier to measure and more powerful training methods using large η values usually only work for batch methods. On the other hand, they also have drawbacks:

- They are much more likely to “get stuck” in local error minima. As they always update in a way which decreases the overall error over all

³Still, the patterns should be presented in random order such that there is no implicit bias towards some of them (which are trained last)

patterns, their trajectory on the error surface is monotonic. In other words, once they have found a minimum, they may never leave it, even though other minima may be much lower.

- For some problems, for example in robotics applications, training data becomes available bit by bit, while the net already is performing its main task (like deciding on a direction in which to move). Here batch training simply is not possible.

Root Mean Square Error

The value of the sum of squares error summed over many patterns naturally depends on the size of the pattern set. To evaluate a network's performance independently of the number of patterns, the sum of squares error can be normalised to a per-pattern per-output-unit basis, which gives the *root mean square* error (see [BISHOP 95], page 197):

$$E^{RMS} = \sum_p \frac{2E^{(p)}}{\sum_k^c (d_k^p - \bar{d})} \quad (4.12)$$

with \bar{d} being the mean target and $E^{(p)}$ the sum of squares error. The value of this measure is 1 for an “average prediction” and 0 for the optimal prediction.

4.3 The Elman network

The Elman network ([ELMAN 90]) is a very simple recurrent net, which differs from a two-layer feed-forward network by having a fully interconnected hidden layer. Each hidden unit thus gets not only activated by all inputs, but also by the previous activation of each hidden layer unit, including itself. This is what gives the network “memory” over arbitrarily long time spans.

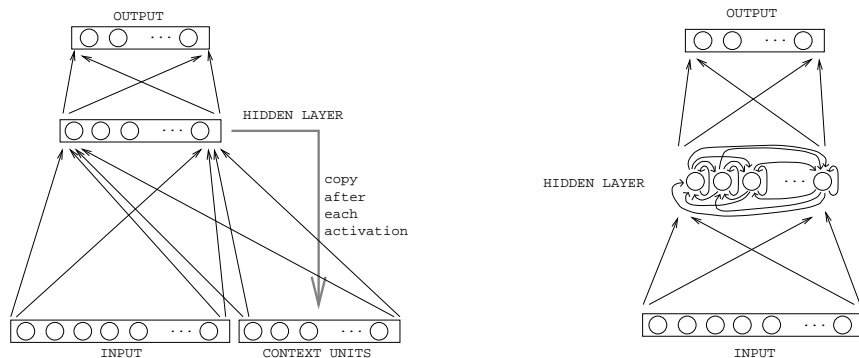


Figure 4.4: The Elman network, with context units (left) and with recurrent connections (right). The two representations are identical if one assumes bottom-up activations without time delay and recurrent connections / context unit activations being delayed until the next bottom-up activation.

Elman himself proposed the representation on the left of figure 4.4. The network is used like a feed-forward net, except that after each forward activation the hidden unit activations are copied to context units, which form part of the input layer. For the first activation, the context units are set to 0.5.

Because of its recurrent nature, the Elman network is especially well suited to work on (time) series of data. One of its standard applications is prediction of the most likely next element in a time series given all previously presented inputs.

4.3.1 Training

To train his network, Elman proposed to use steepest-descent updates after each (time) step with a small learning rate η , treating it exactly like a feed-forward net and regarding the context units as normal inputs. Certainly, this is not correct (see figure 4.5). Except for the first time step, each context-unit weight not only contributes to the current activation of the hidden layer,

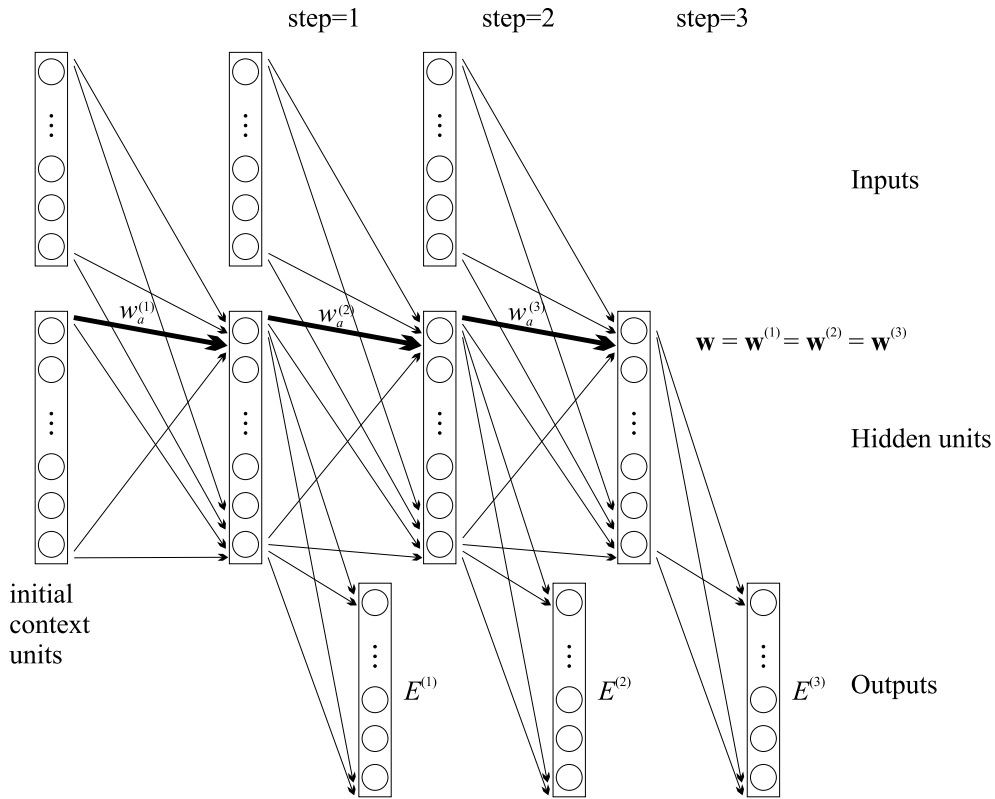


Figure 4.5: The Elman network unrolled in time for three time steps. The context units are omitted except for the first time step, as they are copies of the hidden units from each previous time step. When training the net as proposed by Elman or using RTRL-like procedures, the weights from context-units at different time steps are treated independently, though they are the same.

but also to those of all previous steps.

For example, the derivative of the error by the context-unit weights after step three is

$$\frac{dE^{(3)}}{d\mathbf{w}} = \frac{dE^{(3)}}{d\mathbf{w}^{(1)}} \left(+ \frac{dE^{(3)}}{d\mathbf{w}^{(2)}} + \frac{dE^{(3)}}{d\mathbf{w}^{(3)}} \right) \quad (4.13)$$

but Elman training ignores the last two terms. An illustrative explanation⁴ why this is still a good approximation is that the influence of a weight

⁴Inspired by CHRIS WILLIAMS

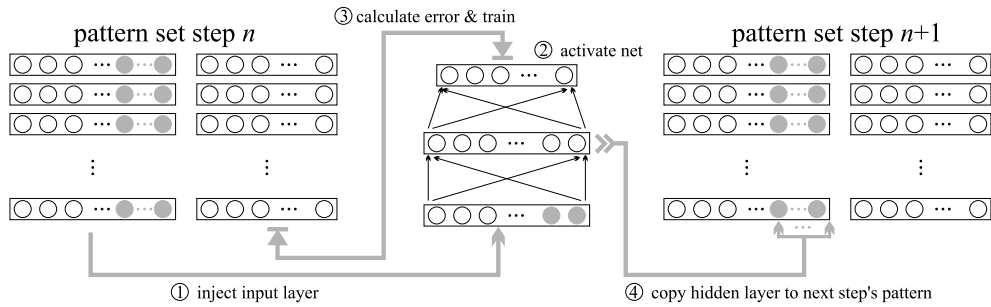


Figure 4.6: Training an Elman net on multiple time series

to any previous activation is on average exponentially smaller than its contribution to the “current” error for commonly used activation functions like the sigmoid (for a more detailed discussion see appendix A).

These approximately correct steepest descent updates are used in the simulation described in chapter 3. I will now very briefly point out that also for Elman networks there are alternative batch training methods, which are very attractive in theory, but suffer from running into local minima like batch methods for MLPs:

4.3.2 Batch methods

If multiple time series are to be learned by an Elman network, they can be trained as a batch, as with standard feed forward networks. In this case, several sets of patterns have to be maintained, one set for each time step. The context units can be treated as if they were part of the pattern, except that they are being modified during training. For every time step of a series which is trained, the hidden layer activation has to be copied to the part of the next time step’s pattern which corresponds to the context units (figure 4.6).

Unfortunately for this kind of batch training the same limitations apply as for training one pattern. Only training methods with a small learning rate

may be applied, as training of some time step is likely to make updates which increase the error for others. One could see this method as pattern–batch time–iterative.

Time batch

If all training data for all time steps and all patterns is known, we may also do batch over time. Using the objective function

$$\text{e.g. } E^{(t)} = \frac{1}{2} \sum_k^c (d_k^{(t)} - a_k^{(t)})^2 \quad (4.14)$$

$$E = \sum_t E^{(t)} \quad (4.15)$$

we sum up the errors of all time steps. The weight derivatives for this objective function simply sum up as $\frac{dE}{d\mathbf{w}} = \sum_t \frac{dE^{(t)}}{d\mathbf{w}}$. This is the basic idea behind what is known as Real–Time Recurrent Learning (RTRL), but what I would simply call *time batch* (see [WILLIAMS & ZIPSER 98] or [HERTZ *et al.* 91], pages 184–186 for more detail).

This batch method does enable us to use more powerful training methods on Elman nets, but like all batch methods, it suffers from being likely to converge to local minima.

Chapter 5

Implementation

As a basis for all experiments conducted during this project I developed a software package written in Common Lisp which provides all necessary functionality for simulations of multi layer feed forward and Elman neural networks. Though in general implementational issues are of minor importance, I would like to point out briefly some aspects which I think deserve to be mentioned. I will not present any in-depth discussion.

Though parallel distributed processing is theoretically attractive and very powerful when implemented in *gray matter* or (silicon) hardware, neural network *simulations* on standard computer systems are very compute intense. Where a parallel (hardware) implementation could calculate the activations of all neurons and their connections in parallel, on serial machines this process has to be emulated by consecutive instructions to a central processor. Even worse, many models demand real valued calculations with highest possible precision, which on most systems are significantly slower than integer operations. Therefore speed was indeed important for the feasibility of this project.

5.1 Why Lisp

It is still widely believed that Lisp would not be suited to applications involving intense numerical computation, but since its invention, much has been improved. As PAUL GRAHAM puts it “Lisp is really two languages: a language for writing fast programs and a language for writing programs fast” ([GRAHAM 96], page 213).

I chose Common Lisp for the second reason but with confidence that speed should be achievable as well. Other properties which are very helpful and partly unique to Lisp are the following:

- *Interactive development*

Most Lisp systems comprise both an interpreter and a compiler. During the development of a program one usually works in the interpreter, which allows a fully interactive form of writing code. The interpreter gives immediate feedback and code and data can be modified while a program runs. Later on, code can be compiled for speed. This is known as *two-stage development*.

- *Unique debugging capabilities*

The previous point leads directly to unique debugging capabilities: The behaviour of a program can be monitored at any point while it runs in the interpreter.

- *Rapid prototyping*

Common Lisp is a very powerful language which provides many tools to write programs fast. Closures and typed data are unique to Lisp (and a few like languages) and allow very versatile constructions.

- *Macro programming*

Lisp makes it very easy to “write programs which write programs”. Through macros it becomes possible to generate code which is tailored

to its specific task at compile time, thus improving performance at run time. But best of all, macros provide a great way to improve clarity and simplicity of a program.

5.2 Design decisions

Though the code was designed solely to implement the experiments conducted during this project, I tried to make it as universal as possible. Some of its limitations and features are:

- Only layered feed forward and Elman networks are supported.
- The number of layers is not limited. Activation functions can be specified per layer. All layer sizes are supported, though they have to be defined at compile-time.
- Data types for activation values, derivatives etc. can be specified globally.

All functions working on networks are implemented as macros, which are configured by a network-specification at compile-time. These macros build tailored functions for networks according to the specification. The main advantages of this concept are that array sizes are known at compile-time which makes unrolling of inner loops possible, and also that some function calls can be saved even with compilers which do not support inlining.

The most important drawback of massive use of macros is that their expansion at compile time uses much CPU time and memory, which can lead to situations where incautious combinations of macros may cause the code to be effectively incompilable. A way out is to optimise the macro definitions themselves such that they expand faster using less memory. Another aspect is that macros can lead to implicit inlining of code, causing possibly unnecessary

duplication of code (which on the other hand is sometimes done deliberately to improve speed, see previous paragraph).

5.3 Speed

Because of the nature of the simulations to be conducted during this project, fast code was indeed important. After many optimisations, one simulation run of 25,000 negotiation rounds as described in section 3.5 took about two CPU-days on a Sun Ultra 5/10 Sparcstation with 128MB main memory and a 269 MHz SUNW UltraSPARC-III CPU. Even if the code had only been slower by some factor below ten (which is usually considered negligible), the experiments could possibly not have been conducted in the way presented here.

Three aspects were crucial for the speed of the code developed:

- *Type declarations, machine data types*

One major difference between Lisp and some other programming languages is that it supports *typed data* as opposed to typed variables. So usually variables do not have to be declared at compile time and types are checked at run time. While this makes Lisp very flexible and development very convenient, run-time type-checking kills speed. In the code developed for this project, all variables of inner loops had to be declared, which partly was only possible through the use of macros as described above.

Also it was important to use only machine data types for the representation of floating point numbers. Lisp supports arbitrarily large numbers, which cannot be represented by a single machine number and thus lead to slow code.

- *Fast array access and fast floating point arithmetic*

The time dominant factor for calculation of a network's activation is building for every neuron i weighted sums of the activations of neurons from the previous layer: $s_i = \sum_j w_{ij}a_j$. As I chose to represent the weight vectors of all units of one layer as a two dimensional array, for every neuron in a layer an iteration through the second dimension of this array has to be done. Thus together with the efficiency of the basic arithmetic operations the speed of this array access is predominant for the overall speed of the neural net activation.

In particular, while the calculation of weighted sums scales as $\mathcal{O}(N^2)$, N being the number of neurons of the network, the complexity of the calculation of the activation function itself only scales like $\mathcal{O}(N)$. Therefore the effort for its computation is neglectable for larger networks, though in itself it may be time consuming.

5.3.1 A speed comparison

To get an impression of the overall performance of the code, I compared it with the April 10, 1996 version of DONALD R. TVETER's back propagation simulator, which was written in C (Developed as part of [TVETER 98], see [BP 99]).

The comparison was only done to benchmark speed. Each program was used to train a 5-5-1 multi layer perceptron network for 100,000 cycles using steepest-descent batch updates, but the learning rate and all other parameters were chosen such that the net would not actually converge to a small error (For details of the settings of both programs see appendix C).

Both runs were done on a Sun Ultra 5/10 Sparcstation with 128MB main memory and a 269 MHz SUNW UltraSPARC-III CPU. `bp` was compiled using `gcc` version 2.8.1 with enabled optimiser (`-O2`). The `NILE` package was compiled using CMU Common Lisp 18b.

Here are the numbers:

- bp:

```
real time      44.230 s
user run time  41.350 s
system run time 0.030 s
```

- NILE:

```
Evaluation took:
33.23 seconds of real time
32.84 seconds of user run time
0.0 seconds of system run time
0 page faults and
67456 bytes consed.
```

I do not want to claim that my implementation was generally faster than others nor do I want to suggest that LISP was in principle faster than C. It is more that I believe that speed is achievable in almost any programming language for which compilers are available that permit certain optimisations. For neural network applications, the most dominant factors are array operations and floating point arithmetic. Any system which produces fast code for both is suitable for development of neural network code, so that in general the choice of the programming language should not be guided by unjustified prejudice.

Chapter 6

Experiments and Results

This chapter is dedicated to a description of the experiments which have been conducted to replicate the simulation described in chapter 3, to an investigation into the effects of variations in its setup, and also to the development of a hypothesis concerning the principles which govern the dynamics of the evolution of language in these simulations.

6.1 Replication of BATALI's simulation

The primary aim of the experiments replicating BATALI's simulation was to evaluate if and to what extent the results reported in [BATALI 98] were reproducible. A total of 21 runs as described in chapter 3 were conducted, each lasting for 25,000 negotiation rounds.

At each negotiation round some measures of the population's development were recorded, and every 5005 negotiation rounds¹ the whole population of agents was dumped to disk for later analysis. The statistics collected at every round differed to some extent from those used by BATALI. In particular, I chose to measure values for speakers instead of hearers, because during

¹every 4000 rounds for the simulation run labelled `mcs-e450 std batali`

every communication episode the latter are being trained and thus are not representative of the population as a whole.

Measuring statistics for the speakers instead of the whole population is computationally attractive because the production mechanism yields most of the measures as a by-product. For each negotiation round, 10 out of 30 possible speakers are selected, and thus per negotiation round averages of speaker's values should sample the population's behaviour appropriately.

6.1.1 Measures for the population's development

- **Speaker Correctness**²

The fraction of communication episodes for which the speaker's output layer is "correct" in that each of its components is within 0.5 of the meaning to be expressed.

Because of the way in which the production method is designed (see 3.4.1, page 32), this is the same as the fraction of "correct" speakers' output layers (see also 3.3.1, page 30) had the speakers "heard" the sequences they generate.

This is almost the same as the fraction of communication episodes in which the speakers' generation method did not hit the cut-off length of twenty characters³, which is why it varies almost inversely to the *length* measure (see below).

- **Speaker RMS**² *Speaker Root Mean Square error*

The average root mean square error of the speakers' output layer for

²Please note that in all figures in this document these measures have been averaged over 100 negotiation rounds in order to improve clarity. Presumably BATALI did the same for production of his figures without explicitly mentioning it.

³except for the case where a speaker's output vector is "correct" after the twentieth character is uttered

the meaning to be expressed in each communication episode (see also section 4.2.9 on page 46).

This measure can be interpreted as a “distance”, being zero for a perfect prediction and 1 for an average prediction of the meaning given a surface form. It is thus more accurate than the correctness value previously described.

Presumably this is the same measure as BATALI’s “error”, except that his seems to be scaled by a factor of 0.5. The description of the measure used for his simulation is not very clear. He defines it as “the average root mean square error between the hearer’s meaning vector and that of the speaker after a communication episode” ([BATALI 98], page 415), which I would interpret as what I call here the *Speaker–Hearer Error*. Still, from the way BATALI uses and interprets his error measure, I assume mine to be equivalent, except for a scaling factor. For all the graphs in this thesis, the RMS values have been cut off above 1.0 to improve clarity⁴.

- **Speaker-Hearer Error**²

An arbitrarily rescaled (factor 3/5) average sum squares error between the output layer of the speaker and the hearer after each communication episode.

This measure can be seen as the distinctness of the population’s agents⁵ as it quantifies the difference on average between a student’s and a teacher’s interpretations of the same sequence, the student having just been trained on the sequence generated by the teacher. Because the absolute value of this measure is of no importance, the scale has been

⁴Recall that the RMS error is 1.0 for an average prediction, but can be higher.

⁵Which is different to BATALI’s “distinctness” which measures how distinct the words of each agent’s language are

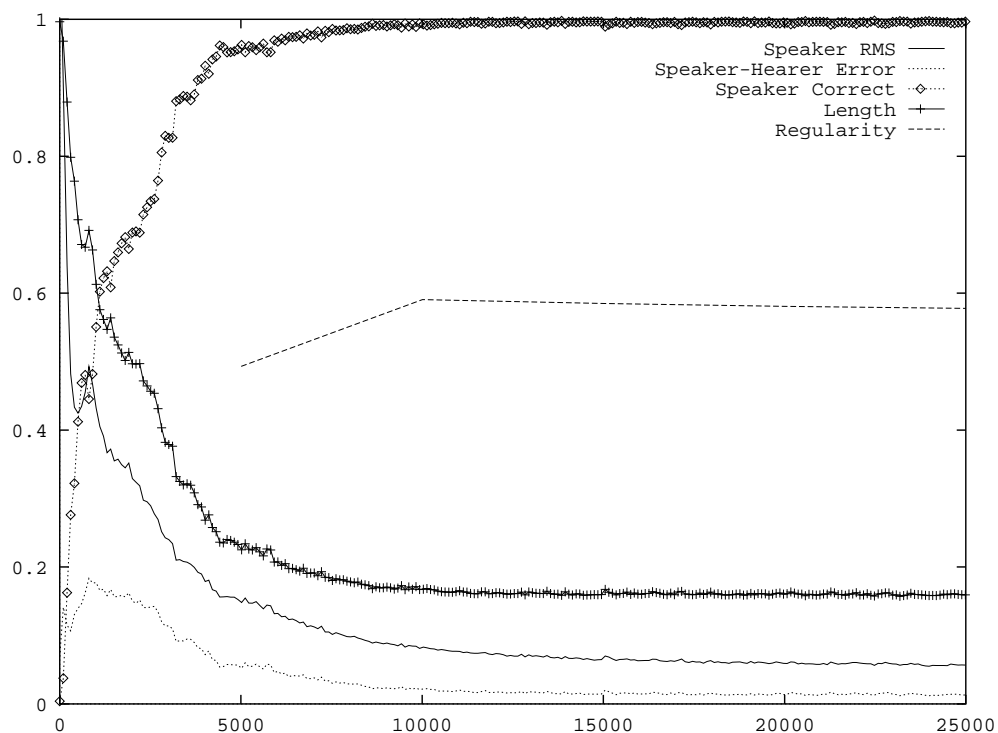


Figure 6.1: Behaviour of the population from replication run `agave std batali 29/06/1999 21:32:32`. Measures collected for each negotiation round have been averaged over 100 rounds in order to improve clarity.

chosen to make the measure fit nicely into the graphs which are to be presented here.

- **Length²**

The average length of sequences generated by speakers during communication episodes, normalised to 1 for the maximum length of 20.

- **Regularity**

An ad hoc measure for the compositional regularity of the agents' languages at times of population dumps. See subsection 6.1.7 on page 68 for details.

BATALI also implemented a distinctness measure which he defined as

“the average fraction of sequences an agent sends for exactly one meaning” ([BATALI 98], page 415). I think this definition is again a bit unclear — presumably what is meant is the fraction of distinct sequences of those sent by an agent for different meanings, averaged over all agents. I have not adopted this measure for the replication because distinct expressions are a natural consequence of the training regime used, and also because during a simulation run this measure does not change much except for an initial sharp rise.

6.1.2 Results from a “best” run

Figure 6.1 shows the measures described above for a “best” run which seems to come closest to the results presented by BATALI in his paper with respect to compositionality (see below).

At the beginning of the simulation, the networks’ average RMS error is about 1.0 for an average prediction (1.1373 is this case), while correctness is near zero and the length of the strings uttered is maximal. This is to be expected because all networks are initialised randomly, and thus can neither recognise each other’s utterances nor produce short and meaningful surface strings.

After the first hundred negotiation rounds, training begins to significantly decrease the error and sequence length. Also, the speaker–hearer error increases for a while, showing that different agents are developing different interpretations of sequences.

As the simulation proceeds, agreement amongst the agents lets the speaker–hearer error decrease again, while error and length values improve. This process continues with error and length converging to some presumably minimal values, the population becoming quite homogeneous according to the speaker–hearer–error.

Some examples of words used by agents at the end of the simulation run

meaning	words and their probabilities
<i>mip hungry</i>	cb 1.0
<i>mip thirsty</i>	cc 1.0
<i>mip silly</i>	dcabb 0.5, acd 0.33, abbd 0.06, abba 0.03, dcabc 0.03, abbbdc 0.03
<i>mip scared</i>	dcc 0.6, dccb 0.36, dc 0.03
<i>you happy</i>	ada 0.63, adad 0.23, adaa 0.13
<i>you sad</i>	aaa 0.86, aaaa 0.13
<i>you angry</i>	bdda 0.66, bdd 0.3, bddd 0.03
<i>you tired</i>	bda 1.0
<i>you excited</i>	daa 1.0
<i>you sick</i>	baa 1.0

Table 6.1: Probabilities (truncated to two decimals) of words being uttered by agents from the population of the 25000th round of `agave std batali 29/06/1999 21:32:32` for some sample meanings

presented here are given in table 6.1. For each of the selected meanings all words which are produced for them within the population are given, together with the probabilities of them being uttered by any agent. A probability of 1.0 for a word means that all agents were using this word for the given meaning.

6.1.3 Almost optimal code

One of the simplest but most significant results from the simulation is that the code defined as the words which emerged within the population is almost optimal in being of nearly minimal length. Because the production method stops producing characters for a given meaning as soon as the sequence produced can be unambiguously associated by the speaker agent with the given meaning, any partial sequence over the alphabet (here A–D) can be used to express a meaning. For example, CC may be code for (*mip thirsty*) while CCA stands for (*me thirsty*). That is, the code includes an implicit stop symbol, which can be thought of as being sent at the end of each word. So the number of possible meanings which can be expressed by words up to and

Sequence length	$H(W)$	$H(C_i)$
1	0.0	0.0
2	4.0	2.0 2.0
3	5.99	1.99 1.99 1.99
4	7.16	1.80 1.68 1.93 1.74
5	0.0	0.0 ...
7	0.0	0.0 ...
12	0.0	0.0 ...

Table 6.2: Information contents $H(W)$ of sequences of different lengths produced by agent 28 of the last round from simulation `agave std batali 29/06/1999 21:32:32`. Also given are the information contents $H(C_i)$ of individual characters of the sequences.

including a length l for an alphabet of size s is

$$n = \sum_{i=1}^l s^i \tag{6.1}$$

An optimal code to express 100 meanings with an alphabet of size $s = 4$ uses all 84 possible words of length up to 3 plus 16 of 256 possible words of length 4. Though the average word length is not a correct measure of optimality for a code with an implicit stop symbol (see section B.5 of the appendix), it is striking that the mean word length of all words uttered for all meanings at round 24999 of run `agave std batali 29/06/1999 21:32:32`, calculated on the basis of word probabilities as exemplified in table 6.1, is 3.14, while the minimal possible word length is $2.92 = (4 \times 1 + 16 \times 2 + 64 \times 3 + 16 \times 4)/100$.

A more accurate measure of the optimality of a code is the mean information content of words of different lengths (see appendix section B.4). Table 6.2 shows the information content $H(C_i)$ for characters of words of different length as used by a typical agent from round 24999 of the simulation run discussed here⁶. The maximum value of $H(C_i)$ is $\log_2 4 = 2$ for an alphabet

⁶Note that I am not absolutely convinced of the correctness of the formulae used here, see appendix B.

of size four as used here. Note that for words of length 2 and 3 the information content is (almost) maximal, while for those of length 4 it is significantly lower, but still quite good.

This almost optimal code should be due to the training and production mechanisms used. When an agent network is trained on a sequence–meaning pair, the Elman training method (see 4.3.1 on page 47) seeks to minimise the error for every position of the sequence. Thus in general for longer sequences the error will be lower than for shorter ones, but over all it will decrease over time for sequences of any length, given that training data is consistent to a certain extent. As the production mechanism stops as soon as an error threshold is reached (defined as the output being “correct”), an overall lower error will lead to shorter sequences being produced.

If many sequence–meaning pairs are trained, the overall error for all of them decreases most if for every character of the sequences the information gain with respect to the meaning space is maximised. Semi–formally, the training mechanism seeks to maximise $P(output|sequence)$, the probability of a correct output vector conditioned on a sequence, while the production mechanisms chooses the *character* for which $P(output|character, sequence)$ is maximised locally. In general, both probabilities depend on the information content of the sequence; the higher this is, the higher the probabilities of correct interpretation.

6.1.4 Homogeneity

Although when the simulation begins the sequences produced by different agents for a particular meaning will differ, statistical divergences will cause certain partial sequences to be produced more often than others for one meaning. The training method will adjust the networks’ weights so as to preferentially associate with the more likely partial–sequence the meanings for which they were produced. The statistically significant partial sequences will on

average cause a lower error for the meanings trained with these sequences, which will consequently lead to the production method preferentially producing them. Over time, these mechanisms will make the population become increasingly homogeneous, in that more and more agents will use the same sequence for the same meaning.

6.1.5 Distinct words

While at the beginning of a simulation words produced by any agent for different meanings are random and often very similar to each other, as the error and word length decrease, the agents develop distinct expressions for all meanings. This phenomenon is natural to the training/production cycle. Training of a network agent decreases its error when associating the sequence on which it is trained with the given meaning. By preferentially associating one particular sequence with a meaning, all other sequences will become less likely to be associated with it, which makes it improbable that the production method will produce an ambiguous sequence for a meaning.

Amongst the languages of agents at times of the population dumps of the simulation run labelled `agave std batali 29/06/1999 21:32:32` (see Appendix E, page 137 onwards), only one agent could be found which would utter the same sequence for more than one meaning. Agent 24 from round 15015 produced `DCCBACCDBCDBCACDCBAC` for both (*mip scared*) and (*they scared*)⁷. Though in early stages of the simulation ambiguous sequences are very likely, these are merely a residue of imperfect learning.

⁷Inspection of the languages from Appendix E also shows for agent 1 from round 5005 the same sequence `DBBBBBBB` for both (*mip excited*) and (*yup excited*). This is due to the cut-off length of 8 characters which was used to produce the tables. With a maximum length of 20 as used in the simulation itself the expressions for the two meanings used by this agent are `DBBBBBBBBBBBBBBBBBBB` and `DBBBBBBBCCCCAADADACA`, respectively

Regularity 57%	<i>me</i> -A 78%	<i>we</i> -D 75%	<i>mip</i> -D 36%	<i>you</i> -A 90%	<i>yall</i> -B 41%	<i>yup</i> -C 70%	<i>yumi</i> -B 54%	<i>one</i> -C 52%	<i>they</i> -C 53%	<i>all</i> -B 97%
<i>happy</i> AD- 59%	dcdA (93 %)	dcD (93 %)	ddcb (66 %)	ADA (63 %)	ADaB (60 %)	AD (100 %)	ADbd (80 %)	ADC (50 %)	ADC (50 %)	ADB (80 %)
<i>sad</i> AA- 52%	AA dA (90 %)	AAD (90 %)	acaD (86 %)	AAA (86 %)	AAaB (83 %)	acab (73 %)	AA (96 %)	acaC (50 %)	ac (83 %)	AAB (100 %)
<i>angry</i> DD- 60%	DDA (100 %)	DDD (86 %)	DD (86 %)	bddA (66 %)	bdd (70 %)	add (96 %)	DDb (43 %)	DDca (93 %)	DDC (90 %)	DDB (56 %)
<i>tired</i> CD- 50%	CDA (100 %)	CDD (96 %)	CD (96 %)	bdA (100 %)	bd (100 %)	bdC (100 %)	bdB (100 %)	CDC (56 %)	CDcb (56 %)	CDB (100 %)
<i>excited</i> DB- 38%	dad (100 %)	D (50 %)	D (50 %)	daA (100 %)	DBa (100 %)	DBC (93 %)	DBd (73 %)	da (80 %)	dabd (50 %)	DB (73 %)
<i>sick</i> CA- 50%	CAA (100 %)	CAD (100 %)	CA (100 %)	baA (100 %)	ba (100 %)	baC (100 %)	baB (100 %)	CAC (63 %)	CAcb (63 %)	CAB (100 %)
<i>hungry</i> CB- 50%	CBA (100 %)	CBD (100 %)	CB (100 %)	bbA (100 %)	bb (100 %)	bbc (100 %)	bbB (100 %)	CBca (56 %)	CBC (60 %)	CBb (100 %)
<i>thirsty</i> CC- 50%	CCA (100 %)	CCD (100 %)	CC (100 %)	bcA (100 %)	bc (100 %)	bcC (100 %)	bcB (100 %)	CCC (53 %)	CCcb (50 %)	CCB (100 %)
<i>silly</i> AB- 43%	dcA (96 %)	dcab (100 %)	dcabb (50 %)	ABA (100 %)	AB (86 %)	ABC (86 %)	ABd (100 %)	acC (86 %)	acb (83 %)	ABB (100 %)
<i>scared</i> DC- 51%	DCac (100 %)	DC (80 %)	DCc (60 %)	bcdA (56 %)	bcd (56 %)	adbC (93 %)	DCB (63 %)	daC (86 %)	DCcC (63 %)	DCbB (60 %)

Table 6.3: The typical language of the population of round 24999 of run `agave std batali 29/06/1999 21:32:32`. For every meaning, the word which is most likely to be uttered by an agent from the population is given with its probability. The most likely pre- and postfixes for both components of the meanings are highlighted.

6.1.6 Compositionality

Table 6.3 shows for every meaning the word which is most likely to be uttered by agents after the last round of the simulation run `agave std batali 29/06/1999 21:32:32` together with its probability. Note that equal words such as **D** for the meanings (*we excited*) and (*mip excited*) do not mean that the agent’s languages were ambiguous. In this case half the population uses the word for one meaning, while the other half uses it for another.

This “language” is representative of those of all agents of the population, in that it consists of the expressions which are used by the majority of them. Its most striking feature, as well as being optimal and unambiguous for each agent, is a certain amount of compositionality as defined in 2.5.1. A major part of the language is regular in that the predicate is represented by the first two characters of each word and the referent is (ambiguously) encoded by the last character. The most likely referents according to this schema are printed bold and uppercase in the table. Also, for every row and column, the overall probability of the hypothetical constituent at hand is given.

Regularity 63%	<i>me</i> -A 40%	<i>we</i> -DC 50%	<i>mip</i> -B 70%	<i>you</i> -C 60%	<i>yall</i> -B 90%	<i>yup</i> -BA 40%	<i>yumi</i> -D 50%	<i>one</i> -A 80%	<i>they</i> -AB 80%	<i>all</i> -C 50%
<i>happy</i> BA- 70%	BA	BADC	BAB	bca	bcaB	BAac	BAc	BAA	BAAB	BAbC
<i>sad</i> AB- 70%	A	ABDC	ABB	ac	acB	ABac	ABc	ABA	ABAB	ABbC
<i>angry</i> BD- 40%	B	BDDC	BDB	bc	bcB	bbc	BDc	bb	bbb	BDbC
<i>tired</i> CD- 90%	CD	CDd	CDdB	CDC	CDcB	CDBA	CDcD	CDA	CDAB	CDb
<i>excited</i> CB- 40%	C	cc DC	CB	cca	ccaB	CBca	ccb	CBA	CBAB	CBC
<i>sick</i> DA- 90%	DA	DAd	DAdB	DAC	DAcB	DABA	DAcD	DAA	DAAB	DAb
<i>hungry</i> DB- 50%	dd	ddc	DBd	dc	dcB	DBc	dcD	DBb	DBbd	DBcd
<i>thirsty</i> DB- 50%	dd A	ddac	DBad	dca	dcba	DBca	dcaD	DBaA	DBAB	DBacd
<i>silly</i> AD- 60%	ADd	ADDC	ADad	aca	acaB	ADBA	ADc	aa	aaAB	ADbC
<i>scared</i> CA- 90%	CA	CAd	CAdB	CAC	CAcB	CABA	CAcD	CAA	CAAB	CAb

Table 6.4: The language from BATALI’s simulation, reformatted to the table layout used here (figure 24.11 from page 419 of [BATALI 98]).

BATALI claims to have found a language emerging from his simulation which is completely regular for the five predicates *tired*, *scared*, *sick*, *sad* and *excited*. They are represented by the first and second position of the words, and referents are encoded as postfixes for many of the meanings (table 6.4)⁸. The comparably higher compositional regularity of his language is also reflected by the regularity measure (see 6.1.7) which for it is 63% while for the maximally regular language⁹ of all runs I have conducted it is just 59%. Note that while for my simulations the regularity measure is based on the probabilities of hypothetical constituents for all agents of a population, for BATALI’s simulation I could only calculate it on the basis of the “sequences used by a majority of the population” ([BATALI 98], page 419) given by him.

As opposed to BATALI’s results, all of the typical languages from the replicative runs I conducted show “irregular” predicate constituents, whereby

⁸Table 6.4 shows a major weakness of my ad hoc method for calculation of the regularity measure: For words of length 2, only affixes of length 1 are considered, which is why for example the regularity of the constituent CD for the predicate *tired* is given as 90%, though it should be 100%. Still, the regular constituents are being highlighted correctly.

⁹of the population at round 10010 of run `agave std batali 29/06/1999 21:32:32`

typically about half the words of a particular predicate are constructed with the “regular” prefix and the other half with another. In table 6.3 this effect can be seen clearly for words of the referents *you*, *yall* and *yup* which deviate from the regular analysis for most predicates. According to my analysis many constituents for themselves are also ambiguous, whereby the language as a whole only becomes unambiguous because of the irregularities described above.

6.1.7 A regularity measure

The “most likely constituents” shown in table 6.3 were calculated using some heuristics which were inspired by manual inspection of the typical languages used by agents. An automated procedure was used to generate all language tables and also to calculate a “regularity measure” for the graphs throughout this thesis.

- For every word, affixes of lengths according to the following table are considered:

word length	prefix length	suffix length
≥ 4	1,2	1,2
3	1,2	1
2	1	1
1	–	–

- For all predicates and referents, the frequencies of all considered prefixes and suffixes are determined.
- For each predicate and referent, the “most probable” constituent is determined by the following heuristic:
 - If the probability of short words (only affixes of length one considered) is higher than the probability of any two-character affix, the most probable one-character affix is selected.

- Otherwise, the most probable two-character affix is taken.

The probabilities of the most likely constituents according to these heuristics are given for each row and column of the language tables. The averaged probability over all affixes is considered to be the 'regularity' of the language as a whole, given in the upper left corner of each language table.

Another plausible analysis could be to consider, instead of affixes, absolute positions in the sequences generated by the agents. For example, in the language shown in table 6.3 the constituent for *they* could also be a C at third position.

Therefore it has to be emphasised that the heuristics developed here follow the strict assumption that constituents developed by the networks are always continuous, and that predicates and referents are encoded as pre- and postfixes, respectively. This assumption by no means has to be correct, it is only motivated by manual inspection. Also it is inconsistent with BATALI who claims that the language he presents in his paper shows discontinuous constituents. I neither find his analysis very plausible nor could I find any such language among those developed by the simulations I conducted.

6.1.8 Why compositionality?

Possibly the most interesting question which arises from these experiments is why compositionality should emerge, though in this case it is contradictory to minimal length (discussed in 6.1.3). Ignoring for a moment that the networks can exploit the additional information content of an implicit stop symbol, $\lceil \log_4 10 \approx 1.6 \rceil = 2$ characters of an alphabet of size four would be needed to encode for the referents and predicates individually. So a perfectly compositional code should have a word length of four, and thus would be highly redundant, as it could encode for $n = \sum_{i=1}^4 4^i = 340$ meanings of which only 100 are used.

First character		Second Character	
Symbol	1 st char		
+	A	Large	A B
×	B	Small	C D
□	C	tiny	none
○	D		

Table 6.5: Agenda for figure 6.2: Symbols and gray scales used to represent the first and second character of surface forms from round 24999 of run `agave std batali 29/06/1999 21:32:32`.

But a redundant code is unnatural to the agents used here. Not only will the networks encode for meanings using substrings, but the training regime will also generally push towards the minimal average length of 2.92. As a consequence, many positions of the strings used will have to encode for parts of the meaning as a whole, yielding less compositionality.

Note that the mean word length of the language given by BATALI is 3.3 (see table 6.4 on page 67) while that of the population of the last round of the run presented here is 3.14 (see also subsection 6.1.3). This suggests that BATALI possibly took the language he presented in his paper from an earlier round. As longer words in general are less contradictory to compositionality as discussed here, this could be an explanation as to why his language should show more compositionality. Indeed it seems to be the case that languages are sometimes more regular for some constituents at earlier stages of the simulation (see for example the languages of agents from round 5005 of the run given in appendix E from page 137 onwards). I would argue that should BATALI have presented a language of a population which had not yet converged on short forms, it would not be a typical result of the simulation.

However, also in my replication runs compositionality does emerge to a certain extent. For a more detailed analysis consider figure 6.2 on page 71 which shows a projection of all meanings in the space of the first three prin-

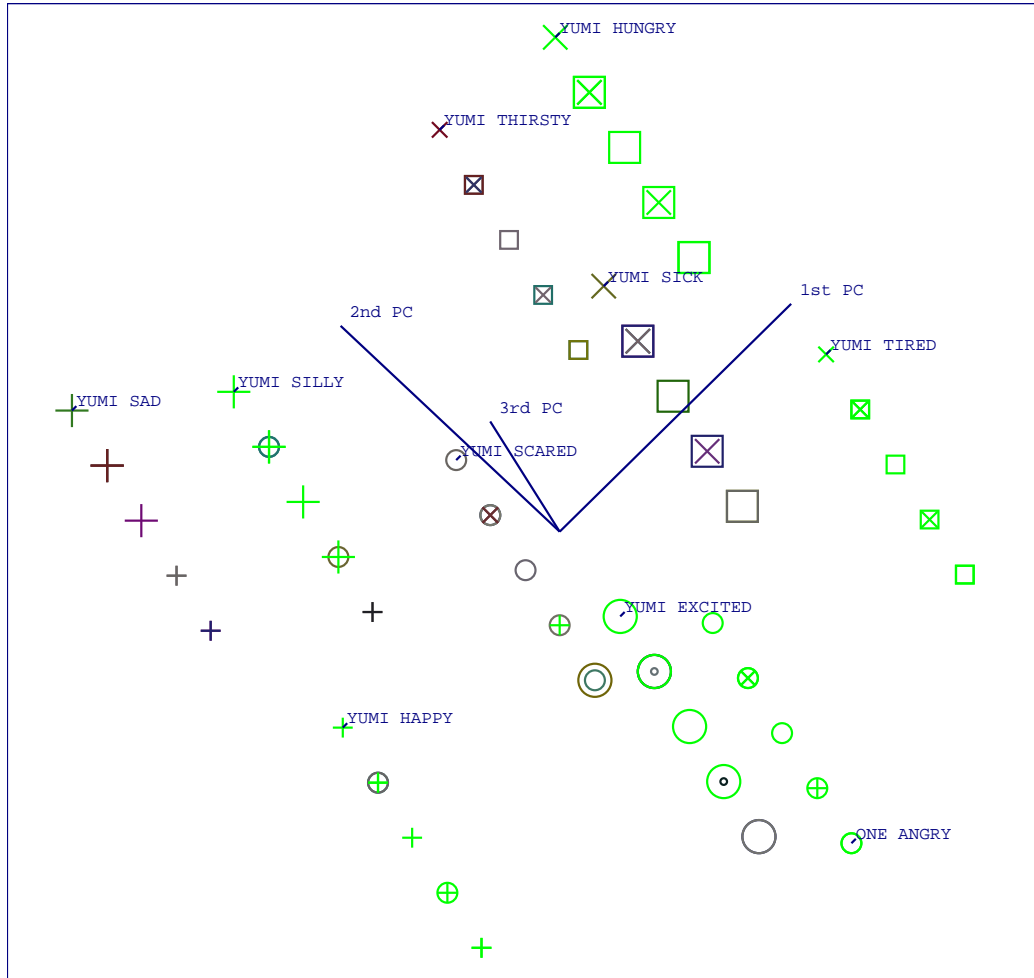


Figure 6.2: A projection of the first three principal components of the meaning space defined by BATALI. Meanings built from the same predicate are clustered as rows, each of the points of a row representing one or many meanings with different referent. Because of the necessary dimensionality reduction (a ten dimensional space is hard to imagine), some meanings with the same predicate but different referent are located at a single point of the first three dimensions shown here; they are distinguishable in higher dimensions. Symbols, sizes and gray value code for the first and second character of the surface forms evolved by `run agave std batali 29/06/1999 21:32:32`, see table 6.5.

principal components of the meaning space¹⁰, labelled according to table 6.5 with the first and second characters which were primarily used by agents from the last round of run `agave std batali 29/06/1999 21:32:32`. It is obvious from figure 6.2 that the characters in first position of the words, visualised as different symbols, already partition the space of meanings “topographically”. Those “columns” of data labelled equally by the first character are further distinguishable by the second position in being of different gray value and/or size.

From the figure shown here it is also obvious that because of how the meanings are constructed, it is advantageous to first distinguish between larger regions of the meaning space, then to identify specific predicates, and then to further distinguish between meanings of the same predicate but different referents.

The population of networks of the simulation presented here has thus collectively achieved what unsupervised neural networks are generally good at: They have found structure in data and developed an almost optimal representation for it. The meanings being componential, this optimal “surface representation” is also structured to a certain extent. In fact, the communicative process between two agents of BATALI’s model resembles a single *auto-associative network* (see for example [BISHOP 95] page 316) in that a complex input vector (the meaning given to the speaker) is compressed to a representation of considerably lower dimensionality (the sequence transmit-

¹⁰The data has been generated from the original meaning vectors as defined by BATALI (see section 3.3 on page 30) using the `pca` program by YOSHIRO MIYATA, ANDREAS STOLCKE *et al.* and has been visualised using `xgobi` [SWAYNE *et al.* 91]. *Principal Components Analysis* (PCA) is a standard technique for dimensionality reduction (see for example [BISHOP 95], pages 310–313), which basically can be used for a projection of data such that the direction along which it varies the most is the first axis, the second axis being the direction orthogonal to the first along which the next largest variation occurs, etc. Without giving any detail, what is important for the question at hand is that PCA gives a linear transformation of the data whose dimensionality can be reduced preserving the most important parts of its structure.

ted to the hearer) before being uncompressed again to a vector (the hearer's meaning vector) which is hopefully similar to the original input vector.

On the other hand, according to these insights the structure of the surface forms is primarily dominated by the particular binary vectors chosen by BATALI for construction of the meaning vectors. The predicates are represented as six presumably randomly chosen bits, in contrast to the referents being built from only four bits in a regular way. Therefore the meanings vary the most in the first six bits. The networks will prefer surface representations of the data which gain the most information about the space of meanings, not necessarily those which are the most regular. It would be interesting to investigate into the effects of differently designed meaning spaces.

6.2 Reproducibility of the results, parameter variation

The results shown in 6.1 are basically reproducible and typical. Appendix F from page 169 onwards shows the basic statistics as well as the final languages of 21 replicate runs.

What is striking is that I could not find a population whose language was as regular as the one presented by `BATALI` (table 6.4, page 67). Though such a highly regular language should not be completely impossible, it does not seem to be consistent with the insights presented in the section 6.1. Except for the speculation in 6.1.8, I cannot provide a plausible explanation for these different results.

I have also investigated the effects of changes to the other parameters of the simulation, namely the population size, the maximum word length before production is cut off, the size of the hidden layer of the agents and the number of characters available.

6.2.1 Population size

I have run a total of 30 simulations with population sizes of 2,7 and 15, each lasting 30,000 negotiation rounds, all other parameters being equal to those of the original simulation.

Essentially, the population size seems to be irrelevant to the outcome of the simulation, except that smaller populations converge much faster both in terms of negotiation rounds and CPU-time. Figure 6.3 shows the statistics of a typical run with just two agents and table 6.6 shows the population's language at the end of the run.

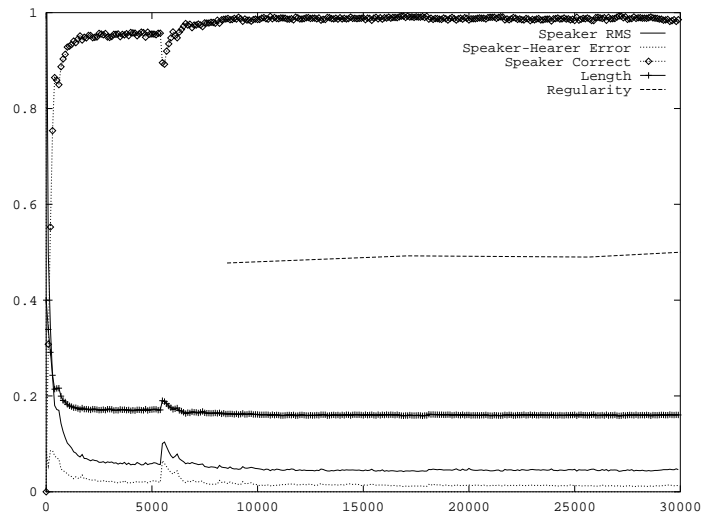


Figure 6.3: Statistics of a simulation of a population of only two agents (run bi-zarr batali popsize 2 30/07/1999 08:02:54)

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
50%	-C 45%	-B 35%	-A 40%	-C 40%	-D 45%	-C 40%	-B 50%	-C 85%	-C 50%	-B 70%
<i>happy</i>	bba (100 %)	bbad (100 %)	badA (100 %)	ADa (100 %)	AD (100 %)	ADC (100 %)	ADB (100 %)	bca (50 %)	bcdadbbb (50 %)	bad (100 %)
<i>sad</i>	AAa (100 %)	AAd (100 %)	abb (100 %)	AAC (100 %)	A (100 %)	aba (100 %)	AA (100 %)	abC (100 %)	ab (100 %)	AAB (100 %)
<i>angry</i>	DBcC (100 %)	DBc (100 %)	bdA (50 %)	DBdC (50 %)	DBdD (50 %)	dca (100 %)	DB (100 %)	dcC (100 %)	dc (100 %)	DBB (100 %)
<i>tired</i>	CDC (100 %)	CDB (100 %)	CD (100 %)	ddaC (100 %)	dda (100 %)	ddaa (100 %)	ddaB (100 %)	CDaC (100 %)	CDa (100 %)	CDd (100 %)
<i>excited</i>	BDd (50 %)	BDd (50 %)	BD (100 %)	daa (100 %)	da (100 %)	daC (100 %)	daB (100 %)	BDcC (100 %)	BDC (100 %)	BDB (100 %)
<i>sick</i>	CCd (100 %)	CCB (100 %)	CC (100 %)	ddeb (100 %)	ddb (100 %)	ddbC (100 %)	ddbB (100 %)	CCcC (50 %)	CCcb (50 %)	CCa (50 %)
<i>hungry</i>	CBcC (100 %)	CBc (100 %)	CB (100 %)	ddcd (100 %)	ddd (50 %)	CBad (100 %)	CBd (100 %)	CBaa (100 %)	CBa (100 %)	CBB (100 %)
<i>thirsty</i>	CAaC (100 %)	CAa (100 %)	CA (100 %)	ddcC (100 %)	dddD (100 %)	CAd (100 %)	CAbd (100 %)	CAC (50 %)	CAC (50 %)	CAB (100 %)
<i>silly</i>	BAaC (50 %)	BAa (100 %)	BA (100 %)	aca (100 %)	ac (100 %)	acC (100 %)	acd (100 %)	BAcC (100 %)	BAC (100 %)	BAB (100 %)
<i>scared</i>	BBaa (100 %)	BB (100 %)	BBc (100 %)	dadd (50 %)	daD (100 %)	beb (100 %)	BBd (100 %)	bcC (100 %)	bc (100 %)	BBB (100 %)

Table 6.6: A typical language for populations of two agents. (From round 29999 of run bi-zarr batali popsize 2 30/07/1999 08:02:54)

6.2.2 Cut off length

The maximal word length can also be decreased without influencing the outcome of the simulation. Usually convergence with a shorter cut-off length is a bit slower in terms of negotiation rounds, presumably because the number of total training cycles is dependent on the cut-off length, and thus shortening it means less training of the agents. Decreasing the maximum word length could also save some CPU time, but as convergence slows down the gain may not be very significant. I have not collected any detailed data on this effect.

6.2.3 Hidden layer size

Effects of variation of the hidden layer size are of particular interest because the number of hidden units determines the networks' memory capacity for interpretation of sequences, as well as the maximal complexity of the mapping between inputs and outputs. For many common applications of connectionist models, networks with smaller hidden layers tend to generalise better over data, while larger hidden layers often lead to networks essentially memorising the data. The question therefore arises whether this principle is also valid for the simulations described here, in the sense that smaller hidden layer sizes would yield more compositional languages.

A total of six runs was conducted with hidden layer sizes of 10 and 20 units. The results of typical runs are given for 10 hidden units in figure 6.4 and table 6.7, and for 20 hidden units in figure 6.5 and table 6.8. The most significant insight is that lower hidden layer sizes do not lead to better generalisation, in the sense of more regular languages. Instead, too small a hidden layer (size 10) in general leads to higher errors, longer words and far less agreement.

A hidden layer size of 20 seems to be already appropriate for the given task, though still agreement amongst the population is not as good as with

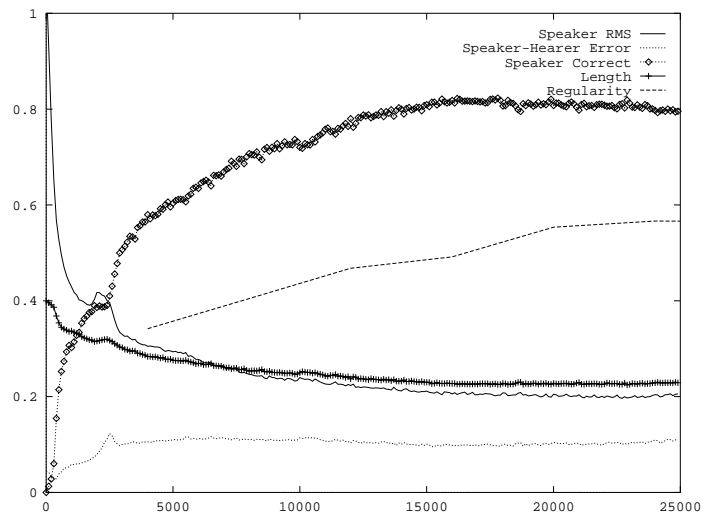


Figure 6.4: A simulation using 30 agents with hidden layers of only 10 units (run bunting batali hiddens 10 18/08/1999 19:10:14)

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
56%	-B 61%	-A 42%	-A 53%	-B 65%	-D 69%	-C 39%	-A 44%	-B 78%	-C 59%	-A 56%
<i>happy</i>	aadB	aad	caaaaaA	CDB	CDD	CD	daA	CDB	CDC	CDaA
CD- 51%	(50 %)	(40 %)	(10 %)	(30 %)	(56 %)	(80 %)	(13 %)	(30 %)	(20 %)	(33 %)
<i>sad</i>	DdB	Ddac	DcA	DB	DdddddD	Dcd	D	DcB	DC	D
D- 90%	(10 %)	(23 %)	(56 %)	(53 %)	(23 %)	(36 %)	(70 %)	(53 %)	(76 %)	(10 %)
<i>angry</i>	ADB	ADc	ac	ADbB	ADb	ccddb	AD	acbB	acC	acdA
AD- 45%	(33 %)	(23 %)	(36 %)	(26 %)	(13 %)	(6 %)	(83 %)	(16 %)	(30 %)	(6 %)
<i>tired</i>	abcB	abc	acacc	BCdB	BCD	BC	addaaaaA	BCB	BCcC	BCA
BC- 49%	(46 %)	(43 %)	(10 %)	(20 %)	(26 %)	(90 %)	(26 %)	(66 %)	(13 %)	(36 %)
<i>excited</i>	aacB	aac	acaA	CCB	CCdD	CC	addaaaaA	CCB	CCC	CCA
CC- 49%	(50 %)	(73 %)	(23 %)	(16 %)	(16 %)	(93 %)	(13 %)	(40 %)	(26 %)	(50 %)
<i>sick</i>	abd	abd	accaaaaA	BDB	BD	BD	addddddd	BDcB	BDC	BDA
BD- 49%	(50 %)	(40 %)	(6 %)	(50 %)	(50 %)	(46 %)	(16 %)	(43 %)	(36 %)	(53 %)
<i>hungry</i>	abB	abbA	BBA	BBdB	BBD	BB	BBdA	BBB	BBC	BBad
BB- 70%	(73 %)	(46 %)	(53 %)	(63 %)	(80 %)	(53 %)	(66 %)	(70 %)	(36 %)	(26 %)
<i>thirsty</i>	abaB	abA	BAA	BAdB	BAD	BAcd	BA dA	BAB	BAC	BA
BA- 70%	(43 %)	(43 %)	(60 %)	(76 %)	(86 %)	(23 %)	(66 %)	(50 %)	(56 %)	(73 %)
<i>silly</i>	aabd	aaad	CAad	cbd	cdD	cdad	dad	cbdB	CAdb	CA d
CA- 36%	(36 %)	(23 %)	(23 %)	(33 %)	(20 %)	(6 %)	(20 %)	(33 %)	(26 %)	(53 %)
<i>scared</i>	aabB	aaac	cac	CB	CBcD	CBa	caccd	CBB	CBa	cac
CB- 45%	(26 %)	(20 %)	(26 %)	(23 %)	(16 %)	(33 %)	(10 %)	(36 %)	(20 %)	(33 %)

Table 6.7: The final language from run bunting batali hiddens 10 18/08/1999 19:10:14 with agents' hidden layers of size 10

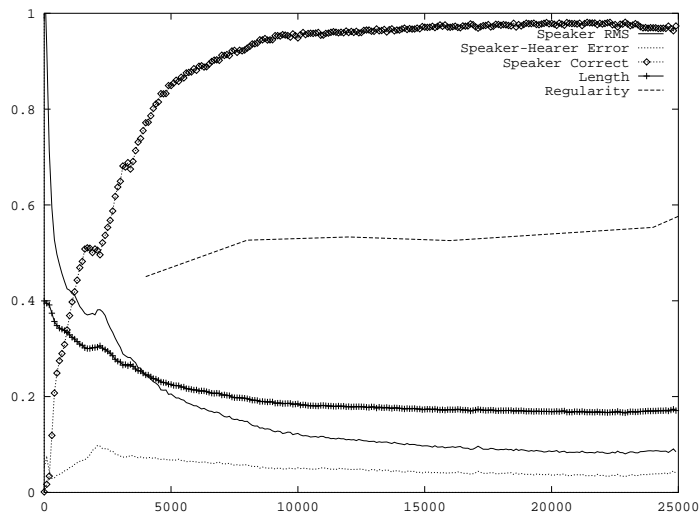


Figure 6.5: A simulation using 30 agents with hidden layers of 20 units (run kite batali hiddens 20 18/08/1999 19:10:44)

Regularity 57%	<i>me</i> -A 55%	<i>we</i> -D 74%	<i>mip</i> -D 43%	<i>you</i> -A 93%	<i>yall</i> -B 55%	<i>yup</i> -C 37%	<i>yumi</i> -D 30%	<i>one</i> -B 81%	<i>they</i> -B 36%	<i>all</i> -C 62%
<i>happy</i> DA- 58%	DAA (96 %)	DAD (73 %)	DA (73 %)	abA (100 %)	ab (86 %)	abC (86 %)	DAba (36 %)	DAaabbB (10 %)	DacbB (16 %)	DAb (66 %)
<i>sad</i> AD- 37%	ADA (93 %)	AD (80 %)	ADb (83 %)	aaA (93 %)	A (83 %)	aaC (50 %)	ADca (43 %)	aaBa (33 %)	aaB (50 %)	ADC (40 %)
<i>angry</i> BD- 50%	BDA (93 %)	BDD (96 %)	BD (96 %)	baA (100 %)	ba (100 %)	bab (80 %)	cacD (53 %)	BDbB (73 %)	BDB (93 %)	BDC (73 %)
<i>tired</i> CD- 50%	CDd (83 %)	CDdc (80 %)	bcdD (66 %)	CDA (100 %)	CDB (100 %)	bcda (96 %)	CD (96 %)	bcdB (80 %)	bcd (96 %)	CDC (96 %)
<i>excited</i> DD- 52%	DDd (63 %)	DD (46 %)	DDc (40 %)	DDbA (36 %)	DDB (40 %)	bbd (63 %)	DD (53 %)	bbb (83 %)	bb (60 %)	DDC (60 %)
<i>sick</i> CA- 50%	CA dA (60 %)	CAD (70 %)	bcaD (73 %)	CA A (100 %)	CAB (96 %)	bcaa (90 %)	CA (100 %)	bcaB (80 %)	bca (93 %)	CAC (73 %)
<i>hungry</i> CC- 69%	CCdA (40 %)	CCD (63 %)	CCcD (63 %)	CCA (90 %)	CCba (46 %)	CCb (90 %)	CC (80 %)	bccB (56 %)	bcc (90 %)	CCC (66 %)
<i>thirsty</i> CB- 69%	CBdA (63 %)	CBd (73 %)	CBcD (46 %)	CBA (100 %)	CBB (46 %)	CBb (50 %)	CB (86 %)	bcb (80 %)	bcbd (36 %)	CBC (53 %)
<i>silly</i> DB- 55%	DBdA (40 %)	DBD (63 %)	DB (76 %)	acA (100 %)	ac (93 %)	acC (93 %)	DBddb (10 %)	DBB (96 %)	DBbd (50 %)	DBdC (43 %)
<i>scared</i> DC- 86%	DCdd (63 %)	DCD (70 %)	DCc (73 %)	DCbA (56 %)	DCB (80 %)	DCbC (80 %)	DC (66 %)	DCcbB (23 %)	DCcB (43 %)	DCca (53 %)

Table 6.8: The final language of run kite batali hiddens 20 18/08/1999 19:10:44 with agents with 20 hidden units

30 hidden layer units, as can be seen from the probabilities of the most probable words in every cell of table 6.8. Still, for both smaller hidden layer sizes the emerging languages show the same basic pattern as those of the original experiment, except for being less “perfect”.

These results suggest that for the standard experiment the hidden layer size could possibly be reduced to about 20–25 in order to cut down CPU–time without unduly influencing the final result.

6.2.4 Alphabet size

Because the alphabet size determines the highest possible information content of each character, and thus could possibly influence the amount of compositional regularity of the emerging language, I also replicated the original experiment with different alphabets, namely of two and ten characters. In theory, two factors could influence the effects of different alphabet sizes:

- **Memory capacity**

For larger alphabets, as more information is encoded in each character, less information has to be stored by the network processing a sequence. Should the memory capacity of a network influence its regularisation capabilities with respect to compositionality, larger alphabets should yield more idiosyncraticity.

Conversely, under this assumption smaller alphabets should show increased compositionality.

- **Alphabet fitting meaning structure**

If the analysis as described in 6.1.8 is correct that under the training regime used here the network agents seek to maximise the information content of each character, a code should be maximally compositional if the number of values in each of the dimension(s) of the meaning space,

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
47%	-H 51%	-G 36%	-H 35%	-B 60%	-C 33%	-I 32%	-G 57%	-E 29%	-J 35%	-D 29%
<i>happy</i> D- 70%	DH (60 %)	Dhd (46 %)	Dj (100 %)	DB (100 %)	DC (100 %)	De (100 %)	D (100 %)	bE (100 %)	ea (100 %)	DD (100 %)
<i>sad</i> A- 80%	AH (73 %)	AhG (46 %)	Aa (96 %)	AB (100 %)	AC (93 %)	Ae (100 %)	A (76 %)	ba (96 %)	AJ (100 %)	AD (96 %)
<i>angry</i> E- 40%	hH (100 %)	he (100 %)	EH (100 %)	cc (100 %)	ce (100 %)	Ec (100 %)	ch (100 %)	Eb (86 %)	E (100 %)	Eg (96 %)
<i>tired</i> J- 39%	hf (63 %)	hfG (63 %)	JfH (96 %)	ctB (53 %)	cf (100 %)	Jfc (83 %)	ctG (100 %)	Jfb (70 %)	Jf (100 %)	fe (100 %)
<i>excited</i> C- 40%	hb (100 %)	hd (100 %)	hj (96 %)	CB (100 %)	Cd (60 %)	Cj (96 %)	CdG (50 %)	bd (50 %)	ef (100 %)	fd (93 %)
<i>sick</i> J- 50%	hi (100 %)	hG (100 %)	JH (100 %)	ci (73 %)	cij (70 %)	Jc (76 %)	cG (100 %)	JE (100 %)	Jd (100 %)	Jch (46 %)
<i>hungry</i> I- 40%	gH (100 %)	gG (100 %)	ig (100 %)	li (93 %)	I (100 %)	Ie (100 %)	IG (100 %)	jj (46 %)	jJ (53 %)	Ij (100 %)
<i>thirsty</i> G- 40%	Gb (100 %)	G (100 %)	Ge (93 %)	iB (100 %)	if (100 %)	jI (93 %)	Gc (100 %)	jb (73 %)	jbg (60 %)	Gf (100 %)
<i>silly</i> B- 59%	BH (100 %)	gd (100 %)	Bg (100 %)	Bc (63 %)	Bcg (43 %)	BI (100 %)	dG (100 %)	B (100 %)	BJ (100 %)	fa (100 %)
<i>scared</i> F- 80%	FH (53 %)	FhG (50 %)	FjH (56 %)	FB (100 %)	FC (100 %)	FI (100 %)	FG (100 %)	bf (100 %)	FJ (60 %)	F (100 %)

Table 6.9: The language of the population of the 60,000th round of a typical run using an alphabet of size ten and network agents with 20 hidden units (run *oriole batali* chars 10 hidden 20 length 8 23/08/1999 18:24:12)

which are considered significant components of it, is expressible by a whole number of characters.

The idea behind this complicated formulation will (hopefully) become clear in the discussion of an alphabet size of 10.

The most basic result is that, in accordance with the considerations stated above, in experiments with just two possible input characters and a hidden layer size of 30 the population does not converge, while it does for 40 hidden units. For ten input characters, the number of hidden layer units could be reduced to 20 without any obvious impact, and further reductions are likely to be possible (I have not evaluated this in detail).

Experiments with 10 and 2 character alphabets do not clearly verify any of the speculations above (see tables 6.9 and 6.10). The languages do not significantly differ in regularity, nor is for 10 characters the most use being made of the fact that the number of available characters exactly matches both the number of predicates and referents. An alphabet of size ten would allow each of these components to be represented by exactly one character

Regularity 50%	<i>me</i> -AA 53%	<i>we</i> -AB 29%	<i>mip</i> -BB 47%	<i>you</i> -AA 32%	<i>yall</i> -AA 33%	<i>yup</i> -BB 35%	<i>yumi</i> -BA 23%	<i>one</i> -AB 43%	<i>they</i> -AA 38%	<i>all</i> -AA 41%
<i>happy</i> BB- 60%	BBbabab (80 %)	BBbAB (40 %)	BBbabaab (40 %)	BBbAA (53 %)	BBbAA (43 %)	B (30 %)	BB (100 %)	bababaAB (70 %)	bababAA (63 %)	BBbabAA (63 %)
<i>sad</i> BB- 57%	aabbaaba (26 %)	aabbabAB (36 %)	BBab (90 %)	BBaab (90 %)	BBAA (86 %)	baabba (40 %)	Bba (100 %)	babba (60 %)	babbaAA (56 %)	BBabb (90 %)
<i>angry</i> AA- 39%	AAababAA (46 %)	AAaba (46 %)	AAabaBB (53 %)	bbbbb (66 %)	bbbb (43 %)	baabaaba (63 %)	AAababab (40 %)	bababAB (50 %)	babababa (46 %)	bbbb (70 %)
<i>tired</i> AB- 54%	aaaAA (93 %)	aaaa (90 %)	aaaBB (66 %)	ABaAA (50 %)	ABAA (50 %)	baabaaBB (63 %)	aaaaBA (43 %)	ABbbaaa (70 %)	ABbaAA (86 %)	ABabAA (90 %)
<i>excited</i> BA- 69%	aaabAA (70 %)	aaabaAB (46 %)	BAbabBB (80 %)	BAabab (46 %)	BAabab (50 %)	BAb (93 %)	bbbbb (53 %)	BAbabba (46 %)	BAba (56 %)	BAabaAA (73 %)
<i>sick</i> AB- 52%	aaabAA (70 %)	aaabb (46 %)	aaabBB (83 %)	BAaabbbb (40 %)	BAaabbb (36 %)	baabaaBB (63 %)	aaabbab (46 %)	ABbbb (96 %)	ABbaabb (80 %)	ABababb (60 %)
<i>hungry</i> AB- 78%	aabAA (73 %)	aaba (66 %)	ABbab (43 %)	BAaabbAA (60 %)	BAaabba (43 %)	ABabBB (70 %)	ABabBA (53 %)	ABbbAB (86 %)	ABbab (50 %)	ABabb (70 %)
<i>thirsty</i> AB- 71%	aabbbAA (40 %)	aabbbAB (23 %)	ABbaabaa (36 %)	BAaabaAA (50 %)	BAaaba (60 %)	baaaaba (36 %)	ABababaa (63 %)	ABbbaAB (73 %)	ABbAA (33 %)	ABabab (50 %)
<i>silly</i> BA- 69%	aabb (30 %)	aabbAB (26 %)	BAbbbB (63 %)	BAaab (60 %)	BAaaba (66 %)	BAaBB (73 %)	bbaaa (96 %)	BAbbba (80 %)	BAbb (66 %)	BAabbb (66 %)
<i>scared</i> BA- 69%	aaabbbb (30 %)	aaabbb (33 %)	BAbaaa (86 %)	BAaab (76 %)	BAAA (83 %)	BAaaa (76 %)	bbbabb (76 %)	BAbaAB (90 %)	BAbaAA (86 %)	BAaaaAA (66 %)

Table 6.10: The typical language from the 60,000th round of a run using an alphabet of only two characters, networks with 40 hidden units and a cut-off length of 20 (run *gyr batali* chars 2 hidden 40 length 20 01/09/1999 19:38:23)

of the words of the language, and the size of the alphabet does not enforce parts of the meaning space to be encoded by several positions of the strings used.

6.3 A generational experiment

One of the principal differences between the setup of BATALI’s simulation and the general framework for language evolution as described in 2.2 is that it does not model changes in the agents of the population. As networks are neither deleted nor newly created, a language emerging from the system is never forced to be trained to any unknowing agent. In terms of “knowledge” of the agents the population stays very homogeneous over time. Another consequence is a semantic bottleneck (see subsection 2.4.2) can only be implemented by having certain meanings never expressed by any agent, as implemented by BATALI (see section 5.3, pages 423–424 of [BATALI 98]).

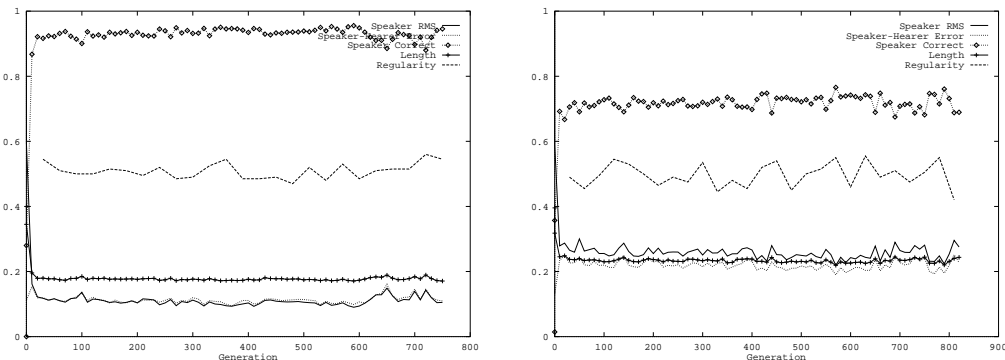


Figure 6.6: Statistics for a generational experiment on the basis of BATALI’s model, without a bottleneck (left) and with the number of meanings for transmission between generations being reduced to 70 of 100 (right). The runs were labelled `bi-zarr gen bot 100 13/08/1999 20:35:24` and `bi-zarr gen bot 70 13/08/1999 20:35:53`, respectively. The measures have been averaged over 20 generations to increase clarity.

In order to study the effects of pure, enforced transmission of the networks’ language over time, I implemented a strictly generational model, where at each generation one freshly initialised student agent is trained on the output of a teacher agent from the previous generation, swapping teacher and student at the next. The initial teacher is initialised randomly. So any language which is to persist through time has to undergo permanent trans-

mission between I- and E-Language (see section 2.4).

6.3.1 Setup

Each student is trained for 5000 passes through the language of the teacher using steepest-descent online updates with a learning rate η of 0.01 as in the simulation described above. The number of training passes is motivated by the fact that in BATALI's simulation convergence is reached at about round 15000, whereby on average each agent has been trained by ten teachers every 30th round ($15000 \times 10/30 = 5000$). A hidden layer size of 30 was used and a cut-off length of 8.

Two experiments have been conducted, one with transmission of all meanings from one generation to the next, and one with a semantic bottleneck randomly selecting (without replacement) 70 out of the 100 possible meanings to be uttered by the teacher of each generation. Figure 6.6 shows the usual statistics for both runs. For both experiments, correctness rises sharply in the first few dozens of generations, while error and length decrease. After that, no significant further change in terms of the figures shown can be observed. The model with bottleneck generally shows a higher error, and the correctness value is roughly 0.7 of that of the experiment without bottleneck, which suggests that those meanings which have not been trained can not be produced properly by an agent.

6.3.2 Results

Tables 6.11 and 6.12 show some representative languages of teachers from each of the simulations. While the language from the simulation without a bottleneck is very similar to those typically emerging from BATALI's simulation, the result from the run with bottleneck clearly reflects what the previously presented statistics suggest: it shows many imperfections, and

Regularity 52%	<i>me</i> -A 40%	<i>we</i> -C 40%	<i>mip</i> -B 80%	<i>you</i> -D 40%	<i>yall</i> -A 60%	<i>yup</i> -D 50%	<i>yumi</i> -A 60%	<i>one</i> -D 100%	<i>they</i> -C 50%	<i>all</i> -B 70%
<i>happy</i> BC- 30%	ddac	dd	ddB	acaa	acA	BC	ddab	BCD	BCC	BCB
<i>sad</i> DA- 50%	DA d	DAC	dbB	DAa- aaaab	DAA	bcab- bcbb	DA	dbD	db	DAB
<i>angry</i> BA- 70%	ddd	ddda	BAB	BAaa	BAA	BA	BAab	BAD	BAC	BAbB
<i>tired</i> CB- 30%	ccdd	ccd	CBdB	adD	adb	cddD	cddA	CBdD	CBd	cdd
<i>excited</i> B- 50%	ddcd	ddC	BbB	acD	ac	BD	acb	BbD	Bb	BdB
<i>sick</i> CB- 30%	ccbacA	ccb	CBbc	caaD	caA	cdBd	edbA	CBbD	CBb	cdB
<i>hungry</i> CB- 30%	cccA	ccC	CBcB	cac	ca	cadc	cad	CBcD	CBC	cdc
<i>thirsty</i> CB- 30%	ccA	ccaa	CBaB	ada	adab- abab	cdaD	cdaA	CBaD	CBa	cda
<i>silly</i> DC- 60%	DCcA	DCC	DC	aad	aa	aab	DCA	DCD	DCdC	DCB
<i>scared</i> AB- 70%	ABac	ABa	AB	adc	A	ABbD	ABaA	ABD	ABC	ABB

Table 6.11: The language of the teacher agent from generation 510 of the generational model without bottleneck (run bi-zarr gen bot 100 13/08/1999 20:35:24)

Regularity 50%	<i>me</i> -C 40%	<i>we</i> -D 50%	<i>mip</i> -D 50%	<i>you</i> -C 70%	<i>yall</i> -B 60%	<i>yup</i> -D 40%	<i>yumi</i> -A 60%	<i>one</i> -B 40%	<i>they</i> -B 30%	<i>all</i> -A 60%
<i>happy</i> AC- 40%	cd	cdaD	cda	ACC	AC	ACd- cccc	ACda- abaA	aaa	aaaB	ACd
<i>sad</i> CC- 50%	CCc- adadb	C	CC	cbca- caaa	cbe	CCbc	cb	CCc	CCd	CCA
<i>angry</i> BC- 50%	BCb	BCa	BC	bbc	bbcdB	acdb- cbcb	bbA	BCc	BCcc- bacB	BCaa- ddaA
<i>tired</i> DD- 50%	baba	babdD	bcdd- bddD	DDbC	DDbB	DD	bbb	DDd	DDdd- bada	DDbd
<i>excited</i> BD- 20%	BDC	BDcd- addD	bcdd- dddD	acb	acbB	adde- ccbD	bbdd- caaA	aacbd	aadbB	abdc
<i>sick</i> DC- 50%	baC	baca- aabb	bcD	DCbC	DCB	DC	bbdA	DCcB	DCc	DCaa- aaaA
<i>hungry</i> DB- 70%	babd- bbdC	babbD	DBD	DBbc- dbbC	DBB	DB	DBbA	DBcB	DBca	DBdd- bbdd
<i>thirsty</i> DA- 70%	baa	baab- dbbb	DAD	DAbC	DAbbac	DAcb- dada	DAb	DAcc	DAc	DA
<i>silly</i> AD- 50%	caC	ca	cada	ADC	ADB	AD	ADbA	aacd- aadB	ADac- cddd	ADA
<i>scared</i> AB- 50%	bdd	bddD	ABac- caca	ABcc- dada	ABc	AB- caD	AB	aaB	aabaa	ABA

Table 6.12: The language of the teacher agent from generation 510 of the generational model with bottleneck (run bi-zarr gen bot 70 13/08/1999 20:35:53)

the number of words which hit the cut-off length of 8 is about equal to the number of meanings which have not been trained.

Clearly this experiment does not show any of the desired effects. The networks seem not to be able to generalise well over meanings which they were not trained on, and the language emerging from a generational model does not show any properties which would depart from those of the previously described simulations. In particular, they do not show any increased preference for compositionally regular languages. The language from the run with bottleneck seems to be of the same quality as the one presented on page 423 of [BATALI 98], but I would argue that neither the one presented by BATALI nor the one shown here exhibits any convincing generalisation over unseen meanings.

6.3.3 Persistence of a language over time

On the other hand what the simulation without bottleneck does show is that once an appropriate language has evolved, it can be successfully transmitted over time without much change, whereby some words even persist through hundreds of generations. Appendix D from page 133 onwards exemplifies this behaviour, showing the languages of the teacher agents of three stages during 90 generations.

6.4 Learnability experiments

Though for the experiments described so far the principle which underlies the networks' learning and acquisition mechanisms seems to be guided by information gain with respect to the meaning space, the languages which evolve from the population of agents do exhibit regularity which at least partly corresponds to human intuitions about compositionality and the measure described in 6.1.7 on page 68.

Therefore those languages which are compositional in the sense used here must have spread within the population of agents (or over generations), and for this to happen they should have some kind of advantage over irregular languages. Supposedly they are easier to learn. The question is if and to what extent these intuitions are correct.

Another question concerns the networks' capacity, given as the size of their hidden layer. For many problems it can be shown that hidden layers of too great a size cause *over fitting* of the networks to the data by basically memorising it instead of generalising over it. On the opposite end, the results presented in 6.2.3 suggest that smaller hidden layers lead to imperfections instead of more regular surface forms. For none of the cases have satisfactory answers been found so far with respect to the influence of the hidden layer size on the networks' ability to learn certain languages.

To answer these questions I have conducted a series of simple experiments where a single Elman network as used in BATALI's simulation is trained on given languages of different regularity. The training error is measured, and after training the network's learned (output-) language is extracted and compared with the input language.

6.4.1 Generating random languages

To facilitate the generation of languages for the experiments to be conducted, their words were assumed to be always four characters long. Optimal compositionality was assumed to be present when the first two characters unambiguously code for the predicate and the last two for the referent. To generate random languages of a certain regularity, first ten two-character sequences, to represent the “regular constituents”, were assigned to each predicate and referent, respectively. Then for each meaning the prefix and suffix were chosen from the corresponding “regular” constituents with a given probability and generated randomly otherwise. Because the languages produced by this method are only approximately of the given regularity, their true regularity is determined retrospectively by the ad hoc measure described in 6.1.7.

6.4.2 Training

Networks of different hidden layer sizes were trained on input languages generated by the previously described method, each being of a certain regularity. For the results to be presented here, the network has been trained for 8000 passes through the artificially generated language using the standard Elman steepest descent pattern- and time-online updates with a learning rate η of 0.01 as before. As in the generational model (see 6.3.1), the number of passes was motivated by convergence of the population in the original simulation, but has been increased to compensate for the fact that the words of the artificially generated language are always four characters long, while those uttered by agents in the generational model can be up to eight characters long, thus potentially yielding a larger number of effective training cycles (see also 6.2.2).

Basically comparable results have been found using time-online pattern-

batch steepest descent updates and conjugate gradient batch updates over time and patterns (See 4.3.1 about training of Elman methods, 4.2.6 about steepest descent updates and 4.2.8 for conjugate gradients).

6.4.3 Measures used

After completion of all passes through the training set (generated language), the network's root mean square error over all words was determined as well as some additional measures. The language of the network was extracted using the production mechanism as described in 3.4.1 for all meanings, recording the sequences generated. For the network's language the following measures were determined:

- **regularity out**

Its regularity according to the measure described in 6.1.7.

- **equal words**

The fraction of words which are string-equal with their corresponding instances from the training-language.

- **similar words**

The average fraction of characters of each word which are equal to those of the training-language, considering for every word only characters up to the length of the shortest of both words from the input- and output-language.

6.4.4 Details of experiments

At every run a language is generated according to the method described in 6.4.1 with the regularity probability given to the generation algorithm drawn from a uniform distribution of $[0 \dots 1]$. The true regularity of the artificial language is determined according to 6.1.7 and the network is trained on it

twice, each time being initialised with random weights. After training, the network’s language is extracted, the measures described above (in 6.4.3) are calculated to be finally averaged over the two sets of training passes in order to minimise fluctuations due to the distribution of the initial weights¹¹.

Experiments have been conducted on Elman networks with hidden layers of 5, 15, 30, 50 and 100 units and four input units as in BATALI’s simulation. For the different hidden layer sizes between 150 and 213 runs were done.

6.4.5 The relation between compositionality and learnability

Figure 6.7 shows the measures defined in 6.4.3 for a network with 30 hidden units when trained on languages of different regularity. This experiment confirms the expectation that regular languages are easier to learn. The training error decreases with increasing regularity of the training language, while the similarity between input- and output-language increases.

On the other hand, the regularity of the output language behaves to a great extent independently of the input language. Variation in the regularity of the training language between roughly 0.25 and 1 only causes variation in the regularity of the network’s output language between 0.4 and 0.6. These results provide a clear picture of why the languages emerging from the populations of the simulations described in 6.1 were predominantly regular in that range. No matter how regular the language that a network is trained on, it will always produce a language of regularity between 0.4 and 0.6.

Under the assumption that those languages which persist in the experiments described in 6.1 and 6.3 are those which are most “natural” to the

¹¹Ideally many more training cycles should have been done with each language in order to get better averages, but as these experiments were conducted towards the end of the time available for this project, this was not possible considering that 50 runs of a network with 30 hidden units already took about two days on the machines available.

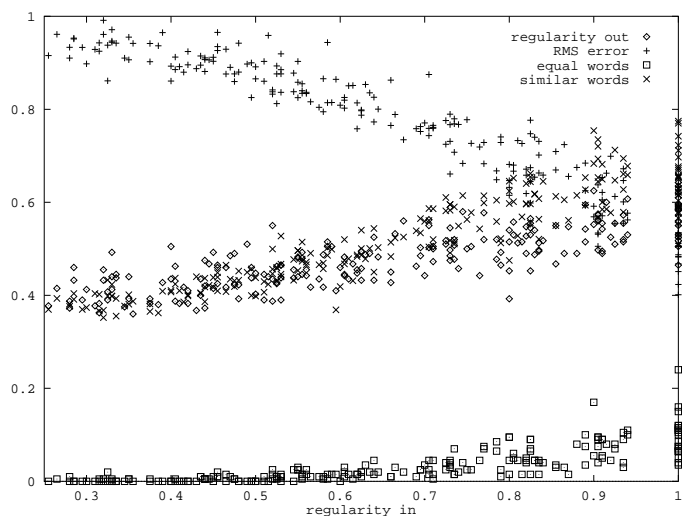


Figure 6.7: Learnability of languages of different regularities when trained on a Batali-style network with 30 hidden units using steepest descent time-online pattern-online updates. (For an explanation of the measures used see 6.4.3)

networks used, in that they are easiest to learn, this also suggests that compositionality as defined here is not what primarily influences the learnability of a language.

Table 6.14 shows the output-language of a network of 30 hidden units after being trained on the completely regular language shown in table 6.13. Even though the number of training passes should definitely be sufficient for a language to be transmitted properly as shown in section 6.3, the language generated by the network shown here is clearly imperfect. This provides more evidence for the assumption that the principle which leads to the observed surface forms is only marginally related to compositionality. Were the opposite the case, the network should be able to reproduce perfectly the compositional input language. In general, the networks used here can not adequately reproduce arbitrary languages, and the particular class of languages which *can* be reproduced as shown in 6.3 does not seem to be that of the regularly compositional ones.

Regularity 100%	<i>me</i> -BC 100%	<i>we</i> -DB 100%	<i>mip</i> -AA 100%	<i>you</i> -CC 100%	<i>yall</i> -CA 100%	<i>yup</i> -AB 100%	<i>yumi</i> -CB 100%	<i>one</i> -BB 100%	<i>they</i> -DD 100%	<i>all</i> -DC 100%
<i>happy</i> DB- 100%	DBBC (100 %)	DBDB (100 %)	DBAA (100 %)	DBCC (100 %)	DBCA (100 %)	DBAB (100 %)	DBCB (100 %)	DBBB (100 %)	DBDD (100 %)	DBDC (100 %)
<i>sad</i> AC- 100%	ACBC (100 %)	ACDB (100 %)	ACAA (100 %)	ACCC (100 %)	ACCA (100 %)	ACAB (100 %)	ACCB (100 %)	ACBB (100 %)	ACDD (100 %)	ACDC (100 %)
<i>angry</i> DA- 100%	DABC (100 %)	DADB (100 %)	DAAB (100 %)	DACC (100 %)	DACA (100 %)	DAAB (100 %)	DACB (100 %)	DABB (100 %)	DADD (100 %)	DADC (100 %)
<i>tired</i> AA- 100%	AABC (100 %)	AADB (100 %)	AAAA (100 %)	AACC (100 %)	AACA (100 %)	AAAB (100 %)	AACB (100 %)	AABB (100 %)	AADD (100 %)	AADC (100 %)
<i>excited</i> AD- 100%	ADBC (100 %)	ADDB (100 %)	ADAA (100 %)	ADCC (100 %)	ADCA (100 %)	ADAB (100 %)	ADCB (100 %)	ADBB (100 %)	ADDD (100 %)	ADDC (100 %)
<i>sick</i> AB- 100%	ABBC (100 %)	ABDB (100 %)	ABAA (100 %)	ABCC (100 %)	ABCA (100 %)	ABAB (100 %)	ABCB (100 %)	ABBB (100 %)	ABDD (100 %)	ABDC (100 %)
<i>hungry</i> CB- 100%	CBBC (100 %)	CBDB (100 %)	CBAA (100 %)	CBCC (100 %)	CBCA (100 %)	CBAB (100 %)	CBCB (100 %)	CBBB (100 %)	CBDD (100 %)	CBDC (100 %)
<i>thirsty</i> BD- 100%	BDBC (100 %)	BDDB (100 %)	BDAA (100 %)	BDCC (100 %)	BDCA (100 %)	BDAB (100 %)	BDCB (100 %)	BDBB (100 %)	BDDD (100 %)	BDDC (100 %)
<i>silly</i> DC- 100%	DCBC (100 %)	DCDB (100 %)	DCAA (100 %)	DCCC (100 %)	DCCA (100 %)	DCAB (100 %)	DCCB (100 %)	DCBB (100 %)	DCDD (100 %)	DCDC (100 %)
<i>scared</i> DD- 100%	DDBC (100 %)	DDDB (100 %)	DDAA (100 %)	DDCC (100 %)	DDCA (100 %)	DDAB (100 %)	DDCB (100 %)	DDBB (100 %)	DDDD (100 %)	DDDC (100 %)

Table 6.13: The completely regular, artificially generated language on which a 30-hidden-unit BATALI-style network was trained which, after training was completed, generated the language shown in table 6.14

Regularity 66%	<i>me</i> -C 50%	<i>we</i> -CC 30%	<i>mip</i> -A 60%	<i>you</i> -CC 70%	<i>yall</i> -C 70%	<i>yup</i> -D 60%	<i>yumi</i> -C 60%	<i>one</i> -BB 30%	<i>they</i> -DD 40%	<i>all</i> -A 60%
<i>happy</i> DB- 90%	DBb	DBdb	DBd	DBCC	DBC	DBaD	DBcb- ccbC	DBba	DB	DBA
<i>sad</i> DC- 70%	DCbc- dbcb	DCbc- dbaa	DCdd- bbaA	dbcc- ccbd	DCcd- ccbd	DCad- ddbD	DCcd- ccbb	dbba- bddd	dbdd- ddda	DCaa- aaaA
<i>angry</i> AD- 50%	ADbc- accC	ADdb- cdbe	aada- cacA	ADbc- ecca	ADcb- acca	abca- ddaD	ADcb- cacC	abbb- dddd	abdd- dabd	aaaa- cacA
<i>tired</i> AA- 90%	AAbc- bbcb	AAbc- bacb	AAAd	AACC	AAC	AAa	AAcb- cccb	AAbd	AADD	AA
<i>excited</i> AD- 90%	ADbc- cccC	ADdb- cdCC	ADda- aabA	ADbc- ccCC	ADC	ADa	AD	ADdd- acab	ADd	ADaA
<i>sick</i> AB- 90%	ABbC	ABdb- caCC	ABd	ABCC	ABC	AB	ABcb- cabC	ABBB	ABAd- ddda	ABab
<i>hungry</i> C- 90%	CbcC	Ccdc- cdCC	CA	Ccc- bcbc	CcC	CD	CC	Cabd- dadd	Caad- ddDD	C
<i>thirsty</i> BD- 40%	bcab- bbbc	bcab- abab	bbda- aaaA	BDCC	BDC	B	BDcb- cbcC	bbbd- bbBB	bb	BDA
<i>silly</i> DC- 90%	DCb	DCbc- dbab	DCd	DCCC	DCC	DCaD	DCcb- cbca	DCBB	DCDD	DC
<i>scared</i> DD- 90%	DDb	DDbc- ccdc	DDA	DDbc- ccCC	DDca	DD	DDC	DDbd	DDaDD	DDac

Table 6.14: Language of a BATALI style network with 30 hidden units after training on an artificial language of maximal regularity (see table 6.13, from repetition 0 of run 0 of batch buzzard learn real batali hidden 30 11/09/1999 12:37:14)

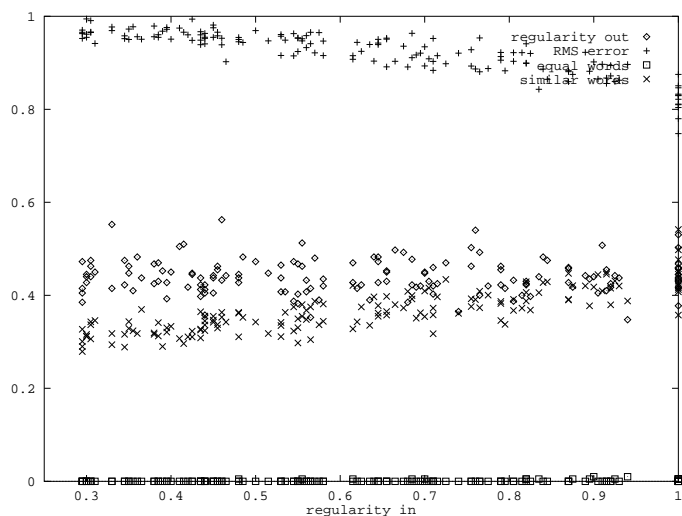


Figure 6.8: Learnability as shown in figure 6.7 but for a network with five hidden layer units

Another conclusion which could be drawn from this experiment is that apparently the regularity measure I developed is suboptimal. Indeed it seems that it would have been more appropriate to find regular patterns at fixed positions of the strings uttered by a network, instead of considering pre- and postfixes defined relative to the length of each word.

Figure 6.8 shows the results of a learnability experiment on a network of hidden layer size 5. Clearly, this network does not have enough capacity to learn the training language appropriately. The error is generally higher (for regular languages) than for a network of 30 hidden units, and the difference in performance between regular and irregular languages is not significant.

6.4.6 Relation between network capacity and learnability

So far it has been shown with a couple of examples that networks of insufficient capacity (too small a hidden layer) cannot appropriately learn languages

regularity in	RMS error			similar words		
	low	high	ratio	low	high	ratio
5 hiddens	0.96	0.85	0.88	0.32	0.43	0.74
15 hiddens	0.95	0.67	0.70	0.36	0.57	0.63
30 hiddens	0.94	0.56	0.59	0.39	0.66	0.58
50 hiddens	0.91	0.50	0.54	0.39	0.67	0.59
100 hiddens	0.86	0.46	0.54	0.39	0.67	0.58

Table 6.15: The relation between hidden layer size and learnability of languages of low and high compositional regularity. For each of the hidden layer sizes the average RMS error and similar words proportion are given for input languages of low and high regularity ($[0.2 \dots 0.3]$ and $[0.9 \dots 1.0]$, respectively) together with the ratio between both values.

of any regularity. For those of presumably ideal capacity it has been shown that they do better on more regular than on irregular languages, ignoring for a moment that the definition of regularity used here is unnatural to the networks. If there exists a relationship of general validity between the networks' capacity and the "complexity" of languages they can learn, networks with even larger hidden layers should learn idiosyncratic languages almost as well as regular ones, and thus should exhibit less correlation between training language complexity and training error / language reproducibility.

The experiments conducted do not support this hypothesis. Table 6.15 shows for different hidden layer sizes the average RMS error and similar words measure for input languages of low and high compositionality ($[0.2 \dots 0.3]$ and $[0.9 \dots 1.0]$, respectively). The ratios given in the table are a measure of the qualitative difference between learnability of idiosyncratic and compositional languages. For hidden layers which are significantly larger than the presumably optimal size of 30 the, ratios do not increase or decrease respectively, which means that even larger networks can not learn completely random languages properly.

It could well be that the networks examined here were still too small to show the expected behaviour, or that the number of training passes was still

too small, which should be checked. For now I can only conclude that this kind of network can not learn arbitrarily complex languages, and that there exists no clear relationship between the hidden layer size and the learnability of languages of different compositional regularity.

Chapter 7

Conclusion

In my opinion, the results presented in chapter 6 still leave much room for interpretation, but there seems to be justification for the following summary:

- Basically, BATALI's results can be reproduced, but only to a limited extent. It remains unclear how he could get the particular results he presented in [BATALI 98], which, compared to those of this replication, are more regular. Because languages of the population sometimes look more regular in parts before having converged onto short forms, BATALI could possibly have presented a language from an earlier stage of the simulation.
- The formation of the surface forms developed by the networks of the simulation's population seems to be dominated by information gain with respect to the meaning space. Pressure towards minimal representations is the predominant force, not regularisation.
- The results are not influenced by the population size, and to a large extent are independent of the production cut-off length.
- A clear dependency could be shown between the networks' capacity in terms of their hidden layer size and the maximum length of sequences

which can be processed.

- Only a marginal correlation between the networks' capacity and their regularisation capabilities in terms of intuitively defined compositionality could be proven.
- “Languages” which “naturally” emerge from a population of networks can be transmitted successfully over hundreds of generations almost without change.
- Though compositional regularity of a language does influence its learnability by networks, it is not the most important factor. Even ideally regular languages cannot be learned as well as languages which emerge from the process of repeated production and acquisition.
- Implementation of a semantic bottleneck in a strictly generational variation of the model leads to imperfections instead of increased regularity.

On the basis of these results I would argue that the simulation described in [BATALI 98] is not particularly well suited to model the emergence of compositionality. It does, however, show fundamental mechanisms of agreement between agents on linguistic forms, leading to almost optimal representations for the predefined meanings.

The simple meaning space does not make necessary the development of abstract, structured representations of it. The agents of the simulations find an almost optimal encoding for its elements (the ten bits of the meaning space), instead of reducing it to its two major components and then finding representations for them. The latter process should be advantageous for more complex, possibly infinite meaning spaces, but it seems not to be for the one used here.

7.1 Perspectives

Irrespective of these results I believe that connectionist methods are very attractive for modelling language evolution. As neurobiological research proceeds, increasingly accurate models of the brain will be developed, and it will remain an interesting challenge to model linguistic processes using these techniques. In particular, the advances in research into language evolution using symbolic representations (see 2.6.2 on page 20) raise the question of whether similar results are achievable in the non-symbolic domain.

Possibly the most significant restraining factor is that neural network implementations in software for serial machines scale at least polynomial in time with respect to the number of neurons, thus limiting the complexity of possible applications. Sophisticated training mechanisms can significantly reduce the effort needed, but only parallel hardware will make highly complex experiments possible.

As a result of the work I have presented here I would like to point out some aspects which I believe should be considered for future work in this area:

- **Large/infinite meaning space**

Interesting linguistic phenomena such as compositionality or recursively defined production rules are presumably only advantageous for representation of significantly large and complex meaning sets. Therefore I would consider them a necessary precondition for any model of language evolution.

The agent model should ideally include some kind of classification system which would reduce the information of the meaning space to its most significant components.

- **Production mechanism**

The production method used in BATALI's simulation, which basically

iterates through all possible characters for all positions of words to be uttered, seems to be not very well motivated and is also computationally unattractive.

It seems much more sensible to use a neural network model which naturally provides bidirectional mappings. One such model is the *Helmholtz machine* (see [DAYAN *et al.* 95]) which uses stochastic units. It can be trained using the *wake-sleep* algorithm described in [HINTON *et al.* 95a], for which a “recurrent” version is also available as presented in [HINTON *et al.* 95b]. Though I cannot give a qualified judgement on the eligibility of the *Helmholtz machine through time*, it seems very attractive on first sight for language evolutionary simulations along the lines of the work presented here.

- **Neurobiological accuracy**

Many of the standard neural network models derived from the perceptron no longer harmonise with insights gained by recent neurobiological research. Other models are much better motivated in this sense. For example, Pulsed Neural Networks (see [MAASS & BISHOP 98], [SCHMANSKY 99]) also allow information to be encoded by the temporal relation of activations (spikes) received by a neuron. On the other hand, they are much more computationally expensive than standard models on serial machines, which could be compensated for by using specialised hardware currently under development.

I think the work by BATALI should be seen as a first interesting step, and the conclusions drawn here should not be taken as evidence that connectionist methods are not feasible as models for language evolution.

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Appendix A

Why and when Elman training does work

The elman network is a simple recurrent network of the same structure as a multi layer feed forward net, but with a fully interconnected hidden layer. For an introduction to the Elman network, see section 4.3 on page 46.

Elman used sigmoid units for all layers, but other activation functions could be used, at least for the output layer, without causing any trouble. For the hidden layer it is important that the activation functions are at least bounded, because otherwise the activations could easily diverge over time, which would make the network both useless and harder to train.

A.1 Training the Elman network

According to Elman his network should be trained using standard back propagation with a fixed learning rate η for each time step, treating context units as ordinary inputs and thus ignoring recurrency.

This means that the back propagation algorithm is to be used to calculate $\frac{dE}{d\mathbf{w}}$ and updates of the weights are to be done in the direction of steepest descent of the error surface, using the standard update-rule $\mathbf{w} \leftarrow -\eta \frac{dE}{d\mathbf{w}}$. In

his paper ([ELMAN 90]) Elman does not give any more detail about training¹, and it is quite obvious that this kind of training is an approximation.

As the activations of the hidden layer units depend on all their previous activations, to train the network correctly we shall in theory not ignore them. But this is just what Elman does and in the next subsection I will try to give an argument why indeed Elman training still is a good approximation of real recurrent back propagation (I am partly repeating here [ROSS 97], pages 6:5–6:7 and [HERTZ *et al.* 91], section 7.2, pages 172–176).

A.1.1 Why and when Elman training does work

Here is a more detailed and hopefully more descriptive version of the calculation of the derivatives of the error by each weight for recurrent back propagation.

First of all we note that for arbitrary recurrent nets every unit has to have an input x_i (which may be zero for non-input units), it can have connections to other units and it can be an output unit, all at the same time. Thus the weighted sum s_i which is input to the activation function is extended by the input x_i :

$$s_i = \sum_j w_{ij} a_j + x_i \tag{A.1}$$

If we assume an equal delay within all neurons and synchronous updates, the activation at time $t + \tau$ will result from activations of other units at time t :

$$a_i^{t+\tau} = g(s_i^t) = g\left(\sum_j w_{ij}^t a_j^t + x_i^t\right) \tag{A.2}$$

¹which may be mainly because at the time of publication of his paper, back propagation had just been invented

which means that the change of activation for that time step is just

$$\tau \frac{da_i}{dt} = g(s_i^t) - a_i^t \quad (\text{A.3})$$

We would like the net to converge to a stable state, so it has to have a stable attractor, such that the activation change and thus the above derivative becomes zero. So for one time t , the new and old activations will be equal.

$$\exists t : a_i^t = g(s_i^t) \quad (\text{A.4})$$

Not very exciting so far. But what will be the $\frac{\partial E}{\partial w_{ij}}$ s which we need to calculate for any kind of standard weight update? First of all, any unit can (in the general case) be an output unit, so we define the error of any unit k as the usual difference between its target and its activation if it is an output unit, and constantly zero if it is not:

$$E_k = \begin{cases} d_k - a_k & : \text{ } k \text{ is an output unit} \\ 0 & : \text{ otherwise} \end{cases} \quad (\text{A.5})$$

Then the sum of squares error is just:

$$\begin{aligned} E &= \frac{1}{2} \sum_k E_k^2 \\ &= \frac{1}{2} \sum_o (d_o - a_o)^2 \quad \text{for all outputs } o \end{aligned} \quad (\text{A.6})$$

As for feed-forward nets, the partial derivative of the error by one specific weight for every output unit depends on the error of that unit and the contribution of the weight we are looking at to the activation of each of the output units:

$$\frac{\partial E^t}{\partial w_{ij}^t} = \sum_k \frac{\partial E^t}{\partial a_k^t} \frac{\partial a_k^t}{\partial w_{ij}^t} \quad (\text{A.7})$$

$$= \sum_k -E_k^t \frac{\partial a_k^t}{\partial w_{ij}^t} \quad (\text{A.8})$$

The partial derivative of the activation function by application of the chain rule depends on its derivative of the sum s_k and all activations “feeding into” s_k at time $t - \tau$. If $w_{ij} = w_{km}$ (the weight we differentiate by), then one factor of the derivative is just a_j . But still w_{ij} could further contribute to the error through recurrent connections, so we sum up over all $w_{km} \frac{\partial a_m}{\partial w_{ij}}$, including $m = j$:

$$\begin{aligned} \frac{\partial a_k^t}{\partial w_{ij}^t} &= \frac{\partial a_k^t}{\partial s_k^{t-\tau}} \frac{\partial s_k^{t-\tau}}{\partial w_{ij}} \\ &= g'(s_k^{t-\tau}) \delta_{ki} a_j^{t-\tau} + \text{if this is just the weight we are looking for} \\ &\quad g'(s_k^{t-\tau}) \sum_m w_{km} \frac{\partial a_m^{t-\tau}}{\partial w_{ij}} \\ &= g'(s_k^{t-\tau}) \left[\delta_{ki} a_j^{t-\tau} + \sum_m w_{km} \frac{\partial a_m^{t-\tau}}{\partial w_{ij}} \right] \end{aligned} \quad (\text{A.9})$$

What this means is exactly what should be obvious from the characteristics of recurrent nets. The current error derivatives depend on all previous activations which contributed to them. One could now continue to show how the derivatives can be calculated by an error-propagation network.

A.1.2 The Elman approximation

But what we are interested in here is how much a simplification it is to “cut off” the calculations after one step as (implicitly) done by Elman. Also, Elman neglects the fact that naturally there should be a per-unit delay, not

just delays of the context units.

Anyway, if we drop all time dependency of all units and connections except the hidden layer’s connections to itself via the context units, and ignore the fact that when training the weights also change over time (which we also ignored in all previous equations), we get the correct derivatives of the error by the recurrent weights (those from the hidden units to the context units) as follows:

We “unroll” A.9 for the output layer (o), the hidden layer (h) and the context units (c) to get the partial derivatives for a context–unit weight w_{ij} (from hidden unit i to context unit j , indexing context units like the corresponding hidden units such that context unit activation $c_j^t = a_j^{t-\tau}$):

Output layer:

$$\frac{\partial E}{\partial w_{ij}} = \sum_o (d_o^t - a_o^t) \frac{\partial a_o^t}{\partial w_{ij}} \quad (\text{A.10})$$

Hidden layer:

$$\frac{\partial a_o^t}{\partial w_{ij}} = g'(s_o^t) \sum_h w_{oh} \frac{\partial a_h^t}{\partial w_{ij}} \quad (\text{A.11})$$

And finally:

$$\frac{\partial a_h^t}{\partial w_{ij}} = g'(s_h^t) \left[c_j^t = a_j^{t-\tau} + \sum_c w_{hc} \frac{\partial a_c^{t-\tau}}{\partial w_{ij}} \right] \quad (\text{A.12})$$

The rightmost sum in A.12 is the one which we drop when doing Elman training, because we do not consider any contributions of any weight to the error which result from previous activations of the context (=hidden) units. Now let us unroll the recurrent connections in time:

$$\frac{\partial a_h^t}{\partial w_{ij}} = g'(s_h^t) a_j^{t-\tau} + \sum_k w_{hk} g'(s_h^t) \frac{\partial a_k^{t-\tau}}{\partial w_{ij}} \quad (\text{A.13})$$

$$\begin{aligned} &= g'(s_h^t) a_j^{t-\tau} + \quad (\text{A.14}) \\ &g'(s_h^t) \sum_k w_{hk} g'(s_k^{t-\tau}) a_j^{t-2\tau} + \\ &g'(s_h^t) \sum_k \sum_l w_{hk} w_{kl} g'(s_k^{t-\tau}) g'(s_l^{t-2\tau}) a_j^{t-3\tau} + \dots + \\ &g'(s_h^t) \sum_k \sum_l \dots \sum_z w_{hk} w_{kl} \dots w_{yz} g'(s_k^{t-\tau}) g'(s_l^{t-2\tau}) \dots g'(s_z^\tau) a_j^0 \end{aligned}$$

If we take n_{hid} to be the number of hidden units and assume averages \bar{w} for all context unit weights, \bar{a} for all context unit activities and \bar{s} for their sums, we can simplify:

$$\frac{\partial a_h^t}{\partial w_{ij}} = \bar{a} g'(s_h^t) \sum_{\alpha=0}^{t/\tau} n_{hid}^\alpha \bar{w}^\alpha g'(\bar{s})^\alpha \quad (\text{A.15})$$

which means that if the sum converges, the proportional error of Elman training is E_{Elman} :

$$c = n_{hid} \bar{w} g'(\bar{s}) \quad (\text{A.16})$$

$$\sum_{\alpha=0}^{t/\tau} c^\alpha = \frac{1}{1-c} \quad (\text{A.17})$$

$$a_j^{t-\tau} \approx \bar{a} \quad (\text{A.18})$$

$$\begin{aligned} E_{Elman} &= 1 - \left(\frac{g'(s_h^t) a_j^{t-\tau}}{g'(s_h^t) \bar{a} \sum_{\alpha=0}^t c^\alpha} \right) \\ &\approx c \\ &\approx n_{hid} \bar{w} g'(\bar{s}) \end{aligned} \quad (\text{A.19})$$

Results so far:

- only for $|c| < 1$ the error for this type of recurrent net does at all converge,
- the smaller $|c|$, the better the Elman approximation and
- if we could approximate c without actually doing recurrent backprop, we could improve the accuracy of Elman training.

First of all we can simplify c , if we decompose the sum \bar{s} into its parts:

$$c = n_{hid} \bar{w} g'(\bar{s})$$

$$g'(\bar{s}) = g'\left(\sum_i w_{mi} a_i\right) = g'(n_{hid} \bar{w} \bar{a}) \quad (\text{A.20})$$

$$x = n_{hid} \bar{w}$$

$$c(x, a) = x g'(\bar{a} x) \quad (\text{A.21})$$

Here is $c(x, a)$ for the sigmoid activation function²:

$$\begin{aligned} c(x, a)_{sigmoid} &= x Dg(ax) (1 - g(ax)) \\ &= x D \frac{1}{1 + e^{-Dax}} \left(1 - \frac{1}{1 + e^{-Dax}} \right) \end{aligned} \quad (\text{A.22})$$

²Thanks to BRUCE EDDY for help with the following equations

$$\begin{aligned}
p &= Dx \\
c(x, a)_{sigmoid} &= p \frac{1}{1 + e^{-pa}} - p \frac{1}{(1 + e^{-pa})^2} \\
&= \frac{pe^{-pa}}{(1 + e^{-pa})^2} \\
&= \frac{pe^{-pa}}{1 + 2e^{-pa} + e^{-2pa}}
\end{aligned} \tag{A.23}$$

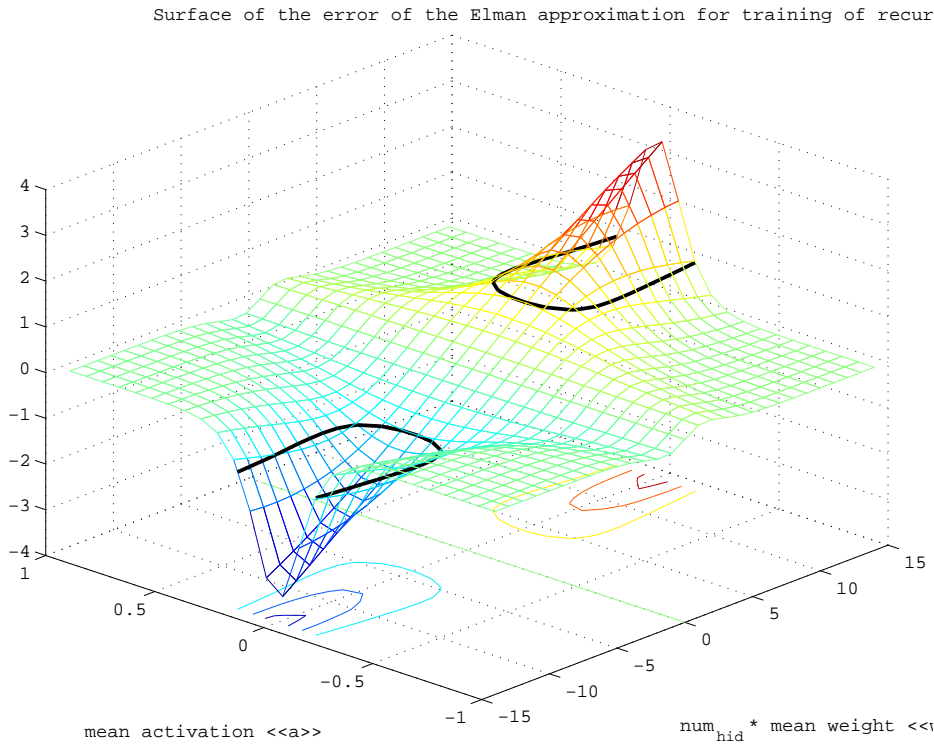


Figure A.1: A 3D plot of the error of Elman training compared with real recurrent back propagation, dependent on \bar{a} , the mean activation, and $x = n_{hid}\bar{w}$, the mean weight of the hidden layer recurrent connections times the size of the hidden layer. The contour line for $|c| = 1$ is marked bold — for all values of \bar{a} and x “within” the contour lines in general Elman training will not find good weight updates

Now that we have an explicit expression for c , we can also give a convergence condition for $\sum_{\alpha=0}^t c^\alpha$:

$$\begin{aligned}
c(x, a)_{sigmoid} &\leq 1 \\
|p e^{-pa}| &\leq |1 + 2e^{-pa} + e^{-2pa}| \\
|p| &\leq |e^{pa} + e^{-pa} + 2| \\
|(p-2)e^{pa}| &\leq |e^{2pa} + 1| \\
0 &\leq |e^{2pa} - (p-2)e^{pa} + 1| \\
\text{set } z &= e^{pa} \\
0 &\leq |z^2 - (p-2)z + 1| \\
&\quad \text{(solving as quadratic)} \\
\left| \frac{1}{2}p - 1 \pm \sqrt{p^2 - 4p} \right| &\leq |z| = |e^{pa}| \\
\left| \frac{\ln(\frac{1}{2}p - 1 \pm \sqrt{p^2 - 4p})}{p} \right| &\leq |a| \tag{A.24}
\end{aligned}$$

This “convergence radius” for $c(x, a)$ is given as the bold contour line in figure A.1.

Appendix B

Information content of codes with implicit stop character

The code evolving from the simulations described in chapters 3 and 6 differs from those commonly studied by information theory by having an implicit stop-symbol¹. The production method (see 3.4.1 on page 32) stops producing characters for a given meaning as soon as the sequence produced so far can be unambiguously associated by the speaker with the meaning. So every substring which can be constructed from the alphabet available can be used to express a meaning. For example, CC may code for (*mip thirsty*) while CCA stands for (*me thirsty*). Though the simulations described here do not actually model the real process of communicating a meaning using the strings evolved, this process would consist of sending the string to code for a meaning plus an additional *stop symbol*.

It is intuitively clear that this additional symbol increases the information

¹Though I hope that the formulae derived here are correct, I have to point out that I could not find any literature about the special case at hand in the time given and therefore the ideas presented are for the most part my own. Because of the limited time for this project and the minor importance of information content for the general discussion in chapter 6, I tried not to spend too much time on these issues, and thus expect at least glitches if not serious mistakes in this discussion. Also I would not consider it to be formally adequate, and indeed it should be redone properly at a later time.

content of the code if compared with one using the same alphabet but no stop symbol. I will give here an account on how to measure the information content of words from a language using such a stop symbol.

B.1 Alphabets, words and the communication channel

Any code (or “language” here) is defined over a set of elementary symbols S (or characters) from an alphabet \mathcal{A} . Words are constructed by concatenation of symbols.

Information theory views the process of communicating a “meaning” as continued transmission of symbols over a channel from a sender to a receiver. Both the sender and the receiver know the code which defines the relation between words (or sequences of elementary symbols) and the meanings to be communicated.

B.2 Efficiency

A basic criterion for the quality of a code used in such a system is its efficiency to encode for the meanings to be communicated using the least number of transmitted symbols. This measure can easily be reduced to how much information on average is being encoded by each of the symbols of the words, or how much information the receiver gains when receiving one symbol. If this information gain is maximised for each character sent, the average length of sequences needed to communicate elements of the meaning space will be minimised, thus the code will become the optimal.

B.2.1 Entropy: Average information per transmitted symbol

A suitable measure for the average information content of each emitted symbol C is the entropy of the distribution of symbols from the alphabet at each position of a sequence (see for example [USHER 84] chapters 1–2 and [BISHOP 95], pages 240–245):

$$H(C) = - \sum_{s \in \mathcal{A}} P(s) \log_2 P(s) \quad [\text{bits}] \quad (\text{B.1})$$

If all symbols from the alphabet are equally probable to be emitted such that $\forall i, j, s_{i,j} \in \mathcal{A} \rightarrow P(s_i) = P(s_j) = \frac{1}{|\mathcal{A}|}$, the entropy becomes maximal:

$$\sum_{s \in \mathcal{A}} P(s) = 1 \quad (\text{B.2})$$

$$\begin{aligned} H(C) &= -\log_2 P(s \in \mathcal{A}) \\ &= -\log_2 \frac{1}{|\mathcal{A}|} \\ &= \log_2 |\mathcal{A}| \end{aligned} \quad (\text{B.3})$$

Conversely this means that the probabilities of symbols of an optimal code will be equal.

B.3 Information content of words

Let a word w of length l be constructed by concatenation (denoted as \circ) of l characters, each a symbol from the alphabet $c \in |\mathcal{A}|$:

$$w = c_1 \circ c_2 \circ \cdots \circ c_l \quad (\text{B.4})$$

then assuming that the probabilities of symbols of a word are independ-

ent, the probability of a word of length l is

$$P(w) = \prod_{i=1}^l P(c_i) \quad (\text{B.5})$$

Under this assumption we can add up the average information of symbols at each of any word's positions to get the average information content of words:

$$H(W) = \sum_{i=1}^l H(C_i) \approx l \times H(C) \quad (\text{B.6})$$

The equations to show this for the general case are quite messy, so I will illustrate this equality for the special case of words with two symbols. The derivation makes use of the fact that probabilities of possible outcomes of an event add up to one: $\sum P(x) = 1$

$$\begin{aligned} H(W, \text{length}(W) = 2) &= - \sum_{c_1 \circ c_2 \in W} P(c_1)P(c_2) \log_2 [P(c_1)P(c_2)] \\ &= - \sum_{c_1 \circ c_2 \in W} P(c_1)P(c_2) \log_2 P(c_1) + P(c_1)P(c_2) \log_2 P(c_2) \\ &= - \sum_{s_1 \in \mathcal{A}} \left[\sum_{s_2 \in \mathcal{A}} P(s_1)P(s_2) \log_2 P(s_1) + P(s_1)P(s_2) \log_2 P(s_2) \right] \\ &= - \sum_{s_1 \in \mathcal{A}} \left[P(s_1) \log_2 P(s_1) \left(\sum_{s_2 \in \mathcal{A}} P(s_2) \right) + P(s_1) \sum_{s_2 \in \mathcal{A}} P(s_2) \log_2 P(s_2) \right] \\ &= - \sum_{s_1 \in \mathcal{A}} P(s_1) \log_2 P(s_1) - \sum_{s_1 \in \mathcal{A}} \left(P(s_1) \sum_{s_2 \in \mathcal{A}} P(s_2) \log_2 P(s_2) \right) \\ &= - \sum_{s_1 \in \mathcal{A}} P(s_1) \log_2 P(s_1) - \sum_{s_2 \in \mathcal{A}} P(s_2) \log_2 P(s_2) \\ &= H(C_1) + H(C_2) \end{aligned}$$

B.3.1 Average code word length of an optimal code

Given that a code has to encode for given number $N(W)$ of expressions, we can give the average code word length l of an optimal code as

$$N(W) = 2^{lH(C)} = (2^{\log_2|\mathcal{A}|})^l = |\mathcal{A}|^l \quad (\text{B.7})$$

$$l = \log_{|\mathcal{A}|}N(W) \quad (\text{B.8})$$

Thus the average code word length is another measure for efficiency of code.

B.4 Information content of words with implicit stop symbol

For words with an implicit stop symbol the above equations can not be applied directly as the probability of the stop symbol is definitely dependent on the previous characters in that it must appear exactly once and at the end of a word. To get the information content under these conditions, one could calculate probabilities of characters of a word conditioned on all previous characters, for example for words of length two $P(w) = P(c_1, c_2) = P(c_1)P(c_2|c_1)$.

I will follow here a simpler approach, based on the observation that the number of meanings N which can be expressed by words W^S of an optimal code up to length l over an alphabet of size $|\mathcal{A}|$ using an implicit stop symbol is the sum of the meanings which can be expressed by every possible substring:

$$N(W^S) = \sum_{i=1}^l |\mathcal{A}|^i \quad (\text{B.9})$$

Using equation B.3 solved for $|\mathcal{A}|$ and equation B.6 for the information

content of words without a stop symbol we get for the general case

$$\begin{aligned}
 N(W^S) &= \sum_{i=1}^l 2^{iH(C_i)} \\
 &= \sum_{i=1}^l 2^{\sum_{j=1}^i H(C_{i,j})} \\
 &= \sum_{i=1}^l 2^{H(W_i)} \tag{B.10}
 \end{aligned}$$

$$H(W^S) = \log_2 N(W^S) = \log_2 \left(\sum_{i=1}^l 2^{H(W_i)} \right) \tag{B.11}$$

Note that the word entropies $H(W_i)$ are to be based on character entropies $H(c_{i,j})$ calculated for the j^{th} position of all words of length i .

B.5 Efficiency of a code with implicit stop symbol

The efficiency of a code with implicit stop symbol can be measured as usual using the entropy of characters, but all possible partial sequences over the given alphabet have to be respected. Given that an optimal code should also be of minimal average code word length, the number of expressible meaning $N(W^S)$ should not be greater than the number of meanings which are actually to be encoded. If it is, the code is redundant.

Equation B.9 gives us the maximum number of meanings which can be encoded by a code with implicit stop symbol up to a length l . Unfortunately it can not be solved directly for l to give us the minimal length for the longest word an optimal code needs to encode for a number of meanings. What helps is the following equality:

$$b^{l+1} = \left[(b-1) \sum_{i=0}^l b^i \right] + 1 \quad (\text{B.12})$$

$$\frac{b^{l+1} - 1}{b - 1} - 1 = \sum_{i=1}^l b^i \quad (\text{B.13})$$

The validity of B.12 can be seen easily, just consider an overrun of some digit in a number system, for example $999 + 1 = [(10 - 1) \sum_{i=0}^3 10^i] + 1 = 1000 = 10^4$.

We can now solve for l :

$$N \geq \frac{|\mathcal{A}|^{l+1} - 1}{|\mathcal{A}| - 1} - 1 \quad (\text{B.14})$$

$$l = \left\lceil \log_{|\mathcal{A}|} [N(|\mathcal{A}| - 1) + 2] - 1 \right\rceil \quad (\text{B.15})$$

Note that the length l is *not* an average length as in B.3.1, but the minimal length of the longest codeword needed.

Appendix C

Details of the speed comparison in subsection 5.3.1

The following configuration was used for **bp** for the the comparison described in 5.3.1:

```
m 5 5 1      * make net

** Algorithmic settings
a a s      * sigmoid units
a d c      * correct derivatives
a u p      * periodic update method. (BATCH)

ci 2        * clear and initialise weights in -2..2

rt {
0 0 0 0 0 0
0 0 0 0 1 1
0 0 0 1 0 1
0 0 0 1 1 0
0 0 1 0 0 1
0 0 1 0 1 0
0 0 1 1 0 0
0 0 1 1 1 1
0 1 0 0 0 1
0 1 0 0 1 0
0 1 0 1 0 0
```

```

0 1 0 1 1 1
0 1 1 0 0 0
0 1 1 0 1 1
0 1 1 1 0 1
0 1 1 1 1 0
1 0 0 0 0 1
1 0 0 0 1 0
1 0 0 1 0 0
1 0 0 1 1 1
1 0 1 0 0 0
1 0 1 0 1 1
1 0 1 1 0 1
1 0 1 1 1 0
1 1 0 0 0 0
1 1 0 0 1 1
1 1 0 1 0 1
1 1 0 1 1 0
1 1 1 0 0 1
1 1 1 0 1 0
1 1 1 1 0 0
1 1 1 1 1 1}
a 0          * no momentum
e 0.000001   * learning rate

t 0.000001   * error limit
r 100000 10000 * 100.000 cycles - write stats every 10.000

```

The NILE code used is:

```

(defun tr-sd-5-5-1-sigm (net
                        train-input train-output
                        error-lim
                        eta
                        &key (max-cycles 0)
                              (momentum (coerce 0.0d0 'type-weight))
                              (write-error-every 1)
                              (write-net-every 0)
                              write-final)
  (declare
    (type type-weight momentum eta)
    (type type-act error-lim)
    (fixnum max-cycles write-error-every write-net-every)
    (optimize (speed 3) (space 2) (safety 0) (debug 0)

```

```

                (compilation-speed 0))
    )
(trainer (netspec 5 5 1) net
  train-input
  train-output
  :batch t

  :method :sd
  :sd-opts (:eta eta
            :momentum momentum)

  :max-cycles max-cycles
  :error-lim error-lim

  :cycle-opts
  (:write-error-every write-error-every
   :write-net-every write-net-every)
  :write-final write-final))

;;; definition of tr-cg-5-5-1-sigm omitted - not used
;;; for speed comparison

(defun demo-par5 (&key (method :sd)
                    (eta 0.1d0)
                    (alpha 0.9d0)
                    random-state
                    (max-cycles 100)
                    (error-lim 0.01d0)
                    (write-error-every 1)
                    (write-net-every 0)
                    (write-final t)
                    (iloc-eta 0.15d0)
                    output-to-file
                    (ext-detect-locmin 0.005d0)
                    (ext-detect-locmin-kick 4.0)
                    (weight-deviation 2.0)
                    calc-test-error)
  (declare
    (single-float weight-deviation)
    (type type-act error-lim)
  )
  (let* ((net
         (my-tenuring (mk-net (netspec 5 5 1)

```

```

:weight-deviation weight-deviation
:runtime-weights t
:runtime-weights-state random-state)))
(train-input (my-tenuring
  (patterns 5
    (0.0 0.0 0.0 0.0 0.0)
    (0.0 0.0 0.0 0.0 1.0)
    (0.0 0.0 0.0 1.0 0.0)
    (0.0 0.0 0.0 1.0 1.0)
    (0.0 0.0 1.0 0.0 0.0)
    (0.0 0.0 1.0 0.0 1.0)
    (0.0 0.0 1.0 1.0 0.0)
    (0.0 0.0 1.0 1.0 1.0)
    (0.0 1.0 0.0 0.0 0.0)
    (0.0 1.0 0.0 0.0 1.0)
    (0.0 1.0 0.0 1.0 0.0)
    (0.0 1.0 0.0 1.0 1.0)
    (0.0 1.0 1.0 0.0 0.0)
    (0.0 1.0 1.0 0.0 1.0)
    (0.0 1.0 1.0 1.0 0.0)
    (0.0 1.0 1.0 1.0 1.0)
    (1.0 0.0 0.0 0.0 0.0)
    (1.0 0.0 0.0 0.0 1.0)
    (1.0 0.0 0.0 1.0 0.0)
    (1.0 0.0 0.0 1.0 1.0)
    (1.0 0.0 1.0 0.0 0.0)
    (1.0 0.0 1.0 0.0 1.0)
    (1.0 0.0 1.0 1.0 0.0)
    (1.0 0.0 1.0 1.0 1.0)
    (1.0 1.0 0.0 0.0 0.0)
    (1.0 1.0 0.0 0.0 1.0)
    (1.0 1.0 0.0 1.0 0.0)
    (1.0 1.0 0.0 1.0 1.0)
    (1.0 1.0 1.0 0.0 0.0)
    (1.0 1.0 1.0 0.0 1.0)
    (1.0 1.0 1.0 1.0 0.0)
    (1.0 1.0 1.0 1.0 1.0))))))
(train-output (my-tenuring
  (patterns 1
    (0.0)
    (1.0)
    (1.0)
    (0.0)

```



```

(1.0)
(0.0)
(0.0)
(1.0)
(1.0)
(0.0)
(0.0)
(1.0)
(0.0)
(1.0)
(1.0)
(0.0)
(1.0)
(0.0)
(0.0)
(1.0)
(0.0)
(1.0)
(1.0)
(0.0)
(0.0)
(1.0)
(1.0)
(0.0)
(1.0)
(0.0)
(0.0)
(1.0)))
(test-input train-input)
(test-output train-output)
(test-error (coerce 0.0d0 'type-act)))
(declare (type type-act test-error))

(ecase method
  (:sd
    (tr-sd-5-5-1-sigm net
      train-input train-output
      (coerce error-lim 'type-act)
      (coerce eta 'type-weight)
      :max-cycles max-cycles
      :momentum (coerce alpha 'type-weight)
      :write-error-every write-error-every
      :write-net-every write-net-every

```

```

                                :write-final write-final))
(:cg
  ;; (tr-cg-5-5-1-sigm net
  ;;           train-input train-output
  ;;           (coerce error-lim 'type-act)
  ;;           :max-cycles max-cycles
  ;;           :interval-location-eta (coerce iloc-eta 'type-weight)
  ;;           :gss-tol 0.000001d0
  ;;           :write-error-every write-error-every
  ;;           :write-net-every write-net-every
  ;;           :write-final write-final
  ;;           :ext-detect-locmin-kick
  ;;           (coerce ext-detect-locmin-kick 'single-float)
  ;;           :ext-detect-locmin (coerce ext-detect-locmin 'type-act)
  ;;           )
  ))
;; now get test error
(if calc-test-error
  (let ((output-layer-act (layer-act-vec (svref net 2)))
        (filehandle (if output-to-file
                          (open "output.dat"
                                :direction :output
                                :if-exists :supersede
                                :if-does-not-exist :create)
                          t)))
    (setq test-error
          (all-pattern-error (netspec 5 5 1) net
                             test-input test-output
                             (array-dimension test-input 0)
                             :write-output-to
                             filehandle))
      (format t "~%Test-error: ~a~%" test-error)
      (if (and filehandle
                (not (eq filehandle 't)))
          (close filehandle))
          test-error))))

```

The test function was invoked as:

```

(time (nile_demos:demo-par5 :eta 0.000001d0
                             :alpha 0.0d0
                             :max-cycles 100000
                             :write-error-every 10000

```

```
:write-final nil))
```


Appendix D

Persistence of a language over time in a generational model

Given here are the languages of the speaker agent at three subsequent population dumps of the generational run labelled `bi-zarr gen bot 100 13/08/1999 20:35:24`. Note that the language is very stable, considering that shown here is a span over 90 generations and that imperfections of training may lead to the production of some words being cut off later, in which case words from different generations mostly still have a common “stem”. Also comparison of these languages and the one from round 510, given in table 6.11 on page 84, shows that many words do not even change over hundreds of generations.

Generation 300

Regularity 49%	<i>me</i> -C 50%	<i>we</i> -C 40%	<i>mip</i> -B 40%	<i>you</i> -C 70%	<i>yall</i> -A 40%	<i>yup</i> -B 40%	<i>yumi</i> -A 90%	<i>one</i> -C 50%	<i>they</i> -B 40%	<i>all</i> -B 40%
<i>happy</i> BC- 50%	ddaC	dd	ddB	BCcC	BCc	BC	ddaaA	BCd	BCdd	BCa
<i>sad</i> DA- 50%	DAd	DAa	dba	DAC	DAcc	bcbbacbc	DA	dbd	db	DAB
<i>angry</i> BA- 70%	ddd	ddda	BAB	BAC	BAcA	BA	BAA	BA d	BA dB	BA bdabad
<i>tired</i> CB- 30%	ccd	ccdaddC	CBdd	adda	adb	cddB	cddA	CBdC	CBd	cdd
<i>excited</i> BB- 40%	ddC	ddcb	BBB	bdC	bd	BBa	bdb	BBC	BB	BBabcadc
<i>sick</i> CB- 30%	ccb	ccbcbC	CBba	cabC	cab	cdbB	cdbA	CBbC	CBB	cdB
<i>hungry</i> CB- 30%	ccC	cccccdC	CBca	cad	ca	cacdbe dd	caA	CBcC	CBc	cdc
<i>thirsty</i> CB- 30%	cca	ccaa	CBaa	ada	aaA	aba	cdaaA	CBaC	CBa	cda
<i>silly</i> DC- 60%	DCC	DCcdccab	DC	aaC	aa	aaB	DCA	DCd	DCdcdcbc	DCB
<i>scared</i> A- 90%	AcC	AC	AcB	AdC	A	AB	AcA	Abd	Abc	AbB

Generation 330

Regularity 52%	<i>me</i> -C 50%	<i>we</i> -C 40%	<i>mip</i> -B 80%	<i>you</i> -C 50%	<i>yall</i> -C 40%	<i>yup</i> -C 40%	<i>yumi</i> -A 80%	<i>one</i> -D 100%	<i>they</i> -B 40%	<i>all</i> -B 50%
<i>happy</i> BC- 50%	ddadC	dd	ddB	BCC	BCcC	BC	ddab	BCD	BCdB	BCB
<i>sad</i> DA- 50%	DAd	DAdbbbb	dbB	DAC	DAcaaaaa	bca	DA	dbD	db	DAB
<i>angry</i> BA- 70%	ddd	dddaa	BAB	BAcccd dd	BAC	BA	BAabccbd	BAD	BA dd	BA a
<i>tired</i> CB- 30%	cedd	ccd	CBdB	add	adb	cddC	cddA	CBdD	CBd	cdd
<i>excited</i> BD- 40%	ddccbC	ddC	bbB	BDC	BDcC	BD	BDA	bbD	bb	BDB
<i>sick</i> CB- 30%	ccb	ccba	CBbB	cab	cabddbcC	edbC	cdbA	CBbD	CBB	cdB
<i>hungry</i> CB- 30%	ccccccC	ccC	CBcc	cadeaadd	ca	caC	caA	CBcD	CBc	cdc
<i>thirsty</i> CB- 30%	ccad	cca	CBaB	adab	ada	abaaaa cb	cdaA	CBaD	CBa	cda
<i>silly</i> DC- 60%	DCcC	DCC	DC	aaC	aa	aab	DCaA	DCcdD	DCd	DCa
<i>scared</i> A- 90%	AcC	AC	AcB	AdC	A	Ab	AcA	AbD	Abc	AbbB

Generation 360

Regularity 54%	<i>me</i> -C 40%	<i>we</i> -CB 20%	<i>mip</i> -B 90%	<i>you</i> -D 60%	<i>yall</i> -A 50%	<i>yup</i> -B 30%	<i>yumi</i> -A 90%	<i>one</i> -D 100%	<i>they</i> -B 50%	<i>all</i> -B 80%
<i>happy</i> BC- 50%	dda	ddbb	ddB	BCcaadD	BCc	BC	ddaA	BCD	BCda	BCB
<i>sad</i> DA- 50%	DA d	DA db	db B	DA c	DA cA	bcaaaaaa	DA	db D	db	DAB
<i>angry</i> BA- 70%	ddd bb bd	ddd bb bd	BA bbbb B	BA c	BA cA	BA	BAA	BAD	BA d B	BAB
<i>tired</i> CB- 30%	ccd	ccdb	CB d B	ad D	adb	cddd	cdde	CB d D	CB d	cdd
<i>excited</i> BD- 40%	dd C	dd CB	bb B	BDD	BD	BDB	BDA	bb D	bb	BD b B
<i>sick</i> CB- 30%	ccb	cebb	CB bb B	cab D	cab	cdbd	cdbA	CB b D	CBB	cd B
<i>hungry</i> CB- 30%	cc C	cccc	CB c B	ca D	ca	cac	caA	CB c D	CB c	cdc
<i>thirsty</i> CB- 30%	cca	ccaa	CB a B	ada	aaA	aba	cdA	CB a D	CB a	cd aB
<i>silly</i> DC- 60%	DCC	DCCB	DC	aa D	aa	aaB	DCA	DCD	DC d B	DCB
<i>scared</i> A- 90%	A c C	A c	A c B	A dccddab	A	AB	A cA	A b D	A bc	A b B

Appendix E

Details of run agave std batali

29/06/1999 21:32:32

Of the 21 simulation runs replicating BATALI's paper, the whole population of agents was dumped to disk every 5005 rounds. These states of the simulation were then analysed. For completeness I am giving here the languages of all agents of all dumps for run agave std batali 29/06/1999 21:32:32 which is analysed in detail in chapter 6.

E.1 Round 5005

Language of agent 1

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>	
48%	-A 50%	-D 40%	-C 40%	-A 90%	-B 30%	-C 50%	-B 50%	-CA 30%	-C 60%	-B 70%	
<i>happy</i> (AD- 50%)	dcadd	dc D	dcddc C	ADA	ADdabcac	AD	dbdde	ADCA	ADC	ADdc	
<i>sad</i> (AA- 90%)	AA adcd	AA ddc	AA cd	AAA	AA	AA cb	AAB	AACA	AAC	AAdbB	
<i>angry</i> (DD- 50%)	DDA	DD	DDC	badadd	bddd	adddab	DDdB	dadc	DD cdcd	DDB	
<i>tired</i> (CD- 40%)	CDA	CDD	CD	bdA	bd	bdcbb	bd B	cacc	CD cba	CDB	
<i>excited</i> (DB- 40%)	daacaad D		DB bbbbbb	daaba A	DB a		DB bbbbbb	DB	da	dab C	DBB
<i>sick</i> (CA- 30%)	CA d	cd da	cbdd aC	ba	ba B	babbcd cC	babd	CA abdb a	CA b	cbdbdbac	
<i>hungry</i> (CB- 40%)	CB a A	CB a	CB	bb A	bb	bbb C	bb B	cacba	CB cab	CBB	
<i>thirsty</i> (CC- 40%)	CC ad	CC dd D	CC	bc A	bc	bcb C	bcbd	cacacc CA	CC b C	CC b B	
<i>silly</i> (AB- 40%)	dcaa A	dc dc abaa	acd	ABA	AB	ABC	AB d	acc	ac	ABB	
<i>scared</i> (DC- 30%)	DC c A	DC c	DC b	bcd A	bcd	adb cC	dbcbaa	caccccd	cc C	dbc	

Language of agent 2

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
50%	-AD 30%	-A 30%	-C 40%	-A 60%	-A 30%	-C 50%	-B 50%	-A 70%	-C 90%	-B 80%
<i>happy</i> (AD- 50%)	dcdada	dcd	dcdcdC	ADA	ADbA	AD	dcdB	ADcA	ADC	ADbbdB
<i>sad</i> (AA- 90%)	AAAD	AAd	AAdC	AAaA	AAbA	AA	AAddB	AAcA	AAC	AAbd
<i>angry</i> (DD- 50%)	DDaaadd	DD	DDC	baadd	bdd	adddddab	DDbd	dadcaA	DDcC	DDb
<i>tired</i> (CD- 40%)	CDA	CDdc	CD	bdac	bd	bdcB	bdbbaddc	caccd	CDbcC	CDbB
<i>excited</i> (DB- 40%)	dcAD	D	DBbbbbba	daab	DBA	DBbC	DB	da	dabC	DBB
<i>sick</i> (CA- 30%)	CAdd	cddA	CAdb	ba	bab	babb	badbB	CA	CAbbabca	cbdbdc
<i>hungry</i> (CB- 40%)	CBaa	CBA	CB	bbacA	bb	bbC	bbba	cacA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCAd	CCbdcbcc	CCb	bcA	bc	bcBc	bcbd	CCA	CC	CCbbdB
<i>silly</i> (AB- 40%)	dcaa	dcabA	acd	ABac	AB	ABC	ABd	acc	ac	ABbB
<i>scared</i> (DC- 50%)	DCca	DCc	DCcccC	bccA	bedc	adbcc	DCbbB	cccc	ccC	DCbcB

Language of agent 3

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
51%	-A 60%	-D 30%	-D 60%	-A 70%	-A 50%	-C 40%	-A 30%	-A 40%	-C 60%	-B 100%
<i>happy</i> (AD- 70%)	dcaad	dcD	ADcdcd	ADA	ADbA	AD	ADbadadc	ADcA	ADC	ADbabbB
<i>sad</i> (AA- 70%)	AAadc	AAddc	AAcd	AAA	AAbacbA	AAbC	AA	acacbbcA	acbcbaC	AAbB
<i>angry</i> (DD- 50%)	DDA	DD	DDdc	baadd	bdddA	addd	DDbd	dadab	DDdcbaa	DDb
<i>tired</i> (CD- 40%)	CDA	CDdc	CD	bdac	bd	bdcB	bdbdaadc	cacc	CDcC	CDbB
<i>excited</i> (DB- 50%)	dcacA	D	DBcacacD	DBaA	DBA	DBca	DB	dac	dabC	DBB
<i>sick</i> (CA- 30%)	CAd	cdda	CABd	ba	bab	babb	bbdA	CA	CAb	cbdB
<i>hungry</i> (CB- 40%)	CBaa	CBA	CB	bbacA	bbA	bbC	bb	cacbab	CBca	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCba	CC	bcA	bc	bcB	bcdbabbA	CCac	CCcb	CCbB
<i>silly</i> (AB- 40%)	dcaaA	dcbaab	acd	ABA	AB	ABC	ABd	aca	ac	ABB
<i>scared</i> (DC- 50%)	DCc	DCcb	DCbcc	beadcc	bedc	adbcc	DCbcdb	cccccc	cccC	DCbbcB

Language of agent 4

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
52%	-A 70%	-A 40%	-B 40%	-A 70%	-A 30%	-B 40%	-B 70%	-A 60%	-C 70%	-B 70%
<i>happy</i> (AD- 50%)	dcaad	dcD	dcdddddB	ADA	ADbA	AD	dcdB	ADcA	ADC	ADbd
<i>sad</i> (AA- 90%)	AAA	AAaA	AA	AAabA	AAbabac	AAcbB	AAb	AAcA	AAC	AAbB
<i>angry</i> (DD- 50%)	DDA	DD	DDdd	badad	bdddA	addd	DDbaB	dad	DDddca	DDb
<i>tired</i> (CD- 40%)	CDA	CDd	CD	bdac	bd	bdbcc	bdbB	cacd	CDbccA	CDbB
<i>excited</i> (DB- 50%)	dcaacadA	D	DBbbbabB	DBaA	DBA	DBacB	DB	dac	dabC	DBbB
<i>sick</i> (CA- 40%)	CAd	CAddb	CAB	ba	bab	babbC	babd	CA	CABdca	cbdddbac
<i>hungry</i> (CB- 40%)	CBaa	CBA	CB	bbA	bbc	bbcB	bb	cacaba	CBcabC	CBB
<i>thirsty</i> (CC- 50%)	CCad	CCdA	CC	bcA	bc	bcBc	bcbd	CCac	CCbcabd	CCbB
<i>silly</i> (AB- 40%)	dcaaA	dcabA	acd	ABA	ABab	AB	ABd	aca	ac	ABB
<i>scared</i> (DC- 40%)	DCcA	DCc	DCcccc	bcc	bcd	abccc	DCcB	cccA	ccC	dbc

Language of agent 5

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
48%	-A 60%	-D 50%	-B 50%	-A 60%	-B 50%	-B 40%	-D 50%	-CA 30%	-C 80%	-B 50%
<i>happy</i> (AD- 50%)	dcaad	dcD	dcddcdC	ADA	ADbA	AD	dcdB	ADcA	ADC	ADbbd
<i>sad</i> (AA- 70%)	AAadc	AAcd	AAcd	AAaab	AAbaB	AAcB	AA	acacabCA	acdcbaaC	AAdcBd
<i>angry</i> (DD- 40%)	DDA	DDc	DDcadc	badadd	bddd	add	DD	daadcadb	dadca	DDbc
<i>tired</i> (CD- 40%)	CDA	CD	CDbc	bdA	bd	bdbcc	bdbB	cacc	CDbcC	CDB
<i>excited</i> (DA- 40%)	DAccD	D	dbbbbbbB	DAcaaac	dba	dbacB	db	DAccba	DAbC	dbB
<i>sick</i> (CA- 30%)	CAd	cddAd	cbddcaab	ba	baB	babB	babD	CAab	CAb	cbdbdbB
<i>hungry</i> (CB- 40%)	CBA	CBadc	CB	bbA	bb	bbcB	bbb	cacb	CBcabC	CBbc
<i>thirsty</i> (CC- 40%)	CCA	CCba	CC	bcab	bcB	bcbbC	bcbbD	cacacCA	CCbC	CCbB
<i>silly</i> (AB- 40%)	dcaaA	dcabD	acdbabbB	ABA	AB	ABc	ABD	aca	ac	ABB
<i>scared</i> (DC- 50%)	DCcA	DCc	DCcccc	bccA	bcd	adbcccc	DCbcD	caccc	ccC	DCbc

Language of agent 6

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
45%	-AD 30%	-D 60%	-C 40%	-A 50%	-A 30%	-CB 40%	-D 40%	-A 30%	-C 50%	-B 80%
<i>happy</i> (AD- 50%)	dcAD	dcD	dcddcC	ADA	ADbA	AD	dcdb	ADcA	ADC	ADbbd
<i>sad</i> (AA- 70%)	AAadd	AAadd	AAcd	AAaA	AAba	AAcB	AA	acaacd	acdbdca	AAdbB
<i>angry</i> (DD- 50%)	DDAD	DDc	DD	baadd	bddd	add	DDba	dad	DDdcbA	DDb
<i>tired</i> (CD- 40%)	CDAd	CD	CDb	bdac	bd	bdcB	bdbC	caccd	CDbC	CDbbcd
<i>excited</i> (DB- 40%)	dcaaacD	D	DBbbcC	daababad	DBA	DBbca	DB	da	dab	DBB
<i>sick</i> (CA- 30%)	CAd	cddD	CABd	ba	bab	babaCB	babD	CA	CABdca	cbdB
<i>hungry</i> (CB- 40%)	CBaa	CBA	CB	bbac	bb	bbcB	bbb	cacb	CBcabC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCbad	CC	bcA	bc	bcBc	bcBd	CCac	CCbC	CCbB
<i>silly</i> (AB- 40%)	dcaaA	dcabD	acd	ABA	AB	ABc	ABD	acc	ac	ABB
<i>scared</i> (DC- 50%)	DCcA	DCc	DCcccc	bcc	bcd	adbcc	DCbbD	cccc	cccd	DCB

Language of agent 7

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
49%	-A 60%	-A 40%	-B 40%	-A 60%	-D 50%	-B 50%	-B 40%	-A 50%	-C 60%	-B 70%
<i>happy</i> (AD- 50%)	dcadd dcd	decddc	ADab	ADba	ADb	ADb	dcdbb	ADcA	AD	ADb
<i>sad</i> (AA- 90%)	AAad	AAAd	AAAD	AAabA	AAba	AAAB	AAAddbba	AAc	AA	AAbbd
<i>angry</i> (DD- 50%)	DDA	DDdA	DD	badad	bdD	adb	DDbBD	dad	DDcdda	DDb
<i>tired</i> (CD- 40%)	CDA	CDc	CD	bdac	bd	bdc	bdBD	caed	CDbC	CDbB
<i>excited</i> (DB- 40%)	dacadb	D	DBcad	daaaaaac	DBa	DBcbaccB	DBBD	da	dab	DB
<i>sick</i> (BA- 30%)	cad	cdddA	cddB	BA	BAbD	BAB	BAbdd	ca	cab	cbd
<i>hungry</i> (CB- 40%)	CBaA	CBA	CB	bbA	bb	bbc	bbbba	cacbA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCbA	CC	bcA	bc	bcB	bcBD	CCac	CCbC	CCbB
<i>silly</i> (AB- 40%)	dcaA	dcab	acd	ABA	AB	ABc	ABd	acc	ac	ABB
<i>scared</i> (DC- 40%)	DCcA	DCc	DCcB	bcdA	bcD	adbcc	DCcbb	cccA	ccC	dbccB

Language of agent 8

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
49%	-A 70%	-D 40%	-C 40%	-A 70%	-A 30%	-CC 30%	-B 50%	-A 50%	-C 80%	-B 70%
<i>happy</i> (AD- 60%)	dcad	dcD	decddcC	ADaA	ADbA	AD	ADbdd	ADcA	ADC	ADdbB
<i>sad</i> (AA- 70%)	AAad	AAdda	AAcd	AAaA	AAbaA	AAcBa	AA	acaac	accbaaaa	AAdbB
<i>angry</i> (DD- 50%)	DDA	DD	DDC	baadd	bdc	daccdd	adda	DDba	dadaab	DDccacdC
<i>tired</i> (CD- 40%)	CDA	CDc	CD	bdA	bd	bdecB	bdB	cacc	CDcBa	CDB
<i>excited</i> (DB- 40%)	dcaeddc	D	DBcad	daacacA	DBA	DBcbbbc	DB	dac	dabC	DBc
<i>sick</i> (CA- 30%)	CAd	cddab	cddba	ba	bab	babaccB	babd	CAa	CAabd	cbdd
<i>hungry</i> (CB- 40%)	CBaA	CBa	CB	bbacA	bbac	bbcbCC	bb	cacA	CBcC	CBbc
<i>thirsty</i> (CC- 40%)	CCA	CCdD	CC	bcA	bc	bcBCC	bcB	caedc	CCbccC	CCbB
<i>silly</i> (AB- 40%)	dcaA	dcabD	acd	ABacac	AB	ABc	ABd	aca	ac	ABB
<i>scared</i> (DC- 50%)	DCcA	DCc	DCb	becad	becd	adbCC	DCcB	cacccc	ccC	DCcB

Language of agent 9

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
51%	-A 60%	-D 50%	-C 40%	-A 80%	-A 30%	-B 40%	-D 60%	-AB 30%	-C 90%	-B 80%
<i>happy</i> (AD- 50%)	dcadd	dcD	decddcC	ADaB	ADbA	AD	dcdbdb	ADca	ADC	ADb
<i>sad</i> (AA- 80%)	AAa	AA	AAdb	AAabab	AAabab	adbdcdca	AAbdD	AAca	AAc	AAb
<i>angry</i> (DD- 50%)	DDA	DD	DDc	baddA	bddd	adddB	DDba	dadabc	DDccbab	DDb
<i>tired</i> (CD- 40%)	CDA	CDD	CD	bdA	bd	bdcB	bdB	cacc	CDbcC	CDB
<i>excited</i> (DB- 50%)	dac	D	DBbbac	daacacA	DBA	DBbac	DB	dabac	DBaC	DBB
<i>sick</i> (CA- 30%)	CAd	cdddD	cdddbb	baA	ba	bababdaa	babD	CAaB	CAabd	cbdbba
<i>hungry</i> (CB- 40%)	CBaA	CBa	CB	bbA	bb	bbcb	bbb	cacbAB	CBC	CBb
<i>thirsty</i> (CC- 40%)	CCad	CCbA	CC	bcA	bc	bcB	bcD	caaba	ABCCbC	CCbB
<i>silly</i> (AB- 40%)	dcaA	dcba	acd	ABA	AB	ABc	ABD	aca	ac	ABB
<i>scared</i> (DC- 50%)	DCcA	DCc	DCbC	bedacA	bedc	adbccc	DCbbbdD	cacccc	ccC	DCb

Language of agent 10

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
55%	-A 70%	-A 50%	-C 40%	-A 70%	-D 40%	-C 80%	-B 70%	-A 60%	-C 70%	-B 80%
<i>happy</i> (AD- 50%)	dcad	dcd	decddcC	ADA	ADbA	AD	dcdbdbb	ADcA	ADC	ADb
<i>sad</i> (AA- 80%)	AAa	AA	AAcd	AAaab	AAabab	adbdcdca	AAbdD	AAcc	AAc	AAbB
<i>angry</i> (DD- 50%)	DDA	DD	DDcb	baaddaa	bddd	adddB	DDba	dadaca	DDcbda	DDb
<i>tired</i> (CD- 40%)	CDA	CDd	CD	bdac	bd	bdcC	bdB	caed	CDbcC	CDB
<i>excited</i> (DB- 40%)	daacd	D	DBcdC	daacacA	DBac	DBcabcc	DB	da	dab	DBc
<i>sick</i> (CA- 30%)	CAAd	cdddA	CAd	ba	baD	badbcdC	baB	CA	CAacaab	cbdB
<i>hungry</i> (CB- 40%)	CBaA	CBA	CB	bacac	bbcab	bbC	bb	cacb	CBcA	CBB
<i>thirsty</i> (CC- 50%)	CCad	CCbA	CC	bcA	bc	bcB	bcD	CCac	CCcb	CCbB
<i>silly</i> (AB- 40%)	dcaA	dcba	acd	ABA	AB	ABc	ABD	aca	ac	ABB
<i>scared</i> (DC- 60%)	DCcA	DCc	DCcbcc	bccA	bcc	adbcc	DCcbB	ccccA	DCcbccc	DCcb

Language of agent 11

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
47%	-A 50%	-A 30%	-C 50%	-A 80%	-A 40%	-B 30%	-D 50%	-CA 30%	-C 70%	-B 60%
<i>happy</i> (AD- 50%)	dcad	dcd	decddcC	ADA	ADbA	AD	dcdb	ADcA	ADC	ADb
<i>sad</i> (AA- 90%)	AAad	AAdddA	AAcd	AAaaA	AAbaA	AA	AAD	AAcA	AAc	AAbd
<i>angry</i> (DD- 50%)	DDA	DDdA	DDC	baddad	bddd	addd	DDD	dadc	DDcaba	DD
<i>tired</i> (CD- 40%)	CDA	CDdc	CD	bdA	bd	bdcB	bdB	caed	CDbC	CDB
<i>excited</i> (DB- 40%)	dcaabb	D	DBbbba	ca	DBA	DBbca	DBba	dac	dabC	DB
<i>sick</i> (CA- 30%)	CAd	cdddabc	cddabca	ba	bab	babB	bbbaD	CAab	CAbdb	cbdd
<i>hungry</i> (CB- 40%)	CBaA	CBA	CB	bbac	bbA	bb	bb	cacab	CBC	CBB
<i>thirsty</i> (CC- 40%)	CCad	CCbad	CC	bcA	bc	bcB	bcD	caCA	CCbC	CCbB
<i>silly</i> (AB- 40%)	dcaabA	dcabd	acd	ABA	AB	ABc	ABD	acc	ac	ABB
<i>scared</i> (DC- 40%)	DCcA	DCc	DCcbcc	bcdA	bcd	adbcb	DCcbb	caccc	ccb	dbcc

Language of agent 12

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>	
49%	-AB 20%	-D 50%	-B 30%	-A 80%	-A 50%	-C 40%	-D 50%	-A 60%	-C 70%	-B 70%	
<i>happy</i> (AD- 50%)	dcad	dcD	dcddc	ADaA	ADbA	AD	dcddb	ADac	ADC	ADbdblB	
<i>sad</i> (AA- 90%)	AAaada	AAbaddD	AAAdc	AAaab	AAbaA	AA	AAb	AAcA	AAc	AAAd	
<i>angry</i> (DD- 50%)	DDaadddd	DDda	DD	badad	bddA	addddd	DDbdD	dad	DDdcaba	DDb	
<i>tired</i> (CD- 40%)	CDa	CDD	CD	bdA	bd	bdbC	bdbD	cacd	CDcC	CDbB	
<i>excited</i> (DB- 40%)	dacacd	AB D		DBbbdbba	dabA	DBA	DBab	DBbD	da	dabC	DB
<i>sick</i> (CA- 30%)	CAadd	cddD	CAdbdd	ba	bab	babC	babD	CA	CAb	cbdd	
<i>hungry</i> (CB- 40%)	CBaa	CBa	CB	bbAa	bbA	bbC	bb	cacaacc	CBca	CBb	
<i>thirsty</i> (CC- 50%)	CCad	CCbaD	CC	bcA	bc	bcB	bcba	CCA	CCbaC	CCbB	
<i>silly</i> (AB- 40%)	dcaAB	dcabda	acdcb	ABacA	ABac	AB	ABD	aca	ac	ABB	
<i>scared</i> (DC- 40%)	DCca	DCc	DCB	bcdaA	bcd	adbcc	DCcdeddb	cccA	ccC	dbc	

Language of agent 13

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>	
52%	-A 70%	-D 40%	-C 40%	-A 90%	-A 30%	-C 50%	-B 50%	-A 70%	-C 50%	-B 90%	
<i>happy</i> (AD- 50%)	dcdA	dcD	dcddC	ADA	ADbA	AD	dcdbd	ADcA	ADC	ADbdblB	
<i>sad</i> (AA- 80%)	AAA	AA	AAcd	AAab	AAba	adbdcbad	AAB	AAcA	AAc	AAbB	
<i>angry</i> (DD- 50%)	DDad	DD	DDC	baddA	bddd	add	DDbd	dadcd	DDcba	DDb	
<i>tired</i> (CD- 40%)	CDa	CDD	CD	bdA	bd	bdbC	bdB	cacd	CDcb	CDbB	
<i>excited</i> (DB- 50%)	daaaadb	D		DBbbbdC	DBaA	DBA	DBC	DB	da	dab	DBB
<i>sick</i> (CA- 30%)	CAd	cdddb	cdbad	ba	bab	babbcbC	babd	CAabA	CAb	cbdbdda	
<i>hungry</i> (CB- 40%)	CBaa	CBa	CB	bbA	bb	bbcB	bbB	cacba	CBC	CBb	
<i>thirsty</i> (CC- 40%)	CCA	CCabD	CC	bcA	bc	bcB	bcdbddc	cacaaaa	CCbC	CCbB	
<i>silly</i> (AB- 40%)	dcaAB	dcbaa	acd	ABA	AB	ABC	ABD	aca	ac	ABB	
<i>scared</i> (DC- 50%)	DCcA	DCc	DCcb	bcda	bcd	adbcc	DCB	cacccc	cccd	DCbcB	

Language of agent 14

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
46%	-D 50%	-D 50%	-C 40%	-A 60%	-A 30%	-B 30%	-B 50%	-A 40%	-C 60%	-B 40%
<i>happy</i> (AD- 50%)	dcaD	dcD	dcddc	ADA	ADbA	AD	dcdb	ADcA	ADC	ADbdblB
<i>sad</i> (AA- 90%)	AAAdadc	AAAd	AAddcbcd	AAA	AA	AAABC	AAAd	AAc	AAcbcdC	AAAdBB
<i>angry</i> (DD- 50%)	DDa	DD	DDC	badad	bdd	adbcdddd	DDb	dadcc	DDcdaba	DDbc
<i>tired</i> (CD- 40%)	CDacD	CD	CDbC	bdac	bd	bdBC	bdbd	caedb	CDbca	CDb
<i>excited</i> (DA- 40%)	DAcaadb	D		DAbaaad	dbA	dbacB	db	DAcb	DAb	dbc
<i>sick</i> (CA- 30%)	CAD	cdddD	CAdbd	ba	bab	babb	babdba	CA	CAbdddcd	cbdbB
<i>hungry</i> (CB- 40%)	CBaa	CBa	CB	bbA	bb	bbcB	bbB	cacbab	CBC	CB
<i>thirsty</i> (CC- 50%)	CCad	CCba	CC	bcA	bc	bcBC	bcdb	CCacA	CCbC	CCBB
<i>silly</i> (AB- 40%)	dcaab	dcabb	acd	ABA	AB	ABC	ABdbadda	aca	ac	ABBB
<i>scared</i> (DC- 50%)	DCca	DCc	DCcbC	bcc	bcd	adbcccc	DCB	cccc	ccC	DCbbc

Language of agent 15

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>	
49%	-AD 30%	-A 30%	-B 50%	-A 60%	-A 40%	-C 50%	-B 40%	-A 50%	-C 90%	-B 50%	
<i>happy</i> (AD- 50%)	dcaD	dcD	dcddC	ADA	ADbA	AD	dcdbbda	ADcA	ADC	ADbdblB	
<i>sad</i> (AA- 90%)	AAAD	AAdd	AAcd	AAab	AA	AAbC	AAAd	AAcA	AAc	AAdbB	
<i>angry</i> (DD- 50%)	DDadddd	DDcd	DD	bdad	bdd	add	DDbddd	dad	DDdC	DDb	
<i>tired</i> (CD- 50%)	CDacdc	CDc	CD	bdac	bdb	bdC	bdbB	CDcc	CDc	CDbB	
<i>excited</i> (DB- 40%)	dcaAD	D		DBcdc	dabA	DBA	DB	DBabadba	da	dabC	DBBB
<i>sick</i> (BA- 30%)	cadadaaa	cddab	cddbB	BAA	BA	BAbC	BAbd	ca	cab	cbdbdb	
<i>hungry</i> (CB- 40%)	CBaa	CBa	CB	bbA	bb	bbC	bbB	cacab	CBC	CBb	
<i>thirsty</i> (CC- 50%)	CCAD	CCba	CCB	bcA	bc	bcB	bcdb	CCac	CC	CCBB	
<i>silly</i> (AB- 40%)	dcaaaaab	dcbaA	acdB	ABA	ABd	AB	ABdaB	aca	ac	ABBB	
<i>scared</i> (DC- 50%)	DCca	DCc	DCcB	bcd	bcc	adbccc	DCcdcbB	cccc	ccC	DCbbc	

Language of agent 16

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
49%	-AD 30%	-D 60%	-C 40%	-A 60%	-D 40%	-B 50%	-B 60%	-A 50%	-C 60%	-B 50%
<i>happy</i> (AD- 50%)	dcAD	dcD	dcddC	ADA	ADadD	AD	dcdb	ADcA	ADC	ADbdblB
<i>sad</i> (AA- 90%)	AAadc	AAcd	AAcd	AAA	AA	AAcB	AAAd	AAcA	AAc	AAdbB
<i>angry</i> (DD- 50%)	DDaadd	DD	DDC	baadd	bdD	addb	DDb	dad	DDcca	DDbdblB
<i>tired</i> (CD- 40%)	CDaccd	CD	CDc	bdac	bd	bdbC	bdbB	caccccc	CDcC	CDbB
<i>excited</i> (DA- 40%)	DAccaadb	D		dbcbbbb	DAba	dba	db	DAc	DAcb	dbBB
<i>sick</i> (CA- 30%)	CAd	cddD	CAdbd	ba	bab	babb	babdaad	CA	CAb	cbdb
<i>hungry</i> (CB- 40%)	CBaa	CBa	CB	bbac	bb	bbcB	bbB	cacba	CBC	CBb
<i>thirsty</i> (CC- 50%)	CCAD	CCad	CC	bcA	bc	bcB	bcdb	CCacB	CCbC	CCBB
<i>silly</i> (AB- 40%)	dcaaa	dcab	acd	ABac	AB	ABc	ABd	aca	ac	ABb
<i>scared</i> (DC- 50%)	DCca	DCc	DCcb	bcda	bcd	adbccc	DCbB	cccc	cccc	DCbcb

Language of agent 17

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>	
49%	-AD 40%	-A 30%	-D 40%	-A 70%	-D 40%	-B 40%	-B 50%	-A 60%	-C 70%	-B 70%	
<i>happy</i> (AD- 50%)	dcdadc	ADdcd	dcdcc	ADaA	ADbaa	AD	dcdB	ADcA	ADC	ADbbd	
<i>sad</i> (AA- 90%)	AAAD	AAadd	AAdc	AAab	AAbA	AA	AAdd	AAcA	AAC	AAd	
<i>angry</i> (DD- 50%)	DDAD	DD	DDD	badcadd	A bdd	add	DDbddd	dadac	DDcbadaa	DDb	
<i>tired</i> (CD- 40%)	CDc	CDdc	CD	bdac	bd	bdcB	bdB	caccd	CDbC	CDB	
<i>excited</i> (DB- 40%)	dacadca	D	DBc	dca dabb	AA	DBa	DBac	DB	da	dabC	DBB
<i>sick</i> (CA- 30%)	CAdd	cddA	CABD	ba	bab	babB	babd	CA	CAB	cbdB	
<i>hungry</i> (CB- 40%)	CBaa	CBA	CB	bbA	bb	bbcc	bbB	cacb	CBC	CBB	
<i>thirsty</i> (CC- 50%)	CCAD	CCbad	CCb	bcA	bc	bcbC	bcbD	CCA	CC	CCbB	
<i>silly</i> (AB- 40%)	dcaababd	dcdcab	acd	ABA	AB	ABaD	AB	ABda	acA	ac	ABd
<i>scared</i> (DC- 50%)	DCca	DCc	DCbc	bedac	bcD	adbcc	DCcdB	ccc	cccd	DCbcB	

Language of agent 18

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
50%	-A 60%	-D 50%	-D 50%	-A 80%	-A 40%	-C 70%	-B 60%	-C 50%	-BC 40%	-BB 50%
<i>happy</i> (AD- 50%)	dcadd	dcD	dcdcd	ADA	ADbA	AD	dcdB	ADca	ADc	ADdB
<i>sad</i> (AA- 90%)	AAA	AAadd	AAcD	AAab	AA	AAbc	AAd	AAC	AAcBC	AABB
<i>angry</i> (DD- 50%)	DDA	DD	DDD	baddA	bddd	add	DDba	dad	DDdcdab	DDb
<i>tired</i> (CD- 40%)	CDac	CDdc	CD	bdA	bd	bdcB	bdB	cacd	CDbcc	CDBB
<i>excited</i> (DB- 40%)	daabaaa	D	DBbbb	daabb	DBA	DBC	DB	da	daBC	DBBB
<i>sick</i> (CA- 30%)	CAD	cdD	cddbac	ba	bab	babB	babd	CAaC	CABcd	cbdD
<i>hungry</i> (CB- 40%)	CBA	CBab	CB	bbA	bb	bbC	bbB	cacb	CBC	CBB
<i>thirsty</i> (CC- 40%)	CCad	CCadd	CC	bcA	bc	bcbC	bcbD	cacbC	CCBC	CCBB
<i>silly</i> (AB- 40%)	dcaA	dcabb	acd	ABA	AB	ABC	ABd	acA	ac	ABb
<i>scared</i> (DC- 40%)	DCcA	DCc	DCcb	bcc	bcd	adbcc	DCB	caccC	ccccBC	dbcb

Language of agent 19

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
51%	-A 40%	-D 50%	-D 40%	-A 70%	-A 30%	-C 70%	-BD 50%	-A 30%	-C 60%	-B 90%
<i>happy</i> (AD- 50%)	dcadd	dcD	dcdcd	ADA	ADdA	AD	dcdB	ADcA	ADc	ADdB
<i>sad</i> (AA- 90%)	AAad	AAAD	AAcd	AAaA	AA	AAbc	AAdb	AAcA	AAC	AAbd
<i>angry</i> (DD- 50%)	DDA	DDdd	DD	badadd	bddd	add	DDbddd	dad	DDcdad	DDb
<i>tired</i> (CD- 40%)	CDA	CDdc	CD	bdA	bd	bdcB	bdB	cac	CDbC	CDBB
<i>excited</i> (DB- 50%)	daaaaa	D	DBbbcd	DBaA	DBA	DBC	DB	da	dab	DBB
<i>sick</i> (CA- 30%)	CAd	cdD	cddb	ba	bab	babB	babD	CAaB	CAB	cbdB
<i>hungry</i> (CB- 40%)	CBA	CBa	CB	bbA	bb	bbC	bbD	cacb	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCad	CCbda	CCbD	bcA	bc	bcbC	bcbD	CCab	CC	CCbB
<i>silly</i> (AB- 40%)	dcaab	dcdab	acd	ABA	AB	ABC	ABd	acA	ac	ABB
<i>scared</i> (DC- 50%)	DCacc	DCc	DCcb	bcc	bcd	adbcc	DCbcb	ccc	cccc	DCB

Language of agent 20

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
51%	-A 40%	-D 50%	-B 40%	-A 90%	-A 40%	-CB 30%	-B 50%	-A 30%	-C 80%	-B 90%
<i>happy</i> (AD- 50%)	dcdA	dcD	dcdcd	ADA	ADbA	AD	dcdB	ADcA	ADC	ADbbd
<i>sad</i> (AA- 90%)	AAadc	AAAd	AAcd	AAA	AA	AACB	AAB	AAcA	AAC	AAB
<i>angry</i> (DD- 50%)	DDA	DD	DDc	bddad	bddd	add	DDba	dad	DDdcb	DDb
<i>tired</i> (CD- 40%)	CDc	CD	CDB	bdA	bd	bdcB	bdB	caccd	CDbC	CDBB
<i>excited</i> (DB- 50%)	dcdcbD	D	DBcad	DBaA	DBA	DBbb	DB	da	dabC	DBB
<i>sick</i> (CA- 30%)	CAd	cdD	CADb	baA	ba	babC	babD	CA	CAabd	cbdB
<i>hungry</i> (CB- 40%)	CBA	CBabd	CB	bbA	bb	bbCB	bbB	cacb	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCad	CCbaD	CC	bcA	bc	bcbcc	bcbD	CCacb	CCbC	CCbB
<i>silly</i> (AB- 40%)	dcaA	dcba	acd	ABaC	AB	ABc	ABd	acc	ac	ABB
<i>scared</i> (DC- 50%)	DCc	DCcb	DCbc	bccA	bcd	adbcc	DCbcb	ccc	cccc	DCB

Language of agent 21

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
50%	-AD 40%	-D 40%	-D 70%	-A 90%	-A 30%	-C 50%	-DB 20%	-A 70%	-C 70%	-BB 50%
<i>happy</i> (AD- 50%)	dcAD	dcD	dcdcdcc	ADA	ADbA	AD	dcdB	ADcA	ADC	ADbbd
<i>sad</i> (AA- 90%)	AAadda	AAAd	AAcd	AAA	AA	AAbc	AAd	AAcA	AAC	AAdB
<i>angry</i> (DD- 50%)	DDAD	DD	DDD	bdadd	bddd	add	DDbddd	dad	DDdcb	DDb
<i>tired</i> (CD- 40%)	CDacdc	CDD	CD	bdA	bd	bdcB	bdB	caccd	CDbC	CDBB
<i>excited</i> (DB- 40%)	dcaAD	D	dcbacd	DBaA	DB	DBC	DBbad	da	dabC	DBB
<i>sick</i> (CA- 30%)	CAdd	cdD	CADb	baA	ba	babB	babD	CA	CAB	cbdD
<i>hungry</i> (CB- 40%)	CBaaa	CBaba	CB	bbaca	bb	bbC	bbB	cacb	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCAD	CCbad	CCbD	bcA	bc	bcb	bcbD	CCA	CC	CCbB
<i>silly</i> (AB- 40%)	dcaaaa	dcbaab	acd	ABA	AB	ABC	ABd	acA	ac	ABB
<i>scared</i> (DC- 50%)	DCcac	DCc	DCbc	bedac	bed	adbcc	DCcb	cccc	cccc	DCB

Language of agent 22

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
46%	-A 60%	-D 40%	-D 40%	-A 70%	-B 30%	-C 50%	-B 50%	-A 30%	-C 60%	-B 40%
<i>happy</i> (AD- 50%)	dcDA	dcD	dcddcb	ADA	ADbbaacc	AD	dcdB	ADcA	ADC	ADbdb
<i>sad</i> (AA- 70%)	AAAdA	AAAdD	AAAcD	AAaA	AAAbbc	AAcbb	AA	acacbcab	acbcacca	AABB
<i>angry</i> (DD- 50%)	DDA	DD	DDdcb	badad	bddd	addd	DDb	dadedcdd	DDdacbd	DDbd
<i>tired</i> (CD- 40%)	CDac	CDc	CD	bdac	bd	bdbcC	bdbdccc	caed	CDbcC	CDBB
<i>excited</i> (DA- 40%)	DAabaad	D	dbcdecac	DAbaab	dba	dbcabC	db	DAc	DAcb	dbb
<i>sick</i> (CA- 30%)	CAd	cddD	CABD	ba	baB	babb	babdd	CA	CAB	cbdbd
<i>hungry</i> (CB- 40%)	CBaA	CBa	CB	bbAa	bb	bbcb	bbB	cacbab	CBC	CBb
<i>thirsty</i> (CC- 50%)	CCad	CCba	CC	bcA	bc	bcbC	cbcd	CCA	CCbC	CCBB
<i>silly</i> (AB- 40%)	dcaA	dcbaa	acD	ABA	AB	ABC	ABd	acc	ac	ABBB
<i>scared</i> (DC- 50%)	DCcA	DCc	DCccc	bcDA	bcd	adbccc	DCcB	cccac	ccC	DCcbcc

Language of agent 23

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
48%	-A 60%	-C 40%	-B 30%	-A 80%	-D 40%	-B 40%	-DA 20%	-C 40%	-C 50%	-B 100%
<i>happy</i> (AD- 60%)	dcad	dcd	dcdB	ADaA	ADbada	ADB	ADbddcdc	ADa	AD	ADbB
<i>sad</i> (AA- 90%)	AAAd	AAAdd	AA	AAab	AAba	AAbc	AAbDA	AAca	AAc	AAb
<i>angry</i> (DD- 50%)	DDA	DDda	DD	badA	bdD	adbcaadd	DDbbdDA	dad	DDcdca	DDb
<i>tired</i> (CD- 40%)	CDA	CDC	CD	bdA	bd	bdc	bdbaadad	caed	CDbeca	CDBB
<i>excited</i> (DA- 30%)	dcacac	dcabdac	D	DAcacabA	dba	dbba	dbadbbdb	DAC	DAb	db
<i>sick</i> (BA- 30%)	cadd	cddab	cdba	BA	BABA	BAB	BABd	ca	cab	cbdB
<i>hungry</i> (CB- 40%)	CBaA	CBa	CB	bbA	bb	bbc	bbba	cacab	CBC	CBb
<i>thirsty</i> (CC- 50%)	CCad	CCbadd	CC	bcA	bc	bcbC	cbcd	CCA	CCbC	CCbB
<i>silly</i> (AB- 40%)	dcaA	dcabab	dcbaBA	ABA	ABabcccc	AB	ABdadba	acc	ac	ABBB
<i>scared</i> (DC- 50%)	DCcA	DCc	DCbc	bcde	bcD	abcccc	DCcdcb	daccccc	DCcbeccc	DCcbccbbB

Language of agent 24

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
52%	-AD 30%	-A 30%	-C 50%	-A 70%	-A 40%	-B 40%	-B 50%	-A 60%	-C 90%	-B 90%
<i>happy</i> (AD- 50%)	dcadd	dcd	dcddc	ADA	ADbA	AD	dcdbdB	ADcad	ADC	ADdbbbd
<i>sad</i> (AA- 90%)	AAAd	AAAdd	AAcd	AAab	AA	AAcbB	AAAB	AAcA	AAc	AAbB
<i>angry</i> (DD- 50%)	DDA	DD	DDC	badad	bdddA	addd	DDbDb	dad	DDcdbad	DDb
<i>tired</i> (CD- 40%)	CDA	CdD	CD	bdA	bd	bdcB	bdB	CDaccbb	CDbC	CDB
<i>excited</i> (DB- 40%)	dcacbc	D	DBcdaC	daabA	DBA	DBca	DBd	da	dabC	DB
<i>sick</i> (CA- 40%)	CAd	CAddb	CABd	ba	bab	babB	babd	CA	CAB	cbdbbbbB
<i>hungry</i> (CB- 40%)	CBaA	CBa	CB	bbac	bb	bbcB	bbB	cacba	CBC	CBb
<i>thirsty</i> (CC- 50%)	CCAD	CCbA	CC	bcA	bc	bcbC	cbcd	CCacb	CCbC	CCbB
<i>silly</i> (AB- 40%)	dcaA	dcadab	acd	ABA	AB	ABc	ABd	aca	ac	ABBB
<i>scared</i> (DC- 40%)	DCcA	DCc	DCbC	bccA	bcd	adbccc	DCbbcd	ccccA	ccC	dbccB

Language of agent 25

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
52%	-A 50%	-D 60%	-D 50%	-A 80%	-A 40%	-B 60%	-BB 30%	-A 70%	-C 50%	-B 90%
<i>happy</i> (AD- 50%)	dcadd	dcD	dcddc	ADaA	ADbA	AD	dcdbdB	ADcA	ADC	ADdbcbdd
<i>sad</i> (AA- 90%)	AAAd	AAAdD	AAcd	AAabA	AAba	AAAB	AAdbda	AAcA	AA	AAbB
<i>angry</i> (DD- 50%)	DDA	DD	DDD	badd	bddd	addd	DDbddd	dad	DDdcba	DDb
<i>tired</i> (CD- 40%)	CDA	CDD	CD	bdac	bd	bdB	bdcdbabb	caed	CDbcC	CDBB
<i>excited</i> (DB- 40%)	dcacdc	D	DBcaD	daaaaadA	DBA	DBcbbbbB	DBdbbbbB	da	dab	DB
<i>sick</i> (BA- 30%)	cadd	cdDa	cdBd	BA	BAb	BAbdbcbB	BAbdd	ca	cab	cbdbbbB
<i>hungry</i> (CB- 40%)	CBaA	CBa	CB	bbA	bb	bbc	bbba	cacbab	CBcab	CBb
<i>thirsty</i> (CC- 50%)	CCad	CCbAd	CC	bcA	bc	bcB	cbcd	CCA	CCbC	CCbB
<i>silly</i> (AB- 40%)	dcaA	dcabD	acd	ABA	ABabA	AB	ABd	aca	ac	ABBB
<i>scared</i> (DC- 40%)	DCcA	DCc	DCb	bcdA	bcd	adbccc	DCcddBB	ccccA	ccC	dbccB

Language of agent 26

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
49%	-A 60%	-D 50%	-C 50%	-A 70%	-D 30%	-CB 30%	-B 50%	-A 50%	-C 70%	-B 80%
<i>happy</i> (AD- 50%)	dcadd	dcD	dcddc	ADA	ADba	AD	dcdB	ADcA	ADC	ADbbd
<i>sad</i> (AA- 70%)	AAAd	AAAdD	AAcd	AAab	AAba	AAAB	AA	acaA	acdcbaC	AAbB
<i>angry</i> (DD- 50%)	DDA	DD	DDdC	badadd	bdddD	bdddab	DDbd	dadab	DDdcbaC	DDb
<i>tired</i> (CD- 40%)	CDA	CDc	CD	bdA	b	bdcbb	bdB	caedC	CDcbca	CDB
<i>excited</i> (DA- 40%)	DAcadbD		dbcadC	DAbA	dbacaD	dbcabca	db	DAc	DAcb	dbb
<i>sick</i> (CA- 30%)	CAd	cddD	cddb	ba	bab	babbac	babd	CAcaadaA	CABdbaaC	cbdbddB
<i>hungry</i> (CB- 40%)	CBaA	CBabdca	CB	bbA	bbe	bbCB	bb	cacba	CBC	CBb
<i>thirsty</i> (CC- 40%)	CCa	CCdD	CC	bcA	bc	bcbCB	cbcd	caebc	CCbC	CCbB
<i>silly</i> (AB- 40%)	dcaA	dcabb	acd	ABA	AB	ABc	ABd	aca	ac	ABBB
<i>scared</i> (DC- 40%)	DCcA	DCc	DCccC	bcc	bcd	bccdbC	DCB	caccd	ccC	dbcc

Language of agent 27

Regularity	me	we	mip	you	yall	yup	yumi	one	they	all
49%	-A 50%	-D 40%	-C 60%	-A 80%	-A 30%	-C 60%	-B 50%	-A 40%	-C 70%	-B 60%
happy (AD- 50%)	dcad	dcD	dcddBc	ADaA	ADbA	AD	dbdcd	ADA	ADC	ADbdb
sad (AA- 80%)	AAA	AA	AAAdC	AAabA	AAbacdab	adbcaebC	AA B	AAcc	AA C	AA BB
angry (DD- 50%)	DDA	DD	DDC	baddA	bdcd	add	DDbd	dad	DDcddada	DDb
tired (CD- 40%)	CDac	CDD	CD	bdA	bd	bdcbcbb	bdB	cacbcc	CDbccC	CDBB
excited (DB- 40%)	daacd	D	DBbbaaC	daacaccc	DBA	DBaC	DB	da	dab	DBBB
sick (CA- 30%)	CAD	cddab	cdbab	baA	ba	babdccb	babd	CAcbcaeb	CAcbdbbb	cbdbd
hungry (CB- 40%)	CBaA	CBa	CB	bbA	bb	bbcbccc	bbB	cacba	CBcbC	CBcb
thirsty (CC- 40%)	CCA	CCD	CC	bcA	bc	bcbccc	cbcd	cacc	CCbC	CCBB
silly (AB- 40%)	dcaA	dcbaa	acb	ABaC	AB	ABC	ABd	acA	ac	ABBB
scared (DC- 40%)	DCac	DC	DCbC	bcdA	bcd	adbcccbC	DCCbB	cacc	ccC	DCbbcbBB

Language of agent 28

Regularity	me	we	mip	you	yall	yup	yumi	one	they	all
51%	-AD 40%	-D 50%	-D 50%	-A 70%	-A 50%	-B 40%	-BD 30%	-A 60%	-C 70%	-B 80%
happy (AD- 50%)	dcadcd	ADdcD	dcdd	ADaA	ADbaA	AD	dcadcd	ADac	ADC	ADbdbdB
sad (AA- 90%)	AAAD	AAda	AAD	AAaab	AAbaAA	AA	AABD	AAcA	AA C	AA B
angry (DD- 50%)	DDa	DD	DDc	bdadA	bdd	add	DDbbadd	dad	DDdaba	DDb
tired (CD- 40%)	CDac	CDcD	CD	bdac	bd	bdB	bdcd	caccd	CDcbccc	CDBB
excited (DB- 40%)	dcAD	D	DBcaa	daaacac	DBA	DBbcc	DBad	da	dab	DB
sick (CA- 30%)	CAdd	cddD	CAbd	baA	ba	baB	badb	CA	CAB	cbdd
hungry (CB- 40%)	CBaa	CBa	CB	bbacA	bb	bbc	bbBD	cacabcaeb	CBcaC	CBB
thirsty (CC- 50%)	CCAD	CCbaa	CC	bcA	bc	bcB	bcBD	CCA	CCbC	CCbB
silly (AB- 40%)	dcaA	dcab	acd	ABaA	ABA	AB	ABad	acA	ac	ABBB
scared (DC- 50%)	DCacc	DCcD	DCc	bcdA	bcd	abccc	DCcdb	ccccA	DCccccC	dbcc

Language of agent 29

Regularity	me	we	mip	you	yall	yup	yumi	one	they	all	
53%	-A 90%	-D 50%	-C 50%	-A 70%	-B 30%	-CC 50%	-B 50%	-C 50%	-C 70%	-B 60%	
happy (AD- 50%)	dcad	dcD	dcddcb	CADab	ADbaceda	ADbcdc	CC	dcddB	ADca	ADC	AD
sad (AA- 90%)	AAA	AA	AAcd	AAabA	AAAbac	AAcb	CC	AAB	AAcC	AA C	AAbcd
angry (DD- 60%)	DDA	DD	DDc	baddad	bdd	addbdca	DDba	DDaabada	DDdcddaba	DDb	
tired (CD- 40%)	CDA	CD	CDb	bdc	bd	bdcB	CC	bdB	caccd	CDbC	CDbbcbcb
excited (DB- 50%)	da	D	DBcaC	daabbA	DBabc	DBbcbca	DB	daabcC	DBcaccbC	DBB	
sick (CA- 30%)	CAdA	cddD	CAbd	ba	baB	babed	babd	CA	CAB	cbdB	
hungry (CB- 40%)	CBa	CBab	CB	bbA	bb	bbc	bbB	cacba	CBcC	CBB	
thirsty (CC- 50%)	CCA	CCd	CC	bcA	bc	bcbCC	cbcd	CCcabC	CCbC	CCbB	
silly (AB- 40%)	dcacaaa	dcdba	acd	ABa	AB	Abc	ABd	acC	ac	ABBB	
scared (DC- 40%)	DCcA	DCc	DCbC	bcdA	bccd	adbccc	CC	DCcbbacd	ccC	ccccb	dbcc

Language of agent 30

Regularity	me	we	mip	you	yall	yup	yumi	one	they	all
50%	-AA 30%	-D 40%	-C 40%	-A 90%	-A 30%	-C 50%	-B 60%	-A 40%	-C 60%	-B 90%
happy (AD- 50%)	dcadd	dcD	dcddcb	ADA	ADbA	AD	dcddB	ADca	ADC	ADbdbdB
sad (AA- 90%)	AAad	AAAdd	AAcdd	AAA	AA	AAbC	AAad	AAcA	AA C	AAdB
angry (DD- 50%)	DDad	DD	DDcd	badadd	bddd	add	DDbd	dad	DDabC	DDb
tired (CD- 40%)	CDA	CD	CDbC	bdA	bd	bdB	bdB	cac	CDcbC	CDB
excited (DA- 40%)	DAaccd	D	dbbbcd	DAabaaa	dbA	dbca	db	DAc	DAb	dbB
sick (CA- 30%)	CAd	cddab	cbddab	ba	bab	bab	babdB	CAab	CAbdb	cbdbbbca
hungry (CB- 40%)	CBAA	CBa	CB	bbA	bb	bbc	bbB	cacba	CBca	CBB
thirsty (CC- 40%)	CCAA	CCba	CC	bcA	bc	bcbcb	cbcd	caccbaeb	CCbcb	CCbB
silly (AB- 40%)	dcaAA	dcbaa	acd	ABa	AB	ABC	ABd	acA	ac	ABBB
scared (DC- 50%)	DCca	DCc	DCcbC	bccA	bcd	adbccC	DCCb	cacc	ccC	DCCbB

E.2 Round 10010

Language of agent 1

Regularity	me	we	mip	you	yall	yup	yumi	one	they	all
58%	-A 80%	-D 60%	-D 40%	-A 90%	-B 40%	-C 60%	-B 70%	-C 50%	-C 70%	-B 90%
happy (AD- 60%)	dcad	dcD	dcddcb	DADA	ADaB	AD	ADbd	ADca	ADC	ADB
sad (AA- 70%)	AAAd	AA	AAcd	AAA	AAaB	adbcedaad	AAbd	aca	AA C	AAB
angry (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDb	DDcaded	DDC	DDbdcddd
tired (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDca	CDC	CDB
excited (DA- 40%)	DAad	D	dbbdc	DAab	dbac	dbca	db	DAc	DAcb	dbB
sick (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAC	CACb	CAB
hungry (CB- 50%)	CBA	CBD	CB	bbA	bb	bbc	bbB	CBca	CBC	CBB
thirsty (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCC	CCcb	CCB
silly (AB- 40%)	dcaA	dcab	acdb	ABa	AB	ABC	ABd	acA	ac	ABBB
scared (DC- 60%)	DCac	DC	DCc	bcdA	bcd	adbccC	DCB	DCccaccC	DCcC	DCbbbbbB

Language of agent 2

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
61%	-A 90%	-D 70%	-D 40%	-A 90%	-B 40%	-C 70%	-B 50%	-CA 60%	-C 80%	-B 100%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddeb	ADA	ADaB	AD	ADbd	ADCA	ADC	ADbdB
<i>sad</i> (AA- 70%)	AAAdA	AAD	AAdc	AAA	AAaB	AAbC	AA	aca	acab	AAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDbd	DDCA	DDC	DDb
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB
<i>excited</i> (DA- 40%)	DAAdA	D	dbbdc	DAA	dba	dbca	dbd	DAc	DAcB	db
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAbB
<i>hungry</i> (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCCA	CCC	CCbB
<i>silly</i> (AB- 40%)	dcA	dcab	acd	ABA	AB	ABC	ABd	acc	ac	ABB
<i>scared</i> (DC- 60%)	DCac	DC	DCcD	bcd	bcdB	adbC	DCB	DCcacc	DCC	DCbB

Language of agent 3

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
59%	-A 80%	-D 70%	-C 40%	-A 90%	-B 50%	-C 70%	-B 50%	-A 60%	-C 60%	-B 90%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddebC	ADA	ADaB	AD	ADbd	ADcA	ADC	ADB
<i>sad</i> (AA- 70%)	AAAdA	AAD	AAdC	AAA	AAaB	AAbC	AA	aca	acab	AAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDbd	DDcA	DDC	DDb
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDcA	CDC	CDB
<i>excited</i> (DB- 40%)	dad	D	DBbdbaba	daA	DBa	DBca	DBd	da	dacb	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAC	CACb	CAB
<i>hungry</i> (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBc	CBcb	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCcA	CCC	CCB
<i>silly</i> (AB- 40%)	dcA	dcab	acbdcb	ABA	AB	ABC	ABd	acc	ac	ABB
<i>scared</i> (DC- 50%)	DCac	DC	DCC	bcd	bcdB	adbC	DCB	dacc	DCcC	DCbbC

Language of agent 4

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
62%	-A 90%	-D 80%	-C 40%	-A 100%	-B 40%	-C 80%	-B 50%	-CA 60%	-C 80%	-B 100%
<i>happy</i> (AD- 60%)	dcdadddA	dcD	ddcC	ADA	ADaB	AD	ADbd	ADCA	ADC	ADB
<i>sad</i> (AA- 70%)	AAAdA	AAD	AAdC	AAA	AAaB	AAbC	AA	aca	acab	AAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDba	DDCA	DDcdacab	DDb
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB
<i>excited</i> (DB- 40%)	dadA	D	DBdcaad	daA	DBa	DBC	DBd	da	daC	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
<i>hungry</i> (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCCA	CCC	CCB
<i>silly</i> (AB- 40%)	dcA	dcab	dcabb	ABA	AB	ABC	ABd	acc	ac	ABB
<i>scared</i> (DC- 50%)	DCacdad	DC	DCC	bcdA	bcd	adbC	DCB	dacc	DCcC	DCbB

Language of agent 5

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
58%	-A 70%	-D 70%	-D 40%	-A 80%	-B 40%	-C 70%	-B 50%	-C 80%	-CB 50%	-B 90%
<i>happy</i> (AD- 60%)	dcdad	dcD	dddccc	ADA	ADaB	AD	ADbd	ADc	ADcd	ADB
<i>sad</i> (AA- 70%)	AAAdA	AAD	AAdc	AAA	AAaB	AAbC	AA	aca	acab	AAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bdd	bddd	add	DDb	DDC	DDcdab	DDbcd
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDC	CDcB	CDB
<i>excited</i> (DB- 40%)	dad	D	DBbd	daA	DBa	DBca	DBd	da	daCB	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAC	CACB	CAB
<i>hungry</i> (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBC	CBCB	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCC	CCCB	CCB
<i>silly</i> (AB- 40%)	dcA	dcab	acd	ABA	AB	ABC	ABd	acc	ac	ABB
<i>scared</i> (DC- 50%)	DCac	DC	DCcb	bcd	bcded	adbC	DCba	dacc	DCc	DCB

Language of agent 6

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
62%	-A 80%	-D 90%	-C 30%	-A 100%	-B 40%	-C 80%	-B 50%	-A 50%	-B 50%	-B 100%
<i>happy</i> (AD- 60%)	dcdA	dcD	dcdC	ADA	ADaB	AD	ADbd	ADcA	ADc	ADB
<i>sad</i> (AA- 70%)	AAAdA	AAD	AAdC	AAA	AAaB	AAbC	AA	aca	acaB	AAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDbd	DDcA	DDc	DDb
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDc	CDcB	CDB
<i>excited</i> (D- 90%)	Dad	D	Dcabddd	DaA	Dba	Dc	Dbd	DA	DacB	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAC	CACB	CAB
<i>hungry</i> (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBcA	CBc	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCc	CCcB	CCB
<i>silly</i> (AB- 40%)	dcaA	dcab	dcabba	ABA	AB	ABC	ABd	acc	ac	ABB
<i>scared</i> (DC- 50%)	DCac	DCbD	DCcb	bcdA	bcd	adbC	DCbB	dacc	DCc	dbbcbB

Language of agent 7

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
59%	-A 80%	-D 70%	-C 40%	-A 90%	-B 40%	-C 80%	-B 40%	-CA 50%	-C 70%	-B 100%
<i>happy</i> (AD- 60%)	dcdA	dcD	dcdG	ADA	ADaB	AD	ADbd	ADcA	ADc	ADB
<i>sad</i> (AA- 70%)	AAAdA	AAD	AAdC	AAA	AAaB	AAbC	AA	aca	acab	AAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDba	DDCA	DDC	DDb
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDcA	CDC	CDB
<i>excited</i> (DA- 40%)	DAd	D	dbbdcd	DAaA	dba	dbC	dbd	DAc	DAcb	db
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAc	CAcb	CAB
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBcA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCcA	CCc	CCB
<i>silly</i> (AB- 40%)	dca	dcab	acd	ABad	AB	ABC	ABd	acc	ac	ABB
<i>scared</i> (DC- 50%)	DCac	DCcda	DCC	bcA	bcd	adbc	DCbbd	dacc	DCc	dbbcbB

Language of agent 8

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
62%	-A 80%	-D 90%	-C 30%	-A 90%	-A 30%	-C 70%	-B 50%	-A 60%	-C 70%	-B 100%
<i>happy</i> (AD- 60%)	dcdA	dcD	dcdC	ADA	ADab	AD	ADbd	ADcA	ADc	ADbdB
<i>sad</i> (AA- 80%)	AAAdA	AAD	AAdcd	AAA	AA	AAb	AAdB	aca	AAC	AABb
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDbd	DDcA	DDC	DDb
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDcA	CDC	CDB
<i>excited</i> (D- 90%)	Dad	DcdabbDD	D	Daab	Dba	DcC	Dbd	DA	Dacb	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAc	CAcb	CAB
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBcA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCc	CCcb	CCB
<i>silly</i> (AB- 40%)	dca	dcab	acd	ABad	AB	ABC	ABd	acc	ac	ABB
<i>scared</i> (DC- 50%)	DCac	DCbD	DCcb	bcA	bcd	adbc	DCbba	dacc	DCC	dbbcbB

Language of agent 9

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
58%	-A 80%	-D 60%	-D 40%	-A 100%	-B 40%	-C 80%	-B 50%	-A 50%	-B 50%	-B 100%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddccbD	ADA	ADaB	AD	ADbd	ADcA	ADc	ADbB
<i>sad</i> (AA- 70%)	AAAdA	AAD	AAdc	AAA	AAaB	AAbC	AA	aca	acaB	AAB
<i>angry</i> (DD- 60%)	DDAd	DDD	DD	bddA	bdd	add	DDbd	DDcA	DDc	DDb
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDc	CDcB	CDB
<i>excited</i> (DB- 40%)	dAdA	D	DBbcd	daA	DBa	DBC	DBd	da	dacB	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAcA	CAc	CAB
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBc	CBcB	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCdb	CC	bcA	bc	bcC	bcB	CCc	CCcB	CCB
<i>silly</i> (AB- 40%)	dcaA	dcab	acdb	ABA	AB	ABC	ABd	acc	ac	ABB
<i>scared</i> (DC- 50%)	DCac	DC	DCcb	bcA	bcd	adbc	DCB	dacc	DCc	DCcbB

Language of agent 10

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
61%	-A 80%	-D 90%	-C 40%	-A 90%	-B 40%	-C 80%	-B 40%	-A 50%	-B 50%	-B 100%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddccB	ADA	ADaB	AD	ADbd	ADcA	ADc	ADbB
<i>sad</i> (AA- 70%)	AAAdA	AAD	AAdc	AAA	AAaB	AAbC	AA	aca	acaB	AAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDba	DDcA	DDc	DDb
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDc	CDcB	CDB
<i>excited</i> (D- 90%)	Daad	DcddddDD	D	DaaA	Dba	DcC	Dbd	DA	Dacb	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAc	CAcB	CAB
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBc	CBcB	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCcA	CCc	CCB
<i>silly</i> (AB- 40%)	dcaA	dcab	acdb	ABA	AB	ABC	ABd	acc	ac	ABB
<i>scared</i> (DC- 50%)	DCac	DCbD	DCcb	bcA	bcd	adbc	DCbba	dacc	DCc	dbbcbB

Language of agent 11

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
58%	-A 90%	-D 70%	-B 30%	-A 90%	-B 40%	-C 70%	-B 50%	-A 50%	-B 50%	-B 100%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddccB	ADA	ADaB	AD	ADbd	ADcA	ADc	ADbB
<i>sad</i> (AA- 80%)	AAAdA	AAD	AAdc	AAA	AAaB	AAb	AA	aca	AAc	AAbB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDba	DDcA	DDc	DDb
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDc	CDcB	CDB
<i>excited</i> (DA- 40%)	DAdA	D	dbbbcd	DAab	dba	dbC	dbd	DAc	DAcb	db
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAc	CAcB	CAB
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBcA	CBc	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCc	CCcB	CCB
<i>silly</i> (AB- 40%)	dcaA	dcab	acd	ABA	AB	ABC	ABd	acc	accB	ABB
<i>scared</i> (DC- 60%)	DCac	DC	DCcB	bcA	bcd	adbc	DCB	DCcA	DCc	DCcbB

Language of agent 12

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
60%	-A 80%	-D 70%	-D 50%	-A 90%	-B 50%	-C 60%	-B 70%	-CA 50%	-C 80%	-B 90%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddecD	ADA	ADaB	AD	ADbd	ADCA	ADC	ADB
<i>sad</i> (AA- 70%)	AAaA	AAD	AAcD	AAA	AAaB	AAbC	AA	aca	acab	AAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDB	DDCA	DDC	DDbB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB
<i>excited</i> (DA- 40%)	DAd	D	dbbdc	DAab	dbaabab	Bdbcaabaa	dbd	DAc	DAcb	db
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
<i>hungry</i> (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCCA	CCC	CCB
<i>silly</i> (AB- 30%)	dcaA	dcdba	acd	ABA	ABaB	acba	AB	acc	ac	ABB
<i>scared</i> (DC- 60%)	DCac	DC	DCc	bcdA	bcd	adbC	DCB	DCccac	DCcC	DCbbbbb

Language of agent 13

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
61%	-A 90%	-D 80%	-C 40%	-A 100%	-D 40%	-C 70%	-B 50%	-CA 60%	-C 80%	-B 90%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddecB	ADA	ADab	AD	ADbd	ADCA	ADC	ADB
<i>sad</i> (AA- 70%)	AAaA	AAD	AAcA	AAA	AAaba	AAbC	AA	aca	acab	AAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDba	DDCA	DDC	DDbB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB
<i>excited</i> (DB- 40%)	dAdA	DBdD	D	daabA	DBa	DBca	DBd	da	dacb	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
<i>hungry</i> (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCCA	CCC	CCB
<i>silly</i> (AB- 40%)	dcaA	dcab	dcabC	ABA	AB	ABC	ABd	acc	ac	ABB
<i>scared</i> (DC- 50%)	DCac	DC	DCC	bcdA	bcd	adbC	DCB	dacc	DCcC	DCbc

Language of agent 14

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
62%	-A 80%	-D 80%	-B 40%	-A 100%	-A 30%	-C 70%	-B 40%	-CA 50%	-C 70%	-B 90%
<i>happy</i> (AD- 60%)	dcdA	dcD	dcdc	ADA	ADab	AD	ADbDbd	ADCA	ADC	ADbd
<i>sad</i> (AA- 90%)	AAaA	AAD	AAcB	AAA	AA	AAb	AAdbba	AAcA	AAc	AAbB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDba	DDCA	DDC	DDbB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB
<i>excited</i> (D- 90%)	DAd	DcDbabda	D	daA	DBa	DBc	DBd	da	dacb	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAC	CACb	CAB
<i>hungry</i> (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCc	CCcb	CCB
<i>silly</i> (AB- 40%)	dcaA	dcab	dcabbac	ABA	AB	ABC	ABd	acc	ac	ABB
<i>scared</i> (DC- 50%)	DCac	DCbD	DCCB	bcdA	bcd	adbC	DCbbd	dacc	DCC	DCbcb

Language of agent 15

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
59%	-A 80%	-D 70%	-B 30%	-A 100%	-B 40%	-C 70%	-B 50%	-CA 50%	-C 90%	-B 80%
<i>happy</i> (AD- 60%)	dcdA	dcD	dddDbad	BADA	ADaB	AD	ADbaB	ADcAc	ADC	ADbd
<i>sad</i> (AA- 80%)	AAaA	AAD	AAc	AAA	AAaB	AAbC	AAdba	aca	AAc	AA
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDbd	DDCA	DDC	DDbB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB
<i>excited</i> (DB- 40%)	daadd	DBdbddda	D	daA	DBa	DBC	DBd	da	dacb	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
<i>hungry</i> (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCCA	CCC	CCB
<i>silly</i> (AB- 40%)	dcaA	dcaba	dcabc	ABA	ABaB	AB	ABd	acc	ac	ABB
<i>scared</i> (DC- 50%)	DCac	DC	DCC	bcdA	bcd	adbC	DCbba	dacc	DCC	DCB

Language of agent 16

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
62%	-A 80%	-D 70%	-C 40%	-A 90%	-B 50%	-C 80%	-B 60%	-CA 70%	-C 80%	-B 90%
<i>happy</i> (AD- 60%)	dcdAA	dcD	ddecB	ADA	ADaB	AD	ADbd	ADCA	ADC	ADB
<i>sad</i> (AA- 70%)	AAaA	AAD	AAc	AAA	AAaB	AAbC	AA	aca	acab	AAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDB	DDCA	DDC	DDbc
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB
<i>excited</i> (DA- 40%)	DAd	D	dbbbd	CDAaB	dbacaba	BdbC	dbd	DAc	DAcb	db
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
<i>hungry</i> (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCCA	CCC	CCB
<i>silly</i> (AB- 40%)	dcaA	dcab	acd	ABA	AB	ABC	ABd	acc	ac	ABB
<i>scared</i> (DC- 60%)	DCac	DC	DCC	bcdA	bcd	adbC	DCB	DCCA	DCcC	DCbB

Language of agent 17

Regularity 58%	<i>me</i> -A 80%	<i>we</i> -D 70%	<i>mip</i> -B 30%	<i>you</i> -A 80%	<i>yall</i> -B 40%	<i>yup</i> -C 70%	<i>yumi</i> -B 70%	<i>one</i> -A 60%	<i>they</i> -C 60%	<i>all</i> -B 90%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddccB	ADA	ADaB	AD	ADbd	ADcA	ADC	ADB
<i>sad</i> (AA- 70%)	AAaA	AAAD	AAcdB	AAA	AAaB	AAbC	AA	aca	acab	AAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bdd	bddc	addbadC	DDB	DDcA	DDC	DDbc
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDcA	CDC	CDB
<i>excited</i> (DA- 40%)	DAd	D	dbbbac	DAab	dba	dbca	dbd	DAc	DAcb	db
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAC	CACb	CAB
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBcA	CBcb	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCcA	CCC	CCB
<i>silly</i> (AB- 30%)	dcA	dcab	acd	ABA	ABaB	acba	AB	acc	ac	ABB
<i>scared</i> (DC- 60%)	DCac	DC	DCc	bcdA	bcd	adbcC	DCB	DCcA	DCcC	DCbcB

Language of agent 18

Regularity 60%	<i>me</i> -A 80%	<i>we</i> -D 70%	<i>mip</i> -D 40%	<i>you</i> -A 100%	<i>yall</i> -B 40%	<i>yup</i> -C 80%	<i>yumi</i> -B 60%	<i>one</i> -CA 50%	<i>they</i> -C 70%	<i>all</i> -B 90%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddccb	ADA	ADaB	AD	ADbd	ADCA	ADC	ADB
<i>sad</i> (AA- 70%)	AAaA	AAAD	AAdc	AAA	AAaB	AAbC	AA	aca	acab	AAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDB	DDCA	DDC	DDbdd
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB
<i>excited</i> (DA- 40%)	DAd	D	dbbcdAd	DAA	dba	dbC	dbd	DAc	DAcb	db
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAC	CACb	CAB
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBcA	CBcb	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCcA	CCC	CCB
<i>silly</i> (AB- 40%)	dcA	dcab	acd	ABA	AB	ABC	ABd	acccc	ac	ABB
<i>scared</i> (DC- 60%)	DCac	DC	DCc	bcdA	bcd	adbc	DCB	DCcac	DCcC	DCcB

Language of agent 19

Regularity 60%	<i>me</i> -A 80%	<i>we</i> -D 70%	<i>mip</i> -C 40%	<i>you</i> -A 90%	<i>yall</i> -B 40%	<i>yup</i> -C 80%	<i>yumi</i> -B 40%	<i>one</i> -CA 60%	<i>they</i> -C 80%	<i>all</i> -B 100%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddcbC	ADA	ADaB	AD	ADbd	ADCA	ADC	ADB
<i>sad</i> (AA- 70%)	AAaA	AAAD	AAdC	AAA	AAaB	AAbC	AA	aca	acab	AAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDba	DDCA	DDC	DDbD
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB
<i>excited</i> (DB- 40%)	dad	D	DBbdd	daab	DBa	DBC	DBd	da	dacb	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBcA	CBcb	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCcA	CCC	CCB
<i>silly</i> (AB- 40%)	dcA	dcab	acd	ABA	AB	ABC	ABd	acc	ac	ABB
<i>scared</i> (DC- 50%)	DCac	DC	DCC	bcdA	bcd	adbcC	DCb	dacc	DCC	DCbc

Language of agent 20

Regularity 60%	<i>me</i> -A 80%	<i>we</i> -D 70%	<i>mip</i> -C 40%	<i>you</i> -A 100%	<i>yall</i> -B 40%	<i>yup</i> -C 80%	<i>yumi</i> -B 70%	<i>one</i> -CA 50%	<i>they</i> -C 70%	<i>all</i> -B 80%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddcbC	ADA	ADaB	AD	ADbd	ADCA	ADC	ADbbd
<i>sad</i> (AA- 70%)	AAaA	AAAD	AAdC	AAA	AAaB	AAbC	AA	aca	acab	AAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDba	DDCA	DDC	DDbD
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB
<i>excited</i> (DB- 40%)	dad	D	DBbdC	daA	DBa	DBC	DB	da	dacb	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBcA	CBcb	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCc	CCcb	CCB
<i>silly</i> (AB- 40%)	dcA	dcab	acd	ABA	AB	ABC	ABd	acc	ac	ABB
<i>scared</i> (DC- 50%)	DCac	DC	DCcb	bcdA	bcd	adbc	DCB	dacc	DCC	DCbbc

Language of agent 21

Regularity 60%	<i>me</i> -A 90%	<i>we</i> -D 70%	<i>mip</i> -C 40%	<i>you</i> -A 100%	<i>yall</i> -A 30%	<i>yup</i> -C 80%	<i>yumi</i> -B 50%	<i>one</i> -CA 60%	<i>they</i> -C 80%	<i>all</i> -B 80%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddcbC	ADA	ADaB	AD	ADbd	ADcA	ADC	ADbbd
<i>sad</i> (AA- 70%)	AAaA	AAAD	AAdC	AAA	AAaB	AAbC	AA	aca	acab	AAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDba	DDCA	DDC	DDbD
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB
<i>excited</i> (DB- 40%)	dad	D	DBbd	daA	DBa	DBC	DBd	da	dacb	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBcA	CBcb	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCcA	CCC	CCB
<i>silly</i> (AB- 40%)	dcA	dcab	acd	ABA	AB	ABC	ABd	acc	ac	ABB
<i>scared</i> (DC- 50%)	DCac	DC	DCdcbcc	DCC	bcdA	bcd	adbcC	DCbbd	dacc	DCcC

Language of agent 22

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
61%	-A 80%	-D 70%	-C 40%	-A 100%	-B 40%	-C 80%	-B 60%	-CA 60%	-C 80%	-B 100%
<i>happy</i> (AD- 60%)	dcdad	dcD	ddecb	ADA	ADaB	AD	ADbd	ADCA	ADC	ADB
<i>sad</i> (AA- 70%)	AAAdA	AAD	AAcD	AAA	AAaB	AAbC	AA	aca	acab	AAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDB	DDCA	DDC	DDbB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB
<i>excited</i> (DB- 40%)	dAdA	D	DBbC	daA	DBa	DBC	DBd	da	dacb	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCCA	CCC	CCbB
<i>silly</i> (AB- 40%)	dcA	dcab	acd	ABA	AB	ABC	ABd	acc	ac	ABB
<i>scared</i> (DC- 50%)	DCac	DC	DCC	bcdA	bcd	adbC	DCB	dacc	DCcC	DCbC

Language of agent 23

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
61%	-A 80%	-D 70%	-C 40%	-A 90%	-B 40%	-C 70%	-B 50%	-CA 70%	-C 90%	-B 100%
<i>happy</i> (AD- 50%)	dcdA	dcD	dcdC	ADA	ADaB	AD	dcdB	ADCA	ADC	ADB
<i>sad</i> (AA- 90%)	AAAdA	AAD	AAcD	AAA	AAaB	AA	AAdbA	AACA	AAC	AAbB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDba	DDCA	DDC	DDbB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB
<i>excited</i> (DB- 40%)	dAd	D	DBbdC	daA	DBa	DBC	DBd	da	dacb	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCCA	CCC	CCbB
<i>silly</i> (AB- 40%)	dcA	dcab	acd	ABA	AB	ABC	ABd	acc	ac	ABB
<i>scared</i> (DC- 50%)	DCac	DCbdc	DCcb	bcd	bcd	adbC	DCbd	dacc	DCC	dbbcB

Language of agent 24

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
58%	-A 80%	-D 70%	-C 30%	-A 90%	-B 40%	-C 80%	-B 50%	-A 60%	-C 60%	-B 90%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddecB	ADA	ADaB	AD	ADbd	ADcA	ADC	ADB
<i>sad</i> (AA- 70%)	AAAdA	AAD	AAcD	AAA	AAaB	AAbC	AA	aca	acab	AAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDbd	DDcA	DDC	DDbB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDcA	CDC	CDB
<i>excited</i> (DB- 40%)	dAd	D	DBdabddA	daA	DBa	DBC	DBd	da	dacb	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAC	CACb	CAB
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCcA	CCC	CCbB
<i>silly</i> (AB- 40%)	dcA	dcab	dcabbC	ABA	AB	ABC	ABd	acc	ac	ABB
<i>scared</i> (DC- 50%)	DCac	DC	DCcb	bcd	bcd	adbC	DCB	dacc	DCC	DCbc

Language of agent 25

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
59%	-A 80%	-D 70%	-B 30%	-A 100%	-B 40%	-C 80%	-B 50%	-A 60%	-C 60%	-B 100%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddecB	ADA	ADaB	AD	ADbd	ADcA	ADC	ADB
<i>sad</i> (AA- 70%)	AAAdA	AAD	AAcD	AAA	AAaB	AAbC	AA	aca	acab	AAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDba	DDcA	DDC	DDbB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDcA	CDC	CDB
<i>excited</i> (DB- 40%)	dAd	D	DBdadca	daA	DBa	DBC	DBd	da	dacb	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAC	CACb	CAB
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCc	CCcb	CCB
<i>silly</i> (AB- 40%)	dcA	dcab	dcabdba	ABA	AB	ABC	ABd	acc	ac	ABB
<i>scared</i> (DC- 50%)	DCac	DC	DCcB	bcdA	bcd	adbC	DCbd	dacc	DCC	DCB

Language of agent 26

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
61%	-A 90%	-D 70%	-B 30%	-A 100%	-A 30%	-C 70%	-B 60%	-CA 70%	-C 80%	-B 80%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddecB	ADA	ADab	AD	ADbd	ADCA	ADC	ADbbD
<i>sad</i> (AA- 80%)	AAAdA	AAD	AAcD	AAA	AA	AAb	AAdbA	aca	AAcd	AAbB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDba	DDCA	DDC	DDbB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB
<i>excited</i> (DA- 40%)	DAAdA	D	dbbdc	DA	dbA	dbC	dbA	DAc	DAcb	db
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCCA	CCC	CCbB
<i>silly</i> (AB- 40%)	dcA	dcab	acd	ABA	AB	ABC	ABd	acc	ac	ABB
<i>scared</i> (DC- 60%)	DCac	DC	DCcd	bcdA	bcd	adbC	DCB	DCCA	DCC	DCbbc

Language of agent 27

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
62%	-A 90%	-D 80%	-B 40%	-A 100%	-B 40%	-C 80%	-B 50%	-CA 70%	-C 80%	-B 100%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddcB	ADA	ADaB	AD	ADbd	ADCA	ADC	ADB
<i>sad</i> (AA- 70%)	AAdaA	AAD	AAdc	AAA	AAaB	AAbC	AA	aca	acab	AAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDba	DDCA	DDC	DDb
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB
<i>excited</i> (DB- 40%)	dadA	DBdac	D	daA	DBa	DBC	DBd	da	dacb	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCCA	CCC	CCB
<i>silly</i> (AB- 40%)	dcA	dcab	dcabB	ABA	AB	ABC	ABd	accA	ac	ABB
<i>scared</i> (DC- 50%)	DCac	DC	DCcB	bcdA	bcd	adbC	DCB	dacc	DCC	DCbB

Language of agent 28

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
62%	-A 80%	-D 80%	-B 40%	-A 100%	-B 40%	-C 80%	-B 60%	-CA 60%	-C 80%	-B 100%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddcB	ADA	ADaB	AD	ADbd	ADCA	ADC	ADB
<i>sad</i> (AA- 70%)	AAdaA	AAD	AAdc	AAA	AAaB	AAbC	AA	aca	acab	AAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDb	DDCA	DDC	DDbdB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB
<i>excited</i> (DB- 40%)	dad	DBdD	D	daA	DBa	DBC	DBd	da	dacb	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAbbbdB
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCCA	CCC	CCB
<i>silly</i> (AB- 40%)	dcA	dcab	dcabB	ABA	AB	ABC	ABd	acc	ac	ABB
<i>scared</i> (DC- 50%)	DCac	DC	DCcB	bcdA	bcd	adbC	DCbB	dacc	DCC	DCB

Language of agent 29

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
59%	-A 80%	-D 70%	-C 40%	-A 70%	-B 40%	-C 80%	-B 60%	-A 60%	-C 70%	-B 90%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddcbC	ADA	ADaB	AD	ADbd	ADc	ADcd	ADB
<i>sad</i> (AA- 70%)	AAdaA	AAD	AAcd	AAA	AAaB	AAbC	AA	acA	acab	AAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bdd	bddcd	add	DDb	DDcA	DDC	DDbcdB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDcA	CDC	CDB
<i>excited</i> (DA- 40%)	DAd	D	dbbbd	DAab	dba	dbC	dbd	DAc	DAcb	db
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAcA	CAC	CAB
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBcA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCc	CCcbC	CCB
<i>silly</i> (AB- 40%)	dcA	dcab	dcabB	ABA	AB	ABC	ABd	acc	ac	ABB
<i>scared</i> (DC- 50%)	DCac	DC	DCcB	bcd	bcdc	adbC	DCB	DCcA	DCc	dbbcc

Language of agent 30

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
60%	-A 90%	-D 80%	-D 40%	-A 90%	-A 40%	-C 70%	-B 40%	-C 70%	-CB 50%	-B 90%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddccb	ADA	ADaB	AD	ADbd	ADC	ADcd	ADbbd
<i>sad</i> (AA- 90%)	AAdaA	AAD	AAdc	AAA	AA	AAbC	AAbd	AAca	AAc	AAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDba	DDca	DDc	DDb
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDC	CDCB	CDB
<i>excited</i> (DB- 40%)	dadA	DBda	D	daA	DBa	DBca	DBd	da	daCB	DB
<i>sick</i> (CA- 60%)	CAA	CAD	CABD	baA	ba	baC	baB	CAC	CACB	CAB
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBC	CBCB	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CCbdc	bcA	bc	bcC	bcB	CC	CCCB	CCB
<i>silly</i> (AB- 40%)	dcA	dcab	dcabbbA	ABA	AB	ABC	ABd	acc	ac	ABB
<i>scared</i> (DC- 50%)	DCac	DC	DCcb	bcd	bcdc	adbC	DCbba	dacC	DCc	DCB

E.3 Round 15015

Language of agent 1

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
61%	-A 80%	-D 70%	-D 60%	-A 80%	-B 60%	-C 80%	-B 50%	-C 60%	-CB 50%	-B 100%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddccbD	ADA	ADaB	AD	ADbd	ADca	ADc	ADB
<i>sad</i> (AA- 70%)	AAdaA	AAD	AAdc	AAA	AAaB	AAbC	AA	aca	acab	AAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bdd	bddB	add	DDb	DDca	DDc	DDbB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDC	CDCB	CDB
<i>excited</i> (DB- 40%)	dad	D	DBbd	daA	DBa	DBC	DBd	da	daCB	DB
<i>sick</i> (CA- 60%)	CAA	CAD	CABc	baA	ba	baC	baB	CAC	CACB	CAB
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBC	CBCB	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CC	CCCB	CCB
<i>silly</i> (AB- 40%)	dcA	dcab	acD	ABA	AB	ABC	ABd	acc	acb	ABB
<i>scared</i> (DC- 50%)	DCac	DC	DCcD	bcd	bcdB	adbC	DCba	dacC	DCc	DCB

Language of agent 2

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
62%	-A 80%	-D 70%	-D 50%	-A 90%	-B 40%	-C 80%	-B 60%	-CA 60%	-C 80%	-B 100%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddeb	ADA	ADaB	AD	ADbd	ADCA	ADC	ADB
<i>sad</i> (AA- 70%)	AAAdA	AAD	AAdc	AAA	AAaB	AAbC	AA	acaa	aca	AAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDB	DDCA	DDC	DDbB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB
<i>excited</i> (DA- 40%)	DAd	D	dbbD	DAA	dba	dbC	dbd	DAc	DAcb	db
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
<i>hungry</i> (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCCA	CCC	CCB
<i>silly</i> (AB- 40%)	dcA	dcab	acD	ABA	AB	ABC	ABd	acc	ac	ABB
<i>scared</i> (DC- 60%)	DCac	DC	DCcD	bcd	bcdbc	adbC	DCB	DCcac	DCC	DCbB

Language of agent 3

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
59%	-A 80%	-D 70%	-B 40%	-A 90%	-B 50%	-C 70%	-B 60%	-C 60%	-CB 50%	-B 100%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddeb	ADA	ADaB	AD	ADbd	ADca	ADc	ADB
<i>sad</i> (AA- 70%)	AAAdA	AAD	AAdc	AAA	AAaB	AAb	AA	aca	acab	AAbB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDB	DDca	DDc	DDbB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDC	CDCB	CDB
<i>excited</i> (DB- 40%)	dAd	D	DBbdbaaB	daA	DBa	DBC	DBd	da	daCB	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAC	CACB	CAB
<i>hungry</i> (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBC	CBCB	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCC	CCCB	CCB
<i>silly</i> (AB- 40%)	dcA	dcab	acB	ABA	AB	ABC	ABd	acc	ac	ABB
<i>scared</i> (DC- 50%)	DCac	DC	DCc	bed	bedB	adbC	DCB	dacC	DCcc	DCbbb

Language of agent 4

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
55%	-A 80%	-D 60%	-C 50%	-A 100%	-A 30%	-C 60%	-B 70%	-CA 50%	-C 70%	-B 90%
<i>happy</i> (AD- 50%)	dcdA	dcD	dcdBdC	ADA	ADab	AD	dbddbbaa	ADCA	ADC	ADbB
<i>sad</i> (AA- 50%)	dcaaaaA	dcdBdadc	AAAdC	AAA	AA	AAb	AAdba	aca	acab	AAbB
<i>angry</i> (CD- 30%)	ddA	dd	CDbacdda	bddA	bdd	add	ddb	cacdaaaa	CDcdacB	CDbbbbad
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB
<i>excited</i> (DA- 40%)	DAd	dbda	dbbdcC	DAA	dbA	adbcabba	db	DAC	DAcd	dbB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
<i>hungry</i> (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCCA	CCC	CCB
<i>silly</i> (AB- 30%)	dcA	dcab	dcabb	ABA	AB	ABC	dbdbcbccacc	ac	ac	ABB
<i>scared</i> (DC- 50%)	DCac	DC	DCC	bcdA	bcd	adbC	DCB	dacc	DCcC	DCbB

Language of agent 5

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
59%	-A 80%	-D 80%	-B 30%	-A 80%	-A 40%	-C 70%	-B 40%	-C 60%	-B 50%	-B 90%
<i>happy</i> (AD- 60%)	dcdA	dcD	dcdc	ADAd	ADA	AD	ADabbdd	ADca	ADc	ADbBd
<i>sad</i> (AA- 60%)	AAAdA	AAD	AAAc	AAA	AA	AAb	AAdba	aca	acaB	AAbB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDbd	DDca	DDc	DDB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDC	CDcB	CDB
<i>excited</i> (D- 90%)	DAd	Dcdbaaba	D	DaA	DbA	Dbc	Dbd	Da	Dac	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAC	CACB	CAB
<i>hungry</i> (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBC	CBCB	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCC	CCcB	CCB
<i>silly</i> (AB- 40%)	dcA	dcab	dcabc	ABA	AB	ABC	ABd	acc	acbc	ABB
<i>scared</i> (DC- 50%)	DCac	DCbD	DCcB	bcd	bcdB	adbC	DCba	dacc	DCc	dbbcB

Language of agent 6

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
58%	-A 80%	-D 80%	-D 40%	-A 90%	-A 30%	-C 70%	-B 40%	-A 60%	-C 60%	-B 90%
<i>happy</i> (AD- 60%)	dcdA	dcD	dcdc	ADA	ADab	AD	ADbd	ADca	ADC	ADbBd
<i>sad</i> (AA- 70%)	AAAdA	AAD	AAdc	AAA	AA	AAb	AAdba	aca	acaB	AAbB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDba	DDca	DDc	DDB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDca	CDC	CDB
<i>excited</i> (DB- 40%)	dAd	D	DBbd	daA	DBA	DBC	DBd	da	dacB	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAC	CACb	CAB
<i>hungry</i> (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBcA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCc	CCcb	CCB
<i>silly</i> (AB- 40%)	dcA	dcab	acD	ABA	AB	ABC	ABd	acc	ac	ABB
<i>scared</i> (DC- 50%)	DCac	DCbD	DCcb	bcd	bcdc	adbC	DCba	dacc	DCC	dbbbbbbB

Language of agent 7

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
63%	-A 80%	-D 80%	-C 50%	-A 100%	-B 40%	-C 80%	-B 50%	-CA 50%	-C 70%	-B 90%
<i>happy</i> (AD- 60%)	dcD A	dcD	dcD C	ADA	ADaB	AD	ADbd	ADCA	ADC	ADB
<i>sad</i> (AA- 70%)	AA dA	AAD	AA dC	AAA	AAaB	AAbc	AA	acac	aca	AAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDba	DDCA	DDC	DDB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB
<i>excited</i> (D- 90%)	Dad	DcDbabba	D	DaA	Dba	Dbc	Dbd	Da	Dacb	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAc	CAcb	CAB
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCCA	CCC	CCB
<i>silly</i> (AB- 40%)	dcaA	dca	dcabC	ABA	AB	ABC	ABd	acc	ac	ABB
<i>scared</i> (DC- 50%)	DCcadca	DCbD	DCC	bedA	bed	adbC	DCB	dacc	DCcC	dbbcccc

Language of agent 8

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
59%	-A 80%	-D 70%	-B 30%	-A 100%	-B 40%	-C 80%	-B 70%	-A 60%	-C 60%	-B 90%
<i>happy</i> (AD- 50%)	dcD A	dcD	dcD B	ADA	ADaB	AD	dbddadbD	ADc	ADcd	ADB
<i>sad</i> (AA- 70%)	AA dA	AAD	AA dC	AAA	AAaB	AAbc	AA	aca	acab	AAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	addacca	DDB	DDcA	DDC	DDbB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDcA	CDC	CDB
<i>excited</i> (DB- 40%)	dad	D	DB bdc	daA	DBa	DBC	DB	da	dacd	DBB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAc	CAcb	CAB
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBcA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCcA	CCC	CCB
<i>silly</i> (AB- 40%)	dcaA	dcab	acd	ABA	AB	ABC	ABd	acc	ac	ABB
<i>scared</i> (DC- 50%)	DCac	DC	DCcB	bedA	bed	adbC	DCB	dacc	DCc	DCbc

Language of agent 9

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
62%	-A 90%	-D 70%	-C 50%	-A 100%	-B 40%	-C 70%	-B 80%	-CA 60%	-C 80%	-B 80%
<i>happy</i> (AD- 60%)	dcD A	dcD	dcD C	ADA	ADaB	AD	ADbaB	ADCA	ADC	ADB
<i>sad</i> (AA- 70%)	AA dA	AAD	AA dC	AAA	AAaB	AAb	AA	aca	acab	AAbB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDB	DDCA	DDC	DDbc
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB
<i>excited</i> (DA- 40%)	DAdA	D	dbb dC	DAA	dBA	dBc	db	DAc	DAcb	dbb
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBcA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCcA	CCC	CCB
<i>silly</i> (AB- 40%)	dcaA	dcab	acd	ABA	AB	ABC	ABd	acc	ac	ABB
<i>scared</i> (DC- 60%)	DCac	DCbdaa	DCC	bedA	bed	adbcccc	DCB	dacc	DCcC	DCbc

Language of agent 10

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
61%	-A 80%	-D 80%	-B 30%	-A 100%	-B 40%	-C 60%	-B 40%	-CA 70%	-C 90%	-B 100%
<i>happy</i> (AD- 60%)	dcD A	dcD	dcD B	ADA	ADaB	AD	ADbd	ADCA	ADC	ADB
<i>sad</i> (AA- 90%)	AA dA	AAD	AA dC	AAA	AAaB	AA	AAdbaba	AACA	AAC	AAbB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDbd	DDCA	DDC	DDB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB
<i>excited</i> (DB- 40%)	dad	DBda	D	daA	DBa	DBC	DBd	da	dacb	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBcA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCcA	CCC	CCB
<i>silly</i> (AB- 40%)	dcaA	dcab	dcabc	ABA	ABaB	AB	ABd	acc	ac	ABB
<i>scared</i> (DC- 50%)	DCac	DC	DCcB	bedA	bed	adbC	DCba	dacc	DCC	DCB

Language of agent 11

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
59%	-A 80%	-D 70%	-B 30%	-A 90%	-A 40%	-C 80%	-B 60%	-CA 60%	-C 80%	-B 90%
<i>happy</i> (AD- 60%)	dcD A	dcD	dcD B	ADad	ADA	AD	ADbd	ADCA	ADC	ADB
<i>sad</i> (AA- 70%)	AA dA	AAD	AA dC	AAA	AAab	AAbc	AA	acaa	aca	AAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDba	DDCA	DDC	DDB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB
<i>excited</i> (DB- 40%)	dad	DBda	D	daA	DBA	DBC	DBd	da	dacb	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBcA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCcA	CCC	CCB
<i>silly</i> (AB- 30%)	dcaA	dcab	dcabc	ABA	ABabA	acbbC	AB	acc	ac	ABB
<i>scared</i> (DC- 50%)	DCac	DC	DCcB	bedA	bed	adbC	DCB	dacc	DCC	DCbc

Language of agent 12

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
59%	-A 80%	-D 70%	-B 50%	-A 80%	-B 50%	-C 70%	-B 70%	-A 50%	-C 60%	-B 90%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddcB	ADA	ADaB	AD	ADbd	ADc	ADcd	CADB
<i>sad</i> (AA- 50%)	AAaA	AAD	AAcB	AAA	AAaB	Acabba	AA	acA	ac	AAbB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bdd	bddB	adddb	DDB	DDcA	DDC	DDbB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDcA	CDC	CDB
<i>excited</i> (DA- 40%)	DAd	D	dbbD	DAA	dba	dbC	db	DAc	DAcb	dbB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAC	CACb	CAB
<i>hungry</i> (CB- 50%)	CBA	CB	CB	bbA	bb	bbC	bbB	CBcA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCc	CCcb	CCB
<i>silly</i> (AB- 40%)	dcaa	dcab	acdB	ABA	AB	ABC	ABd	acc	acbd	ABB
<i>scared</i> (DC- 60%)	DCac	DC	DCcB	bcd	bcde	adbC	DCB	DCcA	DCC	DCbc

Language of agent 13

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
61%	-A 80%	-D 70%	-D 40%	-A 100%	-B 40%	-C 80%	-B 60%	-C 60%	-C 70%	-B 90%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddcb	ADA	ADaB	AD	ADbd	ADca	ADC	ADB
<i>sad</i> (AA- 70%)	AAaA	AAD	AAc	AAA	AAaB	AAbc	AA	aca	acab	AAAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDB	DDca	DDC	DDbB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDca	CDC	CDB
<i>excited</i> (DA- 40%)	DAd	D	dbbD	DAA	dba	dbC	dbd	DAC	DAcb	db
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAC	CACb	CAB
<i>hungry</i> (CB- 50%)	CBA	CB	CB	bbA	bb	bbC	bbB	CBcA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCc	CCc	CCB
<i>silly</i> (AB- 40%)	dcA	dcab	acd	ABA	AB	ABC	ABd	acc	acbd	ABB
<i>scared</i> (DC- 60%)	DCac	DC	DCc	bcdA	bcd	adbC	DCB	DCca	DCcC	DCbc

Language of agent 14

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
60%	-A 80%	-D 70%	-D 40%	-A 100%	-B 40%	-C 80%	-B 60%	-CA 60%	-C 80%	-B 80%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddcb	ADA	ADaB	AD	ADbd	ADCA	ADC	ADB
<i>sad</i> (AA- 70%)	AAaA	AAD	AAc	AAA	AAaB	AAbc	AA	acaaCA	aca	AAAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDB	DDCA	DDC	DDbc
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB
<i>excited</i> (DA- 40%)	DAd	D	dbbD	DAA	dba	dbC	dbd	DAC	DAcb	db
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
<i>hungry</i> (CB- 50%)	CBA	CB	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCc	CCc	CCB
<i>silly</i> (AB- 40%)	dcA	dcab	acd	ABA	AB	ABC	ABd	acc	ac	ABB
<i>scared</i> (DC- 50%)	DCac	DC	DCc	bcdA	bcd	adbC	DCB	dacc	DCcC	DCbc

Language of agent 15

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
60%	-A 80%	-D 70%	-B 30%	-A 90%	-B 50%	-C 80%	-B 70%	-A 50%	-B 50%	-B 100%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddcB	ADA	ADaB	AD	ADbd	ADc	ADcdcd	ADB
<i>sad</i> (AA- 70%)	AAaA	AAD	AAc	AAA	AAaB	AAbc	AA	aca	acaB	AAAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDB	DDcA	DDc	DDbB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDc	CDcB	CDB
<i>excited</i> (DA- 40%)	DAd	D	dbbD	DAA	dba	dbC	db	DAC	DAcB	dbB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACa	CAC	CAB
<i>hungry</i> (CB- 50%)	CBA	CB	CB	bbA	bb	bbC	bbB	CBcA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCc	CCcB	CCB
<i>silly</i> (AB- 40%)	dcA	dcab	acd	ABA	AB	ABC	ABd	acc	acB	ABB
<i>scared</i> (DC- 60%)	DCac	DC	DCcB	bcd	bcdB	adbC	DCB	DCcA	DCc	DCbB

Language of agent 16

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
58%	-A 80%	-D 80%	-B 30%	-A 100%	-B 40%	-C 70%	-B 40%	-A 60%	-C 50%	-B 100%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddcB	ADA	ADaB	AD	ADbd	ADcA	ADC	ADB
<i>sad</i> (AA- 70%)	AAaA	AAD	AAc	AAA	AAaB	AAb	AA	aca	acab	AAbB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDba	DDcA	DDC	DDB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDcA	CDC	CDB
<i>excited</i> (DB- 40%)	dad	DBd	D	daA	DBa	DBC	DBd	da	dacd	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACa	CAC	CAB
<i>hungry</i> (CB- 50%)	CBA	CB	CB	bbA	bb	bbC	bbB	CBcA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCc	CCcb	CCB
<i>silly</i> (AB- 40%)	dcA	dcab	dcabB	ABA	AB	ABC	ABd	ac	acB	ABB
<i>scared</i> (DC- 50%)	DCac	DC	DCc	bcdA	bcd	adbC	DCba	dacc	DCcC	DCB

Language of agent 17

Regularity	me	we	mip	you	yall	yup	yumi	one	they	all
60%	-A 80%	-D 80%	-D 40%	-A 80%	-B 60%	-C 60%	-B 50%	-C 70%	-CB 50%	-B 100%
happy (AD- 60%)	dcdA	dcD	dcdbdcdb	ADA	ADaB	AD	ADbd	ADC	ADcDb	ADbdB
sad (AA- 70%)	AAAdA	AAAD	AAdc	AAA	AAaB	AAb	AA	aca	acab	AAbB
angry (DD- 60%)	DDA	DDD	DD	bdd	bddB	add	DDbd	DDca	DDc	DDbB
tired (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDC	CDCB	CDB
excited (DB- 40%)	dad	D	DBbd	daA	DBa	DB	DBd	da	daCB	DBB
sick (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAC	CACB	CAB
hungry (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBC	CBCB	CBB
thirsty (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCC	CCCB	CCB
silly (AB- 40%)	dcA	dcab	acD	ABA	AB	ABC	ABd	acc	acb	ABB
scared (DC- 60%)	DCac	DCbD	DCcB	bcd	bcdB	adbC	DCB	dacC	DCc	DCbB

Language of agent 18

Regularity	me	we	mip	you	yall	yup	yumi	one	they	all
58%	-A 80%	-D 70%	-B 40%	-A 100%	-D 40%	-C 70%	-B 50%	-CA 50%	-C 70%	-B 90%
happy (AD- 60%)	dcdA	dcD	dcCb	ADA	ADab	AD	ADbd	ADCA	ADC	ADbd
sad (AA- 70%)	AAAdA	AAAD	AAAd	AAA	AAabD	AAb	AA	aca	acab	AAbB
angry (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDba	DDCA	DDC	DDbB
tired (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB
excited (DB- 40%)	dad	DBdd	D	daA	DBa	DBC	DBd	da	dacb	DB
sick (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAC	CACb	CAB
hungry (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB
thirsty (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCCA	CCC	CCB
silly (AB- 40%)	dcA	dcab	dcabB	ABA	AB	ABC	ABd	acc	ac	ABB
scared (DC- 50%)	DCac	DC	DCcB	bcdA	bcd	adbC	DCbd	dacc	DCC	DCB

Language of agent 19

Regularity	me	we	mip	you	yall	yup	yumi	one	they	all
61%	-A 70%	-D 80%	-C 40%	-A 100%	-B 40%	-C 80%	-B 40%	-CA 70%	-C 70%	-B 100%
happy (AD- 60%)	dcdA	dcD	dcdbddd	ADA	ADaB	AD	ADbd	ADCA	ADC	ADB
sad (AA- 70%)	AAAdA	AAAD	AAAdC	AAA	AAaB	AAbC	AA	aca	acab	AAb
angry (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDba	DDCA	DDC	DDbB
tired (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB
excited (DB- 40%)	dad	DBdD	D	daA	DBa	DBC	DBd	da	dacb	DB
sick (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
hungry (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB
thirsty (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCCA	CCC	CCB
silly (AB- 40%)	dcA	dcab	dcabb	ABA	AB	ABC	ABd	acc	ac	ABB
scared (DC- 60%)	DCad	DCdc	DCbaca	DC	bcdA	bcd	adbC	DCba	DCCA	DCC
										DCB

Language of agent 20

Regularity	me	we	mip	you	yall	yup	yumi	one	they	all
61%	-A 80%	-D 70%	-D 40%	-A 100%	-B 40%	-C 80%	-B 60%	-CA 60%	-C 80%	-B 100%
happy (AD- 60%)	dcdA	dcD	dcCb	ADA	ADaB	AD	ADbd	ADCA	ADC	ADB
sad (AA- 70%)	AAAdA	AAAD	AAdc	AAA	AAaB	AAbC	AA	aca	acab	AAb
angry (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDb	DDCA	DDC	DDbB
tired (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB
excited (DB- 40%)	dad	D	DBbd	daA	DBa	DBC	DBd	da	dacb	DB
sick (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
hungry (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB
thirsty (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCCA	CCC	CCB
silly (AB- 40%)	dcA	dcab	acd	ABA	AB	ABC	ABd	acc	ac	ABB
scared (DC- 50%)	DCac	DC	DCc	bcdA	bcd	adbC	DCB	dacc	DCc	DCbB

Language of agent 21

Regularity	me	we	mip	you	yall	yup	yumi	one	they	all
60%	-A 80%	-D 70%	-B 30%	-A 100%	-B 40%	-C 80%	-B 70%	-CA 50%	-C 70%	-B 100%
happy (AD- 60%)	dcdA	dcD	dcCb	ADA	ADaB	AD	ADbd	ADCA	ADC	ADB
sad (AA- 70%)	AAAdA	AAAD	AAdc	AAA	AAaB	AAbC	AA	acac	aca	AAb
angry (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDb	DDCA	DDC	DDbb
tired (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB
excited (DB- 40%)	dad	D	DBbda	daA	DBa	DBC	DB	da	dacb	DBB
sick (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
hungry (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB
thirsty (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCCA	CCC	CCb
silly (AB- 40%)	dcA	dcab	acd	ABA	AB	ABC	ABd	acc	ac	ABB
scared (DC- 50%)	DCac	DC	DCcB	bcdA	bcd	adbC	DCB	dacc	DCC	DCbB

Language of agent 22

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
60%	-A 80%	-D 70%	-B 40%	-A 100%	-A 30%	-C 80%	-B 40%	-CA 60%	-C 80%	-B 100%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddcB	ADaA	ADA	AD	ADbd	ADCA	ADC	ADB
<i>sad</i> (AA- 70%)	AAaA	AAAD	AAdc	AAA	AAab	AAbC	AA	aca	aca	AAb
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDba	DDCA	DDC	DDb
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB
<i>excited</i> (DB- 40%)	dad	DBda	D	daA	DBA	DBC	DBd	da	dacb	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCCA	CCC	CCB
<i>silly</i> (AB- 40%)	dcA	dcab	dcabB	ABA	AB	ABC	ABd	acc	ac	ABB
<i>scared</i> (DC- 50%)	DCac	DC	DCcB	bcdA	bcd	adbC	DCba	dacc	DCC	DCB

Language of agent 23

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
59%	-A 80%	-D 70%	-D 50%	-A 80%	-B 50%	-C 60%	-B 50%	-C 60%	-C 50%	-B 100%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddcb	ADA	ADaB	AD	ADbd	ADC	ADcd	ADB
<i>sad</i> (AA- 70%)	AAaA	AAAD	AAdc	AAA	AAaB	AAb	AA	aca	acab	AAbB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddd	bdd	add	DDb	DDca	DDC	DDbB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDC	CDCb	CDB
<i>excited</i> (DA- 40%)	DA	D	dbbD	DAA	dba	dbC	dbd	DAC	DACb	db
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAC	CACb	CAB
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBca	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCca	CCC	CCB
<i>silly</i> (AB- 40%)	dcA	dcab	acD	ABA	ABdaB	AB	ABd	acc	ac	ABB
<i>scared</i> (DC- 60%)	DCac	DC	DCcD	bcd	bcdB	adbC	DCba	DCcaC	DCC	DCB

Language of agent 24

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
55%	-A 80%	-D 70%	-C 30%	-A 90%	-B 40%	-C 60%	-B 80%	-CA 50%	-C 70%	-B 90%
<i>happy</i> (AD- 50%)	dcdA	dcD	dccC	ADA	ADaB	AD	dcdbB	ADCA	ADC	ADB
<i>sad</i> (AA- 50%)	dcaadaaA	dcdbadaa	AAaC	AAA	AAaB	AAbC	AA	aca	aca	AAb
<i>angry</i> (CD- 40%)	ddA	dd	CDdcd	bddA	bdd	add	ddB	CDcaaca	CDcbacB	CDbbcd
<i>tired</i> (CD- 50%)	CDA	CD	dacdD	CD	bdacaac	bdcadddbC	bdB	CDCA	CDC	CDB
<i>excited</i> (DA- 30%)	DAdacac	dbdabaa	dbba	bdaacA	bdbbcba	addabca	db	Dac	DAcba	dbB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCCA	CCC	CCB
<i>silly</i> (AB- 30%)	dcA	dcab	dccbaab	ABA	AB	ABC	ABd	dbdbcaaa	acc	accb
<i>scared</i> (DC- 50%)	DCacdc	DCbdaac	D	DCcbacd	bcdA	bcd	adbcbacB	DCB	dacc	DCcbacd

Language of agent 25

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
59%	-A 80%	-D 70%	-B 30%	-A 100%	-B 40%	-C 70%	-B 40%	-CA 60%	-C 80%	-B 100%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddcc	ADA	ADaB	AD	ADbd	ADCA	ADC	ADB
<i>sad</i> (AA- 70%)	AAaA	AAAD	AAdc	AAA	AAaB	AAb	AA	aca	acab	AAbB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDbd	DDCA	DDC	DDb
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB
<i>excited</i> (DB- 40%)	dad	DBda	D	daA	DBa	DBC	DBd	da	dacb	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCCA	CCC	CCB
<i>silly</i> (AB- 40%)	dcA	dcaba	dcaB	ABA	AB	ABC	ABd	acc	ac	ABB
<i>scared</i> (DC- 50%)	DCad	DC	DCcB	bcdA	bcd	adbC	DCba	dacc	DCC	DCB

Language of agent 26

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
59%	-A 80%	-D 70%	-D 40%	-A 100%	-B 40%	-C 80%	-B 60%	-C 60%	-CB 40%	-B 90%
<i>happy</i> (AD- 60%)	dcdA	dcD	dcdbdc	ADA	ADaB	AD	ADbd	ADC	ADcd	ADB
<i>sad</i> (AA- 70%)	AAaA	AAAD	AAdc	AAA	AAaB	AAbC	AA	aca	acab	AAb
<i>angry</i> (DD- 60%)	DDA	DD	DDcD	bddA	bdd	add	DDb	DDca	DDc	DDbc
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDC	CDCB	CDB
<i>excited</i> (DA- 40%)	DA	D	dbbD	DAA	dba	dbC	dbd	DAC	DACB	db
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CACB	CAB
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBCA	CBCB	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCca	CCc	CCB
<i>silly</i> (AB- 40%)	dcA	dcab	acD	ABA	AB	ABC	ABd	acc	acbc	ABB
<i>scared</i> (DC- 60%)	DCac	DC	DCcb	bcdA	bcd	adbC	DCB	DCca	DCC	DCbB

Language of agent 27

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
59%	-A 80%	-D 70%	-D 40%	-A 90%	-B 50%	-C 70%	-B 70%	-CA 50%	-C 60%	-B 90%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddcb	ADA	ADaB	AD	ADbd	ADCA	ADC	ADB
<i>sad</i> (AA- 70%)	AAAdA	AAAD	AAAdc	AAA	AAaB	AAb	AA	aca	acab	AAbB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bdd	bddB	add	DDB	DDCA	DDC	DDbB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDc	CDcb	CDB
<i>excited</i> (DB- 40%)	dad	D	DBbd	daA	DBa	DBC	DB	da	dacb	DBB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCCA	CCC	CCB
<i>silly</i> (AB- 40%)	dca	dcab	acD	ABA	AB	ABC	ABd	acc	acb	ABB
<i>scared</i> (DC- 50%)	DCac	DC	DCcb	bcdA	bcd	adbC	DCB	dacc	DCC	DCbc

Language of agent 28

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
62%	-A 80%	-D 70%	-D 40%	-A 100%	-A 30%	-C 80%	-B 70%	-CA 60%	-C 80%	-B 80%
<i>happy</i> (AD- 60%)	dcdA	dcD	dcdb	ADA	ADab	AD	ADbd	ADCA	ADC	ADbbd
<i>sad</i> (AA- 90%)	AAAdA	AAAD	AAAdc	AAA	AA	AAb	AAdbB	AAACA	AAC	AAbbd
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	bddbC	DDB	DDCA	DDC	DDbB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	b	bdC	bdB	CDCA	CDC	CDB
<i>excited</i> (DB- 40%)	dad	D	DBbd	daA	DBA	DBC	DB	da	dacb	DBB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCc	CCcb	CCB
<i>silly</i> (AB- 40%)	dcaA	dcab	acD	ABA	AB	ABC	ABd	acc	ac	ABB
<i>scared</i> (DC- 60%)	DCac	DCbaa	DCcb	bcdA	bcd	adbC	DCba	dacc	DCC	DCB

Language of agent 29

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
61%	-A 90%	-D 70%	-D 40%	-A 70%	-B 50%	-C 70%	-B 70%	-CA 70%	-C 80%	-B 80%
<i>happy</i> (AD- 60%)	dcdA	dcD	dcddbc	ADac	ADa	AD	ADbd	ADCA	ADC	ADB
<i>sad</i> (AA- 70%)	AAAdA	AAAD	AAdc	AAA	AAaB	AAb	AA	aca	acab	AAbB
<i>angry</i> (DD- 60%)	DDA	DD	DDcddD	bdd	bddB	bddbcd	DDB	DDCA	DDC	DDbc
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	b	bdC	bdB	CDCA	CDC	CDB
<i>excited</i> (DA- 40%)	DAd	D	dbbd	DAA	dba	dbC	db	DAc	DAcb	dbB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bcba	bcC	bcB	CCCA	CCC	CCB
<i>silly</i> (AB- 40%)	dcaabaaA	dcdbaaaa	acD	ABA	AB	ABC	ABd	acc	ac	ABB
<i>scared</i> (DC- 60%)	DCA	DC	DCcb	bcd	bcdB	bccC	DCB	DCCA	DCC	DCbc

Language of agent 30

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
61%	-A 80%	-D 70%	-D 40%	-A 80%	-B 60%	-C 80%	-B 60%	-C 60%	-B 50%	-B 100%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddcb	ADA	ADaB	AD	ADbd	ADC	ADcbda	ADB
<i>sad</i> (AA- 80%)	AAAdA	AAAD	AAAdc	AAA	AAaB	AAbC	AA	aca	AAc	AAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bdd	bddB	addcbcd	DDB	DDca	DDc	DDbB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDca	CDc	CDB
<i>excited</i> (DA- 40%)	DAd	D	dbbd	DAA	dba	dbC	dbd	DAC	DAcB	db
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAC	CACB	CAB
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBC	CBCB	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCC	CCcB	CCB
<i>silly</i> (AB- 40%)	dca	dcab	acD	ABA	AB	ABC	ABd	acc	acB	ABB
<i>scared</i> (DC- 60%)	DCac	DC	DCc	bcd	bcdB	adbC	DCB	DCca	DCcc	DCbB

E.4 Round 20020

Language of agent 1

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
61%	-A 80%	-D 70%	-D 50%	-A 90%	-B 50%	-C 80%	-B 60%	-CA 60%	-C 80%	-B 100%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddcb	ADA	ADaB	AD	ADbd	ADCA	ADC	ADB
<i>sad</i> (AA- 50%)	AAAdA	AAAD	acaD	AAA	AAaB	acabbcb	CAA	acaa	ac	AAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDB	DDCA	DDC	DDbB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB
<i>excited</i> (DB- 40%)	dad	D	DBbd	daA	DBa	DBC	DBd	da	dacb	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCCA	CCC	CCB
<i>silly</i> (AB- 40%)	dca	dcab	acD	ABA	AB	ABC	ABd	acc	acb	ABB
<i>scared</i> (DC- 50%)	DCac	DC	DCc	bcd	bcdB	adbC	DCB	dacc	DCcC	DCbB

Language of agent 2

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
60%	-A 80%	-D 80%	-D 50%	-A 100%	-B 40%	-C 70%	-B 60%	-CA 50%	-C 90%	-B 100%
<i>happy</i> (AD- 60%)	dcdA	dcD	dcDc	ADA	ADaB AD	ADbd	ADCA	ADC	ADB	
<i>sad</i> (AA- 50%)	AAAdA	AAD	acaD	AAA	AAaB acab	AA	acaa	ac	AAB	
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDB	DDCA	DDC	DDbB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB
<i>excited</i> (DB- 40%)	dad	D	DBbD	daA	DBa	DBC	DBd	da	daC	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
<i>hungry</i> (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCcC	CCC	CCB
<i>silly</i> (AB- 40%)	dcaA	dca	acD	ABA	AB	ABC	ABd	acc	acb	ABB
<i>scared</i> (DC- 50%)	DCbdabdc	DCbD	DCc	bcdA	bcd	adbC	DCB	dacc	DCcC	dbbcB

Language of agent 3

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
59%	-A 80%	-D 70%	-D 50%	-A 70%	-B 50%	-C 70%	-B 50%	-CA 60%	-C 90%	-B 100%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddcb	ADAd	ADa	AD	ADbd	ADCA	ADC	ADB
<i>sad</i> (AA- 50%)	AAAdA	AAD	acaD	AAA	AAaB acab	AA	acaa	ac	AAB	
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bdd	bddB	add	DDba	DDCA	DDC	DDbB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB
<i>excited</i> (DB- 40%)	dad	D	DBbdaaD	daA	DBa	DBC	DBd	da	dabadC	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
<i>hungry</i> (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCcC	CCC	CCB
<i>silly</i> (AB- 40%)	dcaA	dcab	acD	ABA	AB	ABC	ABd	acc	acb	ABB
<i>scared</i> (DC- 50%)	DCac	DC	DCcb	bcd	bcdB	adbC	DCB	dac	DCc	DCbB

Language of agent 4

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
57%	-A 70%	-D 70%	-D 40%	-A 100%	-B 40%	-C 70%	-B 50%	-A 50%	-B 50%	-B 100%
<i>happy</i> (AD- 60%)	dcd	dcD	ddcb	ADA	ADaB AD	ADbd	ADcA	ADc	ADB	
<i>sad</i> (AA- 50%)	AAAdA	AAD	acaD	AAA	AAaB acabb	AA	acaa	ac	AAB	
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDba	DDcA	DDc	DDbB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDc	CDcb	CDB
<i>excited</i> (DB- 40%)	dad	D	DBbdc	daA	DBa	DBC	DBd	da	dacB	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAC	CACB	CAB
<i>hungry</i> (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBcA	CBc	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCc	CCcB	CCB
<i>silly</i> (AB- 40%)	dcaA	dcab	acD	ABA	AB	ABC	ABd	acc	acB	ABB
<i>scared</i> (DC- 50%)	DCac	DC	DCc	bcdA	bcd	adbC	DCbaB	dac	DCcc	DCB

Language of agent 5

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
59%	-A 80%	-D 70%	-D 50%	-A 80%	-B 40%	-C 70%	-B 70%	-CA 50%	-C 80%	-B 80%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddcb	ADAd	ADa	AD	ADbd	ADCA	ADC	ADB
<i>sad</i> (AA- 50%)	AAAdA	AAD	acaD	AAA	AAaB acab	AA	acac	ac	AAB	
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDB	DDCA	DDC	DDbc
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDc	CDcb	CDB
<i>excited</i> (DA- 40%)	DAd	D	dbbD	DAA	dba	dbC	db	DAc	Dacb	dbB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
<i>hungry</i> (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBcA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCcA	CCC	CCB
<i>silly</i> (AB- 40%)	dcaA	dcab	acD	ABA	AB	ABC	ABd	acc	acB	ABB
<i>scared</i> (DC- 60%)	DCac	DC	DCc	bcd	bcdB	adbC	DCB	DCcacc	DCcC	DCbc

Language of agent 6

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
63%	-A 80%	-D 70%	-B 30%	-A 100%	-B 50%	-C 60%	-B 50%	-CA 70%	-C 90%	-B 100%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddcb	ADA	ADaB AD	ADbd	ADCA	ADC	ADB	
<i>sad</i> (AA- 50%)	AAAdA	AAD	acad	AAA	AAaB acab	AA	acaa	ac	AAB	
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDbd	DDCA	DDC	DDbB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB
<i>excited</i> (D- 90%)	Dad	D	DcdbaadB	DaA	Dba	DbC	Dbd	Da	Dacb	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
<i>hungry</i> (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBcA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCcA	CCC	CCB
<i>silly</i> (AB- 60%)	dcaA	dcab	dcabB	ABA	ABaB	AB	ABd	ABcA	ABcC	ABB
<i>scared</i> (DC- 50%)	DCac	DC	DCc	bcdA	bcd	adbC	DCB	dacc	DCcC	DCbB

Language of agent 7

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
61%	-A 80%	-D 80%	-C 40%	-A 90%	-B 50%	-C 70%	-B 40%	-C 70%	-CB 50%	-B 100%
happy (AD- 60%)	dcD	dcD	dcD	ADA	ADaB	AD	ADbd	ADC	ADcd	ADB
sad (AA- 50%)	AAAd	AAD	acad	AAA	AAaB	acab	AA	acaa	ac	AAbB
angry (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDba	DDca	DDc	DDb
tired (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDC	CDCB	CDB
excited (D- 90%)	Dad	Dcd	dbd	DaA	Dba	DbC	Dbd	Da	DaCB	DB
sick (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAC	CACB	CAB
hungry (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBC	CBCB	CBB
thirsty (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCA	CCCB	CCB
silly (AB- 40%)	dca	dcab	dcab	ABA	AB	ABC	ABd	acc	acb	ABB
scared (DC- 50%)	DCac	DCc	DCC	bcd	bcdB	adbC	DCba	dacC	DCcc	dbbcccB

Language of agent 8

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
59%	-A 80%	-D 70%	-D 50%	-A 100%	-A 30%	-C 70%	-B 60%	-CA 60%	-C 80%	-B 100%
happy (AD- 50%)	dcD	dcD	ddcb	ADaA	ADA	AD	dcdbbB	ADCA	ADC	ADB
sad (AA- 50%)	AAAd	AAD	acad	AAA	AAaB	acab	AA	acac	ac	AAb
angry (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDba	DDCA	DDC	DDb
tired (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB
excited (DB- 40%)	dad	D	DBbD	daA	DBA	DBC	DBd	da	dacb	DB
sick (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
hungry (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB
thirsty (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCCA	CCC	CCB
silly (AB- 40%)	dca	dca	acd	ABA	AB	ABC	ABd	acc	acb	ABB
scared (DC- 50%)	DCc	DC	DCc	bcdA	bcd	adbC	DCB	dacc	DCcC	DCbB

Language of agent 9

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
59%	-A 80%	-D 70%	-D 50%	-A 100%	-A 30%	-C 70%	-B 50%	-CA 60%	-C 80%	-B 100%
happy (AD- 60%)	dcD	dcD	ddcb	ADaA	ADA	AD	ADbd	ADCA	ADC	ADB
sad (AA- 50%)	AAAd	AAD	acad	AAA	AAaB	acab	AA	acac	ac	AAb
angry (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDba	DDCA	DDC	DDb
tired (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB
excited (DB- 40%)	dad	D	DBbD	daA	DBA	DBC	DBd	da	dacb	DB
sick (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
hungry (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB
thirsty (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCCA	CCC	CCB
silly (AB- 40%)	dca	dca	acd	ABA	AB	ABC	ABd	acc	acb	ABB
scared (DC- 50%)	DCc	DC	DCc	bcdA	bcd	adbC	DCB	dacc	DCcC	DCbB

Language of agent 10

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
57%	-A 80%	-D 70%	-B 30%	-A 90%	-A 30%	-C 70%	-B 40%	-CA 60%	-C 80%	-B 100%
happy (AD- 60%)	dcD	dcD	ddcb	ADaA	ADA	AD	ADbd	ADCA	ADC	ADB
sad (AA- 50%)	AAAd	AAD	acad	AAA	AAaB	acab	AA	acac	ac	AAb
angry (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDba	DDCA	DDC	DDb
tired (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB
excited (DB- 40%)	dad	D	DBbD	daA	DBA	DBC	DBd	da	dacb	DB
sick (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
hungry (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB
thirsty (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCCA	CCC	CCB
silly (AB- 40%)	dca	dca	acd	ABA	AB	ABC	ABd	acc	acb	ABB
scared (DC- 50%)	DCc	DC	DCc	bcdA	bcd	adbC	DCB	dacc	DCcC	DCbB

Language of agent 11

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
58%	-A 80%	-D 70%	-D 50%	-A 100%	-B 40%	-C 70%	-B 50%	-CA 50%	-C 70%	-B 80%
happy (AD- 60%)	dcD	dcD	ddcb	ADaA	ADA	AD	ADbd	ADc	ADcd	ADB
sad (AA- 50%)	AAAd	AAD	acad	AAA	AAaB	acab	AA	acac	ac	AAb
angry (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDba	DDCA	DDC	DDb
tired (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB
excited (DB- 40%)	dad	D	DBbD	daA	DBA	DBC	DBd	da	dacb	DB
sick (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
hungry (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB
thirsty (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCCA	CCC	CCB
silly (AB- 40%)	dca	dcab	acd	ABA	AB	ABC	ABd	acc	acb	ABB
scared (DC- 50%)	DCc	DC	DCc	bcdA	bcd	adbC	DCB	dacc	DCcC	DCbC

Language of agent 12

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
58%	-A 80%	-D 70%	-B 30%	-A 80%	-B 60%	-C 60%	-B 60%	-C 60%	-CB 40%	-B 100%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddcB	ADA	ADaB	AD	ADbd	ADcA	ADc	ADB
<i>sad</i> (AA- 50%)	AAAdA	AAD	acad	AAA	AAaB	acabba	AA	acaa	ac	AAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bdd	bddB	addbb	DDB	DDca	DDc	DDbB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDC	CDCB	CDB
<i>excited</i> (DB- 40%)	dad	DBda	D	daA	DBa	DBC	DBd	da	dabdc	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAC	CACB	CAB
<i>hungry</i> (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBC	CBCB	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCc	CCCB	CCB
<i>silly</i> (AB- 60%)	dcaAA	dcab	dcdbabB	ABA	ABaB	AB	ABd	ABcac	ABcbbbbc	ABB
<i>scared</i> (DC- 50%)	DCac	DC	DCc	bcd	bcdB	adbc	DCB	dacC	DCcc	DCbB

Language of agent 13

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
60%	-A 80%	-D 70%	-D 50%	-A 100%	-A 40%	-C 80%	-B 70%	-CA 40%	-C 80%	-B 90%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddc	ADA	ADab	AD	ADbd	ADCA	ADC	ADB
<i>sad</i> (AA- 60%)	AAAdA	AAD	acaD	AAA	AAaB	acabb	AA	acac	aca	AAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDB	DDCA	DDC	DDbB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB
<i>excited</i> (DB- 40%)	dad	D	DBbd	daA	DBa	DBC	DB	da	daC	DBB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
<i>hungry</i> (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBcc	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CC	CCbc	bcA	bcbca	bcC	bcB	CCcc	CCC	CCB
<i>silly</i> (AB- 40%)	dcaA	dcab	acd	ABA	AB	ABC	ABd	acc	accb	ABB
<i>scared</i> (DC- 60%)	DCac	DCd	DCc	bcdA	bcd	adbc	DCB	dacc	DCcC	DCbc

Language of agent 14

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
59%	-A 80%	-D 70%	-D 50%	-A 80%	-B 60%	-C 70%	-B 50%	-A 60%	-C 70%	-B 100%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddcb	ADA	ADaB	AD	ADbd	ADcA	ADC	ADB
<i>sad</i> (AA- 50%)	AAAdA	AAD	acaD	AAA	AAaB	acabb	AA	acaa	ac	AAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bdd	bddB	add	DDba	DDcA	DDC	DDB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDC	CDCb	CDB
<i>excited</i> (DB- 40%)	dad	D	DBbd	daA	DBa	DBC	DBd	da	dabC	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACa	CAC	CAB
<i>hungry</i> (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBcA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCc	CCcb	CCB
<i>silly</i> (AB- 40%)	dcA	dcab	acd	ABA	AB	ABC	ABd	acc	acb	ABB
<i>scared</i> (DC- 50%)	DCac	DC	DCc	bcd	bcdB	adbc	DCB	dacc	DCcC	DCbB

Language of agent 15

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
59%	-A 80%	-D 80%	-B 30%	-A 90%	-B 50%	-C 80%	-B 50%	-A 60%	-C 60%	-B 100%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddcB	ADA	ADaB	AD	ADbd	ADcA	ADC	ADB
<i>sad</i> (AA- 50%)	AAAdA	AAD	acad	AAA	AAaB	acabcbc	CAA	acaa	ac	AAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bdd	bddB	add	DDba	DDcA	DDC	DDB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDC	CDCb	CDB
<i>excited</i> (DB- 40%)	dad	DBdd	D	daA	DBa	DBC	DBd	da	dacb	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACa	CAC	CAB
<i>hungry</i> (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBcA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCc	CCcb	CCB
<i>silly</i> (AB- 40%)	dcA	dcab	dcabB	ABA	ABaB	ABC	AB	acc	acb	ABB
<i>scared</i> (DC- 50%)	DCac	DC	DCc	bcd	bcdB	adbc	DCba	dacc	DCcC	DCB

Language of agent 16

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
59%	-A 80%	-D 80%	-D 50%	-A 90%	-B 50%	-C 70%	-B 60%	-CA 50%	-C 70%	-B 90%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddc	ADA	ADaB	AD	ADbd	ADCA	ADC	ADbdbcdd
<i>sad</i> (AA- 50%)	AAAdA	AAD	acaD	AAA	AAaB	acab	AA	acaa	ac	AAbB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bdd	bddB	add	DDB	DDCA	DDC	DDbB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB
<i>excited</i> (DB- 40%)	dad	D	DBbd	daA	DBa	DBC	DBd	da	dacb	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAC	CACb	CAB
<i>hungry</i> (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBcA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCcA	CCC	CCB
<i>silly</i> (AB- 40%)	dcA	dcab	acd	ABA	AB	ABC	ABd	acc	acb	ABB
<i>scared</i> (DC- 50%)	DCac	DCbD	DCcb	bcdA	bcd	adbc	DCB	dacc	DCC	dbbcbbbb

Language of agent 17

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
58%	-A 80%	-D 80%	-D 30%	-A 90%	-B 50%	-C 70%	-B 50%	-C 70%	-B 40%	-B 100%
happy (AD- 60%)	dcdA	dcD	ddcb	ADA	ADaB	AD	ADbd	ADC	ADcdd	ADbdB
sad (AA- 50%)	AAaA	AAAD	acaD	AAA	AAaB	acab	AA	acaC	ac	AAB
angry (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDbd	DDca	DDc	DDB
tired (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDC	CDCB	CDB
excited (DB- 40%)	dad	DBdD	D	daA	DBa	DBC	DBd	da	dabbdA	DB
sick (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAca	CAc	CAB
hungry (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBC	CBCB	CBB
thirsty (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCC	CCCB	CCB
silly (AB- 40%)	dcaA	dcab	dcbbaca	ABA	AB	ABC	ABd	acc	acb	ABB
scared (DC- 50%)	DCac	DC	DCc	bcd	bcdB	adbC	DCB	daC	DCcc	DCbB

Language of agent 18

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
59%	-A 80%	-D 70%	-B 40%	-A 100%	-A 40%	-C 70%	-B 40%	-CA 60%	-C 80%	-B 100%
happy (AD- 60%)	dcdA	dcD	ddcB	ADaA	ADA	AD	ADbd	ADCA	ADC	ADB
sad (AA- 50%)	AAaA	AAAD	acad	AAaA	AAA	acaba	AA	acaa	ac	AAB
angry (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDba	DDCA	DDC	DDB
tired (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB
excited (DB- 40%)	dad	DBda	D	daA	DBA	DBC	DBd	da	dacb	DB
sick (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
hungry (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB
thirsty (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCCA	CCC	CCB
silly (AB- 40%)	dcaA	dcab	dcabb	ABA	AB	ABC	ABd	acc	acb	ABB
scared (DC- 50%)	DCac	DC	DCcB	bcdA	bcd	adbC	DCba	dacc	DCC	DCB

Language of agent 19

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
62%	-A 80%	-D 90%	-C 40%	-A 100%	-A 30%	-C 70%	-B 40%	-CA 60%	-C 80%	-B 90%
happy (AD- 60%)	dcdA	dcD	ddcB	ADaA	ADA	AD	ADbd	ADCA	ADC	ADB
sad (AA- 70%)	AAaA	AAAD	acaD	AAaC	AAA	AAab	AAbC	AA	acaa	aca
angry (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDba	DDCA	DDC	DDB
tired (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB
excited (D- 90%)	dad	Dcdbaad	DD	DaA	DBA	DbC	Dbd	Da	Dacb	DB
sick (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
hungry (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB
thirsty (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCCA	CCC	CCB
silly (AB- 40%)	dcaA	dcab	dcabb	ABA	ABab	AB	ABd	acc	ac	ABB
scared (DC- 50%)	DCac	DCcbbD	DCC	bcdA	bcd	adbC	DCba	dacc	DCC	dbbc

Language of agent 20

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
60%	-A 80%	-D 80%	-B 30%	-A 100%	-B 40%	-C 70%	-B 40%	-CA 60%	-C 100%	-B 100%
happy (AD- 60%)	dcdA	dcD	ddcB	ADA	ADaB	AD	ADbd	ADCA	ADC	ADB
sad (AA- 50%)	AAaA	AAAD	acad	AAA	AAaB	acab	AA	acaa	ac	AAB
angry (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDba	DDCA	DDC	DDB
tired (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB
excited (DB- 40%)	dad	DBdD	D	daA	DBa	DBC	DBd	da	daC	DB
sick (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
hungry (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB
thirsty (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCCA	CCC	CCB
silly (AB- 40%)	dcaA	dca	dcabB	ABA	AB	ABC	ABd	acc	acbC	ABB
scared (DC- 50%)	DCcaad	DC	DCc	bcdA	bcd	adbC	DCba	dacc	DCcC	DCB

Language of agent 21

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
59%	-A 80%	-D 70%	-D 50%	-A 90%	-B 50%	-C 70%	-B 60%	-C 70%	-CB 50%	-B 100%
happy (AD- 60%)	dcdA	dcD	ddcb	ADA	ADaB	AD	ADbd	ADC	ADcd	ADB
sad (AA- 50%)	AAaA	AAAD	acad	AAA	AAaB	acabb	AA	acaa	ac	AAB
angry (DD- 60%)	DDA	DDD	DD	bdd	bddB	add	DDb	DDca	DDc	DDbB
tired (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDC	CDCB	CDB
excited (DB- 40%)	dad	D	DBbd	daA	DBa	DBC	DBd	da	daCB	DB
sick (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAC	CACB	CAB
hungry (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBC	CBCB	CBB
thirsty (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCC	CCCB	CCB
silly (AB- 40%)	dcaA	dcab	acD	ABA	AB	ABC	ABd	acc	acb	ABB
scared (DC- 50%)	DCac	DC	DCc	bcdA	bcd	adbC	DCB	dacC	DCcc	DCbB

Language of agent 22

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
60%	-A 80%	-D 70%	-D 40%	-A 100%	-A 40%	-C 80%	-B 60%	-CA 50%	-C 60%	-B 100%
<i>happy</i> (AD- 60%)	dcD A	dcD	dcb	ADaA	ADA	AD	ADbd	ADCA	ADC	ADB
<i>sad</i> (AA- 70%)	AAAdA	AAD	AAdc	AAaA	AAA	AAbc	AA	acac	aca	AAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDb	DDCA	DDC	DDbB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDC	CDCb	CDB
<i>excited</i> (DB- 40%)	dad	D	DBbD	daA	DBA	DBC	DBd	da	dacb	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
<i>hungry</i> (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCCA	CCC	CCB
<i>silly</i> (AB- 40%)	dcA	dcab	acD	ABA	AB	ABC	ABd	acc	acb	ABB
<i>scared</i> (DC- 50%)	DCac	DC	DCc	bcdA	bcd	adbC	DCB	dacc	DCcC	DCbB

Language of agent 23

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
59%	-A 80%	-D 80%	-C 30%	-A 90%	-A 30%	-C 70%	-B 50%	-CA 50%	-C 70%	-B 90%
<i>happy</i> (AD- 60%)	dcD A	dcD	dcD	ADad	ADA	AD	ADbd	ADc	ADcd	ADB
<i>sad</i> (AA- 50%)	AAAdA	AAD	acad	AAaA	AAA	AAab	acab	AA	acaa	ac
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDb	DDCA	DDC	DDbB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB
<i>excited</i> (D- 90%)	Dad	Dcad	DD	DaA	DBA	DbC	Dbd	Da	Dacb	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
<i>hungry</i> (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCCA	CCC	CCB
<i>silly</i> (AB- 40%)	dcA	dca	dcabb	ABA	AB	ABC	ABd	acc	acb	ABB
<i>scared</i> (DC- 50%)	DCcadcd	DCcda	DCC	bcdA	bcd	adbC	DCba	dacc	DCcC	dbbcc

Language of agent 24

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
61%	-A 80%	-D 90%	-B 30%	-A 100%	-A 40%	-C 70%	-B 50%	-A 60%	-C 60%	-B 100%
<i>happy</i> (AD- 60%)	dcD A	dcD	dcD	ADaA	ADA	AD	ADbd	ADcA	ADC	ADB
<i>sad</i> (AA- 50%)	AAAdA	AAD	acad	AAaA	AAA	acaba	AA	acaA	ac	AAbB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDb	DDcA	DDC	DDb
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDcA	CDC	CDB
<i>excited</i> (D- 90%)	Dad	Dcd	baad	D	DaA	DBA	DbC	Dbd	DA	Dabd
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAc	CAcb	CAB
<i>hungry</i> (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCc	CCcb	CCB
<i>silly</i> (AB- 40%)	dcA	dcab	dcabb	ABA	AB	ABC	ABd	acc	acb	ABB
<i>scared</i> (DC- 50%)	DCac	DCbD	DCcB	bcdA	bcd	adbC	DCB	dacc	DCC	dbbcB

Language of agent 25

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
58%	-A 80%	-D 70%	-B 40%	-A 100%	-A 30%	-C 70%	-B 50%	-A 60%	-C 60%	-B 100%
<i>happy</i> (AD- 60%)	dcD A	dcD	dcb	ADA	ADab	AD	ADbd	ADcA	ADC	ADB
<i>sad</i> (AA- 50%)	AAAdA	AAD	acad	AAaA	AAA	acab	AA	acaA	ac	AAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDb	DDcA	DDC	DDb
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDcA	CDC	CDB
<i>excited</i> (DB- 40%)	dad	DBda	D	daA	DBA	DBC	DBd	da	dacb	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAc	CAcb	CAB
<i>hungry</i> (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCc	CCcb	CCB
<i>silly</i> (AB- 40%)	dcA	dcab	dcabb	ABA	AB	ABC	ABd	acc	acb	ABB
<i>scared</i> (DC- 50%)	DCac	DC	DCcB	bcdA	bcd	adbC	DCB	dacc	DCC	DCbB

Language of agent 26

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
60%	-A 80%	-D 70%	-D 50%	-A 100%	-B 40%	-C 70%	-B 50%	-CA 60%	-C 80%	-B 100%
<i>happy</i> (AD- 60%)	dcD A	dcD	dcb	ADA	ADaB	AD	ADbd	ADCA	ADC	ADB
<i>sad</i> (AA- 50%)	AAAdA	AAD	acaD	AAaA	AAA	AAaB	acabbbb	AA	acaa	ac
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDb	DDCA	DDC	DDb
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB
<i>excited</i> (DB- 40%)	dad	D	DBbD	daA	DBa	DBC	DBd	da	dacb	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
<i>hungry</i> (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCCA	CCC	CCB
<i>silly</i> (AB- 40%)	dcA	dcab	acD	ABA	AB	ABC	ABd	acc	acb	ABB
<i>scared</i> (DC- 50%)	DCac	DC	DCc	bcdA	bcd	adbC	DCB	dacc	DCcC	DCbB

Language of agent 27

Regularity	me	we	mip	you	yall	yup	yumi	one	they	all
58%	-A 80%	-D 80%	-D 50%	-A 100%	-B 40%	-C 70%	-B 70%	-C 60%	-B 50%	-B 90%
happy (AD- 50%)	dcdA	dcD	dcdbc	ADA	ADaB	AD	dcdbB	ADca	ADc	ADB
sad (AA- 50%)	AAAdA	AAAD	acaD	AAA	AAaB	acab	AA	acaa	ac	AAB
angry (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDb	DDca	DDc	DDbB
tired (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDC	CDcB	CDB
excited (DB- 40%)	dad	D	DBbD	daA	DBa	DBC	DBd	da	dacB	DB
sick (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAC	CACb	CAB
hungry (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBcC	CBc	CBB
thirsty (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCC	CCcB	CCB
silly (AB- 40%)	dcA	dcab	acD	ABA	AB	ABC	ABd	acC	acB	ABB
scared (DC- 50%)	DCac	DCbD	DCcb	bcdA	bcd	adbC	DCB	dacC	DCc	dbbcc

Language of agent 28

Regularity	me	we	mip	you	yall	yup	yumi	one	they	all
59%	-A 80%	-D 70%	-D 40%	-A 90%	-B 50%	-C 80%	-B 60%	-A 50%	-C 60%	-B 90%
happy (AD- 60%)	dcdA	dcD	dcdb	ADA	ADaB	AD	ADbd	ADcA	ADC	ADB
sad (AA- 70%)	AAAdA	AAAD	AAAc	AAA	AAaB	AAbC	AA	acaa	aca	AAB
angry (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDb	DDca	DDc	DDbB
tired (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDc	CDcb	CDB
excited (DA- 40%)	DAd	D	dbbD	DAa	dba	dbc	dbd	DAc	DAcb	db
sick (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACa	CAC	CAB
hungry (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBcA	CBC	CBB
thirsty (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCC	CCcb	CCB
silly (AB- 40%)	dcA	dcab	acD	ABA	AB	ABC	ABd	acc	ac	ABB
scared (DC- 50%)	DCac	DC	DCc	bcd	bcdB	adbC	DCB	dacc	DCcC	DCbc

Language of agent 29

Regularity	me	we	mip	you	yall	yup	yumi	one	they	all
58%	-A 80%	-D 70%	-D 50%	-A 100%	-A 30%	-C 70%	-B 60%	-C 60%	-B 50%	-B 100%
happy (AD- 60%)	dcdA	dcD	dcdb	ADaA	ADA	AD	ADbd	ADC	ADcd	ADB
sad (AA- 50%)	AAAdA	AAAD	AAAc	AAA	AAaB	acab	AA	acaa	ac	AAB
angry (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDb	DDca	DDc	DDbB
tired (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDca	CDc	CDB
excited (DB- 40%)	dad	D	DBbD	daA	DBa	DBC	DBd	da	dacB	DB
sick (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAC	CACb	CAB
hungry (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBC	CBcB	CBB
thirsty (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCC	CCcB	CCB
silly (AB- 40%)	dcA	dcab	acD	ABA	AB	ABC	ABd	acc	acB	ABB
scared (DC- 50%)	DCac	DC	DCc	bcdA	bcd	adbC	DCB	dacC	DCcc	DCbB

Language of agent 30

Regularity	me	we	mip	you	yall	yup	yumi	one	they	all
58%	-A 80%	-D 80%	-B 30%	-A 90%	-B 50%	-C 70%	-B 40%	-A 50%	-B 50%	-B 100%
happy (AD- 60%)	dcdA	dcD	dcdb	ADA	ADaB	AD	ADbdd	ADcA	ADc	ADbbdbbB
sad (AA- 70%)	AAAdA	AAAD	AAAc	AAA	AAaB	AAbC	AA	acaa	acaB	AAB
angry (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDba	DDcA	DDc	DDb
tired (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDc	CDcB	CDB
excited (DB- 40%)	dad	DBbD	D	daA	DBa	DBC	DBd	da	daba	DB
sick (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAC	CACb	CAB
hungry (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBcA	CBc	CBB
thirsty (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCC	CCcB	CCB
silly (AB- 40%)	dcA	dcab	dcabB	ABA	ABaB	AB	ABd	acc	acB	ABB
scared (DC- 50%)	DCac	DC	DCc	bcd	bcdB	adbC	DCba	dacc	DCcc	DCB

E.5 Round 24999

Language of agent 1

Regularity	me	we	mip	you	yall	yup	yumi	one	they	all
60%	-A 80%	-D 90%	-B 30%	-A 80%	-B 40%	-C 70%	-B 50%	-A 50%	-C 60%	-B 100%
happy (AD- 60%)	dcdA	dcD	dcdc	ADad	ADa	AD	ADabdbaB	ADcA	ADC	ADbbdbB
sad (AA- 50%)	AAAdA	AAAD	acAd	AAA	AAaB	acabb	AA	acac	ac	AAB
angry (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDba	DDcA	DDC	DDb
tired (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDcA	CDC	CDB
excited (D- 90%)	Dad	Dcdbaad	DD	DaA	Dba	Dbc	Dbd	DA	Dabd	DB
sick (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAC	CACb	CAB
hungry (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBcA	CBcb	CBB
thirsty (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCcA	CCC	CCB
silly (AB- 40%)	dcA	dcab	dcabB	ABA	AB	ABC	ABd	acc	acB	ABB
scared (DC- 50%)	DCac	DCbD	DCcB	bcd	bcdB	adbC	DCba	dac	DCC	dbbcB

Language of agent 2

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
60%	-A 80%	-D 70%	-D 50%	-A 90%	-B 50%	-C 70%	-B 60%	-C 70%	-B 60%	-B 100%
<i>happy</i> (AD- 60%)	dc d A	dc D	dd cb	AD A	AD a B AD	AD bd AD C	AD cd AD B			
<i>sad</i> (AA- 50%)	AA dA AA D	aca D	AAA	AAA a B acab	AA	aca a ac	AA B			
<i>angry</i> (DD- 60%)	DD A DD D DD	bddA	bdd	add	DD B DD ca DD c	DD b B				
<i>tired</i> (CD- 50%)	CD A CD D CD	bdA	bd	bdC	bd B CD C CD c B CD B					
<i>excited</i> (DB- 40%)	dad	D	DB b D	daA	DB a DB C DB d	da	da B DB			
<i>sick</i> (CA- 50%)	CA A CA D CA	baA	ba	baC	ba B CAC CA c B CAB					
<i>hungry</i> (CB- 50%)	CB A CB D CB	bbA	bb	bbC	bb B CBC CB c B CBB					
<i>thirsty</i> (CC- 50%)	CC A CC D CC	bcA	bc	bcC	bc B CCC CC c B CCB					
<i>silly</i> (AB- 50%)	dcA	dcab	AB b D ABA	AB	ABC AB d	acC	ac B ABB			
<i>scared</i> (DC- 50%)	DC ac	DC	DC cb	bcd	bcd B ad bC DC B	daC	DC c DC b B			

Language of agent 3

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
59%	-A 80%	-D 70%	-D 50%	-A 80%	-B 40%	-C 70%	-B 70%	-CA 60%	-C 80%	-B 90%
<i>happy</i> (AD- 60%)	dc d A	dc D	dd cb	AD ad	AD a AD	AD abd ba	AD CA	AD C	AD bb D	
<i>sad</i> (AA- 50%)	AA dA AA D	aca D	AAA	AAA a B acab	AA	aca a ac	AA B			
<i>angry</i> (DD- 60%)	DD A DD D DD	bddA	bdd	add	DD B DD ca DD c	DD b B				
<i>tired</i> (CD- 50%)	CD A CD D CD	bdA	bd	bdC	bd B CD CA CD C CD B					
<i>excited</i> (DB- 40%)	dad	D	DB bbdd	daA	DB a DB C DB d	da	dab D DB			
<i>sick</i> (CA- 50%)	CA A CA D CA	baA	ba	baC	ba B CACA CA C CAB					
<i>hungry</i> (CB- 50%)	CB A CB D CB	bbA	bb	bbC	bb B CBCA CB C CBB					
<i>thirsty</i> (CC- 50%)	CC A CC D CC	bcA	bc	bcC	bc B CCCA CC C CCB					
<i>silly</i> (AB- 40%)	dcA	dcab	ac D	ABA	AB	ABC AB d	acc	ac B ABB		
<i>scared</i> (DC- 50%)	DC ac	DC	DC cb	bcdA	bcd	ad b C DC B	daC	DC c DC b B		

Language of agent 4

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
57%	-A 70%	-D 80%	-B 30%	-A 90%	-B 50%	-C 60%	-B 60%	-C 70%	-CB 40%	-B 100%
<i>happy</i> (AD- 60%)	dc d A	dc D	dd cB	AD A	AD a B AD	AD bd	AD C	AD cd	AD B	
<i>sad</i> (AA- 50%)	AA dA AA D	aca D	AAA	AAA a B acab	AA	aca a ac	AA B			
<i>angry</i> (DD- 60%)	DD A DD D DD	bddA	bdd	add	DD B DD ca DD c	DD da	DD cb	DD b B		
<i>tired</i> (CD- 50%)	CD A CD D CD	bdA	bd	bdC	bd B CD C CD c B CD B					
<i>excited</i> (DB- 40%)	dad	D	DB dd	daA	DB a DB C DB d	da	dab D DB			
<i>sick</i> (CA- 50%)	CA A CA D CA	baA	ba	baC	ba B CAC CA c B CAB					
<i>hungry</i> (CB- 50%)	CB A CB D CB	bbA	bb	bbC	bb B CBC CB c B CBB					
<i>thirsty</i> (CC- 50%)	CC A CC D CC	bcA	bc	bcC	bc B CCC CC c B CCB					
<i>silly</i> (AB- 40%)	dcA	dcab	dcab B	ABA	AB	ABC AB d	acC	ac B ABB		
<i>scared</i> (DC- 50%)	DC ac	DC	DC c	bcdA	bcd	ad b C DC B	daC	DC cc DC b B		

Language of agent 5

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
58%	-A 80%	-D 80%	-B 30%	-A 100%	-B 40%	-C 60%	-B 40%	-C 70%	-B 50%	-B 100%
<i>happy</i> (AD- 60%)	dc d A	dc D	dd cB	AD A	AD a B AD	AD bd	AD ca	AD c	AD B	
<i>sad</i> (AA- 50%)	AA dA AA D	aca D	AAA	AAA a B acab	AA	aca a ac	AA B			
<i>angry</i> (DD- 60%)	DD A DD D DD	bddA	bdd	add	DD b D DD ca DD c	DD B				
<i>tired</i> (CD- 50%)	CD A CD D CD	bdA	bd	bdC	bd B CD C CD c B CD B					
<i>excited</i> (DB- 40%)	dad	D	DB dd	daA	DB a DB C DB d	da	da B DB			
<i>sick</i> (CA- 50%)	CA A CA D CA	baA	ba	baC	ba B CAC CA c B CAB					
<i>hungry</i> (CB- 50%)	CB A CB D CB	bbA	bb	bbC	bb B CBC CB c B CBB					
<i>thirsty</i> (CC- 50%)	CC A CC D CC	bcA	bc	bcC	bc B CCC CC c B CCB					
<i>silly</i> (AB- 60%)	dcA	dcab	dcab B	ABA	AB a B AB	AB d	AB cdcaC	AB cd	ABB	
<i>scared</i> (DC- 50%)	DC ac	DC	DC c	bcdA	bcd	ad b C DC ba	daC	DC cc DC B		

Language of agent 6

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
61%	-A 80%	-D 90%	-C 30%	-A 100%	-A 40%	-C 60%	-B 40%	-CA 70%	-C 80%	-B 100%
<i>happy</i> (AD- 60%)	dc d A	dc D	dd cD	AD aA	AD A AD	AD bd	AD CA	AD C	AD B	
<i>sad</i> (AA- 50%)	AA dA AA D	aca D	AAA	AAA a B acab	AA	aca a ac	AA B			
<i>angry</i> (DD- 60%)	DD A DD D DD	bddA	bdd	add	DD ba	DD CA	DD C	DD B		
<i>tired</i> (CD- 50%)	CD A CD D CD	bdA	bd	bdC	bd B CD CA CD C CD B					
<i>excited</i> (DB- 40%)	dad	D	DB dd	daA	DB a DB C DB d	da	dab DB			
<i>sick</i> (CA- 50%)	CA A CA D CA	baA	ba	baC	ba B CACA CA C CAB					
<i>hungry</i> (CB- 50%)	CB A CB D CB	bbA	bb	bbC	bb B CBCA CB C CBB					
<i>thirsty</i> (CC- 50%)	CC A CC D CC	bcA	bc	bcC	bc B CCA CC C CCB					
<i>silly</i> (AB- 60%)	dcA	dcab	dcabb	ABA	AB abd AB	AB d	AB CA	AB cd	ABB	
<i>scared</i> (DC- 60%)	DC ac	DC cd	DC	bcdA	bcd	ad b C DC ba	DC cacc	DC cc	DC B	

Language of agent 7

Regularity	me	we	mip	you	yall	yup	yumi	one	they	all
58%	-A 80%	-D 80%	-B 30%	-A 100%	-B 40%	-C 70%	-B 50%	-A 60%	-C 60%	-B 100%
<i>happy</i> (AD- 60%)	dcDA	dcD	ddcB	ADA	ADaB	AD	ADbd	ADcA	ADC	ADB
<i>sad</i> (AA- 50%)	AAAdA	AAAD	acad	AAA	AAaB	acab	AA	acaA	ac	AAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDba	DDcA	DDC	DDB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDc	CDcb	CDB
<i>excited</i> (DB- 40%)	dad	DBdD	D	daA	DBa	DBC	DBd	da	dab	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAC	CACb	CAB
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBcA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCC	CCCB	CCB
<i>silly</i> (AB- 40%)	dcA	dcab	dcabB	ABA	AB	ABC	ABd	acc	acb	ABB
<i>scared</i> (DC- 50%)	DCac	DC	DCc	bcdA	bcd	adbC	DCB	dac	DCcC	DCbB

Language of agent 8

Regularity	me	we	mip	you	yall	yup	yumi	one	they	all
61%	-A 80%	-D 70%	-D 50%	-A 90%	-B 50%	-C 80%	-B 80%	-C 90%	-CB 40%	-B 100%
<i>happy</i> (AD- 50%)	dcDA	dcD	dcDC	ADA	ADaB	AD	dbdcdB	BADC	ADcbdaac	ADbbbbaB
<i>sad</i> (AA- 70%)	AAAdA	AAAD	AAcD	AAA	AAaB	AAcB	AA	acaC	aca	AAB
<i>angry</i> (DD- 60%)	DDA	DD	DDcD	bddA	bdd	add	DDB	DDca	DDc	DDbB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDc	CDcB	CDB
<i>excited</i> (DA- 40%)	DAd	D	dbbD	DAA	dba	dbC	db	DAc	DAbd	dbB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAC	CACB	CAB
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBc	CBcB	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCC	CCCB	CCB
<i>silly</i> (AB- 40%)	dcA	dcab	acD	ABA	AB	ABC	ABd	acC	acb	ABB
<i>scared</i> (DC- 50%)	DCac	DC	DCc	bcd	bcdB	adbC	DCB	daC	DCcc	DCbB

Language of agent 9

Regularity	me	we	mip	you	yall	yup	yumi	one	they	all
58%	-A 80%	-D 80%	-B 40%	-A 90%	-B 50%	-C 80%	-B 40%	-C 60%	-B 50%	-B 100%
<i>happy</i> (AD- 60%)	dcDA	dcD	ddcB	ADA	ADaB	AD	ADbd	ADca	ADc	ADB
<i>sad</i> (AA- 50%)	AAAdA	AAAD	acad	AAA	AAaB	acab	CAA	acaC	ac	AAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDba	DDca	DDc	DDB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDc	CDcB	CDB
<i>excited</i> (DB- 40%)	dad	DBdD	D	daA	DBa	DBC	DBd	da	daB	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAC	CACB	CAB
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBca	CBc	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCC	CCcB	CCB
<i>silly</i> (AB- 40%)	dcA	dcab	dcabB	ABA	AB	ABC	ABd	acc	acb	ABB
<i>scared</i> (DC- 50%)	DCac	DC	DCc	bcd	bcdB	adbC	DCba	daC	DCc	DCB

Language of agent 10

Regularity	me	we	mip	you	yall	yup	yumi	one	they	all
60%	-A 80%	-D 70%	-B 40%	-A 90%	-A 30%	-C 60%	-B 40%	-CA 60%	-C 80%	-B 100%
<i>happy</i> (AD- 60%)	dcDA	dcD	ddcB	ADad	ADA	AD	ADbd	ADCA	ADC	ADB
<i>sad</i> (AA- 50%)	AAAdA	AAAD	acad	AAA	AAab	acab	AA	acaC	ac	AAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDba	DDCA	DDc	DDB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDc	CDB
<i>excited</i> (D- 90%)	Dad	D	DcdBadd	D	DaA	DbA	Db	Dbd	Da	Dabd
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBcA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCA	CCc	CCB
<i>silly</i> (AB- 40%)	dcA	dcab	dcabB	ABA	AB	ABC	ABd	acc	acb	ABB
<i>scared</i> (DC- 50%)	DCac	DC	DCc	bcdA	bcd	adbC	DCba	daC	DCc	DCB

Language of agent 11

Regularity	me	we	mip	you	yall	yup	yumi	one	they	all
59%	-A 70%	-D 80%	-D 40%	-A 80%	-B 60%	-C 70%	-B 70%	-C 70%	-CB 40%	-B 100%
<i>happy</i> (AD- 60%)	dcDA	dcD	dcDC	ADA	ADaB	AD	ADbd	ADC	ADcd	ADB
<i>sad</i> (AA- 50%)	AAAd	AAAdD	acaD	AAA	AAaB	acab	AA	aca	ac	AAB
<i>angry</i> (DD- 60%)	DDA	DD	DDcd	bdd	bddB	add	DDB	DDca	DDc	DDbB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDc	CDcB	CDB
<i>excited</i> (DA- 40%)	DAd	D	dbbD	DAA	dba	dbC	db	Dca	DAbd	dbB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAC	CACB	CAB
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBC	CBCB	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCC	CCCB	CCB
<i>silly</i> (AB- 40%)	dcA	dcab	acD	ABA	AB	ABC	ABd	acc	acb	ABB
<i>scared</i> (DC- 60%)	DCac	DCbD	DCc	bcd	bcdB	adbC	DCB	daC	DCcc	DCbB

Language of agent 12

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
60%	-A 80%	-D 70%	-D 40%	-A 80%	-B 60%	-C 70%	-B 70%	-C 90%	-CB 50%	-B 100%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddeb	ADA	ADaB	AD	ADbd	ADC	ADCB	ADB
<i>sad</i> (AA- 50%)	AAAdA	AAD	acaD	AAA	AAaB	acab	AA	acaC	ac	AAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bdd	bddB	bddcb	DDB	DDca	DDc	DDbB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDC	CDCB	CDB
<i>excited</i> (DA- 40%)	DAd	D	dbbD	DAA	dba	dbC	db	DAcdaC	DAbd	dB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAC	CACB	CAB
<i>hungry</i> (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBC	CBCB	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCC	CCCB	CCB
<i>silly</i> (AB- 40%)	dcA	dcab	dcabb	ABA	AB	ABC	ABd	acC	acb	ABB
<i>scared</i> (DC- 50%)	DCac	DC	DCc	bcd	bcdB	bcC	DCB	daC	DCcc	DCbB

Language of agent 13

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
58%	-A 80%	-D 70%	-D 50%	-A 100%	-B 40%	-C 70%	-B 40%	-A 50%	-C 70%	-B 100%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddeb	ADA	ADaB	AD	ADbd	ADcA	ADC	ADB
<i>sad</i> (AA- 50%)	AAAdA	AAD	acaD	AAA	AAaB	acab	AA	acac	ac	AAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDba	DDcA	DDC	DDbB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDcA	CDC	CDB
<i>excited</i> (DB- 40%)	dAd	D	DBbD	daA	DBa	DBC	DBd	da	dab	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAc	CAcb	CAB
<i>hungry</i> (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBcc	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCcA	CCC	CCB
<i>silly</i> (AB- 40%)	dcA	dcab	acD	ABA	AB	ABC	ABd	acc	acb	ABB
<i>scared</i> (DC- 50%)	DCac	DC	DCcb	bcdA	bcd	adbC	DCba	dac	DCC	DCB

Language of agent 14

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
59%	-A 70%	-D 80%	-D 40%	-A 80%	-B 60%	-C 70%	-B 70%	-C 80%	-CB 40%	-B 90%
<i>happy</i> (AD- 60%)	dcdA	dcD	dcddc	ADA	ADaB	AD	ADbd	ADC	ADCB	ADB
<i>sad</i> (AA- 50%)	AAAd	AAAd	acaD	AAA	AAaB	acab	AA	acaa	ac	AAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDB	DDC	DDcddc	DDbB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDC	CDCB	CDB
<i>excited</i> (DA- 40%)	DAd	D	dbbD	DAA	dba	dbC	db	DAba	DAb	dbbc
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAC	CACB	CAB
<i>hungry</i> (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBC	CBCB	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCC	CCcd	CCB
<i>silly</i> (AB- 40%)	dcA	dcab	acD	ABA	AB	ABC	ABd	acc	acb	ABB
<i>scared</i> (DC- 60%)	DCac	DC	DCc	bcdA	bcd	adbC	DCB	daC	DCcc	DCbB

Language of agent 15

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
59%	-A 80%	-D 70%	-D 50%	-A 100%	-B 40%	-C 70%	-B 80%	-CA 50%	-C 60%	-B 80%
<i>happy</i> (AD- 60%)	dcdA	dcD	dcddc	ADA	ADaB	AD	ADbd	ADC	ADcd	ADbbd
<i>sad</i> (AA- 50%)	AAAdA	AAD	acaD	AAA	AAaB	acab	AA	acac	ac	AAB
<i>angry</i> (DD- 60%)	DDA	DD	DDcd	bddA	bdd	add	DDB	DDCA	DDC	DDbbbbddc
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDc	CDcb	CDB
<i>excited</i> (DA- 40%)	DAd	D	dbbD	DAA	dba	dbC	db	DACA	DAbd	dB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
<i>hungry</i> (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCCA	CCC	CCB
<i>silly</i> (AB- 40%)	dcA	dcab	acD	ABA	AB	ABC	ABd	acc	acb	ABB
<i>scared</i> (DC- 60%)	DCac	DC	DCc	bcdA	bcd	adbC	DCB	DCccccc	DCcC	DCbB

Language of agent 16

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
60%	-A 80%	-D 80%	-B 40%	-A 90%	-A 40%	-C 60%	-B 40%	-CA 60%	-C 90%	-B 100%
<i>happy</i> (AD- 60%)	dcdA	dcD	dcdb	ADad	ADA	AD	ADbd	ADCA	ADC	ADB
<i>sad</i> (AA- 50%)	AAAdA	AAD	acad	AAA	AAaB	acab	AA	acac	ac	AAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDba	DDCA	DDC	DDbB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB
<i>excited</i> (DB- 40%)	dAd	D	DBdD	daA	DBA	DBC	DBd	da	dab	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
<i>hungry</i> (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCCA	CCC	CCB
<i>silly</i> (AB- 60%)	dcA	dcab	dcabB	ABA	ABab	AB	ABd	ABcaacd	ABcd	ABB
<i>scared</i> (DC- 50%)	DCac	DC	DCcb	bcdA	bcd	adbC	DCba	dac	DCC	DCB

Language of agent 17

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>										
58%	-A	80%	-D	80%	-C	30%	-A	90%	-A	40%	-C	60%	-B	50%	-CA	50%	-C	70%	-B	100%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddcb	ADad	ADA	AD	ADbd	ADCA	ADC	ADB										
<i>sad</i> (AA- 50%)	AAAdA	AAD	acad	AAaA	AAA	acab	AA	acaa	ac	AAB										
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDbd	DDCA	DDC	DDb										
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDc	CDcb	CDB										
<i>excited</i> (DB- 40%)	dad	DBdD	D	daA	DBA	DBC	DBd	da	dabd	DB										
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB										
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB										
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCCA	CCC	CCB										
<i>silly</i> (AB- 60%)	dcA	dcab	dcabC	ABA	ABab	AB	ABd	ABcaacdc	ABcd	ABB										
<i>scared</i> (DC- 50%)	DCac	DC	DCC	bcdA	bcd	adbC	DCB	dac	DCcC	DCbB										

Language of agent 18

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>										
57%	-A	80%	-D	80%	-B	30%	-A	80%	-B	50%	-C	70%	-B	50%	-C	60%	-C	40%	-B	100%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddccb	ADaA	ADA	AD	ADbd	ADC	ADcd	ADB										
<i>sad</i> (AA- 50%)	AAAdA	AAD	aca	AAA	AAaB	acab	AA	acaa	ac	AAB										
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bdd	bddB	add	DDba	DDC	DDcd	DDb										
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDC	CDcb	CDB										
<i>excited</i> (DB- 40%)	dad	DBdD	D	daA	DBa	DBC	DBd	da	dabd	DB										
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAC	CACb	CAB										
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBca	CBC	CBB										
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCca	CCC	CCB										
<i>silly</i> (AB- 40%)	dcA	dcab	dcabB	ABA	AB	ABC	ABd	acc	acb	ABB										
<i>scared</i> (DC- 50%)	DCac	DC	DCC	bcd	bcdB	adbC	DCB	dac	DCcC	DCbB										

Language of agent 19

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>										
58%	-A	80%	-D	80%	-B	30%	-A	90%	-A	30%	-C	70%	-A	40%	-CA	50%	-C	70%	-B	90%
<i>happy</i> (AD- 60%)	dcdA	dcD	dcdB	ADad	ADA	AD	ADbd	ADC	ADcd	ADB										
<i>sad</i> (AA- 50%)	AAAdA	AAD	acad	AAA	AAaB	acab	AA	acac	ac	AAB										
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDba	DDCA	DDC	DDb										
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB										
<i>excited</i> (D- 90%)	Dad	Dcdddd	DD	DaA	DBa	DbC	Dbdabab	ADa	Dabb	DB										
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	bab	CACA	CAC	CAB										
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbb	CBCA	CBC	CBB										
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCCA	CCC	CCB										
<i>silly</i> (AB- 40%)	dcA	dcab	dcabB	ABA	AB	ABC	ABd	acc	acb	ABB										
<i>scared</i> (DC- 50%)	DCac	DC	DCC	bcd	bcdB	adbC	DCbA	dac	DCcC	DCbB										

Language of agent 20

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>										
58%	-A	70%	-D	70%	-D	50%	-A	90%	-B	40%	-C	80%	-B	70%	-C	70%	-CB	40%	-B	90%
<i>happy</i> (AD- 60%)	dcd	dcdD	dcdC	ADA	ADaB	AD	ADabdbba	ADC	ADcd	ADbbd										
<i>sad</i> (AA- 60%)	AAAdA	AAD	acad	AAA	AAaB	AA	AAbC	AAbd	aca	acabcccc	AAB									
<i>angry</i> (DD- 60%)	DDA	DD	DDcD	bddA	bdd	add	DDb	DDca	DDc	DDbB										
<i>tired</i> (CD- 50%)	CDA	CD	CDbd	bdA	bd	bdC	bdB	CDC	CDCB	CDB										
<i>excited</i> (DA- 40%)	DAd	D	dbbd	DAA	dba	dbC	db	DAcd	DAbd	dB										
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAC	CACB	CAB										
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBC	CBCB	CBB										
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCC	CCCc	CCB										
<i>silly</i> (AB- 40%)	dcA	dcab	dcabB	ABA	AB	ABC	ABd	acc	acb	ABB										
<i>scared</i> (DC- 50%)	DCac	DC	DCC	bcd	bcdB	adbC	DCB	dac	DCcc	DCbB										

Language of agent 21

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>										
59%	-A	80%	-D	80%	-B	30%	-A	100%	-B	40%	-C	70%	-B	40%	-A	50%	-C	60%	-B	90%
<i>happy</i> (AD- 60%)	dcdA	dcD	dcdc	ADA	ADaB	AD	ADbd	ADcA	ADC	ADB										
<i>sad</i> (AA- 50%)	AAAdA	AAD	acad	AAA	AAaB	acab	AA	acac	ac	AAB										
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDbd	DDcA	DDC	DDb										
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDcA	CDC	CDB										
<i>excited</i> (D- 90%)	Dad	Dcdbaab	D	DaA	DBa	DbC	Dbd	DA	Dabd	DB										
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAC	CACb	CAB										
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBcA	CBC	CBB										
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCC	CCCc	CCB										
<i>silly</i> (AB- 40%)	dcA	dcab	dcabB	ABA	AB	ABC	ABd	acc	acb	ABB										
<i>scared</i> (DC- 50%)	DCac	DCbD	DCCB	bcdA	bcd	adbC	DCbA	dac	DCC	dbbc										

Language of agent 22

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>										
59%	-A	80%	-D	70%	-D	40%	-A	80%	-B	60%	-C	70%	-B	60%	-C	70%	-CB	40%	-B	100%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddcb	ADA	ADaB	AD	ADbd	ADC	ADcd	ADB										
<i>sad</i> (AA- 50%)	AAAdA	AAD	acaD	AAA	AAaB	acab	AA	acaC	ac	AAB										
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bdd	bddB	add	DDbA	DDca	DDc	DDbB										
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDC	CDCB	CDB										
<i>excited</i> (DB- 40%)	dad	D	DBbD	daA	DBa	DBC	DBd	da	dabd	DB										
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAC	CACB	CAB										
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBC	CBCB	CBB										
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCC	CCcB	CCB										
<i>silly</i> (AB- 50%)	dcA	dcab	ABba	ABA	AB	ABC	ABd	acc	acb	ABB										
<i>scared</i> (DC- 50%)	DCac	DC	DCc	bcd	bcdB	adbC	DCB	daC	DCcc	DCbB										

Language of agent 23

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>										
58%	-A	80%	-D	80%	-B	40%	-A	80%	-B	50%	-C	70%	-B	50%	-C	70%	-B	50%	-B	100%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddcB	ADA	ADaB	AD	ADbd	ADC	ADcB	ADB										
<i>sad</i> (AA- 50%)	AAAdA	AAD	acad	AAA	AAaB	acab	AA	acaC	ac	AAB										
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddd	bdd	add	DDba	DDca	DDc	DDbB										
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDC	CDcB	CDB										
<i>excited</i> (DB- 40%)	dad	DBdD	D	daA	DBa	DBC	DBd	da	dabd	DB										
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAC	CACb	CAB										
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBCa	CBC	CBB										
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCC	CCcB	CCB										
<i>silly</i> (AB- 40%)	dcA	dcab	dcabB	ABA	AB	ABC	ABd	acc	acb	ABB										
<i>scared</i> (DC- 50%)	DCac	DC	DCcB	bcd	bcdB	adbC	DCB	daC	DCc	DCbB										

Language of agent 24

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>										
58%	-A	80%	-D	80%	-B	40%	-A	90%	-B	50%	-C	70%	-B	50%	-CA	50%	-C	70%	-B	100%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddcB	ADA	ADaB	AD	ADbd	ADCA	ADC	ADB										
<i>sad</i> (AA- 50%)	AAAdA	AAD	acad	AAA	AAaB	acab	AA	acaC	ac	AAB										
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bdd	bddB	add	DDba	DDCA	DDC	DDbB										
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB										
<i>excited</i> (DB- 40%)	dad	DBdD	D	daA	DBa	DBC	DBd	da	dab	DB										
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAC	CACb	CAB										
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB										
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCCA	CCC	CCB										
<i>silly</i> (AB- 40%)	dcA	dcab	dcabB	ABA	AB	ABC	ABd	acc	acb	ABB										
<i>scared</i> (DC- 50%)	DCac	DC	DCcB	bcdA	bcd	adbC	DCB	dac	DCc	DCbB										

Language of agent 25

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>										
59%	-A	80%	-D	70%	-D	40%	-A	100%	-B	40%	-C	70%	-B	60%	-C	60%	-B	50%	-B	100%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddcb	ADA	ADaB	AD	ADbd	ADC	ADcB	ADB										
<i>sad</i> (AA- 50%)	AAAdA	AAD	acaD	AAA	AAaB	acab	AA	acaC	ac	AAB										
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDbA	DDca	DDc	DDbB										
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDca	CDc	CDB										
<i>excited</i> (DB- 40%)	dad	D	DBb	daA	DBa	DBC	DBd	da	daB	DB										
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAC	CACB	CAB										
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBca	CBC	CBB										
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCC	CCcB	CCB										
<i>silly</i> (AB- 50%)	dcA	dcab	ABbD	ABA	AB	ABC	ABd	acc	acb	ABB										
<i>scared</i> (DC- 50%)	DCac	DC	DCc	bcdA	bcd	adbC	DCB	daC	DCcc	DCbB										

Language of agent 26

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>										
59%	-A	80%	-D	70%	-D	40%	-A	100%	-A	30%	-C	70%	-B	40%	-CA	60%	-C	80%	-B	100%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddcb	ADaA	ADA	AD	ADbd	ADCA	ADC	ADB										
<i>sad</i> (AA- 50%)	AAAdA	AAD	acaD	AAA	AAab	acab	AA	acaC	ac	AAB										
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDbd	DDCA	DDC	DDbB										
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB										
<i>excited</i> (DB- 40%)	dad	D	DBbD	daA	DBa	DBC	DBd	da	dabd	DB										
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB										
<i>hungry</i> (CB- 50%)	CBA	CBD	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB										
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCCA	CCC	CCB										
<i>silly</i> (AB- 50%)	dcA	dcab	ABbbD	ABA	AB	ABC	ABd	acc	acb	ABB										
<i>scared</i> (DC- 50%)	DCac	DC	DCc	bcdA	bcd	adbC	DCba	dac	DCcC	DCB										

Language of agent 27

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
59%	-A 80%	-D 70%	-B 40%	-A 90%	-A 40%	-C 70%	-B 40%	-A 50%	-B 50%	-B 100%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddcB	ADaA	ADA	AD	ADbd	ADcA	ADc	ADB
<i>sad</i> (AA- 50%)	AAAdA	AAD	acad	AAaA	AAA	acab	AA	acaA	ac	AAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bdd	bddb	add	DDba	DDcA	DDc	DDB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDc	CDcB	CDB
<i>excited</i> (DB- 40%)	dad	DBda	D	daA	DBA	DBC	DBd	da	daB	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACa	CAC	CAB
<i>hungry</i> (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBc	CBcB	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCc	CCcB	CCB
<i>silly</i> (AB- 40%)	dcA	dcab	dcabB	ABA	AB	ABC	ABd	acc	acB	ABB
<i>scared</i> (DC- 50%)	DCac	DC	DCcB	bcA	bcd	adbC	DCba	dacc	DCc	DCB

Language of agent 28

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
59%	-A 80%	-D 70%	-D 40%	-A 90%	-A 30%	-C 80%	-B 60%	-A 60%	-C 60%	-B 90%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddcb	ADad	ADA	AD	ADbd	ADc	ADcdcaC	ADB
<i>sad</i> (AA- 70%)	AAAdA	AAD	AAbbabb	AAA	AAab	AAbC	AA	acaA	aca	AAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDB	DDcA	DDC	DDbB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDcA	CDC	CDB
<i>excited</i> (DB- 40%)	dad	D	DBbD	daA	DBA	DBC	DBd	da	dab	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACa	CAC	CAB
<i>hungry</i> (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBcA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCc	CCcb	CCB
<i>silly</i> (AB- 40%)	dcA	dcab	acD	ABA	AB	ABC	ABd	acc	acB	ABB
<i>scared</i> (DC- 50%)	DCac	DC	DCc	bcA	bcd	adbC	DCB	dac	DCcC	DCbc

Language of agent 29

Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
60%	-A 70%	-D 60%	-D 50%	-A 90%	-B 50%	-C 80%	-B 60%	-C 80%	-B 60%	-B 100%
<i>happy</i> (AD- 60%)	dcd	dcdb	ddcb	ADA	ADaB	AD	ADbd	ADC	ADeba	ADB
<i>sad</i> (AA- 60%)	AAAdA	AAD	acaD	AAA	AAaB	AAbC	AA	acaC	aca	AAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bddA	bdd	add	DDB	DDca	DDc	DDbB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDc	CDcB	CDB
<i>excited</i> (DB- 40%)	dad	D	DBbD	daA	DBa	DBC	DBd	da	daB	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CAC	CACb	CAB
<i>hungry</i> (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBC	CBcB	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCC	CCcB	CCB
<i>silly</i> (AB- 40%)	dcaaaaa	dcab	acD	ABA	AB	ABC	ABd	acc	acB	ABB
<i>scared</i> (DC- 50%)	DCac	DC	DCc	bcd	bcdB	adbC	DCB	daC	DCcc	DCbB

Language of agent 30

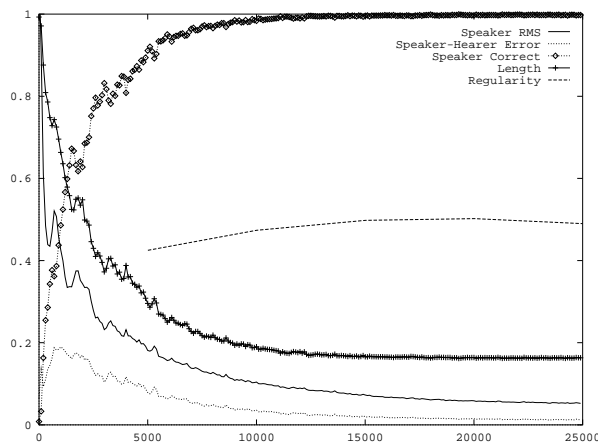
Regularity	<i>me</i>	<i>we</i>	<i>mip</i>	<i>you</i>	<i>yall</i>	<i>yup</i>	<i>yumi</i>	<i>one</i>	<i>they</i>	<i>all</i>
60%	-A 80%	-D 70%	-D 40%	-A 90%	-B 40%	-C 80%	-B 60%	-CA 60%	-C 80%	-B 90%
<i>happy</i> (AD- 60%)	dcdA	dcD	ddcb	ADA	ADabdd	AD	ADbdB	ADCA	ADC	ADbbbbba
<i>sad</i> (AA- 70%)	AAAdA	AAD	AAAdc	AAA	AAaB	AAbC	AA	acaa	aca	AAB
<i>angry</i> (DD- 60%)	DDA	DDD	DD	bdd	bddB	add	DDba	DDCA	DDC	DDB
<i>tired</i> (CD- 50%)	CDA	CDD	CD	bdA	bd	bdC	bdB	CDCA	CDC	CDB
<i>excited</i> (DB- 40%)	dad	D	DBbD	daA	DBa	DBC	DBd	da	dab	DB
<i>sick</i> (CA- 50%)	CAA	CAD	CA	baA	ba	baC	baB	CACA	CAC	CAB
<i>hungry</i> (CB- 50%)	CBA	CBd	CB	bbA	bb	bbC	bbB	CBCA	CBC	CBB
<i>thirsty</i> (CC- 50%)	CCA	CCD	CC	bcA	bc	bcC	bcB	CCCA	CCC	CCB
<i>silly</i> (AB- 40%)	dcA	dcab	acD	ABA	AB	ABC	ABd	acc	ac	ABB
<i>scared</i> (DC- 50%)	DCac	DC	DCc	bcA	bcd	adbC	DCB	dacc	DCcC	DCbB

Appendix F

21 replications of BATALI's simulation

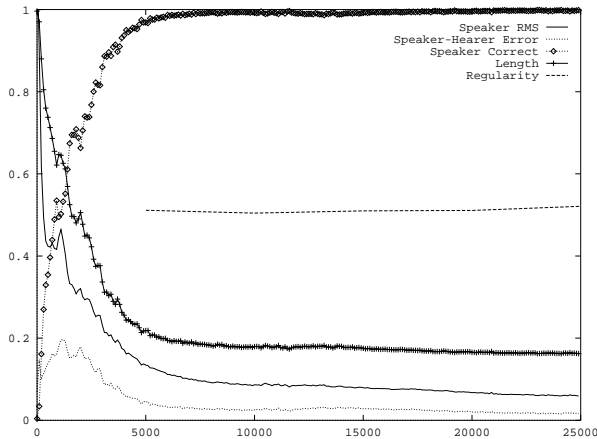
Given here are for 21 replication runs of the simulation described in chapter 3 the statistics described in 6.1.1 as well as the language of the population at the 25000th round of each run.

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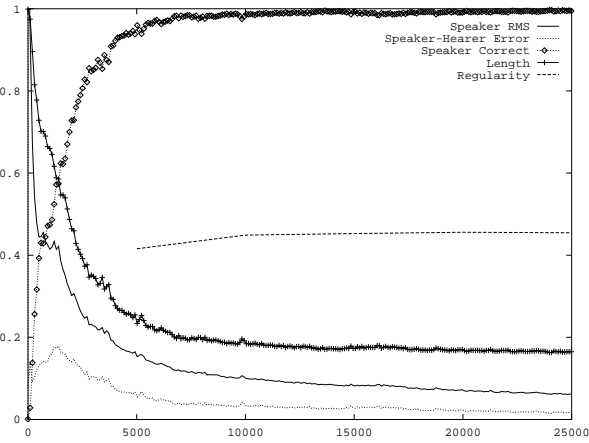
Regularity	ME	WE	MIP	YOU	YALL	YUP	YUMI	ONE	THEY	ALL
48%	-C 70%	-A 38%	-D 36%	-C 57%	-C 46%	-B 76%	-D 39%	-A 60%	-B 45%	-D 44%
HAPPY CD- 30%	caC (96 %)	CDac (70 %)	ddD (93 %)	ccC (100 %)	CDC (100 %)	dbc (100 %)	CD (96 %)	dbdA (50 %)	dbd (50 %)	CDab (56 %)
SAD D- 90%	Da (100 %)	Dac (100 %)	DD (96 %)	DcC (100 %)	DC (100 %)	DcB (100 %)	Dca (90 %)	Dab (100 %)	D (90 %)	Ddc (96 %)
ANGRY BD- 50%	BDC (56 %)	BDC (43 %)	BD (100 %)	bcC (100 %)	bc (100 %)	bcd (100 %)	cdD (100 %)	BDaA (50 %)	BDa (46 %)	BDD (100 %)
TIRED BA- 40%	adC (100 %)	ad (100 %)	BAdc (100 %)	acd (50 %)	acd (50 %)	BAdB (100 %)	adD (100 %)	BAdA (100 %)	BAd (100 %)	adb (96 %)
EXCITED BB- 30%	cad (56 %)	cad (43 %)	BBca (46 %)	ccdC (66 %)	ccd (66 %)	BBcB (66 %)	cdbD (63 %)	BBa (100 %)	BB (100 %)	cbD (100 %)
SICK BA- 40%	adaC (70 %)	adA (70 %)	BaCa (100 %)	acC (100 %)	accd (96 %)	BACB (100 %)	abdc (50 %)	BACc (100 %)	BAC (100 %)	abD (63 %)
HUNGRY AA- 60%	AAC (100 %)	AAA (50 %)	AAaa (46 %)	aca (100 %)	AAbC (70 %)	AAB (70 %)	AA (76 %)	baA (70 %)	baac (40 %)	AAD (73 %)
THIRSTY AB- 59%	ABaC (96 %)	ABA (96 %)	ABab (90 %)	acb (100 %)	ABC (96 %)	ABB (83 %)	AB (76 %)	babA (53 %)	baB (53 %)	ABbD (60 %)
SILLY DB- 32%	caa (60 %)	caab (43 %)	DBbc (93 %)	cca (56 %)	ccab (53 %)	DBbB (70 %)	cdba (96 %)	DBA (100 %)	DB (73 %)	cba (100 %)
SCARED CB- 30%	cabC (53 %)	cab (53 %)	CBbD (50 %)	ccb (86 %)	ccb (63 %)	CBbB (76 %)	CBc (100 %)	bbA (100 %)	bbB (100 %)	CB (100 %)

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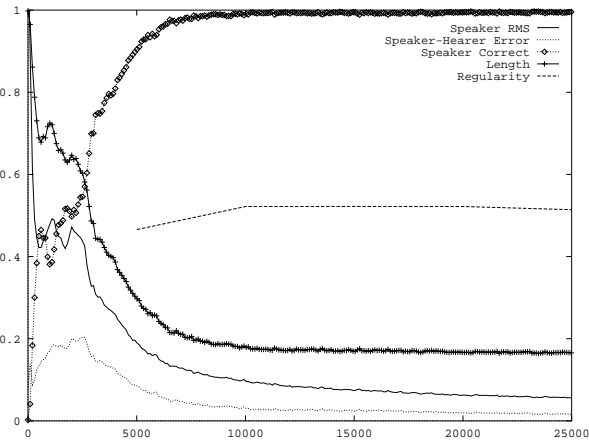
Regularity	ME	WE	MIP	YOU	YALL	YUP	YUMI	ONE	THEY	ALL
52%	-B 53%	-B 32%	-D 56%	-C 66%	-C 47%	-A 40%	-C 62%	-D 61%	-D 48%	-B 62%
HAPPY A- 59%	Adba (76 %)	AdcB (46 %)	A (70 %)	dcdC (83 %)	dC (96 %)	dcdB (63 %)	AdC (56 %)	Acc (100 %)	Ac (83 %)	Aca (100 %)
SAD AB- 60%	ABB (100 %)	ABa (86 %)	AB (96 %)	dcC (100 %)	dcB (100 %)	dbA (96 %)	ABcb (50 %)	ABdD (50 %)	ABD (56 %)	ABc (56 %)
ANGRY AA- 59%	AAAbB (63 %)	AAB (63 %)	AA (93 %)	dcaC (73 %)	dca (73 %)	caaa (46 %)	AAab (63 %)	AAC (96 %)	AAD (100 %)	AAa (66 %)
TIRED CA- 41%	bbba (30 %)	baaB (46 %)	baD (100 %)	ccca (56 %)	CAaC (96 %)	CA (86 %)	baa (80 %)	CAdD (70 %)	CAD (76 %)	CAaB (96 %)
EXCITED DA- 60%	adaB (93 %)	ada (93 %)	adaD (90 %)	DAC (76 %)	Dacb (76 %)	DA (96 %)	DABc (76 %)	DAdc (80 %)	DAD (86 %)	DAB (80 %)
SICK CA- 29%	bba (100 %)	baB (46 %)	babD (66 %)	cca (46 %)	ccab (86 %)	CABc (46 %)	baC (100 %)	ccaD (100 %)	CAC (86 %)	CAB (63 %)
HUNGRY CB- 39%	bbc (100 %)	bc (100 %)	bcD (100 %)	ccb (96 %)	CBc (100 %)	CB (90 %)	bcC (100 %)	CBD (86 %)	CBA (66 %)	CBb (100 %)
THIRSTY CD- 40%	bdB (100 %)	bd (100 %)	bdD (100 %)	ccd (100 %)	CDC (100 %)	CD (93 %)	bdC (100 %)	CDD (66 %)	CDdb (36 %)	CDB (100 %)
SILLY DB- 60%	adbB (56 %)	adbc (100 %)	addc (100 %)	DBcC (56 %)	DBC (53 %)	DB (96 %)	DBbC (53 %)	DBdc (53 %)	DBD (66 %)	DBB (73 %)
SCARED DD- 59%	addb (100 %)	addB (93 %)	addD (96 %)	DDC (100 %)	DDa (83 %)	DD (90 %)	DDbC (50 %)	DDD (60 %)	DDdb (50 %)	DDb (76 %)

agave std batali 28/06/1999 14:25:37



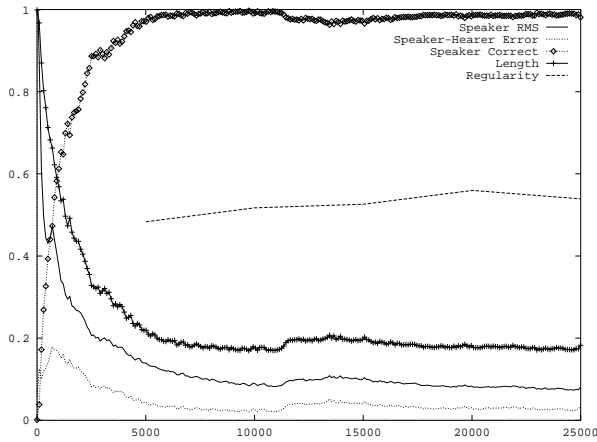
Regularity 45%	ME -B 55%	WE -D 33%	MIP -B 33%	YOU -C 43%	YALL -B 35%	YUP -A 50%	YUMI -B 45%	ONE -A 63%	THEY -D 48%	ALL -C 41%
HAPPY BD- 69%	BDB (60 %)	BDbc (56 %)	BD (93 %)	ccC (93 %)	ccB (90 %)	BDcA (90 %)	BDcB (96 %)	BDA (100 %)	BDD (100 %)	BDC (93 %)
SAD BC- 50%	bbB (100 %)	bb (100 %)	bbd (100 %)	BCC (73 %)	BCcB (70 %)	BC (96 %)	bbc (100 %)	BCd (60 %)	BCa (36 %)	BCb (100 %)
ANGRY CA- 31%	abB (63 %)	abbc (63 %)	dbcB (56 %)	CABc (100 %)	CAB (96 %)	CABa (100 %)	cbB (60 %)	dbb (50 %)	dbb (50 %)	cbba (60 %)
TIRED CA- 20%	aad (100 %)	abD (100 %)	dbcd (76 %)	CAd (76 %)	CAdB (63 %)	dcB (50 %)	acd (93 %)	dabd (76 %)	d (100 %)	dcbb (50 %)
EXCITED CB- 40%	CBaB (63 %)	CBd (66 %)	dbdc (90 %)	ccd (43 %)	C (100 %)	CBA (60 %)	CB (86 %)	dbdA (93 %)	dbD (86 %)	CBa (40 %)
SICK AB- 41%	ABa (96 %)	AB (90 %)	ABca (80 %)	caC (100 %)	caa (100 %)	dcc (100 %)	ABcc (93 %)	dabA (60 %)	dba (86 %)	ABC (80 %)
HUNGRY AC- 39%	aa (100 %)	ACbc (66 %)	ACB (73 %)	aaa (100 %)	ACc (100 %)	dcA (100 %)	AC (96 %)	daA (100 %)	dac (100 %)	ACa (96 %)
THIRSTY AD- 59%	ADB (96 %)	AD (90 %)	ADcB (90 %)	ADa (80 %)	ADac (80 %)	dcd (100 %)	ADcd (66 %)	dad (63 %)	dadc (63 %)	ADC (86 %)
SILLY BA- 69%	BAB (63 %)	BAbc (63 %)	BA (93 %)	cca (50 %)	cca (33 %)	BACa (90 %)	BACB (96 %)	BAA (100 %)	BAD (96 %)	BAC (93 %)
SCARED DD- 39%	add (46 %)	adD (53 %)	DDB (90 %)	cdd (100 %)	cd (100 %)	DDc (63 %)	cdB (100 %)	DDA (100 %)	DD (90 %)	DDcb (60 %)

agave std batali 28/06/1999 14:25:41



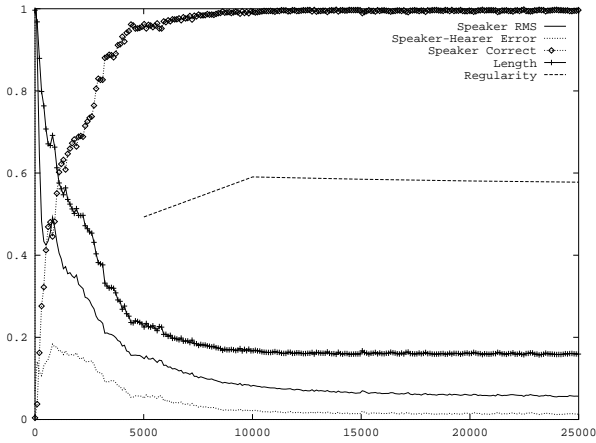
Regularity 51%	ME -B 60%	WE -B 35%	MIP -C 53%	YOU -D 62%	YALL -D 46%	YUP -A 55%	YUMI -A 40%	ONE -D 67%	THEY -C 57%	ALL -A 73%
HAPPY CA- 50%	CAB (53 %)	CAB (46 %)	dca C (93 %)	CAD (50 %)	CA da (50 %)	dcad (53 %)	CA (100 %)	dc D (100 %)	dca (76 %)	CAA (90 %)
SAD CC- 39%	CCB (100 %)	CC (93 %)	CCC (96 %)	cd D (93 %)	cd (100 %)	cde (73 %)	CCd (93 %)	dd D (100 %)	dd C (100 %)	CCA (100 %)
ANGRY AC- 60%	ACB (56 %)	AC bc (43 %)	ACC (100 %)	adc (100 %)	ACD (100 %)	AC ad (50 %)	AC (76 %)	dc C (76 %)	dc C (76 %)	ACA (56 %)
TIRED AB- 44%	ABB (40 %)	ABB (60 %)	bcb b (90 %)	adb b (70 %)	AB db (90 %)	bcb A (56 %)	AB (56 %)	bcb D (96 %)	bcb (63 %)	AB dc (60 %)
EXCITED AA- 40%	AAB (50 %)	AAB (50 %)	dcbb (80 %)	adb c (56 %)	AAD (56 %)	dc A (100 %)	AA (100 %)	dc D (100 %)	dc b (96 %)	AA c (100 %)
SICK BC- 32%	add (50 %)	abcd (90 %)	BCC (76 %)	ad (53 %)	ada (100 %)	BCA (60 %)	abc (93 %)	BCD (100 %)	BC (43 %)	abc A (90 %)
HUNGRY BD- 50%	bbd (86 %)	bb (76 %)	bb C (96 %)	BDD (73 %)	BD da (73 %)	BD (100 %)	abad (100 %)	BD b (100 %)	BDC (100 %)	BDA (70 %)
THIRSTY BA- 58%	bb B (100 %)	bba (96 %)	BA ab (50 %)	BAD (60 %)	BA da (56 %)	BA (90 %)	ab A (63 %)	BA b (96 %)	BAC (90 %)	BAA (70 %)
SILLY CB- 50%	CBB (70 %)	CB ba (60 %)	ddab (70 %)	CBD (53 %)	CB da (53 %)	ddad (56 %)	CB (100 %)	ddb (100 %)	dd (96 %)	CBA (100 %)
SCARED DB- 50%	DBB (63 %)	DB ba (60 %)	DB (100 %)	da D (100 %)	da (100 %)	da A (73 %)	aa A (93 %)	DBD (100 %)	DBC (96 %)	DBA (100 %)

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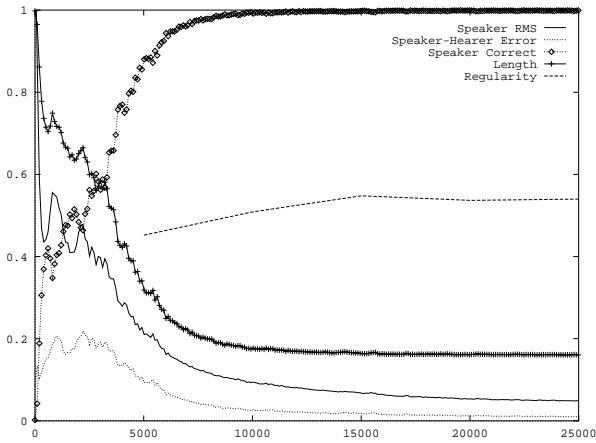
Regularity 53%	ME -C 70%	WE -C 42%	MIP -C 44%	YOU -A 90%	YALL -A 53%	YUP -A 42%	YUMI -D 31%	ONE -B 88%	THEY -B 41%	ALL -D 63%
HAPPY AD- 28%	dc C (90 %)	dc (96 %)	bad C (70 %)	ADA (93 %)	AD b (56 %)	bbd A (66 %)	AD b (43 %)	bb (53 %)	bbd (70 %)	ba D (73 %)
SAD AB- 34%	aa C (70 %)	ABC (93 %)	baa (96 %)	aa A (76 %)	ABA (100 %)	AB b (53 %)	AB (96 %)	bb B (100 %)	ba B (83 %)	ABD (90 %)
ANGRY DB- 39%	dd C (90 %)	D (100 %)	DB d (80 %)	da A (96 %)	da (96 %)	DBA (53 %)	dac (90 %)	DBB (100 %)	DB (76 %)	DB ac (36 %)
TIRED CD- 69%	ddd (40 %)	ddd (56 %)	CDC (100 %)	CD aA (70 %)	CDA (73 %)	CD (100 %)	CD dD (33 %)	CDB (73 %)	CD bc (63 %)	CDD (70 %)
EXCITED BD- 39%	ddad (43 %)	dc b (80 %)	BD d (96 %)	add A (93 %)	add (80 %)	BDA (43 %)	addb (40 %)	BDB (100 %)	BD (60 %)	BD aD (66 %)
SICK CB- 60%	dda C (40 %)	ddb (63 %)	CB cd (50 %)	CB ab (36 %)	CBA (56 %)	CB (96 %)	acd D (56 %)	CB b (96 %)	CB c (60 %)	CB D (100 %)
HUNGRY CA- 90%	CA cC (70 %)	CAC (66 %)	CA cb (76 %)	CAA (66 %)	CAA (26 %)	CA ba (60 %)	CAD (46 %)	CA bB (96 %)	CAB (90 %)	CA db (63 %)
THIRSTY CC- 60%	acd C (33 %)	acd C (46 %)	CCC (86 %)	CC aA (76 %)	CCA (76 %)	CC (73 %)	acd (63 %)	CC bB (56 %)	CC b (53 %)	CCD (93 %)
SILLY AC- 42%	ACC (63 %)	AC cb (43 %)	bac C (43 %)	ACA (66 %)	AC ab (66 %)	bac A (46 %)	A (100 %)	bbc (93 %)	bac (70 %)	AC b (90 %)
SCARED AD- 43%	AD cC (43 %)	AD ccb (23 %)	bcd (56 %)	AD cA (86 %)	AD c (40 %)	bc A (76 %)	AD cb (50 %)	bc B (76 %)	bc (73 %)	bca D (70 %)

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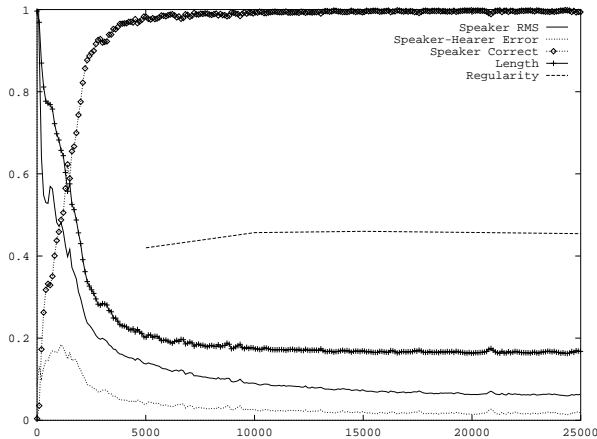
Regularity 57%	ME -A 78%	WE -D 75%	MIP -D 36%	YOU -A 90%	YALL -B 41%	YUP -C 70%	YUMI -B 54%	ONE -C 52%	THEY -C 53%	ALL -B 97%
HAPPY AD- 59%	dcdA (93 %)	dcD (93 %)	ddcb (66 %)	ADA (63 %)	ADaB (60 %)	AD (100 %)	ADbd (80 %)	ADC (50 %)	ADC (50 %)	ADB (80 %)
SAD AA- 52%	AAaA (90 %)	AAAD (90 %)	acaD (86 %)	AAA (86 %)	AAaB (83 %)	acab (73 %)	AA (96 %)	acaC (50 %)	ac (83 %)	AAB (100 %)
ANGRY DD- 60%	DDA (100 %)	DDD (86 %)	DD (86 %)	bddA (66 %)	bdd (70 %)	add (96 %)	DDb (43 %)	DDca (93 %)	DDC (90 %)	DDB (56 %)
TIRED CD- 50%	CDA (100 %)	CDD (96 %)	CD (96 %)	bdA (100 %)	bd (100 %)	bdC (100 %)	bdB (100 %)	CDC (56 %)	CDcb (56 %)	CDB (100 %)
EXCITED DB- 38%	dad (100 %)	D (50 %)	D (50 %)	daA (100 %)	DBa (100 %)	DBC (93 %)	DBd (73 %)	da (80 %)	dabd (50 %)	DB (73 %)
SICK CA- 50%	CAA (100 %)	CAD (100 %)	CA (100 %)	baA (100 %)	ba (100 %)	baC (100 %)	baB (100 %)	CAC (63 %)	CACb (63 %)	CAB (100 %)
HUNGRY CB- 50%	CBA (100 %)	CBD (100 %)	CB (100 %)	bbA (100 %)	bb (100 %)	bbC (100 %)	bbB (100 %)	CBca (56 %)	CBC (60 %)	CBB (100 %)
THIRSTY CC- 50%	CCA (100 %)	CCD (100 %)	CC (100 %)	bcA (100 %)	bc (100 %)	bcC (100 %)	bcB (100 %)	CCC (53 %)	CCcb (50 %)	CCB (100 %)
SILLY AB- 43%	dcA (96 %)	dcab (100 %)	dcabb (50 %)	ABA (100 %)	AB (86 %)	ABC (86 %)	ABd (100 %)	acC (86 %)	acb (83 %)	ABB (100 %)
SCARED DC- 51%	DCac (100 %)	DC (80 %)	DCc (60 %)	bcdA (56 %)	bcd (56 %)	adbC (93 %)	DCB (63 %)	daC (86 %)	DCcC (63 %)	DCbB (60 %)

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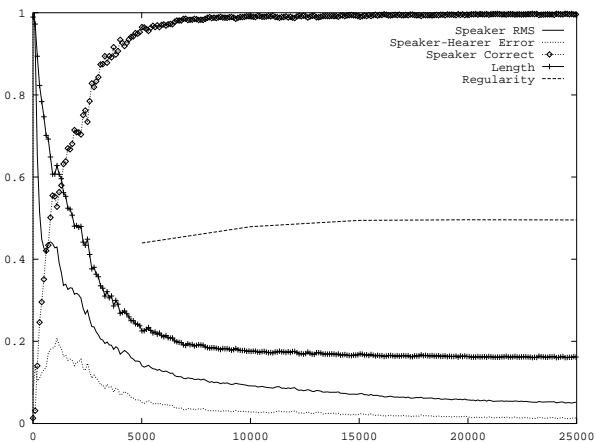
Regularity	ME	WE	MIP	YOU	YALL	YUP	YUMI	ONE	THEY	ALL
54%	-C 53%	-C 65%	-B 43%	-A 80%	-A 61%	-B 42%	-A 34%	-B 91%	-B 38%	-D 59%
HAPPY BB- 40%	acba (100 %)	acb (93 %)	acbB (83 %)	bab (100 %)	BBA (100 %)	BB (86 %)	acbd (100 %)	BBB (56 %)	BBB (43 %)	BBc (100 %)
SAD BC- 59%	acC (50 %)	acC (50 %)	BCc (93 %)	bac (96 %)	BCA (46 %)	BC (63 %)	BCA (53 %)	BCB (50 %)	BCB (50 %)	BCD (76 %)
ANGRY DB- 70%	DBca (86 %)	DBC (96 %)	DBcB (93 %)	DBA (63 %)	DBad (60 %)	DBB (100 %)	DB (100 %)	cbB (56 %)	cbbc (53 %)	DBD (100 %)
TIRED DD- 50%	DDC (43 %)	DDC (56 %)	cbdc (96 %)	DDA (60 %)	DDad (56 %)	cbda (70 %)	DD (100 %)	cbdB (100 %)	cbd (100 %)	DDD (100 %)
EXCITED AB- 40%	ABa (100 %)	ABC (93 %)	AB (86 %)	daA (100 %)	da (100 %)	daB (100 %)	dac (100 %)	ABB (56 %)	ABbd (56 %)	daD (86 %)
SICK DC- 50%	DCcC (50 %)	DCC (53 %)	cbc (100 %)	DCaA (50 %)	DCA (90 %)	cbad (90 %)	DC (100 %)	cbAB (93 %)	cba (80 %)	DCb (100 %)
HUNGRY CC- 70%	CCcC (76 %)	CCC (83 %)	CC (50 %)	caA (100 %)	CCA (100 %)	CCdB (60 %)	dcdA (93 %)	CCB (86 %)	CCbd (53 %)	CCD (53 %)
THIRSTY CD- 49%	caC (100 %)	CDC (83 %)	CD (66 %)	ca (100 %)	cad (100 %)	CDdB (50 %)	dcd (60 %)	CDB (90 %)	Cdbd (53 %)	CDD (63 %)
SILLY BD- 40%	aca (100 %)	acd (86 %)	acdB (96 %)	baA (96 %)	BDA (100 %)	BD (100 %)	acdA (96 %)	BDdB (40 %)	BDB (66 %)	BDc (100 %)
SCARED AD- 40%	aaC (93 %)	ADC (93 %)	AD (90 %)	aaA (53 %)	aad (100 %)	bdd (96 %)	ADA (100 %)	aaB (100 %)	ADB (100 %)	ADD (96 %)

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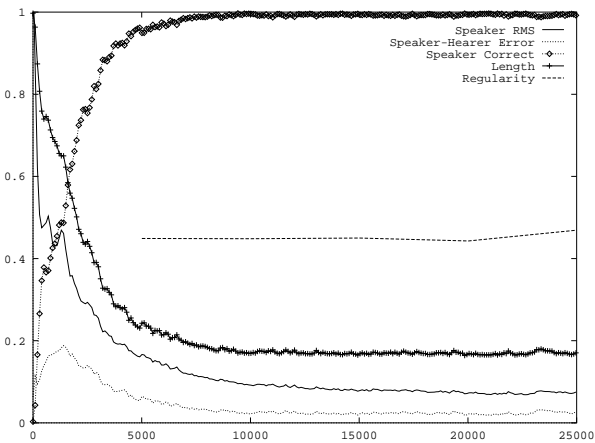
Regularity	ME	WE	MIP	YOU	YALL	YUP	YUMI	ONE	THEY	ALL
45%	-D 66%	-D 42%	-D 39%	-A 48%	-B 54%	-B 48%	-C 33%	-A 46%	-D 38%	-D 58%
HAPPY DB- 61%	DBdD (53 %)	DBD (53 %)	DB (93 %)	bcBA (83 %)	bcB (90 %)	DBc (100 %)	bcbd (86 %)	DBaA (56 %)	DBa (53 %)	DBb (100 %)
SAD DC- 70%	DCdD (53 %)	DCD (53 %)	DC (90 %)	cc (63 %)	ccB (63 %)	DCbB (70 %)	DCC (100 %)	DCaA (50 %)	Dca (60 %)	DCb (73 %)
ANGRY BB- 40%	bdbb (93 %)	BBD (100 %)	abd (100 %)	BBbA (66 %)	BBB (70 %)	abB (96 %)	BB (93 %)	aadb (50 %)	aba (73 %)	BBa (100 %)
TIRED BA- 40%	bdc (100 %)	BAbD (60 %)	adD (96 %)	BACa (96 %)	BAcc (63 %)	adc (100 %)	BA (76 %)	aac (100 %)	ad (96 %)	BACD (100 %)
EXCITED AB- 26%	bdb (93 %)	bdbc (100 %)	ABcD (93 %)	bcA (56 %)	bcaB (53 %)	ABcB (83 %)	bab (53 %)	aab (100 %)	ABc (53 %)	babD (56 %)
SICK AC- 22%	bdD (100 %)	bda (100 %)	ACbD (73 %)	cbA (93 %)	cbB (93 %)	ACbB (70 %)	baa (100 %)	aaA (100 %)	AC (83 %)	baD (96 %)
HUNGRY CA- 39%	cdD (100 %)	cd (100 %)	cda (96 %)	CAc (100 %)	C (100 %)	CA (86 %)	cdC (100 %)	CAA (63 %)	CAaD (63 %)	CAD (96 %)
THIRSTY DD- 35%	DDD (83 %)	DDda (53 %)	DDa (90 %)	cbc (100 %)	cb (96 %)	cbda (76 %)	cbdd (56 %)	acc (100 %)	acd (100 %)	DDac (66 %)
SILLY DA- 59%	ddcD (73 %)	ddc (73 %)	D (93 %)	DAcc (66 %)	DAc (66 %)	DA (96 %)	DAcD (96 %)	DAA (66 %)	DAaD (93 %)	DAD (100 %)
SCARED DA- 35%	ddbD (96 %)	ddb (93 %)	ddba (73 %)	bcc (56 %)	bccd (46 %)	DAB (90 %)	bcd (93 %)	DAab (73 %)	DAbA (83 %)	DAbD (93 %)

agave std batali 02/07/1999 08:11:04



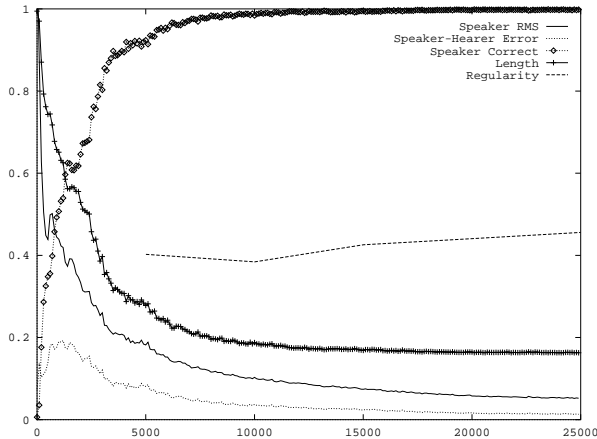
Regularity 49%	ME -C 30%	WE -A 52%	MIP -B 57%	YOU -C 40%	YALL -A 36%	YUP -D 99%	YUMI -A 43%	ONE -C 96%	THEY -D 46%	ALL -D 62%
HAPPY C- 50%	CC (100 %)	Ccad (96 %)	Cdda (56 %)	abaa (83 %)	a (93 %)	acD (100 %)	acA (100 %)	CcC (96 %)	CdD (76 %)	ac (93 %)
SAD AD- 39%	ccd (100 %)	cdaA (56 %)	cda (70 %)	ADC (100 %)	AD (96 %)	ADD (100 %)	ADA (96 %)	cdC (70 %)	cdca (50 %)	ADb (93 %)
ANGRY AA- 39%	ccaa (96 %)	caA (56 %)	caad (53 %)	AAa (100 %)	AA (86 %)	AAD (93 %)	AAc (53 %)	daaC (63 %)	daa (63 %)	AAcD (53 %)
TIRED DC- 30%	bc (96 %)	bcb (100 %)	DCB (100 %)	bcC (96 %)	bab (100 %)	DCD (100 %)	bac (53 %)	DCC (100 %)	DC (100 %)	bacD (56 %)
EXCITED CA- 41%	ccab (86 %)	CAb (100 %)	CA (100 %)	abab (76 %)	abA (76 %)	abaD (100 %)	abcA (83 %)	CAC (60 %)	CAcD (60 %)	CAD (100 %)
SICK BA- 40%	bca (100 %)	BAac (83 %)	daB (100 %)	BAab (80 %)	BAA (83 %)	daD (100 %)	BA (90 %)	daC (100 %)	da (100 %)	BAD (100 %)
HUNGRY BB- 49%	BBcC (70 %)	BBc (83 %)	dbB (100 %)	BBb (100 %)	BBA (100 %)	dbD (100 %)	BB (100 %)	dbC (100 %)	db (100 %)	BBD (100 %)
THIRSTY BD- 40%	bcd (100 %)	BDA (100 %)	ddB (100 %)	BDC (63 %)	BDcd (60 %)	ddD (100 %)	BD (96 %)	ddC (100 %)	dd (100 %)	BDD (100 %)
SILLY CD- 47%	ccb (100 %)	CDbA (100 %)	CDB (73 %)	abdC (100 %)	abd (96 %)	abdD (96 %)	abcd (83 %)	CDbC (100 %)	CDbD (73 %)	CDbb (100 %)
SCARED CB- 50%	CBb (100 %)	CBA (100 %)	CB (96 %)	abbb (100 %)	abb (100 %)	abbD (100 %)	abcb (83 %)	CBC (80 %)	CBcD (80 %)	CBD (100 %)

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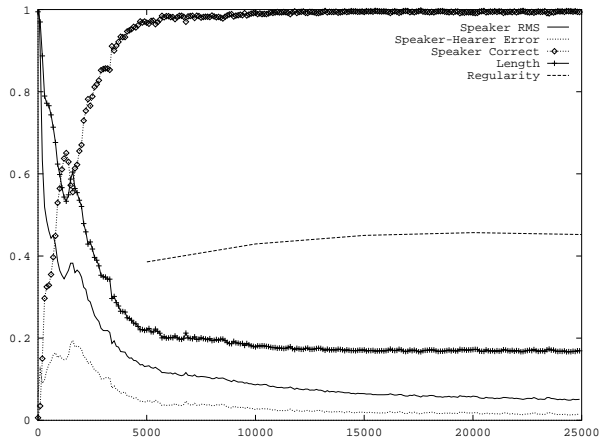
Regularity	ME	WE	MIP	YOU	YALL	YUP	YUMI	ONE	THEY	ALL
46%	-D 64%	-A 42%	-A 51%	-C 53%	-C 55%	-C 34%	-D 40%	-A 74%	-D 35%	-B 35%
HAPPY AA- 20%	dbb (70 %)	dcbbb (26 %)	abd (96 %)	bb (96 %)	bbd (100 %)	adb (76 %)	dab (100 %)	AAbA (60 %)	AAb (63 %)	abB (100 %)
SAD DD- 59%	DDb (63 %)	DDbA (43 %)	DDA (63 %)	DDd (90 %)	DDdC (63 %)	ad (80 %)	DD (80 %)	adA (100 %)	adD (70 %)	DDac (50 %)
ANGRY BA- 38%	bdD (100 %)	bd (100 %)	BAd (43 %)	bba (100 %)	B (100 %)	BAb (86 %)	bdb (96 %)	BAA (96 %)	BA (80 %)	BA d (53 %)
TIRED CB- 64%	CBdD (66 %)	CBd (70 %)	CBA (63 %)	CBcC (73 %)	CBC (73 %)	CBca (96 %)	CB (63 %)	caA (100 %)	caab (60 %)	CBac (33 %)
EXCITED AB- 29%	dbc (43 %)	dbcA (76 %)	AB (53 %)	bcB (100 %)	bc (96 %)	ABC (96 %)	bcD (96 %)	aacb (73 %)	ABa (66 %)	ABcd (53 %)
SICK CA- 40%	dbD (33 %)	dbA (100 %)	CABd (96 %)	ccb (40 %)	ccb (36 %)	CABb (96 %)	cbb (23 %)	CABa (100 %)	CAB (100 %)	cbB (53 %)
HUNGRY CD- 69%	CDD (70 %)	CDdA (63 %)	CDaA (50 %)	CDcC (90 %)	CDC (86 %)	CDca (86 %)	CD (90 %)	cadA (76 %)	caD (80 %)	CDa (53 %)
THIRSTY CC- 37%	dcD (100 %)	dcA (100 %)	cacd (93 %)	CCC (100 %)	CC (100 %)	CCa (56 %)	CCD (76 %)	cacA (96 %)	cac (96 %)	CCad (56 %)
SILLY DA- 40%	dbD (36 %)	D (96 %)	DAA (56 %)	DAcC (70 %)	DAC (70 %)	adC (80 %)	DA (96 %)	aaA (100 %)	aad (100 %)	DAa (60 %)
SCARED AC- 50%	dcB (46 %)	dc (93 %)	ACd (56 %)	ACC (60 %)	ACcd (60 %)	AC (100 %)	dcc (100 %)	aacc (63 %)	ACa (100 %)	ACdc (53 %)

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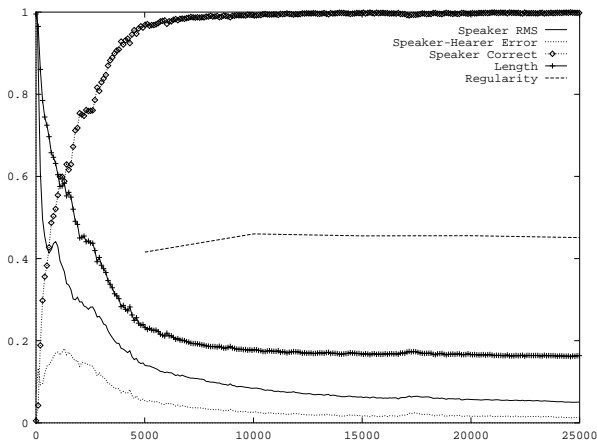
Regularity	ME	WE	MIP	YOU	YALL	YUP	YUMI	ONE	THEY	ALL
45%	-A 57%	-C 52%	-A 38%	-C 53%	-B 41%	-C 55%	-D 45%	-B 62%	-B 44%	-C 36%
HAPPY CB- 64%	CBA (53 %)	CBaC (43 %)	adcb (83 %)	cca (100 %)	C (96 %)	CBC (86 %)	CBd (56 %)	CBB (66 %)	CBbc (53 %)	CBdC (56 %)
SAD AA- 50%	AAA (76 %)	AAaC (73 %)	AA (96 %)	caC (100 %)	ca (100 %)	cab (100 %)	caa (100 %)	AAB (53 %)	AAbc (53 %)	AAc (100 %)
ANGRY BC- 30%	bab (66 %)	babC (66 %)	BcBA (70 %)	cc (56 %)	ccB (100 %)	BCbC (80 %)	BcC (100 %)	bbB (100 %)	bbc (100 %)	BC (100 %)
TIRED BD- 30%	badd (80 %)	BDdd (60 %)	BD (100 %)	dcd (56 %)	dcdB (56 %)	dbd (100 %)	ddD (56 %)	bbdd (93 %)	BDB (100 %)	BDdC (86 %)
EXCITED CD- 30%	bad (83 %)	badC (90 %)	bdc (96 %)	ccd (100 %)	CDB (96 %)	CDbb (96 %)	CDbD (50 %)	bbd (86 %)	bbdc (93 %)	bcd (100 %)
SICK DC- 20%	baA (100 %)	baC (100 %)	bdac (70 %)	DCbC (73 %)	DCB (96 %)	dbC (100 %)	ddc (86 %)	bba (53 %)	bbac (53 %)	bca (100 %)
HUNGRY DA- 40%	DAA (60 %)	DAa (40 %)	bdaA (50 %)	dca (100 %)	Dac (100 %)	dbaC (93 %)	DA (100 %)	dbaa (90 %)	dba (93 %)	DAb (100 %)
THIRSTY DD- 40%	DDaA (76 %)	DDa (76 %)	adA (100 %)	dcC (80 %)	DdC (100 %)	dbbC (90 %)	DD (100 %)	dBB (90 %)	dB (86 %)	DDb (100 %)
SILLY A- 70%	AcA (86 %)	AC (50 %)	A (100 %)	cda (53 %)	cdab (53 %)	AbC (100 %)	Ac (50 %)	ABb (93 %)	AB (100 %)	AcB (100 %)
SCARED AD- 49%	ADdd (56 %)	ADd (66 %)	AD (100 %)	cdC (100 %)	cdd (86 %)	cddb (96 %)	cddD (83 %)	ADB (46 %)	ADB (53 %)	ADcd (76 %)

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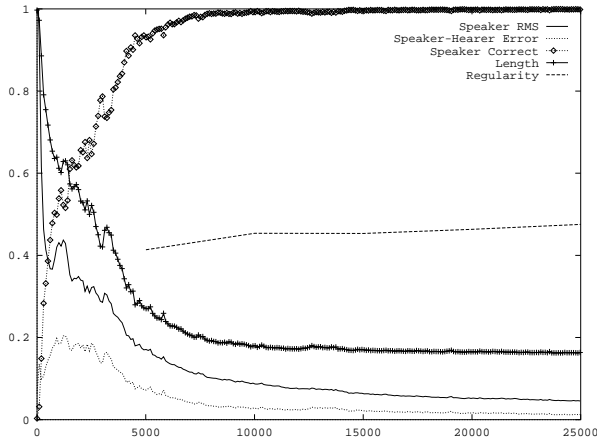
Regularity	ME -A 54%	WE -A 29%	MIP -C 66%	YOU -D 85%	YALL -B 35%	YUP -A 77%	YUMI -D 48%	ONE -D 64%	THEY -A 41%	ALL -A 46%
HAPPY DA- 51%	aad (100 %)	adc (53 %)	adcC (53 %)	DAD (100 %)	D (86 %)	DA (80 %)	DAb (86 %)	DAcD (63 %)	DAc (63 %)	DAA (100 %)
SAD DC- 60%	acA (96 %)	acd (93 %)	acC (100 %)	DCD (100 %)	DCB (80 %)	DC (80 %)	DCa (46 %)	DCc (46 %)	DCc (53 %)	DCA (53 %)
ANGRY DD- 36%	adA (100 %)	add (80 %)	addC (70 %)	DDD (100 %)	DD (83 %)	DDc (83 %)	DDb (36 %)	cdD (66 %)	cddA (66 %)	DDA (100 %)
TIRED CD- 29%	bab (53 %)	bab (40 %)	cab (100 %)	bdbD (56 %)	bdB (53 %)	CDaA (96 %)	bbb (60 %)	CDaD (86 %)	CDA (86 %)	bbbA (63 %)
EXCITED AD- 31%	aaa (100 %)	ADb (90 %)	ADbC (96 %)	dbd (100 %)	dba (53 %)	dbaA (53 %)	ADbD (93 %)	cdb (50 %)	cdb (50 %)	abb (53 %)
SICK CD- 29%	badA (50 %)	bad (50 %)	cad (100 %)	bdD (100 %)	bda (100 %)	CDcA (100 %)	bbD (90 %)	CDcD (80 %)	CDc (93 %)	bbA (100 %)
HUNGRY BC- 30%	baA (100 %)	BCA (100 %)	caa (96 %)	bdcD (93 %)	BCd (100 %)	ccA (96 %)	BC (100 %)	ccD (73 %)	cc (100 %)	BCc (100 %)
THIRSTY CB- 28%	bac (53 %)	bacb (46 %)	caC (100 %)	bdc (86 %)	bdcB (93 %)	CBA (100 %)	bbc (46 %)	CBc (40 %)	CBc (50 %)	bbc (53 %)
SILLY AC- 30%	aac (100 %)	AC (73 %)	ACbC (93 %)	dbcD (96 %)	dbc (96 %)	dbcA (100 %)	ACbD (76 %)	cbD (60 %)	cbdA (60 %)	ACb (43 %)
SCARED AB- 30%	aab (100 %)	ABA (100 %)	ABC (96 %)	dbbD (96 %)	dbB (96 %)	dbbA (96 %)	ABD (93 %)	cbbD (53 %)	ccb (60 %)	AB (90 %)

bi-zarr std batali 27/06/1999 09:28:34



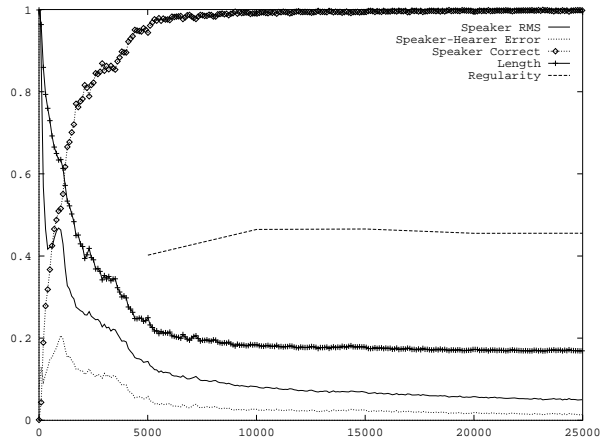
Regularity	ME	WE	MIP	YOU	YALL	YUP	YUMI	ONE	THEY	ALL
45%	-C 84%	-B 43%	-D 64%	-B 61%	-C 35%	-C 42%	-B 72%	-B 50%	-C 33%	-C 36%
HAPPY DC- 29%	DCC (100 %)	DC (100 %)	DCb (90 %)	aba (60 %)	abad (56 %)	aad (96 %)	Dca (96 %)	ada B (70 %)	ada (76 %)	aca (46 %)
SAD DD- 41%	DDC (100 %)	D (86 %)	DD (90 %)	da B (100 %)	da (100 %)	dad (50 %)	dac (100 %)	DDd (96 %)	DDa (96 %)	DDb (93 %)
ANGRY CA- 80%	CAC (96 %)	CA (53 %)	CAdc (63 %)	CAaB (46 %)	CAa (63 %)	aaa (96 %)	CAB (70 %)	CAdd (76 %)	CAd (83 %)	CAbd (73 %)
TIRE BA- 40%	cba C (100 %)	cb (56 %)	cba D (100 %)	bb aB (96 %)	BAb (100 %)	BA (100 %)	cba B (100 %)	BAaa (63 %)	BAa (70 %)	BAC (100 %)
EXCITED CC- 30%	CCd (100 %)	CC (100 %)	CCaD (73 %)	abca (83 %)	ab C (83 %)	aa C (96 %)	CCaB (80 %)	adca (70 %)	ad C (83 %)	aca C (76 %)
SICK CD- 30%	CDC (100 %)	CD (100 %)	CDD (100 %)	bba (93 %)	bbad (100 %)	bad (70 %)	CDB (100 %)	bdaa (46 %)	bda (70 %)	bca (100 %)
HUNGRY BD- 34%	cbd (53 %)	cbd B (50 %)	BDdD (96 %)	bbd B (80 %)	bbd (80 %)	BDdC (100 %)	bcd B (43 %)	BDdB (100 %)	BD (53 %)	bcd (80 %)
THIRSTY BC- 31%	cb C (100 %)	cb B (100 %)	BCcD (63 %)	bb B (100 %)	bb C (100 %)	BCca (83 %)	BCB (100 %)	bd B (100 %)	bd C (100 %)	BC (90 %)
SILLY DB- 30%	DBC (100 %)	DB (100 %)	DBD (100 %)	abd (73 %)	abd (73 %)	add C (93 %)	DBB (100 %)	add B (100 %)	add (100 %)	acd (100 %)
SCARED AC- 31%	cc C (100 %)	cc B (100 %)	ACc (100 %)	ab B (80 %)	abb C (76 %)	ACbC (76 %)	ACbB (66 %)	ad B (80 %)	adb C (80 %)	AC (86 %)

bi-zarr std batali 27/06/1999 09:28:39



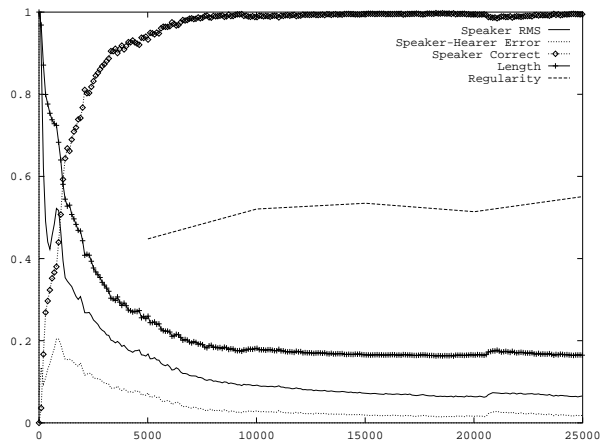
Regularity	ME	WE	MIP	YOU	YALL	YUP	YUMI	ONE	THEY	ALL
47%	-D 41%	-C 56%	-B 76%	-D 64%	-A 36%	-A 58%	-A 47%	-D 64%	-B 42%	-B 71%
HAPPY BA- 30%	BAD (100 %)	BA (93 %)	BAB (100 %)	aca (56 %)	acab (50 %)	ab A (43 %)	BAA (100 %)	ada (53 %)	ada B (53 %)	aba (56 %)
SAD BB- 80%	BBc (96 %)	BB (53 %)	BBdB (93 %)	BBa (53 %)	BBad (53 %)	abb (100 %)	BBdA (86 %)	BBb (60 %)	BBbd (60 %)	BBd (96 %)
ANGRY AA- 30%	bca (100 %)	ba C (100 %)	da B (90 %)	AAD (100 %)	AAA (50 %)	AA (50 %)	ca A (100 %)	da D (100 %)	da (96 %)	AAB (100 %)
TIRE CA- 30%	cc (96 %)	cc C (100 %)	dcc B (66 %)	cca (100 %)	CAdc (86 %)	dcc A (86 %)	CAC (100 %)	dcc (100 %)	dcc (90 %)	CACb (100 %)
EXCITED AC- 30%	bc (100 %)	beb (100 %)	adbc (73 %)	ACbD (100 %)	ACb (100 %)	abc A (66 %)	ACbb (96 %)	adb D (96 %)	ad B (96 %)	abc B (73 %)
SICK CA- 41%	ccb (90 %)	CAbC (90 %)	dc B (66 %)	CAD (53 %)	CAdA (53 %)	dc A (100 %)	CA (83 %)	dda (96 %)	dcba (66 %)	CABb (70 %)
HUNGRY CB- 49%	CBca (46 %)	CBc (60 %)	dbc (96 %)	CBa (100 %)	CBd (100 %)	db A (96 %)	CB (100 %)	db D (100 %)	db (100 %)	CBb (100 %)
THIRSTY CD- 40%	cc D (100 %)	CDC (96 %)	dcd B (100 %)	CDD (100 %)	CDA (100 %)	dcd A (96 %)	CD (100 %)	dd D (100 %)	dcd (96 %)	CDB (100 %)
SILLY BD- 30%	BDD (100 %)	BD (100 %)	BDB (100 %)	acd (60 %)	acdb (56 %)	abd (90 %)	BDA (96 %)	ad D (96 %)	add B (96 %)	abd B (96 %)
SCARED AC- 30%	bc D (100 %)	bd C (100 %)	adc B (70 %)	ACcD (100 %)	ACc (100 %)	abcd (66 %)	ACcb (83 %)	adc D (100 %)	adc (100 %)	abcc (76 %)

bi-zarr std batali 28/06/1999 03:01:14



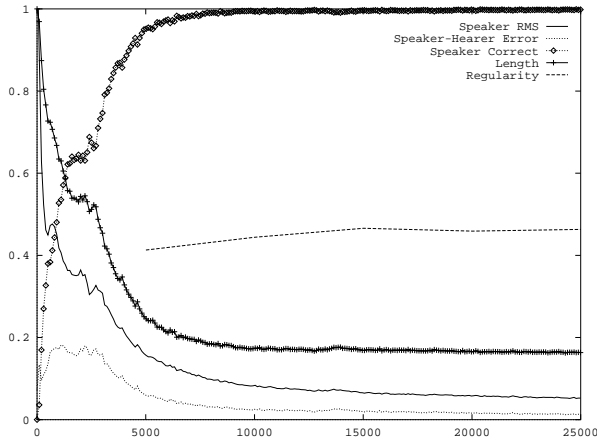
Regularity 45%	ME -C 46%	WE -C 37%	MIP -C 34%	YOU -A 70%	YALL -D 37%	YUP -B 55%	YUMI -C 72%	ONE -C 48%	THEY -D 41%	ALL -A 52%
HAPPY DB- 37%	bcd (56 %)	bcdA (53 %)	DBdaC (63 %)	badA (93 %)	baD (90 %)	DBdaa (56 %)	badC (93 %)	DBdC (86 %)	DBD (73 %)	bdad (60 %)
SAD D- 90%	DC (60 %)	Dca (60 %)	Dda (100 %)	DaA (100 %)	Daac (70 %)	Da (70 %)	bacC (96 %)	Ddd (100 %)	DD (100 %)	Dac (100 %)
ANGRY CD- 31%	ccdd (80 %)	CDdC (86 %)	CDd (80 %)	adA (100 %)	ad (100 %)	add (50 %)	bdd (100 %)	dbcd (96 %)	dbdD (86 %)	CDdA (90 %)
TIRED CB- 40%	ccdb (83 %)	CBd (90 %)	CB (90 %)	abA (100 %)	ab (100 %)	abB (100 %)	abC (100 %)	CBbC (50 %)	CBb (53 %)	CBA (100 %)
EXCITED BD- 30%	bcC (86 %)	bccb (83 %)	BDcb (76 %)	baab (73 %)	babD (70 %)	BDB (100 %)	BDcd (53 %)	dbC (90 %)	dbcb (96 %)	BD (100 %)
SICK CD- 40%	ccdC (76 %)	CDC (100 %)	CD (93 %)	aad (100 %)	acD (96 %)	acdB (96 %)	acdC (96 %)	CDbC (56 %)	CDb (56 %)	CDA (100 %)
HUNGRY AC- 30%	ccaC (43 %)	cca (60 %)	caC (63 %)	aaA (100 %)	ACa (53 %)	ACad (50 %)	ACC (100 %)	ccC (90 %)	cacD (63 %)	caA (90 %)
THIRSTY CA- 40%	ccb (100 %)	CA dC (90 %)	CA (83 %)	aab (100 %)	acb (96 %)	acbB (96 %)	acbC (96 %)	CA b (66 %)	CA bD (53 %)	CA dA (53 %)
SILLY DB- 37%	bcaC (63 %)	bca (63 %)	DBaC (96 %)	baaA (63 %)	baca (96 %)	DBaa (80 %)	baC (96 %)	DBab (70 %)	DBa (93 %)	bdac (60 %)
SCARED BB- 36%	bcb (90 %)	bcbA (23 %)	BBC (80 %)	babA (86 %)	bab (83 %)	BBB (100 %)	BBa (70 %)	dbbC (53 %)	dbb (60 %)	BB (100 %)

bi-zarr std batali 28/06/1999 03:01:19



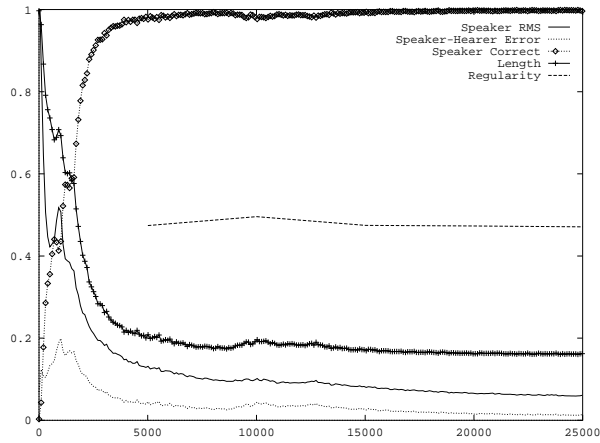
Regularity 55%	ME -C 79%	WE -C 50%	MIP -B 76%	YOU -D 71%	YALL -D 42%	YUP -A 47%	YUMI -B 40%	ONE -C 75%	THEY -A 38%	ALL -A 62%
HAPPY AC- 66%	ACC (70 %)	ACcb (53 %)	ACB (93 %)	ACD (63 %)	ACda (46 %)	ACad (76 %)	ddaa (50 %)	aaC (100 %)	A (96 %)	ACA (80 %)
SAD DB- 50%	DBC (100 %)	DBb (100 %)	abB (96 %)	DBD (60 %)	DBda (60 %)	abd (96 %)	DB (100 %)	abC (100 %)	ab (100 %)	DBA (100 %)
ANGRY CA- 59%	cca (100 %)	CAC (96 %)	CAa (56 %)	CAdc (76 %)	CAD (86 %)	CAdA (86 %)	CA (63 %)	aa (63 %)	aaa (100 %)	CAad (40 %)
TIRED CD- 40%	cccd (86 %)	CDbC (93 %)	baB (80 %)	CDD (63 %)	CDD (36 %)	badA (73 %)	CD (93 %)	badC (96 %)	bad (66 %)	CDbA (53 %)
EXCITED AD- 30%	ccbC (50 %)	ccb (93 %)	ADaB (96 %)	ccD (100 %)	cdc (96 %)	ADad (86 %)	cda (56 %)	aab (100 %)	ADA (90 %)	cdab (46 %)
SICK CB- 40%	cccC (53 %)	CBC (100 %)	baaB (70 %)	CBdc (66 %)	CBd (76 %)	baaA (66 %)	CB (100 %)	baC (100 %)	baA (63 %)	CBA (100 %)
HUNGRY BB- 51%	BBC (53 %)	BBcb (46 %)	BB (100 %)	bdD (100 %)	bd (80 %)	bdb (86 %)	cbB (100 %)	BBaC (60 %)	BBA (83 %)	BBd (96 %)
THIRSTY BC- 59%	BCC (53 %)	BCcb (53 %)	BC (96 %)	bdc (50 %)	bdc (50 %)	BCdA (46 %)	ddB (100 %)	BCdC (93 %)	BCd (43 %)	BCA (93 %)
SILLY D- 69%	DC (100 %)	Dcb (100 %)	DaB (96 %)	DcD (100 %)	Dac (100 %)	Dad (53 %)	D (100 %)	adC (66 %)	adcb (66 %)	DA (56 %)
SCARED DD- 49%	DDcC (76 %)	DDC (80 %)	adB (100 %)	DDD (56 %)	DDda (56 %)	addA (86 %)	DD (100 %)	addC (96 %)	add (83 %)	DDab (56 %)

bi-zarr std batali 28/06/1999 19:43:12



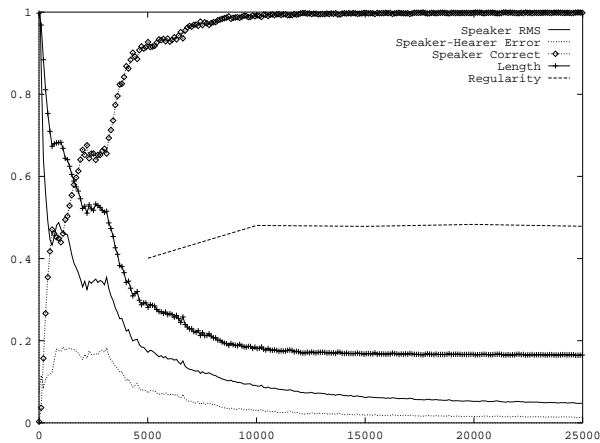
Regularity 46%	ME -D 73%	WE -A 31%	MIP -B 68%	YOU -A 84%	YALL -D 32%	YUP -B 70%	YUMI -D 41%	ONE -A 58%	THEY -B 35%	ALL -B 44%
HAPPY A- 57%	daD (100 %)	dA (100 %)	daB (100 %)	AA (100 %)	A (70 %)	AdB (46 %)	AaD (53 %)	Aab (100 %)	AdbB (93 %)	Adbd (86 %)
SAD AB- 60%	dbaD (90 %)	dbA (90 %)	dbaB (93 %)	ABA (90 %)	ABaD (66 %)	AB (90 %)	ABD (66 %)	ABbA (60 %)	ABB (66 %)	ABdB (66 %)
ANGRY DD- 29%	DDaD (100 %)	DDA (100 %)	DDaB (96 %)	aaA (100 %)	ada (86 %)	adaB (53 %)	ccaD (76 %)	baA (100 %)	bdaa (90 %)	add (100 %)
TIRED BD- 29%	cdD (100 %)	cdc (90 %)	BDd (100 %)	cacA (56 %)	cac (53 %)	BDca (50 %)	ccD (83 %)	bacA (66 %)	BDc (46 %)	ccc (100 %)
EXCITED DD- 39%	DDD (100 %)	DD (100 %)	DDB (100 %)	acA (96 %)	acd (96 %)	adc (70 %)	DDca (56 %)	ba (86 %)	bad (86 %)	DDc (63 %)
SICK BD- 30%	cda (66 %)	cdab (46 %)	BBB (100 %)	caA (100 %)	caD (90 %)	BDaB (93 %)	cca (76 %)	babA (63 %)	BDa (70 %)	ccaB (90 %)
HUNGRY CB- 30%	cdba (93 %)	CBd (100 %)	bbd (100 %)	cabA (90 %)	CBa (100 %)	bbB (100 %)	CB (100 %)	bbA (100 %)	bb (100 %)	CBB (100 %)
THIRSTY BC- 30%	cdb (90 %)	cdbc (93 %)	BCd (96 %)	cab (86 %)	cabC (86 %)	BCB (100 %)	ccbD (60 %)	BCA (100 %)	BC (100 %)	ccB (66 %)
SILLY DB- 40%	DBD (100 %)	DB (93 %)	DBB (93 %)	acbA (86 %)	acb (83 %)	acbB (83 %)	DBca (53 %)	babC (63 %)	bccB (80 %)	DBc (53 %)
SCARED DC- 40%	DCD (100 %)	DC (83 %)	DCB (93 %)	accA (90 %)	acc (76 %)	accB (86 %)	DCa (90 %)	bacc (70 %)	bccd (66 %)	DCc (100 %)

bi-zarr std batali 28/06/1999 19:43:17



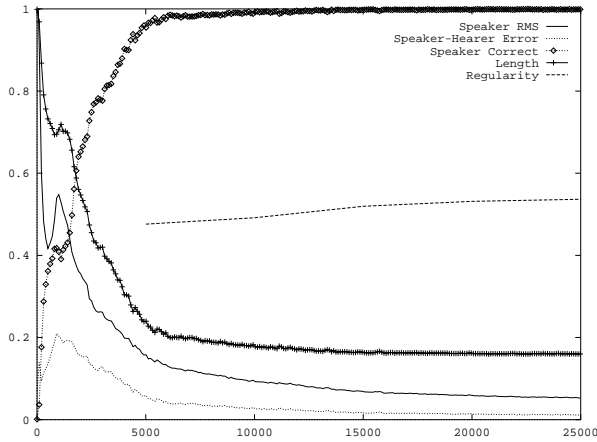
Regularity 47%	ME -A 67%	WE -A 33%	MIP -C 53%	YOU -B 86%	YALL -A 31%	YUP -C 46%	YUMI -A 40%	ONE -B 65%	THEY -C 39%	ALL -D 39%
HAPPY BB- 50%	abA (100 %)	ab (53 %)	abd (93 %)	BBB (100 %)	B (100 %)	BB (100 %)	BBA (63 %)	BBcB (60 %)	BBC (60 %)	BBac (60 %)
SAD BC- 60%	abb (80 %)	abbb (50 %)	abC (100 %)	BCB (93 %)	BCbA (73 %)	BC (83 %)	BCA (63 %)	BCcB (70 %)	BCC (70 %)	BCac (63 %)
ANGRY DB- 40%	aabA (56 %)	aab (56 %)	DBaa (100 %)	baB (56 %)	ba (56 %)	DBab (100 %)	cbA (100 %)	DBB (100 %)	DB (96 %)	DBa (100 %)
TIRED DA- 30%	caA (63 %)	caad (60 %)	DAa (100 %)	cdB (73 %)	cdBA (73 %)	DAd (100 %)	cbd (86 %)	DAB (100 %)	DA (96 %)	cbdc (50 %)
EXCITED AA- 40%	AAA (100 %)	AA (100 %)	AAC (100 %)	bdB (100 %)	bdA (100 %)	dbd (60 %)	AAAd (50 %)	ddB (96 %)	dbd (40 %)	AAAdc (50 %)
SICK CB- 40%	cab (100 %)	CBcA (86 %)	dcaa (60 %)	CBB (66 %)	CBbc (66 %)	dcab (83 %)	CB (100 %)	dcB (100 %)	dc (93 %)	CBcd (50 %)
HUNGRY CC- 58%	cac (100 %)	CCA (50 %)	CCa (50 %)	CCbB (53 %)	CCb (50 %)	CCC (93 %)	CC (63 %)	dccB (73 %)	dcC (73 %)	CCD (83 %)
THIRSTY CD- 40%	cadA (96 %)	cad (96 %)	cadC (93 %)	CDd (80 %)	CD (100 %)	CDc (100 %)	CDA (70 %)	ddcc (70 %)	dcd (80 %)	CDac (66 %)
SILLY AC- 40%	ACA (100 %)	AC (86 %)	ACC (96 %)	bdcB (96 %)	bdc (93 %)	bdcC (86 %)	ACd (43 %)	ddcB (50 %)	dcdA (56 %)	ACD (53 %)
SCARED AD- 40%	ADA (100 %)	AD (83 %)	ADC (90 %)	bddB (93 %)	bdd (90 %)	bddC (86 %)	ADb (93 %)	dd (76 %)	dda (93 %)	ADD (100 %)

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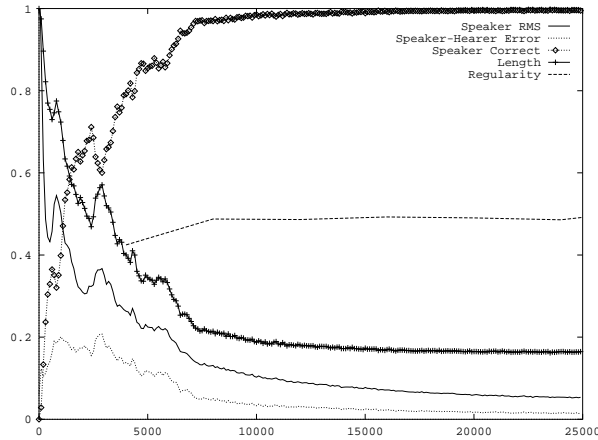
Regularity	ME	WE	MIP	YOU	YALL	YUP	YUMI	ONE	THEY	ALL
47%	-B 72%	-A 42%	-D 63%	-B 75%	-C 48%	-D 38%	-C 64%	-B 45%	-D 42%	-C 55%
HAPPY CB- 50%	aaB (100 %)	aac (90 %)	aacD (93 %)	CBB (76 %)	CBbC (76 %)	CB (100 %)	aacC (90 %)	CBa (100 %)	CBD (100 %)	CBC (100 %)
SAD CC- 39%	aaaB (50 %)	aaA (53 %)	cac (73 %)	CBB (100 %)	CC (86 %)	CCa (83 %)	CCC (100 %)	caB (100 %)	ca (100 %)	CCd (100 %)
ANGRY BC- 40%	baB (93 %)	ba (90 %)	bac (96 %)	BCB (56 %)	BCbC (56 %)	BC (100 %)	dcC (100 %)	bbaB (46 %)	BCa (100 %)	BCC (100 %)
TIRED BD- 30%	daB (86 %)	dabc (86 %)	BDcD (60 %)	dbbB (53 %)	dbC (100 %)	BDcb (86 %)	dcd (100 %)	bbd (100 %)	BDcdb (36 %)	ddC (96 %)
EXCITED AC- 60%	ACaB (50 %)	ACA (50 %)	ACda (56 %)	ACB (60 %)	ACbC (53 %)	bcD (100 %)	AC (93 %)	bbB (96 %)	bbc (100 %)	ACd (60 %)
SICK BD- 30%	dacB (66 %)	dac (63 %)	BDcc (90 %)	dbba (93 %)	dcb (80 %)	BDca (66 %)	dc (93 %)	bbad (73 %)	BDc (33 %)	dca (86 %)
HUNGRY DA- 37%	DAaB (100 %)	DA (90 %)	DAaD (93 %)	dbaB (63 %)	dba (63 %)	ddab (60 %)	DAaa (83 %)	bdaB (66 %)	bda (66 %)	dda (83 %)
THIRSTY DD- 31%	dadB (60 %)	dad (60 %)	DDD (100 %)	dbdB (60 %)	dbd (60 %)	DDbD (60 %)	DDb (43 %)	bdB (100 %)	bdD (100 %)	DD (83 %)
SILLY CD- 50%	aadB (96 %)	aad (90 %)	aadD (93 %)	CDba (60 %)	CDb (63 %)	CD (100 %)	aadC (93 %)	CDa (60 %)	CDaD (56 %)	CDC (100 %)
SCARED AD- 40%	aba (100 %)	ADA (100 %)	AD (86 %)	ab (50 %)	abb (76 %)	cdD (96 %)	ADb (93 %)	abd (100 %)	ADD (96 %)	ADC (86 %)

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Regularity	ME	WE	MIP	YOU	YALL	YUP	YUMI	ONE	THEY	ALL
53%	-A 69%	-B 51%	-C 42%	-D 82%	-B 39%	-D 41%	-B 49%	-A 92%	-A 38%	-B 66%
HAPPY DC- 50%	bcA (100 %)	bc (100 %)	bcC (100 %)	DCD (100 %)	DCc (100 %)	DC (100 %)	bcd (100 %)	DCaA (50 %)	DCA (53 %)	DCB (100 %)
SAD DA- 40%	baA (73 %)	baad (73 %)	Dab (50 %)	ddD (86 %)	dd (96 %)	DAD (100 %)	ddB (96 %)	DAA (100 %)	DA (96 %)	DAB (46 %)
ANGRY CC- 50%	CCc (46 %)	CCc (53 %)	acC (100 %)	CCD (63 %)	CCdB (63 %)	caD (100 %)	CC (100 %)	caA (96 %)	ca (96 %)	CCB (100 %)
TIRED CD- 40%	abc (56 %)	abc (43 %)	acb (80 %)	CDbD (100 %)	CDB (100 %)	CDba (100 %)	CDbb (100 %)	adc (53 %)	adc (46 %)	acbd (80 %)
EXCITED CB- 60%	bcbA (83 %)	bcB (83 %)	bbC (96 %)	CBd (60 %)	CBdB (46 %)	CB (86 %)	CBc (100 %)	CBA (53 %)	CBab (50 %)	CBB (100 %)
SICK AC- 50%	ACA (90 %)	ACaB (90 %)	AC (100 %)	cdcD (96 %)	cdc (96 %)	cda (100 %)	cdcB (96 %)	ACdA (90 %)	ACd (86 %)	ACdB (93 %)
HUNGRY AA- 69%	AAcA (50 %)	AAcB (46 %)	AA (80 %)	cdDa (100 %)	cdbca (40 %)	AAD (56 %)	AAB (100 %)	AAA (80 %)	AAad (66 %)	AAdB (56 %)
THIRSTY AD- 40%	abA (96 %)	ab (83 %)	ADb (53 %)	cdD (66 %)	cdD (100 %)	ADD (100 %)	abd (100 %)	ADA (100 %)	AD (100 %)	ADbd (53 %)
SILLY DB- 50%	bac (100 %)	ba (96 %)	bab (93 %)	DBD (46 %)	DBd (53 %)	DB (100 %)	bad (100 %)	DBA (50 %)	DBA (50 %)	DBB (100 %)
SCARED BB- 50%	BBbA (93 %)	BBB (93 %)	BB (96 %)	bdD (100 %)	bd (100 %)	dbc (80 %)	bdB (100 %)	BBA (100 %)	BBad (96 %)	BBd (100 %)

mcs-e450 std batali



Regularity 49%	ME -C 75%	WE -A 29%	MIP -D 81%	YOU -B 48%	YALL -B 51%	YUP -C 33%	YUMI -B 57%	ONE -C 74%	THEY -D 71%	ALL -A 42%
HAPPY DC- 29%	DCC (100 %)	DC (100 %)	DCD (96 %)	bbb (80 %)	bbbd (83 %)	bcbd (96 %)	DCB (100 %)	bdC (46 %)	bdcD (53 %)	bcad (56 %)
SAD DD- 42%	DDC (100 %)	D (90 %)	DD (90 %)	dbB (100 %)	db (100 %)	dbd (90 %)	dba (100 %)	DDdC (56 %)	DDD (56 %)	DDb (96 %)
ANGRY CB- 40%	cca (96 %)	CBc (96 %)	CBD (56 %)	ccB (100 %)	CBB (100 %)	bcbC (100 %)	CB (86 %)	cc (66 %)	ccD (100 %)	CBd (43 %)
TIRED AC- 40%	cadC (96 %)	cad (86 %)	cadD (93 %)	abB (50 %)	ACaB (76 %)	AC (100 %)	cadB (86 %)	ACC (100 %)	ACD (100 %)	ACad (56 %)
EXCITED BC- 40%	caC (100 %)	cab (86 %)	cabD (96 %)	bbc (96 %)	BCba (100 %)	BC (93 %)	cabB (80 %)	BCC (100 %)	BCD (100 %)	BCA (73 %)
SICK CD- 34%	CDC (100 %)	CD (56 %)	CDbD (80 %)	abc (66 %)	abc (33 %)	acb (100 %)	CDbB (76 %)	adc (63 %)	adc (63 %)	acbd (66 %)
HUNGRY AD- 40%	cdd (46 %)	cdd (53 %)	ADaD (66 %)	abdB (76 %)	abd (96 %)	ADb (100 %)	abda (80 %)	ADd (100 %)	AD (100 %)	ADA (66 %)
THIRSTY AA- 58%	cdaC (50 %)	cdA (50 %)	AAD (53 %)	aba (96 %)	AAB (80 %)	AA (66 %)	AAa (56 %)	AAC (100 %)	AAD (46 %)	AA (33 %)
SILLY BD- 31%	daC (100 %)	da (100 %)	daD (100 %)	bbd (46 %)	bbd (43 %)	BDb (96 %)	daB (100 %)	BDd (100 %)	BD (93 %)	BDA (100 %)
SCARED BA- 60%	caaC (50 %)	caA (53 %)	BAda (50 %)	bba (100 %)	BAB (100 %)	BA (86 %)	BAa (56 %)	BAC (100 %)	BAD (50 %)	BAad (53 %)