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ADVANCED REVIEW

Inductive reasoning 2.0

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Inductive reasoning entails using existing knowledge to make predictions about novel cases. The first part of this review summarizes key inductive phenomena and critically evaluates theories of induction. We highlight recent theoretical advances, with a special emphasis on the structured statistical approach, the importance of sampling assumptions in Bayesian models, and connectionist modeling. A number of new research directions in this field are identified including comparisons of inductive and deductive reasoning, the identification of common core processes in induction and memory tasks and induction involving category uncertainty. The implications of induction research for areas as diverse as complex decision-making and fear generalization are discussed.

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bayesian models, categories, concepts, inductive reasoning, similarity

1 | INTRODUCTION

Inductive reasoning involves making predictions about novel objects or situations based on existing knowledge. These predictions are necessarily probabilistic. For example, if you are told that grizzly bears had a certain kind of enzyme you might be moderately confident, but by no means certain, that this property generalizes to other bears. Most of the reasoning that people do in everyday life is inductive. Predicting whether it is likely to rain tomorrow, how your partner will react to the box of chocolates you purchased as a gift, or whether stock prices will rise in the next 6 months all involve some form of induction. More generally, induction is involved in a range of cognitive activities such as categorization, probability judgment, analogical reasoning, scientific inference, and decision-making. The pervasive nature of induction is one of the reasons why it has become an important area of study for cognitive scientists. The study of induction also addresses one of the core questions of cognitive science, namely how knowledge is generalized from known to unknown cases. Finally, research on inductive reasoning is important because it informs understanding of how children and adults make rational inferences from evidence (Hayes, Goodhew, Heit, & Gillan, 2003; Klauer & Phye, 2008).

Much of what we have learned about the cognitive processes involved in inductive reasoning has come from studies of *category-based induction*. This involves inferring the properties of the members of a conclusion category, based on knowledge about the properties of premise categories. So a property of the premise category of "grizzly bears" might be generalized to the conclusion category of "all bears" because of your knowledge of the relations between these categories.

The review begins with a summary of some key empirical phenomena identified in research on category-based induction. We then outline and evaluate a number of theories that aim to explain the cognitive mechanisms that drive induction. A key feature of the review is to highlight the newest frontiers of inductive research. Much of this work has focused on placing category-based induction in a broader cognitive context—by examining the relationship between induction and other key cognitive processes, such as memory and decision-making, as well as comparing induction to other types of reasoning.

Throughout the review, our focus is on the most recent and exciting theoretical and empirical developments in the field. For those interested in a more comprehensive history of induction research a number of other reviews are available (Hayes, Heit, & Swendsen, 2010; Heit, 2000; Kalish & Thevenow-Harrison, 2014). In this field, there has been sustained interest in examining how inductive processes emerge and develop over the early part of the life span. Hence, wherever possible we will touch on relevant developmental work as well as research with adult reasoners.

2 | PHENOMENA THAT DEPEND ON TAXONOMIC SIMILARITY

Empirical studies of category-based induction with adults and children have identified the touchstone phenomena in Table 1. These are divided into two types. Those in the top panel are typically observed when induction involves generalization of "blank" or unfamiliar properties (e.g., "has property P"). When such properties are used, property generalization is thought to be driven mainly by taxonomic relations between the premises and conclusions. Those in the lower panel involve more complex premise-conclusion relations, sometimes including prior knowledge about the property being generalized or causal knowledge about premises and conclusions. Our list of phenomena is not intended to be exhaustive. Inclusion was determined by the robustness of the phenomena and their significance for theories of induction.

2.1 | Premise—conclusion similarity promotes induction

A robust finding is that the probability of generalizing a novel property from a premise to a conclusion category is a positive function of their perceived similarity (Osherson et al., 1990). Hence, people are more likely to generalize a blank property from leopards to lions than from leopards to koalas. This is one of the first induction principles to emerge developmentally, appearing to be well understood by 13 months of age (Keates & Graham, 2008), although there is an ongoing debate as to whether adults and children compute similarity in the same way when doing induction (Gelman & Davidson, 2013; Sloutsky & Fisher, 2012; Sweller & Hayes, 2014).

2.2 | Premise typicality promotes induction and can lead to asymmetrical inference

Another inductive principle honored by both adults and young children is *premise typicality* (Rhodes, Brickman, & Gelman, 2008; Rips, 1975). Premise instances that are more typical or representative of a general category are more likely to support

TABLE 1 Touchstone inductive phenomena with examples (terms to the left of the/are premises; terms to the right are conclusions. Properties are shown in italics)

	Example of a stronger argument	Example of a weaker argument
Panel A. Phenomena that depend on taxonomic similarity		
1. Premise—conclusion similarity promotes induction (Osherson, Smith, Wilkie, & Lopez, 1990)	Leopards *have property X*/Lions *have property X*	Leopards *have property X*/Koalas *have property X*
2. Premise typicality promotes induction (Rips, 1975)	1. Sparrows *have property X*/Geese *have property X* 2. Vultures *have property X*/Sparrows *have property X*	1. Penguins *have property X*/Geese *have property X* 2. Vultures *have property X*/Quail *have property X*
3. Diversity and sample size of premises promotes induction (Heit, Hahn, & Feeney, 2005)	1. Lions + Mice *have property X*/Mammals *have property X* 2. Lions + Mice + Cows + Bears *have property X*/Mammals *have property X*	1. Lions + Tigers *have property X*/Mammals *have property X* 2. Lions + Mice *have property X*/Mammals have *property X*
Panel B. Phenomena that depend on background knowledge		
1. Domain expertise can alter or reverse standard induction phenomena (example shows preference for nondiverse preferences shown by those with expertise in tree care) (Proffitt, Coley, & Medin, 2000)	Paper birch trees + River birch trees *are affected by disease X* [less diverse premises]/Other trees are affected *by disease X*	White pine + Weeping willow *are affected by disease X* [more diverse premises]/Other trees are affected *by disease X*
2. Property knowledge alters the relations used in induction (Heit & Rubinstein, 1994)	1. Sparrows *have a ulnar artery*/Hawks *have an ulnar artery* 2. Tigers *study their food before attacking*/Hawks *study their food before attacking*	1. Tigers *have an ulnar artery*/Hawks *have an ulnar artery* 2. Sparrows *study their food before attacking*/Hawks *study their food before attacking*
3. Salient relations between premises and conclusions can override similarity-based induction (Hayes & Thompson, 2007)	1. Polar bears + Antelopes *have property X*/Animals have property X 2. Brown bears *have property X* / Buffalo *have property X*	1. Polar bears + Penguins *have property X*/Animals have property X 2. Brown bears + Polar Bears +Grizzly Bears *have property X*/ Buffalo *have property X*

Example studies are cited.

property induction than are less typical premises. Hence, people are more likely to project a property from sparrows to geese than from penguins to geese. Similarly, premise typicality strengthens property projection from specific instances to more general categories (e.g., from sparrows to birds). A related finding is premise–conclusion asymmetry (Osherson et al., 1990), whereby the projection from a typical category member like sparrows to a less typical instance like geese is stronger than projection from geese to sparrows. Note though that such asymmetries can shift with experience and culture. In a classic result, 4-year-olds showed stronger projection of a biological property of humans (e.g., has a "spleen") to other mammals (e.g., dogs), than from dogs to humans (Carey, 1985). This was viewed as evidence that children see humans as a prototypical example of "living things." Recent work, however, shows that this asymmetry is reduced or eliminated in children raised in rural environments or cultures that attach special significance to interactions with the biological world (Herrmann, Waxman, & Medin, 2012).

2.2.1 | Evidence diversity and sample size promotes induction

Philosophers of science have suggested that diverse evidence leads to more robust generalization (Heit et al., 2005). Most adults share this intuition, generalizing properties more strongly from diverse category sets (e.g., lions and mice) than from nondiverse sets (e.g., lions and tigers) (Feeney & Heit, 2011; Lopez, 1995; Osherson et al., 1990). Adults are also more likely to generalize properties shared by many instances than those shared by few instances (often referred to as the *premise monotonicity* effect) (Feeney, 2007; Osherson et al., 1990). Young children also show sensitivity to sample size in induction (Gutheil & Gelman, 1997). However, the developmental results are mixed when it comes to evidence diversity (Heit & Hahn, 2001). Children as young as five show sensitivity to evidence diversity in induction with novel categories but not with familiar natural kinds (Rhodes & Liebenson, 2015). This suggests that young children may represent familiar categories in a different way to adults (i.e., as more homogenous groups containing typical instances).

3 | SIMILARITY-BASED INDUCTION MODELS

The phenomena listed in the top panel of the table can generally be explained by assuming that people mentally compute the similarity between premise and the conclusion categories. One of the first detailed theoretical accounts of this process, the similarity-coverage model (SCM, Osherson et al., 1990), assumes that inductive generalization is determined by (a) the feature overlap between the premise and conclusion categories, and (b) the average maximum similarity of premises to a more general category that includes the premises and conclusions (e.g., in generalizing from sparrows to geese, "birds" is an inclusive category). The similarity component is sufficient to explain premise-conclusion similarity. Other phenomena require similarity *and* coverage. Premise typicality, for example, arises because typical premises have higher mean similarity to the inclusive category (i.e., better coverage) than less typical premises. Similarly, more diverse premises provide better coverage of an inclusive category than less diverse premises.

As well as the phenomena in Table 1 top panel, the similarity-coverage model can explain a range of other inductive reasoning effects and reasoning fallacies (Osherson et al., 1990). In all of these cases, however, people have relatively little knowledge about the relevant categories or the property being generalized. When such knowledge is present, many additional inductive phenomena are observed (see lower panel of Table 1). Similarity-based models struggle to explain these effects.

4 | INDUCTIVE PHENOMENA THAT DEPEND ON BACKGROUND KNOWLEDGE

4.1 | Domain expertise can alter or reverse standard induction phenomena

There are many cases where prior experience in the domain from which premise and conclusion categories are drawn can alter the effects summarized in the top panel of Table 1. Many studies have compared inductive reasoning in cultural groups with different levels of experience in a particular conceptual domain. One important line of work compares inductive reasoning in indigenous and cultural groups who have close contact with the biological world with reasoning by urban undergraduates. In many cases, signature inductive phenomena (e.g., premise diversity) are absent or reversed in those with more biological knowledge (Medin & Atran, 2004; Proffitt et al., 2000). Analogous shifts in reasoning have been found within cultures, when domain novices are compared with those who have formal training and/or extensive experience in a domain (Bailenson, Shum, Atran, Medin, & Coley, 2002; Shafto & Coley, 2003). This pattern holds for child "experts" as well (Coley, 2012). In many cases, domain experts prefer to make inductive inferences based on their deeper knowledge of causal and ecological relations between premise and conclusion categories rather than on general heuristics such as typicality and diversity. Notably, violations of the standard induction phenomena among experts are only found for stimuli that lie within the domain of expertise. Fish experts, for example, used causal knowledge to generalize a novel disease property ("has a disease called sarca") but used taxonomic similarity to generalize a novel blank property ("has a property called sarca") (Shafto & Coley, 2003). Hence, even in domain experts, taxonomic similarity often functions as a default guide for induction when the arguments involves less familiar categories or properties.

4.2 | Property knowledge alters the relations used in induction

The selective generalization of properties is also observed in nonexperts when the properties are familiar (i.e., nonblank) (Bright & Feeney, 2014a; Hayes & Heit, 2013; Hayes & Lim, 2013; Heit & Rubinstein, 1994). Heit and Rubinstein, for example, found that anatomical properties (e.g., "has an ulnar artery") were more likely to be generalized from sparrows to hawks than from tigers to hawks but that for behavioral properties (e.g., "studies its food before attacking") the pattern reverses. At a minimum, this suggests that property knowledge can alter the way that people compute the similarity between base and target stimuli (birds are likely to have similar biological features but predators are likely to have similar hunting behaviors). As discussed below, such effects may point to the operation of inductive mechanisms that cannot be reduced to similarity computations.

4.3 | Salient relations between premises and conclusions can override similarity-based induction

Many of the induction effects listed in the top panel of Table 1 can be altered or reversed when premises and conclusions are presented in certain contexts (Medin, Coley, Storms, & Hayes, 2003; Ransom, Perfors, & Navarro, 2015). Medin et al. (2003) found that the diversity effect can be reversed when the diverse premise categories share a distinctive relation. For example, a novel property was judged less likely to generalize from polar bears and penguins (high diversity set) to other animals than from polar bears and antelopes (low diversity set) to other animals. Similarly, in *nonmonotonicity* via *property reinforcement*, a property shared by multiple categories (e.g., grizzly bears, brown bears, and polar bears) was less likely to generalize to other animals than the property of a single category (e.g., grizzly bears). Such effects suggest that people look for shared distinctive relations between premise categories when doing induction (e.g., arctic habitat seems a likely contender in the nondiversity example). If the relation is not shared by the conclusion category then it is unlikely to be generalized.

Causal relations between premise and conclusion categories exert an especially powerful influence on induction, often overriding the effects of similarity (Rehder, 2006, 2009). In studies with artificial categories, Rehder (2006) orthogonally manipulated typicality and diversity and the presence of causal relations between instance features and category membership. Similarity-based induction disappeared when generalization could be based on causal relations. Children as young as five appear capable of appreciating the inductive potency of causal relations (Bright & Feeney, 2014b; Hayes & Thompson, 2007).

The presence of causal relations can also lead to asymmetries in induction, with generalization from causes to effects (e.g., a property of carrots passing to rabbits) viewed as stronger than generalization from effects to causes (e.g., a property of rabbits generalizing to carrots) (Medin et al., 2003). Similarly, they can lead to conjunction fallacies such as perceiving that the properties of a causal agent (e.g., cows) are just as likely to generalize to multiple conclusion categories (e.g., milk and ice cream) as to a single category (Feeney, Shafto, & Dunning, 2007; Medin et al., 2003).

5 | THEORETICAL EXPLANATIONS OF KNOWLEDGE EFFECTS

Because the similarity-coverage model assumes that induction is driven primarily by the taxonomic similarity of premise and conclusion categories (and their superordinates) it has difficulty accounting for the effects of experience, premise context, property, and causal knowledge on induction. It may be that the model could be adapted to accommodate some of these effects by assuming that different similarity metrics are applied in different types of arguments but the details have yet to be specified, and little of the explanatory work would be done by the core SCM mechanisms (Medin et al., 2003). Because of these difficulties, there has been a shift toward broader theoretical frameworks for explaining induction.

5.1 | Bayesian models

Many researchers have suggested that induction is best thought of as a form of Bayesian belief revision (Chater, Oaksford, & Hahn, 2010; Heit, 1998; Kemp & Tenenbaum, 2009; Tenenbaum & Griffiths, 2001). In the first effort to apply Bayesian modeling to key inductive phenomena, Heit (1998) assumed that when generalizing a novel property between familiar categories (e.g., from sparrows to crows) people will access their prior knowledge about the distribution of familiar properties. They will know, for example, that certain properties are true of all birds including sparrows and crows, but that other properties are limited just to the premise or the conclusion. The inductive problem is to determine which of these distributions the

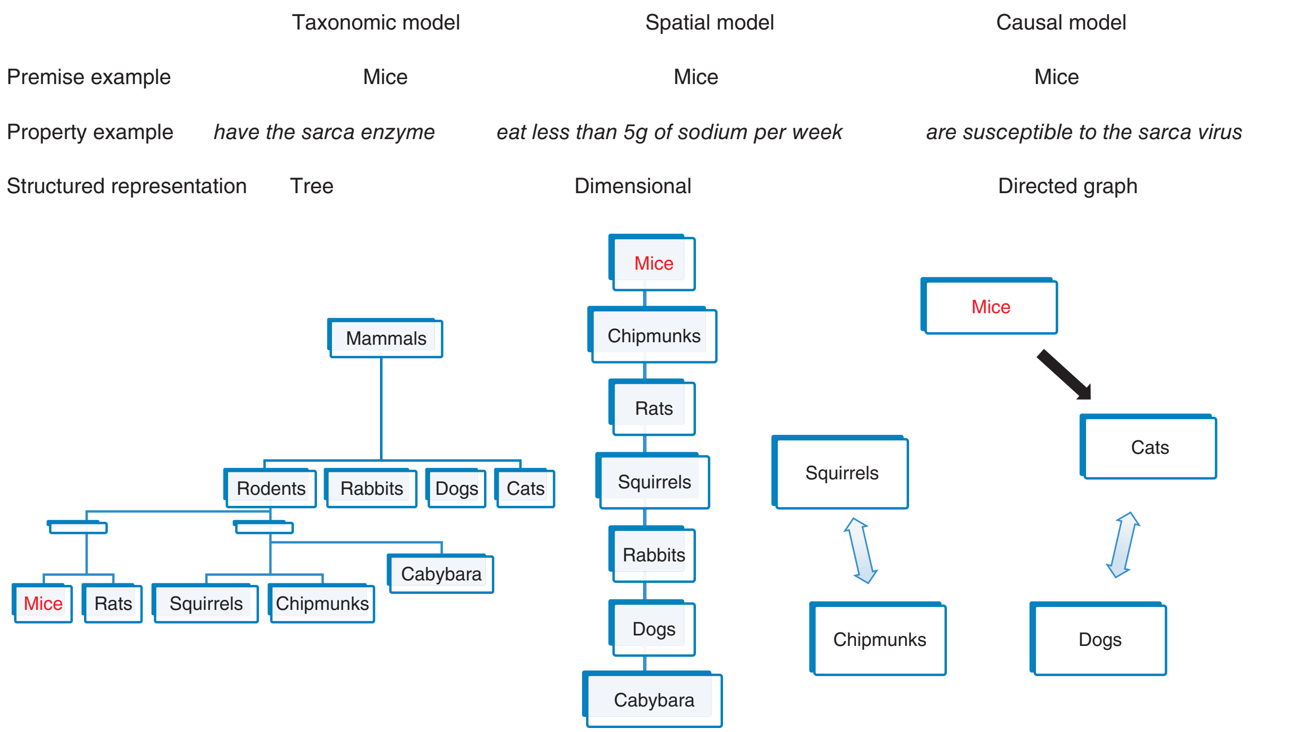

FIGURE 1 Examples of tree, dimensional, and causal-structured representations. Adapted from Kemp and Tenenbaum (2009). Solid arrows show predator–prey relations. Light arrows show shared habitat relations

novel property most closely resembles. To solve the problem the Bayesian model treats the premises in an inductive argument as evidence, which is used to revise beliefs about the prior hypotheses according to Bayes' theorem. Once these beliefs have been revised the plausibility of the conclusion is estimated.

This model successfully predicts many of the key results in the first panel of Table 1. It can be extended to arguments with familiar properties by assuming that such properties prime the retrieval of specific types of priors. So when asked whether a biological property of hawks is more likely to generalize to sparrows or tigers people will retrieve prior knowledge about anatomical properties, whereas inductions about behavior will prime knowledge about familiar behavioral properties.

Like other early Bayesian induction models (Tenenbaum & Griffiths, 2001), Heit's model does not provide details about how prior probabilities are computed. It is also not clear whether the model gives priority to causal relations. Some of these issues are addressed in the *Structured Statistical* approach (Kemp & Tenenbaum, 2009), which assumes that induction involves making an inference about the probability of a conclusion given the observed premises. Critically, this approach assumes that the priors used as inputs into Bayesian calculus are based on intuitive theories. These are instantiated as structured representations of the distribution of features across categories. Different kinds of structured representations are retrieved depending on the property being generalized. This idea is illustrated in Figure 1. When induction involves taxonomic properties, the default structure is a hierarchical tree. For spatial or quantitative properties, categories are represented according to their distance in dimensional space based on the relevant property (e.g., size). Causal properties are represented in a directed causal graph. Each structure leads to the activation of a different set of priors about the distribution of known features. For example, in the causal case knowing that a mouse has a disease may lead to retrieval of knowledge of relevant food-chain relations, activating many features of cats. In the case of blank properties, different conceptual domains are associated with different default representations. The tree structure, for example, is seen as the default for generalizing blank properties in biological categories (Kemp & Tenenbaum, 2009). Once priors are derived from the appropriate structured representation, a Bayesian inference mechanism is used to derive feature inferences.

This model has been applied to a range of induction datasets, including many of the key findings from both panels of Table 1. In general, the fit of the structured statistical models is impressive compared to other quantitative models like similarity-coverage. Critically, the relative fit of models based on different structured representations depended on the property being generalized. Bayesian predictions based on taxonomic "tree" priors produced a good fit to induction involving genetic properties but a poor fit to induction with disease properties. Predictions based on a causal model showed the opposite trend.

The structured statistical approach is impressive in that it provides a clear mechanism for deriving prior probabilities from background knowledge, and allows for the flexible application of different kinds of knowledge. Although it can deal with causal relationships that can be represented in a chain or web it is not clear how the model would deal with cases of induction where premises and conclusion categories are seen as similar because they fulfill similar causal *roles* (e.g., hawks and tigers are similar because they both take the role of predator). Perhaps the main weakness of the structured statistical model though is a by-product of one of its major strengths, namely its flexible application of different knowledge structures. The model says little about how people ensure that they retrieve the correct structured representation for a given problem. When told that mice have a certain disease it seems likely that people would consider a range of possible routes for property generalization (e.g., taxonomic, predator–prey relations, and ecological relations), each of which is associated with a different structured representation for generating priors. Exactly how a particular representation is selected and others discarded, is not specified. This resembles the problem of "knowledge selection" in other domains like category learning (Heit & Bott, 2000).

5.2 | Relevance theory and the role of sampling assumptions

Relevance theory (Medin et al., 2003) was devised with the specific aim of predicting and explaining context sensitivity and causal knowledge effects in induction. The core assumption is that people evaluating inductive arguments actively compare premise and conclusion categories, and (in the multiple premise case) different premises. This process activates distinctive relations between these categories that serve as candidates for inductive projection. Causal relations are assumed to be more distinctive than taxonomic or thematic relations. When familiar properties are used these further specify the relevant dimensions on which premises and conclusions should be compared, so that different kinds of properties (e.g., biological vs. behavioral) can produce different patterns of inductive projection.

A positive feature of relevance theory is that it applies the same general principles to explain the touchstone effects involving taxonomic similarity and the effects of context and knowledge. For example, a property of lions and tigers is less likely to project to other animals than a property of polar bears and lions, because the less diverse set activates a distinctive property ("large cats") that is not shared by most instances of the conclusion. The same mechanism predicts that the even more diverse set of polar bears and penguins will be less potent for the same conclusion. The effects of causal relations are explained using similar mechanisms. A projection from grass to cows is strong because the premise-conclusion order suggests a very distinctive causal process (ingestion).

The relevance approach has yielded a number of interesting empirical findings (Bright & Feeney, 2014a; Feeney, Coley, & Crisp, 2010; Feeney & Heit, 2011; Medin et al., 2003), but until recently, no formal versions of the theory had been proposed. A promising new approach views relevance theory in the context of people's beliefs about how and why premises have been sampled from the set of possible observations. These sampling assumptions are instantiated in a formal Bayesian model of belief revision (Ransom et al., 2015; Shafto, Goodman, & Griffiths, 2014; Voorspoels, Navarro, Perfors, Ransom, & Storms, 2015). A key insight is that reasoners often assume that the premises presented in an inductive argument have been selected *intentionally* by a helpful agent to highlight a salient property of the premises.

According to the Bayesian sampling model "helpful" sampling leads to a very different pattern of property generalization than if random sampling is assumed. For example, when people assume that the premise set (grizzly bears, brown bears, and polar bears) has been selected to highlight a specific property, the sample provides more evidence for a specific conclusion (that this is a specific property of bears) than for more general conclusions (that the property is shared by other animals). Hence, this approach can readily explain nonmonotonicity via property reinforcement (Medin et al., 2003). It has also been shown to predict novel phenomena involving negative evidence. For example, Voorspoels et al. (2015) showed that adding negative evidence to a premise set can increase belief in conclusions about how far a property can be generalized. For example, those who learned that "Mozart's music elicits alpha waves" but that "falling rocks do note elicit alpha waves" were more likely to conclude that "Metallica's music elicits alpha waves," than those who were only given positive evidence. Notably, when steps are taken to undermine helpful sampling assumptions (i.e. by convincing reasoners that the premises were generated randomly) property reinforcement and negative evidence effects disappear. A computational Bayesian model which allowed for different types of sampling assumptions provided a good fit to these data. Another notable finding is that the helpful sampling assumption appears to emerge early in development; by 3 years of age children frequently assume that the information presented to them in inductive problems has been selected by a helpful teacher (Bonawitz & Shafto, 2016; Gweon, Tenenbaum, & Shultz, 2010).

So far, the Bayesian model incorporating helpful sampling has only been applied to a subset of the phenomena in Table 1. In principle, it could be applied to other effects such as causal nondiversity. Recent work also shows how the approach can be extended beyond contexts where premises are seen as intentionally sampled by a helpful agent. For example, a modified version of the model can explain why people generalize properties in different ways depending on the strategy that they use to collect evidence (Hayes, Banner, & Navarro, 2017; Lawson & Kalish, 2009).

5.3 | Connectionist models

Connectionist models propose that semantic cognition in general, and inductive reasoning in particular, are emergent properties of a connected system of processing units. The weights between these connections are modified through error-driven learning. Processing units are organized in hierarchical layers, reflecting different types of input from the environment. Units in lower level layers may be activated by perceptual object features, whereas units in higher order layers are activated by the presence of the whole object, object labels or abstract features (e.g., "is living"). Activation between layers is interactive such that activation of a lower level layer can affect that of a high level layer and vice versa.

The first detailed connectionist account of induction was the feature-based induction model (FBIM) (Sloman, 1993). FBIM is implemented as a connectionist network that learns associations between input nodes representing the features of the premise categories and an output node for the property to be considered. The conclusion activates the same output node in proportion to the features shared with the premise. Generalization increases as a function of similarity between the premise and conclusion, but is reduced by the presence of "rich" conclusion categories that contain many features. The model offers a connectionist account of many of the phenomena in panel A of Table 1. Although it was not designed to explain the knowledge-based effects in the lower panel of the table, it is conceivable that it could be extended to capture some of these phenomena. For example, the model allows feature weighting in proportion to the number of categories under consideration, so that features shared by all premise categories would have the greatest weight. This could explain the effects of property reinforcement manipulations reported by Medin and colleagues. It is not clear, however, how FBIM could accommodate the effects of property knowledge or casual links between premises and conclusions.

The connectionist networks outlined by Rogers and McClelland (2004, 2014) go further in explaining knowledge-based effects in induction. Changes to patterns of induction based on property knowledge are explained by assuming that properties serve as contextual cues. For example, the reasoner learns that in the presence of biological properties, taxonomic similarity is a better predictor of generalization whereas in the presence of behavioral properties, other ecological relations may be more predictive. Similarly, the salient impact of causal features on induction is explained by the learning of patterns of "coherent covariation" between object features. For example, features such as wings, feathers, and hollow bones co-occur frequently because they all reflect part of the evolved ability to fly. Hence, such "causal" features will acquire strong connection weights and exert a strong influence on property induction. Connectionist models are extremely flexible and powerful learning machines, capable of producing a range of "high-level" cognitive phenomena without assuming that learners develop implicit theories of category structure. However, there has not been a sustained effort on the part of connectionist theorists to explain the full range of inductive phenomena summarized in Table 1.

5.4 | Summary

Since our previous WIRES review, considerable progress has been made in explaining the more complex aspects of human induction. When we last reviewed this literature, relevance theory was a popular heuristic framework but had not been implemented formally. This issue has been addressed by Bayesian models that accord an important role to participants' sampling assumptions.

Nevertheless, there is still important work to be done. One challenge for Bayesian models is to explain developmental *change* in induction. While several studies have shown that young children often reason in a manner consistent with Bayesian principles (Bonawitz & Shafto, 2016; Gweon et al., 2010), the challenge is to explain why young children sometimes reason differently to older children and adults (Rhodes & Liebenson, 2015). Is this because of age differences in priors, changes in the belief revision mechanism or both?

A more general issue is the extent to which the models reviewed represent qualitatively different kinds of theoretical explanations. For example, some have argued that models of optimal Bayesian inference can be reduced to patterns of interactive activation in connectionist networks (McClelland, Mirman, Bolger, & Kaitan, 2014). Alternately, there are data demonstrating dissociations between these types of knowledge—with people relying on structured knowledge when they have the time and capacity to do so but falling back on associative relations when under load (Bright & Feeney, 2014a). Further progress will result from detailed empirical work and comparisons between competing formal models which take account of factors such the psychological plausibility of the model assumptions and the trade-off between model complexity and flexibility with quantitative fit. Ultimately, these models will also need to explain how inductive processes are involved in other cognitive tasks. New developments in this area are reviewed in the next section.

6 | NEW DIRECTIONS IN INDUCTION RESEARCH

Induction is increasingly being viewed in a broader context, in terms of its relations to other types of judgments and decisions. Kemp and Jern (2013), for example, have catalogued how property induction is related to a range of other tasks including category learning and identification, object recognition and naming. Here, we focus on two recent lines of work investigating relations between inductive and deductive reasoning, and between the processes involved in induction and recognition memory.

6.1 | Relations between induction and deduction

Induction is not the only kind of reasoning. The traditional alternative to induction is deduction, which is linked to making valid inferences that are 100% certain given a set of premises, and do not depend on, or ideally even use, other background knowledge. So, at first glance, deduction seems very different from induction, which is probabilistic and knowledge-rich. But, where do you draw the line between induction and deduction, and how are they related? Heit (2007) has distinguished between two different approaches; the problem view and the process view. According to the problem view, induction and deduction refer to different kinds of reasoning problems that people solve. For example, deductive problems could be defined as arguments that are logically valid according to the rules of a well-specified logic, and other arguments could be referred to as inductive problems. Alternately, deductive problems could be defined as those with 100% (or perhaps 99.9%) likely conclusions, inductively strong problems could be those with very highly probable conclusions (perhaps 75–99.9%), and other problems could be considered weak.

Unlike the problem view, the process view is concerned with cognitive processes. The question of interest is what processes underlie induction and deduction, and whether these are the same or different. Some researchers have suggested that induction and deduction depend on the same cognitive processes. This approach will be referred to as the one-process view. Several influential research programs embody the one-process view, by applying a common framework to both inductive and deductive problems. For example, the similarity-coverage model and FBIM would, without additional assumptions, account for some deductive reasoning phenomena. Oaksford and Chater (2007, 2012) have outlined a Bayesian model in which both inductive and deductive reasoning are driven by an assessment of the conditional probability of a conclusion given the evidence. Lassiter and Goodman (2015) suggest that a common reasoning process underlies both kinds of reasoning but that people impose different evidence thresholds when they judge an argument conclusion to be “plausible” (e.g., in induction) as opposed to “necessary” (e.g., in deduction).

In contrast, two-process accounts assume that heuristic and analytic processes contribute to reasoning (De Neys, 2015; Evans & Stanovich, 2013; Handley & Trippas, 2015; Sloman, 2014). Both induction and deduction could be influenced by these two processes, but in different proportions. Although the details vary in different versions of two-process accounts, induction judgments are typically assumed to be most strongly influenced by heuristic processes that tap into knowledge of similarity relations and background causal knowledge. In contrast, deduction judgments are typically assumed to be influenced by more deliberative analytic processes that focus on consistency with logical principles. Two-process accounts have provided an explanatory framework for many results (e.g., content effects, individual differences, effects of time pressure). Unlike single-process theories, only a few two-process theories have been implemented computationally (Klauer, Beller, & Hütter, 2010; Oberauer, 2006).

Studies that pit one- and two-process accounts against each other are becoming more common (Heit & Rotello, 2010; Lassiter & Goodman, 2015; Rotello & Heit, 2009; Singmann & Klauer, 2011). The general method, adapted from Rips (2001), is to take a set of arguments and have one group judge whether the arguments are deductively valid and another group judge whether they are inductively strong. Heit and Rotello found that different variables affect deduction vs. induction judgments; logical validity itself has a greater effect on deduction judgments, whereas more superficial variables such as similarity and the length of an argument (the similarity and sample size phenomena in Table 1) have a greater effect on induction (Heit & Rotello, 2010; Rotello & Heit, 2009). They implemented a two-dimensional model of reasoning (Figure 2) that successfully accounted for these results by assuming that deduction and induction rely on differing proportions of two kinds of underlying information, which could be the outputs of analytic and heuristic processes.

While these results are impressive, they may not be the end of the story. Simply demonstrating task dissociations whereby inductive and deductive judgments are affected by different task manipulations may not be decisive evidence against all single-process models of reasoning (Newell & Dunn, 2008). Recent work comparing single and dual reasoning processes has adopted methods such as “state-trace analysis” which allows for more direct inferences about the number of processes that underlie inductive and deductive judgments (Singmann & Klauer, 2011; Stephens, Dunn, & Hayes, in press). Stephens, Dunn and Hayes used a signal detection framework to generate a number of formal single- and dual-process models of reasoning, and reported that some versions of a single-process model (as well as some dual-process models) are capable of explaining both inductive and deductive data, including those reported by Heit and Rotello (Stephens et al., in press).

Clearly, there is some way to go in clarifying the relations between inductive and deductive reasoning. Nevertheless, substantial progress has been made toward this goal. This work has stimulated the development of new paradigms for comparing reasoning tasks and computational versions of both single- and dual-process models of reasoning. It has also encouraged studies of the neural bases of induction and deduction (Goel & Dolan, 2004; Heit, 2015). Such studies have relied on the

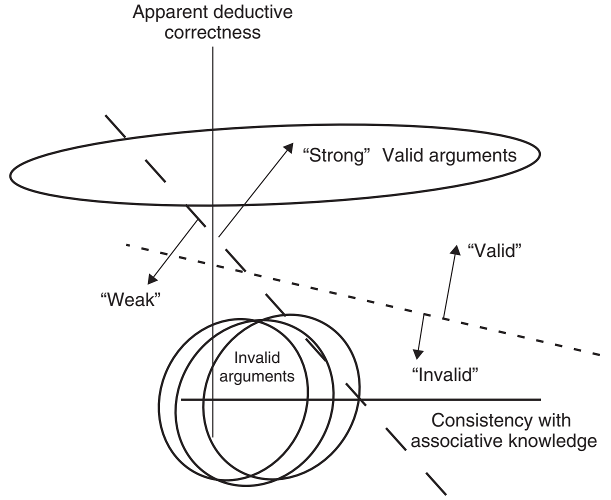

FIGURE 2 Two-dimensional model of reasoning, showing arguments varying in apparent deductive correctness (y-axis) and consistency with associative knowledge (x-axis). The dotted line shows the decision boundary for judging whether an argument is deductively valid or invalid. The dashed line shows the decision boundary for judging whether an argument is inductively strong or weak. Adapted from Heit and Rotello (2010)

FIGURE 3 Example of the experimental design used by Dunsmoor and Murphy (2014) (CS = Conditioned stimulus; GS = Generalization stimulus)

method of "forward inference," for example, concluding in favor of dual-process models when different patterns of brain activity are evident for inductive vs. deductive judgments (Henson, 2006).

Another important link between induction and deduction is in studies of belief bias, in which participants are typically asked to make deductive judgments about logical syllogisms (Evans, Barston, & Pollard, 1983). Although explicitly not an inductive task—for which the use of background knowledge would be normative—belief bias studies use knowledge-rich materials to observe the impact of prior beliefs on deductive conclusions, for example, concluding in favor of a believable conclusion that is not deductively valid. In a further link to induction, Dube, Rotello, and Heit (2010) have proposed a signal detection account of the belief bias in deductive reasoning.

6.2 | Relations between induction, memory, and decision-making

Our understanding of induction has also been enriched over the past decade by work examining links between inductive reasoning and other key cognitive domains such as memory and decision-making. In the case of memory, there have been two important developments. First, methods originally developed for studying memory and perception, such as signal-detection analysis, have been increasingly applied to study reasoning (Heit, Rotello, & Hayes, 2012). Second, empirical work and computational modeling have revealed overlaps between the fundamental processes involved in induction and recognition memory, as well as important differences between them. Heit and Hayes (Hayes & Heit, 2013; Heit & Hayes, 2011), for example, developed a task where instances (e.g., pictures of dogs) were presented under induction instructions (these items all have a novel property X) or recognition instructions (memorize the items). This was followed by a test set containing old and new instances for which participants made either induction (does this item have property X?) or recognition decisions (did you see this item before?). Perhaps unsurprisingly, people were more likely to make a positive response to new test items in induction than recognition. Across test items, however, the probability of making a positive response in induction

BOX 1

INDUCTIVE PRINCIPLES AND THE GENERALIZATION OF FEAR

The importance of induction in everyday life is illustrated by work showing that inductive phenomena affect how people generalize learned fear. Fearful or traumatic experiences often generalize beyond the specific details of the original experience. This is particularly so in clinical anxiety disorders such as post-traumatic stress disorder, panic, or phobias (Bouton, Mineka, & Barlow, 2001). Laboratory studies of fear acquisition typically employ a Pavlovian conditioning paradigm in which some initially neutral conditioned stimulus (CS) is paired with an unpleasant unconditioned stimulus (US). Over repeated CS–US pairings, the CS comes to elicit a "fearful" conditioned response.

Dunsmoor and Murphy have shown that the generalization of conditioned fear is consistent with inductive principles (Dunsmoor & Murphy, 2014). Their experimental design is illustrated in Figure 3. Two groups of volunteers were conditioned with pictures from an animal category (e.g., birds, CS+) followed by electric shock. On other trials members of a different category (e.g., mammals, CS−) were not followed by shock. Generalization of fear was tested by presenting new members of the category that was previously associated with shock (generalization stimuli). Crucially, one group was trained with typical instances and tested with atypical instances, while another was trained with atypical instances and tested with typical instances. Consistent with premise typicality effects (Table 1), those in the typical CS + group showed greater generalization of conditioned fear (measured by changes in skin conductance) than those trained with an atypical CS+.

These results show that higher-order forms of reasoning, like inductive inference, are involved in the way that people generalize learned fear. Future work could examine how other inductive processes are implicated in fear generalization (Dunsmoor & Murphy, 2015).

and recognition was highly correlated, suggesting a common decision component in the two tasks. Modeling of decisions and reaction times found that assessment of the total similarity of a test probe to previously experienced exemplars was important in both induction and recognition (Hawkins, Hayes, & Heit, 2016; Heit & Hayes, 2011). The main difference between the tasks was in the amount of time that people spent assessing similarity; decisions about new items in recognition were typically more "cautious" than those in induction. Such work suggests that many cognitive tasks that differ from induction at a descriptive level may in fact share many core processes.

So far, our discussion of induction has focused on cases where the properties of objects known to belong to a category are generalized to other category exemplars. But how do we make inductive predictions when we are unsure about the category membership of our premises? This situation arises in many cases of everyday decision-making. For example, imagine that an individual finds a rash on their arm. The rash could be a harmless skin condition. However, it could be a symptom of something more serious like skin cancer. How does an individual factor this uncertainty into their judgments and predictions (e.g., the likelihood that the rash will spread, whether to visit a doctor)?

Normative (Bayesian) approaches (Anderson, 1991) suggest that all category alternatives should be considered. People should estimate the probabilities of the predicted property for each category alternative (e.g., harmless skin condition, cancer) and then weight each according to the likelihood of the object being in that category. Early empirical work on this issue suggested that people do not reason this way. Experimental studies with natural (Murphy & Ross, 2005) and artificial categories (Murphy & Ross, 2010) have found that people often ignore uncertainty about category membership, basing predictions solely on the category to which an object is most likely to belong (a heuristic termed "single-category" reasoning).

Recent work has questioned the generality of this heuristic, demonstrating that whether or not people consider multiple category alternatives in inference depends on a range of factors (Chen, Ross, & Murphy, 2014; Griffiths, Hayes, & Newell, 2012; Hayes & Newell, 2009; Murphy & Ross, 2010). These include experience with the alternative categories and the consequences of ignoring less likely categories. For example, if one of the category alternatives has relatively low probability but has potentially serious consequences (e.g., skin cancer in the above example) it is likely to be factored into inductive predictions. A somewhat counter-intuitive finding is that people may be more likely to consider multiple uncertain categories in induction when the task requires less conscious deliberation. Chen, Murphy and Ross, found that people engage in single-category reasoning when asked to make an explicit inductive prediction about an object that could belong to one of several different categories. However, when asked to carry out an analogous "implicit" prediction task (judging the trajectory of a moving object that had similarities to two known categories of moving objects), people appeared to factor in both uncertain alternatives (Chen, Ross, & Murphy, 2013, 2016). Because there are numerous differences between the explicit and implicit induction tasks, the explanation of these results remains unclear. Nevertheless, the work holds out the intriguing prospect that "thinking less" about an inductive prediction can lead people to reason in a way that is closer to normative prescriptions.

7 | CONCLUSION

Over the past decade, research on induction has become both deeper and broader. A deeper understanding of induction has been achieved through the development of more comprehensive and sophisticated computational models. These have helped to reveal new dimensions of induction, such as the role of evidence sampling, missing from earlier theories. At the same time, there has been a proliferation of research examining links between induction and other important cognitive activities. Our review has sampled only a few of these new lines of induction research (See Sidebar for another example). Induction characterizes the rich, knowledge-laden inferences that are pervasive in everyday reasoning, while at the same time having important theoretical links to other cognitive activities. Hence, the study of inductive reasoning will continue to be a central topic in cognitive science research.

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CONFLICT OF INTEREST

The authors have declared no conflicts of interest for this article. This material includes work by Evan Heit while serving at the National Science Foundation (US). Any opinion, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

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