65 Naive Physics: Building a Mental Model of How the World Behaves

JASON FISCHER

ABSTRACT To navigate and interact with the world, we must have an intuitive grasp of its physical structure and dynamics. Where should I push to open this door? Can I place this box on top of the others, or will the stack be unstable? Although the natural laws governing physical behavior can be challenging to comprehend in a mathematical sense, we implicitly employ approximate physical models in everyday life to predict objects' physical behaviors and adjust our actions accordingly. Our commonsense understanding of how the world will behave—termed *naive physics*—emerges early in life and is expanded and refined by experience throughout our development and into adulthood. We draw on naive physics in nearly all aspects of everyday life, and doing so often feels effortless and automatic. We "see" that a piece of furniture is too heavy to lift or that a surface is too slippery to walk on safely. Just how accurate are our physical intuitions? Do we carry out rich mental simulations of physical dynamics, or do we rely on heuristics that are effective in many scenarios but could break down in others? What brain machinery supports naive physics? This chapter explores these questions from the vantage points of behavioral and neuroimaging research.

The Development of Physical Cognition in Infancy

Contrary to the once popular Piagetian notion that young infants understand little about the physical structure of the world, research over the past several decades has demonstrated that even in the first months of life, infants have basic expectations about how objects will behave. At just 2.5 months old, infants are surprised when an object seems to jump from one location to another without traversing the space in between, or when one object seems to pass through another. What are the building blocks of these early-emerging physical intuitions? Spelke and colleagues (Spelke, Breinlinger, Macomber, & Jacobson, 1992; Spelke & Kinzler, 2007) argue that we are born with an innate knowledge of some basic principles governing object motion, and this knowledge provides the mental scaffolding for learning more sophisticated physical concepts over the course of development. They propose that the core system of object representation comprises three principles: cohesion (objects move as connected, bounded units), continuity (an object moves along one connected path over space and time), and contact (objects must touch in order to influence each other's motion). Even very young infants apply these principles to individuate objects and predict their motion but initially fail to properly apply other physical principles, such as gravitational and inertial constraints. The emergence of these latter principles appears to hinge on experience—as children learn how particular objects behave in particular circumstances, they acquire piecemeal knowledge that builds upon the core principles. Over the first years of life, children's intuitions regarding gravity and inertia become steadily more adult-like but remain inconsistent across scenarios (Kaiser, Proffitt, & McCloskey, 1985). Likewise, children's sensitivity to the features that discriminate objects (e.g., shape, size, or color) relies on experience with specific events. Young infants fail to make use of such cues to individuate objects (Xu & Carey, 1996), and as infants learn about the attributes relevant for predicting an object's behavior, they often do so in an event-specific fashion that fails to transfer to new scenarios (Wang, Baillargeon, & Paterson, 2005). By contrast, infants rarely display misconceptions about cohesion, continuity, and contact—these principles form the stable core of our physical knowledge that endures throughout development and into adulthood.

How is children's physical knowledge expanded and refined over the course of development? Baillargeon and colleagues have proposed that children's physical representations are enriched through rule learning via explanation-based processes (Baillargeon, 2002; Wang, Zhang, & Baillargeon, 2016). Infants must first notice that two events for which they have similar models have contrastive outcomes that cannot be predicted based on current knowledge. They then search for the conditions that lead to each outcome, engaging in hypothesis-testing behaviors with objects that violated their expectations (Stahl & Feigenson, 2015). Finally, infants attempt to generate an explanation to be incorporated as a new variable that differentiates the outcomes of the two events. This framework supports the learning of event categories (e.g., occlusion, support, collision, and containment) and the relevant variables for interpreting those events (e.g., the shapes and sizes of objects and the spatial relationships between them). Because the same variable can be learned separately and at different times for different events, knowledge about a given variable does not always transfer across event categories. For example, 9-month-old infants attend to the height of an object placed in a container (and are surprised when a tall object fits completely in a short container) but not the height of an object placed in a tube, even when the containment and tube events are visually identical (Wang, Baillargeon, & Paterson, 2005). Hence, most 9-month-olds have not yet identified height as a relevant variable in tube events, even though they have done so for containment events (perhaps because of more experience with containers). After further revision based on experience, infants' rules become sufficiently abstract to unify variables learned under different conditions.

Even before the 1-year mark, infants acquire a broad and diverse catalog of physical knowledge in a systematic fashion. For example, infants incrementally learn increasingly sophisticated notions of support. As early as 3 months old, infants demonstrate an understanding that two objects must be in contact for one to support the other. Infants then come to understand that the spatial arrangement of the objects matters (the supported object must be on top), and ultimately, at about 12 months old, they understand roughly where an object's center of mass must be located relative to a supporting surface in order to be stable (Baillargeon, 1998). Between 5 and 7 months, infants also begin to display expectations about how falling objects will accelerate, and they become sensitive to the causal roles of one object striking and launching another. And infants' learning is not limited to rigid body interactions. By 5 months old, most infants are able to differentiate a liquid from a solid on the basis of movement cues and cohesiveness (Hespos, Ferry, Anderson, Hollenbeck, & Rips, 2016) and have expectations for how nonsolid substances will accumulate when poured (Anderson, Hespos, & Rips, 2018). By about 11 months old, infants can infer the weight of an object based on how much it compresses a soft material (Hauf, Paulus, & Baillargeon, 2012).

The above examples point to a systematic acquisition of physical knowledge during the first years of life, built around a stable core of object-motion principles. Just how sophisticated do our physical inference abilities become in adulthood? Do we ultimately rely on a catalog of situation-specific physical knowledge, or can we employ more generalized processes to predict physical dynamics across a range of scenarios? And what brain machinery supports naive physics? The remainder of this chapter explores these questions.

Physical Inference Abilities in Adults

In adulthood, the apparent effortlessness with which we predict and reason about object dynamics in daily life belies some striking misconceptions about physical behavior that are revealed upon closer inspection. A classic example comes from McCloskey, Caramazza, and Green (1980), where college students were asked to draw the trajectory of a ball as it exited a curved tube. Many participants drew a curved path, indicating curvilinear motion even in the absence of any external forces. Similarly, many participants indicated that a ball being twirled at the end of a string would follow a curved path when the string was cut. These findings show that people's predictions can be starkly at odds with the physical behaviors they see in the world every day (and in fact, people perceive straight paths to be more natural looking than curved ones when viewing, rather than diagramming, the outcomes of the same scenarios (Kaiser, Proffitt, & Anderson, 1985). In a number of other scenarios, such as when a ball is released from a pendulum (Caramazza, McCloskey, & Green, 1981) or dropped by someone who is walking (McCloskey, Washburn, & Felch, 1983), people draw trajectories that are inconsistent with Newtonian dynamics. People also tend to make systematic errors when predicting how a liquid will be oriented within a tilted container (Vasta & Liben, 1996) or when indicating which of two objects is heavier after observing a collision between them (Gilden & Proffitt, 1989; Todd & Warren, 1982). While this is a surprising pattern of errors to observe in adults, it is consistent with the notion that physical knowledge is acquired in an event-specific fashion. Just as with infants, adults rarely hold misconceptions about the principles of cohesion, continuity, and contact, but judgments of object motion that incorporate gravity and inertia can be highly idiosyncratic. For example, while people tend to make errors regarding the path that a ball will take as it exits a curved tube, they are much more accurate at indicating how water will exit the same tube (Kaiser, Jonides, & Alexander, 1986), perhaps as a result of more experience with the latter scenario. These errors seem to suggest that even in adulthood, we are unable to integrate our learning about various physical scenarios into a unified model of object behavior. Instead, people might construct ad hoc theories of physical behaviors on the fly (Cook & Breedin, 1994) or rely on an incorrect, non-Newtonian model of physics (Clement, 1982; McCloskey, Caramazza, & Green, 1980).

78951_11442_ch04_1P.indd 780 8/2/19 6:23 PM

A puzzle remains, though: How are we able to interact so effectively with our everyday environments if our physical predictions draw on idiosyncratic and sometimes incorrect conceptions about object behavior? Recent studies that have tested how people interact with moving objects shed some light on this matter. Using displays like those in Caramazza, McCloskey, and Green (1981), Smith, Battaglia, and Vul (2013) asked people to predict the path a ball would take after it was clipped from a swinging pendulum. Participants' predictions were tested in three ways: (1) drawing the path of the ball, (2) positioning a bin to catch the ball after it was released, and (3) cutting the ball free at the appropriate time so that it would land at a specified location. Results from the first task replicated previous findings that people often make idiosyncratic errors when drawing the path of the ball. However, performance on the latter two tasks revealed a different pattern of errors—participants' biases were less idiosyncratic and more consistent with a correct application of Newtonian mechanics. Other work has shown that in a variety of scenarios, people can be highly accurate and precise when executing actions on falling objects (Zago & Lacquaniti, 2005). People also perform better at judging how a liquid will behave in a container when asked to imagine the action of tilting the container rather than just giving a verbal description (Schwartz & Black, 1999). It may be the case, then, that the implicit physical inferences that support action tap into knowledge separate from that which we use to explicitly describe or diagram the workings of physical systems. When trying to catch the ball cut from the pendulum, people may place the bin in the correct position even without an explicit understanding of why the ball should end up there. Other studies using three-dimensional computer-generated stimuli or videos of object interactions have also found more accurate physical inferences than similar studies that used two-dimensional or schematic stimuli (Flynn, 1994; Hamrick, Battaglia, Griffiths, & Tenenbaum, 2016). The availability of naturalistic cues to the geometry and material properties of objects may be another factor that promotes access to implicit (and more consistently Newtonian) physical knowledge. The errors that people make when explaining the workings of physics nonetheless remain intriguing (Why would implicit and explicit physical predictions draw on distinct knowledge?), but they do not reflect a limit on our ability to make accurate predictions in the real-life scenarios where we use physical inferences to guide behavior.

If we can make accurate, approximately Newtonian physical predictions in at least some circumstances, what mental functions support this ability? One proposal is that we possess a mental "intuitive physics engine" that carries out simulations of physical dynamics (Battaglia, Hamrick, & Tenenbaum, 2013; Ullman, Spelke, Battaglia, & Tenenbaum, 2017). Here, *mental simulation* refers to playing physical dynamics forward in time as a video game physics engine would. Based on an initial scene configuration (e.g., scene layout, object geometry, material properties, and velocities), a mental simulation would step forward through successive states of the scene as physical interactions play out. Such a simulation would likely operate under a number of simplifying assumptions to make efficient simulation tractable, just as video game physics engines do. For example, collision detection may be based on simplified information about an object's three-dimensional shape (e.g., its convex hull) rather than fine-scaled geometry, and objects may only be actively simulated when in motion (akin to "sleep" and "wake" states in a video game physics engine). The end state of a simulation could answer questions such as "Where will the ball land?," and simulating a scenario multiple times over a range of initial parameters could answer questions such as "How should I roll this ball so it will end up in the desired location?" Importantly, this conception of mental simulation does not in itself implicate any particular brain areas or timescales (simulation need not progress in real time) and does not imply that simulation outcomes are always accurate or free of bias. Indeed, recent work has shown that in a number of scenarios both the successes and failures in human judgments are modeled well by probabilistic physics simulations that make similar patterns of errors (Bates, Battaglia, Yildirim, & Tenenbaum, 2015; Battaglia, Hamrick, & Tenenbaum, 2013). Hegarty (2004) has also argued in favor of a mental simulation account of physical inference based on tasks in which participants reason about multicomponent physical systems (e.g., a rope connected to a weight, threaded through a number of pulleys). Participants are slower to make judgments about components that are farther from the beginning of the causal chain, which suggests they step sequentially through the system to determine its behavior rather than simultaneously evaluating the components as a whole.

While probabilistic physics simulations provide good models of human performance under many conditions, there is ample reason to question whether mental simulation is the sole or primary means by which we form physical predictions in many everyday situations. Davis and Marcus (2016) point out that there are many scenarios in which physical outcomes are difficult or inefficient to infer through simulation but are trivial to infer from a rule-based standpoint. For example, to know whether water will spill out of a canteen, it is sufficient simply to know whether the canteen is open or closed. Mental simulation of the water's motion within

78951_11442_ch04_1P.indd 781 8/2/19 6:23 PM

the canteen would be impractical, and there is no need for the level of detail that a simulation would provide. In scenarios like these, commonsense physical reasoning may be achieved through knowledge-based analysis that relies on a large number of rules, rather than mental simulation (Davis, Marcus, & Frazier-Logue, 2017). Ultimately, it is likely that we draw on some combination of qualitative reasoning and dynamic simulation to form physical predictions. The conditions under which each is used, and the limits of each in terms of precision, processing speed, and adaptability to novel scenarios, will be important to flesh out in future research. Regardless of exactly how precise our naive physics system is or what algorithms it is built on, there is no doubt we possess some fundamental physical knowledge that allows us to survive and engage with the world. This raises the question of what neural machinery underlies our physical-reasoning abilities.

A Physics Engine in the Brain

Research to identify and characterize the brain regions that support naive physics is in the early stages, but emerging evidence points to a set of regions in the frontal and parietal cortex. A recent functional magnetic resonance imaging (fMRI) study (Fischer, Mikhael, Tenenbaum, & Kanwisher, 2016) contrasted brain activity from tasks that required physical inference (predicting the direction that an unstable tower of blocks would fall or predicting the trajectory of a bouncing billiard ball) with tasks that did not require physical inference but were otherwise matched on a host of factors. This study revealed a set of brain regions that are reliably engaged when people observe and predict the unfolding of physical events: bilateral frontal regions (dorsal premotor cortex, or PMd, and the supplementary motor area, or SMA), bilateral anterior parietal regions (postcentral sulcus, or PoCS) and the anterior intraparietal sulcus (aIPS), and the left supramarginal gyrus (SMG). Neuroimaging studies using textbook-style tasks have implicated similar regions in more explicit, abstract physical reasoning. A study in which subjects were asked to solve mechanical-reasoning puzzles found that a similar frontoparietal network of regions was engaged (Jack et al., 2013), and another study on the representation of abstract physics concepts (e.g., gravity, potential energy, and wavelength) found information related to these concepts in premotor and anterior parietal areas, among others (Mason & Just, 2016). Thus, although the behavioral work discussed above has established important distinctions between explanation-based physical problem-solving and the implicit physical inferences that we carry out in daily life, these two facets of physical cognition may draw on some common brain machinery.

The brain regions recruited for physical inference appear to largely overlap with those commonly implicated in action planning and tool use (Gallivan & Culham, 2015). This raises the possibility of a close relationship between action planning and naive physics, and neuropsychological findings from patients with apraxia reinforce this notion. *Apraxia* refers to a pattern of impairments following brain damage that affect the ability to perform meaningful gestures and execute the appropriate actions for particular tools. While apraxia has often been framed as a motor condition, there is evidence that the core impairments in apraxia are in mechanical reasoning and action planning, rather than motor execution per se. When patients with apraxia are presented with novel tools, they show difficulties not only in executing appropriate actions with the tools but also in selecting the appropriate tool for a task based on its geometry (Goldenberg & Hagmann, 1998). The latter task requires mechanical reasoning but not fine-scaled motor execution. Lesions that result in impaired mechanical reasoning in apraxic patients fall in the same frontal and parietal regions as those implicated in physical reasoning in healthy participants (Goldenberg & Spatt, 2009).

The precise degree to which physical inference and action planning engage a common set of brain regions remains to be established by studies that measure both simultaneously. But to the degree that the two functions recruit common brain resources, why might the cortical systems for physical prediction and action planning be closely linked? Perhaps the most fundamental reason is that action planning inherently requires physical prediction. In order to plan appropriate actions, we must have a mental model of how objects will behave when we interact with them, taking into account physical variables such as the objects' shapes, sizes, and material properties. Indeed, there is evidence that many such variables are encoded within the frontal and parietal regions described above. Premotor cortex encodes object mass, both when preparing to lift an object (Gallivan, Cant, Goodale, & Flanagan, 2014) and when observing object interactions in the absence of any intention to perform an action (Schwettmann, Fischer, Tenenbaum, & Kanwisher, 2018). The aIPS encodes visual and somatosensory information about object shape, size, and orientation (Murata, Gallese, Luppino, Kaseda, & Sakata, 2000; Sakata, Taira, Murata, & Mine, 1995). The PMd, the SMA, and the anterior parietal cortex also show tuning to the gravitational

78951_11442_ch04_1P.indd 782 8/2/19 6:23 PM

constant, responding most strongly when viewing a falling object that accelerates at a rate consistent with natural gravity (Indovina et al., 2005). These variables that are crucial for anticipating objects' behaviors when preparing actions are the same as those we draw on for physical prediction more broadly.

As a result of the interdependence between action planning and physical inference, the two may share cortical machinery in a manner analogous to the relationship between the spatial attention and eye movement systems (Corbetta et al., 1998). Just as covert attention can be deployed off-line from the actual execution of saccades, predictive models in the action-planning system may run off-line from motor execution to simulate the outcomes of physical interactions (Schubotz, 2007). It is critical to note the distinction between this idea and motor simulation theories of perceptual and conceptual processing. Motor simulation theories hold that in a variety of domains, such as object recognition, language processing, and action understanding, covert engagement of the motor system—imaging oneself acting—is required in order to perceive and interpret information in those domains. Theories of this sort have been refuted by empirical evidence showing that disruptions of the motor system do not reliably lead to impairments in perceptual or conceptual processing (Mahon & Caramazza, 2008; Vannuscorps & Caramazza, 2016). The account of physical reasoning presented here does not invoke the notion of imagining one's own actions as a means of understanding physical behavior. The idea is simply that the same physical prediction mechanisms that support action planning may be called upon to subserve physical reasoning more broadly. For example, imagine picking up a bag of tortilla chips and a jar of salsa while grocery shopping. Without much thought, you use a soft grip to handle the chips—any more pressure would crush them—but a firm grip to pick up the salsa so the heavy jar won't slip out of your hand. The same physical inference mechanisms that informed these nuanced actions could alert you to the likelihood of the chips being crushed when you see the checkout attendant pack the salsa on top of the chip bag. Thus, the limits of motor execution need not constrain the kinds of physical behaviors that can be predicted using resources shared with the action-planning system. Interactions between objects that are out of reach may still be understood using the same predictive models that would be applied if the objects were targets of action. A possible reinterpretation of the *mirror neuron* responses implicated in motor simulation is that they reflect predictions regarding the physical outcomes of observed behaviors.

Ventral Stream Contributions to Naive Physics

While the work discussed above implicates dorsal cortical regions in carrying out physical predictions, the ventral temporal cortex may play a complementary role, computing the object and scene attributes that form the basis for such predictions. In both humans (Cant & Goodale, 2011; Hiramatsu, Goda, & Komatsu, 2011) and monkeys (Goda, Tachibana, Okazawa, & Komatsu, 2014), information about objects' material properties is encoded in the ventral visual pathway. While early visual cortex encodes image-level details that serve as cues to objects' materials, higher-order areas (the posterior inferior temporal (IT) cortex in monkeys; the posterior collateral sulcus/fusiform gyrus in humans) represent more abstract information about dimensions, such as hardness, roughness, and elasticity. The same higher-order ventral regions encode object weight when it can be inferred from surface-texture cues (Gallivan et al., 2014). These material representations can be modified by visuohaptic experience (Goda, Yokoi, Tachibana, Minamimoto, & Komatsu, 2016) and thus may carry supramodal information about objects' material properties to support functions like physical prediction and action planning. Ventral representations of scene elements may also factor importantly into physical prediction—for example, by signaling the orientation of gravity. Humans use visual information (in addition to vestibular input) to infer the direction of gravity (Dichgans, Held, Young, & Brandt, 1972), and Vaziri and Connor (2016) have found that individual neurons in macaque anterior IT cortex are tuned to gravity-aligned scene elements, which may help establish a gravitational reference frame in which to carry out physical predictions.

It remains to be seen whether the object and scene information carried in the ventral visual stream contributes directly to the implicit physical predictions that guide our behavior in everyday life. While a variety of information from the ventral stream would, in principle, be useful for physical prediction, such information may also be present in a more flexible and rapidly accessible format in the dorsal stream (Jeong & Xu, 2017; Vaziri-Pashkam & Xu, 2017). In particular, object representations in posterior parietal cortex that support visually guided action may support physical prediction as well. If these object representations existed solely for the sake of guiding motor behaviors, one might expect them to maintain strict viewpoint specificity (Craighero, Fadiga, Umiltà, & Rizzolatti, 1996) since different object orientations require different actions (James, Humphrey, Gati, Menon, & Goodale, 2002). Instead, these dorsal object representations contain viewpoint-invariant information (Jeong & Xu, 2016; Konen & Kastner, 2008), suggesting they could support a broader range of abilities, such as tracking the stable properties of objects as they move and interact.

Conclusions

Over the past several decades, a flurry of research has led to major strides in understanding the computational and neural basis of our naive physics abilities. Still, many key questions remain. Beyond allowing us to predict the behavior of objects and plan actions accordingly, how do our physical intuitions shape the way we interpret and engage with the world? Research in computer vision has suggested that naive physics may have a pervasive role even at the earliest stages of visual processing, helping to segment the surfaces and objects in a scene (Zheng, Zhao, Joey, Ikeuchi, & Zhu, 2013). How does our naive physics system interact with other aspects of cognition? Recent work has shown that physical cognition is dissociable from social cognition (Kamps et al., 2017), and the two may even be in a mutually inhibitory relationship, limiting our ability to use both in conjunction (Jack et al., 2013). Addressing these broader questions will be key to understanding how our physical intuitions shape our everyday experience.

REFERENCES

Anderson, E. M., Hespos, S. J., & Rips, L. J. (2018). Five-month-old infants have expectations for the accumulation of nonsolid substances. *Cognition, 175*, 1–10.

Baillargeon, R. (1998). Infants' understanding of the physical world. In M. Sabourin, F. Craik, & M. Robert (Eds.), *Advances in psychological science: Biological and cognitive aspects* (Vol. 2, pp. 503–529). Hove, UK: Psychology Press/Erlbaum.

Baillargeon, R. (2002). The acquisition of physical knowledge in infancy: A summary in eight lessons. In U. Goswami (Ed.), *Blackwell handbook of childhood cognitive development* (Vol. 1, 46–83). Oxford, UK: Blackwell.

Bates, C., Yildirim, I., Tenenbaum, J. B., & Battaglia, P. (2015). Humans predict liquid dynamics using probabilistic simulation. In Dale, R., Jennings, C., Maglio, P., Matlock, T., Noelle, D., Warlaumont, A., & Yoshimi, J. (Eds.), *Proceedings of the 37th Annual Conference of the Cognitive Science Society* (pp. 172–178). Austin, TX: Cognitive Science Society.

Battaglia, P. W., Hamrick, J. B., & Tenenbaum, J. B. (2013). Simulation as an engine of physical scene understanding. *Proceedings of the National Academy of Sciences, 110*(45), 18327–18332.

Cant, J. S., & Goodale, M. A. (2011). Scratching beneath the surface: New insights into the functional properties of the lateral occipital area and parahippocampal place area. *Journal of Neuroscience, 31*(22), 8248–8258.

Caramazza, A., McCloskey, M., & Green, B. (1981). Naive beliefs in "sophisticated" subjects: Misconceptions about trajectories of objects. *Cognition, 9*(2), 117–123.

Clement, J. (1982). Students' preconceptions in introductory mechanics. *American Journal of Physics, 50*(1), 66–71.

Cook, N. J., & Breedin, S. D. (1994). Constructing naive theories of motion on the fly. *Memory & Cognition, 22*(4), 474–493.

Corbetta, M., Akbudak, E., Conturo, T. E., Snyder, A. Z., Ollinger, J. M., Drury, H. A., et al. (1998). A common network of functional areas for attention and eye movements. *Neuron, 21*(4), 761–773.

Craighero, L., Fadiga, L., Umiltà, C. A., & Rizzolatti, G. (1996). Evidence for visuomotor priming effect. *Neuroreport, 8*(1), 347–349.

Davis, E., & Marcus, G. (2016). The scope and limits of simulation in automated reasoning. *Artificial Intelligence, 233*, 60–72.

Davis, E., Marcus, G., & Frazier-Logue, N. (2017). Commonsense reasoning about containers using radically incomplete information. *Artificial Intelligence, 248*, 46–84.

Dichgans, J., Held, R., Young, L. R., & Brandt, T. (1972). Moving visual scenes influence the apparent direction of gravity. *Science, 178*(4066), 1217–1219.

Fischer, J., Mikhael, J. G., Tenenbaum, J. B., & Kanwisher, N. (2016). Functional neuroanatomy of intuitive physical inference. *Proceedings of the National Academy of Sciences, 113*(34), E5072–E5081.

Flynn, S. B. (1994). The perception of relative mass in physical collisions. *Ecological Psychology, 6*(3), 185–204.

Gallivan, J. P., Cant, J. S., Goodale, M. A., & Flanagan, J. R. (2014). Representation of object weight in human ventral visual cortex. *Current Biology, 24*(16), 1866–1873.

Gallivan, J. P., & Culham, J. C. (2015). Neural coding within human brain areas involved in actions. *Current Opinion in Neurobiology, 33*, 141–149.

Gilden, D. L., & Proffitt, D. R. (1989). Understanding collision dynamics. *Journal of Experimental Psychology: Human Perception and Performance, 15*(2), 372–383.

Goda, N., Tachibana, A., Okazawa, G., & Komatsu, H. (2014). Representation of the material properties of objects in the visual cortex of nonhuman primates. *Journal of Neuroscience, 34*(7), 2660–2673.

Goda, N., Yokoi, I., Tachibana, A., Minamimoto, T., & Komatsu, H. (2016). Crossmodal association of visual and haptic material properties of objects in the monkey ventral visual cortex. *Current Biology, 26*(7), 928–934.

Goldenberg, G., & Hagmann, S. (1998). Tool use and mechanical problem solving in apraxia. *Neuropsychologia, 36*(7), 581–589.

Goldenberg, G., & Spatt, J. (2009). The neural basis of tool use. *Brain, 132*(Pt. 6), 1645–1655.

Hamrick, J. B., Battaglia, P. W., Griffiths, T. L., & Tenenbaum, J. B. (2016). Inferring mass in complex scenes by mental simulation. *Cognition, 157*, 61–76.

Hauf, P., Paulus, M., & Baillargeon, R. (2012). Infants use compression information to infer objects' weights: Examining cognition, exploration, and prospective action in a preferential-reaching task. *Child Development, 83*(6), 1978–1995.

Hegarty, M. (2004). Mechanical reasoning by mental simulation. *Trends in Cognitive Sciences, 8*(6), 280–285.

Hespos, S. J., Ferry, A. L., Anderson, E. M., Hollenbeck, E. N., & Rips, L. J. (2016). Five-month-old infants have general knowledge of how nonsolid substances behave and interact. *Psychological Science, 27*(2), 244–256.

Hiramatsu, C., Goda, N., & Komatsu, H. (2011). Transformation from image-based to perceptual representation of materials along the human ventral visual pathway. *NeuroImage, 57*(2), 482–494.

Indovina, I., Maffei, V., Bosco, G., Zago, M., Macaluso, E., & Lacquaniti, F. (2005). Representation of visual gravitational motion in the human vestibular cortex. *Science, 308*(5720), 416–419.

Jack, A. I., Dawson, A. J., Begany, K. L., Leckie, R. L., Barry, K. P., Ciccia, A. H., & Snyder, A. Z. (2013). fMRI reveals reciprocal inhibition between social and physical cognitive domains. *NeuroImage, 66*, 385–401.

James, T. W., Humphrey, G. K., Gati, J. S., Menon, R. S., & Goodale, M. A. (2002). Differential effects of viewpoint on object-driven activation in dorsal and ventral streams. *Neuron, 35*(4), 793–801.

Jeong, S. K., & Xu, Y. (2016). Behaviorally relevant abstract object identity representation in the human parietal cortex. *Journal of Neuroscience, 36*(5), 1607–1619.

Jeong, S. K., & Xu, Y. (2017). Task-context-dependent linear representation of multiple visual objects in human parietal cortex. *Journal of Cognitive Neuroscience, 29*(10), 1778–1789.

Kaiser, Mary Kister, Jonides, J., & Alexander, J. (1986). Intuitive reasoning about abstract and familiar physics problems. *Memory & Cognition, 14*(4), 308–312.

Kaiser, Mary Kister, Proffitt, D. R., & Anderson, K. (1985). Judgments of natural and anomalous trajectories in the presence and absence of motion. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 11*(4), 795–803.

Kaiser, Mary Kister, Proffitt, D. R., & McCloskey, M. (1985). The development of beliefs about falling objects. *Perception & Psychophysics, 38*(6), 533–539.

Kamps, F. S., Julian, J. B., Battaglia, P., Landau, B., Kanwisher, N., & Dilks, D. D. (2017). Dissociating intuitive physics from intuitive psychology: Evidence from Williams syndrome. *Cognition, 168*, 146–153.

Konen, C. S., & Kastner, S. (2008). Two hierarchically organized neural systems for object information in human visual cortex. *Nature Neuroscience, 11*(2), 224–231.

Mahon, B. Z., & Caramazza, A. (2008). A critical look at the embodied cognition hypothesis and a new proposal for grounding conceptual content. *Journal of Physiology-Paris, 102*(1–3), 59–70.

Mason, R. A., & Just, M. A. (2016). Neural representations of physics concepts. *Psychological Science, 27*(6), 904–913.

McCloskey, M., Caramazza, A., & Green, B. (1980). Curvilinear motion in the absence of external forces: Naive beliefs about the motion of objects. *Science, 210*(4474), 1139–1141.

McCloskey, M., Washburn, A., & Felch, L. (1983). Intuitive physics: The straight-down belief and its origin. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 9*(4), 636–649.

Murata, A., Gallese, V., Luppino, G., Kaseda, M., & Sakata, H. (2000). Selectivity for the shape, size, and orientation of objects for grasping in neurons of monkey parietal area AIP. *Journal of Neurophysiology, 83*(5), 2580–2601.

Sakata, H., Taira, M., Murata, A., & Mine, S. (1995). Neural mechanisms of visual guidance of hand action in the parietal cortex of the monkey. *Cerebral Cortex, 5*(5), 429–438.

Schubotz, R. I. (2007). Prediction of external events with our motor system: Towards a new framework. *Trends in Cognitive Sciences, 11*(5), 211–218.

Schwartz, D. L., & Black, T. (1999). Inferences through imagined actions: Knowing by simulated doing. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 25*(1), 116–136.

Schwettmann, S., Fischer, J., Tenenbaum, J., & Kanwisher, N. (2018). Neural representation of the intuitive physical dimension of mass. Presented at the *Vision Sciences Society Annual Meeting*. Saint Pete Beach, FL.

Smith, K., Battaglia, P., & Vul, E. (2013). Consistent physics underlying ballistic motion prediction. In Knauff, M., Pauen, M., Sebanz, N., & Wachsmuth, I. (Eds.), *Proceedings of the 35th Conference of the Cognitive Science Society* (pp. 3426–3431). Austin, TX: Cognitive Science Society.

Spelke, E. S., Breinlinger, K., Macomber, J., & Jacobson, K. (1992). Origins of knowledge. *Psychological Review, 99*(4), 605–632.

Spelke, E. S., & Kinzler, K. D. (2007). Core knowledge. *Developmental Science, 10*(1), 89–96.

Stahl, A. E., & Feigenson, L. (2015). Observing the unexpected enhances infants' learning and exploration. *Science, 348*(6230), 91–94.

Todd, J. T., & Warren, W. H. (1982). Visual perception of relative mass in dynamic events. *Perception, 11*(3), 325–335.

Ullman, T. D., Spelke, E., Battaglia, P., & Tenenbaum, J. B. (2017). Mind games: Game engines as an architecture for intuitive physics. *Trends in Cognitive Sciences, 21*(9), 649–665.

Vannuscorps, G., & Caramazza, A. (2016). Typical action perception and interpretation without motor simulation. *Proceedings of the National Academy of Sciences, 113*(1), 86–91.

Vasta, R., & Liben, L. S. (1996). The water-level task: An intriguing puzzle. *Current Directions in Psychological Science, 5*, 171–177.

Vaziri, S., & Connor, C. E. (2016). Representation of gravity-aligned scene structure in ventral pathway visual cortex. *Current Biology, 26*(6), 766–774.

Vaziri-Pashkam, M., & Xu, Y. (2017). Goal-directed visual processing differentially impacts human ventral and dorsal visual representations. *Journal of Neuroscience, 37*(36), 8767–8782.

Wang, S., Baillargeon, R., & Paterson, S. (2005). Detecting continuity violations in infancy: A new account and new evidence from covering and tube events. *Cognition, 95*(2), 129–173.

Wang, S., Zhang, Y., & Baillargeon, R. (2016). Young infants view physically possible support events as unexpected: New evidence for rule learning. *Cognition, 157*, 100–105.

Xu, F., & Carey, S. (1996). Infants' metaphysics: The case of numerical identity. *Cognitive Psychology, 30*(2), 111–153.

Zago, M., & Lacquaniti, F. (2005). Cognitive, perceptual and action-oriented representations of falling objects. *Neuropsychologia, 43*(2), 178–188.

Zheng, B., Zhao, Y., Joey, C. Y., Ikeuchi, K., & Zhu, S.-C. (2013). Beyond point clouds: Scene understanding by reasoning geometry and physics. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 3127–3134). Portland, OR: IEEE.

-1—
0—
+1—
78951_11442_ch04_1P.indd 786 8/2/19 6:23 PM