Individual variability in pattern recognition and set shifting under the influence of ambiguity priming

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Introduction

Perceiving patterns where none exist and missing patterns that do exist both commonly occur in real-world situations characterized by uncertainty, while optimal pattern detection lies at the center of this cognitive-behavioral continuum. Humans use causal inference from pre-existing data in order to generate hypotheses, recognize patterns, and make decisions; a simple but reliable test for this type of casual inference is a "blicket detector," which reacts in the presence of certain objects or combinations of objects but not others.

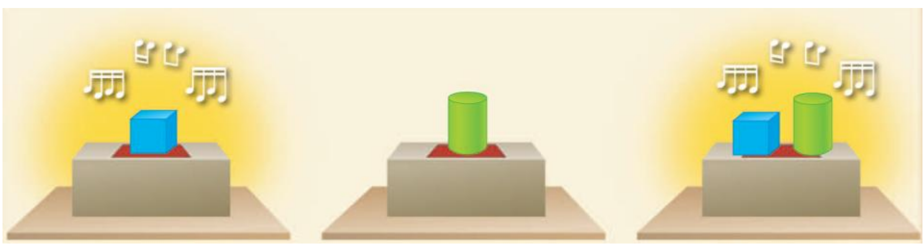
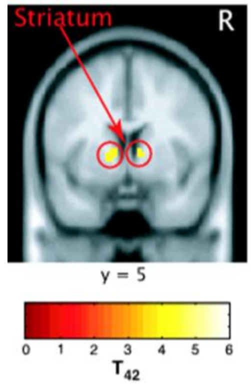


Figure 1. A sample blicket detector experiment.[4] Given that the causality is deterministic, sufficient information can be gathered to infer that the blue cube alone activates the machine.

When studied in a controlled environment, decision making often involves manipulated, deterministic variables, but in reality, most decisions are made in conditions of uncertainty, where feedback is often unreliable. A neuroeconomic study[5] suggested that conditions of increased ambiguity were associated with greater midbrain (i.e. striatum and amygdala) activation, which implied that as feedback becomes less accurate, people become more reliant on their emotions or instincts rather than logical processes which have traditionally been associated with the prefrontal cortex in the forebrain.

Figure 2 (next page). Shift in midbrain activity in accordance with ambiguity in the neuroeconomic study. Although ambiguity was not quantified, the plots under B show a general signal increase in the midbrain as ambiguity increased.



In addition, a study[2] done by Chiarello (1990) on semantic priming, or the effect in which words assist the recognition of other related words, showed that for some types of semantic relationships, the left visual field (LVC) influenced priming effects to a greater extent than the right visual field (RVC). This in turn suggested that priming led to a shift in brain activity toward the right hemisphere which dictates the left visual field, even though the data was purely behavioral. This study also supported the notion that the left side of the brain is associated with more precise semantic tasks, while the right side is associated with broader semantic tasks, which may lend support to a similar lateralization of brain function from ambiguity-related factors.

One way to expand on the notion of causal inference in learning patterns is by investigating the threshold of change in circumstances that must be passed before humans adapt to new patterns. The flexibility of changing mental rules, or set shifting, is sensitive to ambiguity priming, the process in which a prolonged period of uncertainty followed by the sudden discovery of a definite pattern leads to perseveration toward the initial pattern.

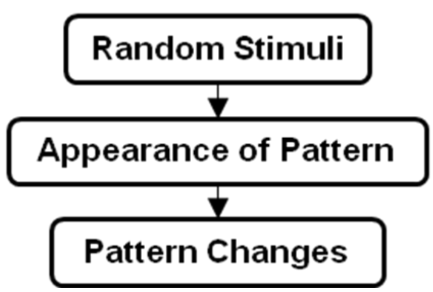


Figure 3. The ambiguity priming process.

An experiment that made use of ambiguity priming involved having participants viewing a series of dots on a flat screen and judging the direction in which they were moving, either left or right. Only a certain percentage of the dots (50% in lower ambiguities, 6% in higher ambiguities) were “coherent,” or moving together in the same direction, while the remaining incoherent dots remained static and flickered on and off for the purpose of distraction. Results from the experiment led to an emphasis on individual variability. During ambiguity priming trials, the task began at a high ambiguity to instill a state of confusion in the participant before drastically lowering the ambiguity to “plant” the pattern, allowing participants to see the direction in which the dots were moving. After priming, the participants were expected to have greater difficulty adjusting to changes in the motion of the dots than if the priming did not occur.

Another essential component of decision making is feedback – an analysis of a quantitative relationship between feedback ambiguity and pattern detection, through modeling, may lend further insight into human cognition by offering predictive power in regard to individual behavior during decision making.

Objective

The intent of this study was to observe individual differences in pattern recognition and set shifting under varying situations, including the problem of whether these differences were primarily due to state or trait. Our aims included finding a correlation between the performance-ambiguity differential and susceptibility to ambiguity priming, associating different states with activations in different regions of the cerebral cortex and midbrain, and producing computational models to differentiate individuals based on behavioral signals in pattern recognition and ambiguity priming.

Materials and Methods

The setup for the experiment involved programming a graphical pattern detection task in MATLAB R2010a with the Psychophysics Toolbox Version 3 extension. The task, themed on role-play cyber security to facilitate emotional engagement, required participants to deduce the correct answer choice, based on the pattern in its properties, from each list of communications.

	Time	**Destination**	**File Size**	**Alert**
1	3:00	Seattle	<100	ET Trojan Sality Variant Downloader
2	9:00	Chicago	100+	FTP Satan Scan
3	15:00	Los Angeles	-	STOR overflow attemptINFO web bug
4	21:00	New York	-	Rar Encrypted File Transfer
5	-	Miami	-	Suspicious Browser Redirect

Table 1. Each communication has a number of properties, including time, destination, file size, and alert. In the table, the possible values for each property are displayed by column.

Immediately after each response, participants were given feedback for a period of time, which allowed them to narrow down the answer. The pattern changed periodically after several correct responses in a row, and the objective was to find a certain number of patterns. User interaction with the program was limited to three separate keyboard keys – two for switching between answer options and one for selecting an answer option. For standardization, each participant was also required to complete a standardized tutorial to learn the task. Preliminary testing involved isolating and manipulating variables (demonstrated below) such as ambiguity level, number and complexity of the answer options, pattern operator types, and visual representation to define an adaptive difficulty method; the sequence of values for these variables were permuted in a random order to prevent order effects. Controlled variables were automatically set to their default values.

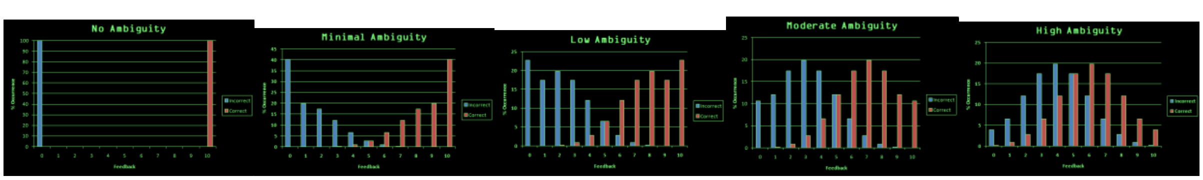


Figure 5. The ambiguities were defined as approximate Gaussian distributions centered at specific points along the feedback scale, with higher being more positive. The graphs represent, for ambiguity levels from 0 to 4, the probabilities of each feedback based on whether the answer choice was correct or incorrect. The default value was 0.

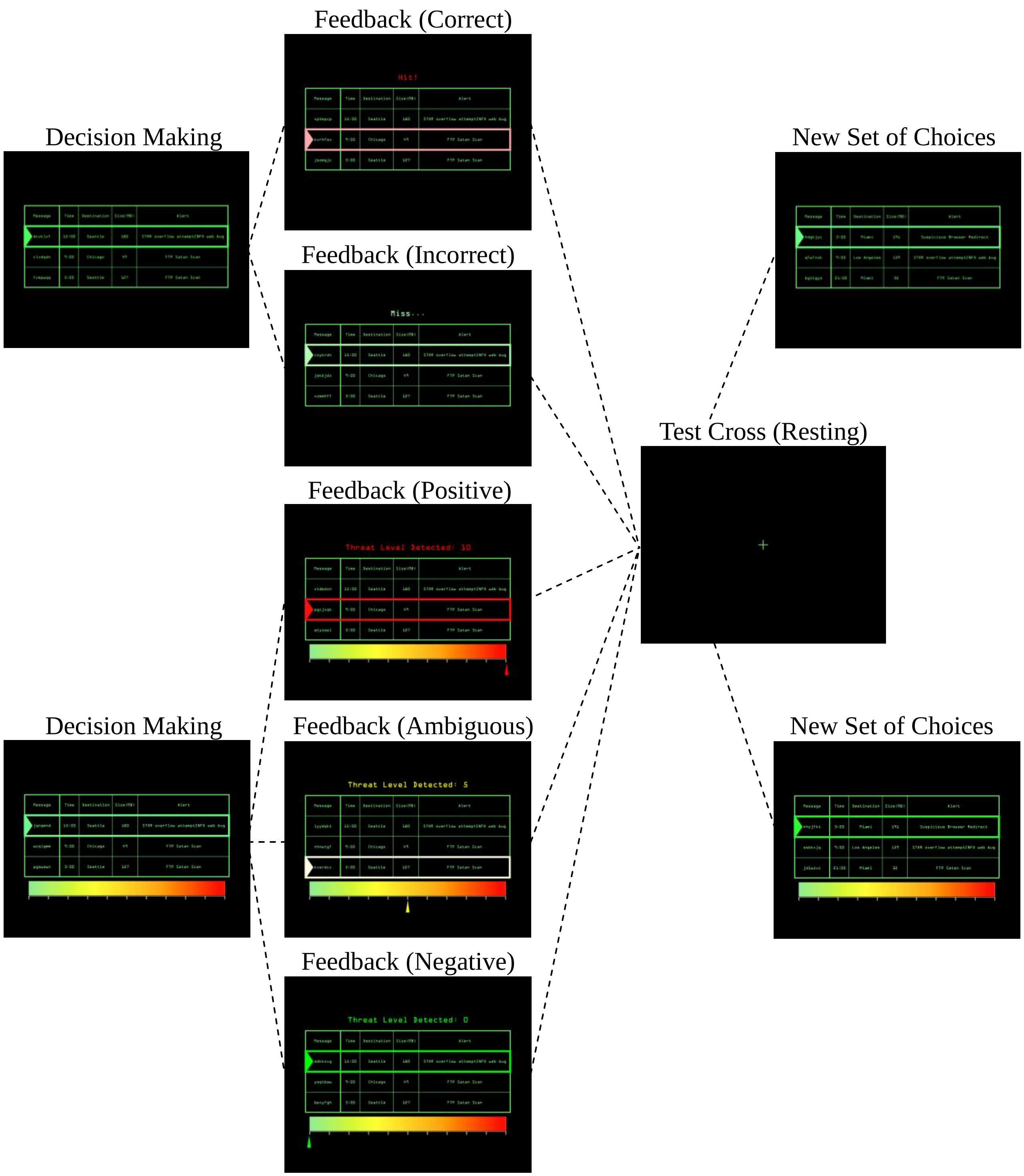


Figure 6. Possible sequences of events in the Deterministic and Probabilistic feedback modes. Ambiguity was a major defining component of the latter – as the ambiguity level increased, the feedback was more likely to fall into a gray area. Feedback was shown for exactly 2.5 seconds; the test cross was shown for exactly 0.5 seconds.

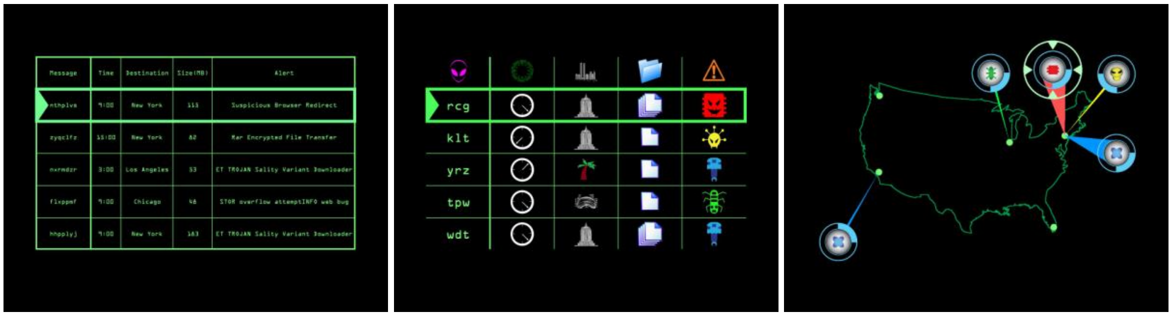


Figure 4. Three forms of visual representation, from left to right: Semantic, Pictorial, and Graphical. In the latter, the placement of the answer options varied with each set of communications; we hypothesized that this fact would lead longer pattern recognition times. The default value was the Semantic mode.

Finally, the number of answer choices, the number of properties, and the pattern operator type were combined together into a vector of variables instead of being tested separately. The rationale was that these variables may not influence performance independently of one another. The pattern operator was either Normal, Conjunctive, or Disjunctive for each pattern – Normal was the singular operator in which the pattern was determined by one property, while Conjunctive and Disjunctive patterns depended on two properties and were based on a logical AND and a logical OR, respectively. The permutations for the values in this vector were represented by a 3-dimensional matrix, which was in turn stored in an array of hashes.

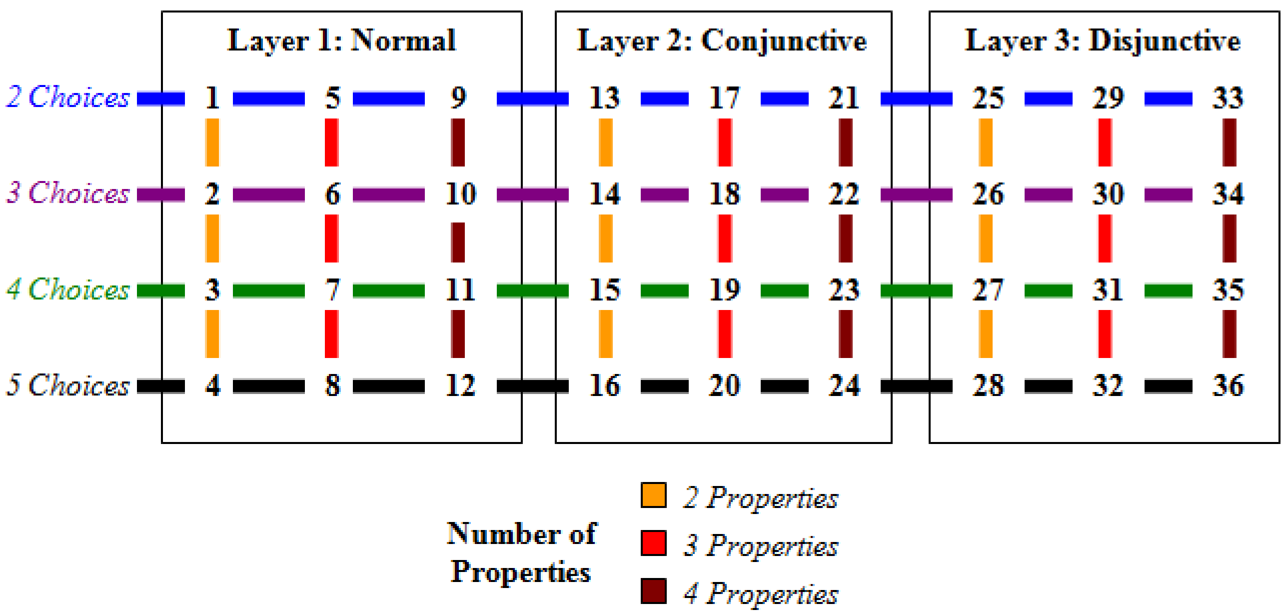


Figure 7. A diagram of the possible hashes, with values from 1 to 36. Each represents a distinct combination of 1 of 4 possible numbers of answer choices, 1 of 3 possible numbers of properties, and 1 of 3 possible pattern operators.

$$H = (N-1) + 4(P-2) + 12(A-1)$$
$$(A, P, N) = \left(\left\lceil \frac{H}{12} \right\rceil, \quad \left\lceil \frac{H-12(A-1)}{4} \right\rceil + 1, \quad H - 12(A-1) - 4(P-2) + 1\right)$$

Equation 1. The hash function H outputs the hash from 1 to 36 based on the number of answer choices N, the number of properties P, and the pattern operator number A (from 1 to 3, in order from Normal to Disjunctive). Below it, the inverse hash function recovers the variable vector from the hash. Brackets represent taking the ceiling (or least integer) function of the enclosed quantity.

In the experiment, participants were tested both on regular pattern detection with variable ambiguity and on the ambiguity priming task. The program recorded behavioral data such as the accuracy and timestamps of each response and, for a number of trials, also interfaced with a Hitachi ETG-4000 optical topography system for measuring the neurobiological response using near-infrared spectroscopy (NIRS).

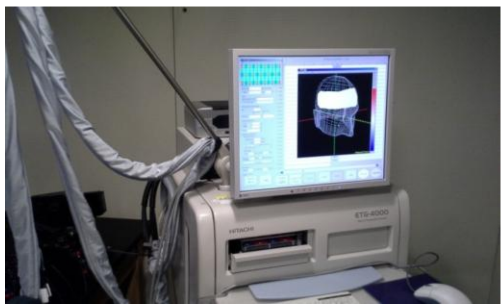


Figure 8. The Hitachi ETG-4000 optical topography system. After position calibration, a wireframe model of the head is shown on-screen.

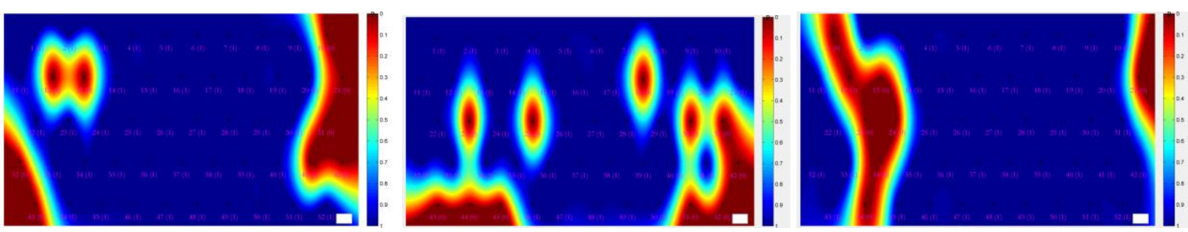


Figure 9. After temporal synchronization of the transistor-transistor logic (TTL) pulse onsets with the behavioral timestamps, the localized cortical activation is contrasted between various feedback ambiguities and various states of activity including decision-making, positive feedback, negative feedback, and rest, using the NIRS Analysis Package (NAP) developed by our lab. These visual maps show relative changes in concentration of i) oxygenated hemoglobin, ii) deoxygenated hemoglobin, and iii) total hemoglobin by channel position.

Results

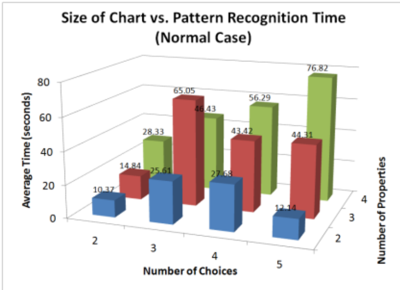
Note: Pattern recognition time is operationally defined as the time elapsed from the appearance of the pattern to the selection of the first correct answer in the streak. Time spent in the feedback and test cross screens is included and totals 3 seconds per response. Asterisks indicate outliers and are not included in the statistical measures.

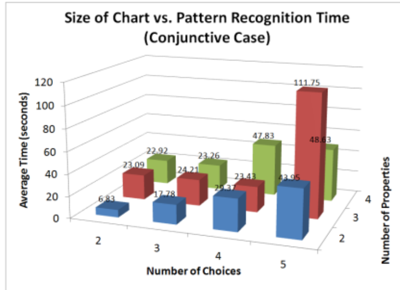
Trial	Ambiguity				
	0 (None)	1 (Minimal)	2 (Low)	3 (Moderate)	4 (High)
1	72.8	154.8	59.7	372.8	399.5
2	90	21.9	239.6	263.2	172.9
3	360.2*	56.2	20.4	280.8	161.3
4	130.8	103.2	48.7	116.8	220.5
5	48.4	668.5*	1160.8*	123.3	363.2
6	14.7	172.1	34.4	72.4	439.6
7	67.1	46.1	222.4	178.7	805.2*
8	27.3	22.7	25.4	60	121.4
9	35.6	38.3	54.2	21.6	27.5
Average	60.8	76.9	88.1	165.5	238.2

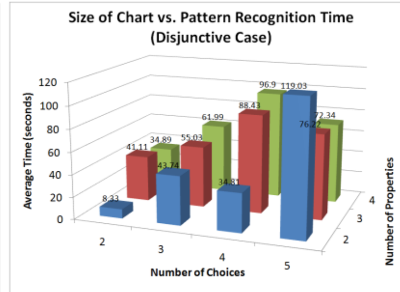
Trial	Pattern Recognition Time by Visual Mode		
	Semantic	Pictorial	Graphical
1	37.9	27.3	72.7
2	37.8	46.2	46.6
3	17.3	40.9	55.1
4	32.7	37.7	153.3*
5	57.4	30.9	38
6	244.6*	52.9	125.8*
7	54.4	41.2	27.5
8	41.2	60.1	36.1
9	65.3	39.9	24.4
10	28.3	69.1	20.5
11	56	45.2	267.5*
12	15.2	79.8	25.6
13	26.9	29	25.1
14	29.9	17.1	19.6
15	97.1	23	31
16	48.6	49.4	63.6
17	241*	50.5	64.9
18	11.8	34.8	20.8
19	36.9	15.8	63.1
20	34	67.8	51.9
Average	40.48333	42.93	40.38235
Standard Deviation	20.55415	17.26762	18.17417

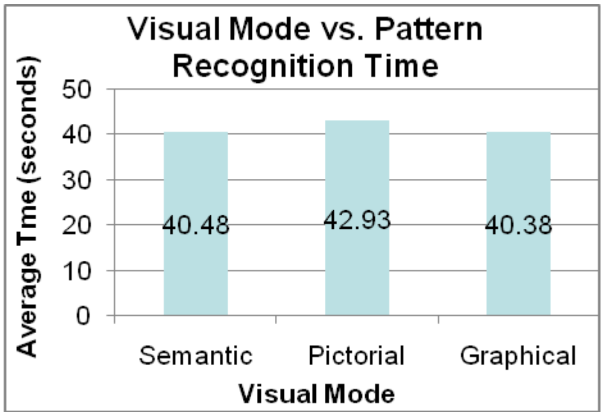
Sample data from testing the variable vector of answer options, properties, and operator type:

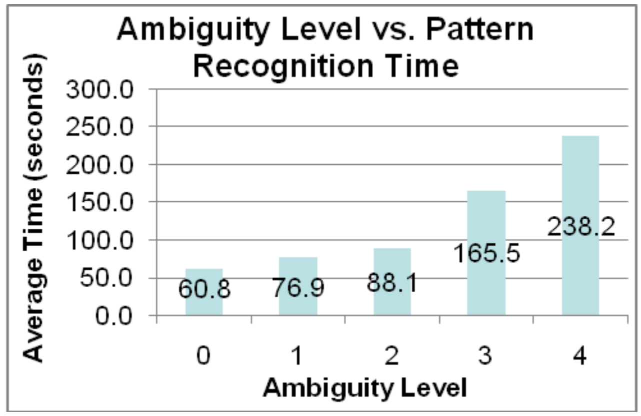
Pattern Number	Answer Options	Properties	Operator	Time to find pattern (sec)	Time spent on pattern (sec)
1	3	4	Disjunctive	194.94	207.34
2	4	2	Normal	62.93	82.71
3	4	4	Disjunctive	89.48	112.78
4	2	4	Conjunctive	5.85	26.22
5	4	2	Conjunctive	10.81	25.88
6	4	2	Disjunctive	5.97	26.75
7	5	4	Conjunctive	138.69	161.2
8	2	2	Disjunctive	3.47	12.79
9	3	4	Conjunctive	20.31	38.57
10	3	4	Normal	8.7	29.33
11	3	4	Disjunctive	155.34	164.79
12	2	3	Normal	6.91	14.44
13	5	2	Conjunctive	80.57	98.28
14	5	4	Disjunctive	74.39	92.76
15	2	3	Conjunctive	71.11	79.68











The graph of the relationship between ambiguity level and pattern detection time seems to suggest an exponential relationship of the form

$$t \propto (A+1)^n ; t \approx k(A+1)^n + c$$

Equation 2. t represents time, while A represents ambiguity level. k, c, and n are all constants.

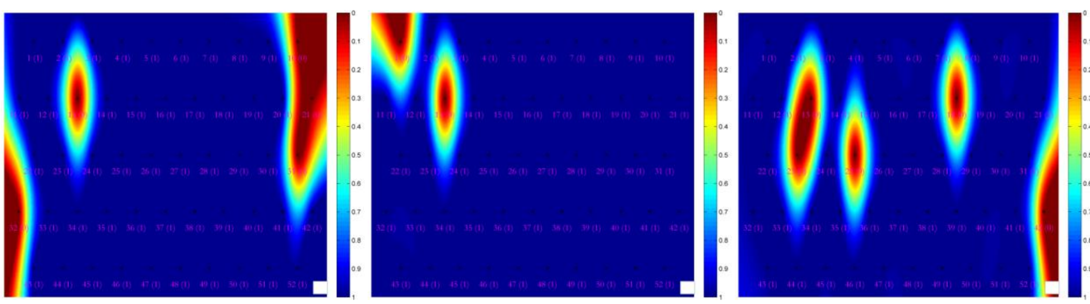


Figure 10. Maps showing activation of, from left to right, oxygenated, deoxygenated, and total hemoglobin when comparing cortical response of one test subject to low and high ambiguity.

The ambiguity also provided interesting NIRS results. In accordance with the hypothesis, there seems to be a hemispheric shift over increasing ambiguity. Although it is possible that the shift in hemispheric activity is because of noise due to the increased difficulty, the decrease in left hemispheric activity provides strong evidence that the shift is related to ambiguity, as opposed to noise. In the situation of noise, there would be the same amount of activity in the left hemisphere, so it is safe to say that the shift is related to ambiguity.

In order to analyze the NIRS data in NAP, we had to set conditions for comparison. The conditions were set as shown by the numbers below:

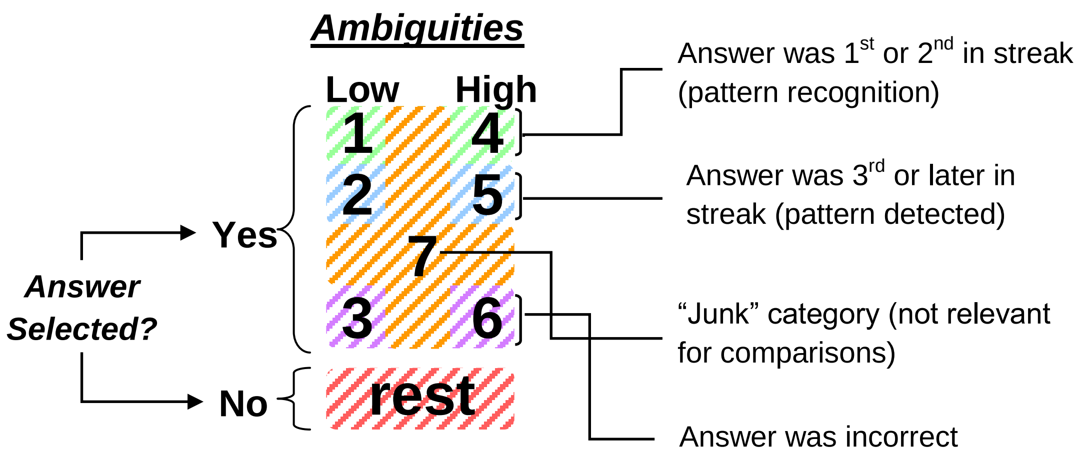
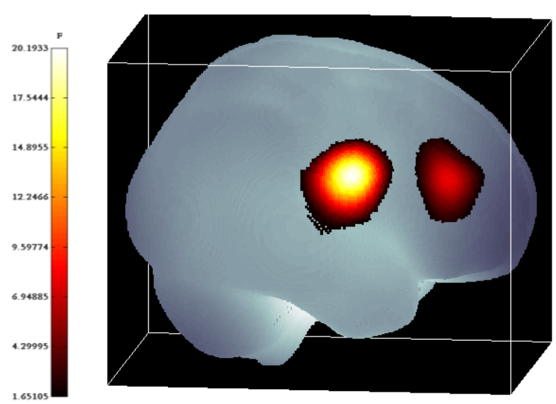
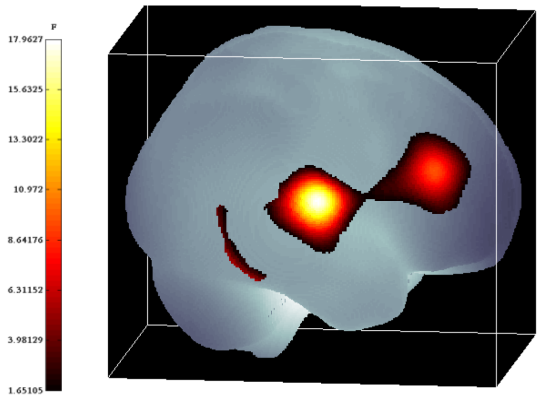


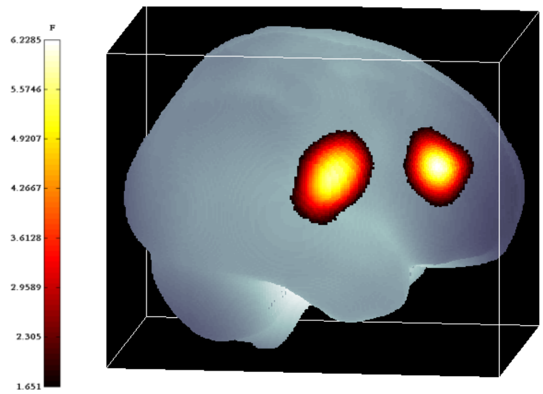
Figure 11.

The main comparisons between the conditions were: condition 1 versus condition 4, condition 2 versus condition 5, and condition 3 versus condition 6.

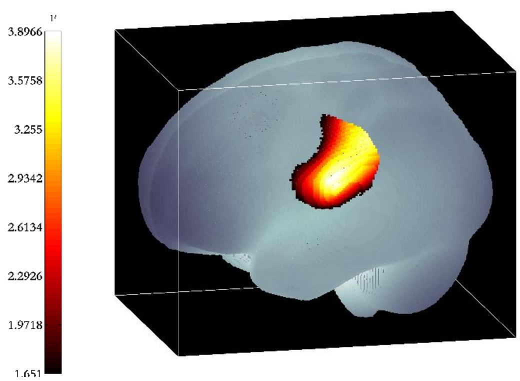


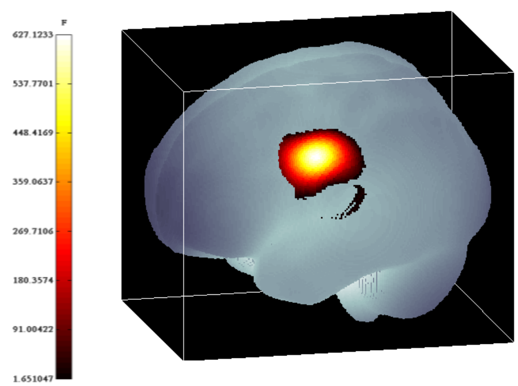
The figure above shows the contrast between condition 1 and condition 4 deoxy. The deoxy activity in the right hemisphere is greater for lower ambiguities, thus indicating more oxy activity in the right hemisphere for higher ambiguities. The location of activity is nearly the same for the contrasts between condition 2 and 5 (below left) and between condition 3 and 6 (below right).

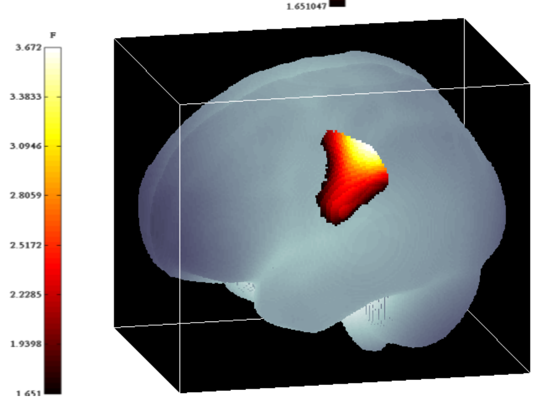




The initial oxygenated hemoglobin brain maps also affirmed the hypothesis. The same conditions were compared, except in this case there was more oxygenated hemoglobin in the left hemisphere for the lower ambiguity patterns. The brain maps are shown in order below (1 vs. 4, 2 vs. 5, 3 vs. 6).







Models

For individual comparison, a number of models based on statistical inference may be applied to the behavioral data. These include:

1. Recursive probability model
2. Regime switching model (Markov Tracking/Guessing)
3. Bayesian updating model
4. State-space model (SSM) (still in early stages)

<u>Recursive probability model</u>

This model is founded on the logistic growth equation. In essence, I realized that a sigmoidal curve was necessary due to the fact that early in the pattern the probability of getting the answer correct is near the probability of guessing (1/i where i = number of choices).

The logistic growth function is defined as:

$$\frac{dN_t}{dt} = r_{\max} N_t \left(\frac{K - N_t}{K} \right) = r \left(1 - \frac{N}{K} \right)$$ where K is p=1 and N is actually a probability.

The main issue with the logistic growth function is that it is continuous with respect to time. In our case, we do not have a continuous function nor can we use time as a step.

To deal with the continuous function issue, I simply created a recursive model that takes a discrete step size of “s”.

Below is the derivation:

$$p(t + \Delta t) = p(t) + \frac{dp_t}{dt} \Delta t = p(t) + p(t) \mathrm{r} \left(1 - \frac{p}{1} \right) s$$ (**Notice how the carrying capacity K is p=1)

Thus $p(t+1) = p(t)[1 + rs(1 - p(t)]$ where $p(0) = \frac{1}{i}$.

Next I needed to deal with *r* and *s*.

I’ll start with the solution to the step size issue. It is important to note that the ambiguity of a given pattern is not known by the participant; however, they do know that a feedback of 10 means they are more likely correct than a feedback of 6. So we can think of step size as how accurate the feedback is. If an individual chooses the correct selection and get a feedback over 5 then they are moving a certain number of steps forward. Meanwhile, if they get an answer correct but get a low feedback, then they are moving backwards. Furthermore, for incorrect selections, the same phenomenon exists, except the magnitude of the steps is dependent on the number of choices (*i*).

$$S_{n-1} \xrightarrow{\textbf{feedback}} \begin{cases} \textbf{correct} & s_n = s_{n-1} + \dfrac{f-5}{h_1} \\[2ex] \textbf{incorrect} & s_n = s_{n-1} + \dfrac{5-f}{h_2(i-1)} \end{cases}$$

The diagram above indicates how the step size is calculated. The constants *h1* and *h2* are simply place holders that can adjust the magnitude of step based on the data.

The final calculation that is left is *r*.

The *r* value determines how quickly the growth occurs in a sense. A higher *r* value would mean that a participant would be able to detect the pattern faster. Therefore the *r* value is based on the chart size and ambiguity. After looking into the 3-dim data I decided to create a chart difficulty variable that is based on the number of choices (*i*) and the number of properties (*j*).

$$D = \sum_{i=1}^{j} [L(i)-1][i-1] \longrightarrow L = \{4, 5, 2, 5\}$$

Furthermore, the ambiguity is affected by the difficulty, so, based on initial data, I set *r* as follows:

$$r_{\max} = \left(\frac{F}{F_0}\right)^z (A+1)^{-kD}$$

k in this case is small, due to the fact that D can approach values of 50.

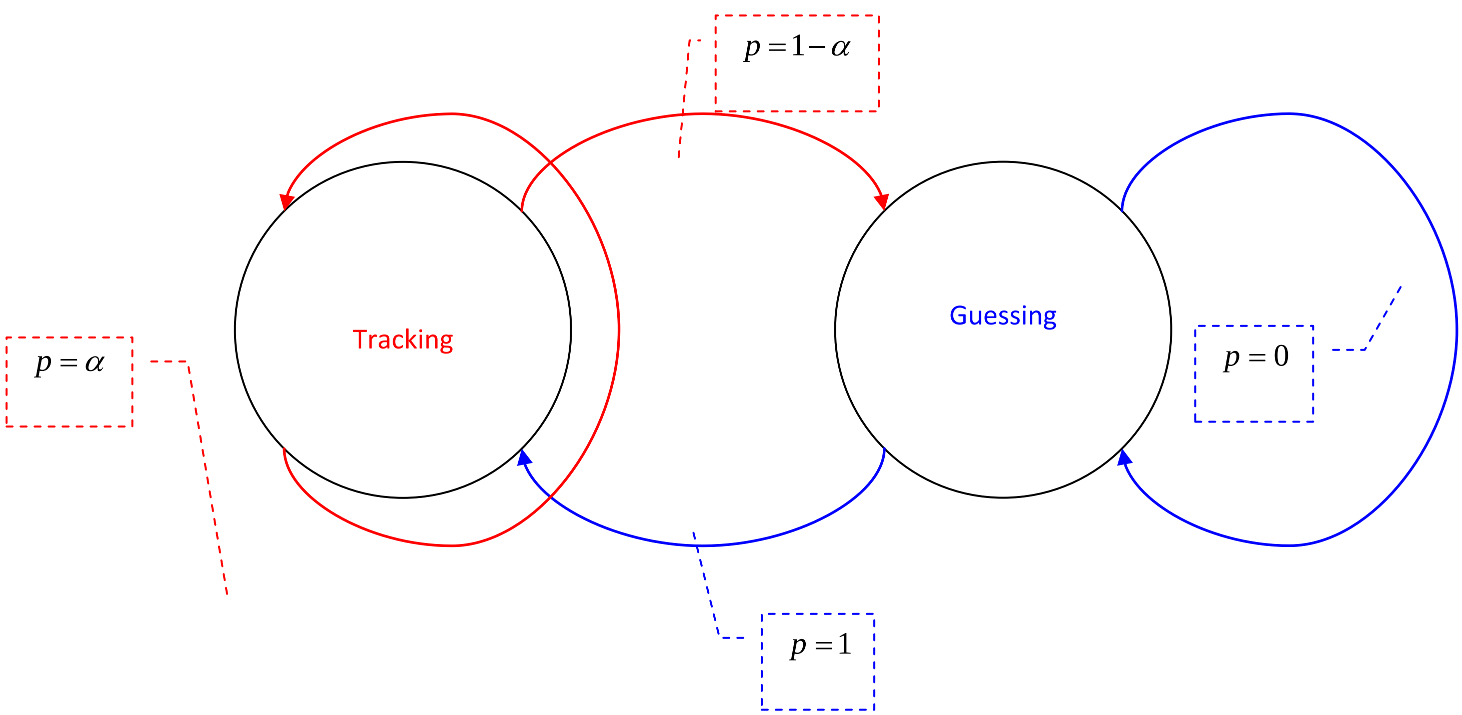
The F represents the F value calculated from the NIRS trials. For behavioral trials F can either be ignored or left variable (will get to later). Essentially, the F value represents how well an individual performs at a certain ambiguity in relation to their performance at lower ambiguities. This allows us to create a component of individual variability that is related to the observed hemispheric shifts.

The final recursive equation is:

$$\boxed{p_n = p_{n-1} + p_{n-1}\left(\frac{F}{F_0}\right)^z (A+1)^{-kD}(1-p_{n-1})s_n}$$

Equation 3.

Regime switching model (Markov Tracking/Guessing)



The model on the previous page indicates a general way to look at the task. The alpha values in reality actually change as an individual receive more and more feedback; however, from a general standpoint, a Markov chain is easier to model and the alpha values may be a possible substitute for F values in the recursive probability model. The tracking mode can be determined in two ways: recognition of pattern or attempted detection of pattern. If the tracking mode is set to be simply the recognition of the pattern, the model is extremely simple. All the answers within the streak would be counted as tracking and the rest as guessing. In this case the alpha value would be determined by calculating the expected value required to match the behavioral data. The other tracking mode would also involve tracking of incorrect patterns. This version of analysis would require looking at the individual selections and seeing if 3 or more in a row shared the same information. In a sense, this model would be much more powerful.

After developing these models, it would be useful to create another model to fix conditions. This model would include correct tracking, incorrect tracking, and guessing at the various ambiguities.

<u>Bayesian updating model</u>

A simple Bayesian model would constantly update probabilities by repeatedly utilizing Bayes' Rule:

$$p(B_k \mid A) = \frac{p(A \mid B_k)\, p(B_k)}{\sum_{i=1}^{n} p(A \mid B_i)\, p(B_i)}$$

Equation 4. Bayes' Rule applied to the behavioral data. *A* is the previous feedback or some other representation of the current state, B_k represents the occurrence of outcome *k* (such as a correct or incorrect response), and *n* is the total number of possible outcomes.

$p(B_k)$ is known as the prior and is subject to estimation in the initial step. $p(A \mid B_k)$ is known as the likelihood and is taken from statistical measures of the behavioral data. $p(B_k \mid A)$, the posterior, is substituted into the prior $p(B_k)$ of the next iteration; this process may be repeated indefinitely using a sequence of A's in a process known as Bayesian updating.

State-space model (SSM)

Because the task consists of a series of states, each which has an input and an output and can be represented by variables as axes, a SSM may be a good fit. One option is to use Shannon entropy to quantify probabilities for possible outcomes as microstates.

Discussion

The initial data suggested that higher comparative ambiguity led to a larger increase in right hemispherical activity of the brain during the semantic version of the task, which may be consistent with Chiarello's research. However, more investigation is needed.

By modeling the effect of ambiguity on pattern detection, it would be possible to determine the probability of detecting a pattern based on the state of the game and previous data. These probabilities in turn would allow observation of false positive and false negative instances and offer insight into the characteristics of optimal pattern detectors. In addition, quantitative models would be able to lay the groundwork for a more sensitive Bayesian adaptive algorithm able to fit the variables of the task to the nuances of each participant.

Future directions for this study include psychotherapy for schizophrenia, which is associated with apophenia or the perception of false patterns, and Asperger's syndrome[7], which exhibits a larger performance gap than normal between lower and higher relative ambiguities and, according to the hypothesis, a higher susceptibility to ambiguity priming.

Pattern detection in the presence of ambiguous feedback also provides applications outside of cognitive psychology, such as in the medical field for medical and psychological diagnoses. Doctors and psychologists could benefit from a deeper understanding of human tendencies in these situations where lines are blurred. In the diagnosis of mental disorders this proves to be of utmost importance due to the fact that many patients often have a range of symptoms from multiple disorders or have symptoms that are common to many disorders, thus introducing a factor of ambiguity. Although a large part of this problem lies in the actual classification of the disorders, it is important to note that an understanding of human pattern detection in cases of ambiguous feedback could help pinpoint in what direction a potential doctor/psychologist would lean. This predictive power would help decrease the amount of false positives and false negatives in regard to the diagnosis of disorders and diseases. Other applications include machine learning from probabilistic inputs and stock market predictions based on economic indicators.

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