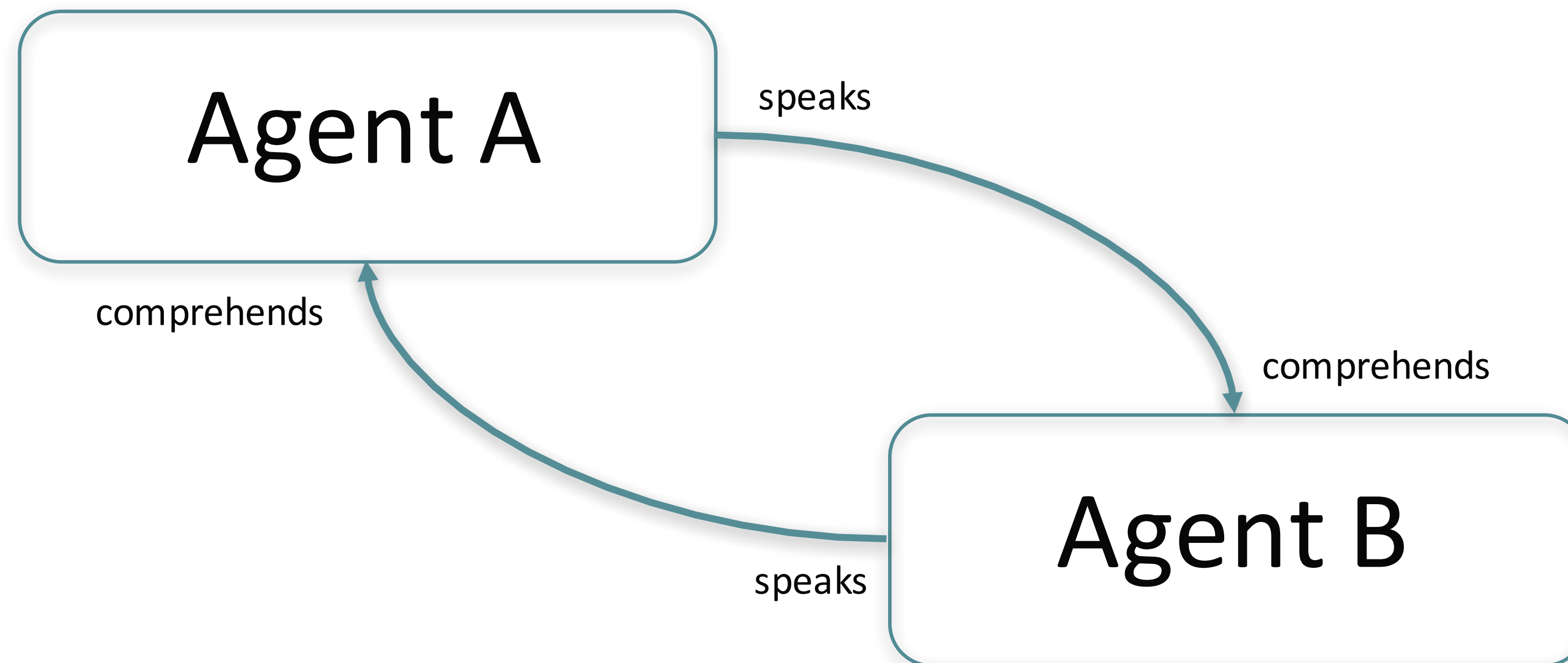


Constraints on Information Processing in Language Comprehension and Production

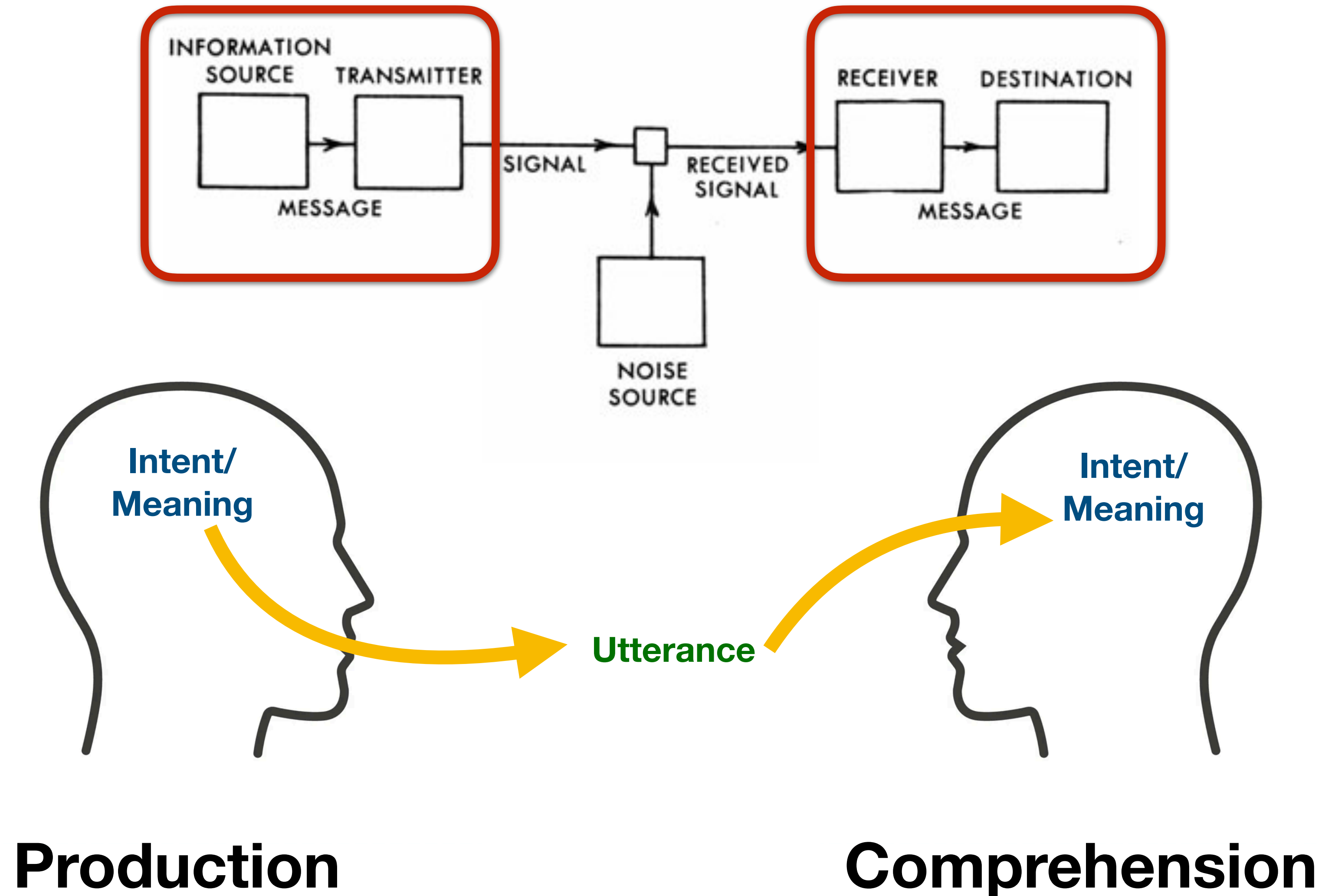
Richard Futrell
Department of Language Science
University of California, Irvine
@rljfutrell

ILFC Seminar
2023-12-13

Natural Language as an Information-Theoretic Code

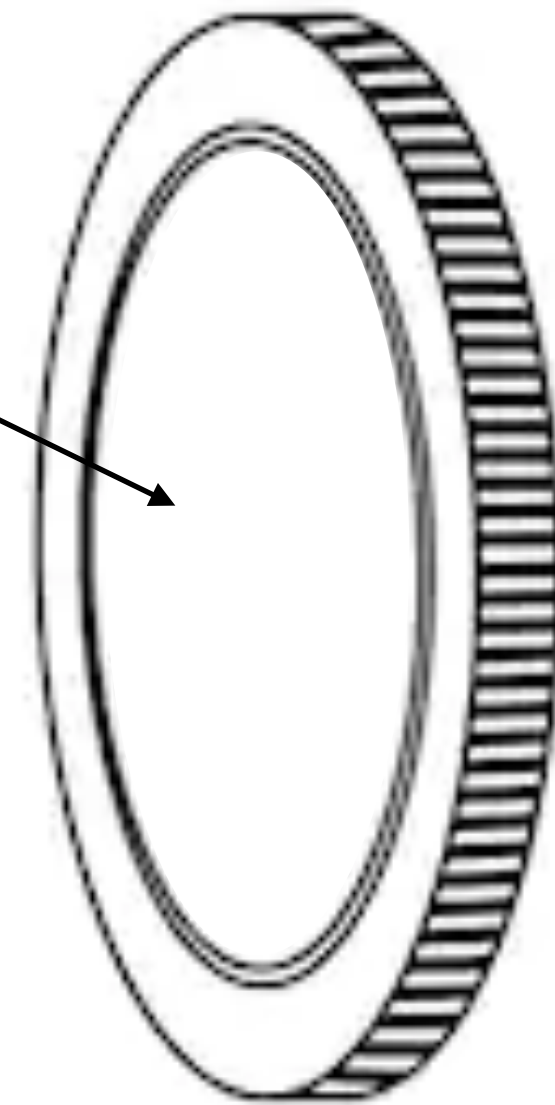


Natural Language as an Information-Theoretic Code



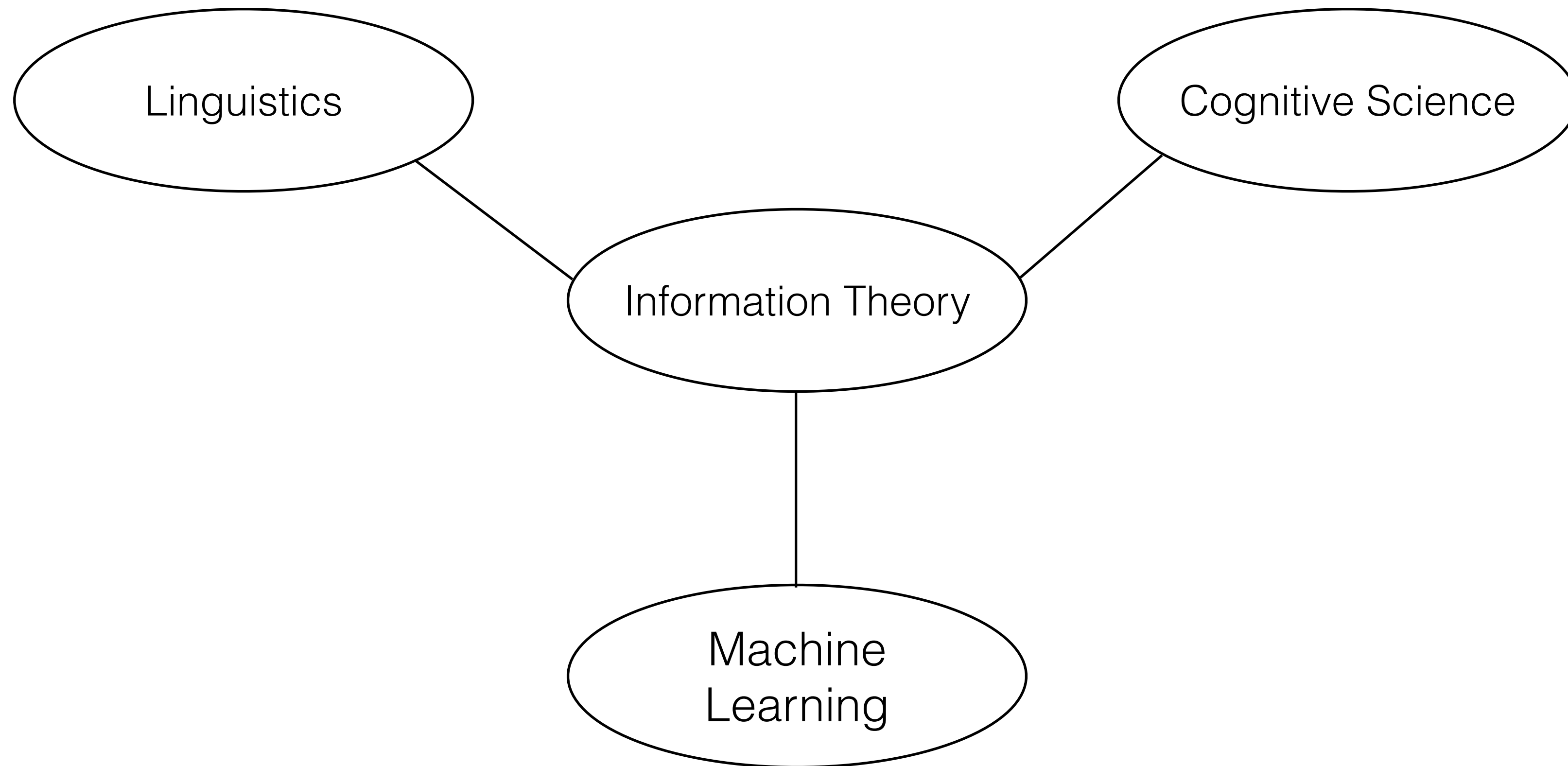
Research Program

Models of language
processing



Models of how
processing shapes
language structure

A Nexus Between Fields



Goals Today

- Develop and test models of **language comprehension** and **language production** based on **maximizing efficiency *subject to constraints***.
 - Show that a **bottleneck on memory** yields detailed patterns of comprehension difficulty for nested clauses.
 - Show that a **bottleneck on control** yields accessibility effects in incremental production of words.
- On both sides, a **predictive language model** ends up playing a central role.

Outline

- Introduction
- Information Theory for Language Processing
- Memory Bottleneck in Language Comprehension
- Control Bottleneck in Language Production
- Conclusion

What is Information?

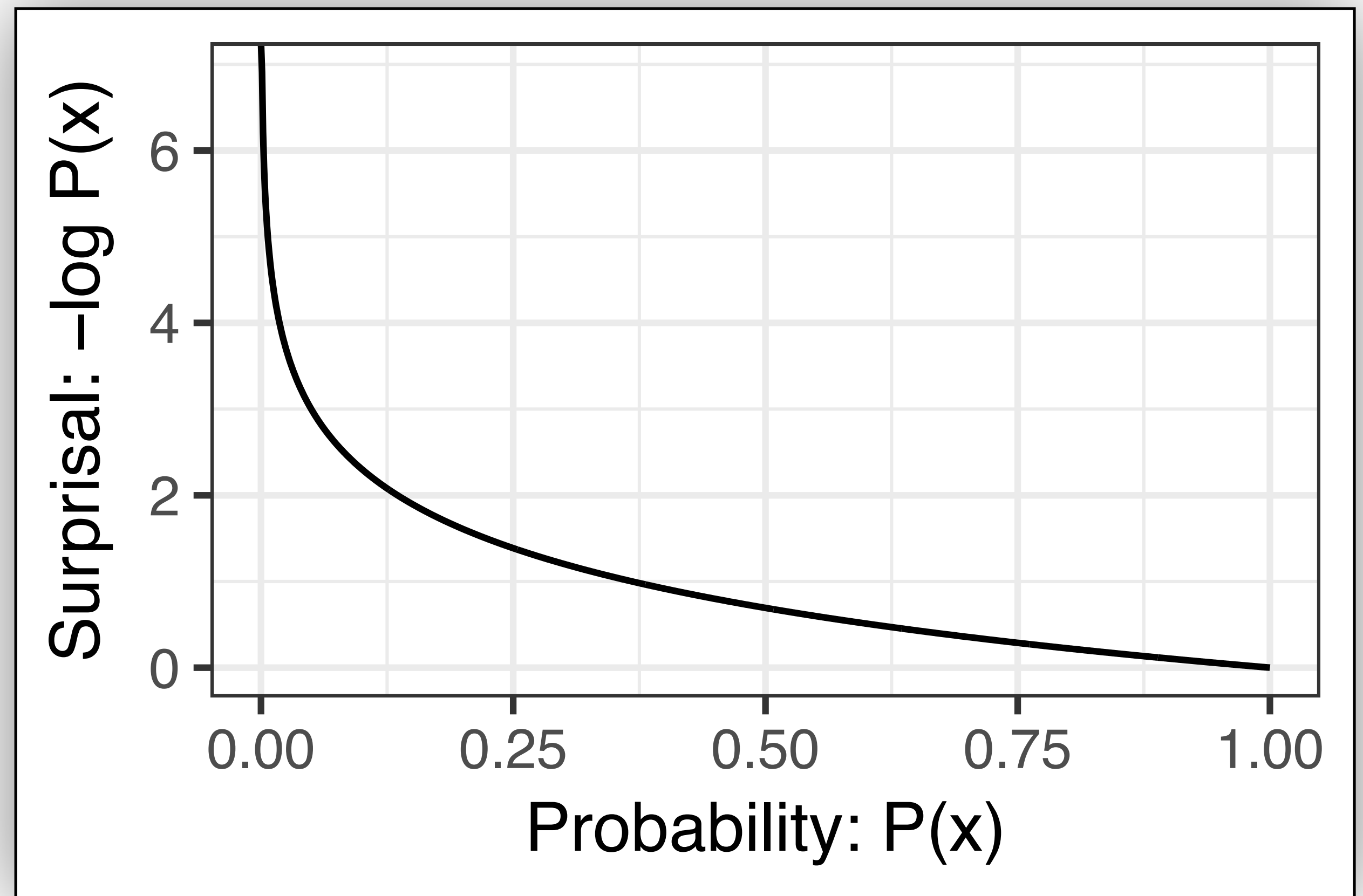
- The children went outside to... *play*
011101

Amount of information ~ Amount of surprise

- The children came inside to... *play*
011101110001011101

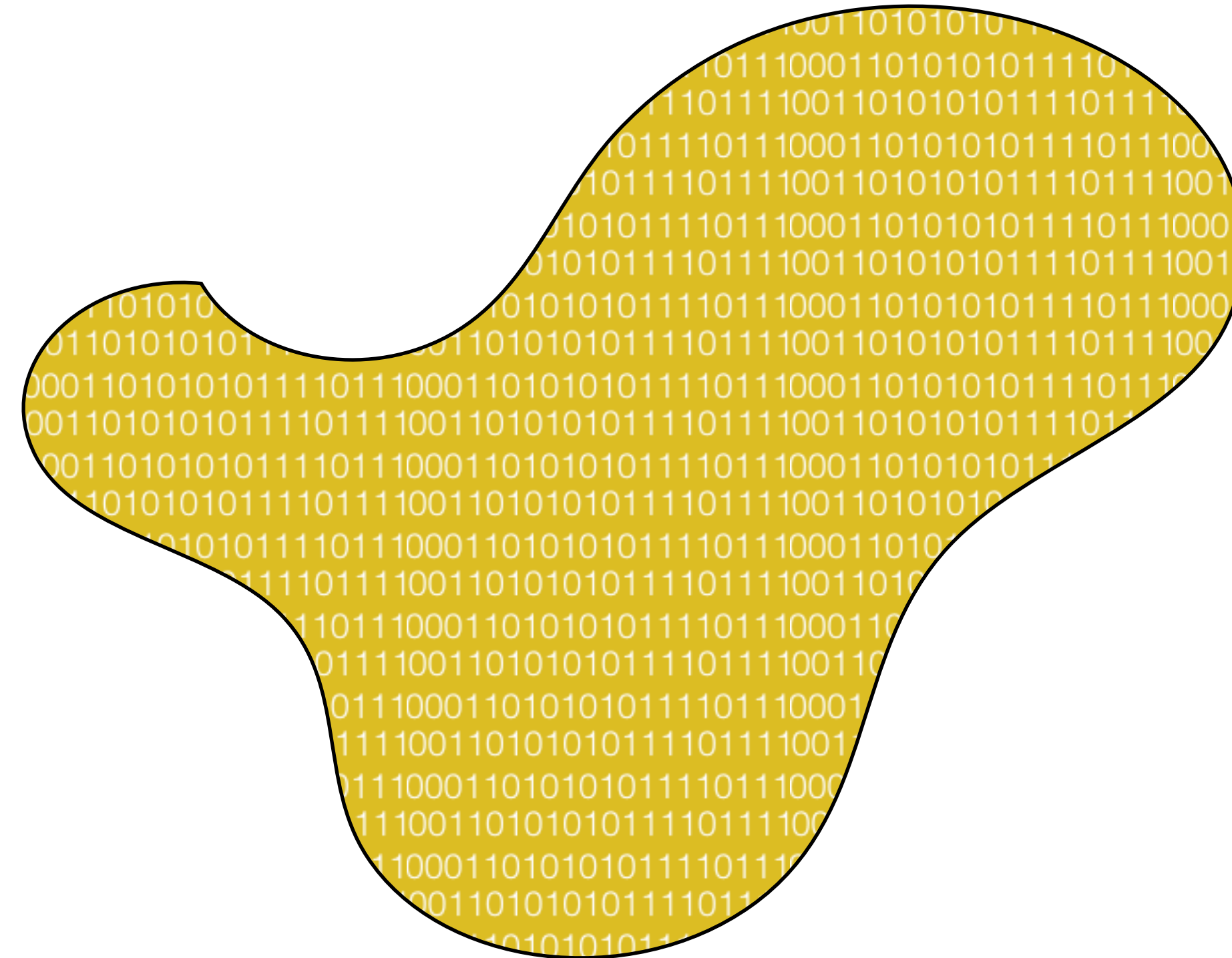
Basic Information Theory: Surprisal

- The **amount of information** in a word (or anything!) depends on how *surprising* it is in context.
- Information content is quantified as **surprisal**:
 - $S(\textit{word} \mid \textit{context}) = -\log_2 P(\textit{word} \mid \textit{context})$
(measured in bits)
- Surprisal is also the **length of the shortest binary representation** that encodes the word in context.



A Closer Look at Surprisal

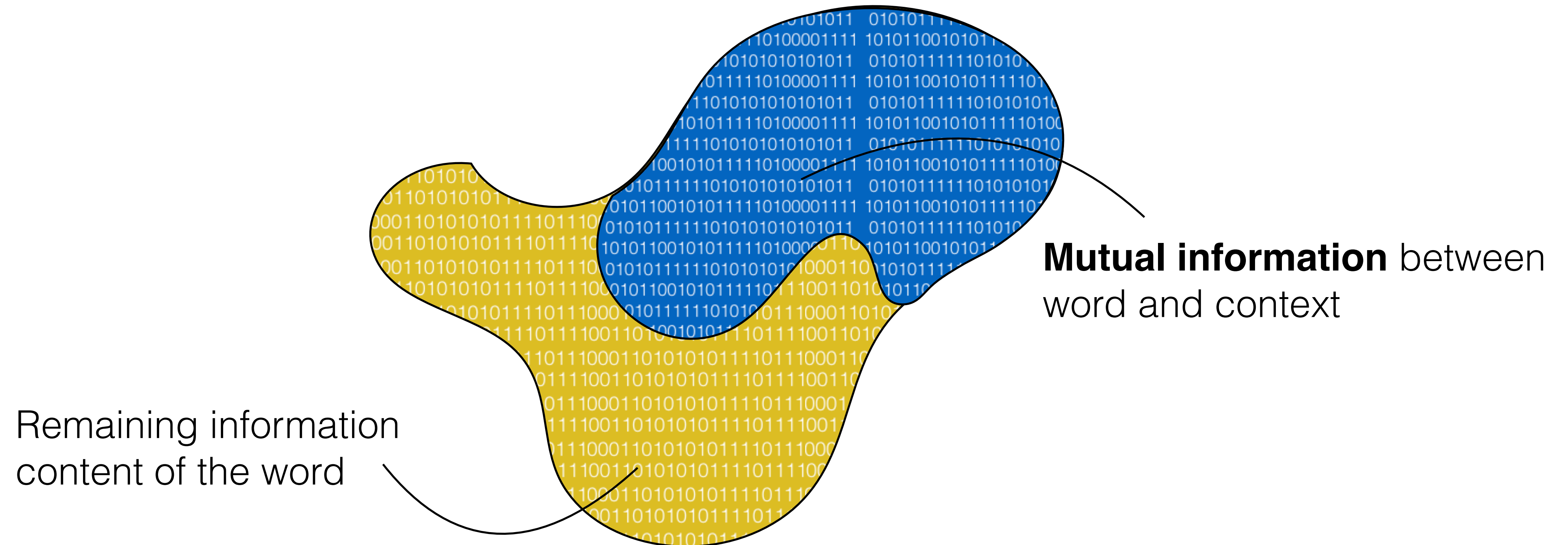
play



Information content
of **play**
 $S(\text{play})$

A Closer Look at Surprisal

The children went outside to play...



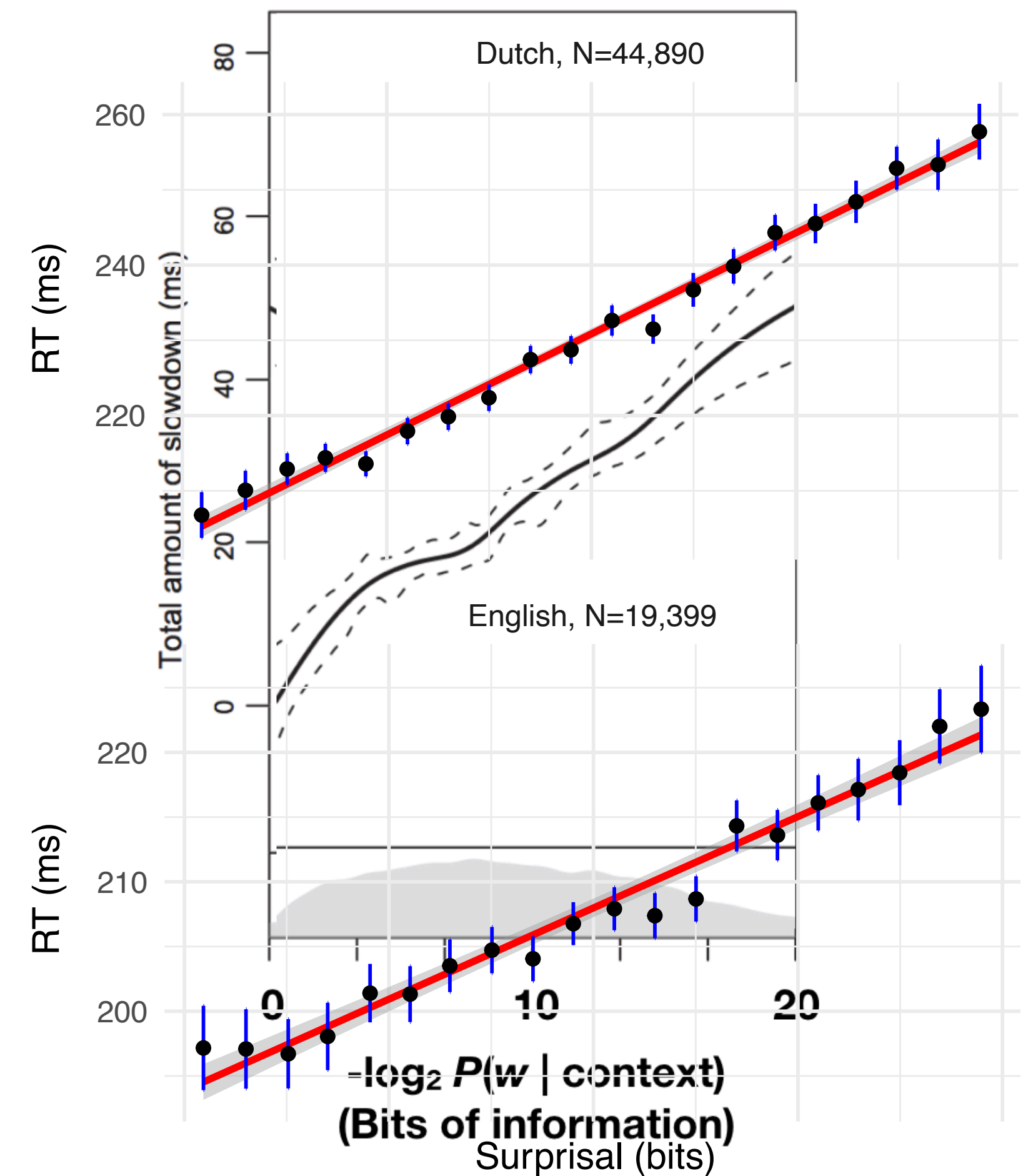
Information content of **play** in **context**
 $S(\text{play} \mid \text{context})$

Information Theory in Psycholinguistics

- **Surprisal Theory**: (Hale, 2001; Levy, 2008; Smith & Levy, 2013)
 - $RT(\textit{word} \mid \textit{context}) = k S(\textit{word} \mid \textit{context})$.
- **Idea**: Each bit of information content takes a fixed time for processing.

Information Theory in Psycholinguistics

- **Surprisal Theory:** (Hale, 2001; Levy, 2008; Smith & Levy, 2013)
 - $RT(\textit{word} \mid \textit{context}) = k S(\textit{word} \mid \textit{context})$.
- **Idea:** Each bit of information content takes a fixed time for processing.
- Surprisal theory and variants have **high predictive value** for reading times and N400 signals (Smith & Levy, 2013; Frank & Bod, 2011; Frank, 2016; Wilcox et al., 2020; Shain, 2019; Li & Futrell, 2022)
- Predicts classic garden path effects, although **underestimating effect size** (Hale, 2001; Levy, 2008; but see van Schijndel & Linzen, 2022)



Surprisal and Language Models

- Optimal representations are based on a **predictive language model**

$$S(\textit{word} \mid \textit{context}) = -\log P(\textit{word} \mid \textit{context})$$

- Fitting a language model to predict words in context *is equivalent to* finding optimal compressed representations of words in context.
- What do you get if you train a giant neural network to minimize surprisal?



As a language model, I don't have emotions, so I can't be "stumped" in the way that you mean. But I do have a knowledge cutoff, meaning that I am only aware of information that



Information Theory and Language Processing

- Surprisal Theory is a good start, but...
 - It does not account for **memory limitations**, and often **underestimates reaction times**.
 - It does not say anything about how **linguistic structure** interacts with processing difficulty.
 - It's not clear what it has to say about **production**.
- What happens when we consider optimal representations **under cognitive constraints?**

Outline

- Introduction
- Basics of Information-Theoretic Psycholinguistics
- **Memory Bottleneck in Language Comprehension**
- Control Bottleneck in Language Production
- Conclusion



Michael Hahn

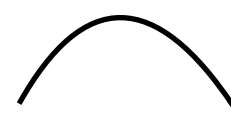





Ted Gibson



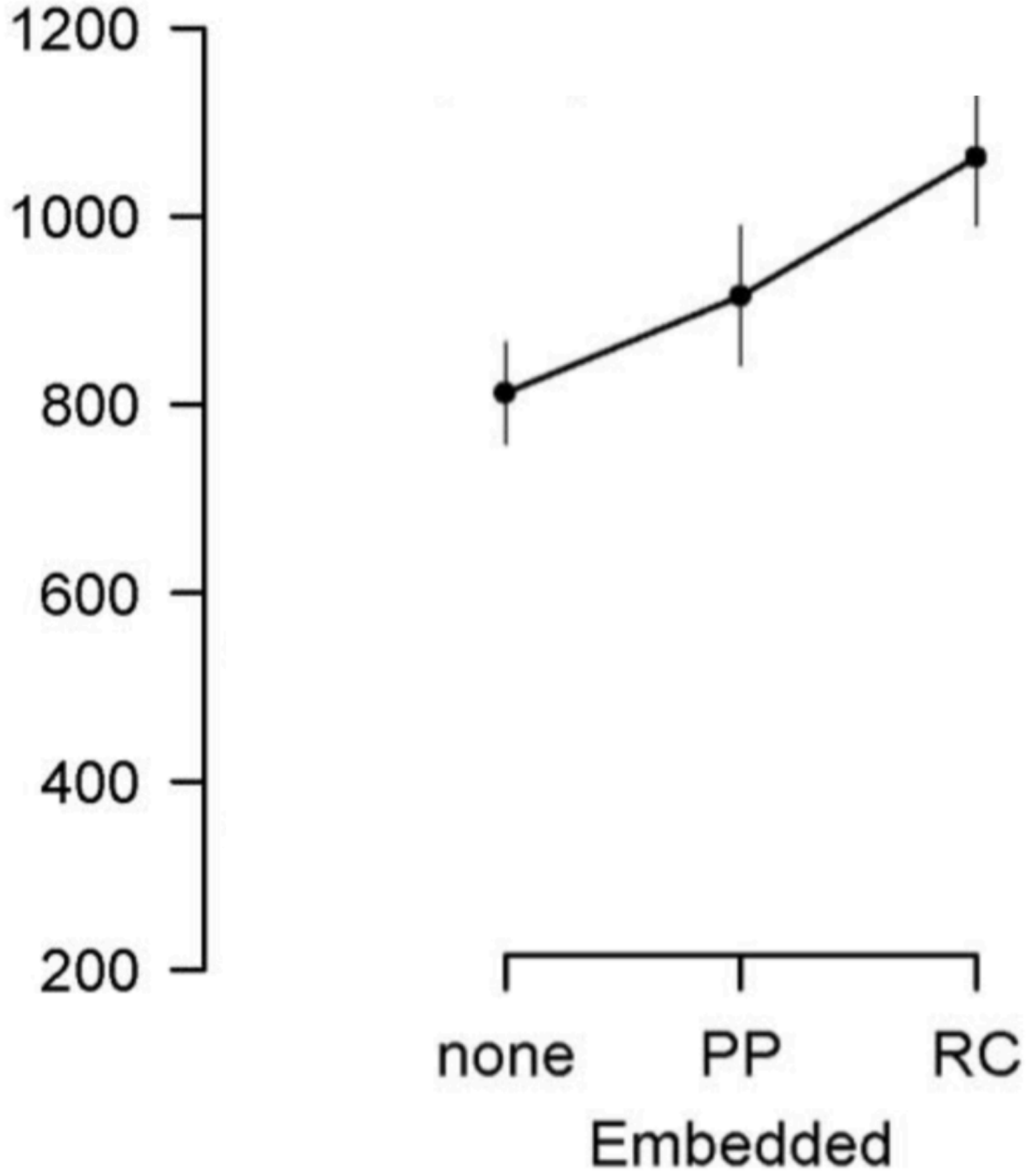
Roger Levy

Memory Effects in Sentence Processing




- Bob threw  out the trash. 👍
- Bob threw the trash  out. 👍
- Bob threw  out the old trash that had been sitting in the kitchen. 👍
- Bob threw the old trash that had been sitting in the kitchen  out. 👎

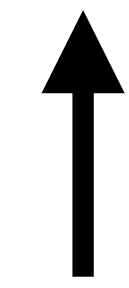
The Dependency Locality Theory (Gibson, 1998, 2000)

Self-Paced Reading Times



Memory Effects in Sentence Processing

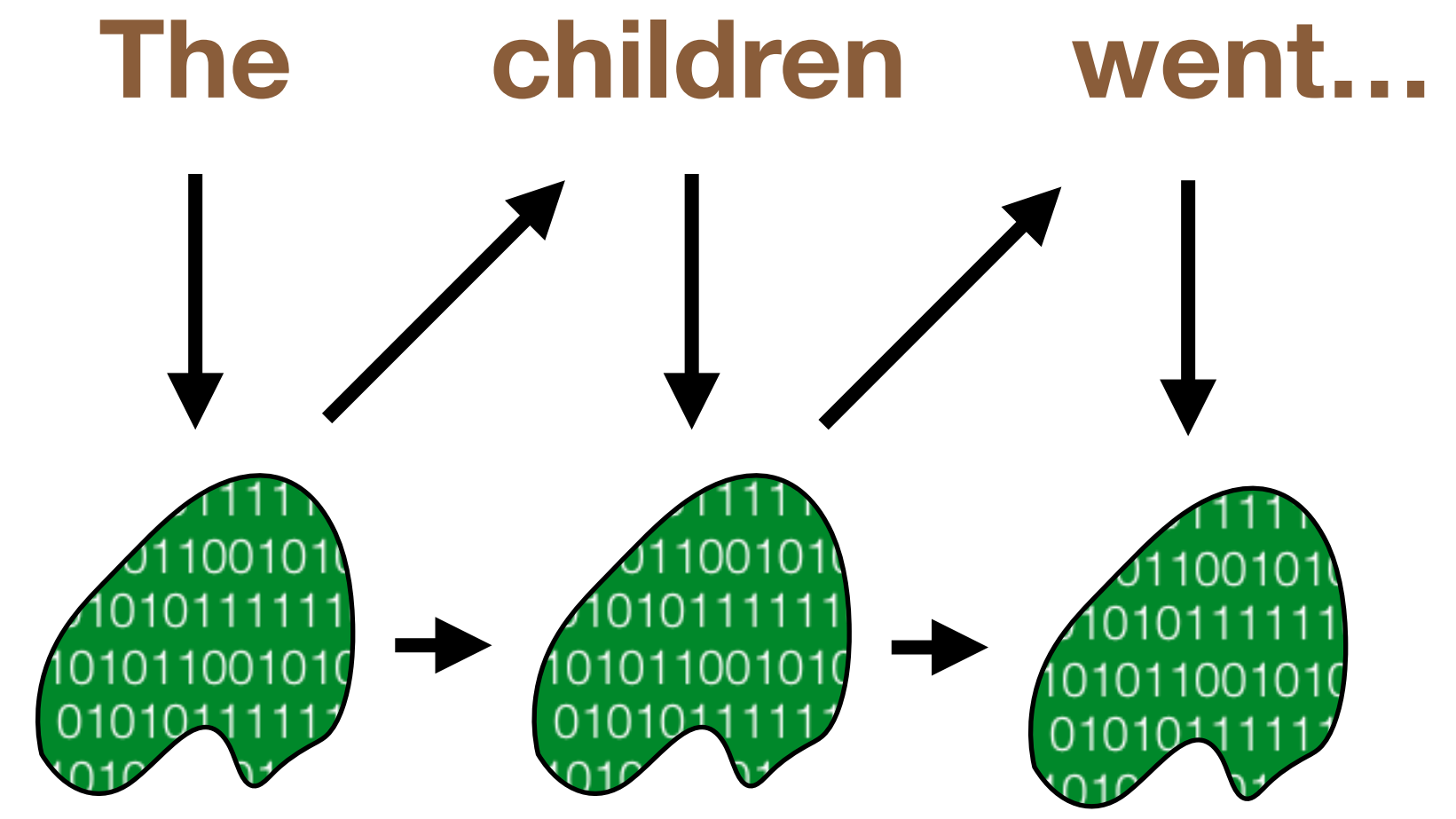
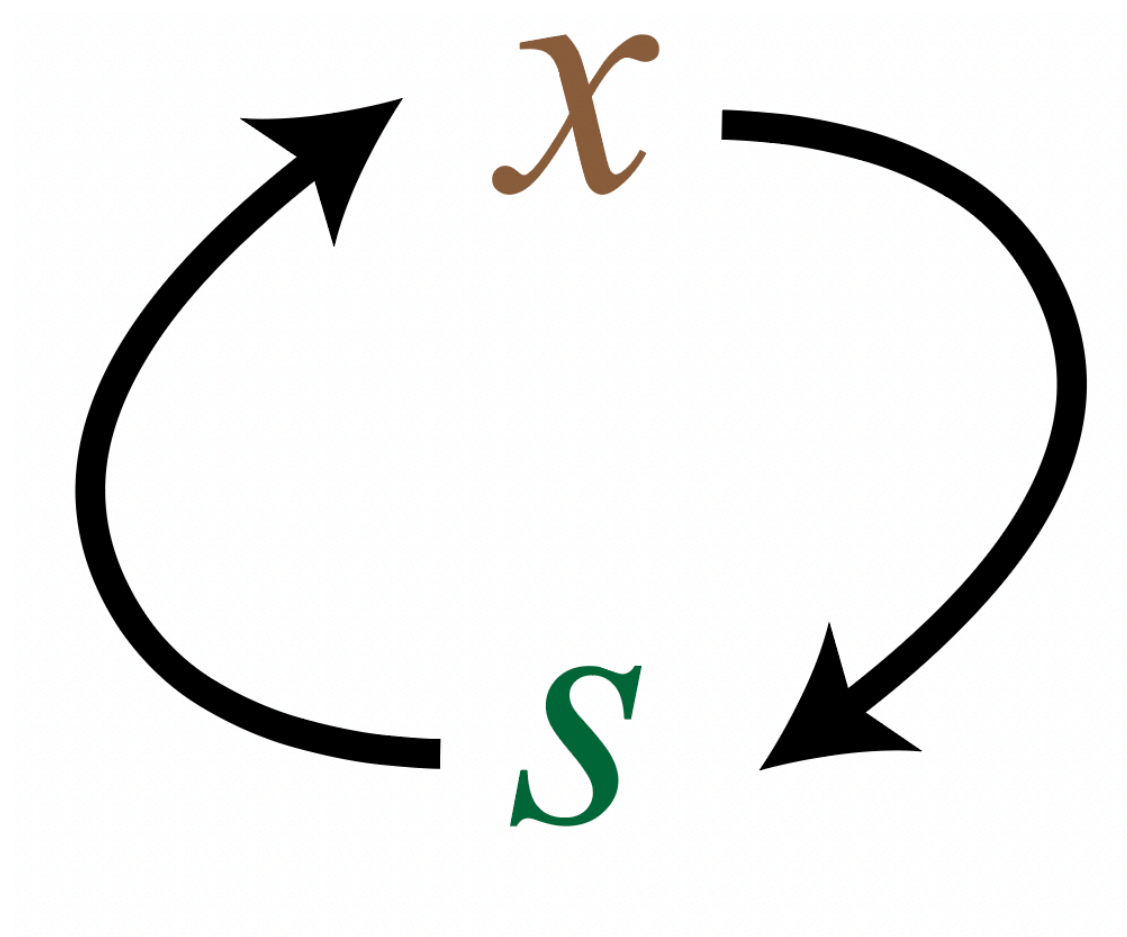
- The apartment was well-decorated. 👍

- The apartment that the maid cleaned was well-decorated. 👍

- The apartment that the maid who the service sent over cleaned was well-decorated. 👎👎👎👎👎




RT trouble starts here

Memory in Language Comprehension

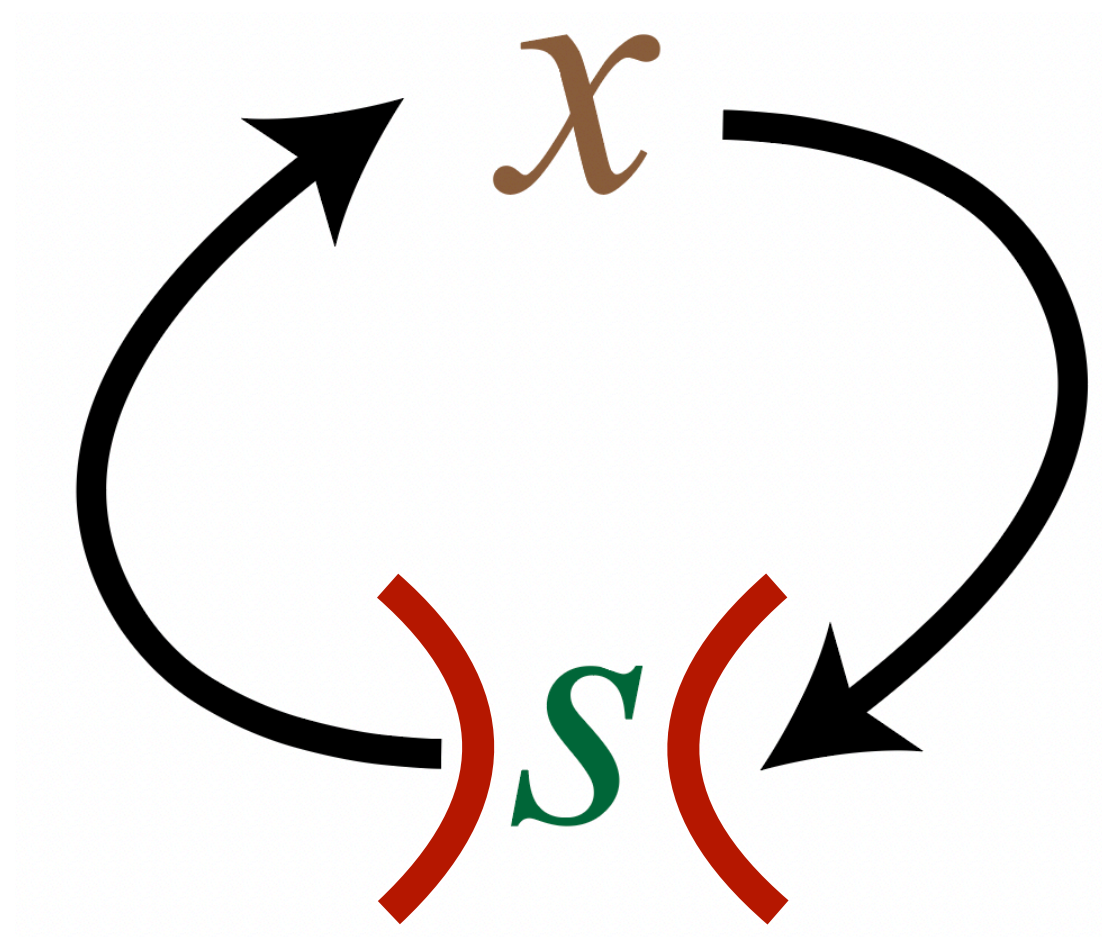
Word
Memory State



Memory in Language Comprehension

Word

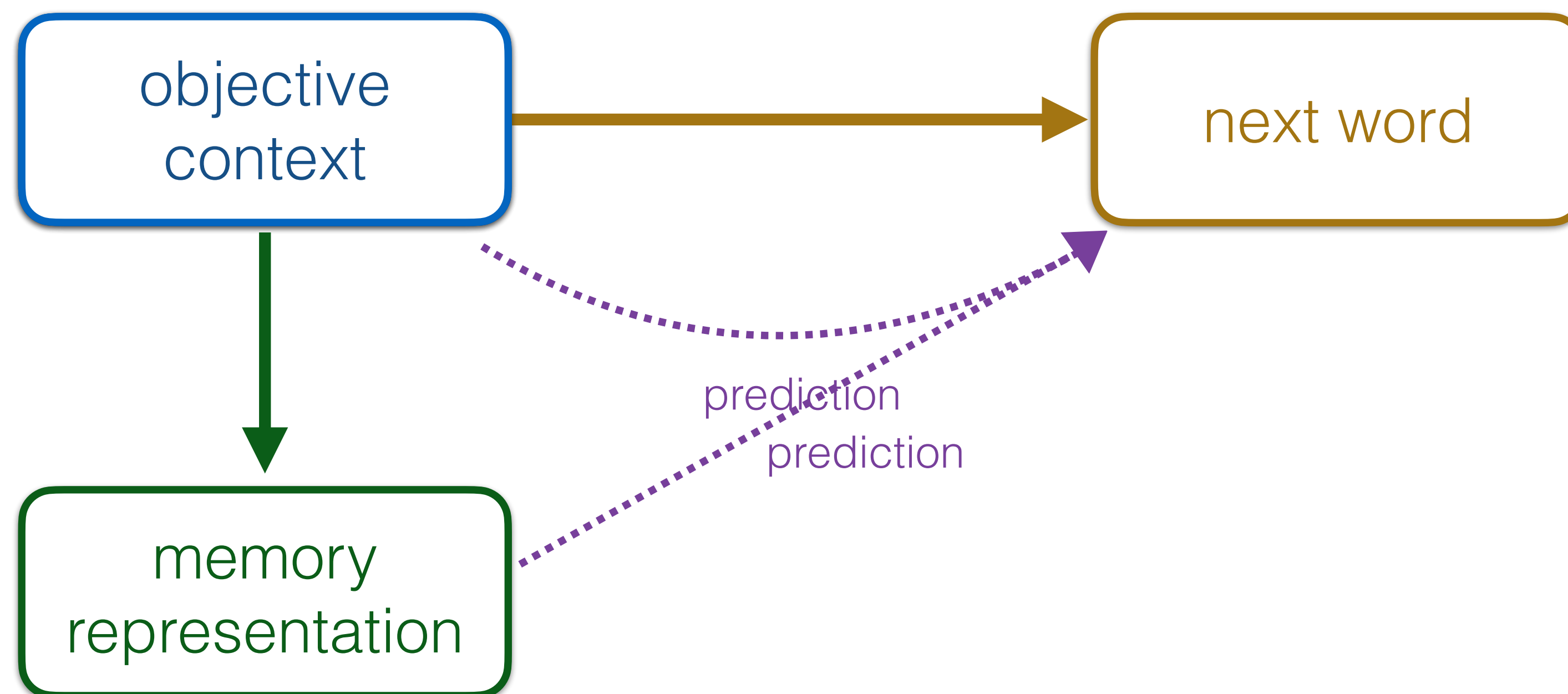
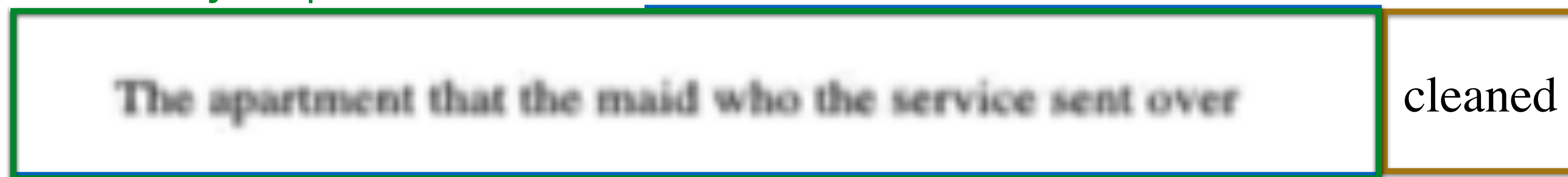
Memory State



How to fit a memory bottleneck into Surprisal Theory?

- Surprisal: $RT(w|context) = S(w|context)$
- Lossy context: surprisal: $S(w|context) \neq S(w|memory\ representation)$

memory representation



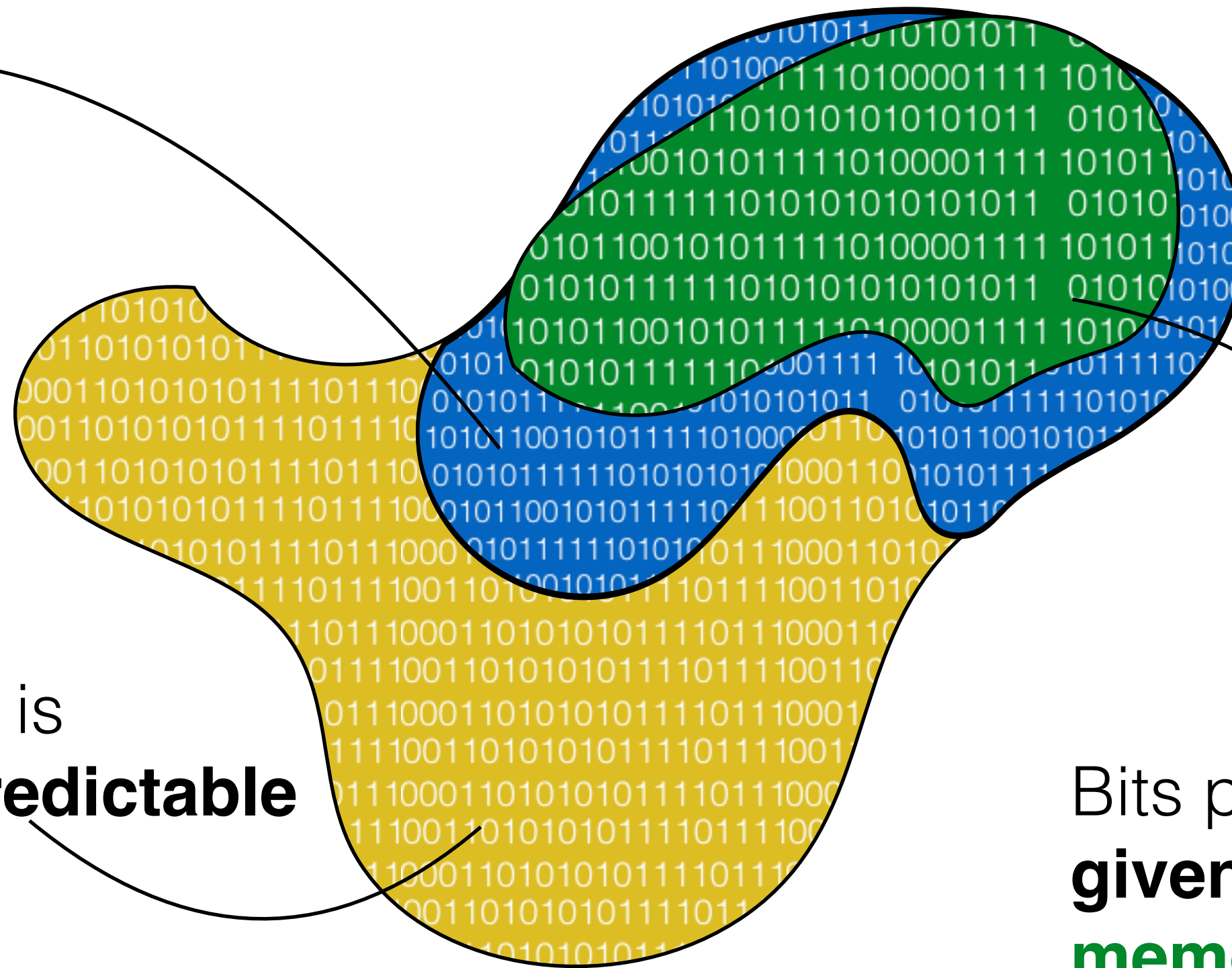
Lossy-Context Surprisal

The maid cleaned...

Lossy context surprisal $S(\text{cleaned} | \text{The maid})$

Memory cost
due to memory
limitations

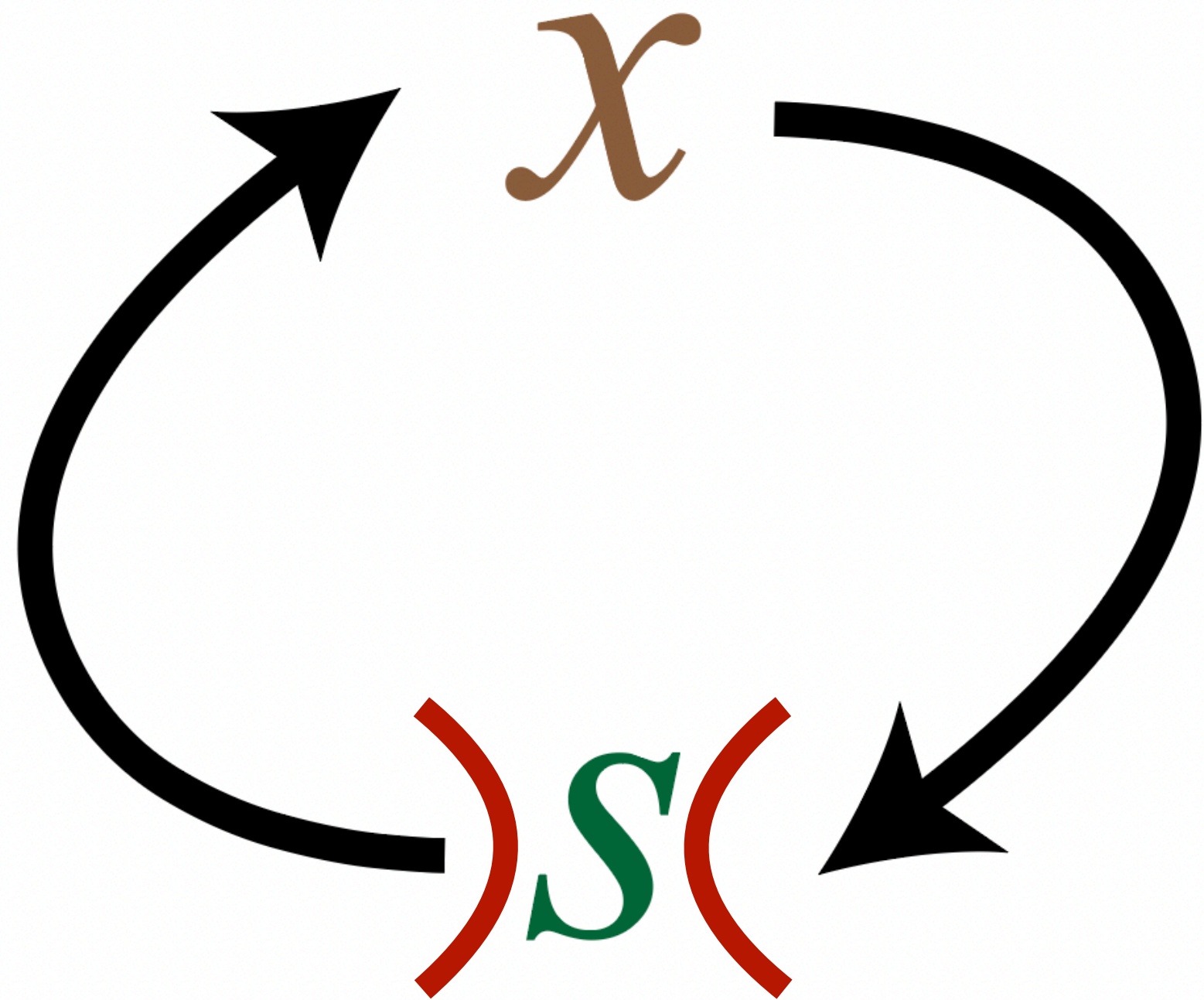
Processing difficulty is
the **number of unpredictable
bits.**



Bits predictable
**given the
memory state**

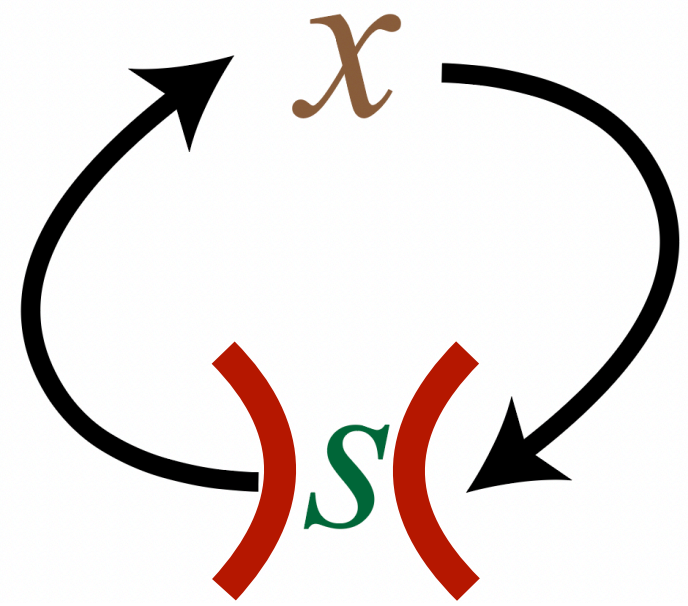
$$S(\text{word} | \text{memory}) = S(\text{word} | \text{context}) + \text{Memory cost}$$

Uses of Lossy-Context Surprisal



- By constraining memory in various ways, we can account for...
- Certain **dependency locality effects** (Futrell, Gibson & Levy, 2020)
- Cross-linguistic patterns in **structural forgetting** (Futrell, Gibson & Levy, 2020)
- General **reading times** in eyetracking corpora, with neural network implementation (Kuribayashi et al., 2022)
- Novel patterns in comprehension of **nested clauses**. (Hahn, Futrell, Levy & Gibson, 2022)

Processing with Constrained Memory



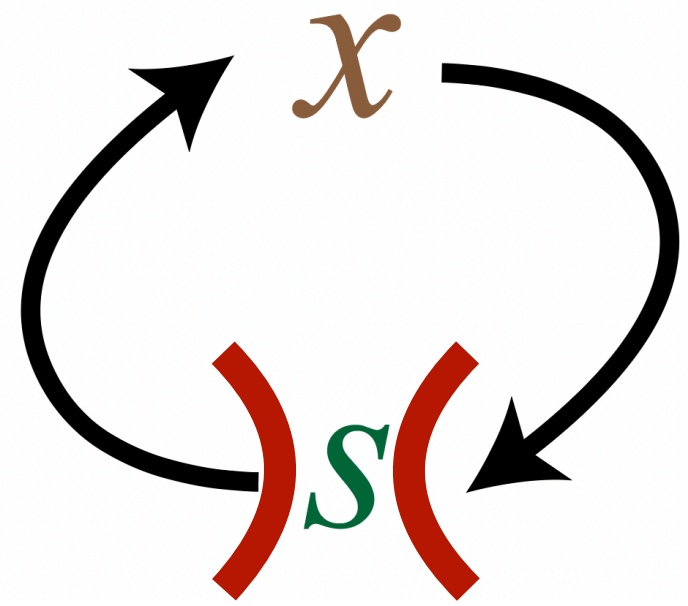
- Idea: Only a certain maximum number of words can be retained in memory.
- Predictions about upcoming words are **optimal subject to the constraint** that not all context words can be represented.

Context

The report that the doctor annoyed the patient...

was interesting

Processing with Constrained Memory



- Idea: Only a certain maximum number of words can be retained in memory.
- Predictions about upcoming words are **optimal subject to the constraint** that not all context words can be represented.

Lossy Context

The report ??? the doctor annoyed the patient...

Context c

The report that the doctor annoyed the patient...

The report **by** the doctor annoyed the patient.

The report **about** the doctor annoyed the patient.

$P(c)$



was interesting

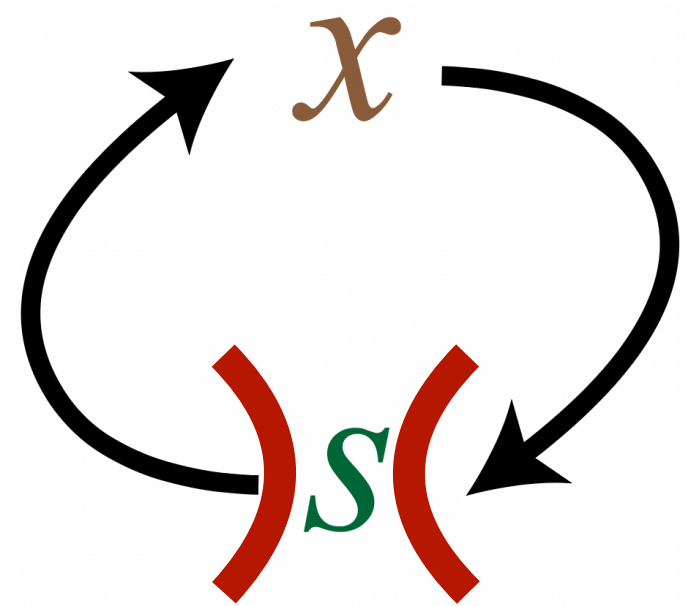


was interesting



was interesting

Predictions about Embedded Clauses



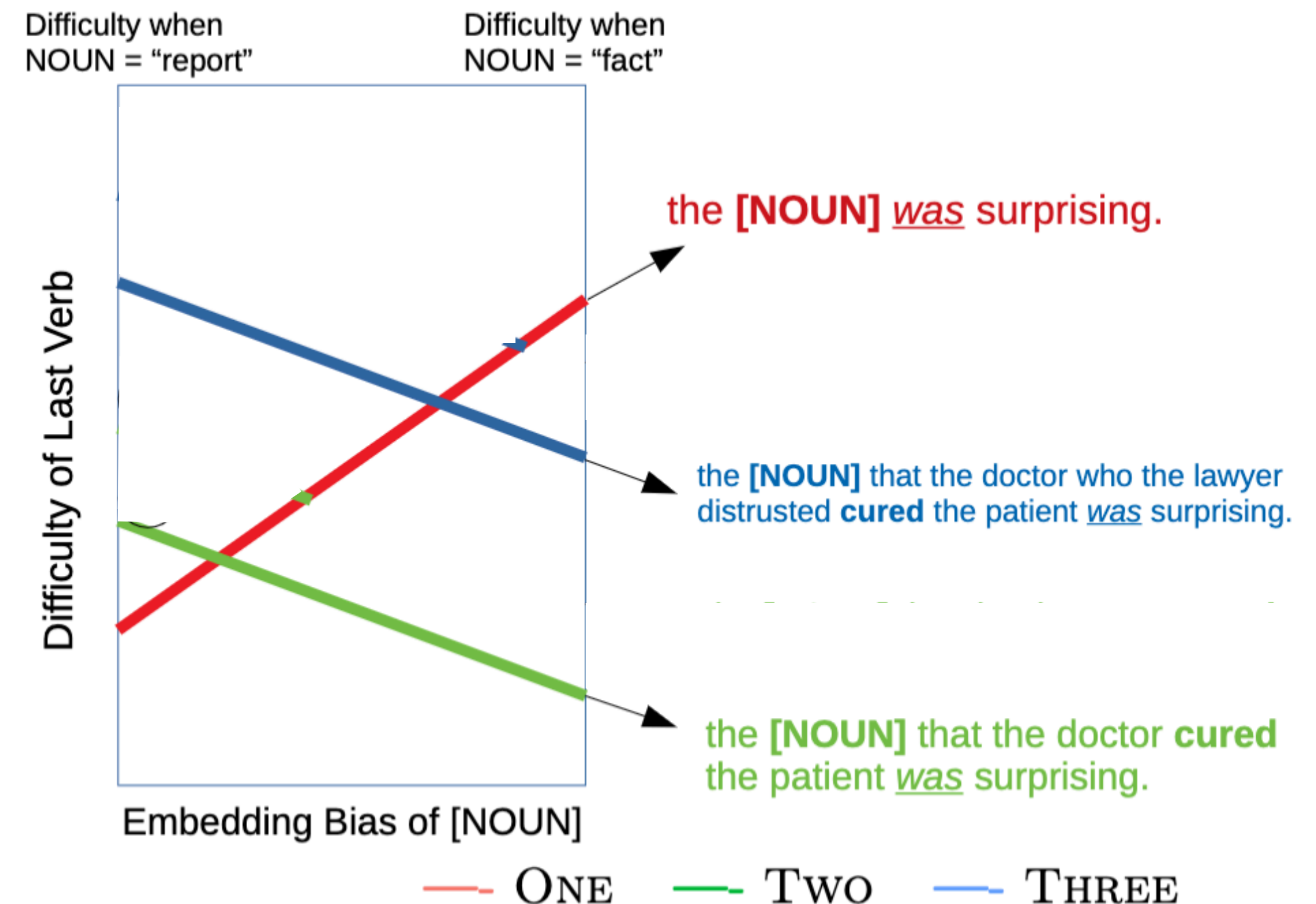
- Prediction: The difficulty of multiple embedding depends on the **embedding bias** of the noun.

Low Embedding Bias

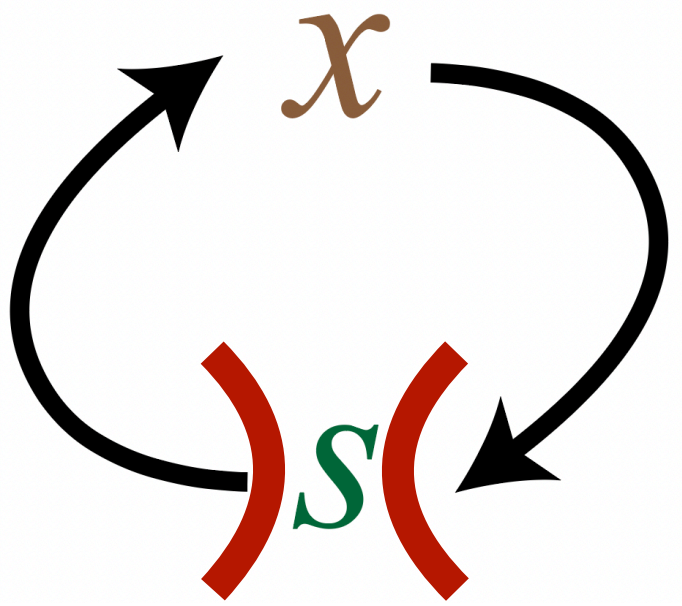
	Context c	$P(c)$
True (c^*)	The report that the doctor annoyed the patient...	██████████
Variants	The report by the doctor annoyed the patient.	██████████
	The report about the doctor annoyed the patient.	██
	...	

High Embedding Bias

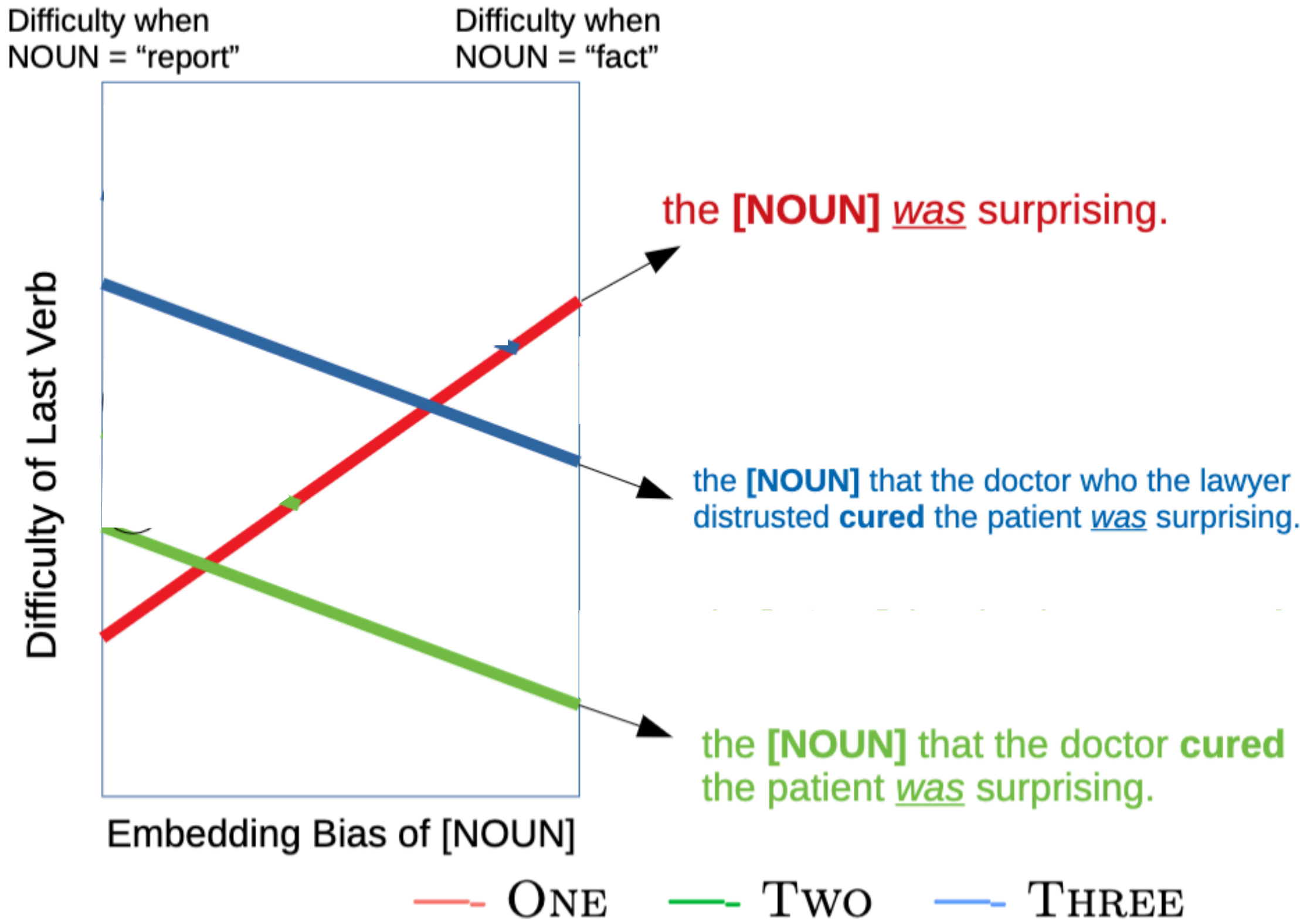
	Context c	$P(c)$
True (c^*)	The fact that the doctor annoyed the patient...	██████████
Variants	The fact of the doctor annoyed the patient.	██
	The fact about the doctor annoyed the patient.	██
	...	



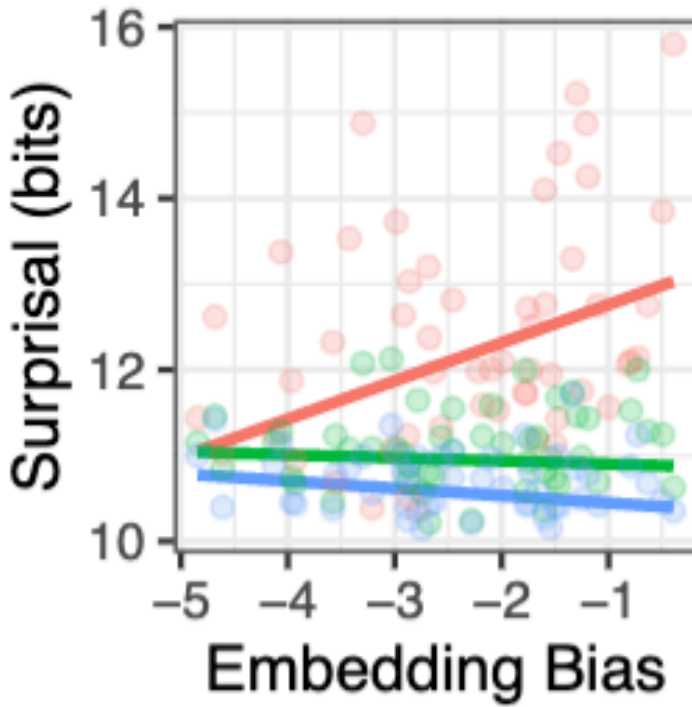
Predictions about Embedded Clauses



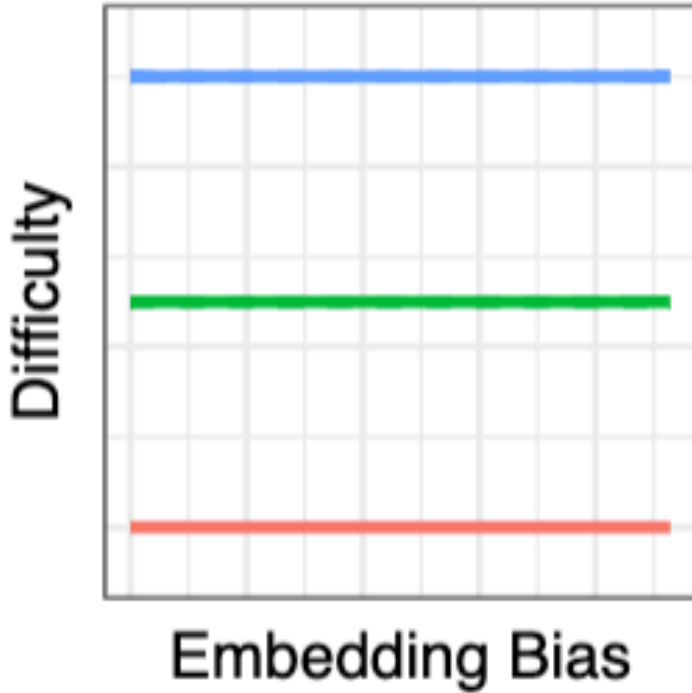
- Prediction: The difficulty of multiple embedding depends on the **embedding bias** of the noun.



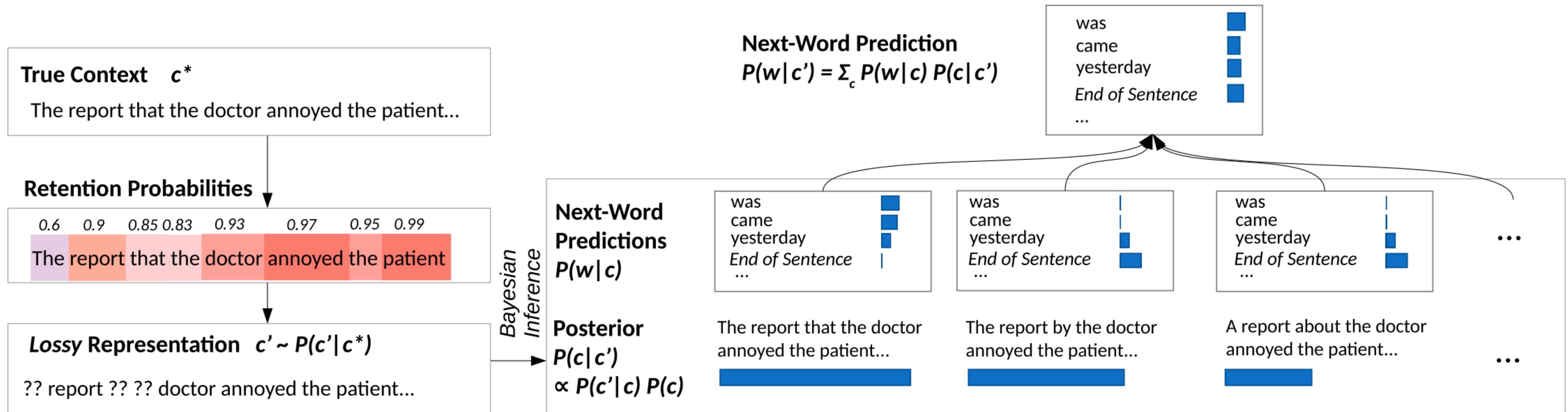
Surprisal Theory



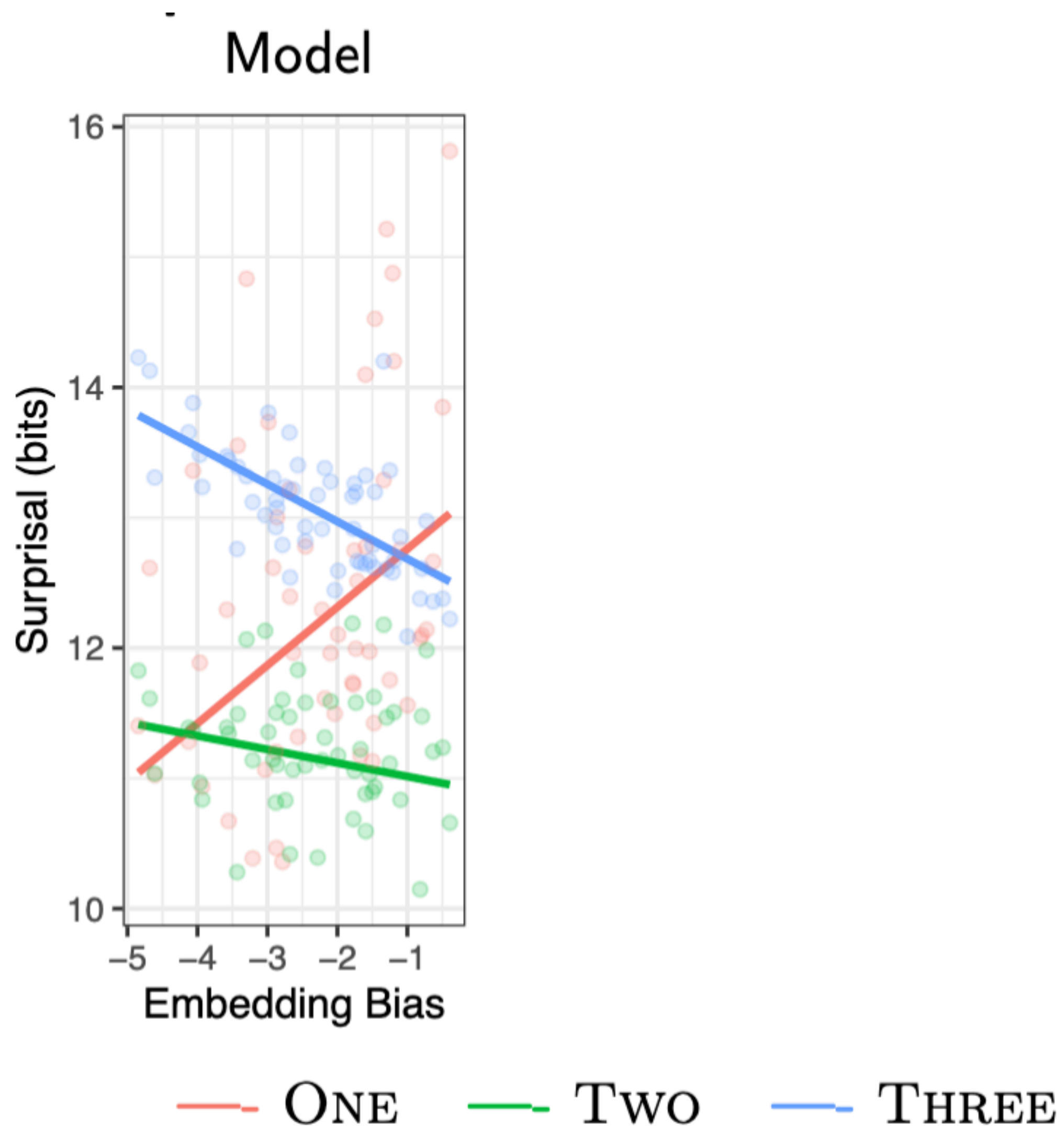
DLT



Model Implementation

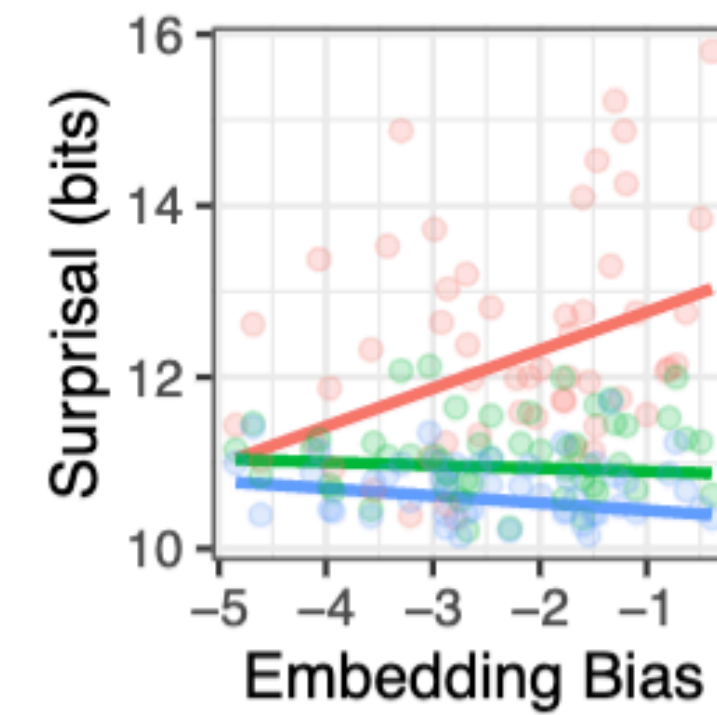


Reading Time Experiment Results

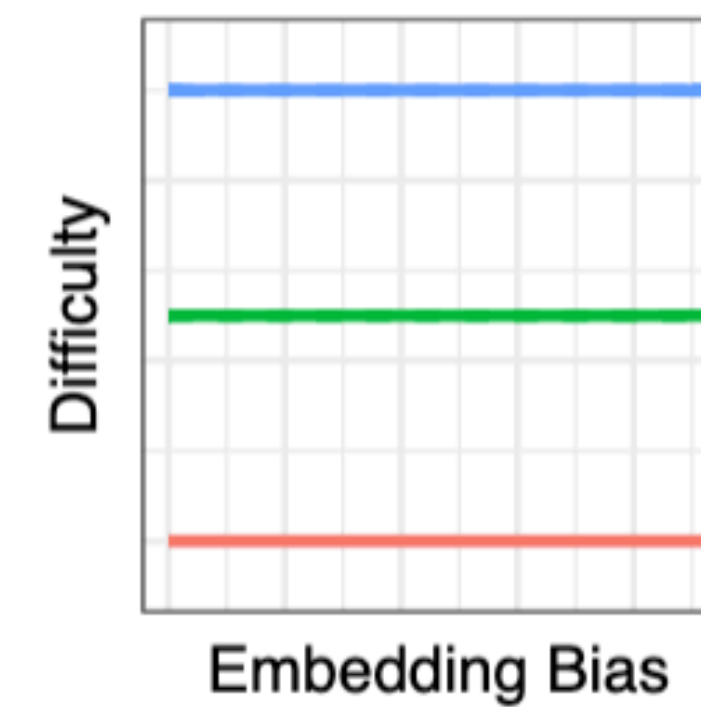


Previous Models

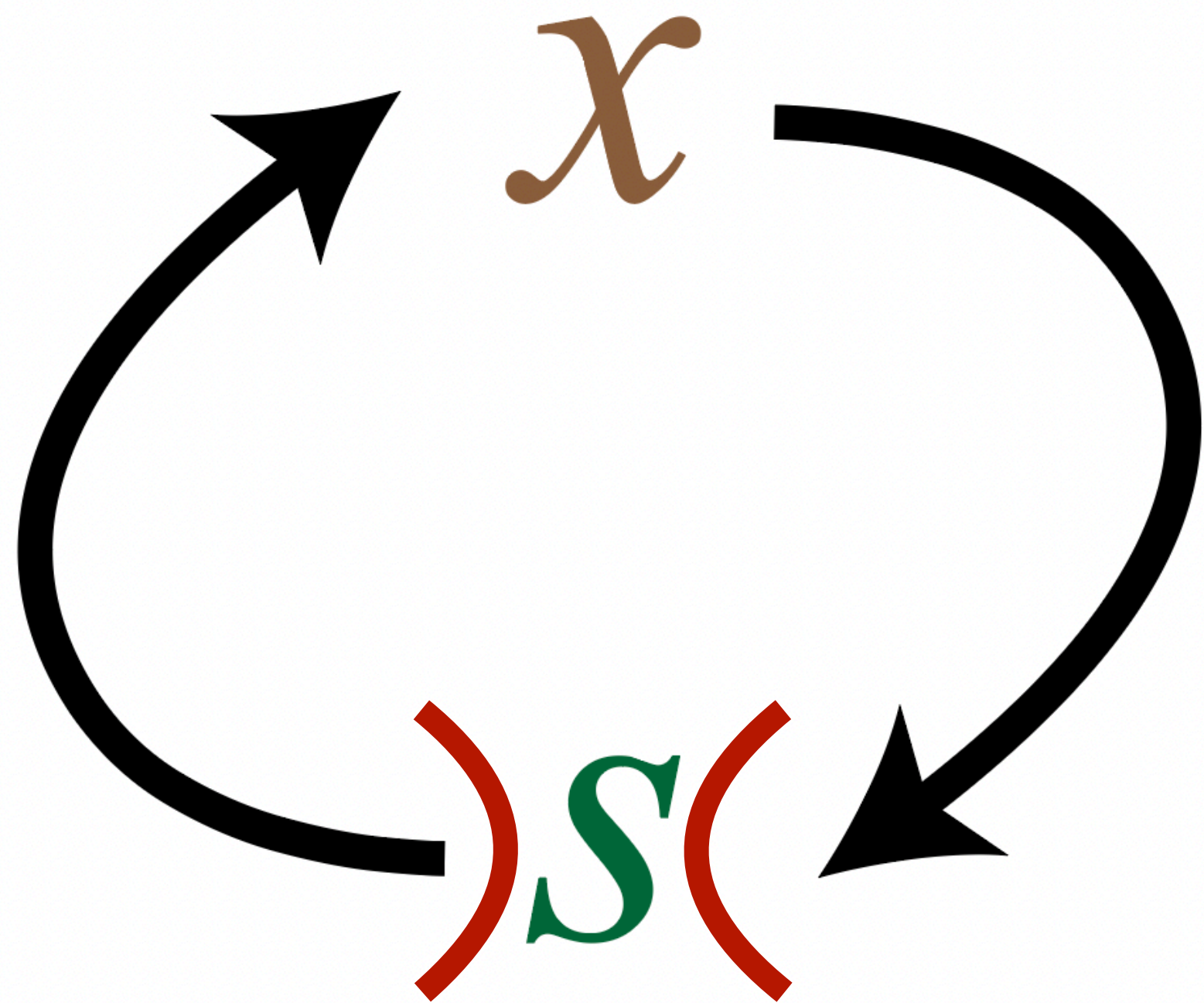
Surprisal Theory



DLT



Memory Bottleneck in Language Comprehension



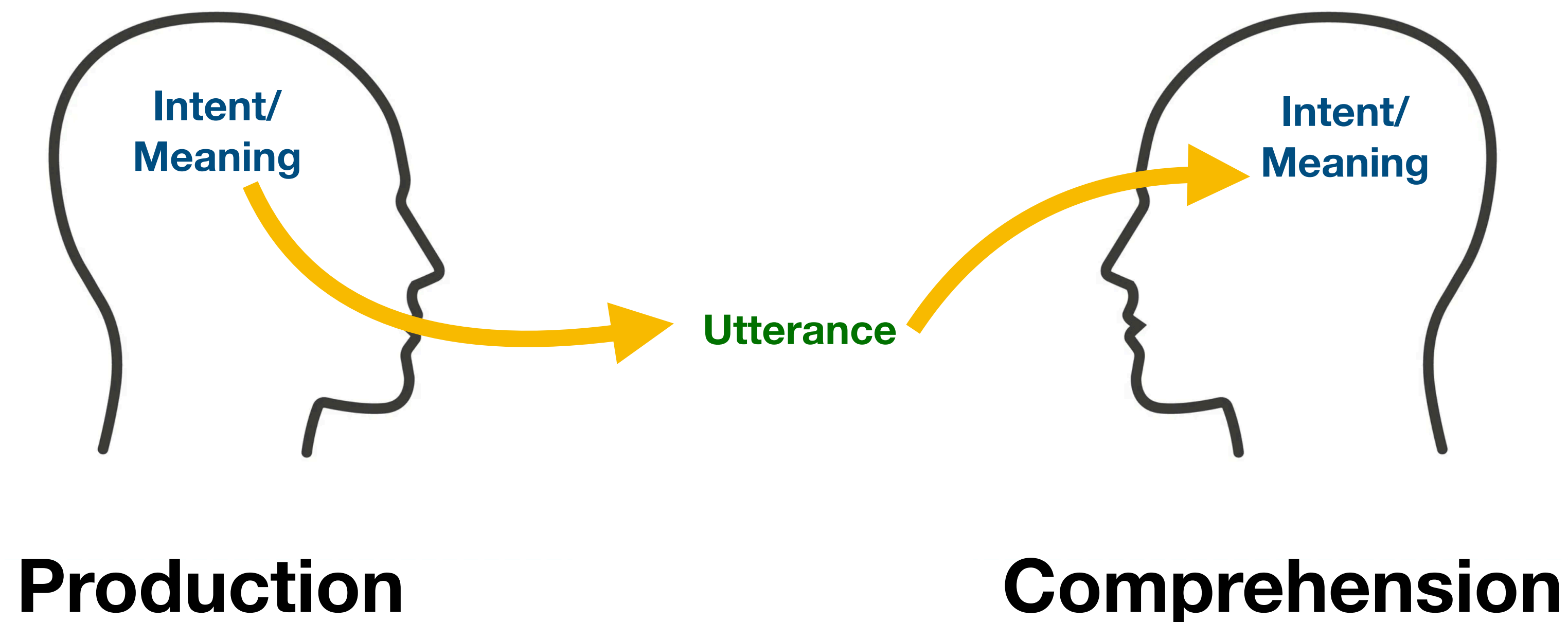
- We considered language comprehension difficulty based on **surprisal** given a **lossy memory representation of context**.
- Predicts RT **better than a less constrained language model**.
- Comprehension can be modeled as **maximally efficient subject to memory constraints**.

Outline

- Introduction
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Information Theory and Language Production

- Information-theoretic models of language processing have mostly focused on **comprehension**.
- What can we say about **production**?

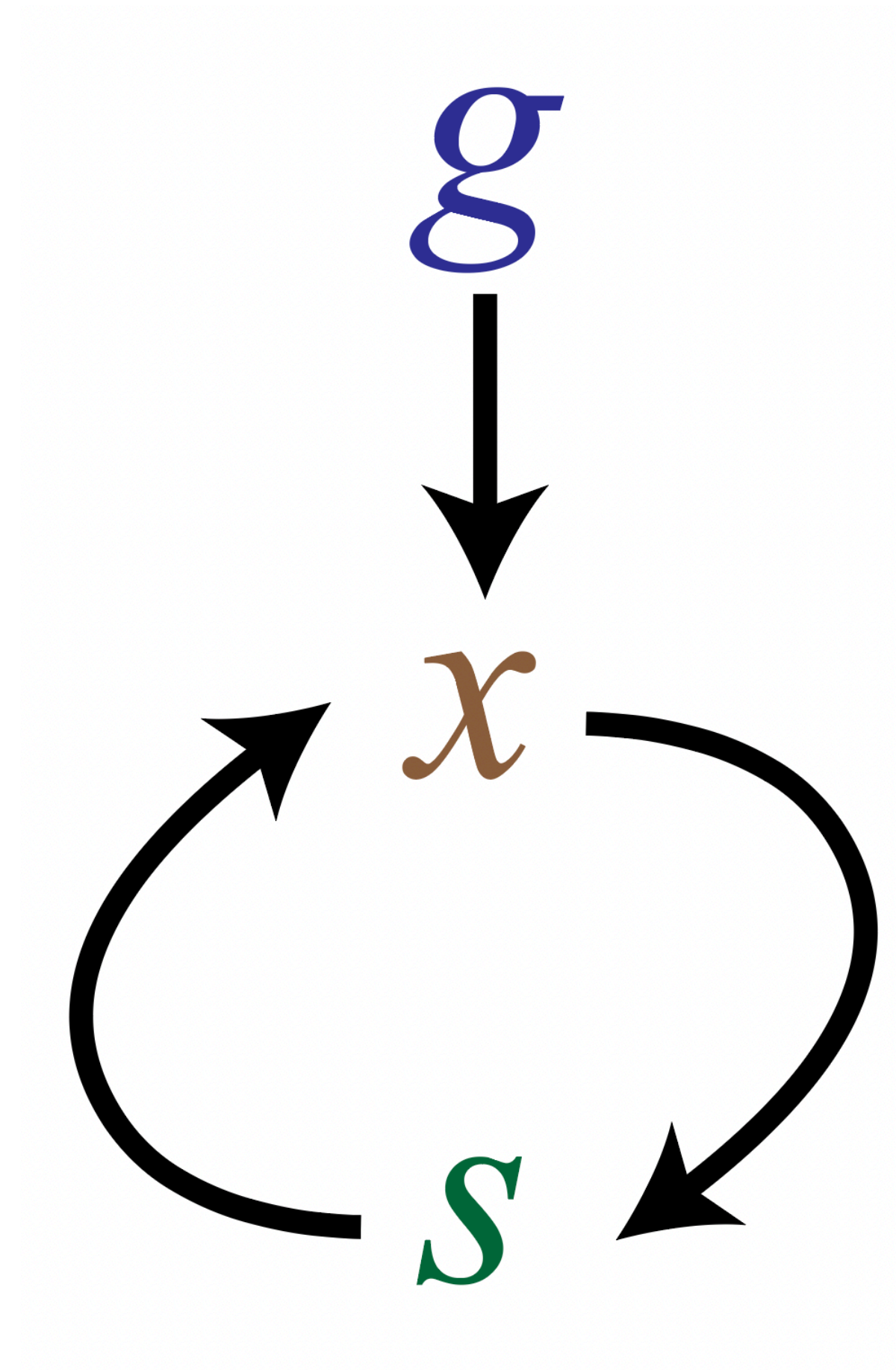


From Comprehension to Production

**Communicative
Goal**

Word

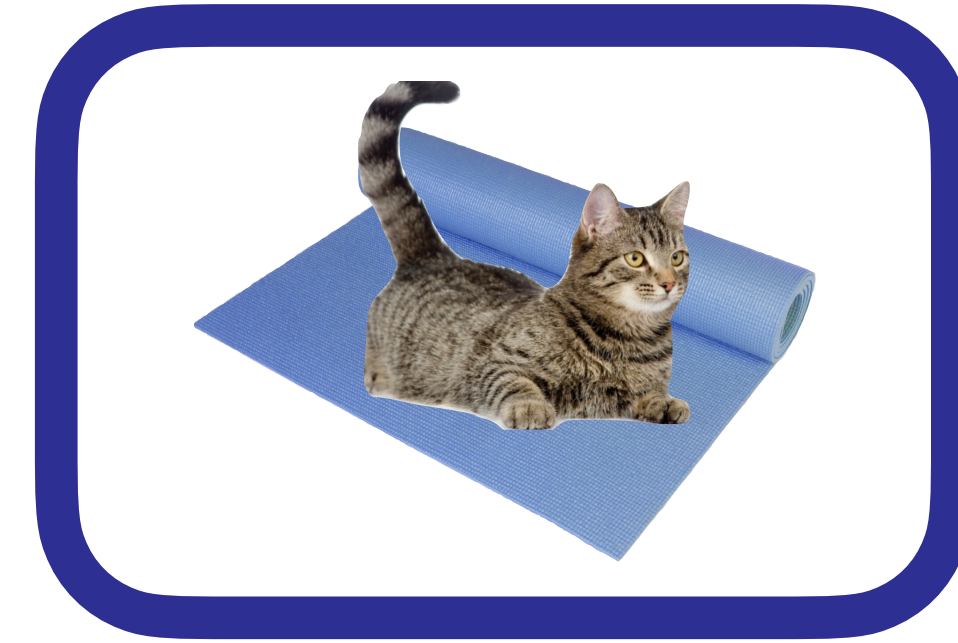
Memory State



Picture of Language Production

Goal

=



Word

x

cat $\sim P(\cdot | g, s)$ (Policy)

State

=

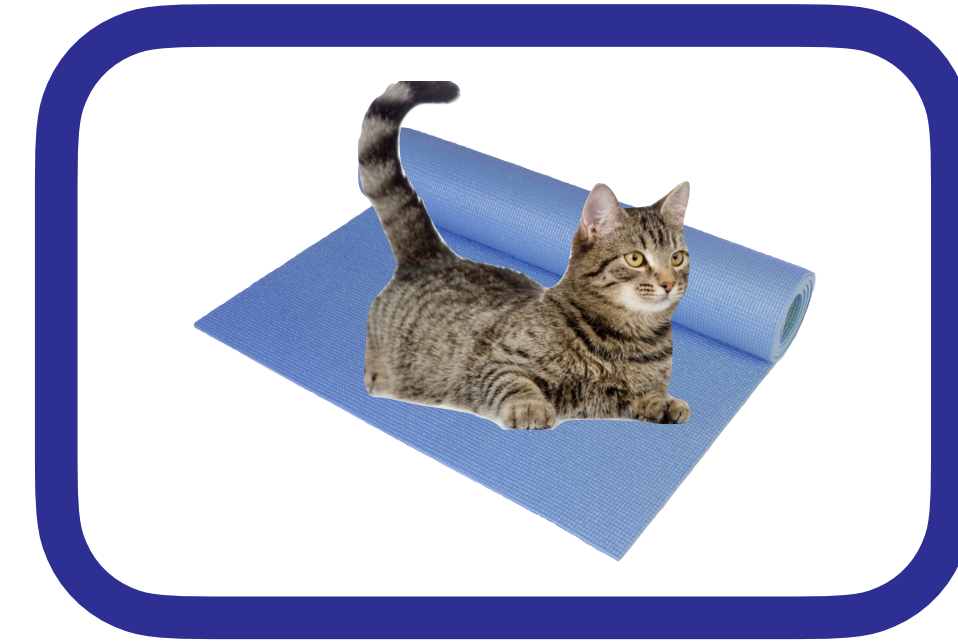
the

Picture of Language Production

Goal

g

=



Word

x

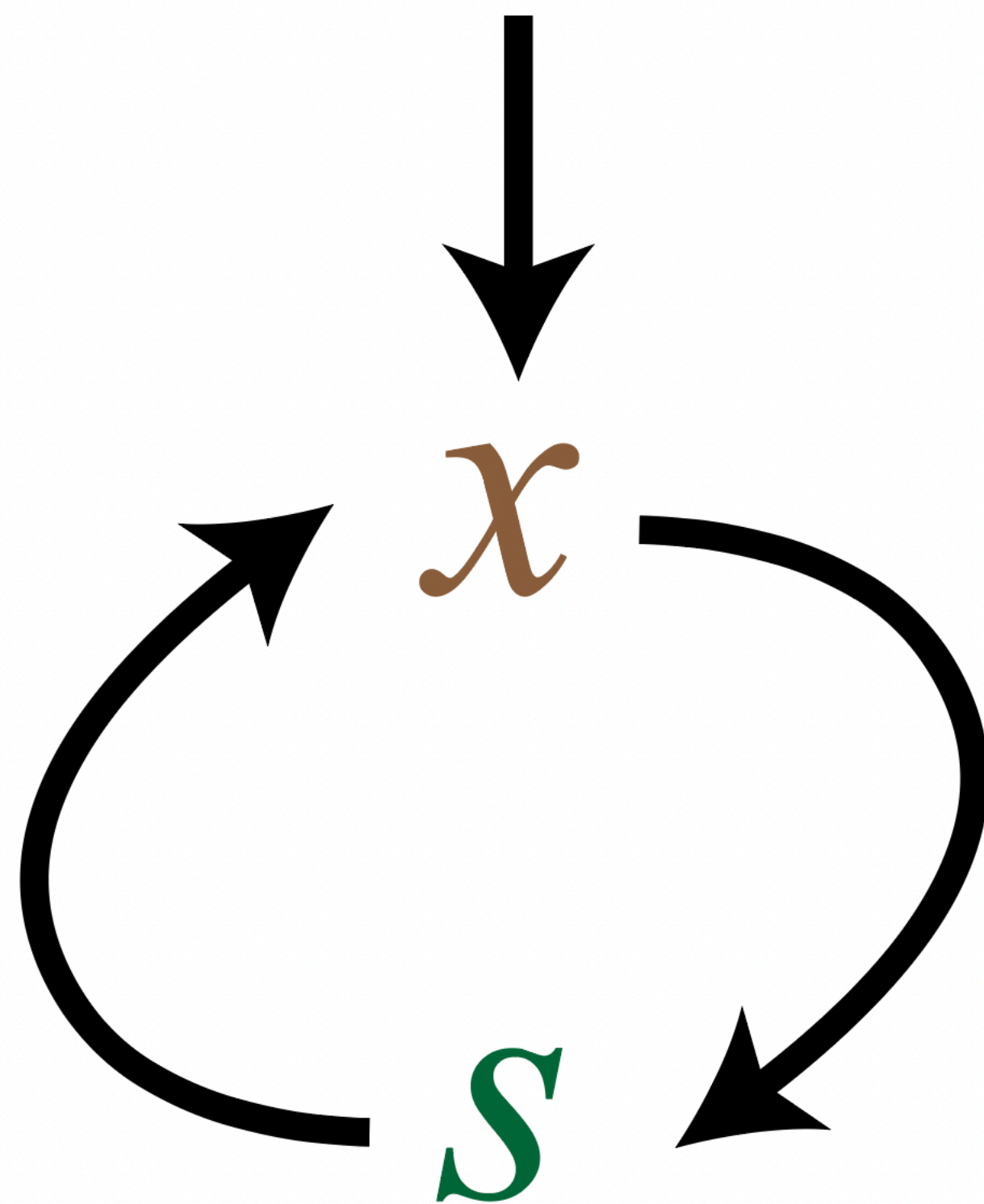
$\text{sat} \sim P(\cdot | g, s)$ (Policy)

State

s

=

the cat

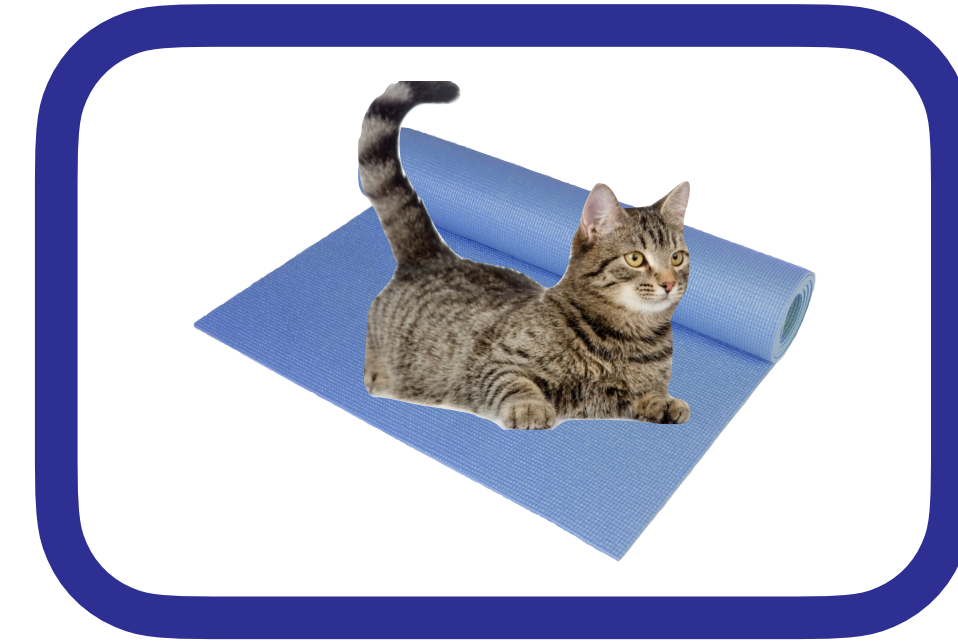


Picture of Language Production

Goal

g

=



Word

x

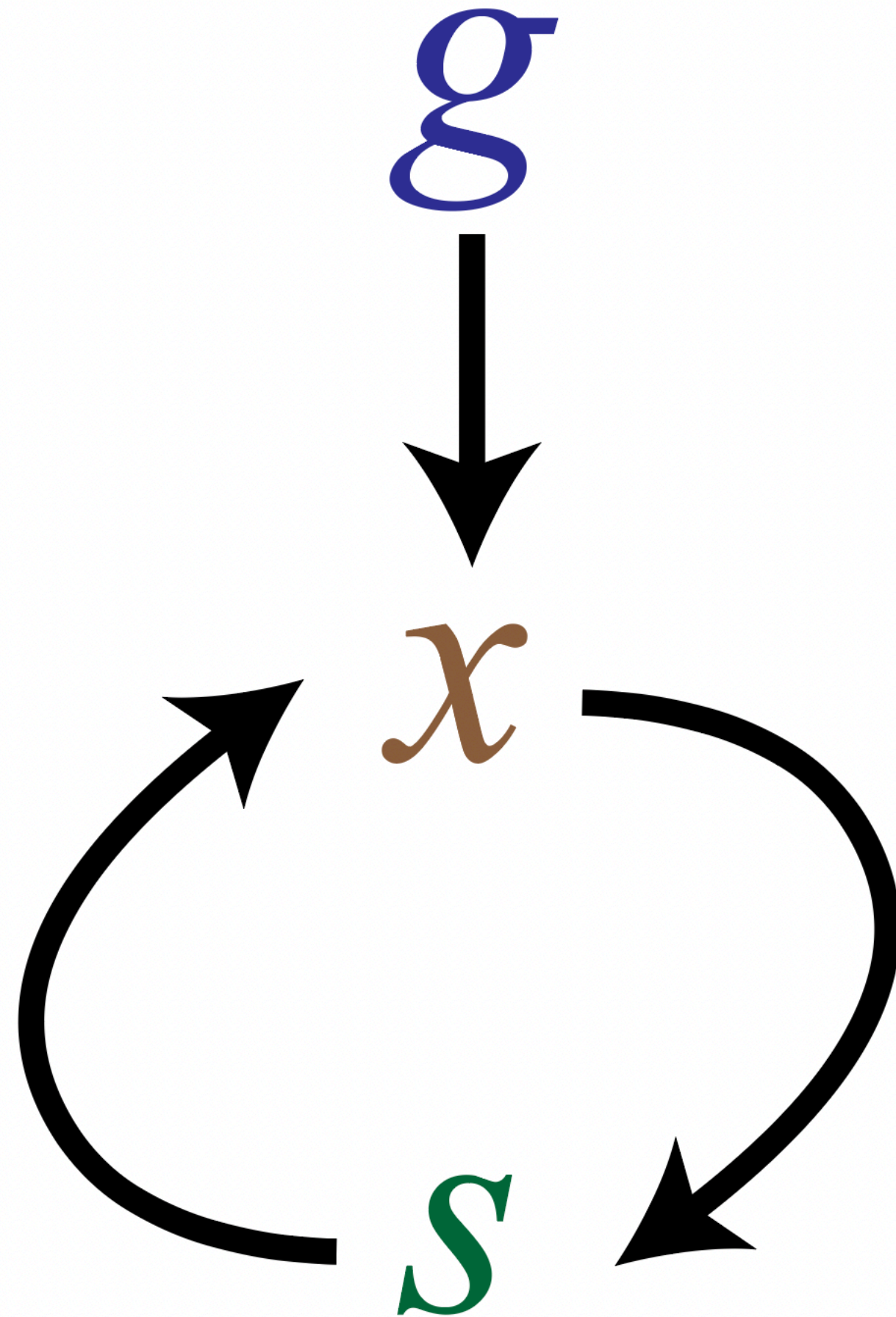
$on \sim P(\cdot | g, s)$ (Policy)

State

s

=

the cat sat

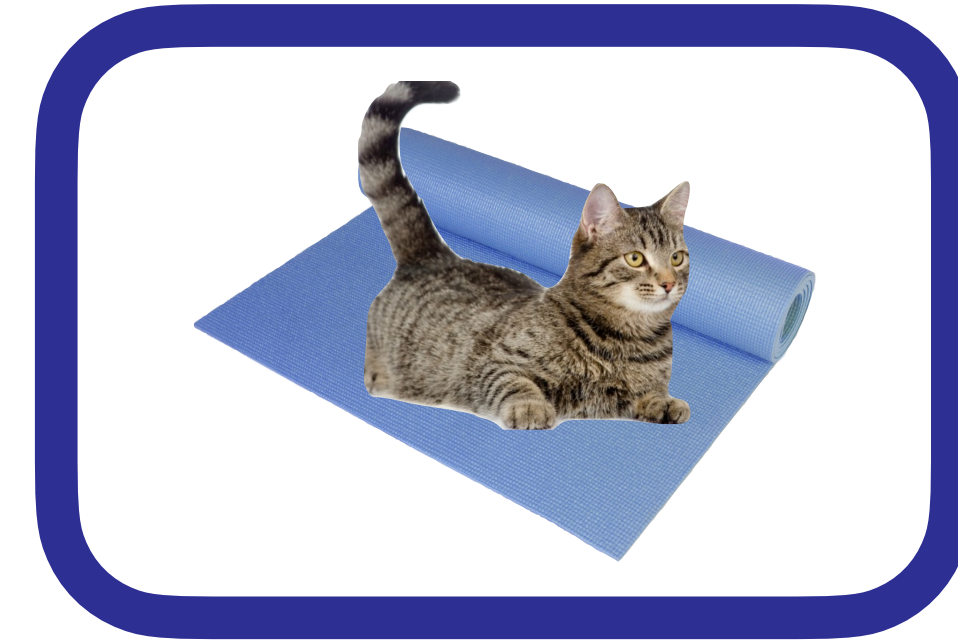


Picture of Language Production

Goal

g

=



Word

x

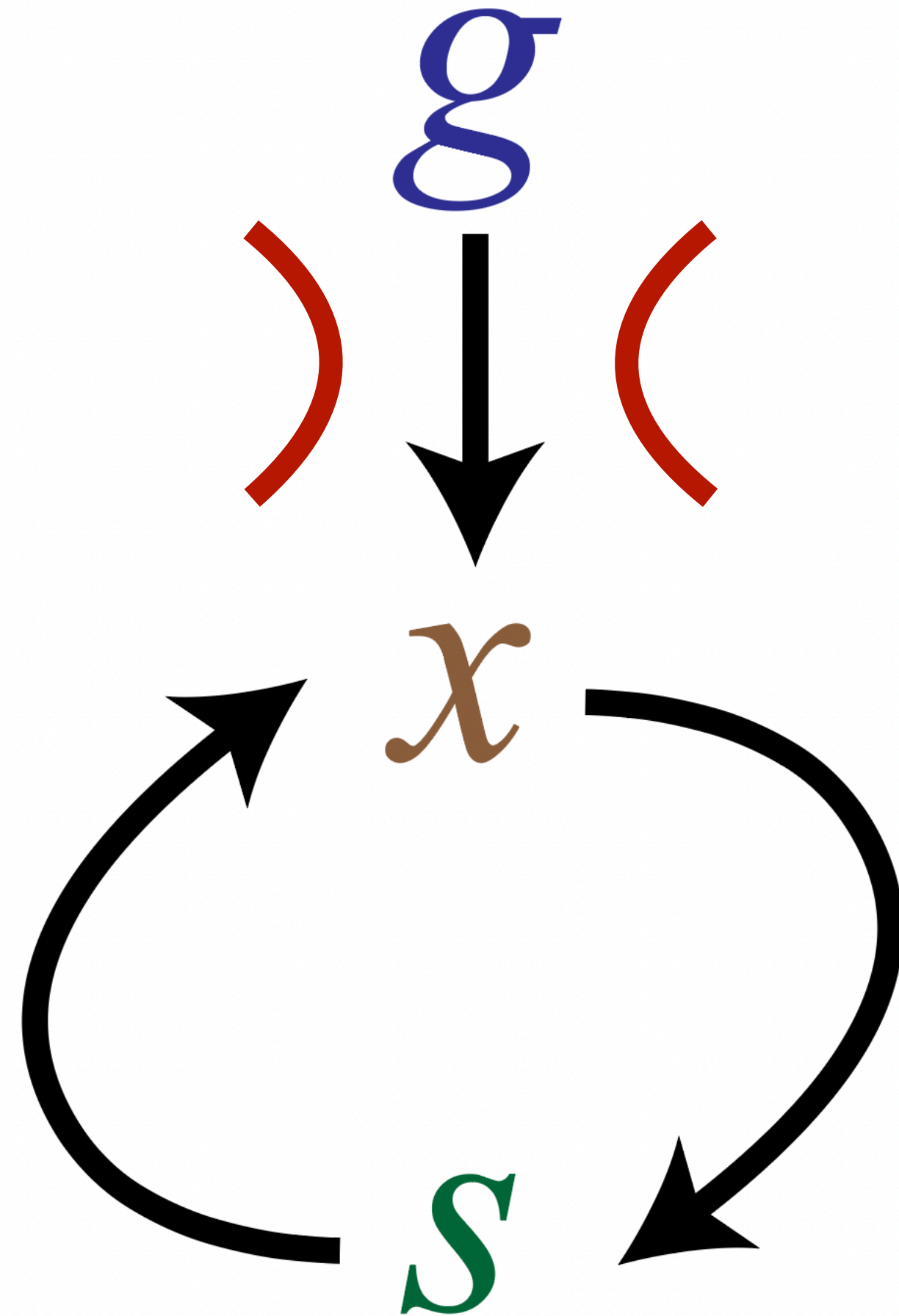
$\sim P(\cdot | g, s)$ (Policy)

State

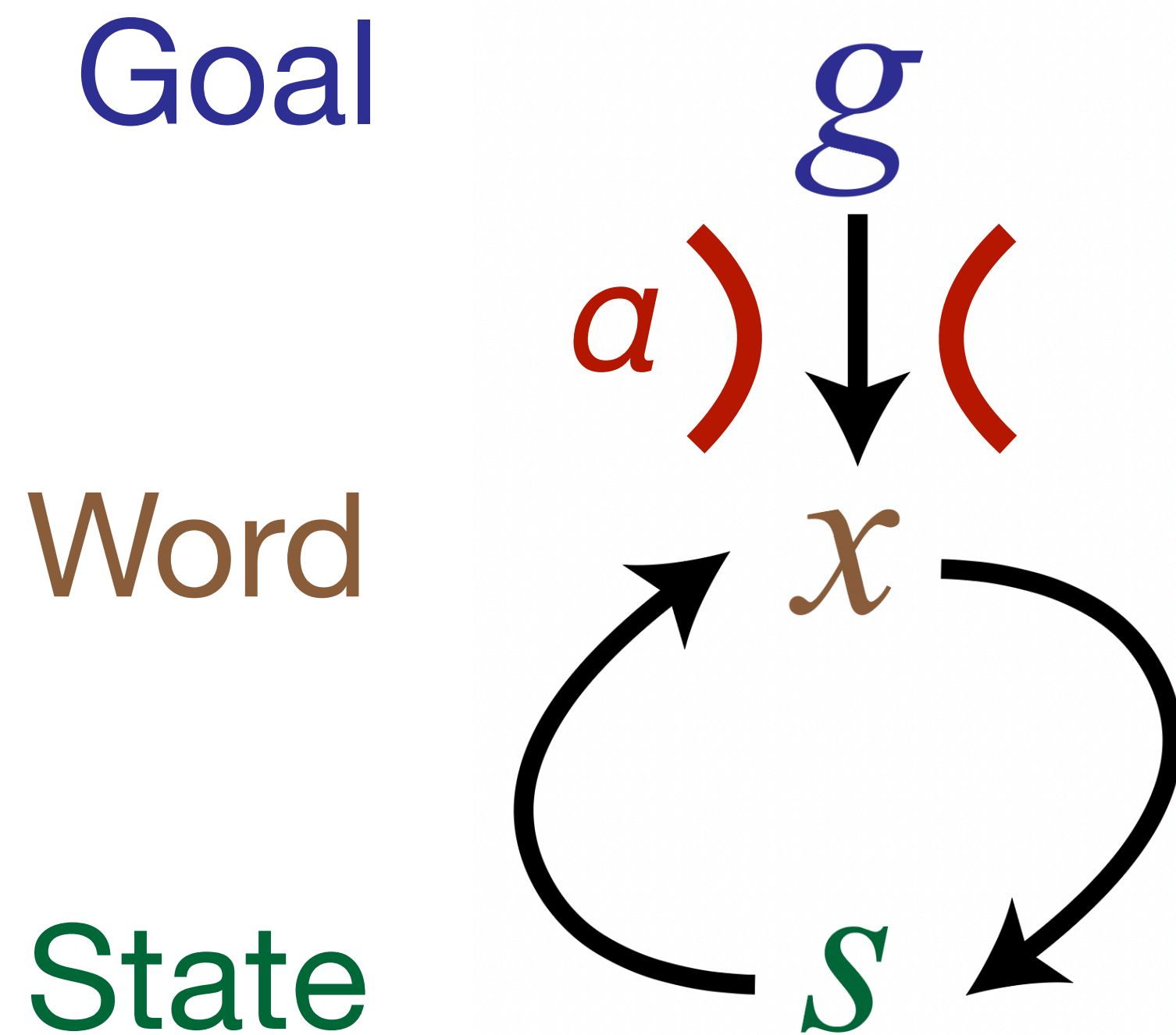
s

=

the cat sat on

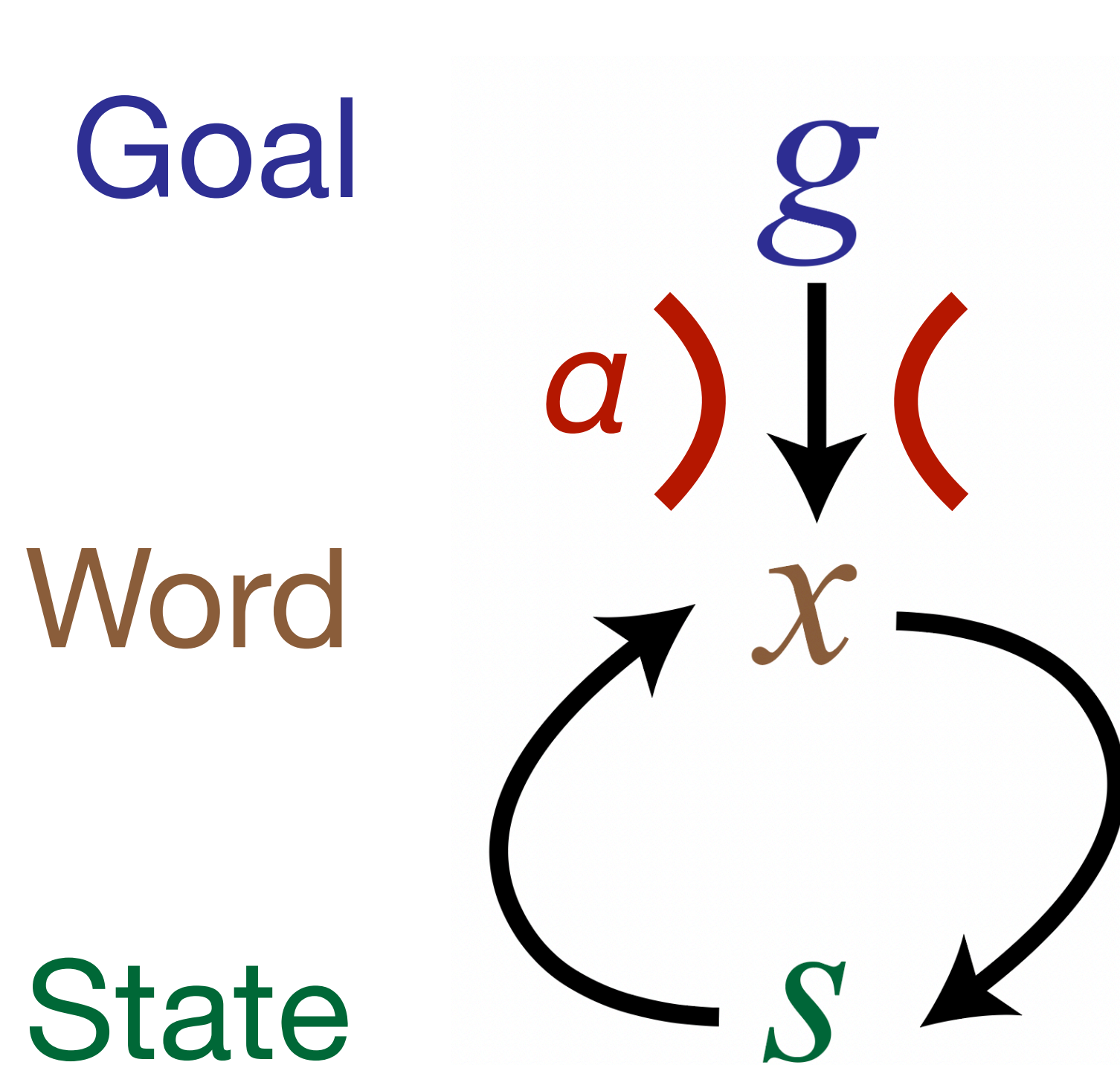


Optimization Problem for Language Production



- Idea: You can only use so much information about the goal per word, due to a constraint on **cognitive control**.
 - Cognitive control operates under a **bandwidth constraint: 50 bits/ms** (Fan, 2014; Zénon et al., 2019)
- So, find a policy that
 - Maximizes **communicative accuracy**
 - Subject to a **constraint on the mutual information** of g with x in each timestep.

Constrained Optimal Policy



Policy

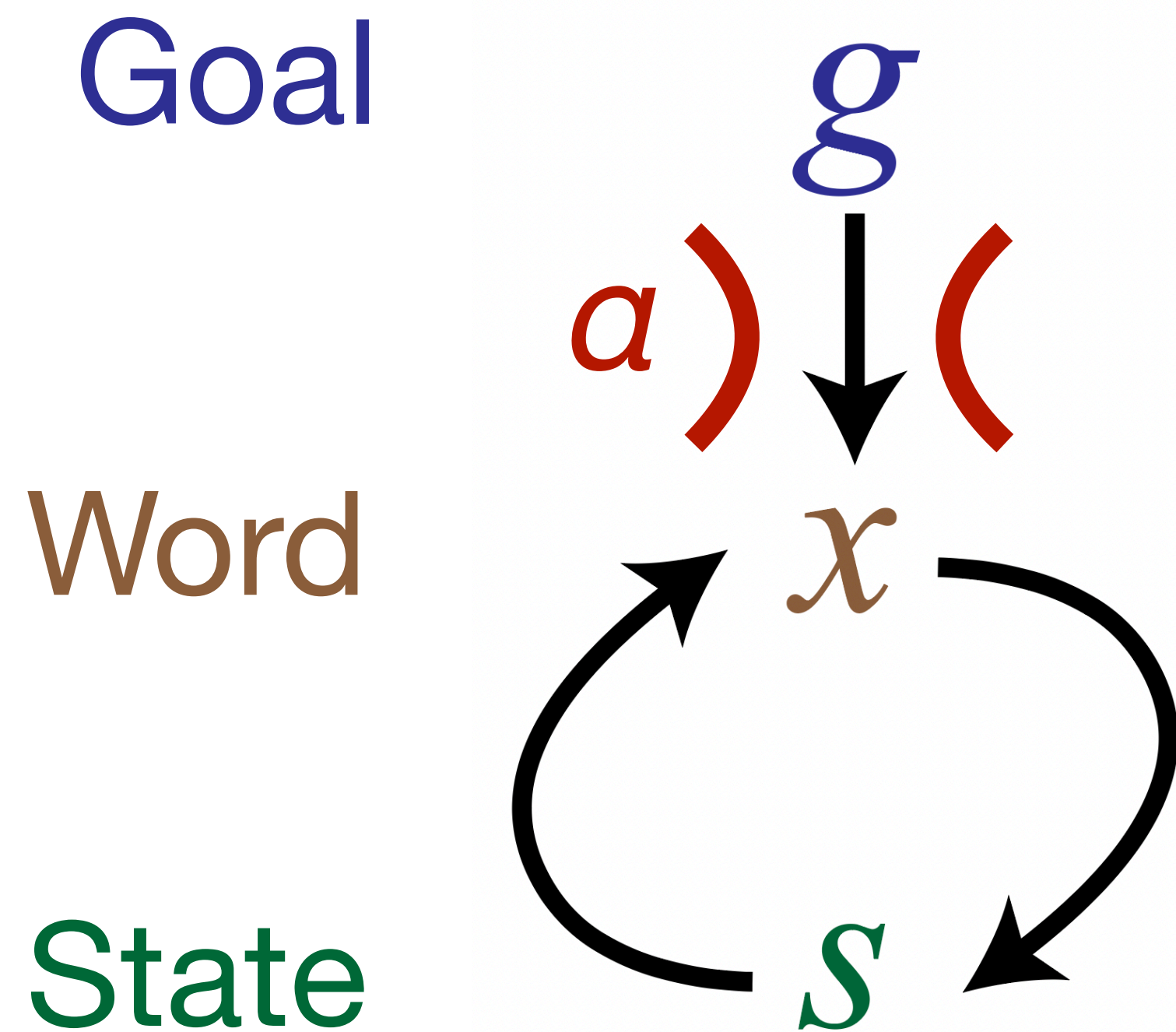
Surprisal

Control Signal

$$P(\text{word} \mid \text{goal}, \text{state}) \propto \exp \{ \log P(\text{word} \mid \text{state}) + \alpha u(\text{word} \mid \text{goal}, \text{state}) \}$$

- A word is produced if...
 - It is **low surprisal** given the memory state.
 - It is **communicatively accurate**.
- The trade-off of these factors is controlled by the bandwidth of cognitive control, α .

Uses of the Rate-Distortion Theory of Control



- We can use this production model to explain...
- **Frequency** and **semantic interference** effects in word production (Futrell, 2020; Futrell, 2023, PNAS)
- **Semantic substitution errors** (Upadhye & Futrell, 2022) and use of **filled pauses** (Futrell, 2023, PNAS)
- **Accessibility effects** in use of optional complementizers in English (Futrell, 2023, CogSci)
- **Accessibility effects** in use of Mandarin classifiers (Futrell, 2023, CogSci)

Mandarin Classifiers

- In certain phrases, Mandarin nouns must be preceded by a **classifier** which can be either **specific** or **generic**.

一 台 电脑
one MACHINE computer
'one computer'

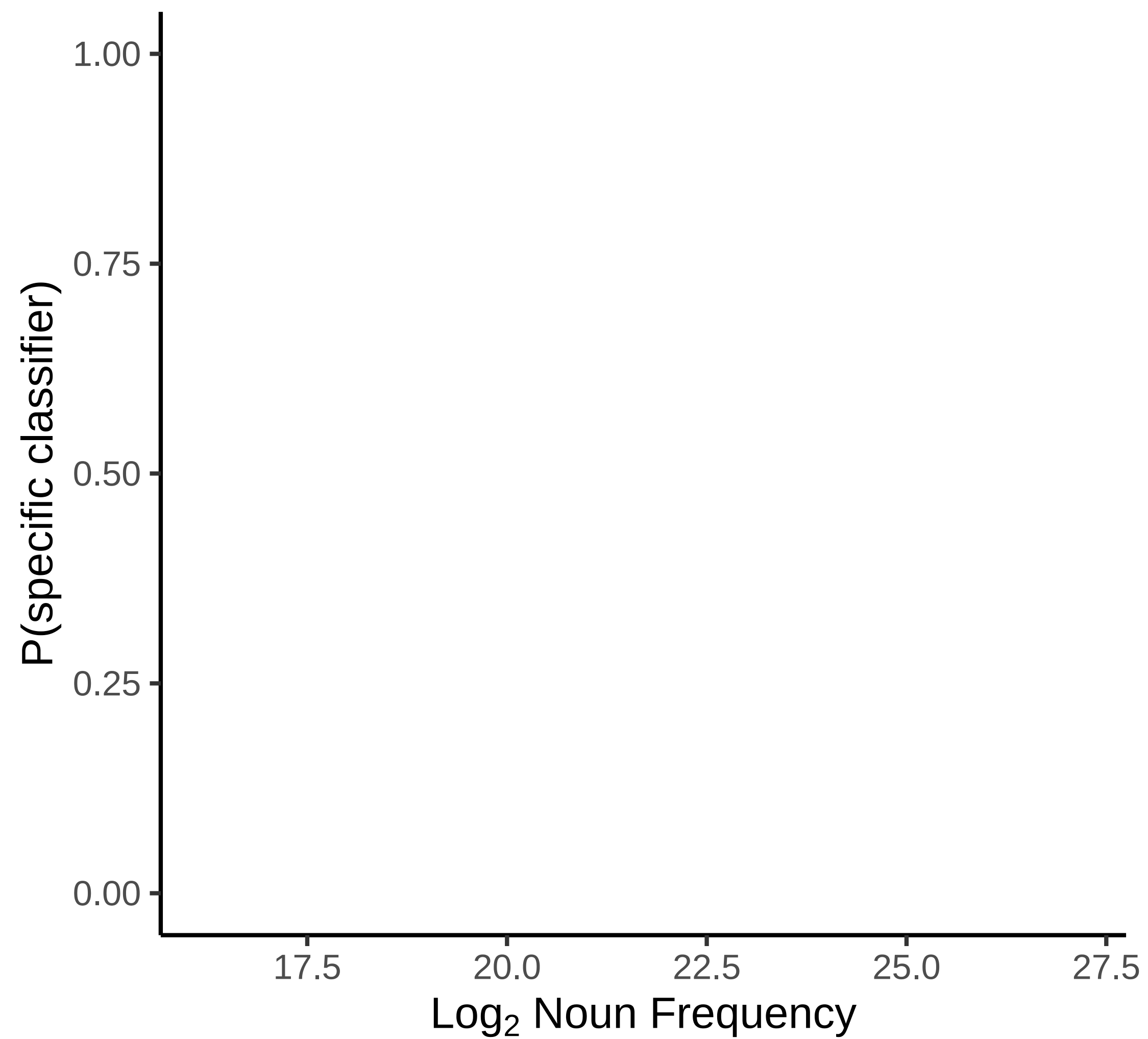
一 个 电脑
one GENERIC computer
'one computer'

一 只 猫
one ANIMAL cat
'one cat'

一 个 猫
one GENERIC cat
'one cat'

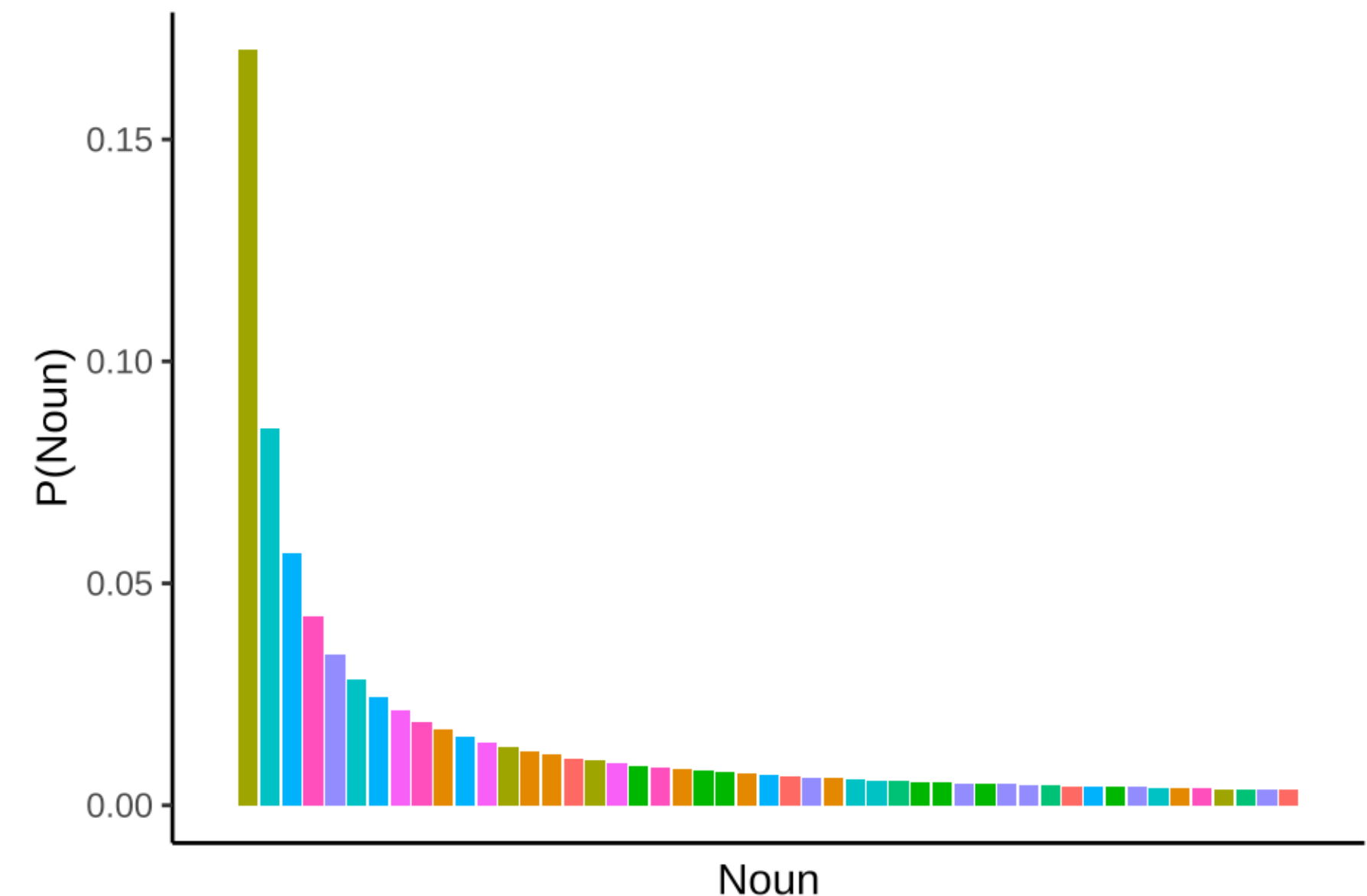
An Accessibility Effect in Mandarin Classifiers

A. Zhan & Levy (2019) Experiment



Mandarin Classifier Simulation

- Set up a toy language where every utterance consists of CLASSIFIER + NOUN, where CLASSIFIER can be generic or specific.
- $N=200$ different nouns, each assigned to one of 10 different specific classifiers.
- Probability distribution on nouns is Zipfian.
- Derive the constrained optimal policy.



$$P(\text{word} \mid \text{goal, state}) \propto \exp \left\{ \log P(\text{word} \mid \text{state}) + \alpha u(\text{word} \mid \text{goal, state}) \right\}$$



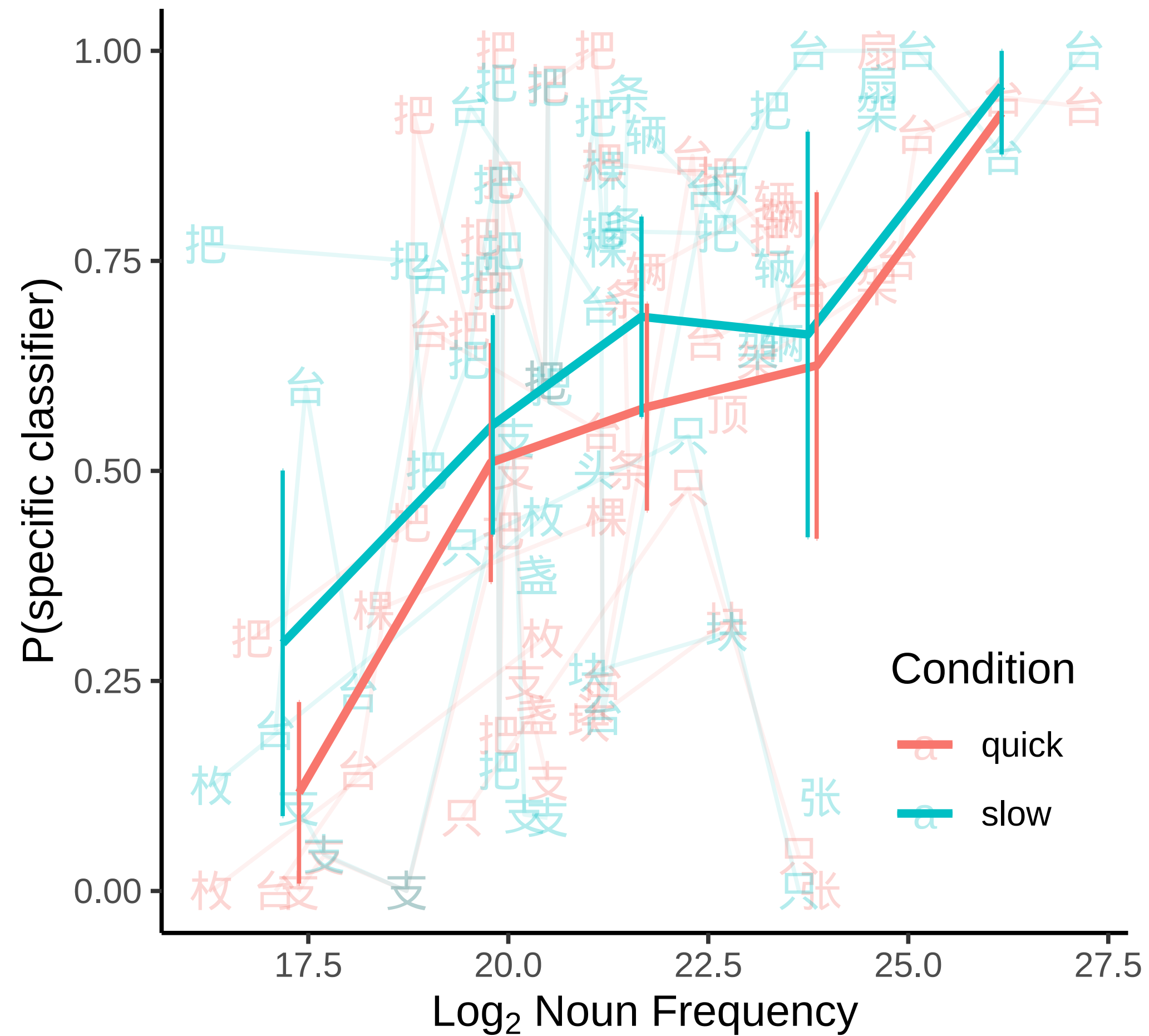
Favors generic classifier



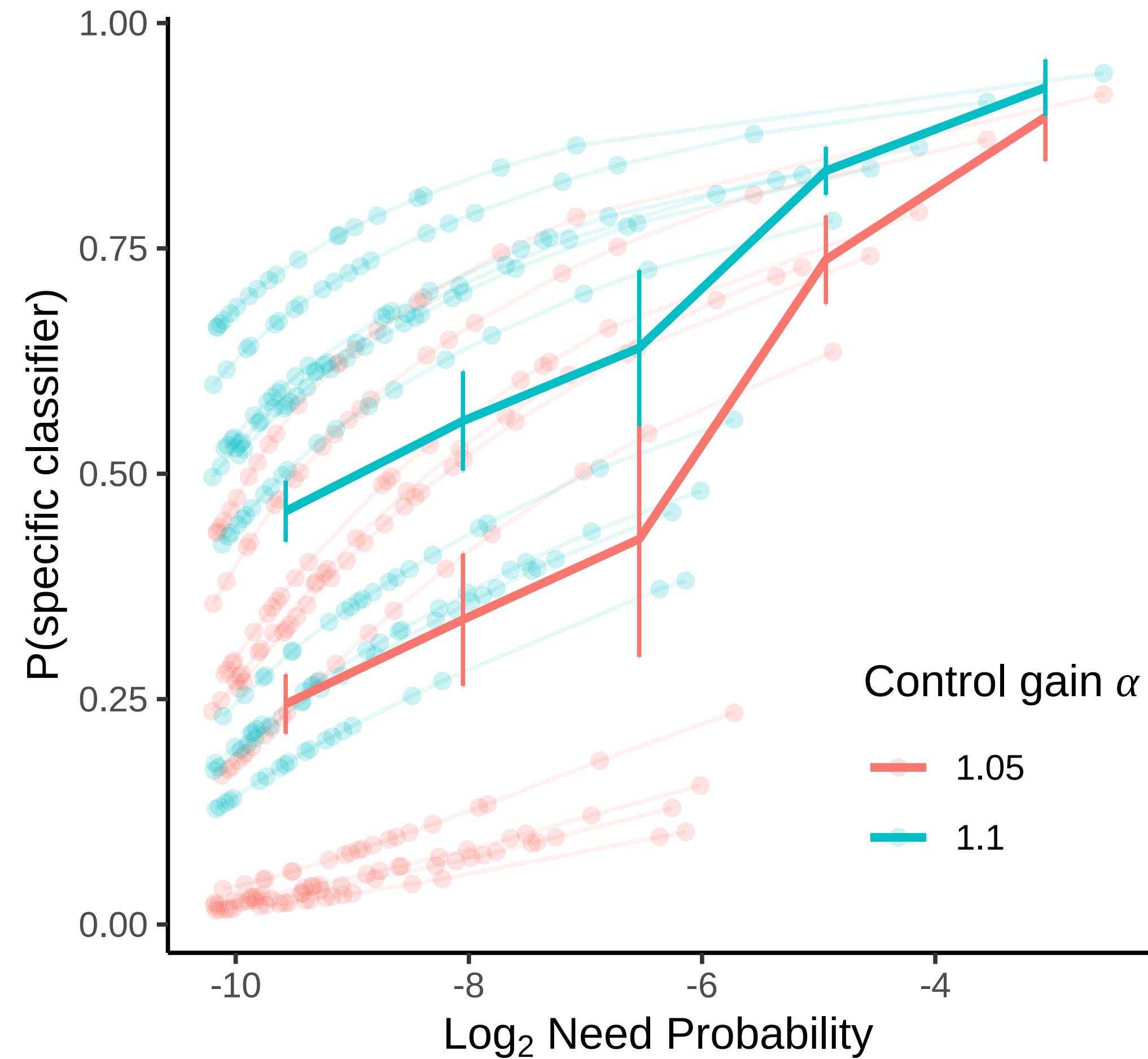
Favors specific classifier

Mandarin Classifier Result

A. Zhan & Levy (2019) Experiment

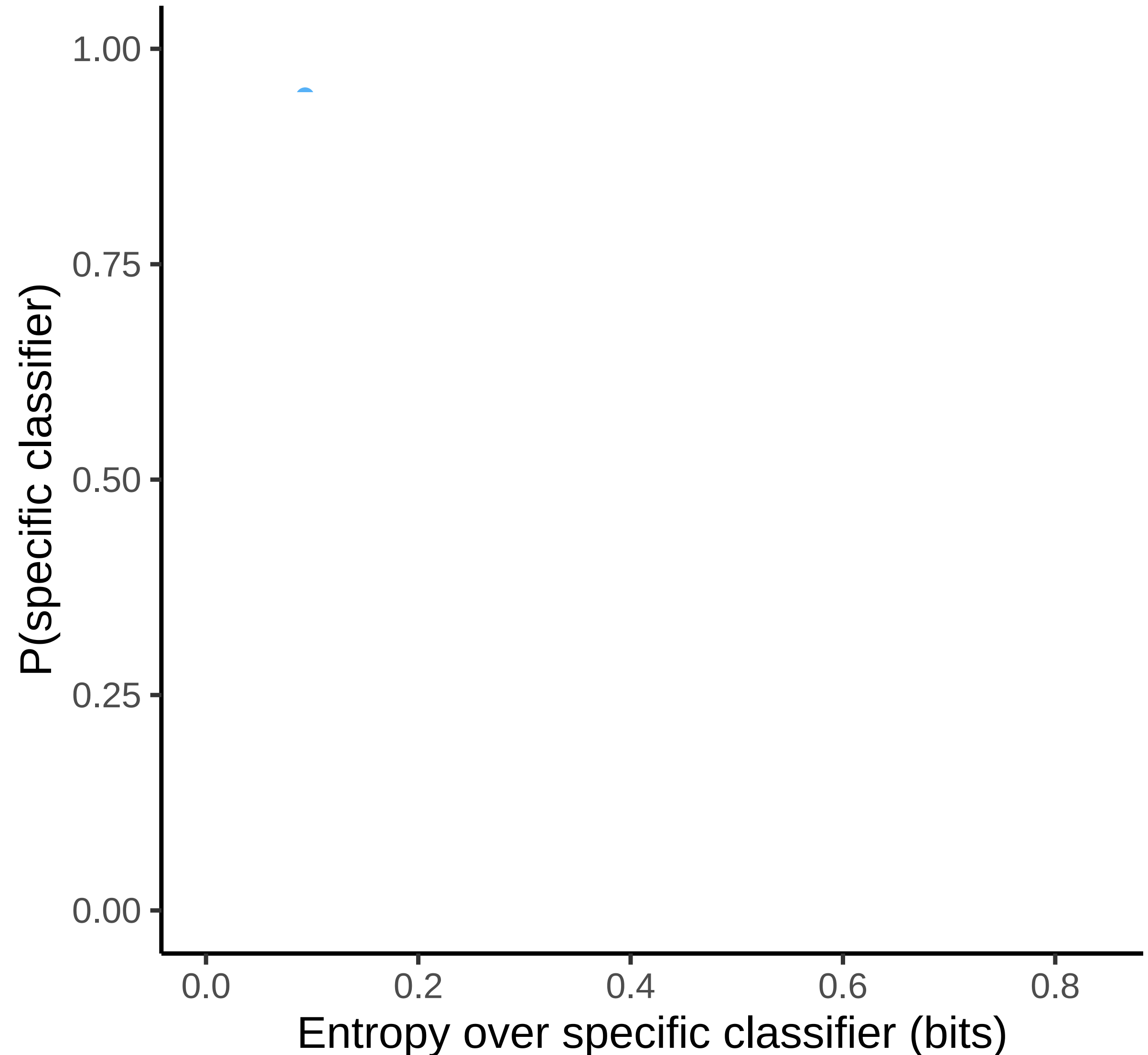


B. Model Simulation

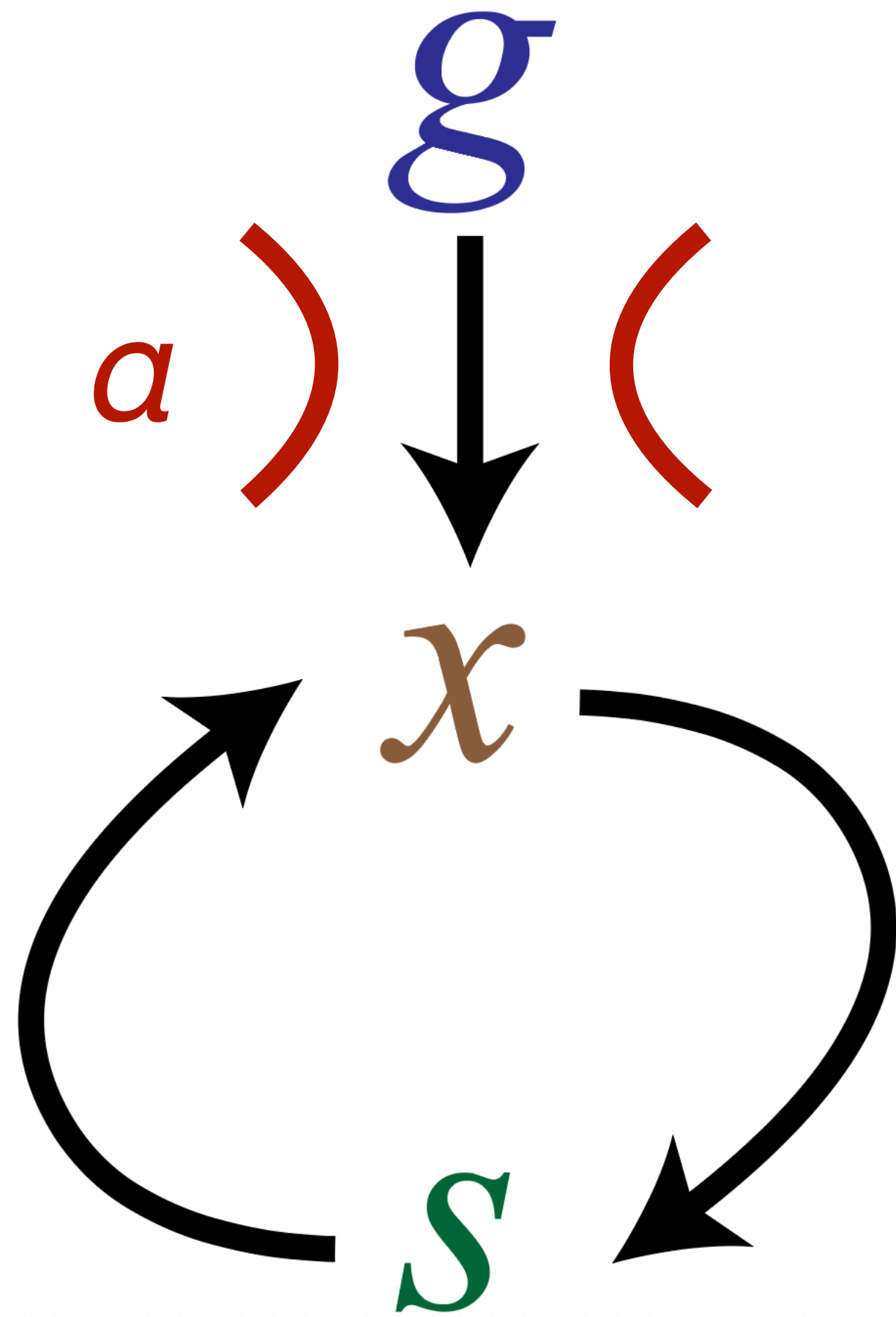


Mandarin Classifier Result

- Production of specific classifier is rare when the model has uncertainty about which specific classifier it should use.
- Matches the intuitive idea of “accessibility.”



Control Bottleneck in Language Production



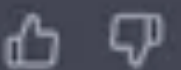
- An information-theoretic model captures **accessibility-based production** effects.
- A constrained optimal production policy ends up including a **language model** as a component...

$$P(\text{word} \mid \text{goal}, \text{state}) \propto \exp \{ \log P(\text{word} \mid \text{state}) + \alpha u(\text{word} \mid \text{goal}, \text{state}) \}$$

- Really, it's a language model plus a reward model:
 - As in Reinforcement Learning from Human Feedback (RLHF)



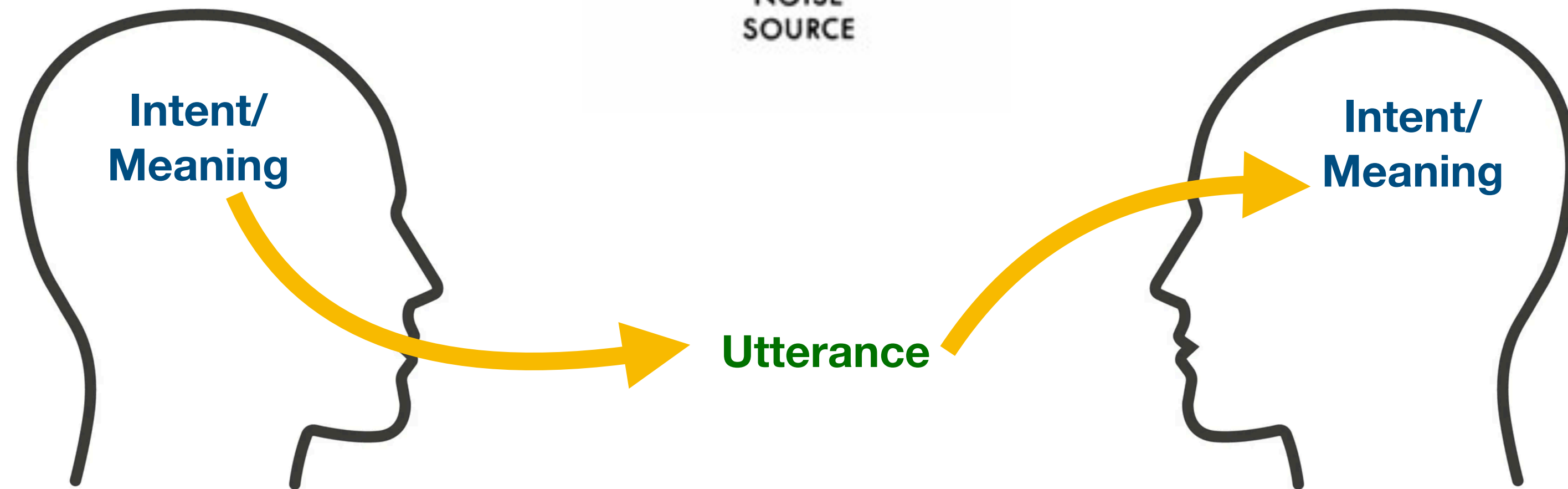
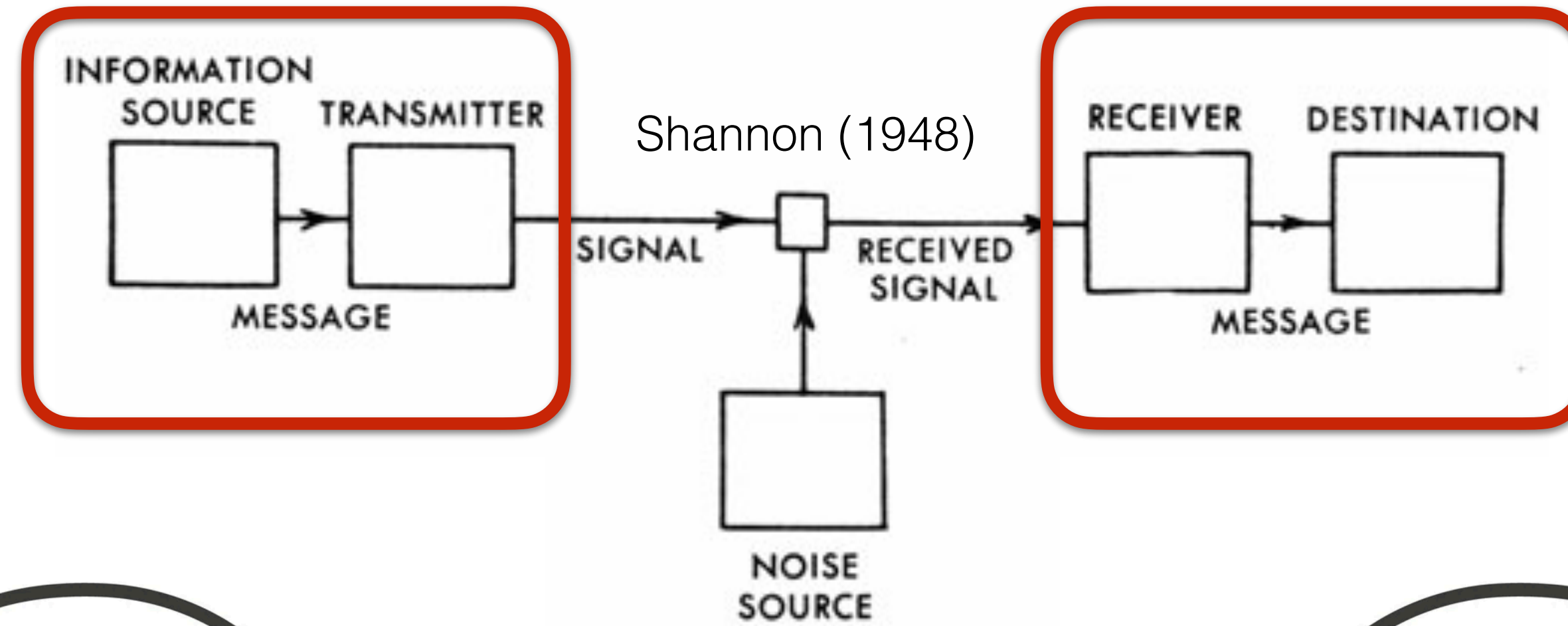
As a language model, I don't have emotions, so I can't be "stumped" in the way that you mean. But I do have a knowledge cutoff, meaning that I am only aware of information that



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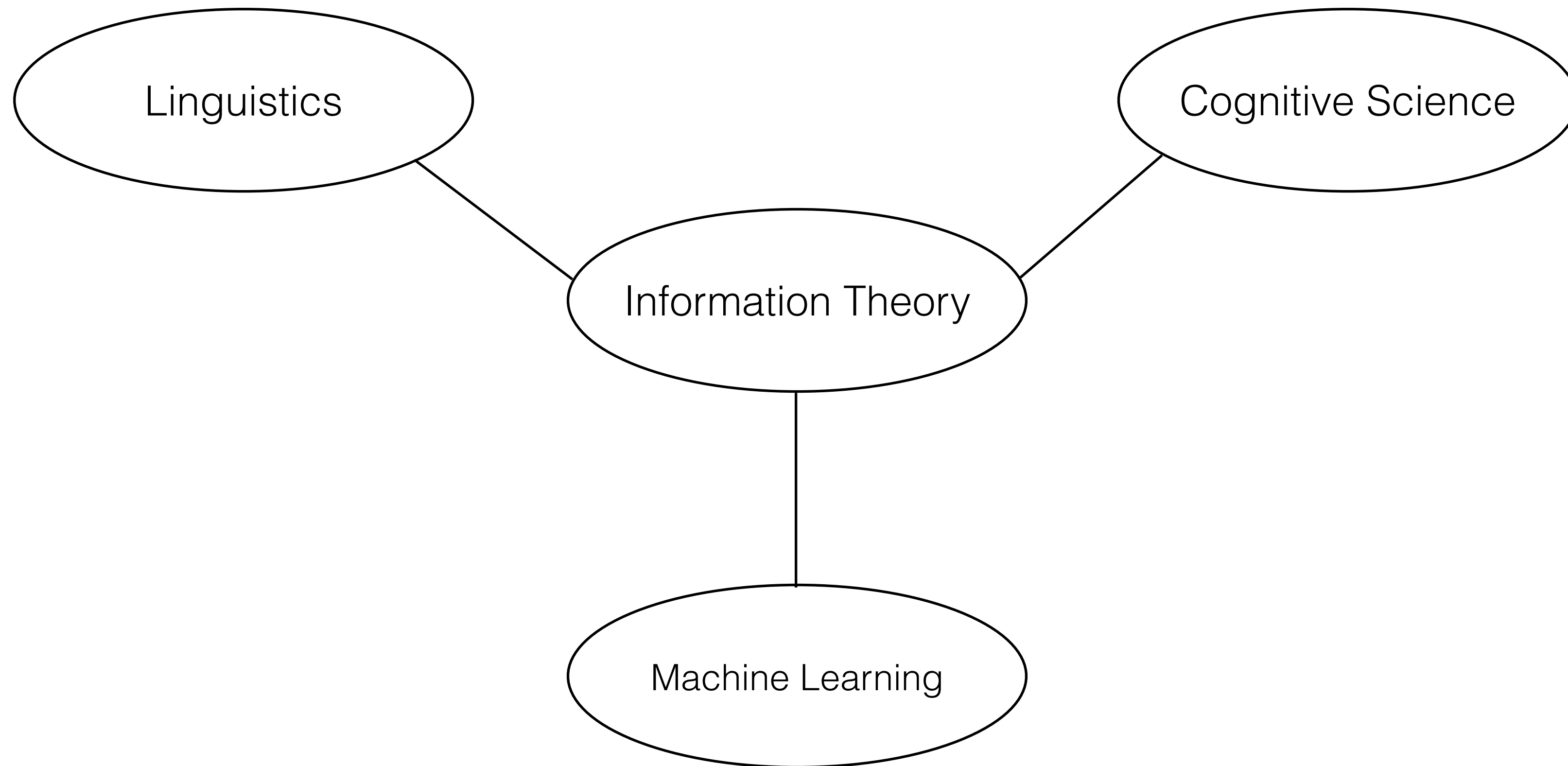
Natural Language as a Code



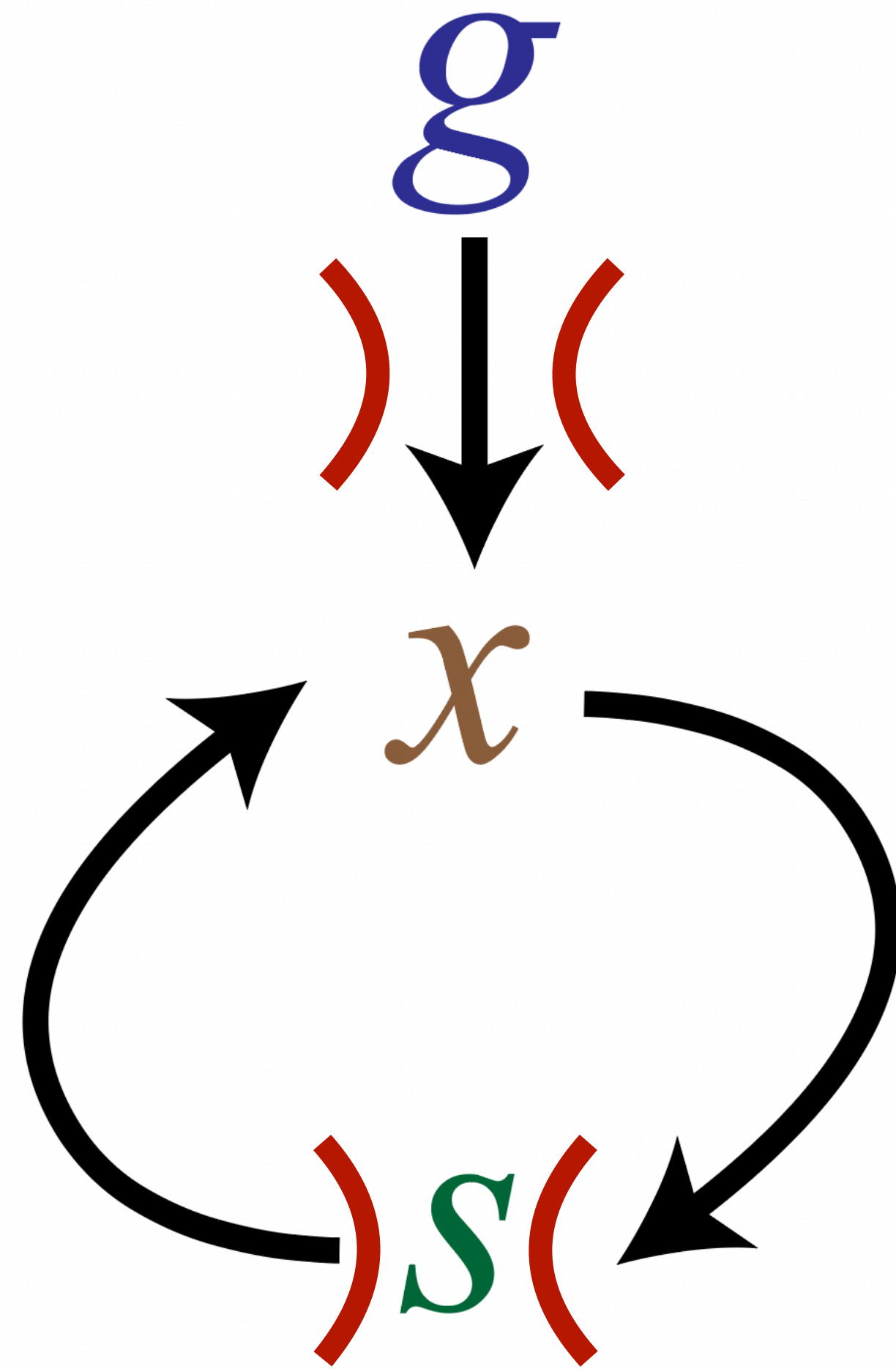
Production

Comprehension

A Nexus Between Fields



Conclusion



- We can model language processing as optimal *subject to constraints*...
 - On incremental memory.
 - On control.
- **Language models** $P(\textit{word} \mid \textit{context})$ emerge as a key part of both comprehension and production.
 - Comprehension: They define the **information content** of each word to be processed.
 - Production: They emerge under a **constraint on cognitive control**.
- Information-theoretic psycholinguistics is an open field!

Acknowledgments

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- Thanks for your attention!

To find out more...

- On **lossy-context surprisal** as a model of human processing difficulty:
 - Richard Futrell, Edward Gibson, and Roger Levy. 2020. Lossy-context surprisal: An information-theoretic model of memory effects in sentence processing. *Cognitive Science* 44.
 - Michael Hahn, Richard Futrell, Roger Levy, and Edward Gibson. 2022. A resource-rational model of recursive sentence processing. *PNAS*.
 - Richard Futrell (2019). Information-theoretic locality properties of natural language. In *QuaSy*, pp. 2-15.
 - Richard Futrell, William Dyer, and Gregory Scontras (2020). What determines the order of adjectives in English? Comparing efficiency-based theories using dependency treebanks. In *ACL*.
 - Karthik Sharma, Richard Futrell, and Samar Husain (2021). What determines the order of verbal dependents in Hindi? In *CMCL*.
 - Michael Hahn, Judith Degen, and Richard Futrell. Explaining patterns of word and morpheme order as an efficient tradeoff of memory and surprisal. *Psychological Review*.
- On **RDC production model**
 - Richard Futrell (2021). An information-theoretic account of semantic interference in word production. *Frontiers in Psychology*.
 - Shiva Upadhye & Richard Futrell (2022). An information-theoretic account of semantic substitution errors in speech. In *InfoCog*.
 - Richard Futrell (2023). An information-theoretic account of accessibility effects in incremental language production. In *CogSci*.
 - Richard Futrell (2023). Information-theoretic principles in incremental language production. *PNAS*.