潘晚坷

上海师范大学

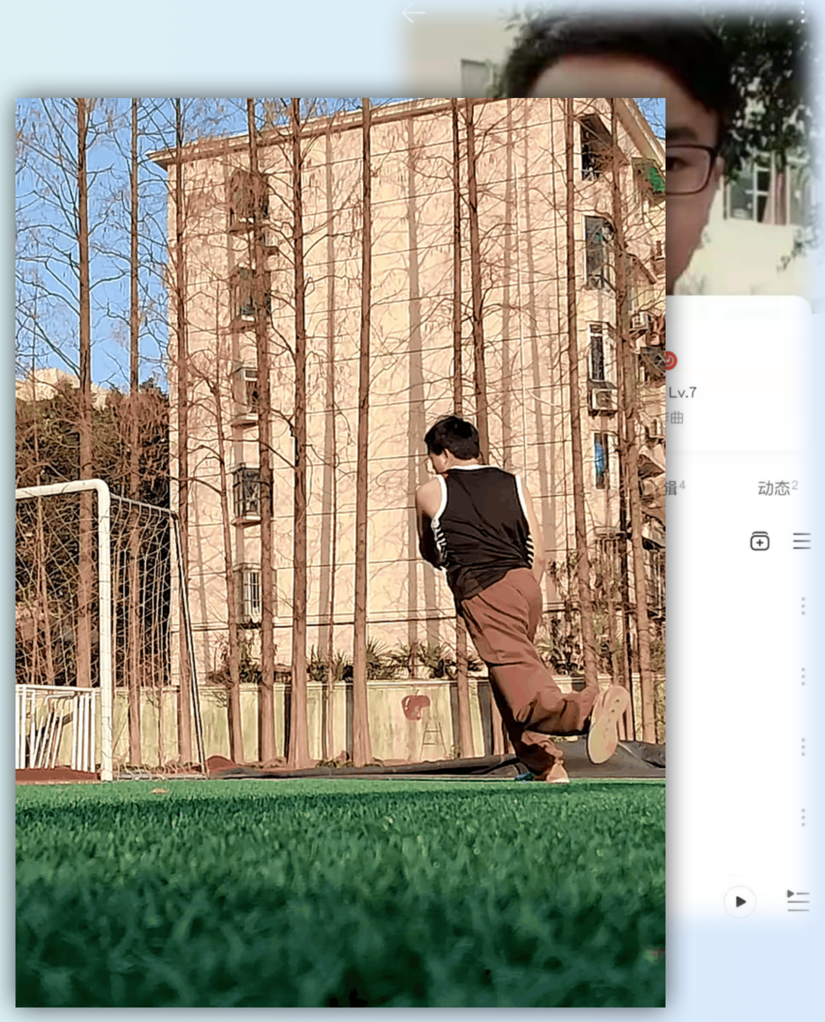
基础心理学：社会计算认知

导师：胡天翊副教授

研究主题：谣言传播

关注主题：行为决策，计算神经，
进化，复杂科学，哲学

兴趣爱好：音乐，跑酷，围棋



Biased evaluations emerge from inferring hidden causes

Shin, Y. S., & Niv, Y. (2021)

Nature Human Behaviour

https://doi.org/10.1038/s41562-021-01065-0

2021. 4. 29

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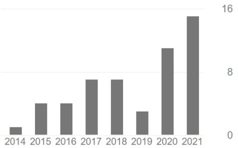

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Neural correlates of social perception on response bias YS Shin, H Kim, S Han Brain and cognition 88, 55-64	2	2014
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Reinforcement learning in the brain Y Niv Journal of Mathematical Psychology 53 (3), 139-154	568	2009
Orbitofrontal cortex as a cognitive map of task space RC Wilson, YK Takahashi, G Schoenbaum, Y Niv Neuron 81 (2), 267-279		
Reinforcement learning: the good, the bad and the ugly P Dayan, Y Niv Current opinion in neurobiology 18 (2), 185-196		
Hierarchically organized behavior and its neural foundations: a reinforcement learning perspective MM Botvinick, Y Niv, AG Barto Cognition 113 (3), 262-280		
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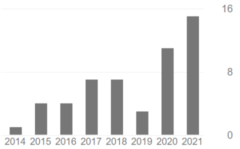

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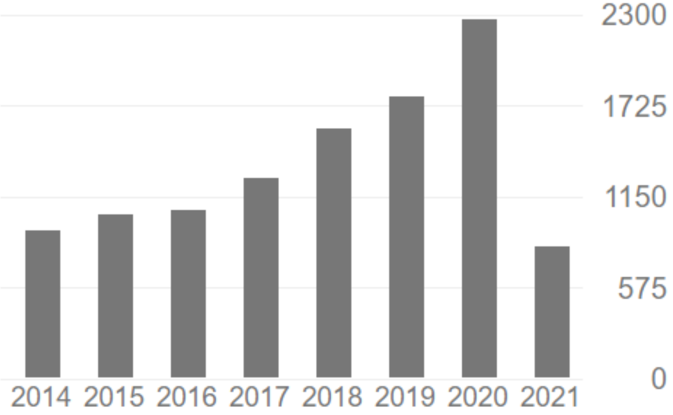

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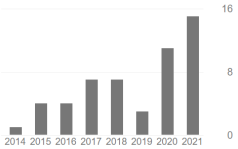

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Opening burton's clock: Psychiatric insights from computational cognitive models D Bennett, Y Niv	5	2018
The two cultures of computational psychiatry D Bennett, SM Silverstein, Y Niv JAMA psychiatry 76 (6), 563-564	25	2019

Biased evaluations

Negativity bias

Introduction

Biased evaluations

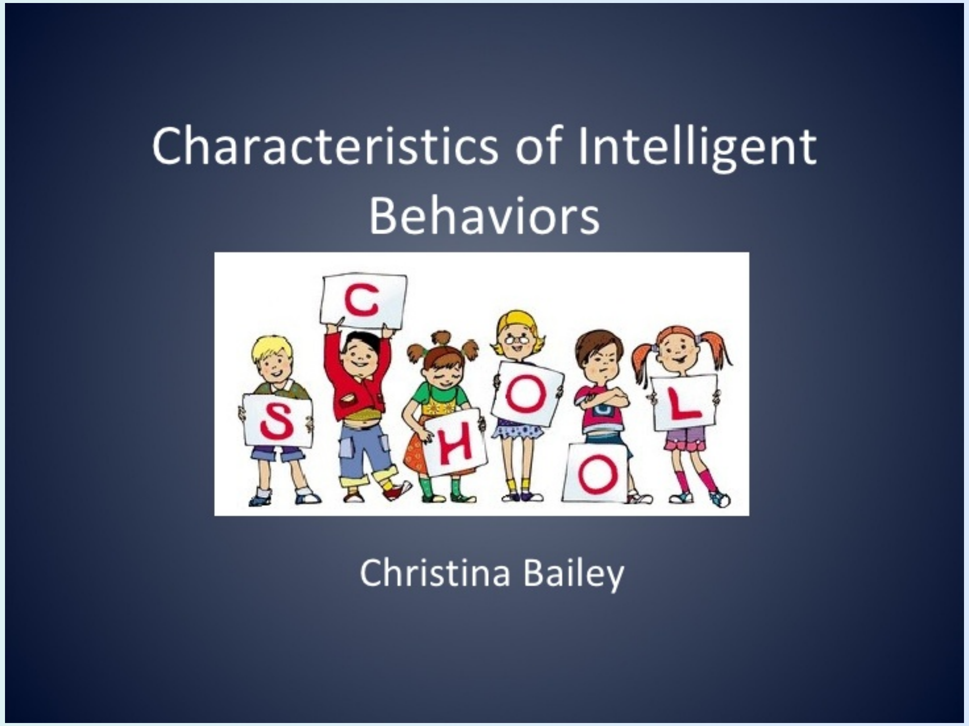
Negativity bias

Diagnosticity of information

An intelligent person defined by the diagnostic intelligent behaviors even when unintelligent behaviors are observed more frequently.

Positive events are often the default, making negative events more diagnostic.

Similarity between negative words is judged to be lower than between positive words(Alves, 2015).



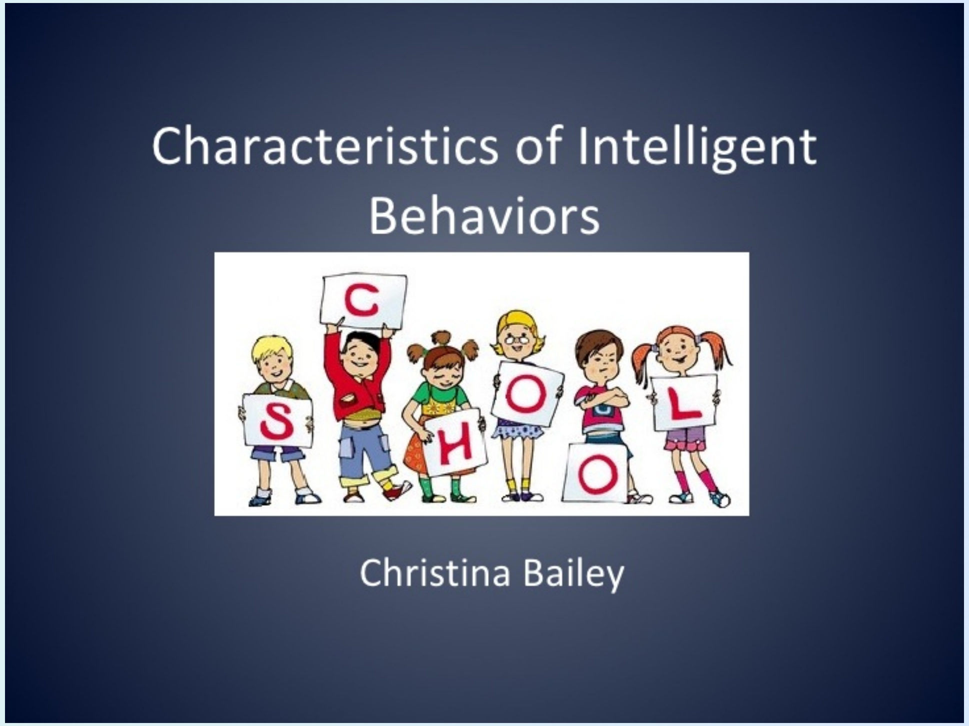
Introduction

Biased evaluations

Negativity bias

Diagnosticity of information

Rare Heterogeneity Wight



Introduction

Biased evaluations

Negativity bias

Diagnosticity of information

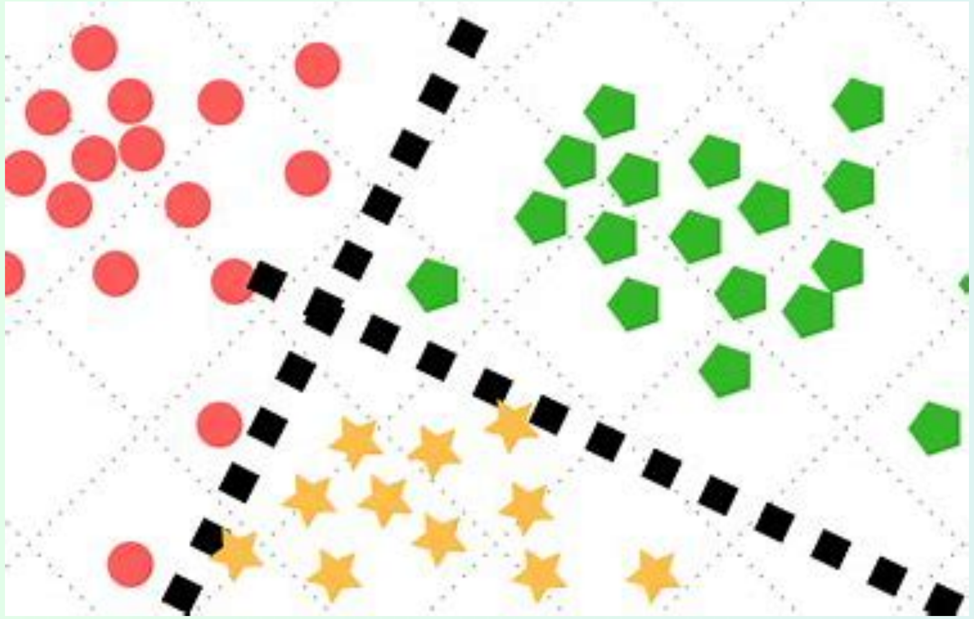
Impression formation

Introduction

Hidden causes

Post-hoc impression

Introduction



Hidden causes

Post-hoc impression

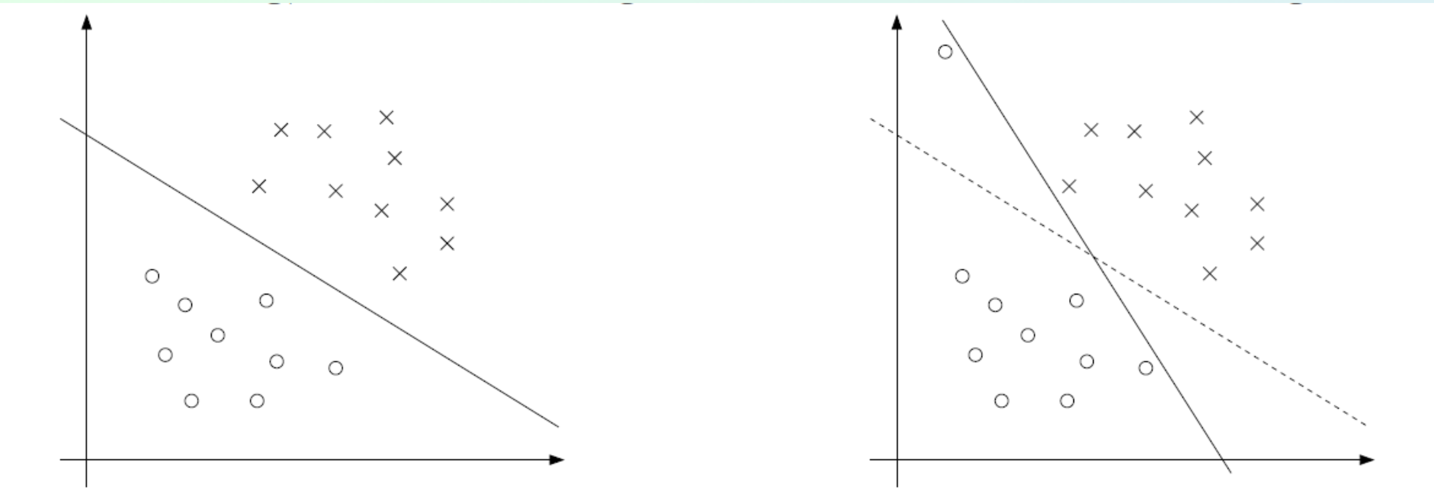
Latent causes

We cannot remember every single things. Therefore, we might lump together different similar experiences.

e.g. processing of a positive word is faster due to a large cluster of positivity.

Reason cause post reasoning.

Introduction



Hidden causes

Post-hoc impression

Latent causes

Sparsity of events

Sparse events get less similarity.

Sparse events produce more latent causes.

Sparse events carry more weight evaluation.

Introduction

Biased evaluations

Negativity bias

Diagnosticity of information

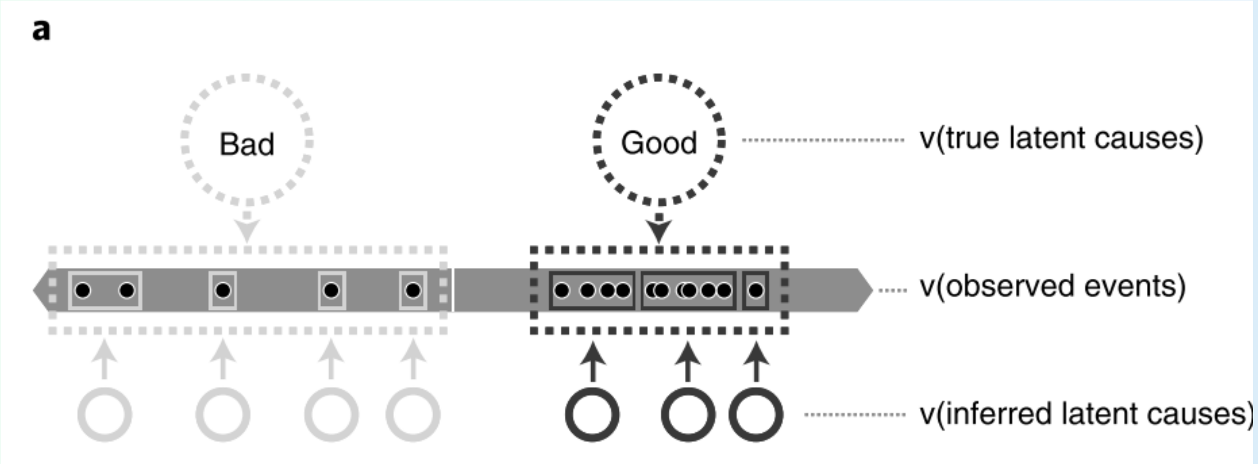
Impression information

Hidden causes

Post-hoc impression

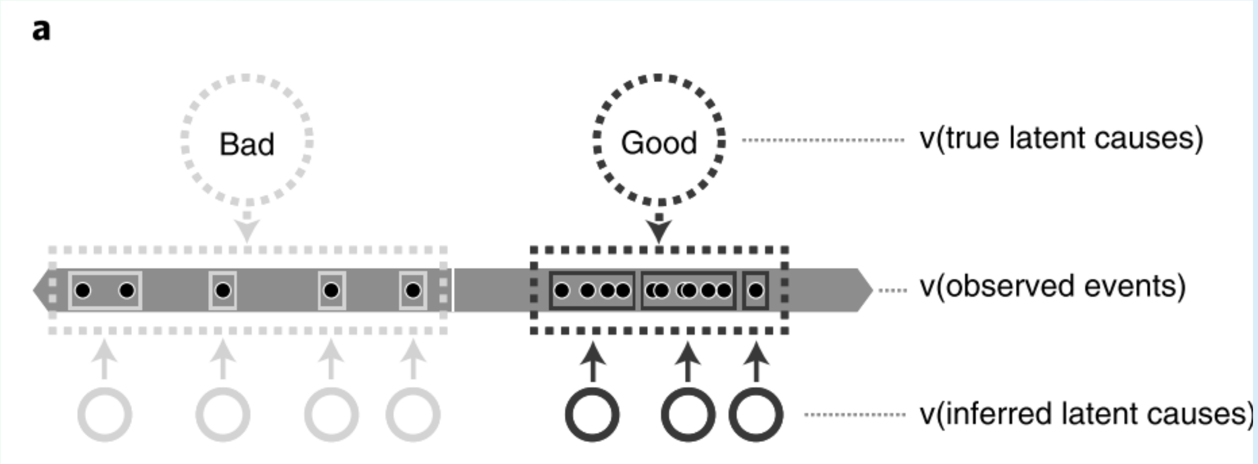
Latent causes

Sparsity of events



Hypothesis

The negativity bias emerges from the combination of normative segmentation of information into causes based on similarity and incorrectly weighted averaging over latent causes.



Experimental Procedure

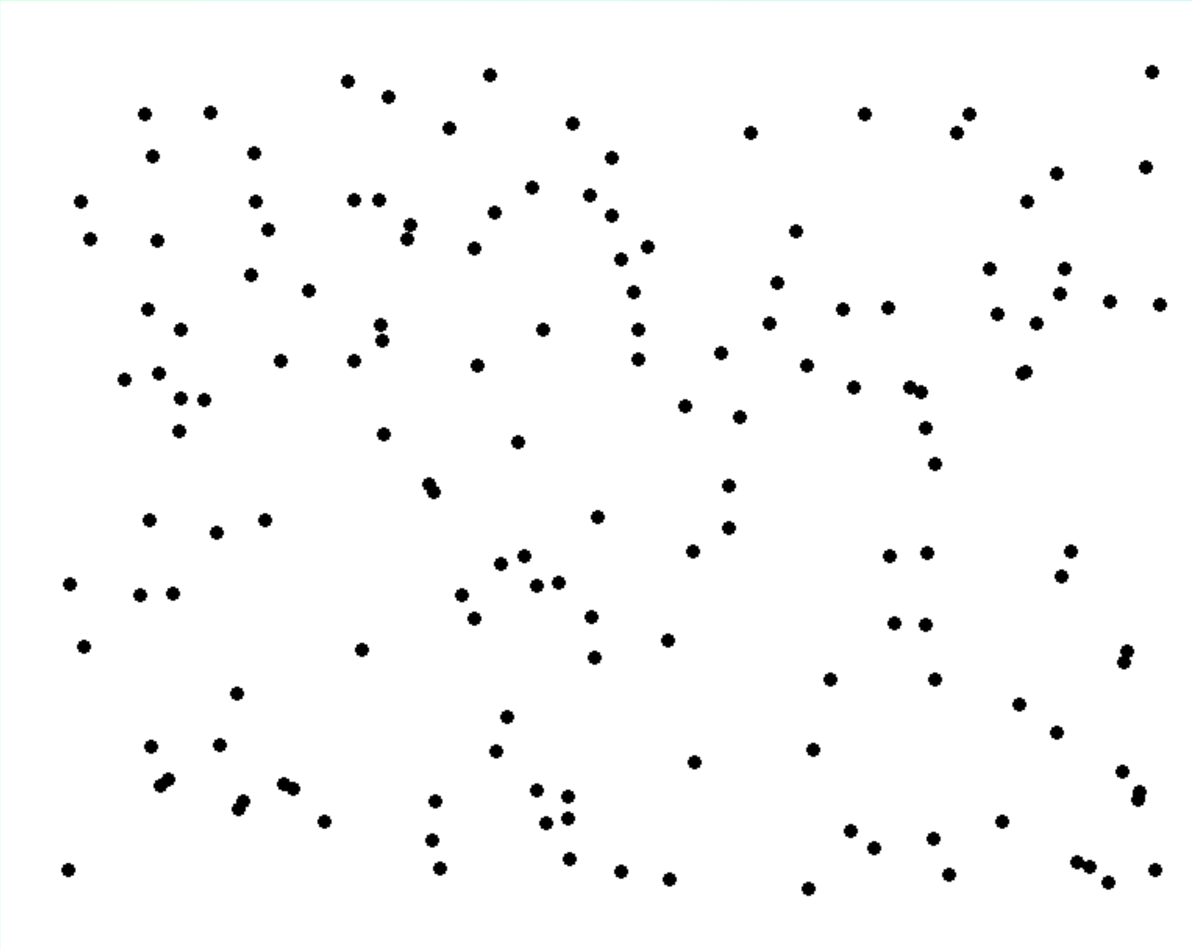
You were visiting different schools for fundraiser events.

Your job was to log the donation amounts.

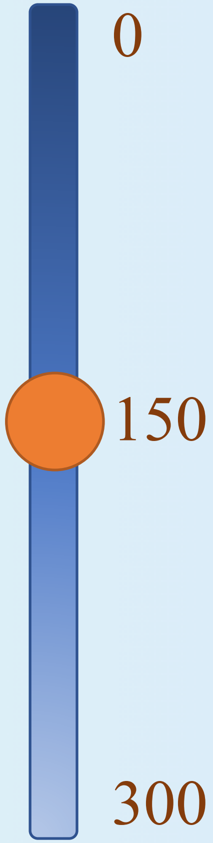
40 donors making donations in each school.

Each donor made a single donation with coins, ranging from 1 to 300 coins.

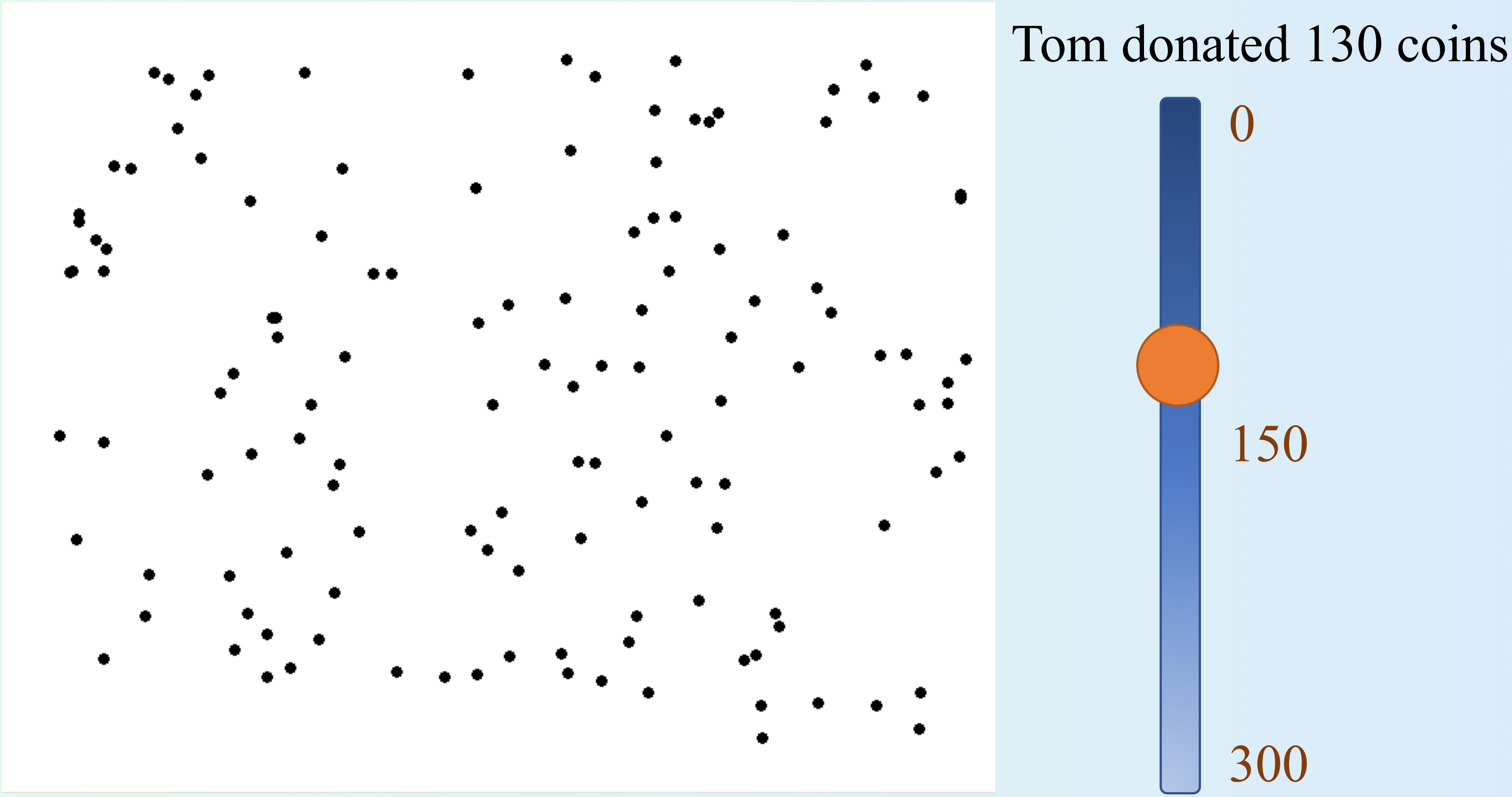
Experimental Procedure



Gregory donated 150 coins



Experimental Procedure



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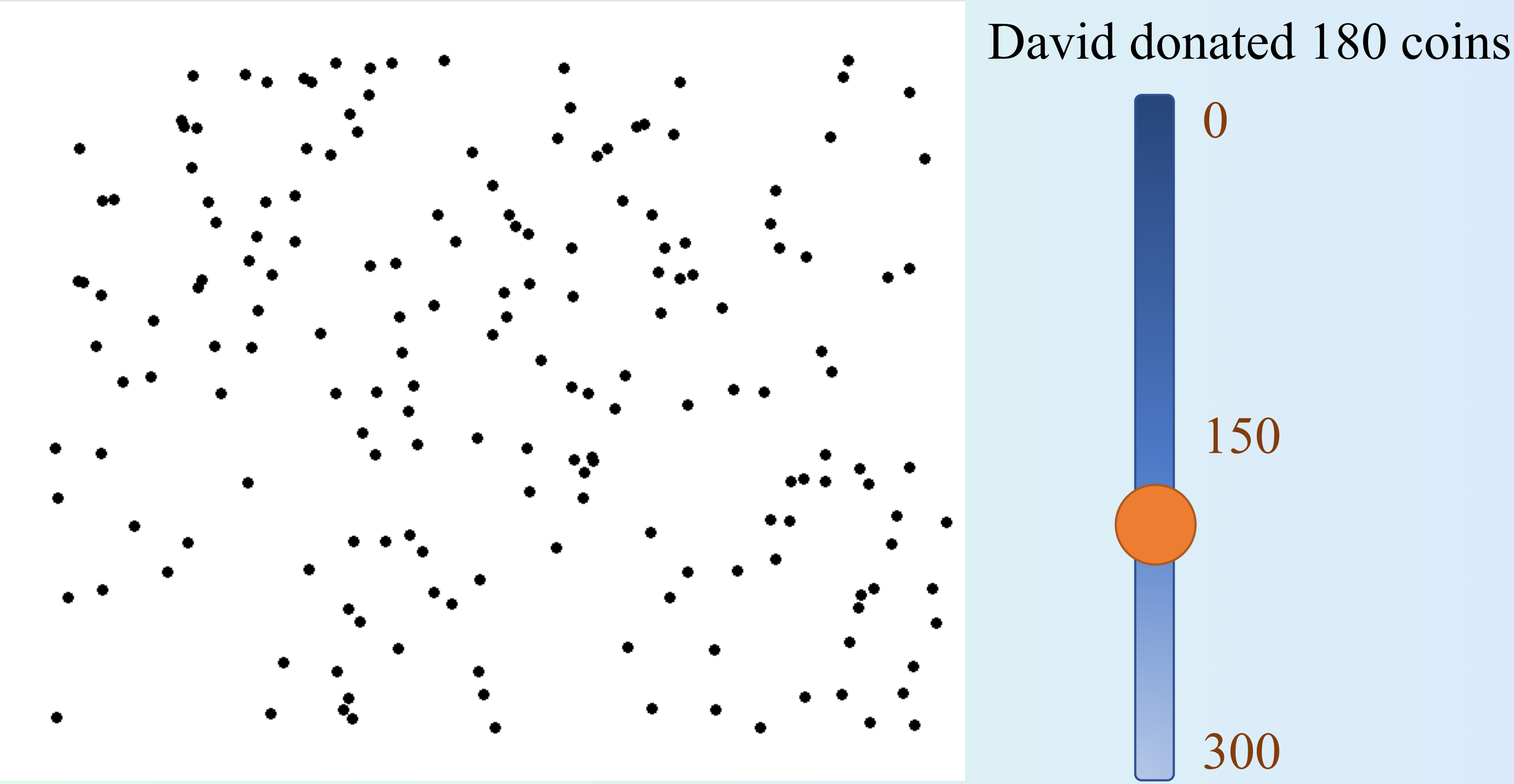
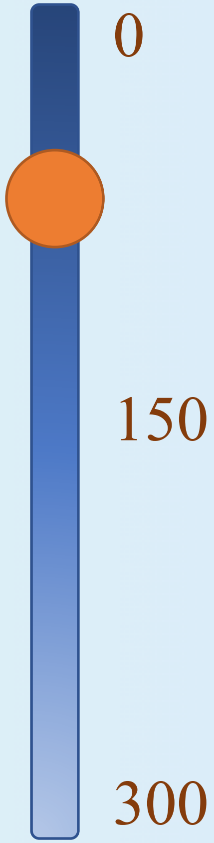
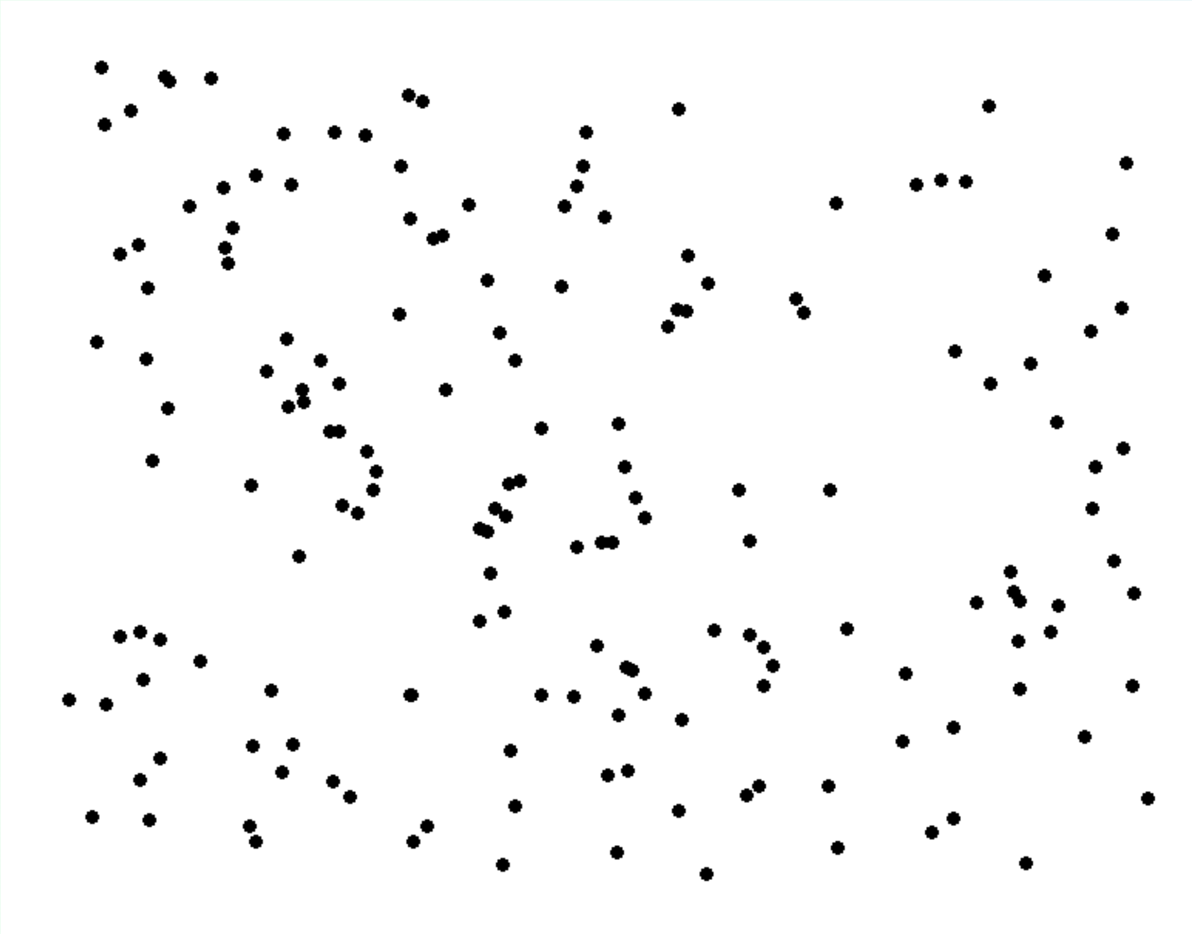


Experimental Procedure

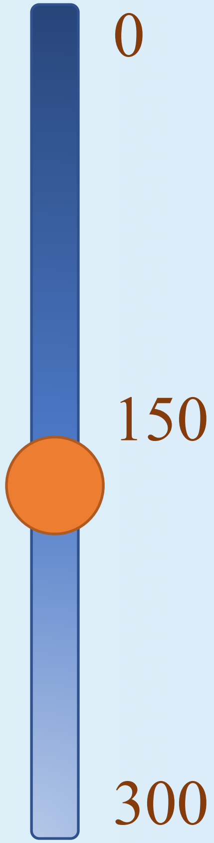
Thomas donated 60 coins



Experimental Procedure

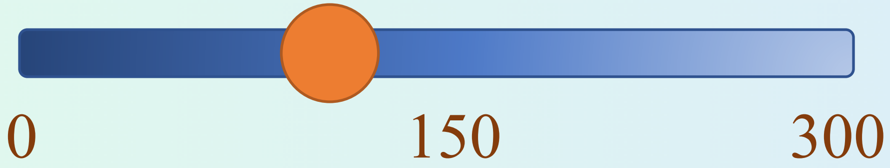


Belly donated 170 coins

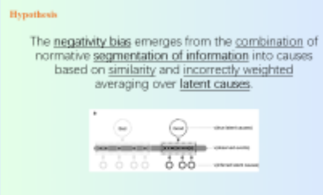


Experimental Procedure

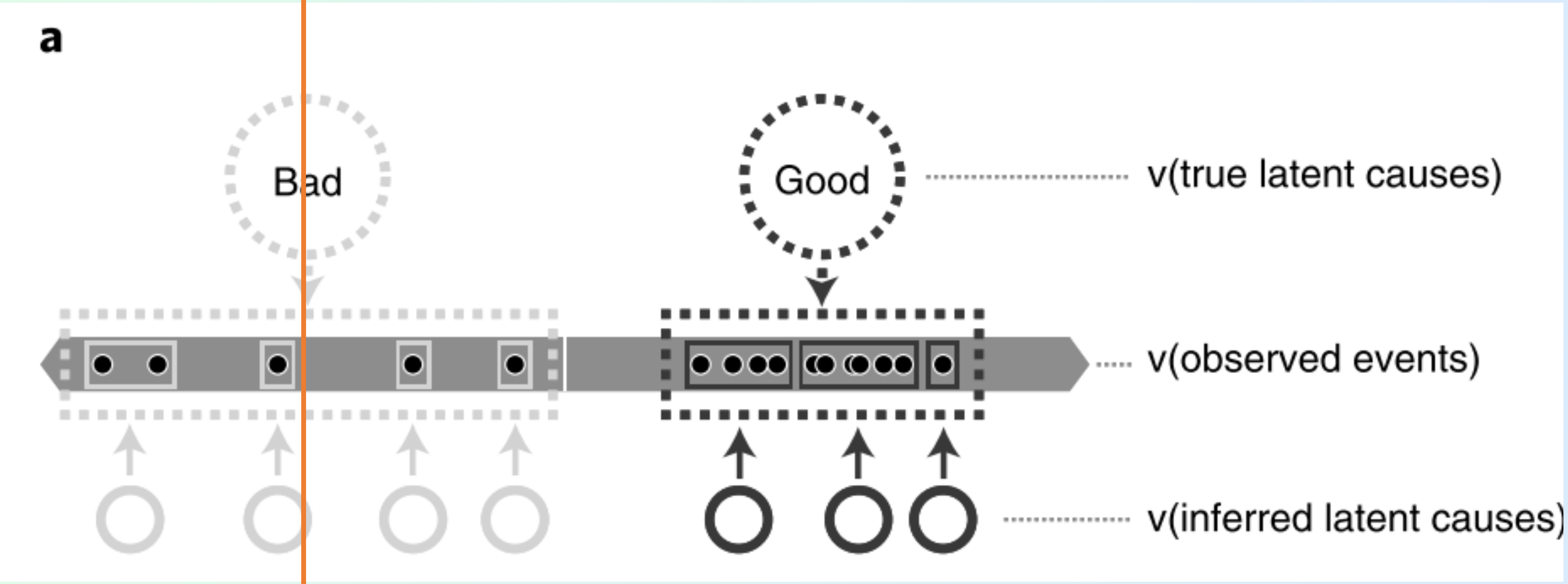
How many the average donation amount is?

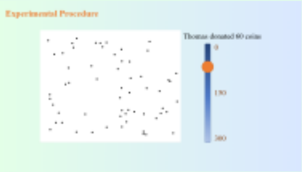


Experiment Design



Negativity bias: estimate of average donation amount was low than **true mean(150)**



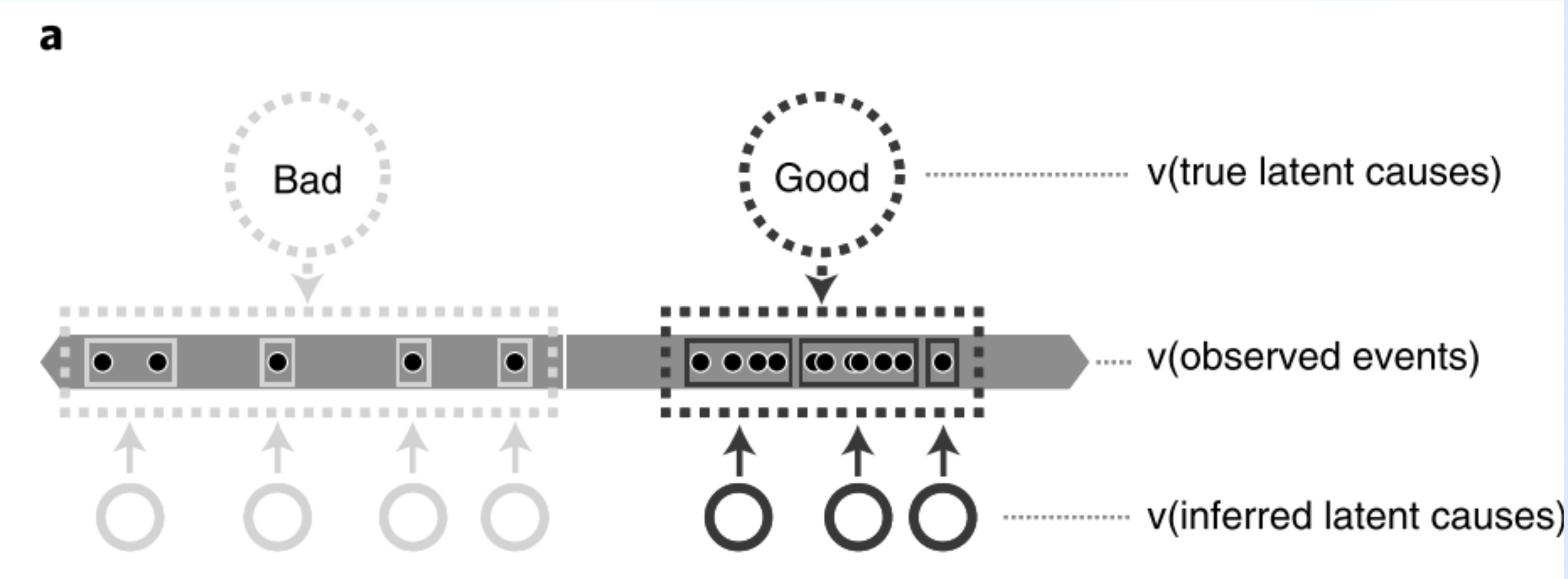


Sparse:
diagnostic
information

Dense

Experiment Design

Impression: Thomas is “stingy”



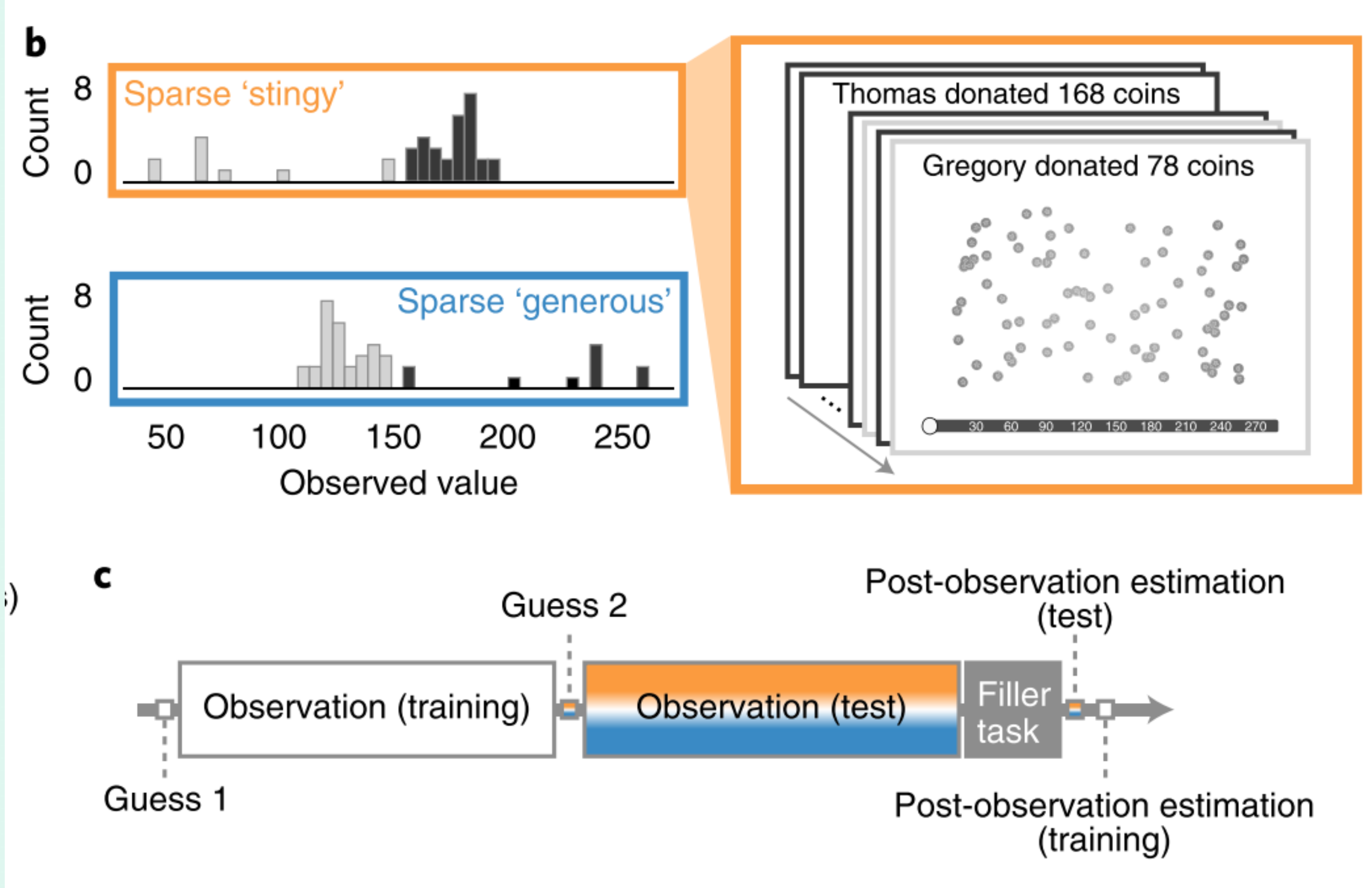
Post-hoc impression:
to infer other people

Latent cause:

Experiment Design

Tow conditions:

Experimental procedure:



Results: Experiment 1A (N = 76)

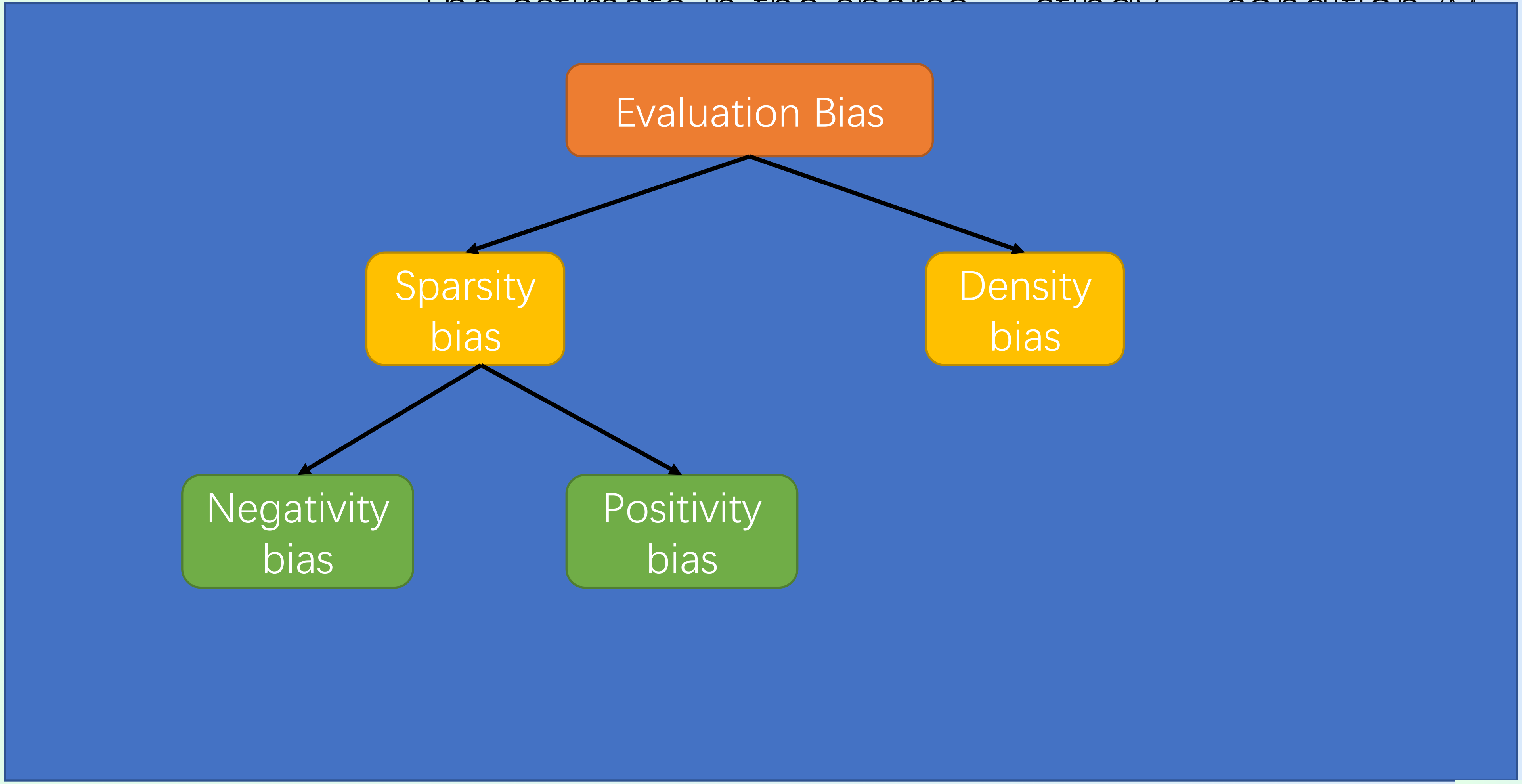
The estimate in the sparse 'stingy' condition ($M = -0.020$)
significantly below ($t(74) = -2.744$, $P = 0.008$)
the estimate in the sparse 'generous' condition ($M = 0.024$)

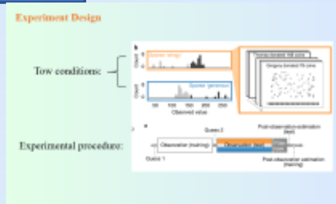
The results suggested that sparse donation amount caused the sparsity bias

Results: Experiment 1A (N = 76)

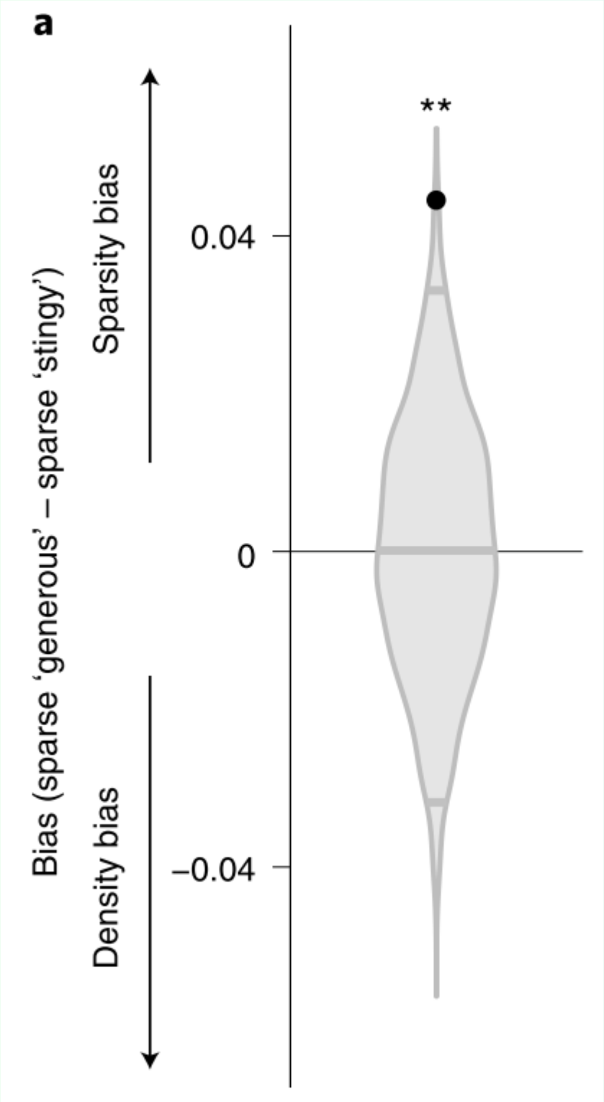
The estimate in the sparse ‘stingy’ condition (M −0.020)

= 0.024)





Results: Experiment 1A (N = 76)



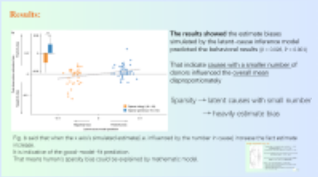
The estimate in the sparse 'stingy' condition (M = −0.020) significantly below ($t(74) = -2.744$, $P = 0.008$) the estimate in the sparse 'generous' condition(M = 0.024)

The results suggested that sparse donation amount caused the sparsity bias($t(41) = 2.772$, $P = 0.008$)

But how do we know the sparse condition lead to latent cause and then lead to the sparsity bias?

Figure a. y axis is bias (sparse 'generous' – sparse 'stingy')

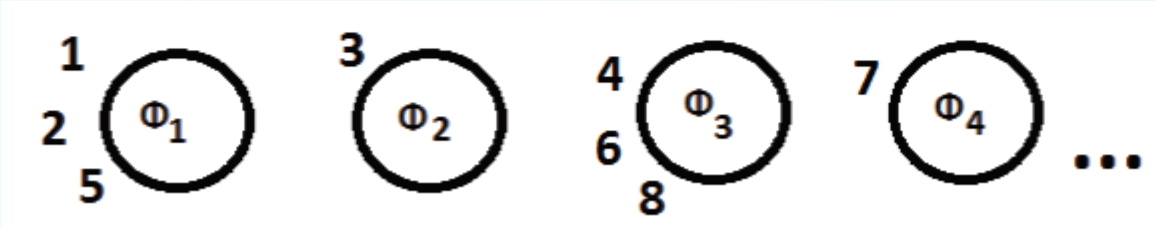
- Density bias means that estimate appeal to be consistent with the majority other than the true mean.
- Sparsity bias means that estimate appeal to the extreme value other than the true mean.

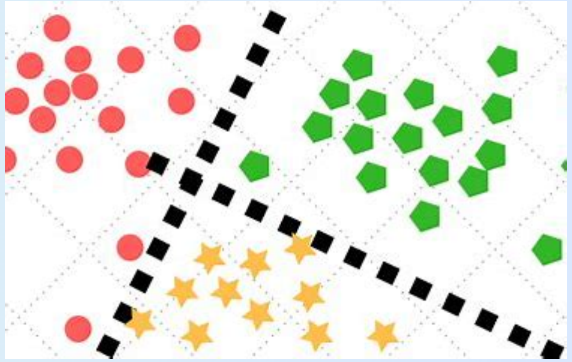


Model: (Gershman & Blei, 2012)

How do we connect our data to latent cause?

Chinese Restaurant Process

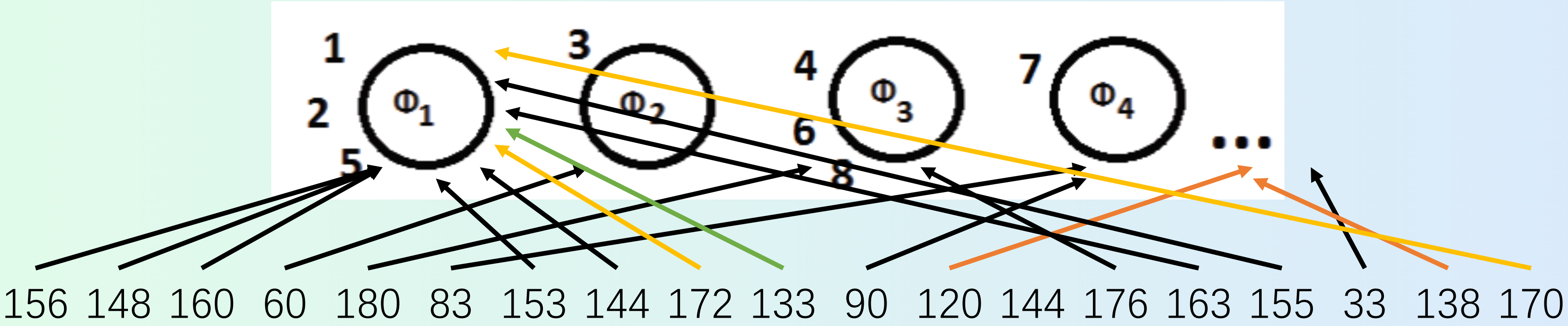




Input: donations by each donor

Output: distribution over the number of latent cause

Model:



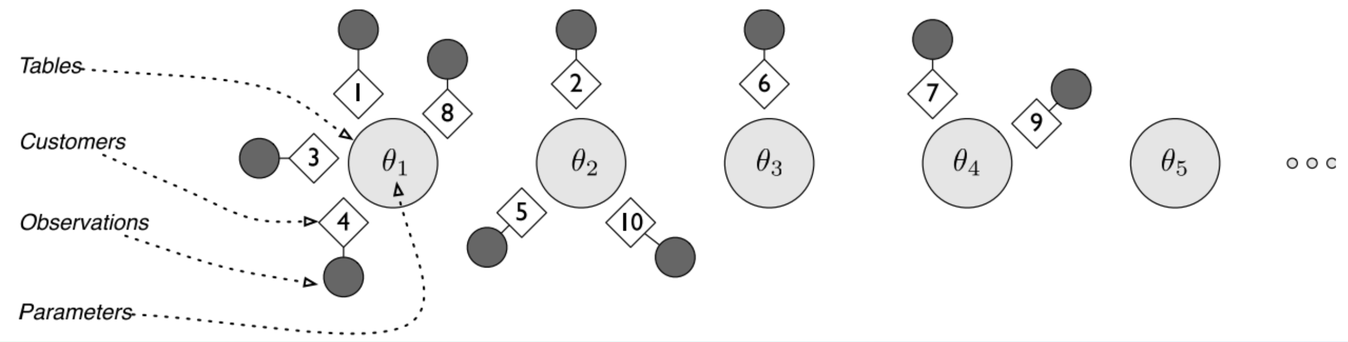
Input: donations by each donor

Output: the number of latent cause

+ estimation

Algorithm: (Gershman & Blei, 2012)

Chinese Restaurant Process



$$p(Z = k) = \begin{cases} \frac{n_k}{\sum n_k + \alpha} & \text{if } k \text{ is an old cause} \\ \frac{\alpha}{\sum n_k + \alpha} & \text{if } k \text{ is a new cause} \end{cases},$$

Z denote the choice to latent cause(table)
k is table indexes
α influence the prior tendency to new table
n_k is the number of observations in table k

Algorithm:

Chinese Restaurant Process

CPR Process

$$p(Z=k)=\begin{cases}\frac{n_k}{\sum n_k+\alpha} & \text{if } k \text{ is an old cause}\\ \frac{\alpha}{\sum n_k+\alpha} & \text{if } k \text{ is a new cause}\end{cases},$$

CPR Mixture

$$p(x_t \in k|\{x_i\}_k)=\sum_{h'\in H} p(x_t \in k|\{x_i\}_k, h')p(h'|\{x_i\}_k)$$

$$p(h'|\{x_i\}_k)=\frac{p(\{x_i\}_k|h')p(h')}{\sum_{h\in H} p(\{x_i\}_k|h)p(h)},$$

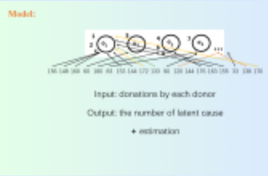
$$p(\{x_i\}_k|h')=\prod_{i:x_i\in \text{cause } k} p(x_i|h').$$

$$p(x_i|h')=\begin{cases}\frac{1}{|h'|} & \text{if } x_i\in h'\\ 0 & \text{otherwise}\end{cases}.$$

$$p(x_t\in k|\{x_i\}_k)=\frac{\sum_{h':\{x_i\}_k, x_t\in h'} \frac{1}{|h'|^{n_k}}p(h')}{\sum_{h:\{x_i\}_k\in h} \frac{1}{|h|^{n_k}}p(h)}.$$

- Chinese restaurant process is the **prior** over groupings (CRP; Aldous, 1985; Pitman, 2002).
- the posterior provides
  a distribution over the number of clusters,
  the assignment of data to clusters,
  and the parameters associated with each cluster

the average donation estimated by model



Algorithm:

Bayesian inference model

Which table is chosen

$$p(Z=k|x_t) = \frac{p(x_t|Z=k)p(Z=k)}{\sum_{k'=1}^{t} p(x_t|Z=k')}.$$

posterior

How much the donation is

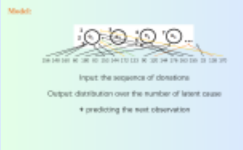
$$p(Z=k) = \begin{cases} \frac{n_k}{\sum n_k + \alpha} & \text{if } k \text{ is an old cause} \\ \frac{\alpha}{\sum n_k + \alpha} & \text{if } k \text{ is a new cause} \end{cases},$$

prior

$$p\left(x_t \in k | \{x_i\}_k\right) = \frac{\sum_{h':\{x_i\}_k, x_t \in h'} \frac{1}{|h'|^{n_k}} p(h')}{\sum_{h:\{x_i\}_k \in h} \frac{1}{|h|^{n_k}} p(h)}.$$

likelihood

Algorithm:



Bayesian inference model

$$p(Z = k|x_t) = \frac{p(x_t|Z = k)p(Z = k)}{\sum_{k'=1}^{t} p(x_t|Z = k')}.$$

$$p(Z = k) = \begin{cases} \frac{n_k}{\sum n_k + \alpha} & \text{if } k \text{ is an old cause} \\ \frac{\alpha}{\sum n_k + \alpha} & \text{if } k \text{ is a new cause} \end{cases},$$

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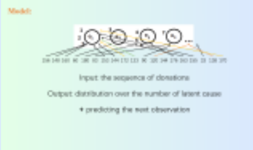
$$p(x_t \in k|\{x_i\}_k) = \sum_{h' \in H} p(x_t \in k|\{x_i\}_k, h')p(h'|\{x_i\}_k)$$

Algorithm:



Bayesian inference model

$$p(Z=k|x_t)=\frac{p(x_t|Z=k)p(Z=k)}{\sum_{k'=1}^{t}p(x_t|Z=k')}.$$

$$p(Z=k)=\begin{cases}\frac{n_k}{\sum n_k+\alpha} & \text{if } k \text{ is an old cause}\\ \frac{\alpha}{\sum n_k+\alpha} & \text{if } k \text{ is a new cause}\end{cases},$$

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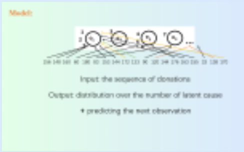
$$p(x_t\in k|\{x_i\}_k)=\sum_{h'\in H}p(x_t\in k|\{x_i\}_k,h')\boxed{p(h'|\{x_i\}_k)}$$

$$\boxed{p(h'|\{x_i\}_k)}=\frac{p(\{x_i\}_k|h')p(h')}{\sum_{h\in H}p(\{x_i\}_k|h)p(h)},$$

Algorithm:



Bayesian inference model

$$p(Z=k|x_t) = \frac{p(x_t|Z=k)p(Z=k)}{\sum_{k'=1}^{t} p(x_t|Z=k')}.$$

$$p(Z=k) = \begin{cases} \frac{n_k}{\sum n_k + \alpha} & \text{if } k \text{ is an old cause} \\ \frac{\alpha}{\sum n_k + \alpha} & \text{if } k \text{ is a new cause} \end{cases},$$

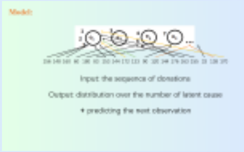
$$p(x_t \in k|\{x_i\}_k) = \frac{\sum_{h':\{x_i\}_k, x_t \in h'} \frac{1}{|h'|^{n_k}} p(h')}{\sum_{h:\{x_i\}_k \in h} \frac{1}{|h|^{n_k}} p(h)}.$$

$$p(x_t \in k|\{x_i\}_k) = \sum_{h' \in H} p(x_t \in k|\{x_i\}_k, h')p(h'|\{x_i\}_k)$$

$$p(h'|\{x_i\}_k) = \frac{\boxed{p(\{x_i\}_k|h')}p(h')}{\sum_{h \in H} p(\{x_i\}_k|h)p(h)},$$

$$\boxed{p(x_i|h')} = \begin{cases} \frac{1}{|h'|} & \text{if } x_i \in h' \\ 0 & \text{otherwise} \end{cases}.$$

Algorithm:



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$$\boxed{p(x_i|h')}=\begin{cases}\frac{1}{|h'|} & \text{if } x_i\in h'\\ 0 & \text{otherwise}\end{cases}.$$

$$\boxed{p(\{x_i\}_k|h')}=\prod_{i:x_i\in\text{cause }k}p(x_i|h').$$

Algorithm:

Bayesian inference model

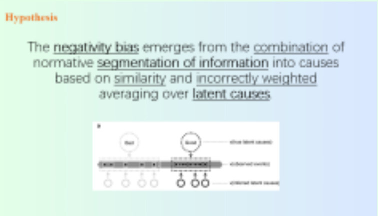
$$p(Z=k|x_t) = \frac{p(x_t|Z=k)p(Z=k)}{\sum_{k'=1}^{t} p(x_t|Z=k')}.$$

evaluation of each latent-cause

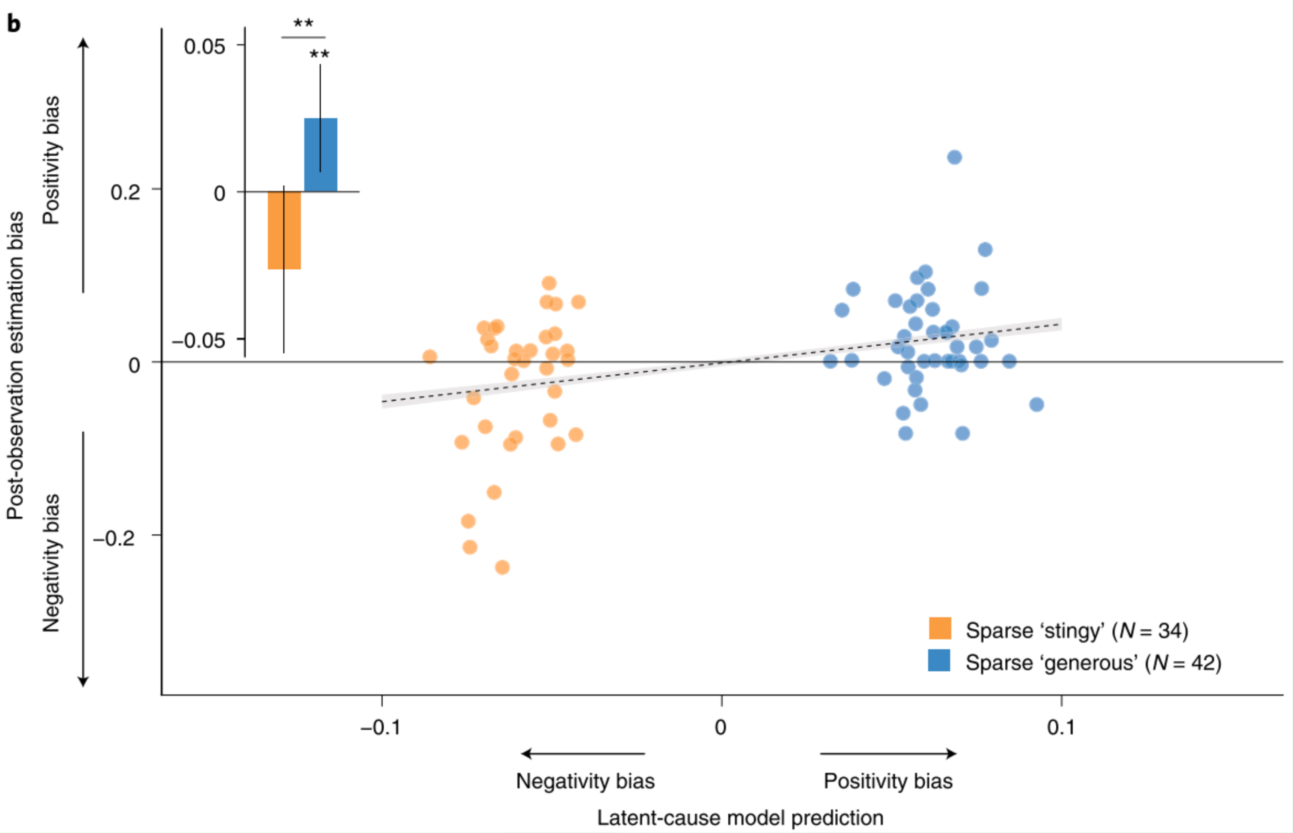
evaluation of a group

weighted by the log number of events

estimation bias



Results:

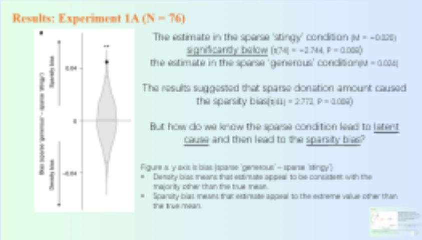


The results showed the estimate biases simulated by the latent-cause inference model predicted the behavioral results ($\beta = 0.028$, $P < 0.001$)

That indicated causes with a smaller number of donors influenced the overall mean disproportionately

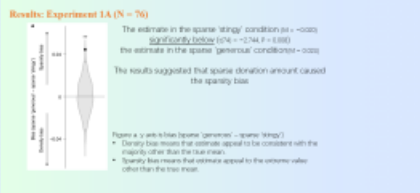
Sparsity → latent causes with small number → heavily estimate bias

Fig. b said that when the x axis' s simulated estimate(i.e. influenced by the number in cause) increase the fact estimate increase.
It is indicative of the good-model-fit prediction.
That means human' s sparsity bias could be explained by mathematic model.

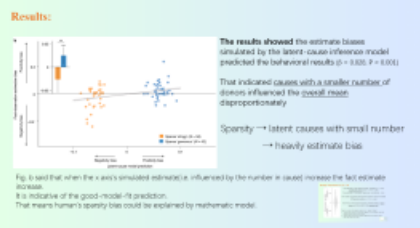


Results:

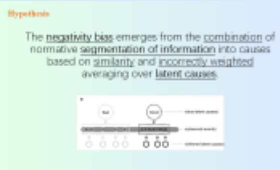
- The behavioral results found sparsity bias



- The fitting model showed the simulated biases predict individual behavioral biases



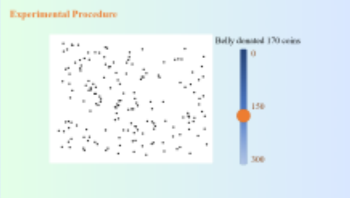
That indicated that latent-cause inference could be the mechanism by which sparse events become overweighted in the overall estimate



Exp1B

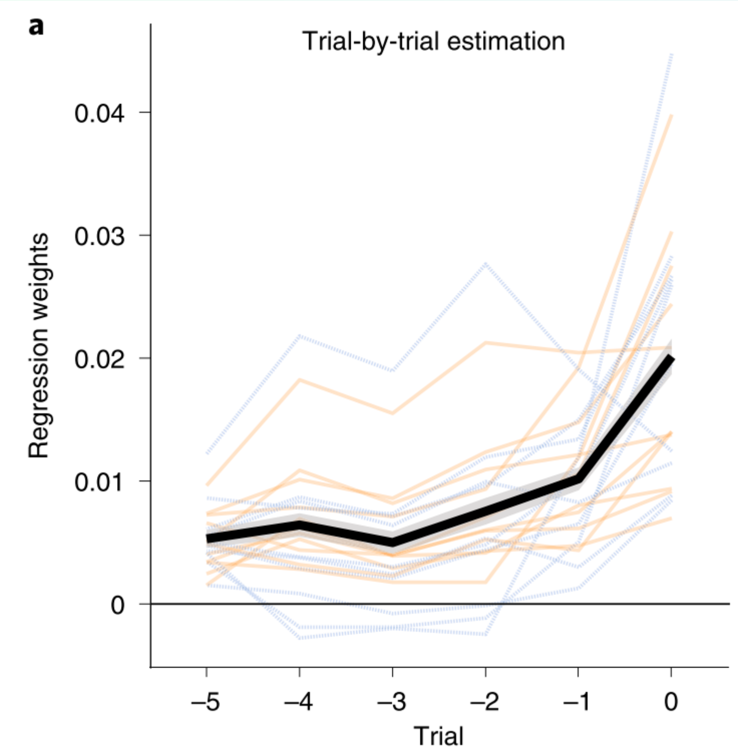
If somebody expertise in math or guess out the experimental purpose?

So, asking participants to report their average estimate on every trial

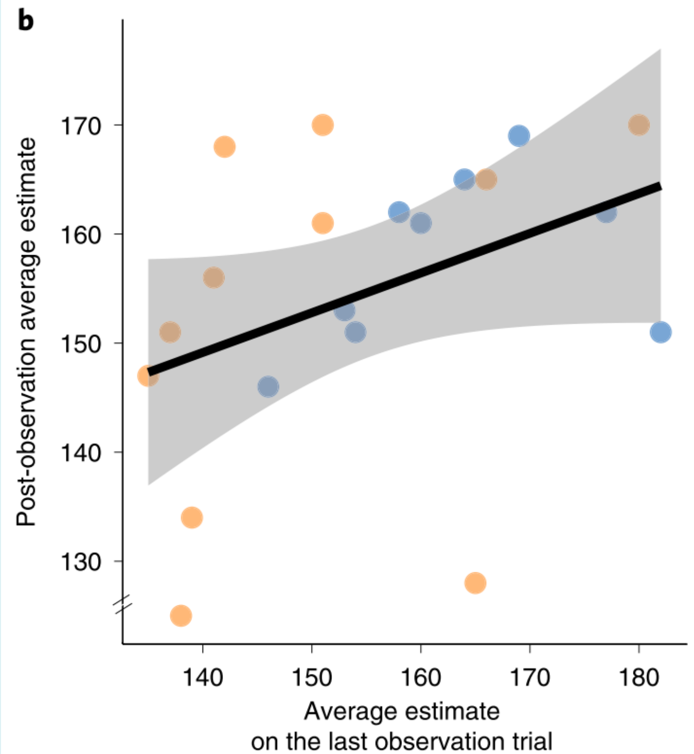


The results showed that estimates were <u>no longer significantly</u> different across conditions(sparse 'stingy' $N = 10$, $M = 0.032$; sparse 'generous' $N = 12$, $M = 0.012$; $t(20) = 0.984$, $P = 0.337$)

Exp1B: linear regression



recency bias



β = 5.362, P = 0.082

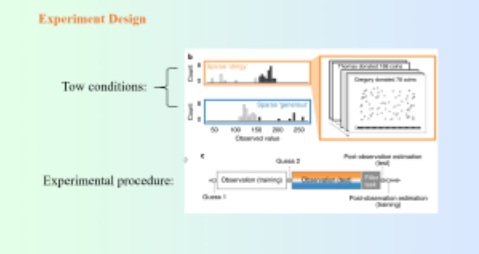
That indicate the sparsity in the distribution induces biases <u>only when the average values are not tracked on a trial-by-trial basis</u>

Exp2A.1-4

There are two limitations

Uneven number of events
in the two causes

Sparse events(surprising)
elicit higher prediction errors



Pearce, J. M. & Hall, G. A model for Pavlovian learning: variations in the effectiveness of conditioned but not of unconditioned stimuli. Psychol. Rev. 87, 532–552 (1980).

Exp2A.1-4

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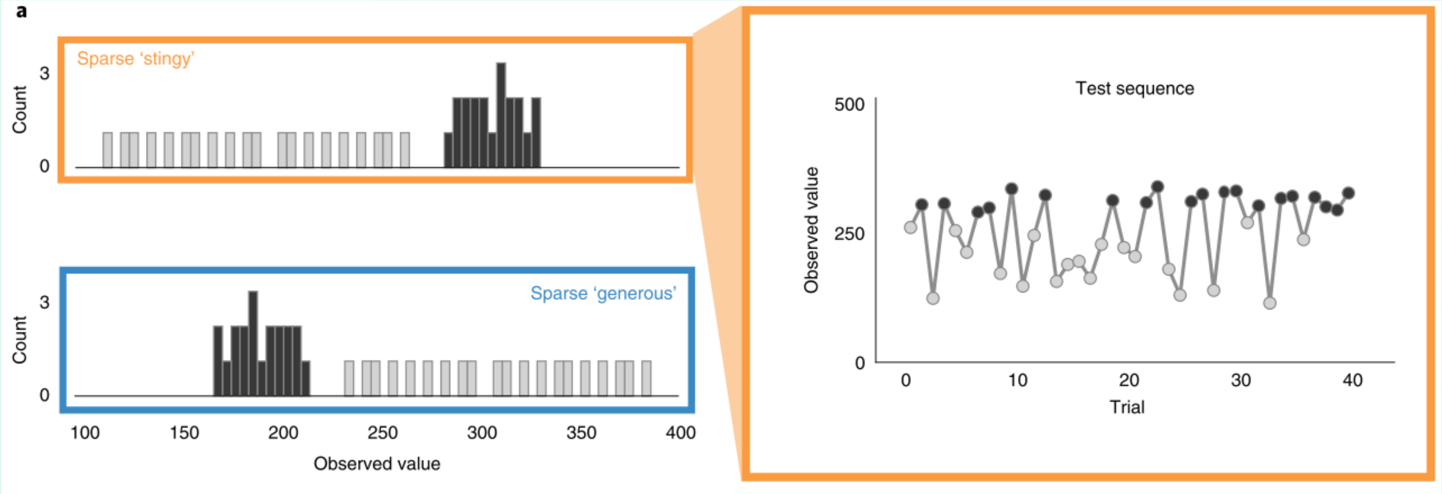
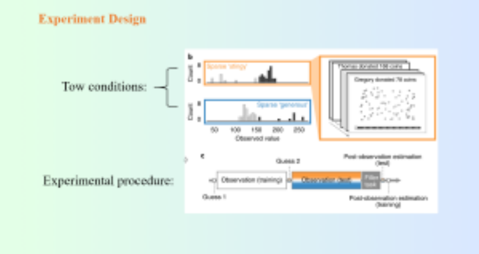




Pearce, J. M. & Hall, G. A model for Pavlovian learning: variations in the effectiveness of conditioned but not of unconditioned stimuli. Psychol. Rev. 87, 532–552 (1980).

Algorithm:

Pearce–Hall model

$$v_{t+1} = v_t + \boxed{a_{t+1}} \times S \times x_t,$$

- a is the associability parameter
- S denotes salience of the cue
- x represents the observed amount

$$\boxed{a_{t+1}} = (1 - \eta) \times a_t + \eta \times |x_t - v_t|.$$

- η is learning rate
- xt – vt is prediction error

Pearce, J. M. & Hall, G. A model for Pavlovian learning: variations in the effectiveness of conditioned but not of unconditioned stimuli. Psychol. Rev. 87, 532–552 (1980).

Algorithm:

Pearce–Hall model

$$v_{t+1} = v_t + a_{t+1} \times S \times x_t,$$

0.05 0 0.1 1 0.5

$$a_{t+1} = (1 - \eta) \times a_t + \eta \times |x_t - v_t|.$$

0.1 0 0.2 0.5 0

Algorithm:

Pearce–Hall model

$$v_{t+1} = v_t + a_{t+1} \times S \times x_t ,$$

0.05	0	0.1	1	0.5
0.197	0.05	0.21	1	0.7

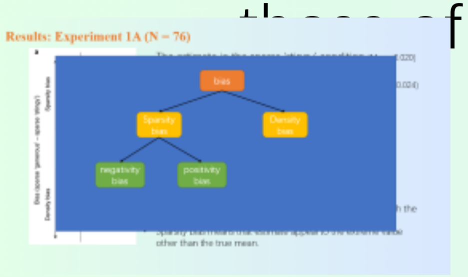
$$a_{t+1} = (1 - \eta) \times a_t + \eta \times |x_t - v_t| .$$

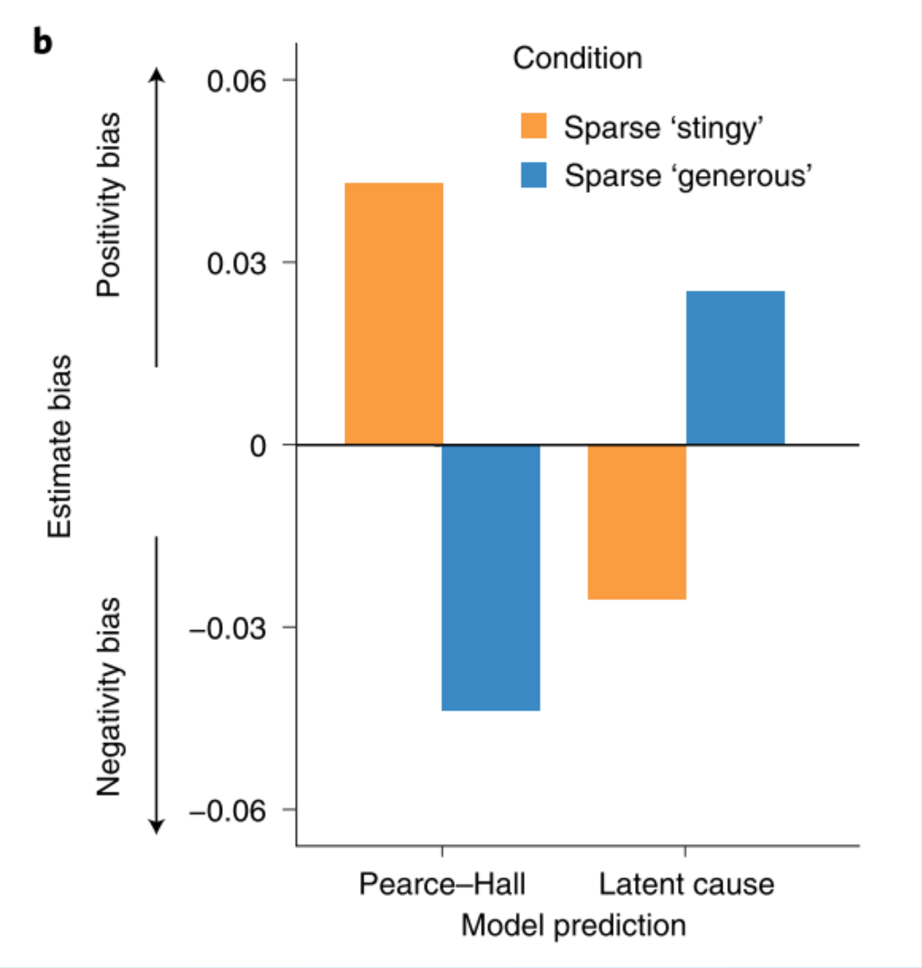
0.1	0	0.2	0.5	0
0.21	0.08	0.2	0.7	0.05

Exp2A-1 N = 70

The results showed

- The estimate in the sparse 'stingy' condition (M = −0.023, N = 26) was <u>significantly lower than</u> that in the sparse 'generous' condition (M = 0.018, N = 44; t(68) = −2.511, P = 0.014)
- These results were in the direction predicted by the <u>latent-cause</u> inference model and <u>opposite to</u> those of the <u>Pearce–Hall model</u>.





Exp2A2-4

To strengthen this finding,

three independent sets of replications were conducted

(experiment 2A-2, N = 67; experiment 2A-3, N = 260; experiment 2A-4, N = 229)

	n	'stingy'	n	'generous'	t	p
2A-2	28	−0.014	39	0.017	−2.137	0.036
2A-3	133	−0.009	127	0.013	−2.556	0.011
2A-4	118	−0.005	111	0.021	−3.098	0.002

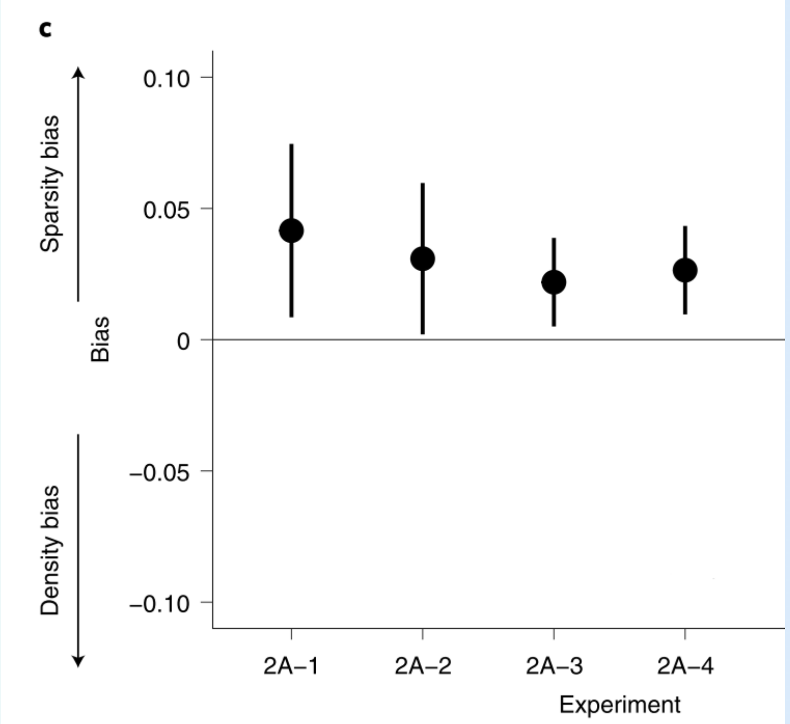
Exp2A2-4

An additional meta-analytic Bayes factor analysis

Sparsity bias vs. density bias: BF_{+0} = 17,732

Negativity biases: BF_{+0} = 636.584

Positivity biases: BF_{+0} = 4.556



Exp2B&C

Is there the sparsity bias in the non-social domain

So, asking participants to log coffee beans(Exp2B)

or to log gamble coins (Exp2C) ?

	n	‘below-average’	n	‘above-average’	t	p
2B(N = 81)	38	0.015	51	0.001	−1.654	**0.102**
2C (N = 101)	43	0.048	50	0.030	−1.822	**0.071**

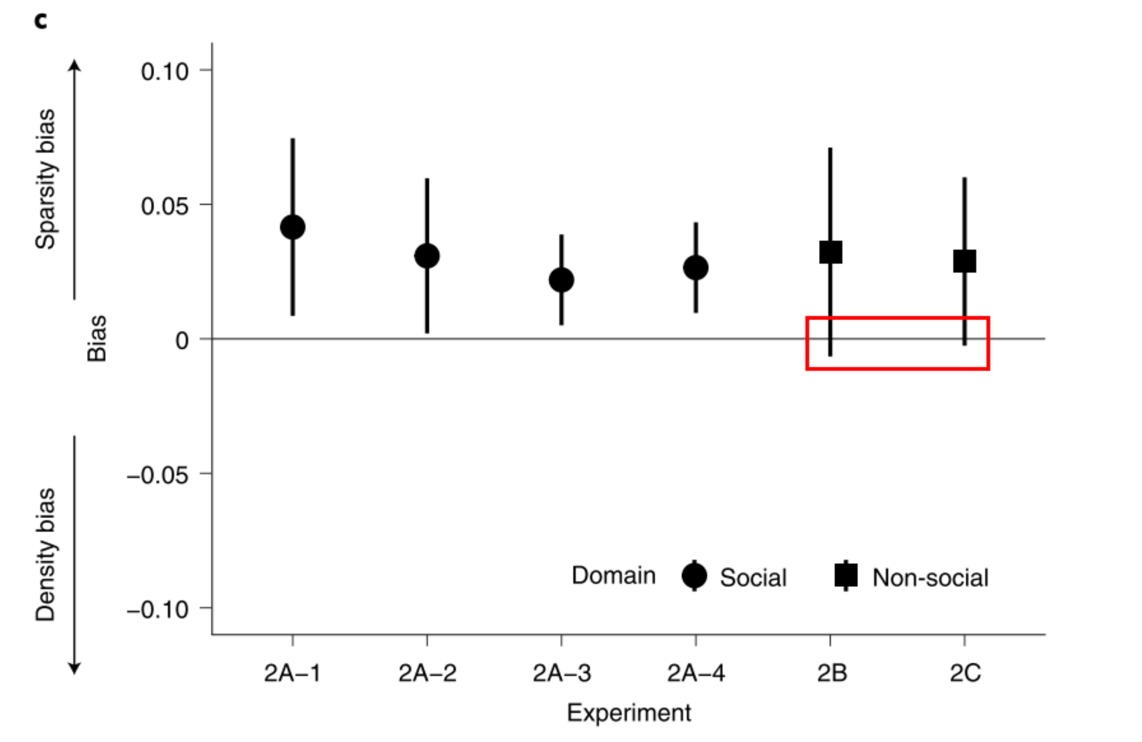
Results:

Mixed-effects linear regression model

Dependent variable: normalized estimates

Fixed effects: sparsity and social (‘social’ or ‘non-social’) conditions

Random effects: experiments 2A-1, 2A-2, 2A-3, 2A-4, 2B and 2C (N = 808)

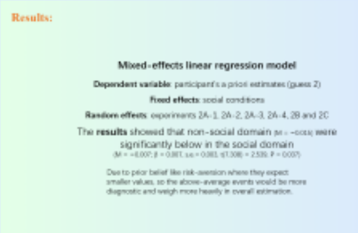


The **results** showed that

no significant interaction(P = 0.695)

sparse ‘below-average’ condition (BF_{0+}= 4.902)

<u>sparse ‘above-average’ condition</u> (BF_{0+}= 16.153)



Enlightenment

Negativity bias < sparsity bias ---- related to attention bias etc.

Valence

Nonsocial condition

Model:

Latent variables and clustering(e.g. HGF)

Cognitive mechanism and diagnosis

Dimensionality and limitation

Weight:

Surprising vs. sparse

Strong and weak synapse

Scholl, B., Thomas, C. I., Ryan, M. A., Kamasawa, N., & Fitzpatrick, D. (2021). Cortical response selectivity derives from strength in numbers of synapses. *Nature*, *590*(7844), 111–114. https://doi.org/10.1038/s41586-020-03044-3

Design:

Find more potential mechanisms

Konovalov, A., & Ruff, C. C. (2021). Enhancing models of social and strategic decision making with process tracing and neural data. WIREs Cognitive Science, 32. https://doi.org/10.1002/wcs.1559

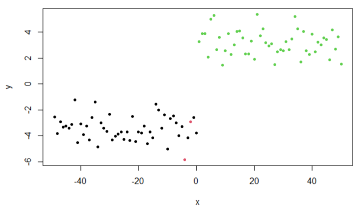
Thanks

Algorithm:

```
> library(nimble)
> # 通过rCRP函数随机生成样本
> # 通过dCRP函数返回样本分布的似然
> rCRP(n=1, conc = 2, size=30)
 [1]  1  2  3  2  4  2  5  3  2  6  3  7  4  8  8  9  6  2 10  2
[21] 10  1  3  2  8  8  1  3  3  6
> # n是采样几次，即采样多少个样本，现阶段只能为1；
> # alpha也称concentration，即这里的conc参数，conc越大，越可能产生新的桌子；
> # size为样本量，比如这里选择输产生一个包含30个客人的样本.
>
> z = list(c(1,1,1),c(1,2,3),c(1,1,2),c(1,2,2),c(1,3,3))
> for (i in z){
+   j = dCRP(x=i, conc = 1, size=3)
+   print(j)
+ }
[1] 0.3333333
[1] 0.1666667
[1] 0.1666667
[1] 0.1666667
[1] 0.1666667
>
> # x是样本数据，其指为类别编号(table or cluster)；
> # 参数conc，也就是alpha
> # size为样本量.
> # 参考自：https://zhuanlan.zhihu.com/p/66036062
```

```
# install_github("jirotubuyaki/CRPClustering")
# (https://github.com/jirotubuyaki/CRPClustering
# https://cran.r-project.org/web/packages/CRPClustering/vignettes/CRPClustering-vignette.pdf
library(CRPClustering)
n=100
df = matrix(c(1:n - 50,rnorm(50,-3,1),rnorm(50,3,1)),ncol=2)
z_result <- crp_gibbs(
                      data = as.matrix(df),
                      mu=c(0,0),
                      sigma_table=10,
                      alpha=2,
                      ro_0=0.1,
                      burn_in=10,
                      iteration=30
                      )
x= as.data.frame(df)$V1
y= as.data.frame(df)$V2
plot(x,y,pch=20,col=as.factor(z_result))
```

cluster <dbl>	mu_k.1 <dbl>	mu_k.2 <dbl>
2	-39.461884	-2.999849
3	-6.082211	-8.860235
5	27.859146	2.774889



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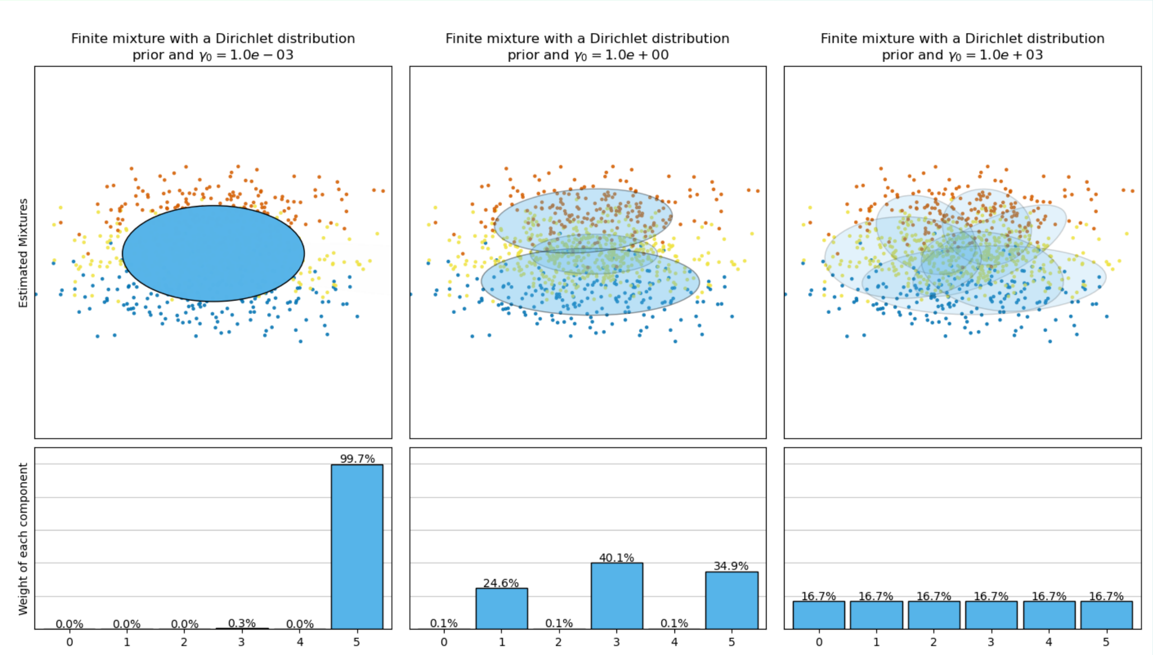

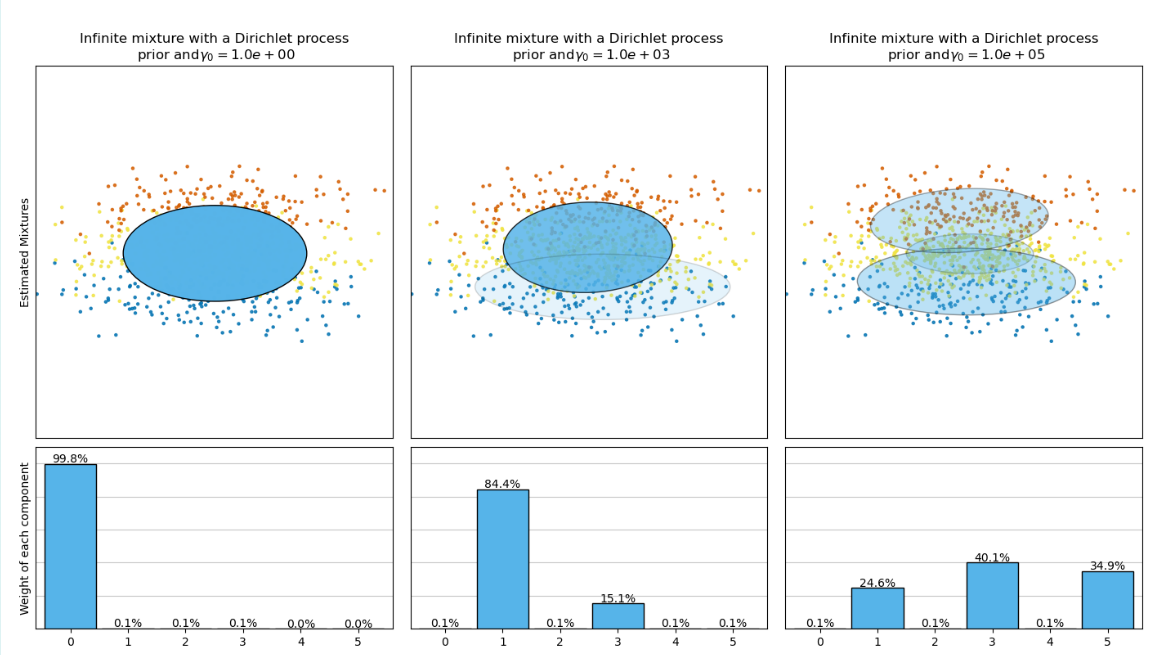

- https://scikitlearn.org/stable/auto_examples/mixture/plot_concentration_prior.html?highlight=bayesiangaussianmixture
- https://rdrr.io/cran/DPpackage/
- https://rdrr.io/cran/msBP/
- https://stuartlacy.co.uk/2019/09/26/dirichlet-process-mixture-models-part-iii-chinese-restaurant-process-vs-stick-breaking/

Algorithm:

Gershman, S. J., & Blei, D. M. (2012). A tutorial on Bayesian nonparametric models. *Journal of Mathematical Psychology*, *56*(1), 1–12. https://doi.org/10.1016/j.jmp.2011.08.004

$$p(Z=k|x_t) = \frac{p(x_t|Z=k)p(Z=k)}{\sum_{k'=1}^{t} p(x_t|Z=k')}.$$

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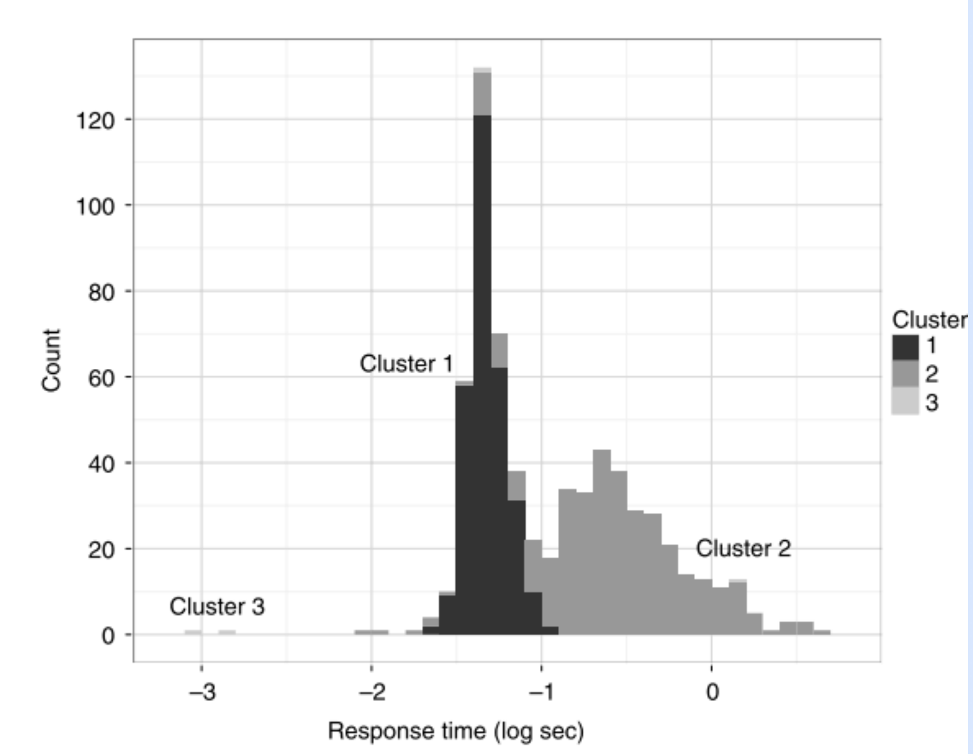
$$p\left(x_t \in k|\{x_i\}_k\right) = \frac{\sum_{h':\{x_i\}_k, x_t \in h'} \frac{1}{|h'|^{n_k}} p(h')}{\sum_{h:\{x_i\}_k \in h} \frac{1}{|h|^{n_k}} p(h)}.$$

$$P(y_{n+1}|\mathbf{y}_{1:n}) = \sum_{\mathbf{c}_{1:n+1}} \int_\theta P(y_{n+1}|c_{n+1},\theta) \times P(c_{n+1}|\mathbf{c}_{1:n})P(\mathbf{c}_{1:n},\theta|\mathbf{y}_{1:n})\mathrm{d}\theta.$$

$$P(c_n=k|\mathbf{c}_{1:n-1}) = \begin{cases} \dfrac{m_k}{n-1+\alpha} & \text{if } k \le K_+ \\ & \text{(i.e., } k \text{ is a previously occupied table)} \\ \dfrac{\alpha}{n-1+\alpha} & \text{otherwise} \\ & \text{(i.e., } k \text{ is the next unoccupied table)} \end{cases}$$



Results:

Mixed-effects linear regression model

Dependent variable: participant’ s a priori estimates (guess 2)

Fixed effects: social conditions

Random effects: experiments 2A-1, 2A-2, 2A-3, 2A-4, 2B and 2C

The **results** showed that non-social domain (M = −0.015) were significantly below in the social domain
(M = −0.007; β = 0.007, s.e.= 0.003, t(7.308) = 2.539, P = 0.037)

Due to prior belief like risk-aversion where they expect smaller values, so the above-average events would be more diagnostic and weigh more heavily in overall estimation.

Negativity bias:

Trends in Cognitive Sciences

CellPress

Opinion

Why Good Is More Alike Than Bad: Processing Implications

Hans Alves,[1,2,*] Alex Koch,[1,2,*] and Christian Unkelbach[1]

Humans process positive information and negative information differently. These valence asymmetries in processing are often summarized under the observation that 'bad is stronger than good', meaning that negative information has stronger psychological impact (e.g., in feedback, learning, or social interactions). This stronger impact is usually attributed to people's affective or motivational reactions to evaluative information. We present an alternative interpretation of valence asymmetries based on the observation that positive information is more similar than negative information. We explain this higher similarity based on the non-extremity of positive attributes, discuss how it accounts for observable valence asymmetries in cognitive processing, and show how it predicts hitherto undiscovered phenomena.

Trends

Valence asymmetries describe differences in how humans process positive and negative information. They are evident at all stages of information processing and have been summarized under the observation that 'bad is stronger than good'.

Many researchers have argued that valence asymmetries result from internal affective reactions. Because negative information is more relevant for well-being, it elicits a strong affective reaction, which triggers deeper and more elaborate processing.

Processing Positive and Negative Information

COGNITION AND EMOTION
https://doi.org/10.1080/02699931.2018.1549022

Routledge
Taylor & Francis Group

Check for updates

The differential similarity of positive and negative information – an affect-induced processing outcome?

Hans Alves, Alex Koch and Christian Unkelbach

Social Cognition Center Cologne, University of Cologne, Köln, Germany

ABSTRACT

People judge positive information to be more alike than negative information. This good-bad asymmetry in similarity was argued to constitute a true property of the information ecology (Alves, H., Koch, A., & Unkelbach, C. (2017). Why good is more alike than bad: Processing implications. *Trends in Cognitive Sciences*, *21*, 69–79). Alternatively, the asymmetry may constitute a processing outcome itself, namely an influence of phasic affect on information processing. Because no research has yet tested whether phasic affect influences perceived similarity among stimuli, we conducted 5 Experiments that also tested whether phasic affect can account for the higher judged similarity among positive compared to negative stimuli. In three experiments, we affectively charged pictures of different Pokemon by pairing them with monetary gains and losses (Exp. 1a, 1b) as well as positive and negative trait words (Exp. 2); yet, the evaluative charge did not differentially influence perceived similarity among the Pokemon. Experiment 3 replicated the basic similarity asymmetry among positive and negative words, and found that it was unaffected by externally induced phasic affect. Experiment 4 showed that phasic affect had no influence on perceived similarity of non-evaluative words either. We conclude that albeit a weak influence of phasic affect on perceived similarity of stimuli cannot be ruled out entirely, it can most likely not account for the typically medium to large sized asymmetry in similarity among positive and negative stimuli.

ARTICLE HISTORY
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Valence; affect; similarity; information processing