Physical object representations for perception and cognition

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Abstract

Theories of perception typically assume that the goal of sensory processing is to output simple categorical labels or low-dimensional quantities, such as the identities and locations of objects in a scene. But humans perceive much more in a scene: We perceive rich and detailed three-dimensional (3D) shapes and surfaces, substance properties of objects (such as whether they are light or heavy, rigid or soft, solid or liquid), and relations between objects (such as which objects support, contain or are attached to other objects). These physical targets of perception support flexible and complex action, as the substrate of planning, reasoning, and problem solving. In this chapter we introduce and argue for a theory of how people perceive, learn, and reason about objects in our sensory environment in terms of what we call physical object representations (PORs). We review recent work showing how this account explains many human judgments in intuitive physics, provides a basis for object shape perception when traditional visual cues are not available, and, in one domain of high-level vision, suggests a new way to interpret multiple stages of hierarchical processing in the primate brain.

Introduction

The goal of this chapter is to introduce a computational framework for studying the form and content of physical object representations (PORs) in the mind and brain. By PORs, we mean the basic system of knowledge that supports perceiving, learning and reasoning about all the objects in our environment -- their shapes, appearances, affordances, substances, and the way they react to forces applied to them. PORs can be considered as an interface between perception and cognition, linking what we perceive to how we plan our actions and talk about the world. Despite their fundamental role in perception, many important questions about object representations remain open. What kind of information formats or data structures underlie PORs, so as to support the many ways in which humans flexibly and creatively interact with the world? How can properties of objects be inferred from sensory inputs, and how are they represented in neural circuits? How can these representations integrate sense data across vision, touch, and audition?

After introducing the computational ingredients of POR theory from a reverse-engineering perspective, we review recent work that is beginning to answer some of these questions. We focus on three case studies: (1) how PORs can explain human judgments in intuitive physics, across a broad range of physical outcome prediction scenarios; (2) how PORs provide a substrate for physically-mediated object shape perception in scenarios where traditional visual cues fail, and a natural substrate for
multimodal (visual-haptic) perception and crossmodal transfer; (3) how in one domain of high-level vision -- face perception -- PORs might be computed by neural circuits, and how thinking in terms of PORs suggests a new way to interpret multiple stages of processing in the primate brain.

**Physical object representations (PORs)**

How, in engineering terms, can we formalize PORs? There are two main aspects to our proposal. First is a working hypothesis about the contents of PORs. We draw on tools developed for video game engines (Gregory, 2014), including graphics (Blender Online Community, 2015) and physics engines (Coumans, 2010; Macklin, Müller, Chentanez, & Kim, 2014), and planning engines from robotics for grasping and other humanoid motions (Miller & Allen, 2004; Todorov, Erez, & Tassa 2012; Toussaint, 2015). These tools instantiate simplified but algorithmically tractable models of reality that capture our basic knowledge of how objects work, and how our bodies interact with them. In these systems, objects are described by just those attributes needed to simulate natural-looking scenes and motion over short time scales (~2 seconds): three-dimensional (3D) geometry, substance or mechanical material properties (e.g., rigidity), optical material properties (e.g., texture), and dynamical properties (e.g., mass). Video game engines provide causal models in the sense that the process by which the data (i.e., natural-looking scenes) are generated has some abstract level of resemblance to its corresponding real-world process, but in a form that is efficient enough to support real-time interactive simulation.

Second, we embed these simulation engines within probabilistic generative models. Physical properties of an object are not directly observable in the raw signals arriving at our sensory organs. These properties, including 3D shape, mass, or support relations, are latent variables that need to be inferred given sense inputs; they are products of perception. Probabilistic modeling provides the mathematical language to rigorously and unambiguously specify the domain and task being studied, and to explain how, given sensory inputs, latent properties and relations in the underlying physical scene can be reliably inferred, through some form of approximate Bayesian inference (see Kersten & Schrater, 2001 for an in-depth treatment of this perspective). The probabilistic models we build to capture PORs can be seen as a special case of “probabilistic programs”, or generalizations of directed graphical models (Bayesian networks) that define random variables and conditional probability distributions relating variables using more general data structures and algorithms than simply graphs and matrix algebra (see Ghahramani, 2015, or Goodman & Tenenbaum, 2016, for an introduction).
The POR framework is closely related to “analysis-by-synthesis” (AxS) accounts of perception: the notion that perception is fundamentally about inverting the causal process of image formation (Helmholtz and Southall, 1924; Rock, 1983). On this view, perceptual systems model the causal processes by which natural scenes are constructed, as well as the process by which images are formed from scenes; this is a mechanism for the hypothetical “synthesis” of natural images, in the style of computer graphics, by using a graphics engine. Perception (or “analysis”) is then the search for or inference to the best explanation (or plausible explanations) of an observed image in terms of this synthesis, which in the POR framework can be implemented using Bayesian inference.

Most mechanisms for approximating Bayesian inference that have traditionally been proposed in analysis by synthesis (e.g., Markov Chain Monte Carlo, or MCMC) seem implausible when considered as an algorithmic account of perception: They are inherently iterative and almost always far too slow relative to the dynamics of perception in the mind or brain. We draw on recent advances in machine learning and probabilistic programming (including deep neural networks, particle filters or sequential importance samplers, data-driven MCMC, approximate Bayesian computation, and hybrids of these methods) to construct efficient and neurally plausible approximate algorithms for the physical inference tasks specified with our probabilistic models.

While our focus in this chapter is perception, the domain of the POR framework is more general. With a causal model of the world (including its state-space structure i.e., object dynamics and interactions in a physics engine) and a planner based on a body model, the POR framework transforms the physical environment around us into something computable, naturally supporting many aspects of cognition including reasoning, imagery, and planning for locomotion and object manipulation, via simulation-based inference and control algorithms. In this sense, PORs express functionality somewhat analogous to the “emulators” of emulation theory (Grush, 2004), an earlier proposal for an integrated account of perception, imagery and motor planning which also fits broadly within a Bayesian approach to inference and control. A key difference is the language of representation for state, dynamics and observation. Emulation theory was formulated using classical ideas from estimation and control, such as the Kalman Filter: body and environment state are represented as vectors, dynamics are linear, and observations are linear functions of the state with Gaussian added noise. The computations supported are simpler but much less expressive than in the POR framework, where state is represented with structured object and scene descriptions, dynamics using physics engines, and observation models using graphics engines. PORs can thus explain how cognitive and perceptual processes operate over a much wider range of
physical scenarios, varying greatly in complexity and content, although they require more algorithmic machinery to do so.

**Intuitive physical reasoning**

![Figure 1](image.png)

**Figure 1.** (A, B). How would you pick up the apples indicated while maintaining a stable arrangement of the other objects? It is easy to see that you will likely need to touch more objects (and probably use two hands) in panel A, while the apple in panel B can be removed on its own, with just one hand. (C) An orangutan building a tower with large lego-like blocks. (D) A schematic of the POR framework applied to intuitive physical reasoning with a tower of wooden blocks. From left to right, the input image; inference to recover the 3D scene and physical properties of objects; physics engine simulation to predict near-future states given the inferred initial configuration; questions that can be answered and tasks that can be performed based on such simulations.

Having overviewed the basic components of PORs, we now turn to recent computational and behavioral work exploring their application in several domains. We begin with intuitive physics, in the context of scene understanding. When looking at a scene consisting of multiple objects, such as the stack of apples in Figure 1A, we immediately understand how these objects support each other. We can predict whether the stack would topple if the middle apple at the bottom row were removed, and plan how to pick the designated apple without making the rest unstable. We can also “see” that picking the apple in Figure 1B is much easier and can be achieved with just one action using just one hand (as opposed to the two hands or a more complex sequence...
of actions needed for the stack in Figure 1A). These abilities are likely shared across other species, particularly non-human primates (Figure 1C), and they can be used to think about many different kinds of physical scenarios: For instance, can you arrange a set of objects into a stable tower, using wooden blocks (Figure 1D) or Lego blocks (as in Figure 1C) or stones or bricks or cups or even apples?

The POR framework was first introduced to answer these kinds of questions, in a form similar to how we characterize it here, by Battaglia, Hamrick and Tenenbaum (2013). Battaglia et al. showed that approximate probabilistic inferences over simulations in a game-style physics engine could be used to perform many different tasks in blocks-world type scenes. While physics engines are designed to be deterministic, Battaglia et al. (2013) found that human judgments were best captured using a probabilistic model that combined the deterministic dynamics of the physics engine with probability distributions over the uncertain geometry of objects’ initial configurations and/or shapes, their physical attributes (e.g., their masses) and perhaps the nature of the forces at work (e.g., friction, or perturbations of the supporting surface).

In one version of this model (Figure 1D), input images comprised one or more static 2D views of a tower of blocks in 3D that might fall over under gravity, and the task was to make various judgements about what would or could happen in the near future. Object shapes and physical properties were assumed to be known, but the model had to estimate the 3D scene configuration for the blocks. This inference step used AxS with a top-down stochastic search-based (MCMC) procedure: Block positions in 3D are iteratively and randomly adjusted until the rendered (synthesized) 2D images approximately match the input images; multiple runs of this procedure yield slightly different outputs representing samples from an approximate Bayesian posterior distribution on scenes given images. Once these physical object representations are established, they support a wide range of dynamical inferences that go well beyond the purely static content in the perceptual input. How likely is the tower to fall? If it falls, how much of the tower will fall? In which direction will the blocks fall? How far will they fall? If the table supporting the tower were bumped, how many or which of the blocks would fall off the table? If the tower is unstable, what kind of applied force or other action could hold it stable?

To see how these judgments are computed, consider answering the questions “How likely is the tower to fall?” or “How much of this tower is likely to fall?”. The model runs a number of forward simulations using the physics engine (implemented by Battaglia et al. in Bullet, Coumans, 2010), starting from the sample of configurations returned by the probabilistic 3D scene inference procedure. These simulations run until all objects stop moving, or some short time limit has elapsed. The distribution of their outcomes
represents a sample of the Bayesian posterior predictive distribution on future states, conditioned on the input image and the model’s representation of physics. Predictive judgments such as those above can then be calculated by simply querying each sample and aggregating: e.g., the model's judgment of “how likely is the tower to fall?” is calculated as the average number of simulations in which the tower fell (relative to the total number of simulations ran); “how much of the tower is likely to fall?” is calculated by averaging the proportion of blocks that fell in each simulation.

Strikingly, Battaglia et al. (2013) found that only a few such posterior samples (they estimated typically 3-7 samples per participant, per trial), generated from the highly approximate simulations of video game physics engines under perceptual uncertainty, were sufficient to account for human judgments across a wide range of tasks with high quantitative accuracy. In the last several years, a growing number of behavioral and computational studies have developed approximate probabilistic simulation models of the PORs underlying our everyday physical reasoning abilities. Studies have examined intuitive judgments of mass from how towers do or don’t fall (Hamrick, Battaglia, Griffiths, and Tenenbaum 2016); predictions about future motions (Smith, Dechter, Tenenbaum and Vul, 2013a; Smith, Battaglia and Vul, 2013b) and judgments of multiple physical properties (e.g. friction as well as mass) and latent forces such as magnetism, from how objects move and collide in planar motion (Ullman, Stuhlmuller, Goodman and Tenenbaum, 2018; see also the seminal earlier work on probabilistic inference in collisions by Sanborn, Mansinghka, and Griffiths. 2013); and predictions about the behavior of liquids such as water and honey (Bates, Yildirim, Battaglia and Tenenbaum, 2015, submitted; Kubricht et al., 2016), and granular materials such as sand (Kubricht et al., 2017), falling under gravity. Taken together, these studies show how the POR framework provides a broadly applicable, quantitatively testable and functionally powerful computational substrate for everyday intuitive physical scene understanding.

How might PORs and their associated computations be implemented in neural hardware? As a first step towards addressing this question, a recent fMRI study in humans aimed to localize cortical regions involved in many of the intuitive physics judgments discussed above (Fischer, Mikhael, Tenenbaum, & Kanwisher, 2016). Fischer et al. found a network of parietal and premotor regions that was differentially activated for physical reasoning tasks in contrast to difficulty-matched non-physical tasks (such as color judgments, or social predictions) with the same or highly similar stimuli. These regions were consistent across multiple experiments controlling for different task demands and across different visual scenarios. A recent fMRI study in macaque monkeys found a similar brain network differentially recruited for analogous physical vs. non-physical stimulus contrasts, in a passive-viewing paradigm (Sliwa & Freiwald, 2017). These networks closely overlap with networks for action planning and
tool use in humans (see Gallivan & Culham, 2015 for a review) and the mirror neuron system in monkeys (Rizzolatti & Craighero, 2004), consistent with the proposal that PORs provide a bridge between perception and cognitive functions of action planning, reasoning and problem solving. Future experimental work using physiological recording, informed by some of the more neurally grounded models discussed later in this chapter, can now target neural populations in these brain networks in order to elucidate the neural circuits underlying intuitive physics.

Physics-mediated object shape perception

Figure 2. (A) Example pairs of unoccluded objects, and cloth-occluded matches in different poses. (B) An example trial from Yildirim, Siegel, & Tenenbaum (2016), where the task is to match the unoccluded object to one of the two occluded objects. (C) A schematic of the POR framework applied to the object-under-cloth task. From left to right, the input image; inference to recover the 3D shape of the unoccluded object and imagining a cloth positioned above it; physics engine simulation to predict dropping of
the cloth on the object shown at two different angles; and graphics to predict what the resulting scene would look like. (D) A multisensory causal model combining a graphics engine with a grasp planning engine. (E) Example novel objects from Yildirim and Jacobs (2013) rendered visually and photographed after 3D printing using plastic.

We now turn to the role of PORs in a more purely perceptual task: perceiving object shape. Vision scientists traditionally study many cues as routes to 3D shape, such as contours, shading, stereo disparity, or motion. But physics can also be an essential route to shape, especially when these traditional cues are unavailable. Consider seeing an object that is heavily or even entirely occluded, as when draped by a cloth (Figure 2A and 2B). It is likely you haven’t seen airplanes or bicycles occluded under a cloth before, but still it is relatively easy to pair an unoccluded object with its randomly rotated and occluded counterpart.

Most contemporary approaches to visual object perception emphasize learning to “untangle” or become invariant to sources of variation in the image (DiCarlo & Cox, 2007; Serre, Oliva, & Poggio, 2007). On this account, a processing hierarchy (such as a deep neural network) progressively transforms sensory inputs until reaching an encoding that is diagnostic for a particular object shape or identity, and invariant to other factors (Riesenhuber & Poggio, 1999). These approaches can perform very well when trained to ignore a given class of variations, but to achieve optimal performance, they must be trained anew (or at least “fine-tuned”) independently for every new kind of invariance. They do not show instantaneous (“zero-shot”) invariance for new ways an object might appear, such as those arising from an occluding cloth.

The POR framework provides a different approach, in which the goal is not learning invariances but explaining variation in the image with respect to the causal process generating images from 3D physical scenes (e.g., Mumford, 1997; Yuille & Kersten, 2006). For the object-under-cloth task, this process can be captured by composing (1) a physics engine simulating how cloth drapes over 3D rigid shapes, (2) a graphics engine simulating how images look from the resulting scenes (occluded or unoccluded), and (3) a probabilistic inference engine. The inference engine inverts the graphics process to recover 3D shapes from unoccluded 2D images, and then imagines likely 2D images under different ways these shapes could be rotated and draped under cloth (Figure 2C). Yildirim et al. (2016) presented preliminary evidence that such a mechanism fits human judgements in a match-to-sample task, akin to Figure 2B, across four difficulty levels. In contrast, a deep neural network trained for invariant object recognition, but not specifically for scenes involving cloth-based occlusion, could fit the easiest human judgments but failed to generalize above chance to the harder judgments. These results
illustrate a key advantage of the POR framework: the ability to generalize to novel settings not by requiring further training but by combining or composing existing causal models.

The POR framework supports combining causal models not only across multiple visual cues but also across sensory modalities. This is because the contents of PORs are not specific to vision or any single modality, but instead capture the physical properties of objects that are the root causes of sense data in every modality, via appropriate modality-specific “rendering” engines (such as a graphics engine in vision). Embedded in a framework for probabilistic inference to invert these renderers, PORs provide a basis for perceiving shape from any form of sense data, as well as for multisensory integration and cross-modal perception. Consider the POR-based model shown in Figure 2D: Starting from a probabilistic generative model over part-based body shapes in 3D, the multisensory causal model combines a visual graphics engine that generates the 2D appearance of each shape viewed in given pose with a touch or haptic rendering engine, based on a kinematic grasp planner, that generates the way a shape feels in the hand given a certain grasp trajectory. Bayesian inference then allows the model to estimate a 3D shape that explains inputs from either visual or haptic channels alone, or both, as well as to automatically and in a “zero-shot” manner transfer from objects first encountered in one modality (e.g., visually) to recognize how they would be perceived in another modality (e.g., haptically). Yildirim and Jacobs (2013) found that this model accounted for the performance of human participants in a visual-haptic crossmodal categorization task (example stimuli shown in Figure 2E). These results were extended to a visual-haptic shape similarity judgment task (Erdogan, Yildirim, & Jacobs, 2015).

The idea that shared neural representations support object perception across multiple sensory modalities is consistent with a number of fMRI studies (e.g., Amedi, Jacobson, Hendler, Malach, & Zohary 2002; James et al., 2002; Lacey, Tal, Amedi, & Sathian, 2009; Tal & Amedi, 2009; Lee Masson, Bulthé, Op de Beeck, & Wallraven, 2016). The POR framework provides explicit hypotheses as to what the format of such multisensory neural representations might be. Erdogan, Chen, Garcea, Mahon, & Jacobs (2016) used fMRI to test one such hypothesis introduced in their earlier computational work (Erdogan et al., 2015). In addition to finding that visual and haptic exploration of novel objects gave rise to similar patterns of BOLD activity in the lateral occipital cortex (LOC), they also found that this activity could be cross-modally decoded to the part-based 3D object structure mentioned above (Erdogan et al., 2015). Further experimental work along these lines, aiming to quantitatively test specific POR models and ideally extending into physiological recordings from neural populations, could lead to a more precise understanding of the neurocomputational basis of multisensory perception and crossmodal transfer.
Reverse-engineering ventral visual stream computations using PORs

Figure 3. (A) Samples from a modern 3D graphics model of a human face, yielding near photorealistic 2D images (NVIDIA & University of Southern California’s Institute for Creative Technologies). Across the three images of this face, in addition to knowing that identity is preserved, we can also appreciate the details of the face’s 3D shape and texture, the subtleties of expression, that vary or remain constant across images. (B) Despite their unfamiliarity, most observers can match the identity of the naturalistic face on the left to one of the textureless faces (“sculptures”), which must rely on a sense of 3D shape. (C) Schematic of the efficient AxS approach including a probabilistic generative model of face image formation (panel ii) and the recognition network (panel i). Layers f1 through f6 indicate the different components of the recognition network. Trapezoids show single or multiple transformations. Yildirim et al. (2018) found that transformations across the model layers f3, f4, and f5 closely captured the transformations observed in the neural data from ML/MF (middle lateral and middle
fundus areas) to AL (anterior lateral area) to AM (anterior medial area) (Freiwald & Tsao, 2010).

We now turn to discussing how the POR framework can illuminate aspects of the neural circuits underlying perception. Even though traditional AxS methods can recover PORs from sense inputs, these algorithms (based on top-down, iterated stochastic search) do not readily map onto neural computation. Many authors have thus preferred feedforward network models, most recently deep convolutional neural networks (CNNs), which are both more directly relatable to neural circuit-level mechanisms and more consistent with the fast bottom-up processing observed in perception. However, CNNs, typically trained for invariant object recognition or “untangling”, do not explicitly address the question of how vision recovers the causal structure of scene and image formation. Therefore, neither traditional approaches to AxS nor modern CNNs really answer the challenge: How do our brains compute rich descriptions of scenes with detailed 3D shapes and surface appearances, in much less than a second?

A new class of computational models aim to combine the best aspects of these two approaches, by using CNNs or recurrent networks to map images to their underlying scene descriptions, thereby accomplishing otherwise computationally costly inference in one or a few bottom-up passes on the image (Eslami et al., 2018; Kulkarni, Kohli, Tenenbaum, & Mansinghka, 2015; George et al., 2017, Yildirim, Kulkarni, Freiwald, & Tenenbaum 2015). Yildirim, Freiwald and Tenenbaum (2018) developed one such approach using the POR framework and tested it as a computational theory of multiple stages of processing in the ventral visual stream, a hierarchy of processing stages in the visual brain (Conway, 2018). This model consists of two parts: A generative model based on a multistage 3D graphics program for image synthesis (Figure 3C), and a recognition model based on a CNN that approximately inverts the generative model, stage by stage (Figure 3C). The recognition network is different from conventional CNNs for vision in two ways. First, it is trained to produce the inputs to a graphics engine, the latent or unobservable variables of the probabilistic model, instead of predicting class labels such as face identities. And second, it is trained in a self-supervised fashion, with inputs and targets internally synthesized by the probabilistic graphics component; no externally generated labels are needed. This approach differs from other recent efficient AxS approaches (Eslami et al., 2018; Kulkarni et al., 2015) and their earlier counterparts (Dayan, Hinton, Neal, & Zemel, 1995) in that it is based on a probabilistic graphics engine (instead of a generic function approximator) and therefore more closely captures the causal structure of how 3D scenes give rise to images.
Yildirim et al. (2018) tested their approach in one domain of high-level perception, the perception of faces. Faces give rise to a rich sense of 3D shape in addition to percepts of a discrete individual's identity (see Figures 3A, 3B), and face perception has been extensively studied in both psychology and neurophysiology, thus providing a rich source of data and constraints for modeling. The sense of a face’s 3D shape also crosses between visual and haptic modes of perception (Dopjans, Wallraven, & Bulthoff, 2009), as in the examples discussed above.

Yildirim et al. compared two broad classes of hypotheses for how we perceive the 3D shape of a face, and how these computations are implemented in the primate ventral stream: (1) the efficient AxS hypothesis implemented in their recognition network, which posits that the targets of ventral stream processing are latent variables in a probabilistic causal model of image formation, and (2) the “untangling” hypothesis implemented in standard deep CNNs for face recognition, which posit that the target of ventral stream processing is an embedding space optimized for discriminating among facial identities. Their recognition network implementing the AxS hypothesis recapitulated transformations across multiple stages of processing in IT cortex from ML/MF to AL to AM -- the three sites in the monkey face patch system -- with respect to the similarity structure of the population-level activity in each stage (Freiwald & Tsao, 2010). Alternative models, including a number implementing the “untangling” hypothesis, did not capture these transformations. The efficient AxB model also accurately matched human error patterns in psychophysical experiments, including experiments designed to determine how flexibly humans can attend to either the shape or texture components of a face stimulus (Figure 3B). Finally, the recognition model suggested an interpretable account of some intermediate representations in this hierarchy: in particular that middle face patches (ML/MF) can be interpreted as computing intermediate surface representations, such as intrinsic images (normal maps or depth maps for surface geometry and albedos for surface color) or a 2.5D sketch.

The efficient AxS approach thus offers a potential resolution to the issue of interpretability in systems neuroscience (Yamins and DiCarlo, 2016). In addition to assessing accounts of the brain in terms of how much variance in neural firing rates they explain, the efficient AxS approach suggests that computational neuroscientists could aim for at least “semi-interpretable” models of perception, where populations of neurons in some stages (such as ML/MF and AM) can be understood as stages in inverting a causal generative model, even while other populations of neurons (such as AL) might be better explained as implementing valuable hidden-layer non-linear transforms between more interpretable parts of the system.

**Conclusion and future directions**
We believe that there is promising, if preliminary, evidence for the centrality of PORs in the mind and brain. The strongest aspect of this proposal so far is theoretical: PORs offer a solution to problems both old (e.g. multimodal perception) and new (e.g. the cloth draping task presented above), which are difficult to explain with alternative accounts in either cognitive neuroscience or AI. There remain, however, significant challenges. Empirical work has only begun to test strong predictions of the POR framework; far more behavioral and physiological data are needed. As we have noted, PORs provide a rich foundation for structuring perception and behavior, but this comes with a heavy computational burden. The efficient AxS approach is one possible way that the brain might handle this complexity, but again more study is needed, especially relating dynamics of processing in these models to dynamics of neural computation.

The POR framework also offers new research directions for studying aspects of complex behavior production and object manipulation. An important advantage of the POR framework is that having causal models of the world allows for flexible action planning, reasoning, and intelligent object manipulation. To illustrate, we revisit the grasping engine shown in Figure 2D in its broader context. This grasping engine implements a planner based on a simulatable body model (similar to forward models typically invoked in models of motor control, Jordan & Rumelhart, 1992; Wolpert & Flanagan, 2009; Wolpert & Kawato, 1998). Such a model allows embodied agents to evaluate the consequences of its actions by simulating them internally before (or without ever) actually performing them. Many organisms likely use this approach, e.g., performing simulations for making a judgment about the action “Can I jump?”. Brecht (2017) suggested that the microcircuits in the mammal somatosensory cortex implement a simulatable body model that can be used for action planning and decision making. The POR framework provides a toolset to capture these computations in engineering terms using existing simulation engines (e.g., see Yildirim, Gerstenberg, Saeed, Toussaint, & Tenenbaum, 2017 for a proof-of-concept implementation in the context of complex object manipulation).

Perhaps the most important open question is also the most challenging: How could simulations with richly structured generative models, such as graphics engines, physics engines, and body models, be implemented in neural mechanisms? Recent developments in machine learning and perception suggest intriguing possibilities, based on deep learning systems that are trained to emulate a structured generative in an artificial neural network architecture. Deep networks that emulate graphics engine were mentioned above; while they do not yet come close to the full functionality of traditional graphics engines, their performance in narrow domains can be surprisingly impressive and continues to improve. In intuitive physics, hybrids of discrete symbolic
and distributed representations, such as neural physics engines (Chang, Ullman, Torralba, & Tenenbaum, 2016), interaction networks (Battaglia, Pascanu, Lai, & Rezende, 2016) and other graph networks (Battaglia et al., 2018), and hierarchical relation networks (Mrowca et al. 2018), have received much attention lately. These systems assume discrete symbolic representations for each object and its relations with other objects, and vectorial representations for the rules of physical interactions between objects; this allows the dynamics of object motion and interaction (e.g., collisions) to be learned efficiently end-to-end from simulated data. Artificial neural networks such as these can be considered partial hypotheses for how graphics and physics might be implemented in biological neural circuits; they are almost surely wrong or at best incomplete, but they suggest a way forward. Further work is needed to test these models empirically, and to develop their capacities; currently they are very limited in the scope of physics they can learn (e.g., a limited class of rigid body interactions, such as billiard balls colliding on a table). Nevertheless, with these advances, and building on the example of the efficient AxS approach and other research linking artificial neural networks to neural representations in the brain, we see promise in linking the POR framework to neural computation in perception, and well beyond.

References


