Role of Working Memory on Strategy Use in the Probability Learning Task

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Abstract

Extensive research on probability learning has reported on the ubiquity of the probability matching strategy—choosing options in proportion to their probability of being correct. The current paper explores why the optimal strategy in this task (always choosing the higher probability option) is not intuitive for participants, by examining their decisions in relation to their working memory capacities. We hypothesize that probability matching is a by-product of an automatic recency-based strategy produced by limits in working memory storage and that deliberate strategizing mediated by working memory processing can override recency in favor of optimal responding. A variant of the Expectancy-Valence Learning Model is fit to participant data from a two-choice probability learning task using hierarchical Bayesian modelling. Point estimates of the best-fitting parameter values are then correlated with working memory measures. Results indicate close relations between them, providing support for our hypothesis.

Keywords: working memory; probability learning; recency

Introduction

Decisions in life often condense into simple binary choices—to react or not to react, to speak or not to speak, to do or not to do. An important factor influencing such decision making is the outcomes of previous similar decisions. However, our abilities to integrate the histories of outcomes is strongly constrained by the attentional and processing limits of our working memory (WM), thus compromising the quality of our decision making. Indeed, several researchers have focused on differences in decision making between situations when information is gathered over sequential experience (where the narrow window of WM is likely to have an impact) and when it is obtained from simultaneous description (which is relatively uninfluenced by WM capacity; Hertwig, Barron, Weber, & Erev, 2004). The former is more typical of real-life, emphasizing the importance of examining the role of WM limits. In the current paper, we investigate how limits in storage and processing mechanisms of WM influence behavior on binary choices through the probability learning task.

Probability Learning Task

The probability learning task is a simple experimental paradigm involving multiple trials of choosing between two mutually exclusive and exhaustive outcomes (Vulkan, 2000). For instance, in each trial, participants may be asked to predict which of two presented light bulbs will turn on (Humphreys, 1939). Typically, the two options have pre-determined and unequal probabilities of occurring—e.g., Bulb A will turn on with 0.7 probability, and Bulb B with 0.3 probability. Each trial is independent; hence the optimal strategy is to choose the higher probability side (once it has been identified) 100% of the time. This is known as probability maximizing—in our example such a strategy would lead to 70% accuracy.

However, participants rarely perform this relatively simple strategy of exploring for the high payoff option and then exploiting via probability maximizing. Rather, a typically observed behavior is probability matching—choosing options in proportion to their probability of occurrence. Participants therefore tend to choose Bulb A 70% of the time and Bulb B 30%, leading to a lower accuracy level of 58% (.7×.7 + .3×.3). This behavior typically persists even after enough samples have been drawn to identify the higher probability option with at least some level of certainty (Arrow, 1958). Probability matching has been given wide attention as a supposed lapse of judgement for which several explanations have been proposed, without much consensus regarding the underlying mechanism (Feher da Silva, Victorino, Caticha, & Baldo, 2017).

Working Memory and Probability Matching

One of the primary explanations of probability matching is the recency effect. Human short-term retention abilities are limited, creating a narrow window of recent experience which makes information highly susceptible to time-based decay (Kareev, 1995). In the current task, this constraint encourages decisions to be based on smaller samples of information (most likely the very recent samples), which, given the law of large numbers, is likely to produce probability matching behavior (Plonsky, Teodorescu, & Erev, 2015; Rakow & Newell, 2010). For example, if participants retain only one previous trial in their short-term window and make utility calculations and decisions based on this previous trial, they would exhibit perfect matching. Several studies have fit such one-outcome-based win-stay-lose-shift strategies to decision making with surprising success despite their relative simplicity (Nowak & Sigmund, 1993). More sophisticated reinforcement learning models (such as the EVL and PVL models; Busemeyer & Stout, 2002; Erev & Roth, 1998) also incorporate a recency weighting which discounts the influence of older outcomes. Such findings suggest that probability matching behavior could be a result of overweighting recent outcomes, produced by their higher activation in the attentional window.

It must be noted that most studies find that probability matching does not persist—when enough trials are presented, participants are often able to switch to the optimal strategy of maximizing. For instance, Restle (1961) found that probability matching disappeared after 1000 trials. Other studies have emphasized that switching to the optimal strategy is more likely if participants are provided with higher monetary payoffs, regular feedback, and more intense practice (Shanks, Tunney, & Mccarthy, 2002). An interpretation of this is that probability matching (produced e.g. by short-term recency) is a default response, which can be overridden in favor of maximizing through conscious deliberation. This dual process hypothesis is supported by correlations between SAT scores and maximizing on a descriptive version of this task (West & Stanovich, 2003).

These features of probability learning behavior—recency-based responding and deliberate strategy shift to maximizing—are likely to be mediated by WM capacity. Several models of WM consist of two core functions, storage and processing (frequently known as the span and control of attention respectively; Cowan, 2008). Here, we refer to storage as the ability to temporarily hold information in an active attentional state, protected from time-based decay and other interference. Decay in storage capacity is likely to produce recency-based performance in the probability learning task, as it constrains the number of previously observed outcomes that are in a readily accessible state when making a new decision (Ricker, Vergauwe, & Cowan, 2016). The processing component of WM directs attentional use, focusing it on goal-relevant information. An important function of WM processing is the inhibition of automatic but incorrect responding, as suggested by correlations with performance on the antisaccade and Stroop tasks (Kane & Engle, 2003; Unsworth, Schrock, & Engle, 2004). In our task, this component is perhaps responsible for resisting convenient recency-based responding and deducing the optimal strategy by steering and focusing attention toward task-relevant information (which could include independence of trials and the existence of a higher probability option).

Based on this previous research, in our study, we hypothesize the following to be correlated: (1) recency-based responding and WM storage capacity, and (2) strategy shift to maximizing and WM processing abilities.

Previous Studies and the Current Experiment

Several experiments have previously linked WM with performance on probability learning or other similar tasks (Gaissmaier, Schooler, & Rieskamp, 2006; Kareev, 1995; Rakow & Newell, 2010). These studies have reported mixed results—some have found positive correlations between WM capacity and maximizing, while others have reported the opposite. Through this paper, we attempt to resolve this debate. Further, unlike previous studies, our primary motivation is to model the interaction of the two WM components in producing recency-based responding and suppressing it in favor of the optimal strategy.

For our task, we used the light bulb setting described earlier. Participants chose between two bulbs and received feedback (i.e., which bulb lit up) after each trial. To model probability learning behavior, we used the Strategy-Shift Expectancy-Valence Learning (SS-EVL) model–a variant of the original EVL model (Busemeyer & Stout, 2002). Recency and strategy shift parameters extracted from this model were correlated with WM scores. Since such statistical analysis is likely to be noisy, our study has a larger sample size than that of previous experiments.

Methods

Participants

One hundred and thirty-one undergraduate students of Indiana University served as participants and were compensated with course credit. Of these, data of eight participants was excluded due to failure to perform at least one of the tasks.

Tasks and Procedure

The experiment consisted of five computer-based tasks (four WM and one probability learning). Each session lasted around 60 minutes and began with administration of the WM tasks.

Memory tasks. Participants performed four WM tasks in the following order: symmetry span, digit span, visual array, and operation span.

WM storage was measured with the digit span and visual array tasks. The digit span is a simple number recall task classically used as a measure of short-term memory (method similar to Quinn, Tuci, Harvey, Di Paolo, & Wood, 2005). The visual array task requires detecting rapid color changes in an array of 4, 6, 8, or 10 colored squares (method similar to Cowan, Fristoe, Elliott, Brunner, & Saults, 2006). Here, task performance depends on temporary storage of colors, and has been frequently used as a measure of storage (Cowan et al., 2006; Shipstead, Redick, Hicks, & Engle, 2012).

The symmetry span and operation span tasks require simultaneous usage of memory and processing and were used as measures of WM processing (methods similar to Oswald, Mcabee, Redick, & Hambrick, 2014). The memory component of these tasks involves the retention of presented items (spatial positions of colored squares for symmetry span and letters for operation span). Memory items are interpolated with processing components (symmetry or arithmetic accuracy judgements respectively) that interfere with rehearsal of memory items.

These specific working-memory tasks were selected because they not only represent the functional components of working memory (i.e., storage and processing), but also use different content modalities—symmetry span and visual array are visuo-spatial tasks, while digit span and operation span are verbal-numeric tasks.

Probability learning task. Participants performed three probability learning games, each involving 100 trials. During each game, participants were presented with an image of a 'bulb-box', a device containing two lightbulbs (Bulb A and Bulb B). Participants were informed that on each trial one of the two bulbs would turn on and it was their task to guess the correct bulb. For every correct guess, participants gained one point and for every incorrect guess, they lost one point. Number of points won by participants was revealed at the end of each game. To motivate participants to aim for higher points and achieve optimal decisions, participants were rewarded with between 0 to 3 nutrition bars based on performance. The probability with which the two bulbs lit up remained constant within each game but varied from game to game. Three probability contingencies were used—0.60, 0.70, and 0.80—the order of which was determined randomly. Bulb A or Bulb B was set as the more frequent bulb in each game with equal probability. Participants were informed that each 'bulb-box' game had a different underlying 'program' controlling it to minimize tendencies of using previous games as priors for future ones. To further combat this, the color of the lightbulbs was changed from game to game.

Results

Probability matching (selecting the bulbs in proportion to how often they light up) was observed in the aggregated data of participants, decreasing with successive games (Figure 1).

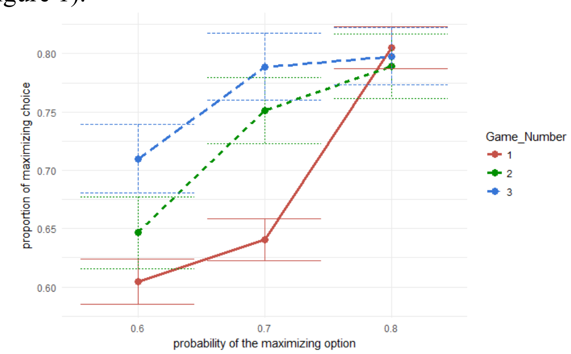

Figure 1: Proportion of maximizing choices averaged across trials (data for all game and probability contingencies)

Further, we found that participants were more likely to choose the maximizing option as the number of trials played increased within each game (Figure 2).

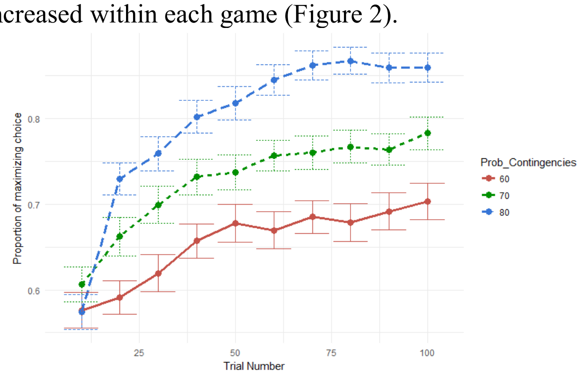

Figure 2: Averaged proportion of maximizing responses across trials

We then calculated correlations between WM scores and frequency of maximizing responding. Maximizing responding was calculated as the proportion of times the maximizing option was selected in a game. Significant correlations were obtained for scores on visual array ($r(123) = 0.2$, p=.03) and spatial span tasks ($r(123) = 0.19$, p=.04), while correlations with digit span ($r(123) = 0.09$, p=.36) and operation span ($r(123) = 0.19$, p=.07) were weaker. Stronger correlation with the visuo-spatial WM tasks (as opposed to the verbal ones) could arise if participants were retaining previous outcomes as visuo-spatial information (e.g. *left* bulb, *right* bulb, *right* bulb…).

These positive correlations between WM and optimal responding are in line with our hypotheses. They are consistent with results from some previous studies on WM and probability learning (Rakow & Newell, 2010; West & Stanovich, 2003); but contradict others which have found negative correlations (Gaissmaier et al., 2006; Kareev, 1995).

Modelling

Correlation measures provide us a small peak into the relationship between WM capacity and probability matching. However, they do not reveal the relation between WM capacity and the use of recency or strategy shift to maximizing. We therefore modelled the data using a modified EVL model and correlated parameters with WM scores. We also employed a Baseline Bernoulli model for comparison.

Model Descriptions

Strategy-Shift Expected-Valence Learning Model (SS-EVL). Variants of the EVL model have been previously used to model probability learning (Feher da Silva et al., 2017; Schulze, van Ravenzwaaij, & Newell, 2015) and other reinforcement learning tasks (such as the Iowa and Soochow Gambling Tasks; Ahn, Busemeyer, Wagenmakers, & Stout, 2008). Its parameters typically include consistency c and recency A. In our version of the model, we accommodate a strategy shift toward maximizing through a third parameter—timepoint of shift T.

The model assumes that on every trial, participants assign a utility value to the two lightbulbs—1 if it is correct on that trial, and 0 otherwise. Therefore, in a trial, utility $u(t)$ gained from bulb j based on outcome x is defined by:

$$u_j(t) = \begin{cases} 1 & if\ x(t) = j, \\ 0 & if\ x(t) \neq j \end{cases}$$

This utility is then incorporated into the running expected utility E_j of the two options using a weighted utility updating rule (Rescorla & Wagner, 1972) which discounts older outcomes with a recency parameter A. Larger the value of A, greater is the influence of older outcomes:

$$E_j(t) = A \cdot E_j(t-1) + (1-A) \cdot u(t)$$

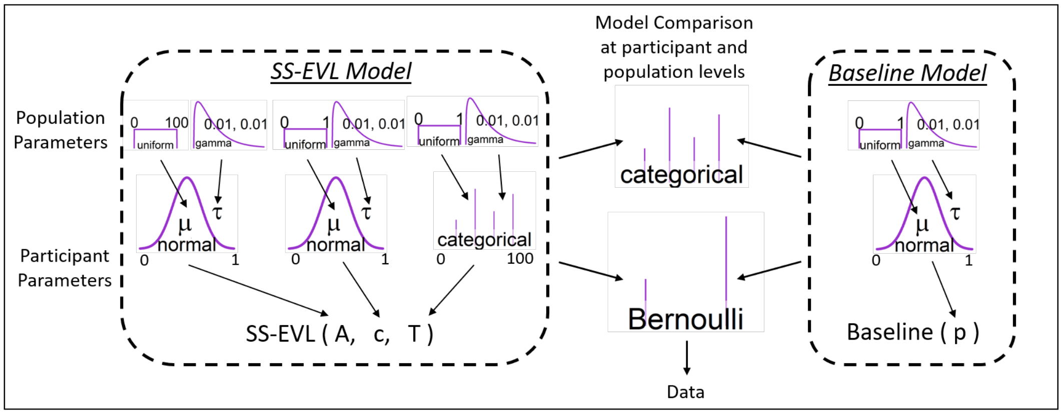

Figure 3: Structure and priors of the hierarchical Bayesian model

The expected utility calculations are then used to make a choice decision D based on Luce's choice rule (Luce, 1959) incorporating exploration θ:

$$\Pr[D(t+1)=j] = \frac{e^{\theta(t) \cdot E_j(t)}}{\sum_{k=1}^{2} e^{\theta(t) \cdot E_k t)}} \;;\quad \theta(t) = \left(\frac{t}{10}\right)^c$$

$\theta(t)$ represents the extent to which participants make choice decisions based on calculated utilities. If $\theta(t) = 0$, decisions are random and as $\theta(t)$ increases, decisions are highly sensitive to utilities. The value of θ is dependent on the free consistency parameter *c,* which is constrained between 0 and 1. Though we do not use this parameter for future WM analysis, it is essential to incorporate it in the model—it provides for a cleaner estimate of recency by accounting for the influence of exploration in participant data.

Finally, we assume that at some trial *T*, participants identify and shift to the maximizing strategy. Therefore, from this trial onward, the expected utilities of the maximizing and non-maximizing options are set to 1 and 0 respectively. Hence, the running utility E_j is revised such that:

$$\boldsymbol{for\ t > T:} \qquad E_j(t) = \begin{cases} 1 \ \ if\ j = maximizing\ option, \\ 0\ if\ j\ \neq maximzing\ option \end{cases}$$

Baseline Model. A simple Bernoulli baseline model was also fit to data. The Baseline model has only one parameter—probability that participants choose the maximizing option, $p(j=1)$. Therefore, the model predicts unequal probabilities of choosing between the two bulbs, which are independent of outcomes observed by participants and constant across trials.

In our task, participants could be using varied strategies (e.g., looking for patterns in outcomes or random guessing). This model serves to filter out such participants who are better modelled by a random Bernoulli process than by a recency model which assumes positive dependency on observed outcomes. Thus, this model is not intended to be a process model of the underlying mechanism, but rather a useful cache for unaccounted strategies. If a larger number of participants are better fit by this model than the SS-EVL, it suggests that our proposed mechanism of probability matching is not dominant in the population.

Model Fitting

We used Bayesian hierarchical modelling for parameter fitting and model comparison (see Figure 3 for details about prior and multilevel structure). We combined the two models into a single hyper-model and employed a categorical distribution to determine the strategy used by each participant— on each MCMC timestep, for each trial, it sampled from one or the other model based on its probability of being the true process underlying that participant's data. In a similar way, we also estimated the population level posterior probability for each model. The analysis was implemented on JAGS via R. We drew 200,000 samples via three MCMC chains. Inspection of diagnostic plots indicated convergence for most parameters.

Here we only fit data from the first probability learning game of each participant because of considerable order and practice effects in future games.

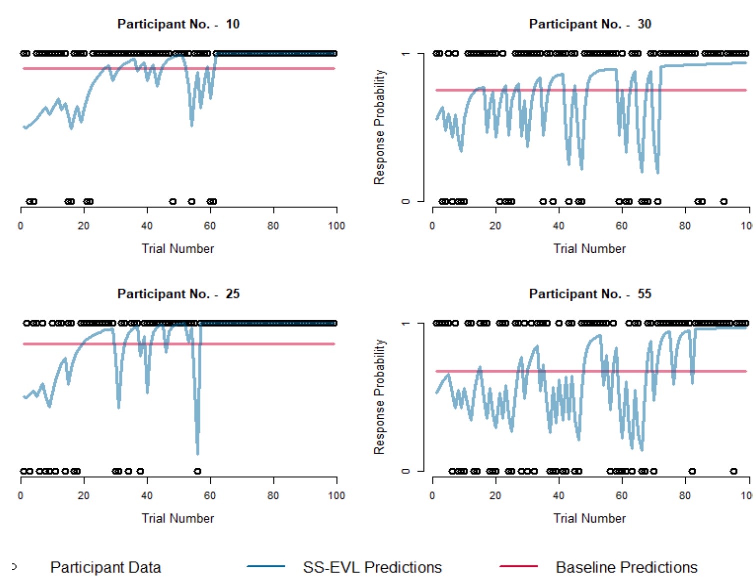

Figure 4: Model fitting of individual participants

Model Comparisons

Overall, the SS-EVL model outperformed the Baseline, with a posterior probability *P(model=SS-EVL|D)* of 0.71. Further, 85 out of 123 participants were categorized as employing an SS-EVL strategy (for examples of individual fit, see Figure 4). SS-EVL also better captured the participants' average pattern of performance across trials (Figure 5).

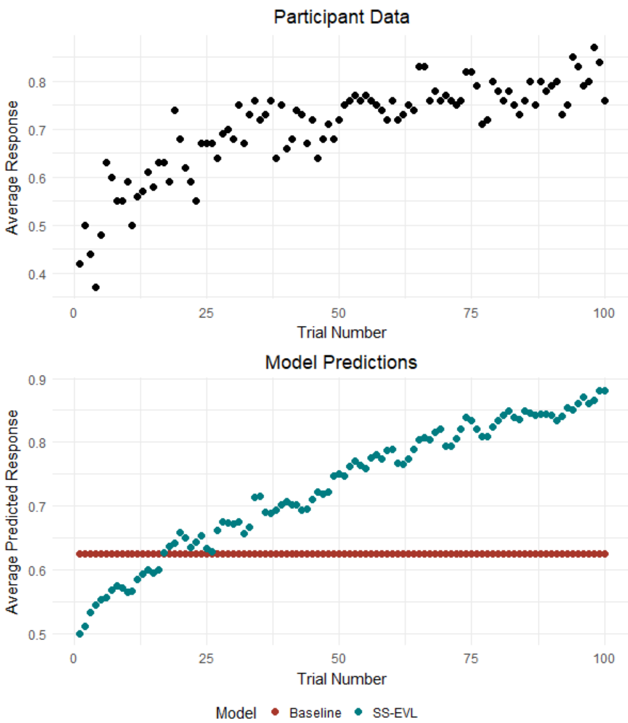

Figure 5: Average participant data and model predictions across trials

Correlations with WM scores

To test our hypothesis that WM components correlated with strategy use, we analyzed those participants who were better fit by the SS-EVL model. Point estimates (modes) of two SS-EVL parameters were correlated with WM scores—recency A and timepoint of strategy shift T (Table 1). As in the behavioral correlations reported above, visual array and symmetry span were more strongly correlated than other measures. Of the two measures of WM storage, only visual array showed indication of correlation with recency, providing partial support for hypothesis 1 that overweighting of recent outcomes is a by-product of WM storage limits. As predicted in hypothesis 2, measures of WM processing shared a significant negative correlation with timepoint shift—participants with higher WM processing abilities were likely to shift toward the maximizing strategies within fewer trials.

Discussion

Our study demonstrates the process by which WM components work together to produce typical probability learning behaviour. The picture that emerges suggests that the limits of the WM store intensify weighting of recent events, producing default responses that require greater WM processing to inhibit them in favor of the optimal strategy. In the real world, such a tendency toward recency makes sense as it allows us to adapt to our dynamic and temporally autocorrelated environment, where making decisions based on older information is often unsuccessful and recent events are a good indicator of the current state of the world (Plonsky et al., 2015). It appears that the two components of WM thus work together to produce appropriate everyday behavior—limits in the WM store allow for quick recency-based responses to environmental stimuli while WM processing acts as a correctional mechanism, stepping in to replace the recency-based strategy if an optimal strategy is found.

It would therefore be hasty to call probability matching a lapse in judgement (Vulkan, 2000)—participants do not fail to arrive at successful decisions in the probability learning task because of some cognitive failure. Rather, they do not always use the optimal strategy because the task itself is not representative of natural environments: unlike typical real-world situations, here the event probabilities are stationary across trials, and the trials are independent of one another. Participants therefore must deploy deliberate processing to resist responding automatically based on assumed environmental structures where recency would be best. While binary decisions may be common to our everyday life, the probability structure underlying this task is not, making the optimal strategy unintuitive. Future work can examine participant performance using real-world probability structures—for instance having the probabilities of the bulbs shift or be autocorrelated across trials (Gaissmaier & Schooler, 2008).

As mentioned earlier, previous studies have found mixed

Table 1: Correlations between WM obtained parameter values

	WM storage measures		WM processing measures	
	Visual Array	Digit Span	Symmetry Span	Operation Span
Recency *(A)*	0.19^{+}	0.08	0.18^{+}	0.11
Timepoint of shift *(T)*	−0.16	−0.11	-0.24^{*}	-0.20^{+}
$^{+}$p<.1. *p<.05. **p<.01. ***p<.001 N=85				

results when relating WM to performance in similar tasks—some have obtained positive correlations, providing support to our results (e.g., Rakow & Newell, 2010; West & Stanovich, 2003), while others have obtained the opposite (e.g., Gaissmaier et al., 2006; Kareev, 1995). While, the differing results could be due to difference in task structure—the studies reporting negative correlations use a correlation-detection task, which involves estimating two probabilities and not just one (for details of the task, refer to Kareev, 1995)—this is an unlikely explanation since our model would still predict positive correlations for such a task structure. Therefore, a more likely possibility is that participants employ different strategies (such as pattern matching, random responding etc.), producing different results. In the current paper, we only focused on recency-based responding—the SS-EVL model fit participants for this specific strategy and our results suggested that it was the dominant strategy in our sample when compared to a Bernoulli baseline. We then correlated the obtained parameter estimates for participants best fit by this model with WM scores, therefore excluding any effect of other strategies. However, future work must model other possible strategies, determine their frequency in the sample and their relation to WM capacity.

Further work must also be done to narrow in on the mechanisms underlying these decisions. While our model estimates the timepoint at which the strategy-shift toward maximizing occurs, it does not uncover the mechanism that produces this shift. Our correlational evidence argues that this mechanism is associated with the processing component of WM, but we do not know what operation within this component leads to optimal strategizing and why it reaches a threshold at a particular timepoint. Identifying the likely mechanisms at work in making decisions based on recent and older information will help us understand the role of limited WM storage and processing in these common choice settings.

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