

CHAPTER 4

Case-Based Decision Neuroscience: Economic Judgment by Similarity

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It is said that the only constant in life is change. We are routinely faced with different situations, no two exactly alike. We visit new places, try new foods, meet new people, find new jobs, and invent new products. You have probably never read this very sentence before. The pervasiveness of novelty can be paralyzing if one is not prepared for it. By their nature, unfamiliar situations challenge our ability to draw on past experience. And by our nature, humans make do.

In general, how do we appraise courses of action in various contexts? We could form projections of what's likely to happen as a result of each action in a context and combine that with an evaluation of how desirable those outcomes are. Or we could lean on the automatic attitudes drilled into us by extensive experience. These are the two prevailing theories in neuroeconomics, expressed mathematically in terms of expected utility and reinforcement learning. The biggest success story of decision neuroscience to date has been in uncovering neural instantiations of these decision-making rules.

How might these two systems go awry when there is little direct experience to work from? The former relies heavily on a cognitive map or mental structure but does not have much to hang its structure on. The latter depends vitally on preexisting experience, but this direct experience is unavailable. The capacity to cope in new circumstances is an important but tricky skill.

A plausible alternative is to recall how well or poorly similar actions turned out in similar contexts in the past. Such an approach to decision-making enables us to draw on the variety of disparate experiences we acquire over time and respond gracefully to the novelty and complexity that pervades real life. It imposes fewer assumptions about the structure of the world compared with sophisticated probabilistic judgments, while squeezing more information out of background knowledge than simple value caching.

I lay out a “case-based” system combining theory and empirical evidence from economics, psychology, neuroscience, statistics, and computer science. Value judgment by similarity corresponds to an economic model called case-based decision theory (CBDT), inspired in part by a computational problem-solving process known as case-based reasoning (CBR). This theory has links to nonparametric statistics, suggesting why and when the system works well. Recent evidence from neuroscience indicates that we use this kind of

system and implicates the hippocampus and related medial temporal lobe (MTL) regions as neural loci. This can be thought of as a complementary narrative to what has been described as episodic control (Dayan, 2008; Lengyel & Dayan, 2008).

JUDGMENT AND DECISION-MAKING FROM SIMILARITY

Judgments based on similarity are ubiquitous. Consciously and unconsciously, we map athletes onto predecessors to forecast performance (“LeBron James is the next Michael Jordan”—ESPN), we react to people based on group stereotypes, we talk about new businesses in terms of existing analogues (describing various start-ups as the Ubers of food delivery, flowers, laundry, lawn care, marijuana, and mortgage lending), we evaluate products based on brand lines, we search historic economic events for relations to modern ones (“The Great Recession is just like the Great Depression”—Forbes), we hold to legal precedent as a guide for future cases, and we pitch new TV shows or movies as mixtures of old concepts (“The pitch [for Hollywood movie *Man’s Best Friend*] was ‘*Jaws* with Paws’ ... Investors were told that if the movie *Jaws* was a huge success, a similar plot but on land with a dog could also be a huge success.”—Reid Hoffman).

People are psychologically attuned to similarity. This is for good reason. In a sense, all learning is premised on finding similarity. Heraclitus said that “you cannot step twice into the same river,” which is not only a deep philosophical truth but also an evolutionary problem. If every instant is unique, how can we learn and make decisions from experience? We are thus tasked with recognizing useful parallels that allow us to generalize from the past.

At its best, similarity-based judgment constitutes an ecologically valid heuristic for summarizing a vast landscape of information in service of decision-making. A neural network trained to classify handwritten digits holds the potential to perform well on digits it has never seen before, provided it has access to data on similarity between digits (as implicitly evaluated by the classification probabilities from another neural network; Hinton, Vinyals, & Dean, 2015). It has never encountered a “3,” but knowing that certain “2’s” are visually similar while “1’s” are quite different implicitly contains a fair amount of information about what exactly a “3” looks like. This is precisely the kind of quality required for good transfer learning. This aspect of similarity is intimately tied to our propensity to associate and connect and categorize. We may not be wired to easily navigate probabilistic state spaces, but we are able to effortlessly form comparisons and associations between concepts in our memory.

This is not to say that similarities are always well founded. The movie *Man’s Best Friend* turned out to be terrible, for instance. Classic examples of irrationality can be explained by indiscriminate similarity judgment. When asked how likely it is that the outspoken socially involved philosophy major Linda is a bank teller or a feminist bank teller, people respond that she is more likely to be the latter than the former (Tversky & Kahneman, 1983). Although this belief violates the laws of probability, Linda better

resembles our idea of a feminist bank teller and so we judge that possibility to be more likely (Bar-Hillel, 1974; Kahneman & Tversky, 1972). We can be unconsciously misled by superficial connections, even when we are experts. Prominent venture capitalist Paul Graham was quoted as saying “I can be tricked by anyone who looks like Mark Zuckerberg. There was a guy once who we funded who was terrible. I said: ‘How could he be bad? He looks like Zuckerberg!’” While this was said in jest, such biases are plausible. Gilovich (1981) asked professional sportswriters and varsity football coaches to predict the success of fictitious young players based on written profiles. In one manipulation, a player won an award named after a famous pro who either played in the same position or a different position. Success ratings turned out to be higher when the pro played in the same position.

For better or worse, we often form evaluations based on examples considered similar to our present situation. A body of research in economics explores the theme of valuation based on similarity. This work centers on a theoretical framework that reflects the mental contagion of value.

Case-based decision theory

CBDT is a model of decision-making, which takes past experiences as its primitives and weights those experiences based on their similarity to the current choice situation. It was developed and originally axiomatized by Gilboa and Schmeidler (1995a) as a psychologically plausible complement to expected utility theory. In order to apply classical expected utility theory, the agent must hold subjective probabilities over all pertinent states of the world. In many situations, this state space and its associated probabilities can be extremely complicated, intricate, or unnatural to construct. When deciding on a new restaurant to visit for dinner, one might not naturally estimate probability distributions over the quality of food and service for each place. Instead, one might simply call to mind their experiences at places thought to be roughly similar. From the start, Bayesian decision theory was primarily considered appropriate inside what Savage (1954) called a *small world*, where knowledge is plentiful. CBDT was meant to tackle decision-making in large worlds.

The primitive concepts of CBDT are a set of past cases and subjective similarity assessments between each case and the current situation. The agent’s memory M is a set of cases formally described as triples (q, a, r) , where q represents the problem situation, a is the action taken, and r is the result. The agent evaluates an action by combining the utilities of outcomes that occurred when that action was taken in the past. These utilities are weighted by the similarity between the current situation (with description p) and each past case (with description q), $s(p, q)$:

$$U(a) = \sum_{(q,a,r) \in M} s(p, q)u(r).$$

Table 4.1 Case-based decision theory calculation example

City	s(city, Paris)	s(city, Sydney)	Utility
Montreal	0.8	0.1	5
Los Angeles	0	0.5	6
Vancouver	0.5	0.5	10

Gilboa and Schmeidler (1997a) generalized this to allow similarity between cases to depend on acts as well as descriptions, so $U(a) = \sum_{(q,b,r) \in M} s((p,a), (q,b))u(r)$, and Gilboa, Schmeidler, and Wakker (2002) provided two additional axiomatic derivations clarifying its empirical content. A variant also formulated in Gilboa and Schmeidler (1995a) uses averaged similarity:

$$V(a) = \sum_{(q,a,r) \in M} \frac{s(p,q)}{\sum_{(q',a,r) \in M} s(p,q')} u(r).$$

To illustrate, suppose you are deciding which city to visit for a vacation and have narrowed the options down to Paris and Sydney. Though you have been to neither, you recall your past trips to Montreal, Los Angeles, and Vancouver, as laid out in Table 4.1. Though French-speaking urban Montreal was chilly, you had a decent time there (utility 5). You feel the city is quite similar to Paris (similarity 0.8) but hardly at all like Sydney (similarity 0.1). LA was hot, which you like, and occasionally smoggy, which you do not, but it was pleasant overall (utility 6). You consider LA to moderately resemble Sydney (similarity 0.5) but not Paris (similarity 0). The metropolis of Vancouver was special with its beautiful mountains, oceans, and fresh air—your favorite trip by far (utility 10). The city seems to you halfway between Paris and Sydney (similarity 0.5 each). As a standard case-based decision-maker, the projected utility of visiting Paris is $0.8 \times 5 + 0 \times 6 + 0.5 \times 10 = 9$, while the projected utility of visiting Sydney is $0.1 \times 5 + 0.5 \times 6 + 0.5 \times 10 = 8.5$, a calculation about which you reminisce on your flight to Paris. (If you were using the averaged variant, this decision would be reversed.)

Similarity functions

What might the similarity function look like? Goldstone and Son (2005) organize psychological models of similarity into four types: geometric, feature-based, alignment-based, and transformational. (Research in machine learning has developed more computationally sophisticated takes on these styles; see for example, Chen, Garcia, Gupta, Rahimi, & Cazzanti, 2009.)

Geometric models represent objects as multidimensional points in a metric space. The similarity between objects is calculated as inversely related to the distance between them

in this space. A basic form may be found in models of generalization gradients originating from experiments on behavioral responses to stimuli varying in simple physical dimensions like wavelength of light (Ghirlanda & Enquist, 2003; Spence, 1937). Similarity of behavioral response is usually described as decreasing in the distance of stimulus qualities with exponential decay, $s(x, y) = \alpha \exp(-|x - y|/\beta)$, or Gaussian decay, $s(x, y) = \alpha \exp(-(x - y)^2/\beta^2)$, where α and β are scaling parameters. While having the appeal of parsimony, these models are typically applied to low-level stimuli and imply properties such as symmetry that are at odds with experimental results in other circumstances.

Feature-based models represent objects as collections of features. Similarity is based on a linear combination of the common and distinctive features of each object and is not in general symmetric. In Tversky's (1977) contrast model, $s(x, y) = \theta f(X \cap Y) - \alpha f(X - Y) - \beta f(Y - X)$, where X and Y are the feature sets of stimuli x and y , f is a monotonically increasing function, and θ , α , and β are nonnegative weights. With additional restrictions, stimulus similarity based on the contrast model forms a natural category structure that can be compactly represented in a hierarchical tree. In the ratio model, $s(x, y) = f(X \cap Y)/(f(X \cap Y) + \alpha f(X - Y) + \beta f(Y - X))$, normalizing similarity between 0 and 1.

Alignment-based models involve more complex mappings of features based on higher-order structure mapping. Similarity depends on the degree to which object features can be structurally aligned. For example, Goldstone's (1994) model of "similarity, interactive activation, and mapping" comprises a neural network that learns about the correspondences between stimulus features. Each node reflects the hypothesis that given features map onto each other across stimuli, with excitatory and inhibitory activation encouraging an exclusive one-to-one correspondence. Similarity is based on the weighted mean of feature proximity weighted by activation of the node representing the feature pair.

Transformational models are based on topological warping operations such as rotation, scaling, and translation. Similarity is computed from transformational distance, the degree of warping required to transform one stimulus into another. This may be defined in simple ways such as the minimum number of transformations needed (Imai, 1977), or in more complicated ways like Kolmogorov complexity, the length of the shortest computer program that describes the necessary transformations (Hahn, Chater, & Richardson, 2003). This style of model is typically applied to perceptual stimuli.

Empirical studies of case-based decision theory

CBDT has been applied to study consumer behavior (Gilboa & Schmeidler, 1993, 1997b, 2003; Gilboa, Postlewaite, & Schmeidler, 2015), brand choice (Gilboa & Pazgal, 1995), individual learning (Gilboa & Schmeidler, 1996), social learning (Blonski, 1999; Heinrich, 2013; Krause, 2009), sequential planning (Gilboa & Schmeidler, 1995b), asset pricing (Guerdjikova, 2006), real estate (Gayer, Gilboa, & Lieberman, 2007), portfolio

choice (Golosnoy & Okhrin, 2008), technology adoption (Eichberger & Guerdjikova, 2012), manufacturing capacity (Jahnke, Chwolka, & Simons, 2005), macroeconomic expectations (Pape & Xiao, 2014), and Japanese TV drama watching (Kinjo & Sugawara, 2016). The idea of similarity between strategic games on both structural and perceptual levels has been used to analyze learning, transfer, and spillover across different games and institutional setups (Bednar, Chen, Liu, & Page, 2012; Cason, Savikhin, & Sheremeta, 2012; Cooper & Kagel, 2003; Cownden, Eriksson, & Strimling, 2015; Di Guida & Devetag, 2013; Guilfoos & Pape, 2016; LiCalzi, 1995; Mengel & Sciubba, 2014; Rankin, Van Huyck, & Battalio, 2000; Samuelson, 2001; Sarin & Vahid, 2004; Spiliopoulos, 2013; Steiner & Stewart, 2008).

Experimental tests specifically conducted on CBDT have yielded encouraging results. Ossadnik, Wilmsmann, and Niemann (2013) ran a ball and urn experiment with a twist. Every ball had three separate payoffs on it, identified by colors (which were the same across balls). On each trial, participants had to choose a color. A ball was drawn from the urn (which contained a known number of balls) and only the payoff associated with the chosen color was revealed. After a number of trials, a second round began in which a few balls were removed from the urn without being revealed. Later on, a third round began in which several balls were similarly added to the urn. Given the limited information available and the high number of possible ball-color-value combinations, full Bayesian updating would be difficult. The experimenters found that, as compared with maximin-type criteria and simple model-free reinforcement learning, the data conformed best to CBDT supposing that similarity across trials was proportional to the number of balls in common.

Participants in the study of Grosskopf, Sarin, and Watson (2015) were in the role of a company having to choose production levels for an economic good. The amount of profit for a given production level depended on “market conditions,” which were represented by a list of five symbols. In each round, participants had access to only a few past cases, which were combinations of market conditions (case descriptions), production choices (actions), and profit levels (outcomes). Similarity between the vectors of past and present market conditions was taken to be the number of symbols in common, a special case of Tversky’s (1977) contrast model. CBDT described participant behavior better than a heuristic, which ignored market conditions and chose the production level yielding the highest past value.

Bleichrodt, Filko, Kothiyal, and Wakker (2017) used a special design to test the core of CBDT without making any structural assumptions about similarity. Participants made choices on the basis of hypothetical case banks, one of which consisted of true values and would be used for payment. Cases dealt with the monthly value appreciation of real estate investments in various parts of the Netherlands. Participants had to choose between gambles with payoffs based on the appreciation percentage of a new piece of real estate. This experimental design allows certain functions of similarity weights to be estimated, which

can be used to test the implications of CBDT from binary choices alone. CBDT predicts that people choose by combining, in a specific way, the hypothetical memory with their personal assessment of similarity across types and locations of real estate. The theory's axioms impose behavioral restrictions reflecting the consistency of similarity weights across decisions. These restrictions were generally satisfied by the data.

Pape and Kurtz (2013) combined CBDT with the ALCOVE neural network model to analyze classification learning. In this model, the relative importance of each feature dimension is updated from feedback, with overall learning rate, aspiration level, and degree of imperfect recall estimated as model parameters. A simulated case-based agent predicted the speed of learning well across categorization schemes of various difficulty levels (Nosofsky & Palmeri, 1996; Nosofsky, Gluck, Palmeri, McKinley, & Glauthier, 1994). Moreover, additive similarity was found to fit the data better than averaged similarity.

CBDT is attractive because it forces us to link choice to the set of cases in our memory in a way that offers a platform for the impact of memory and associations in economic modeling. Particularly in the most complex of situations, all cases may not be immediately recalled. Rather, we have to engage in mental search. Evaluation may derive from finite samples drawn from memory, as some theories posit. At the extreme, people often retrieve only a single case to work from. If the probability of retrieval is proportional to the similarity between cases, then the averaged case-based assessment constitutes the expectation of retrieved value. When we take into account that people draw small samples from similar cases in memory (Qian & Brown, 2005), regularly observed biases affecting judgment and decision-making can be parsimoniously explained (Gayer, 2010; Hertwig, Barron, Weber, & Erev, 2004; Marchiori, Di Guida, & Erev, 2015; Stewart, Chater, & Brown, 2006).

Computational models of association can be integrated with CBDT to produce a unified model for studying the effects of framing on economic decisions. After all, such phenomena are about altered patterns of mental association stemming from the way a problem is presented. In novel conditions, the case-based estimate represents a kind of half-educated guess. It is stitched together, Frankenstein-like, from whatever comes to mind. It is not an exceptionally consistent estimate and is prone to being jostled by the vagaries of memory. Preferences are therefore unstable, cobbled-together assessments of value that shift as different memories are emphasized. In this vein, Gonzalez and colleagues have developed case-based (aka instance-based) models that incorporate similarity and selective retrieval in the ACT-R architecture to predict and explain a variety of economic choices (Dutt & Gonzalez, 2012; Dutt, Arló-Costa, Helzner, & Gonzalez, 2014; Gonzalez, 2013; Gonzalez & Dutt, 2011; Gonzalez, Lerch, & Lebiere, 2003; Harman & Gonzalez, 2015; Lebiere, Gonzalez, & Martin, 2007; Lejarraga et al., 2012, 2014). Some of this work focuses explicitly on framing, accounting for variation in preferences based on differences in the retrieval process (Gonzalez & Mehlhorn, 2016).

COMPUTATIONAL CHARACTERIZATIONS

Case-based reasoning

The idea of computational connections should not be entirely surprising as CBDT was conceived of with a certain computational backdrop in mind—a problem-solving process known as CBR that stores training data and waits to make judgments until a new problem is posed (Stanfill & Waltz, 1986; Riesbeck & Schank, 1989; Aha, Kibler, & Albert, 1991; Kolodner, 1992, 1993). The heart of CBR lies in solving new problems by reusing and adapting solutions to similar old problems. It is captured by the “CBR cycle” consisting of the 4 *R*’s: Retrieve, Reuse, Revise, and Retain (Richter & Weber, 2013). When a new problem is encountered, similar past cases are *retrieved* from the case base, their information is *reused* to construct solutions, their solutions are *revised* to fit current needs, and the new experience is *retained* for future use.

CBR has been fruitfully applied to commercial tasks as diverse as customer service, vehicle fault diagnosis and repair, and aircraft part construction (Watson & Marir, 1994; Leake, 1994, 1996; Montani & Jain, 2010, 2014). For example, a critical task in the aerospace industry is to precisely bond together composite materials using extreme heat and pressure in an autoclave. However, the right way to arrange these materials in the autoclave is complicated because its heating properties are not perfectly understood, and identical examples are unavailable because product designs are always changing. The company Lockheed successfully tackled this problem with a software system called Clavier, which recommended new layouts by adapting previous similar layouts. Clavier proved useful even with a small case base, and with more experience its “performance ‘grew’ to approach that of the most experienced autoclave operator in the shop” (Hennessy & Hinkle, 1992).

Why has CBR proven so successful? It can be flexibly applied to a wide range of problems, even difficult ones encountered for the first time. CBR is a type of lazy learning, meaning that the answer is only generated when a new query arises. This just-in-time approach is helpful when faced with an infinite number of unencountered and unforeseen possibilities. We are commonly forced to perform in novel circumstances where causal relationships are not well understood but background knowledge can still prove useful, and CBR can support transfer learning here (Aha, Molineaux, & Sukthankar, 2009; Klenk, Aha, & Molineaux, 2011). We can further understand case-based decision-making by comparing control systems from a statistical standpoint.

Bias—variance trade-off

CBDT shares properties with nonparametric estimation. The case-based estimate is a similarity-weighted sum of case values. It takes the same kind of form as a nonparametric kernel estimate, which is a kernel-weighted sum of data points. The similarity function plays the role of the kernel, assessing how close the new input value is to each of the old

input values in psychological space, and then blending the old output values accordingly. The case-based estimate with averaged similarity especially mimics the Nadaraya–Watson kernel regression estimator, a locally weighted average of data points. If only a single case is retrieved due to cognitive limitations, the model coincides with nearest-neighbor interpolation. Case-based estimation may not be as agnostic as statistical technique about the domain of application since background information is contained in the shape of the similarity function. It may also exhibit properties such as asymmetry (Tversky, 1977) that are atypical in statistical applications. Nonetheless, formal links have been established between case-based and kernel-based methods (Gilboa, Lieberman, & Schmeidler, 2011; see also Hüllermeier, 2007). We may thus view CBDT from one angle as a nonparametric estimate of value. This link helps us see why and when the case-based estimate is useful.

A case-based controller exhibits a different statistical trade-off than model-free and model-based controllers. This entails a distinct pattern of advantages and disadvantages. A case-based system stakes out an intermediate position between model-free and model-based systems on the bias–variance spectrum.

Case-based control employs knowledge derived from unsupervised or other subtler forms of learning to a greater degree than a model-free system. It better leverages experience by casting a wider net in the sea of memory. In other words, it engages in greater generalization from other circumstances to its present condition. Simplistic reinforcement learning models relinquish this power and neglect background relationships between acts or contexts. Continuous state or action spaces provide extreme examples of the need to generalize. Continuity has been a classic issue in reinforcement learning partly because it implies that an agent never encounters the exact same action or state more than once. Incorporating the values of similar actions in similar contexts sharpens predictions. A kernel approach turns out to be robust to convergence problems that other solutions suffer from in continuous state spaces (Gershman & Daw, 2017; Ormoneit & Sen, 2002). Generalizing does come with the cost of statistical bias as the extra data reflect circumstances that may only be marginally relevant and can significantly degrade performance when poorly selected. In line with this, nonparametric estimators carry an intrinsic smoothing bias, which results from using data far from the focal point to reduce the estimator variance. But when one has almost no direct experience, using imperfectly relevant knowledge is worthwhile. For this reason, statisticians regulate smoothing bias via choice of bandwidth and find that the optimal window is larger when the sample is small. The benefit of even limited or noisy additional information is high when facing new stimuli.

However, a case-based controller is not as bold as a model-based controller. Model-based estimates impose strong assumptions in order to hone their predictions and reduce the portion of generalization error stemming from variance. This is the benefit of a cognitive map. But it comes at the cost of bias from two sources. First is the coarsening inherent

in the construction of any mental model. All practical models must be simplifications, otherwise they would be far too complicated to represent. Second is the more egregious misspecification resulting from a mistaken understanding of the world. This issue is made worse by conditions of limited experience, when little data are available to constrain the map. Like nonparametric objects, case-based estimates avoid structure in order to mitigate bias but yield to the error from variance. A model-based system goes out on a limb in an attempt to make sharp predictions across new circumstances. In this sense, the model-based controller is the staunch one that sticks to its guns, while the case-based controller exhibits a more flexible and graceful judgment. A drawback is that the latter will learn more slowly—it hesitates to draw inferences even when those inferences may be justifiable—but as the maxim goes, it is better to be approximately right than definitely wrong. When traveling through new and complex surroundings, where the risk of a misstep can be high, clinging stubbornly to potentially outmoded conclusions is especially maladaptive.

[Gilboa, Samuelson, and Schmeidler \(2013\)](#) construct a unified model containing multiple classes of reasoning. They show that an agent may exhibit cycles where Bayesian reasoning is used until an unexpected event occurs, at which point case-based and rule-based reasoning take the lead until more data are collected and a new probabilistic model is formed. CBR can thus be inductively rational in the face of the unexpected. [Lengyel and Dayan \(2008\)](#) show that a kind of episodic memory-based control can outperform model-based control when the world is novel and complex. Erroneous or misspecified aspects of the model-based belief structure, represented as inferential noise, produce costly mistakes particularly when problems are multistage and experience is limited. Researchers at Google DeepMind recently demonstrated that in the low-data regime, such episodic control prevails over other state-of-the-art algorithms in complicated sequential decision-making tasks like video games ([Blundell et al., 2016](#)), especially when the feature mapping can also be trained ([Pritzel et al., 2017](#)).

Despite these useful characterizations of case-based control, our understanding of how similarity is realistically learned and processed in the brain has more to say. This understanding could inspire further hybrid models that draw out the economic implications of lifelike neural architectures. The idea of a case-based system dovetails with recent interest in the role of the MTL, and specifically the hippocampus, in decision-making. This region might be considered a primary neural locus for the processes of learning and memory that instantiate a case-based system.

NEURAL PATHWAYS

Generalization and the hippocampus

Hippocampal function is traditionally conceived in terms of spatial knowledge and episodic memory. However, growing attention is being paid to how its associational

processing flexibly subserves the learning and construction of value, especially in novel and complex situations (Seger & Peterson, 2013; Shohamy & Turk-Browne, 2013; Wimmer & Shohamy, 2011). Though the canonical view of feedback learning focuses on the basal ganglia, recent work suggests expanding the previously overlooked role of the MTL. Dopamine-driven striatal learning turns out to be limited, for example, when feedback is delayed or withheld. The hippocampal region, which appears to play a central role in generalization, is then required to bind information about cues and outcomes across time and space. While the striatum is responsible for encoding stimulus–response links, the hippocampus is responsible for encoding stimulus–stimulus links. The MTL supports generalization by this process of bundling stimulus representations into associative networks, within which items are considered similar neurally and psychologically based on shared connections.

We tend to view memory as dealing with the past, but it actually exists to help us predict the future. The process of association carried out by the hippocampus has two purposes from a decision-making perspective: First is to retrieve relevant memories, particularly those elements corresponding to value, in service of present decisions; second is to construct, modify, and consolidate memory in service of future decisions.

The hippocampus tugs the mental strings connected to an encountered configuration of stimuli in an attempt to anticipate forthcoming stimuli and rewards. The ingredients needed for decision-making and value learning appear to be represented in the hippocampus. Human neuroimaging has revealed concurrent value and choice signals in area CA1 of the hippocampus shortly before choices are made, as well as outcome signals following choice (Lee, Ghim, Kim, Lee, & Jung, 2012). Striking evidence for a control system distinct from standard dopaminergic and striatal mechanisms comes from feedback learning experiments, which involve comparisons and dissociations with Parkinson's disease (PD) patients and MTL amnesics (Reber, Knowlton, & Squire, 1996; Moody, Bookheimer, Vanek, & Knowlton, 2004; Shohamy, Myers, Onlaor, & Gluck, 2004, 2009). Foerde, Race, Verfaellie, and Shohamy (2013) documented a double dissociation on a standard probabilistic learning task with either immediate or delayed feedback. When faced with immediate feedback, PD patients were impaired while amnesics performed as well as controls, whereas with delayed feedback, PD patients performed as well as controls while amnesics were impaired. Remarkably, the delay difference producing the effect was not long (1 s vs. 7 s).

Consistent with the idea that a case-based system is most advantageous under novelty, Poldrack et al. (2001) showed that control appears to be transferred from MTL to the striatum as classification learning proceeds. Moreover, several studies demonstrate involvement of the hippocampus in spillover of value to stimuli and actions that are new but similar to those observed or taken in the past (Kahnt, Park, Burke, & Tobler, 2012; Wimmer, Daw, & Shohamy, 2012). Barron, Dolan, and Behrens (2013) created especially novel stimuli, which were new combinations of familiar foods, such as an

avocado and raspberry smoothie. This forced participants to construct assessments of the novel goods via combination of past experiences. Activity in the hippocampus was found to be related to this construction process.

Though the exact mechanisms by which the MTL comes to generalize value are as yet unknown, any theories must respect the fundamental associative nature of hippocampal function (Horner & Burgess, 2013). As a multimodal convergence zone, it takes in signals from many regions. By the manner in which the hippocampus recognizes stimulus bundles, it links lower level stimuli to higher level associations and concepts, illustrated by sparse coding cells, extreme versions of which are popularly known as “grandmother cells” or “Jennifer Aniston neurons” (Kreiman, Koch, & Fried, 2000; Quiroga, Reddy, Kreiman, Koch, & Fried, 2005, 2008, 2014). It thus exerts some control over one’s degree of conceptual granularity, thereby impacting degrees of generalization. One proposed mechanism of generalization that fits this picture is integrative encoding, wherein episodes with overlapping elements are integrated into a linked network of mnemonic associations (Shohamy & Wagner, 2008). Retrieval under novel circumstances then activates this network and can indirectly draw upon associations between concepts or stimuli that were never directly experienced together (Walther, 2002), mechanically similar to the creation of false memories (Roediger & McDermott, 1995). Even bumblebees may similarly merge memories after feedback learning (Hunt & Chittka, 2015). Indeed, when a new memory is formed, older memories with overlapping events are reactivated (Schlichting, Zeithamova, & Preston, 2014), alongside the rewards tied to those older memories (Kuhl, Shah, DuBrow, & Wagner, 2010; Wimmer & Büchel, 2016).

Stimulus associations and the hippocampus

A large body of human and animal studies reveals that whenever stimuli are separated in time and space, the hippocampus is central to connecting them to each other as well as their spatial and temporal context (Staresina & Davachi, 2009). This is especially the case when the configurations are stable and consistent (Mattfeld & Stark, 2015). The hippocampus is engaged during sequence learning (Schendan, Searl, Melrose, & Stern, 2003), and lesions impair the ability to learn and remember temporal regularities (Curran, 1997; Farovik, Dupont, & Eichenbaum, 2010; Schapiro, Gregory, Landau, McCloskey, & Turk-Browne, 2014). It is usually crucial for “trace conditioning” in which there is a significant interval between the end of the conditioned stimulus and beginning of the unconditioned stimulus presentation (Bangasser, Waxler, Santollo, & Shors, 2006; Cheng, Disterhoft, Power, Ellis, & Desmond, 2008) and also seems involved in “delay conditioning” when there is a long delay between conditioned and unconditioned stimulus onset even if they overlap (Berger, Alger, & Thompson, 1976; Christian & Thompson, 2003; Green & Arenos, 2007; Tam & Bonardi, 2012). Computational models are able to

predict hippocampal learning in such paradigms by focusing on how its stimulus representations change over the course of a trial (Ludvig, Sutton, Verbeek, & Kehoe, 2009, 2008; Moustafa et al., 2013).

When new stimulus configurations are encountered, the hippocampus binds the components together and associates them with past bundles of stimuli, whether learning is explicit or implicit (Degonda et al., 2005; Rose, Haider, Weiller, & Büchel, 2002). The ultimate goal is to make better predictions through generalization. Accordingly, when there is reason to believe that different stimuli will foreshadow similar prospects, these stimuli actually become represented more similarly by neural activity patterns, so that they will be treated similarly in further processing. The stimuli come to activate similar networks and also become embedded and integrated more strongly within these networks, leading them to be better remembered (Kuhl et al., 2010; LaRocque et al., 2013; Staresina, Gray, & Davachi, 2009). Intriguingly, the degree of this representational overlap for a given memory is negatively related to the strength of its unique episodic reinstatement, suggesting a trade-off between integration of the memory into the network and retrieval of its specific details (Tomparry & Davachi, 2017).

This enhanced pattern similarity can be triggered in multiple ways. Most directly, cues that are associated with the same outcome are mentally bundled together, and information learned about one is generalized to the others. This phenomenon of acquired equivalence relies on the hippocampal formation (Bódi, Csibri, Myers, Gluck, & Kéri, 2009; Coutureau et al., 2002; Myers et al., 2003; Preston, Shrager, Dudukovic, & Gabrieli, 2004). The stimuli come to be coded more similarly in the hippocampus (McKenzie et al., 2014) and become easier to confuse with each other (Meeter, Shohamy, & Myers, 2009). Stimuli that merely appear close together in time and context, absent outcomes, are like-wise informationally linked. This sensory preconditioning also depends on the hippocampal formation (Port & Patterson, 1984; Wimmer & Shohamy, 2012), and so might higher-order conditioning, when the original cue is conditioned before cues are paired (Gilboa, Sekeres, Moscovitch, & Winocur, 2014). Such stimuli become represented more similarly by MTL activity patterns (Hsieh, Gruber, Jenkins, & Ranganath, 2014; Schapiro, Kustner, & Turk-Browne, 2012), and pattern similarity at the time of retrieval is related to one's subjective sense of temporal and contextual proximity between the objects (Ezzyat & Davachi, 2014), as well as successful memory for their order (DuBrow & Davachi, 2014).

Neural pattern similarity in the temporal lobe appears representative of psychological similarity (Charest, Kievit, Schmitz, Deca, & Kriegeskorte, 2014; Davis & Poldrack, 2014; Davis, Xue, Love, Preston, & Poldrack, 2014), perhaps because psychological category structure may be represented in such a dimension-reduced and hierarchical manner that it can be smoothly mapped onto a two-dimensional neural substrate (Huth, Nishimoto, Vu, & Gallant, 2012; Kriegeskorte et al., 2008). There is some evidence that hippocampal coding for nonsemantic item-context bundles also follows

a hierarchical structure. McKenzie et al. (2014) recorded activity from neuronal ensembles of rats in a learning task and found context to be of primary importance to coding similarity, followed by position of items within the environment, followed by the item valence (reward status), and lastly the item identity itself. These results can help us understand how similarity is constructed on deep levels.

Neural computations of the hippocampus

Some of the mechanisms contributing to such high-level patterns are reasonably well understood. Computational theories describe the associative retrieval and encoding functions of the hippocampal region in terms of information processing by each of its anatomical substructures in turn (Gluck & Myers, 2001; Hasselmo & Eichenbaum, 2005; Marr, 1971; McNaughton & Nadel, 1990; Treves & Rolls, 1994). Input from the neocortex is first processed through hippocampal afferents in a specialized manner, with the perirhinal and lateral entorhinal cortices supporting item memory and the parahippocampal and medial entorhinal cortices supporting context memory (Diana, Yonelinas, & Ranganath, 2013, 2007; Kragel, Morton, & Polyn, 2015; Libby, Hannula, & Ranganath, 2014; Reagh & Yassa, 2014). The entorhinal cortex (EC) acts as a primary gateway between the hippocampus and the rest of the brain. Information travels through a loop with recurrence and multiple paths (Andersen, Bliss, & Skrede, 1971): The EC projects to the dentate gyrus (DG), area CA3 (through the perforant pathway), and area CA1; DG projects sparsely to CA3 via mossy fibers; CA3 exhibits a relatively large amount of recurrent collaterals feeding back onto itself, and projects to CA1 via Schaffer collaterals; and CA1 projects out of hippocampus via subiculum and EC back out to neocortex, and via fornix to other regions in cortex.

A computational linchpin is area CA3, thought to form a recurrent autoassociative network that reconstructs complete memories from partial inputs (Gluck & Myers, 1997). In this process of pattern completion, the presentation of cues reinstates networks of activity based on the nexus of associated places, times, histories, concepts, and outcomes, particularly those that are most pivotally and centrally connected. Pattern completion by CA3 is integral to both memory retrieval and encoding, though they invoke different neural paths. Mice and rats with lesions to CA3 are impaired on spatial learning tasks especially when given a smaller number of cues with which to retrieve the full memory (Gold & Kesner, 2005; Nakazawa et al., 2002) and single-unit recording shows CA3 output as being closer to stored representations than to degraded input patterns (Neunuebel & Knierim, 2014). This sort of retrieval is predominantly initiated by direct input from the EC and is accordingly disrupted by lesions of the perforant pathway (Lee & Kesner, 2004), though some evidence suggests that dentate granule cells also help with pattern completion (Gu et al., 2012; Nakashiba et al., 2012). However, the projection from the EC is too weak to handle the encoding of new memories.

Autoassociative encoding can be powerful enough to yield one-shot learning, in which a single trial alone is enough to firmly store a memory (Day, Langston, & Morris, 2003; Nakazawa et al., 2003; Rutishauser, Mamelak, & Schuman, 2006). Incoming patterns must be separated if they are to be stored distinctively, which is considered a function of the DG (Bakker, Kirwan, Miller, & Stark, 2008; Leutgeb, Leutgeb, Moser, & Moser, 2007; McHugh et al., 2007; Schmidt, Marrone, & Markus, 2012). Encoding is indeed driven by the mossy fibers from the DG, and new learning is disturbed if these are inactivated, although retrieval is usually spared (Lassalle, Bataille, & Halley, 2000; Lee & Kesner, 2004). The mossy fiber synapses come close to the bodies of CA3 pyramidal neurons and are sometimes called “detonator synapses” because they hold the ability to forcefully induce associative plasticity among CA3 neurons and their afferents (Brandalise & Gerber, 2014; Chierzi, Stachniak, Trudel, Bourque, & Murai, 2012; Lee et al., 2013; Lysetskiy, Földy, & Soltesz, 2005; Rebola, Carta, Lanore, Blanchet, & Mulle, 2011).

Reencoding must normally happen when the stimuli anticipated by cued associations fail to match the stimuli actually encountered—that is, when there is a prediction error. Signals of expectancy violation have been detected in the hippocampus with a range of methods (Fyhn, Molden, Hollup, Moser, & Moser, 2002; Hannula & Ranganath, 2008; Honey, Watt, & Good, 1998; Knight, 1996; Kumaran & Maguire, 2006, 2007) and appear to be associative in that they are based on unexpected combinations of stimuli rather than merely novelty of stimuli alone (Kafkas & Montaldi, 2015; Shohamy & Wagner, 2008). These signals have been localized to area CA1, which is ideally placed to act as a comparator or match–mismatch detector, as it receives sensory information about the environment from the EC along with the associative predictions formed by CA3 (Chen, Olsen, Preston, Glover, & Wagner, 2011; Duncan, Ketz, Inati, & Davachi, 2012). Such signals are likely needed to switch between the retrieval and encoding modes of CA3 autoassociation. When expectations are not met, encoding is triggered and memories are updated, by either strengthening or weakening connections and representations as needed. The mnemonic representations of items that fail to materialize when expected become weaker, making them easier to forget (Kim, Lewis-Peacock, Norman, & Turk-Browne, 2014). These associative prediction errors guide learning in many circumstances, of which novelty is an important class (Kumaran & Maguire, 2007, 2009). In this way, the prediction error induces plasticity to adaptively enhance learning under novelty, complementing the adaptive properties of choice under novelty discussed earlier.

INTERACTIONS BETWEEN SYSTEMS

Many doors are open for interaction between control systems. The hippocampus is anatomically embedded in multiple dopaminergic pathways. The neurophysiological record shows direct connections between the hippocampal formation and the ventral

striatum (Floresco, Todd, & Grace, 2001; Legault, Rompré, & Wise, 2000; Lisman & Grace, 2005) and possibly dorsal striatum (Finch, 1996; Finch, Gigg, Tan, & Kosoyan, 1995; Jung, Hong, & Haber, 2003; La Grutta & Sabatino, 1988; Sabatino, Ferraro, Liberti, Vella, & La Grutta, 1985; Sørensen & Witter, 1983) and Scimeca and Badre (2012) discuss several ways the striatum could support retrieval. Direct dopaminergic projections from the ventral tegmental area (VTA) have been shown to enhance long-term potentiation in the hippocampus to support plasticity and encoding (Duncan, Tompary, & Davachi, 2014; Lisman & Grace, 2005; Shohamy & Adcock, 2010; Wittmann et al., 2005). Recent evidence indicates that dopamine release from the locus coeruleus also plays a pivotal role in hippocampal signaling (Kempadoo, Mosharov, Choi, Sulzer, & Kandel, 2016; Takeuchi et al., 2016), especially for one-shot learning in highly novel contexts (Wagatsuma et al., 2018). Dopamine modulates hippocampal plasticity on time-scales from minutes to hours (Bethus, Tse, & Morris, 2010; Frey et al., 1990; Lisman, Grace, & Düzel, 2011; O'Carroll, Martin, Sandin, Frenguelli, & Morris, 2006), improving memory encoding and consolidation (Apitz & Bunzeck, 2013; Axmacher et al., 2010; Imai, Kim, Sasaki, & Watanabe, 2014; Kafkas & Montaldi, 2015; McNamara, Tejero-Cantero, Trouche, Campo-Urriza, & Dupret, 2014; Murayama & Kitagami, 2014; Rosen, Cheung, & Siegelbaum, 2015; Rossato, Bevilacqua, Izquierdo, Medina, & Cammarota, 2009). Memory strength can thus be easily enhanced by reward, and information acquisition itself can provide pseudorewards or bonuses (Kakade & Dayan, 2002), strengthening memory via similar neural pathways (Bunzeck, Doeller, Dolan, & Düzel, 2012; Gruber, Gelman, & Ranganath, 2014; Kang et al., 2009; Wittmann, Daw, Seymour, & Dolan, 2008, 2007).

In the other direction, the hippocampus can activate dopaminergic neurons in the VTA by sending CA1 novelty signals through the subiculum, nucleus accumbens, and ventral pallidum (Bunzeck & Düzel, 2006; Lisman & Grace, 2005). Contextual information straight from CA3 also travels through lateral septum to the VTA (Luo, Tahsili-Fahadan, Wise, Lupica, & Aston-Jones, 2011). Hippocampal pattern completion, replay of experience, and autobiographical recollection evoke or reinstate representations of value in the striatum to help accurately consolidate memories and associations relating to stimuli (Han, Huettel, Raposo, Adcock, & Dobbins, 2010; Schwarze, Bingel, Badre, & Sommer, 2013) or rewards (Kuhl et al., 2010; Lansink, Goltstein, Lankelma, McNaughton, & Pennartz, 2009; Speer, Bhanji, & Delgado, 2014).

Growing evidence reveals that episodic memory can guide value-based decision-making and is starting to shed light on how the hippocampus and striatum interact in the process (Pennartz, Ito, Verschure, Battaglia, & Robbins, 2011). In a simple value learning paradigm, Duncan and Shohamy (2016) documented behaviorally that contextual familiarity encouraged the retrieval and use of past episodes in decision-making. Murty, FeldmanHall, Hunter, Phelps, and Davachi (2016) showed that cues were used to adaptively guide lottery choice when learned cue–outcome associations were strong.

Wimmer and Büchel (2016) cued the retrieval of single past episodes in which stimuli were associated with rewards and found that risk preferences were biased by reactivation of the reward values, which were represented in the striatum. Gluth, Sommer, Rieskamp, and Büchel (2015) found that evaluation of snack food was biased toward items that were better remembered, and they observed corresponding value signals in the striatum, hippocampus, and ventromedial prefrontal cortex (vmPFC). They further found that this bias was mediated by hippocampal–vmPFC functional connectivity. Several other studies have observed that the strength of hippocampal–striatal connectivity during reward learning and at rest is related to value generalization (Gerraty, Davidow, Wimmer, Kahn, & Shohamy, 2014; Kumaran, Summerfield, Hassabis, & Maguire, 2009; Wimmer & Shohamy, 2012; Wimmer et al., 2012). Thus, the distributed neural representation of stimuli, values, and their associations depends crucially on what type of information must be retrieved and applied.

Interactions between case-based and model-free systems

Both competitive and cooperative links have been observed between case-based and model-free behaviors, as well as their presumed neural substrates.

Several experiments indicate competitive links between MTL-dependent declarative learning and striatum-dependent procedural learning (Moody et al., 2004; Poldrack & Packard, 2003; Poldrack, Prabhakaran, Seger, & Gabrieli, 1999), which may be mediated by PFC (Poldrack & Rodriguez, 2004). Rats with hippocampal lesions actually perform better on procedural learning tasks (Eckart, Huelse-Matia, & Schwarting, 2012). It may be that hippocampal context–outcome associations interfere with striatal action–outcome contingencies that could be more important in such circumstances over the long run (Cheung & Cardinal, 2005). Collins, Ciullo, Frank, and Badre (2017) imposed working memory load by increasing the number of stimuli to be learned and found that this strengthened model-free reward prediction errors. Wimmer, Braun, Daw, and Shohamy (2014) used a drifting probabilistic reward learning task in which a unique incidental picture accompanied each trial. Better episodic memory for the pictures on a surprise memory test the following day was negatively correlated with reward and reinforcement learning rate during the task. For individual trials on which the picture was successfully remembered, reward had a weaker influence on the subsequent choice, and reward prediction error signals in the putamen were negligible.

At the same time, cooperative links have been demonstrated in similar paradigms (Ferbinteanu, 2016). Bornstein, Khaw, Shohamy, and Daw (2017) showed that decision-making in a multiarmed bandit task was biased by incidental reminders of past trials, consistent with a version of model-free reinforcement learning that incorporates episodic sampling. Aberg, Müller, and Schwartz (2017) found that delivered and anticipated rewards were positively related to associative memory encoding, and

valence-dependent asymmetries in these effects were modulated by individual differences in sensitivity to reward versus punishment. [Dickerson, Li, and Delgado \(2011\)](#) observed that prediction errors in feedback learning correlated positively with activity in both the putamen and the hippocampus. In some experiments centered on either episodic memory encoding or probabilistic reward learning, activity in the hippocampus appears to positively correlate with activity in the putamen on feedback trials when stimuli are successfully remembered later ([Sadeh, Shohamy, Levy, Reggev, & Maril, 2011](#); [Wimmer et al., 2014](#)). In a probabilistic learning task with feedback accompanied by incidental trial-unique images, [Davidow, Foerde, Galván, and Shohamy \(2016\)](#) found that stronger episodic memory encoding was correlated with enhanced reinforcement learning among adolescents but not adults. Moreover, functional hippocampal–striatal connectivity was positive only for adolescents. Thus the process of development may play an important role in how these systems interact. [Kahnt et al. \(2012\)](#) looked at value updating in a perceptual association paradigm, augmenting a standard reinforcement learning model with a similarity-based generalization gradient. They found that hippocampal–striatal connectivity was negatively correlated with the width of the generalization window, suggesting a discriminative mechanism.

The exact nature of such interactions thus remains an open question. Computational theory may help suggest possible mechanisms, especially cooperative ones. Various strands of the artificial intelligence literature synergistically combine CBR with model-free reinforcement learning to enhance transfer learning. This is particularly valuable when state and action spaces are large or continuous ([Santamaría, Sutton, & Ram, 1997](#)). Similar past cases can accelerate learning by contributing to initial guesses of the value function, which can then be revised according to temporal difference learning, retaining its promises of long-run convergence ([Drummond, 2002](#); [Gabel & Riedmiller, 2005](#); [Sharma et al., 2007](#); [Bianchi, Ribeiro, & Costa, 2008, 2009](#); [Celiberto, Matsuura, Mañtaras, & Bianchi, 2010, 2011](#)). Once learning has converged in a task, the optimal policy can be abstracted for transfer to future tasks ([Von Hessling & Goel, 2005](#)). In return, reinforcement learning is able to influence the retrieval of cases by helping with on-line assessment of the best similarity metrics for CBR ([Juell & Paulson, 2003](#)). Cases may be stored preferentially when the agent is attaining high rewards ([Auslander, Lee-Urban, Hogg, & Munoz-Avila, 2008](#)) and selectively pruned when they hinder prediction or exceed storage ([Gabel & Riedmiller, 2005](#); [Wilson & Martinez, 2000](#)).

Such computational models suggest further possibilities for neural interplay between case-based and model-free systems. Along related lines, an influential body of work has been inspired by the well-known Dyna architecture ([Sutton, 1990](#)), which is used to explain hippocampal replay of recent memories during rest ([Johnson & Redish, 2007](#); [Kurth-Nelson, Economides, Dolan, & Dayan, 2016](#)). Modified temporal difference algorithms with offline replay of previously experienced sequences allow extra practice,

substantially speeding up early learning (Johnson & Redish, 2005; Johnson & Venditto, 2015).

Another important form of generalization relies on eligibility traces, which are computational accessories to temporal difference learning attached to states or actions that facilitate their value updates across temporal gaps (Barto, Sutton, & Brouwer, 1981; Sutton & Barto, 1998). Given its responsibilities in connecting stimuli across delays, the hippocampus may be involved in instantiating eligibility traces (Ludvig et al., 2009). Implementation could happen by means of synaptic tagging, in which recently active synapses are tagged for increased susceptibility to long-term potentiation or depression over longer periods of time (Frey & Morris, 1997; Izhikevich, 2007). Dopamine firing patterns do appear to reflect eligibility traces (Pan, Schmidt, Wickens, & Hyland, 2005), and we have seen how strongly entangled the hippocampus is with various dopamine circuits. However, such hypotheses remain to be empirically verified. Notably, eligibility traces are most beneficial in non-Markovian environments. Among other reasons, this could occur when agents are unsure of what to attend to in an unfamiliar setting, rendering the state space only partially observable.

Interactions between case-based and model-based systems

Model-based decision-making relies on sophisticated forecasting, typically involving the estimation of state transition probabilities. One source of these subjective probabilities may be a case-based system (Blok, Medin, & Osherson, 2003; Taylor, Jong, & Stone, 2008).

Some evidence supports the existence of a hippocampal process for learning transition probabilities that operates in parallel with the striatum and is linked to model-based decision-making (Bornstein & Daw, 2012, 2013). Hippocampal similarity-based learning is also thought to be one mechanism for learning word transition probabilities of artificial grammars (Opitz & Friederici, 2004). Such belief updating may be premised on sequential association learning (Amso, Davidson, Johnson, Glover, & Casey, 2005) and the binding of regularities across time and space as discussed earlier. Consistent with a key role for association, Doll, Shohamy, and Daw (2015) found that generalization in an acquired equivalence task was correlated with use of a model-based strategy in a separate sequential learning task. Theoretically, probabilities constructed from stimulus associations might reflect the successor representation (Dayan, 1993), which assesses the expected future visitations of states based on their sequential cooccurrence. This can be done latently prior to the introduction of reward and sheds light on how cognitive maps may be neurally instantiated in the hippocampus (Stachenfeld, Botvinick, & Gershman, 2014, 2017). The successor representation could explain why sensitivity to contingency degradation is impaired in rats with lesions of the hippocampal region but sensitivity to outcome devaluation is spared (Corbit & Balleine, 2000; Corbit, Ostlund,

& Balleine, 2002). A mild disparity in these sensitivities occurs even under normal circumstances in humans, which may be explained by a hybrid successor representation/model-based mechanism (Momennejad et al., 2017). Moreover, the temporal context model of episodic memory can be viewed as estimating the successor representation (Gershman, Moore, Todd, Norman, & Sederberg, 2012), revealing a deep connection between episodic memory and reinforcement learning.

Outcome projection based on similar cases is common in the world at large and has proven successful when facing complex problems. As John Locke said, “in things which sense cannot discover, analogy is the great rule of probability.” Similarity-based approaches can help accurately predict college admissions (Klahr, 1969), movie revenue (Lovallo, Clarke, & Camerer, 2012), and legal case outcomes (Teitelbaum, 2014). Historically, weather forecasting was done by seeing how conditions evolved on similar recorded days (Kruizinga & Murphy, 1983). In general, this method of “reference class forecasting” suggested by Kahneman and Tversky (1982) has been found helpful in project management to the point where it is officially endorsed by the American Planning Association, particularly for “nonroutine projects ... and other local one-off projects”—in other words, novel problems with limited past data. One branch of decision theoretic models formalizes the idea by constructing probabilities from similarity-weighted frequencies of past outcomes—a kernel estimate of event occurrence. Billot, Gilboa, Samet, and Schmeidler (2005) provide an axiomatized representation of probabilities as similarity-weighted frequencies. Others have relaxed their assumptions in various ways, such as by allowing beliefs to depend on the database size, having multiple beliefs to reflect ambiguity (Eichberger & Guerdjikova, 2010), and combining similarity-weighted frequencies with a prior in a nested Bayesian framework (Bordley, 2011). Theoretical predictions from these models await empirical testing.

Another line of research focuses on a more flexible form of forecasting based on imagination. Imagining potential outcomes in detail can help agents evaluate options, and the hippocampus plays a significant role in this mental simulation (Buckner & Carroll, 2007; Gilbert & Wilson, 2007; Suddendorf & Corballis, 2007). Just as the hippocampus enables us to reconstruct vivid scenes from past episodes, it also helps us to conjure up potential future scenarios from reconstituted episodes (Schacter, Addis, & Buckner, 2007, 2008, 2012). In the process, it may interact with vmPFC to integrate related events in a flexible and prospectively useful form (Benoit, Szpunar, & Schacter, 2014; Weilbacher & Gluth, 2017; Zeithamova & Preston, 2010; Zeithamova, Dominick, & Preston, 2012). Future events are imagined in more detail when they would occur in familiar or recently experienced settings, revealing their origins in past episodes (Szpunar & McDermott, 2008). Envisioning future events recruits similar temporal and prefrontal regions as envisioning the past (Addis, Wong, & Schacter, 2007; Okuda et al., 2003; Schacter & Addis, 2007; Szpunar, Watson, & McDermott, 2007), and hippocampal amnesics typically exhibit impaired episodic prospection (Klein, Loftus, & Kihlstrom, 2002; Hassabis, Kumaran,

& Maguire, 2007; Addis, Sacchetti, Ally, Budson, & Schacter, 2009; Andelman, Hoofien, Goldberg, Aizenstein, & Neufeld, 2010; Kwan, Carson, Addis, & Rosenbaum, 2010; Race, Keane, & Verfaellie, 2011, 2013). Such imaginative prospection may be goal-relevant and enhanced by reward (Bulganin & Wittmann, 2015), though not always adaptively (Gershman, Zhou, & Komers, 2017). Animals in choice experiments exhibit a phenomenon known as vicarious trial and error, in which they pause at choice points and orient themselves toward potential options, as if they were envisioning the future implications of taking a given path (Johnson, van der Meer, & Redish, 2007; Muenzinger, 1938; Tolman, 1938). This behavior appears to rely on the hippocampus (Hu & Amsel, 1995; Hu, Xu, & Gonzalez-Lima, 2006), and hippocampal activity represents positions traveling down each path ahead of the animal (Johnson & Redish, 2007).

This type of goal-relevant simulation sometimes plays a role in intertemporal choice, as the constructed representation of future reward may feed into previously identified frontoparietal control regions associated with a preference for longer-term options (McClure, Laibson, Loewenstein, & Cohen, 2004). Rats with hippocampal lesions tend to pick smaller, immediate rewards (Abela & Chudasama, 2013; Cheung & Cardinal, 2005; Mariano et al., 2009; McHugh, Campbell, Taylor, Rawlins, & Bannerman, 2008; Rawlins, Feldon, & Butt, 1985). People who are prompted to consciously imagine spending a delayed reward in the future tend to choose the delayed option more often, and the strength of this bias is correlated with simulation richness (Benoit, Gilbert, & Burgess, 2011; Daniel, Stanton, & Epstein, 2013; Lebreton et al., 2013; Lin & Epstein, 2014; Liu, Feng, Chen, & Li, 2013; Peters & Büchel, 2010). Hippocampal amnesics do not display this effect, although their intertemporal choices appear to be comparable to controls who are not prompted to use imagination (Palombo, Keane, & Verfaellie, 2014; though see Kwan et al., 2015), in accordance with multiple process hypotheses. From a theoretical standpoint, associative neural network models of region CA3 naturally generate standard reward discounting curves derived from the predicted similarity representations they produce with respect to future states (Laurent, 2013).

A final intriguing angle centers on analogical reasoning, which depends on higher-order structural similarity and enables powerful generalization (Gentner, James Holyoak, & Kokinov, 2001; Holyoak, 2012; Kolodner, 1997). Analogizing appears to be a problem-solving ability near the peak of cognition and decision-making. Raven's Matrices, which test abstract relational reasoning, rank highly among mental tests in their *g*-loading (Jensen, 1998). The flexible application and recombination of past cases invokes more conscious processing involving our evolutionarily well-developed PFC (Krawczyk, 2012; Zeithamova & Preston, 2010). Analogical thinking has been tested in other species as well, and only chimpanzees have succeeded at a level modestly comparable to humans (Zentall, Wasserman, Lazareva, Thompson, & Rattermann, 2008). Notably, successful chimps were those with prior training in symbolic representations like language or tokens. Thus, high-level relational comparisons may be key to both

generalization and intelligence. These skills make a difference even at the frontier of human ability. The brokerage firm Merrill Lynch was styled after cofounder Charlie Merrill's experience in the supermarket industry (Gavetti, Levinthal, & Rivkin, 2005), and mathematician Stefan Banach often said that "good mathematicians see analogies between theorems or theories; the very best ones see analogies between analogies."

CONCLUSION

Decision neuroscience has been guided by the formal characterization of habitual and goal-directed control in terms of model-free and model-based systems. Research emerging from multiple fields points to the importance of alternative memory-based mechanisms in learning and valuation, straining the boundaries of the traditional dichotomy. I have reviewed the behavioral and neural evidence characterizing these "case-based" mechanisms from several angles.

Empirical research in psychology and economics shows that evaluation often occurs on the basis of similarity judgments (Gilovich, 1981). Theoretical work from economics, psychology, and computer science describes how decisions can be made by drawing on similar past cases (Gilboa & Schmeidler, 1995a; Kolodner, 1992). Computational and statistical perspectives reveal that such methods have different properties than typical model-free and model-based rules, analogous to nonparametric techniques (Gilboa et al., 2011). In particular, case-based evaluation makes fewer assumptions about problem structure than model-based evaluation, while still generalizing beyond the circumstances of past observations more than model-free evaluation. As a result, case-based approaches can be adaptive compared to other systems in novel and complex settings (Gilboa et al., 2013). This provides a normative justification for such alternative mechanisms and suggests under which conditions we might expect them to be mobilized.

The hippocampus and broader MTL structures are natural candidates to subserve a case-based system. Recent work in neuroscience indicates that these regions are involved in value-based judgment to a previously unrecognized extent. The hippocampus can reinstate memories of stimulus and reward associations when triggered by task-relevant or external cues (Wimmer & Büchel, 2016), and it sometimes even represents value signals directly (Gluth et al., 2015). Hippocampal involvement occurs especially with stimuli that are novel or natural objects (Barron et al., 2013) or when learning occurs over relatively long timescales (Foerde et al., 2013). Case-based computations could also support or compete with those of model-free or model-based systems, and both types of interaction have been observed (Bornstein & Daw, 2013; Wimmer et al., 2014).

A number of open questions follow from this perspective:

- Can tighter correspondences be found between brain activity and computational theory for a case-based system? Representations of value derived from reinforcement learning and expected utility have been observed in the striatum and prefrontal cortex

(Daw & O’Doherty, 2013; Knutson, Taylor, Kaufman, Peterson, & Glover, 2005), as have more exotic quantities such as regret (Lohrenz, McCabe, Camerer, & Montague, 2007). Case-based decision theory provides another quantitative account of value that may help explain neural activity.

- How does the interaction between hippocampal and striatal functions depend on the properties of the decision problem? In some tasks, the hippocampus reinstates contextual features to support striatal value representations (Wimmer & Büchel, 2016), while in other tasks, value signals appear to be represented in the hippocampus itself (Gluth et al., 2015). The distributed representation of value likely depends on properties of the stimulus and environment, such as familiarity and complexity, but clear principles are still to be laid out.
- What other adaptive properties might normatively justify contributions of episodic memory to decision-making? Computational noise in a model-based system can stem from stringent memory demands, so episodic control may exhibit more robust performance due to lower cognitive costs (Lengyel & Dayan, 2008). Such arguments may suggest new predictions about how factors like cognitive load affect learning and behavior.

To address these questions will require moving beyond traditional neuroeconomic paradigms in which artificial stimuli are presented repeatedly and value is learned incrementally. Neuroimaging techniques with high spatial resolution must also be used to measure brain activity in humans because the size, shape, and cytoarchitecture of the hippocampus make it difficult to image.

Evaluation based on similarity has arisen time and again across the behavioral and computational sciences. I have attempted to synthesize a wide range of relevant theoretical and empirical findings into a cohesive foundation for neuroeconomics to build on. These ideas reveal the need for studies that reflect the novel, unstructured, non-Markovian, discontinuous—in short, *messy*—nature of the world at large. Decision-making under such conditions may call upon different sets of mechanisms than those traditionally considered. The transparency and simplicity of most neuroeconomic experiments may obstruct our view of what happens when matters are not so tidy—and we live in an untidy world.

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