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The Impact of Presentation Order on the Attraction Effect in Decision-making

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Abstract

The attraction effect in decision-making is a famous example of how preferences are influenced by the availability of other options. One emerging hypothesis for the effect is that biases in attention influence preferences. In the past, these ideas have been explored indirectly through computational modeling and eye tracking. In the present paper, we directly manipulate attention through presentation order, presenting choice options sequentially. Our results show that presentation order has a large impact on the effect – some presentation orders enhance the effect and other orders reverse the effect. To understand these results, we fit a dynamic model, called the Multiattribute Linear Ballistic Accumulator model, to the choice and response time data. Modeling results reveal that presentation order influences the allocation of attention on the positive and negative differences between options. In sum, our results show that attention has a direct impact on the attraction effect.

Keywords: preferential choice; context effects; order effects; response time modeling; Bayesian parameter estimation

Introduction

Everyday we make hundreds of choices. Some are seemingly trivial -- what cereal should I eat for breakfast? Others have long lasting implications -- what stock should I invest in? Despite their obvious differences, these two decisions have one important thing in common; both can be sensitive to context. That is, our preferences for existing alternatives can be altered by the introduction of new alternatives.

Context effects -- preference changes depending on the availability of other options -- have attracted a great deal of attention among consumer researchers studying high-level decision tasks. In recent work, context effects have also been shown in low-level domains such as perception (Trueblood, Brown, Heathcote, & Busemeyer, 2013). This suggests that context effects are a general feature of human choice behavior and calls for a common theoretical explanation that applies across paradigms. One emerging hypothesis is that context effects occur because of biases in attention. When comparing options, one might pay attention to some features more than others and this in turn influences preferences. This idea has been explored using dynamic models that implement attention-weighting mechanisms such as Multi-alternative Decision Field Theory (MDFT, Roe, Busemeyer, & Townsend, 2001), the Leaky Competing Accumulator model (LCA, Usher & McClelland, 2004), and the Multiattribute Linear Ballistic Accumulator model (MLBA; Trueblood, Brown, and

Heathcote, 2014). In addition, Noguchi and Stewart (2014) used eye tracking to examine the role of visual attention in context effects. Their results suggest that alternatives are compared in pairs and specific patterns of gaze transitions are correlated with context effects. Further, recent work in economics has proposed that context effects might arise due to "rational inattention" (Woodford, 2012). The basic idea is that attention is a scarce resource and places constraints on the amount of information individuals can process during a decision. Taken together, this set of results strongly suggests attention is crucial to context effects. No previous work has directly manipulated attention in the attraction effect.

In the present paper, we directly manipulate attention by presenting choice options sequentially. Studies of context effects typically involve choices among three alternatives where one option is identified as the "target", one option is the "competitor", and the third option is the "decoy". For example, suppose there are two options (X and Y) in a choice, which are almost equally attractive. If an alternative D is introduced that is similar to alternative X, but inferior, it makes X more attractive. This is known as the attraction effect (Huber, Payne, & Puto, 1982). In this example, X is the target, Y is the competitor, and D is the decoy. In all past studies of the attraction effect, the alternatives X, Y, and D were presented simultaneously and were visible to participants until they made a choice. In the current experiment, we presented the options X, Y, and D one at a time, thus manipulating what participants saw first, second, and last. Our goal is to understand if changes in attention (as manipulated by presentation order) influence final choices.

Our experiment uses a perceptual version of the attraction effect where participants judge which of three rectangles has the largest area, with height and width as the attributes. The experiment uses the same rectangle stimuli as Trueblood et al. (2013). Using a perceptual version of the attraction effect has a number of advantages including the ability to collect sufficient choice and response time data for computational modeling. In addition, the rectangle attraction task is well established in the literature and the results have been replicated in adults (Farmer, Warren, El-Deredy & Howes, 2016), children (Zhen & Yu, 2016), and non-human primates (Parrish, Evans, & Beran, 2015).

Experiment

Participants

Fifty undergraduate students from Vanderbilt University voluntarily participated in this computer-based experiment

in the laboratory at the time of their choosing and received course credit for their participation.

Methods

Participants were told that they would be shown three rectangles presented one at a time, and that they would have to choose the rectangle that they believed to have the largest area by pressing one of the three indicated keys. There was no value tied to the choice of rectangle (i.e., representation of an earned dollar amount), and participants did not receive feedback for their decisions.

Each rectangle stimulus had various dimensions of height and width, which both acted as attribute dimensions. The dimensions of the rectangles were set by numbers of pixels. The target, competitor, and decoy rectangles were determined by the following procedure. First a set of horizontally oriented rectangles, denoted H, were chosen out of a bivariate normal distribution with a mean of 50 pixels for height and a mean of 80 pixels for width with a variance of 2 pixels. This noise allowed for variation in the rectangles across trials. A second set of rectangles, denoted V, were defined in terms of H, but were oriented vertically. Specifically, the height of the V rectangles was defined as the width of the H rectangles plus a random number selected from the interval [-2,2]. The width of the V rectangles was then calculated so that the V and H rectangles had equal area. In half of the trials, the target rectangle T_H was defined using the H rectangles and in the other half of the trials the target T_V was defined using the V rectangles. Thus, the orientation of the target (i.e., horizontal or vertical orientation) was counterbalanced so that half of the trials consisted of the horizontally longer target, T_H, and half of the experimental trials consisted of the vertically longer target, T_V. The competitor rectangles, C, were defined in the opposite manner of the target rectangles so that they were given the same area but were oriented opposite to the target (i.e. vertically if the target was horizontal and horizontally if the target was vertical). The decoys used in this experiment were "range" decoys, options that are a little weaker than the target on the target's weakest attribute. Let D_H denote a horizontally oriented decoy similar to T_H and D_V denote a vertically oriented decoy similar to T_V. A range decoy D_H has the same width as T_H but a shorter height since height is the shortest (weakest) dimension of a horizontally oriented target. Likewise, the D_V decoy has the same height as T_V but a shorter width since width is the shortest (weakest) dimension of a vertically oriented target (see Figure 1 for a schematic of the choice options). The shortest dimension of each decoy was defined as the shortest dimension of the corresponding target minus a random number selected from the interval [7,9].

Each experimental trial began with a fixation cross appearing at the center of a white screen for 0.250 ms. This was followed by the appearance of the numbers "1", "2", and "3" from left to right on the screen to indicate that one rectangle will appear above each number. Participants made their choice by pressing the corresponding "1", "2", or "3"

key at the top of the keyboard. Black rectangles were shown one at a time. Each rectangle was shown above one of the numbers for 1.0 second before disappearing. The location of each rectangle was randomized across trials. The order of appearance for the rectangles was randomized in a controlled manner, such that experimental trials of each order appeared an equal number of times.
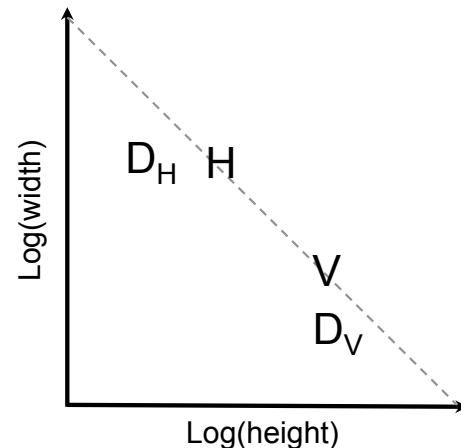

Figure 1: Schematic of the choice options in the rectangle attraction effect task. The options H (horizontally oriented rectangles), V (vertically oriented rectangles), and decoys D_H and D_V are plotted in a two-dimensional attribute space defined by the logarithm of height and width. The dotted line indicates options that should objectively be indifferent because they have the same area. In the attraction effect, preference for H and V can be affected by the presence of either D_H or D_V.

Each participant completed 720 randomized trials that were divided into eight blocks of 90 trials each. Within the 90 trials of each block, there were 30 filler trials and 10 trials for each of the possible six orders the rectangles could be presented. These six orders are as follows: TCD, CTD, TDC, CDT, DTC, and DCT. Within these orders, there were two variations, one where T_H served as the target and one where T_V served as the target to minimize effect based on orientation of the target rectangle. The 30 filler trials were meant to serve as an estimate of accuracy for participants. Each filler trial had a clearly larger rectangle that would allow participants to make a correct choice.

Results

One participant's data were removed due to computer error. Overall, the mean accuracy of participants' performance on filler trials was 66.62% correct with two participants falling two standard deviations below average. However, these participants' data were not removed. This data is analyzed using the *relative choice share for the target*, or RST, which is defined as the number of target options selected divided by the total number of target plus competitor options selected (i.e., T/(C+T), Berkowitsch, Scheibehenne, Rieskamp, 2014). For the results described below we

collapsed across the two different orientations of the target. The attraction effect was still observed with an average of 51.10% target chosen, significantly different from 50% target chosen, the theoretical RST if the decoy had no influence (t(48) = 2.77, p = 0.008).

Although the attraction effect was not observed for each presentation order, each presented order of rectangles were also significantly different from the 50% theoretical RST, refer to Table 1. Figure 2 shows a bar graph of the RST values for each of these orders. A one-way ANOVA showed a significant main effect of order (F(5,288) = 18.27, p < 0.001). In particular, the orders CTD, CDT, and DTC showed the attraction effect, with RSTs significantly higher than 50%, and the orders TCD, TDC, and DCT had RSTs significantly lower than 50% (a reverse attraction effect).

Table 1. The RST value as a percentage, the t-value, and the p-value for each order.

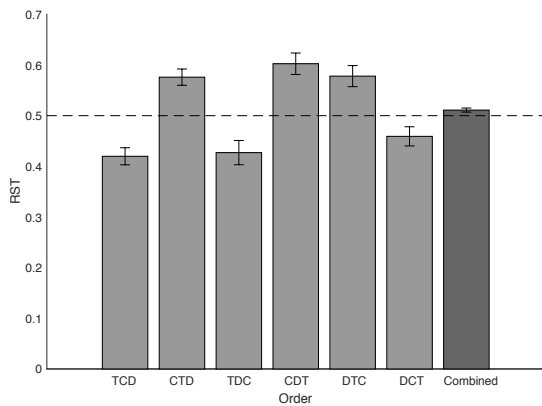| Order	RST (%)	$t(48)$	p-value
TCD	41.99	-4.75853	< 0.001
CTD	57.62	4.7803	< 0.001
TDC	42.71	-3.0831	0.003
CDT	60.25	4.8931	< 0.001
DTC	57.81	3.7921	< 0.001
DCT	45.93	-2.1742	0.035

Figure 2: Results show the RST for each presentation order of the rectangles as well as collapsed across all orders (combined). The dotted line at 0.5 indicates equal preference for the target and competitor. Bars above the dotted line show the standard attraction effect. Bars below the dotted line show a reversed attraction. Error bars show the standard error of the mean.

Modeling

In order to better understand how presentation order influences choices in the attraction effect, we fit the MLBA model (Trueblood et al., 2014) to the choice and response time (RT) data. MLBA is a dynamic model that explains why context effects occur in multi-alternative choice. This model explains how preferences are constructed through a dynamic process of comparing the different features of available options. Context effects occur because of differences in the amount of attention given to specific comparisons (for example, if two options are difficult to discriminate on a particular feature, an individual pays more attention to that feature).

Model Details

MLBA is an extension of the Linear Ballistic Accumulator (LBA) model developed by Brown and Heathcote (2008). The LBA accounts for choice and RTs using independent accumulators that race toward a threshold. The accumulators are linear and accumulate information deterministically. At the beginning of each trial, each accumulator starts at a randomly determined amount of evidence drawn from a uniform distribution on the interval $[0, A]$. The accumulators increase at speeds defined by a set of drift rates, until one of the accumulators reaches the threshold b. The option associated with the accumulator that reaches the threshold first is selected. On each trial, the drift rates are drawn from normal distributions with different means and the same standard deviation, $s = 1$. The model also has a non-decision time parameter T_0 that accounts for encoding and motor response times. The MLBA model adds to the LBA model by specifying how drift rates arise from the evaluation of choice options.

Consider three alternatives (indexed as i, j, k) that have two attributes, P and Q, where P_i and Q_i denote the value of option i on the two attributes. The mean drift rate d_i for option i is defined as: $d_i = \gamma V_{ij} + \gamma V_{ik} + I_0$. The term V_{ij} represents a comparison between options i and j. Likewise, V_{ik} represents a comparison between options i and k. The term I_0 is a positive constant to ensure that at least one of the three mean drift rates is positive, avoiding non-termination in the LBA model. For our purposes, we can fix $I_0 = 1$. The parameter γ is a scaling parameter that ensures that drift rates are in the appropriate range for the LBA model.

In the valuation function V_{ij}, option i is the focal option and option j is evaluated relative to it. Let (u_{Pi}, u_{Qi}) and (u_{Pj}, u_{Qj}) be the subjective values for options i and j. In our experiment, the attribute dimensions, P and Q, are the height and width of the rectangles in pixels. A pair of options were experimentally defined as indifferent in they have equal area, for example, $P_i \times Q_i = P_j \times Q_j$. We define the subjective values simply as the logarithm of the number of pixels for each dimension (e.g., $u_{Pi} = \log(P_i)$). Please see Trueblood et al. (2014) for other possible mappings from objective to subjective values. The valuation function V_{ij} is defined by the difference in the subjective values of the options:

$$V_{ij} = w_{Pij} (u_{Pi} - u_{Pj}) + w_{Qij} (u_{Qi} - u_{Qj})$$

where the weights w_{Pij} and w_{Qij} reflect the amount of attention given to a particular comparison.

Based on research showing that visual attention (e.g., fixation duration) increases with decreasing discriminability of items (Gould, 1967, 1973), we hypothesize that attention weights are larger when attribute values are more similar and smaller when they are more distinct. Using Shepard's (1987) law of generalization, we define the attention weights as

$$w_{Pij} = \exp(-\lambda_+ \mid u_{Pi} - u_{Pj} \mid) \text{ if } u_{Pi} \geq u_{Pj}$$
$$w_{Pij} = \exp(-\lambda_- \mid u_{Pi} - u_{Pj} \mid) \text{ if } u_{Pi} < u_{Pj}$$

$$w_{Qij} = \exp(-\beta \, \lambda_+ \mid u_{Qi} - u_{Qj} \mid) \text{ if } u_{Qi} \geq u_{Qj}$$
$$w_{Qij} = \exp(-\beta \, \lambda_- \mid u_{Qi} - u_{Qj} \mid) \text{ if } u_{Qi} < u_{Qj}$$

where λ_+ and λ_- are free parameters that allow for attention to be asymmetric. That is, the attention weights are different when comparing positive differences in attribute values (i.e., the parameter λ_+) and negative differences in attribute values (i.e., the parameter λ_-). This follows from work showing that similarity judgments often violate symmetry (Tversky, 1977) as well as modifications to Shepard's law that allow for such violations (Nosofsky, 1991). The parameter β is a bias parameter that allows for attributes to be weighted differently. For example, in consumer choice, the attribute of price might receive more weight than the attribute quality. With rectangles, Holmberg and Holmberg (1969) suggested an "elongation effect" where height plays a more important role in area judgment than width.

In summary, the MLBA has the following free parameters: accumulator start-point A, threshold b, non-decision time T_0, drift rate scaling γ, positive attention parameter λ_+, negative attention parameter λ_-, and bias β.

Hierarchical Bayesian Parameter Estimation

We fit the MLBA model with hierarchical Bayesian parameter estimation methods using DE-MCMC (Turner, Sederberg, Brown, & Steyvers, 2013). We note that, as far as we are aware, this is the first time the MLBA (or any dynamic model of context effects) has been fit to both choice data and the full distribution of RT data. In the past, dynamic models of context effects have only been evaluated by qualitative measures or when quantitative fitting was performed, only choice data was used. Thus, we see the present work as a significant methodological step forward in the evaluation of dynamic models of context effects.

In our experiment, there are six order conditions: TCD, CTD, TDC, CDT, DTC, and DCT. We hypothesized that order would influence attention and thus we had separate attention parameters λ_+ and λ_- for each condition. We also fit six γ scaling parameters, one for each condition. We allowed for different scaling parameters across conditions to accommodate the different attention weights, which directly

impact the magnitude of the drift rates. The remaining parameters were assumed to be the same across conditions.

In our model, we had both group-level (or hyper parameters) and individual-level parameters. The individual-level parameters were drawn from normal distributions defined by the hyper parameters. Let μ_x and σ_x represent the hyper mean and standard deviation of the group-level normal distribution for parameter x. The priors for the hyper means were the following: $\mu_b \sim N(1, 0.5)$, $\mu_A \sim N(1, 0.5)$, $\mu_{T0} \sim N(0.25, 0.25)$, $\gamma \sim N(5, 1.5)$, $\lambda_+ \sim N(0.5, 1.5)$, $\lambda_- \sim N(0.5, 1.5)$, $\beta \sim N(1, 1.5)$. The priors for all of the hyper standard deviations σ_x were defined as Gamma(1,1) distributions expect for the standard deviation for non-decision time, which was Gamma(1, 0.5). We ran 24 MCMC chains for 2500 iterations with a burn-in of 500 iterations. All chains converged.

Results

To assess the fit of the model, we calculated the correlation between choice and mean RT data with model predictions. The model predictions were calculated by using the mean of the posterior distributions of the individual parameters. The correlation between the choice data and model predictions was 0.886 ($p < 0.001$). The correlation between the mean RT data and the model predictions was 0.588 ($p < 0.001$). Thus, the model does a good job at capturing general trends in the data.

We also examined how well the model accounted for the average choice data for each condition. Figure 3 shows the mean choice proportions for each option in the 12 different choice sets used in the experiment. The 12 choice sets arise from the two possible placements of the decoy (D_H or D_V) in each of the six order conditions. The model predictions were calculated using the mean of the posterior distributions of the individual parameters.

To understand how presentation order influences choices in the attraction effect, we examined the values of the attention weights for the six conditions (see Table 2). Specifically, we examined the posterior means of the group-level attention weight parameters (λ_+ and λ_-) for each condition. We did not see any obvious trends in the attention weights when we examined them individually. However, the ratio of the positive weight to the negative weight revealed an interesting pattern. In the conditions that exhibited the standard attraction effect (i.e., CTD, CDT, and DTC), the ratio was smaller than the conditions that exhibited an inverse attraction effect (i.e., TCD , TDC, DCT). This suggests that presentation order influences the amount of attention given to positive and negative differences in attribute values. When the attraction effect is observed, more attention is placed on negative differences as compared to when the reverse attraction effect occurs.

Discussion

Our goal in the present paper was to explore the role of attention in the attraction effect through direct manipulation. We manipulated attention through presentation order,
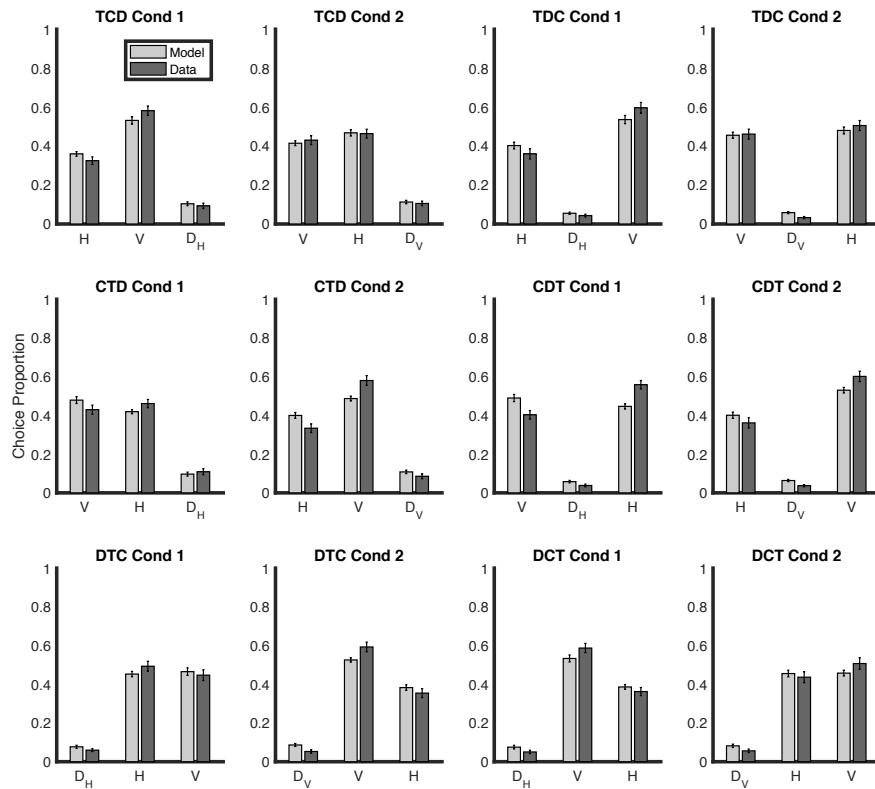
Figure 3. Observed choice proportions and model predictions for 12 choice sets in the rectangle attraction effect task. Each choice set consists of three options (the target, competitor, and decoy). There are two choice sets for each order condition due to the two possible placements of the decoy (either near the horizontally oriented rectangle or the vertically oriented rectangle). The model predictions are shown in light gray and observed choice proportions in dark gray.

presenting the options sequentially rather than simultaneously. The sequential presentation of the options had a large impact on choices – some presentation orders enhanced the attraction effect whereas other presentation orders reversed the attraction effect. To better understand why presentation order impacted choices, we used computational modeling. We fit the MLBA model to choice and response time data. Model fits revealed differences in the attention weights for different presentation orders. For the presentation orders that showed a standard attraction effect, there was increased attention on negative differences as compared to the presentation orders that showed a reverse attraction effect.

Recently, researchers have discovered large individual differences in context effects (Liew, Howe, & Little, 2016; Trueblood, Brown, & Heathcote, 2015). Some individuals show the standard effects, but others do not. For some individuals, the effects are even reversed. This has lead to the conclusion that context effects are fragile (Trueblood et al., 2015). This raises two important questions: (1) Why are

the effects fragile? and (2) What underlies individual differences in the effects? The present work provides one possible explanation. The effects are fragile because they result from biases in attention. Small shifts in attention can have dramatic influences on choice. It is possible that individual differences in the effects arise because of individual differences in attention.

Table 2: Posterior means of the group-level attention weight parameters for the six order conditions.

Condition	λ_+	λ_-	λ_+/λ_-
TCD	1.50	4.25	2.83
CTD	2.05	4.51	2.20
TDC	0.92	2.06	2.24
CDT	1.39	2.52	1.81
DTC	1.86	3.43	1.84
DCT	1.11	2.48	2.23

The results of our experiment also pose a challenge to a recent rational model of context effects that claims the effects are a consequence of expected value maximization given noisy observations (Howes, Warren, Farmer, El-Deredy, & Lewis, 2016). In our experiments, simply changing the presentation order of the same set of options has a dramatic influence on choices. It is unclear how a rational model could account for the influence of presentation order on the effects.

In sum, we have demonstrated that presentation order, which influences attention, can both strengthen and weaken the attraction effect. The MLBA model suggests that presentation order changes the allocation of attention between positive and negative differences between options. These findings provide an explanation for individual differences in context effects and also pose a challenge to recent rational models of the effects.

Acknowledgments

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