Case-Based Decision Neuroscience

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Abstract

I present a potential third instrumental system for value-based decision making that is premised upon similarity between past and present episodes. It can be mathematically described by the economic model of case-based decision theory accompanied by the computational background of case-based reasoning. This case-based system stands between model-free and model-based systems in its position on the bias-variance tradeoff and holds advantages over both when faced with novel and complex problems. The hippocampus and related MTL structures provide the neural substrate upon which case-based calculations are thought to be performed in the process of forming connections and associations between stimuli. This neuroscientific understanding sheds light on how such calculations can also contribute to model-free and model-based decisions.

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It’s 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 as 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 doesn’t have much to hang its structure on. The latter depends vitally on pre-existing 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. This system for 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.

Value judgment by similarity corresponds to a third economic model called case-based decision theory, inspired in part by a computational problem-solving process known as case-based reasoning. This model has links to nonparametric statistics, suggesting why and when the system works well. Recent evidence from neuroeconomics suggests that we use this kind of system and implicates the hippocampus and related medial temporal lobe regions as neural loci. I lay out the multilayered argument for a distinct third “case-based” decision system combining theory and evidence from economics, psychology, neuroscience, statistics, and computer science. This can be thought of as a complementary narrative to what others have described as episodic control (Dayan, 2008; Lengyel and Dayan, 2007).
Judgment by similarity

Judgments based on similarity are ubiquitous. Consciously and unconsciously, we map job candidates and sports players onto predecessors to describe and 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 analogs (various startups have been described as the Ubers of food delivery, flowers, laundry, women’s haircuts, 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 contributed article), 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 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 et al. 2014). 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 learning transfer. This dimension reduction aspect of similarity is intimately tied to our propensity to associate and connect and categorize, and draws upon their powers. We may not be wired to easily navigate probabilistic state spaces, but we are wired to effortlessly form comparisons and associations between concepts in our memory. Memories and associations are immediately recognizable as
the foundations of a brain; one is even tempted to say that a brain is memories and associations. Psychological similarity is a simple representation of holistic evaluation buried within our minds. If you hear that the TV show *Curb Your Enthusiasm* is like *Seinfeld* (as they share creators), despite having no direct experience you immediately have an understanding of the complex brand of observational humor to expect if you watch it.

This isn’t to say that similarities are always well-founded. The movie *Man’s Best Friend* turned out to be terrible. We can be unconsciously misled by superficial connections, even when we are experts and the stakes are high. 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!’ ” Though he later disavowed it as a joke, such biases are plausible. In fact Gilovich (1981) asked professional sportswriters and varsity football coaches to predict the success of fictitious young players based on experimental profiles. In one manipulation, the profile described a player as having won an award named after a famous pro player who either played the same position or a different position. When the pro and youth played in the same position, Gilovich found that participants gave the young player better ratings. Pattern matching is natural, seductively so. Classic findings in behavioral economics are explained by the indiscriminate tendency to gauge similarity. When asked how likely it is that 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, a claim which violates the laws of probability (Tversky and Kahneman, 1983). What’s happening is that Linda more closely resembles our idea of a feminist bank teller than merely a prototypical bank teller. We engage in attribute substitution and answer queries about probability with assessments of similarity (Bar-Hillel, 1974). This has the side effect of base-rate neglect, and lies at the heart of the representativeness heuristic (Kahneman and Tversky, 1972).

When something is linked with other examples, it is ascribed the characteristics associated with those examples, one such characteristic being value. In Gilovich’s study, it is more instinctive to mentally link football players in the same position, and in doing so, have the famous player’s success spread to the concept of the young player. Economic valuation based on similarity has received little attention. Nonetheless, economists have been slowly exploring this theme, developing a model that is akin to
value-oriented categorization and embodies this mental contagion of value.

Case-based decision theory

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 (1995) as an alternative to expected utility intended to be more realistic in some circumstances. In order to apply classical expected utility theory, the agent must hold subjective probabilities over all pertinent states of the world. In many situations, though, 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 only considered genuinely appropriate inside what Savage (1954) called a small world, where experience was plentiful. CBDT was meant to tackle decision making in grand worlds.

The primitive concepts of CBDT are a set of past cases and subjective similarity assessments between each case and the current situation. Formally, each case is a triple \((q, a, r)\), where \(q\) represents the problem situation, \(a\) is the action taken, and \(r\) is the result. The agent’s memory \(M\) is a set of these cases. The agent assesses the value of an action by combining the values of past outcomes when that action was taken weighted by the similarity between the current situation (with description \(p\)) and each past case (with description \(q\)), \(s(p, q)\):

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

Gilboa and Schmeidler (1997a) provided a generalization allowing similarity between cases to depend on acts in addition to descriptions, so \(U(a) = \sum_{(q, b, r) \in M} s((p, a), (q, b))u(r)\), and Gilboa et al. (2002) modernized the axiomatization for clarity and to support empirical testing. A variant also formulated in Gilboa
and Schmeidler (1995) 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 big vacation and have narrowed the options to Paris, France, or Sydney, Australia. Though you’ve been to neither, you think back to your past trips to Montreal, Los Angeles, and Vancouver, as laid out in Table 1. Though it was chilly, you had a decent time in French-speaking urban Montreal (utility 5), a city you feel 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 don’t, and the people were a mixed bag, 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, with its beautiful mountains, oceans, and fresh air, was fantastic, 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.)

<table>
<thead>
<tr>
<th>city</th>
<th>s(city, Paris)</th>
<th>s(city, Sydney)</th>
<th>utility</th>
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<tbody>
<tr>
<td>Montreal</td>
<td>0.8</td>
<td>0.1</td>
<td>5</td>
</tr>
<tr>
<td>Los Angeles</td>
<td>0</td>
<td>0.5</td>
<td>6</td>
</tr>
<tr>
<td>Vancouver</td>
<td>0.5</td>
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<td>10</td>
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What does the similarity function look like? 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 (Spence, 1937; Ghirlanda and Enquist, 2003). 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, \(s(x,y) = \alpha \exp(-(x - y)^2/\beta^2)\). While having the appeal of parsimony, these models apply more to low-level stimuli and imply properties such as symmetry which are at odds with experimental results in other
circumstances. Tversky (1977) constructed similarity functions that depend on the common and distinct features of the comparates, and are not in general symmetric. In the 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 \( \theta \), \( \alpha \), and \( \beta \) are non-negative 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. The relevant stimulus qualities themselves may be selected based on some dimension reduction process applied to the high-dimensional attribute space of the original stimuli.

CBDT has been applied to study consumer theory (Gilboa and Schmeidler, 1993; Schmeidler and Gilboa, 1994; Gilboa and Schmeidler, 1997b; Gilboa et al., 2015), brand choice (Gilboa and Pazgal, 1995), social learning (Blonski, 1999; Krause, 2009; Heinrich, 2013), asset pricing (Guerdjikova, 2006), real estate (Gayer et al., 2007), portfolio choice (Golosnoy and Okhrin, 2008), technology adoption (Eichberger and Guerdjikova, 2012), manufacturing capacity (Jahnke et al., 2005), macroeconomic expectations (Pape and Xiao, 2014), and Japanese TV drama watching (Kinjo and Sugawara, 2014). 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 (LiCalzi, 1995; Rankin et al., 2000; Samuelson, 2001; Cooper and Kagel, 2003; Sarin and Vahid, 2004; Steiner and Stewart, 2008; Bednar et al., 2012; Cason et al., 2012; Di Guida and Devetag, 2013; Guilfoos and Pape, 2013; Spiliopoulos, 2013; Mengel and Sciubba, 2014; Cownden et al., 2015).

The few experimental tests carried out on CBDT have yielded encouraging results. Ossadnik et al. (2013) ran a ball and urn experiment with a twist. Every ball had three colors on it, each associated with a separate payoff. On each trial, participants had to choose a color, after which a ball was drawn from the urn (containing a known number of balls) and the payoff associated with only that 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, and later, for a third round several balls were similarly added to the urn. Given the limited information and high number of possible ball-color-value combinations, full Bayesian updating would be untenable. The experimenters found that, as compared with maximin-type criteria and simple reinforcement learning, the
data conformed best to CBDT supposing the similarity across trials was proportional to the number of balls in common with that trial.

Participants in the study of Grosskopf et al. (2008) were in the role of a company having to choose production levels for a 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 only a few past cases, which were combinations of market conditions (case descriptions), production choices (actions), and profit levels (outcomes). It would not be possible to rigorously identify a tractable state space for this problem. All the ingredients for a case-based decision were present, though. Participant choices were accurately described by CBDT with similarity between the vectors of past and present market conditions taken to be the number of symbols in common, a special case of Tversky’s (1977) contrast model.

Bleichrodt et al. (2013) used a clever design to test the core of CBDT without making any structural assumptions about similarity. Participants made choices on the basis of sets of hypothetical case banks, one of which consisted of true values and was used for payment. This allowed them to back out functions of similarity weights which can be used to test the implications of CBDT from binary choices alone. Each case bank comprised a few instances of different kinds of real estate in different parts of the Netherlands as well as their value appreciation over the previous few years. Participants had to choose between gambles with payoffs based on the appreciation percentage of a new piece of real estate. CBDT predicts that they choose by combining in a specific way the hypothetical memory with their personal assessment of similarity across types and locations of real estate. These predictions imply formal restrictions reflecting the consistency of similarity weights across decisions, implications that were generally satisfied by the data.

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, we can parsimoniously
explain regularly observed biases affecting judgment and decision making (Marchiori et al., 2015; Stewart et al., 2006; Gayer, 2010; Hertwig et al., 2004).

An exciting possibility is to integrate computational models of association with CBDT and attempt to produce a unified model for studying the effects of framing and priming on economic decisions. After all, these 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 and CBDT is a cobbled-together assessment that shifts as different memories are emphasized. Priming would have the greatest effect here by altering the search path, and the availability heuristic may be thought of in these terms. Pape and Kurtz (2013) took an early step in this direction by hybridizing CBDT with the ALCOVE neural network model to simulate human classification learning. They found a simulated case-based agent fits past data well (Nosofsky et al., 1994; Nosofsky and Palmeri, 1996), more so with additive similarity over averaged similarity, and were able to estimate model parameters including learning rate, aspiration level, and degree of imperfect recall.

Case-based reasoning

The idea of computational linkages should not be entirely surprising as CBDT was conceived of partly with a certain computational backdrop in mind — a problem-solving process known as case-based reasoning (CBR) that stores training data and waits to make judgments until a new problem is posed. 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 Rs: Retrieve, Reuse, Revise, and Retain (Richter and 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. People have used this method (sometimes in conjunction with others such as RL, as we will see later) to address challenging practical matters. Aside from the host of quasi-academic applications of case-based reasoning (Montani and Jain, 2010, 2014), over 100 commercial software applications were identified
decades ago (Leake, 1994, 1996; Watson and Marir, 1994), a number that has since grown to include various household names. These examples span domains as diverse as aircraft part construction, vehicle fault diagnosis and repair, computer purchasing, and customer service. Currently, recommendation engines used by Netflix and Amazon to suggest movies to watch or products to purchase run on collaborative filtering techniques that look for similarities between users based on their rating patterns.

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 problem arises. This just-in-time approach is ideal 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. Using what has been learned in one task to tackle another is known in computer science as transfer learning. The computational literature has many examples showing CBR can address transfer learning (Aha et al., 2009). The form of CBR that most resembles CBDT, called instance-based learning, can be theoretically characterized as a “weak but general” learner (Griffiths and Bridge, 1995b,a). But we can further characterize case-based decision making when we compare valuation systems from a statistical standpoint.

**Bias-variance tradeoff**

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 of the conditional mean, 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 weighting function. It may also exhibit properties such as asymmetry (Tversky, 1977) which are
outside the usual assumed confines particularly if the non-averaged variant is used. Nonetheless, formal links have been established between case-based and kernel-based methods (Gilboa et al. 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 decision maker (CBDM) exhibits a different statistical tradeoff than model-free and model-based decision makers. 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.

A CBDM employs knowledge derived from unsupervised or other subtler forms of learning to a greater degree than a model-free system. He casts a wider net in the sea of his memory to leverage experience. In other words, the CBDM engages in greater generalization from other circumstances to his present condition. Standard reinforcement models relinquish this power and neglect background relationships between acts or contexts. Continuous action spaces are an extreme example of the need to generalize. Continuity has been a classic (albeit surmountable) problem in reinforcement learning partly since the probability that any particular action has been taken before is zero. Incorporating the values of similar actions in similar contexts sharpens predictions, and to the extent that the extra data helps predict an action value, including it is a net gain. A kernel approach also turns out to be robust to convergence problems that other solutions suffer from in continuous state spaces (Ormoneit and Sen, 2002).

Generalizing does come with the cost of statistical bias as the extra data reflects circumstances that may only be marginally relevant and can significantly degrade performance when poorly chosen. 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 indirectly 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 CBDM is not as bold as a model-based decision maker. Model-based estimates impose 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 hold. Second are more egregious forms of misspecification resulting from a mistaken understanding of the world. This issue is worsened by conditions of limited experience, when there is only a tiny island of solid reality to grab onto.

Case-based estimates, which take on properties of nonparametric objects, avoid structure in order to mitigate bias but submit to the error from variance. A model-based system goes out on a limb in an attempt to make sharp predictions across circumstances. In this sense, the model-based decision maker is the staunch one who sticks to his guns, while the CBDM exhibits a more flexible and graceful judgment. A drawback is that a CBDM’s learning will be slower – he hesitates to draw inferences even when those inferences may be justified – but as the maxim goes, it’s better to be approximately right than definitely wrong. Especially when travelling through new and complex surroundings, where the risk of a misstep can be high, clinging stubbornly to potentially outmoded conclusions is a maladaptive way to proceed. Lengyel and Dayan’s (2007) simulation results show that a kind of episodic controller can perform better than a model-based controller when the world is tough to fully grasp. Erroneous or misspecified aspects of the model-based belief structure, represented as inferential noise, produce costly mistakes, particularly when the problems are multi-stage and experience is limited. Under these conditions the episodic controller prevails. Gilboa et al.’s (2013) unified model containing multiple classes of reasoning shows that under some conditions, 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 is collected and a new probabilistic model is formed. Case-based reasoning can thus be inductively rational in the face of the unexpected.

Despite these useful characterizations of case-based decision making, our understanding of how similarity is realistically learned and processed in the brain has remained untapped. This understanding could inspire more hybrid models that draw out the economic implications of lifelike connectionist theories. The idea of a case-based system dovetails with recent interest in the role of the medial temporal lobe, 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.
Generalization and the hippocampus

Hippocampal function is traditionally conceived in terms of spatial knowledge (which I will largely ignore in what follows) and episodic memory, but less attention has been devoted in neuroeconomics to considering how the flexible background associations it forms from past cases subserve generalized valuation and decision making in new situations (Wimmer and Shohamy, 2011; Seger and Peterson, 2013; Shohamy and Turk-Browne, 2013). Though the canonical view of feedback learning focuses on the basal ganglia (BG), recent work suggests expanding the previously overlooked role of the medial temporal lobe (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. As we will see, the MTL supports generalization by this process of bundling stimulus representations into associative networks, within which items are considered similar neurally and psychologically because of 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 ingredients needed for decision making and value learning appear to be represented in the hippocampus. Human imaging 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 et al., 2012). The hippocampus also seems to be involved in spillover of value to similar actions (Wimmer et al., 2012), and in constructing assessments of novel options via combination of past experiences (Barron et al., 2013). The most striking evidence for a control system distinct from standard dopamine and striatum dependent mechanisms comes from feedback learning experiments which in-
volve comparisons and dissociations with Parkinson’s disease (PD) patients and MTL amnesics (Reber et al., 1996; Moody et al., 2004; Shohamy et al., 2004, 2009). In an emblematic study, Foerde et al. (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 second vs 7 seconds).

Though the exact mechanism by which the MTL comes to generalize value is as yet unknown, any theories must respect the fundamental associative nature of hippocampal function (Horner and 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 et al., 2000; Quiroga et al., 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 and 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). Even bumblebees may similarly merge memories (Hunt and Chittka, forthcoming). Indeed, when a new memory is formed, older memories with overlapping events are reactivated (Schlichting et al., 2014), alongside the rewards tied to those older memories (Kuhl et al., 2010).

**Hippocampal binding**

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 and Davachi, 2009). This is especially the case when the configurations are stable and consistent (Mattfeld and Stark, 2015). The hippocampus is usually crucial for trace conditioning when there
is a significant interval between the end of the conditioned stimulus and beginning of
the unconditioned stimulus presentation (Bangasser et al., 2006; Cheng et al., 2008),
but also seems involved in delay conditioning when there is a long delay between
conditioned and unconditioned stimulus onset even if they overlap (Berger et al.,
1976; Christian and Thompson, 2003; Green and Arenos, 2007; Tam and Bonardi,
2012), as predicted by computational models (Ludvig et al., 2008, 2009; Moustafa
et al., 2013). It is engaged during sequence learning (Schendan et al., 2003), and
lesions of it impair the ability to learn and remember regularities (Curran, 1997;
Farovik et al., 2010; Schapiro et al., 2014).

When new stimulus configurations are encountered, the hippocampus binds the
components together and associates them with past bundles of stimuli, explicitly
or implicitly (Rose et al., 2002; Degonda et al., 2005). 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 for
the purposes of prediction and also become embedded and integrated more strongly
within these networks leading them to be better remembered (Staresina et al., 2009;
Kuhl et al., 2010; LaRocque et al., 2013). This enhanced pattern similarity can be
triggered in multiple ways.

Most directly, cues that are associated with the same outcome are mentally bun-
dled together, and information learned about one is generalized to the others. This
phenomenon of acquired equivalence relies on the hippocampal formation (Coutureau
et al., 2002; Myers et al., 2003; Preston et al., 2004; Bódi et al., 2009). The stimuli
come to be coded more similarly in the hippocampus (McKenzie et al., 2014) and
become easier to confuse with each other (Meeter et al., 2009). Stimuli that merely
appear close together in time and context, absent outcomes, are likewise informa-
tionally linked. This sensory preconditioning also depends on the hippocampal formation
(Port and Patterson, 1984; Wimmer and Shohamy, 2012), as does higher order condi-
tioning, when the original cue is conditioned before cues are paired, at least sometimes
(Gilboa et al., 2014). Such stimuli become represented more similarly by MTL activ-
ity patterns (Schapiro et al., 2012; Hsieh et al., 2014), and pattern similarity at the
time of retrieval is related to one’s subjective sense of temporal and contextual prox-
imity between the objects (Ezzyat and Davachi, 2014), as well as successful memory
Neural pattern similarity in the temporal lobe appears representative of psychological similarity (Davis and Poldrack, 2014; Davis et al., 2014; Charest et al., 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 (Kriegeskorte et al., 2008; Huth et al., 2012). There is some evidence that hippocampal coding for nonsemantic item-context bundles also follows a hierarchical structure, as McKenzie et al. (2014), when recording from neuronal ensembles of rats in a learning task, 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 level.

Neural computations of the hippocampus

The machinery that generates such high level patterns is 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 (Marr, 1971; McNaughton and Nadel, 1990; Treves and Rolls, 1994; Gluck and Myers, 2001; Hasselmo and Eichenbaum, 2005). 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 et al., 2007, 2013; Libby et al., 2014; Reagh and Yassa, 2014; Kragel et al., 2015). 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 et al., 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. The computational linchpin is area CA3, thought to form a recurrent autoassociative network reconstructing complete memories (and perhaps heteroassociatively retrieving sequences) – represented as patterns of neuronal firing.
– from partial inputs. In this process of pattern completion, the presentation of cues reactivates 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 (Nakazawa et al., 2002; Gold and Kesner, 2005), and single-unit recording shows CA3 output as being closer to stored representations than to degraded input patterns (Neunuebel and Knierim, 2014). This sort of retrieval is predominantly initiated by direct input from the EC, and accordingly is disrupted by lesions of the perforant pathway (Lee and Kesner, 2004), though some recent evidence suggests that old dentate granule cells also help with pattern completion (Nakashiba et al., 2012; Gu 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 (Nakazawa et al., 2003; Day et al., 2003; Rutishauser et al., 2006), necessary to, for example, episodic memory. Incoming patterns must be separated if they are to be stored distinctively, which is a classic function of the DG (McHugh et al., 2007; Leutgeb et al., 2007; Bakker et al., 2008; Schmidt et al., 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 et al., 2000; Lee and Kesner, 2004). The mossy fibers 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 (Lee et al., 2013; Brandalise and Gerber, 2014; Chierzi et al., 2012; Lysetskiy et al., 2005; Rebola et al., 2011).

Re-encoding 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 (Knight, 1996; Honey et al., 1998; Fyhn et al., 2002; Kumaran and Maguire, 2006, 2007; Hannula and Ranganath, 2008), and appear to be associative in that they are based on unexpected combinations of stimuli rather than merely novelty of stimuli alone (Shohamy and Wagner, 2008; Kafkas and Montaldi, 2015).
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 et al., 2011; Duncan et al., 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 et al., 2014). These associative prediction errors guide learning in many conditions, of which novelty is an important subgroup (Kumaran and 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.

What to learn and store is itself a choice, and because memory exists in order to improve future decision making, the choice of what to encode ought to reflect the value of information. Even when the prospect of external reward does not accompany some piece of information, it may nonetheless pay off in the future. Acquiring information provides pseudorewards or bonuses (Kakade and Dayan, 2002) for this reason, and information seeking itself is considered motivating. The mechanism by which this happens is partly shared with motivation from reward (Wittmann et al., 2007, 2008; Bunzeck et al., 2012; Kang et al., 2009; Gruber et al., 2014), and the MTL and BG act in concert to achieve these effects. The hippocampus is anatomically embedded in the midbrain dopaminergic circuit, which is vital to its function. The hippocampus can activate dopaminergic neurons in the VTA by sending CA1 novelty signals from the subiculum through the nucleus accumbens and ventral pallidum (Lisman and Grace, 2005; Bunzeck and Düzel, 2006). Direct dopaminergic projections from the VTA then enhance LTP in the hippocampus to support plasticity and encoding (Wittmann et al., 2005; Lisman and Grace, 2005; Shohamy and Adcock, 2010; Duncan et al., 2014) on timescales of minutes to hours (Frey et al., 1990; O’Carroll et al., 2006; Bethus et al., 2010; Lisman et al., 2011), ultimately improving retrieval (Rossato et al., 2009; Axmacher et al., 2010; Apitz and Bunzeck, 2013; Imai et al., 2014; Murayama and Kitagami, 2014; Kafkas and Montaldi, 2015). Intrinsic and extrinsic rewards alike activate components of this circuit, and reactivation of experience in the hippocampus can be enhanced by real or anticipated reward (Singer and Frank,
The neurophysiological evidence shows direct connections between the hippocampus/EC and the ventral striatum (Floresco et al., 2001; Legault et al., 2000; Lisman and Grace, 2005) and, albeit less confidently, dorsal striatum (Sørensen and Witter, 1983; Finch, 1996; Finch et al., 1995; La Grutta and Sabatino, 1988; Sabatino et al., 1985; Jung et al., 2003). In addition, several kinds of information flow along multiple pathways besides the mesolimbic for different purposes. For instance, contextual information straight from CA3 travels through lateral septum to the VTA (Luo et al., 2011) linking it to reward. Moreover, many key learning processes in the hippocampus are simultaneously mediated by other systems and neurotransmitters such as acetylcholine, serotonin, and norepinephrine (Hasselmo, 1995), which may explain MTL learning even when dopaminergic activity is disrupted. The hippocampal region thus has ample opportunity to interact with other, potentially striatal-dependent control systems via direct anatomical projections or indirect loops including other regions altogether. In fact, during associative tasks and at rest, the hippocampus is functionally connected to the striatum (Ross et al., 2011; Kahn and Shohamy, 2013; Mattfeld and Stark, 2015) and the strength of this connection is related to its influence on choice (Wimmer and Shohamy, 2012; Wimmer et al., 2012). Transfer of learning relates to connectivity between hippocampus, vmPFC, and striatum (Kumaran et al., 2009; Gerraty et al., 2014). Hippocampal pattern completion, replay of experience, and autobiographical recollection evoke or reinstate representations of value in the striatum so as to help accurately consolidate reward memories and associations (Lansink et al., 2009; Kuhl et al., 2010; Speer et al., 2014). Many doors are open for multiplex interactions between case-based and model-free or model-based systems.

**Interactions between case-based and model-free affiliate processes**

Several experiments indicate competitive links between the processes which seem to underlie case-based and model-free systems (Poldrack and Packard, 2003), even on nonspatial tasks. A negative functional relationship has frequently been found between the MTL and striatum during feedback learning (Jenkins et al., 1994; Poldrack et al., 1999, 2001; Moody et al., 2004). Rats with hippocampal lesions actually
perform better on procedural learning tasks (Eckart et al., 2012), and sometimes on delayed reinforcement tasks, ostensibly because hippocampal context-outcome associations may interfere with striatal action-outcome contingencies that could be more important under certain circumstances (Cheung and Cardinal, 2005). More direct evidence comes from Wimmer et al.’s (2014) 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 in which the picture was successfully remembered, reward had a weaker influence on the subsequent choice, and reward prediction error signals in the putamen were almost nil.

At the same time, cooperative links have been demonstrated also. Prediction errors in one feedback learning experiment correlated positively with activity in both the putamen and the hippocampus (Dickerson et al., 2011). More direct evidence here, too, comes from the reward learning task of Wimmer et al. (2014) with incidental pictures. They discovered that on trials when incidental pictures were remembered, activity in the hippocampus was significantly correlated with activity in the putamen, a result corroborated by other research (Sadeh et al., 2011).

Thus whether interaction is seen as competitive or cooperative depends on the job at hand. The striatum can support hippocampal case-based operations at the expense of some of its own responsibilities. The hippocampus can help striatal model-free generalization in return. Kahnt et al. (2012) looked at value updating in a perceptual association paradigm, augmenting a standard RL model with a similarity-based generalization gradient. They found that hippocampal-striatal connectivity predicted the width of the generalization window, though with a negative correlation. Notwithstanding the basic sensory nature of the task, this suggests the hippocampus could at times control generalization by restricting percept identity. Control over conceptual granularity at a more abstract level could facilitate hierarchical learning (Dietterich, 2000; Sutton et al., 1999).

An important form of generalization relies on eligibility traces, which are computational accessories to TD learning attached to states or actions that facilitate their value updates across temporal gaps (Barto et al., 1981; Sutton and Barto, 1998). Given its responsibilities in connecting stimuli across delays, the hippocampus may instantiate eligibility traces. Implementation could happen by means of synaptic
tagging, in which recently active synapses are tagged for increased susceptibility to LTP or LTD over longer periods of time (Frey and Morris, 1997; Izhikevich, 2007). Dopamine firing patterns do appear to reflect eligibility traces (Pan et al., 2005), and we have seen how strongly entangled the hippocampus is with midbrain dopamine circuits. Notably, eligibility traces are most beneficial when the world is non-Markovian, such as occurs when the state space is partially observable, likely to be applicable in unfamiliar settings due to attentional limitations.

Interactions between the striatum and hippocampus may be modulated by PFC, potentially leading to either interference or support. Path analysis of one feedback learning experiment revealed that negative striatal-hippocampal functional connectivity was mediated by paths to and from PFC regions (Poldrack and Rodriguez, 2004). Negative paths between PFC and MTL suggest the former exerted inhibitory control over the latter. In another task, experimenters posited that instructions, from one’s own rules or others’ teachings, could produce training signals from the hippocampus and PFC that bias striatal learning towards consistency with the instructions (Doll et al., 2009). The validity of these instructions may lead to better or worse task performance. Others have proposed that striatal reward prediction errors could be used to adjust PFC-dependent memory retrieval strategies (Scimeca and Badre, 2012). This mechanism would enhance hippocampal retrieval.

A recent strand of the artificial intelligence literature combines CBR with model-free RL synergistically to produce augmented versions of RL that are more adept at transfer learning, and expedite performance in new tasks or changing conditions. This is particularly valuable when the curse of dimensionality bites harshly, such as when state and action spaces are continuous (Santamaria et al., 1997). Similarity-weighted case values can jumpstart learning by serving as initial guesses of the value function, which can then be revised according to TD learning (Sharma et al., 2007; Drummond, 2002; Gabel and Riedmiller, 2005). Alternatively, suitably similar cases may be used as heuristics to accelerate RL (Bianchi et al., 2009; Celiberto et al., 2010, 2011), which involves biasing action choice akin to ε-greedy policies while retaining Q-learning of action values (Bianchi et al., 2008). These methods have proven successful in various test beds such as real-time strategy games, robotic soccer, and first-person shooters, with each domain demanding a different blend of skill. The agent can hit the ground running while retaining RL’s promises of long run convergence. RL is able to return the favor by helping with online assessment of the best similarity metrics for CBR,
which can mean altering the weights placed on prespecified dimensions that contribute to similarity assessment (Juell and Paulson, 2003). Learning is intertwined when both directions are joined, wherein cases judged to be similar inform and enhance decision making, and then assessment of similarity is adjusted depending on the results. Cases may be stored preferentially when the agent is attaining high rewards (Auslander et al., 2008), and pruned or reduced when they hinder prediction or exceed storage (Wilson and Martinez, 2000; Gabel and Riedmiller, 2005). Once learning has converged in one task, the optimal policy can be summarized and abstracted for transfer to future tasks (e.g. via decision tree; Von Hessling and Goel 2005). These models suggest intriguing possibilities for the neural interplay between case-based and model-free systems. Perhaps similar styles of algorithm are instantiated by the hippocampus and striatum or other structures in tandem. Along these lines, inspired by neural observations of hippocampal replay of recent memories during rest, (Johnson and Redish, 2005) have explored modified TD algorithms with offline replay of previously experienced sequences to allow offline practice, significantly speeding up early learning (see also Johnson and Venditto 2015).

**Interactions between case-based and model-based affiliate processes**

Neural evidence suggests that a variety of model-based decision processes may be tied to or subserved by hippocampal computations. Some work points to positive functional connectivity between the caudate and the hippocampus during probabilistic learning (Dickerson et al., 2011). Sensitivity to contingency degradation is impaired in rats with lesions of the hippocampal region (although sensitivity to outcome devaluation is spared; Corbit and Balleine 2000; Corbit et al. 2002). Generalization in an acquired equivalence paradigm correlates with use of a model-based system in a separate decision task (Doll et al., 2015). PD patients show activation of the hippocampus and suppression of the caudate in the Tower of London planning problem, while controls show the opposite pattern, even though both groups perform comparably and exhibit PFC activation (Dagher et al., 2001). Thus the hippocampus may be able to support planning in concert with PFC, independently of, and compensating for, the striatum if need be.
Model-based decision making relies on estimating state transition probabilities. One source of these subjective probabilities may be a case-based system (Blok et al., 2003; Taylor et al., 2008). While the hippocampus does provide a spatial map that can be used in support of or in conflict with flexible goal-directed behavior driven by the caudate or PFC (McDonald and White, 1993, 1994; Packard et al., 1989; Packard and McGaugh, 1996; Schroeder et al., 2002; Voermans et al., 2004; Brown et al., 2012; Brown and Stern, 2013), cognitive mapping more broadly construed also appears to be subserved by MTL regions. Hippocampal similarity-based learning is thought to be one mechanism for learning word transition probabilities of artificial grammar (Opitz and Friederici, 2004). The kind of novelty signals represented in area CA1 could be used to update various probabilistic beliefs. Consistent with this idea, some evidence suggests the existence of a hippocampal process for learning transition probabilities that has been linked to model-based decisions (Bornstein and Daw, 2012, 2013), parallel to striatal or PFC subregions (Amso et al., 2005; Gläscher et al., 2010). Such updating might be premised on sequential association learning (Amso et al., 2005) and the binding of regularities across time and space as discussed earlier, playing a greater role when patterns are highly consistent (Mattfeld and Stark, 2015). Computationally, this process might be sophisticatedly described as learning of the successor representation (Dayan, 1993), which represents the expected discounted future visitations of states and requires attending to their sequential co-occurrence. This can be done latently prior to the introduction of reward. Intriguingly, the successor representation has been linked to the temporal context model of episodic memory by Gershman et al. (2012).

As John Locke stated, “in things which sense cannot discover, analogy is the great rule of probability.” Techniques based on this principle are common in the world at large, and have proven successful when facing complex problems. The analog method is a historically used approach to weather forecasting, in which the future is predicted by seeing how conditions evolved on similar recorded days (Kruizinga and Murphy, 1983). Similarity-based approaches can help accurately predict college admissions (Klahr, 1969), movie revenue (Lovallo et al., 2012), and legal case outcomes (Teitelbaum, 2014). In general, this method of reference class forecasting suggested by Kahneman and Tversky (1977) has been found helpful in project management to the point where it is officially endorsed by the American Planning Association, particularly for “non-routine projects ... and other local one-off projects” – in other
words, novel problems with limited past data. In one specification with the same justification as similarity based valuation, probabilities might be usefully constructed from frequencies of observed outcomes weighted by the similarity of past conditions—a kernel estimate of event occurrence. Billot et al. (2005) provide an axiomatized representation of probabilities as similarity-weighted frequencies. Central to their treatment is the concatenation axiom, which states that the belief resulting from two databases combined must be a convex combination of the beliefs resulting from each of those databases separately. This is a remarkably sharp characterization that transparently clashes with Bayes’ rule, which entails beliefs must be convex combinations of the potential posteriors induced by continuations of observed data (Shmaya and Yariv, 2008). Having a duplicated set of observations would make a Bayesian learner more confident than having a single set, for instance, but this confidence is prohibited by the concatenation axiom. While we might expect such a restriction to be violated in many circumstances, it could hold under novelty when there is limited opportunity to check internal consistency, just as people respond that there are more murders in Detroit than in Michigan when asked separately even though Detroit is in Michigan (Kahneman and Frederick, 2002). Nevertheless, attempts have been made to relax this restriction, such as allowing beliefs to depend on the database size, having multiple beliefs to reflect ambiguity (Eichberger and Guerdjikova, 2010), and combining similarity-weighted frequencies with a prior in a nested Bayesian framework (Bordley, 2011). Theoretical implications from any these models await empirical testing.

Cognitive maps and models may be very flexibly drawn up to assist forecasting and drive decision making, and one line of thinking focuses on the role of the hippocampus in mental simulation of outcomes (Gilbert and Wilson, 2007; Suddendorf and Corballis, 2007; Buckner and Carroll, 2007). Just as the hippocampus enables us to retrieve vivid scenes from past episodes, so, too, does it enable us to conjure up potential future scenarios from reconstituted episodes (Schacter et al., 2007, 2008, 2012), interacting with vmPFC to integrate related events in a flexible and prospectively useful form (Zeithamova and Preston, 2010; Zeithamova et al., 2012; Benoit et al., 2014). Future events are imagined in more detail when they would occur in familiar or recently experienced settings, revealing their origins in past episodes (Szpunar and McDermott, 2008). Envisioning future events recruits similar temporal and prefrontal regions as envisioning the past (Okuda et al., 2003; Schacter and Addis, 2007; Szpunar et al., 2007; Addis et al., 2007), and hippocampal amnesics are
typically quite impaired in episodic prospection (Talland, 1965; Klein et al., 2002; Hassabis et al., 2007; Addis et al., 2009; Andelman et al., 2010; Kwan et al., 2010; Race et al., 2011, 2013).

Options can then be evaluated by imagining potential outcomes. Animals in choice experiments exhibit a phenomenon known as vicarious trial and error, in which they pause at choice points and orient themselves, sometimes in motion, toward potential options, as if they were envisioning the future implications of taking a given path (Muenzinger, 1938; Tolman, 1938; Johnson et al., 2007). This behavior appears to depend on the hippocampus (Hu and Amsel, 1995; Hu et al., 2006), the neural activity of which represents positions travelling down each path ahead of the animal (Johnson and Redish, 2007). A similar behavioral manifestation of deliberation has been seen in a human decision making experiment with mouse tracking (Sullivan et al., 2014). 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 fronto-parietal control regions associated with a preference for longer term options (McClure et al., 2004). Rats with hippocampal lesions tend to pick smaller, immediate rewards (Rawlins et al., 1985; Cheung and Cardinal, 2005; McHugh et al., 2008; Mariano et al., 2009; Abela and Chudasama, 2013). 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 (Peters and Büchel, 2010; Benoit et al., 2011; Lebreton et al., 2013; Daniel et al., 2013; Liu et al., 2013; Lin and Epstein, 2014). 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 et al. 2014; though see Kwan et al. 2015), in accordance with multiple process hypotheses.

A final, extremely intriguing angle centers on analogical reasoning (Gentner et al., 2001; Holyoak, 2012), based on higher-order structural similarity. While the MTL alone is needed for relational encoding, the PFC becomes involved during highly flexible application and recombination of past cases (Zeithamova and Preston, 2010). Hofstadter (2001) considers analogy to be sufficiently important as to call it the core of cognition. In fact, analogizing appears to be a problem solving ability at the cutting edge of cognition and decision making. People have made their fortunes from analogical insight, such as Charlie Merrill, who styled Merrill Lynch after his experience in the supermarket industry (Gavetti et al., 2005). Raven’s Matrices, which
test abstract relational reasoning, rank highly among mental tests in their g-loading (Jensen, 1997). These explicit forms of analogy invoke more conscious processing involving our evolutionarily well-developed PFC (Krawczyk, 2012). Analogical thinking has been tested in other species as well, and only chimpanzees have succeeded at a level modestly comparable to humans (Zentall et al., 2008). Notably, successful chimps were those with prior training in symbolic representations like language or tokens. A similar pattern was found in human children, as 3-year olds were able to perform comparably to 5-year olds on some analogical tasks if relational labels were available. These results suggest that lower-level relational understanding can help an agent ascend the hierarchy of abstract relational comparisons, the height of which may simultaneously capture intelligence and generalization. Famed mathematician Stefan Banach often said that “good mathematicians see analogies between theorems or theories; the very best ones see analogies between analogies.” These skills make a difference at the frontier of human ability.

**Conclusion**

In this paper, I present a potential third instrumental system for value-based decision making that is premised upon similarity between past and present cases. It can be mathematically described by the economic model of case-based decision theory accompanied by the computational background of case-based reasoning. This case-based system stands between model-free and model-based systems in its position on the bias-variance tradeoff and holds advantages over both when faced with novel and complex problems. The hippocampus and related MTL structures provide the neural substrate upon which case-based calculations are thought to be performed in the process of forming connections and associations between stimuli. This neuroscientific understanding sheds light on how such calculations can also contribute to model-free and model-based decisions.

Ultimately the striatum, hippocampus, prefrontal cortex, and the rest of the brain work together as a complete decision making circuit that has, I argue, as one special case simple RL, as another special case EUT, and as a third special case CBDT. I believe these constitute three extremes that are useful conceptual frames for parcelling computational goals, neural substrates, and behavioral phenomena. The proposed case-based system has distinct computational properties, a distinct primary neural
locus, and has proven to be experimentally dissociable under at least some circumstances. There appears to be enough modularity to justify such a viewpoint (Dayan, 2008; Lengyel and Dayan, 2007).

A caveat is in order here. The similarity-based mechanisms discussed do not obviate the need to rely on background knowledge; they merely allow an agent to make use of it in a way that is a bit more agnostic about the structure of the world. One-shot learning by the hippocampus, for instance, is in the same spirit as the professor who, as the story goes, impressed his students by skimming a new book in one minute and summarizing for them its complete contents. When the students praised him for reading so quickly, he replied that it had actually taken him thirty years to read the book. What he meant was that the knowledge required to accomplish the feat had taken thirty years to accumulate. Case-based decisions cannot take place on a truly blank slate. Similarity assessments hinge critically on a person’s underlying schemas (Murphy and Medin (1985); Medin et al. (1993). Tversky (1977) notes that “an essay is like a fish,” because both have a head, body, and tail – but woe betide the student who tries to submit a salmon as his term paper. Nevertheless, the concept of similarity retains appeal and feels like a meaningful concept enough that we repeatedly gravitate towards it in both cognitive modeling and everyday life. Any complete account of decision making must acknowledge this.

Decision making based on similarity has a long and diverse pedigree. It has deep roots in both social science and personal intuition. I have attempted to provide some grist for the mill by synthesizing a grab bag of 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, discontiguous – in short, messy – nature of the world at large. Learning and decision making under challenging conditions call upon different sets of mechanisms. The transparency and simplicity of most neuroeconomic experiments may obstruct our view of what happens when matters are not so tidy. And, for better or worse, we live in an untidy world.
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