Simulating Language
7: Hierarchical models and learning to learn

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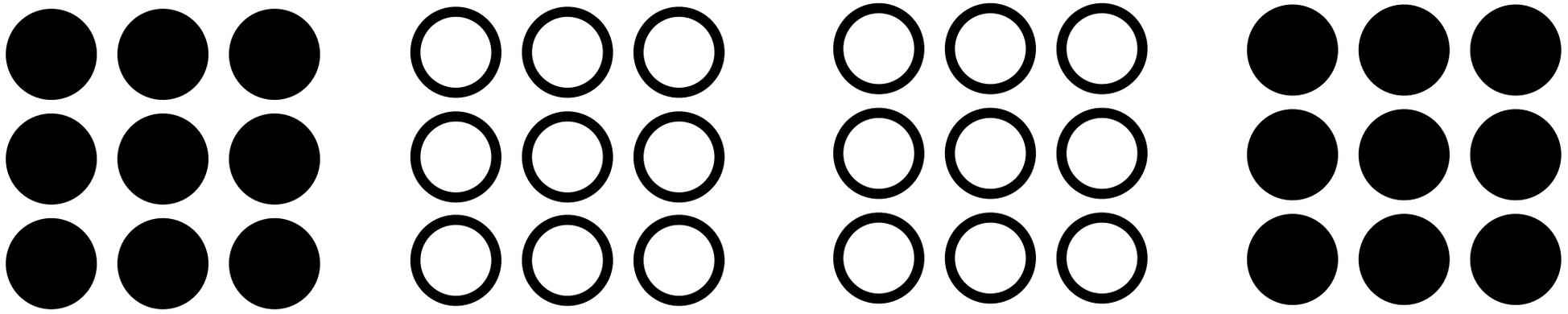
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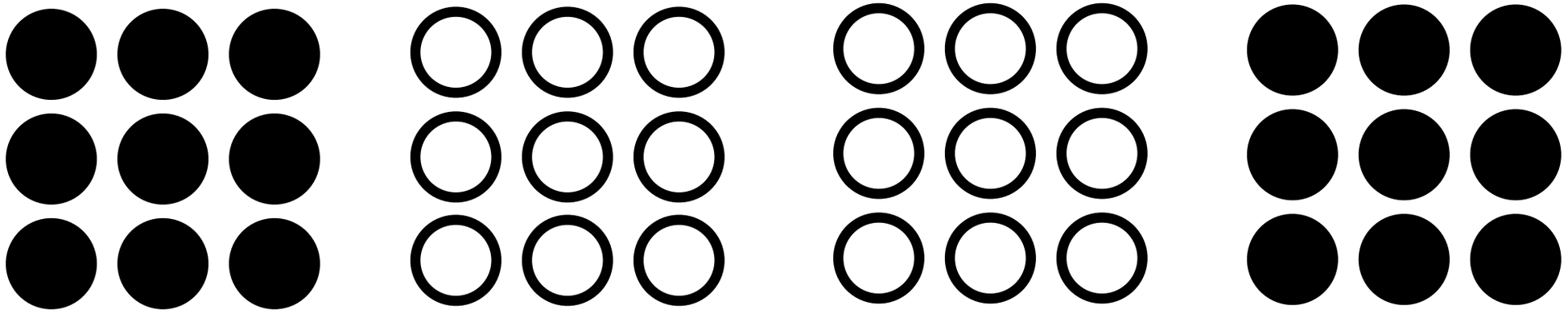
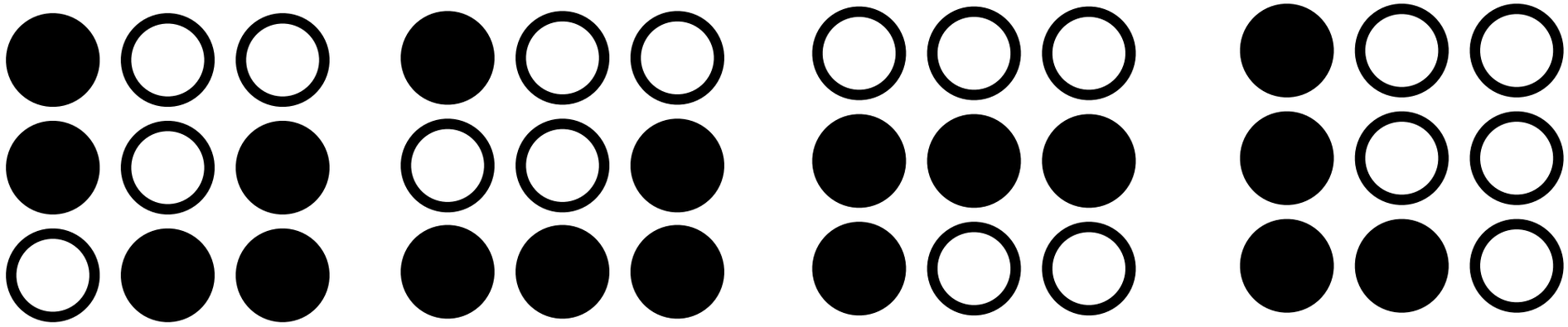


Option 1: Bag E contains marbles, beyond that I cannot say

Option 2: Bag E contains a mix of roughly equal numbers of black and white marbles

Option 3: Bag E contains either exclusively black marbles, or exclusively white marbles



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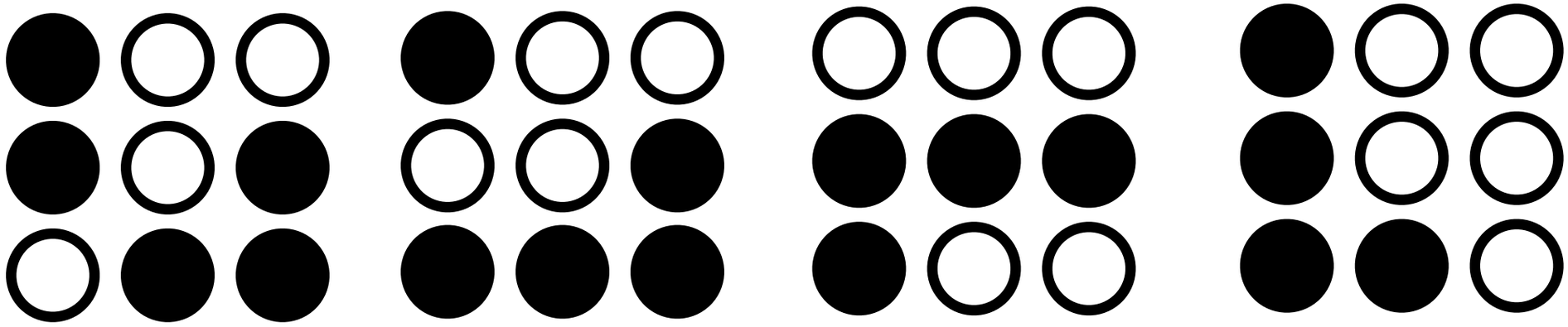
Y
Z



Option 1: Bag Z contains marbles, beyond that I cannot say

Option 2: Bag Z contains a mix of roughly equal numbers of black and white marbles

Option 3: Bag Z contains either exclusively black marbles, or exclusively white marbles

The prior

$$P(h \mid d) \propto P(d \mid h)P(h)$$

Priors include

- Expectations about word meanings (week 3)
- Expectations about regularity / variability (weeks 4-5)
- Expectations about degeneracy / holism / compositionality (week 7)

Where does the prior come from?

$$P(h \mid d) \propto P(d \mid h)P(h)$$

- Could be due to very general constraints on learning (e.g. the simplicity prior used last week)

- Could be due to learning in another domain (e.g. a regularity preference because you've learned the universe tends to be predictable?)

- Could be domain-specific expectations that you are somehow born with (see upcoming weeks for a model of this!)

- **Could be learned domain-specific expectations**

Motivating examples involving language, not marbles: reminder of some stuff from lecture 2

Quine (1960): meaning underdetermined by data

- The four legged animal
- The two legged animal
- Some part of either (the leg, the hat, …)
- Some property of some part (the length of the leg, the material of the hat)
- Nothing to do with what you're seeing ("I'm hungry")
- Something weirder (a wet nose and a waggable tail, but only until Scotland win the World Cup)

There are in principle **infinitely many possible meanings** for "doggy" which would be consistent with this usage, and **any possible sequences of usages**

Learners must have **some** constraints on word meaning

Minimally: to rule out the extremely wacky word meanings

But maybe they are more detailed:

- Expectations about meanings (e.g. words refer to whole objects, words refer to basic-level categories, words generalise by shape of referent, …: Macnamara, 1972; Markman, 1989; Landau, Smith & Jones, 1988)

- Expectations about words (e.g. word meanings are mutually exclusive: Markman & Wachtel, 1988)

- …

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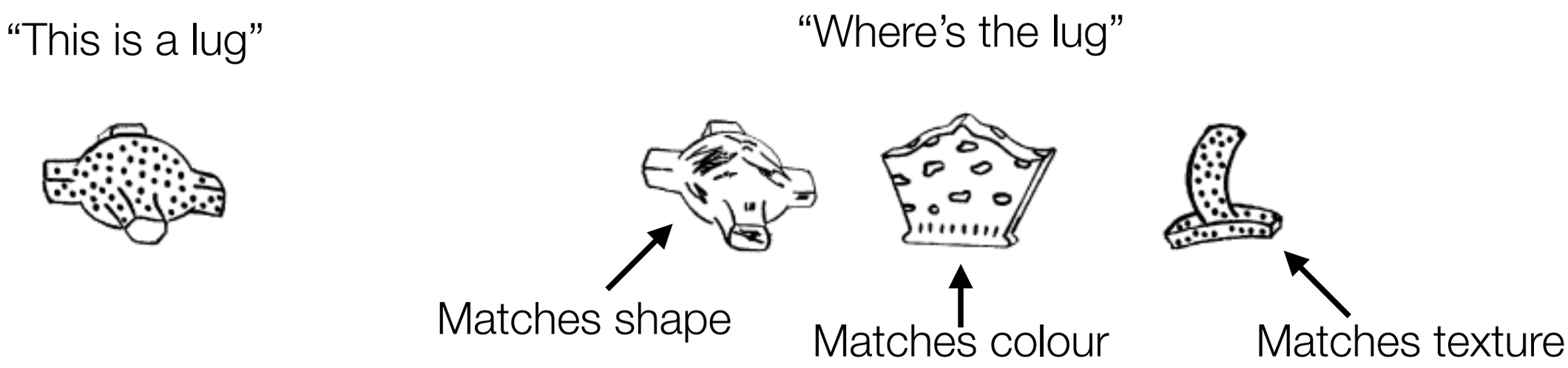
- …

The shape bias

- In English, shape of objects is the most reliable cue to category membership, and therefore the most reliable cue to object names
  - i.e. concrete count nouns tend to generalise by shape, not texture, colour, material etc: cups are cup-shaped, chairs are chair-shaped, trousers are trouser-shaped, …

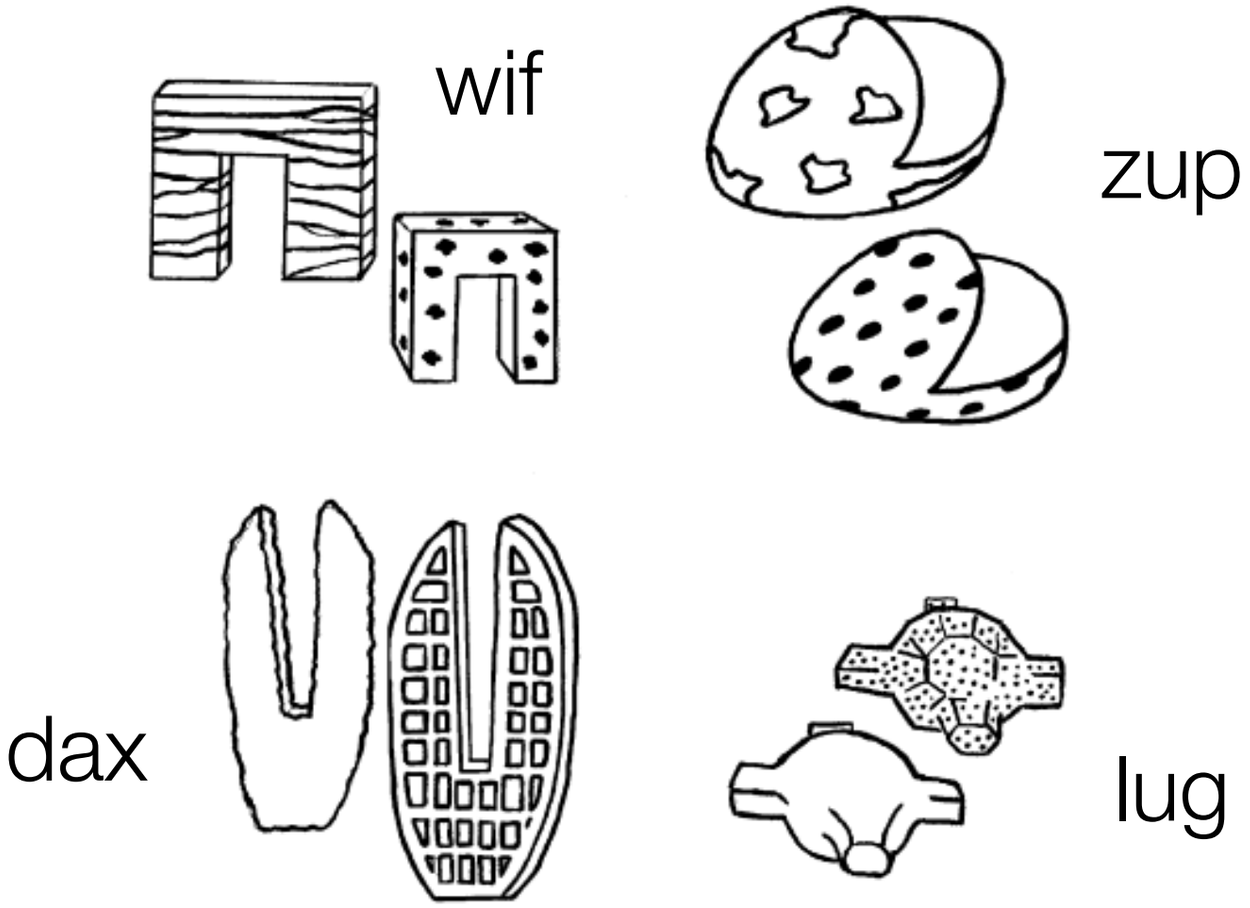
- Children aged 3+ seem to be aware of this, and systematically generalise new object names by shape (e.g. Landau et al., 1988): **the shape bias**



Learning the shape bias (L. Smith et al, 2002)

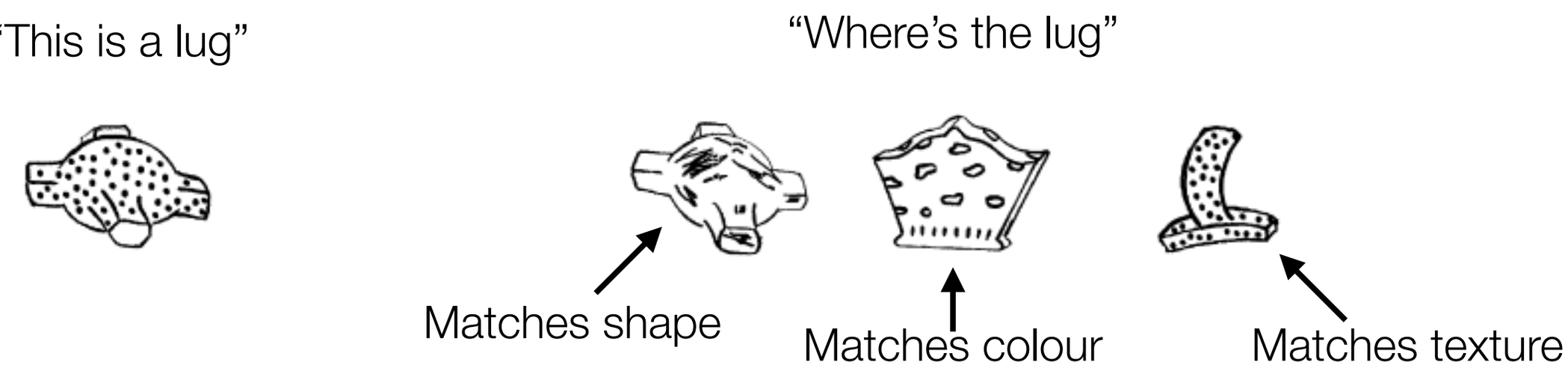
- 18 month old English-speaking children (i.e. too young to show the shape bias)

- Experimental group get 7 week training programme on novel objects whose labels generalise by shape



Learning the shape bias (L. Smith et al, 2002)

- Week 8: first-order generalisation test with trained label and 3 novel objects

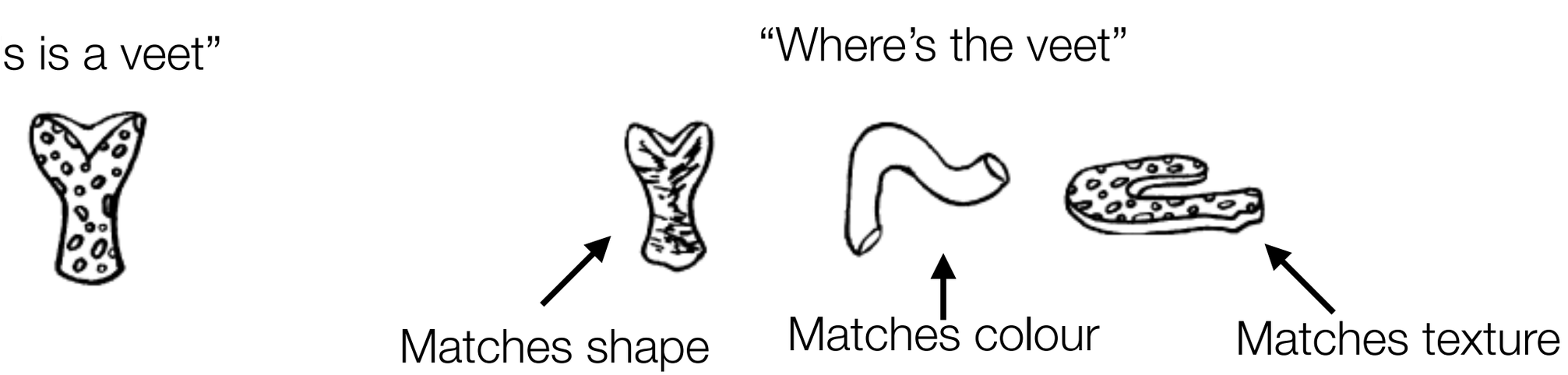


- Control group: 36% generalise by shape (i.e. chance)

- Trained children: 88% generalise by shape

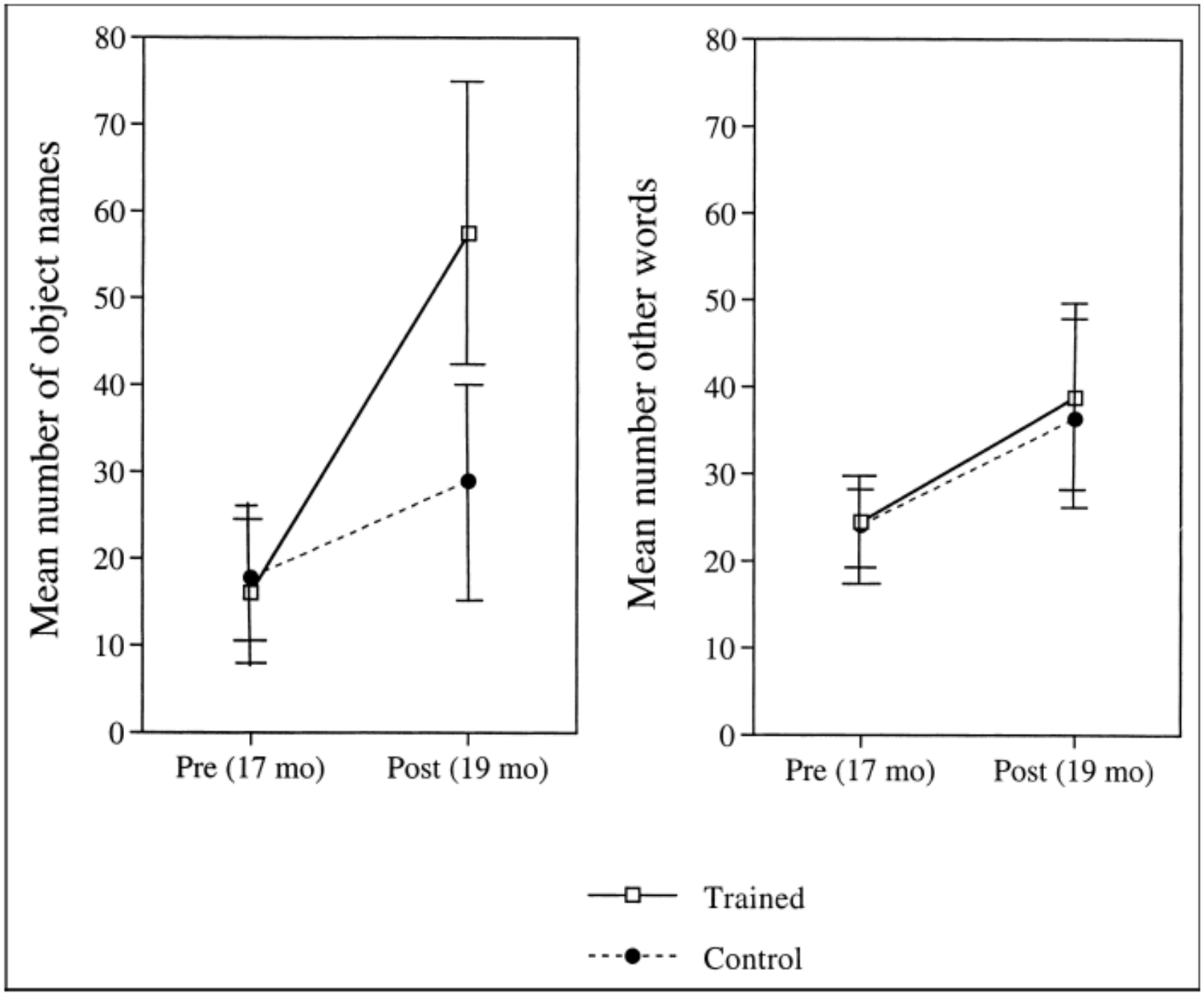
Learning the shape bias (L. Smith et al, 2002)

- Week 9: second-order generalisation test with **novel** label and 3 novel objects



- Control group: 34% generalise by shape (i.e. chance)
- Trained children: **70% generalise by shape**

Learning the shape bias (L. Smith et al, 2002)



How do we capture this in a model?

- Rather than being fixed, the prior is itself learned (and the learned prior can therefore guide subsequent learning)

- We can model learning the prior as a process of Bayesian inference in the usual way

- Of course this means we need a prior over our prior, which is why these models are called **hierarchical**

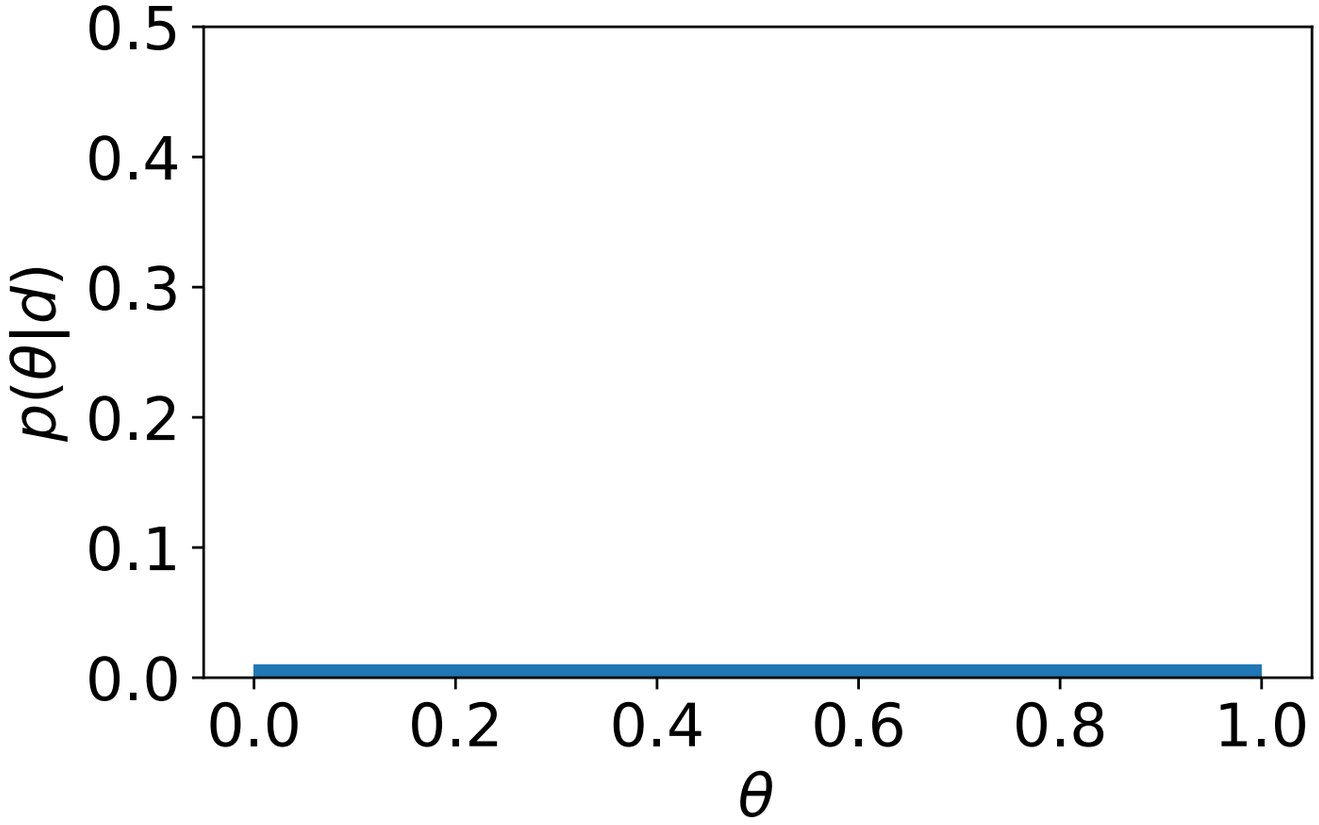
Level 3 γ

Level 2 α

Level 1 θ

Data d

$\alpha = 1$



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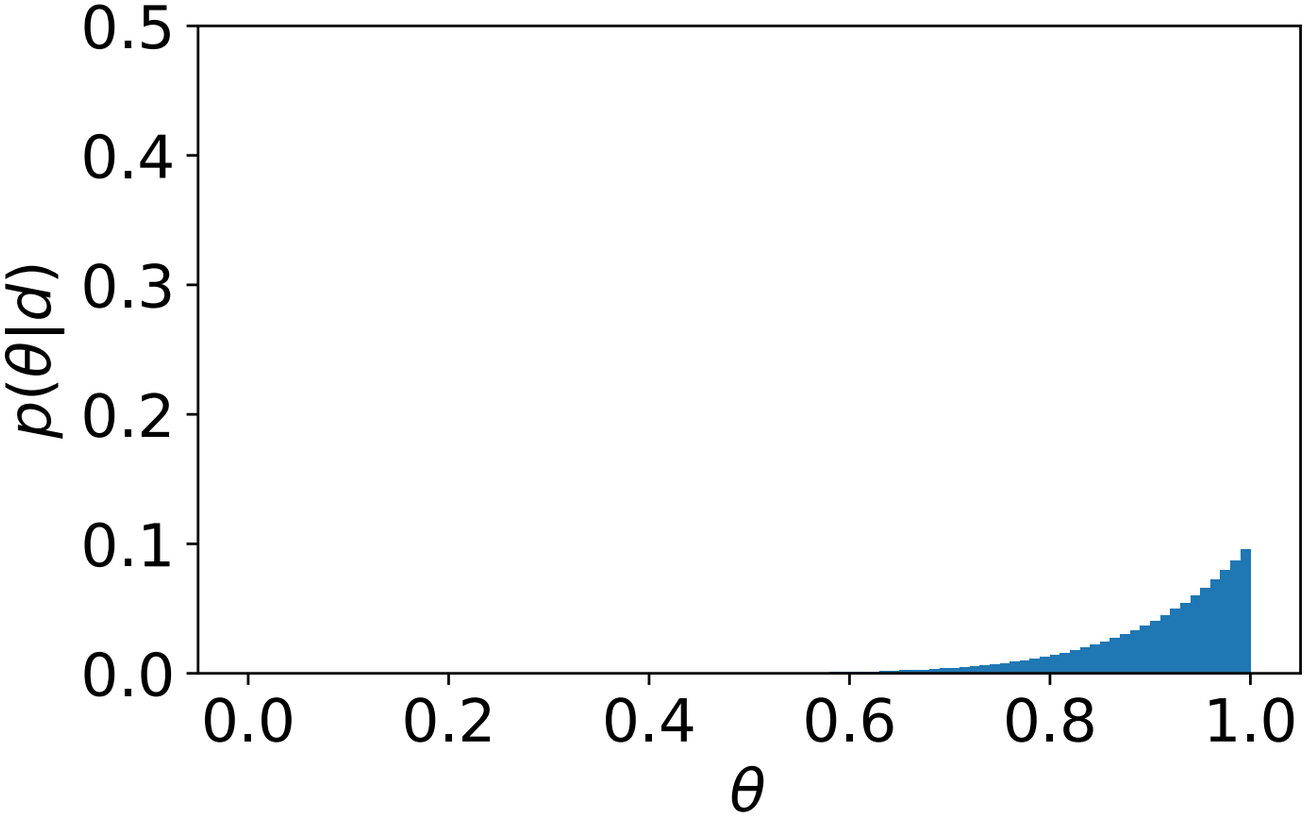
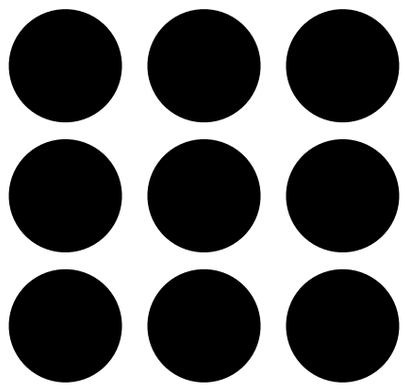
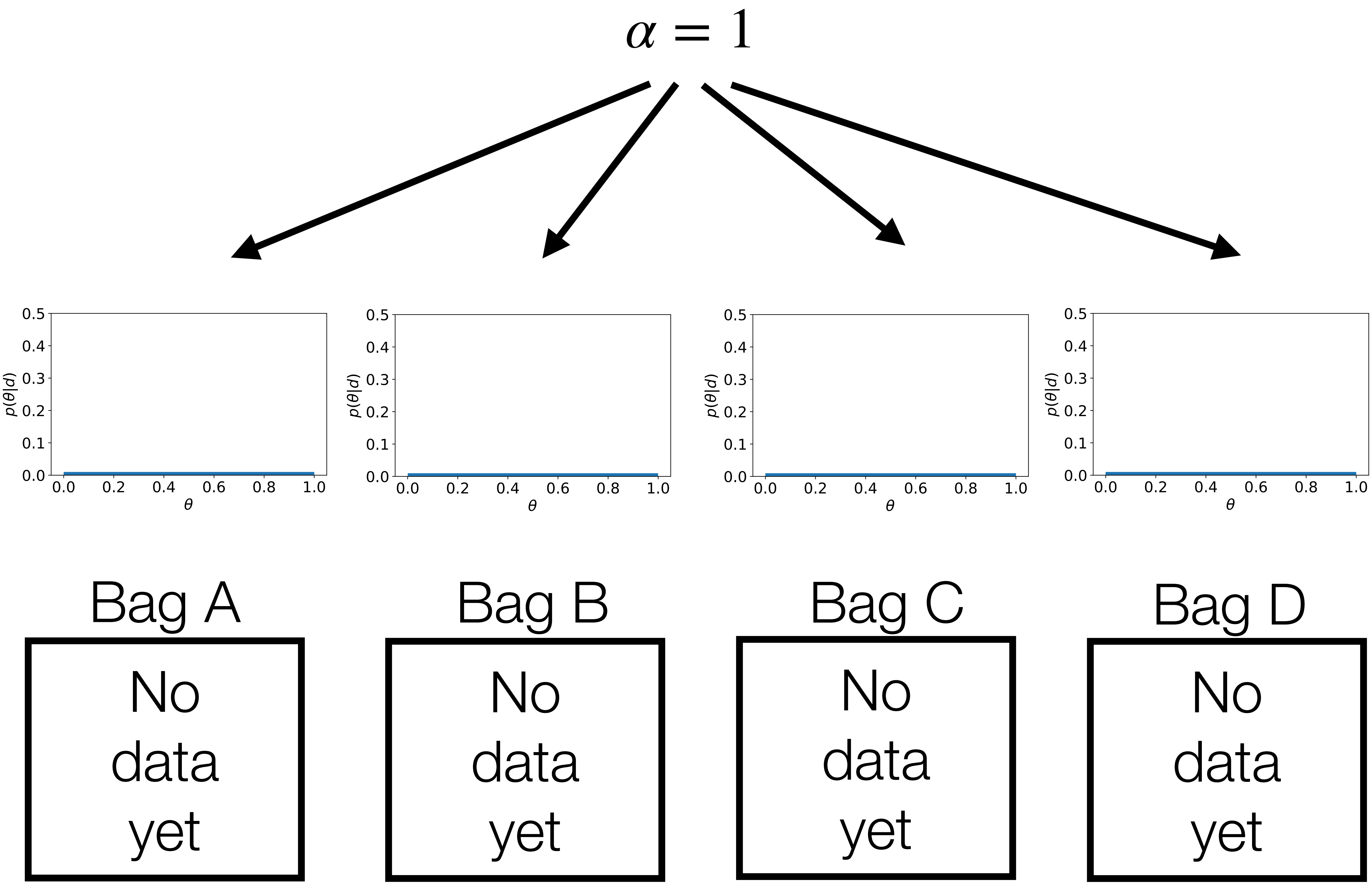
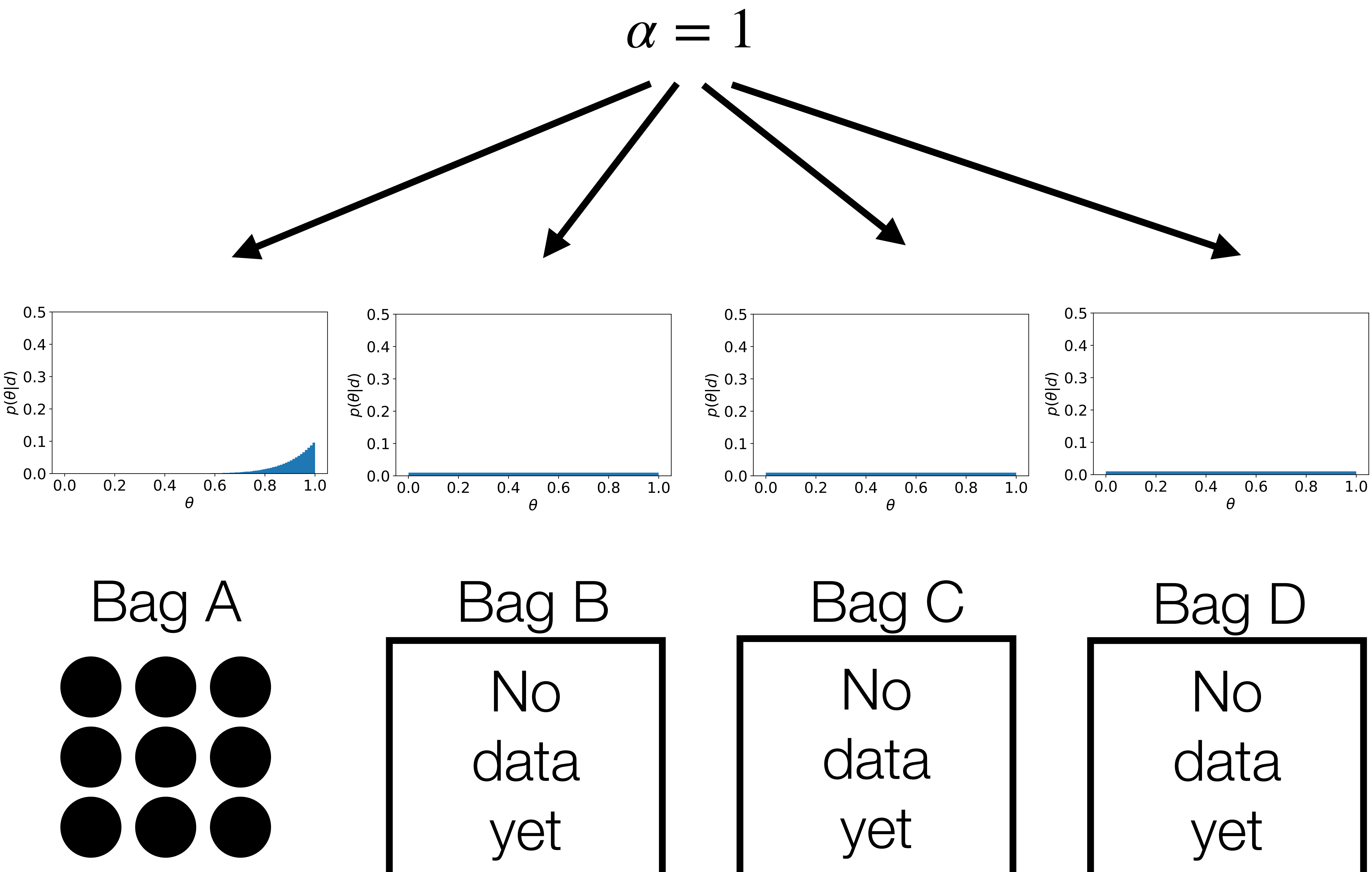
$\alpha = 1$



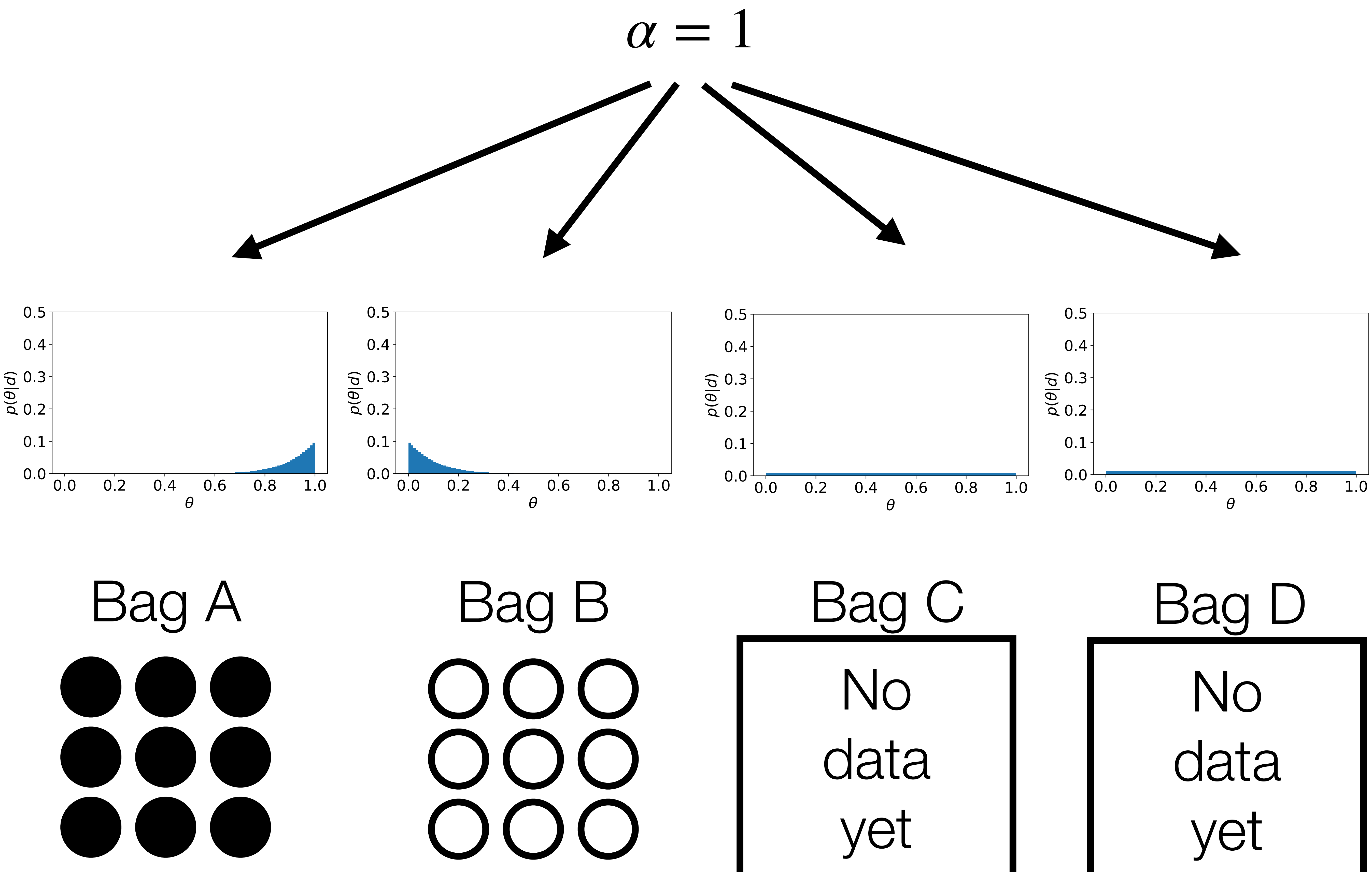




α = 1
p(θ|d)
0.0
0.1
0.2
0.3
0.4
0.5
0.0 0.2 0.4 0.6 0.8 1.0
θ
Bag A
Bag B
Bag C
Bag D
No data yet
No data yet
No data yet
No data yet



$\alpha = 1$
0.5
0.4
0.3
0.2
0.1
0.0
$p(\theta|d)$
0.0 0.2 0.4 0.6 0.8 1.0
θ
Bag A
Bag B
Bag C
Bag D
No data yet
No data yet
No data yet



α = 1
0.5
0.4
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0.1
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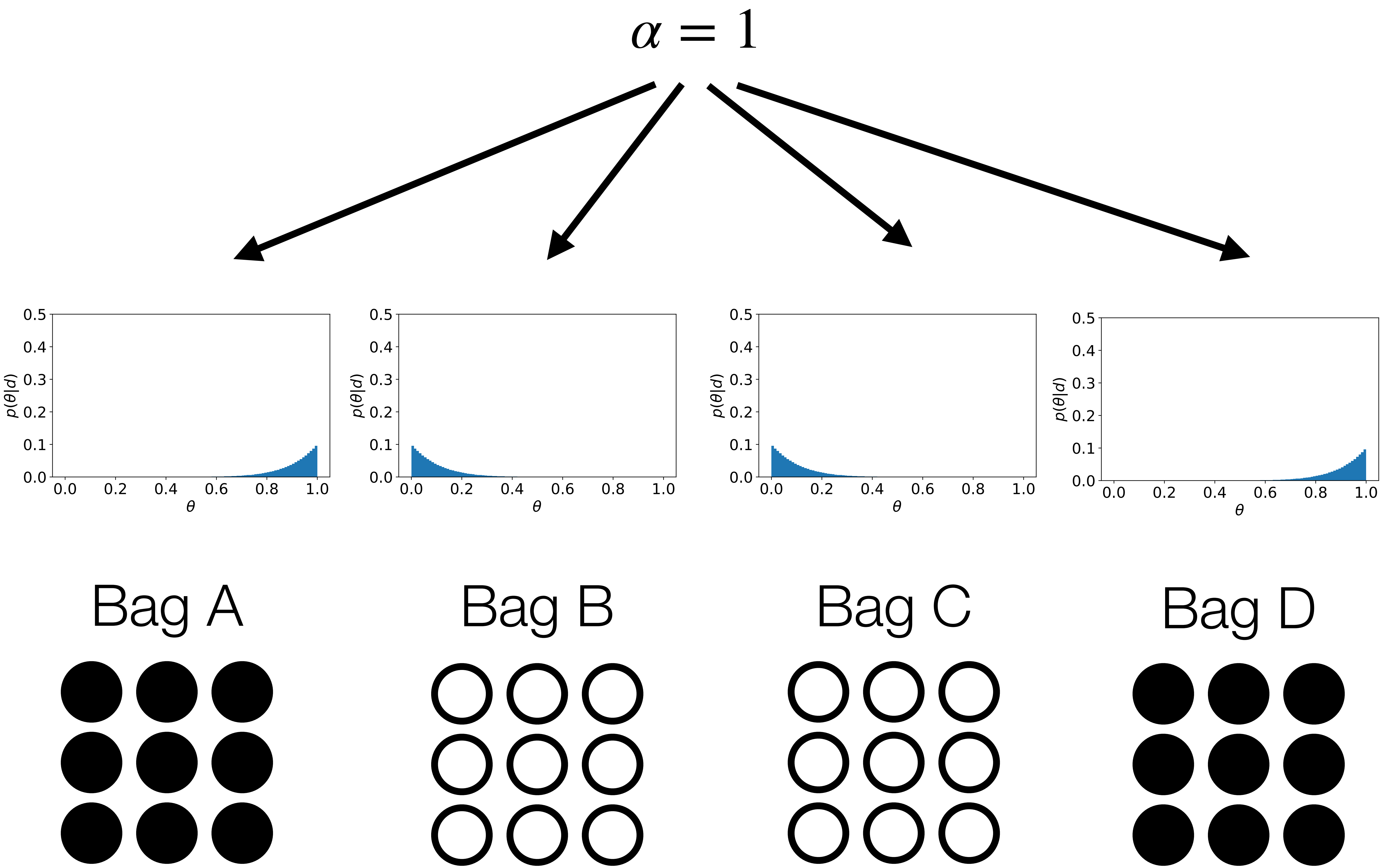
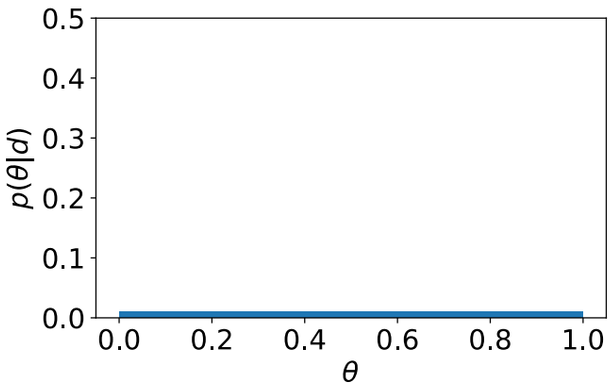
p(θ|d)
0.0 0.2 0.4 0.6 0.8 1.0
θ
Bag A
Bag B
Bag C
No data yet
Bag D
No data yet



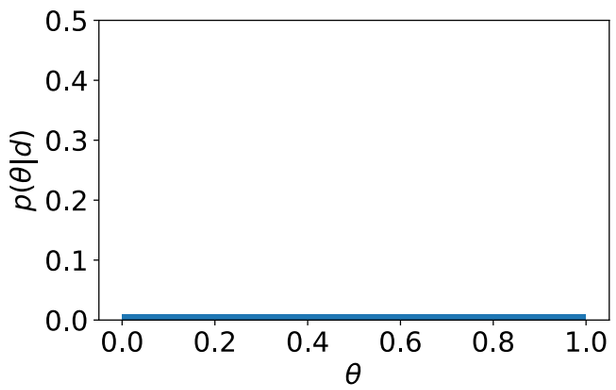
$\alpha = 1$
$p(\theta|d)$
θ
Bag A
Bag B
Bag C
Bag D

$$\alpha = ???$$



Bag A

No data yet



Bag B

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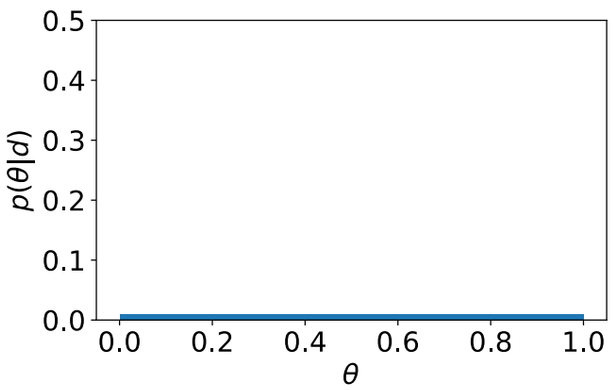

Bag C

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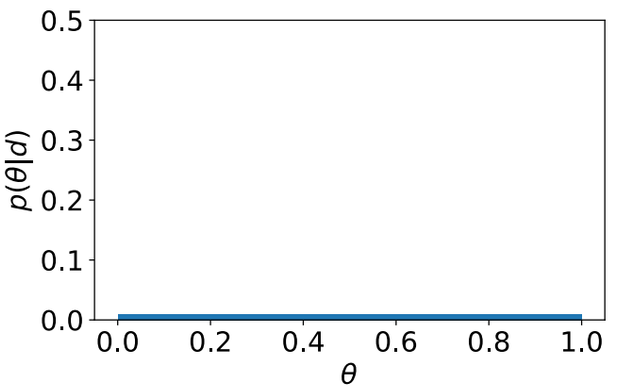

Bag D

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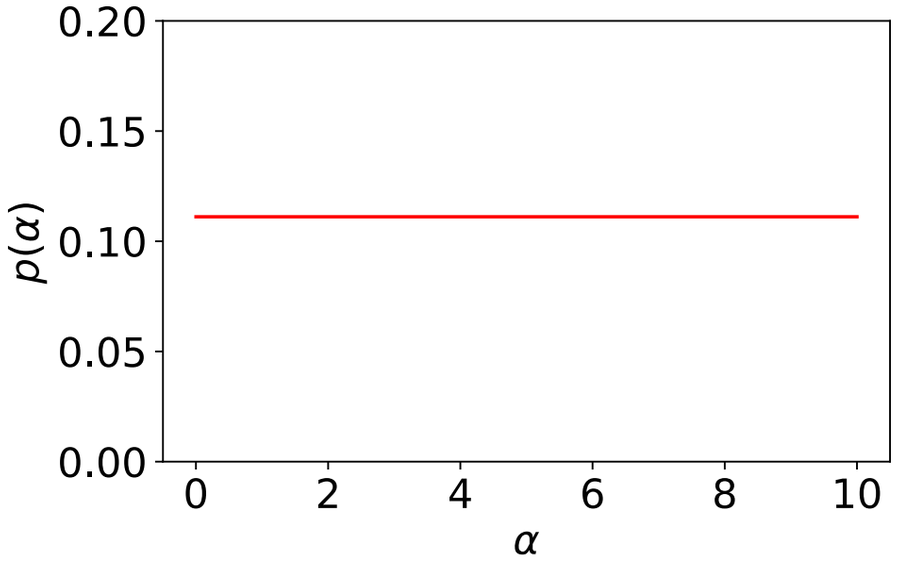

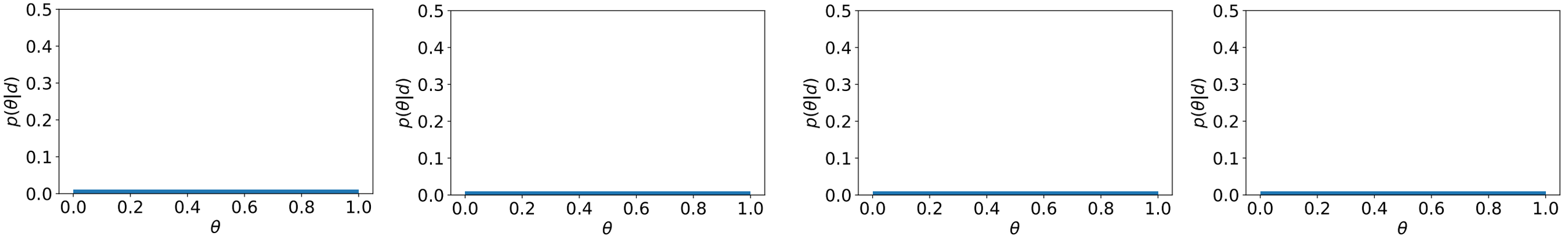

Bag A

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Bag B

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Bag C

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Bag D

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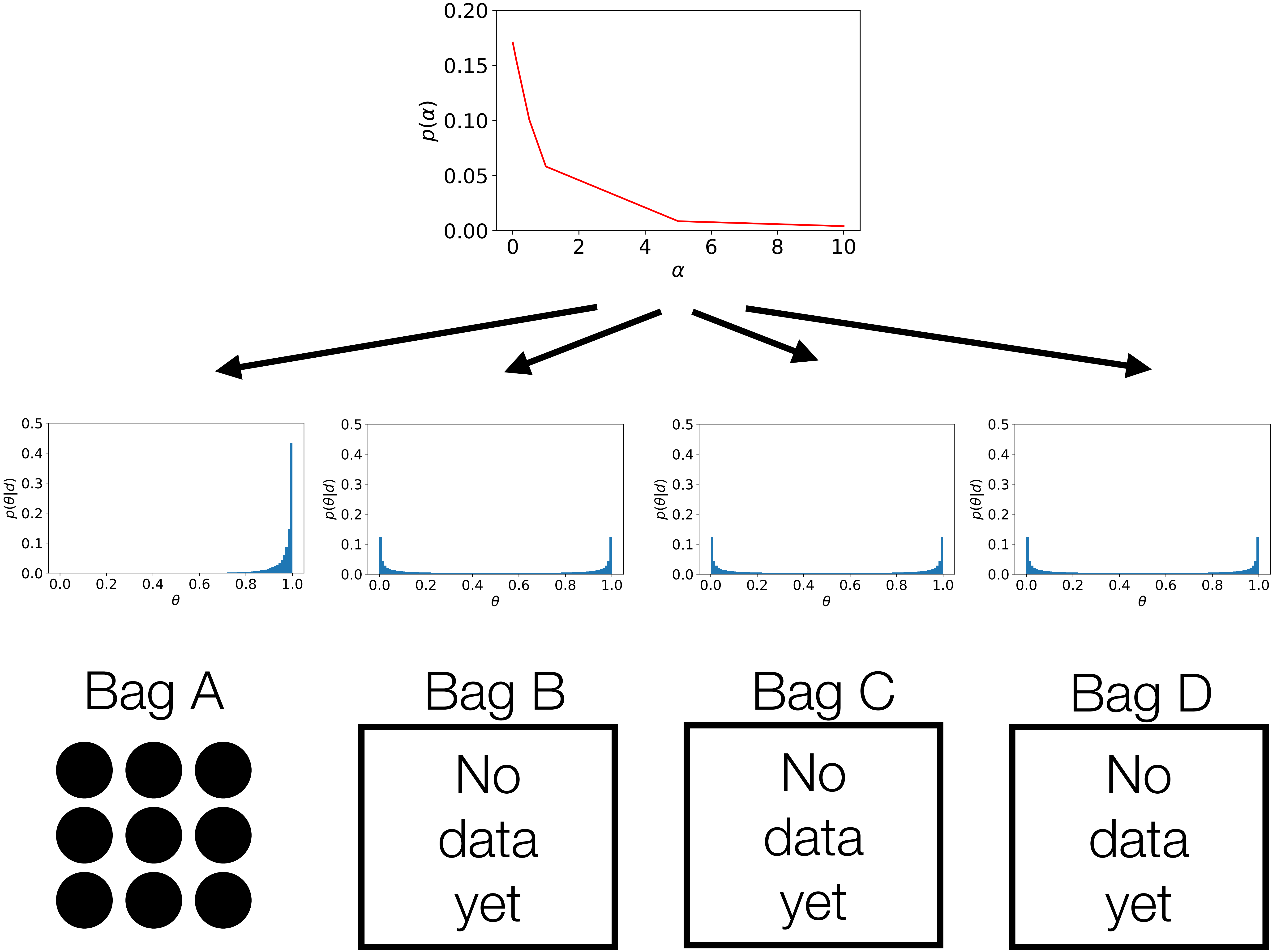

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$p(\alpha)$
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α
0.5
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0.2
0.1
0.0
$p(\theta|d)$
0.0
0.2
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0.6
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1.0
θ
Bag A
Bag B
No data yet
Bag C
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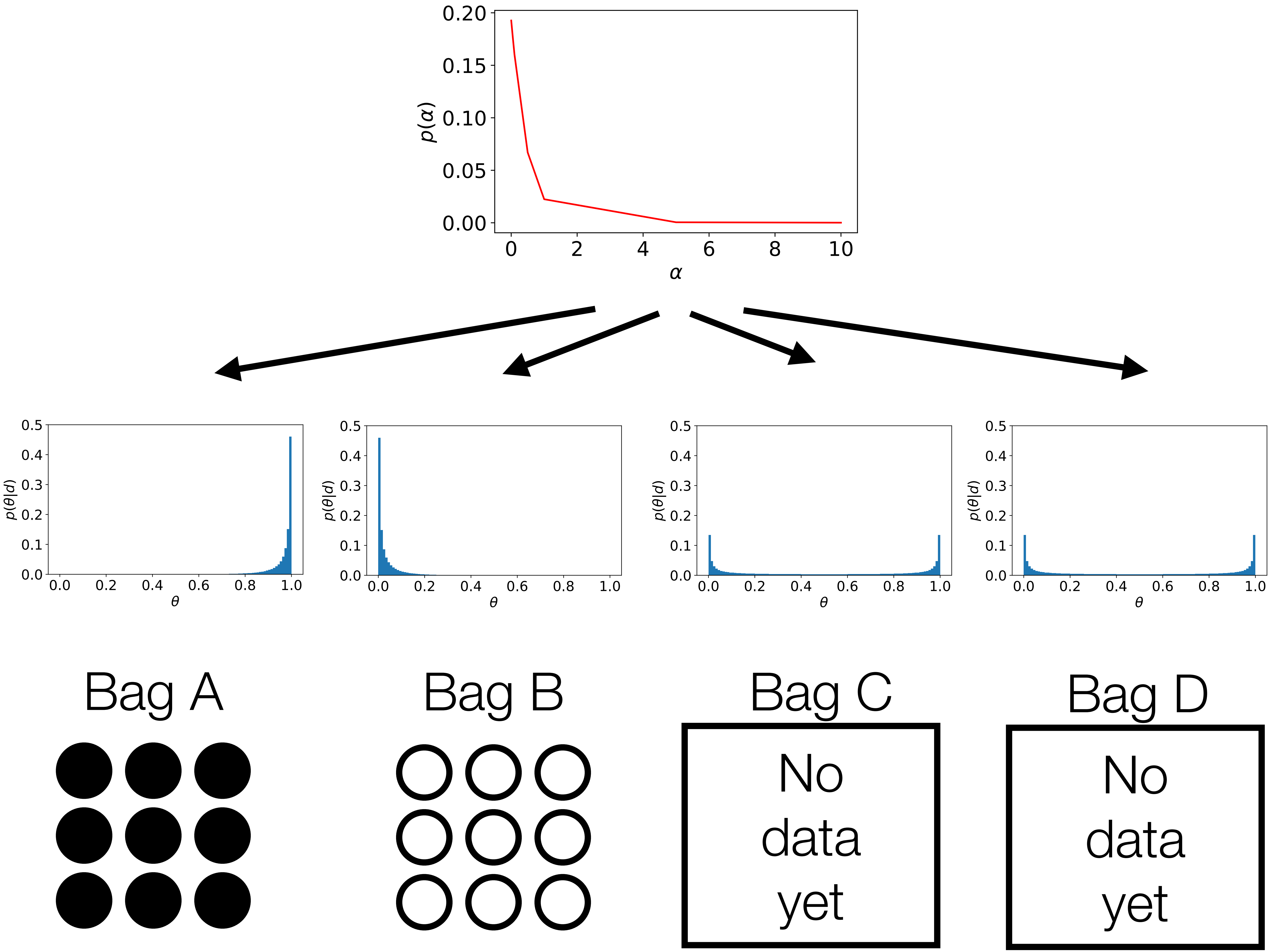

0.20
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p(α)
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α
0.5
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0.0
p(θ|d)
0.0
0.2
0.4
0.6
0.8
1.0
θ
Bag A
Bag B
Bag C
No data yet
Bag D
No data yet

The same thing in maths for those that prefer it

The familiar non-hierarchical model

$$P(\theta \mid d) \propto P(d \mid \theta) P(\theta)$$

The same thing in maths for those that prefer it

The familiar non-hierarchical model

$$P(\theta \mid d) \propto P(d \mid \theta) P(\theta \mid \alpha)$$

The same thing in maths for those that prefer it

The familiar non-hierarchical model

$$P(\theta \mid d) \propto P(d \mid \theta) P(\theta \mid \alpha)$$

Hierarchical model, inferring α

$$P(\alpha \mid d) \propto P(d \mid \alpha) P(\alpha)$$

The same thing in maths for those that prefer it

The familiar non-hierarchical model

$$P(\theta \mid d) \propto P(d \mid \theta) P(\theta \mid \alpha)$$

Hierarchical model, inferring α

$$P(\alpha \mid d) \propto P(d \mid \alpha) P(\alpha)$$

The same thing in maths for those that prefer it

The familiar non-hierarchical model

$$P(\theta \mid d) \propto P(d \mid \theta) P(\theta \mid \alpha)$$

Hierarchical model, inferring α

$$P(\alpha \mid d) \propto \int_{\theta} P(d \mid \theta) P(\theta \mid \alpha) P(\alpha)$$

The same thing in maths for those that prefer it

The familiar non-hierarchical model

$$P(\theta \mid d) \propto P(d \mid \theta) P(\theta \mid \alpha)$$

Hierarchical model, inferring α

$$P(\alpha \mid d) \propto \int_{\theta} P(d \mid \theta) P(\theta \mid \alpha) P(\alpha)$$

Hierarchical model, inferring θ

$$P(\theta \mid d) \propto \int_{\alpha} P(d \mid \theta) P(\theta \mid \alpha) P(\alpha)$$

These learned biases are probably **everywhere**

Just a hunch, but I think we might be massively underestimating the power of learned biases to shape learning and explain the surprising precocity of language learners

- Basic level bias, shape bias, …
- Mutual exclusivity - develops over time (Halberda, 2003), is weaker in bilingual children (Houston-Price et al., 2010)
- Syntactic categories
- Correlations between semantic/phonological cues and syntactic category (e.g. in English, nouns tend to be longer than verbs, 4-year-olds know this: Cassidy & Kelly, 1991)
- Pragmatic inference?
- Structure dependence in syntax??
- …

Summary and next up

- Priors can be learned
- We can capture this as Bayesian inference, using a hierarchical model
- There is strong evidence that humans learn to learn in this way
- Several options available on the readings page for this lecture, from brief and non-technical to long and somewhat technical
- Lab: a simple hierarchical learning model

References

Cassidy, K. W. , & Kelly, M. H. (1991). Phonological information for grammatical category assignments. *Journal of Memory and Language, 30,* 348-369.

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Smith, L.B., Jones, S.S., Landau, B., Gershkoff-Stowe, L. & Samuelson, L. (2002). Object Name Learning Provides On-the-Job Training for Attention. *Psychological Science, 13,* 13-19.