What deep learning can tell us about higher cognitive functions like mindreading?

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Abstract
Can deep learning (DL) guide our understanding of computations happening in biological brain? We will first briefly consider how DL has contributed to the research on visual object recognition. In the main part we will assess whether DL could also help us to clarify the computations underlying higher cognitive functions such as Theory of Mind. In addition, we will compare the objectives and learning signals of brains and machines, leading us to conclude that simply scaling up the current DL algorithms will not lead to human level mindreading skills. We then provide some insights about how to fairly compare human and DL performance. In the end we find that DL can contribute to our understanding of biological computations by providing an example of an end-to-end algorithm that solves the same problems the biological agents face.
Introduction

It has been shown that deep learning (DL) provides currently the best set of models for the neural representation of visual images in high-level visual cortex of monkeys (Yamins et al., 2014) and humans (Khaligh-Razavi & Kriegeskorte, 2014). Importantly, these models have been shown to outperform a wide range of neuroscientific and computer vision models developed by vision scientists over the last decades. The application of DL networks, inspired by biological neural networks, has helped us to achieve a better understanding of vision (Hassabis et al., 2017; VanRullen, 2017). The successful application of DL in vision leads to the question whether these models could help us to also gain insights into other aspects of human cognition. It is presently unclear whether DL can lead to improved understanding of other cognitive processes beyond vision.

In this perspective we will first very briefly review how DL has helped us to study visual object recognition in the primate brain (see Kriegeskorte, 2015; Yamins & DiCarlo, 2016 for more thorough reviews). This positive case example of how to combine DL with neuroscience is then, in the main part of the paper, followed by the question whether DL could also help us to understand the emergence of higher cognitive functions such as Theory of Mind (or mindreading, see below). Then we open up a discussion about the learning signals available to biological brains and machines and how to actually compare the two. We end up by discussing that DL has provided end-to-end algorithms which solve similar tasks as biological agents are facing, and such examples help to guide the search of brain’s computational strategies.

Marrying biology and AI: The success story in vision

DL as a model for primate vision

Visual object recognition in primates is mediated by a hierarchy of transformations along the occipitotemporal cortex (DiCarlo et al., 2012). Intriguingly, it has been shown that these transformations are quite similar to the hierarchy of transformations learned by the deep neural networks (DNN) trained to recognize objects on natural images. Several pieces of work have demonstrated a direct correspondence between the
hierarchy of the human visual areas and the layers of the DNNs (Gülcu 2015, Seibert, 2016, Cichy et al., 2016; Eickenberg 2016). Moreover, recent magnetoencephalography work has shown with millisecond resolution that activity in the deeper layers of the DNN predict brain signals later in time (Cichy et al., 2016; Seeliger et al., 2017). These results have led to the conclusion that DNNs provide a good model for understanding how visual object recognition happens in the primate brain [Kriegeskorte 2015, Yamins & Di Carlo, 2016]. Besides being a good model, the DNNs have made it possible to address a number of empirical, neuroscientific questions. For example, using a DNN as a computational model enabled us to demonstrate that gamma band activity not only signals coherent object representations (i.e. the “final product”), as suggested by classic theories, but rather has a direct role in the incremental building-up of these representations along the ventral visual pathway (Kuzovkin et al., 2017).

While DL has offered an algorithmic model for (feedforward) visual object recognition in brains, these developments do not provide a full understanding of biological vision (Cox, 2014; Kriegeskorte, 2015; VanRullen, 2017). Most importantly, in biological vision at least part of the processing is done by feedback connections (Roelfsema, 2006), although the exact computational role of feedback is less clear (See Bastos et al, 2012 for one particular view). The DL networks commonly used in machine vision are feedforward, although there is a recent trend towards incorporating feedback (e.g. Wen et al., 2018). Also, it is important to note that the DL networks still explain only a part of the variability of the neural responses happening in real brains. Hence, the present-day DL networks cannot be seen as the ultimate model of biological visual processing (e.g. Kriegeskorte, 2015; Rajalingham et al, 2018). Nevertheless, the work with DL has illuminated how relatively simple transformations applied throughout a hierarchy of processing stages can be associated with successful object recognition.

What has made DL successful for investigating biological vision?

The recent developments in DL have been made possible by increased computational power, refinements to the algorithms, and availability of large data-sets necessary for training DL networks (LeCun et al., 2015). Beyond these factors there are several specific aspects to consider that have enabled DL to be helpful for investigating biological vision. There are three aspects to highlight: 1) Appropriate training data: DNNs are a good model for biological object recognition as they are trained on datasets that are directly relevant for biological vision: natural images (i.e. Imagenet (Deng et al., 2009)); 2) A training objective that is similar to biological vision: Machine vision has the straightforward goal to accurately recognize objects in a scene (or to segment or
localize them) which resembles the goal of the biological vision (see below for a more nuanced view); 3) Good neuroscientific comparison data: It has become much more straightforward to measure the activity of biological vision systems. In the case of vision we have a fairly good understanding of the areas involved in vision, how they are connected and organized. Decades of work on the visual system have revealed the visual processing hierarchy which can and has been compared to the hierarchy of transformations learned by DL systems (Gülcu 2015, Seibert, 2016, Cichy et al., 2016; Eickenberg 2016). In the case of vision all these aspects together were needed for DL to inform us about the mechanisms underlying visual object recognition. We argue that time is ripe to apply DL models to other questions where all these aspects are available (e.g. the problem of how animals perform spatial navigation). For other problems, however, all these aspects still need to be advanced. One of these topics, where we see the limits of present-day DL, is mindreading.

Challenges ahead: using DL to study other aspects of cognition

Studying vision with the help of DL seems justified - both the artificial and the biological visual systems solve a similar task with a similar performance, both are hierarchical and require the transformation of features from simple to more complex. From this perspective, using DL to investigate the computations underlying mindreading might seem a bit far-fetched as mindreading seems quite different from vision: mindreading is an essential ability of humans to infer the mental states of others such as for example their perceptual states, beliefs, knowledge, desires, or intentions (for review Apperly, 2010). While we share basic visual processes with most other mammals, it is thought that the scope and complexity of mindreading skills sets us apart from most of the animal kingdom (Call & Tomasello, 2008). Hence even if one would agree that DNNs are useful for understanding vision, it is unclear whether DNNs have anything to tell us about mindreading. How could this ability to understand what others think and intend emerge from artificial neural networks (Lake et al., 2017; Baker et al., 2017)? On the other hand, diverse research supports the view that mindreading to a large extent is an acquired skill, just like reading (Apperly, 2010; Heyes & Frith, 2014). And if mindreading skills require training, similarly to vision, then DL networks could help to unravel at least some of the computations underlying mindreading. To highlight this aspect of being learned we will use the term “mindreading” instead of “theory of mind” in this manuscript (see also Apperly, 2010; Heyes & Frith, 2014).
We feel that mindreading will be an important topic to study with the modern tools offered by DL for two several reasons. First, if the goal is to build artificial agents that think and behave at (least at) the level of humans, then there might not be a way around studying mindreading. This is because at least according to some prominent views about communication, mindreading is necessary for the emergence of meaningful communication and language (Tomasello, 2010; 2014; Scott-Phillips 2014; Mercier & Sperber, 2017). This perspective suggests that training agents with DL on huge text corpora will never lead to agents who are able to communicate with humans or with each other in a meaningful fashion. Hence, the only way to build these agents is to first understand and build in mindreading capabilities. However, this is a daunting task, as there is still much unclarity about mindreading in humans and animals (e.g. Siegal, 2008; Call & Tomasello, 2008; Apperly, 2010; Heyes & Frith, 2014; Scott & Baillargeon, 2017). Second, given that there is still much controversy about mindreading even in humans, we believe that modern DL tools can actually help to better understand mindreading. This is because in artificial systems one can add and modify single components of the system. For example, one could see how having an external memory (i.e. separately from the deep neural network) can help the agents in acquiring basic mindreading skills. Similarly, as discussed in the next section, one can see whether and which mindreading skills can emerge through reinforcement learning. Third, similarly to how we require mindreading skills to understand other humans, we will need mindreading skills in AI systems for them to understand human intentions, for example in human-machine interaction (see Rabinowitz et al., 2018). For these reasons we think there will be a surge of DL works into mindreading. In this perspective article we want to discuss how DL could contribute to studying mindreading. We will first delineate some problems in studying mindreading with DL. Next we will offer one particular way for studying mindreading with DL. We will conclude that the present day DL algorithms are not sufficient for acquiring human like mindreading skills and describe some of these learning signals relevant for acquiring mindreading skills in biological brains.

DL to study the emergence of mindreading

As noted above, progress in machine vision has been so beneficial for the study of biological vision because of comparable training data and similar training objectives for biological and machine vision algorithms. On top of that in the case of vision there is appropriate neuroscientific data to compare to the outcomes of DNN. All of these aspects are yet missing or severely underdeveloped in mindreading research. What would constitute good training data for teaching artificial agents how to read other
minds? Which neuroscientific data could one compare the artificial models to? And, most importantly, what would be the training objective?

To make any meaningful comparison between the AI agents and the biological agents with regard to mindreading, one needs to find a task that is similar or at least comparable to both (as in vision, where often the task for both biological and artificial agents is to recognize objects). Although there are several classic tasks for studying human mindreading (e.g. the Sally and Anne task), they depend on language and executive functions (see Apperly, 2010, for a review). However, we believe that as a first step it is necessary to study the core mindreading skills possessed already by preverbal infants and non-human animals (Baillargeon et al., 2010; Call & Tomasello, 2008). For example, in the early 2000s Brian Hare, Josep Call and Michael Tomasello performed an excellent series of experiments demonstrating that chimpanzees exhibit at least some characteristics of mindreading (Hare et al., 2000; 2001). The experiments involved two chimpanzees, a dominant (D) and a subordinate (S) chimpanzee. (Chimpanzee social status is organized hierarchically, i.e. some animals are more dominant than others.) When the same piece of food is available for both D and S, the dominant almost always obtains it. In the experiments the two chimpanzees were set into separate cages facing each other. Between them, there was a space containing two walls. During the experiment, pieces of food were presented. In the critical condition one piece of food could only be seen by the subordinate and not by the dominant chimpanzee. Could the subordinate take advantage of the fact that the dominant chimpanzee could not perceive one piece of food? The results demonstrated that the S chimpanzee indeed obtained more food in this condition. Hence, the S chimpanzee was able to take into account what the D chimpanzee could and could not see: One chimpanzee could take another chimpanzee’s perspective.

This was an elegant experiment as it demonstrated that the chimpanzees possess at least some basic form of mindreading (Call & Tomasello, 2008). For us, the experiment is even more exciting given that such competitive settings are easy to implement with AI agents because in this task there is a clear goal to optimize for: obtaining food. Of course we do not think that “obtaining food” is the sole goal driving mindreading skills in primates (see next section), but having such a clear goal provides a tangible starting point for studying mindreading with deep reinforcement learning (DRL), where the DNN learns through rewards (e.g. points, Mnih et al., 2015; Silver et al., 2016). In particular, one could implement two agents (“subordinate” and “dominant”) who are competing for reward and try to see whether the behavior of the artificial agents reveals some rudimentary skills of perspective taking, similar to the chimpanzee work (Hare et al 2000; 2001). One could also open up the internal representations of the artificial
networks and see whether the networks have learned anything about the other agent. In short, we believe that implementing this task with AI agents provides a way to study the computations underlying mindreading. Importantly, as data is available for chimpanzee performance on these task (Hare et al 2000; 2001), comparing biological and AI agents becomes feasible.

In our work with very simple DRL agents we observed that the “subordinate agent” can learn to take into account the behavior of the “dominant agent”. For example, when the “dominant” was in the field of view of the “subordinate”, the subordinate went for the food if the dominant could not see the food similarly to what has been observed in chimpanzees (Hare et al 2000). We acknowledge that our agents learned these skills through trial-and-error over a long training period (Labash et al., in preparation) while chimpanzees can master the task in the first trial (Hare et al 2000; 2001). However, the chimpanzees had learned about social hierarchies and about the behavior of other chimpanzees in their daily life over many years. Hence, the fact that the subordinate AI agents learned to take into account the behavior of the dominant AI agent demonstrates that part of mindreading skills can indeed be learned through reinforcement learning. It is important to note that we are not claiming that DRL would capture all aspects of mindreading. We simply feel that by understanding the capabilities and limitations of DRL in acquiring mindreading we will better understand the computational demands of mindreading, just as DNNs have led to a better understanding of vision.

This task based on (Hare et al 2000; 2001) is far from ideal when it comes to comparing biological and AI agents. First, such competitive paradigms are not natural for humans. This means that comparison to human behavior is lacking and that with this particular task one cannot study more complex forms of mindreading. Also, it is hard to study the brains of awake chimpanzees, hence elucidating neural mechanisms underlying this form of mindreading is hindered. This is unfortunate as it precludes any comparison between the representations in brains and representations learned by the AI agents. As noted above, our understanding of vision has benefitted from DL exactly because one can make such direct comparisons between the representations in DNNs and in biological vision (Kriegeskorte, 2015; Yamins & DiCarlo, 2016). To make this happen in the domain of mindreading, one needs to design simpler tasks that capture mindreading skills but are not dependent on language (Scott & Baillargeon, 2017, see also Rabinowitz et al., 2018). Finally, to acquire mindreading skills the AI agents probably need to be equipped with the learning signals available to human infants. In the next section we will describe some of these learning signals relevant for acquiring mindreading skills in biological brains.
Goals, rewards and learning in brains and machines

For training AI agents it is important to determine the goal the agent should optimize for. Hence, one key question for creating AI algorithms that could be informative about biology is “what is the goal of the respective biological system” (Cox, 2014; Marblestone et al., 2016; Scholte et al., 2017). In vision, the goal “to recognize objects” could be a good proxy for what the ventral visual stream is optimized for (Yamins & DiCarlo, 2016), although it is certainly not the only goal of biological vision (Cox, 2014; Scholte et al., 2017). “Recognizing objects” is a goal that is also quite easy to implement in AI. That is one reason why AI has been very useful for the research on vision. In contrast, there is no clear goal function for training AI algorithms for mindreading skills. This is because the generic functions that mindreading skills might be optimized for (e.g. communication, deception) are themselves complex to formulate and hard to implement in AI (but for some important first steps see Foerster et al., 2016; 2017; Sukhbaatar & Fergus, 2016; Mordatch & Abbeel, 2017; Rabinowitz et al., 2018). Most likely, such higher cognitive functions arise from the combination of many different neural processes that obey their own cost functions (Marblestone et al., 2016). In the last section we offered a potential goal in the acquisition of mindreading skills: In the context of multi-agent competition (Tampuu et al., 2017), mindreading could emerge through a process of an agent trying to maximize the probability of reward (e.g. food intake) while avoiding competitive interference by other agents (Labash et al., in preparation). However, we are of course not implying that maximizing the probability of food rewards is the sole goal that would lead to mindreading skills to emerge. In this section, we would like to provide a better understanding of the goals and learning signals that drive biological agents and how these differ from learning in machines.

In the present-day AI approaches it is fashionable to learn directly from data without coding prior knowledge into the network, hence “innate biases” may sound a bit like heresy (see Marcus, 2018, for a discussion about innateness in AI). However, these small biases enable the organism to learn about aspects of the world that have been important for the species over the course of evolution, not those that are the most salient, novel or statistically dominant in the current environment. By providing the agent with genetically pre-defined bias one can speed up learning the relevant features of its environment (Ullman et al., 2012; Marblestone et al., 2016). For example, recognizing
and distinguishing other human beings is important and hence there is an innate bias for attending to faces (Johnson, 2005; Reid et al., 2017). In particular, preferences for faces over similarly configured non-face objects are present in neonatal infants (Farroni et al., 2005) and even in fetuses in the third trimester of pregnancy (Reid et al., 2017). This bias is most likely a subcortical detector for stimuli with face-like configurations (Johnson, 2005; Reid et al., 2017) that directs the attention of the organism (e.g. through an eye-movement) towards faces. These subcortical detectors bias the cortical learning system to process more input about faces and hence the organism learns faster about them (Johnson, 2005; Johnson et al., 2015).

Similar biases likely exist for drawing infant’s attention to speech: they direct the learning resources of the infant to the speech signal. Speech signals are more interesting and arousing for the infant than other environmental sounds (Perszyk & Waxman, 2018) and hence lead to quicker learning about them. Further innate biases likely exist for directing the infant’s attention to hands (Ullman et al., 2012), eyes and gaze-direction (Grossmann, 2017), and biological motion (Simion et al., 2008). For us humans, such innate biases are a key component of start-up software such as “intuitive psychology” (Lake et al., 2016). These biases also make humans more intrinsically motivated to learn about other humans (Oudeyer & Kaplan, 2009; Schmidhuber, 2010).

In sum, the innate part about mindreading is that over the course of human evolution external learning signals have been adjusted so that the infant brain is very sensitive to other people (Burkart et al, 2009; Hawkes, 2014): stimuli such as faces, eyes and infant-directed speech aid and guide learning in the infant brain. In other words, other people and their behavioral signals are more important for human infants than other environmental cues. We believe that this sensitivity to the behavior of others makes the organism learn more about the behavior and states of other people and hence provides one key cornerstone for developing mindreading skills. Instead of wanting to avoid any kind of innateness in AI agents, one should embrace at least some innate biases that are known to make humans smart (Marcus, 2018). Equipping AI agents with a preferential sensitivity to other agents might be necessary to even come close to human-like mindreading skills.

Our suggestion is not yet realized by the recent work of Rabinowitz and colleagues (2018). In their approach Rabinowitz et al., 2018 train a neural network to learn mindreading skills while predicting the behavior of an agent in a gridworld. Although this study represents one of the first efforts to equip artificial agents with mindreading faculties, the authors themselves acknowledge severe limitations. In their approach, the agent who was learning mindreading had full observability of the other agent and
environment, it was trained in a supervised manner, and it did not act on the environment (so it can hardly be called an agent). These important aspects limit the biological plausibility of both the task and teaching signals used in the learning process. It could be argued that if training through supervision works then there is no need for “innate biases” to make the systems sensitive to other agents. However, based on our analysis we feel that whenever organisms (or artificial mindreading agents) are put to complex environments, they benefit from these biases that direct their attention and processing resources to particular features of the environment. Future research will need to show the range and limits of mindreading skills that can emerge purely through supervision.

This is not to say that supervision plays absolutely no role in animal or human learning. Social supervision shows to animals and humans “how things are done around here”: when a lion cub follows her mother she learns about optimal foraging and navigation; when she observes her mother during buffalo hunt, she learns to hunt; when she performs rough and tumble play with her siblings, she learns to fight and defend. Similarly, human children observe, imitate, play and learn through these behaviors (Gopnik, 2017). Recently, the AI community has taken up the challenge to use imitation and observation of others as a teaching signal (e.g. Borsa et al., 2017; Bansal et al., 2017; Stadie et al., 2017).

Taken together, the training signals for AI agents are very primitive as compared to the teaching signals a human baby obtains from the environment. Even when the AI agent is trained by both external rewards (points) and internal rewards (prediction errors) as done in some recent works (Pathak et al., 2017, Bellemare et al., 2016), the biological learning signals are more diverse. Two conclusions follow from this discussion. First, simply scaling up the current efforts for developing AI will not lead to human level intelligence (or, more narrowly, to mindreading skills). Rather, the AI algorithms need to be supported with at least some biases in order to learn from social agents. Second, comparing AI agents learning from points and humans learning from a multitude of social and intrinsic cues is unfair and not very informative. We next turn to the question how to make these comparisons a bit more adequate.
General Discussion

Comparing AI and biological agents

Motivated by the success of deep learning in large-scale tasks, which in some cases rival or even surpass the human level (Mnih et al., 2015; Silver et al., 2017), some research is beginning to compare the efficiency of animal and machine algorithms (Lake et al., 2017). However, it is not clear which metric and set of inputs or tasks should be used in such comparisons. For example, current AI agents can learn to play Atari video games from scratch in just a few minutes and achieve higher scores than most humans. But it remains unclear how much of their success can be attributed to the data (e.g. amount and richness of learning experiences), the algorithm (e.g. learning and decision making rules), the computational resources (e.g. amount of memory), and even hardware (e.g. physical ability to respond fast and efficiently). To obtain conclusions about the efficiency of the algorithms used by machines and animals it is necessary to at least account for the distinct training and computational resources available to each of them.

Computational complexity theory is a branch of theoretical computer science which aims to compare the efficiency of algorithms, and that can offer us some insights (Arora & Barak, 2009). Here the main idea is to measure efficiency in terms of how an algorithm taxes on different resources when the complexity of a task increases. For example, time complexity studies how much time an algorithm takes to solve instances of a problem when the size of the input changes.

Following the analogy with complexity theory, we propose that a more meaningful comparison between machine and animal algorithms will require a systematic study of how the algorithms’ performance scales when taxing on different computational resources. Given the different availability to computational resources (time, memory, bandwidth, etc...) between machines and animals, and specially the vast array of prior information available to animals, this strategy will require to go beyond simply reporting the final performance and time needed to solve a task, but rather a series of tasks that parametrically change the demands on the available resources.

This type of analyses can give us a better understanding which modules from DL are likely to be critical in animal brains (modules exploiting similar computational resources)
and which are likely to be specific to artificial systems (modules exploiting very different computational resources). Thus, we believe that limiting artificial systems to possess similar computational resources (in amount and type) to those available by animals will help to constrain the emergent algorithms and representations to be closer to those used by brains. Also any comparison between AI and biological agents should be conducted in ethologically relevant tasks for the animals.

Deep learning as an end-to-end algorithmic framework: the importance of having one example

One of the crucial achievements that DL has made possible is to provide examples of end-to-end algorithms able to solve large-scale tasks at human level.

Operating at the algorithmic level rather than at the detailed implementation level has allowed researchers to train systems that learn to link distant processing domains. For example, it is now very common to train systems that link complex sensory input to decision making (including motor output) through many and varied processing stages (e.g. Mnih et al., 2015; Silver et al., 2017). The end-to-end character of the system and its training enforces a high level of coherence in the representations and algorithms used along the different stages of processing. We believe this adds a very important global constraint that is very difficult to address in models of isolated brain areas. In such studies of computational modelling the main objective has typically been to provide a good fit for the detailed neuronal dynamics, rather than their function within an overall goal.

In other words, building end-to-end systems that need to work in real-world tasks forces the different parts of the system to learn efficient representations that need to match between these different modules to achieve a complex goal. While the implementation level is absolutely necessary to address questions such as which aspects of neuronal dynamics and circuits could instantiate similar algorithms and representations, this is a complementary level of analysis that can be better pursued either jointly (Skorheim et al., 2014; Rao & Sejnowski, 2011; Florian, 2007; Neymotin et al., 2013; Izhikevich, 2007) or after having some educated guesses about the algorithmic level of the system. Just as an example of the latter, inspired by the beneficial role of some level of stochasticity in the weights of neural networks during training (which makes the network more robust towards perturbations) one could be prompted to search for the actual
origin and computational role of noise in neurons and synapses during learning, rather than trying to average them out as a mere nuisance.

Thus, having the example of a working algorithm (where one can open the representations and analyze them in detail), facilitates the task of identifying some efficient representations and necessary computational steps that the brain also needs to solve similar problems.

Summary and Conclusions

DL algorithms and brains share the capability to learn from experiences and they both use multilayer distributed representations for processing information. The connectionist nature of DL and its spectacular success in large-scale tasks offers a framework against which to contrast current computational theories of how the brain achieves its success in similar tasks.

Using DL to study visual object recognition has been a success story. Just a few years ago one could claim that nobody knows how biological visual recognition works, but now DL has provided a working model for at least some aspects of biological vision (VanRullen, 2017). DNNs offer a framework for understanding how one can go from pixels to meaningful object categorization. Furthermore, there is a good match between the representations learned in artificial and in biological vision systems. Hence, the DNNs have led to a better understanding of visual object recognition in the brain: they provide so far the best computational theory of biological vision (Kriegeskorte 2015, Yamins & Di Carlo, 2016). The success of DNNs in vision has generated a hope that DL could lead to similar progress in understanding higher cognitive functions. However, it is also possible that the case of vision is not typical: in vision there is abundant training data, good neuroscientific comparison data and a clear training objective. As a case example where it might be more complicated for DL to lead to an understanding of biological computations we considered the topic of mindreading. Mindreading “performance” does not obey a simple cost function, there is less neuroscientific data to compare to and there are no databases for training the AI agents. Nonetheless, this does not imply that AI cannot contribute to understanding the algorithms underlying mindreading in the brain. We foresee that if one includes the bias of being more sensitive to humans (and other agents) and endows the agents with other components (e.g. external memory), these agents will be more successful in mindreading tasks. Having AI agents that are closer to humans in mindreading will help us to understand how mindreading skills are learned in the human brain. Discovering which algorithmic
components are necessary for acquiring mindreading abilities will contribute to resolving many debates surrounding the cognitive and biological basis of mindreading (e.g. Siegal, 2008; Call & Tomasello, 2008; Apperly, 2010; Heyes & Frith, 2014; Scott & Baillargeon, 2017).

In this perspective we have focused on how certain similarities between biological and artificial neural networks can be exploited to gain understanding on how the brain might solve some computational problems. Obviously, these systems are also different in many important respects (Lake et al., 2016). Thus, it is essential to remark that we should not take DL architectures and their learning algorithms as the ultimate brain-like learning system, but simply as working examples that can guide our search for how the brain really works. So far DL remains our best source for working algorithms in large-scale tasks similar to those that animals have to solve. Given the difficulty in monitoring all the relevant variables in real brains and the inaccessibility to the brain's masterplans, the fact that we can open these artificial algorithms and analyze them in detail provides a source of inspiration that we can not afford to not explore.

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