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Examining the Transfer of Function Representations

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Abstract

A transfer task was used to test whether people rely on rules or associations to learn a function. The primary function that everyone received was an inverse absolute value function. The secondary transfer functions that had a similar rule were flip conditioned or shift conditioned version of the primary function. The secondary function representing association was a parabola condition shaped function, which had input-output pairs closest to the primary function. It is expected that since the Parabola condition has less deviations from the trained function that if people favor associations then it would be easier, despite it having a very different rule than the primary function. The flip condition is the farthest from the primary function followed by the shift condition, but they have a similar shape, rule-wise to the primary function so if people have the least trouble on these functions then they might favor rules. The subjects had the most trouble with the Parabola condition so seem to favor rules when learning a function.

Examining the Transfer of Function Representations

by

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Thesis

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Introduction

Without relying on a clock or a sundial, how might a person maintain a sense of time using the position of the sun? Perhaps they might associate that when the sun is at its highest with noon or sunset with dusk. Maybe they just form a general sense of time so that at any position of the sun they can make an approximation of the time that is within reason. Or perhaps they hold their hand out to the horizon and use each finger to represent a segment of time while knowing that when the sun is at its highest it is noon and when it is at its lowest it is dusk or dawn.

These questions are examples of a function learning task. A function learning task involves relating continuous input values to continuous output values. This means that a person would only encounter so many example values during training and can still be tested on new values within the training range, which is called interpolation. Being tested on values outside of the training range is referred to as extrapolation. Interpolation and extrapolation are new values that have not been encountered before so require more than recalling the correct answer. Interpolation and extrapolation have been extensively studied in hopes of it revealing how people represent a function when given only a few training values, followed by feedback.

The leading theories or function learning will be discussed followed by how those theories are compared to each other. An evaluation of whether the method of comparison of theories is mathematical valid and the presentation of a new method to compare theories.

The two main theories of function learning are that people form input-output associations or they form rules, like an equation that accurately maps the input to the correct output. In the example above about using the sun to tell time, using a rule method could involve if the sun is a given height over the horizon then there is a certain rate that relates that given height and the time. An example of an association method to learn a function using the same example could involve associating the sun at its highest position with noon.

A rule-based model could be some form of regression model the chooses the parameters of the function that minimize error (Busemeyer, Byun ,Delosh, & McDaniel, 1997). An example of association-based model could be one that remembers the connections between the training input and output and uses a similarity rule such as distance of the new test item and the training values to produce a response like the Associative Learning Model, ALM (Busemeyer et al., 1997). This type of model can account for interpolation accuracy. Accuracy can be thought of as deviations of the response of the subject or model and the answer produced by the function. This type of model may not account for unfamiliar values that are very dissimilar to the values the subjects were trained on during extrapolation (Busemeyer et al., 1997). This model fails to extrapolate beyond the training range producing the same response for increasingly extreme test values (Busemeyer et al., 1997). This flattening out during extrapolation is not often seen in the subjects' responses but neither is the pure replication of the function implied in the training values (Busemeyer et al., 1997). This hinted that people are doing a mixture of rule and association methods to produce their responses. EXAM (Extrapolation Associative Model) was created to overcome ALM's limitations in extrapolation (Busemeyer et al., 1997). It creates local rules between associated input-output pairs and uses these rules to extrapolate.

When given training trials that imply two contradicting linear functions, some subjects seemed to extrapolate in a manner that is consistent with representing both of the functions at once, which lead to the belief that people could be forming simple rules and relating certain input ranges to those previously formed rules to produce their response (Kalish, Lewandowsky,&

Kruschke, 2004). This allows a complex function to be broken down into a number of simpler linear functions (Kalish et. al., 2004). POLE (Population of Linear Experts) is a model that does just that (Kalish et. al., 2004). EXAM and POLE were compared to each other seeing how they differed using large testing gaps between training regions. EXAM smooths these regions and POLE allows multiple discontinuous functions (McDaniel, Dimperio, Griego, & Busemeyer, 2009).

It seemed that the next step was to find the model that is the right combination of rule and association methods. This model was to be compared to subjects' data to see how far its predictions deviated in interpolation and extrapolation. However, it is not the case that interpolation and extrapolation by itself is diagnostic of what strategy people are using. Gaussian Process model, representing associative learning, and Bayesian regression model, representing rule-based learning, have been mathematically shown to produce the same function (Lucas, Griffiths, Williams, & Kalish, 2015). The similarity rule used to judge whether a new test value is similar to a given training value can be simple, such as the distance between the values, or a complex rule relating the two. An example could be that it will be reasonable to associate the position of the sun at sunrise and sunset with each other. They are similar because the sun is at its lowest position but in very different cardinal directions and this can cause dawn and dusk to be more similar with each other than dawn and noon. A complex similarity rule or something other than a radial basis function can be used to produce complex extrapolation patterns with associative models (Kalish, 2013).

Since interpolation and extrapolation can't be used to determine which method people are using when learning a function, a transfer learning framework will be used. Transfer learning involves taking the information learned in one task and using it in another task. Tasks are not always seen as isolated from one another and using the knowledge gathered from one task could help with tackling a similar task (Canini, Shashkov, & Griffiths, 2010). An example of a transfer learning task could be if people use their knowledge of how to predict time by the position of the sun to a new task such as predicting time by the position of the moon. Helie & Ashby (2012) looked at whether people were using a rule or association based representation in category learning by presenting an indirect category learning task, where the category was not given, to see if this knowledge could be transferred to help the subjects perform a category learning task. Function learning falls within the realm of category learning with category learning requiring a categorical response and function learning requiring a response of a particular magnitude. Applying transfer learning to function learning could reveal if a primary function is learned followed a secondary function, then do the subjects struggle more if the secondary function has a very different rule. A different rule could mean the functions have a very different shape with higher degree of complexity, even if the associated input-output pairs are relatively similar or if the opposite is true.

The function chosen as the primary function is an inverse absolute value function because people are good at learning simple linear functions. The only problem would be that it is already known that people learn linear functions faster with a basis toward linearly increasing functions so the results might not reflect the transfer of knowledge just the well-studied basis that people already have against more complicated nonmonotonic functions, such as quadratic and periodic functions (Busemeyer et al., 1997). McDaniel, Dimperio, Griego, & Busemeyer (2009) used absolute values functions to see how people extrapolated between training regions when comparing two competing models so these functions might be the right level of complexity.

Everyone was given the primary function but then were split into 3 groups and each group received a different secondary transfer function. The groups presented the inverted primary function, the flip condition and the shift conditioned primary function, the shift condition, are being tested to see whether people rely on rules to aid their performance. The parabola condition was presented the parabola condition as the secondary transfer function to be tested to see if people rely on associations learned in the primary function to aid their performance. It is less likely that people learned the rule of the parabola condition rather than the rule of the inverse absolute value functions.

Since people struggle on more complex functions, tick marks were used. When given tick marks, subjects' performance was higher when given complex functions then subjects that were not aided by tick marks (Kalish, 2013). The tick marks form discrete landmarks that might allow one to make associations with local rules in between. In the example of estimating the time based off the sun's position, a person could use their fingers to form a standardized distance representing a certain amount of time, grounded by associations such as the rising sun with dawn and the sun at its highest with noon.

The vertex is included in the training values. It is thought that including the vertex might help since it is a critical point where the function completely changes direction. If people create local approximations between training examples and the vertex in not included in the set of training points then people will not form the pointed tip of the vertex and instead interpolate a flat line between the two most central training points (McDaniel et al., 2009). This might affect the subjects' perception of the absolute value and Parabola condition functions they are asked to learn It is also the case that they might not view the change in rule as a single change to the whole function but as multiple changes to multiple functions due to knowledge partitioning

(Kalish et al., 2004). If people partition the function into smaller more manageable functions and the training examples are kept separate across transfer task then people might be able to represent both the primary function and the transfer function at the same time as overlapping functions (Kalish, et al., 2004). Kalish, et al. showed that two functions can be captured by a few subjects if the training points do not contradict each other (2009). This transfer task will require them to reuse the same training examples which will directly contradict the primary function. If the subjects use this method then they have more learning experience from the primary function and they might be slow to change in the transfer task (McDaniel et al., 2009). The participants are given evenly spaced training examples because people tend to learn them better than densely spaced training examples (McDaniel, Fadler, Pashler, 2013).

If people rely on a rule then simple transformations, that displace the learned input-output pairs, should be easily learned as a simple alteration of the rule or equation. If people rely on associations then they will display a low absolute mean error for a very different functions, rule-wise, if the input-output pairs are relatively similar. Similar is defined as low average absolute deviations of the training values from one of the transfer functions and the primary function. The parabola condition has an average absolute deviation of 47.59 from the primary function. The shift condition has an average absolute deviation of 100 from the primary function. The flip condition has an average absolute deviation of 154.76 from the primary function. If people rely on associations then it is expected that the parabola condition will have the lowest error followed by the Shift condition and the flip condition, which has the greatest distance between input-output pairs. The shift condition of the primary function is a slight change in the rules that displaces the input-output pairs like the inverse but to a lesser extent. If people rely on rules the Shift condition will be the easiest followed by the flip condition which flip conditions and slightly shift conditions the primary function with the parabola condition being the hardest despite being the closest to the primary function.

Methods

Participants

There were 60 students taking an introductory psychology class at Syracuse University for class credits.

Procedure

All of the participants were trained on an inverse absolute value function in Phase 1 then they are trained on a secondary transfer function during Phase 2. The participants are told that they are going to be shown a new function. In both phases the participants are given 21 evenly spaced training examples in random order, which includes the vertex or apex of the function, in 6 blocks. There are 4 training blocks followed by a test block and 2 more training and the final test block for each phase.

The stimulus is presented as a vertical bar to the left of the screen. There are 9 tick marks on the stimulus bar. The stimulus bar changes color across phases. Responses are collected by a horizontal bar on the bottom of the screen. There are 9 tick marks on the response bar. When a participant clicks on the response bar a small blue box appears at that location on the response bar. The participant can adjust their response until they decide to click on a red box to the right to confirm their selection. If their response is correct, then they are praised and allowed to continue but if their response is incorrect then they are presented the correct response as a small rectangular feedback bar in the correct position in the response bar. They must click the feedback bar in order to continue. This can be seen in Figure 1.

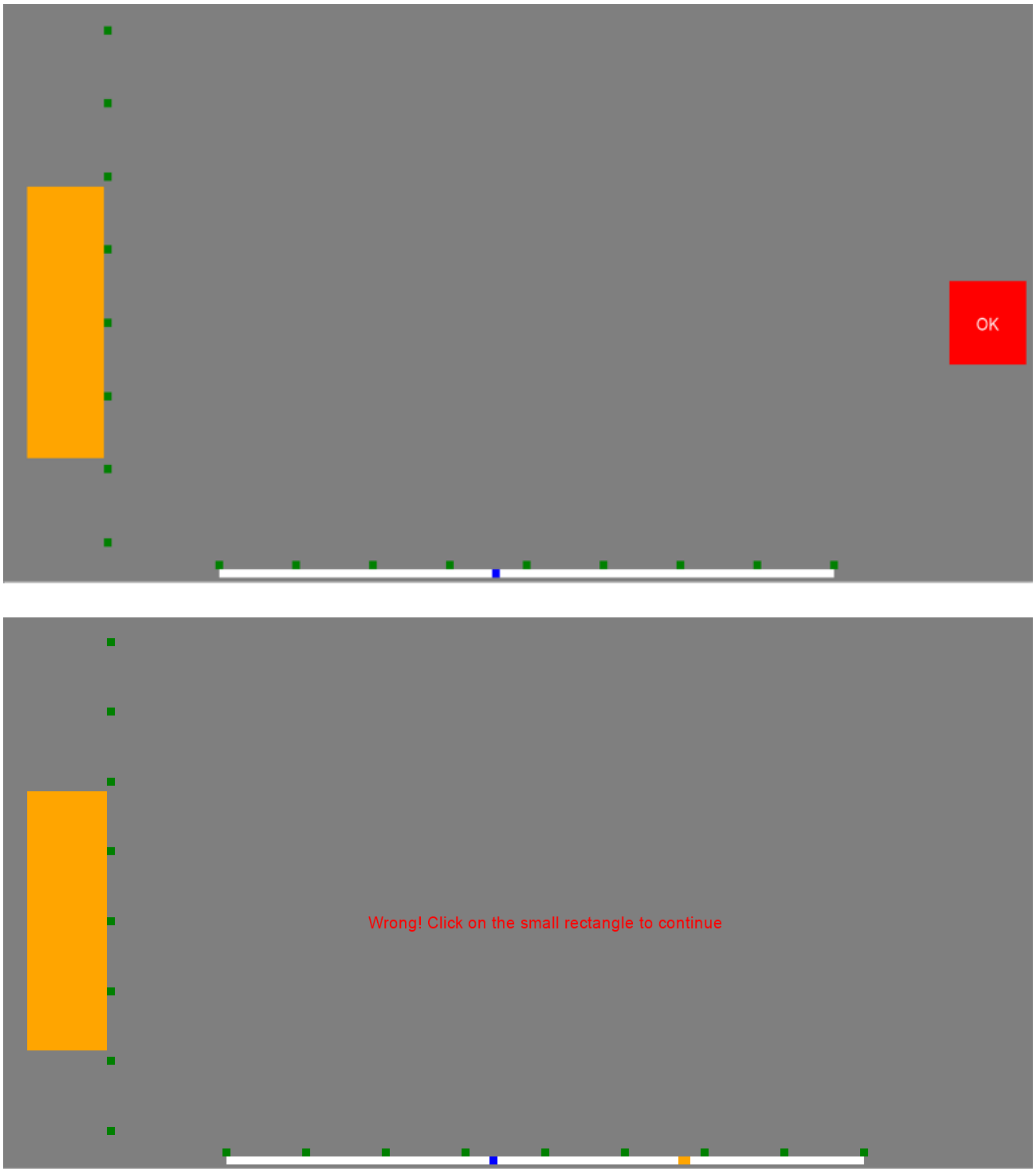

Figure 1: In the top image is a screen shot of the experiment. The stimulus bar is shown in yellow with the 9 tick marks. The response bar is shown in white on the bottom of the screen with 9 tick marks. The small blue square represents where the participant clicked on the response bar. The OK button is displayed to the right side of the screen. The bottom image is a screen shot of the experiment that a subject would see if they got the answer wrong. The stimulus and response bar are the same as the top image. The OK button is missing because they already submitted their answer. The small yellow square on the response bar represents the range of correct responses. They are given a message that informs them that they were wrong and how to continue.

Design

Phase 1

During Phase 1 all participants are shown an inverse absolute value function, y=200-|x-350| The apex of the function is located at the coordinates of (350,200). The training range is between 100-600 or a range of 500 centered on the vertex of the function. There are 21 training examples that are presented 6 times, during which feedback is given. There are also 4 interpolation trials during which no feedback is given for new input values within the training range. Extrapolation is tested on both sides of the vertex, the lower range being 25-100 and the upper half being 600-700. There are 6 extrapolation trials with 3 being on either side of the vertex beyond the training range.

Phase 2

The participants are split into 3 groups for Phase 2. There are 3 transfer conditions during the second phase which include: 3 transfer groups. The flip condition is given a function that is a simple transformation of the primary function, being a reflection across the x axis, that displaces many of the input-output pairs: y=50+|x-350|. There were 21 participants in the flip condition. The parabola condition is given a function that is very different from the primary function in terms of rules, being a parabola condition instead of absolute value function, but having similar input-output pairs as the primary function $\mathrm{y} = 200 - .0065(\mathrm{x} - 350)^2$. There were 19 people in the parabola condition. The parabola condition that was chosen was selected because a wider parabola condition misses the training examples near the vertex and a steeper parabola condition descended too fast, going out of the range of possible responses in the extrapolation regions. The shift condition given is a downward shift condition of the primary function: y=100-|x-350|.There were 20 people in the shift condition. In figure 2 all the functions have been graphed. For all the functions, the vertex or apex of the function is located at 350 in the x coordinate and the stimulus values are the same for each of the 3 transfer groups. The training and testing blocks are the same as Phase 1.

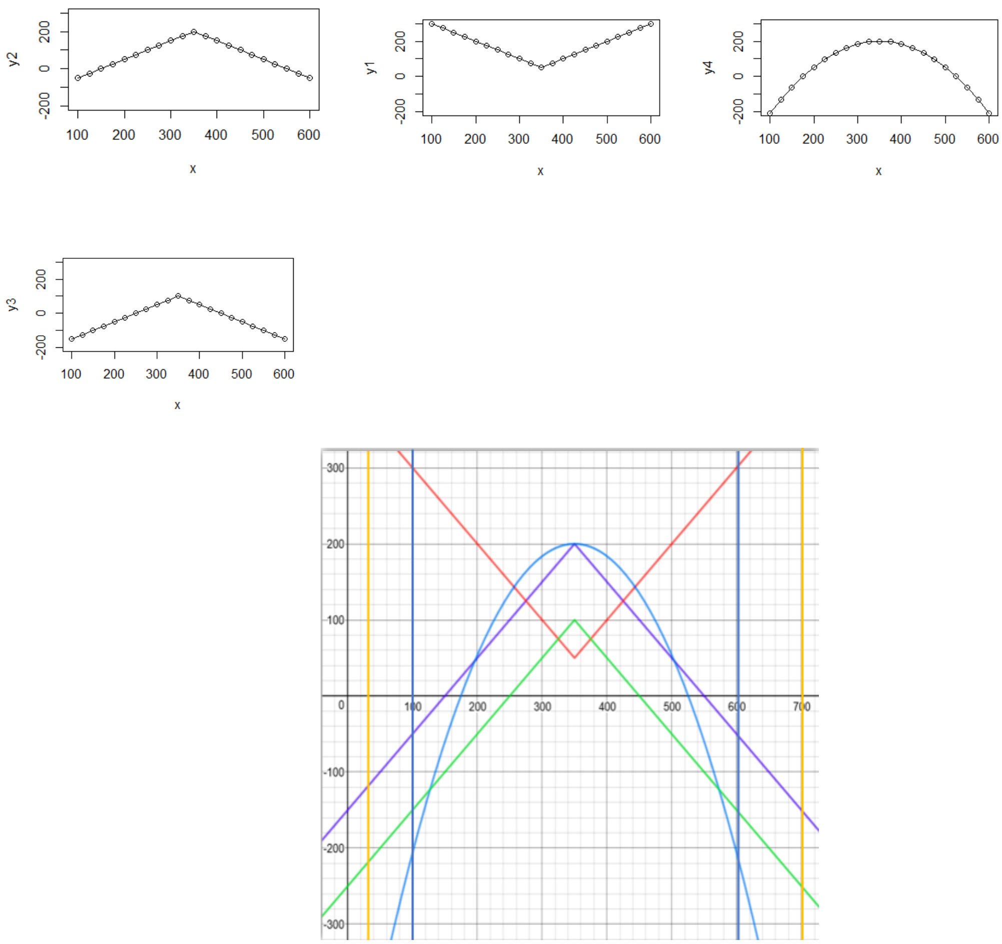

Figure 2: The top images are the functions that are being used. Each dot in one of the top images is one of 21 training values. The function in the first top image is the primary function that everyone is given. The function in the second top image is the function for flip condition. The function in the second to the last top image is for parabola condition. The function in the top last image is the function for shift condition. The x and y axis are the same so that they can be compared. The bottom picture is the same functions overlapping and includes both the training and extrapolation regions which have been marked with the vertical blue and yellow lines.

Results

The absolute mean error for each person, in each block or phase, was compared across conditions to see if they are notably different and whether it mattered which transfer function people were given. Absolute mean error is defined as mean absolute distance from their response and the correct response.

A Bayesian analysis was used because using a frequentist analysis there is a level of uncertainty in how representative the sample is to the population and the characteristics of the population distribution around the sample are assumed but are used to draw the ultimate conclusion (Kruschke 2015). The data will take the form of the absolute mean error or deviation from the function they are given. A Bayesian split plot (Kruschke 2015) using Jags (Plummer 2003), was used. This is similar to a frequentist ANOVA test. The means of each group and the estimated difference between the two groups using the estimated means and variance. The parameters are shared variance of all the groups since is it a homoscedastic model. The posterior was created by using the broad prior and the data in an MCMC sampling process. There were 2,000 burn-in steps where the chains converge toward the posterior before the 50,000 steps that were saved. The chains were inspected to see that they were well mixed. A broad uninformed prior centered on zero was used. A ROPE (Region of Practical Equivalence) was used to make these comparisons. A response within 15 pixels was considered the same, since the correct feedback range was 15 pixels which was considered to be the same as the right answer in the experiment. If all the HDI, High Density Interval, of the estimated difference between the estimated grand means parameters within the ROPE, Region of Practical Equivalence, then they are credibly the same, which allows one to accept the null. The entire HDI must be out of the ROPE for the groups' performance to be considered credibly different (Kruschke 2015).

First the training trials in phase 1, the primary function, are compared to see if there are any difference between the groups at the beginning due to subject differences. It will also make the analysis seem more familiar by the time phase 2, the secondary transfer conditions, are analyzed.

The training trials in phase 1 are compared across blocks. The conditions represent which group subjects were assigned for the later transfer function but in phase 1 everyone received the same function.

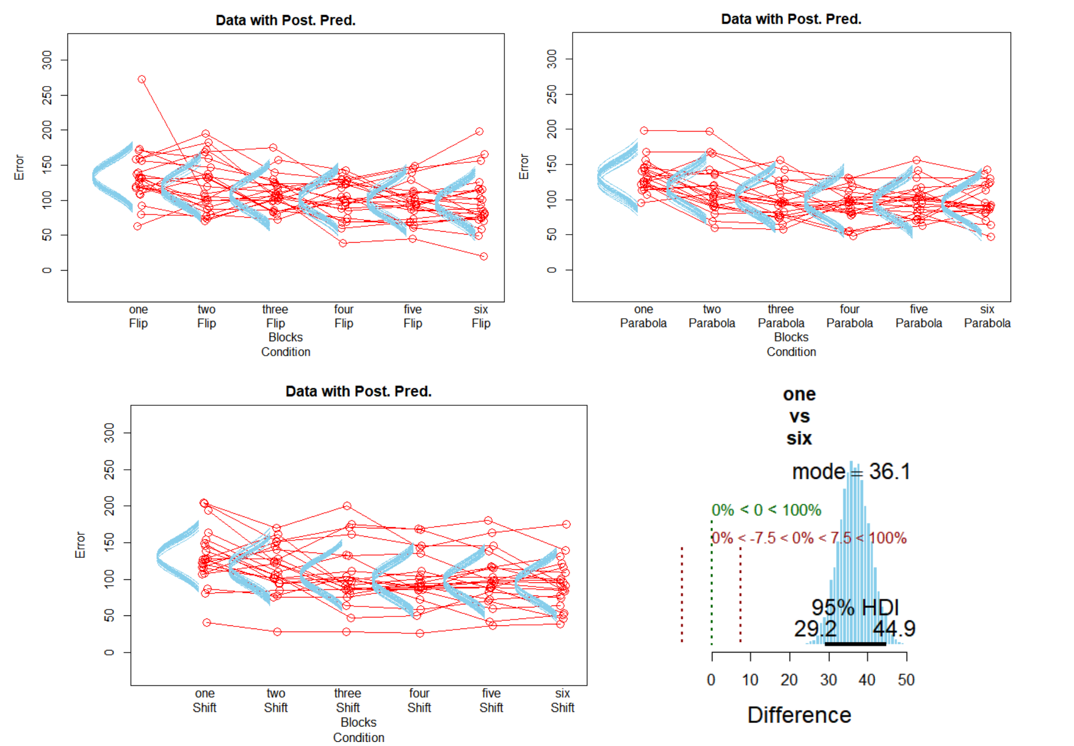

Figure 3: The mean of each subject per block is shown for the 3 conditions in phase 1 for the training trials. The top left image is the flip condition and the top right image is the parabola condition. The bottom image is the shift condition.

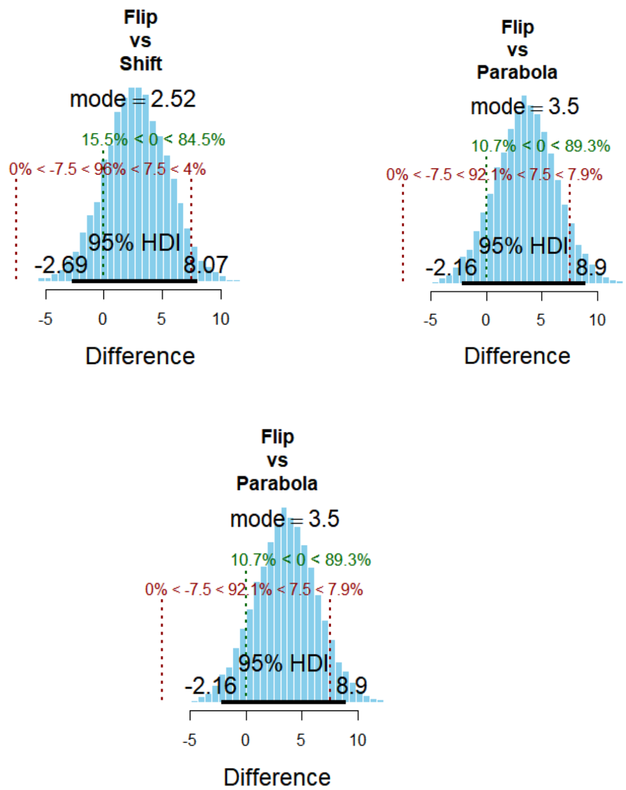

Figure 4: The posterior distributions of difference of 3 conditions in phase 1 for the training trials are shown with a ROPE of 15. The ROPE is centered on 0 with half of which being on either side. In the leftmost image the estimated difference parameter for flip condition compared to shift condition is shown as a posterior distribution with a 95% High Density Interval (HDI) and a mode. In the middle image the flip condition is compared to parabola condition. In the last image. parabola condition is compared to shift condition.

In Figure 3 the bottom right image shows a credible difference between training block 1 and training block 6 for phase 1. The shallow curves in each condition shows the learning curve across blocks for phase 1. The absolute mean deviation of each condition was calculated using the same MCMC process and the absolute mean deviations of the subjects in that condition. This estimated parameter of absolute mean deviation performance score for each condition was compared to each other to obtain the posterior distribution of difference between conditions.

Since the entire HDI is not outside of the ROPE none of the conditions were found to be credible different during phase 1, learning the primary function, see Figure 4.

Next to be examined was the difference of the conditions in phase 2 since it is of greatest interested as to whether people transferred knowledge if they were given a rule or association-based transfer task.

The difference in the transfer conditions was compared to see if the rule and association-based conditions affected the amount of learning between the first and the last training block.

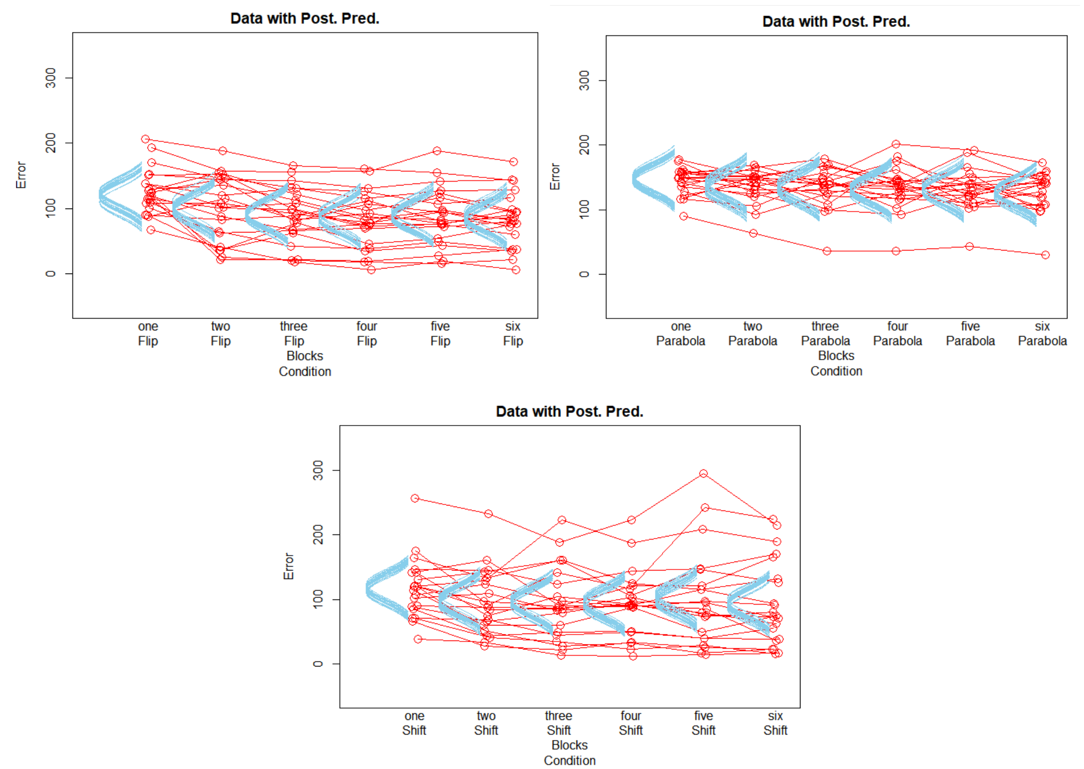

Figure 5: The mean of each subject per block is shown for the 3 conditions in phase 2 for the training trials. The top left image is the flip condition and the top right image is the parabola condition. The bottom image is the shift condition.

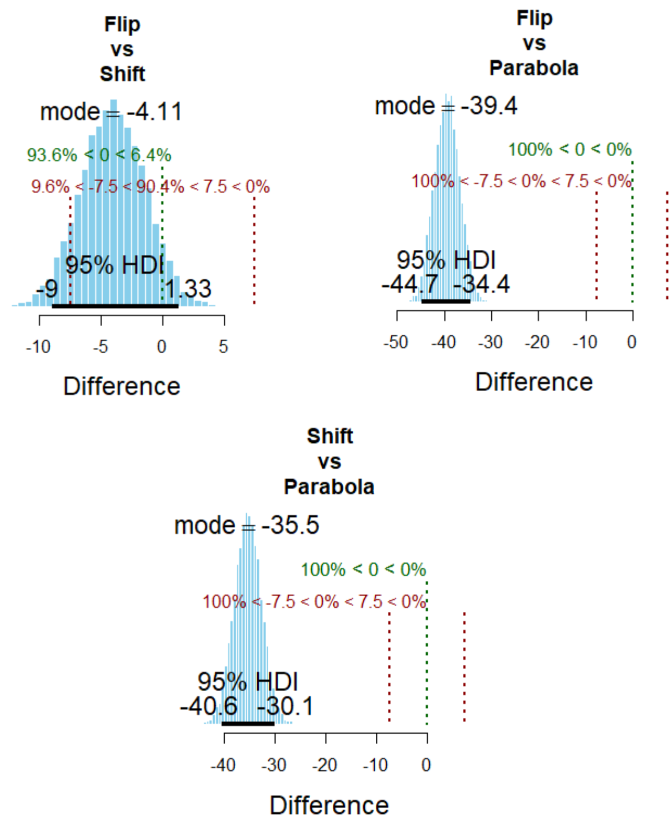

Figure 6: The posterior distributions of difference of 3 conditions in phase 2 for the training trials are shown with a ROPE of 15. In the leftmost image flip condition is compared to shift condition. In the middle image flip condition is compared to parabola condition. In the last image. parabola condition is compared to shift condition.

The performance of flip condition and the shift condition are not credibly different from each other since the HDI is included in the ROPE. The performance of parabola condition is credibly different than both the flip condition and the shift condition since the entire HDI is excluded from the ROPE. The parabola condition was credibly harder than both the flip condition and the shift condition. The performance of the flip condition and the shift condition were not creditably more difficult from each other, see Figure 6.

Next, the presence of learning was investigated by seeing if the first and the last training block are credibly different. Subjects were tested to see if more learning occurred between the first and that last training block depending on the condition.

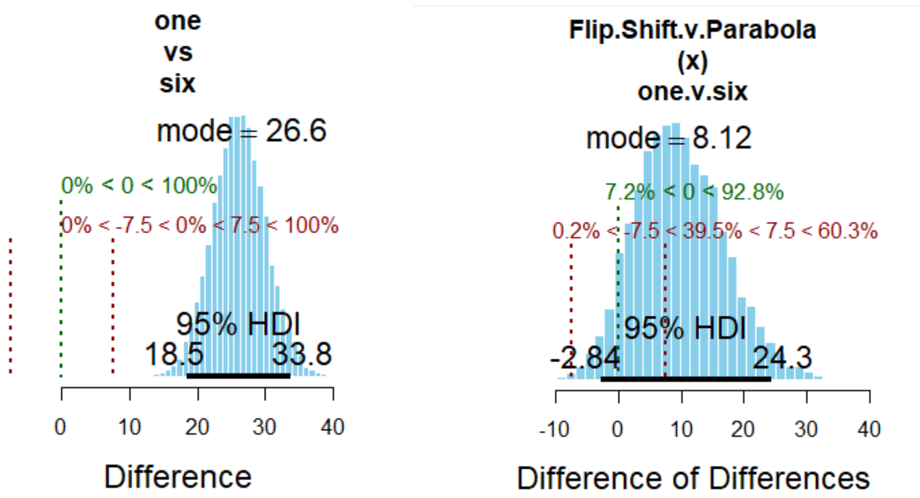

Figure 7: The left image is the posterior distribution of the difference between the first and the last training blocks in Phase 2 regardless of condition for the training trials. The right image is the interaction between the 2 rule-based conditions (flip condition and shift condition) and the association-based condition (parabola condition) and the difference between the first and the last training blocks.

There was a difference in absolute mean error between the first and the last training block for everyone in phase 2 so there was some amount of learning happening across blocks. The performance of the flip condition and shift condition are compared to the parabola condition to see if more learning occurred if one was given a rule or association-based transfer condition. There was a large overlap of the HDI and the ROPE indicating that the amount learned is not determined by whether the subjects were given a rule or association-based condition, see Figure 7.

Subjects performance on the transfer task was tested to see if it was better than the primary function depending on whether they were given a rule or association-based transfer task.

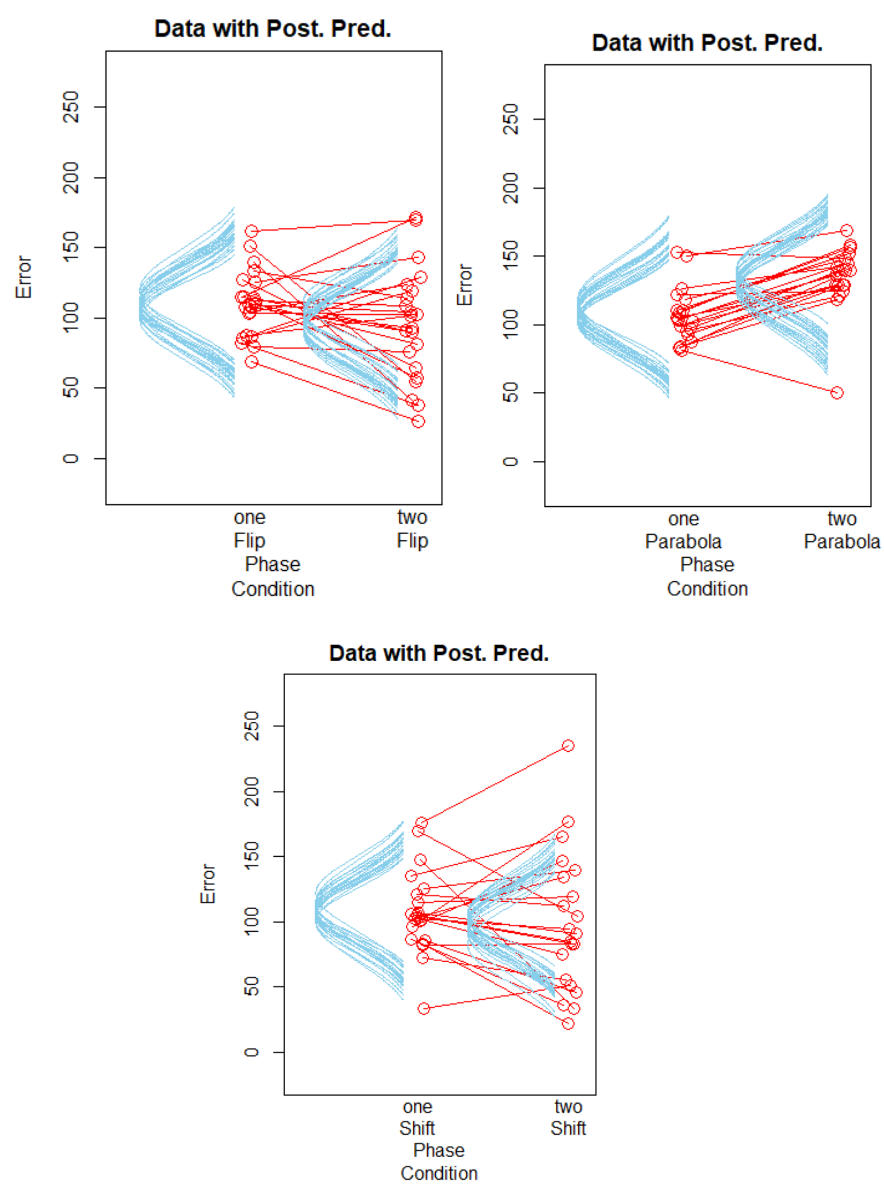

Figure 8: The leftmost image is the mean error for each person in both Phase 1 and Phase 2 in flip condition for the training trials. The predicted distribution is shown in blue with red lines connecting each individual in both phases for each of the images. The middle image is the mean error for each person in both Phase 1 and Phase 2 in parabola condition. The last image is the mean error for each person in both Phase 1 and Phase 2 in shift condition.

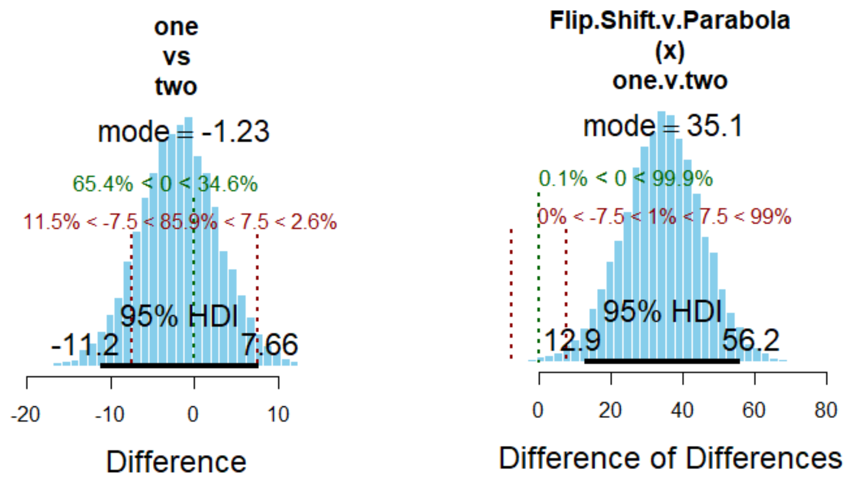

Figure 9: The left image is the posterior distribution of the difference between Phase 1 and Phase 2 regardless of condition for the training trials. The right image is the interaction between the 2 rule-based conditions (flip condition and shift condition) and the association-based condition (parabola condition) and the difference between Phase 1 and Phase2.

Phase 2 was not easier than phase 1 because they were not credibly different. Whether a person was given a rule or association did have a credible effect on the difference in phase 1 and phase 2. This can be seen in Figure 9

Discussion

This study provides evidence in support of people favoring rules over associations. The performance in the two rule transfer conditions (flip condition and shift condition) performances were not credibly different but the association condition (parabola condition) performance was credibly different than both the of the rule transfer conditions when examining the training trials. When comparing the performance of the training trials in transfer conditions, the flip condition and the shift condition were not credibly different even through the average absolute distance of the output values generated from the functions are varying degrees of distance from the primary function. This might mean that the fact they are more similar to each other due to having a similar functional rule as the primary function since they do not share having a similar proximity to the primary function. The association transfer condition (parabola condition) was harder than the rule transfer conditions (flip condition and the shift condition). This can be seen in Figure 6 Since the parabola condition was hardest, having similar input-output pairs but a very different rule, than the shift condition and the flip condition, that have similar rules, but the input-output pairs are more displaced, this provides evidence for people using rules. Helie and Ashby (2011) also observed that people favor rules over associations in their transfer category experiment.

A study that is more focused on the test trials might reveal how these transfer conditions affect the subjects' extrapolated guesses or their representation of the function. One could ask whether a single person produces a stable guess across test trials. This could be a measure of how much they truly believe their guess is predictive of the function. Feedback in the training trials might cause subjects to second guess their representation of the function and recreate it, readjusting their extrapolated guesses. In the training trials this could be seen as learning, producing closer and closer approximations to the correct answer, but in the testing trials these stable changes in their guesses are adjustments to their representation of the function or what they perceive the function to be. Stable regularities in the subjects' extrapolated patterns could reveal any believed regularities in training trials and might change as the training examples change to reflect other functions. Kattner, Cox , & Green varied the training task to see how it affected performance on unseen test items in a category learning task (2016). With additional testing blocks one could see how the subjects adjust their representations of the function as they learn the training trials. The function could even be allowed to change without being announced to see how the subjects adjust their representation, extrapolation patterns to match one or neither of the functions. In life a function might be affected by novel outside influences and the function might change suddenly.

The learning rate for the training trials ideally could have been steeper. The difference across 6 training blocks of learning was around 26 pixels as can be seen in Figure 3. This is not even double the range that was needed to be considered different. The range of correct responses for the full training range for both the primary function and the Flip condition and the Shift condition was 250 pixels. This could mean that not much learning occurred across training blocks. This could imply that people did not learn the primary function so did not likely transfer their knowledge representations to the secondary transfer functions.

Determining whether subjects are using rules or associations is ambiguous, when using extrapolation and interpolation patterns (Lucas, et al., 2015). This study provides evidence toward people favoring rules over associations, but it does not rule out people using a combination of rule and association methods. It also, does not necessarily point to one of the models such as POLE or EXAM. With more sophistication maybe these distinctions can be made. This was simply the first attempt of applying transfer learning to function learning to overcome the ambiguity of rules and associations.

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Internship Experience

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- Applied electroencephalography (EEG) preparation and data acquisition
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- Aided in multivariate pattern-classification analysis to EEG data

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- Help track problematic behaviors recorded by the nurses

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- Observe and participate in normal social worker duties
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Supplemental Instructor (SI) Fall Semester 2015
Purdue University Northwest Hammond, Indiana

- Provided SI sessions for behavioral statistics
- Attended behavioral statistics class to coordinate SI sessions with instructor

Awards

- Ronald E. McNair Scholar