¹ Explaining contingency judgements with a computational model of instance-based memory

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10   Abstract

11   The purpose of this experiment is to create a simulated version of a study done by Crump,

12   Hannah, Allan, and Hord (2007). Our model replicated several key findings, such as the

13   effects of $\triangle$P and outcome density. We created a model using RStudio, based on

14   MINERVA 2, which is a simulation model of episodic memory (Hintzman, 1986).

15   MINERVA 2 assumes that each experience leaves an individual memory trace. Our model

16   was presented with four different conditions. two were high outcome density and two were

17   low outcome density conditions. Low outcome density refers to a trial in which fewer

18   outcomes were presented than cues. High outcome density refers to trials where more

19   outcomes were presented than cues. Four types of trials can be presented to the model.

20   The model can be presented with a cue and no outcome, no cue and no outcome, a cue and

21   an outcome, or no cue and an outcome. Our model was shown all four combinations. It

22   was then asked to predict, based on all of the combinations that it had been presented

23   with, whether an outcome would occur given that cues were presented first with no

24   outcomes. We hypothesized that Just like the human participants in the original study, our

25   computer model also had higher contingency ratings when more outcomes were presented

26   than cues (high outcome density). In contingent conditions ($\triangle$P=.467), contingency

27   ratings were much higher overall than noncontingent conditions ($\triangle$P=0), which, as

28   intended, paralleled the original results. However, it did so with regard to a higher

29   expectation overall than that of the original study.

30   *Keywords:* memory, contingency judgments, MINERVA II, instance theory

31   Word count: 2180

Explaining contingency judgements with a computational model of instance-based memory

Introduction

Imagine that you are driving down a highway. Your current speed is sixty miles per hour. Suddenly, traffic slows down and you see two police cars pass by. "I guess there was an accident", you think to yourself as you anticipate a longer commute than expected. You later pass the cars involved, and also arrive twenty minutes late to work. Why did you predict that a car crash had occurred? Why did you predict that you would have a longer commute time? These types of questions are asked by researchers when studying contingency judgements. A contingency judgement can be defined as one's perception of whether a particular stimulus predicts a particular outcome. The purpose of studying human contingency judgements is to be able to gain a better understanding of the way that people learn about the causal relationships between events (Beckers, De Houwer, & Matute, 2007).

In order to study this further, we created a model using RStudio. The model attempts to help us understand the way in which contingency judgements are made. Our model is based on MINERVA 2, which is a simulation model of episodic memory. Specifically, MINERVA 2 assumes that each experience leaves an individual memory trace Hintzman (1986). Our model focuses on evaluating the percentage of information remembered after cues and outcomes are first presented. The model is first presented a set amount of cues and outcomes, and its memory is then checked by asking the model to predict whether an outcome will occur given that a cue was presented or not.

Our experiment is based on a research study performed by Crump et al. (2007). While this study involved presenting humans with a contingency task, our computer model attempts to replicate the findings of the study, and expand upon it. The findings of the original study explain that people are generally normative. In other words, people generally act in an expected way when making contingency judgements, and this is referred to as the

$\triangle$P rule (Allan, 1993). For instance, if someone changes the brightness of their phone

screen and it becomes brighter, a person will likely be able to tell that an increase occurred

rather than a decrease, or no change. This would be expected, or normative, behavior. By

the same token, human beings are not robots, and each person has their own biases. For

instance, one may rate contingency as significantly higher or lower than actuality. These

biases result in a departure from expectations during research. This phenomenon is

explained by the outcome density effect. This states that when more outcomes occur, they

lead participants to more strongly predict that there is a contingency occurring in order to

create the outcomes, even if there is not necessarily a true contingency between events. For

instance, if someone is shown a circle followed by a square 95 percent of the time, they are

more likely to predict that the circle indicates that a square will be presented later, even if

the order was randomly generated and no connection between the two cues was intended.

What psychological mechanisms are involved in making contingency judgements?

Several theories can be used to explain the way in which contingency judgements work.

MINERVA 2 assumes that repeated exposure to the same information creates multiple

copies rather than strengthening the same memory. This is called multiple-trace theory.

While this theory is assumed for the purposes of this study, many other models attempt to

explain how contingency judgments are formed. One of these is called rule-based theory.

This theory looks at people or even animals as intuitive statisticians who extract

contingency information by applying formulas (Allan, 1993). In other words, animals and

humans act as "calculators" unwittingly. Another theory is associative theory, which looks

at contingency learning as a result of Pavolvian associations formed between all previously

presented events (Allan, 1993). This is based on the Rescorla-Wagner model of learning,

which explains that learning diminishes as the conditioned stimulus becomes more familiar.

This makes the case that contingencies are learned through the repeated presentation of

stimuli. For instance, in Crump et al. (2007), when a red circle is presented after a blue

square, participants learn to associate the circle with the square and form a judgement that

the circle is contingent upon the prior presentation of the square. Signal detection theory

deals with measuring one's ability to differentiate between actual information and random

patterns that distract from it. Based on this theory, contingency judgements are formed

based on how well one is able to separate noise (random pairings) from actual

contingencies. Several factors may influence whether or not one is able to make an accurate

contingency judgement. First, there is a minimum amount of change necessary for one to

tell whether something is different from before. For instance, if someone only changes the

brightness on their phone by 1% would one be able to notice? There is also a minimum

amount of stimulation required in order for someone to be aware that something is

happening. This can occur if a significant amount of time is elapsed between two events, as

one may be less likely to predict that one event caused another. For example, if you eat

spoiled food but do not get sick until three weeks later, you may be less likely to predict

that the food caused the illness than if you got sick the next day. Further, noise

interference also plays a role. This is anything that distracts the participant in some way

while they are trying to focus on the contingency task. Other thoughts, sounds, or objects

in sight can create noise in one's memory. These factors can take away from or add to a

participant's memory of the task. Noise may reduce contingency judgement accuracy.

MINERVA II

MINERVA II is a computational instance theory of human memory (Hintzman, 1984,

1986, 1988). It is conceptually similar to other global-similarity models of memory (Eich,

1982; Murdock, 1993). MINERVA II and related models have been applied to explain

many kinds of cognitive phenomena and processes such as recognition memory (Arndt &

Hirshman, 1998), probability judgment and decision-making (Dougherty, Gettys, & Ogden,

1999), artificial grammar learning (Jamieson & Mewhort, 2009a), serial reaction time task

performance (Jamieson & Mewhort, 2009b), associative learning phenomena (Jamieson,

Crump, & Hannah, 2012), and computational accounts of semantic knowledge (Jamieson,

111 Avery, Johns, & Jones, 2018).

112 In MINERVA 2, memory is a matrix M. Each row represents a memory trace, and
113 the columns represent features of the trace.

114 How do we compute $\triangle$P? $\triangle$P is defined as the contingency between the cue-outcome
115 pairs over trials. "C" and "O" denote cue and outcome, respectively. "~C" denotes that a
116 cue does not occur, and "~O" denotes that an outcome does not occur (Crump et al., 2007).

117 $$\triangle P = P(O|C) - P(O|\tilde{}C) = \frac{A}{A+B} - \frac{C}{C+D}$$

118 How does encoding work? Individual events are represented as feature vectors E, and
119 new events are stored to the next row in the memory matrix M. Individual features are
120 stored with probability L, representing quality of encoding.

121 How does retrieval work? A probe (feature vector for a current event in the
122 environment) is submitted to memory, and causes traces to activate in proportion to their
123 similarity to the probe. Similarity between each trace and the probe is computed with a
124 cosine:

125 $$S_i = cos(\theta) = \frac{A\dot{B}}{||A||||B||}$$

126 $$S_i = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}}$$

127 Where A is a probe and B is a memory trace in M.

128 Activation as function of similarity raised to a power of three.

129 $$A_i = S_i^3$$

130 Each trace is then weighted by its activation (cubed similarity) to the probe, and
131 summed to produce an echo.

132 $$C_j = \sum_{i=1}^{m} A_i \times M_{ij}$$

133 How is a contingency judgment computed? We take the raw values in the outcome
134 portion of the echo as measures of expectation for the outcome given the cue.

Methods

We used RStudio to create a model of memory. Our model was presented with two types of streams, non-contingent and contingent. Non-contingent refers to trials where $\triangle P$ is 0. This means there is no relationship between the cues and outcomes shown, regardless of outcome density. In other words, cues do not predict outcomes, or vice-versa. Contingent refers to trials where $\triangle P$ is .467, where the presence of a cue does foreshadow the presence of an outcome. Each type of stream contained two conditions, low outcome density and high outcome density. Low outcome density refers to a trial in which fewer outcomes were presented than cues. High outcome density refers to trials where more outcomes were presented than cues. Four types of trials can be presented to the model. The model can be presented with a cue and no outcome, no cue and no outcome, a cue and an outcome, or no cue and an outcome. Our model was shown all four combinations. It was then asked to predict, based on all of the combinations that it had been presented with, whether an outcome would occur given that cues were presented first with no outcomes.

MINERVA 2 is a multiple-trace model as it assumes that each experience leaves an individual memory trace Hintzman (1986). In other words, repeated exposure to the same information creates multiple copies rather than strengthening the same memory. MINERVA 2 is mostly focused on long-term memory. However, there is assumed to be a temporary buffer (short-term memory) that relays information to long-term memory Hintzman (1988). The model was programmed in R and the code is presented in Appendix 1.

The original experiment by Crump et al. (2007). involved a blue square being presented as the cue and a red circle being presented as the outcome. Our model presents cues and outcomes to the model as sets of 0s and 1s. 0 being not present, 1 being present. If a cue was presented first (1), it may have either been followed by an outcome (1), or no outcome (0). If no cue was presented first (0), it was either followed by no outcome, or an

161 outcome. In theory, the more cues and outcomes presented, the more accurate the model

162 will be at predicting the presence or absence of each.
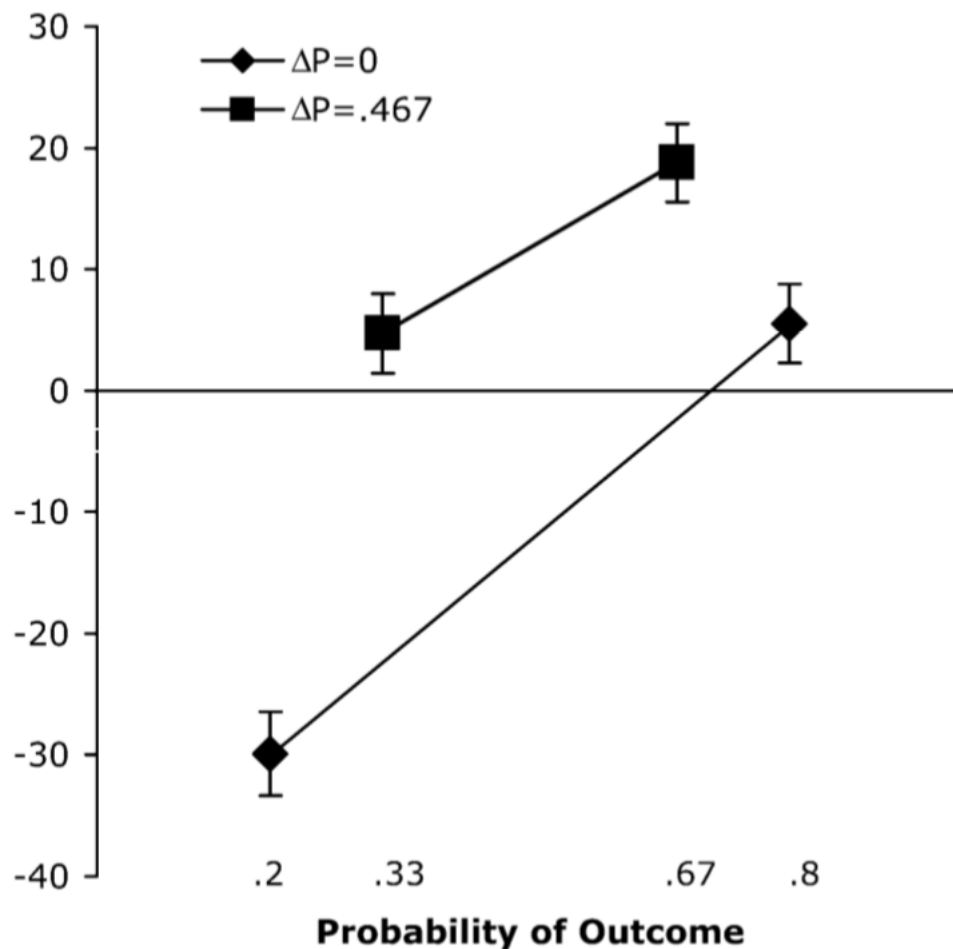
163 **Simulation 1**

164 **Results**

Figure 1. Original results reprinted from Crump et al. (2007)

165   The original results from Crump et al. (2007) are shown in Figure 1. The figure

166 shows that, for non-contingent conditions ($\triangle$P=0, diamond shape), contingency ratings

167 were lower for both low and high outcome density conditions. Participants' contingency

168 ratings were highest overall during contingent conditions ($\triangle$P=.467, diamond shape).

169 However, regardless of stream condition, contingency ratings were always higher when

170 outcome density was larger. This trend indicates that the $\triangle$P effect is present. As shown

171 in the figure, some participants gave negative contingency ratings. This is of particular

172 note, as each condition contained an outcome density greater than or equal to 0. This

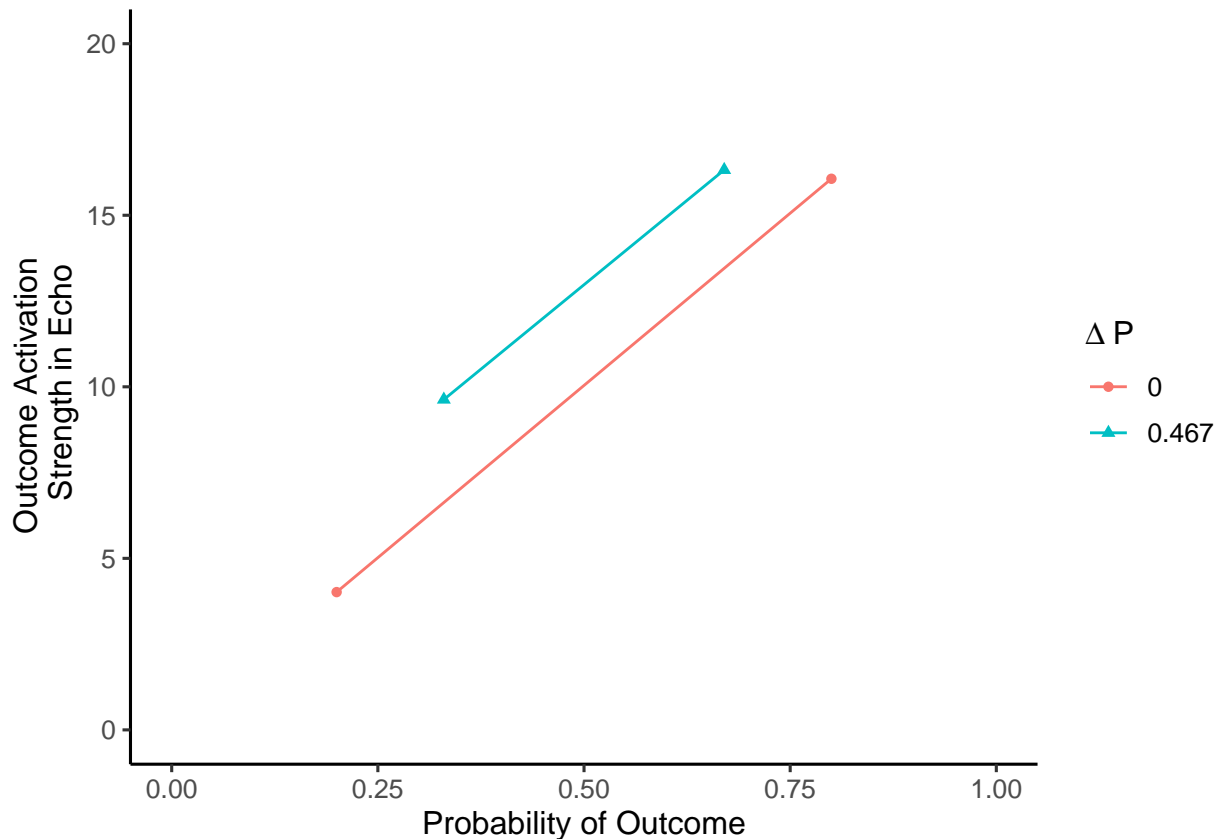173 shows that the outcome density effect is present.

Figure 2. Mean Contingency Ratings Based on Outcome Density

174   Did our MINERVA model produce a similar $\triangle$P effect and outcome density effect to

175 those found in the Crump et al. (2007) study? The results of the model simulations are

176 shown in Figure 2. For both contingent ($\triangle$P=.467) and non-contingent ($\triangle$P=0) streams of

177 data, contingency ratings (Outcome Activation Strength in Echo) were lower when less

178 outcomes were presented (low outcome density, lower Probability of Outcome). Just like

179 the human participants in the original study, our computer model also had higher

180 contingency ratings when more outcomes were presented than cues (high outcome density,

181 greater Probability of Outcome). In contingent conditions, contingency ratings were much

182 higher overall than non-contingent conditions, which, as intended, paralleled the results of

183 the original study.

Discussion

185   The purposes of this experiment were to create a simulated version of the Crump et

186 al. (2007) study. In general, our model was able to replicate several attributes of the

187 in-person study, such as the $\triangle$P conditions and the outcome densities associated with

188 them. This suggests that aspects of contingency judgments can be explained in terms of

189 memory processes.

190   By studying contingency judgements, we can gain a better understanding of factors

191 that influence learning, memory, and eventually decision making. Our results indicate that

192 there is a relationship between the number of times a result is shown, and one's prediction

193 of whether or not they will get that an outcome will occur based on a certain cue. This

194 general principle may have implications in the world of mental health, such as with

195 disorders such as anxiety and depression. For instance, it could be the case that one

196 develops depressive symptoms due in part to what they expect to happen (outcomes),

197 based on previous experiences (cues). Of course, it would require a substantial amount of

198 further research to properly examine how previous experiences shape mental disorders.

Limitations

200   Our model contains several key differences when compared with the original study

201 done by Crump et al. (2007). One major difference between our model and the in-person

202 study is that our simulation did not produce any negative ratings. Specifically, the outcome

density effect was not present. Several factors may explain this result, such as the fact that no human participants were present for our study. In the low outcome density condition ($\triangle$P=0) of the original study, human beings gave negative ratings. This was likely due to the outcome density effect. This phenomenon was not present in our simulation data. Another factor that may explain this result is overlooked variables when creating our model. It is possible that we neglected to code for some aspect of attention or memory.

Future Research

In order to create a model that produces results that are more accurate to the original study, we plan on creating a negative contingency condition. This condition would set $\triangle$P equal to -.467, meaning that the precense of a cue would predict the absence of an outcome. This has the potential to make the model more likely to give negative ratings of contingency.

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