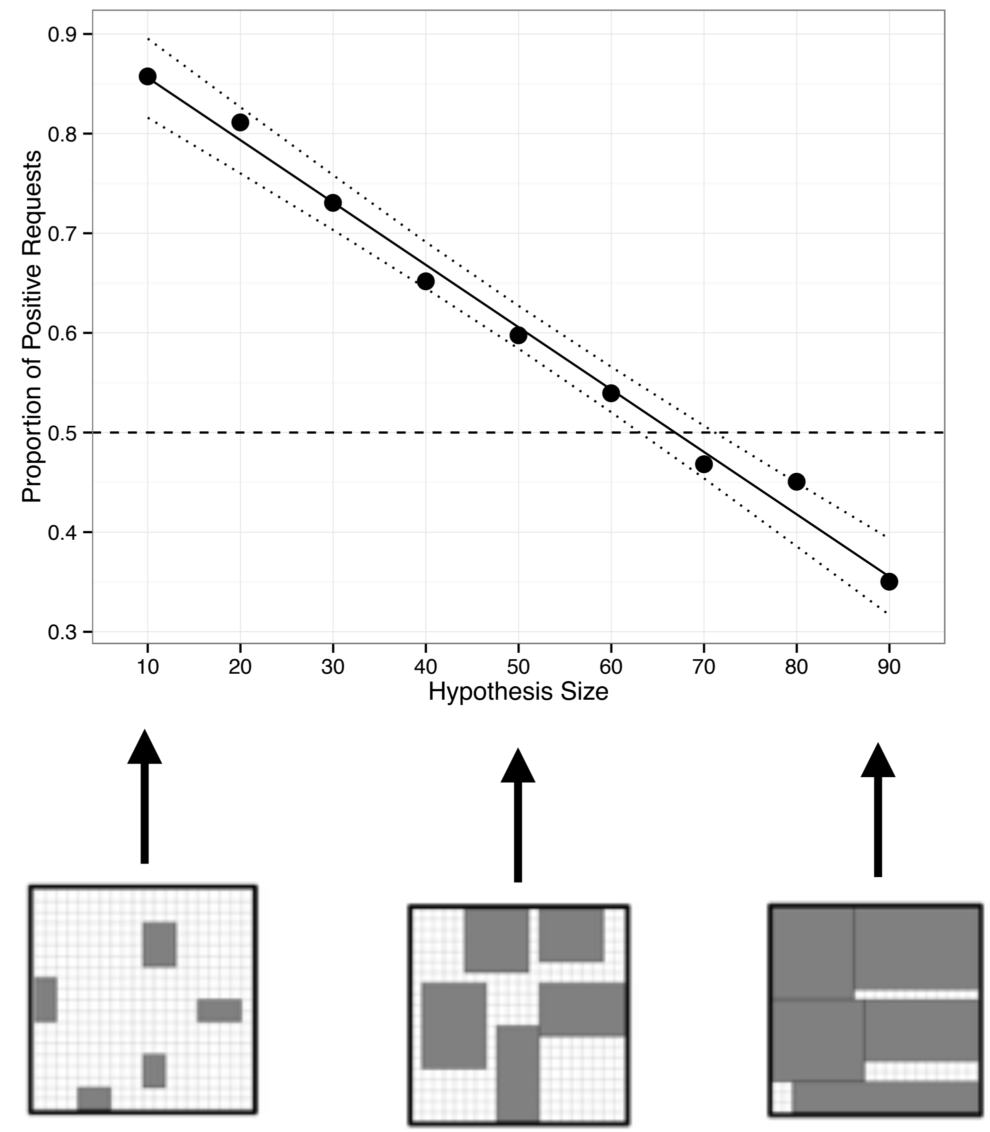
On the origins of data

Dan Navarro
University of Adelaide

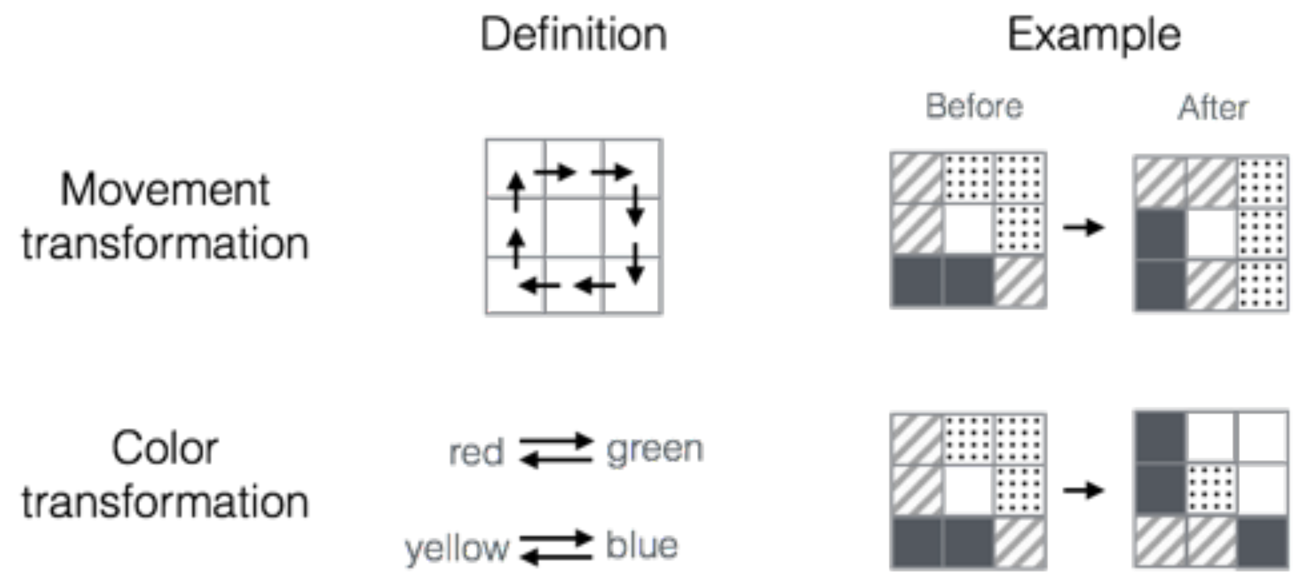
The lab has been busy lately, and I really wanted to talk about all their good work…

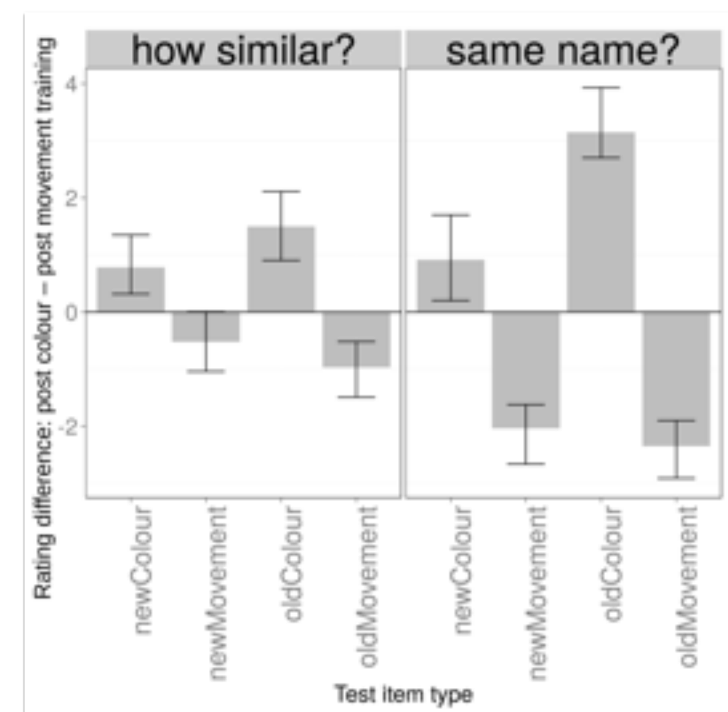
Drew has cool stuff looking at the kind of evidence people prefer to learn from…



Hendrickson, Navarro & Perfors (under revision). Sensitivity to hypothesis size during information search. *Decision*

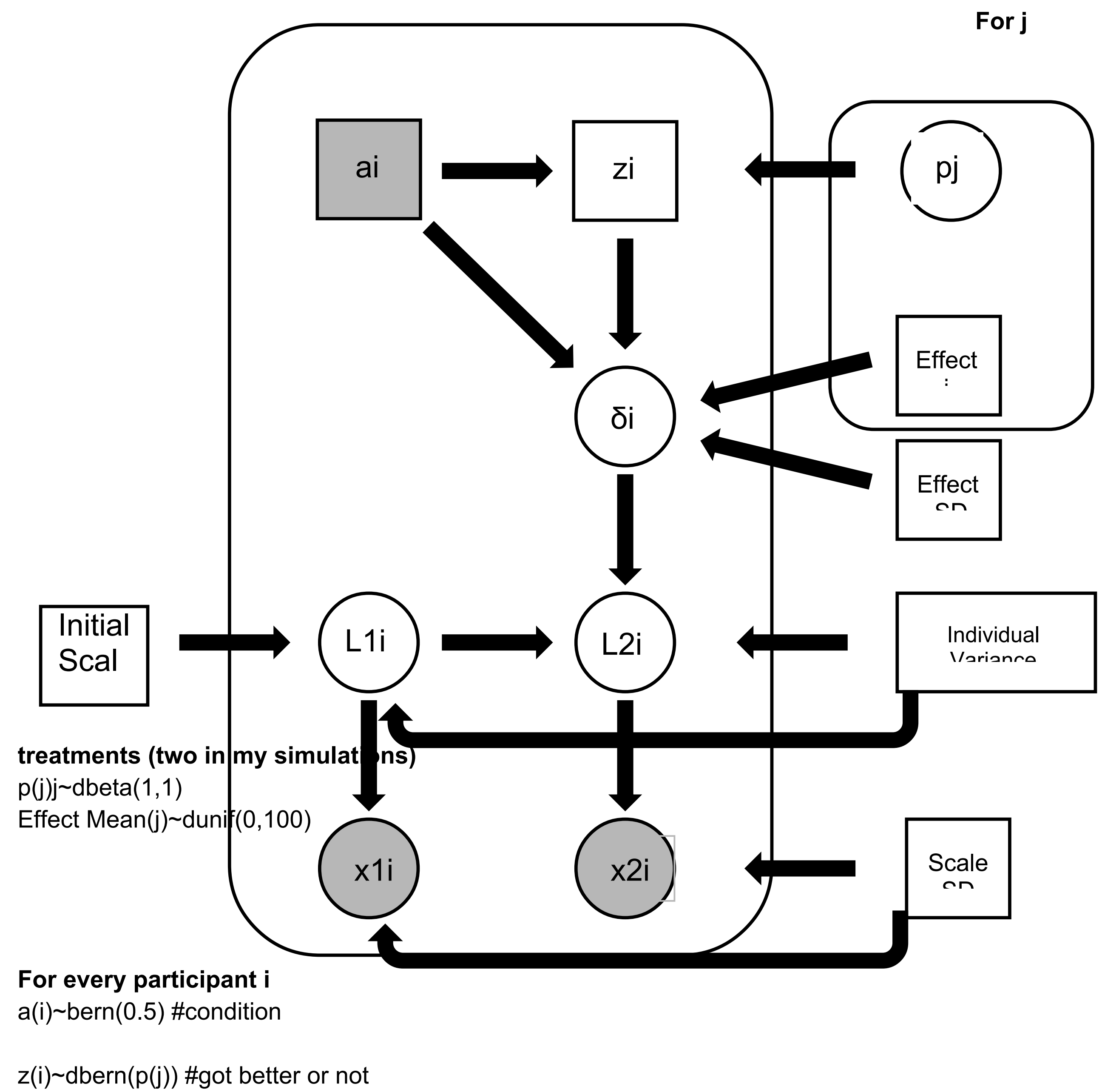
Steve has cool stuff looking at how people learn (and use) "admissable" stimulus transformations



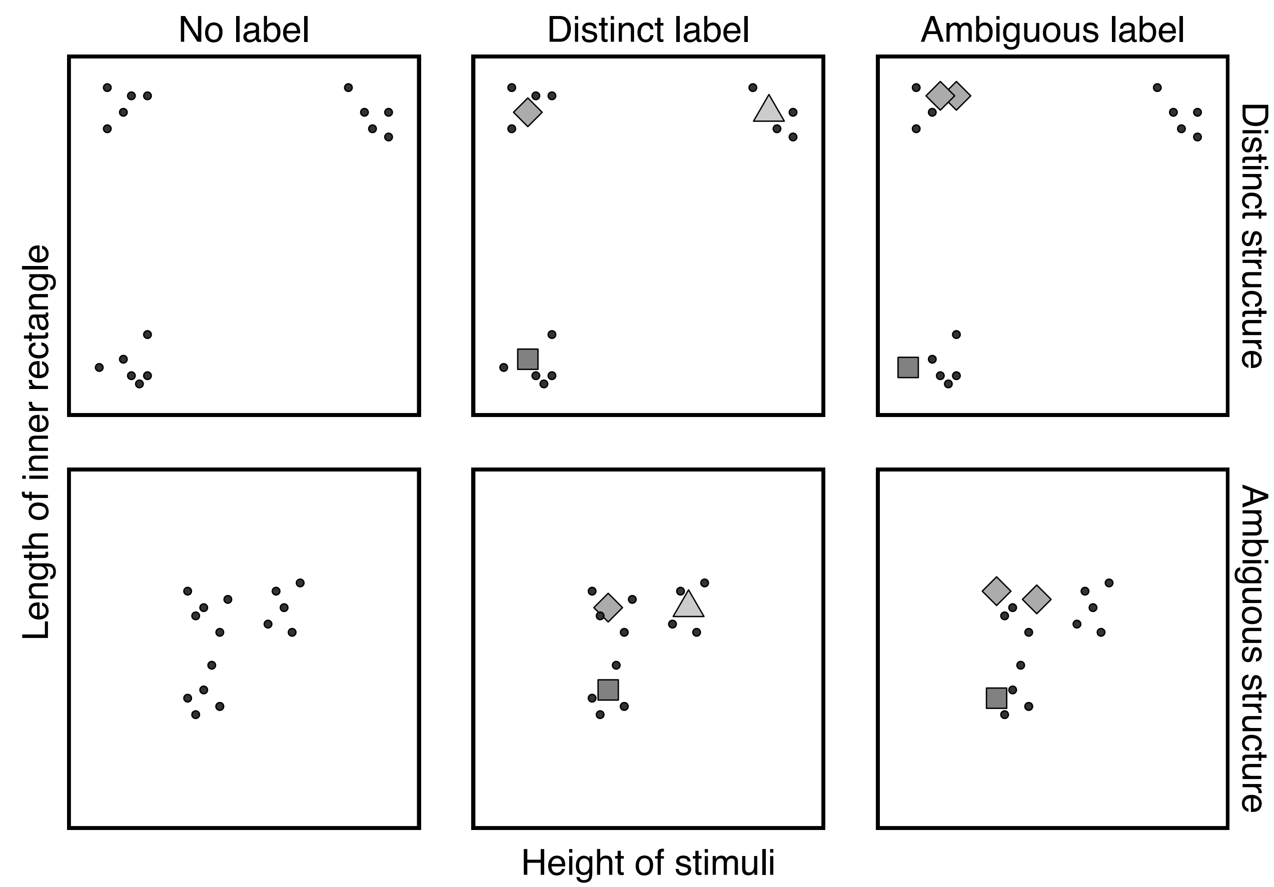


Langsford, Navarro, Perfors & Hendrickson (under review). Transformation learning and its effect on similarity. *JEP:LMC*

Lauren has some scarily effective ideas about how the analysis of clinical trials could be done better…

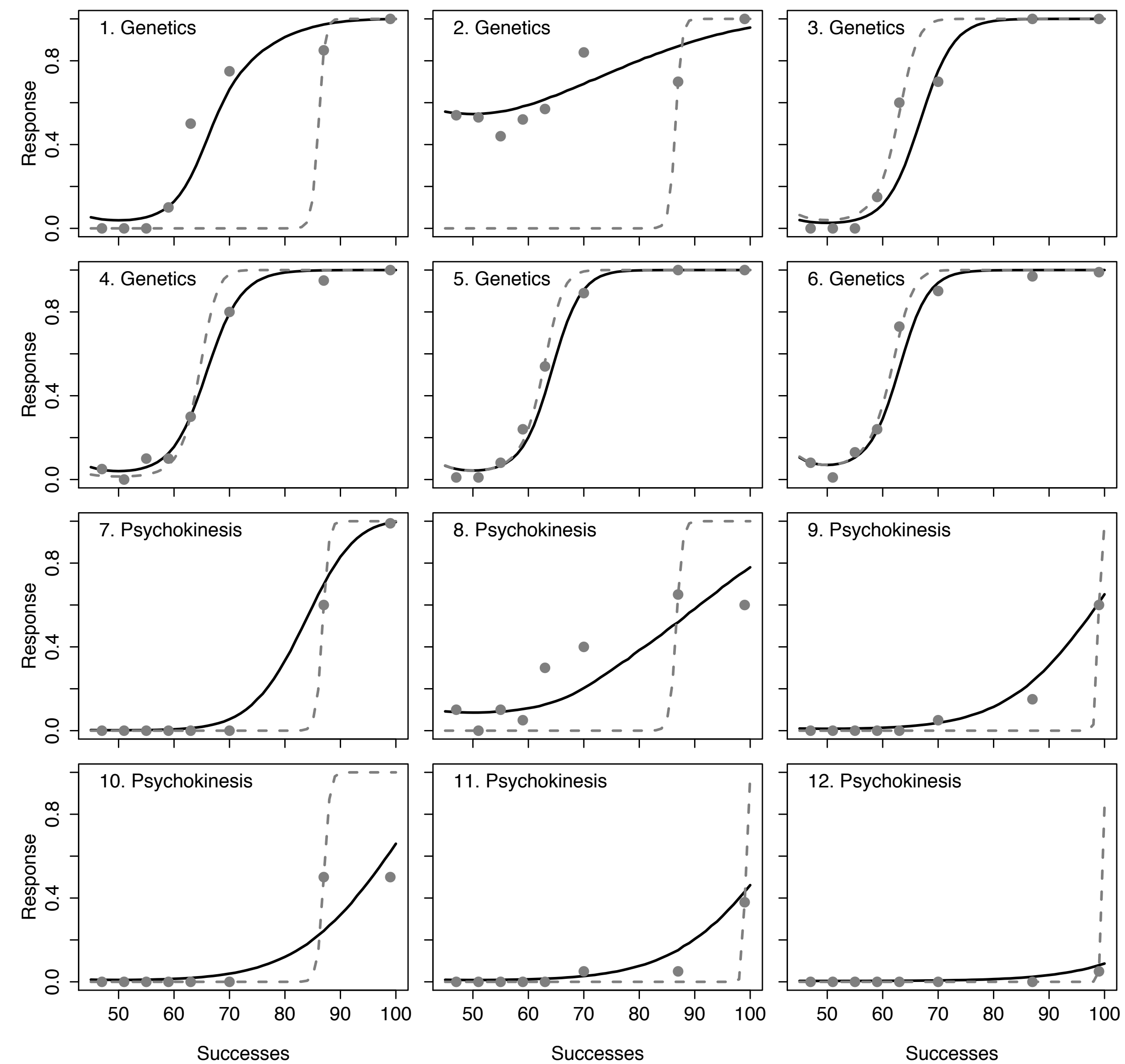


Wai Keen thinks much of the semi-supervised learning literature is missing the point…



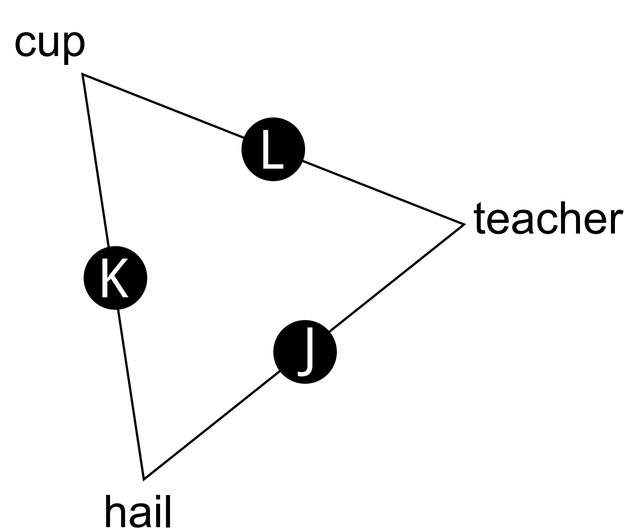
Vong, Perfors & Navarro (in press). The helpfulness of category labels in semi-supervised learning depends on category structure. *Psychonomic Bulletin and Review*

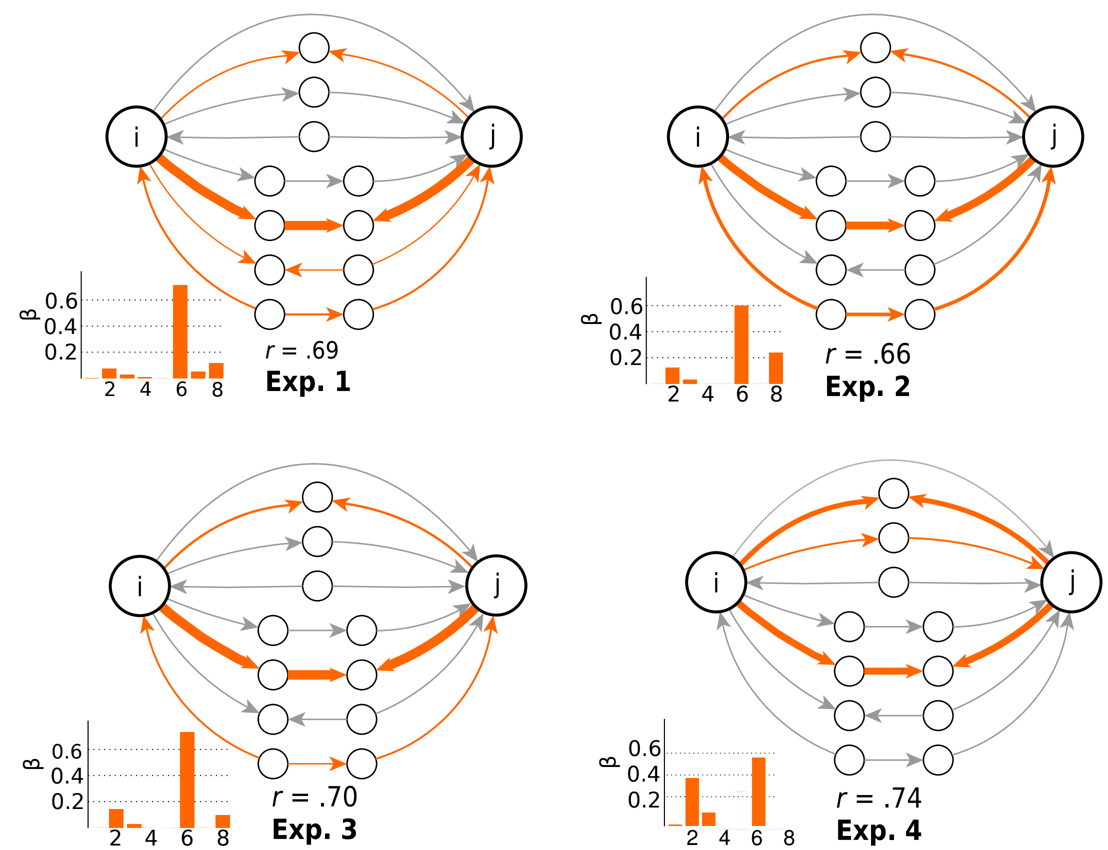
Sean has an awesome rant about how Bayesian cognitive modeling ought to work



Tauber, Navarro, Perfors & Steyvers (in preparation). Bayesian models of cognition revisited: Letting go of optimality and letting data drive psychological theory. *Psych Review?*

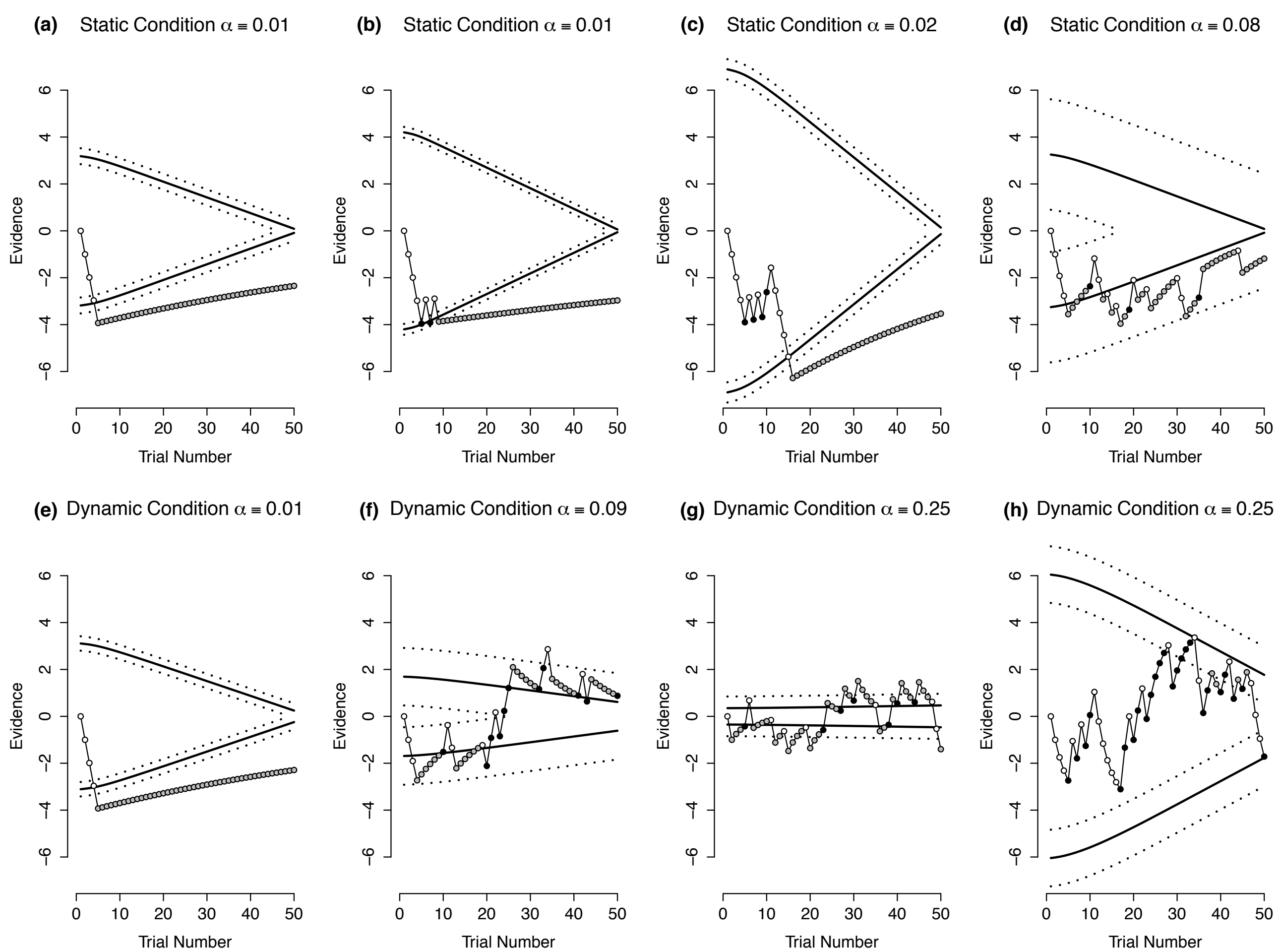
Simon has a semantic network model for predicting similarities between very unrelated words

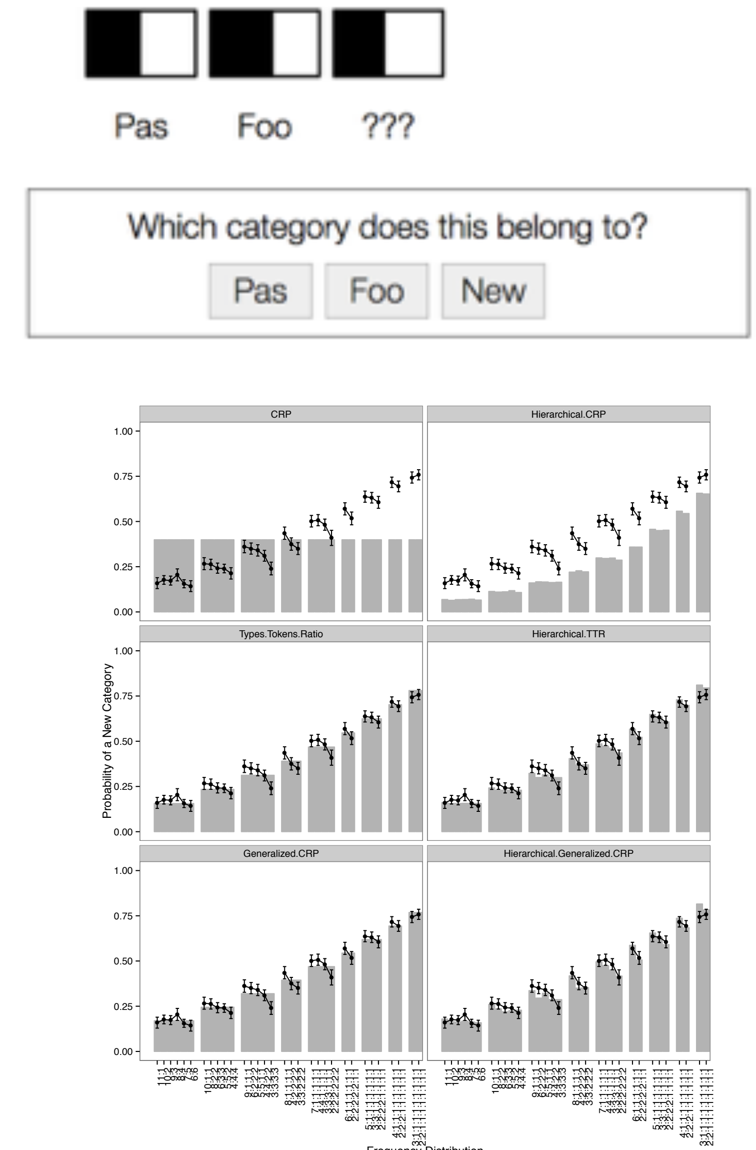




De Deyne, Navarro, Perfors, Storms (submitted?). Structure at every scale: A semantic network account of the similarities between very unrelated concepts. *JEP:G*

(Even I've been doing research)





Navarro, Newell & Schulze (under revision). Learning and choosing in an uncertain world: An investigation of the explore-exploit dilemma in static and dynamic environments. *Cognitive Psychology*

Navarro & Kemp (in preparation). None of the above: A Bayesian account of the section of novel categories. *Psych Review?*

In the end, I had to ignore most people and concentrate on one line of work…

:-(

Navarro, Dry & Lee (2012). Sampling assumptions in inductive generalization. *Cognitive Science*

Hendrickson, Perfors & Navarro (in preparation). One cat, two cats: Sampling models in different category learning tasks produce qualitatively different inductive generalisations

Ransom, Perfors & Navarro (in press). Leaping to conclusions: Why premise relevance affects argument strength. *Cognitive Science*

Voorspoels, Navarro, Perfors, Ransom & Storms (under revision). How do people learn from negative evidence? Non-monotonic generalizations and sampling assumptions in inductive reasoning. *Cognitive Psychology*

Perfors, Navarro & Shafto (in preparation). Stronger evidence isn't always better: The role of social inference in evidence selection and interpretation.

Navarro, Dry & Lee (2012). Sampling assumptions in inductive generalization. *Cognitive Science*

Drew Hendrickson, Perfors & Navarro (in preparation). One cat, two cats: Sampling models in different category learning tasks produce qualitatively different inductive generalisations

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Wouter Voorspoels, Navarro, Perfors, Ransom & Storms (under revision). How do people learn from negative evidence? Non-monotonic generalizations and sampling assumptions in inductive reasoning. *Cognitive Psychology*

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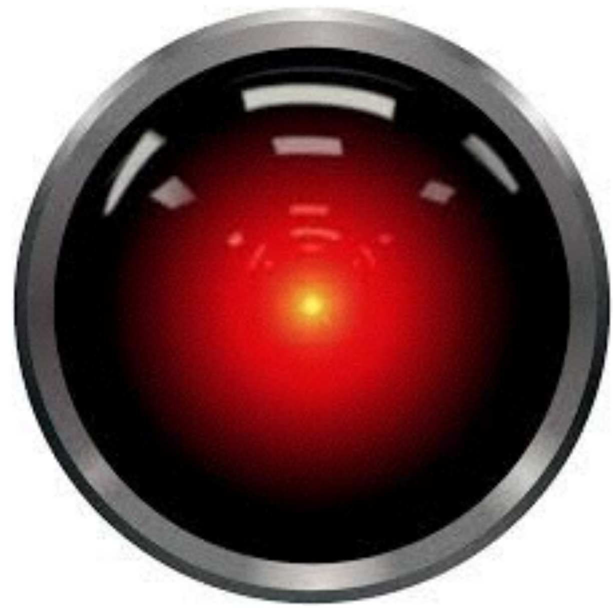
So… I want to build a smart machine, and I want it to do human-like inductive reasoning



So… I want to build a smart machine, and I want it to do human-like inductive reasoning

I want it to have **common sense**

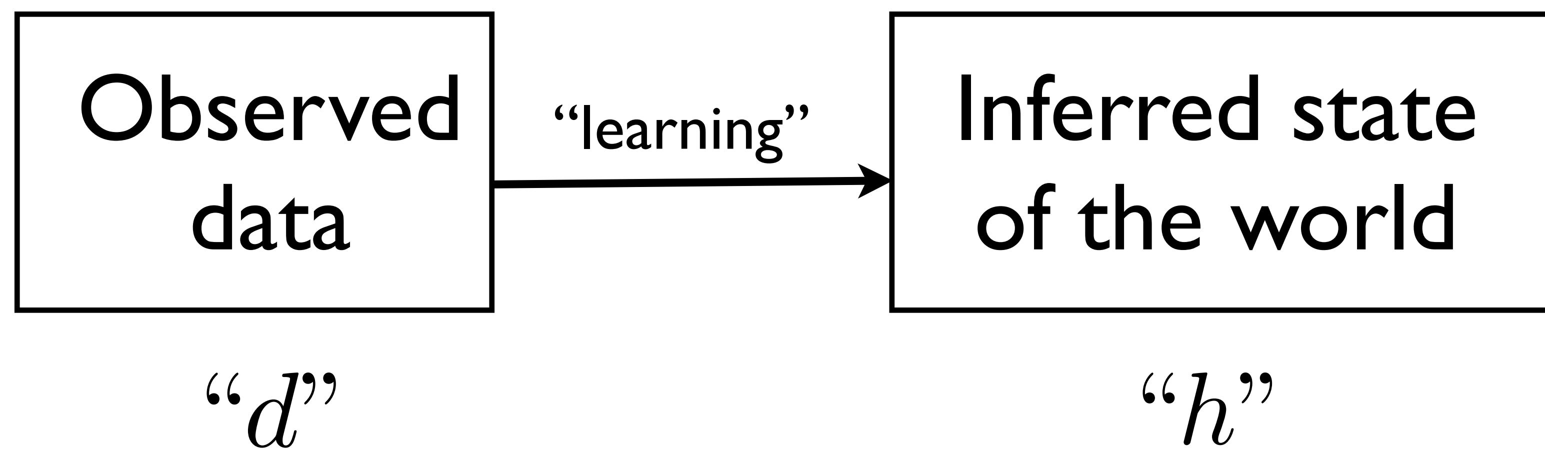
So I have to ask…

Why isn't inductive inference simple?

Why isn't inductive inference simple?

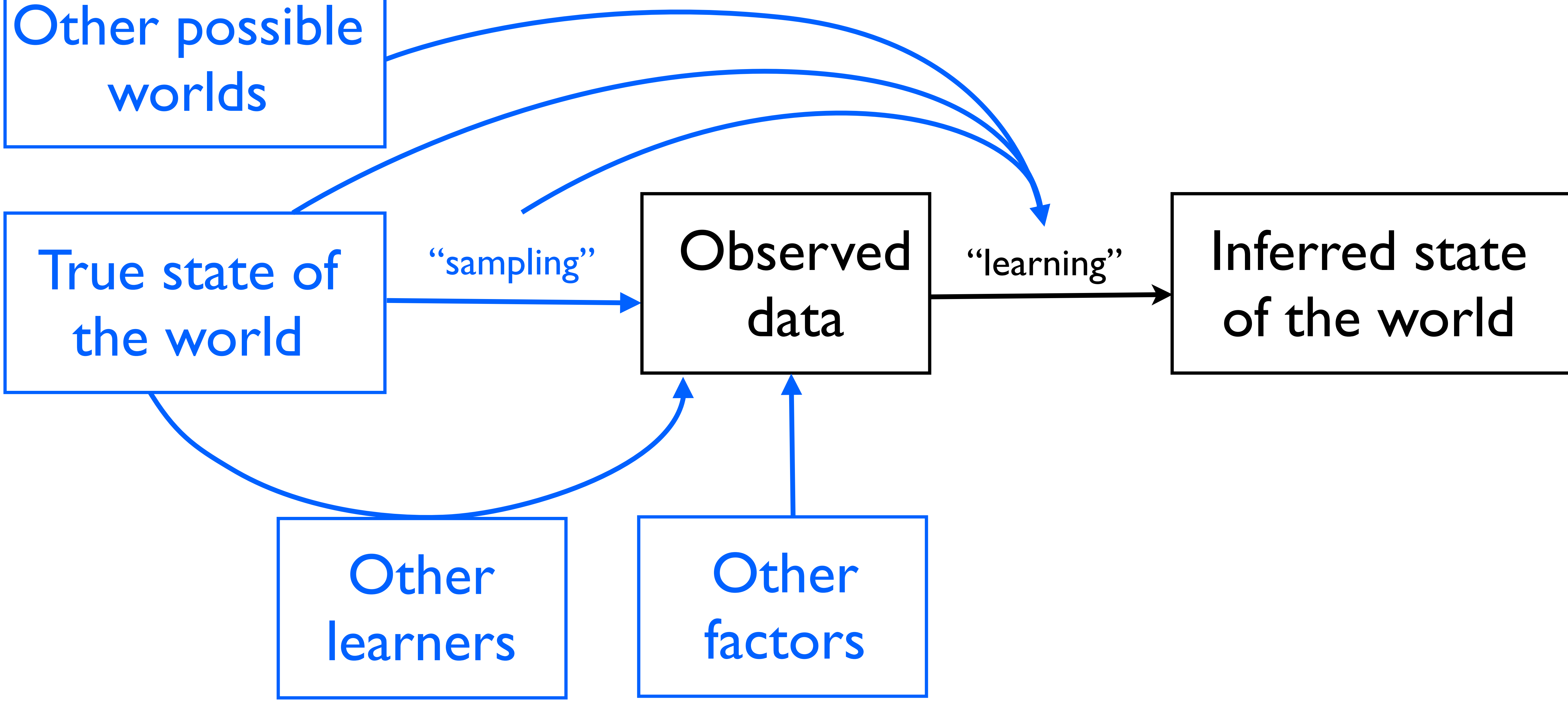
$$P(h|d) = \frac{P(d|h)P(h)}{P(d)}$$

A simple learning rule...



$$P(h|d) = \frac{P(d|h)P(h)}{P(d)}$$

… hides a lot of complexity



And what this means is that even "simple" problems become surprisingly tricky…

$$P(h|d) = \frac{P(d|h)P(h)}{P(d)}$$

Sampling assumptions in simple generalisation problems

Navarro, Dry & Lee (2012). Sampling assumptions in inductive generalization. *Cognitive Science*

Hendrickson, Perfors & Navarro (in preparation). One cat, two cats: Sampling models in different category learning tasks produce qualitatively different inductive generalisations

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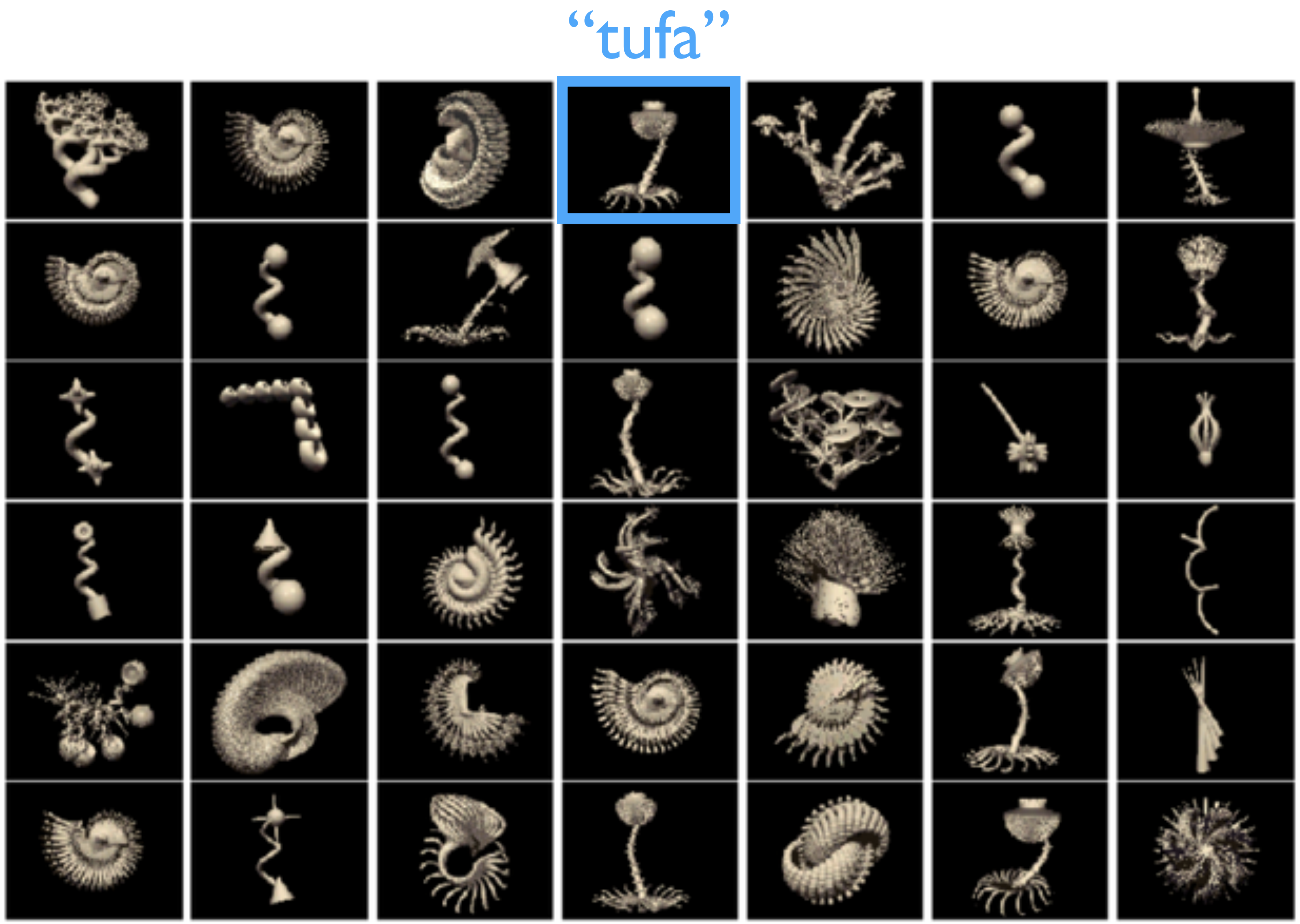
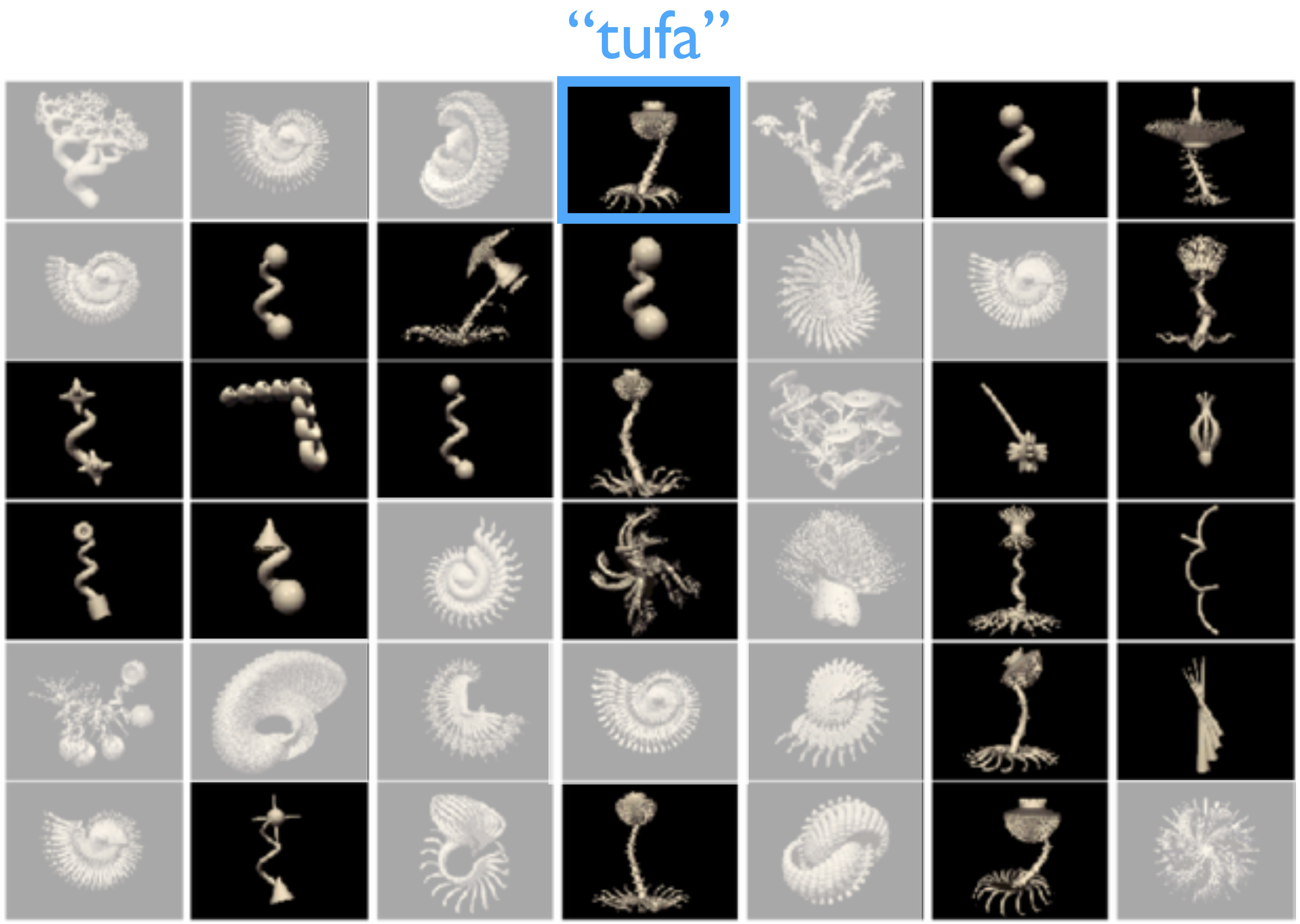

"tufa"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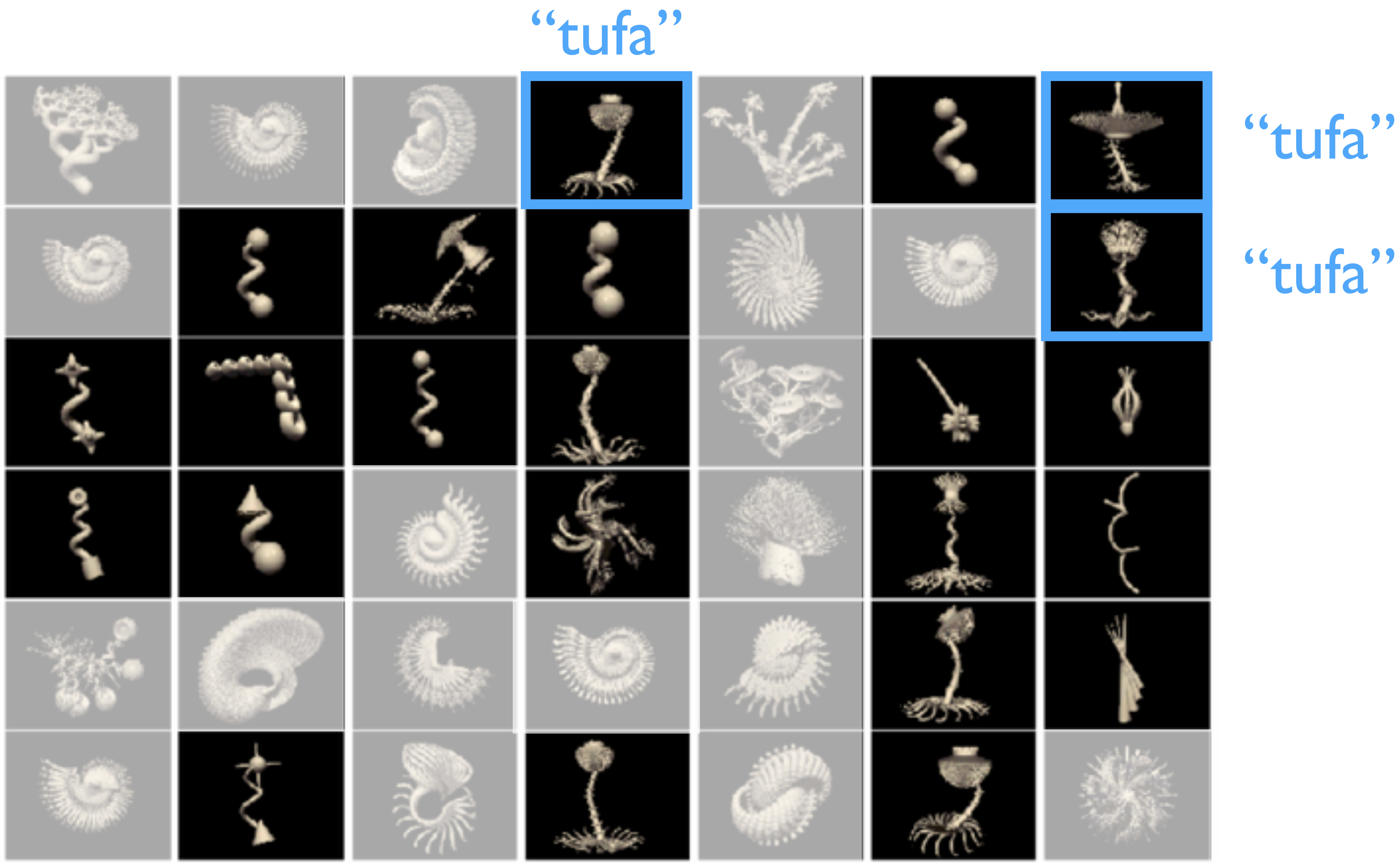
"tufa"
"tufa"
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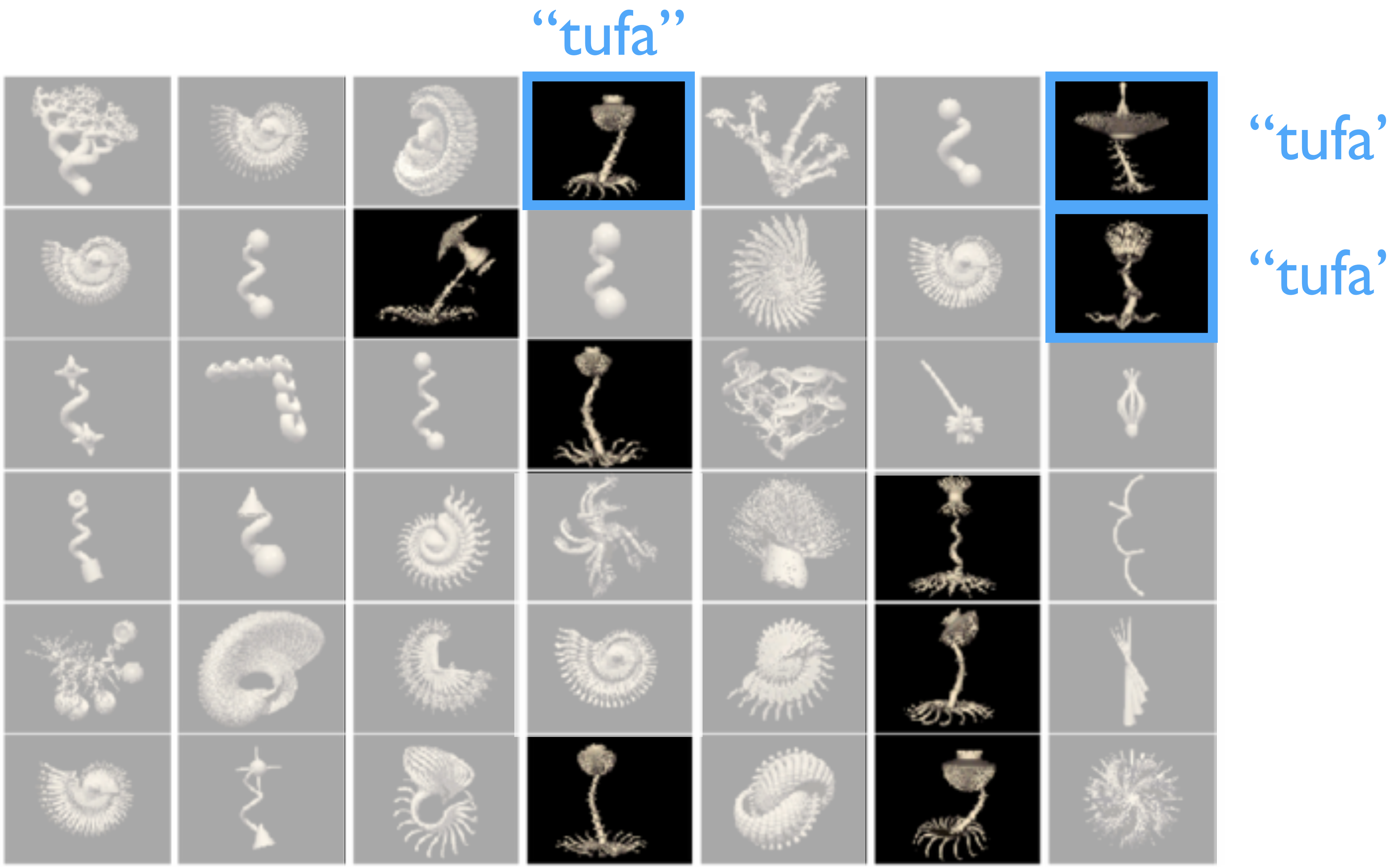
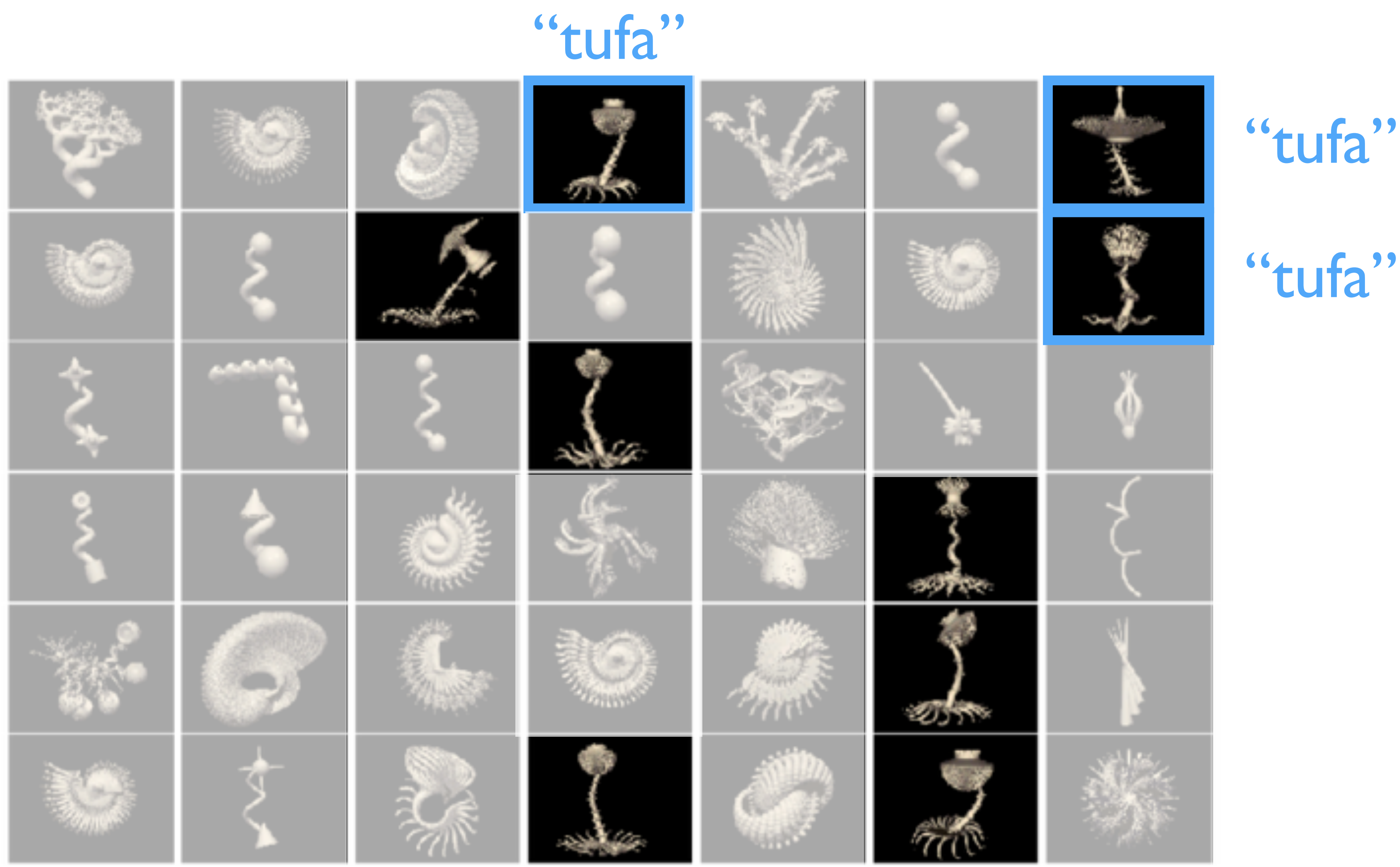


“tufa”
“tufa”
“tufa”

Why <u>should</u> generalizations become narrower with more positive examples?

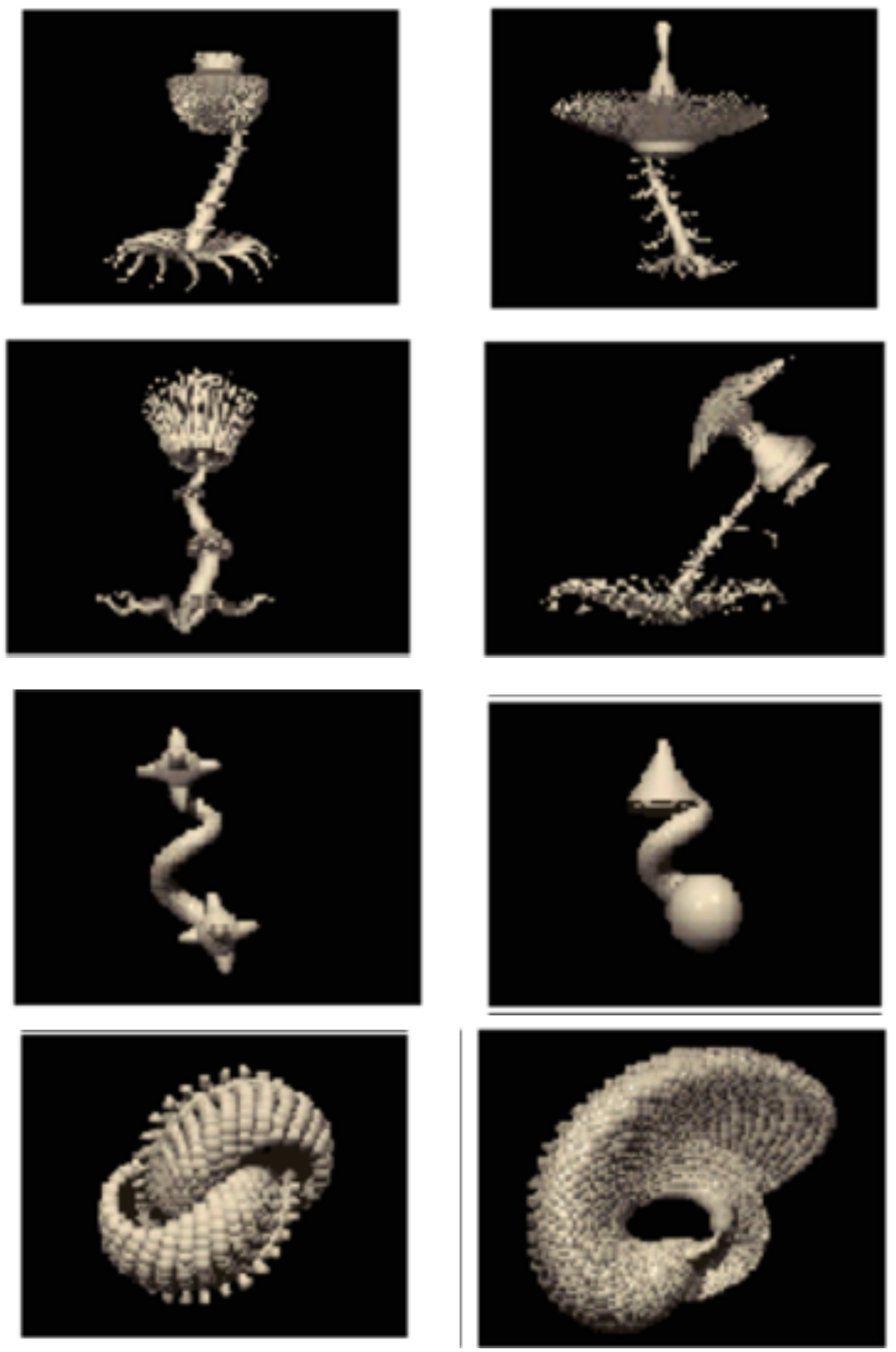


There is a puzzle here…

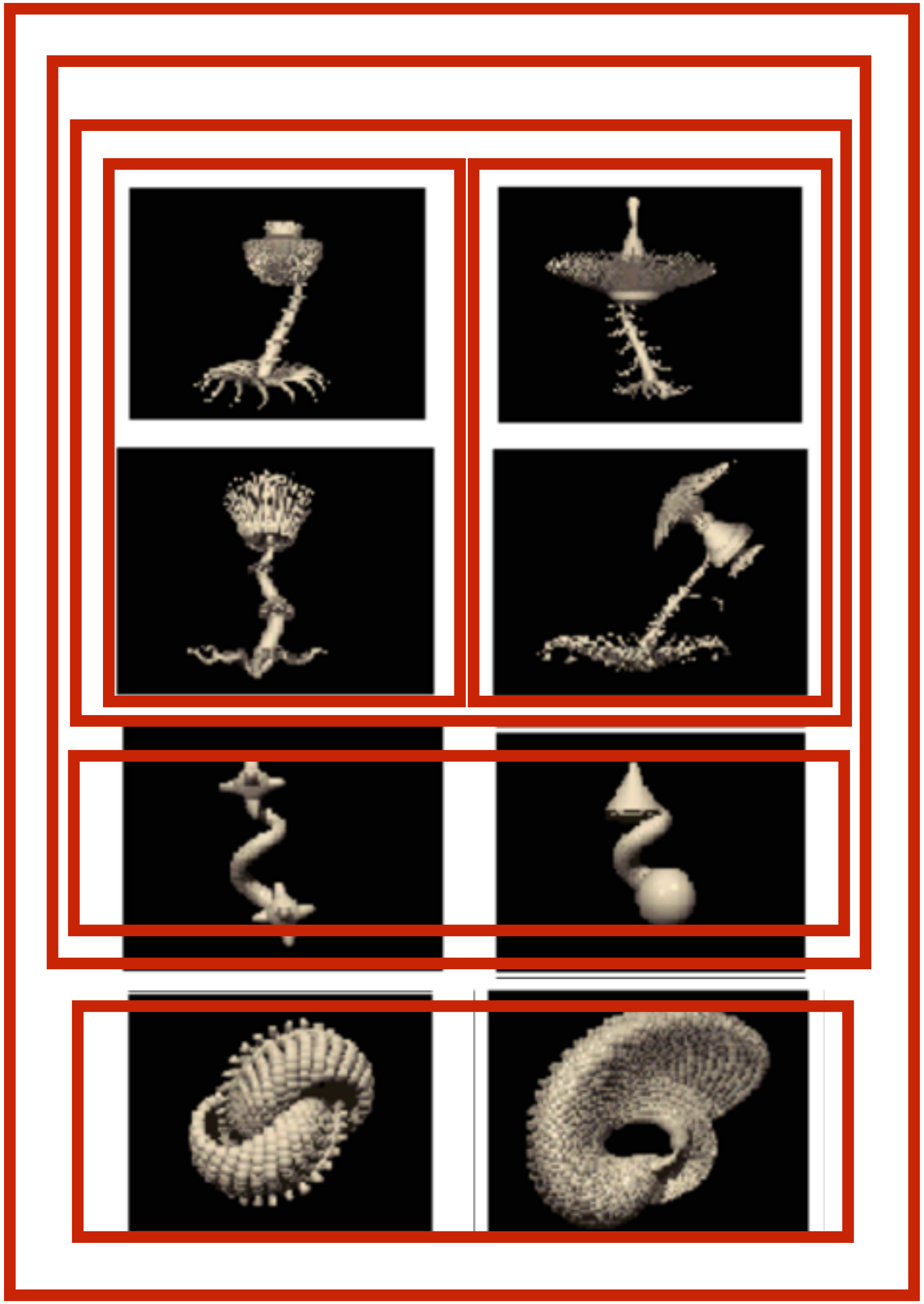
"The null hypothesis is never proved or established, but is possibly disproved, in the course of experimentation. Every experiment may be said to exist only **to give the facts a chance of disproving the null hypothesis.**"

- R.A. Fisher

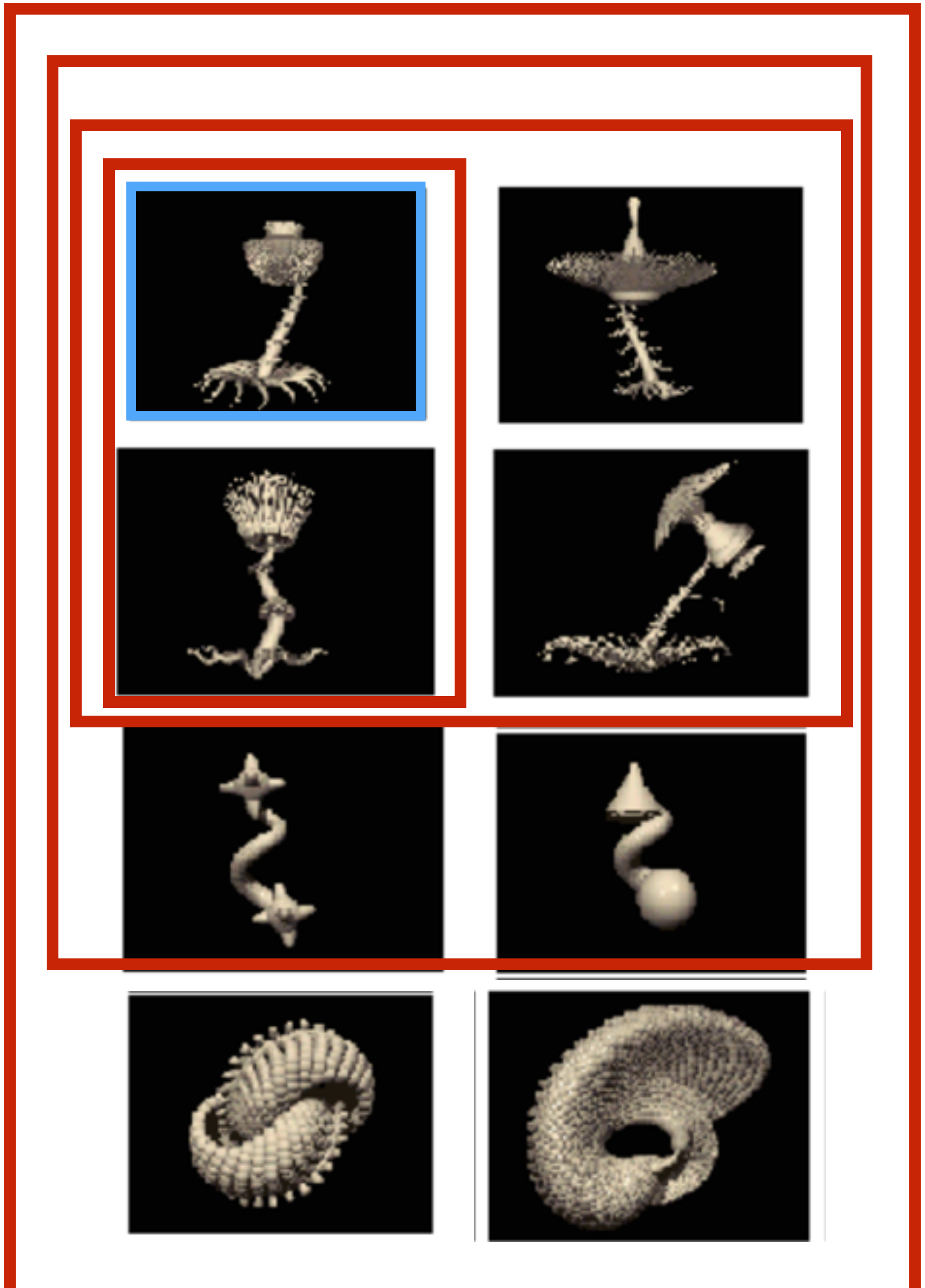
Okay let's reason like a falsificationist…



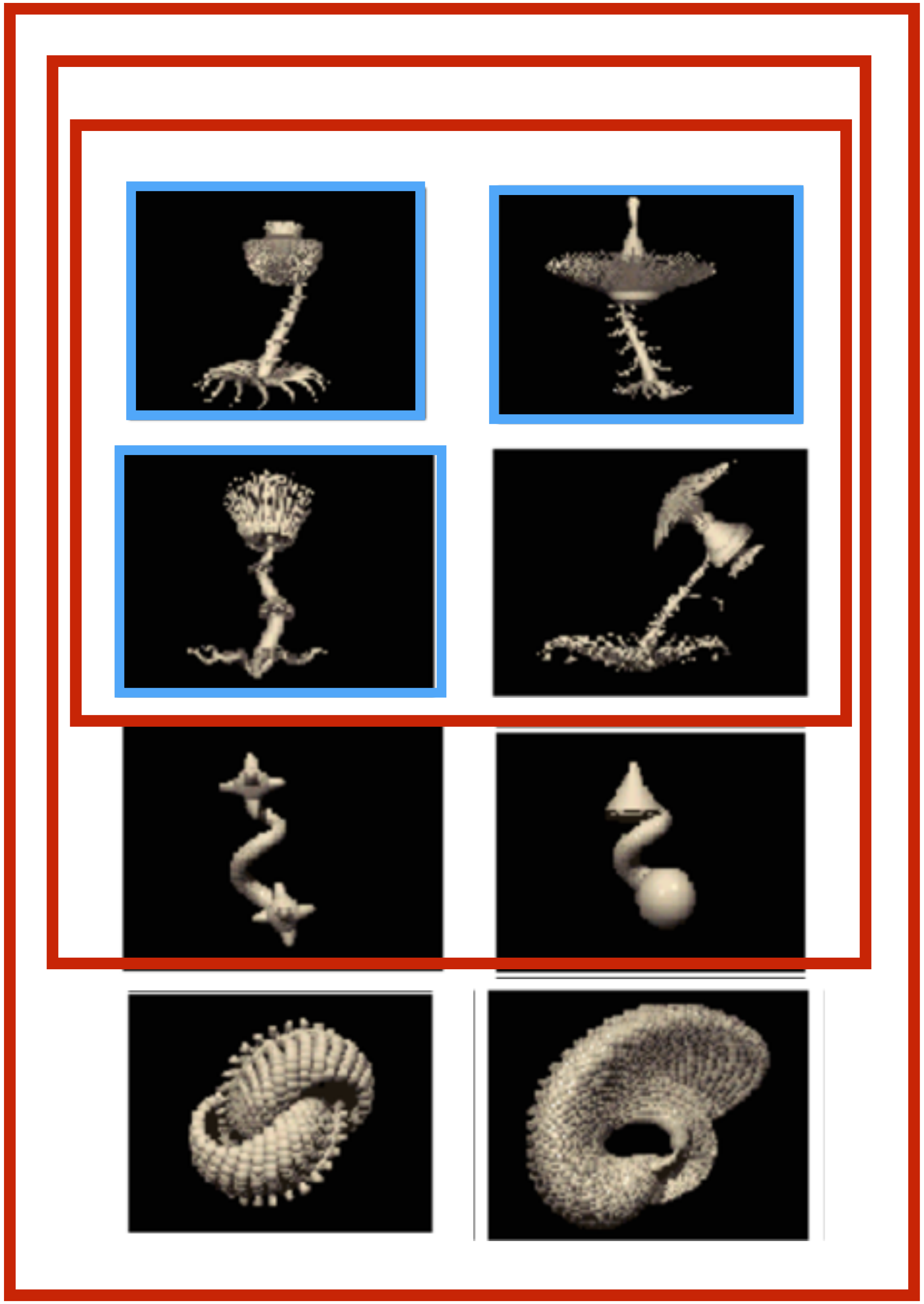
Here are some objects



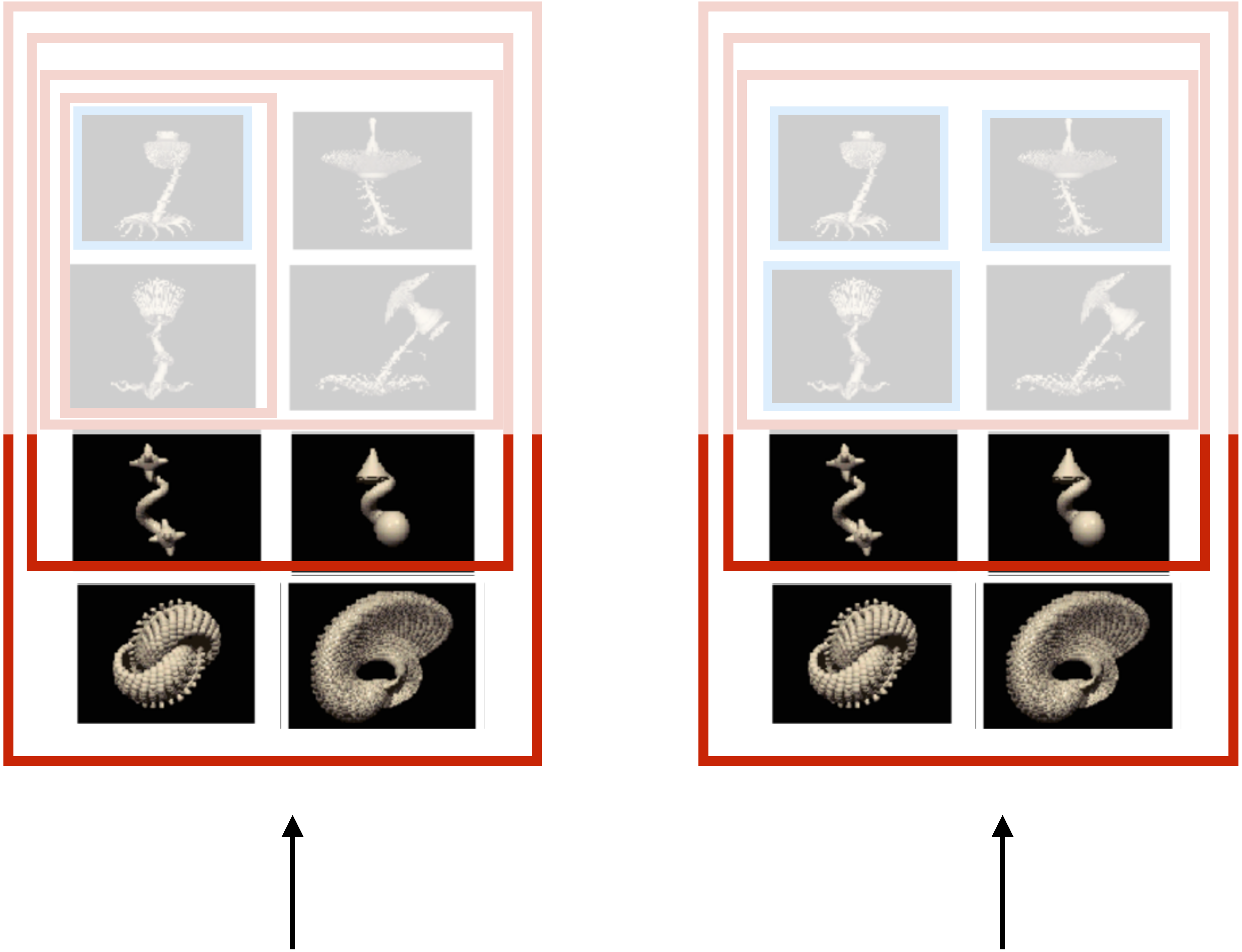
And seem plausible a priori hypotheses for the extension of a novel category



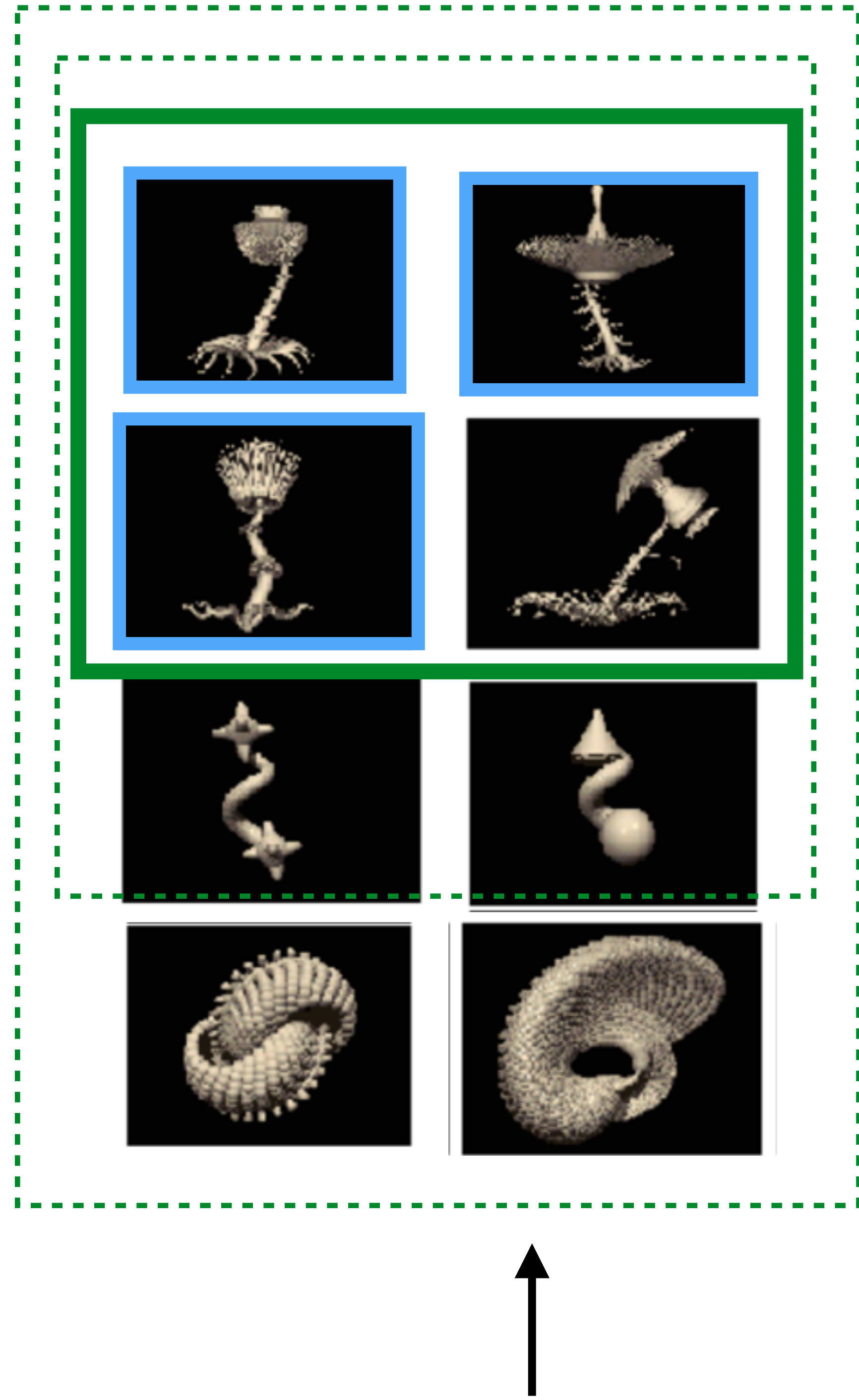
The first labelled object eliminates some hypotheses



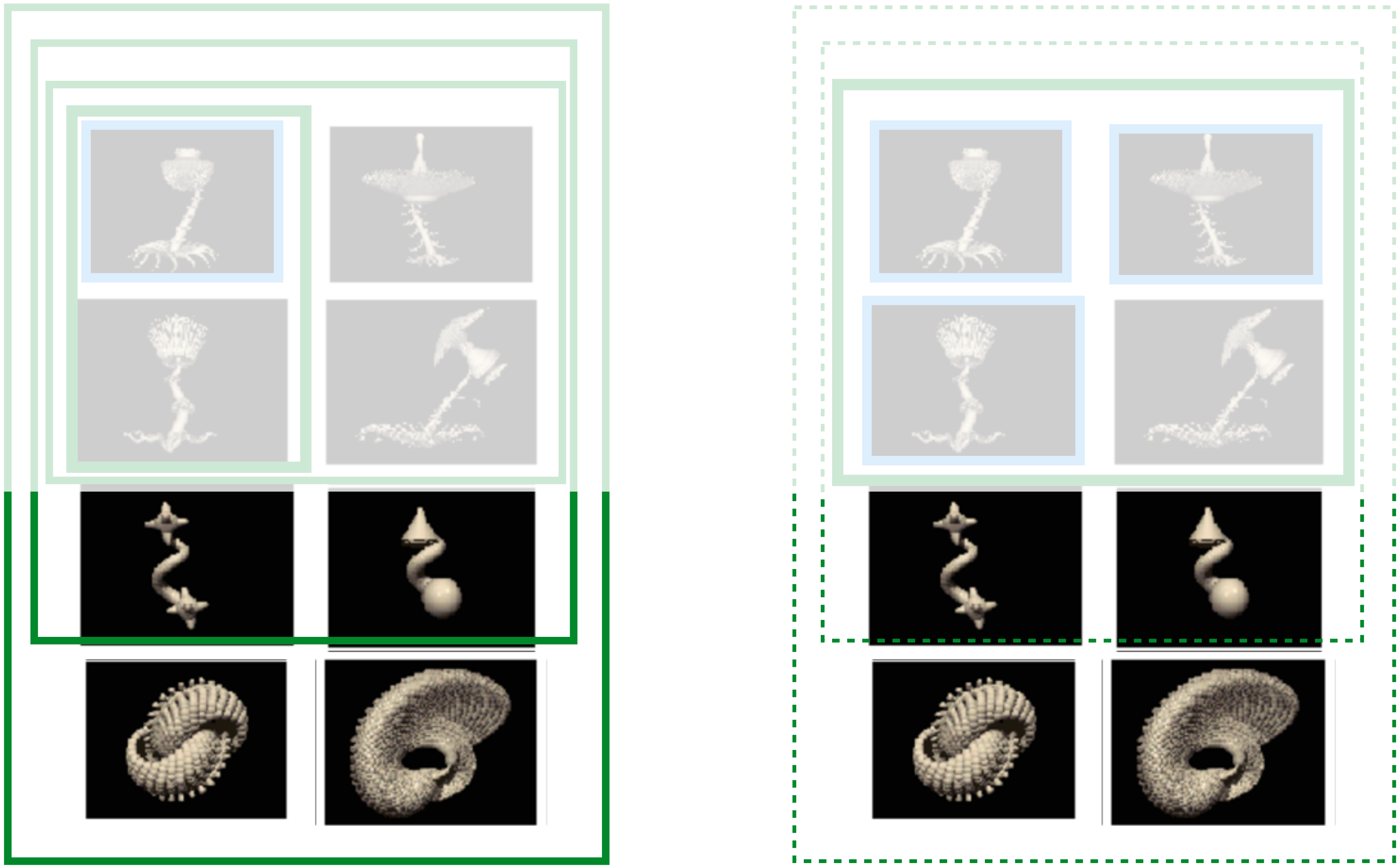
… and two more



Generalization to these items should be the same in both cases. It is not



Ockham's razor: the smaller hypothesis provides a simpler explanation for why all the observed tufas look so damn similar



Generalizations should tighten around the positive exemplars as the sample size increases

A tale of two Bayesians

$$P(h|d) = \frac{P(d|h)P(h)}{P(d)}$$

$$P(h|d) = \frac{P(d|h)P(h)}{P(d)}$$

Bayes' rule: $$P(h|x) \propto P(x|h)P(h)$$

Posterior degree of belief

Prior degree of belief

A Bayesian "scores" hypotheses by asking how likely they think it is that we data x would be if hypothesis h were true?

$$\Big\downarrow$$

$$P(h|x) \propto P(x|h)P(h)$$

The likelihood is the learner's **theory** about the problem they're solving

$$P(h|x) \propto P(x|h)P(h)$$

Different theories, different learning

$$P(h|d) = \frac{\boxed{P(d|h)}P(h)}{P(d)}$$

$$P(h|d) = \frac{\boxed{P(d|h)}P(h)}{P(d)}$$

Two very simple theories…

Weak sampling: “select an item at random and then provide the category label”

Two very simple theories…

Weak sampling: “select an item at random and then provide the category label”

Strong sampling: “make sure you pick an item that actually belongs to the target category”

… produce two different learning rules

Weak sampling:

$$P(x|h) \propto \begin{cases} 1 & \text{if } x \in h \\ 0 & \text{otherwise} \end{cases}$$

Strong sampling:

$$P(x|h) = \begin{cases} \frac{1}{|h|} & \text{if } x \in h \\ 0 & \text{otherwise} \end{cases}$$

And qualitatively different behaviour

Weak sampling:

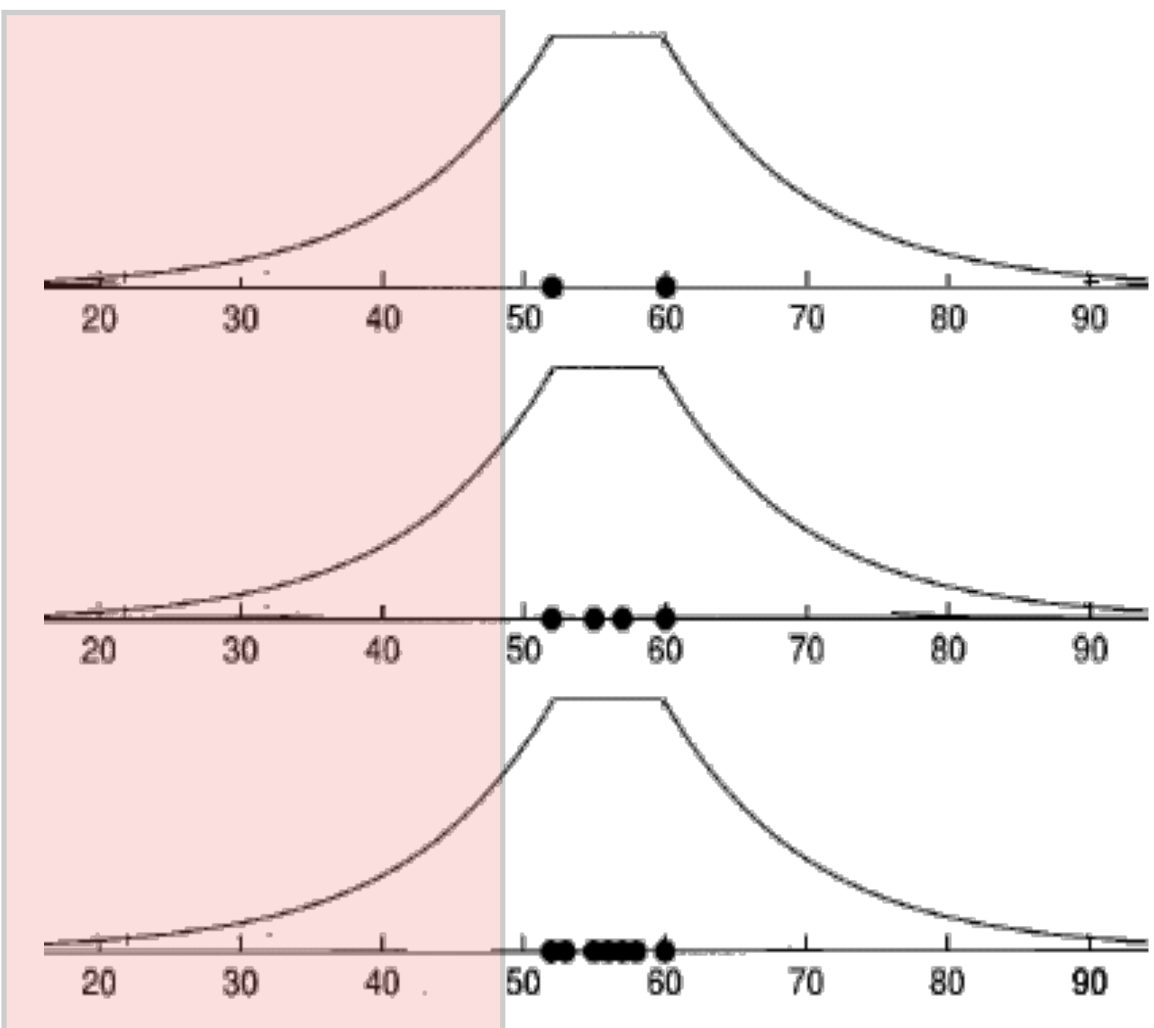
Act like a falsificationist

Strong sampling:

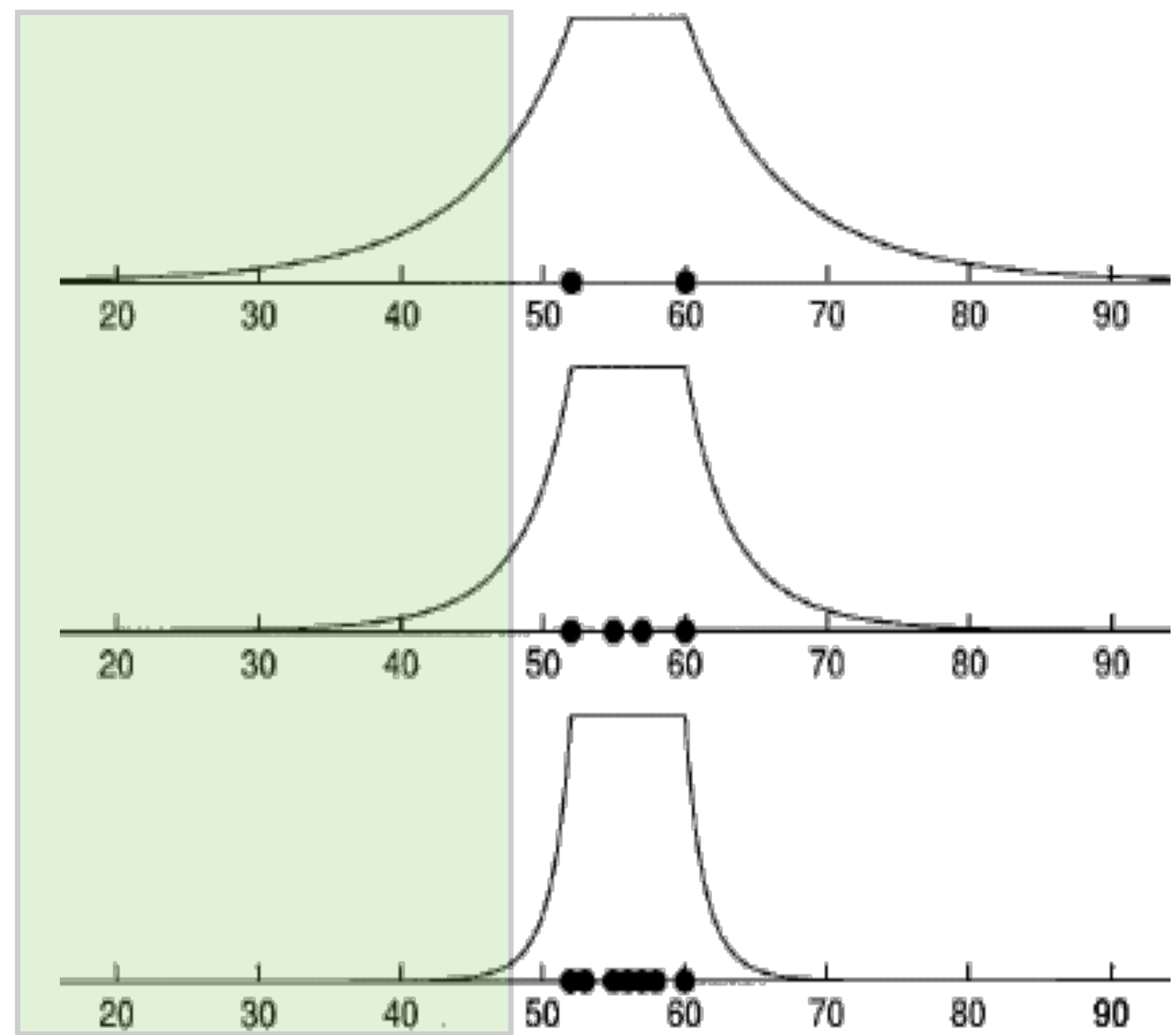
Apply Ockham's razor: prefer small/simple hypotheses

Here's the testable prediction about generalisation gradients…

weak sampling



strong sampling



And a series of experimental tests…

- Navarro, Dry & Lee (2012):
  - Two experiments, stimuli varied on one dimension
  - N=22 & N=20 undergraduates
  - Non traditional stimulus presentation
  - Response measure: Probability judgments

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- Vong, Hendrickson, Perfors & Navarro (2013)
  - As above, but with N=318 workers on AMT

And a series of experimental tests…

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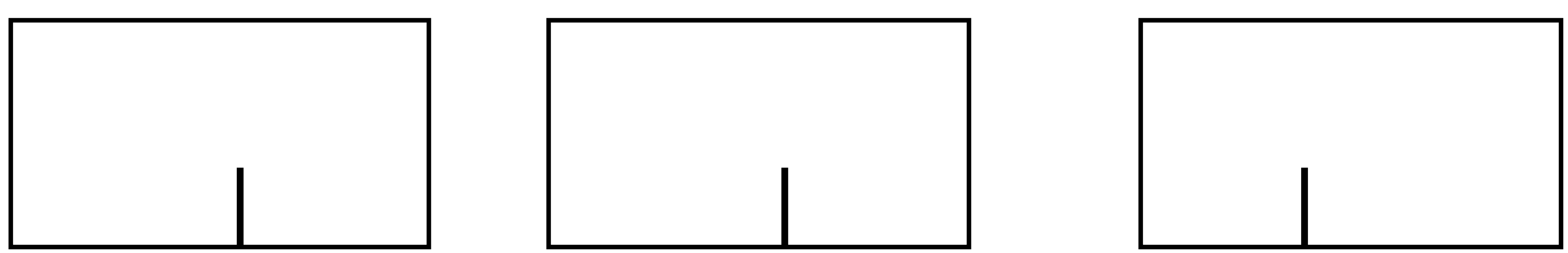
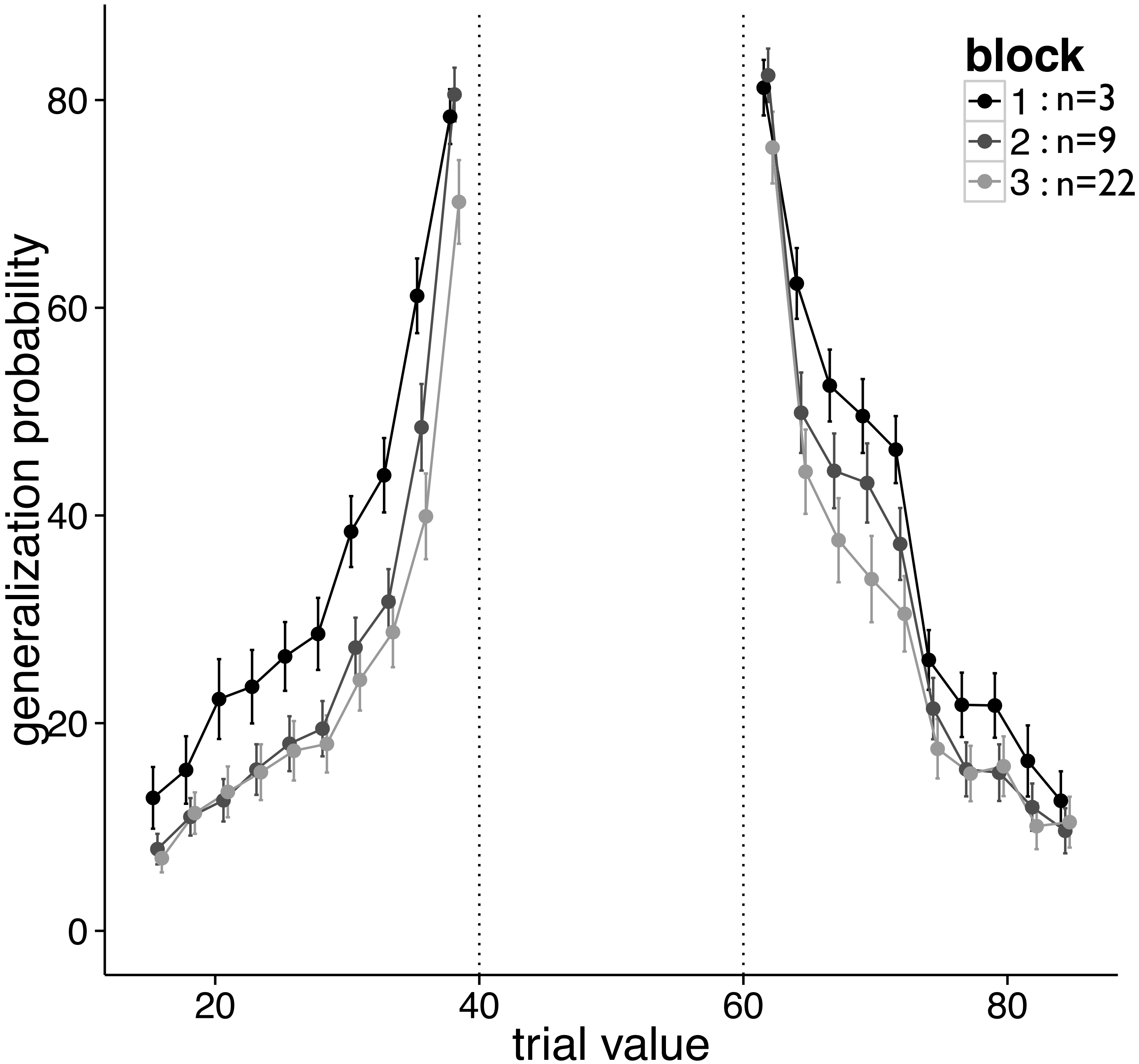
- Vong, Hendrickson, Perfors & Navarro (2013)
  - As above, but with N=318 workers on AMT
- Hendrickson, Perfors & Navarro (in preparation)
  - One experiment (N=470) on AMT
  - Participants shown traditional categorisation stimuli (below)
  - Response measures: probability judgment & categorisation decisions

stimuli:

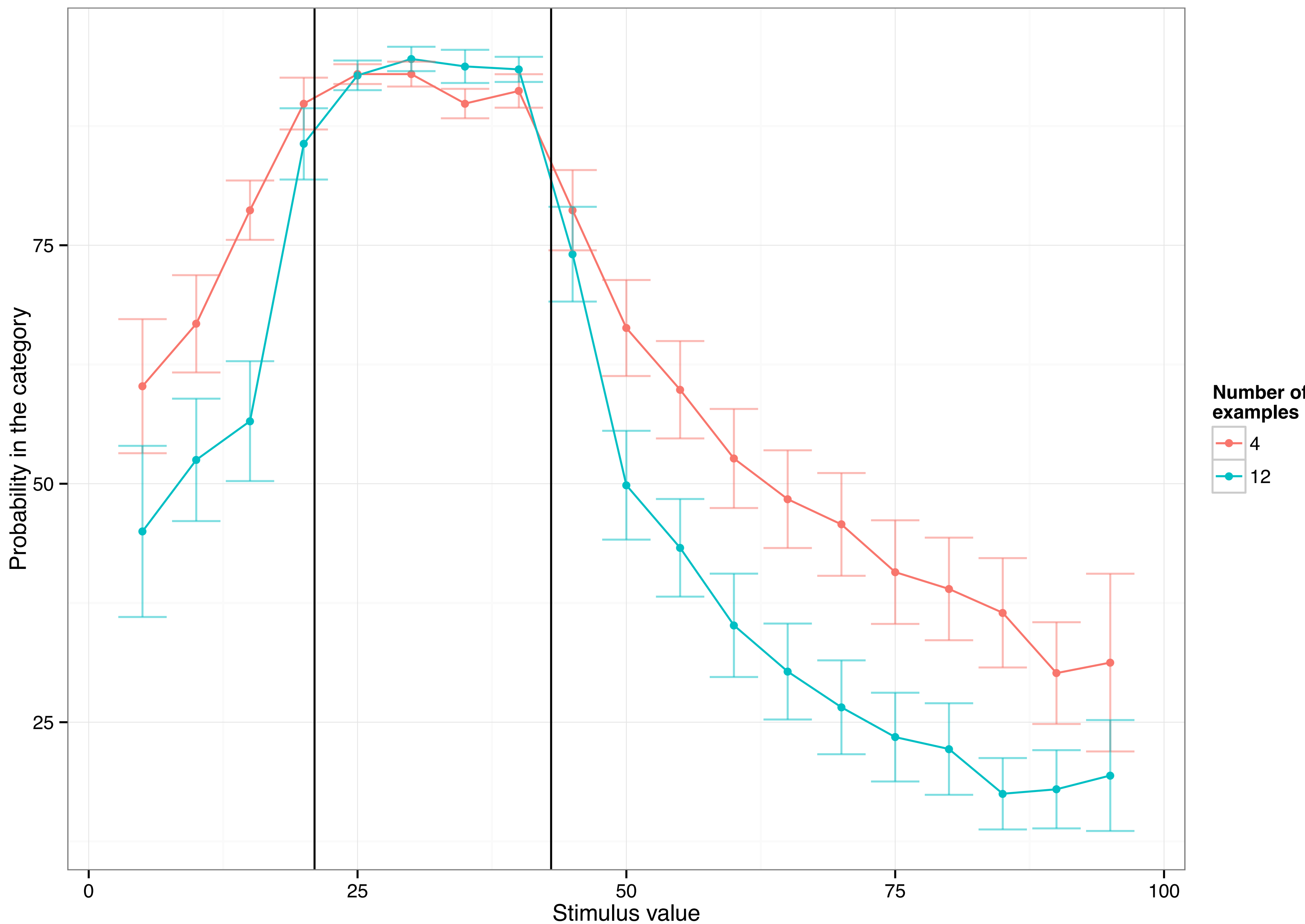


Looks like strong sampling…



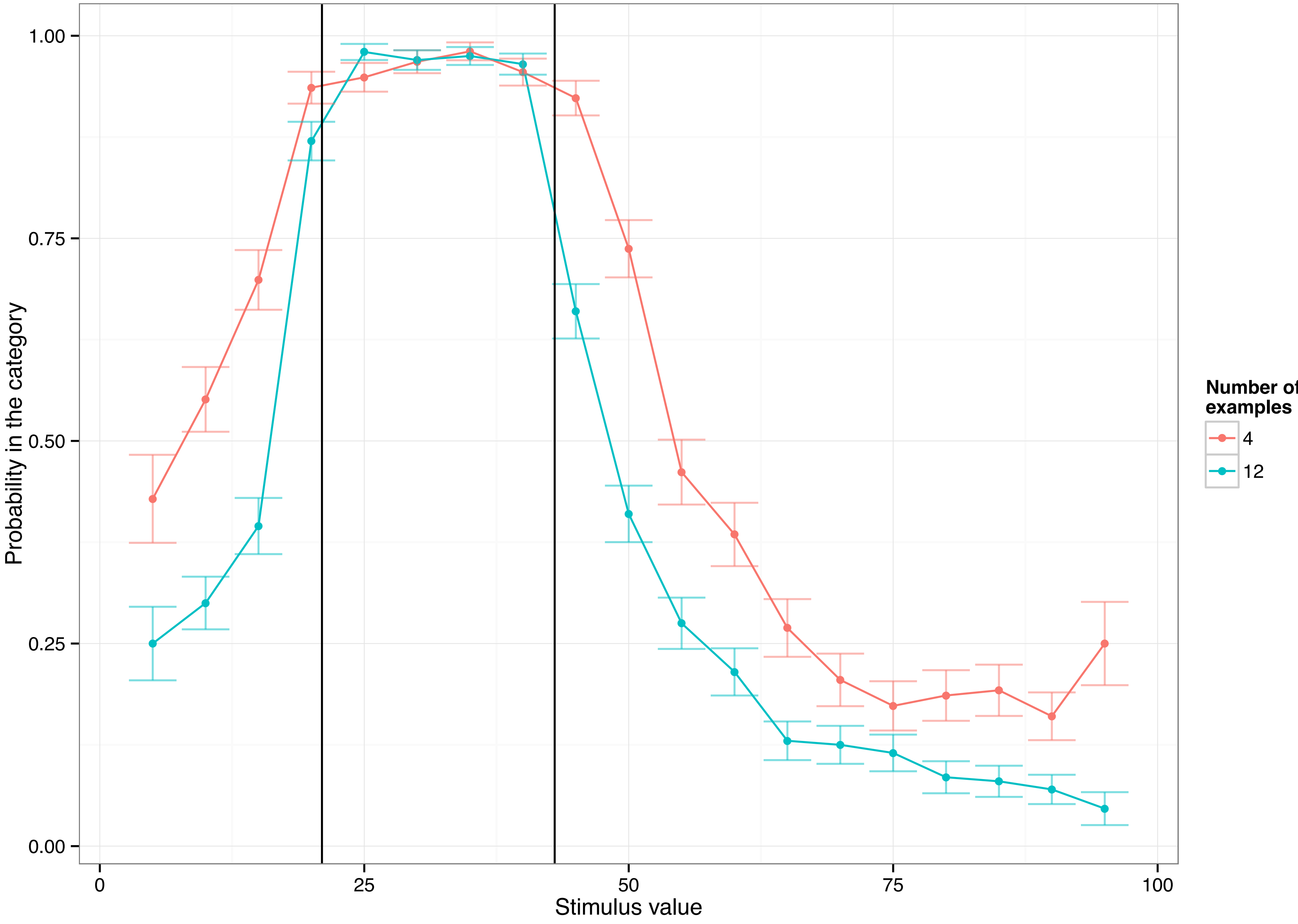
Vong, et al (2013) - probability judgment with "toy" task

Looks like strong sampling…



Hendrickson, et al (in prep) - probability judgments

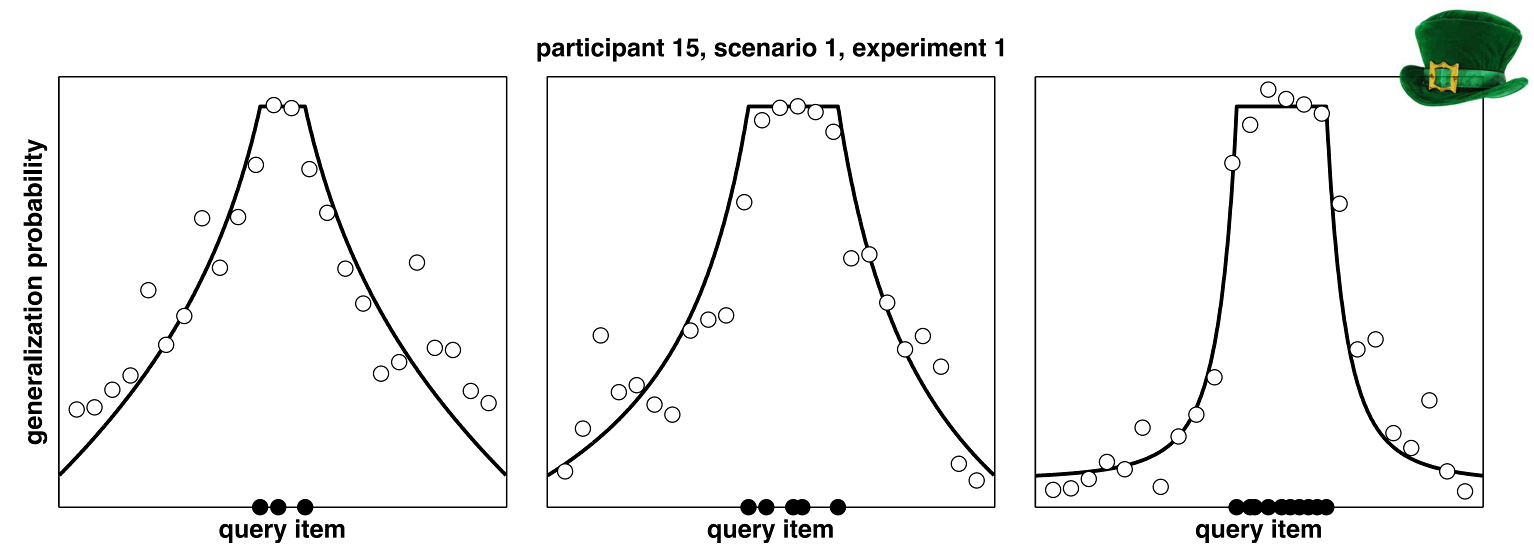
Looks like strong sampling…



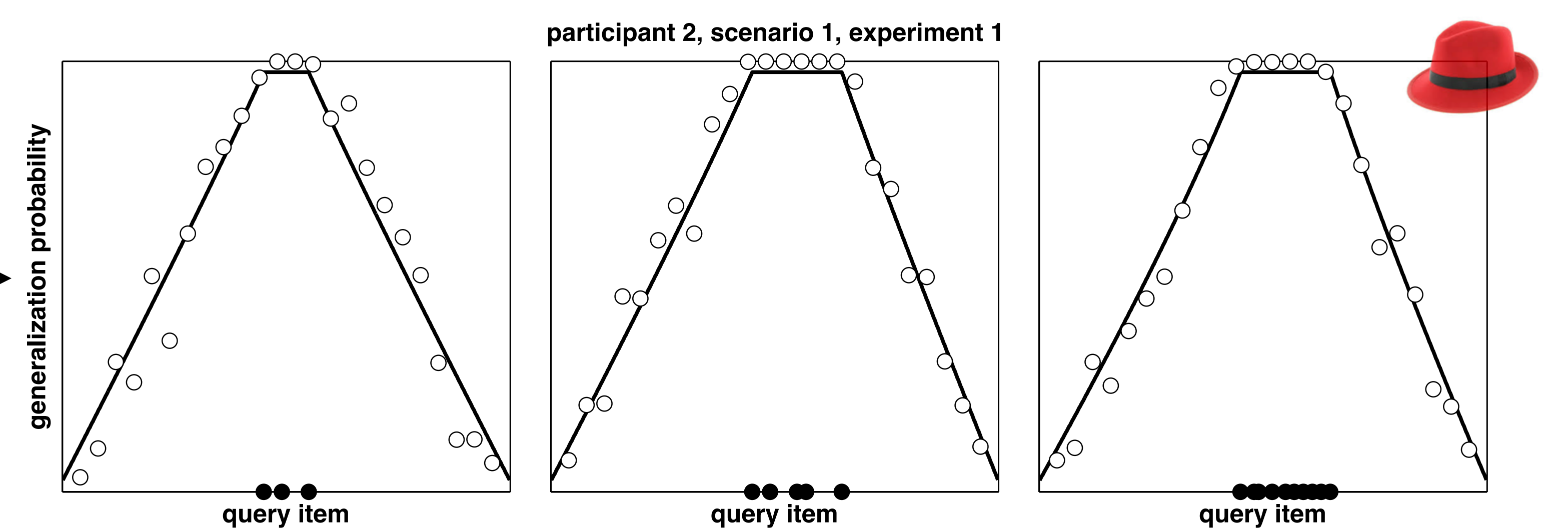
Hendrickson, et al (in prep) - categorisation data

But there are individual differences:

Sensitivity to sample size in simple generalisation

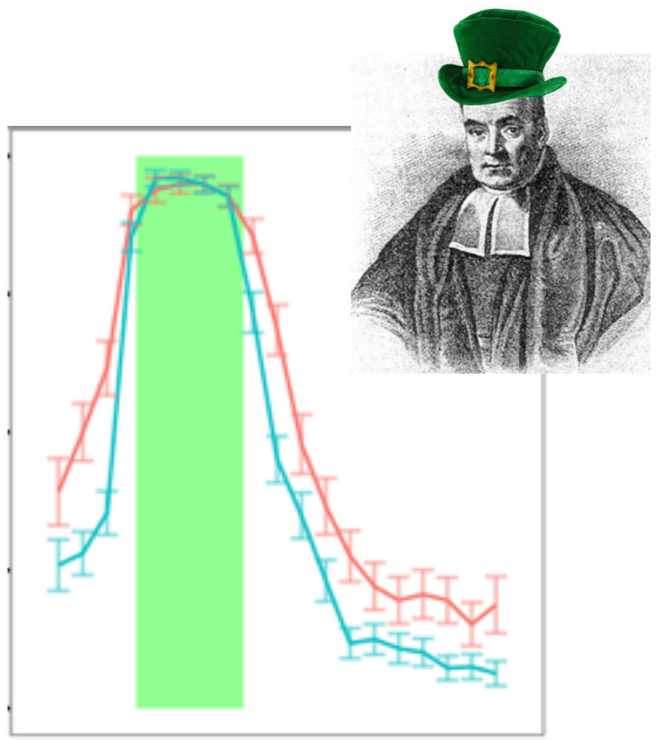


Insensitivity to sample size in simple generalisation



Navarro et al (2012)

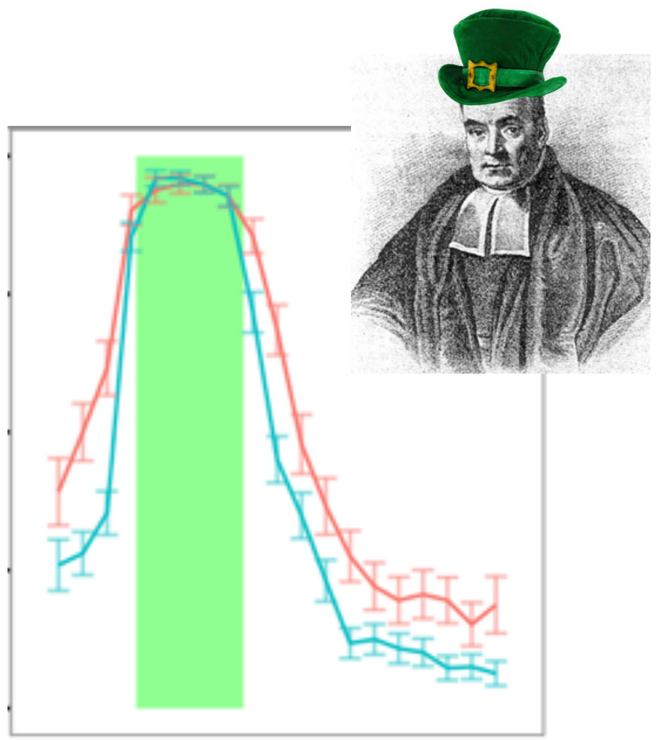
And there are <u>task</u> differences:



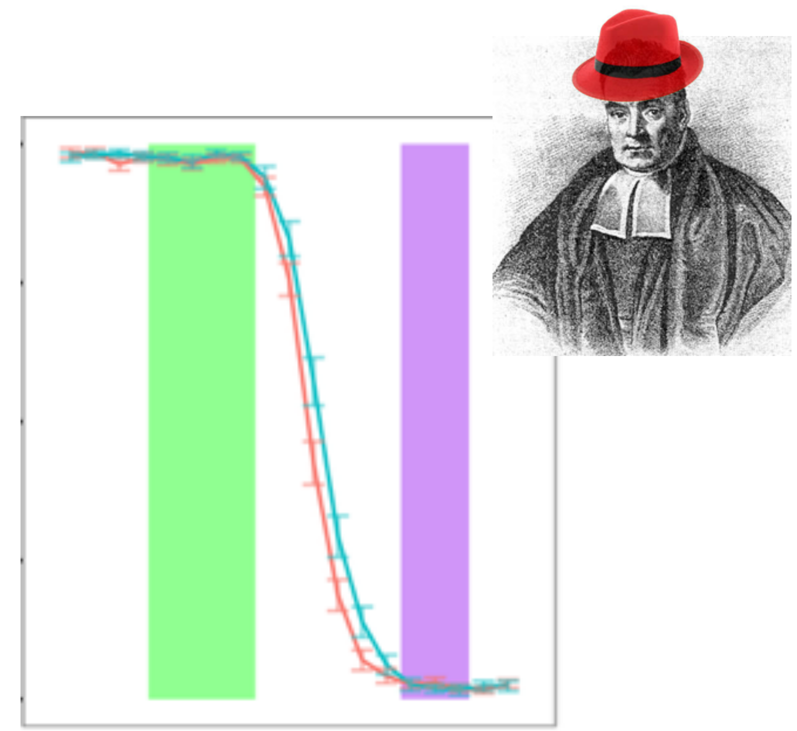
“Concept learning” designs where people see positive examples from one category produce the strong sampling “tightening” effect

Hendrickson, et al (in prep)

And there are task differences:



"Concept learning" designs where people see positive examples from one category produce the strong sampling "tightening" effect



"Classification" designs where people see labelled examples from two categories show no tightening, only a weak base rate effect (in the opposite direction)

Hendrickson, et al (in prep)

- The tightening effect predicted by strong sampling does happen
- But there are differences across individuals and across tasks

- The task differences make sense if you assume people are forming theories about how the experiment(er) designed the task
- This starts to feel like <u>social</u> cognition…

Relevance, social cognition and inductive reasoning

Navarro, Dry & Lee (2012). Sampling assumptions in inductive generalization. *Cognitive Science*

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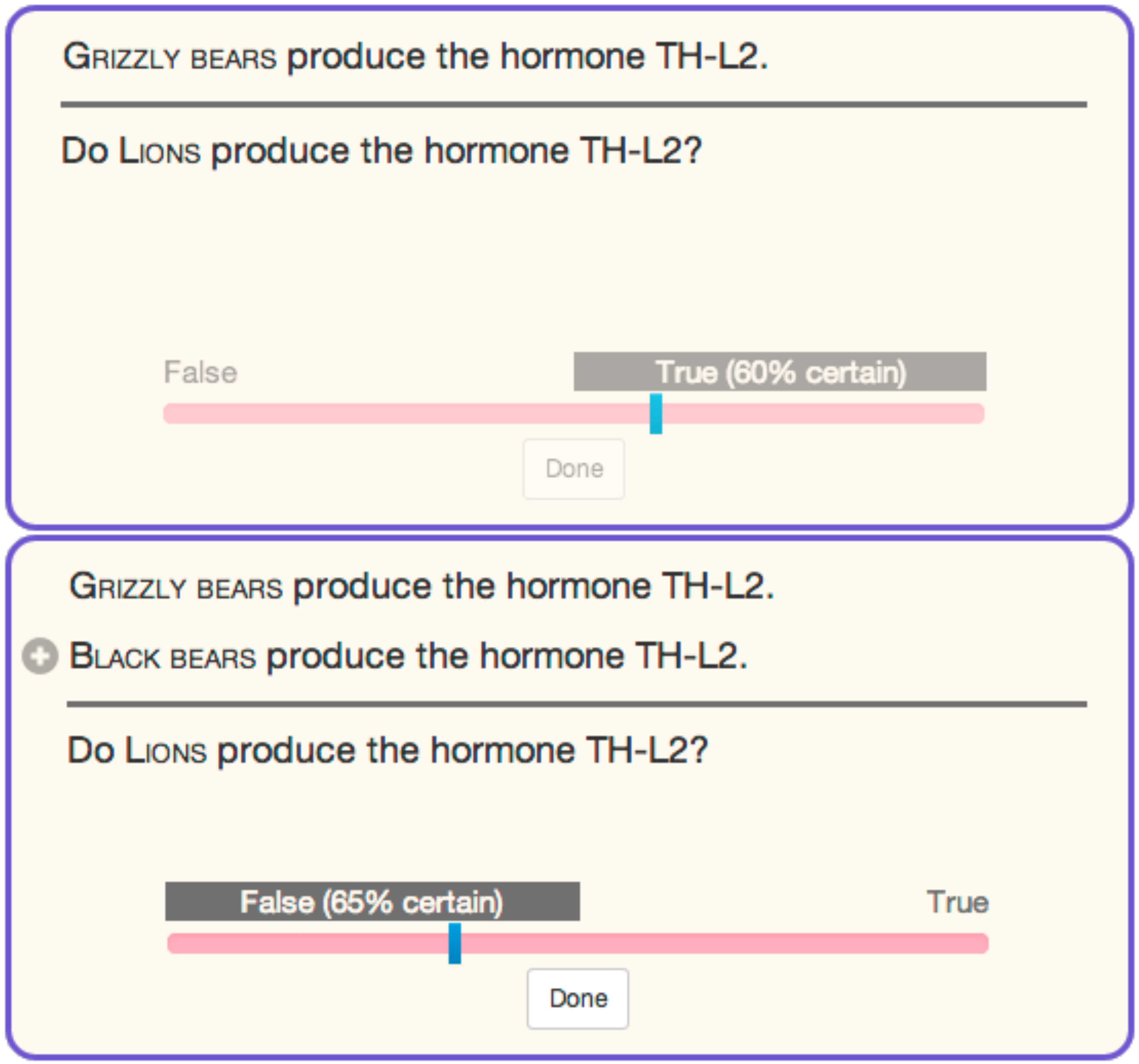
Grizzly bears produce the hormone TH-L2.

Do Lions produce the hormone TH-L2?

False | True (60% certain)

Done


Grizzly bears produce the hormone TH-L2.
Do Lions produce the hormone TH-L2?
False
True (60% certain)
Done
Grizzly bears produce the hormone TH-L2.
Black bears produce the hormone TH-L2.
Do Lions produce the hormone TH-L2?
False (65% certain)
True
Done

Grizzly Bears → Lions

Grizzly Bears + Black Bears → Lions

Adding the "Black Bears" premise weakens the argument?

Grizzly Bears → Lions

Grizzly Bears + Black Bears → Lions

Tigers → Ferrets

Tigers + Lions → Ferrets

Same thing with the "Lions" premise

Grizzly Bears → Lions

Grizzly Bears + Black Bears → Lions

Tigers → Ferrets

Tigers + Lions → Ferrets

Orangutans → Gorillas

Orangutans + Chimpanzees → Gorillas

Conversely, the "Chimpanzee" premise strengthens the argument here

Grizzly Bears + Black Bears

Tigers + Lions

Orangutans + Chimpanzees

In all cases the additional premise concentrates beliefs around a target category, e.g. bears, cats, primates

Is this “tightening” effect related to the tightening in the “tufa” generalisation problem?

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Does it depend on the learner’s theory about how the argument was constructed?

Is this “tightening” effect related to the tightening in the “tufa” generalisation problem?

Does it depend on the learner’s theory about how the argument was constructed?

Can we produce qualitative shifts in people’s reasoning by manipulating their theory about how the argument was made?

Previous experience?
(filler trials)

Cover story?	Relevant cover story, Relevant fillers	
	Neutral cover story, Relevant fillers	Neutral cover story, Random fillers
		Random cover story, Random fillers

Cover story manipulation

- Relevant: people were told that the "additional" premise was chosen by a helpful teacher
- Neutral: people were told nothing about how the second premise was generated

- Random: people were told that the second premise was selected at random from the set of true facts.

Eagles → Doves
Elephants → Deer
Kangaroos → Wombats

Three “filler” arguments

Eagles → Doves
Elephants → Deer
Kangaroos → Wombats

Eagles + Hawks → Doves
Elephants + Cows → Deer
Kangaroos + Koalas → Wombats

… with a relevant second premise

(positive premises from the same category suggest strong sampling)

Eagles → Doves
Elephants → Deer
Kangaroos → Wombats

Eagles + Hawks → Doves
Elephants + Cows → Deer
Kangaroos + Koalas → Wombats

Eagles - Tortoises → Doves
Elephants + Anteaters → Deer
Kangaroos - Flamingos → Wombats

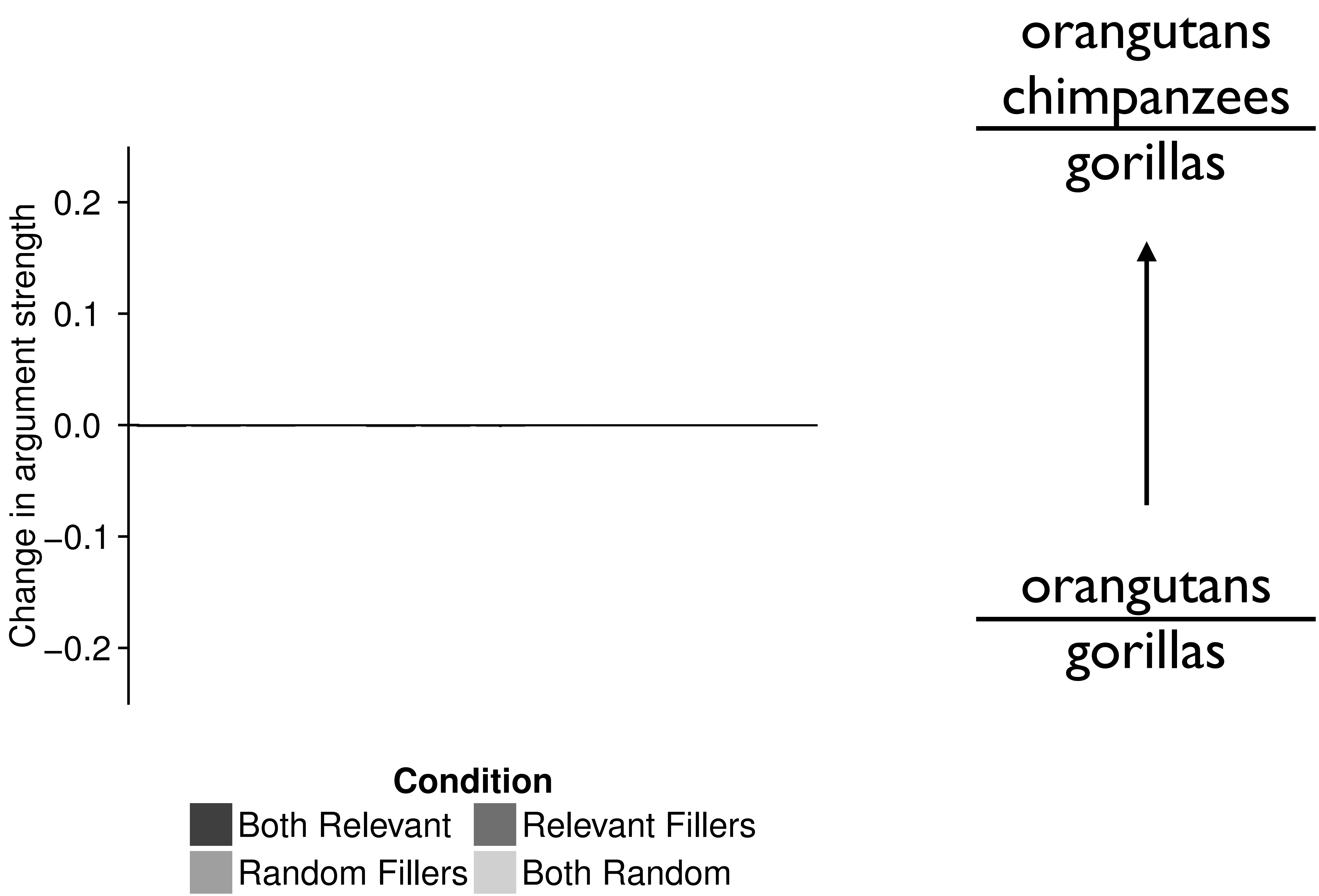
… or a random one

(negated premises unrelated to the topic suggest weak sampling)

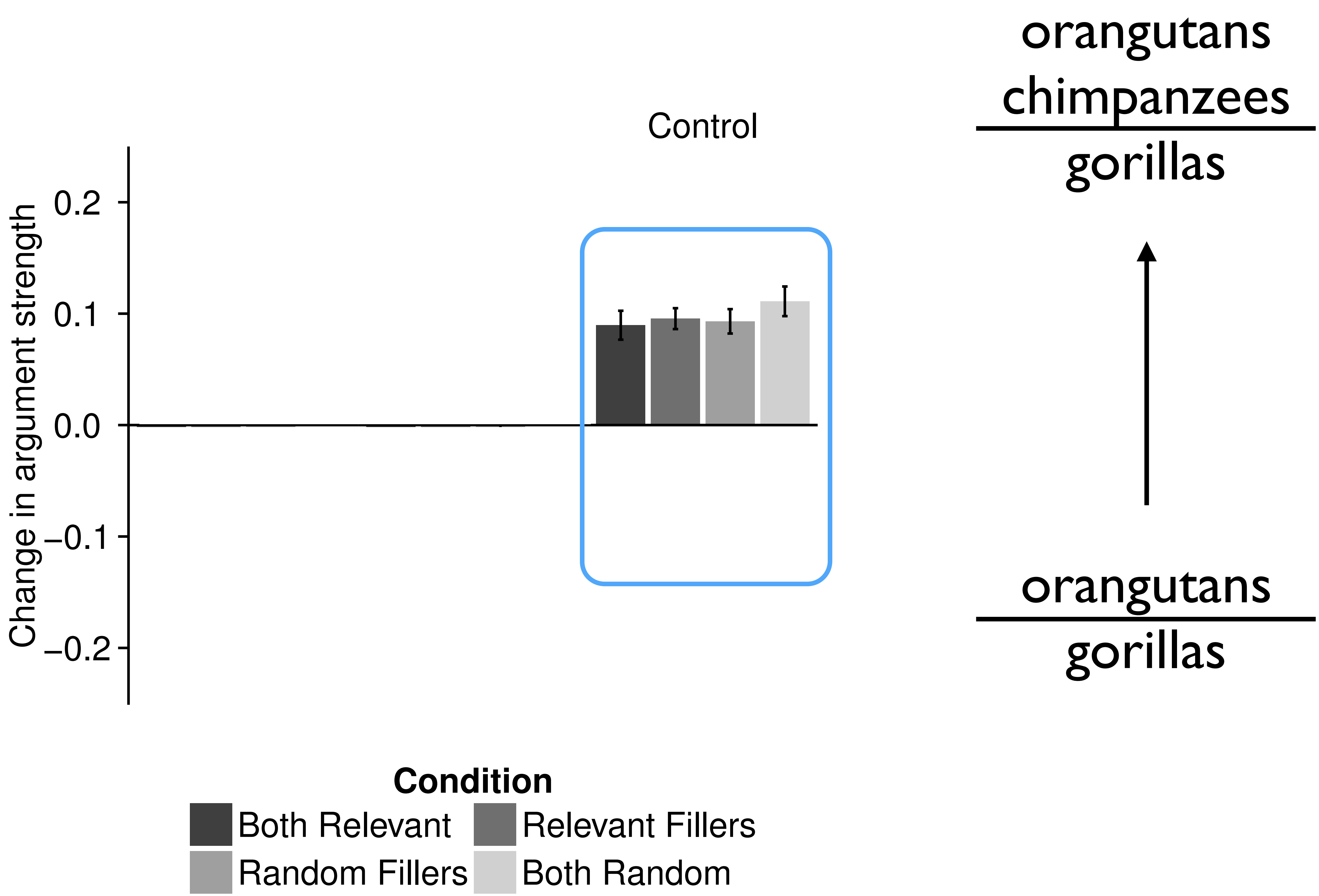
Stimulus ordering was fixed and designed to ensure that fillers (mostly) preceded targets:

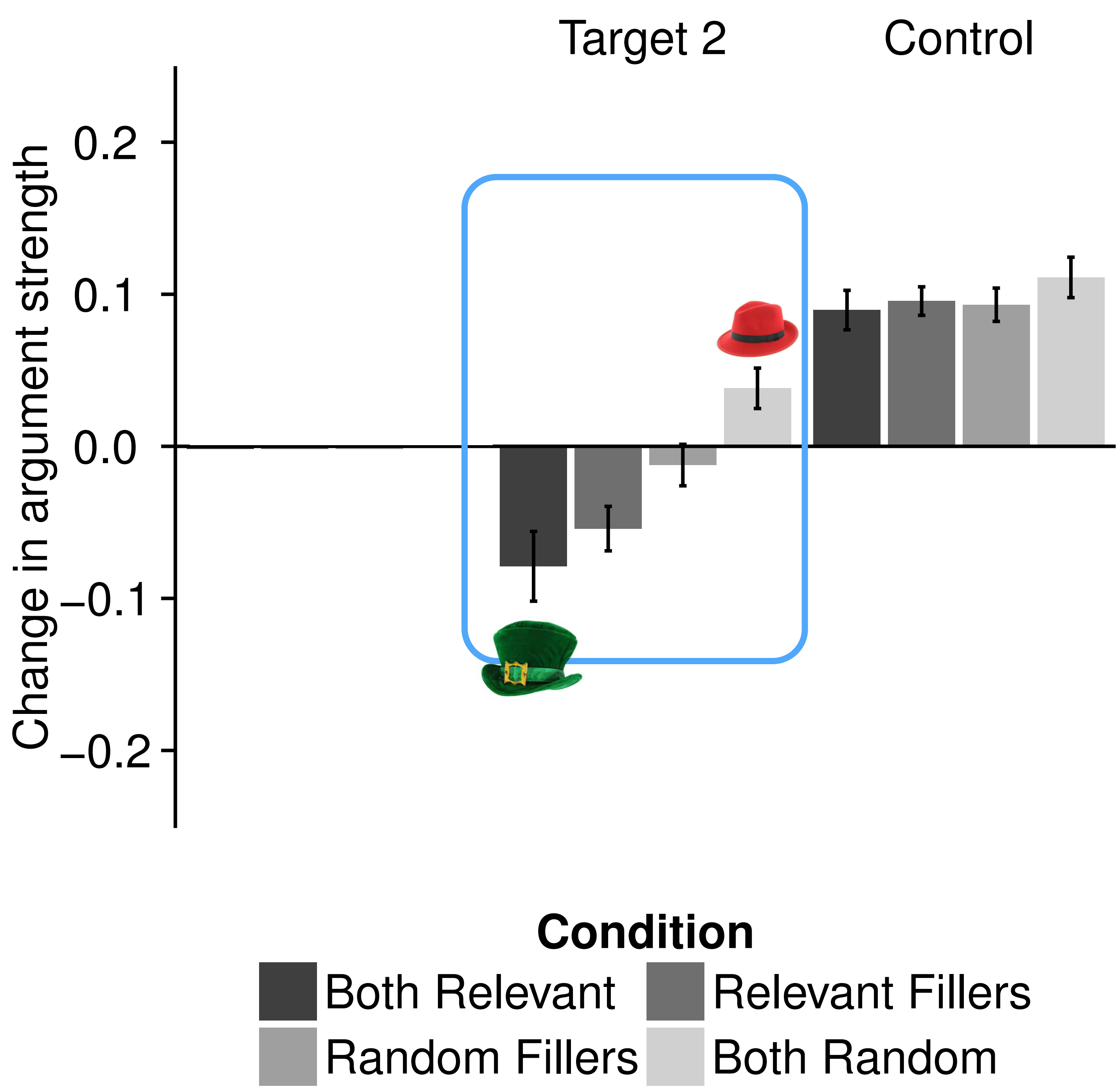
	Additional example	
First generalisation	HELPFUL	RANDOM
EAGLES → DOVES	+HAWKS	−TORTOISES
ELEPHANTS → DEERS	+COWS	+ANTEATERS
TIGERS → FERRETS	+LIONS	+LIONS
KANGAROOS → WOMBATS	+KOALAS	−FLAMINGOS
GRIZZLY BEARS → LIONS	+BLACK BEARS	+BLACK BEARS
ORANGUTANS → GORILLAS	+CHIMPANZEES	+CHIMPANZEES

Participants were 296 people recruited through MTurk



Change in argument strength
0.2
0.1
0.0
−0.1
−0.2
Condition
Both Relevant
Relevant Fillers
Random Fillers
Both Random
orangutans
chimpanzees
gorillas
orangutans
gorillas


Control
Change in argument strength
0.2
0.1
0.0
−0.1
−0.2
orangutans
chimpanzees
gorillas
orangutans
gorillas
Condition
Both Relevant
Relevant Fillers
Random Fillers
Both Random

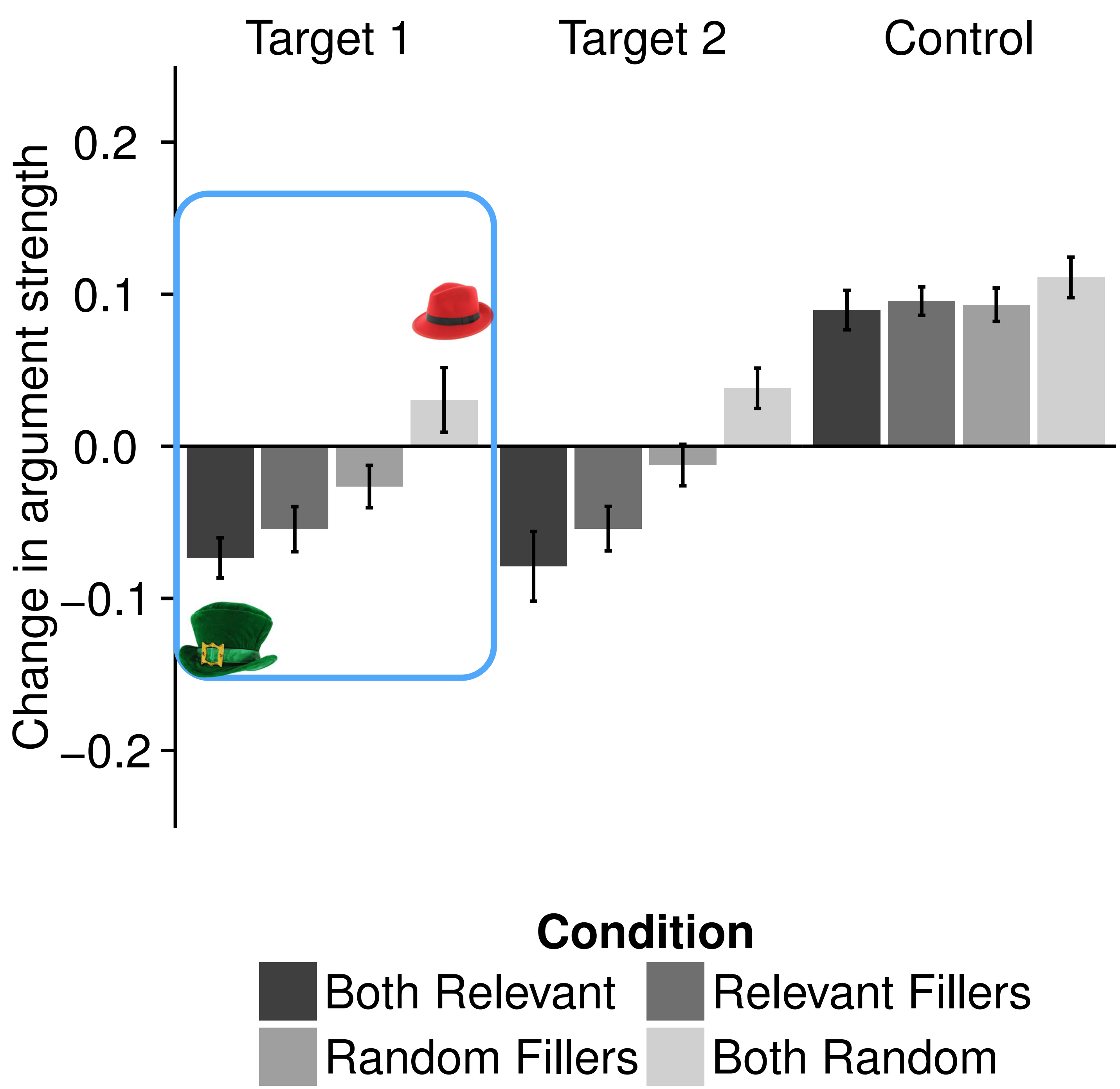


grizzly bears
black bears

lions

grizzly bears

lions



tigers
lions
---
ferrets

↑

tigers
---
ferrets

(Bayesian) data analysis: hypothesis tests for order restricted models

Model	Order restrictions
NO EFFECT	$\mu_1 = \mu_2 = \mu_3 = \mu_4$
FILLERS ONLY	$\mu_1 = \mu_2 < \mu_3 = \mu_4$
STORY ONLY	$\mu_1 < \mu_2 = \mu_3 < \mu_4$
BOTH	$\mu_1 < \mu_2 < \mu_3 < \mu_4$
RANDOM EFFECT	$\mu_1 \neq \mu_2 \neq \mu_3 \neq \mu_4$

Clear effect of cover story on targets, possibly also an effect of filler type

		Bayes Factor (: NO EFFECT)	
Model	Order restrictions	Target 1	Target 2
NO EFFECT	$\mu_1 = \mu_2 = \mu_3 = \mu_4$	-	-
FILLERS ONLY	$\mu_1 = \mu_2 < \mu_3 = \mu_4$	740:1	12,000:1
STORY ONLY	$\mu_1 < \mu_2 = \mu_3 < \mu_4$	4,100:1	17,000:1
BOTH	$\mu_1 < \mu_2 < \mu_3 < \mu_4$	2,900:1	30,000:1
RANDOM EFFECT	$\mu_1 \neq \mu_2 \neq \mu_3 \neq \mu_4$	520:1	4,600:1

Null effect for the control item

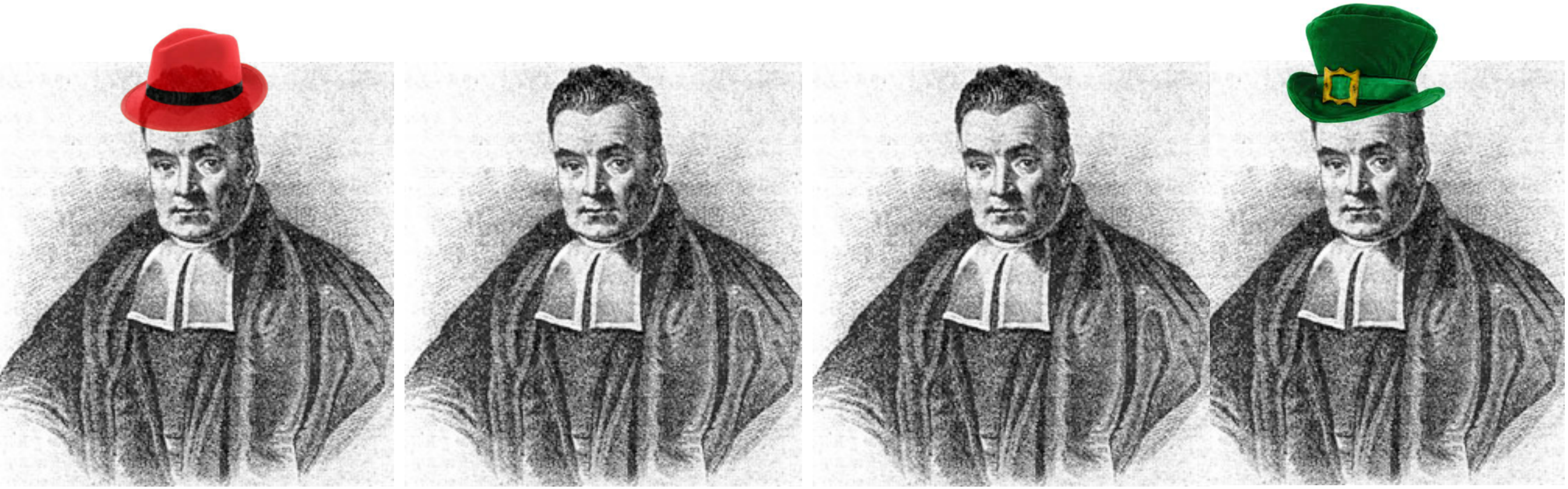
		Bayes Factor (: NO EFFECT)
Model	Order restrictions	Control
NO EFFECT	$\mu_1 = \mu_2 = \mu_3 = \mu_4$	-
FILLERS ONLY	$\mu_1 = \mu_2 < \mu_3 = \mu_4$	$< 1 : 1$
STORY ONLY	$\mu_1 < \mu_2 = \mu_3 < \mu_4$	$< 1 : 1$
BOTH	$\mu_1 < \mu_2 < \mu_3 < \mu_4$	$< 1 : 1$
RANDOM EFFECT	$\mu_1 \neq \mu_2 \neq \mu_3 \neq \mu_4$	$< 1 : 1$

Should we model this as a difference between two Bayesian learners?

A weakly sampling falsificationist

A strongly sampling Ockhamist

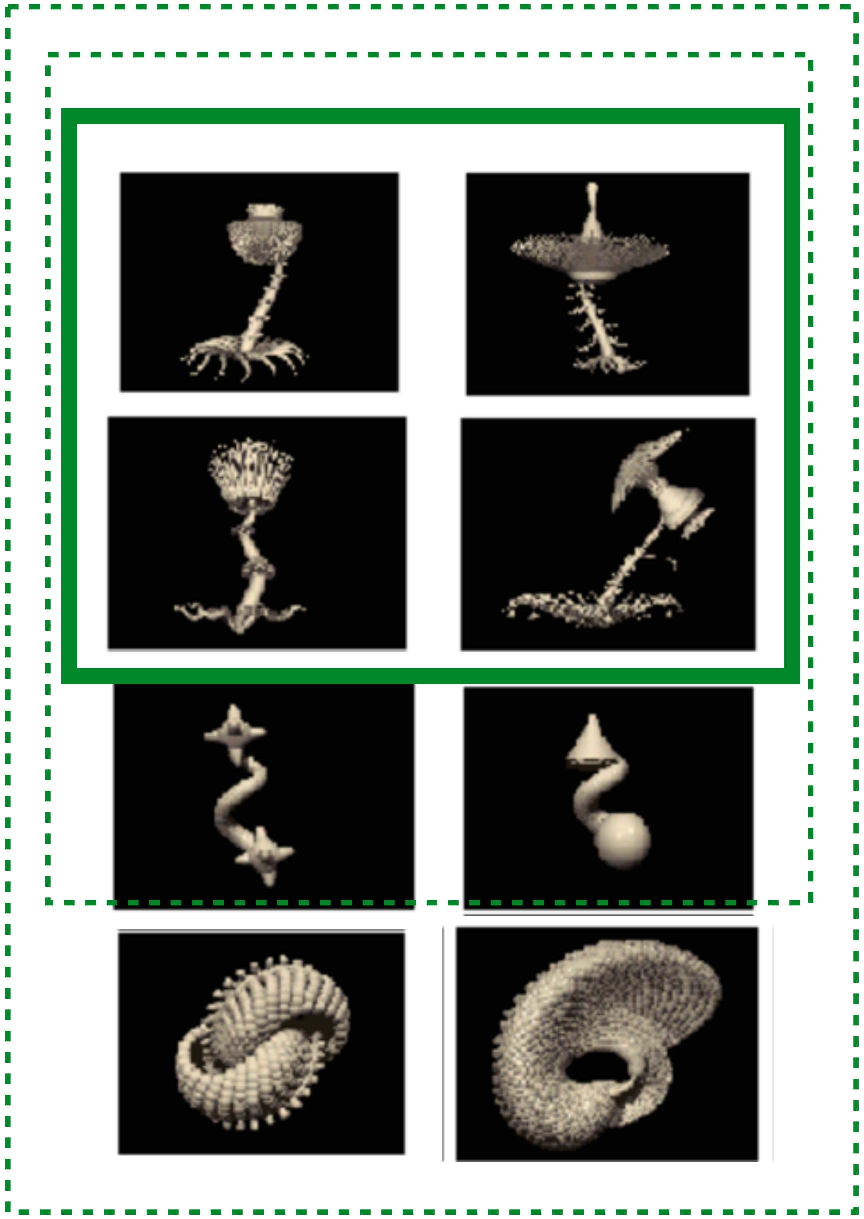
Or posit a continuum of Bayesians?



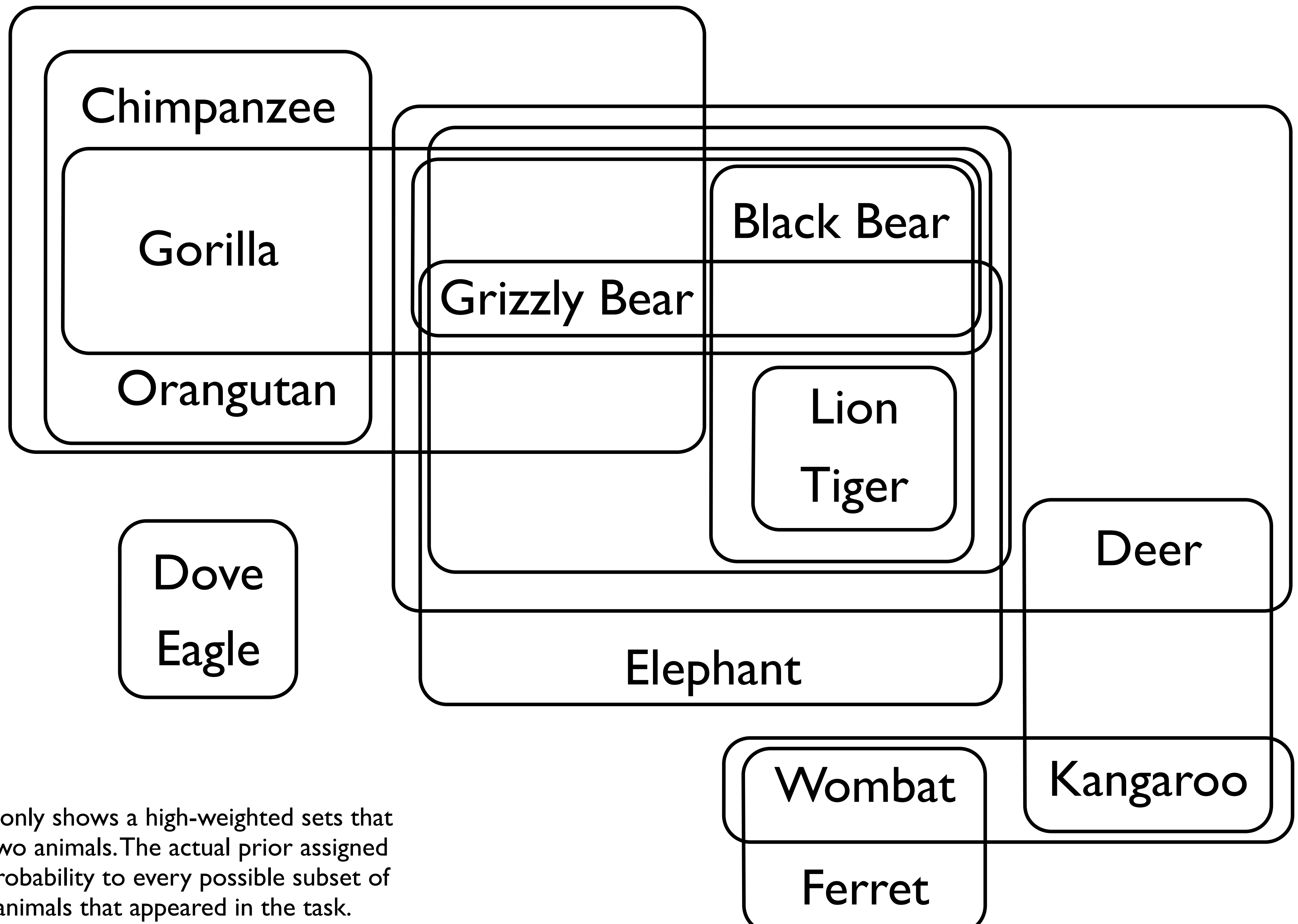
θ=0 θ=.33 θ=.67 θ=1

"weak" "strong"

And what shall our Bayesians use for their hypothesis space and priors?

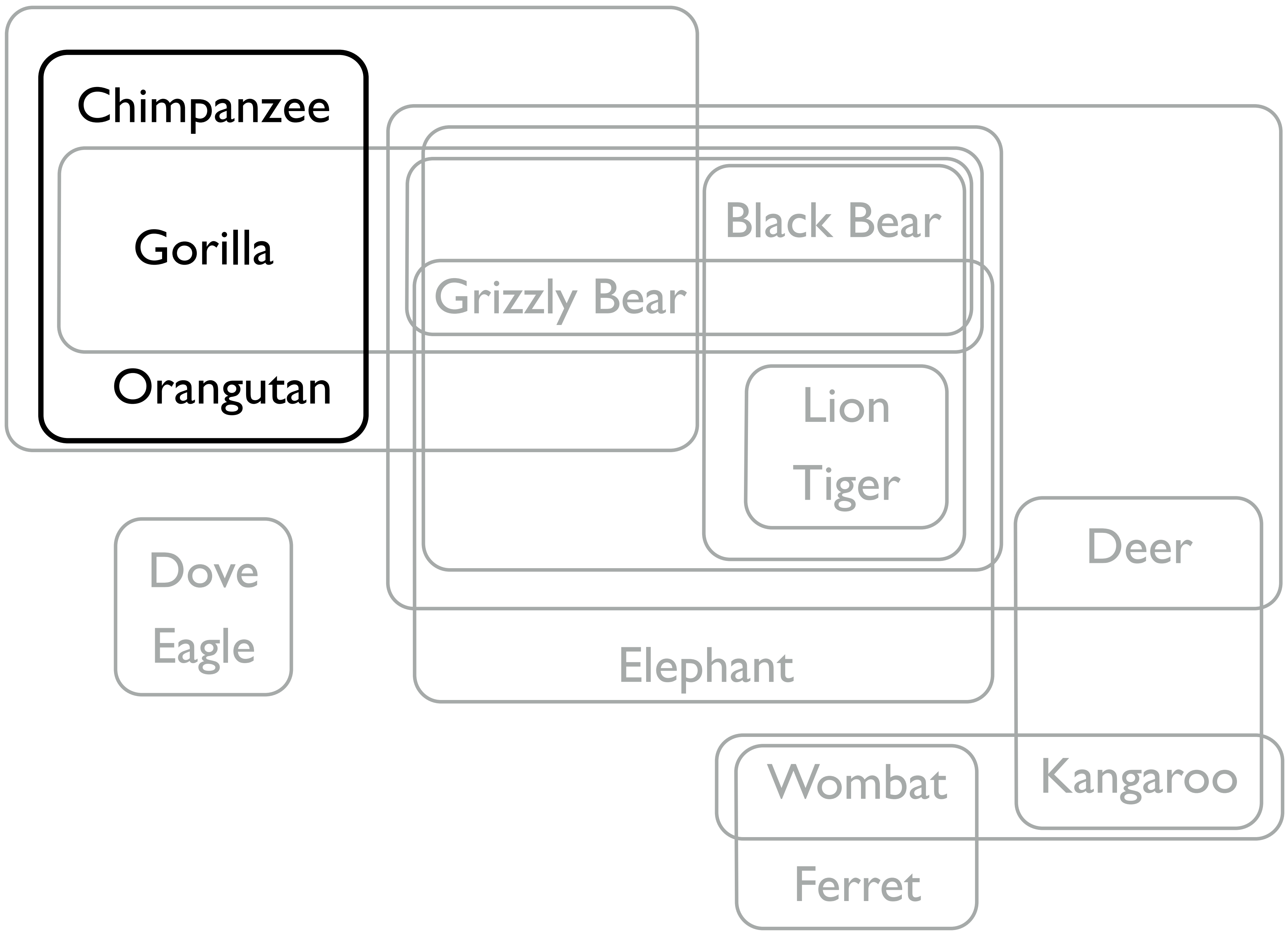


Assume any subset of items is a legitimate hypothesis, with weights inferred from similarity judgments

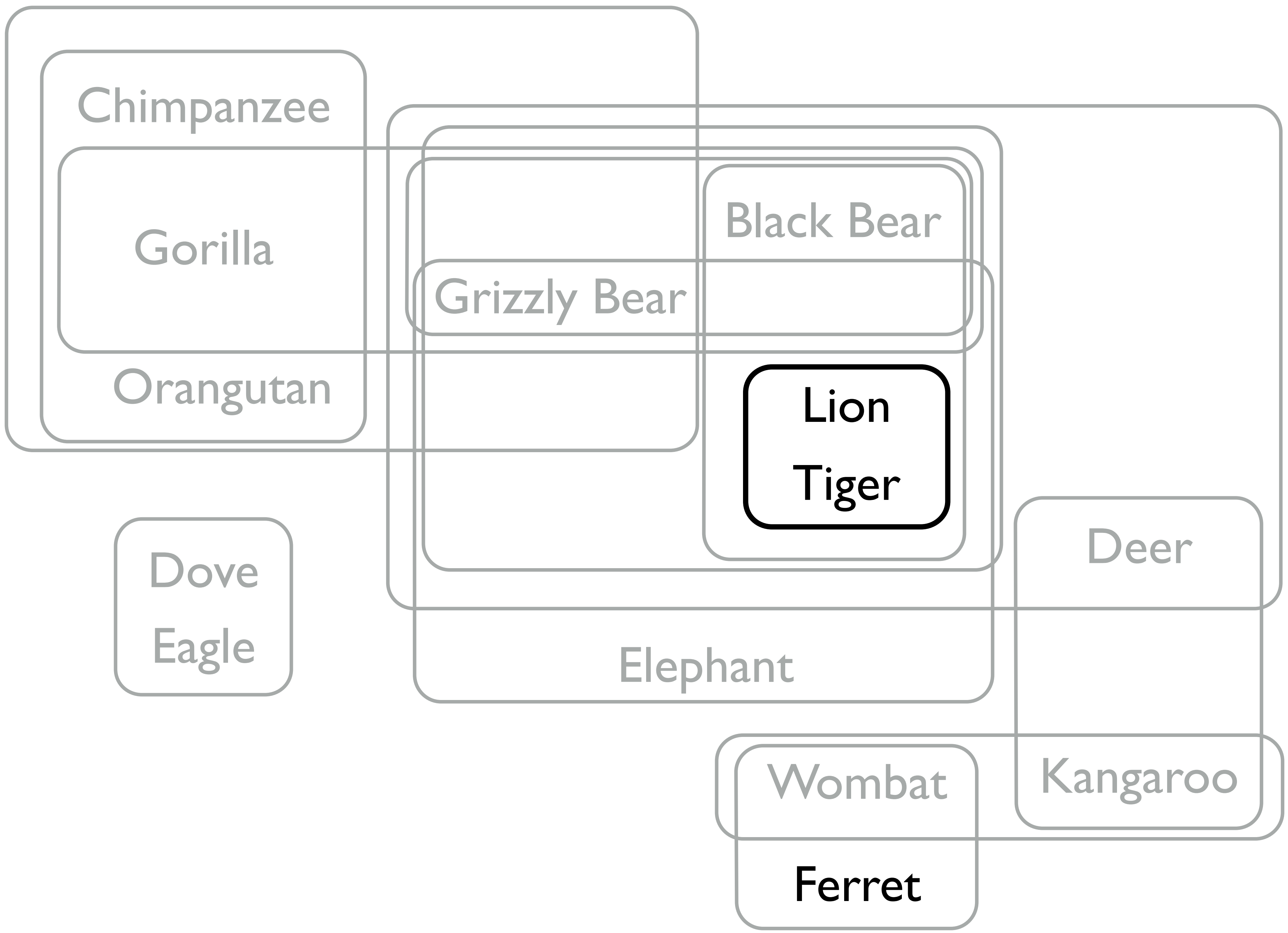


*This illustration only shows a high-weighted sets that contain at least two animals. The actual prior assigned non-zero prior probability to every possible subset of the set of all animals that appeared in the task. Qualitative features of model predictions are robust to the specific choice of prior: anything even semi-reasonable seems to work

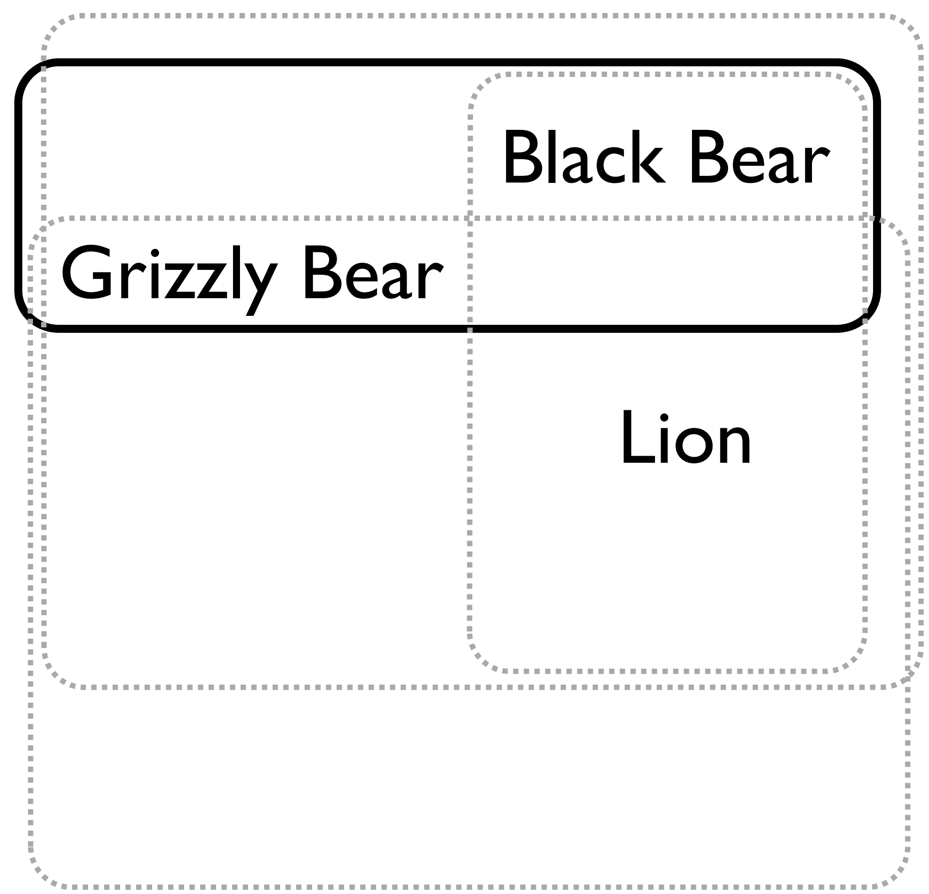
(Chimpanzee, Gorilla, Orangutan)



(Lions, Tigers) but not Ferrets

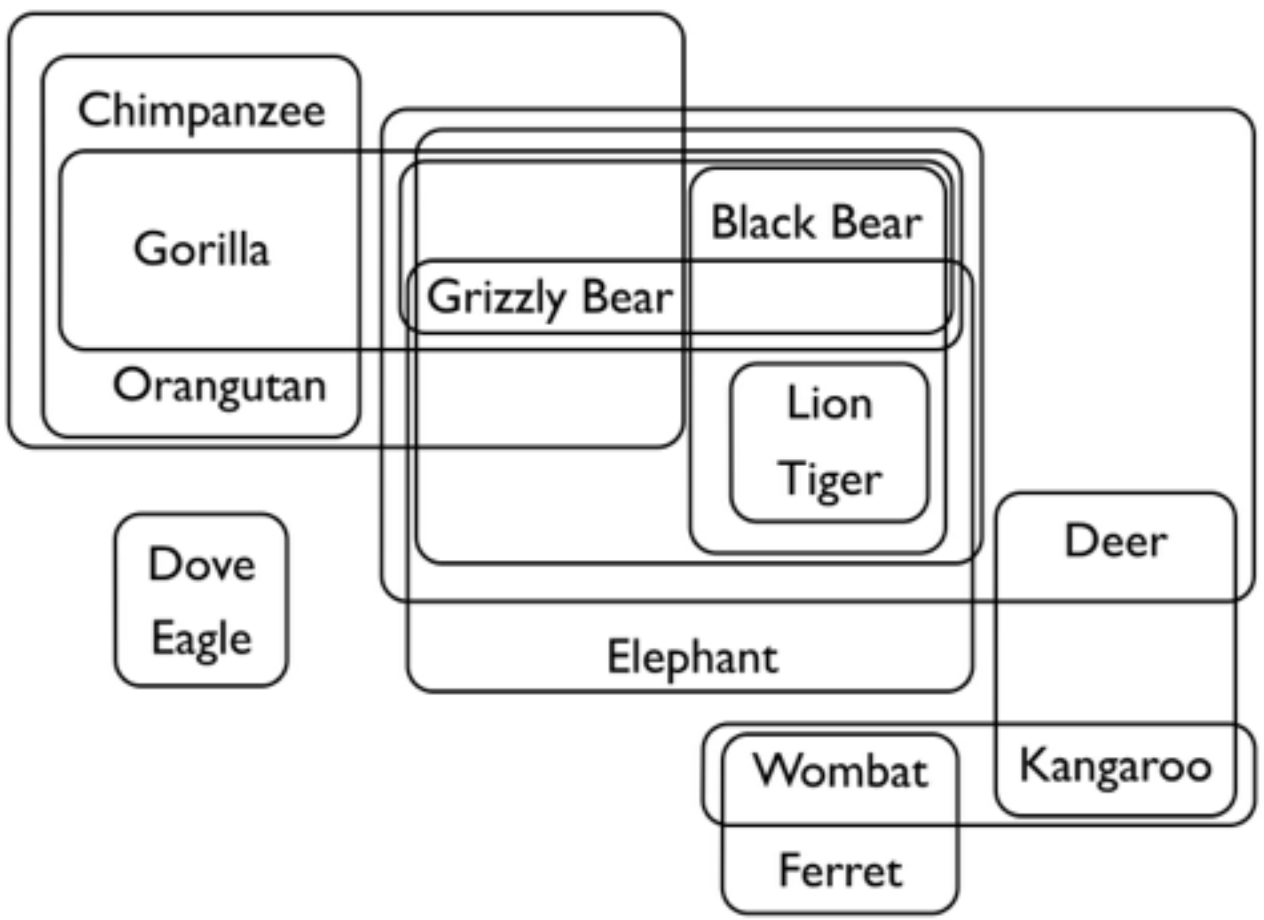


(Grizzly Bears, Black Bears) but not Lions?



There are many high weighted features involving these three, but overall the prior puts the bears together more often

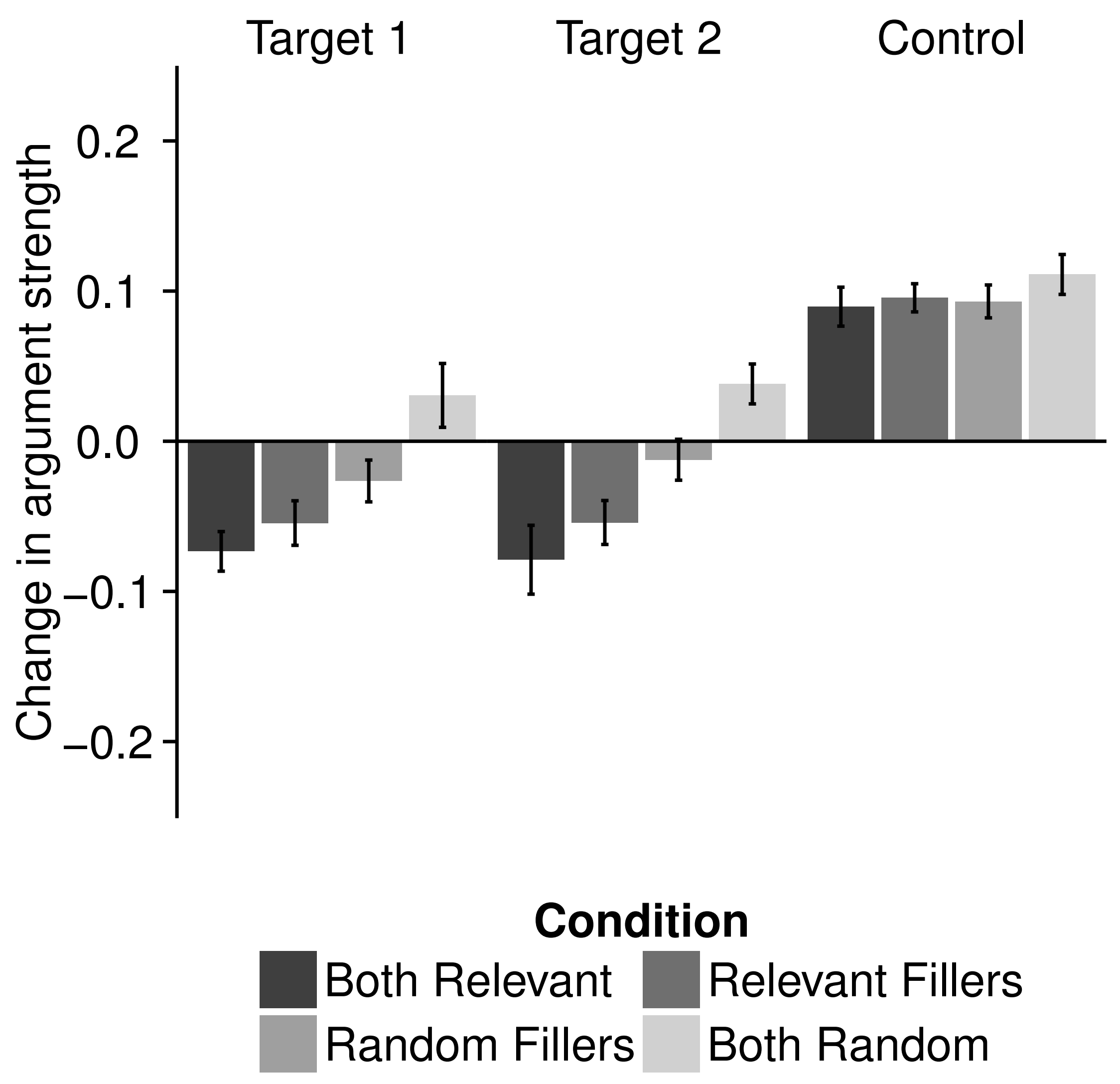
The prior explains why there are structural differences between the targets and the control



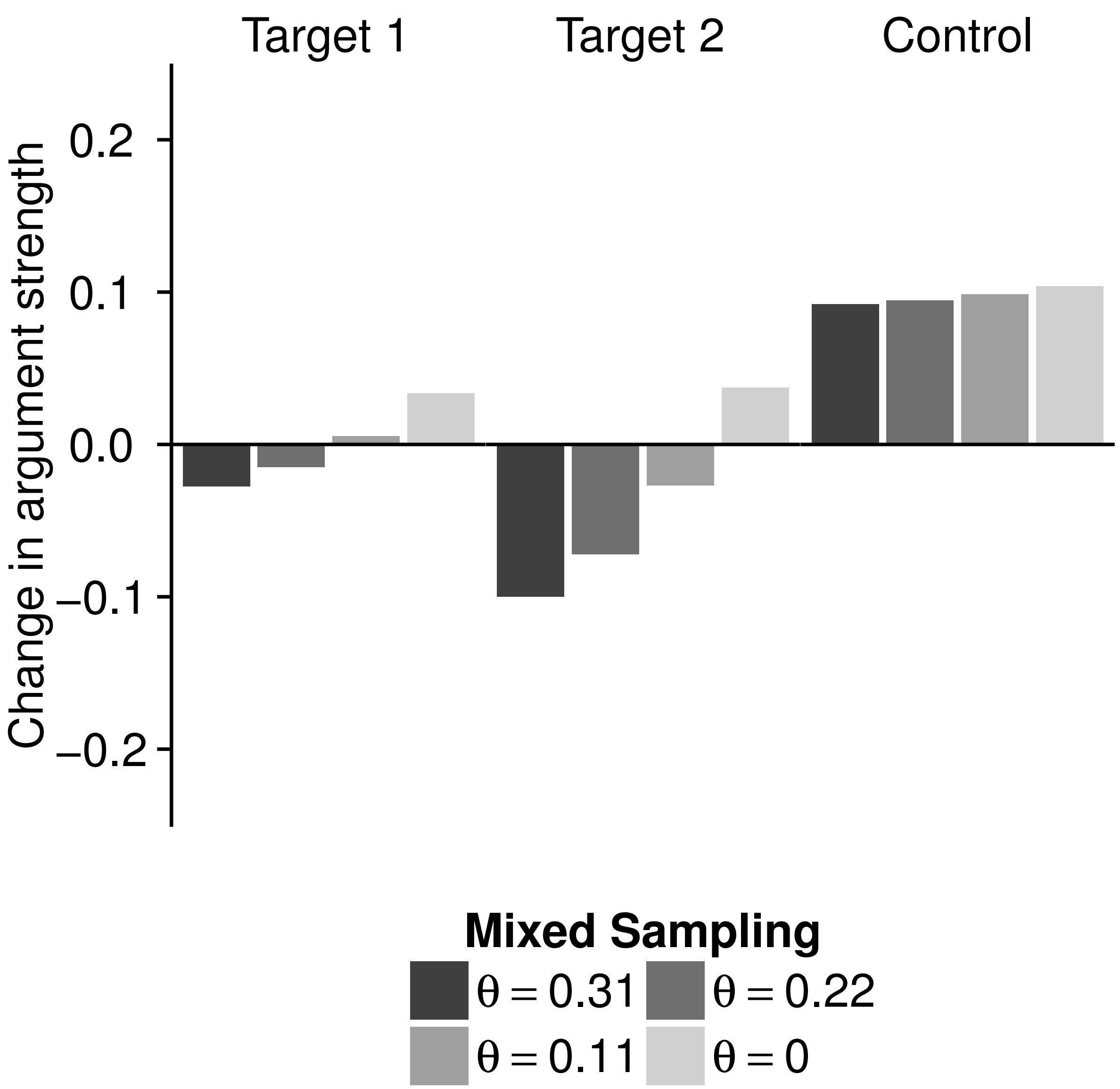
The likelihood describes how "adding more premises" can have different effects across conditions

Empirical data

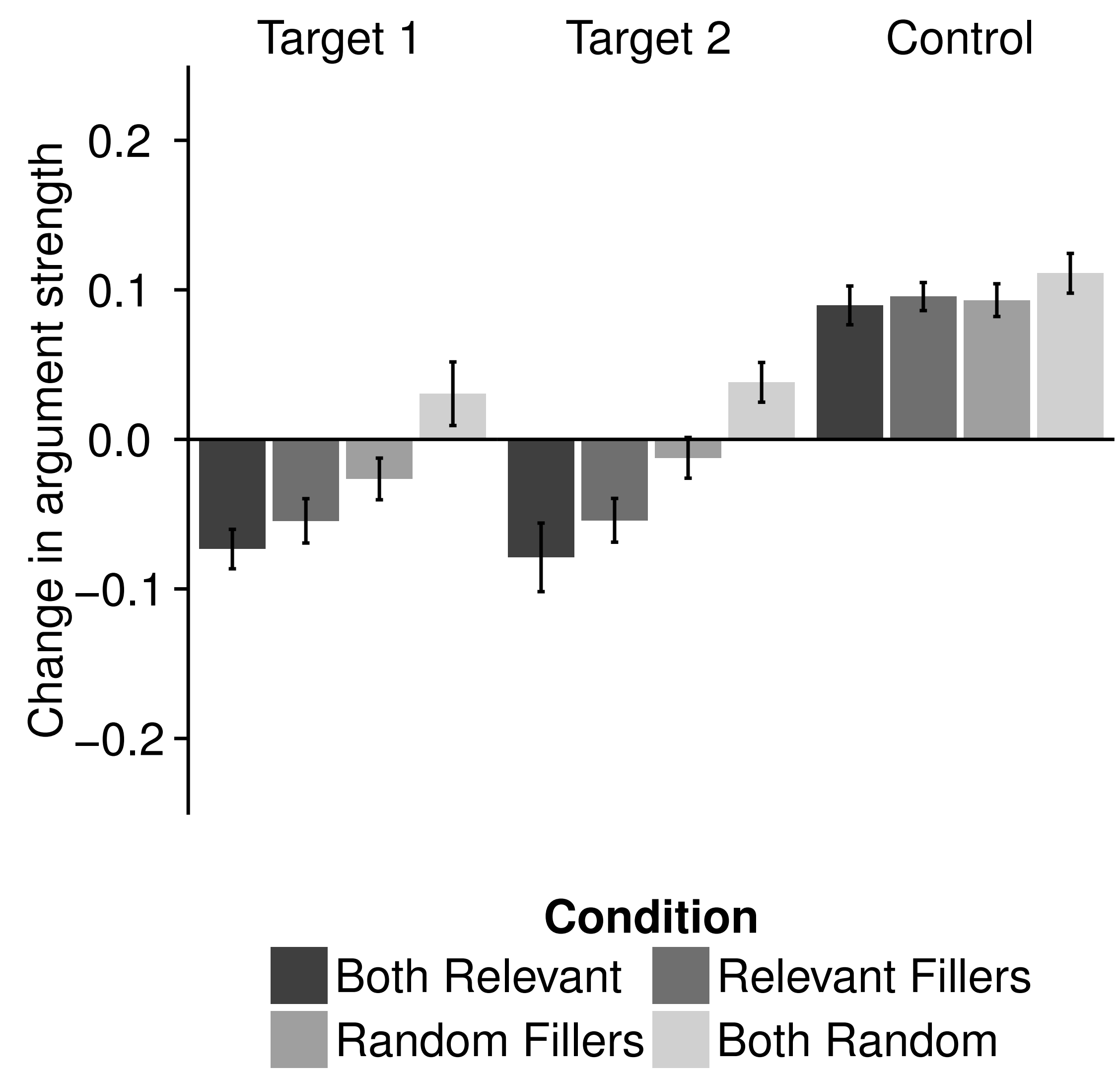
Does the model work???



Model fits



Empirical data



- It’s not just about the evidence facts provide for a conclusion, it’s also about how you think those facts were put together

- Bayesian models explain the reversal as a shift in the sampling assumption

- This is encouraging, so…

How to take a helpful hint…
(the curious power of negative evidence)

Navarro, Dry & Lee (2012). Sampling assumptions in inductive generalization. *Cognitive Science*

Hendrickson, Perfors & Navarro (in preparation). One cat, two cats: Sampling models in different category learning tasks produce qualitatively different inductive generalisations

Ransom, Perfors & Navarro (in press). Leaping to conclusions: Why premise relevance affects argument strength. *Cognitive Science*

Voorspoels, Navarro, Perfors, Ransom & Storms (under revision). How do people learn from negative evidence? Non-monotonic generalizations and sampling assumptions in inductive reasoning. *Cognitive Psychology*

Perfors, Navarro & Shafto (in preparation). Stronger evidence isn't always better: The role of social inference in evidence selection and interpretation. Previously rejected from *JEP:G*

You want to infer whether all ravens are black.
Which of these observations is more helpful?

Law of contraposition makes these two statements logically equivalent

Raven → Black

¬Black → ¬Raven

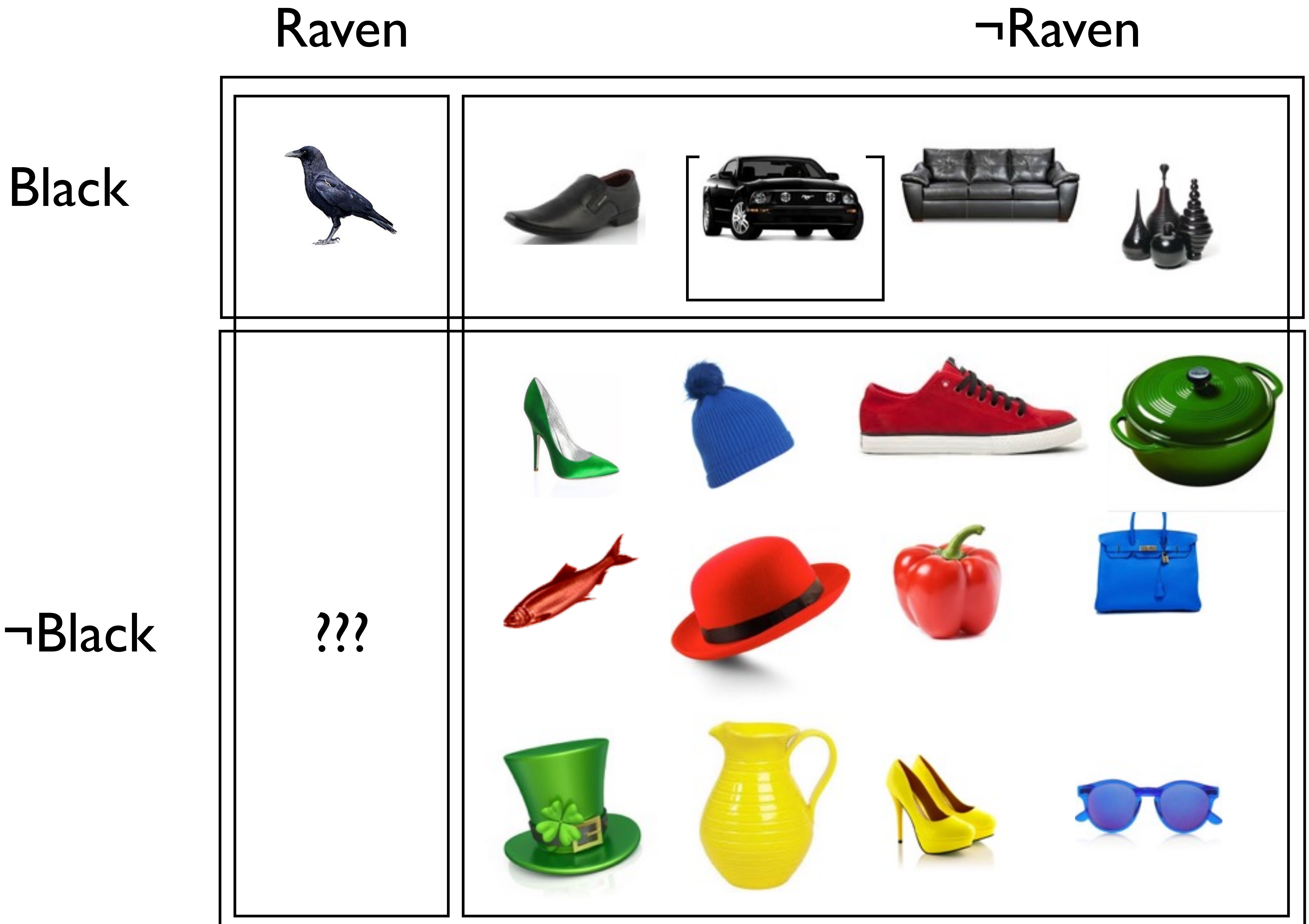
Okaaaay…. apparently these are the same?

$\text{Raven} \rightarrow \text{Black}$ $\neg\text{Black} \rightarrow \neg\text{Raven}$

(raven, black)

(¬black, ¬raven)

	Raven	¬Raven
Black		
¬Black	???	


Raven
¬Raven
Black
¬Black
???

Category size/frequency matters, theoretically & empirically

- Positive (labelled) categories are small
    - Oaksford & Chater (1998), Navarro & Perfors (2011), etc.
- Sampling from a small category is more powerful
    - Good (1960), Klayman & Ha (1987), Oaksford & Chater (1998), Navarro & Perfors (2011), Austerweil & Griffiths (2011), etc
- People treat positive evidence as more informative than negative evidence
    - Wason (1960, 1968), many many others…
    - So it all makes sense! And…

Paradox resolved!

A black raven is very informative

A non-black non-raven has non-zero but negligible evidentiary value

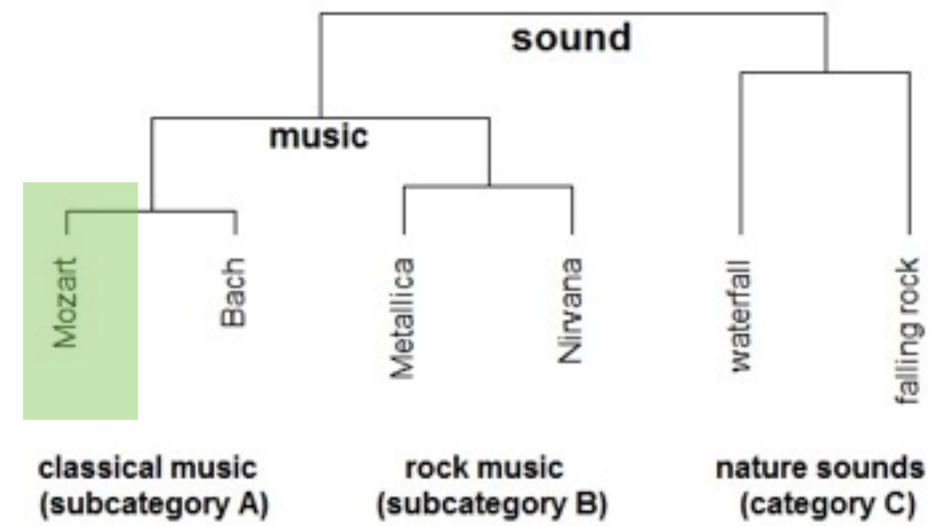
So we'll just some empirical work, with some *obviously* predictable results…

Mozart produces alpha waves

The sound of a falling rock does not

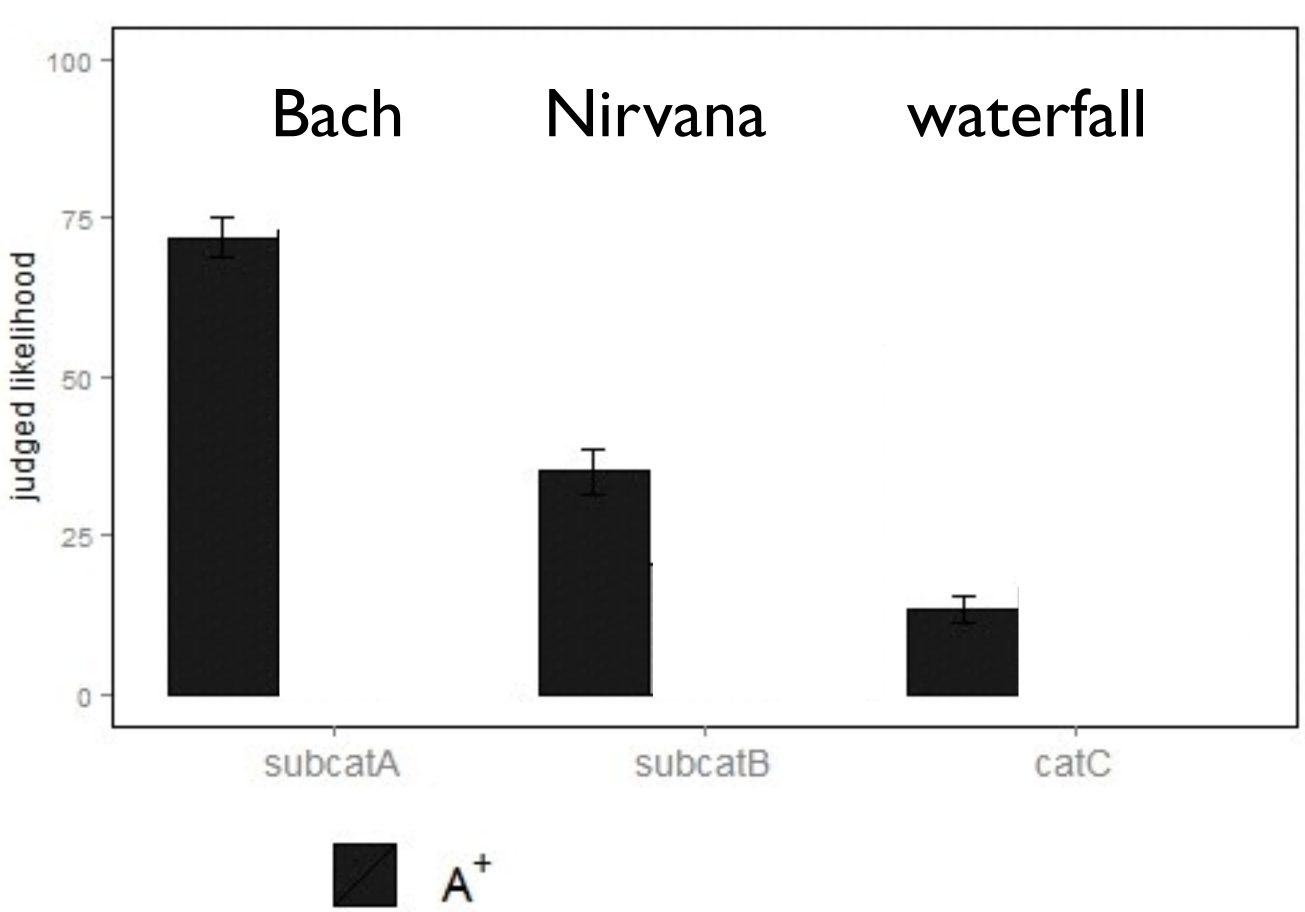
	music	¬music
alpha		
¬alpha	???	 This ought to be about as utterly useless as the green shoes thing

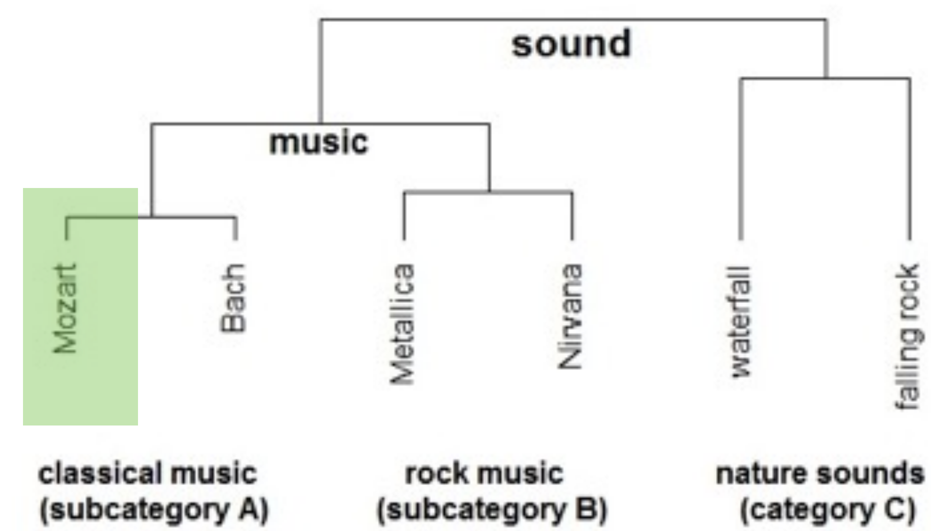
Okay, we start by telling people that Mozart does produce alpha waves…



Mozart+

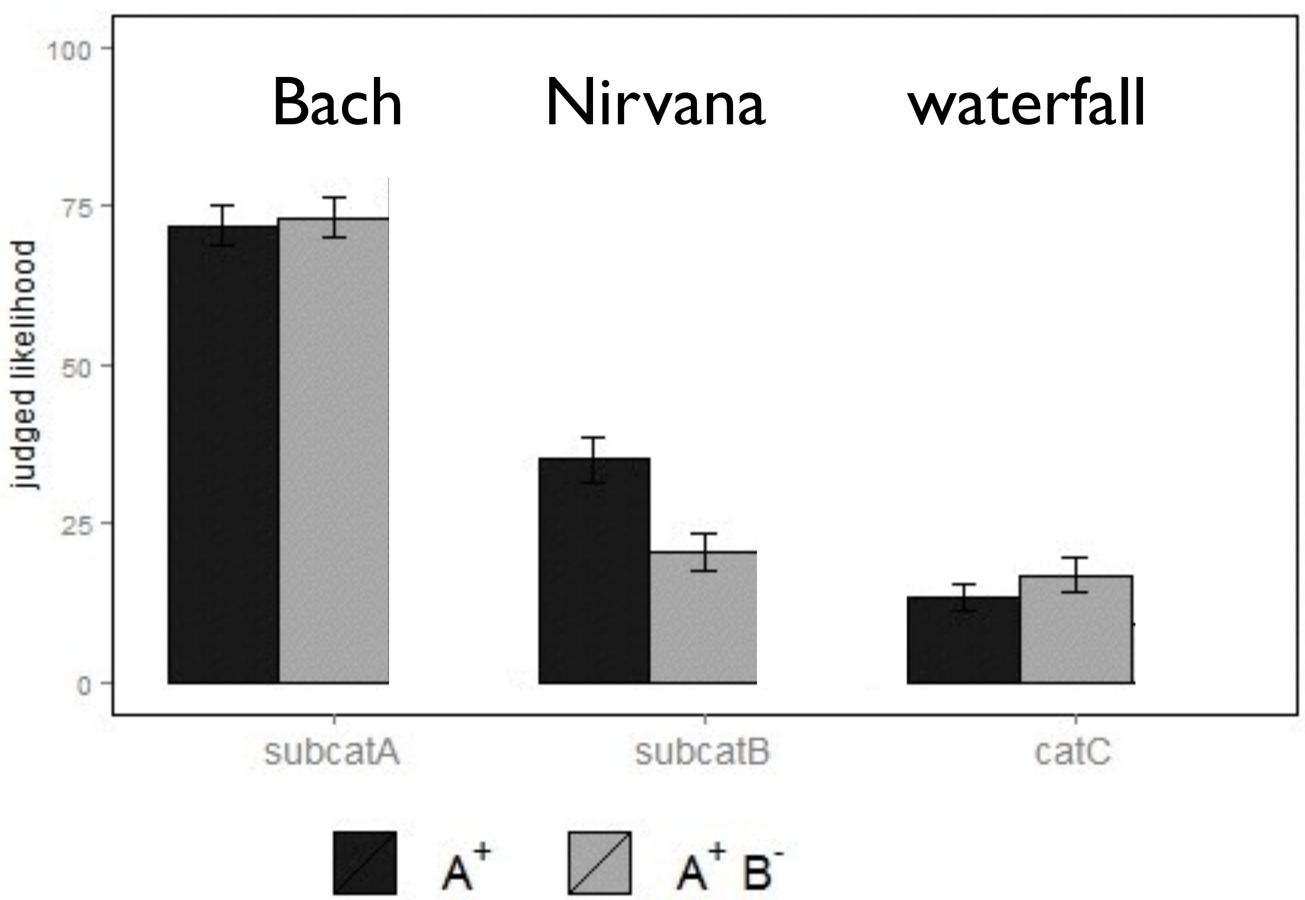
… and they generalise in a way that seems terribly sensible

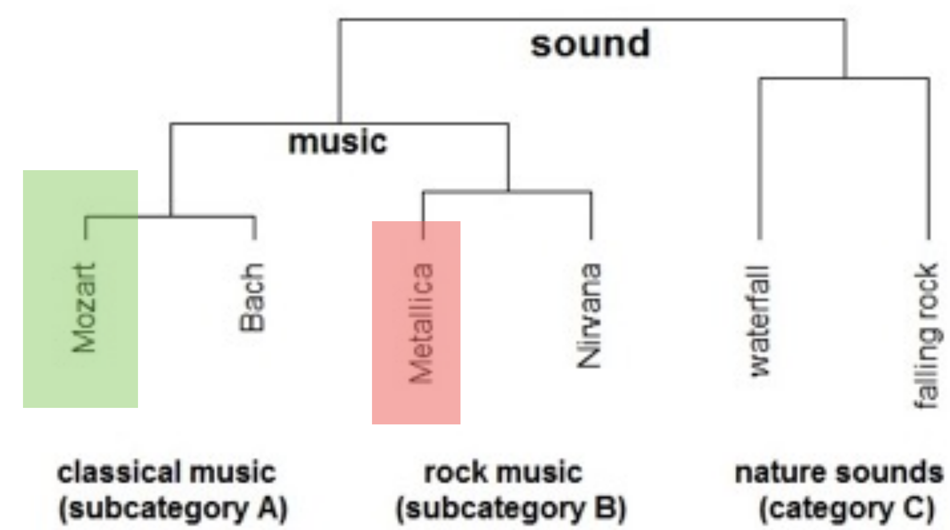




Mozart+

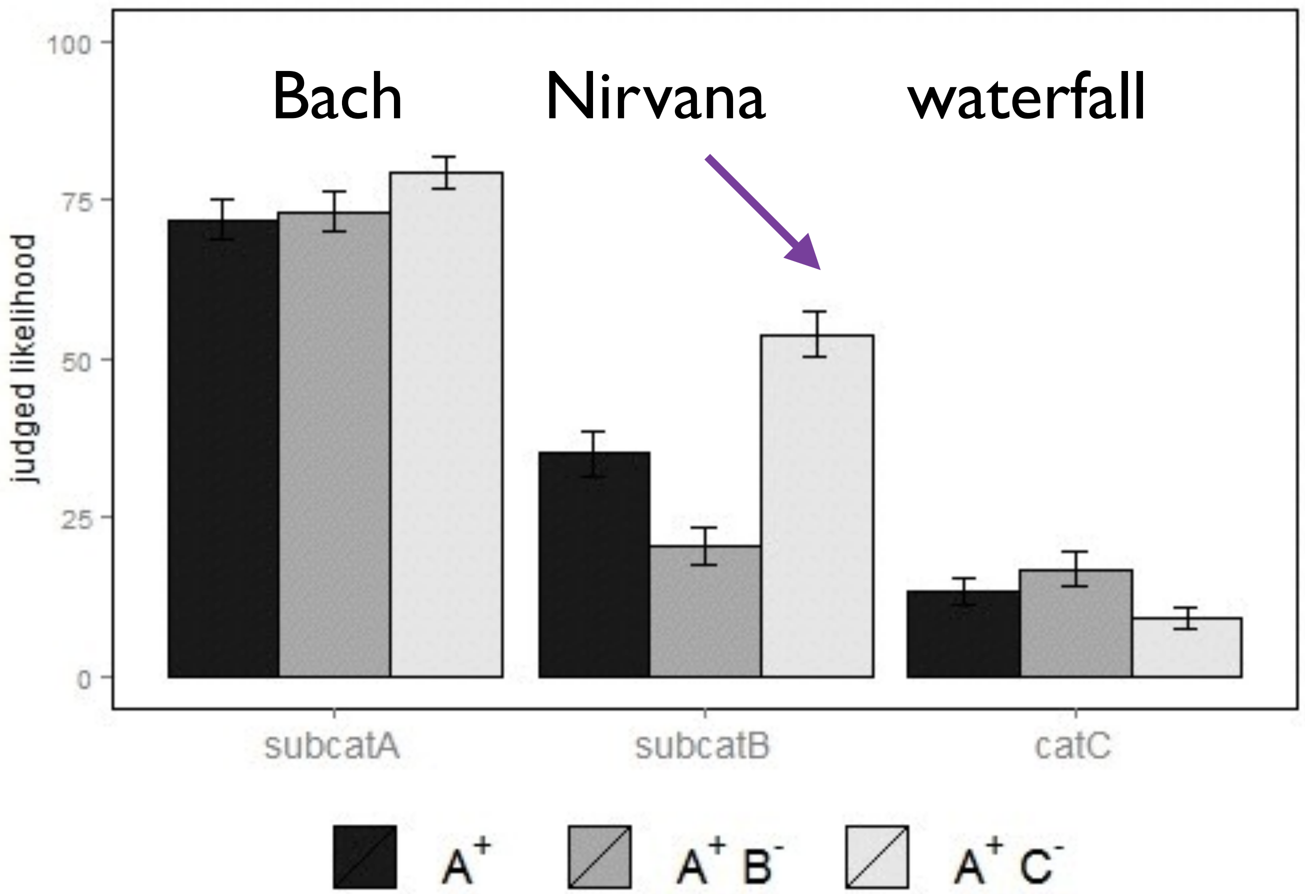
Adding Metallica as a negative example has a small effect (yay!)

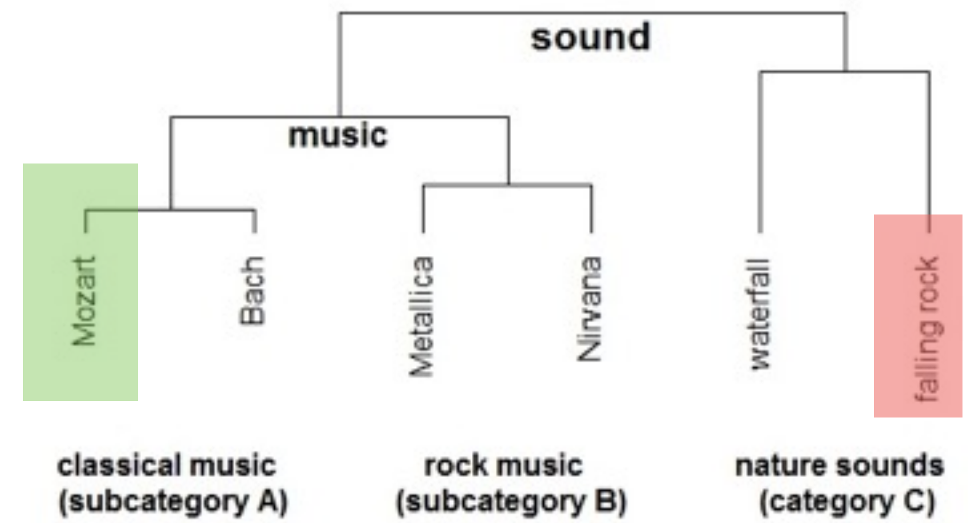




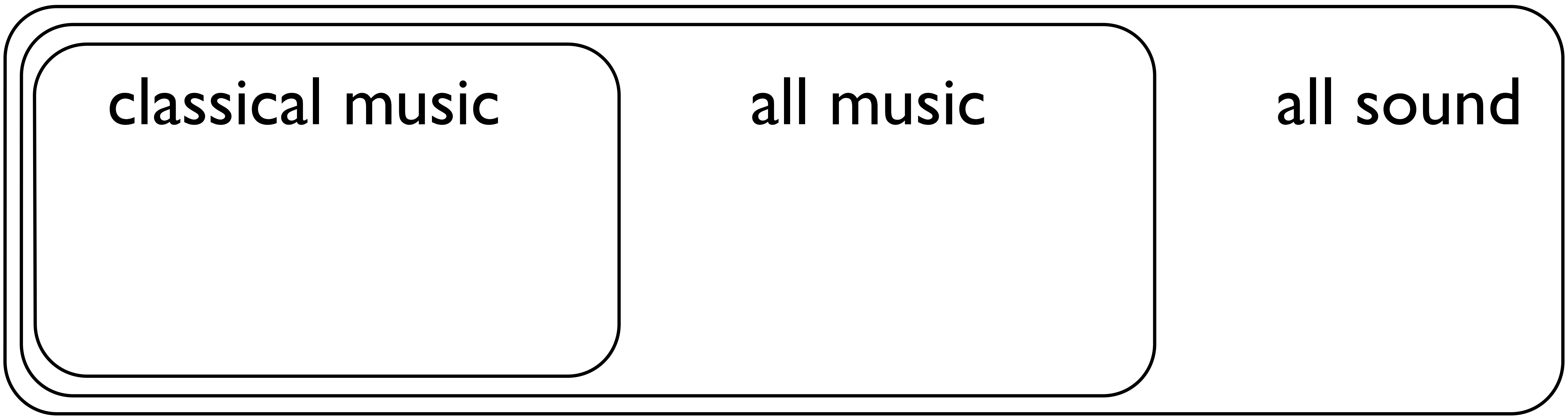
Mozart+ Metallica-

OKAY WTF HUMANS I HATE YOU ALL.

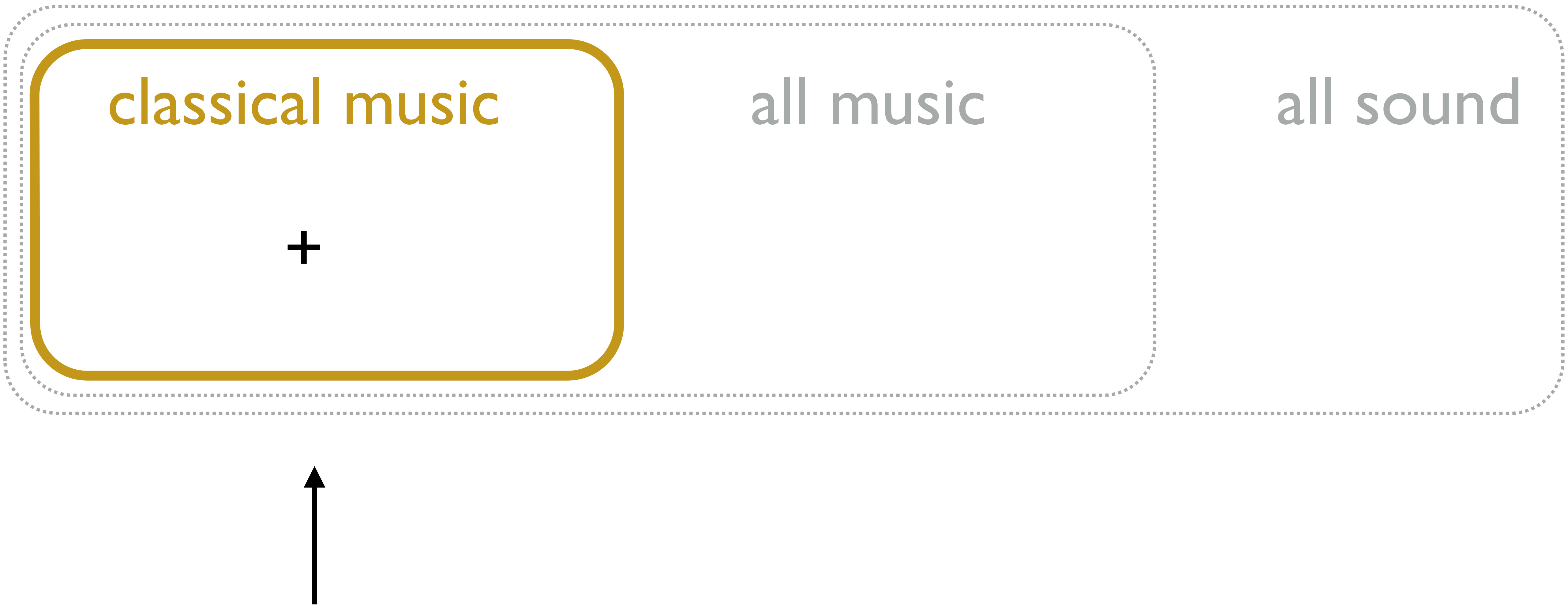




Mozart+ Falling Rock-

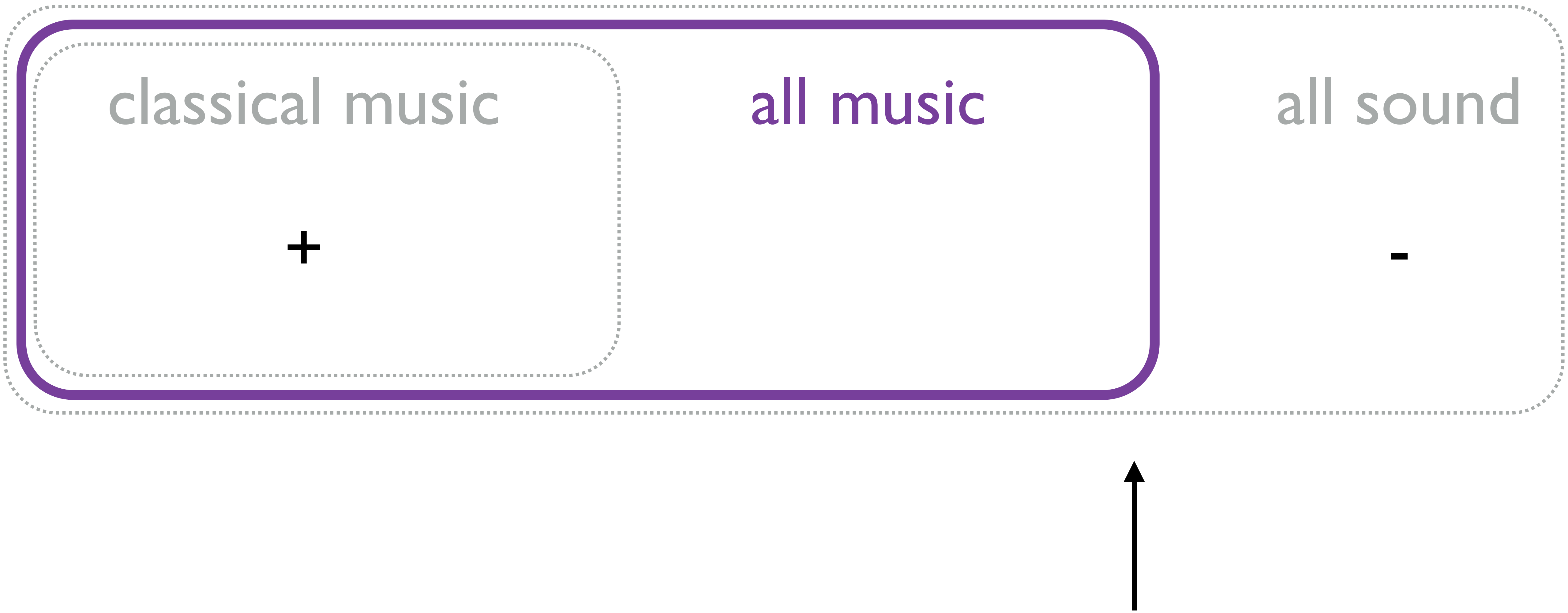


three relevant hypotheses for the extension of the alpha waves property



positive example of classical music means people strongly endorse the narrow category

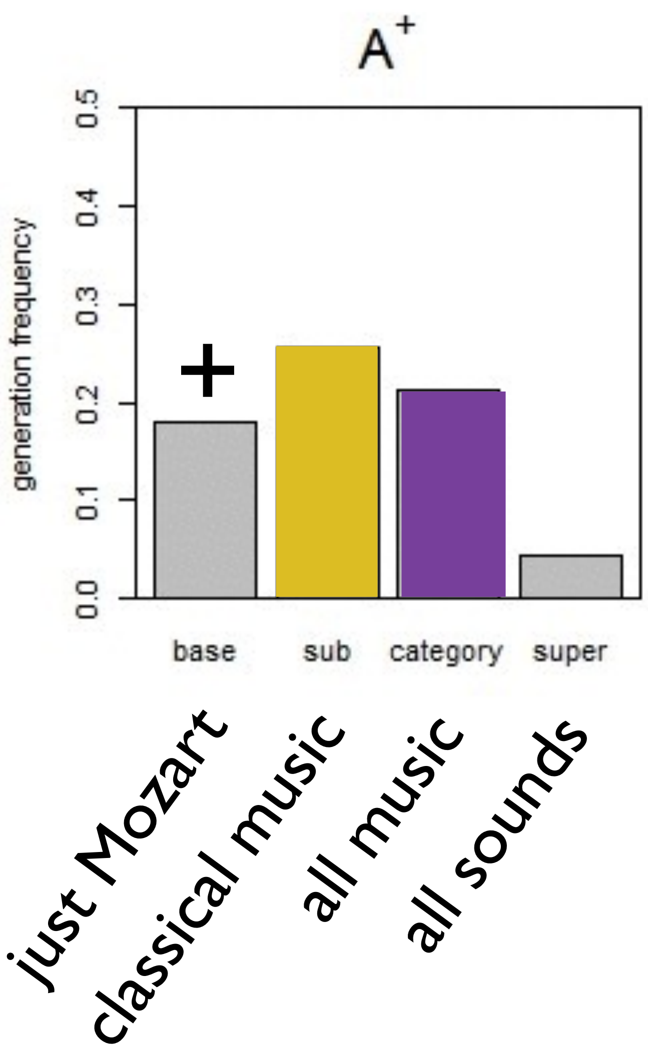
but add a negative observation from a distant category and you get a huge belief revision?



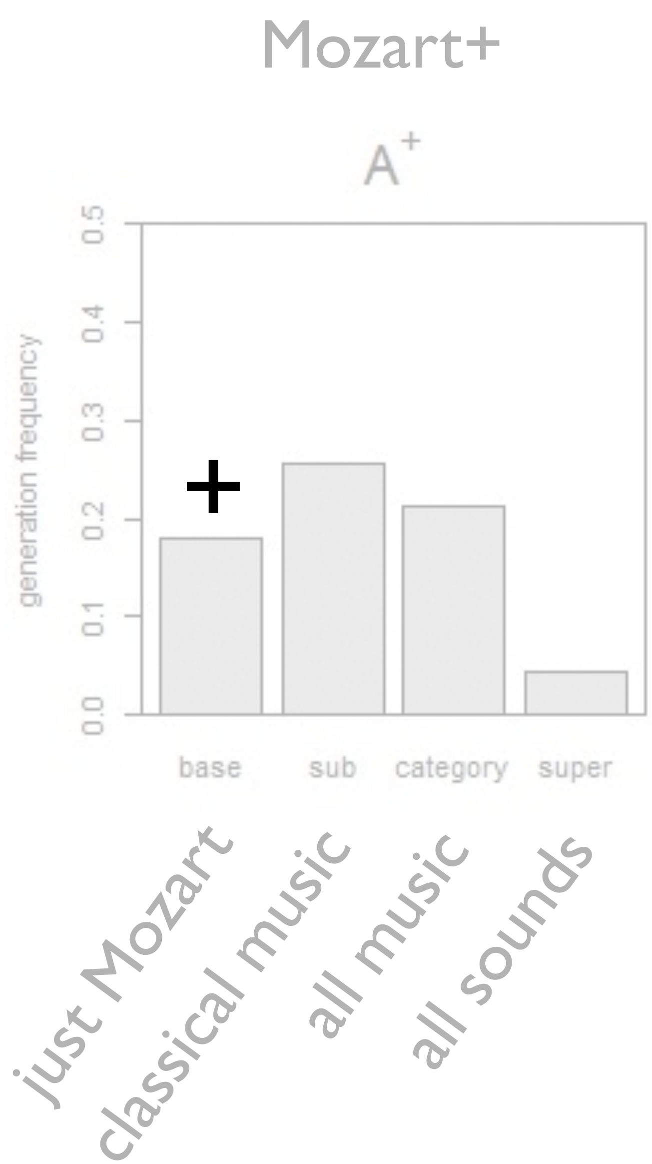
Apparently people make a (pragmatic?) inference that the negative observation is used to demarcate the category boundary

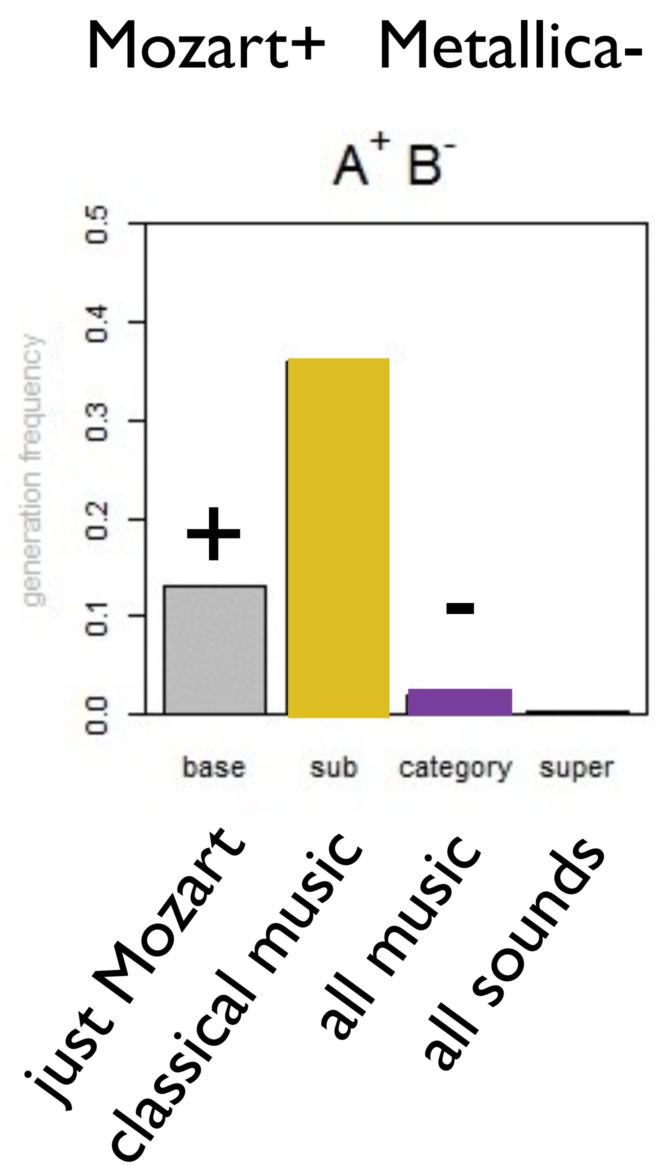
Well, let's ask them what they think the true extension of the property is…

Mozart+

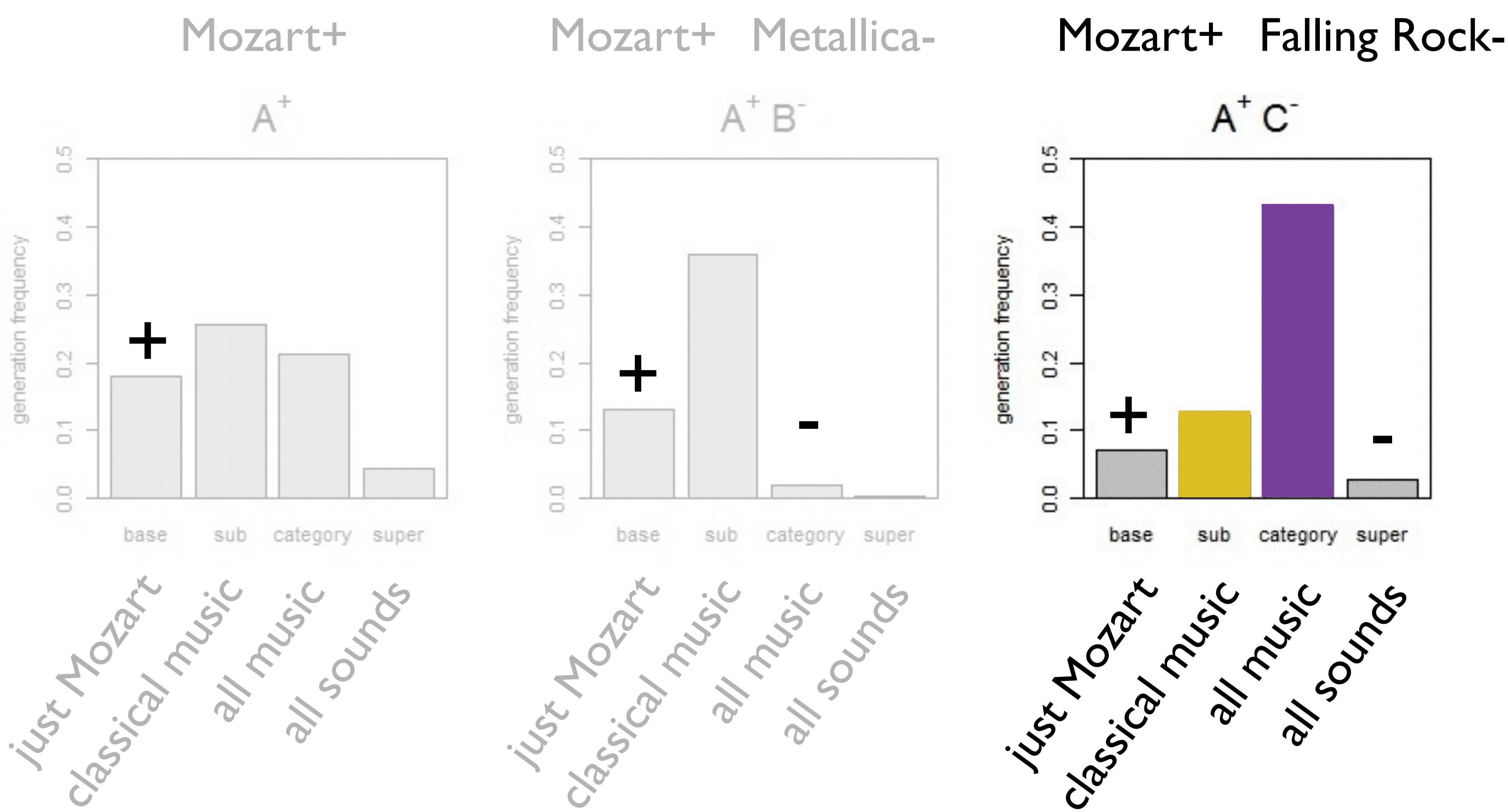


Well, let's ask them what they think the true extension of the property is…





And there it is.



(aside: the actual experiment used many different arguments)

topic	premises			conclusions		
	subcat A	subcat B	cat C	A-member	B-member	C-member
MUSIC	Mozart	Metallica	falling rock	Bach	Nirvana	waterfall
PAINTERS	Rubens	Dahli	woodcarver	Van Eyck	Warhol	sculpturer
PUBLIC FIGURES	actors	librarians	moles	politicians	programmers	pheasants
SHIPS	freight ships	hovercrafts	cars	cruise ships	sail boats	rocks
GLASS	window glass	bottle glass	art glass	car glass	drinking glass	jewelry glass
DISPLAYS	LCD	television	paintings	plasma	traffic signs	book page
WATER BODIES	Atlantic	Balaton	mustard gass	Mediterranean	Silverlake	olive oil
WIND	flute	guitar	crying child	clarinet	violin	door
FRUIT	strawberries	banana's	grass blades	cranberries	apples	oak leafs
WATER BIRDS	ducks	sparrows	elephants	seagulls	blackbirds	camels
INSECTS	moths	spiders	lizzards	flies	centipede	goldfish
POLAR ANIMALS	polar bears	deer	sow bug	pinguins	parakeet	ant

(aside: the actual experiment used many different arguments)

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MUSIC	Mozart	Metallica	falling rock	Bach	Nirvana	waterfall
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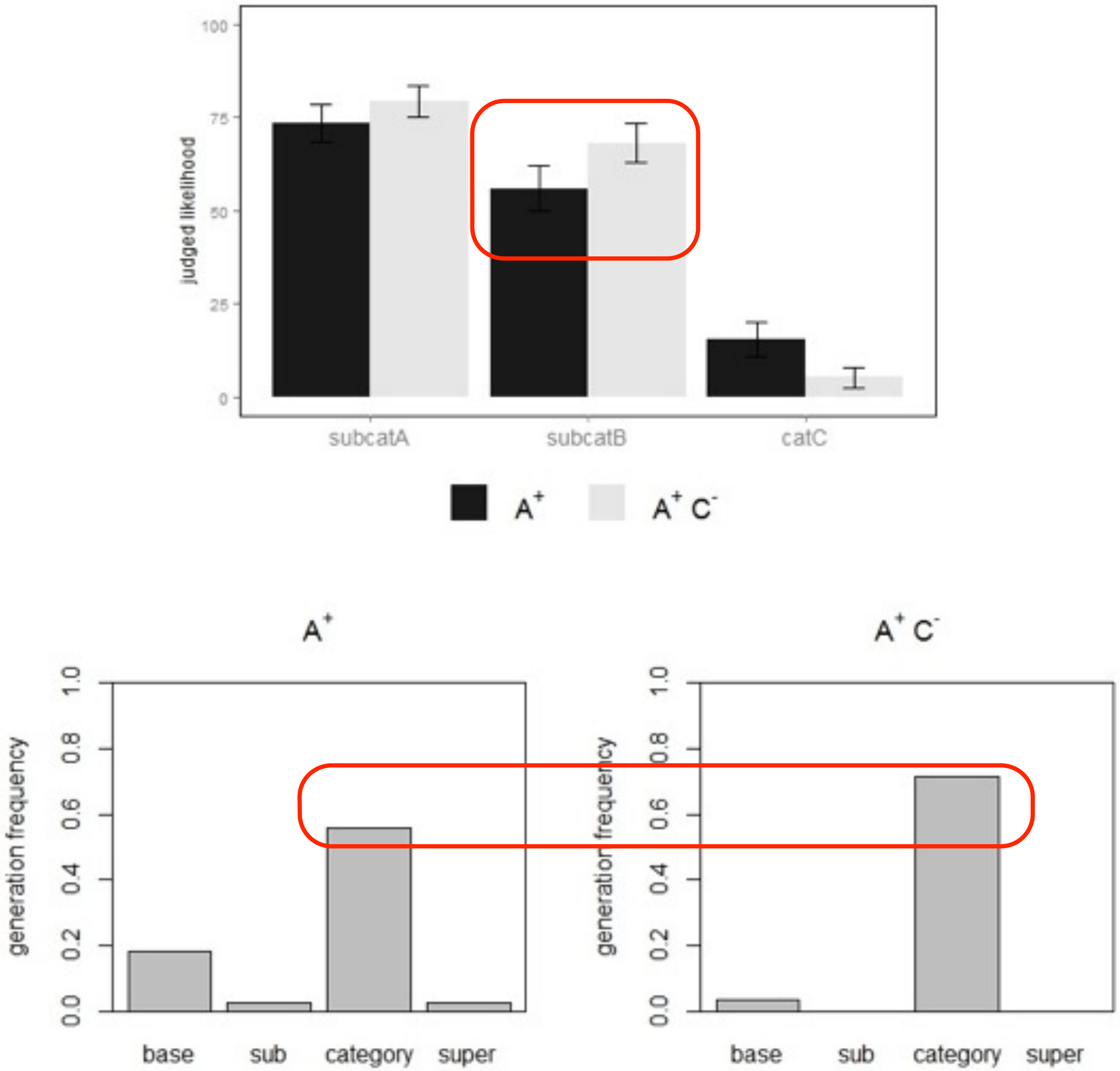
INSECTS	moths	spiders	lizzards	flies	centipede	goldfish
POLAR ANIMALS	polar bears	deer	sow bug	pinguins	parakeet	ant

plus we ran an entire pseudo-replication with different items

topic	premises			conclusions	
	subcat A	cat C	A-member	B-member	C-member
MAMMALS	dog (+)	magpie (-)	wolf	donkey	blackbird
BIRDS	crow (+)	tuna fish (-)	raven	swan	halibot
FISH	salmon (+)	lizzard (-)	codfish	goldfish	snake
INSECTS	bee (+)	sparrow (-)	ant	cricket	pigeon

(and yes, the replication worked)



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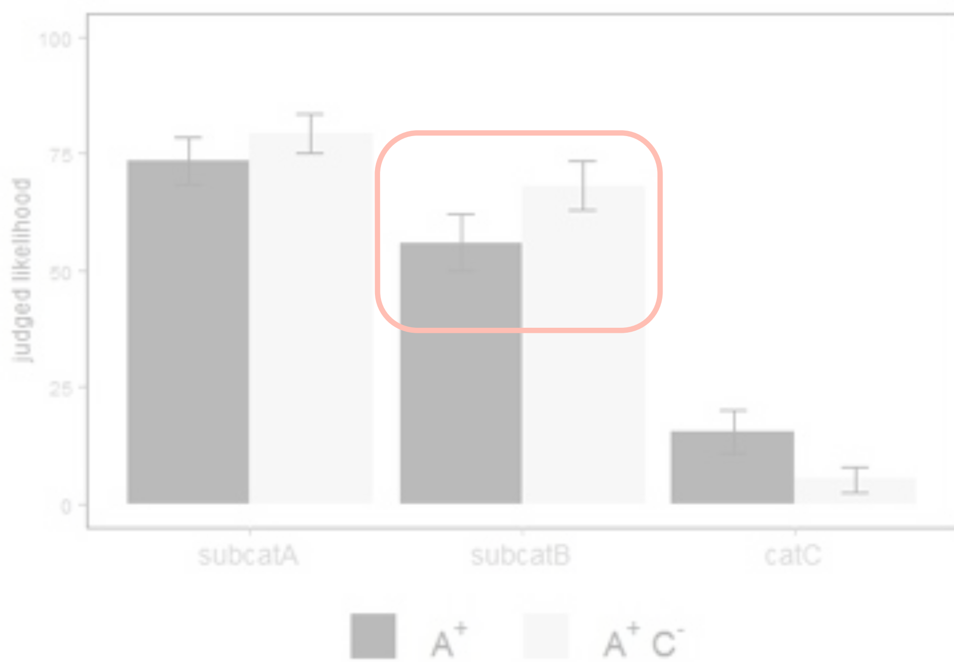
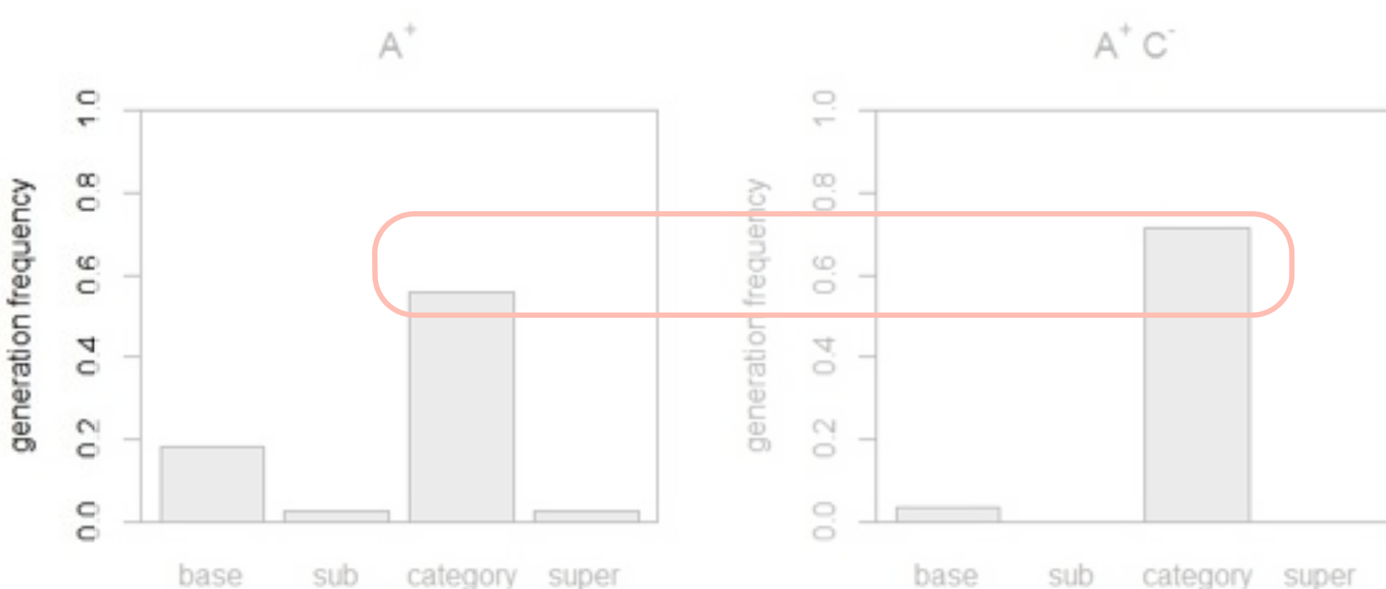
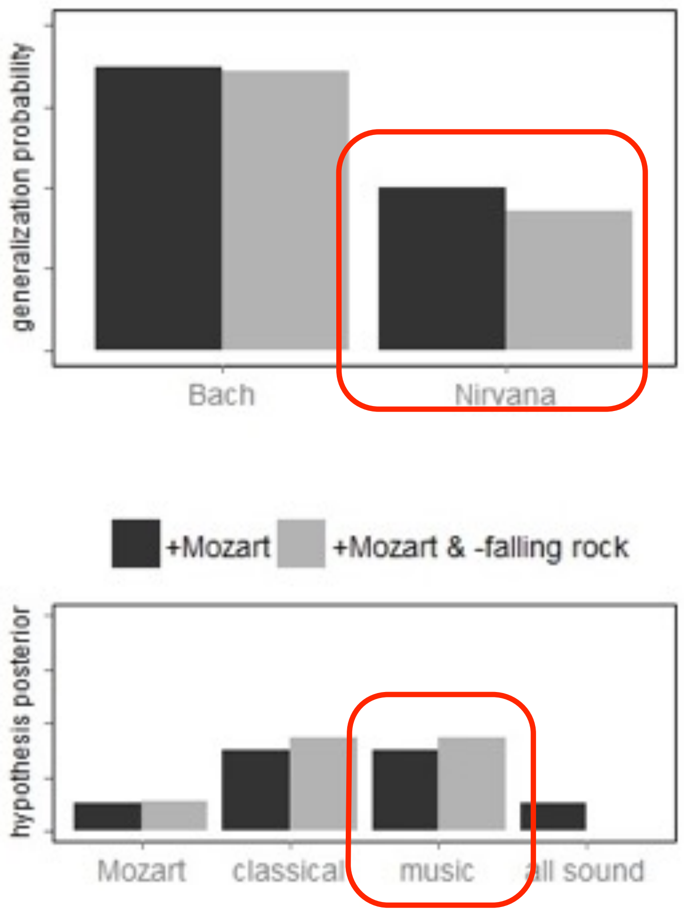




The big question is how to account for the results…

Does the weak sampling model capture the effect?

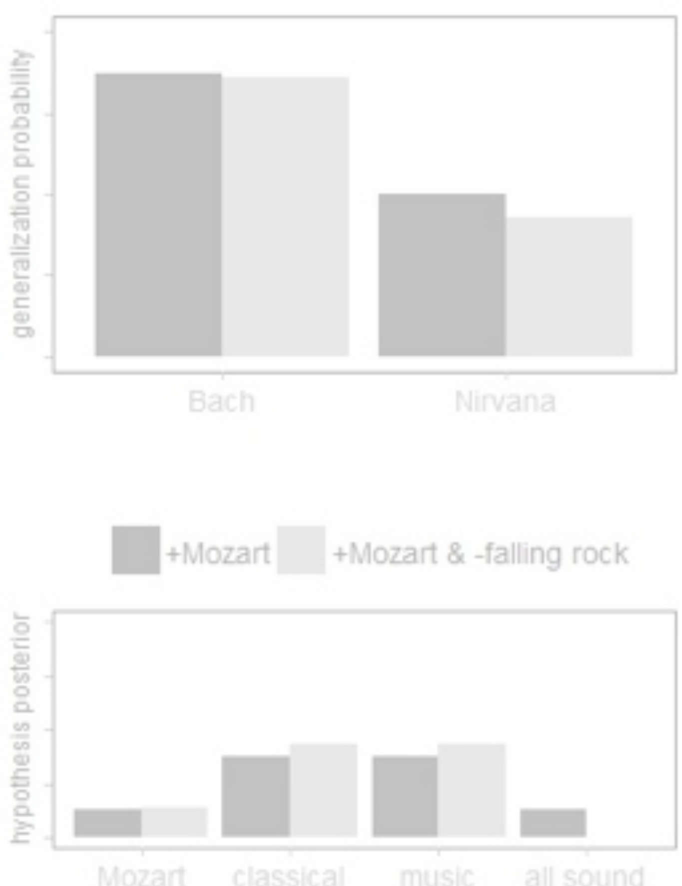
Weak sampling



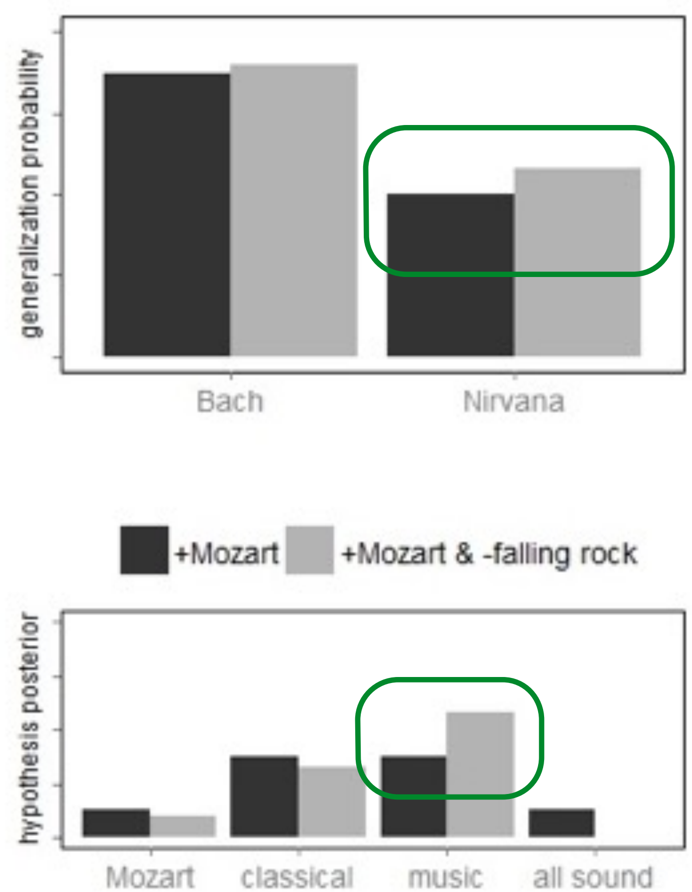
No, it predicts a null effect

Okay, does the "strong sampling" model capture the effect?

Weak sampling



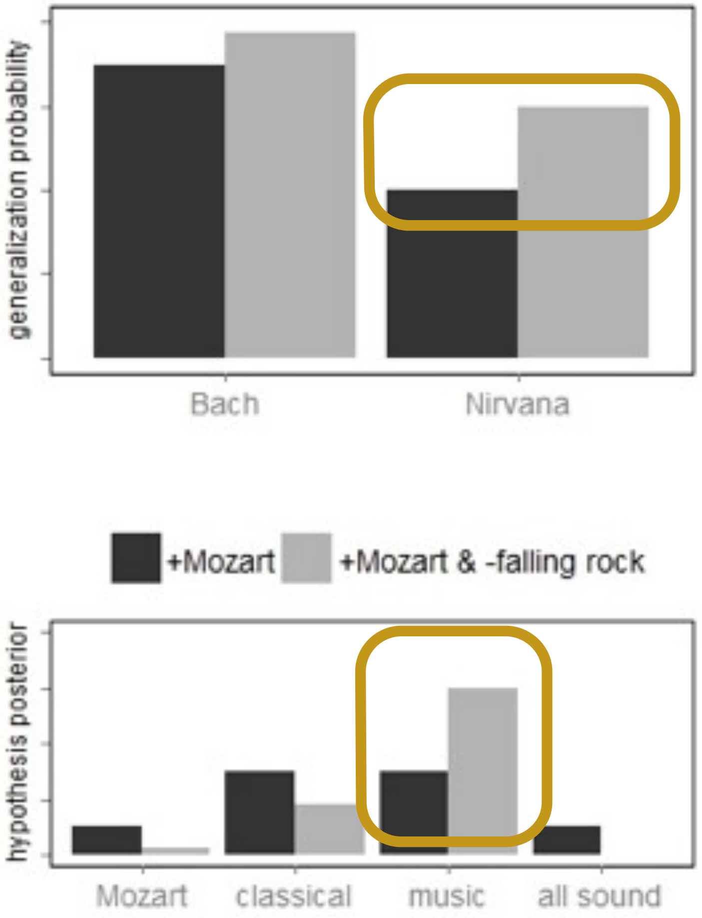
Strong sampling



Yes, but the effect is much smaller than the empirical one

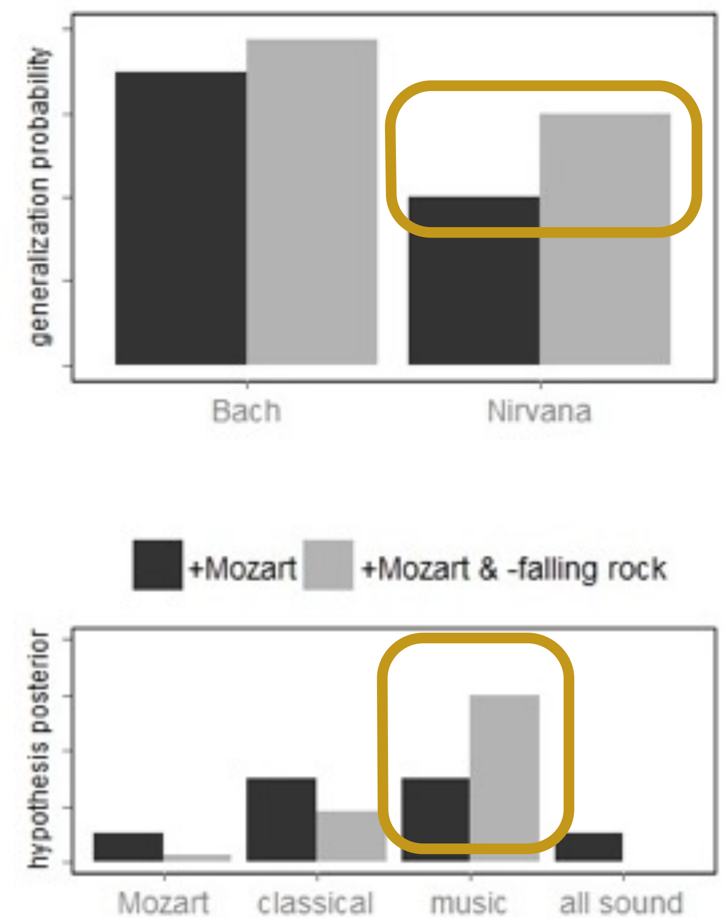
(people are out-Bayesing Bayes??)

Well, here's a model that gets the effect size right…



But Bayes is going to need a fancier hat…

<u>Pedagogical</u> sampling



Weak sampling

An argument consists of random true statements about the world

Weak sampling

An argument consists of random true statements about the world

Strong sampling

An argument consists of randomly selected facts particular to a target category

Weak sampling

An argument consists of random true statements about the world

Strong sampling

An argument consists of randomly selected facts particular to a target category

Pedagogical / persuasive sampling

An argument consists of purposefully chosen facts designed to convince an intelligent reasoner of the truth of some proposition

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

The data x selected by the communicator…

… is designed to maximise the learner's posterior degree of belief in hypothesis h

If that's right, then the same manipulation we used in the previous study should work…

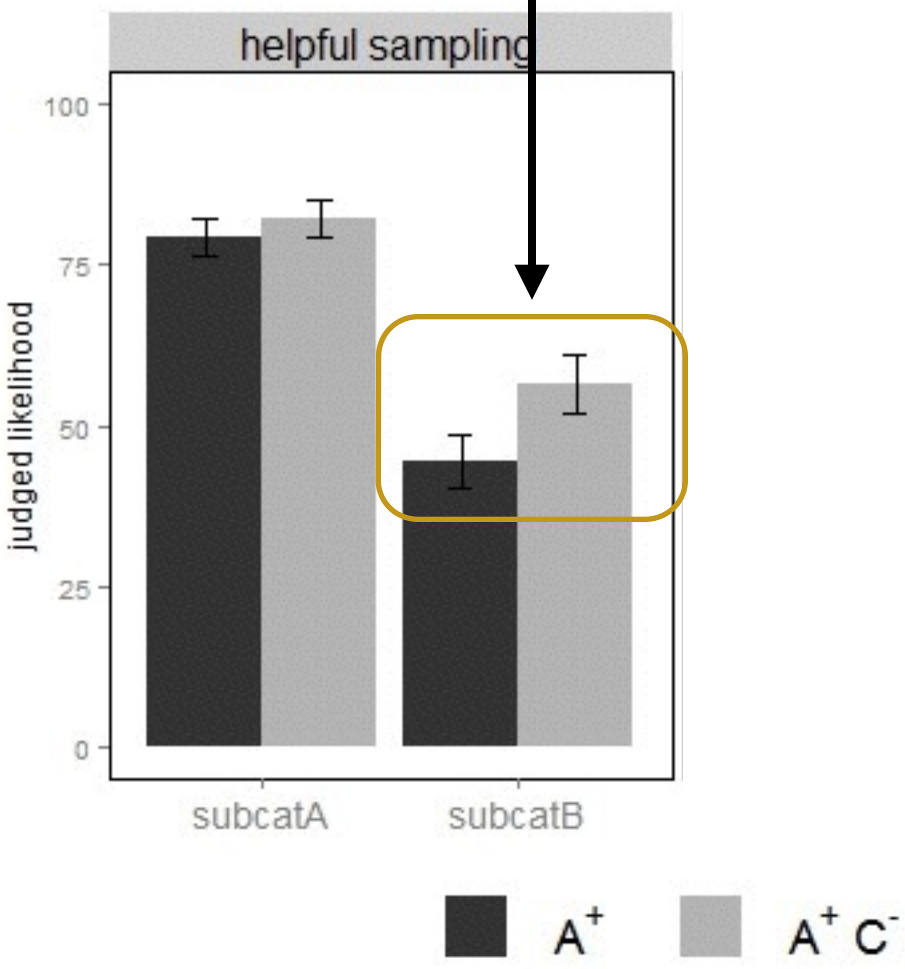
If the negative example is perceived as a "helpful hint" we should continue to get the effect

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

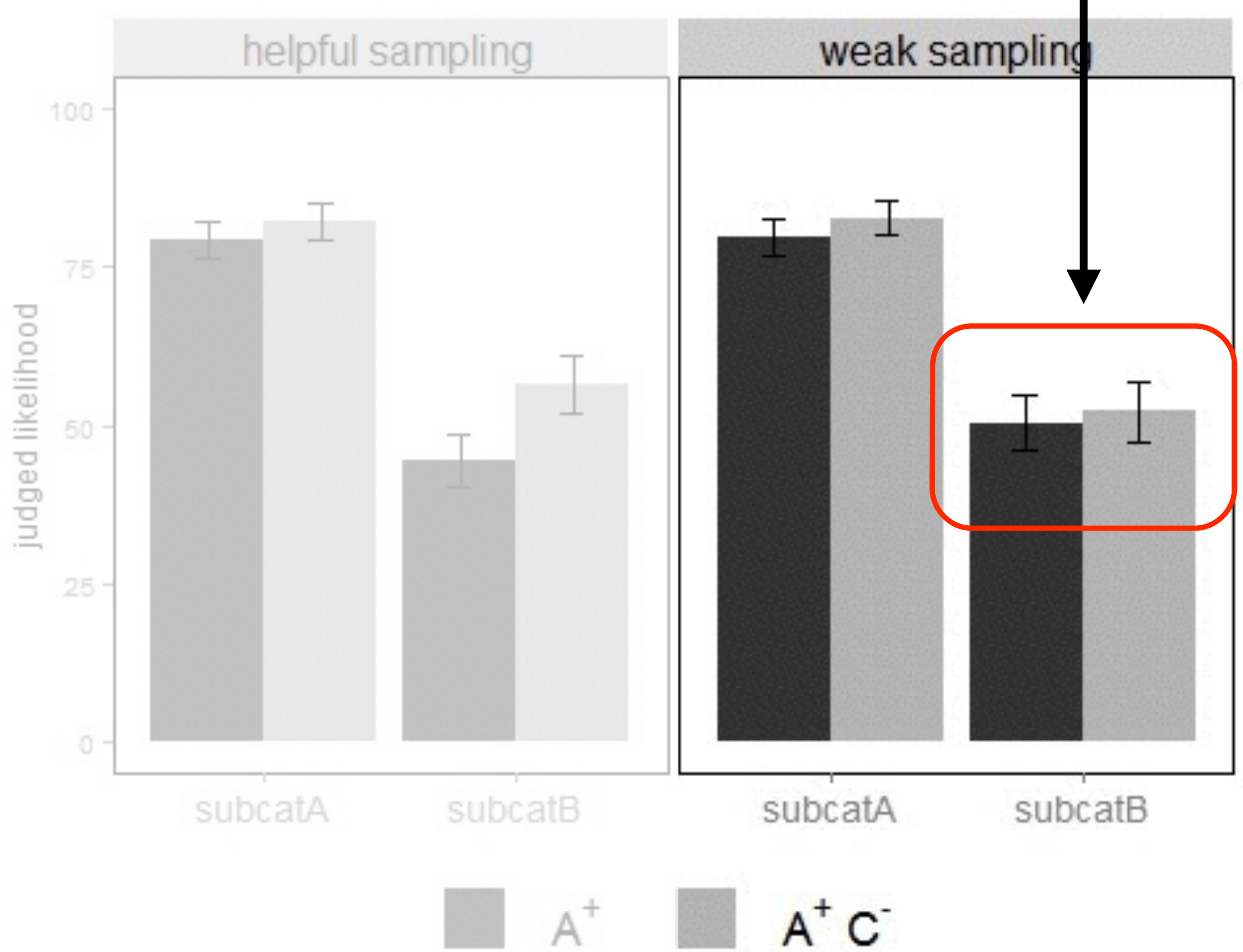
	premise 1 (+)	premise 2 (-)	A-member	B-member
	topics			
MUSIC	Mozart	waterfall	Bach	Nirvana
FRUIT	strawberries	grass blades	blackberry	apple
BIRDS	ducks	elephants	swan	blackbird
TYPES OF WATER	Atlantic ocean	tap water	Mediterranean	Lake Balaton
	fillers weak sampling			
	premise 1	premise 2	conclusion 1	conclusion 2
EXAMPLE	sheep (+)	dogs (-)	horses	chickens
TRIAL 1	aluminium (+)	lead (+)	copper	tin
TRIAL 2	Earth (+)	weather satelite (-)	Uranus	Sun
FILLER	physicists (+)	engineers (+)	mathematicians	carpenters
FILLER	cobras (+)	iguanas (-)	pythons	sea turtles
	fillers helpful sampling			
	premise 1	premise 2	conclusion 1	conclusion 2
EXAMPLE	sheep (+)	cows (+)	horses	pigs
TRIAL 1	aluminium (+)	brass (-)	copper	lead
TRIAL 2	Earth (+)	Mars (+)	Uranus	Sun
FILLER	cobras (+)	pythons (-)	vipers	anacondas
FILLER	physicists (+)	mathematicians (+)	chemists	carpenters

200 participants on MTurk

Adding negative evidence as a "hint" produces the effect, as before



Presenting it as an arbitrary fact makes the effect vanish…



- The social aspect to inductive reasoning is central
  - By default, people seem to "read" an inductive argument as if it were put together for a <u>purpose</u>
- Pedagogical sampling as normative standard
  - In real life, arguments <u>aren't</u> collections of facts
  - They're acts of <u>persuasion</u>
  - If so, shouldn't "normative" accounts reflect that?



Let’s make the social aspect explicit:

The role of goals and social reasoning when aggregating expert opinions

Navarro, Dry & Lee (2012). Sampling assumptions in inductive generalization. *Cognitive Science*

Hendrickson, Perfors & Navarro (in preparation). One cat, two cats: Sampling models in different category learning tasks produce qualitatively different inductive generalisations

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You're a journalist writing an article about expert opinions about climate change…

You're a journalist writing an article about expert opinions about climate change…

93% likely

95% likely

97% likely

92% likely

99% likely

91% likely

89% likely

You're a journalist writing an article about expert opinions about climate change…

93% likely

95% likely

97% likely


5% likely

92% likely

99% likely

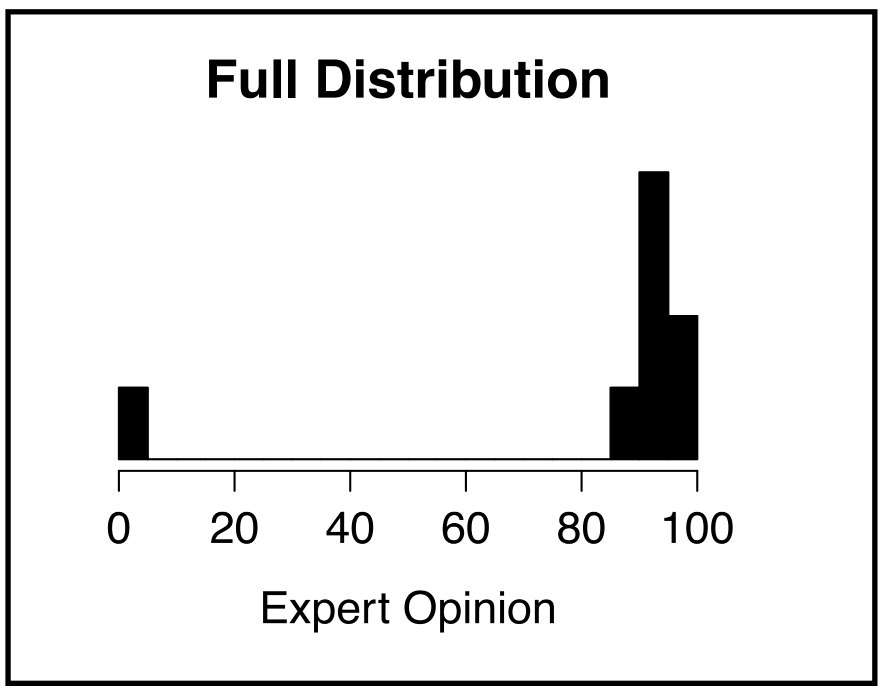
91% likely

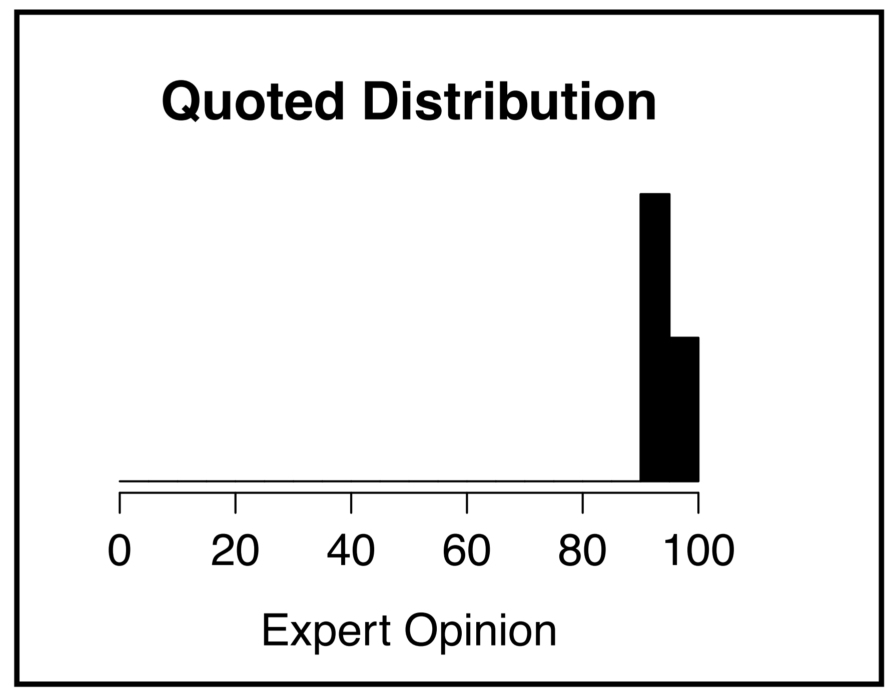
89% likely

Here's your full distribution of expert opinion

Your editor says the article only has room for (at most) three quotes. Who to choose??

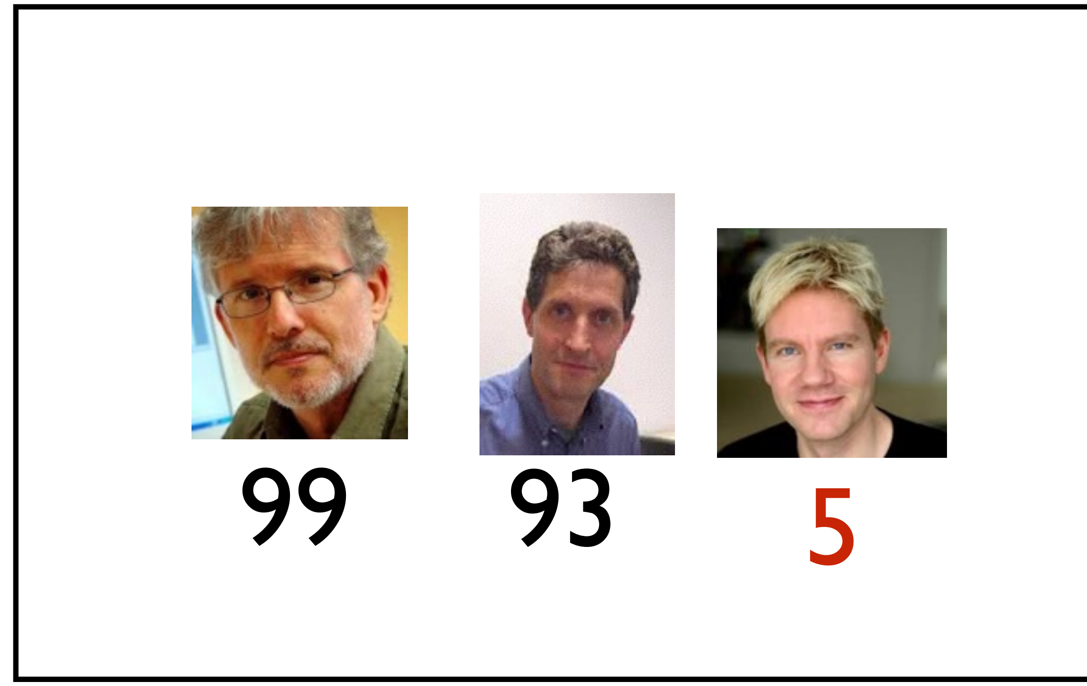
Do you quote only from the consensus?

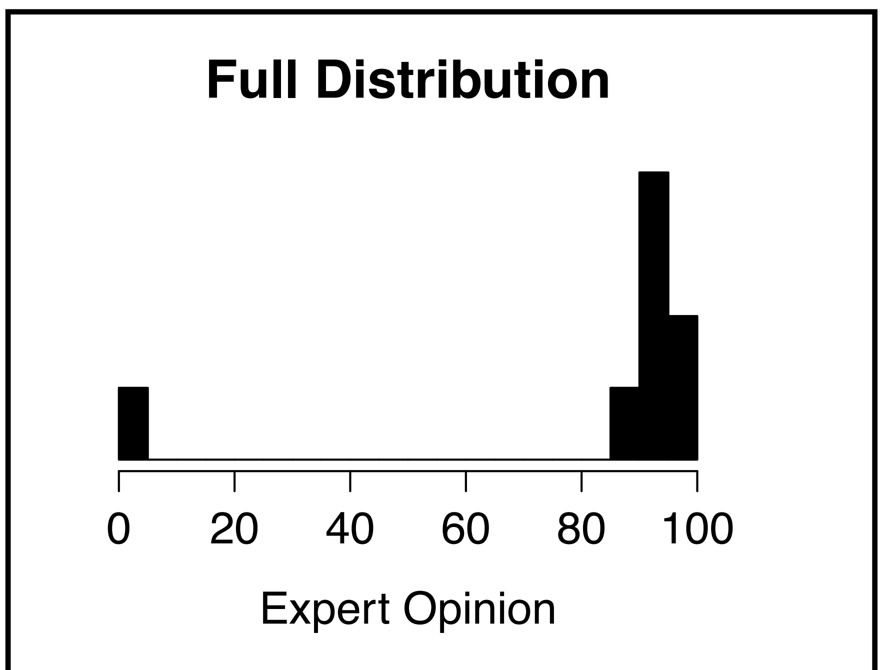


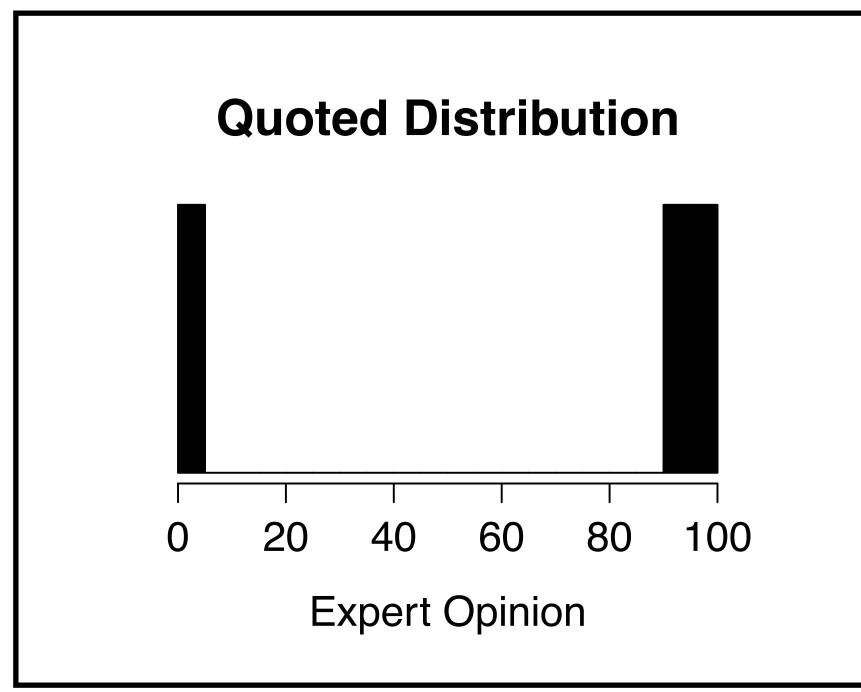


(maximises distributional similarity)

Or do you include the dissenter?

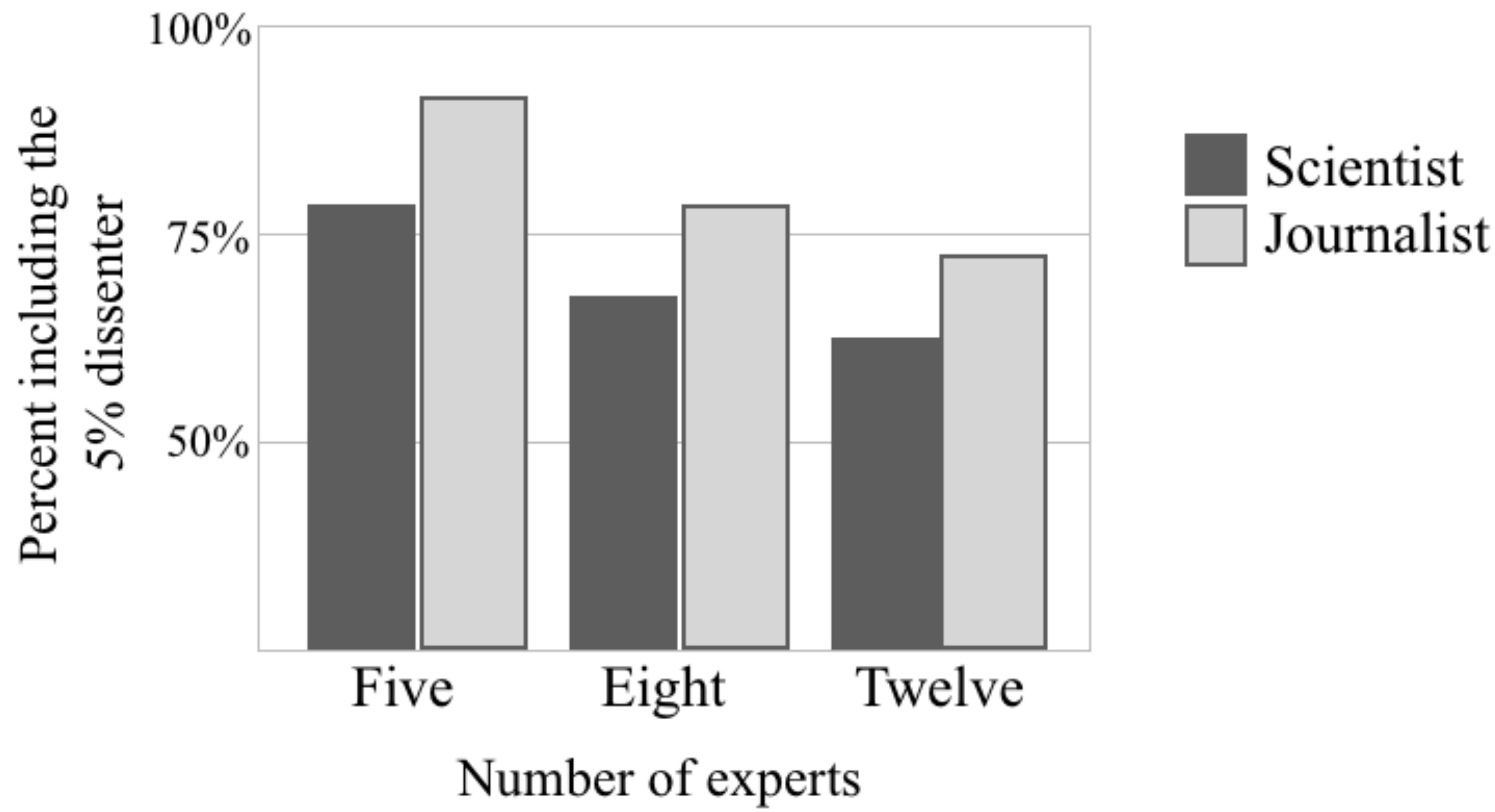


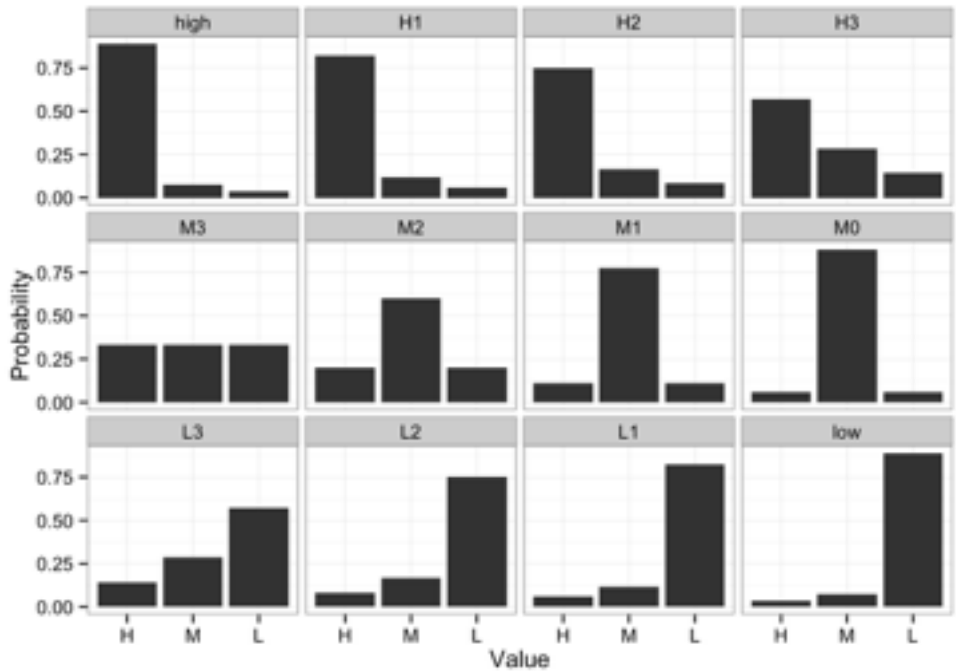




("full spectrum" but terrible approximation)

Some empirical data. Even when outnumbered 11 to 1, most people choose to quote the contrarian.





A hypothesis space of possible expert distributions

A hypothesis space of possible expert distributions

A hypothesis space of possible journalistic agendas

"Helpful" → Communicate the true distribution

"Bias high" → Communicate a distribution with highest/lowest mean

"Bias low" → Communicate a distribution with highest/lowest mean

Select evidence to manipulate
the reader's beliefs

Bayesian writer

Bayesian reader

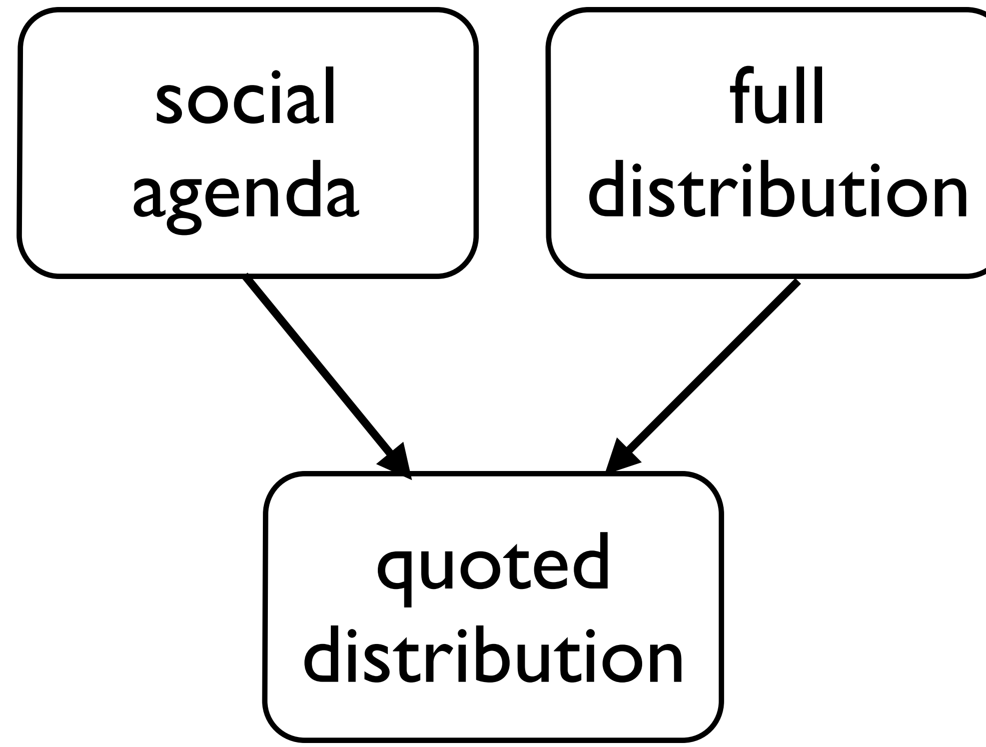
Select evidence to manipulate
the reader's beliefs


Bayesian writer

Bayesian reader

Guess the true distribution AND
infer the journalistic agenda

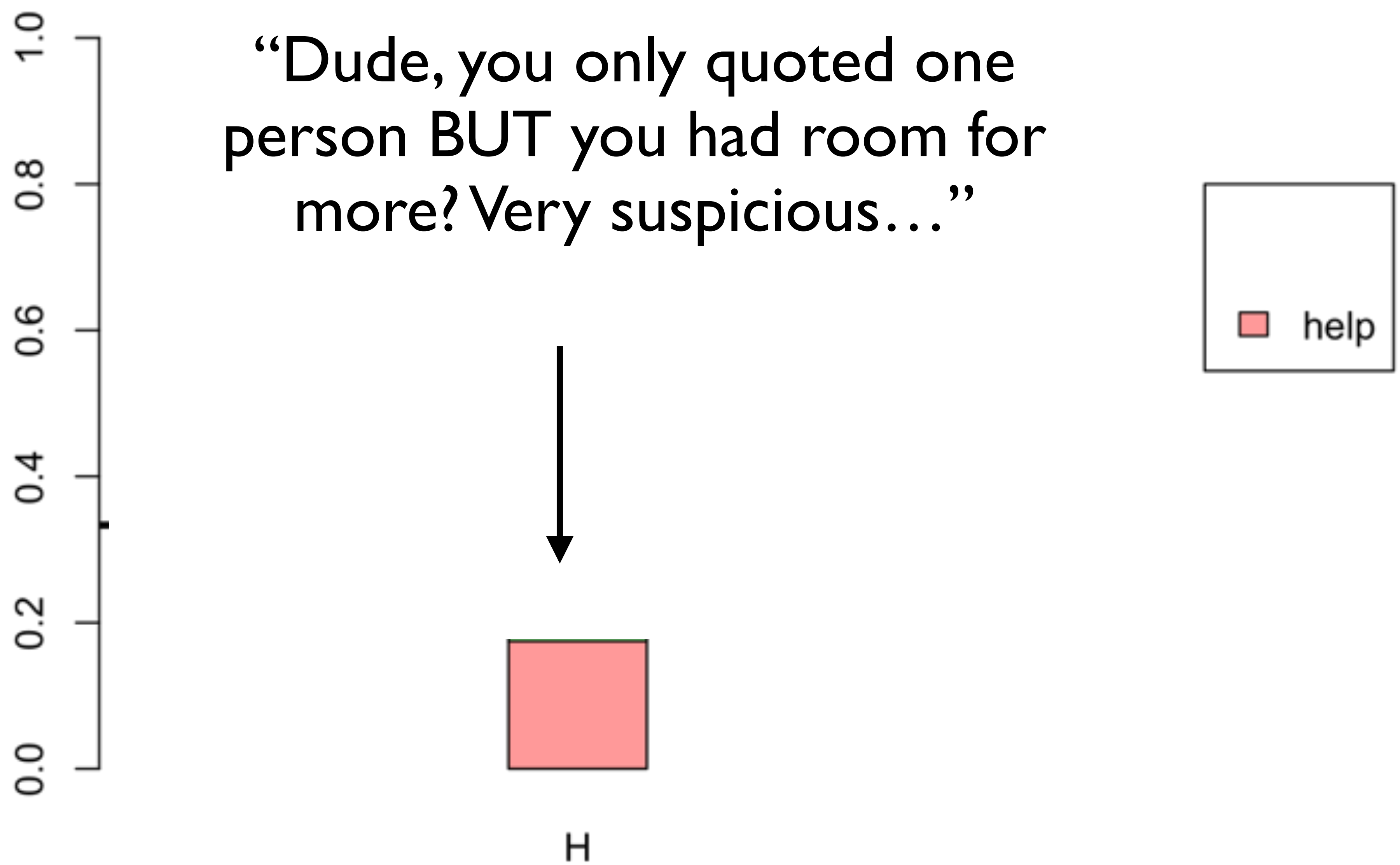
So what does a Bayesian reader infer about the Bayesian writer?



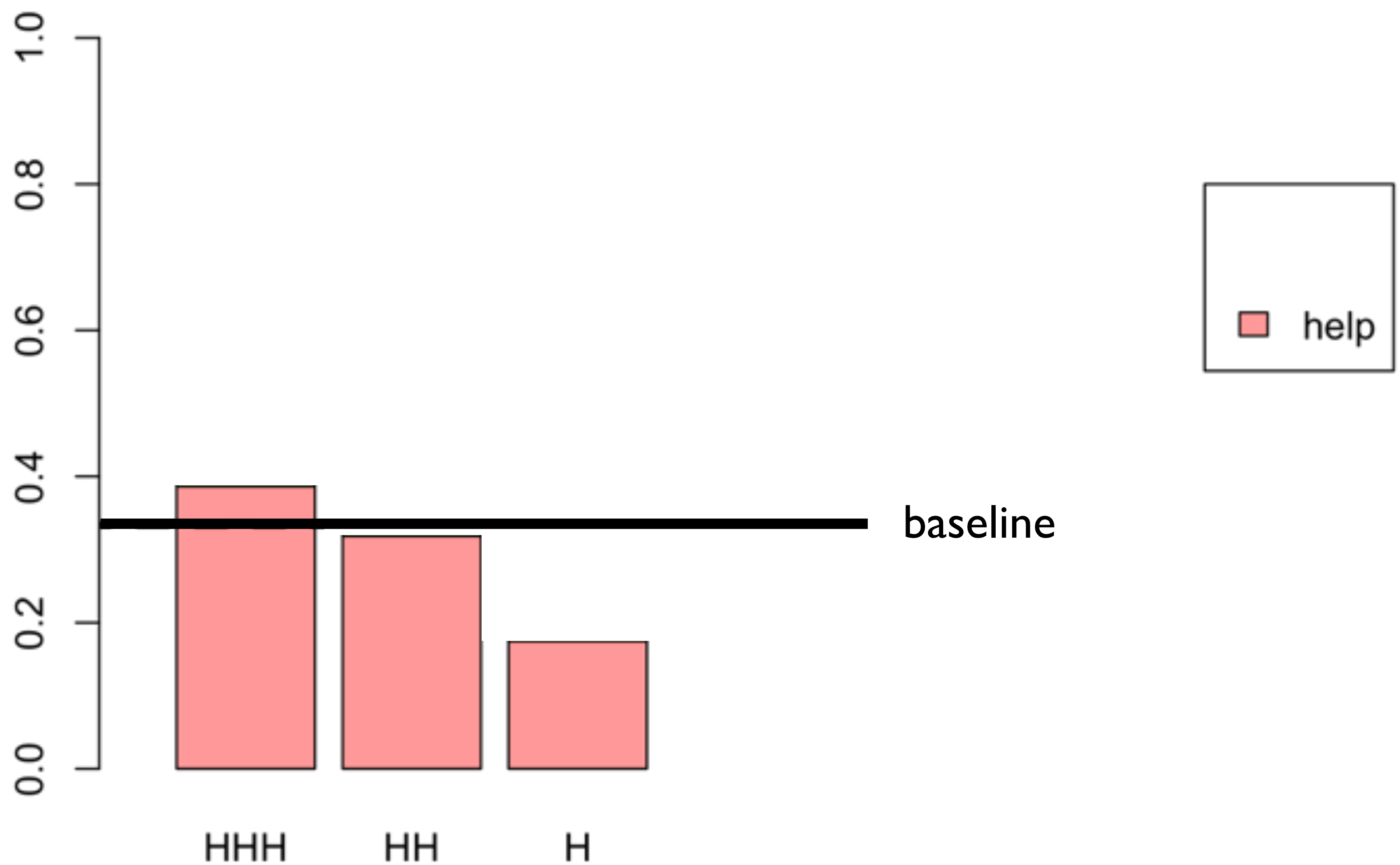
(I'll assume uniform priors over possible agendas and over possible distributional hypotheses)

Quoting one expert only looks suspicious

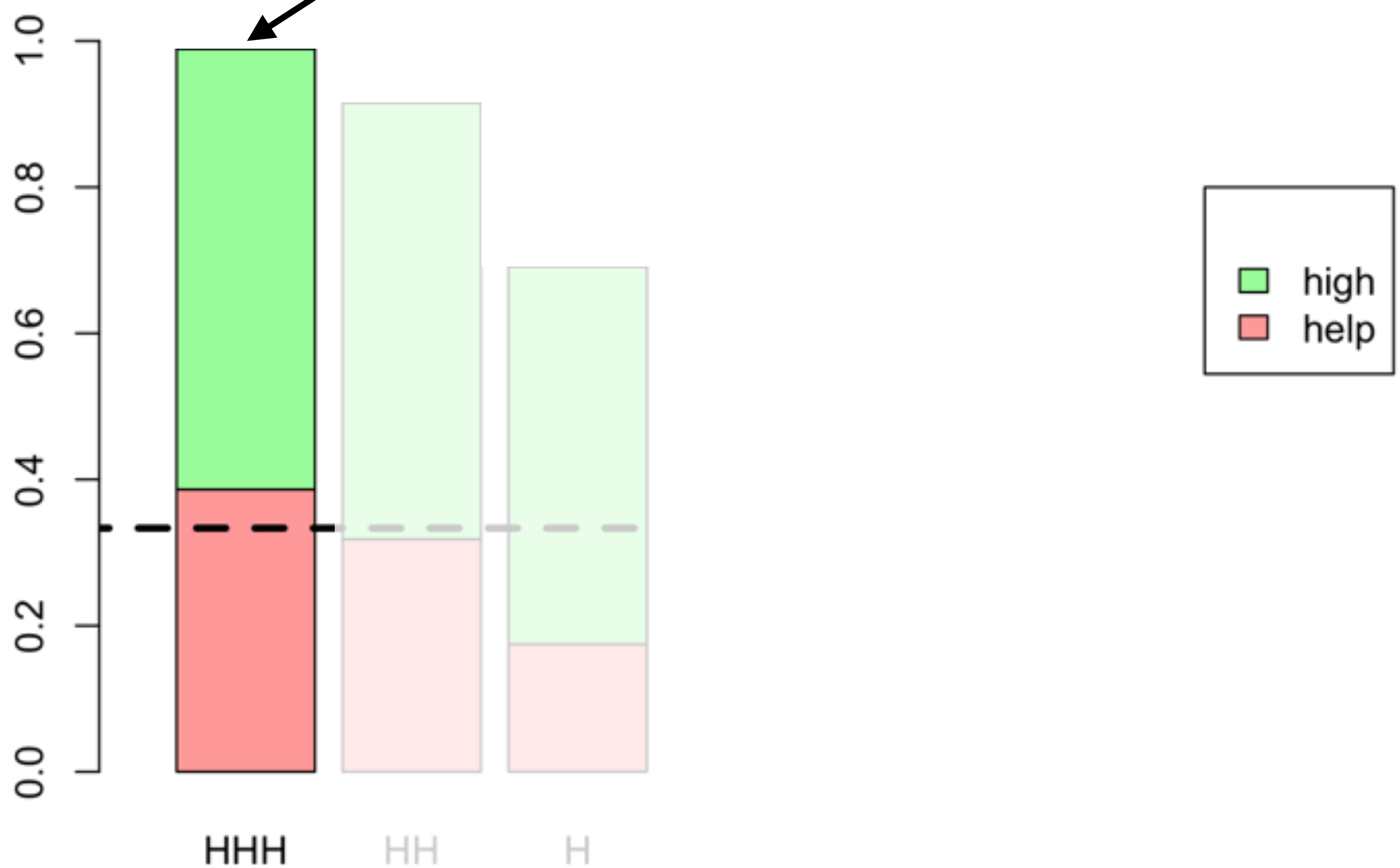
"Dude, you only quoted one person BUT you had room for more? Very suspicious…"



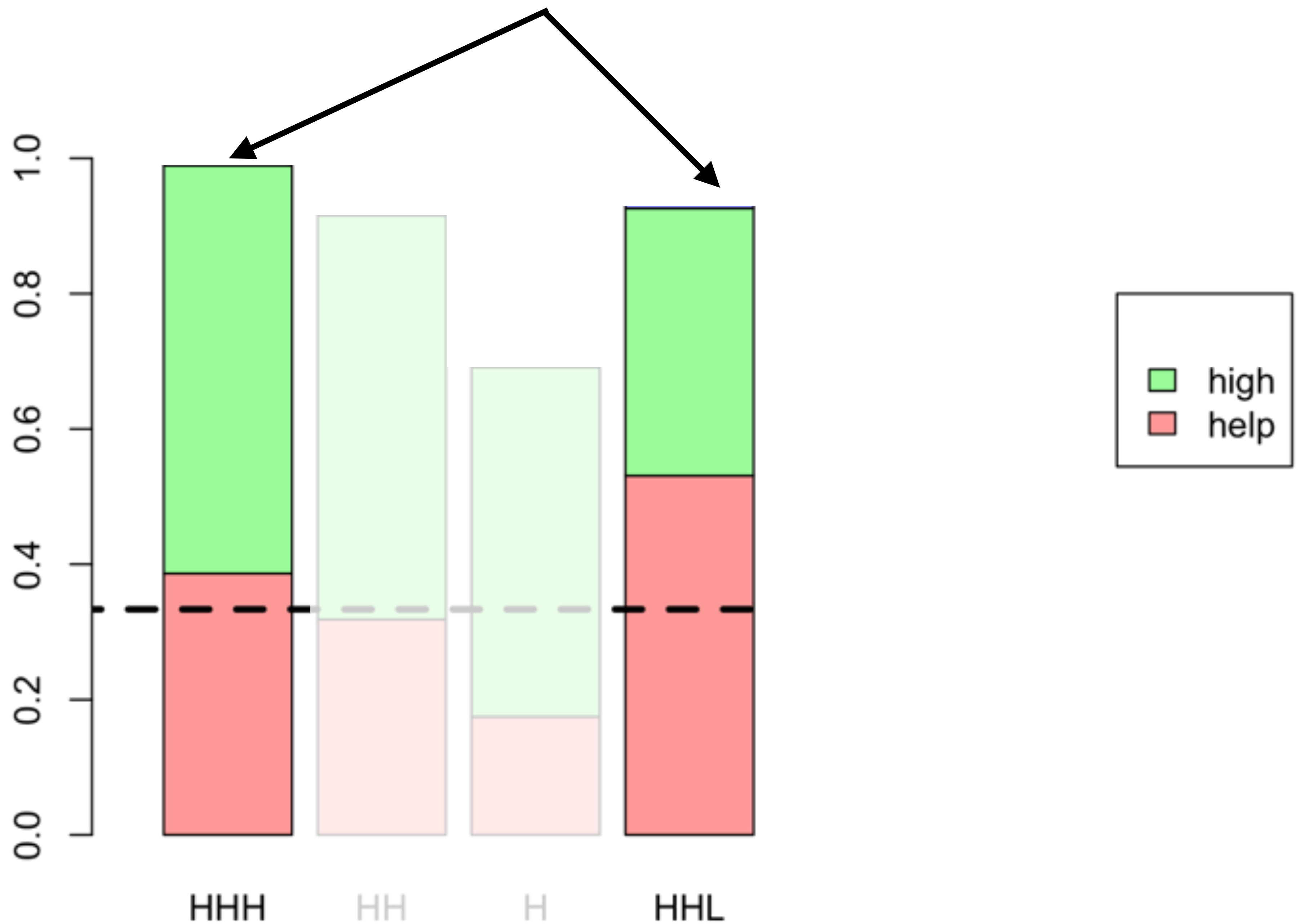
Anything less than maximum number of experts causes a deterioration of trust



But when all the quoted experts agree, the reader thinks you're probably biased

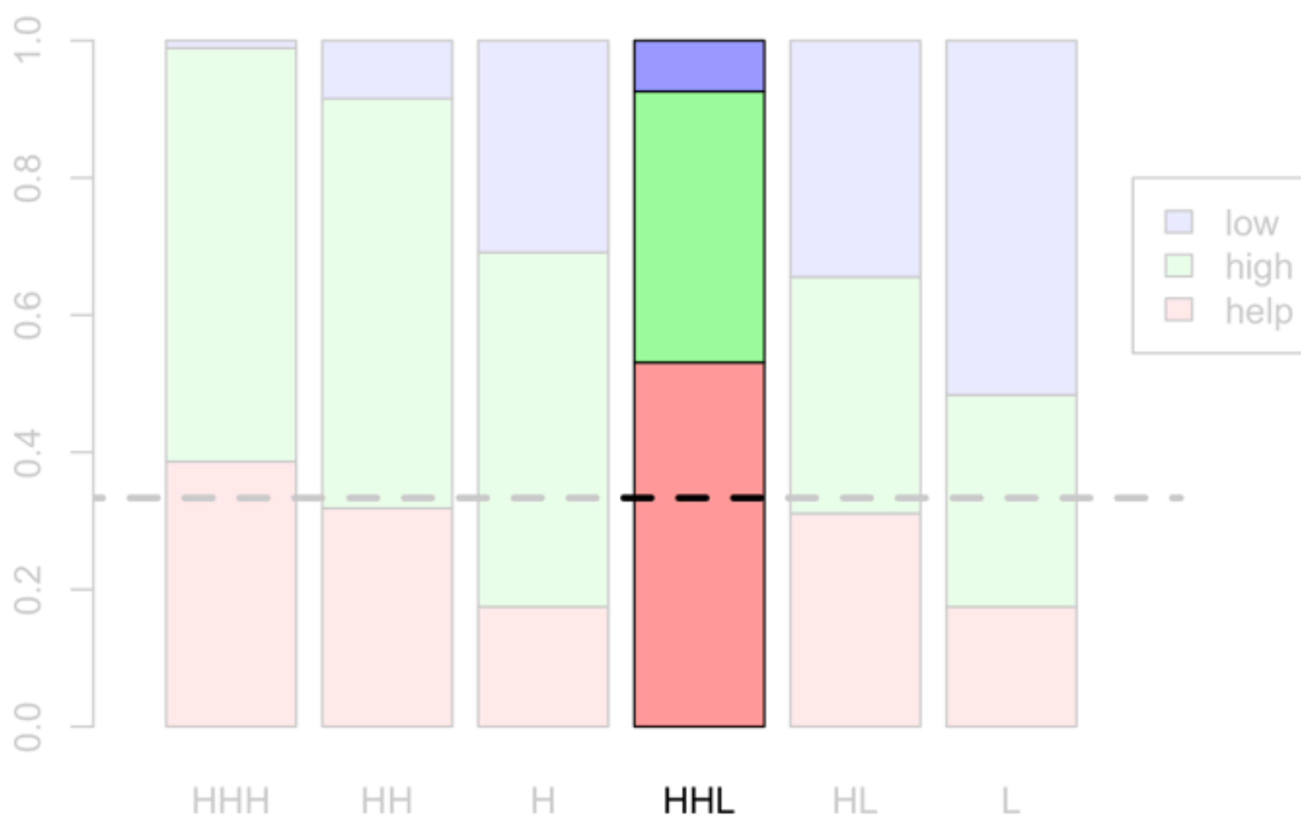


You can increase the reader's trust by including the contrarian



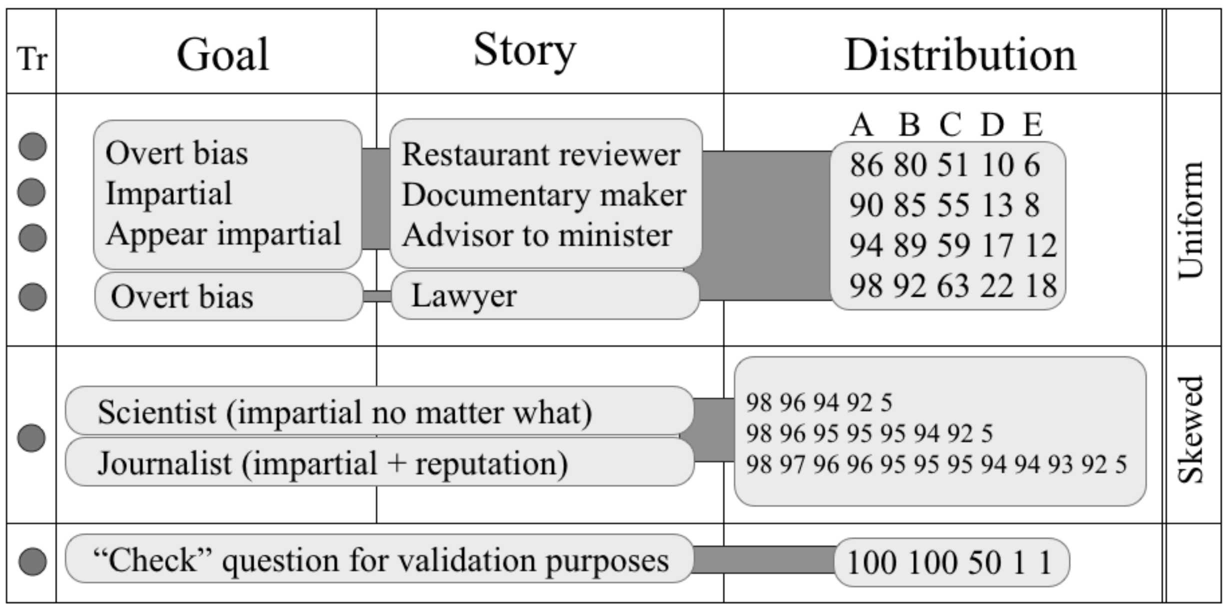
A Bayesian journalist who cares about their reputation has a strong motivation to pursue “he says she says” journalism

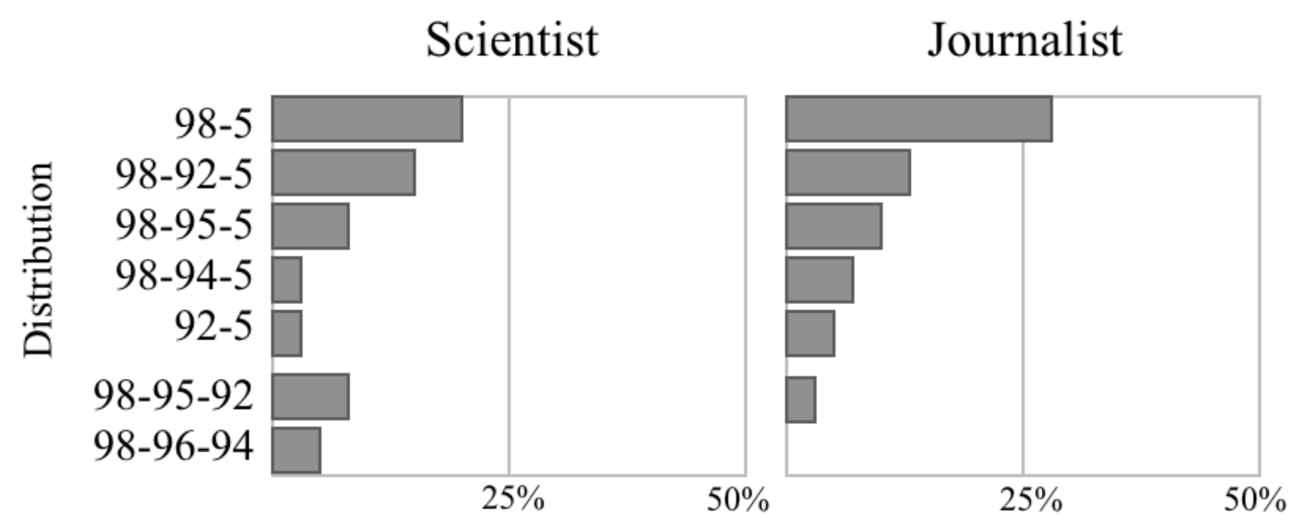
A Bayesian journalist who cares about their reputation has a strong motivation to pursue "he says she says" journalism

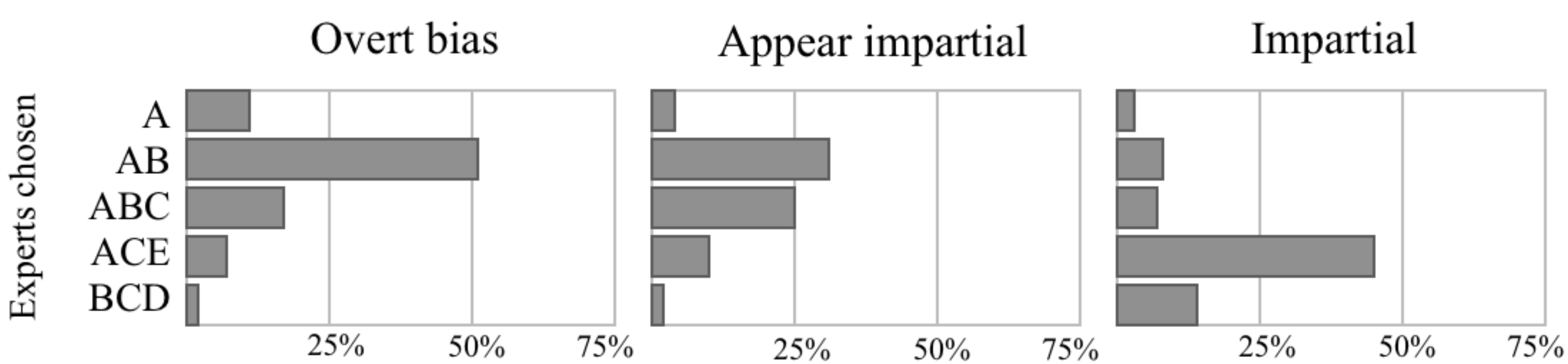


Because a Bayesian reader can't tell the difference between journalistic bias and expert consensus

Oh, and we have a heap of other data and modelling on this too, but I have no time…

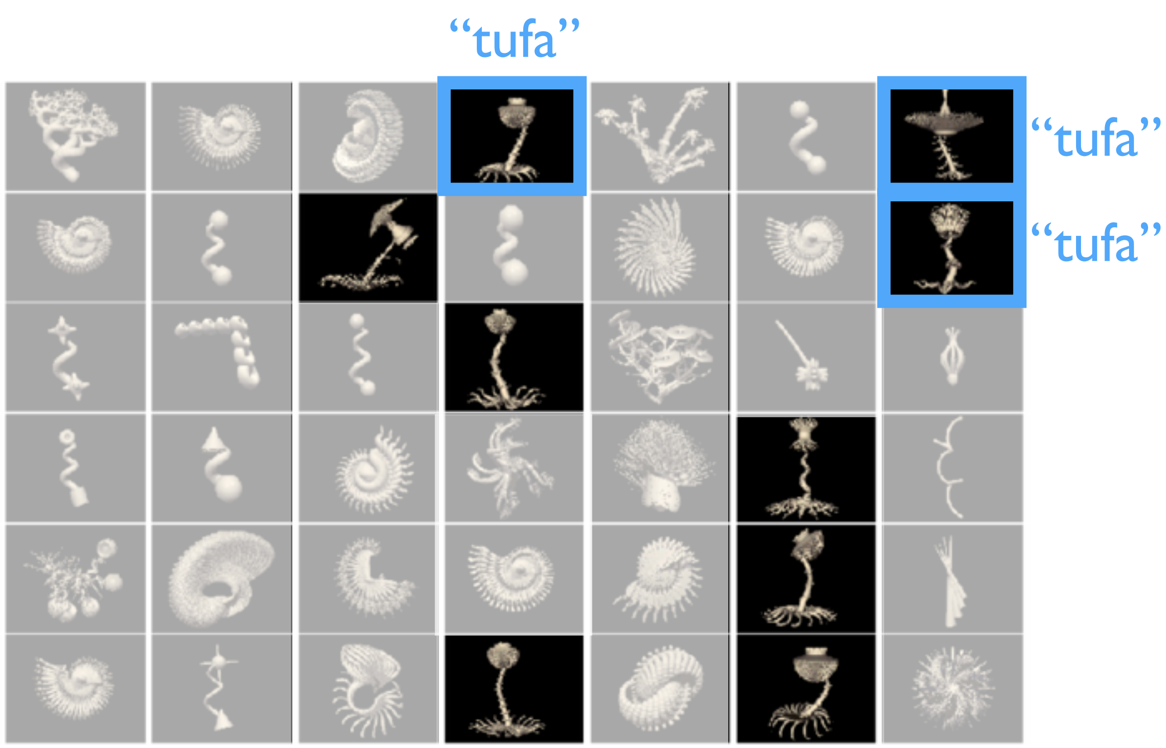


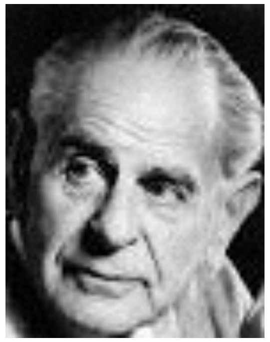




A few final thoughts about human reasoning and Bayesian reasoning

Traditional accounts of learning and inference specify norms that implicitly rely on something like falsificationist reasoning

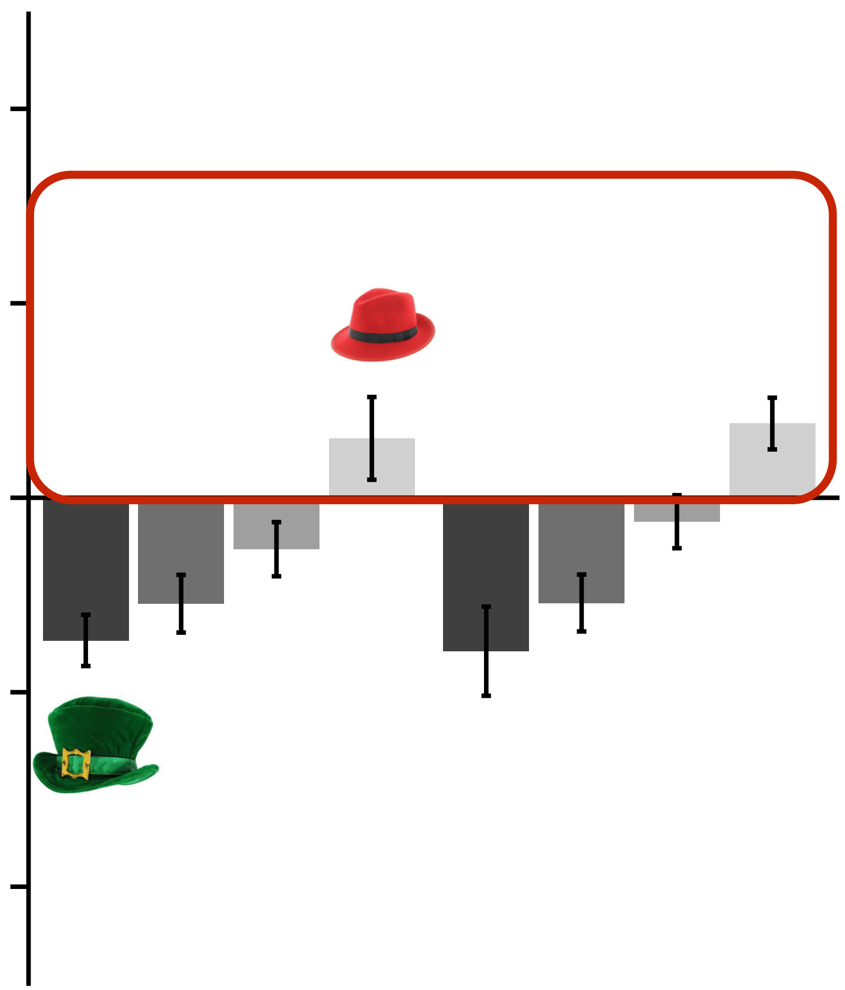




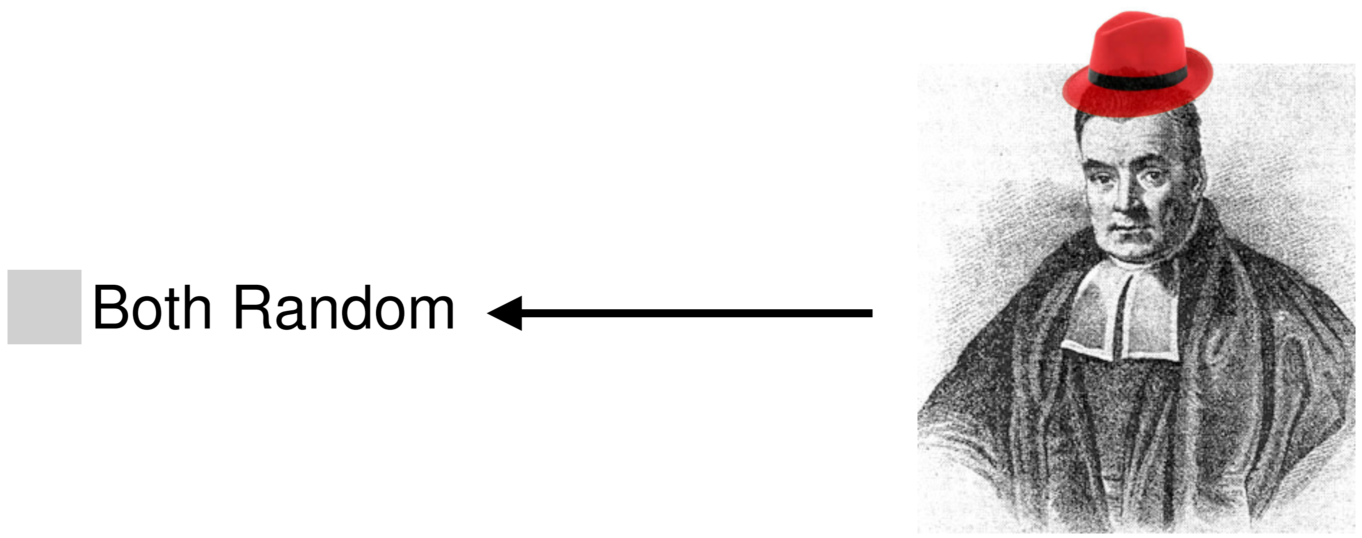
falsificationist learning

weak sampling

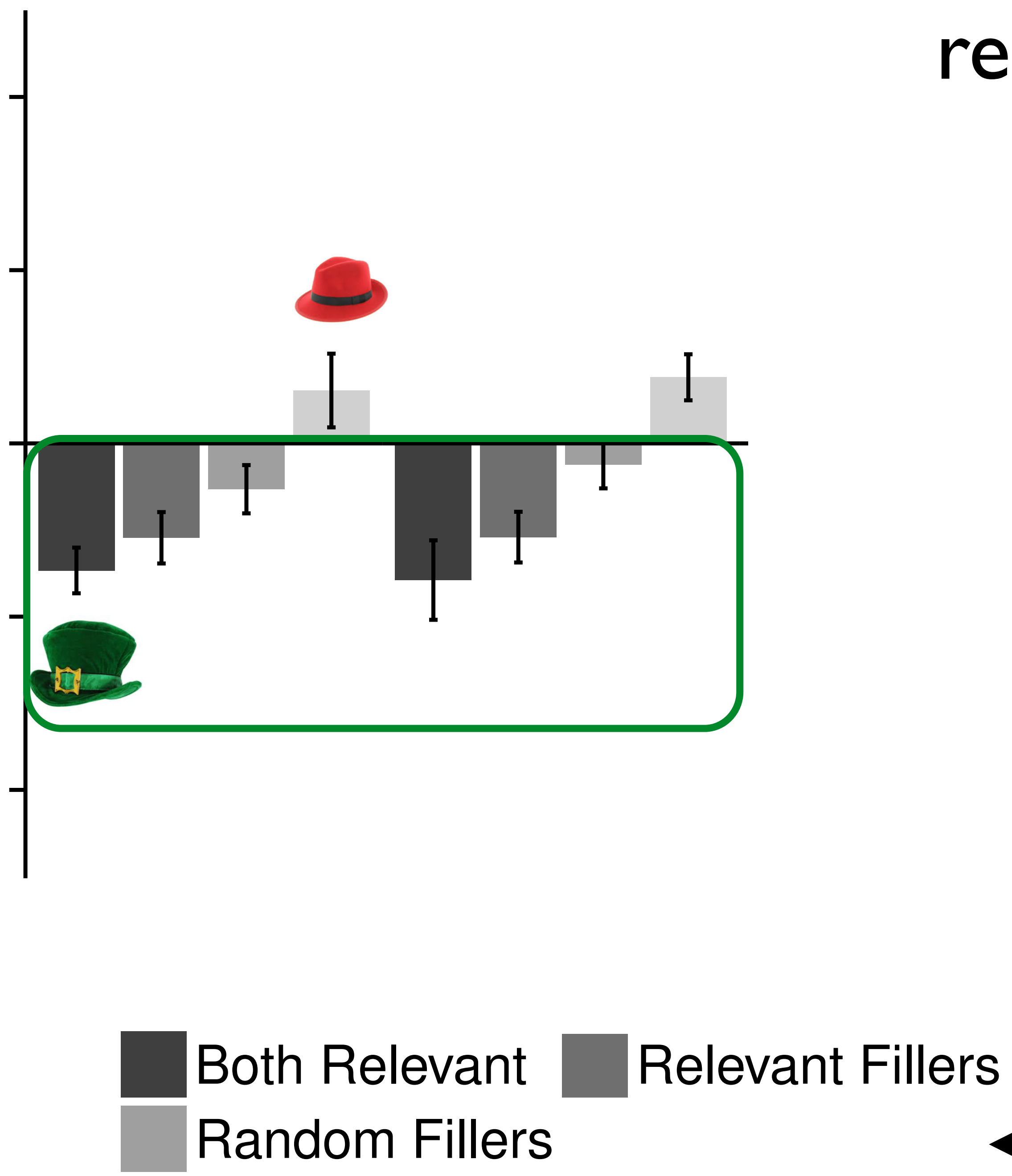
But why?



… it **only** makes sense when evidence is selected in an arbitrary and random fashion



In real life, isn't ANYTHING ELSE a more reasonable theory for the origin of the data????



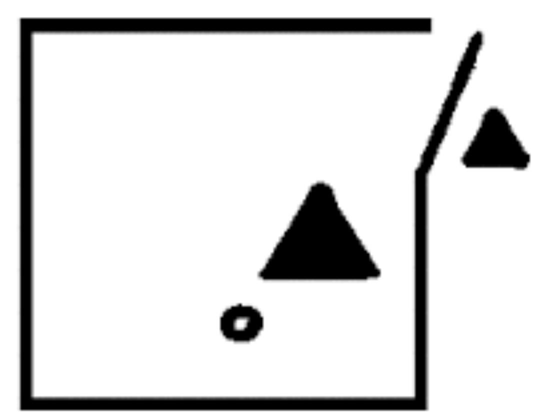
"Common sense" inference requires people to learn from complex (and smart) data sources…

We need to disentangle facts from agendas

We need to
detect trickery

We need to detect novelty and invariances in a dynamic world

We need to read the intention of other agents



Understanding human common sense reasoning requires something a lot richer

Thanks!