

Computational Models in the Debate Over Language Learnability

Frederic Kaplan^{a,*}, Pierre-Yves Oudeyer^b and Benjamin Bergen^c

^a *Ecole Polytechnique Fédérale de Lausanne, EPFL-CRAFT, Lausanne, Switzerland*

^b *Sony Computer Science Laboratory Paris, Paris, France*

^c *Department of Linguistics, University of Hawaii, Honolulu, HI, USA*

Computational models have played a central role in the debate over language learnability. This article discusses how they have been used in different 'stances', from generative views to more recently introduced explanatory frameworks based on embodiment, cognitive development and cultural evolution. By digging into the details of certain specific models, we show how they organize, transform and rephrase defining questions about what makes language learning possible for children. Finally, we present a tentative synthesis to recast the debate using the notion of learning bias. Copyright © 2008 John Wiley & Sons, Ltd.

Key words: language acquisition; poverty of stimulus; generative models; statistical learning; embodiment; active learning; selection for learnability

LANGUAGE ACQUISITION AS A COMPUTATIONAL PROBLEM

What makes language learning appear so easy for children? This question is at the centre of one of the most lively debates in modern linguistics and psychology (Gold, 1967; Pinker, 1989; Seidenberg, 1997; Wexler & Culicover, 1980). Interestingly, computers have had a pervasive influence on the way we understand the process of language acquisition and on the question of language learnability in particular. By asking what children can learn from the input they are exposed to, linguists have implicitly framed the problem of language acquisition as a machine learning question. Machine learning theory formalizes learning problems in the following manner:

- There is a learner whose objective is to discover/model a mapping from a space A to a space B .
- Learning happens as examples of pairing of points $x \in A \mapsto y \in B$ are provided to the learner by the environment.

*Correspondence to: Frederic Kaplan, Ecole Polytechnique Fédérale de Lausanne, EPFL-CRAFT, Lausanne, Switzerland. E-mail: frederic.kaplan@epfl.ch

In machine learning terms, a language learner is confronted with two types of task. The first is to learn the structure of the language they are exposed to: the mapping they have to learn is from the space of sentences S to the binary space coding for syntactic correctness/incorrectness $B = \{\text{correct}, \text{notcorrect}\}$. The second task is to learn to assign semantic content to these sentences: the mapping is from S to the space of meanings M or vice versa.

Framing language acquisition in these formal terms has allowed researchers to pursue mathematical and computational studies of language learning. These studies have played a central role in the controversies about language learnability and have been used by different explanatory frameworks, often to support contradictory views. More than this, although, computational models have from the beginning defined the terms of the debate. In each successive model, the computational problems of language acquisition described above have been progressively reframed in novel ways. This article discusses the role of these models in different 'stances' towards language acquisition, from generative views to more recently introduced approaches focusing on embodiment, cognitive development and cultural evolution. After offering a brief overview of these different approaches, the article enters into the details of several specific computational models in order to articulate in a precise manner the role they play in the debate.

STANCES

The Generative Stance

The generative stance has dominated modern linguistics during the second half of the 20th century. In this view, the central problem of language acquisition is the learning of syntax. Syntax provides the basis for distinguishing well-formed from ill-formed sentences and permits the creation of an in principle infinite set of well-formed utterance. Thus, most of the modelling effort of the generative stance has concerned the first learning problem that we mentioned: learning a mapping between the space of sentence S to the binary space code for syntactic correctness/incorrectness (Gold, 1967; Wexler & Culicover, 1980). This has led to the Poverty of Stimulus hypothesis, which claims that the input available to children underdetermines what they learn about language (Chomsky, 1975, 1980; Marcus, 1999), especially because children do not receive explicit feedbacks as they learn. In formal terms, this means that models of the syntactic input that infants receive, used as training examples to general syntactic learning systems, could not account for the precise and fast learning that human infants display given. Researchers then proposed that this could only be solved by adding some human-language-specific biases to the learning systems. Likewise, subsequent arguments were developed that state that language learning, including semantic mapping, is not possible without a substantial genetic preprogramming of specific neural circuits (Gallistel, 2000; Pinker & Bloom, 1990). Jumping to the conclusion that language is simply not learnable by general means, many authors have tended to reduce the role of learning in language development to a very small contribution (Piattelli-Palmarini, 1989), like the setting of a few parameters as in the Principles and Parameters theory (Chomsky & Halle, 1968) or as ordering of innate constraints, as in Optimality Theory (Archangeli & Langendoen, 1997). However, for a decade or so, the Poverty of Stimulus hypothesis has been empirically challenged by other approaches.

The Statistical Stance

The Poverty of Stimulus hypothesis was first challenged by a number of computational experiments showing how rather general statistical induction machine learning techniques could in practice extract linguistic patterns in the flow of sounds, words and sentences (e.g. Elman, 1990; Seidenberg, 1997; Solan, Horn, Ruppin, & Edelman, 2005): 'Rather than involving hypothesis testing about grammatical rules, learning involves accumulating information about statistical and probabilistic aspect of language' (Seidenberg & MacDonald, 1999). Compared with the generative approach that focuses on the so-called competence aspect of the linguistic faculty, the statistical learning stance stresses the importance of performance—actual production and comprehension of utterances. On this view, the use of language and not grammaticality judgments is the core of linguistic knowledge. A recent review (Elman, 2005) argues convincingly that in the field of language development, such computational models have clearly shown that there is often much more information in the linguistic input that children encounter than previously thought. This structure can be captured by state-of-the-art general machine learning algorithms. In other words, the 'Stimulus' is richer than expected. Likewise, learning a mapping between two streams of data—learning to pair linguistic form with meaning—has been addressed as a problem of evaluation of statistical occurrences based on cross-situational inference (e.g. Siskind, 1996). The so-called probabilistic constraint approach (Seidenberg & MacDonald, 1999) has made strides in showing that adults store vast amounts of statistical information, in particular distributional information, about the behaviour of lexical items in their language. In English, for instance, verbs seem to provide strong constraints that are used for resolving syntactic ambiguities. Yet, some authors argued that despite these successes, this machine learning perspective fails to capture several important characteristics of human language learning (e.g. Marcus, 1998), and others have argued that framing the debate on language learnability in statistical terms ignores other critical components of learning (see below).

The Embodied and Social Cognition Stance

Most computational approaches to language acquisition do not take into account, at least in their models, the embodied and social dimension of this process. Yet, the fact that language and concepts are acquired through the use of a physical body and the fact that language is an interactive process taking place between individuals situated in social and physical environments could not help but constrain language learning. This is particularly important for the second problem we mentioned concerning language acquisition: associating semantic content with sentences. Naturally, expanding the scope of investigation beyond isolated and idealized linguistic knowledge significantly complicates the nature of models and the explanations they offer. However, at the same time, and more interestingly, the body, physical and social context, and goals of the learning agent can serve as a set of biases, which dramatically affect what a learner can and will learn. To investigate this view, researchers have for instance endowed artificial agents with a virtual incarnation of the human biological system underlying spatial relations (for spatial preposition learning) or physical action (for action verb learning), or whatever the relevant semantic domain is (e.g. Bailey, 1997; Regier, 1996). Similar experiments have also been conducted with physical robots (Cangelosi, Smith, & Smith, 2006; Dominey, 2005; Roy & Pentland, 2002; Steels & Kaplan, 2000; Sugita & Tani, 2005). In such approaches,

the meaning of a word is a schematic (that is, abstracted) representation of concrete perceptual, motor and other experiences. Broadly, when a computational learner already includes a model of the human motor system, this makes the learning of verbs of motion, like *push* or *appuyer*, much easier, since it constrains the space of possible meanings. Likewise, in the domain of spatial relations terms, the system endowed with human-like visual capacities need only to figure out where to make categorical distinctions in the semantic domain, and learn how to pair these conceptualizations with the phonology of the words denoting these categories. The key point of such models stress is that taking into consideration the embodiment and social environment of learners radically improves accounts of language learning because the inherent biases they introduce facilitate processes that would in principle be exponentially harder than anything learning machines could do.

The Developmental Stance

The three previous stances are subject to the critique that they only consider specific linguistic problems in isolation, and ignore the developmental processes that surround and support the acquisition of language. In these frameworks, language development is most often considered in terms of sequence of competencies without much explanation of how the child gets from one to another. Developmental models try to fill this gap, by investigating how a computational learner can learn in an incremental and open-ended manner (see Lungarella, Metta, Pfeifer, & Sandini, 2003; Oudeyer, Kaplan, & Hafner, 2007; Prince, Helder, & Hollich, 2005; Weng *et al.*, 2001, as well as Berthouze & Kaplan, 2005; Berthouze & Metta, 2004; Kaplan & Oudeyer, 2006 for current trends in this emerging field). Similarly, computational approaches to language acquisition belonging to the previous stances generally consider the problem of learning the structure present in an input stream as a passive process: learners are 'exposed to' /given learning examples. On the contrary, developmental accounts argue that human infants actively explore their environment, in particular the linguistic environment, and thereby influence the linguistic input that they can potentially observe (Berlyne, 1960; Smith & Gasser, 2005; White, 1959). By doing so, they can control the complexity of their learning experiences to ensure the input feeds into the learner's current developmental state, instead of having to cope directly with the full-fledged complexity of the language. This new line of models, although still in its infancy, offers a constructive novel perspective on the language learnability question.

The Cultural Evolution Stance

The four previously outlined stances towards human language learning do not take into account language evolution. The generative stance argues that since only specially tuned or biased learning machines can acquire the syntax of human languages, humans must also have such language-specific biases in order to successfully acquire language. The cultural evolution approach turns this argumentation on its head, and proposes instead that languages have evolved culturally so as to become easily learnable by individuals with pre-existing non-language-specific cognitive capabilities. This line of thinking is explored by yet another kind of computational models that involve language creation and evolution in populations of individuals (Brighton, Kirby, & Smith, 2005; Kirby, 2001; Oudeyer, 2005a; Zuidema, 2003).

Table 1. Stances

Stance	Focus	Key points
Generative	Grammaticality, classes of grammar	Theoretical models show that certain classes of languages are not learnable without feedbacks. Therefore, innate learning circuits specific to language are necessary to compensate for 'the poverty of the stimulus'
Statistical learning	Statistical structures of existing language and general learning methods to induce them	Semantics and grammatical functions can be extracted from distributional information presented in child-directed speech. The 'Stimulus' is richer than expected. This information can be derived from noisy data using, for instance, connectionist networks, without explicit feedback
Embodied and social cognition	Role of physical and social constraints	Robotic and computational models illustrate how embodied and social constraints radically transform the problem of learning language. These models support the idea that it is the common substrate of the human motor control and perceptual systems that drive children's rapid and flexible acquisition of verbs and nouns
Developmental	Developmental processes, active learning, motivation	Robotic and computational models illustrate how computational learners can actively control the complexity of their learning experiences and follow a developmental path instead of having to cope immediately with the full-fledged complexity of language
Cultural evolution	Adaptation of language to human cognition	Models involving populations of interacting learners explore the hypothesis that languages have evolved culturally so as to become easily learnable by individuals with preexisting non-language specific cognitive capabilities

The computational models used by these five stances are rather diverse. They share neither exactly the same assumptions nor the same types of implementation and more importantly they do not address the same issues in the language learnability controversy. Table 1 presents a broad summary of these differences. In the following sections, we will discuss five computational models, one belonging to each of these stances. This will more clearly illustrate how they are used in the debate. Inevitably, the choice of any particular models as representative of a given stance will have drawbacks. Nevertheless, we believe that characterizing specific models in greater detail will help elucidate the similarities and the differences among these various approaches and, more importantly, the role that computational models play in the debate over language learnability.

GENERATIVE STANCE: A THEORETICAL MODEL

In 1967, Gold wrote a theoretical article discussing the question: 'For which classes of language does a learning algorithm exist?' (Gold, 1967, p. 448). To our knowledge, this model is the first known attempt to capture the notion of learnability. In this article, Gold explicitly casts the problem of language learnability as a machine learning problem. He defines a language as a set of

strings over some finite alphabet. A class of languages will be considered learnable if there is an algorithm capable of identifying it 'in the limit'. This means that after some finite time, the algorithm will systematically guess properly which language it is (i.e. a finite number of incorrect guesses are allowed).

From his investigation, Gold concludes that the class of context-sensitive language is learnable (in the sense previously defined) if the learner is informed which strings are in the language and which strings are not. Without this information not even the class of regular languages is learnable. However, Gold remains cautious about the conclusions that can be drawn from such a theoretical analysis. If it is true that most children are rarely informed when they make grammatical errors (which means that they learn syntax solely from positive utterances), and if one accepts the formal notions he introduced as a model of learnability, then his studies must lead to one of the following conclusions.

1. 'The class of possible natural languages is much smaller than one would expect from our present model of syntax' (p. 453). This can mean, for instance, that even if English is context sensitive, it is not true that just any context-sensitive language can occur naturally. Likewise, it can imply (and this is the conclusion that most people retain from this study) that the child starts out with constraining information about the language she will have to learn.
2. 'The child receives negative instances by being corrected in a way we do not recognize' (p. 453). If indeed the child is being presented information of such a kind, then the class of primitive recursive languages, which includes context-sensitive language, becomes learnable. Negative evidence may for instance occur when the child does not get the desired response to an utterance. Gold admits that 'it is difficult to interpret the actual training program of a child in terms of the naive model of language assumed here'.
3. 'The child may learn that a certain string is not acceptable by the fact the it never occurs in a certain context' (p. 454). This would be the equivalent of a negative instance.

The Model in the Debate

Several empirical studies with young infants have argued that children show sensitivity to structures for which there is no evidence in the input and sensitivity to grammatical constraints at the youngest ages at which they can be tested (Crain, 1991). There is not sufficient space in this article to review all the kinds of argument that have been taken as evidence for the innateness of grammar. However, Gold's analysis of learnability is a representative example of the kind of formal models that have been used to defend the Poverty of Stimulus hypothesis (Chomsky, 1975, 1980; Marcus, 1999). Interestingly, for Gold himself, this possible interpretation of the model is only one of the several.

STATISTICAL LEARNING STANCE: A CONNECTIONIST MODEL

'Claims about what cannot be learned by the child need to be assessed in terms of the kinds of statistical information available to the child and learning mechanism that are able to extract non-obvious regularities from it' (Seidenberg & MacDonald, 1999, p. 10). This assertion from Seidenberg and MacDonald's comprehensive review of the domain stresses the perspective shift introduced by

the statistical learning stance. In the past 15 years, a number of empirical (non-computational) studies have demonstrated that distributional information that could be used to induce semantic and grammatical categories does in fact exist in child-directed speech, and that learners are sensitive to it (Brent & Cartwright, 1996; Mintz, Newport, & Bever, 2002; Redington, Chater, & Finch, 1998; Saffran, 2001). Computational modelling has crucially turned these observations into an actual formal framework that addresses language learnability.

Elman's simple recurrent networks (Figure 1) have played a major role in this debate (Elman, 1990, 2004, 2005; Elman *et al.*, 2001). Layers in these networks are composed of one or more units. Information flows from input units to the hidden units and then to the output units. In addition, at every time step t , units from the hidden layer receive input from the so-called context layer, which simply stores the activation of the hidden (intermediary) units from time $t - 1$. The crucial part of the network is the recurrence from the activation of the hidden units to the context layer. This amounts to incorporating some memory into the neural network, and even though only the last internal state is stored, the memory capacity is potentially much deeper.

For instance, in one set of simulations, a network was trained to predict upcoming words, given a corpus of sentences that had been generated by an artificial, natural-like, grammar (Elman, 1990). The network was presented one word at a time and had to predict the next word based on the input layer and the context units. No other information was available for learning. The success or failure of prediction could be verified when the next item was processed. This network, in which learning and testing phases are part of a single process, learned to predict in a context-appropriate manner all the words that were grammatically possible. Moreover, a closer look at the hidden unit vector showed that it performed a hierarchical categorization of the words present in that language. Figure 2 plots three (of the 70 actual) dimensions of the network's 'mental space'. The state space is partitioned into different regions that correspond to both grammatical and semantic categories. Hierarchical relationship between categories (dog within non-human animal within animal within nouns) is shown by nesting relationship in space. Thus, the network has learned relevant grammatical and semantic properties of each word and uses these to generate expectations about successive words in the sentences. Finally, in such experiments, the rate of acquiring new words is initially slow because no category structure has yet emerged. However, once a critical mass is achieved, the acquisition rate accelerates. Elman (2004) has argued that this effect could be related to the vocabulary burst (4–9 words a day (Smith & Gasser, 2005)) often documented for children around 18 months.

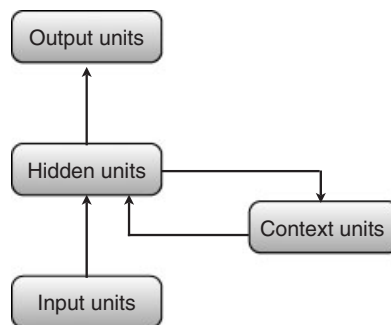


Figure 1. Elman's simple recurrent network (adapted from Elman, 2004).

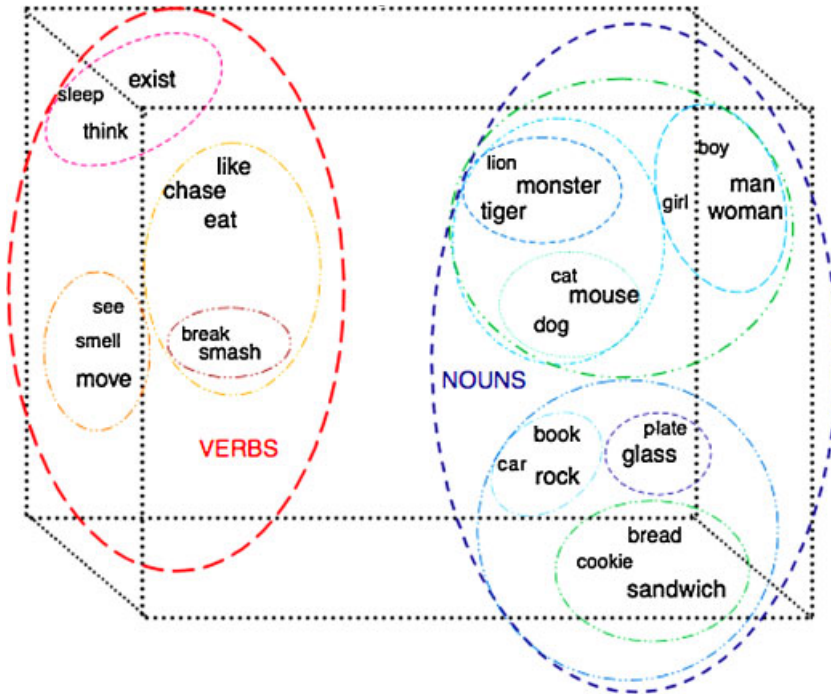


Figure 2. Schematic visualization in 3D of the high-dimensional state space described in the hidden unit layer of Elman's simple recurrent network (reprinted from Elman, 2004). This figure is available in colour online at www.interscience.wiley.com/journal/icd

The Model in the Debate

Compared with the generative stance, models like this one explore a radically different approach, shifting from symbolic to non-symbolic models of learning, from innate grammatical rules to emergent grammatical structure, from discontinuity between acquisition and processing to continuity between the two processes. It could be argued that the core issue addressed by the generative stance, learning a complex grammar, is not yet really addressed convincingly by the statistical and connectionist approaches (see, for instance, Marcus, 1998). Researchers like Elman argue that the learning potential of recurrent networks has not yet been fully explored and that simulations involving complex sentences have already shown that recurrent networks can learn agreement relations that span multiple embeddings and long distance filler-gap dependencies (e.g. Christiansen & Chater, 1999). What is important for us is that simple recurrent networks not only illustrate a statistical view of language acquisition but also significantly restructure the debate on language learnability in concrete terms—connectionist approaches can tangibly be shown to have or not have certain learning capacities.

EMBODIED AND SOCIAL STANCE: A COMPUTATIONAL MODEL OF ACTION VERB LEARNING

Humans learning language are unlike most artificial learning machines in that they are *situated* in a real-world environment, *embodied* in an immensely complex

physical organism, and learn language as part of their development of means to achieve social and material goals. All cognitively normal children acquire words beginning around 12 months of age and will acquire on average 10 words per day until adulthood, often on the basis of single or indirect exposure, and mostly without explicit instruction (Bloom, 2000). They begin with words whose meanings are directly grounded in their situated, embodied experiences. Children's first words (Bloom, 1993) consist of words denoting concrete objects (*ball, bottle, juice, mommy, baby, horse*, etc.), words cuing social interactions (*yes, no more, up, bye-bye, uh-oh*, etc.), words denoting concrete events and actions (*go, get, sit*, etc.), words denoting concrete sounds (*woof, moo, choo-choo*, etc.), and concrete prepositions and demonstratives (*out, that, here*, etc.). Importantly, languages cut up the world in different ways, so that a particular form-meaning pairing in one language such as English *push* or *on* might be split into different words in another language, such as French *appuyer* 'push [a button]' and *pousser* 'push [an object]' or German *auf* 'on [a horizontal surface]' and *an* 'on [a vertical surface]'. This means that language learners must have the ability to construct categories on the basis of linguistic input—they cannot be pre-wired (as, for instance, suggested by Nelson (1973)).

How can a computational approach tackle the effects of embodiment in language acquisition? Bailey's (1997) model of action verb learning is a representative example. The specific task addressed by the model is the following: 'Given a set of pairings of actions and verbs, learn the bidirectional mapping between the two so that future actions can be labelled and future commands can be acted out' (p. 2). Thus, the model includes an active motor control mechanism (and not just passive description of actions) based on the so-called *x-schemas* represented using the Petri net formalism (Figure 3). An *x-schema* for sliding an object on a tabletop may for instance represent that the sequence initially begins by either grasping the object or placing the palm against it and then proceeds to move in a given direction with a given force. Each schema is then summarized as a collection of features (posture, direction, force, etc.). The system is then presented with pairs of actions and labels in the form of verbs that could be used to describe those actions in a language to be learned. Learning to use these verbs thus consists in learning which parameters of the motor actions are relevant to the use of which verb labels. In some cases, the system can discover that particular verbs, like *push*, are best modelled as corresponding to two distinctive senses: *push* may correspond not only (1) to sliding actions which usually use the palm (or in suitable contexts might use the index finger) and which tend to be directed away from the body or downward but also (2) to actions such as pushing on a flat surface in which there is no motion but instead a steady application of significant force, almost always involving a palm posture. When tested on English, the system achieves about 80% accuracy for both labelling actions and executing actions when given a label, and its success rates on other languages that partition the same semantic space in radically different ways, like Russian and Farsi, are nearly as promising.

The Model in the Debate

Bailey's model and others investigating similar approaches introduce a novel element into the language learnability debate, concerning the question of how children can learn to use verbs, like *push* and *pull*, after hearing just a few examples. These models flesh out the idea that it is the common substrate of the human motor control system that drives children's rapid and flexible acquisition of action verbs.

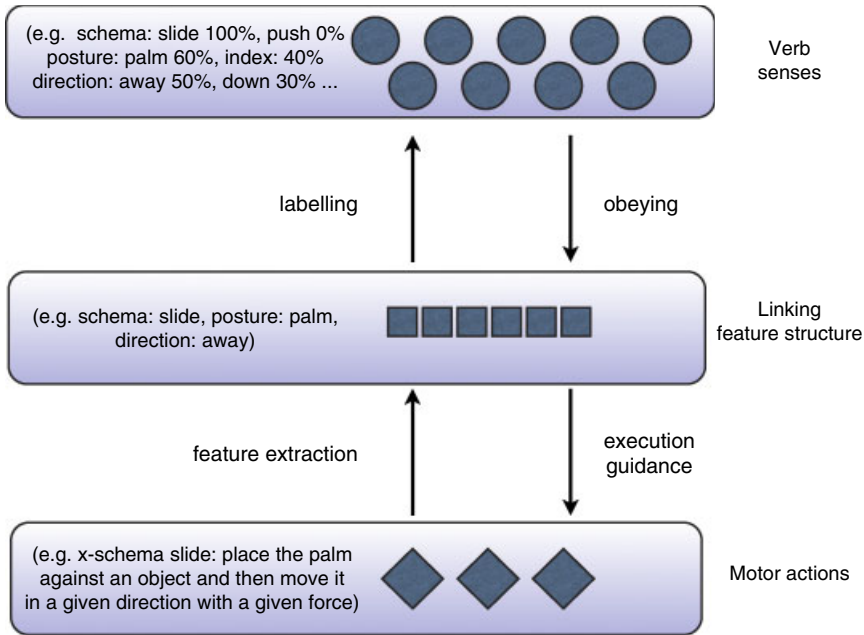


Figure 3. The model of motion verb learning described by Bailey (adapted from Bailey, 1997).

The Gavagai problem

This is not to imply that the problem of word-learning thereby becomes trivial—there are still significant computational issues like when to conflate representations into single, more general categories, and of course, there is the *gavagai* problem (Quine, 1960). The *gavagai* problem, roughly, is the difficulty that language learners in principle have in determining what in the world is referred to by a given, novel chunk of language. Suppose a child hears *push* in situations in which her mother pushes her on a swing. How is she to determine what *push* denotes—is it the swing, her mother, the grass below, her feeling of temporary weightlessness, or perhaps the action the mother is performing? In addition to cross-situational inference (mentioned above), attention seems to be an important component of the grounding of word meaning. Namely, human learners have the capacity to determine with some degree of reliability what objects or locations others are attending to. Removing this ability interferes with word learning, and endowing it upon machine language learners facilitates word learning significantly (Yu, Ballard, & Aslin, 2005). The utility of joint attention in language learning is just another way that having a situated, grounded agent makes a theoretically implausible learning problem run-of-the-mill (see also Tomasello, Carpenter, Call, Behne, & Moll, 2004). A specific review of computational models dealing with this issue can be found in Kaplan and Hafner (2006).

Linguistic grounding and conceptual metaphor

In many respects, Bailey's model offers a simplistic view of what word learning is. Learning a word is unlikely to consist only of pairing its phonology with an embodied representation of its meaning. For instance, it implies learning to use it

in specific contexts and not others, with some people and not others, etc. Another weakness of models like Bailey's is that they usually address only rather specific language learning problems. Some modellers now try to tackle other dimensions of embodied language learning that occur at later stages of linguistic development. Once language learners have a core set of basic words, and concepts to go with them, they then move on to more complex words, grounded indirectly on the basis of these basic words. Two important ways that new words can be grounded in previous ones are through *linguistic grounding* and *conceptual metaphor*. In the first case, a new word can be introduced through language—*A puppy is a baby dog. A polar bear is a white bear who lives in the snow*. Knowledge of individual words and their meanings can be used to construct new semantic representations, through any one of a broad set of compositional mechanisms (Bergen & Feldman, 2006). In the second case, words learned through direct associations with grounded perceptual, motor, and other experiences can serve as the basis for abstract language and concepts through metaphorical mappings (Lakoff & Johnson, 1980). The concept of quantity, and the metaphorical language describing it, as in *stock prices rose* or *my anxiety has flattened out*, has been convincingly argued to arise on the basis of systematic correlations in early childhood experience between concrete source domains and abstract target domains (Grady, 1997). In this particular case, increases in height systematically (though not exceptionlessly) correlate with increases in quantity—consider the early childhood experiences of pouring milk into a glass or piling blocks on top of one another. Thus, abstract words and the concepts they denote can be learned through concrete ones, which are themselves grounded in the real-world experiences of situated, embodied agents.

Relatedness with nativist views

Figure 4 offers a schematic overview of the embodied and social cognition approach. It could be argued that such a view is eventually not so different from notions of semantic bootstrapping developed by Pinker and other nativists (Pinker, 1984, 1994) if some innate language-specific knowledge is added to the process. Indeed, the notion of biases helping language acquisition is common to both approaches. We will come back to this similarity in the last part of this article.

DEVELOPMENTAL STANCE: A ROBOTIC EXPERIMENT

Computational learners studied in the previous stances are all passive learners: they are exposed to a pre-specified set of data examples that were generated for the particular task under study. This formalization of the learning process might be misleading. During the last 10 years, the machine learning community has begun to investigate architectures that permit incremental and active learning (e.g. Belue, Bauer, & Ruck, 1997; Cohn, Ghahramani, & Jordan, 1996; Denzler & Brown, 2001; Hasenjager, Ritter, & Obermayer, 1999; Mackay, 1992; Paas & Kindermann, 1995; Plutowsky & White, 1993; Thrun & Pratt, 1998; Watkin & Rau, 1992). Active learners are machines that search and select specific training examples. More specifically, a few researchers have started to address the problem of designing intrinsic motivation systems to drive active learning, inspired by research in developmental psychology and neuroscience. The idea is that a robot controlled by such systems would be able to autonomously explore its environment not to fulfil predefined tasks but driven by some form of intrinsic motivation that pushes it to search for situations where learning happens

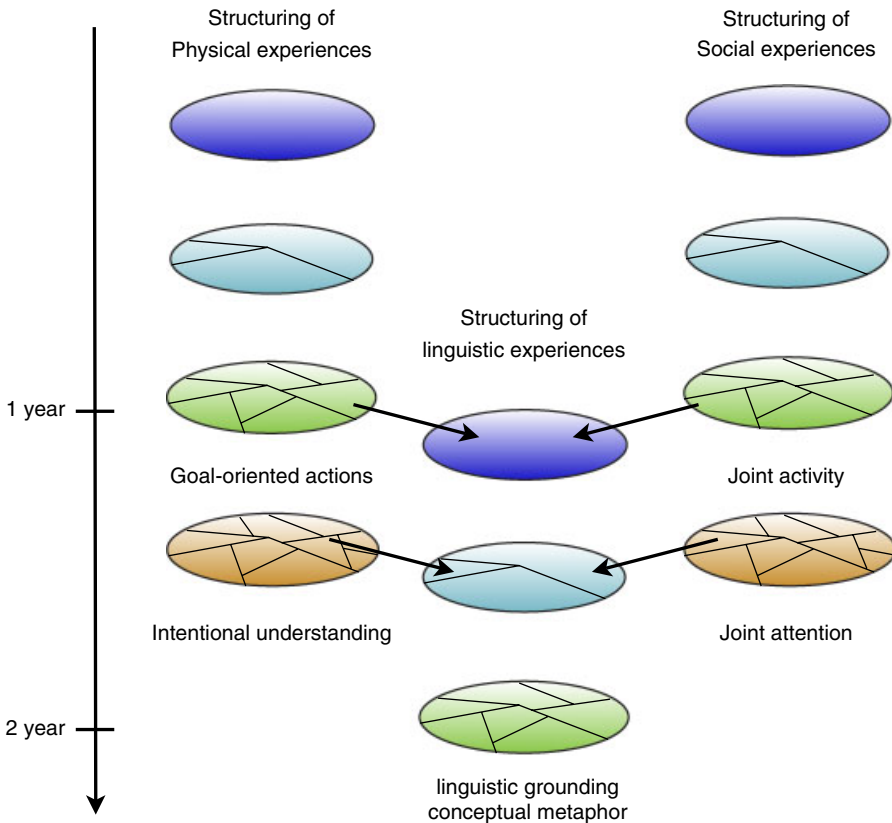


Figure 4. Language acquisition is made possible through two types of biases. During their first year, children progressively structure their physical and social experiences into meaningful elements. Just before they utter their first words, they have developed skills permitting goal-oriented actions, intentional understanding and joint attention. These skills create sufficiently strong constraints to facilitate the acquisition of word meaning and to bootstrap the development of language. During the second year, linguistic experiences get structured and increase in complexity partly through purely linguistic processes (linguistic grounding), partly through structuring coming from the physical or social experiences (conceptual metaphor). This figure is available in colour online at www.interscience.wiley.com/journal/icd

efficiently (Barto, Singh, & Chentanez, 2004; Huang & Weng, 2002; Marshall, Blank, & Meeden, 2004; Oudeyer & Kaplan, 2006; Schmidhuber, 1991, 2006; Weng, 2002). Technically, such control systems can be viewed as particular types of reinforcement learning architectures (Sutton & Barto, 1998), where rewards are not provided externally by the experimenter but self-generated by the machine itself. The term 'intrinsically motivated reinforcement learning' has been used in this context (Barto *et al.*, 2004).

We will discuss an experiment in which a robot exploits its own learning biases through active learning and thus controls the complexity of its learning situations (Oudeyer & Kaplan, 2006). In this experiment, the robot actively seeks out sensorimotor contexts where it can learn given its morphological and cognitive biases. Although a passive strategy would lead to very inefficient learning, an active strategy permits the learner to discover and exploit learning situations

fitted to its biases. In this experiment, a four-legged robot is placed on a playmat. The robot can move its arms, its neck and its mouth, and can produce sound. Various toys are placed near the robot, as well as a pre-programmed 'adult' robot that can respond vocally to the other robot in certain conditions (Figure 5).

More precisely, the robot is equipped with seven continuous motor channels that can control various actuators (movement of the head, neck, legs and production of sounds) and with five sensory channels, corresponding to the various sensors. The presence (or absence) of an object in the mouth of the robot, the presence (or absence) of a visual tag within the field of view, sensor indicating whether something is oscillating or not in the close range of the infra-red distance sensor, mean pitch of the sound that is heard when a sound is actually perceived by the microphone and duration of the sound that is heard. On the playmat, two toys are present: an 'elephant ear' that the robot can possibly bite but that does not produce perceivable reactions when it is bashed and a suspended soft toy that it can bash with the arm but which is too far for biting. The pre-programmed 'adult' robot imitates the sounds produced by the other robot with a different voice that shifts the pitch down. (The fact that parents help scaffolding young infant's learning by imitating them is well documented (Smith & Gasser, 2005).)

At the beginning of an experiment, the robot does not know anything about the structure of its sensorimotor space (which actions cause which effects). Given the size of the space, exhaustive exploration would take a very long time and random exploration would be inefficient. However, this robot is equipped with an algorithm that permits intelligent exploration based on an evaluation of what the robot can or cannot learn at the current stage of its development.

The robot can be described as having two modules: (1) one module implements a predictor M that learns to predict the sensorimotor consequences when a given action is executed in a given sensorimotor context; and (2) another module is a metapredictor $\text{meta}M$ that learns to predict the errors that machine M makes in its predictions: these meta-predictions are then used as the basis of a measure of the potential interest of a given situation. Using its metaprediction system, the artificial agent can learn how to learn by exploiting its own learning biases. The system is designed to be *progress driven*. It avoids both predictable and unpredictable situations in order to focus on the ones that are expected to maximize the decrease in prediction error. To obtain such a behaviour, the metaprediction system computes the local derivative of the error rate curve of M and generates an estimation of the expected learning progress linked with a particular action in a particular context. In order to really evaluate learning progress, error obtained in one context must be compared with errors obtained in similar situations (if not the robot may oscillate between hard and easy situations and evaluate these changes as progress). Therefore, the metaprediction system must also be equipped with a self-organized classification system capable of structuring an infinite continuous space of particular situations into higher-level categories (or kinds) of situations. Figure 6 summarizes the key components of such progress-driven systems (see Oudeyer & Kaplan, 2006; Oudeyer *et al.*, 2007 for more details).

Figure 7 represents how progress-driven learning operates on an idealized problem. Confronted with four contexts characterized by different learning profiles, the motivation for maximizing learning progress results in avoiding situations that are already predictable (context 4) or too difficult to predict (context 1), in order to focus first on the context with the fastest learning curve (context 3) and eventually, when the latter starts to reach a 'plateau', to switch the second most promising learning situation (context 2). Situations of maximal progress are called 'progress niches'. Progress niches are not intrinsic properties



Figure 5. A four-legged robot is placed on a playmat. The robot can move its arms, its neck and its mouth, and can produce sound. Various toys are placed near the robot, as well as a pre-programmed 'adult' robot that can respond vocally to the other robot in certain conditions. This figure is available in colour online at www.interscience.wiley.com/journal/icd

of the environment. They result from a relationship between a particular environment, a particular embodiment (sensors, actuators, feature detectors and techniques used by the prediction algorithms) and a particular time in the developmental history of the agent. Once discovered, progress niches progressively disappear as they become more predictable.

During each robotic experiment, which lasts approximately half a day, the flow of values of the sensorimotor channels is stored, as well as a number of features that help us to characterize the dynamics of the robot's development. The evolution of the relative frequency of the use of the different actuators is measured: the head pan/tilt, the arm, the mouth and the sound speakers (used for vocalizing), as well as the direction in which the robot is turning its head. Figure 8 shows the data obtained during a typical run of the experiment.

It is possible to summarize the evolution of these behavioural patterns using the concept of stages, where a stage is defined as a period of time during which some particular behavioural patterns occur significantly more often than random and did not occur significantly more often than random in the previous stages. These behavioural patterns correspond to combinations of clear deviations from the mean in the curves in Figure 8.

1. At the beginning of the experiment, the robot has a short initial phase of random exploration and body babbling. During this stage, the robot's behaviour is equivalent to the one we would obtain using random action selection: we clearly observe that in the vast majority of cases, the robot does not even look at or act on objects; it essentially does not interact with the environment.
2. Then there is a phase during which the robot begins to focus successively on playing with individual actuators, but without knowing the appropriate affordances: first there is a period where it focuses on trying to bite in all directions (and stops bashing or producing sounds), then it focuses on just

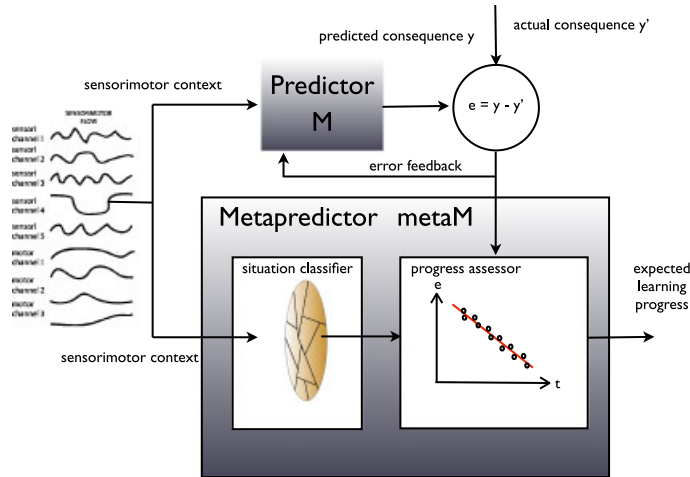


Figure 6. An intrinsic motivation system including a predictor M that learns to anticipate the consequence y of a given sensorimotor context and a metapredictor $metaM$ learning to predict the expected learning progress of M in the same context. The interestingness of a given context is defined as the associated expected learning progress, and actions are chosen in order to reach maximally interesting sensori-motor contexts. Once the actual consequence is known, M and $metaM$ get updated. $metaM$ re-evaluates the error curve linked with this context and computes an updated measure of the learning progress (local derivative of curve). In order to classify similar contexts, $metaM$ includes a hierarchical self-organizing classifier. This figure is available in colour online at www.interscience.wiley.com/journal/icd

looking around, then it focuses on trying to bark/vocalize towards all directions (and stops biting and bashing), then on biting, and finally on bashing in all directions (and stops biting and vocalizing).

3. Then, the robot comes to a phase in which it discovers the precise affordances between certain action types and certain particular objects: it is now focusing either on trying to bite the biteable object (the elephant ear) or on trying to bash the bashable object (the suspended toy).
4. Finally, the robot comes to a phase in which it focuses on vocalizing towards the 'adult' robot and listens to the vocal imitations that it triggers. This interest for vocal interactions was not pre-programmed, and results from exactly the same mechanism that allowed the robot to discover the affordances between certain physical actions and certain objects. The fact that the interest for vocal interaction appears after the focus on biting and bashing comes from the fact that this is an activity that is a little bit more difficult to learn for the robot, given its sensorimotor space and this environment.

The Model in the Debate

In which sense does this experiment contribute to the debate over language learnability? Is the present architecture intended to be a model of child development?

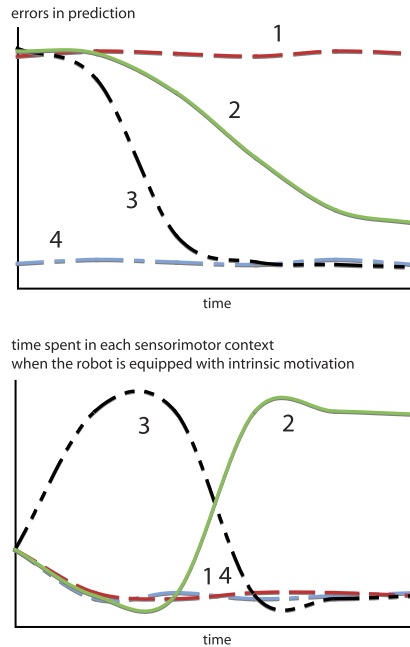


Figure 7. Confronted with four contexts characterized by different learning profiles, the motivation for maximizing learning progress results in avoiding situations already predictable (context 4) or too difficult to predict (context 1), in order to focus first on the context with the fastest learning curve (context 3) and eventually, when the latter starts to reach a 'plateau' to switch to the second most promising learning situation (context 2). This intrinsic motivation system allows the creation of an organized exploratory strategy necessary to engage in open-ended development. This figure is available in colour online at www.interscience.wiley.com/journal/icd

Intrinsic motivation in developmental psychology and neuroscience

There is substantial evidence that children are not passive learners but are intrinsically motivated to progress in learning. In the 1960s, psychologists like White argued that activities enjoyable for their own sake may be accounted for by the existence of intrinsic psychobiological human motivation (White, 1959). In the same period, Berlyne proposed that exploration might be triggered and rewarded for situations that include novelty, surprise, incongruity and complexity. He also observed that the most rewarding situations were those with an intermediate level of novelty, between already familiar and completely new situations (Berlyne, 1960). Gibson (1988) discussed the putative role of intrinsic motivation forces that impel infants to actively seek out new knowledge: 'A baby is provided with an urge to use its perceptual systems to explore the world'. Novel investigations in neuroscience concerning neuromodulation systems have complemented these findings. Although most experiments in this domain focus on the involvement of particular neuromodulators like dopamine for predicting extrinsic reward (e.g. food), some work lends credence to the idea that such neuromodulators might also be involved in the processing of types of intrinsic motivation associated with novelty and exploration (Dayan & Belleine, 2002; Kakade & Dayan, 2002). In particular, some studies suggest that dopamine responses could be interpreted as reporting 'prediction error' (and not only 'reward prediction error'). At a more global level, Panksepp has compiled a set of

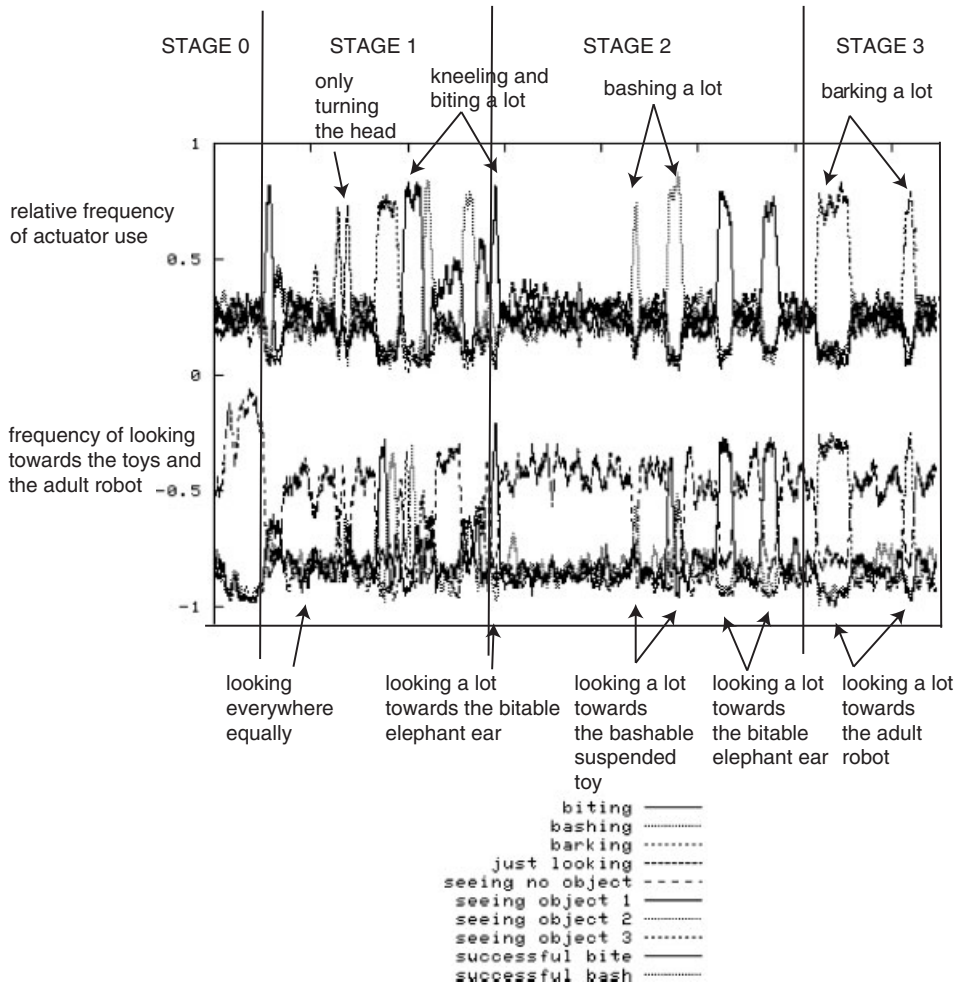


Figure 8. Results obtained after a typical run of the Playground Experiment. Top curves: relative frequency of the use of different actuators (head pan/tilt, arm, mouth, sound speaker). Bottom curves: frequency of looking towards each object and in particular towards the 'adult' pre-programmed robot.

evidence, suggesting the existence of a SEEKING system responsible for exploratory behaviours. 'This harmoniously operating neuroemotional system drives and energizes many mental complexities that humans experience as persistent feelings of interest, curiosity, sensation seeking and, in the presence of a sufficiently complex cortex, the search for higher meaning' (Panksepp, 1998). All these views support the idea that children engage themselves spontaneously in situations characterized by some 'appropriate' level of novelty and that this tendency could play a crucial role in development.

Not a model of child development

However, the experiment described above, like the other experiments we have considered in this article, is not intended to be a model of child development. It is

a tool for thought. It permits an exploration of the mechanisms that can allow a system to actively exploit its own learning biases in order to learn more efficiently. This experiment shows that a form of active learning can lead to an organized exploration characterized by successive stages. In the present case, the notion of progress niche can help us think about the following hypothetical developmental scenario in which 'the discovery of communication' takes place. If children indeed show some form of intrinsic motivation for maximizing learning progress, they will get successively interested in playing with and manipulating objects or situations of increasing complexity, the choice of which is determined by their potential returns in terms of learning progress. At a certain point in their development, children should discover that interacting with others, for example, by producing and listening for sounds, is an important source of learning progress, a new progress niche. This discovery will make them more and more interested and involved in social activities.

Interpreting developmental patterns

Developmental patterns illustrated in Figures 7 and 8 are reminiscent of many developmental sequences observed in language development. Let us consider a concrete example taken from the literature of children's early vocalization. Figure 9 plots the consonant sounds infants use most often during the first 18 months. During the first six months, labial sounds ([f]/[v]) predominate. However, alveolar sounds ([t]/[d], [s]/[z]) become dominant during the next three months and continue to dominate afterwards. During the first year, velar consonants ([k]/[g]) progress gradually (but remain at an intermediary level) with an extremum around between 9 and 12 months (Smith & Oller, 1981). How can we interpret such a pattern? Can it be traced back to the way the child progressively masters her vocal tract? Is it due to the evolution in stimulation that the child experiences? Or to the new types of social interaction? Or to progresses in perceptual capabilities? Or to anatomical changes? If we consider the child as an active learner, a possible scenario is that children initially produce mainly labial sounds because at the beginning they are the ones that result in the fastest learning progress. This needs of course to be investigated further by connecting such a developmental algorithm with a reasonably realistic model of the vocal tract. Ideally this model should also capture the physiological changes that happen during the child's first year. As we have seen in the experiment, cognitive and morphological biases play a crucial role in the organizing sensorimotor exploration. But, in this view, these biases do not have to be specific to language.

Active learning models are likely to permit a whole range of reinterpretations of existing developmental data (we have discussed elsewhere how progress-driven learning provides an interpretation of developmental sequences in early imitation (Kaplan & Oudeyer, 2007a, 2007b)). Many diverse lines of experimental data can potentially be explained in common terms if we consider children not as passive learners exposed to input streams but on the contrary as active seekers of progress niches, who learn how to focus on what is learnable in the linguistic inputs they encounter and on what can be efficiently grasped at a given stage of their cognitive and physiological development. We will now consider another important and largely ignored dimension of language learnability: languages themselves may have adapted to become learnable.

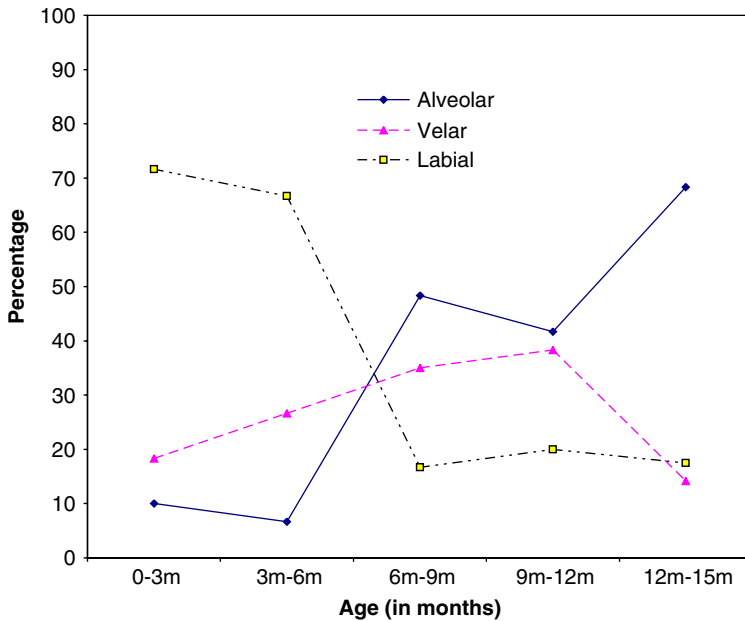


Figure 9. Evolution of the consonant sounds produced between 0 and 15 months (adapted from Smith and Oller (1981)). This figure is available in colour online at www.interscience.wiley.com/journal/icd

CULTURAL EVOLUTION STANCE: A GENERATIONAL MODEL

Computational approaches to language acquisition rarely address issues related to the evolution of linguistic forms and structures. However, it could be argued that the two problems are integrally related, and that language learnability cannot be understood outside of the context of language evolution. The core idea of these models is to simulate and observe how languages adapt over time to the learning and other usage constraints of the learners/users. There already exists a vast number of computational models of the emergence and evolution of language (see Cangelosi & Parisi, 2002; Kirby, 2002; Steels, 2003 for general overviews of the field). Successful experimental and theoretical results have been obtained in the domains of lexicon formation (e.g. Hutchins & Hazlehurst, 1995; Kaplan, 2001, 2005; Ke, Minett, Au, & Wang, 2002; Shoham & Tenenholz, 1997; Smith, Kirby, & Brighton, 2003; Steels, 1996; Steels & Belpaeme, 2005), phonological evolution (De Boer, 2001; Oudeyer, 2005b, 2005c, 2006) and grammatical aspects of language acquisition (Steels & Beule, 2006; Steels, De Beule, & Neubauer, 2005). Among these models, a number have studied the impact of learning biases upon the evolution of linguistic structures, and in particular, cultural selection for better learnability. Zuidema (2003) presented abstract simulations of the formation of syntactic structures and observed the influence of cognitive constraints upon the generated syntax. Brighton *et al.* (2005) surveyed several simulations of the origins of syntax (Kirby, 2001) which were re-described in the light of this paradigm of cultural selection for learnability.

This section describes a computer experiment that illustrates cultural selection for learnability in the field of phonology (this model is described in detail in

another article (Oudeyer, 2005a)). This example shows how phonological structures can be culturally selected so as to become easily learnable. It models the cultural formation of syllable systems, which are thought to be a fundamental unit of the complex phonological systems of human languages (MacNeilage, 1998), and relies on the interactional framework developed by De Boer (2001) called the 'imitation game'. This model involves a population of artificial agents that can produce, hear and learn syllables, based on computational models of the auditory system and a motor apparatus that are linked by abstract neural structures. These abstract neural structures are implemented as a set of prototypes or templates, each being an association between a motor program that has been tried through babbling and the corresponding acoustic trajectory. Thus, agents store in their memory only acoustic trajectories that they have already managed to produce themselves. The crucial property of these neural structures is that they are not language/phonology specific. Exactly the same learning machinery could be used to learn, for example, hand-eye coordination or walking behaviour. This learning system has biases (for example, one of them was that the number of prototypes that could be stored was limited), as do all learning systems (Mitchell & Weinmann, 1997), but they are general and not specific to language. The set of prototypes is initially empty for all agents, and grows progressively through babbling. The babblings of each agent can be heard by nearby agents, and this influences their own babbling. Indeed, when an agent hears an acoustic trajectory, this activates the closest prototype in its memory and triggers some specific motor exploration of small variation of the associated motor program. This means that if an agent hears a syllable *S* that it does not already know, two cases are possible: (1) he already knows a quite similar syllable and has a great chance to stumble upon the motor program for *S* when exploring small variations of the known syllable, and (2) he does not already know a similar syllable and so there is little chance that he will incorporate in its memory a prototype corresponding to *S*. This process means that if several babbling agents are put together, some islands of prototypes, i.e. networks of very similar syllables, will form in their memory and they will develop a shared skill corresponding to the perception and production of the syllables in these networks. Nevertheless, the space of possible syllables was large in these experiments, and so the first thing that was studied was whether agents in the same simulation could develop a large and shared repertoire of syllables. This was shown to be the case (Oudeyer, 2005a). Interestingly, if one runs multiple simulations, each population of agents will end up with their own particular repertoire of syllables.

Then, a second experiment was run: some fresh agents were introduced to syllable systems that were created by another population of interacting agents, and other fresh agents were introduced to a syllable system that was generated artificially as a list of random syllables. Performance in learning was measured as the ability to faithfully imitate syllables. The results, illustrated in Figure 10, were that the fresh agents were always good at learning the syllable systems developed by other similar agents, but on the contrary rather bad at learning the random syllable systems. In other words, the syllable systems developed culturally by agents were adapted to their preexisting cognitive biases, and the random systems were not. Thus, the syllable systems evolved and were selected in a cultural Darwinian process so as to fit to the ecological niche defined by the cognitive structures of agents, fitness here being learnability. The end result is that evolved syllable systems have a particular structure and there is a close match between them and the intrinsic biases of the learning system. This could

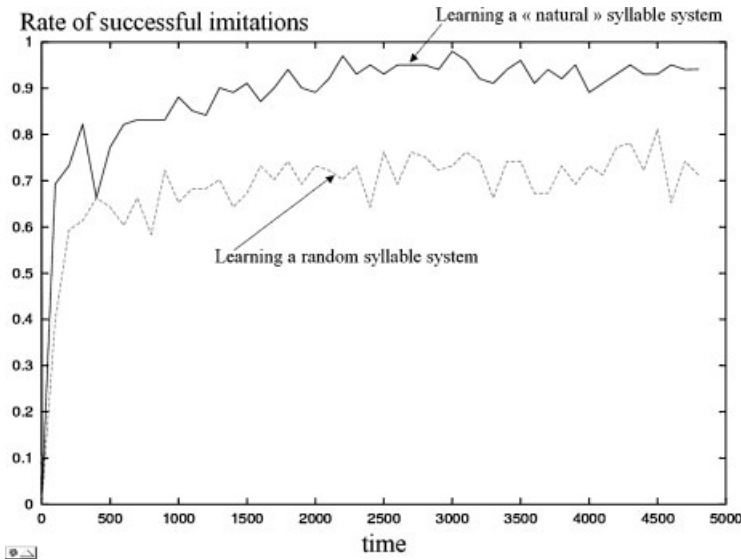


Figure 10. Evolution of the rate of successful imitations for a child agent that learns a syllable system established by a population of agents (top curve), and for a child agent that learns a syllable system established randomly by the experimenter (bottom curve). The child agent can only perfectly learn the vocalization systems that evolved in a population of agents. Such vocalization systems were selected for learnability (reprinted from Oudeyer (2005a)).

lead an external observer to think that the learning system has innate phonology-specific learning biases. However, this is not the case: the learning system is just a standard sensorimotor learning system and language has evolved to fit its preexisting biases.

The model in the debate: generational models like this one offers an alternative to the idea that specific innate traits have been selected in order to make language learning possible. They propose instead that languages have been culturally selected to adapt to pre-existing non-language-specific cognitive capabilities. Such a hypothesis would have been difficult to defend without the use of illustrating computational experiments such as the one presented here.

TENTATIVE SYNTHESIS AROUND THE NOTION OF BIAS

Computational models of language learning have significantly structured the debate on language learnability. Over the years, they have helped to refine our intuitions, suggest novel lines of empirical investigation with humans, and build concepts that shed a different light on children's remarkable learning capacities. Yet, have they solved the innateness controversy? The innateness question has a long and passionate history, filled with misunderstandings (Deacon, 1997; Marler, 2004). In the recent years a growing number of researchers have insisted on the importance of reconsidering this debate from novel perspectives, taking development in its full sense (Elman *et al.*, 2001; Karmiloff-Smith, 1992; Thelen & Smith, 1994) or articulating differently the gene-environment question (Marcus,

2004). Indeed, the models we have discussed in this article invite a recasting of the innateness debate in new terms. We would like to suggest that the notion of bias, as a cornerstone of the different approaches considered here, is a good candidate for a synthesis.

- Language-specific learning biases: generative models insist on the necessity of innate language specific biases to learn complex syntax.
- Generic learning biases: like any machine learning technique, connectionist models extracting structures from sequential inputs are also characterized by learning biases (there are things they can learn and others that they cannot). The fact that they can learn some aspects of language means that at least some types of linguistic structure fits their biases. However, contrary to generative models, these biases are argued to be generic and not specific to language.
- Physical and social biases: in addition to learning biases, embodied and social models illustrate how language acquisition is facilitated by physical and social biases.
- Active exploitation of biases: robotic experiments based on developmental models illustrate how computational learners can discover and exploit their own learning, physical and social biases in order to select and exploit what is efficiently learnable in its environment.
- Cultural selection based on learners' biases: computational models of cultural evolution investigate the hypothesis that languages themselves have evolved to fit into the ecological niches created by the biases of their learners.

Language acquisition results from highly dynamic and deeply interacting processes. Children's learning biases are best understood as resulting from a developmental history mixing embodiment factors (neural, anatomical) and cognitive factors. In the same way, children, possibly driven by a type of innate impulse, may actively seek out learnable situations adapted to these biases, but languages themselves have culturally evolved to be learnable. Clearly, in such a co-evolving process, cultural and genetic components will interact tightly. The very idea of disentangling genetic versus cultural components becomes unrealistic once we recognize development to be a complex dynamical process and culture as a continuously evolving system. It is unreasonable to expect a given learning trend or piece of linguistic knowledge to demonstrably result from either a single bit of innate linguistic knowledge or a single relevant fact about the input to which the child is exposed. But in order to understand the learning and evolutionary dynamics underlying language acquisition, we need a new scientific vocabulary; one that digs deeper than *innate* and *learned*. Computational models, like the ones presented in this article, help refine our intuitions, suggest novel lines of empirical investigation with humans, and build concepts that shed a reinvigorating light on children's fantastic learning capacities.

ACKNOWLEDGEMENTS

This research benefits from additional support from the ECAGENTS project funded by the Future and Emerging Technologies programme (IST-FET) of the European Community under EU R&D contract IST-2003-1940.

REFERENCES

- Archangeli, D., & Langendoen, D. T. (1997). *Optimality theory: An overview*. Oxford, UK: Blackwell.
- Bailey, D. (1997). *When push comes to shove: A computational model of the role of motor control in the acquisition of action verbs*. Ph.D. thesis, UC Berkeley.
- Barto, A., Singh, S., & Chentanez, N. (2004). Intrinsically motivated learning of hierarchical collections of skills. *Proceedings of the 3rd international conference on development and learning (ICDL 2004)*, Salk Institute, San Diego.
- Belue, M., Bauer, K., & Ruck, D. (1997). Selecting optimal experiments for multiple output multi-layer perceptrons. *Neural Computation*, 9, 161–183.
- Bergen, B., & Feldman, J. (2006). *It's the body, stupid! Concept learning according to cognitive science*. Technical report, ICSI Technical Report TR-06-002.
- Berlyne, D. (1960). *Conflict, arousal and curiosity*. New York: McGraw-Hill.
- Berthouze, L., & Kaplan, F. (2005). Introduction: The fifth international workshop on epigenetic robotics. *Proceedings of the fifth international workshop on epigenetic robotics: Modeling cognitive development in robotic systems*. Lund University cognitive studies (Vol. 123). Nara, Japan.
- Berthouze, L., & Metta, G. (2004). Introduction: The fourth international workshop on epigenetic robotics. *Proceedings of the fourth international workshop on epigenetic robotics: Modeling cognitive development in robotic systems*. Lund University cognitive studies (Vol. 117). Genova, Italy.
- Bloom, L. (1993). *The transition from infancy to language: Acquiring the power of expression*. New York: Cambridge University Press.
- Bloom, P. (2000). *How children learn the meanings of words*. Cambridge, MA: MIT Press.
- Brent, M., & Cartwright, T. (1996). Distributional regularity and phonotactic constraints are useful for segmentation. *Cognition*, 61, 93–125.
- Brighton, H., Kirby, S., & Smith, K. (2005). Cultural selection for learnability: Three hypotheses underlying the view that language adapts to be learnable. In M. Tallerman (Ed.), *Language origins: Perspective on evolution*. Oxford: Oxford University Press.
- Cangelosi, A., & Parisi, D. (2002). *Simulating the evolution of language*. Berlin: Springer.
- Cangelosi, A., Smith, A. M., & Smith, K. (Eds.). (2006). *The evolution of language: Proceedings of the 6th international conference on the evolution of language*. Singapore: World Scientific.
- Chomsky, N. (1975). *Reflections on language*. New York: Pantheon.
- Chomsky, N. (1980). *Rules and representations*. Oxford: Basil Blackwell.
- Chomsky, N., & Halle, M. (1968). *The sound pattern of english*. New York: Harper Row.
- Christiansen, M., & Chater, N. (1999). Toward a connectionist model of recursion in human linguistic performance. *Cognitive Science*, 23, 157–205.
- Cohn, D., Ghahramani, Z., & Jordan, M. (1996). Active learning with statistical models. *Journal of Artificial Intelligence Research*, 4, 129–145.
- Crain, S. (1991). Language acquisition in the absence of experience. *Behavioral and Brain Sciences*, 14, 597–650.
- Dayan, P., & Belleine, W. (2002). Reward, motivation and reinforcement learning. *Neuron*, 36, 285–298.
- De Boer, B. (2001). *The origins of vowel systems*. Oxford: Oxford University Press.
- Deacon, T. (1997). *The symbolic species*. New York: W. Norton and Co.
- Denzler, J., & Brown, C. (2001). Information theoretic sensor data selection for active object recognition and state estimation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2(24), 145–157.
- Dominey, P. F. (2005). Emergence of grammatical constructions: Evidence from simulation and grounded agent experiments. *Connection Science*, 17(3–4), 289–306.
- Elman, J. (1990). Finding structure in time. *Cognitive Science*, 14, 179–211.
- Elman, J. (2004). An alternative view of the mental lexicon. *Trends in Cognitive Sciences*, 8(7), 301–306.
- Elman, J. (2005). Connectionist models of cognitive development: Where next? *Trends in Cognitive Sciences*, 9(3), 113–117.
- Elman, J., Bates, E., Johnson, M., Karmiloff-Smith, A., Parisi, D., & Plunkett, K. (2001). *Rethinking innateness—A connectionist perspective on development*. Cambridge, MA: MIT Press.

- Gallistel, P. (2000). The replacement of general-purpose learning models with adaptively specialized learning modules. In M. Gazzaniga (Ed.), *The cognitive neurosciences*, (2nd ed.) (pp. 1179–1191). Cambridge, MA: MIT Press.
- Gibson, E. J. (1988). Exploratory behavior in the development of perceiving, acting and the acquiring of knowledge. *Annual Review of Psychology*, 39, 1–41.
- Gold, E. (1967). Language identification in the limit. *Information and Control*, 10, 447–474.
- Grady, J. E. (1997). Theories are buildings revisited. *Cognitive Linguistics*, 8(4), 267–290.
- Hasenjager, M., Ritter, H., & Obermayer, K. (1999). Active learning in self-organizing maps. In E. Oja & S. Kaski (Eds.), *Kohonen maps* (pp. 57–70). Amsterdam: Elsevier.
- Huang, X., & Weng, J. (2002). Novelty and reinforcement learning in the value system of developmental robots. In C. Prince, Y. Demiris, Y. Marom, H. Kozima, & C. Balkenius (Eds.), *Proceedings of the 2nd international workshop on epigenetic robotics: Modeling cognitive development in robotic systems* (pp. 47–55). Lund University cognitive studies (Vol. 94). Edinburg, UK.
- Hutchins, E., & Hazlehurst, B. (1995). How to invent a lexicon: The development of shared symbols in interaction. In N. Gilbert & R. Conte (Eds.), *Artificial societies: The computer simulation of social life* (pp. 157–189). London: UCL Press.
- Kakade, S., & Dayan, P. (2002). Dopamine: Generalization and bonuses. *Neural Networks*, 15, 549–559.
- Kaplan, F. (2001). *La naissance d'une langue chez les robots*. Paris: Hermes Science.
- Kaplan, F. (2005). Simple models of distributed co-ordination. *Connection Science*, 17(3–4), 249–270.
- Kaplan, F., & Hafner, V. (2006). The challenges of joint attention. *Interaction Studies*, 7(2), 129–134.
- Kaplan, F., & Oudeyer, P.-Y. (2006). Trends in epigenetic robotics: Atlas 2006. In F. Kaplan, P.-Y. Oudeyer, A. Revel, P. Gaussier, J. Nadel, L. Berthouze, H. Kozima, C. Prince, & C. Balkenius, C. (Eds.), *Proceedings of the sixth international workshop on epigenetic robotics: Modeling cognitive development in robotic systems*. Lund University cognitive studies (Vol. 128). Paris, France.
- Kaplan, F., & Oudeyer, P.-Y. (2007a). The progress-drive hypothesis: An interpretation of early imitation. In C. Nehaniv & K. Dautenhahn (Eds.), *Models and mechanisms of imitation and social learning: Behavioural, social and communication dimensions* (pp. 361–377). Cambridge, MA: Cambridge University Press.
- Kaplan, F., & Oudeyer, P.-Y. (2007b). Un robot motivé pour apprendre: Le rôle des motivations intrinsèques dans le développement sensorimoteur. *Enfance*, 59(1), 46–58.
- Karmiloff-Smith, A. (1992). *Beyond modularity: A developmental perspective on cognitive science*. Cambridge, MA: MIT Press.
- Ke, J., Minett, J., Au, C.-P., & Wang, W. (2002). Self-organization and selection in the emergence of vocabulary. *Complexity*, 7(3), 41–54.
- Kirby, S. (2001). Spontaneous evolution of linguistic structure: An iterated learning model of the emergence of regularity and irregularity. *IEEE Transactions on Evolutionary Computation*, 5(2), 102–110.
- Kirby, S. (2002). Natural language and artificial life. *Artificial Life*, 8, 185–215.
- Lakoff, G., & Johnson, M. (1980). *Metaphors we live by*. Chicago: University of Chicago Press.
- Lungarella, M., Metta, G., Pfeifer, R., & Sandini, G. (2003). Developmental robotics: a survey. *Connection Science*, 15(4), 151–190.
- MacKay, D. (1992). Information-based objective functions for active data selection. *Neural Computation*, 4, 590–604.
- MacNeilage, P. (1998). The frame/content theory of evolution of speech production. *Behavioral and Brain Sciences*, 21, 499–548.
- Marcus, G. (1998). Can connectionism save constructivism? *Cognition*, 66, 153–182.
- Marcus, G. (1999). *Poverty of the stimulus arguments* (pp. 660–661). Cambridge: MIT Press.
- Marcus, G. (2004). *The birth of the mind: How a tiny number of genes creates the complexities of human thought*. New York: Basic Books.
- Marler, P. (2004). Innateness and the instinct to learn. *Anais da Academia Brasileira de Ciencias*, 76(2), 189–200.
- Marshall, J., Blank, D., & Meeden, L. (2004). An emergent framework for self-motivation in developmental robotics. *Proceedings of the 3rd international conference on development and learning (ICDL 2004)*, Salk Institute, San Diego.

- Mintz, T., Newport, E. L., & Bever, T. G. (2002). The distributional structure of grammatical categories in speech to young children. *Cognitive Science*, 26, 393–424.
- Mitchell, B., & Weinmann, L. (1997). Creative design for the www. *SIGGRAPH 1997*. Lecture notes.
- Nelson, K. (1973). Structure and strategy in learning to talk. *Monograph of the Society for Research in Child Development*, Vol. 38 (12). Chicago: University of Chicago Press.
- Oudeyer, P.-Y. (2005a). How phonological structures can be culturally selected for learnability. *Adaptive Behavior*, 13(4), 269–280.
- Oudeyer, P.-Y. (2005b). The self-organisation of combinatoriality and phonotactics in vocalisation systems. *Connection Science*, 17(3–4), 325–341.
- Oudeyer, P.-Y. (2005c). The self-organization of speech sounds. *Journal of Theoretical Biology*, 233(3), 435–449.
- Oudeyer, P.-Y. (2006). Self-organization in the evolution of speech. *Studies in the evolution of language*. Oxford: Oxford University Press.
- Oudeyer, P.-Y., & Kaplan, F. (2006). Discovering communication. *Connection Science*, 18(2), 189–206.
- Oudeyer, P.-Y., Kaplan, F., & Hafner, V. (2007). Intrinsic motivation systems for autonomous mental development. *IEEE Transactions on Evolutionary Computation*, 11(2), 265–286.
- Paas, G., & Kindermann, J. (1995). Bayesian query construction for neural network models. In G. Tesaro, D. Touretzky, & T. Leen (Eds.), *Advances in neural processing systems* (Vol. 7, pp. 443–450). Cambridge, MA: MIT Press.
- Panksepp, J. (1998). *Affective neuroscience: The foundations of human and animal emotions*. Oxford: Oxford University Press.
- Piattelli-Palmarini, M. (1989). Evolution, selection and cognition: From learning to parameter setting in biology and language. *Cognition*, 31, 1–44.
- Pinker, S. (1984). *Language learnability and language development*. Cambridge: Harvard University Press.
- Pinker, S. (1989). *Learnability and cognition: The acquisition of argument structure*. Cambridge, MA, USA: MIT press.
- Pinker, S. (1994). *The language instinct*. London: Penguin Books.
- Pinker, S., & Bloom, P. (1990). Natural language and natural selection. *Behavioral and Brain Sciences*, 13(4), 707–784.
- Plutowsky, M., & White, H. (1993). Selecting concise training sets from clean data. *IEEE Transactions on Neural Networks*, 4, 305–318.
- Prince, C., Helder, N., & Hollich, G. (2005). Ongoing emergence: A core concept in epigenetic robotics. In L. Berthouze, F. Kaplan, H. Kozima, H. Yano, J. Konczak, G. Metta, J. Nadel, G. Sandini, G. Stojanov, & C. Balkenius (Eds.), *Proceedings fifth international workshop on epigenetic robotics: Modeling cognitive development in robotic systems*. Lund University cognitive Studies (Vol. 123). Nara, Japan.
- Quine, W. (1960). *Word and object*. Cambridge, MA: MIT Press.
- Redington, M., Chater, N., & Finch, S. (1998). Distributional information: a powerful cue for acquiring syntactic categories. *Cognitive Science*, 26, 393–424.
- Regier, T. (1996). *The human semantic potential: Spatial language and constrained connectionism*. Cambridge, MA: MIT Press.
- Roy, D., & Pentland, A. (2002). Learning words from sights and sounds: A computational model. *Cognitive Science*, 26, 113–146.
- Saffran, J. (2001). Words in a sea of sounds: The output of infant statistical learning. *Cognition*, 81, 149–169.
- Schmidhuber, J. (1991). Curious model-building control systems. *Proceeding of international joint conference on neural networks* (Vol. 2, pp. 1458–1463). Singapore: IEEE.
- Schmidhuber, J. (2006). Developmental robotics, optimal artificial curiosity, creativity, music, and the fine arts. *Connection Science*, 18(2), 173–187.
- Seidenberg, M., & MacDonald, M. (1999). A probabilistic constraints approach to language acquisition and processing. *Cognitive Science*, 23, 569–588.
- Seidenberg, M. S. (1997). Language acquisition and use: Learning and applying probabilistic constraints. *Science*, 275, 1599–1604.
- Shoham, Y., & Tennenholtz, M. (1997). On the emergence of social conventions: Modeling, analysis, and simulations. *Artificial Intelligence*, 94(1–2), 139–166.

- Siskind, J. (1996). A computational study of cross-situational techniques for learning word-to-meaning mappings. *Cognition*, 61(1–2), 1–38.
- Smith, B. L., & Oller, D. K. (1981). A comparative study of premeaningful vocalizations produced by normally developing and Down's syndrome infants. *Journal of Speech and Hearing Disorders*, 46, 46–51.
- Smith, K., Kirby, S., & Brighton, H. (2003). Iterated learning: A framework for the emergence of language. *Artificial Life*, 9(4), 371–386.
- Smith, L., & Gasser, M. (2005). The development of embodied cognition: Six lessons from babies. *Artificial Life*, 11, 13–30.
- Solan, Z., Horn, D., Ruppín, E., & Edelman, S. (2005). Unsupervised learning of natural languages. *Proceedings of the National Academy of Sciences*, 102(33), 11629–11634.
- Steels, L. (1996). A self-organizing spatial vocabulary. *Artificial Life Journal*, 2(3), 319–332.
- Steels, L. (2003). Evolving grounded communication for robots. *Trends in Cognitive Science*, 7(7), 308–312.
- Steels, L., & Belpaeme, T. (2005). Coordinating perceptually grounded categories through language: A case study for colour. *Behavioral and Brain Sciences*, 28, 469–529.
- Steels, L., & Beule, J. D. (2006). Unify and merge in fluid construction grammar. In C. N. L. Lyon & A. Cangelosi (Eds.), *Emergence and evolution of linguistic communication*. Lecture notes in computer science. Berlin: Springer.
- Steels, L., De Beule, J., & Neubauer, N. (2005). Linking in fluid construction grammars. *Proceedings of BNAIC. Transactions of the Belgian royal society of arts and sciences* (pp. 11–18). Brussels.
- Steels, L., & Kaplan, F. (2000). Aibo's first words: The social learning of language and meaning. *Evolution of Communication*, 4(1), 3–32.
- Sugita, Y., & Tani, J. (2005). Learning semantic combinatoriality from the interaction between linguistic and behavioral processes. *Adaptive Behavior*, 13(1–2), 33–52.
- Sutton, R., & Barto, A. (1998). *Reinforcement learning: An introduction*. Cambridge, MA: MIT Press.
- Thelen, E., & Smith, L. B. (1994). *A dynamic systems approach to the development of cognition and action*. Boston, MA, USA: MIT Press.
- Thrun, S., & Pratt, L. (1998). *Learning to learn*. Dordrecht: Kluwer.
- Tomasello, M., Carpenter, M., Call, J., Behne, T., & Moll, H. (2005). Understanding and sharing intentions: the origins of cultural cognition. *Behavioral and Brain Sciences*, 28(5), 675–735.
- Watkin, T., & Rau, A. (1992). Selecting examples for perceptrons. *Journal of Physics A: Mathematical and General*, 25, 113–121.
- Weng, J. (2002). A theory for mentally developing robots. *Second international conference on development and learning*. Silver Spring, MD: IEEE Computer Society Press.
- Weng, J., McClelland, J., Pentland, A., Sporns, O., Stockman, I., Sur, M., et al. (2001). Autonomous mental development by robots and animals. *Science*, 291, 599–600.
- Wexler, K., & Culicover, P. W. (1980). *Formal principles of language acquisition*. Cambridge: MIT Press.
- White, R. (1959). Motivation reconsidered: The concept of competence. *Psychological Review*, 66, 297–333.
- Yu, C., Ballard, D. H., & Aslin, R. N. (2005). The role of embodied intention in early lexical acquisition. *Cognitive Science*, 29(6), 961–1005.
- Zuidema, W. (2003). How the poverty of the stimulus solves the poverty of the stimulus. In S. Becker & K. Obermayer (Eds.), *Advances in neural information processing* (Vol. 15, pp. 51–68). Cambridge, MA: MIT Press.