Computational Pragmatics

And another Bayesian Application in NLP

CSCI 1460: Computational Linguistics
Guest Lecture — 29 September 2022

Fall 2022
Charles Lovering

Lecture #	Date	Topic
0	9 Sept	Intro Lecture
1	13 Sept	Tasks and Metrics
2	15 Sept	Text Classifiers Part 1: Models
3	20 Sept	Text Classifiers Part 2: Features
4	22 Sept	Tokenization
5	27 Sept	Distributional Hypothesis
	29 Sept	Guest Lecture (Charlie Lovering): Computational Pragmatics
6	4 Oct	Topic Modeling
7	6 Oct	Deep Learning 101
8	11 Oct	Language Modeling Part 1: Ngram Models
9	13 Oct	Language Modeling Part 2: Neural Architectures
10	18 Oct	Language Modeling Part 3: Pretraining and Finetuning
11	20 Oct	Guest Lecture (Julia Netter): Risks of LM Misuse
12	25 Oct	Statistical Machine Translation
13	27 Oct	Neural Machine Translation
14	1 Nov	Guest Lecture (Dan Garrette): Technical and Societal Challenges of Multilingual NLP

Neural NLP

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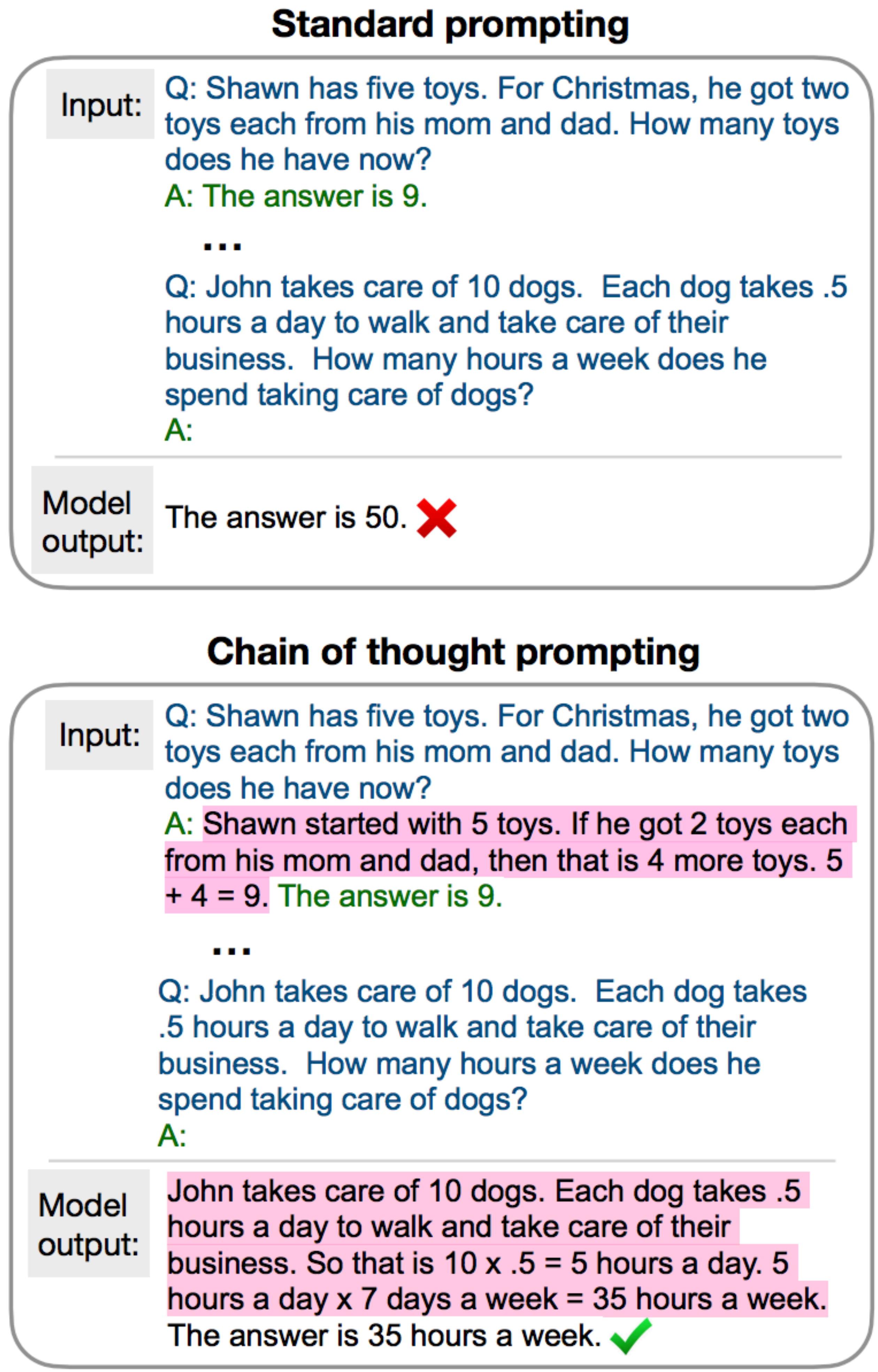
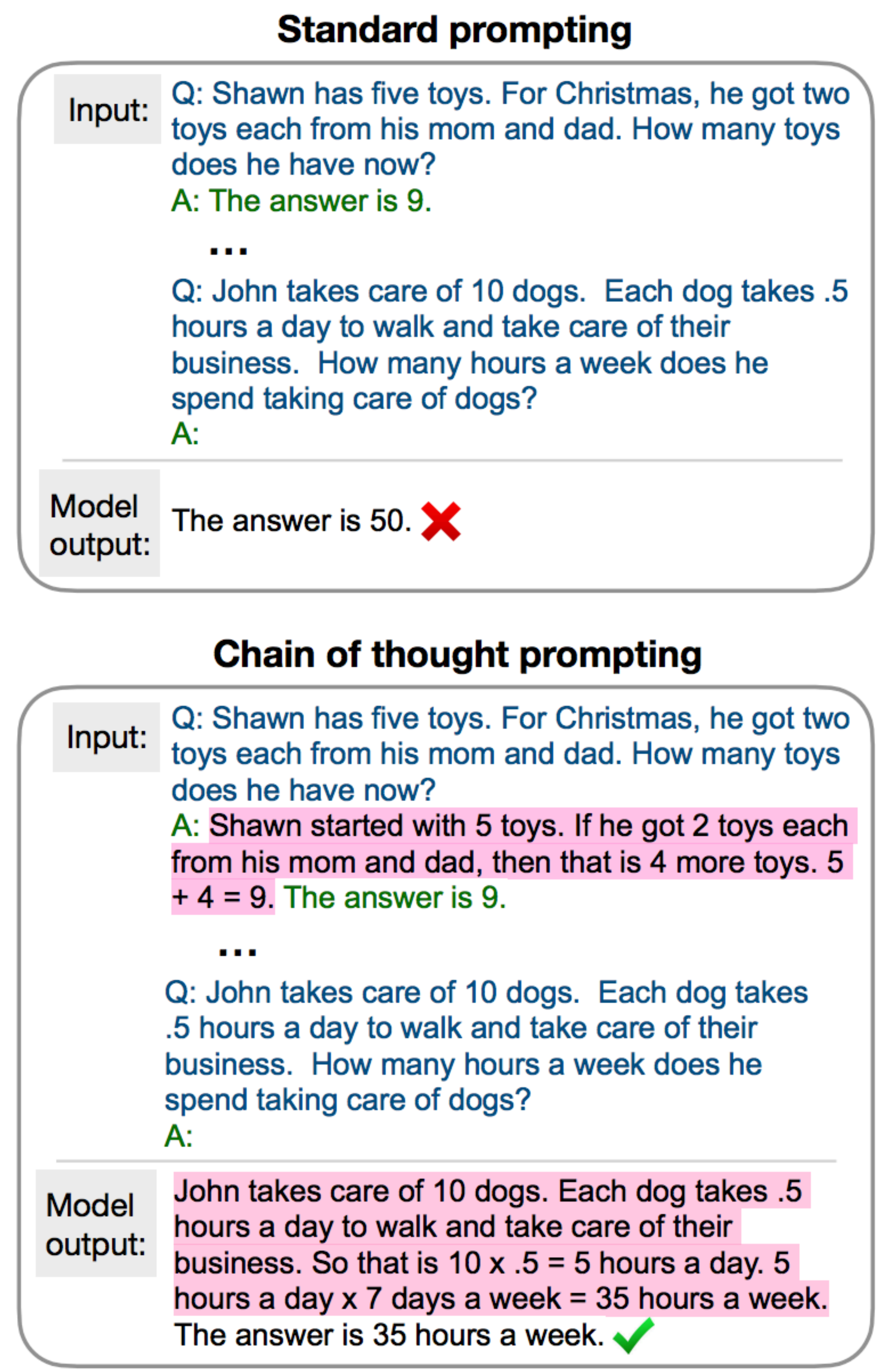
Left: https://www.midjourney.com/showcase/

Model: Midjourney

Author: Deeds


milkyway in a glass bottle, 4K,
unreal engine, octane render


Standard prompting
Input:
Q: Shawn has five toys. For Christmas, he got two toys each from his mom and dad. How many toys does he have now?
A: The answer is 9.
...
Q: John takes care of 10 dogs. Each dog takes .5 hours a day to walk and take care of their business. How many hours a week does he spend taking care of dogs?
A:
Model output:
The answer is 50.
Chain of thought prompting
Input:
Q: Shawn has five toys. For Christmas, he got two toys each from his mom and dad. How many toys does he have now?
A: Shawn started with 5 toys. If he got 2 toys each from his mom and dad, then that is 4 more toys. 5 + 4 = 9. The answer is 9.
...
Q: John takes care of 10 dogs. Each dog takes .5 hours a day to walk and take care of their business. How many hours a week does he spend taking care of dogs?
A:
Model output:
John takes care of 10 dogs. Each dog takes .5 hours a day to walk and take care of their business. So that is 10 x .5 = 5 hours a day. 5 hours a day x 7 days a week = 35 hours a week. The answer is 35 hours a week.



Left: https://www.midjourney.com/showcase/
Model: Midjourney
Author: Deeds

Right: https://arxiv.org/pdf/2201.11903v1.pdf
Model: T5-like, gpt3-like models (google internal)

Pragmatics

Very-low Data

Pragmatics

Rational Speech Acts

Very-low Data

I went to the bank.

https://en.wikipedia.org/wiki/Pragmatics

I went to the bank.

https://en.wikipedia.org/wiki/Pragmatics

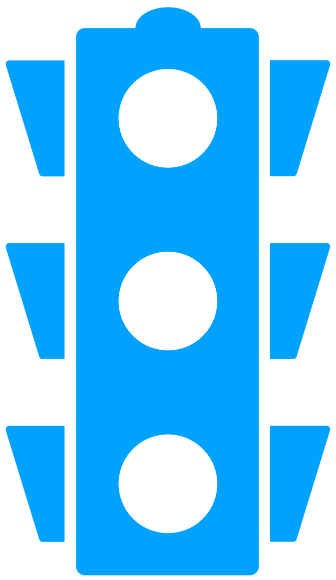
I went to the bank.

https://en.wikipedia.org/wiki/Pragmatics

You have a green light.

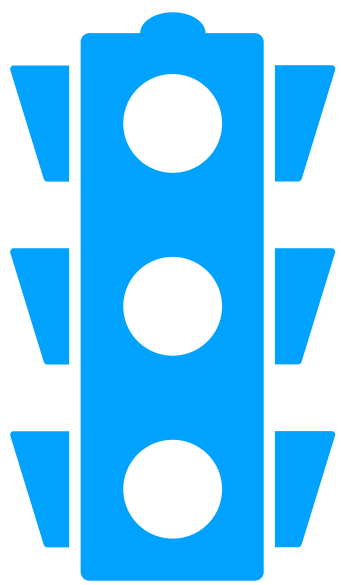
https://en.wikipedia.org/wiki/Pragmatics

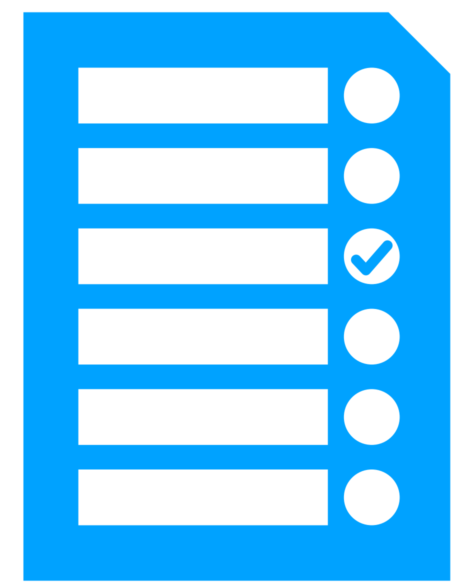
You have a green light.



https://en.wikipedia.org/wiki/Pragmatics

You have a green light.





https://en.wikipedia.org/wiki/Pragmatics

Scales

The big mouse;
the small elephant

Hyperbole

Damn, those shoes must cost a million dollars.

Metaphor

He was a beast out there on the court.

Sarcasm

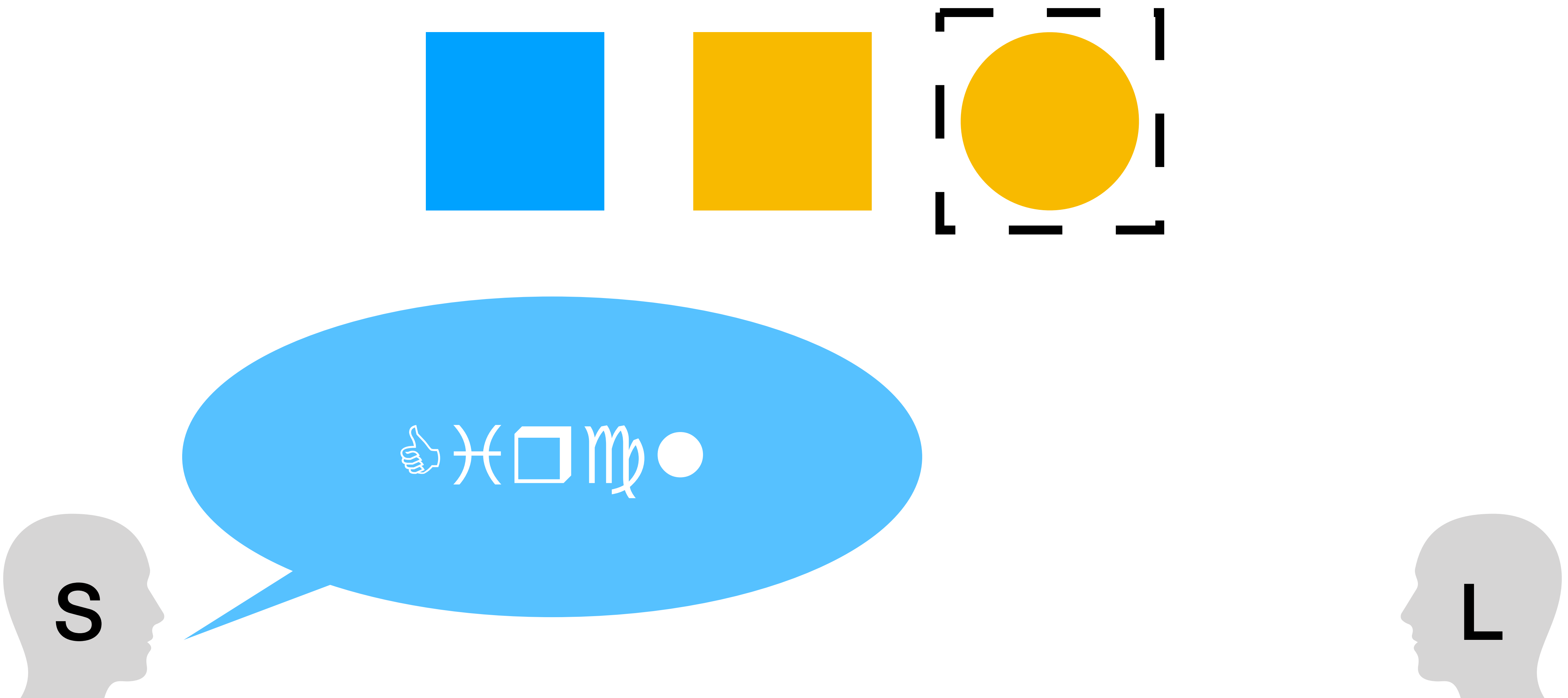
Digging this hole is so much fun.

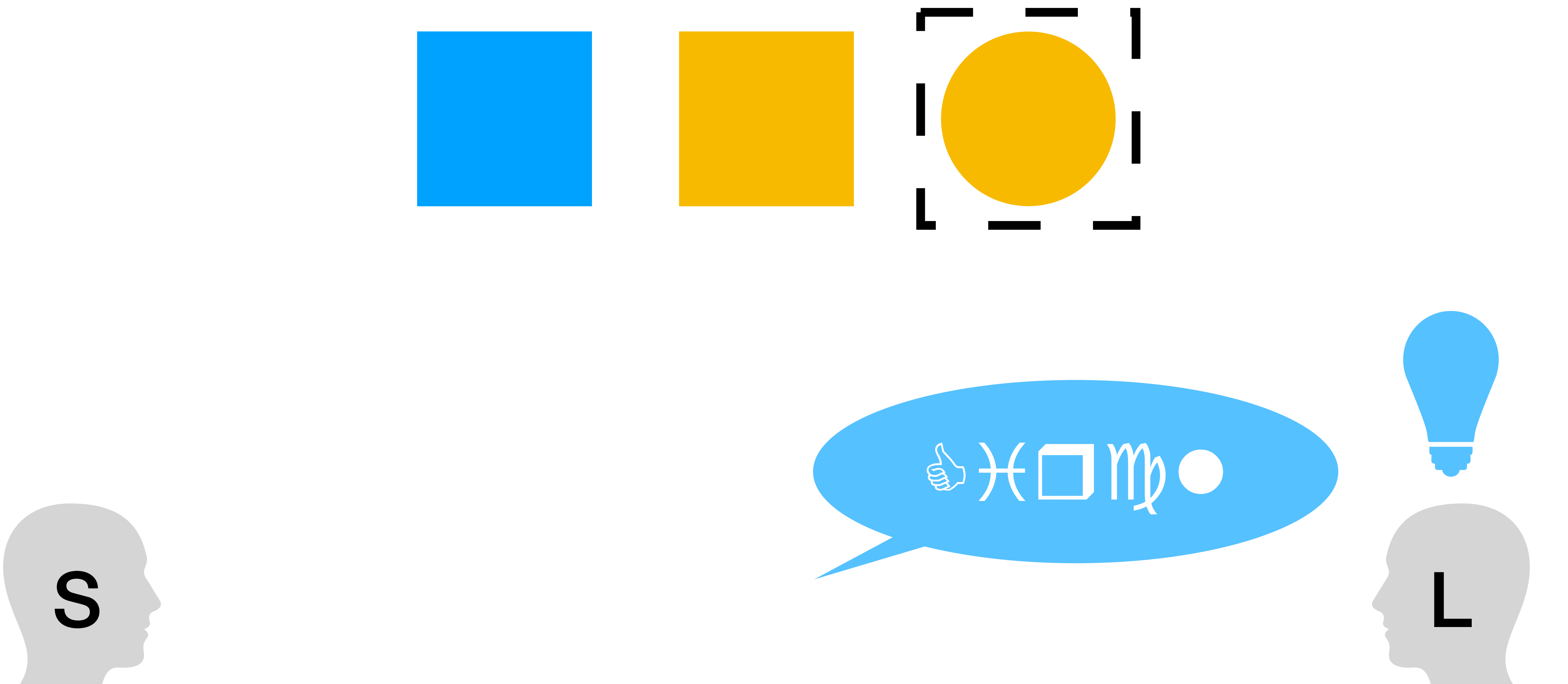
https://en.wikipedia.org/wiki/Pragmatics

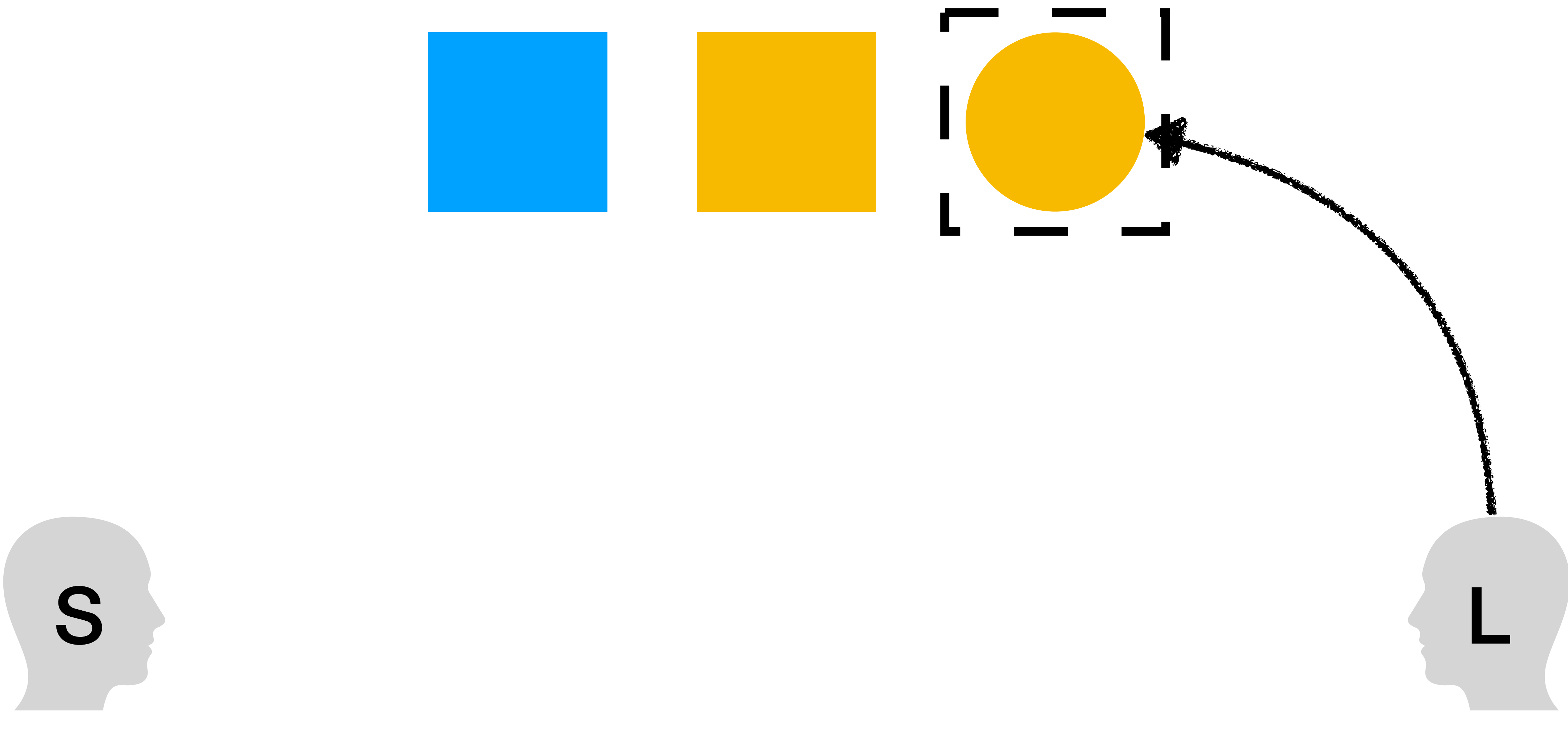
Reference Games


S
L

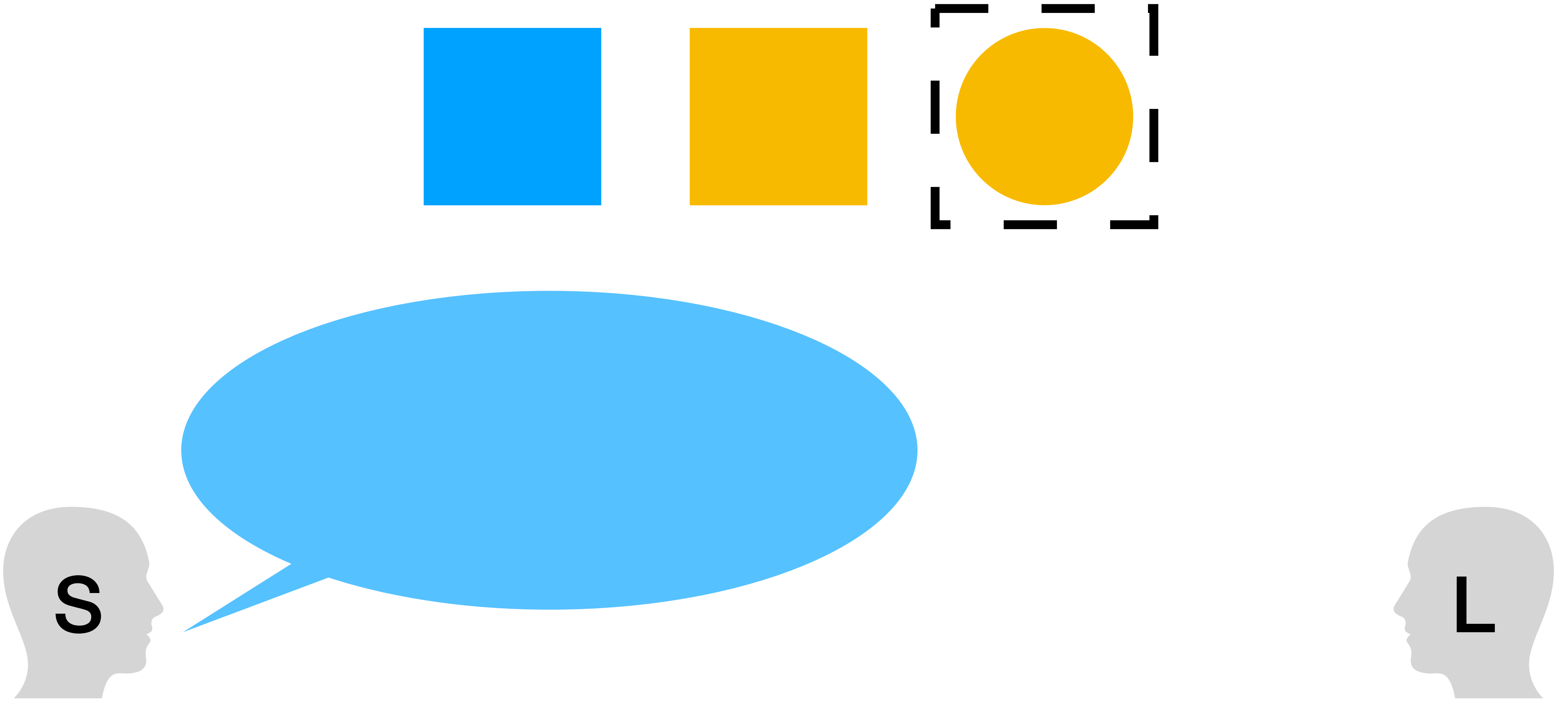

S
L


S
L

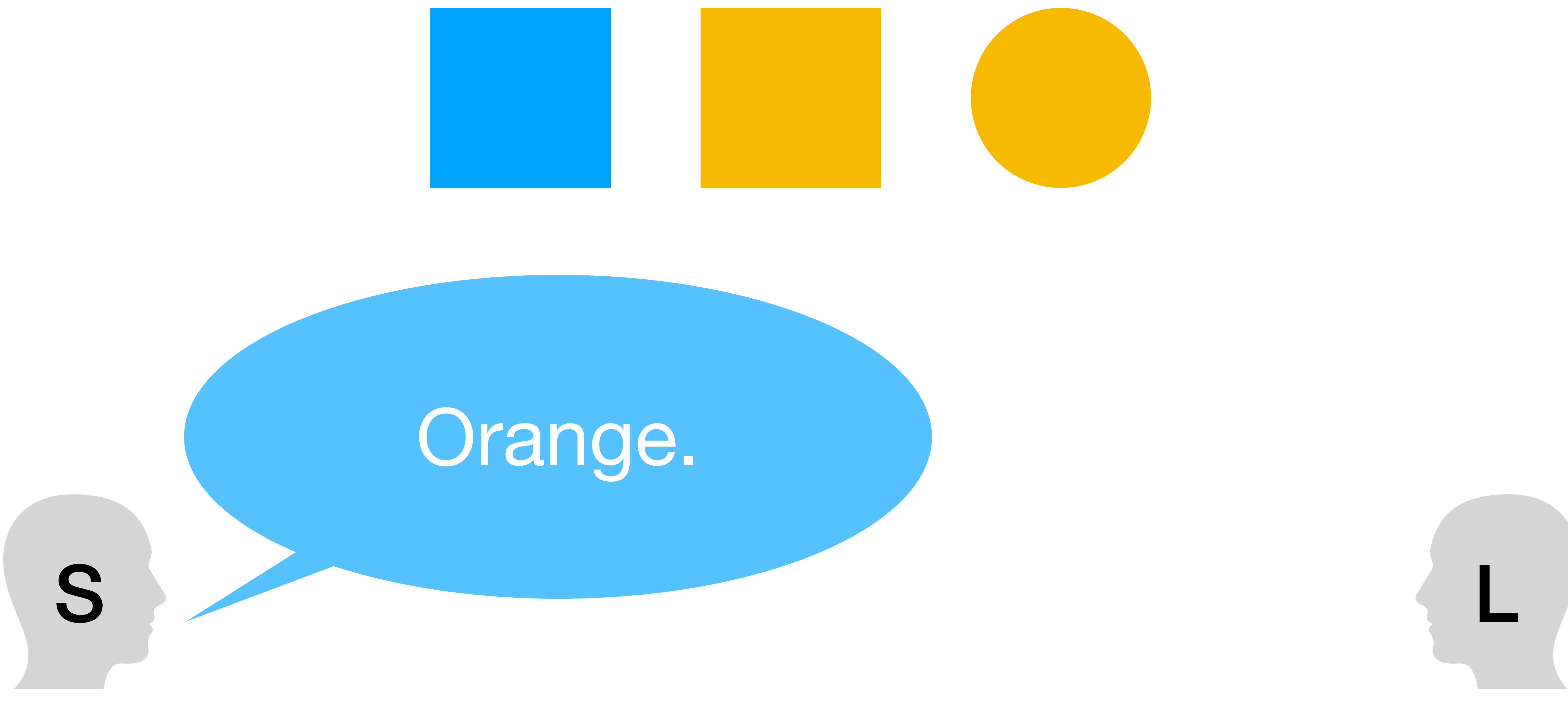

S
L


S
L

What would you say to get a “listener” pick the selected item?



What would you pick?



$$P_{\text{Literal}}(r \mid m) = \frac{\text{Eval}(r, m) \times P(r)}{\sum_{r' \in \text{Context}} \text{Eval}(r', m) \times P(r')}$$

$$P_{\text{Literal}}(r \mid m) = \frac{\text{Eval}(r, m) \times P(r)}{\sum_{r' \in \text{Context}} \text{Eval}(r', m) \times P(r')}$$

referent (an item)

message

$$P_{\text{Literal}}(r \mid m) = \frac{\text{Eval}(r, m) \times P(r)}{\sum_{r' \in \text{Context}} \text{Eval}(r', m) \times P(r')}$$

If message applies
to a given referent

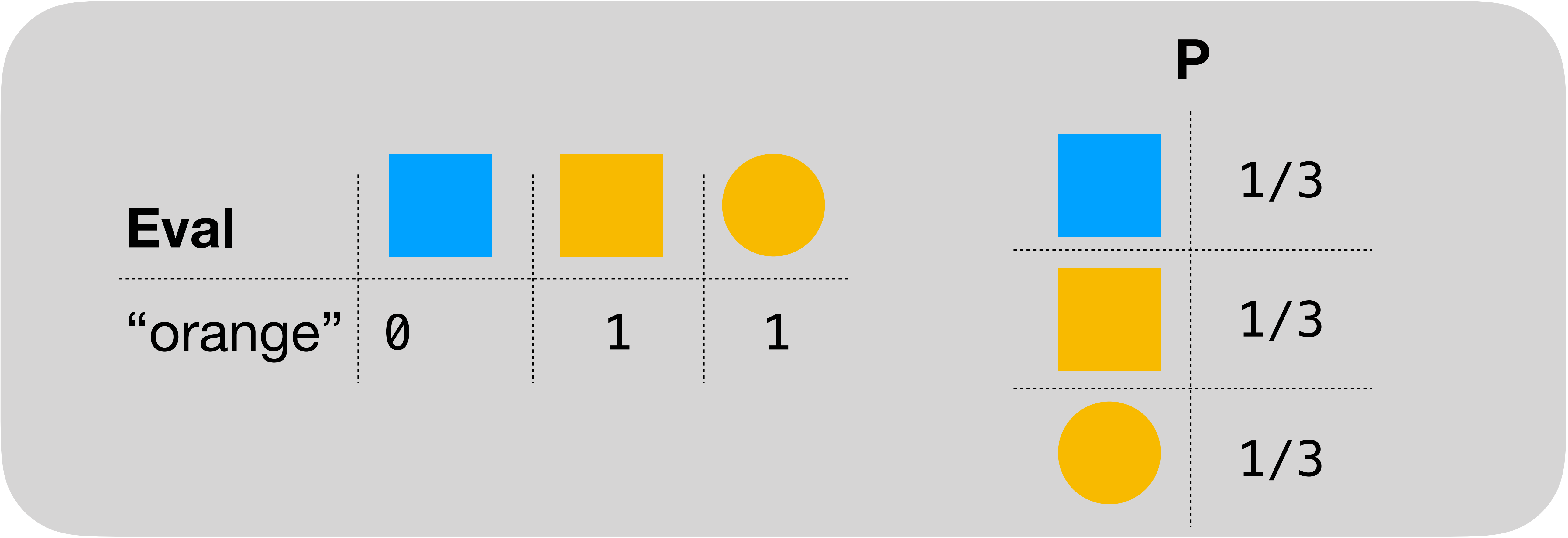
$$P_{\text{Literal}}(r \mid m) = \frac{\text{Eval}(r, m) \times P(r)}{\sum_{r' \in \text{Context}} \text{Eval}(r', m) \times P(r')}$$

Prior of the referent.

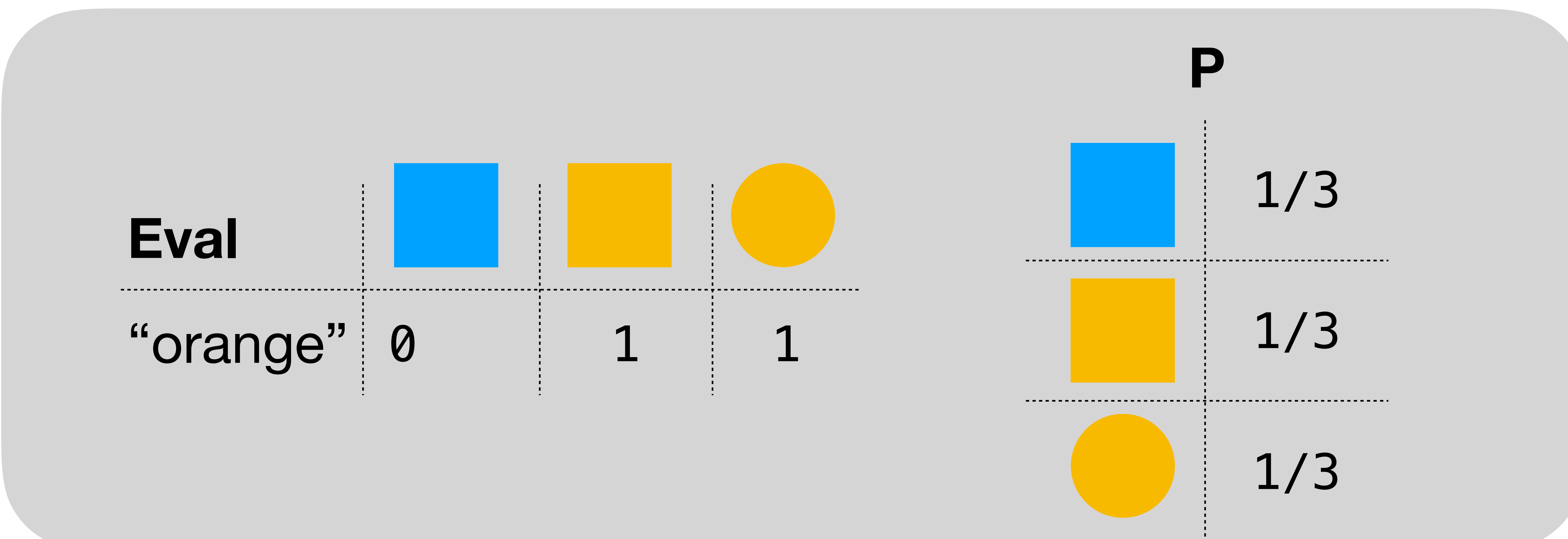
$$P_{\text{Literal}}(r \mid m) = \frac{\text{Eval}(r, m) \times P(r)}{\sum_{r' \in \text{Context}} \text{Eval}(r', m) \times P(r')}$$

Normalizing across referents in context

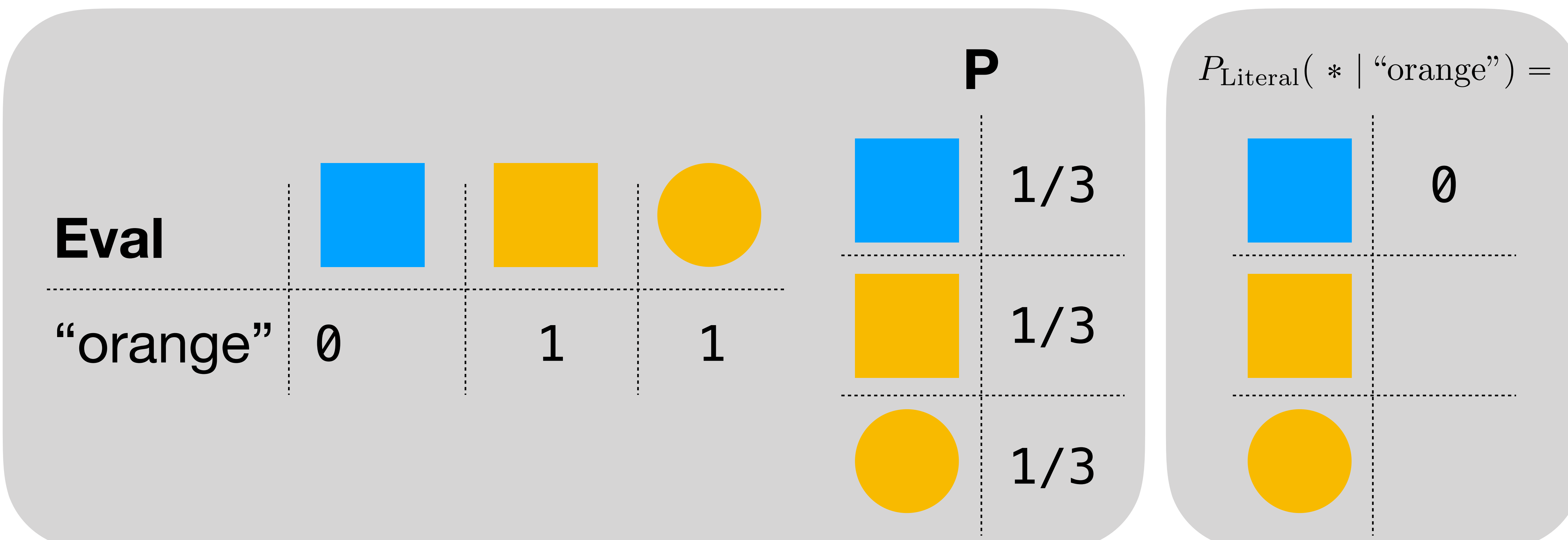
$$P_{\mathrm{Literal}}(r \mid m) = \frac{\mathrm{Eval}(r, m) \times P(r)}{\sum_{r' \in \mathrm{Context}} \mathrm{Eval}(r', m) \times P(r')}$$



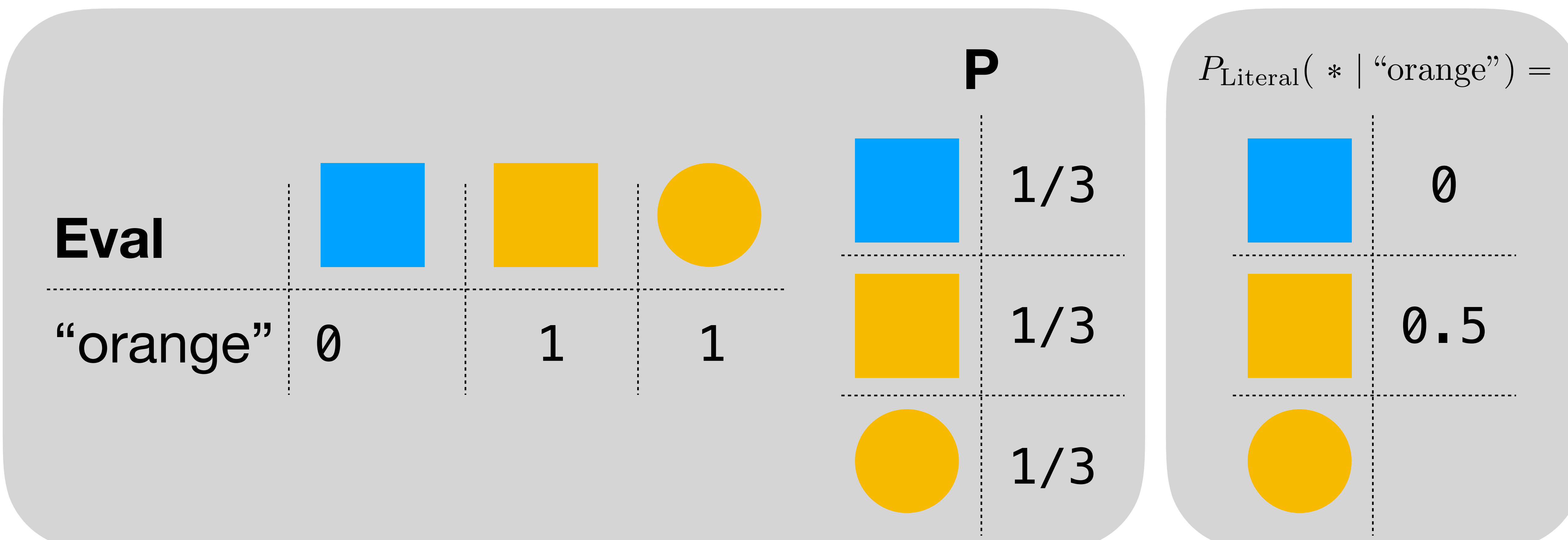
$$P_{\text{Literal}}(\blacksquare \mid \text{“orange”}) = \frac{\text{Eval}(\blacksquare, \text{“orange”}) \times P(r)}{\sum_{r' \in \text{Context}} \text{Eval}(r', m) \times P(r')}$$



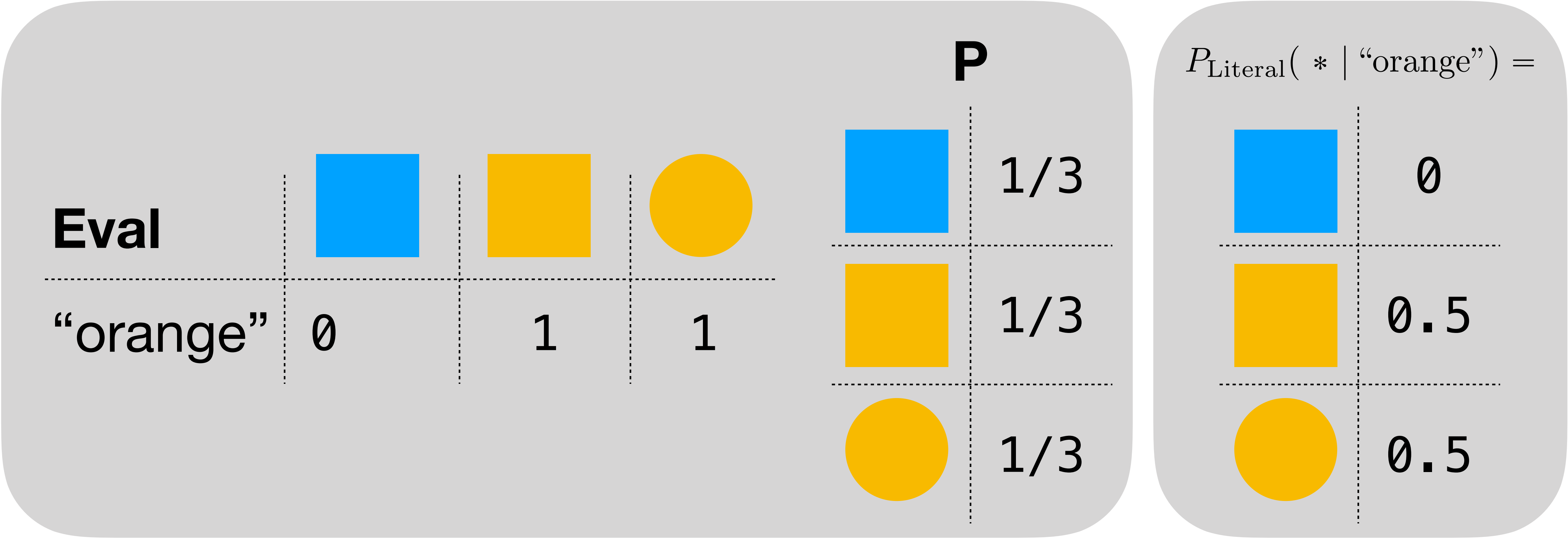
$$
\begin{aligned}
P_{\text{Literal}}(\blacksquare \mid \text{“orange”}) &= \frac{\text{Eval}(\blacksquare, \text{“orange”}) \times P(r)}{\sum_{r' \in \text{Context}} \text{Eval}(r', m) \times P(r')} \\
&= \frac{0 \times \frac{1}{3}}{\sum_{r' \in \text{Context}} \text{Eval}(r', m) \times P(r')} \\
&= 0.
\end{aligned}
$$



$$
\begin{aligned}
P_{\text{Literal}}({\color{orange}\blacksquare} \mid \text{“orange”}) &= \frac{\text{Eval}({\color{orange}\blacksquare}, \text{“orange”}) \times P(r)}{\sum_{r' \in \text{Context}} \text{Eval}(r', m) \times P(r')} \\
&= \frac{1 \times \frac{1}{3}}{1 \times \frac{1}{3} + 1 \times \frac{1}{3}} \\
&= 0.5
\end{aligned}
$$

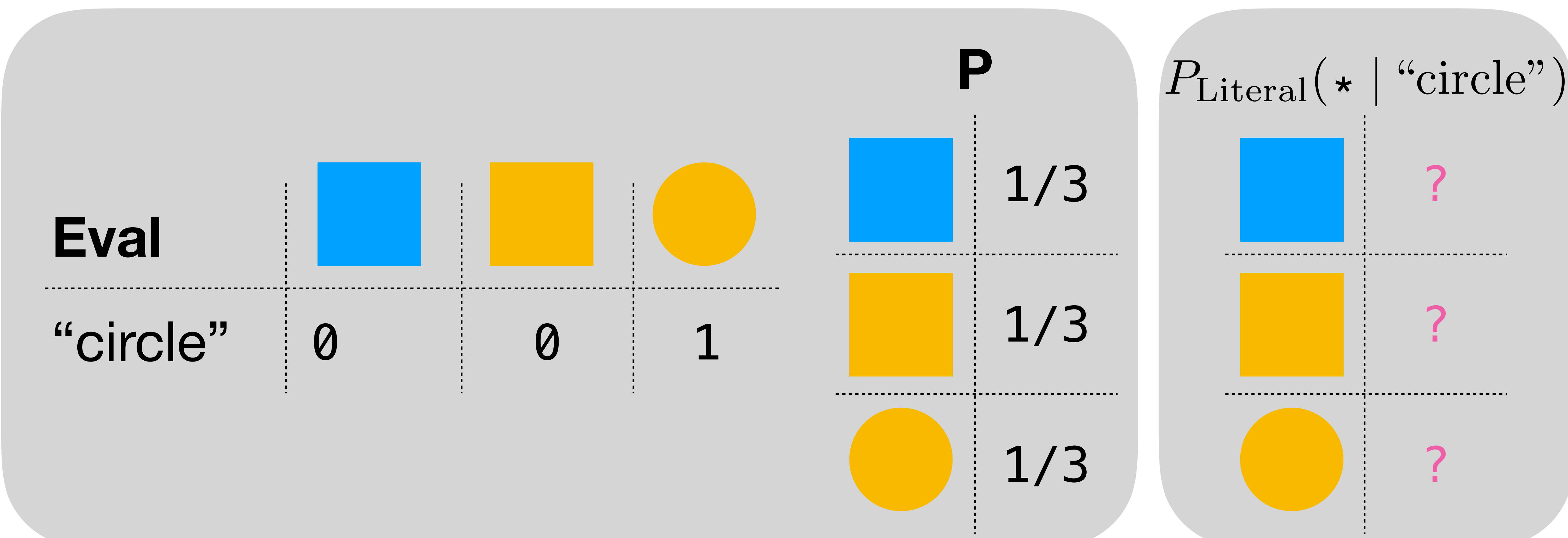


$$
\begin{aligned}
P_{\text{Literal}}(\blacksquare \mid \text{“orange”}) &= P_{\text{Literal}}(\bullet \mid \text{“orange”}) \\
&= \frac{\text{Eval}(\bullet, \text{“orange”}) \times P(r)}{\sum_{r' \in \text{Context}} \text{Eval}(r', m) \times P(r')} \\
&= \frac{1 \times \frac{1}{3}}{1 \times \frac{1}{3} + 1 \times \frac{1}{3}} \\
&= 0.5
\end{aligned}
$$



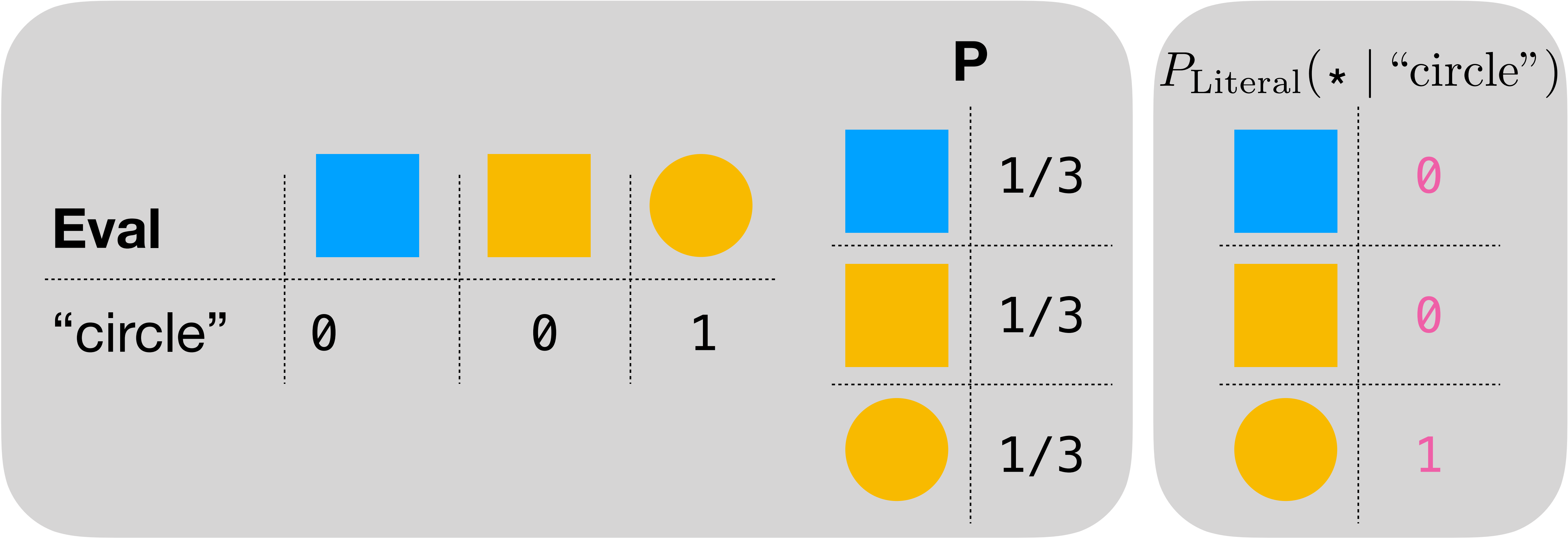
$$P_{\text{Literal}}(r \mid m) = \frac{\text{Eval}(r, m) \times P(r)}{\sum_{r' \in \text{Context}} \text{Eval}(r', m) \times P(r')}$$

$$P_{\text{Literal}}(\, * \mid \text{“circle”}\,)$$



$$P_{\text{Literal}}(r \mid m) = \frac{\text{Eval}(r, m) \times P(r)}{\sum_{r' \in \text{Context}} \text{Eval}(r', m) \times P(r')}$$

$$P_{\text{Literal}}(\star \mid \text{“circle”})$$

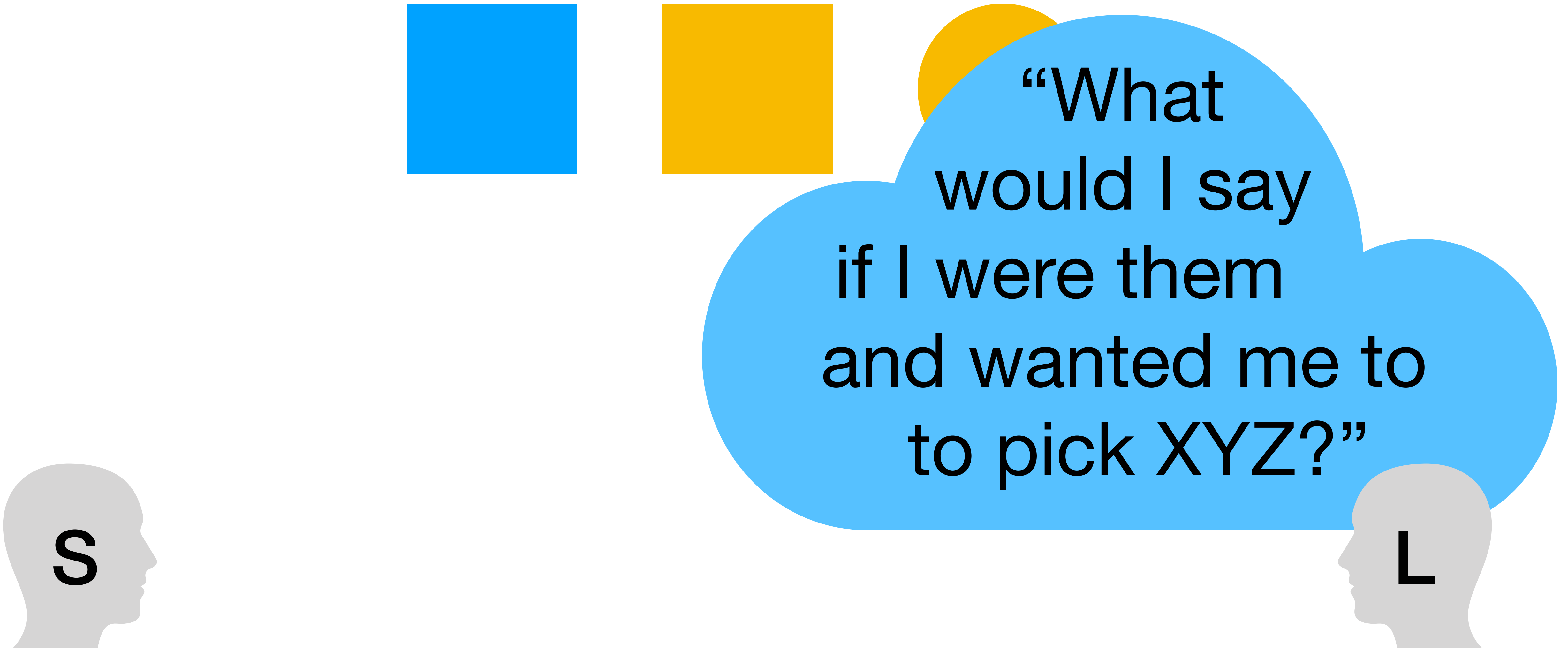


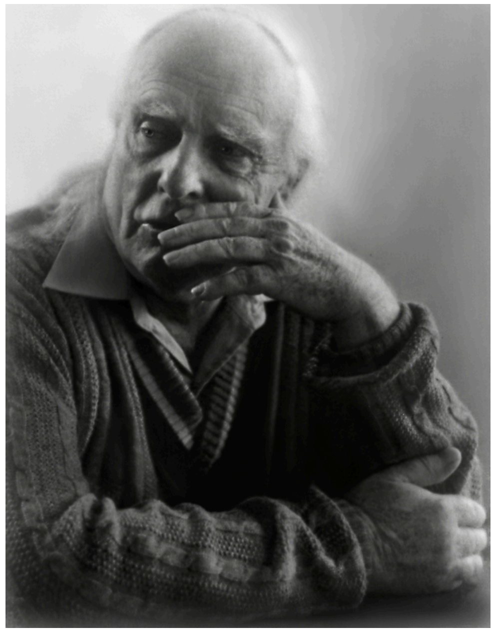
What’s next?

Gricean Principles

https://www.academia.edu/download/52084711/Grice-Logic.pdf

https://www.goodreads.com/photo/author/1961539.Paul_Grice


“What
would I say
if I were them
and wanted me to
to pick XYZ?”
S
L



While not being ambiguous, and saying only what is needed.

$P_{\text{Literal}}(r \mid m) =$	P of a referent given a message, understood literally
$P_{\text{S}}(m \mid r) =$	P of a message, assuming the message will be heard by a literal listener.
$P_{\text{L}}(r \mid m) =$	P of a referent, assuming the message was sent by a pragmatic speaker.

$$P_{\text{Literal}}(r \mid m) = \frac{\text{Eval}(r, m) \times P(r)}{\sum_{r' \in \text{Context}} \text{Eval}(r', m) \times P(r')}$$

$$P_{\text{S}}(m \mid r) =$$

P of a message, assuming the message will be heard by a literal listener.

$$P_{\text{L}}(r \mid m) =$$

P of a referent, assuming the message was sent by a pragmatic speaker.

$$P_{\text{Literal}}(r \mid m) = \frac{\text{Eval}(r, m) \times P(r)}{\sum_{r' \in \text{Context}} \text{Eval}(r', m) \times P(r')}$$

$$P_{\text{S}}(m \mid r) = \frac{P_{\text{Literal}}(r|m)}{\sum_{m' \in \text{Messages}} P_{\text{Literal}}(r|m')}$$

$$P_{\text{L}}(r \mid m) =$$

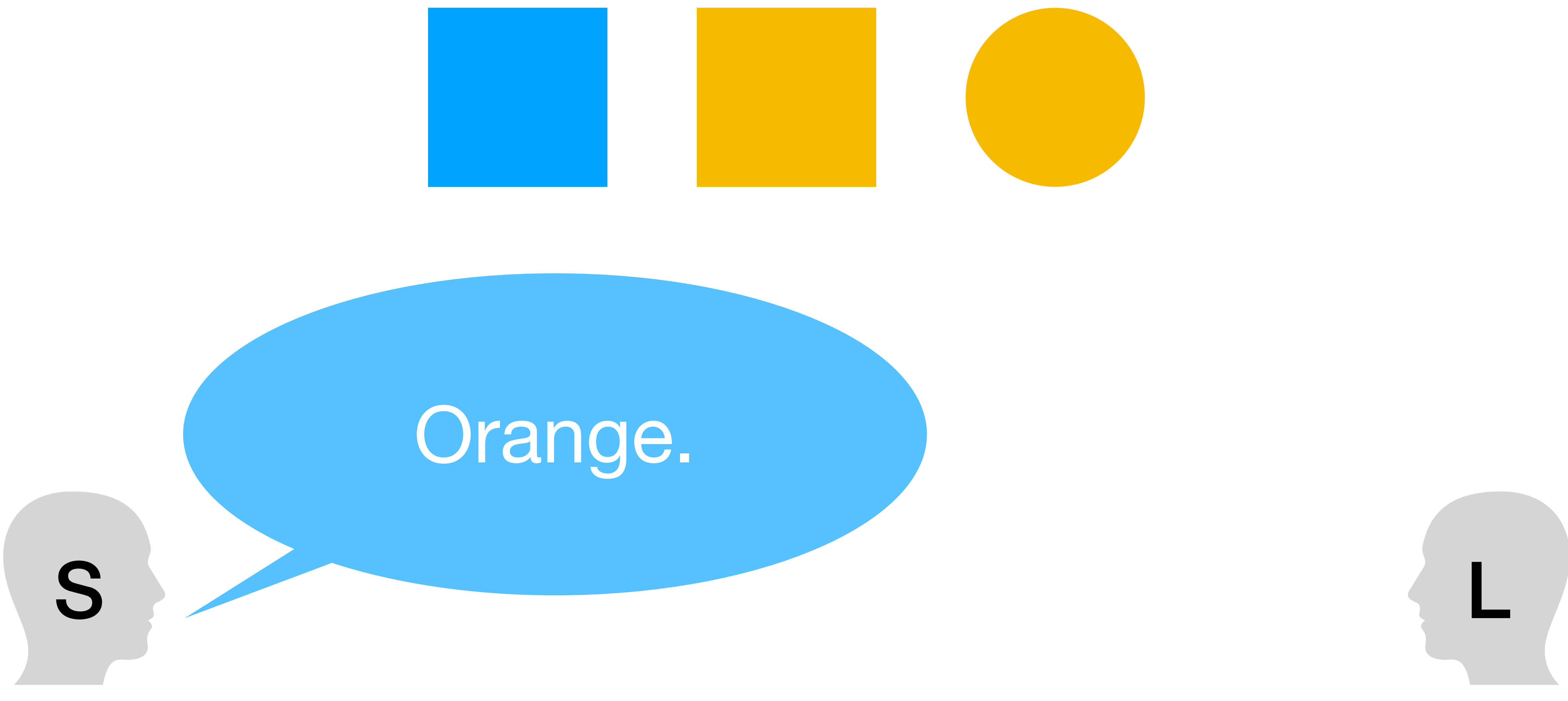
P of a referent, assuming the message was sent by a pragmatic speaker.

$$P_{\text{Literal}}(r \mid m) = \frac{\text{Eval}(r, m) \times P(r)}{\sum_{r' \in \text{Context}} \text{Eval}(r', m) \times P(r')}$$

$$P_{\text{S}}(m \mid r) = \frac{P_{\text{Literal}}(r|m)}{\sum_{m' \in \text{Messages}} P_{\text{Literal}}(r|m')}$$

$$P_{\text{L}}(r \mid m) = \frac{P_{\text{S}}(m \mid r) \times P(r)}{\sum_{r' \in \text{Context}} P_{\text{S}}(m \mid r) \times P(r')}$$

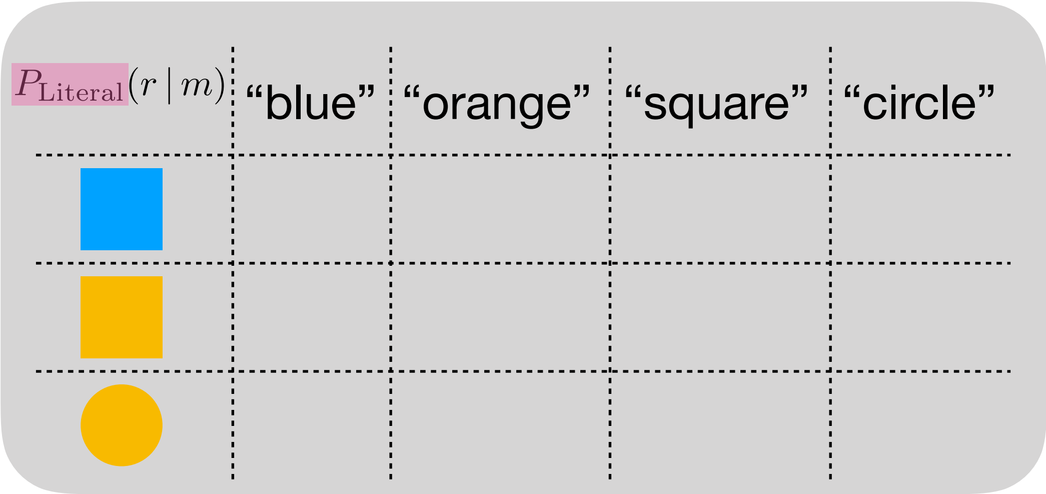
What would you pick?



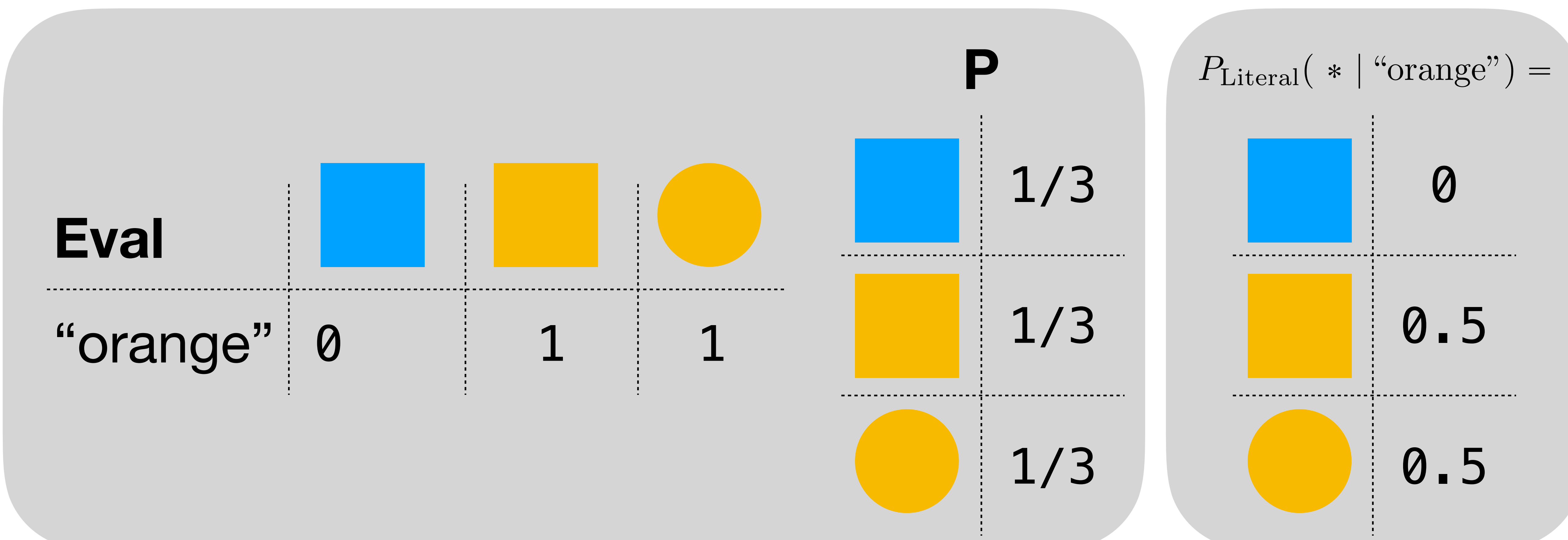
$$P_{\text{Literal}}(r \mid m) = \frac{\text{Eval}(r, m) \times P(r)}{\sum_{r' \in \text{Context}} \text{Eval}(r', m) \times P(r')}$$

$$P_{\text{S}}(m \mid r) = \frac{P_{\text{Literal}}(r|m)}{\sum_{m' \in \text{Messages}} P_{\text{Literal}}(r|m')}$$

$$P_{\text{L}}(r \mid m) = \frac{P_{\text{S}}(m \mid r) \times P(r)}{\sum_{r' \in \text{Context}} P_{\text{S}}(m \mid r) \times P(r')}$$



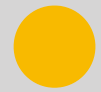
$$
\begin{aligned}
P_{\text{Literal}}(\blacksquare \mid \text{“orange”}) &= P_{\text{Literal}}(\bullet \mid \text{“orange”}) \\
&= \frac{\text{Eval}(\bullet, \text{“orange”}) \times P(r)}{\sum_{r' \in \text{Context}} \text{Eval}(r', m) \times P(r')} \\
&= \frac{1 \times \frac{1}{3}}{1 \times \frac{1}{3} + 1 \times \frac{1}{3}} \\
&= 0.5
\end{aligned}
$$



$$P_{\text{Literal}}(r \mid m) = \frac{\text{Eval}(r, m) \times P(r)}{\sum_{r' \in \text{Context}} \text{Eval}(r', m) \times P(r')}$$

$$P_{\text{S}}(m \mid r) = \frac{P_{\text{Literal}}(r|m)}{\sum_{m' \in \text{Messages}} P_{\text{Literal}}(r|m')}$$

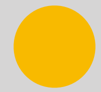
$$P_{\text{L}}(r \mid m) = \frac{P_{\text{S}}(m \mid r) \times P(r)}{\sum_{r' \in \text{Context}} P_{\text{S}}(m \mid r) \times P(r')}$$

$P_{\text{Literal}}(r \mid m)$	"blue"	"orange"	"square"	"circle"
	1	0	0.5	0
	0	0.5	0.5	0
	0	0.5	0	1

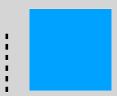
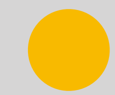
$$P_{\text{Literal}}(r \mid m) = \frac{\text{Eval}(r, m) \times P(r)}{\sum_{r' \in \text{Context}} \text{Eval}(r', m) \times P(r')}$$

$$P_{\text{S}}(m \mid r) = \frac{P_{\text{Literal}}(r|m)}{\sum_{m' \in \text{Messages}} P_{\text{Literal}}(r|m')}$$

$$P_{\text{L}}(r \mid m) = \frac{P_{\text{S}}(m \mid r) \times P(r)}{\sum_{r' \in \text{Context}} P_{\text{S}}(m \mid r) \times P(r')}$$

$P_{\text{Literal}}(r \mid m)$	"blue"	"orange"	"square"	"circle"
	1	0	0.5	0
	0	0.5	0.5	0
	0	0.5	0	1

$$P_{\text{S}}(m \mid r) = \frac{P_{\text{Literal}}(r|m)}{\sum_{m' \in \text{Messages}} P_{\text{Literal}}(r|m')}$$

$P_{\text{S}}(m \mid r)$			
"blue"	?	?	?
"orange"	?	?	?
"square"	?	?	?
"circle"	?	?	?

$$P_{\text{Literal}}(r \mid m) = \frac{\text{Eval}(r, m) \times P(r)}{\sum_{r' \in \text{Context}} \text{Eval}(r', m) \times P(r')}$$

$$P_{\text{S}}(m \mid r) = \frac{P_{\text{Literal}}(r|m)}{\sum_{m' \in \text{Messages}} P_{\text{Literal}}(r|m')}$$

$$P_{\text{L}}(r \mid m) = \frac{P_{\text{S}}(m \mid r) \times P(r)}{\sum_{r' \in \text{Context}} P_{\text{S}}(m \mid r) \times P(r')}$$

$P_{\text{Literal}}(r \mid m)$	“blue”	“orange”	“square”	“circle”
🟦	1	0	0.5	0
🟧	0	0.5	0.5	0
🟠	0	0.5	0	1

$$P_{\text{S}}(\text{“orange”} \mid r) = \frac{P_{\text{Literal}}(r|\text{“orange”})}{\sum_{m' \in \text{Messages}} P_{\text{Literal}}(r|m')}$$

$$P_{\text{S}}(\text{“orange”} \mid \blacksquare) = \frac{P_{\text{Literal}}(\blacksquare|\text{“orange”})}{P_{\text{Lit}}(\blacksquare|\text{“blue”}) + P_{\text{Lit}}(\blacksquare|\text{“orange”}) + P_{\text{Lit}}(\blacksquare|\text{“square”}) + P_{\text{Lit}}(\blacksquare|\text{“circle”})}$$

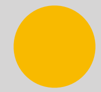
$$= \frac{0}{1 + 0 + 0.5 + 0} = 0.$$

$P_{\text{S}}(m \mid r)$	🟦	🟧	🟠
“blue”	0	?	?
“orange”	?	?	?
“square”	?	?	?
“circle”	?	?	?

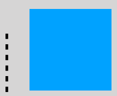
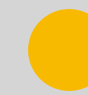
$$P_{\text{Literal}}(r \mid m) = \frac{\text{Eval}(r, m) \times P(r)}{\sum_{r' \in \text{Context}} \text{Eval}(r', m) \times P(r')}$$

$$P_{\text{S}}(m \mid r) = \frac{P_{\text{Literal}}(r|m)}{\sum_{m' \in \text{Messages}} P_{\text{Literal}}(r|m')}$$

$$P_{\text{L}}(r \mid m) = \frac{P_{\text{S}}(m \mid r) \times P(r)}{\sum_{r' \in \text{Context}} P_{\text{S}}(m \mid r) \times P(r')}$$

$P_{\text{Literal}}(r \mid m)$	"blue"	"orange"	"square"	"circle"
	1	0	0.5	0
	0	0.5	0.5	0
	0	0.5	0	1

$$P_{\text{S}}(m \mid r) = \frac{P_{\text{Literal}}(r|m)}{\sum_{m' \in \text{Messages}} P_{\text{Literal}}(r|m')}$$

$P_{\text{S}}(m \mid r)$			
"blue"	0	?	?
"orange"	?	?	?
"square"	?	?	?
"circle"	?	?	?

$$P_{\text{Literal}}(r \mid m) = \frac{\text{Eval}(r, m) \times P(r)}{\sum_{r' \in \text{Context}} \text{Eval}(r', m) \times P(r')}$$

$$P_{\text{S}}(m \mid r) = \frac{P_{\text{Literal}}(r \mid m)}{\sum_{m' \in \text{Messages}} P_{\text{Literal}}(r \mid m')}$$

$$P_{\text{L}}(r \mid m) = \frac{P_{\text{S}}(m \mid r) \times P(r)}{\sum_{r' \in \text{Context}} P_{\text{S}}(m \mid r) \times P(r')}$$

$P_{\text{Literal}}(r \mid m)$	"blue"	"orange"	"square"	"circle"
$\textcolor{#00A0FF}{\blacksquare}$	1	0	0.5	0
$\textcolor{orange}{\blacksquare}$	0	0.5	0.5	0
$\textcolor{orange}{\bullet}$	0	0.5	0	1

$$P_{\text{S}}(\text{“orange”} \mid r) = \frac{P_{\text{Literal}}(r \mid \text{“orange”})}{\sum_{m' \in \text{Messages}} P_{\text{Literal}}(r \mid m')}$$

$$P_{\text{S}}(\text{“orange”} \mid \textcolor{orange}{\blacksquare}) = \frac{P_{\text{Literal}}(\textcolor{orange}{\blacksquare} \mid \text{“orange”})}{P_{\text{Lit}}(\textcolor{orange}{\blacksquare} \mid \text{“blue”}) + P_{\text{Lit}}(\textcolor{orange}{\blacksquare} \mid \text{“orange”}) + P_{\text{Lit}}(\textcolor{orange}{\blacksquare} \mid \text{“square”}) + P_{\text{Lit}}(\textcolor{orange}{\blacksquare} \mid \text{“circle”})}$$

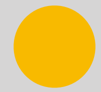
$$= \frac{0.5}{0 + 0.5 + 0.5 + 0} = 0.5$$

$P_{\text{S}}(m \mid r)$	$\textcolor{#00A0FF}{\blacksquare}$	$\textcolor{orange}{\blacksquare}$	$\textcolor{orange}{\bullet}$
"blue"	?	?	?
"orange"	0	0.5	?
"square"	?	?	?
"circle"	?	?	?

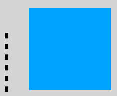
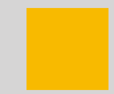
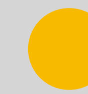
$$P_{\text{Literal}}(r \mid m) = \frac{\text{Eval}(r, m) \times P(r)}{\sum_{r' \in \text{Context}} \text{Eval}(r', m) \times P(r')}$$

$$P_{\text{S}}(m \mid r) = \frac{P_{\text{Literal}}(r|m)}{\sum_{m' \in \text{Messages}} P_{\text{Literal}}(r|m')}$$

$$P_{\text{L}}(r \mid m) = \frac{P_{\text{S}}(m \mid r) \times P(r)}{\sum_{r' \in \text{Context}} P_{\text{S}}(m \mid r) \times P(r')}$$

$P_{\text{Literal}}(r \mid m)$	"blue"	"orange"	"square"	"circle"
	1	0	0.5	0
	0	0.5	0.5	0
	0	0.5	0	1

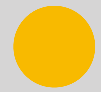
$$P_{\text{S}}(m \mid r) = \frac{P_{\text{Literal}}(r|m)}{\sum_{m' \in \text{Messages}} P_{\text{Literal}}(r|m')}$$

$P_{\text{S}}(m \mid r)$			
"blue"	?	?	?
"orange"	0	0.5	?
"square"	?	?	?
"circle"	?	?	?

$$P_{\text{Literal}}(r \mid m) = \frac{\text{Eval}(r, m) \times P(r)}{\sum_{r' \in \text{Context}} \text{Eval}(r', m) \times P(r')}$$

$$P_{\text{S}}(m \mid r) = \frac{P_{\text{Literal}}(r|m)}{\sum_{m' \in \text{Messages}} P_{\text{Literal}}(r|m')}$$

$$P_{\text{L}}(r \mid m) = \frac{P_{\text{S}}(m \mid r) \times P(r)}{\sum_{r' \in \text{Context}} P_{\text{S}}(m \mid r) \times P(r')}$$

$P_{\text{Literal}}(r \mid m)$	"blue"	"orange"	"square"	"circle"
	1	0	0.5	0
	0	0.5	0.5	0
	0	0.5	0	1

$$P_{\text{S}}(\text{“orange”} \mid r) = \frac{P_{\text{Literal}}(r|\text{“orange”})}{\sum_{m' \in \text{Messages}} P_{\text{Literal}}(r|m')}$$

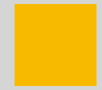
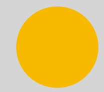
$$P_{\text{S}}(\text{“orange”} \mid \bullet) = \frac{P_{\text{Literal}}(\bullet|\text{“orange”})}{P_{\text{Lit}}(\bullet|\text{“blue”}) + P_{\text{Lit}}(\bullet|\text{“orange”}) + P_{\text{Lit}}(\bullet|\text{“square”}) + P_{\text{Lit}}(\bullet|\text{“circle”})}$$

$$= \frac{0.5}{0 + 0.5 + 0 + 1} = 0.33$$

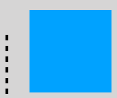
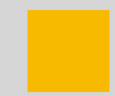
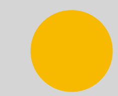
$$P_{\text{Literal}}(r \mid m) = \frac{\text{Eval}(r, m) \times P(r)}{\sum_{r' \in \text{Context}} \text{Eval}(r', m) \times P(r')}$$

$$P_{\text{S}}(m \mid r) = \frac{P_{\text{Literal}}(r|m)}{\sum_{m' \in \text{Messages}} P_{\text{Literal}}(r|m')}$$

$$P_{\text{L}}(r \mid m) = \frac{P_{\text{S}}(m \mid r) \times P(r)}{\sum_{r' \in \text{Context}} P_{\text{S}}(m \mid r) \times P(r')}$$

$P_{\text{Literal}}(r \mid m)$	"blue"	"orange"	"square"	"circle"
	1	0	0.5	0
	0	0.5	0.5	0
	0	0.5	0	1

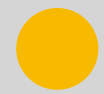
$$P_{\text{S}}(m \mid r) = \frac{P_{\text{Literal}}(r|m)}{\sum_{m' \in \text{Messages}} P_{\text{Literal}}(r|m')}$$

$P_{\text{S}}(m \mid r)$			
"blue"	?	?	?
"orange"	0	0.5	0.33
"square"	?	?	?
"circle"	?	?	?

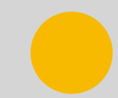
$$P_{\text{Literal}}(r \mid m) = \frac{\text{Eval}(r, m) \times P(r)}{\sum_{r' \in \text{Context}} \text{Eval}(r', m) \times P(r')}$$

$$P_{\text{S}}(m \mid r) = \frac{P_{\text{Literal}}(r|m)}{\sum_{m' \in \text{Messages}} P_{\text{Literal}}(r|m')}$$

$$P_{\text{L}}(r \mid m) = \frac{P_{\text{S}}(m \mid r) \times P(r)}{\sum_{r' \in \text{Context}} P_{\text{S}}(m \mid r) \times P(r')}$$

$P_{\text{Literal}}(r \mid m)$	"blue"	"orange"	"square"	"circle"
	1	0	0.5	0
	0	**0.5**	0.5	0
	0	**0.5**	0	1

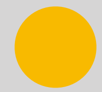
$$P_{\text{S}}(m \mid r) = \frac{P_{\text{Literal}}(r|m)}{\sum_{m' \in \text{Messages}} P_{\text{Literal}}(r|m')}$$

$P_{\text{S}}(m \mid r)$			
"blue"	?	?	?
"orange"	0	0.5	0.33
"square"	?	?	?
"circle"	?	?	?

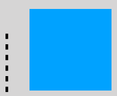
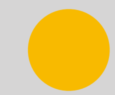
$$P_{\text{Literal}}(r \mid m) = \frac{\text{Eval}(r, m) \times P(r)}{\sum_{r' \in \text{Context}} \text{Eval}(r', m) \times P(r')}$$

$$P_{\text{S}}(m \mid r) = \frac{P_{\text{Literal}}(r|m)}{\sum_{m' \in \text{Messages}} P_{\text{Literal}}(r|m')}$$

$$P_{\text{L}}(r \mid m) = \frac{P_{\text{S}}(m \mid r) \times P(r)}{\sum_{r' \in \text{Context}} P_{\text{S}}(m \mid r) \times P(r')}$$

$P_{\text{Literal}}(r \mid m)$	"blue"	"orange"	"square"	"circle"
	1	0	0.5	0
	0	0.5	0.5	0
	0	0.5	0	1

$$P_{\text{S}}(m \mid r) = \frac{P_{\text{Literal}}(r|m)}{\sum_{m' \in \text{Messages}} P_{\text{Literal}}(r|m')}$$

$P_{\text{S}}(m \mid r)$			
"blue"	0.67	0	0
"orange"	0	0.5	0.33
"square"	0.33	0.5	0
"circle"	0	0	0.67

$P_{\mathrm{S}}(m \mid r)$	■	■	●
"blue"	0.67	0	0
"orange"	0	0.5	0.33
"square"	0.33	0.5	0
"circle"	0	0	0.67

$$P_{\mathrm{L}}(r \mid m) = \frac{P_{\mathrm{S}}(m \mid r) \times P(r)}{\sum_{r' \in \mathrm{Context}} P_{\mathrm{S}}(m \mid r) \times P(r')}$$

$$P_{\mathrm{L}}(\blacksquare \mid \text{“orange”}) = \frac{P_{\mathrm{S}}(\text{“orange”}) \mid \blacksquare) \times P(\blacksquare)}{\sum_{r' \in \mathrm{Context}} P_{\mathrm{S}}(\text{“orange”}) \mid r') \times P(r')}$$

$$= \frac{0.5 \times 0.33}{0 \times 0.33 + 0.5 \times 0.33 + 0.33 \times 0.33} = \frac{1/2}{1/2 + 1/3} = \frac{3}{5}.$$

$$P_{\mathrm{L}}(r \mid m) = \frac{P_{\mathrm{S}}(m \mid r) \times P(r)}{\sum_{r' \in \mathrm{Context}} P_{\mathrm{S}}(m \mid r) \times P(r')}$$

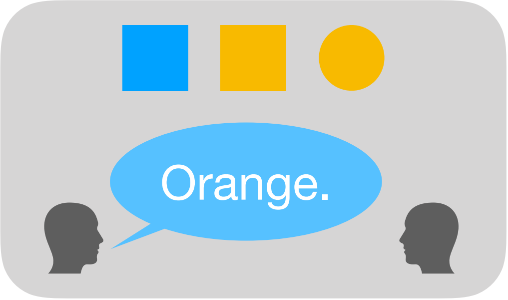
$P_{\mathrm{S}}(m \mid r)$	$\blacksquare$	$\blacksquare$	$\bullet$
"blue"	0.67	0	0
"orange"	0	0.5	0.33
"square"	**0.33**	0.5	0
"circle"	0	0	0.67

$$P_{\mathrm{L}}(\blacksquare \mid \text{“orange”}) = \frac{P_{\mathrm{S}}(\text{“orange”}) \mid \blacksquare) \times P(\blacksquare)}{\sum_{r' \in \mathrm{Context}} P_{\mathrm{S}}(\text{“orange”}) \mid r') \times P(r')}$$

$$= \frac{0.5 \times 0.33}{0 \times 0.33 + 0.5 \times 0.33 + 0.33 \times 0.33} = \frac{1/2}{1/2 + 1/3} = \frac{3}{5}.$$

$$P_{\mathrm{L}}(\bullet \mid \text{“orange”}) = \frac{P_{\mathrm{S}}(\text{“orange”}) \mid \bullet) \times P(\bullet)}{\sum_{r' \in \mathrm{Context}} P_{\mathrm{S}}(\text{“orange”}) \mid r') \times P(r')}$$

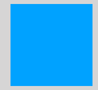
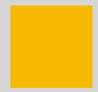
$$= \frac{0.33 \times 0.33}{0 \times 0.33 + 0.5 \times 0.33 + 0.33 \times 0.33} = \frac{1/3}{1/2 + 1/3} = \frac{2}{5}.$$

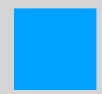
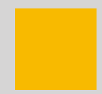
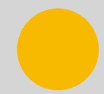


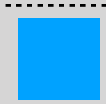
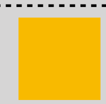
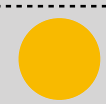
$$P_{\mathrm{L}}(\blacksquare \mid \text{“orange”}) = 0,$$

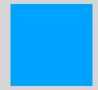
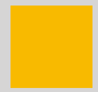
$$P_{\mathrm{L}}(\blacksquare \mid \text{“orange”}) = \frac{3}{5},$$

$$P_{\mathrm{L}}(\bullet \mid \text{“orange”}) = \frac{2}{5}.$$

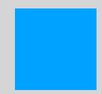
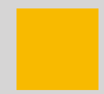
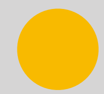
$P_{\text{Literal}}(r \mid m)$	"blue"	"orange"	"square"	"circle"
	1	0	0.5	0
	0	0.5	0.5	0
	0	0.5	0	1

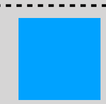
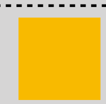
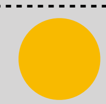
$P_{\text{S}}(m \mid r)$			
"blue"	0.67	0	0
"orange"	0	0.5	0.33
"square"	0.33	0.5	0
"circle"	0	0	0.67

$P_{\text{L}}(r \mid m)$	"blue"	"orange"	"square"	"circle"
	1	0	0.4	0
	0	0.6	0.6	0
	0	0.4	0	1

$P_{\text{Literal}}(r \mid m)$	“blue”	“orange”	“square”	“circle”
	1	0	0.5	0
	0	0.5	0.5	0
	0	0.5	0	1

Transpose + Normalize

$P_{\text{S}}(m \mid r)$			
“blue”	0.67	0	0
“orange”	0	0.5	0.33
“square”	0.33	0.5	0
“circle”	0	0	0.67

$P_{\text{L}}(r \mid m)$	“blue”	“orange”	“square”	“circle”
	1	0	0.4	0
	0	0.6	0.6	0
	0	0.4	0	1

$P_{\text{Literal}}(r \mid m)$	"blue"	"orange"	"square"	"circle"
	1	0	0.5	0
	0	0.5	0.5	0
	0	0.5	0	1

$P_{\text{S}}(m \mid r)$			
"blue"	0.67	0	0
"orange"	0	0.5	0.33
"square"	0.33	0.5	0
"circle"	0	0	0.67

Transpose + Normalize

$P_{\text{L}}(r \mid m)$	"blue"	"orange"	"square"	"circle"
	1	0	0.4	0
	0	0.6	0.6	0
	0	0.4	0	1

What would you pick?

$$P_{\text{Literal}}(r \mid m)$$

$P_{\text{Literal}}(r \mid m)$	Pepperoni	mushroom	Cheese	Plain
	1.0	0.5	0.33	0.0
	0.0	0.5	0.33	0.0
	0.0	0.0	0.33	1.0

$$P_{\text{S}}(m \mid r) :$$

$P_{\text{S}}(m \mid r)$			
Pepperoni		?	
mushroom		?	
Cheese		?	
Plain		?	

$$P_{\text{Literal}}(r \mid m)$$

$P_{\text{Literal}}(r \mid m)$	Pepperoni	mushroom	Cheese	Plain
	1.0	0.5	0.33	0.0
	0.0	0.5	0.33	0.0
	0.0	0.0	0.33	1.0

$$P_{\text{S}}(m \mid r) :$$

$P_{\text{S}}(m \mid r)$			
Pepperoni		0	
mushroom		0.6	
Cheese		0.4	
Plain		0	

$$P_{\text{Literal}}(r \mid m)$$

$P_{\text{Literal}}(r \mid m)$	Pepperoni	mushroom	Cheese	Plain
	1.0	0.5	0.33	0.0
	0.0	0.5	0.33	0.0
	0.0	0.0	0.33	1.0

$$P_{\text{S}}(m \mid r) :$$

$P_{\text{S}}(m \mid r)$			
Pepperoni		0	
mushroom		0.6	
Cheese		0.4	
Plain		0	

0 / 0 + 0.5 + 0.33 + 0 = 0
1/2 / (0 + 1/2 + 1/3 + 0) = 1/2 / (1/2 + 1/3) = 3 / (2 + 3) = 3 / 5 = 0.6
1/3 / (0 + 1/2 + 1/3 + 0) = 1/3 / (1/2 + 1/3) = 2 / (2 + 3) = 2 / 5 = 0.4
0 / 0 + 0.5 + 0.33 + 0 = 0

Aside #1

Handle length +
how pragmatic
you want to be.

$$P_{\text{Literal}}(r \mid m) = \frac{\text{Eval}(r, m) \times P(r)}{\sum_{r' \in \text{Context}} \text{Eval}(r', m) \times P(r')}$$

$$P_{\text{S}}(m \mid r) = \frac{\exp(\alpha(\log P_{\text{Literal}}(r|m) + C(m)))}{\sum_{m' \in \text{Messages}} \exp(\alpha(\log P_{\text{Literal}}(r|m') + C(m')))}$$

$$P_{\text{L}}(r \mid m) = \frac{P_{\text{S}}(m \mid r) \times P(r)}{\sum_{r' \in \text{Context}} P_{\text{S}}(m \mid r) \times P(r')}$$

Aside #2

Learn the "evaluate" function from data.

Learning in the Rational Speech Acts Model

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Abstract

The Rational Speech Acts (RSA) model treats language use as a recursive process in which probabilistic speaker and listener agents reason about each other's intentions to enrich the literal semantics of their language along broadly Gricean lines. RSA has been shown to capture many kinds of conversational implicature, but it has been criticized as an unrealistic model of speakers, and it has so far required the manual specification of a semantic lexicon, preventing its use in natural language processing applications that learn lexical knowledge from data. We address these concerns by showing how to define and optimize a trained statistical classifier that uses the intermediate agents of RSA as hidden layers of representation forming a non-linear activation function. This treatment opens up new application domains and new possibilities for learning effectively from data. We validate the model on a referential expression generation task, showing that the best performance is achieved by incorporating features approximating well-established insights about natural language generation into RSA.

Literal speaker. Learned RSA is built on top of a *log-linear model*, standard in the machine learning literature and widely applied to classification tasks [19, 27].

$$S_0(m \mid t, c; \theta) \propto \exp(\theta^T \phi(t, m, c)) \qquad (4)$$

Aside #3

There are probabilistic programming languages that support 'neat' implementations.

[4]:
```
@Marginal
def speaker(state):
    alpha = 1.
    with poutine.scale(scale=torch.tensor(alpha)):
        utterance = utterance_prior()
        pyro.sample("listener", literal_listener(utterance), obs=state)
    return utterance
```

Finally, we can define the pragmatic_listener, who infers which state is likely, given that the speaker chose a given utterance. Mathematically:

$$P_L(s|u) \propto P_S(u|s)P(s)$$

In code:

[5]:
```
@Marginal
def pragmatic_listener(utterance):
    state = state_prior()
    pyro.sample("speaker", speaker(state), obs=utterance)
    return state
```

https://pyro.ai/examples/index.html

Aside #4

Add more layers for
Better performance.

Understanding the Rational Speech Act model

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Abstract

The Rational Speech Act (RSA) model, which proposes that probabilistic speakers and listeners recursively reason about each other's mental states to communicate, has been successful in explaining many pragmatic reasoning phenomena. However, several theoretical questions remain unanswered. First, will such a pragmatic speaker–listener pair always outperform their literal counterparts who do not reason about each others mental states? Second, how does communication effectiveness change with the number of recursions? Third, when exact inference cannot be performed, how does limiting the computational resources of the speaker and listener affect these results? We systematically analyzed the RSA model and found that in Monte Carlo simulations pragmatic listeners and speakers always outperform their literal counterparts and the expected accuracy increases as the number of recursions increases. Furthermore, limiting the computation resources of the speaker and listener so they sample only the top k most likely options leads to *higher* expected accuracy. We verified these results on a previously collected natural language dataset in color reference games. The current work supplements the existing RSA literature and could guide future modeling work.

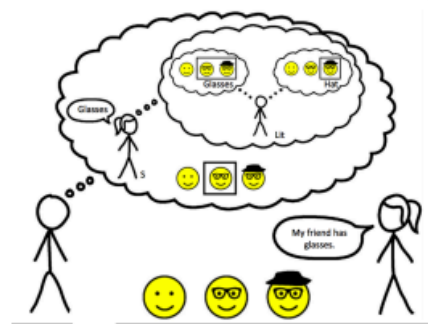

Figure 1: Pragmatic reasoning in a reference game. The speaker says my friend has glasses. The listener needs to guess which one is the speaker's friend. Adapted from Goodman and Frank (2016).

RESEARCH ARTICLE

Reasoning in Reference Games: Individual- vs. Population-Level Probabilistic Modeling

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Variation across ppl

Abstract

Recent advances in probabilistic pragmatics have achieved considerable success in modeling speakers' and listeners' pragmatic reasoning as probabilistic inference. However, these models are usually applied to population-level data, and so implicitly suggest a homogeneous population without individual differences. Here we investigate potential individual dif-

Pragmatics

Very-low Data

Pragmatics

Very-low Data

Bayesian Language of Thought

1,2	2,4

1,2	2,4
1,2,3	2,4,6
1,1,1	2,2,2

1,2,3	1,2,3

1,2,3	1,2,3
9,7,8	7,8,9

4,5	4

4,5	4
4,5,9	4,9
4,5,9,2	4,9

4,5	4
4,5,9	4,9
4,5,9,2	4,9
4,5,9,3,2,16,9	4,9,16,9

Bayesian Language of Thought =

Set of primitives

Prior function

Inference Scheme

A Set of primitives

- And
- Or
- Not
- Pair
- If
- Recurse
- Head

A Set of primitives

And
Or
Not
Pair
If
Recurse
Head
Tail
ForEach
Filter
Eq…

A Set of primitives

And	0..9
Or	+
Not	-
Pair	/
If	sqrt
Recurse	…
Head	
Tail	
ForEach	
Filter	
Eq…	

A Set of primitives

And	0..9	Forward
Or	+	Backward
Not	-	Left
Pair	/	Right
If	sqrt	Goto
Recurse	…	penup
Head		pendown
Tail		begin_fill
ForEach		end_fill
Filter		
Eq…		

How likely does H
make the observed D

$$P(H)P(D|H)$$

Prior: How likely is the H?
Inversely related to
description length

1,2	2,4
1,2,3	2,4,6
1,1,1	2,2,2

$$H_1 = \mathrm{ForEach}(x, x * 2 * 2 + 2 - 2 - x * 2)$$

$$H_2 = \mathrm{ForEach}(x, x * 2)$$

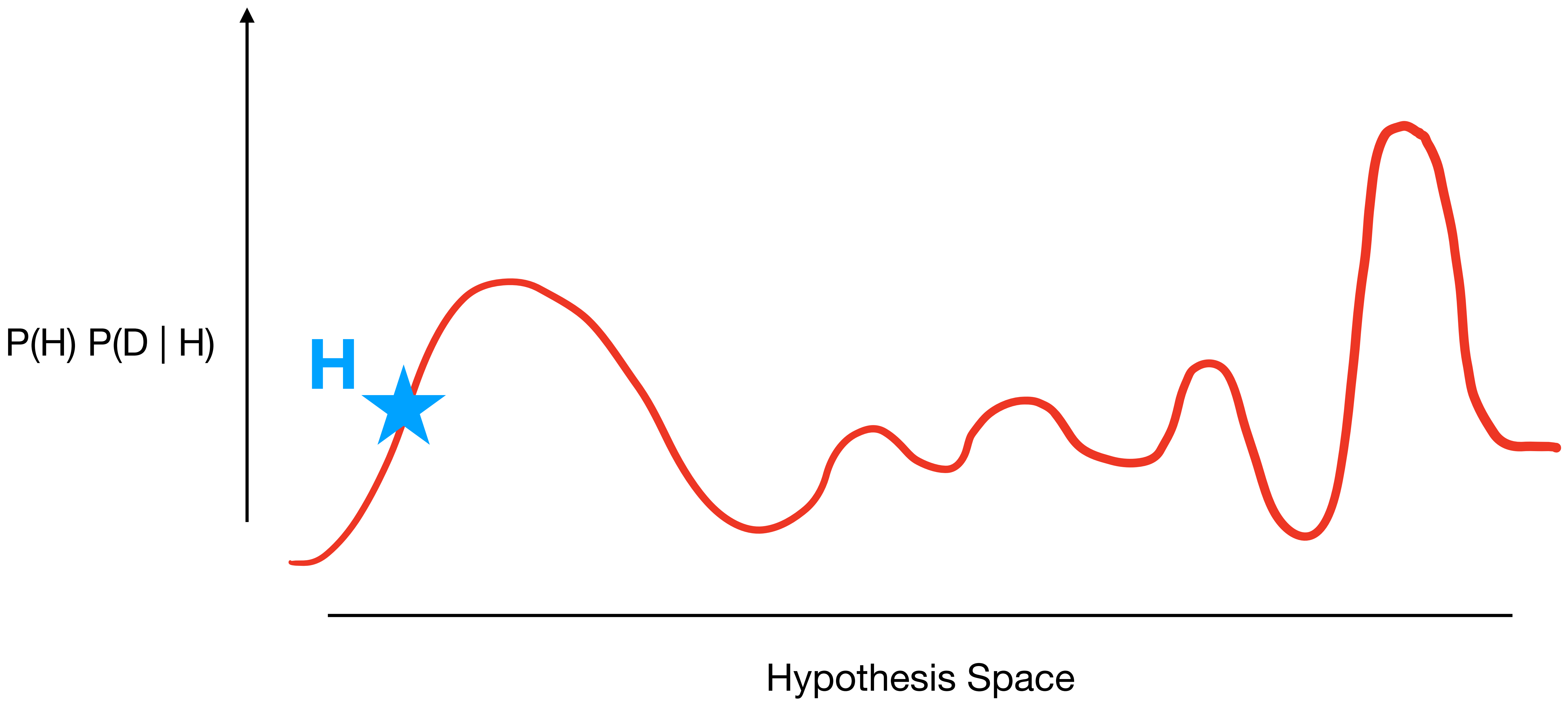
$$P(H_1) < P(H_2)$$

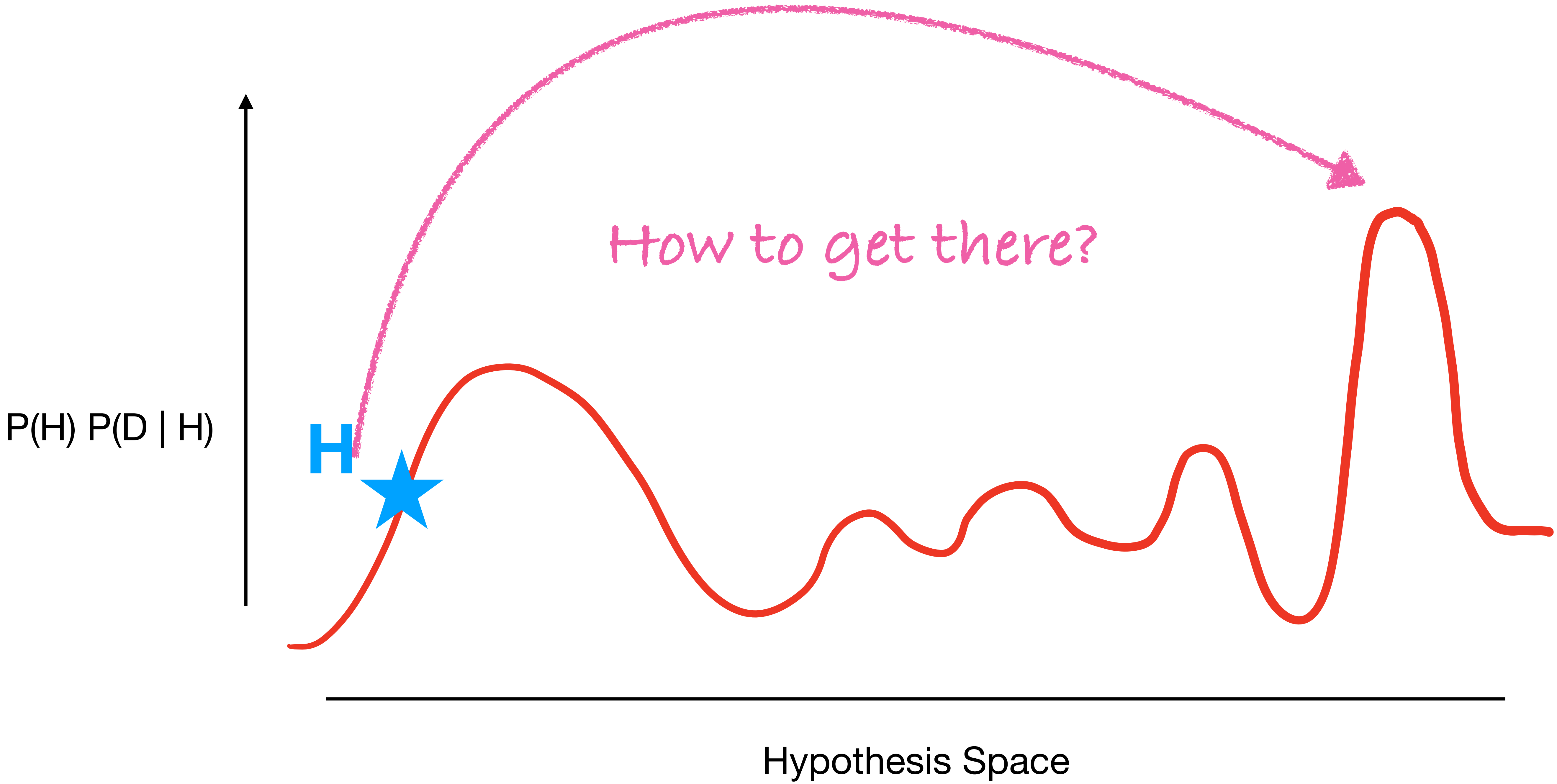
4,5	4
4,5,9	4,9
4,5,9,2	4,9
4,5,9,3,2,16,9	4,9,16,9

$$H_1 = \mathrm{ForEach}((x, i), \mathrm{If}(\mathrm{Eq}(i \bmod 2, 0), x, \varnothing))$$

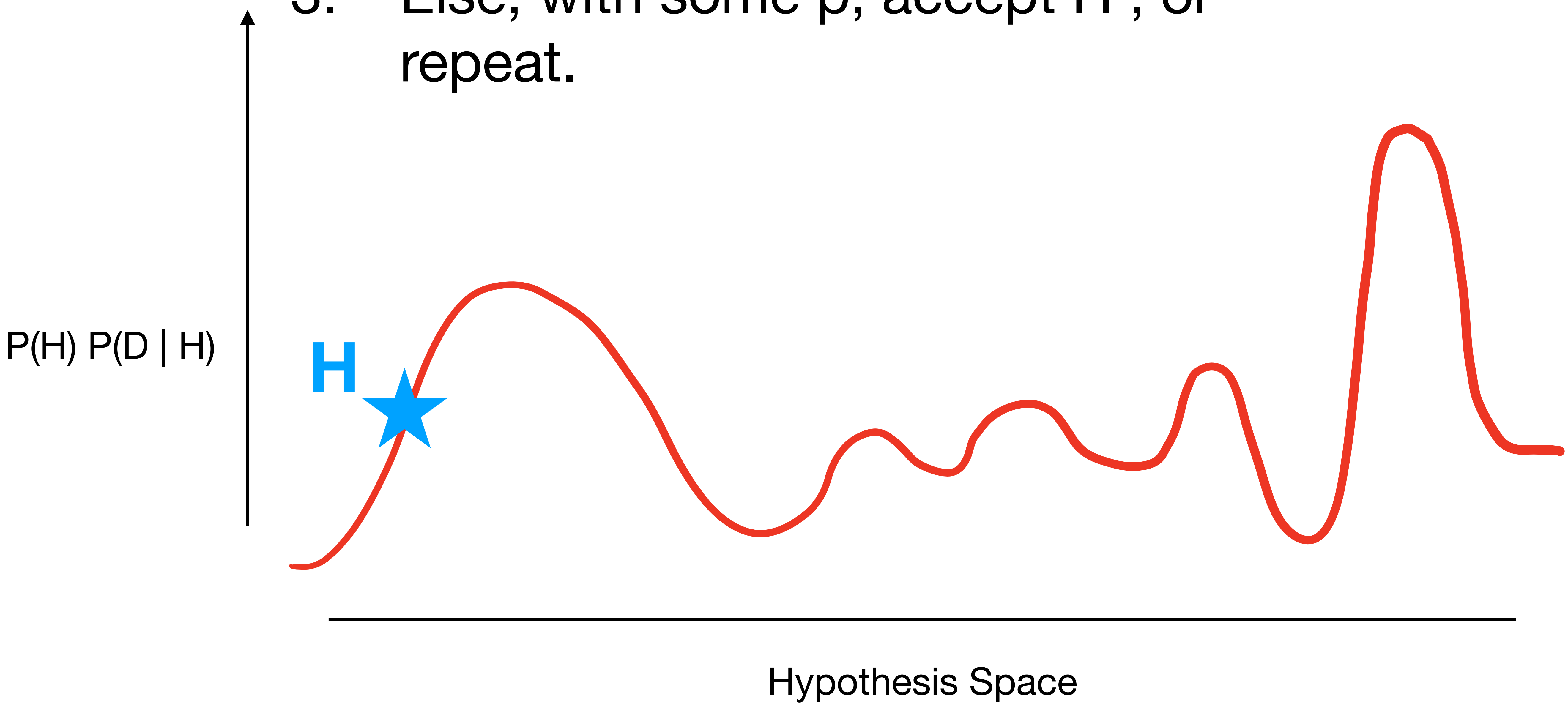
$$H_2 = \mathrm{ForEach}(x, x * 2)$$

$$P(D|H_1) > P(D|H_2)$$

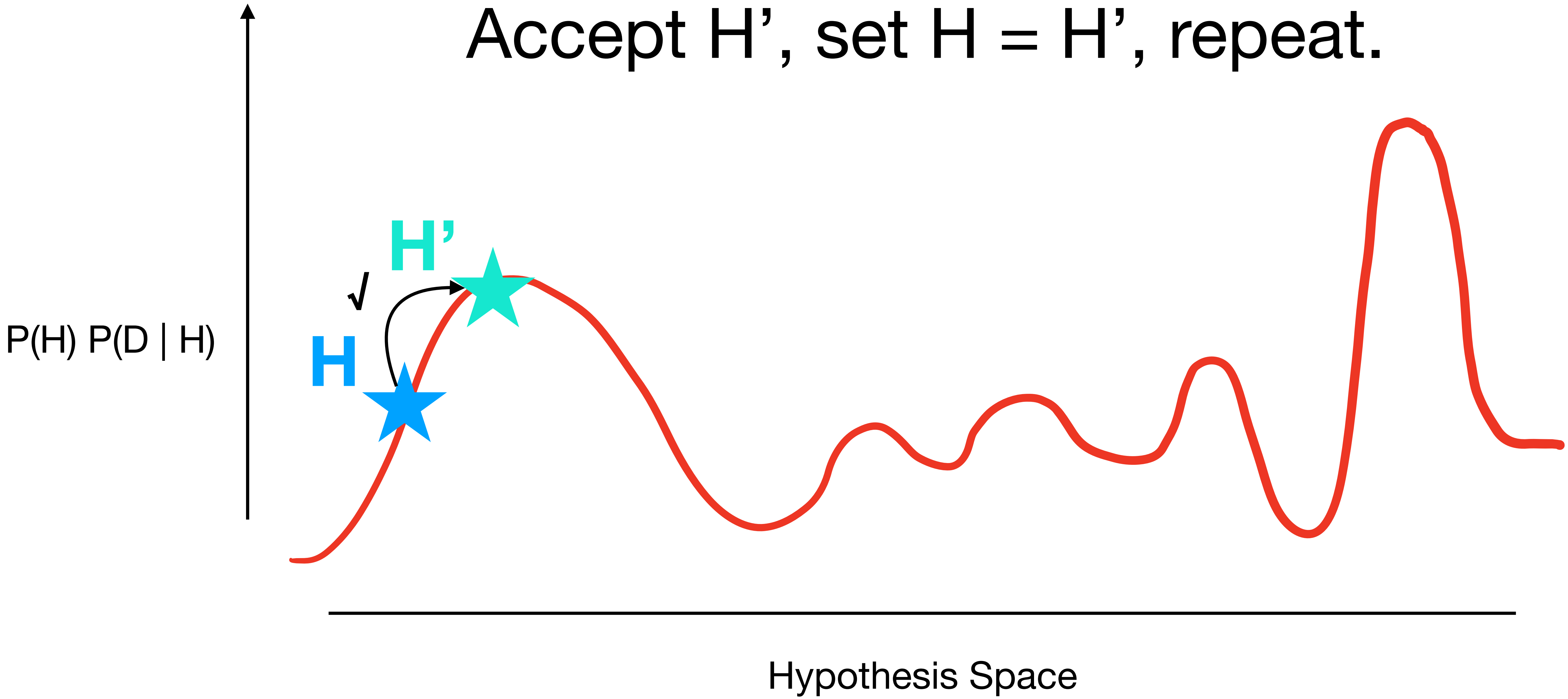

P(H) P(D | H)
H
Hypothesis Space


How to get there?
P(H) P(D | H)
H
Hypothesis Space

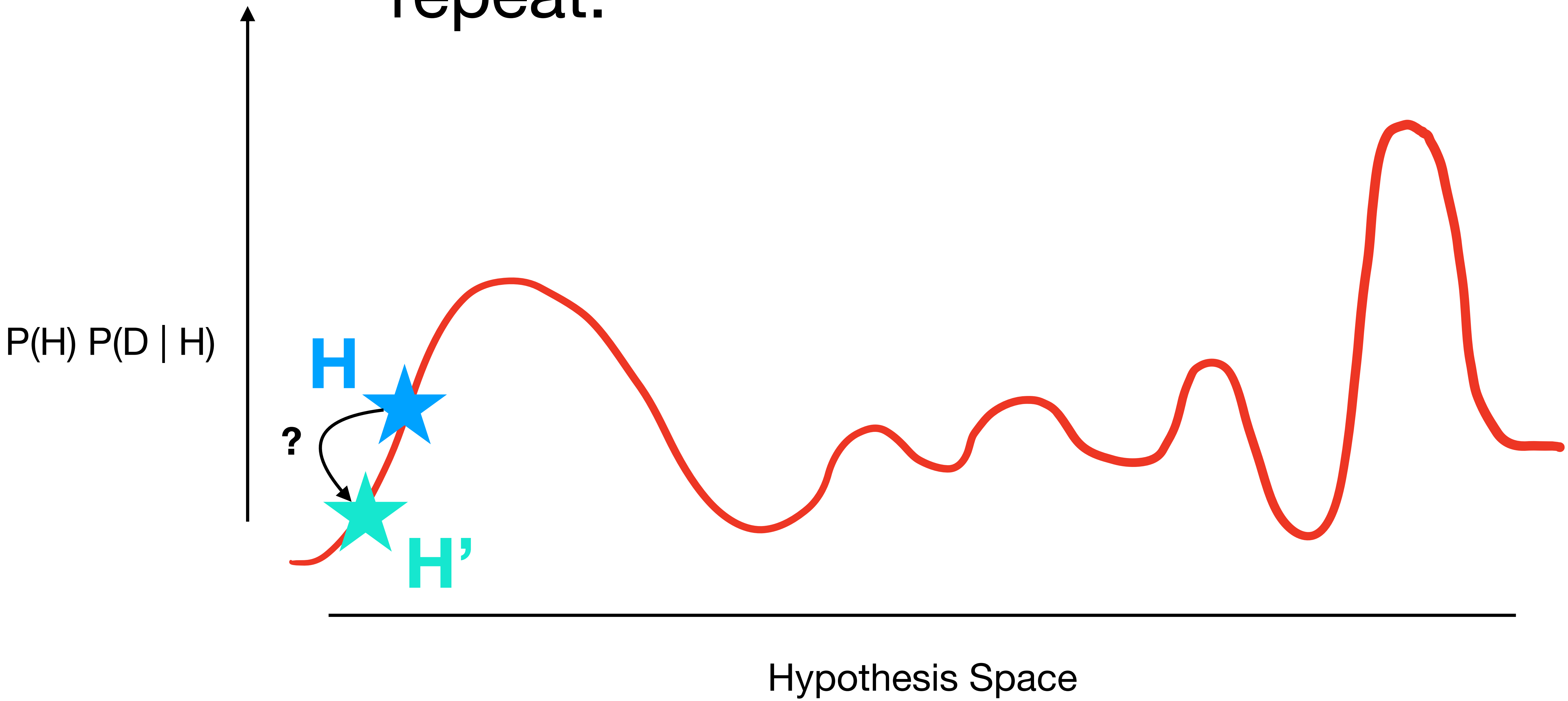
1. Make a random change to H —> H’
2. If $\frac{P(H')P(D|H')}{P(H)P(D|H)}$ > 1, accept H’
3. Else, with some p, accept H’, or repeat.



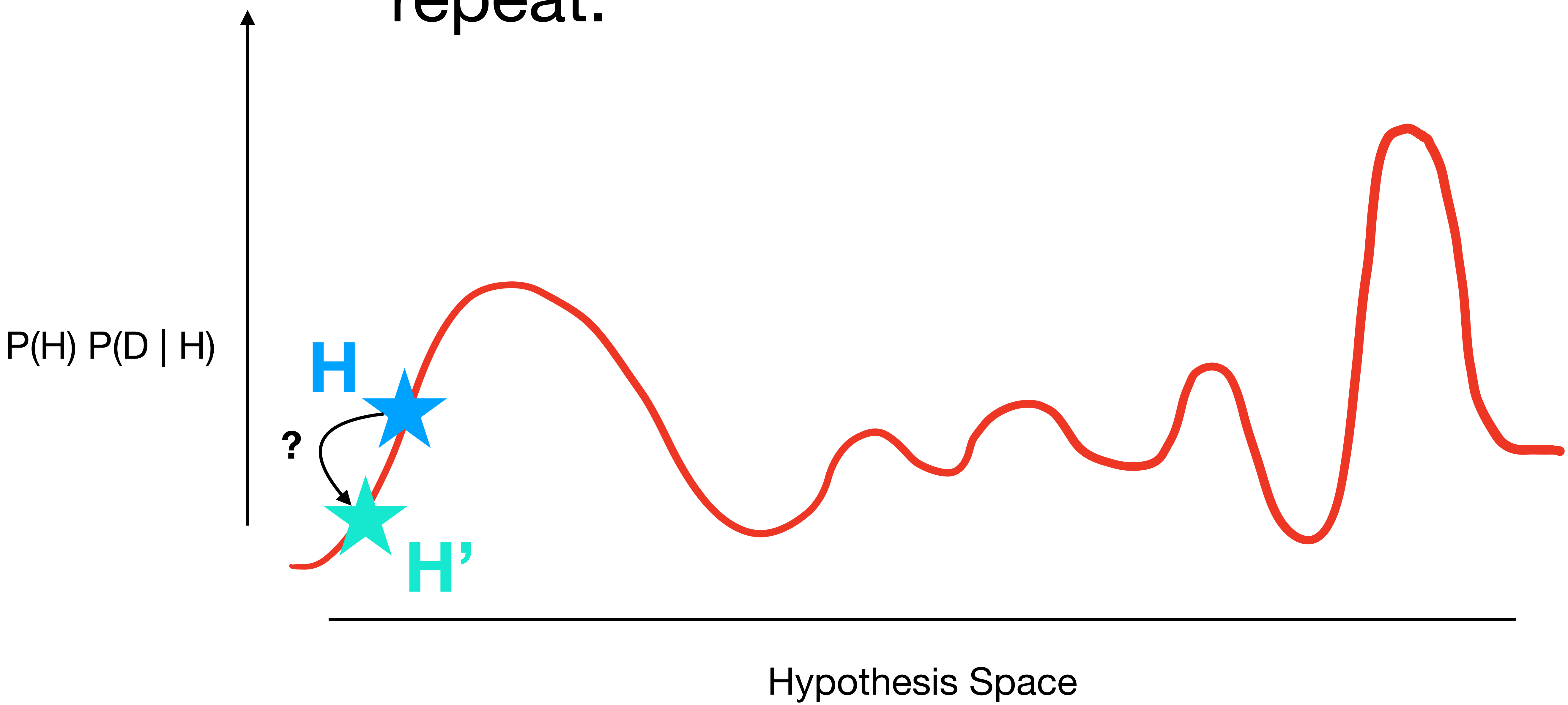
Accept H’, set H = H’, repeat.



Accept H’ with *p* setting H = H’, repeat.



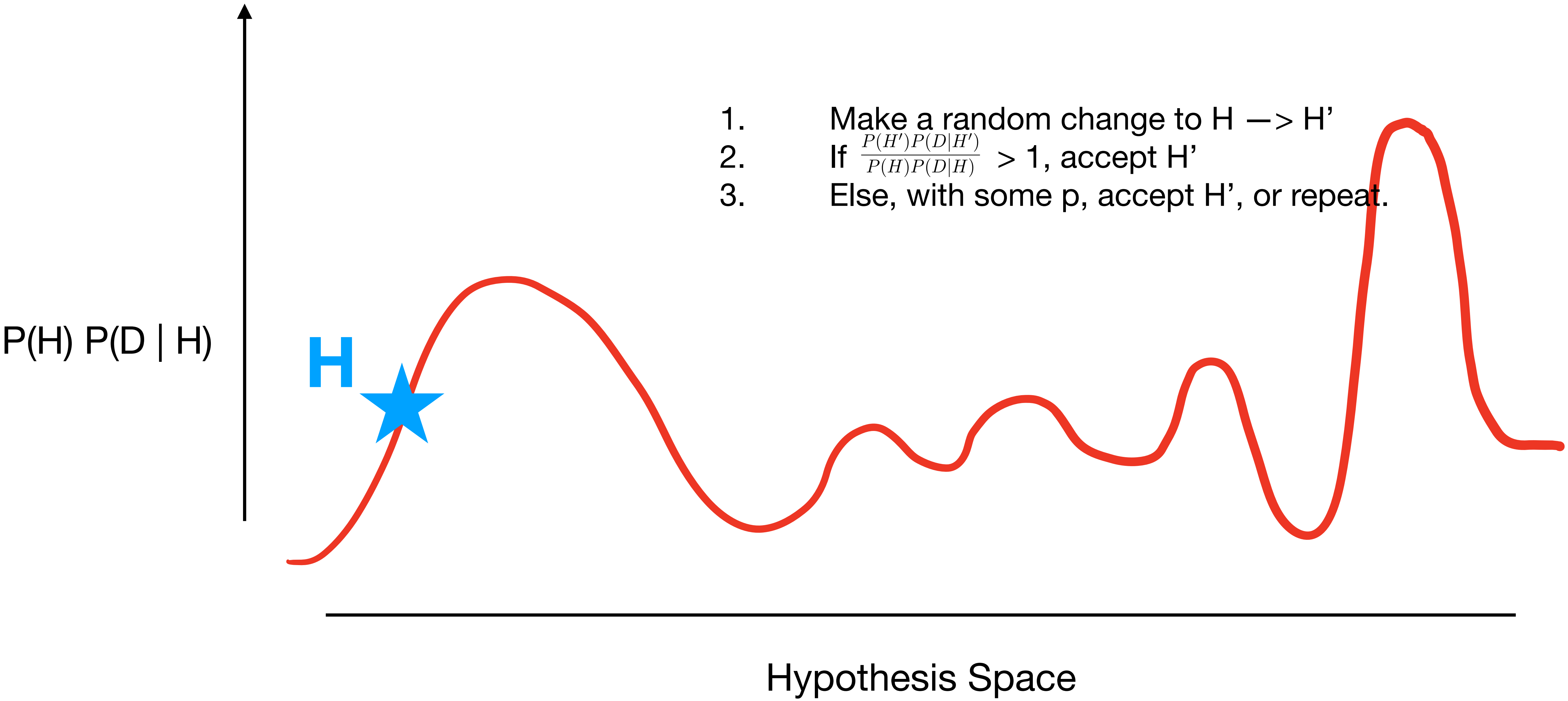
Accept H' with p setting H = H', repeat.



Note: In some schemes, p is fixed, in some, it is simply the ratio.

Hastings Algorithm

1. Make a random change to H —> H’
2. If $\frac{P(H')P(D|H')}{P(H)P(D|H)}$ > 1, accept H’
3. Else, with some p, accept H’, or repeat.



```
git clone https://github.com/piantado/Fleet
cd Fleet/Models/Sorting
module load eigen/3.4.0 mpi/openmpi_4.1.1_gcc_10.2_slurm20 gcc/10.2 clang/7.1.0
make
./main
```

1,2,3	1,2,3
9,7,8	7,8,9

1 minute

```
λx.if_s(
    (reverse(x)<x),
    pair(
      tail(x),
      head(x)),
    x
)
```

1,2,3	1,2,3
9,7,8	7,8,9

3 minutes

```
λx.tail(
    if_s(
        (x<tail(x)),
        tail(
            pair(
                reverse(x),
                head(
                    recurse(reverse(x))))),
        pair(x,head(x)))
)
```

References / Things to read
For Pragmatics & RSA

https://wmonroeiv.github.io/pubs/yuan2018understanding.pdf
https://web.stanford.edu/~cgpotts/temp/potts-lagb2019-rsa-tutorial-handout.pdf
https://arxiv.org/pdf/1510.06807.pdfhttps://journals.plos.org/plosone/article/file?id=10.1371/journal.pone.0154854&type=printable

References / Things to read
For Bayesian Language of Thought

One model for the learning of language
DreamCoder
https://github.com/piantado/Fleet
https://en.wikipedia.org/wiki/Metropolis%E2%80%93Hastings_algorithm
https://www.cambridge.org/core/journals/behavioral-and-brain-sciences/article/building-machines-that-learn-and-think-like-people/A9535B1D745A0377E16C590E14B94993

Thanks!