Pragmatics, probabilities & psychologists: A Bayesian perspective on some reasoning problems

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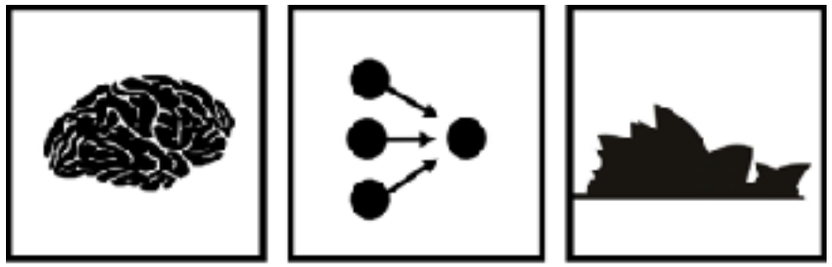

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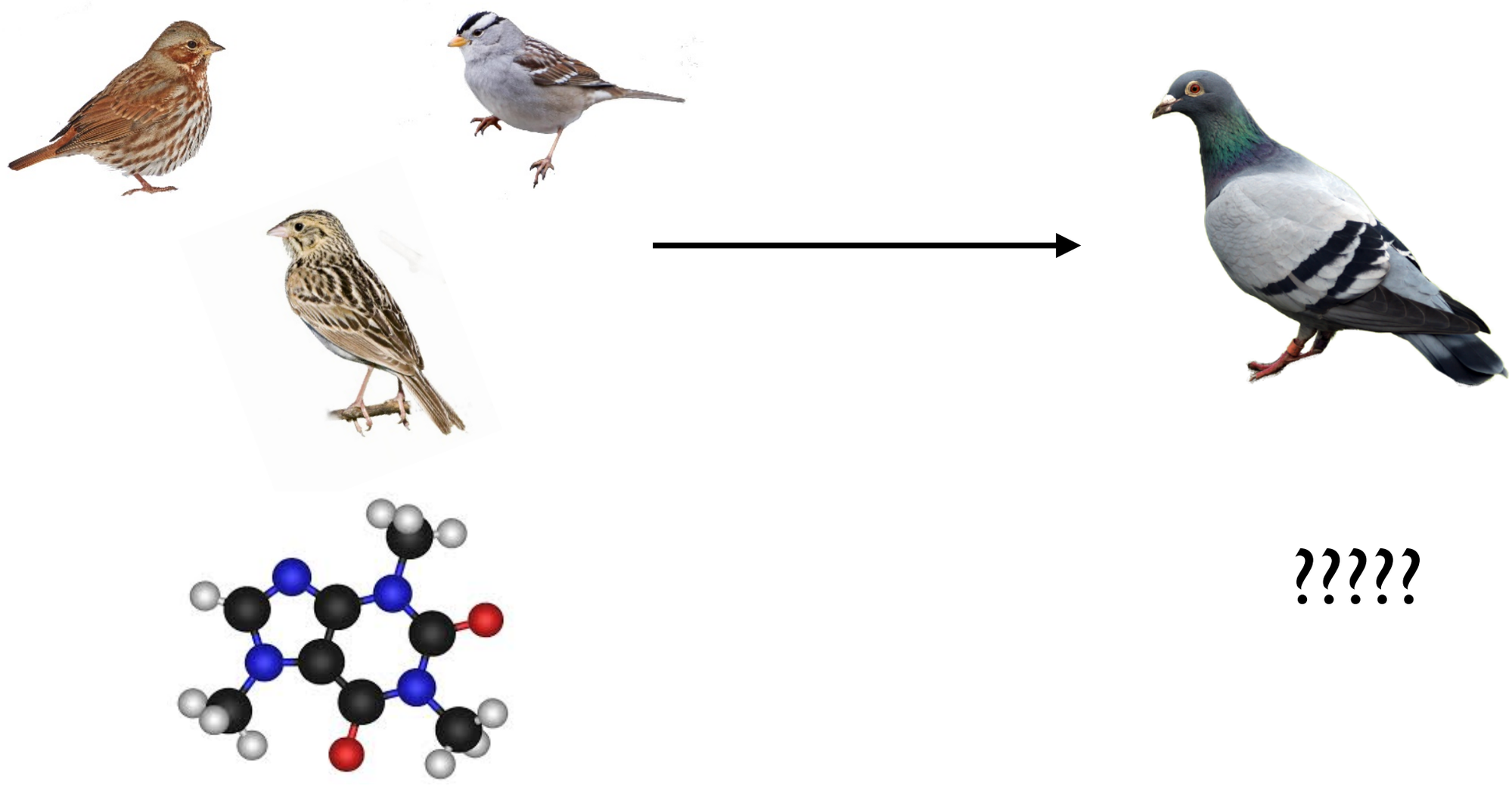
What are the connections between human reasoning and statistical inference?

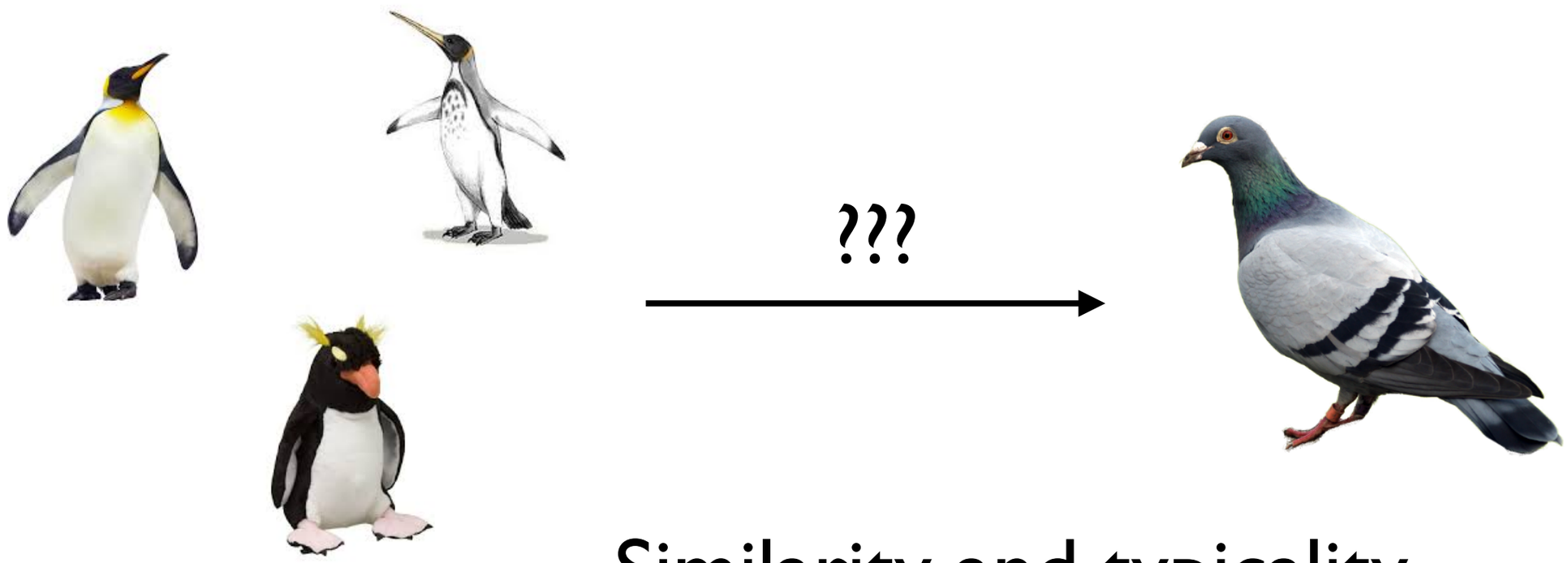
What should we do with this *sample* of evidence?

These birds have plaxium blood

The problem of inductive generalisation



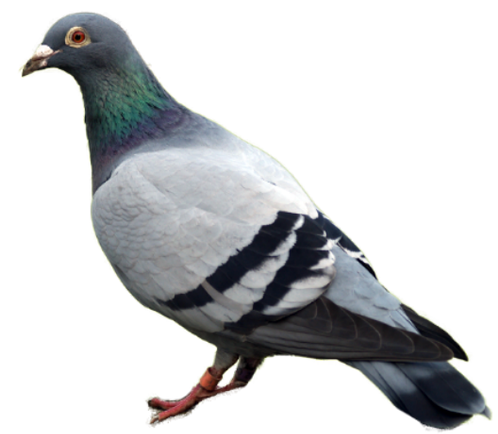
What factors shape our inductive inferences?



Similarity and typicality of the sample

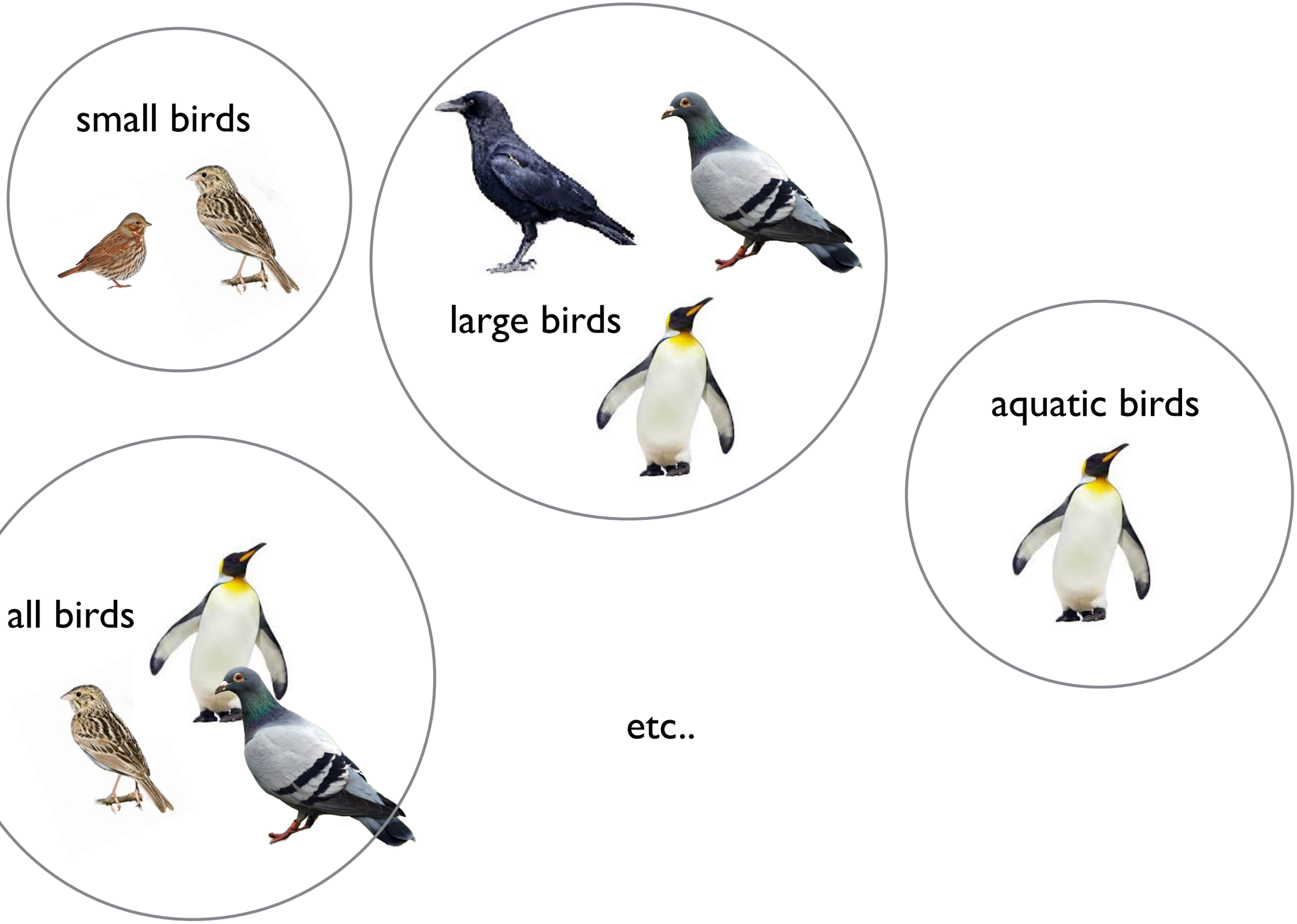
What factors shape our inductive inferences?

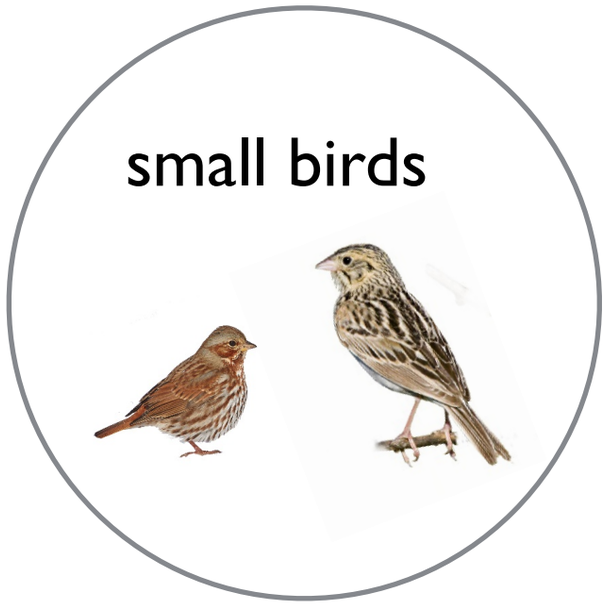
???



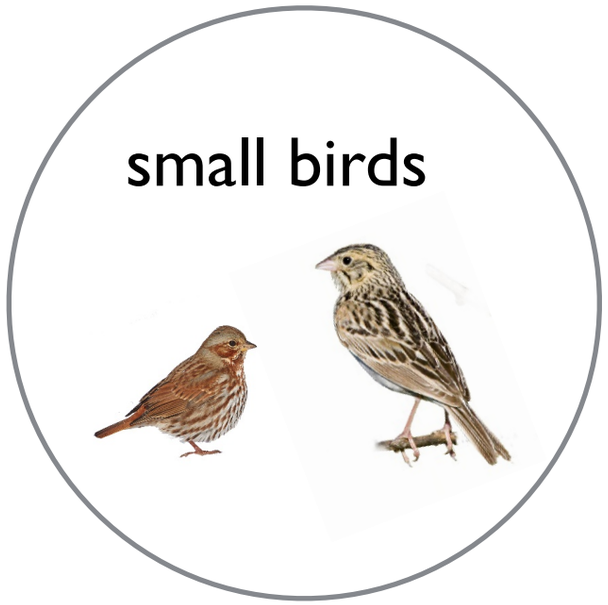
Size and diversity of the sample

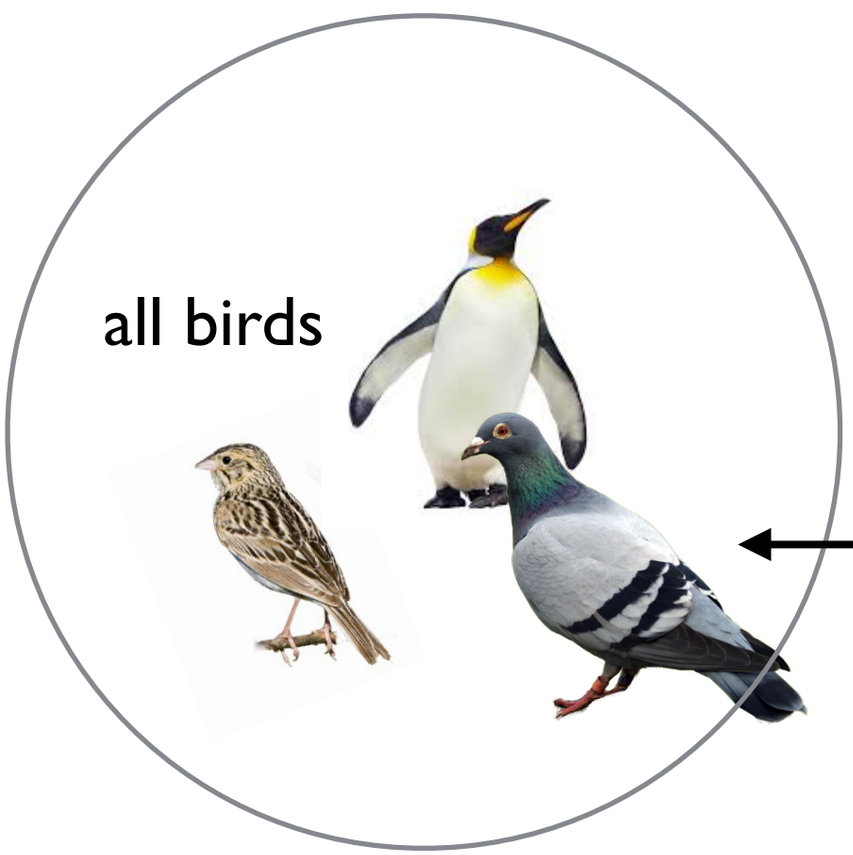
Reasoners consider hypotheses





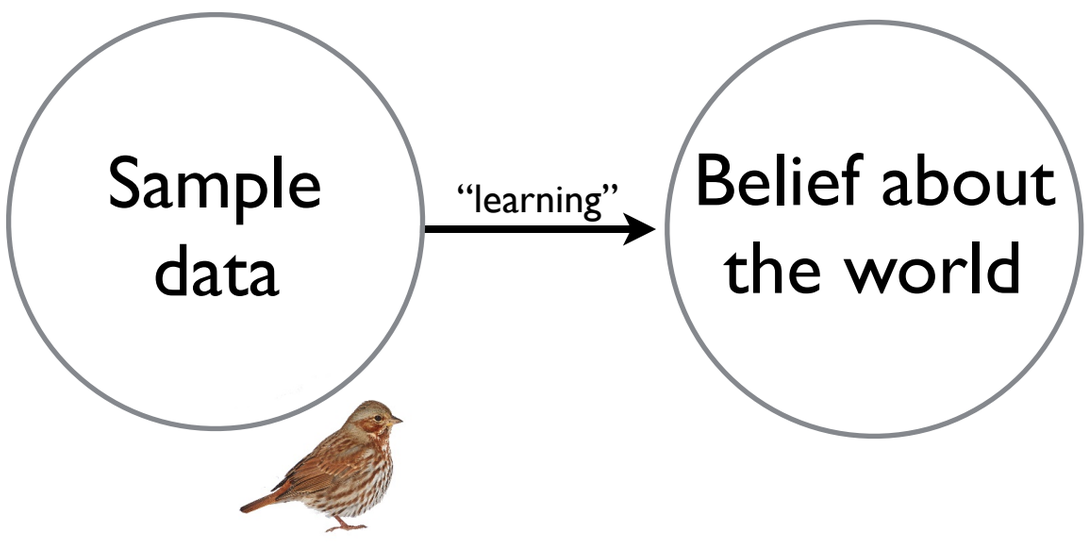
The sample rules out some and not others…





Inductive generalisation is based on hypotheses consistent with the sample

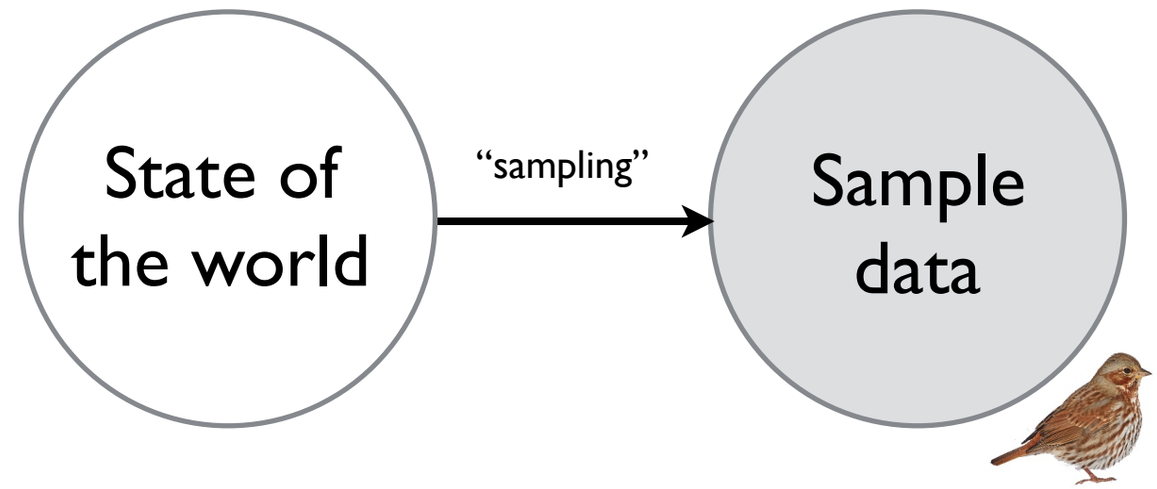
Traditional view of reasoning

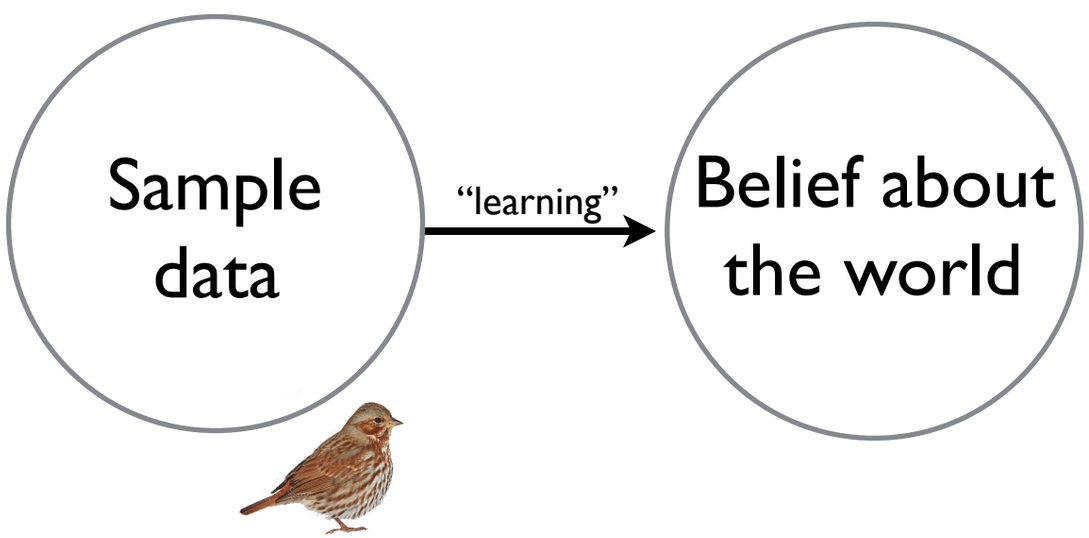


Properties of the sample shape learning

Reasoning as intuitive statistics

$$P(h|d) = \frac{P(d|h)P(h)}{\sum_{h' \in \mathcal{H}} P(d|h')P(h')}$$

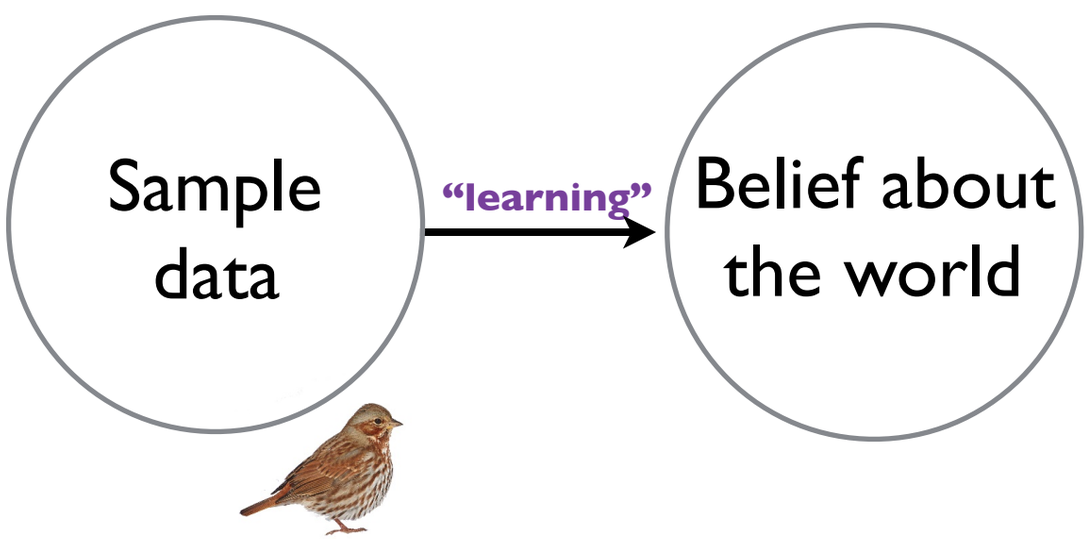


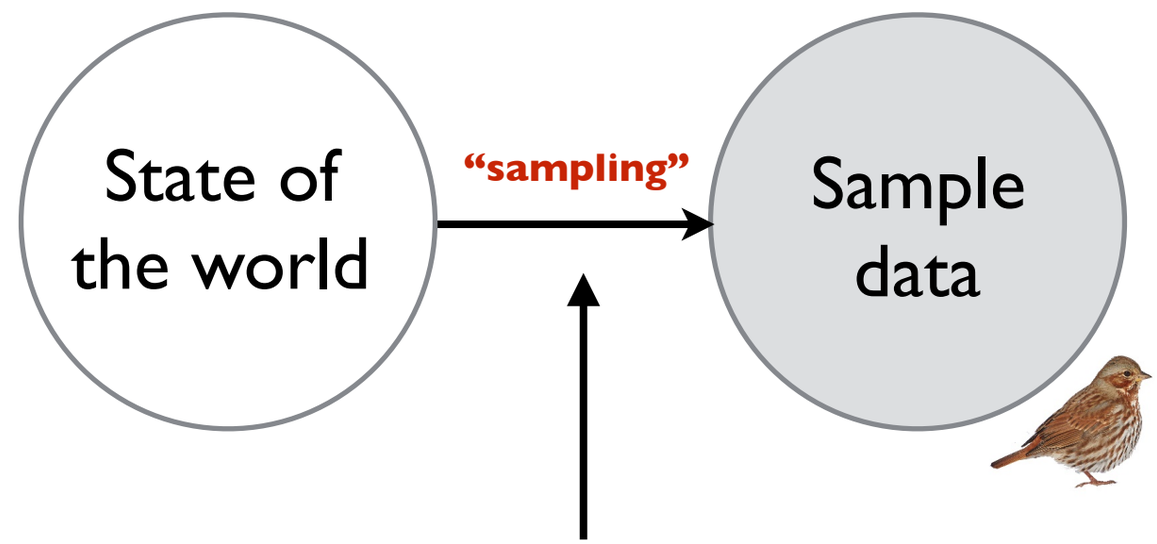


Properties of the sample shape learning

Critical prediction: Learning depends on *sampling*

$$P(h|d) = \frac{P(d|h)P(h)}{\sum_{h' \in \mathcal{H}} P(d|h')P(h')}$$





The evidentiary value of the sample depends on how the learner thinks it was generated, or how it came to their attention

Properties of the sample shape learning

Epistemic vigilance: Statistical reasoning about untrustworthy data

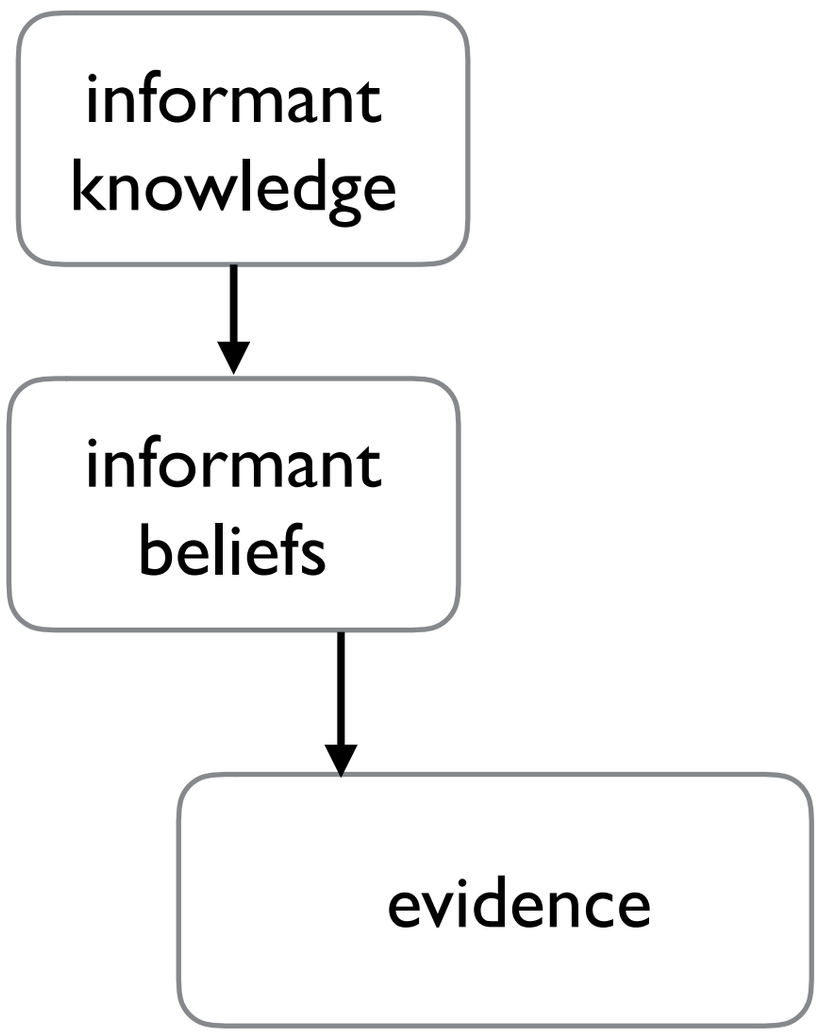
These birds have plaxium blood

Does this bird have plaxium blood?

This is silly, but "it's all made up" is *absolutely* a legitimate sampling assumption

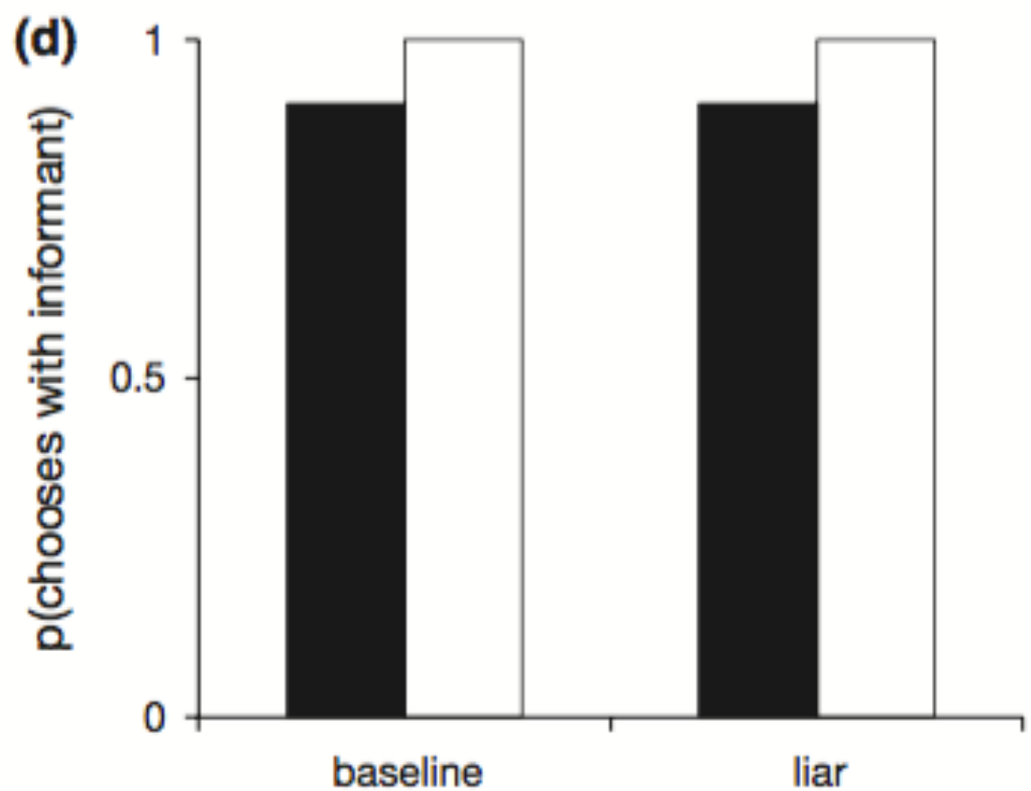
Does this bird have plaxium blood?

The price of inductive freedom is epistemic vigilance



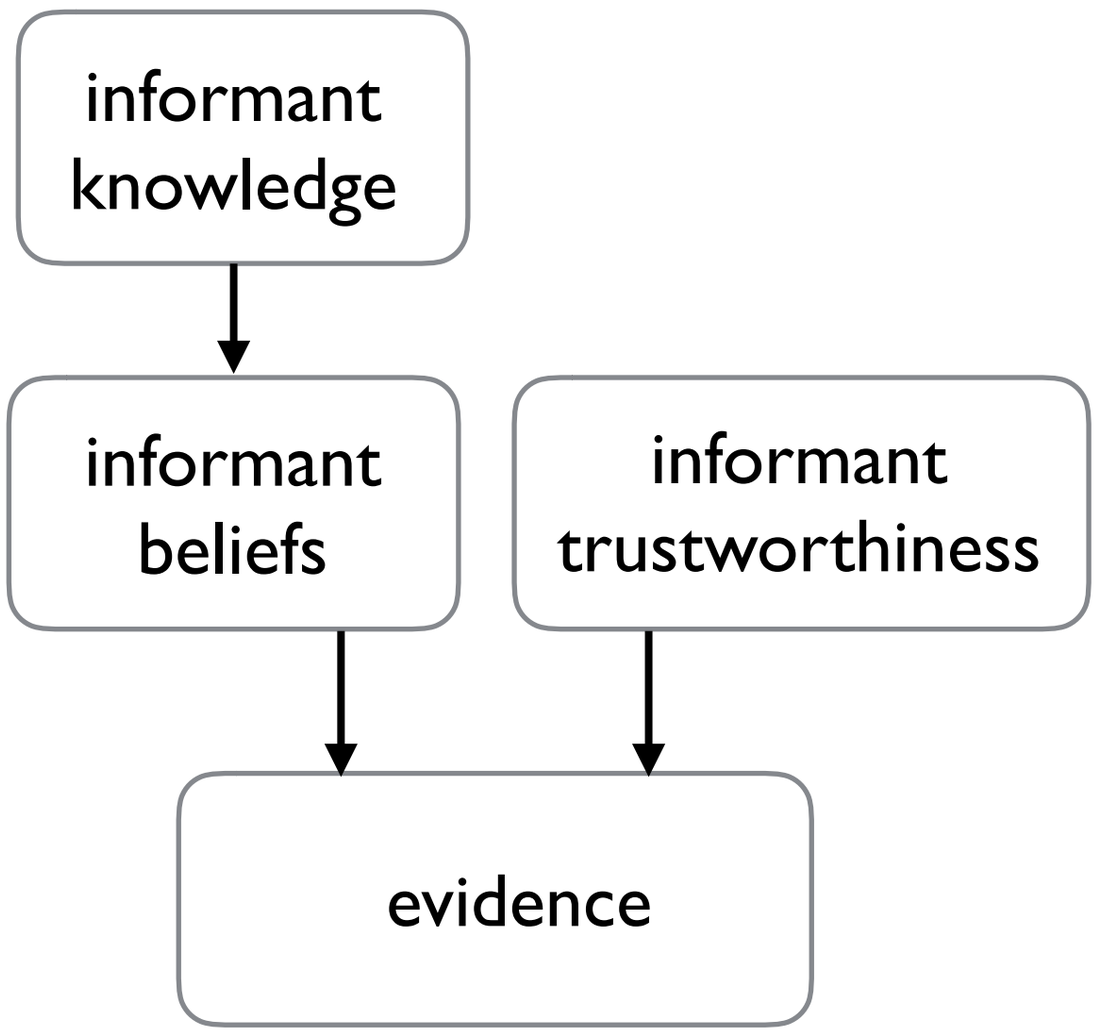
Shafto, Eaves, Navarro & Perfors (2012) *Developmental Science*

Three year olds are easily deceived…



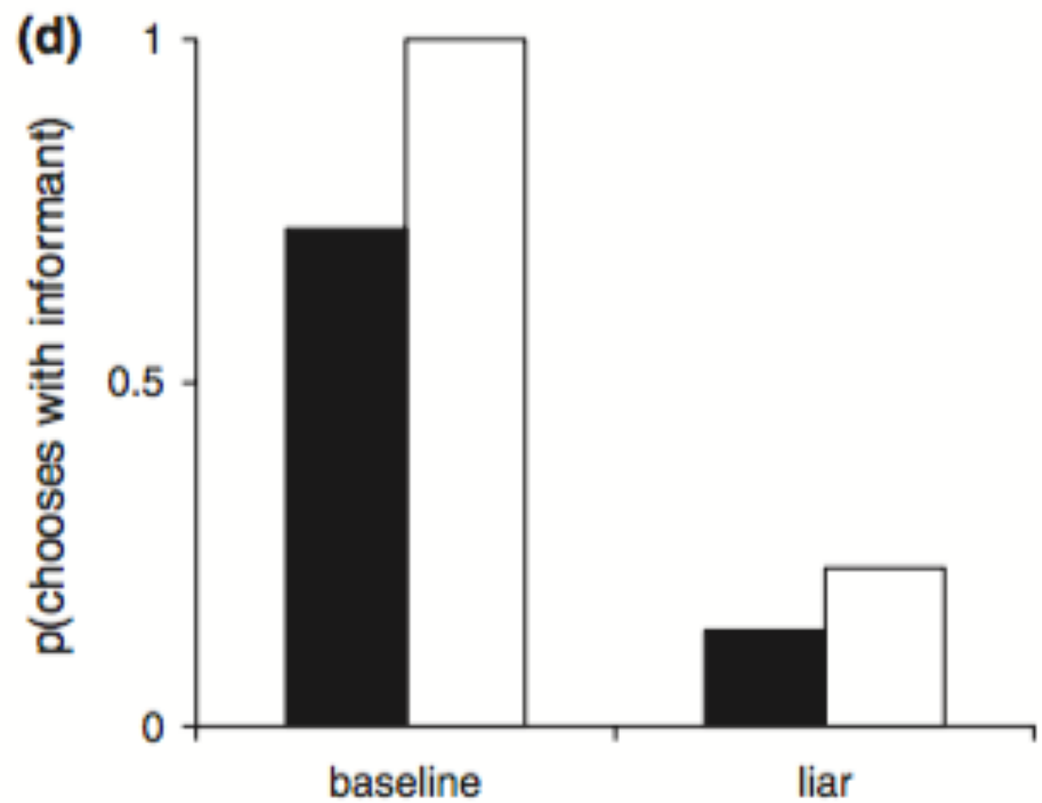
Mascaro & Sperber (2009)

The price of inductive freedom is epistemic vigilance



Shafto, Eaves, Navarro & Perfors (2012) *Developmental Science*

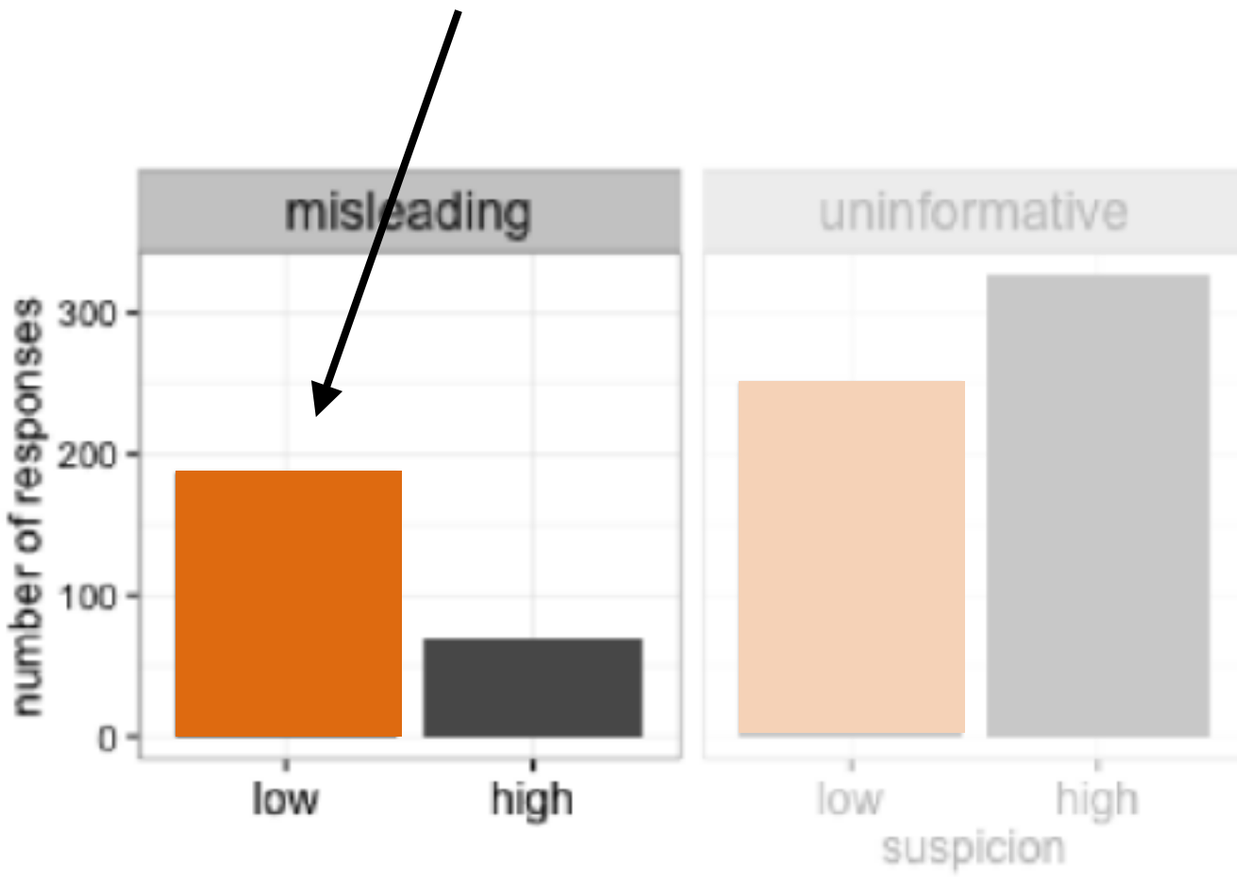
… but four year olds are savvy statisticians



Mascaro & Sperber (2009)

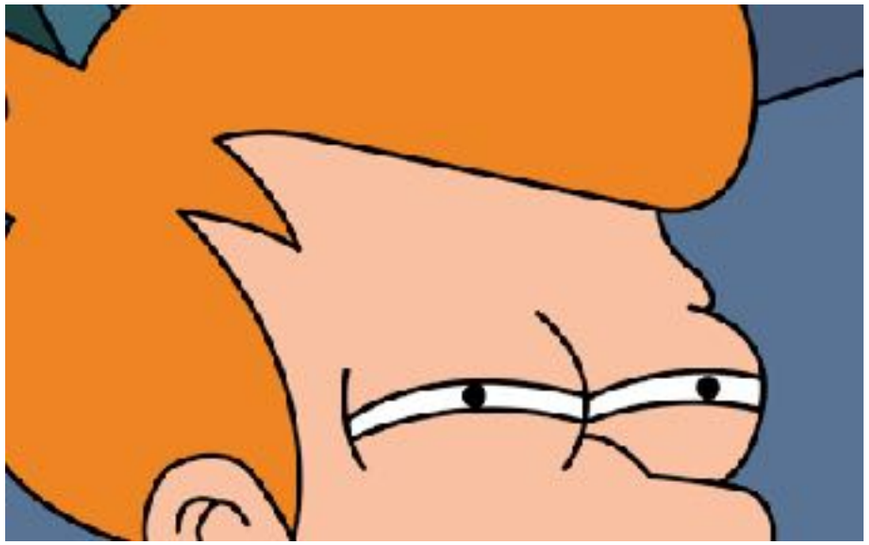
Why epistemic vigilance?

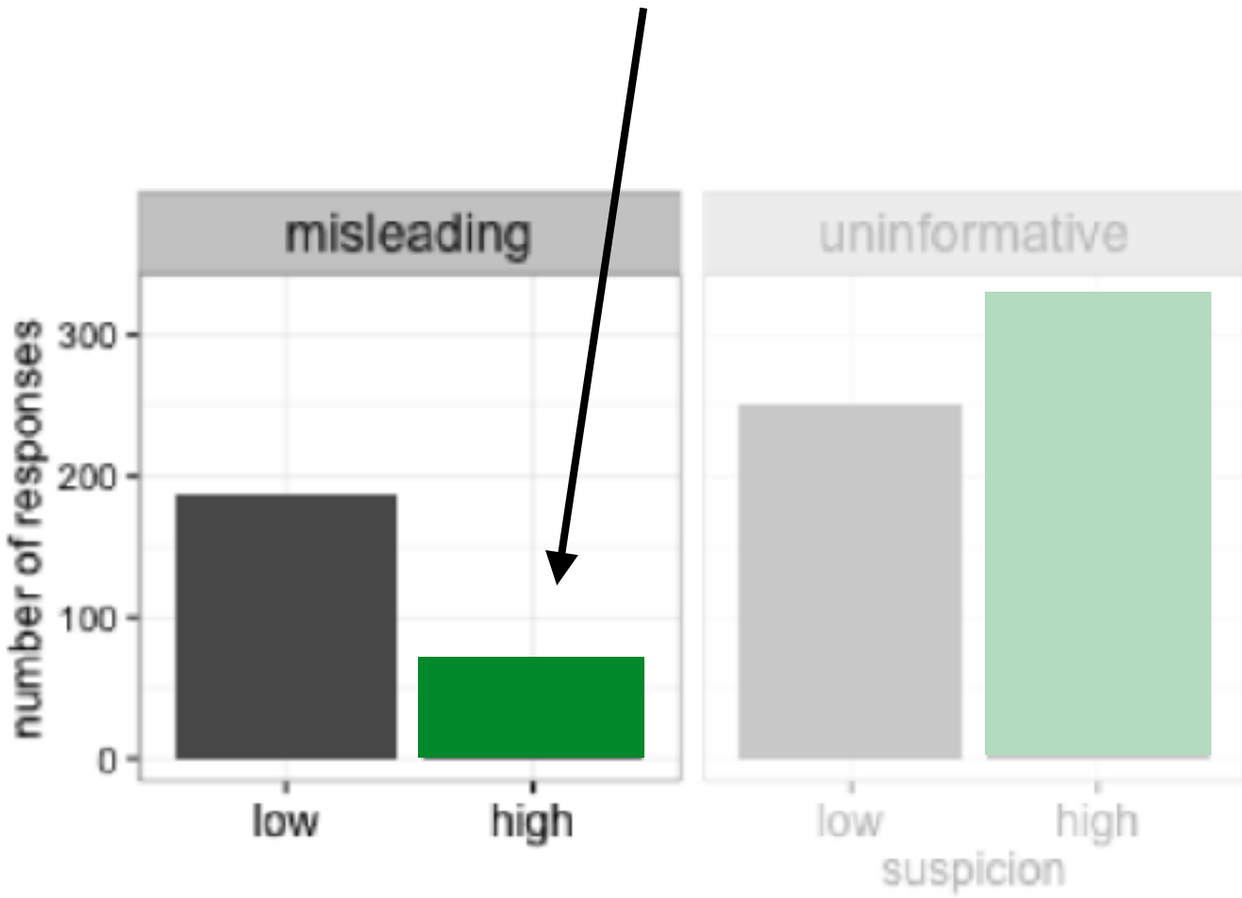
People will try to "mislead with a half truth" if the listener is naive…



Ransom, Voorspoels, Perfors & Navarro (2017)

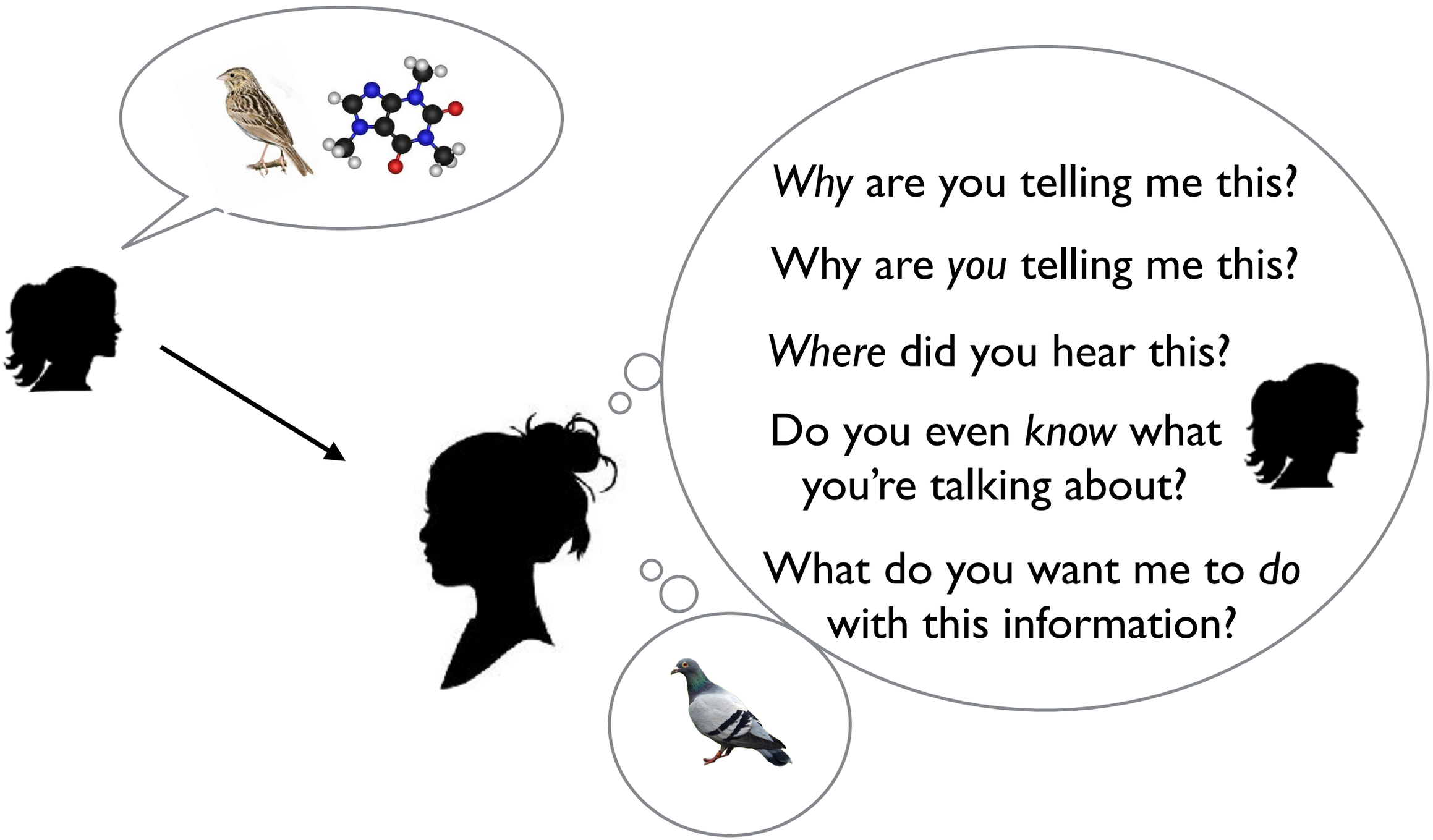
They rarely try this when the listener is suspicious!





Ransom, Voorspoels, Perfors & Navarro (2017)

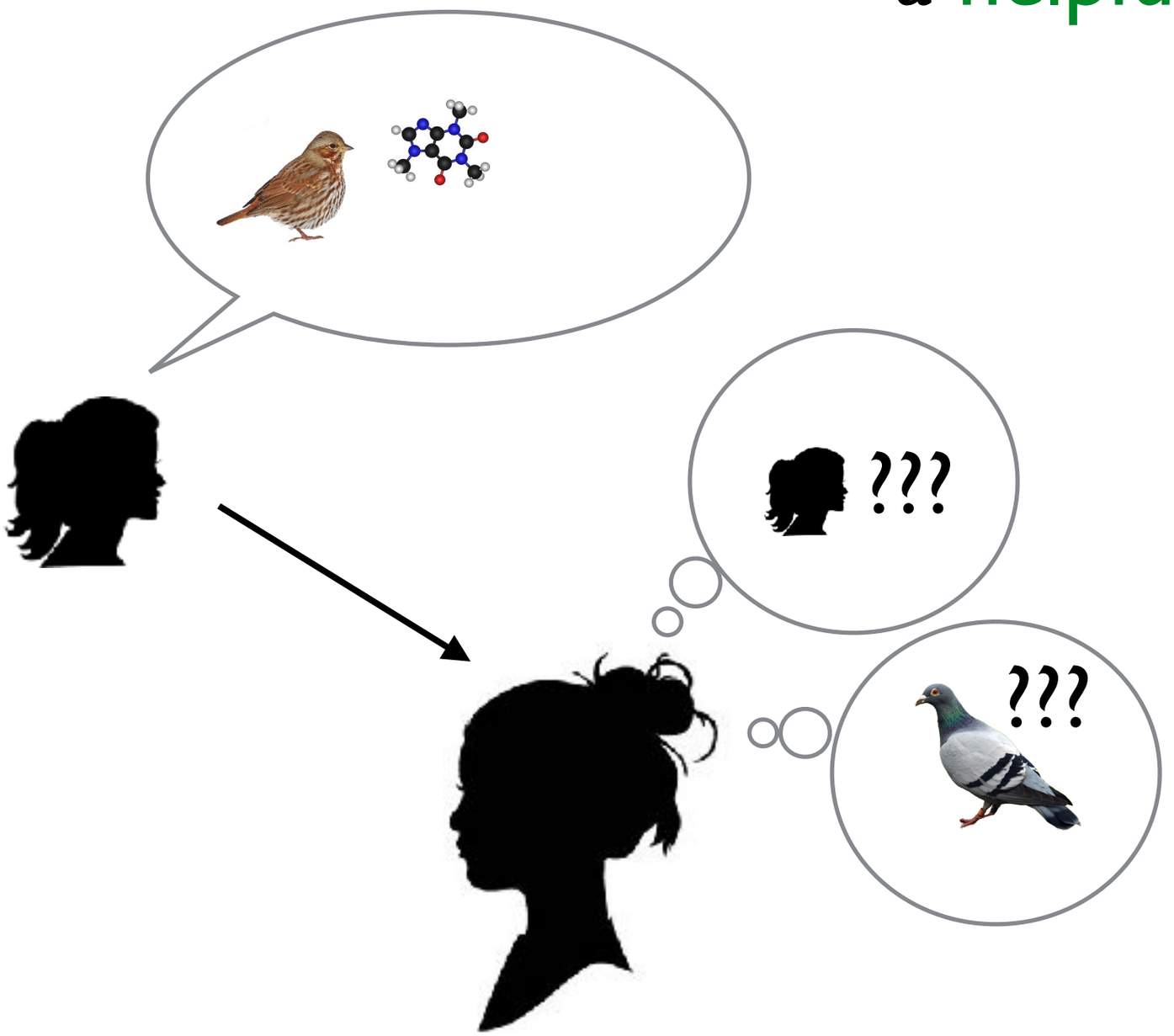
Everyday reasoning *about the world* is intertwined with *social reasoning* about other people



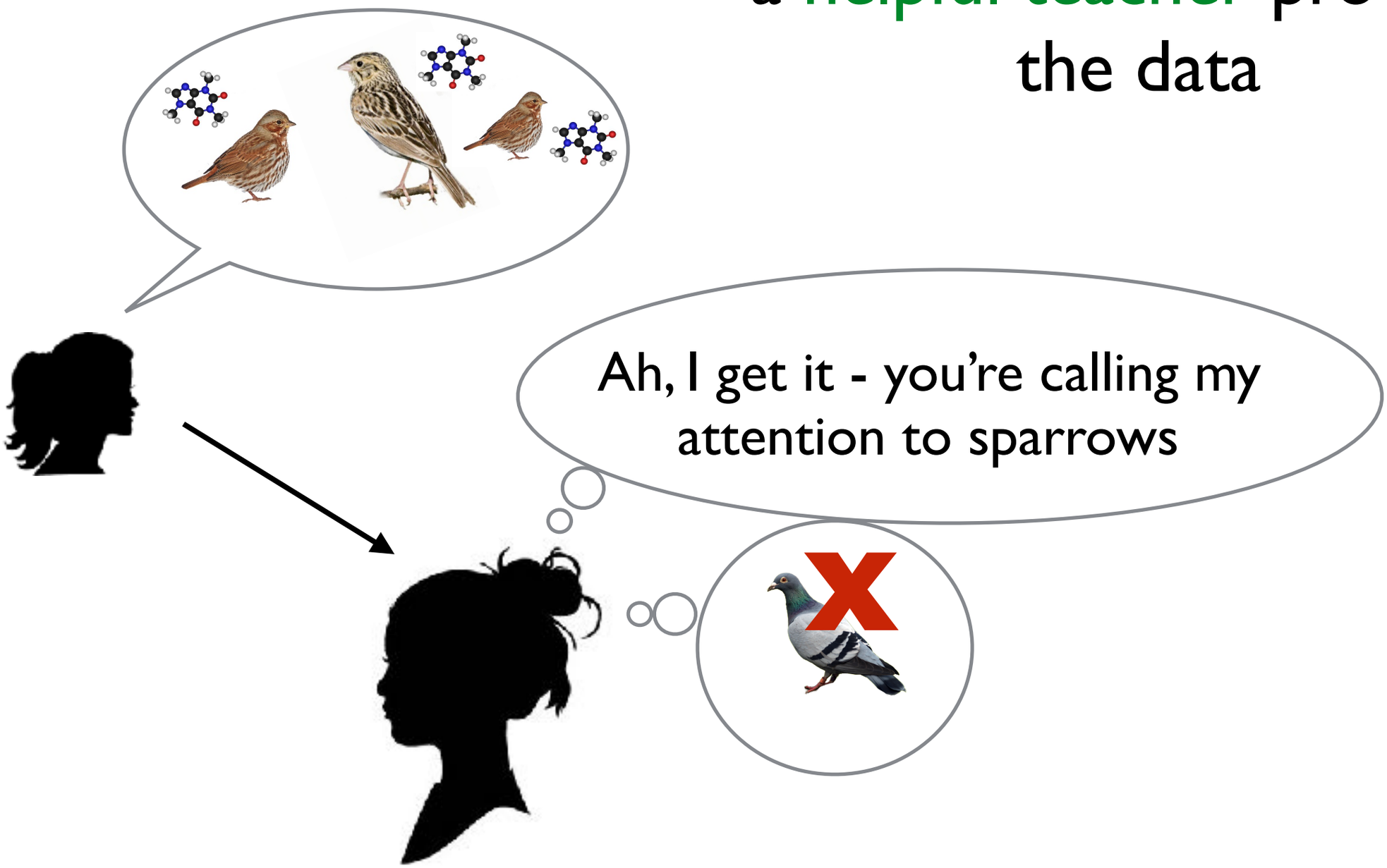
What does all this buy us?
Taking a hint from a helpful teacher

Ransom, Perfors & Navarro
(2016). *Cognitive Science*

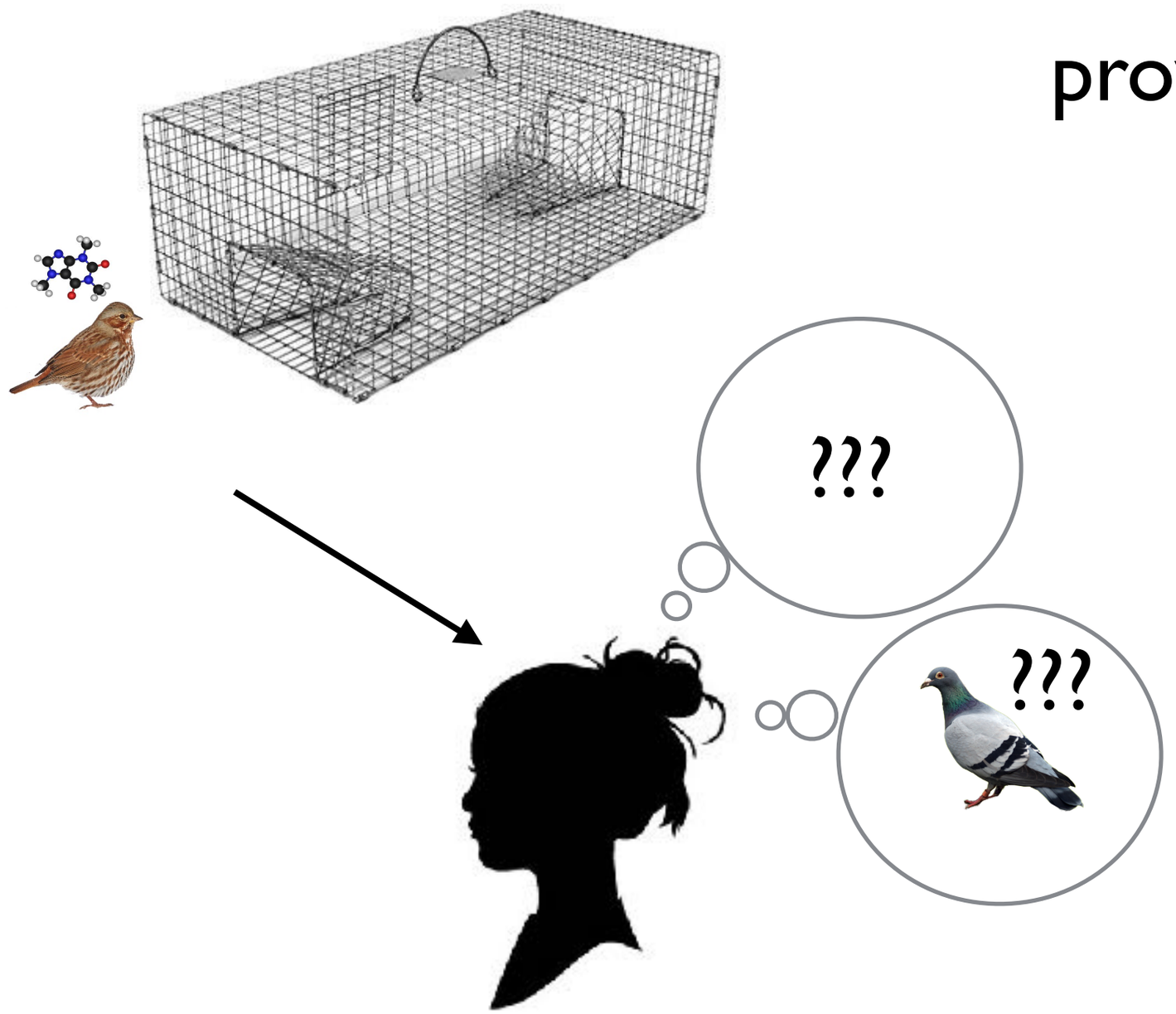
Inductive reasoning when a helpful teacher provides the data



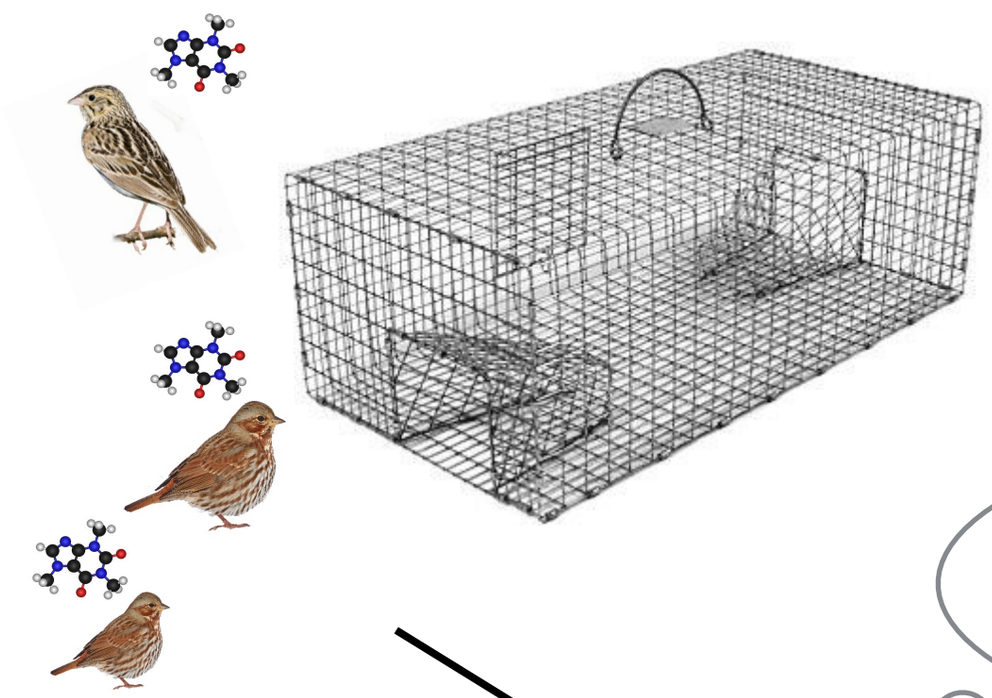
Inductive reasoning when a helpful teacher provides the data



Inductive reasoning when an indifferent world provides the data



Inductive reasoning when an indifferent world provides the data



Sampling mechanism:

Random:

"select items at random"

Helpful:

"select items to efficiently communicate an idea"

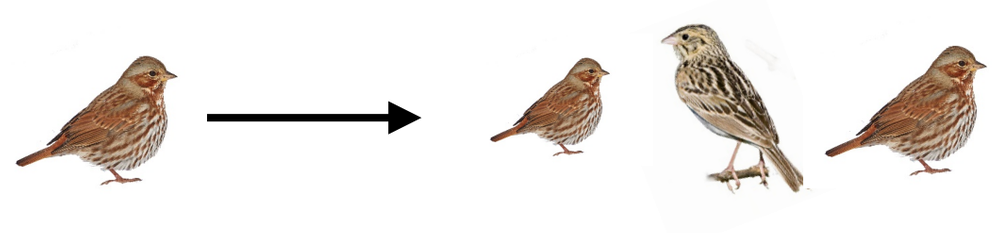
Prediction:

Random:

Adding positive instances has minimal effect if they're too similar to things I already know about

Helpful:

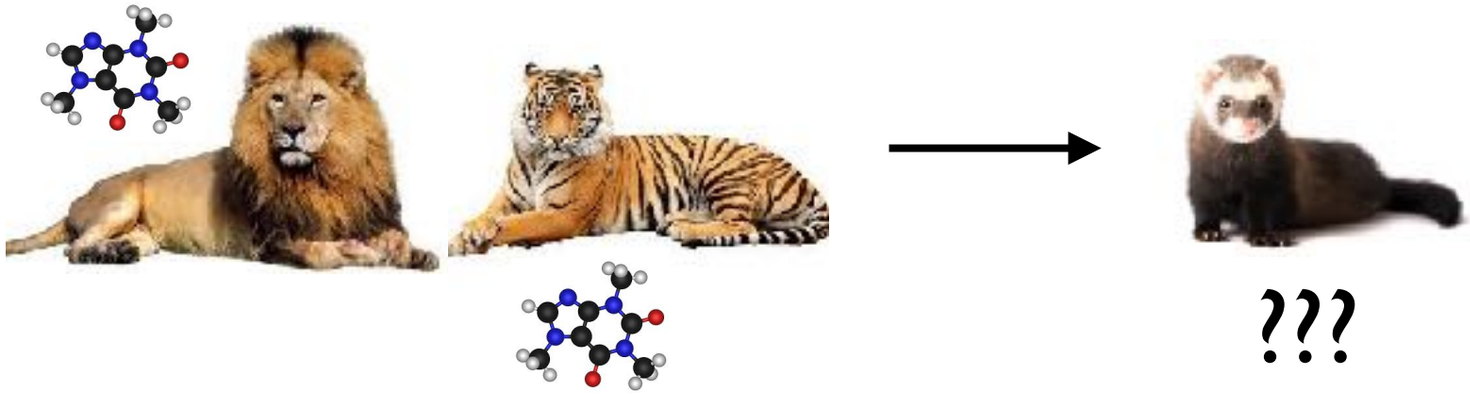
Adding positive instances from the same category conveys *intent*, and drives attention to that category



Previous experience?
(filler trials)

Cover story?

Helpful cover story, filler trials imply helpful	
Neutral cover story, filler trials imply helpful	Neutral cover story, filler trials imply random
	Random cover story, filler trials imply random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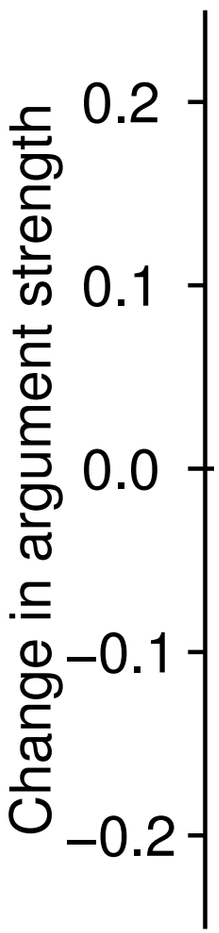
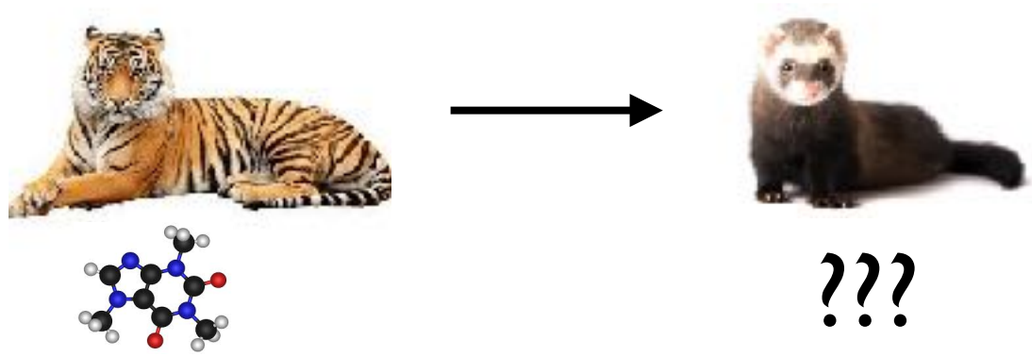

Change in argument strength
0.2
0.1
0.0
−0.1
−0.2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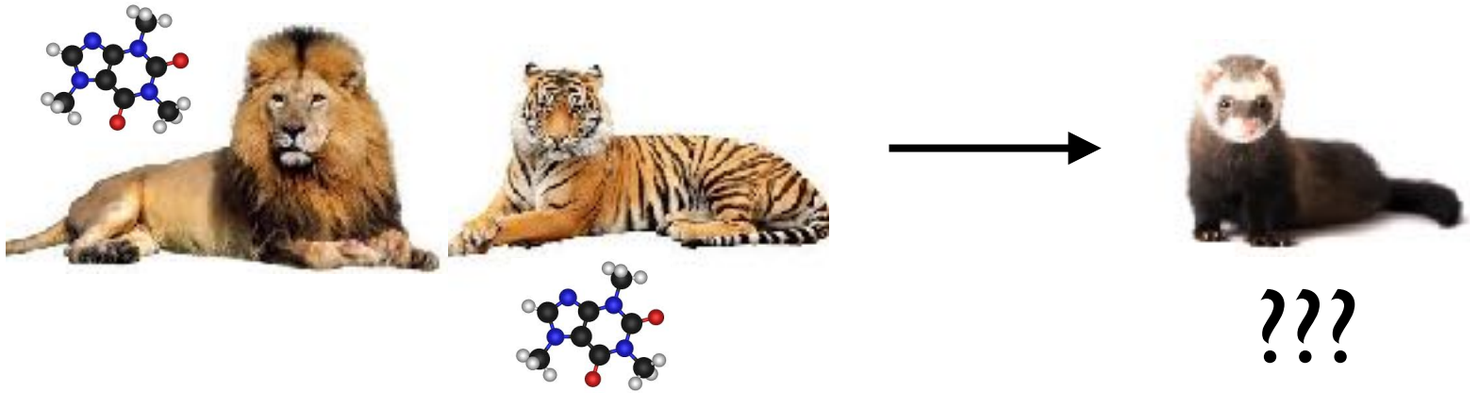
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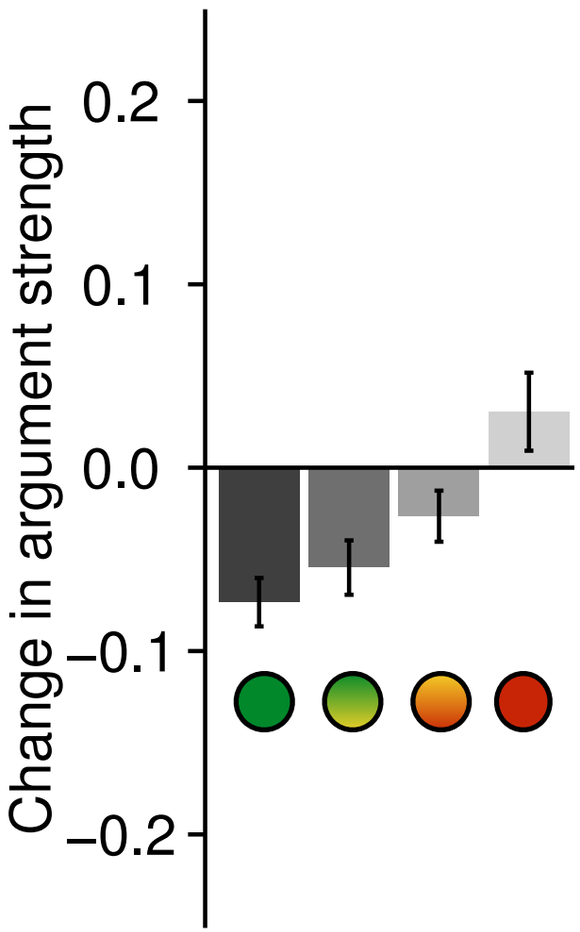
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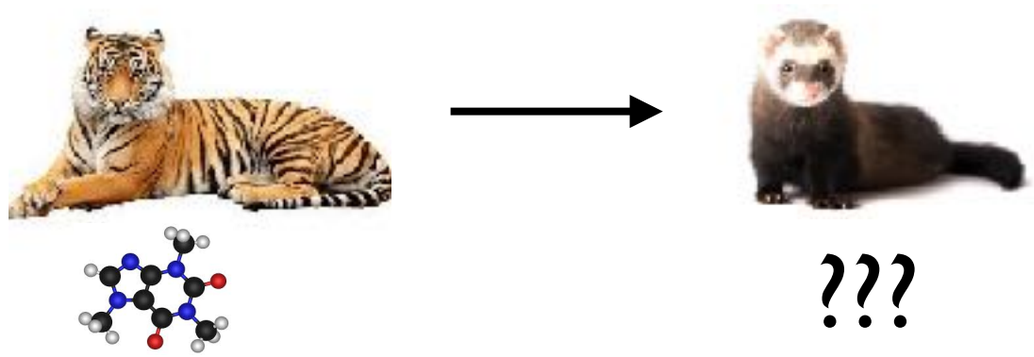
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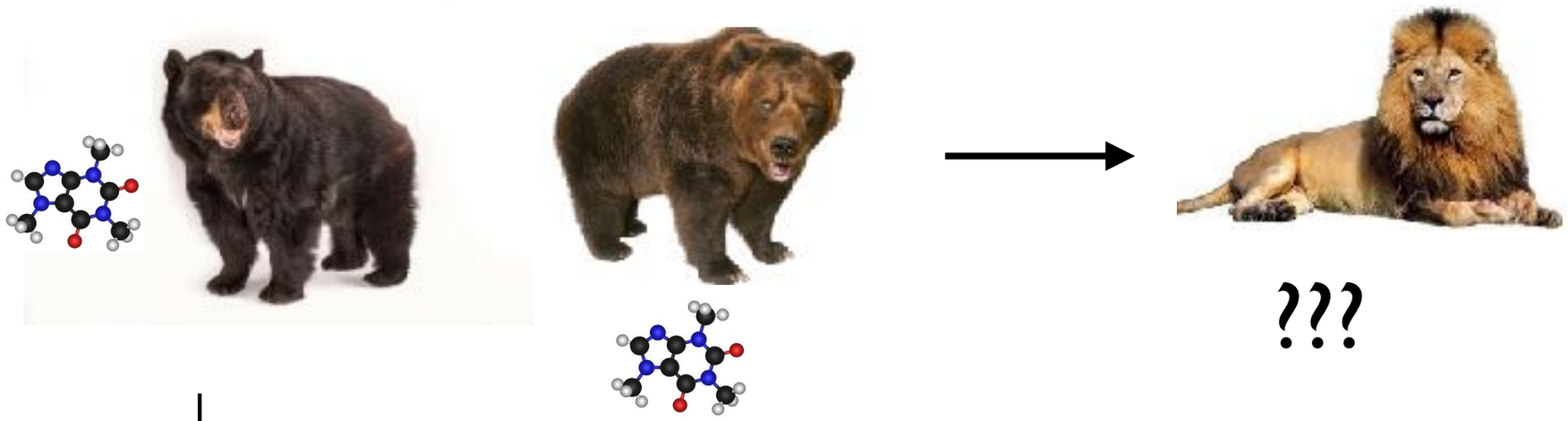
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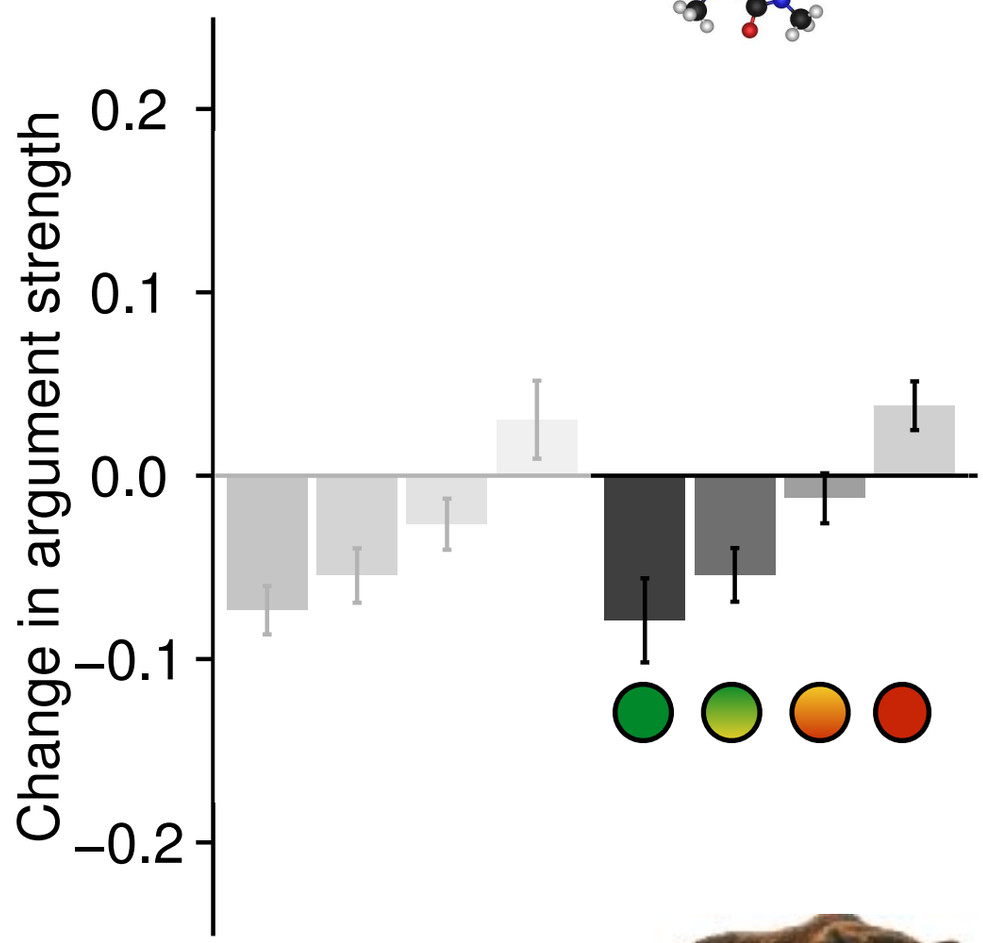
Change in argument strength
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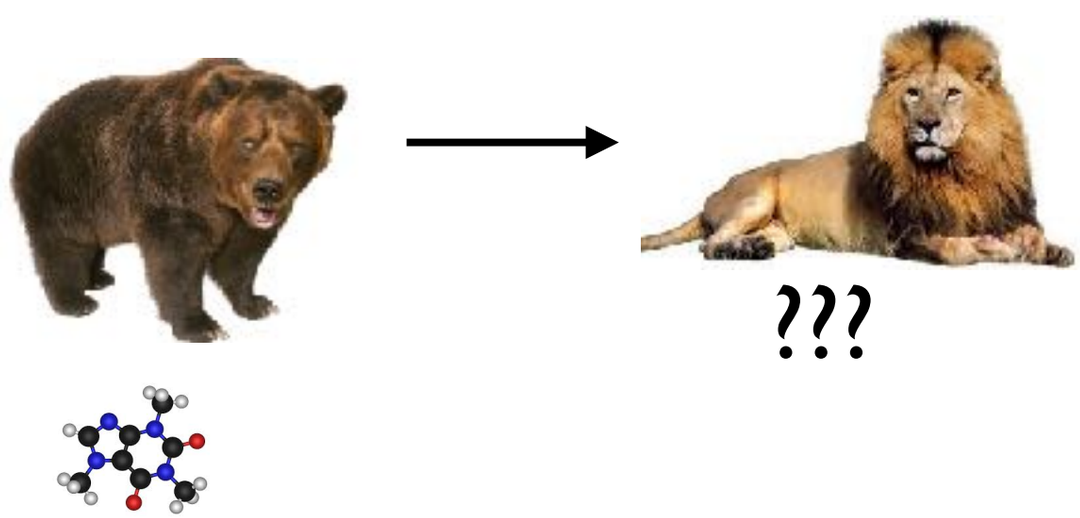
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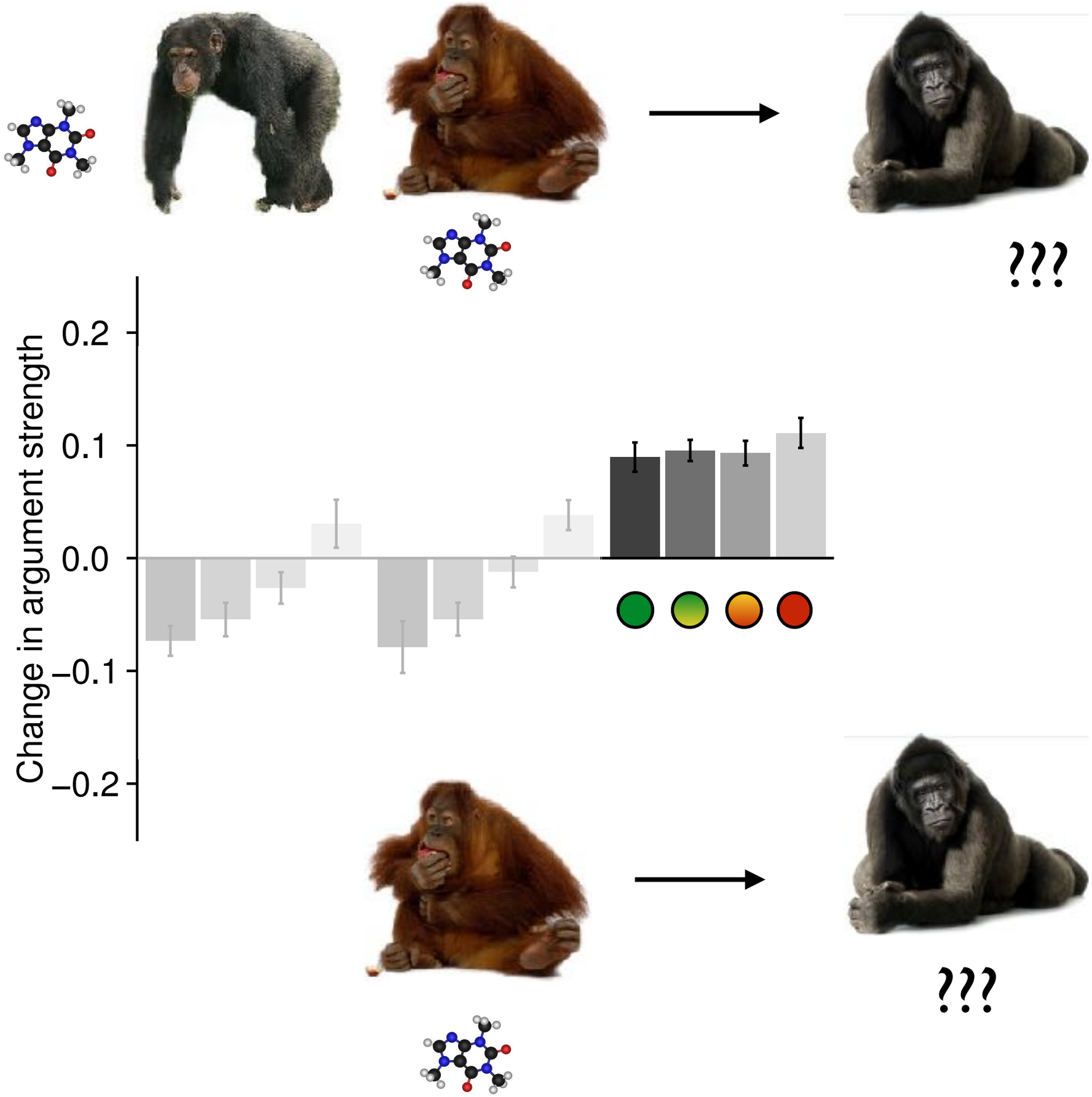
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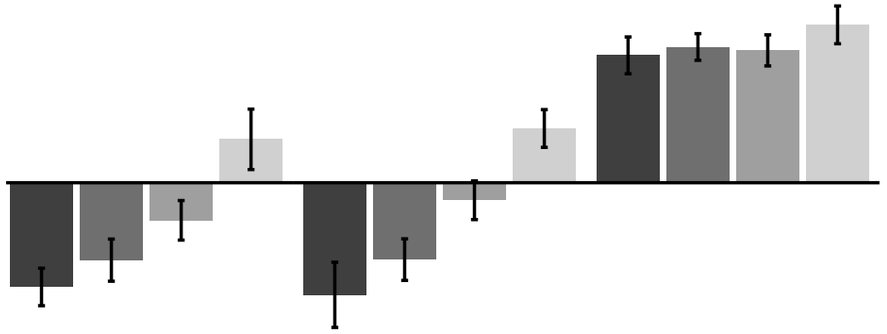
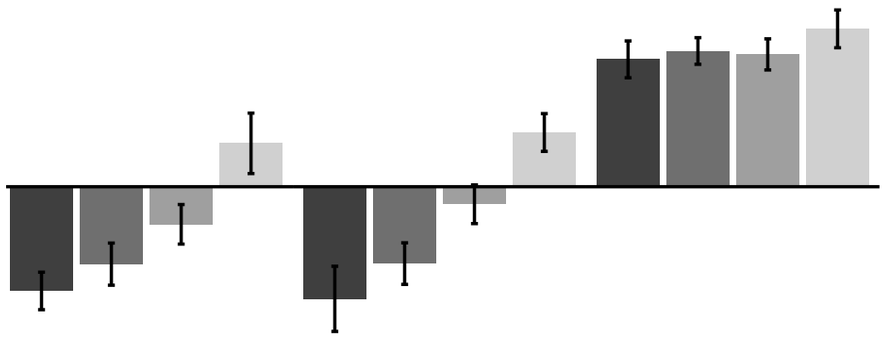
Change in argument strength
0.2
0.1
0.0
−0.1
−0.2
???

Humans

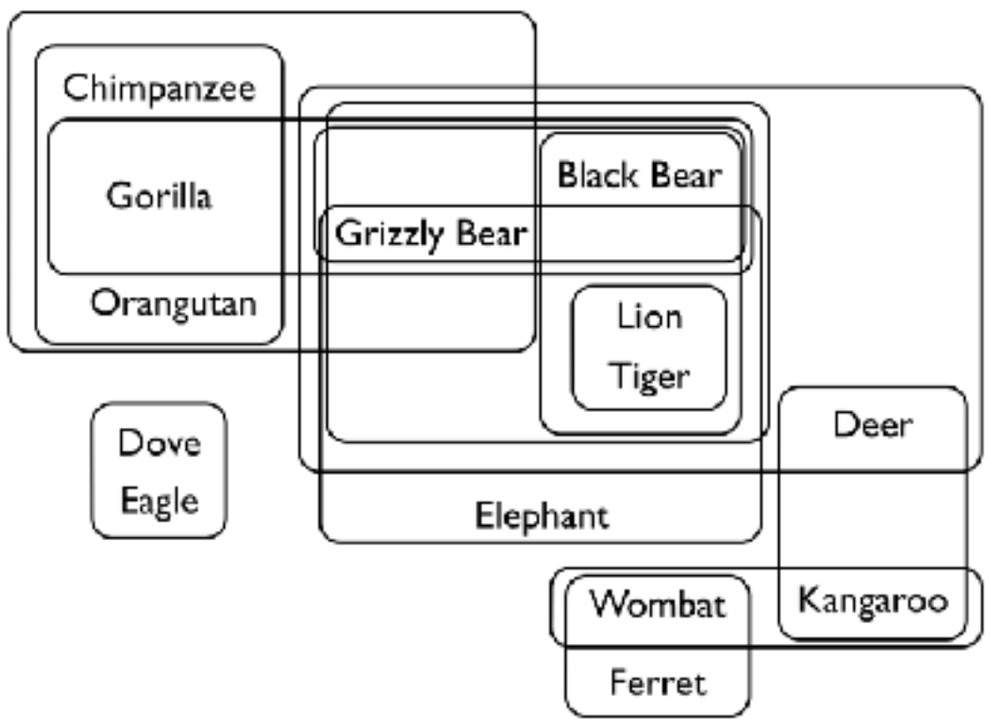


Bayes

Humans



Knowledge about animal categories (*theory of the world*) creates structural differences between the different arguments



The sampling model (*theory of the context*) describes how "adding more data" can have different effects across conditions and arguments

Using negative evidence to take hints from helpful teachers

Voorspoels, Navarro, Perfors, Ransom & Storms (2015). *Cognitive Psychology*

Positive evidence

Mozart produces alpha waves in the brain

This seems helpful!

Negative evidence

This… not so much

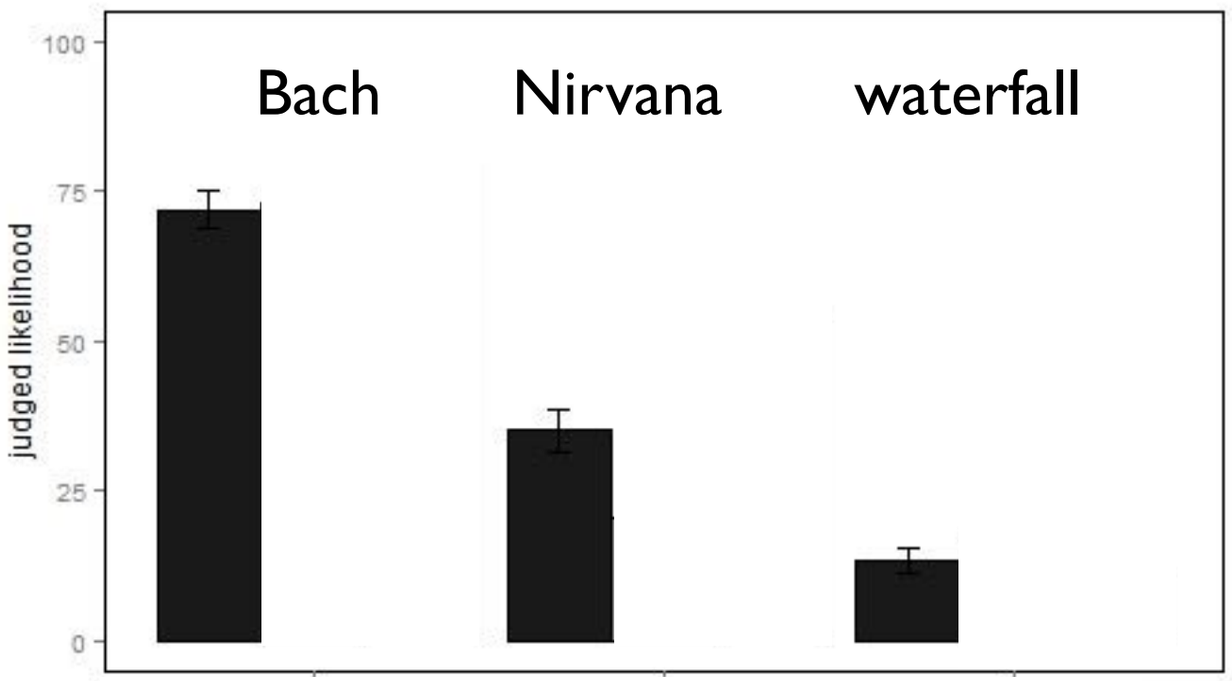
The sound of a falling rock does not

see Hempel (1945), Good (1960), etc

Okay, we start by telling people that Mozart does produce alpha waves…

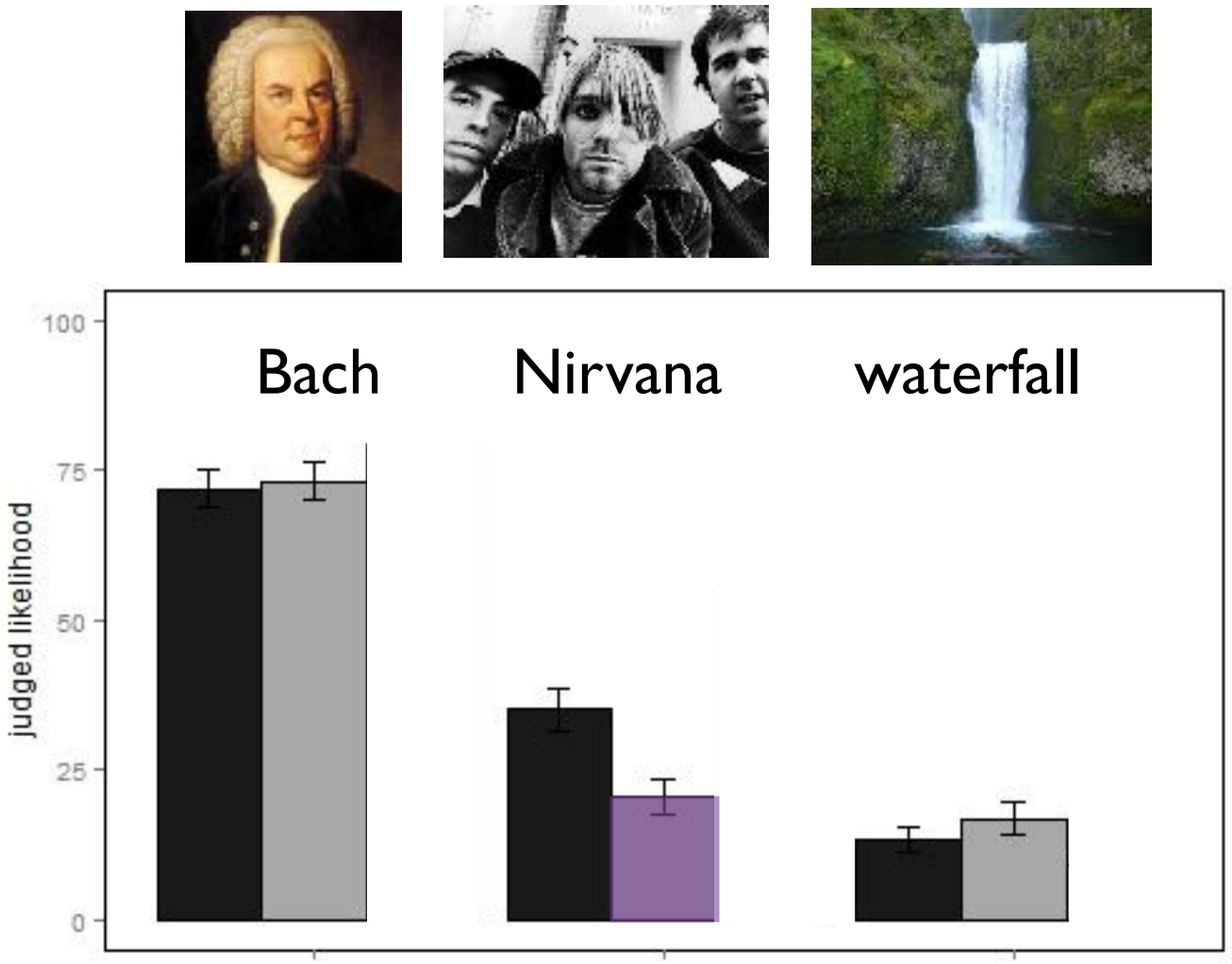
+Mozart





+Mozart

… and they reason sensibly

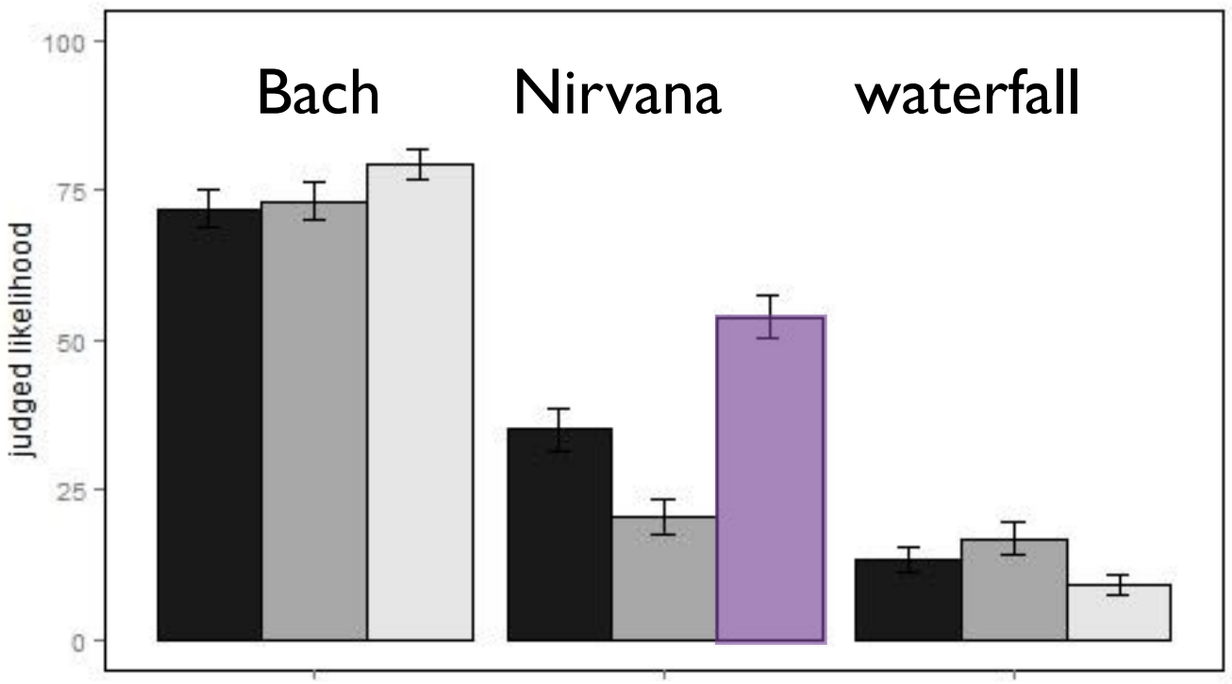


+Mozart

-Metallica

Adding Metallica as a negative example has a modest, sensible effect on inferences about Nirvana



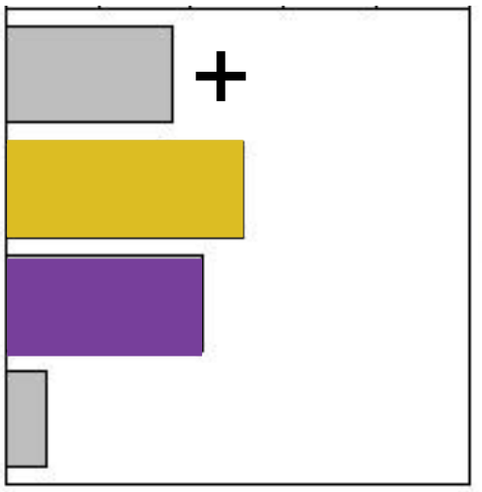


Um.

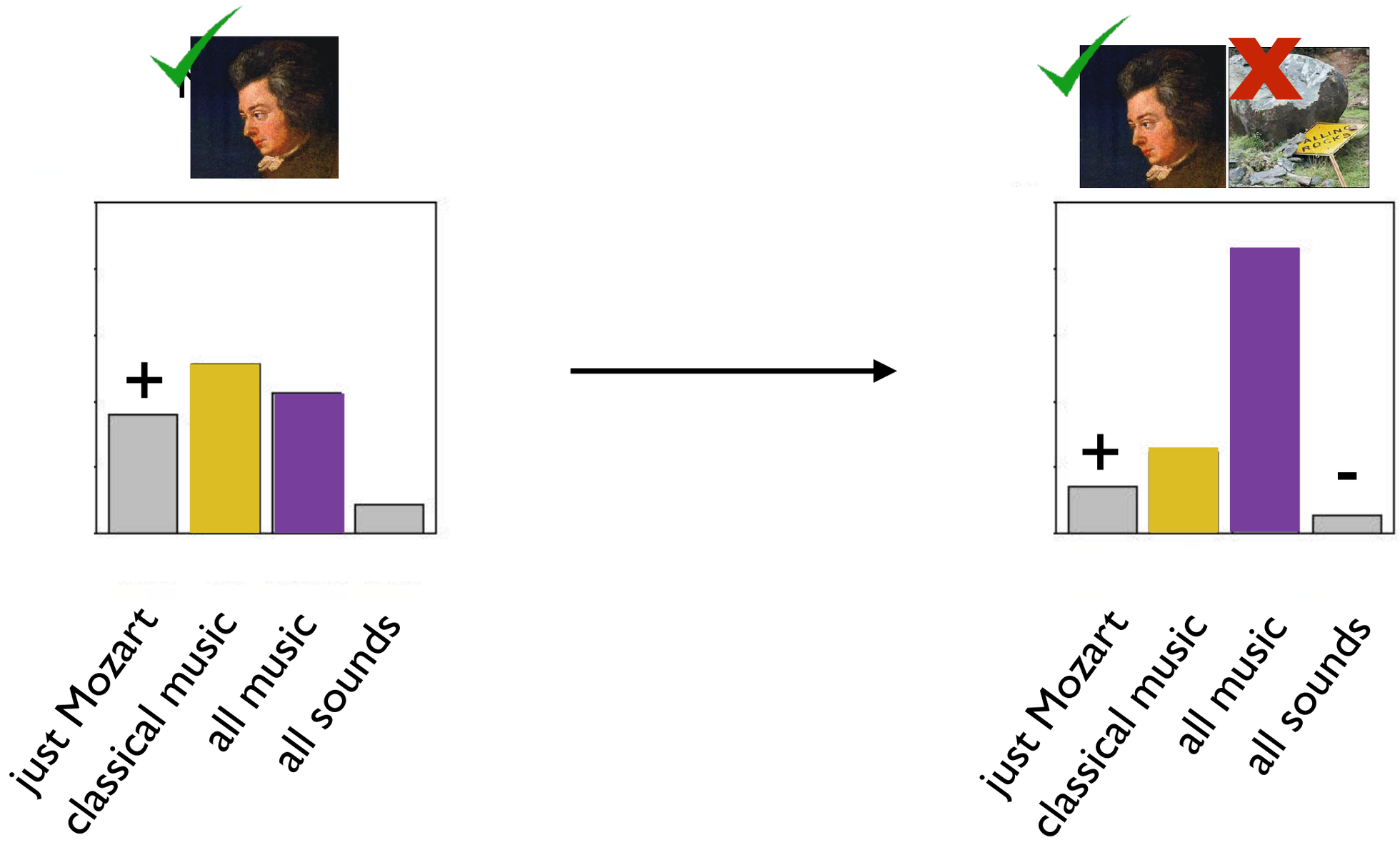
+Mozart

-Falling rock

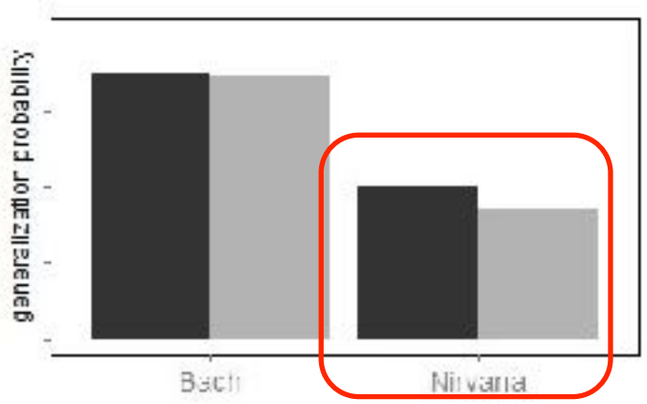
just Mozart
classical music
all music
all sounds

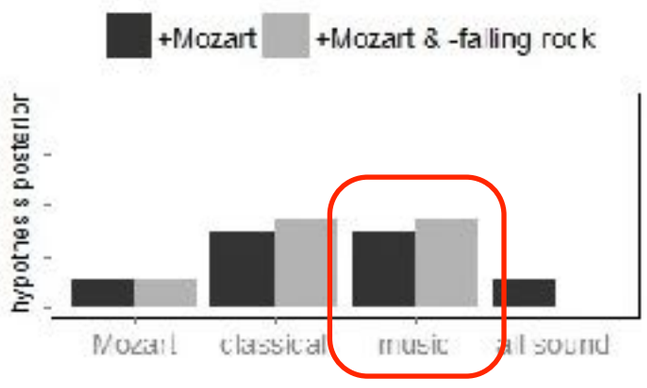


Negative evidence is interpreted as marking the category boundary

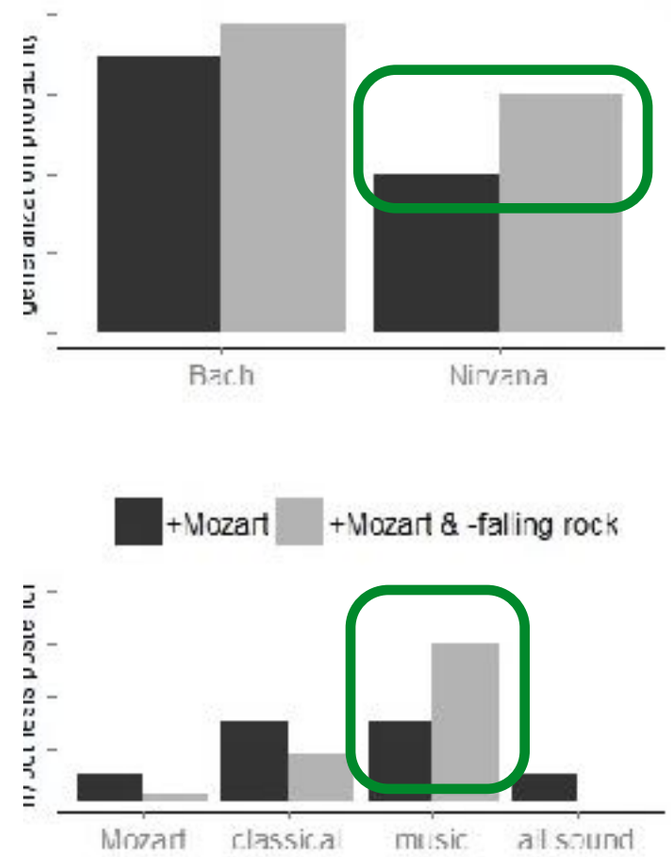


Bayesian reasoners with a random sampling assumption do *not* produce the effect





Bayesian reasoners with a helpful sampling assumption *do* produce the effect

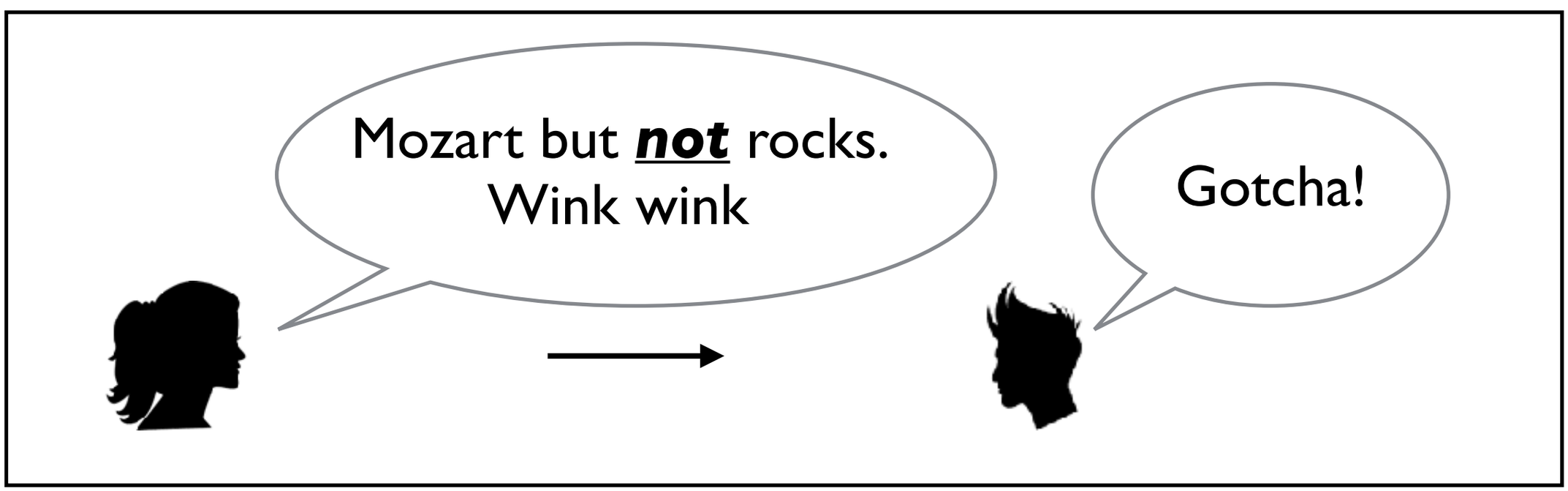


What does it mean to be "helpful" anyway?

$$P(x|h) \propto P(h|x)^{\alpha}$$

The data x sampled by the <u>communicator</u>…

… is designed to maximise the <u>learner's</u> degree of belief in hypothesis h



Prediction:

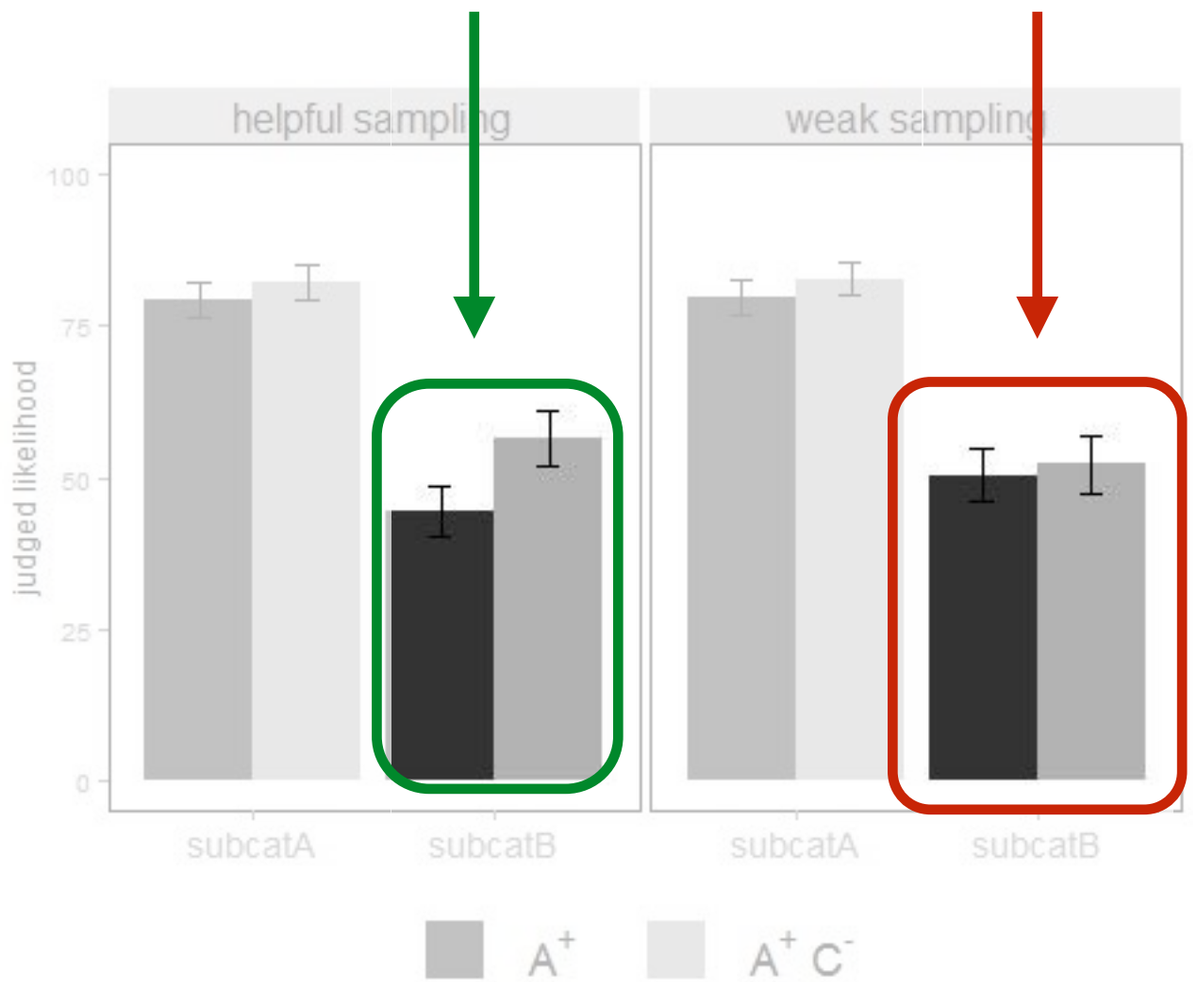
If the negative evidence is perceived as a helpful hint we should continue to get the effect →

If it is construed as an arbitrary fact, the effect should vanish →

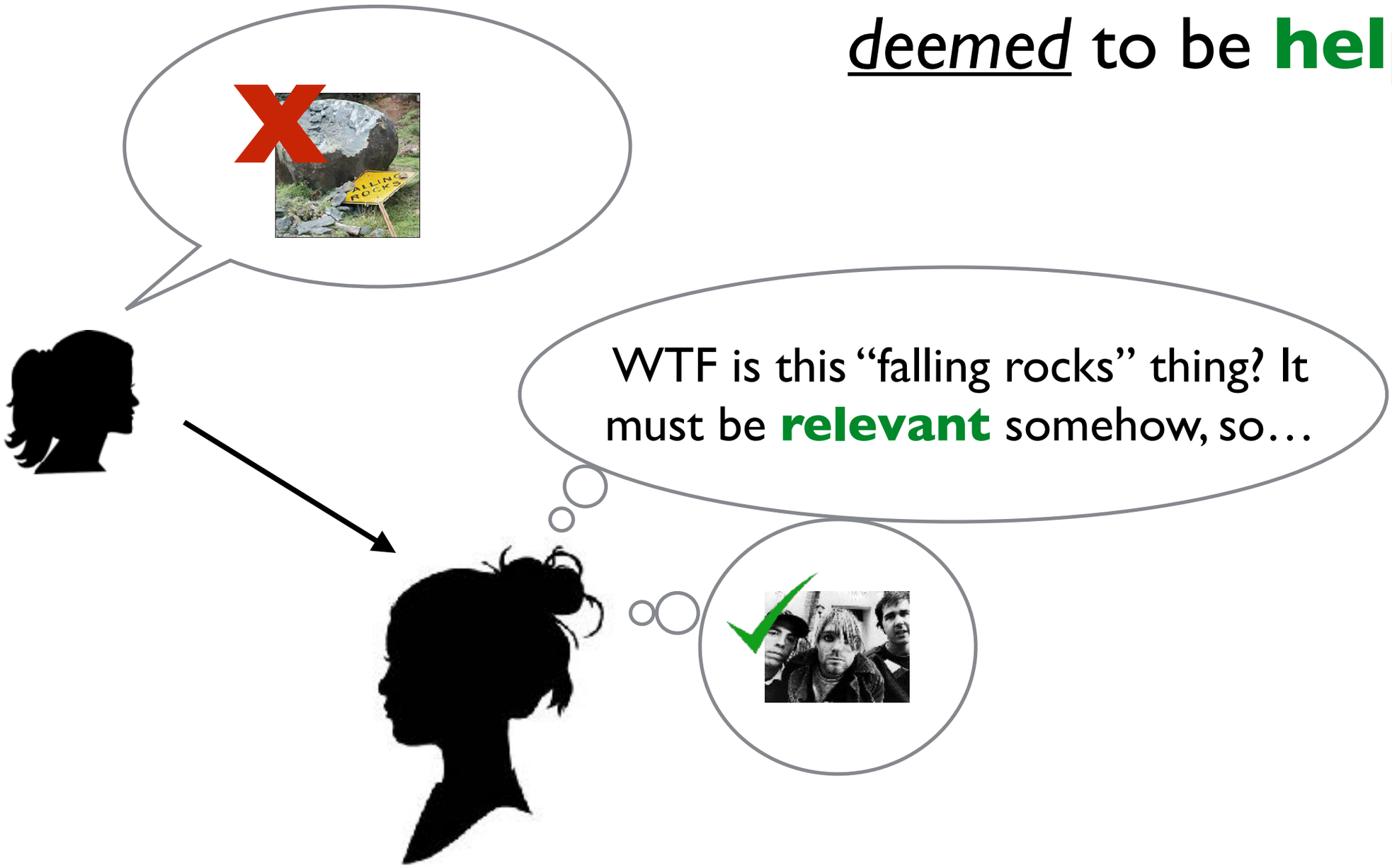
Here's the experimental results:

Hint

Arbitrary



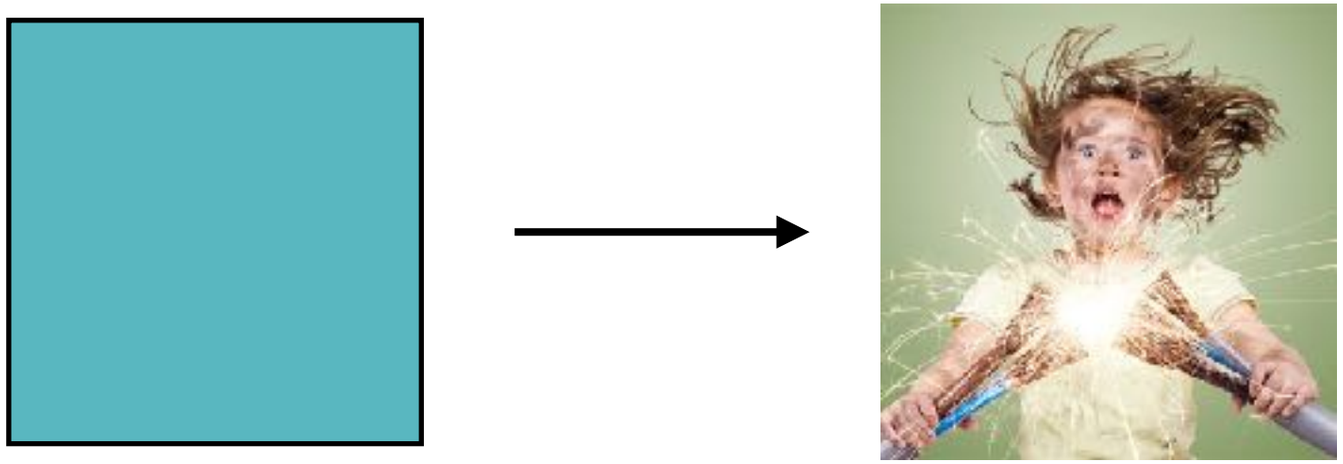
Superficially useless information can have a huge effect when it is *deemed* to be **helpful**



Extension: Negative evidence, fear conditioning & inductive reasoning

(work in progress!)

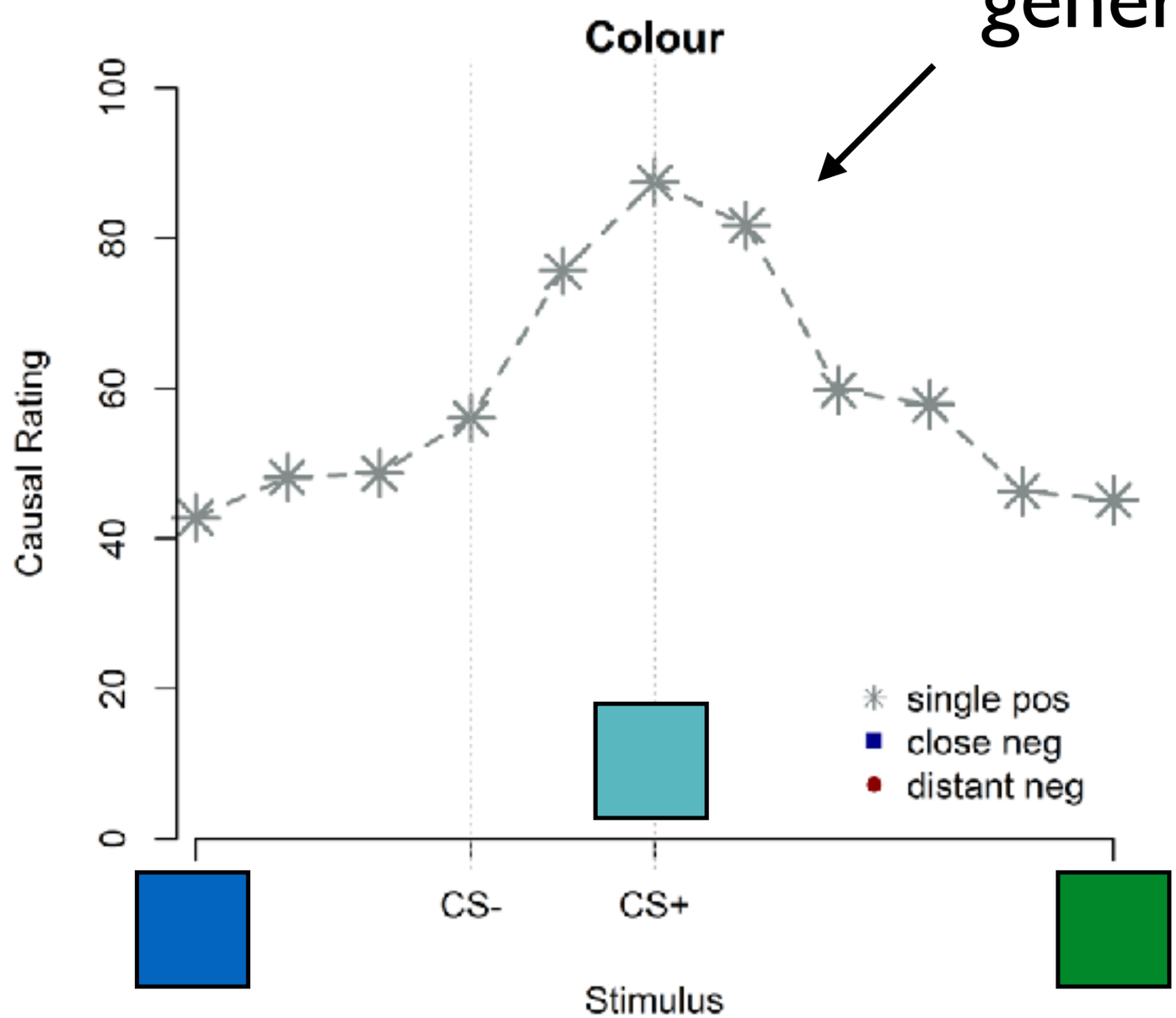
Fear conditioning*



CS US

Lee, Lovibond, Hayes & Navarro (in prep)

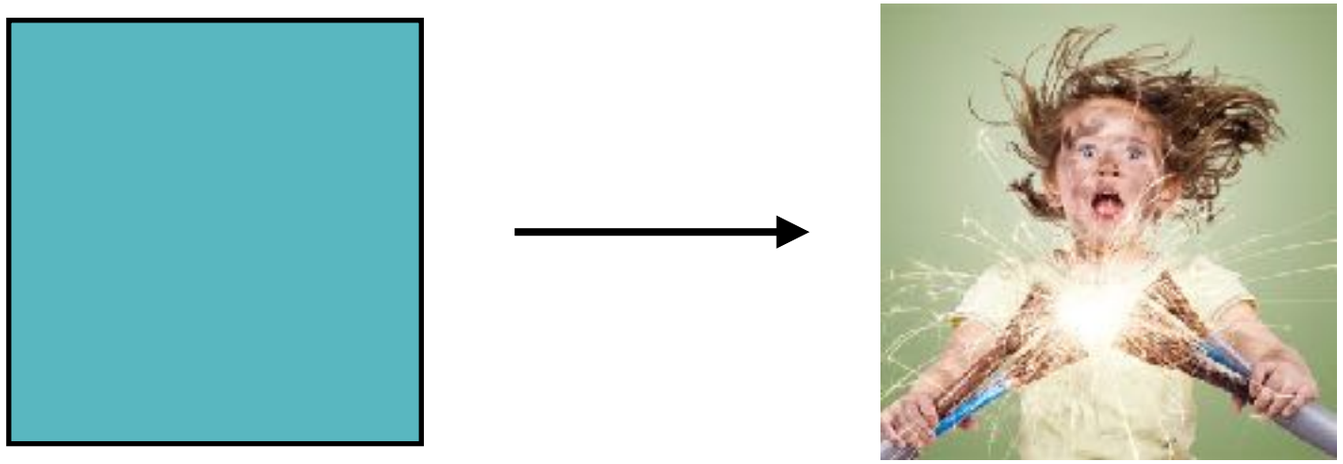
Similarity based generalisation



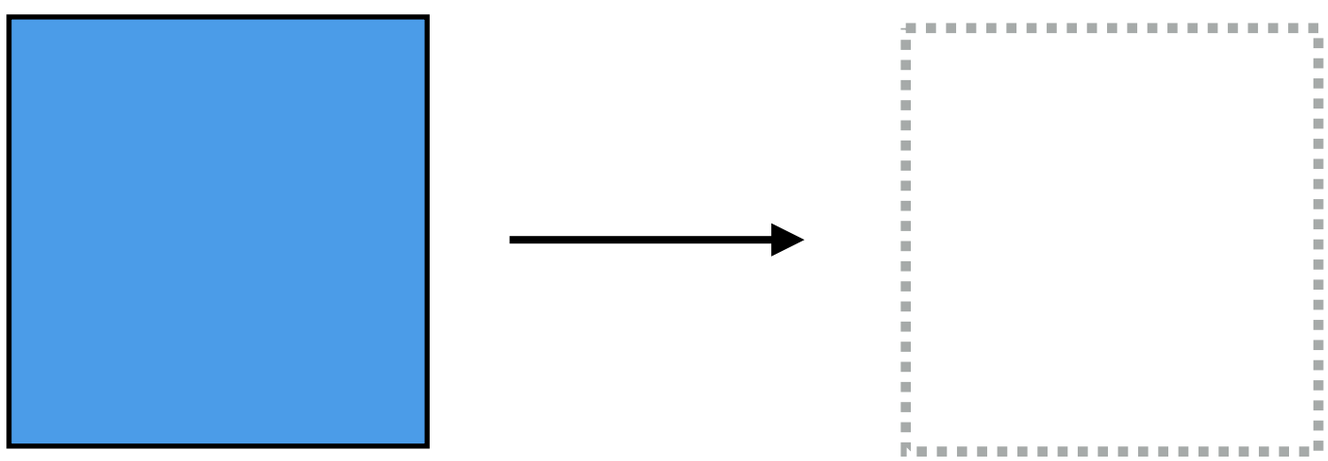
Lee, Lovibond, Hayes & Navarro (in prep)

Negative evidence along the same dimension ("*near*" CS-)

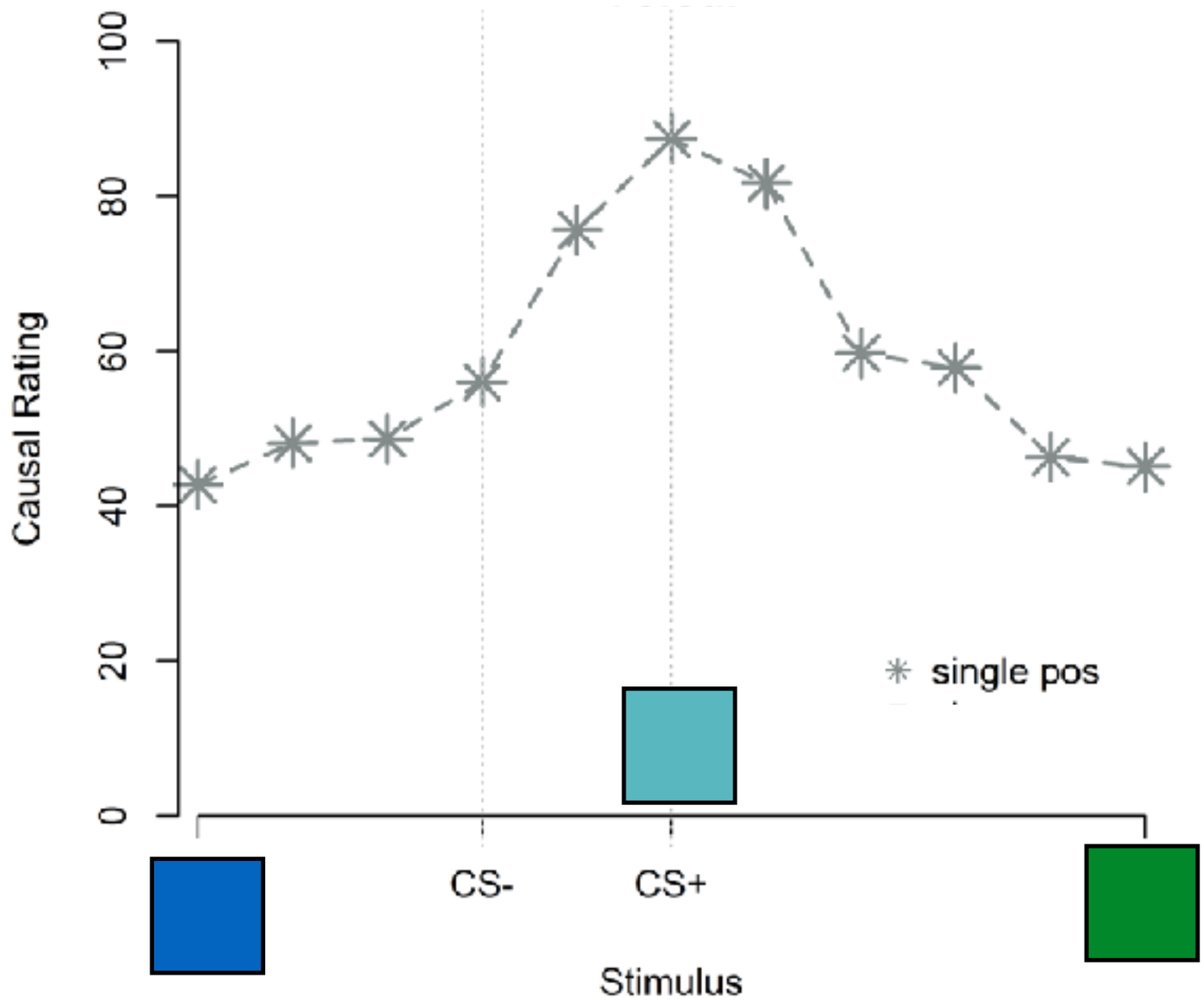
CS+



CS-

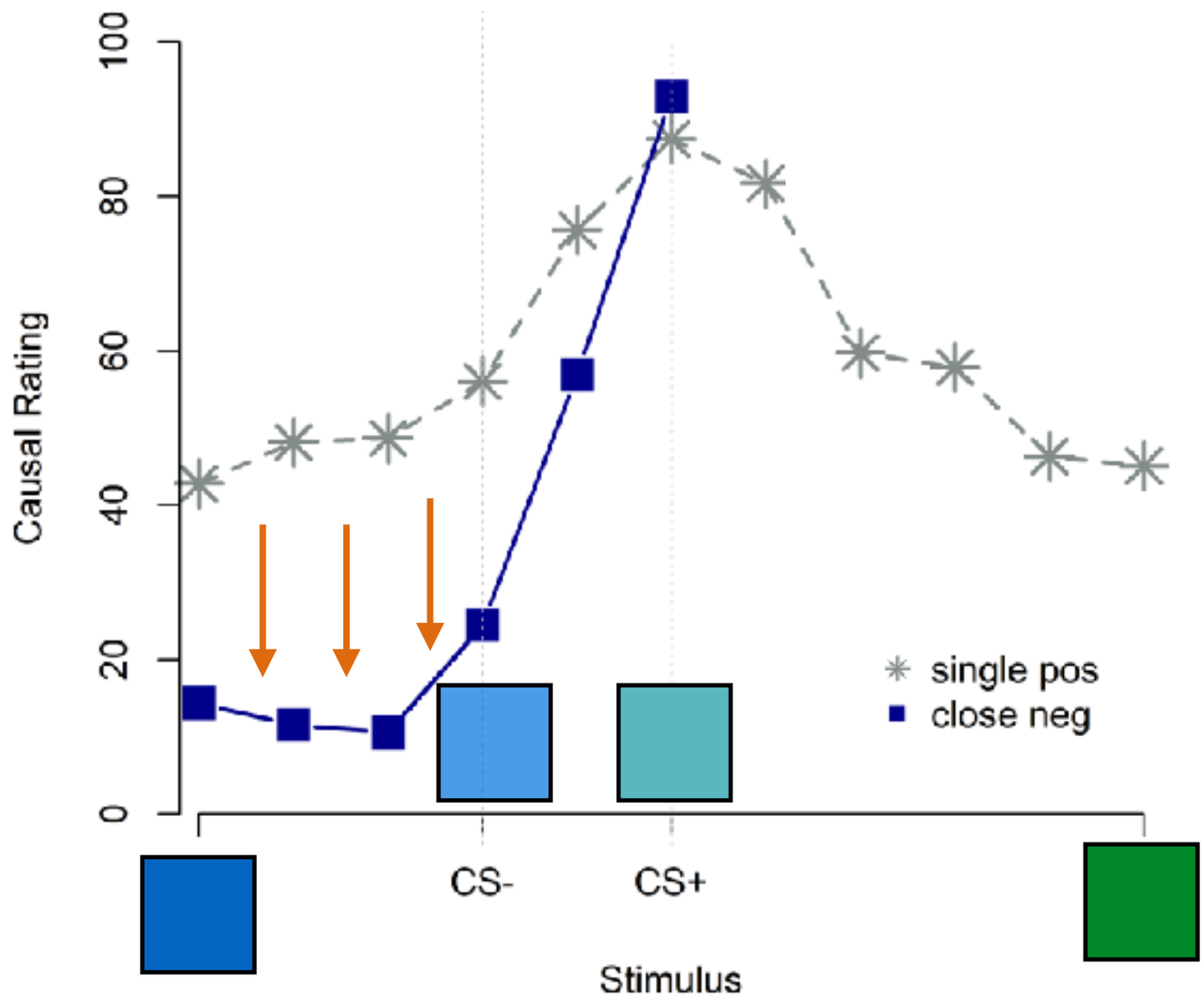


Lee, Lovibond, Hayes & Navarro (in prep)



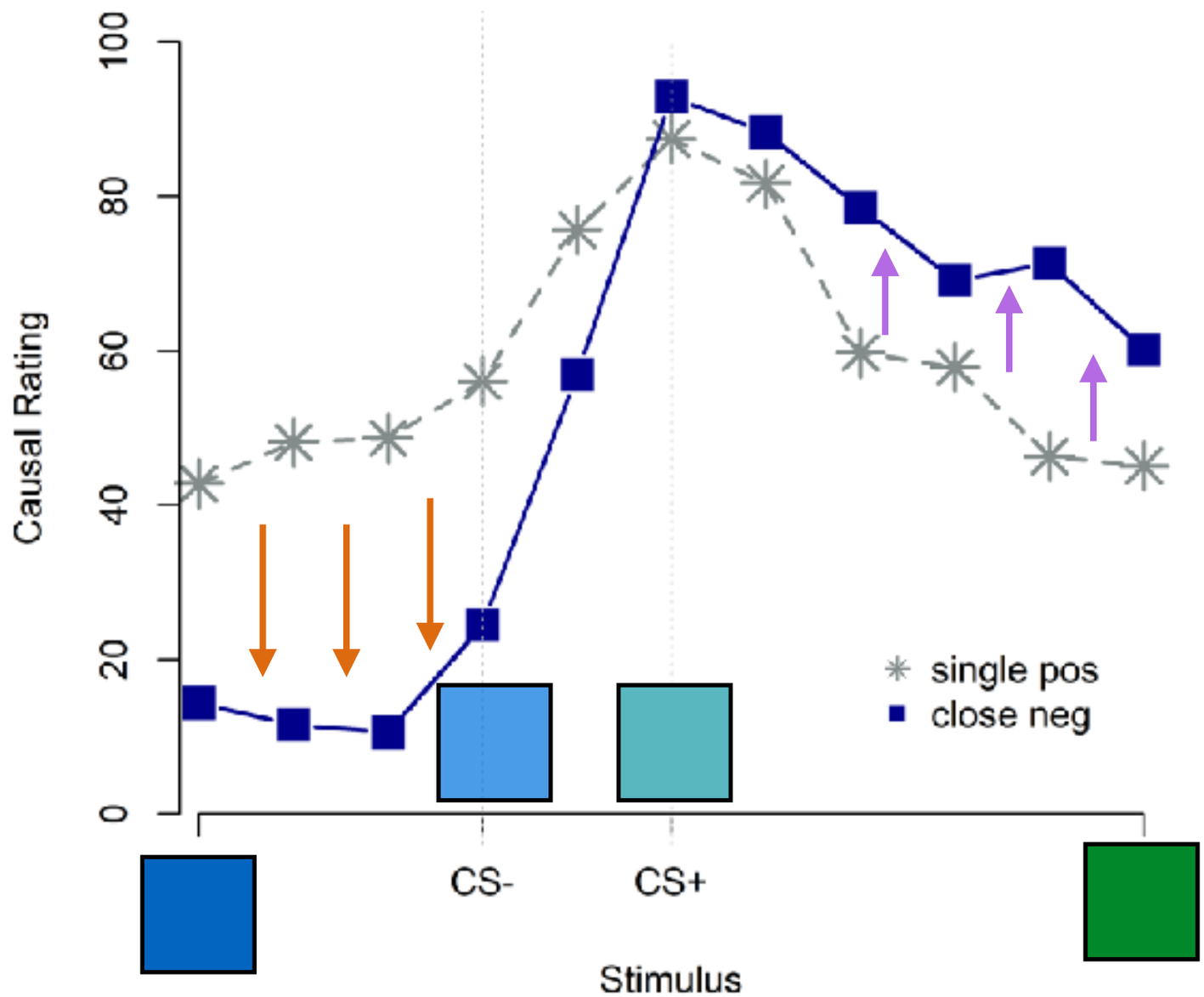
Lee, Lovibond, Hayes & Navarro (in prep)

CS- decreases generalisation on this side



Lee, Lovibond, Hayes & Navarro (in prep)

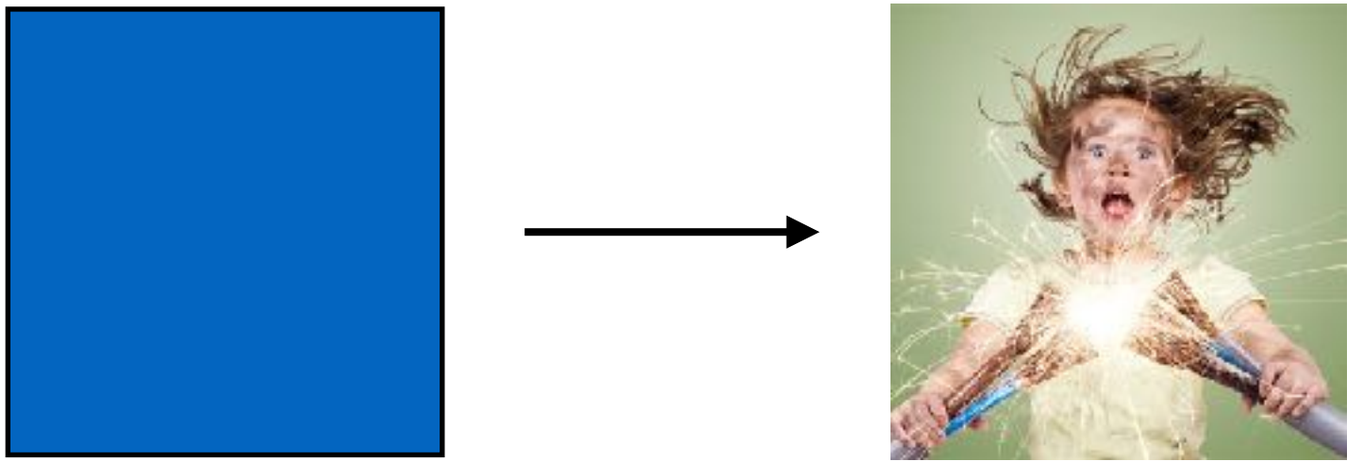
CS- increases generalisation on this side



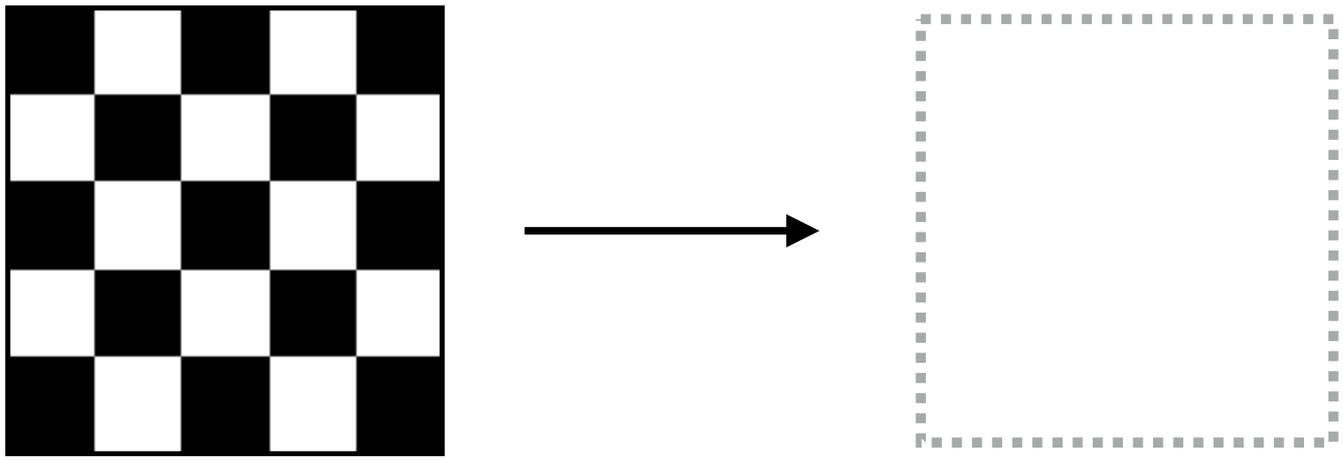
Lee, Lovibond, Hayes & Navarro (in prep)

What happens when the "*far*" CS- has no value on the blue-green dimension?

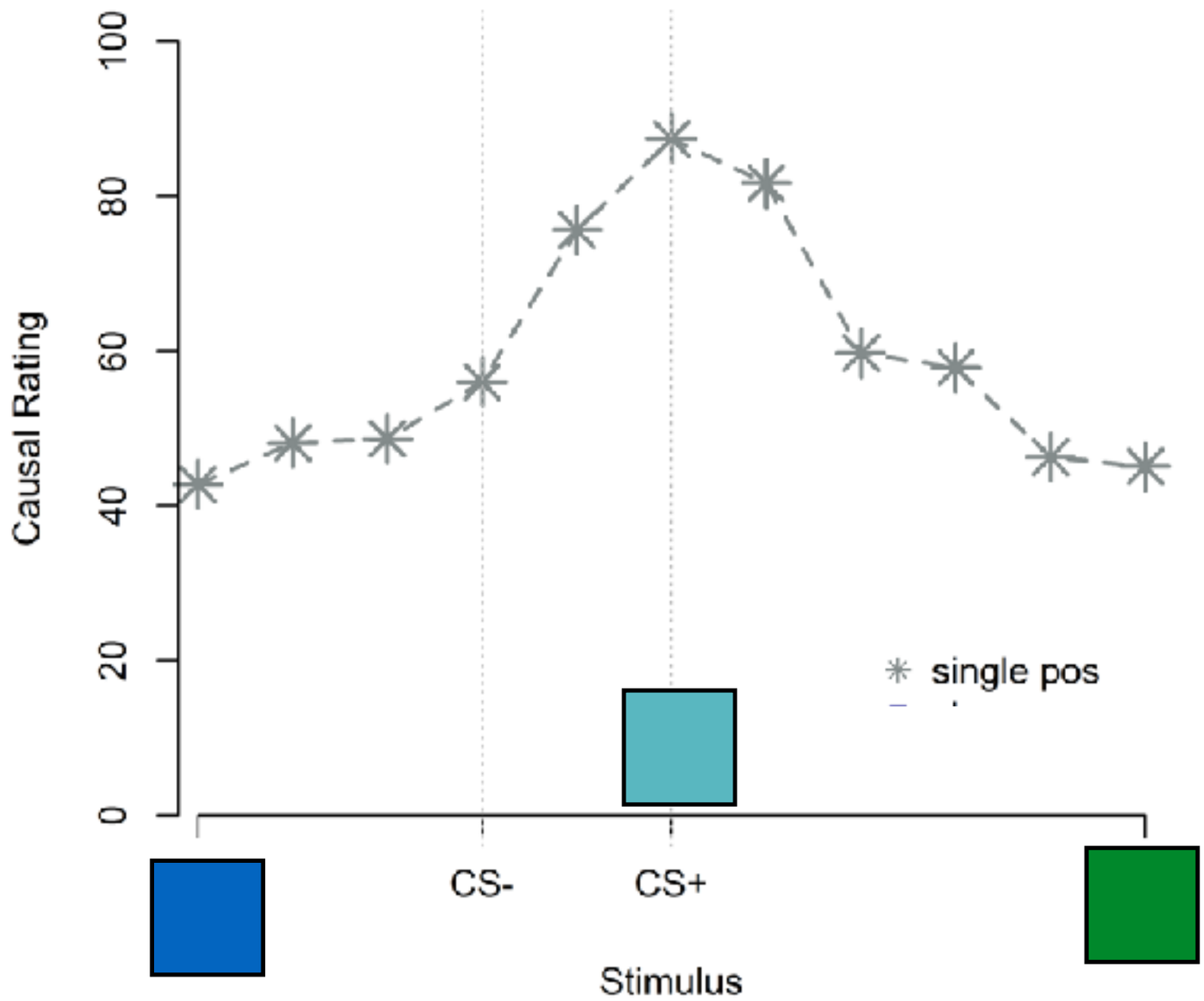
CS+



CS-

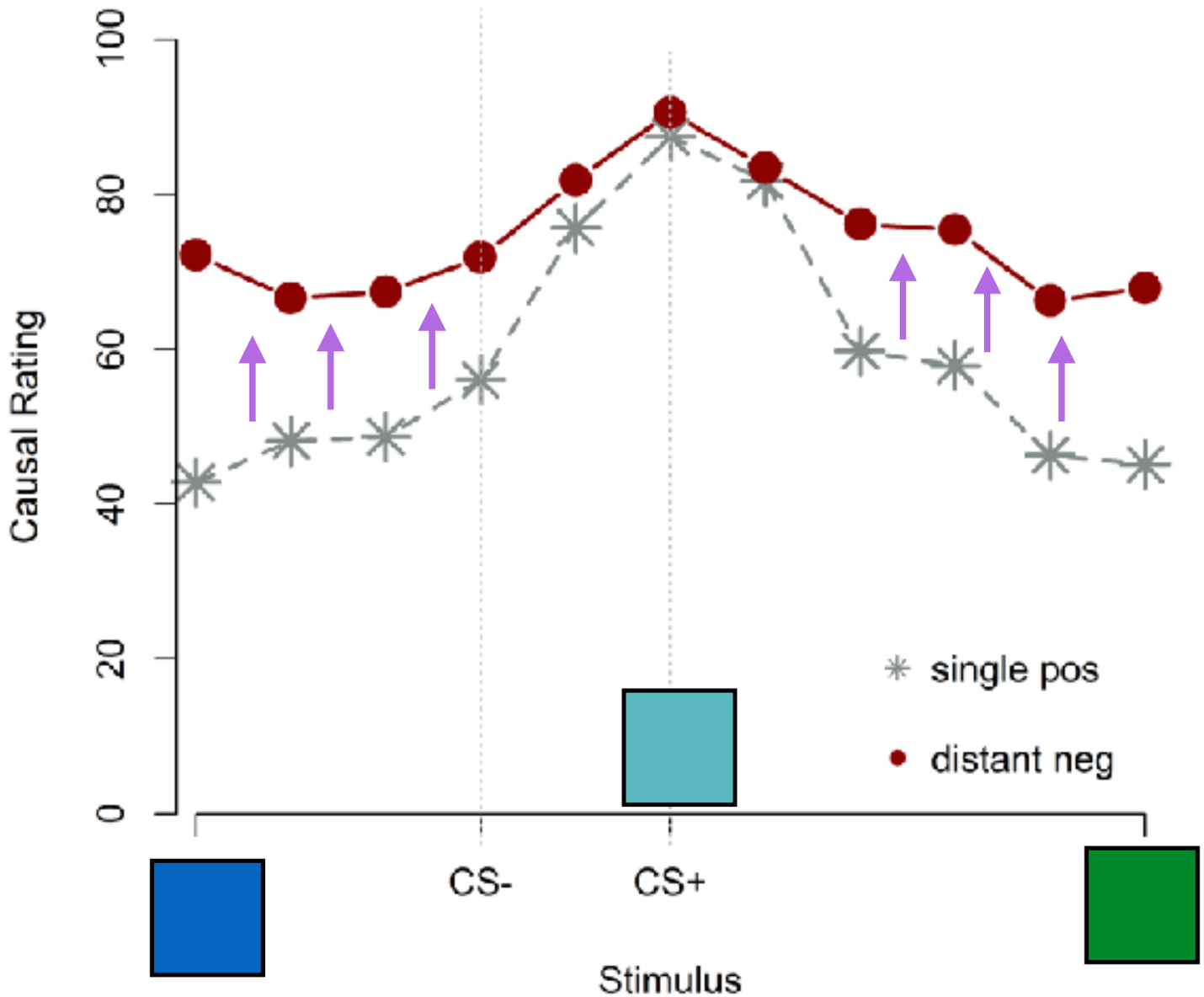


Lee, Lovibond, Hayes & Navarro (in prep)



Lee, Lovibond, Hayes & Navarro (in prep)

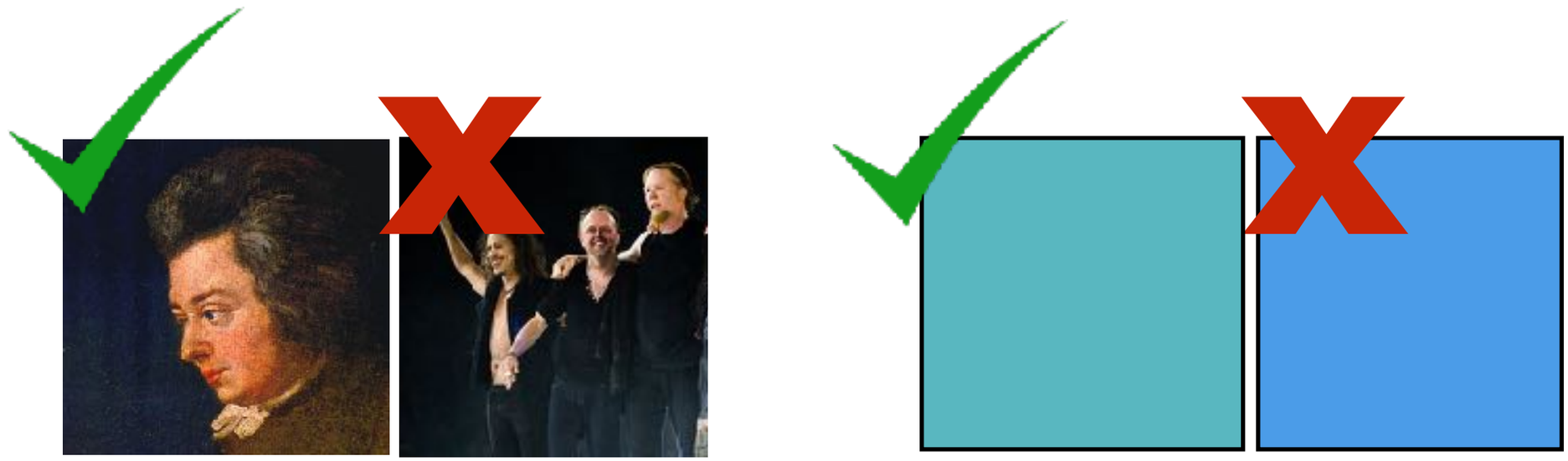
CS- increases generalisation across the whole dimension



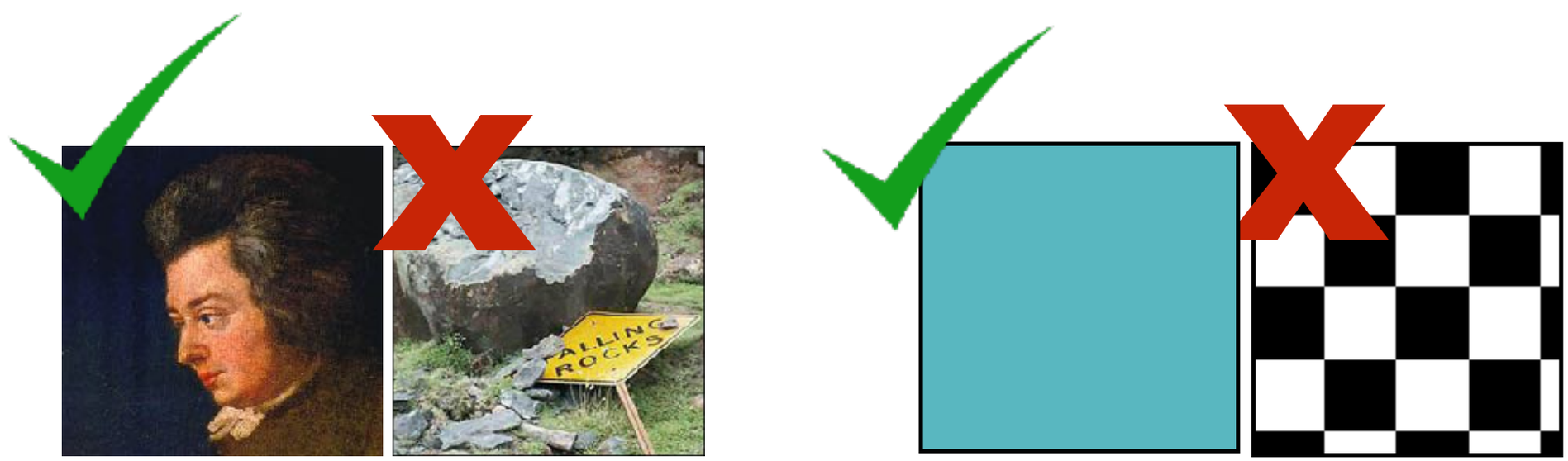
Lee, Lovibond, Hayes & Navarro (in prep)

These are essentially the same design

Near negative

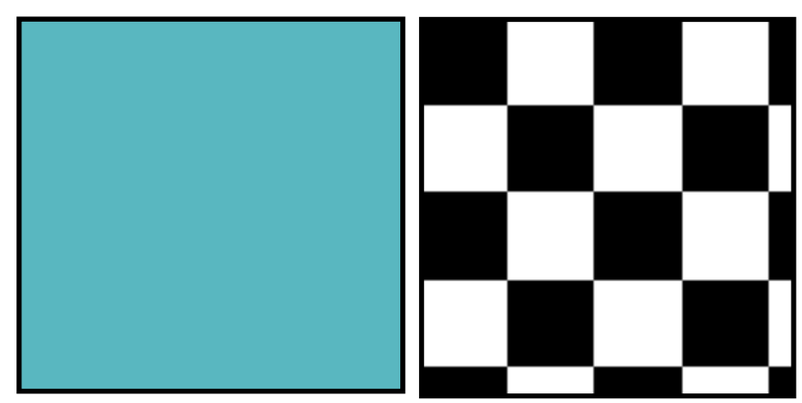


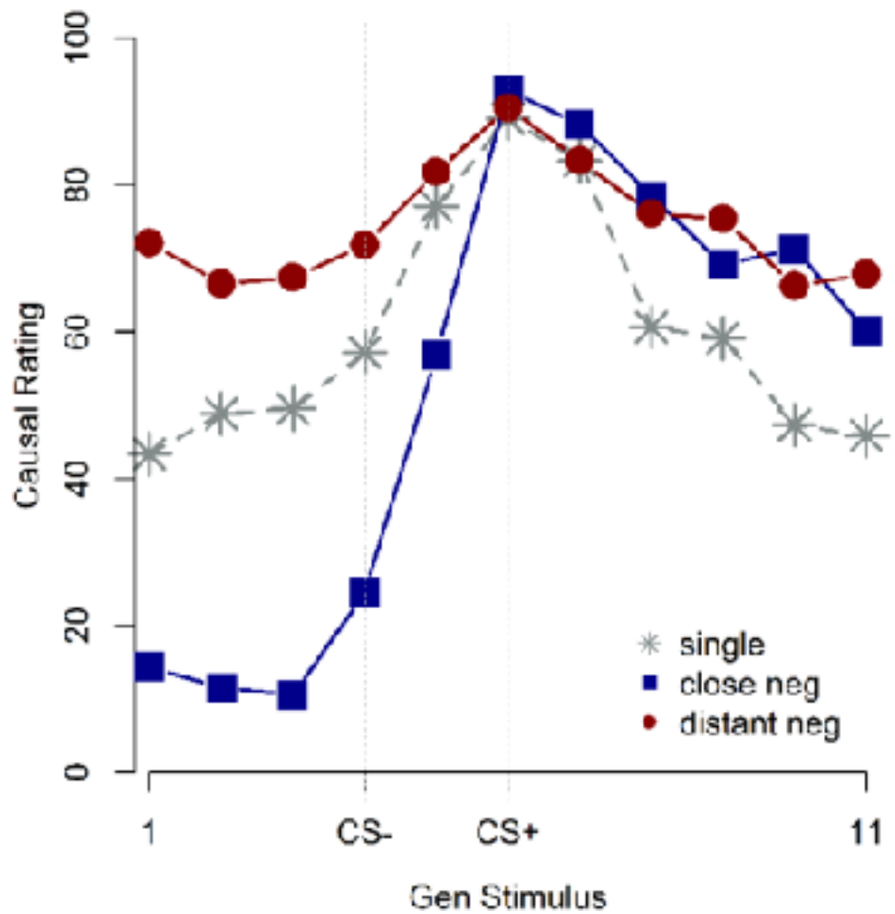
Distant negative



We needed a fancy sampling assumption for this

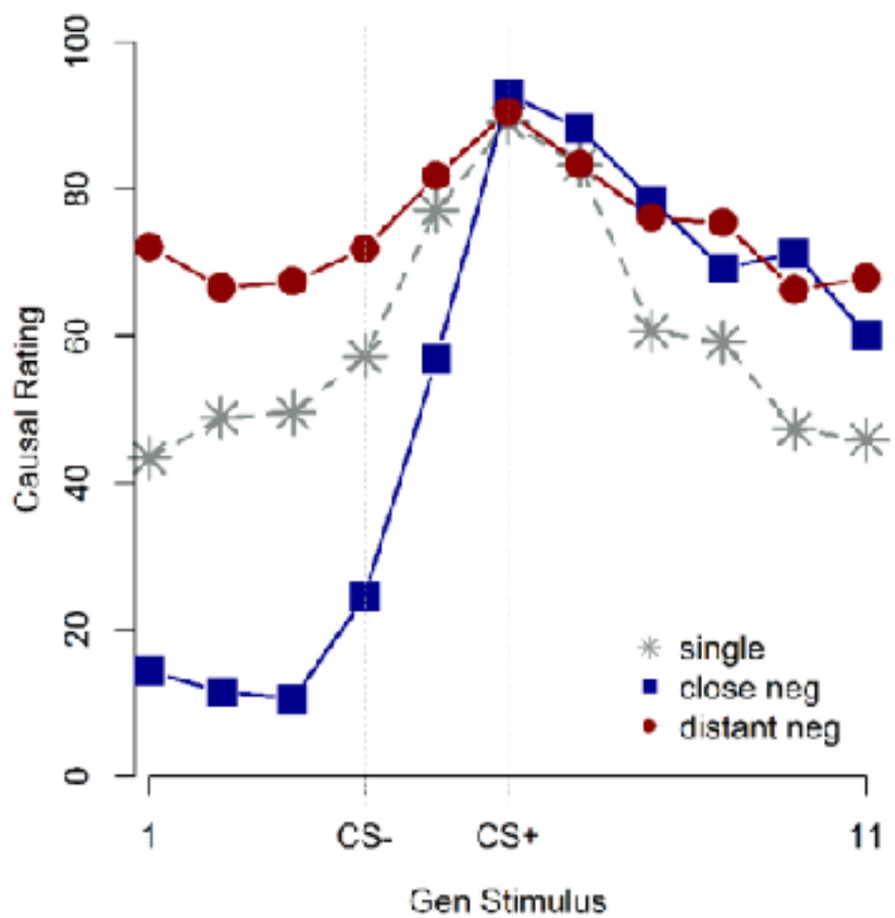
What about this?

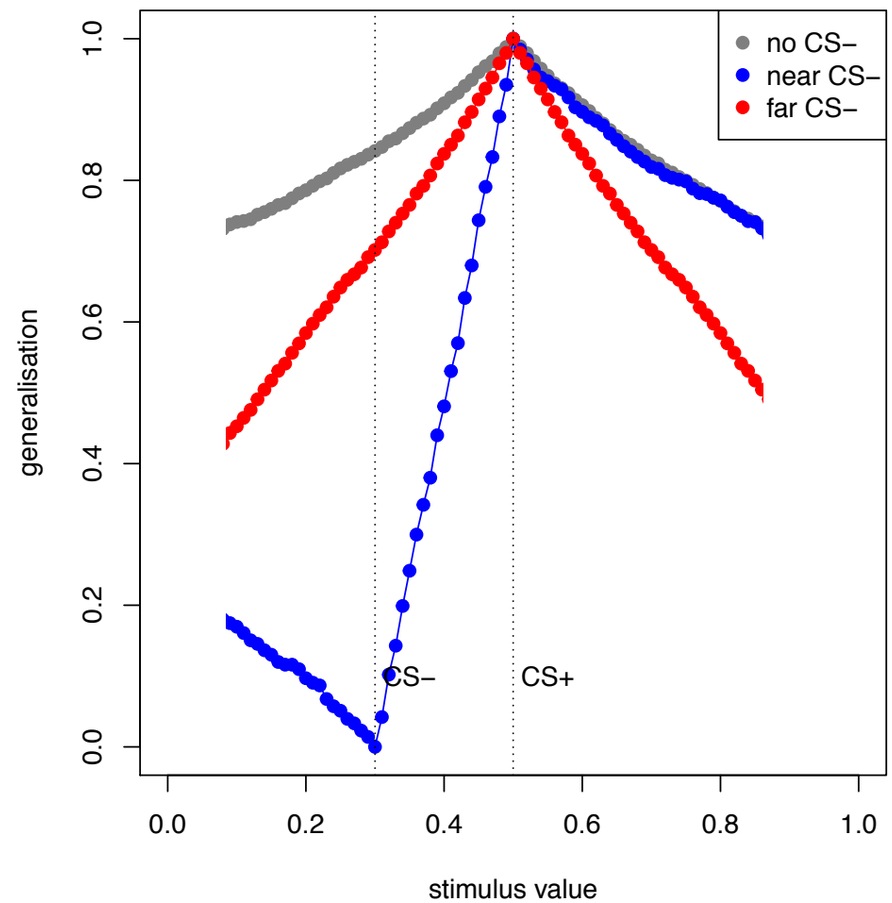




Lee, Lovibond, Hayes & Navarro (in prep)

Bayesian reasoning with random sampling produces the wrong pattern

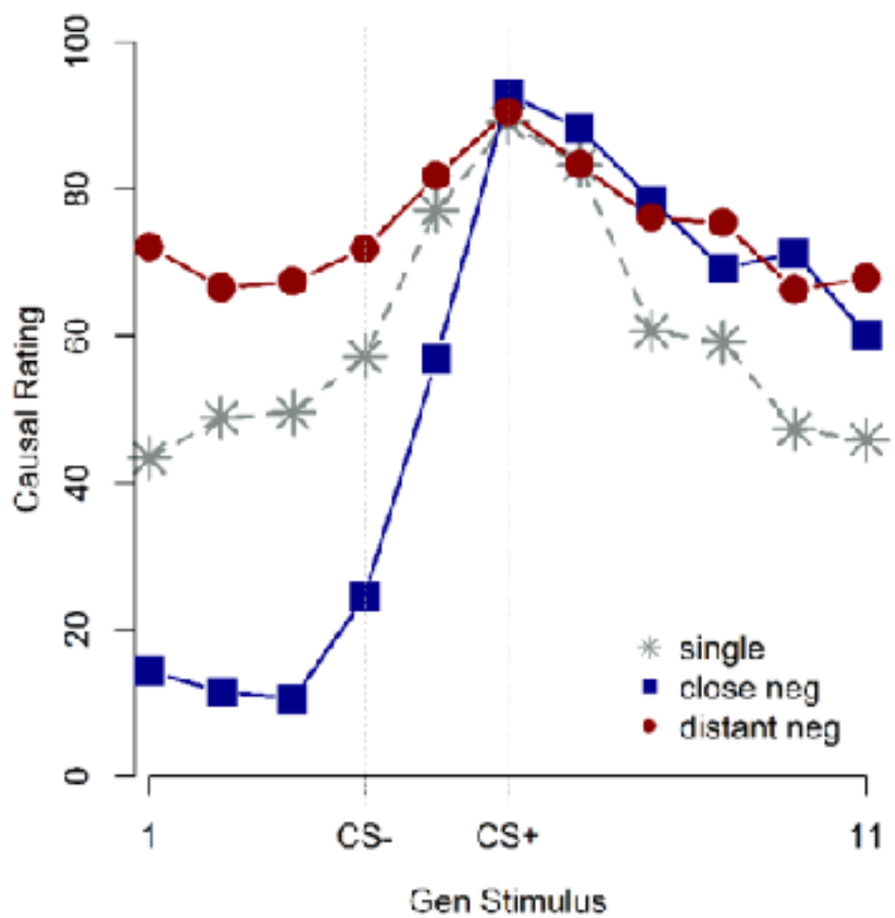


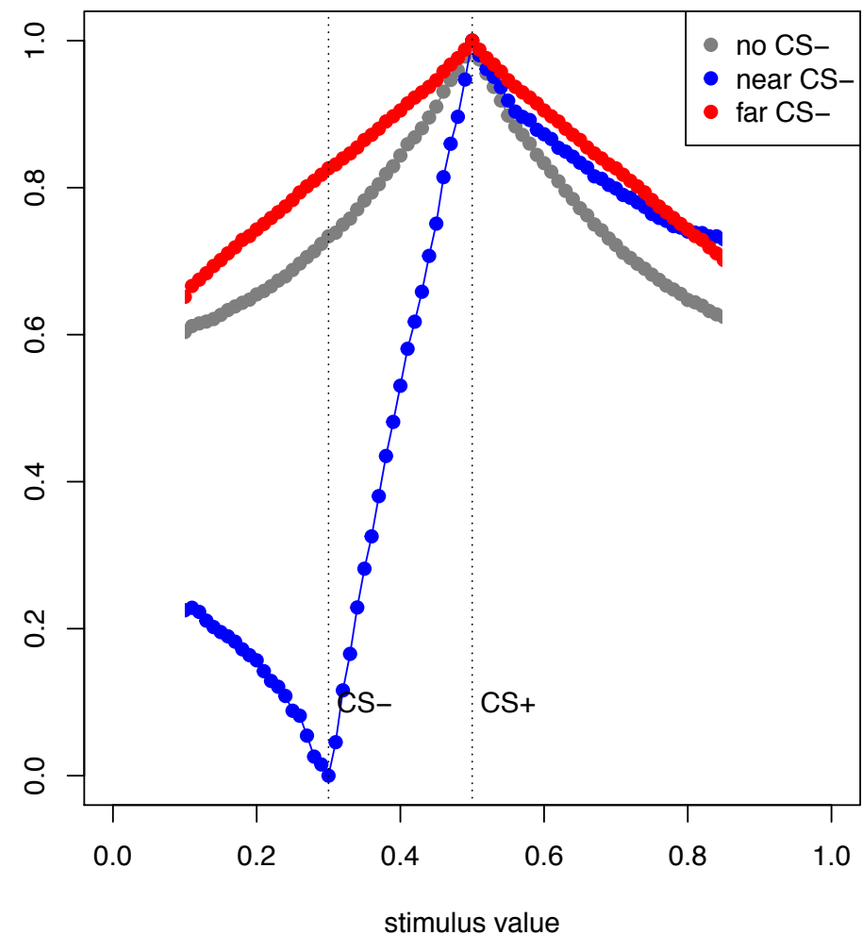


(aside: compare to animal results, Switalski et al 1966)

Lee, Lovibond, Hayes & Navarro (in prep)

Bayesian reasoning that assumes an intentional* sampling process works*





Lee, Lovibond, Hayes & Navarro (in prep)

Taking the *wrong* hint because your teacher is a jerk

(another work in progress!)

Linda is 31 years old, single, outspoken, and very bright. She majored in philosophy. As a student, she was deeply concerned with issues of discrimination and social justice, and also participated in anti-nuclear demonstrations.

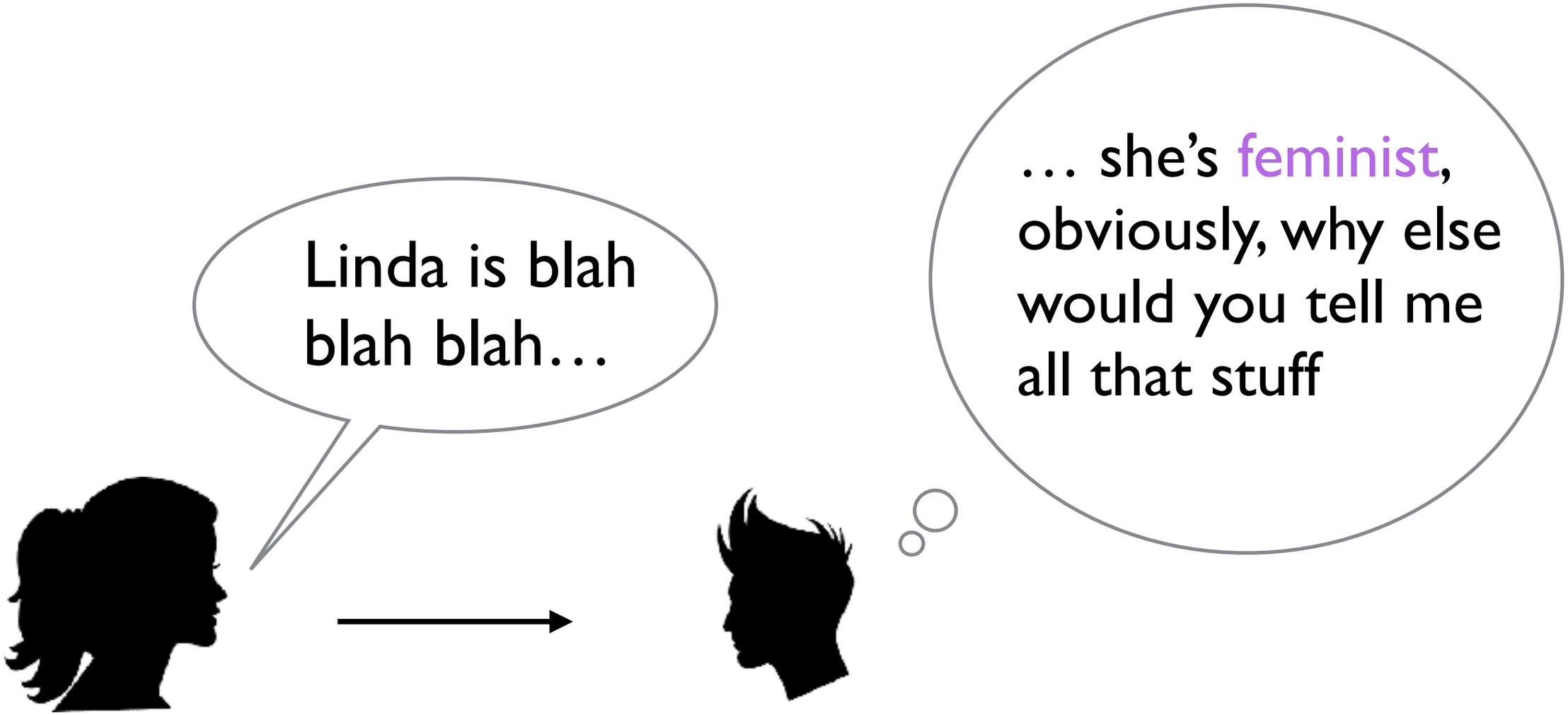
Which is more probable?

(a) Linda is a bank teller

(b) Linda is a feminist bank teller

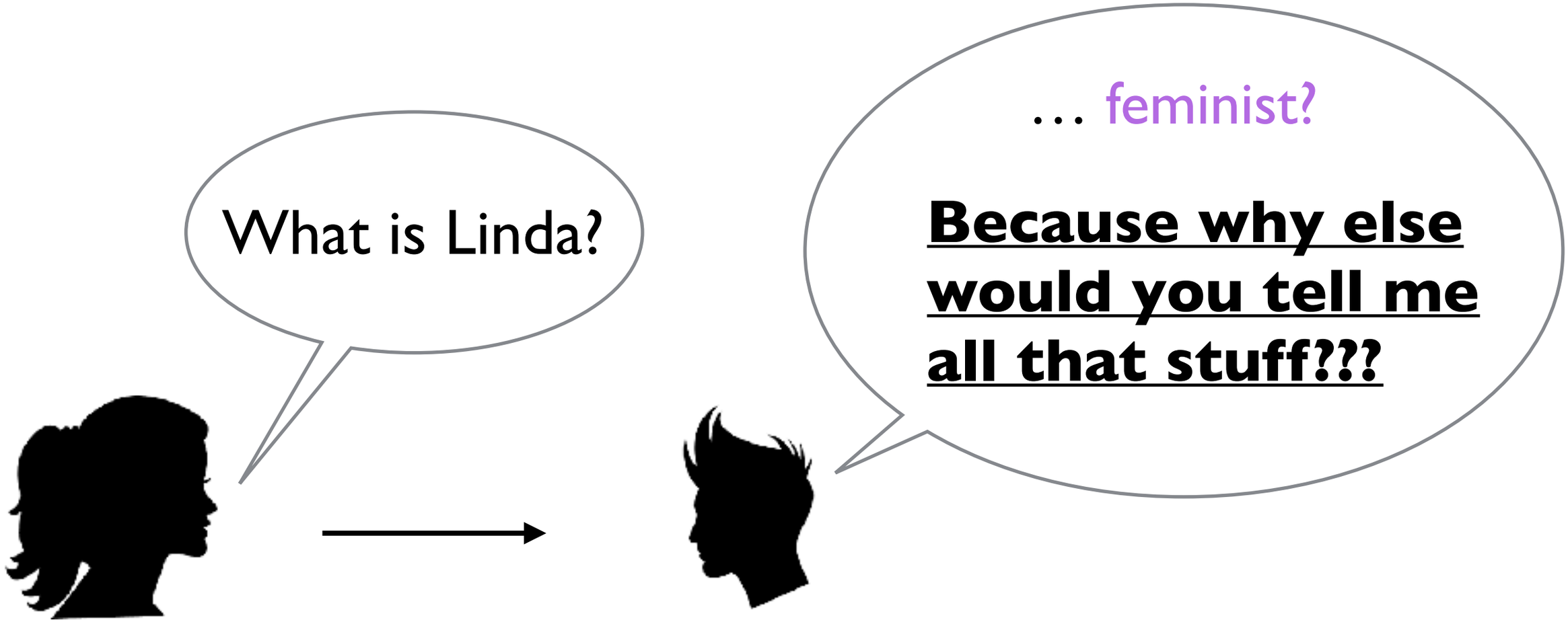
Kahneman & Tversky (1983)

The social/pragmatic account

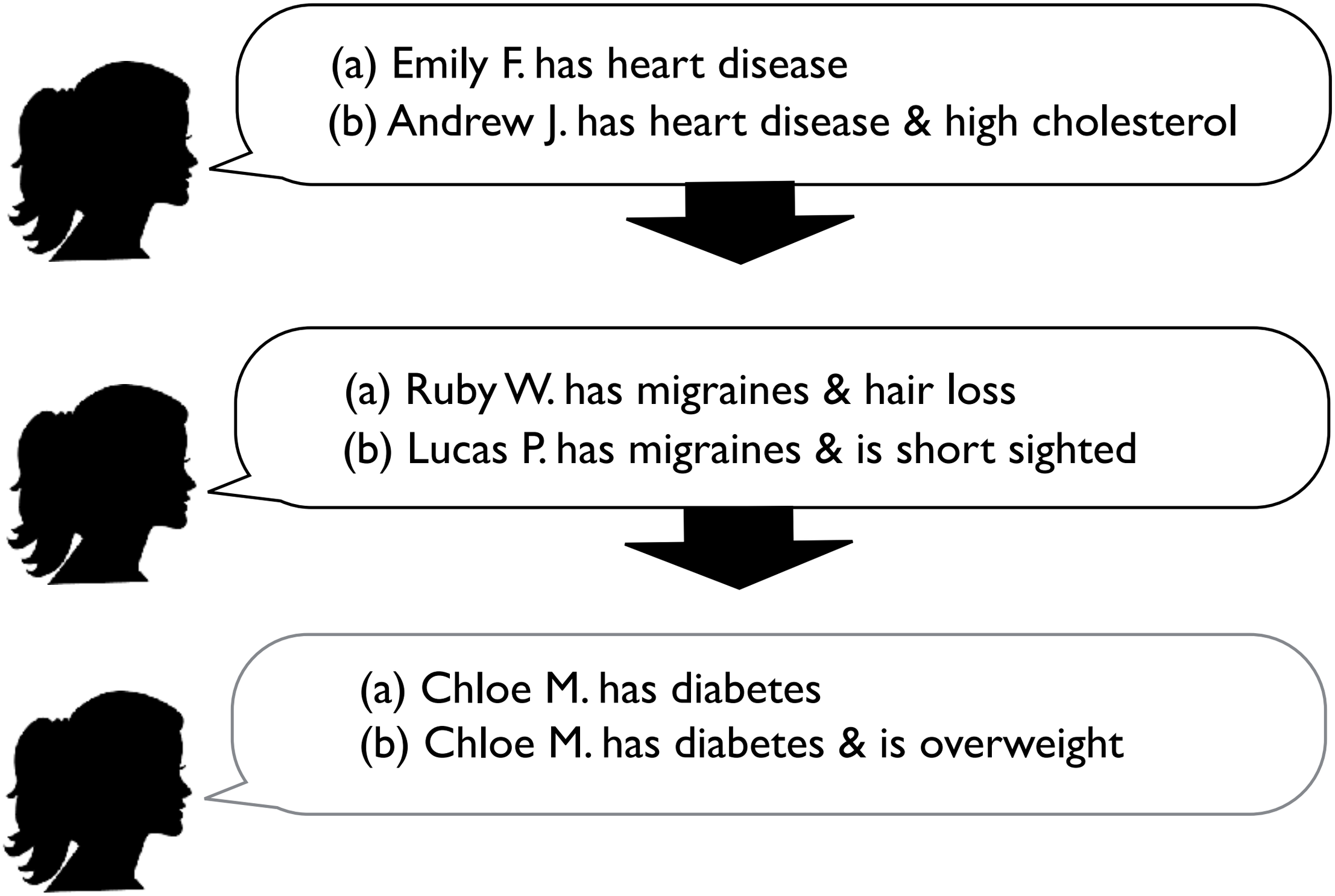


see Hertwig & Gigerenzer (1999)

The social/pragmatic account



see Hertwig & Gigerenzer (1999)



Social / pragmatic context

Navarro, Tingey, Perfors & Keshwa (in prep)

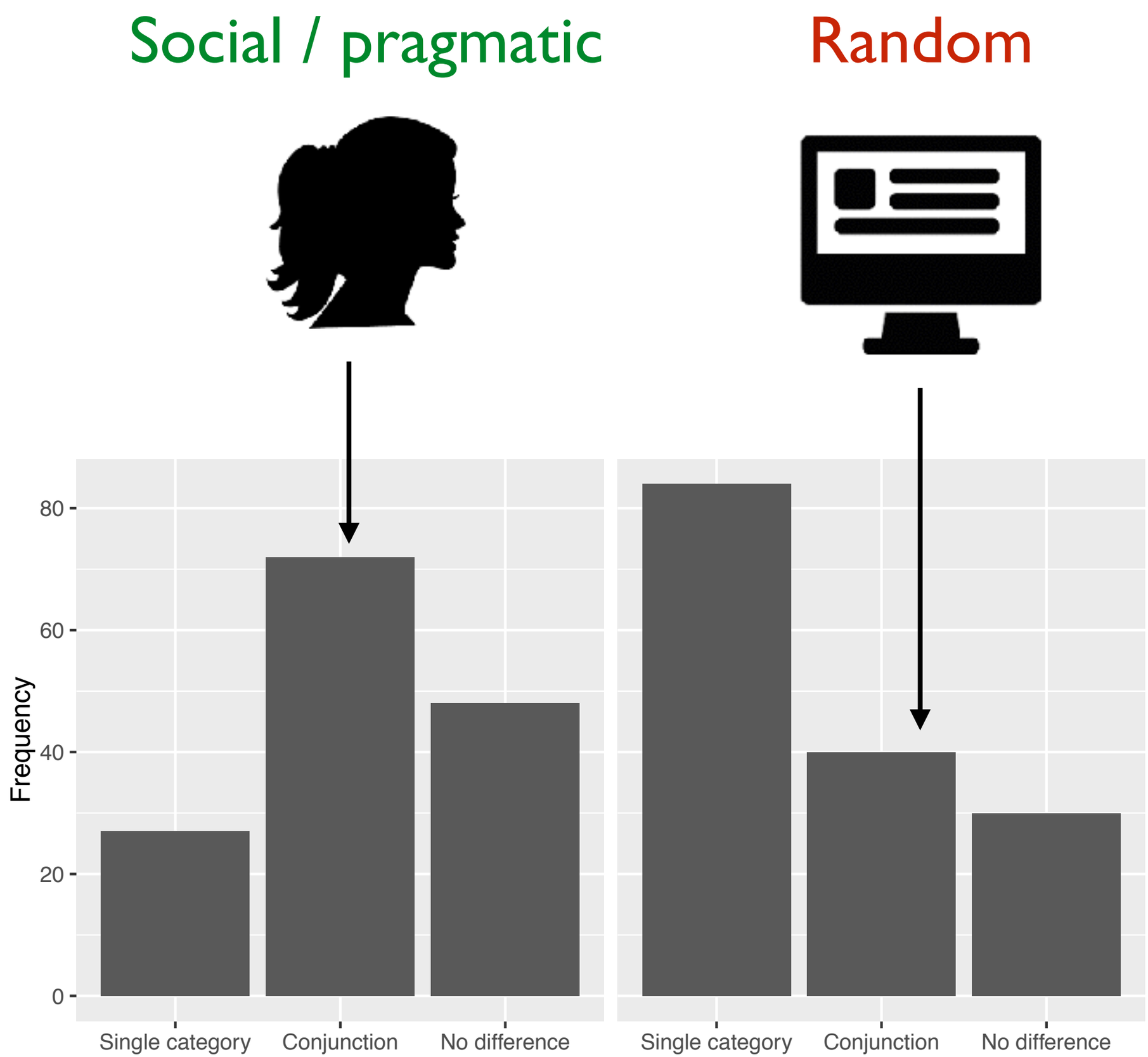
(a) Emily F. has diabetes
(b) Andrew J. is anaemic + Charlotte L. is hypertensive

(a) Sophie P. is short sighted + Jack N. has anxiety
(b) Ethan K. is overweight + Jack N. has anxiety

(a) Chloe M. has diabetes
(b) Chloe M. has diabetes + Chloe M. is overweight

Random / disconnected fact condition

Navarro, Tingey, Perfors & Keshwa (in prep)



Navarro, Tingey, Perfors & Keshwa (in prep)

The "taboo" task

Generate a description that implies but does not openly state that "Linda is a feminist":

Linda is 31 and has had a rough upbringing, growing up with an abusive father which restricted her mother and her freedom. This upbringing was what made her decide to major in sociology and psychology within university. She has strong views on politics and other similar matters that affect men and women. She regularly attends rallies and protests on the weekend.

Navarro, Tingey, Perfors & Keshwa (in prep)

The "taboo" task

Generate a description that implies but does not openly state that "Paula is a bank teller":

Paula is 30, and loves buying clothes even at her age of 30. She is in contact with money so much that she has been able to calculate the exact change given before the cashier has given it to her. Her skills in counting are ingrained within her brain that she cannot turn it off, due to years dealing with cash

Navarro, Tingey, Perfors & Keshwa (in prep)

The "taboo" task

Generate a description that implies but does not openly state that "Brenda is a feminist & bank teller":

Brenda is 32 years old, methodical, logical, and passionate about her beliefs. She is very good with both people and numbers and is often able to spot errors. She is trusted by her friends to handle the money when planning an overseas trip. She is also a very individual woman and looks up to celebrities such as Emma Watson

Navarro, Tingey, Perfors & Keshwa (in prep)

Several different versions

"Feminist / Bank Teller",
"Engineer / Jazz Musician",
"Introvert / Chef",
"Journalist / Anxious Person",
"Painter / Accountant",
"Extrovert / Statistician”,
"Pacifist / Boxer",
"Butcher / Empath",
"Writer / Mechanic"

Navarro, Tingey, Perfors & Keshwa (in prep)

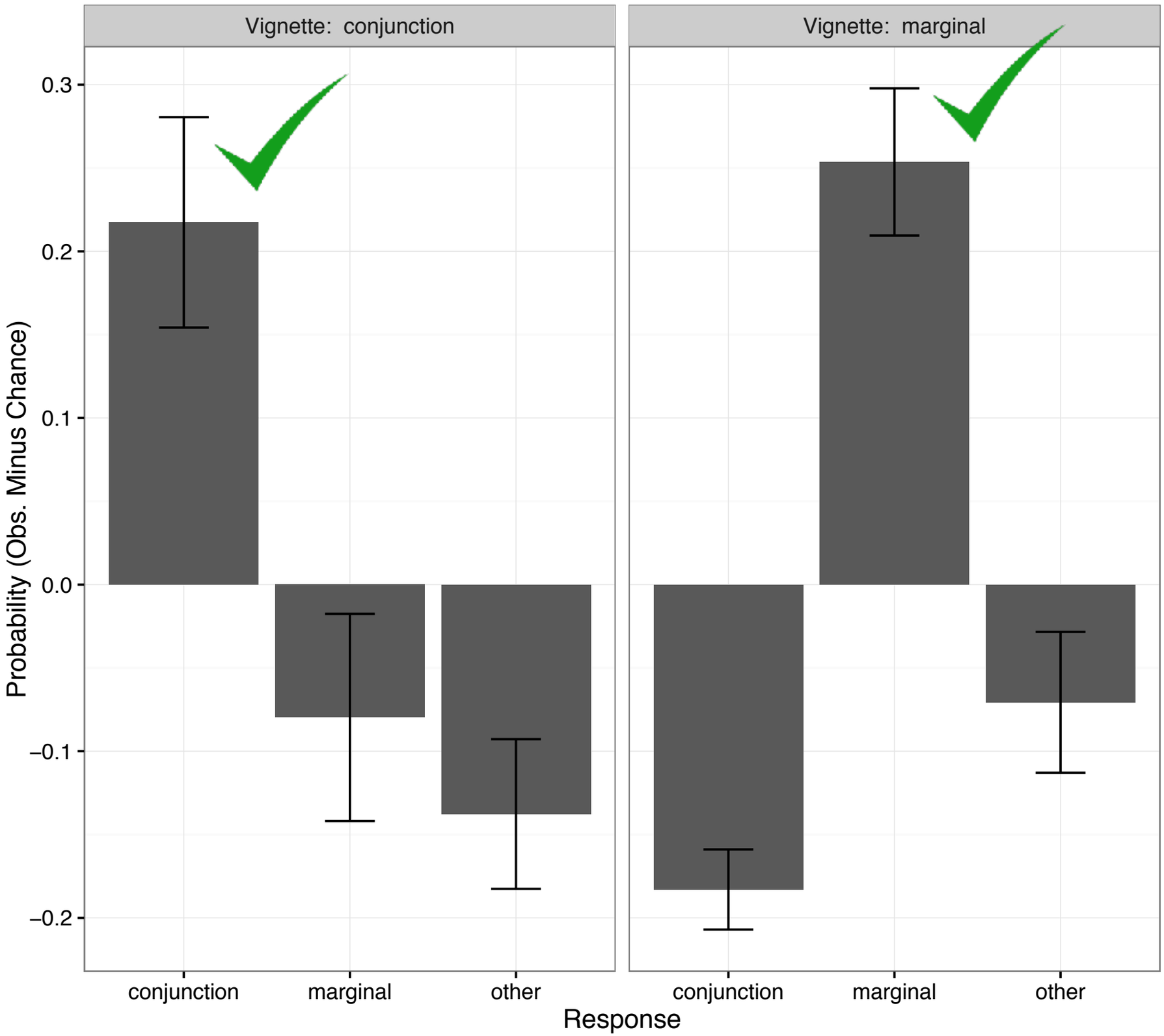
“Mind reading” task:

Isabelle is 41 years old and is very bright and good with numbers. Her creative flair has always been a passion although until recently she didn’t act on it. As a women with two professions she works extremely hard and ensures that her conflicting logical and free spirited natures are harmonious in all aspects of life.

Which of the following do you believe the writer was trying to communicate when they wrote this description:

- ○ Isabelle is a painter
- ○ Isabelle is an accountant
- ○ Isabelle is both a painter and an accountant
- ○ None of the above

Navarro, Tingey, Perfors & Keshwa (in prep)



Navarro, Tingey, Perfors & Keshwa (in prep)

Standard conjunction task:

Ryan is 26. He spends his spare time unwinding and sitting on a couch at the end of the day reading or watching a movie. He has a small but tight knit group of friends. He likes talking to them individually and dislikes group outings.

How likely is it that this person belongs to each of the following categories? Please give an estimate of the probability from 0 to 100% for each category (0 being impossible and 100 being certain).

Teacher: [ ] %

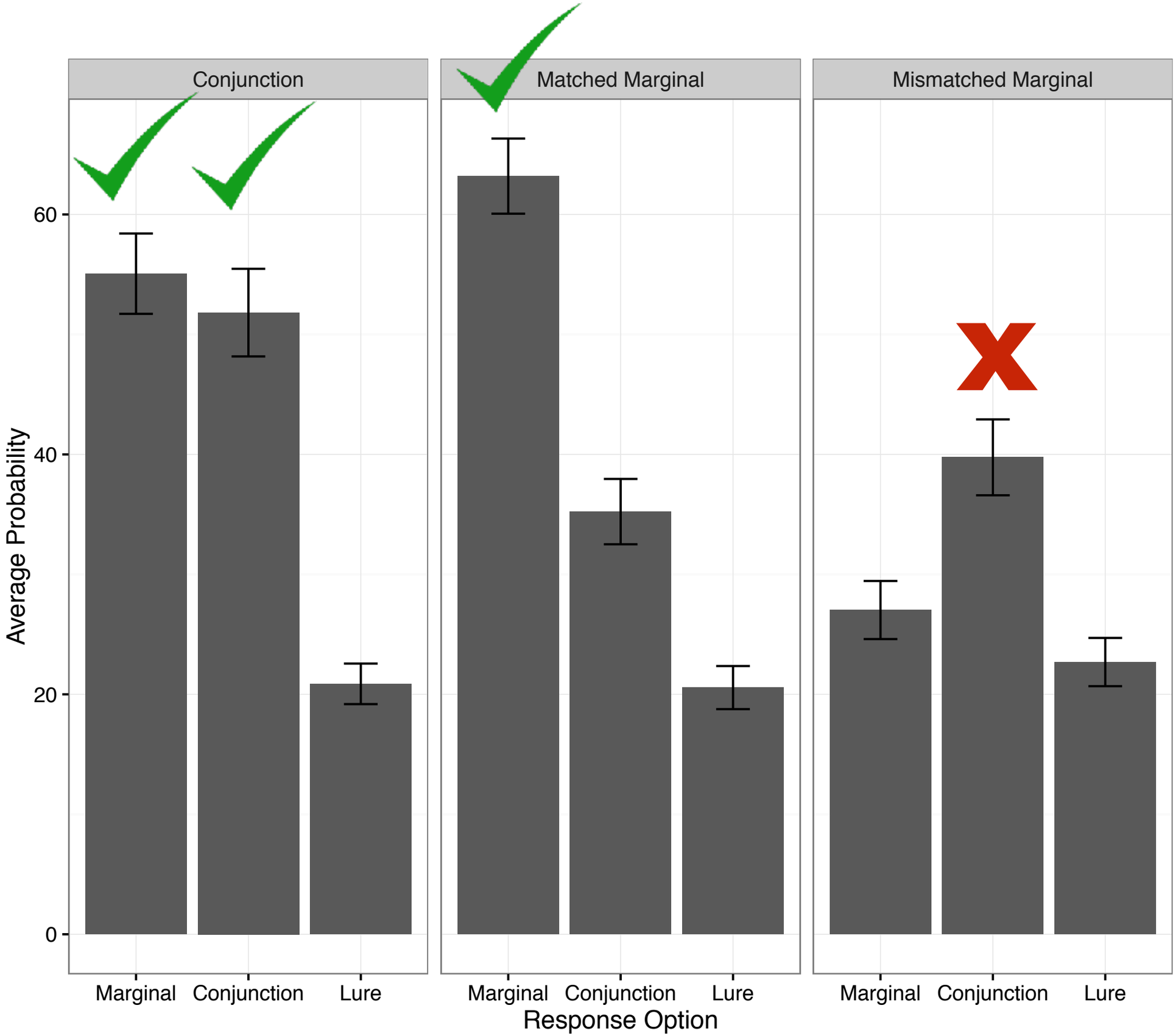
Introvert: [ ] %

Activist: [ ] %

Chef and Introvert: [ ] %

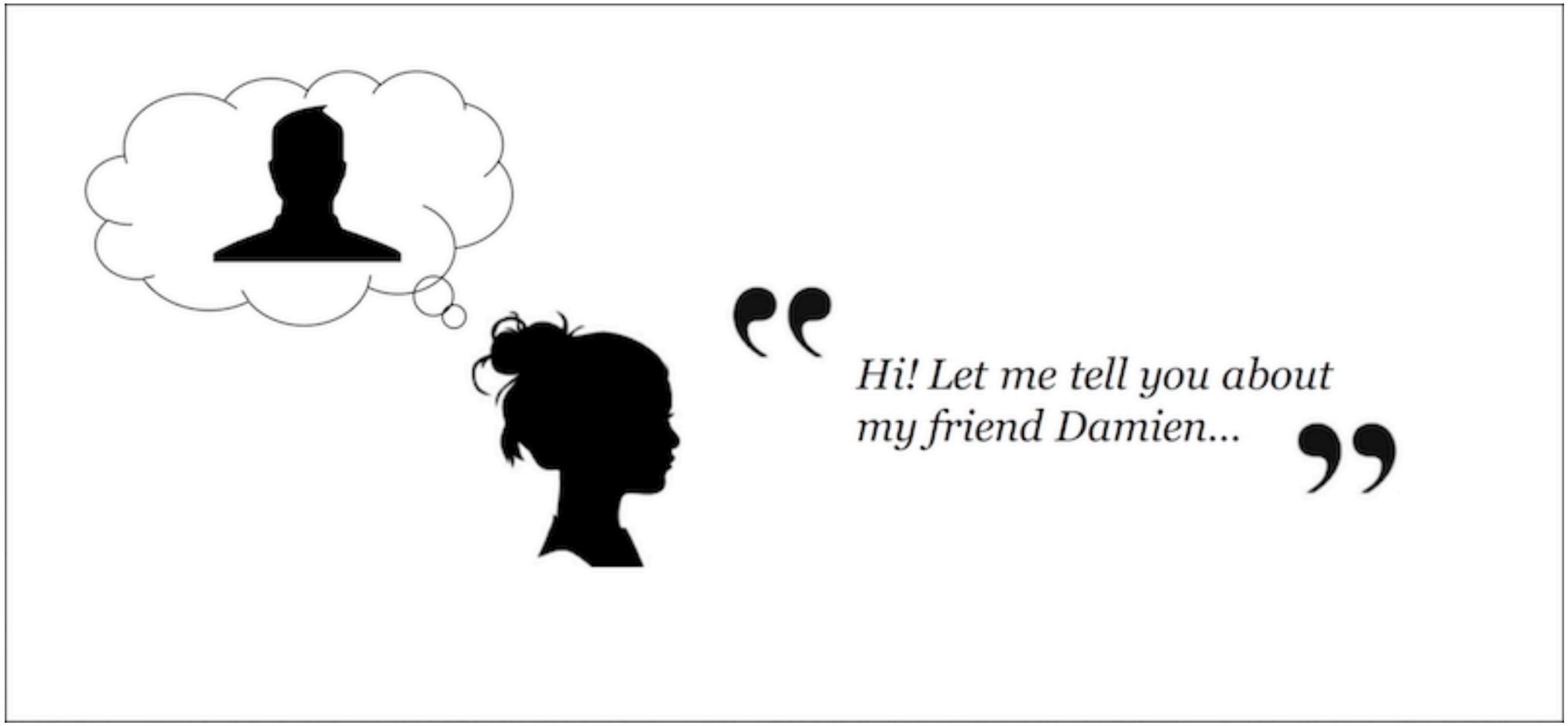
Neurosurgeon and pessimist: [ ] %

Navarro, Tingey, Perfors & Keshwa (in prep)

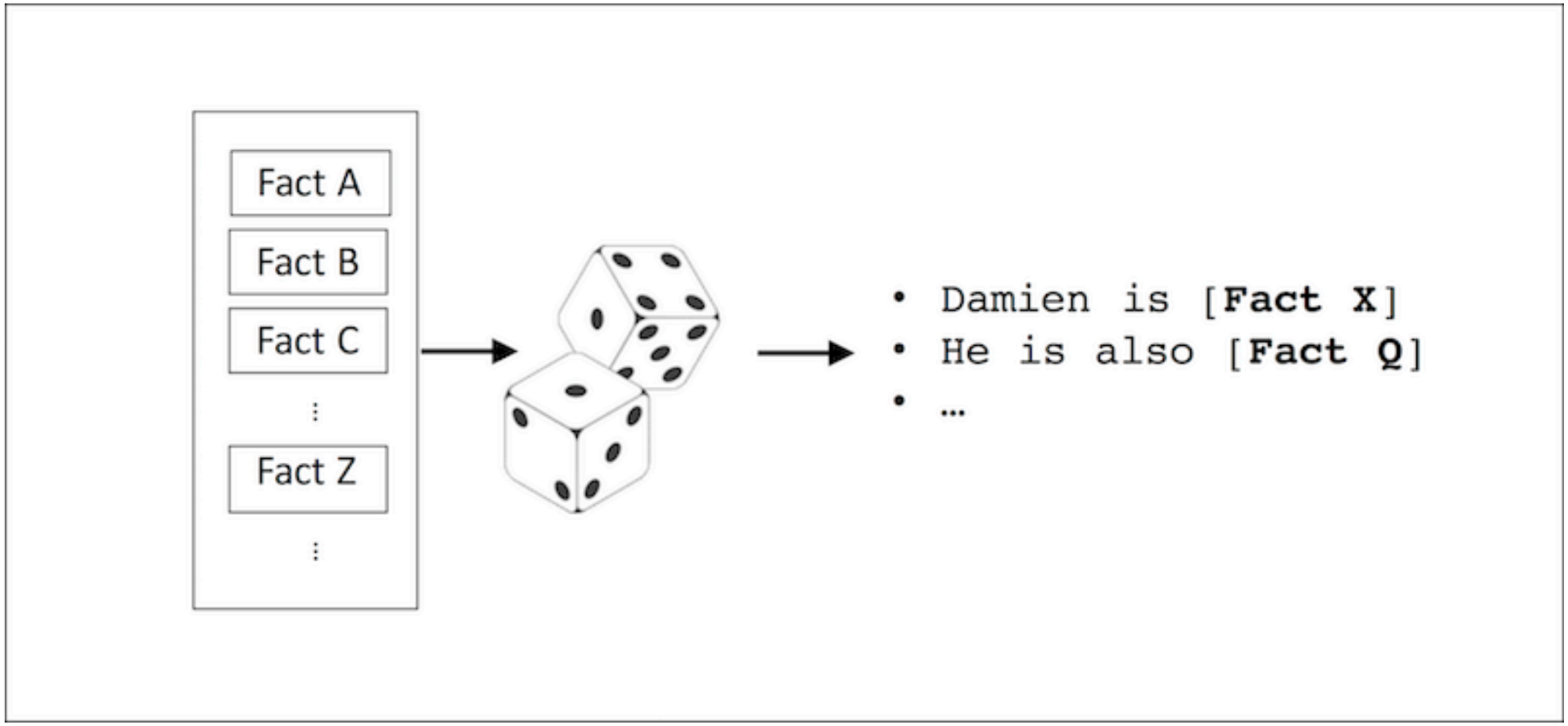


Navarro, Tingey, Perfors & Keshwa (in prep)

In progress: social vs random vignettes



In progress: social vs random vignettes



More tensions between social and random sampling: variations on the Monty Hall Dilemma

(yet another work in progress!)

The Monty Hall dilemma

A suitably constrained host:

	If A is correct	If B is correct	If C is correct
Host opens A	**0%**		
Host opens B		**0%**	
Host opens C			**0%**

Host won't open
the prize door

A suitably constrained host:

	If A is correct	If B is correct	If C is correct
Host opens A	**0%**	**0%**	**0%**
Host opens B		0%	
Host opens C			0%

Nor will they open the door you chose (A)

A suitably constrained host:

	If A is correct	If B is correct	If C is correct
Host opens A			
Host opens B	**50%**		**100%**
Host opens C	**50%**	**100%**	

Otherwise random

A suitably constrained host: a Bayesian reason to switch

	If A is correct	If B is correct	If C is correct
Host opens A			
Host opens B	**50%**	**0%**	**100%**
Host opens C			

* this is the correct solution to the original problem as stated by vos Savant

An indifferent host chooses randomly

	If A is correct	If B is correct	If C is correct
Host opens A	33%	33%	33%
Host opens B	33%	33%	33%
Host opens C	33%	33%	33%

An indifferent host: a Bayesian reason for indifference

	If A is correct	If B is correct	If C is correct
Host opens A			
Host opens B	**33%**	**33%**	**33%**
Host opens C			

A malicious host who never offers a bet when your choice was wrong!

	If A is correct	If B is correct	If C is correct
Host opens A			
Host opens B	**p%**		
Host opens C			
Host does not open a door		**100%**	**100%**

A malicious host with discretion: a Bayesian reason to stay

	If A is correct	If B is correct	If C is correct
Host opens A			
Host opens B	**p%**	**0%**	**0%**
Host opens C			
Host does not open a door			

A helpful host with discretion:

	If A is correct	If B is correct	If C is correct
Host opens A	0%	0%	0%
Host opens B		0%	
Host opens C			0%
Host does not open a door			

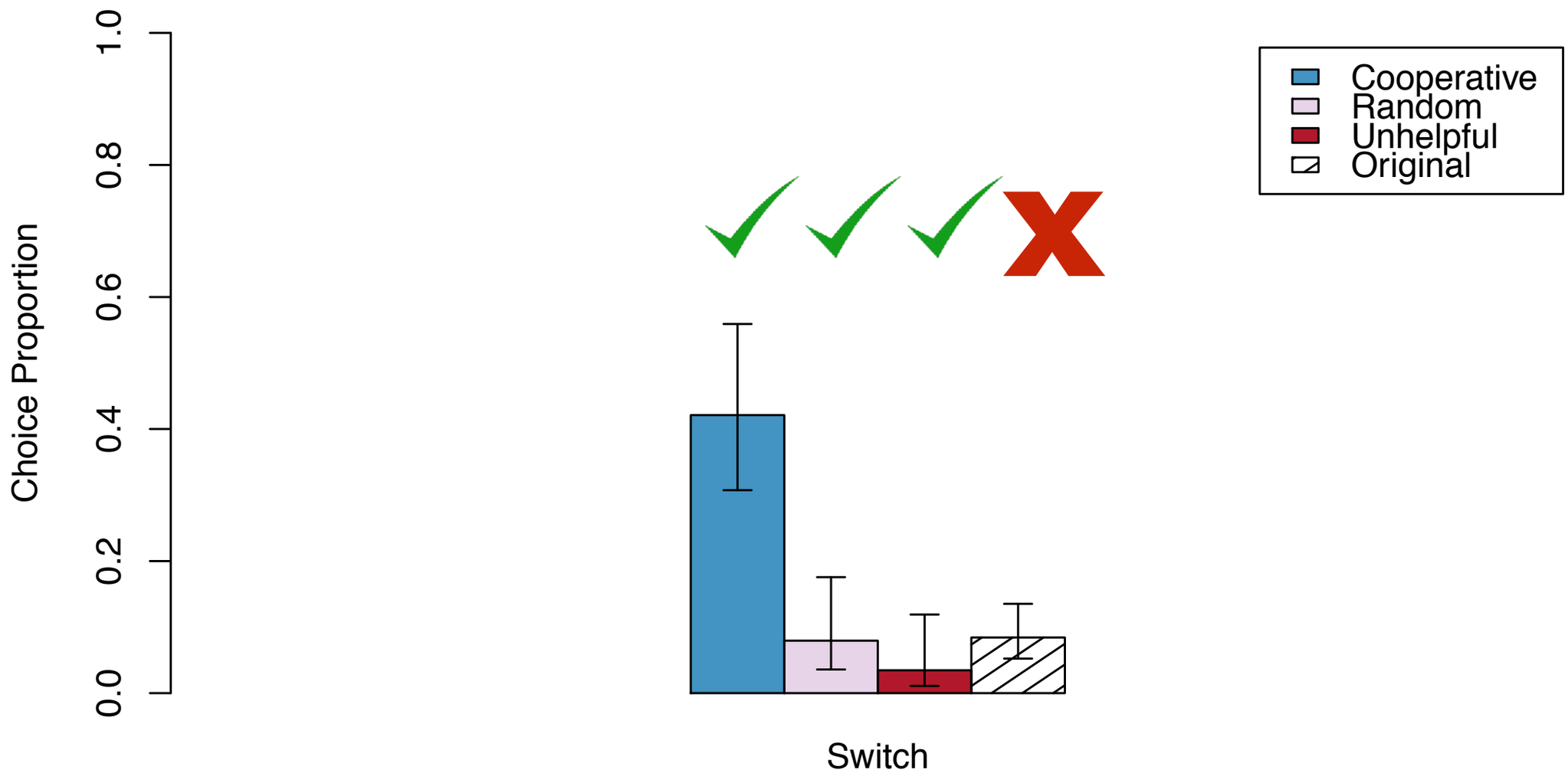
A helpful host with discretion:

	If A is correct	If B is correct	If C is correct
Host opens A	0%	0%	0%
Host opens B		0%	
Host opens C			0%
Host does not open a door	**100%**	**0%**	**0%**

A helpful host with discretion: A Bayesian reason to switch

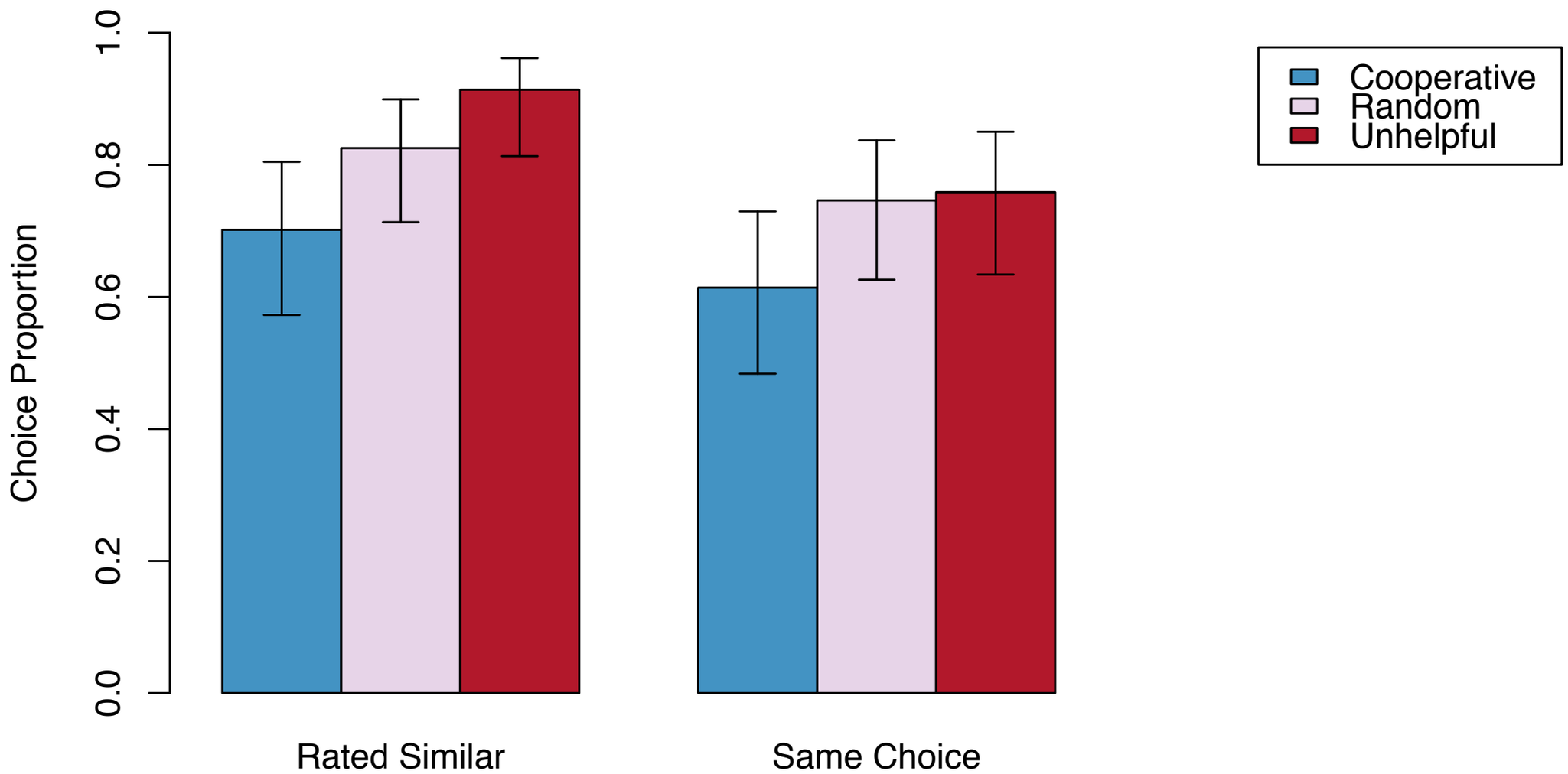
	If A is correct	If B is correct	If C is correct
Host opens A			
Host opens B	**0%**	**0%**	**100%**
Host opens C			
Host does not open a door			

Probability of switching



Perfors, Navarro, Benders & Donkin (in limbo)

People (incorrectly?) view the original MHD as most similar to the malicious version



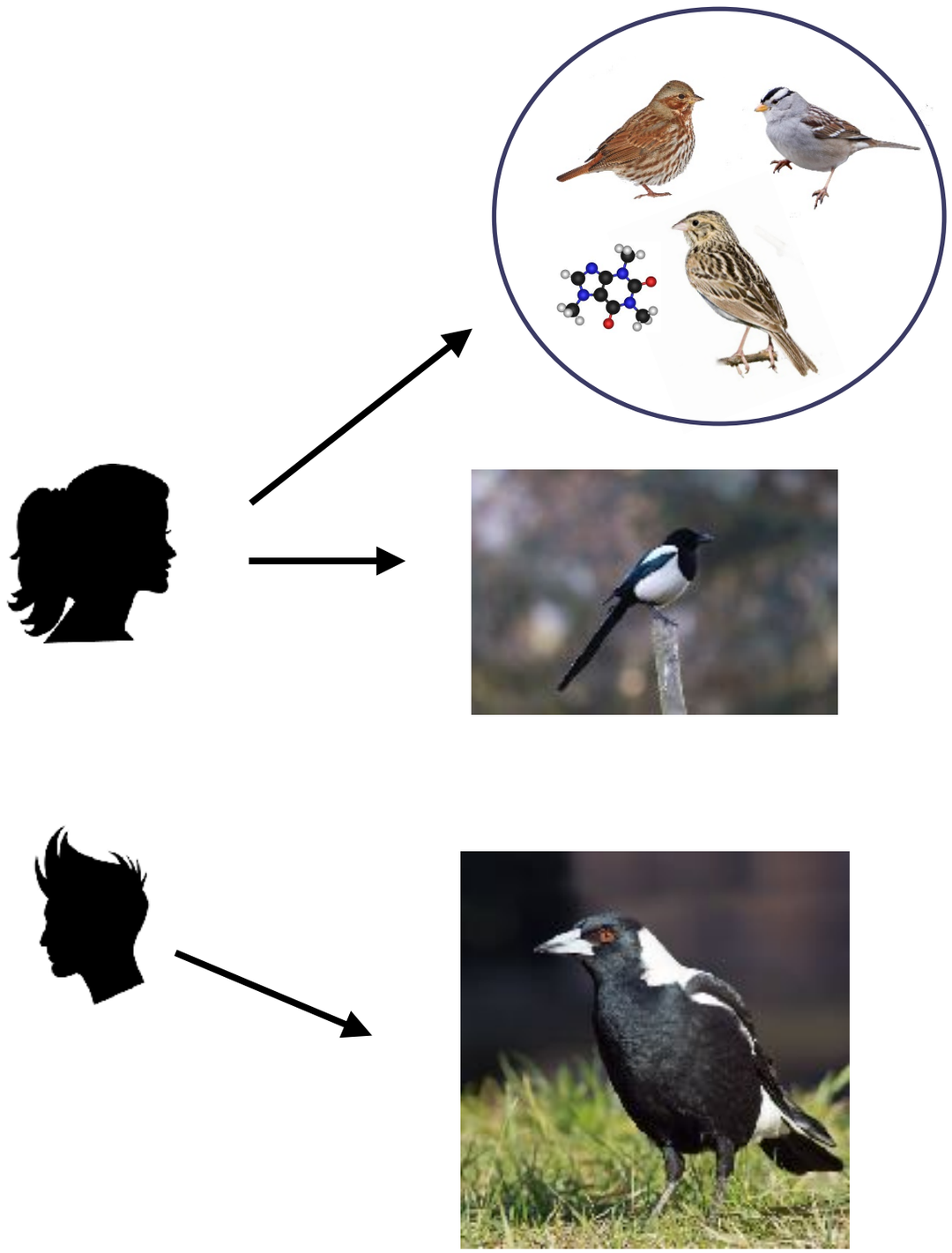
Perfors, Navarro, Benders & Donkin (in limbo)

Possibly people are treating MHD as a "social reasoning" problem, and thinking that the host is malicious?

Can people be sensitive to conditional sampling without requiring a social component?

(also in progress, but almost finished)

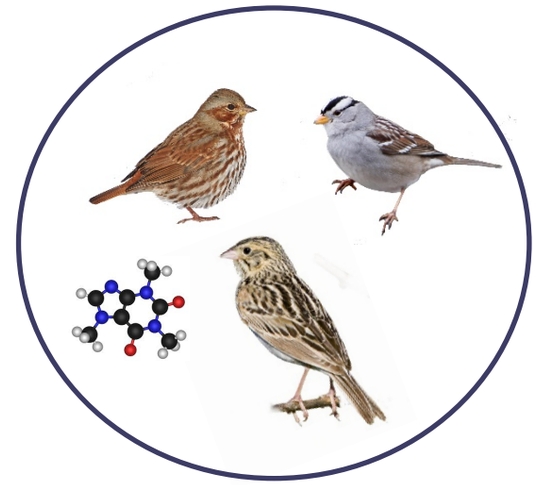
Most of these effects rely on sampling by people



This problem can be solved using social cognition

Maybe this is <u>all</u> social reasoning?

Sampling across spatial locations

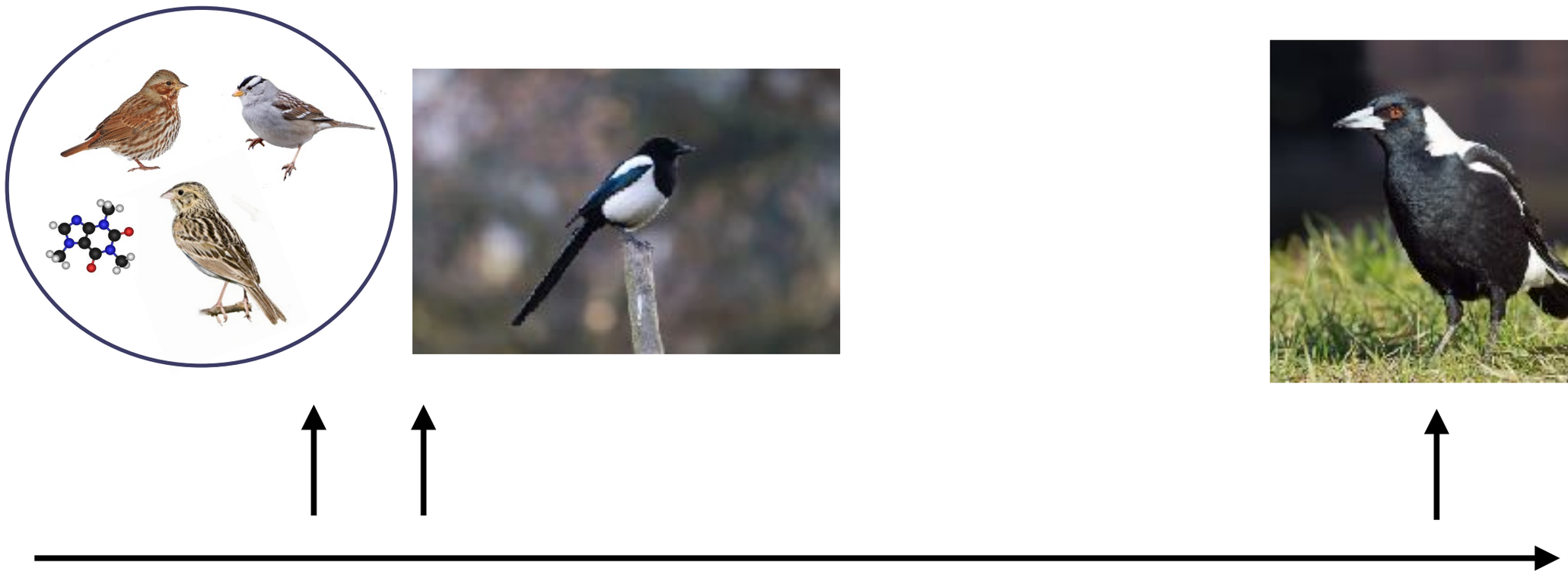


Eurasian magpie

Australian magpie

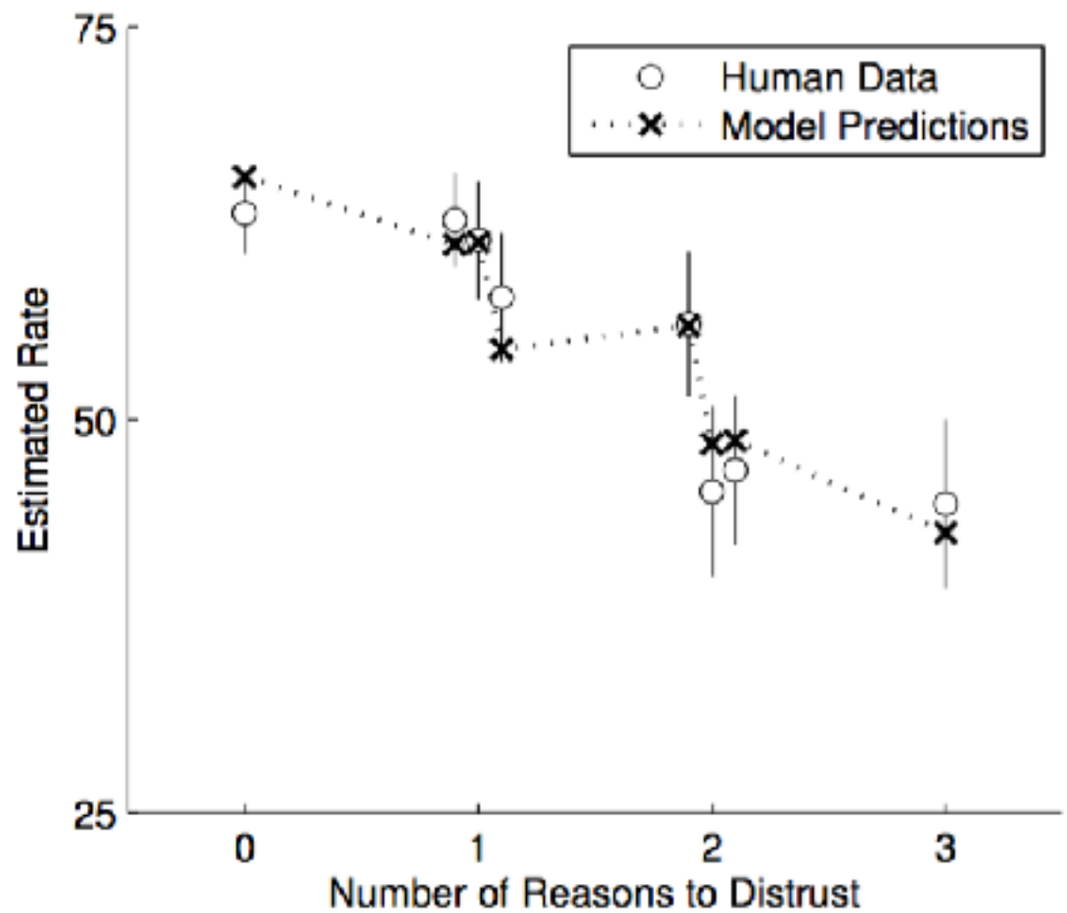
Not social cognition

Sampling across time



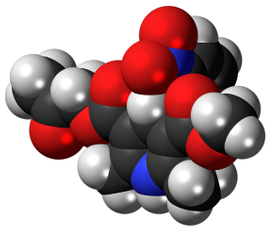
Not social cognition

You are currently classifying predators according to whether they pose a threat to humans. *Your team*, working at *this location recently* collected 200 observations and found that 50 (25%) of them met this criterion. This week, you have made another 4 observations, of which 3 (75%) met the above criterion. What proportion of predators in the area do you estimate pose a threat to humans?



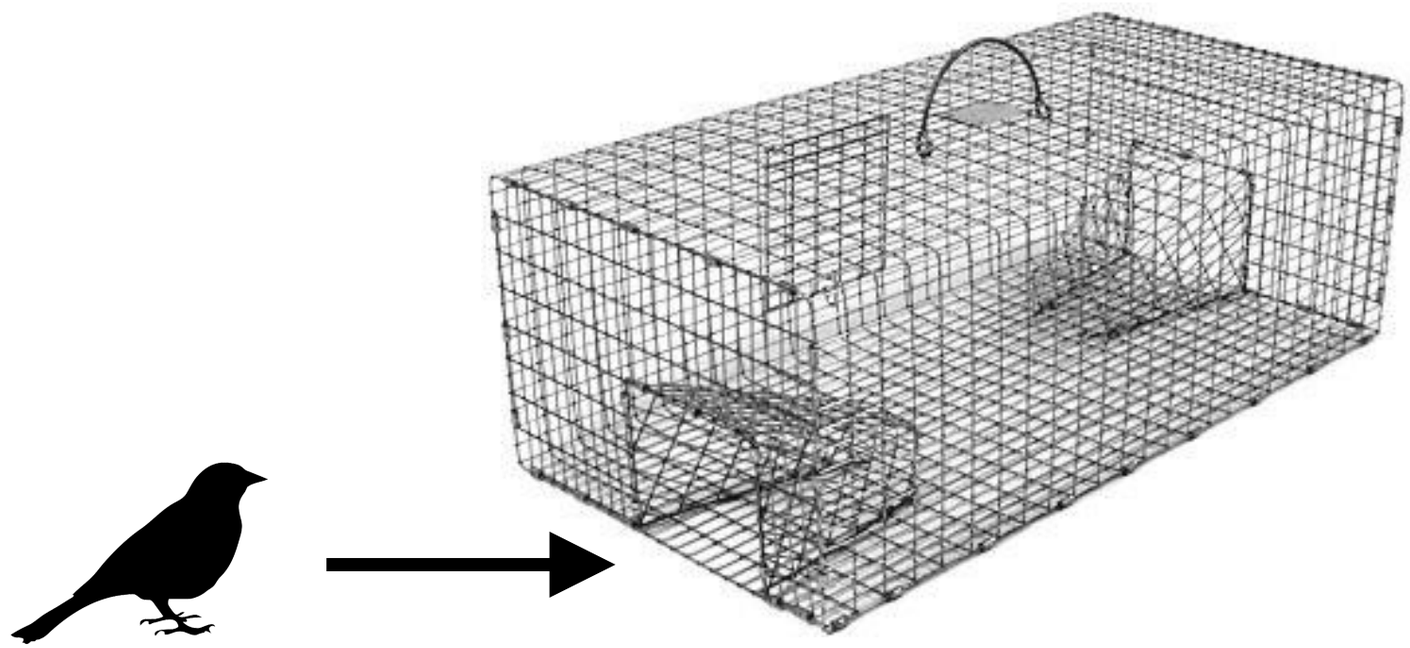
Welsh & Navarro (2012). *Organisational Behavior and Human Decision Processes*

Let's make this a little more sneaky…



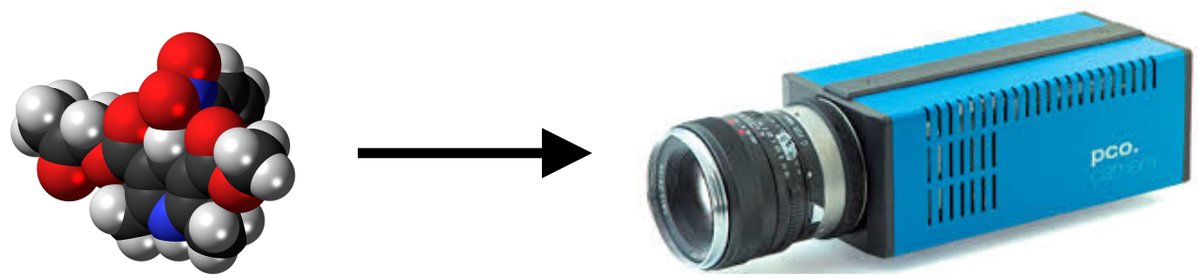
20 *small* birds with *plaxium* blood (SP+)

Hayes, Banner & Navarro (2017)



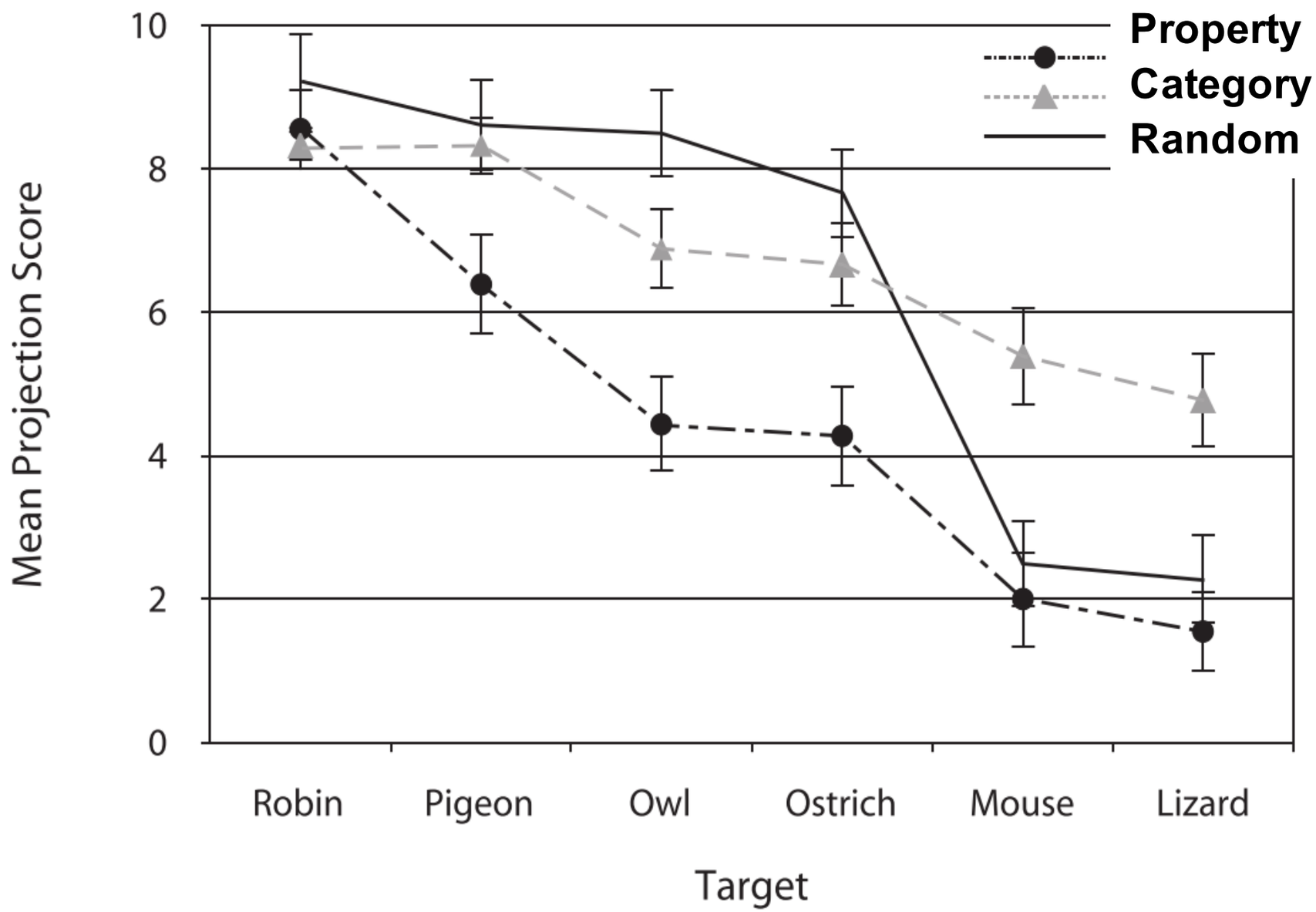
Category sampling: select items based on category membership (i.e. small birds)

Hayes, Banner & Navarro (2017)



Property sampling: select items based on possession of the property (i.e. plaxium blood)

Hayes, Banner & Navarro (2017)

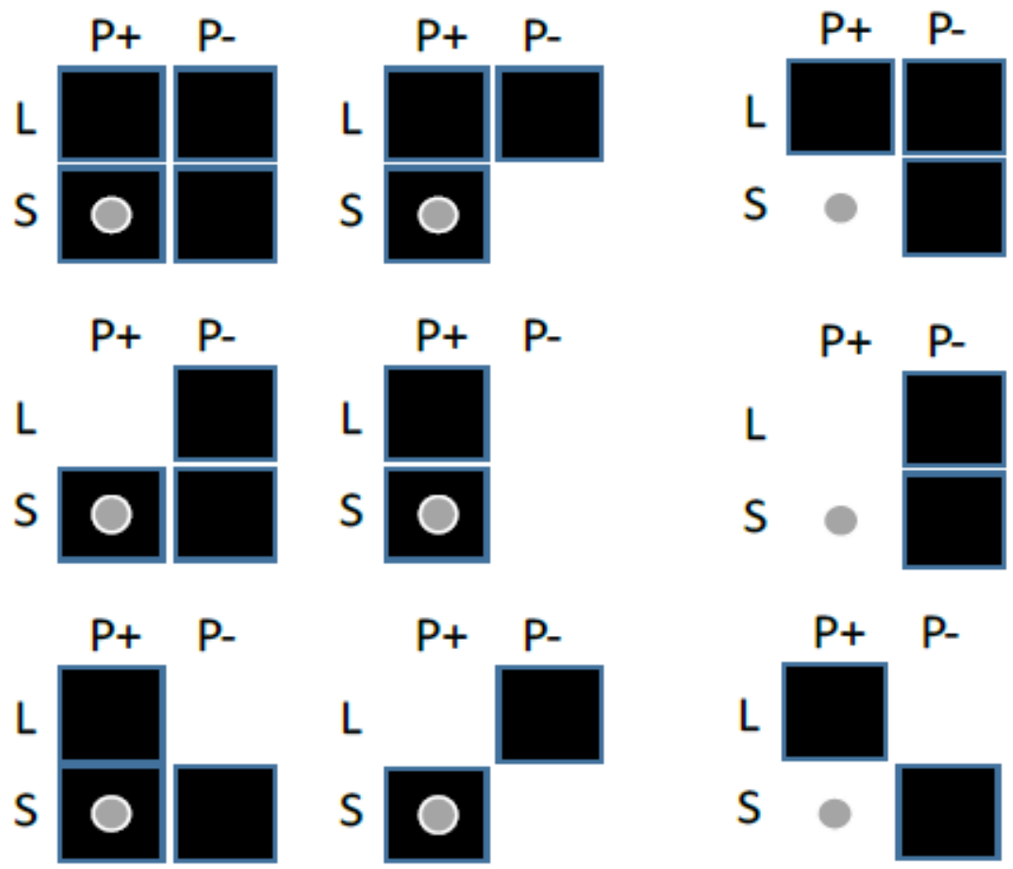


category

property

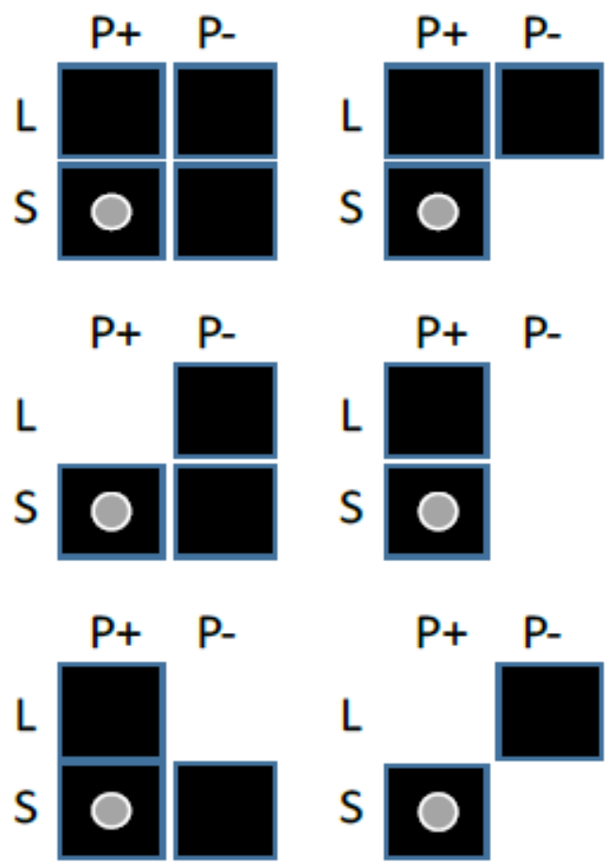
Lawson & Kalish (2009)

Hypotheses a reasoner might consider



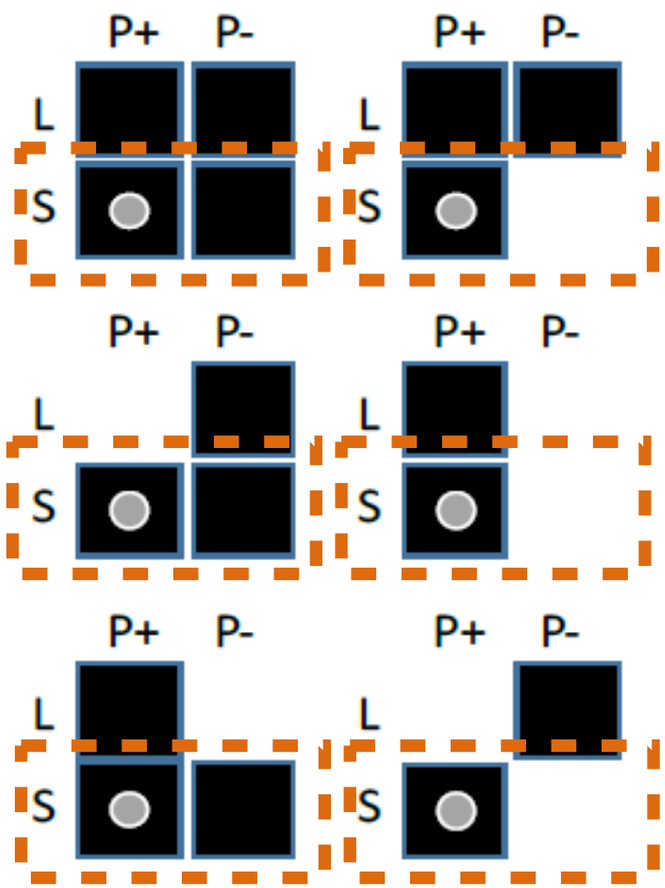
Hayes, Banner & Navarro (2017)

Hypotheses consistent with the data



Hayes, Banner & Navarro (2017)

Category sampling

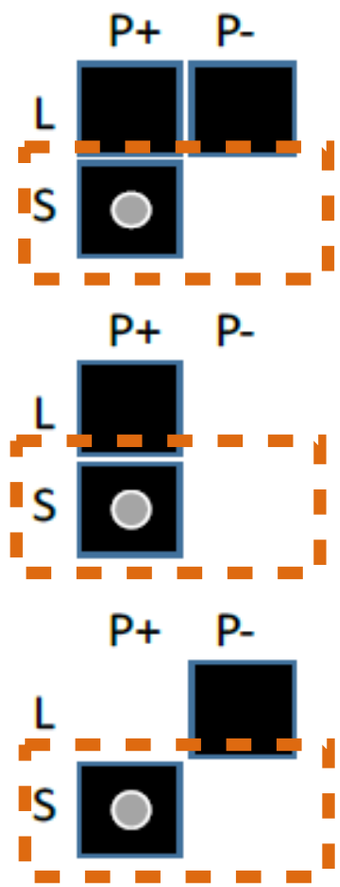


Frame explains absence of LP+ and LP-

Hypothesis must account for absence of SP-

Hayes, Banner & Navarro (2017)

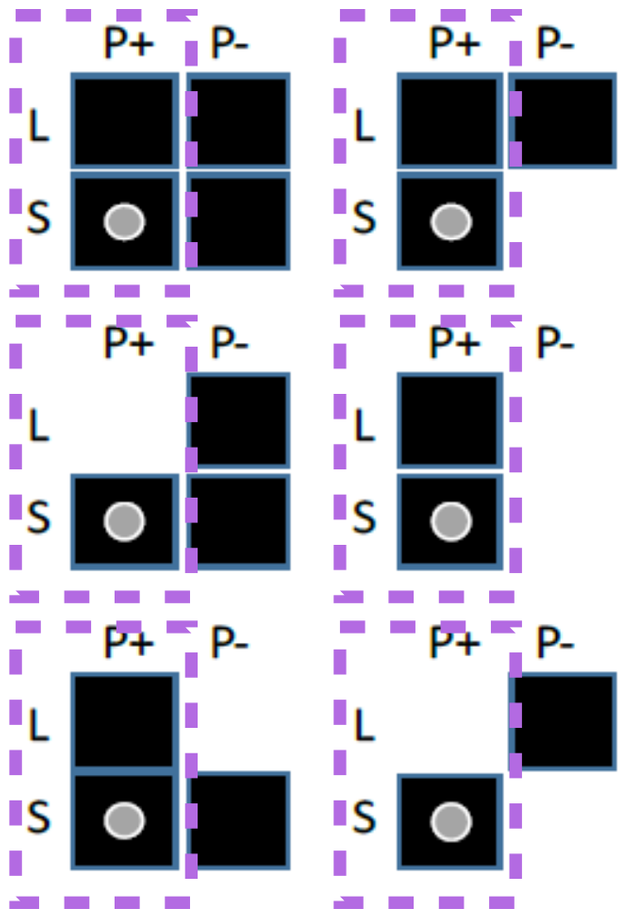
Category sampling



2 of 3 hypotheses allow LP+
… so generalisation to large birds is *very plausible*

Hayes, Banner & Navarro (2017)

Property sampling

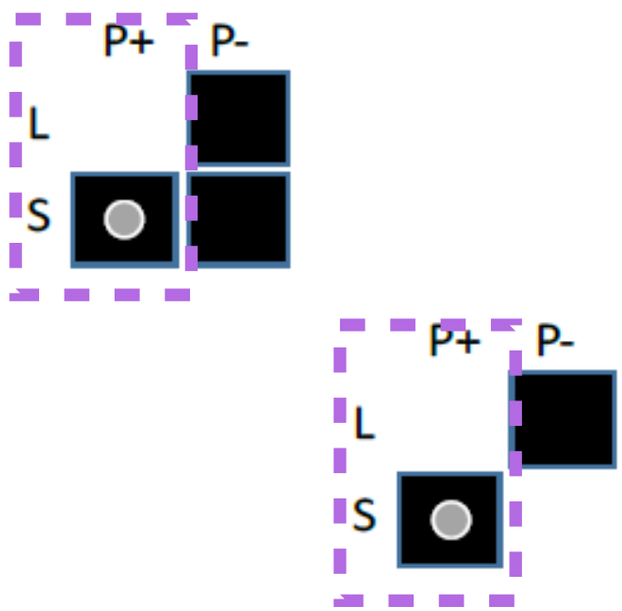


Frame explains absence of SP- and LP-

Hypothesis must account for absence of LP+

Hayes, Banner & Navarro (2017)

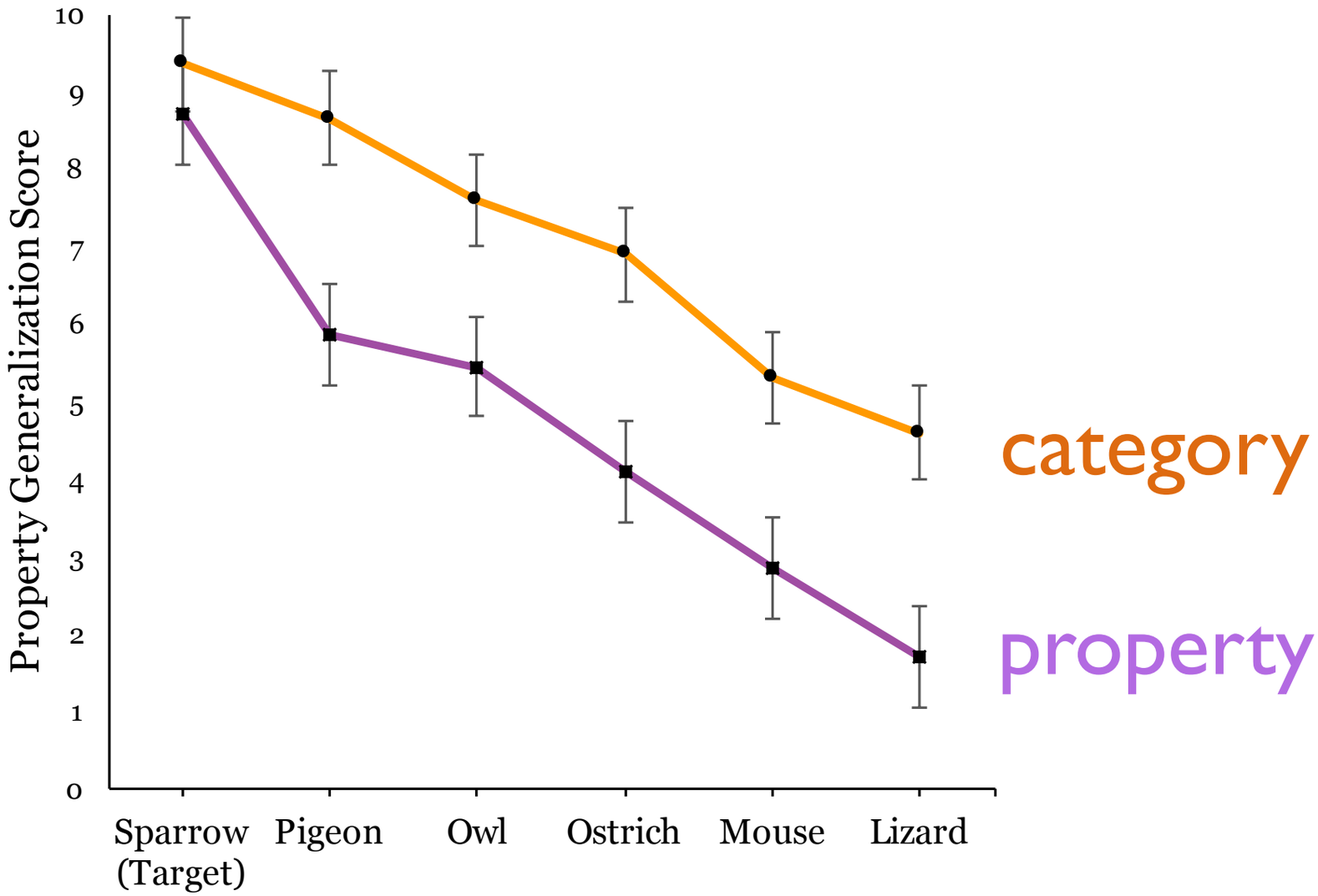
Property sampling



No remaining hypotheses allow LP+… so generalisation to large birds is *very implausible*

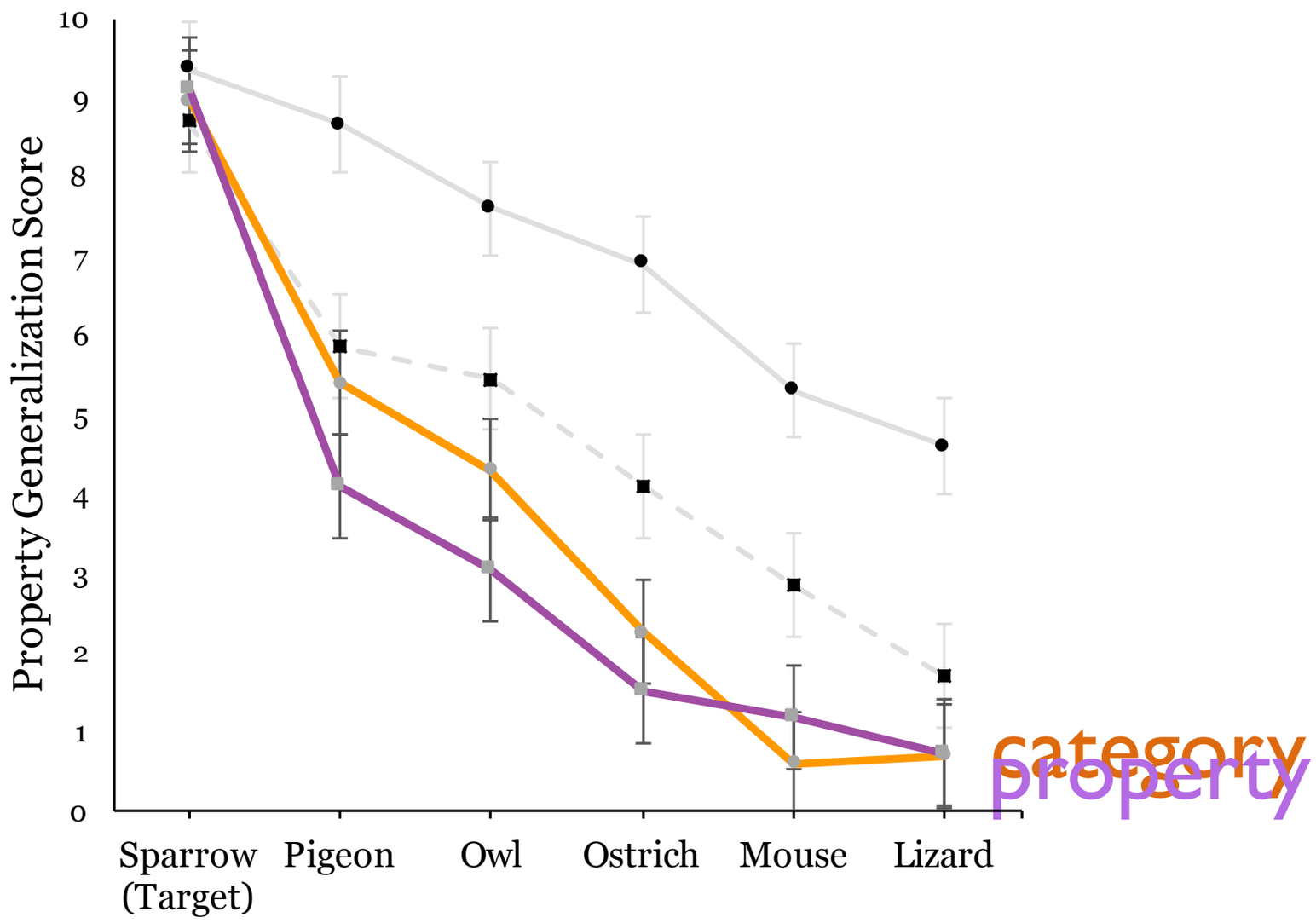
Hayes, Banner & Navarro (2017)

Replication of L&K 2009



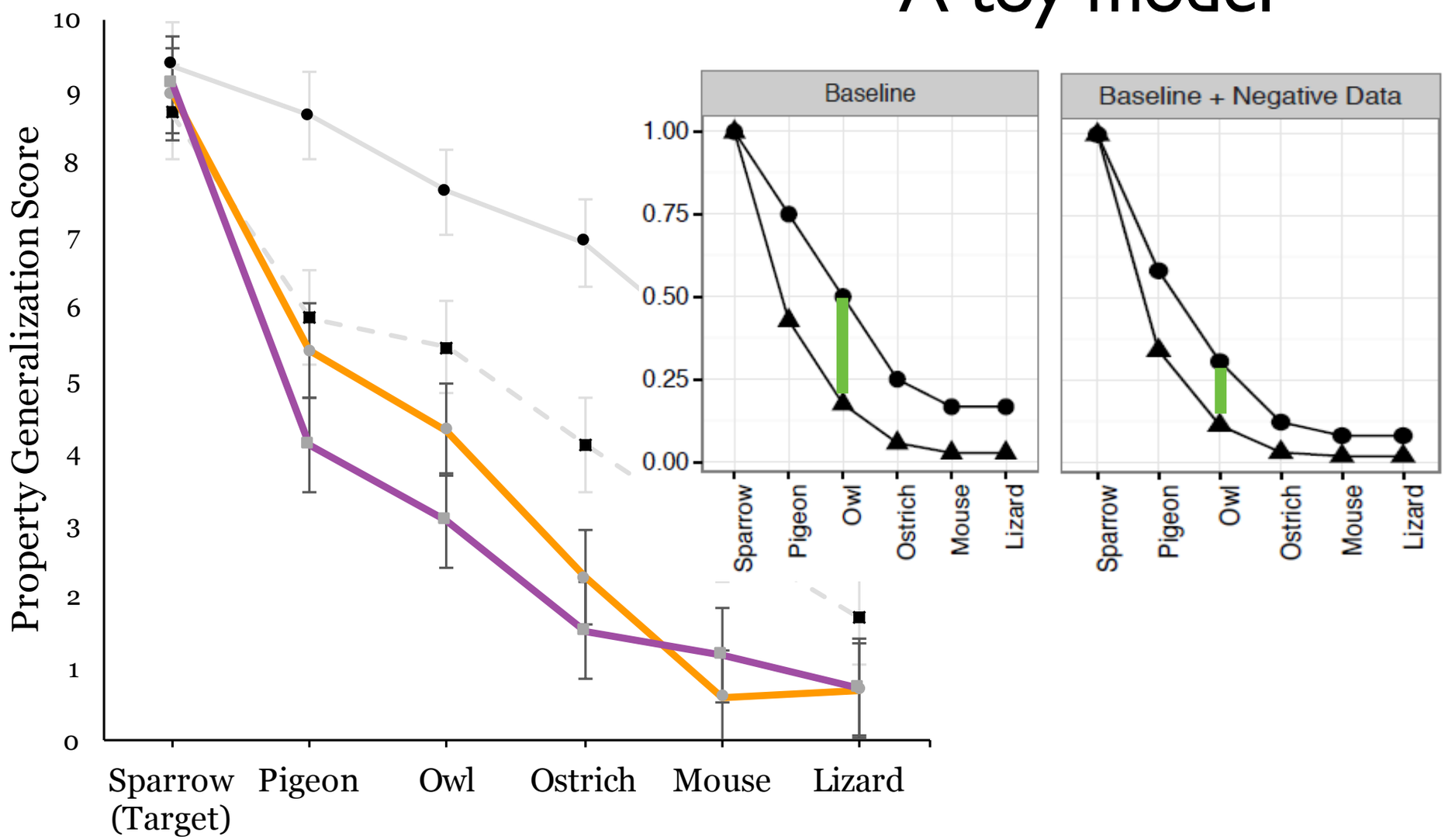
Hayes, Banner & Navarro (2017)

Explicit negative evidence (actual LP-) attenuates value of *implicit* negative evidence (no LP+)



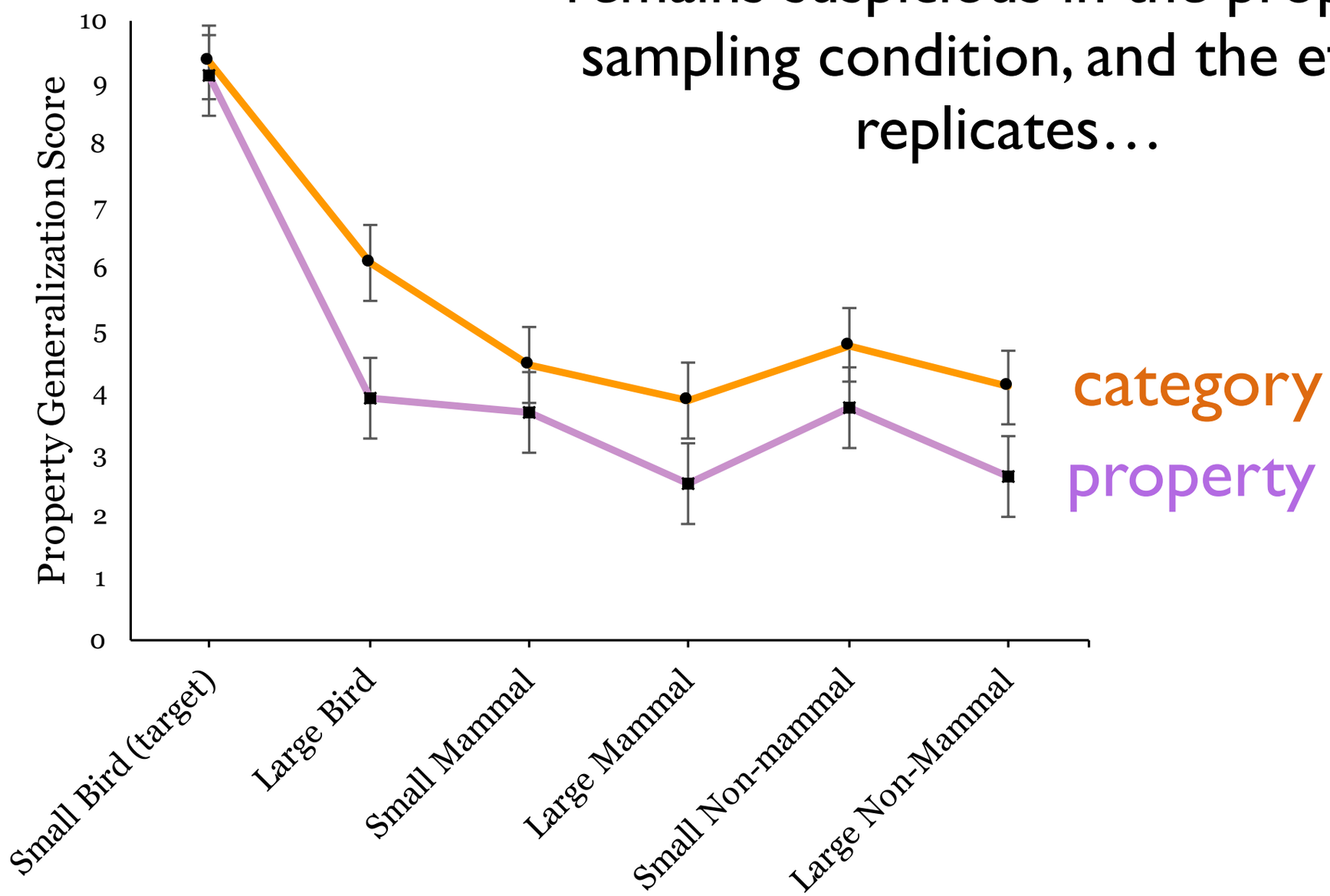
Hayes, Banner & Navarro (2017)

A toy model



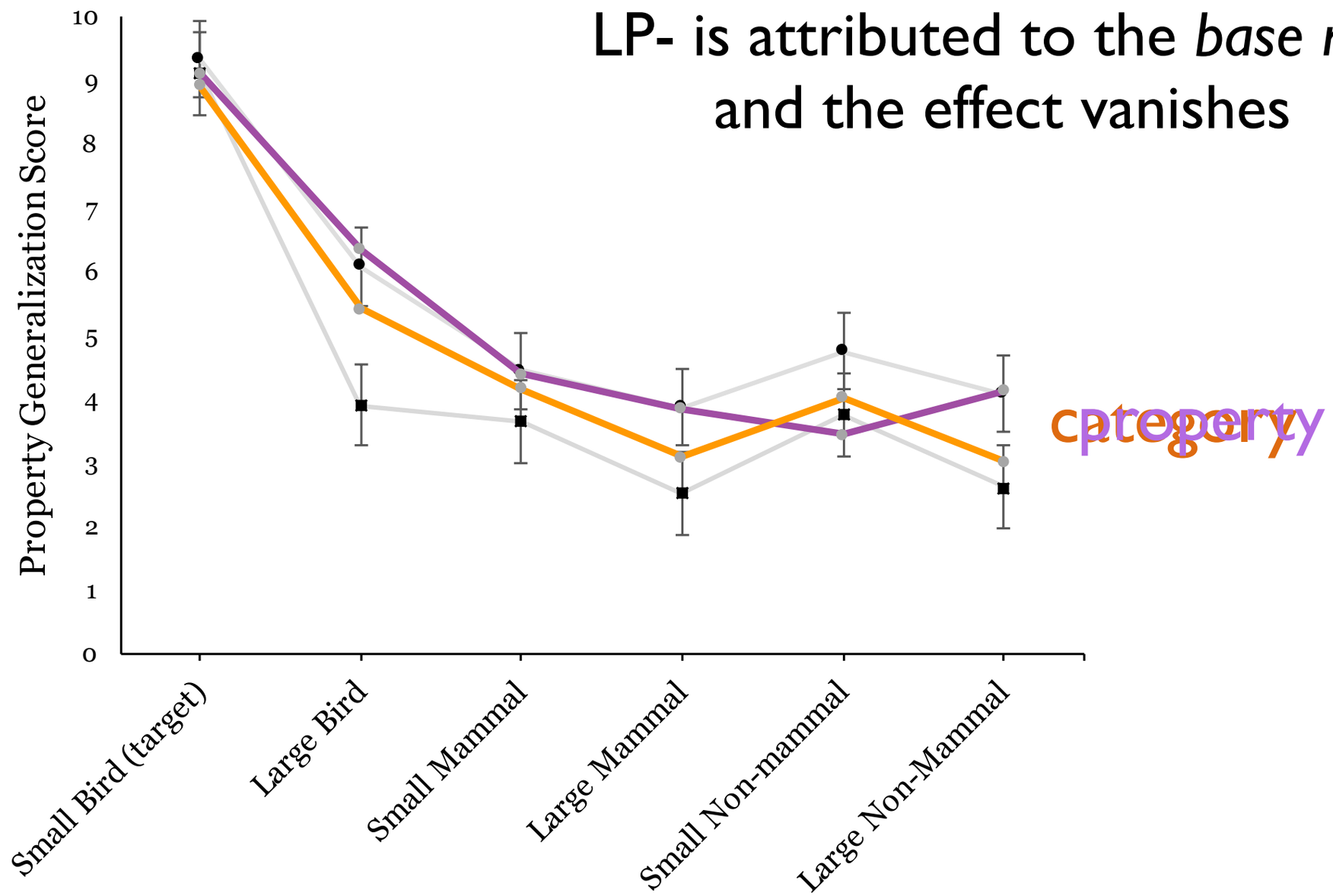
Hayes, Banner & Navarro (2017)

If we tell people large birds are common, then the absence of LP+ remains suspicious in the property sampling condition, and the effect replicates…



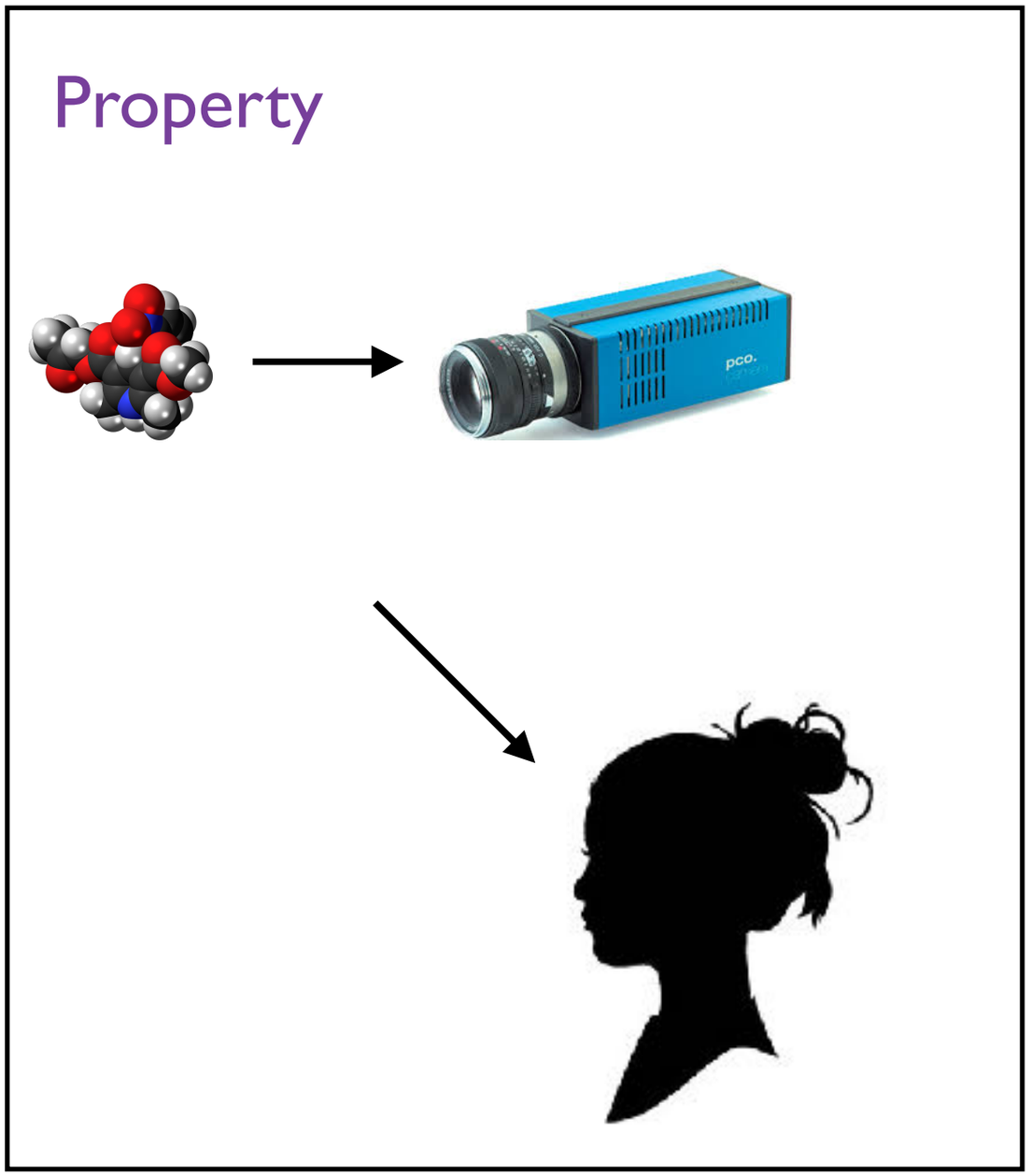
Hayes, Banner & Navarro (2017)

But if we tell people large birds are rare, then the absence of LP+ and LP- is attributed to the *base rate* and the effect vanishes



Hayes, Banner & Navarro (2017)

People pay attention to *mechanistic* constraints on sampling processes (not just social cues), and this shapes our reasoning in a sensible way

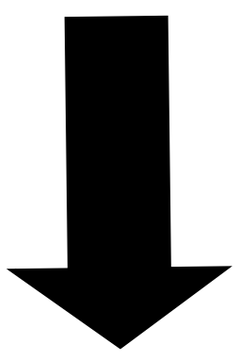


Hayes, Banner & Navarro (2017)

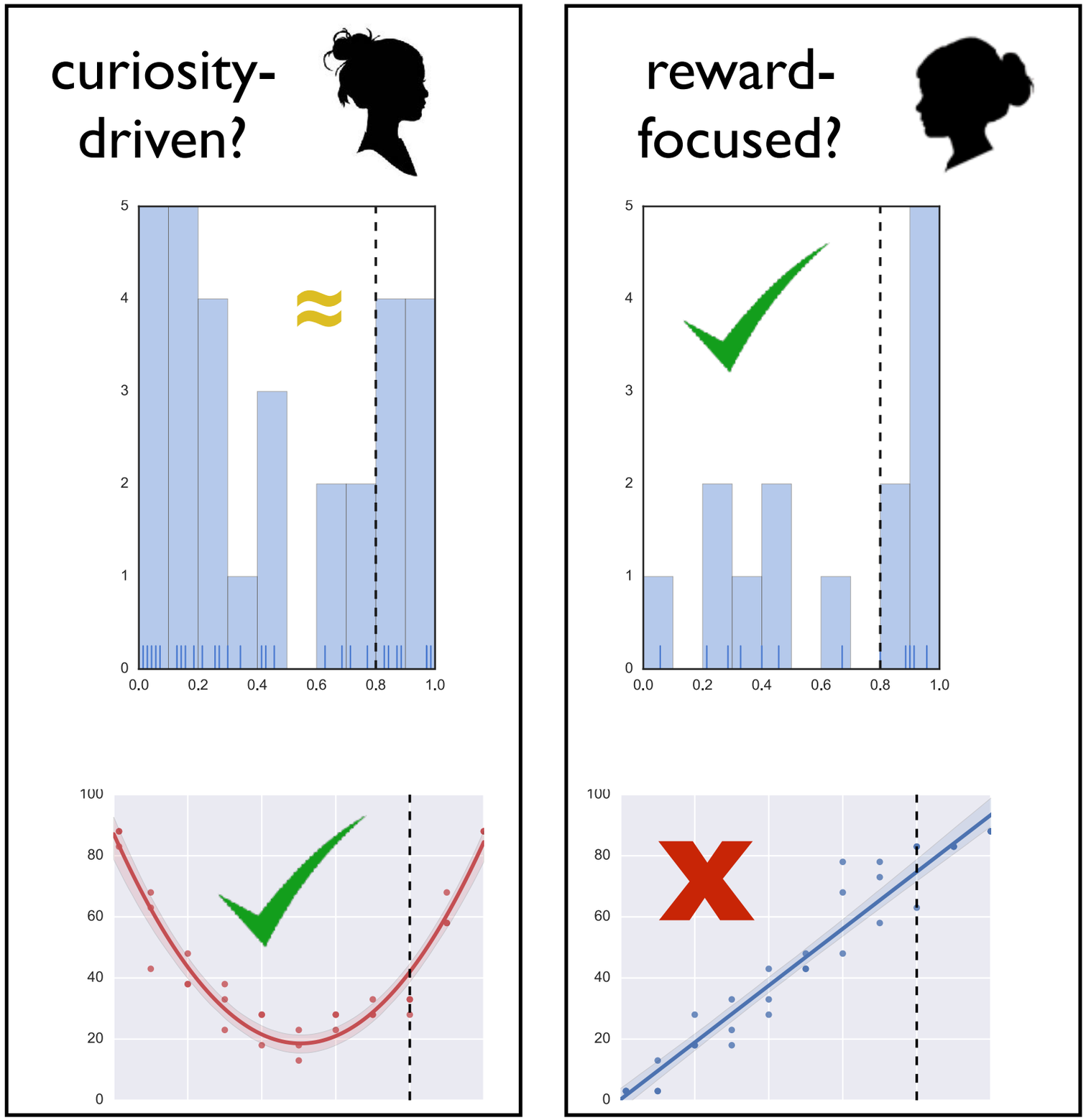
More extensions?

Choice: What drives people's active sampling?

instrumental learning task

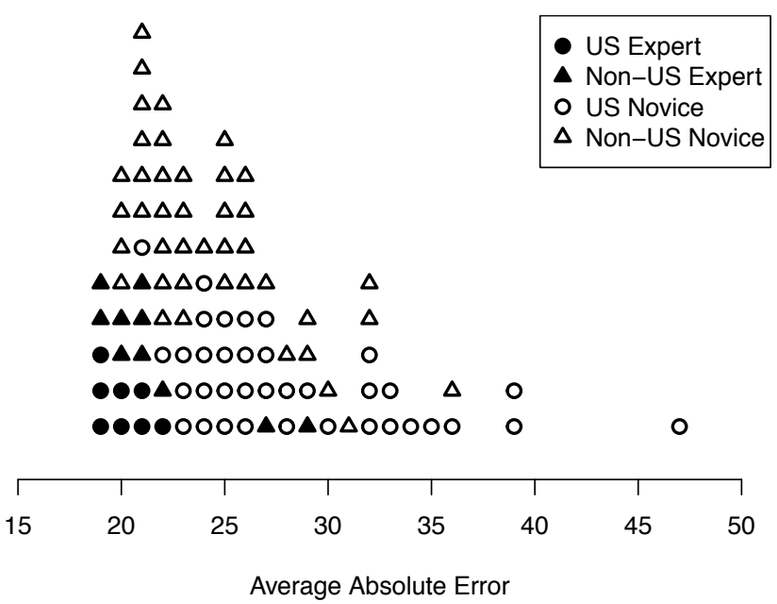


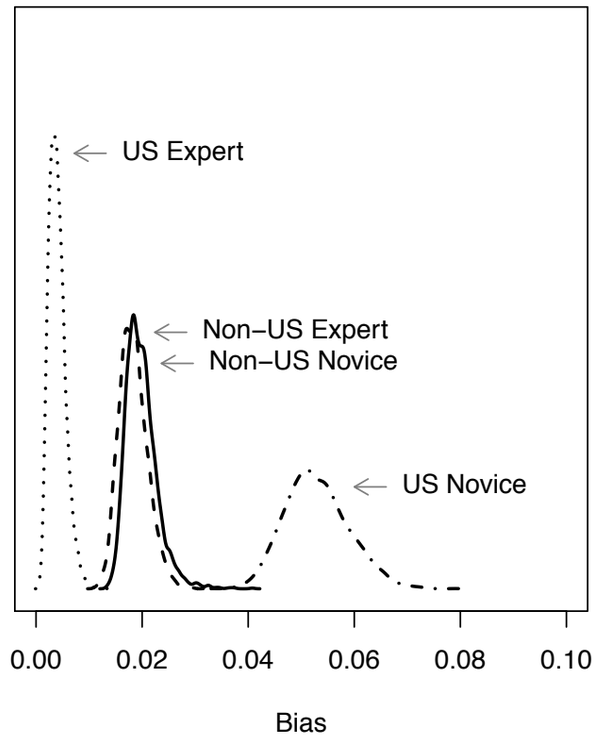
transfer task

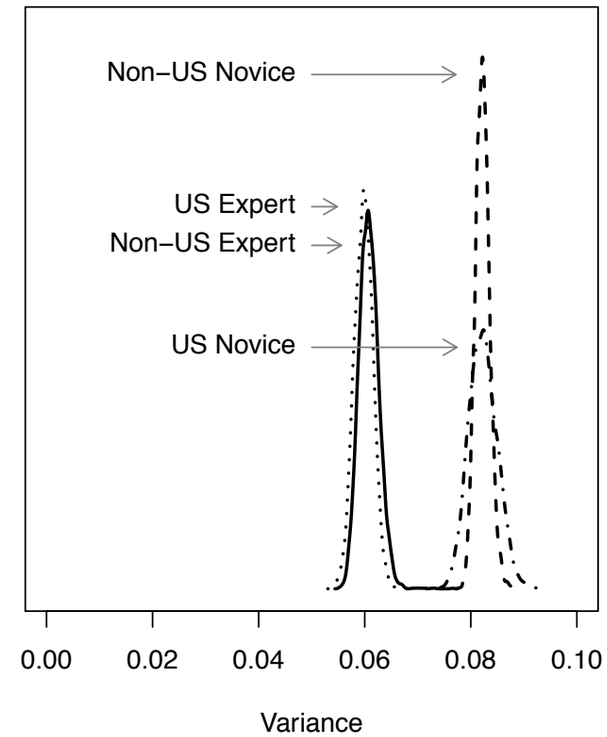


with Sean Tauber and Ben Newell

Law: Evidence sampling and expertise in the courtroom

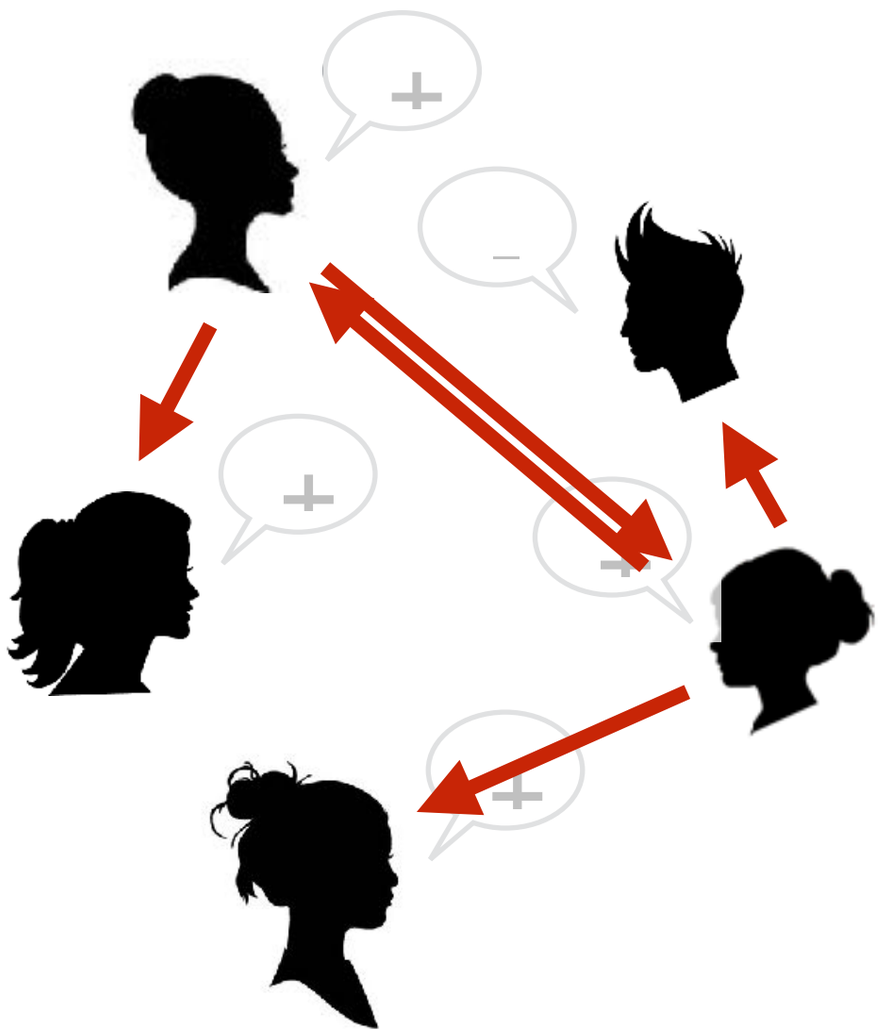


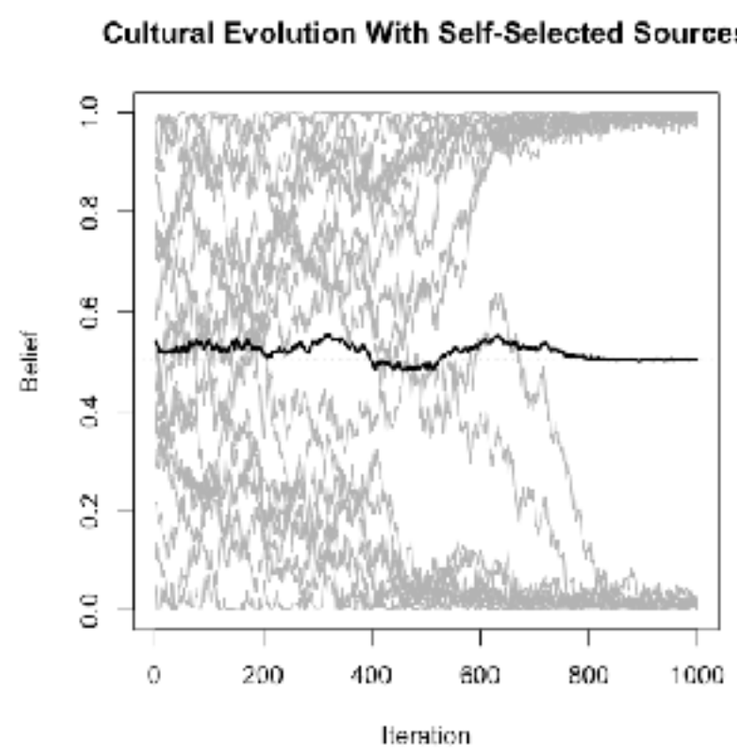


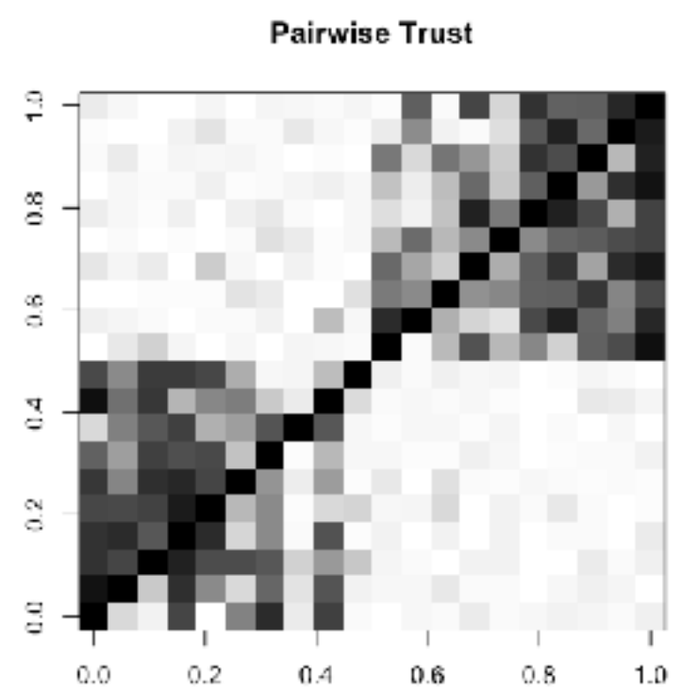


Martire, Edmonds, Navarro & Newell (2017)
Martire, Growns & Navarro (under review)

Society: Trust-based sampling via self-organising social networks (fake news…)

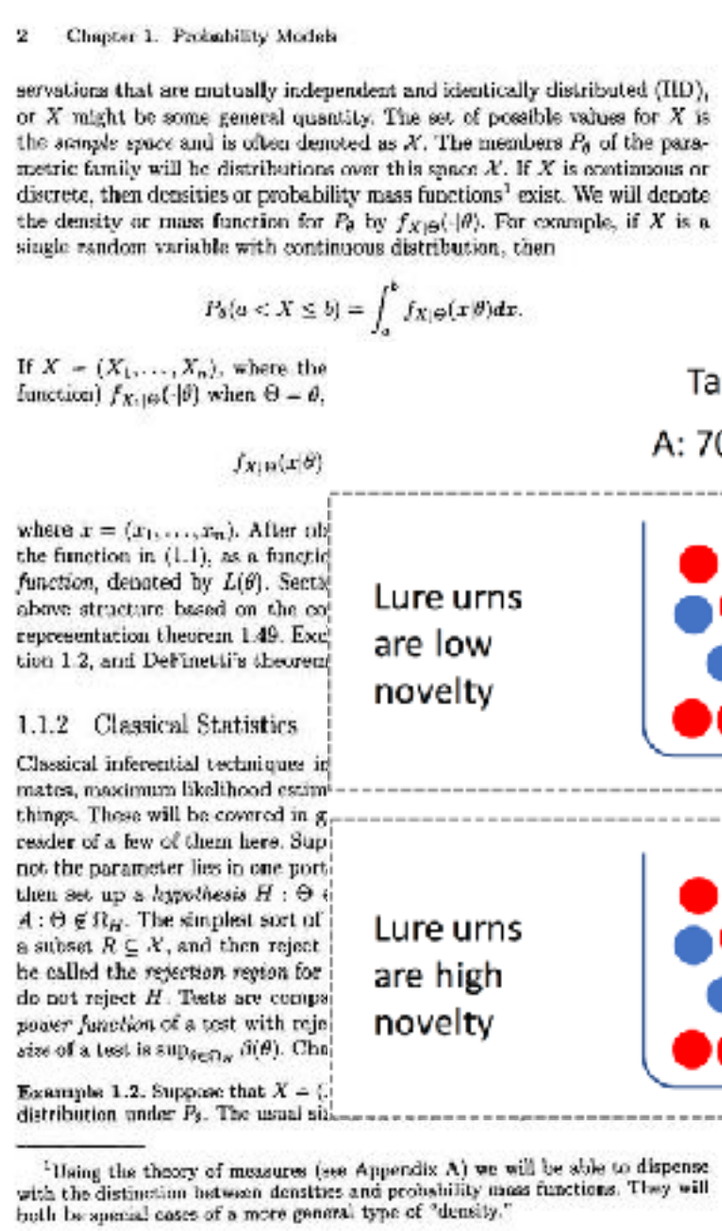






with Amy Perfors

Development: Exploratory versus goal-directed sampling by preschoolers



2 Chapter 1. Probability Models

servations that are mutually independent and identically distributed (IID), or X might be some general quantity. The set of possible values for X is the *sample space* and is often denoted as $\mathcal{X}$. The members P_θ of the parametric family will be distributions over this space $\mathcal{X}$. If X is continuous or discrete, then densities or probability mass functions[1] exist. We will denote the density or mass function for P_θ by $f_{X|\Theta}(\cdot|\theta)$. For example, if X is a single random variable with continuous distribution, then

$$P_\theta(a < X \leq b) = \int_a^b f_{X|\Theta}(x|\theta)dx.$$

If $X = (X_1, \ldots, X_n)$, where the
function) $f_{X|\Theta}(\cdot|\theta)$ when $\Theta = \theta$,

$$f_{X|\Theta}(x|\theta)$$

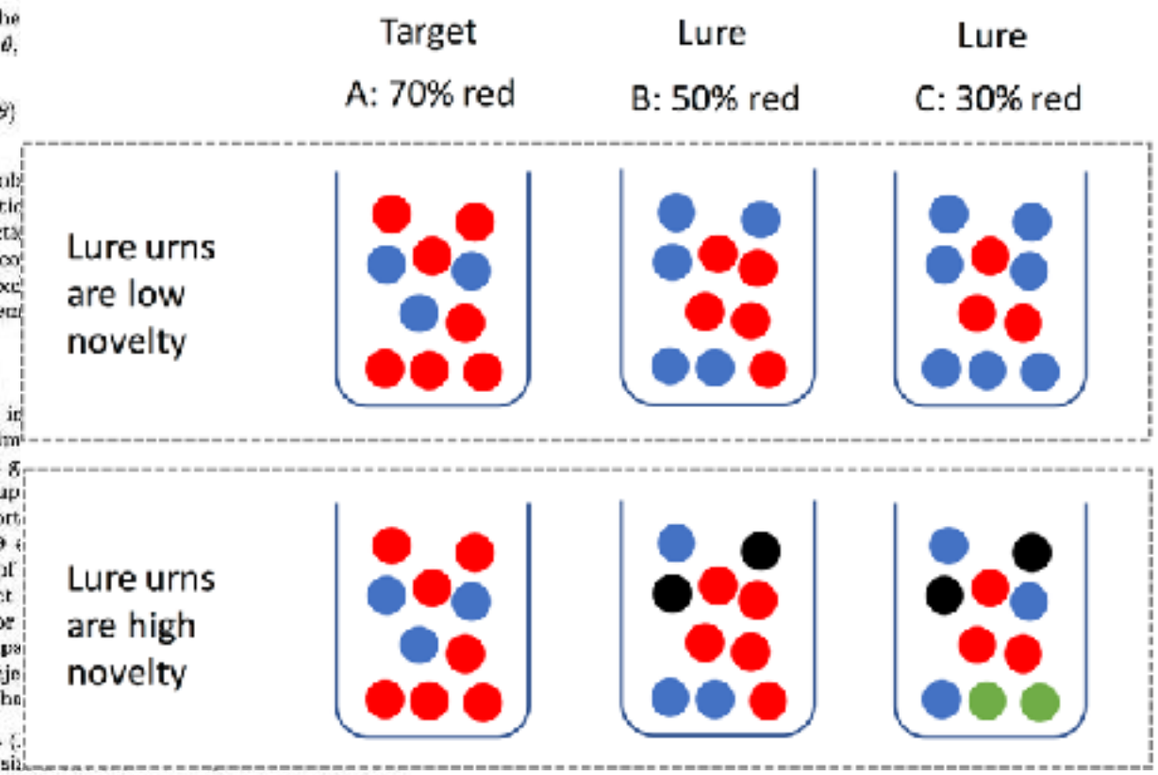
where $x = (x_1, \ldots, x_n)$. After ob
the function in (1.1), as a functio
function, denoted by $L(\theta)$. Secti
above structure based on the co
representation theorem 1.49. Exe
tion 1.2, and DeFinetti's theorem

1.1.2 Classical Statistics

Classical inferential techniques in
mates, maximum likelihood estim
things. These will be covered in g
reader of a few of them here. Sup
not the parameter lies in one port
then set up a *hypothesis* $H : \Theta \in$
$A : \Theta \notin \Pi_H$. The simplest sort of
a subset $R \subseteq \mathcal{X}$, and then reject
be called the *rejection region* for
do not reject H. Tests are compa
power function of a test with reje
size of a test is $\sup_{\theta \in \Pi_H} \beta(\theta)$. Cha

Example 1.2. Suppose that $X = (.$
distribution under P_θ. The usual si

[1] Using the theory of measures (see Appendix A) we will be able to dispense with the distinction between densities and probability mass functions. They will both be special cases of a more general type of "density."



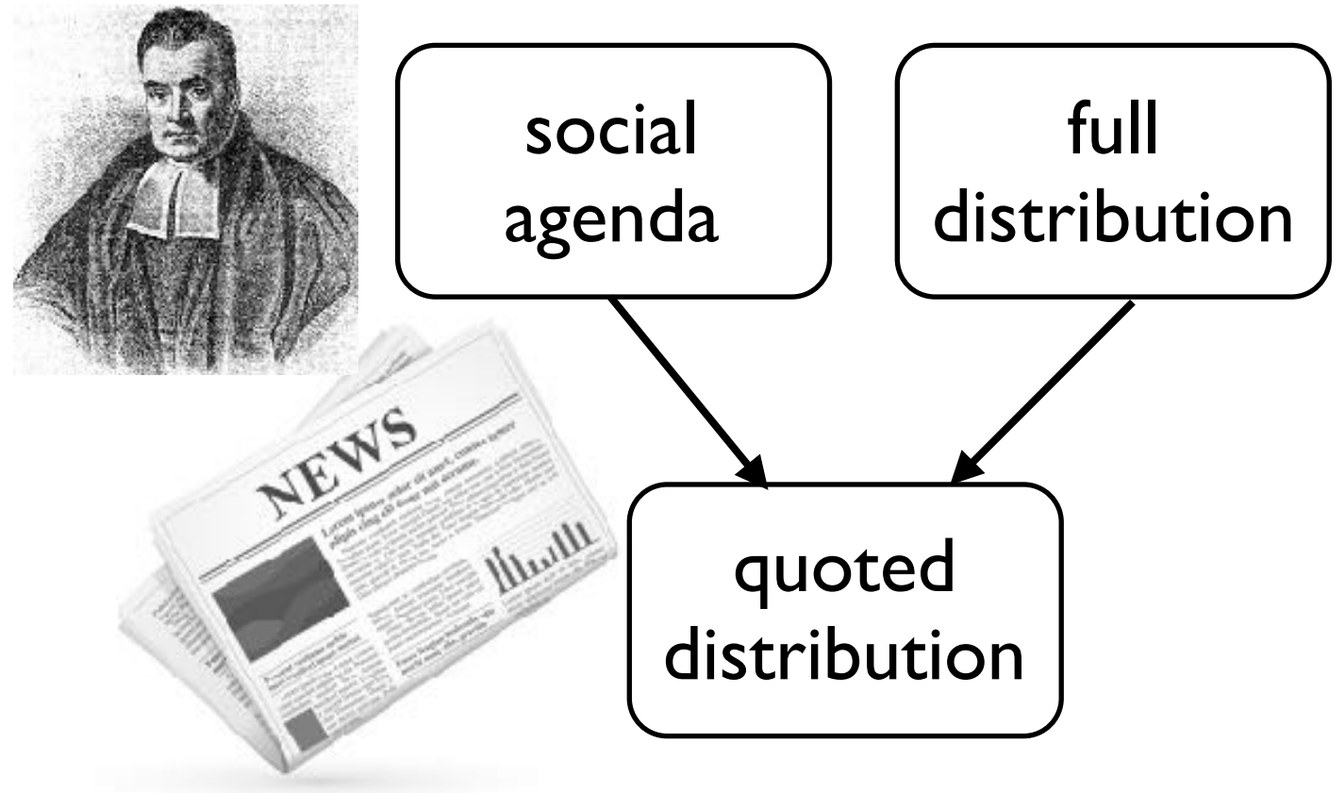
with Candy Liu, Jenny Richmond & Amy Perfors

Wrap-up:

On the origins of data and the rationality* of human reasoning

People are smart. Limited, but smart.

"*Common sense*" reasoning is infuriatingly cunning, and requires people to learn from complex data sources (e.g., other people)



We need to disentangle facts from agendas

with Amy Perfors and Pat Shafto

We need to detect trickery

social agenda

full distribution

quoted distribution

too many collaborators to list

social agenda

full distribution

quoted distribution

We need to know when to reject the rules we're given

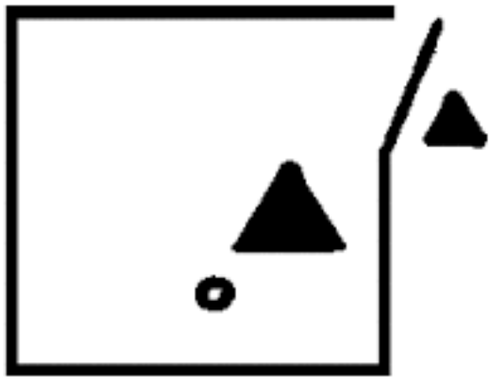
with Charles Kemp

social agenda

full distribution

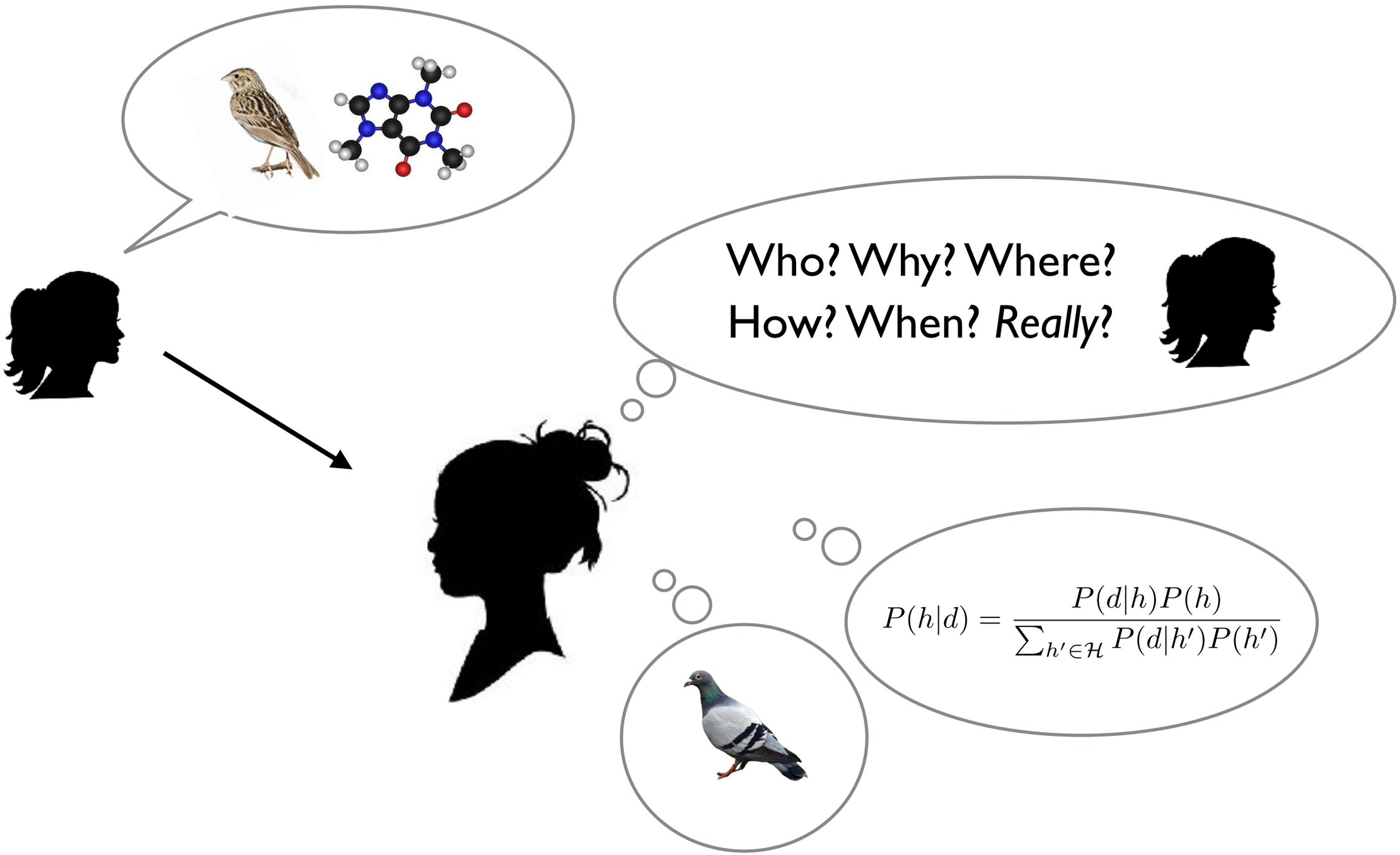
quoted distribution

We need to read the intention of potentially malicious agents



too many collaborators to list

Common sense reasoning requires uncommonly rich statistical models



Thanks!