COMPUTATIONAL MODELS OF TASTE PREFERENCES IN RATS AS A FORM OF NATURALISTIC DECISION-MAKING

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Research in decision-making has traditionally focused on understanding perceptual tasks, in which competing sets of inputs are presented simultaneously. But few studies have explored more naturalistic decisions, such as those in taste preference, where an animal samples one stimulus and has the choice to either stay or switch to another based on its intrinsic value. Given that this choice occurs across time, we ask: how do previous experiences with stimuli affect future experiences with same or different stimuli? In order to test memory’s influences on decision-making, we used Matlab to incorporate synaptic depression into an Izhikevich/LIF hybrid network modeling taste preferences in rats in two different ways: input depression and post-input depression. We compared each memory model to our control non-memory model and found that adding depression post-input created larger interactions between stimuli (post-input: n = 3453, r = -.11, p < .0001 vs. no memory: n = 4264, r = .04, p < .01), while the input depression model did not (n = 415, r = .05, p > .28). All models manipulated the distribution of time spent at stimuli. These results indicate that taste preference models, and likely other preference-related tasks, are highly susceptible to previous influences. In the future, we will incorporate other types of short and long-term memory and compare these results with experimental data to determine which model is the best biological fit.
1. INTRODUCTION

We seek to explore the role of short-term memory in taste preferences of rats as a model for decision-making, specifically naturalistic decisions.

Decision-making can be divided up into two categories: perceptual and naturalistic. Perceptual decisions are those where an animal is presented with two or more sensory stimuli simultaneously and one stimulus clearly prevails over another. Most naturalistic decisions, including those of taste preference are defined differently: an animal is presented with one option and must make a choice (or preference) to either stay or switch to another option in a much more real world situation.

Given that taste preferences are a form of naturalistic decision-making, a larger goal is to uncover a broader understanding of decision-making in general. While previous research has focused on perceptual decision-making, little research has elucidated naturalistic decision-making or the role of memory in naturalistic decisions.

1.0.1 Experimental Research

Decision-making

Traditional research in decision-making has been produced in a wide variety of areas: neuroscience, psychology, business, and economics. This makes sense, given that decision-making, other than merely being an interesting phenomenon, is an integral part of our lives. The definition of a decision, according to Gold and Shadlen, is a deliberative process that results in the commitment to a categorical proposition (2007). Areas of the brain thought to be involved in decision-making are far and wide and include the orbitofrontal cortex (OFC), ventromedial pre-frontal cortex (vmPFC), anterior cingulate cortex (ACC), parietal cortex, the amygdala, insular cortex, and the ventral striatum (Pearson, 2014).

Two theoretical concepts that have defined a large area of theoretical decision-making are Signal Detection Theory (SDT) and Sequential Analysis (Gold and Shadlen, 2007). The former is based on conditional probabilities: $P(E | h_1)$ and $P(E | h_2)$, where E is the evidence, h is the stimulus that leads to the evidence, and $P(E | h_1)$ is the likelihood of E given h1 (Gold and Shadlen, 2007). In neuroscience, this can be used to describe a particular motor response, the output (E), for example, given a visual stimulus, the input (h1). The latter of the two concepts, sequential analysis, builds upon the base of SDT. In this case, there are multiple pieces of evidence for different stimuli that build up over time. Not only is the animal choosing between $P(E | h_1)$ and $P(E | h_2)$, but also whether to commit to one process or another (Gold and Shadlen, 2007; Wald, 1947; Wald and Wolfowitz, 1948).

Previously, these concepts have defined all types of decision-making. However, doing so potentially creates wrongful assumptions. First, much of the research on decision-making is focused on perceptual tasks. One of the most famous perceptual decision experiments was a visual discrimination task in which macaque monkeys were required to distinguish motion in one of two directions and received a juice reward for being correct (Newsome et al., 1989). In such a case, the stimulus (h1) could be motion moving in a certain direction and E could be a directional neuron firing in response to a stimulus. As more and more evidence is collected, the animal "commits" to a certain direction, where most of the direction is moving. This is also called "ramping up" (Gold and Shadlen, 2007), the increase in evidence favoring one direction or another until the animal reaches a threshold and commits. On the other hand, naturalistic decision-making may not truly fit this paradigm. Again, as stated previously, naturalistic decision-making is what we would consider the everyday use of decision-making; that is, a realistic choice in which an animal is presented with multiple stimuli and must make a choice to try one or all of them. In these cases, there is no "right" answer. The true decision is for the animal to stay at, a gaze, a tastant, or a location, for example, or to switch to something else. Value-based decision-making falls under this category. Another problem lies with the idea of the "ramping up" of evidence; in naturalistic decisions, the stay or switch behavior may be better modeled by state transitions driven by noise rather than integration or ramping up of evidence (Miller and Katz, 2010, 2013). Assuming that there is noise in the system.
(which is true for many animal behaviors), the noise itself has been shown to drive highly optimal state transitions and likely explains trial-to-trial variability (Miller and Katz, 2010).

**Memory**

Another issue with applying perceptual decision-making to naturalistic is that in perceptual tasks, an animal perceives two or multiple stimuli at the same time (Newsome, 1996; Shadlen and Newsome, 2001). On the other hand, in naturalistic decisions, these stimuli are presented across time. An animal, for example, samples one stimulus before making the decision to switch to another. Given that an animal spends time switching back and forth between stimuli over a period of time, we would expect some kind of cellular memory to be involved (often absent from decision-making research). Specifically, we focus on naturalistic decisions occurring over many seconds to hundreds of seconds, so short-term memory is a likely candidate involved (Figure 1.1).

The two main types of short-term memory that fit these shorter time constants are synaptic augmentation and depression. Synaptic augmentation is a relatively uncommonly researched phenomenon, and it is similar to synaptic facilitation where increased firing in a subsequent time period increases the probability of vesicle release in the future. The main difference is that augmentation occurs over seconds rather than milliseconds, so it is more plausible than facilitation (Zengel, 1980). Depression, on the other hand, decreases the probability of vesicle release after firing. Augmentation and facilitation generally make a signal more apparent, while depression creates sensory adaptation. In addition, it has been shown that facilitation decreases "switch" behavior, while increases it (Miller, 2013a). Evidence has been shown that forms of short-term memory can manipulate decision-making (Deco et al., 2009) and it is likely that naturalistic decision-making is even more likely to benefit from incorporating memory into a model. This would be done by taking a standard decision-making circuit model and adapting it to a stay or switch circuit, while also incorporating the memory of previous stimuli into the decision-making process.
Foraging and Taste Preferences

One issue that must be addressed is the choice of behavior to analyze in trying to better understand decision-making. We already established that we would like to delve into naturalistic decisions, and one type of such decision is taste preference. Taste processing was chosen to research because tastes fit into easily measurable categories, "aversive or rewarding," that match up with an ingestion or expulsion of the food (Berridge and Grill, 1983). In addition, taste processing does not require operant conditioning, which can rewire the brain and complicate results. While there is little research on decision-making of taste preferences, there are several findings on the effect of certain types of memory on taste. Conditioned-taste aversion (CTA), for example, is a phenomenon where a noxious stimulus is paired with a taste. An animal begins by consuming a tastant normally, and when a noxious stimulus is paired with it, the original tastant becomes unpalatable. Again, here is an example of a taste preference changing over time, so memory likely plays a role in this. Furthermore, Katz and Moran demonstrate a change in population activity of the conditioned tastant over time (2014).

Foraging is a relatively new area of research that also utilizes stay or switch behavior. Foraging is described as "a prototype of environmentally based switching between action patterns to optimize resource gathering" (Adams et al., 2012). Evolutionary pressures could have dictated what was easier or more difficult to forage based on the effort required to leave one area, search for food in another area, and the value of the new food. Kolling et al. emphasizes that the cost of foraging is critical to decision making. It is not a binary option, but rather it involves (1) the value of the encounter (i.e. level of nutrition), (2) average search value, and (3) the cost of leaving (2012). Pearson et al. found that when monitoring
foraging, the ACC increased activity as the reward diminished and the animal got closer and closer to leaving, indicating a threshold for leaving a foraged area. And during the decision, the ACC fired in phasic bursts rather than firing continuously, emphasizing that the standard model of integration ("ramping up") must be much more complex to parallel actual firing (2014).

Memory

To further explore taste preference decision-making, we will be creating multiple models. We first determine the type of short-term memory to incorporate into the model. Current models of memory tend to be quite specific (i.e. modeling NMDA channels or calcium influx) or quite general (i.e. after a cell fires, increase conductance) (Weinberg and Smith, 2012; Song et al., 2008; Hennig, 2013). While it is more biologically accurate and relevant to include more specific memory models, given the lack of in depth research on decision-making circuitry, as previously mentioned, it is likely more beneficial at this point to pursue a more general model. Therefore, we chose a standard short-term memory model (See Materials and Methods; Dayan and Abbott, 2001; Hennig, 2013; Song et al., 2008).

These findings create a framework for the role of memory in taste preferences of rats after having accounted for problems in adapting previous models to this current model (perceptual to naturalistic). It is also clear that there is a lack of research on the role of memory in decision-making, especially in naturalistic decisions such as taste preferences. However, there are enough findings in each of those areas: decision-making, memory, the taste system, and computational modeling to successfully model this network.

1.1 In summary, we seek to:

1. Create multiple viable models for stay-or-switch behavior in taste preferences of rats
2. Explore combinations of cellular short-term memory and their influence on this stay-or-switch system
2. MATERIALS AND METHODS

Unlike standard decision-making models that use a neural integrator and "ramp up" evidence over time, we created a computational model that fits the stay-or-switch behavior we hypothesize.

2.0.1 Emulate experimental research on taste preferences

What is the structure of this decision-making model we seek to implement? First and foremost, we are emulating experimental research on taste preferences from a gustatory lab completed by Don Katz. In this experiment, Male Long Evans rats were anesthetized with ketamine and xylazine cocktail followed by a surgical removal of the scalp. Microelectrode assemblies were drilled into the skull and lowered to the gustatory cortex (GC). Testing took place in an isolated chamber with a video camera to record the animal’s orofacial region. Electrophysiological recordings were also collected. The animal received the stimulus through a nose poke; fine poly-imide tubes eject food under the pressure of nitrogen directly into the mouth. The stimulus is delivered over a period of about 90 ms. The rat then decides whether or not to try the same stimulus again - delivered at least 5 seconds after the previous delivery over a two minute period - or switch to the other (Figure 2.1).

![Figure 2.1. The animal tries two different stimuli (A,B) over multiple trials.](image)

2.0.2 Computational Modeling

**Decision-Making Models**

Three unique models were developed to explore the role of memory in naturalistic decisions. Though unique, each model has the same general structure that attempts to model the experimental research procedure above. An animal completes six trials, each consisting of hundreds of switches during that time. Each trial is the same, except the palatability, coded by a variable, of one of the stimuli increases from trial to trial (0.00, 0.04, 0.08, 0.12, 0.16, 0.20). The other palatability remains static at a low bias (0.05). The trials are independent from one other.
The animal, coded by a small-scale neural network, begins at one of two stimuli, each coded with a unique palatability. A poisson input determines the amount of excitability of switch cells. Thalamic input feeds stay and inhibitory cells. There is an initial input pulse at the beginning of each trial, followed by a larger constant current following that. When the switch "pool" has an excitability of at least five times that of the stay "pool", the animal switches to the other stimulus. This process repeats over the course of a ten-minute trial.

1. Non-memory network: This is the simplest model, and it serves as the control. There is no interaction between the two stimuli, other than the coded palatabilities. In such a case, the memory of the previous stimulus plays little role in the memory of the subsequent. The palatability of one stimulus should not affect the palatability of the other.

2. Cellular memory network: post input depression: Both the stay and switch cells now have cellular memory - depression, specifically. Again, depression states that if a cell fires, it will be less likely to fire in the future (Equation 2.3, 2.4). This leads to a hypothesized interaction between one stimulus and the other. The animal should stay at the stimulus with the higher palatability and switch more frequently from the other, lower palatability stimulus.

3. Cellular memory network: input depression: The input current itself is depressed. This leads to a hypothesized interaction between one stimulus and the other, though likely smaller than Model 2. The animal should stay at the stimulus with the higher palatability and switch more frequently from the other, lower palatability stimulus.

Izhikevich and Leaky Integrate-and-Fire

The computational model is based on a decision-making network with hundreds of cells coded in Matlab. Matlab was chosen because of its ease in mathematical coding and analytics, as well as graphing abilities. Based on experimental data, the generally accepted ratio between excitatory and inhibitory cells is 4:1 (Izhikevich, 2003). We implemented a hybrid of the Izhikevich model (2003) and the leaky integrate-and-fire (LIF) model (Gerstner, 1996). There are a number of different possible models that could have been used, but the Izhikevich model allows for a large amount of customization and the LIF model is a classical model used. The former can create multiple types of neuronal spikes in a short amount of time at a 1ms resolution or smaller, leading to high efficiency. Given that there is not much information on decision-making circuitry (and because the areas are quite widespread), we stick with a regular spiking neuron.

In order to add cellular memory to the model, a conductance matrix was included (Dayan and Abbott, 2001), as memory alters the conductance of the system. Conductances were created using a matrix with a uniformly distributed set of pseudorandom numbers multiplied by conductance strengths connecting excitatory to excitatory, excitatory-inhibitory, inhibitory-excitatory, and inhibitory-inhibitory conductances. Inhibitory-excitatory connections were the strongest, followed by excitatory-inhibitory, excitatory-excitatory, and finally inhibitory-inhibitory (zero conductance).

Current was generated using a standard sigmoid (Dayan and Abbott, 2001) that incorporated the palatability of the present stimulus for excitatory stay cells, a switch current for excitatory switch cells, and a base current for inhibitory cells. This current, in addition to the conductances of the cells, then causes firing in all of the cells. Subsequently, each cell’s synaptic gating variable (proportion of post-synaptic receptors available) was altered depending on whether or not the cell fired. When no cellular memory is implemented, the synaptic gating variable is reset to 1 each time the cell fires (100% of the post-synaptic cell’s receptors are open), and decays over time based on a synaptic time constant in any other case.
If the pre-synaptic cell fires:

\[ S = 1, \]  \hspace{1cm} (2.1)

where \( S \) is the synaptic gating variable value of the cell

Otherwise:

\[ S = S \times \exp \left( \frac{-dt}{\tau_{S}} \right) \]  \hspace{1cm} (2.2)

* Solution to the differential equation, as inputed in Matlab code

**Cellular Memory Equations**

As was previously stated, two of our models include depression as a form of cellular memory in the model**. Whereas in the non-memory network, the synaptic gating variable increases to 1 (100\% bound) when the cell fires, depression in the memory network makes the cell less likely to fire. So the synaptic gating variable should then, decrease, after firing. In the time that the cell does not fire, the synaptic variable slowly increases back to 1, as a function of the probability of release (fixed/constant) and the depression level. A depression value of 1 indicates no depression, while 0 indicates full depression, and the cell cannot fire.

If the pre-synaptic cell fires:

\[ S = S + prD(1 - S); \quad D = D(1 - pr) \]  \hspace{1cm} (2.3)

where \( pr \) is the probability of release and \( D \) is the depression variable

Otherwise:

\[ S = S \times \exp \left( \frac{-dt}{\tau_{S}} \right); \quad D = 1 + (D - 1) \times \exp \left( \frac{-dt}{\tau_{D}} \right) \]  \hspace{1cm} (2.4)

where \( pr \) is the probability of release and \( D \) is the depression variable

**Only the excitatory cells (hold and switch cells) are being depressed.**
3. RESULTS

Fig. 3.1. a. Non-memory distributions (x-axis: frequency, y-axis: time) show positive skew. S1 (Stimulus 1) duration histogram at a low palatability (palatability = 0.05) b. S2 (Stimulus 2) at a low palatability (palatability = 0). c. S1 duration histogram remains static at a low palatability (palatability = 0.05) d. S2 at a high palatability (palatability = 0.20) show a few very long durations

3.0.3 Non-memory stay-or-switch network

Behavioral output of the non-memory network shows a relatively positively skewed distribution of durations at both stimuli (S1 = Stimulus 1, S2 = Stimulus 2) independent of palatability (Figure 3.1.a-d). With a palatability value of 0.05 for S1 and 0 for S2 at low palatability, and 0.05 for S1 and 0.20 for S2 at high palatability there is an apparent difference in distribution between the S1 and S2 but not necessarily between palatabilities.

S2 shows much higher durations than S1, again, independent of palatability. And durations at S1 are relatively invariant compared to S2.
The non-memory model shows a lack of interaction between durations at both stimuli (Figure 3.2.a,b). As palatability increases, the mean duration spent at S2 increases, but S1 stays fixed. This makes sense, given that only their palatability levels are coded to create any sort of difference across time. S2 is increasing in palatability from trial to trial, explaining the increase in mean duration time (3.2.a), unlike S1, which is static. But again, the palatability of S1 does not change given S2 and vice versa.

However, when S1 is plotted at the nth duration against S2 at the nth duration for all trials, there is a correlation for both at low palatability (Figure 3.2.c; $r = .33$, $p < .00001$). High palatability of S2 and low palatability of S1 shows a small correlation, as well (Figure 3.2.d; $r = .16$, $p < .001$). It is important to keep in mind, though, that these durations are over quite small differences in time (140 to 240 ms). Interestingly enough, when the larger values ($t > 300$ms) were removed from the correlation at high palatability, there was not a significant correlation ($r = -.13$, $p > .05$). So it appears that the much higher S2 values play a role in correlating with the S1 values. But it is unclear why this is different between low and high palatability.

**Fig. 3.2.** a. S1 vs. S2 across multiple palatability trials b. S1 vs. S2 over a sample trial c. Correlation between S1 at nth duration and S2 at nth duration for low palatability ($r = .33$, $p < .00001$) d. Correlation between S1 at nth duration and S2 at nth duration for high palatability ($r = .16$, $p < .001$)
durations. In addition, it is surprising in itself that there exist correlations for the non-memory model, given that there are not visible interactions between trials (Figure 4.2b). And the discrepancy between Figure 3.2a and 3.2d could be that there are generally small interactions within trials between S1 and S2, but not necessarily as palatability increases. In fact, the correlation between S1 and S2 across palatabilities was very small (n = 4264, r = .04, p < .01).

3.0.4 Cellular memory: Post input depression stay-or-switch network

**Fig. 3.3.** Post input depression distributions (x-axis: frequency, y-axis: time) a. S1 duration histogram at a low palatability (palatability = 0.05) b. S2 at a low palatability (palatability
We hypothesized that adding cellular memory to our non-memory model would increase interactions between durations at both stimuli. The stronger the palatability of one stimulus, the longer the animal should spend at that stimulus. And the opposite should occur in conjunction with this cellular memory at the other stimulus. There are two ways we would see this occur. In the case of the non-memory model, we noted that there were correlations within a trial between the stimuli, but not between trials. If we see correlations between palatability and time spent at the stimulus (between trials), then we have achieved the memory interaction we are looking for.

Figures 3.3.a-d show typical stimulus duration distributions for S1 and S2, respectively. There is a significant visual difference between this S1 and the S1 distribution in the non-memory model. S2 distributions, on the other hand, does not have as apparent of a difference in distribution. It appears that the cellular memory creates a bimodal distribution from a unimodal one (Figure 3.3.a, 3.1.a).

We took a look at how depression may be changing the times of durations and distributions over time. As expected, the value of the depression variable syncs up with switch on and switch off times (Switch on time is the time that the animal begins the switch, and switch off time is the time that the animal either switches back to the other stimulus or is not sampling either, Figure 3.4). There also appear to be large chunks of time where the animal is not sampling either stimulus. That length of time, visually appears to depend on the behavior of the depression variable (Figure 3.4)
Fig. 3.4. Stay/switch behavior syncs with depression variable over time. Gaps in between the stay/switch lines indicate points where the animal is not consuming either stimulus.
Fig. 3.5. For all parts of figure, x-axis: "nth" duration, y-axis: duration time (ms) a. S1 duration over time at a low palatability (palatability = 0.05), S2 is at a low palatability (palatability = 0.00) b. S1 duration over time at a low palatability (palatability = 0.05), S2 is at a high palatability (palatability = 0.20). c. S1 against S1 for a sample trial shows "competition"
A more visual interpretation of the interaction, and one that can relate back more realistically to taste preferences themselves, shown in Figure 3.5.c. In effect, there is a competition between one stimulus and the other. That is, when one stimulus has just hit a 'peak' – a long duration, the other stimulus does not also hit a peak at that same or often next nth duration. And as palatability strengthens, one stimulus dominates peaking, while the other has very few peaks (Figure 3.5.a, 3.5.b).

Interestingly, we do not see a large correlation between S1 at the nth duration and S2 at the nth duration ($r = -0.09, p < 0.0001$). But this could be explained in one way by there being clusters within the correlation plot (Fig 3.6.a). The output is such that the animal slowly increases (and sometimes slowly decreases) time spent at one stimulus until there appears to be an exponential-like increase in time spent, as in S2 distributions in the non-memory model (Figure 3.5; Figure 3.1). Though a negative correlation makes sense, since an interaction should theoretically lead the animal to spend lesser time at one stimulus and greater at the other (Figure 3.7). On the other hand, the non-memory model has little interaction as palatability increases (Figure 3.2a). We also found that as palatability increased, there was a small correlation between S1 and S2 (Figure 3.7; $n = 3453, r = -0.11, p < 0.0001$).

![Fig. 3.6. Correlation between S1 at nth duration and S2 at nth duration for low palatability across multiple runs ($r = -0.09 p < 0.0001$); No significant correlation at high palatability](image-url)
Fig. 3.7. S1 vs S2 across multiple palatability trials shows interaction for the post-input depression model (n = 3453, r = -.11, p < .0001).

**Longer duration cellular memory network**

The non-memory model is not only flawed in interactions between stimuli, but also in realistic timing of durations. It’s unlikely that an animal would spend only 300 ms (distribution of Fig 4.1.a,b), say, for example, at a stimulus, especially if it was tasty. The memory model has a much more frequent output of "peaks", which more typically span 1-5 seconds (for both stimuli, instead of just 1). Even still, we have to question whether this itself is biologically plausible. In turn, we created an extension of the memory model that has much longer durations at a time. Doing so required lowering the current to the switch pool cells (so that they would be less likely to switch and therefore have longer durations). One question we had to answer was whether doing so affected the interactions between stimuli. And while not quantitatively explored, increasing duration length only slightly affected these interactions comparatively (Figure 3.8). As palatability increases, there is a visible interaction, though slightly noisier in comparison to the non-memory model.
3.0.5 Cellular memory: Input depression stay-or-switch network

We expect to see an interaction between stimuli in the input depression cellular network, though perhaps not as strong as in the post-input network. The input network showed a much greater resemblance in distribution to the non-memory network than the post-input network (Figure 3.9.a-d). Even when the depression was increased to increase the effect on the post-input network, the results were negligible. Duration times were much smaller than the post-input network or the non-memory network.

Fig. 3.8. S1 vs. S2 across multiple palatability trials for a longer duration network (max duration = 50 seconds)

Fig. 3.9. Input depression distributions (x-axis: frequency, y-axis: time) a. S1 duration histogram at a low palatability (palatability = 0.05) b. S2 at a low palatability (palatability = 0). c. S1 duration histogram remains static at a low palatability (palatability = 0.05) d. S2 at a high palatability (palatability = .20)
Over a sample trial, there appears to be a slight interaction between stimuli - though not always and is not correlated (Figure 3.10, 3.11; r = .01, p > .05).

Fig. 3.10. S1 and S2 plotted against each other for a given trial shows some interaction, but not a significant amount.

Fig. 3.11. Input depression network shows relatively little interaction, or memory, as palatability increases (n = 415, r = .05, p > .28)
3.0.6 Kolmogorov-Smirnov results: Differences in distributions between models

Multiple Kolmogorov-Smirnov tests were performed to compare distributions of all three models. However, due to the size of the data points for each distribution (500+) and the noise inputted in the network, all models were found to be significantly different from one another. Further information and plots of CDF (used to calculate the KS test) are included in the Appendix.
4. DISCUSSION

Three unique models were developed and analyzed to determine which of the three would optimally suit a naturalistic taste preference decision-making circuit. We argued that a model incorporating memory should theoretically fill this position.

The first model, the non-memory network, showed that within a trial, the stay and switch behavior was correlated when the animal was faced with two stimuli of similar, low palatability. However, if the animal was faced with one stimulus of a low palatability and one stimulus of a high palatability, the correlation decreased. In addition, there was no relationship between a difference in palatability of the stimuli as a function of time spent at those stimuli. In other words, if an animal was first presented with two stimuli that were relatively untasty, the animal might spend an equal time at both (or around that). But if one of the weaker stimuli was replaced after each trial with a taster stimulus, we would expect that the animal would spend more and more time there and less time at the less tasty stimulus. One interesting aspect of the model is that the animal seems to spend a more plausible time at S2 than S1 (Fig 3.1). For S1, the animal never spends more than 800 ms at the stimulus. But at S2, the animal spent up to 20 seconds at one time for a trial at a high palatability. The "peaks" within the non-memory network are consistent with the synaptic gating variable being set to 100% each time a cell fires – so the more a stay cell fires, the more likely it will fire again. Consequently, if stay cells are strong, switch cells get weaker and durations are longer.

Out of the three models, the post-input depression network best reflected a naturalistic circuit for several reasons (Fig 5.1). Most importantly, adding cellular memory created interactions between the stimuli. As palatability increased, the animal spent more time at that stimulus and less time at the other stimulus with a fixed palatability. What exactly in the depression model is causing this interaction that we do not see with the other models? The palatability is coded as a variable which adds to the stay current. This is why we see longer durations in the non-memory model for S2 – because of the increase in palatability from trial to trial. If the palatability is high, stay cells are more excited and therefore fire, keeping the animal at that stimulus. But in the non-memory model, nothing is stopping the switch cells from also firing. Any cell that fires in the non-memory model is going to be more likely to fire subsequently, because its synaptic gating variable is then set to 1 (100% bound) – which then adds to the current for the next iteration. In the case of the depression model, both the stay and switch cells must have an optimal level of firing in order to "win" over the other. If a stay or switch cell fires, it will be less likely to fire subsequently. A lack of firing leads to a higher current, as the depression variable increases again with time, which leads to the cell being more likely to fire. And so there is a strong interplay between the stay cells and the switch cells. At a higher palatability, the stay cells have a stronger current, so they will likely fire for longer, but then will be subsequently less likely to fire at points due to depression. At a lower palatability, they will get less current in the first place. Or the switch cells may initially gain strength and fire, and then lose strength and allow the stay cells to fire. At some point, with the "peaks" we observe, it is likely that the switch cells have weakened enough for a significant amount of time that the stay cells beat them out and fire for a long time (Fig 4.5.e, 4.5.f). We also have to keep in mind that our depression time constant is 9.2 seconds – a much longer time in comparison to cell firing or even many of the durations, and so this temporary weakening is entirely plausible. When we looked at switching over time against the depression variable (Fig 4.4), those gaps in time when the animal is doing nothing is most likely due to something more interesting. The circuit tells the animal to stop tasting a stimulus, as the stay cells are weakened. But the switch cells are also too weakened to switch and begin tasting the other stimulus. However, these large gaps are artifacts of the model itself, so it is unclear whether this would actually occur biologically at this point.
The final model, input depression showed relatively little interaction between the two stimuli. Even when the probability of release and voltage to the decision-making network were increased, there were negligible effects on the behavior output. It appears that either depression must occur in the network itself to have an effect on the interaction of the stimuli, or there are some flawed characteristics to this model that need to be reexamined.

Fig. 4.1. Mean durations plotted against trial number - each subsequent trial refers to an increase in palatability. The post-input memory network appears to be the only model with interactions between stimuli. **Legend:** T1 = Stimulus 1 (S1); T2 = Stimulus 2 (S2)

There remain two questions we must address from these observations: 1) How biologically plausible is this model? and 2) Why are any of these models better than traditional decision-making models? For the biological plausibility aspect, we used a depression time constant of 9.2 seconds (Song et al., 2008) and the same ratio of excitatory to inhibitory cells in the cortex, as found in previous research (Dayan and Abbott, 2001). The use of the LIF and Izhikevich models are arguably as plausible as other computational models, if not more. At the current time, we do not have substantial experimental data that backs up these stay/switch behaviors to compare against. However, we know that memory plays a role in taste preference from multiple studies on conditioned taste aversion (Katz and Moran, 2014; Welzl et al., 2001; Lamprecht et al., 1997).

Of course, there are a few issues with the model. First, duration times are quite low. Even in the cases where there are peaks at 50s or 100s, there are many more times where the animal samples the stimulus for <500 ms. To rephrase that in terms of behavioral output, any duration under one second is likely the animal choosing to taste the stimulus and quickly switching to the other or stopping the consumption of that stimulus. Without experimental data, we cannot for sure say that this is unrealistic. But based on our
observations of taste decisions in animals, this does not seem likely, at least not likely to occur so frequently. One problem with simply reducing the current to the switch cells to make durations longer for that stimulus is that each element that is changed in the model has an effect on other elements. Often times, when the current was reduced too much, the system failed to produce any behavioral output (zero switching). In order to make adjustments to the code, there must be a balance between the achieved goal and keeping the system biologically realistic. In addition, adding memory appears to reduce the correlation between S1 and S2 durations, unlike the non-memory model. At this point, it is not quite clear why this happens.

It has long been supposed that ramping up of evidence is indeed the correct way to model decisions (Gold and Shadlen, 2007). But, as stated previously, this may not be true in the case of naturalistic decisions.

The decision is not the value of the stimulus itself, but rather to stay at that stimulus or switch to another (Miller and Katz, 2010, Kolling et al., 2012, Pearson et al., 2014). We argue that even though our model is just in the beginning phases, it is likely a better indicator of naturalistic decisions than p

Future directions should include further developing the memory model to be more biologically realistic. One interesting type of model that could be explored would be a memory model that feeds back to the input. For example, the post-input cells would get depressed, which would then feed back to the input and depress the input. This would combine the input depression and post-input models, and is seen in many areas of the cortex rather than a feed forward network. Other forms of short-term memory, including facilitation/augmentation, and long-term potentiation should also be explored.
5. APPENDIX

5.0.7 Statistical Results

Kolmogorov-Smirnov Test and CDF

Fig. 5.1. CDFs of all models; all models have unique distributions (see zoomed in figures below), causing a rejection of the null hypothesis of the KS-test)
Fig. 5.2. Two sample non-memory models against each other (NM1, NM2), post-input depression (M3). Noise causes non-memory models to have unique distributions, leading to a rejection of the null hypothesis of the KS-test
Fig. 5.3. Two sample non-memory models against each other (NM1, NM2), post-input depression (M3). When noise was removed from the non-memory model, the two models did not pass the KS-test.
5.0.8 References


