Regret Theory Predicts Decoy Effects in Risky and Multi-attribute Choice

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Abstract

Regret Theory (Loomes & Sugden, 1982) is a theory of decision making based on the idea that people consider not only outcome utility, but also future regret or rejoicing, which depends on both the chosen option and foregone options. Regret theory was originally proposed as a theory of choice under uncertainty. Here, we demonstrate that Regret Theory also predicts the widely studied attraction, compromise, and similarity context effects. First, we show that it predicts attraction effects in choice among gamble triples. Second, we apply Regret Theory to non-gamble multi-attribute choice settings and show that both predicts these context effects and predicts a within-subject dissociation between the compromise and similarity effects previously observed in empirical studies. Regret Theory provides a foundation for a unified account of risky and multi-attribute choice, and we believe the form we present here provides the simplest account to date that explains phenomena in both domains.

Keywords: decision making; regret theory; decoy effects; risky choice; multi-attribute choice

Introduction

Two domains of decision making attracting significant scientific attention are *risky choice* and *multi-attribute choice*. In both task domains, people's decisions appear to deviate from those predicted by rational choice theories in systematic ways. For example, in risky choice among economic gambles, phenomena such as the *reflection effect* and the *certainty effect* can in some circumstances violate expected utility theory (Savage, 1954; von Neumann & Morgenstern, 1947). In multi-attribute choice, contextual decoy effects such as the *attraction* and *compromise* effects violate *independence of irrelevant alternatives*, a rational choice axiom which holds that the preference between options A and B should not be affected by a third option D.

Several models account for risky choice phenomena, including Prospect Theory and its descendants (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992); these models now number in the dozens (Bhatia, Loomes, & Read, 2021). Similarly, models have been developed to account for decoy effects in multi-attribute choice, including Decision Field Theory (DFT) (Busemeyer & Townsend, 1993) and comparison-based models (e.g. Howes, Warren, Farmer, El-Deredy, & Lewis, 2016). There are also attempts to develop unified models, including Salience Theory (Bordalo, Gennaioli, & Shleifer, 2013), Divisive Normalization (Glimcher, 2022), and extensions of DFT (Bhatia, 2014).

We make two contributions. First, we demonstrate that an existing model of risky choice, Regret Theory, predicts contextual decoy effects in economic gambles (Wedell, 1991). Furthermore, the model makes these predictions using a constrained and simple form and with the same quantitative parameter settings that provide good fits to the risky choice tasks that motivated Prospect Theory. Second, we show that Regret Theory predicts the attraction, compromise, and similarity effects in multi-attribute choice, assuming that the decision maker is uncertain about how attributes will combine to yield future value. We also show that while the model can predict all three effects, it cannot *simultaneously* account for the similarity effect and the other two decoy effects, a dissociation also found in humans (Liew, Howe, & Little, 2016).

Background & Related Work

Multi-attribute choice & contextual decoy effects Prior work has shown that in choices among three two-attribute options, preference between two options can be influenced by the attributes of a third option, violating an axiom of classical decision theory: *independence of irrelevant alternatives*. These violations primarily occur for choices with two options A & B—which tradeoff two attributes in different ways but have similar composite value[1]—and a third *decoy* option: D. Empirical studies have revealed *decoy effects*: placements of D in attribute space that have a predictable influence on the preference between A and B (Figure 1):

- **Attraction effect** People are more likely to select an option that dominates D (Huber, Payne, & Puto, 1982).
- **Compromise effect** When D positions one of the options as a compromise between extremes, people are more likely to select the compromise option (Simonson, 1989).
- **Similarity effect** When D has similar attribute values (and a similar composite value) to one of the options, people are more likely to select the other (non-similar) option (Tversky, 1972). Prior work suggests that this effect is negatively correlated with the attraction and compromise effect (Spektor, Bhatia, & Gluth, 2021; Liew et al., 2016).

Although they have been studied most in the context of consumer choice, decoy effects also appear in many other set-

[1]For example, a weighted sum of the attribute values.

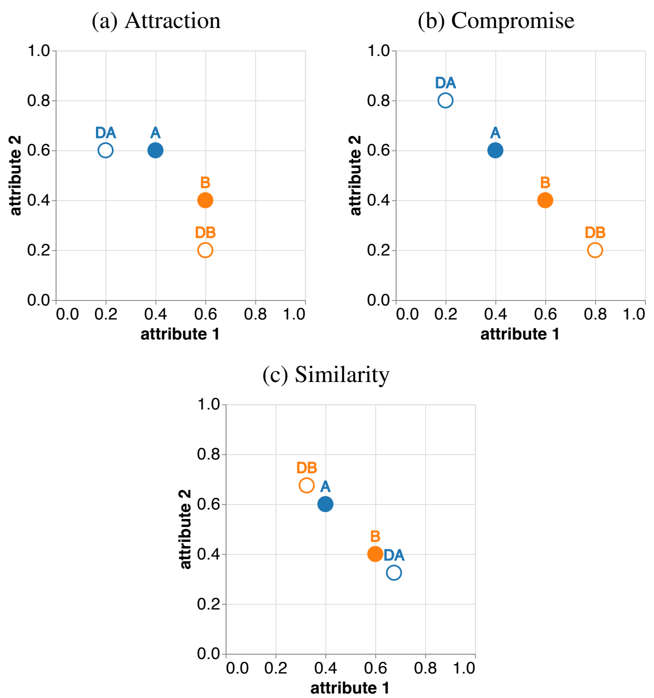


Figure 1: *The structure of decoy effects for options with two attributes.* Holding constant the positions of A and B, people's choices can be influenced by the position of a third option D. When a decoy is placed at DA people choose A more often, and when decoys are placed at DB people choose B more often. The option with the choice share that is increased by the decoy is the *target*, and the option with the choice share that is decreased is the *competitor*.

tings including perceptual decision making tasks (Trueblood, Brown, Heathcote, & Busemeyer, 2013), voter choice (Sue O'Curry & Pitts, 1995), judgements about the strength of eyewitness testimony (Trueblood, 2012), and motor planning (Farmer, El-Deredy, Howes, & Warren, 2015).

Models of decoy effects A long tradition of sequential sampling models such as the Multi-attribute Linear Ballistic Accumulator model (Trueblood, Brown, & Heathcote, 2014) have been applied to decoy effects. A different approach proposed by Howes et al. (2016) shows that decoy effects can emerge from the optimal integration of noisy ordinal comparisons of attributes across options. Another approach proposes that a decision maker has a population of independent utility functions, and decoy effects emerge from voting geometry when aggregating across that population (Bergner, Oppenheimer, & Detre, 2019).

Several families of models have been applied to both the risky choice effects described by Kahneman and Tversky (1979) and the decoy effects described above. These include DFT (via MDFT (Roe, Busemeyer, & Townsend, 2001)), Salience Theory[2] (Bordalo, Gennaioli, & Shleifer, 2012), and Divisive Normalization (Glimcher, 2022). While these prior works have each applied a theory to both domains, the analyses used instantiations of the theory that are specific to either risky or multi-attribute choice. In this work we present a single instantiation (Eq. 10) that can be applied to both domains simultaneously, and our analysis uses a consistent set of parameters across domains. In addition, the model we present differs from the models mentioned above in that it does not compare options to the average of the alternatives, but instead performs pairwise comparisons between individual options.

Regret Theory

Regret Theory hypothesizes that when making a decision, people anticipate the future regret or rejoicing that they will experience as a consequence. This anticipation modifies the expected utility of possible outcomes, which in turn affects the agent's choice. We will use the following notation to describe how Regret Theory can be applied to both risky and multi-attribute choice problems:

- The agent must choose among a set Z of I distinct options (*actions* in Loomes & Sugden's original terminology): $Z = \{A_1, \ldots, A_{I-1}, A_I\}$
- Each option is defined as a set of possible outcomes that can occur after choosing that option: $A_i = \{x_{i1}, x_{i2}, \ldots x_{iN}\}$.
- $S = A_1 \times A_2 \times \cdots \times A_I$ is the set of possible future world *states* (unique combinations of outcomes).
- The probability of state S_j is the product of the probabilities of the outcomes that occur in that state[3]: $P(S_j) = \pi_j = \prod_i^I P(x_{ij})$.
- The *choiceless utility* of an outcome x_{ij} is $C(x_{ij})$, and refers to the subjective value derived from experiencing x_{ij}, irrespective of the other options and outcomes.
- The key quantity of interest for Regret Theory is the anticipated (dis)satisfaction of experiencing one outcome and missing out on another, which Loomes & Sugden call the *modified utility*. The modified utility of experiencing an outcome x_{ij} and missing out on another outcome x_{kj} is $M(x_{ij}, x_{kj})$.

While the original definition of Regret Theory is general and does not commit to specific choices of C and M, in this work we use the following instantiations:

[2] Note that while Salience Theory and Regret Theory are known to be equivalent in some cases for choice among two options, no such equivalence has been established for choice among more than two options (Herweg & Müller, 2021)

[3] We focus here on the case of statistically independent outcomes, but Generalized Regret Theory does not require that outcomes are independent.

$$C(x) = \begin{cases} x^c & \text{if } x \geq 0 \\ -(|x|^c) & \text{if } d < 0 \end{cases} \quad (1)$$

Where c is a free parameter in the interval $(0,1]$. This function is applied to each outcome independently, and captures diminishing marginal value.

$$M(x_{ij}, x_{kj}) = C(x_{ij}) + R\left(C(x_{ij}) - C(x_{kj})\right) \quad (2)$$

The function R is applied to the difference between the subjective value the agent would experience in the state j if it chose option A_i and the subjective value that the agent *could have* obtained had it chosen the alternative option A_k.

We explore two forms for R:

$$R^{-}(d) = \begin{cases} 0 & \text{if } d \geq 0 \\ -(|d|^r) & \text{if } d < 0 \end{cases} \quad (3)$$

$$R^{+}(d) = \begin{cases} d^r & \text{if } d \geq 0 \\ 0 & \text{if } d < 0 \end{cases} \quad (4)$$

Eq. 3 only considers *regret* (when the choiceless utility of the chosen option is less than the alternative option), and Eq. 4 only considers *rejoicing* (when the choiceless utility of the chosen option is greater than the alternative option). In both cases r is a free parameter in the interval $[1,\infty)$.

For example, consider a choice between gamble A which pays \$11 with probability 0.5 or \$3 otherwise, and gamble B which pays \$13 with probability 0.5 or \$0 otherwise. If the agent chooses B, then it will expect to experience regret if B pays out less than A, and rejoice if B pays out higher than A. Table 1 enumerates all 4 possible world states that could occur and the differences d that would result from choosing A or B in each state.

For choices among two options, the *expected modified utility* of choosing A_i instead of a alternative A_k is:

$$E(A_i, A_k) = \sum_j \pi_j M(x_{ij}, x_{kj}) \quad (5)$$

Applying Regret Theory to choice among more than two options. When there are more than two options, each option can be compared to all of the alternatives, requiring a generalization of M (Eq. 2) that reduces multiple comparisons to a single summary value. Loomes and Sugden (1987) defined such a function in Generalized Regret Theory: $M^*(A_{ij}, Z_j - \{A_{ij}\})$ which describes the modified utility of choosing the option A_i from a set of possible options Z if the world state S_j occurs. We adopt the following for M^*:

$$M^*(A_{ij}, Z_j - \{A_{ij}\}) = C(x_{ij}) + \underset{k \neq i}{\downarrow} \left[R\left(C(x_{ij}) - C(x_{kj})\right)\right] \quad (6)$$

where $\downarrow: \mathbb{R}^{I-1} \rightarrow \mathbb{R}$ is a reduction operation (e.g, *max* or *min*). Note that M^* is equivalent to M for any $\downarrow \in \{max, min, mean\}$ for two option problems.

Table 1: *Example of future possible world states for a risky choice problem.* A choice between gamble A which pays \$11 with probability 0.5 or \$3 otherwise, and gamble B which pays \$13 with probability 0.5 or \$0 otherwise. $C(x_{Aj})$ is the choiceless utility of choosing A if world state j comes to pass, and d_{Aj} denotes the difference between the choiceless utility of the chosen and unchosen option if A was chosen. Negative values of d represent regret, and positive values represent rejoicing. For simplicity, we use $c = 1$ for this example.

World state S_j	$P(S_j) = \pi_j$	$C(x_{Aj})$	$C(x_{Bj})$	d_{Aj}	d_{Bj}
S_1	0.25	11	13	-2	2
S_2	0.25	11	0	11	-11
S_3	0.25	3	13	-10	10
S_4	0.25	3	0	3	-3

Substituting this instantiation of M^* for M in equation 5, the expected modified utility of selecting option A_i from the set of possible options Z is:

$$E(A_i, Z) = \sum_j \pi_j M^*(A_{ij}, Z_j - \{A_{ij}\}) \quad (7)$$

Extending Regret Theory to Multi-attribute Choice

Wedell (1991) studied the attraction effect using economic gambles (risky choices among three options, each with one attribute), so the model presented in Eq. 7 can be applied to those choices as-is (see Fig. 2 for results, described below). However, most studies that have examined decoy effects used choices among options with *two* attributes and no explicit statement about probabilistic outcomes.

A common approach for aggregating an option's attributes in multi-attribute choice is to use a weighted sum of the attributes using a subjective weight for each attribute:

$$U(A) = \sum_l^L w_l a_l \quad (8)$$

A fixed weight for each attribute implies that decision makers are certain about each attribute's future contribution to utility. But this is not necessarily the case: it is possible that changes in the decision maker's environment or tastes could change the relative importance of the attributes. For example, when purchasing a house, several attributes might affect your ultimate enjoyment of the house, such as the number of rooms and the size of the yard. But the way these attributes contribute to later satisfaction can be affected by factors that are uncertain at the time of purchase: e.g, changing family circumstances could affect need for a yard. The key intuition is that we do not know for certain how the attributes of our chosen options will contribute to our future satisfaction.

To capture this intuition, we replace the single set of attribute weights $\{w_1, \ldots, w_l\}$ from Eq. 8, with a distribution W over sets of attribute weights. The results we present use the following simple categorical distribution, which permits futures where one attribute is more valuable than the other, but in expectation all attributes are equally valuable (future work will explore the implications of other distributions):

$$\begin{cases} P(\{w_1 = 0.1,\ w_2 = 0.9\}) = & \frac{1}{2} \\ P(\{w_1 = 0.9,\ w_2 = 0.1\}) = & \frac{1}{2} \end{cases}$$

Each set of attribute weights describes a possible future where the attributes contribute differently to the total satisfaction. These possible futures can be incorporated into the space of possible world states: for any combination of outcomes there is one world state for each possible set of attribute weights. Thus the set of world states is now defined as $S = W \times A_1 \times A_2 \times \ldots \times A_I$ (see table 2 for an example).

Now we can define the choiceless utility of an outcome x in a particular world state S_j in which the attribute weights are $w_1,\ w_2,\ \ldots\ w_L$:

$$C_j^*\ (x) = \sum_l w_{jl} C(a_l) \tag{9}$$

Replacing C with C_j^* in equation 7 completes the extension to problems with more than one attribute:

$$E(A_i, Z) = \sum_j \pi_j \left[\underset{k \neq i}{\downarrow} R\left(C_j^*(x_{ij}) - C_j^*(x_{kj})\right) \right] \tag{10}$$

Note that if we constrain the attribute weights so that $\sum_l w_{jl} = 1$, then $C_j^* = C$ for outcomes with only one attribute (as in the risky choice settings examined above).

Evaluating Regret Theory's predictions

Model implementation & fitting

To evaluate this extension of Regret Theory, we implemented the model in Python using the Jax (Bradbury et al., 2018) and Equinox (Kidger & Garcia, 2021) libraries.

To enable fitting to empirical choice data, we compute the expected modified utility of each option (see equation 10), and then apply a softmax function to the resulting values.

$$P(\text{choose } A_i) = \frac{e^{\beta E(A_i, Z)}}{\sum_{k \in Z} e^{\beta E(A_k, Z)}} \tag{11}$$

where β is a free parameter that controls the concentration of the choice probabilities.

Additionally, to allow fitting with gradient-based optimization we used smooth approximations of the *max* and *min* functions during parameter fitting (however, after fitting we replaced the approximations with the exact versions when generating the plots in this manuscript).

For each $\downarrow \in \{max, min, mean\}$ and $R \in \{R^+, R^-\}$, we fit parameters using the L-BFGS-B algorithm as implemented by JaxOpt (Blondel et al., 2021). We repeated the fitting procedure with 500 random initializations to mitigate the risk of local optima, keeping the best fitting parameters across all combinations of $\downarrow$ functions, R functions, and initializations. The best fitting parameters for the data sets we explore below are given in Table 4.

Risky choice phenomena

To verify that the model preserves the original Regret Theory's ability to capture the risky choice phenomena, and to understand which parameter values yield the best predictions in this domain, we fit models to the human choice data reported in Kahneman and Tversky (1979). We fit a single set of parameters to all problems except those with non-monetary outcomes (problems 5, 6, & 9) and those involving multi-stage gambles (problems 10, 11 & 12). The parameters were fit to the *modal choice* for each problem using a binary cross entropy loss function, resulting in a set of parameters that reproduces the modal human choice for every problem in the dataset (see Table 4 for parameter values).

Attraction effect in the risky choice setting

We explored the model's predictions for the attraction effect in the risky choice setting by fitting to the empirical data reported in Wedell (1991). We retained the c and r values obtained from fitting the Prospect Theory data and fit only $\downarrow$ and β to the new data.[4] Wedell (1991) does not report per-problem choice data, so we fit to the aggregate choice data. We fit a single set of parameters that minimized the sum of squared errors between the reported choice proportions for each condition / decoy position combination, and the model's predicted choice probabilities averaged by condition / decoy position (see Table 4 for best-fit parameter values).

The empirical data and model predictions are plotted in Fig. 2. Note that although the empirical data show a baseline preference for A (the choice share of A is greater than 0.5 in all conditions), the choice share of A is higher in the *atA* condition where the decoy is dominated by A, and lower in the *atB* condition where the decoy is dominated by B (the attraction effect). This pattern appears in all conditions except for *Rprime*, which is a control condition where the decoy is equally dominated by both A and B (in this condition *atA* and *atB* decoys are indistinguishable). The model correctly predicts this pattern of results: a higher choice share of A when the decoy is dominated by A, and a lower choice share of A when the decoy is dominated by B in all conditions except for *Rprime* where there is no difference between decoy positions.

Decoy effects in multi-attribute choice setting

Following Dumbalska, Li, Tsetsos, and Summerfield (2020), we generated a set of multi-attribute choice problems in order to systematically evaluate the effect of the decoy posi-

[4] it is necessary to re-fit β because it is sensitive to the scale of outcomes, and the scales of these two datasets differ considerably

Table 2: *State space for a multi-attribute choice problem.* Consider a choice between two cars. Car A is less fuel efficient (0.4 units of fuel efficiency) but more comfortable (0.6 units of comfort), while Car B is more efficient (0.6 units of fuel efficiency) but less comfortable (0.4 units of comfort). If the agent is uncertain about whether efficiency or comfort will be more important in the future, then they may be uncertain about which car will provide more satisfaction. If they choose Car A and efficiency turns out to be more important then they will experience regret, but if comfort turns out to be more important then they will experience rejoicing. This table enumerates three possible features, and the regret or rejoicing the agent would expect to experience having chosen Car A or Car B. For example, in future state S_1 the utility of Car A is $0.1 \times 0.4 + 0.9 \times 0.6 = 0.58$ and the utility of Car B is $0.1 \times 0.6 + 0.9 \times 0.4 = 0.42$, so the agent would expect to experience rejoicing if they chose Car A and regret if they chose Car B. $C(x_{Aj})$ is the choiceless utility of choosing Car A if world state j comes to pass, assuming $c = 1$, and d_{Aj} is the difference between the choiceless utility of the chosen and unchosen option if A was chosen. Negative values of d represent regret, and positive values represent rejoicing.

World state S_j	$P(S_j) = \pi_j$	Attribute weights	$C^*_j(A)$	$C^*_j(B)$	d_{Aj}	d_{Bj}
S_1	0.5	$\{w_{\text{fuel}} = 0.1,\ w_{\text{comfort}} = 0.9\}$	0.58	0.42	0.16	-0.16
S_2	0.5	$\{w_{\text{fuel}} = 0.9,\ w_{\text{comfort}} = 0.1\}$	0.42	0.58	-0.16	0.16

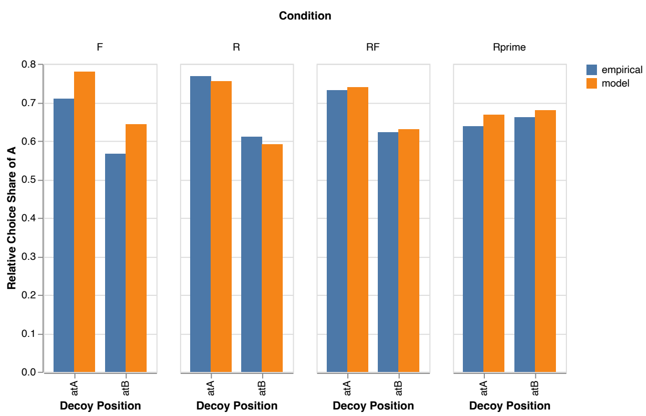


Figure 2: *Empirical data vs model predictions for Wedell (1991).* Relative Choice Share of A is computed as $\frac{P(ChooseA)}{P(ChooseA)+P(ChooseB)}$. The model predictions in this plot were produced by a single set of parameters.

tion. We used fixed values for A $(x = 12,\ y = 19)$ and B $(x = 19,\ y = 12)$, and evaluated the models preferences for the choice set $\{A, B, D\}$ for every decoy D in a 30 by 30 grid (see Figure 3). We again reused the c and r values obtained from fitting to the Kahneman and Tversky (1979) data. β was chosen manually to maximize the readability of the effects in the heatmap figures (see Table 4).

In (a) we can see an attraction effect: the choice probability of A is high when the decoy is dominated by A, and the choice probability of A is low when the decoy is dominated by B and vice-versa. We can also see the compromise effect in this plot: the choice probability of A is high when the decoy is placed in the top left along the diagonal (positioning A as the middle of the three options), and the choice probability of B is high when the decoy is placed in the bottom right along the diagonal (positioning B as the middle of the three options). Note that (a) does not show a similarity effect: the choice probability of A is low when the decoy is close to B near the diagonal (where the decoy would have a similar total x + y value to the other options), and vice versa.

However, in (b) we can see that a model that uses different R and $\downarrow$ does predict a similarity effect: the choice probability of A is high when the decoy is close to B along the diagonal, and vice versa. We can also see a reversed compromise effect: the choice probability of A is low when the decoy is placed in the top left along the diagonal (which places A as the middle option), and the choice probability of B is low when the decoy is placed in the bottom right along the diagonal (which places B as the middle option).

Discussion & Limitations

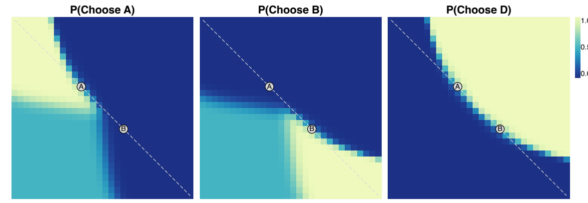
The dissociation of the similarity effect from the attraction and compromise effects we found in our simulations is consistent with prior work suggesting that individual participants rarely exhibit all three decoy effects. Liew et al. (2016) clustered participants based on their choice behavior and found 3 clusters: one which demonstrated both attraction and compromise effects but not the similarity effect, and two other clusters which demonstrated the similarity effect and a reversed compromise effect but no attraction effect.

These two patterns of behavior map onto the two plots shown in Figure 3 where a model using $R = R^-$ and $\downarrow = max$ predicts the attraction and compromise effects. This combination of R and $\downarrow$ leads the model to focus on comparisons where the option under consideration is the worst among all options: R^- will evaluate to 0 for comparisons where the option under consideration is equal to or better than the alternative, and a negative number in all other cases. This means that the *max* in Eq. 10 will evaluate to 0 unless the option is worse than both alternatives. In contrast, a model with the same r, c, and β, but $R = R^+$ and $\downarrow = min$ predicts the similarity effect and a reversed compromise effect. This combination of R and $\downarrow$ leads the model to focus on comparisons where the option

Table 3: Free parameters

	Domain	Interpretation
c	$(0, 1]$	Agent's diminishing marginal utility (smaller values mean utility diminishes more quickly).
r	$[1, \infty)$	Agent's sensitivity to regret / rejoicing (receiving less / more than if it had chosen differently).
$\downarrow$	$\mathbb{R}^{I-1} \rightarrow \mathbb{R}$	How the agent aggregates across comparisons when there are more than two possible options
R	$\{R^+, R^-\}$	Whether the agent considers only rejoicing or only regret (see equations 4 and 3).
W	Dirichlet$(k = L)$	Agent's distribution over weights w_l for attributes $l \in L$.
β	$(0, \infty)$	How concentrated the agent's choice probabilities are on the option with the highest expected modified utility.

(a) Attraction & Compromise ($R = R^-$, $\downarrow = max$)



(b) Similarity ($R = R^+$, $\downarrow = min$)

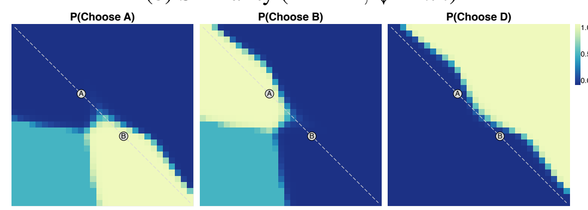


Figure 3: Heatmaps depicting the model's preferences for the choice set $\{A, B, D\}$ for every position of D in a 30 by 30 grid. Each plot depicts the model's probability of choosing an option as a function of the decoy's position. For example, the color of a cell in the left-most plot, labeled $P(Choose\ A)$, indicates the probability that the model will select option A if the decoy D is placed at that cell. The probabilities for each cell sum to 1 across the three plots. All cells across all plots use exactly the same values for all parameters except for R and $\downarrow$ (see table 4 for complete list of parameter values).

under consideration is the best among all options: R^+ will evaluate to 0 for comparisons where the option under consideration is equal to or worse than the alternative, and a positive number in all other cases. This means that the *min* in Eq. 10 will evaluate to 0 unless the option is better than both alternatives. This is particularly interesting because it suggests that decoy effects may be driven by a decision maker's focus on different comparisons for each option: focusing on the least favorable comparisons for each option yields the attraction and compromise effects, while focusing on the most favorable comparisons yields the similarity effect and a reversed compromise effect.

A limitation of the current work is that we have focused on fitting the model to aggregated choice data. Future work will fit to individual level data to understand how individual differences and experimental contexts affect the salience of favorable vs. unfavorable comparisons, and the extent to which this explains the dissociation between the attraction, compromise, and similarity effects observed in previous work like Liew et al. (2016). In addition, while we have focused on three of the most commonly studied decoy effects (attraction, compromise, and similarity), future work could explore Regret Theory's predictions about other decoy effects such as the phantom decoy effect (Pettibone & Wedell, 2000).

Table 4: Fitted parameters

Dataset	c	r	$\downarrow$	R	β
K&T (1979)	0.564	2.600	N/A	R^-	336.486
Wedell (1991)	0.564	2.600	*max*	R^-	0.151
Figure 3 (a)	0.564	2.600	*max*	R^-	20.000
Figure 3 (b)	0.564	2.600	*min*	R^+	20.000

Conclusion

Using simulation experiments, we have shown that an existing theory of risky choice (Regret Theory) can be extended with a simple assumption—uncertainty about how the attributes of options combine to yield future utility—to offer a single model of risky choice phenomena and contextual choice phenomena. The effects predicted include those that motivated Prospect Theory as well as the attraction, compromise, and similarity effects. They also include the empirically observed within-subject dissociation between the compromise and similarity effects. Moreover, this model suggests an explanation for the dissociation in terms of individual-level variation in the salience of favorable vs. unfavorable comparisons to the option under consideration.

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