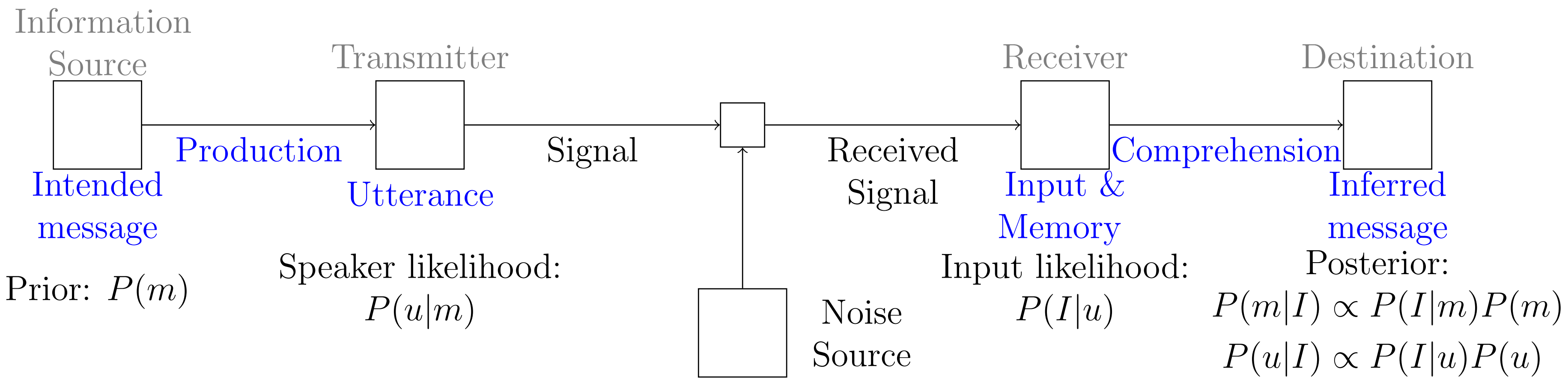
Noisy-channel sentence comprehension theory



Roger Levy

9.19: Computational Psycholinguistics

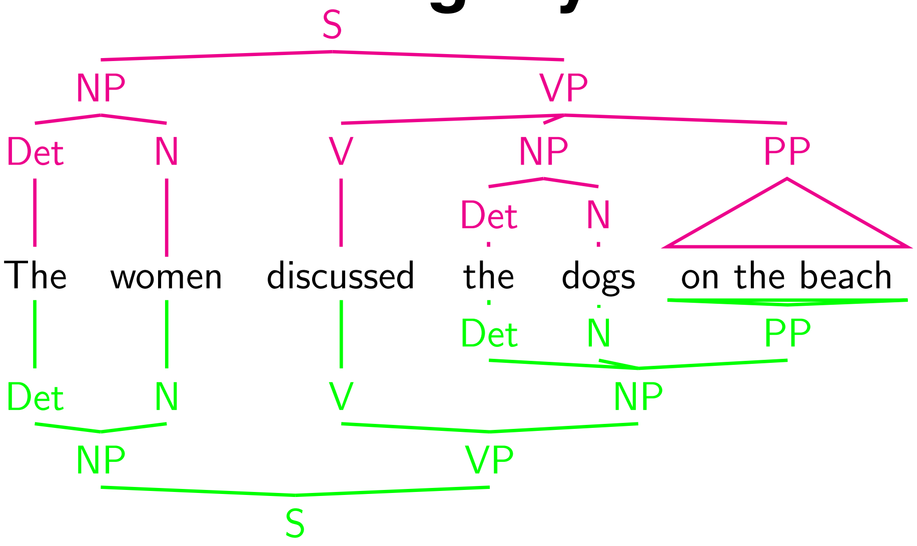
13 November 2023

Today's agenda

- Review principles of rational analysis and its application to theory of language comprehension
- Examine a phenomenon challenging for surprisal theory
- Propose a noisy-channel processing theory, using information theory and probabilistic grammars
- Develop a hypothesis within the theory for the challenging phenomenon
- Empirically test a key prediction of the theory

Challenges for efficient linguistic communication

Ambiguity



Environmental noise

Memory Limitations

Incomplete knowledge of one's interlocutors

Rational analysis

(Anderson, 1990, 1991)

Rational analysis

- Background assumption: cognitive agent is optimized via evolution and learning to solve everyday tasks effectively

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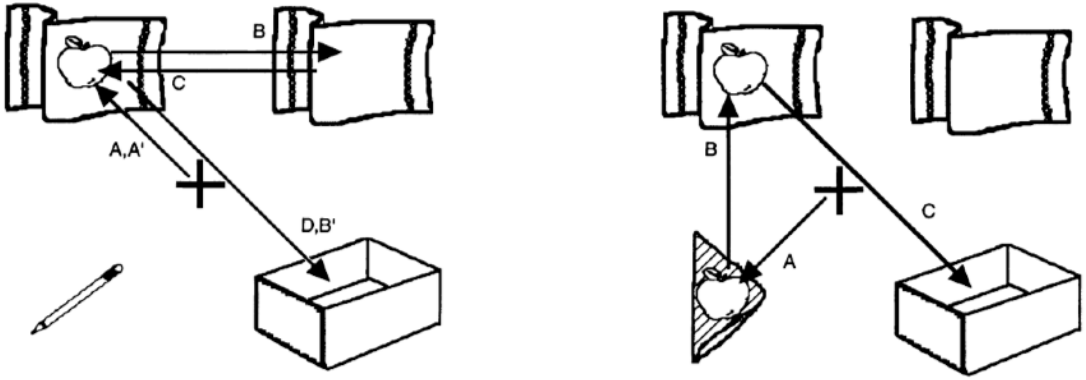
3. Make minimal assumptions re: computational limitations
4. Derive predicted optimal behavior given 1—3
5. Compare predictions with empirical data
6. If necessary, iterate 1—5

(Anderson, 1990, 1991)

Efficient comprehension as rational, goal-driven

- Online sentence comprehension is hard
- But lots of information sources can be usefully brought to bear to help with the task
- Therefore, it would be *rational* for people to use *all information sources available*, whenever possible
- This is what *incrementality* is
- We have lots of evidence that people do this often
- How do we reconcile these information sources?

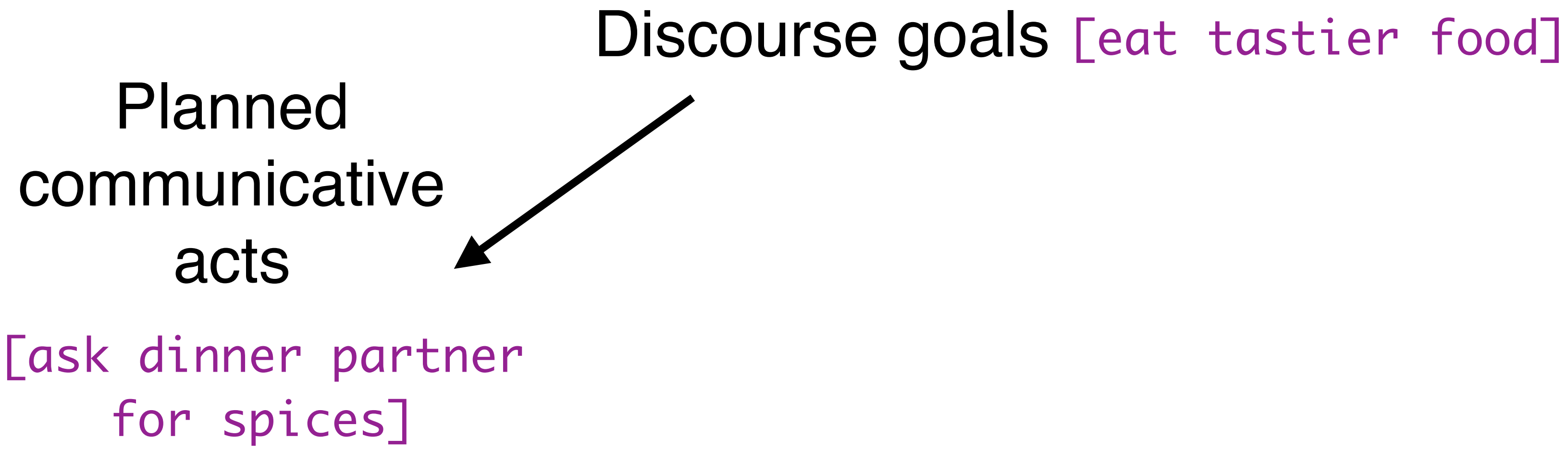


"Put the apple on the towel in the box." *(Tanenhaus et al., 1995, Science)*

Comprehenders as reverse engineers

Discourse goals `[eat tastier food]`

Comprehenders as reverse engineers



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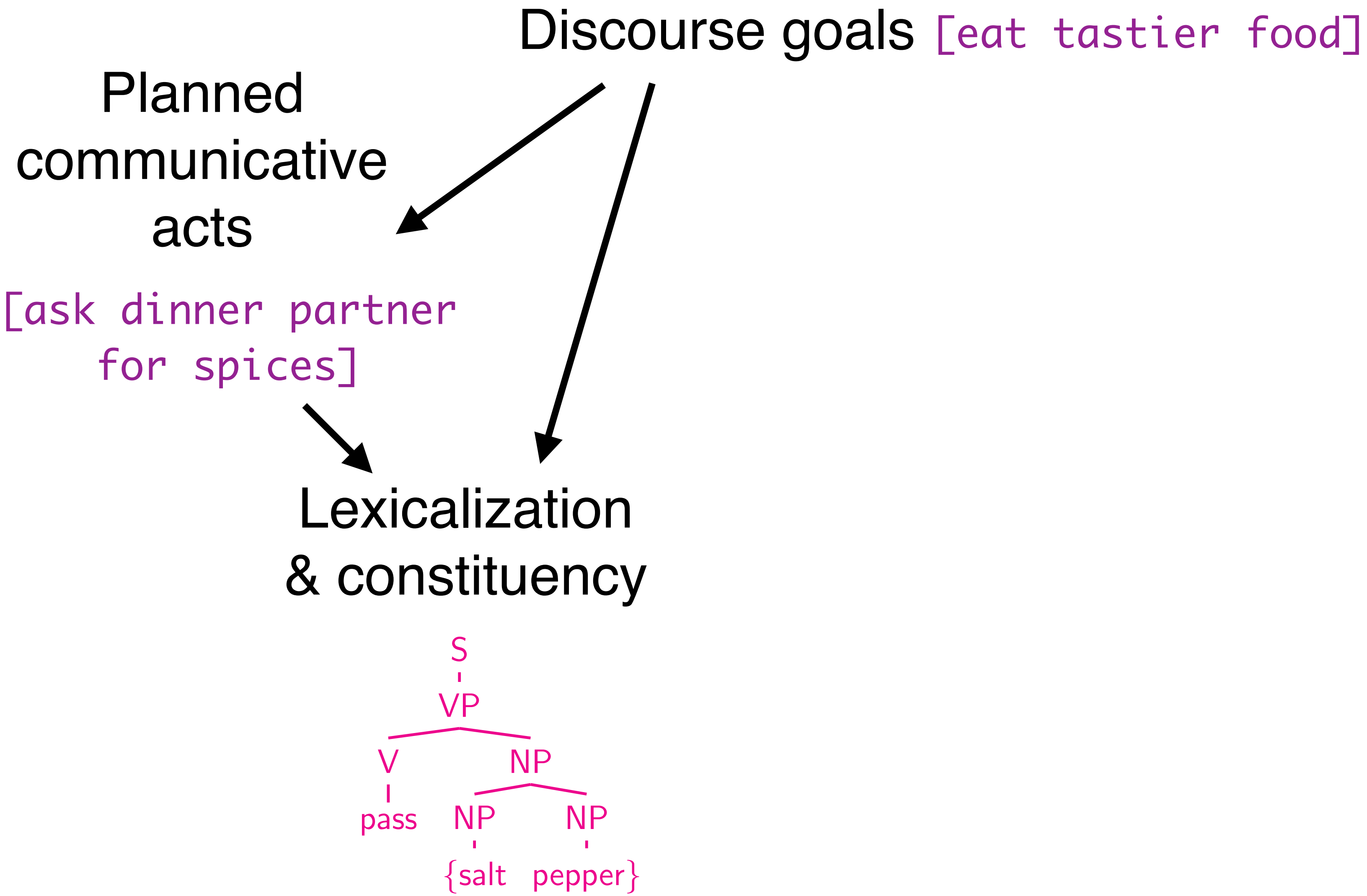

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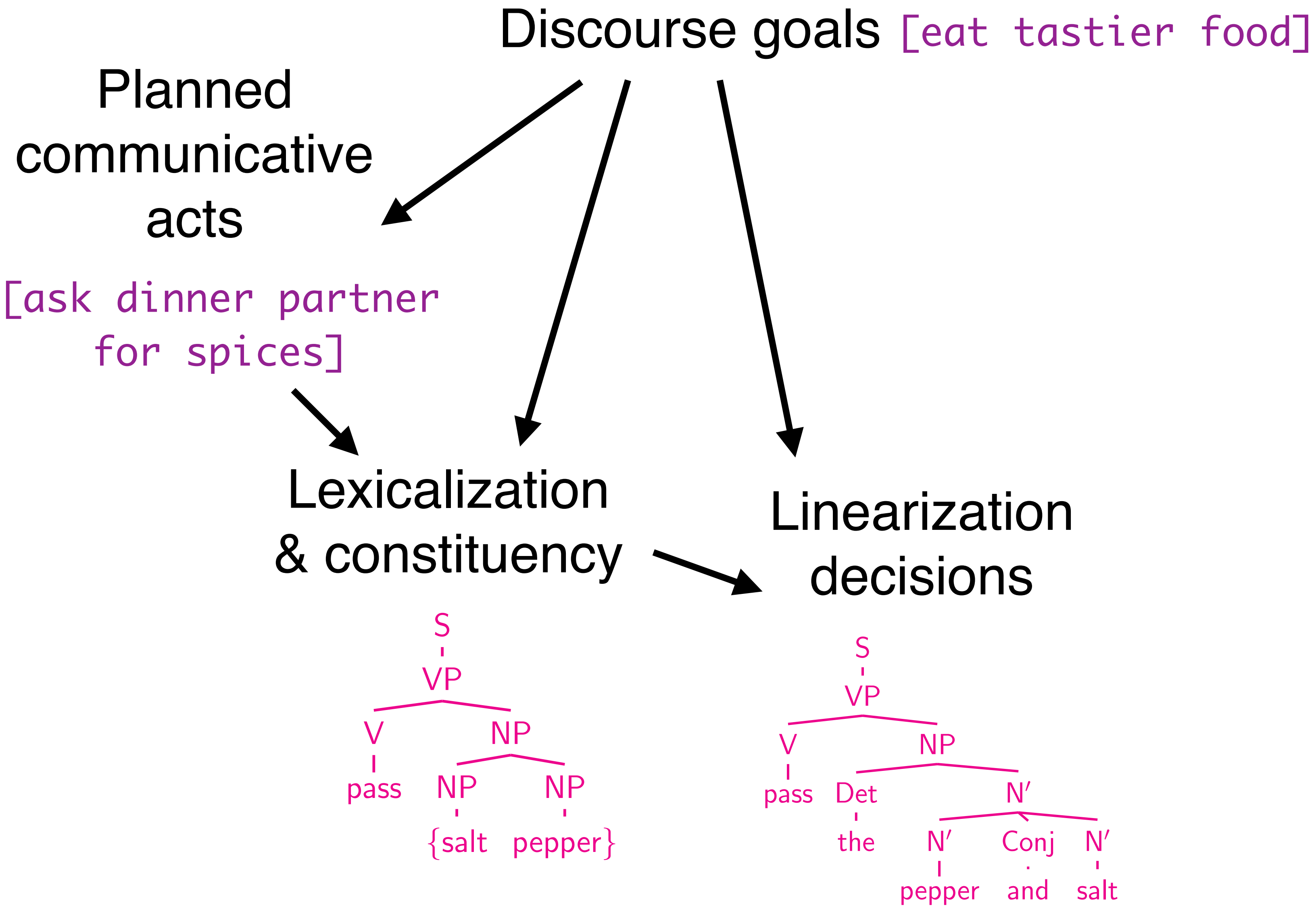

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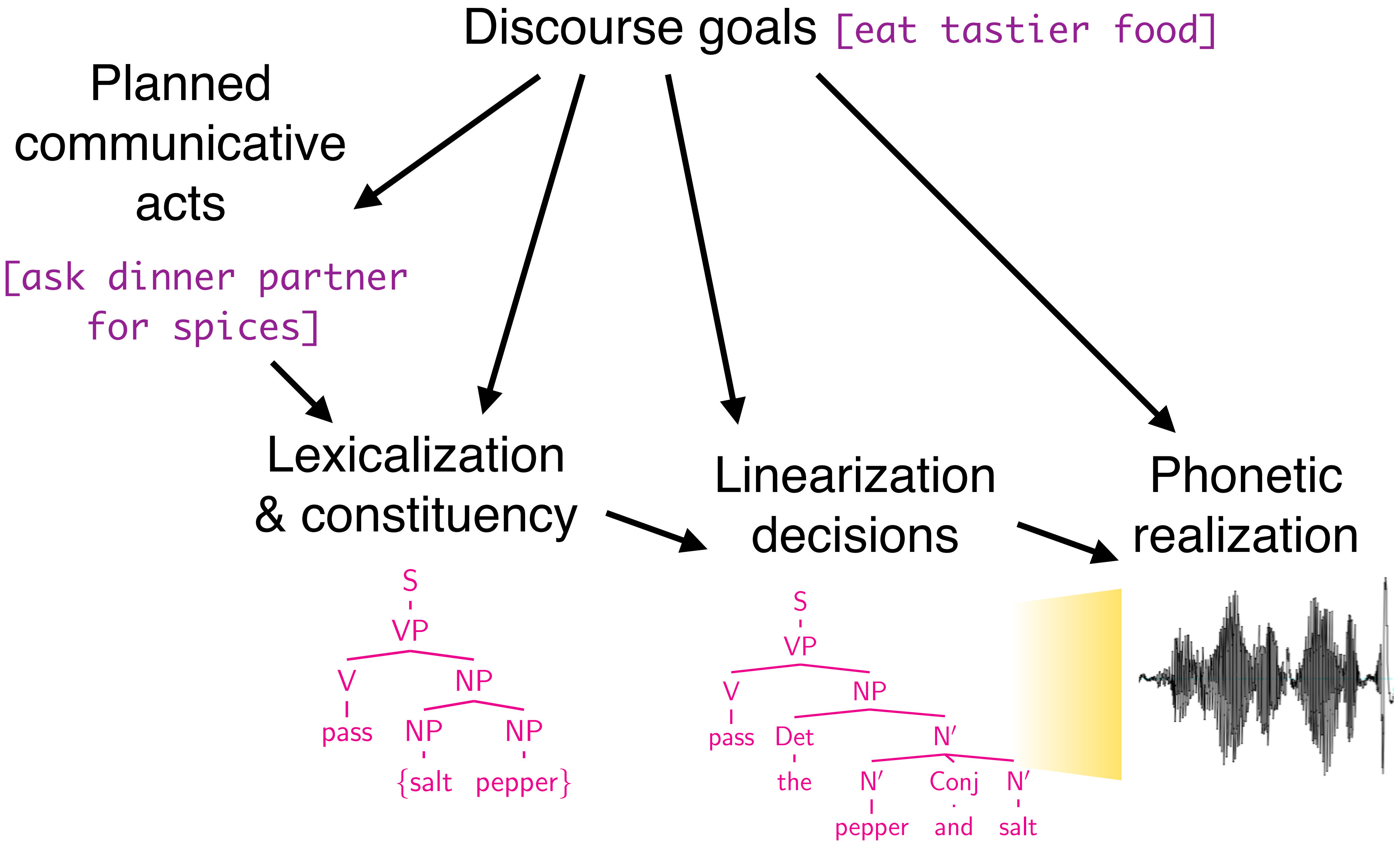

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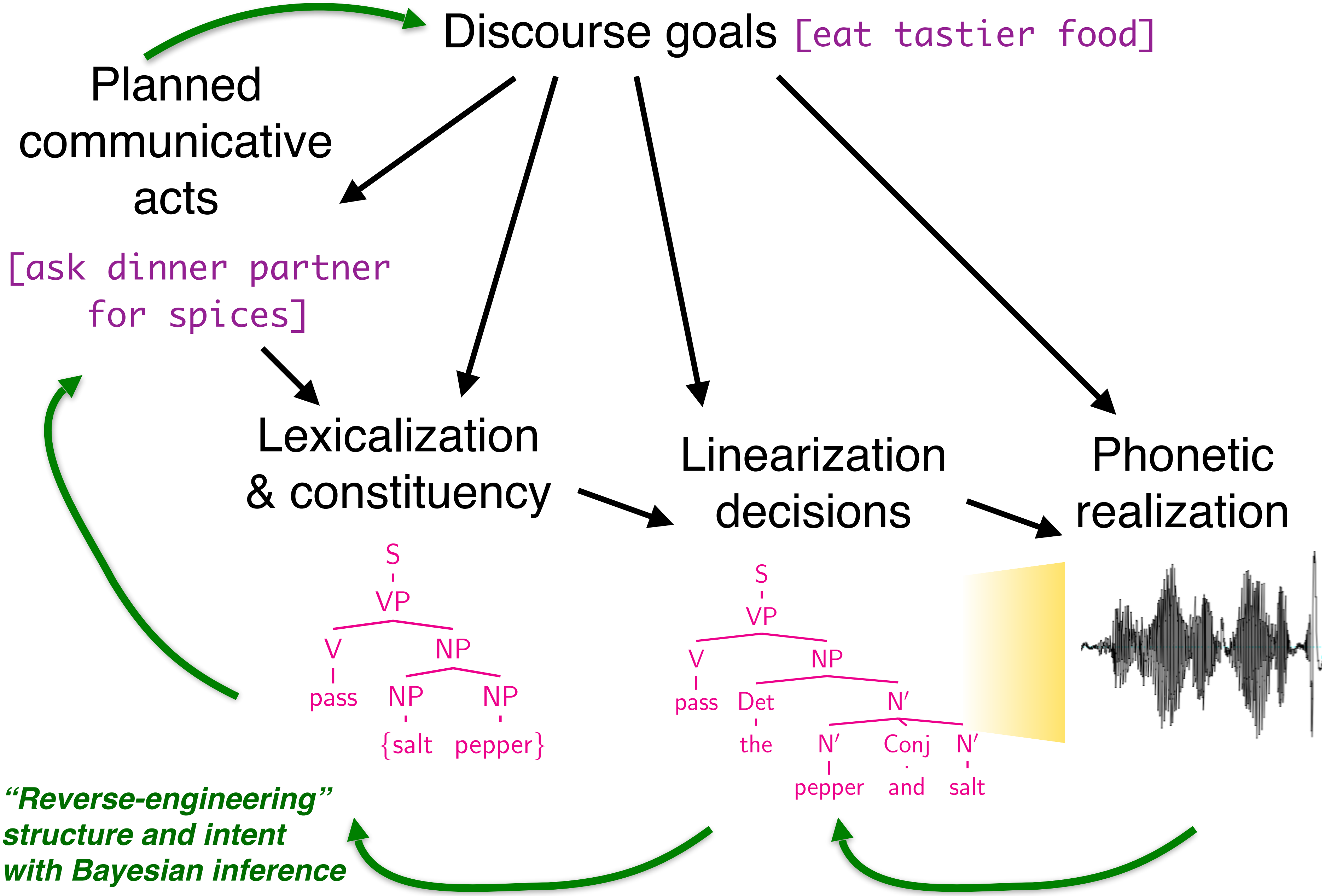

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“Reverse-engineering” structure and intent with Bayesian inference

Surprisal summary: psycholinguistic evidence

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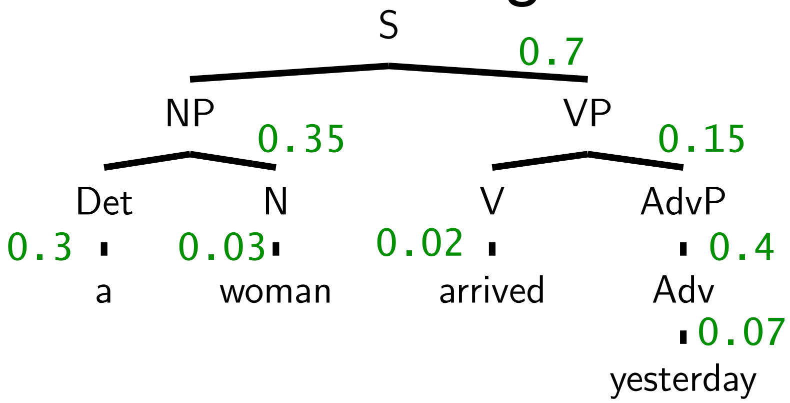

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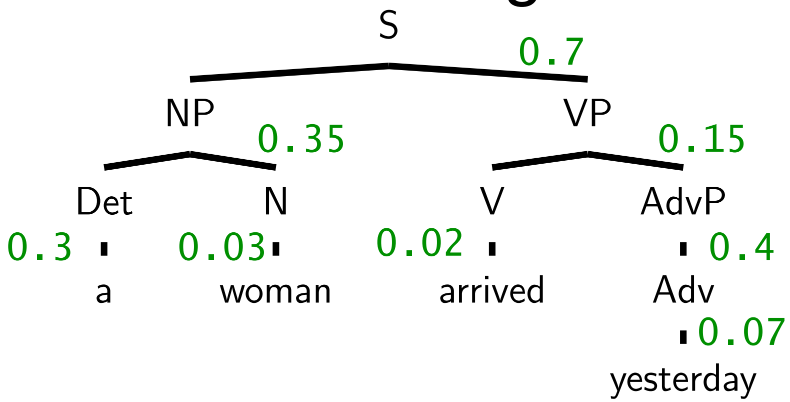

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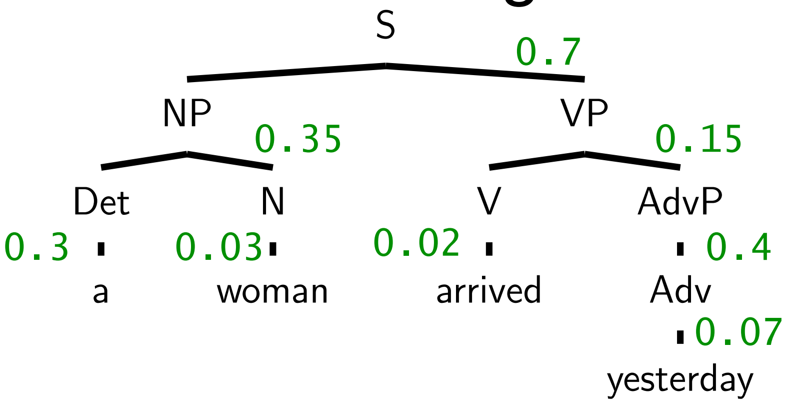

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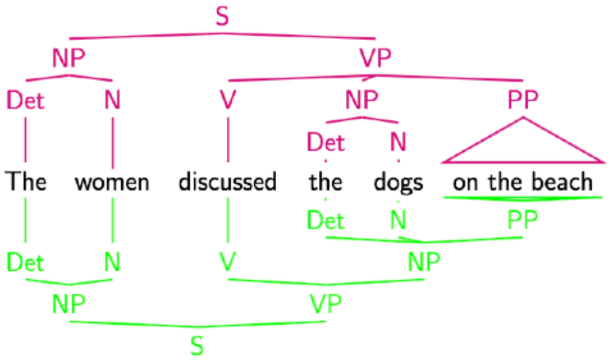

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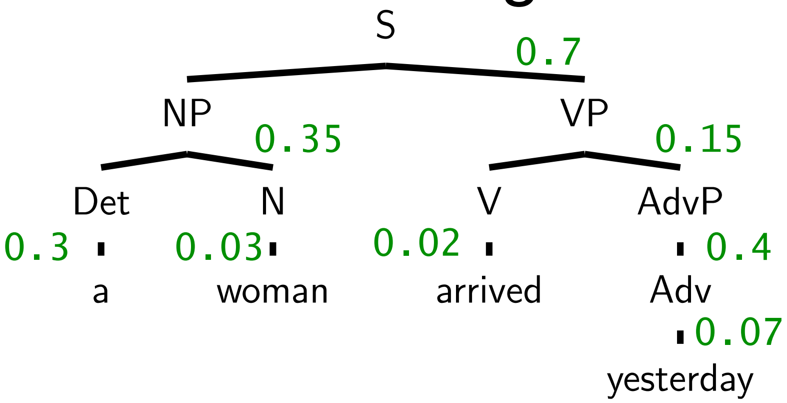

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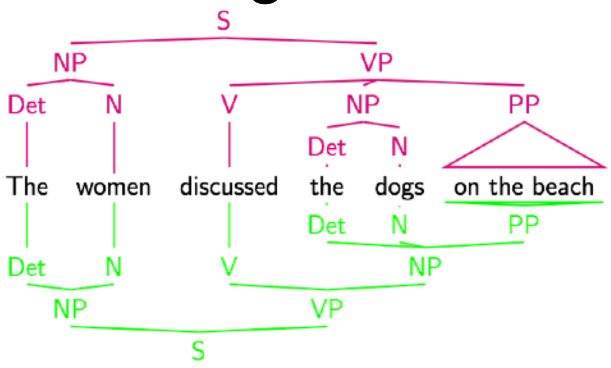

- Garden-pathing

When the dog scratched the vet removed the muzzle.

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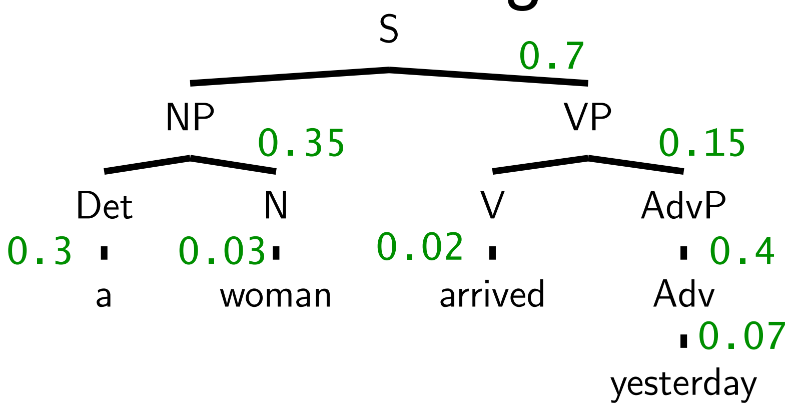

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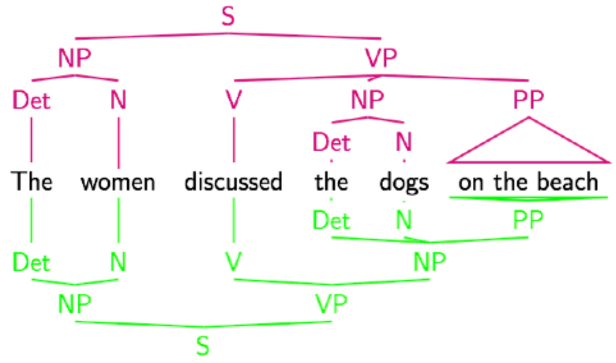


- Garden-pathing

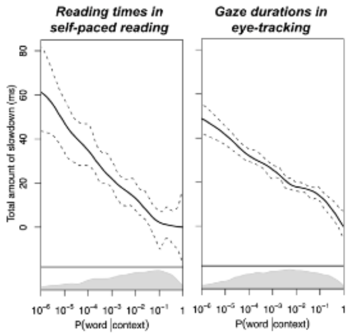
When the dog scratched the vet removed the muzzle.

- Prediction & reading times

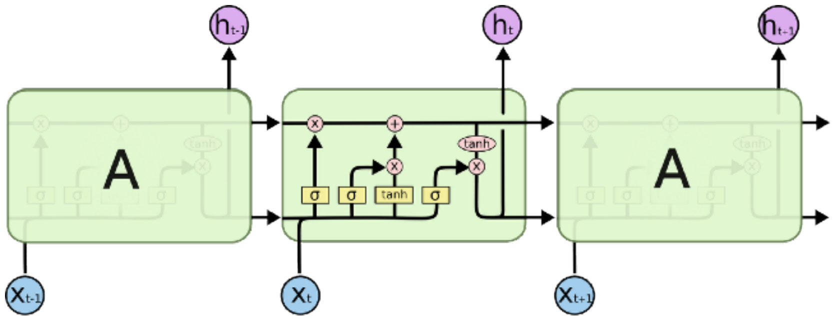
my brother came inside to…

the children went outside to…

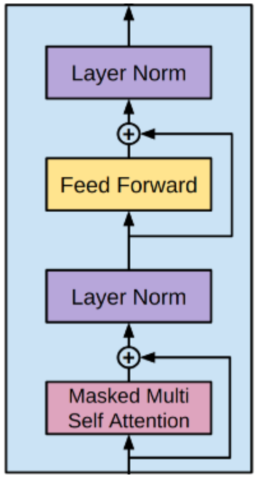
play



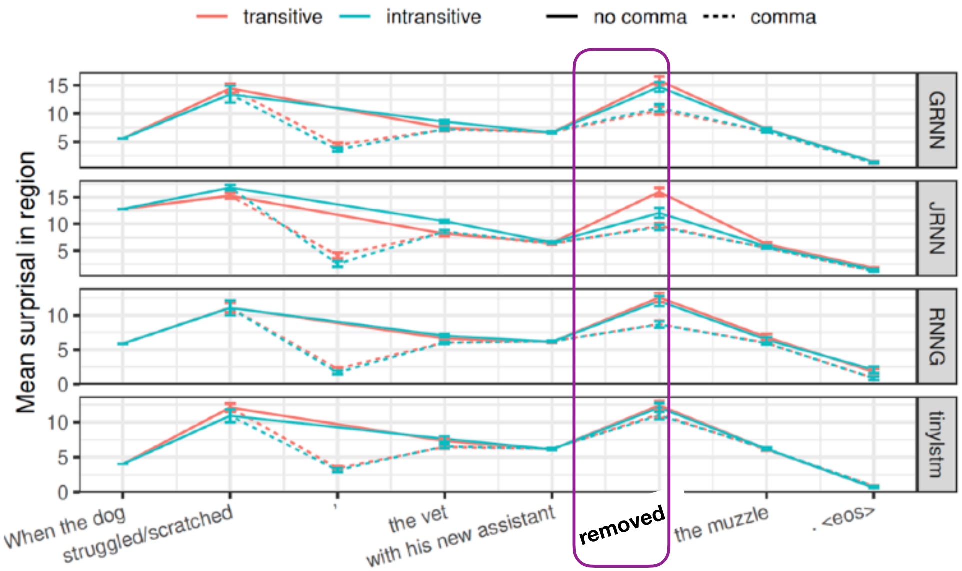
Syntax-like surprisal from deep-learning models



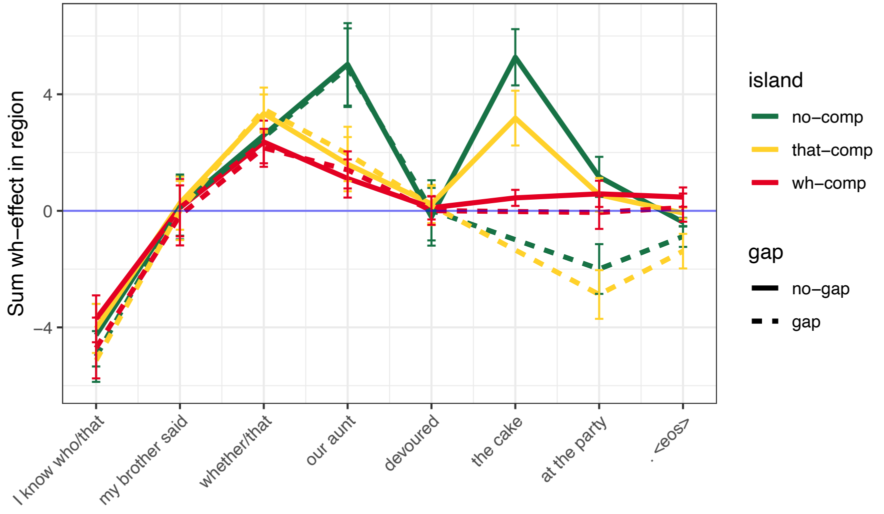
(Elman, 1990; Hochreiter & Schmidhuber, 1997)



(Vaswani et al., 2017; Radford et al., 2018, 2019)



(Futrell et al. 2019, NAACL)



(Wilcox et al., 2018, BlackBox NLP)

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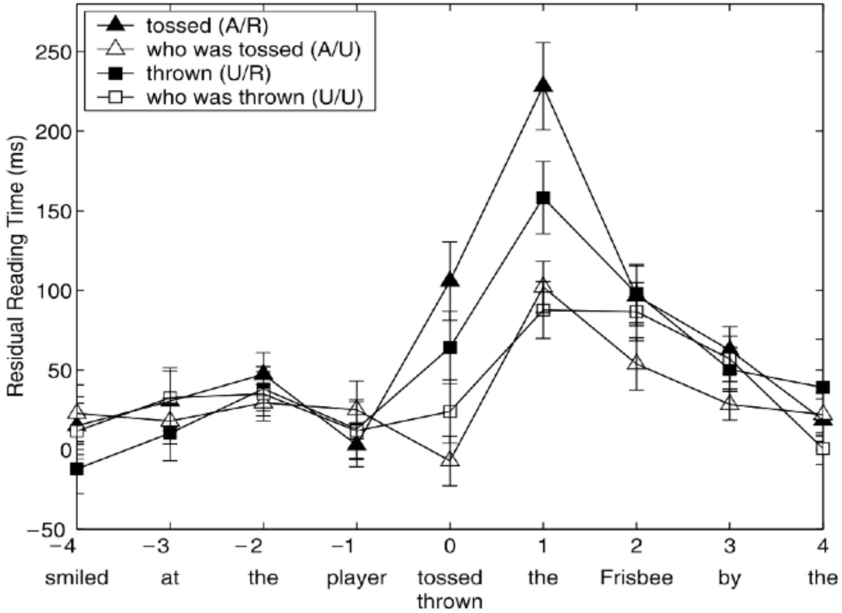

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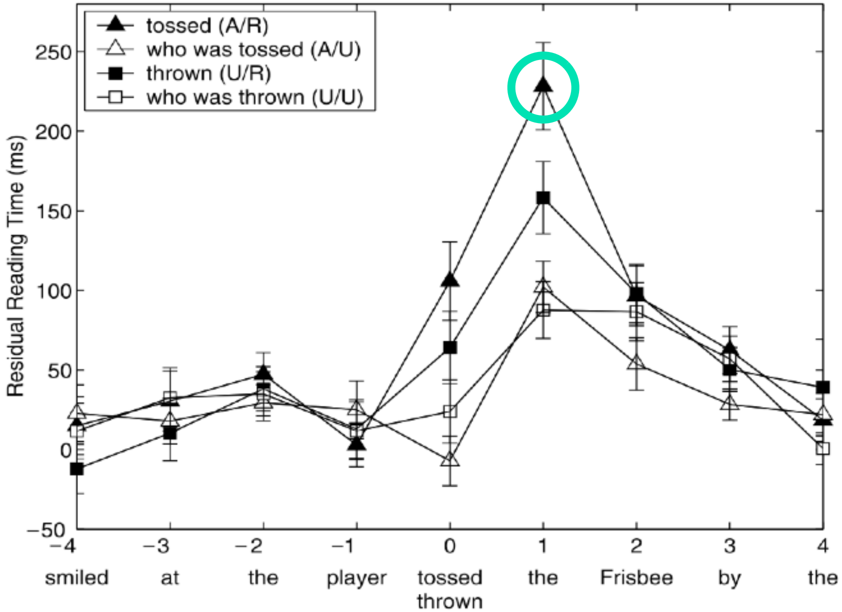

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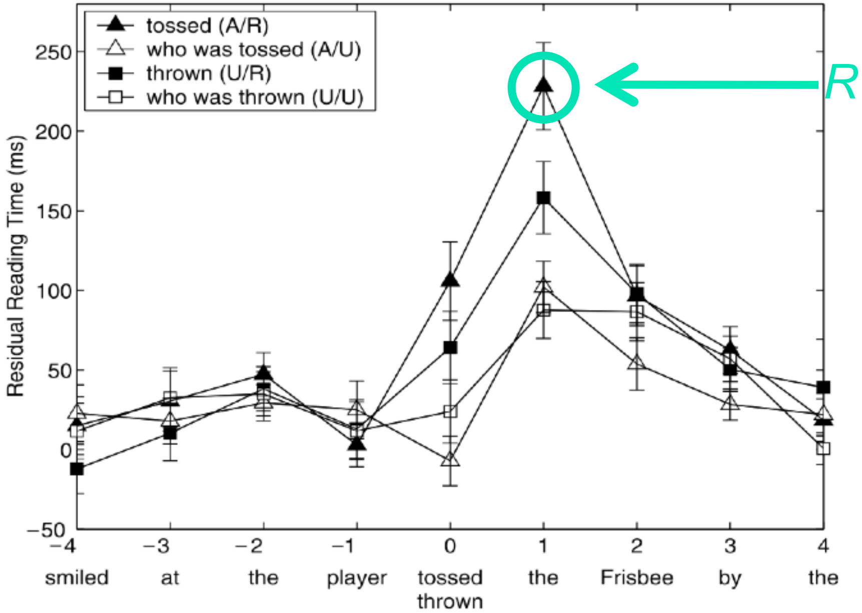

RT spike in (a)

Tabor et al. (2004, JML)

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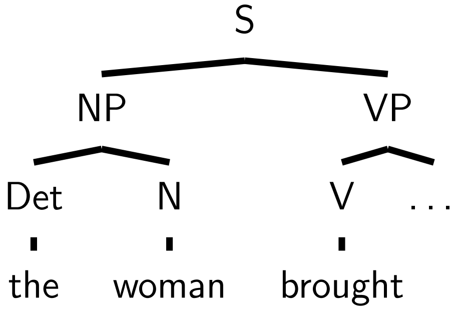

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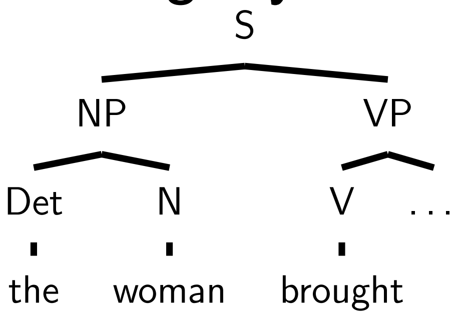

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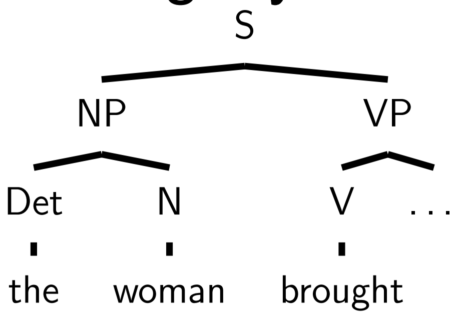

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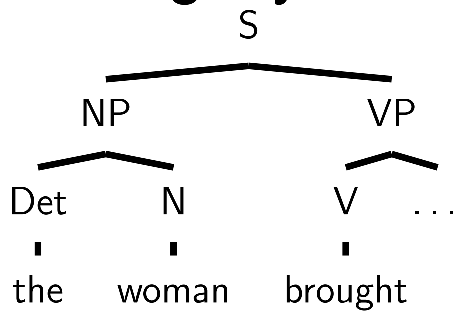

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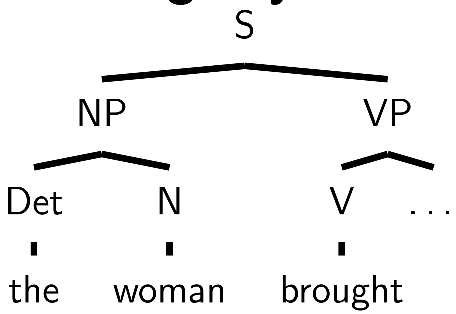

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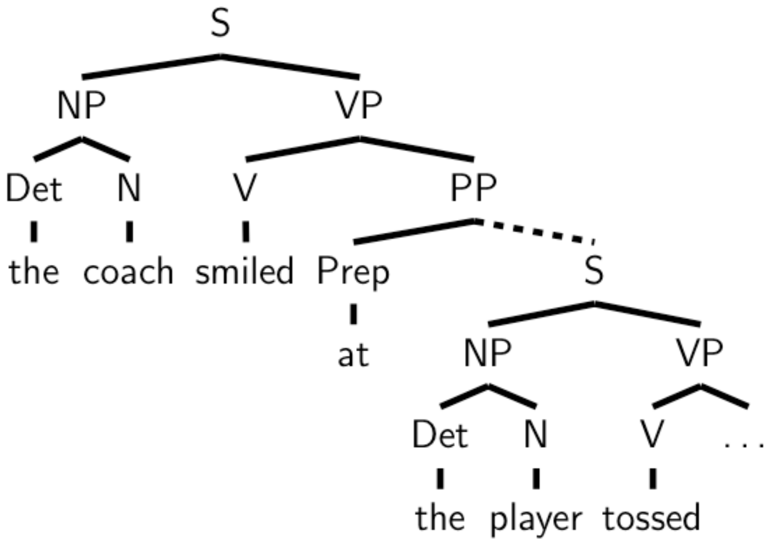

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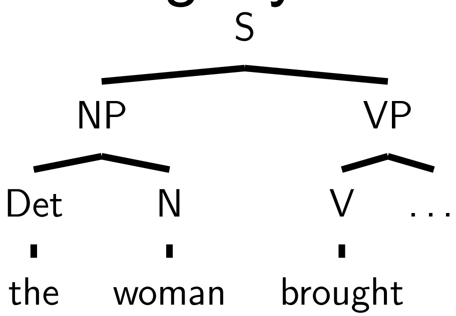

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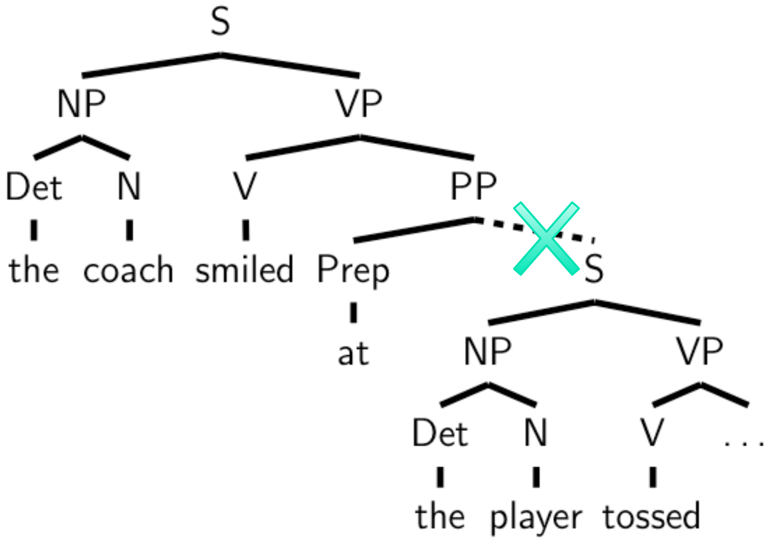

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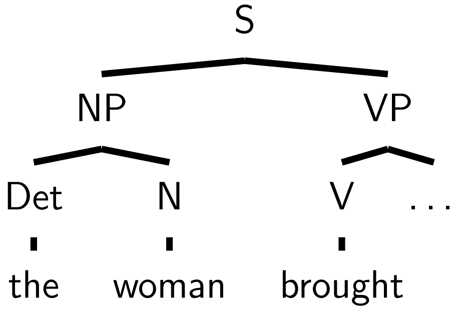

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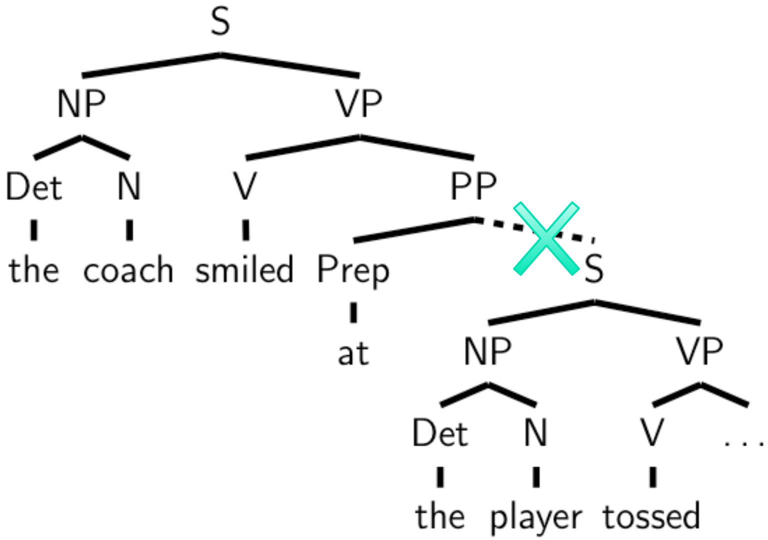

- *A challenge for rational models:* ***failure to condition on relevant context***

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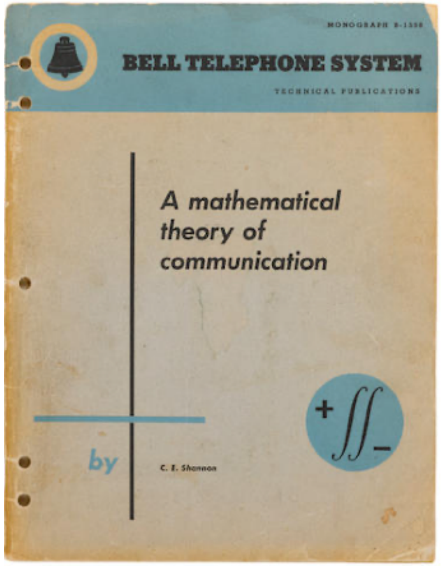
- Intuitively seems patently wrong…
  - We sometimes *misread* things
  - We can also *proofread*
- Leads to two questions:

  1. What might a model of sentence comprehension under uncertain input look like?
  2. What interesting consequences might such a model have?

Noisy-channel theory of language processing

(Shannon, 1948)



MONOGRAPH B-1598

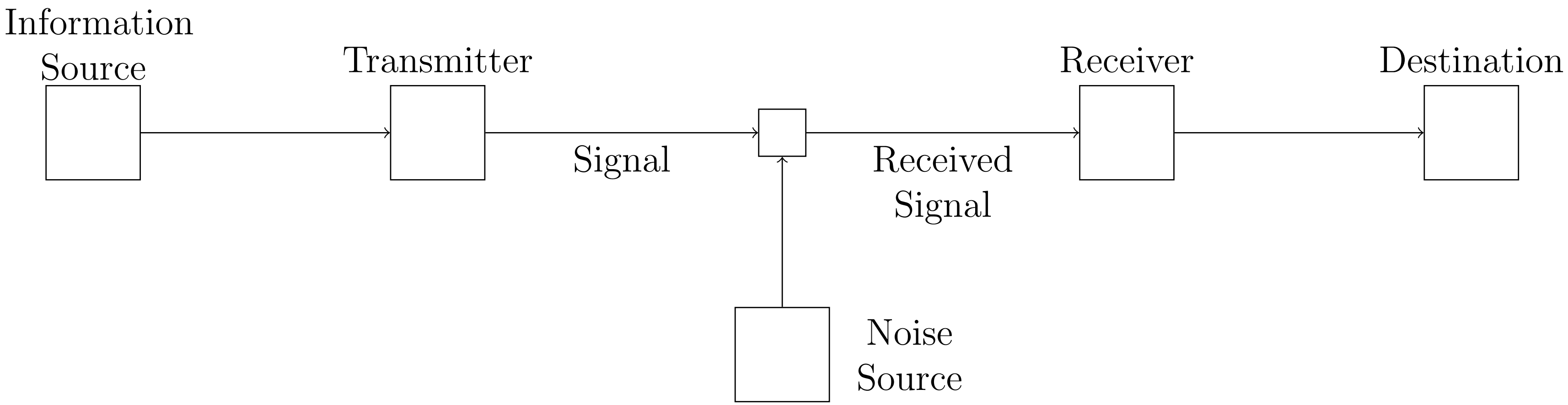
BELL TELEPHONE SYSTEM

TECHNICAL PUBLICATIONS

A mathematical theory of communication

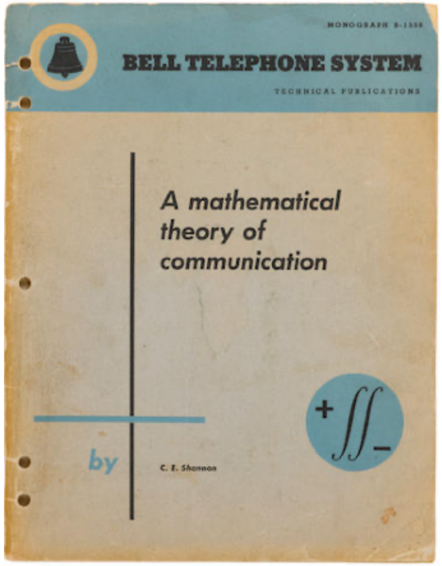
by

C. E. Shannon



Noisy-channel theory of language processing

(Shannon, 1948)



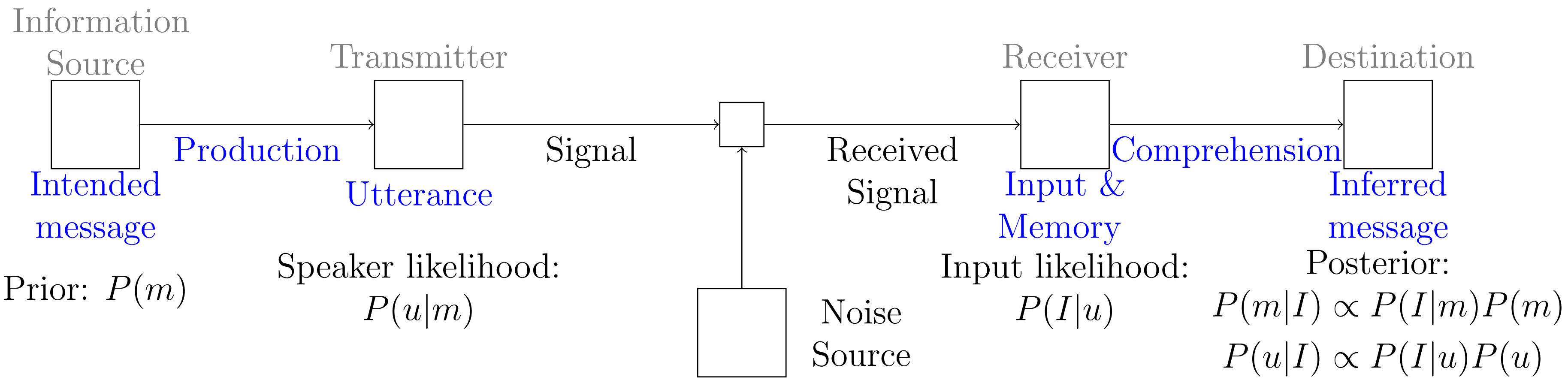
MONOGRAPH B-1598

BELL TELEPHONE SYSTEM

TECHNICAL PUBLICATIONS

A mathematical theory of communication

by C. E. Shannon



Prior: $P(m)$

Speaker likelihood: $P(u|m)$

Input likelihood: $P(I|u)$

Posterior:
$$P(m|I) \propto P(I|m)P(m)$$
$$P(u|I) \propto P(I|u)P(u)$$

(Levy, 2008; Gibson et al., 2013)

Noisy-channel sentence processing

$$P_G(T|\mathbf{w}) \propto P(\mathbf{w}|T)P(T) = P(T,\mathbf{w})$$

Levy (2008, EMNLP)

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$$= P_C(\mathbf{w}) \underbrace{\int_I \frac{P_C(I|\mathbf{w})P_T(I|\mathbf{w}^*)}{P_C(I)}\,dI}_{\propto Q(\mathbf{w},\mathbf{w}^*)}$$

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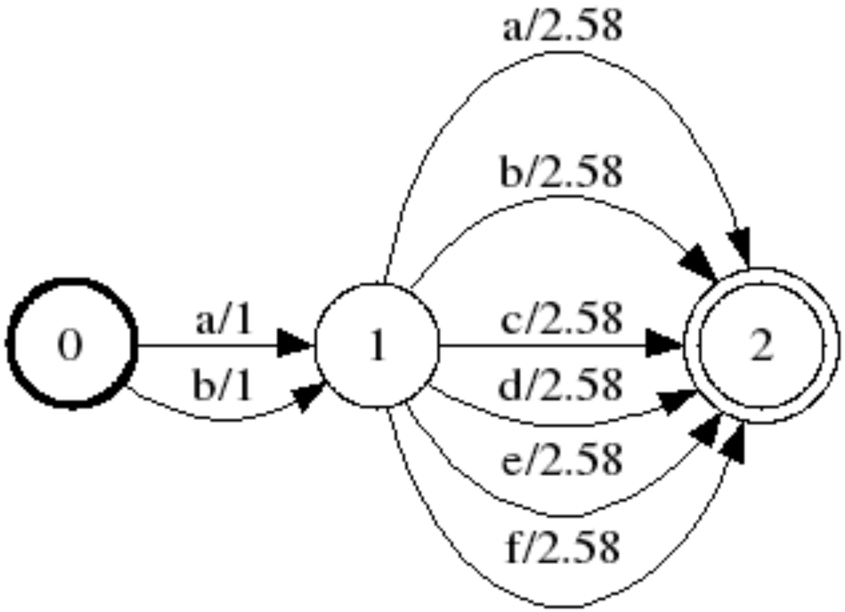

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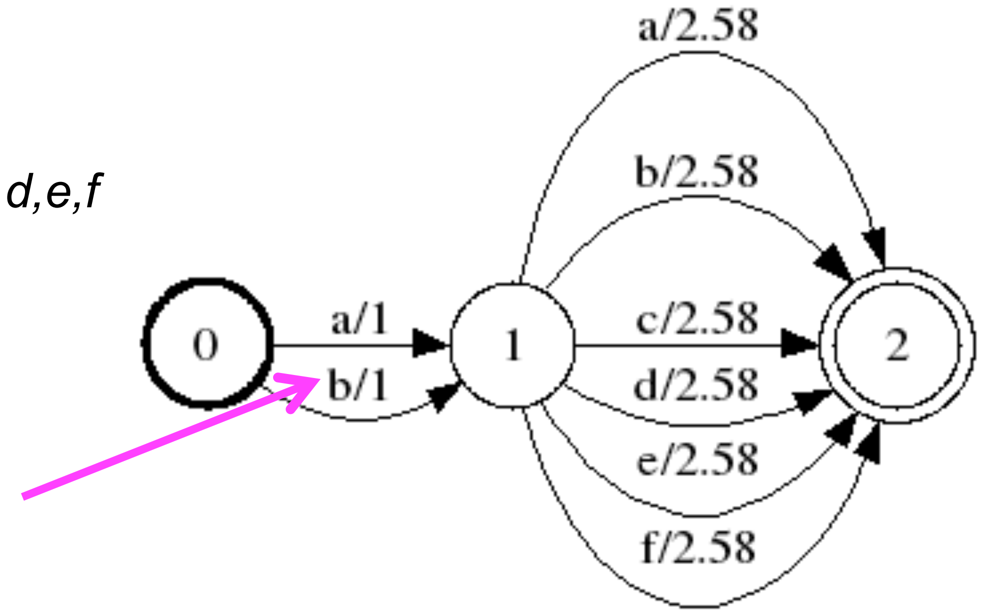

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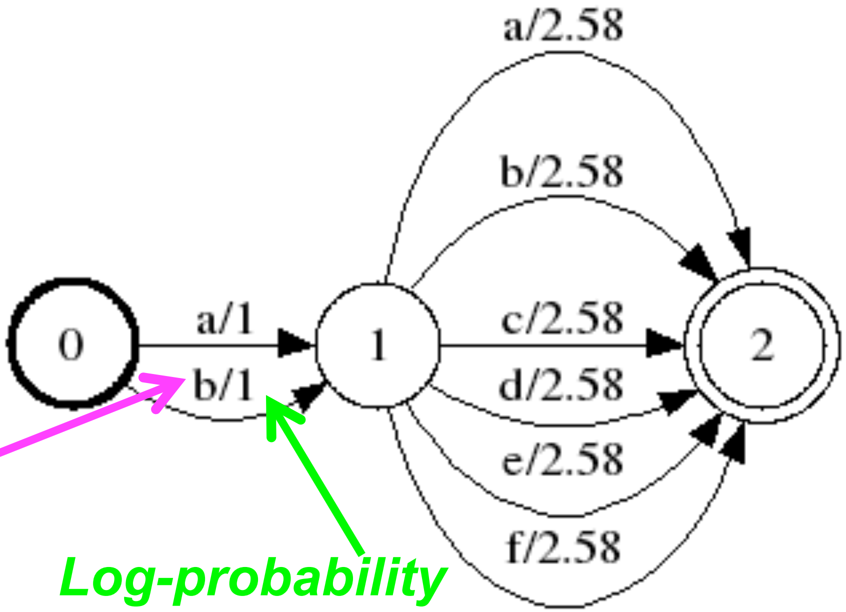

Input symbol

Log-probability (surprisal)

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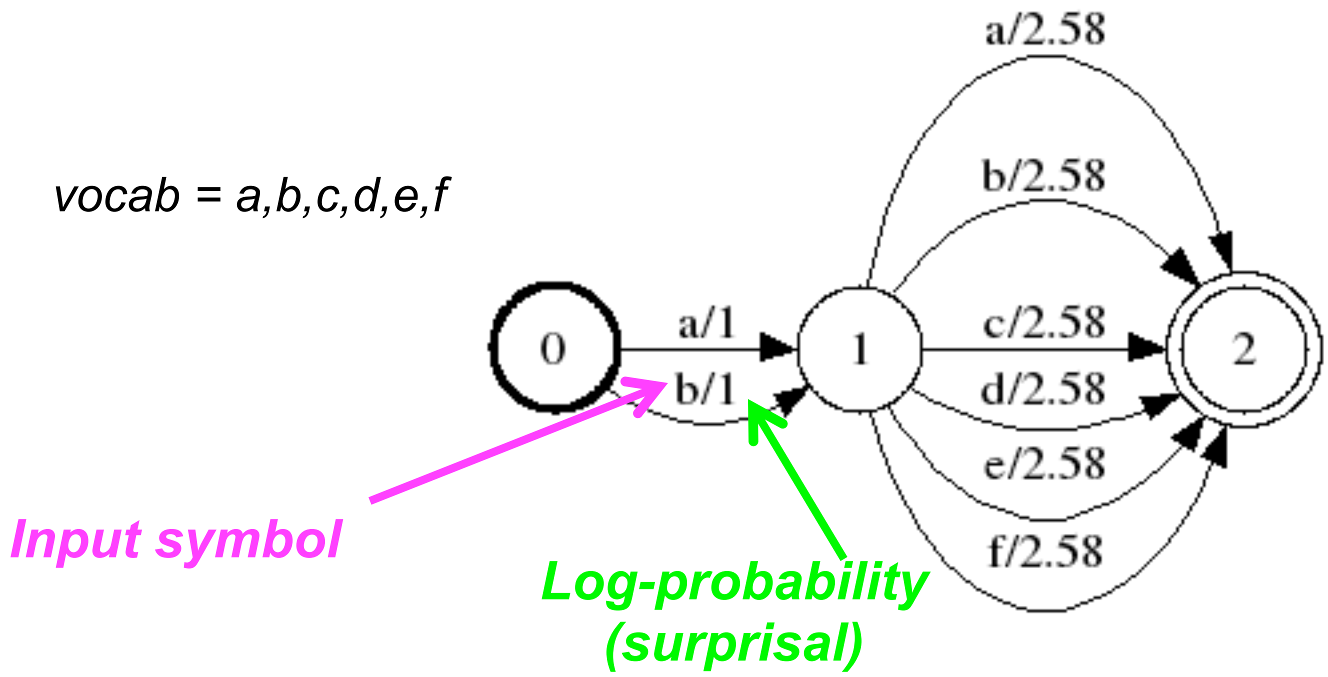
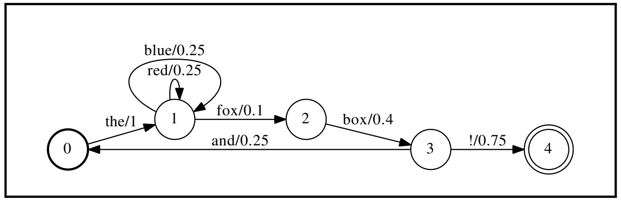


- "Word 1 is a or b, and I have no info about Word 2"

Weighted finite-state automata



A WEIGHTED FINITE-STATE AUTOMATON (WFSA) consists of a tuple (Q, V, S, R) such that:

- Q is a finite set of STATES $q_0 q_1 \ldots q_N$, with q_0 the designated START STATE;
- Σ is a finite set of terminal symbols;
- $F \subseteq Q$ is the set of FINAL STATES;
- Δ is a finite set of TRANSITIONS each of the form $q \overset{i}{\rightsquigarrow} q'$, meaning that "if you are in state q and see symbol i you can consume it and move to state q'";
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- $w_{1\ldots N} \in \Sigma^N$ is ACCEPTED or RECOGNIZED by an automaton iff there is a PATH of transitions $\underset{1\ldots N}{\rightsquigarrow}$ to a final state $q^* \in F$ such that

$$q_0 \underset{1}{\overset{w_1}{\rightsquigarrow}} \underset{2}{\overset{w_2}{\rightsquigarrow}} \ldots \underset{N-1}{\overset{w_{N-1}}{\rightsquigarrow}} \underset{N}{\overset{w_N}{\rightsquigarrow}} q^*$$

- The WEIGHT of such a path $\underset{1\ldots N}{\rightsquigarrow}$ is the product of the weights of each of the transitions, together with the weight of the final state:

$$P(q_0 \underset{1}{\overset{w_1}{\rightsquigarrow}} \underset{2}{\overset{w_2}{\rightsquigarrow}} \ldots \underset{N-1}{\overset{w_{N-1}}{\rightsquigarrow}} \underset{N}{\overset{w_N}{\rightsquigarrow}} q^*) = \rho(q^*) \prod_{i=1}^{N} \lambda(\underset{i}{\rightsquigarrow}) \tag{1}$$

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- A generative probabilistic grammar determines beliefs about *which strings are likely to be seen*
    - Probabilistic Context-Free Grammars (PCFGs; Booth, 1969)
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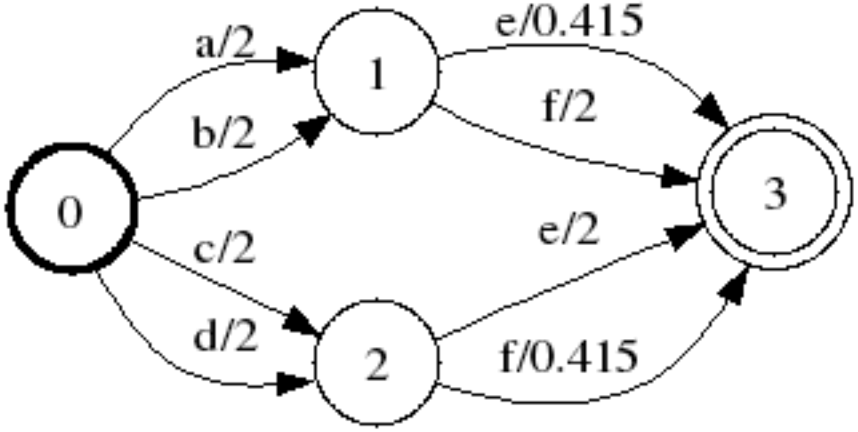

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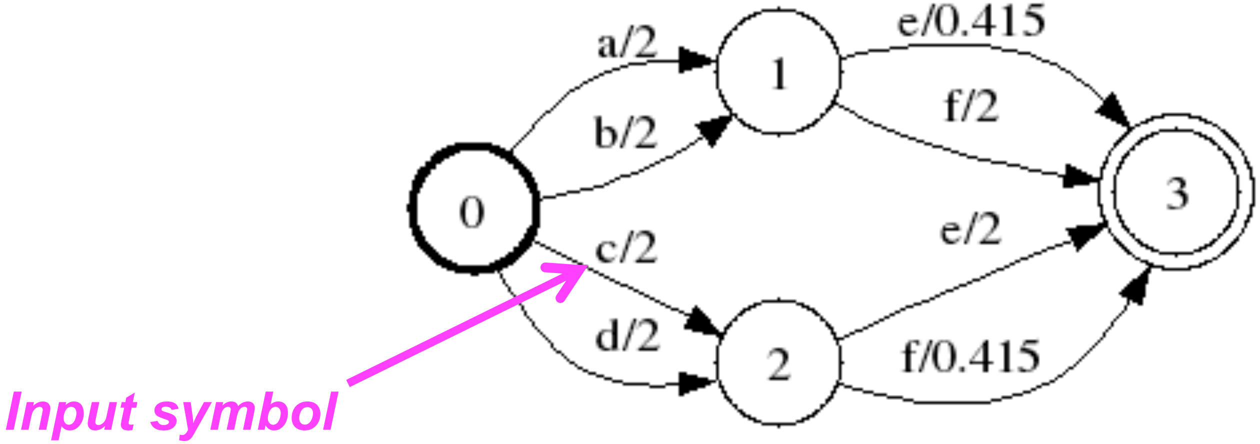

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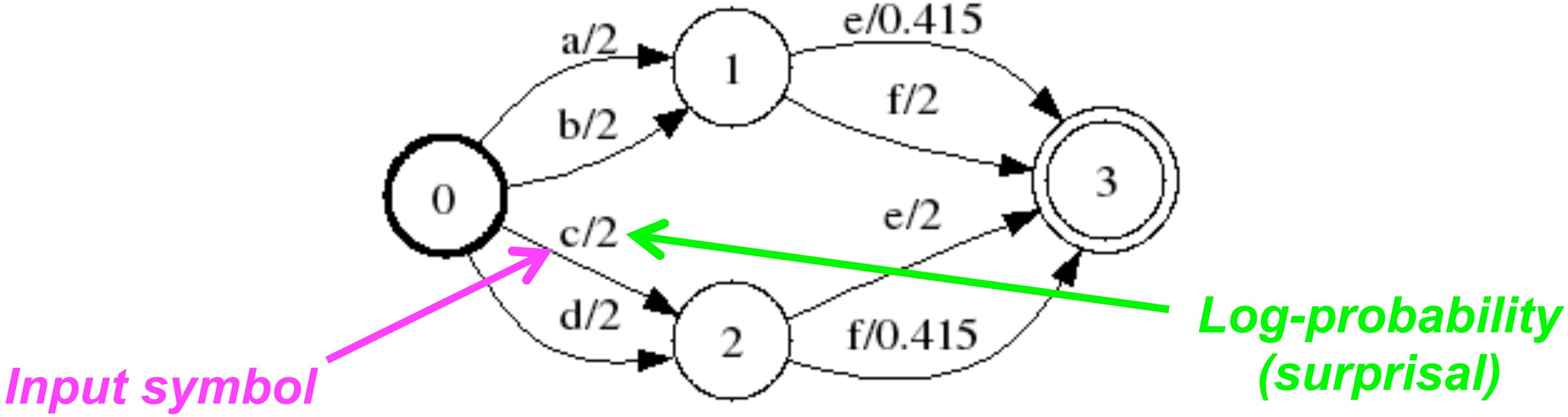

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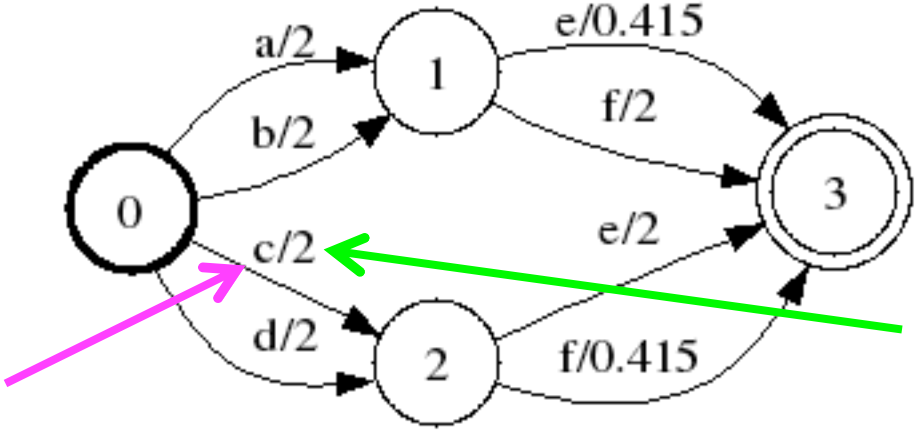

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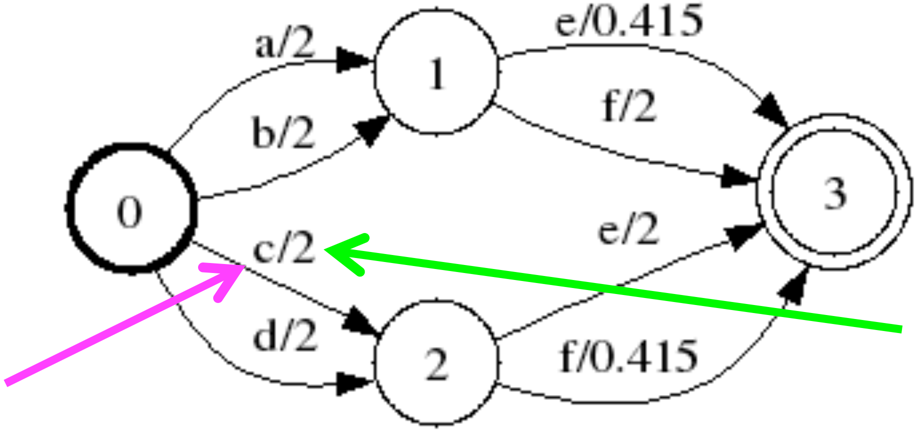

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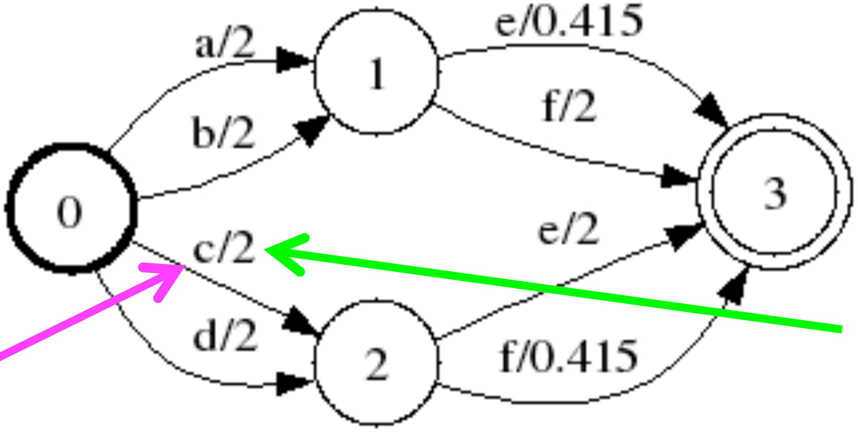

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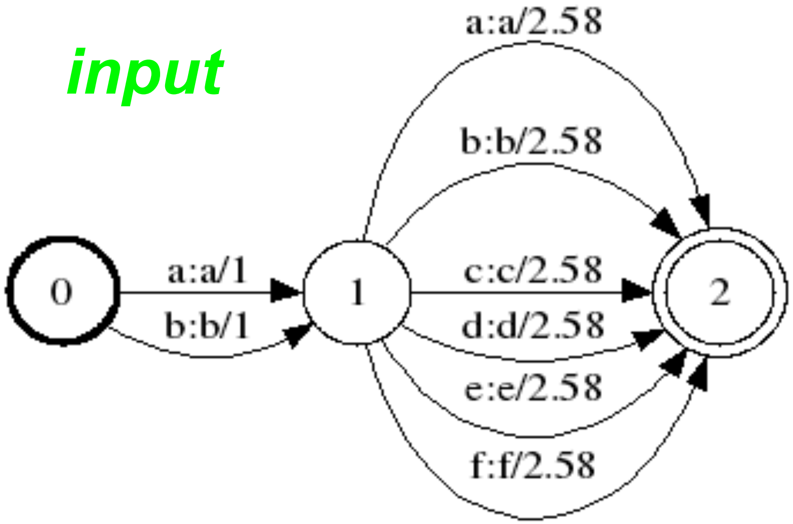

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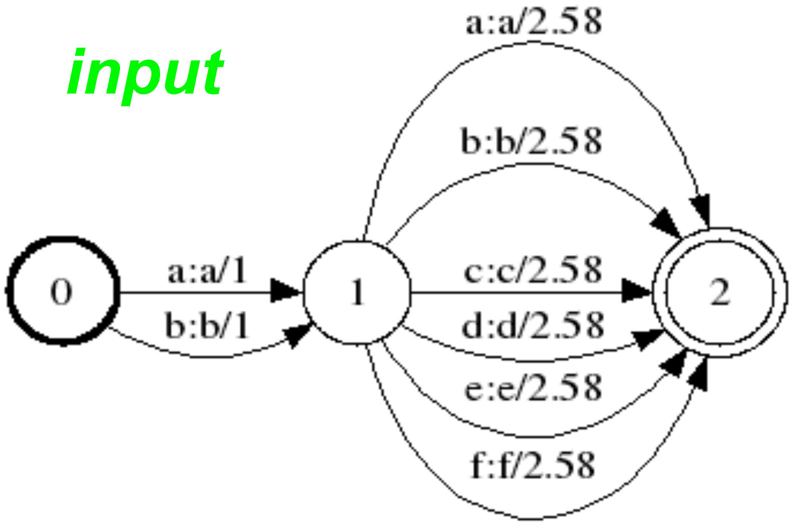
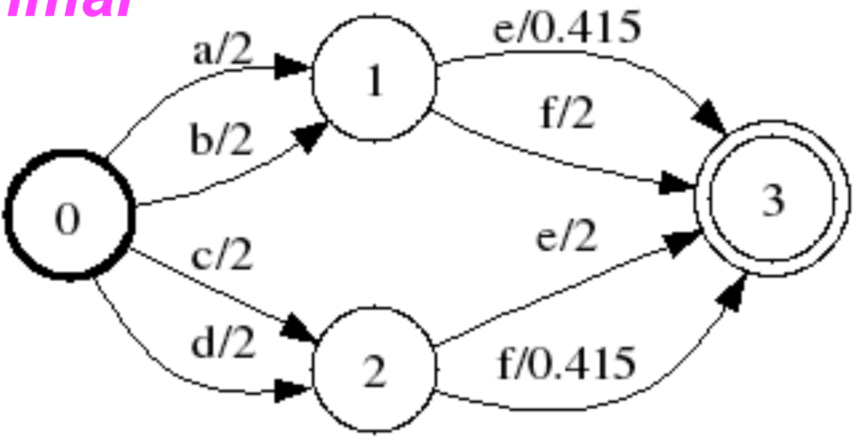


+

grammar



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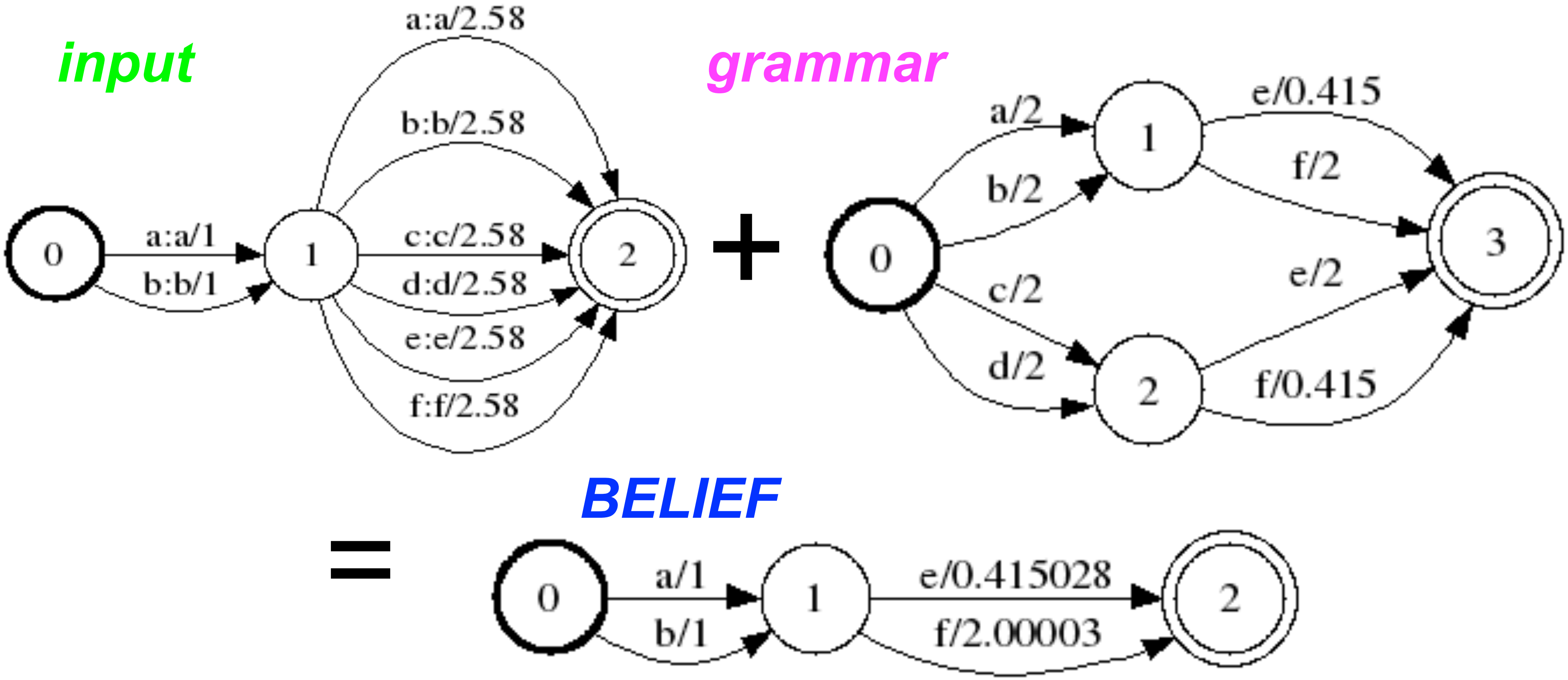

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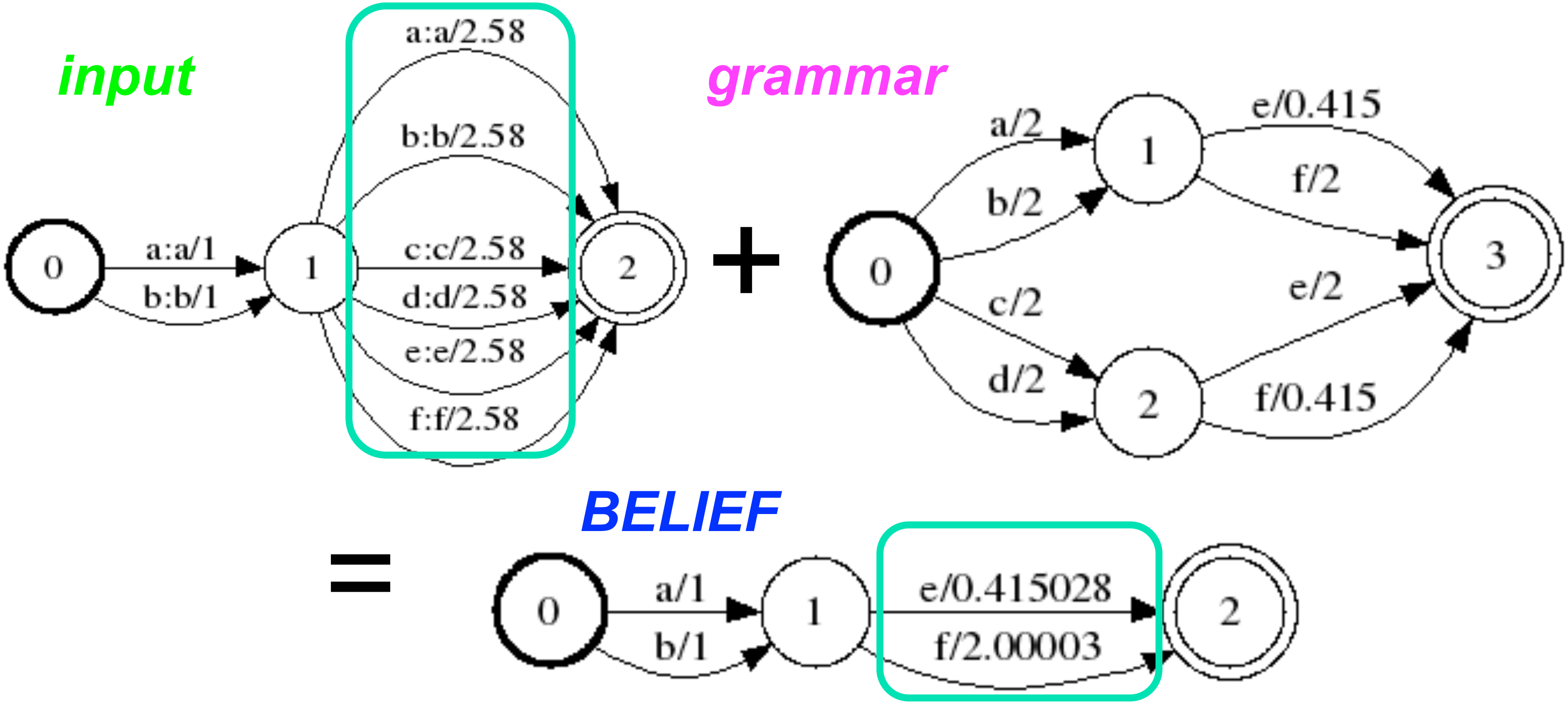

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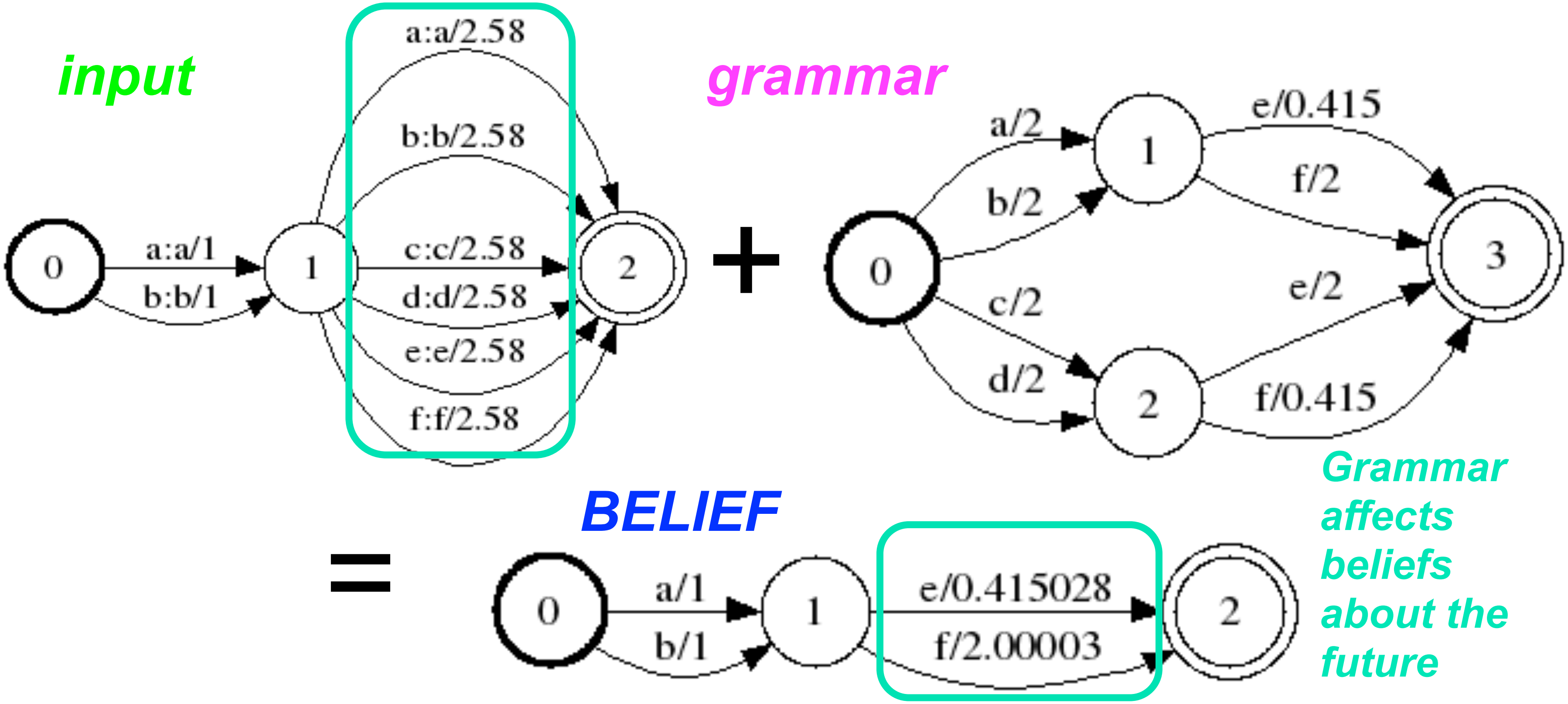
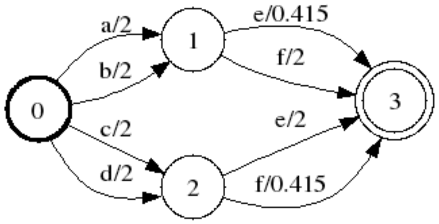


Grammar affects beliefs about the future

Revising beliefs about the past

- When we’re uncertain about the future, grammar + partial input can affect beliefs about what will happen
- With uncertainty of the past, grammar + future input can affect beliefs about *what has already happened*



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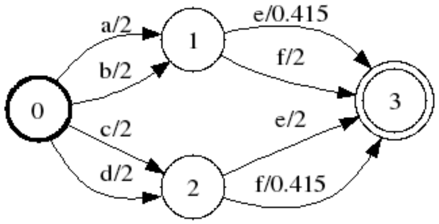

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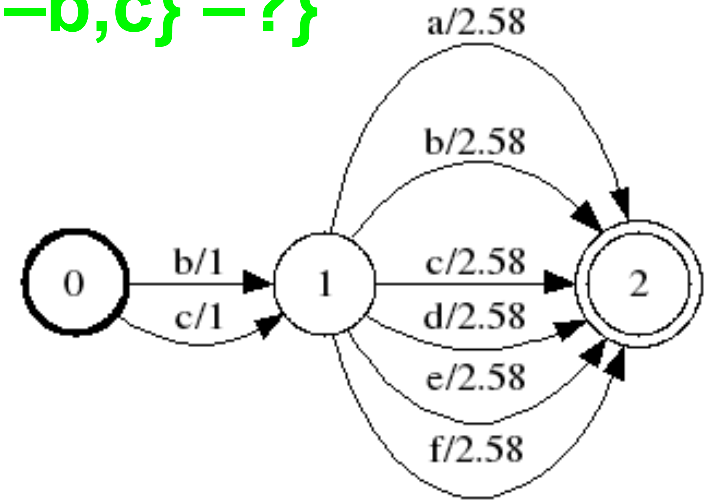

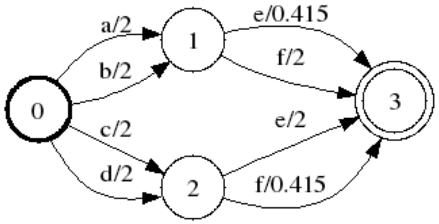

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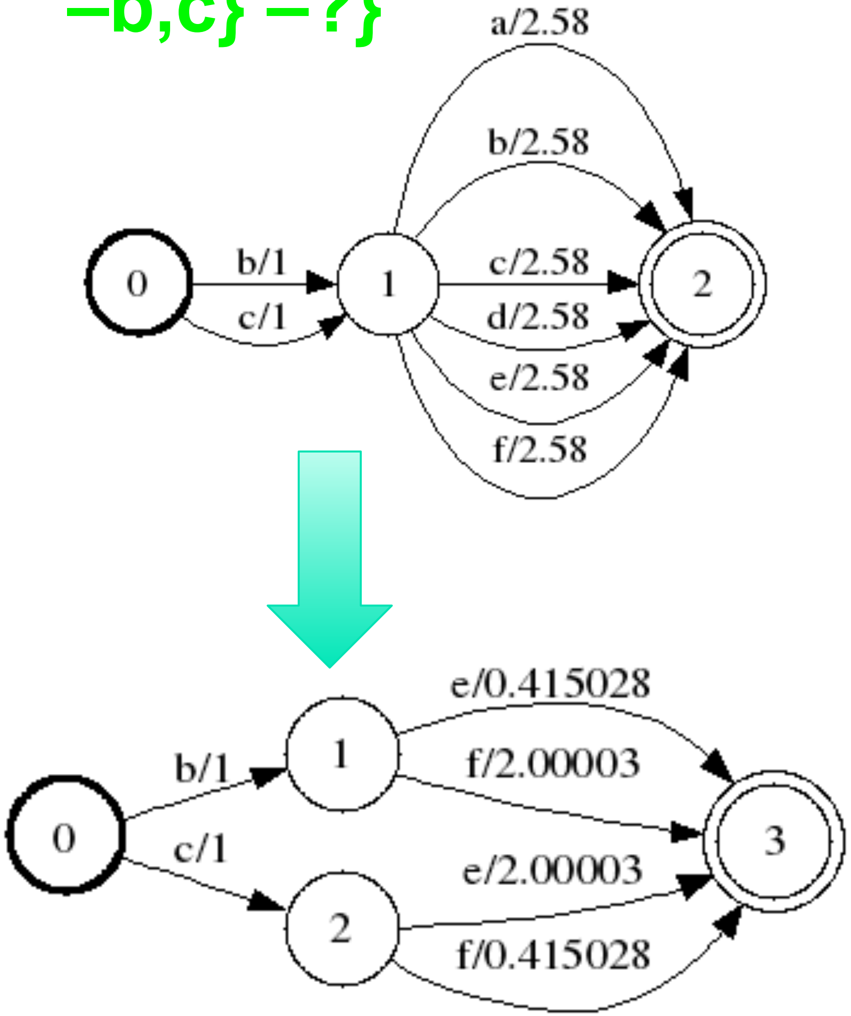

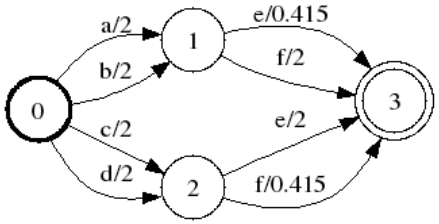

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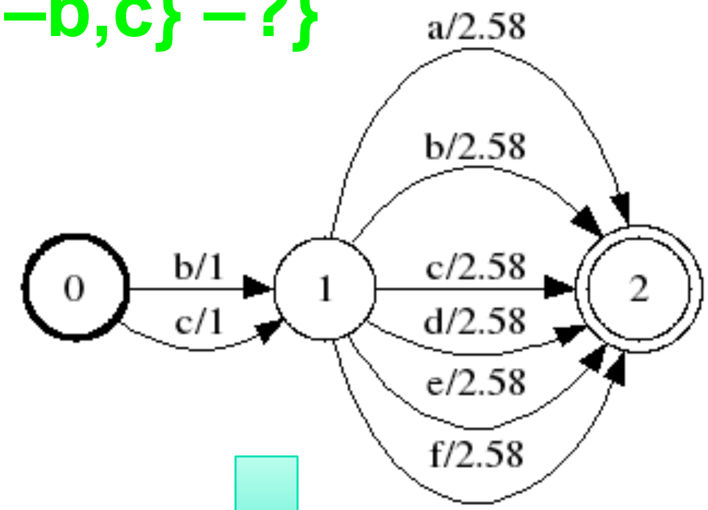

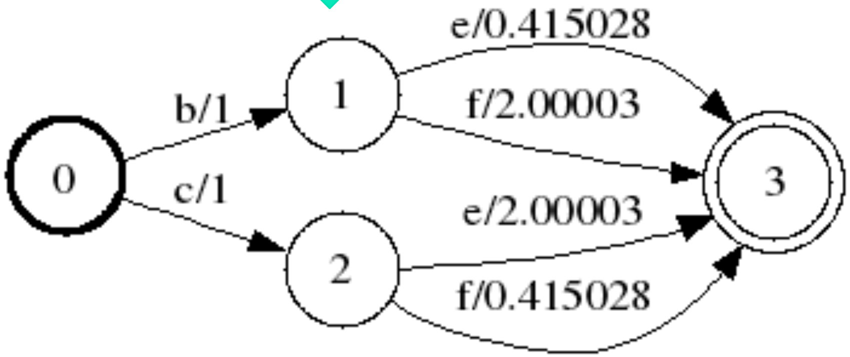

words 1 + 2

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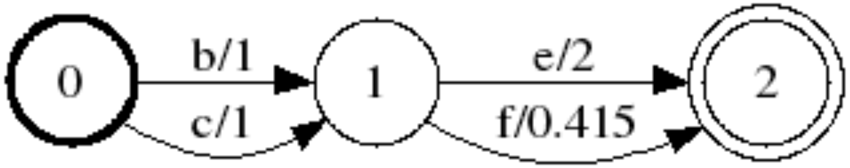

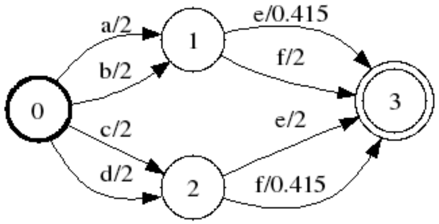

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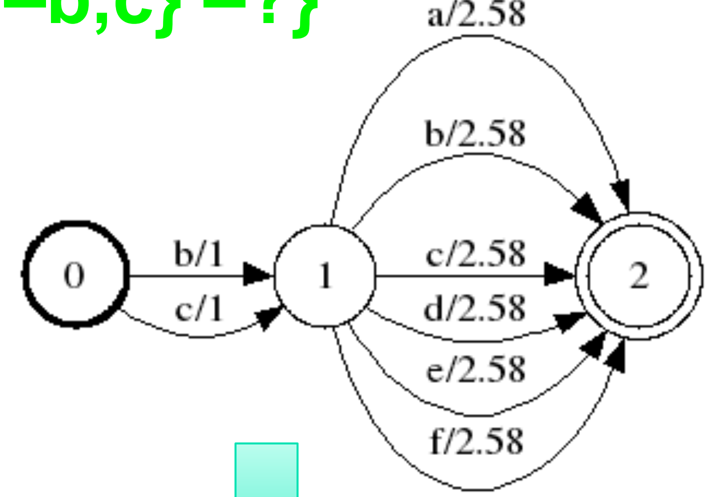

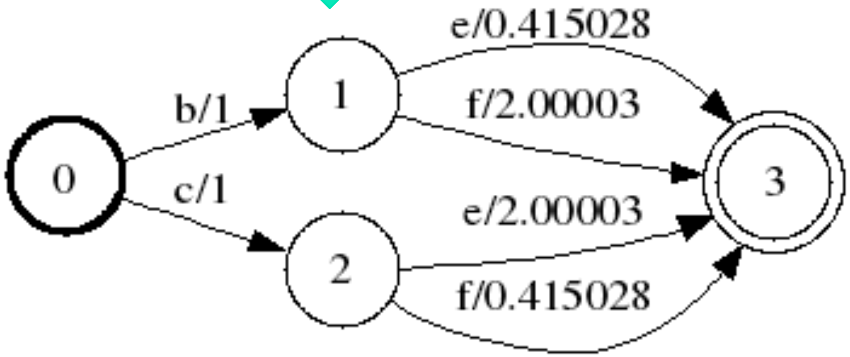

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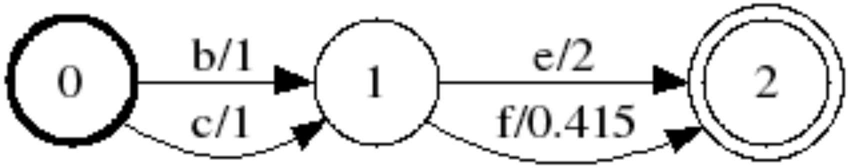

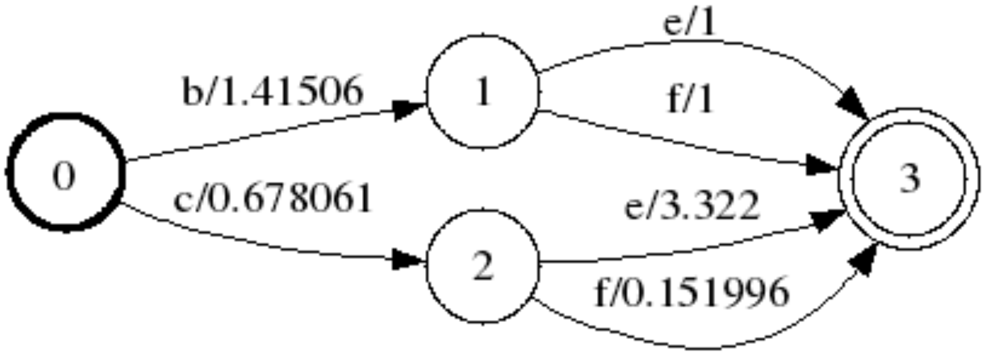

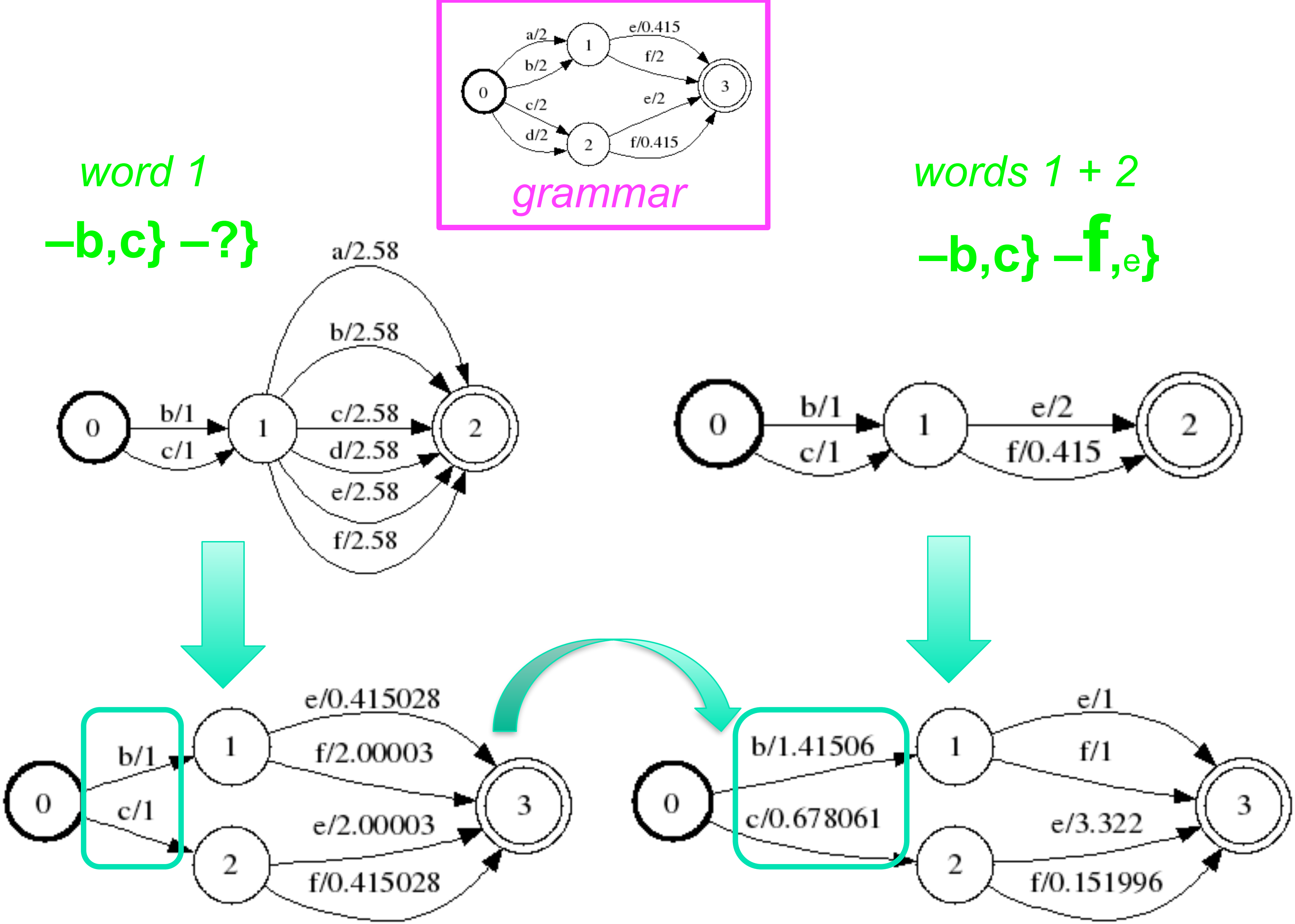

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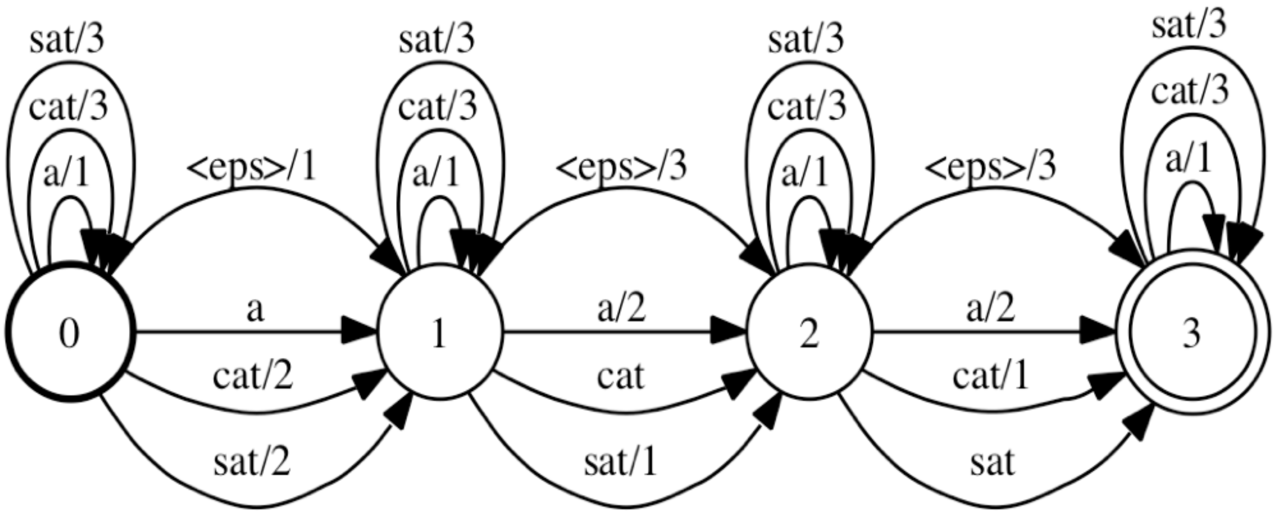

Result of K_{LD} applied to **w*** = ***a cat sat***

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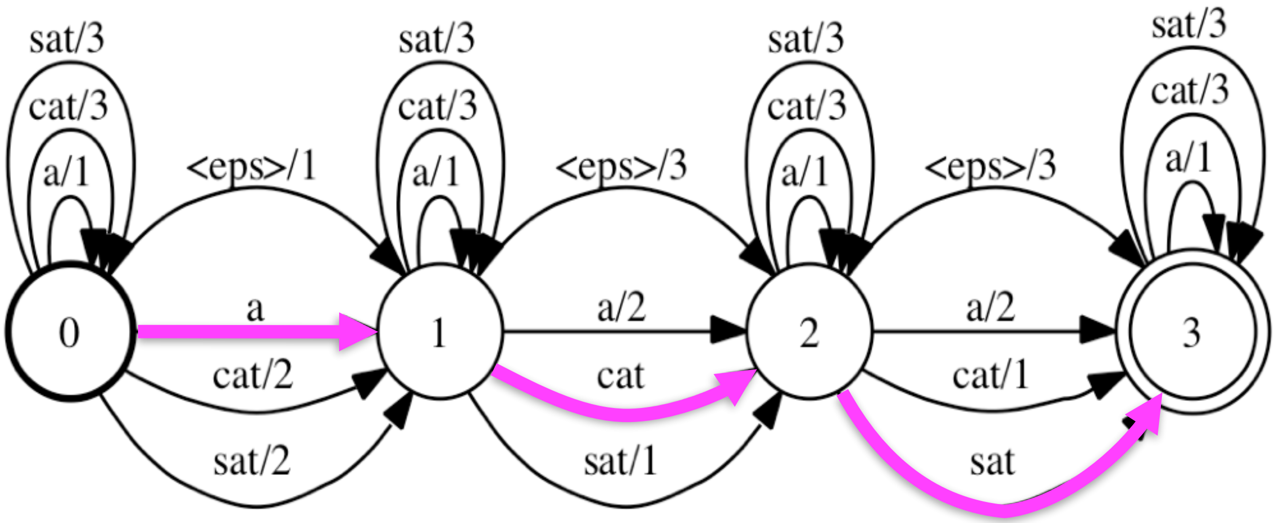

Cost(*a cat sat*)=0

Result of K_{LD} applied to **w*** = ***a cat sat***

The noisy-channel model (**FINAL**)

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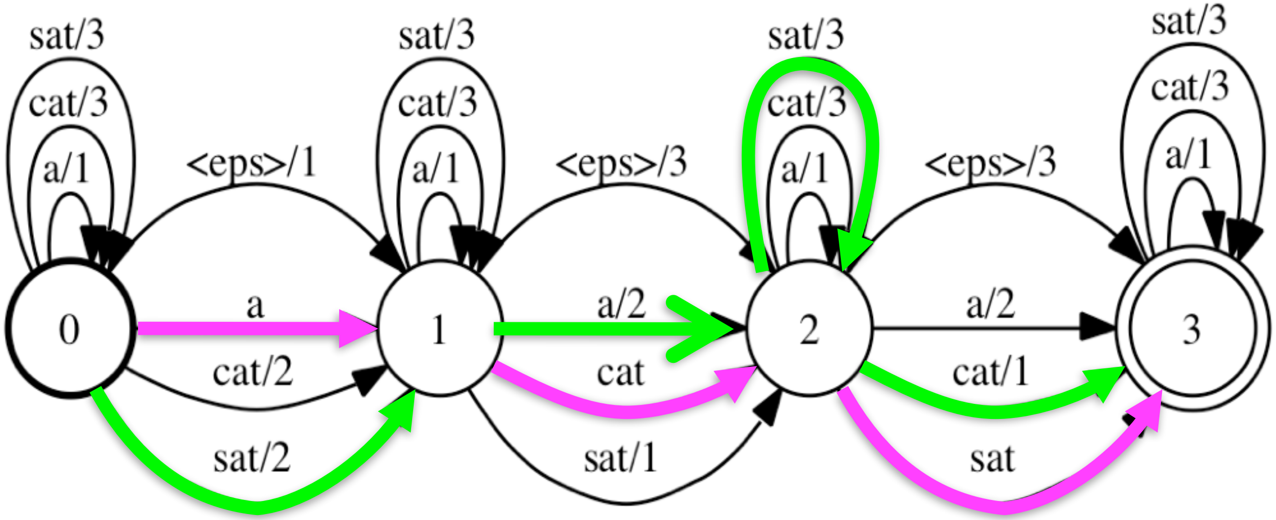
Cost(*a cat sat*)=0

Cost(*sat a sat cat*)=8



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Rational analysis

- Background assumption: cognitive agent is optimized via evolution and learning to solve everyday tasks effectively

1. Specify precisely the goals of the cognitive system
2. Formalize model of the environment adapted to
3. Make minimal assumptions re: computational limitations
4. Derive predicted optimal behavior given 1—3
5. Compare predictions with empirical data
6. If necessary, iterate 1—5

(Anderson, 1990, 1991)

Incremental inference under uncertain input

The coach smiled at the player ***tossed*** *the frisbee*

Incremental inference under uncertain input

- Near-neighbors make the “incorrect” analysis “correct”:

The coach smiled at the player ***tossed*** *the frisbee*

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(and?)

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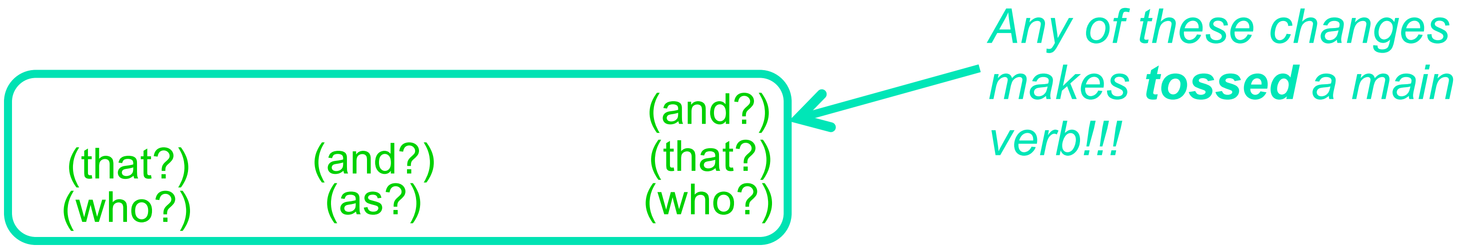

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*Any of these changes makes **tossed** a main verb!!!*

*The coach smiled at the player **tossed** the frisbee*

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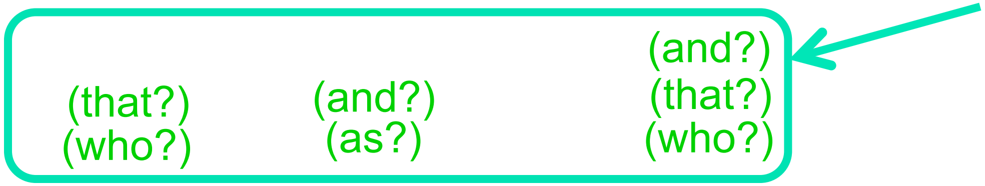

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*Any of these changes makes **tossed** a main verb!!!*

*The coach smiled at the player **tossed** the frisbee*

- Hypothesis: the boggle at “tossed” involves *what the comprehender wonders whether she might have seen*

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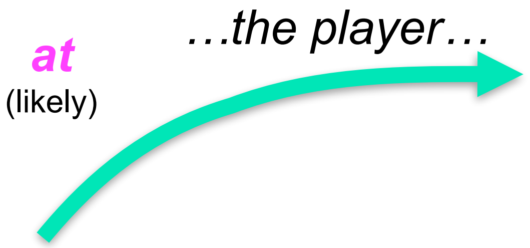

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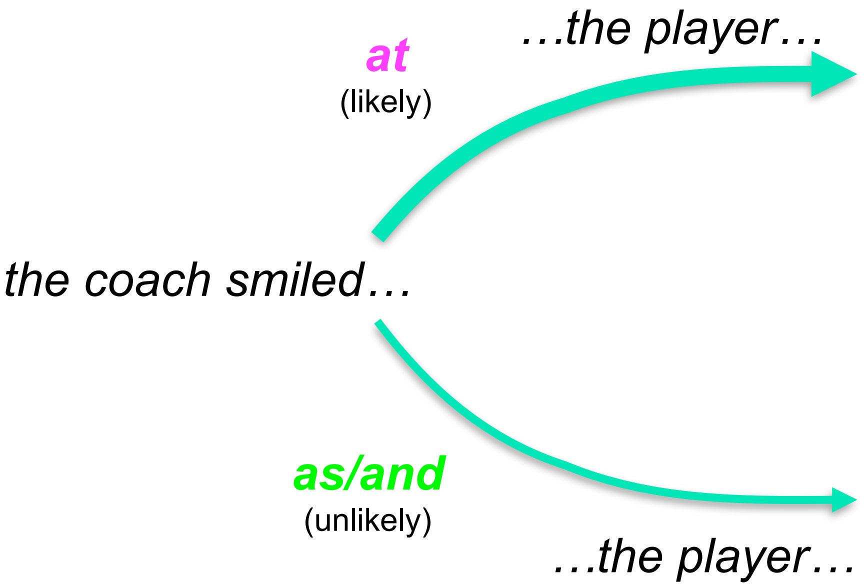

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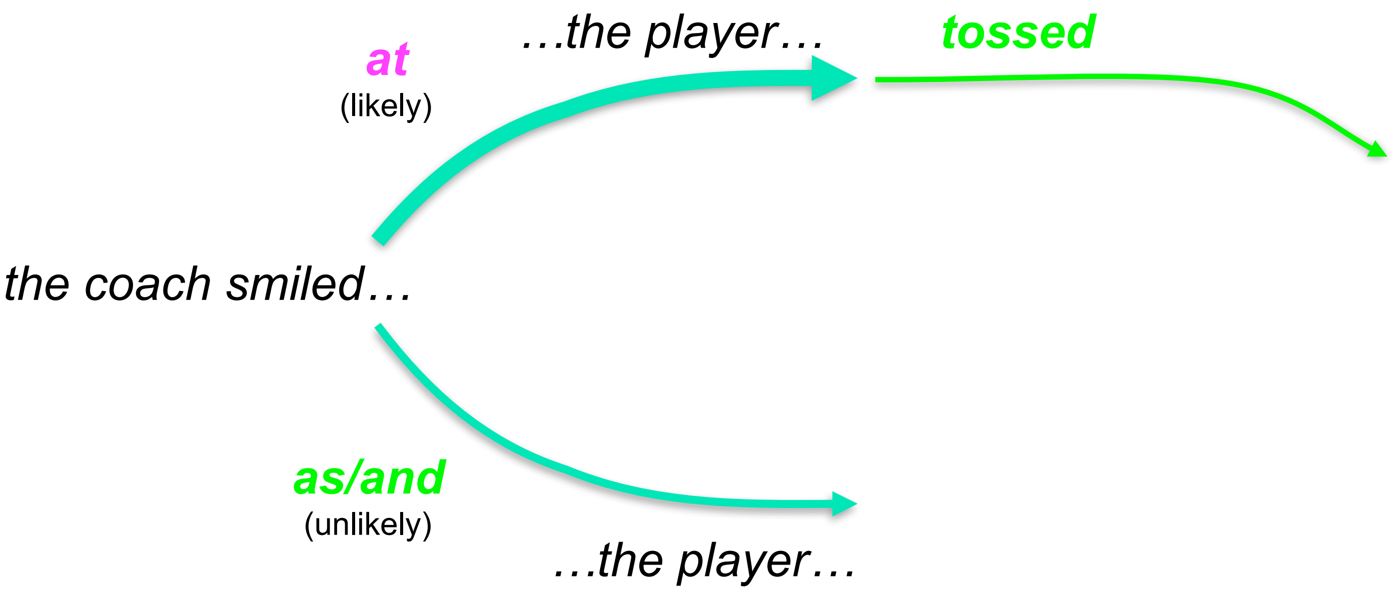

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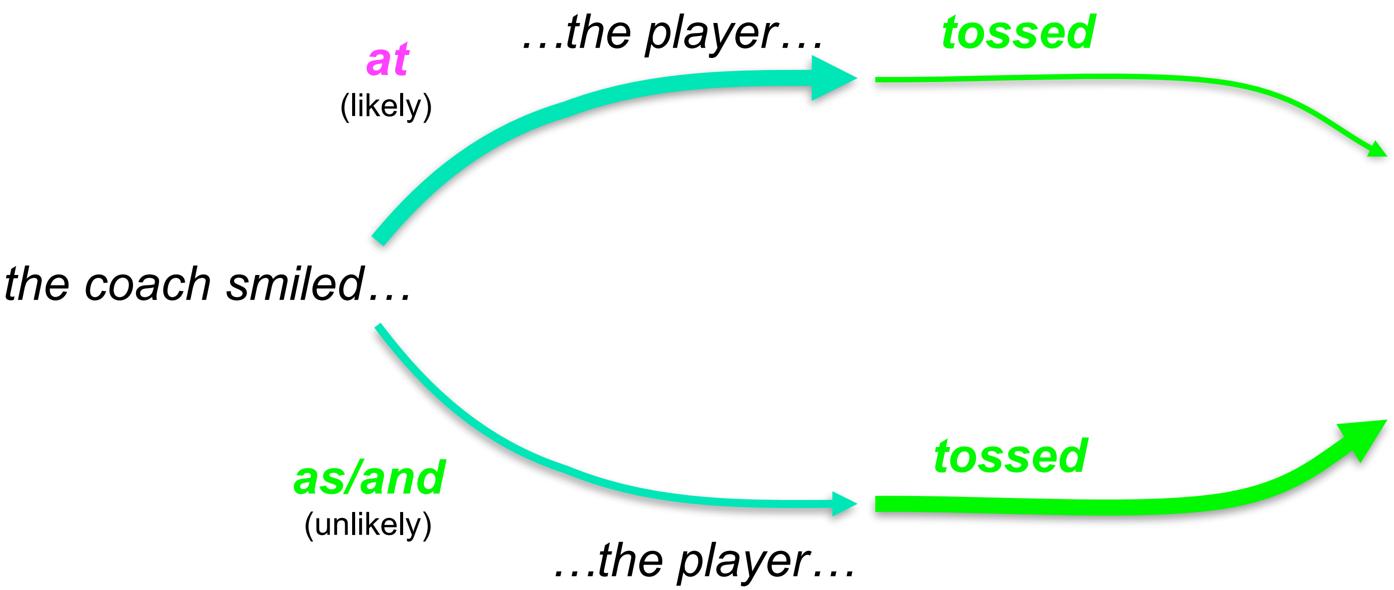

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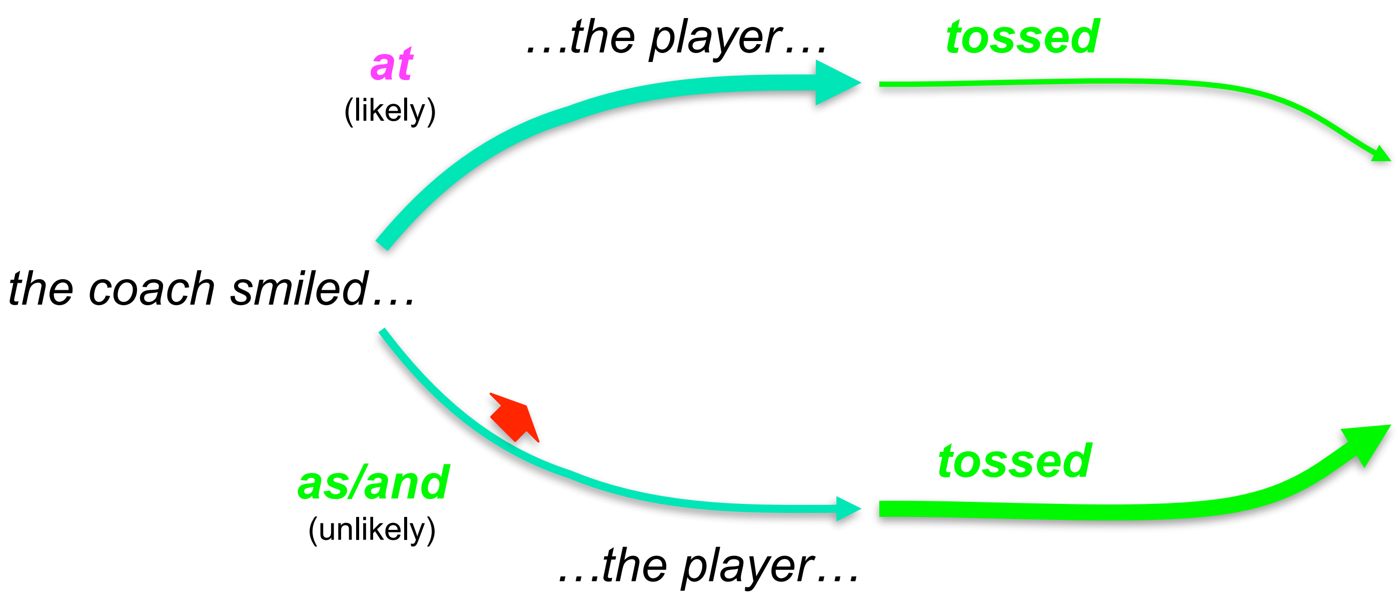

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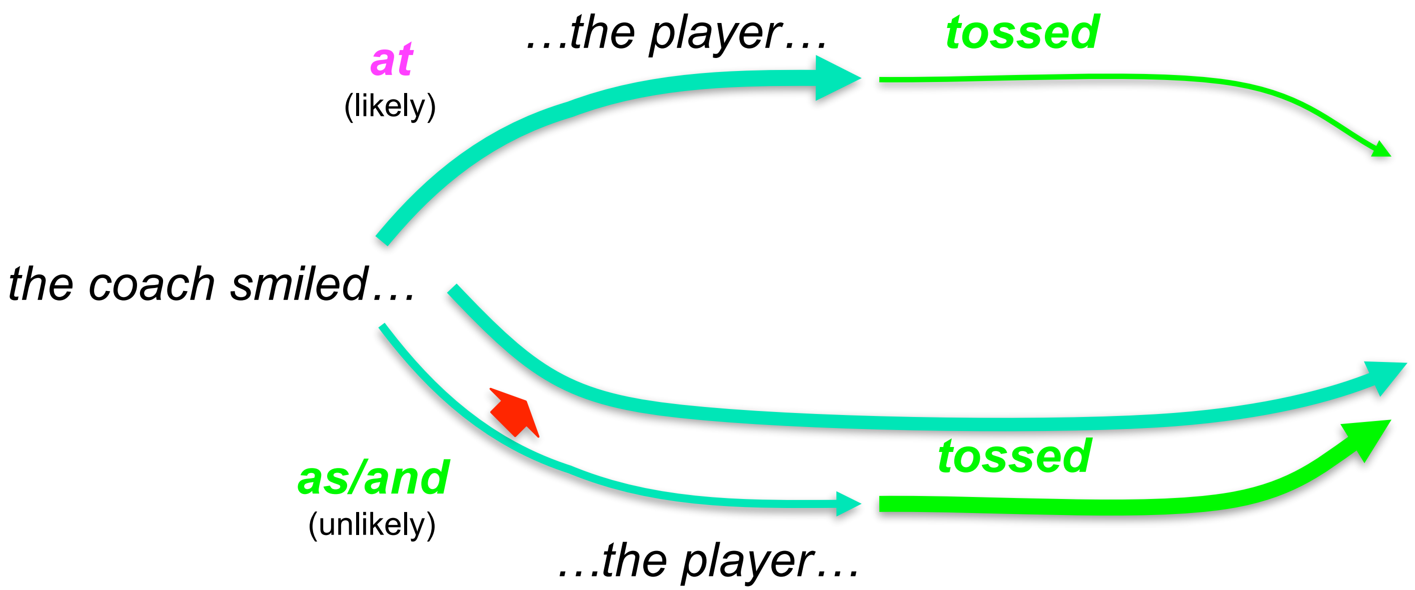

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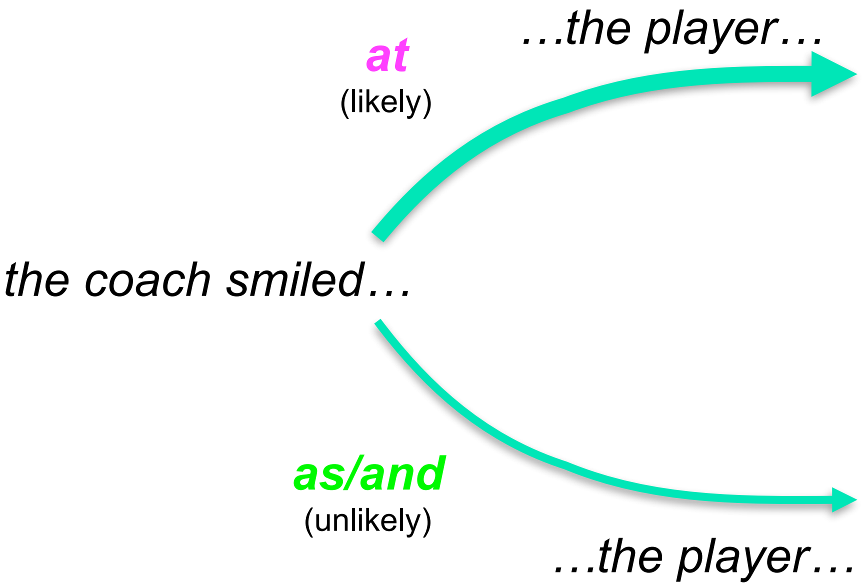

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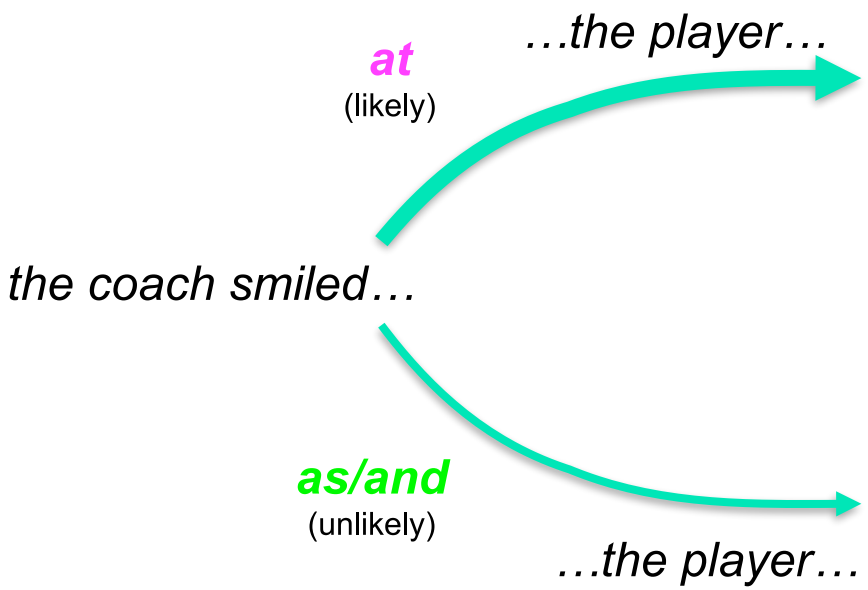

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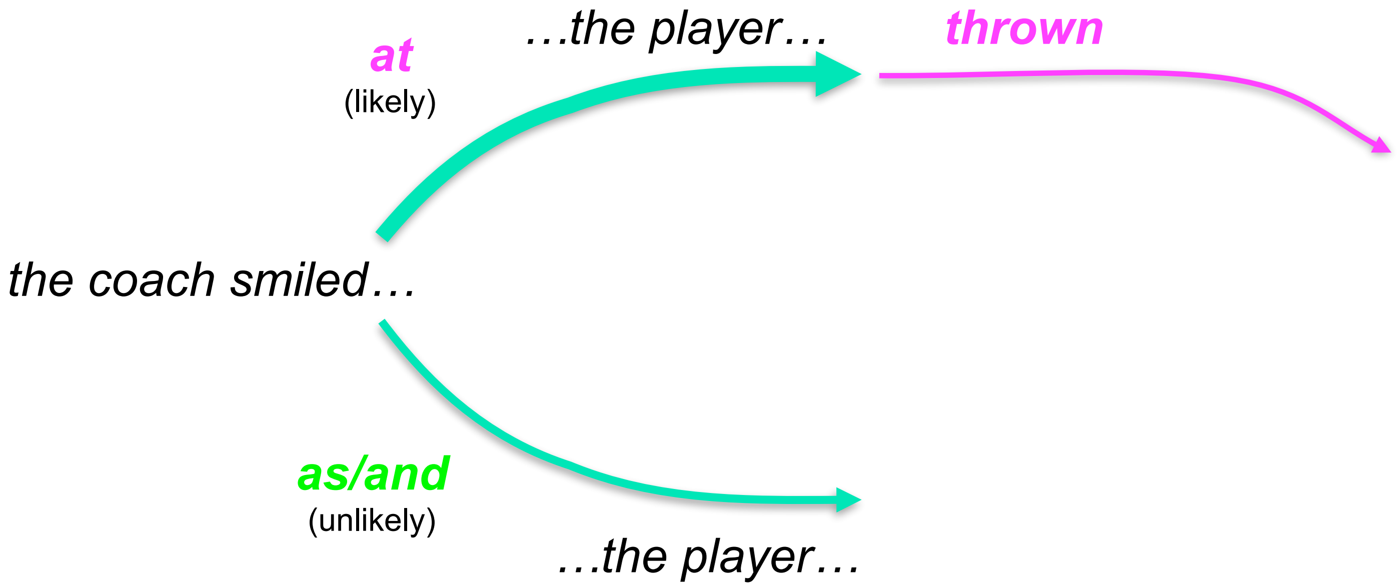

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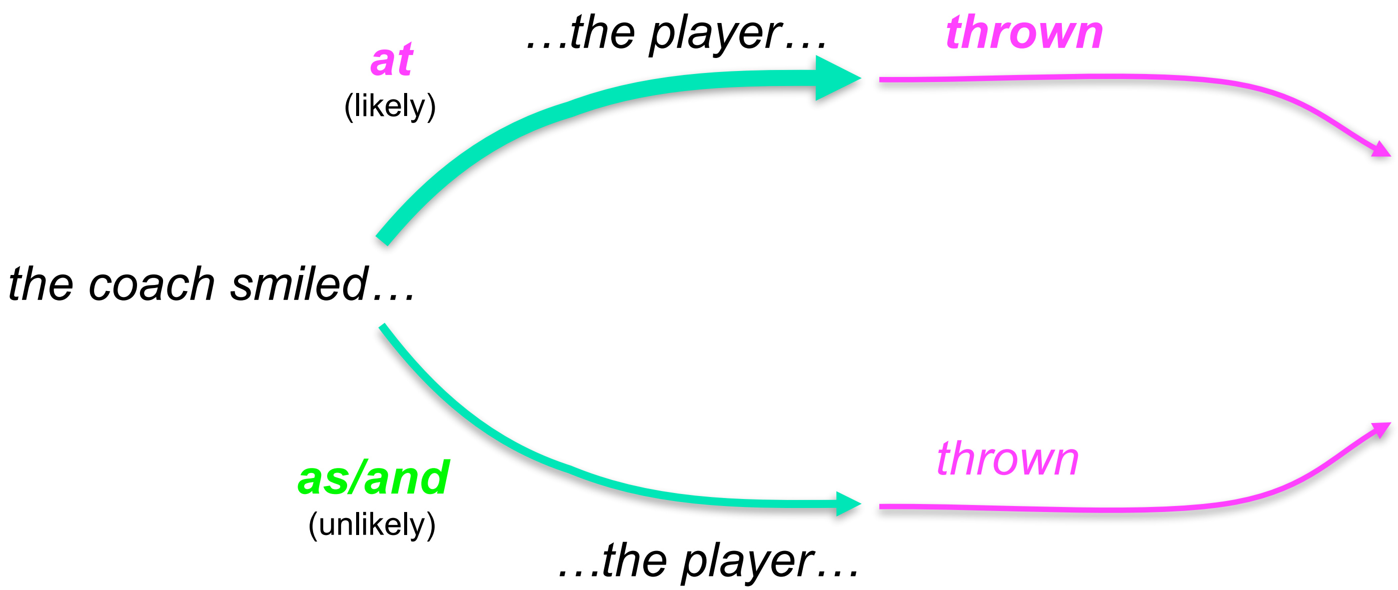

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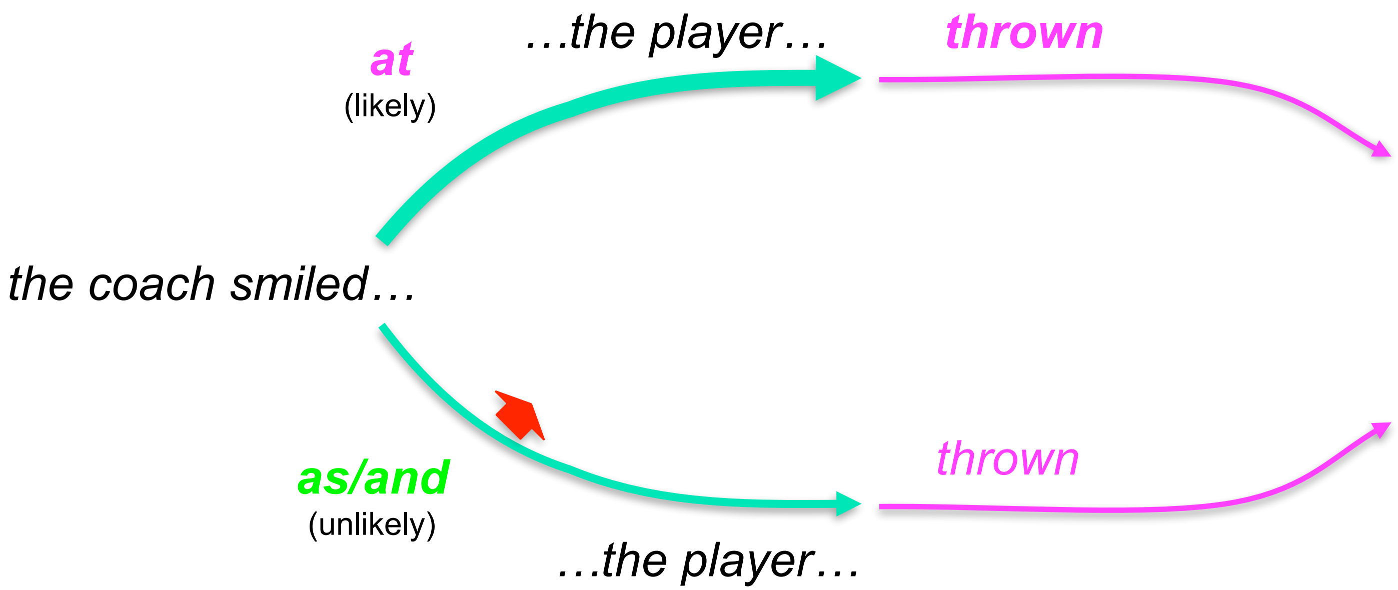

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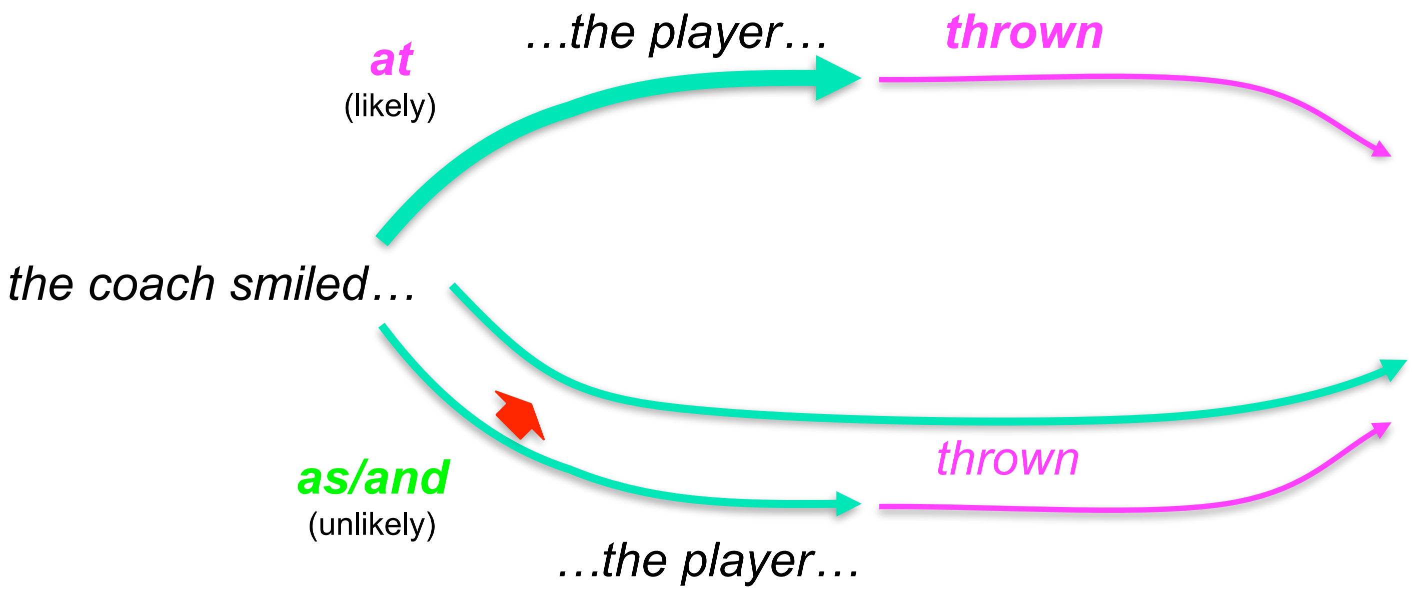

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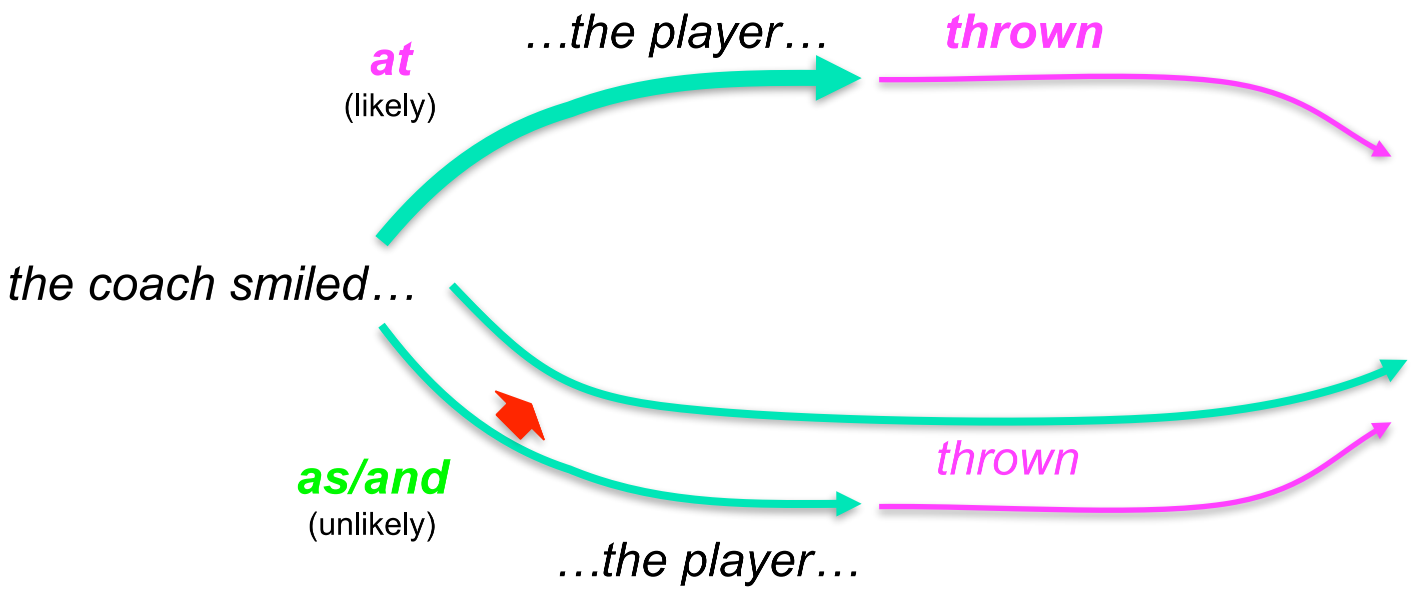

- *tossed* is more likely to happen along the bottom path
  - This creates a large shift in belief in the *tossed* condition
- *thrown* is very unlikely to happen along the bottom path
  - As a result, there is no corresponding shift in belief

Ingredients for the model

$$P(\mathbf{w}|\mathbf{w}^*) \propto \underbrace{P_C(\mathbf{w})}_{\text{Prior}}\underbrace{Q(\mathbf{w}, \mathbf{w}^*)}_{\text{Expected evidence}}$$

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- Q(**w**,**w***) comes from K_{LD} (with minor changes)
- P_C(**w**) comes from a probabilistic grammar (this time finite-state)
- We need one more ingredient:
  - a **quantified signal** of the alarm induced by word w_i about changes in beliefs about the past

Quantifying alarm about the past

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- *Relative Entropy* (KL-divergence) is a natural metric of change in a probability distrib. (Levy, 2008; Itti & Baldi, 2005)

$$D(P\,||\,Q) = \sum_x P(x)\,\log\frac{P(x)}{Q(x)}$$

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- The change induced by w_i is the ***error identification signal*** EIS_i, defined as

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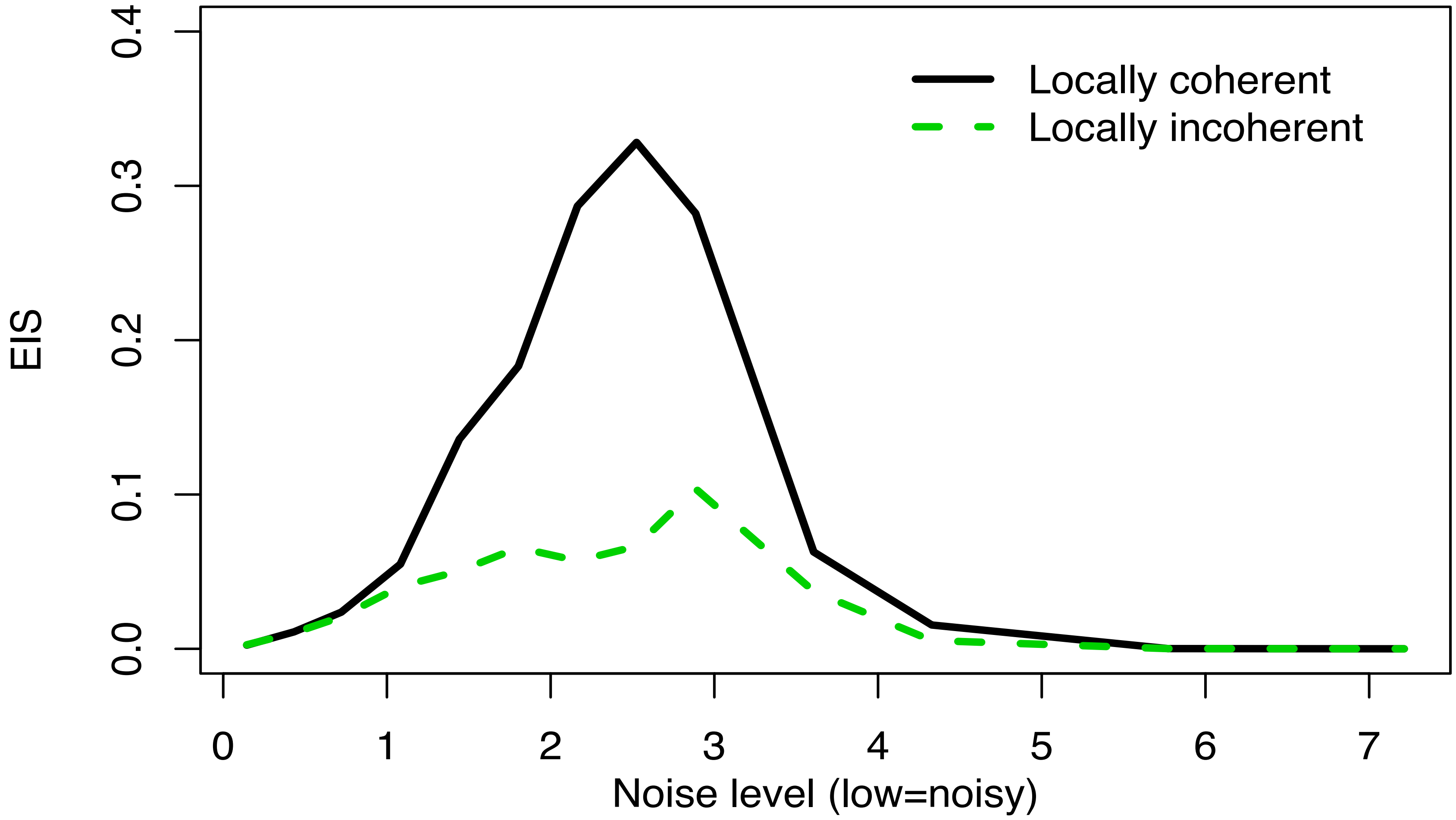
Results on local-coherence sentences

- Locally coherent: *The coach smiled at the player tossed the frisbee*
- Locally incoherent: *The coach smiled at the player thrown the frisbee*



(All sentences of Tabor et al. 2004 with lexical coverage in model)

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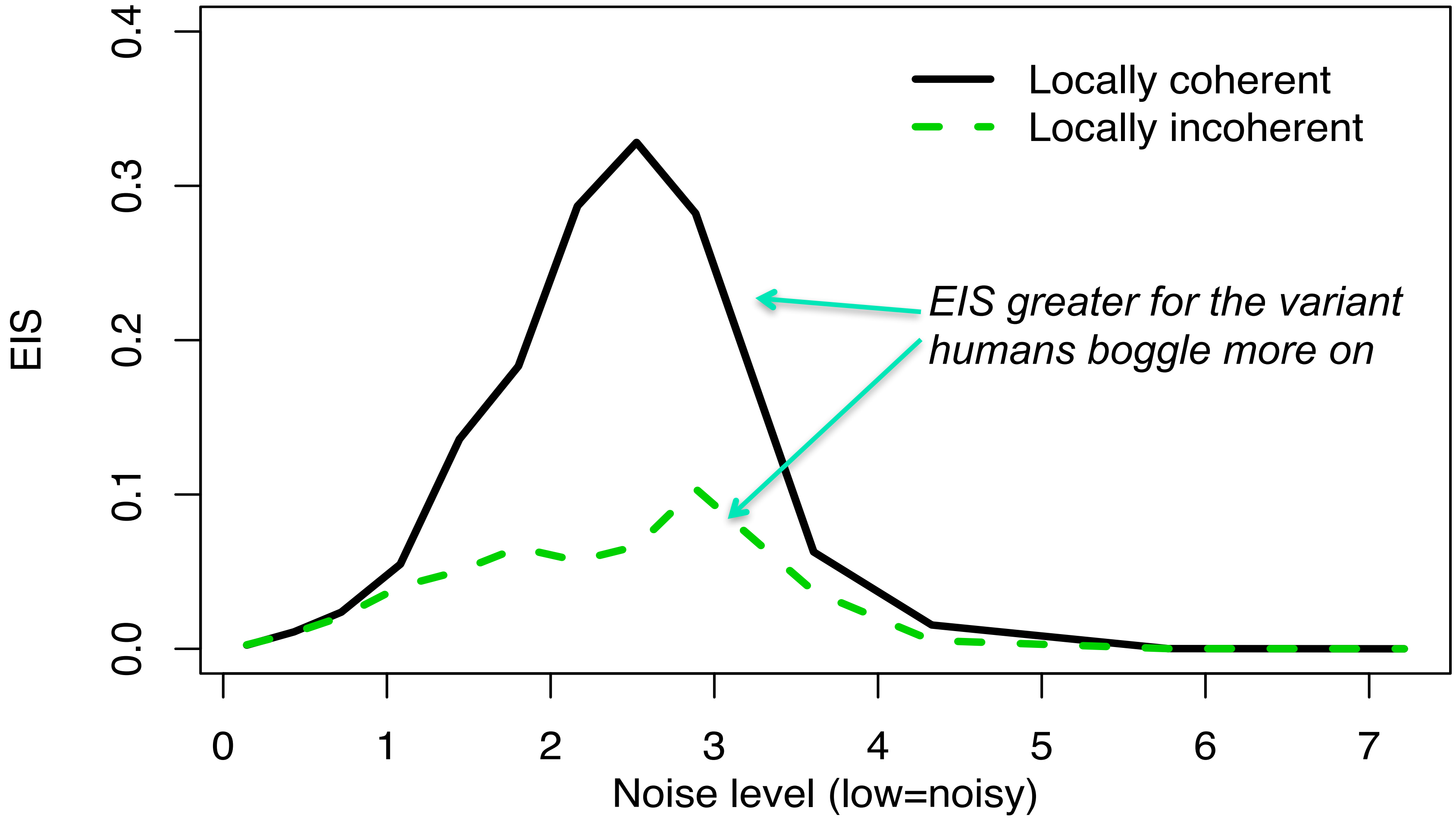

EIS greater for the variant humans boggle more on

(All sentences of Tabor et al. 2004 with lexical coverage in model)

Today's summary

- Reviewed principles of rational analysis and its application to theory of language comprehension
- Examined a phenomenon challenging for surprisal theory
- Proposed a noisy-channel processing theory, using information theory and probabilistic grammars
- Developed a hypothesis within the theory for the challenging phenomenon
-

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Prediction 2: hallucinated garden paths

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While the clouds crackled, above the glider soared a magnificent eagle.

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- There’s a garden-path clause in this sentence…

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- Try reading the sentence below:

`While the clouds crackled, above the glider soared a magnificent eagle.`

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- There's a garden-path clause in this sentence…
- …but it's interrupted by a comma.
- Readers are ordinarily very good at using commas to guide syntactic analysis:

  While the man hunted, the deer ran into the woods

  While Mary was mending the sock fell off her lap

  - "With a comma after *mending* there would be no syntactic garden path left to be studied." (Fodor, 2002)

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  - “With a comma after *mending* there would be no syntactic garden path left to be studied.” (Fodor, 2002)
- We’ll see that the story is slightly more complicated.

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- This sentence is comprised of an initial intransitive subordinate clause…

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`While the clouds crackled, above the glider soared a magnificent eagle.`

- This sentence is comprised of an initial intransitive subordinate clause…
- …and then a main clause with *locative inversion*.

  (c.f. `a magnificent eagle soared above the glider`)

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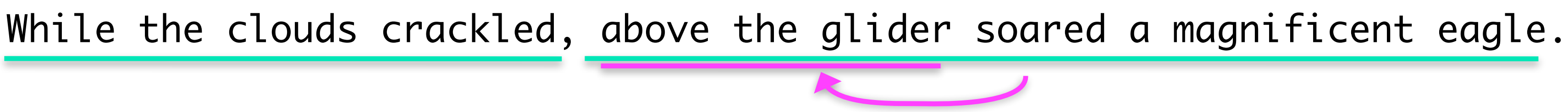

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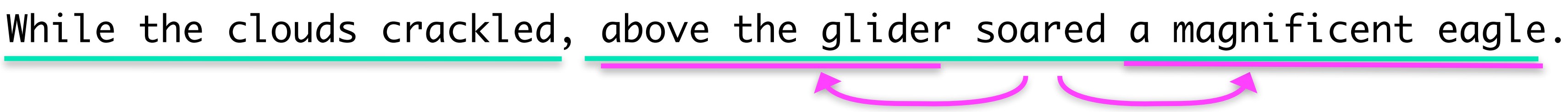

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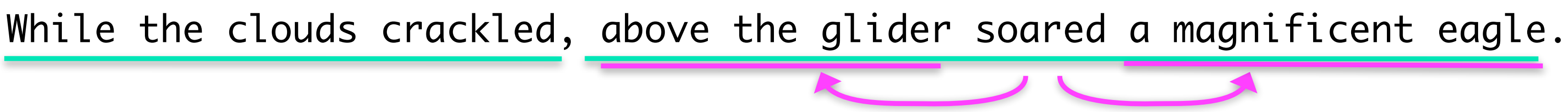

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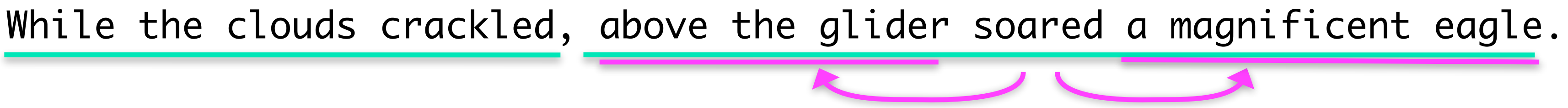
  (c.f. a magnificent eagle soared above the glider)
- Crucially, the main clause’s initial PP would make a great dependent of the subordinate verb…

Prediction 2: hallucinated garden paths



While the clouds crackled, above the glider soared a magnificent eagle.

- This sentence is comprised of an initial intransitive subordinate clause…
- …and then a main clause with *locative inversion*.

  (c.f. a magnificent eagle soared above the glider)
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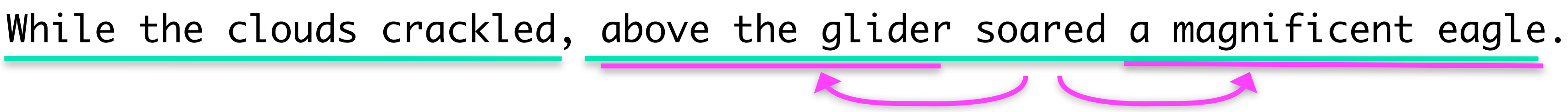

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- Inferences through *…glider* should thus involve a tradeoff between perceptual input and prior expectations

While the clouds crackled…

- Inferences as probabilistic paths through the sentence:
  - Perceptual cost of ignoring the comma
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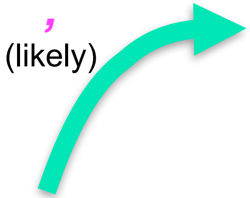

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(likely)

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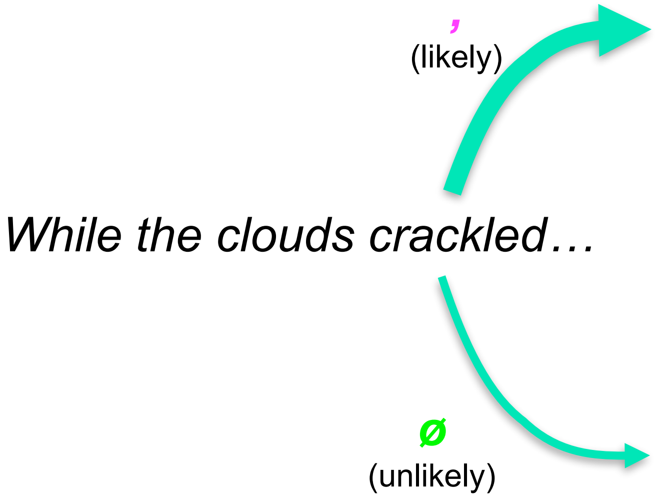

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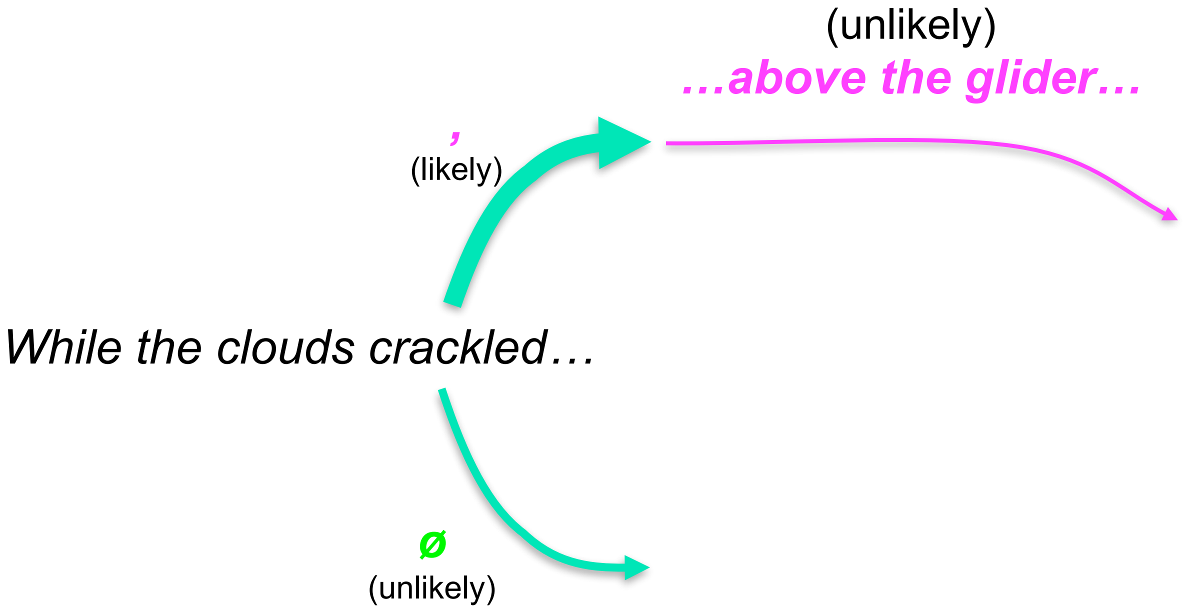

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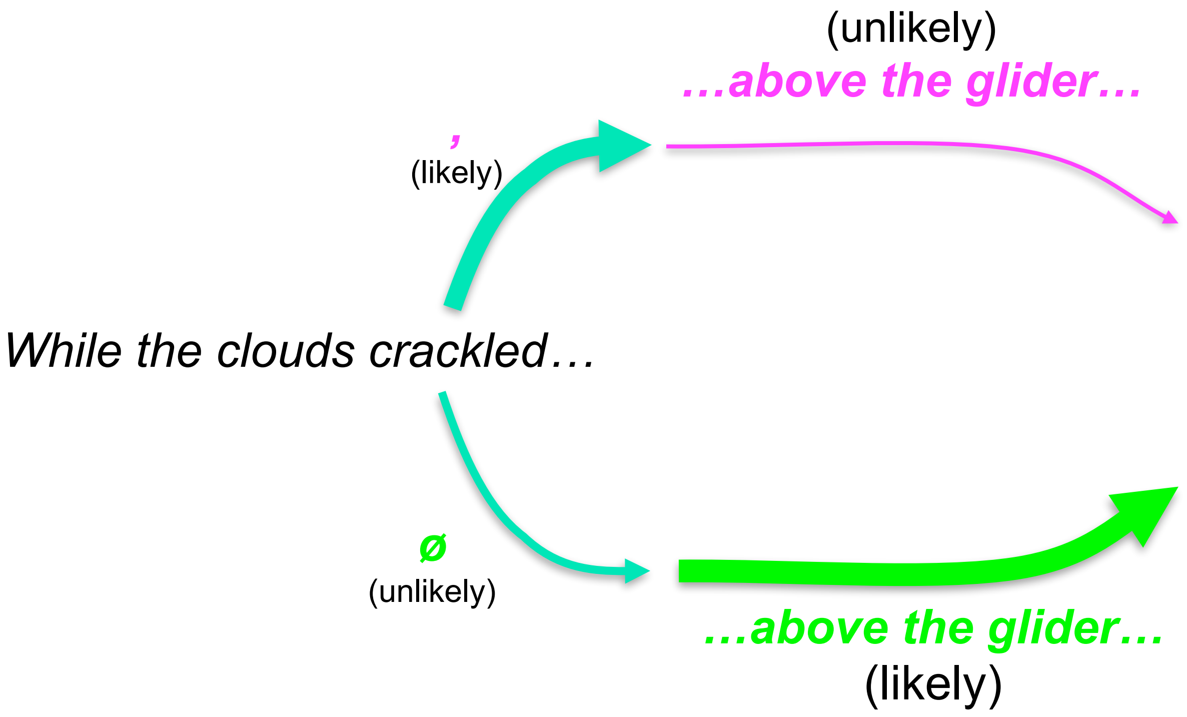

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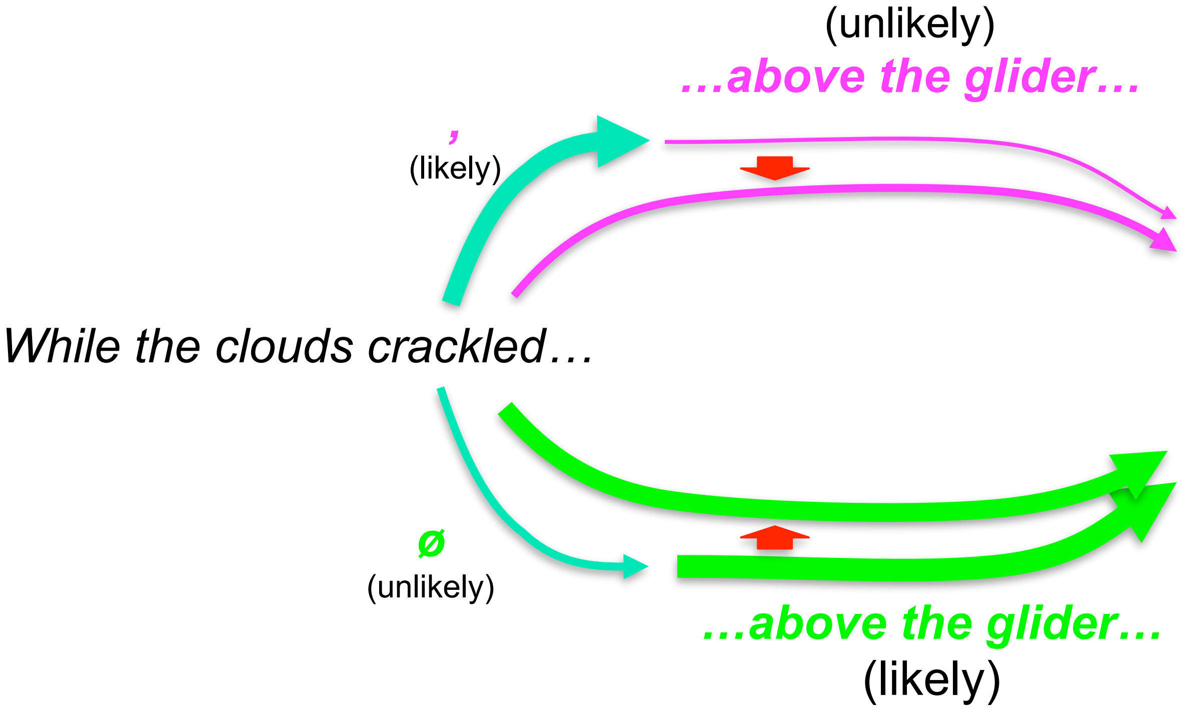

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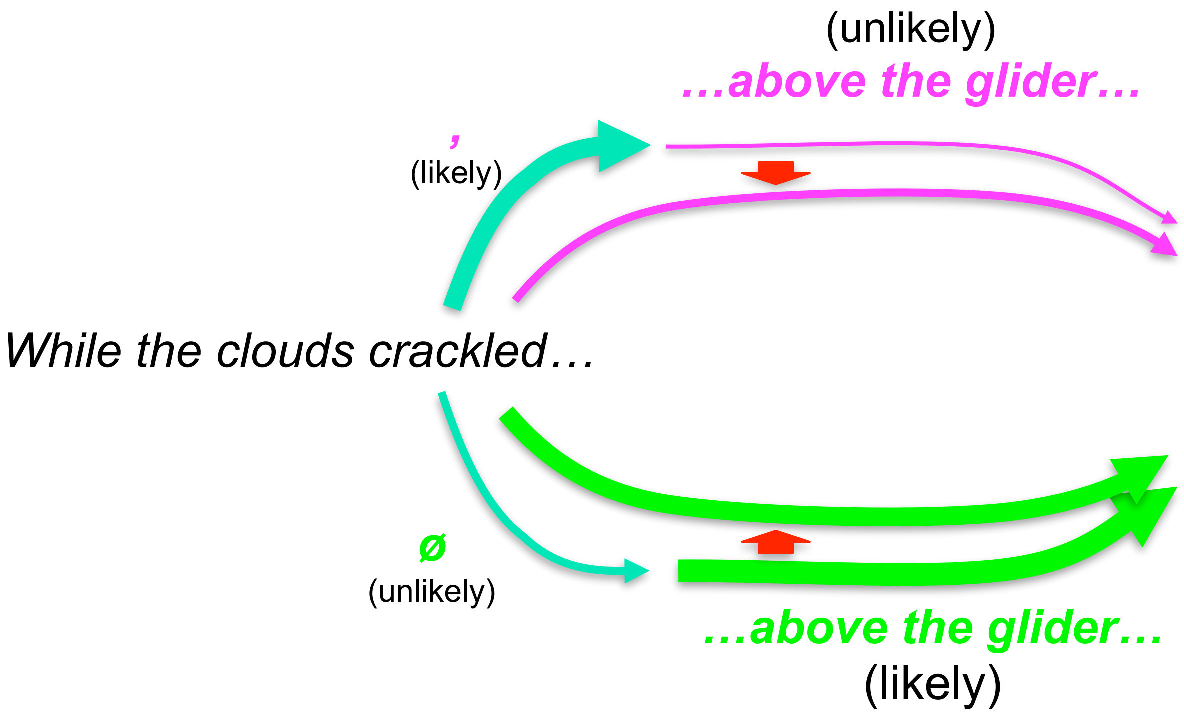

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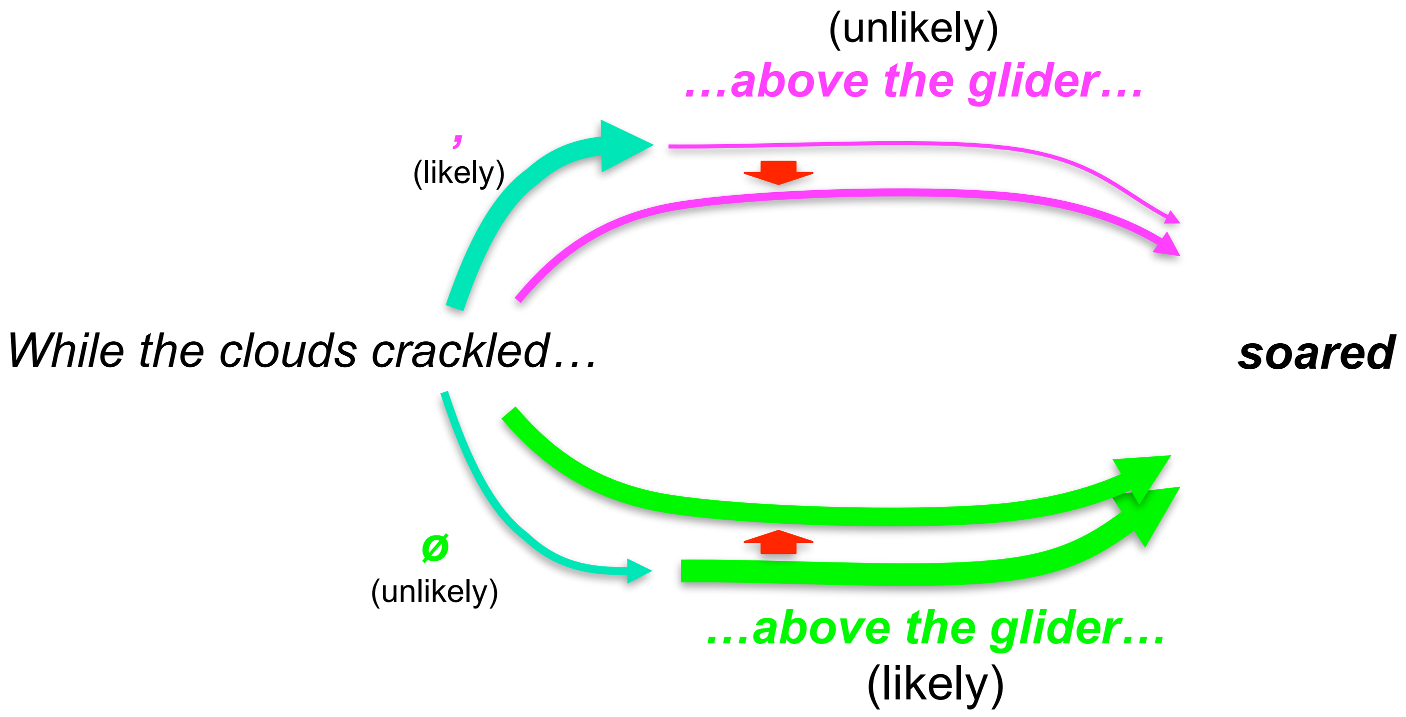

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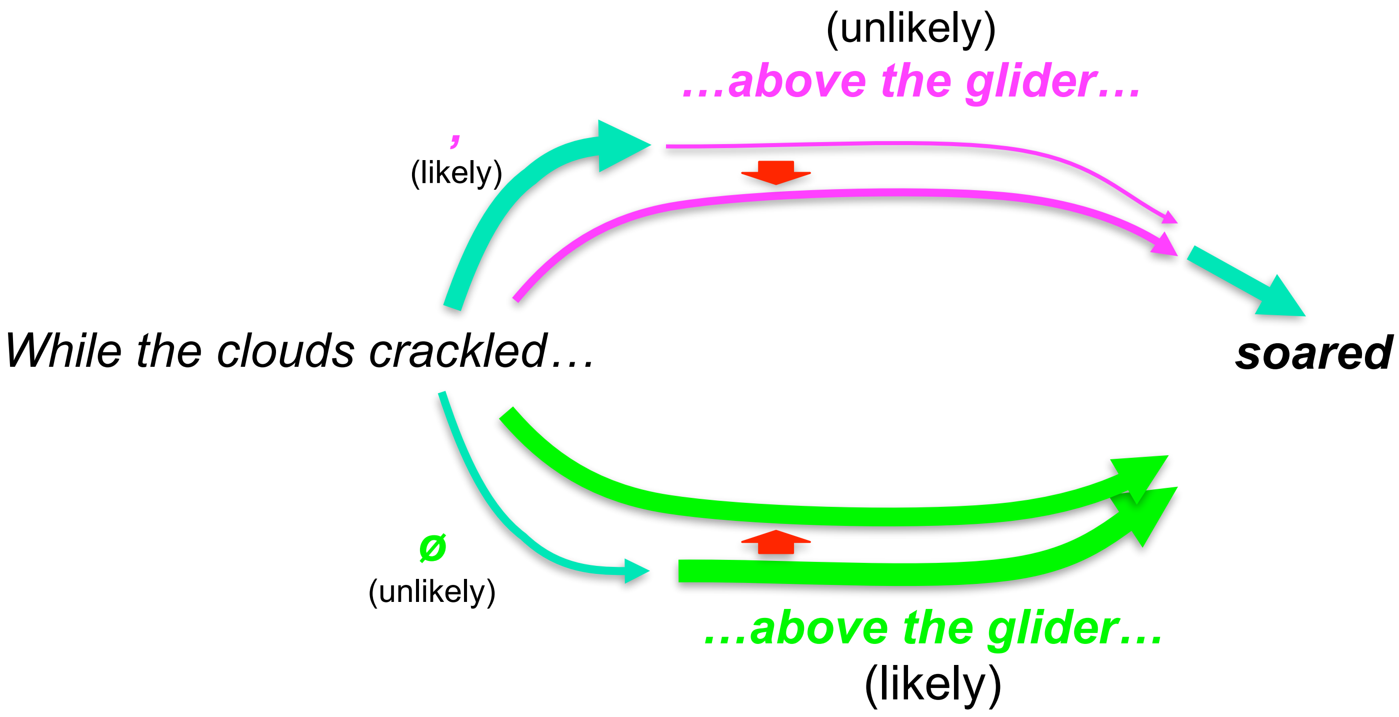

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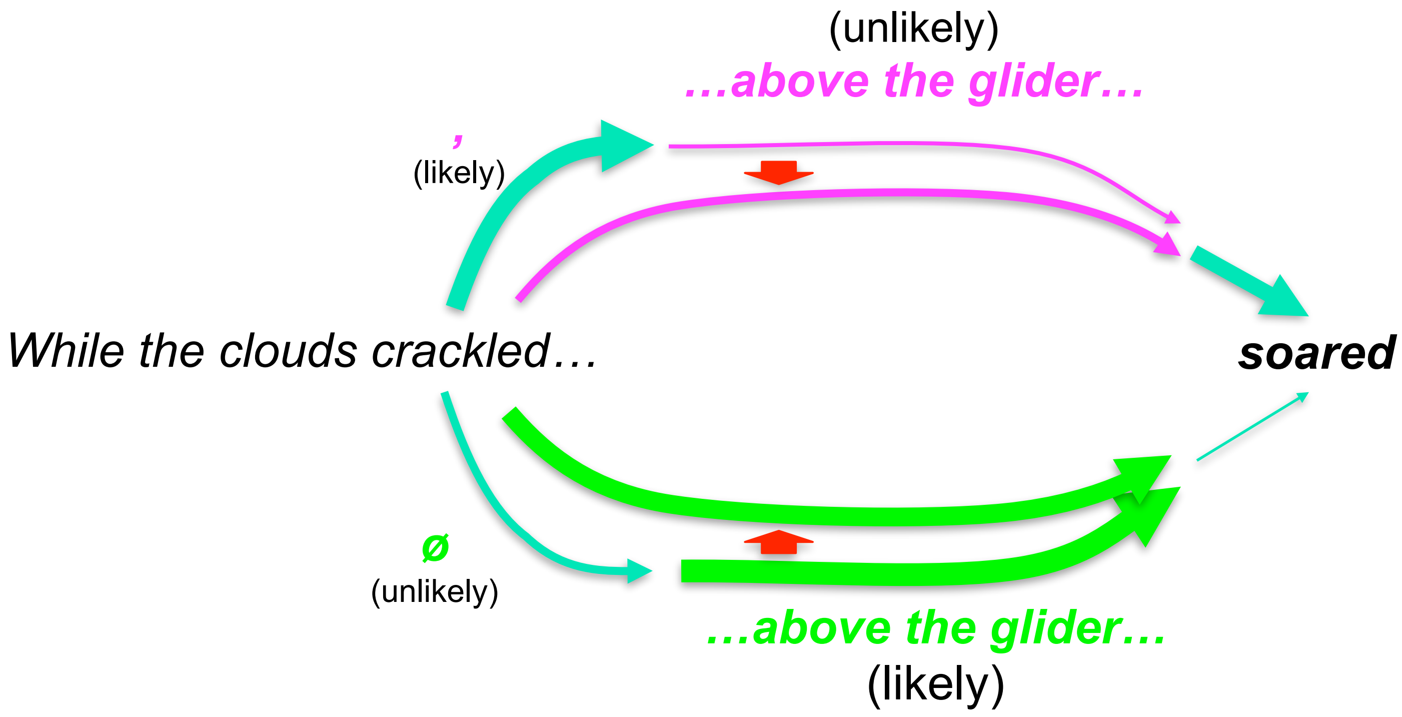

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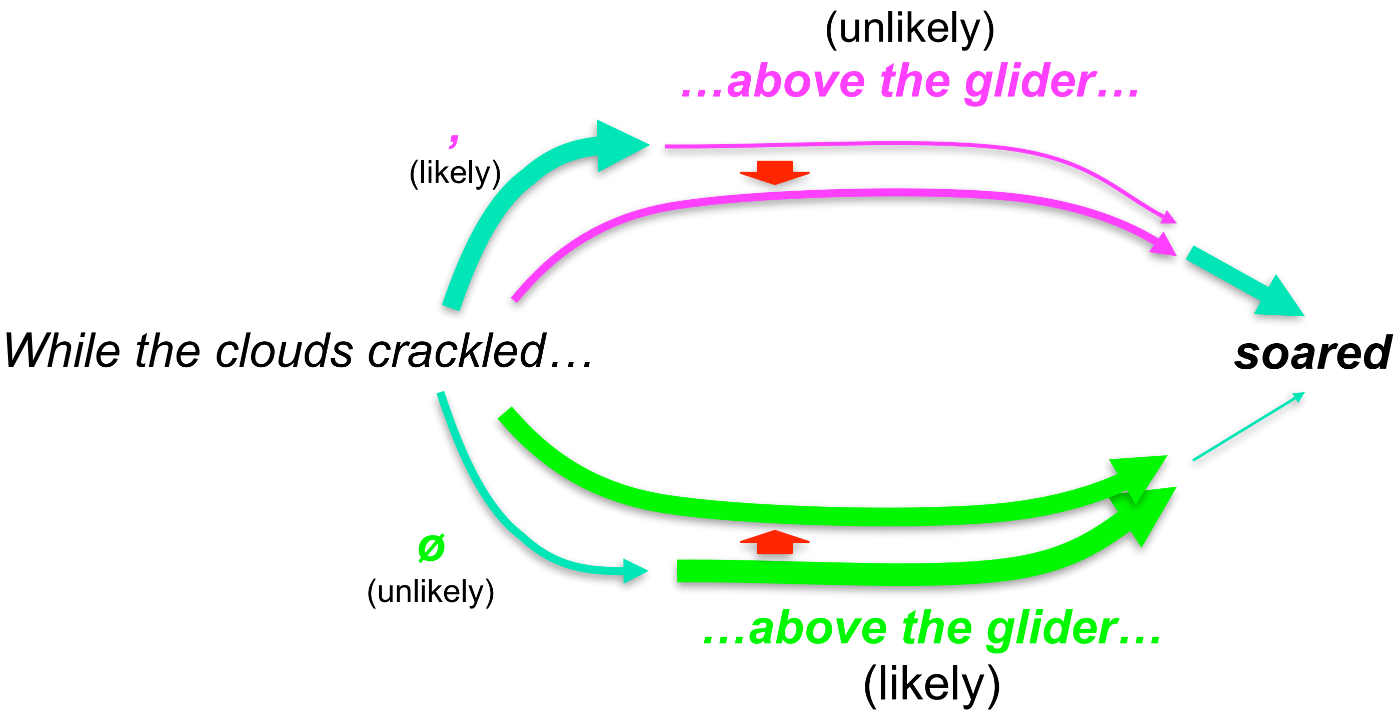

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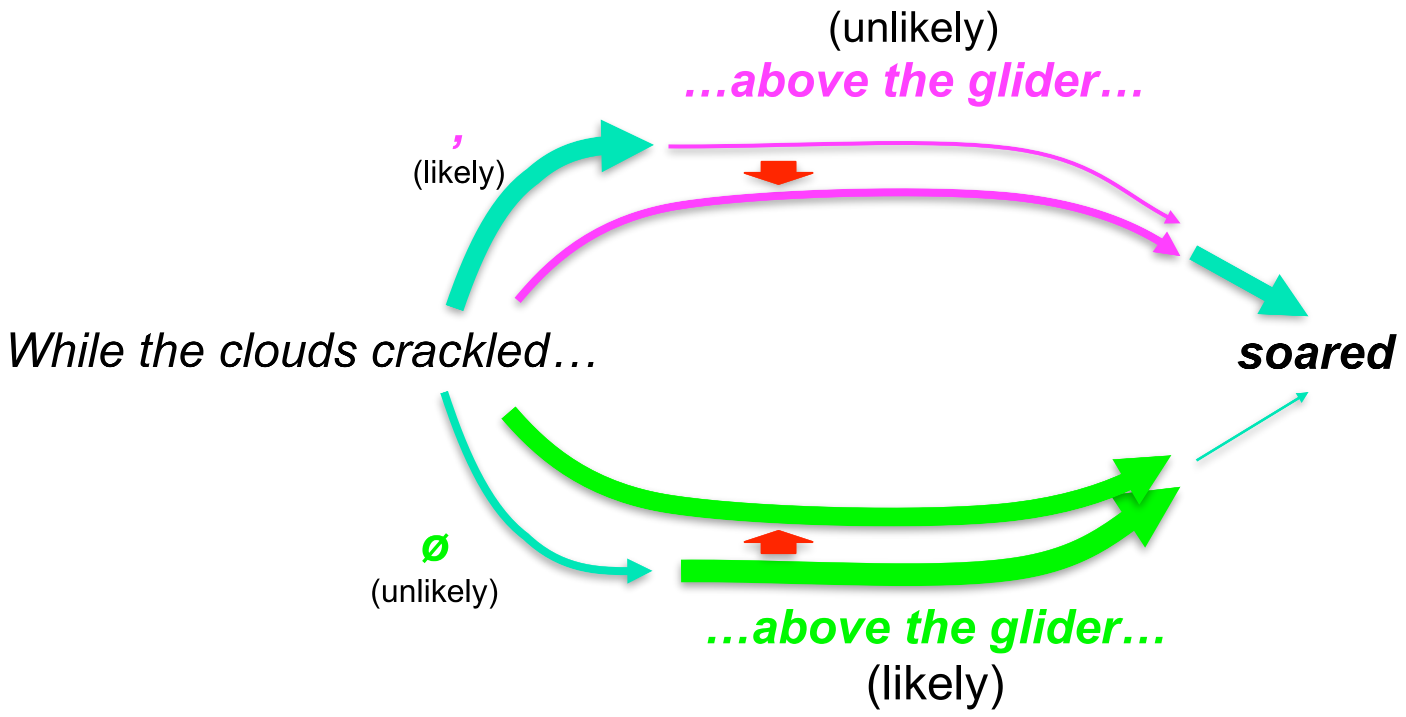

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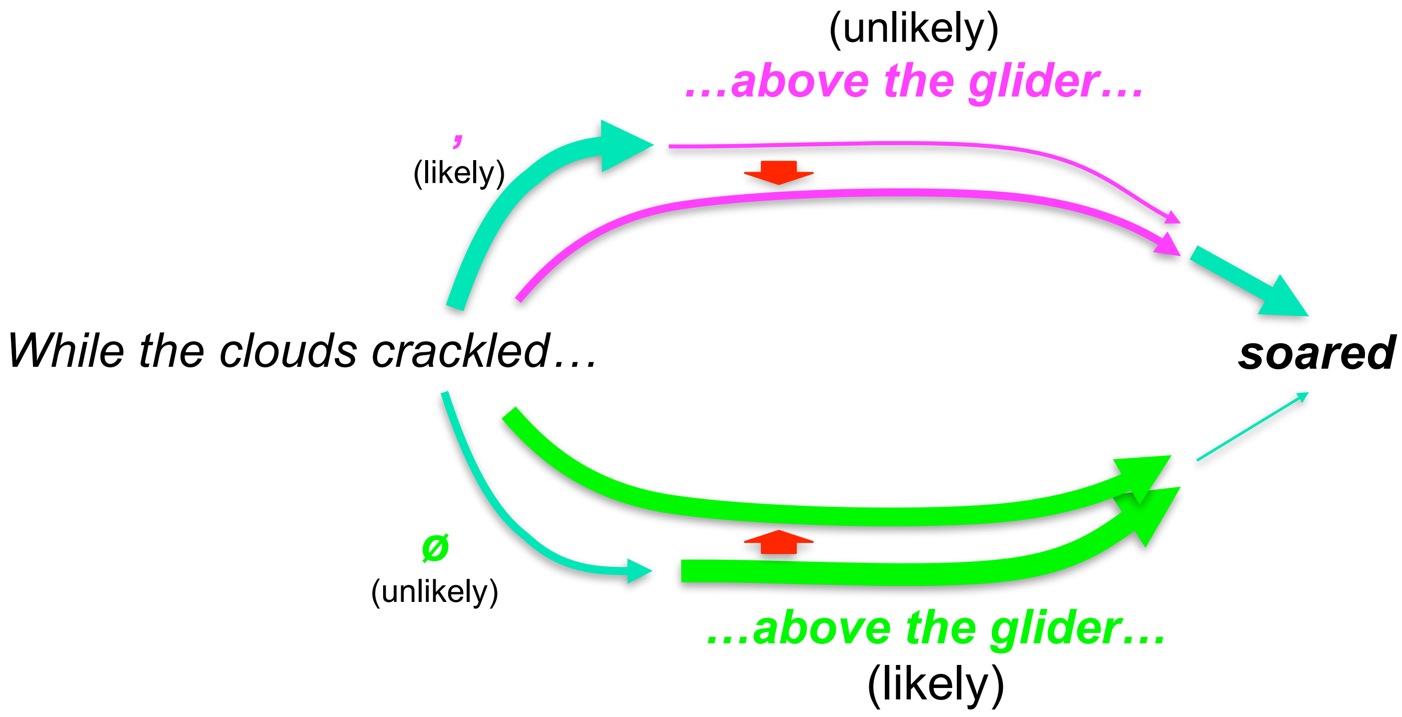

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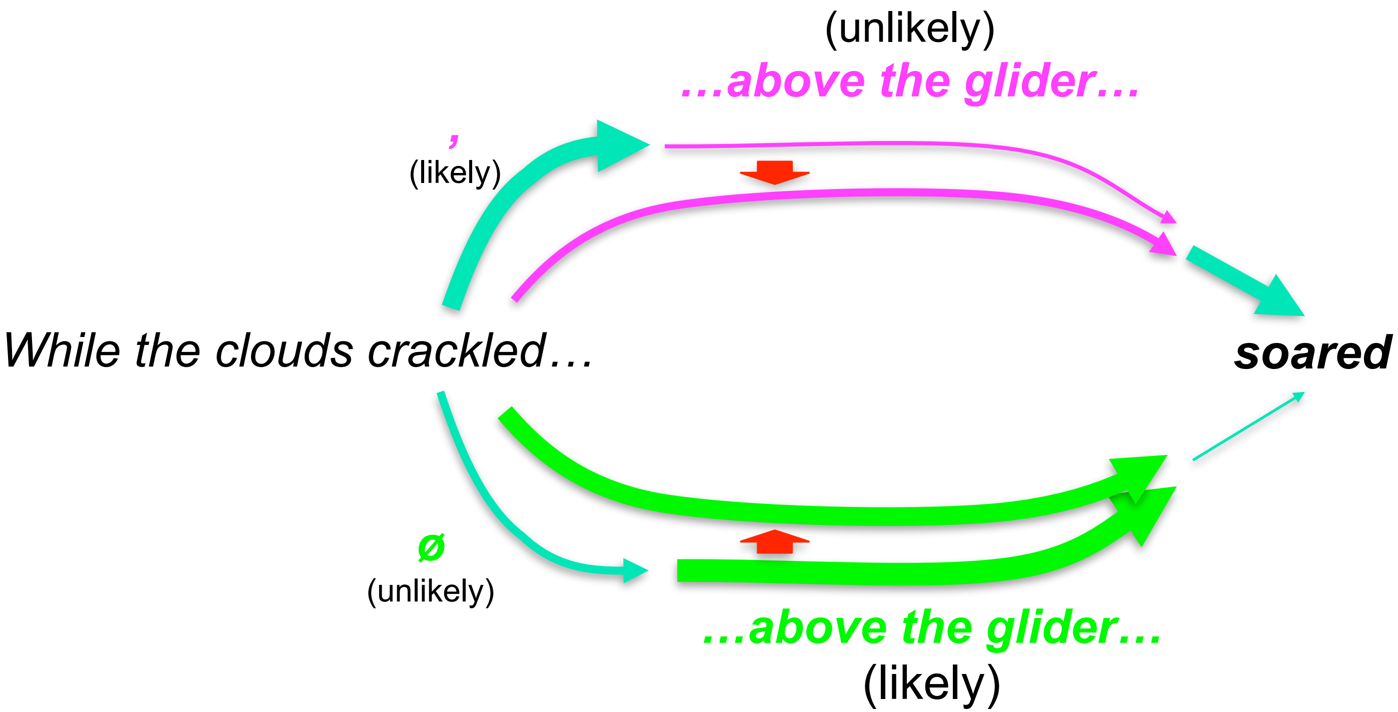

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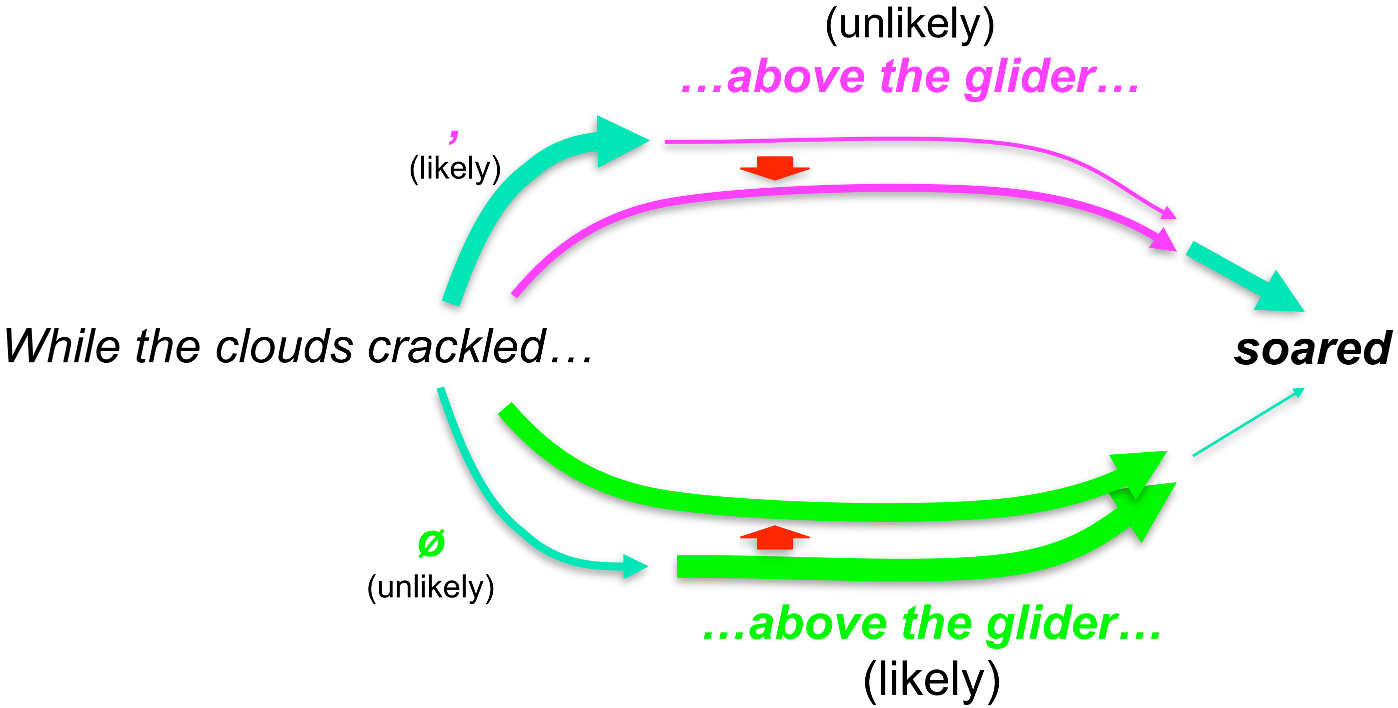

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Prediction 2: hallucinated garden paths

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- Two properties come together to create “hallucinated garden path”
  1. Subordinate clause into which the main-clause inverted phrase would fit well
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- The phrase *in the distance* fulfills a similar thematic role as above the glider for crackled

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Prediction 2: Hallucinated garden paths

- Methodology: word-by-word self-paced reading

- Readers aren’t allowed to backtrack

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```
While-----------------------------------------------------------------
```

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```
while-the--------------------------------------------------------------
```

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```
while-the-clouds-------------------------------------------------------
```

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```
while-the-clouds-crackled,---------------------------------------------
```

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```
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- Simple test of whether beliefs about previous input can be revised

Model predictions

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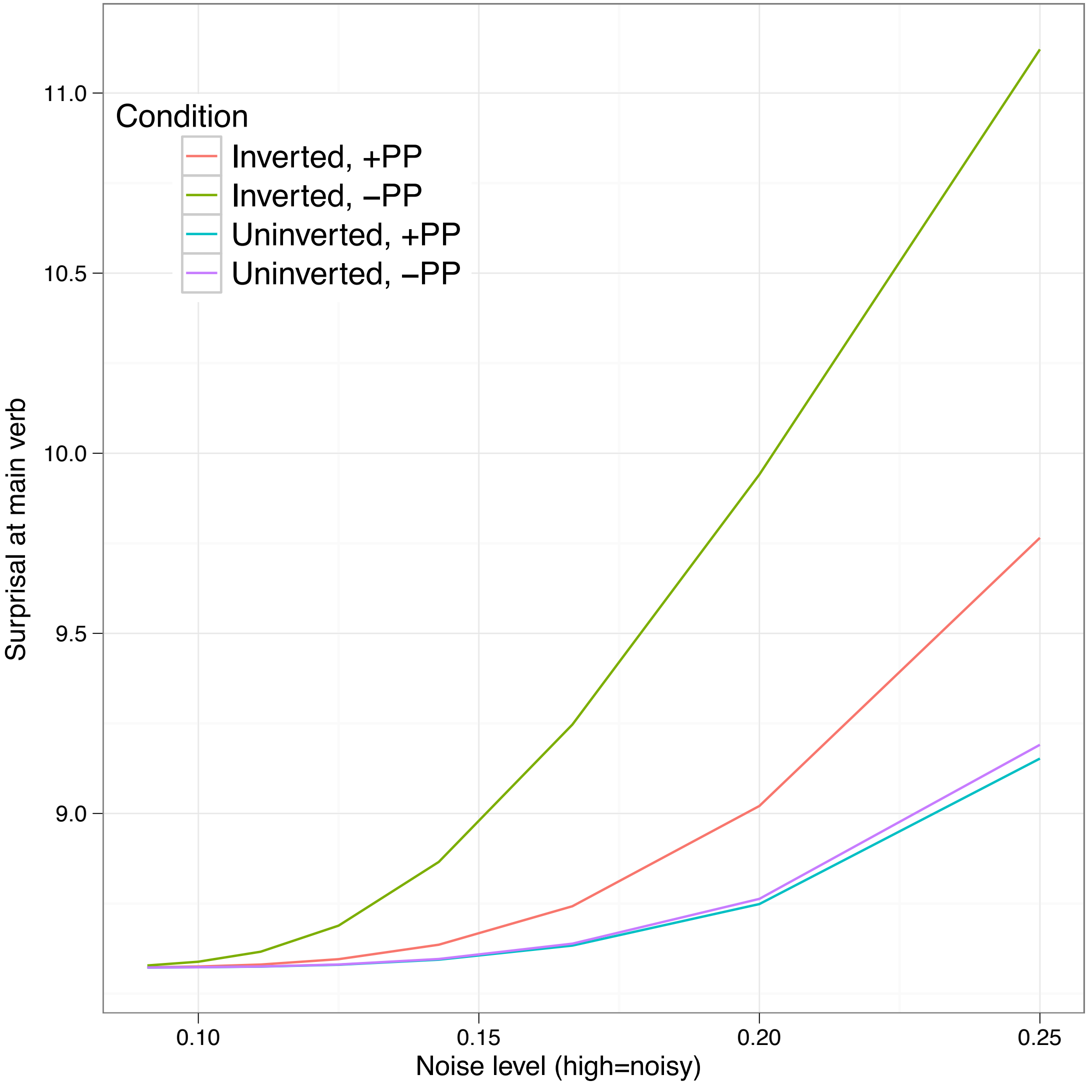
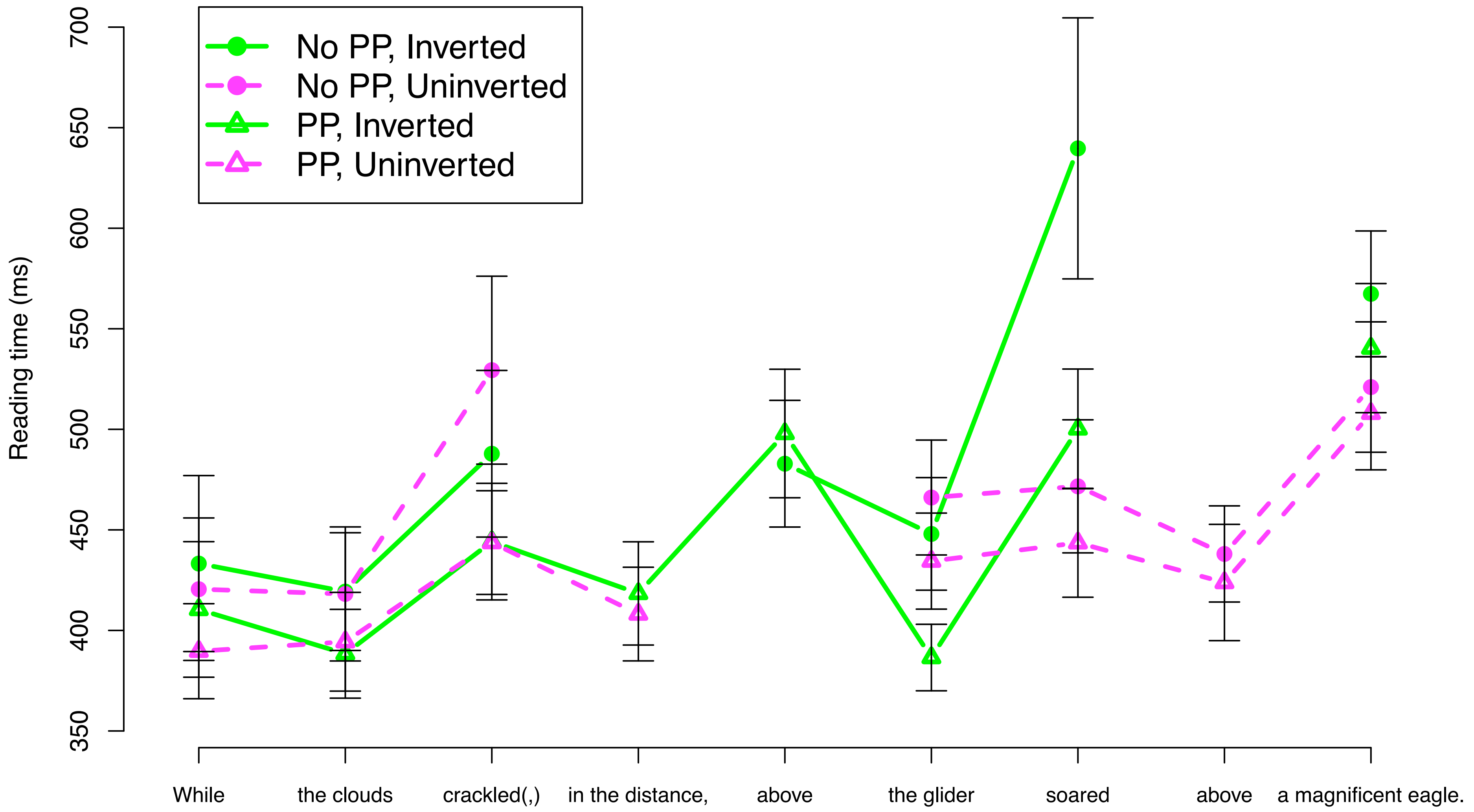


Results: whole sentence reading times



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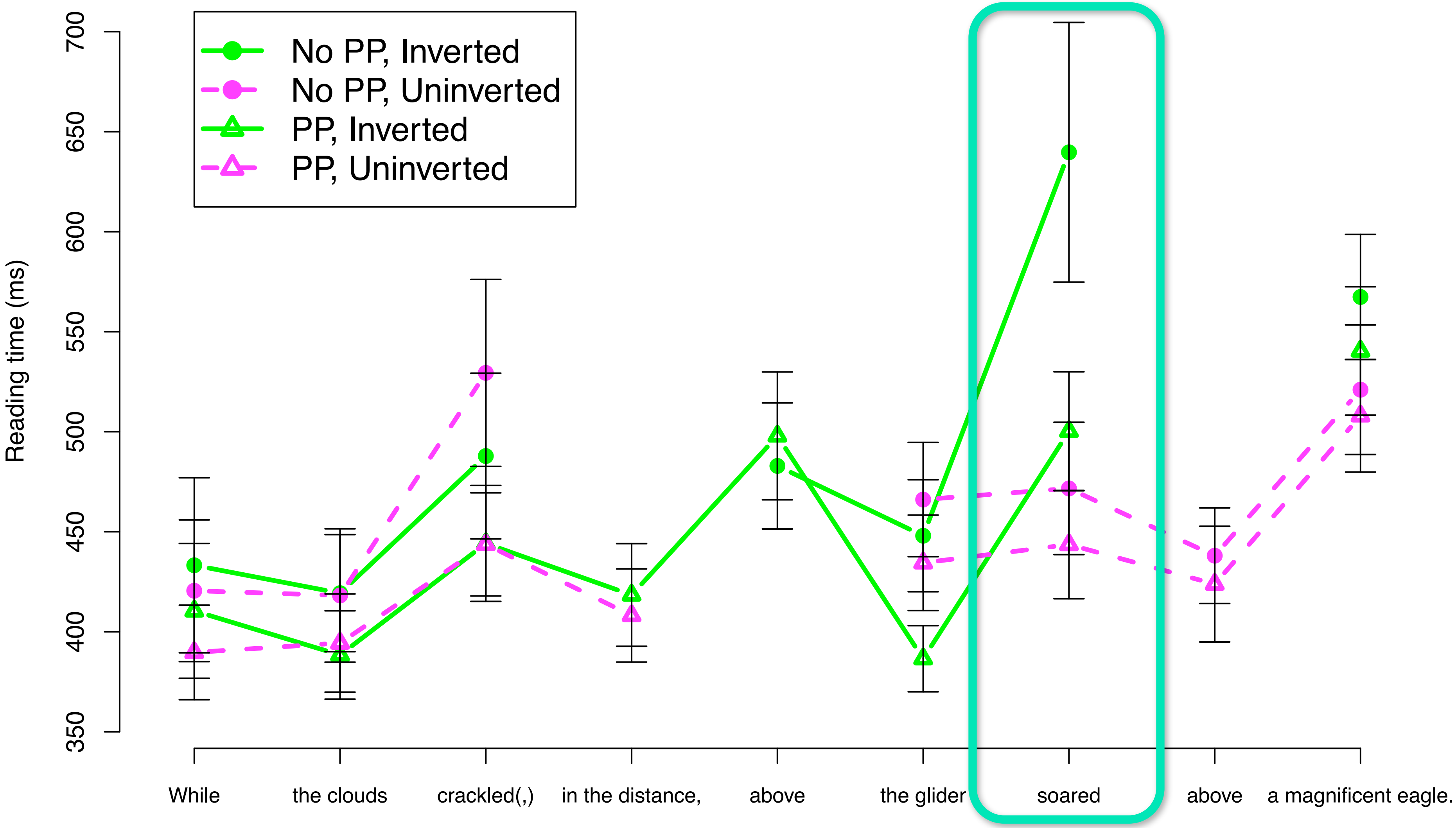

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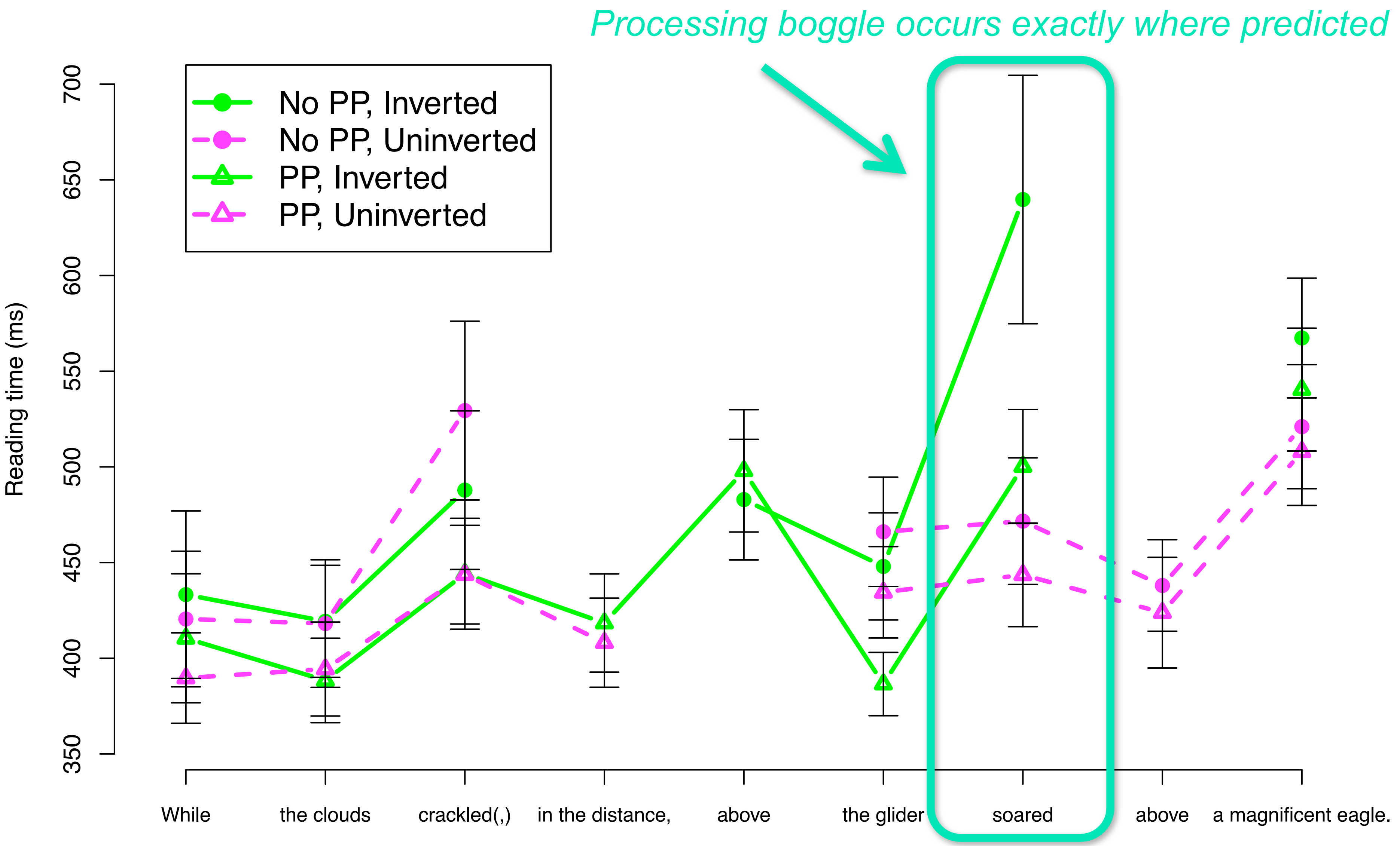
Processing boggle occurs exactly where predicted

Hallucinated garden-path summary

- The *at/toward* study showed that comprehenders *note the possibility of* alternative strings and *act on it*
- This study showed that comprehenders can actually *devote resources to* grammatical analyses inconsistent with the surface string

Hallucinated garden paths cont'd

- Sure, but punctuation's weird stuff
- What about *real words*?

- At least sometimes, bias *against* N N interpretation

(*Frazier & Rayner, 1987; Macdonald, 1993*)

Hallucinated garden paths cont’d

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I know that the desert trains could resupply the camp.

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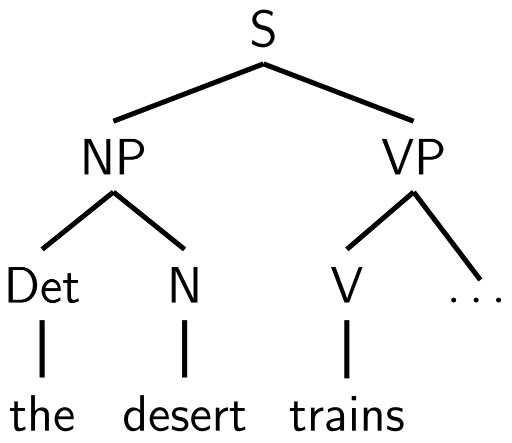

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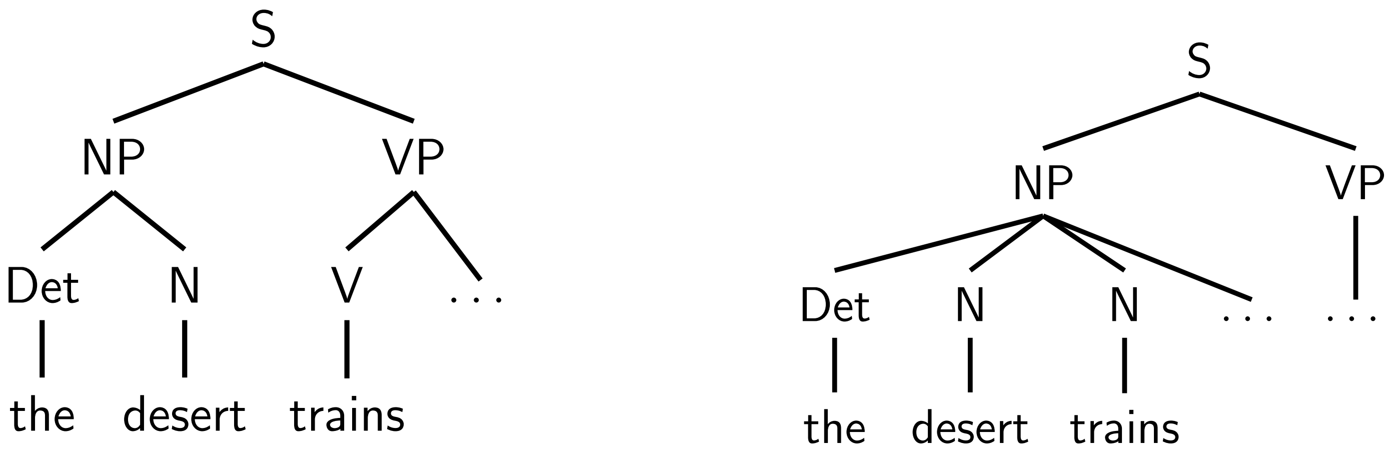

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Hallucinated GPs with words

Could be "intern chauffeured"

Could NOT be "inexperienced chauffeured"

(Bergen, Levy, & Gibson, 2012)

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- We use a contextual bias against NN and toward NV to test for GP hallucinations involving wordform change

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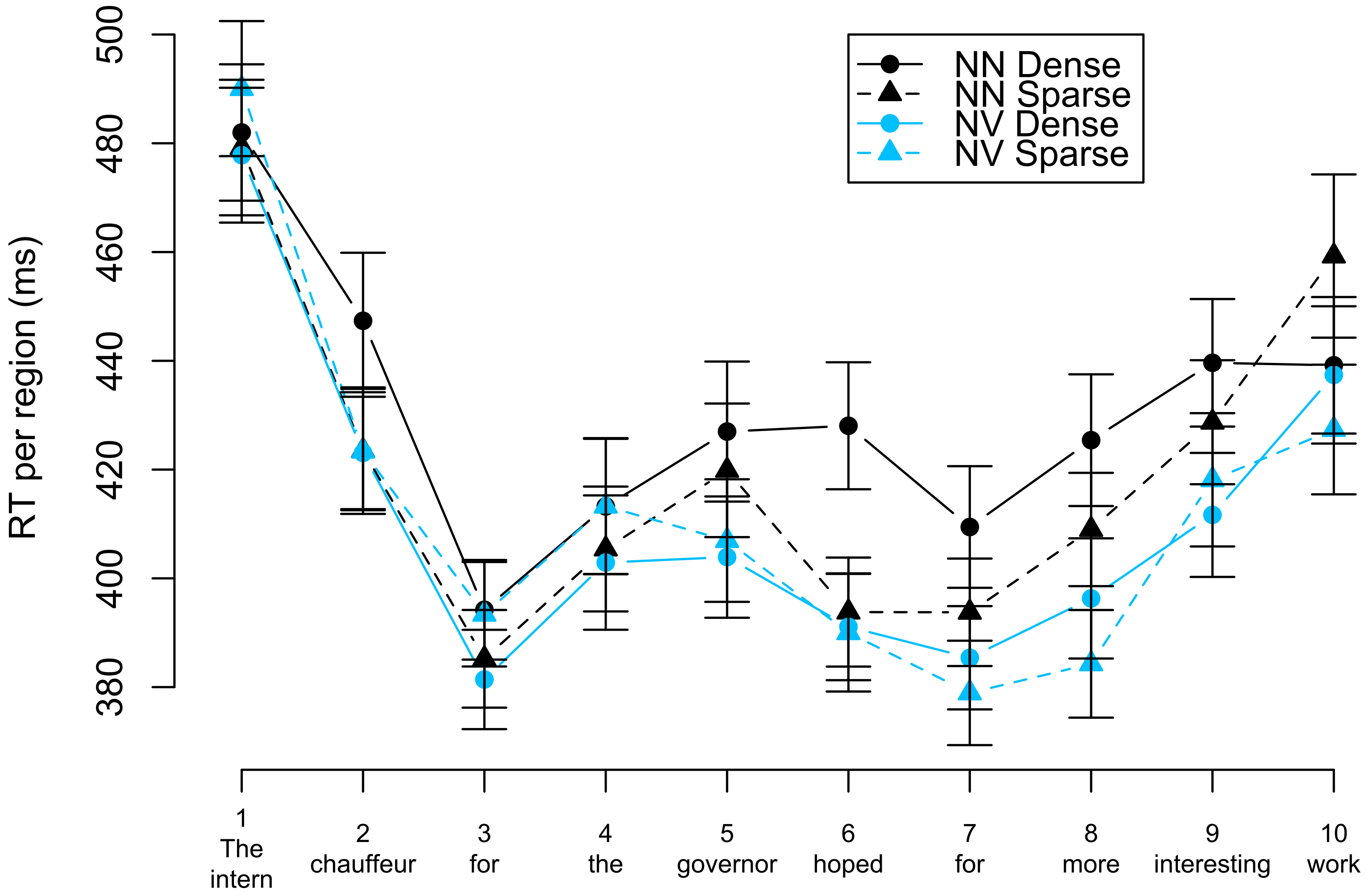
Some interns chauffeured for the governor but hoped for more interesting work.
[NV, "sparse" neighborhood]

(Bergen, Levy, & Gibson, 2012)

Results

- RT spike at disambiguating region for NN Dense



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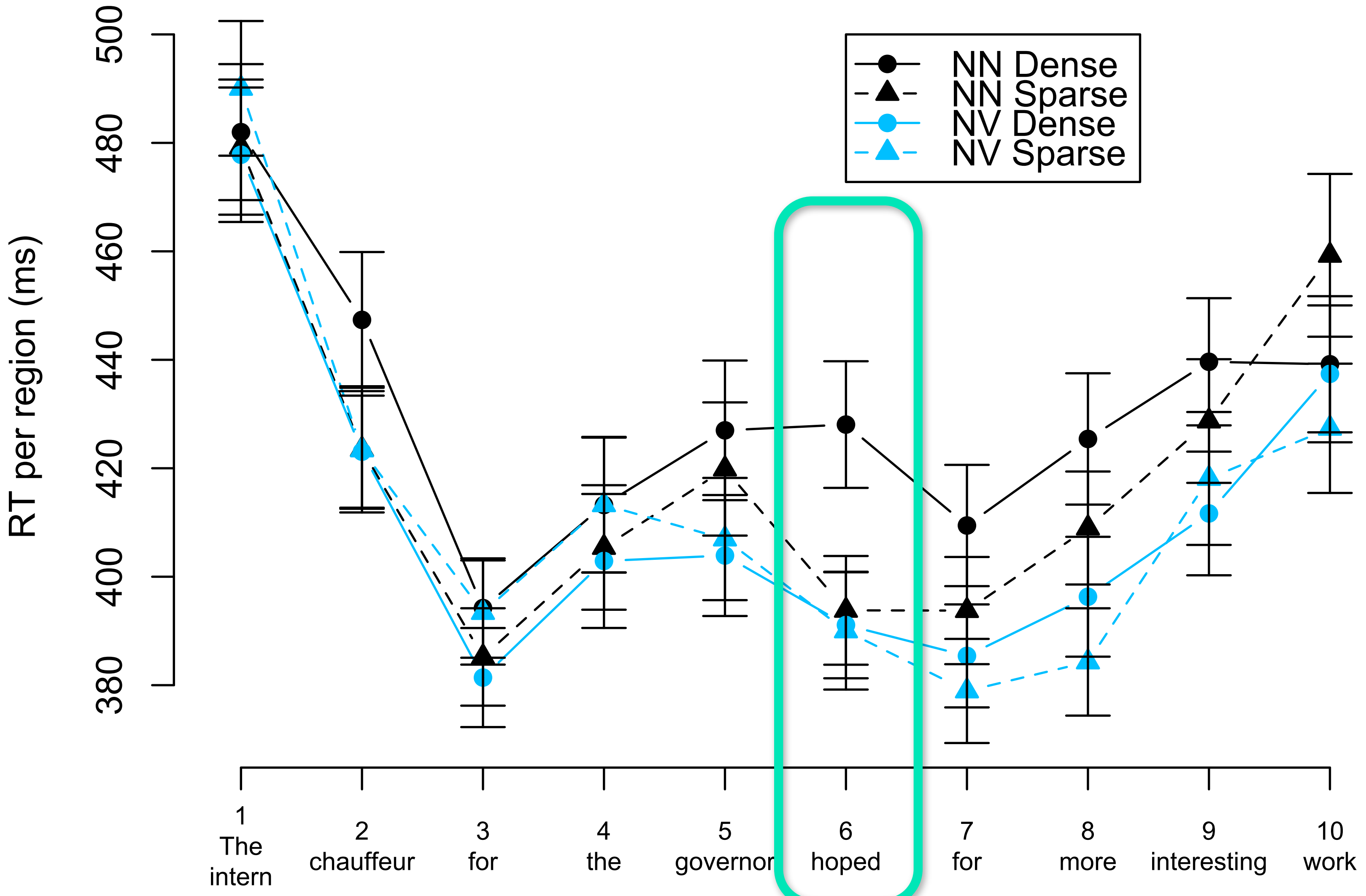

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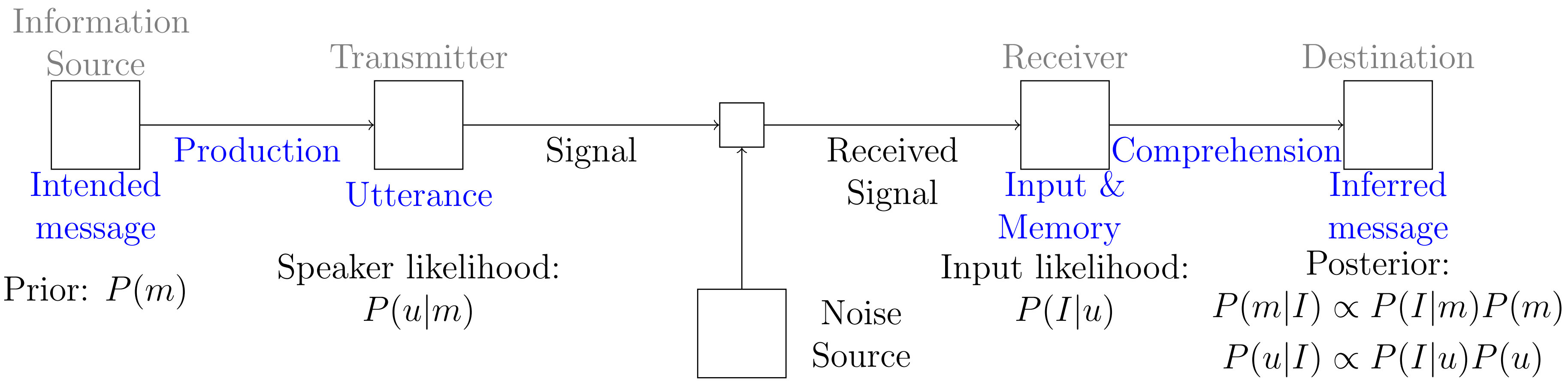
Noisy-channel theory of language processing



(Shannon, 1948; Levy, 2008; Gibson et al., 2013)

Simple question-answering

(Ferreira, 2003; Gibson et al., 2013)

Simple question-answering

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Did the woman lose something?

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Did the girl kick something? **No**

The businessman benefited from the tax law.

Did the tax law benefit from anything?

(Ferreira, 2003; Gibson et al., 2013)

Simple question-answering

`The woman lost the diamond.`

Did the woman lose something? **Yes**

`The ball kicked the girl.`

Did the girl kick something? **No**

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`The cook baked a cake Lucy.`

Was something baked for Lucy? **No** *(Yes?)*

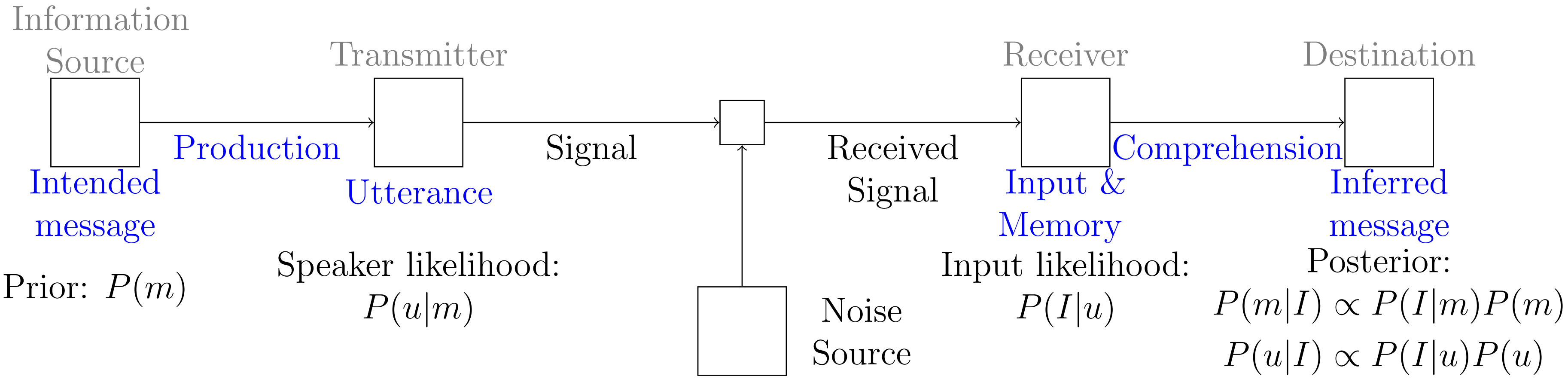
Over 2/3 of answers!

(Ferreira, 2003; Gibson et al., 2013)

Noisy-channel semantic interpretation?

`The cook baked a cake Lucy.`

Was something baked for Lucy?



Information Source

Intended message

Prior: $P(m)$

Production

Transmitter

Utterance

Speaker likelihood: $P(u|m)$

Signal

Noise Source

Received Signal

Receiver

Input & Memory

Input likelihood: $P(I|u)$

Comprehension

Destination

Inferred message

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$$P(m|I) \propto P(I|m)P(m)$$

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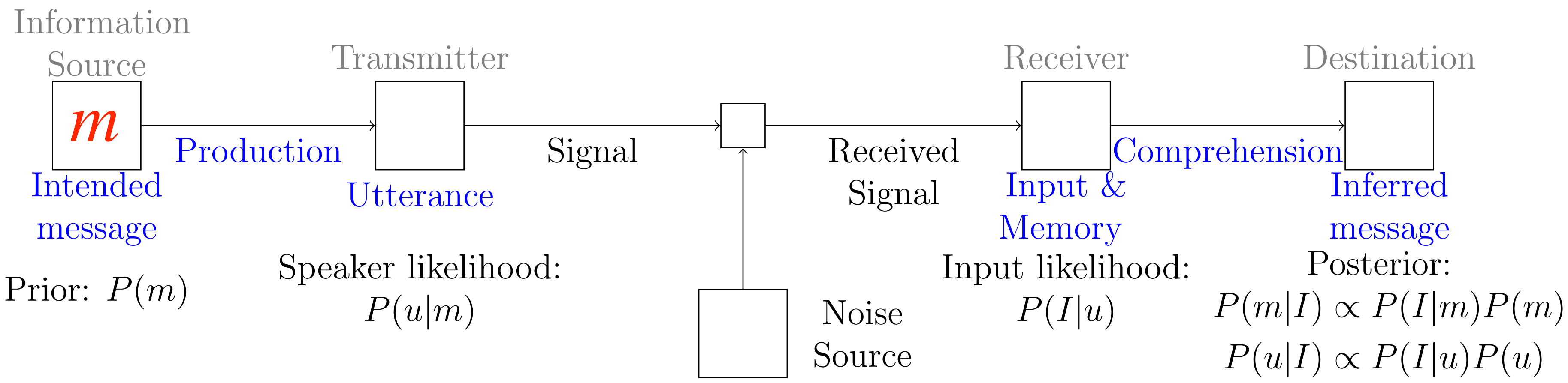

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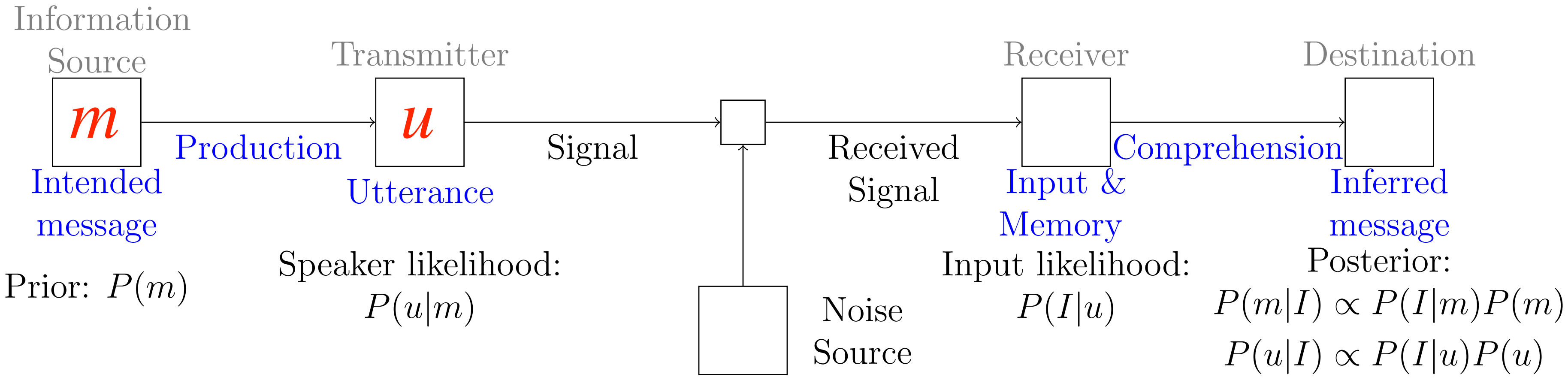

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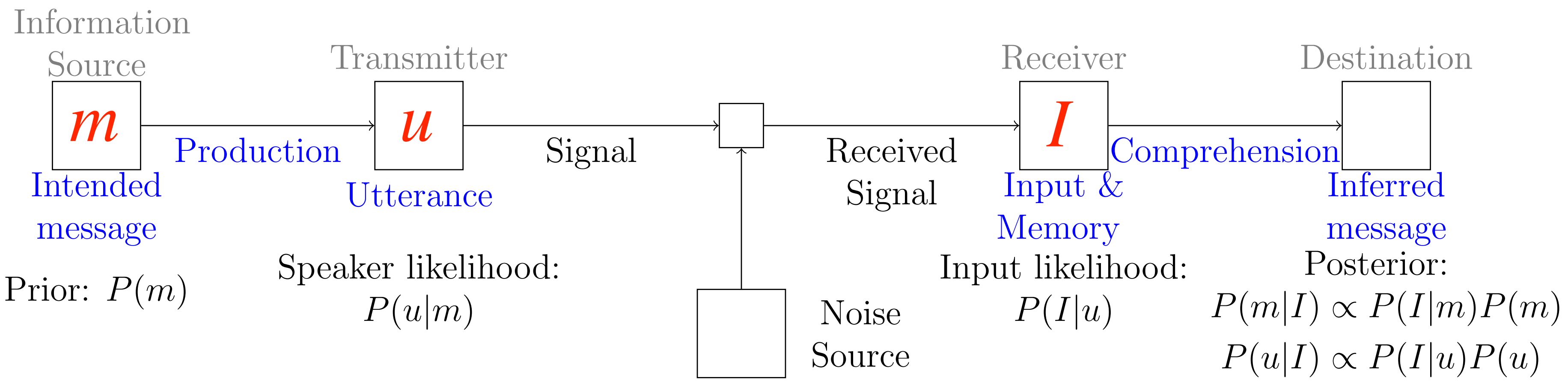

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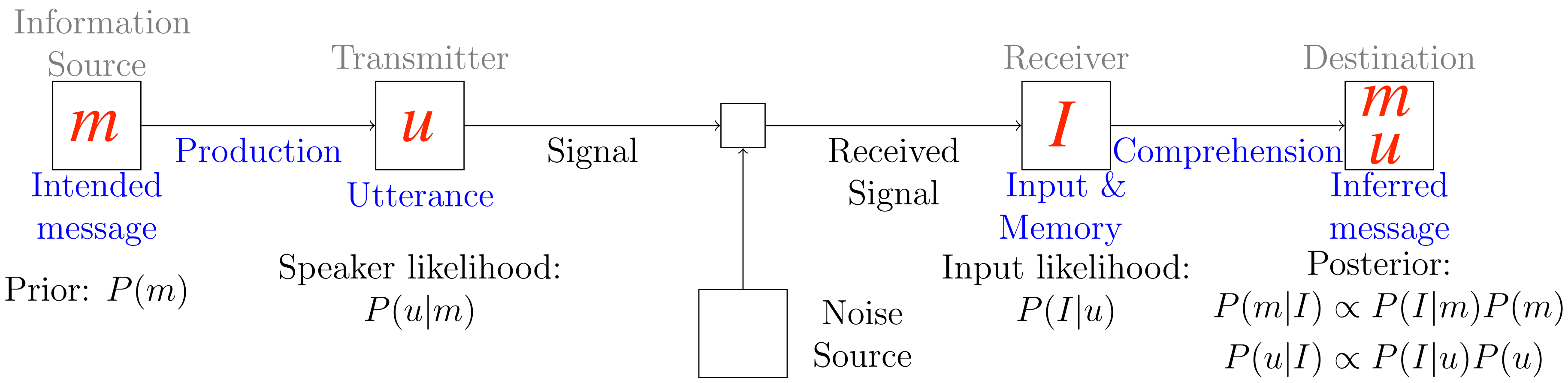

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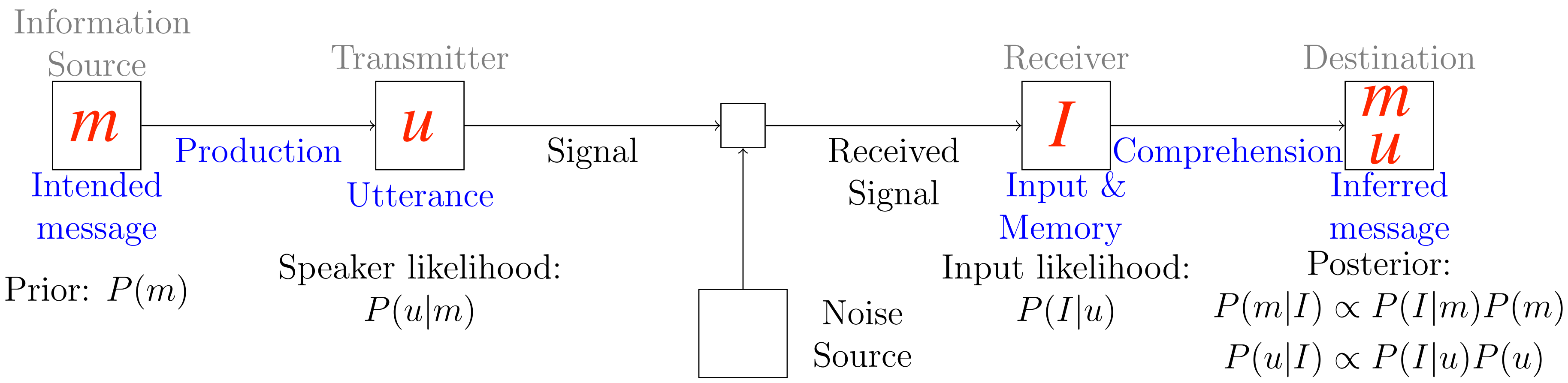

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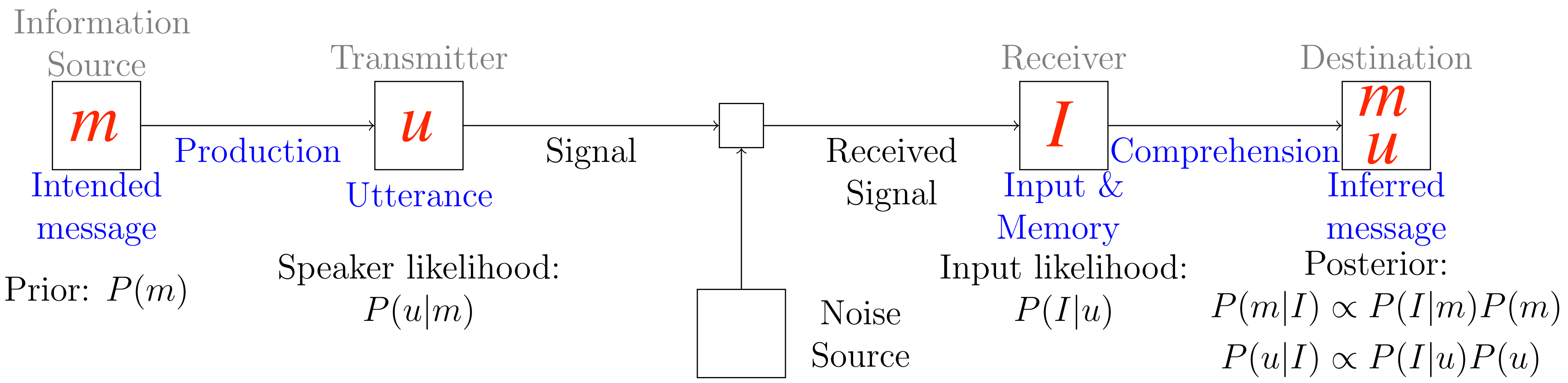

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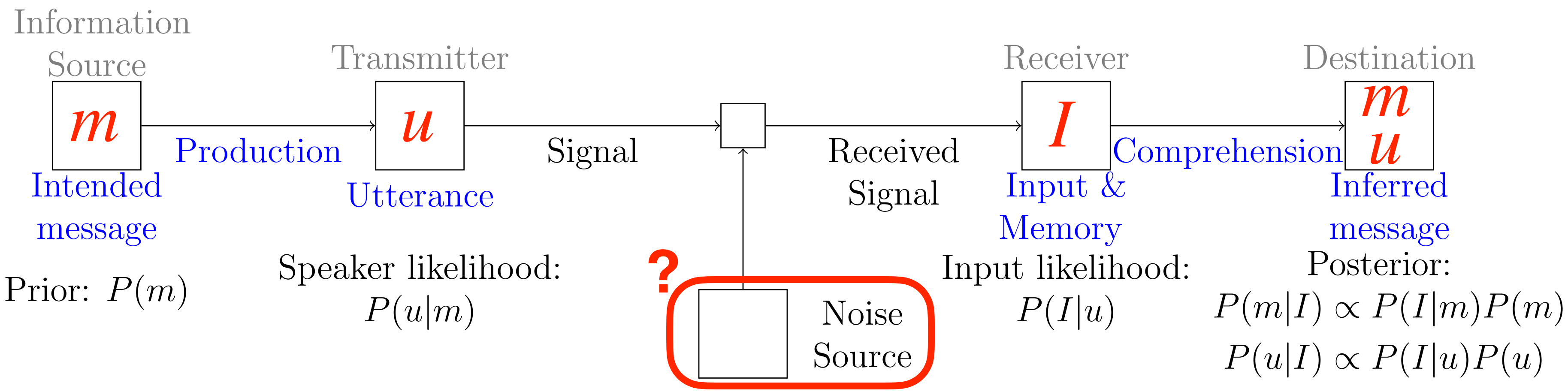

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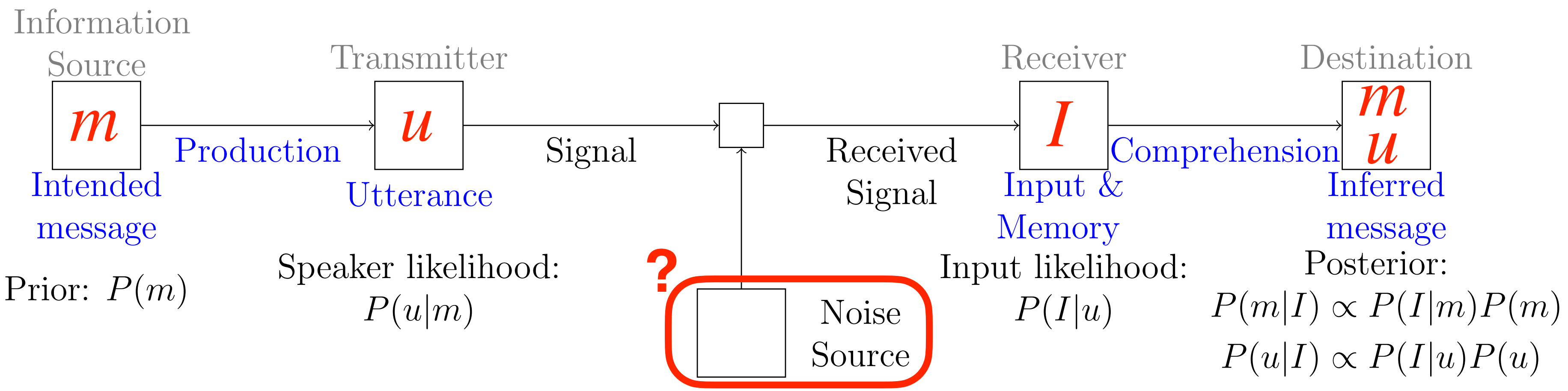

In two semantically plausible "neighbor" sentences, the answer is "yes":

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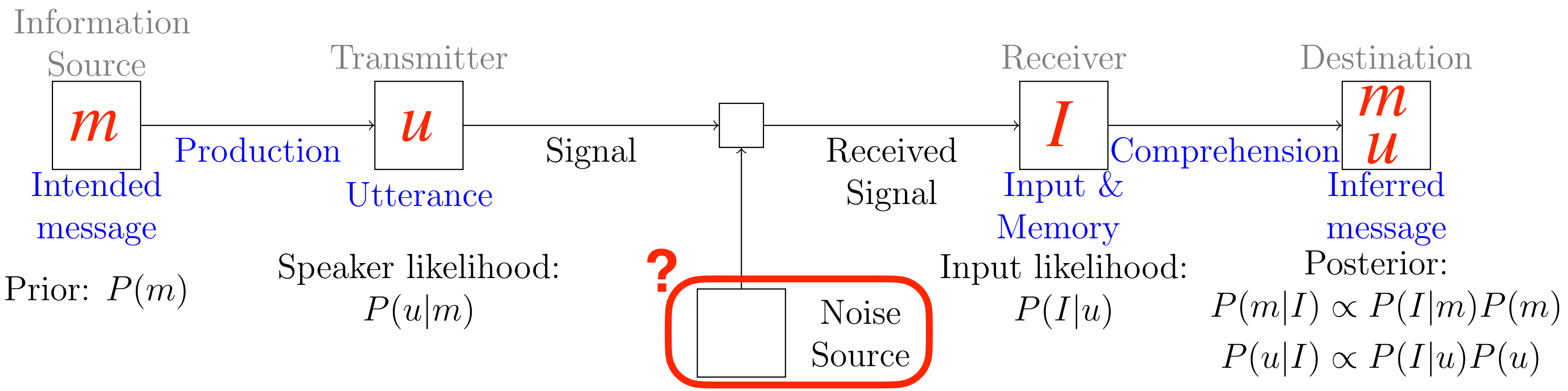
m? *Was something baked for Lucy?*



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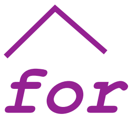

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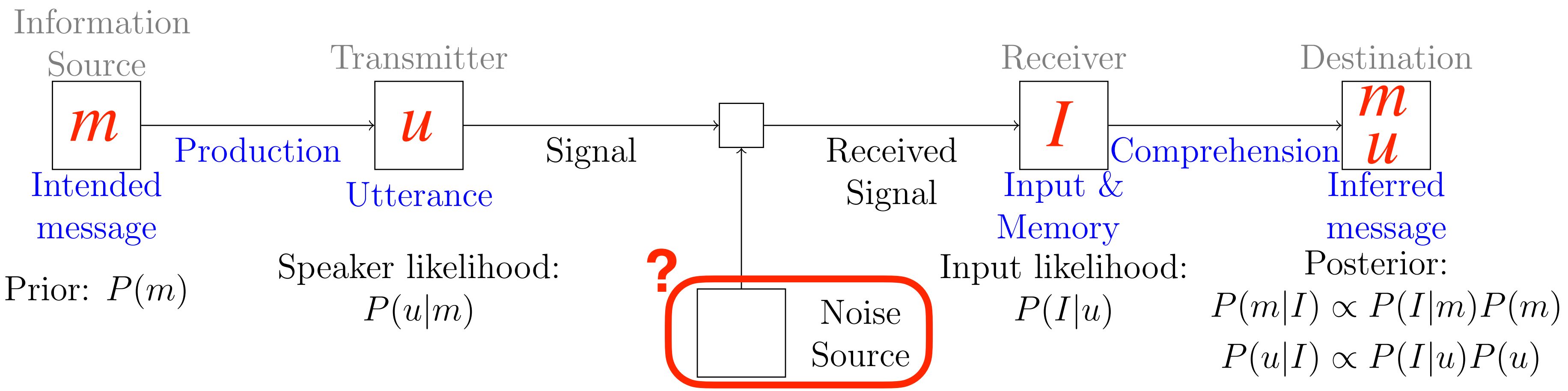
m? *Was something baked for Lucy?*



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The cook baked a cake $\hat{}$ Lucy.

for

Hypothesized noise operation: **deletion**

Noisy-channel semantic interpretation?

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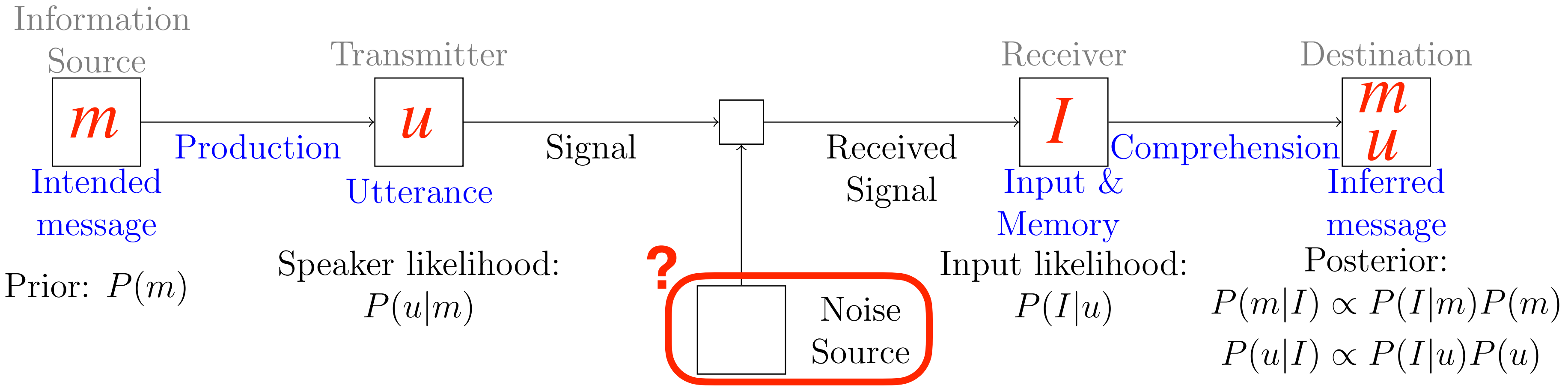

In two semantically plausible "neighbor" sentences, the answer is "yes":

`The cook baked a cake Lucy.`

`for`

Hypothesized noise operation: **deletion**

`The cook baked a cake Lucy.`

`Lucy a cake`

Noisy-channel semantic interpretation?

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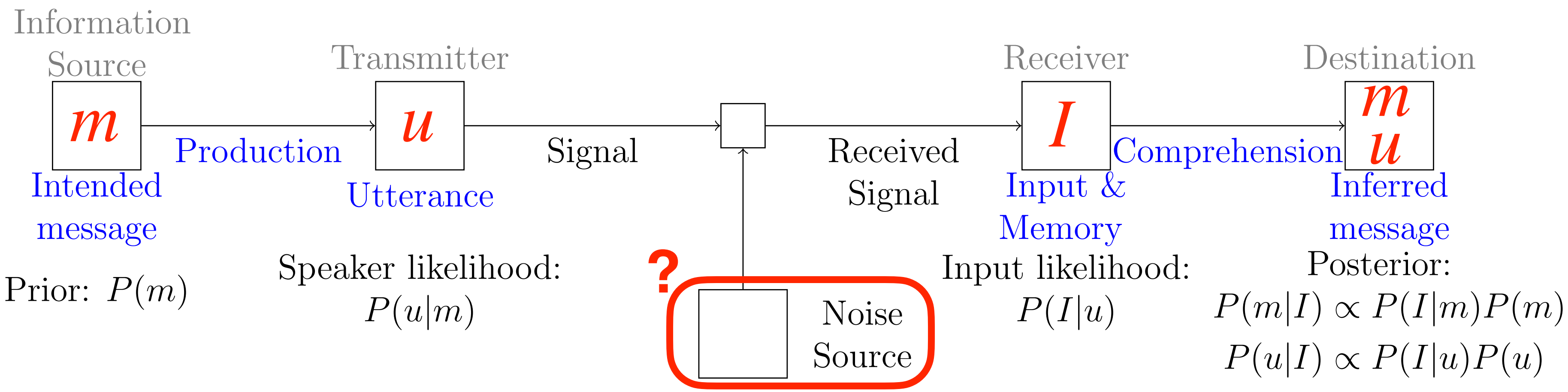

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m

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Prior: $P(m)$

Production

Transmitter

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Signal

?

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Received Signal

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In two semantically plausible "neighbor" sentences, the answer is "yes":

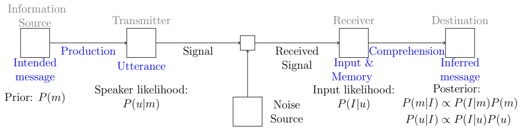
`The cook baked a cake ^ Lucy.`

Hypothesized noise operation: **deletion** ***`for`***

`The cook baked a cake Lucy.`

Hypothesized noise operation: **exchange** ***`Lucy a cake`***

Predictions for implausible sentences



$$P(m \mid I) \propto \underset{\text{Noise operation}}{\underline{P(I \mid m)}}\,\underset{\text{Plausibility}}{\underline{P(m)}}$$

(Gibson et al., 2013)

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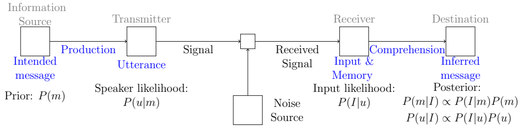

$$P(m|I) \propto \underline{P(I|m)}\,\underline{P(m)}$$

Noise operation Plausibility

Non-literal interpretation?

	Double Object/Benefactive-*for* alternation	***Deletion/ insertion***	***Exchange***
Implausible	**`The cook baked a cake Lucy.`**	Yes	Yes
	`The cook baked Lucy for a cake.`	Yes	Yes

(Gibson et al., 2013)

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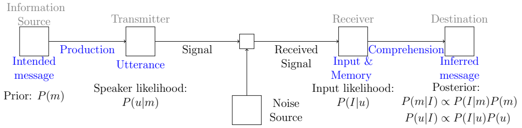

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	Double Object/Benefactive-*for* alternation	***Non-literal interpretation?***	
		Deletion/ insertion	***Exchange***
Implausible	`The cook baked a cake Lucy.`	Yes	Yes
	`The cook baked Lucy for a cake.`	Yes	Yes
Plausible	`The cook baked Lucy a cake.`	No	No
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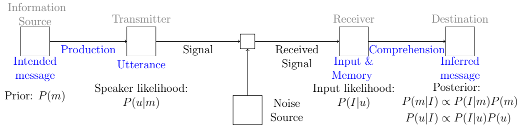
(Gibson et al., 2013)

Predictions for implausible sentences



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		Non-literal interpretation?	
		Deletion/ insertion	***Exchange***
	Double Object/Benefactive-*for* alternation		
Implausible	**`The cook baked a cake Lucy.`**	Yes	Yes
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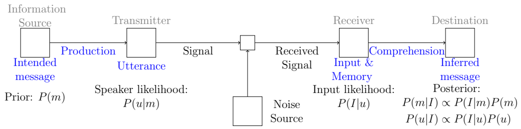
	`The cook baked a cake for Lucy.`	No	No
	Active/Passive alternation		
Implausible	**`The ball kicked the girl.`**	No	Yes
	`The girl was kicked by the ball.`	No	Yes

(Gibson et al., 2013)

Predictions for implausible sentences



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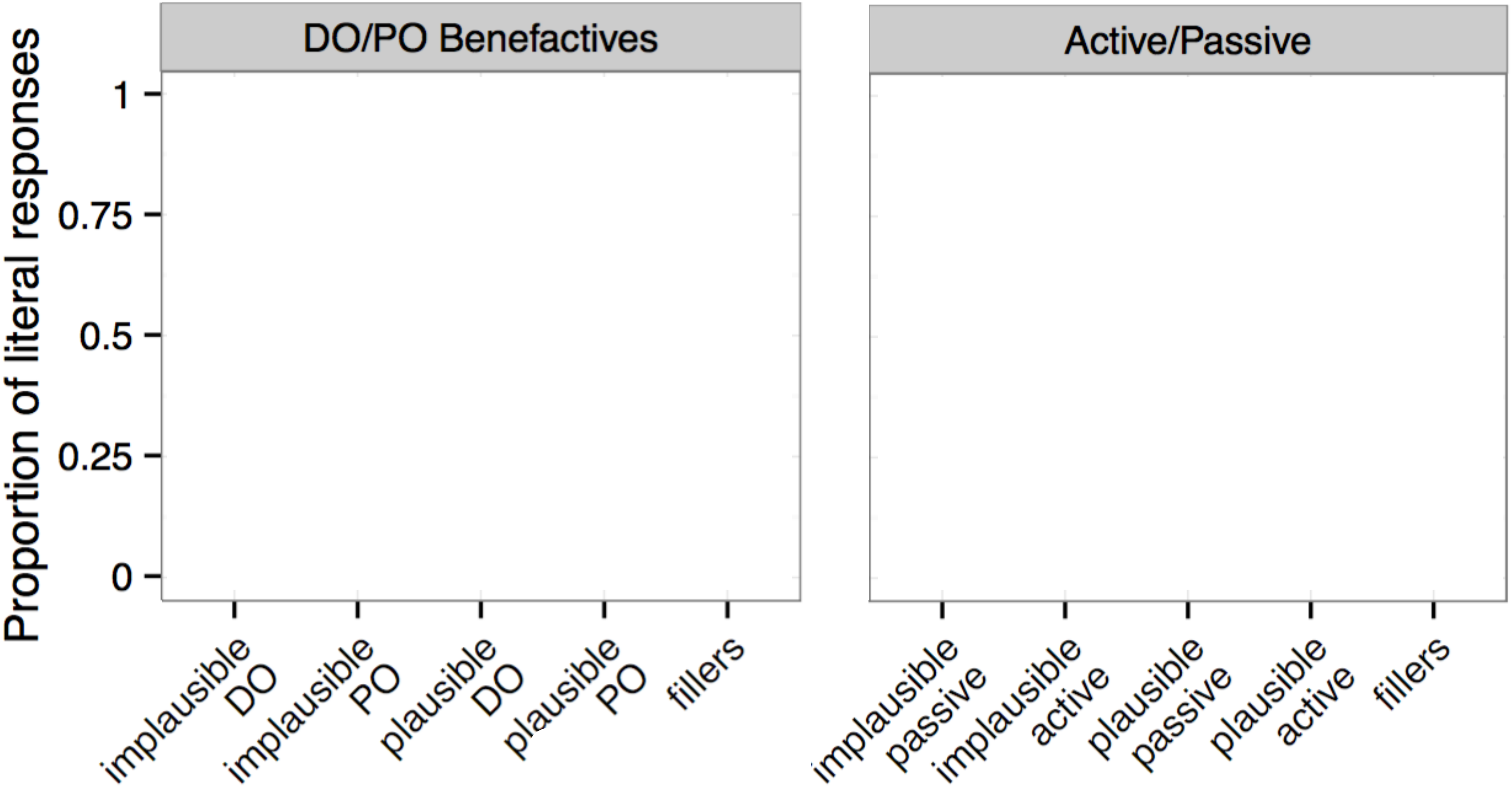
(Gibson et al., 2013)

Literal vs. non-literal interpretation rates

Non-literal interpretations for implausible sentences?

Insertion/Deletion	*Exchange*	*Insertion/Deletion*	*Exchange*
Yes	Yes	No	Yes



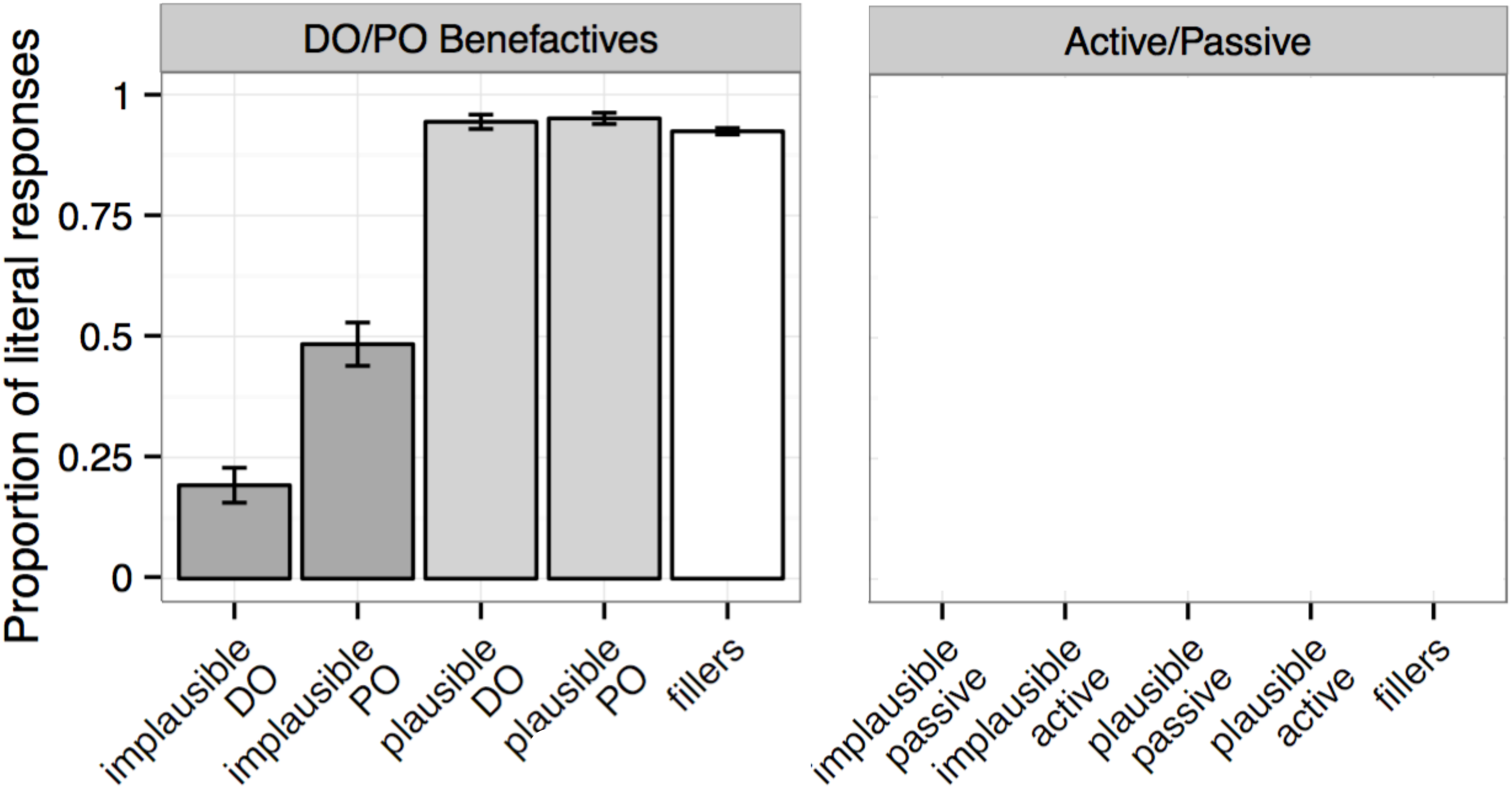
(Gibson et al., 2013; data from replication by Poppels & Levy, 2016)

Literal vs. non-literal interpretation rates

Non-literal interpretations for implausible sentences?

Insertion/Deletion ***Exchange*** ***Insertion/Deletion*** ***Exchange***

Yes **Yes** **No** **Yes**



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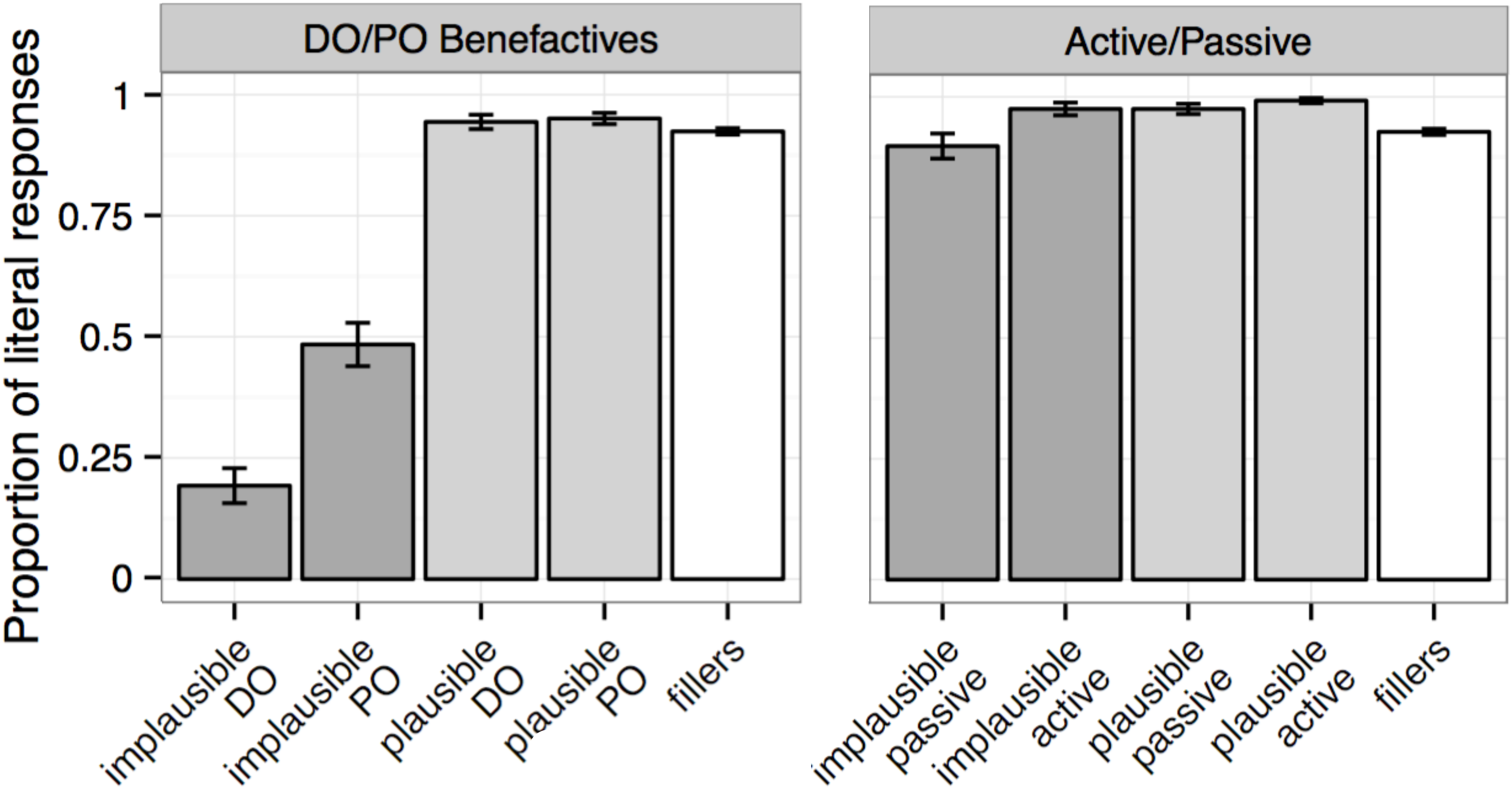
Literal vs. non-literal interpretation rates

Non-literal interpretations for implausible sentences?

Insertion/Deletion | ***Exchange*** | ***Insertion/Deletion*** | ***Exchange***

Yes | **Yes** | **No** | **Yes**



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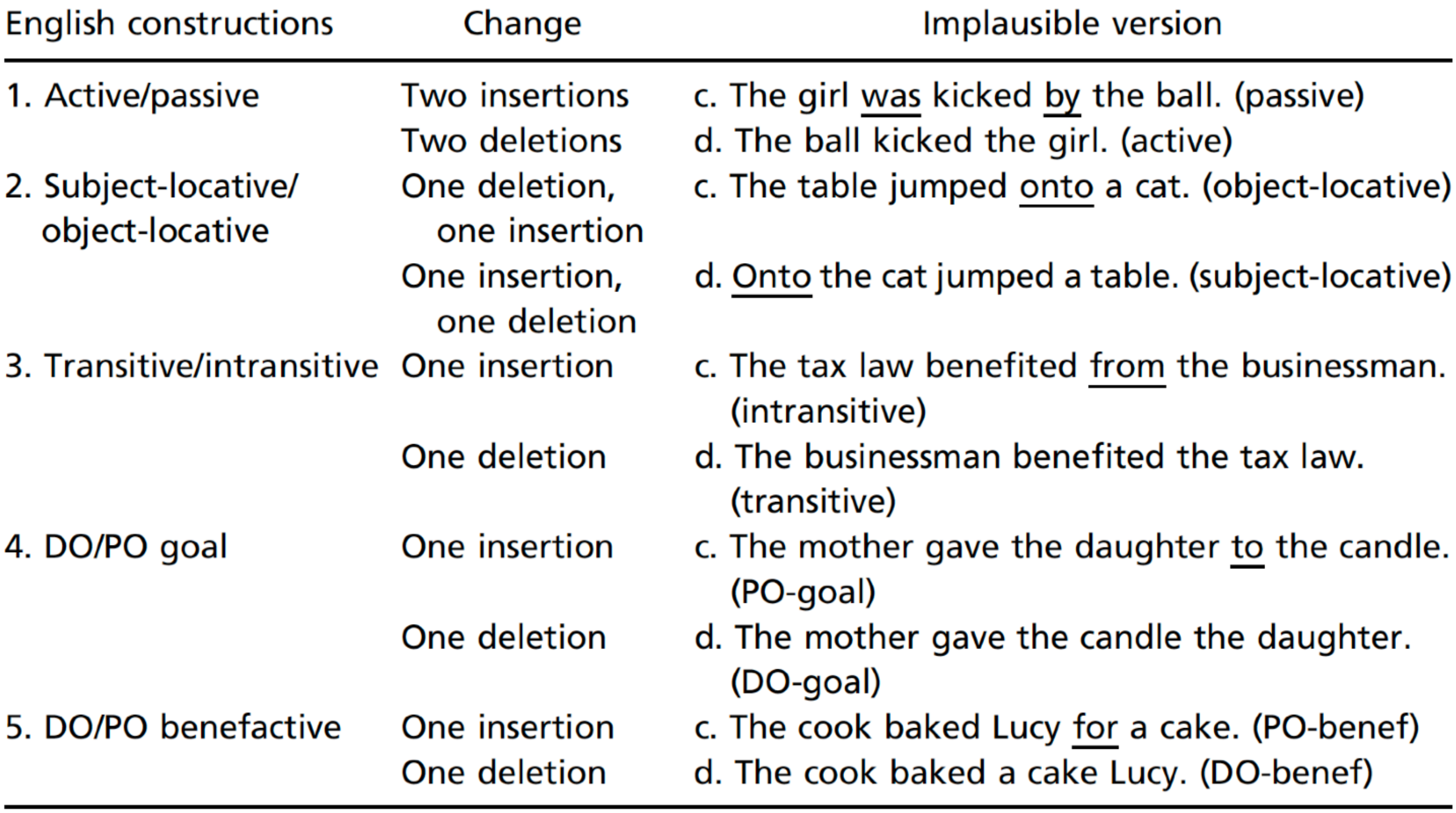
Five alternations in an insertion/deletion model



English constructions	Change	Implausible version
1. Active/passive	Two insertions	c. The girl was kicked by the ball. (passive)
	Two deletions	d. The ball kicked the girl. (active)
2. Subject-locative/ object-locative	One deletion, one insertion	c. The table jumped onto a cat. (object-locative)
	One insertion, one deletion	d. Onto the cat jumped a table. (subject-locative)
3. Transitive/intransitive	One insertion	c. The tax law benefited from the businessman. (intransitive)
	One deletion	d. The businessman benefited the tax law. (transitive)
4. DO/PO goal	One insertion	c. The mother gave the daughter to the candle. (PO-goal)
	One deletion	d. The mother gave the candle the daughter. (DO-goal)
5. DO/PO benefactive	One insertion	c. The cook baked Lucy for a cake. (PO-benef)
	One deletion	d. The cook baked a cake Lucy. (DO-benef)

c=inferred insertion   d=inferred deletion

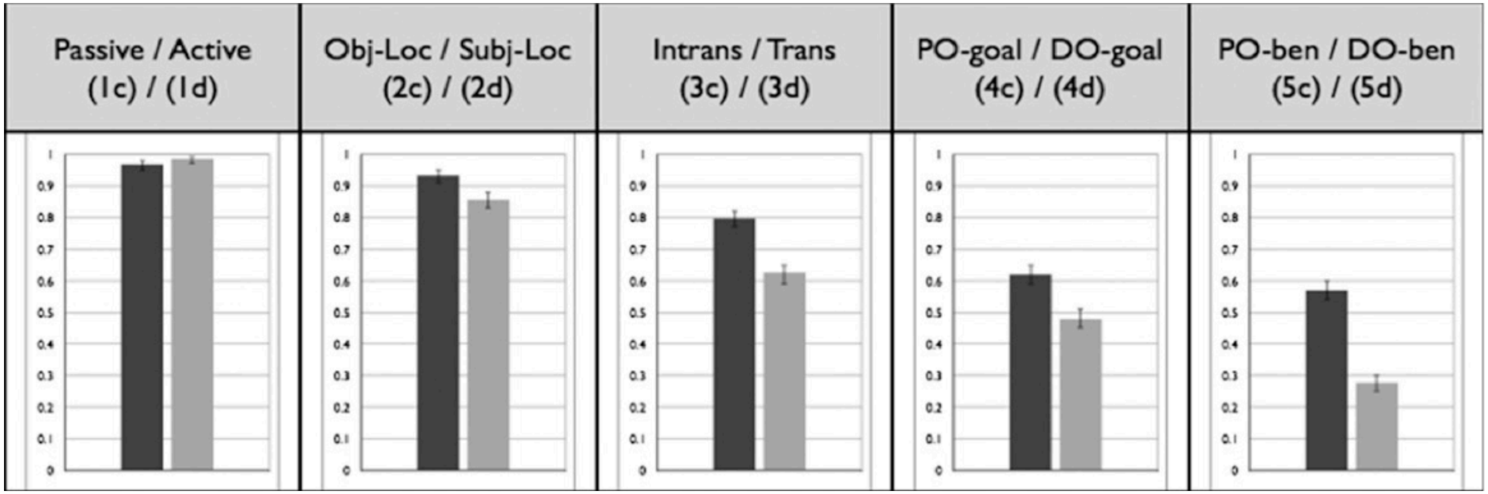
(Gibson et al., 2013; plausible versions not shown here)

Five alternations in an insertion/deletion model

$$P(m \mid I) \propto \underbrace{P(I \mid m)}_{\text{Noise operation}}\underbrace{P(m)}_{\text{Plausibility}}$$

Base experiment

20 experimental items, 60 plausible & grammatically normal fillers → 10/80 implausible trials



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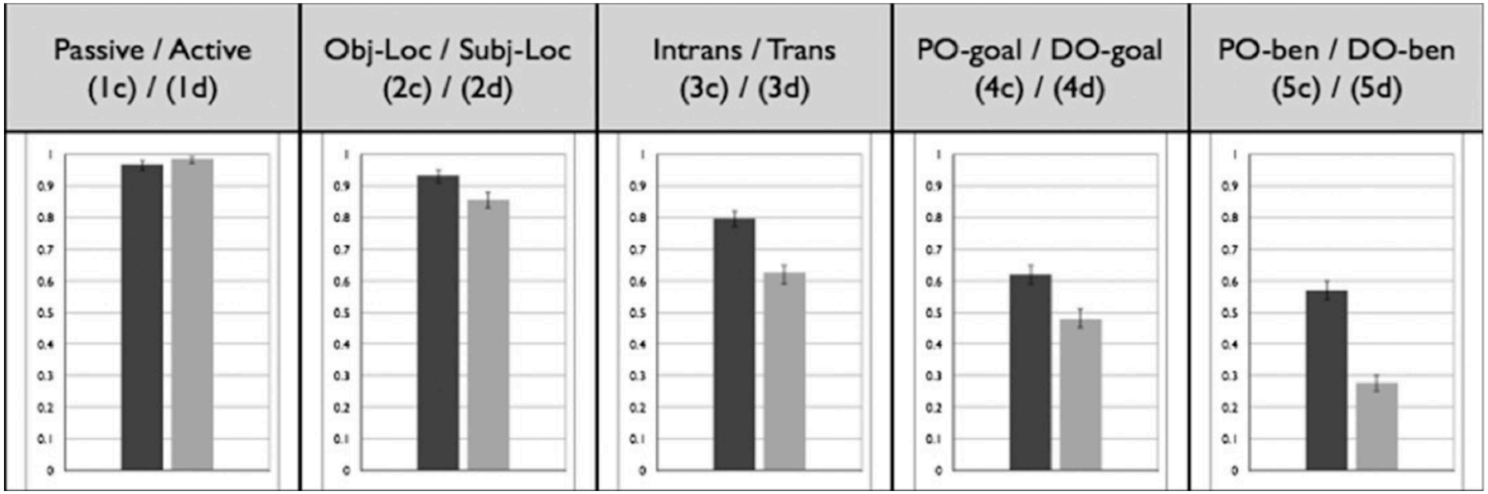

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Fillers with syntactic errors

"A legislator lied to the consultant a new bill"

"A bystander was the fireman by rescued in the nick of time"

(Gibson et al., 2013)

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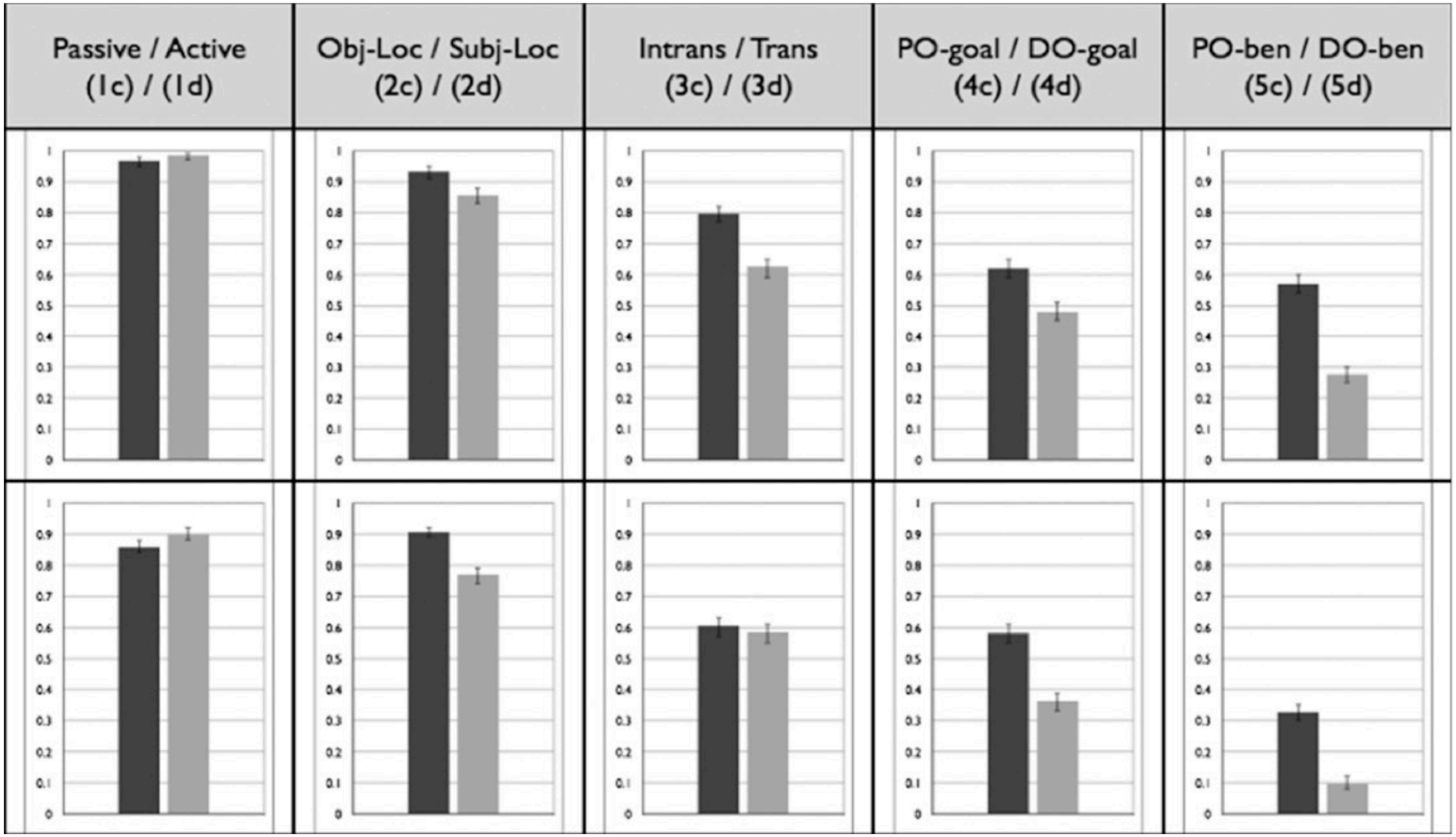

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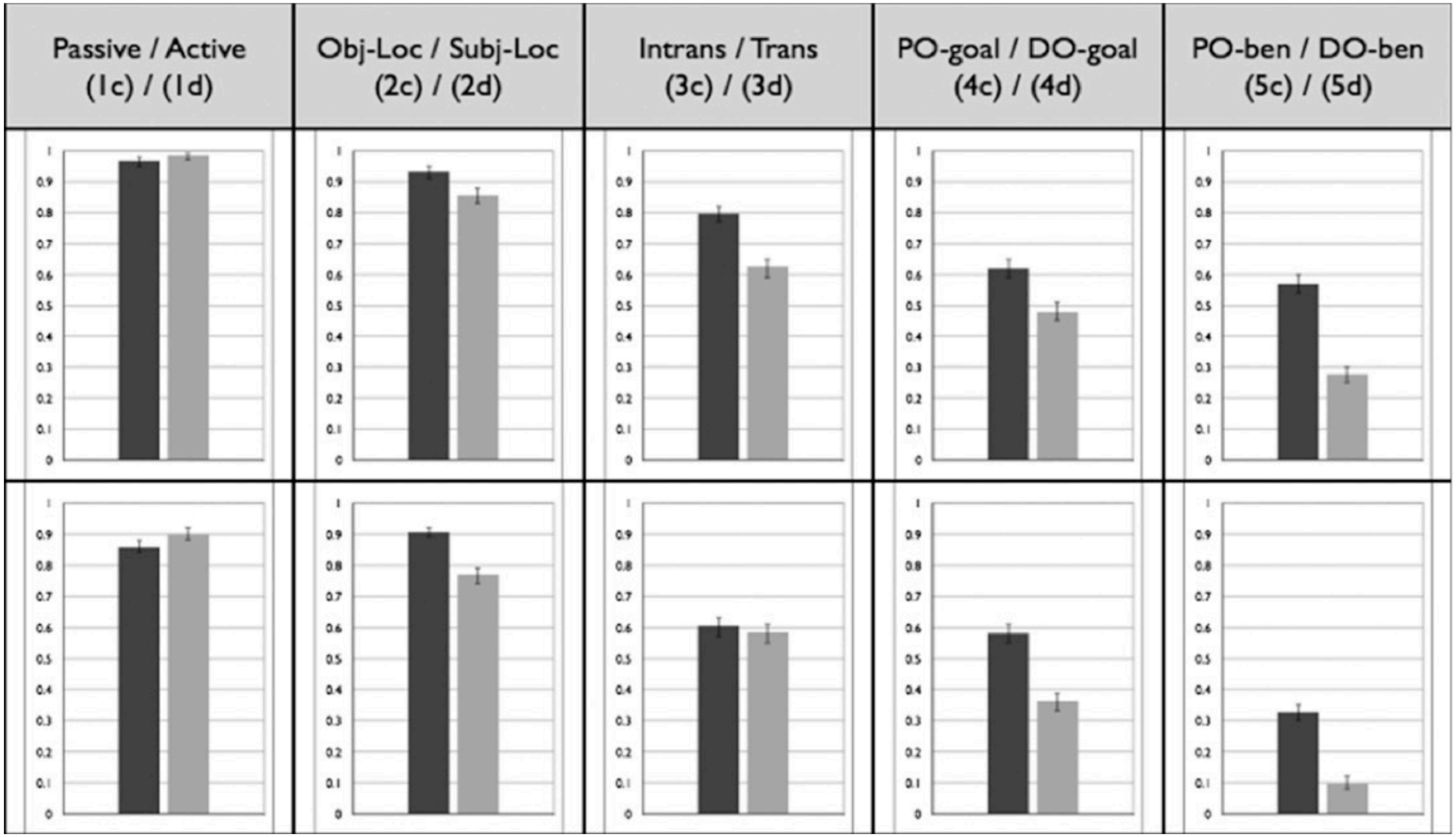
Noise operation

Plausibility



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Many implausible trials

100 experimental items, 60 plausible & grammatically normal fillers → 50/160 implausible trials

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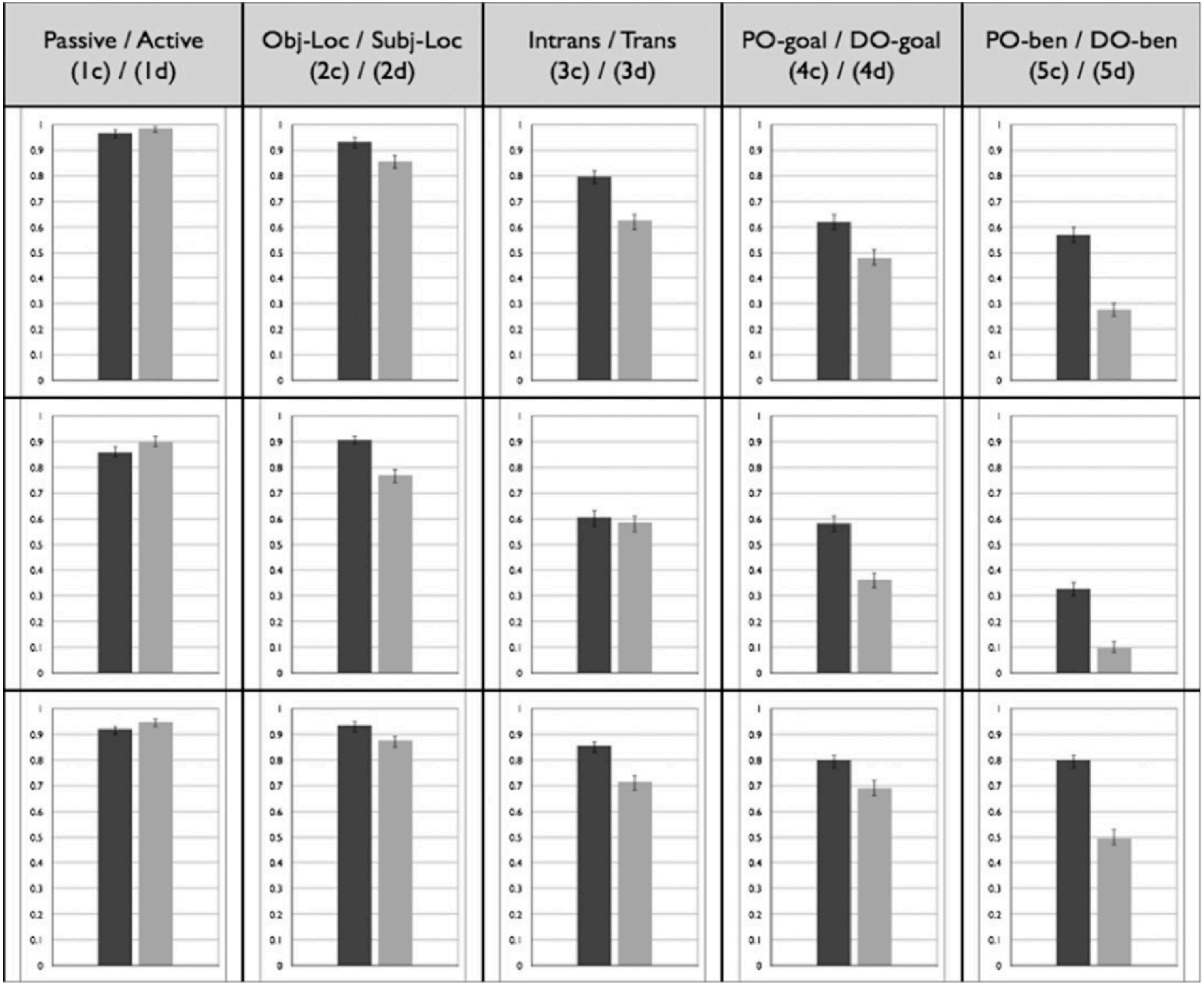

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Inferring deletions versus insertions

$$P(m \mid I) \propto \underbrace{P(I \mid m)}_{\text{Noise operation}}\underbrace{P(m)}_{\text{Plausibility}}$$

The cook baked a cake for Lucy.

↓

The cook baked a cake Lucy.

The cook baked Lucy a cake.

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Inferring deletions versus insertions

$$P(m \mid I) \propto \underbrace{P(I \mid m)}_{\text{Noise operation}}\underbrace{P(m)}_{\text{Plausibility}}$$

1 Delete

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Inferring deletions versus insertions

$$P(m \mid I) \propto \underbrace{P(I \mid m)}_{\text{Noise operation}}\underbrace{P(m)}_{\text{Plausibility}}$$

① Delete ② Choose deletion location

The cook baked a cake ~~for~~ Lucy.

↓

The cook baked a cake Lucy.

The cook baked Lucy a cake.

↓

The cook baked Lucy for a cake.

Inferring deletions versus insertions

$$P(m\,|\,I) \propto \underbrace{P(I\,|\,m)}_{\text{Noise operation}}\underbrace{P(m)}_{\text{Plausibility}}$$

1 Delete

2 Choose deletion location

`The cook baked a cake ~~for~~ Lucy.`

↓

`The cook baked a cake Lucy.`

1 Insert

`The cook baked Lucy a cake.`

↓

`The cook baked Lucy for a cake.`

Inferring deletions versus insertions

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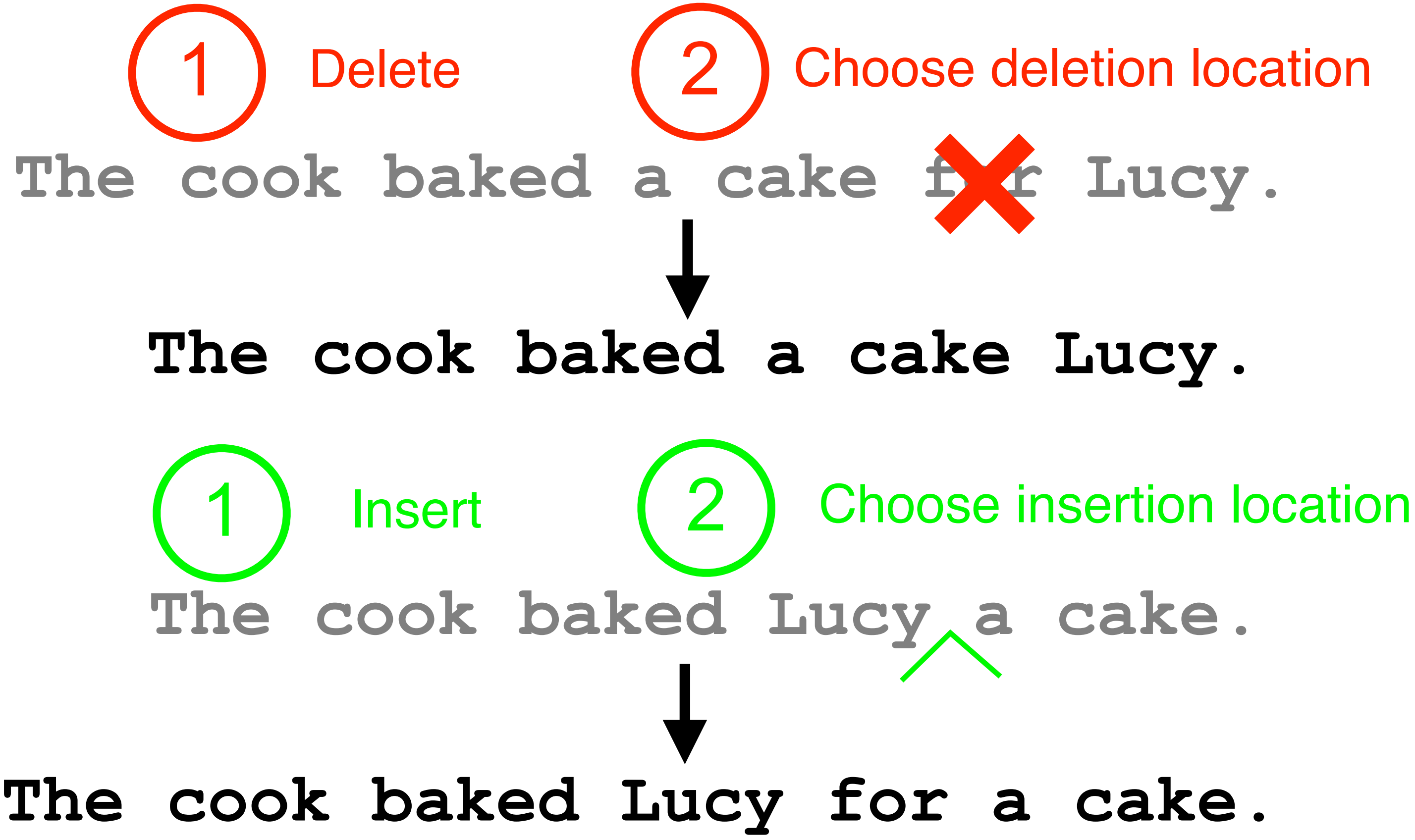

1 Delete

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The cook baked a cake ~~for~~ Lucy.

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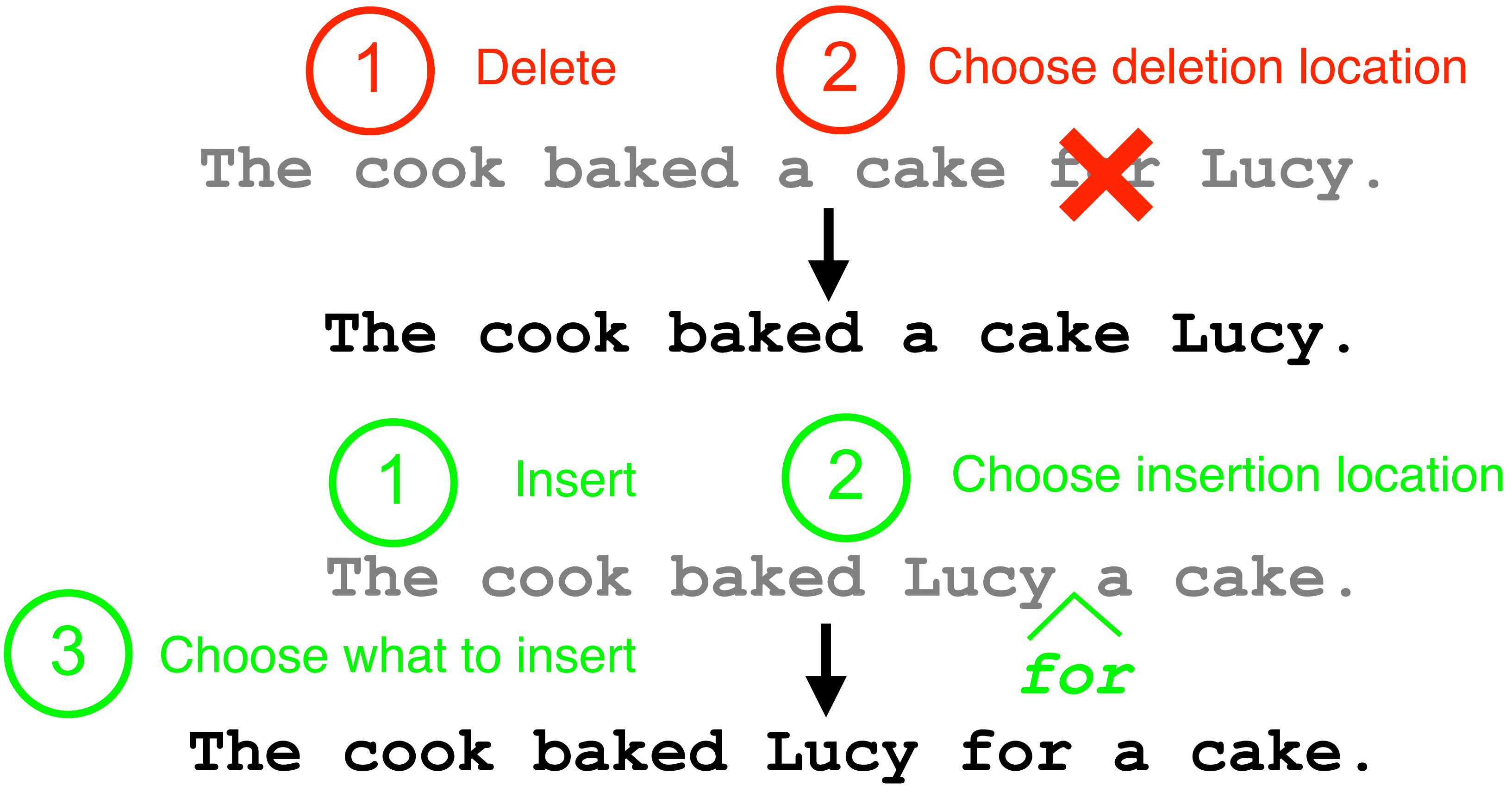

1 Delete

2 Choose deletion location

The cook baked a cake ~~for~~ Lucy.

The cook baked a cake Lucy.

1 Insert

2 Choose insertion location

The cook baked Lucy a cake.

3 Choose what to insert

for

The cook baked Lucy for a cake.

Inferring deletions versus insertions

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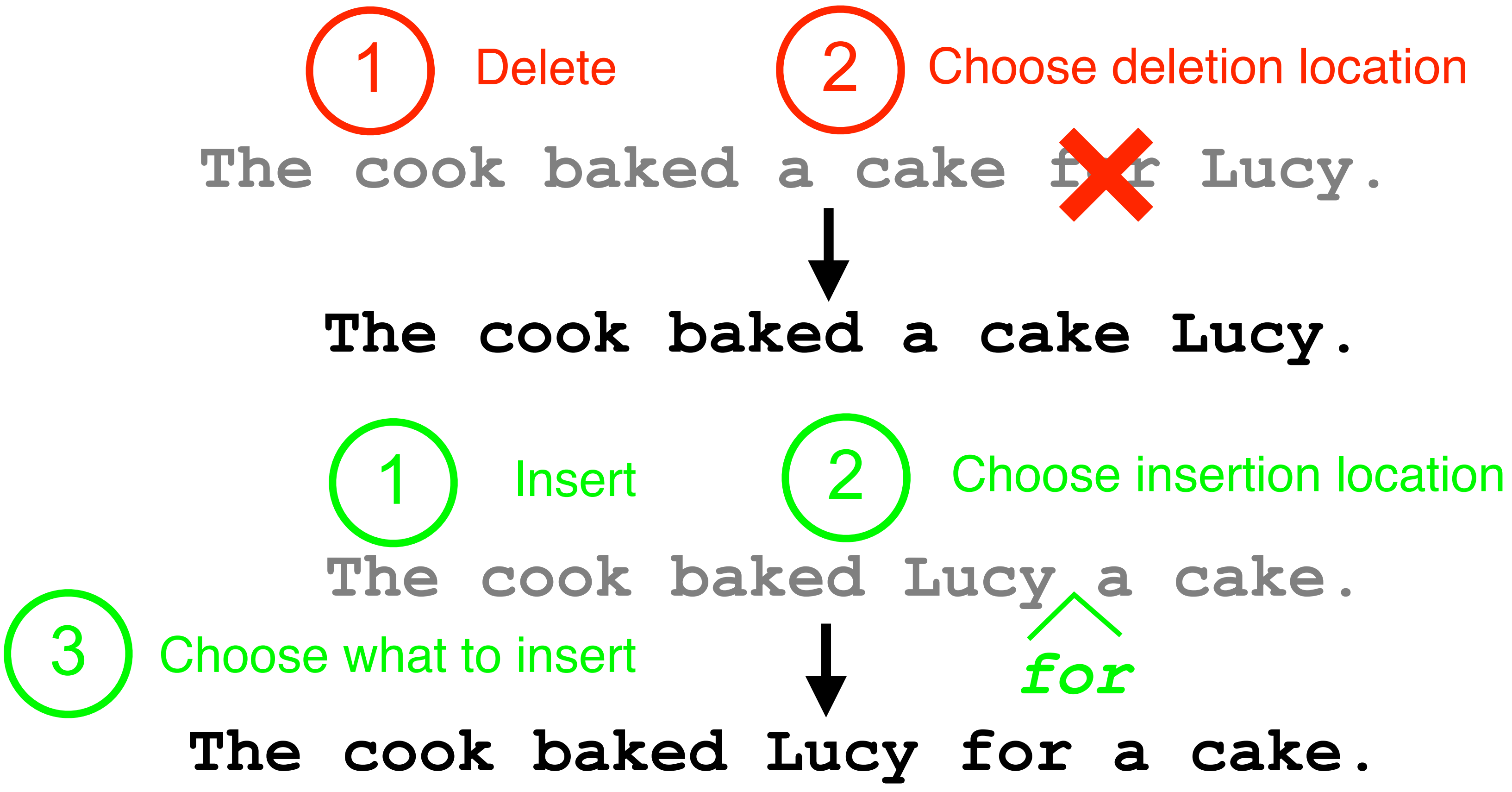

1 Delete

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The cook baked a cake Lucy.

1 Insert

2 Choose insertion location

The cook baked Lucy a cake.

3 Choose what to insert

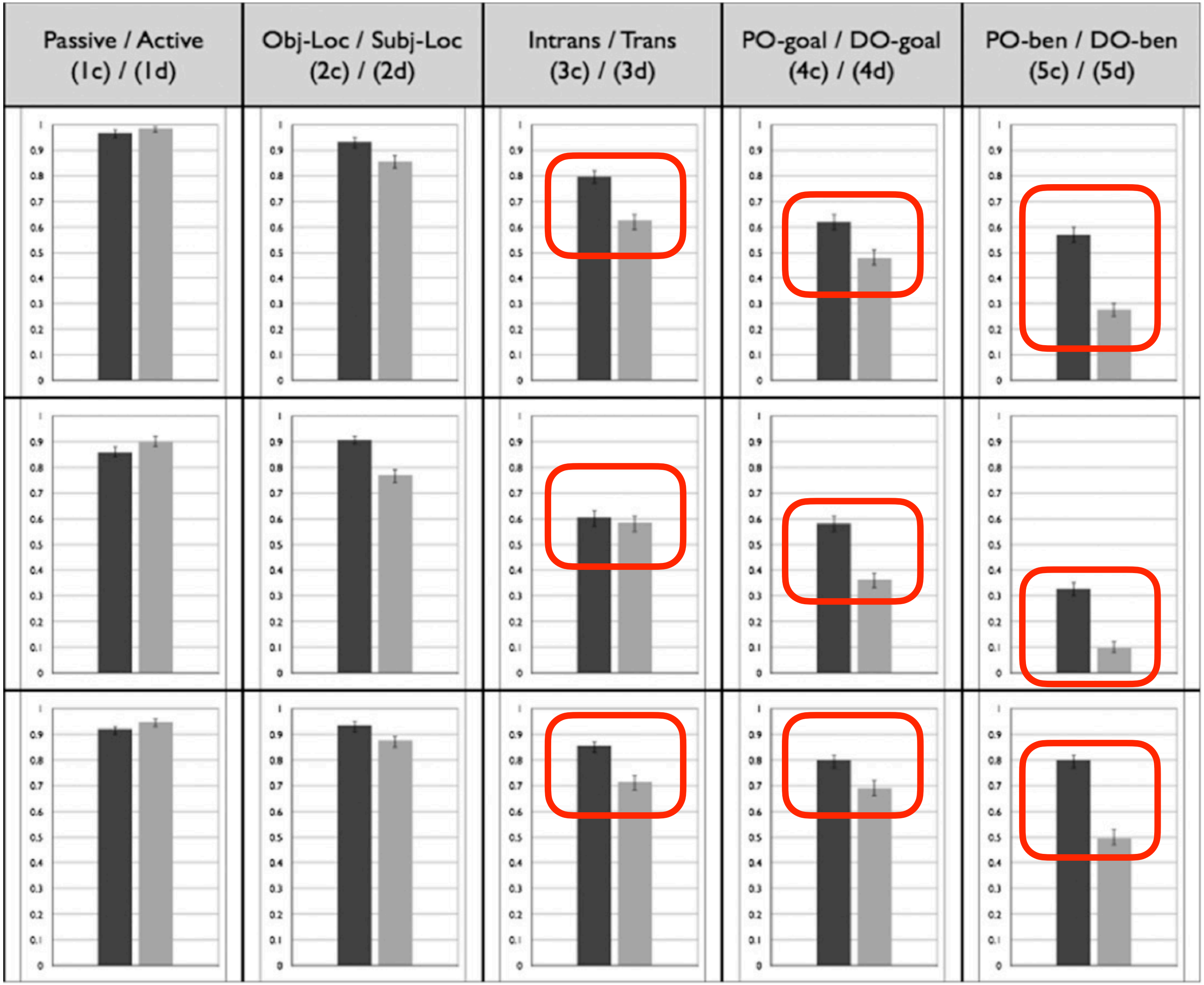
for

The cook baked Lucy for a cake.

Noisy-channel prediction: inferring deletions should be intrinsically easier than inferring insertions!

Five alternations in an insertion/deletion model

$$P(m\,|\,I) \propto \underbrace{P(I\,|\,m)}_{\text{Noise operation}}\underbrace{P(m)}_{\text{Plausibility}}$$



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In the real world (2008)

I’m not going to solely blame all of man’s activities on changes in climate.

Sarah Palin (images credit Gage Skidmore)

(Credit to Colin Phillips for bringing these examples to light)

In the real world (2008)

I’m not going to solely blame all of man’s activities on changes in climate.

Sarah Palin (images credit Gage Skidmore)

I'm not one to attribute every activity of man to climate change.

(Credit to Colin Phillips for bringing these examples to light)

Corpora of speech errors

Anticipations	John dropped his cuff of coffee reek long race
Perseverations	John gave the goy (=gave the boy) Spanish speaping people
Exchanges	teep a cape (=keep a tape) the nipper is zarrow Fancy getting your model renosed (=nose remodeled)

(Fromkin, 1971; Garrett, 1975, inter alia)

Revisiting the possibility of exchanges

This is a problem that I need to talk about Joe with.

(Poppels & Levy 2016)

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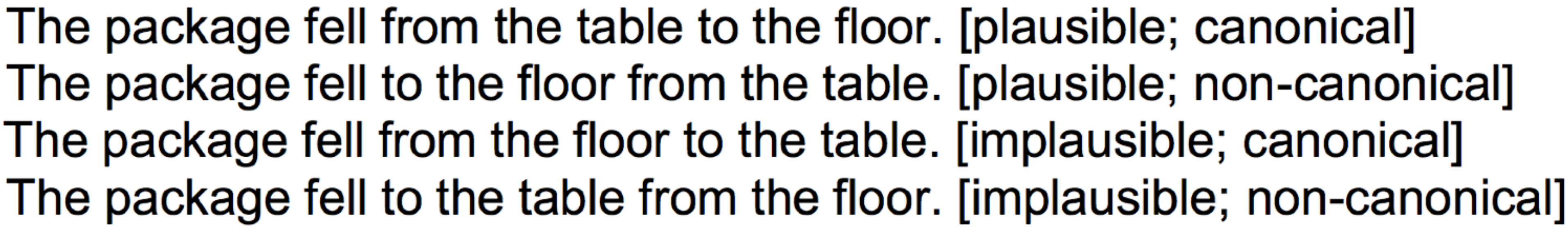

The package fell from the table to the floor. [plausible; canonical]
The package fell to the floor from the table. [plausible; non-canonical]
The package fell from the floor to the table. [implausible; canonical]
The package fell to the table from the floor. [implausible; non-canonical]

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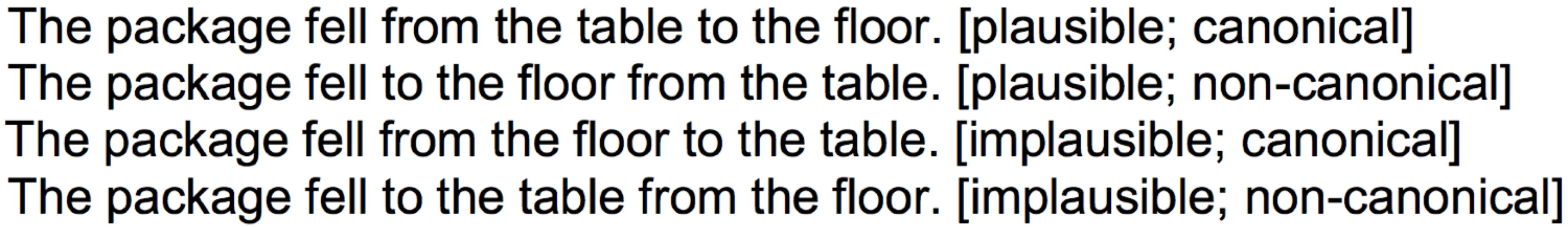

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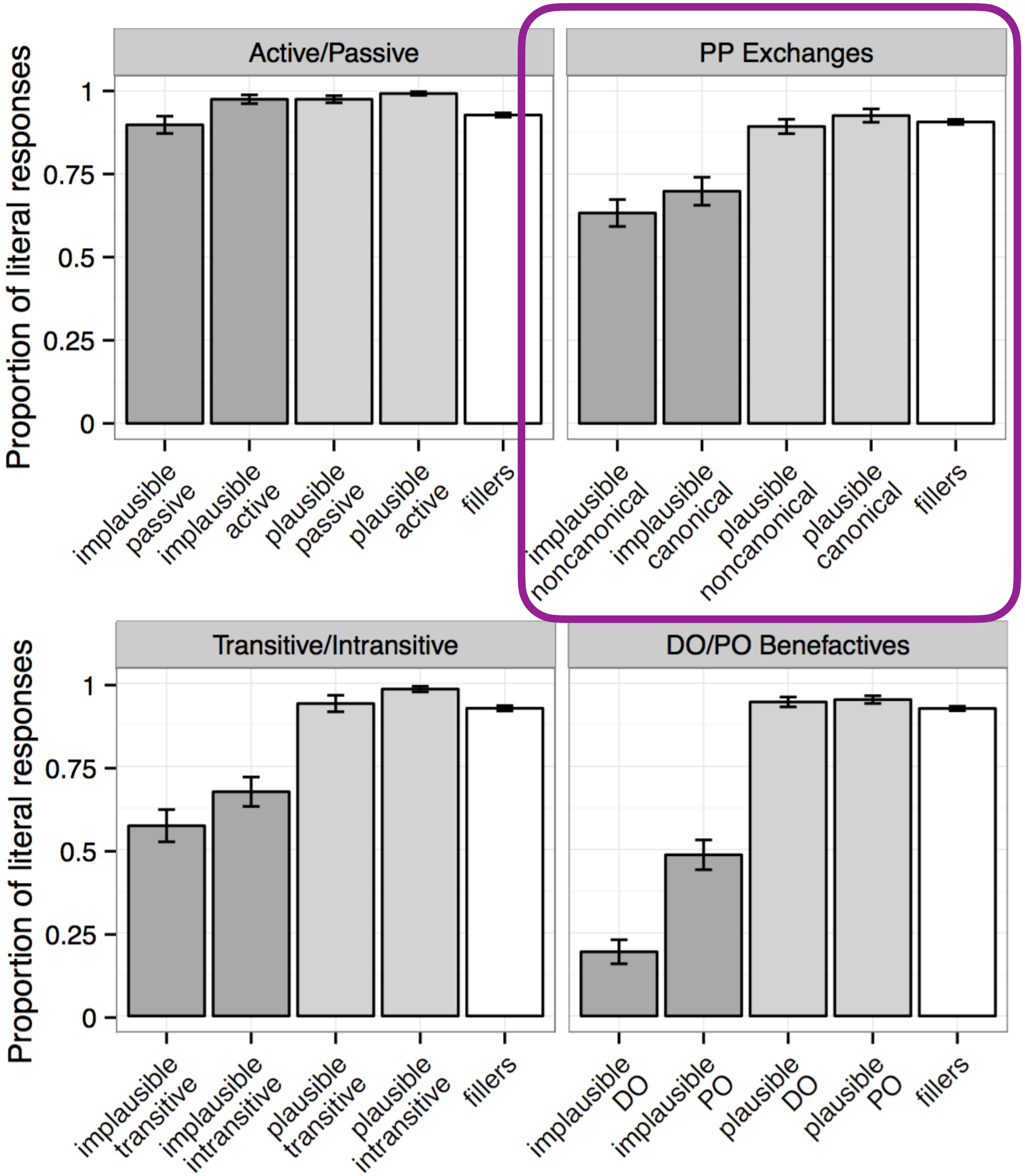
Did something fall to the floor?

(Poppels & Levy 2016)

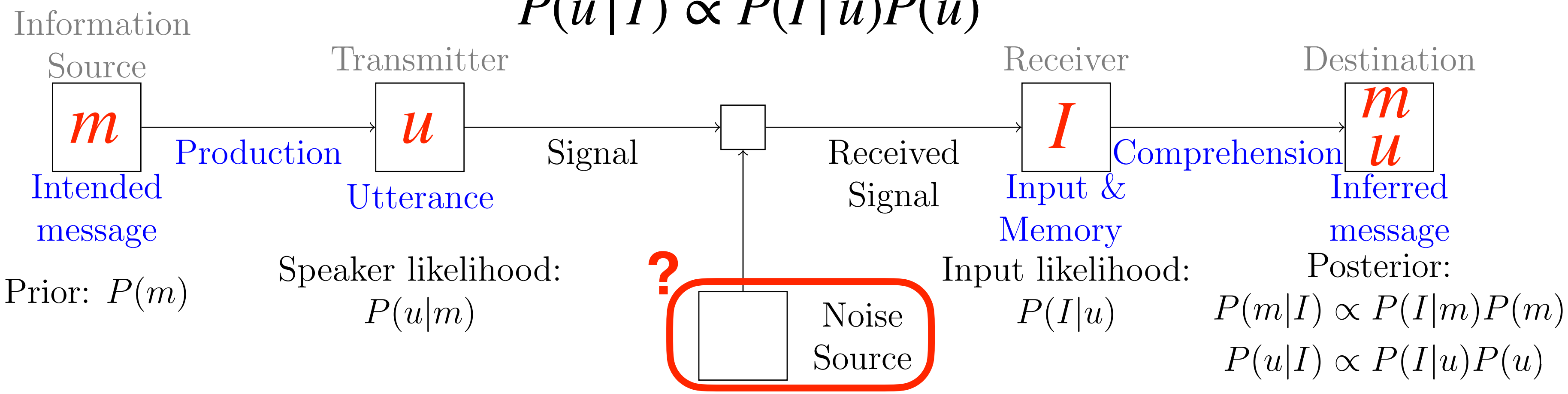
Exchanges in the noise model



(Poppels & Levy 2016)

Probing inferred intended utterances

$$P(u \mid I) \propto P(I \mid u)P(u)$$



(Ryskin et al., 2018)

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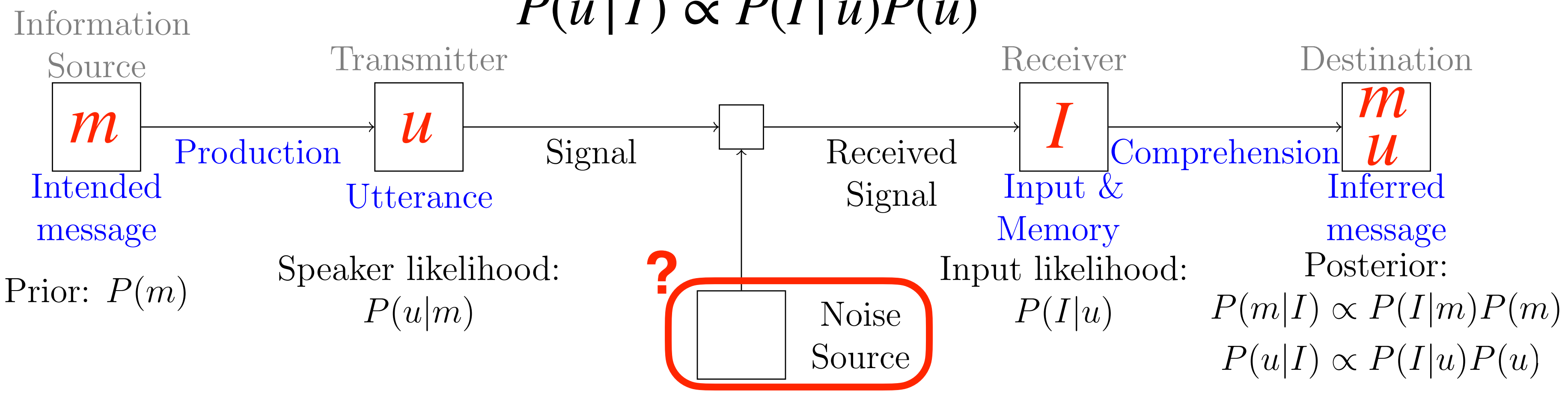

Experiment "cover story": read transcriptions of speech that might have errors, retype with edits if they think the speaker might have meant something else

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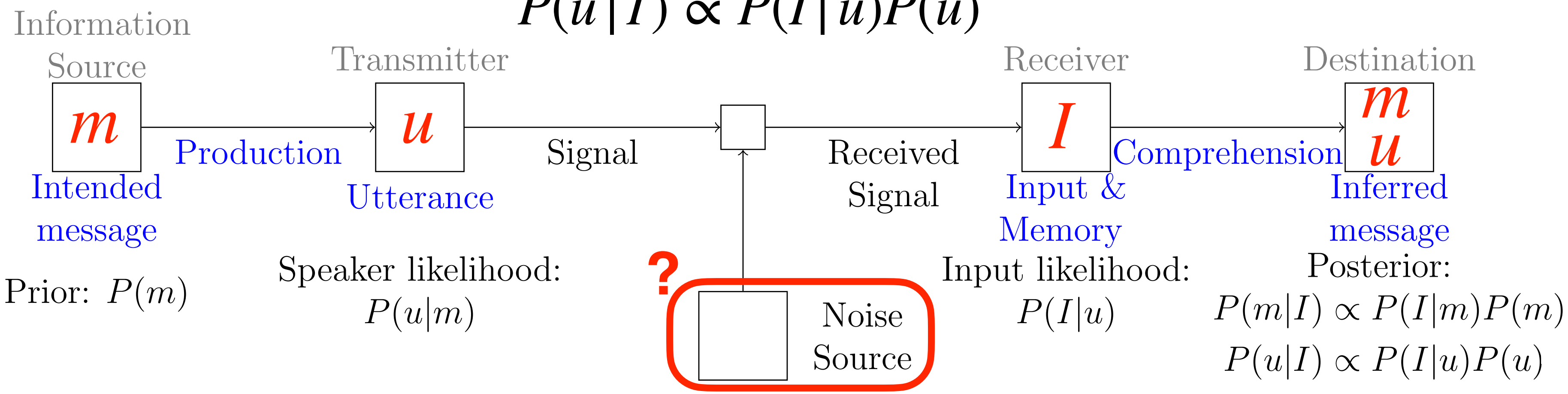

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(Ryskin et al., 2018)

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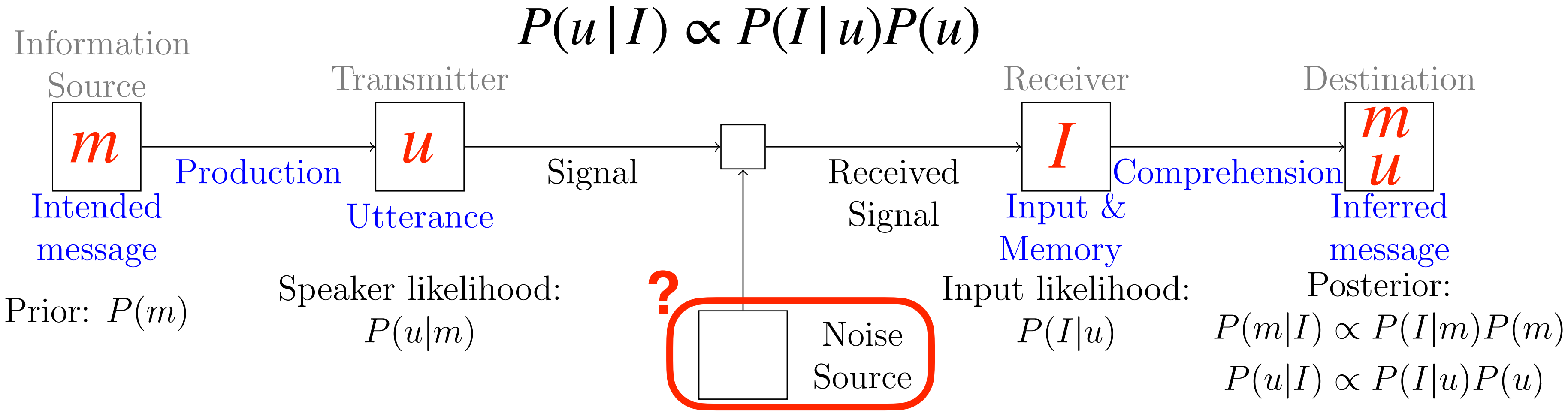

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`The ball kicked the girl.`

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No error

(*Ryskin et al., 2018*)

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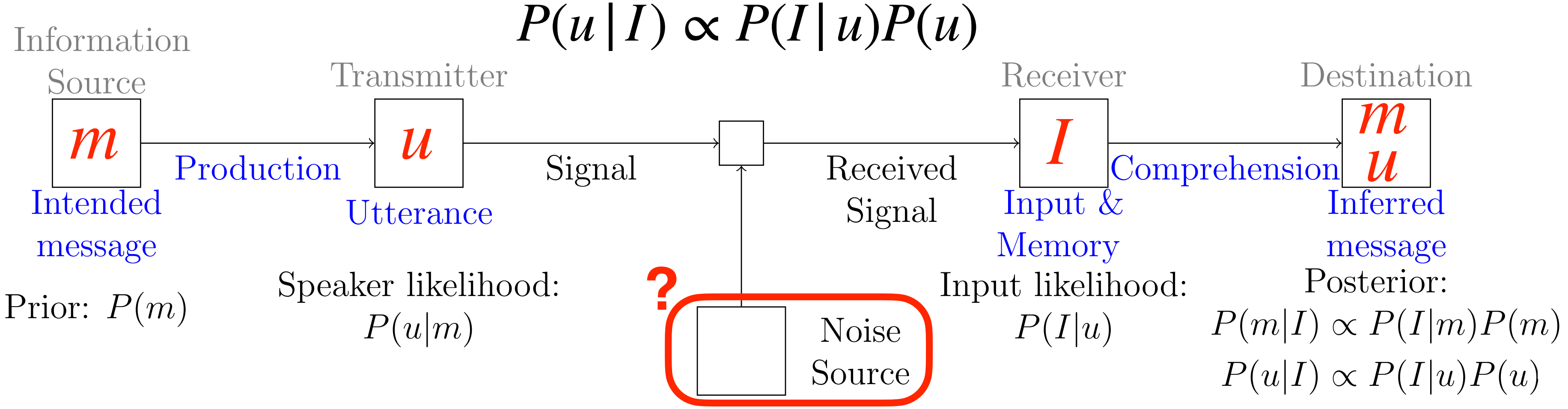

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`The ball kicked the girl.`

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Exchange

(Ryskin et al., 2018)

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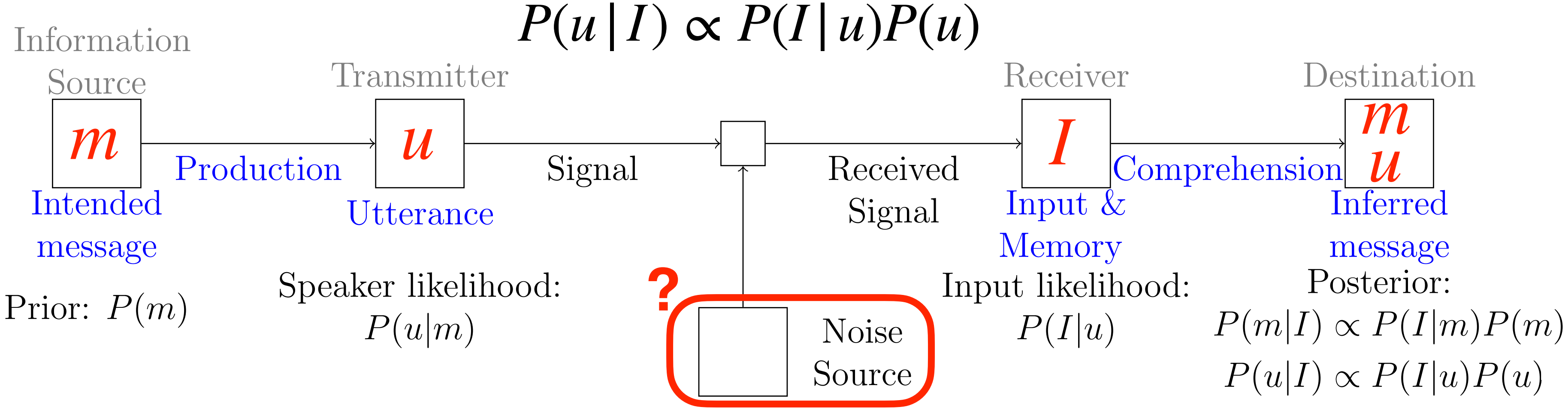

Information Source

m

Production

Intended message

Prior: $P(m)$

Transmitter

u

Utterance

Speaker likelihood: $P(u|m)$

Signal

?

Noise Source

Received Signal

Receiver

I

Input & Memory

Input likelihood: $P(I|u)$

Comprehension

Destination

m

u

Inferred message

Posterior:

$P(m|I) \propto P(I|m)P(m)$

$P(u|I) \propto P(I|u)P(u)$

Experiment "cover story": read transcriptions of speech that might have errors, retype with edits if they think the speaker might have meant something else

`The ball kicked the girl.`

`The ball kicked the girl.`

No error

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Exchange

`The ball was kicked by the girl.`

Deletion

(Ryskin et al., 2018)

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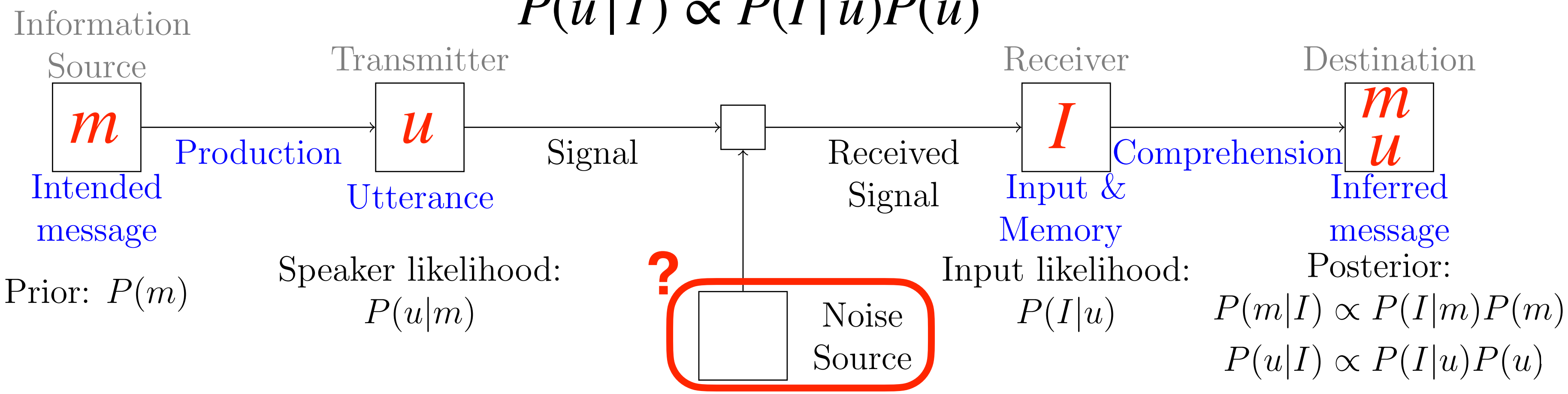

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`The ball kicked the girl. The judge gave the athlete to the prize.`

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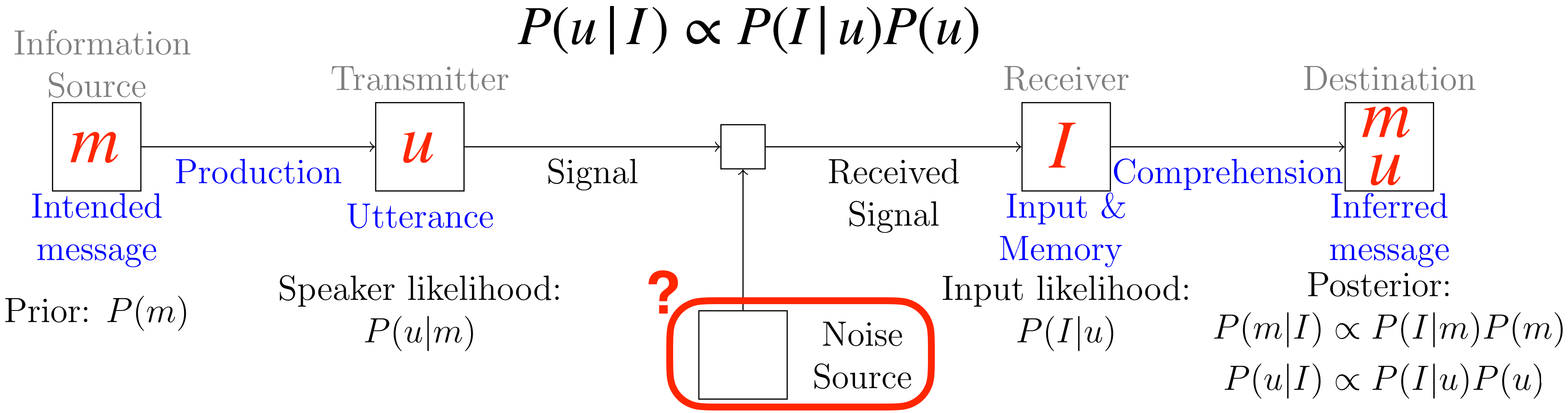

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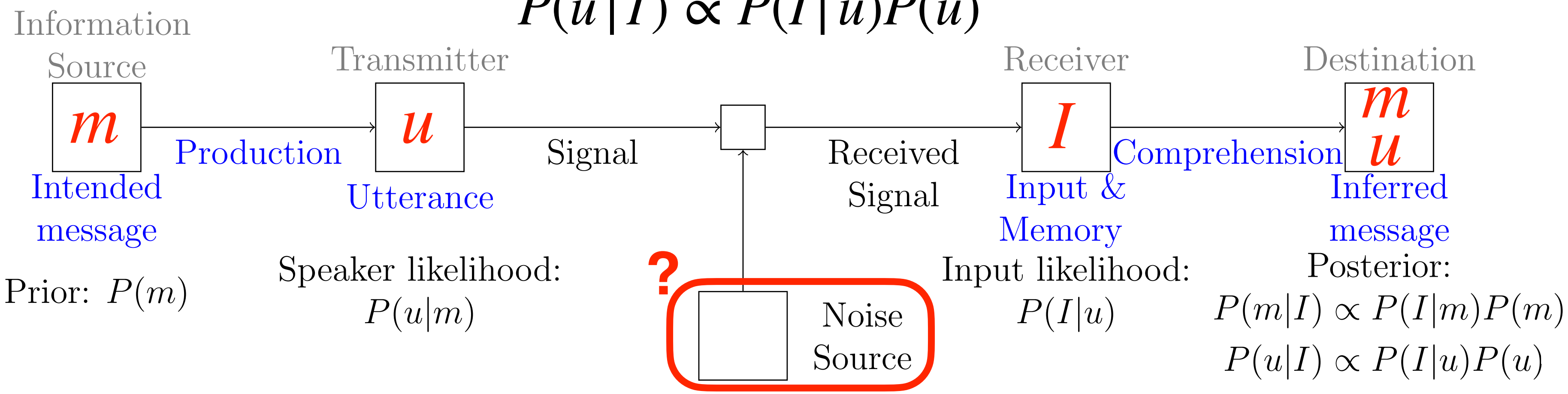

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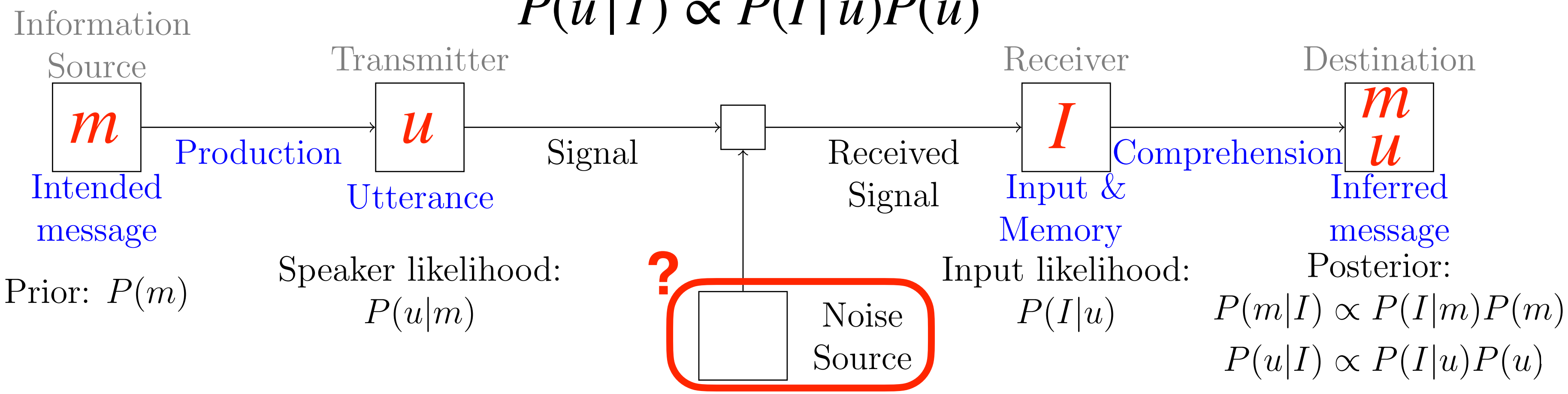

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The ball kicked the girl. No error	The judge gave the athlete the prize. Insertion
The girl kicked the ball. Exchange	The judge gave the athlete a prize. Insertion
The ball was kicked by the girl. Deletion	The judge gave the prize to the athlete. Exchange

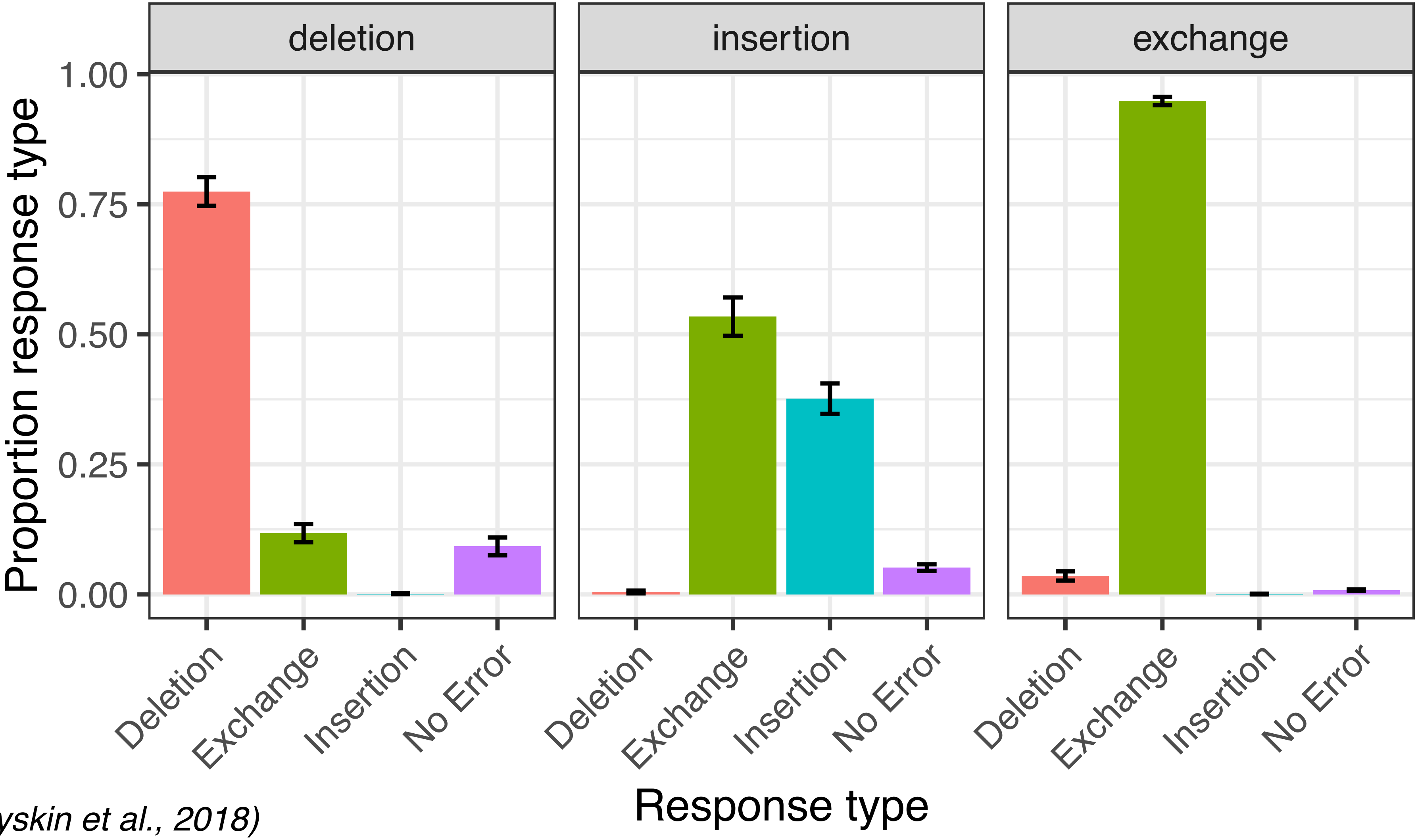
(Ryskin et al., 2018)

Probing inferred intended utterances

"The corrupt politicians profited the bribes."

"The actor handed the director to the script."

"The bowl broke the grandfather."



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Noisy-channel interpretation summary

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  - More implausible sentences in environment→less non-literal inference
- *However*, status of exchange errors in the noise model remains a mystery

Structural Forgetting and the Noisy Channel

(Futrell & Levy, 2017; Futrell et al., 2020)

(Slide courtesy Richard Futrell)

Structural Forgetting and the Noisy Channel

1. The apartment that the maid who the cleaning service sent over was well-decorated.

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1. *The **apartment** that the **maid** who the **cleaning service sent over was well-decorated**. 👍

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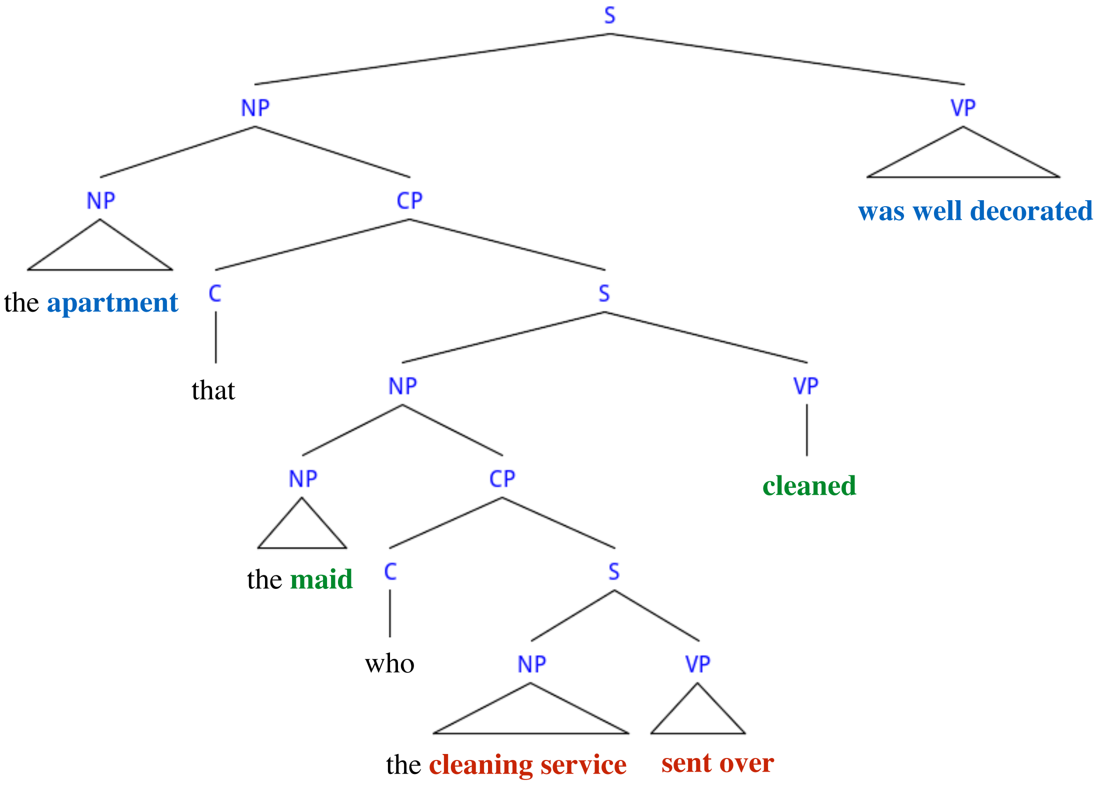

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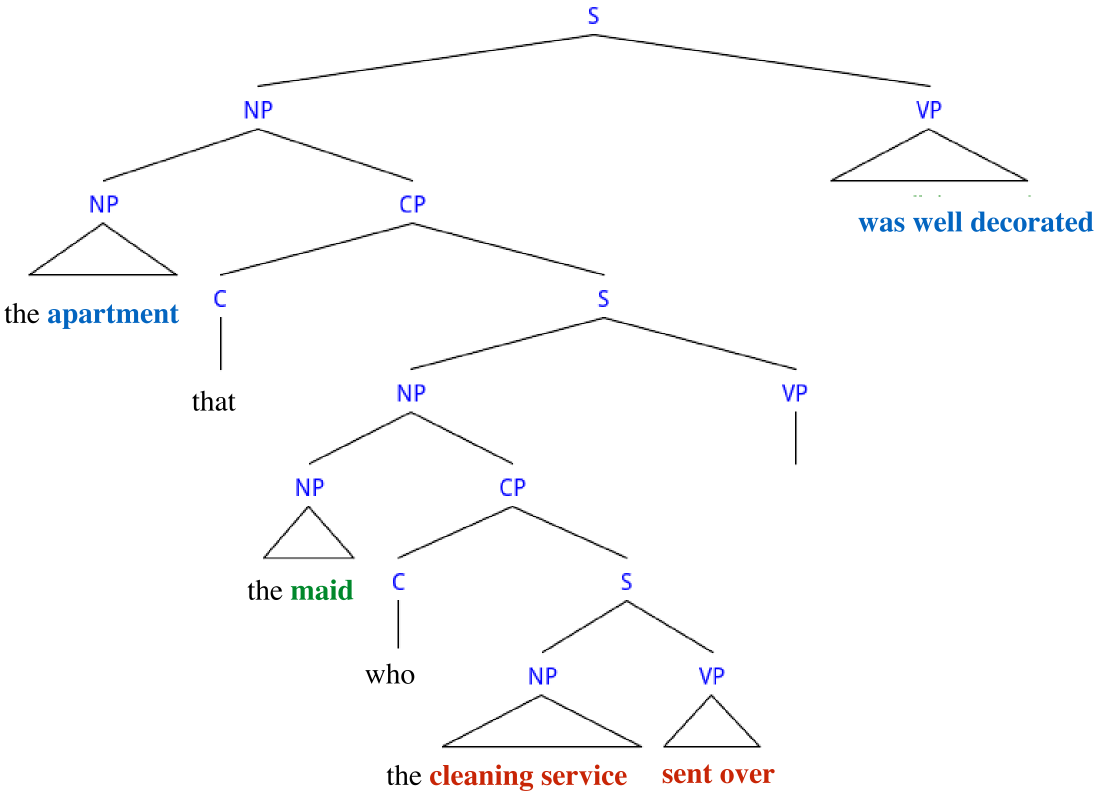

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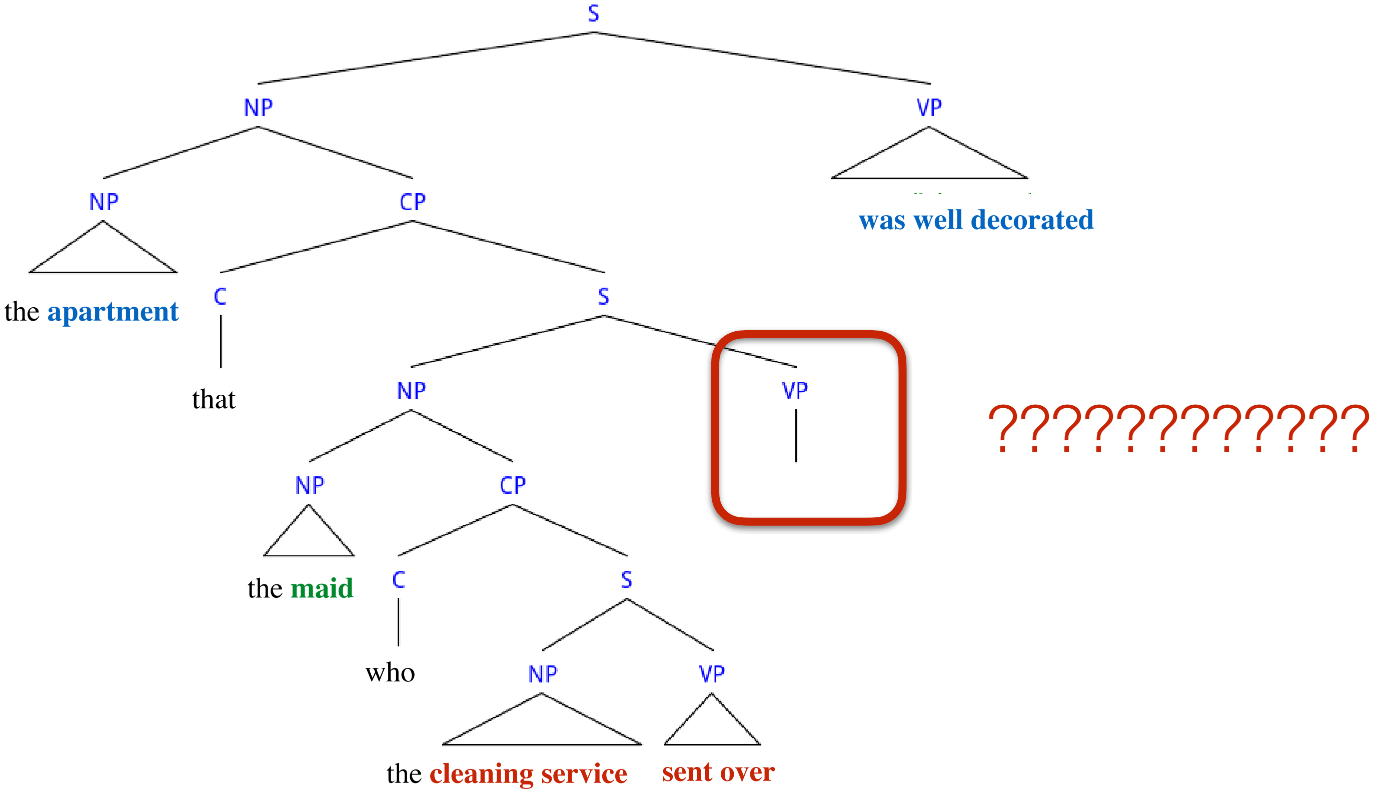

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- **Structural forgetting effect**: part of the sentence is forgotten by the time you get to the end (Gibson & Thomas, 1999; Frazier, 1985; Fodor, p.c.)

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- **Structural forgetting effect**: part of the sentence is forgotten by the time you get to the end (Gibson & Thomas, 1999; Frazier, 1985; Fodor, p.c.)
- The ungrammatical sentence seems better than the grammatical one.
  - A "**grammaticality illusion**": how could we define grammaticality in this case?

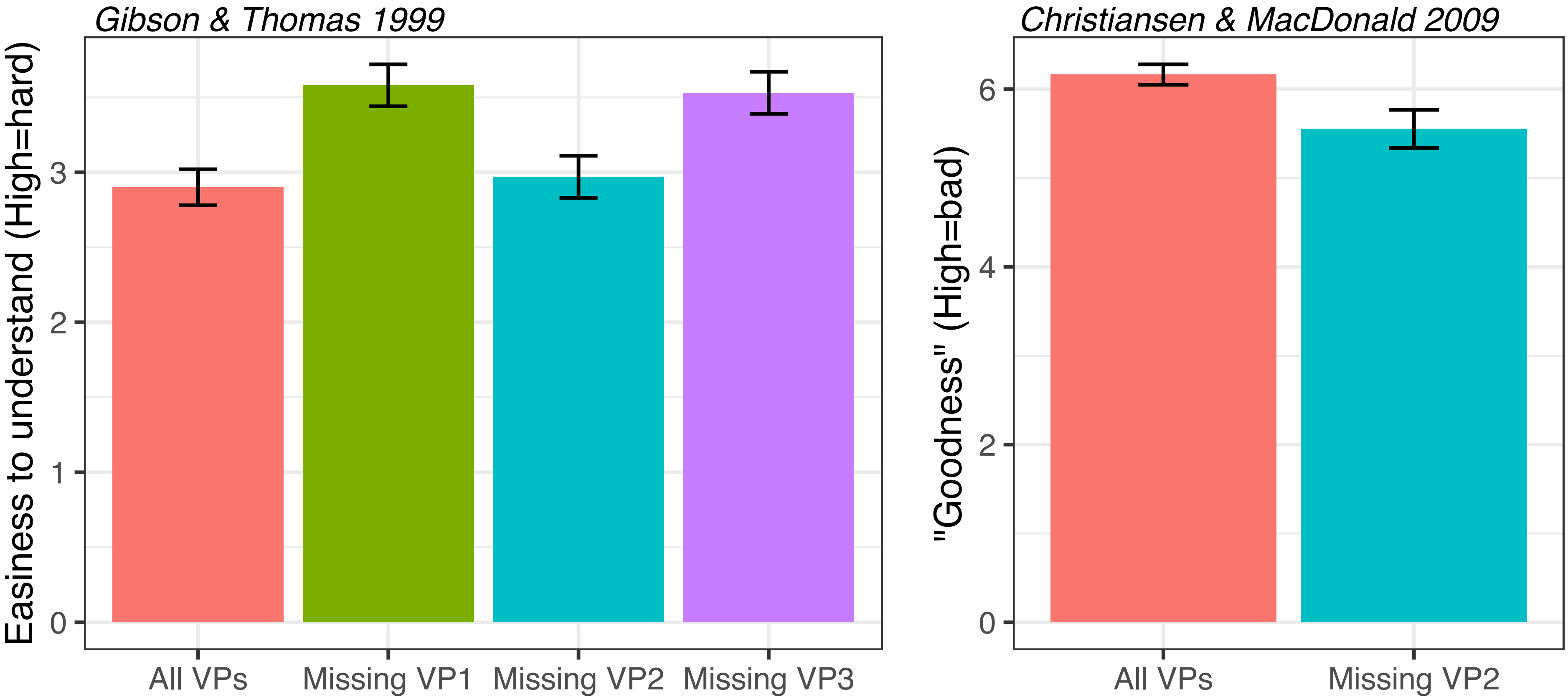
(Slide courtesy Richard Futrell)

Gibson & Thomas 1999: whole-sentence reading

The ancient manuscript that the graduate student who the new card catalog had confused a great deal was studying in the library was missing a page.

Christiansen & MacDonald 2009: word-by-word self-paced reading, follows by rating

The chef who the waiter who the busboy offended appreciated admired the musicians.



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- But the effect is **language-dependent** (Vasishth et al., 2010; Frank et al., 2016).

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- What is the difference between English and German?

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  - But why?

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- These contexts are more common in German than English (Roland et al., 2007).

(Slide courtesy Richard Futrell)

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  - English: the maid [that cleaned the apartment]
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  - English: the maid [that cleaned the apartment] **80%**
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  - English: the maid [that cleaned the apartment] **80%**
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  - German: das Dienstmädchen, [das die Wohnung reinigte]
    die Wohnung, [die das Dienstmädchen reinigte]

(Slide courtesy Richard Futrell)

Noisy-Context Surprisal Account of Structural Forgetting

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- Structural forgetting means the ungrammatical sentence with two verbs is **easier to process** than the grammatical sentence with three verbs:

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$C($ The **apartment** that the **maid** who the **cleaning service** **sent over** **was well-decorated**. $)$ $<$

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(Slide courtesy Richard Futrell)

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$$C(\texttt{NOUN THAT NOUN THAT NOUN VERB VERB}) <$$
$$C(\texttt{NOUN THAT NOUN THAT NOUN VERB VERB VERB})$$

(Slide courtesy Richard Futrell)

Noisy-Context Surprisal Account of Structural Forgetting

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$$C(2\ \text{VERBS}) < C(3\ \text{VERBS})$$

(Slide courtesy Richard Futrell)

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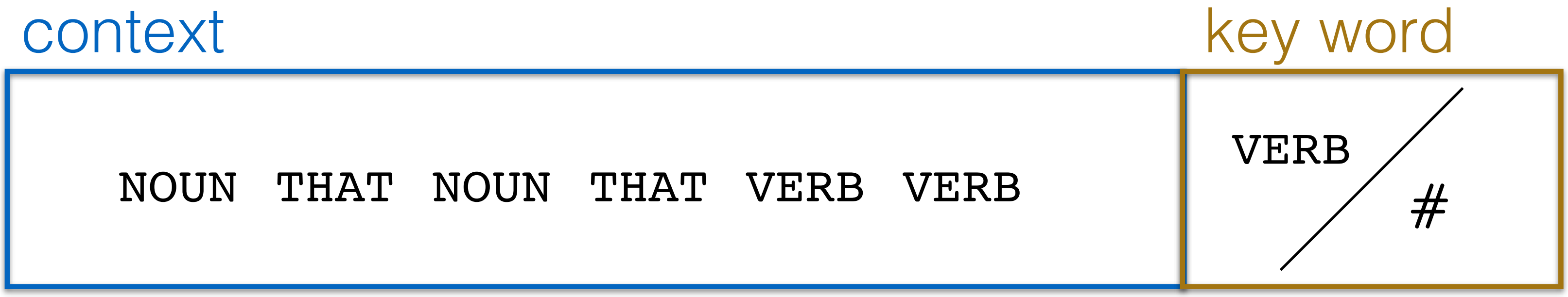

context

NOUN THAT NOUN THAT VERB VERB

key word

VERB / #

(Slide courtesy Richard Futrell)

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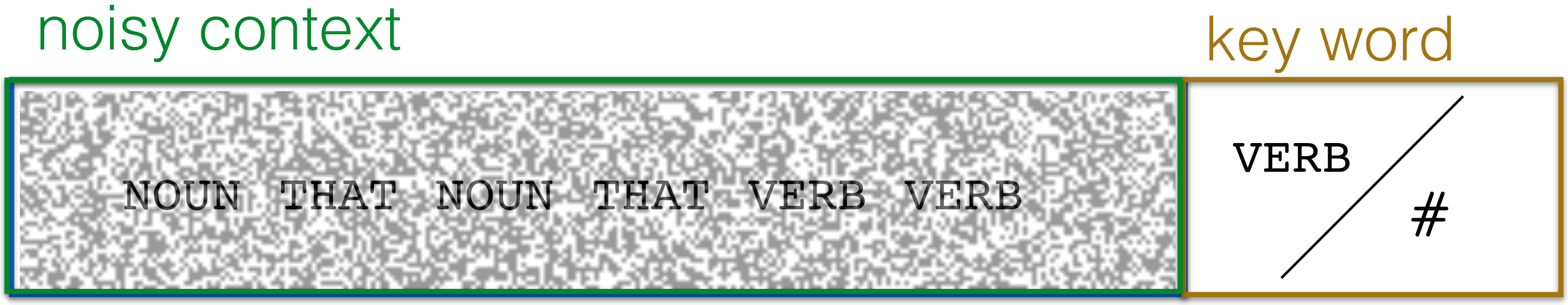

noisy context

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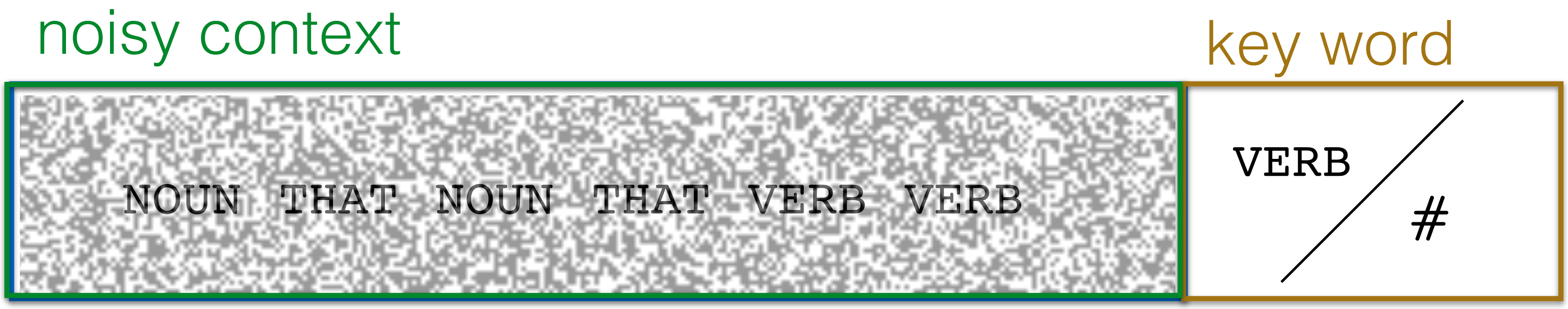

noisy context

NOUN THAT NOUN THAT VERB VERB

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- Correct noise based on prior about the language.

(Slide courtesy Richard Futrell)

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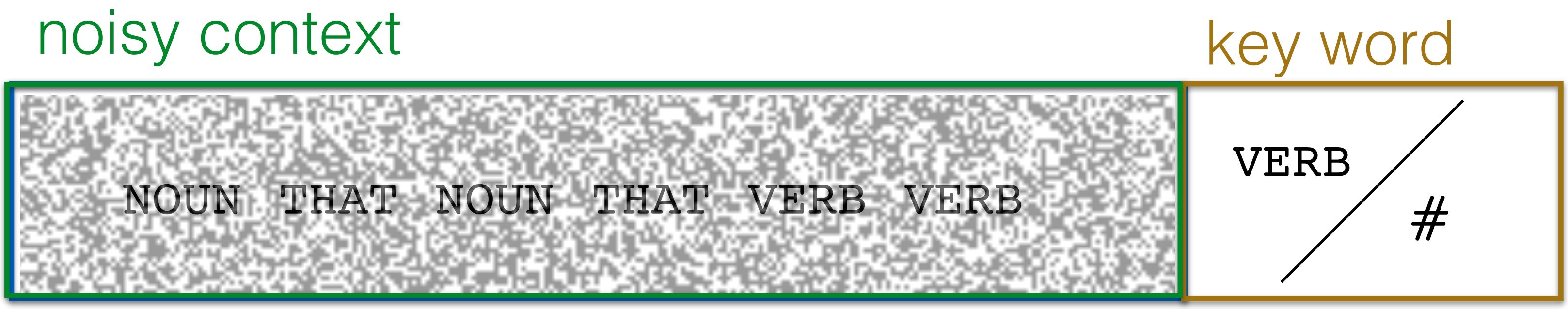
$$C(2\ \text{VERBS}) \ < \ C(3\ \text{VERBS})$$



- Correct noise based on prior about the language.
- Higher probability for verb-final RCs in German,
  - so more likely to make the right prediction.

(Slide courtesy Richard Futrell)

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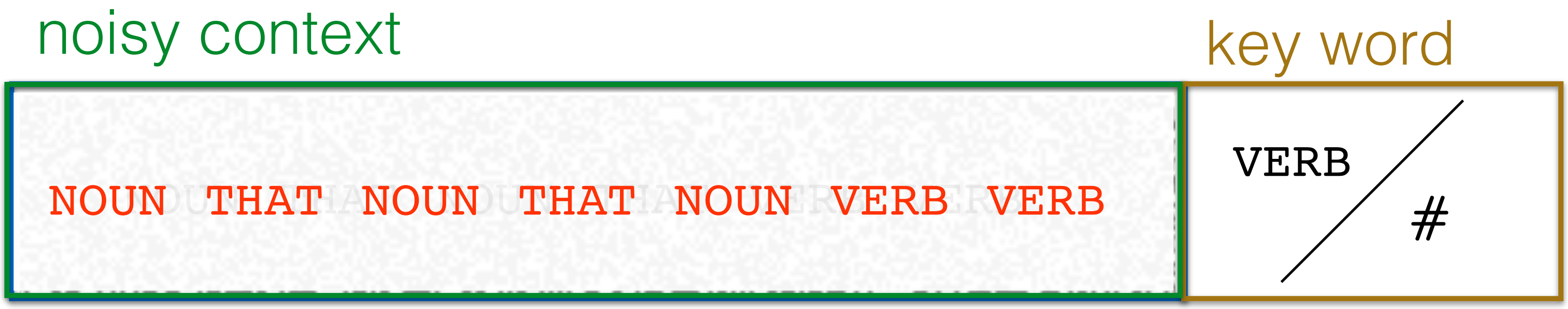

noisy context

key word

NOUN THAT NOUN THAT NOUN VERB VERB

VERB

#

- Correct noise based on prior about the language.
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(Slide courtesy Richard Futrell)

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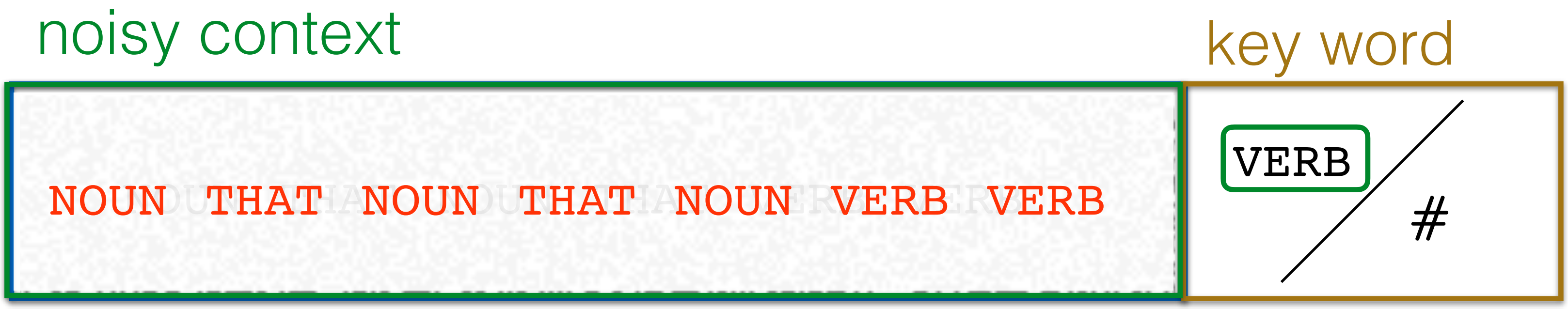

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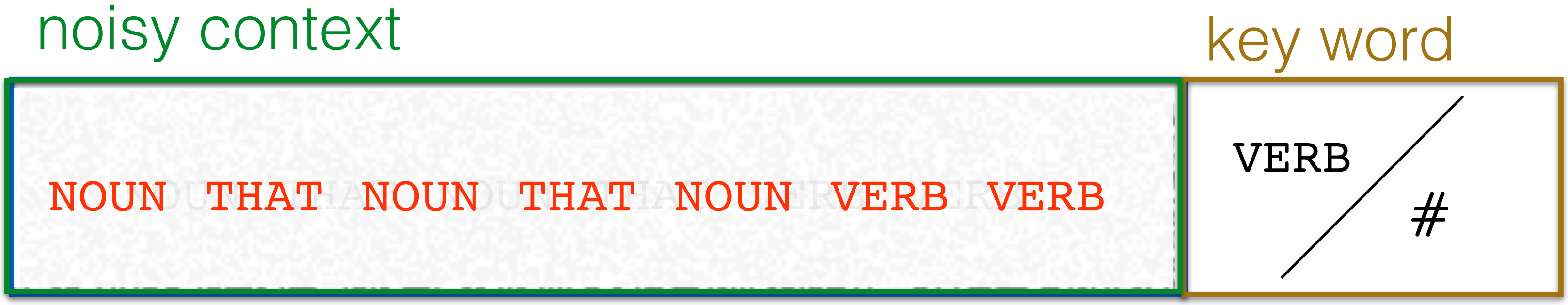

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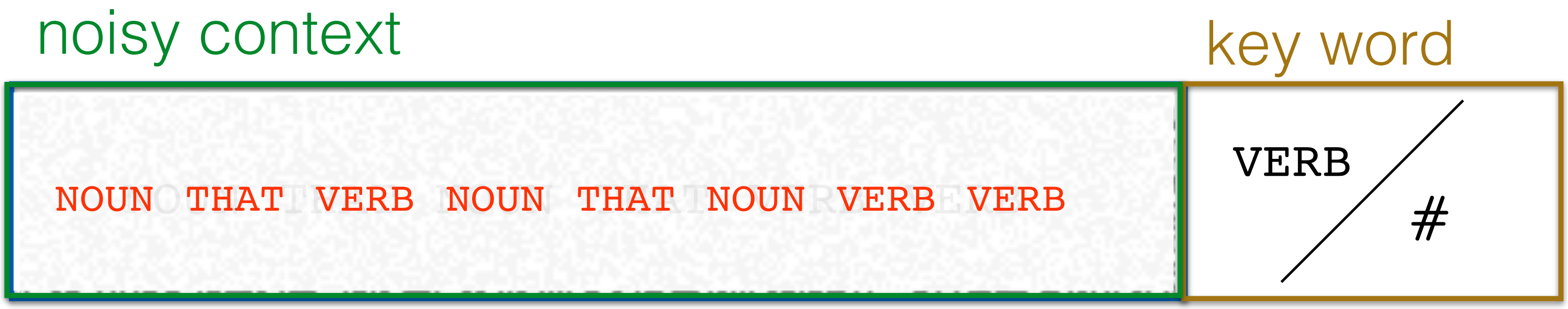

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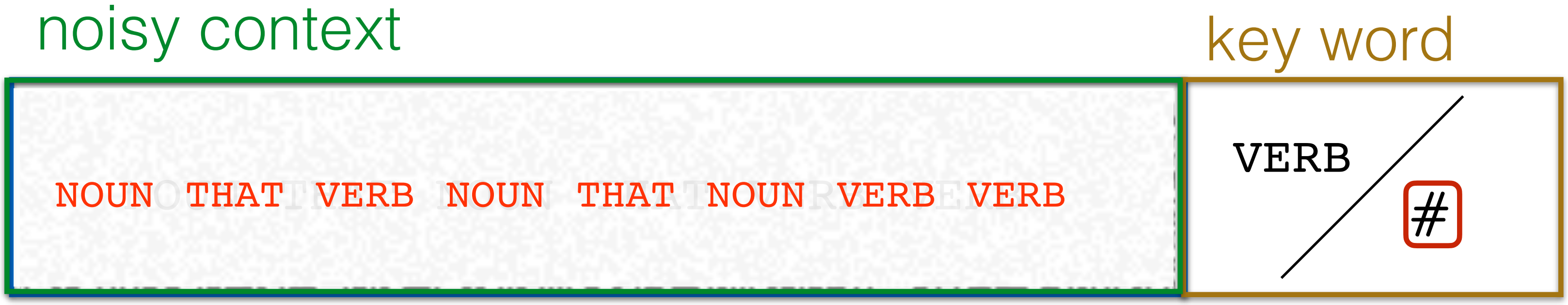

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Rule	Probability
S -> NP VERB	1
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NP -> NOUN RC	mr
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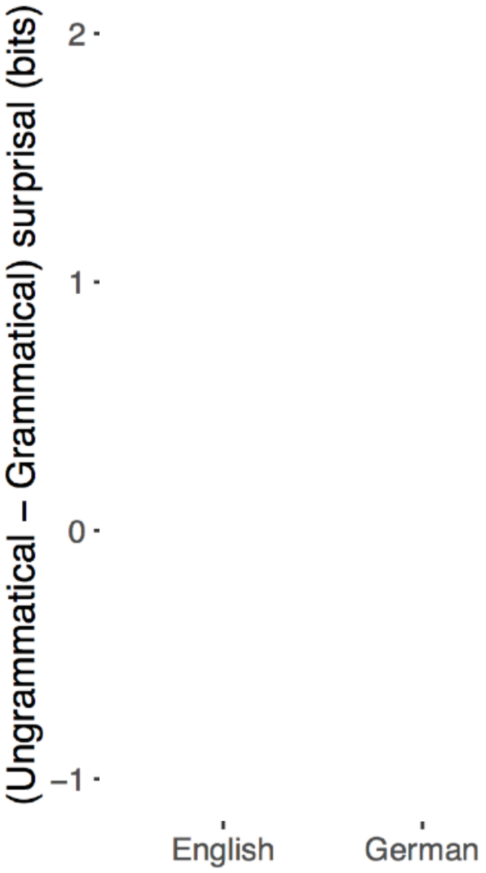

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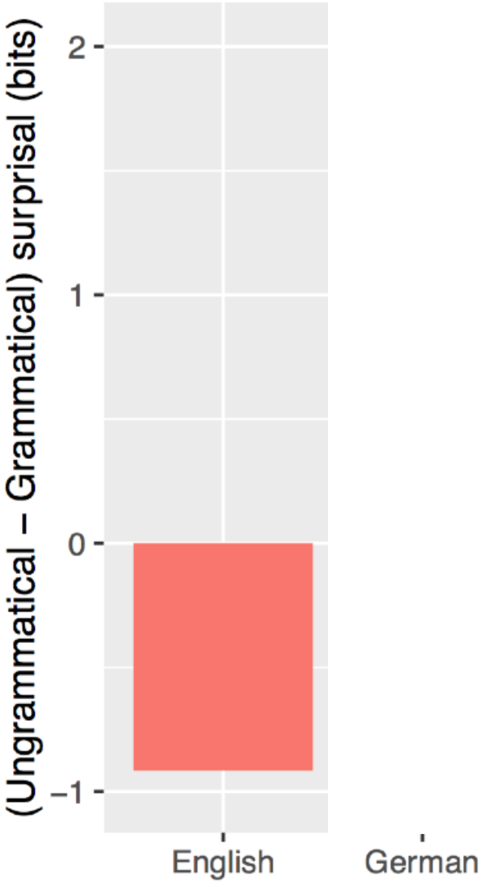

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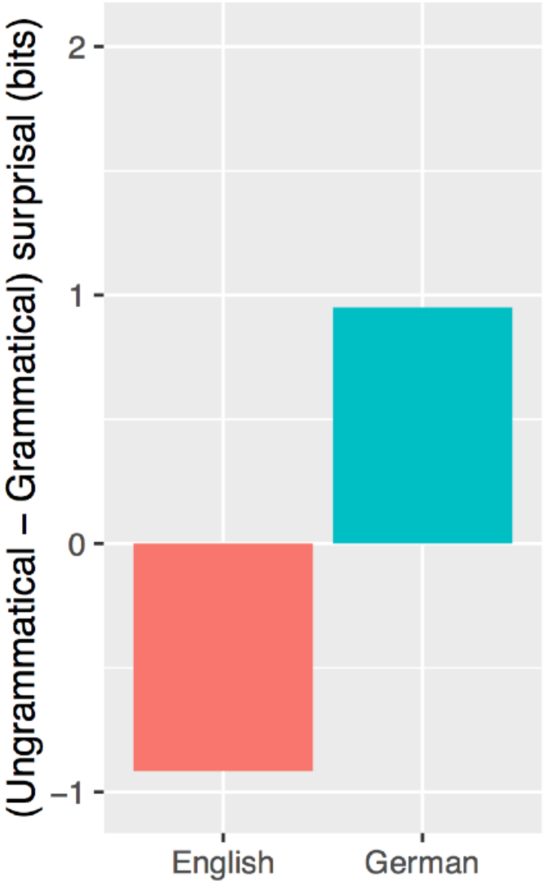

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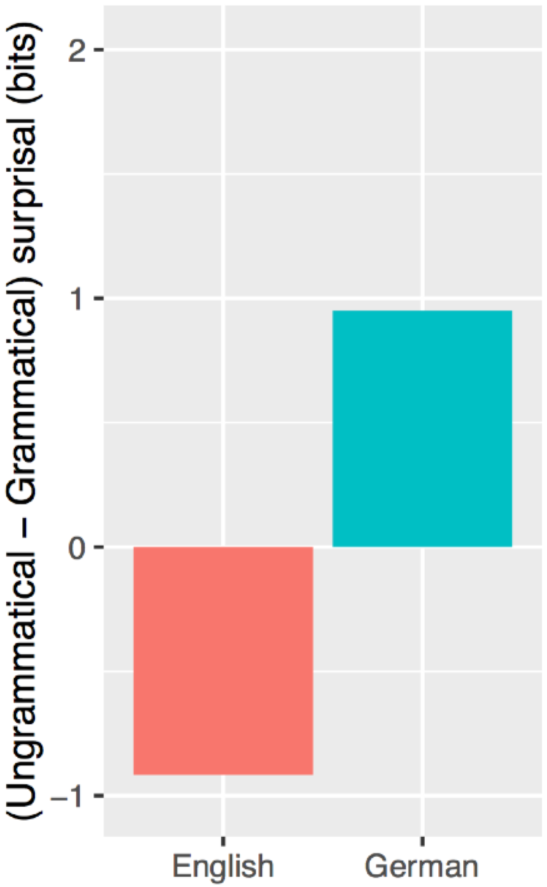

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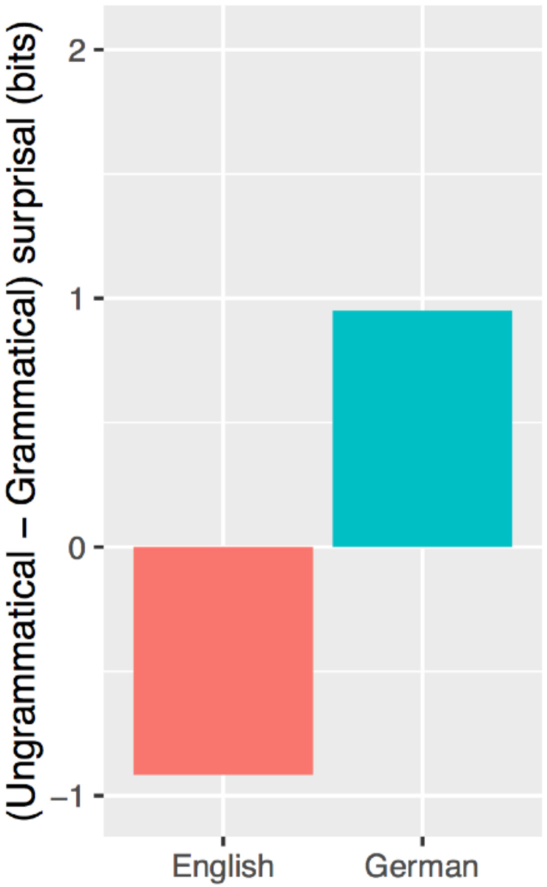

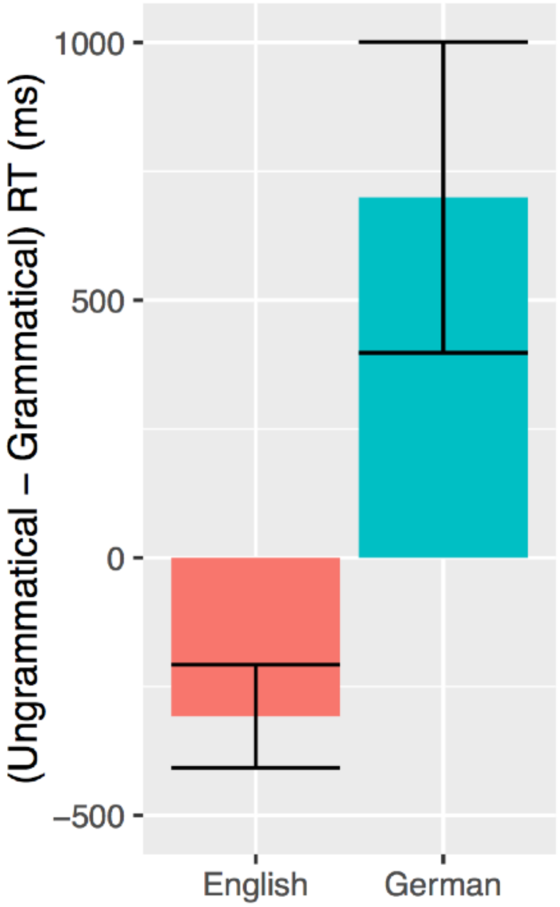

Vasishth et al. (2010)

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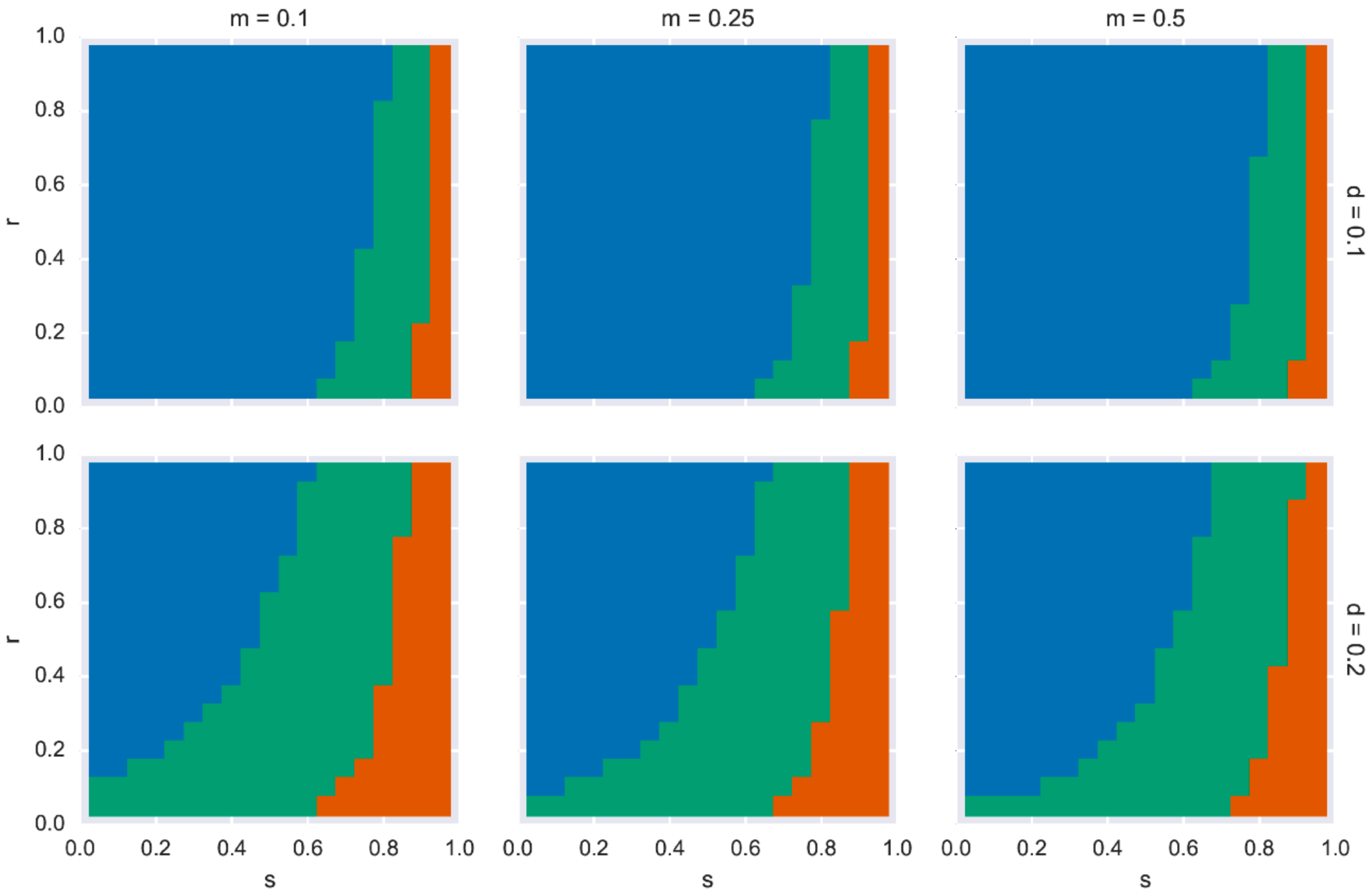
Robustness to choice of model parameters

m Modifier probability

s Probability of English RC being verb-final

d Probability of context token deletion

🟩 = English+German-like pattern



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- Probability that a context is remembered depends on its prior probability.
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- The model has an explicit grammar (competence), but cannot apply it correctly (performance).

(Slide courtesy Richard Futrell)

Structural Forgetting and the Noisy Channel

(Futrell & Levy, 2017)

Structural Forgetting and the Noisy Channel

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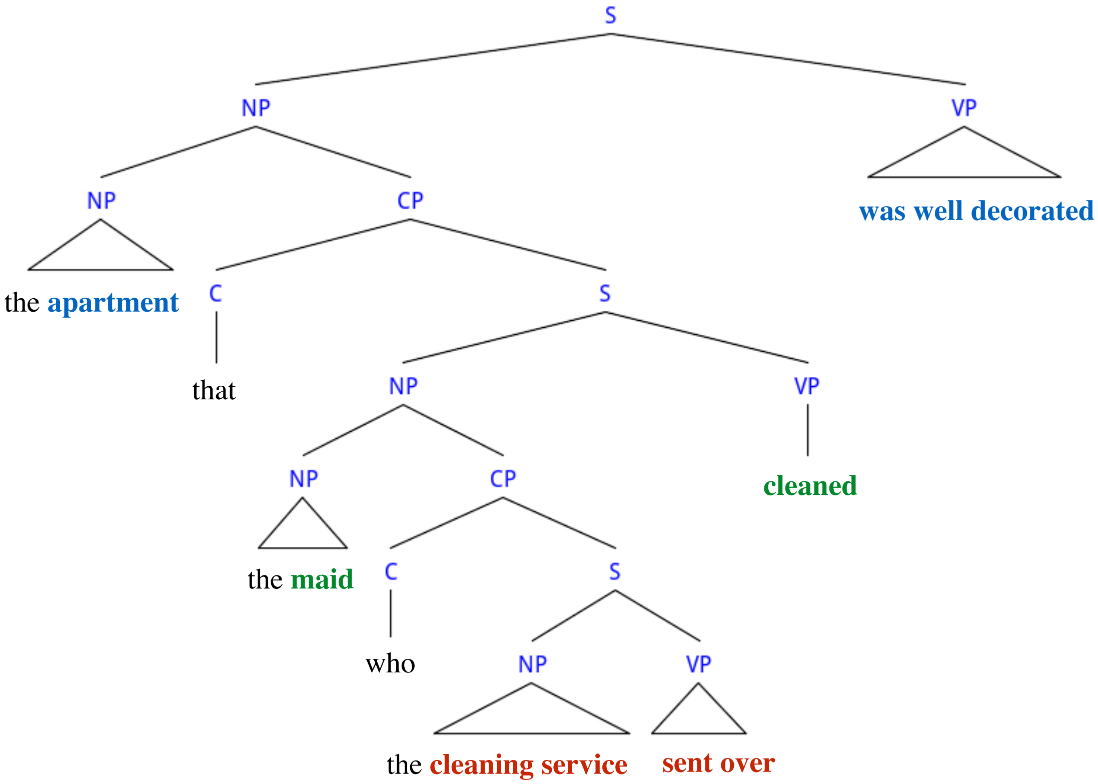

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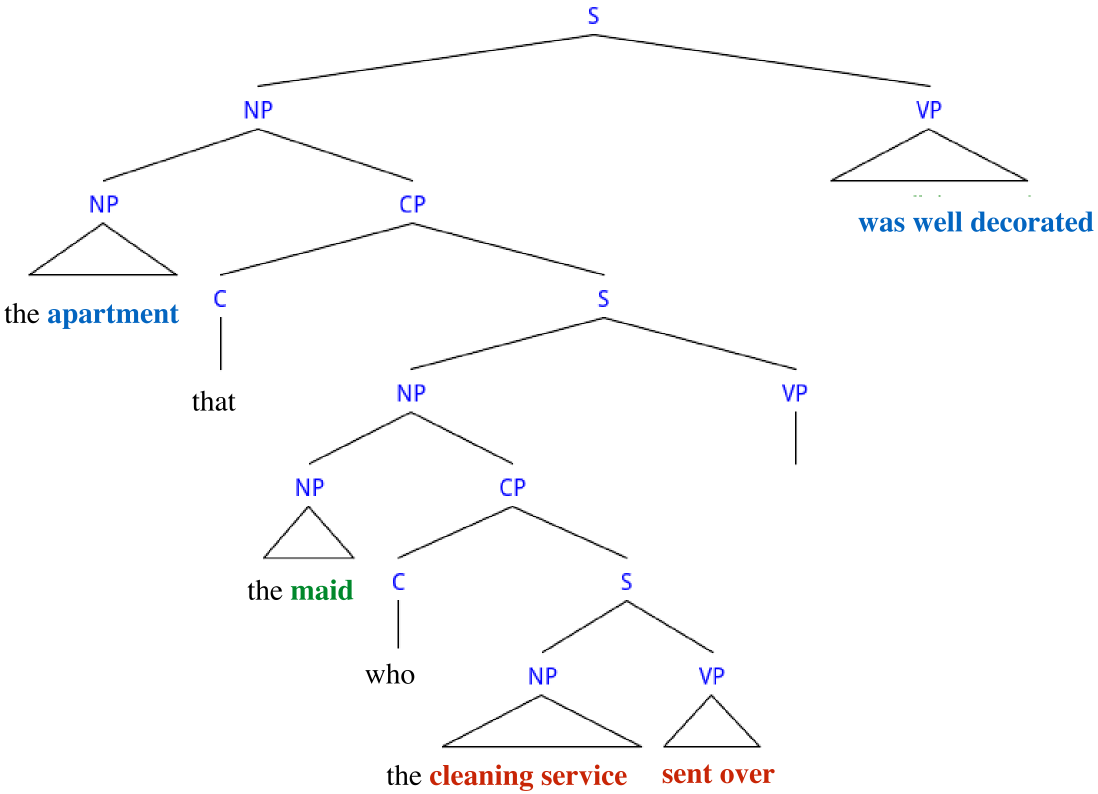

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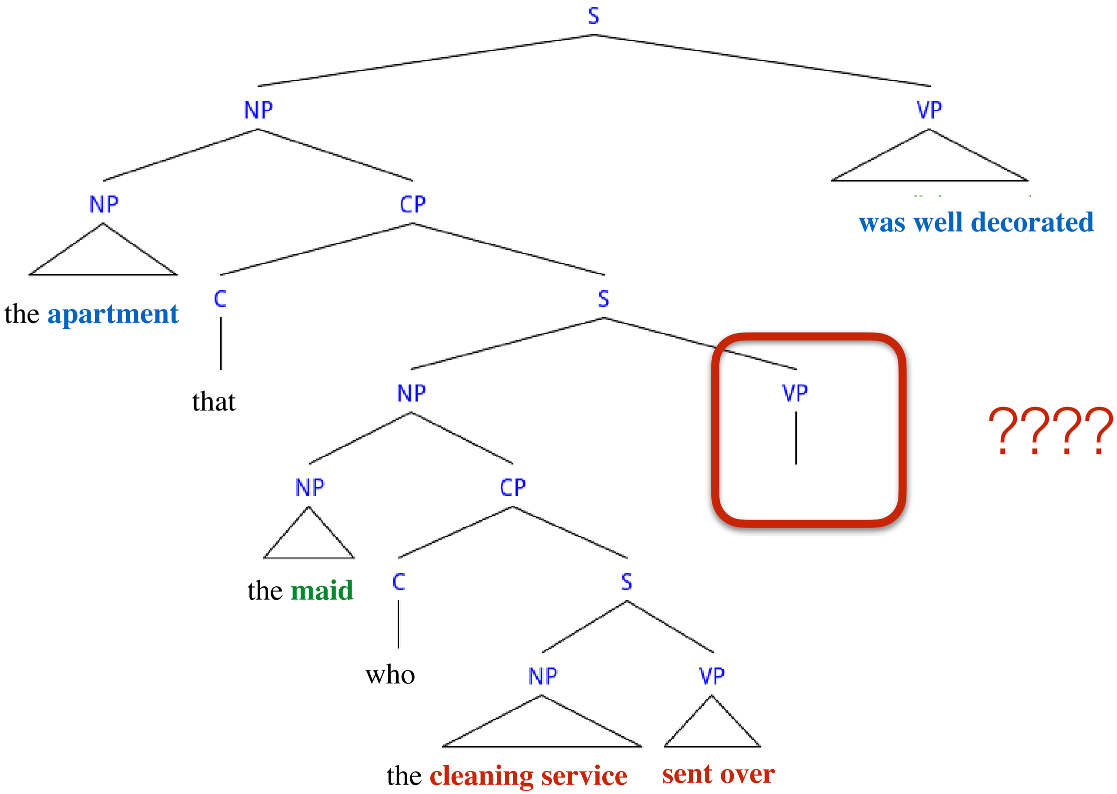

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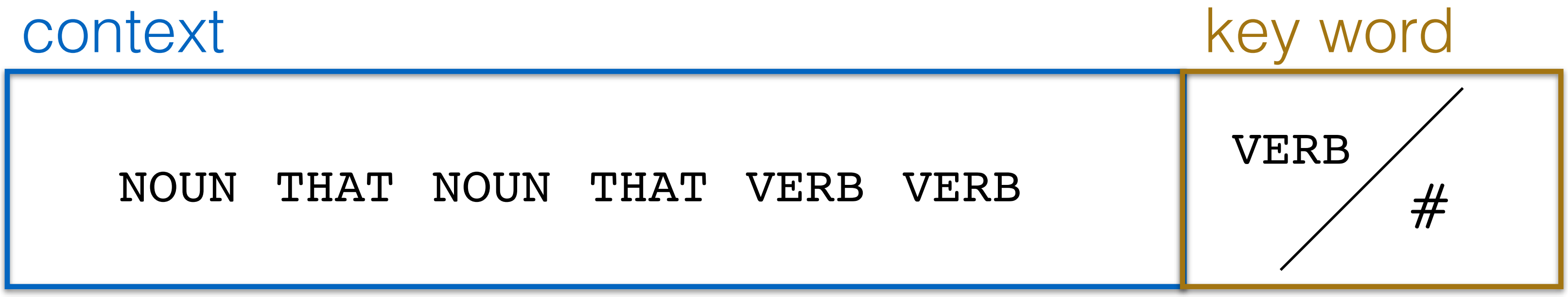

context

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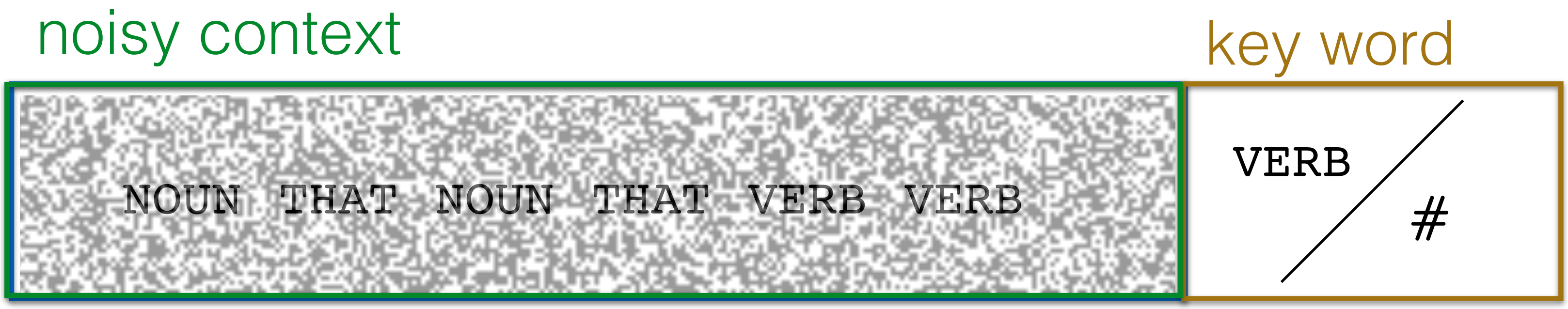

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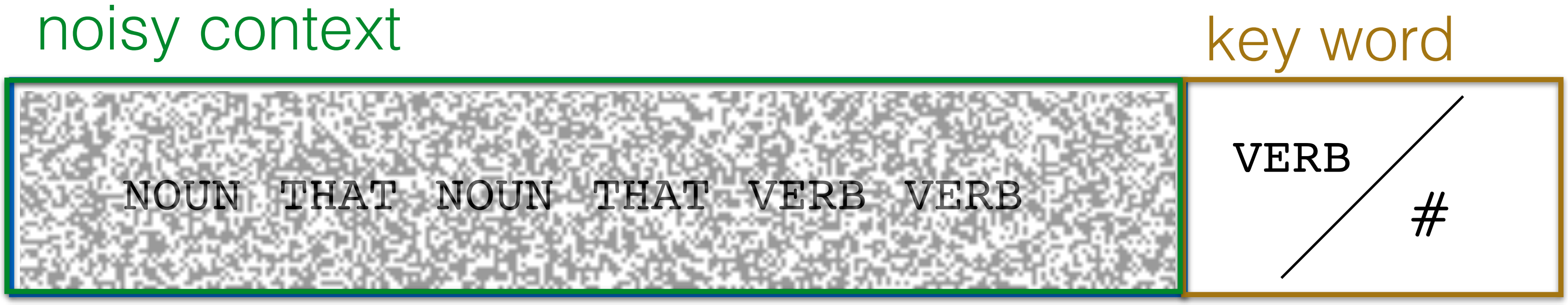

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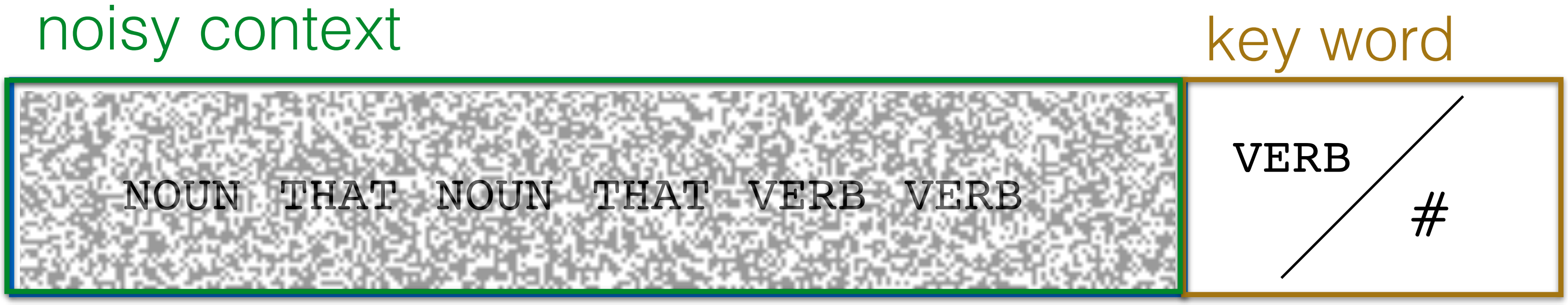

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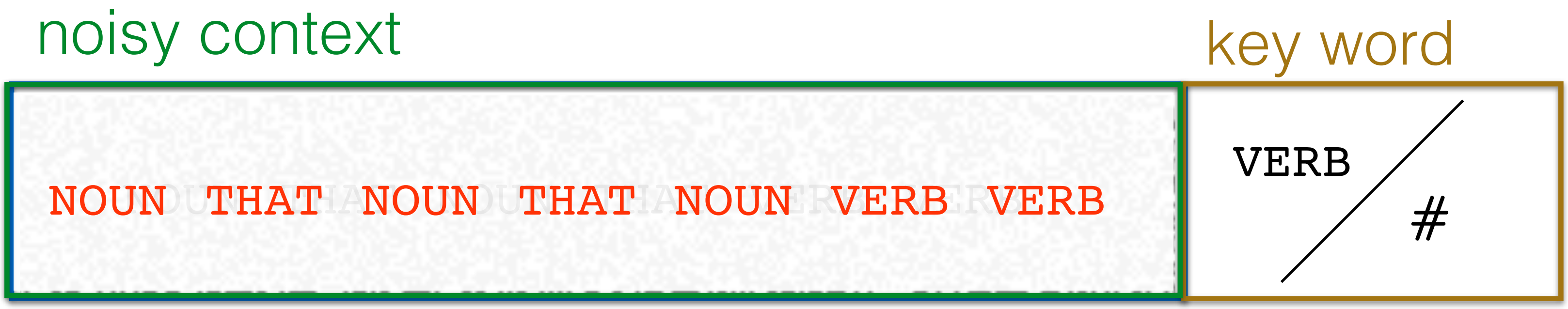

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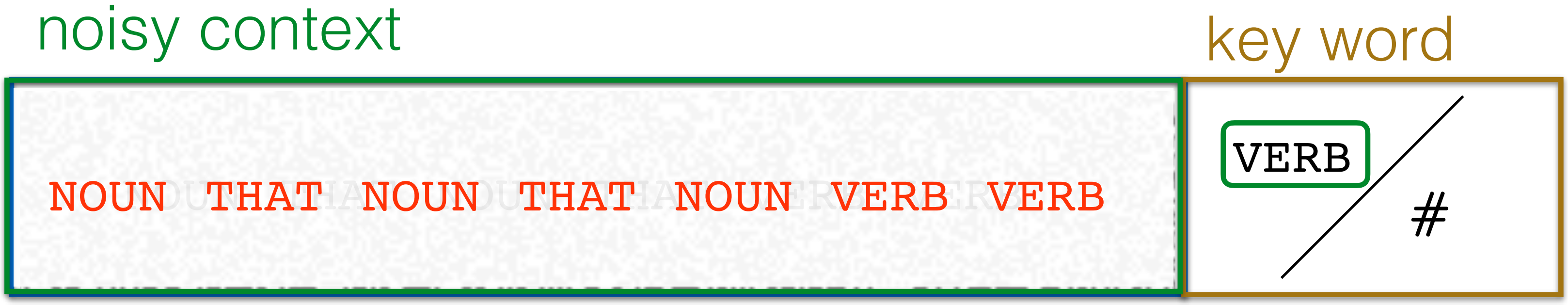

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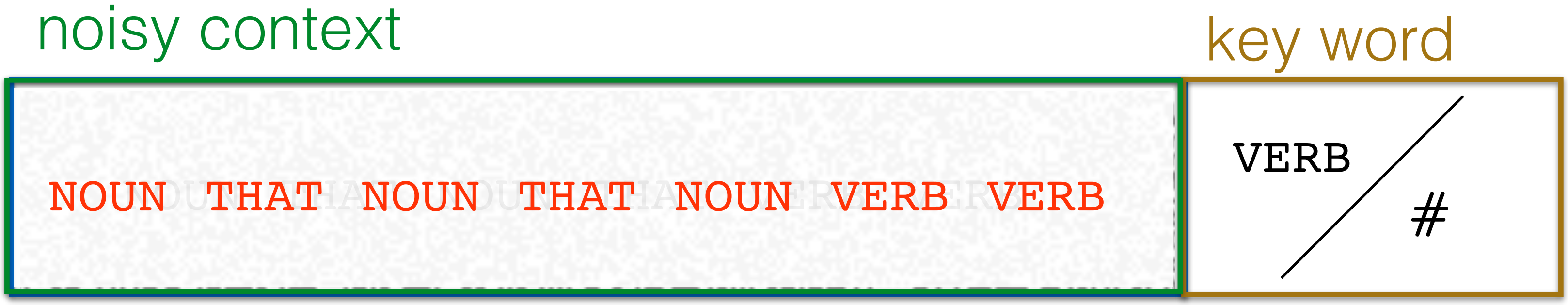

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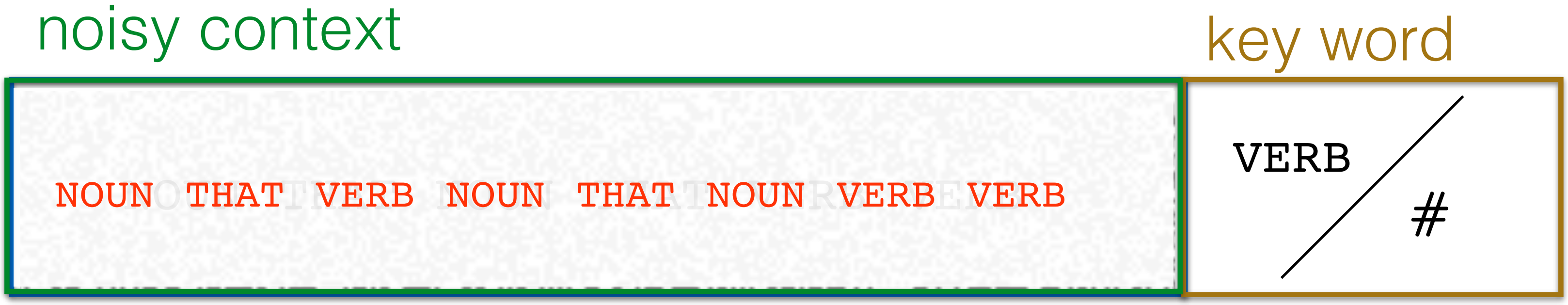

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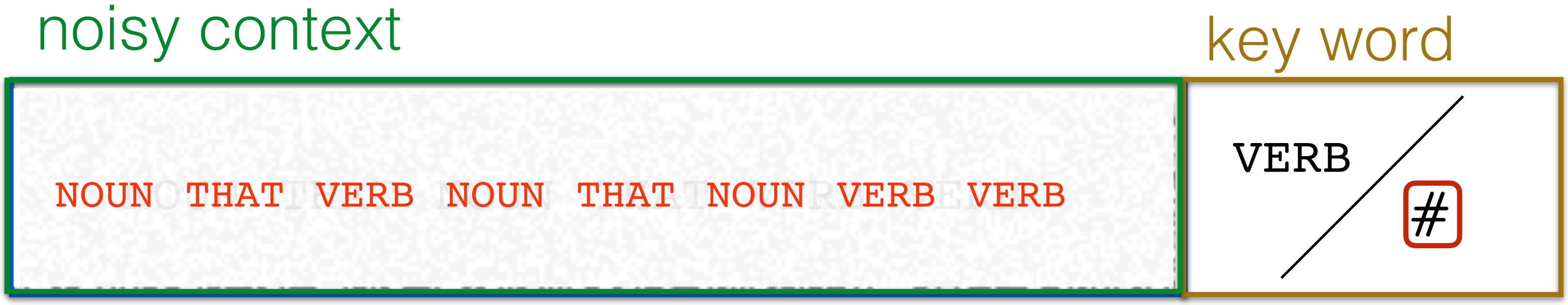

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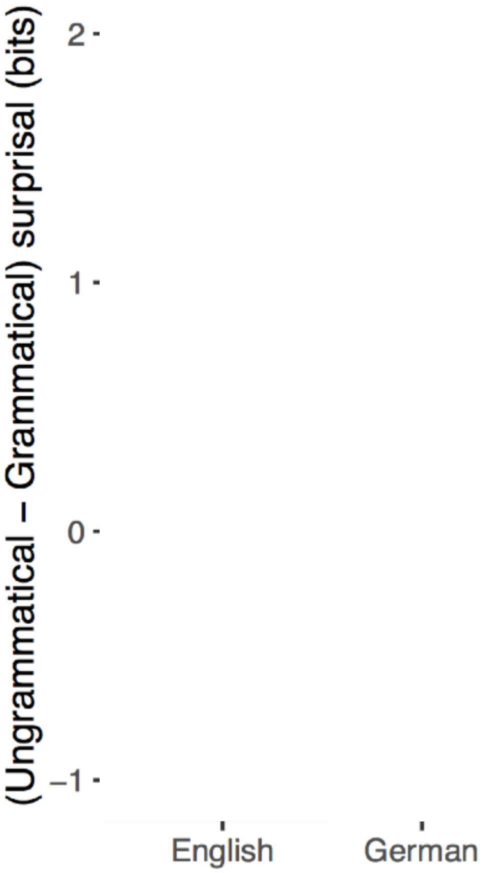

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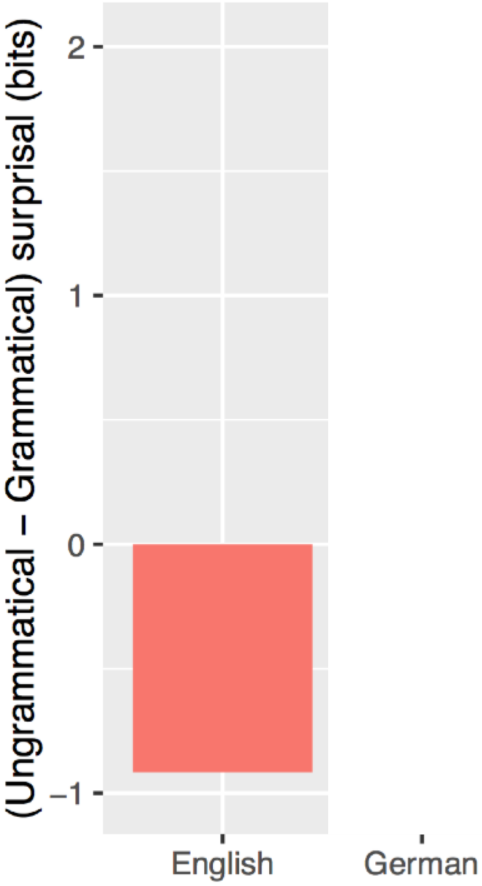

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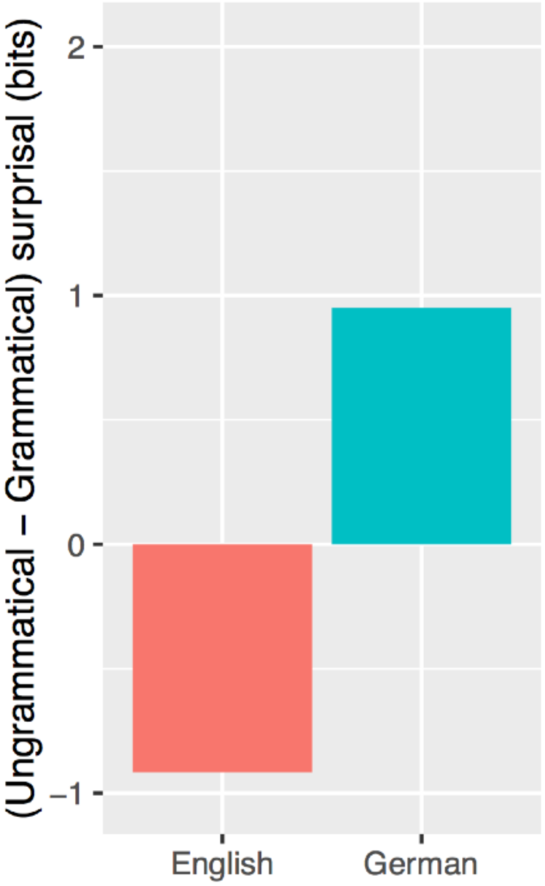

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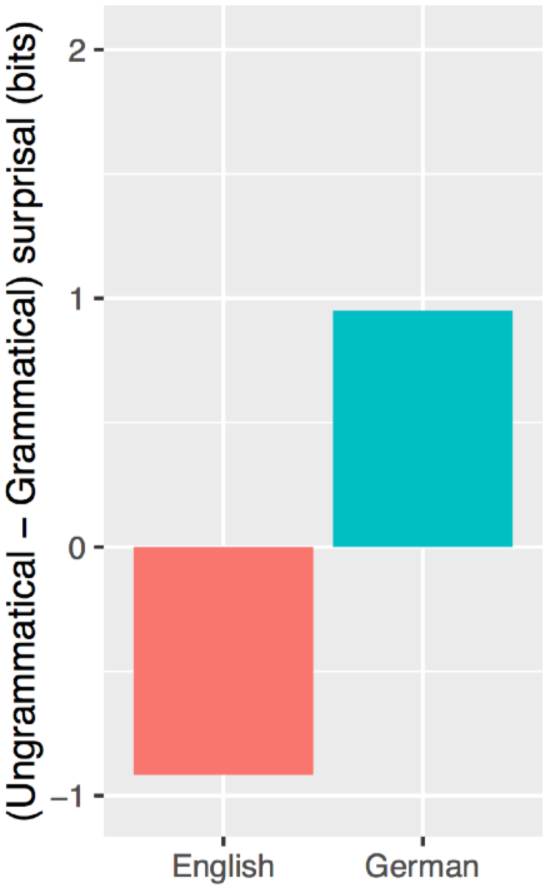

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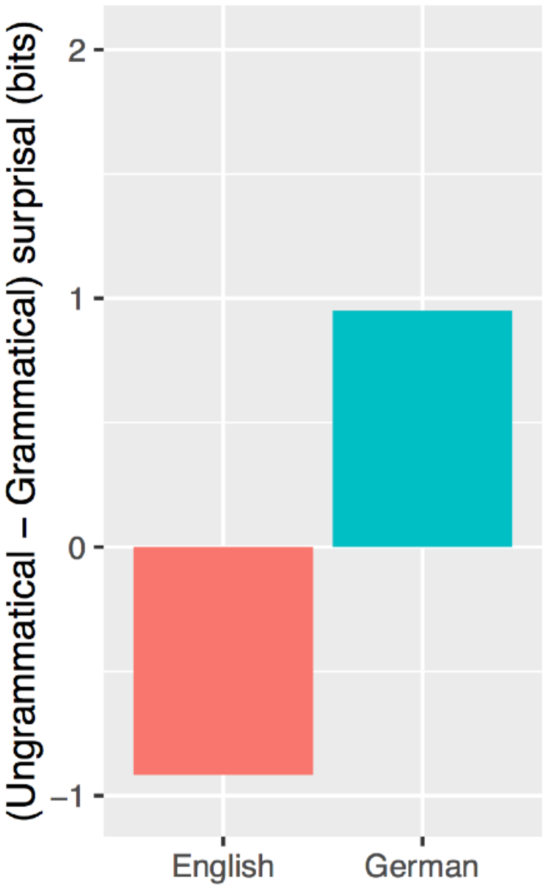

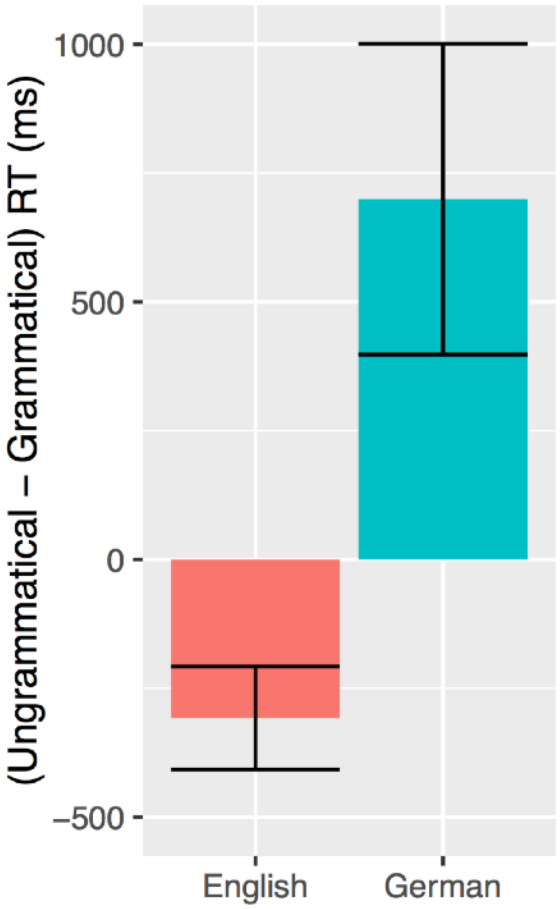

Vasishth et al. (2010)

Noisy-Context Surprisal Account of Structural Forgetting

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- Probability that a context is remembered depends on its prior probability.
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- Probability that a context is remembered depends on its prior probability.
  - Noisy-context surprisal *explains* the behavior of the RNN in Frank et al. (2016): the RNN is using a lossily compressed / noisy representation of context.
- The model has an explicit grammar (competence), but cannot apply it correctly (performance).

Dependency length and noisy-channel surprisal

(Hawkins, 1994; Gibson, 1998, 2000; Gildea & Temperley, 2007, 2009; Park & Levy, 2009; Futrell et al., 2015)

Dependency length and noisy-channel surprisal

- Syntactic dependencies vary in linear distance

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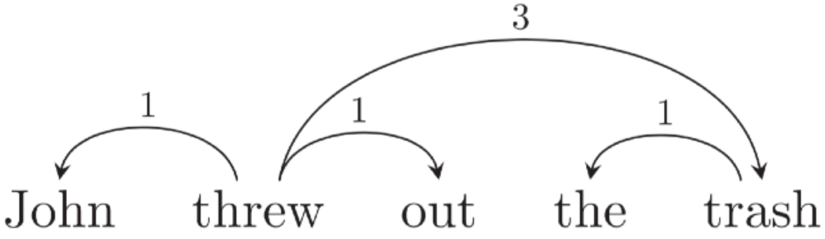

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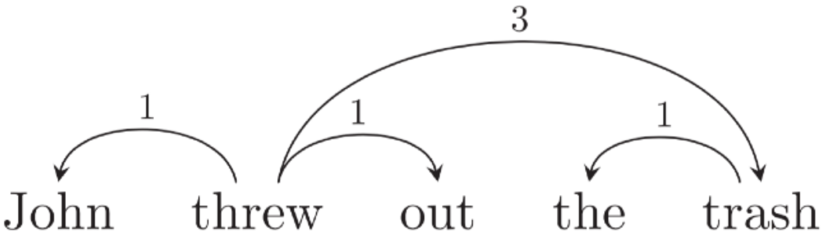

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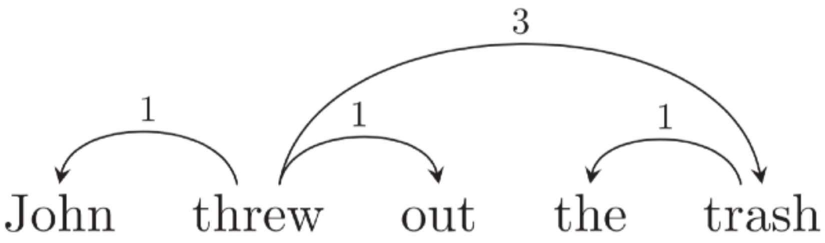

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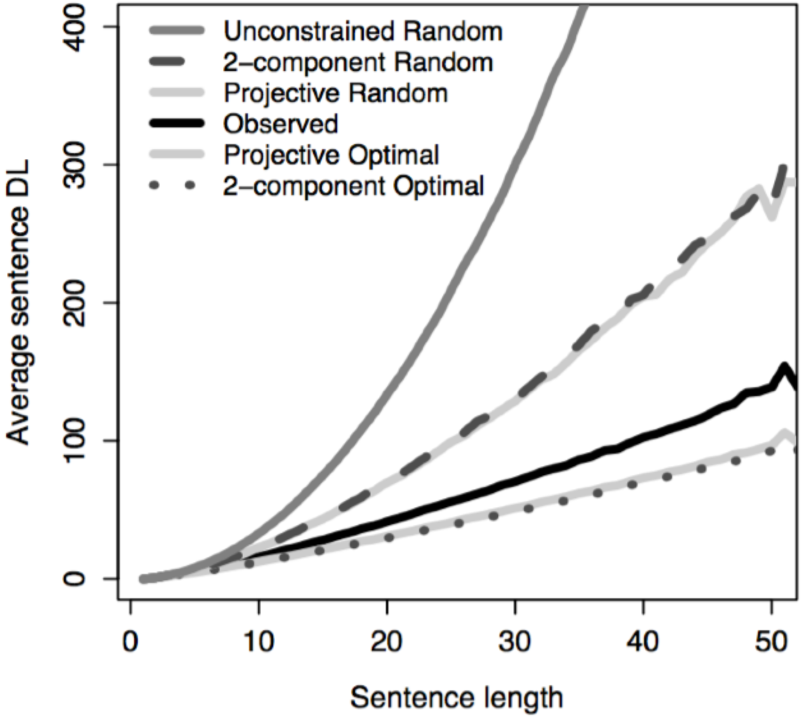

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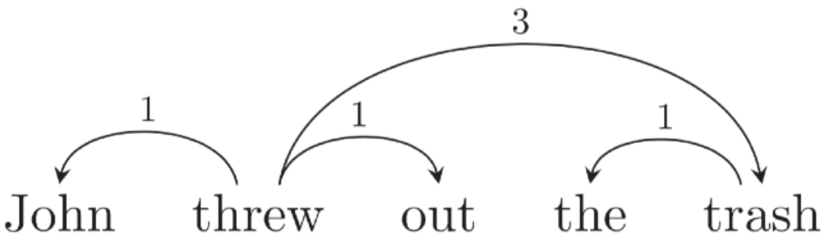

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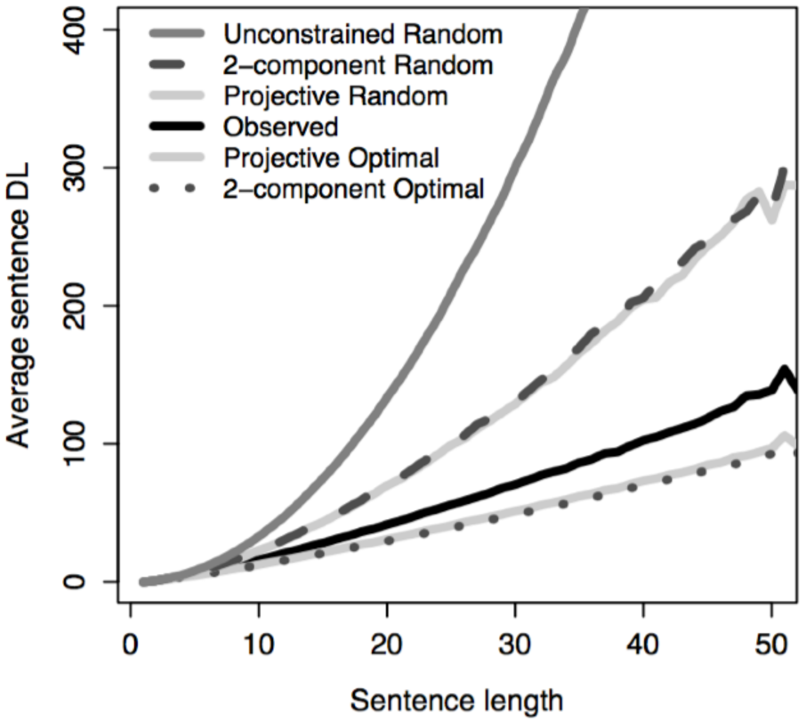

Random-linearization dependency lengths

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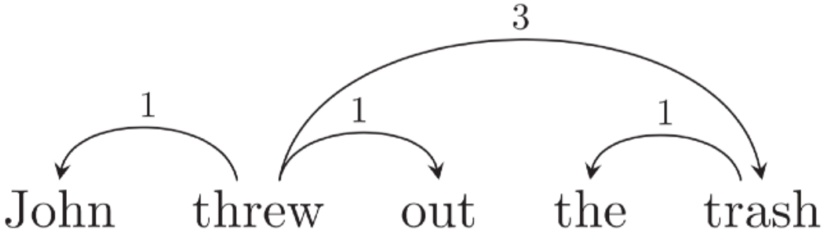

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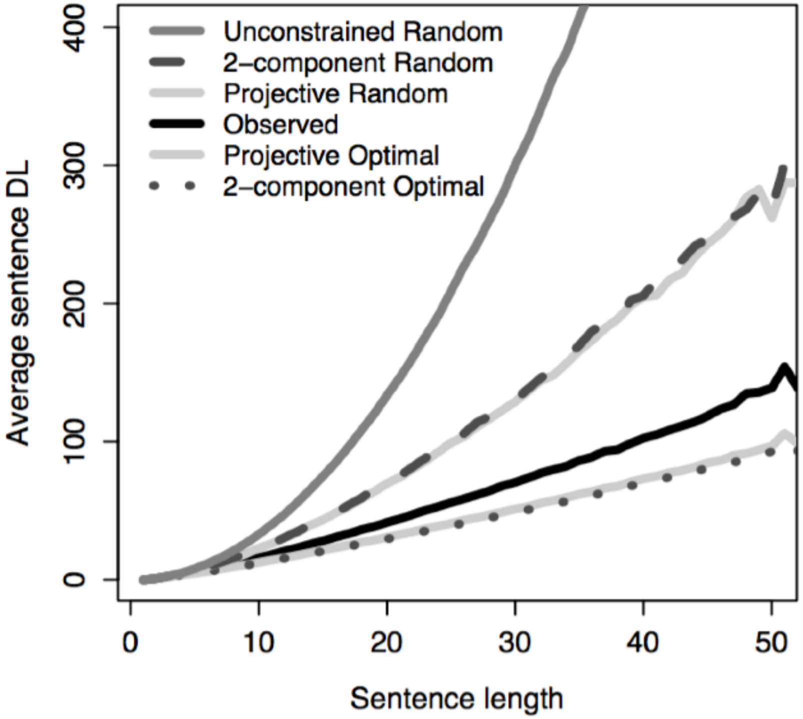


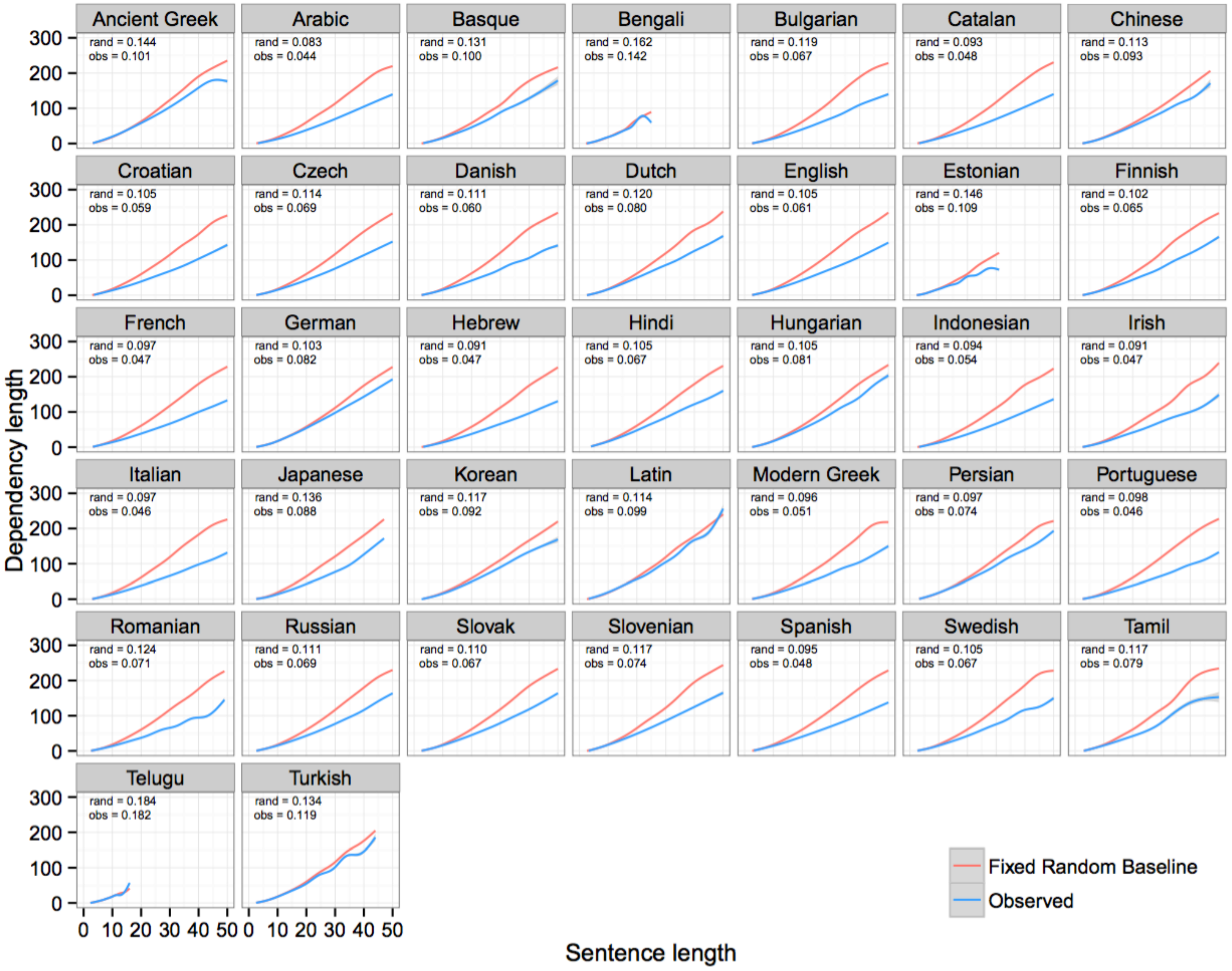
Random-linearization dependency lengths

Observed dependency lengths

(Hawkins, 1994; Gibson, 1998, 2000; Gildea & Temperley, 2007, 2009; Park & Levy, 2009; Futrell et al., 2015)

(Futrell et al., 2015)

Dependency lengths are short across languages!



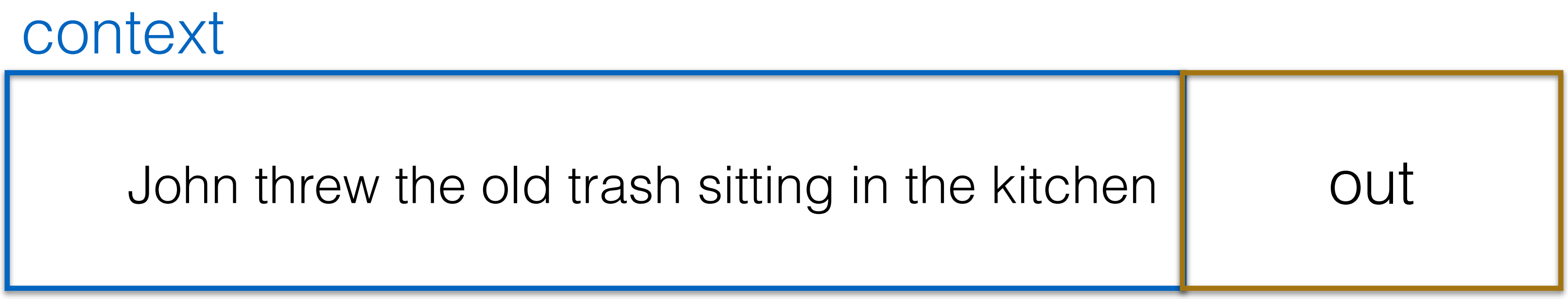
Dependency lengths and the noisy channel

- Here: dependency length minimization can be derived from a combination of surprisal & noisy-channel theory

Richard Futrell

(Futrell & Levy, 2017)

From noisy-channel & surprisal to dependency length minimization



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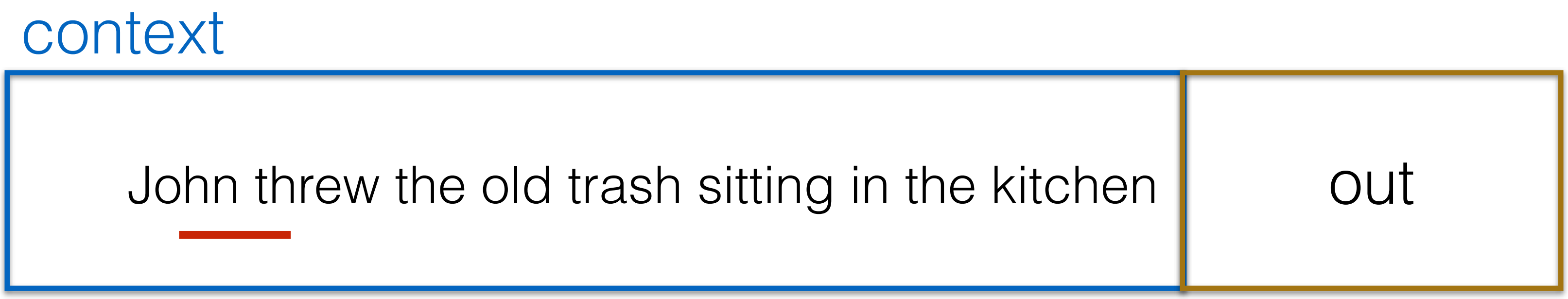

context

John threw the old trash sitting in the kitchen

out

(Futrell & Levy, 2017)

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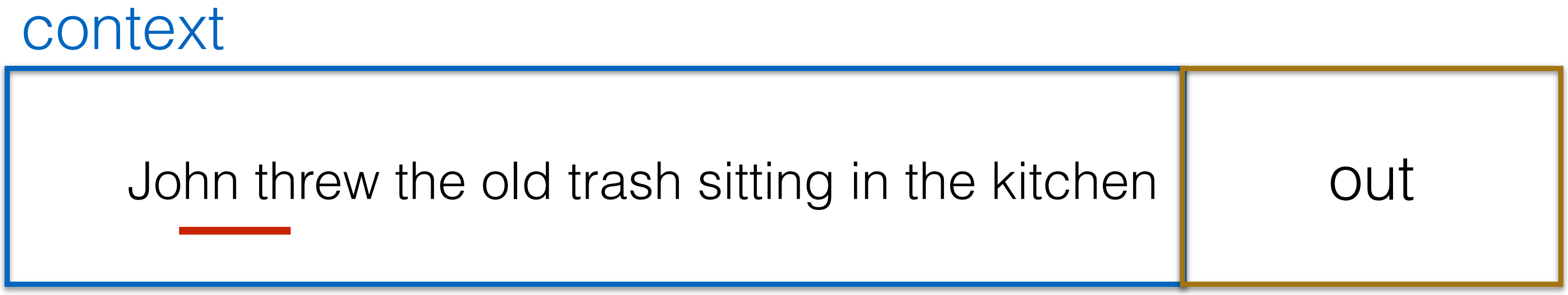

- Suppose we have an **increasing noise rate** the longer a word has been in memory.

(Futrell & Levy, 2017)

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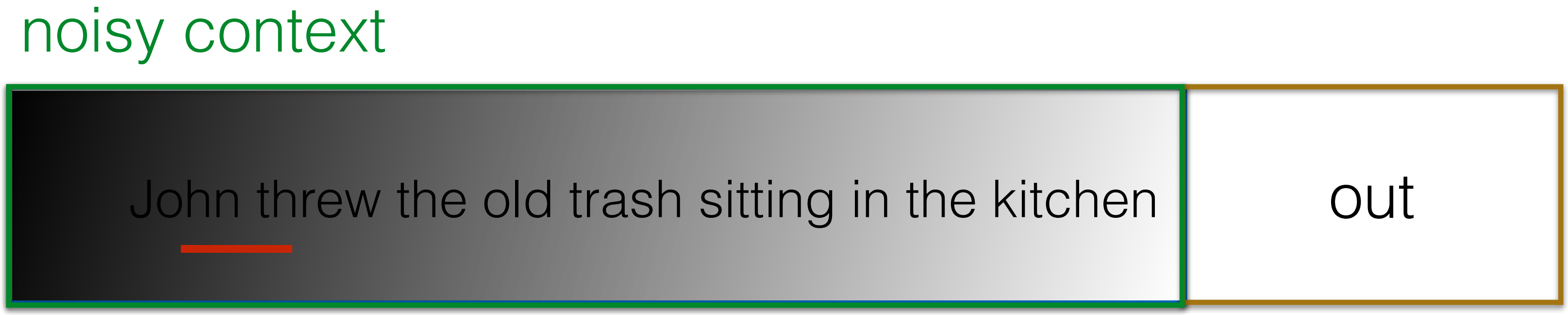

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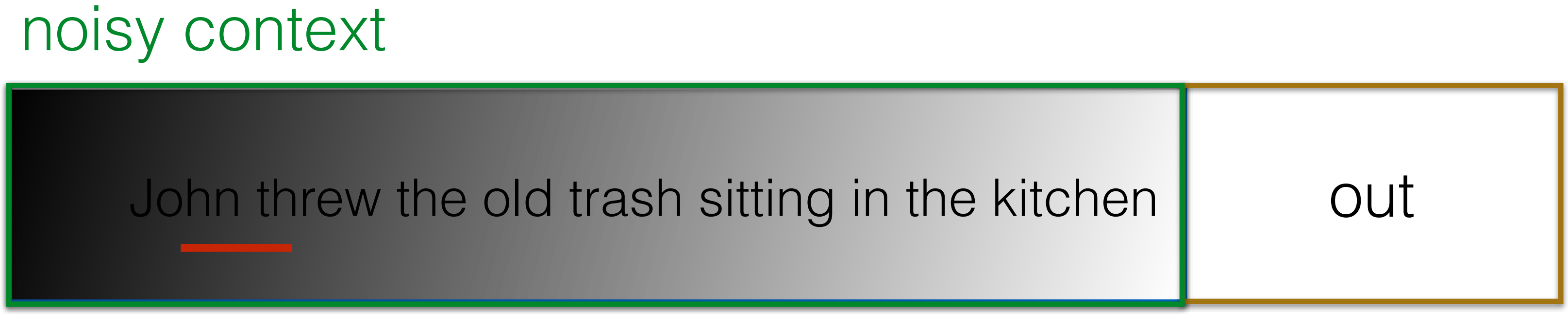

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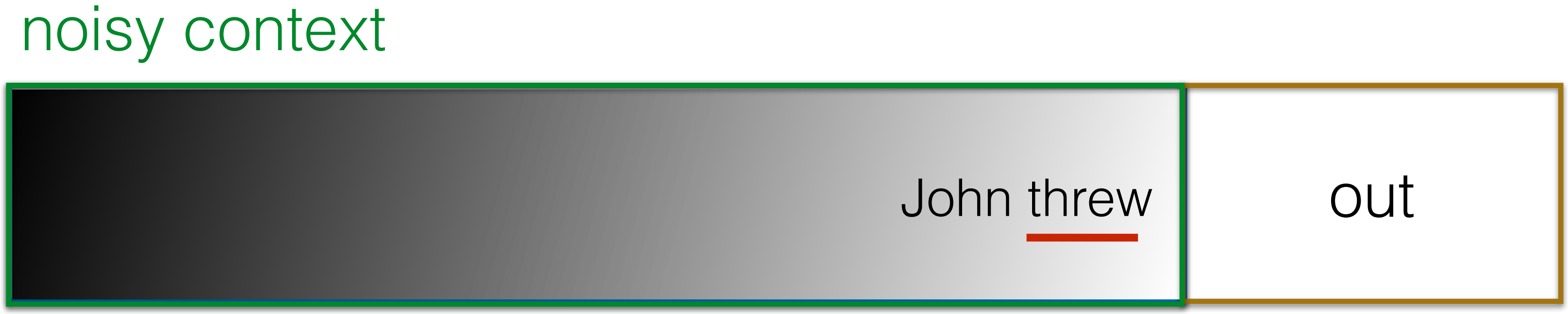

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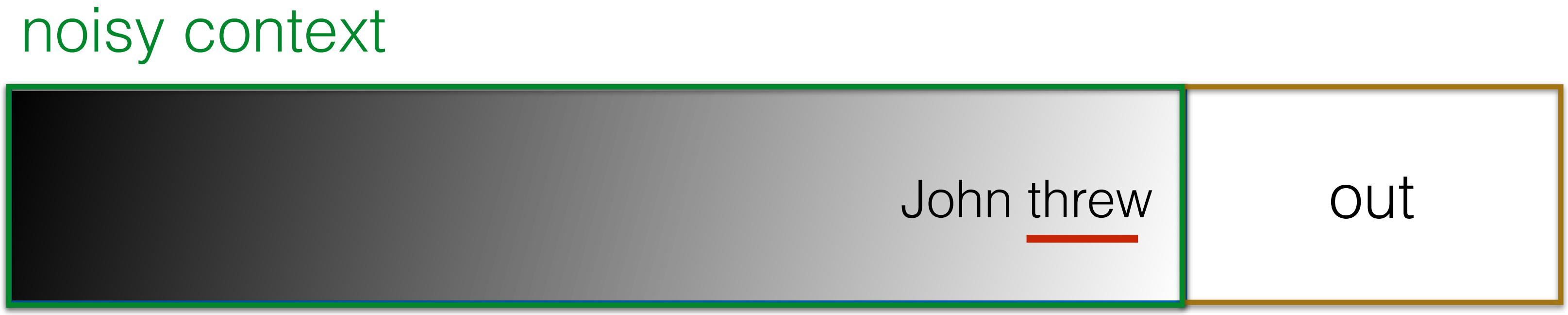

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(Futrell & Levy, 2017)

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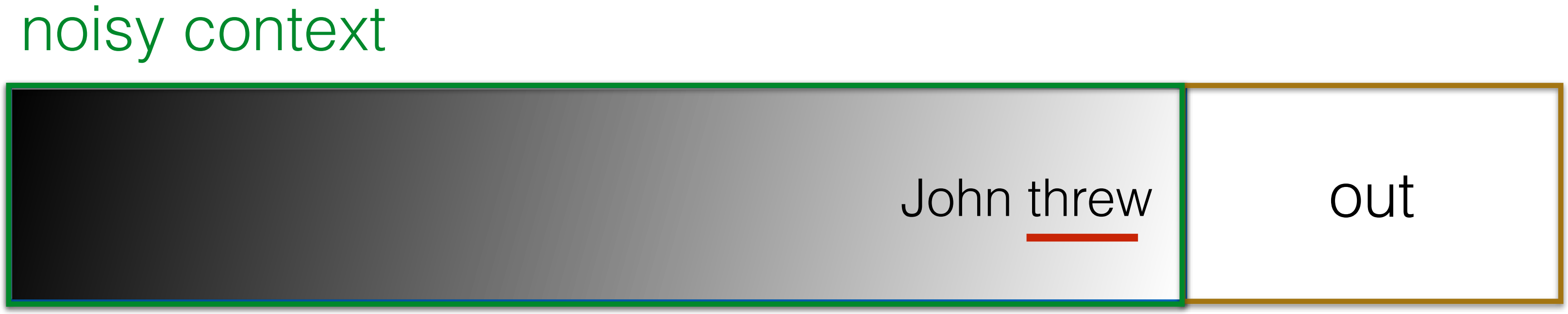

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- We call this **information locality** (following Gildea & Jaeger, 2015).

(Futrell & Levy, 2017)

Derivation of Information Locality

(Futrell & Levy, 2017)

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- Erasure noise decreases the influence of context:

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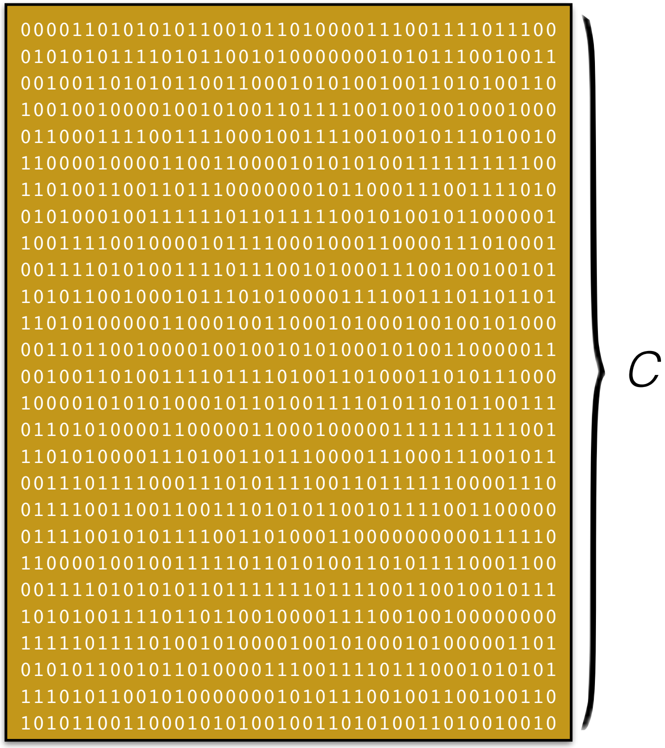
h(out)



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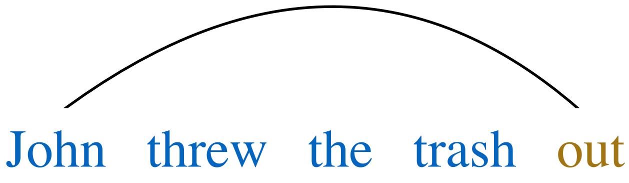
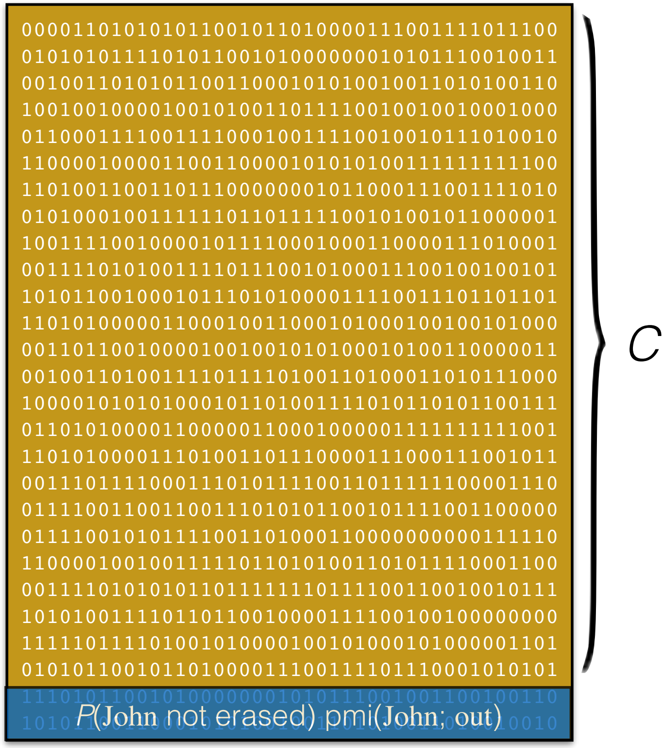


h(out) - *P*(John not erased) pmi(John; out)



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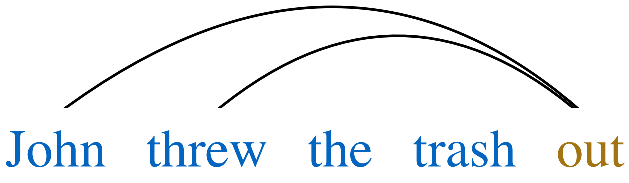

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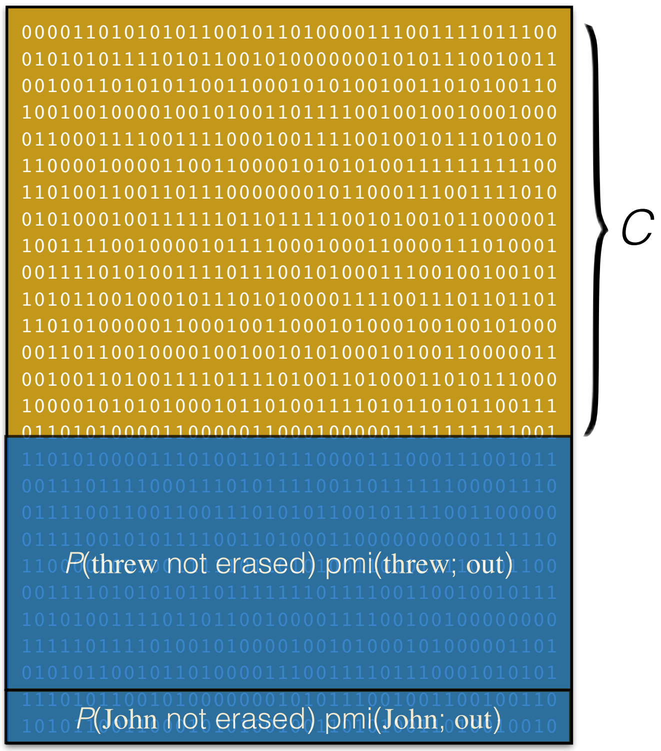
C
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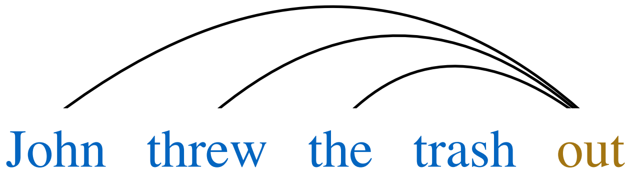

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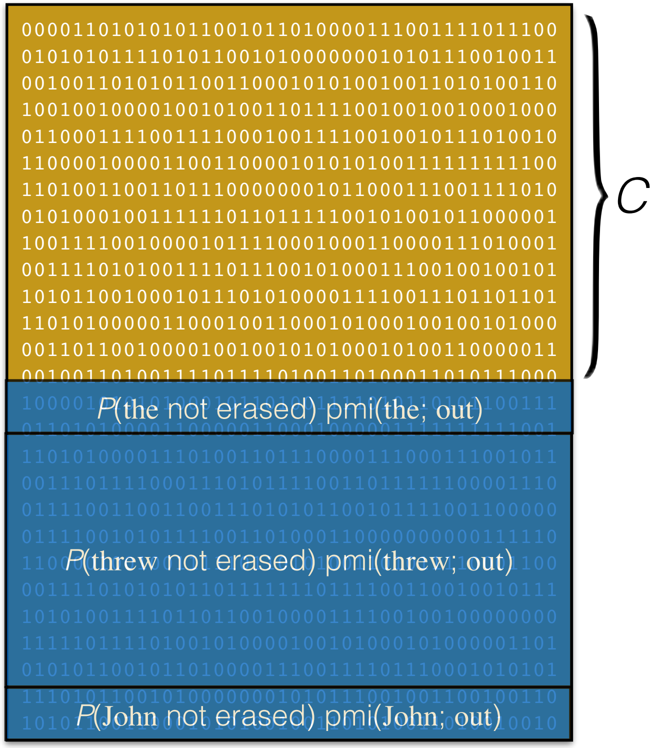
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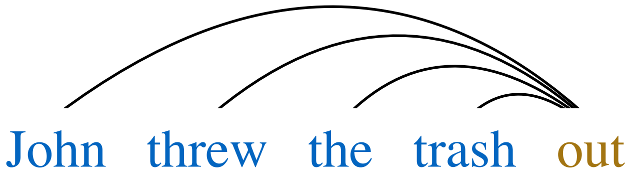

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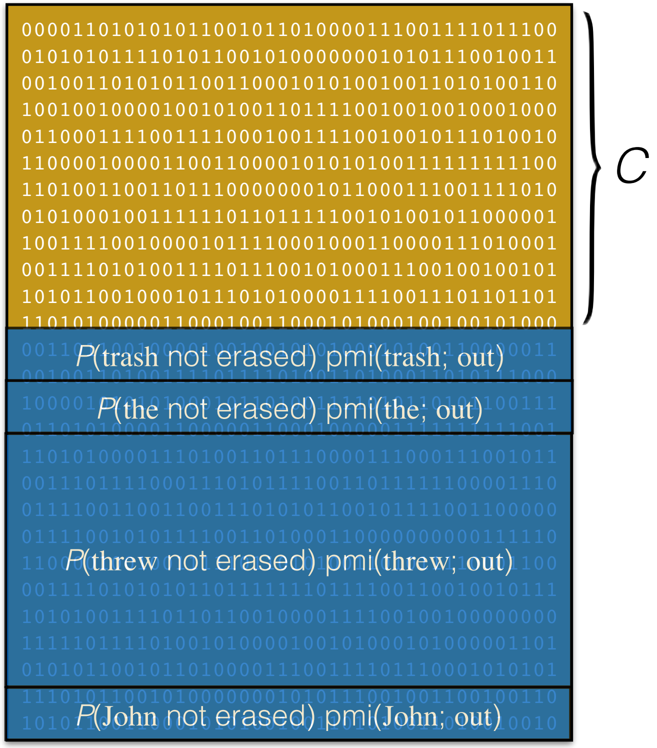
- *P*(trash not erased) pmi(trash; out)



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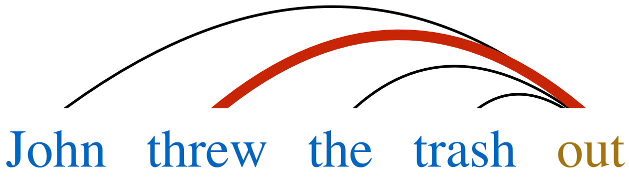

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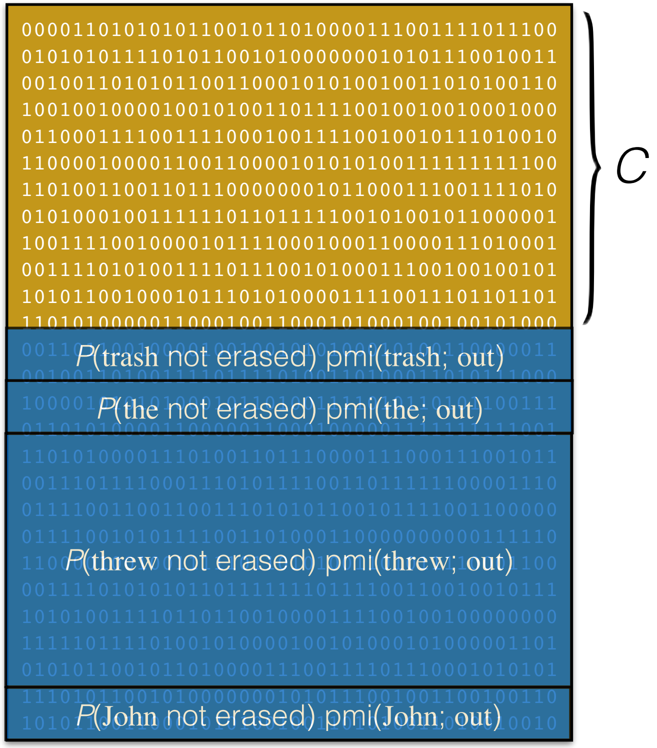
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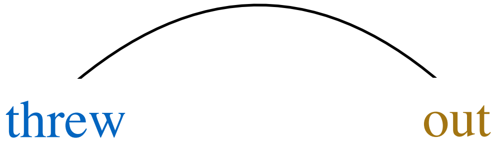

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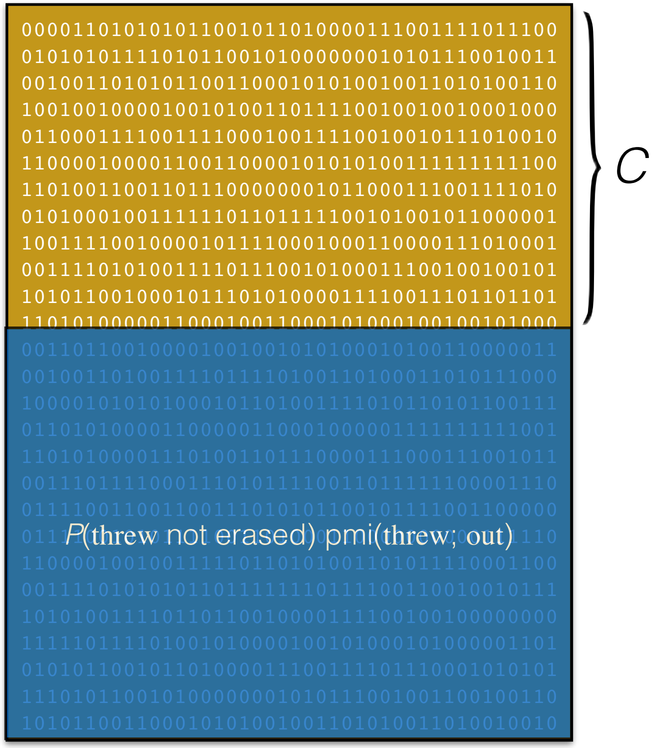

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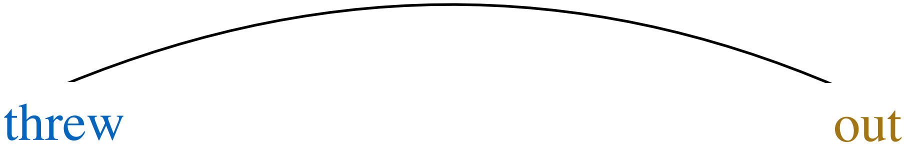

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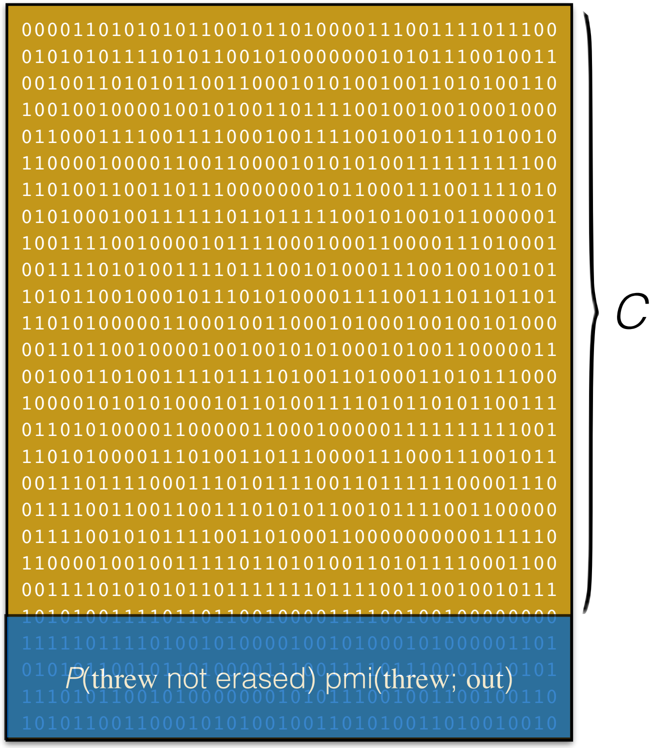

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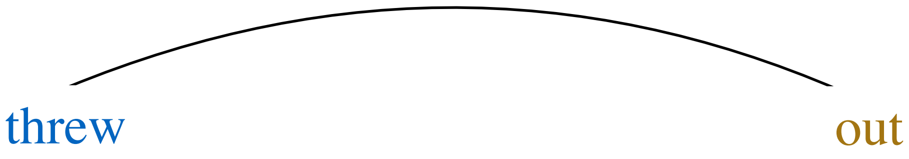
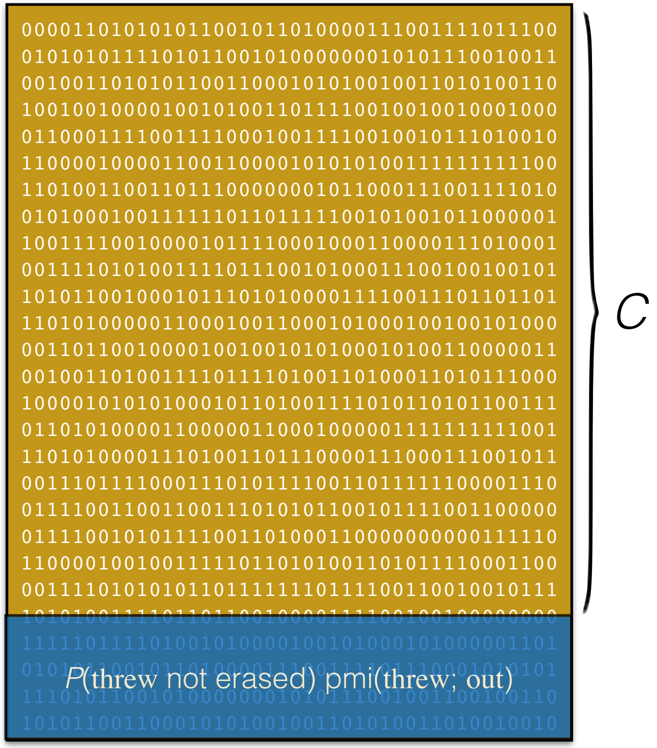


h(out) - P(threw not erased) pmi(threw; out)

- When context items are far, their cost-reducing influence decreases.



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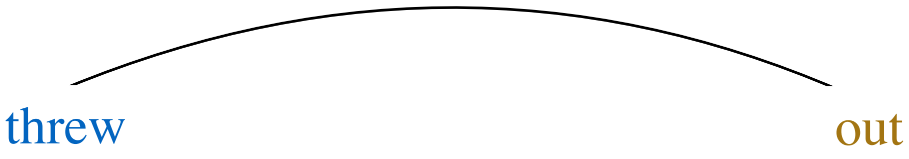

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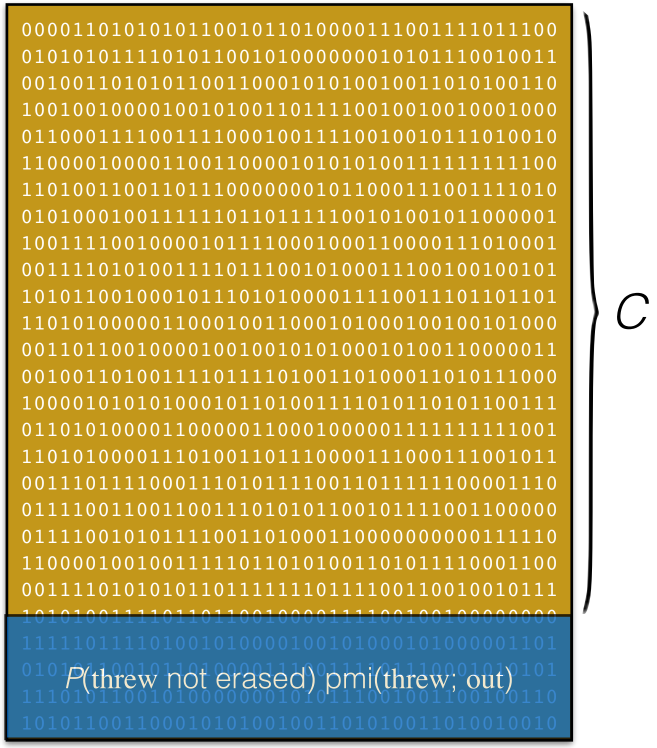

- When context items are far, their cost-reducing influence decreases.
  - Similar to the concept of decay in cue effectiveness (Qian & Jaeger, 2012)

(Futrell & Levy, 2017)

Information Locality

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Information Locality

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- We will show that the hypothesis is true in dependency corpora.

(Futrell & Levy, 2017)

Do Dependencies Have High Mutual Information?

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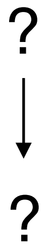

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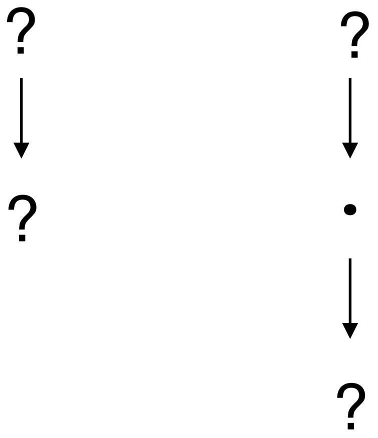

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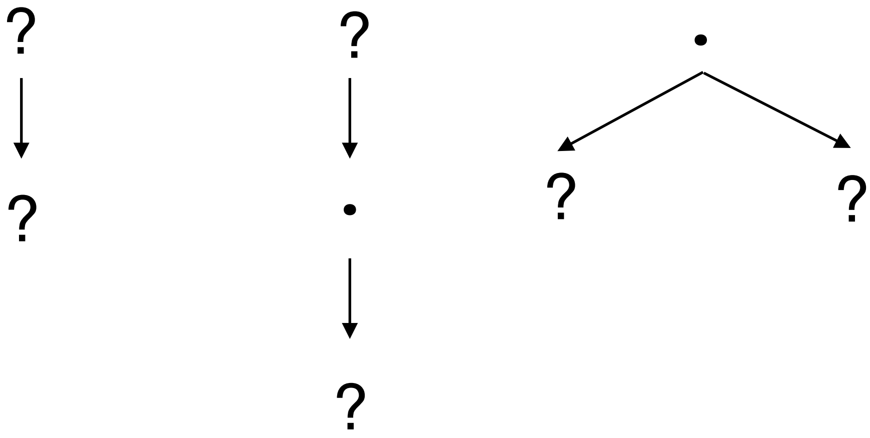

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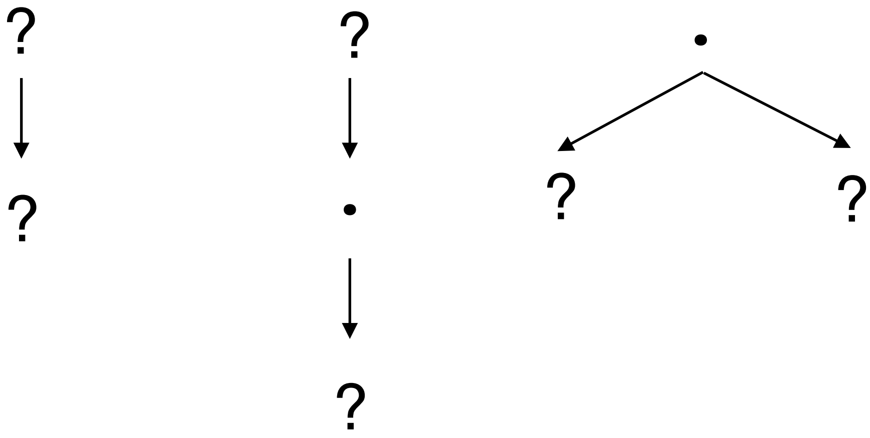

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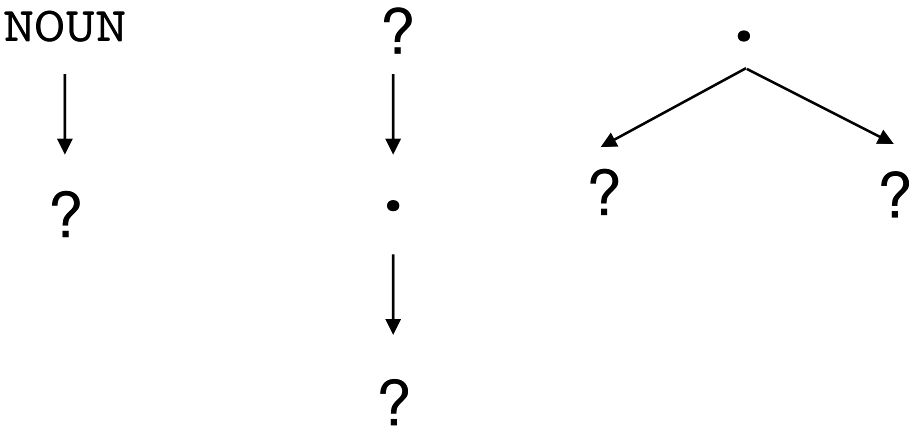

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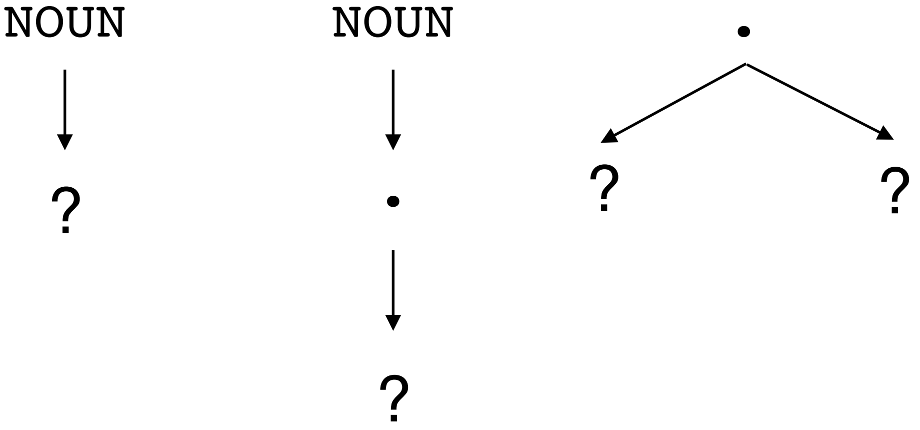

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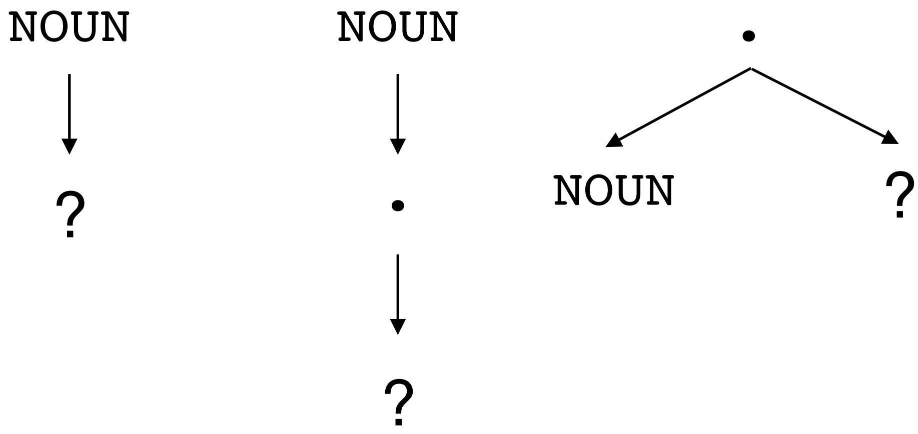

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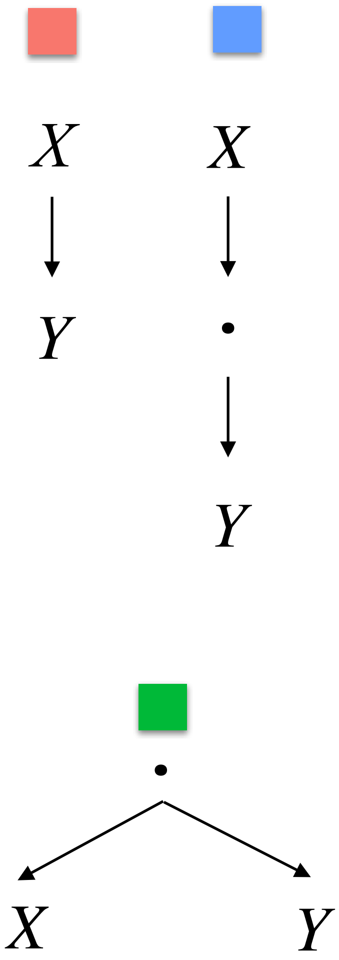

Mutual information (bits)
0.4
0.2
0.0
Ancient Greek
Arabic
Basque
Bulgarian
Catalan
Chinese
Church Slavonic
Croatian
Czech
Danish
Dutch
English
Estonian
Finnish
French
Galician
German
Gothic
Hebrew
Hindi
Hungarian
Indonesian
Irish
Italian
Japanese
Kazakh
Latin
Latvian
Modern Greek
Norwegian (B)
Persian
Polish
Portuguese
Romanian
Russian
Slovak
Slovenian
Spanish
Swedish
Tamil
Turkish
Uyghur
Vietnamese

(Futrell & Levy, 2017)

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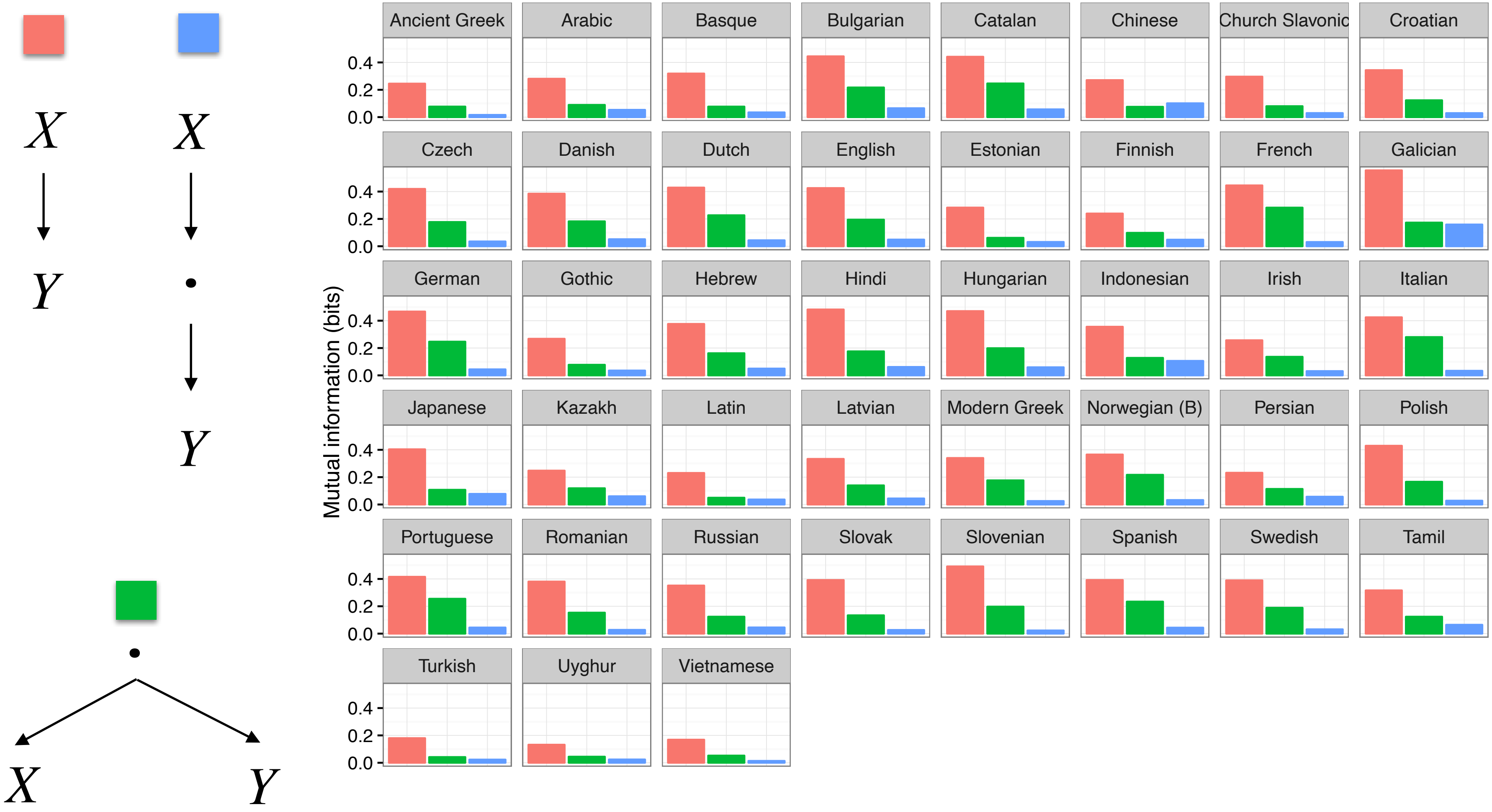

(Futrell & Levy, 2017)

Comprehension as exploration of input

- Broader ongoing goal: develop eye-movement control model integrating the insights discussed thus far:
  - Probabilistic linguistic knowledge
  - Uncertain input representations
  - Principles of adaptive, rational action
- *Reinforcement learning* is an attractive tool for this

(Bicknell & Levy, 2010, 2012ab)

A rational reader

- Very simple framework:
  - Start w/ prior expectations for text (linguistic knowledge)
  - Move eyes to get perceptual input
  - Update beliefs about text as visual arrives (Bayes’ Rule)
- Add to that:
  - Set of *actions* the reader can take in discrete time
  - A *behavior policy*: how the model decides between actions

(Bicknell & Levy, 2010, 2012)

A first-cut behavior policy

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- Actions: *keep fixating*; *move the eyes*; or *stop reading*
- Simple behavior policy with two parameters: α and β
- Define *confidence* in a character position as the probability of the most likely character

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```
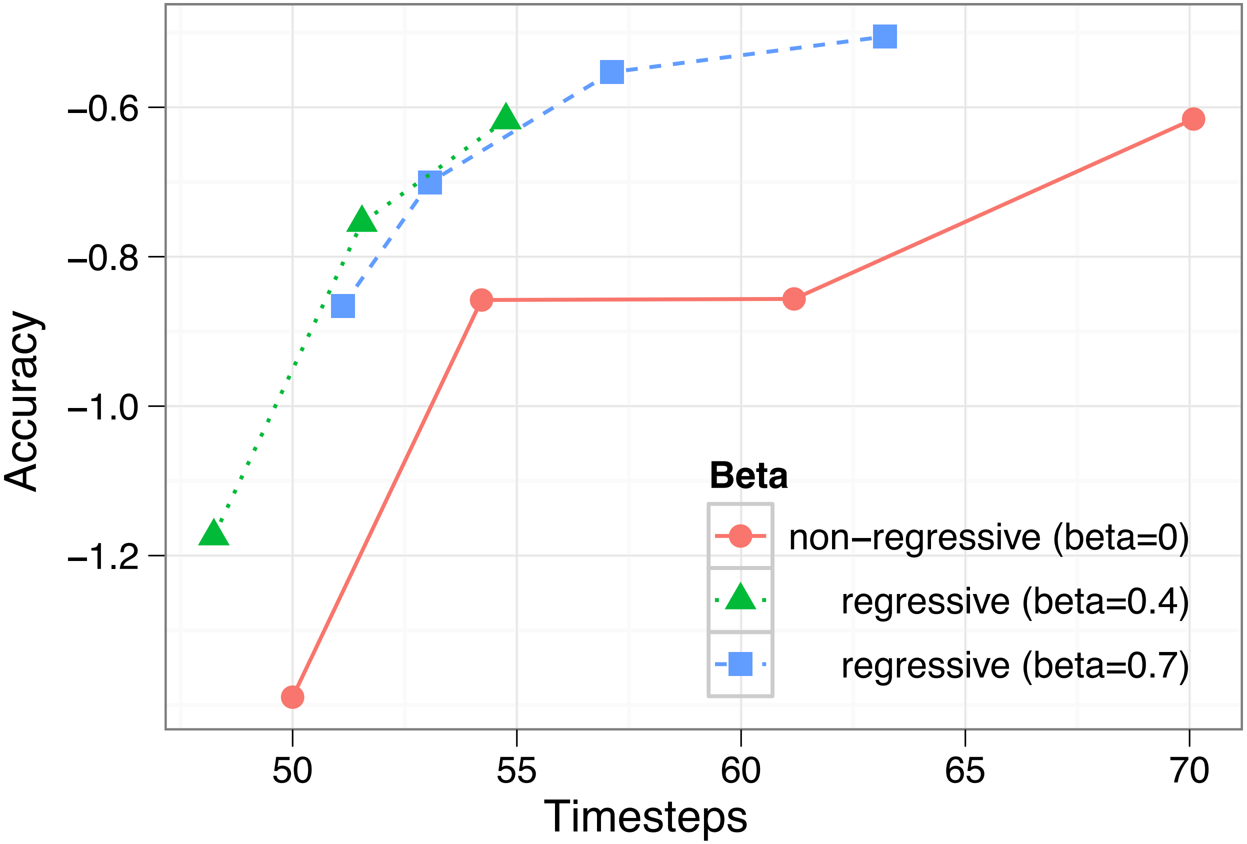

Confidence=0.59

- Move left to right, bringing up confidence in each character position until it reaches α
- If confidence in a previous character position drops below β, regress to it
- Finish reading when you're confident in everything

(Non)-regressive policies

- *Non-regressive policies* have *β=0*
- Hypothesis: non-regressive policies strictly dominated
- Test: estimate *speed* and *accuracy* of various policies on reading the the Schilling et al. (1998) corpus



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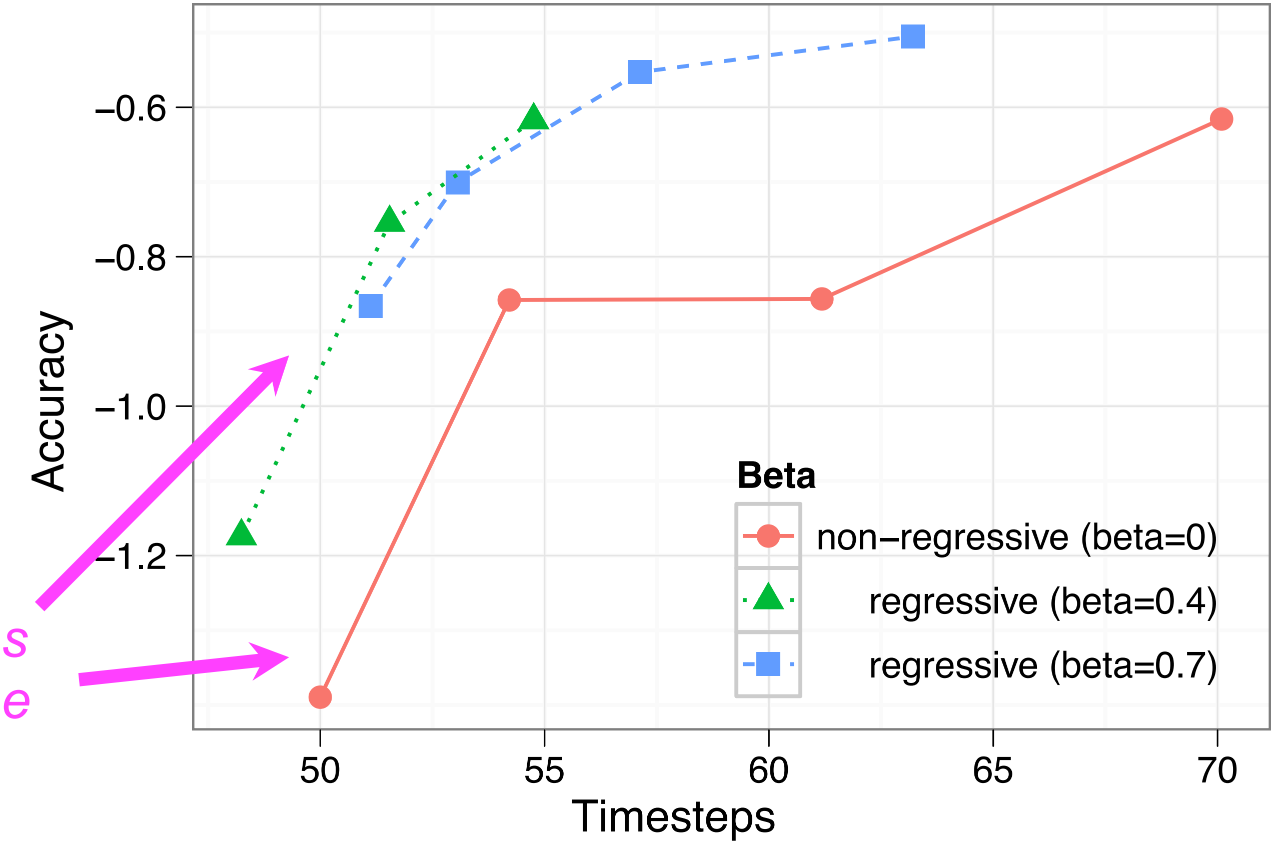

Non-regressive policies always beaten by some regressive policy

Goal-based adaptation

(Bicknell & Levy, 2010)

Goal-based adaptation

- Open frontier: modeling the adaptation of eye movements to specific reader goals

- We set a *reward function:* relative value γ of speed (finish reading in T timesteps) versus accuracy (guess correct sentence with probability L)

- PEGASUS simplex-based optimization (Ng & Jordan, 2000)

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γ	α	β
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0.1		
0.4		

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0.025	0.90	0.99
0.1	0.36	0.80
0.4	0.18	0.38

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γ	**α**	**β**	**Timesteps**	**Accuracy**
0.025	0.90	0.99	41.2	P(correct)=0.98
0.1	0.36	0.80	25.8	P(correct)=0.41
0.4	0.18	0.38	16.4	P(correct)=0.01

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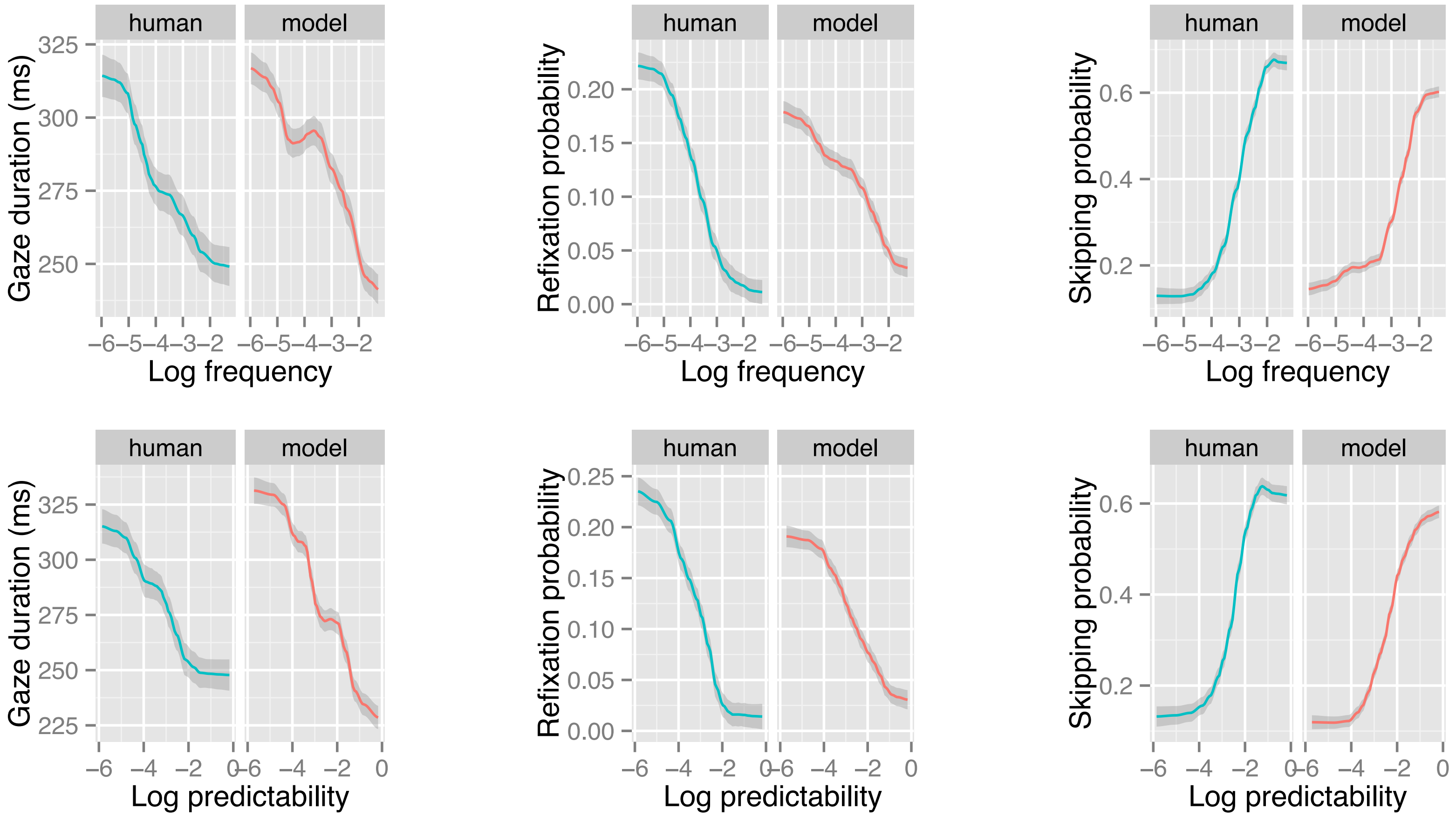
- The method works, and gives intuitive results

(Bicknell & Levy, 2010)

Empirical match with human reading

- Benchmark measures in eye-movement modeling:

frequency



predicts size and shape of all effects

predictability

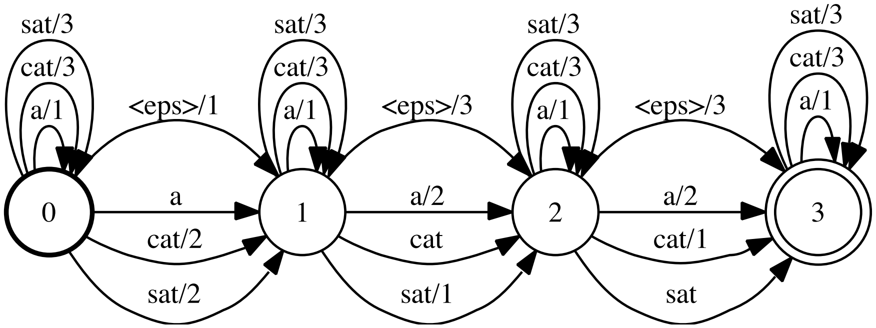
Bicknell & Levy (2012)

Success at empirical benchmarks

- Other models (E-Z Reader, SWIFT) get these too, but *stipulate* rel’nship between word properties & “processing rate”
- We *derive* these relationships from simple principles of noisy-channel perception and rational action

Noisy-channel processing: summary

- Noisy-channel models help us understand
  - Basic capabilities of human language comprehension
  - Outstanding puzzles in syntactic processing
- These models open up a rich typology of new sentence processing effects
- There is growing evidence for these effects
- These models pose new theoretical opportunities and architectural challenges for the study of human linguistic cognition



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