22 Abstract Concepts

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22.1 Introduction

One of the characteristics of human intelligence is the ability of thinking and reasoning about abstract concepts like “knowledge” and “beauty.” This ability is at the core of human innovation and creativity. In fact, it is required for fundamental capabilities such as the retrieval of past thoughts and memories, relational reasoning and problem-solving in current situations, and the processing of thoughts linked to the future (e.g., design, planning). Indeed, abstract concepts constitute an essential part of human language, where abstract words are often used in daily conversations to represent emotions, events, and situations that occur in physical environments and social interactions among people.

Human language includes concrete concepts, such as “water” or “glass,” that are linked to objects that can be objectively defined and understood. These are usually studied through a bottom-up approach that involves five major levels of analysis: phonetic, lexical, semantic, syntactic, and pragmatic. In contrast, abstract concepts like “love” or “freedom” don’t have specific physical referents; hence, they are more ambiguous, and their notion can significantly variate across individuals (Borghi et al. 2018). In this chapter, abstract concepts are broadly defined as higher-order, or complex, thoughts that are not bounded to a single, perceptually derived piece of information and that do not exist at any particular time or place (Barsalou 2003).

Even if the most common and intuitive definition of abstraction is opposite to that of concreteness, abstract and concrete concepts are not a dichotomy. They are considered part of a continuum (Barsalou and Wiemer-Hastings 2005), in which entities can have both abstract and concrete features in different proportions ranging from highly abstract (e.g., “justice”) to highly concrete (e.g., “stone”). The continuum view has gained strength in recent years, after growing evidence in support of embodied and grounded theories of cognition. In fact, a number of proposals have argued that abstract concepts can be grounded in a sensorimotor system as concrete concepts (see Pexman 2019) characterized by a continuum from unembodied (fully symbolic) to strongly embodied (Meteyard and Vigliocco 2008). A fundamental assumption of this view is that abstract concepts can be linked to embodied perceptions and learned through a process of progressive abstraction (Gentner and Asmuth 2019).

The embodied theories of the development of abstract thinking and reasoning constitute the theoretical resource for the design of artificial agents capable of abstract and symbolic processing, which is required for higher cognitive functions such as natural language understanding. This is one of the current challenges for the fast-growing field of cognitive robotics, in which future robots are expected to take on tasks once thought too complex or delicate to automate, especially in the fields of social care, companionship, therapy, domestic assistance, entertainment, and education (Matarić and Scassellati 2016; Di Nuovo et al. 2016).

This chapter aims at stimulating new research in cognitive robotics and artificial intelligence toward the creation of smarter robots that will be capable of understanding and manipulating abstract concept and words, thus overcoming the current limitations in human-robot communication by using natural language, which is the most intuitive of the user interfaces (Di Nuovo et al. 2018). To this end, section 22.2 provides a multidisciplinary background, briefly exploring recent embodied theories for the development of abstract concepts in humans. Section 22.3 will present pioneer work on cognitive robotics models of abstract words by implementing in robots the grounding transfer mechanism.

However, abstract concepts are not a single entity. They can be categorized into different domains that can be acquired using different strategies. Indeed, section 22.4 will present a different strategy for the embodied learning of numerical concepts that combines gestures and action with words, such as in the use of finger-counting representations to augment teaching a child (or a robot) about numbers. Numbers are a special domain of abstract concepts that constitute the building blocks of mathematics, a language of the human mind that can express the fundamental workings of the physical world and make the universe intelligible. Section 22.5 will present cognitive robotics models of emotion, another group that requires special attention among the abstract concepts since recent proposals that emotions can play an effective intermediary role for learning and grounding abstract concepts. Section 22.6 will discuss the current limitations in abstract cognition and robotics research. Finally, section 22.7 will give conclusions and identify future directions.

22.2 Education, Neuroscience, and Psychology Views on the Development of Abstract Concepts

Abstract concepts cover a vast domain, ranging from numbers to emotions and from social roles to mental state concepts. Anthropologists, cognitive scientists; developmental, social, and cognitive psychologists; educationalists; linguists; neuroscientists; and philosophers have extensively investigated how abstract concepts are acquired, used, and represented in the brain. This heterogeneity is one of the main reasons why it has been difficult to find a comprehensive theory that can account for the multiplicity of abstract concepts. This section will explore current views in education, neuroscience, and psychology characterized by an embodied approach to the development of abstract concepts.

The developmental psychologist Jean Piaget, whose work had an extensive influence on both theory and practice in education, argued that children develop abstract reasoning skills as part of their last stage of development, known as the formal operational stage, which usually occurs around the age of twelve (Piaget 1972). Specifically, this is the age at which most children transition from the concrete operational stage to the formal operational stage. However, brain-imaging studies have provided new evidence that there is a continuous neural development during adolescence that may last longer than what was theorized by Piaget. In particular, abstract reasoning requires maturational changes in some brain regions, such as the prefrontal cortex, which may last until late adolescence (Giedd and Rapoport 2010). Educational studies confirm that some tests of prefrontal lobe activity highly correlate with scientific reasoning ability and the capacity to reject scientific misconceptions and adopt correct ideas (Kwon and Lawson 2000). Other developmental psychologists (Harwood, Miller, and Vasta 2011) have argued that the development of abstract reasoning is not just a natural developmental stage; rather, it is the product of culture, experience, and teaching. Hayes and Kraemer (2017) explored cognitive neuroscience studies and presented evidence suggesting that sensorimotor processes can strengthen learning associated with the fundamental abstract concepts for understanding science, technology, engineering, and mathematics (STEM). On this basis, they proposed that embodied exercises could improve STEM pedagogy by situating abstract concepts in a concrete context, thus correlating intangible ideas with corporeal information. In doing so, rich multimodal distributed neural representations are forged, giving students a better chance at succeeding in the "hard" sciences, which are universally considered to be among the most abstract constructions of the human mind.

Numerous cognitive neuroscience studies suggested that both concrete and abstract concepts might be bodily grounded because they share similar mechanisms and modalities of representations, as both abstract and concrete concepts activate brain systems for action and perception (Gallese 2009). Behavioral and neurophysiological studies demonstrated a causal link between the motor system and the comprehension of both concrete and abstract language, where abstract concepts are acquired via a simulation process that calls on neural systems used in perceiving and acting on related concrete events (Glenberg et al. 2008). These results, also linked to the use of mirror neurons, support the embodied simulation theory (Gallese and Sinigaglia 2011), which provides a unitary explanation of basic abstract cognition, indicating that people reuse their own mental states or processes, represented in a bodily format, when functionally attributing them to others.

In the embodied cognition domain, at least three proposals have been offered to explain how abstract concepts could be acquired.

The first was proposed in the seminal work by Lakoff and Johnson (1980), who suggested that the meanings of abstract concepts could be grounded through conceptual metaphors (e.g., "love is a journey"), which help to embody abstract concepts into the sensorimotor experience. The linguistic and psychological evidence supporting the conceptual metaphors from the perspective of embodied simulations can be found in a review by Gibbs (2011). In this proposal, the evidence from the embodied cognition experiments should be explained in the light neural theory of thought and language; thus, he proposed that while children learn these metaphors, they develop conceptual metaphor neural circuits in connection to embodied experience, and these characterize abstract concepts. However, other authors (e.g., Murphy 1996; Dove 2011) criticized the developmental plausibility of this explanation, noting that children reach a mature metaphorical comprehension only quite late in middle childhood, at around ten years old. Several studies, however, show that metaphorical thinking emerges much earlier and constantly progresses, along with children's knowledge and information-processing abilities (Vosniadou 1987). But it is not clear whether these earlier developments in children's metaphorical thinking might contribute to the grounding of abstract concepts.

The second proposal assumes that the abstract concepts are mediated by language—that is, the conceptual grounding is augmented by concrete words (Dove 2014). In this context, the WAT (words as social tools) theory proposes a multiple representation view (Borghi et al. 2019), which attributes a major role to language and sociality in the acquisition of abstract concepts. Specifically, it hypothesizes that more abstract concepts are mainly linguistically acquired and induce in us a higher necessity to rely on others because of their complexity and our feelings of incompetence. Borghi et al. (2011) tested this idea in a study with adults, showing that learning novel abstract concepts was facilitated by verbal explanations (motor linguistic information) and not by manual actions, whereas the pattern was opposite for concrete concepts. By this view, the acquisition of language is a prerequisite for embodying abstract concepts. However, this proposal that abstract meaning is grounded through language is difficult to reconcile with strongly embodied developmental theories, like that of Glenberg and Gallese (2012), but it could be well associated with weak embodiment or hybrid models.

Howell, Jankowicz, and Becker (2005) suggested that children are likely to learn the first concrete words via direct experience. Later, abstract words are acquired, and their meanings are grounded by linguistic experience and by relationships to words learned earlier. According to Howell et al.'s model, children's representations of lexical cooccurrence information become increasingly sophisticated. Dove (2011) proposed a hybrid model in which language provides the child with new representational capacities (e.g., linguistic perceptual symbols) that support the learning of all kinds of concepts and are particularly helpful with characterizing abstract concepts.

Finally, a relatively recent idea is the proposal that abstract meaning is grounded through emotions (Vigliocco et al. 2013). The argument is that emotional experience should be considered a primary source of the embodied information that supports the development of abstract thinking and reasoning. Indeed, it forms a continuum that goes from sensorimotor experience that strongly characterizes concrete word representations to emotional experiences that dominate representations of abstract words (Moffat et al. 2015; Siakaluk, Knol, and Pexman 2014). Statistically, abstract words tend to have a stronger intensity of valence (good/bad, pleasant/unpleasant) than concrete words, making emotions an effective intermediary for learning and grounding abstract concepts (Altarriba, Bauer, and Benvenuto 1999). In this proposal, introspective emotion states could help the grounding of abstract meanings in embodied experience. Indeed, a significant step in forming abstract thinking occurs when, around two years of age, children start to learn words to express their emotions, mapping nonconcrete language to their felt experience for the first time. Kousta et al. (2011, 26) argued that "emotion may provide a bootstrapping mechanism for the acquisition of abstract words" because this process of learning labels for internal emotion states supports children in comprehending that words can identify entities that do not have an external, perceptual substantiation. Analyzing ratings of acquisition for abstract words by age, Kousta et al. (2011) showed that abstract words with a higher intensity of valence (e.g., "joy," "grief") were acquired earlier than neutral abstract words (e.g., "fashion," "space"). Since emotional development continues throughout childhood, it seems likely that early grounding in emotion may be more about valence than about more complex emotions, which develop later. However, the mechanism for the later acquisition of neutral abstract words is not fully explained by this proposal. Perhaps this might be facilitated through experiencing their use in the context of other words.

One of the current trends in the recent literature on abstract concepts focuses on the identification of the different domains and their corresponding brain representations (Borghi et al. 2017). In this respect, Desai, Reilly, and van Dam (2018) conducted a meta-analysis of the neural basis of four types of abstract concepts (numerical and emotional concepts and two higher-order abstract processes, morality judgments and theory of mind). Desai et al.'s (2018) analysis showed that the representation of abstract concepts is more widespread than is often assumed. Importantly, representations of different types of abstract concepts differ in important aspects, with each of the domains examined being associated with some unique areas of the brain. They found significant overlaps in the activation of morality and theory of mind concepts, which are likely processed when referring to social and episodic memories or to emotions and imagery. However, recent evidence suggests that defining concepts in terms of sole concreteness/abstractness is a simplification. Borghi et al. (2019) interviewed over three hundred adults and identified four domains of abstract concepts: philosophical-spiritual (e.g., sanctity), self-sociality (e.g., courtesy), emotive/inner states (e.g., anger), and physical, spatial, temporal, and quantitative (e.g., numbers).

Among the abstract domains, number concepts received special attention because of the strong relationship between the human mind and numerical cognition, which has made the latter a subject of research in the various disciplines that study the human mind and its development (Di Nuovo and Jay 2019). Their special role was confirmed by developmental, cross-cultural, and neuroscientific evidence that converges in the conclusion that number concepts occupy a range of positions on the continuum between abstract and concrete conceptual knowledge (Fischer and Shaki 2018). This includes the strong connection between spatial and mathematical domains (Young, Levine, and Mix 2018). Therefore, the study of numerical cognition can be a way to explore neuronal mechanisms of high-level brain functions (Nieder 2016). In fact, the observation of numerical practice within a situation can provide a provisional basis for pursuing the explanation of cognition as a nexus of relations between the mind at work and the world in which it works.

Number cognition is one of the skills that can be extended through embodied experiences from a rather limited set of inborn skills to an ever-growing network of abstract domains (Lakoff and Nuñez 2000). The early numerical practice is usually accompanied by gestures that are considered a window onto children's number knowledge because children spontaneously use gestures to convey information that is not necessarily found in their speech (Goldin-Meadow 1999). Within the human body, a special role is attributed to fingers, including a significant influence on the development of our system of counting. For example, we likely use a base-ten system because of the number of fingers we have. Indeed, recent research on the embodiment of mathematics has evidenced fingers as natural tools that play a fundamental role, from developing number sense to becoming proficient in basic arithmetic processing (Soylu, Lester, and Newman 2018).

These behavioral observations are confirmed by recent neuroimaging research in which empirical studies suggest there is a neural link or even a common substrate for the representation of numbers and fingers in the brain (for a review, see Peters and De Smedt 2018). Neuroimaging data show neural correlates of finger and number representations located in neighboring or even overlapping cortex areas, suggesting that fingers may have a role in setting up the biological neural networks for more advanced (i.e., abstract) mathematical computations (Moeller et al. 2011). Importantly, several studies (e.g., Sato et al. 2007; Tschentscher et al. 2012) empirically showed the existence of a permanent neural link between the finger configurations and their cardinal number meaning in adults.

Emotions play a very important role in many aspects of our lives, including decision-making, perception, learning, and behavior, and emotional skills are an important component of human intelligence. The research on emotion concepts is intrinsically tied to the more general and controversial debate about the nature of emotion itself (Adolphs 2016). However, direct links between the body and the emotions have been long established. James (1894) provided the canonical example of such a link: "We know that we 'fear' a bear by perceiving changes in our own bodily state." There is neuroscientific evidence that emotion changes the operating characteristics of cognition and action selection (Pessoa et al. 2019) and that there is, in fact, emotional activation before, during, or shortly after learning enhances memory (McGaugh 2018) and alters judgment (Gasper and Danube 2016). Given the importance of the body and its neural representation in emotion, it is perhaps unsurprising that the domain of emotion concepts has long been highlighted as a natural application for theories of embodied cognition. Indeed, almost all emotion theories consider that emotions are embodied via somatosensory, interoceptive, or motor information (Niedenthal and Ric 2017). Importantly, modern theories not only focus on embodiment but propose that emotions involve a cascade of events, with somatosensory and motor resources recruited at multiple time points in the perception, understanding, experience, and production of emotions (Winkielman, Coulson, and Niedenthal 2018).

22.3 Cognitive Robotics Models of Abstract Words

The design of cognitive robots that are capable of learning new words and concepts typically adopts an embodied and grounded approach. Chapter 20 introduced the "direct-grounding" approaches for developing language models in robots and presented applications of this strategy to learning more concrete words—that is, when the robot learns the names of objects it can perceive or words for actions it is performing or observing. For instance, robots can simulate the early stages of language development via the interaction of infants with caregivers (for a review, see Asada [2016]). Interestingly, Kawai et al. (2020) proposed a hidden Markov model to explain the development of syntactic categories that fit the developmental psychological experiments at different ages and for different languages.

The abstract/concrete continuum view of concepts suggests that the learning of higher-order, more abstract words may be obtained by extending the strategies and models for the grounding of concrete words. However, in the scientific literature only very few examples explore such an extension.

Recently, Cangelosi and Stramandinoli (2018) offered a review of two main strategies for grounding concepts without the sensorimotor experience of direct physical referents. In the "grounding-transfer" strategy (Cangelosi and Riga 2006), new concepts and words are learned by the robot in successive stages, via combining words whose meanings have been previously acquired through direct grounding. For example, a robot can learn the word "mermaid" if instructed to merge the previously acquired grounded meanings of "woman" and “fish” and then transfer the result to the new word without ever seeing such a fantastic animal. In the alternative strategy, the robot learns abstract concepts by associating words to gestures and actions—for example, the use of finger counting to teach a child (or a robot) to count. In this section, we review some examples of the first strategy, while the second strategy is discussed in the next section, which presents cognitive robotics models of number cognition.

Recurrent neural networks (RNNs) are particularly suitable structures for modeling abstract concept learning since the recurrent connections allow the network to handle the sequence of progressive abstraction. Two main types of RNN were proposed: the Elman type, with a recursion on the hidden layer (Elman 1990), and the Jordan type, with a recursion from the output to the input (Jordan 1986).

From the “grounding transfer” view, Stramandinoli, Marocco, and Cangelosi (2012, 2017) investigated the problem of grounding intermediate abstract concepts—that is, higher-order actions that can be obtained by combining concrete motor concepts. Stramandinoli, Marocco, and Cangelosi (2012) performed experiments on a cognitive model for the humanoid robot iCub based on an RNN of the Elman-type, which permit the learning of higher-order concepts based on temporal sequences of action primitives and word sentences. The training of the model is incremental. The mechanism includes two stages: 1) the basic-grounding (BG) and 2) higher-grounding (HG) transfer mechanisms. During the BG, the robot learns a set of action primitives (e.g., “PUSH,” “GRASP” or “PULL,” “NEUTRAL”) using embodied and situated strategies. Two different stages were implemented for the HG training to enable different levels of the combination between basic and complex actions. In the first HG stage (i.e., HG-1), a sequence of previously learned words (e.g., “RECEIVE [is] PUSH [and] GRASP [and] PULL”) are provided to guide the hierarchical organization of the basic concepts directly grounded in sensorimotor experience (e.g., “PUSH,” “GRASP,” or “PULL”) in order to learn novel concepts (e.g., “GIVE”). Subsequently, the network receives as input the higher-order word “receive” and targets the outputs previously stored. During the second HG stage (i.e., HG-2), the robot learns three new higher-order words (“accept,” “reject,” “keep”) consisting of a combination of basic action primitives and higher-order words acquired during the previous HG-1 stage (e.g., “KEEP [is] PICK [and] NEUTRAL”). HG-2 adds a further hierarchical combination of words from both concrete concepts (BG) and the first level of abstraction words (HG-1). This training methodology is extremely flexible and permits designers to freely add novel words to the known vocabulary of the robot or to completely rearrange the word-meaning associations.

In follow-up work, Stramandinoli, Marocco, and Cangelosi (2017) proposed a partial RNN (Jordan-type) for learning the relationships between motor primitives and objects and performed experiments on the iCub robot for investigating the grounding of more abstract action words, such as “use” or “make.” Abstract action words represent a class of terms distant from the immediate perception that describe actions with a general meaning and that can refer to several events and situations. Therefore, they cannot be directly linked to sensorimotor experience through a one-to-one mapping with their physical referents in the world. The grounding of abstract action words is achieved through the integration of the linguistic, perceptual, and motor input modalities, recorded from the iCub sensors, in a three-layer RNN model (figure 22.1). The iCub robot first develops some basic perceptual and

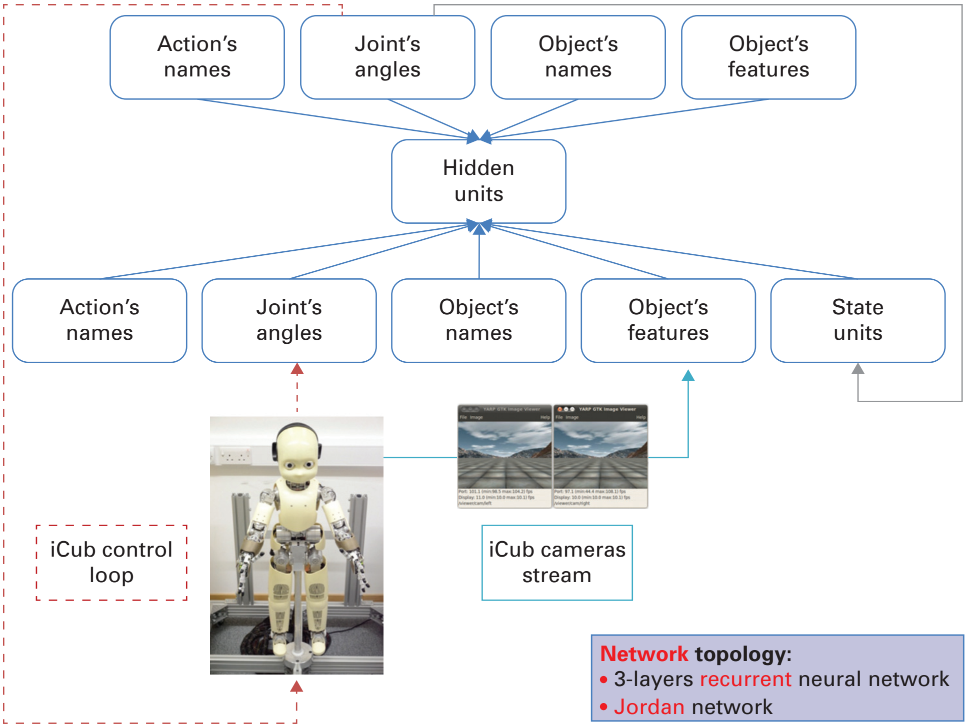

Figure 22.1
The partially recurrent neural network model for language abstraction.

motor skills, such as "PUSH," "PULL," and "LIFT," necessary for initiating the physical interaction with the environment, and then it can use such knowledge to ground language. The training of the model is incremental and consists of three stages:

1. Prelinguistic—the robot is trained to recognize a set of objects (e.g., "KNIFE," "HAMMER," "BRUSH," and so on) and learn object-related action primitives (e.g., "CUT," "HIT," "PAINT," and so on) by combining low-level motor primitives. For example, the action primitive "cut" is built by iterating the "push-pull" sequence several times.

2. Linguistic-perceptual training—this is the first stage of language acquisition. The model is trained to associate labels with the corresponding object and actions (two-word sentences consisting of a verb followed by a noun—e.g., "CUT [with] KNIFE"). These words are directly grounded in perception and motor experience.

3. Linguistic abstract training—abstract action words (e.g., "USE, "MAKE") are grounded by combining and recalling the perceptual and motor knowledge previously linked to basic words (i.e., the previous linguistic-perceptual training). To derive the meaning of abstract action words, the robot, guided by linguistic instructions (e.g., "USE a KNIFE"), organizes the knowledge directly grounded in perception and motor knowledge. This phase of training represents the abstract stage of language acquisition when new concepts are formed by combining the meaning of terms acquired during the previous stages of training.

Novel lexical terms can be continually acquired throughout the robot's development via new sensorimotor interactions with the environment that correspond to new linguistic descriptions. At the end of the training, the robot was able to perform the behavior triggered by the linguistic description and the perceived object. The presence of clusters in the hidden units of the model suggested the formation of concepts from the multimodal data received as input by the network.

22.4 Cognitive Robotics Models of Numerical Concepts: Development and Representation

To explore embodied abstract cognition, cognitive robotics allows building embodied calculators that can merge abstract and concrete interpretations of numbers. This section concisely reviews some of the major computational models that were created to simulate the development of numerical cognition in artificial cognitive systems and robots. A more detailed review of the topic can be found in Di Nuovo and (Jay 2019).

In pure computational modeling, one of the milestones is the work of Ahmad, Casey, and Bale (2002), who introduced a very complex multinetwork modular system following a mixture-of-experts approach. A peculiar aspect of the counting subsystem was a module for "pointing" to the next object to count "like a finger," which was one of the first times that embodiment was included, even if its implications were not explicitly studied. The proposed architecture included two subsystems for subitizing and counting, which were realized by interconnecting several constituent modules, including connectionist networks that were trained independently. The main constituent architectures included, other than the multilayer feedforward neural network, recurrent connections of both Elman and Jordan types in the counting subsystem, and two self-organizing map (Kohonen 2001) architectures in the subitizing subsystem. The construction of this system also followed the assumption that subitizing is an innate capability, while counting should be learned via examples. This model has shown good adherence to the children's data but also some inconsistency. For example, the simulation has a higher frequency of counting no objects compared to when children, who rarely make this error, count.

Chen and Verguts (2010) studied the interaction between the representations of number and space, presenting a bioinspired connectionist model that exhibited the SNARC effect in the parity judgment and number comparison tasks. The model was able to simulate not only the SNARC effect but also several other experimental data effects, including the spatial attention bias known as the Posner-SNARC effect and, after lesion, the spatial dysfunction found in patients with left-hemisphere damage. However, the "space representation" was hand-wired in such a way that it exhibited properties suggested by neuroscientific data.

The first attempt to use robots to explore embodied aspects of the interactions between numbers and space, made by Ruciński (2014), reproduced three psychological phenomena connected with number processing: size and distance effect, the SNARC effect, and the Posner-SNARC effect. The architecture was split into two neural pathways: "ventral," which elaborates on the identity of objects and makes decisions according to the task and processes the language, and "dorsal," which processes the spatial information—that is, locations and shapes of objects and sensorimotor transformations that provide direct support for visually guided motor actions. The results show that the embodied approach generated a more biologically plausible model by replacing arbitrary parts of the Chen and Verguts model with elements that have direct physical connection and, therefore, more realistic interpretation.

In another experiment, Ruciński (2014) presented a new cognitive developmental robotics model to simulate aspects of the earlier work on gesture in counting by Alibali and DiRusso (1999), and indeed experimental results showed that pointing gestures significantly improved the counting accuracy of the humanoid robot iCub. The architecture was a recurrent neural network of the Elman type, with two input layers: one for the items to count—that is, a binary vector—and another for the proprioceptive information—that is, the arm and hand encoder values. The model was trained via backpropagation through time. Statistical analysis of the results showed adherence to the experimental data of Alibali and DiRusso.

Recently, Di Nuovo et al. conducted several experiments (De La Cruz et al. 2014; Di Nuovo, De La Cruz, and Cangelosi 2014; Di Nuovo et al. 2014) with the iCub humanoid robot to explore whether the association of finger counting with number words and/or visual digits could serve to bootstrap numerical cognition in a cognitive robot. The models (e.g., figure 22.2) were based on three RNNs of the Elman type, which were trained separately and then merged to learn the classification of the three inputs: finger counting (motor), digit recognition (visual), and number words (auditory)—that is, the triple-code

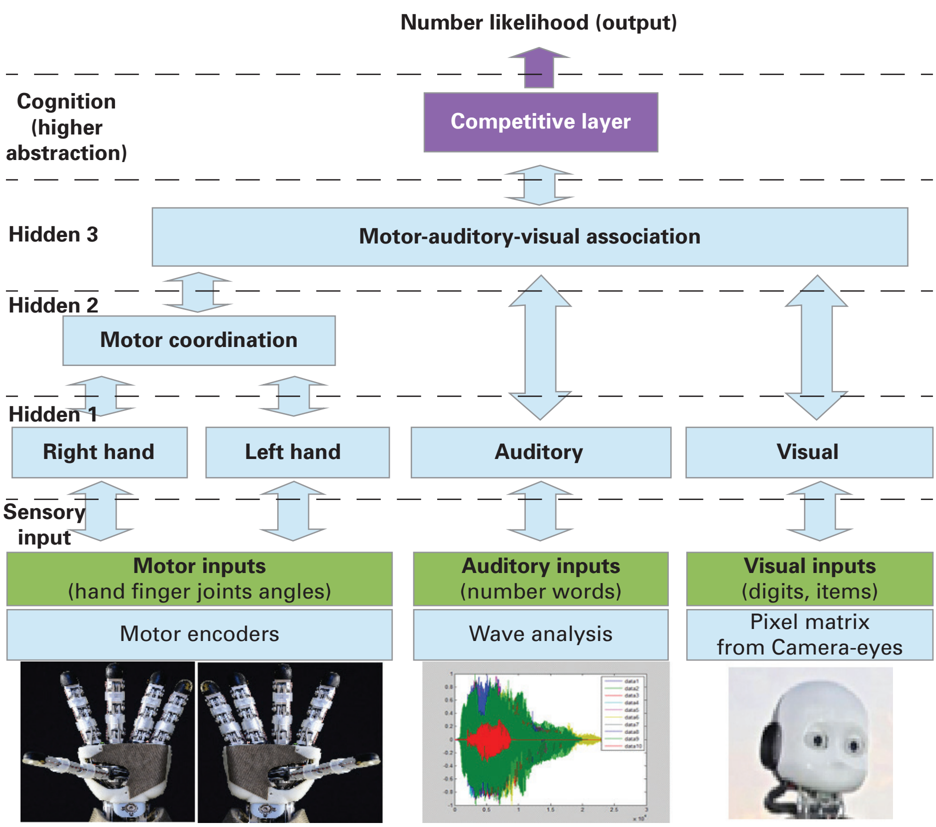

Figure 22.2
A schematic representation of the deep architecture for number cognition showing an integration of the models proposed by the several investigations of Di Nuovo et al. (2014).

model (Dehaene 1992). Also, the model mimics the two-hemisphere organization of the brain. Results of the various robotic experiments show that learning finger sequencing together with number word sequences speeds up the building of the neural network's internal links, resulting in a qualitatively better understanding (higher likelihood of the correct classification) of the real number representations.

Optimal cluster analysis (figure 22.3) showed that the internal representations of the finger configurations form the ideal basis for the building of an embodied number representation in the robot. Furthermore, it has been shown that such a cognitive developmental robotic model can subsequently sustain the robot's learning of the basic arithmetic operation of addition. However, this operation was implemented with an additional handcrafted layer just to show the possible further abstraction offered by the model.

Further investigation increased the biological adherence of the models and demonstrated the potential benefits, in terms of learning efficacy and efficiency, when used with deep-learning approaches, which are inspired by the complex layered organization and functioning of the cerebral cortex (Bengio 2009). Di Nuovo, De La Cruz, and Cangelosi (2015) created a model (e.g., figure 22.3) with an improved setup of the network weights employing restricted Boltzmann machines (RBMs) and the contrastive divergence-learning algorithm.

Follow-up studies (Di Nuovo 2017, 2018) focused on extending the simulation by incorporating the neural link observed between visual and motor areas in neuroscientific studies. Particularly, Di Nuovo (2018) investigated the long short-term memory architecture (Graves 2012) for learning to perform addition with the support of the robot's finger counting. Interestingly, the model showed similarities with studies with humans (children and adults) by performing an unusual number of split-five errors, which can be linked to the five finger representations (Domahs, Krinzinger, and Willmes 2008).

Di Nuovo and McClelland (2019) investigated the perceptual process of recognizing spoken digits in deep convolutional neural networks embodied in the iCub robot. Simulation results showed that the robot's fingers boost the performance by setting up the network and augmenting the training examples when these were numerically limited. This is a

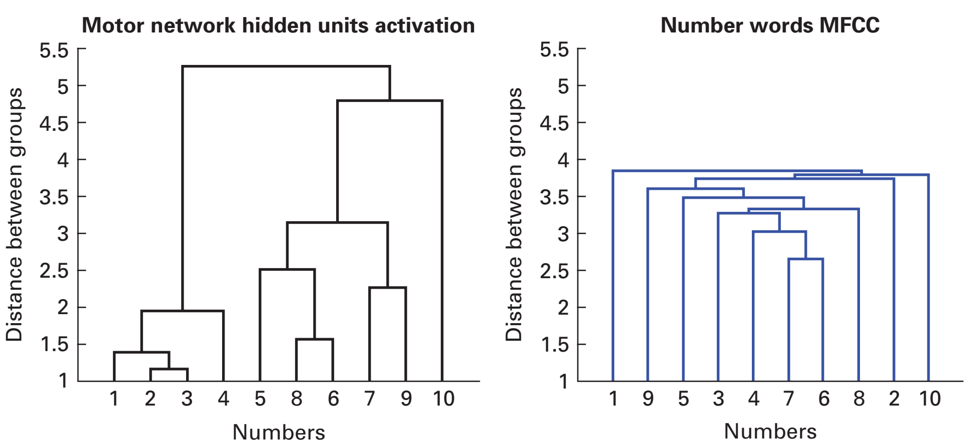

Figure 22.3
Optimal leaf-order dendrogram of hidden-unit activation for finger configurations (*left*) and of number words (*right*).

common scenario in robotics, where robots will likely learn from a small amount of data. The embodied representation (finger encoder values) was compared to other representations, showing that fingers can represent the real counterpart of that artificial representation and can maximize learning performance. The results are associated with some behavior observed in several human studies in developmental psychology and neuroimaging. Overall, the hand-based representation provided our artificial system with information about magnitude representations that improved the creation of a more uniform number line, as seen in children (Gunderson, Spaepen, and Levine 2015). Importantly, this is the first time that a cognitive developmental robotics model has demonstrated effectiveness when compared against the standard approach for a benchmark machine-learning problem—that is, the Google Tensorflow Speech Recognition data set.

22.5 Cognitive Robotics Models of Emotions

The idea that robots may have emotions has captured the imagination of many researchers in the field of artificial intelligence, who have identified the crucial importance of emotions in the design of more intelligent and sociable robots (e.g., Breazeal 2004b; Fellous and Arbib 2005; Ziemke and Lowe 2009). The behavior-based robotic (BBR) has been a common approach for emotion-aware robots, which can use emotions as internal variables, which drive their external actions, mostly by correcting their operations according to the signals gained from their sensors (Arkin 2005). BBR ideas stimulated the design of robots capable of expressing emotional cues, such as the Kismet, Mexi, iCub, and Emys (Breazeal 2004a; Parmiggiani et al. 2012; Esau et al. 2003; Kędzierski et al. 2013). However, the mechanical expression of physical cues is just a preliminary step for the successful modeling of emotions; thus, emotionally capable cognitive architectures are necessary for enhancing the implementation of believable, autonomous, adaptive, and context-aware artificial agents (Hudlicka 2011).

Despite the theoretical agreement that the next generation of cognitive architectures must integrate emotion and cognition to define realistic models of human-machine interaction, in practice the computational modeling of emotion has been often underrated in cognitive architecture research. Models account for emotion as well as some other aspects of cognition, but usually, they are not aiming to be comprehensive architectures (see Rodríguez and Ramos 2015).

The computational modeling of emotion is frequently associated later with the addition of an emotion module that can influence some of the components of the general cognitive architecture (see Reisenzein et al. 2013). A notable example is SOAR (Laird 2012), which was not designed to model emotions; nevertheless, two different computational emotion models have been built upon SOAR: EMA (Marsella and Gratch 2009) and PEACTIDM (Marinier, Laird, and Lewis 2009). These two models represent the two principal alternative paths available to model emotions in cognitive architectures, and they also illustrate how theoretical assumptions in psychology can influence modeling choices. A general cognitive architecture designed to include emotions as flexible motivators for action is LIDA (Franklin et al. 2014), but this has only been considered at a conceptual level since modeling of emotions has not been implemented yet.

Pessoa (2017) identified two main categories of applications for emotion models in robotics: 1) to provide robots urgency to take action and make decisions, 2) to aid understanding of emotion in humans or to generate humanlike expressions. For the first category, significant applications of emotion-enabled general cognitive architectures have not yet been created for use with robots, even if general cognitive architectures have been used to control complex robots—for example, SOAR in the REEM robot (Puigbo et al. 2015). For the second category, it should be noted that many contributions in the robotics literature are loosely connected with the neuropsychological aspects of emotions, and the great majority fall under the category of pure machine-learning exercises, such as computer vision for facial expression recognition. Discussion and examples of recent contributions to modeling emotions in robotics can be found in the first volume of the book by Esposito and Jain (2016).

An example of the first category can be found in eMODUL, a perceptual system of emotion-cognition interaction specifically designed for robotics by Belkaid, Cuperlier, and Gaussier (2019). The eMODUL system is situated in its physical and social environment, and its components constantly appraise events from the body and the world, with a particular interest in emotionally relevant stimuli that affect other computational/cognitive processes (e.g., allocation of resources, organization of behavior). The system continuously processes emotionally modulated signals and reintegrates them into the information processing flow for higher-order processing. Valence extraction consists of the evaluation (appraisal) of the emotional values of complex representations. Therefore, the system sensations and actions are no longer neutral and objective but rather emotionally colored. For example, when occurring on the sensation space, emotional modulation affects perception and memory. When occurring on the action space, it can modulate action selection and motor expression. In terms of the system autonomy, these two types of modulations, respectively, have an impact on the allocation of cognitive/computational resources and the organization of appropriate behavior with regard to the system's survival, well-being, and task/goal demands. The authors provide two experimental examples of the application of the eMODUL system with artificial neural networks, in which emotional modulation consists of increasing or decreasing the synaptic efficacy of targeted populations of the neurons involved in these processes. The first experiment is in the context of a survival problem, in which a hunger modulation makes the robots more determined to access the resources and feed. The second is a visual search task designed similarly to the common experimental paradigm in psychology, in which the emotional (frustration or boredom) modulation of attention increases the robot's performance and fosters exploratory behavior to avoid deadlocks.

As an example of the second category, Prescott et al. (2019) included emotional signals in a neuroscience-inspired multimodal computational architecture for the autobiographical memory system, named the mental time travel model, to control the iCub robot. The model allows for retrieving past events, including their emotional associations, and projecting them into an imagined future by using the same system. This architecture proves useful for the social capabilities of robots by enabling face, voice (including emotion), action, and touch gesture recognition through interaction with humans. Using this system for imagining future events should allow for simulating and visualizing actions as well as planning actions before actual execution. This work is still at an early stage; however, experiments show that deploying emotionally mediated memory models into a brain-inspired control architecture for the iCub robot has enhanced the robot's capability for recognizing social actors and actions.

22.6 Open Issues in Abstract Cognition and Robotics Research

In the interdisciplinary literature, most contributions recognize that to fully account for the representation of abstract concepts an extension beyond a purely grounded approach is needed. Pecher and Zeelenberg (2018) raised doubts on whether sensorimotor grounding alone can fully explain abstract concepts because recent evidence indicates that even concrete concepts are not always grounded in sensorimotor processes.

Another open issue has been highlighted by (Pexman 2019), who noted that so far none of the proposals for grounding abstract meaning have yet been tested in child studies. It will be important to investigate whether children's early abstract concepts are grounded through metaphor, language cooccurrence, and emotion. To this end, developmental robotics modeling can provide a powerful tool to collect preliminary information to evaluate or compare existing theories and to make novel experimental predictions that can be tested on humans (see chapter 3 for details). In particular, they could provide computational evidence in the debate on language development between "nativists" and "empiricists" (see chapter 20, section 1.1) by modeling the alternate theories and analyzing the resulting robot behavior in comparison to children's behavior.

To this end, computational models have the advantage of being fully specified in any implementation aspect, which makes them easily reproducible and verifiable, and they can produce detailed simulations of human performance in various situations and, for example, be used in experiments with any combination of stimuli. Furthermore, models can be lesioned (e.g., links between neurons can be cut) to simulate cognitive dysfunctions, and performance can be compared to the behavior of patients to gain information and insights into diagnosis and treatment that might be difficult to discover otherwise.

However, the cognitive robotics models proposed so far have been relatively naive because they focused on simulating only a particular aspect, verified with dummy tasks in simplified scenarios, and provided little evidence of their generalization ability in alternative, realistic settings. They considered only the concepts (e.g., metaphorical concepts such as "to grasp an idea") that have been empirically investigated in humans and found to be grounded in action and perception systems. Thus, we have yet to see if we might be able to extend these conclusions to other kinds of abstract concepts such as "politics" or "metaphysics." This is also the case with emotion modeling, which has predominantly been studied in terms of replicating human social behavior, while very little has been done to improve robots' abstract thinking. Significant improvement in the complexity of the models and, moreover, the test scenarios is needed before cognitive robotics modeling can be considered a reliable tool in education, neuroscience, and psychology research.

The reason for this lack of reality can be attributed not only to the limitations of current robotic platforms but also to the unavailability of raw data from children's experiments. Indeed, there are no open "benchmark" databases for cognitive robotics, unlike the typical open data behavior in machine learning. Robotic modelers can use only postprocessed data and statistical analyses for designing and validating models.

22.7 Conclusion

All these studies provided valuable information about the simulation of artificial learning and demonstrated the value of the cognitive robotics approach for studying aspects of abstract cognition. These findings reveal a novel way to achieve the humanization of artificial learning strategies, in which embodiment can make the robot's training more efficient and understandable for humans.

Further multidisciplinary research is required to gather data from children and get a better understanding of the underlying processes and strategies of abstract thinking and reasoning. It seems likely that there are developmental differences in the acquisition of the different types of concepts; therefore, hybrid models that combine sensorimotor experience and language appear to be viable options that should be investigated. In this respect, cognitive robotics can contribute to the theoretical development of abstract concepts acquisition and use in humans—that is, by providing a simulated environment for testing hypotheses—and benefit from the resulting discoveries to create innovative models of humanlike learning and social interaction.

To advance knowledge in this interdisciplinary field, we remark that closer collaboration among researchers in the multiple disciplines involved is necessary to share expertise and codesign studies. Importantly, we envision the need for real ad hoc joint experiments and for artificial simulations to obtain well-matched data comparing robots' and children's tasks. Furthermore, the availability of open databases will favor the engagement of the machine-learning community, as has occurred in other applied fields, such as computer vision, speech recognition, and DNA sequencing.

Additional Reading and Resources

- Book exploring the ways in which embodied and grounded cognition theories can be expanded into abstract words: Borghi, Anna, and Ferdinand Binkofski. 2014. *Words as Social Tools: An Embodied View on Abstract Concepts*. New York: Springer.
- This book presents a collection of studies that relate to various theoretical frameworks for abstract concepts, from neuroimaging to computational modeling and from behavioral experiments to corpus analyses: Bolognesi, Marianna, and Gerard Steen, eds. 2019. *Human Cognitive Processing, Vol. 65: Perspectives on Abstract Concepts: Cognition, Language and Communication*. Amsterdam: John Benjamins.
- Special issue with a collection of experimental and modeling papers on abstract concepts: Borghi, Anna M., Laura Barca, Ferdinand Binkofski, and Luca Tummolini. 2018. "Varieties of Abstract Concepts: Development, Use and Representation in the Brain." *Philosophical Transactions of the Royal Society B* 373 (1752): 20170121.
- Pearl, Lisa S., and Jon Sprouse. 2015. "Computational Modeling for Language Acquisition: A Tutorial with Syntactic Islands." *Journal of Speech, Language, and Hearing Research* 58 (3): 740–753.
- Source code and data for Di Nuovo and McClelland (2019): "Developing the Knowledge of Number Digits in a Child-Like Robot." *Nature Machine Intelligence* 1 (12): 594–605.

http://doi.org/10.17032/shu-180017. Number Understanding Modelling in Behavioral Embodied Robotic Systems (NUMBERS): http://doi.org/10.17032/shu-180017.

• Data set on concrete/abstract decision data for ten thousand English words in Pexman, P. M., et al. 2017. "The Calgary Semantic Decision Project: Concrete/Abstract Decision Data For 10,000 English Words." *Behavior Research Methods* 49:407–417. https://doi.org/10.3758/s13428-016-0720-6.

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