Simulating Language
2: Word learning

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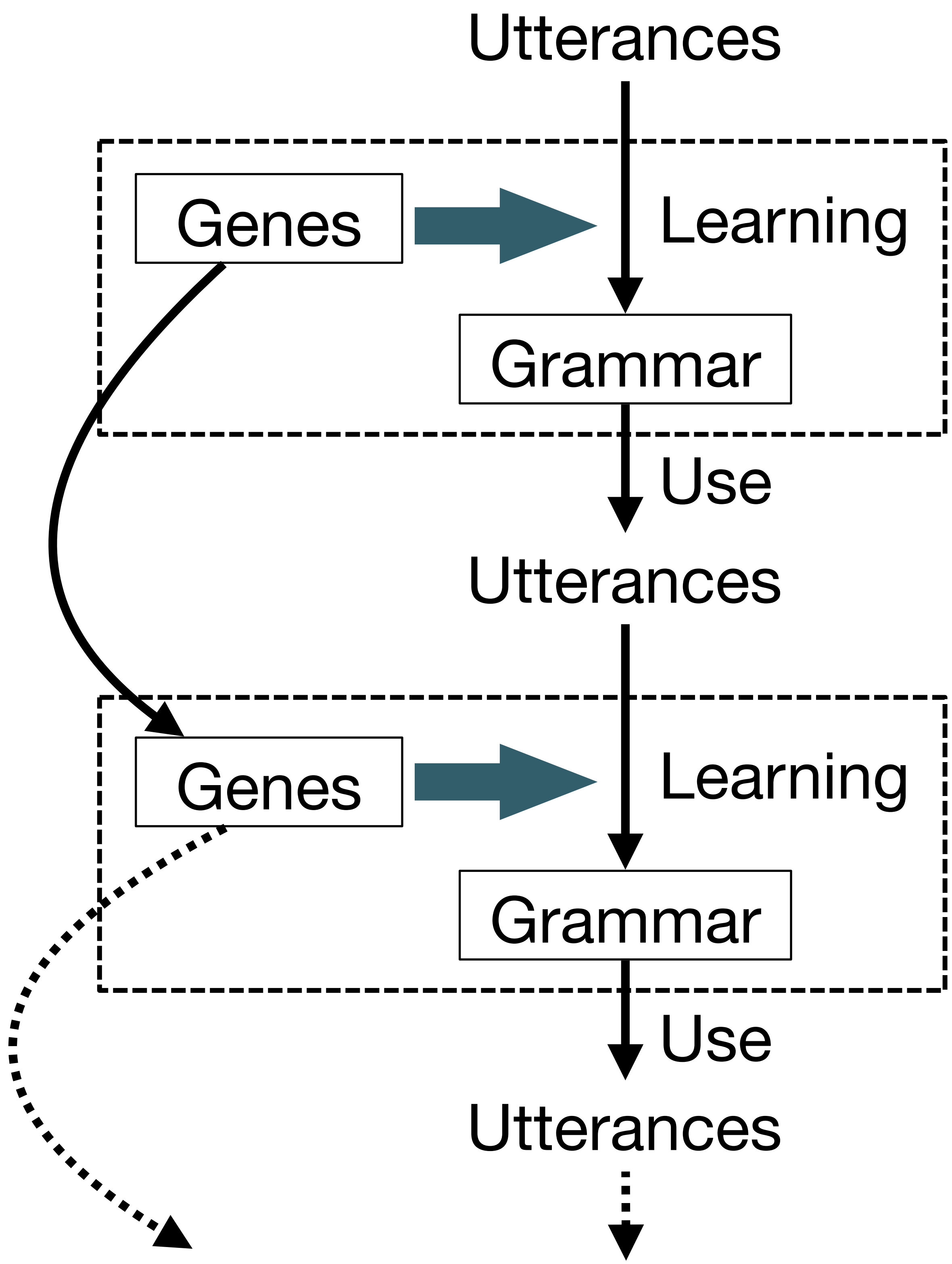
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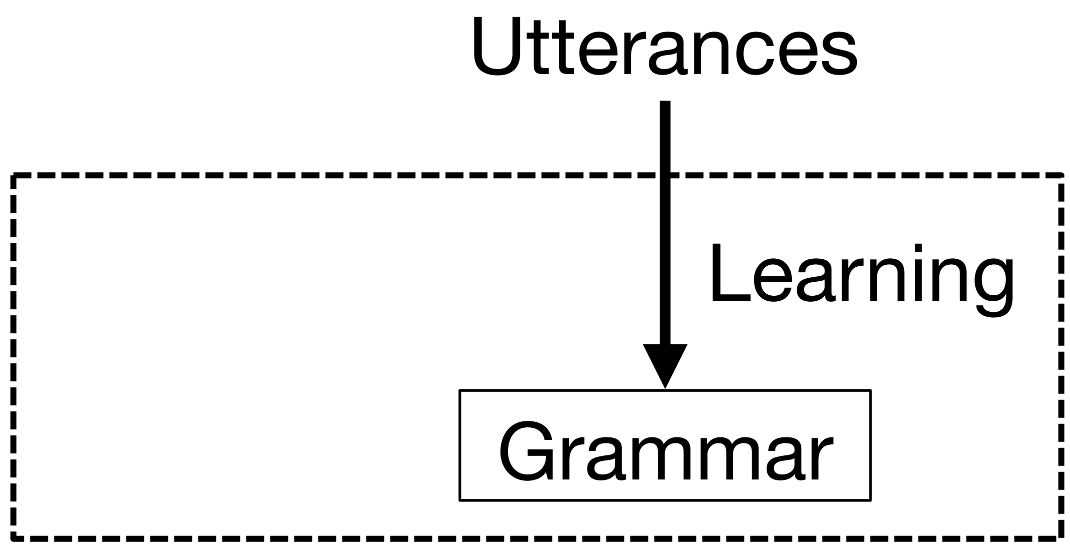
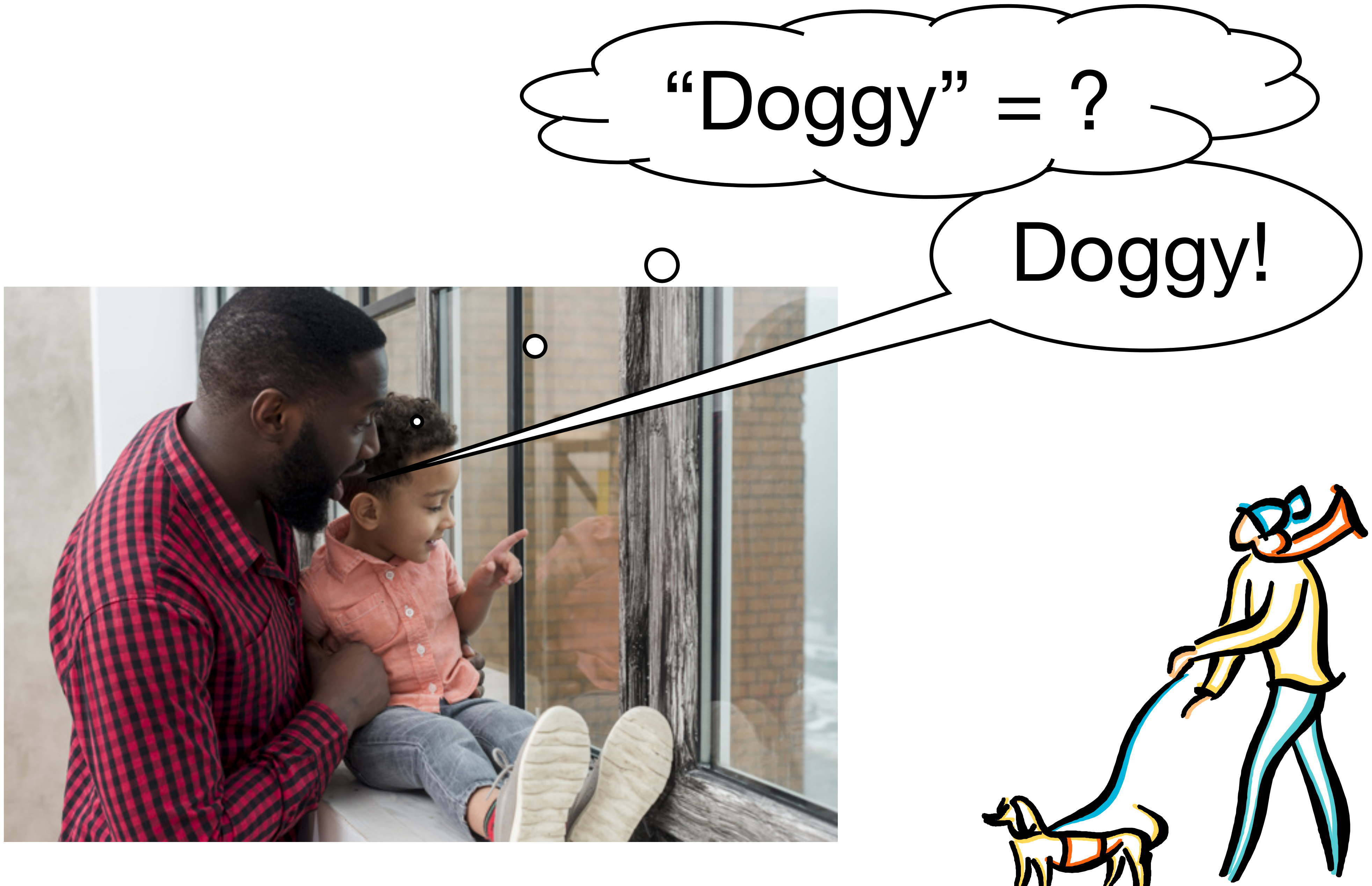


$$P(h|d) \propto P(d|h)P(h)$$

Word learning

Learning the meaning of words



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)

- …

If the constraints on learning are minimal, how is rapid word learning possible?

If the constraints on learning are strong, how do we learn words that don't fit the constraints?

Word learning as *Bayesian inference*

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

- Xu, F., & Tenenbaum, J. B. (2007) Word learning as Bayesian Inference. Psychological Review, 114, 245-272

- You are trying to use evidence provided by *instances of word use* to infer *unobservable word meaning*

hypotheses = word meanings

data = labelling events

likelihood = how word meanings lead to labelling events

prior = the kind of meanings I expect words to have

This is a *fep*

What does *fep* mean?

A. Dalmatian

B. Dog

C. Animal

These are also *feps*

What does *fep* mean?

A. Dalmatian

B. Dog

C. Animal

Here are 3 *daxes*

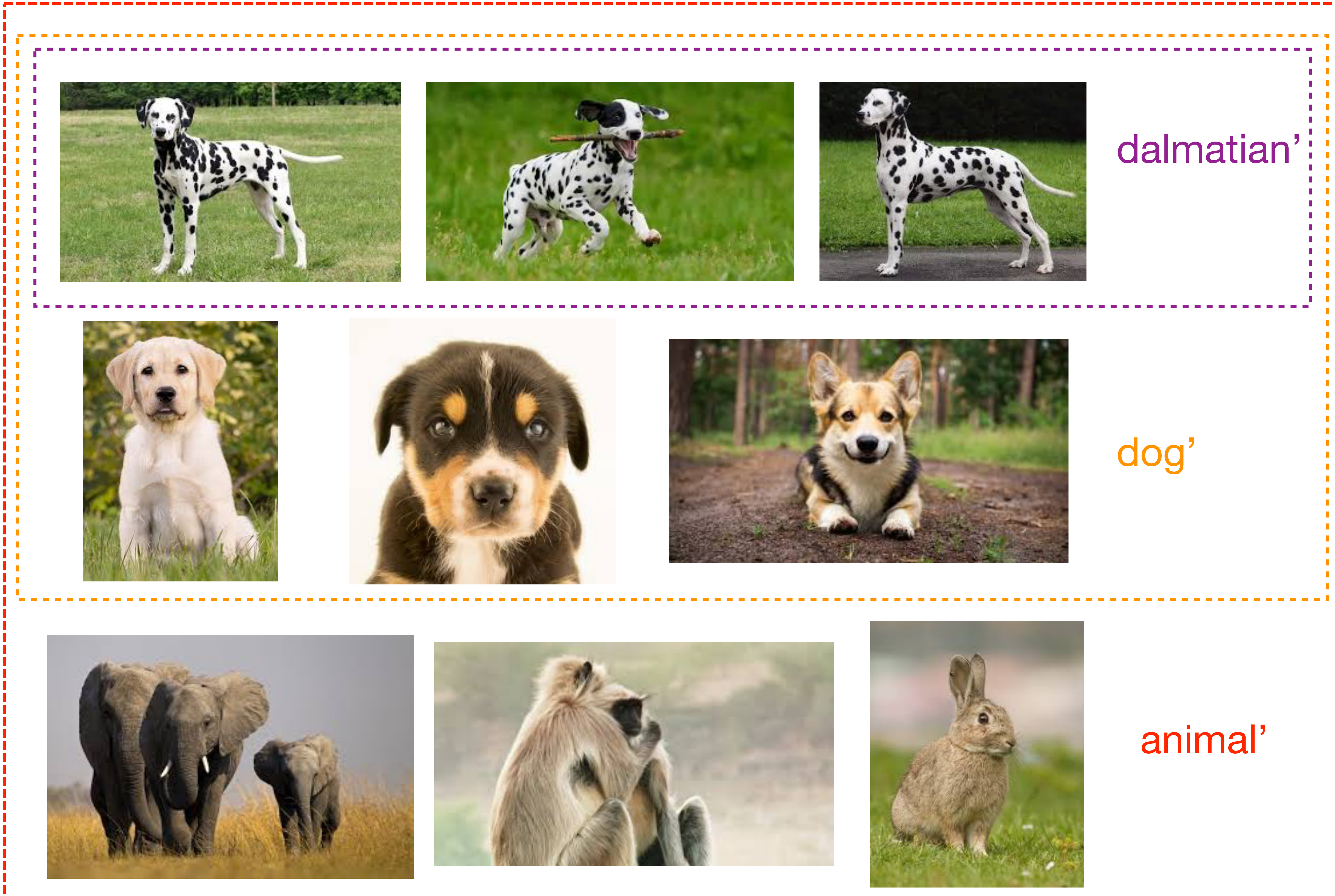
What does *dax* mean?

A. Dalmatian

B. Dog

C. Animal

Did you infer different meanings for *fep* and *dax*?
What factors influenced your decision?


dalmatian’
dog’
animal’

Quantifying a *suspicious coincidence*

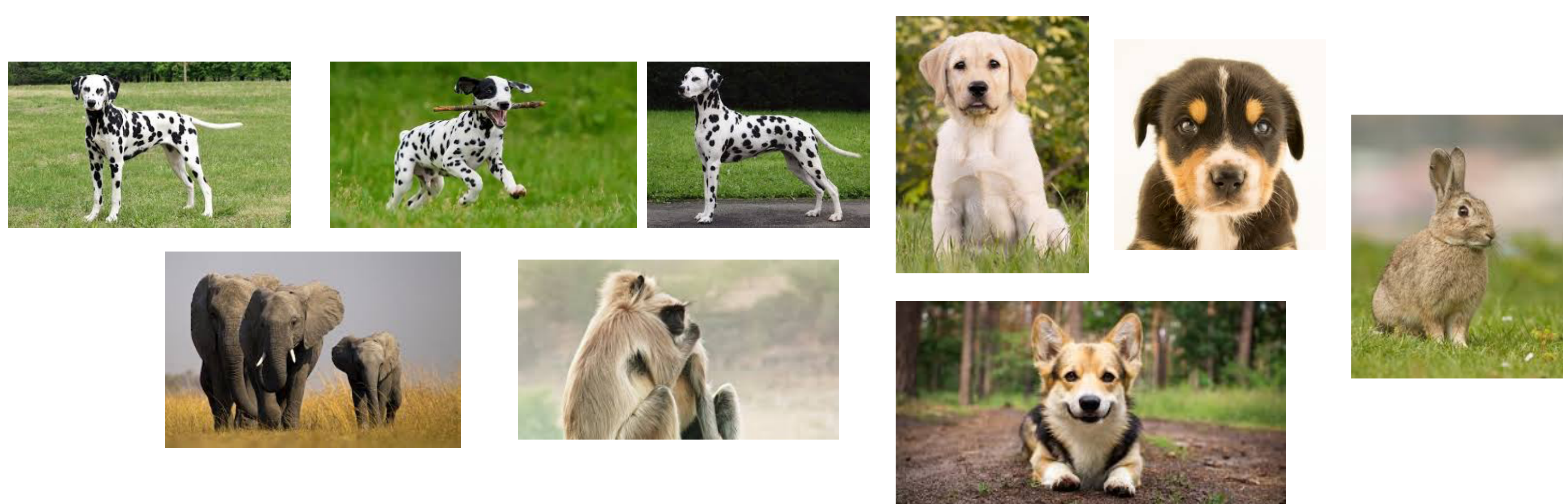
$$P(h|d) \propto P(d|h)P(h)$$

3 hypotheses under consideration

fep=dalmatian’

fep=dog’

fep=animal’



Quantifying a *suspicious coincidence*

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

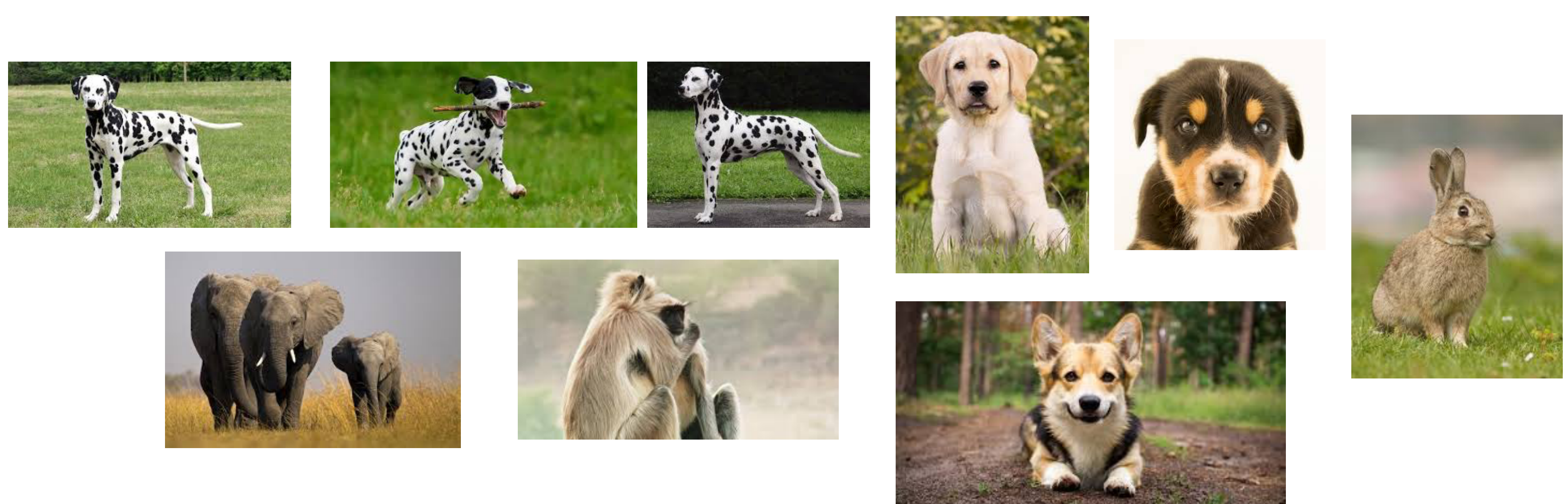
"*fep*"

Likelihood: P( | *fep*=dalmatian') = ???

fep=dalmatian'

fep=dog'

fep=animal'



Quantifying a *suspicious coincidence*

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

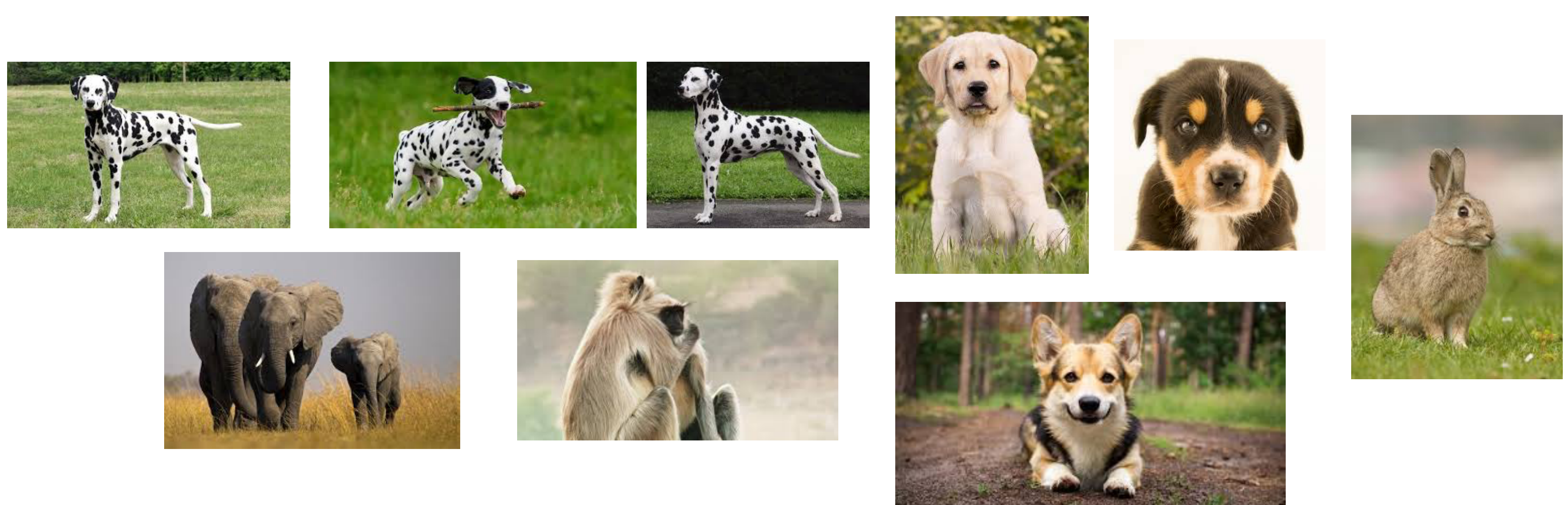
“*fep*”

Likelihood: P( | *fep*=dog’) = ???

fep=dalmatian’

fep=dog’

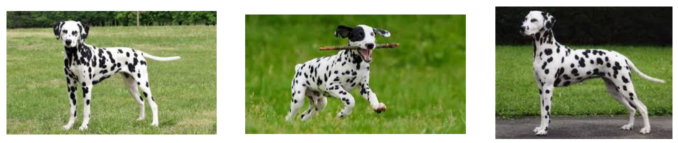
fep=animal’



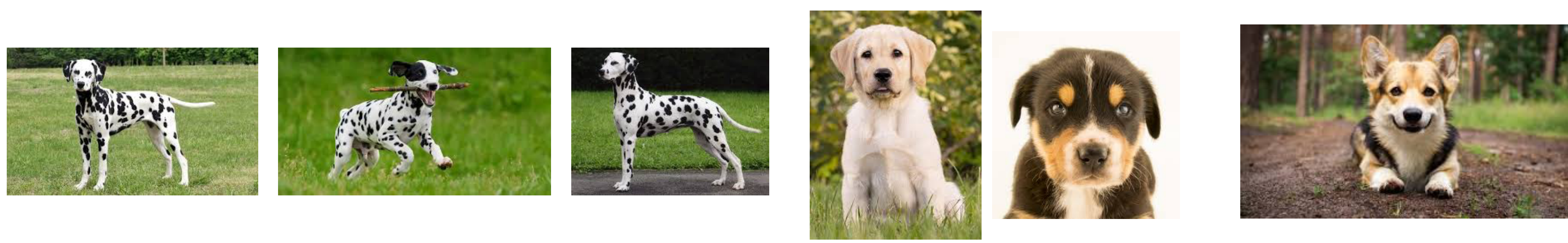
Quantifying a *suspicious coincidence*

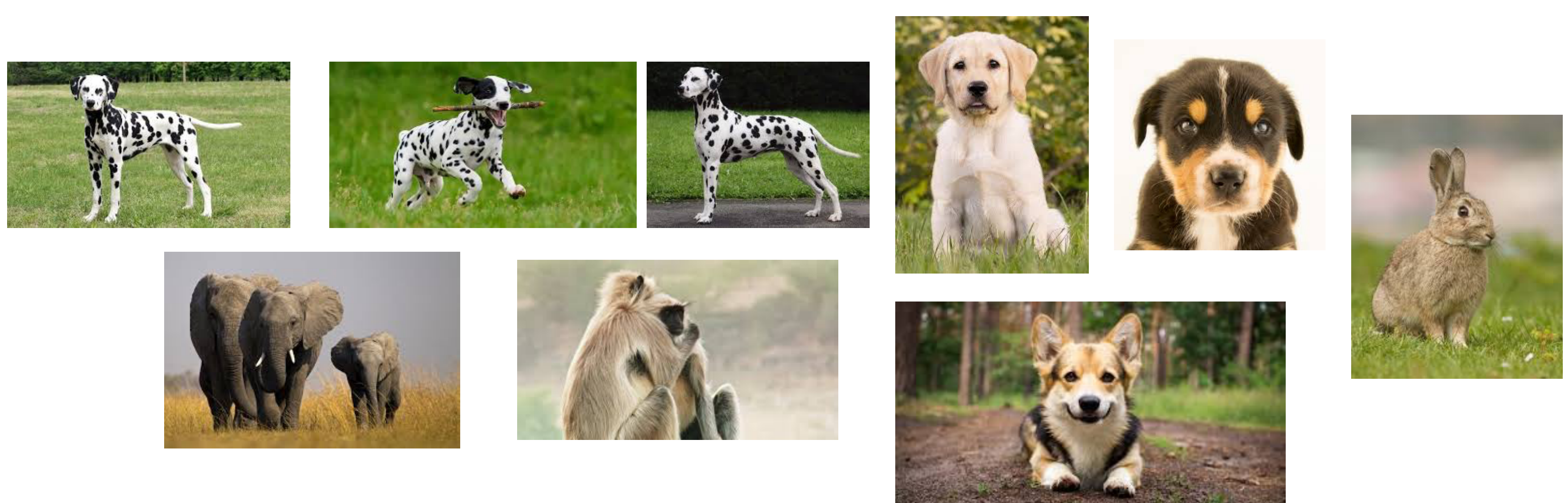
$$P(h|d) \propto P(d|h)P(h)$$

“fep” *“fep”* *“fep”*

Likelihood: P( | *fep*=dalmatian’) = ???

fep=dalmatian’ 

fep=dog’ 

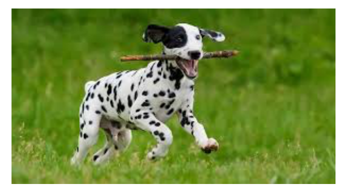
fep=animal’ 

Quantifying a *suspicious coincidence*

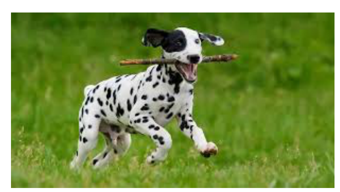
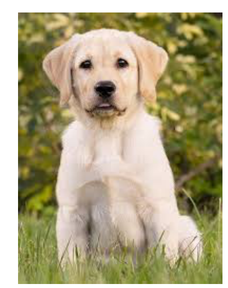
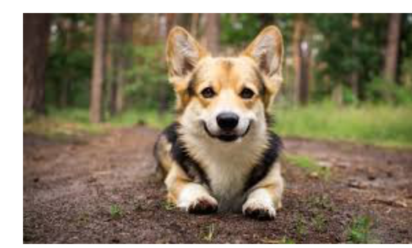
$$P(h|d) \propto P(d|h)P(h)$$

Likelihood: P(“*fep*”  “*fep*”  “*fep*”  | *fep*=dog’) = ???

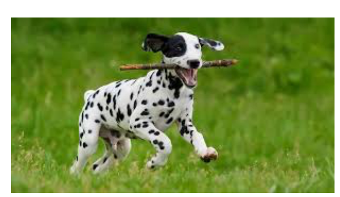
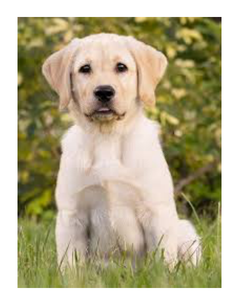
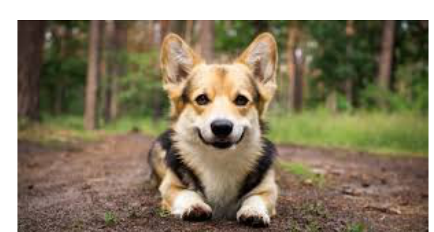
fep=dalmatian’

fep=dog’

fep=animal’

Quantifying a *suspicious coincidence*

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

“*fep*”

P( | *fep*=dalmatian’) = 1/3

“*fep*”

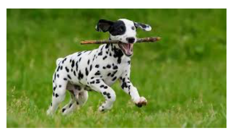
P( | *fep*=dog’) = 1/6

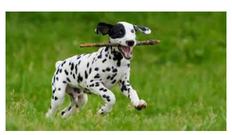
“*fep*”

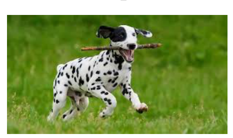
P( | *fep*=animal’) = 1/9

Quantifying a *suspicious coincidence*

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

P(“*fep*”  “*fep*”  “*fep*”  | *fep*=dalmatian’) = 1/3 x 1/3 x 1/3 = 1/27

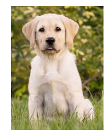
P(“*fep*”  “*fep*”  “*fep*”  | *fep*=dog’) = 1/6 x 1/6 x 1/6 = 1/216

P(“*fep*”  “*fep*”  “*fep*”  | *fep*=animal’) = 1/9 x 1/9 x 1/9 = 1/729

Quantifying a *suspicious coincidence*

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

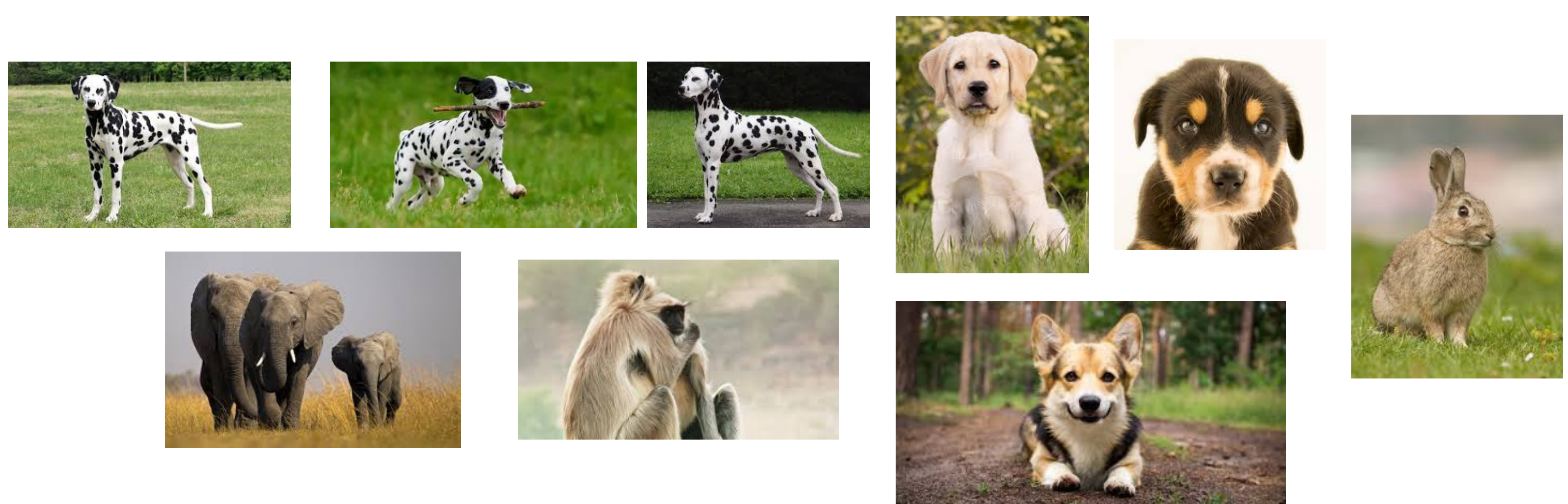
“*dax*” “*dax*” “*dax*”

Likelihood: P(   | *dax*=dalmatian’) = ???

fep=dalmatian’

fep=dog’

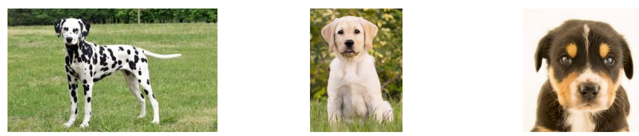
fep=animal’



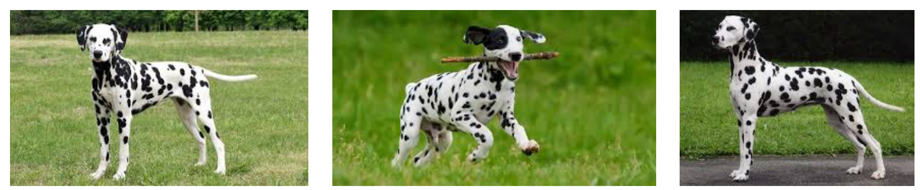
Quantifying a *suspicious coincidence*

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

“dax” *“dax”* *“dax”*

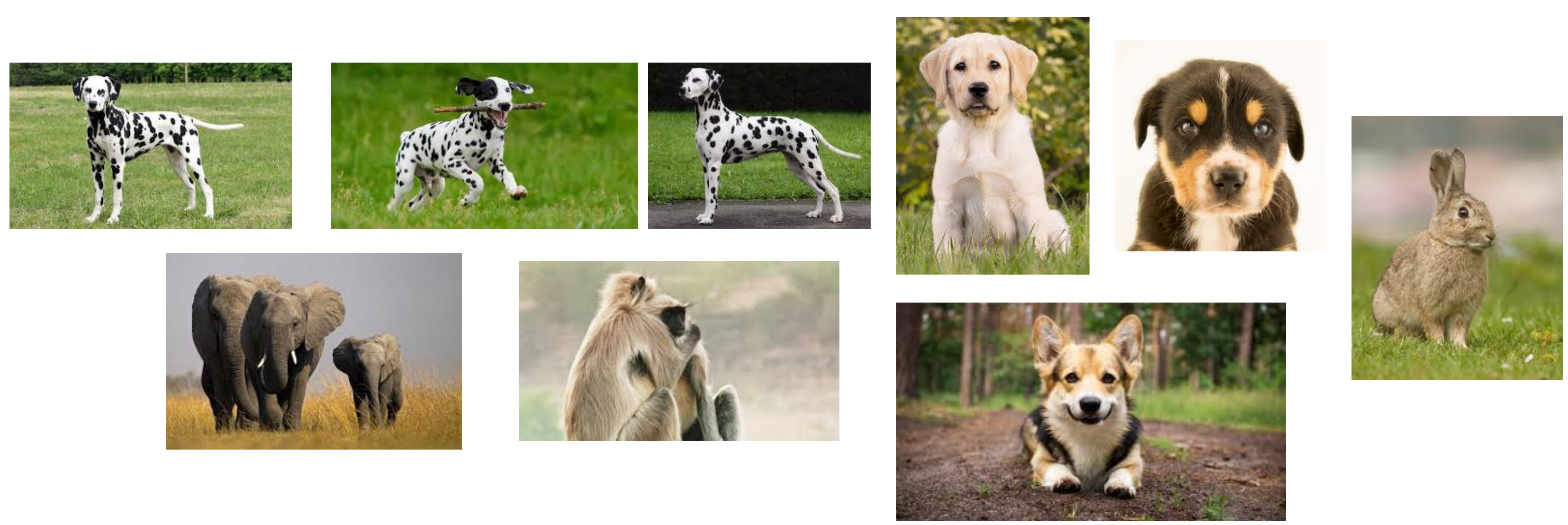
Likelihood: P( | *dax*=dog’) = ???

fep=dalmatian’



fep=dog’

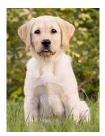
fep=animal’



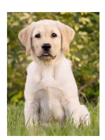
Quantifying a *suspicious coincidence*

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

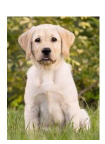
“*dax*” “*dax*” “*dax*”

P(   | *dax*=dalmatian’) = 1/3 x 0 x 0 = 0

“*dax*” “*dax*” “*dax*”

P(   | *dax*=dog’) = 1/6 x 1/6 x 1/6 = 1/216

“*dax*” “*dax*” “*dax*”

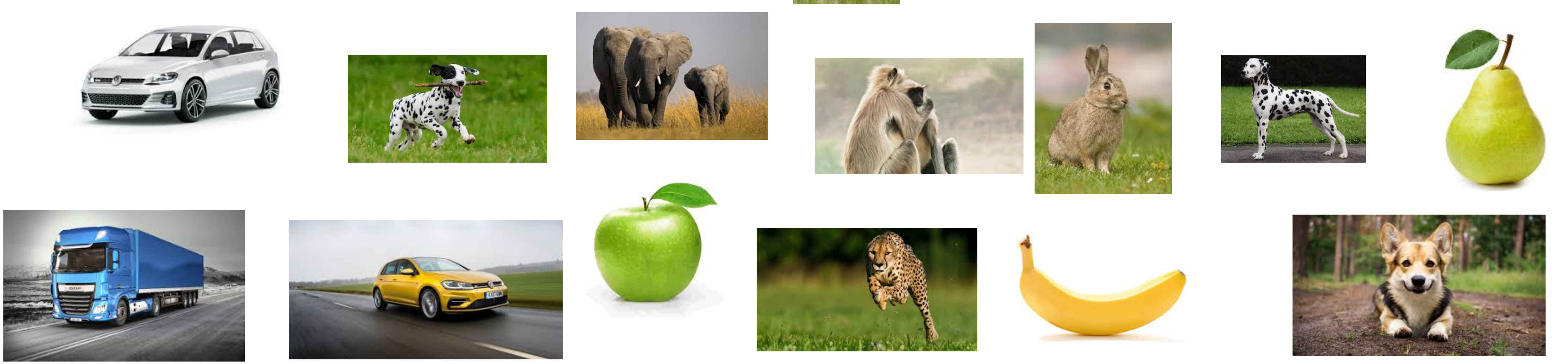
P(   | *dax*=animal’) = 1/9 x 1/9 x 1/9 = 1/729

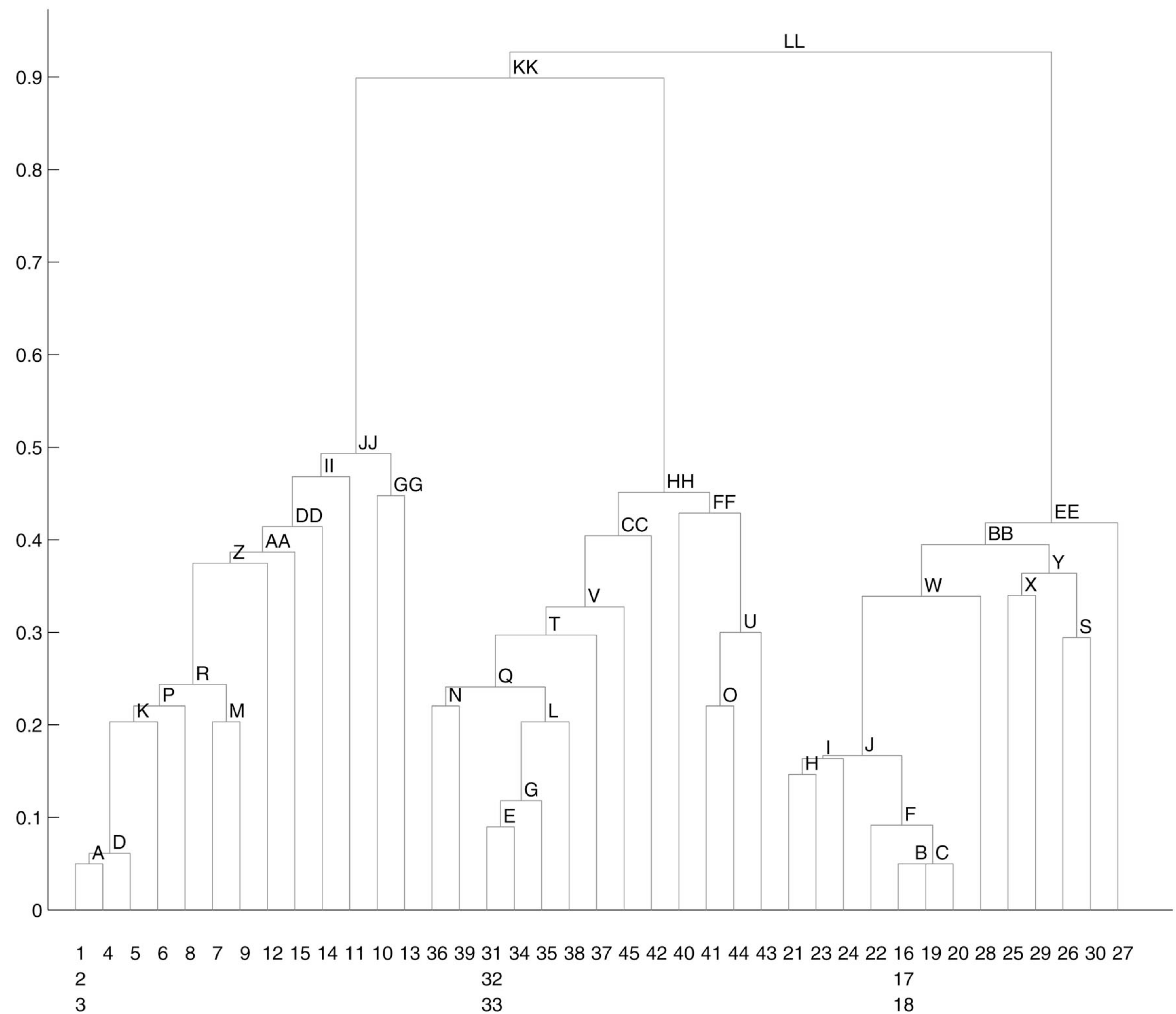
Xu, F., & Tenenbaum, J. B. (2007) Word learning as Bayesian Inference. Psychological Review, 114, 245-272

Their task

These are *feps*

Show me all the *feps*





0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
LL
KK
JJ
II
GG
HH
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AA
Z
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1 4 5 6 8 7 9 12 15 14 11 10 13 36 39 31 34 35 38 37 45 42 40 41 44 43 21 23 24 22 16 19 20 28 25 29 26 30 27
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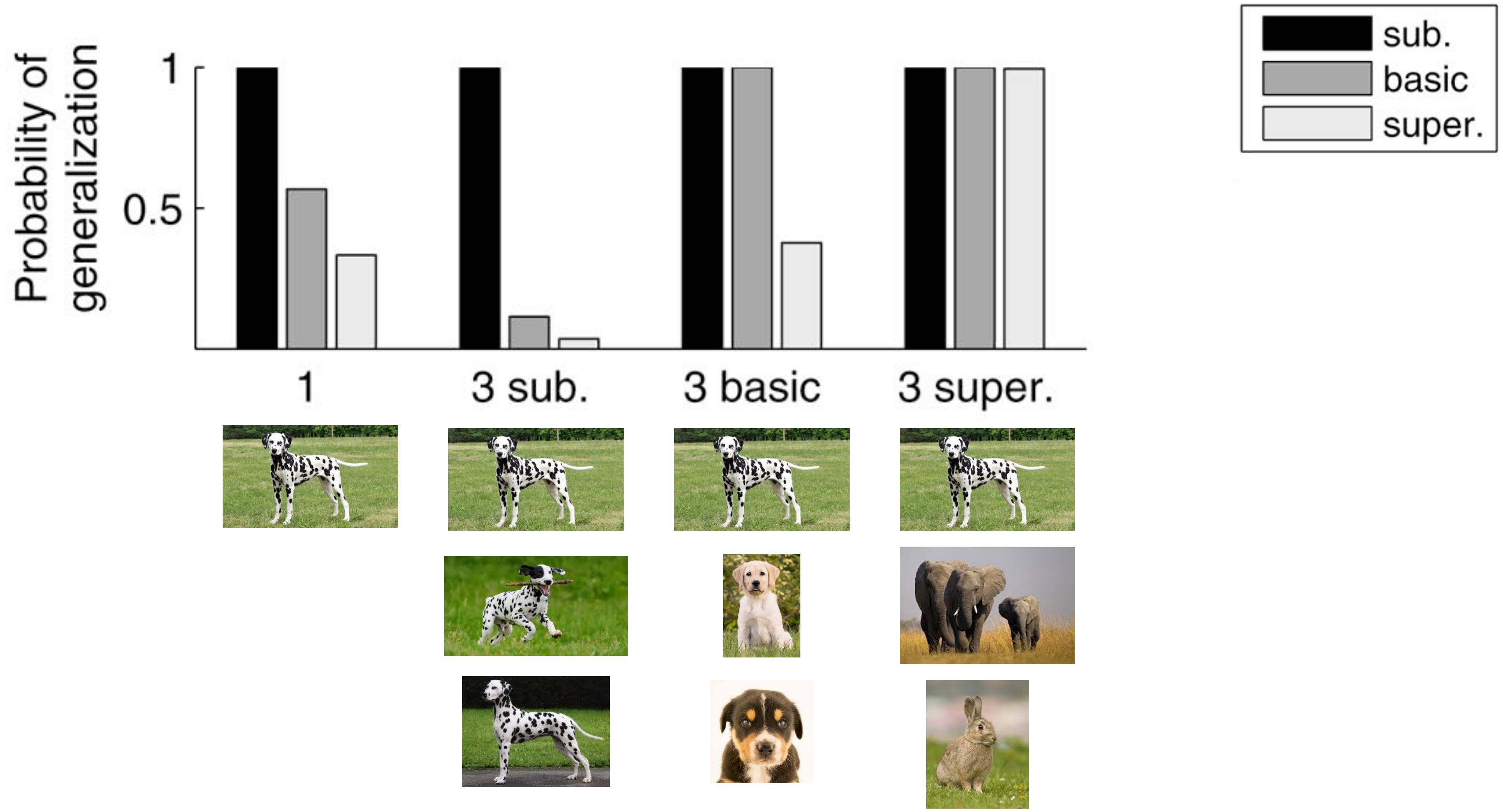
17
18

Model predictions

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

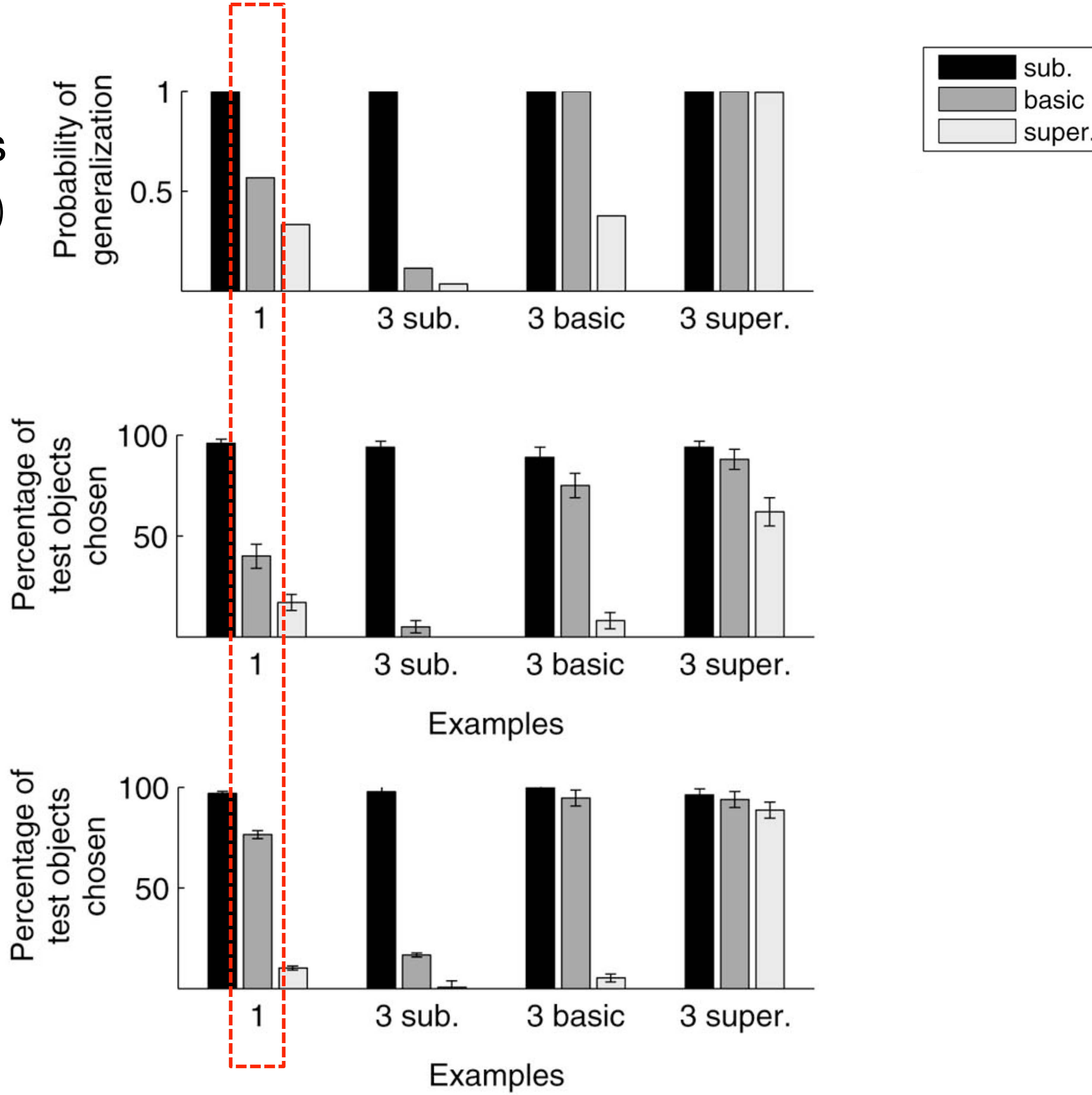


Model predictions

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

Children

Adults



Add a basic-level bias

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

Uniform prior

P(*fep*=dalmatian’) = P(*fep*=dog’) = P(*fep*=animal’)

Prior with a basic-level bias

P(*fep*=dog’) > P(*fep*=dalmatian’) = P(*fep*=animal’)

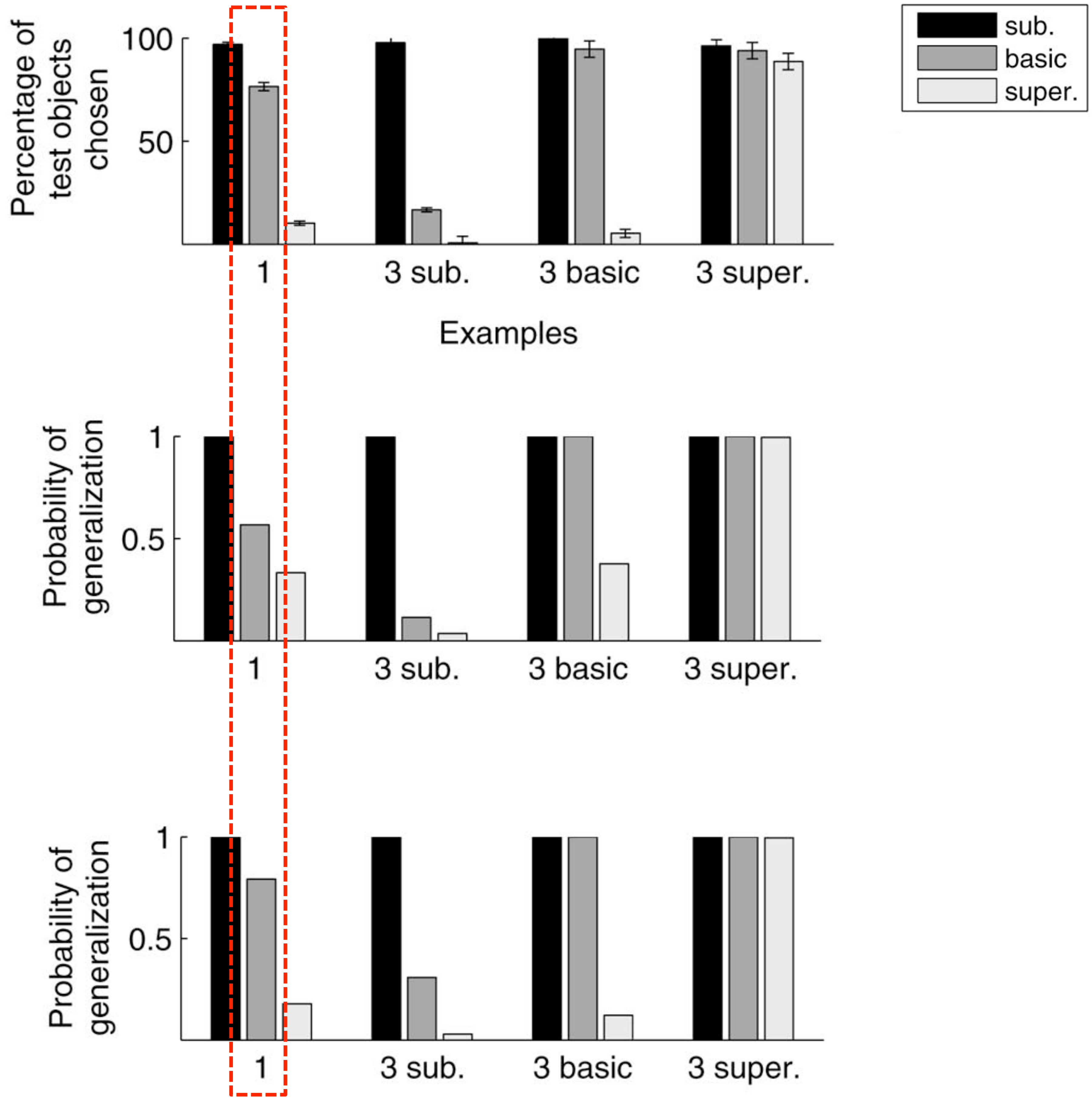
Adults

Model without basic-level bias

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

Model **with** basic-level bias

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



Why might adults and children come to this word learning task with different priors?

Coming up next!

- Lab: a simple Bayesian model of word learning
  - Basic framework for Bayesian models
  - Play around with suspicious coincidences, the prior
- Next lecture: a Bayesian model of frequency learning
  - No pre-reading for lecture 3: catch up on the intro to probabilities and Bayes set for today…
  - …or read Xu & Tenenbaum (2007), it's very rich

References

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Markman, E. M., & Wachtel, G. F. (1988). Children's use of mutual exclusivity to constrain the meanings of words. *Cognitive Psychology, 20,* 121–157.

Quine, W. V. O. (1960). *Word and object.* Cambridge, MA: MIT Press.

Xu, F., & Tenenbaum, J. B. (2007) Word learning as Bayesian Inference. *Psychological Review, 114,* 245-272.