Memory and Representativeness

Bordalo et al. (2019) NBER WP

Discussed by Silvio Ravaioli

February 25, 2020

The Model

Cocktail party summary of the model

Representativeness example as in Tversky and Kahneman (1972)

- Description of an introvert man
- How likely he is a librarian or a food delivery driver?

50 years after, we are still looking for a good explanation for it

- This bias comes from a "kernel of truth:" based on our experience, $Pr(\text{introvert}|\text{librarian}) > Pr(\text{introvert}|\text{food driver})$, so the trait introvert is "diagnostic"
- When asked to assess $Pr(\text{librarian}|\text{introvert})$, we sample from our memory of introvert people, and introvert-librarian come to mind more easily

Cocktail party summary of the model

Representativeness example as in Tversky and Kahneman (1972)

- Description of an introvert man
- How likely he is a librarian or a food delivery driver?

50 years after, we are still looking for a good explanation for it

- This bias comes from a "kernel of truth:" based on our experience, $Pr(\text{introvert}|\text{librarian}) > Pr(\text{introvert}|\text{food driver})$, so the trait introvert is "diagnostic"
- When asked to assess $Pr(\text{librarian}|\text{introvert})$, we sample from our memory of introvert people, and introvert-librarian come to mind more easily

Interference in Judgment by Representativeness

Selective recall (episodic memory)
Two forms of interference in the retrieval process

- Interference across types **within** a group (base-rate neglect)
  Within introvert people, a librarian is more stereotypical than a farmer - recalled more often
- Interference **across** groups (contrast)
  The type (farmer) relatively more common in other groups (extroverts) is less diagnostic - recalled less often

The Model 1/3 - Setup

- Memory database: probability space, with event space Ω and probability measure P
- Joint distribution of two random variables T (type) and G (groups) defined on (Ω, P)
- Task: assess conditional probabilities $Pr(\text{type}|\text{group})$
- Example: guess the occupation based on the personality $Pr(\text{t=librarian} \mid \text{g=introvert})$

The Model 2/3 - Ease of recall

Generalized (distorted) agent

$$\tilde{P}(t|g) = P(t|g)\frac{M\Big(P(t|g), P(t|-g)\Big)}{\mathbb{E}(M)}$$

Higher M: easier to recall t when thinking about g

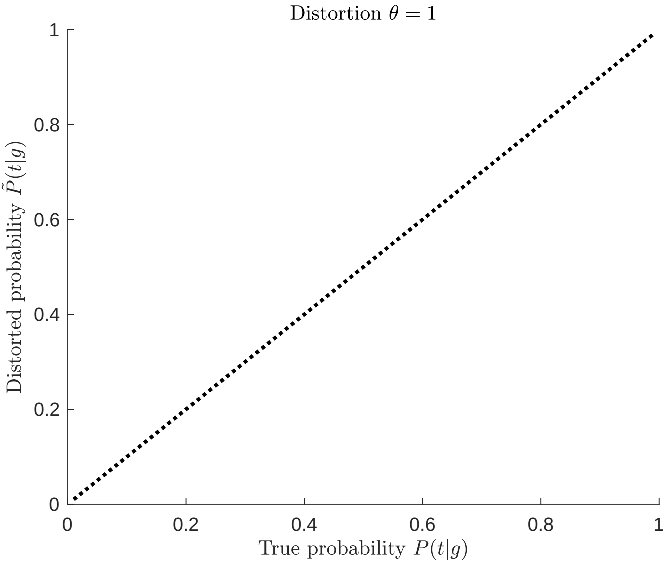
$$\frac{\partial M}{\partial P(t|g)} > 0 \qquad \frac{\partial M}{\partial P(t|-g)} > 0$$

Example of functional form for the ease of recall M:

$$M\Big(P(t|g), P(t|-g)\Big) = \left[\frac{P(t|g)}{P(t|-g)}\right]^{\theta}$$

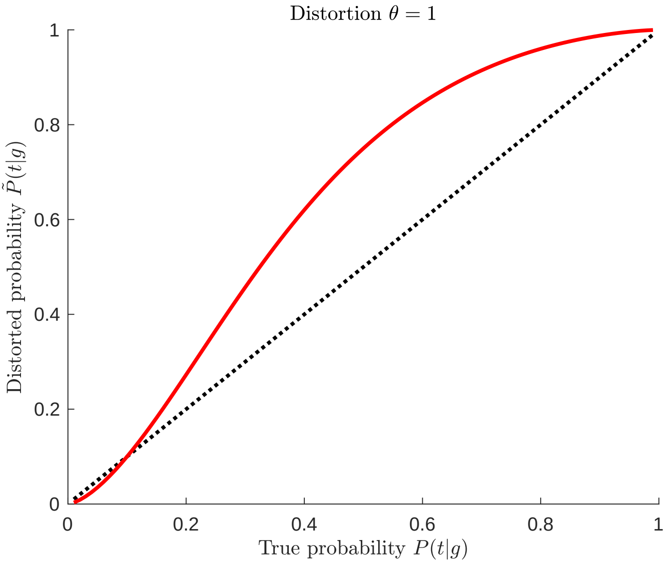
where $\theta \geq 0$ captures the distortion of judgments [BCGS 2016]

The Model 2/3 - Ease of recall (Simulation)



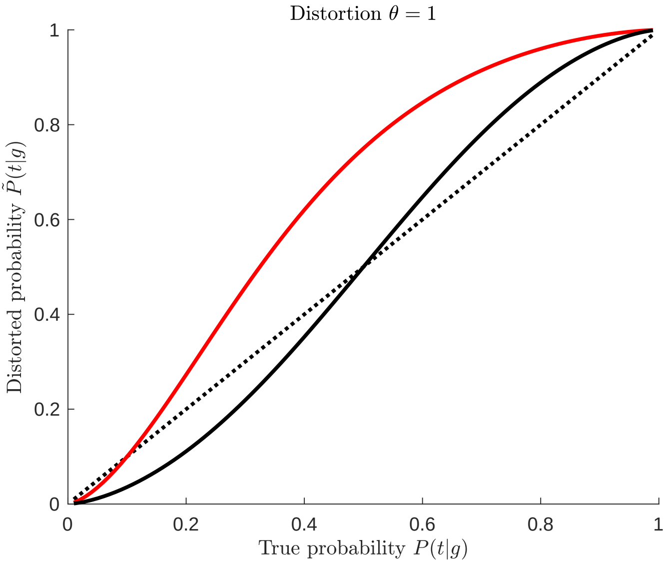
Lines for $p(t|-g)$ = 0.1 (red), $p(t|-g)$ = 0.5 (black), $p(t|-g)$ = 0.9 (blue)

The Model 2/3 - Ease of recall (Simulation)



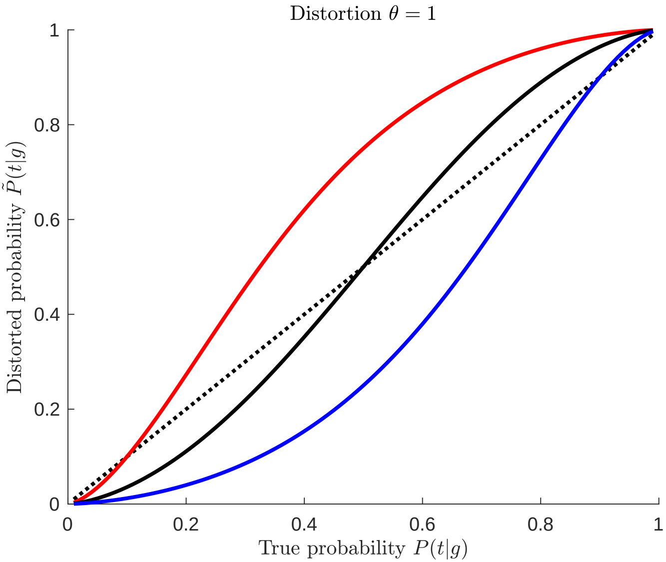
Lines for $p(t|-g)$ = 0.1 (red), $p(t|-g)$ = 0.5 (black), $p(t|-g)$ = 0.9 (blue)

The Model 2/3 - Ease of recall (Simulation)



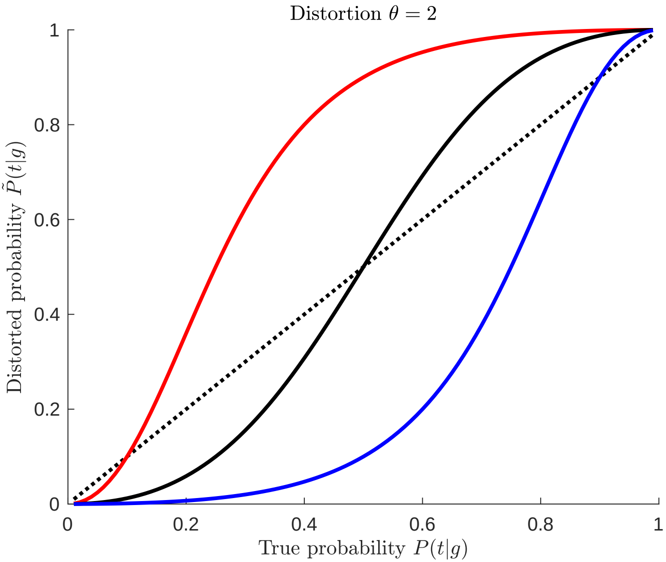
Lines for $p(t|-g)$ = 0.1 (red), $p(t|-g)$ = 0.5 (black), $p(t|-g)$ = 0.9 (blue)

The Model 2/3 - Ease of recall (Simulation)



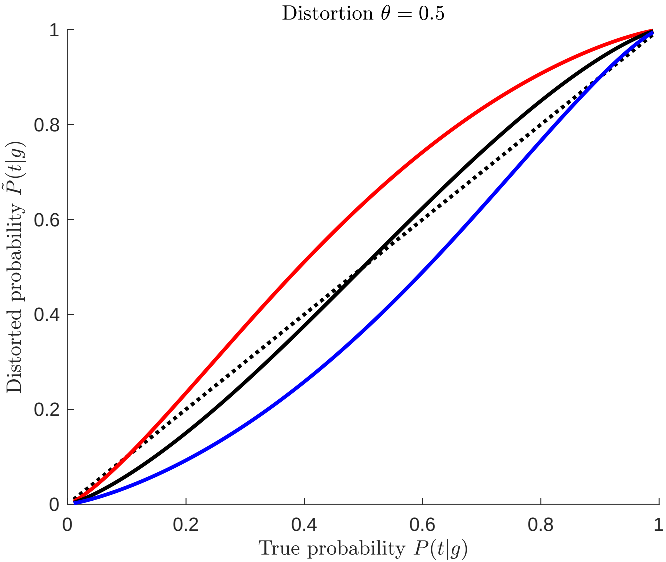
Lines for $p(t|-g)$ = 0.1 (red), $p(t|-g)$ = 0.5 (black), $p(t|-g)$ = 0.9 (blue)

The Model 2/3 - Ease of recall (Simulation)



Lines for $p(t|-g) = 0.1$ (red), $p(t|-g) = 0.5$ (black), $p(t|-g) = 0.9$ (blue)

The Model 2/3 - Ease of recall (Simulation)



Lines for $p(t|-g)$ = 0.1 (red), $p(t|-g)$ = 0.5 (black), $p(t|-g)$ = 0.9 (blue)

The Model 3/3 - Predictions

Representativeness is captured by the ratio $\frac{P(t|g1)}{P(t|g2)}$

1. (Exp 1) The ratio $\frac{\tilde{P}(t1|g1)}{\tilde{P}(t2|g1)}$ increases when we increase $Pr(t2|g2)$ (add more blue words)
2. (Exp 2) The ratio $\frac{\tilde{P}(t1|g1)}{\tilde{P}(t2|g1)}$ decreases when we increase $Pr(t1|g2)$ (add more orange words)
3. (Exp 3) The ratio $\frac{\tilde{P}(t1|g1)}{\tilde{P}(t2|g1)}$ is higher
   when we cue $g2$ ($t1$ is representative $P(t1|g2) = 0$)
   than $g3$ ($t1$ is NOT representative $P(t1|g3) = 1$)

where $P(t1|g1) = P(\text{orange}|\text{number})$ [study 1/2]

Memory and Representativeness

Bordalo et al. (2019) NBER WP

Discussed by Silvio Ravaioli

February 25, 2020

Possible issues with the model

- Definition of types and groups (and their complements). In general, we do not have a distinction between types and groups (they are just two RVs that characterize each stimulus)
- If we have >2 dimensions (as in the third study: color/size/category, but without recall), is there interaction between dimensions?
- Not according to the factor $M\Big(P(t|g), P(t|-g)\Big)$, but some types can be more representative of various sub-groups (further distortion)
- Not obvious why we want to assume the comparison $g/-g$ instead of a series of pairwise comparisons $g1/g2$

More testable predictions?

We have now "a foundation for the kernel of truth" - but can we get a micro-foundation?

- **Natural connection with Vlaev's paper!**
- The model talks about about recall from the memory database but it is very agnostic about *how* this happens
- What mental *process* would generate the function M?
- Connection with the memory literature (stimuli recall task) Are representative stimuli recalled more often?
- Connection with models of sampling Predictions in terms of response time (number of samples required to stop)

The Experiments

Study 1.

Participants are shown a sequence of 50 abstract images that vary along two dimensions, **content** and **color**. They are randomly assigned to one of two treatments:

- condition in which they see 10 orange numbers, 15 blue numbers and 25 gray shapes (*gray* treatment)
- condition in which they see the same 10 orange numbers and 15 blue numbers, but also 25 blue words (the blue treatment)

Participants are asked several questions:

1. "An image was randomly drawn from the images that were just shown to you. The chosen image showed a number. What is the likely color of the chosen image?"
2. "What is the probability the number is orange?"
3. "How many orange numbers were shown to you?"
4. "How many blue numbers were shown to you?"

Study 1.

Predictions:

1. If $\gamma > 0$, the blue treatment reduces the assessed likelihood that the randomly drawn number is blue in Q1 and Q2 relative to the gray treatment. If $\gamma = 0$ there is no treatment effect.
2. If $\gamma > 0$, the blue treatment reduces the share of blue numbers recalled in Q3 and Q4 relative to the gray treatment. There is also a positive correlation at the individual level between the share of blue numbers recalled from Q3 and Q4 and the assessed likelihood of the number being blue in Q1 and Q2. If $\gamma = 0$ there is no treatment effect.

Study 2.

Strength of contextual interference is manipulated by creating five new variants of the *decoy data*.

- Denote by $blue_k$ a treatment in which k blue words are replaced with orange words.
- The authors allow for six such treatments varying the frequency of orange words $k \in \{0, 1, 3, 6, 10, 22\}$.

Prediction:

- If $\gamma > 0$, the assessed probability that a random number is orange in Q1 and Q2 and the share of recalled orange numbers in Q3 and Q4 decrease with the number of orange words k in the decoy distribution. If $\gamma = 0$ there is no treatment effect.

Study 3.

The authors test whether the features of the task that shape perceptions of similarity affect memory retrieval and thus probability judgments, even if they are normatively irrevelant.

- Following the design of Study 1, images are characterized by G (content) and T (color).
- Additionally, the images vary in font size $T' \in \{small, large\}$
- All orange numbers are large and all blue numbers are small, while all words are blue and large.

Two treatment groups are different in questions asked:

1. "What is the likely color of a randomly drawn number?"
2. "What is the probability of a randomly drawn number being orange?”

Study 3.

Prediction:

1. If $\gamma > 0$, the share of recalled orange/large numbers and the assessment of the probability that a random number is orange/large is higher in the color treatment than in the size treatment. If $\gamma = 0$ there is no treatment effect.

Results

Study 1: Baseline Experiment.

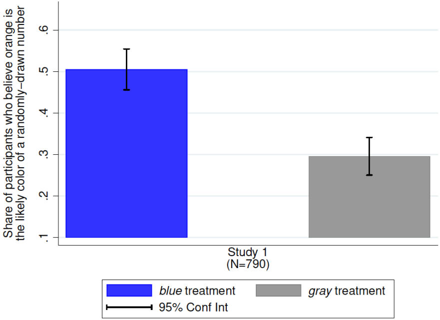
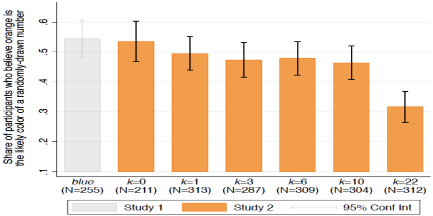
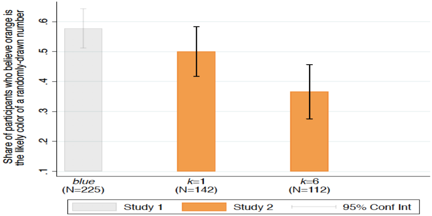


Figure 1: Share of participants who believe that the likely color of a randomly-drawn number is orange for the *blue* and *gray* treatments of Study 1.

Study 2: Varying Relative Likelihood.



(a) Conducted with MTurk



(b) Conducted in Laboratory

Figure 2: Share of participants who believe that the color of a randomly-drawn number is most likely orange for the *blue* treatments with $k = 0, 1, 3, 6, 10, 22$.

Study 3: Modulating Recall through Cues.

Table 5: Regression estimates of treatment effects in Study 3

	OLS: Y=1 if "orange OR large is likely"	OLS: Y= 1 if more orange OR large numbers recalled	0.5-Q-Reg: Y= Share of orange OR large to total numbers recalled	0.5-Q-Reg: Y= Probability that a randomly-drawn number is orange OR large
	(1)	(2)	(3)	(4)
1 if color cue	.2296***	.1168***	.04**	.05**
	(.0343)	(.0341)	(.0178)	(.0218)
Wave dummy	yes	yes	yes	yes
Constant	.1808***	.1953***	.41***	.35***
	(.0293)	(.0291)	(.0152)	(.0186)
Observations	647	647	647	647
Adj./Ps. R^2	0.06	0.02	0.01	0.01