Abstract

"The meaning of a word is its use in the language". In the first half of the 20th century Ludwig Wittgenstein introduced this idea into philosophy and especially in the last few decades, related disciplines such as psychology and linguistics started embracing the view that that natural language is a dynamic system of arbitrary and culturally learnt conventions. From the end of the nineties on, researchers around Luc Steels transferred this notion of communication to the field of artificial intelligence by letting software agents and later robots play so-called language games in order to self-organize communication systems without requiring prior linguistic or conceptual knowledge. Continuing and advancing that research, the work presented in this thesis investigates lexicon formation in humanoid robots, i.e. the emergence of shared lexical knowledge in populations of robotic agents. Central to this is the concept of referential uncertainty, which is the difficulty of guessing a previously unknown word from the context. First in a simulated environments and later with physical robots, this work starts from very simple lexicon formation models and then systematically analyzes how an increasing complexity in communicative interactions leads to an increasing complexity of representations and learning mechanisms. We evaluate lexicon formation models with respect to their robustness, scaling and their applicability to robotic interaction scenarios and one result of this work is that the predominating approaches in the literature do not scale well and are not able to cope with the challenges stemming from grounding words in the real-world perceptions of physical robots. In order to overcome these limitations, we present an alternative lexicon formation model and evaluate its performance.

Contents

Part I

Introduction

Chapter 1

Investigating the emergence of communication systems

One of the most important findings of cognitive science has been the insight that even supposedly simple mental tasks such as recognizing objects or performing arm movements are actually the result of a complex interplay between a highly interwoven network of cognitive processes, the body, and the physical world and the social environment. And it turned out that the capability to use symbolic language – one of the few features (if not the only) that sets us apart from the animal kingdom – is not an isolated mental skill either but relies on and emerges from large parts of the cognitive apparatus that is available to us. Progress in neuroscience and related areas has given us quite some understanding of the underlying mechanisms of perception, motor control, memory, etc., but theories of "how language works" are just beginning to emerge.

Coming from an artificial intelligence background, we want to explore the question of "how language could work" by designing artificial robotic agents that learn to communicate with each other about things in their environment. This involves finding solutions to a wide variety of challenges: how can we build robots that are able to perceive the world, that construct persistent mental representations of what they experience, that interact socially with each other and – most importantly – that have the capability to communicate? Endowing our agents with a "capability to communicate" does not mean that we will give them a pre-existing language. We will instead investigate how they can self-organize communication systems through local conversations, i.e. how they can agree on a shared language in order to communicate successfully.

The work presented in this thesis will not cover the whole complexity of human language (which would include grammar, morphology, etc.) but we will focus on lexicon formation. That means we will show how agents can learn ~~names for objects in their environment (i.e. words similar to proper names~~

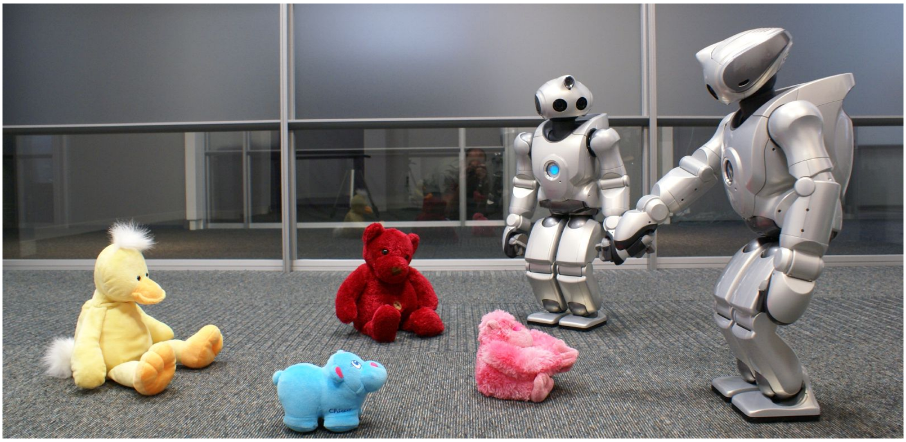

Figure 1.1: Example of a communicative interaction between two agents. The robots perceive objects in their shared environment through their built-in cameras and subsequently engage in a conversation about one of the objects. Over the course of repeated such interactions, populations of agents are able to coordinate their conceptual repertoires for recognizing and classifying objects as well as a shared language for communicating about them.

such as "John", adjectives such as "green" and nouns such as "block") from each other. We will start from very simple models and then demonstrate how the increased complexity of communicative challenges and agent architectures leads to more complex word learning models. In series of controlled experiments we will evaluate the performance of these models as well as the influence of internal and external factors – both in simulated environments where agents have idealized abstract perceptions of the world and with actual physical robots, which will allow us to analyse the impact of embodiment on the dynamics of the interactions.

Let us give an example of how such an experiment could look like. Figure 1.1 shows two robotic agents that are placed in an office environment with a set of toy objects in front of them. The robot at the right will take the role of the speaker and the other the role of a hearer. The communicative goal of the speaker will be to draw the attention of the hearer to one of the objects (e.g. the pink monkey). For this, he will first have to classify the visual experience of the object with respect to how similar it is to mental representations of previously experienced objects (i.e. he has to recognize the pink monkey as a `monkey`, as something `pink`, as `the closest object`, etc.) – or, in case he has never before seen a similar looking object, construct such a representation. Then, the speaker will use words from his own private linguistic inventory that he associates with the recognized concepts and that he thinks of will serve his communicative goal best (and again invent words when he does not know how to express the concepts). The hearer will then try to interpret the utterance using his own sensory experience of the scene and his own private conceptual and linguistic repertoires. The hearer infers the communicative goal of the speaker by finding the object that fits best the concepts associated to the words heard. It can of course happen that both agents connect different meanings to the words of the utterance. To avoid potential misunderstandings, the hearer points to the object that he understood and the speaker will either signal a confirmation (if the object pointed at was indeed the one he intended) or otherwise point to the correct object. It might furthermore happen that the hearer does not know one of the words at all or is otherwise not able to infer the topic of the conversation – also in this case the speaker will point to the object he had in mind, allowing the hearer to learn the meaning of the word.

For taking part in such interactions, the robots certainly need to be endowed with a powerful set of mental capabilities and we will analyze what these have to be. Building robotic systems that are able to self-organize linguistic communication systems from scratch is a very exciting – and also extraordinarily difficult – engineering challenge. It involves dealing with high levels of complexity in the interaction of the different cognitive processes and we will explore how (by going from simple models to more advanced ones) the complexity of different dynamics can be handled and explained. In addition to that, we will take inspiration from psychologists and linguists such as Bloom (2000); Bowerman & Levinson (2001); Tomasello (1999, 2003, 2008) who discuss human intelligence and language as a result of capabilities for engaging in social activities, for constructing mental representations about the world and other general learning mechanisms. We will demonstrate how their theories about language and cognition can be operationalized in computational models and additionally use these models to verify hypotheses coming out of these research fields. In this chapter we will lay out the theoretical foundations for this work. Chapter 2 will introduce the methods and tools that were used for our experiments and then Chapter 3 will sum up this introduction by giving an overview of the work.

This thesis' investigations are a truly multidisciplinary endeavour: we will borrow ideas from artificial intelligence, robotics, psychology, linguistics and philosophy and – although our contribution is clearly rooted in artificial intelligence – we also want to be relevant to all of these disciplines. Before we begin, let us set the stage by outlining the theoretical and methodological basis for our experiments as well as embed the work in the literature (those readers who are familiar with the research field of artificial language evolution can safely skip this part and continue with Chapter 2).

1.1 Basic assumptions

The question of what language is, how it is learnt, how it changes, which cognitive mechanisms are involved, etc. (in short: how it works) is far from being settled – in fact, the study of language is probably the field within the cognitive sciences with the biggest variety of competing theories. Many ideas that were considered to be state of the art in the recent past are nowadays seen as outdated by younger scholars but still receive attention and support by major parts of the scientific community. Due to this absence of a common theoretical basis, it is very likely that the particular view on language taken in thesis is not shared by many linguists, psychologists and philosophers. However, defending this view against competing theories would be beyond the scope of this thesis. Instead, we explicitly enumerate our basic assumptions and then go on from there – we'll leave the discussion of these premises to the referenced literature.

Additionally, we will discuss the empirical methods chosen for our experiments. Trying to answer questions about language and cognition by building and running computational models is a rather new approach and scientific standards still have to be agreed upon. Over their long history, related disciplines have established a set of principles and rules of what can be considered a valid contribution to their fields: insights are either gained by conducting carefully controlled experiments with human subjects (with the methods for experiment design and data interpretation well defined) or by systematically analyzing human languages. With the subjects of the investigations here being computer programs embodied in robots and emerging artificial communication systems, the methods of psychology and linguistics can't be applied and the question is how results of our research can be a contribution to the understanding of human language. Furthermore, even within the modeling community there is only little consensus of how to do experiments and how to reach progress (and there are many examples with poor scientific quality). It is thus understandable that many psychologists and linguistics hesitate to accept results from modeling work. But since we want to use computational modeling for understanding how language works and furthermore want the work to be relevant to people outside of artificial intelligence, a thorough and consistent methodology needs to be followed.

1.1.1 Communication and language acquisition as a social act

Communication is commonly understood (by computer scientists, but also many others) as a process in which a sender sends information to a receiver. Information is encoded into a message and transmitted over a medium to the receiver, which then decodes the message again. When for example a speaker says "the dog is hungry" the information that the dog is hungry (e.g. $\texttt{dog(x)} \wedge \texttt{hungry(x)}$) is encoded into an English sentence. The hearer is able to decode the sentence because he speaks the same language, i.e. he uses the same rules to produce and interpret utterances.

However, uttering a sentence such as above is something else than sole transmission of information. According to Tomasello (1999), it is part of a co-operative activity that both speaker and hearer are involved in: built on a *common ground* (the interlocutors' mutual understanding of each others knowledge and goals, Clark & Brennan, 1991), speaking is an action in which the speaker attempts to affect the mental states of the hearer – usually by drawing the attention of the listener to something in the world (e.g. an object, an event, a property of an object etc.). Uttering the sentence "the dog is hungry" is an action that could have several communicative goals (depending on their shared environment and previous discourse): the speaker could want his child to feed the dog, he could want a stranger to leave his property, or warn a friend of a potentially dangerous animal. The speaker does not say all this – he implicitly assumes that the hearer will infer the communicative intention and perform the desired action.

Where does then the human capacity for performing communicative acts and interpreting them come from and how do children learn the language of their parents? In the *nativist view* (Chomsky, 1957; Hauser, Chomsky & Fitch, 2002; Pinker & Bloom, 1990), language development is seen as the result of genetically predefined abilities that are independent from the development of other skills. All humans are born with an innate "language organ" (the *language acquisition device*) and learning the language of a particular culture means adapting parameters of an "universal grammar". Although the nativist view occupied generations of linguists and although it is probably still one of the most widespread theories around, we find its assumptions so fallacious and unnatural that we will not discuss it here – for a review of arguments against nativism refer e.g. to Tomasello (2005) and to the majority of the other theoretical literature listed in our references (e.g. Steels, 2003a).

Piaget (1952) saw the non-social interaction with the environment as the main source of language development: because parents usually make sure that a rabbit is in the field of view of a child when they say the word "rabbit", children can passively learn the associations between words and their meanings in a similar way as they learn other facts about the external world. In this tradition, the *constraints* approach (e.g. Gleitman, 1990; Markman, 1992) proposes (possibly innate) learning mechanisms (i.e. constraints) that enable the child to *map* what it hears to what it sees. But "learning a word is a social act. When children learn that rabbits eat carrots, they are learning something about the external world, but when they learn that *rabbit* refers to rabbits, they are learning an arbitrary convention shared by a community of speakers, an implicitly agreed-upon way of communicating" (Bloom, 2000, p. 55).

We will hence adopt the *social-pragmatic view* in this thesis: "In the social-pragmatic view, young children are not engaged in a reflective cognitive task in which they are attempting to make correct mappings of word to world based on adult input, but rather they are engaged in social interactions in which they are attempting to understand and interpret adult communicative intentions – so as to make sense of the current situation" (Tomasello, 2001, p. 135). The major cognitive skill involved in language learning is thus not a set of learning constraints but "their understanding that other persons have intentions towards their intentional states" (Tomasello, 2001, p. 135). So when a child hears the word "rabbit", it learns the meaning of this word not because she sees a rabbit, but because she can interpret the communicative intentions of the adult. In addition to the ability to engage in communicative interactions, to establish shared attention and to culturally learn from such interactions, language learning requires an "...unique motivation to share psychological states with others and unique forms of cognitive representation for doing so" (Tomasello, Carpenter, Call, Behne & Moll, 2005, p. 675) – humans are thus intrinsically motivated to engage in collaborative interactions and to cooperate.

Consequently, language learning does not rely on a specific *language acquisition device*, but on skills that evolved and developed for other purposes: the ability to infer the intentions of others, the ability to acquire concepts, and certain general learning and memory capabilities.

1.1.2 Language as a complex adaptive system

A language is not a self-contained body of fixed rules that are internalized by everybody who speaks the language (as it is the case in many engineered communication systems in computer science), but it is a set of conventions shared by a community of language users. What words mean and how they are to be combined into proper sentences according to the grammar of a language is not dictated by authorities or institutions such as for example dictionary publishers. Instead, each single convention is established and adapted through ongoing linguistic behavior (conversations). New words, phrases and grammatical constructions continuously enter a language, word meanings can change over time and expressions can even disappear from a language (see e.g. Croft, 2000; Deutscher, 2005). Language learning and language change happens in local dialogues between speakers of the language in order to adapt to changing communicative needs (e.g. when new artifacts or knowledge enter a culture), as a result of contact with other language communities or to improve expressiveness in general.

This has lead researchers to conceptualize language as a *complex adaptive system* (Steels, 2000) and investigate it by means of analytical models and computer simulations. The global phenomenon of a coherent and shared language is understood in terms of the local interactions between language users – in a similar way that the properties of a gas can be analyzed as the result of the physical interaction of molecules, the functioning of a cell as the interplay between complex enzyme networks, or market dynamics based on models of single economic actors (see for example Castellano, Fortunato & Loreto, 2009, for a review of how methods from statistical physics have been applied to a big variety of social dynamics).

The basic idea is that shared linguistic communication systems *emerge* through processes of *self-organization*. Words and grammatical constructions are mutually *adopted* by agents and consequently *propagate* in the population. No agent has a complete view over the language but each agent maintains its own set of inventories, shaped only through local interactions with other agents (no agent can directly control the linguistic behavior of the whole population). A language community is an open system, i.e. new agents can enter at any time and new communicative challenges may arise. When existing inventories are not not adequate, agents adapt or extend them (e.g. by inventing words or by adopting existing linguistic items for other uses). Furthermore, there are

are selectionist *feedback* relationships between the use of linguistic entities and their success so far in communication – words that are consistently used to successfully reach communicative goals are more likely to spread in the population, leading to self-organized *coherence*. Oudeyer & Kaplan (2007) thus also conceptualized language evolution as a *Darwinian process*. Finally, language spontaneously becomes more complex, driven by the need to optimize communicative success and handle an agent's constraints of the physical and cognitive apparatus.

Steels (2006b) introduced the term *semiotic dynamics* for the approach of understanding language as a function of the local behavior of agents: "I argue that it's the study of semiotic dynamics: the processes whereby groups of people or artificial agents collectively invent and negotiate shared semiotic systems, which they use for communication or information organization" (p. 32). The emergence of language is investigated by making precise computational models of how agents communicate and learn from each other and by identifying the internal and external factors involved in the self-organization of communication systems.

1.1.3 Computational models as a tool for studying language evolution

Building operational models of (robotic) agents that are able to self-organize a language (which is the main goal of the work presented here) is in itself a very interesting and nontrivial challenge. Finding well-working solutions to this problem is definitely a contribution to robotics and artificial intelligence because it shows that and how such systems can be engineered. Furthermore, searching for the structures and algorithms that are needed for the successful emergence of particular communication systems in specific environments can lead to new intuitions and insights about cognition and language – an approach that can be seen as "understanding by doing" and that is advocated in robotics by e.g. Pfeifer & Bongard (2006).

Beyond that, linguistic, psychological or philosophical theories of how certain cognitive processes can be explained and integrated using computational modeling. Understanding a cognitive system in terms of a running computer simulation forces a researcher to make the assumptions of the underlying theory explicit enough so that it can be expressed fully in a formal programming language. Successfully running the simulation can be seen as an existence proof that the assumed mechanisms in principle yield similar results compared to phenomena observed in human language. Additionally, computational models serve as illustrations of theories because they clearly depict how certain proposed mechanisms can function together.

The method of building artificial systems in order to understand nature feels very natural for researchers in artificial intelligence and robotics (since building systems is what they anyway do). However, psychologists and linguists (who submit themselves to rigorous scientific procedures based on controlled experiments with human subjects) are often reluctant to accept such work as contributions to their fields due to difficulties in judging the results: First, it is often not clear why one particular computational model and not another one should be the correct explanation of a real-world phenomenon. Second, operationalizing hypothesized cognitive mechanisms into structures and algorithms requires simplifications and the question is how the results from such simplified models can be generalized to human language and cognition. Third, computer modeling experiments are often not described in enough detail so that they could be understood and repeated by other researchers.

Acknowledging the need for more careful experimentation standards in order to be relevant for researchers outside of computer science, scholars such as Cangelosi & Parisi (2002a); Schlesinger & Parisi (2001); Steels (2006a) started defining sets of criteria for how to do computer simulations in the field of artificial language evolution in a scientific way. These efforts are still in the beginning but it seems that the modeling community started paying more attention to the concerns mentioned above in the recent years. Two types of questions are usually asked in language evolution related computer modeling work: First, how can we explain the emergence of a complex natural language like communication system? And second, which out of two (or more) competing linguistic theories receive the most support from a computer simulation?

The first kind of experiments searches for the cognitive mechanisms and external factors that are required for the successful development of a particular communication system or for another phenomenon observed in human language. A particular computational model is implemented and two falsifiable predictions can be made: (i) The model is able to reproduce the expected behavior. (ii) The model is the simplest one (with the minimal set of assumed cognitive mechanisms) that is able to show the expected behavior. Steels (2006a, p.324) proposed four steps involved in setting up computer simulations: "(1) The researcher hypothesises that a certain set of cognitive mechanisms and external factors are necessary to see the emergence of a specific feature of language. (2) The mechanisms are operationalized in terms of computational processes, and (simulated) 'agents' are endowed with these processes, (3) A scenario of agent interaction is designed, possibly embedded in some simulation of the world. The scenario and the virtual world capture critical properties of the external factors as they pose specific communicative challenges. (4) Systematic computer simulations are performed, demonstrating that the feature of interest indeed emerges when agents endowed with these mechanisms start to interact with each other." Additionally, it is usually shown that particular mechanisms or factors are crucial for the desired behavior to emerge by comparing simulations that include them with simulations that don't. Solutions that work well are compared to those that work less well, allowing to understand the role of a particular factor in the investigated phenomenon.

Most work in the computer modeling field is concerned with such "how?" and "why?" types of questions. New experiments often increase the complexity of the communicative task or of the evolved communication systems and thus extend our body of expertise in engineering agent simulations and add a further building block to our understanding of artificial language evolution. However, as discussed above, researchers outside the field have difficulties accepting such results, even when obtained through very careful experimentation. But some experiments get a wider recognition in the other areas of cognitive science – instead of asking “how?” questions, competing theories set up by philosophers, linguists or psychologists are compared with respect to their performance in a particular communicative tasks in a particular environment. The basic assumptions of each theory are implemented in separate computational models and then measures are defined to compare the outcome of the different simulations. The model that runs with the highest communicative success, the least cognitive effort, etc. will receive the most support – given that the assumptions of the theories are properly represented in their respective computational models. Well-known examples for such kinds of studies were presented by Hurford (1989) and Steels & Belpaeme (2005).

In this thesis, we will follow both approaches. For the same interaction protocol and within the same simulated and physical environments we will implement and test different agent architectures (different cognitive structures and mechanisms, different modes of information processing, different invention and learning procedures, etc.). In each of these experiments, the assumptions and scaffolds will be made very explicit and we will show the consequences (by defining a set of measures that will allow us to compare these different solutions) of adding complexity to the agents and consequently to their evolved communication systems.

1.2 Simulating the self-organization of language

A large body of research on the emergence and evolution of artificial communication systems developed over the past 15 years. There are now numerous collections of papers (e.g. Briscoe, 2002; Cangelosi & Parisi, 2002b; Cangelosi et al., 2006; D.M. Smith et al., 2008; Hurford et al., 1998; Steels, 2012b) and several attempts of reviewing the research in the field (e.g. Christiansen & Kirby, 2003; Kirby, 2002; Steels, 1997b, 1998c, 2000, 2001, 2003a,b, 2006b). We particularly mention the efforts of Steels (2005a) who mapped out different communication systems according their complexity toward grammar and of Wagner et al. (2003) who provide an extensive classification of computational modeling approaches according to whether agents are situated/ non-situated and whether the evolved languages are structured/ unstructured. Since we are here interested in the cognitive mechanisms that are involved in language, we will survey some of the existing literature (without at all trying to be exhaustive) with respect to how they model capacities for communication.

1.2.1 Biologically inspired communication systems

A significant share of scholars in the field of artificial language evolution had their roots in *artificial life*: criticizing classical artificial intelligence for the failure of its *knowledge-oriented* approach to deliver what it had promised, the focus was put on *behavior-oriented* AI, emphasizing the need for autonomous, adaptive and self-sustaining systems that self-organize their behavior in the sensori-motor interaction with the environment (Brooks, 1990, 1991; Pfeifer & Scheier, 1999; Steels, 1994; Steels & Brooks, 1994).

Rooted in the paradigm of behavior based robotics, many researchers have investigated the emergence of *signaling systems* both in populations of physical and simulated robots. The focus in this field is on how agents can learn to exchange signals as distinct responses to situations in their environment – in a similar way as for example animals emit alarm calls in the presence of predators (e.g. Seyfarth et al., 1980). And agents are not directly given a communicative task but a general co-operative problem (e.g. food foraging or navigation) and communication may arise in order to become better at solving the task (see Nolfi, 2005 for a review of this approach).

The behavior of the agents is usually determined by the structure and connection weights of artificial neural networks that are connected to the sensors and actuators of physical or simulated robots. The main force that drives development is artificial genetic evolution, i.e. the structure (and sometimes the weights) of the agents' neural networks are represented by genes and selection based on an external fitness criterion leads to the improvement of behavior from generation to generation (see e.g. chapter 9 of Mitchell, 1997 for an introduction to genetic algorithms). The underlying assumption in such kind of experiments is always that the successful use of communication has a positive influence on the reproductive success of the agents, i.e. the environment and the task have to be designed in such a way that communication is beneficial.

For example Werner & Dyer (1992) presented a model in which simulated agents have to solve a mate finding task. Evolutionary pressure to communicate is put on the agents by giving them only limited individual knowledge about their environment and thus they benefit from sharing it. Similarly, Cangelosi & Parisi (1998) had agents interact in a simulated grid world with both poisonous and edible mushrooms and they learn to signal the presence of the different kinds of mushrooms because avoiding poisonous food increases their fitness. More recently, Marocco & Nolfi (2007) gave simulated robots a collective navigation problem and (without initially communicating) the agents evolved to rely on different communication modalities to improve their performance in the task.

However, it still needs to be shown how the approach of evolutionary robotics can be scaled up to more complex and human language-like communication systems. Although these models have shown how basic signaling behaviors can arise out of the need to solve more general problems, the restriction to neural network representations has limited the behavior of the agents to be very simple and the need for large numbers of trials for the genetic algorithms usually prohibits the use of real physical robots.

1.2.2 Cognitive models and linguistic communication systems

Recognizing that "...pushing the behaviour-based paradigm in the direction of higher cognition has been more difficult" (Steels, 2003c, p. 2381), there was soon again a return from that approach back to more classical methods of artificial intelligence. Without giving up the principles of adaptation, self-organization and situatedness, emphasis was put on how agents can construct mental representations and on the cognitive mechanisms that are needed for that. So instead of investigating the (linguistic) behavior of agents as the result of a monolithic (neural) control structure, the interplay of powerful cognitive processes and structures for perception, memory, learning, problem solving and social interaction is analyzed.

For example in the so-called *Naming Game* (Steels, 1995; Steels & McIntyre, 1998) it is shown which cognitive mechanisms are needed for the emergence of a repertoire of names for pre-given atomic meanings (e.g. individual objects) in a population of simulated agents. And the *Talking Heads* experiment (Steels, 1998a, see also Steels & Kaplan, 1999a,b, 2002) demonstrates what the required ingredients are so that categorical distinctions such as red/green or big/small can be constructed by agents embodied in robotic pan-tilt cameras and how these categories can become shared in the population through language. More recently, Loetzsch, van Trijp & Steels (2008a); Steels & Loetzsch (2009) showed with the *Perspective Reversal Experiment* that an additional cognitive capability (i.e. to be able to imagine a scene from the perspective of the interlocutor) is required for agents embodied in freely roaming Sony Aibo robots to successfully bootstrap a communication system about ball movement events.

The experiments above don't involve grammar, i.e. their linguistic repertoires are only lexical. It could be envisioned how to implement them without the need to explicitly model cognitive representations and processes (for example in a pure connectionist fashion). But when it comes to the self-organization of grammar, this is hardly imaginable. De Beule & Steels (2005); Steels (2012a); Steels & De Beule (2006); Steels et al. (2005) presented with *Fluid Construction Grammar* a formalism for the representation of grammatical knowledge, mechanisms for the use of that knowledge in production and interpretation as well as learning operators for acquiring and adapting grammatical constructions. Based on that formalism, De Beule (2008) demonstrated how compositionality, hierarchy, and recursion can emerge in a population of (simulated) agents and Steels (2005b) as well as Steels & Wellens (2006) showed that grammar can emerge in order to reduce the computational complexity of semantic interpretation. The probably most impressive experiment involving Fluid Construction Grammar so far is the *Case Marking* experiment (Steels, 2002b; van Trijp, 2008): agents embodied in pan-tilt cameras observe dynamical real-world scenes consisting of multiple objects and puppets to each other. When describing these scenes to each other (e.g. with sentences similar to "Jill slides blocks to Jack"), the challenge is to grammatically mark the roles of the several objects in the event.

Chapter 2

Building blocks of situated communicative interactions

Let us now introduce some of the building blocks that form the basis of all experiments in this thesis. We will start with a detailed characterization of the communicative interactions between agents and how the agents can learn from them. Then we will discuss different ways of representing linguistic knowledge, i.e. how word forms can be connected to meanings and what impact the structure of this association has on the complexity of the learning task. And finally, we give an overview how word meanings can be grounded in robots, i.e. how persisting conceptual representations can be constructed by robotic agents and how they co-evolve with language. For all of these mechanisms and representational structures we will motivate their underlying design choices from various perspectives. But we will not give formal definitions yet and leave that to the description of the actual experiments later in this thesis.

2.1 Language games: the social context

Following the assumption that communication is a social act in which a speaker uses language to affect the mental states of a hearer (see Section 1.1.1 above) and that a shared language is constructed and shaped in repeated conversations (Section 1.1.2), we will design all of our experiments around one particular such type of interaction, called a *language game*. This term is commonly associated to Wittgenstein (1967), who made an analogy between the use of language in dialogue and playing a game (e.g. a ball-game; in both cases there are sets of context-dependent rules for each interaction step), and it is Steels (1995, 2001) who is recognized for adopting Wittgenstein's concept of language games to the modeling of communicative interactions between artificial agents.

2.1.1 Distributed co-ordination in language games

Language games are played by populations of autonomous *agents* that are modeled as software programs (utilizing standard agent-based techniques of artificial intelligence, see e.g. Russel & Norvig, 1995; Wooldridge & Jennings, 1995). Each agent maintains its own set of initially empty *inventories* (e.g. ontologies, lexicons, etc.) for memorizing acquired knowledge. The agents have built-in mechanisms for using these inventories to produce and interpret language in a rather automatic way, *diagnostics* and *repair strategies* for detecting and overcoming problems in their internal information processing and *alignment mechanisms* to adapt their inventories in order to perform better in future interactions. The agents make their own decisions solely based on internal goals and states, their perception of the environment and their interaction with others – i.e. there is no central control, agents can't directly effect mental states of others nor have they access to others' mental states (there is no telepathy) and no agent has an overview over the whole population.

The agents are situated in a *world* to which they are connected via sensors and actuators. The external goal that is given to the agents is to communicate about things in the world. Thus, the environment creates a *communicative task* for the agents and part of designing an experiment is defining what things in the world will be presented to the agents. The world is usually not static, i.e. the configuration of the scenes presented to the agents may continuously change. As mentioned before, we will investigate models of lexicon formation both in simulated worlds and with physical robots in real environments. For our simulated environments will not try to set up virtual worlds in which simulated robots interact in but we completely scaffold all problems of perception and categorization by generating pre-conceptualized scene descriptions that are directly perceived by the agents. An example scene consisting of two objects created by such a world generator could look like this:

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green(obj-1), small(obj-1), square(obj-1), red(obj-2), small(obj-2), circle(obj
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In contrast, in our experiments with physical environments, real robots perceive actual objects through their cameras (see Chapter 7).

A language game follows a strict script. That is, the agents conform to routinized dialogue patterns that consist of distinct actions applicable only to specific contexts and which constrain how to interpret utterances. An example of such a routinized dialogue is the procedure for running into a person that one knows: (in western English-speaking cultures) it starts with a greeting phrase ("hi", "hello", etc.), usually accompanied by eye contact and optionally complemented by a hand shake or other greeting gestures. Then the chances are very high that one of the interlocutors will take initiative and say "How are you?", a question which the other person is not supposed to answer honestly but to reply with "fine", "great", etc., optionally followed by ", and you?" (which doesn't need be replied). Only after these compulsory steps the two persons can start to have a real conversation. And it is not OK to end the dialogue by just going away, it has to be announced (e.g. "Well, I have to leave.") and concluded by a final phrase such as "see you later", "goodbye", etc.

Another example is the routine for buying a train ticket at a counter. After an optional greeting, the customer will utter his request. Because the ticket seller already knows that the customer will most likely want to buy a ticket, it is enough to say for example: "One ticket to London for tomorrow morning please" (the "please" does not add any information but is compulsory). The seller will then issue the ticket, if necessary asking for more details. When the ticket gets printed, the seller will say a price (e.g. "seventeen pounds"), which functions (since the customer could also read the price from the electronic display in front of him) as a request to hand over the money. The interaction ends with both involved persons thanking each other and optional greetings.

The type of game that we are going to use for our experiments is not not embedded in complex activities such as meeting another person on the street or buying a train ticket. The underlying purpose of the dialogue lies solely in the communication itself and in providing rich opportunities for learning and alignment. The game is thus a rather idealized interaction scenario with only one goal: drawing attention to an object in the external environment. But it doesn't lack realism: we will discuss below that children indeed learn many words from such interactions and it is also very close to one of the games discussed by Wittgenstein (1967), in which parents teach children words by pointing at an object and uttering a name for it. A situation in which somebody points at a thing (e.g. a cow) and tells its name (e.g. "cow") with the purpose of teaching the word to a child can be conceptualized as a game because in order for the child to successfully learn the name for the object it has know how the game works, i.e. that the parent is telling something about the thing that he is pointing at (it could be also that pointing at a cow and uttering "cow" is an action that the parent performs in order to make the cow go away or to get milk from it, but that's not the case – the game is about learning words and the child has to know this in order to make sense of the action).

Figure 2.1 shows a schematic view of the language game that our agents are going to play (we will discuss each of mechanisms mentioned below in much more detail in the description of the actual experiments – here we only will outline the general dialogue script that is shared by all experiments throughout this thesis). Two agents are randomly drawn from the population and together establish a *joint attentional scene* (Tomasello, 1995) – a situation in which both agents attend to the same set of objects in the environment and in which both agents know that the respective other agent is attending to the same set of objects. Once such a state is reached, the game starts. One of the agents is randomly assigned to take the role of the speaker and the other the role of the hearer. Both agents perceive then a *sensory context* from the joint attentional scene and keep it in their short-term memory (visual perception and joint attention with real robots is enormously difficult and we will dedicate the whole Chapter 7 to that; in our experiments involving simulated environments

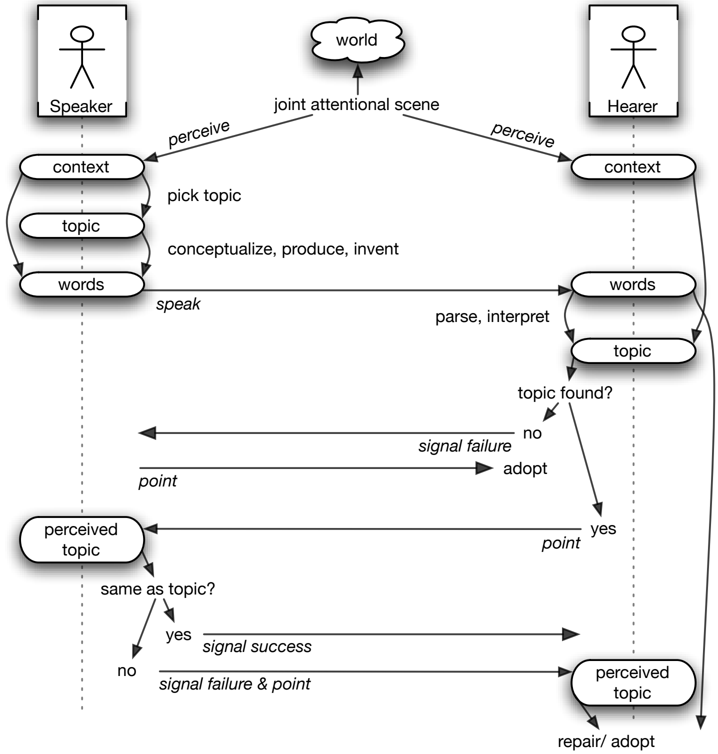


Figure 2.1: Flow of one language game. A speaker and a hearer follow a routinized script. The speaker tries to draw the attention of the hearer to a physical object in their shared environment. Both agents are able to monitor whether they reached communicative success and thus learn from the interaction by pointing to the topic of the conversation and giving non-linguistic feedback. Populations of agents gradually reach consensus about the meanings of words by taking turns being speaker and hearer over thousands of such games.

all these issues will be scaffolded and both agents will perceive the same scene description that is generated by the world generator mentioned above).

Next, the speaker randomly picks one object from his context to be the *topic* of the interaction – his communicative goal will be to draw the attention of the hearer to that object. For this he constructs an utterance, which involves first coming up with a mental representation of the meanings to express (*conceptualization*) and then finding words that cover these meanings. When the speaker does not have the necessary categories or words in his inventories, he *invents* them. Additionally, the speaker uses himself as a model of the hearer and by listening to himself (*re-entrance*), he checks whether the words he came up with are clear and precise enough to be understood (given his own inventories). Once the speaker is satisfied with the constructed utterance, he speaks out the words to the hearer. The hearer then *parses* the utterance and tries to find the object from his own perception of the scene that he believes to be most probable given his interpreted meanings. He will point then to that object and the speaker will either confirm that this was indeed the object he intended to talk about (and signal *communicative success*) or he will point to his chosen topic (and thus signal *communicative failure*). It could also happen that the hearer is confronted with a novel word or that his interpretation doesn't match any of the objects in his context. In this case, the hearer signals a communicative failure and the speaker then also points to the object he intended. In both cases, the hearer is able to learn from the interaction by *adopting* the words heard and associating them with the topic pointed at by the speaker (and, if necessary, also inventing categories that are needed to conceptualize the topic). Finally, at the end of each interaction both agents *adapt* their inventories based on the sensory context, the topic, the words used and the outcome of the game in order to be more successful in future interactions (*alignment*). The population of agents plays *series* of such language games. Each agent starts with initially empty inventories and has never before seen any of the objects in the world. Each agent tries to optimize his own communicative success and cognitive effort and thus coherent mental representations and shared language emerge (solely through processes of invention, adoption and alignment) as a side-effect of the game.

Finally some terminology issues: this type of game has often been called *Guessing Game*, either because the hearer has to guess the topic of the utterance and point to it or because the hearer can not know what aspect of an object the speaker intended with a particular word (referential uncertainty, see below). When the focus is on the kind of languages learnt, our game could be also called *Object Naming Game* because it is about naming objects (in contrast to describing objects and their relations to other objects or their roles in events). We will avoid possible confusions by always using the term "language game" when referring to this particular interaction pattern.

2.1.2 Other social learning scenarios

The language game paradigm has proved to be very successful in demonstrating how groups of artificial agents can establish a shared set of conventions through self-organization processes. However, when it comes to explaining human communication, it has been – rightfully – criticized for two reasons: First, it happens very rarely that humans have to construct a communication system from scratch and the normal case is that children learn the existing language of their parents' culture. And second, the explicit feedback that our agents give each other (including pointing and correnctions) is not necessary for children to learn the meanings of words.

Because our agents start without any prior language, speakers have to invent words whenever their lexicons are not sufficient for their communicative needs. And when multiple speakers independently invent words for the same thing, a large number of competing words are spreading in the population, before eventually one word "wins" and a convention is established (as we will see further below). Although some psychologists have demonstrated that humans are indeed able to bootstrap and align symbolic communication systems in similar ways (e.g. Galantucci, 2005; Healey et al., 2007), it is not the normal situation that children are confronted with in language acquisition – they are born into a culture with an established language and parents also won't adopt inventions made by their children.

An alternative to this *horizontal transmission* of language is the *iterated learning model* (Kirby, 2001; Smith, Kirby & Brighton, 2003; see also Steels, 2002a for a comparison with the language game framework). Instead of focusing on how language propagates within members of the same generation, it investigates *vertical transmission* from one generation to the next. Following an inductive machine learning approach, training sets consisting of meaning-form pairs created from a parent are used to train the inventories of a child, which then becomes the parent for the next generation. The language of the first generation is usually initialized randomly.

However, the purely inductive nature of iterated learning leaves out crucial aspects of communication such as joint attention, shared context and communicative goals. Furthermore, languages also change within generations and these changes can't be explained with effects of vertical transmission because they rely on processes of coordination and alignment.

The agents in our language game experiments always give each other non-linguistic corrective feedback, i.e. the speaker either confirms that the topic pointed at by the hearer was the intended one or he points to the right topic. But children don't necessarily need such social scaffolds in order to learn the language of their parents – they are smart enough to make sense of the communicative intentions of speakers, even when just overhearing conversations of others. Lieven (1994) extensively reviews cross-cultural differences in the social interactions from that children learn language and the conclusion is that parents in some cultures give extensive feedback, others almost not: "children are clearly not having to learn language from something like a television set; but nor are they being presented with a graded set of syntax lessons" (Lieven, 1994, p. 73).

Some researchers investigated other types of games with less explicit feedback. Best known are *Description Games* in which the speaker describes a scene and the hearer either agrees that it is a good description for the current scene or he disagrees. The disadvantage is that the speaker has no way to verify whether the hearer indeed understood him (the fact that the hearer agreed does not mean that they had a similar understanding of the words used). But description games actually need to be played when the topic of a conversation is not an object (which can be pointed at) but for example an aspect of an event or other relations between objects (which can't be pointed at). The lacking consensus between speaker and hearer on what the topic of the conversation is makes self-organizing a shared language harder and the problem is usually tackled with *cross-situational* learning techniques (discussed further below). Vogt & Coumans (2003) have compared the performance of the language game introduced above with so-called "selfish games", in which there is no feedback at all (so it's like learning language from a television set). Their conclusion is that selfish games are – albeit viable – much more difficult.

Even if children don't need extensive teaching and feedback, it nevertheless helps them. For example Chouinard & Clark (2003) demonstrated that learning improves when parents reformulate erroneous utterances of their children. And Tomasello & Todd (1983) compared lexical learning rates in trials where mothers directed the attention of their children at novel objects with trials where they just followed into what their child was looking at – the results suggest that joint attention supports lexical acquisition. Bloom (2001) puts it this way: "The natural conclusion here is that these naming patterns on the part of adults really are useful, they just aren't necessary. Environments differ in how supportive they are, and word learning is easier when speakers make the effort to clarify their intent and exclude alternative interpretations. But children are good enough at word learning that they can succeed without such support " (p. 1099).

Our agents don't have a 'theory of mind', i.e. hearers have no non-linguistic pragmatic means available to them for figuring out what the speaker intends. And they don't have additional heuristics for determining whether they reached their communicative goal, because they use language only to direct attention (it would be for example easier when the speaker would not try to draw attention to an object but try to request the hearer to bring him the object – if the hearer brings another one then he knows that he said something wrong). The only way for our agents to deal with these limitations is thus is to establish joint attention and to use pointing as a means to check whether the words were used correctly. So our language game is, in a way, designed to overcome our agents' lack of social intelligence by making it easy to verify whether communicative goals were reached. And again Bloom (2001): "Because of this, the best way to teach a child an object name is to make it as clear as possible that you are intending to refer to the referent of that name; and the best way to do this is to point and say the word. In this way, the child can infer that the speaker means to pick out the dog when using this new word, 'dog', and the meaning will be quickly and accurately learned" (p. 1099).

2.1.3 Evaluating the performance of language games

How can we then compare the performance of the different language game experiments that we're going to do, i.e. how do we assess the development of our agents' *communicative competence*? Intuitively, we would say that a person who knows more words than somebody else and who complies better with the rules of for example English is a better speaker of the language. The underlying conception is that a language is some homogeneous public entity, casted into dictionaries and internalized by its speakers. But even a person who learnt the English dictionary by heart and follows all rules of the language can still find himself in a situation where he will not understand what other English speakers say. The person could for example attend a mathematics conference and (although he understands all the words) have no clue what they are talking about. Or he could meet a group of adolescents who use slang words that did not make it into the dictionaries yet.

Despite still ongoing debates about the historical distinction between linguistic *competence* and *performance* (Chomsky, 1965), most linguists and philosophers agree now that mastering a language is not about knowing the words and rules, but about reaching communicative goals: "We forget that there is no such thing as a language apart from the sounds and marks people make, and the habits and expectations that go with them. 'Sharing a language' with someone else consists in understanding what they say, and talking pretty much the same way they do" (Davidson, 2005, p. 131).

Therefore, we will make make *communicative success* our main criterion for performance in language games. That is, the focus is not on the content our agents' inventories, but how they use this knowledge in communication. As detailed before (Section 2.1.1), our language game script allows both the speaker and the hearer to determine whether the communicative goal (drawing attention to an external object) was reached. After each interaction in an experiment's ongoing series of dialogues, we will determine how the agents assessed their success in communication and record it using the following measure:

> *Measure 2.1: Communicative success*
>
> *Measures the fraction of successful games as assessed by the agents. An interaction is a success when the hearer is able to point to the topic intended by the speaker (see Figure 2.1, page 24). After each successful interaction the value of 1 is recorded, for each failure 0. Values are averaged over the last n interactions (n=250 if not stated otherwise).*

Throughout this thesis, we will record such data along repeated series of language tames (together with data of many other measures) to generate graphs such as in Figures 2.2a–2.2c. How to read then these graphs? The recorded values (in this case for the communicative success measure) are plotted over the number of interactions along the x-axis. So in this example the agents reach an average communicative success of about 80% after 1000 interactions, which then later on increases to about 95%.

Three things are important when interpreting such graphs. First, the fact that it takes 1000 interactions to reach 80% success does not mean that each agent played 1000 games up to that point. In the example the population consisted of 10 agents, and with each time two agents participating in an interaction, 1000 interactions means that each agent played 200 games on average, being speaker in about 100 interactions. Second, values are averaged over an average window. The example graphs show the same results for average windows of 1, 100 and 1000. Many authors in the field of artificial language evolution include graphs such as Figure 2.2a in their papers (no averaging). But we believe that the noisy curve in that example does not add any information and makes comparisons with other graphs harder. We will thus use higher averaging windows (usually 250, but sometimes even higher), which produce

Figure 2.2a: Example for the evolution of communicative success over time. Values were recorded for 10 different series of the same experiment, each consisting of 10000 interactions. The size of the average window for recording the values of each series is 1, i.e. values within a series are not averaged.

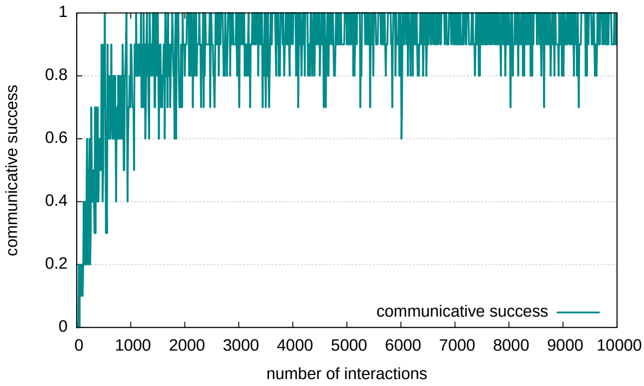


Figure 2.2b: A graph of communicative success in the same experimental run as above, but with values averaged over the last 100 interactions in each series. Error bars are standard deviations across the 10 repeated series of the same experiment.

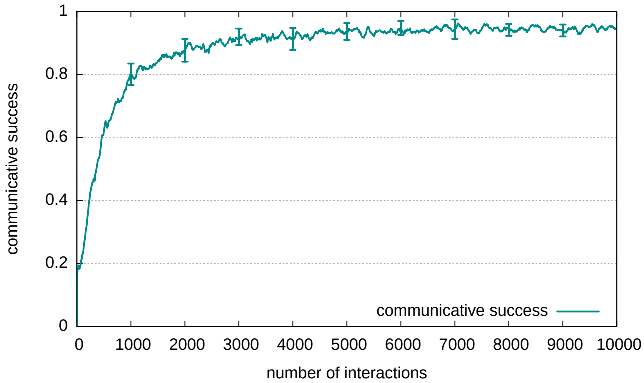
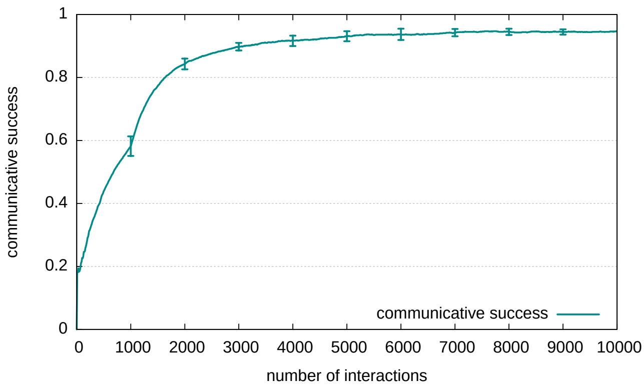


Figure 2.2c: The same as above, but with an average window of 1000. Note that this curve seems to be "delayed" compared to the other two as a result of the bigger averaging window. Another side-effect of averaging is the little "bend" in the curve at around interaction 1000.



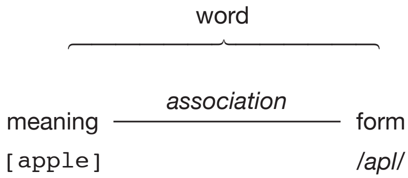


Figure 2.3: A diagram that illustrates our notion of the term "word" as referring to the whole association of a meaning to a form.

cleaner curves. The disadvantage of heavy averaging is, as it is shown in the other two graphs (Figure 2.2b and 2.2c), that the curves are a bit "behind" the non-averaged data (so this has to be kept in mind). And, finally, third, we will always repeat the same experiment 10 times and average the results of each series to rule out effects of randomness (the agents will always talk about different scenes, each time with other randomly chosen partners, leading always to varying dynamics). The error bars in Figures 2.2b and 2.2c still give a hint on how values vary across the different series (they indicate the standard deviation of the values at that interaction number in all 10 series).

Of course communicative success is not the only measure we are interested in (we will introduce others later). Part of self-organizing a language is also that agents improve their cognitive economy. That means that inventory sizes will converge to an optimal number of elements that are needed to cope with the communicative task (making processing faster) and the number of changes in the agent's inventories will decrease. And we will compute measures of *coherence* that indicate how similar the inventories of the population's agents are. But, as we will see, it is possible (and in the case of embodied agents unavoidable) that agents have very different conceptual and linguistic inventories but still communicate successfully. Thus: "What matters, the point of language or speech or whatever you want to call it, is communication, getting across to someone else what you have in mind by means of words that they interpret (understand) as you want them to" (Davidson, 2005, p. 120).

2.2 Words: representing linguistic knowledge

We have introduced the social context in which our communicative interactions are going to take place. Next, we're going to define what it means for our agents to "know a language". Since the focus of our thesis is on lexicon formation (which leaves out many crucial aspects of natural language such as grammar and morphology), our agents' linguistic inventories are single *lexicons*, consisting solely of *words*. Words are couplings between a *meaning* and a *form* (see Figure 2.3) and we will consistently use the term *word* to refer to the whole of this association (and not to the form). What meanings are and where they come from will be the topic of the next Section 2.3. For now we will treat them as sets of unstructured symbols (or *categories*, *attributes*, *features*, *conceptual entities*, whatever you want to call them) such as `object-34`, `category-17`, `red-2` and so on. Forms are random character strings that are created by speakers whenever they invent a new word. Throughout our thesis, these forms will be built from three random consonant/ vowel pairs such as for example in “nuzega” or “firopa”.

2.2.1 Saussurean signs

For the coupling between meaning and form we rely on the concept of the the *Saussurean Sign* (de Saussure, 1967). It is a bi-directional relation between a concept (in the sense of some entity of thought, *signified*) and a form (a sound, a gesture, etc., *signifier*). Bi-directional means that the same representation is used to parse and produce utterances (which is not self-evident – it is easy to imagine non-reciprocal communication systems in which agents use different representations for parsing and producing or in which agents lack the capability to either parse or produce). The connection between the signified and the signifier is arbitrary, i.e. there is nothing in the concept of a donkey that determines the sound “donkey” (in fact, different cultures arbitrarily connect very different forms to similar concepts of donkeyness, e.g. “Esel” in German). It’s important to note that Saussurean Signs don’t link actual sounds waves to physical objects existing in the world but both the signifier and the signified are mental patterns of reoccurring sensory experiences of sounds and objects. Furthermore, and this will be more clear later on, it is not the signs directly that determine what we speak or how we interpret utterances – it is the differences in meaning and form between within a whole system of signs that govern the speech of individuals (*parole* in Saussure’s terms). That is, speakers don’t follow explicit rules (in a classical artificial intelligence rule system sense) such as `"if donkey visible → produce sound ‘donkey’"` – instead, they consider their whole system of signs and their differences in meaning to eventually use the sign that *distinguishes* the donkey from the other objects in the scene.

We’ll assume Saussurean signs to be an appropriate construct for the representation of form-meaning couplings in our work (especially the notion of bi-directionality, arbitrariness and the importance of relative differences to other signs), and we think that this is not a controversial choice. But there is still the question of where this particular nature of words comes from. To investigate this, Hurford (1989) compared different strategies for lexicon formation in computer simulations. Learners either separately imitated the production and speaking behavior of others or used observed speaking behavior both in production and interpretation. The latter strategy clearly had advantages because it makes it easier for the agents to learn. Additionally, Oliphant (1996) carried out similar simulation studies which demonstrated that Saussurean communication is favourable in populations of repeatedly interacting agents (e.g. as in our language games), especially when the populations are spatially organized. These experiments clearly show that the Saussurean nature of words has advantages over other communication systems. But the authors discuss these results under the assumption that Saussurean communication evolved by means of natural selection, a view that is challenged nowadays (see Bloom, 2000, pp. 74–78 for a discussion). As an alternative, the bi-directional use of signs can be seen as a consequence of our theory of mind: “Children’s ability to reproduce intentional communicative actions via some form of cultural or imitative learning involves a role reversal – the child has intentions towards the other person's intentional states – which leads to the creation of linguistic conventions" (Tomasello, 2001, p. 153). So we don't directly imitate the linguistic behavior of others, that is, we don't imitate the production of the sound "donkey" in the presence of a donkey but we imitate the action of saying "donkey" as a method for directing attention to donkeys. "Once a child believes that the adult's use of the word *dog* was used with the intent to refer to a dog, then she could use the same means (saying 'dog') to satisfy this goal" (Bloom, 2000, p. 76).

Finally, how are we going to implement our agents' systems of Saussurean signs in terms of data structures? We'll choose the most simple representation possible: a lexicon is represented as a list of words, each having a meaning, a form and a score reflecting how successful that word was used in past interactions. As we will see later, the lexicon is usually part of a larger *semiotic network*, a complex network (Strogatz, 2001) that connects an agent's sensory experiences to forms and back and whose overall behavior is the result of a coupling of different processes that each have their own dynamics. There are many representations thinkable that are more cognitively plausible than lists of words. For example Kosko (1988) implemented a two-layer neural network that can store paired data associations and Billard & Hayes (1999) developed DRAMA (dynamical recurrent associative memory architecture) specifically for representing words in robots. We prefer our representation over more integrated solutions because it gives us full control over processes of language use and learning. We assume that these structures could be easily transferred into more natural representations (e.g. neural networks).

2.2.2 Increasing complexity in the coupling between form and meaning

Words are couplings between meaning and form. We'll treat forms as simple random strings and what meanings are will be explained in the next section. We will turn now to the nature of this coupling, i.e. how a form is coupled to meaning and how words in a lexicon relate to each other. This structure is part of an agents cognitive infrastructure, especially his mechanisms for production/ interpretation, learning and alignment. And it has direct consequences on the dynamics of the language game experiments, i.e. how quick the agents reach communicative success and coherence. Depending on the "degrees of freedom" in what the agents can associate to a form, in how words with equivalent meanings/forms relate to each other, and in how agents combine different words into utterances, various kinds (and degrees) of *ambiguities* arise in an agent's lexicon. For example in all of these models it happens that different forms for the same meaning spread in the population (because agents independently invent them), causing *synonyms* (the same meaning is associated to multiple forms) to occur in the agent's lexicon. Similarly, different

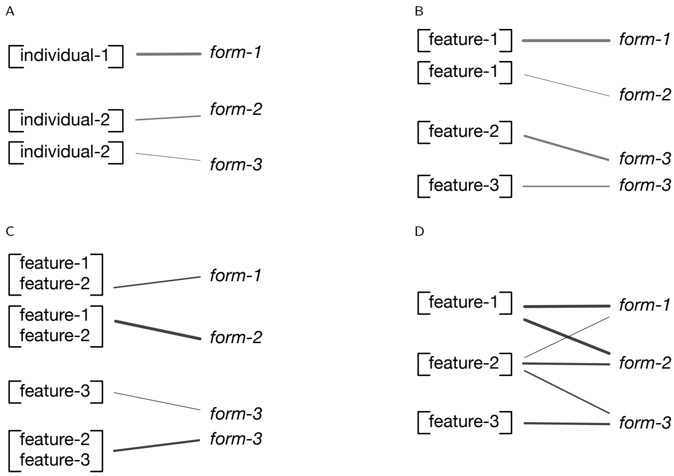


Figure 2.4: Increasing complexity in the nature of the coupling between form and meaning. Hypothetical example lexicons of one agent are shown for four different models of lexicon formation. Line widths denote different connection weights (scores). A: One-to-one mappings between names and individuals in the Naming Game. There can be competing mappings involving the same individual (synonyms). B: One-to-one mappings between words and single categories in Guessing Games. Additionally to synonymy, there can be competing mappings involving the same words (homonymy). c: Many-to-one mappings between sets of categories and words. In addition to synonymy and homonymy, words can be mapped to different competing sets of categories that partially overlap each other. D: Flexible word meaning representations. Competition is not explicitly represented but words have flexible associations to different categories that are shaped through language use.

contexts and other reasons might cause an agent to adopt multiple meanings to the same form (*homonymy*).

What does it mean for an agent to have for example a synonym in his lexicon? Technically, an agent that learnt two different forms f_1 and f_2 for the meaning m_1 will not store them in the same word with connections to both forms, but he maintains two separate representations $w_1 : m_1 \Leftrightarrow f_1$ and $w_2 : m_1 \Leftrightarrow f_2$. Part of the self-organization process in the series of language games is that the whole population eventually agrees on one single form for a particular meaning (and vice versa). In order to reach this goal, each agent individually tries to optimize his own lexicon by preferring the most conventionalized associations and eliminating *competing* synonymous and homonymous words. We will introduce various algorithms that achieve this – all of them rely on scoring each word depending on how successful it is used in communication. When enough agents in the population start preferring a particular form-meaning association, it will prevail over the others, causing each individual agent to remove competing synonyms and homonyms.

Furthermore, other ambiguities arise from the use of *multi-word* utterances (it can become unclear which word covers which meaning), from *specificity* relations (whether a new word refers to the whole object, to it's kind or a general property of it), and others. The degrees of freedom in what to associate to a new form can be interpreted as the *complexity* of a lexicon formation model and we will classify a variety of models according this degree of freedom. For now, Figure 2.4 illustrates the nature of the coupling between meaning and form for four of them.

The simplest of these four models, the *Naming Game* (Steels, 1995; Steels & McIntyre, 1998; Figure 2.4A), is historically also the oldest. The task in this game is to agree on a set of names for established individuals (for example proper names such as "John" and "Mary" for individual persons). Agents jointly perceive sets of uniquely identifiable objects such as for example `object-3`, `object-8`, `object-4`; or (as in Steels, 1995) unambiguously interpretable positions on a spatial grid relative to the speaker (e.g. `front`, `side`, `behind`, `left`, etc). Words are thus one-to-one associations between a representation for an individual and a name. Since both speaker and hearer have the same representations of individuals (the world they perceive consists already of pre-conceptualized symbolic representations for unique objects or locations), the hearer immediately knows which concept to associate to a novel word after the speaker pointed to it. But synonymy can occur because different speakers might invent different names for the same object (for example in Figure 2.4A the words `individual-2`⇔*form-2* and `individual-2`⇔*form-3* are synonymous).

Figure 2.4B illustrates a next class of models. It is commonly referred to as a *Guessing Game* and was first introduced by Steels (1996a). It takes away the scaffold that objects are represented as unique concepts by letting the agents perceive scenes in which objects are sets of pre-conceptualized discrete categories as for example in:

```
object-1: [weight heavy] [size medium] [shape square]
object-2: [weight light] [size small] [shape round]
object-3: [weight heavy] [size tall] [shape square]
```

The speaker then searches for a category that *discriminates* the chosen topic from the other objects in the context (for example `[size medium]` discriminates `object-1` from the rest, `[weight light]` or `[shape round]` discriminate `object-2`, etc.) and then uses a single word to express that meaning (the game stops when no discriminative category can be found). So the words acquired by the agents are comparable to adjectives for basic categories such as "red", "small" or "round". The representation of words is identical to those of Naming Games (a one-to-one mapping between an atomic category and a form), but further difficulties arise because the hearer does not know which sensory quality (or channel) a novel word refers to. Consequently, homonyms may appear in addition to synonyms because a hearer might adopt different interpretations of the same word (for example in the agent in Figure 2.4B interprets the form *form-3* both as `feature-2` and as `feature-3`). Because the words in this game still "name" single categories, such experiments are sometimes called Naming Games as well, reserving the term Guessing Game for the language game script.

Van Looveren (1999, 2000) presented two further innovations: first, *multi-word* utterances were introduced: objects don't need to be discriminated anymore by a single category but combinations of categories can be expressed by different words (e.g. "red" and "small" when some other objects in the context are also red and some others also small, but none of them red and small at the same time). This leads to the additional difficulty that when a hearer is confronted with two novel words at the same time then he does not know which word covers which part of the inferred meaning (such a situation is usually seen as too difficult: hearers only learn when there is only one unknown word so that they can infer its meaning using the know words and the context). Second, meanings of words can be *structured*: instead of expressing a single individual or category, words are many-to-one mappings between forms and sets of discrete categories (see Figure 2.4C). Due to this, another challenge arises for the hearer: he does not know to which subset of the topic's feature he has to associate a new word. As a result, the agents' lexicons do not only contain homonyms but also competing words where the meaning of one is the subset of another (e.g. in Figure 2.4C there are two words with the form *form-3*: one that expresses only `feature-3` and one that covers both `feature-2` and `feature-3`).

In order to scale up the above three lexicon formation models towards more complex meaning spaces and in order to allow for the emergence of more natural communication systems, Wellens & Loetzsch (2012); Wellens, Loetzsch & Steels (2008) proposed another lexicon representation as shown in Figure 2.4D. The main innovation is to tackle ambiguities in what words mean with a *flexible* coupling between meaning and form: whereas agents in the previous models try to figure out the meaning of a word by adopting multiple associations between a form and its alternative meanings (and then use word scoring techniques to rule out all of them except one), here the uncertainty is put in the word representation itself. Instead of having a single score for the whole coupling between a form and a set of categories, each connection to a category is scored separately, which allows the meaning of a word to gradually change towards its conventional use in the population. Figure 2.4D tries to illustrate this: an agent's lexicon is represented as a many-to-many association between categories and forms, with each connection scored separately.

2.3 Meanings: grounded word semantics

In addition to the social context of the communicative interactions and the nature of word representations, the notion of "meaning" is central to the understanding of communication in general and models lexicon formation in particular. In our simulated language game experiments, as discussed before, the world of the agents already provides shared pre-conceptualized meanings consisting of (sets of) symbols such as `object-34`, `category-17` or `red-2`. With the meanings already being "in the world", they are also immediately shared by all agents in the population and the question what meanings are and where

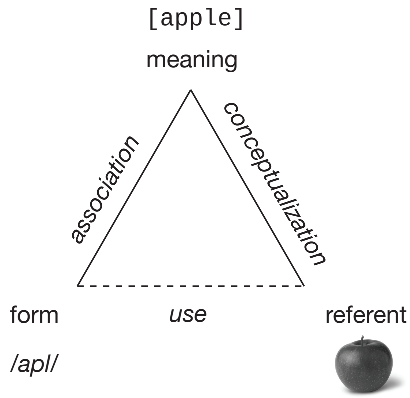


Figure 2.5: Diagram of a semiotic triangle. The relation between a meaning, a form and a referent loosely resemble the definition of a sign by Peirce (1931).

they come from is not posed – the focus is rather on reaching consensus on which meanings to connect to which forms. However, objects in the real world – which is also the world of our robots – do not come with universally shared properties directly accessible to observers. Instead, each agent has to construct "meanings" as his own interpretation of a scene from its sensori-motor interaction with the environment.

2.3.1 From Saussure to Peirce

A widely accepted notion of meaning is that they are not something to be found in the world, but that they are used to *refer* to things in the world: "The traditional view, emerging first in Aristotle, is that the meaning of a word is what determines its reference. ... Hence the meaning of *dog* determines which things are and are not dogs, and knowing the meaning of dog entails knowing what things are dogs and are not dogs" (Bloom, 2000, p. 18).

Adding referents to De Saussure's (1967, see also Section 2.2.1 above) definition of a sign as a relation between a meaning and a form, Peirce (1931) introduced the concept of a sign as a triadic relationship between a form, a meaning and a referent (see Figure 2.5). Peirce originally used the term *representamen* for the *shape* (form) of the sign and *interpretant* for its *sense* or *concept* (meaning). For the referent, which is a physical object in the world but which also can be abstract, Peirce used the term *object*.

The relation between form an meaning is, analogous to the Saussurean sign, an arbitrary conventionalized bi-directional association between a meaning and a form. And although finding the appropriate meaning underlying a form or finding the form that expresses a meaning of course requires some look-up process, these associations can be considered to be "stored" in the lexicon of an agent. In contrast, the relation between meanings and referents is of a different nature. Word meanings are representations that allow to determine to which referents a word applies and to which not. Therefore, finding out whether a specific meaning is applicable to a specific referent in the context is an active process that in each interaction again establishes the relation between a meaning and a referent. We call the process of determining the meanings that are applicable to a referent *conceptualization* and the reverse process of applying the meanings underlying an utterance to a situation in order to determine a referent *interpretation*.

The third relation in Figure 2.5 between forms and referents is even less direct. The meaning representations maintained by each agent are not accessible by other agents – they can only observe forms and referents. Meanings thus constitute an intermediate layer that allows agents to relate the same words to similar referents in the world, i.e. *use* a word in the same way: "For a large class of cases – though not for all – in which we employ the word 'meaning' it can be defined thus: the meaning of a word is its use in the language" (Wittgenstein, 1967, Part I, Section 43). For example, the meaning of "red" is a shared convention how to classify the world into things that are red and things that are not. Moreover, meaning representations are constructed individually by each agent from sensory experiences of specific referents. And because every agent has a different history of interactions with the world and other agents, two agents will never connect exactly the same meaning representation to the same form. Intuitively, every two humans will also have slightly different opinions about which border cases of red objects should be considered red, but they will still use "red" successfully in most of the cases to refer to red object. As we will see later, conceptual coherence, i.e. the similarity between meanings acquired by different agents, is not necessarily a prerequisite for successful communication. It is enough that we all use a word to refer to the same things – further cognitive overlap is not necessary.

Furthermore, conceptualizing a referent or interpreting a meaning never happens in a vacuum. Words can be used differently in different contexts (for example "the red block" can be used to refer to an orange block when all other objects are blue, but not when there is another red block). And more importantly, the interpretation of words depends also on the social context, i.e. the previous discourse and the kind of communicative interaction. As discussed above in Section 2.1.1, the language game played determines how words have to be interpreted to yield a referent. "We must therefore explicitly acknowledge the theoretical point that linguistic reference is a *social* act in which one person attempts to get another person to focus her attention on something in the world" (Tomasello, 1999, p. 97). In our experiments, the type of communicative interaction is fixed (see Figure 2.1, page 24) and the implicit communicative goal underlying each utterance is to draw attention to a single object in the environment of the robots. Consequently, when an agent says for example "red small", then the built-in convention is to interpret these words as "please point to the object that is small and red".

The question of how to represent and process word meanings is very closely related to the *symbol grounding problem* (Harnad, 1990), which his "... , generally speaking, the problem of how to causally connect an artificial agent with its environment such that the agent's behavior, as well as the mechanisms, representations, etc. underlying it, can be intrinsic and meaningful to itself, rather than dependent on an external designer or observer" (Ziemke, 1999, p. 177).

The debate around this problem was started by Searle (1980) with the Chinese room argument as a critique to early paradigms in artificial intelligence that envisioned the possibility of intelligence based solely on the manipulation of idealized *physical symbol systems* (Newell, 1980; Newell & Simon, 1976) and since that has occupied many philosophers and cognitive scientists. However, when adopting the notion of meaning discussed above as a functional relation between forms, internal representations and referents, then "... one may argue that argue that the semiotic symbol is *per definition* grounded, becasue the triadic relation (i.e. the semiotic symbol) already bears symbols meaning with respect to reality" (Vogt, 2002a, p. 434). We will thus not take part in this debate and rather focus on the technical challenge of the acquisition of meanings through the interaction of a physical body with the environment and on processes for conceptualization and semantic interpretation, which together "solve the symbol grounding problem" Steels, 2008; Steels, Loetzsch & Spranger, 2007.

2.3.2 Mental representations for categorization

Peirce's definition of a sign can be discussed without subscribing to any theory of what word meanings are and how they are represented in an agent, a question which has occupied philosophers, logicians, linguists and psychologists for a very long time. We will not delve into the history of this debate but rather stick with contemporary notions of meaning in the cognitive sciences that are based on the concept of *categories*, as advanced by scholars such as Lakoff (1987), Harnad (1987) or Barsalou (1999). A category is a representation that allows to classify objects according to some criterion or "a category exists whenever two or more distinguishable objects or events are treated equivalently" (Mervis & Rosch, 1981, p. 89). We call the long-term memory of categories that are acquired by an agent an *ontology*.

Categories are abstractions from the continuous sensori-motor interaction with the environment that have proved to be useful for an agent, for example in communication: "one purpose of categorization is to reduce the infinite differences among stimuli to behaviorally and cognitively usable proportions. It is to the organism's advantage not to differentiate one stimulus from others when that differentiation is irrelevant for the purposes at hand" (Rosch et al., 1976, page 384). Consequently, well-tuned category systems contribute to the cognitive economy of an agent because they limit the number of sensori-motor patterns that have to memorized and they can be processed independently of the context in which they were created and the objects and the events that they stand for, a phenomenon which Gärdenfors (2005) calls the "detachment of thought". Finally, categories are not only used for language, but also for a big variety of other cognitive activities such as for example planning. Some scholars such as Peirce (1931, p. 2.302) even claim that "we think only in signs".

Early psychological studies by Rosch (1973) have shown that many categories do not have strict borders but that membership to a category is continuous. For example, the category `red` does not unambiguously divide all things in the world into a set of objects that are red and into another set of objects that are not red, but instead provides a graded judgement of *how* red an object is. And at least for 'basic level' categories, Rosch (1973) demonstrated that the gradedness of this classification is a function of the similarity to a *prototype*, which can be understood as a point in a sensori-motor space that defines the center of the category. Such a space is defined by multiple dimensions representing continuous sensory or other qualities and multiple categories defined by points in that space. For example color categories can be represented as points in a two- or threedimensional color space and color categorization of an object then means to find the category that has the closest geometric distance to a stimulus. Along that line, Gärdenfors (2000) introduced the theoretic framework of 'conceptual spaces' for an operationalized geometric account of categorization and provided examples for many domains, such as for example in (Gärdenfors & Williams, 2001).

As mentioned before, we will not to equip our agents with pre-existing engineered sets of categories but endow them with mechanisms for the autonomous creation of truly grounded ontologies. For that, most work on category formation in the field of artificial intelligence has been done (very successfully) using techniques of machine learning (Mitchell, 1997). Such learning methods always require data sets of example stimuli together with their correct classification (usually labelled manually by a human) and then a classifier (for example based on a neural network or a K-nearest neighbor algorithm) is trained so that it eventually can reproduce the classificaton that is implicit in the example set. However, there are three problems with such approaches: First, in open-ended interaction and learning scenarios where the things to expect in the environment are not known in advance, proper training sets may not be easily available at all. Second, once classifiers are trained, they don't adapt and thus the learnt classification may become inappropriate when new types of objects occur in the environment (which is the case for humans and for our robots). And third, the categories learnt with machine learning techniques are still induced by a designer because he used his own (human) category system to create the labelled data sets. For a further discussion of the problems involved in applying machine learning techniques to autonomous category formation, refer to (Steels, 1997a).

We will thus need mechanism that allow our agents to gradually construct and shape their ontologies from the continuous interaction with the environment and other agents, in a similar way to the self-organization of lexicons discussed above. One method for this introduced by Steels (1996b) are *discrimination trees* (we will disscuss them in Chapter 9). He presented simulated agents with generated contexts consisting of objects characterized by real-valued features and in order to be successful in discriminating one object from the other objects in such a generated context, they created categories by further and further sub-dividing the range of feature values into smaller and smaller regions (hence the term discrimination tree). Discrimination trees were then implemented by Steels (1997a); Steels & Vogt (1997) on wheeled LEGO robots to create categories for distances measured with infrared sensors and later by (Steels & Kaplan, 1999a,b, 2002) in the Talking Heads experiment (discussed further below) for visual features such as color, size and position obtained by pan-tilt cameras directed at a whiteboard with objects. Also with LEGO robots, Vogt (2002b, 2003) conducted similar experiments, but instead of discrimination trees, categories were created as prototypes in the sensory space of a bigger range of distance sensors. Finally, the formation of color categories using various prototype-based approaches was studied extensively by Steels & Belpaeme (2005) who presented agents with perceptions of sets of color chips and by Bleys, Loetzsch, Spranger & Steels (2009) who used the same robotic setup with humanoid robots as in this thesis.

2.3.3 Categories and language

Because the agents in our experiments will construct and shape their ontologies exclusively for the purpose of being successful in the given task of communicating about objects in their environment, both the adequateness of each agent's individual category system as well as the coherence between different agents' ontologies directly have an impact on the overall communicative success of the population, which in return means that success in communication is a also a good measure for driving the self-organization of the category systems. Consequently, effective mechanisms for orchestrating the co-evolution of conceptual and linguistic inventories through a tight coupling are crucial for successful communication (see Steels, 1998b for a discussion and review of early experiments).

The perceptual, conceptual and linguistic representations that are maintained by each agent for producing and parsing utterances can be viewed as a *semiotic network* as shown in Figure 2.6. Long-term memories of meanings are connected to forms through persistent associations that are stored in the agent's lexicon. For production and parsing, a look up process retrieves the best form connected a meaning and vice versa. In contrast, representations of sensory experiences that are created by perceptual processes for referents are only memorized over the course of a single interaction. They become dynamically connected to meanings through processes of conceptualization and semantic interpretation. Each of the connections between representations in a semiotic network is weighted. Scores of form meaning associations reflect how well a word was used in the past and conceptualizations are scored based both on how well a category discriminates a referent from the context and on success in previous interactions. Producing or parsing an utterance then amounts to finding an optimal path through the network, either by always following connection with highest weight or by searching for the highest cumulative score.

The biggest challenge in maintaining semiotic networks lies the coupling between the alignment dynamics of meanings and of words. The communicative success perceived by an agent only provides an overall measure for the appropriateness and degree of conventionalization of all the representations

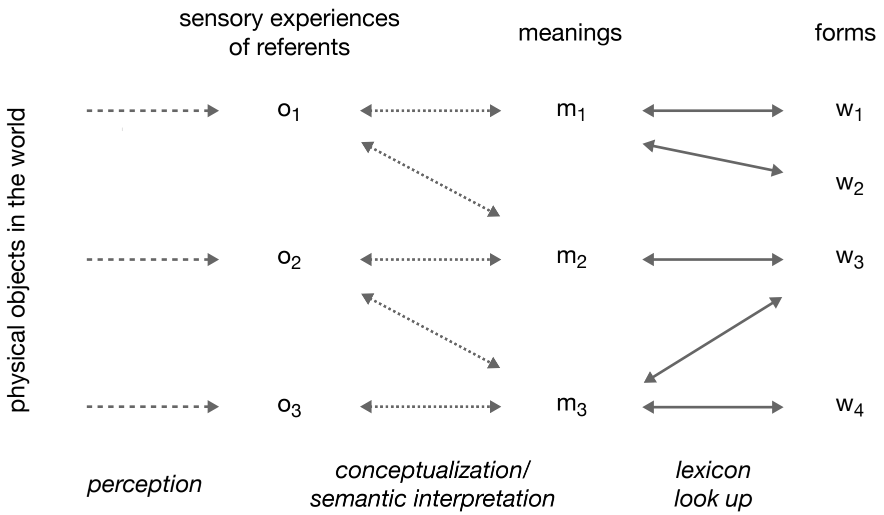


Figure 2.6: A schematic model of an agent's semiotic network. Perceptual processes yield representations of sensory experiences that then become connected to meaning representations through processes of conceptualization and semantic interpretation. Forms are connected to meanings through a lexicon look up process.

along a particular path through the semiotic network. For example when an interaction fails, an agent has no guaranteed way of attributing the failure in order to repair its network – it could be both due to an inappropriate category, due to a wrong word, or due to a disadvantageous connection weigth that prevented the agent from using the 'right' path through the network. Similarly, also positive communicative feedback only acts on both the involved categories and words and as we will see later on, it needs many interactions to disentangle the fortune of particular categories from those of the words connected to them.

By letting agents create and align meanings in a way so that they fit well with the linguistic conventions in a population, we give language a very prominent role in the formation of categories, which is not an uncontroversial choice. Next to language that imposes and structures concepts, there are at least two other important factors: First, while it is very unlikely for most of the categories to be innate, the genetic endowment of agents certainly constrains the morphology of the body and its perceptual apparatus. And similar sensorimotor interactions with the environment lead to a similar structuring of reality. Second, the structure of the world itself also constrains concept formation. Some patterns in the world occur more often than others and some distinctions are more salient than others, and for efficient communication it makes sense to reflect these patterns in the language. How these three factors are weighted is an ongoing debate in the cognitive sciences and we will not take a stance in this discussion. In our experiments, language, the body and the world play an equally important role.

Nevertheless, the previously unpopular theory of *linguistic relativity* which proposes a strong influence of language on the nature of categories (or Sapir-Whorf hypothesis, Whorf & Carroll, 1956) started to receive more an more support recently (see for example Levinson, 2001 for a review of empirical evidence and arguments). And there is quite of number of computational studies demonstrating that the shaping of categories through language is beneficial for the self-organization of communication systems. For example (Cangelosi & Harnad, 2002) showed in an experiment where simulated agents were interacting in a toy-world consisting of mushrooms (with some of them being poisonous) that agents that have to construct their sensori-motor categories solely by trial-and error interactions with the environment have an evolutionary disadvantage compared to those whose categories are shaped through language.

A related question is whether the learning of word meanings requires the pre-existence of categories (learnt or innate) or whether, in the other extreme, the mental world is exclusively structured through language. In humans, linguistic development is preceded by a phase in which mental representations are constructed solely from the non-linguistic interaction with the world. However, concepts such as number systems or as simple as color categories are clearly culturally transmitted and thus even if language initially relies on pre-existing representations, in later stages there is a co-evolution of categories and words and we will also pursue that strategy in our experiments. In support, Clark (2004) reviewed empirical evidence (for the domain of space) on how children first build on conceptual representations acquired in pre-linguistic stages and how these representations are refined or build upon later when learning the underlying representational structure of the parent's language.

Finally, the issue of planning and interpretating multi-word utterances is also linked to the interplay between categories and language. First of all, we need to define what the meaning of an utterance is: in interpretation, it is the combined meanings of all the words involved in parsing. Consequently, when an agent connects many different meanigns to the same word forms, then many different sets of categories can result from applying a lexicon. Semantic interpretation of such a list of categories will then look for the object that fits all categories best. In production, conceptualization processes try to find a set of categories that disriminate the chosen topic from the other objects in the context. Lexicon application then needs to find a combination of words that *cover* each of the categories in the meaning, a process which again can yield multiple combinations of words.

In general, agents trace their semiotic networks in parallel for the involved representations and additional conceptualization and lexicon processes need to check whether combined sets of categories and words are applicable to a context, meaning or utterance. How exactly linguistic and semantic representations are to be processed is implicitely hidden in the language game and shared by all agents. For advancing this work towards grammatical language, more explicit means of representing how to apply categories are certainly needed and a good candidate for this is the *IRL* framework Spranger, Loetzsch & Pauw

(2010a); Spranger, Pauw & Loetzsch (2010b); Spranger, Pauw, Loetzsch & Steels (2012b); Steels & Bleys (2005); Van Den Broeck (2008) which enables agents to autonomously construct compositional semantic structures that configure the interplay of cognitive categorization operations and categories.

Chapter 3

Models of lexicon formation

In this thesis we will systematically analyze the performance of different classes of lexicon formation models. Starting simple, we will confront our agents with more and more challenging communicative tasks and each time examine what additional representational mechanisms and learning strategies are required to reach communicative success and coherence. In doing so, we will follow the increasing complexity of models that we laid out in Section 2.2.2 (page 32).

In order to be able to evaluate the impact of the additional challenges stemming from embodiment and real-word perception, we will first investigate lexicon formation in simulated worlds: throughout Part **??**, agents will be presented with idealized simulated perceptions of varying complexity. To set the stage, we will briefly review models for the naming of individual objects in Chapter 4. From there on, we discuss strategies for dealing with ambiguity that arises from conceptualization, multi-word utterances and structured meanings in Chapter 5. Motivated by these results, we introduce a flexible model of word meaning representation and learning in Chapter 6.

Part **??** then discusses embodied models of lexicon formation. We will first introduce the robotic experimental setup with its mechanisms for visual perception and social cognition in Chapter 7. Then we look at how robots can construct notions of object individuality as a prerequisite for aligning sets of proper names in Chapter 8, and how more general categories can be grounded trough language games in Chapter 9. Finally, in Chapter 10 we apply the model from Chapter 6 to real-word embodiment and analyze its performance.

3.1 Guessing the meaning of novel words

Because there is no direct relationship between word forms and referents and ~~due to the nature of words as arbitrary relationships between meanings and~~

forms, hearers are faced with the challenge of guessing the meaning of novel words. When the hearer does not know a word (and can not infer its meaning using the other words in the utterance and the context), then he non-linguistically signals a communicative failure and the speaker will then point to the intended referent. Although this pointing will unambiguously establish shared reference, the hearer does not know which aspect of the referent is covered by the unknown word: it could be its color, its size, or even a combination thereof.

The degree of this uncertainty depends on the nature of the coupling between meaning and form. When single word forms map to single categories that stand for unique referents as a whole, then there is no uncertainty for the hearer at all and he just needs to associate a novel word to his conceptualization of the individual object. But as soon as words refer to categories such as `red` or `small`, hearers need to infer which category was meant upon hearing a novel word. This problem gets multiplied when the language game involves multi-word utterances (and when thus it is not clear which word covers which part of the meaning) or when word meanings are allowed to be structured (a word can refer to single categories or combinations of categories, see Section 2.2.2 on page 32).

The challenge of dealing with this uncertainty is usually linked to the problem of *referential indeterminacy* and a thought experiment carried out by Quine (1960): he discussed an imagined situation in which a field linguist tries to learn a language unfamiliar to him from a native speaker. As they walk through a forest, they encounter a rabbit and the native points to it and says the word "gavagai". The linguist then forms the reasonable hypothesis that the word means `rabbit`, but Quine makes point that he can not be sure what the meaning of "gavagai" is and that there is potentially an infinite number of possible meanings: it could mean "Let's go hunting", "There will be a storm tonight", "dinner", and so on.

Children also face the problem of referential uncertainty when learning their mother tongue. Nevertheless, they learn words extraordinarily quickly, from only a very few or even one exposures. This phenomenon is called "fast-mapping" and was extensively studied by Carey (1978). Although it can take years for children to home in to the proper meaning of words in all their nuances, children make very good initial guesses about what words refer to. In the literature, there is an enormous amount of empirical studies showing that children prefer some interpretation of novel words over others. For example Akhtar, Carpenter & Tomasello (1996) showed that in a object naming task with toy objects, 24-month-old children tend to associate unknown words with objects that are novel in the context. Similarly, Smith, Jones & Landau (1996) demonstrated that three-year-old children rely on relative saliency when selecting features for learning names for objects with attached parts.

Citing these findings, many researchers have concluded that children thus must be endowed with (possibly innate) word learning *biases* or *constraints* (Gleitman, 1990; Markman, 1992). In this theory, constraints greatly reduce the hypothesis space of possible meanings and only due to that make the task of learning a language achievable. For example Macnamera (1982) proposed the *whole object bias*: children assume that a novel label is likely to refer to the whole object and not to its parts, substance, or other properties. Furthermore, Landau, Smith & Jones (1998) suggested the *shape bias* – children initially use object shape as the main categorization ground and only later on incorporate other properties such as its function. And with the *mutual exclusivity constraint* (Markman & Wachtel, 1988), children assume category terms are mutually exclusive, i.e. a novel word can not refer to a property of an object for which the child already knows a word. Similarly, Clark (1987) formulated the *principle of contrast* (every two forms contrast in meanings) and the *principle of conventionality* (for each meaning, there is a conventional form that speakers expect to be used in the language community).

All these studies clearly show that children indeed consistently prefer some interpretations of novel words over others and as we will see, implicitly using some of these strategies such as the principle of contrast or the mutual exclusivity constraint in our lexicon formation experiments will also help to reach coherence in the population. There is, however, a debate whether it is necessary to assume language specific biases or constraints to explain these empirical results or whether they can be the consequence of other, possibly more general, cognitive mechanisms.

Most prominently, Tomasello (1999, 2003) argues that no special mechanisms are needed and that word learning to a large extend relies on the children's general ability to understand the intentions of their caregivers in naturally occurring social interactions (Tomasello, 2001) and in the motivation to participate in joint activities and to share psychological states with others (Tomasello, Carpenter, Call, Behne & Moll, 2005). We share the stance that "These findings are consistent with the view that fast mapping emerges from a general capacity to learn socially transmitted information – including, but not limited to, the meanings of words" (Bloom, 2000, p. 34ff).

Others have explained children's word learning skills with the ability to observe statistics in co-occurrences between objects and words, a theory called *cross-situational learning*. For example Akhtar & Montague (1999) presented children with novel objects that varied in shape and texture. By consistently labelling objects of similar properties "a modi one", children associated the quality that remained constant across trials to the new word. In a more recent study, (Smith & Yu, 2008) showed similar effects for associating novel words to more holistic concepts such as `ball` and `dog`.

Inspired by this empirical evidence, scholars such as Siskind (1996) and Smith, Smith, Blythe & Vogt (2006) operationalized their understanding of cross-situational learning in computational studies on lexicon formation. In this technique, a learner initially derives a set of possible *candidate* meanings from the context and stores all of them with a novel word. In subsequent exposures to the same word in other contexts, the hearer eliminates all those meanings that are not consistent with the context (i.e in the intersection with the meanings derived from the current context) until unambiguous mappings are found. There are, however, a number of problems with this approach. Requiring observation of many word - context pairs, the time to gain usable word meanings by far exceeds the number of exposures that children need on average. Second, in order to enumerate all possible meanings of a novel word and for using the technique of intersecting meanings across contexts, the learners need fully established category systems that do not change, which is often not the case when for example robotic agents co-evolve their ontologies with lexicons in the learning process. Consequently, most computational experiments on cross-situational learning have been done in simulated worlds where the environment already provides pre-conceptualized atomic meanings that are shared between speaker and hearer (with exceptions such as in De Beule, De Vylder & Belpaeme, 2006). Third and finally, models of cross-situational learning usually consider single-word utterances and unstructured word meanings. Scaling to more complex communicative challenges as introduced in this thesis has proved to be difficult (Vogt & Coumans, 2003).

In general, we find the notion of a *hypothesis* space that gets *pruned* over the course of many interactions problematic. We will show in this thesis that lexicon formation models that consider word learning as an enumeration and subsequent elimination of alternative hypotheses will not scale well with increasing population sizes, meaning spaces, and the challenges of embodiment. Instead we will argue for models in which learners construct and gradually shape word meanings (Bowerman & Choi, 2001). The hypothesis is that "…the use of words in repeated discourse interactions in which different perspectives are explicitly contrasted and shared, provide the raw material out of which the children of all cultures construct the flexible and multi-perspectival – perhaps even dialogical – cognitive representations that give human cognition much of its awesome and unique power" (Tomasello, 1999, p. 163). Although in this view learners also make guesses at the meaning of novel words, they are different in nature. Children cannot have at hand all the concepts and perspectives that are embodied in the words of the language they are learning – they have to construct them over time through language use. "For example, many young children overextend words such as *dog* to cover all four-legged furry animals. One way they home in on the adult extension of this word by hearing many four-legged furry animals called by other names such as *horse* and *cow*" (Tomasello, 2003, pp 73–74).

3.2 Scaling, robustness and the challenge of real-world perception

The second focus of this thesis is on *scaling* and *robustness* of lexicon formation models. We will investigate how well models perform with increasing communicative challenges and by that try to find the boundaries in which they are applicable. Many of the models reviewed here only have been tried in “easy enough” environments and tasks and we will systematically analyze under which conditions they fail and why. Most importantly, we will test all our models with respect to how well they scale with larger population sizes. Virtually every model in the literature works properly when the number of agents in the population is two, because then each agent is part of every interaction and conventions thus become easily shared. But whereas many models scale well to small population sizes of 5 to 10 agents, they often become impractical for populations of 100 or 1000 agents due to fundamental shortcomings in the way how words and meanings are represented and processed. Similarly, scaling with meaning spaces is an issue. We will evaluate population dynamics in worlds with increasing number of objects and rising complexity and structuredness of (simulated) perceptions.

On the other hand, we will argue that under the condition that some crucial dynamics are in place, lexicon formation models are robust with respect to the particular strategies chosen for invention, adoption and alignment. For example, many algorithms have been proposed for updating the inventories of agents after an interaction based on the outcome of the game, and we will dissect which of them are really required to reach success and coherence.

Related to scaling and robustness is the issue of the influence of real-world perception on lexicon formation models. First of all, not providing agents with shared symbolic perceptions adds the additional complexity of category formation, which creates new kinds of dynamics when ontologies and lexicons are constructed in parallel and interdependently. For example, strategies for updating word confidences also need to take into account that underlying categories also may have shifted their meaning. Or when an interaction fails, there is the hard decision to make whether the categories involved were inappropriate or whether the word forms were simply not conventionalized.

Furthermore, embodiment creates other kinds of uncertainties that need to be dealt with. Agents can view a scene from different angles, lighting conditions may vary and thus the perceptions that two different robots have of the same physical object will never be the same. Even a single robot will perceive an object differently over the course of time due to camera noise, robot motion and general uncertainty in computer vision systems. Nevertheless, human concepts, such as, for example, the color red, are robust to such influences – we will recognize an object as red under very different lighting conditions and even subjects with color deficiencies are often able to communicate about colors.

Concretely, embodied lexicon formation models need to cope with *perceptual deviation*, i.e. that specific continuous features (e.g. position, shape, width and height, color information, etc.) computed by the vision system for an object differ drastically between the perception of speaker and hearer. For example one robot might perceive the height of an object as being `0.72` and the other one as `0.56`. This will inevitably cause each agent to have a different notion of a word such as “high”. We will make the point that investigating lexicon formation with real robots leads to more robust and realistic models, which in turn also perform better in simulated environments.

Part II

Strategies for lexicon formation in simulated worlds

Chapter 4

Establishing names for unique objects

To set the stage, we will now briefly introduce the lexicon formation model that is commonly referred to as the “Naming Game”. In such a language game, agents learn to associate single word forms to atomic, unstructured meanings which are provided by a shared simulated environment. Whereas in the initial publication by Steels (1995) the meanings were pre-conceptualized spatial categories such as `left` and `front`, later on (e.g. in Steels & McIntyre, 1998) shared concepts for unique individual objects such as `obj-4` and `obj-17` were normally used. Since then, the Naming Game has become a general vehicle for investigating the emergence and spread of conventions in a population, where conventions not necessarily need to be form-meaning associations but can be any trait that is negotiated in a population, such as for example preferences or beliefs.

No other lexicon formation model has been as extensively investigated as the Naming Game and we will not re-discuss all these results. We will rather introduce it here as a baseline for all the other experiments in this thesis and only focus on aspects that we will also need later on.

4.1 Basic strategies for representing, processing and learning of words

In all experiments in this thesis, language users are modelled as software agents following standard practices in the field of Artificial Intelligence (see e.g. Wooldridge & Jennings, 1995). That is, each agent has its own private state and autonomously responds to changes in the environment and to actions of other agents. It is important that agents do not have access to mental ~~representations of other agents (i.e. there is no telepathy). Instead, they are~~

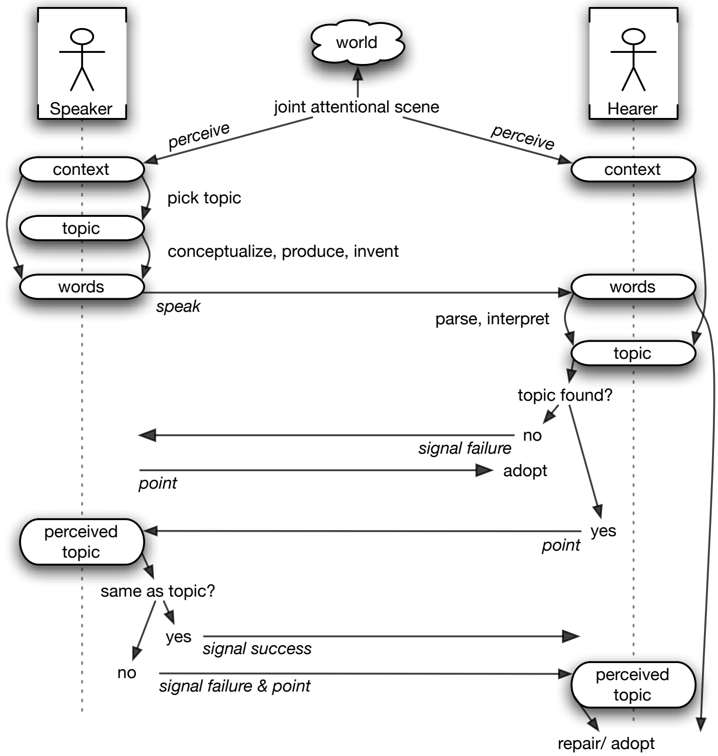


Figure 4.1: Main steps and mechanisms involved in a communicative interaction (see also Figure 2.1).

only able to observe the actions of their interlocutors such as utterances, pointing, non-linguistic feedback and so on.

At the begin of an experimental run, the population $P := \{a_1, a_2, \ldots\}$ is created (we will by default use a population size $|P| = 10$) and the agents $a_i \in P$ are initialized with empty linguistic (and conceptual) inventories. Before each communicative interaction, two agents are randomly drawn from this population and assigned the communicative roles of speaker and hearer. To play a language game, the speaker and hearer follow a built-in script that is shown again in Figure 4.1 (see also Section 2.1.1, page 22).

This particular type of language game will form the basis of all experiments in this thesis and the particular lexicon formation models will only differ in their strategies for representing, processing and learning of lexicons and ontologies. We will now define these mechanisms for the Naming Game and later on only discuss the differences to this model:

Lexicon representation. Each agent a in the population $P := \{a_1, a_2, \ldots\}$ maintains a lexicon $L(a) := w_1(a), w_2(a), \ldots$ consisting of a set of words $w(a)$. A word is represented as a three tuple $w := \langle m(w), f(w), \gamma(w) \rangle \in \mathcal{M} \times \mathcal{F} \times \mathbb{R}$, which is an association of a meaning $m(w) \in \mathcal{M}$ to a form $f(w) \in \mathcal{F}$ with an association weight $\gamma(w)$ representing the agent's confidence in that association. $\mathcal{M}$ is the set of possible word meanings, $\mathcal{F}$ the set of possible word forms and $\gamma(w)$ a real value with $0 \leq \gamma(w) \leq 1$.

Perception. The world in which the agents interact consists of shared atomic meanings $m \in \mathcal{M}$, which can be anything but are typically seen as 'individual objects'. In each interaction both the speaker and hearer are provided with the vector of all meanings in the world as their perception of the scene. By default, the number of meanings in the world $|\mathcal{M}|$ is 10 and thus, the context for each agent always consists of 10 'objects':

```
(obj-1 obj-2 obj-3 obj-4 obj-5 obj-6 obj-7 obj-8 obj-9 obj-10)
```

Topic selection. The speaker randomly selects one of the objects in the context as the topic of the interaction.

Conceptualization. In the Naming Game, the world already provides pre-conceptualized meanings and consequently, the meaning chosen as the topic is the meaning m to be expressed.

Production. The speaker looks up his lexicon for all words that have m as their meaning and from these selects the word with the highest association score. When multiple words for meaning m have the highest score, a random choice is made.

Invention. When the lexicon does not contain a word for meaning m, then a new word $w = \langle m, f, \gamma_i \rangle$ with a new unique form f and an initial word score γ_i of 0.5 is created and stored in the lexicon of the agent. The new form f is guaranteed to be unique during an experimental run (no word form is invented twice) and typically consists of three random consonant-vowel combinations (e.g. "fuzobi" or "kalige"). After invention, production is repeated with the updated lexicon.

Utterance. The single form produced by the speaker, possibly after invention, is sent as the utterance to the hearer.

Parsing. The hearer looks up his lexicon for the word that matches the utterance (with no possibility of associating multiple meanings to a form, there is always only one or no such word). The meaning of that word is the meaning parsed by the hearer.

Interpretation. In the Naming Game, the parsed meaning is immediately treated as the topic understood by the hearer, no further semantic interpretation is necessary.

Pointing, communicative success and feedback. When the hearer is able to parse the utterance and to interpret a topic, he points to the topic by sending the meaning such as `obj-7` to the speaker. The speaker compares the received meaning with his own intended topic and signals a communicative success when this is the case and a communicative failure otherwise. When the hearer does not know the word uttered, he immediately signals a communicative failure and the speaker then points to the intended topic.

Adoption. Both when the hearer does not know a word form f or when he pointed to the wrong topic (which does not happen in the Naming Game), the speaker will point to the intended topic m. The hearer then adopts the new convention by storing a new word $w = \langle m, f, \gamma_i = 0.5\rangle$ in his own lexicon.

Consolidation. Based on the outcome of the game, the speaker and hearer update their lexicons in order to be more successful in future interactions. When the interaction failed, then both agents update the score of the word used in production respectively in parsing by the value $\Delta_f = -0.1$. Words with a score of 0 or smaller are removed from the lexicon. In the case of communicative success, the scores of the words used are updated by $\Delta_s = 0.1$ (and set to 1.0 if the result is greater) and the scores of all words in the lexicon that have the same form are updated by $\Delta_i = 0.1$ (*lateral inhibition*, again, words with a score of 0 or below are removed from the lexicon).

4.2 Alignment dynamics

With all these mechanisms in place, the population is able to successfully create and align a shared lexicon for the meanings in the world through series of such languages games. Figure 4.2 shows an example of 15 consecutive interactions from game 100 on. Within these early stages of the alignment process, most interactions fail, although in some of them words are used that both the speaker and hearer know. Interaction 100 was played between agent 5 and agent 9 and the speaker picks `obj-3` as the topic of the conversation. The word chosen by the speaker is “bukopa”, which in turn is successfully interpreted by the hearer as `obj-3`, eventually making the interaction a success. In contrast, interaction 101 is an example of a failed game. The speaker agent 3 utters “wosogi” for the meaning `obj-3`, which the hearer agent 7 does not know yet. Note that in the Naming Game, an interaction is immediately a success when the hearer knows the word, because agents directly perceive the meanings from the world and thus never associate a ‘wrong’ meaning to a form in adoption.

Furthermore, even within these few games the population uses three different forms for `obj-3`. This is because speakers independently invent words for new meanings and hearers adopt words from different speakers for the same meanings. To illustrate this, Figure 4.3 shows the lexicon of agent 1 after game 250 and after game 2500. After interaction 250, the agent associates up to five different word forms to each of the meanings, which get reduced to one per meaning after 2500 interactions.

From the perspective of the population, Figure 4.4a shows snapshots of the first four agents’ lexicons for three different meanings after 250 played games.

#	speaker	topic speaker	utterance	hearer	topic hearer	success?
100	agent 5	`obj-3`	*"bukopa"*	agent 9	`obj-3`	yes
101	agent 3	`obj-3`	*"wosogi"*	agent 7		no
102	agent 6	`obj-7`	*"tevaso"*	agent 2		no
103	agent 9	`obj-8`	*"razitu"*	agent 4		no
104	agent 6	`obj-5`	*"salusu"*	agent 8	`obj-5`	yes
105	agent 2	`obj-3`	*"xiliza"*	agent 7	`obj-3`	yes
106	agent 7	`obj-1`	*"ligita"*	agent 8		no
107	agent 9	`obj-9`	*"navino"*	agent 3	`obj-9`	yes
108	agent 5	`obj-10`	*"pinobe"*	agent 8		no
109	agent 1	`obj-10`	*"sifubi"*	agent 3		no
110	agent 10	`obj-6`	*"kiduze"*	agent 6	`obj-6`	yes
111	agent 5	`obj-10`	*"pinobe"*	agent 1		no
112	agent 10	`obj-7`	*"dezosa"*	agent 6		no
113	agent 1	`obj-1`	*"sewapa"*	agent 7		no
114	agent 10	`obj-7`	*"dezosa"*	agent 3		no

Figure 4.2: Overview of 15 consecutive interactions from game 100 on. It shows the agents that are interacting, the topic chosen by the speaker, the utterance formed, the topic understood by the hearer (when successfully parsed) and whether the agents reached communicative success.

Their lexicons show a very low coherence, with the numbers of associations and their forms greatly varying. Whereas all four agents at least already have adopted an association with the same form for `obj-2` and `obj-3` ("resere" and "fodato"), this is not the case for `obj-1`: Of all the four forms associated by agent 1 to this meaning, only one ("sewapa") is shared with one other agent.

However, due to the strategies of 1) updating word scores based on the outcome of the game, of 2) laterally inhibiting competing associations, and of 3) preferring words with higher scores, the population quickly reaches coherence. Figure 4.4b shows the lexicons of the same four agents after 2000 interactions. For each of the three meanings, the population agreed on a single form with 1.0 as the association score. Which of the forms from the early stages 'survives' this selection process can not be completely determined by looking at the lexicons in Figure 4.4a, but it is clear that associations which are known to more agents and which have a higher average score in the population are more likely to become conventionalized.

Figure 4.5 shows for each form connected by the population to the meaning `obj-3` the average association scores across all agents. The form that eventually wins ("sezeba") is created very early on and competes with the form "bukopa" for dominance until around interaction 1000, after which "sezeba" asserts itself and "bukopa" slowly starts loosing the competition, before it gets eliminated at around interaction 1800. All other four forms initially created by the population are quickly lowered in score, and the last one ("wosogi") is removed by the last agent at round interaction 900. Nevertheless, individual agents might

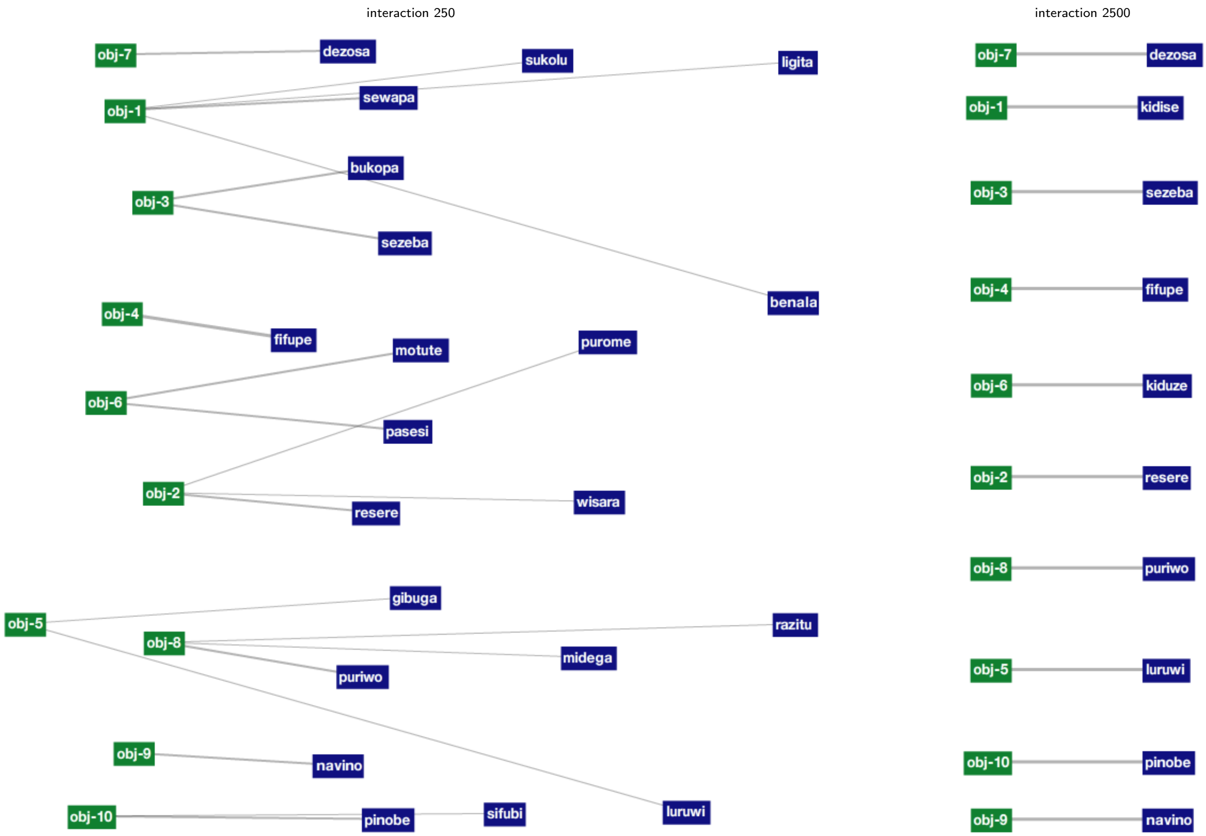


Figure 4.3: Network representation of the complete lexicon of the first agent in the population after 250 interactions (left) and 2500 interactions (right). In each network, word meanings are drawn on the left and forms on the right. Each line represents a word in the lexicon of the agent, the line widths denote the strength of the association.

undergo much different dynamics. Figure 4.6 shows the scores of words in the lexicon of agent 1 for the meaning `obj-3`. This agent did not have the winning form "sezeba" in his lexicon between interactions 400 and 500, only after which he re-adopted it and used it most of the time. Similarly, the already eliminated form "bukopa" gets adopted again after interaction 1000 and because agent 1 successfully uses the word one time in the role of the hearer (as speaker he would have chosen the still higher-scored form "sezeba"), the previously more successful "sezeba" becomes reduced in score due to lateral inhibition.

Furthermore, Figure 4.7 shows the evolution of association scores of all words in the lexicon of agent 1. Despite the previous example (which is in fact rare), most words that reach a certain score above the initial words score of 0.5 win the competition over their competitors and all other words become quickly removed. After around interaction 1200, the lexicon does not change

meaning	agent 1		agent 2		agent 3		agent 4	
obj-1	*"zasala"*	0.50	*"milozo"*	0.50	*"botewi"*	0.50	*"zasala"*	0.30
	"milozo"	0.30	*"zasala"*	0.50	*"zasala"*	0.50	*"botewi"*	0.50
					"milozo"	0.30		
					"legubu"	0.30		
obj-2	*"zaxiwu"*	0.80	*"zaxiwu"*	0.60	*"dovege"*	0.40		
obj-3	*"gokaso"*	0.40	*"malixe"*	0.50	*"dotopi"*	0.50	*"dotopi"*	0.30
	"dotopi"	0.40	*"dotopi"*	0.40	*"nobaxo"*	0.40		
	"malixe"	0.40	*"fivine"*	0.50	*"fivine"*	0.50		

Figure 4.4a: Forms associated to three different meanings by the first four agents of a population of 10 after 250 interactions.

meaning	agent 1		agent 2		agent 3		agent 4	
obj-1	*"milozo"*	1.00	*"milozo"*	1.00	*"milozo"*	1.00	*"milozo"*	1.00
obj-2	*"zaxiwu"*	1.00	*"zaxiwu"*	1.00	*"zaxiwu"*	1.00	*"zaxiwu"*	1.00
obj-3	*"gokaso"*	1.00	*"gokaso"*	1.00	*"gokaso"*	1.00	*"gokaso"*	1.00

Figure 4.4b: Associations to three meanings after 2000 interactions.

anymore and all conventionalized forms remain at a score of 1.

Finally and most importantly, the alignment dynamics of the population can be analyzed quantitatively. As already discussed in Section 2.1.3 on page 27, communicative success, i.e. the fraction of interactions in which the speaker reached his communicative goal, is our main criterion for evaluating the performance of language game experiments. Figure 4.8 shows the evolution of this measure over 2500 consecutive interactions: after 600 interactions, in 80% of the games communicative success is reached, and after about 1500 interactions, success reaches and remains at 100%. A second crucial measure is lexicon size, i.e. the average number of words in the lexicon of each agent (also shown in Figure 4.8). After an initial phase of invention and adoption, at around interaction 300, each agent knows about 22 word forms. After that, word score update based on success and lateral inhibition reduce the number of words, before it reaches 10 at around interaction 1500. A lexicon size of 10 is considered to be 'optimal', because there are 10 different meanings in the world and an inventory of 10 words for these meanings is the most cognitively

Measure 4.1: Lexicon size

Measures the average number of words known by the population. The number of meaning-form associations in each agent's lexicon is counted and averaged over the number of agents:

$$v = \frac{\sum_{i=1}^{|P|} |L(a_i)|}{|P|}$$

Values v are averaged over the last 250 interactions.

Figure 4.5: Evolution of words in the population for the meaning obj-3. Each line shows for a single form the corresponding word scores averaged over all agents that know the form.

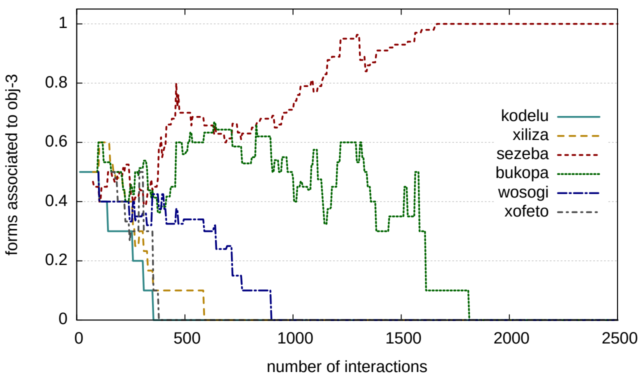
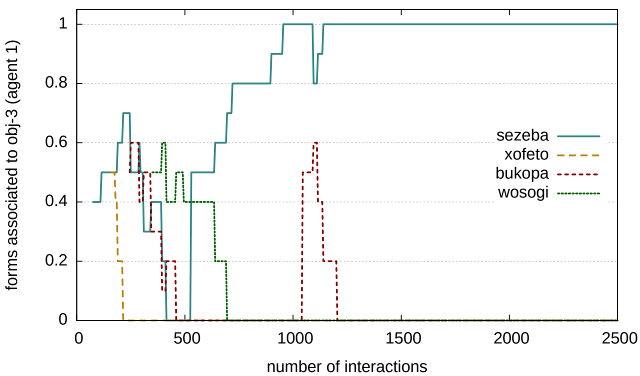


Figure 4.6: Scores for forms associated by the first agent to the meaning obj-3.



efficient means to communicate about these meanings in terms of processing and ambiguities.

Additionally, we will use measures of coherence, stability, and ambiguities in inventories for evaluating the performance of language games in this thesis (see Figure 4.9). Lexicon coherence externally compares the lexicons of speaker and hearer with respect to how similar they are in terms of the fraction of shared form-meaning associations. Coherence reaches 100% soon after 1500 interactions, but the curve slightly lags behind communicative success because even when agents already consistently use the same forms for a particular meaning, there are still varying competing forms that still need to be eliminated by lateral inhibition (see also Figures 4.5-4.7).

Frequency of lexicon changes provides a measure for the stability of the agents' lexicons by counting how often agents add or remove words in their lexicons. At the beginning, speakers invent words or hearers adopt words in almost every interaction, and after around interaction 500, when lateral inhibition results in a peak in the number of words that are removed, the slope of stability increases. But similar to coherence, complete stability is only reached much later than complete communicative success (at around interaction 2000), because lower-scored competing words still need to be removed from the lexicons.

Measure 4.2: Lexicon coherence between speaker and hearer

Provides a measure for how similar the lexicons of the interacting agents are. The degree of lexicon overlap between the speaker s and the hearer h of the current interaction is computed as the fraction of form meaning associations that are shared by speaker and hearer and all words known by speaker and hearer:

$$v = \frac{|L(s) \cap L(h)|}{|L(s)| + |L(h)|}$$

Association weights of words are ignored when forming the intersection between the two lexicons. Values v are averaged over the last 250 interactions.

A slightly more precise measure for coherence in the population would be to compare the lexicons of all agents. But because computing coherence between all pairs of agents would be very costly, we chose to use coherence between speaker and hearer as a approximation for population coherence.

Measure 4.3: Frequency of lexicon changes

Measures how stable the agents' lexicons are. For each interaction in which either the speaker or the hearer add or remove a word from their inventories, a value of 1 is recorded, for all others 0. Values are averaged over the last 250 interactions.

Measure 4.4: Average number of forms per meaning (synonymy)

The average number of forms associated to each meaning by an agent is averaged over all agents in the population:

$$v = \sum_{i=i}^{|P|} \frac{|L(a_i)|}{|\{m : m \in \mathcal{M} \ \wedge \ \exists w(w \in L(a_i) \wedge m_w(w) = m)\}|} \ / \ |P|$$

Values v are averaged over the last 250 interactions.

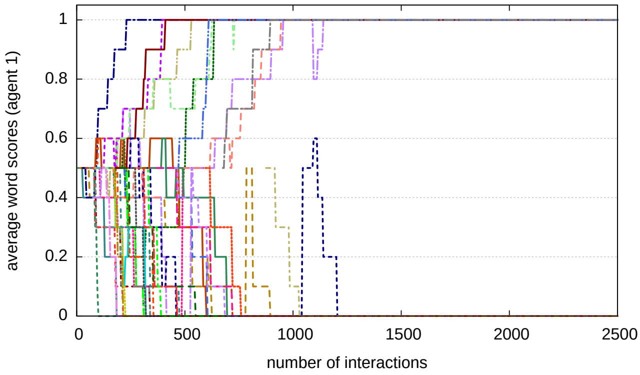


Figure 4.7: Evolution of the first agent's lexicon over 2500 interactions. Each line represents the score of a single word as it changes over time.

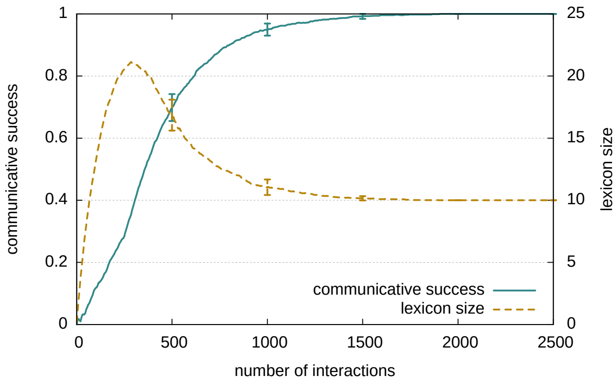


Figure 4.8: Main dynamics of the Naming Game. Communicative success (measure 2.1, page 28) and lexicon size (measure 4.1) are averaged over 10 repeated series of 2500 interactions.

Finally, the average number of forms associated to each meaning is a indicator for ambiguities in the agents' lexicons. This measure is often also referred to as *synonymy*, but the 'synonyms' in the lexicons of our agents are of a different quality than those found in the real world: here there are competing forms for exactly the same meaning, whereas in natural languages they are rather seen as words with similar meanings, but still carrying semantic distinctions. In the Naming Game, synonymy is directly correlated with lexicon size, because the number of meanings to be expressed is fixed and there are no word meaning ambiguities in adoption. The curves for lexicon size and number of forms per meaning look exactly the same. When lexicon size peaks at interaction 300 with 22 words, the degree of synonymy is 2.2, and at the optimal size of 10 words, there is only one form per meaning.

4.3 Other alignment strategies & scaling

The main challenge for aligning lexicons in the Naming Game is the elimination of competing word forms for the same meanings (synonymy). The common strategy used for this is to update association scores based on communicative success and to laterally inhibit competing forms. However, other strategies are possible and in Figures 4.10a-4.10c we will compare four of them with the update dynamics discussed above (in the graphs called "update + lateral inhibition").

First, a strategy that we call "no alignment" does not change association scores at all at the end of an interaction (the parameters for word score in case of success Δ_s, in case of failure Δ_f and for lateral inhibition Δ_i are all set to 0). But still, although later than with the other strategies, the population reaches almost complete communicative success after 2500 interactions. Nevertheless, average lexicon size increases to a stable level of above 50, without ever decreasing again. Since all associations remain at their initial word score of 0.5, speakers essentially make a random choice when producing for a specific meaning. What happens is that every form ever invented by a speaker needs to be learnt by all other agents in the population in order to reach success.

The second strategy "update based on success" only updates the associations used by the speaker and hearer for producing and parsing (and performs no lateral inhibition, $\Delta_s = 0.1$, $\Delta_f = -0.1$, $\Delta_i = 0$). Communicative success is reached much faster than with the default "update + lateral inhibition" strategy, but again lexicon size does not reach the optimum of 10 but remains at a stable plateau of about 33 words on average. This is because once a form wins over its competitors, there is no chance for synonyms to be lowered in score (which in this strategy is only possible through use in a failed interaction). As a result, a number of 'successful' forms for each meaning will reach a score of 1.0 and speakers will randomly choose from them, as with the previous strategy. All other associations will not be used anymore, but remain in the lexicons of the agents.

These 'unused' words can be eliminated with the third strategy "update + constant decay". In addition to updating scores of used words based on the outcome of the game with $\Delta_s = 0.1$, $\Delta_f = -0.1$ and $\Delta_i = 0$, the score of each association in the lexicon is changed by a parameter $\Delta_d = -0.05$ divided by the number of words in the lexicon. When words reach a score of 0 or below, they are removed from the lexicon. This in a way creates 'blind' lateral inhibition dynamics, since words which are not successfully used slowly become removed and only words who are frequently used in successful interactions survive. However, there are two problems with this strategy. First, the choice of parameter Δ_d is very difficult. If it's too high, then words that are well conventionalized but that happened not to be used often enough can get accidentally removed. And if it's too low, then synonyms become removed only very late. Second, this strategy only works when the meanings expressed by the agents are equally distributed over time: words for specialized meanings that occur less often are very unlikely to survive with these dynamics.

Finally, a fourth strategy "competitor elimination on first success" again does not update word scores at all. Instead, on the first occasion that a word is used successfully, all associations with competing forms are immediately removed from an agent's lexicon (this behavior can be emulated by choosing the parameters $\Delta_s = 0$, $\Delta_f = 0$ and $\Delta_i = -0.5$). Surprisingly, agents reach complete success and stability also with this strategy, although a bit later than with the other ones. On the other hand, agents need to remember less words (lexicon size peaks at about 16) and they don't need to maintain word scores, which increases cognitive economy, especially when scaling to larger population sizes.

Other alignment strategies such as that the speaker always imitates the last word heard for a meaning have been investigated by Kaplan (2005), and he also found that the default strategy "update + lateral inhibition" is the best solution for dampening competing forms for meanings in the Naming Game. Furthermore, this strategy is very robust with respect to the actual parameters chosen for updating word scores. In the literature, the values of $\Delta_s = 0.1$, $\Delta_f = -0.1$ and $\Delta_i = -0.2$ are often been given some significance, but that choice is not crucial at all. As shown in Figure 4.11a, almost the same communicative success is reached for parameter Δ_i for the whole range of values from 0 to 1. This parameter only affects how soon agents remove synonyms from their lexicons, and as demonstrated in Figure 4.11b, an optimal lexicon size is reached quickly for the big range of values $-1 \leq \Delta_i \leq -0.1$.

Similarly, actual values for the score update parameter in the case of communicative failure Δ_f have no real effect on communicative success and lexicon size in the range of $-0.2 \leq \Delta_i \leq 0$ (see Figures 4.11c and 4.11d). Only when Δ_f is too high, then the alignment process has difficulties to take off, because new words immediately get removed again from an agent's lexicon on the first occasion that the word was used unsuccessfully, which can easily happen with new conventions in a population. Along the same lines, the choice of the association score update parameter in case of success Δ_s is quite arbitrary. For values $0.05 \leq \Delta_s \leq 1$ communicative success is more or less the same (see Figure 4.11e), only when Δ_s is too small, negative updates from lateral inhibition and on communicative failure do not get balanced anymore so that words have more difficulties to reach high scores.

Finally, the Naming Game scales very well with increasing population sizes, as demonstrated in Figures 4.12a and 4.12b. To keep the curves comparable, values are plotted along the x axis over the number of games played by each agent instead of the overall number of interactions as in the graphs before. For example, for a population of 500 agents to play 100 interactions per agent, $100 * 500/2 = 25000$ games need to be played, because two agents take part in every interaction. The evolution of communicative success takes the form of a s-curve for all population sizes. After an initial phase with low success, in which a lot of new forms become invented, more and more conventions assert themselves and the slope of the curve steepens, before eventually a plateau of complete success is reached. The curve for lexicon size looks identical for all population sizes, with maximums naturally being higher for larger populations, because more agents independently invent words for the same meanings.

We do not show graphs for scaling with increasing world complexity, because the Naming Game scales linearly with the number of objects in the world. With no ambiguity for the hearer in guessing what the meaning of an unknown word is, the words for each meaning are negotiated independently.

Consequently, aligning words for 20 meanings in the world takes double as long than for 10 meanings. This is also the reason for why Naming Game dynamics are often investigated for a single meaning – additional meanings do not any complexity to the model.

Much more is known about the dynamics of Naming Game-like models of distributed conventionalization processes (in fact, the Naming Game is by far the most investigated lexicon formation model), but with lesser relevance for the experiments in our thesis, we will not discuss these results in depth. There are proofs that the model always convergences (De Vylder & Tuyls, 2006; Ke et al., 2002) (which is reassuring to know for our work), and convergence times (Kaplan, 2005) and scaling laws (Baronchelli et al., 2006) are well understood. Since it is somehow an unnatural assumption that in large populations all agents communicate with and learn from each other with equal probability, the impact of communication network structures where some agents are more central than others has been studied by Dall'Asta, Baronchelli, Barrat & Loreto (2006). Furthermore, the emergence of atomic conventions has been studied in stochastic game-theoretic frameworks (Shoham & Tennenholtz, 1997), with Markov processes (Ke et al., 2002) and in connectionist neural networks (Hutchins & Hazlehurst, 1995). Finally, the impact of stochasticity in perception, pointing, memory and utterance perception (i.e. there is a probability of error in transmission) has been investigated by Steels & Kaplan (1998).

Figure 4.9: Lexicon coherence (measure 4.2), frequency of lexicon changes (measure 4.3 and average number of forms per meaning (measure 4.4) and averaged over 10 repeated series of 2500 interactions.

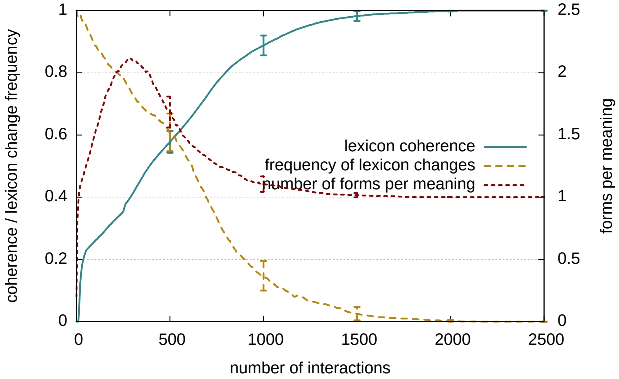


Figure 4.10a: Comparison of four different alignment strategies: lexicon size.

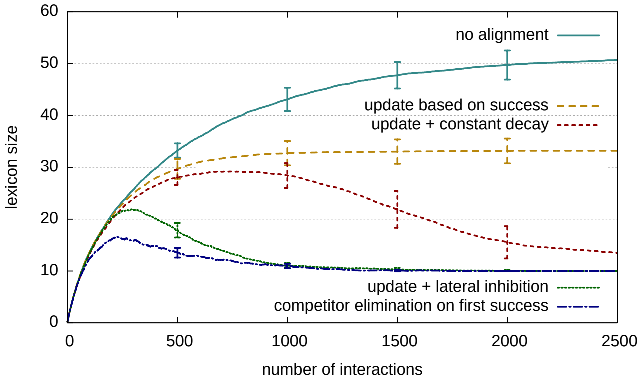


Figure 4.10b: Comparison of four different alignment strategies: communicative success.

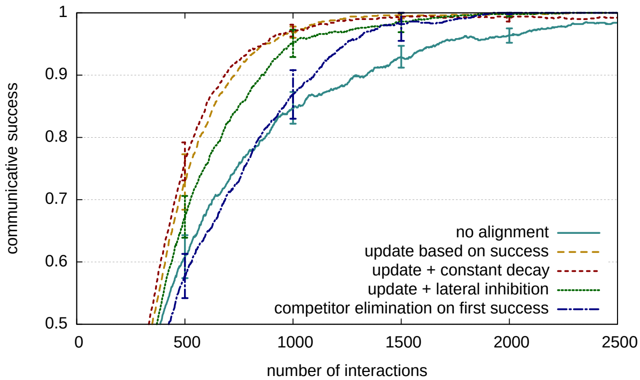


Figure 4.10c: Comparison of four different alignment strategies: frequency of lexicon changes.

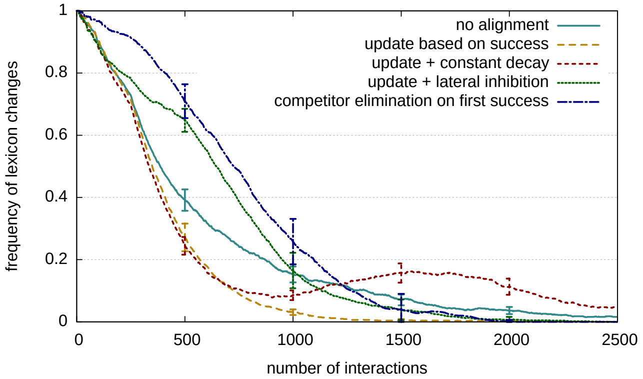


Figure 4.11a: The impact of different values for the word score update parameter Δ_i on communicative success.

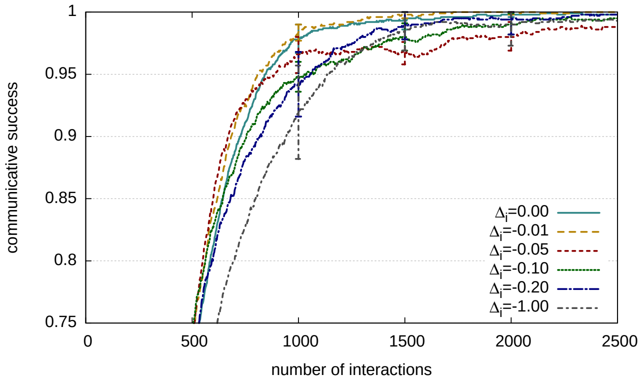


Figure 4.11b: The impact of different values for the word score update parameter Δ_i on lexicon size.

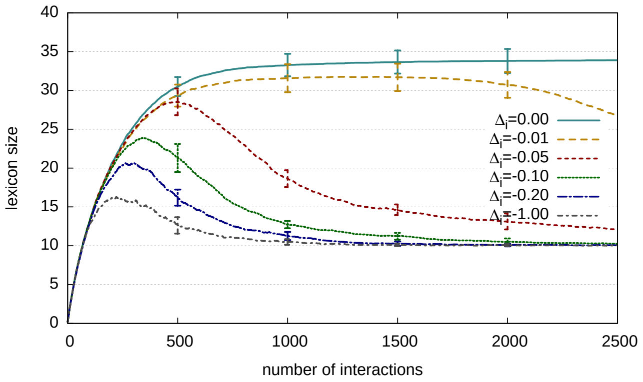


Figure 4.11c: The impact of different values for the word score update parameter Δ_f on communicative success.

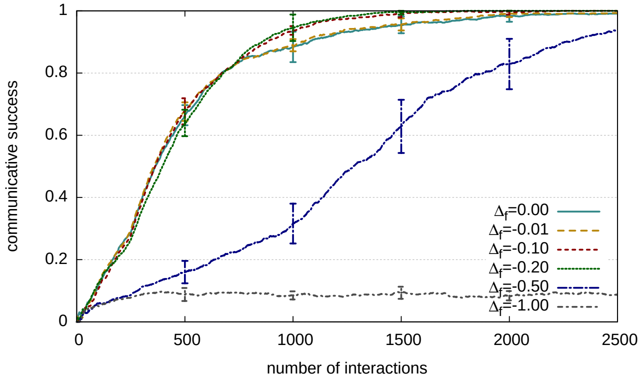


Figure 4.11d: The impact of different values for the word score update parameter Δ_f on lexicon size.

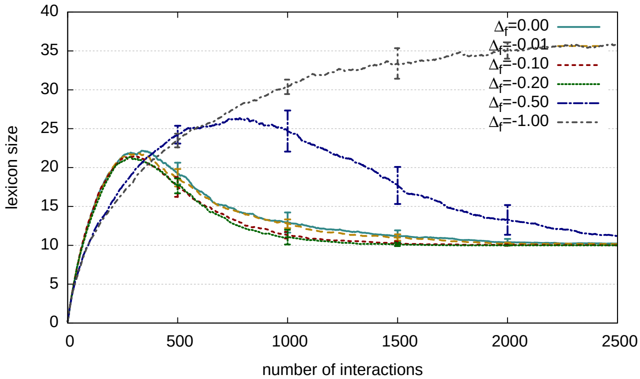


Figure 4.11e: The impact of different values for the word score update parameter Δ_s on communicative success.

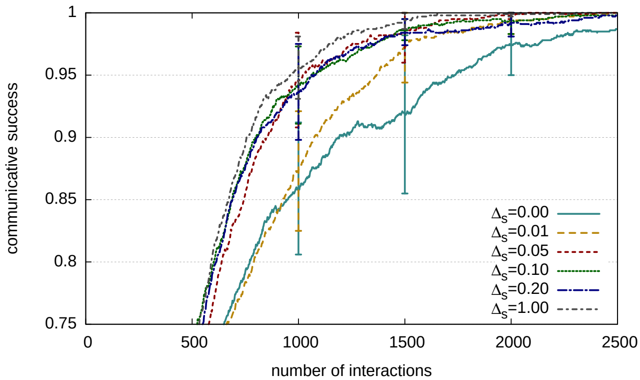


Figure 4.12a: Scaling of communicative success with increasing population size.

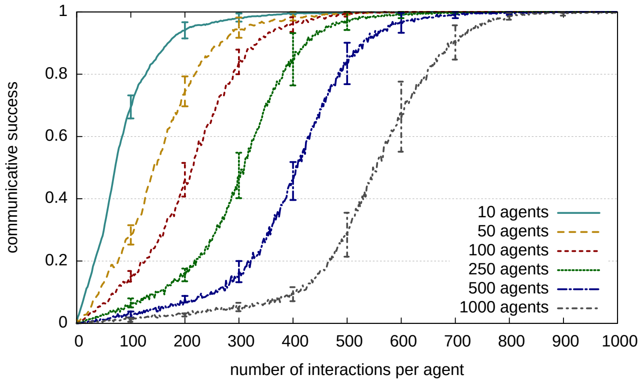
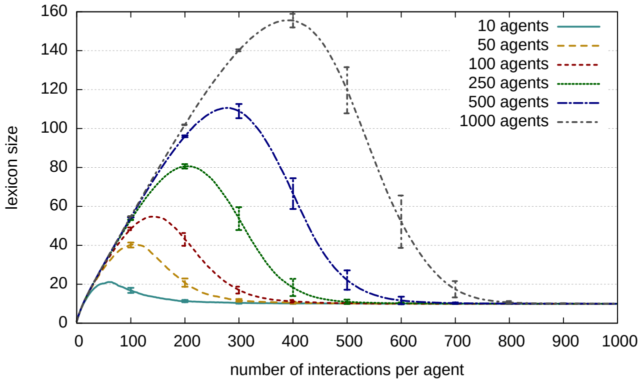


Figure 4.12b: Scaling of lexicon size with increasing population size.



Chapter 5

Challenges of ambiguity in word meaning

Next we investigate a variety of models that take the Naming Game from the previous chapter one step further in complexity. Rather than having the world provide unique categories that then directly become the meanings underlying an utterance, objects in the world are now characterized by a set of properties, as shown in the exemplary context in Figure 5.1. Unlike in the Naming Game, object labels such as `obj-142`, `obj-143`, etc. can not be used as meanings, because they do not remain the same for objects across contexts – instead they serve as a "pointer" that serves as a reference to an object during a game. For setting objects apart, each of them has a set of properties such as `green`, `big`, and so on. As discussed in Section 2.2, these properties can be seen as *categories*, *attributes*, or *features*, and they are essentially unstructured symbols that are part of the world and that are thus automatically shared between the agents of the population. We will call them categories for the remainder of this thesis.

Figure 5.1: Example of a simulated world perception. Objects have a temporary identifier for establishing reference (`obj-142`, `obj-143`, etc.) and are characterized by a set of categories (`green`, `big`, etc).

In order to draw attention to one of such objects, the speaker needs to construct a set of categories that allow the hearer to distinguish the object from all other objects in the context. This process is called *conceptualization* (see Section 2.3.1) and the resulting category set serves as the meaning that is then verbalized by the speaker. For example in the scene of Figure 5.1, the category `green` can be used to distinguish `obj-142` from all other objects, because no other object has this property. Similarly, the categories `small` and `sweet` are each sufficient to discriminate `obj-144` from the rest. However, only the combined meanings `red` ∧ `big` and `red` ∧ `sour` distinguish `obj-143` from the other objects, because each single category of this object is also found in one of the others.

This additional conceptualization layer creates a variety of further ambiguities, and the degree of these uncertainties depends on the nature of word representations (see Section 2.2.2 on page 32). Most importantly, a hearer perceiving a novel form can not know directly which meaning to adopt. For example, upon hearing "fabesi" for `obj-144` in the scene of Figure 5.1, the hearer can infer from the context that the word does not mean `red` (because `obj-143` is also red), but he is left with the uncertainty whether the speaker meant `small` or `sweet`. Furthermore, when word meanings are not restricted to single categories but can be structured, the number of potential meanings multiplies because any discriminating combination of categories is a meaning candidate. Finally, when utterances are allowed to contain multiple words, there is the additional uncertainty in guessing which word carries which meaning. And from the perspective of a single agent, it is undecidable which words contributed to communicative failure when updating word scores at the end of a game.

In this chapter we will analyze a number of strategies for dealing with these challenges. After briefly introducing the world simulation that we are going to use in Section 5.1, we will investigate four lexicon formation models that differ in two aspects. First, whether word meanings are restricted to single categories (unstructured word meanings) or whether forms can be associated to sets of categories (structured word meanings). And second, whether agents can use multiple words to express a meaning (multi-word utterances) or whether they use only a single word (single-word utterances):

	single-word utterances	multi-word utterances
unstructured meanings (single categories)	Section 5.2	Section 5.4
structured meanings (category sets)	Section 5.3	Section 5.5

5.1 A simple world simulator

A simple world simulation provides our agents with artificial perceptions such as illustrated in Figure 5.1. In each interaction, a set of objects $O = \{o_1, o_2, \ldots\}$, each containing a number of distinct categories, is randomly created and perceived by both the speaker and hearer. The number of objects in a context O is randomly chosen to be in the range $cs_{min} \leq |O| \leq cs_{max}$. The set of available categories in the world $C := \{c_1, c_2, \ldots\}$ is constant throughout an experimental run and each object $o \subset C$ consists of a fixed number $|o|$ of categories from C that are randomly drawn. The world simulator guarantees that no two objects in a context have the same set of categories.

Throughout this and the next chapter, by default the number of available categories $|C|$ is 15, the number of categories per object $|o|$ is 10, the minimum number of objects in a context cs_{min} is 2, and the maximum context size cs_{max} is 5. An example context that was created with these parameters is shown below:

object	categories
obj-53	c-4 c-2 c-6 c-12 c-9 c-1 c-14 c-5 c-3 c-15
obj-54	c-10 c-5 c-11 c-9 c-3 c-2 c-8 c-6 c-7 c-14
obj-55	c-7 c-5 c-6 c-2 c-15 c-8 c-10 c-13 c-4 c-3
obj-56	c-10 c-2 c-4 c-7 c-1 c-5 c-6 c-3 c-9 c-13

5.2 Single words for single categories

We first look at how populations of agents can agree a set of names for single categories in language games with single- word utterances. The additional challenge for reaching coherence compared to the Naming Game will be that agents will associate word forms to multiple meanings, in addition to connecting multiple forms to the same meanings.

5.2.1 Conceptualization, interpretation & the interplay with word processing

Most of the strategies for representing and processing words, for playing a language game and for learning are identical to those in the Naming Game (see Section 4.1 on page 53). Here, we will only discuss the differences.

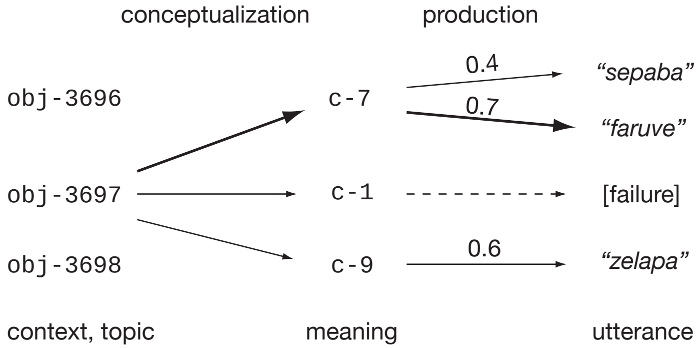


Figure 5.2: Example of a semiotic network in production. Conceptualization constructs three different meanings, and the lexicon is applied independently to each of them. The path that leads to the utterance with the highest word score is drawn with a thicker line.

Lexicon representation. Form meaning representations are represented in an identical way as in the Naming Game. The set of possible word meanings $\mathcal{M}$ amounts to the set of available categories in the world C.

Conceptualization. Given the topic chosen by the speaker and the perceived context, the conceptualization process computes all categories that part of the topic but not of the other objects. For example with this context

object	categories
`obj-3696`	`c-3 c-15 c-11 c-2 c-6 c-10 c-14 c-4 c-13 c-8`
`obj-3697`	`c-1 c-9 c-13 c-7 c-3 c-8 c-4 c-11 c-6 c-10`
`obj-3698`	`c-2 c-14 c-10 c-11 c-15 c-12 c-5 c-6 c-13 c-8`

and `obj-3697` as the topic, conceptualization comes up with three alternative meanings: `c-7`, `c-1` and `c-9`. When no such category can be found, then conceptualization fails, the speaker signals a communicative failure, and the next interaction starts.

Production and the interplay with conceptualization. As in the Naming Game, the speaker looks up his lexicon for all words that have the category resulting from conceptualization as their meaning and from these selects the word with the highest association score. The difference, however, is that conceptualization often results in multiple meanings. The lexicon is looked up for each of them in parallel, and in the end the meaning-utterance combination with the highest word score is selected. Figure 5.2 illustrates this approach. The lexicon is independently applied to the three different meanings `c-7`, `c-1` and `c-9`, and while this agent does not have a word for `c-1`, he knows one word for `c-9` and two words for `c-7`. Of all these utterances, "faruve" is then chosen by the speaker because it involved the word with the highest score of 0.7.

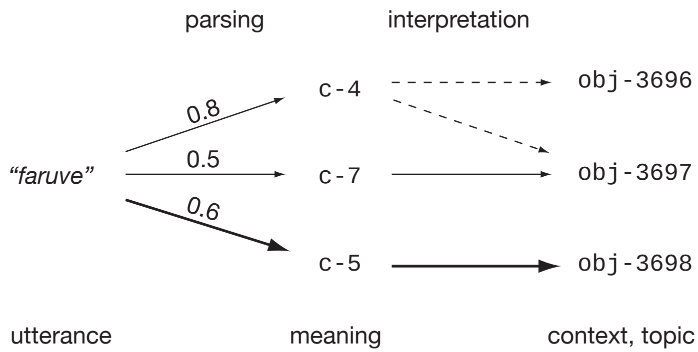


Figure 5.3: Example of a semiotic network in parsing. The lexicon of this agent contains three different meanings for "faruve", which are each interpreted independently. The path with the highest word score that leads to a single interpreted topic is drawn with a thicker line.

As a consequence of this, it is the lexicon that 'selects' the meanings that are verbalized, which we will later see is a good strategy. By using the scores of the involved words as a criterion for which meaning to choose, the speaker increases his chance to be understood, because higher word scores also mean that the population reached more consensus about how to name a particular category.

Invention. Only when production completely fails, i.e. the speaker does not have a word for any of the conceptualized meanings, a new word is created for a randomly chosen meaning and production is retried again.

Parsing. The hearer retrieves all words from his own lexicon that match the utterance. Each of these meanings is then independently interpreted in the context.

Interpretation and the interplay with parsing. A meaning is interpreted in the context by retrieving all objects that share the category. When multiple objects found for a meaning (and thus the parsed meaning does not discriminate an object from the rest), then interpretation for that particular meaning fails. Again, this process is interconnected with lexicon application. Out of the successful interpretations, the where the involved form-meaning association has the highest score is eventually selected.

An example of this is shown in Figure 5.3. Although the association from "faruve" to `c-4` has the highest score, it is not selected because the semantic interpretation of `c-4` results in two different referents. Instead, the next highest word with the meaning `c-5` is chosen, yielding `obj-3698` as the topic interpreted by the hearer. Through this, the context constrains ambiguity in the lexicon by excluding words meanings that are not in line with the current scene.

#	speaker	topic	meaning	utterance	hearer	meaning	topic	success?
500	agent 6	`obj-1783`			agent 2			no
501	agent 1	`obj-1785`	`c-6`	*"ziraxo"*	agent 8	`c-5`	`obj-1785`	yes
502	agent 1	`obj-1787`	`c-15`	*"wimure"*	agent 9	`c-13`	`obj-1788`	no
503	agent 6	`obj-1789`	`c-15`	*"namuvo"*	agent 5	`c-3`		no
504	agent 8	`obj-1792`			agent 9			no
505	agent 10	`obj-1797`	`c-14`	*"xazapo"*	agent 5	`c-14`	`obj-1797`	yes
506	agent 8	`obj-1799`	`c-9`	*"kugoma"*	agent 9	`c-9`	`obj-1799`	yes
507	agent 7	`obj-1803`			agent 4			no
508	agent 7	`obj-1805`	`c-6`	*"ziraxo"*	agent 4	`c-6`	`obj-1805`	yes
509	agent 3	`obj-1806`	`c-8`	*"namuvo"*	agent 9			no
510	agent 2	`obj-1810`	`c-1`	*"bikuse"*	agent 4	`c-12`		no
511	agent 6	`obj-1812`			agent 4			no
512	agent 10	`obj-1817`	`c-8`	*"gubawo"*	agent 5	`c-4`		no
513	agent 8	`obj-1819`	`c-7`	*"vatage"*	agent 10	`c-7`	`obj-1819`	yes
514	agent 6	`obj-1822`			agent 7			no

Figure 5.4: Overview of 15 consecutive interactions from game 500 on. It shows the agents that are interacting, the topic chosen by the speaker, the conceptualized meaning that was chosen, the utterance, the meaning parsed by the hearer together with the interpreted topic, and whether the agents reached communicative success.

Recovery from failure & adoption. Three cases are distinguished when an interaction fails. First, when the hearer could not come up with a topic (either because he did not know the word or because interpretation returned multiple objects), then he re-conceptualizes the scene for the topic pointed at by the speaker and for each resulting meaning stores an association to the form heard in his lexicon. Second, when the hearer pointed to the wrong object (and is consequently corrected by the speaker), then he checks whether another path in his processing led to the correct topic. For example in Figure 5.3, the alternative path "faruve" $\longrightarrow$ `c-7` $\longrightarrow$ `obj-3697` would have resulted in the topic intended by the speaker but was not chosen because the score of the involved word was not the highest. In such a case, nothing happens and this particular path is treated specially in consolidation (below). And third, when the hearer pointed to the wrong object and no other correct path in processing existed, then the hearer also re-conceptualizes the scene and adds new words for all the resulting meanings to his lexicon (except those for which already an association to the form heard exists).

Consolidation. The consolidation strategy is very similar to the Naming Game. After a failed interaction, the score of the word used is lowered in score. After a success, the score of the responsible word increased and those of words with competing forms are laterally inhibited. The parameters for this update are also the same, with $\Delta_s = 0.1$, $\Delta_f = -0.1$ and $\Delta_i = -0.2$.

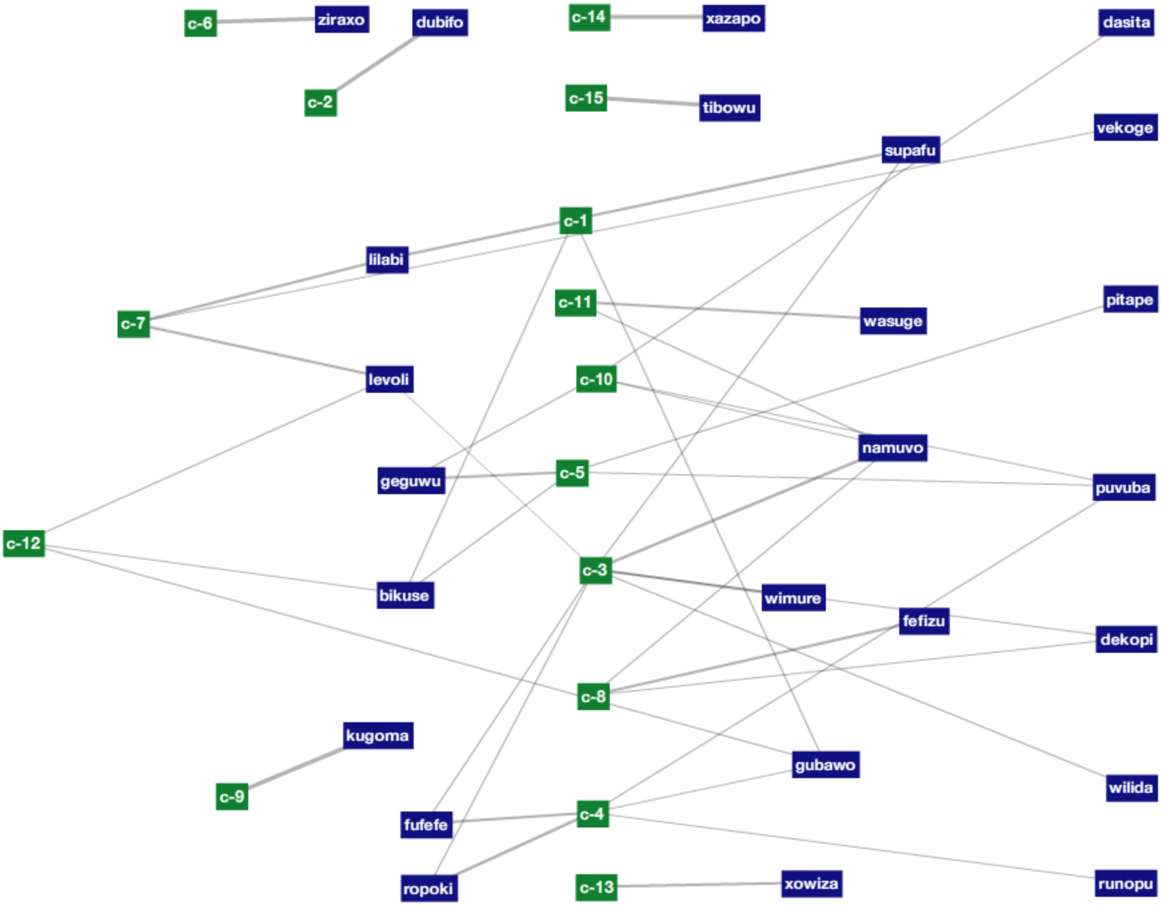


Figure 5.5: Network representation of the complete lexicon of the first agent in the population after 1500 interactions. Each line represents a word in the lexicon of the agent and connects the meaning of the word with its form. The line widths denote the strength of the association.

However, there two differences. First, since now there is also the possibility that multiple meanings are associated to the same form, they also need to be reduced, which is done using the same lateral inhibition as for competing forms. Second, when the hearer pointed to the wrong topic but another path in his processing lead to the correct topic (as described above), then the score of the word involved is updated as if the interaction would have been a success (i.e. the score of the word is increased and words with competing forms or meanings are inhibited).

5.2.2 Dynamics and strategies for reducing ambiguity

Figure 5.4 shows an example of 15 consecutive language games in a population of 10 agents that follow the strategies described in the previous section. There are a variety of differences to the Naming Game. First, it can happen that the speaker is not able to produce an utterance because conceptualization fails (for example in interaction 500). Second, even when the hearer is able to parse an utterance, it can happen that non of the resulting meanings yield a unique object in the context (e.g interaction 503). Third, even when the hearer is able to infer a referent, it might still be a different one than intended by the speaker (e.g. interaction 502). And fourth, even when speaker and hearer reach communicative success, their understanding of the word used might still be different. For example in interaction 501, the speaker conceptualizes `obj-1785` as `c-6`. The hearer parses the utterance as `c-5`, but by chance this gets interpreted as the same object as intended speaker and consequently, both agents assume that they used the word "ziraxo" correctly and will update word scores accordingly.

These additional uncertainties are clearly reflected in early states of the agents' lexicons. Figure 5.5 shows a snapshot of the lexicon of the first agent in the population after 1500 interactions. Although this agent has already settled on the forms for some categories (mostly at the top of the graph), many meanings in that lexicon are not only linked to multiple forms as before, but because hearers adopt multiple meanings for forms in the case of failure, there are also many forms that are connected to multiple meanings. In order to establish an unambiguous one-to-one mapping of single forms to single meanings, alignment dynamics need to reduce these competing forms and meanings over the course of many interactions.

Once more, Figure 5.6a compares the forms associated by four agents in the population to three categories after 1500 interactions. Because the number of potential word meanings (15 categories) is bigger than in the Naming Game in the previous chapter (10 objects), and because due to the uncertainty in meaning the same forms become associated to multiple categories, there are more competing forms for each category in the lexicons (compare Figure 4.4a, page 59). Analogously, competing meanings for three forms in the lexicons of the same four agents are shown in Figure 5.6b. The degree of competition between meanings is less than for forms, as we also see later on. Finally, partial lexicons at the end of the alignment process are shown in Figure 5.7a and 5.7b. Competing forms and meaning have been completely eliminated and unambiguous mappings from single categories to single forms have been established.

The increased competition between words in the alignment process is even more visible in the next two graphs. Figure 5.8a shows the changing scores of all words in the population with the meaning `c-2`. Although the winning form "dubifo" is created very early and although only a few other words are ever used successfully (i.e. their score increases above the initial word score of 0.5), 25 other forms spread in the population during the first 25000 interactions and slowly become eliminated. Similarly, Figure 5.8b shows the competition

meaning	agent 1		agent 2		agent 3		agent 4	
c-1	*"lilabi"*	0.50	*"dasita"*	0.40	*"dasita"*	0.50	*"bixina"*	0.60
	"bikuse"	0.20	*"lazixe"*	0.30	*"lilabi"*	0.50	*"namuvo"*	0.30
	"gubawo"	0.30	*"xowiza"*	0.30	*"bixina"*	0.10	*"vugumi"*	0.30
	"supafu"	0.40	*"lilabi"*	0.20	*"xowiza"*	0.40	*"lazixe"*	0.30
							"bikuse"	0.20
							"ropoki"	0.10
							"runopu"	0.30
							"dekopi"	0.30
							"supafu"	0.10
c-2	*"dubifo"*	1.00	*"wimure"*	0.50	*"sipuva"*	0.30	*"wimure"*	0.40
			"supafu"	0.50	*"dubifo"*	0.50	*"vekoge"*	0.40
			"fuxefa"	0.10			*"vugumi"*	0.50
			"tigasi"	0.10			*"lazixe"*	0.50
			"dubifo"	0.50			*"dutiru"*	0.10
							"dubifo"	0.50
c-3	*"wimure"*	0.50	*"wimure"*	0.50	*"pitape"*	0.50	*"levoli"*	0.50
	"levoli"	0.30	*"vatage"*	0.50	*"gubawo"*	0.30	*"wimure"*	0.40
	"fufefe"	0.30	*"dekopi"*	0.50	*"miwupa"*	0.20	*"vugumi"*	0.30
	"namuvo"	0.40	*"miwupa"*	0.50	*"geguwu"*	0.60	*"supafu"*	0.30
	"supafu"	0.30	*"ropoki"*	0.50	*"sekero"*	0.30	*"tigasi"*	0.10
	"ropoki"	0.30	*"fuxefa"*	0.50			*"lazixe"*	0.20
	"dekopi"	0.20	*"bikuse"*	0.40			*"geguwu"*	0.20
	"wilida"	0.20	*"puvuba"*	0.30				
			"namuvo"	0.40				

Figure 5.6a: Forms associated to 3 different meanings by the first four agents of a population of 10 after 1500 interactions.

of meanings for the form "dubifo" in the population. Before the category `c-2` eventually wins, the agents have tried out 10 other meanings.

The overall performance of a population of 10 agents that follows the above strategies to agree on forms for single meanings in single-word utterances is shown in Figure 5.9. First, discriminative success as a measure for often the speaker is able to conceptualize the scene is constant at around 55% through the entire run. That means that in 45% of the interactions the scenes computed by the world simulator (15 categories, 10 categories per object, 2-5 objects per scene) are too "difficult" to discriminate the topic from the other objects using a single category only. Consequently, communicative success as defined in measure 2.1 can only reach the same level as discriminative success, which it does after about 5000 interactions. In order to still be able to see how

> *Measure 5.1: Discriminative success*
>
> *Measures the fraction of interactions in which the speaker was able to construct a meaning for the current topic in the context. For each interaction with at least one successful conceptualization, the value of 1 is recorded, for all others 0. Values are averaged over the last 250 interactions.*

form	agent 1		agent 2		agent 3		agent 4	
"levoli"	c−12	0.30	c−12	0.40			c−11	0.50
	c−7	0.40					c−7	0.50
	c−3	0.30					c−3	0.50
							c−4	0.40
"lilabi"	c−1	0.50	c−1	0.20	c−1	0.50	c−7	0.40
	c−7	0.50						
"dubifo"	c−2	1.00	c−5	0.10	c−2	0.50	c−11	0.40
			c−2	0.50			c−2	0.50

Figure 5.6b: Meanings associated to 3 different forms by the first four agents of a population of 10 after 1500 interactions.

meaning	agent 1		agent 2		agent 3		agent 4	
c−1	*"lilabi"*	1.00	*"lilabi"*	1.00	*"lilabi"*	1.00	*"lilabi"*	1.00
c−2	*"dubifo"*	1.00	*"dubifo"*	1.00	*"dubifo"*	0.80	*"dubifo"*	1.00
c−3	*"geguwu"*	1.00	*"geguwu"*	0.90	*"geguwu"*	1.00	*"geguwu"*	1.00

Figure 5.7a: Forms associated to 3 different meanings by the first four agents of a population of 10 after 5000 interactions.

successfully the agents use their linguistic knowledge, we introduce the measure of communicative success given discriminative success, which basically 'ignores' interactions in which the speaker could not construct a meaning. This success in language reaches full 100% after about 5000 interactions. Finally, average lexicon sizes show similar dynamics compared to the Naming Game. During an initial phase, in which many words are invented adopted, the average number of form-meaning associations in each agent's lexicon reaches a peak of slightly over word. Then, competing forms and meanings become eliminated from the lexicons, before lexicon size a stable level of 15 words, which is optimal given that there are 15 categories in the world to express.

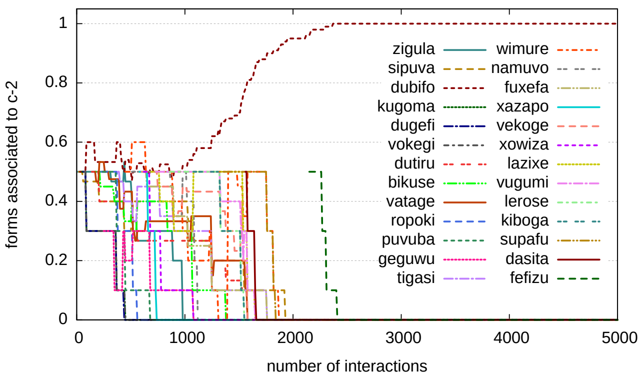
As demonstrated in Figure 5.10, it takes much longer to reach full coherence and lexicon stability than to reach complete communicative success, because even when the population already agreed on which forms to use for which meanings, there are still a big number of (now unused) words with competing forms and meanings left in the lexicons, which only slowly become removed. At the peak of lexicon size, there are more than four forms associated to each

> *Measure 5.2: Communicative success given discriminative success*
>
> *Out of the interactions in which the speaker was able to conceptualize, measures the fraction of games in which communicative success was reached (compare measure 2.1, page 28). In all interactions with discriminative success, a value of 1 is recorded upon communicative success and 0 in the case of failure. In interactions where the speaker could not conceptualized, the value of the previous interaction is recorded (and 0 in the beginning). Values are averaged over the last 250 interactions.*

form	agent 1		agent 2		agent 3		agent 4	
"geguwu"	c-3	1.00	c-3	1.00	c-3	1.00	c-3	1.00
"lilabi"	c-1	1.00	c-1	1.00	c-1	1.00	c-1	1.00
"dubifo"	c-2	1.00	c-2	1.00	c-2	1.00	c-2	1.00

Figure 5.7b: Meanings associated to 3 different forms by the first four agents of a population of 10 after 5000 interactions.

Figure 5.8a: Evolution of words with the meaning c-2 in the population. Each line shows for a single form the corresponding word scores averaged over all agents that connect the form to c-2.



meaning. And because conceptualization results on average in 2.6 different meanings (if it succeeds), the average number of meanings connected to each form reaches about 2.2 at this point. The number of meanings per form is often also called 'homonymy', but we find this term misleading because in natural language homonyms tend to coexist in a language, whereas in our experiments they are subject to competition.

The impact of different alignment strategies for updating word scores based on the outcome of the game on the performance in language games is very similar to in the Naming Game (see Section 4.3 on page 62) and we will not analyze it again. Obviously, competing meanings for forms need to be dampened, which here underlies the same dynamics as the dampening of competing forms.

We want to highlight the importance of another strategy, especially since it is usually not incorporated in similar alignment mechanisms. When the hearer has pointed to the wrong object, he inspects his parsing and interpretation

Measure 5.3: Average number of meanings per form (homonymy)

The average number of meanings associated to each form by an agent is averaged over all agents in the population:

$$v = \sum_{i=1}^{|P|} \frac{|L(a_i)|}{|\{f : f \in \mathcal{F} \ \wedge \ \exists w(w \in L(a_i) \wedge f_w(w) = f)\}|} \ / \ |P|$$

Values v are averaged over the last 250 interactions.

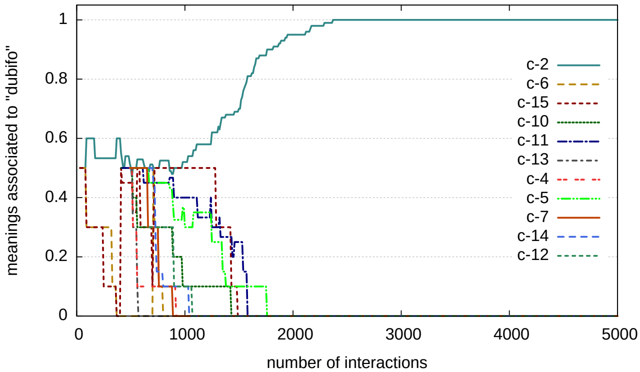


Figure 5.8b: Evolution of words with the form "dubifo" in the population. Each line shows for a single meaning the corresponding word scores averaged over all agents that associate this meaning to "dubifo".

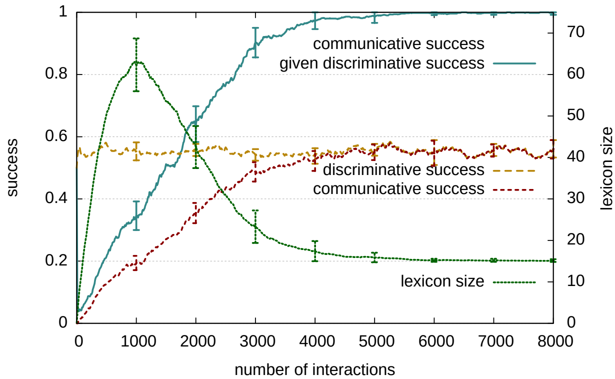


Figure 5.9: Main dynamics in a population of 10 agents. Discriminative success (measure 5.1), communicative success (measure 2.1), discriminative success on successful discrimination (measure 5.2) and lexicon size (measure 4.1) are averaged over 10 repeated series of 8000 interactions.

processing whether another path through the semiotic network resulted in the correct topic intended by the speaker (see Section 5.2.1, paragraph "Recovery from failure & adoption" above). When this is the case, he does not re-conceptualize the scene and adopt new meanings, but to the contrary, treats that path as if it would have been a communicative success.

Figures 5.11a and 5.11b show the impact of using this strategy on communicative success and lexicon size. To make the difference more clear by increasing ambiguities in the lexicons, the number of categories in the world has been set to 50, with the rest of the parameters the same as before. While communicative success is only slightly higher for agents that use the strategy over others that do not, the maximum lexicon size is reduced from about 430 to about 310, and at the same time the point of maximum lexicon size is reached earlier. Additionally, the degrees of synonymy and homonymy are also significantly lower and the lexicon stabilizes more quickly, which all suggests that this strategy speeds up alignment by reinforcing knowledge that already existed in their inventories but that was not conventionalized enough to win over competitors.

Figure 5.10: Lexicon structure and stability in a population of 10 agents. The average number of forms per meaning (measure 4.4), the number of meanings per form (measure 5.3), lexicon coherence (measure 4.2 and stability (measure 4.3) are averaged over 10 repeated series of 8000 interactions.

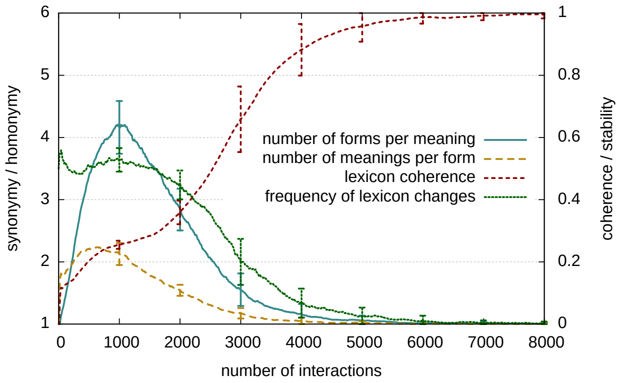
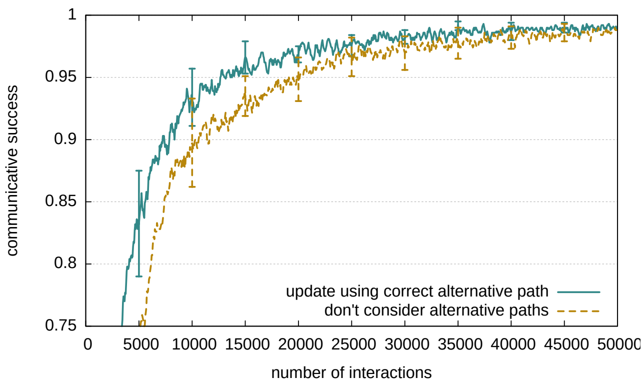


Figure 5.11a: Communicative success in a world of 50 categories for a population in which hearers update their lexicons considering correct alternative paths in their processing and in which they do not.



Furthermore, the way how alternative conceptualizations are handled by the speaker and hearer has a dramatic impact on the dynamics of the language games. First, it matters whether the speaker tries to apply his lexicon to all meanings that were constructed by conceptualization (we call this strategy “speaker: process all”), or whether he selects a random meaning and applies his lexicon to this one (“speaker: process one”). As discussed above in Section 5.2.1 (see also Figure 5.2), all meanings are processed in parallel by the speaker. Second, it has a big impact whether after a failure the hearer adopts words for all re-conceptualized meanings (“hearer: adopt all”, default) or for a random meaning (“hearer: adopt 1”).

Each of these strategies has their advantages and disadvantages, and Figures 5.12a – 5.12e analyze for all four combinations of them communicative success, lexicon size, the number of meanings per form, lexicon coherence and stability in a population of 10 agents. Again, in order to make differences more visible, the number of categories in the world is 50 instead of 10, which greatly increases ambiguities (as we will discuss further below).

Communicative success and lexicon stability are reached by far the quickest when the speaker processes all meanings. Because this allows speakers to

Figure 5.11b: Lexicon size in a world of 50 categories for a population in which hearers update their lexicons considering correct alternative paths in their processing and in which they do not.

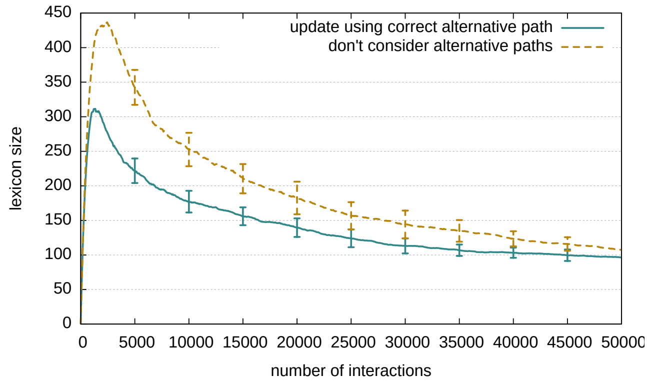
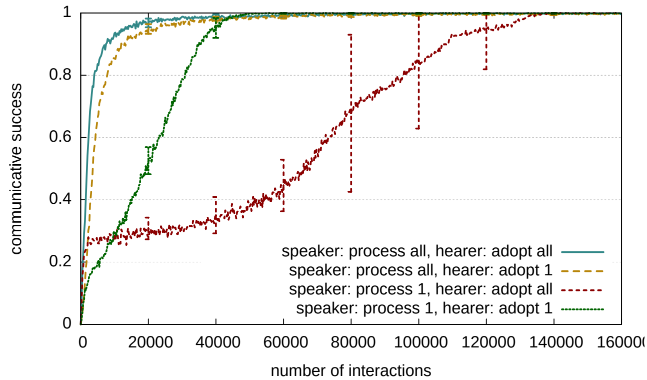


Figure 5.12a: The impact of four different strategies for handling alternative conceptualizations on communicative success.



prefer meanings for which he has 'good' words that are already more conventionalized, the population can start to communicate very successfully about a few meanings. On the downside, it takes longer for the population to agree on words for all categories in the world. Only when conceptualization exclusively comes up with meanings that are not well conventionalized, agents will be forced to communicate about them, which delays complete alignment. As a consequence, lexicon coherence rises very slowly (and does not reach 100% within the 160000 games played) and the frequency of lexicon changes does not reach 0 for a very long time.

When speakers process only one randomly selected meaning, then it takes much longer to reach communicative success. The population has to learn words for all possible meanings simultaneously, which greatly increases ambiguities and causes high frequencies of lexicon changes for long periods of time. On the positive side, because all meanings are tried out with equal change, only with this strategy the agents can reach 100% lexicon coherence and complete stability within the 160000 language games.

Hearers that adopt all re-conceptualized meanings upon recovering from a communicative failure initially have higher lexicon sizes and higher degrees of competing forms and meanings, because of course more words get created in the lexicons of the agents. And it takes much longer for these measures to

Figure 5.12b: The impact of four different strategies for handling alternative conceptualizations on lexicon size.

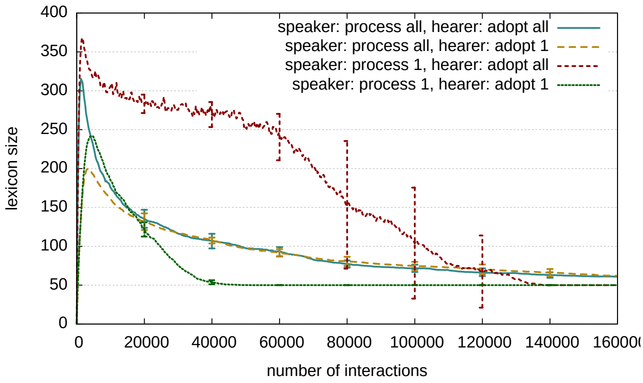
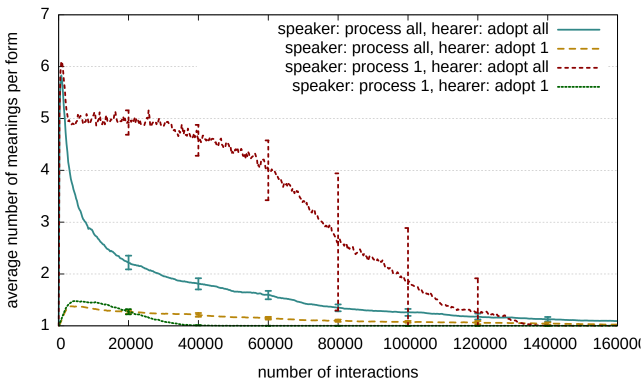


Figure 5.12c: The impact of four different strategies for handling alternative conceptualizations on the number of meanings per form. The curve for the number of forms per meaning looks very similar and is thus not shown.



reach optimal values, because many new words become added every time an interaction fails. But surprisingly, adopting all meanings leads the quickest to success and stability when combined with the "speaker: process all" strategy. When speakers use meanings with more conventionalized meanings, there is less general uncertainties and hearers can afford to introduce words for all meanings and later let the context help to disambiguate between them. However, when combined with the "speaker: process 1" strategy, then the opposite happens. Ambiguities are so great that words become added or removed from the lexicons in almost every interaction up to about game 6000 and it takes the longest to reach communicative success.

In contrast, when hearers only adopt a word for one randomly selected reconceptualized meaning, then lexicon size and form and meaning ambiguities are much lower. Instead of relying on the lexicon to sort out the meanings of words through use in different contexts, hearers make single random guesses and the words immediately disappear again when they do not by chance are in line with similar guesses by other agents in the population. But because ambiguities in the lexicon are avoided, this 'random' walk strategy works reasonably well and when combined with the "speaker: process 1" strategy, complete coherence is reached by far the quickest.

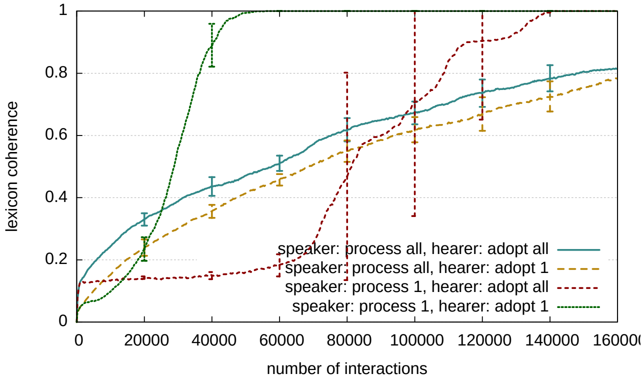


Figure 5.12d: The impact of four different strategies for handling alternative conceptualizations on lexicon coherence.

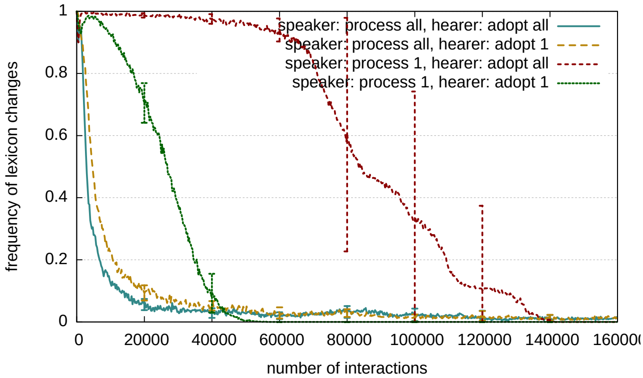


Figure 5.12e: The impact of four different strategies for handling alternative conceptualizations on the frequency of lexicon changes.

5.2.3 Scaling out

With word meanings being one-to-one mappings between forms and meanings as in the Naming Game, and with a relatively simple world simulation (15 categories, 10 categories per object, 2 to 5 objects per context) the model exhibits similar scaling behavior with increasing population sizes compared to the Naming Game. Figures 5.13a and 5.13b show communicative success given discriminative success and lexicon size for population sizes from 10 to 200. Success evolves in a similar, yet flatter s-curve, and lexicon size displays an initial peak that is slowly reduced in subsequent interactions. The additional ambiguities in what words mean result in a higher maximum lexicon sizes (e.g. 240 for 100 agents, compared to 55 in the Naming game (although there for 10 meanings, see Figure 4.12b on page 69).

Much more interesting is the scaling with increasing complexity of the world. Figure 5.14a demonstrates that discriminative success increases when more categories available to the world simulator. When object perceptions are created from $|C| = 40$ categories or more (and the number of categories per scene remains 10, the number of objects per context 10, and context sizes between 2 and 5), then object perceptions differ enough so that speakers can discriminate

Figure 5.13a: *Communicative success given discrimination (measure 5.2) for five different population sizes. Results are averaged over 10 series of varying length, but each with 4000 interactions per agent.*

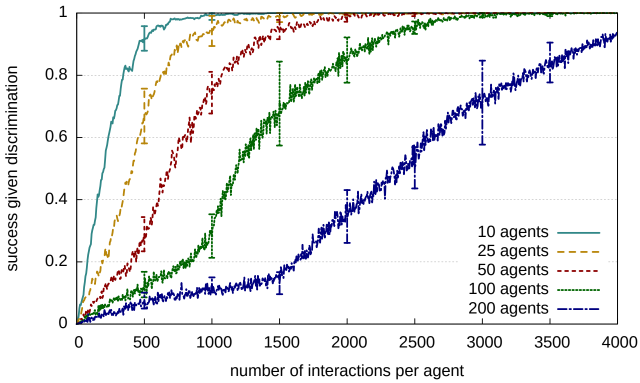
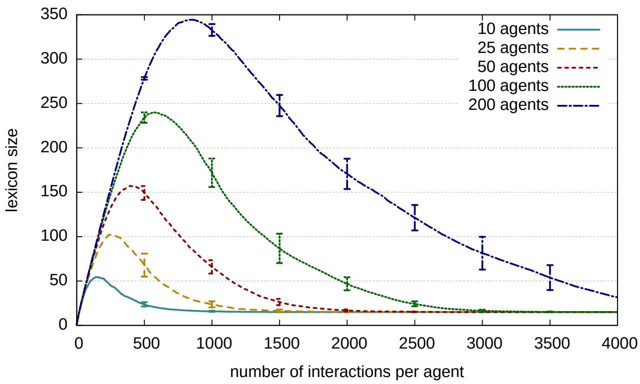


Figure 5.13b: *Lexicon size (measure 4.1) for five different population sizes. Results are averaged over 10 series of varying length, but each with 4000 interactions per agent.*



topics with a single category even for context sizes of 4 and 5, and consequently discriminative success reaches 100%.

But while discriminative success increases, word meaning ambiguities also rise in the population. As shown in Figure 5.14b, the number of different ways how a scene can be conceptualized climbs from about 2 for 15 categories to almost 8 for 100 categories. This means that in a world with 15 categories, hearers that try out a newly adopted word in production have an almost 50% chance of using the meaning that was intended by the previous speaker. In a world with 100 categories, this probability is only about 12.5%.

The coupling of the number of categories in the world with ambiguity in re-conceptualization is also clearly reflected in the lexicons of the agents, as

Measure 5.4: Number of alternative conceptualizations

Measures in how many ways the current topic can be conceptualized in the current scene and thus provides a means to quantify referential ambiguity. In each interaction in which the speaker is able to discriminate the topic from the other objects in the scene, the number of resulting meanings is recorded. In case of discriminative failure, the value from the previous interaction is recorded (initially 0).

Figure 5.14a: Discriminative success (measure 5.1) with increasing numbers of categories in the world. Results were obtained by running 10 series of 500 language games and then sampling the average discriminative success over the last 250 interactions each.

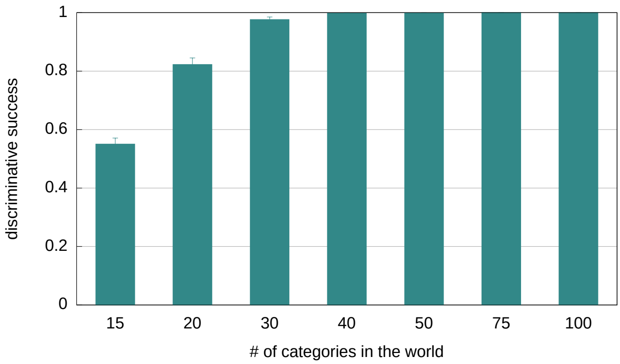
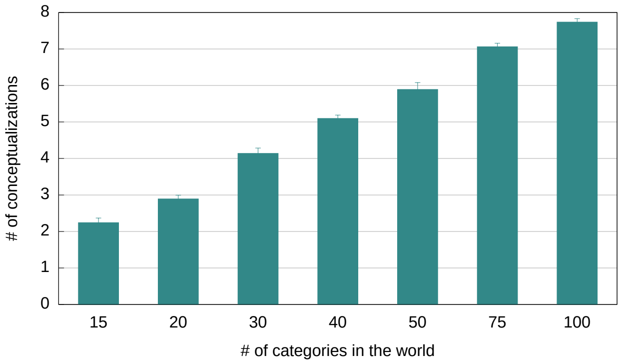


Figure 5.14b: Number of alternative conceptualizations per scene (measure 5.4) for world simulators with increasing number of categories.



illustrated in Figure 5.15a. For all different world simulations, the maximum average number of meanings per form (reached in the initial phase when most words get invented and adopted) is always about as high as the average number of alternative conceptualizations.

Despite such high levels of ambiguity, communicative success scales well with the number of categories in the world and as Figure 5.15b shows, communicate success quickly reaches very high levels of over 95%. However, after an initial steep increase, the curve flattens and complete success is in fact only achieved for worlds with less than 50 categories (the same holds for coherence, not shown).

This is due to the default strategy of selecting meanings based on how well they can be expressed with an agent's lexicon (see above). With increasing numbers of alternative conceptualizations, speakers can more easily rely on categories for which well-established forms exist and avoid those which turned out to be difficult to talk about. As a consequence, the fraction of categories that are frequently used by the population decreases, and only when no other conceptualizations are possible, less conventionalized meanings are used. This, in turn, slows down the alignment process for these less-frequent categories, because there are less opportunities to try them out and eliminate competing forms and meanings. Therefore, the only slowly decreasing lexicon sizes shown

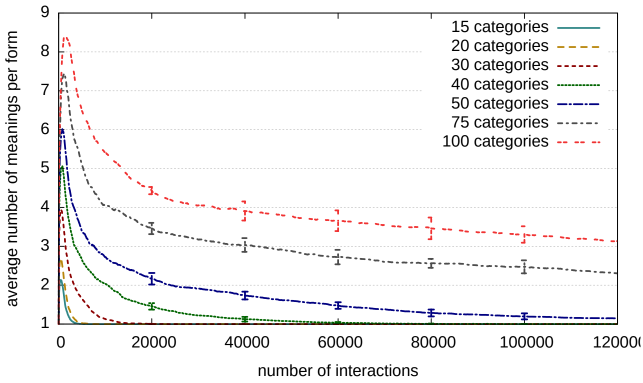


Figure 5.15a: The average number of meanings per form (measure 5.3) for increasing numbers of categories in the world. Results are averaged over 10 series of 120000 interactions.

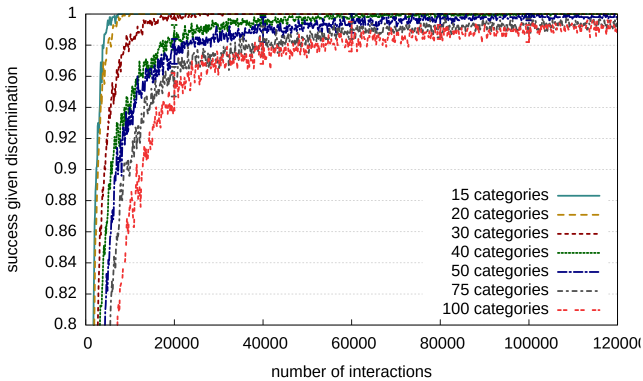


Figure 5.15b: Communicative success given discriminative success for increasing numbers of categories in the world.

in Figure 5.15c are not in conflict with the high levels of success exhibited in Figure 5.15b. They simply reflect the fact that most of the words in the agents lexicon are only rarely used and are thus not subject to competitor dampening mechanisms.

Quite different dynamics emerge when speakers are not allowed to decide which of the alternative conceptualizations to express in an utterance but when they randomly select a meaning, as shown in Figures 5.16a – 5.16d (see Section 5.2.2 above for a discussion of the difference between these strategies). In

Measure 5.5: Succeeded with different meanings

Measures the fraction of interactions in which agents reached communicative success although the hearer parsed the utterance into a different meaning than the one that was conceptualized by the speaker. After each interaction, the value of 1 is recorded when communicative success was reached (see measure 2.1) and when the meaning that underlies the utterance produced by the speaker differs from the meaning that was used by the hearer to interpret the topic. Otherwise, a value of 0 is recorded. Values are averaged over the last 250 interactions.

Figure 5.15c: Lexicon size for increasing numbers of categories in the world. The speaker uses a randomly selected conceptualization to produce an utterance.

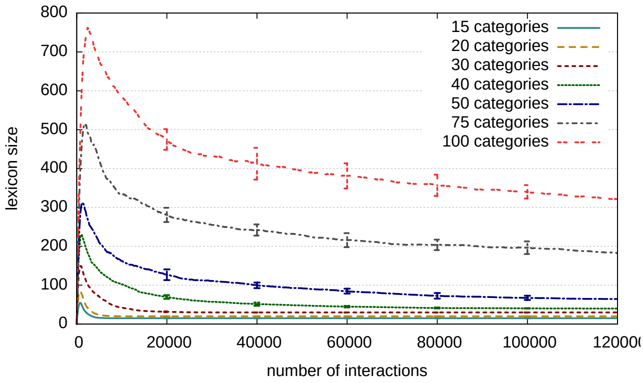
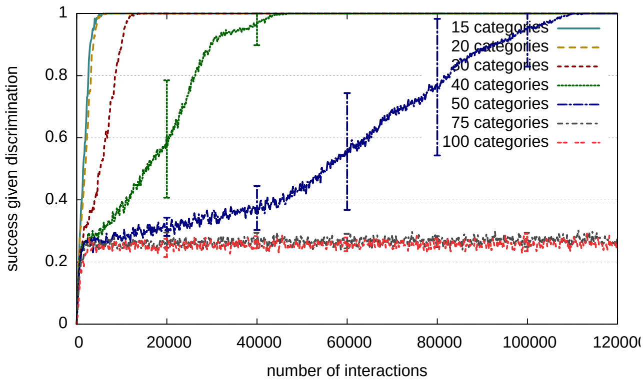


Figure 5.16a: Communicative success given discriminative success for increasing numbers of categories in the world. The speaker uses a randomly selected conceptualization to produce an utterance. Results are averaged over 10 series of 120000 interactions.



worlds with 50 categories or less, complete communicative success is reached within the run of 120000 interactions (Figure 5.16a) and lexicons are reduced to unambiguous mappings of single forms to single categories (Figure 5.16b). And because each category has an equal chance of being used in communication, the lexicons quickly reach complete stability (Figure 5.16d).

Interestingly, alignment dynamics completely break down for worlds with more than 50 categories. From 75 categories on, communicative success stays at a stable level of 25% and the frequency of lexicon changes remains at almost 100%, which means that the lexicons undergo constant change without reaching any coherence. This is due to the combination of two factors. First, with increasing numbers of possible conceptualizations, the chance that the speaker and hearer communicate successfully but use different meanings also increases. As shown in Figure 5.16c, this happens in 20% of the successful interactions in worlds with 75 or 100 categories. That also means that in every fifth successful interaction the agents incorrectly assess whether they used their words correctly and they will wrongly increase the scores of the involved words and inhibit scores of competitors. Combined with the second factor of increased form and meaning ambiguities in the lexicons (for example the number of meanings per form goes beyond 6 from 75 categories on, Figure 5.16b), the feedback loop of communicative success on the lexicon collapses because

Figure 5.16b: Average number of meanings per form for increasing numbers of categories in the world. The speaker uses a randomly selected conceptualization to produce an utterance.

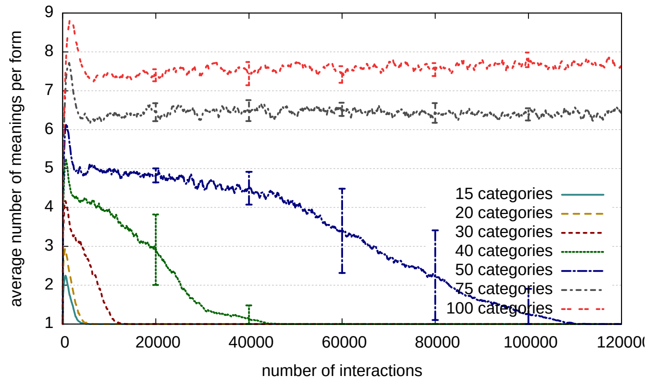
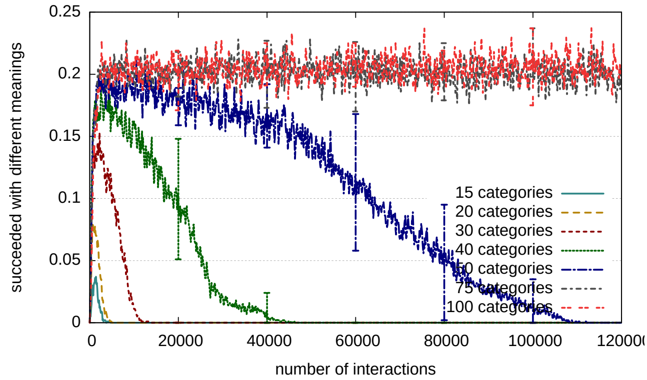


Figure 5.16c: The fraction of interactions in which communicative success is reached although the speaker and hearer used different meanings (measure 5.5) for increasing numbers of categories in the world. The speaker uses a randomly selected conceptualization to produce an utterance.

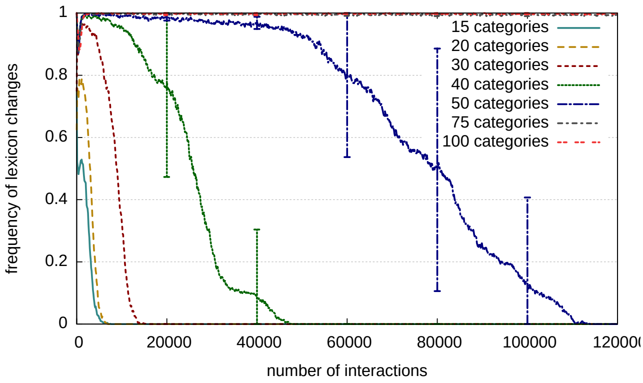


agents are not able anymore to consistently prefer to use the right forms for the right meanings.

5.3 Holistic coding of structured word meanings

Next, we will remove the restriction that word meanings can only be single categories. With the previous model, agents reached only 55% discriminative success, which means that in 45% of the scenes a single category was not sufficient to discriminate the topic from the other objects in the context. To overcome this limitation, we will now allow agents to construct structured meanings, i.e. sets of categories that together distinguish an object from the context.

Figure 5.16d: *Frequency of lexicon changes for increasing numbers of categories in the world. The speaker uses a randomly selected conceptualization to produce an utterance.*



5.3.1 Constructing and interpreting compositional meanings

All strategies for playing the game, production and parsing, learning, and so on are identical to those of the previous section. The only difference lies in the way how meanings are constructed and interpreted and in the extension of word meanings to category sets.

Conceptualization. The goal of the conceptualization process is to construct meanings $\{m_1, m_2, \ldots\}$ as the minimal category sets that are part of the topic $o_t \in O$ but that differ in at least one category from all other objects in the context $O \setminus \{o_t\}$:

$$\{m : m \subseteq o_t \ \wedge \neg \exists o(o \in O \setminus o_t \wedge m \subseteq o\}$$

'Minimal' means that the process only yields the shortest category sets that satisfy the conditions above. In practice, the algorithm first searches for category sets of length 1, then of length 2, and so on, until at least one solution is found.

For example, with this as the context

object	categories
`obj-826`	`c-11 c-3 c-9 c-13 c-15 c-2 c-4 c-10 c-6 c-14`
`obj-827`	`c-6 c-9 c-14 c-10 c-11 c-3 c-13 c-2 c-8 c-15`
`obj-828`	`c-14 c-6 c-4 c-7 c-15 c-11 c-5 c-9 c-13 c-8`
`obj-829`	`c-3 c-11 c-9 c-12 c-5 c-7 c-14 c-13 c-8 c-6`
`obj-830`	`c-11 c-10 c-9 c-1 c-13 c-14 c-7 c-8 c-15 c-5`

and `obj-828` as the topic, conceptualization constructs the three different meanings `(c-4 c-8)`, `(c-4 c-7)` and `(c-4 c-5)`. The category `c-4` is not sufficient to discriminate `obj-828` from the rest, because it is also part of `obj-826`. Only `c-5`, `c-7` and `c-8` are part of the topic, but not of `obj-826`, and all other pairs of categories in `obj-828` can also be found in other objects.

As a second example, the discrimination of `obj-904` in the context

object	categories
obj-901	c-14 c-8 c-13 c-10 c-15 c-6 c-5 c-11 c-1 c-12
obj-902	c-9 c-8 c-5 c-6 c-11 c-10 c-7 c-14 c-3 c-15
obj-903	c-5 c-1 c-15 c-12 c-4 c-13 c-11 c-9 c-7 c-3
obj-904	c-10 c-6 c-9 c-13 c-8 c-15 c-12 c-5 c-11 c-14

yields eight alternative meanings that each consist of three categories: `(c-9 c-13 c-14)`, `(c-6 c-9 c-12)`, `(c-10 c-9 c-12)`, `(c-9 c-12 c-14)`, `(c-9 c-8 c-12)`, `(c-6 c-9 c-13)`, `(c-10 c-9 c-13)` and `(c-9 c-13 c-8)`.

Structured word meanings. Instead of mapping to single categories, words are now associations between single forms and sets of categories, i.e. the space of possible word meanings $\mathcal{M}$ is now a subset of all combinations of C. Invention, adoption and alignment are as before.

Interpretation. Each meaning resulting from parsing is interpreted in the context by retrieving all objects that share the categories in the meaning. Again, interpretation of a meaning fails when multiple topics are found and the path through semiotic network with the highest word score is eventually selected.

5.3.2 Holistic coding as a bad strategy

Because the world simulation guarantees that each object in the context differs from all objects in at least one category, the more powerful conceptualization capabilities lead to 100% discriminative success. With the default world simulation parameters, the number of categories per constructed meaning is one in 55% of the scenes, two in 42% of interactions and three in another 3%.

For most of the scenes, the number of alternative conceptualizations is between one and four, but sometimes more than 10 meanings are conceptualized:

# of meanings	1	2	3	4	5	6	7	8	9	10	>10
frequency	25%	15%	16%	15%	7%	7%	4%	3%	3%	1%	4%

Nevertheless, using a separate word for each possible combination of categories is not a very successful strategy for establishing a communication system. Figure 5.17 gives an example of 20 communicative interactions in a population of 10 agents. Although already 2500 language games have been played, only about half of the interactions are successful. Even for single categories some games still fail (interactions 4500 and 4516) and when multiple categories are involved, the speaker and the hearer rarely associate the same meanings to a form.

#	speaker	topic	meaning	utterance	hearer	meaning	topic	success?
4500	agent 5	obj-15741	c-8	*"timune"*	agent 3			no
4501	agent 7	obj-15746	c-11	*"leredi"*	agent 5	c-11	obj-15746	yes
4502	agent 2	obj-15748	c-14	*"wekobi"*	agent 4	c-14	obj-15748	yes
4503	agent 7	obj-15750	c-5 c-4 c-6	*"budume"*	agent 1			no
4504	agent 3	obj-15755	c-13 c-1	*"gikoxe"*	agent 4	c-9 c-5	obj-15757	no
4505	agent 2	obj-15759	c-8	*"vafeme"*	agent 4	c-8	obj-15759	yes
4506	agent 2	obj-15761	c-2	*"lipuki"*	agent 6	c-2	obj-15761	yes
4507	agent 7	obj-15764	c-3 c-5	*"gapeti"*	agent 6	c-13 c-10	obj-15768	no
4508	agent 6	obj-15769	c-13	*"madado"*	agent 5	c-13	obj-15769	yes
4509	agent 10	obj-15772	c-9 c-2	*"fovodu"*	agent 9	c-9 c-6	obj-15772	yes
4510	agent 1	obj-15777	c-9 c-10	*"xesisu"*	agent 2	c-10 c-9	obj-15777	yes
4511	agent 2	obj-15781	c-7 c-13	*"wefigu"*	agent 9	c-13 c-7	obj-15781	yes
4512	agent 10	obj-15790	c-11 c-12	*"nulafu"*	agent 8			no
4513	agent 8	obj-15791	c-13 c-10	*"putoni"*	agent 5	c-3 c-8	obj-15793	no
4514	agent 4	obj-15795	c-6 c-13	*"fovodu"*	agent 5			no
4515	agent 4	obj-15801	c-2	*"lipuki"*	agent 6	c-2	obj-15801	yes
4516	agent 3	obj-15805	c-1	*"pexepo"*	agent 2			no
4517	agent 5	obj-15807	c-3 c-1	*"wubimi"*	agent 6	c-3 c-4	obj-15806	no
4518	agent 10	obj-15811	c-4	*"vafuxa"*	agent 5	c-4	obj-15811	yes
4519	agent 7	obj-15815	c-15 c-6	*"sovota"*	agent 10	c-1 c-8	obj-15813	no

Figure 5.17: Overview of 20 consecutive interactions in a population of 10 agents from game 4500 on. It shows the agents that are interacting, the topic chosen by the speaker, the conceptualized meaning that was chosen, the utterance, the meaning parsed by the hearer together with the interpreted topic, and whether the agents reached communicative success.

5.4 Multi-word utterances for atomic meanings

Since single-word utterances for structured meanings are obviously a bad strategy, we will now extend the model to compositional utterances in which different words cover different parts of the meaning. As an intermediate step, word meanings are again unstructured as in Section 5.2 above, i.e. each word in the utterance expresses exactly one category. The challenge lies in recovering from partial processing, that is when a speaker only knows words for some parts of the meaning or when a hearer only knows meanings for some of the words in the utterance.

5.4.1 Producing and parsing multiple words and learning from partial processing

The strategies for playing the game, conceptualization, interpretation and alignment are identical to the previous sections and we will again only highlight the differences. For producing multi-word utterances, conceptualization of course needs to construct compositional meanings, i.e. sets of categories

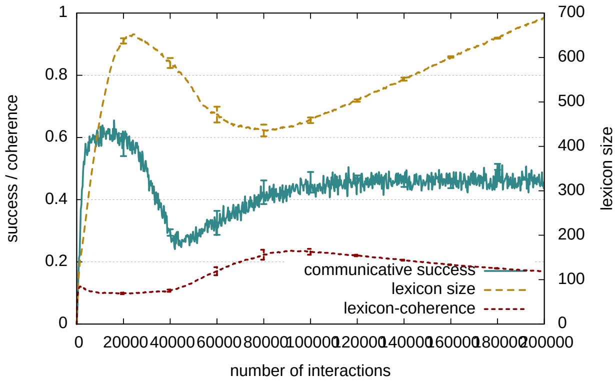


Figure 5.18: Communicative success (measure 2.1), lexicon size (measure 4.1) and lexicon coherence (measure 4.2) in a population of 10 agents. Results are averaged over 5 runs of 200000 interactions.

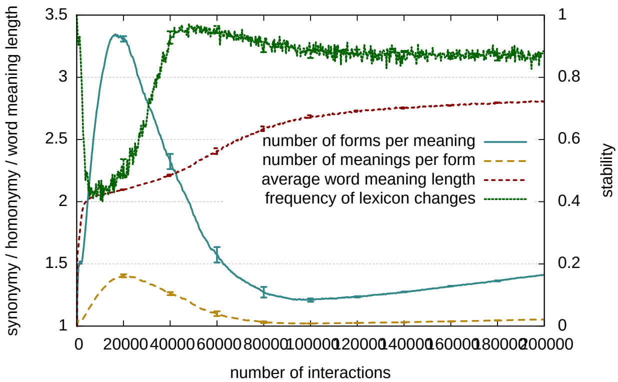


Figure 5.19: Lexicon structure and stability. The average number of forms per meaning (measure 4.4), the average number of meanings per form (measure 5.3, the average word meaning length (measure 5.6) and the frequency of lexicon changes (measure 4.3) are averaged over 5 runs of 200000 interactions.

as in the previous Section 5.3. But as already said, word meanings are again single categories.

Production. With multiple words expressing different parts of a meaning m', production is a bit more complicated than a simple lexicon lookup. First, all applicable words, i.e. words which express one category of the meaning $A := \{w : w \in L(a) \wedge m(w) \in m'\}$ are retrieved from the lexicon. Then, all possible combinations of these applicable words that do not overlap in meaning are computed $X := \{x : x \subseteq A \wedge \neg\exists w_1, w_2 (w_1 \in x \wedge w_2 \in x \wedge m(w_1) = m(w_2))\}$,

> *Measure 5.6: Average word meaning length*
>
> *Measures the average number of categories in the meaning of each word of an agent's lexicon averaged over all agents in the population:*
>
> $$v = \sum_{i=1}^{|P|} \frac{\sum_{j=1}^{|L(a_i)|} |m(w_j(a_i))| \ / \ |L(a_i)|}{|P|}$$
>
> *Values v are averaged over the last 250 interactions.*

while excluding solutions that are subsets from other solutions $U = \{u : u \in X \wedge \neg\exists x(x \in X \backslash u \wedge u \subset x)\}$. From these combinations, the one with the highest average word score is selected.

Invention. When no complete combination of words (i.e. one that covers all categories in the meaning) can be found for any of the conceptualized meanings, then the speaker selects the partial combination that has the least unexpressed categories and the highest average word score and if there is only one unexpressed category, invents a new word for it.

Parsing and interpretation. An utterance u consisting of several forms $u := \{f_1, f_2, \dots\}$ is parsed by again retrieving all applicable words $A := \{w : w \in L(a) \wedge f(w) \in u\}$, forming combinations that do not overlap in meaning as before and excluding subsets of other solutions. The meaning underlying an utterance is formed by concatenating all meanings of a word combination. Again, all resulting meanings are interpreted in the context as before and the path leading to a single interpreted object with the highest average words scores is chosen.

Re-conceptualization with partial meanings. To recover from communicative failure, it is again first checked whether another path in processing lead to the correct topic. If not and if the utterance contains only a single unknown form, then a new word is adopted for that form (when there are multiple unknown forms, then nothing happens, because the ambiguity of which meaning to assign to which form is too high). In order to determine possible meanings for the unknown form, the scene is re-conceptualized using the topic pointed at and the meanings that resulted from the partial parse. That is, from all constructed meanings only those are considered that contain all categories from the partial meaning. For all meanings where the difference between the partial meaning and the meaning amounts to one category, a new word associating the unknown form to the category is added to the lexicons of the agents.

Consolidation & dampening competing forms and meanings. The update of category scores is very similar to as before, except that now multiple words need to be updated. All words that were involved in producing or parsing the utterance are increased in score on communicative success and decreased in case of failure and the competing forms and meanings of the applied words are laterally inhibited.

5.4.2 Interdependent word alignment dynamics

Multi-word utterances introduce one major additional complexity in the dynamics of lexicon alignment compared to the models in the previous Sections 5.2 and 5.3: how well a convention spreads in the population does not only depend on how well it was used in previous interactions, but also on the other words that is was used with together in an utterance. The additional challenge

#	speaker	topic	meaning	utterance	hearer	meaning	topic	success?
1000	agent 8	obj-3513	c-1 c-7	*"sasito kasuvi"*	agent 4	c-13 c-7	obj-3513	yes
1001	agent 7	obj-3519	c-8 c-7	*"wuveso lawabe"*	agent 3	c-7 c-12	obj-3517	no
1002	agent 10	obj-3521	c-12 c-10	*"sopusa boluto"*	agent 7	c-8 c-2	obj-3523	no
1003	agent 6	obj-3526	c-9	*"tibape"*	agent 4	c-2	obj-3526	yes
1004	agent 2	obj-3528	c-12	*"fidasa"*	agent 8	c-12	obj-3528	yes
1005	agent 1	obj-3530	c-7 c-1	*"dolage lawabe"*	agent 7	c-7 c-4	obj-3532	no
1006	agent 7	obj-3536	c-6 c-10	*"ruxize rofoxa"*	agent 4	c-6		no
1007	agent 7	obj-3539	c-8 c-9	*"sopusa ruxize"*	agent 3			no
1008	agent 8	obj-3543	c-12	*"fidasa"*	agent 4	c-2		no
1009	agent 4	obj-3546	c-4 c-1	*"dolage bofixo"*	agent 3	c-6		no
1010	agent 5	obj-3549	c-6	*"rofoxa"*	agent 9	c-6	obj-3549	yes
1011	agent 8	obj-3554	c-5 c-10	*"lesisi lesisi"*	agent 6			no
1012	agent 8	obj-3558	c-1 c-8 c-3	*"zaduba lesisi kasuvi"*	agent 1	c-9 c-11		no
1013	agent 3	obj-3563	c-1 c-7	*"zepese kurawi"*	agent 2	c-5 c-5		no
1014	agent 6	obj-3565	c-5	*"zepese"*	agent 9	c-5	obj-3565	yes

Figure 5.20: Overview of 15 consecutive interactions from game 1000 on. It shows the agents that are interacting, the topic chosen by the speaker, the conceptualized meaning that was chosen, the utterance, the meaning parsed by the hearer together with the interpreted topic, and whether the agents reached communicative success.

that speakers and hearers have to face is the ambiguity in deciding which word of the utterance were responsible for communicative failures.

Figure 5.20 illustrates this by showing 20 consecutive interactions in a population of 10 agents using the strategies described in the previous section. For example in interaction 1005, both the speaker and the hearer share the same form "lawabe" for the meaning `c-7`. However, the other word "dolage" in the utterance is associated to `c-1` by the speaker and to `c-4` by the hearer. Since the hearer then interprets the overall meaning as referring to `obj-3532`, the interaction leads to a communicative failure. In alignment, both agents can not know which word was responsible for the misinterpretation and reduce the scores of both words. It is left to many subsequent interactions in which the words are used together with other words to reach coherence in the population.

Similarly, it can happen that agents reach communicative success although they use different word meanings and consequently falsely increase the scores of form-meaning associations as the result of a game. For example in interaction 1000, the speaker conceptualizes the scene as `c-1 c-7` and then and the hearer parses the resulting utterance as `c-13 c-7`. Since interpretation of that meaning leads to the same topic `obj-3513`, speaker and hearer will both wrongly increase the scores of both words used, also leaving it to later interactions to home in on the correct meanings.

Figure 5.21a: Main measures of alignment. Communicated success (measure 2.1) and lexicon size (measure 4.1) are averaged over 10 repeated series of 6000 language games.

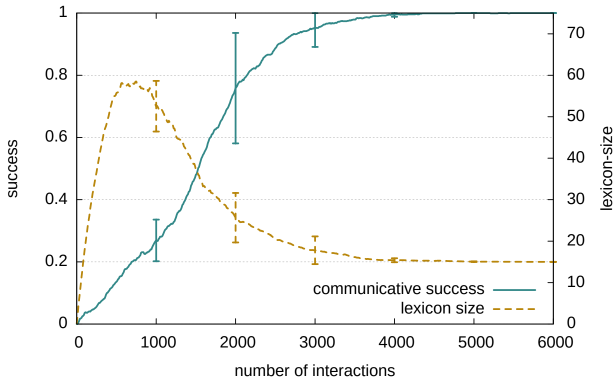
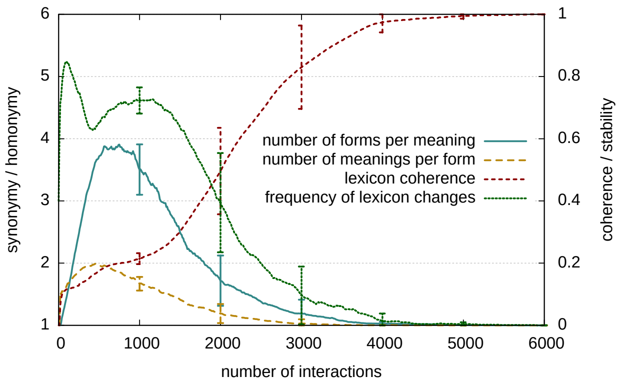


Figure 5.21b: Evolution of lexicon structure. The average number of forms per meaning (measure 4.4), the number of meanings per form (measure 5.3), lexicon coherence (measure 4.2 and stability (measure 4.3) are averaged over 10 repeated series of 6000 interactions.



The overall dynamics look very similar to the language games with single word utterances for single categories in section 5.2 (compare Figure 5.9), which is surprising due to the increased difficulties in lexicon alignment. It can be however explained with the higher (100%) discriminative success resulting from the ability to use multiple categories to conceptualize a scene, out-weighted by two other factors: First, hearers that perceive multiple unknown words will not adopt them, since they associate only one form to one category. And second, a higher number of interactions needed to resolve the ambiguities mentioned above. As shown in Figure 5.21a, the population reaches 100% communicative success and an optimal lexicon size after about 4000 interactions.

For the same reasons as above, the evolution of the lexicon structure (Figure 5.21b) is also very similar to the single-category version of the model (compare Figure 5.10). The same also holds for all other alignment dynamics and the scaling with population size and meaning complexity, which is why we will not repeat them again.

5.5 Multi-word utterances and structured meanings

We will now come to the language game model game that this chapter has lead up to: the combination of structured word meanings with multi-word utterances. It adds one new challenge to the model in the previous section: There is not only the ambiguity of deciding which word covers which meanings, but additionally there is the ambiguity in specificity. Upon hearing a novel word, agents need to decide whether the word refers to a single category, a combination of categories, or the complete meaning as a whole.

5.5.1 Mapping forms to structured meanings

Again, most of the strategies for playing the language game are identical to the previous sections, the main change is to allow word forms to be associated to sets of categories.

Production. Very similar to the strategires described in Section 5.4.1 above for single world utterances for structured meanings, production means to find the applicable combination of words that *covers* the meaning m' with the highest average word score. For that, all words whose meaning is a subset of the meaning to be expressed $A := \{w : w \in L(a) \wedge m(w) \in m'\}$ are retrieved from the lexicon. Then, all possible combinations of these applicable words that do not overlap in meaning are computed $X := \{x : x \subseteq A \wedge \neg\exists w_1, w_2(w_1 \in x \wedge w_2 \in x \wedge m(w_1) = m(w_2))\}$, while excluding solutions that are subsets from other solutions $U = \{u : u \in X \wedge \neg\exists x(x \in X \backslash u \wedge u \subset x)\}$. From these combinations, the one with the highest average word score is selected.

Invention. When no combination of words in the lexicon of the speaker can cover the complete meaning, then the partial combination that has the least unexpressed categories and the highest average word score is selected and a new word is invented for the remaining uncovered categories.

Adoption. Also similarly to as described in Section 5.4.1, a hearer that doesn't know one (and only one) of the word forms in the utterance, re-conceptualizes the scene using the meanings obtained from partially parsing the utterance. From all parses where such a re-conceptualization is possible in the current scene, a new word is created associating the uncovered part to the re-conceptualized meaning.

5.5.2 Increased ambiguity in word meanings

Allowing for structured word meanings while keeping all other mechanisms for lexicon representation and processing untouched vastly increases the difficulty for the population to reach a coherent communication system. Word forms not only compete for the right category (as in the language games with unstructured meanings) or holistic meanings that discriminate a topic (as in Section 5.3), but now they can be associated to an arbitrary set of categories.

Consequently, hearers perceiving a novel word need to keep track of a large number of alternative hypotheses what the word could mean and hope that these competing meanings get reduced as a result of subsequent interactions. This process is made more difficult by the fact that the meanings that get associated to a novel form depend on the potentially wrong partial meanings that were retrieved from partially parsing the known forms in the utterance. For example in interaction 503 of the series of language games is shown in Figure 5.22, the speaker conceptualized the topic as `c-10 c-9` and the hearer interpreted one of the two words in "vaquero rixate" as `c-6`. Whatever the reconceptualized meaning then was, the hearer will most likely have associated another meaning to the unknown word than the one that was intended by the speaker.

Additionally, even when both agents know all the words of the utterance, they can't know which words were responsible in the case of a communicative failure. The default strategy of reducing all involved words in score can be beneficial as in interaction 502 where the speaker and hearer used the different meanings `c-14 c-13` and `c-12 c-10` for the word "zidipa", but there are also other cases such as interaction 507, when at least one of the words of the utterance "pamadu sobowi" was associated by both agents to the meaning `c-3`.

This uncertainty is clearly reflected in the lexicons of the agents. Figure 5.23a shows an example of the word forms associated to three different meanings by four different agents at an early stage of in the evolution of the population. Whereas at least all of the four agents already somehow associate "vepolu" to the meaning `c-1`, no agreement whatsoever exists on the other two meanings `c-2` and `c-1 c-2`. Similarly, the same agents also associate very different meanings to the same forms in the early stages the language games (Figure 5.23b). For example "fufilo" is associated by two agents to single categories, by the other two to a combinations of two categories – and non of these meanings match.

Figure 5.24 displays the complete lexicon of a single agent after 500 interactions. It nicely illustrates the high number of meanings connected to single forms and also the high number forms connected to some meanings. In order to reduce this ambiguity, words need to be tried out in many different context so that competing forms and meanings can be eliminated through lateral inhibition. Two typical competition dynamics are given in Figures 5.25a and 5.25b. The first plots all the different meanings associated by all the agents in the population to the form "gesino" with their average association scores. The meaning that eventually wins at around interaction 10000 is `c-11`, but in the process 36 other competing meanings get adopted and need to be eliminated.

A much more typical evolution of a word form is shown in Figure 5.25b. Here, the form "xiziwo" attracted 18 different meanings that one after the

#	speaker	topic	meaning	utterance	hearer	meaning	topic	success?
500	agent 8	obj-9728	c-12 c-5	*"lumase"*	agent 5	c-4 c-5	obj-9728	yes
501	agent 7	obj-9733	c-14 c-13	*"zidipa"*	agent 2	c-12 c-10		no
502	agent 7	obj-9736	c-4	*"xatise"*	agent 9	c-13		no
503	agent 2	obj-9742	c-10 c-9	*"vavuro rixate"*	agent 10	c-6		no
504	agent 10	obj-9743	c-8	*"xezibe"*	agent 8			no
505	agent 5	obj-9747	c-15	*"ritere"*	agent 4	c-9		no
506	agent 3	obj-9750	c-1	*"sobowi"*	agent 10	c-1	obj-9750	yes
507	agent 10	obj-9753	c-1 c-3	*"pamadu sobowi"*	agent 5	c-3 c-5		no
508	agent 7	obj-9759	c-3 c-9	*"vevovo"*	agent 9			no
509	agent 8	obj-9766	c-4 c-2	*"xezibe fukisa"*	agent 2			no
510	agent 2	obj-9771	c-8 c-5 c-3	*"xozipi kurake nitara"*	agent 3	c-10 c-13 c-15	obj-9767	no
511	agent 8	obj-9772	c-9	*"pamadu"*	agent 2	c-6	obj-9772	yes
512	agent 3	obj-9776	c-3	*"xuzara"*	agent 1			no
513	agent 1	obj-9777	c-1	*"gawupa"*	agent 6			no
514	agent 9	obj-9779	c-13 c-14	*"bogasi manuga"*	agent 2	c-14 c-14		no
515	agent 6	obj-9784	c-10 c-6	*"nitara giberu"*	agent 8	c-6		no
516	agent 1	obj-9789	c-1 c-13	*"liraxe"*	agent 10			no
517	agent 1	obj-9795	c-5 c-13	*"vavuro fekuvu"*	agent 8			no
518	agent 7	obj-9797	c-11	*"fufilo"*	agent 10	c-11	obj-9797	yes
519	agent 1	obj-9800	c-13 c-11	*"xavaxi"*	agent 7	c-7		no

Figure 5.22: Overview of 20 consecutive interactions in a population of 10 agents from game 500 on. It shows the agents that are interacting, the topic chosen by the speaker, the conceptualized meaning that was chosen, the utterance, the meaning parsed by the hearer together with the interpreted topic, and whether the agents reached communicative success.

meaning	agent 1		agent 2		agent 3		agent 4	
`c-1`	*“fufilo”* *“furamu”* *“fukisa”* *“vepolu”* *“gawupa”* *“ninide”*	0.30 0.30 0.20 0.50 0.20 0.20	*“suniwu”* *“menula”* *“ninide”* *“woxowo”* *“vepolu”*	0.50 0.50 0.10 0.40 0.10	*“vepolu”*	0.80	*“letibe”* *“gawupa”* *“vepolu”*	0.10 0.10 0.60
`c-2`	*“letibe”*	0.60	*“wudeso”*	0.50	*“zoxuko”* *“dapuvo”*	0.20 0.40	*“wudeso”*	0.50
`c-1 c-2`	*“zilexe”* *“vekupa”* *“beleno”* *“zifuxa”*		*“suloko”*	0.70	*“xomexo”* *“zepeke”* *“suloko”*	0.50	*“fazufi”*	

Figure 5.23a: Forms associated to 3 different meanings by the first four agents of a population of 10 after 1500 interactions.

form	agent 1		agent 2		agent 3		agent 4	
“zuwika”	`c-15` `c-8`	0.50 0.50	`c-8`	0.40			`c-8`	0.50

“nokuwi”	`c-14 c-4`
	`c-15 c-9`
	`c-13 c-14`
	`c-9 c-10`
	`c-14 c-9`
		0.50
		0.50
		0.50
		0.50
		0.50
			`c-13 c-5`
			`c-13 c-11`
				0.40
				0.50				

“fufilo”	`c-8`
	`c-3`
	`c-10`
	`c-1`
		0.40
		0.50
		0.30
		0.30
			`c-13 c-14`
			`c-6 c-11`
			`c-6 c-13`
			`c-6 c-10`
				0.30
				0.50
				0.50
				0.30
					`c-4`	0.30	`c-6 c-11`	0.20

“nilebo”	`c-3 c-11`
	`c-12 c-11`
	`c-11 c-4`
	`c-14 c-11`
	`c-3 c-7`
		0.50
		0.50
		0.50
		0.50
		0.50
			`c-14`	0.30	`c-14`
					`c-4`
						0.50
						0.50		

“fukisa”	`c-14`
	`c-1`
		0.50
		0.20
			`c-14`	0.30	`c-14`	0.50	`c-13`
							`c-14`
							`c-5`
							`c-7`
								0.50
								0.30
								0.10
								0.10

Figure 5.23b: Meanings associated to 5 different forms by the first four agents of a population of 10 after 1500 interactions.

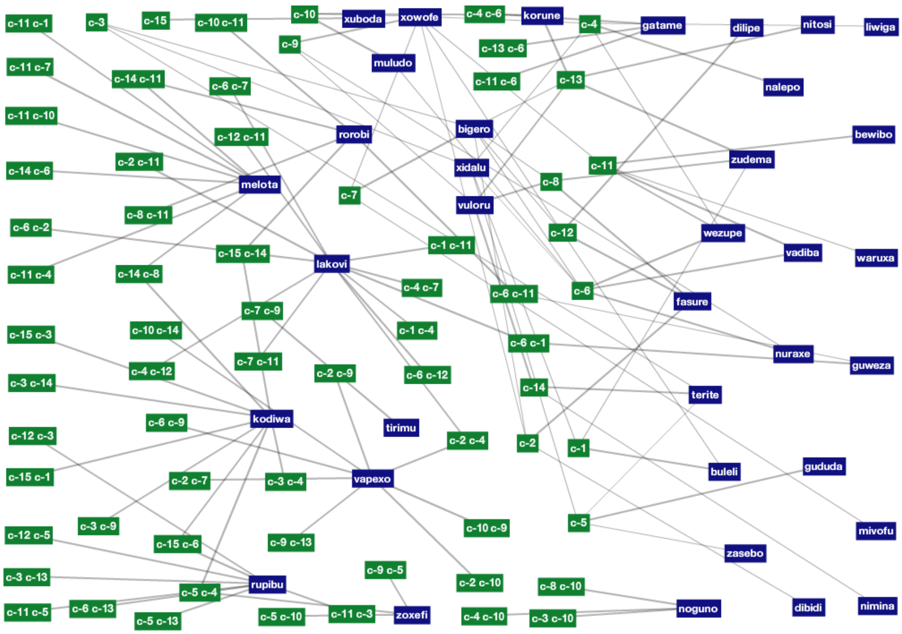


Figure 5.24: Network representation of the complete lexicon of the first agent in the population after 500 interactions. Each line represents a word in the lexicon of the agent and connects the meaning of the word with its form. The line widths denote the strength of the association.

Figure 5.25a: Evolution of words with the form "gesino" in the population. Each line shows for a single meaning the corresponding word scores averaged over all agents that associate this meaning to "gesino".

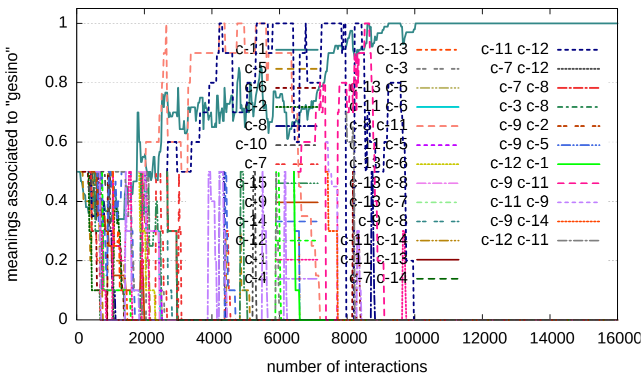


Figure 5.25b: Evolution of words with the form "xiziwo" in the population.

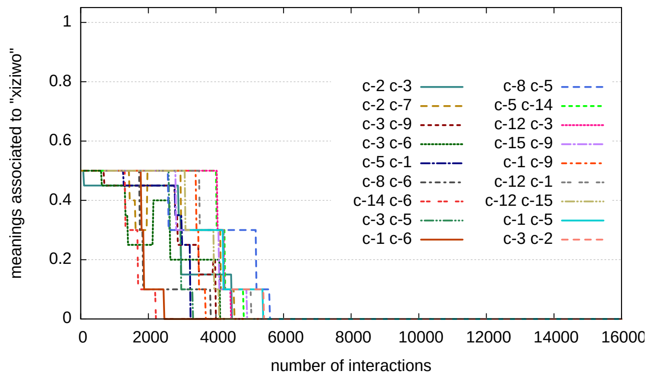
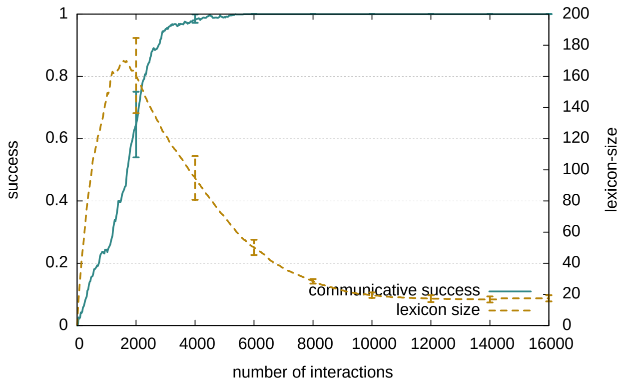


Figure 5.26a: Main measures of alignment. Communicated success (measure 2.1) and lexicon size (measure 4.1) are averaged over 10 repeated series of 16000 language games.



other decrease in score until it finally disappears from the population at around interaction 5500.

The overall dynamics in populations using these kinds of lexicon representations and learning strategies are given in Figures 5.26a and 5.26b and the look very similar to the ones in the the same diagram for agents using unstructured meanings from the previous section (see Figures 5.21a and 5.21b on page 98). Complete communicative success is reached after about 5000 interactions and the evolution of lexicon size shows the typical shape where first a high number of words become evented before later alignment reduces many of them again.

For reasons that we will briefly discuss in Section 5.5.4 below, the number of words in the lexicons of each agent converges to 15, which is also the total number of categories in the simulated world. Consequently, the average number of meanings per form and the average number of forms per meaning also converge to one. The increased ambiguity shows in the maximum lexicon size of about 160 words that each agent has in its inventory at around interaction 2000 (compared to about 60 in Figure 5.21b), a much slower increasing lexicon coherence and much longer sustained high frequencies of lexicon changes.

Figure 5.26b: Evolution of lexicon structure. The average number of forms per meaning (measure 4.4), the number of meanings per form (measure 5.3), lexicon coherence (measure 4.2 and stability (measure 4.3) are averaged over 10 repeated series of 16000 interactions.

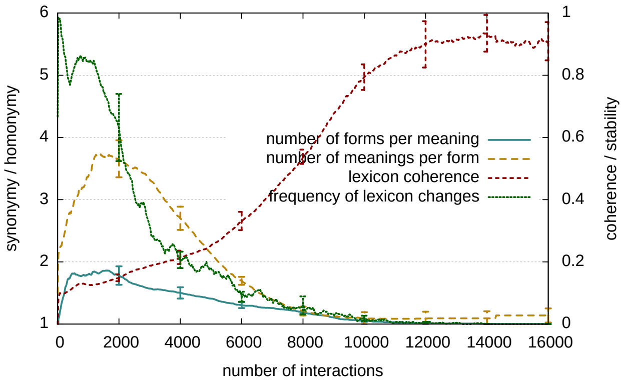
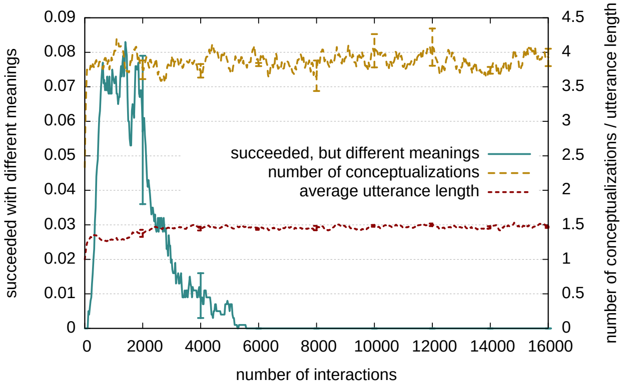


Figure 5.27: Causes for ambiguity. The fraction of interactions in which communicative success is reached although the speaker and hearer used different meanings (measure 5.5), the number of conceptualizations (measure 5.4) and average utterance length (measure 5.7) are averaged over 10 repeated series of 16000 language games.



Some of the challenges that lead to these high uncertainties are uncertainties in Figure 5.27. The average number different meanings that can be used to discriminate a topic from the other objects in the scene is about 4 (because the world does not change during an experimental run). Furthermore, agents will communicate successfully while having different understandings of the meanings in more that 5 percent of the cases during the first 2000 interactions. In this interactions they will wrongly increase the association scores of the words, while reducing the scores of competing combinations. And finally, the average utterance length starts at 1 (the first that speakers will invent cover the complete uncovered meaning) and gradually converges to 1.5 at around interaction 2000.

5.5.3 The limits of random search

The simulation parameters that were used for the experiments throughout this chapter are more or less standard in the body of research that has been done on language game experiments in simulated environments. The size of the pop-

> *Measure 5.7: Average utterance length*
>
> *Measures the average utterance length, i.e. the number of different word forms contained in the utterance produced by the speaker. Values are averaged over the last 250 interactions.*

ulation is 10 agents, simulated world perceptions consist of two to five objects, each characterized by 10 categories out of an overall fixed set of 15 categories. However, when increasing the complexity of the scenario slightly beyond these values, then the strategy of keeping high number of hypotheses of what words mean in the lexicons of the agents turns out to be a strong limitation for scaling up. We now briefly analyze the scaling behavior for increasing population sizes and context sizes.

The Figures 5.28a, 5.28b and 5.28c compare lexicon size, frequency of lexicon changes and communicative success for populations of 10 to 100 agents. In order to be able to compute these graphs within the memory and computing time limits of contemporary computer hardware, speakers and hearers use the "process 1" respectively "adopt 1" strategy for handling alternative conceptualizations and for adopting word meanings (see page 86 et sqq.).

For all five different population sizes, the agents managed to reach the "optimal" lexicon size of 15 words, a stable lexicon that does not change anymore, and 100% communicative success. However, reaching success and coherence takes prohibitively long and agents have to make huge efforts to align with each other. The average maximum lexicon size in populations of 100 agents is around 700 words, almost 50 times as much as the final lexicon size of 15 words. Each agent adds or removes a word to / from his lexicon in more than 80% of his first 7000 interactions. And only every tenth out of the first 5000 interactions succeeds.

It is fair to say that although all involved measures converge, the alignment strategy of memorizing and later eliminating words does not scale at all with increasing population size. Agents have to go through long periods of random search until some words start being successfully used by a critical fraction of the population. The high variance across different experimental runs for population sizes above 25 (indicated by the error bars in Figures 5.28a, 5.28b and 5.28c) supports this. In some runs, this "critical" moment is reached much earlier than in others, suggesting that random factors play an important role in these dynamics. For the case of the Naming Game, Baronchelli et al. (2006) have characterized this phenomenon as a "sharp transition" from an unordered to an ordered state.

For challenging the model with an increasing complexity of the world, it is enough to increase the number of objects that speakers and hearers perceive in a single interaction. We chose context size parameters in such a way that

Figure 5.28a: Lexicon size (measure 4.1) for five different population sizes. Results are averaged over 10 series of varying length, but each with 16000 interactions per agent.

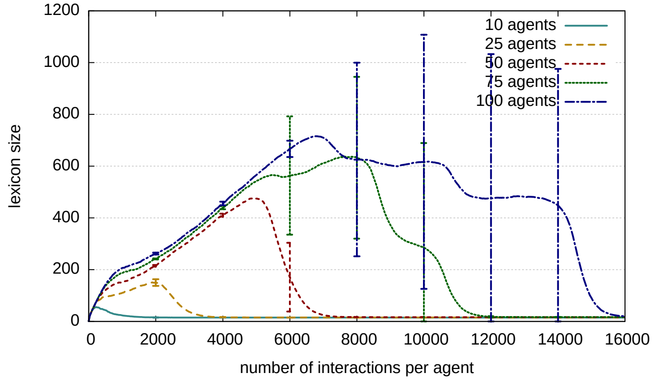


Figure 5.28b: Frequency of lexicon changes (measure 4.3) for five different population sizes. Results are averaged over 10 series of varying length, but each with 16000 interactions per agent.

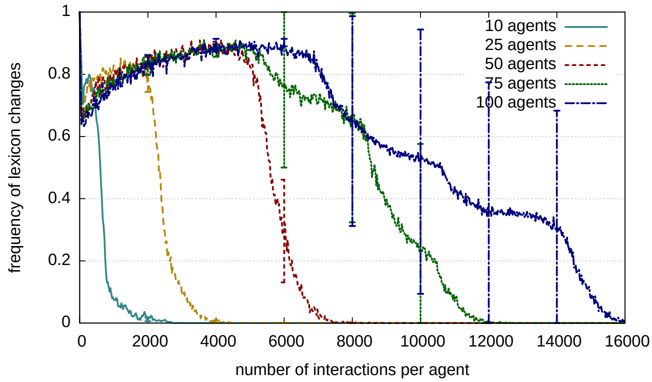


Figure 5.28c: Communicative success (measure 2.1) for five different population sizes. Results are averaged over 10 series of varying length, but each with 16000 interactions per agent.

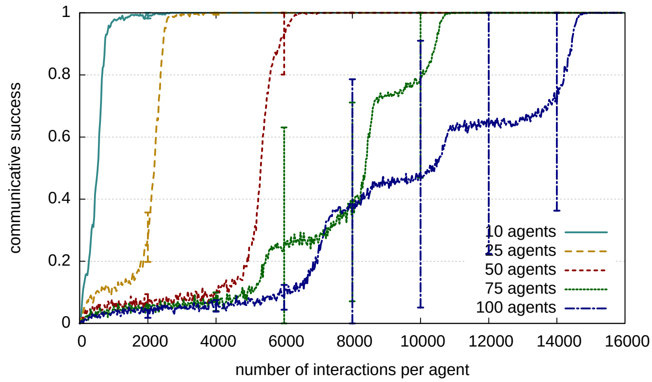


Figure 5.29a: Number of alternative conceptualizations per scene (measure 5.4) for world simulators with increasing number of objects per scene.

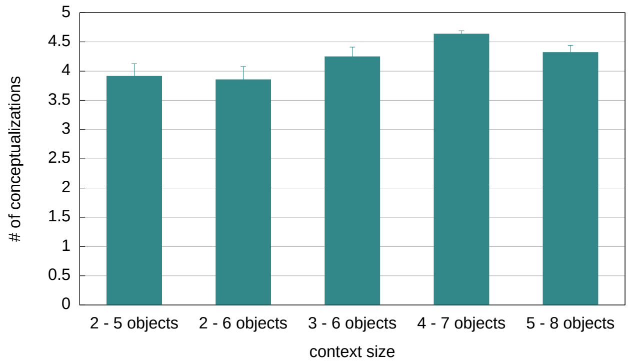
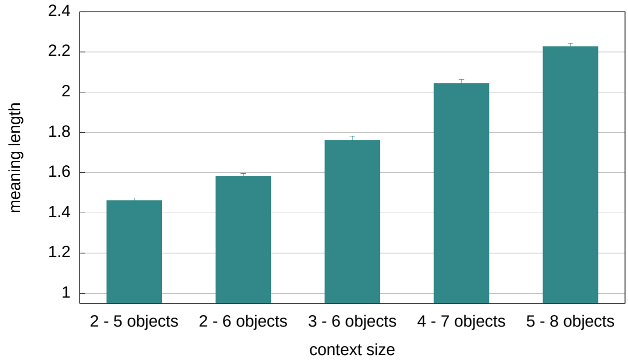


Figure 5.29b: Average meaning length (measure 5.8) for world simulators with increasing number of objects per scene.



the average number of ways to conceptualize a scene (and thus the referential uncertainty) stays more or less the same. Starting from the standard condition in this chapter in which contexts consisting of 2 to 5 objects, to contexts with between 5 and 8 objects, there are on average around four alternative conceptualizations per scene (see Figure 5.29a).

Nevertheless, a higher number of objects in a context means that more categories are needed to discriminate a topic from the other objects in the context, which is illustrated in Figure 5.29b. The average number of categories that speakers need to conceptualize a scene rises from about 1.5 in contexts of 2 to 5 objects to about 2.2 in contexts with 5 to 8 objects (see Figure 5.29b).

This small increase complexity causes a drastic increase in the amount of work that agents have to do in order to keep track of word meanings, leading to an even worse scaling behavior than with population size (see Figures

Measure 5.8: Average meaning length

Measures the average meaning length, i.e. the number categories contained in the meaning that was conceptualized speaker and used in production. Values are averaged over the last 250 interactions.

Figure 5.30a: Lexicon size (measure 4.1) for world simulators with increasing number of objects per scene. Results are averaged over 10 series of 80000 interactions.

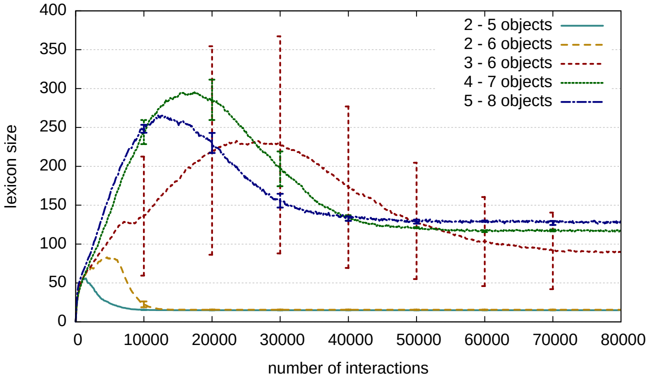


Figure 5.30b: Frequency of lexicon changes (measure 4.3) for world simulators with increasing number of objects per scene. Results are averaged over 10 series of 80000 interactions.

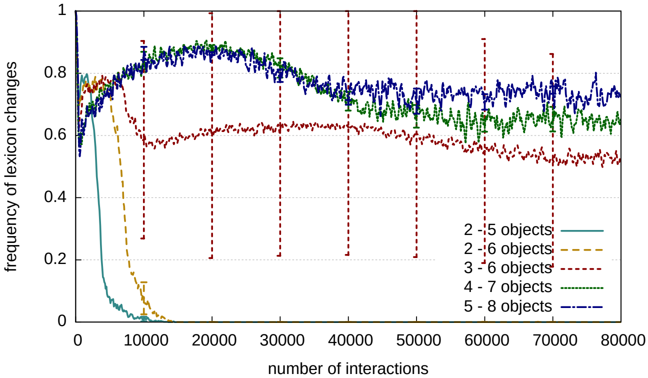
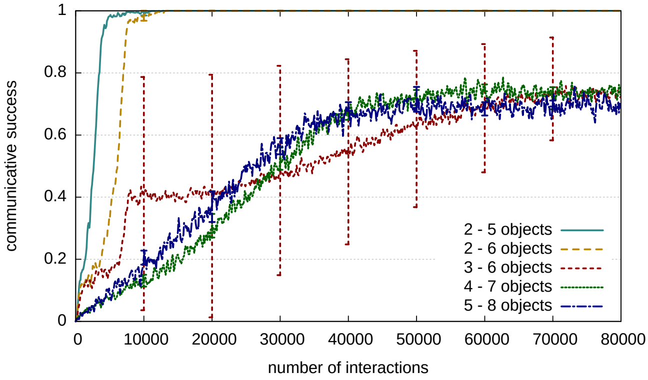


Figure 5.30c: Communicative success (measure 2.1) for world simulators with increasing number of objects per scene. Results are averaged over 10 series of 80000 interactions.



meaning	agent 1		agent 2		agent 3		agent 4	
c-1	*"vepolu"*	1.00	*"vepolu"*	1.00	*"vepolu"*	1.00	*"vepolu"*	1.00
c-2	*"letibe"*	1.00	*"letibe"*	1.00	*"letibe"*	1.00	*"letibe"*	1.00
c-1 c-2	*"beleno"* *"zifuxa"*	0.10 0.10	*"suloko"*	0.20				

Figure 5.31a: Forms associated to 3 different meanings by the first four agents of a population of 10 after 5000 interactions.

form	agent 1		agent 2		agent 3		agent 4	
"xavuto"	c-8	0.50	c-8	0.70	c-8	0.30	c-8	0.60
"buxoxo"	c-8	0.10	c-8	0.10				
"vewuxa"	c-13	1.00	c-13	1.00	c-13	1.00	c-13	1.00
"vaxutu"	c-3 c-12	1.00	c-3	1.00	c-3	1.00	c-3	1.00
"godefe"	c-11 c-8 c-13 c-8 c-13 c-3	0.30 0.50 0.50	c-14 c-9 c-2 c-14	0.30 0.30			c-13 c-6	0.20

Figure 5.31b: Meanings associated to 3 different forms by the first four agents of a population of 10 after 5000 interactions.

5.30a, 5.30b and 5.30c). Only for the first two world simulator configurations (perceived contexts consist of between 2 and 5 objects, respectively 2 and 6 objects) the population of again 10 agents is able to reach complete success and lexicon stability. The high variance indicated by the error bars across different runs for contexts with between 3 and 6 objects indicates that in this case the population was able to converge in some of the runs whereas in others not. Anyway, for all other configurations, the lexicon representation and the strategies for alignment simply don't work.

5.5.4 Bias towards atomic word meanings

Although the agents are endowed with the capacity to represent and process compositional word meanings, the lateral inhibition dynamics used by the agents to gradually reduce alternative hypotheses constitute a bias towards unstructured word meanings.

The lexicon snapshots of the same four agents from Figures 5.23a and 5.23b but 3500 interactions later at interaction 5000 (Figures 5.31a and 5.31b) illustrate this. All four agents agreed on the same forms "vepolu" and "letibe" for the atomic meanings `c-1` and `c-2` and all converged to the highest score of 1.0 for these associations. On the contrary, there is no conventionalized form for the structured meaning `c-1 c-2` and the three words that remained in the population have very low association scores. Looking form the other direction, word forms that are connected to single categories are so with higher scores than those that map to structured meanings. An interesting and rare exception is the form “vaxutu”. While all other agents connect the meaning `c-3` to it, the first agent uses the two categories `c-3 c-12`.

The explanation for this effect is something that De Beule & Bergen (2006) called a frequency effect. Lateral inhibition after a successful language game operates equally on all words that also could have been applied, and consequently words connected to single categories have an advantage in these dynamics. In the example above, the words expression the category combination `c-1 c-2` are in direct competition with the words expressing `c-1` or `c-2` for all conceptualizations that contain these two categories. However, words expressing `c-1 c-2` can only be used in such situations, whereas words expressing single categories can be used in a much wider variety of contexts (basically all conceptualizations that contain that category). They thus can be tried out more frequently, and consequently can spread more quickly the population and be part of more successful interactions. Which means that they will have higher combined scores than their structured counterparts and finally win the competition over them.

Chapter 6

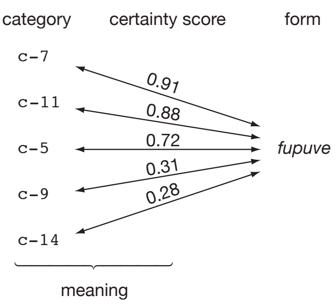
Flexible representations for word learning

Without antedating the discussion of the results of the previous chapter (this will be happen in Chapter 11), we want to highlight two major shortcomings. First, it is a bad strategy to enumerate many alternative hypotheses about what words mean in the lexicons of the agents. Because the conceptualized structured meanings can be any subset of the available categories, referential uncertainty exponentially increases with the number of categories. Turning this into an exponentially increasing competition between word meanings does not scale. Second, the alignment dynamics of the experiments in the previous chapters contain a bias towards atomic words meanings. However, in natural language words are not only about single categories such as red or small but most of them carry complex structured meanings, a fact that a lexicon representation should be able to capture.

The lexicon formation model introduced in this chapter tries to address these two shortcomings by capturing uncertainty in the representation of word meanings themselves[1]. Instead of having competing mappings to different sets of categories for the same word, words now have flexible connections to different categories that are constantly shaped by language use. This is achieved by keeping an *(un)certainty score* for every category in a form-meaning association instead of scoring the meanings as a whole (Figure 6.1). This representation is strongly related to both fuzzy set theory (Zadeh, 1965) with the degree of membership interpreted as the degree of (un)certainty, and prototype theory (Rosch, 1973). Although this representation is identical to a fuzzy set, in what follows, we refer to the representation as a *weighted set* to avoid confusion since we will redefine many set theoretic operations. By allowing the

[1]Some parts of this chapter (mainly Section 6.1) are adapted from Wellens, Loetzsch & Steels (2008), see also Wellens & Loetzsch (2007, 2012)

Figure 6.1: Illustration of a single flexible word representation. The form "fupuve" is associated to 5 different categories with individual certainty scores.



certainty scores to change, the representation becomes adaptive and the need to explicitly enumerate competing hypotheses disappears.

6.1 Processing and aligning flexible word representations

Again, the overall strategies for playing language games are identical to those in the previous two chapters. Also, the same simulated world from the experiments in the previous chapter is used. Interacting agents jointly perceive a simulated scene consisting of 2 to 5 objects, which themselves are represented by subsets from a list of 15 categories. We repeat here an example context of such joint perception from Section 5.1 (page 73):

object	categories
obj-53	c-4 c-2 c-6 c-12 c-9 c-1 c-14 c-5 c-3 c-15
obj-54	c-10 c-5 c-11 c-9 c-3 c-2 c-8 c-6 c-7 c-14
obj-55	c-7 c-5 c-6 c-2 c-15 c-8 c-10 c-13 c-4 c-3
obj-56	c-10 c-2 c-4 c-7 c-1 c-5 c-6 c-3 c-9 c-13

The difference to the experiments in the previous two chapters lies in the nature of word representations and how they are processed, invented, adopted and aligned.

Weighted sets. Perceptions of objects and words in the lexicon have *weighted sets* as the same underlying representation. This allows for example production processes to use a *similarity* measure to find the best combination of words that expresses a topic. Each weighted set is a list of mappings of a category (denoted `category` below) to a real-valued *certainty score* between 0 and 1 (called `certainty` in the remainder of this section).

Similarity between weighted sets. It is possible to define a weighted similarity measure for the above representation, taking the certainty scores as weights. Given two weighted sets of categories as input, the measure returns a real number between -1 and 1, respectively denoting disjunction and equality. This weighted similarity measure lies at the core of the model and requires detailed elaboration but we first need to define some additional functions. Assume a function `Categories(A)` that takes as input a weighted set A and returns the normal set B containing only the categories from A, and a function `CertaintySum(A)` that takes as input a weighted set A and returns a real number representing the sum of all the certainty scores. We can then define the following operations as slight modifications from those in fuzzy set theory:

```
Function Intersection(A, B):

ForEach (category & certainty) in A
    If Find category in Categories(B)
    then Add (category & certainty) to intersection;
End ForEach;

Return intersection;


Function Difference(A, B):

ForEach (category & certainty) in A
    If not Find category in Categories(B)
    then Add (category & certainty) to difference
End ForEach;

Return difference;
```

Note that in contrast to its definition in fuzzy set theory, function `Intersection` is not commutative because it returns all shared categories between A and B but with certainty scores from A. With these definitions we can define the weighted similarity measure as follows:

```
Function Similarity(A, B):

sharedSum ← CertaintySum(Intersection(A, B))
                × CertaintySum(Intersection(B, A);
diffSum ← CertaintySum(Difference(A, B)
              × CertaintySum(Differenc(B, A));
similarity ← (sharedSum - diffSum)
                  / CertaintySum(A) × CertaintySum(B);

Return similarity;
```

Given two weighted sets A and B, `Similarity` first takes all shared categories and all disjoint categories between A and B. By using the `CertaintySum` function we allow the certainty scores to weight in. It is clear that sharing categories is beneficial for the similarity and not sharing categories is not. Intuitively, `Similarity(A,B)` will be higher the more categories are shared between A and B and the higher their certainty scores are. Correspondingly, the more categories are not shared by A and B and the higher their certainty scores, the lower the result will be. Some examples:

```
Similarity(((a 1.0) (b 0.5) (c 0.7)), ((a 0.5) (b 0.5) (c 0.7)))
     = (2.2 × 1.7 - 0 × 0) / 2.2 × 1.7 = 1

Similarity(((a 1) (b 1) (c 1)), ((d 1) (e 1) (f 1)))
    = (0 × 0 - 3 × 3) / 3 × 3 = -1

Similarity(((a 0.9)), ((a 1) (b 0.1) (c 0.2)))
    = (0.9 × 1 - 0 × 0.02) / 0.9 × 1.3 = 0.77

Similarity(((a 0.5) (b 0.5) (c 0.5)), ((a 0.5) (c 0.5) (d 0.5)))
    = (1 × 1 - 0.5 × 0.5) / 1.5 × 1.5 = 0.33
```

Conceptualization. In the experiments in the previous chapter, agents conceptualized a scene by finding minimal sets of categories that *discriminate* the topic from the rest of the objects in the scene. To allow for more adaptive alignment dynamics, this now is part of lexicon application. For this, all the objects in the scene are converted to weighted sets, with constant certainty scores of 0.5.

Production. A speaker that tries to produce gradually adds words to the utterance so that the combined words are most similar to the topic and most dissimilar to the other object in the context:

```
Function Produce(context, topic, lexicon):

bestNewWord ← nil; // the current best new candidate word
utterance ← nil; // The utterance will gradually be combined in here
productionScores ← nil;

Loop
    ForEach word in (lexicon \ words in utterance) do
        meaningOfUtterance ← FuzzySetUnion(ForEach word in utterance
                                            collect Meaning(word));
        meaningOfExtendedUtterance ← FuzzySetUnion(meaningOfUtterance
                                                   + Meaning(word));
        objectSimilarities ← ForEach object in context
                              collect Similarity(meaningOfExtendedUtterance,
                                                 object));

        topicSimilarity ← GetSimilarity(topic, objectSimilarities);
        closestOtherSimilarity ← Max(objectSimilarities \ topicSimilarity);
        Add (topicSimilarity − closestOtherSimilarity) to productionScores;
    End ForEach;
    bestNewWord ← word with highest score in productionScores;
    If ProductionScore(bestCandidate) > average of ProductionScores(utteranc
        then Add bestNewWord to utterance;
        Else Break from Loop;
End Loop;

Return utterance;
```

The ForEach loop will fill productionScores with a score for each unused word in the lexicon denoting not just its similarity to the topic but taking into account its similarity to the rest of the context. For example if the topic is a red object, but all other objects in the context are also red it doesn't really help that much to use the word red. The bestNewWord is thus the word with the highest score in productionScores. If the productionScore for bestNewWord improves the average of the productionScores for the utterance so far it gets added to the utterance, if not the search stops. In the end utterance is that subset of the lexicon that strikes the optimal balance between being most similar to the topic and being most distant from the other objects of the context. This results in context sensitive multi-word utterances and involves an implicit on-the-fly discrimination using the lexicon.

Interpretation. Parsing an utterance amounts to looking up the meaning of all uttered words, taking the fuzzy union (as defined in Zadeh, 1965) of their categories and measuring similarity between this set and every object in the context:

```
Function Interpret(utterance, context):

interpretedMeaning ← Fuzzy Union of all meanings for known words in utteranc
objectSimilarities ← ForEach object in context
                            collect Similarity(interpretedMeaning, object);
topic ← object with highest score in objectSimilarities;

If similarityScore of topic > 0
    then Return topic;
```

Invention. After finding the best possible combination of words to describe the topic, the speaker first interprets his own utterance himself. In this process – which is also called *re-entrance* (Steels, 2003d) – the speaker takes himself as a model of the hearer and thus can check potential misinterpretations, allowing him to rephrase or remedy the utterance. When re-entrance leads the speaker to a different object than his own, which means that no combination of words can discriminate the topic in the current context, refinement of the lexicon is needed. The speaker invents a new form and associates to it, with very low initial certainty score, all so far unexpressed categories of the topic. Because word meanings can shift, it might not be necessary to introduce a new word. Chances are that the lexicon needs a bit more time to be shaped further. Therefore the more similar the meaning of the utterance is to the topic, the less likely a new word will be introduced:

```
Function Invention(utterance, topic, context):

interpretedTopic ← Interpret(utterance, context);
If interpretedTopic ≠ topic
then
    interpretedSimilarity ← Similarity(utterance, interpretedTopic);
    topicSimilarity ← Similarity(utterance,topic);
    randomNr ← Random(0 1) // A random number between 0 and 1
    If (interpretedSimilarity − topicSimilarity) > randomNr
    then
        newMeaning ← Categories of (topic \ Meaning(utterance))
        newWord ← makeWord(randomString, newMeaning);
        Return newWord;
```

Adoption. When the hearer encounters one or more novel words in the utterance, then he needs a way to associate an initial representation of meaning with the novel forms. For that, the first interprets the words he knows and tries to play the game without adopting the novel forms. At the end of the game, when he knows the topic from communicative feedback, the hearer associates all unexpressed categories with all novel forms. Just as in invention, the initial certainty scores start out very low, capturing the uncertainty of this initial representation. Excluding the categories of the already known words is the only constraint shaping the initial representation. Note that there is no explicit enumeration of competing interpretations:

```
Function Adoption(utterance, topic, novelForms):

newMeaning ← Categories of (topic \ Meaning(utterance))
ForEach form in novelForms do
    Add makeWord(form, newMeaning) to lexicon;
```

Alignment. After each interaction, the speaker and hearer determine which parts of the meanings of the used words were beneficial (the ones shared with the topic) and which not (the disjoint categories):

```
Function Align(agent, topic, utterance)

topicCategories ← Categories(topic);
sharedCategories ← Categories(utterance) ∩ topicCategories;
disjointCategories ← Categories(utterance) \ topicCategories;

// Update certainty scores
ForEach word in utterance
   ForEach category in Meaning(word)
      If category in sharedCategories
      then IncrementScore(word, category);
      Else DecrementScore(word, category); // Also removes categories if sco
If not CommunicatedSuccessfully(agent)
then // Make words more specific, only the hearer does this
   ForEach word in utterance
      do Associate disjointCategories to word;
```

Certainty scores are slightly shifted every time a word is used in production or interpretation. The certainty score of the categories that raised the similarity are incremented (*entrenchment*) and the others are decremented *erosion*. Categories with a certainty score equal or less than 0 are removed, resulting in a more general word meaning. In failed games the hearer adds all unexpressed categories of the topic, again with very low certainty scores, to all uttered words, thus making the meanings of those words more specific.

6.2 Continuous shaping of word meanings

When using this similarity based lexicon application, word meanings become immediately useful. As shown in Figure 6.2, the agents of the population have very different notions of what each word means in the beginning, but nevertheless they communicate very successfully from this early on. This is because words are understood even when most of their meanings are not conventionalized – it is enough to reach a successful interpretation of an utterance when the similarity of the words to the topic is the highest among all the referents.

For example in the first shown interaction 500, the speaker associates 9 different categories to the form "satitu", whereas the hearer connects only 4 categories to it. Furthermore, only the two categories `c-2` and `c-5` are shared between the tho agents, and nevertheless they are able to communicate successfully. Stretching existing word meanings so to rather unconventional uses in production and broadly applying words in interpretation (i.e. the ability to use linguistic items beyond their core meanings) is what Langacker (2000) calls *extension*.

This flexible word application also clearly shows the other interactions in Figure 6.2. Although speakers and hearers often have some shared categories in the words that they use, most of the time word meanings drastically differ, both in the categories and certainty scores themselves but also in the specificity

#	speaker + topic	word meanings speaker	word meanings hearer	hearer + topic	succ.
500	agent 7 obj-1495	*"satitu"* (c-2$^{.19}$, c-1$^{.10}$, c-3$^{.10}$, c-13$^{.10}$, c-5$^{.10}$, c-6$^{.03}$, c-8$^{.02}$, c-4$^{.02}$, c-11$^{.02}$) *"fobigu"* (c-7$^{.27}$, c-5$^{.11}$, c-8$^{.10}$, c-4$^{.10}$, c-11$^{.10}$)	*"satitu"* (c-8$^{.20}$, c-5$^{.20}$, c-2$^{.10}$, c-1$^{.10}$) *"fobigu"* (c-7$^{.22}$, c-8$^{.20}$, c-4$^{.13}$, c-3$^{.05}$)	agent 3 obj-1495	yes
501	agent 1 obj-1497	*"satitu"* (c-5$^{.26}$, c-1$^{.26}$, c-11$^{.17}$, c-4$^{.17}$, c-10$^{.13}$)	*"satitu"* (c-5$^{.29}$, c-8$^{.20}$)	agent 6 obj-1497	no
502	agent 7 obj-1499	*"xamexu"* (c-8$^{.17}$, c-14$^{.17}$, c-12$^{.17}$, c-15$^{.17}$) *"bovaze"* (c-8$^{.20}$, c-5$^{.20}$, c-9$^{.17}$, c-1$^{.11}$) *"dugobo"* (c-6$^{.17}$, c-1$^{.17}$, c-3$^{.06}$)	*"xamexu"* (c-8$^{.20}$, c-12$^{.17}$, c-11$^{.04}$, c-13$^{.02}$, c-7$^{.02}$) *"bovaze"* (c-8$^{.32}$, c-9$^{.32}$, c-1$^{.24}$, c-10$^{.02}$, c-7$^{.02}$) *"dugobo"* (c-1$^{.20}$, c-5$^{.10}$, c-6$^{.10}$)	agent 6 obj-1499	yes
503	agent 7 obj-1501	*"satitu"* (c-2$^{.14}$, c-1$^{.13}$, c-3$^{.13}$, c-13$^{.13}$, c-5$^{.13}$) *"zepasa"* (c-4$^{.17}$, c-11$^{.13}$, c-7$^{.07}$, c-8$^{.07}$, c-5$^{.04}$)	*"satitu"* (c-1$^{.39}$, c-5$^{.30}$) *"zepasa"* (c-2$^{.13}$, c-1$^{.13}$, c-3$^{.10}$, c-13$^{.10}$, c-5$^{.10}$, c-7$^{.07}$, c-8$^{.07}$, c-11$^{.02}$, c-4$^{.02}$, c-10$^{.02}$)	agent 2 obj-1501	yes
504	agent 9 obj-1505	*"mimigo"* (c-6$^{.13}$)	*"mimigo"* (c-7$^{.17}$, c-8$^{.13}$, c-2$^{.10}$, c-4$^{.10}$, c-3$^{.06}$, c-12$^{.02}$, c-13$^{.02}$, c-11$^{.02}$)	agent 4 obj-1505	no
505	agent 9 obj-1508	*"satitu"* (c-5$^{.26}$, c-1$^{.17}$, c-4$^{.13}$, c-11$^{.06}$, c-10$^{.06}$, c-13$^{.02}$, c-2$^{.02}$)	*"satitu"* (c-5$^{.44}$, c-1$^{.17}$, c-3$^{.10}$, c-8$^{.03}$)	agent 5 obj-1508	yes
506	agent 2 obj-1510	*"mimigo"* (c-3$^{.20}$, c-7$^{.20}$, c-2$^{.20}$, c-8$^{.20}$, c-4$^{.20}$)	*"mimigo"* (c-8$^{.17}$, c-2$^{.13}$, c-7$^{.10}$, c-1$^{.10}$, c-6$^{.10}$, c-5$^{.10}$, c-4$^{.02}$)	agent 4 obj-1510	yes
507	agent 9 obj-1512	*"guruto"* (c-8$^{.47}$, c-12$^{.47}$, c-14$^{.34}$, c-15$^{.34}$)	*"guruto"* (c-8$^{.41}$, c-12$^{.34}$, c-14$^{.19}$, c-15$^{.12}$)	agent 8 obj-1512	yes
508	agent 3 obj-1516	*"tozafu"* (c-12$^{.20}$, c-1$^{.20}$, c-15$^{.10}$, c-14$^{.10}$)	*"tozafu"* (c-8$^{.26}$, c-7$^{.17}$, c-12$^{.17}$, c-9$^{.10}$, c-10$^{.10}$, c-1$^{.10}$)	agent 1 obj-1516	no
509	agent 10 obj-1519	*"tozafu"* (c-2$^{.13}$, c-8$^{.13}$, c-9$^{.06}$, c-6$^{.06}$, c-5$^{.06}$, c-15$^{.02}$, c-12$^{.02}$, c-14$^{.02}$, c-1$^{.02}$)	*"tozafu"* (c-8$^{.23}$, c-2$^{.07}$)	agent 6 obj-1519	yes
510	agent 2 obj-1521	*"zoveza"* (c-1$^{.26}$, c-10$^{.17}$, c-3$^{.10}$) *"fobigu"* (c-6$^{.06}$, c-7$^{.06}$, c-2$^{.06}$)	*"zoveza"* (c-1$^{.17}$, c-7$^{.13}$, c-6$^{.10}$, c-5$^{.10}$, c-2$^{.10}$, c-8$^{.10}$, c-3$^{.04}$, c-10$^{.04}$) *"fobigu"* (c-3$^{.23}$, c-7$^{.17}$, c-4$^{.07}$)	agent 4 obj-1521	yes
511	agent 7 obj-1523	*"fobigu"* (c-7$^{.30}$, c-5$^{.14}$, c-8$^{.02}$, c-4$^{.02}$, c-11$^{.02}$)	*"fobigu"* (c-4$^{.36}$, c-7$^{.23}$, c-8$^{.23}$, c-2$^{.13}$, c-3$^{.13}$)	agent 9 obj-1523	no
512	agent 9 obj-1525	*"fobigu"* (c-4$^{.31}$, c-7$^{.25}$, c-8$^{.17}$, c-3$^{.17}$, c-5$^{.10}$, c-1$^{.10}$, c-10$^{.10}$, c-2$^{.07}$) *"zepasa"* (c-7$^{.26}$, c-8$^{.26}$, c-4$^{.07}$)	*"fobigu"* (c-6$^{.10}$, c-7$^{.10}$) *"zepasa"* (c-2$^{.17}$, c-1$^{.17}$, c-13$^{.13}$, c-5$^{.13}$, c-4$^{.06}$, c-3$^{.02}$, c-7$^{.02}$, c-8$^{.02}$)	agent 2 obj-1525	yes
513	agent 4 obj-1529	*"guruto"* (c-12$^{.35}$, c-8$^{.35}$, c-15$^{.19}$, c-14$^{.19}$)	*"guruto"* (c-8$^{.23}$, c-15$^{.20}$, c-12$^{.20}$, c-14$^{.20}$)	agent 5 obj-1529	yes
514	agent 1 obj-1532	*"bovaze"* (c-7$^{.13}$, c-8$^{.13}$, c-1$^{.13}$, c-10$^{.13}$, c-9$^{.13}$)	*"bovaze"* (c-8$^{.23}$, c-9$^{.20}$, c-5$^{.14}$, c-1$^{.05}$)	agent 7 obj-1532	yes

Figure 6.2: Overview of 15 consecutive interactions in a population of 10 agents from game 500 on. It shows

of words. For example in interaction 509, the speaker associates 9 categories to the form “tozafu”, whereas the speaker only connects two categories to it.

Nevertheless, agents communicate already successfully in the majority of the shown early interactions. Interestingly (and very different from the experiments in the previous chapter), agents that use multiple words in an utterances are more likely to reach their communicative goal than agents that use only single words. For example in interaction 502, the speaker uses the three different words “xamexu”, “bovaze” and “dugobo”, and although the hearer has a very different understanding what these words mean, the interaction results in a communicative success. The reason for this is that using more words doesn’t increase the danger of using them in a wrong “wrong” way as in the experiments before, but quite to the contrary adds to the chances of being understood by being more expressive. When words are not very conventionalized yet but some coherence exists, then the more words are used, the higher the chance that the overall similarity to the similarity to objects in the context selects the correct topic.

In addition the flexible lexicon application, the similarity-based alignment mechanisms are the second key factor for the dynamics of this lexicon formation model. Instead of deleting competing hypotheses on word meanings from their lexicons, agents gradually refine and shift the meanings of their words to better conform future uses. Figure 6.3 shows a network representation of a single agent’s lexicon at interaction 500 and then at interaction 10000. Compared to the similar Figure 5.24 (page 103) from the last chapter for the same simulated environment, there are much less word forms in the lexicon after 500 interactions. During the next 9500 interaction, this agent carefully entrenches his association scores (denoted by the line widths). Whereas in the beginning words forms are associated to many categories, words later become more specialized and associate less categories with higher scores. As a consequence, more words enter the lexicon as the existing words cover fewer potential meanings. Also different from the previous competition based dynamics, most of the word forms from the lexicon at interaction are still around at interaction 10000.

Analogously, Figures 6.4a and 6.4b further illustrate the same effects by showing the categories and association scores for the first 5 forms for the 4 agents out of a population of 10 agents at 500 and 5000 interactions. Furthermore, Figures 6.5a–6.5c show three typical evolutions of words of a single agent. In Figure 6.5a, the form “lonigo” gets associated to 8 different categories within the first 4000 interactions. From very early on, the two categories `c-1` and `c-2` become dominant and from interaction 4000 on, all other categories become eliminated and the certainty scores for `c-1` and `c-2` continuously increase. For the form “duropi” (Figure 6.5b), it takes a bit longer to find it’s later meaning. After around 3000 interactions, the three categories `c-1`, `c-2` and `c-4` emerge, of which `c-2` has difficulties to become conventionalized and eventually disappears shortly after interaction 12000. That particular word is

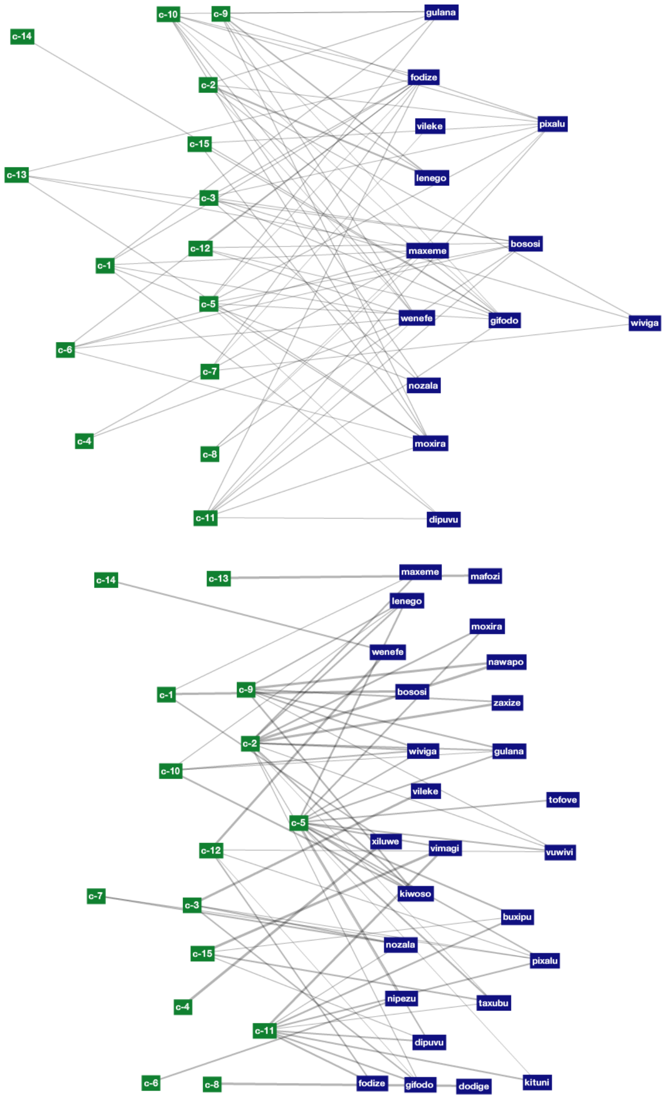


Figure 6.3: A network visualization of the lexicon of a single agent at interaction 500 (top) and interaction 10000 (bottom). For each word denoted by its form, all categories that are associated to the form are shown. The line width represents the certainty scores of these associations.

therefore an example of a word that changes its specificity from being more specific (covering three categories) to more general (covering two categories). An example for the contrary is the word "lonigo" in Figure 6.5c. This one starts out being very general (covering only the single category `c-7`) and later on acquires more meanings (`c-3` at interaction 5000 and `c-2` at interaction 8000), thus becoming more specific.

Finally, the overall alignment dynamics for agents that use flexible word representations and learning mechanisms are shown in Figure 6.6a. Compared to Figure 5.26a on page 104, two things are clearly visible. First, agents start communicating successfully from a bit earlier on but more importantly, never reach 100 percent communicative success. This is due to the fact that agents often stretch their existing words in order to apply in difficult contexts instead of inventing new words, which is interpreted differently by hearers in about two percent of the cases. Second, the typical bell-curved evolution of lexicon size does not occur at all. Instead of inventing and adopting lots of words in the beginning and pruning them later on, agents grow their lexicons much more conservatively. Most of the words enter the lexicons in the first few thousand interactions, but even new words emerge as the lexicons specialize.

Additionally, Figure 6.6b investigates word usage in more depth. First, the overall distance of the words in the utterance to the the topic decreases from 1 in the beginning to almost 0.5 (complete category overlap), showing that agents indeed manage to shape their words to be more applicable in future conversations. Second, the average number of categories covered per word decreases from about 5 to a stable level of 3.5 as part of the entrenchment process. This shows that the word representations are suitable for maintaining structured word meanings, which was not the case for the competition based models from the previous chapter because they contained a frequency-bias towards atomic word meanings.

> *Measure 6.1: Lexicon coherence between speaker and hearer II*
>
> *Provides a measure for how similar the lexicons of the interacting agents are. After each interaction, the similarity between the lexicons of the speaker and the hearer is computed as the average of the output of the `similarity` function for each word form that both agents have in their lexicon and of 0 for all others.*
>
> *Again, the lexicon similarity between speaker and hearer is only an approximation of the population coherence, but is used because its is much more efficiently computed than a measure that involves comparing the lexicons of all agents.*

6.3 Robust scaling dynamics

To demonstrate that the lexicon formation model introduced in this chapter also performs well when the complexity of the interaction scenario increases, we repeat the scaling studies from the previous Chapter (see Section 5.5.3, page 105).

First, Figures 6.7a–6.7c present the main alignment dynamics for increasing population sizes of up to 100 agents. It clearly shows that the model scales well with the number of agents in the population. Agents communicate successfully from very early on and high levels of coherence are reached in all conditions. This is in stark contrast to the same analysis for the models in the previous chapter (see Figure 5.28c), where agents needed to go through thousands of interactions of random search without any success whatsoever. Furthermore, the average lexicon size increases with bigger populations because more words get independently invented and adapted by the population. Since there is no explicit mechanism for synonymy damping, these words stay in the population and specialize on more specific meanings.

A growing number of objects per scene has almost no effect on the dynamics of the game (see Figures 6.8a–6.8c). This is because more alternative conceptualizations of a scene do not result in a higher hypothesis space that needs to be explored but instead only puts a little more burden on the similarity based lexicon application.

And finally, Figures 6.9a–6.9c show what happens when the number of categories in the world simulation increases. More categories mean that agents invent more words and thus it takes longer to align their meanings, but nevertheless the model copes well with an increasing meaning space.

Measure 6.2: Distance utterance to topic

Measures how well the words of the utterance cover the topic. After each interaction, the average of the `similarity` function is computed between all words used by the speaker and the utterance. Results are averaged over the last 250 interactions.

Measure 6.3: Average number of categories per word

Measures how specific words are. For all words in an agents lexicon, the average number of categories that are associated to a form with a non-zero certainty score is computed. Results are averaged over all agents of the population and the last 250 interactions.

form	agent 1		agent 2		agent 3		agent 4	
"sidigu"	c-8	0.34	c-6	0.32	c-6	0.20	c-8	0.39
	c-6	0.34	c-8	0.17	c-7	0.20	c-3	0.32
	c-5	0.26	c-5	0.17	c-3	0.10	c-5	0.32
	c-7	0.17	c-3	0.09	c-8	0.10	c-2	0.17
	c-3	0.17	c-4	0.05	c-5	0.10	c-6	0.09
			c-1	0.04				
"wefugu"	c-8	0.30	c-8	0.13	c-1	0.13	c-4	0.17
	c-7	0.22			c-2	0.13	c-7	0.17
	c-1	0.13			c-11	0.10	c-11	0.02
	c-2	0.02			c-8	0.10	c-6	0.02
	c-12	0.02			c-7	0.10		
	c-9	0.02			c-6	0.02		
	c-5	0.02			c-15	0.02		
					c-4	0.02		
"vufaxe"	c-5	0.43	c-5	0.38	c-5	0.57	c-9	0.30
	c-9	0.25	c-9	0.35	c-9	0.40	c-2	0.30
	c-2	0.14	c-12	0.20	c-12	0.17	c-5	0.14
	c-12	0.08	c-14	0.11	c-2	0.15	c-12	0.06
							c-14	0.06
"bivura"	c-8	0.24	c-5	0.31	c-3	0.17	c-7	0.20
	c-7	0.19	c-9	0.11	c-7	0.17		
	c-1	0.17	c-1	0.10	c-4	0.13		
	c-2	0.14	c-14	0.10	c-1	0.13		
	c-4	0.09	c-12	0.10	c-8	0.07		
	c-5	0.06	c-6	0.09	c-5	0.07		
	c-3	0.06	c-8	0.06	c-2	0.02		
			c-7	0.06				
"kunite"	c-5	0.13	c-9	0.10	c-2	0.20	c-5	0.13
	c-6	0.13	c-5	0.10	c-4	0.13	c-1	0.10
	c-9	0.10	c-7	0.10	c-5	0.10	c-3	0.10
	c-10	0.10	c-3	0.10	c-3	0.10	c-4	0.10
	c-2	0.10	c-4	0.06	c-1	0.10	c-2	0.10
	c-8	0.10	c-1	0.06			c-10	0.02
	c-7	0.02	c-6	0.06			c-8	0.02
	c-3	0.02	c-2	0.06				

Figure 6.4a: Word meanings maintained first four agents of a population of 10 for the first 5 forms after 500 interactions. Word representations are shown with their association scores to different meanings (compared to previous similar charts where competing word meanings were shown).

form	agent 1		agent 2		agent 3		agent 4	
"sidigu"	c−8	0.68	c−8	0.60	c−5	0.66	c−8	0.73
	c−5	0.59	c−5	0.57	c−8	0.63	c−5	0.68
	c−3	0.57	c−3	0.55	c−3	0.59	c−3	0.50
	c−6	0.48	c−6	0.33	c−6	0.46	c−6	0.43
							c−2	0.16
"wefugu"	c−7	0.60	c−7	0.64	c−4	0.59	c−8	0.55
	c−8	0.56	c−8	0.51	c−2	0.46	c−7	0.53
	c−1	0.21	c−4	0.44	c−8	0.45	c−4	0.46
			c−2	0.36	c−7	0.45	c−2	0.40
			c−1	0.32	c−1	0.26	c−1	0.13
"vufaxe"	c−5	0.80	c−5	0.77	c−5	0.84	c−9	0.74
	c−9	0.44	c−9	0.73	c−9	0.67	c−5	0.72
			c−12	0.27	c−12	0.29	c−12	0.22
"bivura"	c−3	0.53	c−3	0.70	c−3	0.67	c−5	0.61
	c−5	0.53	c−7	0.64	c−5	0.67	c−3	0.58
	c−6	0.51	c−5	0.55	c−7	0.37	c−6	0.50
	c−8	0.38	c−6	0.54	c−8	0.32	c−8	0.36
	c−7	0.31	c−8	0.48	c−6	0.31	c−7	0.29
"rotapo"	c−2	0.80	c−2	0.83	c−2	0.86	c−2	0.82
	c−5	0.53	c−5	0.54	c−5	0.46	c−5	0.54
					c−3	0.03		

Figure 6.4b: Word meanings for the same 4 agents as in Figure 6.4a above, but 4500 interactions later (at interaction 5000).

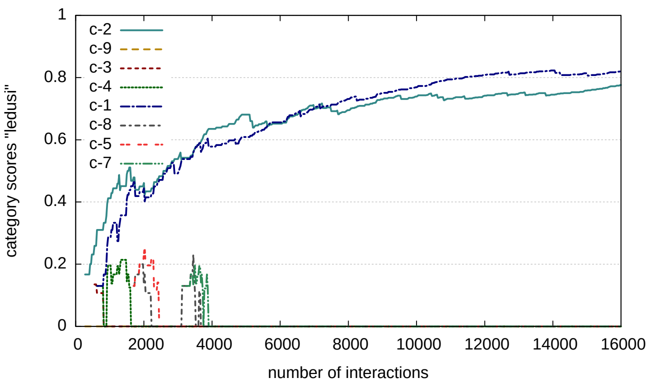


Figure 6.5a: Slowly adapting word meanings of a single word of a single agent over time. The certainty scores of the associations of the form "lonigo" to its categories are shown over the course of 16000 interactions. Not that each agent only takes part in every fifth interaction on average.

Figure 6.5b: Adapting word meanings of another word over time.

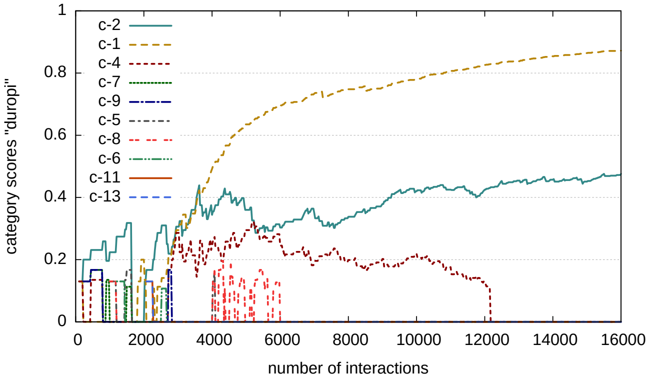


Figure 6.5c: Adapting word meanings of yet another word over time.

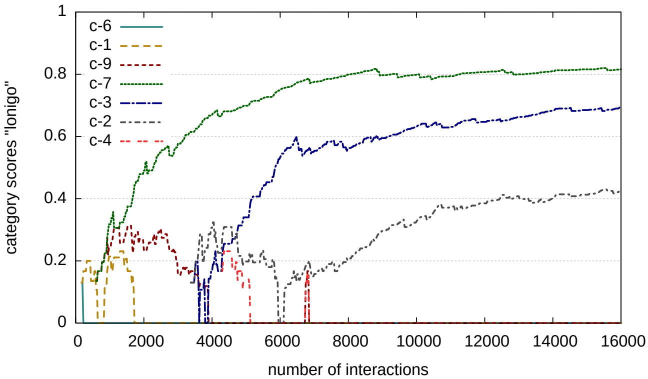


Figure 6.6a: Communicative success (measure [2.1]), lexicon size (measure [4.1]) and lexicon coherence (measure [6.1]) in a population of 10 agents averaged over 10 repeated series of 16000 language games. Each measure is averaged over the last 250 interactions.

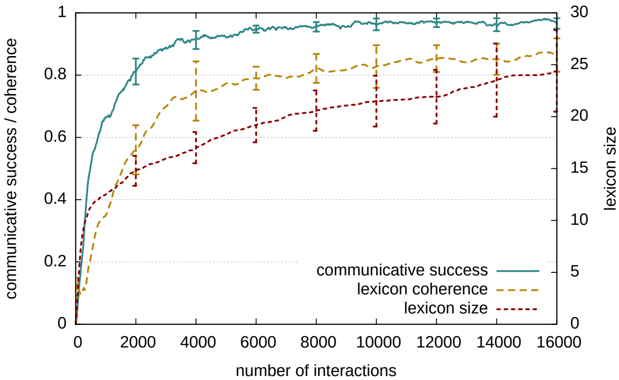


Figure 6.6b: The distance of the utterance to the topic (measure 6.2), the average number of categories covered per word (measure 6.3) and the average utterance length (measure 5.7) are averaged over 10 repeated series of 16000 language games

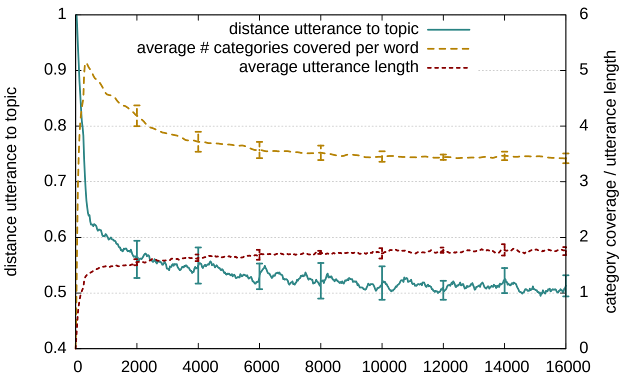


Figure 6.7a: Communicative success (measure 2.1) for five different population sizes. Results are averaged over 10 series of varying length, but each with 8000 interactions per agent.

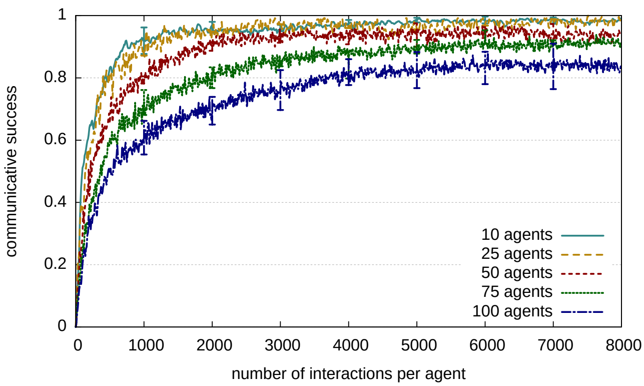
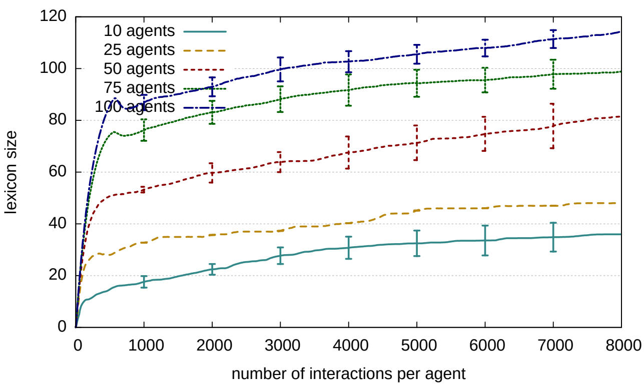


Figure 6.7b: Lexicon size (measure 4.1) for five different population sizes. Results are averaged over 10 series of varying length, but each with 8000 interactions per agent.



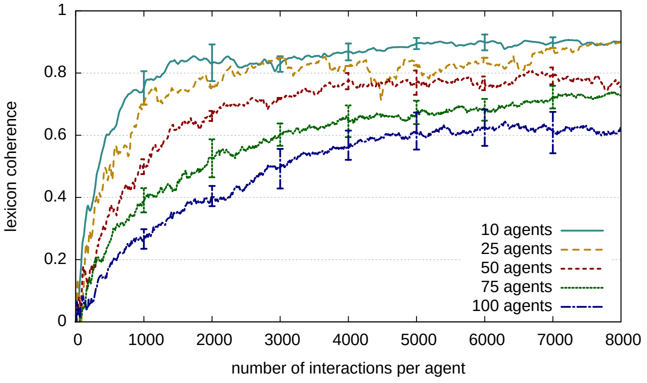


Figure 6.7c: Lexicon coherence (measure 6.1) for five different population sizes. Results are averaged over 10 series of varying length, but each with 8000 interactions per agent.

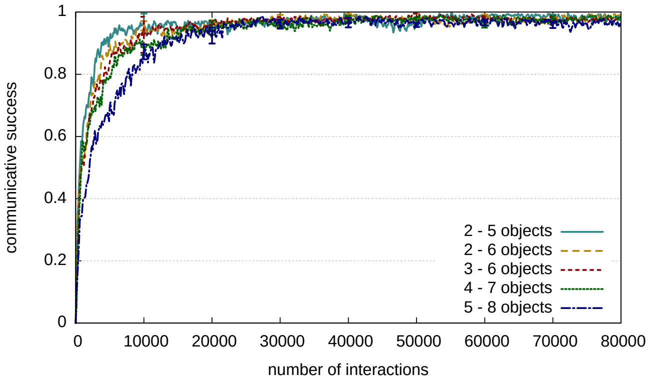


Figure 6.8a: Communicative success (measure 2.1) for world simulators with increasing number of objects per scene. Results are averaged over 10 series of 80000 interactions.

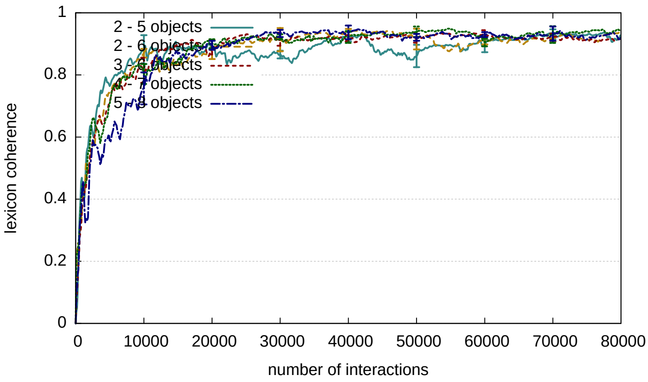


Figure 6.8b: Lexicon coherence (measure 6.1) for world simulators with increasing number of objects per scene. Results are averaged over 10 series of 80000 interactions.

Figure 6.8c: Lexicon size (measure 4.1) for world simulators with increasing number of objects per scene. Results are averaged over 10 series of 80000 interactions.

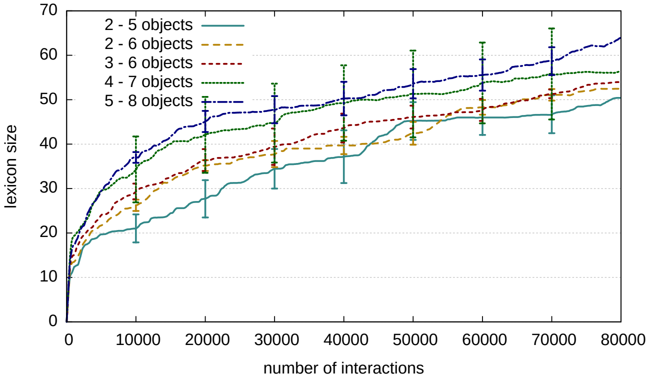


Figure 6.9a: Communicative success (measure 2.1) for world simulators with increasing number of available categories. Results are averaged over 10 series of 80000 interactions.

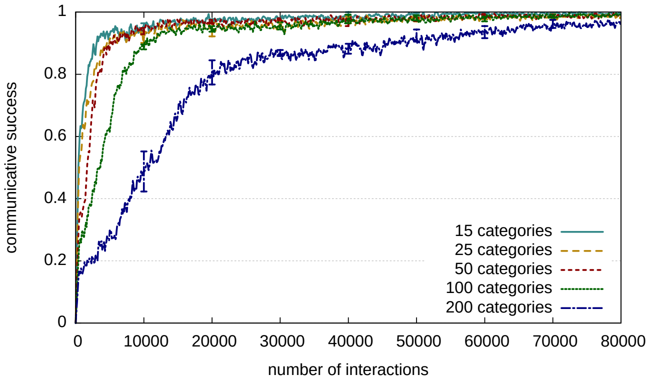


Figure 6.9b: Lexicon size (measure 4.1) for world simulators with increasing number of available categories. Results are averaged over 10 series of 80000 interactions.

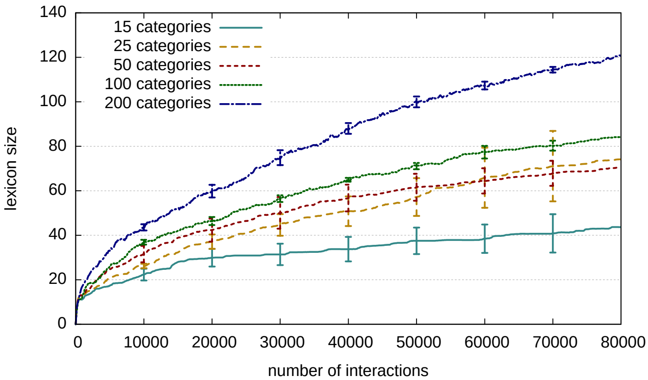
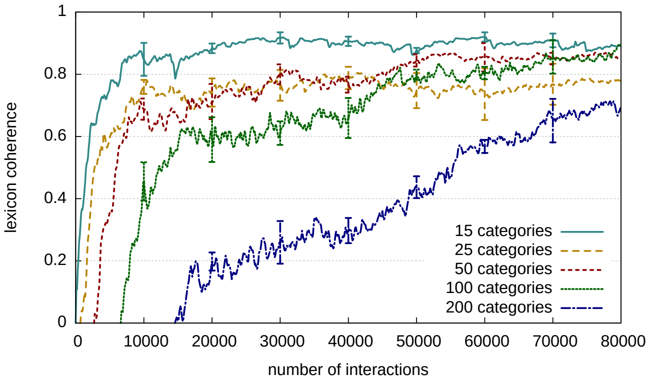


Figure 6.9c: Lexicon coherence (measure 6.1) for world simulators with increasing number of available categories. Results are averaged over 10 series of 80000 interactions.



Part III

Lexicon formation in embodied agents

Chapter 7

Embodiment in humanoid robots

In this third part we will apply the lexicon formation models from the previous three chapters with to real-world situated interactions of autonomous robots. We will discuss mechanisms and representations for conceptualization that allow to link words to the visual perceptions of the robots and we will analyze what impact the additional challenges and complexities coming from embodiment and conceptualization have on the performance of these models. But in order to do that, we will first dedicate one chapter to the perceptual and social skills that we endowed the robots with for engaging in grounded language games[1].

We used two "Sony humanoid robots" (Fujita et al., 2003, see Figure 7.1) for all of our robotic experiments. They are about 60 cm high, weigh approximately 7 kg and have 38 degrees of freedom (4 in the head, 2 in the body, 5×2 in the arms, 6×2 in the legs and 5×2 in the fingers). The main sensors are three CCD cameras in the head, of which we used here one. The camera delivers up to 30 images per second, has an opening angle of about 120° and a resolution of 176×144 pixels. It uses the $YCrCb$ color space (Y: luma or brightness, Cr: chroma red and Cb: chroma blue) with 8 bits per channel. Furthermore, the robots have three accelerometers and gyro sensors in the trunk and one accelerometer in each foot. The feet are equipped with force feedback sensors to detect ground contact. The batteries have enough capacity for about an hour of autonomous operation.

We endowed the robots with a vision system for recognizing and tracking objects in their environment. This system is explained in Section 7.1 and Section 7.2 introduces a set of social skills for engaging in language games

[1] Some parts of of the first two sections of this chapter are taken from Loetzsch, Spranger & Steels (2012) and additionally appeared in shorter form in Spranger, Loetzsch & Steels (2012a).

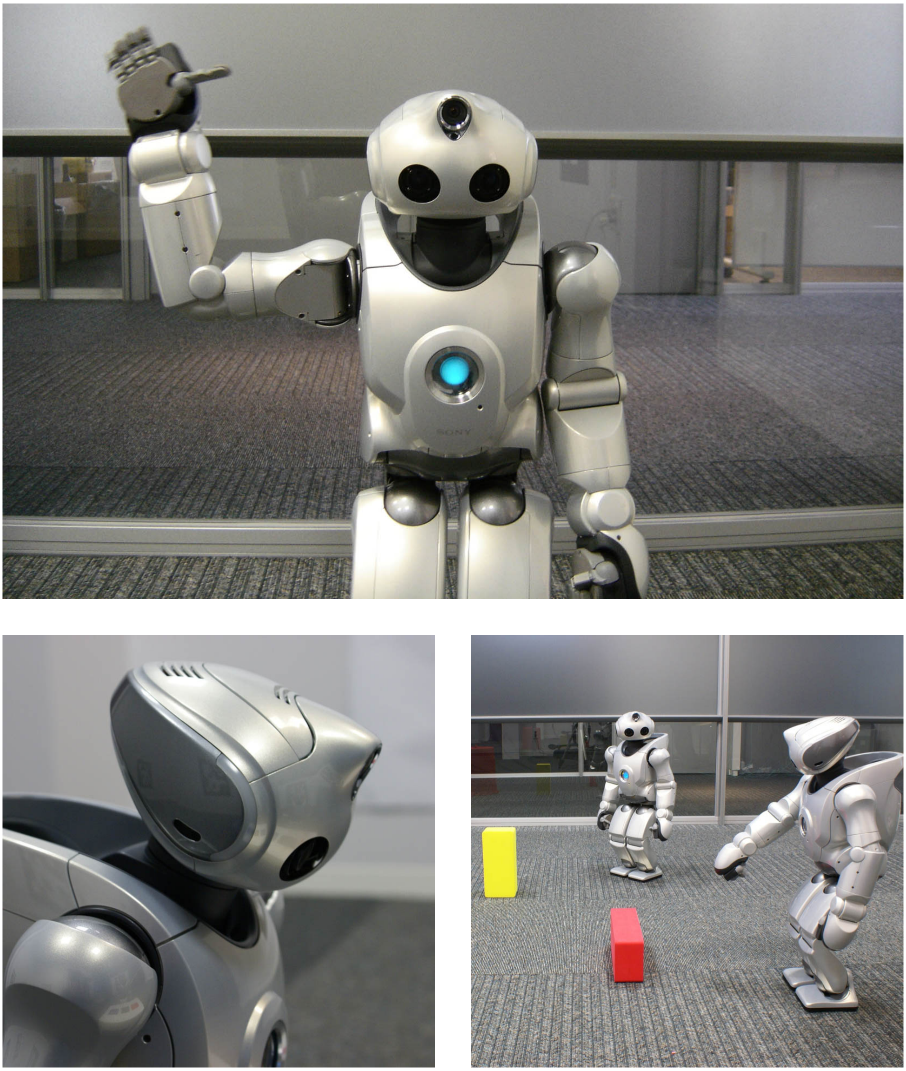


Figure 7.1: The Sony humanoid robot.

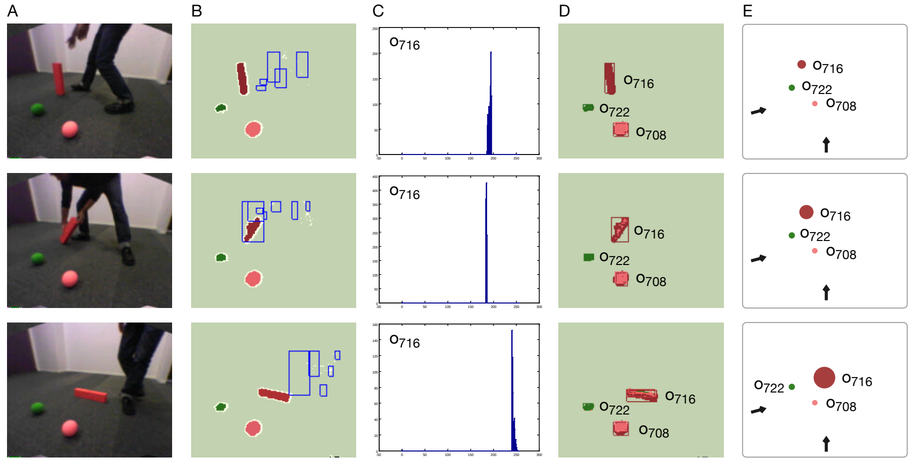


Figure 7.2: Image processing steps for three subsequent points in time. A: Source images provided by the camera of the robot. B: Foreground/ background classification and motion detection (blue rectangles). Foreground regions are then associated to existing object models or become seeds for new object representations. C/D: The changing histogram of the green-red channel for object o_{716} is used to track o_{716} in space and time and thus to create a persistent model of the object. E: Knowing the offset and orientation of the camera relative to the body, the robots are able to estimate the position and size of objects in the world. Black arrows denote the positions of the two robots perceiving the scene.

that were programmed into the robots. Finally, in Section 7.3 we describe the overall experimental setup, i.e. how more high-level cognitive processess for conceptualization and language interact with the sensori-motor capabilities of the robots, and we characterize some properties of the sensory experiences that the robots construct.

7.1 Visual object recognition and tracking

The environment of the robots consists of a variety of physical objects such as toys, cones, barrels and cuboids (see Figure 7.13, page 157) that are initially unknown to the robots. Objects are frequently added to the scene and removed again. In addition, objects are moved within a scene and their appearance may alter. For example the red block in Figure 7.2A is standing up in the beginning and is then put down, changing the perception of the object from being high and thin to low and broad. In addition, perceiving objects is made difficult by partial occlusions and other interfering factors such as human experimenters manipulating the objects in front of the robots.

A prerequisite for building the internal cognitive structures needed for communicating about objects is that the robots have mechanisms for constructing perceptual representations of the objects in their immediate surroundings from the raw sensations streaming from the robots' sensors. Constructing such representations involves three sub-systems: First, low-level vision routines process raw camera images to yield basic *percepts* – connected regions that differ from the background of the environment. Figure 7.2B gives an example and the mechanisms involved are explained in Section 7.1.1 below. Second, these foreground regions are tracked in subsequent camera images despite changing positions and appearances of the objects. In order to do so, the vision system needs to establish a correspondence between an internal *object model* and the image regions that refer to the same physical object, a process known in robotics as *anchoring* (Coradeschi & Saffiotti, 2003; Loutfy et al., 2005). For example as illustrated in Figure 7.2D, the changing raw sensations for the red block in Figure 7.2A are continously connected to the same *anchor* o_{716}. We used *Kalman Filters* for maintaining such persistent object models (Section 7.1.2). Third, when needed in communicative interactions, the vision system encodes a set of visual properties about each object model. In this particular setup these properties are the object's position in a robot egocentric reference system, an estimated width and height and color information, as shown in Figure 7.2E. This process is discussed further in Section 7.1.3.

7.1.1 Detecting foreground regions in images

The robots do not know in advance what kind of objects to expect in their environment. Thus, the assumption is made that everything that was not in the environment before is considered to be a potential object. The system, therefore, gathers statistical information about the environment's background in a calibration phase and image regions that sufficiently differ from the background are treated as candidates for object models. For generating a statistical model of the scene background, the robots observe the experiment space without objects for some time (see Figure 7.3) and perceive a series of calibration images such as in Figure 7.4A. For all three color channels $c \in \{Y, Cr, Cb\}$ the mean $\mu_{c,\vec{p}}$ and variance $\sigma^2_{c,\vec{p}}$ of the image intensities at every image pixel $\vec{p}$ are computed over all calibration images. After the calibration phase the robots are presented with objects, resulting in raw camera images such as in Figure 7.4B. The generated background statistics are used to classify all image pixels as being foreground or background. A pixel is considered foreground when the difference between the image intensity $i_c(\vec{p})$ and the mean of that pixel is bigger than the pixel's standard deviation ($\mid i_c(\vec{p}) - \mu_{c,\vec{p}} \mid > \sigma_{c,\vec{p}}$) for one of the color channels $c \in \{Y, Cr, Cb\}$. As a result, a binary image as shown in Figure 7.4C is generated with all foreground pixels having the value of 1 and all others 0.

This binary image is further noise-reduced using standard image operators (dilatation, erosion, see for example Parker, 1996; Soille, 1993) as illustrated in Figure 7.4D. First, noise is removed through applying a 3×3 erosion operator. Second, the change in size of regions caused by the erosion operator is compensated by applying a 3×3 dilation operator. Then a segmentation algorithm scans the filtered image and computes for all connected foreground pixels a surrounding polygon, the bounding box, and color histograms of the pixels contained in the region (for each color channel, from the original im-

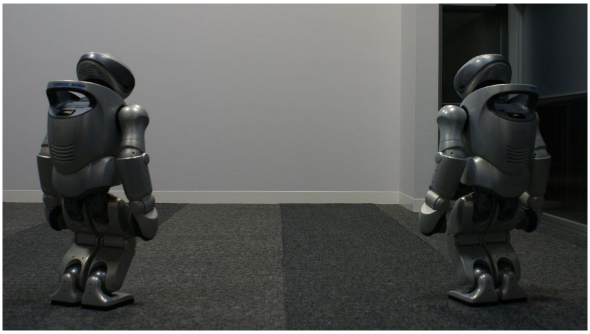


Figure 7.3: Calibration phase of the vision system. Both robots are shown an empty environment for some extended period of time, allowing them to observe the statistical characteristics of the scene background.

age). Color histograms M^c represent frequencies of image intensities on the color channel c, computed either over complete images or parts of them in the case of foreground regions. The whole range of intensities is divided into m bins $k \in \{1, \ldots, m\}$ of equal size. The number of pixels that have intensities falling into each bin $M^c(k)$ is counted using a function $h(i_c(\vec{p}))$ that assigns the intensity i_c of a pixel $\vec{p}$ to a bin k. Normalized histograms $\hat{M}^c(k)$ are computed from such histograms by dividing each frequency $M^c(k)$ by the number of pixels sampled, resulting in a representation where the sum of all $\hat{M}^c(k)$ for $k \in \{1, \ldots, m\}$ is equal to 1, allowing to interpret $\hat{M}(h(i_c(\vec{p})))$ as the probability of an image intensity to occur in an image (or a sub-region). Figure 7.4E shows the estimated bounding boxes and average colors extracted from the regions.

Objects frequently occlude each other, due to particular spatial placement, but also when moved around in the scene. For example the green cube is partly overlapping the blue cuboid in the right bottom of Figure 7.4B and thus the segmentation algorithm creates only one foreground region for both objects. Provided that there is an established object model (see next Section 7.1.2) for at least one of the objects, it is possible to further divide such regions. Each pixel in a foreground region is assigned to the most similar color model of previously perceived objects as shown in Figure 7.4F. Given the normalized color histograms M_I^c of all pixels in the current image I and $M_1^c, \ldots, M_n^c$ of the n previously established object models, the likelihood p_j of a pixel $\vec{p}$ in a foreground region to belong to a color model j can be calculated:

$$p_j(\vec{p}) = M_j^Y(h(i_Y(\vec{p}))) \cdot M_j^{Cr}(h(i_{Cr}(\vec{p}))) \cdot M_j^{Cb}(h(i_{Cb}(\vec{p})))$$

Based on this probability, each pixel is either classified to belong to the model j with the highest likelihood $\text{class}(\vec{p}) = \arg\max_{j=1..n}(p_i(\vec{p}))$ or, when the highest p_j is smaller than a threshold t or when no previous model exists, to a "no model" class. Classified pixels are again segmented into connected regions. As shown in Figures 7.4G and 7.4H, the initially connected foreground region for the blue and green objects in the right bottom of the image could be divided into separate regions due to the use of previous color models.

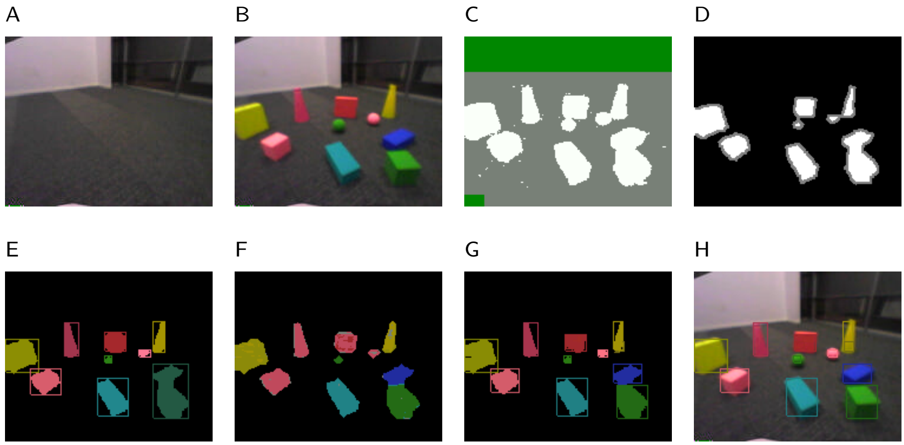


Figure 7.4: From foreground regions to object models. A: A raw camera image taken during the calibration phase. B: A camera image of a scene containing objects. C: The result of foreground/ background classification. White pixels are foreground, green pixels were not classified. D: The noise-reduced classification image. E: The segmented foreground regions drawn in their average color and with bounding boxes. Note that the partially overlapping blue and green blocks in the right bottom of the original image are segmented into the same foreground region. F: Classification of foreground pixels using existing color models. Pixels are drawn in the average color of the most similar object model. G: Bounding boxes and average colors of the segmented classification image. Note that the use of previous color models helped to generate separate percepts for the blue and green blocks at the right bottom of the image. H: Kalman filtered object models. The state bounding boxes are drawn in the average color of the model. I: Computation of position and size in a robot-egocentric reference system. The width and height of objects is indicated by the width and height of the triangles.

The resulting subdivided foreground regions are called *percepts*. They represent the result of the low-level image processing mechanisms acting separately on each image without incorporating past knowledge (except for the color information of previous objects). A percept P is defined as $P := \langle x_P, y_P, w_P, h_P, M_P^Y, M_P^{Cr}, M_P^{Cb}, n_P \rangle$ with x_P, y_P describing the center of the percepts bounding rectangle in image coordinates, w_P and h_P the width and height of the bounding rectangle in pixels, M_P^Y, M_P^{Cr} and M_P^{Cb} the normalized histograms for the three color channels and n_P the number of pixels contained in the region.

In order to improve the tracking algorithm described in the next Section, we also implemented a component for identifying regions in the image where motion has occured. Image intensities $i_{c,t}(\vec{p})$ at time t are compared to those of images taken at time $t-1$. A pixel $\vec{p}$ is classified as subject of motion when the difference is bigger than the standard deviation $\sigma_{c,\vec{p}}$ of this pixel's intensities calculated during the calibration phase ($\mid i_{c,t}(\vec{p}) - i_{c,t-1}(\vec{p}) \mid > \sigma_{c,\vec{p}}$) for one of the color channels $c \in \{Y, Cr, Cb\}$. The resulting classification image is noise-reduced and segmented into regions of motion as shown in Figure 7.2B. This information is used to loosen the parameters for the association of percepts to object models. If there is motion in a particular region of the image, then object models are allowed to move and change color more drastically than if there is no motion.

7.1.2 Maintaining persistent object models

For maintaining a set of stable and persistent models of the objects in their environment, the robots have to associate the percepts extracted from each raw image to existing object models. Furthermore, they have to create new models when new objects enter the scene and eventually delete some models when objects disappear. This task is difficult because objects can move and the detection of regions through foreground/background separation is noisy and unreliable. Extracted properties such as size or position may highly vary from image to image and it can happen that objects are only detected in some of the images streaming from the camera.

The internal object model O_t of an object at time step t (whenever a new camera image is processed) is defined as $O_t := \langle id_O, s_{O,t}, \Sigma_{O,t}, M^Y_{O,t}, M^{Cr}_{O,t}, M^{Cb}_{O,t}\rangle$, with id_O being an unique id serving as an anchor for the object, $s_{O,t}$ a state vector capturing spatial properties, $\Sigma_{O,t}$ the 8×8 state covariance matrix and $M^Y_{O,t}$, $M^{Cr}_{O,t}$ and $M^{Cb}_{O,t}$ normalized color histograms. A state vector s is defined as $s_{O,t} := \begin{pmatrix} x_{O,t} & y_{O,t} & w_{O,t} & h_{O,t} & \dot{x}_{O,t} & \dot{y}_{O,t} & \dot{w}_{O,t} & \dot{h}_{O,t}\end{pmatrix}^T$, with $x_{O,t}, y_{O,t}$ describing the center of the object in the image, $w_{O,t}$ and $h_{O,t}$ the object's width and the height in pixels and $\dot{x}_{O,t}$, $\dot{y}_{O,t}$, $\dot{w}_{O,t}$ and $\dot{h}_{O,t}$ the change variables (speed of change in position and size).

We use Kalman Filters (Kalman, 1960) to model the spatial component $s_{O,t}$ of object models. In every time step t all Kalman Filter states $s_{O,t-1}$ and $\Sigma_{O,t-1}$ of the last time step $t-1$ are used to *predict* a new a priori state $\overline{s}_{O,t}$ and a state covariance matrix $\overline{\Sigma}_{O,t}$ given the 8×8 state transition matrix A and the process noise covariance matrix Q:

$$\begin{aligned} \overline{s}_{O,t} &:= A s_{O,t-1} \\ \overline{\Sigma}_{O,t} &:= A \Sigma_{O,t-1} A^T + Q \end{aligned}$$

We found it sufficient to use a constant state transition matrix A, which predicts every dimension via its change variable and a constant noise covariance matrix $Q = 1^{-5} \cdot I_8$.

Next attempts are made to associate percepts to existing models. Since the position, dimension and color of objects change over time, no a priori known invariant properties of objects allow to decide which percept belongs to which model. Instead, a similarity score $\hat{s}$ based on position and color is used. The score reflects a set of assumptions and heuristics, which are based on intuitive notions of how objects behave, so that experimenters can change the scene, without having to adjust to particular properties of the vision system. First it is assumed that an object can not randomly jump in the image or disappear at one point in space and appear at another. Consequently, a spatial similarity

$\hat{s}_{euclid}$ can be defined using the Euclidean distance between the center of a percept P and the predicted position $\overline{x}_{O,t}, \overline{y}_{O,t}$ of a model O

$$\hat{s}_{euclid}(P, O) := 1 - \frac{\sqrt{(x_P - \overline{x}_{O,t})^2 + (y_P - \overline{y}_{O,t})^2}}{l}$$

with l being the length of the image diagonal in pixels. The result of $\hat{s}_{euclid}$ is 1 when the two points are identical and 0 when they are in opposite corners of the image. Since objects are assumed to move in a predictable fashion, a threshold t_{space} restricts the radius around a model in which percepts are associated – the spatial association score $\hat{s}_{space}$ equals to $\hat{s}_{euclid}$ when it is bigger than t_{space} and 0 otherwise. Second, it is assumed that objects do not change their color in a random fashion. An object's color histogram that has a very high value in a certain bin will not have a zero value in that bin in the next image. Percepts and object models can thus be compared using a color similarity $\hat{s}_{color}$. It is based on the Bhattacharyya coefficient BC (Aherne et al., 1998; Bhattacharyya, 1943) that is used as a similarity measure between two normalized histograms M and M':

$$BC(M, M') := \sum_{k=1}^{m} \sqrt{M(k) \cdot M'(k)}$$

Using the color histograms M_P^c of a percept P and the histograms $M_{O,t-1}^c$ of a previous model O, a similarity measure combining all three color channels is defined as:

$$\hat{s}_{Bhatt}(P, O) := \prod_{c \in \{Y, Cr, Cb\}} BC(M_P^c, M_{O,t-1}^c)$$

The association score $\hat{s}_{color}(P, O)$ then yields the result from the above measure when it is bigger than a threshold t_{color} or 0 otherwise. In order to allow more rapid changes in space and color when objects move, the two association thresholds t_{space} and t_{color} are loosened when motion has been detected within the area spawned by a state.

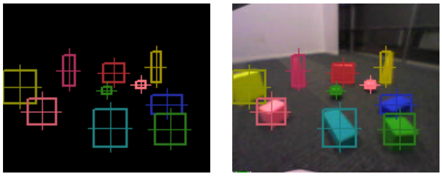
The overall similarity score between a particular percept and an existing object model is then defined as:

$$\hat{s}(P, O) = \hat{s}_{space}(P, O) \cdot \hat{s}_{color}(P, O)$$

Each percept is associated with the internal state that has the highest association non-zero score $\hat{s}$ with respect to that percept. If no such state exists (when either the spatial or color similarity is below the threshold), then the percept is stored in a list of unassociated percepts.

The Kalman Filter states are *updated* given the associated percepts, which are beforehand combined into a single percept. Percepts are combined by computing a bounding polygon and a histogram representing the color frequency in the combined region. Using the predicted a priori state vector $\overline{s}_{O,t}$ and state

Figure 7.5: Kalman filtered object models. The state bounding boxes are drawn in the average color of the model and the state covariance is visualized with the thin cross in the center of each model.



covariance $\overline{\Sigma}_{O,t}$ as well as the spatial components p of the combined percept $p := \begin{pmatrix} x_P & y_P & w_P & h_P \end{pmatrix}^T$, the a posteriori state s_t and the a posteriori state covariance matrix $\Sigma_{O,t}$ are computed

$$\begin{aligned} K_{O,t} &= \overline{\Sigma}_{O,t} H^T H \overline{\Sigma}_{O,t} H^T + R \\ s_{O,t} &= \overline{s}_{O,t} + K_{O,t}(p - H\overline{s}_{O,t}) \\ \Sigma_{O,t} &= (I - K_{O,t}H)\overline{\Sigma}_t \end{aligned}$$

with R as the constant 4×4 measurement covariance matrix (with $R = 1^{-1} \cdot I_4$) and H a constant 8×4 matrix relating the measurement space and the state space (with $h_{i,j} = 1$ for all $i = j$ and 0 for all others). In principle H and R are allowed to change over time, but the above estimates resulted in sufficient tracking performance. Additionally, the color histograms of a state S are updated using

$$M^c_{O,t}(k) := (1 - \alpha) M^c_{O,t-1}(k) + \alpha M^c_P(k)$$

for all color channels $c \in \{Y, Cr, Cb\}$, all histogram bins $k \in \{1, \ldots, m\}$ and with $\alpha \in [0, 1]$ being the influence of the combined percept.

New object models are created from unassociated percepts. All unassociated percepts lying in the same foreground region are combined and used as a seed for a new model which is assigned a new unique ID. In order to avoid creating models from percepts generated for body parts of the experimenter, new models are only created when no motion was detected. Models that have not been associated with percepts for some time are deleted. This mainly happens when objects disappear from the scene and consequently no percepts are associated with them. As a result of the modeling process, Figure 7.5 shows the object models at the time when the percepts in Figure 7.4 were generated.

7.1.3 Computing object features

From each object model, a set of features such as color, position and size are extracted. These feature vectors are called *sensory experiences* and are used by the agents to construct the different conceptual entities needed for engaging in the different kind of language games introduced in this thesis.

The two robots can perceive the environment from arbitrary angles, which makes the position and size of objects in the camera image bad features for communicating about objects. For example the width of an object in the image

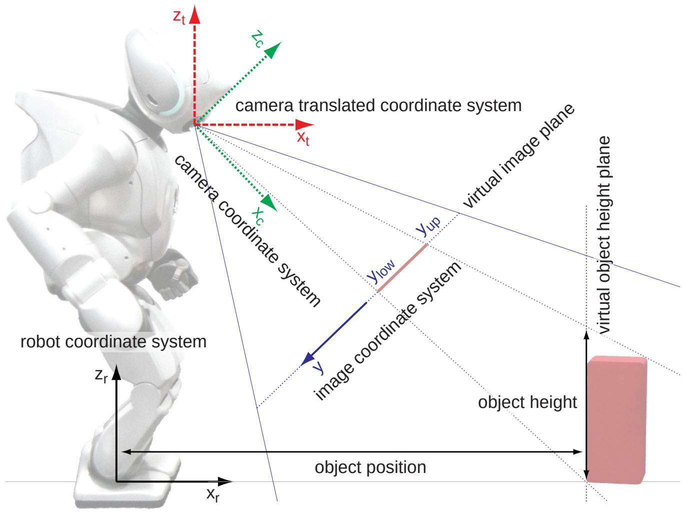


Figure 7.6: Computation of object positions on the ground plane, size estimation and the involved coordinate systems. Note that all systems except the image coordinate system are three dimensional.

depends on how far the object is away from the robot and is thus not at all shared by the robots. In order to be independent from how objects are projected onto camera images, spatial features are computed in an egocentric coordinate system relative to the robot. However, without the use of stereo vision or a priori known object sizes, positions can not be determined solely from camera images. But given the reasonable assumption that objects are located on the ground, they can be calculated by geometrically projecting image pixels onto the ground plane using the offset and rotation of the camera relative to the robot as shown in Figure 7.6. The egocentric robot coordinate system originates between the two feet of the robot, the z axis is perpendicular to the ground and the x axis runs along the sagittal and the y axis along the coronal plane. First, a virtual image projection plane orthogonal to the optical axis of the camera is used to relate image pixels in the two-dimensional image coordinate system to the three-dimensional camera coordinate system (which has its origin in the optical center of the camera, with the x axis running along the optical axis and the y and z an axis being parallel to the virtual image plane). Given the camera resolution height and width r_w and r_h (in pixels) as well as the horizontal and vertical camera opening angle ϕ_v and ϕ_h, the x_i and y_i coordinates of an image pixel can be transformed into a vector $\vec{v}_c$ in the camera coordinate system

$$\vec{v}_c = \begin{pmatrix} 1 \\ -\frac{x_i}{r_h} \cdot \tan\frac{\phi_h}{2} \\ \frac{y_i}{r_v} \cdot \tan\frac{\phi_v}{2} \end{pmatrix}$$

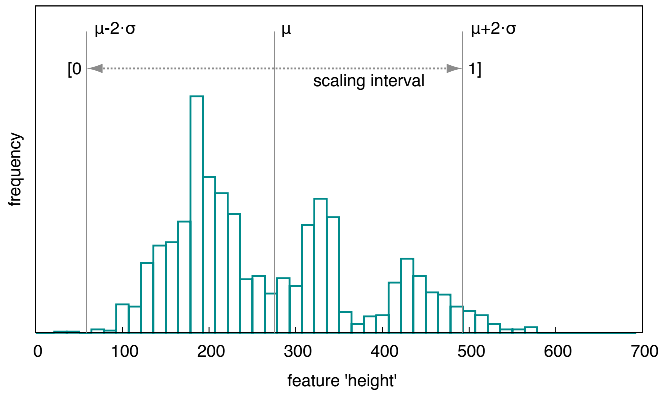


Figure 7.7: Scaling of feature values. The distribution of the 'height' feature sampled over all objects of the geometric objects data set (see Section 7.3.2 on page 156) is used to define an interval $[\mu - 2\sigma, \mu + 2\sigma]$ *for scaling feature values into the interval* $[0, 1]$.

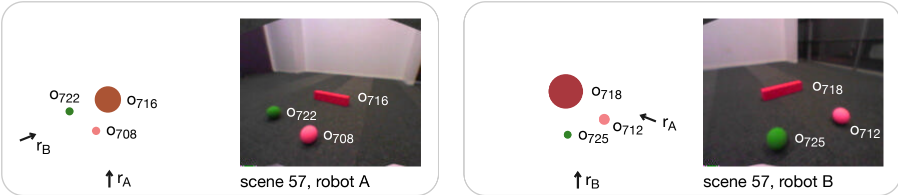
that "points" to the pixel on the virtual projection plane. Given the orientation of the camera relative to the robot represented by the 3×3 rotation matrix R_c, a vector $\vec{v}_c$ can be rotated into a vector $\vec{v}_t$ in the camera translated coordinate system (which originates in the center of the camera, with the axes being parallel to the robot coordinate system) with $\vec{v}_t = R_c \cdot \vec{v}_c$. Furthermore, given the offset from the origin of the robot coordinate system to the center of the camera $\vec{t}_c$, the position of a pixel projected onto the ground plane $\vec{v}_r$ in the egocentric robot coordinate system can be computed by intersecting the ray $\vec{v}_t$ with the ground plane using simple geometric triangulation: The equation

$$\vec{v}_r = a \cdot \vec{v}_t + \vec{t}_c$$

with the unknown scalar a has exactly one solution for x_r and y_r when the pixel designated by $\vec{v}_t$ lies below the horizon. The operating system of the Sony humanoid readily provides estimates for R_c and $\vec{t}_c$ that are computed from joint sensor values.

Using these transformations, the position features `x` and `y` (in mm) are extracted from an object model by projecting the pixel at the center of the lower edge of the object's bounding box onto the ground plane. For estimating a `width` feature, the lower left and right corner of a the bounding box are transformed into positions relative to the robot and the distance between them is calculated. For the computation of `height`, the ray of the pixel on the middle of the upper bounding box edge is intersected with a virtual plane perpendicular to the ground and through the position of the object as shown in Figure 7.6. The extraction of color features from object models is also straightforward. The feature `luminance` is computed as the mean of an internal state's color histogram M_t^Y, `green-red` as the mean of M_t^{Cr} and `yellow-blue` from M_t^{Cb}.

The values of the `x` and `y` features are ususally in the range of meters, `width` and `height` can range from a few centimeters up to half a meter and values on color channels are within the interval $[0, 255]$. In order to be able to handle all



feature	experience robot A						experience robot B							
	o708		o716		o722		o712			o718			o725	
x	464	0.43	821	0.69	686	0.59	607	0.53	*0.11*	925	0.76	*0.08*	432	0.40
y	151	0.61	17	0.51	453	0.82	-301	0.28	*0.33*	137	0.60	*0.09*	115	0.58
width	47	0.31	150	1.00	46	0.30	62	0.46	*0.15*	196	1.00	*0.00*	45	0.29
height	116	0.35	138	0.42	67	0.19	109	0.33	*0.02*	186	0.58	*0.16*	135	0.41
luminance	126	0.76	72	0.30	81	0.37	130	0.79	*0.03*	57	0.17	*0.13*	85	0.41
green-red	206	0.81	187	0.72	101	0.29	206	0.81	*0.00*	196	0.76	*0.04*	98	0.28
yellow-blue	119	0.53	110	0.47	99	0.38	121	0.55	*0.02*	123	0.57	*0.10*	97	0.37

Figure 7.8: Snapshots of the sensory experiences of both robots at the end of the image sequence in Figure 7.2. Top: The camera images at that point in time are overlaid with the object anchors maintained by the tracking system. Left of them, the positions of objects and other robots in the egocentric reference system of each robot are shown. Each object is drawn as a circle in its average color, with the radius representing the object's width. The positions of the two robots (see Section 7.2.3 below) are indicated using black arrows. Bottom: The actual feature values are shown in each first column and feature values scaled to the interval $[0, 1]$ *in each second column. On the right side of the table, the third columns give for each scaled feature the difference between the perception of robot A and B.*

features independently from the dimensions of their domains, feature values are scaled to be within the interval $[0, 1]$ using the statistical distributions of feature values as illustrated in Figure 7.7 In theory the robots could gradually build up such distributions by seeing many different objects over the course of time, in practice the distributions are sampled from objects of recorded data sets (see Section 7.3.2). Given the mean μ and standard deviation σ of the distribution of a feature over a (large) number of objects, a scaled value is computed by mapping values in the interval $[\mu - 2\sigma, \mu + 2\sigma]$ onto $[0, 1]$ and clipping all others. Figure 7.8 gives an example of the sensory experiences of the two robots. For each object, both the unscaled and scaled feature values are given.

7.1.4 Visual perception in humans and robots

The psychological and neurobiological literature on vision contains a lot of evidence for correlates of these three sub-systems in the human brain. First, there are dedicated neural assemblies along the visual stream from the retina to the primary visual cortex that detect basic visual features on a number of separable dimensions such as color, orientation, spatial frequency, brightness and direction of movement. These *early vision* processes operate independently from attention to objects and features "are registered early, automatically, and in parallel across the visual field " (Treisman & Gelade, 1980, p. 98). From there on, two separate visual pathways (also known as the "what" and "where" systems) are responsible for identifying objects and encoding properties about them (see Mishkin et al., 1983 for an early review): A dorsal stream (the "where" system) connecting the primary visual cortex and the posterior parietal cortex is responsible for the primitive individuation of visual objects, mainly based on spatial features. "Infants divide perceptual arrays into units that move as connected wholes, that move separately from one another, and that tend to maintain their size and shape over motion" (Spelke, 1990, p. 29). These "units" can be understood as "pointers" to sensory data about physical objects that enable the brain for example to count or grasp objects without having to encode their properties. They can be compared to the *anchors* mentioned above and are subject of a large number of studies: Marr (1982) calls them *place tokens*, Pylyshyn (1989, 2001) *visual indexes*, Ballard et al. (1997) *deictic codes* and Hurford (2003) discusses them from an artificial intelligence and linguistics perspective as *deictic variables*. In a second ventral stream (the "what" system) running to the infero-temporal cortex, properties of objects are *encoded* and temporarily stored in the *working memory* (Baddeley, 1983) for the use in other cognitive processes. What these properties are depends on top-down attentional processes – for example different aspects of objects have to be encoded when a subject is asked to count the number of "big objects" vs. the number of "chairs".

In addition to findings from neuroscience, there is also a variety of previous work in robotics to rely on. The most widely known setups for grounding symbolic representations in visual data for the purpose of communication is probably the Talking Heads experiment (Steels, 1998a, see Belpaeme et al., 1998 for details of the vision system). Static scenes consisting of geometric shapes on a blackboard are perceived by robotic pan-tilt cameras and the vision system is able to extract features such as color, size and position from these shapes. Siskind (1995) describes a computer program for creating hierarchical symbolic representations for simple motion events from simulated video input and in (Siskind, 2001) from real video sequences (see also Baillie & Ganascia, 2000; Dominey & Boucher, 2005; Steels & Baillie, 2003 for very similar systems and Chella et al., 2000, 2003 for a comparable framework inspired by the *conceptual spaces* of Gärdenfors, 2000).

Furthermore, there is a vast literature on object detection and tracking algorithms for other purposes than symbol grounding (see Yilmaz, Javed & Shah, 2006 for an extensive review). And the vision system introduced here does not reinvent the wheel but makes use of well-established techniques such as color histograms and Kalman filters. It differs, however, from many other approaches in the notion of what is considered to be an object. The types of objects that are expected to occur in the world are often explicitly represented in the vision system, for example by using pre-specified color ranges for identifying different object classes in images (e.g. Pérez et al., 2002), by matching (sometimes learnt) object templates with images (e.g. Hager & Belhumeur, 1998) or by engineering dedicated algorithms tailored for recognizing specific classes of objects (e.g. Jüngel, Hoffmann & Lötzsch, 2004).

In contrast, our robots have no preconceptions of what to expect in their environment and thus can detect and track any type of object, using only two assumptions: First, everything appearing in the environment that sufficiently distinguishes itself from the background and that was not there before is considered to be an object. Second, objects have to be on the ground for being able to make reliable position and size estimates. Furthermore, what makes the approach presented here quite special is the tight integration of visual perception with other cognitive mechanisms such as social behavior (see below), conceptualization and language (as discussed in the next chapters).

7.2 Joint attention & mechanisms for social learning in robots

Robots learning a language are not only grounded in the physical world through their sensorimotor apparatus but also socially grounded in interactions with others. In addition to perceptual capabilities for detecting and tracking objects in their environment they need a set of social skills for engaging in communicative interactions with each other. This includes mechanisms for joint attention and pointing as well as behavioral scripts for structured conversations. Joint attentional scenes (Tomasello, 1995) "are social interactions in which the child and the adult are jointly attending to some third thing, and to one another's attention to that third thing, for some reasonably extended length of time" (Tomasello, 1999, p. 97). Establishing joint attention means in our robotic experiments that two robots taking part in a language game must (1) share a physical environment, (2) attend to a set of objects in their surrounding, (3) track whether the respective other robot is able to attend to the same set of objects and (4) be able to manipulate attention by pointing to distal objects and perceiving these pointing gestures (see Figure 7.9).

7.2.1 Social robotics

How social mechanisms can be implemented in robots is a research area in its own. Scientist in this field are mainly interested in how social skills can improve communication and collaboration between humans and robots (Breazeal, 2002). Additionally, by trying to endow robots with social behaviors that appear "natural" to human observers, they want to understand what social cues humans are responding to. For reviews, refer to Dautenhahn, Odgen & Quick (2002) who developed taxonomies for different degrees of robots' embodiment and "social embeddedness", Fong, Nourbakhsh & Dautenhahn (2002) who give a general survey of socially interactive robots, and Vinciarelli et al. (2009) who

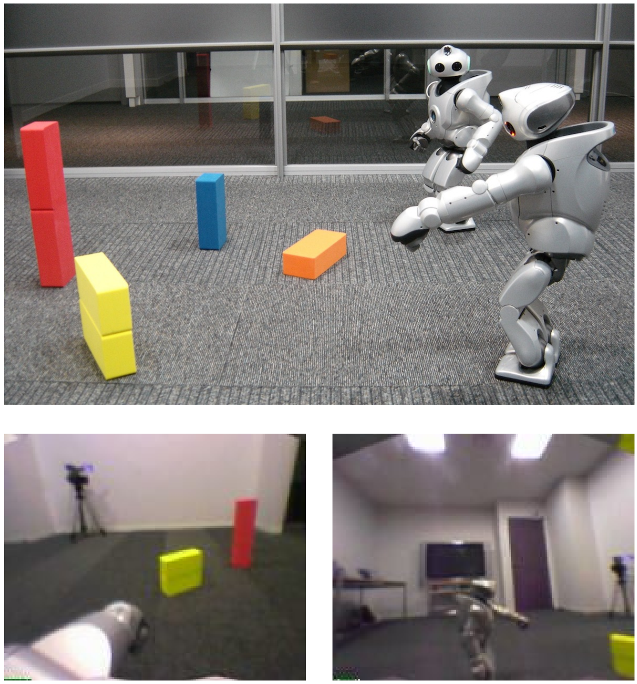


Figure 7.9: Demonstration of a Sony humanoid robot drawing the attention of the other robot to an object in the shared environment by pointing at it. The images at the right show the scene as seen through the camera of the pointer (top) and the robot observing the pointing (bottom). However, please note that the robots are not able to detect pointing gestures using their built-in cameras. Instead, they directly transmit x, y coordinates of the object pointed at.

review the field of "social signal processing", i.e. the detection of social cues in human behavior. For an overview of skills that are prerequisites for joint attention and the state of the art in robotic experiments trying to implement these skills, refer to Kaplan & Hafner (2006). Some examples of work relevant for the experiments in this paper are listed below.

Scassellati (1999) endowed the "Cog" robot (Brooks et al., 1999) with capabilities for finding human faces, extracting the location of the eye within the face, and determining if the eye is looking at the robot for maintaining eye contact (or mutual gaze). Marjanovic, Scassellati & Williamson (1996) showed how the same robot could learn to control his arm for pointing at distal objects in the surrounding space, guided by the camera of the robot. Gaze recognition was investigated among many others by Kozima & Yano (2001). They demonstrated how the "Infanoid" robot is able to track gaze direction in human faces and use this information to identify objects that humans are looking at. Joint attention is established by alternatingly looking at distal objects and the faces. Nagai et al. (2003) modeled the transitions between different developmental stages that infants are going through in the process of learning to engage in joint attentional scenes, resulting in the robot being able to determine which object a human caregiver is looking at.

For recognizing pointing gestures performed by humans, Kortenkamp, Huber & Bonasso (1996) developed a robot that can detect and track the 3D positions of arm and shoulder joints of humans in dynamic scenes, without requiring the humans to wear special markers. By searching along the vector defined by the detected arm joints, the robot can determine which object the experimenter was pointing at. Similarly, Martin et al. (2009) used pointing gestures to instruct a mobile robot where to navigate to. Colombo, Del Bimbo & Valli (2003) used multiple cameras for tracking humans pointing at areas on walls in a room. Nickel & Stiefelhagen (2007) equipped a robot with stereo cameras and use color and disparity information and Hidden Markov Models to track both the direction of gaze and the position where a human is pointing at. Haasch et al. (2005) apply the ability to recognize pointing gestures for teaching words for objects in a domestic environment and Imai, Ono & Ishiguro (2004) showed how the robot "Robovie" could combine mechanisms for establishing mutual gaze and pointing at objects to draw the attention of humans to a poster in the environment of the robot. Finally, Hafner & Kaplan (2005) demonstrated how recognition of pointing gestures could be learned in Aibo robots. One robot performs a hard-wired pointing gesture and the other one has to detect whether it was to the left or to the right.

Additionally there is considerable research into implementing and learning the necessary behaviors for engaging in structured conversations. Breazeal (2003) investigated turn taking with the Kismet robot, focussing on the factors regulating the exchange of speaking turns so that the communication seems natural to human interlocutors. Cassell et al. (1999) discussed how non-verbal gestures and gaze can support turn taking behaviors in multimodal dialogs with the embodied conversational agent (ECA) "Gandalf", trying to replicate findings from psychologic data. A bit more on the theoretical side, Iizuka & Ikegami (2003) followed a Dynamic Systems approach for understanding processes of cognition and action (Thelen & Smith, 1994) to understand turn-taking in wheeled mobile robots in terms of the underlying dynamics of recurrent neural networks. Recent work on communication with ECAs is reviewed by Kröger et al. (2009) for the co-ordination of communicative bodily actions across different modalities and by Kopp (2010) for the alignment of communicative behaviors between interlocutors.

7.2.2 Implementing language games in robots

Language games are coordinated by behavioral scripts (see Section 2.1.1, page 22). Every agent in the population knows the language game script and individually reacts to changes in the environment and actions of the other robot. For example the speaker triggers the action of pointing to the intended topic when the hearer signals that he did not understand the utterance. The scripts are implemented in the form of finite-state machines: actions are performed depending on the current state in the game flow, the perception of the environment and the history of the interaction (see also Loetzsch, Risler & Jüngel, 2006).

Joint attention is monitored by an external computer program, that has access to the world models of both interacting robots. This system initiates the interaction between two agents as soon as both agents observe the same set of objects. It is the task of the human experimenter to find spatial setups in which joint attention is possible, the program only monitors whether robots are seeing the same set of objects. But in the literature there are also other proposals for establishing joint attention in embodied language game experiments. For example Steels & Vogt (1997) programmed sophisticated signaling protocols into LEGO robots. A robot that decides to become a speaker emits an infrared signal and the other robot then aligns its position so that it faces the speaker. The robots "point" to objects by orienting themselves toward them. In the Talking Heads experiment (Steels, 1998a), the speaker directly controls the view direction of the hearer's camera in order to make sure that their cameras perceive the same objects on the whiteboard. An agent points to an object by letting the other agent's camera zoom in on it. In contrast, establishing joint attention in social language learning scenarios between humans and robots is usually easier because the human experimenter (as a well-trained social being) is good at monitoring the attention of the robot and can for example (as in Dominey & Boucher, 2005) point to an object by moving it.

For constructing a naming system robots need non-linguistic means of conveying information, such as pointing to an object or conveying notions of success, failure and agreement in communication. For demonstration purposes robots were equipped with behaviors for pointing at objects (see Figure 7.9). We used motion teaching for creating a set of 18 pointing motions for different areas in front of the robot. Depending on the x, y coordinate of the object to point at, the pointing routines selects and performs one of these pre-taught motions.

Nevertheless, in the communicative interactions underlying the experiments presented here, robots use a different mechanism in order to avoid further difficulties stemming from uncertainties in pointing (see Steels & Kaplan, 1998 for a disscussion of the impact of such uncertainties on the performance in language games). When a robot wants to point to an object in the environment, he directly transmits the x_o, y_o coordinates of the intended object o to the interlocutor. Since robots model object positions in their own (egocentric) coordinate systems, additional steps have to be taken to interpret these coordinates. Most importantly the robot has to know the position x_r, y_r and orientation θ_r of the robot that is pointing r (see next Section 7.2.3 for details on how robots estimate these values). With this information robots transform the coordinates into their own coordinate system:

$$\vec{v} = \begin{pmatrix} \cos\theta_r & -\sin\theta_r \\ \sin\theta_r & \cos\theta_r \end{pmatrix} \begin{pmatrix} x_o \\ y_o \end{pmatrix} + \begin{pmatrix} x_r \\ y_r \end{pmatrix}$$

The robot interpreting the pointing is determining the intended object by choosing the object in his world model that is closest to $\vec{v}$. Furthermore, although we implemented gestures for giving non-linguistic communicative feedback (nodding the head for success and shaking for failure) and we used the built-in speech synthesizer of the Sony humanoid robots for producing utterances, feedback signals whose meaning is shared and utterances are directly passed between interlocutors.

The mechanisms presented in this Section provide simple solutions to required capacities for social language learning that are not meant to be in themselves proposals as to how these skills could be implemented. Nevertheless, we claim that the realism of this study does not suffer from this simplicity: humans rely on extremely powerful mechanisms for perceiving and sharing intentions within interactive situations (Tomasello et al., 2005) and similarly our solutions provide us with the technical prerequisites for letting our robots learn from communicative interactions.

7.2.3 Robot pose estimation

A requirement for the pointing mechanisms described above is a quite precise estimate of the position and orientation of the other robot. For that, robots localize themselves with respect to landmark objects in the environment and transmit their position with respect to these landmarks to the other robot. This way both agents establish mutual knowledge about their position. We use carton boxes enhanced with visual markers (see Figure 7.10) as landmark objects. The unique, black and white, barcode-like, 2D-patterns attached to carton boxes are tracked using the ARToolKitPlus library (Wagner & Schmalstieg, 2007), which is an improved version of ARToolKit (Kato & Billinghurst, 1999; Kato et al., 2000), especially adapted for mobile devices.

From each camera image, a histogram of the pixel luminance is computed. This histogram is then used to derive a threshold for creating a binary image as shown in the top right of Fig. 7.10. The binary image is passed to the tracking library, which searches it for marker patterns and determines the four vertices of the polygon surrounding the marker in the image (see bottom left of Fig. 7.10). Provided with the camera resolution width and height (in pixels), the width and height camera opening angle (in deg) and the widths of the markers used on the carton boxes (in mm), the tracking library is able to make an orientation and position estimate from the edges of the detected patterns, which is then iteratively enhanced by matrix fitting. As a result, the system returns for each detected marker pattern a unique ID and a matrix describing the position and orientation of the marker relative to the camera of the robot (for details of the pose estimation algorithm see Kato & Billinghurst 1999).

To transform the camera relative marker position and orientation into robot egocentric coordinates, they are transformed using the offset and orientation of the camera relative to the ground point of the robot (see Section 7.1.3). Finally, for each marker attached to a carton box, the offset and orientation relative to the center of the box, which is a priori known, is used to determine the position and orientation of the box in egocentric coordinates. To filter out noise and recognition errors, the resulting box poses are averaged over the last n images. Also, when two markers of the same box are detected in the same image, their resulting box poses are averaged. The output of the landmark modeling system is a list of objects consisting of an ID (an ID of the box, not

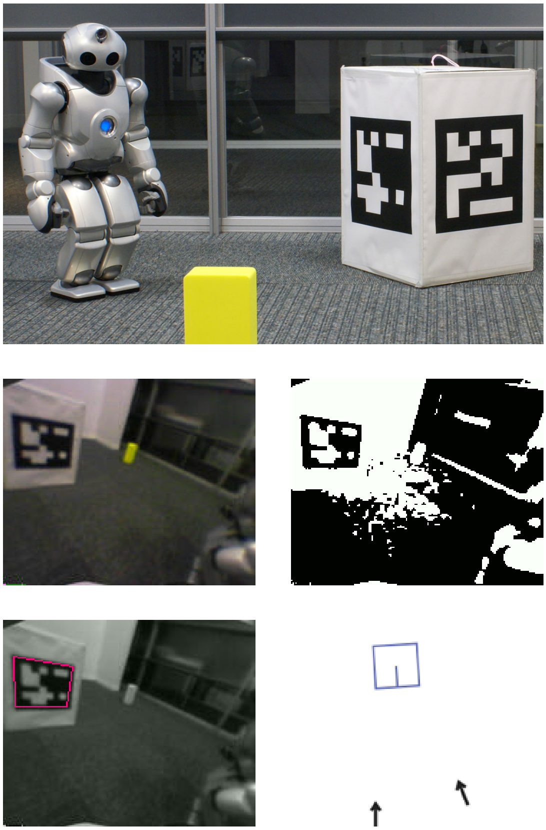


Figure 7.10: Using objects enhanced with visual markers for estimating the position and orientation of the other robot. Top: Example of a carton box that is enhanced with 2D patterns. Center left: A carton box with markers as seen through the camera of a Sony humanoid robot. Center right: Binary image generated from the original image. Bottom left: The marker as detected by the ARToolKit tracking system. Bottom right: Both robots send the position and orientation of the carton box (blue) to each other and are thus able to deduce the position and orientation of the respective other robot.

to confuse with the ID of the marker patterns) and a pose $\vec{b} := \begin{pmatrix} x_b & y_b & \theta_b \end{pmatrix}$ of the carton box in robot egocentric coordinates.

In order to determine the position x_r, y_r and orientation θ_r of the respective other robot, the robots use the carton boxes as global landmarks (see bottom right of Fig. 7.10). About five times per second they exchange the poses of the boxes they have seen over a wireless network connection. Given that both robots see the same box (all robots use the same box IDs for the same visual markers), they can compute the pose of the other robot from the box pose $\vec{b}$ as perceived by the robot (in egocentric coordinates) and the $\vec{b}'$ as sent by the other robot (in the coordinate system of the other robot):

$$\begin{pmatrix} x_r \\ y_r \\ \theta_r \end{pmatrix} := \begin{pmatrix} x_b - \cos(\theta_b - \theta'_b) \cdot x'_b + \sin(\theta_b - \theta'_b) \cdot y'_b \\ y_b - \cos(\theta_b - \theta'_b) \cdot x'_b + \sin(\theta_b - \theta'_b) \cdot x'_b \\ \theta_b - \theta'_b \end{pmatrix}$$

When both robots see multiple boxes the results of the above transformation are averaged.

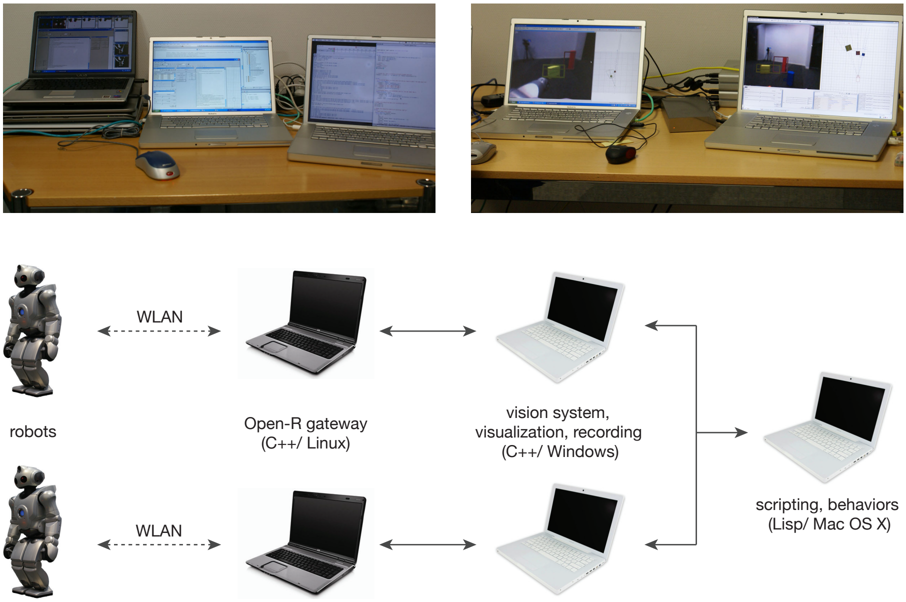


Figure 7.11: Computational infrastructure. Top left: five computers were involved in conducting the experiments. Top right: real-time visualizations of the vision system. Bottom: schematic view of the connections between the different subsystems. The robots communicate with gateway computers over a wireless network and the computers are connected trough an Ethernet network.

7.3 Experimental setup

Integrating all the mechanisms for visual perception and behavior control into a complete setup for doing language game experiments is a challenging but also interesting task in its own (see Thórisson, 2007 for a discussion of "integrated A.I. systems"). It requires computational infrastructure for connecting single components into a fast and robust system and proper modularization is needed in order to be able to develop and test algorithms and behaviors separately. Furthermore, for understanding the complex dynamics of the experimental setup and for detecting problems or errors, it is crucial to have visualizations for each single step in the information processing. Finally, in order to be able to do repeatable experiments and for testing components without actually working on a real robot, mechanisms for recording and replaying each intermediate result of the system are a necessity.

7.3.1 Computational infrastructure

The components of the experimental setup are distributed over five different machines (see Figure 7.11), which is mainly due to the fact that the software involved was written for different operating systems. The vision system runs in real-time on an external Microsoft Windows PC (one for each robot). It was developed on the basis of the 2004 version of the framework used by the GermanTeam (Röfer et al., 2004) for participating in the RoboCup (Kitano et al., 1997) Sony Four Legged League. The GermanTeam's framework is written in C++ and consists of an architecture for modularizing tasks, mechanisms for exchanging data across processes and platforms and a set of powerful debugging mechanisms (Röfer, 2003). Besides that, the framework contains the program *RobotControl*, an application for visualizing nearly every aspect of the vision system (see top right image of Figure 7.11) and for debugging and testing components. RobotControl is also used for recording data to external hard drives and it translates requests from the language game system (see below) into representations that are used by the robotic software.

The software running on the Sony humanoid robots was provided by the members of the Sony Intelligent Systems Research Labs and we used it without modification. Running on top of the Aperios operating system, Open-R (Fujita & Kageyama, 1997; Ishida et al., 2001) is responsible for collecting data from sensors and controlling actuators. There are high-level behavioral primitives for issuing walking commands, gazing at points in space, performing arm movements, speech output and more. In the background the system constantly monitors the body stability and tries to balance walking and other motions, as described in (Nagasaka et al., 2004). Furthermore, there is a security system that triggers a save body posture when the robot is falling.

The communication between the Sony humanoid robots and the RobotControl program is mediated by a gateway software running on separate Linux computers. This mediator exchanges data with the robot using Open-R interprocess communication over a wireless network and with the Windows software over an Ethernet connection. It translates images and other sensor data coming from the robot into the representations used in the GermanTeam's framework and converts behavior commands coming from RobotControl into data structures understood by Open-R. Finally, Lisp programs based on the Babel framework (Loetzsch, 2012; Loetzsch et al., 2009, 2008b; Steels & Loetzsch, 2010) and running on a Macintosh computer under Mac OS X were responsible for central control of the experiments. There are scripts for coordinating the behaviors of the two robots, for organizing the recording of data and for provinding the language game framework with the world models constructed by the robots' vision systems.

In our embodied language game experiments, agents play tens of thousands of language games to reach communicative success and coherence. Since running communicative interactions on real robots is extremely time consuming – albeit possible, as demonstrated in the Talking Heads experiment (Steels & Kaplan, 1999b) – and in order to be able to do repeatable and controlled experiments, we prerecorded data sets of world models constructed by the robots in joint attentional scenes. In each interaction, a random scene is drawn from one of the prerecorded data sets and the recorded world models of robot A and B are presented to the speaker and hearer (in random assignment). Agents

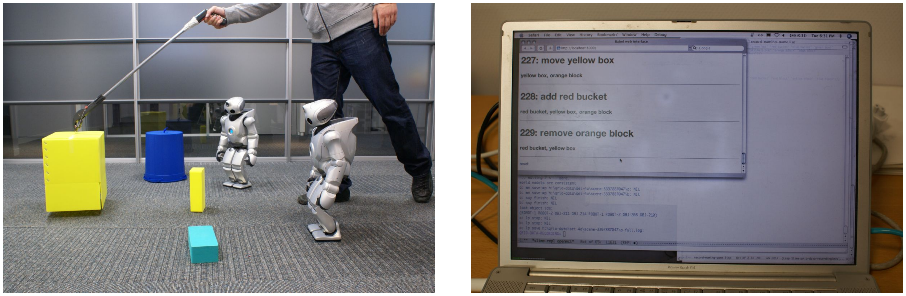


Figure 7.12: Recording data sets. Left: a human experimenter systematically adds objects to or removes them from the space infront of the robot. Right: in order to make sure that all objects occur together with equal distribution in the recorded data set, a computer program running on an external computer instructs the human experimenter how to modify the scene.

point to objects by transmitting the x, y coordinates of the objects (in their own egocentric reference systems). The recorded world models also contain the position and orientation of the other robot, allowing the agent receiving the pointing to transform these coordinates into his own coordinate system, as explained above in Section 7.2.2.

For recording data sets, the two robots are first placed in an empty environment and they are given time to calibrate their vision system as described in Section 7.1.1 (page 138). Afterwards the robots are presented with a global landmark so that they can establish their mutual position and orientation (see Section 7.2.3). Then a human experimenter adds objects to the space observed by the robots. Each time the robots establish joint attention (as defined in Section 7.2.2), both robots (technically: the RobotControl programs connected to them) store a snapshot of their world model at that time. After each recorded scene a human experimenter systematically modifies the space infront of the robots by either adding or removing an object, by moving an object to another location or by changing its orientation (see left image of Figure 7.12). In order to exclude effects of object frequencies on the performance in language games, the software controlling the recording process program keeps track of which objects occured how often (and in which combinations) and instructs the human experimenter how to modify the scene, as shown in the right image of Figure 7.12.

7.3.2 Data sets and their characteristics

All of the grounded language game experiments in this thesis use the same collection of 532 snapshots of the robot's sensory experiences recorded as discussed above. In each of these scenes, the environment contained between two and four objects: two objects are present in 143 scenes (26.9%), three in 268 scenes (50.3%), and four in 121 scenes (22.7%). The objects presented to the robots were drawn from a set of 20 medium sized (between about 15 and and

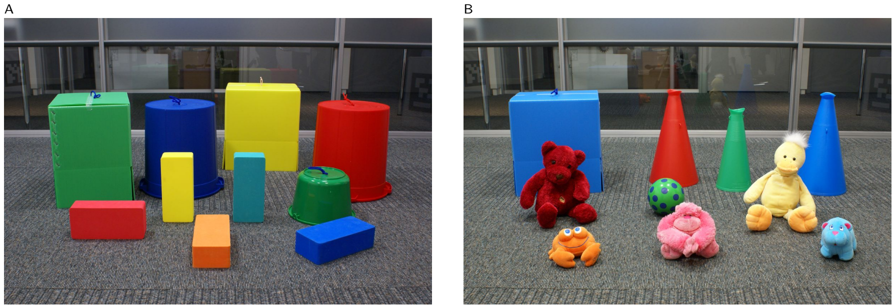


Figure 7.13: Sets of objects that were presented to the robots for recording different data sets. A: ten geometric objects (carton boxes, buckets, foam bricks). B: ten toy-like objects (cones, a ball, animals).

40 cm in width, height and length) solid colored carton boxes, foam bricks, plastic buckets and cones, stuffed animals and a ball (see Figure 7.13).

The 532 recorded scenes are grouped in three different data sets: A first set consists of 215 scenes recorded with ten geometric objects shown in Figure 7.13A and a second set of 149 scenes was recorded with 10 more toy-like objects shown in Figure 7.13B. These two sets were initially recorded for experiments on grounded naming of individual objects (see the next Chapter 8) and thus the objects differ enough in shape, color and size so that in principle they can be distinguished by the robots by these features. Furthermore, in order to rule out frequency effects, the distribution and co-occurrence of objects across the data set is quite uniform.

Another 168 scenes were recorded with objects from the first two sets, but with the possibility of the same physical object occurring twice in a scene. For example a big number of these scenes contain two foam bricks of the same color and size that are not distinguishable as individual objects but need to be discriminated by their orientation or position. Whereas the experiments on the grounded naming of individual objects are done with the first two sets (only one at the time, the second set is only used to show that the proposed mechanisms work independent from the chosen objects), all other grounded lexicon formation experiments use all scenes from the combined three data sets.

Figure 7.14 shows five example scenes from the geometric objects data set. It illustrates how objects are added and removed from the environment and how the appearance and spatial configuration of the objects changes from scene to scene. For example the orange block (o_{65} for robot A, o_{60} for robot B) is standing in the first scene and then laying down from the next scene on, drastically changing its appearance in the process. And the position of the blue bucket (o_{58}/ o_{55}) changes toward the left in subsequent scenes. Furthermore, Figure 7.14 demonstrates that the vision system is able to establish object persistence (see Section 7.1.2, page 141) – the IDs of the objects remain the same from scene to scene despite changing object positions and appearances.

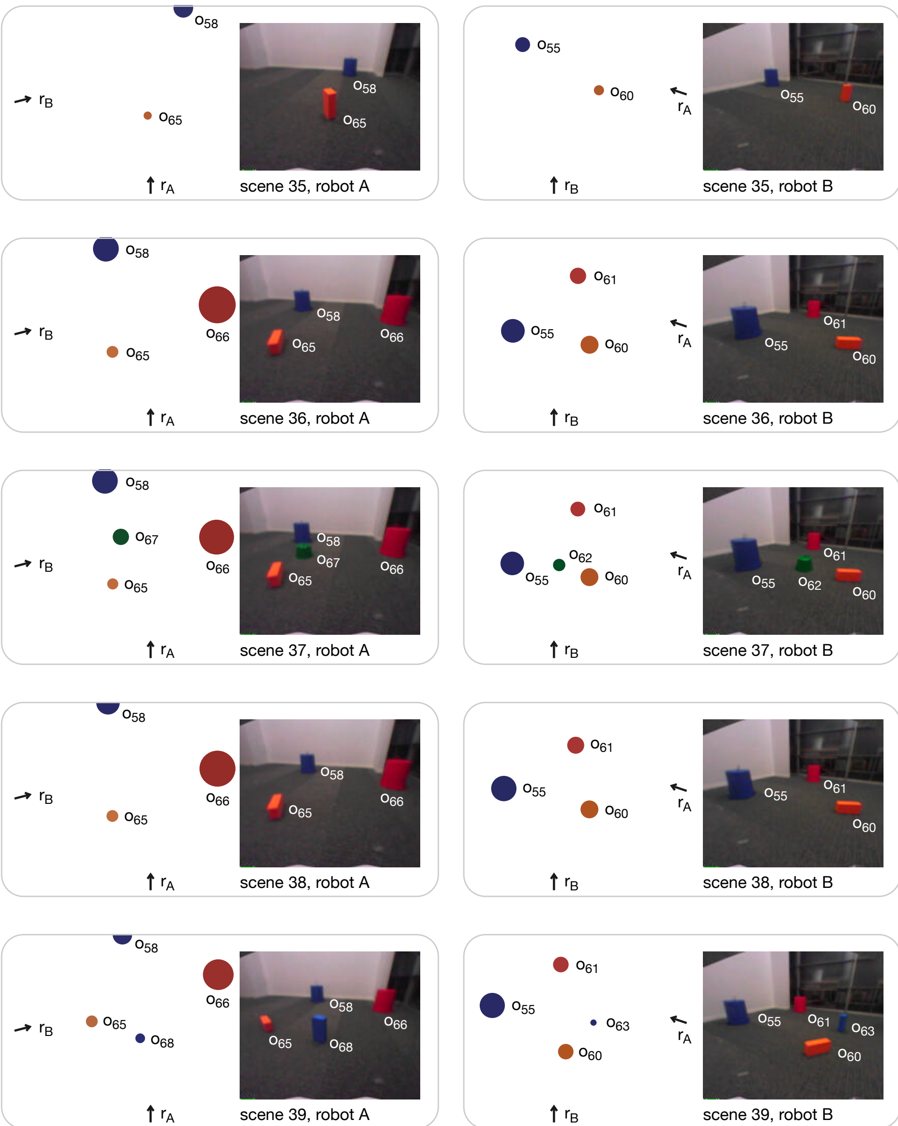


Figure 7.14: Example scenes from the geometric objects data set.

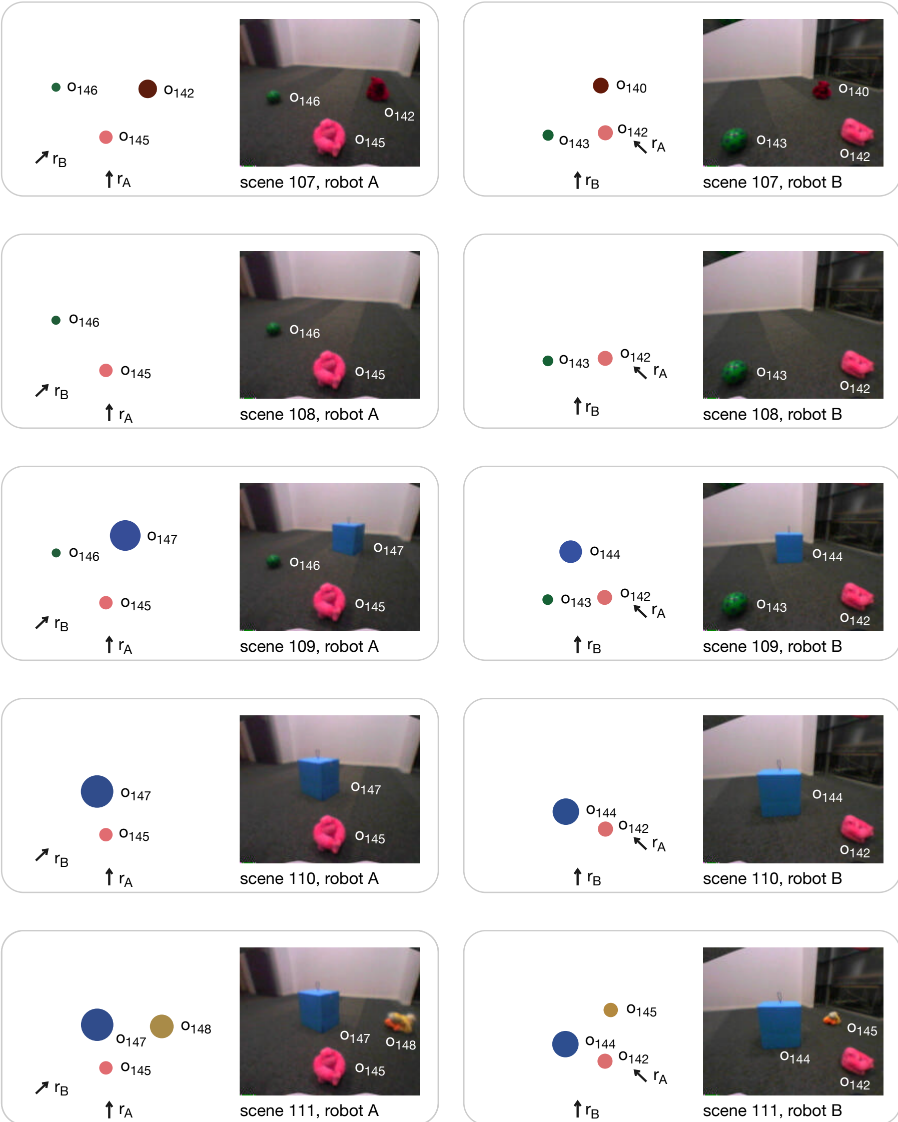


Figure 7.15: Example scenes from the toy data set.

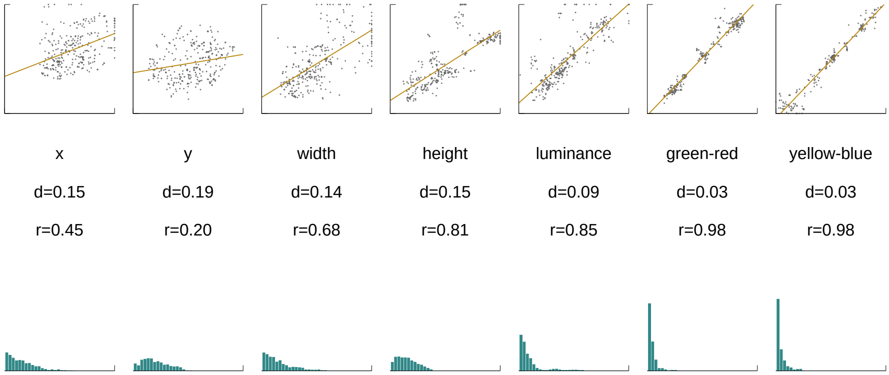


Figure 7.16: Perceptual deviation between robot A and B across all data sets. Top: for each visual feature, the scaled values of all objects in all scenes as perceived by robot A are plotted along the x-axis against the corresponding perceptions of robot B along the y-axis. Center: the average difference d and the correlation coefficient r between the perceptions of robot A and B across all objects is shown for each feature. Bottom: histogram of the distances (x-axis from 0 to 1) between feature values as perceived by both robots across all objects of all scenes.

Similarly, five example scenes from the toy object set are shown in Figure 7.15.

One challenge for lexicon formation models stemming from real-world perception is *perceptual deviation*, i.e. that the continuous features computed by the vision system for an object differ drastically between the perception of speaker and hearer. This is because agents can view a scene from different angles, because lighting conditions may vary, and due to noise (even a single robot will perceive the same object differently over the course of time due to camera noise, robot motion and general uncertainty in computer vision systems). For example the lying down orange block in Figure 7.14 (from scene 36 on) is perceived much more narrow by robot A than by robot B. And the blue block in scene 39 (o_{68}/ o_{63}) is seen from different sides by the two robots so that their perception of width differs. Furthermore, Figure 7.8 on page 146 shows quantitative differences between the perceptions of the two robots for a single scene. For example, the red bar (object o_{716}/ o_{718}) is perceived as much brighter by robot A (the `luminance` feature has a value of 0.30) than by robot B (0.13). Or the height of the green ball is seen smaller by robot A (o_{722}, 0.19) than by B (o_{725}, 0.41).

The amount of perceptual deviation between speaker and hearer varies for different visual features, as illustrated in Figure 7.16. Solely by looking at the graphs in the top row that plot the feature values as perceived by one robot against the values perceived by the other robot, some features look much more reliable than others. Perceptual deviation can be quantified by the linear distances between the two perceptions of an object (shown as a histogram in the bottom of Figure 7.16 and as the average distance d across all objects in the middle of that Figure) or as a by a correlation coefficient r between feature values across all objects and scenes.

Perceptual deviation is the lowest for the color features `green-red` and `yellow-blue` ($d = 0.03$ and $r = 0.98$ for both), which makes them the most reliable features for categorizing objects. This consistency can be explained by the lighting independence of color values in the $YCrCb$ color space and by the relatively homogeneous coloring of the objects in the world. Perceived luminance ($d = 0.09$, $r = 0.85$) is slightly lower because robots view scenes from different angles and thus shadows etc. are perceived differently. Furthermore, the size features `height` ($d = 0.15$, $r = 0.81$) and `width` ($d = 0.14$, $r = 0.68$) are perceived less reliably. Because the perception of object heights is rather viewpoint independent, perceptual deviation for the `height` feature results mainly from noise and body pose uncertainty in the triangulation mechanisms described in Section 7.1.3 (Note that the histogram for that feature in Figure 7.16 does not have its peak at 0 but later, indicating that noise is indeed the main source of deviation here). However, the `width` of objects varies depending on from which side an object is looked at and thus perceptual deviation for this feature is higher than for `height`. Finally, consistency is lowest for the spatial position features `x` ($d = 0.15$, $r = 0.45$) and `y` ($d = 0.19$, $r = 0.20$) because these features clearly depend on the view that the robots have on the a scene. We nevertheless included the position features for two reasons: First, in some scenes they are still the best means to discriminate a target object from the rest of the context and second, they provide a tough challenge for grounded lexicon formation models.

For successful communication, respresentations of categories and words and their processing mechanisms need to be robust enough to deal with perceptual deviation. The underlying meanings of words need to be flexibly interpreted so that speaker and hearer still can understand each other, even if they have different perceptions of a scene. And agents need to learn that some visual features are more reliable than others and thus should be prefered for categorizing objects.

Another property of real-world perception is the *structuredness* of sensory experiences. This involves two phenomena: First, feature values are not uniformly distributed across all perceptions. As shown on the diagonal of Figure 7.17, some features such as `x`, `y` and `width` have more uniform distributions than others such as `green-red` and `yellow-blue`. The "clusters" in the distributions of the color features reflect clusters in the colors of objects in the world of the robots where not all colors occur uniformly, whereas no such peaks are to be found in the histograms of the spatial features because the position and orientation are varied by the experimenter in each scene. Note also how the three bottom-most covariance plots in Figure 7.17 show a clear separation of different color classes in the $YCrCb$ color space. Alignment mechanisms for the co-evolution of ontologies and lexicons can benefit from such clusters in perception for reaching shared category systems.

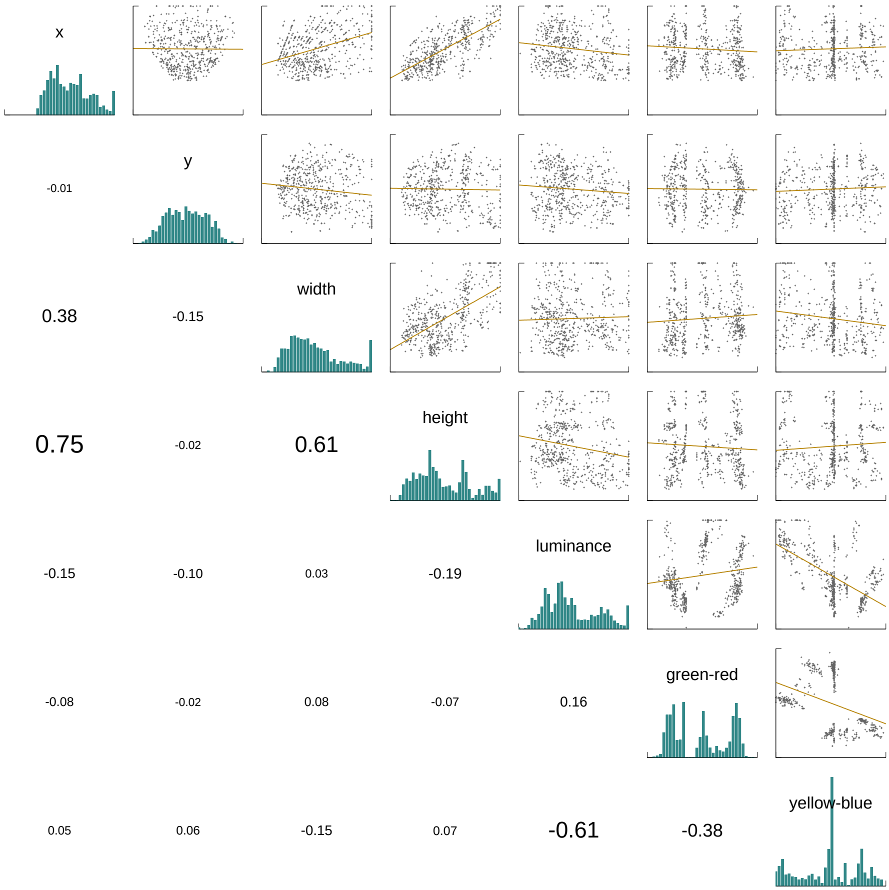


Figure 7.17: Structure in the distribution and correlation of feature values. Along the diagonal, the distribution of the scaled feature values across for all perceived objects of all scenes and both robots is shown as histograms. In the top right part, values for all objects of one feature are plotted against another featuer for all pairs of features. In the bottom left part, the correlation coefficients accross all objects, scenes and robots are shown for all pairs of features.

Second, as illustrated by the covariance plots and correlation coefficients in Figure 7.17, feature values are not independent of each other. For example because in the world captured by our data sets yellow objects tend to bright and blue objects tend to be dark, there is a strong negative correlation of -0.61 between the `luminance` and `yellow-blue` features. Similarly, because objects that are wider are usually also higher, there is a big positive correlation of 0.61 between `width` and `height`. The strongest correlation of 0.75 exists between the `x` feature and `height`, which is probably due to a systematic error in height estimation and because bigger objects were usually placed more in the back of the scene by the experimenter in order to avoid occlusions. Finally, clusters in the world as discussed above for the color of objects lead to (random) correlations such as the one between `green-red` and `yellow-blue`. As we will see, such correlations pose a major difficulty for reaching conceptual coherence in a population of agents because different agents may relate a word form to categories on different sensory features while still using these words successfully.

Chapter 8

Individual names for physical objects

Using the robotic setup from the previous chapter, we will now investigate what it takes to extend the non-grounded Naming Game from Chapter 4 to a *Grounded Naming Game*[1]. The main question is: How can a population of robotic agents agree on a set of *individual names* for physical objects in their environment? Naming in this context means assigning different forms to different individual physical objects in the world – in the same way as we give names such as "John" to particular persons or "Alexanderplatz" to specific places – and as opposed to labeling classes of objects (e.g. "block" or "teddy bear"). The key difference to the non-grounded Naming Game is that the agents do not have access to shared pre-conceptualized individual objects (represented by a set of essentially meaningless symbols, e.g. {`obj-1`, `obj-4`, `obj-12`}). Instead, each agent has to build and maintain conceptual representations that allow him to classify and individuate different sensory experiences with respect to which particular physical object they belong to.

Populations of agents play the same kind of game as described in Section 2.1.1 (page 22). But instead of using artificial perceptions from a simulated world, agents perceive physical world scenes through the bodies of two humanoid robots. Consequently, the *semiotic network* that underlies the processes of language processing and alignment needs to be extended. Sensory experiences of objects are classified based on their similarity to a set of *prototypes* (Edelman, 1998), which are then combined as *prototypical views* into *individuals*, which are in turn connected to *names*. We will describe the processes to build and coordinate these representations in Section 8.1 below. In addition, heuristics are needed to decide that two very different sensory ex-

[1] Parts of this chapter were taken from Loetzsch, Spranger & Steels, 2012; Steels & Loetzsch, 2012; Steels, Loetzsch & Spranger, 2012.

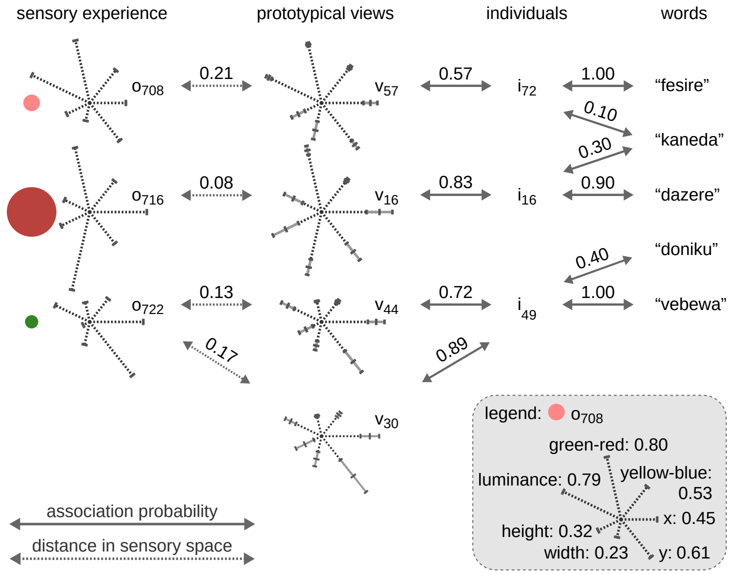


Figure 8.1: A schematic view of part of a single agent's semiotic network. Sensory experiences of objects in the current scene are matched with prototypes of past experiences based on distance in sensory space. Different prototypical views are connected to individuals, which are then linked to words with different connection weights. Agents establish semiotic networks and update the weights as a side effect of the game. Sensory experiences and prototypical views are visualized by their feature vectors. The length of each dimension represents the feature mean value and standard deviations are indicated with error bars. Note that the agents do not memorize sensory experiences – instead they capture their invariant properties in prototypical views.

periences (and thus different conceptual representations) are about one and the same physical object and two examples of such heuristics are presented in section 8.2. Finally, further aspects of the subtle interplay between language use and the construction of semiotic networks are discussed in section 8.3.

8.1 Extending the semiotic network

The semiotic network maintained by each agent a in the population $P = \{a_1, a_2, \ldots\}$ is a memory of prototypical views, individuals and names with weighted connections among them (Figure 8.1). As in all of our non-grounded language game experiments, they are initially empty and are gradually constructed by the agents as a side effect of the game. Nodes can be added or removed and weights between nodes change based on the outcome of the game.

In order to decide which name to use for a chosen topic, the speaker determines the prototypical view that best matches the topic and then finds the most suitable name by tracing his network, each time following the connection with the highest score. That word is then transmitted to the hearer, who interprets it by tracing pathways in his own network but in the other direction. He starts from the name, looks up the individuals associated with this name, then the possible prototypical views associated with these individuals, and then the object that has the highest similarity with one of these prototypical views. The hearer then points to this object so that the speaker can give non-linguistic feedback on success or failure. The question how prototypes, individuals and words are added or removed and how connection weights in the semiotic network are updated is discussed below.

8.1.1 Capturing object properties with prototypes

In every language game, the speaker and hearer perceive each perceive a different set of sensory experiences $E := \{e_1, e_2, \dots\}$ constructed by the two robots about the physical objects in a shared scene from a recorded data set (see section 7.3.2, page 156). A sensory experience $e := \langle o(e), \vec{f}(e)\rangle$ is represented by an object anchor o together with a vector $\vec{f} := \begin{pmatrix} f_1(e) & \dots & f_7(e)\end{pmatrix}^T$ of seven continuous visual features `x`, `y`, `width`, `height`, `luminance`, `green-red` and `yellow-blue` scaled into the interval $[0, 1]$ (see figure 7.8, page 146).

The invariant properties of sensory experiences are captured in terms of prototypes (Edelman, 1995, 1998) and the prototype corresponding to a perception is found using a nearest neighbor computation. This is motivated by psychological findings of Mervis & Rosch (1981); Rosch (1973) who demonstrated that membership to "basic level" categories is continuous and a function of the similarity to a prototype. As will be shown below, agents create different prototypes for different views of the same physical object – which is why these prototypes are called prototypical views. Furthermore, agents do not have access to a clear training set of examples and counter examples that would allow them to deduce exact distinctions between objects (the machine learning approach). Instead, each of them has to independently construct his own inventory of prototypical views over the course of many interactions with different objects in different contexts.

The prototypical views $V(a) := \{v_1, v_2, \dots\}$ maintained by an agent a (also dubbed the "chorus of prototypes" by Edelman, 1995) are modeled as three tuples $v := \left\langle \vec{f}(v), \sigma\left(\vec{f}(v)\right), \gamma(v)\right\rangle$, with $\vec{f}(v)$ a vector of feature values as above, $\sigma\left(\vec{f}(v)\right)$ the variance of feature values (see below) and $\gamma(v) \in [0, 1]$ a score reflecting the outcome of interactions involving that prototypical view. Furthermore, an agent's semiotic network contains a set of individual $I(a) := \{i_1, i_2, \dots\}$, each of them linked to one or more prototypical views: $i(a) \subset V(a)$. A distance function s computing the distance between a sensory experience e and a prototypical view v is defined as the average difference of feature values:

$$s(e, v) := \frac{\sum_{i=1}^{i \le 7} |\,(f_i(e) - f_i(v))\,|}{7}$$

Many other distance functions such as i.e. Euclidean distance could be used as well, but since it did not have a significant impact on the performance of the model, we chose to use the simplest measure. In order then to determine the best matching prototypical view for a particular sensory experience e, the nearest neighbor $nn\Big(e, V(a)\Big) : E \times V \to V$ is computed by calculating the distances s to all prototypical views $V(a)$ maintained by the agent a and selecting the one with the lowest distance. Similarly, the closest object in a scene for a particular prototypical view is determined with the nearest neighbor $nn\Big(v, E(a)\Big) : V \times E \to E$ by computing the distances to all sensory experiences and also choosing the one with the smallest distance.

How are then new prototypes learnt, i.e. how is it decided not to associate a sensory experience to the closest existing prototypical view but to create a new one for that object? One possibility would be to use *sensory distance* itself as a criterion – when the distance to the closest prototype is bigger than a fixed threshold, then a sensory experience would be considered to belong to another individual object. The problem with this approach is that some physical objects in the world vary heavily in their appearances, spanning large areas in sensory space, whereas other objects can be very close to each other in terms of sensory distance. Therefore, any fixed threshold would lead to some objects being captured by different prototypes and some prototypes would cover multiple distinct objects. A better criterion is *discrimination*: "only the comparisons or contrasts between the objects are interesting: if the world consisted of just one object, it would not really matter how that object were represented" (Edelman, 1995, p. 51). An agent observing a scene can safely assume that the sensory experiences of different physical objects belong to different individuals and thus must have the closest distance to different prototypes. If this condition is violated, i.e. two sensory experiences are associated to the same prototypical view, then the agent uses one of them as a seed for a new prototypical view and links it to a newly introduced individual. For example, if there are two sensory experiences e_1 and e_2 and two existing prototypes v_1 and v_2 such that $s(e_1, v_1) = 0.15$, $s(e_1, v_2) = 0.1$, and $s(e_2, v_1) = 0.2$, then a new prototype will be built based on e_2 because v_2 is the closest prototype to both e_1, and e_2 and e_2 is further away from v_2 than e_1. Consequently, agents have to see objects together in order to make a difference between them. Suppose for example there is a orange cube and a red cube of equal size and both objects never occur together in a scene – it would be very likely that the agents do not create different prototypical views for these two objects, treating the different colors as a natural variance in the appearance of a single individual object.

As mentioned above, new prototypical views are created from actual sensory experiences, with the initial prototype features $\vec{f}(v_{new})$ as a copy of the respective object features $\vec{f}(e)$. But that particular sensory experience might have been a rather bad exemplar of the physical object, i.e. it could be that its features are very different from the average appearance of that object. An agent seeing an object the first time can not know of course whether this experience is *prototypical* (Rosch & Mervis, 1975) for that object (sometimes also

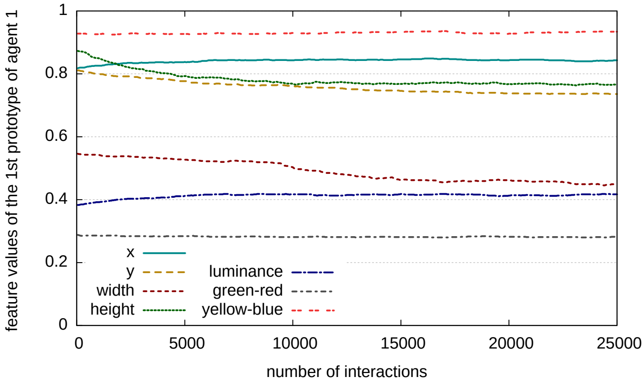


Figure 8.2: Adjustment of a prototypical view over time. The changing feature values of the first prototypical view of the first agent in the population are measured in a single series of 25000 language games and plotted along the x-axis.

called *representative* or *central*). That's why prototypes have to get adjusted later on to better reflect the distributional properties defining that physical object. In every interaction in that a prototypical view v_t at time t is the nearest neighbor to a sensory experience e, the prototype feature values $\vec{f}(v_t)$ and variance $\sigma\left(\vec{f}(v_t)\right)$ are recursively updated for all features f_i:

$$\begin{aligned} f_i(v_t) &= \alpha \cdot f_i(v_{t-1}) + (1-\alpha) \cdot f_i(e) \\ \sigma\left(f_i(v_t)\right) &= \alpha \cdot \left(\sigma\left(f_i(v_{t-1})\right) + \left(f_i(v_t) - f_i(v_{t-1})\right)^2\right) + (1-\alpha) \cdot \left(f_i(e) - f_i(v_t)\right)^2 \end{aligned}$$

with $\alpha = 0.995$ being a stability factor, weighting the impact of new experiences. Especially in the beginning when not all physical objects have been encountered yet it might happen that prototypical views span multiple physical objects in sensory space. Therefore – as a conservative strategy – feature values are only shifted when the distance between the experience and the prototype is not too far away from the standard deviation of that feature: $|f(o) - f(v)| - \sigma^2\left(f(v)\right) < \epsilon$, with $\epsilon = 0.1$ (this is also the only reason why prototype feature variances are maintained). Figure 8.2 gives an example for this adjustment process. It is shown how the feature values of a single prototypical change over time, stabilizing towards the end. Apparently the sensory experience used to create this particular prototype was less representative for that object, especially in the `x`, `width` and `height` features, which get adjusted the most in the beginning.

As a result, the agents independently self-organize their prototypical views in a clustering process, exploiting structure in the world (Rosch et al., 1976) that is observed through the statistical distributions of features in sensory experiences. Note that our model does not depend on the choice of this particular mechanism for maintaining prototypes – other techniques such as for example Radial Basis Function networks (Poggio & Girosi, 1990) or Kohonen maps (Kohonen, 1982) could be used equally well. Figure 8.3 shows how the sensory distance s between the prototypes used by speaker and hearer for the same object changes over time. When prototype features are not adjusted, then the average distance decreases a bit in the beginning (because more prototypical

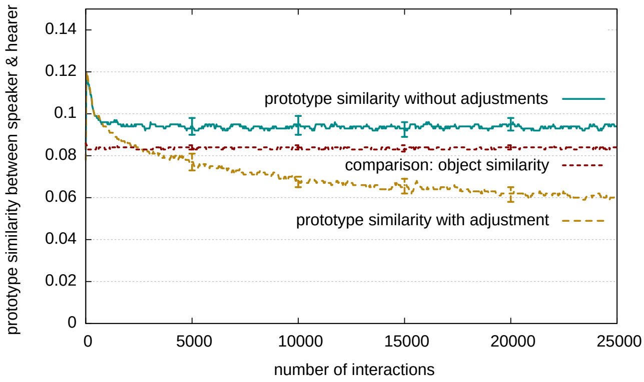


Figure 8.3: The average similarity between the prototypical views used by the speaker and hearer for the objects in the current scene (measure 8.2) are shown for agents with and without adjustment. For comparison, the average sensory distance between the objects in the contexts of speaker and hearer (measure 8.1) is plotted too.

views get learnt, automatically decreasing the distance between prototypes) and remains constant at around 0.095, which is even higher than the average distance between the sensory experiences of speaker and hearer (≈ 0.085). Otherwise – when feature values are adjusted – the similarity between prototypes further decreases to approach ≈ 0.06. The average distance does not reach zero because the two agents can have significantly different perceptions of objects – an agent that (unnaturally) would have access to the perceptions of both robots for a scene would not necessarily associate the same prototypical view to the different sensory experiences for the same physical object, as discussed further down.

Even with these adjustment mechanisms it is not guaranteed that a prototypical view is connected exclusively to the sensory experiences of the same physical object. In fact it happens quite often that prototypes find a niche in the sensory space where there are close to different objects. However, if this is the case, then the words associated to these prototypical views via connected individuals are also less successfully used in language games because the hearer interpreting them more often points to the wrong object. This can be used as a criterion to further shape an agent's semiotic network: After each successful interaction, both speaker and hearer increase the score $\gamma(v)$ of the prototype

Measure 8.1: Object similarity

The distance s between the sensory experiences of speaker $E(sp)$ and hearer $E(h)$ of the objects in the current scene is computed and averaged over the objects in the scene:

$$\textit{object similarity} := \frac{\sum_{i=1}^{i \leq |E|} s\left(e_i(sp), e_i(h)\right)}{|E|}$$

The correspondence between the objects in the two world models is established by letting the speaker point at each object and the hearer determining the respective sensory experience by interpreting the pointing (see section 7.2.2, page 150).

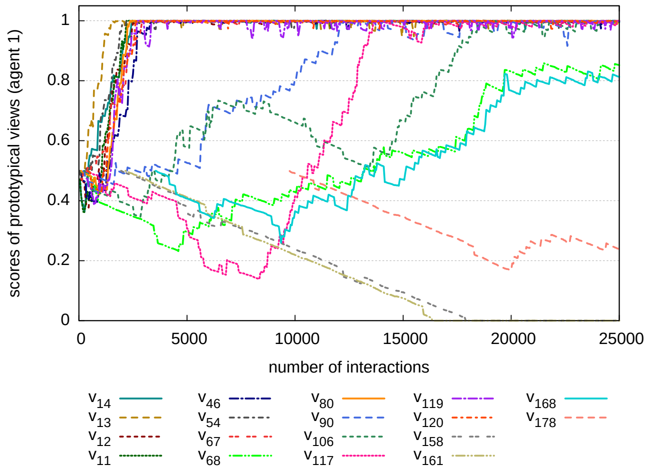


Figure 8.4: Evolution of a single agent's prototype scores. The scores of all prototypical views in the semiotic network of agent 1 out of a population of 10 agents are recorded in a single run of 25000 interactions and plotted along the x-axis.

v that they associated to the topic by the fixed delta of 0.025, and in each interaction that failed they decrease the score by the same amount. Prototypes that reach a score of 0 or below are removed from the agent's semiotic network, together with the individuals and words connected to them (unless they still have links to other prototypes/ individuals in the network). Furthermore, in order to "forget" prototypes that occupy regions in the sensory space where they are almost never used, the scores of all prototypes are reduced in each interaction by a constant decay factor of $0.01/|V(a)|$. Figure 8.4 illustrates these dynamics. Most prototypical views immediately reach a score of 1, but some of them fail to be consistently used in successful interactions so that a few prototypes eventually get deleted.

8.1.2 Linking individuals to words

The words in a semiotic network connect individuals to forms. Besides that, the lexicon representations are exactly the same as in the non-grounded Naming Game (Chapter 4 on page 53). An agent's lexicon $L(a)$ is a set of words, represented by three tuples $w := \langle i, f, \gamma \rangle \in I(a) \times \mathcal{F} \times \mathbb{R}$. Each word associates

Measure 8.2: Prototype similarity

Prototype similarity measures the average sensory distance between the prototypical views associated by the speaker sp and hearer h to the objects in the current scene $E(sp)$ and $E(h)$:

$$\textit{prototype similarity} := \frac{\sum_{i=1}^{i \leq |E|} s\left(nn\left(e_i(sp), V(sp)\right),\ nn\left(e_i(h), V(h)\right)\right)}{|E|}$$

Correspondence between the sensory experiences of speaker and hearer is established by pointing. Results are averaged over the last 250 interactions.

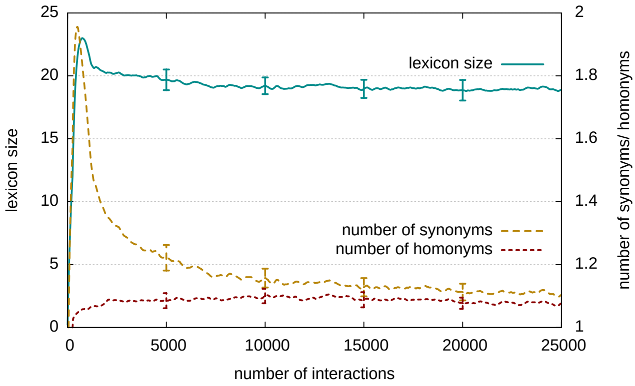


Figure 8.5: Lexicon size and the average number of synonyms and homonyms averaged over all 10 agents of the population. Error bars are standard deviations over 10 repeated experimental runs of 25000 interactions each. See measures 4.1, 4.4 and 5.3 (page 59 ff.)

an individual $i \in I(a)$ to a form $f \in \mathcal{F}$ with an association weight γ representing the agent's confidence in that association. $\mathcal{F}$ is the set of possible word forms and γ is a real value with $0 \leq \gamma \leq 1$.

A speaker tracing his semiotic network in search for a name for the chosen topic first determines the closest prototype and the linked individual and then finds the word in his lexicon connected to this individual that has the highest score. When a speaker does not have a name for an individual $i \in I(a)$, he generates a new unique name f_{new} by making a random combination of syllables and adds the association $\langle i, f_{new}, \gamma_{init} \rangle$ to his semiotic network with an initial weight $\gamma_{init} = 0.5$. A hearer encountering a new name will signal a communicative failure, the speaker then points to the intended object and the hearer determines the corresponding individual. A new association between that individual and the name heard is added to the lexicon with the same initial score of 0.5. In order to reflect how well a name is conventionalized in the population, both speaker and hearer increase the weight of the association used by $\Delta\gamma_{succ} = 0.1$ after a successful language game and decrease the word score by $\Delta\gamma_{fail} = 0.1$ in unsuccessful interactions. Furthermore, synonyms (associations of the same individual to different forms) are dampened using lateral inhibition: After each successful interaction both involved agents decrease the weights of all associations with the same individual but different forms by $\Delta\gamma_{inhib} = 0.2$.

Agents start with initially empty lexicons and since words are learnt in local interactions between randomly chosen members of the population, many different word forms for the same physical objects are created independently by different speakers. In a population of 10 agents, on average two different individuals get associated to a form in the first few hundred interactions (see figure 8.5). Lateral inhibition quickly reduces synonymy, eventually decreasing and stabilizing the average number of associations in each agent's lexicon. However – different from the non-grounded Naming Game – independent creation of word forms is not the only cause for the creating of synonyms. As discussed above, different agents develop very different sets of prototypes and thus there is no guarantee that a name is used exclusively for the sensory experiences of

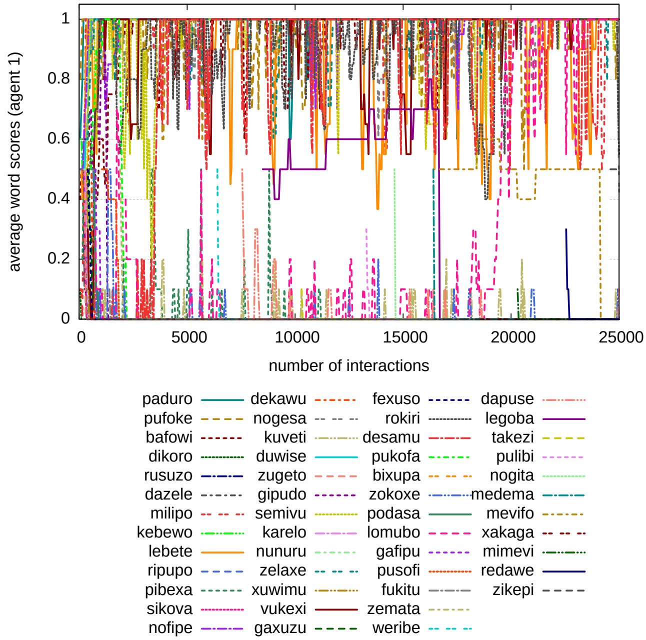


Figure 8.6: A single agent's lexicon as it changes over time. For each word form in the lexicon of the first agent the word scores of all associations involving that form are averaged and plotted along the x-axis (in a single run). The population size for this graph is limited to five in order to restrict the number of word forms.

one particular physical object – even though a hearer adopting a novel word knew the object that was intended by the speaker through pointing. It might for example happen that one speaker has a suboptimal prototypical view that gets associated to the sensory experiences of two different physical objects in different sensory contexts. Therefore the word connected to that prototype and linked individual would be used by the agent for different physical objects (note that his is not homonymy because that name is connected to only one individual and prototype). Another hearer that uses the name for only one physical object (because the linked prototypical view is associated to only one object in the world) might happen to interact with the agent. When the speaker uses the word for another object than understood by the hearer, then the communication will fail and the speaker will point to the object intended, eventually causing the hearer to adopt a synonym for the individual linked to that object (given that he knew already another name for that individual). Consequentially, the average number of synonyms in the agents' lexicons never completely reaches zero (compare to Figure 4.9 on page 66) but remains at a level of about 0.1 as shown in Figure 8.5.

Prototypical views associated to different physical objects is also one of the two causes for homonyms, i.e. different individuals connected to the same name (a phenomenon also absent in the non-grounded Naming Game). The hearer in the example above will connect the name to both the individual that was initially understood and to the individual connected to the object pointed at. A second cause for homonymy is that agents can associate multiple prototypical views to the same physical object as explained below. A hearer then might adopt the same name to different individuals linked to the same object. On average every 10th name an agent's lexicon is homonymous (see figure 8.5).

The suboptimal interrelation between individuals and physical objects and the fact that prototypical views and individuals can get removed from an agent's semiotic network are responsible for a much higher degree of change in the lexicon than in the non-grounded Naming Game (see Figure 8.6 compared to Figure 4.7 on page 4.7). Although most words are created and adopted in the first few hundred interactions and quickly aligned trough lateral inhibition, there are some words that enter the lexicon much later and even consistently successful words are sometimes used in interactions that fail (resulting in their scores going down from 1 and then quickly up again).

8.1.3 Similarity is not enough

With all the introduced mechanisms for creating and maintaining semiotic networks the agents are able to establish successful communication systems. As illustrated by the example interactions in Figure 8.7 (and different from all experiments in simulated environments in Chapters 4 and 5), they do so by sharing not any mental representations other than word forms – perceptions, prototypical views and individuals are internal to the semiotic networks of each agent. Note ids of objects can reoccur in later interactions (for example the objects `obj-144` and `147` are perceived both by the agents in interaction 500 and 502). This is due to the nature of embodied perception as being from a recorded data set of robotic perceptions (see Section 7.3.2). However, these ids are for illustration purposes only. They are not processed or stored by the interacting agents, even not for pointing.

Figure 8.8 shows the overall dynamics in a population of 10 agents playing 25000 language games. After about 2500 interactions (which means that on average each agent took part in 500 games) they are able to successfully draw the attention of the hearer to the intended object and later on communicative success rises to above 95%. The number of prototypical views (and the equal number of individuals – individuals are automatically created and linked to newly introduced prototypes) rises quickly in the beginning and then more

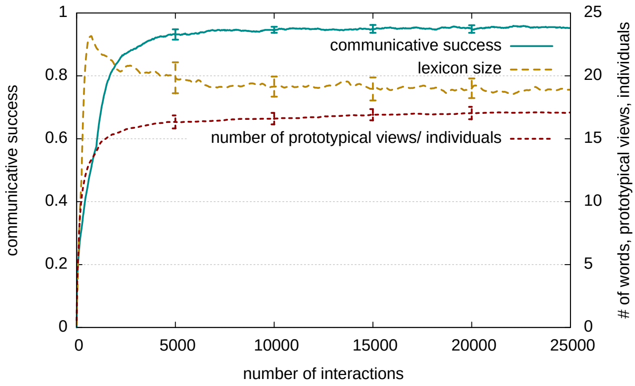
> *Measure 8.3: Number of prototypical views*
>
> *The number of prototypical views in each agent's semiotic network is counted and averaged over the number of agents in the population: number of prototypical views* $:= \sum_{i=1}^{i \leq |P|} |V(a_i)| \;/\; |P|$. *Values are averaged over the last 100 interactions.*

> *Measure 8.4: Number of individuals*
>
> *The number of individuals in each agent's semiotic network is counted and averaged over the number of agents in the population: number of individuals* $:= \sum_{i=1}^{i \leq |P|} |I(a_i)| \;/\; |P|$. *Values are averaged over the last 100 interactions.*

#	speaker	topic speaker	prototypical speaker	view	individual speaker	utterance	hearer	individual hearer	prototype hearer	topic hearer	success?
500	agent 3	obj-144	v-1		i-1	*"vomegi"*	agent 1	v-26	i-26	obj-147	yes
501	agent 5	obj-148	v-122		i-122	*"zedaba"*	agent 4				no
502	agent 5	obj-147	v-101		i-101	*"fimuzu"*	agent 4	v-45	i-45	obj-144	yes
503	agent 1	obj-138	v-98		i-98	*"wifote"*	agent 10	v-59	i-59	obj-139	yes
504	agent 1	obj-136	v-28		i-28	*"rebama"*	agent 10	v-103	i-103	obj-137	yes
505	agent 4	obj-163	v-107		i-107	*"tasuse"*	agent 6	v-53	i-53	obj-159	yes
506	agent 4	obj-162	v-47		i-47	*"bibeno"*	agent 6	v-31	i-31	obj-153	yes
507	agent 1	obj-152	v-84		i-84	*"birupu"*	agent 6				no
508	agent 1	obj-157	v-29		i-29	*"bibeno"*	agent 6	v-31	i-31	obj-153	yes
509	agent 4	obj-173	v-68		i-68	*"tavoke"*	agent 2	v-58	i-58	obj-177	yes
510	agent 4	obj-175	v-107		i-107	*"tasuse"*	agent 2				no
511	agent 6	obj-43	v-49		i-49	*"fepaka"*	agent 4	v-54	i-54	obj-52	yes
512	agent 6	obj-44	v-105		i-105	*"tunite"*	agent 4				no
513	agent 9	obj-9	v-39		i-39	*"vomegi"*	agent 7	v-23	i-23	obj-9	yes
514	agent 9	obj-3	v-37		i-37	*"kogise"*	agent 7	v-108	i-108	obj-6	yes
515	agent 5	obj-148	v-87		i-87	*"vubeta"*	agent 6	v-90	i-90	obj-152	yes
516	agent 5	obj-152	v-92		i-92	*"wifote"*	agent 6	v-17	i-17	obj-155	no
517	agent 4	obj-179	v-107		i-107	*"tasuse"*	agent 7				no
518	agent 4	obj-182	v-83		i-83	*"zozeri"*	agent 7	v-19	i-19	obj-177	yes
519	agent 7	obj-147	v-79		i-79	*"gudute"*	agent 4				no

Figure 8.7: Overview of 20 consecutive interactions from game 500 on. It shows the agents that are interacting, the topic picked by the speaker, the prototypical views and individuals used by both agents, the utterance formed, the topic understood by the hearer (when successfully parsed) and whether the agents reached communicative success.

Figure 8.8: Communicative success (measure 2.1) and inventory sizes (measures 4.1, 8.3 and 8.4) in a population of 10 agents playing 25000 language games. Error bars are standard deviations over 10 repeated runs of 25000 interactions each.



slowly toward the end (because agents still see new objects and because they optimize their inventories based on communicative success) to finally reach a number of about 17. The lexicon size peaks in the beginning and later on approaches the number of individuals, with out reaching it due to a stable amount of synonyms and homonyms in the lexicon.

However, there are only ten different physical objects in the world (see section 7.3.2, page 156), but the agents associate 17 individuals to them, 1.7 on average. This is because objects in the world can drastically vary in their appearances – both over time and within the same scene when viewed by the two robots from different angles. For example a red bar can look very narrow when standing and wide when lying down. And colors of objects can be different from different viewing angles. As a result, different prototypes are created for the sensory experiences of the same object in different orientations or viewing angles because the similarity between these views is lower than to other prototypes (a standing red block could be more similar to a standing orange block than to the same red block lying down).

Similarity based on prototypes is thus not enough for creating individual concepts and names about physical objects that often change their view. The language self-organized by agents endowed with the mechanisms discussed so far cannot be interpreted as a set of individual names but rather as words naming different views of objects. Further mechanisms are therefore needed to establish object identity.

8.2 Heuristics for establishing object identity

The sensory experiences of objects themselves don't reveal whether they belong to the same or different individuals. For example it could be that perceptions of something big and red and something small and red are about the same physical object, and at the same time experiences of big blue and small blue things could belong to different individuals. However, heuristics that exploit other knowledge about the interaction with objects can be employed and we

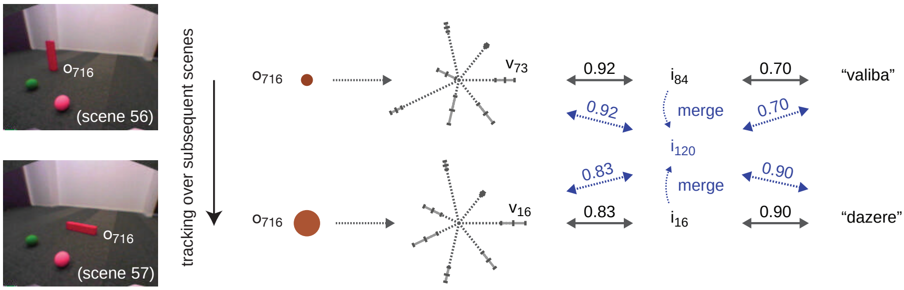


Figure 8.9: The 'object tracking' heuristic. The red bar changes its appearance from one scene to the next, resulting in different prototypical views being associated with the respective sensory experiences. The vision system is able to track the object during the movement via the same anchor o_{716}, making it possible to assume that the two prototypical views are about the same physical object and thus their connected individuals can be merged.

demonstrate how two of them can help the agents to optimize their semiotic networks in order to establish object identity.

The "object tracking" heuristic makes the assumption that if an agent observes how an object changes its appearance, he can infer that the resulting different views must be about the same individual. For example if see somebody painting his red car in green, we will know that it is still the same object. And we have no problems following the plot of a fairy tale in which a frog turns into a prince as long we can witness this transformation. Second, the "same name" heuristic assumes that objects that are referred to with the same name must be the same individual. Imagine seeing someones child and learning her the name and much later meeting a person with the same name. Even though the child grew much taller, wears different clothes, has different hairstyle etc., we will assume that it is the same person. The number of heuristics employed by humans is without doubt much bigger. For example we sometimes can assume that things observed in a fixed location are the same, that the dog being frequently walked by our neighbor is always the same dog although we have difficulties discriminating dogs, and so on.

8.2.1 Observing objects change

The vision system is able to track objects over space and time as detailed in see section 7.1 (page 137). Figure 8.9 shows how the sensory experiences for an object that changes its appearance from one scene to the next gets associated to different prototypical views of a particular agent: The nearest neighbor of o_{716} is v_{73} (linked to i_{84}) in scene 56 and v_{16} (linked to i_{16}) in scene 57. Knowing that these different perceptions are about the same physical object (established through the anchor o_{716}), the agent can assume that the two individuals i_{84} and i_{16} must be about the same object and thus can be "merged". The semiotic network of the agent is then rearranged by introducing a new individual i_{120}, linking i_{120} with all words or prototypical views that were connected to the

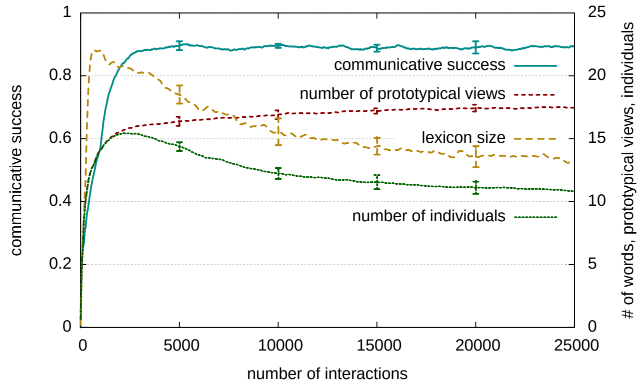


Figure 8.10: Communicative success (measure 2.1) and inventory sizes (measures 4.1, 8.3 and 8.4) in a population of 10 agents that use the object tracking heuristic.

original individuals and finally removing i_{84} and i_{16} from the network. The previously independent names "valiba" and "dazere" are now synonyms and later interactions will determine what the winning name for the new individual is. In order to avoid merging prototypes that have not found their final position in sensory space yet, only individuals views that were independently used in successful interactions are merged – the weights of all links to the individuals in questions (both the scores of prototypes and words) have to be higher than a threshold value of 0.9. Finally, it is worth mentioning how the agents come to observe subsequent scenes: Two agents randomly drawn from the population always play two interactions with each other, the first one on a random scene from the data set and the next one on the following scene in the set.

Figure 8.10 shows what happens when the object tracking heuristic is used by a population of 10 agents playing series of 25000 language games. The number of prototypical views remains 17 (compare figure 8.8), but some of the linked individuals get merged, reducing their number from 17 to 11. There are 10 different physical objects in the world and the result therefore shows clearly that the heuristic enabled the agents to develop true individual concepts that combine different views of objects. Communicative success is still very high but slightly lower than in figure 8.8 (≈90% instead of 95%). This is mainly due to a problem of alignment: Those agents in the population that already merged two different views of an object into a single individual will communicate less successfully with those who didn't do this step yet because the former will use only one single name for the object and the latter two different ones. Furthermore, it also may happen that prototypical views that are in some contexts not about the same physical object get merged because of a suboptimal configuration of prototypes in sensory space, making the merged individual less successful than the two separate ones before.

8.2.2 Different individuals with same name

Agents that view a scene from different angles can have very different perceptions of the same object due to shadows, different sides of the object facing the camera, different distances to the robots, and so on. Consequently, it can hap-

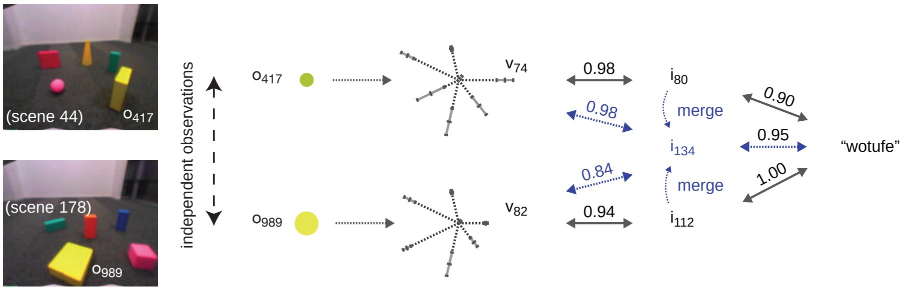
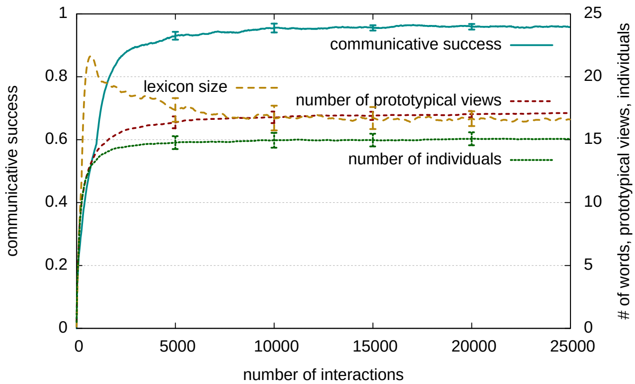


Figure 8.11: The 'same name' heuristic. Independent experiences of different views of the yellow block have led to two separate prototypical views that are both connected to the homonymous word "wotufe". Assuming that individuals that have the same name must be about the same physical object, the connected individuals can be merged.

Figure 8.12: Communicative success (measure 2.1) and inventory sizes (measures 4.1, 8.3 and 8.4) in agents that use the same name heuristic.



pen that a hearer adopts a name for a different individual than if he would have perceived the scene from the viewpoint of the speaker, creating a homonym as a result. This information also can be used to optimize semiotic networks as illustrated in figure 8.11. An agent has established stable links between the name "wotufe" and the individuals i_{80} and i_{112} thus can assume that the connected prototypical views v_{74} and v_{82} are about the same physical object. Similar to the object tracking heuristic, the two individuals get merged by rerouting existing network connections a new individual i_{134}. As discussed in section 8.1.2 above, homonymy can also arise due to misaligned prototypes. That's why the merging operation is only done when the name and the connected prototypes are stable and successful, i.e. the connections to the original individuals have a score higher or equal than 0.9.

Agents that use this heuristic on average merge two pairs of individuals, reducing their number form 17 to about 15 as shown in figure 8.12. The optimal level of 10 individuals (compare figure 8.10) is not reached because the agents create only a small number of homonyms (see figure 8.5) when interacting in the particular environment used in this experiment. Communicative success is as high as in figure 8.8 (>95%) because this way of rearranging the semiotic

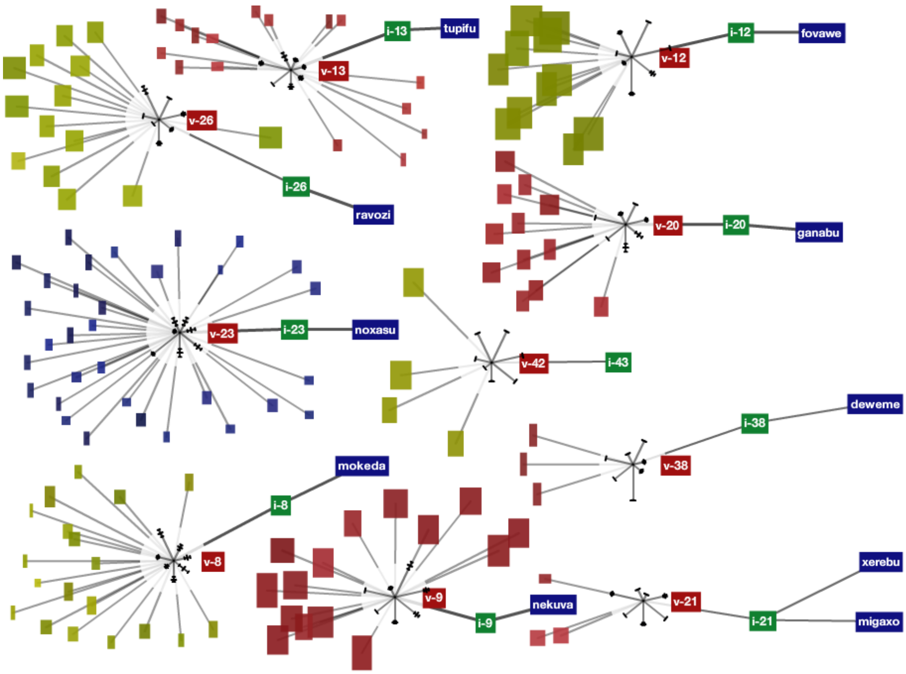


Figure 8.13: Visualization of a single agent's semiotic network after 500 interactions. Words are represented as blue rectangles, individuals in green and prototypical views in red. The thickness of the connecting edges represents connection weights. Visualizations of past sensory experiences are drawn in their average color, width and height and are connected to the closest prototypical view with the smallest distance. Note that agents don't keep sensory experiences in memory – here it is done for visualization purposes only.

network does not change the behavior of the agent – the homonymous names were used successfully before and changing their internal structure does not change how they are used.

8.3 Alignment dynamics

Agents that independently construct and align their semiotic networks can self-organize successful communication systems and using heuristics helps them to establish object identity. Figures 8.13 and 8.14 show an actual network of a single agent after 500 and 10000 interactions. To keep the graphics readable, the populations size was limited to 10 and a data set consisting of only five different physical objects (three small blocks in yellow, red, blue and two big boxes in yellow and red) was used.

After 500 interactions, this agent had created 10 different prototypical with corresponding individuals – among them two separate ones for the small yellow block (v_8 and v_{26}), two for the big yellow block (v_{42} and v_{12}), two for the big red box (v_{20} and v_9), and three for the small red block (v_{76}, v_{13} and v_{71}). 9500

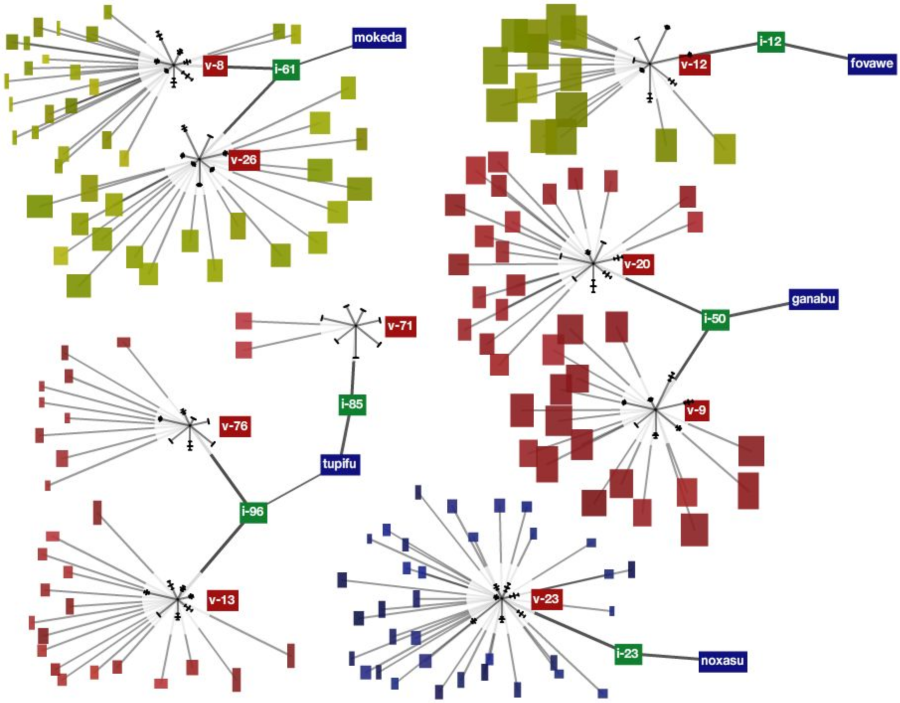


Figure 8.14: The semiotic network of the same agent as in Figure 8.13 after 10000 interactions.

interactions later, the prototypical view v_{42} disappeared from the semiotic network because its region in sensory space was taken over by one of the other prototypical views for yellow blocks. It was already not connected to a word form in interaction 500 and consequently also not used and thus subsequently removed to to the constant decay of prototype scores.

Using the object tracking heuristic, three pairs of prototypical views got merged into individuals (i_{61} for small yellow blocks, i_{96} for small red blocks and i_{50} for big red boxes), reducing their number to six. Finally, synonymy has been completely dampened in this network and the homonymous name "tupifu" is stably linked to the individuals i_{96} and i_{85}, resulting in a lexicon size of five names for five physical objects. When the series of language games would have continued after interaction 10000, it could have happened that the individuals i_{85} and i_{96} get merged due to the "same name" heuristic.

8.3.1 Crucial factors

We don't claim that the particular mechanisms for maintaining semiotic networks as introduced above are the only possible solution to the problem of how a population of agents can self-organize a set of individual names for physical objects. Many strategies (i.e. for the adjustment of prototypical views, lexicon update, etc.) were tested to improve measures such as communicative success and inventory sizes. But other design choices seemed to have little impact on the overall performance – making the system robust in a wide range of parameters. For example the model works well when using different kinds of physical objects (different data sets, see section 7.3.2), other sets of visual features, different distance measures for nearest neighbor computation, other mechanisms for damping synonymy, and generally different values for thresholds or changes in updating scores.

However, three different strategies for updating semiotic networks were found to be crucial for the dynamics of our model. Figures 8.15–8.17 compare the performance in agents that don't use these strategies with a baseline condition (agents maintain their networks as discussed before and use the object tracking heuristic). First, homonymy damping (similar to the damping of synonyms, the scores of words with the same form but different meanings are reduced after each successful interaction) seems to destabilize the construction of semiotic networks. As discussed above, agents sometimes successfully use the same name for different individuals and the damping of homonymy would force them to use different names instead. As a result, words are more often added or removed (figure 8.16) and the number of prototypes is slightly higher than in the baseline configuration (figure 8.17) due to higher fluctuations. This finding is interesting because in many other models of embodied lexicon formation the damping of homonymy is crucial.

Second, it is important that agents keep words that reached zero score in a separate memory. This prevents speakers from creating new names all the time (it is still better to use a word that had little success in the past than a completely new word because at least some of the agents might know the word) and allows hearers to guess the meanings of words even when their confidence in the names is low. Agents not memorizing words with zero score consequently reach much less communicative success (figure 8.15) and maintain a lower, less optimal number of prototypes (figure 8.17) due to less reinforcement from language. The frequency of lexicon changes is lower (figure 8.16) because re-adding a zero score word to the set of actively used connections or removing a word from this set is also counted as a lexicon change.

Third, adjustment of prototypes (adapting their feature values to better capture the statistical distribution of associated sensory experiences) is crucial too. Agents not doing this will create less prototypical views that are less representative for the objects associated to them (see also figure 8.3, page 170) and consequently reach less communicative success (figure 8.15).

8.3.2 Scaling with population size

One of the most important properties of language evolution models is how they scale with increasing population sizes – and this one scales very well. We ran populations of 10, 50, 100, 500 and 1000 agents that use the object tracking heuristic and compared their performance (figures 8.18–8.20). Populations of different sizes naturally require different numbers of language games to be

Figure 8.15: The impact of three different strategies for updating the semiotic network on communicative success (see text). As a baseline, parameters and strategies are as discussed above and agents use the object tracking heuristic. Results are averaged of 20 runs of 25000 language games.

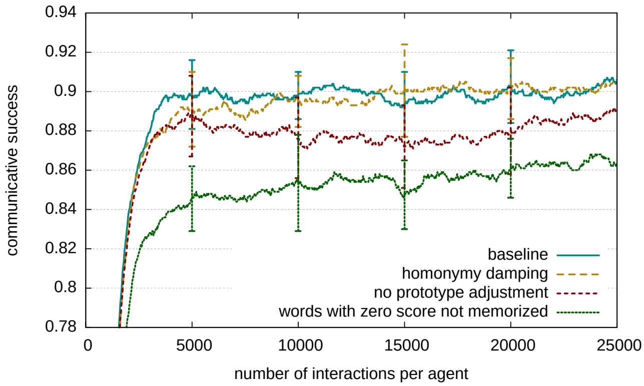


Figure 8.16: The influence of three different update strategies on lexicon change frequencies (how often agents add to or remove words from their lexicons, see measure 4.3 on page 61).

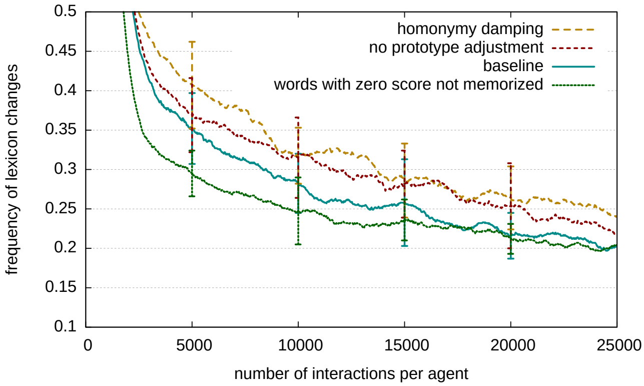
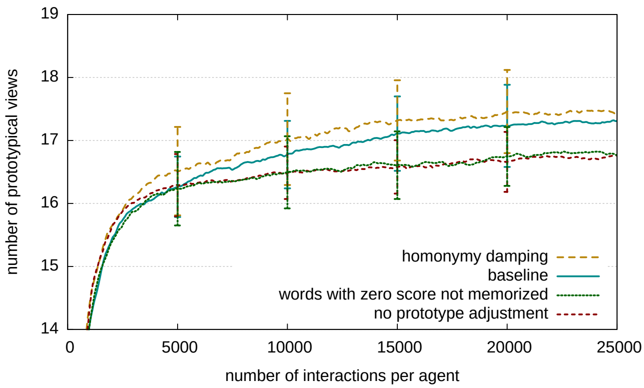


Figure 8.17: The average number of prototypical views in each agent's semiotic network for three different update strategies.



played for aligning their inventories: in order to make the results comparable, values on the x-axis are not the usual absolute number of language games played but the average number of interactions per agent. Because always two agents take part in an interaction, the number of interactions per agent is on average the absolute number of interactions divided by half of the population size. Thus, 10 agents played 25000 language games, 50 agents 125000 interactions, 100 agents 250000 and so on.

The same high level of success as in figure 8.10 is reached by populations of all sizes (figure 8.18), but reaching it takes the longer the bigger the number of agents. This is due to the fact that different speakers independently invent more names and thus the alignment of names takes more interactions. The maximum lexicon size before synonymy damping kicks in is about 25 in a population of 10 agents but ≈125 for 1000 agents (figure 8.20). Despite the different number of synonyms introduced by populations of different sizes, their lexicons remain equally stable once synonyms have been inhibited (figure 8.19). The remarkably good scaling of performance is explained with the fact that the agents independently construct their inventories of prototypical views and individuals (their size in fact remains the same for different population sizes) – the delay in communicative success for bigger populations is mainly due the additional difficulty of aligning the higher number of names.

Figure 8.18: Communicative success in populations of different sizes playing a population size dependent number of games. Results are averaged over 8 repeated runs each. Note that values along the x-axis are for the number of interactions played per agent (see text).

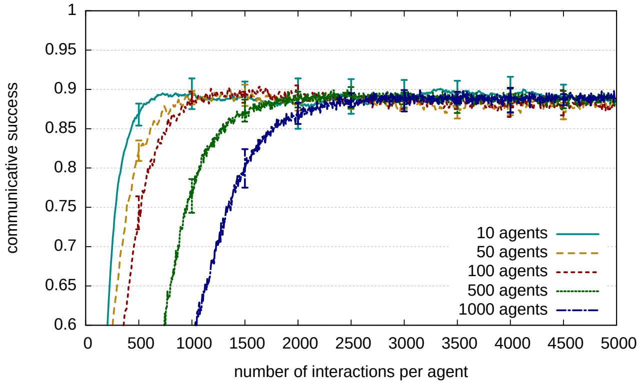


Figure 8.19: The impact of population size on the frequency lexicon changes over the average number of games played by each agent.

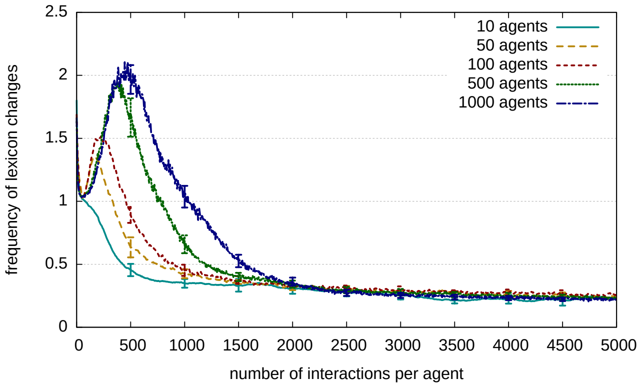
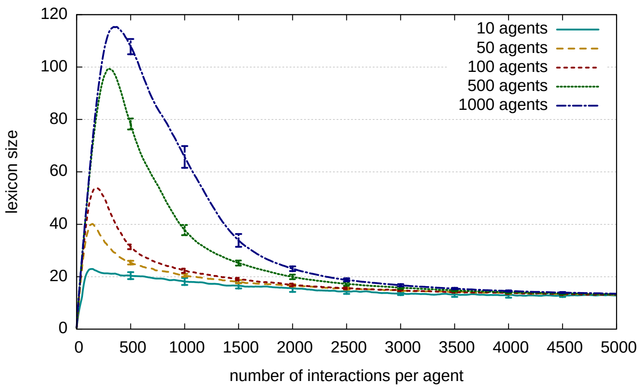


Figure 8.20: The impact of population size on lexicon sizes plotted over the number of interactions per agent.



Chapter 9

Constructing and sharing grounded categories

In the previous Chapter we investigated what it takes to do apply the non-grounded Naming Game from Chapter 4 (page 53) to a robotic setup and it turned out that – although word representations and alignment mechanisms remained unchanged – quite complex cognitive representations and mechanisms were needed for acquiring grounded notions of individual objects. In this chapter we will investigate how the multi-word utterances and structured word representations from Chapter 5 (page 71) can be connected to categories that are grounded in the world of our robots and how these categories can be aligned through language.

This will introduce three major challenges in constructing and maintaining of semiotic networks. First, agents need to be able to construct ontologies of meaningful *perceptual categories* such as `red` and `small` from their sensory experiences. Second, they need conceptualization mechanisms that find combinations of these categories that discriminate the topic from the other objects in the context. And third, word alignment dynamics need to take into account that each agent individually constructs such categories from noisy perceptions and thus the success of words in the population also depends on how conventionalized the underlying categories are.

9.1 Categorization strategies

We discussed in detail what it means to "construct grounded categories" in Section 2.3.1 on page 36 and also listed a few common techniques to implement categorization mechanism in robots in the subsequent Section 2.3.2. Since the focus of our work is on lexicon formation, we will only briefly cover this topic. In order to show that the lexicon formation strategies are independent from the categorization strategies, we will introduce and compare two grounded category representations, namely *discrimination trees* and *prototypes*, which

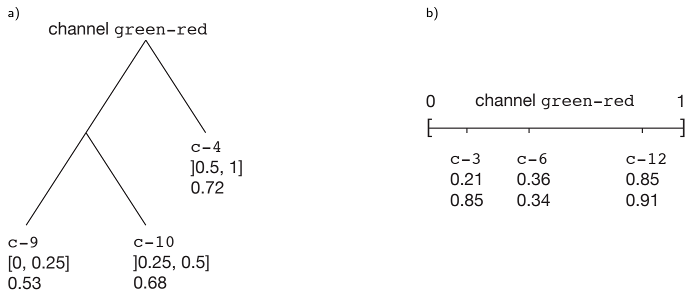


Figure 9.1: Assigning areas on sensory channels to categories using a) discrimination trees and b) prototypes

both assign intervals on sensory channels to categories and thus allow for distinctions such as `small` vs `big`, `green` vs. `red`, and so on.

For all experiments in this chapter, we use the same robotic setup and the same overall language game script as in the previous chapter. As in all of the previous chapters, we will only describe the differences in strategies.

Discrimination trees. This categorization technique was introduced by Steels, 1997a, 1998b; Steels & Kaplan, 1999b; Steels & Vogt, 1997 for the Talking Heads experiment. Categories are formed by recursively splitting a sensory channel into intervals of same length (see Figure 9.1a), that is, an ontology $O(a)$ of an agent a consists of a set of categories $c(a)$ that assign an interval $]min, max], 0 \leq min < max \leq 1$ to a sensory channel with a score δ that reflects how successful the category was used in previous communicative interactions. In the example in Figure 9.1a, the category `c-9` covers the interval between 0 and 0.25 on the `green-red` channel and thus can be used to refer to "very green" objects. A category is *applicable* to an object when the sensory value for the channel of the category falls within the interval of the category.

Prototypes. As an alternative category representation we also implemented something that resembles the continuous category membership of the basic level categories of Rosch (1973) and which was applied in similar form to Lego robots by Vogt (2003). In this strategy, a category $c(a)$ is characterized by a single point $0 \leq v \leq 1$ on a sensory channel and again a score δ that reflects communicative success. The points on the sensory channel spans a one-dimensional Voronoi region, i.e. a category is applicable to an object if it is closest to the perceived sensory value of the object among all prototypes on the same channel. In the example of Figure 9.1b, the prototypical value of the category `c-6` is 0.36, with a score of 0.34. Considering the values of the other categories on the `green-red` channel, this means that all objects that have a sensory value between 0.29 (the middle between `c-3` and `c-6`) and 0.61 (between `c-6` and `c-12`) will be categorized as `c-6`.

Conceptualization. Speakers who attempt to construct a meaning representation that discriminates the topic from the other objects in the sensory context follow the same strategy as in the non-grounded version of the experiment in Chapter 5 (see Section 5.2.1 on page 73). That is, they try to find combinations of categories that are applicable to the topic but not to the other objects. The only difference is that in the non-grounded version the categories are already part of the perceived simulated objects, whereas in the grounded version each agent individually needs to determine which of his categories are applicable and which not.

Saliency & conventionalization. When dealing with real-world perceptions, some combinations of categories are better conceptualizations of a scene than others. This is for three reasons: first, the perceived difference between the topic and the other objects in the context can be very different for different channels and thus categories on these perceptual channels lead to a more contrasting descriptions of an object. This can be captured by computing a *saliency* measure as the minimum distance on the channel of a category between the topic and the other objects in the context. Second, some categories are better conventionalized in the population and thus it is beneficial to prefer them over other categories. This is captured by the aforementioned category score score that is updated as an outcome of the game (see below). And third, in the case of prototypes, the distance between perceived channel values and the prototype can be used as a measure of how well a category expresses a topic. These criteria are combined into a meaning score by multiplying the measures and averaging the result over all categories of a meaning.

Extending the ontology. All agents start without any categories and obviously mechanisms are needed to extend ontologies. For this, Steels & Kaplan (1999b) used a failure in conceptualizing a scene as a trigger to invent new categories. The problem with this strategy is that agents might continue to use less suited categories that nevertheless allow conceptualization and thus get stuck with suboptimal solutions. A better strategy is to create new categories whenever they would increase the overall meaning score. For this, agents conceptualize a scene with their existing categories but also also try to conceptualize with new categories that were created for the most salient channels. Only when a new category leads to a meaning with a higher combined meaning score, then it is added to the ontology.

Production, parsing and word learning. All other mechanisms for processing and maintaining semiotic networks in production, interpretation and alignment remain unchanged from Chapter 5. We will immediately assume the case of multi-word utterances for structured word meanings.

Ontology alignment. After each interaction, the speaker and hearer update the scores of the categories involved in their respective meaning representations to reflect how well they are conventionalized in the population. For that, the scores of the categories that were part of the meaning that was expressed by

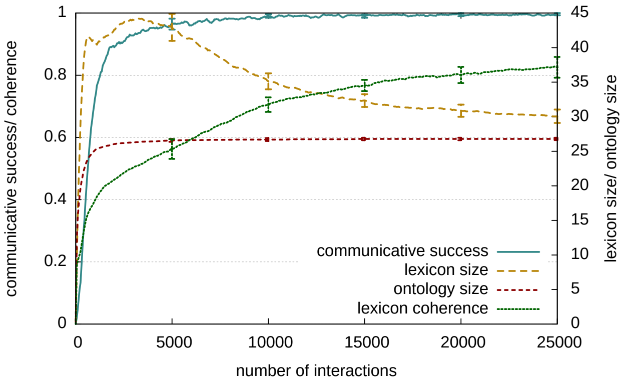


Figure 9.2: Main alignment dynamics with discrimination trees and shared perceptions. Communicative success (measure 2.1), lexicon size (4.1), ontology size (9.1) and discrimination tree lexicon coherence (measure 9.2) are averaged across 10 repeated series of 25000 interactions.

the speaker and interpreted by the hearer are increased by a fixed value of 0.02 in case of success and decreased by 0.02 in case of failure. Categories with a score of 0 are removed from the ontology. Furthermore, when prototypes are used for categorization, their values are slightly shifted towards the perceived value of the topic in order to better reflect the distribution of feature values in the environment (analogously to the shifting of prototypes described in Section 8.1.1 on page 167).

9.2 Problems in aligning fixed form-meaning mappings

To demonstrate that the categorization mechanisms and the interplay of categories and words indeed work, we first ran the model with a modification in which both the speaker and hearer artificially have the same perception of a scene and thus perceptual differences do not play a role. That is, before each interaction, both agents are fed with the perception of the same randomly chosen robot from a recorded scene.

The overall alignment dynamics for agents that use discrimination trees are shown in Figure 9.2. In the first few thousand interactions, the agents quickly acquire a set of around 25 categories, a number that later only slightly increases because we limited the depth of discrimination trees to two (higher depths also work well). Compared to the non-grounded version of this experiment (see

Measure 9.1: Ontology size

Measures the number of categories in the ontology of agents averaged over all agents of the population:

$$v = \frac{\sum_{i=1}^{|P|} |O(a_i)|}{|P|}$$

Values v are averaged over the last 250 interactions.

Figure 9.3: Main alignment dynamics with prototypes and shared perceptions. Communicative success (measure 2.1), lexicon size (4.1), ontology size (9.1) and lexicon coherence for prototypes (measure 9.3) are averaged across 10 repeated series of 25000 interactions.

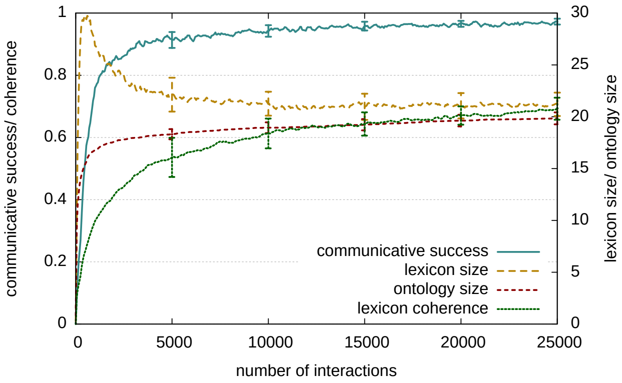


Figure 5.26a on page 104), communicative success and coherence are reached as quickly or even quicker and the maximum number of words that the agents invent or adopt is only 50% higher than the number of categories (compared to around 800% in the non-grounded version).

On the first sight this is surprising, since there is the additional challenge of creating grounded categories. However, because speaker and hearer always have the same perception of a scene and because they use the same way to split the sensory channels into categories, all agents in the population end up adopting the same categories. Furthermore, because the incorporation of saliency in the criteria for selecting meanings from alternative conceptualizations, speaker and hearer almost always conceptualize a scene in the same way (only due to different category scores different conceptualizations can occur, which accounts for the fact that a very small fractions still fail after 10000 interactions). Consequently, the problem of referential uncertainty almost does not exist when agents have shared perceptions because the distributional structure of sensory values across the objects largely narrows down the hypothesis space.

When prototypes are used for categorization, the results are very similar (see Figure 9.3). The number of categories created and thus lexicon size are

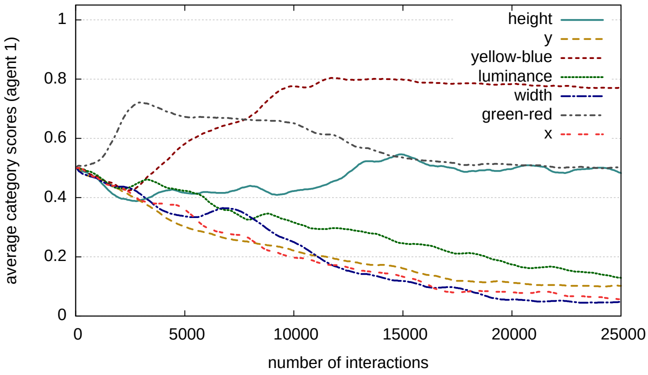
Measure 9.2: Lexicon coherence for discrimination trees

Provides a measure for how similar the meanings underlying the lexicons of the interacting agents are. This measure is identical to measure 4.2 on page 61, with the assumption that two categories in the ontologies of two different agents are "equal" when they cover the same interval on the same sensory channel.

Measure 9.3: Lexicon coherence for prototypes

Measures the prototype similarity between the word meanings of the speaker and hearer of an interaction. The average distance between the prototype values of the meanings of the words that overlap in form between speaker and hearer is divided by the average number of words in the two agents' lexicons.

Figure 9.4: Success of categories in communication per sensory channel. For all categories of the first agent in the population, the average scores of all categories are plotted per channel along the x axis.



slightly lower. Because now each agent individually partitions sensory channels in varying number of categories and thus more different conceptualizations of a scene are possible, coherence and communicative success are slightly lower than when using discrimination trees.

However, when removing the scaffold of providing the agents with the same perception of a scene, agents that use the strategies described in the previous section are much less successful in agreeing on communication systems. Responsible for this is the high perceptual deviation, i.e. the differences in the visual perceptions of physical objects by the two interacting robots. This difference is systematically higher for some sensory channels that for others (see Figure 7.16 on page 160). The correlation between the perception of robots is highest for the `yellow-blue` and `green-red` sensory channels, and it is lowest for the `x` and `y` channels. By incorporating feedback from the use in language, agents learn to rely more on highly correlating channels, as shown in Figure 9.4. The average category scores are highest for categories on the `yellow-blue` and `green-red` channels and lowest for categories on the `width`, `x` and `y` channels, which directly mirrors the distributions in sensory deviation.

Nevertheless, although the alignment mechanisms are sensitive to different degrees of sensory deviation, the lateral inhibition based word meaning selection process is constantly faced with the problem of inconsistent categorization and "wrong" feedback, which adds great difficulties to the problems already inherent in the lexicon formation model. This is illustrated in Figure 9.5, which shows traces of 20 interactions from game 5000 on. For example in interaction 5005, both agents assume the meaning of "wofoza" to be a category that cov-

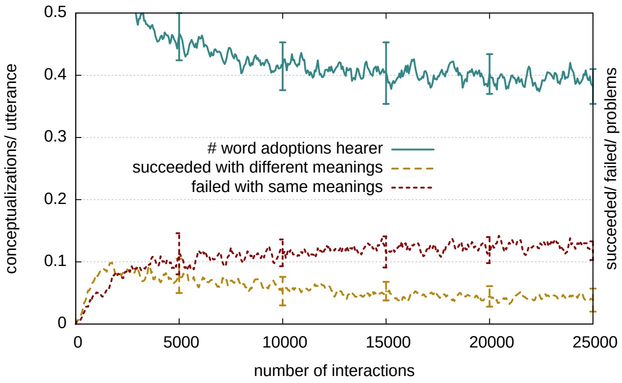
Measure 9.4: Number of word adaptions hearer

Another measure for lexicon stability. Whenever the hearer adopts a new word meaning as the result of a failed communicative interaction, the value of 1 is recorded, otherwise 0. Values are averaged over the last 250 interactions.

#	speaker	topic	meaning	utterance	hearer	meaning	topic	success?
5000	agent 6	obj-69	[y-1: 0.26]	*"nakexo"*	agent 10			no
5001	agent 4	obj-7	[yellow-blue-2: 1.00] [green-red-2: 1.00]	*"renefi romive"*	agent 2	[yellow-blue-2: 1.00] [green-red-2: 1.00]	obj-7	yes
5002	agent 7	obj-31	[width-1: 0.18]	*"zanuta"*	agent 6			no
5003	agent 3	obj-18	[y-2: 0.04]	*"luxoza"*	agent 7	[luminance-1-2: 0.28]		no
5004	agent 10	obj-160	[height-1: 0.64]	*"mazilu"*	agent 3	[height-1: 0.76]		no
5005	agent 9	obj-134	[height-2: 0.94]	*"wofoza"*	agent 10	[height-2: 0.48]		no
5006	agent 1	obj-3	[luminance-2: 0.28]	*"tetupi"*	agent 2	[yellow-blue-2: 0.98] [height-1: 0.62]		no
5007	agent 7	obj-131	[yellow-blue-2: 1.00] [green-red-2: 1.00]	*"romive renefi"*	agent 4	[green-red-2: 1.00] [yellow-blue-2: 1.00]	obj-133	yes
5008	agent 5	obj-174	[green-red-1: 1.00]	*"xubifu"*	agent 7	[green-red-1: 0.98]	obj-178	yes
5009	agent 10	obj-57	[green-red-1: 1.00]	*"xubifu"*	agent 5	[green-red-1: 1.00]	obj-47	yes
5010	agent 5	obj-49	[green-red-2: 0.98]	*"renefi"*	agent 9	[green-red-2: 0.98]		no
5011	agent 1	obj-110	[green-red-1-1: 0.38]	*"gawude"*	agent 4	[green-red-1-1: 0.36]	obj-111	yes
5012	agent 9	obj-7	[width-2: 0.26]	*"renefi"*	agent 3	[green-red-2: 1.00]	obj-9	yes
5013	agent 8	obj-163	[green-red-2: 1.00]	*"renefi"*	agent 10	[green-red-2: 1.00]	obj-159	yes
5014	agent 2	obj-120	[yellow-blue-1: 1.00]	*"radila"*	agent 5	[yellow-blue-1: 1.00]	obj-120	yes
5015	agent 9	obj-35	[height-1-1: 0.44]	*"busimu"*	agent 10	[y-2: 0.06]	obj-44	yes
5016	agent 9	obj-172	[green-red-2: 1.00]	*"renefi"*	agent 1	[green-red-2: 1.00]	obj-176	yes
5017	agent 2	obj-215	[yellow-blue-1: 1.00]	*"radila"*	agent 5	[yellow-blue-1: 1.00]	obj-218	yes
5018	agent 10	obj-163	[green-red-2: 0.98] [luminance-1-2: 0.36]	*"pogupu renefi"*	agent 1	[green-red-2: 0.98]		no
5019	agent 1	obj-87	[green-red-2: 1.00]	*"renefi"*	agent 4	[green-red-2: 1.00]	obj-87	yes

Figure 9.5: Overview of 20 consecutive interactions in a population of 10 agents from game 5000 on. It shows the agents that are interacting, the topic chosen by the speaker, the conceptualized meaning that was chosen, the utterance, the meaning parsed by the hearer together with the interpreted topic, and whether the agents reached communicative success.

Figure 9.6: Sources of alignment problems. The frequency of word adoptions by the hearer (measure 9.4), the number of interactions in which agents succeeded but used different meanings (measure 5.5) and the number of times interactions failed with the same meaning (measure 9.5) are averaged over 10 repeated series of 25000 interactions



ers the interval between 0.5 and 1 on the **height** channel, but nevertheless the interaction fails, because the category was not applicable to the hearer's perception of the scene. Analogously, interaction 5012 is an example of the opposite. Although the categories that are associated by speaker and hearer to the form "renefi" are on different sensory channels, the communication still resulted in a communicative success. In both cases, the wrong entities in the semiotic networks of both agents are increased or respectively decreased in score, which makes it very hard to reach coherence.

More than 10 percent of the interactions fail despite the meanings that were conceptualized or interpreted cover the same categories on the same interval on the same channels, as shown in Figure 9.6. And initially 10 percent and later 5 percent of the interactions succeed although the meanings covered different intervals or other channels. With this inconsistent feedback, hearers still adopt new word meanings in 40 percent of the interactions even after 10000 interactions. As a consequence, the agents are not able to construct stable and coherent lexicon representations, as illustrated by the lexicon snapshots in Figure 9.7. Although after 5000 interactions on average each agent already took part in 1000 interactions, non of the first 10 word meanings of agent 1 are shared by agent 2 and 3.

Measure 9.5: Communicative failure with same meanings

Measures the fraction of interactions in which agents did not reach communicative success although the hearer parsed the utterance into a the same meaning as the one that was conceptualized by the speaker. After each interaction, the value of 1 is recorded when communicative success was not reached (see measure 2.1) and when the meaning that underlies the utterance produced by the speaker is identical (categories on the same sensory channel cover the same categories) to the meaning that was used by the hearer to interpret the topic. Otherwise, a value of 0 is recorded. Values are averaged over the last 250 interactions.

form	agent 1		agent 2		agent 3	
"poxiga"	[yellow-blue-2: 1.00] [green-red-2: 1.00]	0.50	[yellow-blue-1: 1.00] [green-red-2: 1.00] [y-1: 0.22]	0.50 0.30	[y-1: 0.22]	0.30
"watave"	[x-1: 0.22]	0.40				
"genuke"	[height-1: 0.78]	0.30	[luminance-1-1: 0.26]	0.30		
"wavimu"	[luminance-1-2: 0.28]	0.50			[height-1-2: 0.38]	0.40
"pifizi"	[yellow-blue-1: 1.00] [green-red-1: 1.00]	0.30	[height-1-1: 0.36] [luminance-1-2: 0.38]	0.30 0.30	[luminance-2: 0.14] [green-red-1-1: 0.32]	0.50 0.20
"tubafi"	[y-2: 0.12]	0.20				
"gazomi"	[width-1: 0.16]	0.20	[luminance-1: 0.32]	0.30	[width-1: 0.16]	0.40
"gapemu"	[x-1: 0.22]	0.40	[y-2: 0.10]	0.40	[green-red-1: 1.00] [y-1: 0.22]	0.50
"runese"	[y-2: 0.12]	0.20	[yellow-blue-2: 1.00] [width-1-2: 0.34]	0.40	[yellow-blue-2: 1.00] [width-1-1: 0.28] [green-red-1-1: 0.32]	0.30 0.40
"kuvuka"	[width-1-2: 0.28]	0.50	[width-2: 0.26]	0.10		

Figure 9.7: The associated categories and word association scores of the first 10 words of agent 1 (out of a population of 10 agents) and the corresponding meanings in the lexicons of agents 2 and 3 after 5000 interactions.

Not surprisingly, the overall alignment dynamics completely break down when agents individually perceive real-world scenes (see Figure 9.8a and 9.8b). Lexicon coherence hovers between 10 and 15 percent, and due to the permanent adoption of new word meanings, later inhibition dynamics are not able to stop a continuous increase in lexicon size. The communicative success for agents that use prototypes (70%) is slightly higher than when discrimination trees are used (60%), which is because discrimination trees cut sensory channels at fixed points, whereas prototypes allow to cut sensory channels into intervals that are more robust against perceptual deviation. For example discrimination tree category can never cover an interval between 0.35 and 0.6, wheres a prototype can. When for a specific channel many values occur around the value of 0.5, then the prototype is better applicable to these objects.

Given such low levels of coherence and communicative success, we omit the analysis of scaling behavior for this model.

Figure 9.8a: Main alignment dynamics for agents that use discrimination trees for categorization. Communicative success (measure 2.1), lexicon size (4.1), ontology size (9.1) and discrimination tree lexicon coherence (measure 9.2) are averaged across 10 repeated series of 25000 interactions.

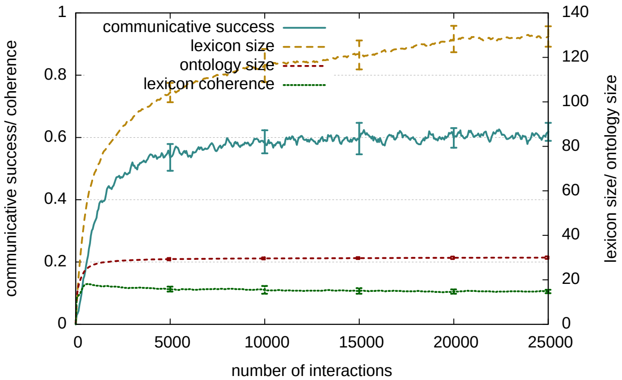
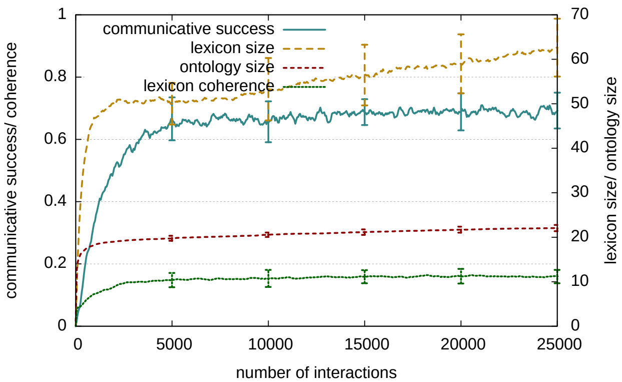


Figure 9.8b: Main alignment dynamics with prototypes. Communicative success (measure 2.1), lexicon size (4.1), ontology size (9.1) and lexicon coherence for prototypes (measure 9.3) are averaged across 10 repeated series of 25000 interactions.



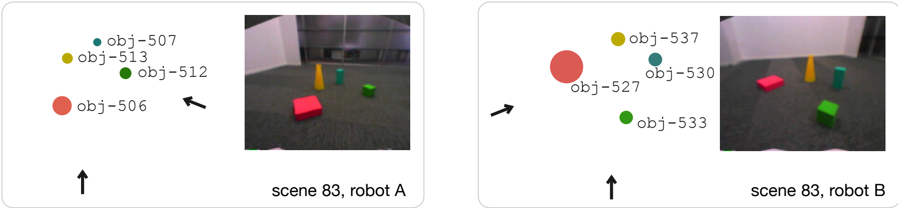
Chapter 10

Flexible word meaning in embodied agents

In the previous chapter we demonstrated that word alignment strategies which rely on competition between alternative word meaning hypotheses are not applicable to embodied scenarios in which speakers and hearers have substantially different perceptions of the objects in their environment. As the final experiment of this thesis, we will now tackle this problem by applying the flexible word representations from Chapter 6 to the robotic setup that we used in the last 3 chapters[1].

For comparability with the simulated version of this model, we assume a categorization strategy that, similarly to discrimination trees, splits sensory channels into four discrete regions. Agents are then provided with sensory contexts that contain for each object all applicable categories. An example of such sensory contexts from the perspectives of two robots in a scene is shown in Figure 10.1. As discussed in the previous chapter, perceptual deviation inevitably causes both agents to categorize the same physical objects differently, and indeed for all objects except the yellow cone the applicable categories differ on four channels.

Everything else, i.e. the lexicon representation, the mechanisms for production and interpretation, alignment strategies and even actual parameters for certainty score updates and so on, are identical to the experiments in Chapter 6 (page 113).



obj-512	obj-507	obj-513	obj-506	obj-533	obj-530	obj-537
x-3	x-4	x-4	*x-2*	*x-2*	x-4	x-4
y-1	*y-2*	*y-3*	*y-3*	*y-2*	*y-1*	*y-2*
width-2	*width-1*	width-2	*width-3*	width-2	*width-2*	width-2
height-2	*height-2*	height-4	height-2	*height-3*	*height-3*	height-4
luminance-2	*luminance-2*	luminance-3	luminance-2	luminance-2	*luminance-3*	luminance-3
green-red-2	green-red-1	green-red-3	green-red-4	*green-red-1*	green-red-1	green-red-3
yellow-blue-2	yellow-blue-3	yellow-blue-1	*yellow-blue-2*	yellow-blue-2	yellow-blue-3	yellow-blue-1

Figure 10.1: Interval based categorization. On the top, the an example scene as seen through the cameras of the two robots and the object models constructed by the vision system are shown. On the bottom, the categories that are applicable to each object are shown. Those categories that are different between the two robots are printed in italics.

10.1 Dealing with perceptual deviation

With flexible word representations, agents do not try trying to find the "correct" mapping from a form to a meaning among a set of competing hypothesis, but rather capture the uncertainty how to conceptualize objects in the word representations themselves. Figure 10.2 shows a partial snapshot of the early lexicons of four agents after 500 interactions. Although there is some initial coherence, very different categories are associated to each form by different agents, very often even from the same sensory channel.

Nevertheless, as already discussed in Chapter 6, agents are able to use these highly un-conventionalized word meanings successfully from very early on, because the similarity based lexicon application does not require all categories of a meaning to be applicable to the topic – it is enough that the similarity of the words of the utterance to the topic is highest compared to the all other objects in the context. This is illustrated in Figure 10.3, which lists 10 consecutive language games from interaction 2000 on. All of these interactions succeed, although the category sets that speaker and hearer connect to the words in the utterance are often very different. Furthermore (as we already observed in non-grounded version), using multi-word utterances does not increase the risk of communicative failure but rather decreases it, because the likelihood of finding the right topic is the higher the more (partially conventionalized) words are used in the similarity-based lexicon application.

[1] Some parts of this chapter are adapted from Wellens, Loetzsch & Steels (2008), see also Wellens & Loetzsch (2007, 2012)

form	agent 1		agent 2		agent 3		agent 4	
"weviwa"	green-red-2	0.22	y-2	0.13	height-2	0.26	y-2	0.17
	yellow-blue-4	0.20	height-3	0.13	green-red-2	0.24	yellow-blue-4	0.13
	luminance-2	0.14	width-3	0.04	yellow-blue-4	0.17	luminance-2	0.10
	x-4	0.13	x-4	0.02	y-2	0.04	green-red-2	0.10
	height-2	0.05	luminance-4	0.02			height-2	0.08
			green-red-3	0.02			x-3	0.02
			yellow-blue-1	0.02			y-4	0.02
							height-3	0.02
							luminance-1	0.02
"vumaza"	width-2	0.26	width-2	0.30	y-3	0.25	green-red-2	0.14
	x-2	0.17	luminance-2	0.14	green-red-4	0.17	yellow-blue-4	0.14
	y-2	0.17	x-3	0.10	width-2	0.17	width-2	0.14
	height-1	0.17	y-4	0.10	yellow-blue-3	0.08	x-2	0.10
	luminance-2	0.13	height-2	0.10			y-2	0.10
	green-red-1	0.06	green-red-3	0.10			y-3	0.10
	x-3	0.02	yellow-blue-3	0.10			width-1	0.10
	green-red-2	0.02	y-3	0.06			height-2	0.10
	yellow-blue-4	0.02	height-3	0.02			luminance-2	0.10
			green-red-1	0.02			x-3	0.02
			yellow-blue-4	0.02			height-3	0.02
							luminance-3	0.02
							green-red-1	0.02
"wedilo"	width-2	0.13	x-4	0.13	luminance-2	0.11	x-3	0.23
	x-2	0.10	width-4	0.13	x-3	0.10	y-2	0.13
	y-3	0.10	height-4	0.11	yellow-blue-3	0.10		
	height-2	0.10	luminance-4	0.02	y-4	0.10		
	luminance-2	0.10	green-red-3	0.02	width-2	0.10		
	green-red-4	0.10	yellow-blue-1	0.02	height-3	0.10		
	yellow-blue-3	0.10	yellow-blue-4	0.02	luminance-3	0.10		
	y-2	0.06			green-red-3	0.10		
	x-3	0.02			yellow-blue-1	0.10		
	height-3	0.02			x-4	0.05		
	luminance-3	0.02			width-3	0.03		
	green-red-1	0.02						
	yellow-blue-4	0.02						
"lugefe"	luminance-2	0.29	luminance-2	0.20	luminance-2	0.17	x-3	0.13
	x-4	0.20	x-3	0.20	x-2	0.10	yellow-blue-4	0.13
	yellow-blue-4	0.07	green-red-1	0.13	y-3	0.10	y-1	0.10
			yellow-blue-3	0.11	width-2	0.10	width-3	0.10
			height-3	0.02	height-3	0.10	height-4	0.10
			yellow-blue-4	0.02	yellow-blue-3	0.10	green-red-1	0.10
					green-red-4	0.06	luminance-2	0.06
					x-3	0.02	y-3	0.06
					width-1	0.02	width-2	0.02
					height-2	0.02	height-2	0.02
					green-red-2	0.02	luminance-1	0.02
					yellow-blue-4	0.02	green-red-2	0.02
"zubere"	y-2	0.20	width-2	0.20	x-2	0.17	x-2	0.23
	yellow-blue-3	0.13	x-2	0.20	y-3	0.17	yellow-blue-3	0.04
	x-3	0.11	y-2	0.10	luminance-3	0.07		
	height-3	0.02	luminance-4	0.10				
	green-red-4	0.02	green-red-4	0.10				
			yellow-blue-3	0.10				

Figure 10.2: The meanings of the first five words of agent 1 (out of a population of 10 agents) and the corresponding categories in the lexicons of agents 2, 3 and 4 after 5000 interactions. The numbers right to the categories are scores of the association to the category.

#	speaker + topic	word meanings speaker	word meanings hearer	hearer + topic	succ.
2000	agent 5 obj-7	*"kaloli"* (luminance-2$^{.24}$, green-red-1$^{.19}$, yellow-blue-3$^{.03}$, width-2$^{.03}$, y-3$^{.02}$, width-1$^{.02}$, height-1$^{.02}$, luminance-4$^{.02}$) *"ketelu"* (y-3$^{.28}$, luminance-2$^{.23}$)	*"kaloli"* (luminance-2$^{.45}$, height-3$^{.20}$, yellow-blue-3$^{.18}$) *"ketelu"* (luminance-2$^{.05}$, yellow-blue-4$^{.04}$)	agent 7 obj-8	yes
2001	agent 8 obj-17	*"xazafu"* (green-red-3$^{.61}$, yellow-blue-1$^{.49}$) *"zisedu"* (width-2$^{.36}$, y-3$^{.31}$, x-2$^{.22}$)	*"xazafu"* (green-red-3$^{.49}$, yellow-blue-1$^{.42}$, luminance-4$^{.22}$, height-2$^{.15}$) *"zisedu"* (y-2$^{.38}$, width-2$^{.22}$, yellow-blue-2$^{.07}$)	agent 9 obj-17	yes
2002	agent 4 obj-18	*"bekamo"* (width-2$^{.41}$, green-red-4$^{.28}$, yellow-blue-2$^{.15}$, luminance-3$^{.14}$, y-2$^{.07}$, x-2$^{.05}$) *"pawegu"* (x-3$^{.20}$, width-2$^{.17}$, luminance-2$^{.10}$, y-2$^{.09}$)	*"bekamo"* (green-red-4$^{.44}$, width-2$^{.27}$, luminance-3$^{.25}$, yellow-blue-2$^{.23}$, y-2$^{.11}$, height-1$^{.03}$) *"pawegu"* (height-2$^{.31}$, width-2$^{.15}$)	agent 3 obj-20	yes
2003	agent 1 obj-17	*"xazafu"* (green-red-3$^{.49}$, yellow-blue-1$^{.43}$, luminance-4$^{.08}$)	*"xazafu"* (green-red-3$^{.56}$, yellow-blue-1$^{.47}$)	agent 6 obj-17	yes
2004	agent 10 obj-100	*"bekamo"* (green-red-4$^{.40}$, width-2$^{.27}$, luminance-3$^{.14}$, yellow-blue-2$^{.08}$, height-2$^{.05}$) *"pawegu"* (y-2$^{.17}$, yellow-blue-3$^{.17}$, x-4$^{.10}$, width-3$^{.10}$, height-3$^{.10}$, luminance-2$^{.10}$, green-red-1$^{.10}$, yellow-blue-2$^{.10}$, x-3$^{.05}$, green-red-4$^{.05}$) *"xivima"* (luminance-2$^{.40}$, yellow-blue-3$^{.35}$, x-3$^{.06}$, width-3$^{.06}$, height-3$^{.06}$, green-red-4$^{.06}$)	*"bekamo"* (x-2$^{.28}$, yellow-blue-2$^{.27}$, width-2$^{.24}$, green-red-4$^{.13}$, y-3$^{.10}$, luminance-3$^{.10}$) *"pawegu"* (x-4$^{.13}$, width-3$^{.13}$, height-3$^{.13}$, y-2$^{.13}$, x-2$^{.03}$, luminance-2$^{.02}$, yellow-blue-2$^{.02}$) *"xivima"* (luminance-2$^{.41}$, yellow-blue-3$^{.26}$, y-3$^{.13}$, green-red-4$^{.13}$, height-3$^{.06}$, x-2$^{.02}$, height-2$^{.02}$, green-red-1$^{.02}$)	agent 8 obj-99	yes
2005	agent 3 obj-17	*"xazafu"* (green-red-3$^{.65}$, yellow-blue-1$^{.54}$, luminance-4$^{.24}$)	*"xazafu"* (green-red-3$^{.49}$, yellow-blue-1$^{.43}$, luminance-4$^{.24}$, height-2$^{.11}$)	agent 9 obj-17	yes
2006	agent 4 obj-109	*"xazafu"* (green-red-3$^{.49}$, yellow-blue-1$^{.43}$, luminance-4$^{.22}$)	*"xazafu"* (green-red-3$^{.50}$, yellow-blue-1$^{.44}$, luminance-4$^{.09}$)	agent 1 obj-109	yes
2007	agent 5 obj-81	*"pokosa"* (height-2$^{.26}$, x-2$^{.22}$, y-4$^{.10}$, width-2$^{.10}$, height-3$^{.10}$, green-red-2$^{.10}$) *"doteza"* (y-2$^{.26}$, width-2$^{.19}$, x-3$^{.17}$)	*"pokosa"* (yellow-blue-3$^{.27}$, green-red-1$^{.17}$, width-2$^{.15}$, y-2$^{.11}$, height-3$^{.10}$, x-2$^{.07}$) *"doteza"* (green-red-1$^{.13}$, x-3$^{.13}$, height-1$^{.13}$, y-3$^{.10}$, luminance-3$^{.10}$, yellow-blue-2$^{.06}$, y-2$^{.02}$, width-1$^{.02}$, luminance-4$^{.02}$, yellow-blue-3$^{.02}$)	agent 8 obj-81	yes
2008	agent 2 obj-152	*"xazafu"* (green-red-3$^{.48}$, yellow-blue-1$^{.48}$)	*"xazafu"* (green-red-3$^{.62}$, yellow-blue-1$^{.49}$)	agent 8 obj-148	yes
2009	agent 1 obj-104	*"regowo"* (yellow-blue-4$^{.44}$, green-red-2$^{.40}$)	*"regowo"* (yellow-blue-4$^{.28}$, y-3$^{.22}$, green-red-2$^{.19}$)	agent 5 obj-107	yes

Figure 10.3: Overview of 10 consecutive interactions in a population of 10 agents from game 2000 on. It shows

form	agent 1		agent 2		agent 3		agent 4	
"weviwa"	`yellow-blue-4` `green-red-2`	0.74 0.53	`yellow-blue-4` `green-red-2`	0.73 0.55	`yellow-blue-4` `green-red-2`	0.68 0.38	`yellow-blue-4` `green-red-2`	0.70 0.58

"vumaza"	`yellow-blue-3`
	`width-2`
		0.35
		0.17
			`width-2`
			`x-2`
			`y-2`
			`yellow-blue-2`
			`luminance-2`
			`green-red-1`
				0.21
				0.09
				0.06
				0.06
				0.02
				0.02
					`x-2`
					`y-3`
					`width-2`
						0.34
						0.32
						0.18
							`width-2`
							`x-2`
							`y-3`
							`luminance-2`
								0.46
								0.19
								0.08
								0.06

"wedilo"	`yellow-blue-3`
	`green-red-4`
	`luminance-2`
	`y-2`
	`width-3`
		0.70
		0.62
		0.38
		0.04
		0.04
			`yellow-blue-3`
			`green-red-4`
			`luminance-2`
				0.68
				0.54
				0.43
					`yellow-blue-3`
					`green-red-4`
					`luminance-2`
						0.67
						0.50
						0.41
							`yellow-blue-3`
							`green-red-4`
							`luminance-2`
								0.68
								0.53
								0.43

"lugefe"	`luminance-2`	0.55	`luminance-2`
			`width-2`
				0.59
				0.21
					`luminance-2`
					`green-red-1`
					`y-3`
						0.51
						0.22
						0.03
							`luminance-2`
							`y-3`
								0.43
								0.06

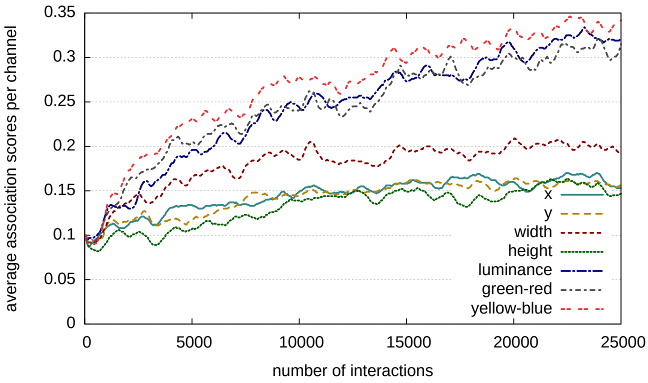
"zubere"	`height-2`
	`width-2`
	`y-2`
		0.34
		0.17
		0.04
			`height-2`
			`width-2`
			`x-2`
				0.55
				0.07
				0.07
					`height-2`
					`width-2`
					`y-2`
						0.35
						0.22
						0.21
							`height-2`
							`width-2`
							`x-2`
								0.55
								0.21
								0.08

Figure 10.4: Meanings of the same words as in Figure 10.2 at interaction 10000.

Carefully shaping these categories in subsequent interactions, agents reach high coherence in their lexicons. Figure 10.4 shows the lexicons of the same agents 9500 interactions later, and it turns all first five words from interaction 500 survived in the lexicons of all the agents, and a consensus on a core set of categories has been reached. Furthermore, the aligned lexicons contain words of different degrees of specificity (unlike the competition based lexicon formation models, which had a bias towards atomic word meanings) – the lexicons in Figure 10.4 contain both very general and very specific words. As an example for a general word, “lugefe” is consistently associated to the single category `luminance-2`, which makes it applicable to all “dark” objects. In contrast, “wedilo” is an example for a very specific word, it is associated by all four agents to the tree categories `yellow-blue-3`, `green-red-4` and `luminance-2`, which makes the word only applicable to dark purple or pink objects. In between, words such as “weviwa” (“turquoise”) or “zubere” (“small”) cover two categories.

Note that categories on channels such as `yellow-blue` and `green-red` have higher association scores than others. Similarly to the experiments in the previous two chapters, agents rely more on categories on channels with smaller perceptual deviation, which is further illustrated in Figure 10.5. The average association scores between forms and categories are highest for categories on the `yellow-blue`, `luminance` and `green-red` channels, which again matches their observed correlations across all the perceptions of both robots (see Figure 7.16 on page 160). Furthermore, some categories on channels with higher perceptual deviation end up being removed from all the words in the lexicon, as shown in Figure 10.6.

Figure 10.5: Success of categories in communication per sensory channel. For all categories of the first agent in the population, the average association scores to the connected forms are plotted per channel along the x axis.



Finally, Figures 10.7a–10.7d provide four examples of the changing association of word forms to different categories, demonstrating the capability to gradually shift word meanings in order to make them more applicable to the objects in the world. A word that constantly changes its dominant meaning is shown in Figure 10.7a. It is invented or adopted at around interaction 6000 and subsequently undergoes many meaning shifts. Over time, the highest association scores are to `height-3` (interaction 7000), `yellow-blue-2` (interaction 16000), `width-2` (21000 - 36000) and `luminance-2` (40000). In addition to that, many other categories are associated with the word, but are immediately discarded again. The situation stabilizes towards the end, giving the word the final meaning "narrow, dark, yellow". In contrast, Figure 10.7b is an example of a rather unsuccessful word. The initial meanings disappear quite soon and at around interaction 5000, a stable set of three categories arises. This meaning does not seem to spread and the word loses all its categories after 22000 interactions. Thereafter the agent does not use the word himself in production, but other agents in the population still use it, leading to new associations with categories, which eventually also don't turn out to be successful.

An example for a word that changes from being very specific to very general is shown in Figure 10.7c. Except for some quickly disappearing other associations, this word is initially only connected to `width-2`. Over the course of more interactions, more and more categories are associated (`luminance-3` at around interaction 3000, `green-red-4` at interaction 7000 and finally `height-2` at interaction 22000). So this word changed from being very general ("thin") to very specific ("thin, low, bright and red"). In contrast, the word in Figure 10.7d is an example of the opposite. It starts being very specific, with connections to `green-red-4`, `yellow-blue-2`, `height-2`, `width-2`, `luminance-3` ("orange, small and bright"). It looses most of its categories, becoming very general ("orange") towards the end.

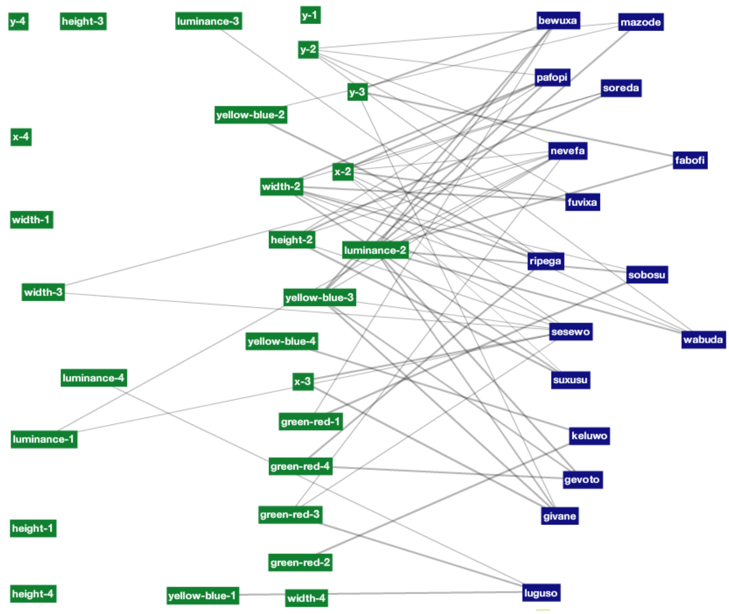


Figure 10.6: Network visualization of the he lexicon of the first agent of the population after 20000 interactions. For each word form, all categories that are associated to the form are shown. Line width denote association weights.

10.2 Success without coherence

Throughout this thesis, the flexible word representations and alignment strategies are the only lexicon formation model that could be applied without modification to a setup with physical robots in a real world. Figure 10.8 shows the overall alignment dynamics, which look very similar to the non-grounded version (Figure 6.6a on page 127). Already after a few hundred interactions agents communicate successfully in more than 50% of the cases, and by further extending and refining their lexicons agents reach about 90% communicative success, which is remarkably high for grounded language games. Even more so than in the non-grounded version, lexicon coherence is not a prerequisite for communicative success – it is even below zero in the first 2000 interaction (due to it's computation using the set similarity measure) and grows only slowly later on. This again shows that the similarity based lexicon application allows agents to stretch their initial word meanings to broad use cases and thus allows them to communicate successfully.

Furthermore, the word usage dynamics (Figure 10.9) look almost identical to their non-grounded counterpart (Figure 6.6b on page 128). The distance between the words of the utterance and the topic quickly decreases, and on average two words that cover on average 4 categories are part of each utterance.

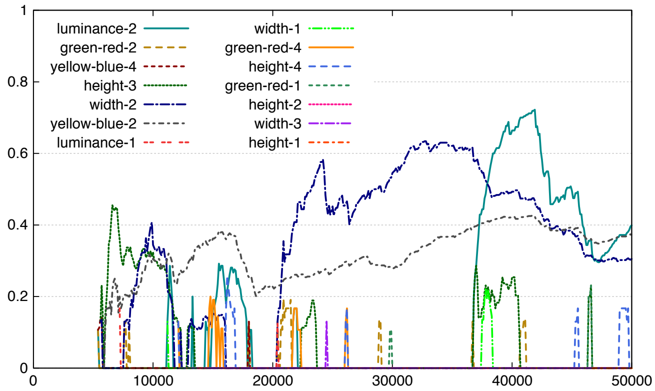


Figure 10.7a: Example of the evolution of a single word of a single agent over time (interactions). Along the x-axis, the association scores to each category of the word are plotted.

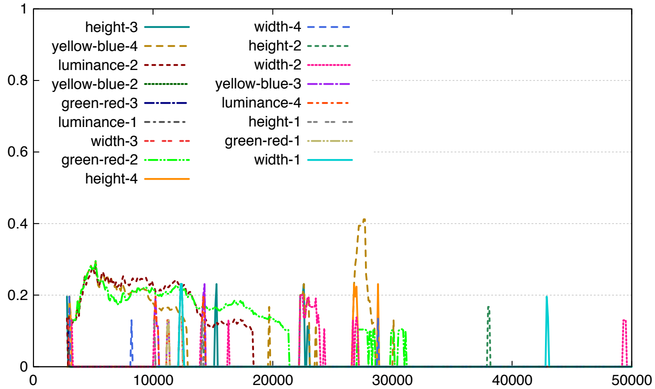


Figure 10.7b: Example of the evolution of a second word over time.

Finally, Figures 10.10a–10.10c investigate the scaling with population size and it shows that the model scales even slightly better with increasing population sizes than the non-grounded version (compare page 206). Without having looked into it, we speculate that this is because the physical world of our robots is more structured than the simulate world, which provides an external structure for the word meanings and thus makes the alignment task easier.

Figure 10.7c: Example of the evolution of a third word over time.

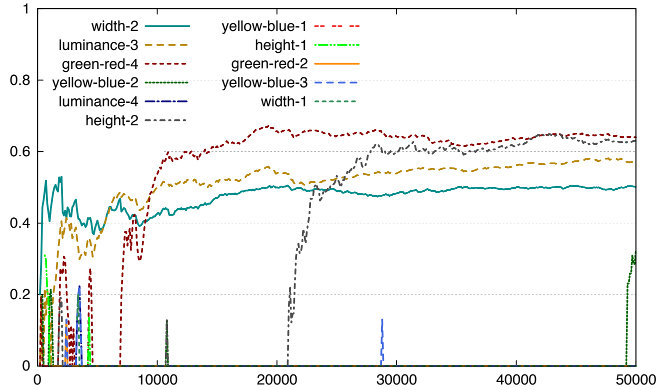


Figure 10.7d: Example of the evolution of a fourth word over time.

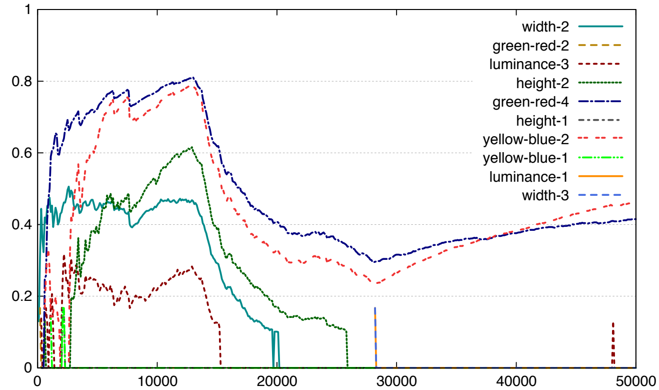


Figure 10.8: Communicative success (measure 2.1), lexicon size (measure 4.1) and lexicon coherence (measure 6.1) in a population of 10 agents averaged over 10 repeated series of 20000 language games.

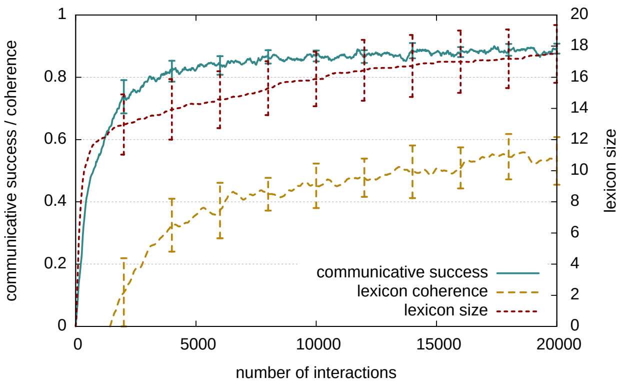


Figure 10.9: The distance of the utterance to the topic (measure 6.2), the average number of categories covered per word (measure 6.3) and the average utterance length (measure 5.7) are averaged over 10 repeated series of 20000 language games.

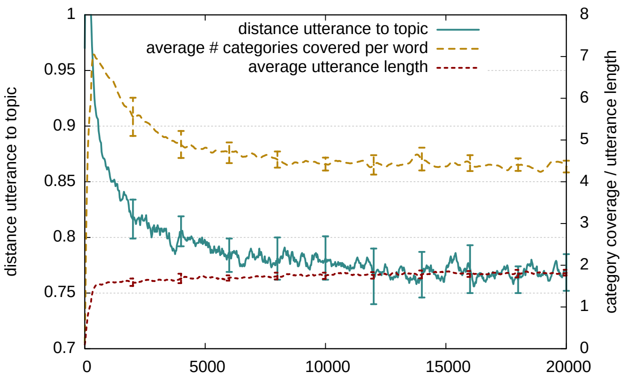


Figure 10.10a: Communicative success (measure 2.1) for five different population sizes. Results are averaged over 10 series of varying length, but each with 8000 interactions per agent.

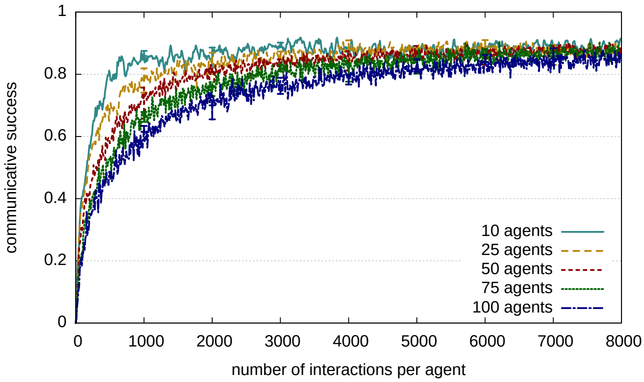


Figure 10.10b: Lexicon size (measure 4.1) for five different population sizes. Results are averaged over 10 series of varying length, but each with 8000 interactions per agent.

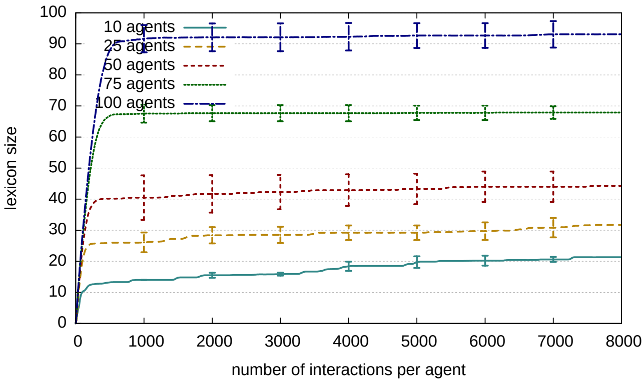
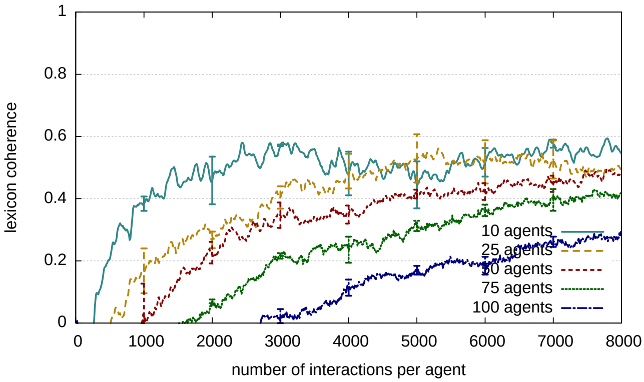


Figure 10.10c: Lexicon coherence (measure 6.1) for five different population sizes. Results are averaged over 10 series of varying length, but each with 8000 interactions per agent.



Part IV

Conclusion

Chapter 11

Summary & discussion

In this thesis we systematically analyzed the performance of different classes of lexicon formation models both in an simulated environment and with an embodiment in physical humanoid robots. Starting from simple lexicon representations and strategies for language processing, learning and alignment, we confronted our agents with increasingly more challenging communicative tasks and examined each time what additional representational mechanisms and learning strategies were required in order to reach communicative success and coherence.

We evaluated each of the models with respect to their alignment dynamics and scaling and especially focused on how well the models can cope with the challenges of referential uncertainty and real-word perception. To allow for a just comparison between models, we tried (where possible) to keep most of the parameters and machinery constant across all of the experiments. Throughout this thesis, we used the same population size, the same language game script, the same diagnostics and repair strategies for learning from failed interactions, the same performance measures, and the same world simulation respectively robotic interaction scenario.

11.1 Word meaning representations and referential uncertainty

We started our investigations in Part II with a series of experiments in which all aspects related to language grounding such as perception, categorization and social interaction were scaffolded. Instead, agents were interacting in a simulated environment in which objects consisted of pre-conceptualized (sets of) symbols such as `object-1`, or `category-2`. As a consequence, the meanings to be expressed were already "in the world" and thus were also immediately shared by all agents of the population.

Individual objects, unstructured meanings, single-word utterances. To set the stage and to introduce the building blocks of all language game experiments in this thesis, in Chapter 4 we briefly introduced the *Naming Game*, which is the most simple and most studied lexicon formation model in the literature. The task in this model is to learn to associate single word forms to atomic, unstructured meanings which are provided by a shared simulated environment.

Words are represented as scored mappings between forms and meanings. Because different agents can independently invent different word forms for the same objects, agents will adopt many of these forms and consequently there is a competition between words that share their forms (*synonymy*) and alignment mechanisms are needed that eliminate competing words. *Lateral inhibition* can be used to achieve this, and we showed that (at least for a wide range of values) the choice for the actual score update parameters is not at all crucial for reaching coherence as long as there is some feedback loop that makes sure that a successful use in communication increases the likelihood of a word to be used in future interactions.

Referential uncertainty does not play a role because when an agent does not know a word form, then pointing will reveal the object, which itself then um-ambiguously serves as the meaning to be associated to the novel form. Consequently, the model scales very well with increasing population size and scales even linearly with the number of objects in the world.

Categories, unstructured meanings, single-word utterances. Next, in Section 5.2 we took away the scaffold that the wold simulator provides agents with unique object identifiers. Instead, perceived objects are characterized by sets of categories and therefore *conceptualization* mechanisms that find sets of categories that discriminate the topic from the other objects in the context need to be added. Production and parsing strategies now select from multiple possible conceptualizations of a scene and we compared several strategies with respect to the number of meanings that are used in production and adoption. We showed that none of them has clear advantages, but that it is beneficial when learning and alignment mechanisms take alternative paths in the semiotic network into account.

In this first category-based experiment we limited word meanings to single categories and allowed agents to use only one word per utterance. With our chosen word simulation parameters (15 categories, 10 categories per object, between 2 and 5 objects per scene), this means that conceptualization fails in about 45% of the cases because no single category can be found that is solely applicable to the topic.

Besides that, referential uncertainty arises to an extend that hearers hearing a novel form must pick from potentially many candidate categories and due to that, lexicons start containing multiple associations from the same form to different meanings (sometimes called *homonymy*), which are then later dampened using lateral inhibition. This slight increase in complexity already caused agents to take significantly longer to reach communicative success and coherence, agents enumerated a lot of different mappings in their lexicons before they got pruned by alignment, and already this simple model does not scale well with increasing number of categories in the world.

Categories, structured meanings, single-word utterances. In the next experiment in Section 5.3 we allowed word forms to be associated to sets of categories while still keeping the limitation of one word per utterance. Using structured word meanings resulted in 100% discriminative success because speakers could now use multiple categories to distinguish a topic from the other objects in the context.

Nevertheless, because with single-word utterances each different combination of categories needs to be expressed by a different word forms, agents accumulate hundreds of different words in their lexicons without reaching any communicative success or coherence, which illustrates that single-word utterances for structured meanings is obviously a bad strategy.

Categories, unstructured meanings, multi-word utterances. As an intermediate step towards the full complexity of the final experiment of Chapter 5, in Section 5.4 we first analyzed a model with multi-word utterances for unstructured meanings. That is, the same word representations as in Section 5.2 are used, but production and parsing mechanisms were enabled to deal with multi-word utterances.

One additional challenge lies in the recovering from partial processing, that is when a speaker only knows words for some parts of the utterance or when a hearer only knows meanings for some of the words in the utterance. But more importantly, multi-word utterances introduce *interdependent alignment dynamics*: how well a convention spreads in the population does not only depend on how well it was used in previous interactions, but also on the other words that it was used with together in the utterance. When an interaction fails, the agents can not know which word or words of the utterance was responsible for the communicative failure and consequently it can happen that well-conventionalized words become punished as part of the alignment process. Nevertheless, the gain from being able to discriminate in 100 percent of the interactions balances these difficulties so that the overall alignment and scaling dynamics are similar compared to the model with unstructured word meanings and single-word utterances.

Categories, structured meanings, multi-word utterances. The full-blown complexity of "Guessing Game"-like experiments was then investigated in Section 5.5, in which multi-word utterances were combined with word meanings consisting of sets of categories. In addition to the ambiguity of deciding which words cover which categories, referential uncertainty drastically increases because now there is also ambiguity in *specificity*: Upon hearing a novel word, agents need to decide whether the word refers to a single category, a combination of categories, or the complete meaning as a whole.

As a result of that, agents enumerate large numbers of words with high degrees of synonymy and homonymy in their lexicons and that need to be eliminated by lateral inhibition in order to reach coherence. Alignment is additionally made difficult by the fact that the feedback loop from communicative success to the lexicon becomes less reliable: In the first 2000 interactions, agents communicate successfully although different word meanings were used in up to 8 percent of the cases, causing the wrong word associations to be increased and decreased by lateral inhibition.

Although with the default world simulation parameters and the standard population size of 10 agents the overall alignment dynamics look similar to the previous experiments (with delayed success and higher intermediate lexicon sizes), performance quickly breaks down when moving beyond the boundaries of these parameters. We showed that for increasing population sizes and for increasing context sizes (which increases both the number of alternative conceptualizations and therefore referential uncertainty as well as the average number of categories and therefore the ambiguity in which parts of meanings words cover), success in the game and coherence is reached not at all or only after thousands of interactions in which agents do not communicate successfully at all. The high variance in performance across different experimental runs indicates that agents go through extended periods of *random search* until some words start being successfully used by a critical fraction of the population.

Furthermore, the lateral inhibition dynamics constitute a bias towards unstructured word meanings. Although agents have the capability to present and process structured word meanings and although indeed many words are initially connected to sets of categories, only words that cover single categories survive in the lexicons of the agents, which we attributed to the disadvantage of interdependent alignment dynamics that words with structured word meanings have.

Categories, flexible word representations. Finally, in Chapter 6 we introduced a lexicon formation model that addresses these shortcomings by capturing uncertainty in the representation of word meanings themselves. Instead of having competing mappings to different sets of categories for the same word, words now have flexible connections to different categories that are constantly shaped by language use, which we achieved by keeping an *(un)certainty score* for every category in a form-meaning association instead of scoring the meanings as a whole. By allowing the certainty scores to change, the representation becomes adaptive and the need to explicitly enumerate competing hypotheses disappears.

We showed that agents which use such representations and the accompanying processing and alignment strategies enjoyed high communicative success from early on, with conservatively growing lexicons that contain stable structured word meanings. And repeating the scaling experiments from the previous chapter, we demonstrated that the model easily copes with the same increasing communicative challenges that the lateral inhibition base models struggled with.

We identified two key factors for this drastic increase in performance. First, the similarity based lexicon application allows agents to communicate successfully even when word meanings are not yet conventionalized. Both speakers and hearers are able to "stretch" their existing word meanings to uses that are far away from the actual meanings of the words, because for the successful interpretation of an utterance it enough that the overall similarity of the words in the utterance to the topic is higher than to the other objects in the context. And second, the similarity-based alignment mechanisms allow agents to gradually refine and shift the meanings of their words to better conform future uses, without having to eliminate competing hypotheses on word meanings.

11.2 Grounded word meanings and challenges from real-word perception

In the third part of this thesis we applied the lexicon formation models from the previous three chapters to real-world situated interactions of two Sony humanoid robots. The key difference to the experiments in simulated environment is that the world does not provide pre-conceptualized categories anymore, and instead distinctions such as small vs. big, red vs blue, thing vs. toy. vs teddy bear have to be constructed from the raw sensory experiences of the robots, which adds further complexities to the mechanisms for constructing and maintaining semiotic networks and which introduces new challenges such as perceptual deviation.

Programming robots to play language games about objects in their environment is in itself a very difficult but also very interesting engineering task and in Chapter 7 we documented our various state-of-the-art solutions to problems of visual perception, object tracking, joint attention and social interaction, their integration into a robust whole system and the overall experimental setup that allowed us to conduct repeated and controlled embodied language games experiments.

Grounded object identity, single word utterances. In Chapter 8 we then investigated what it takes to extend the Naming Game from Chapter 4 to our robotic setup. We endowed our agents with the ability to capture the invariant properties of sensory experiences of objects with prototypes, that is points in the sensory space that are applied using a nearest neighbor computation and that adapt and shift in order to better capture the statistical distributions of visual object features across multiple perceptions of the same object.

However, individual physical objects can drastically change their appearance, both over time and within the same scene when viewed by the two robots from different angles, and as a result agents end up establishing multiple prototypes for different "views" of the same physical object. In order to successfully construct mental representations of individual objects (and therefore real proper names), additional heuristics are needed. We demonstrated that by exploiting temporal-spatial continuity and the lexicon itself as sources for associating separate prototypical views of the same physical object to an individual, the number of words in the lexicons of the agents matched the actual number of distinct physical objects in the world.

The non-grounded Naming Game is the simplest lexicon formation model that can be imagined and therefore proved to be an "E. coli paradigm" for investigating alignment strategies, mathematical proofs of convergence, impact of network structure and so on. Furthermore, it has also led to views that proper names are semantically simpler than words for kinds of objects (e.g. "red" or "block") and that they might be precursors of compositional communication systems (as for example in Steels, 2005a). Nevertheless, we showed that the dynamics of the Grounded Naming Game differ drastically from the non-grounded version and that the underlying semantics of proper names are much more complex, which suggests that proper names are "more likely to be late developments in the evolution of language. In the historical evolution of individual languages, proper names are frequently, and perhaps always, derived from definite descriptions, as is still obvious from many, such as, *Baker*, *Wheeler*, *Newcastle*" (Hurford, 2003, p. 266).

Grounded categories, competing form-meaning mappings. Next, in Chapter 9 we tried to apply the lateral inhibition based lexicon formation models from Chapter 5 to our embodied setup, which required two changes to the mechanisms for constructing and maintaining of semiotic networks: First, agents need to be able to construct ontologies of meaningful *perceptual categories* such as `red` and `small` from their sensory experiences. And second, word alignment dynamics need to take into account that each agent individually constructs such categories from noisy perceptions and thus the success of words in the population also depends on how conventionalized the underlying categories are. In order to demonstrate that the learning and alignment mechanisms are independent from the chosen categorization strategy, we implemented two different category representations (one based on discrimination trees and a second using prototypes on single sensory channels) and showed that the interplay of categories and words indeed works well when interlocutors artificially have the same perception of a scene.

However, when the scaffold of shared perception is removed, alignment dynamics more or less break down. Agents continuously adopt new word meanings and thus do not reach stable lexicons and high communicative success (maximum 60% with discrimination trees and 70% with prototypes), which we explained with the high degree of perceptual deviation. Differences in the visual perception of physical objects by the two interacting agents frequently prevent interlocutors from successfully applying already conventionalized word meanings, which in turn increases the problem of "wrong" feedback from communicative success (interactions often fail although very similar categories were used and many interactions succeed with very different underlying meanings).

A lexicon formation model that tries to select from alternative form meaning couplings is therefore not applicable to a scenario where inconsistent categorization happens as a result of perceptual deviation. This also explains the low overall communicative success for a population of 5 agents in the Perspective Reversal experiment (Loetzsch, van Trijp & Steels, 2008a; Steels & Loetzsch, 2009), which had similar word alignment strategies and an embodiment in Sony Aibo robots. But more importantly, although also very similar (and even improved) word representations and learning mechanisms were used, this means that we were not able to reproduce the results of the Talking Heads experiment (Steels & Kaplan, 1999b) using our robotic setup. We speculate that this is due to the fact that perceptual deviation did not play a role in that experiment because the two robotic cameras were looking from almost the same angle at objects on a whiteboard and thus speaker and hearers always had a very similar perception of a scene.

Grounded categories, flexible word representations. The flexible word representations and alignment strategies from Chapter 6 are the only lexicon formation model throughout this thesis that could be applied to embodied agents without modification. As we showed in the (therefore short) Chapter 10, the overall performance and scaling behavior looks almost identical to the non-grounded version despite the same levels of perceptual deviation as in the previous experiments. High communicative success is reached within relatively few interactions, and rich word meanings of different specificity emerge that reflect the distribution of object properties in the world. This is possible because the model is not only able to capture the uncertainty of what words mean but also the uncertainty of how to categorize objects across different contexts in the word meaning representation itself.

Many, if not even most experiments in the field of artificial language evolution that follow a constructivist cultural learning approach (including most of the experiments on the emergence of grammatical communication systems or the grounding of richer semantics) use some kind of lateral inhibition-based alignment strategies and therefore often fail to scale beyond very simple communicative tasks. Given our results, we argue that language learning should not be considered as an enumeration and subsequent elimination of alternative hypotheses but rather as a process in which learners construct and gradually shape their conceptual and linguistic inventories over time. New members of a linguistic community that try to learn the language do not spend years of randomly searching a hypothesis space before they start being able to communicate successfully. Instead, we acquire simple operational approximations of novel linguistic items very quickly and refine them later on over the course of repeated interactions.

11.3 Acknowledgements

The research reported here was carried out at the Sony Computer Science Laboratories in Paris and Tokyo and at the Artificial Intelligence Laboratory Vrije Universiteit Brussel and it was funded by the European FP6 project *ECAgents* and the FP7 project *ALEAR*. Sincere thanks go to Masahiro Fujita, Hideki Shimamura, and their team at Sony CSL Tokyo for allowing us to work with the fantastic Sony humanoid robots and their support.

The work presented in this thesis could not have been carried out without the joint effort of a great team, and I especially want to thank three people that who had a substantial part in designing and setting up the experiments.

First, I did not enter a new completely field with this thesis but could already rely on the extensive body of research by Luc Steels and his previous collaborators. Next to teaching me how to program in Lisp and of course to organizing funding, in 2007 together we began a project of "deconstructing" language games that formed a starting point for the experiments in Chapter 5. Furthermore, he was deeply involved in the design of the Grounded Naming Game (Chapter 8, Steels & Loetzsch, 2012).

Second, there was a very fruitful and inspiring collaboration with Pieter Wellens from the VUB AI lab. Next to many other joint work, we developed the machinery for conducting language game experiments that is underlying all experiments in this thesis (as part of the Babel2 framework; Loetzsch, Wellens, De Beule, Bleys & van Trijp, 2008b; Steels & Loetzsch, 2010), and we devised the flexible word meaning representations and applied them to our the robotic setup (Chapters 10 and 6, Wellens & Loetzsch, 2012; Wellens, Loetzsch & Steels, 2008).

And third, all work on the Sony humanoid robots from Chapter 7 (Spranger, Loetzsch & Steels, 2012a) was done together with Michael Spranger from the Sony CSL Paris. He had a major share in developing the visual object tracking system and together we built all the machinery for having the robots play language games, conducted endless series of interactions, and analyzed the resulting data to create the data sets used in this thesis.

Moreover, I want to thank all the other colleagues at Sony CSL and the VUB AI Lab for great discussions and advice, but more importantly, for being a fantastic group to work with (in order of appearance): Frederic Kaplan, Verena Hafner, Pierre-Yves Oudeyer, Joachim De Beule, Wouter Van den Broeck, Joris Bleys, Vanessa Micelli, Simon Pauw, Katrien Beuls, and Katja Gerasymova.

Finally, I have to thank the Mathematisch-Naturwissenschaftliche Fakultät II of the Humboldt-Universität zu Berlin for setting a strict time limit for submitting PhD-theses, which eventually forced me to hand in mine.

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