

Choosing fast and slow: explaining differences between hedonic and utilitarian choices

Nisheeth Srivastava (nsrivastava@ucsd.edu), Edward Vul (evul@ucsd.edu)

Department of Psychology, UC San Diego
La Jolla, CA 92093 USA

Abstract

This paper examines the psychological differences between hedonic and utilitarian patterns of preference behavior. Instead of using latent variables like self-control and emotion to explain these differences, we show that they emerge as natural consequences of solving two different, but related problems within an inductive framework of preference learning. We show that hedonic decisions involve tracking the variability of a binary variable, whereas utilitarian decisions require the maintenance of a distribution over a vector of object labels. Computational experiments show that this difference in cognitive representation ensures that hedonic decisions have a lower cognitive sampling cost, which makes them less effortful. Further experiments reveal differences in error rates as a function of deliberative effort between the two paradigms. Deliberative effort benefits utilitarian choices, but not hedonic ones. Overall, our work demonstrates the critical role of cognitive representations in extracting strikingly different behavior patterns from simple models of information processing.

Keywords: consumer choice; preference formation; cognitive modeling; agent-based modeling

Introduction

Consumer research has identified separate patterns of consumption for items that people ostensibly judge useful and those that they consider pleasurable. For instance, buying a bar of soap can be considered a utilitarian choice, whereas buying an oil painting would be considered a hedonic choice (Alba & Williams, 2013). Naturally, such labeling is not rigorous: it is perfectly possible for the purchase of an expensive brand of soap to be a hedonic decision, whereas the bulk purchase of oil paintings for an interior decoration company would be a utilitarian decision. Despite the lack of a clear delineation between hedonic and utilitarian *goods*, the psychological difference between hedonic and utilitarian modes of purchase and consumption is intuitive.

The distinction between hedonic and utilitarian decisions has been of considerable practical interest in the field of marketing, and has motivated theoretical and empirical scrutiny by psychologists. In psychology, this distinction has been attributed to two “systems” of choice: the implicit System 1 that automatically and instinctually makes quick decisions, and the explicit System 2 that slowly, but deliberatively arrives at a more thoughtful answer. The psychological distinction between hedonic (System 1) and utilitarian (System 2) has been characterized primarily by two empirical distinctions. First, hedonic decisions are easier to make while utilitarian decisions are more effortful and deliberate. Second, hedonic judgments tend to be more error-prone than utilitarian ones (Kahneman, 2011). Although a view of two systems with these decision properties is appealing, such an account

does not offer a formal characterization of how prior experience is used to inform either kind of decision, nor does it offer a predictive account of which situations will encourage one or another system, and what judgments those systems might prefer in consumer decisions.

In contrast to psychology, marketing research has been less concerned with characterizing the difference between hedonic and utilitarian decisions, but rather with encouraging hedonic consumption. The general substance of this research is that, because short-term pleasure is the appeal of a hedonic product, those aspects of a choice that increase the influence of emotions or urges on decision making and decrease self-control will increase hedonic behavior (Keinan & Kivetz, 2008). However, this view remains underspecified: What is self-control, why does it apply to hedonic decisions and utilitarian decisions differently, and how can emotions and urges be operationalized meaningfully in formal treatments?

Our general goal in this paper is to develop a formal account of what it means to make hedonic and utilitarian decisions that can explain how the same set of prior experiences can yield such discrepant patterns of behavior and preference when subject to different decision rules.

Our contribution

We adapt a recently developed a computational account of preference formation (Srivastava & Schrater, 2012). By augmenting this computation with simple algorithmic specifications we clarify the difference between hedonic and utilitarian preferences while simultaneously explaining many effects described in consumer research and social psychology.

Our primary contribution is the demonstration that hedonic decisions require agents to make stochastic decisions about a binary variable (“do I want this?”), whereas utilitarian decisions require them to make such decisions about a more complex value distribution (“how much do I value this?”). This computational difference immediately forces utilitarian decisions to have greater sample complexity, with interesting and wide-ranging consequences. Further, very general algorithmic methods for computing both types of decisions suffer varieties of regret that are congruent with the ‘hot’ and ‘cold’ regret distinctions outlined by (Keinan & Kivetz, 2008).

The fit between our theory and a diverse set of research findings suggest that it captures fundamental features of the distinction between hedonic and utilitarian decisions, which makes it a useful tool for deriving policy insights for influencing decisions in one direction or another. Our results also formalize an intuitive link between the hedonic/utilitarian divide in consumer research and fast/slow dual-process cogni-

tive theories.

A cognitive account of consumer preferences

It is widely acknowledged that consumers are not economically rational in expressing their preferences. The most predictive thing we can say about consumption preferences is that they are arbitrary, but coherent (Ariely, Loewenstein, & Prelec, 2003). A researcher cannot know what preference a subject will express for a particular object in a particular choice context, but *ceteris paribus*, they can be reasonably sure that if the subject has expressed preference for one object over another once, they will do so again.

The existence of idiosyncratic but consistent preferences seems to suggest that they are dynamically constructed, an idea that has been expressed prominently in the heuristics literature that has proceeded from Tversky's EBA theory (Tversky, 1972). However, *process* theories of changing preferences have not historically been very predictive, relying on large numbers of latent parameters to describe, but not predict data (Busemeyer & Townsend, 1993; Brown & Heathcote, 2008). We believe that this stems, in large part, because such theories are predicated on a psychophysical value representation (often termed ‘subjective utility’). If we assume that a person assigns some psychophysical ‘utile’ to various objects, then we have two problems in constructing a learning theory of preferences, (i) how to develop a scale for comparing utiles of two different options, and (ii) how to determine the normalization constant that tells us how much to credit each new experience for changing the underlying ‘utile’ state. These problems have made such ‘subjective utility’ learning accounts struggle with the idiosyncratic non-transitivity of preferences.

Our own recent work (Srivastava & Schrater, 2012) has offered a solution by showing how option desirability can be learned from experience without using option-specific subjective utilities, and how doing so solves both the value representation and credit assignment problems endemic to older solutions. All that is needed is to let go of the assumption that people track hedonic value on some internal scale, and to postulate that they track multiple samples of a single binary ‘like/don’t like’ variable instead. In this paper, we build upon this theoretical base to make specific predictions about consumer preferences, which explains, as we shall see, the principal differences between hedonic vs utilitarian choice. Our account hinges on the crucial representational distinction between binary hedonic decisions, and high-dimensional utilitarian ones which typically consider costs, benefits, and tradeoffs associated with a choice. We begin with a Marrian specification of our model at both the computational and algorithmic levels.

Computational specification

We model preference formation as a Bayesian observer directly learning which option among the ones offered is ‘best’ from memories of previous decisions: what was chosen and

what were the options. This learning is bootstrapped by inferring the situational *context* of the underlying choice from the set of options available, thus allowing for some generalization across option sets.

Computing magnitude of desire. How desirable a particular option is takes on a probabilistic interpretation in this account, formally expressed as $p(r|x, o)$, where r is a binary variable indicating preference (‘this option was chosen/best’), x is the option, and o is the current observation (primarily the set of options available right now). Our theory predicts that this quantity is obtained by marginalizing over evidence contained in the set of latent contexts \mathcal{C} ,

$$D(x) = p(r|x, o) = \frac{\sum_c^{\mathcal{C}} p(r|x, c)p(x|c)p(c|o)}{\sum_c^{\mathcal{C}} p(x|c)p(c|o)}, \quad (1)$$

where it is understood that the *context* probability $p(c|o) = p(c|\{o_1, o_2, \dots, o_{t-1}\})$ is a distribution on the set of all possible contexts incrementally inferred from the agent’s observation history. Here, $p(r|x, c)$ encodes the probability that the item x was preferred to all other items present in choice instances linked with the context c , $p(x|c)$ encodes the probability that the item x was present in choice sets indexed by the context c and $p(c)$ encodes the frequency with which the observer encounters these contexts.

The observer also continually updates $p(c|o)$ via recursive Bayesian estimation,

$$p(c^{(t)}|o^{(1:t)}) = \frac{p(o^{(t)}|c)p(c|o^{(1:t-1)})}{\sum_c^{\mathcal{C}} p(o^{(t)}|c)p(c|o^{(1:t-1)})}, \quad (2)$$

reflecting adaptations in situational frequencies as a function of movement through the world.

But how can such a theory account for economic decisions, where objects are not abstract, but have concrete monetary values associated with them? In (Srivastava, Vul, & Schrater, 2014), we show how augmenting the framework above with a set of categorical labels $m \in \mathcal{M}$ denoting money magnitudes yields a workable theory of money-minded economic decisions without committing to psychophysical evaluation of the hedonic worth of money. In this extended account, following a similar probabilistic calculus as in Equation 1, the inferred value of x becomes $p(r|x)$ can be calculated as,

$$p(r|x, o) = \frac{\sum_m^{\mathcal{M}} \sum_c^{\mathcal{C}} p(r|x, m, c)p(x|m)p(m|c)p(c|o)}{\sum_m^{\mathcal{M}} \sum_c^{\mathcal{C}} p(x|m)p(m|c)p(c|o)}, \quad (3)$$

with the difference from the earlier expression arising from an additional summation over the set \mathcal{M} of monetary labels that the agent has experience with. Natural interpretations for the computations involved in this theory are visually schematized in Figure 1.

Computing what to pay. Asking how much someone *desires* an option, the quintessential hedonic question, is different from asking if they would be willing to buy it at a particular price, which is the typical framing of a utilitarian decision. The former corresponds to the term $p(r|x)$, as we define

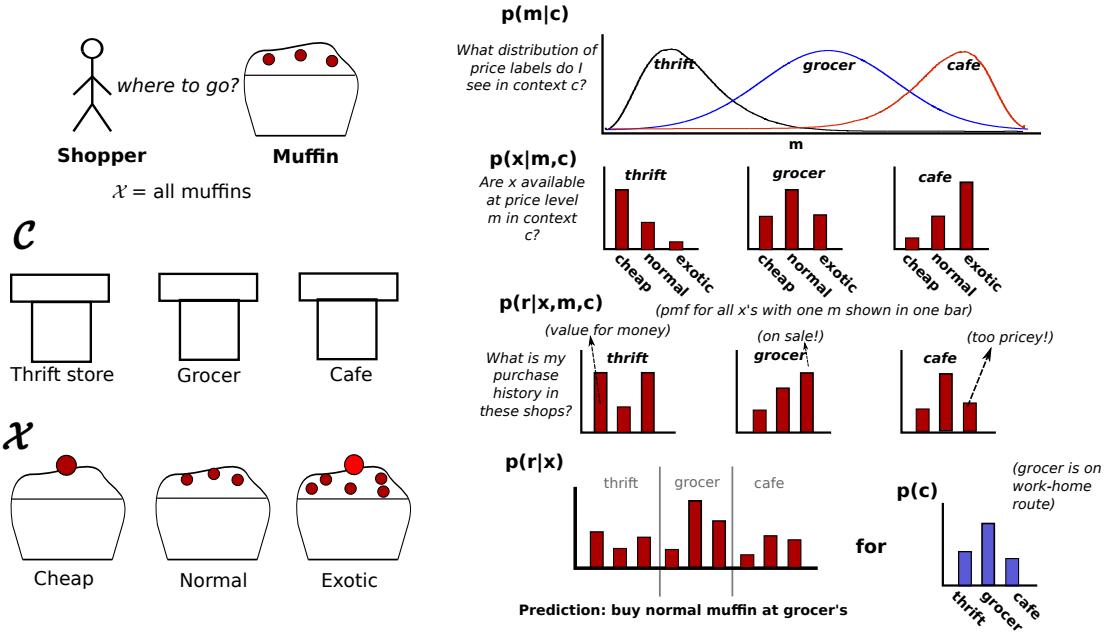


Figure 1: An illustration of the interplay between the stochastic components of our model of preference formation.

above. We suggest that the latter corresponds to assessing $p(m|r=1,x)$, a probability distribution on the set of money labels \mathcal{M} conditioned on prior experience with having seen successful transactions ($r=1$) of the option x . Since the contribution of all terms where $r=0$, i.e. the transaction is not completed, is identically zero this term can be computed as,

$$p(m|r,x) = \frac{\sum_C p(x|m,c)p(m|c)p(r|c)p(c)}{\sum_m^{\mathcal{M}} \sum_C p(x|m)p(m|c)p(c)}, \quad (4)$$

where $p(m|c,r) = p(m|c)$ because the distribution of money labels in a context has no causal relationship with subject preferences and $p(x|m,r,c) = p(x|m,c)$ because the prior history of purchases is contingent on r being 1 in all relevant cases.

This quantity corresponds to a stochastic representation of the willingness to pay (WTP) various amounts of money m to purchase an object x . Since utilitarian decisions are made keeping cost considerations up front, it is reasonable to believe that this quantity is more salient in making them.

Algorithmic specification

The computational goals of preference formation we have described above require accumulation of evidence associated with all previous contexts at the time a new decision is to be made. Clearly, this is not realistic - it is more likely that animals sample evidence from a subset of previous experience. Which samples are recalled and which aren't is best specified at the algorithmic level of description, in the shape of a rudimentary memory model.

A simple memory model. The basic mechanism of evidence accumulation influences the shape of the distribution $p(c|o)$ via memory sampling. Following our own prior

work (Srivastava & Schrater, 2014), we model the process of memory recall as the activation of a subset Q of decision-relevant memory particles. Using this notation, a general belief formation model could be expressed as,

$$p(c) = \sum_{q \in Q} p(c|q)p(q), \quad (5)$$

where $c \in C$ are the latent contexts available in memory and $q \in Q$ are memory *particles* corresponding to past choice selections. Here, the probability distribution $p(q)$ - which we call the *memory prior* - encodes the likelihood of recalling the memory of experience q , while the distribution $p(c|q)$ encodes beliefs about outcomes learned during the experience corresponding to the memory particle q . For our purposes, we assume a trivial bijective mapping between c and q - each memory particle is assumed to be associated with a unique context.

This memory-sampling variant of $p(c|o)$ plugs directly as the prior in the Bayesian context probability update for $p(c|o)$ in Equation 2, which then itself plugs into the two computations in Equations 1 and 4 that we are interested in analyzing. Note, though, that we are able to use the memory model so easily because of one additional assumption: that the context-specific memories recalled are episodic, and therefore convey all context-relevant information once the context itself has been activated in memory¹.

¹This assumption simplifies our analysis by ignoring the memory dependence of our other intermediate probability terms. While it is likely that such dependence exists, its effects will work in the same direction as the basic results of our approach, since it would further impoverish the preference representation we are already imposing sampling constraints on.

Specifying an endogenous decision rule. The final step in our algorithmic specification involves specifying the decision rules that agents forming preferences via our account would use to make decisions. One strategy would be to use a race-to-threshold approach, wherein evidence in favor of various alternatives accumulates until the most likely candidate reaches a threshold, at which point it is emitted as the choice. This basic intuition is shared by several existing computational models of the choice process, but because thresholds and differential evidence accumulation rates are usually free parameters, such an approach would reduce our ability to obtain model predictions.

Instead, we adopt a volatility-sensitive decision rule. Since our account proposes that preferences are dynamically generated at the time of a decision, choosing to stop accumulating evidence when the currently accumulated preference has stabilized is a rational strategy. For the case where we are considering simply whether we want an option or not $p(r|x)$, measuring this volatility is simply a question of tracking $\Delta p(r|x)/\Delta k$, the rate of change of desirability as a function of sample count. For decisions about a suitable price to pay for an option, we can measure volatility as the KL divergence between successive $p(m|x)$ values.

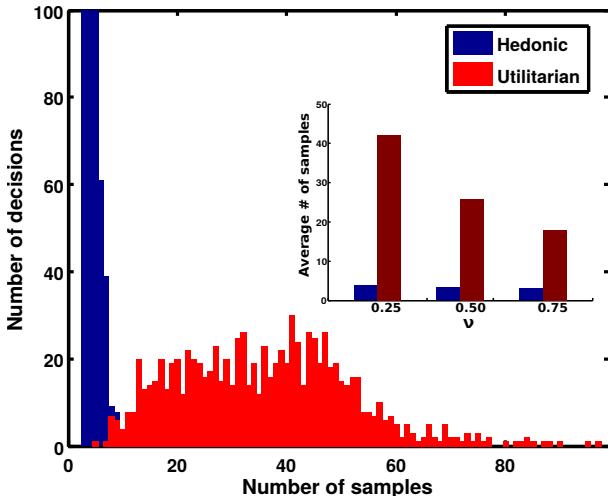


Figure 2: Hedonic decisions require fewer memory samples than utilitarian decisions, based on the set of computations defined by our theory. This explains the phenomenology of easy hedonic decisions, and effortful utilitarian ones.

Finally, even these criteria ultimately require thresholds. We use the large-sample ($n = 1000$) volatility of both these measures to endogenously estimate thresholds δ for our volatility estimates. Since the large-sample estimate is expected to converge to the true posterior distribution, we can assume that the minimal volatility δ_{min} seen in this regime is simply noise, and so can be generalized across multiple decisions. On the other hand, volatility seen in the first 5 samples can be taken as an upper bound δ_{max} for either measure. Then, we define the volatility threshold to be $\delta_{min} + v(\delta_{max} - \delta_{min})$. Setting v to aggressively low values will yield highly conservative agents, while setting it high will yield much more

impulsive ones.

Experiments

Having set up our decision model, we now turn to operationalizing the specific questions we want to ask it. As we anticipated in the introduction, two questions stand out: (i) why are hedonic decisions fast/easy and utilitarian decisions slow/difficult? (ii) why are hedonic decisions more error prone?. We probe these questions using two separate computational experiments.

Decision complexity as a function of sample size

In our framework, the effortfulness of decisions is related to the number of memory samples needed to make them. Thus, we can directly compare the number of samples necessary for a hedonic *how much do I want this?* decision with that needed for a utilitarian *how much should I pay for this?* decision.

Figure 2 shows the result of a simulation experiment we conducted to make this comparison². We randomly³ initialized the input probability distributions for our model to construct 1000 different agent histories associated with preferences in a world with 5 unique contexts and 5 unique money labels, and calculated the minimum number of samples needed for the corresponding output distributions to trigger our decision rules.

It is immediately obvious that our model replicates the basic phenomenology of decisions involving the hedonic $p(r|x)$ being easier, and utilitarian $p(m|r,x)$ decisions being effortful. This conclusion holds across a wide range of values for the parameter v (see inset in Figure 2) and across a large randomized repertoire of agent histories. A possible concern here could be the fact that we are using two different decision rules for both decision categories, using a first order derivative to compute volatility for the hedonic decision, and a KL divergence for the utilitarian one. In the absence of a common quantitative scale, how can we possibly compare results across two separate measurement instruments? We agree that it would have been nicer if there could have been a single quantitative basis for measuring volatility in both cases, but note that we have been careful in designing both stopping rules as functions of the range of the individual measures themselves, obviating the need for a common measurement scale. Thus, these empirical results are valid and, in emerging from the operation of a general parameter-free preference formation model, render transparent the previously opaque distinction between the two classes of consumption decisions we are studying.

²y-axis is artificially truncated at 100 to show details of the sample distribution; the first bar in the original figure rises as high as 600, reflecting the need for very few samples to reach stable desirability inferences.

³The context probability $p(c)$ was generated via 5 draws from a $U(0,1)$ distribution, followed by normalization; the money distribution $p(m|c)$ was initialized similarly, and normalized across contexts; the price distribution $p(x|m,c)$ was first initialized as a 5×5 matrix that was identically 0.1 and then randomly seeded with a single high value in each column, then normalized; the prior choice distribution $p(r|x,m,c)$ was initialized similarly.

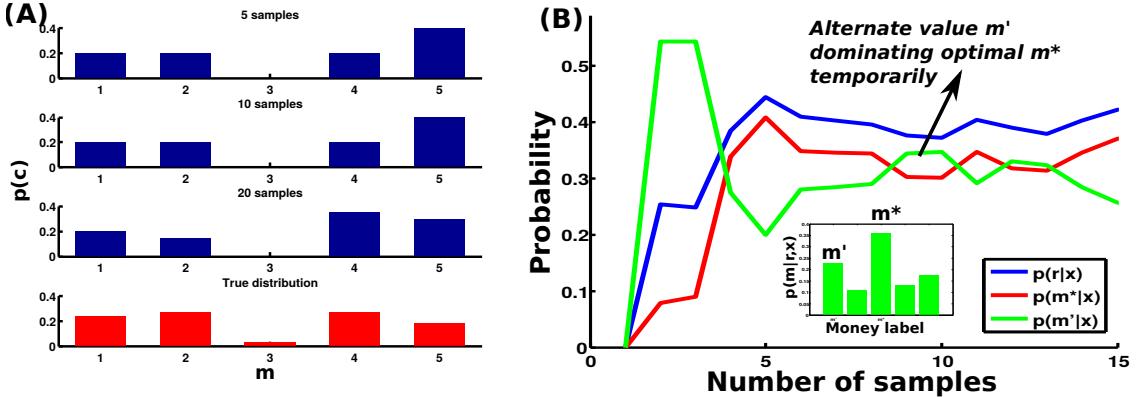


Figure 3: (A)Sampling from memory can introduce short-term biases in estimates of quantities used in preference inference, (B) Such biases influence decisions involving money labels more than decisions involving desirability, since multiple money labels compete for viability, and memory biases make determining the distribution mode difficult.

Figure 3 further clarifies the mechanism responsible for this difference. It should be intuitively evident that dynamic accumulation of choice information will create a series of intermediate probability densities that do not reflect the asymptotic ‘true’ distributions that people would arrive at given infinite time and infallible memory (see panel A for an illustration of a run through one such sampling trial). Deviations from true intermediate distributions will lead inevitably to distortions in the preference formation process. In the example shown in panel B, the blue line plots the time course of the hedonic $p(r|x)$ distribution. Because the accumulation process for this distribution tracks only the volatility of a binary variable, it has fewer ways of failing to converge than the process for the utilitarian $p(m|r,x)$ distribution, which requires an entire vector of stochastic variables to behave nicely for a useful decision to emerge. Thus, in a nutshell, we propose that utilitarian decisions are harder because the measure of the stochastic cognitive representation that people use to make them has a much greater cardinality than the one they use for making hedonic decisions.

Error-proneness as a function of impulsivity

The second computational experiment we conducted analyzed patterns for errors in both classes of decisions. To do this, we first had to operationalize errors in our framework. For the utilitarian case, this was simple: we compared the mode of the $p(m|x)$ distribution at the stopping point with that in the large sample limit, and counted all situations wherein they did not match up. For the hedonic case, we sampled a binary choose/don’t choose outcome from both the stopping point desirability and the large sample limit, and counted all situations where they did not match up.

In both classes of decisions, errors would cause regret that was either of the ‘miss’ variety, viz. ‘I wish I had chosen this’ or of the ‘guilt’ variety, viz. ‘I wish I hadn’t chosen this’, reflected symmetrically in the relationship between the small and large sample predictions. Further, the error fraction, the fraction of simulations in which error of any of these four

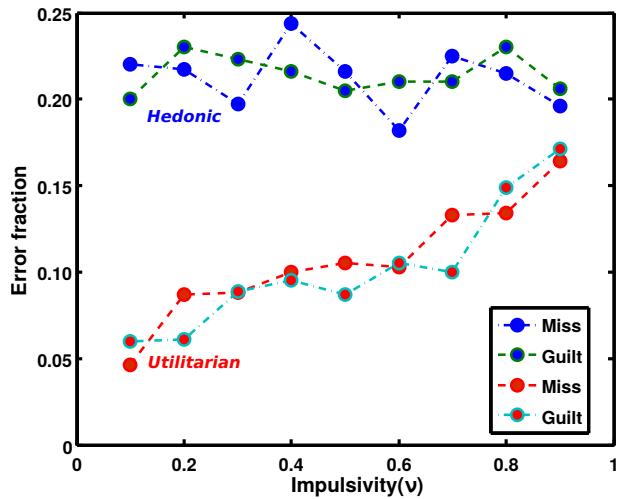


Figure 4: Greater impulsivity leads to more errors in utilitarian calculations, but not in hedonic ones. However, the base rate for error in hedonic calculations remains higher than in utilitarian calculations.

varieties was seen, is expected to depend on the impulsivity parameter v ; more impulsive decisions should be more error-prone.

In a further series of 1000×9 randomized simulations, we assessed the frequency with which these errors occur in our sample for 9 evenly spaced values of v using the endogenous stopping rules as before. Our simulations results follow a pattern previously observed empirically by (Frederick, 2005). As illustrated in Figure 4, we find that (i) hedonic judgments are more error-prone, but (ii) this error-proneness does not reduce with greater deliberative effort (measured as the inverse of the impulsivity parameter v). In contrast, (iii) utilitarian judgments are less error-prone overall, and (iv) grow less error-prone with greater deliberative effort.

This overall pattern of results is also congruent with our earlier finding that the informational sample complexity of hedonic decisions being extremely low, which makes them more sensitive to sample bias, and also indifferent to the availability of greater cognitive resources. Once somebody’s mind

is made up about the hedonic aspects of a consumption decision, further thinking won't budge them. In contrast, utilitarian decisions, due to their greater sample complexity, benefit through greater opportunity for deliberation.

Finally, a speculative point: if someone is implicitly aware of the differential sensitivity to deliberative effort in the two paradigms, regret caused by failing to compute utilitarian calculations correctly will be 'hot', since they will perceive this to be a personal failure, while that experienced by anhedonia will be 'cold', since no amount of extra effort could have made things better. This distinction tracks the varieties of counterfactual regret previously outlined by (Kahneman, 1995).

Discussion

Thanks in part to Kahneman's lucid book (Kahneman, 2011), it has become fashionable to describe cognition as consisting of two systems: one quick, automatic, and habitual, and one slow, deliberate and cognitive. Remarkably, our results are generally convergent with such two system descriptions, but derive the differences in the two systems from task-relevant information-processing requirements within the same overall cognitive model. Thus, these results, while presented here specifically in the context of preference formation, also support a more general view that the two system description is not ontologically deep - it describes phenomena that can equally well be encompassed by single-process theories.

Our analysis also ties into a body of consumer and social psychology research that tracks adaptations in impulse regulation when people face series of decisions (Keinan & Kivetz, 2008). Theories of self-control have chiefly revolved around the observations that when people feel that they have been too prudent, they experience 'miss' regret and subsequently choose to indulge themselves, and when they think they have been too indulgent, they experience 'hot' guilt and become more calculating (Baumeister, 2002).

While our current model does not directly address these behaviors, it could do so if we posit that people can over-ride the endogenous volatility-based threshold we used. For instance, somebody who is stressed for time will make a quick decision that he may immediately afterward try to change, suggesting that his decision was made while the underlying preference was still volatile. In such an extended account, the volatility criterion would serve as the default controller, but could be adjusted or over-ridden by executive control to account for other task requirements. In such a setting, Bayesian learning of the threshold itself, working on top of the model we have defined, would accommodate the self-regulatory behaviors outlined above by increasing the desirability threshold to account for misses and decreasing the WTP threshold to account for guilt.

Multiple other tangential findings from the consumer research literature can also be accommodated within our theory. For instance, the facts that consumers placed under cognitive load make more hedonic decisions (Shiv & Fedorikhin,

1999), and that they do so when choices are temporally proximal (Milkman, Rogers, & Bazerman, 2010) are explained directly via the differential sample complexity of the two types of choices: Given limited time, people will rationally prefer the low complexity choice strategy. A more intriguing phenomenon is that subjects are less likely to make hedonic choices under simultaneous presentation of options than sequential (Read, Loewenstein, & Kalyanaraman, 1999). Under our account, since simultaneous choice expands the size of the sample space required to make a desirability computation, it increases the sample complexity of the hedonic approach, thus making people less likely to use it.

To conclude, in this work, we show that differences in hedonic vs utilitarian preference patterns can be explained simply by differences in how evidence for both classes of decisions accumulates via sequential memory sampling.

Acknowledgments: NS was funded by the Institute of New Economic Thinking; NS and EV were funded NSF CPS Grant #1239323.

References

- Alba, J. W., & Williams, E. F. (2013). Pleasure principles: A review of research on hedonic consumption. *Journal of Consumer Psychology*, 23(1), 2–18.
- Ariely, D., Loewenstein, G., & Prelec, D. (2003). "coherent arbitrariness": Stable demand curves without stable preferences. *The Quarterly Journal of Economics*, 118(1), 73–105.
- Baumeister, R. F. (2002). Yielding to temptation: Self-control failure, impulsive purchasing, and consumer behavior. *Journal of Consumer Research*, 28(4), 670–676.
- Brown, S. D., & Heathcote, A. (2008). The simplest complete model of choice response time: linear ballistic accumulation. *Cognitive psychology*, 57(3), 153–178.
- Busemeyer, J. R., & Townsend, J. T. (1993). Decision field theory: a dynamic-cognitive approach to decision making in an uncertain environment. *Psychological review*, 100(3), 432.
- Frederick, S. (2005). Cognitive reflection and decision making. *Journal of Economic perspectives*, 25–42.
- Kahneman, D. (1995). Varieties of counterfactual thinking. *What might have been: The social psychology of counterfactual thinking*, 375–396.
- Kahneman, D. (2011). *Thinking, fast and slow*. Macmillan.
- Keinan, A., & Kivetz, R. (2008). Remedyng hyperopia: The effects of self-control regret on consumer behavior. *Journal of Marketing Research*, 45(6), 676–689.
- Milkman, K. L., Rogers, T., & Bazerman, M. H. (2010). Ill have the ice cream soon and the vegetables later: A study of online grocery purchases and order lead time. *Marketing Letters*, 21(1), 17–35.
- Read, D., Loewenstein, G., & Kalyanaraman, S. (1999). Mixing virtue and vice: Combining the immediacy effect and the diversification heuristic. *Journal of Behavioral Decision Making*, 12(4), 257–273.
- Shiv, B., & Fedorikhin, A. (1999). Heart and mind in conflict: The interplay of affect and cognition in consumer decision making. *Journal of consumer Research*, 26(3), 278–292.
- Srivastava, N., & Schrater, P. R. (2012). Rational inference of relative preferences. In *Advances in neural information processing systems* (pp. 2303–2311).
- Srivastava, N., & Schrater, P. R. (2014). Frugal preference formation. In *Proceedings of the 36th annual meeting of the cognitive science society*.
- Srivastava, N., Vul, E., & Schrater, P. R. (2014). Magnitude-sensitive preference formation. In *Advances in neural information processing systems* (pp. 1080–1088).
- Tversky, A. (1972). Elimination by aspects: A theory of choice. *Psychological review*, 79(4), 281.