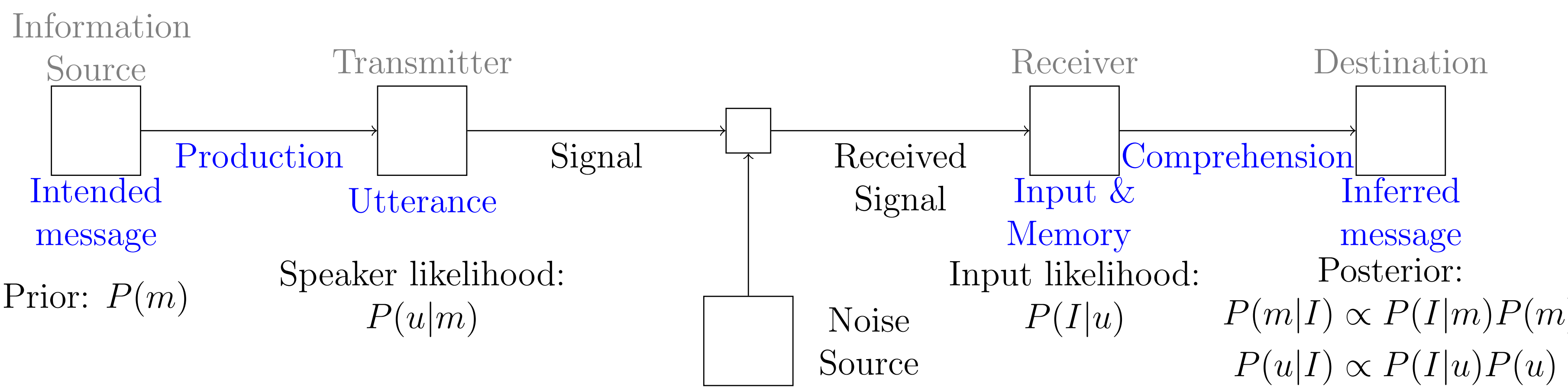
# Noisy-channel sentence comprehension theory II




Roger Levy

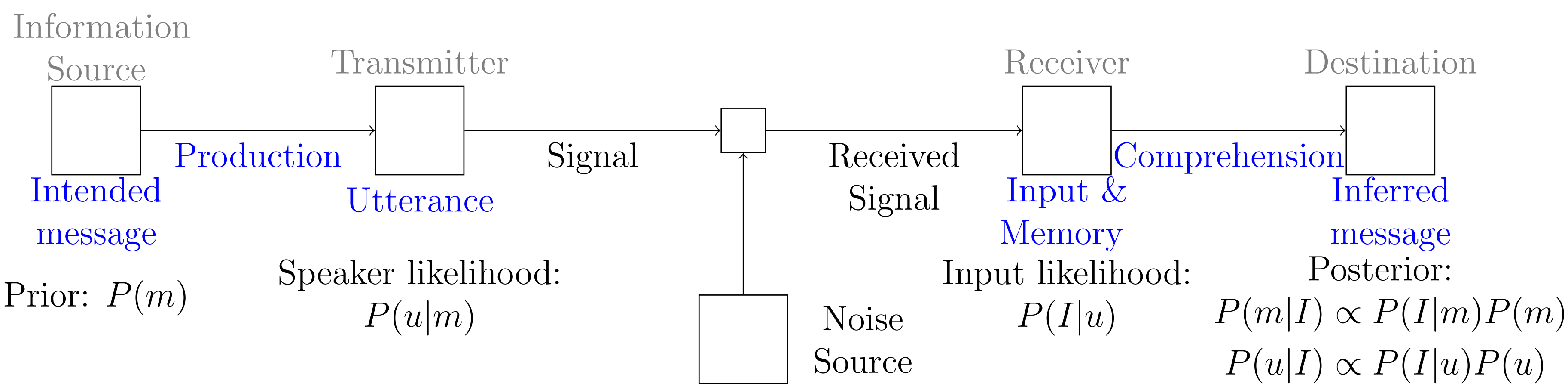
9.19: Computational Psycholinguistics

22 November 2021

# Today's agenda

- Explaining patterns of global utterance interpretation in the noisy-channel sentence processing theory
- Explaining "structural forgetting" effects by combining the noisy-channel theory with surprisal

# Noisy-channel theory of language processing




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

# Simple question-answering

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

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**`The woman lost the diamond.`**

*Did the woman lose something?*

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**The ball kicked the girl.**

*Did the girl kick something?*

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*Did the tax law benefit from anything?*

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**`The cook baked a cake Lucy.`**

*Was something baked for Lucy?*

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**`The cook baked a cake Lucy.`**

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

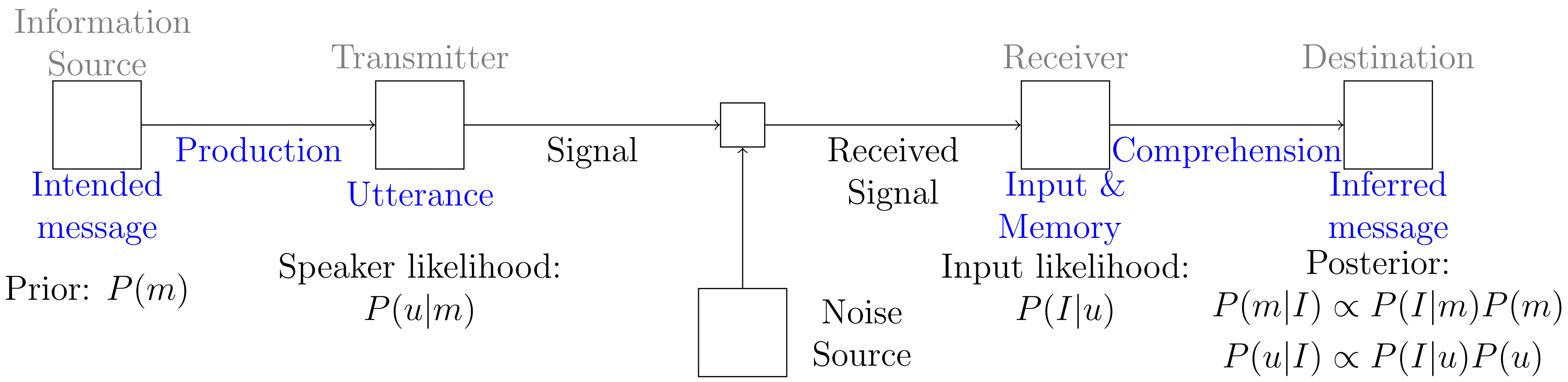
***Over 2/3 of answers!***

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

# Noisy-channel semantic interpretation?

**`The cook baked a cake Lucy.`**

*Was something baked for Lucy?*



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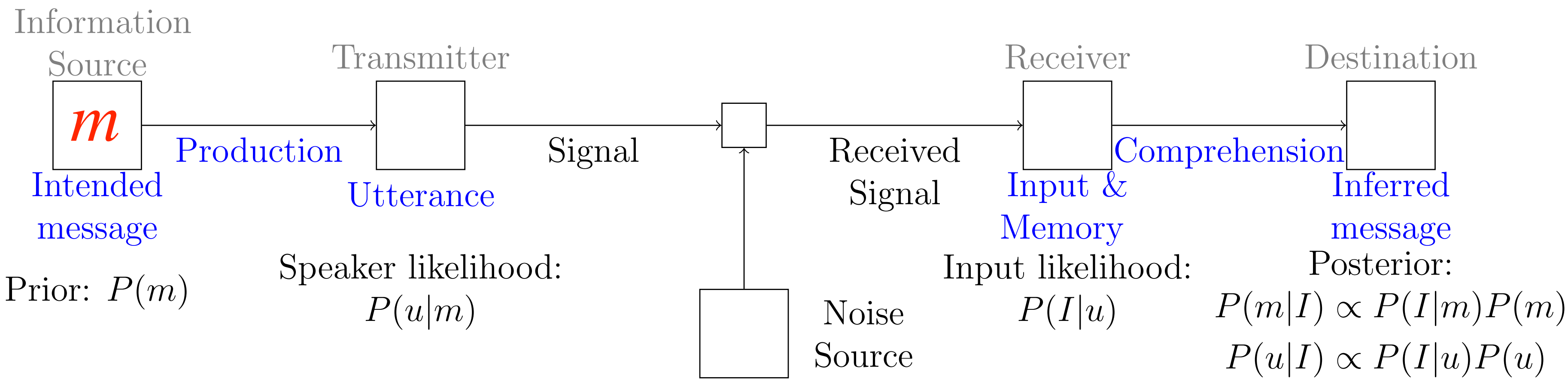

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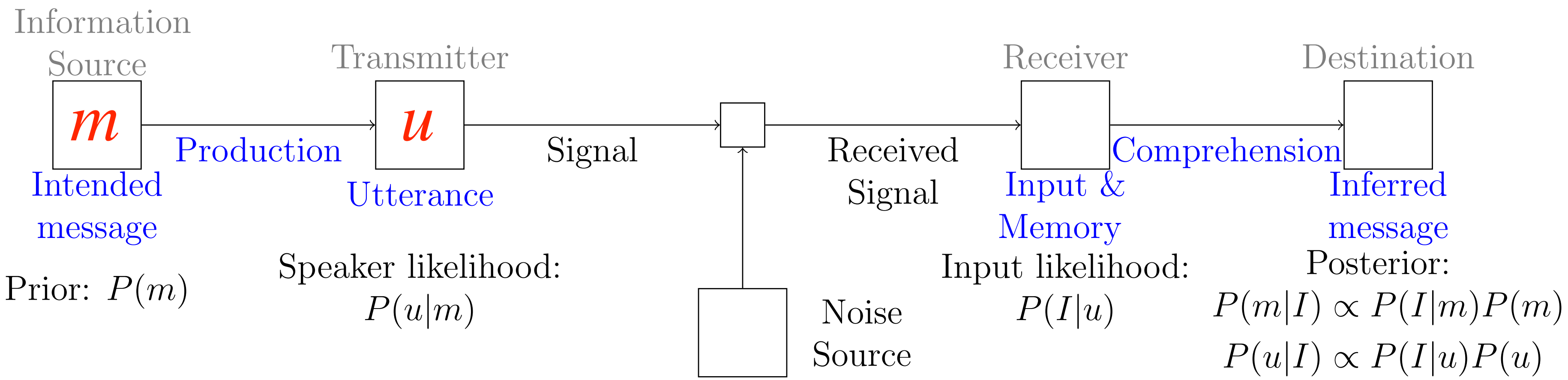

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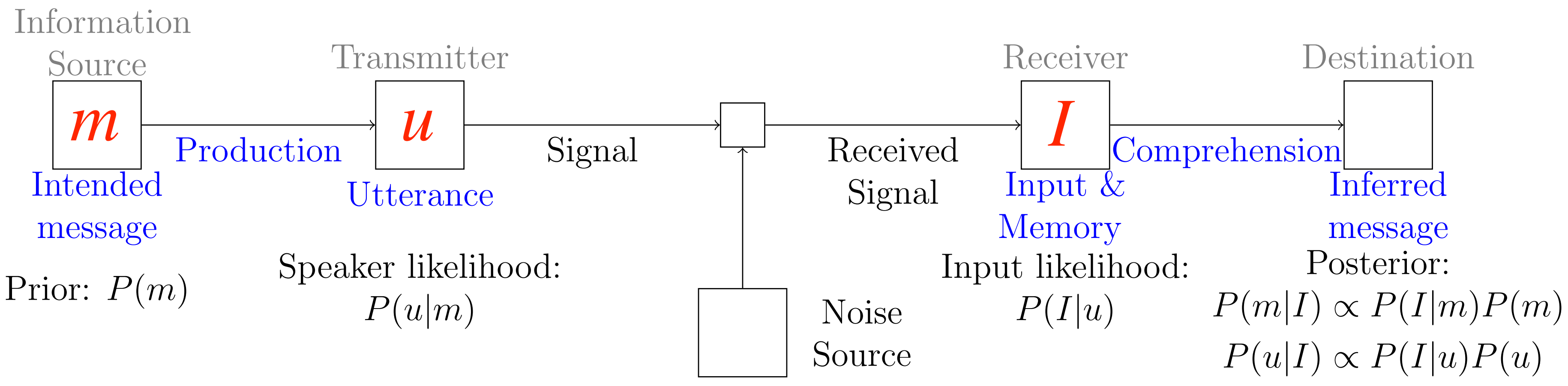

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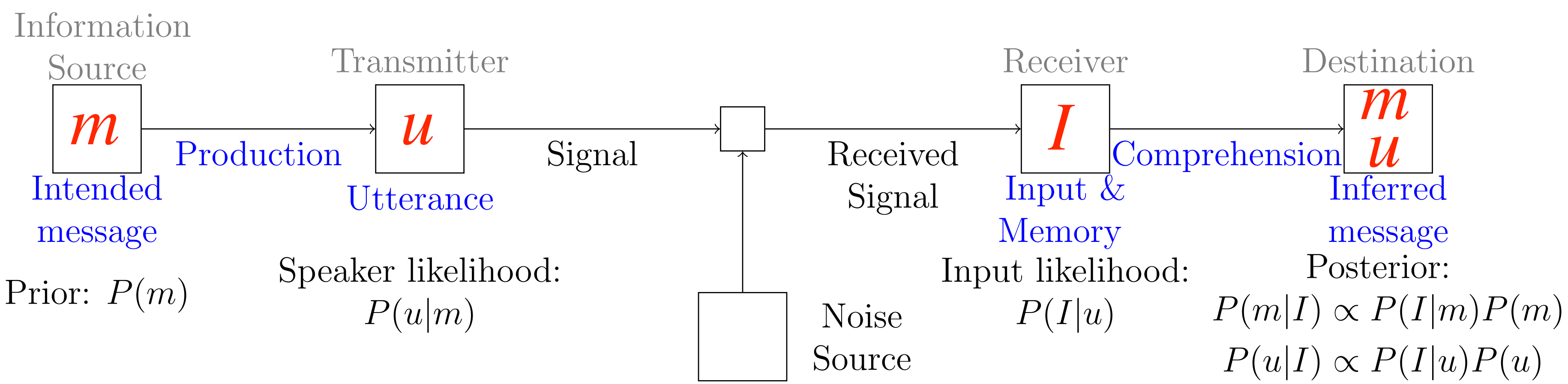

# Noisy-channel semantic interpretation?

*I* ← **`The cook baked a cake Lucy.`**

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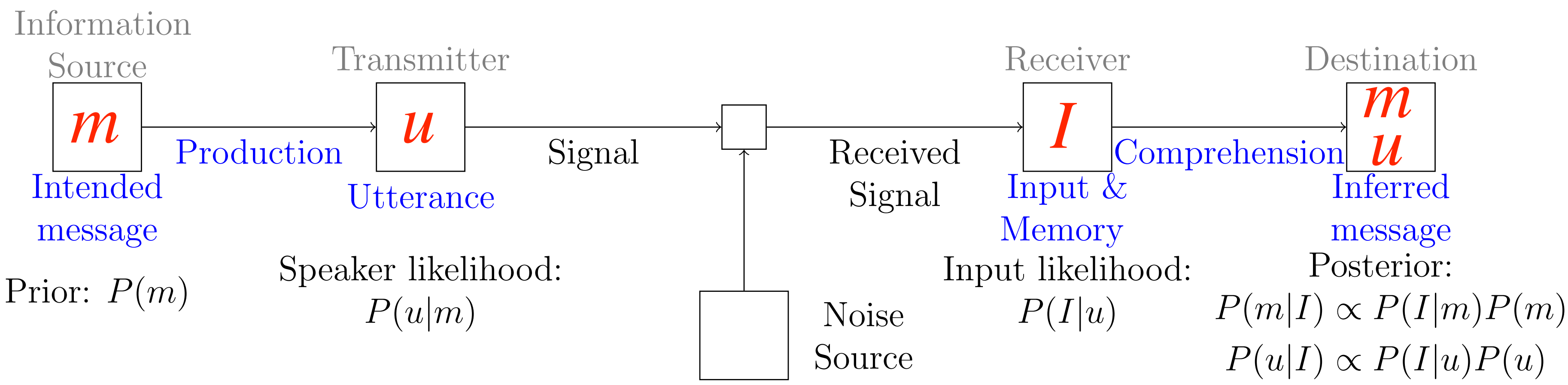
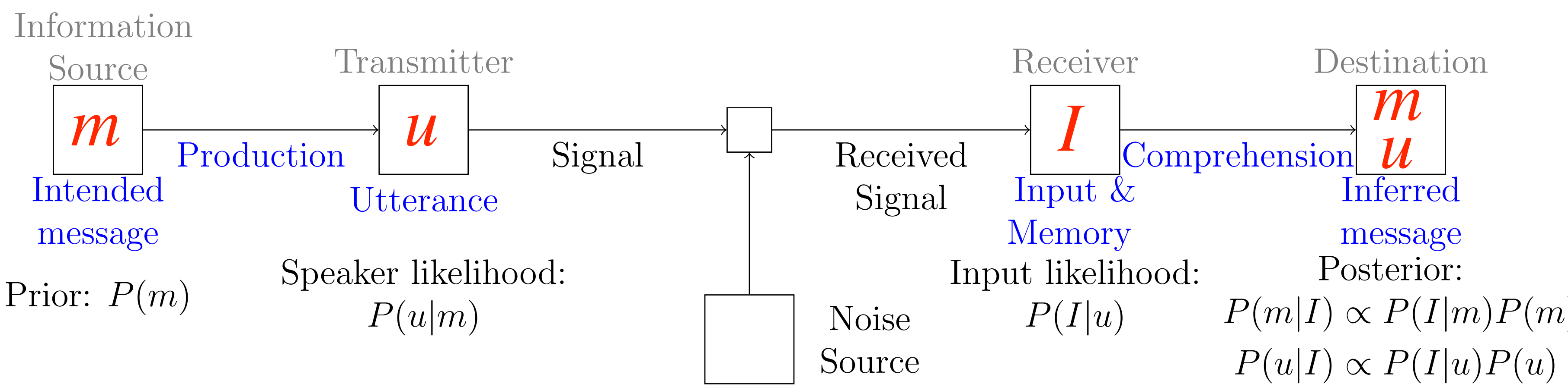


# Noisy-channel semantic interpretation?

$I \leftarrow$ **`The cook baked a cake Lucy.`**

$m$? *Was something baked for Lucy?*



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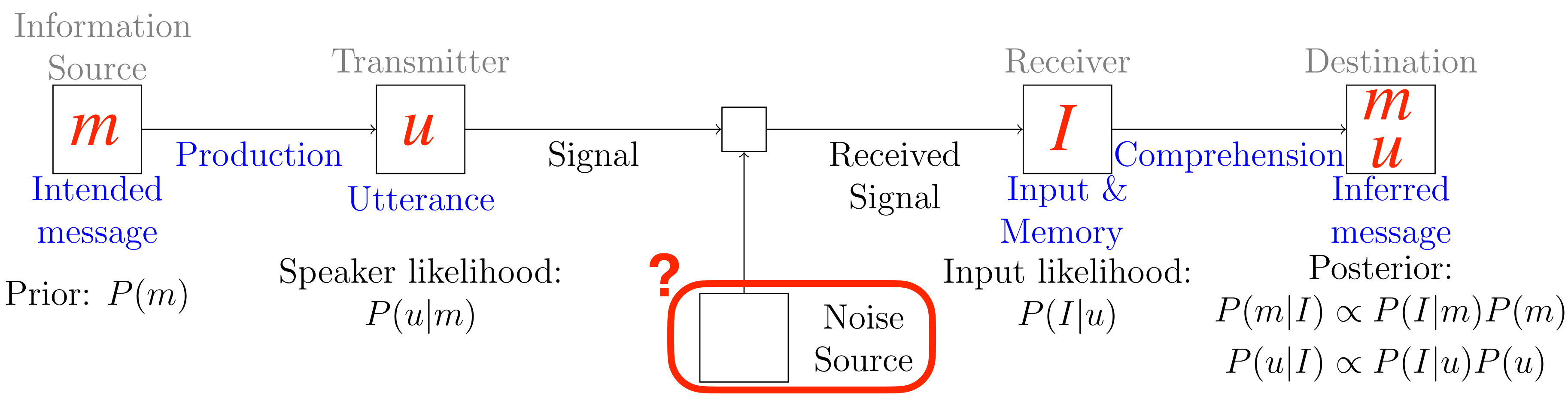

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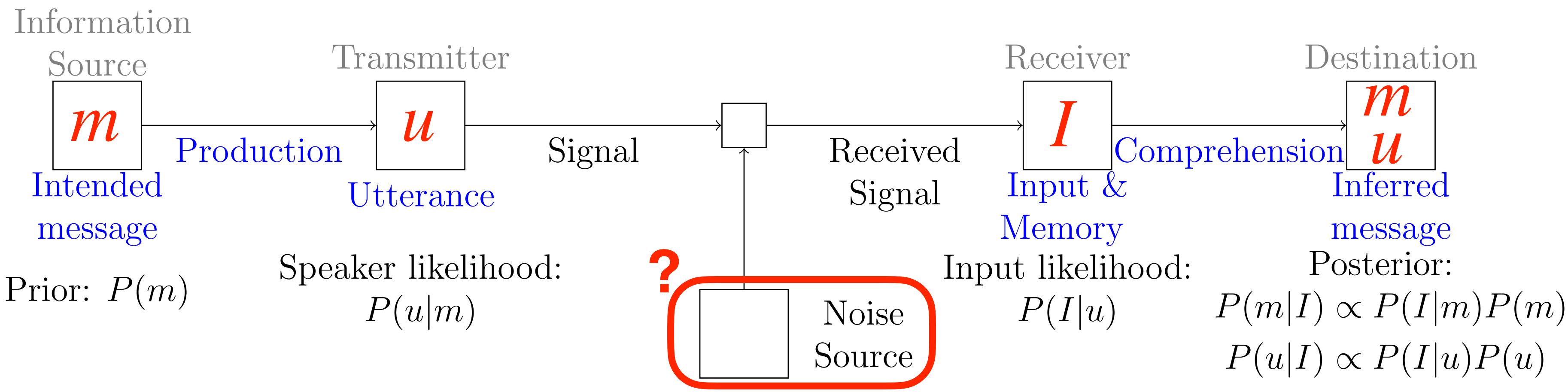


In two semantically plausible "neighbor" sentences, the answer is "yes":

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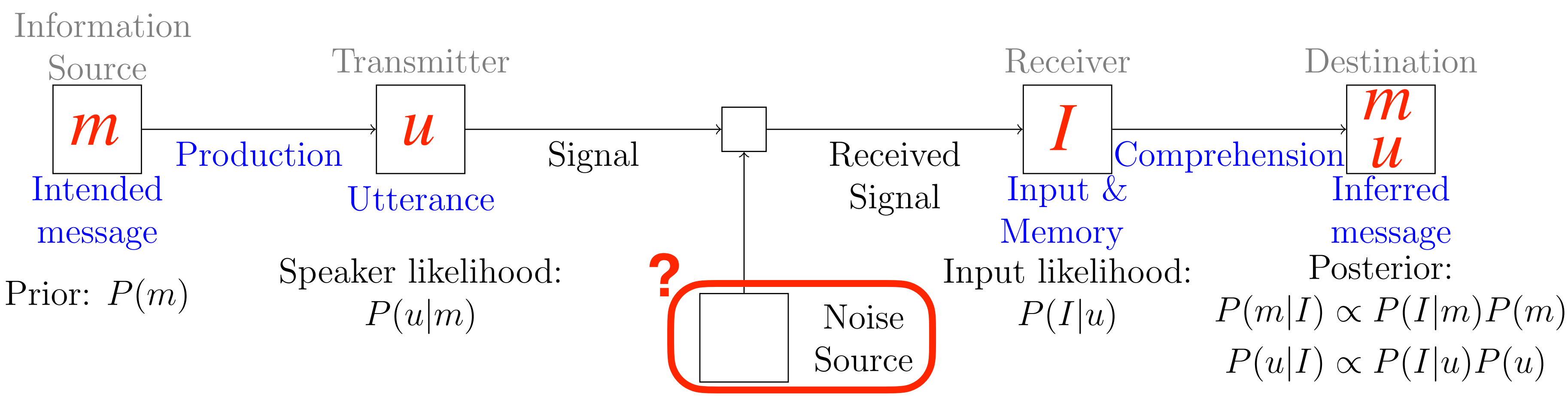


In two semantically plausible "neighbor" sentences, the answer is "yes":

**`The cook baked a cake Lucy.`**

***`for`***

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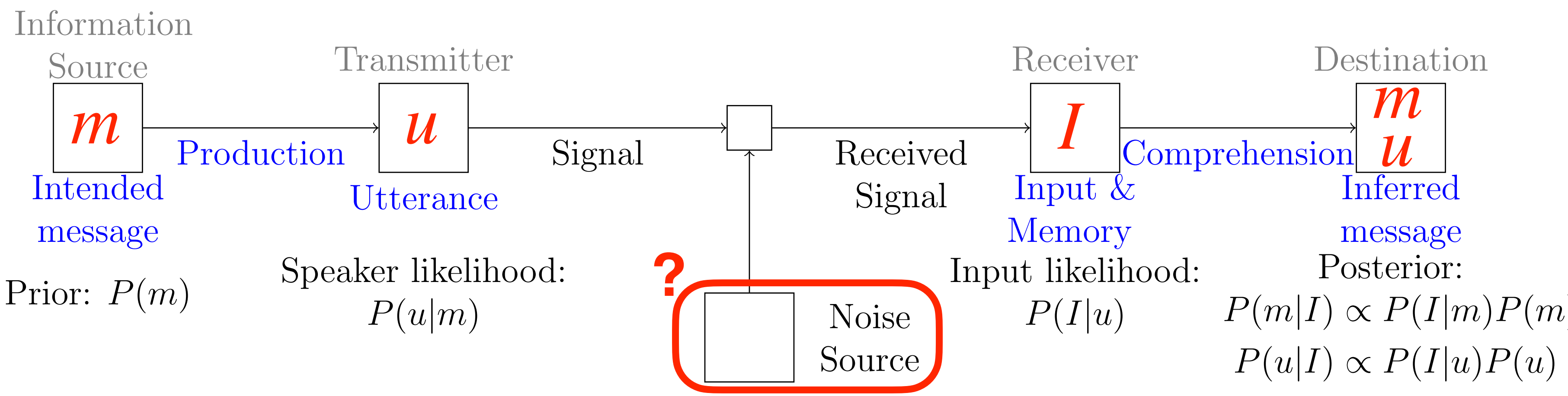


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*for*

Hypothesized noise operation: **deletion**

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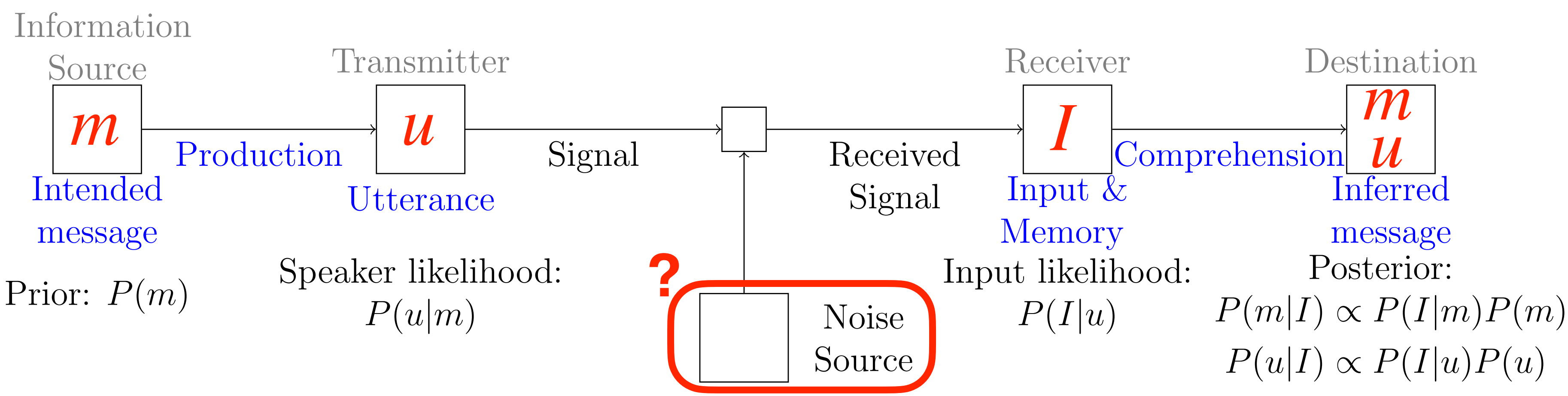


In two semantically plausible "neighbor" sentences, the answer is "yes":

`The cook baked a cake Lucy.`

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

`The cook baked a cake Lucy.`

*`Lucy a cake`*

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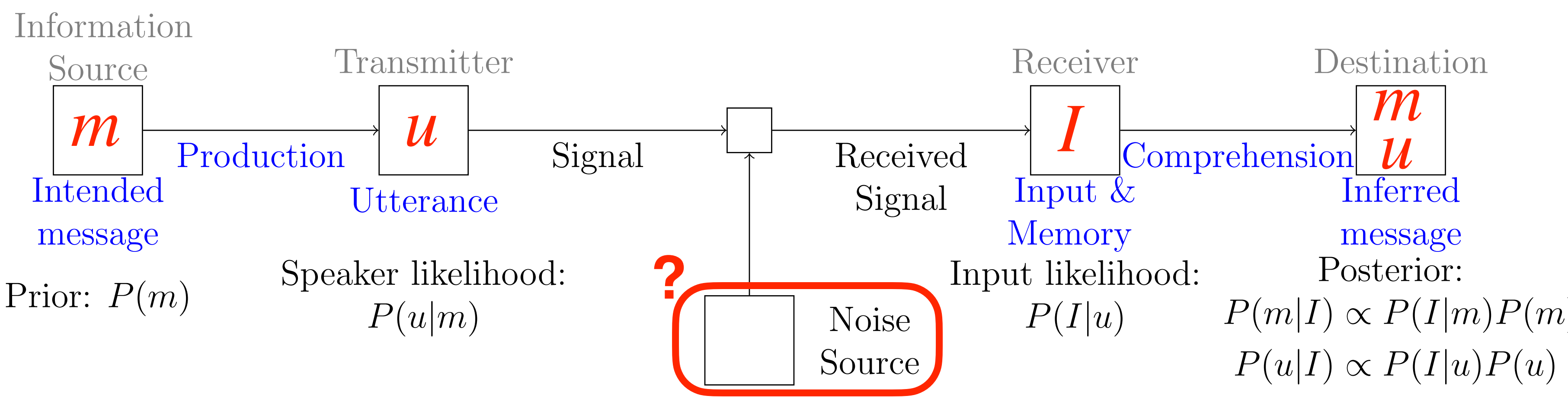



In two semantically plausible "neighbor" sentences, the answer is "yes":

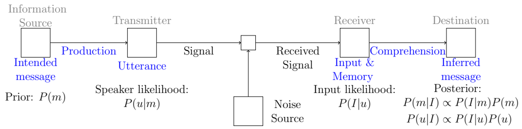
**`The cook baked a cake Lucy.`**

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

**`The cook baked a cake Lucy.`**

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

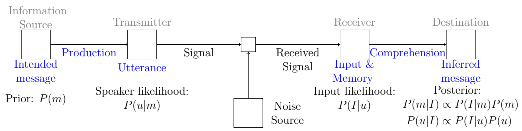
# Predictions for implausible sentences




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

(Gibson et al., 2013)

# Predictions for implausible sentences

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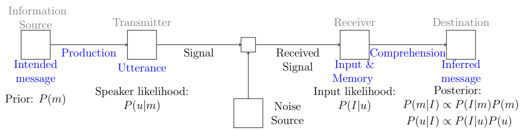
***Non-literal interpretation?***

| 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)*

# Predictions for implausible sentences

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| | | ***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 |
| | **`The cook baked a cake for Lucy.`** | No | No |

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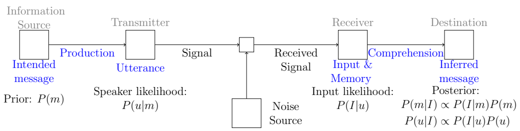


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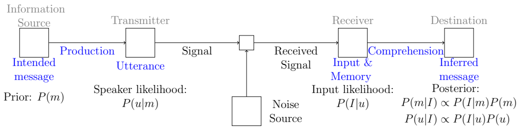
| | | ***Deletion/ insertion*** | ***Exchange*** |
|---|---|---|---|
| Implausible | **The cook baked a cake Lucy.** | Yes | Yes |
| | **The cook baked Lucy for a cake.** | Yes | Yes |
| Plausible | **The cook baked Lucy a cake.** | No | No |
| | **The cook baked a cake for Lucy.** | No | No |

Active/Passive alternation

| | | ***Deletion/ insertion*** | ***Exchange*** |
|---|---|---|---|
| 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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| | | ***Deletion/ insertion*** | ***Exchange*** |
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| Implausible | **`The cook baked a cake Lucy.`** | Yes | Yes |
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**Active/Passive alternation**

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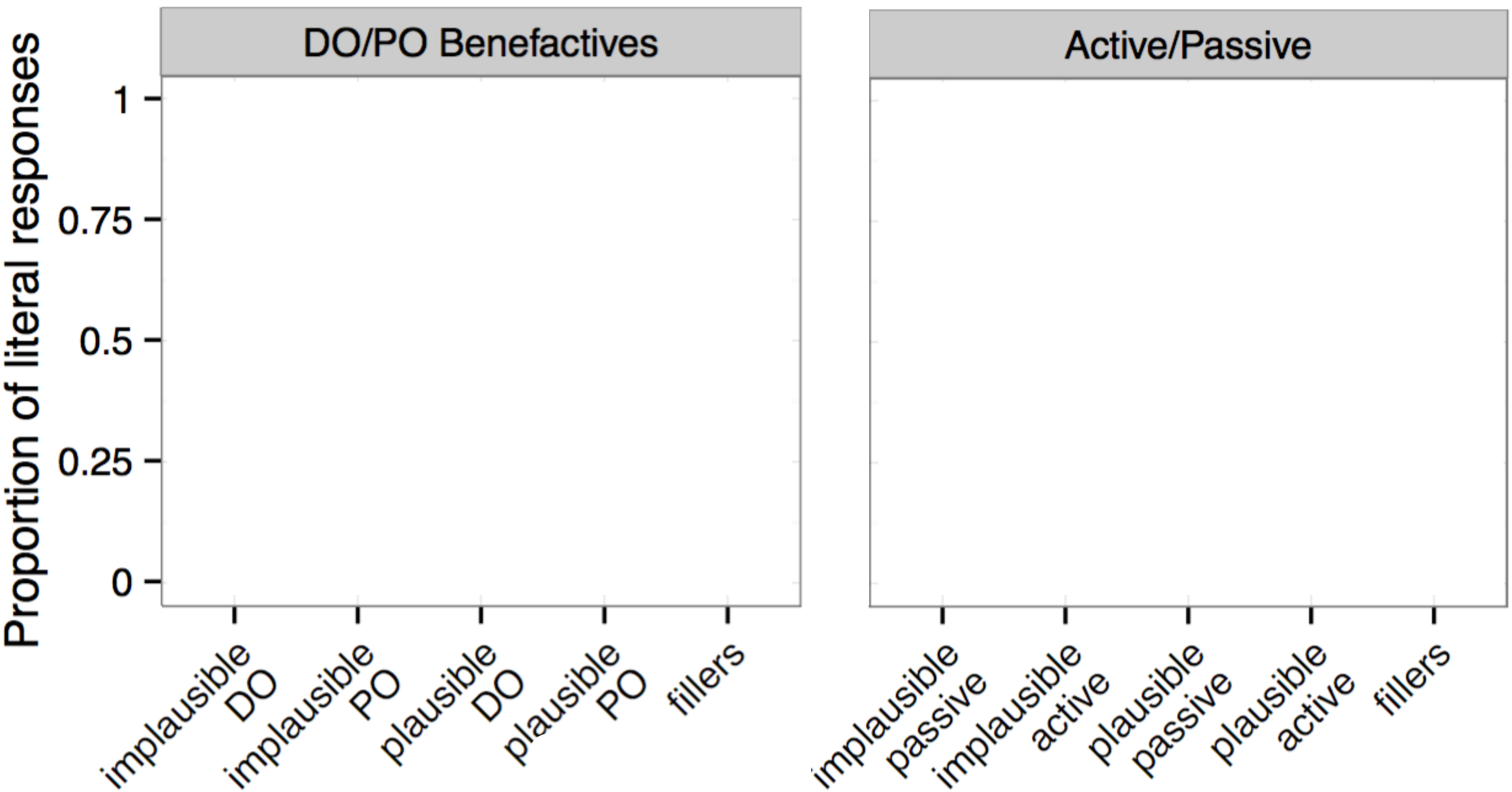
*(Gibson et al., 2013)*

# 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

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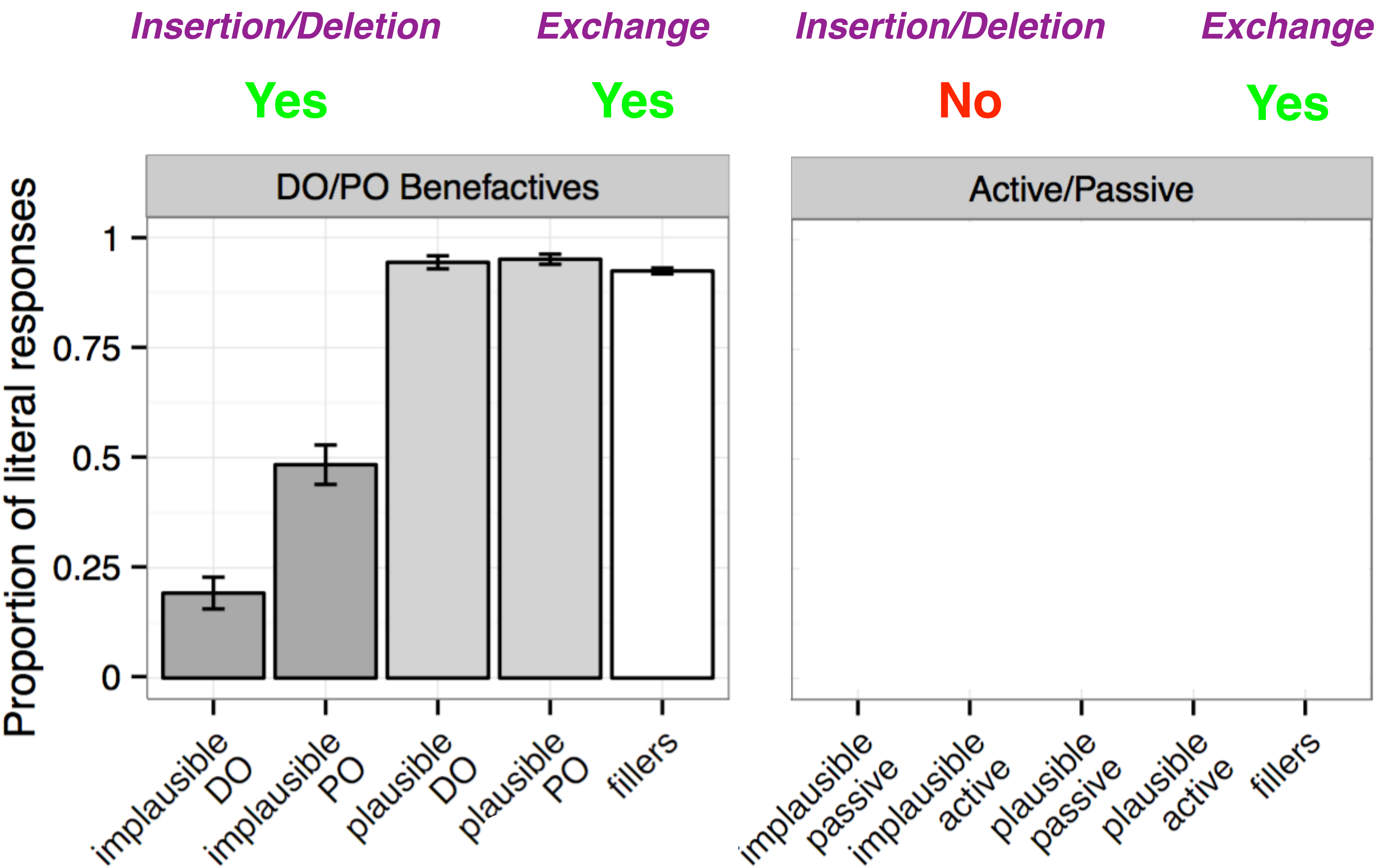


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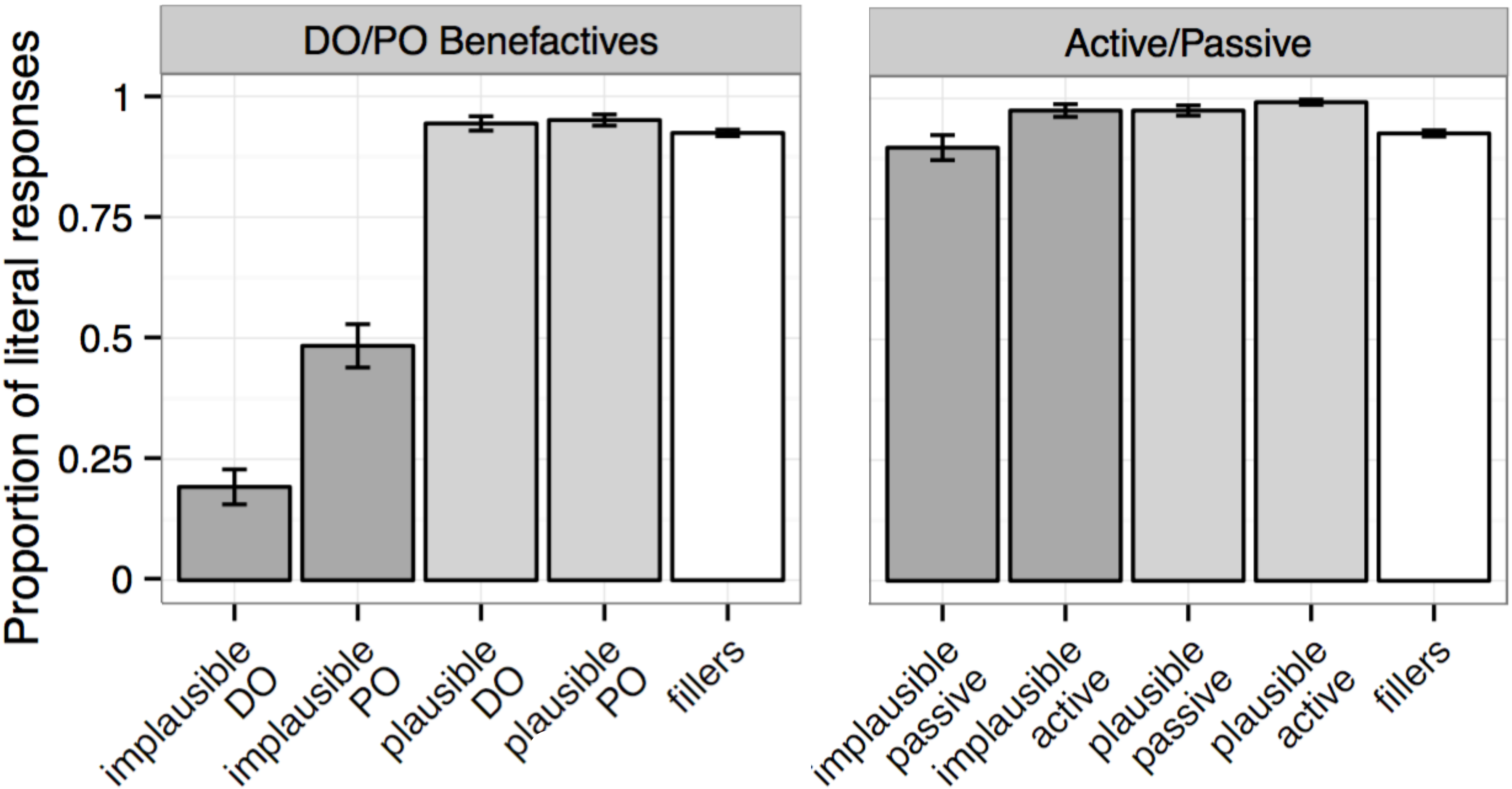


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# Five alternations in an insertion/deletion model

| 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

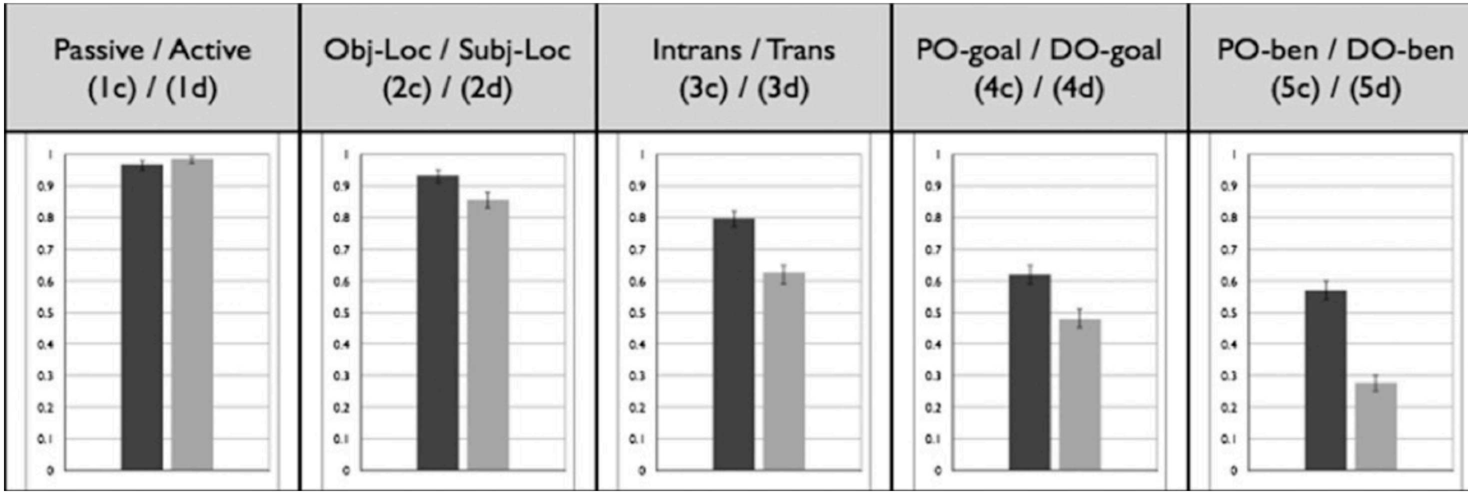
$$P(m \mid I) \propto \underline{P(I \mid m)}\,\underline{P(m)}$$

Noise operation

Plausibility

***Base experiment***

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

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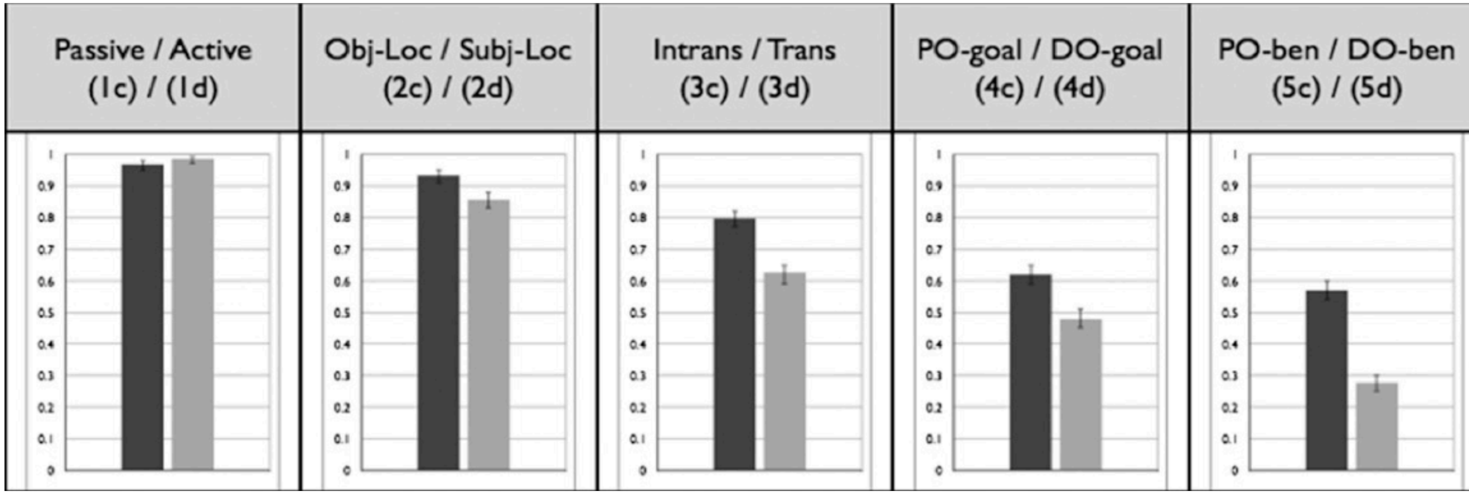


***Fillers with syntactic errors***

*"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)

# Five alternations in an insertion/deletion model

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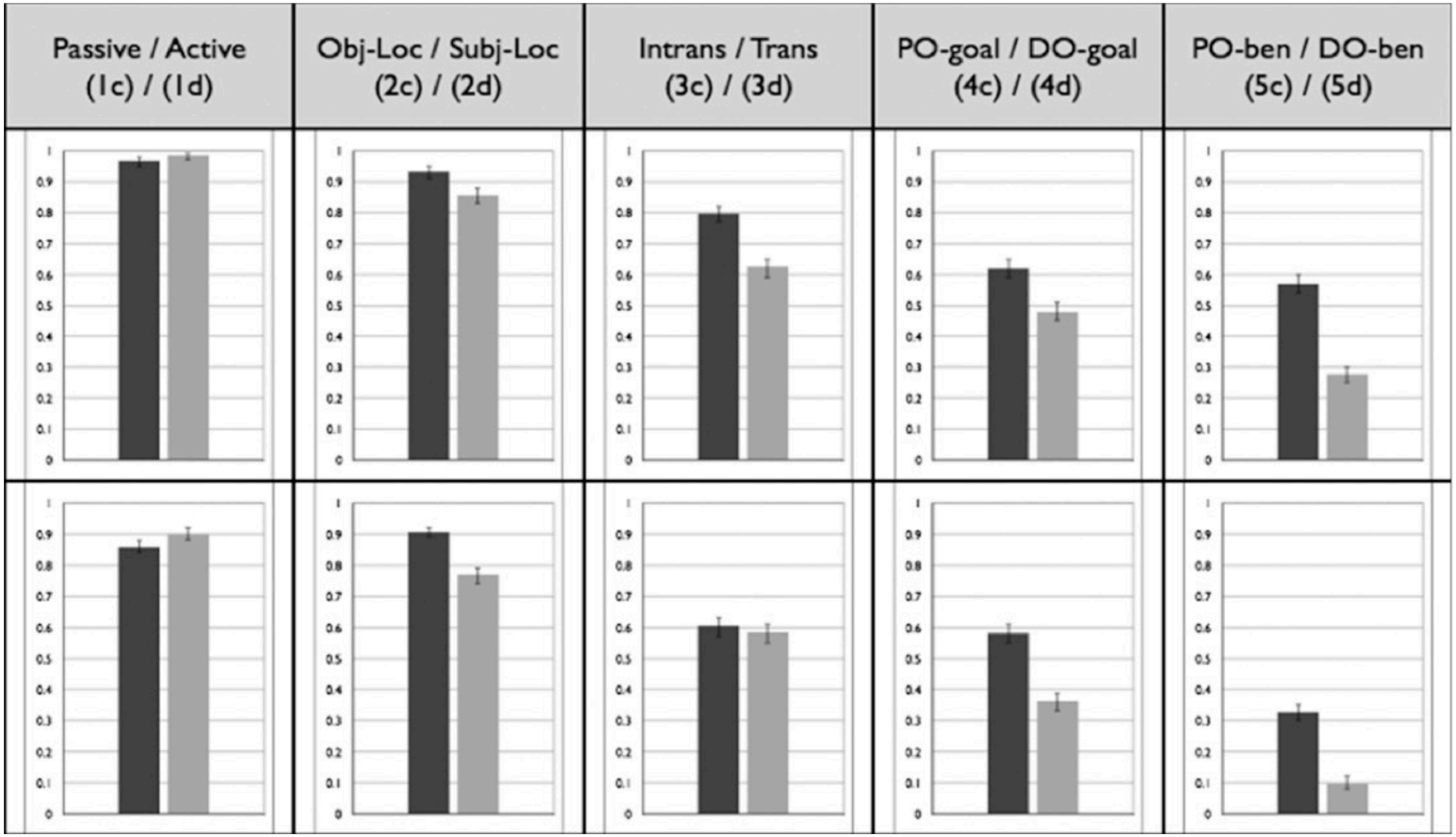


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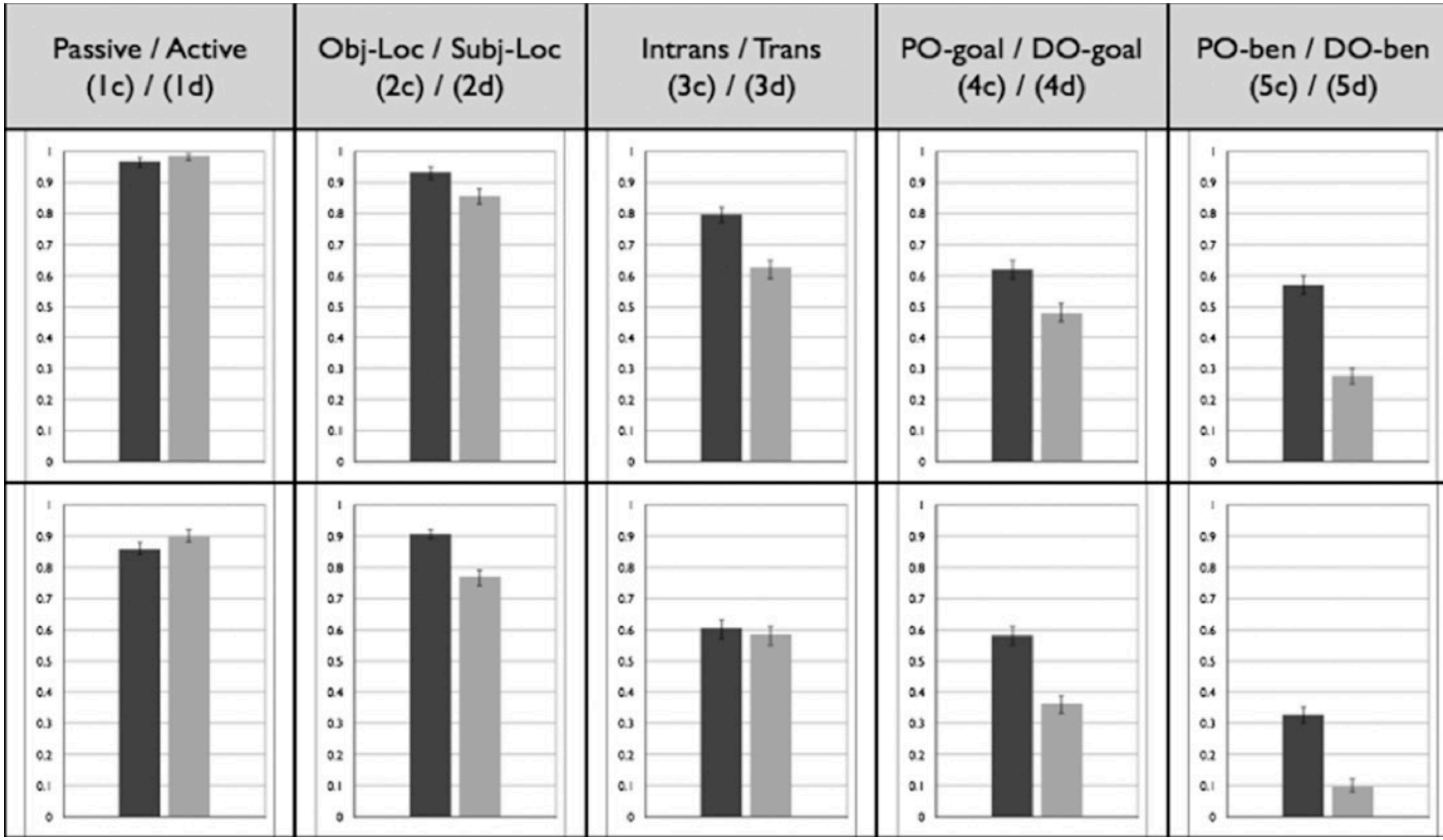


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***Many implausible trials***

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

*(Gibson et al., 2013)*

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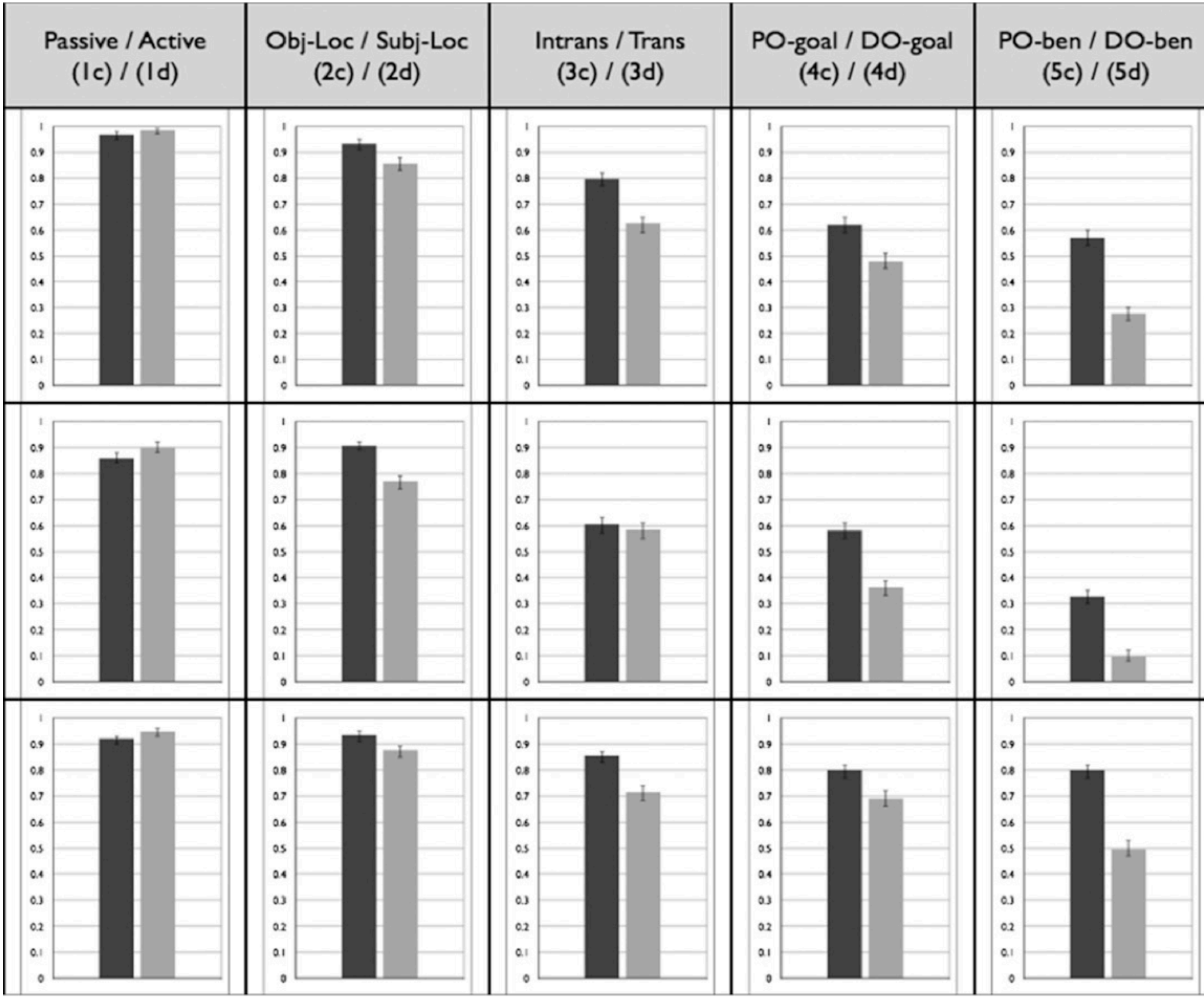


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# Inferring deletions versus insertions

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

The cook baked a cake for Lucy.

$\downarrow$

**The cook baked a cake Lucy.**

The cook baked Lucy a cake.

$\downarrow$

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

# Inferring deletions versus insertions

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

1 Delete

The cook baked a cake for Lucy.

↓

**The cook baked a cake Lucy.**

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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.`

$\downarrow$

**`The cook baked a cake Lucy.`**

`The cook baked Lucy a cake.`

$\downarrow$

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

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↓

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↓

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

# Inferring deletions versus insertions

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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.`

`The cook baked Lucy for a cake.`

# 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.`**

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

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

1 Delete  2 Choose deletion location

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

↓

**`The cook baked a cake Lucy.`**

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

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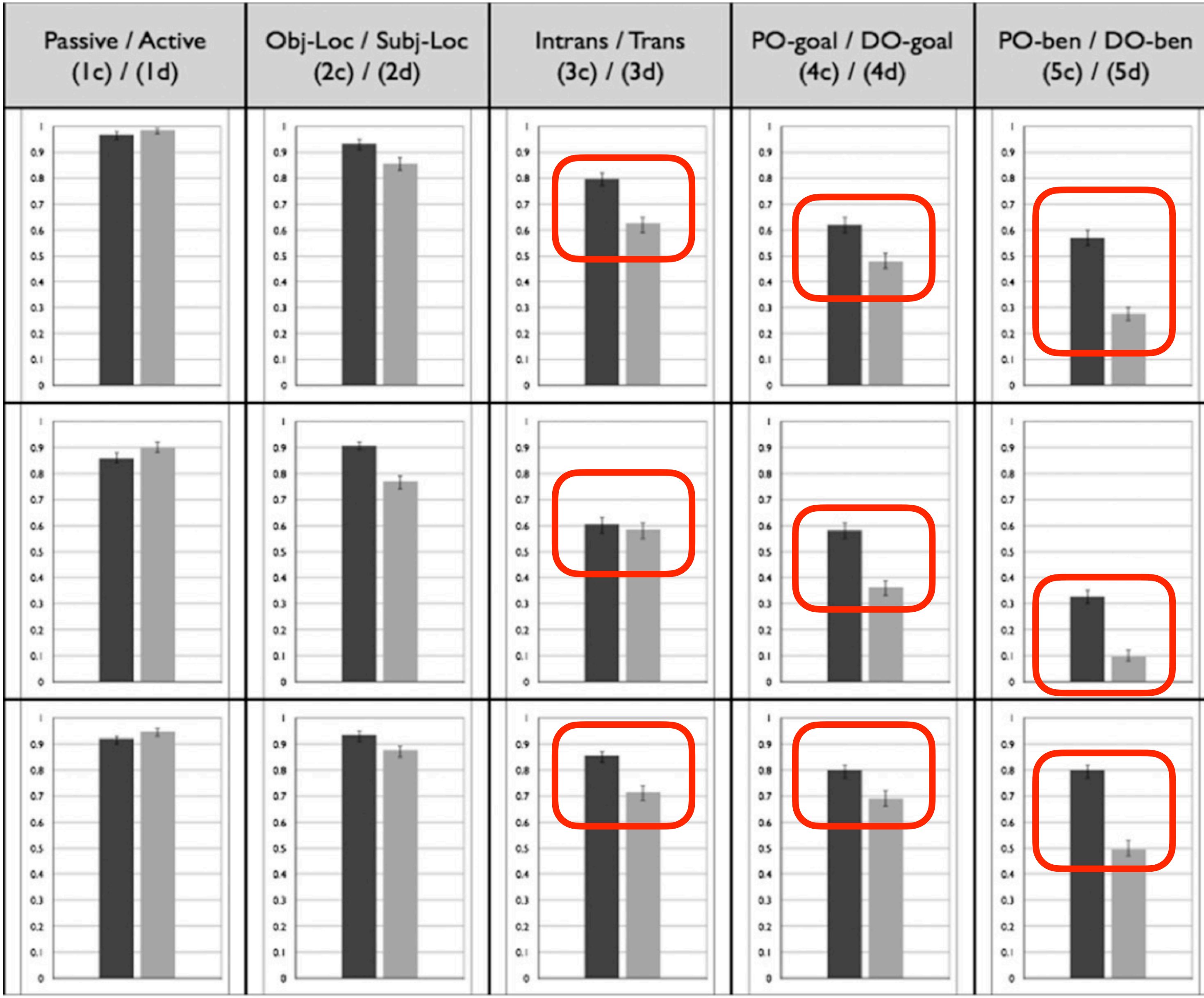


*(Gibson et al., 2013)*

# 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)*

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

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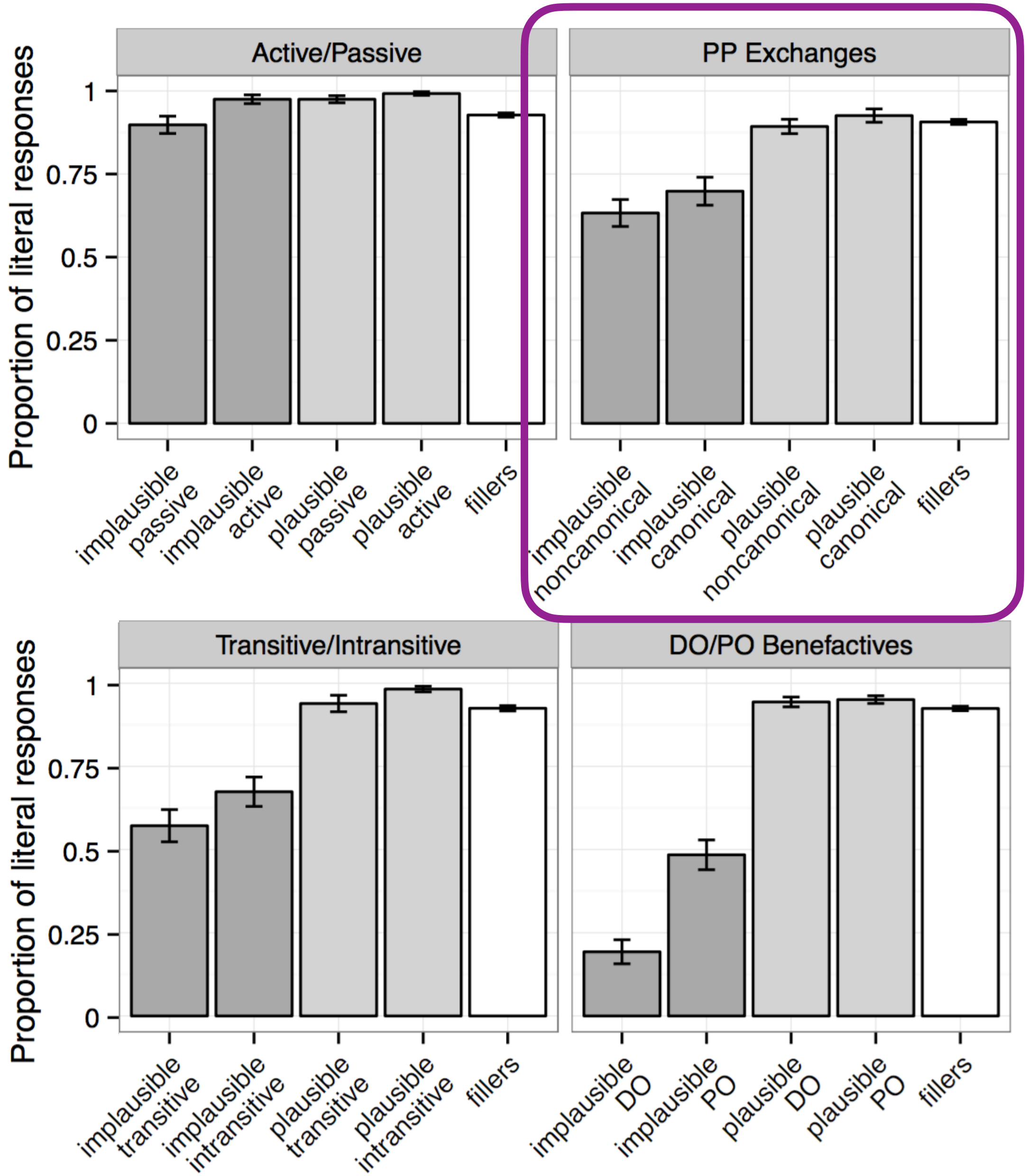
The package fell to the table from the floor. [implausible; non-canonical]

***Did something fall to the floor?***

*(Poppels & Levy 2016)*

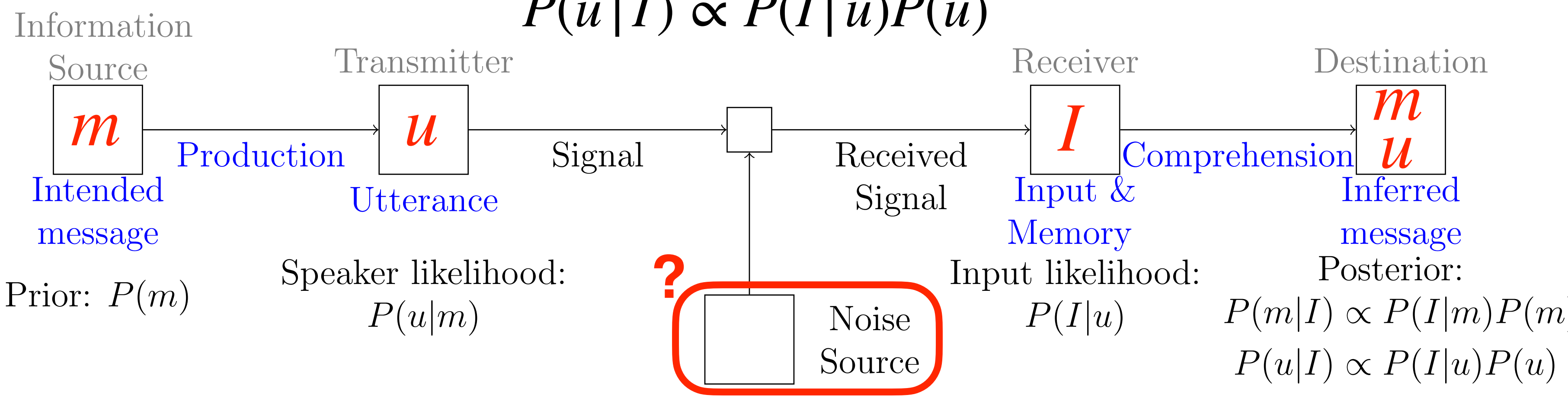
# Exchanges in the noise model




*(Poppels & Levy 2016)*

# Probing inferred intended utterances

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

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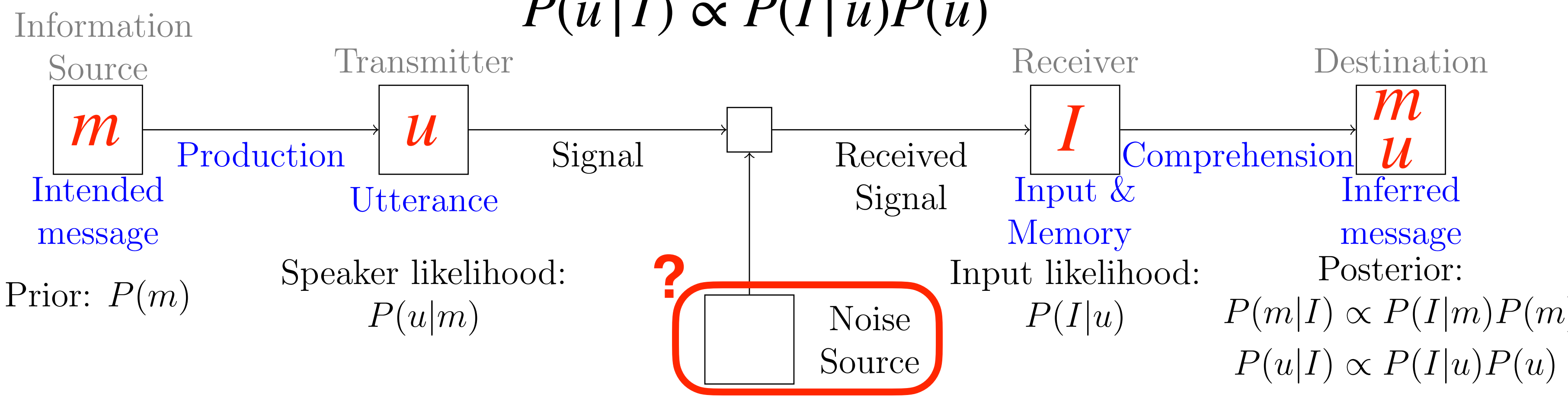


Experiment "cover story": read transcriptions of speech that might have errors, retype with edits if they think the speaker might have meant something else

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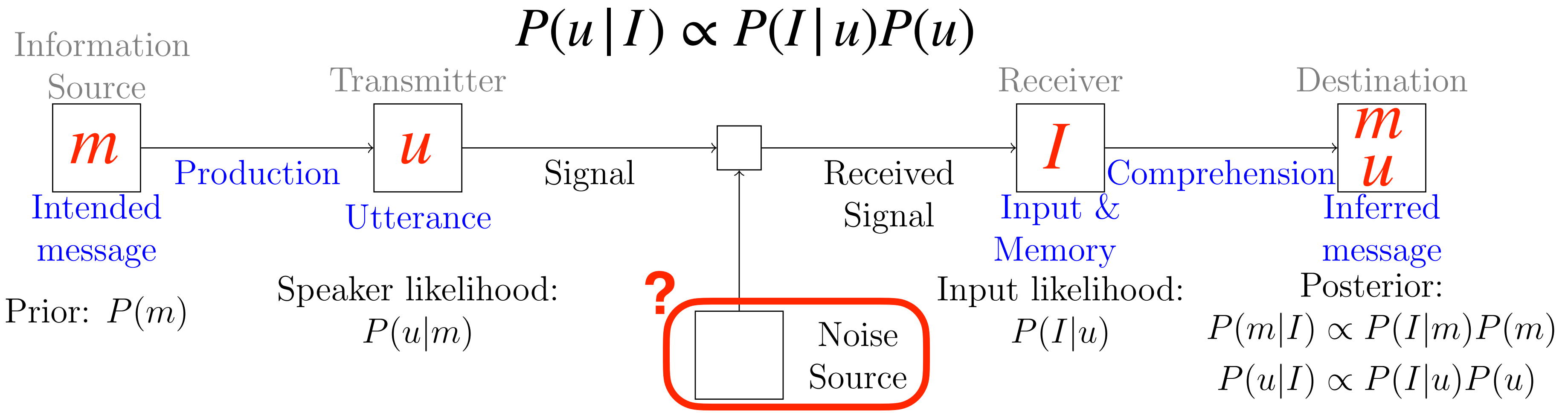


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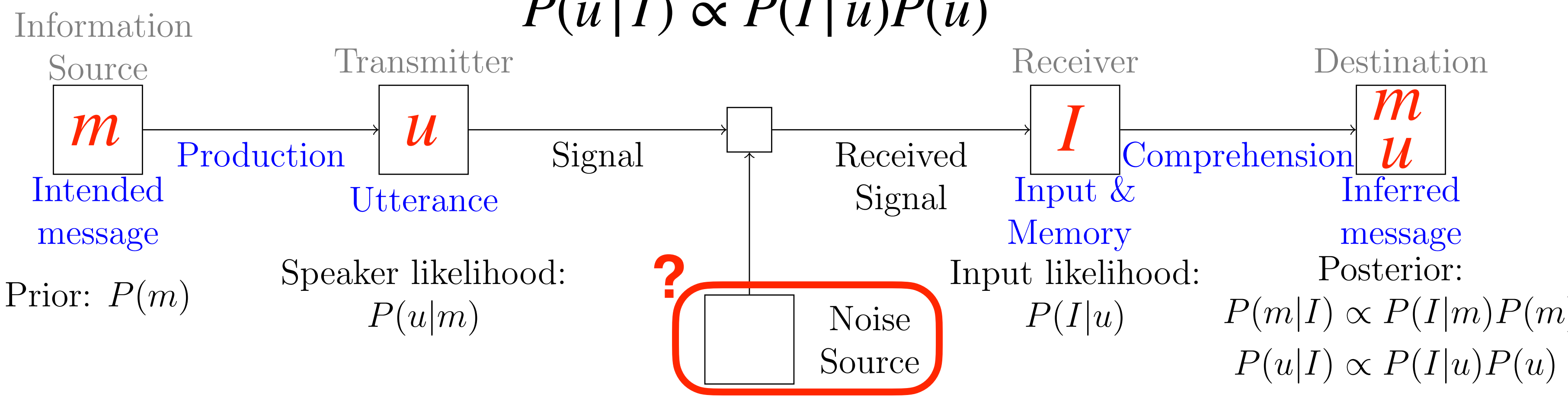


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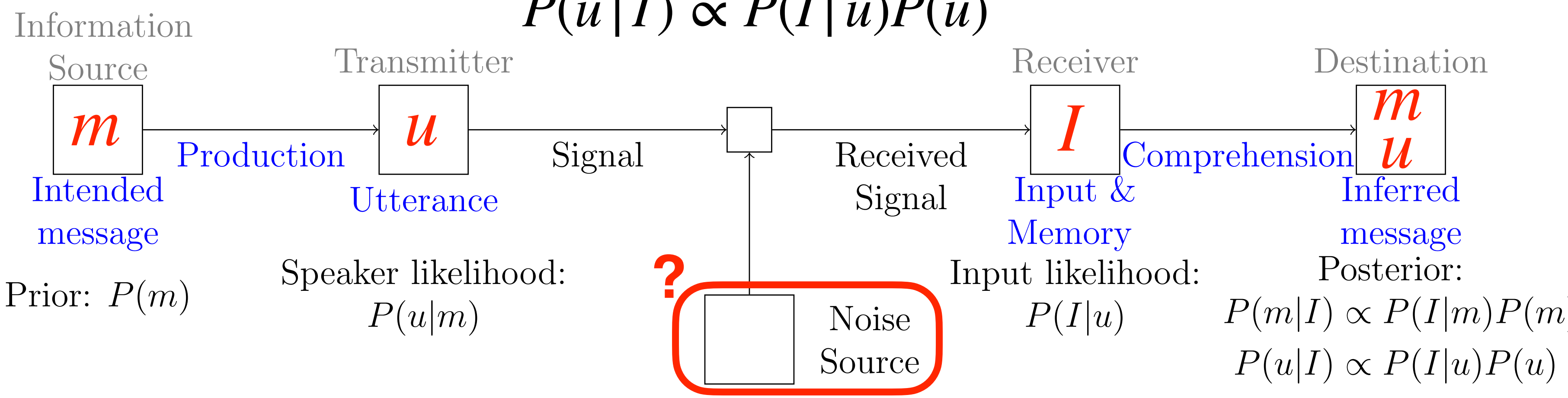


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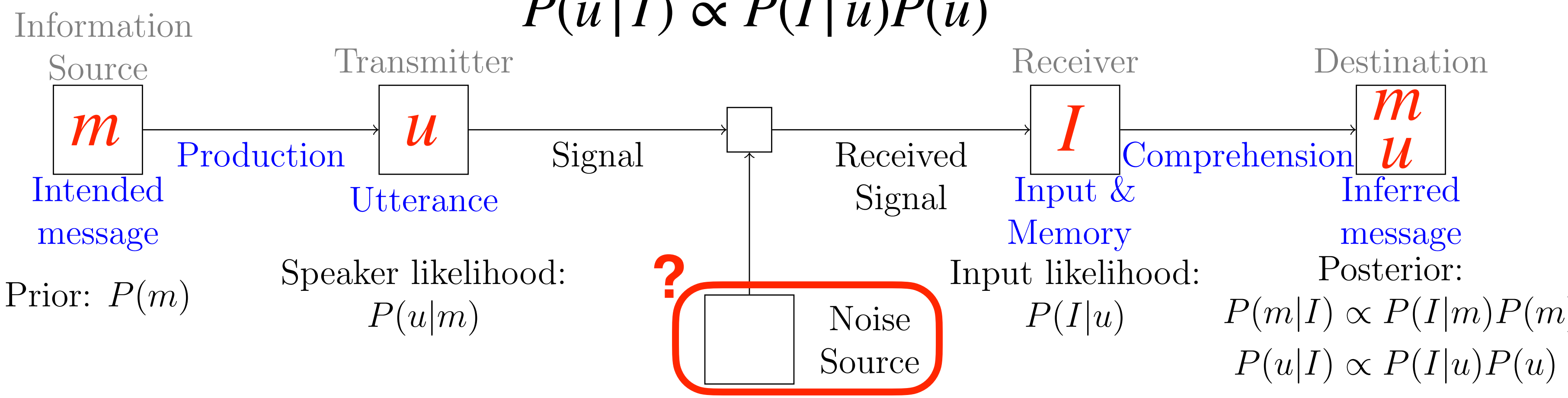


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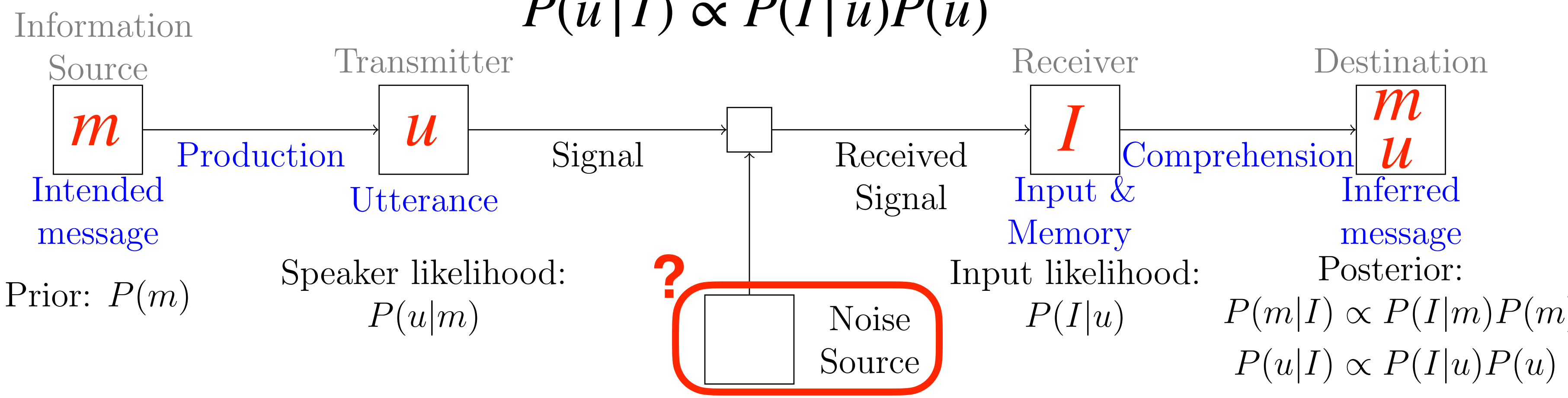


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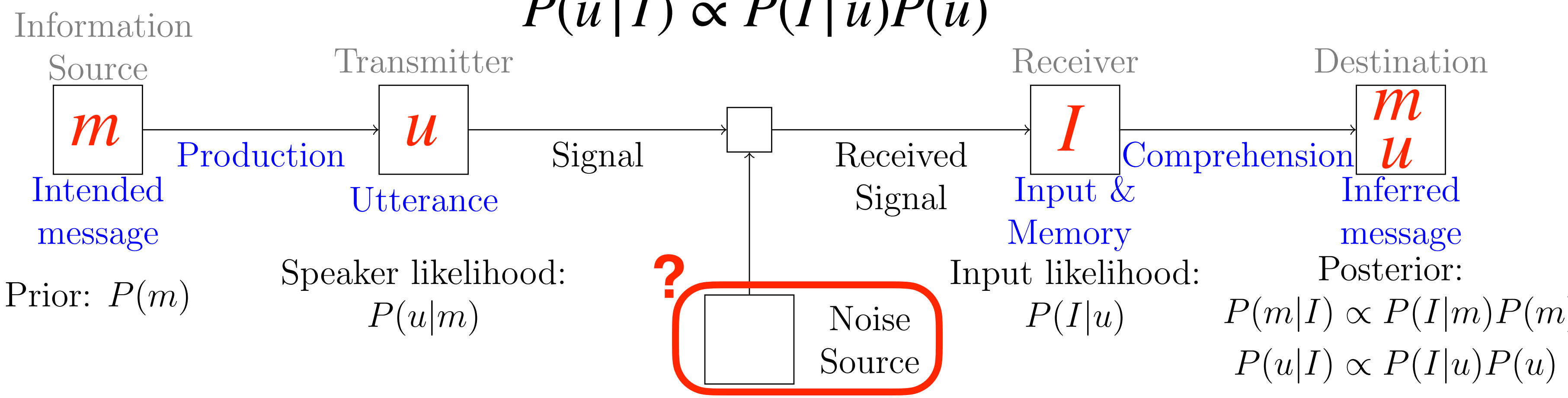


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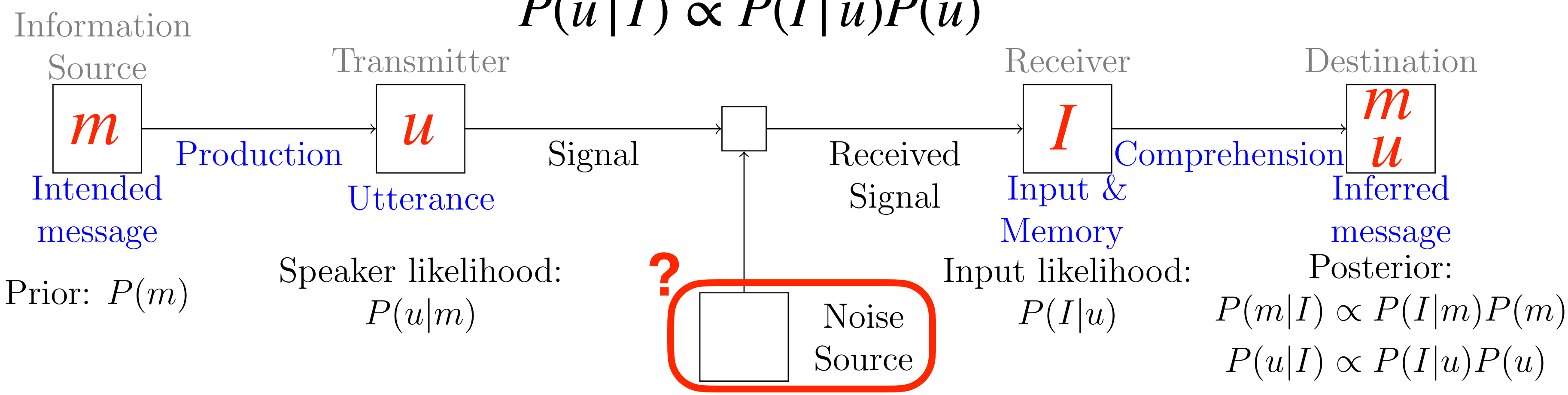


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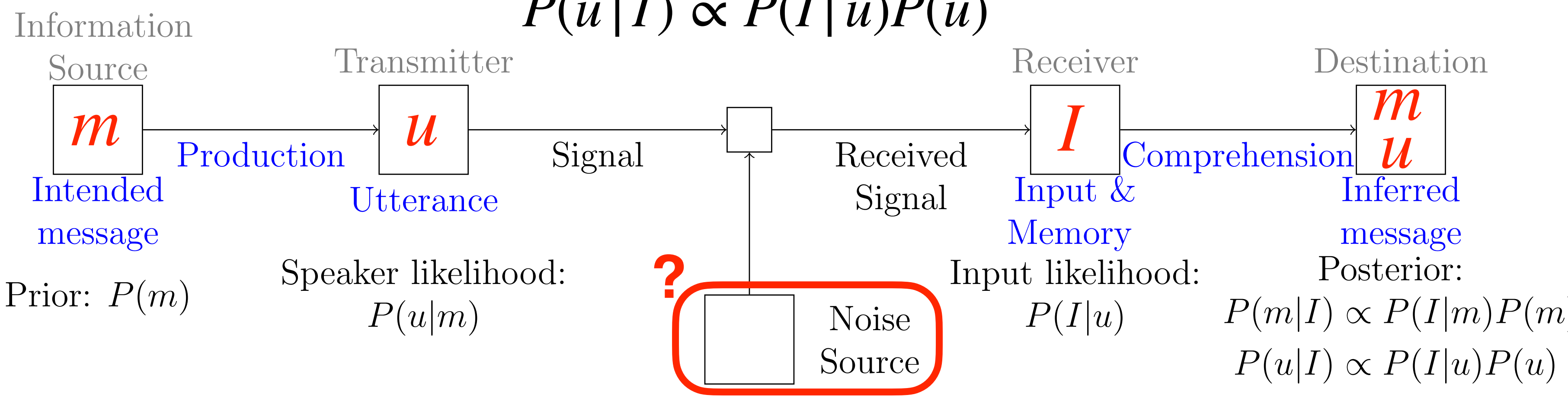


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| | |
|---|---|
| `The ball kicked the girl.`<br>No error | `The judge gave the athlete the prize.`<br>Insertion |
| `The girl kicked the ball.`<br>Exchange | `The judge gave the athlete a prize.`<br>Insertion |
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*(Ryskin et al., 2018)*

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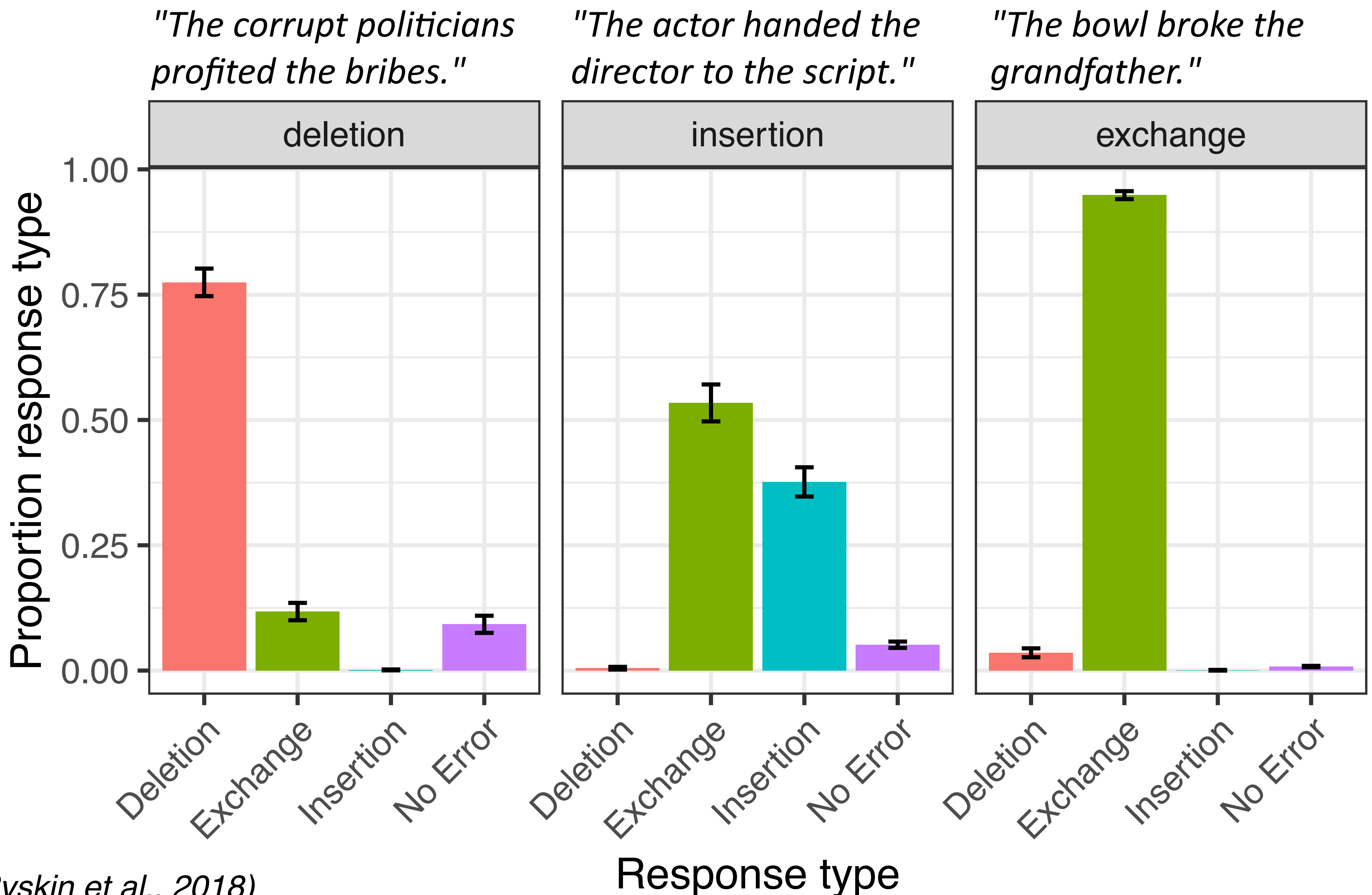


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- *However*, status of exchange errors in the noise model remains a mystery

# 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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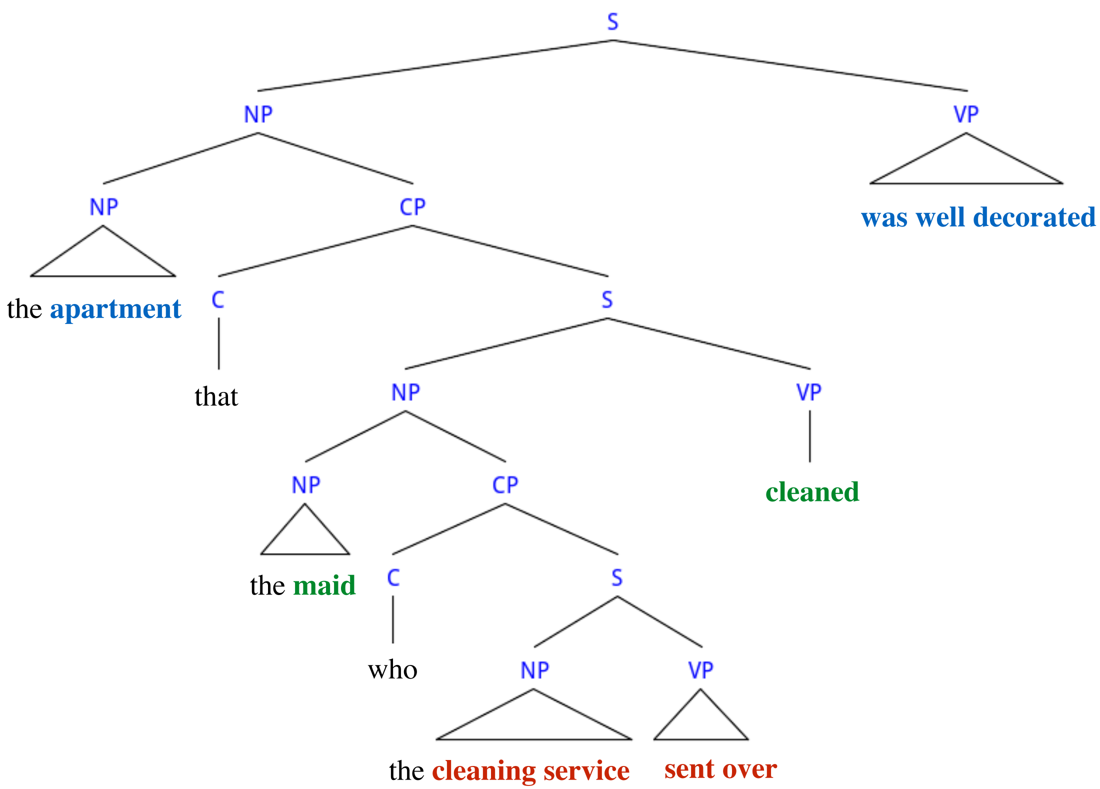


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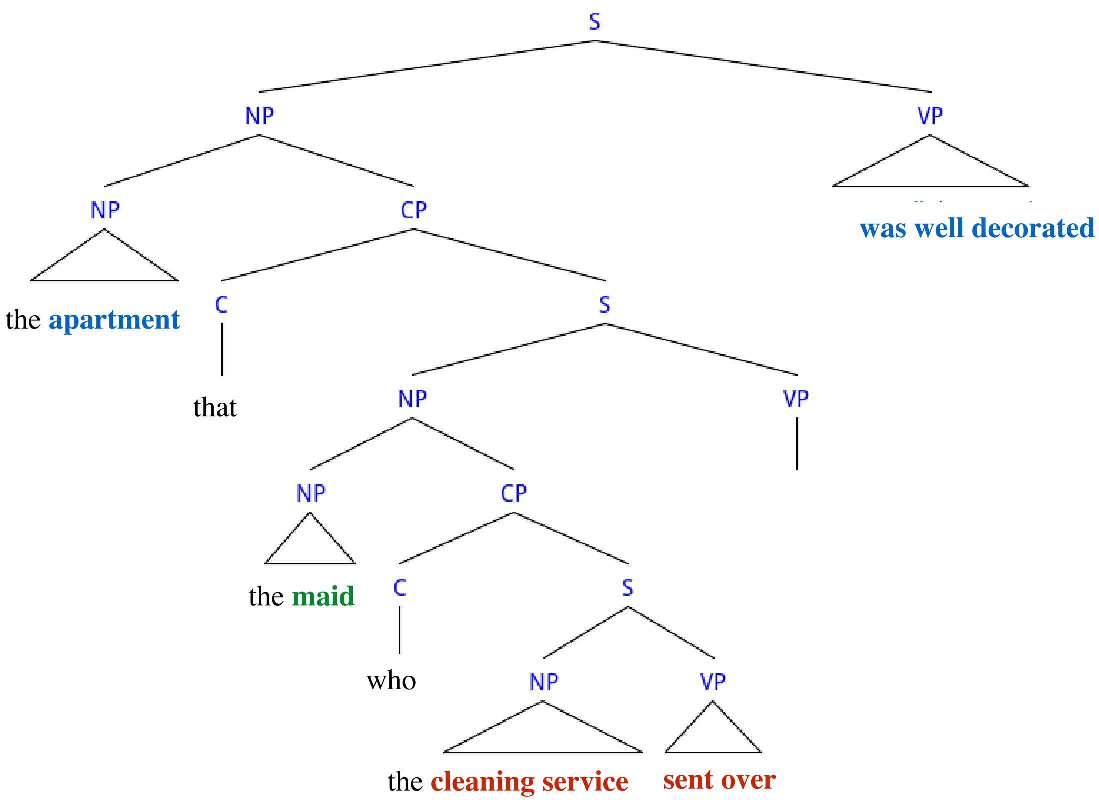


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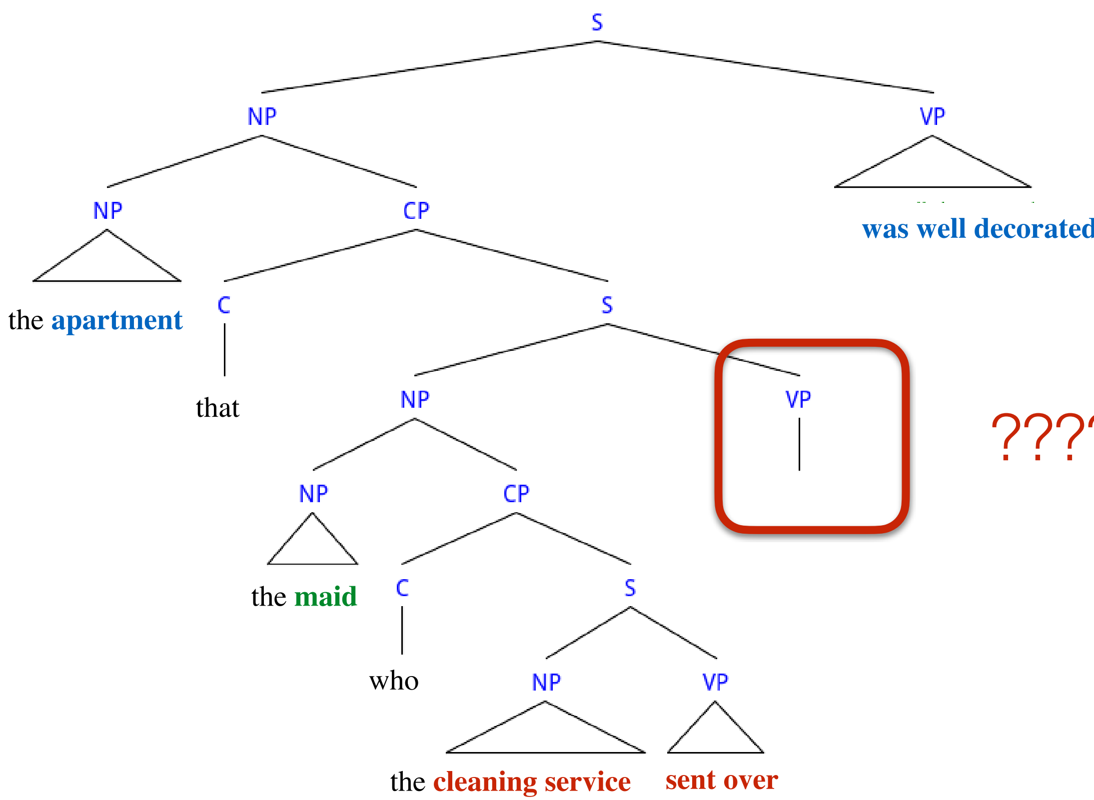


????????????

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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?

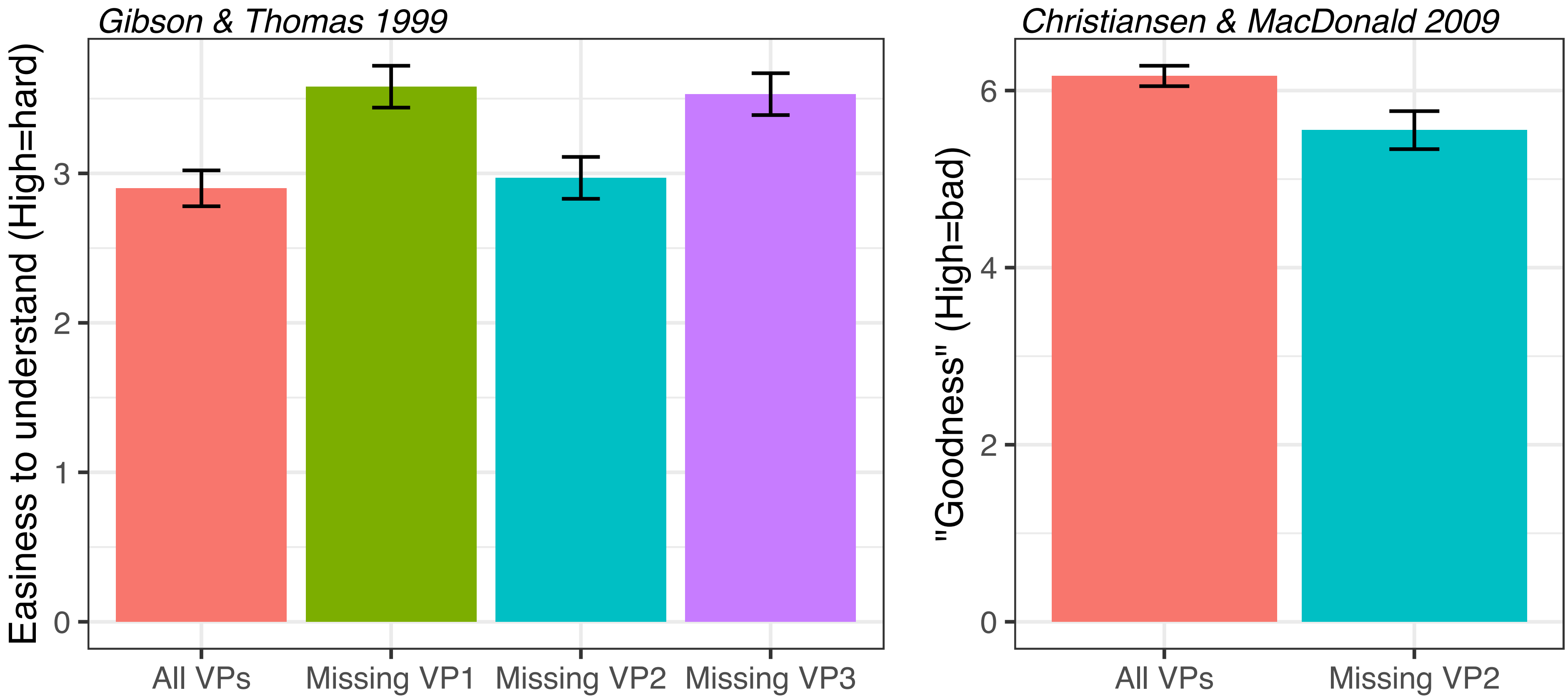
*(Slide courtesy Richard Futrell)*

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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# Structural Forgetting

1. *Die **Wohnung**, die das **Zimmermädchen**, das der **Reinigungsdienst übersandte**, **war gut eingerichtet**. 👎

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  - English: the maid [that cleaned the apartment]
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*(Slide courtesy Richard Futrell)*

# Noisy-Context Surprisal Account of Structural Forgetting

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$$C(\texttt{NOUN THAT NOUN THAT NOUN VERB VERB}) <$$
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$$C(2\ \textsc{verbs}) < C(3\ \textsc{verbs})$$

*(Slide courtesy Richard Futrell)*

# Noisy-Context Surprisal Account of Structural Forgetting

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

context

`NOUN THAT NOUN THAT VERB VERB`

key word

`VERB / #`

*(Slide courtesy Richard Futrell)*

## Noisy-Context Surprisal Account of Structural Forgetting

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- Correct noise based on prior about the language.

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## Noisy-Context Surprisal Account of Structural Forgetting

$$C(2\ \textsc{verbs}) \;<\; C(3\ \textsc{verbs})$$


- Correct noise based on prior about the language.
- Higher probability for verb-final RCs in German,
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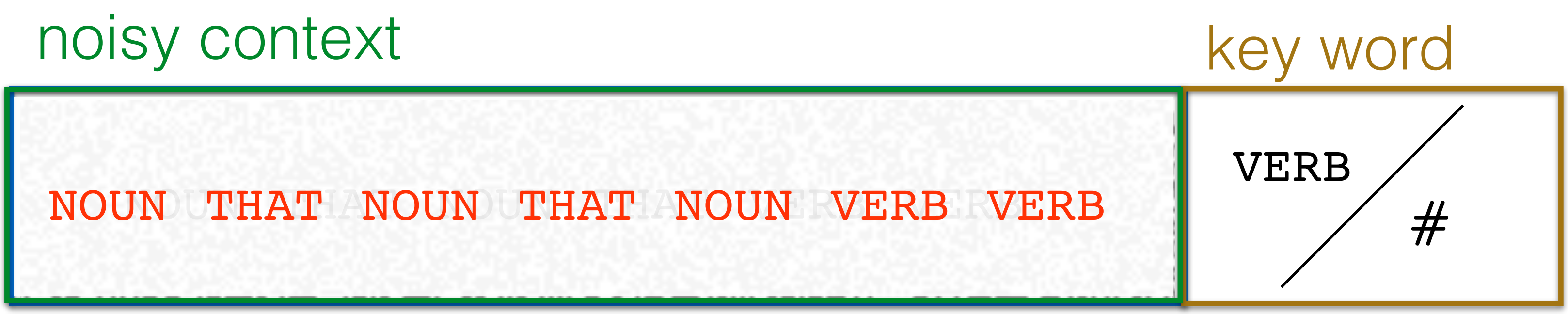


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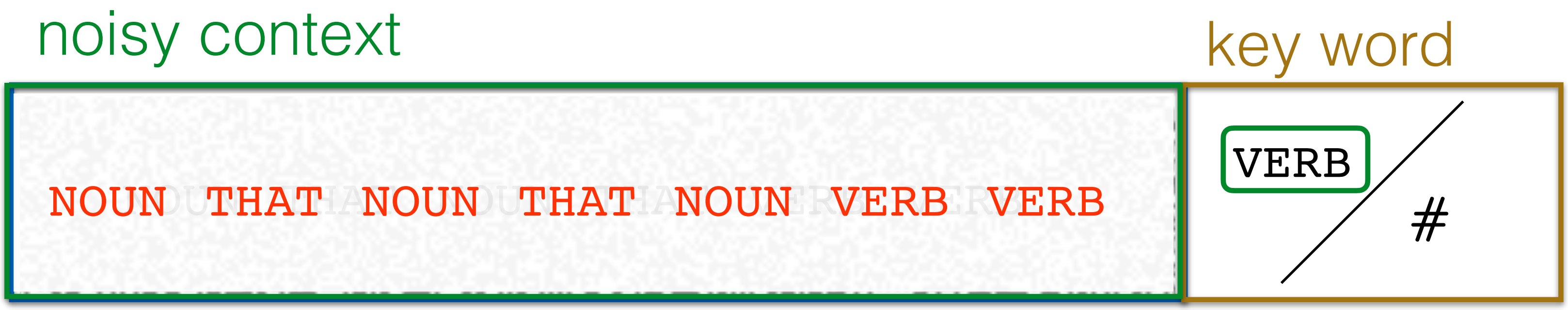


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$C(2 \text{ VERBS}) < C(3 \text{ VERBS})$

noisy context

NOUN THAT NOUN THAT NOUN VERB VERB

key word

VERB / #

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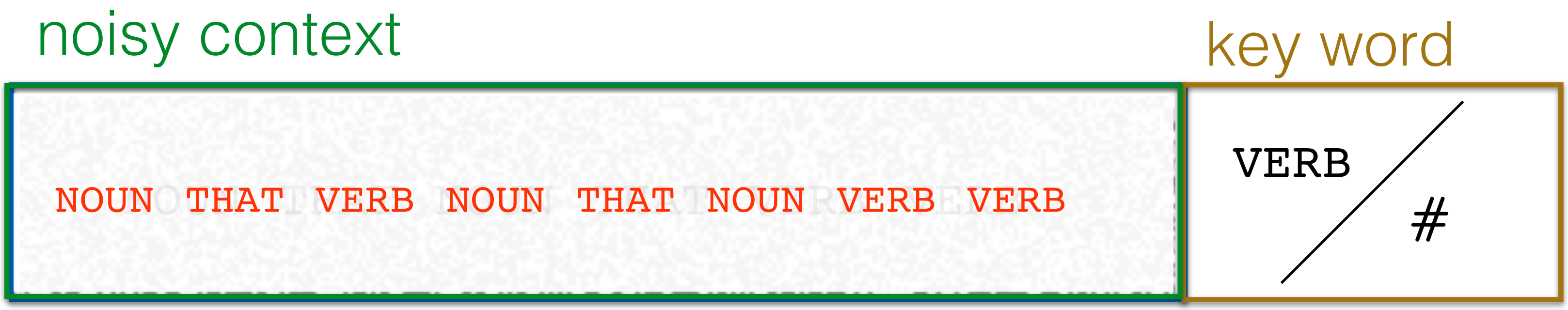


- Correct noise based on prior about the language.
- Higher probability for verb-final RCs in German,
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(Slide courtesy Richard Futrell)

## Noisy-Context Surprisal Account of Structural Forgetting

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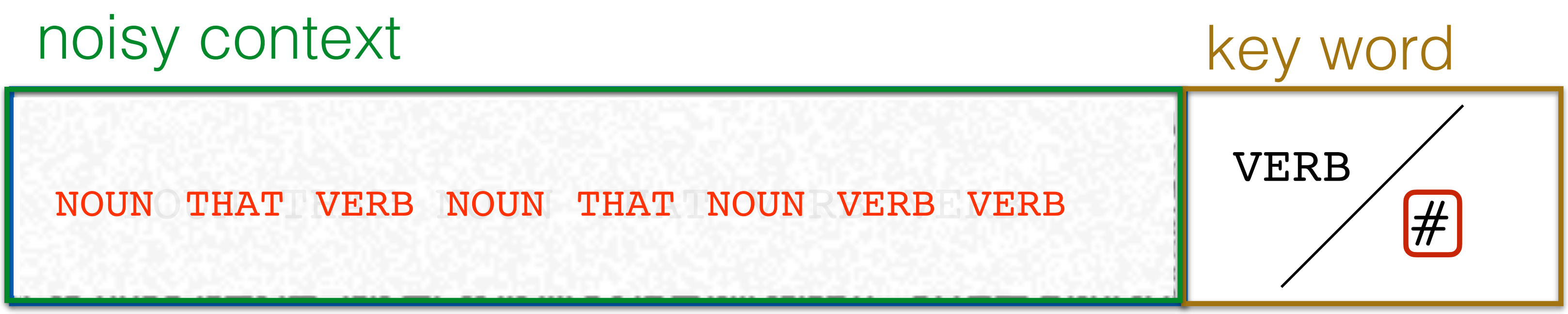


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| **Rule** | **Probability** |
| --- | --- |
| S -> NP VERB | 1 |
| NP -> NOUN | 1-*m* |
| NP -> NOUN RC | *mr* |
| NP -> NOUN PP | *m*(1-*r*) |
| PP -> PREP NP | 1 |
| RC -> THAT VERB NP | *s* |
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NOUN VERB

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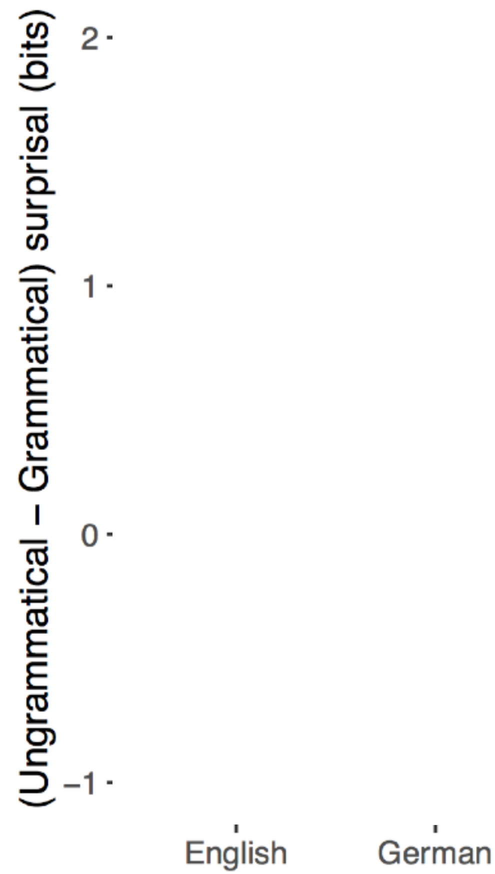


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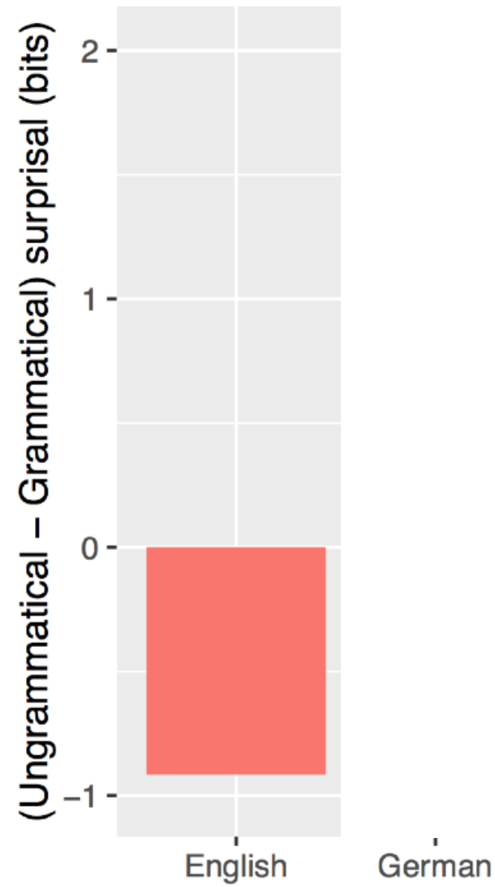


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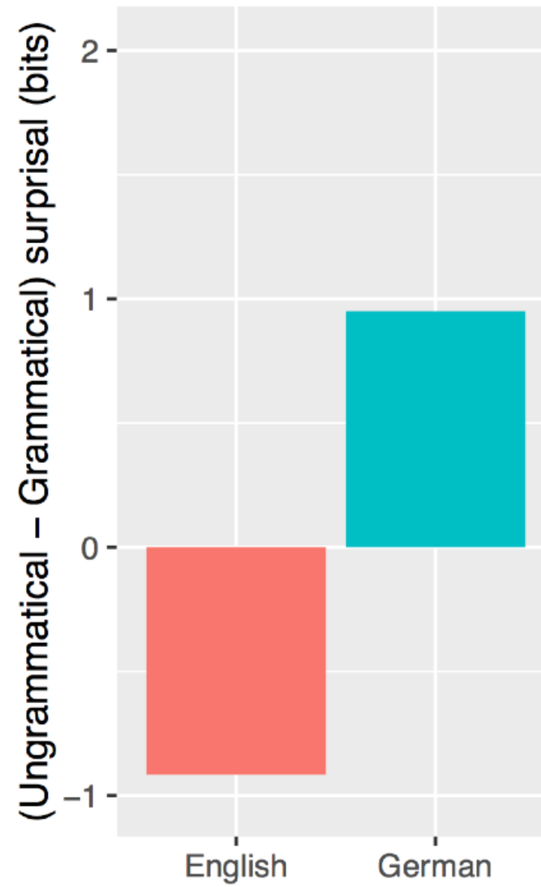


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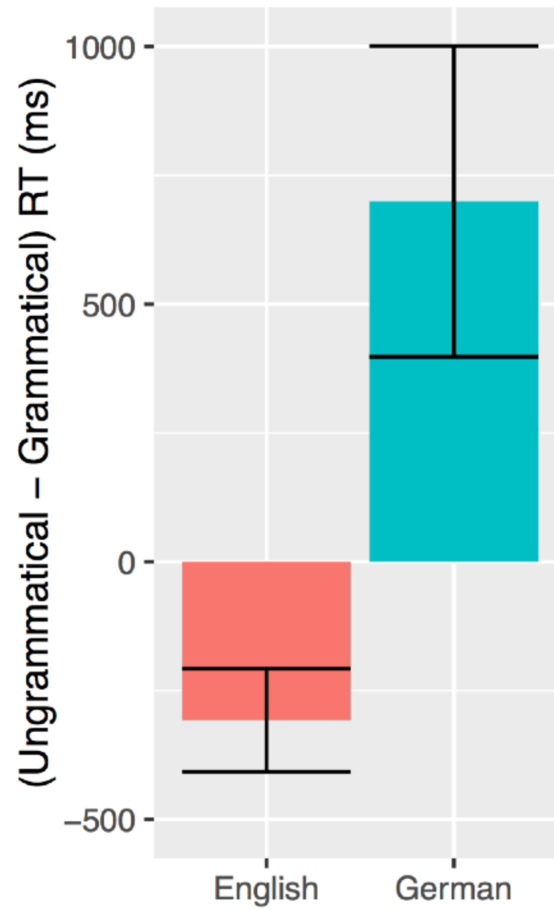


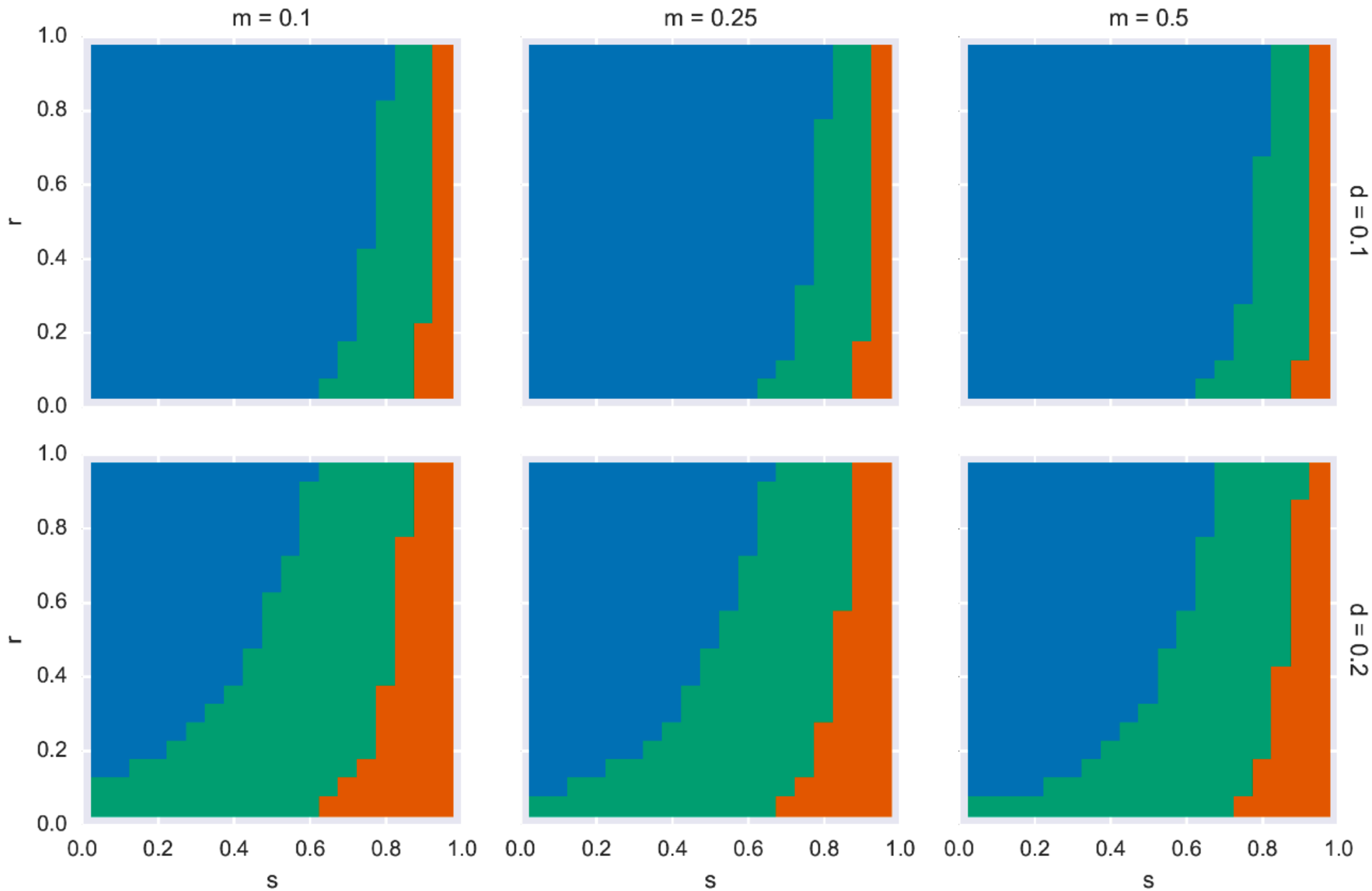

Vasishth et al. (2010)

*(Slide courtesy Richard Futrell)*

# 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




(Futrell & Levy, 2017)

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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).

*(Slide courtesy Richard Futrell)*

# Summary for today

- Applied noisy-channel sentence processing theory to global utterance interpretation
  - Broad support for noisy-channel predictions in patterns of "non-literal" utterance interpretation
  - A puzzle remains regarding the role of *exchange errors* in comprehenders' noise model
- Examined cross-linguistic pattern of "structural forgetting" effects, offered an account by combining noisy-channel theory + surprisal theory

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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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- We'll see that the story is slightly more complicated.

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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:
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(likely)

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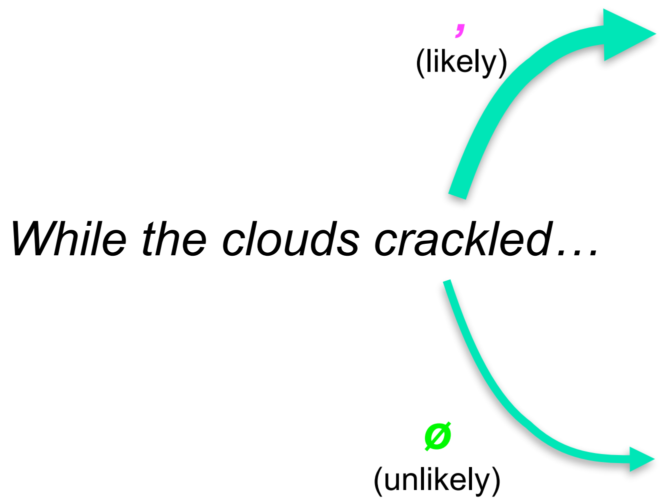


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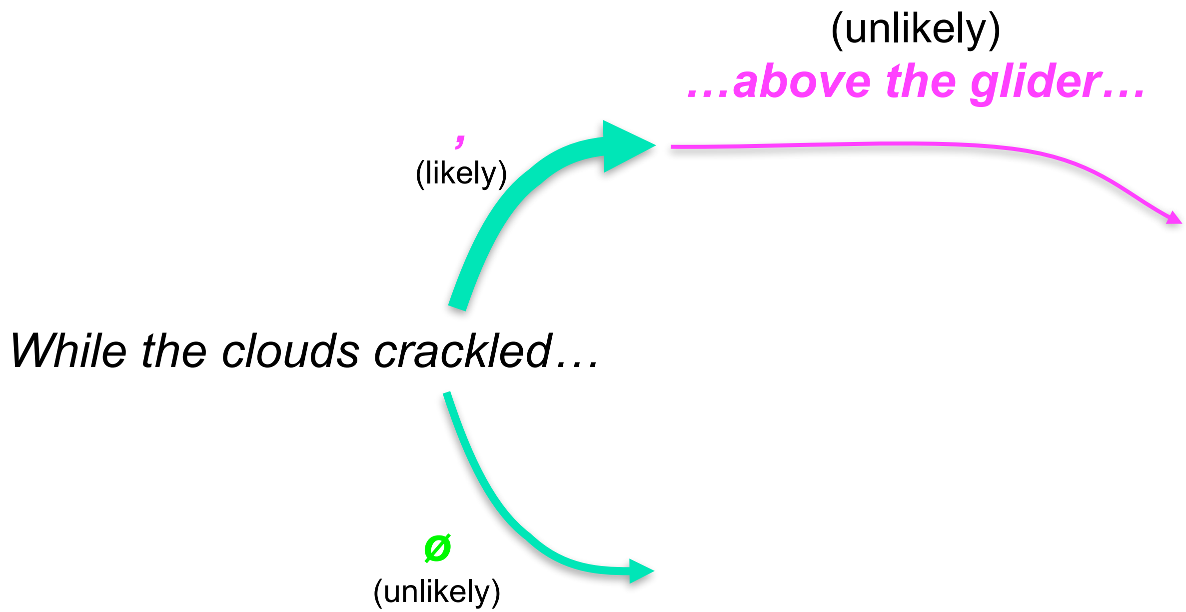


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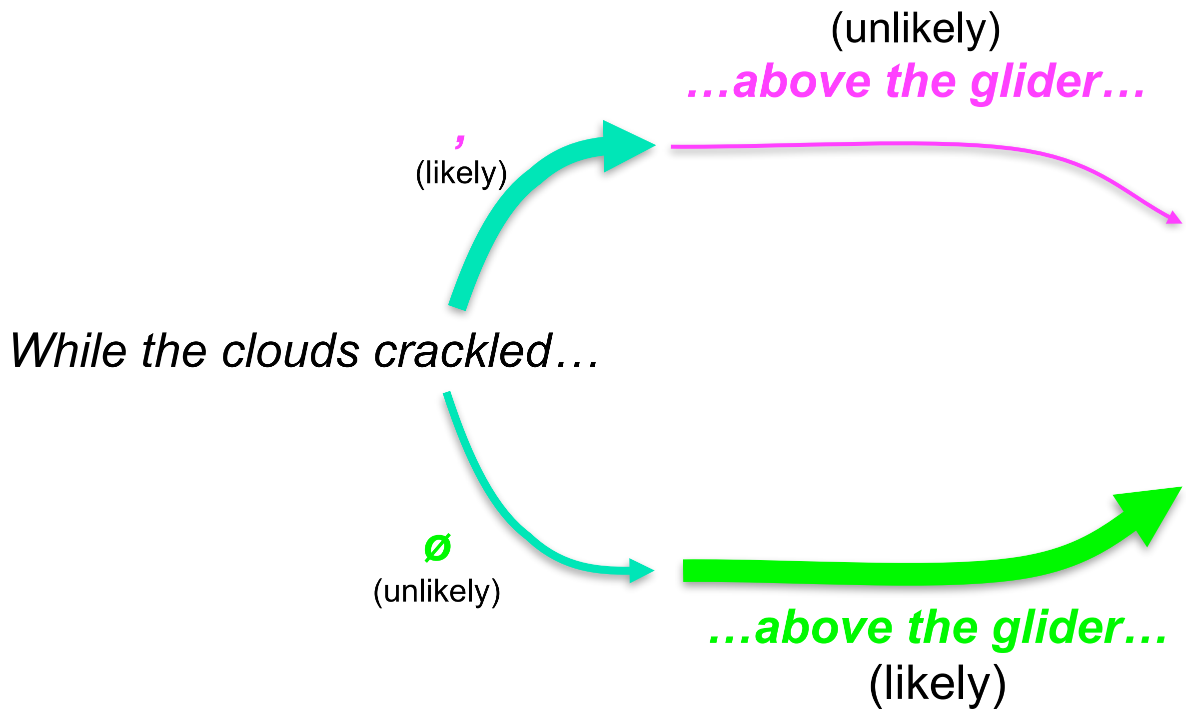


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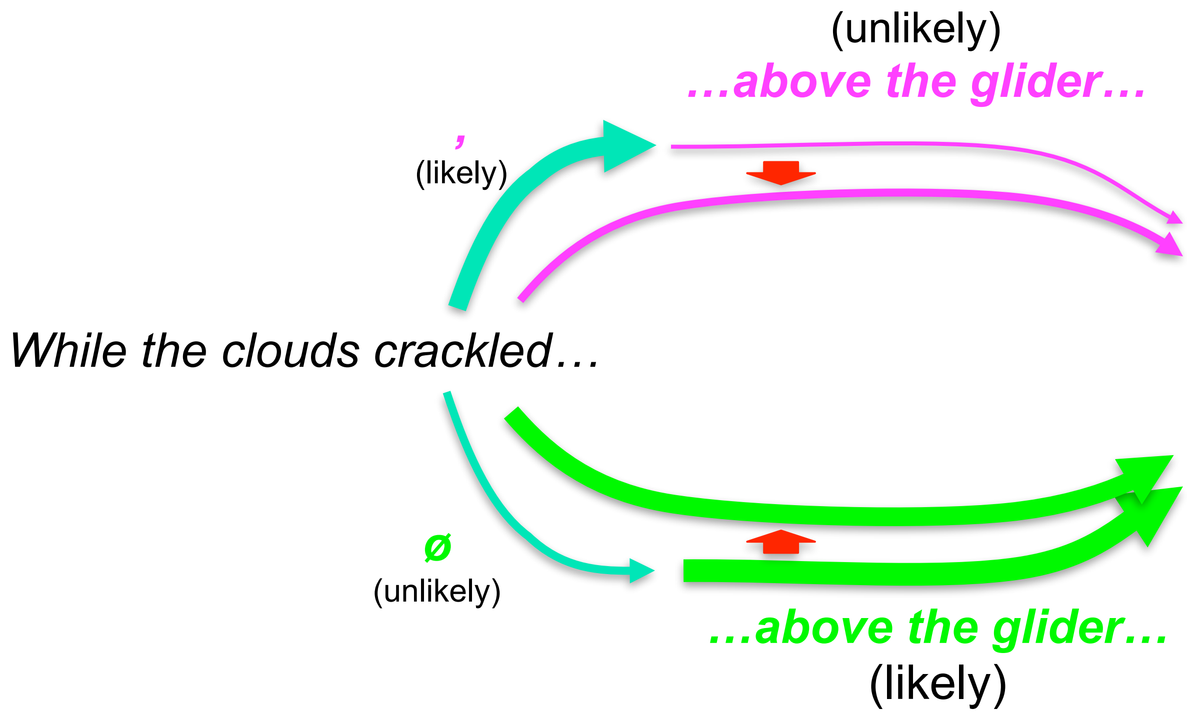


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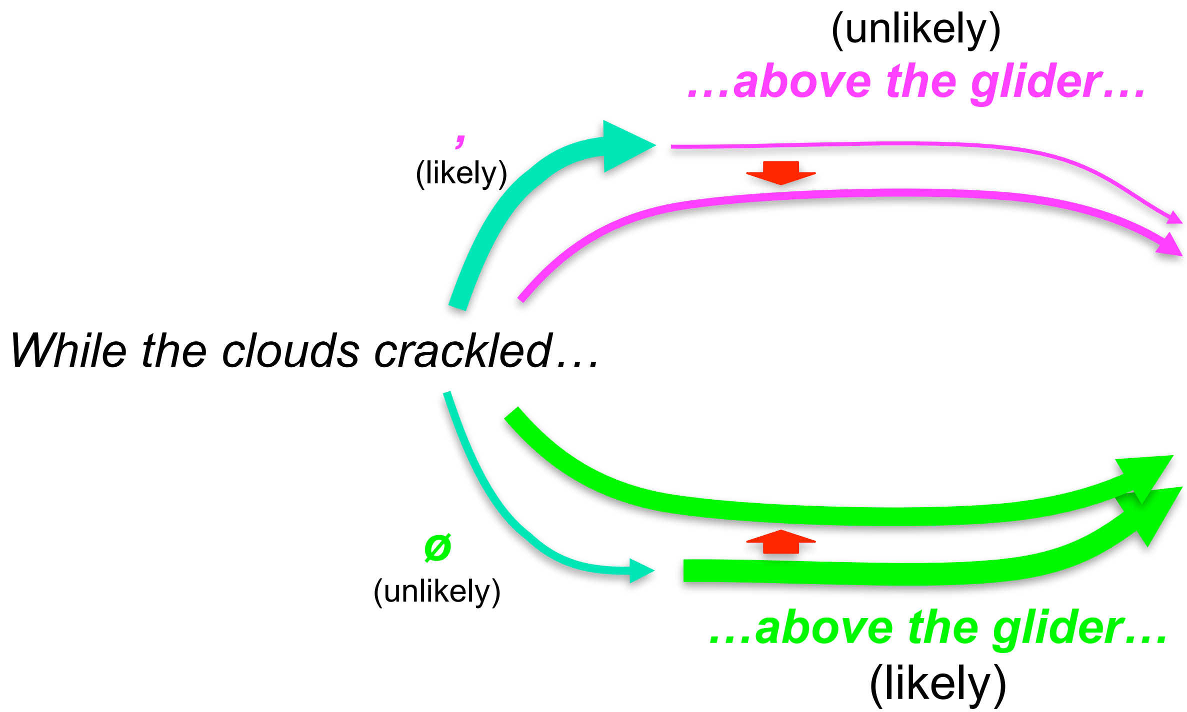


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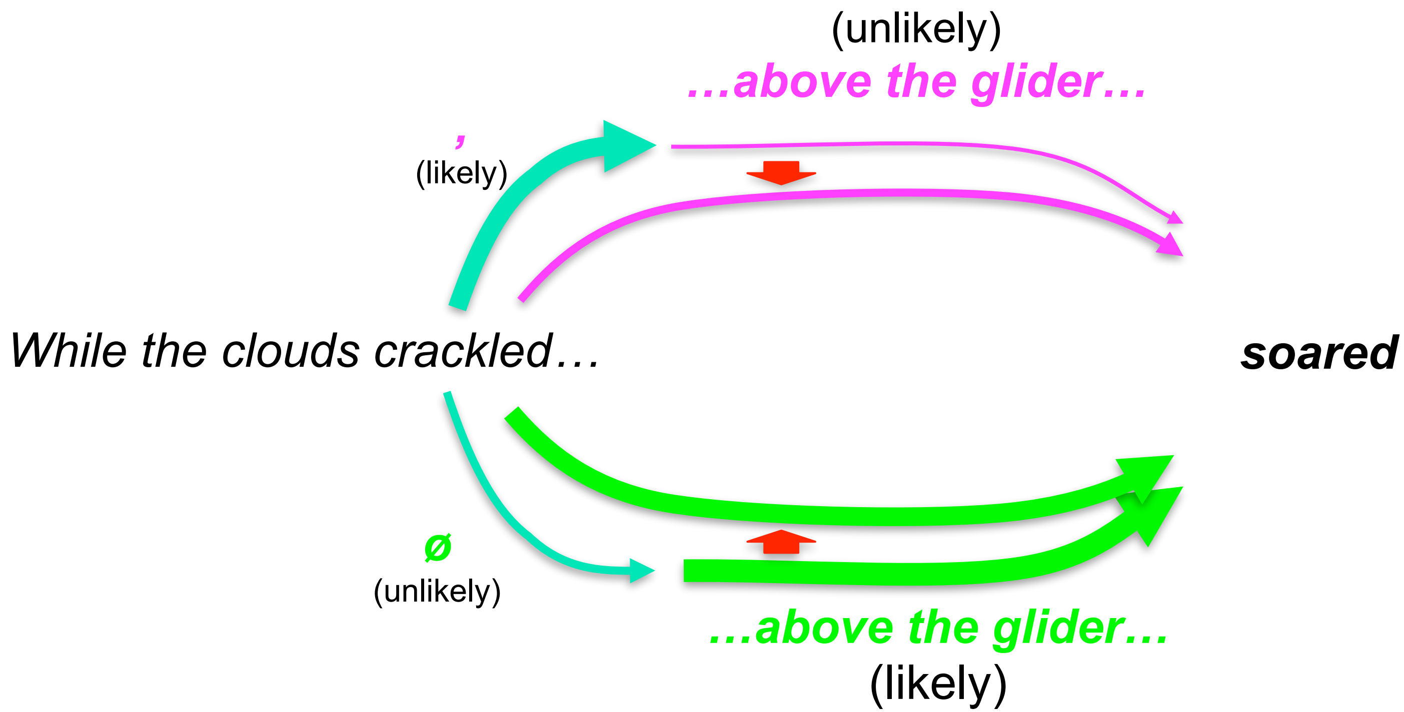


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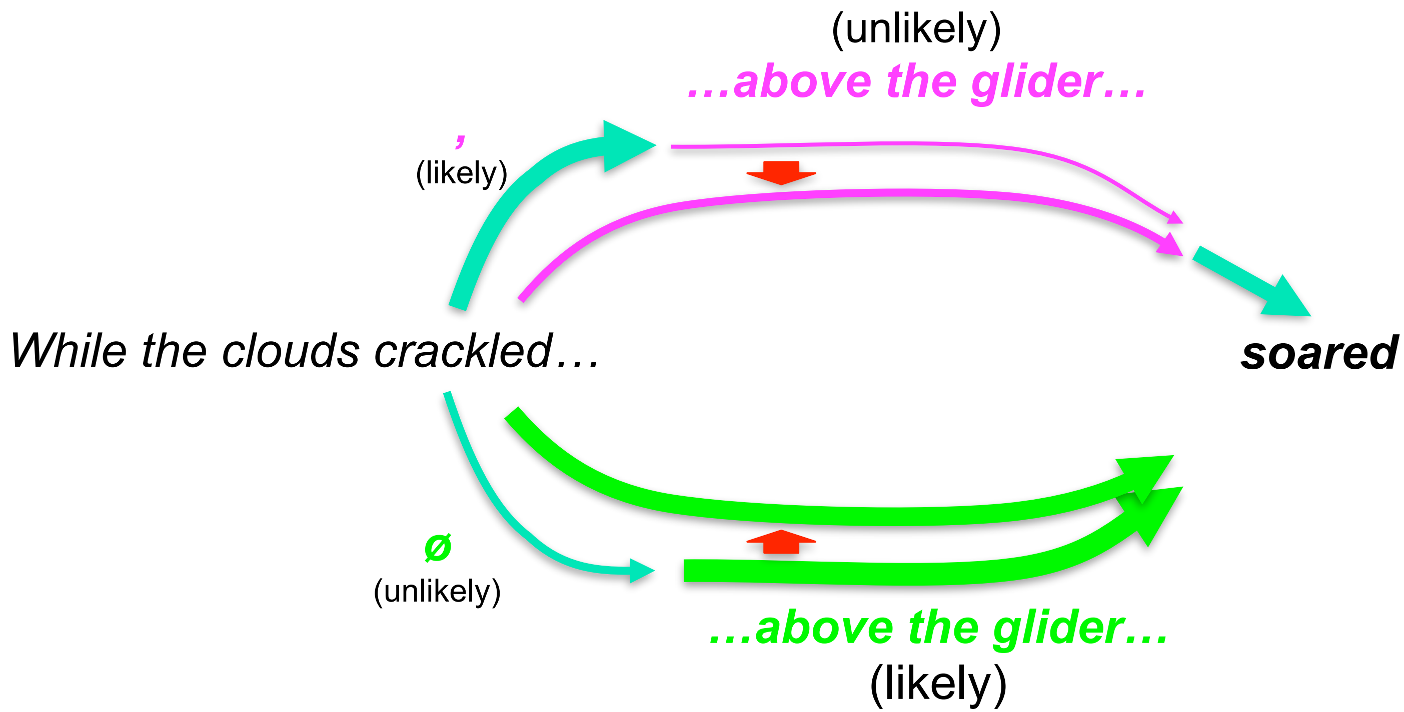


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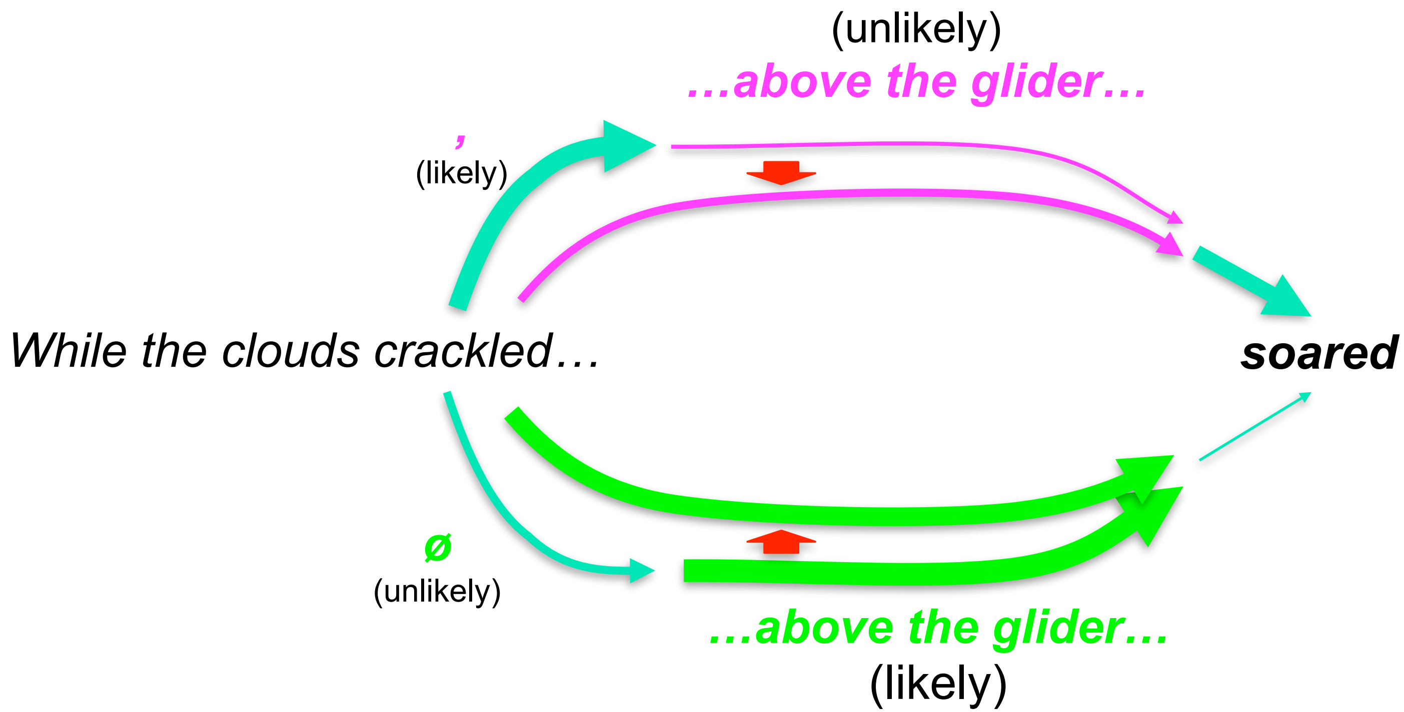


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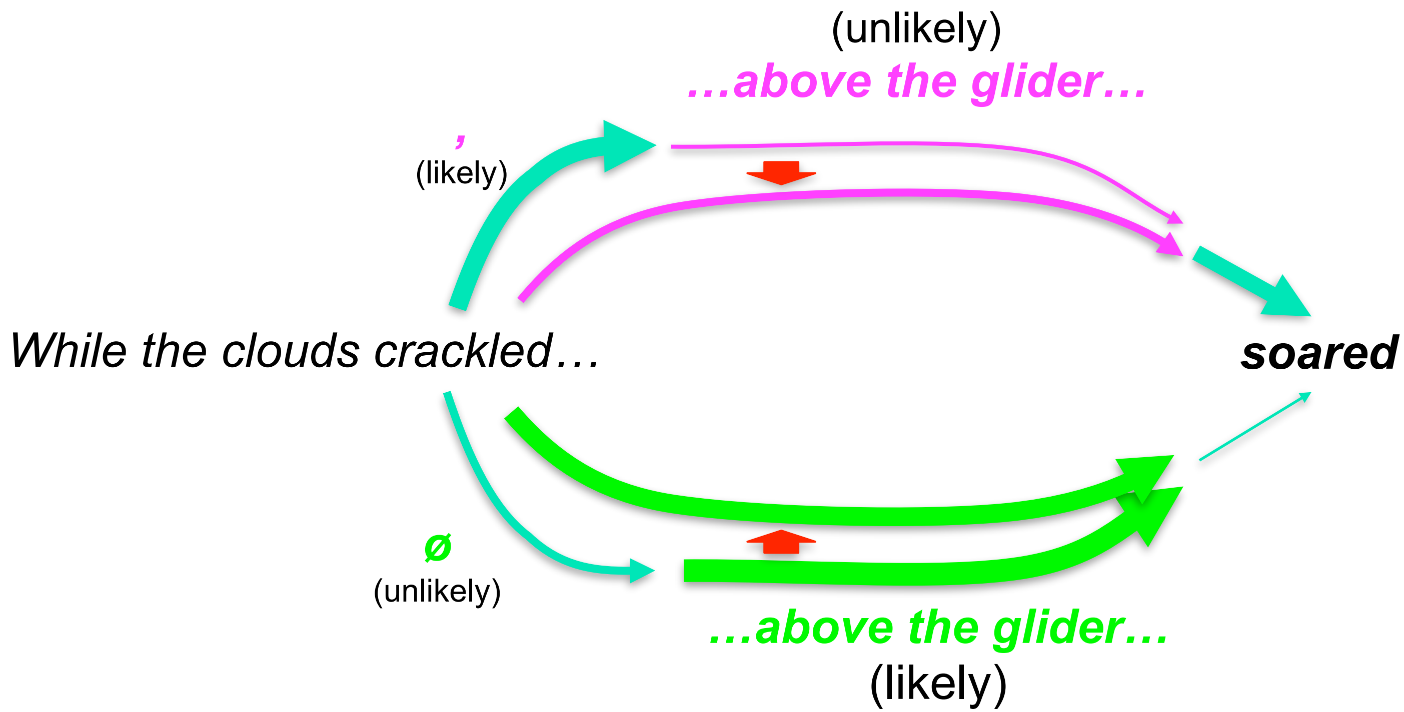


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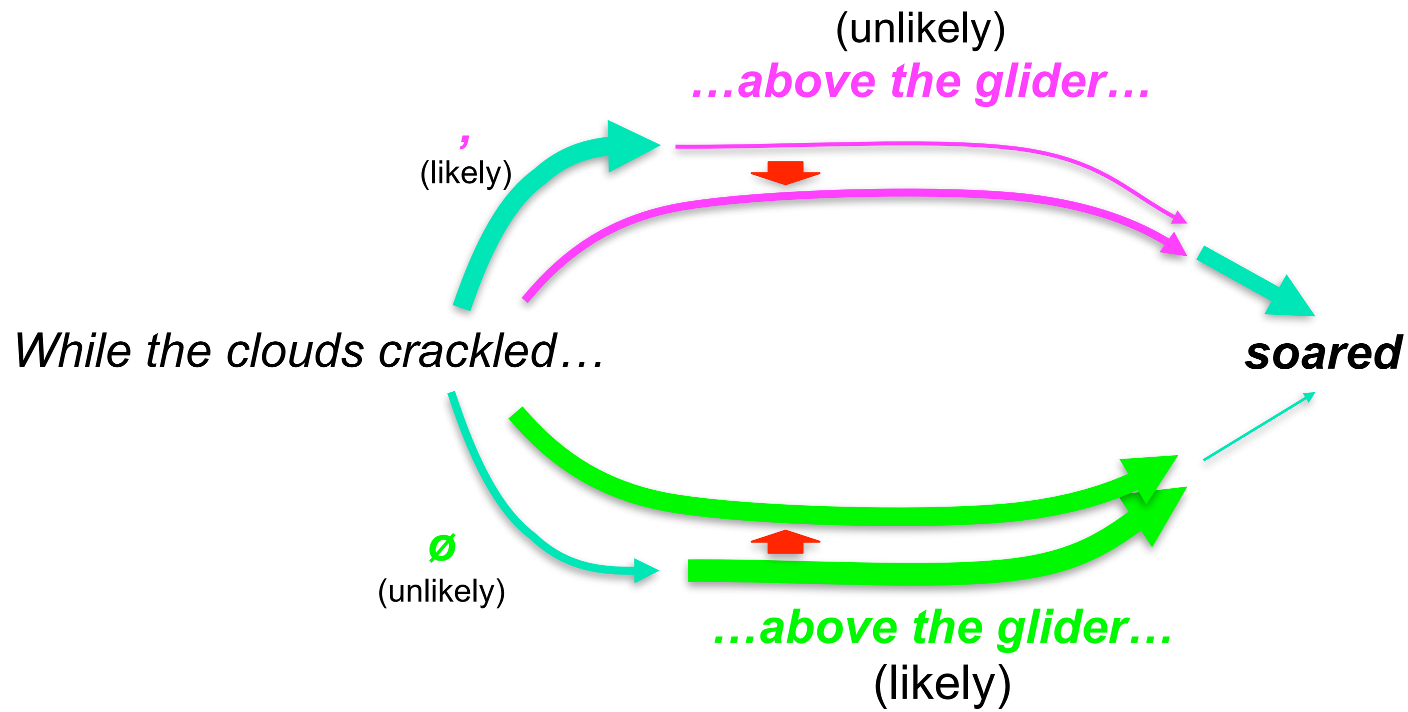


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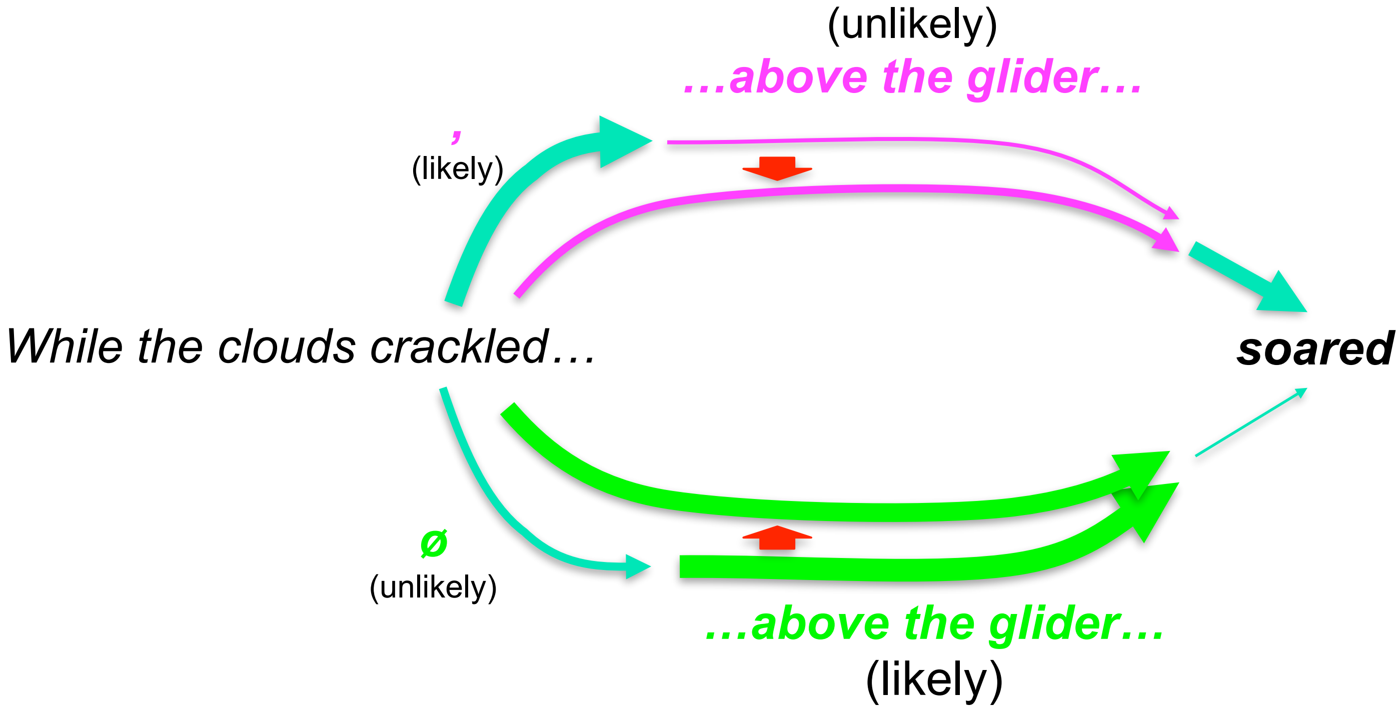


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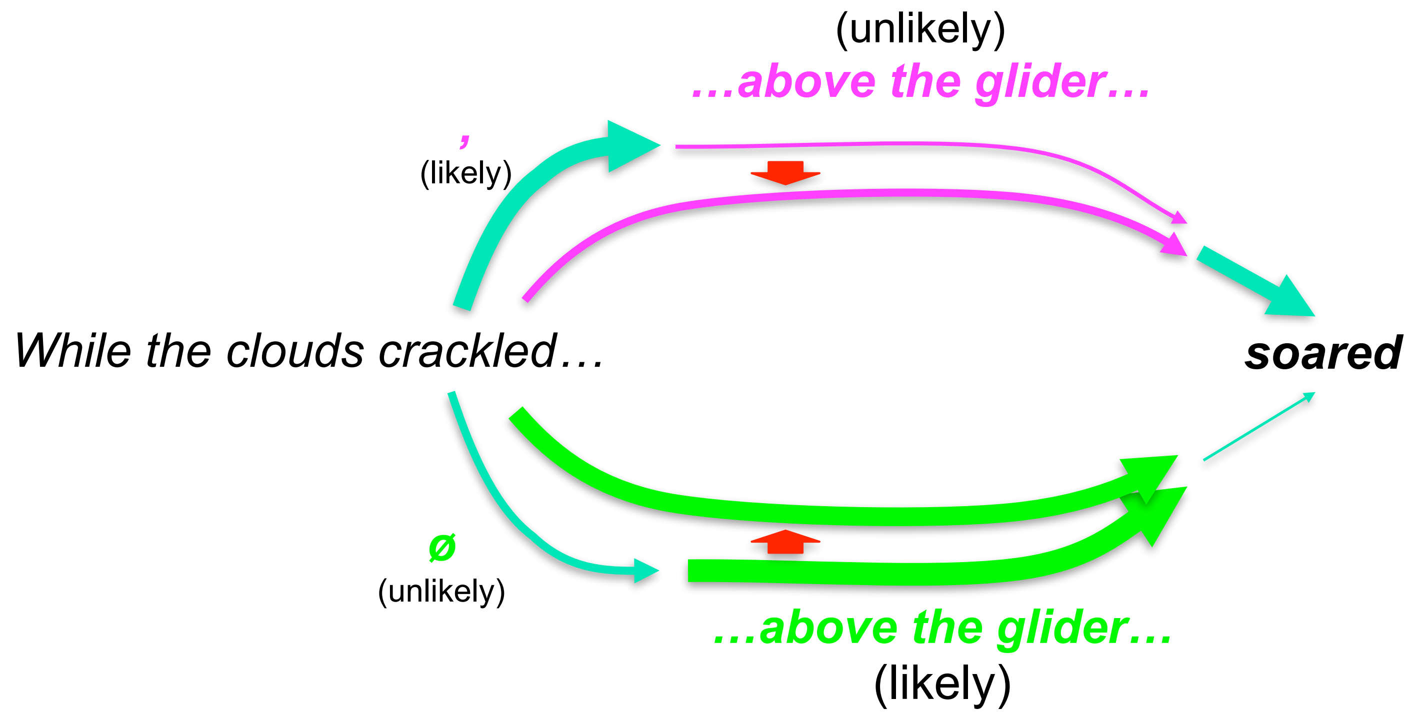


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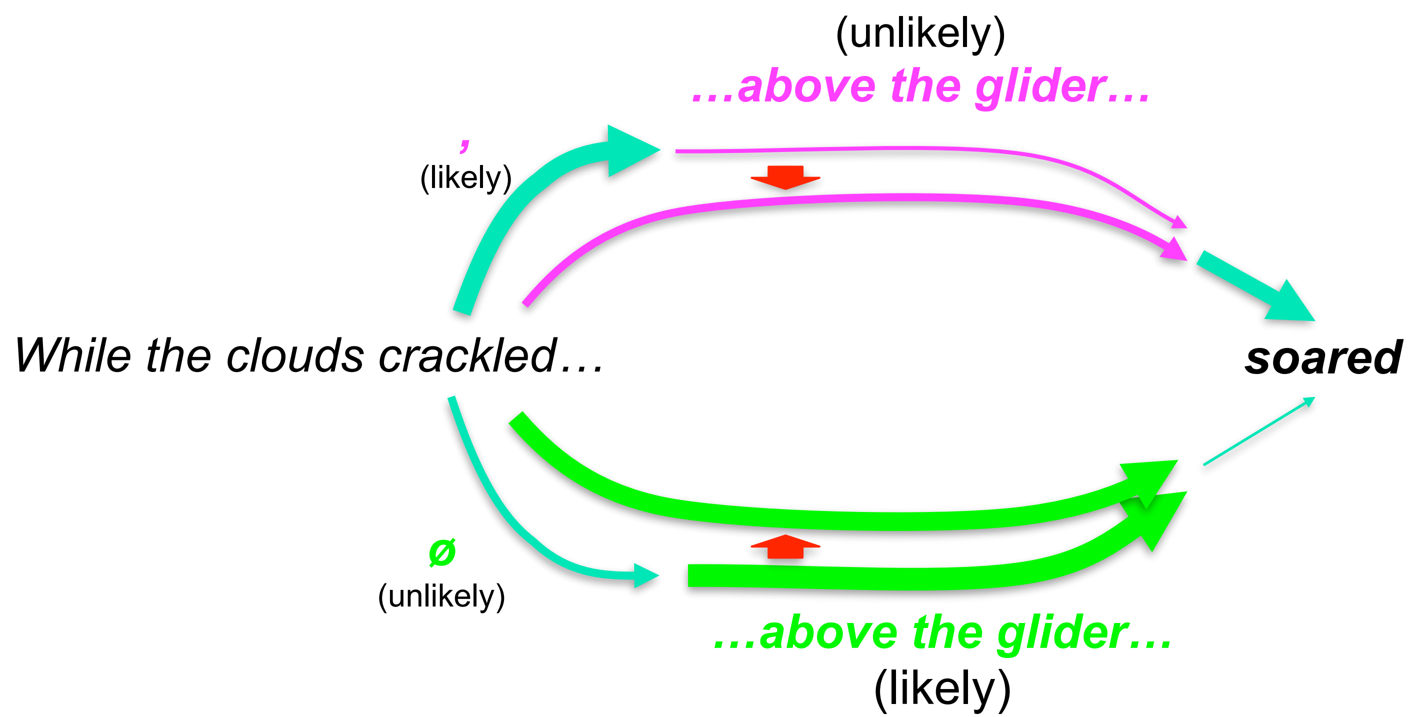


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while-------------------------------------------------------------------
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While-the---------------------------------------------------------------
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```
While-the-clouds-------------------------------------------------------
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```
While-the-clouds-crackled,---------------------------------------------------
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# Prediction 2: Hallucinated garden paths

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

`While-the-clouds-crackled,-above-the-glider---------------------------------`

- Readers aren’t allowed to backtrack

# Prediction 2: Hallucinated garden paths

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

`While-the-clouds-crackled,-above-the-glider-soared---------------------`

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- So the comma is visually *gone* by the time the inverted main clause appears

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

`While-the-clouds-crackled,-above-the-glider-soared---------------------`

- Readers aren't allowed to backtrack
- So the comma is visually *gone* by the time the inverted main clause appears
- Simple test of whether beliefs about previous input can be revised

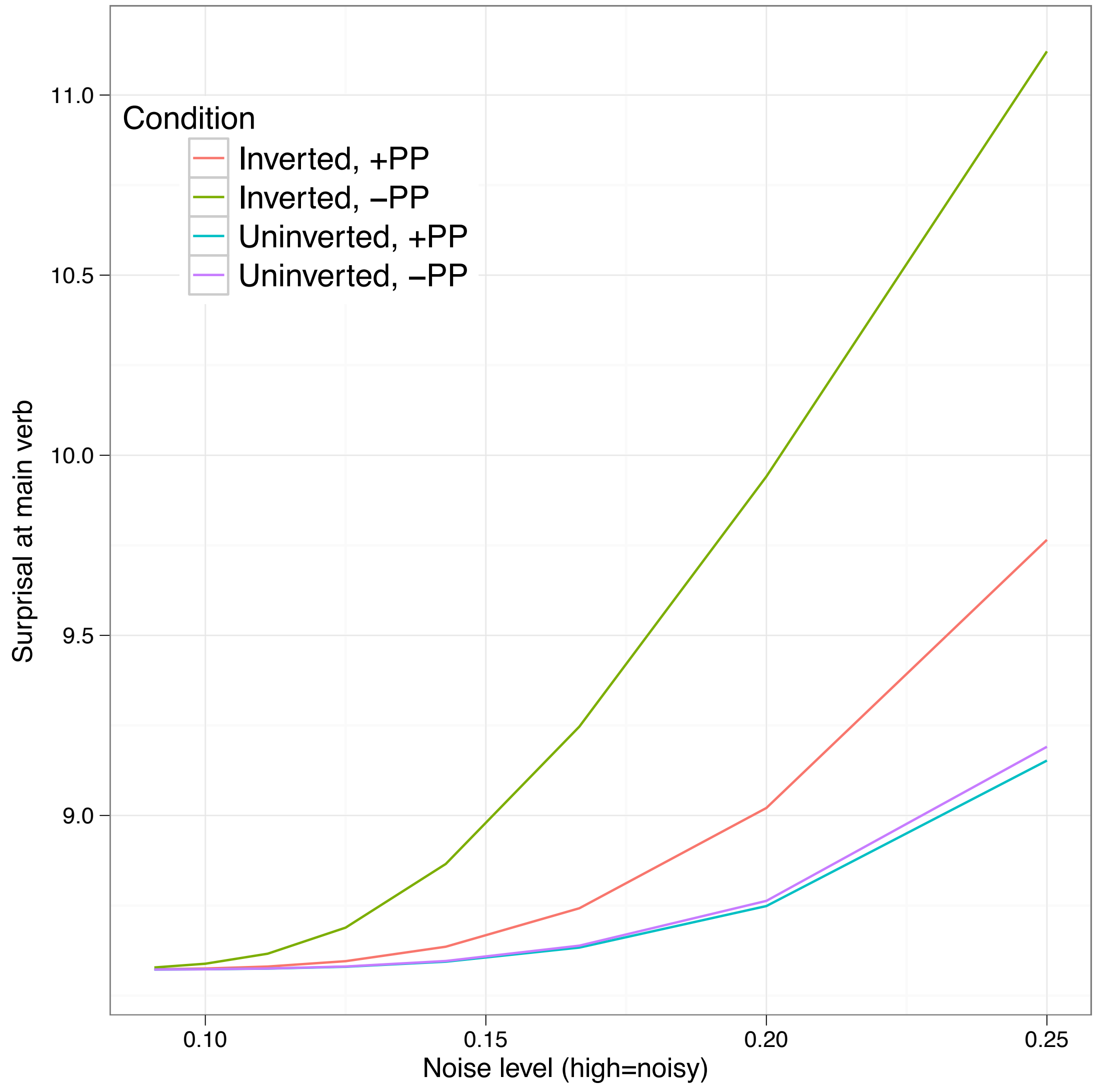
# Model predictions

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

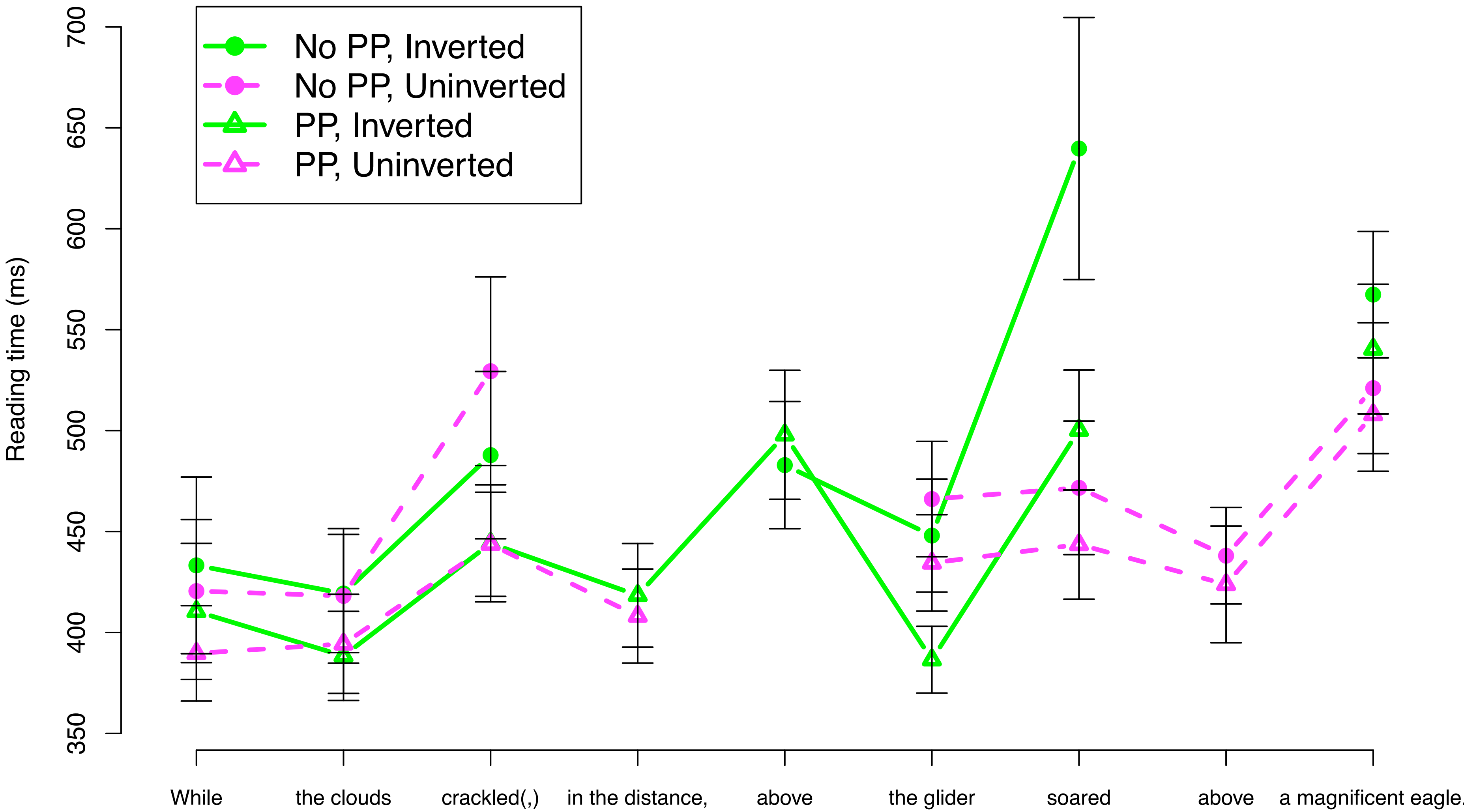
While the clouds crackled in the distance, above the glider soared a magnificent eagle.

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

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



# Results: whole sentence reading times



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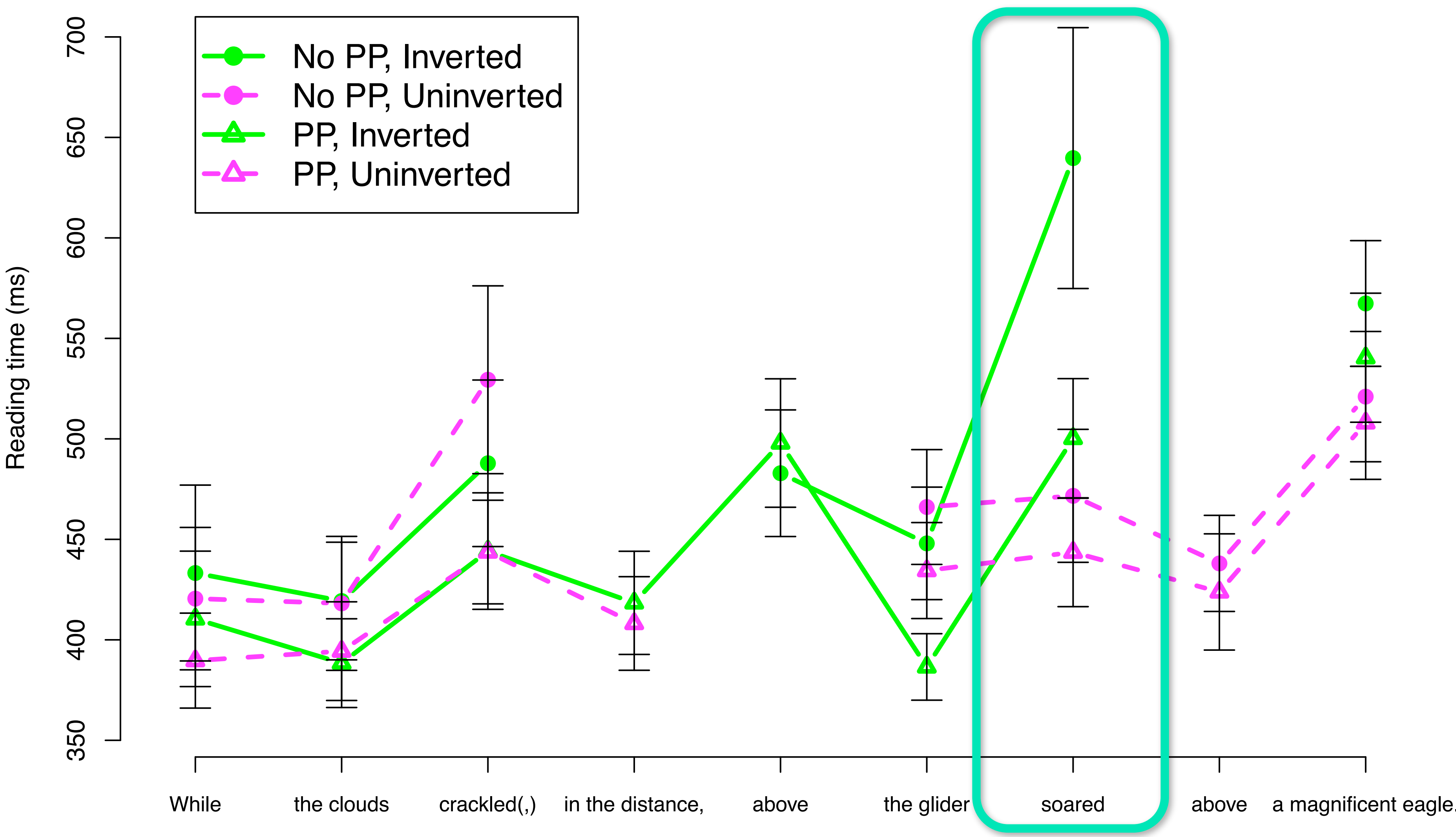

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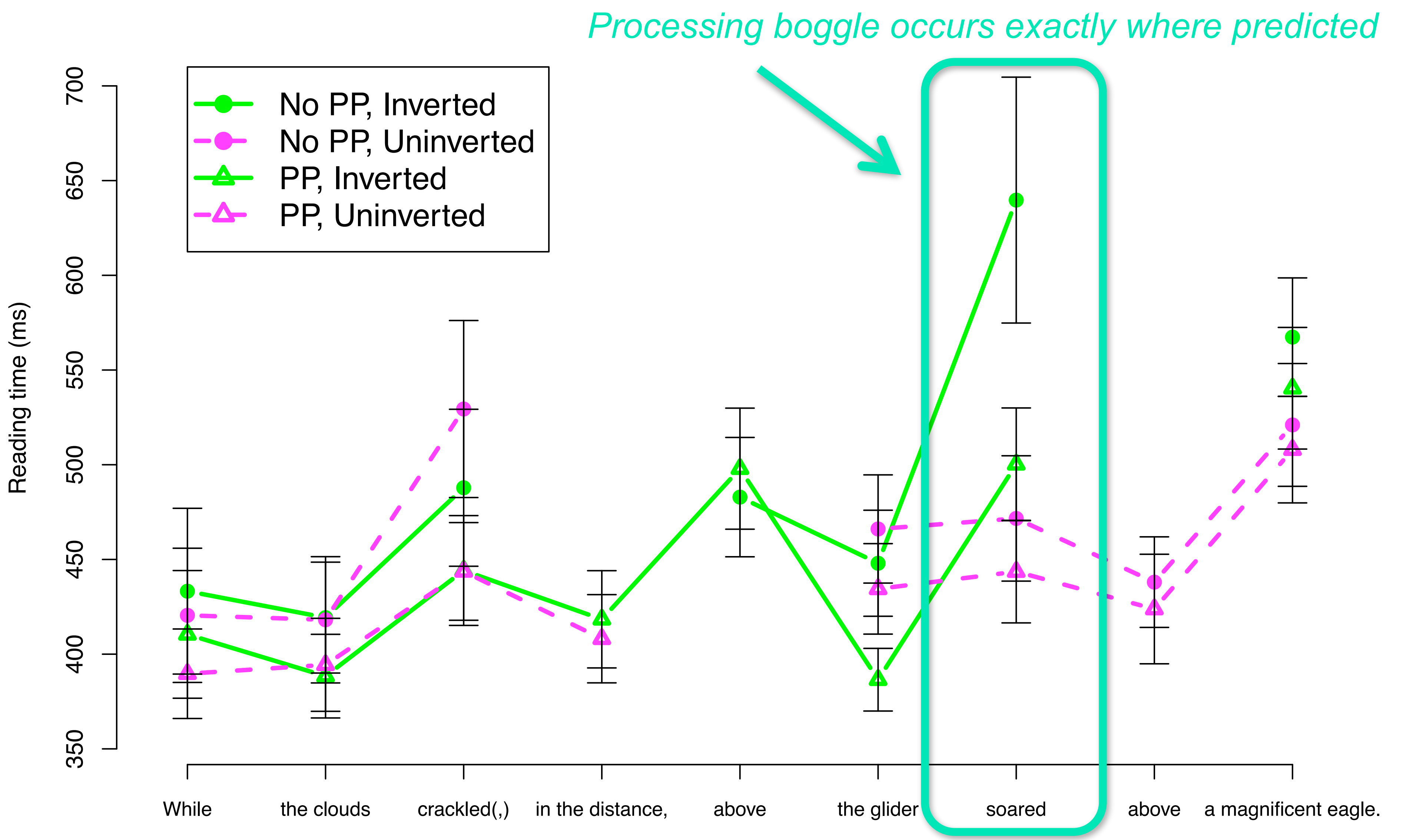

# Hallucinated garden-path summary

- 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

- Sure, but punctuation's weird stuff
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*I know that the desert trains could resupply the camp.*

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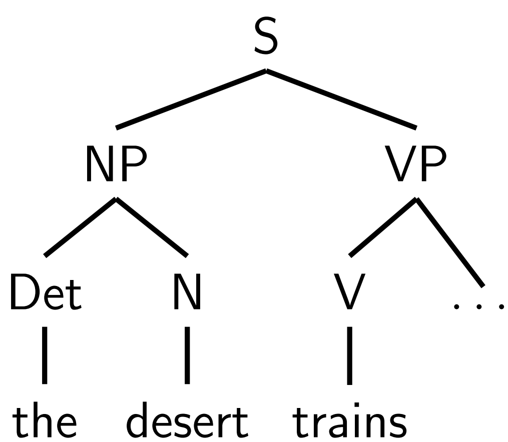


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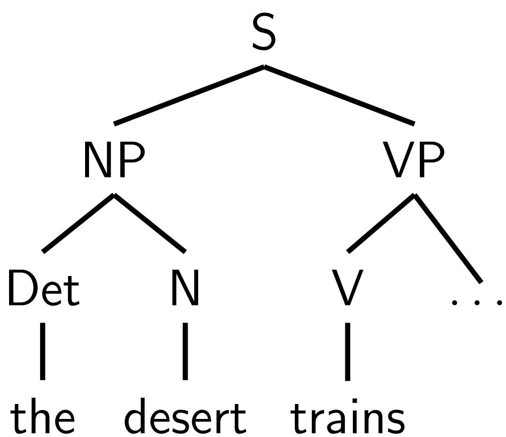


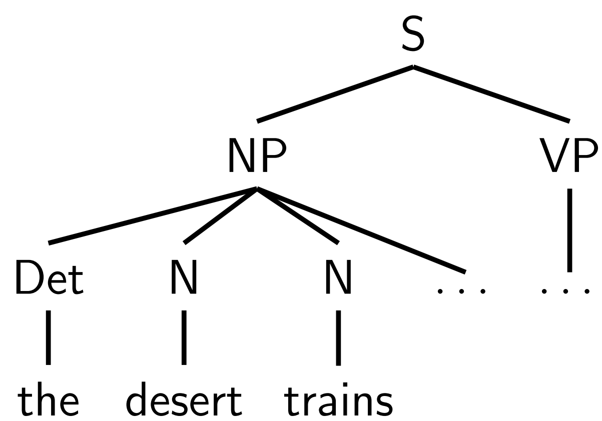


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# Hallucinated GPs with words

*Could be "intern chauffeured"*

*Could NOT be "inexperienced chauffeured"*

(*Bergen, Levy, & Gibson, 2012*)

# Hallucinated GPs with words

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

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*Could NOT be "inexperienced chauffeured"*

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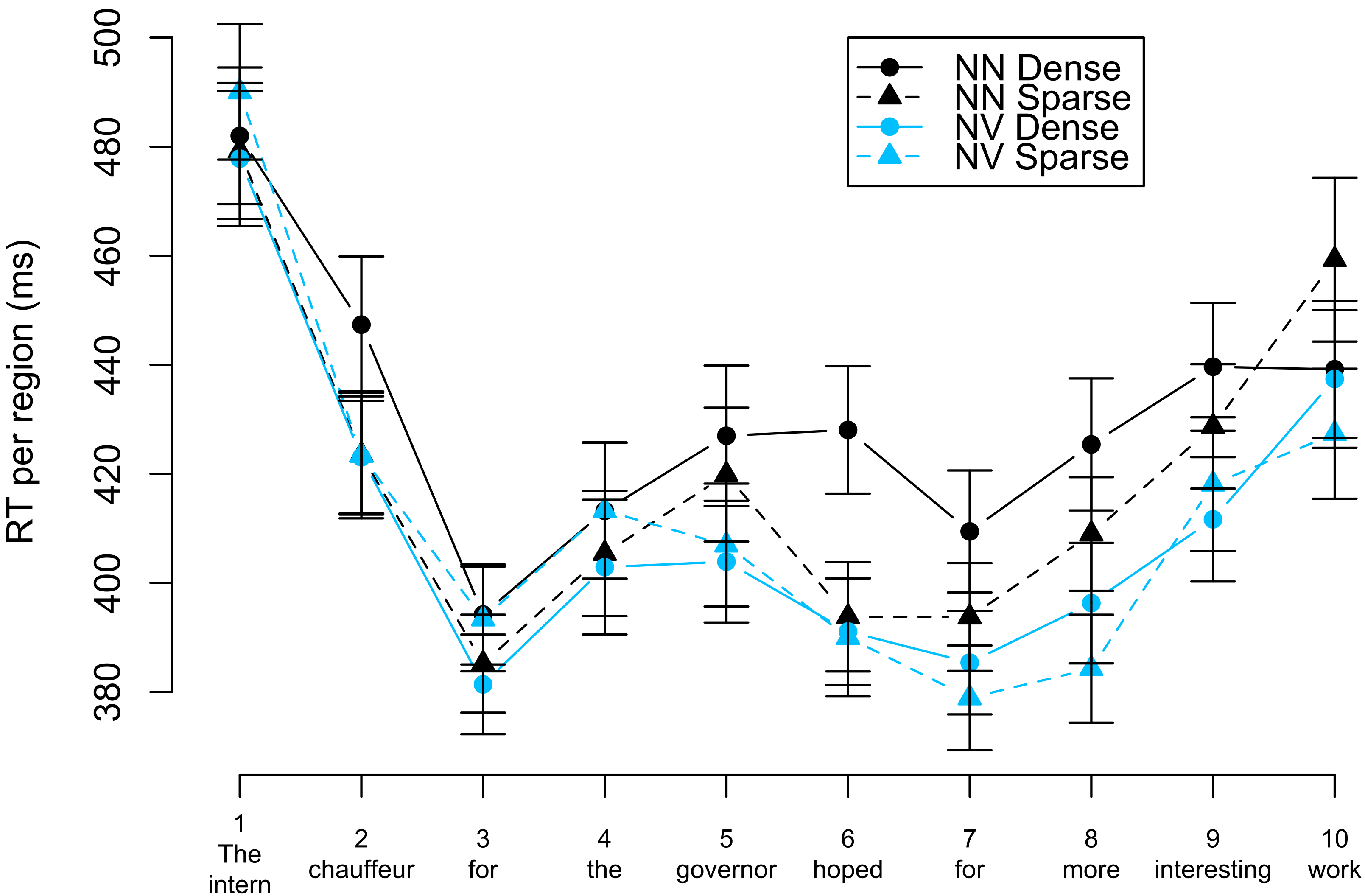
[NN, "sparse" neighborhood]

*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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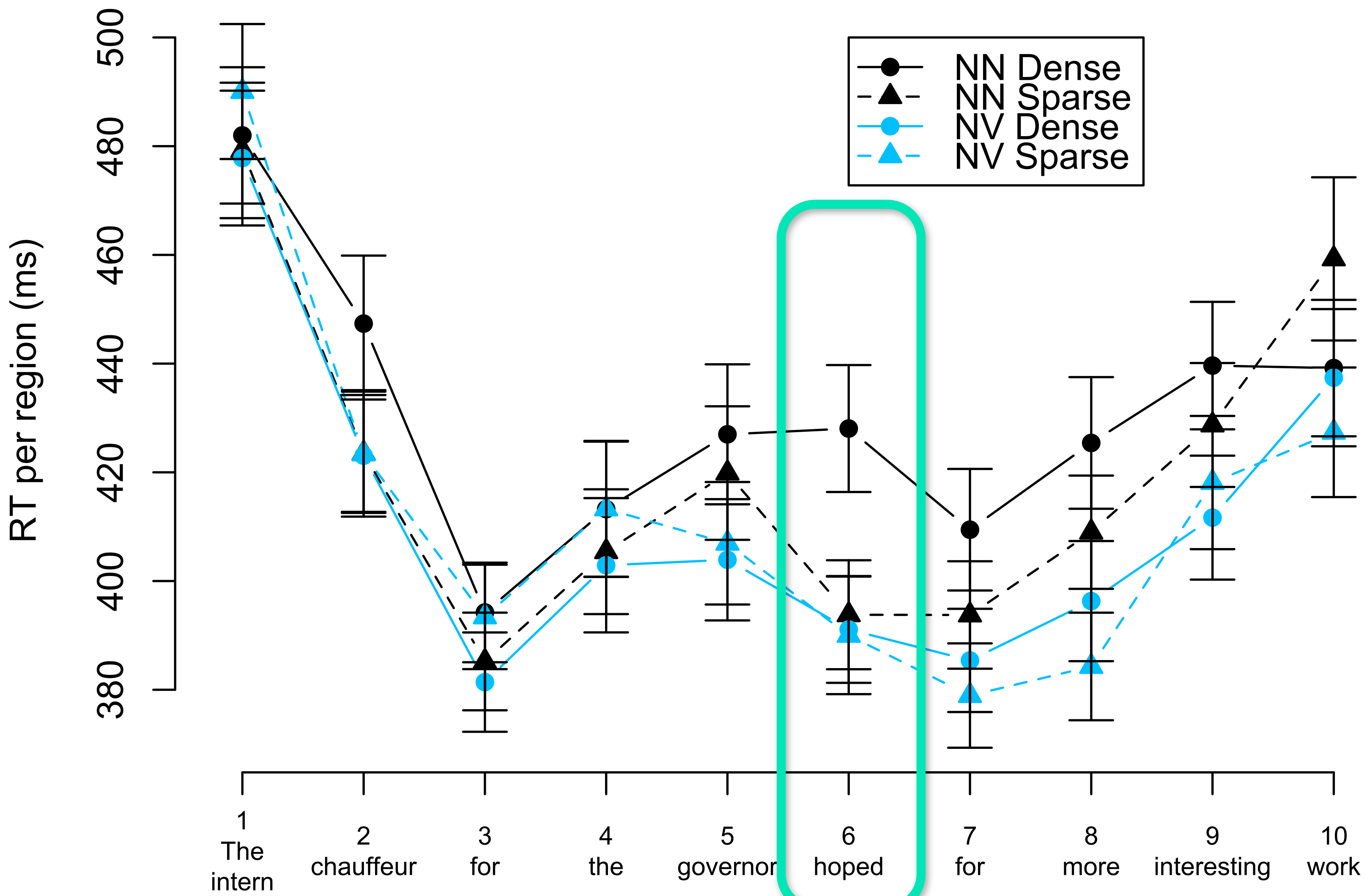


*(Bergen, Levy, & Gibson, 2012)*

# Structure of the noise model

- Gibson et al. (2013) explored noise model with restricted noise operations: word *insertions* and *deletions*

| **Sentence** | **Plausibility** | **Insertions** | **Deletions** |
|---|---|---|---|
| The cook baked Lucy a cake. | Plausible | 0 | 1 |
| The cook baked Lucy for a cake. | Implausible | 1 | 0 |
| The cook baked a cake for Lucy. | Plausible | 1 | 0 |
| The cook baked a cake Lucy. | Implausible | 0 | 1 |

# Structure of the noise model

| Sentence | Construction | Edits |
|---|---|---|
| The girl was kicked by the ball. | passive | 2I |
| The ball kicked the girl. | active | 2D |
| The tax law benefited from the businessman. | intransitive | 1I |
| The businessman benefited the tax law. | transitive | 1D |
| The cook baked Lucy for a cake. | Prepositional Object (PO) benefactive | 1I |
| The cook baked a cake Lucy. | Double Object (DO) benefactive | 1D |

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*Often "corrected" to plausible interpretation inconsistent with literal meaning*

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*Consistently given literal interpretation*

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# 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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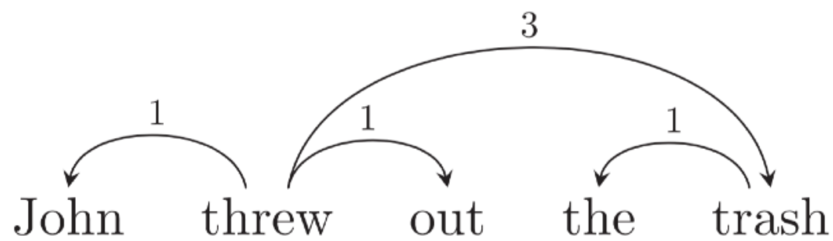


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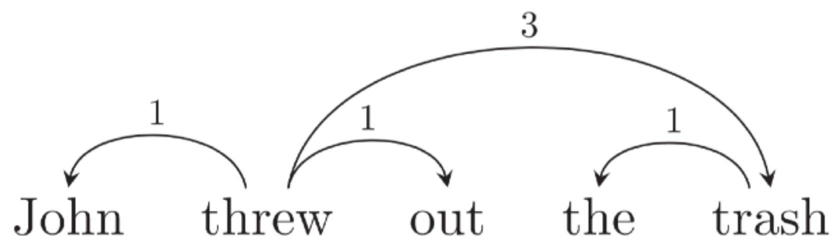


- Idea with long history: short dependencies preferred

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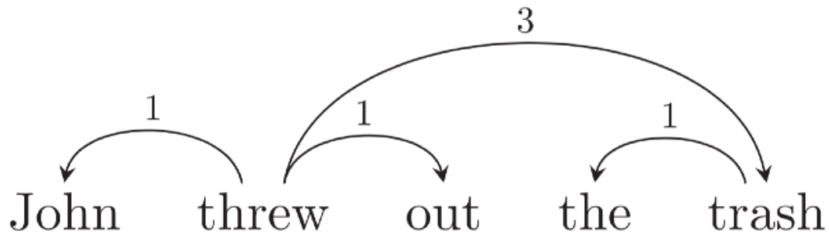


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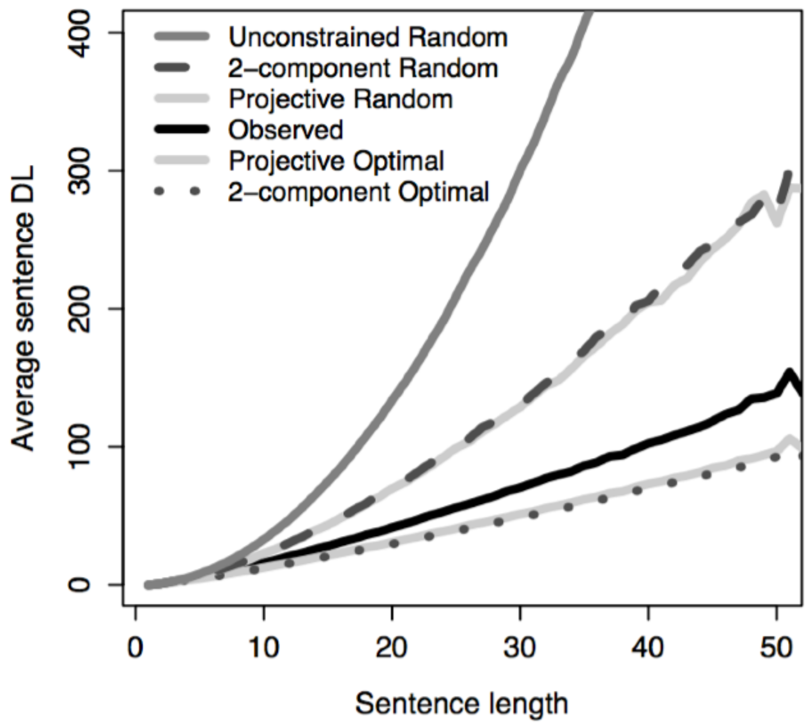


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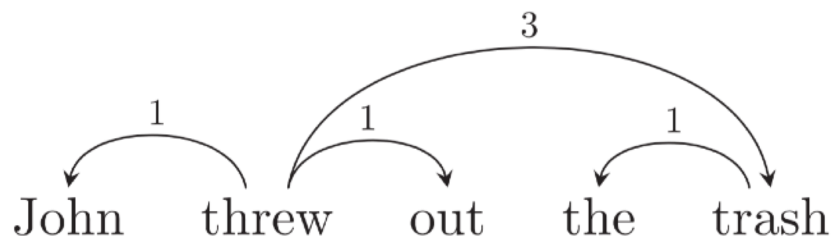


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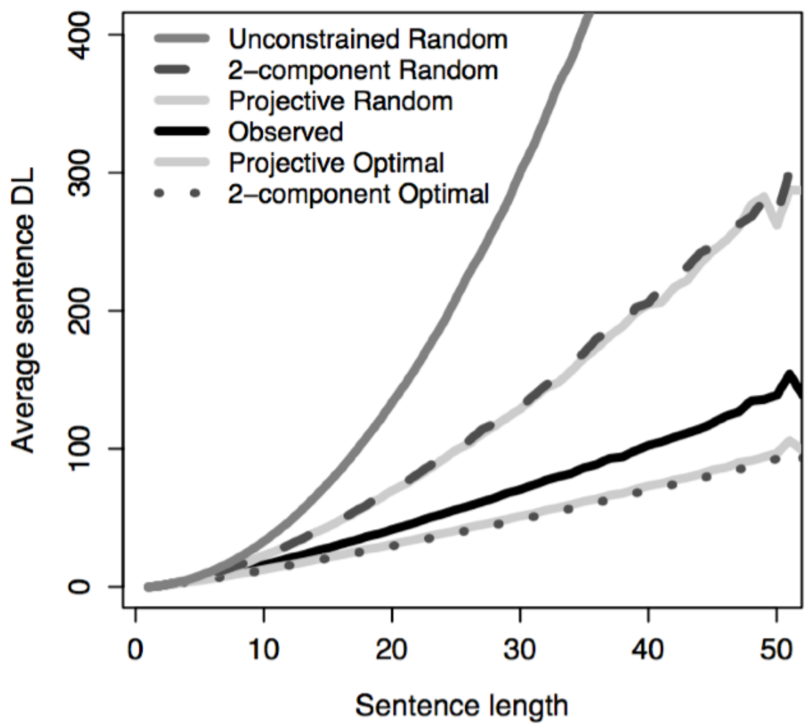


Random-linearization dependency lengths

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

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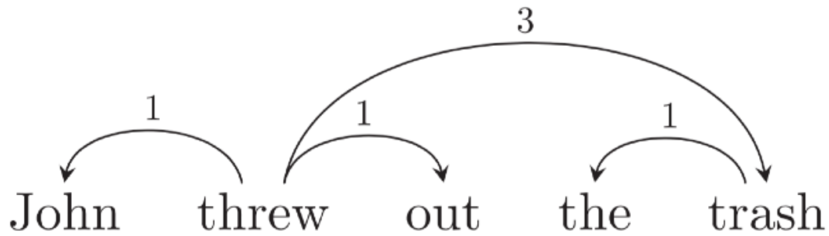


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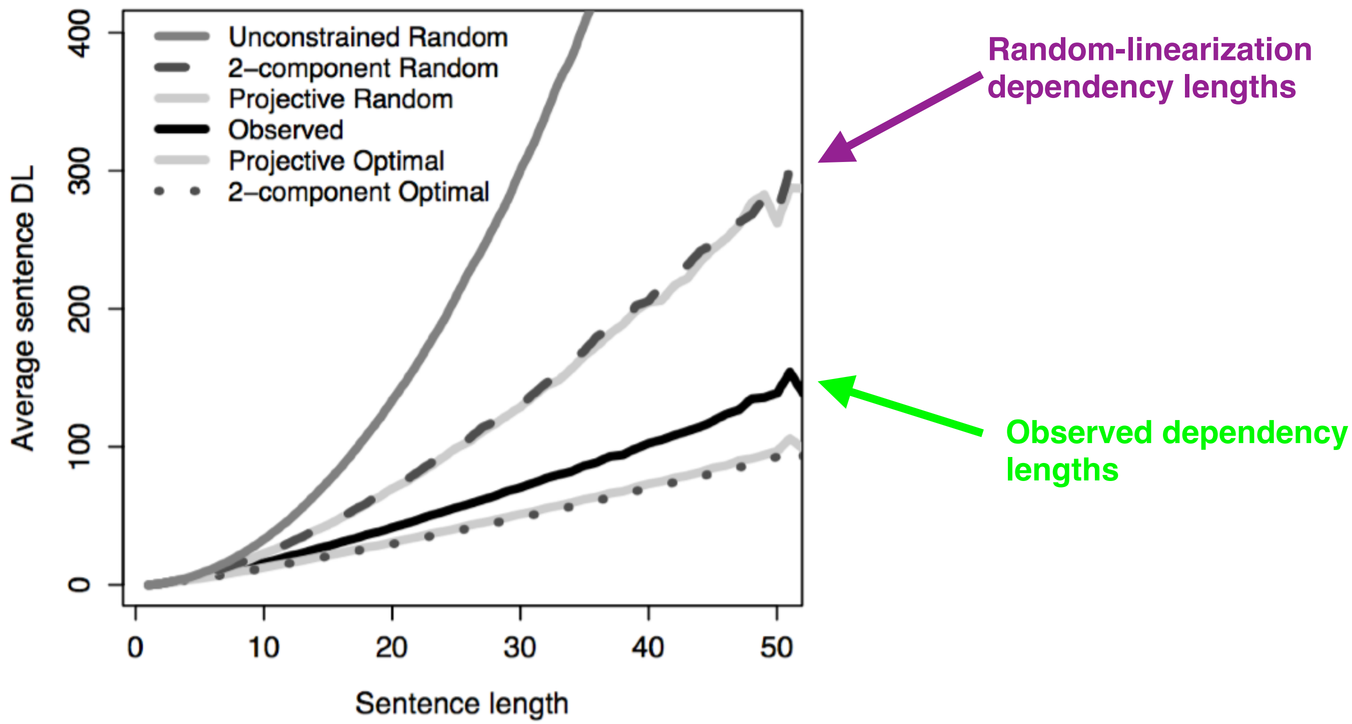


(Hawkins, 1994; Gibson, 1998, 2000; Gildea & Temperley, 2007, 2009; Park & Levy, 2009; Futrell et al., 2015)

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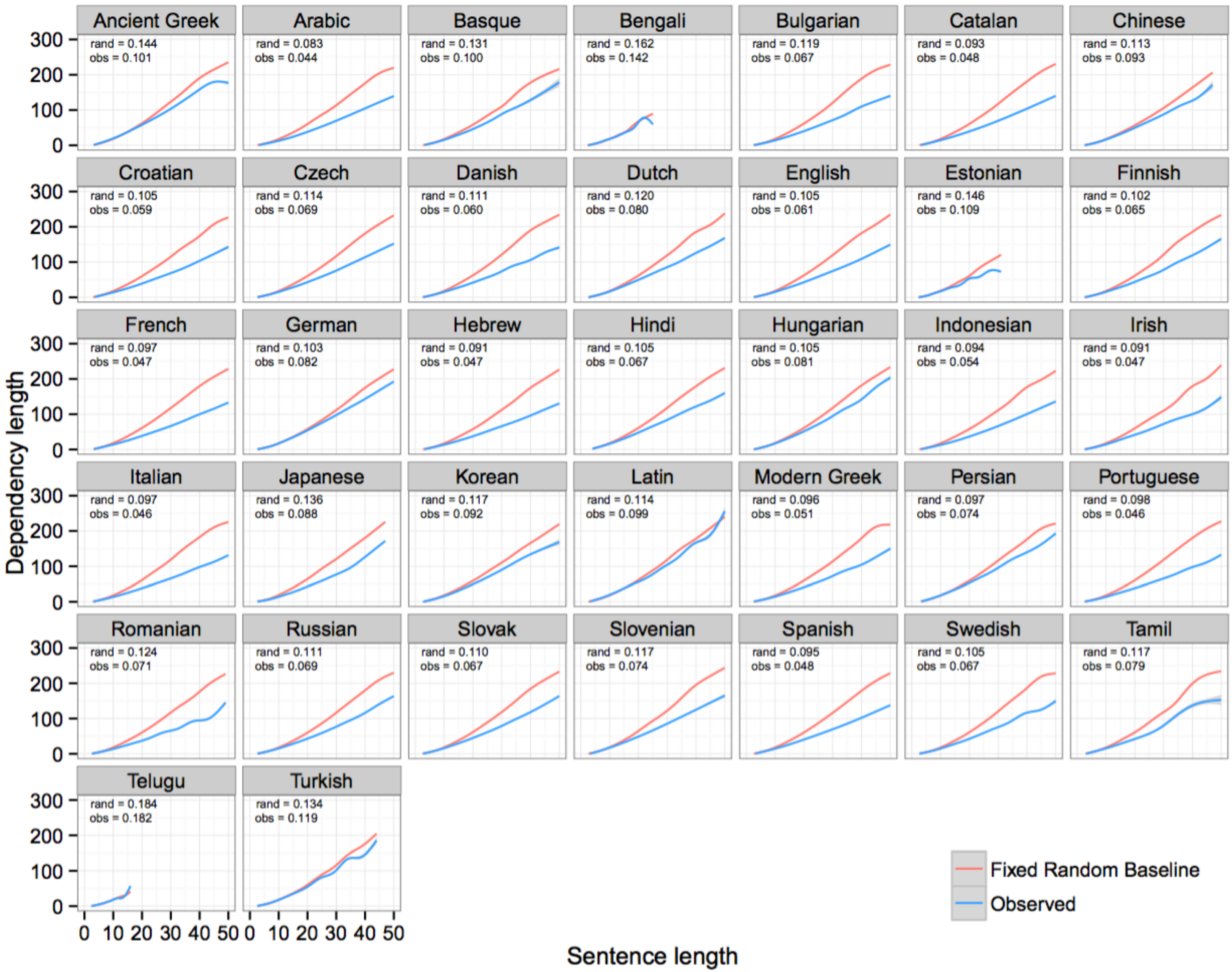
# Dependency lengths are short across languages!



# Dependency lengths and the noisy channel

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

(Futrell & Levy, 2017)

# From noisy-channel & surprisal to dependency length minimization

context

| John threw the old trash sitting in the kitchen | out |
|---|---|

(Futrell & Levy, 2017)

*(Slide courtesy Richard Futrell)*

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

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## From noisy-channel & surprisal to dependency length minimization

noisy context


- Suppose we have an **increasing noise rate** the longer a word has been in memory.
- When "threw" is far from "out", then it is less likely to reduce the surprisal of "out": more likely to be affected by noise.

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- When "threw" is far from "out", then it is less likely to reduce the surprisal of "out": more likely to be affected by noise.
- Noisy-context surprisal increases when **words that predict each other are far apart**.

(Futrell & Levy, 2017)

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- Noisy-context surprisal increases when **words that predict each other are far apart**.
- We call this **information locality** (following Gildea & Jaeger, 2015).

(Futrell & Levy, 2017)

*(Slide courtesy Richard Futrell)*

# Derivation of Information Locality

(Futrell & Levy, 2017)

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- Erasure noise decreases the influence of context:

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$$C(w|\text{context}) \approx h(w) - \sum_{w' \in \text{context}} P(w' \text{ not erased}) \text{pmi}(w; w')$$

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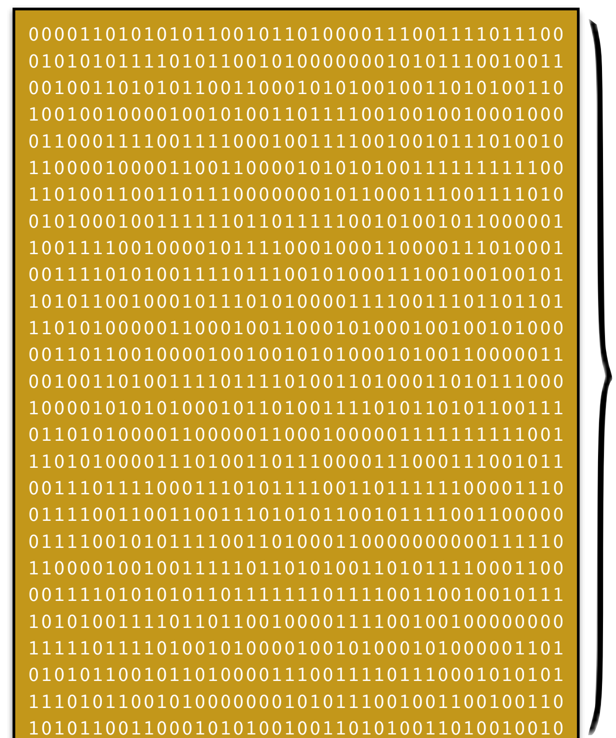
$h$(out)



$C$

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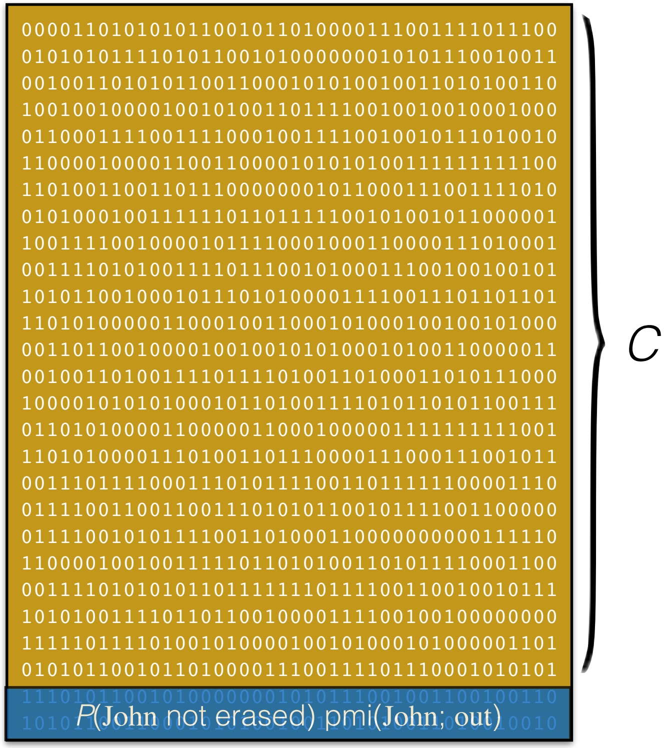
$h$(out) - $P$(John not erased) pmi(John; out)

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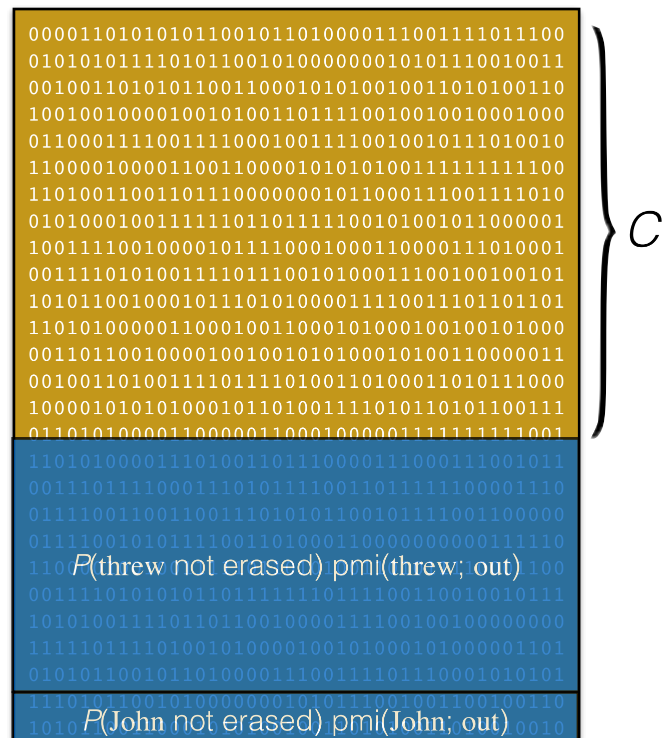


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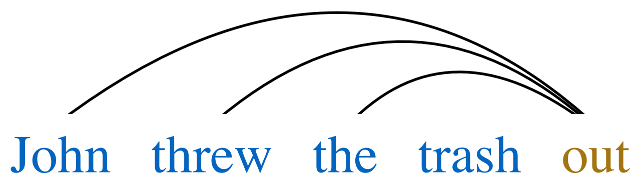


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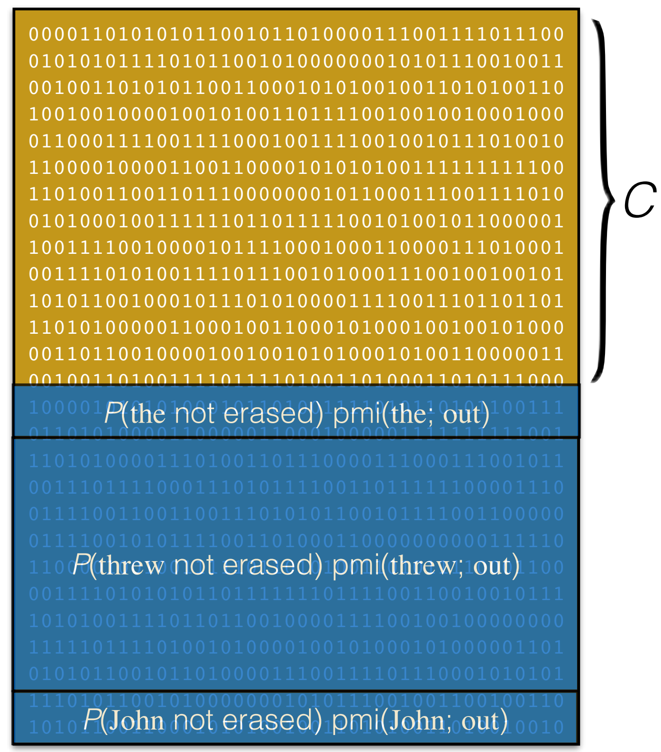


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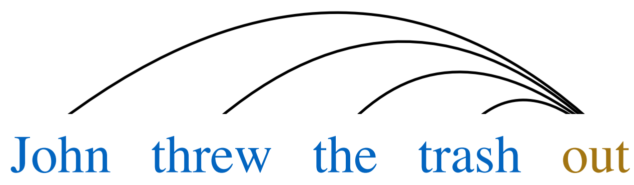


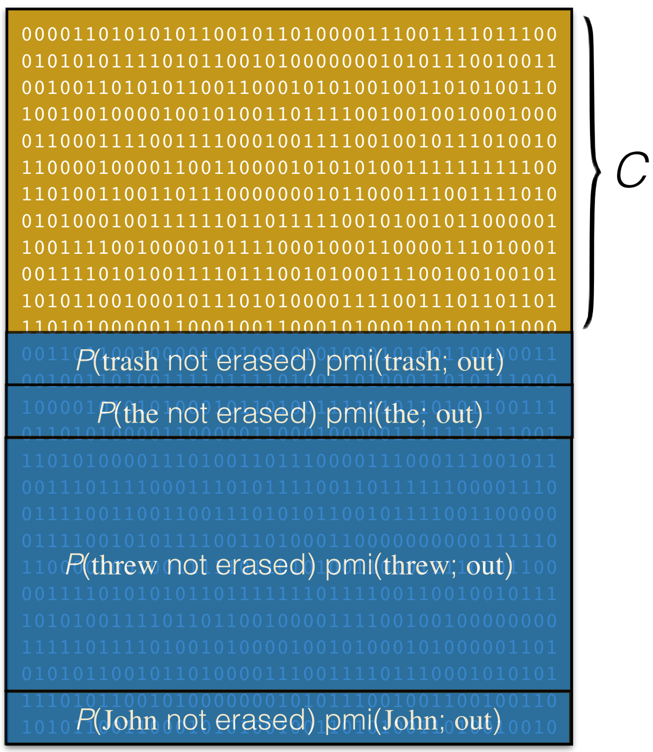


$h$(out) - $P$(John not erased) pmi(John; out)

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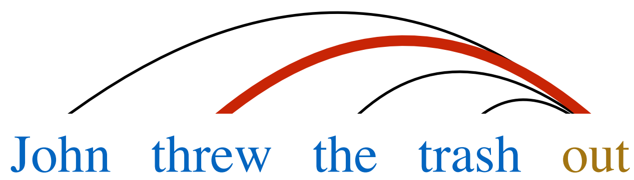


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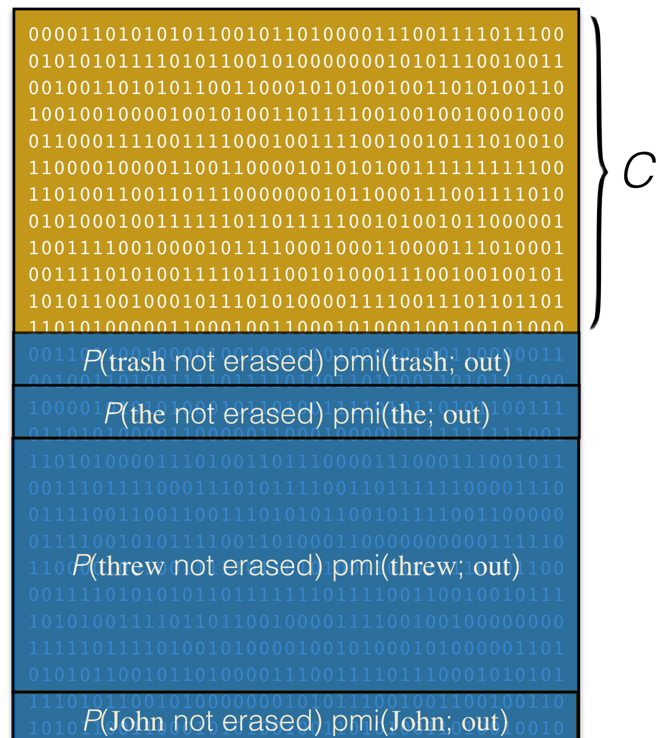
$\boxed{\text{- } P(\text{threw not erased}) \text{ pmi(threw; out)}}$

- $P$(the not erased) pmi(the; out)

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




(Futrell & Levy, 2017)

(Slide courtesy Richard Futrell)

# Derivation of Information Locality

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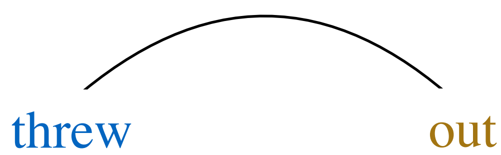
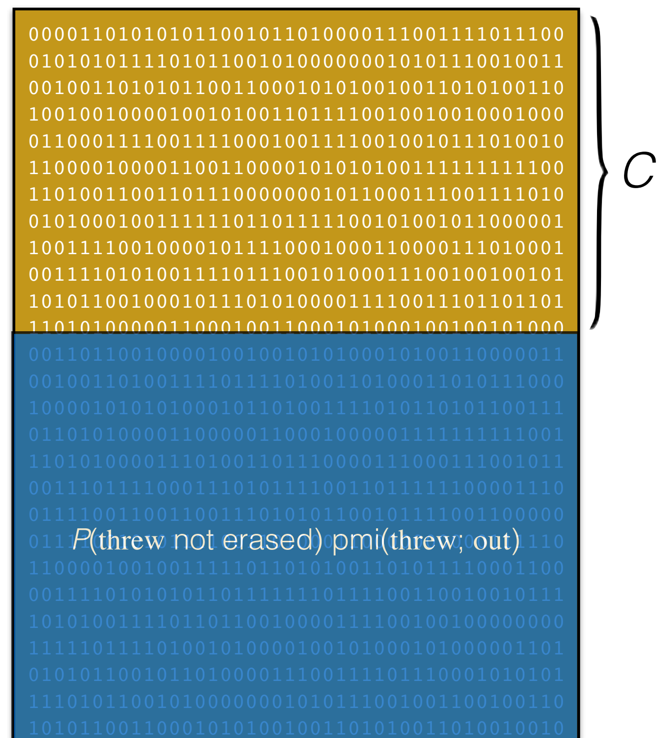



$h$(out) - $P$(threw not erased) pmi(threw; out)




(Futrell & Levy, 2017)

*(Slide courtesy Richard Futrell)*

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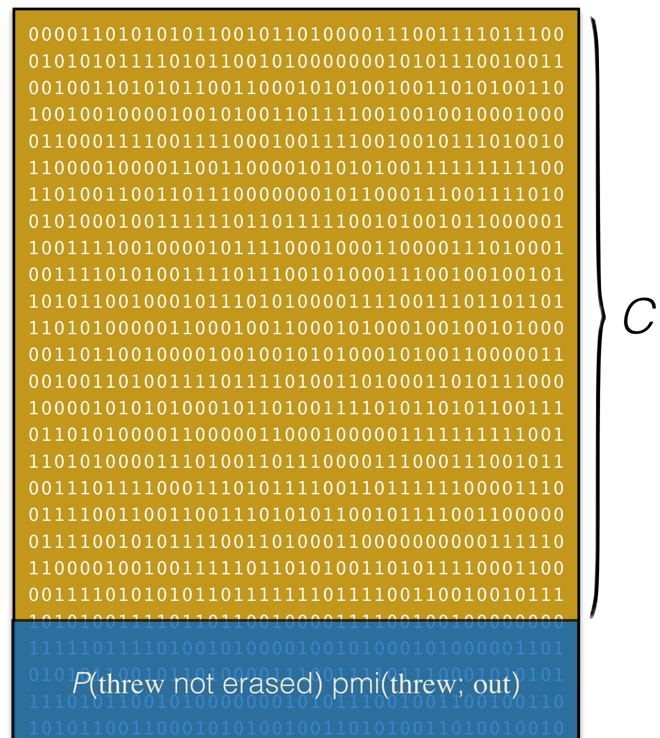


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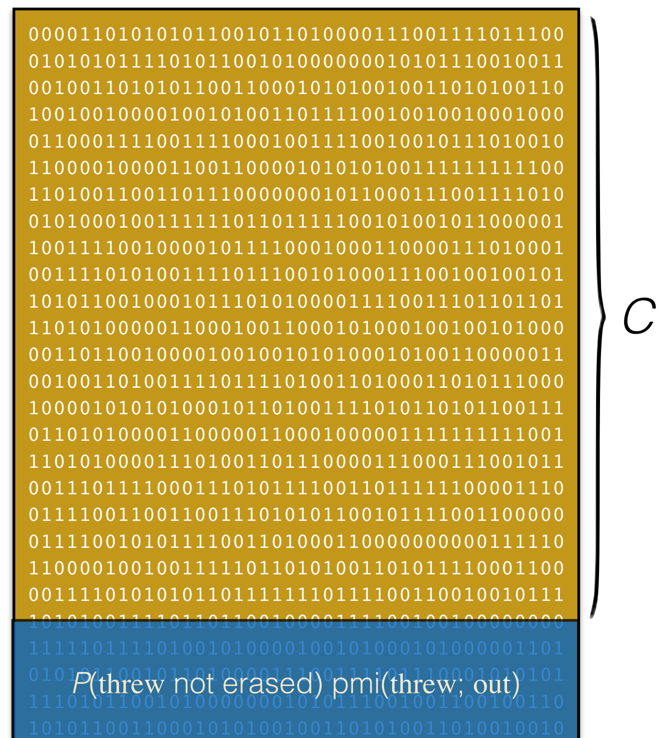


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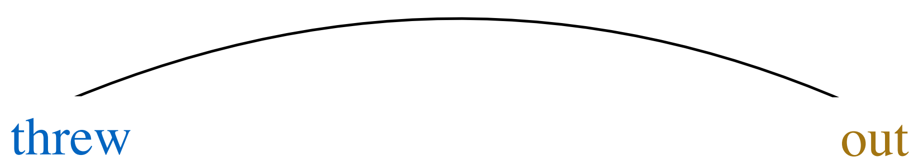


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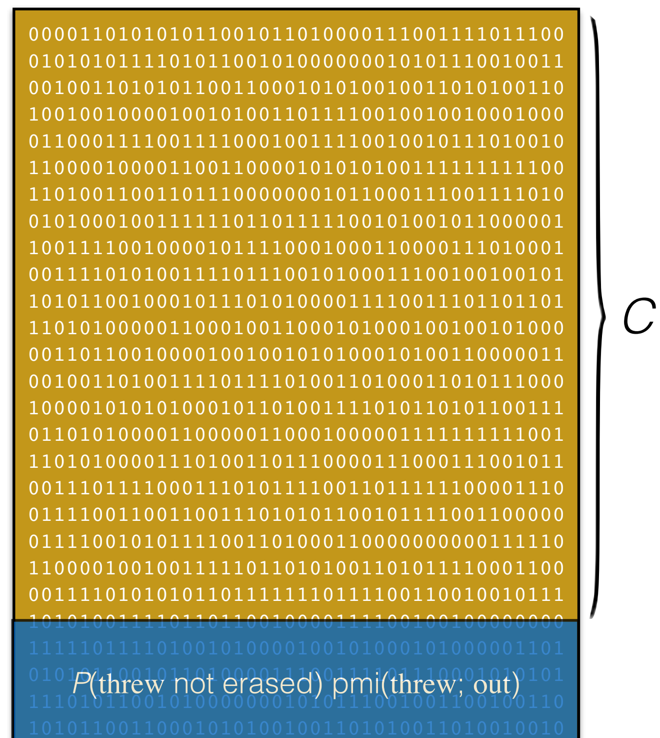
- When context items are far, their cost-reducing influence decreases.
  - Similar to the concept of decay in cue effectiveness (Qian & Jaeger, 2012)

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- **Information locality:** prediction of processing difficulty when words that predict each other (have high mutual information) are far apart.

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

(Futrell & Levy, 2017)

*(Slide courtesy Richard Futrell)*

# Do Dependencies Have High Mutual Information?

(Futrell & Levy, 2017)

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?

$\downarrow$

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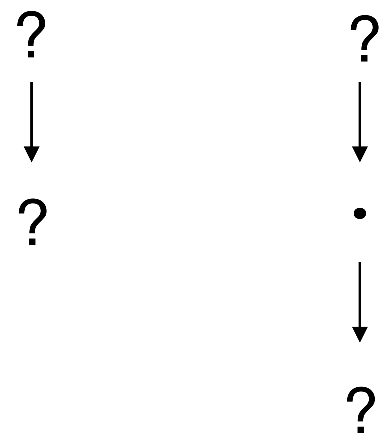


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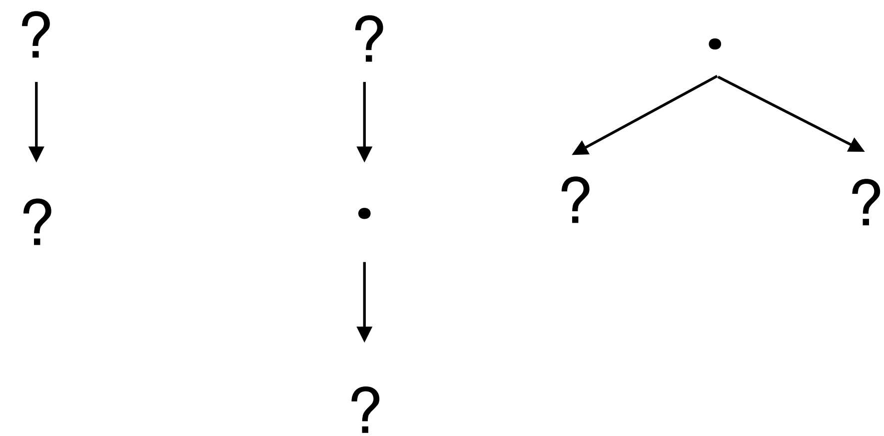


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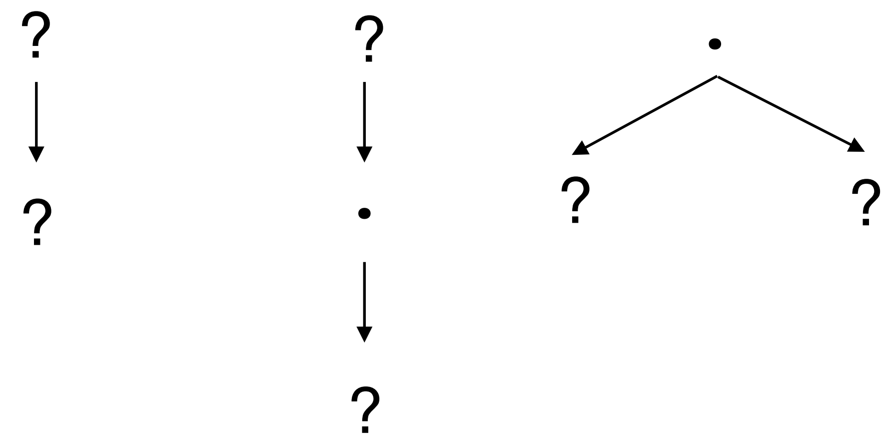


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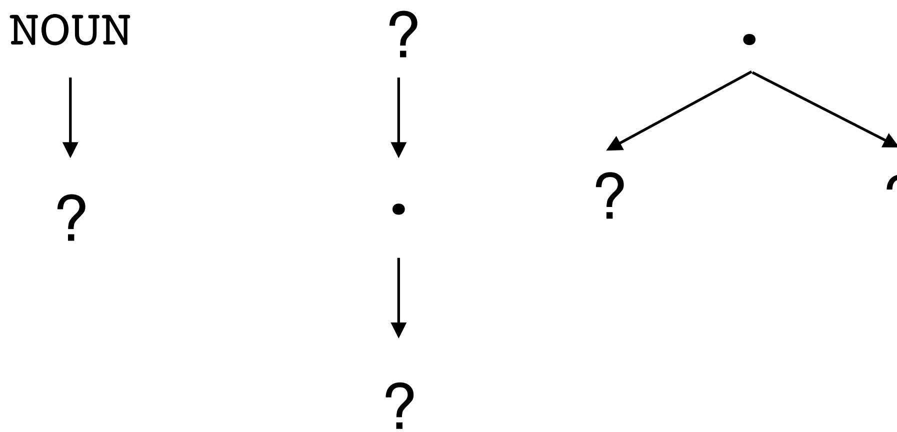


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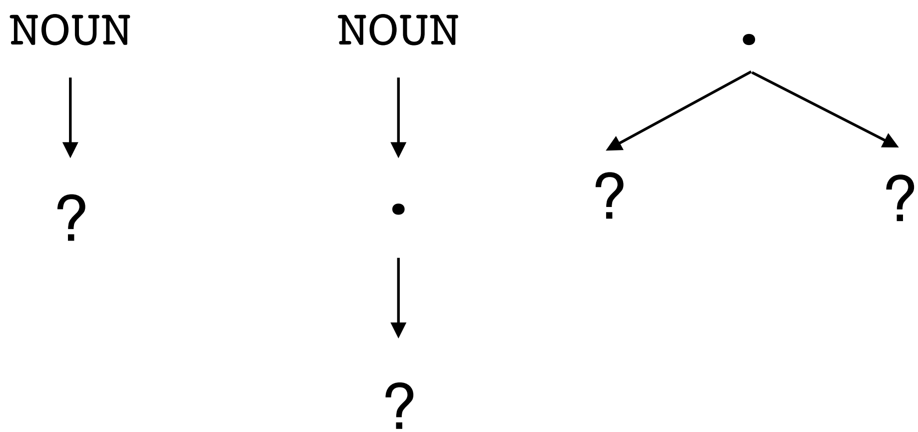


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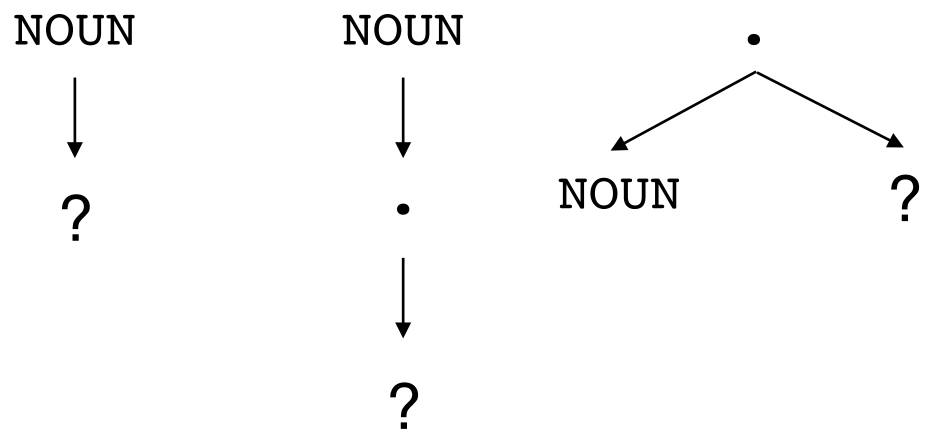


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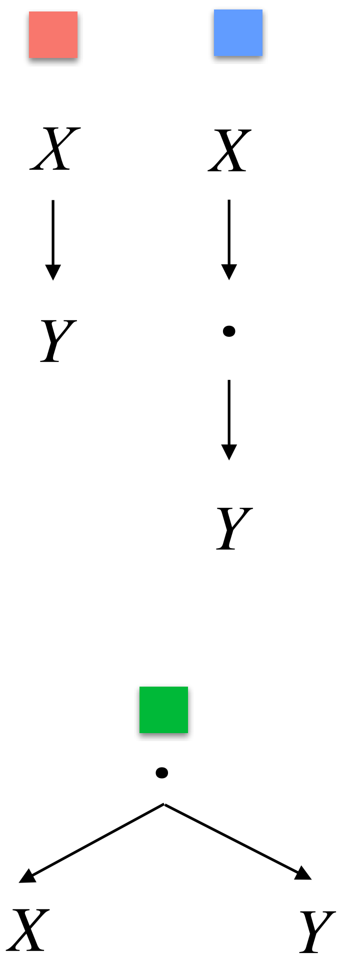



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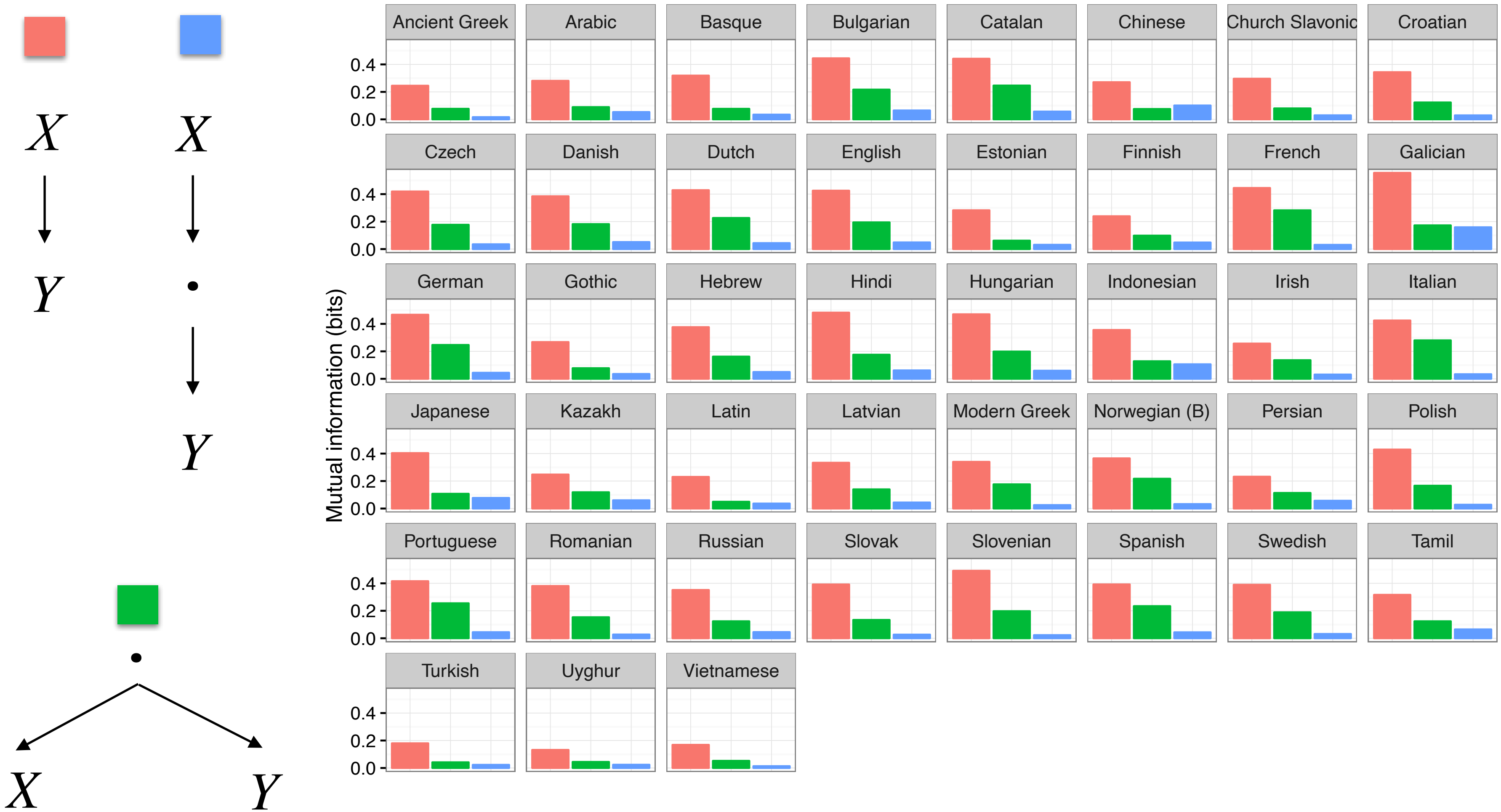


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# Comprehension as exploration of input

- 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*
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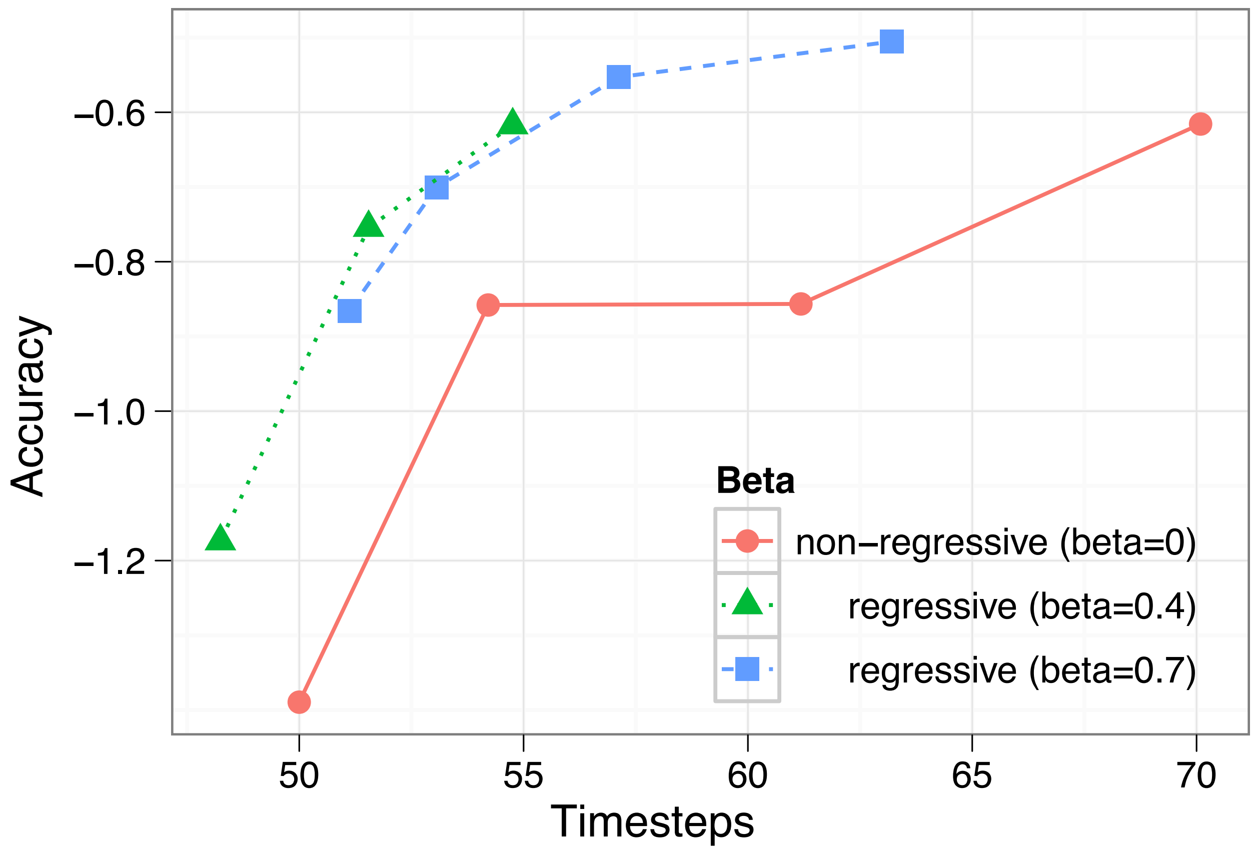
**Confidence=0.59**

- Move left to right, bringing up confidence in each character position until it reaches $\alpha$
- If confidence in a previous character position drops below $\beta$, 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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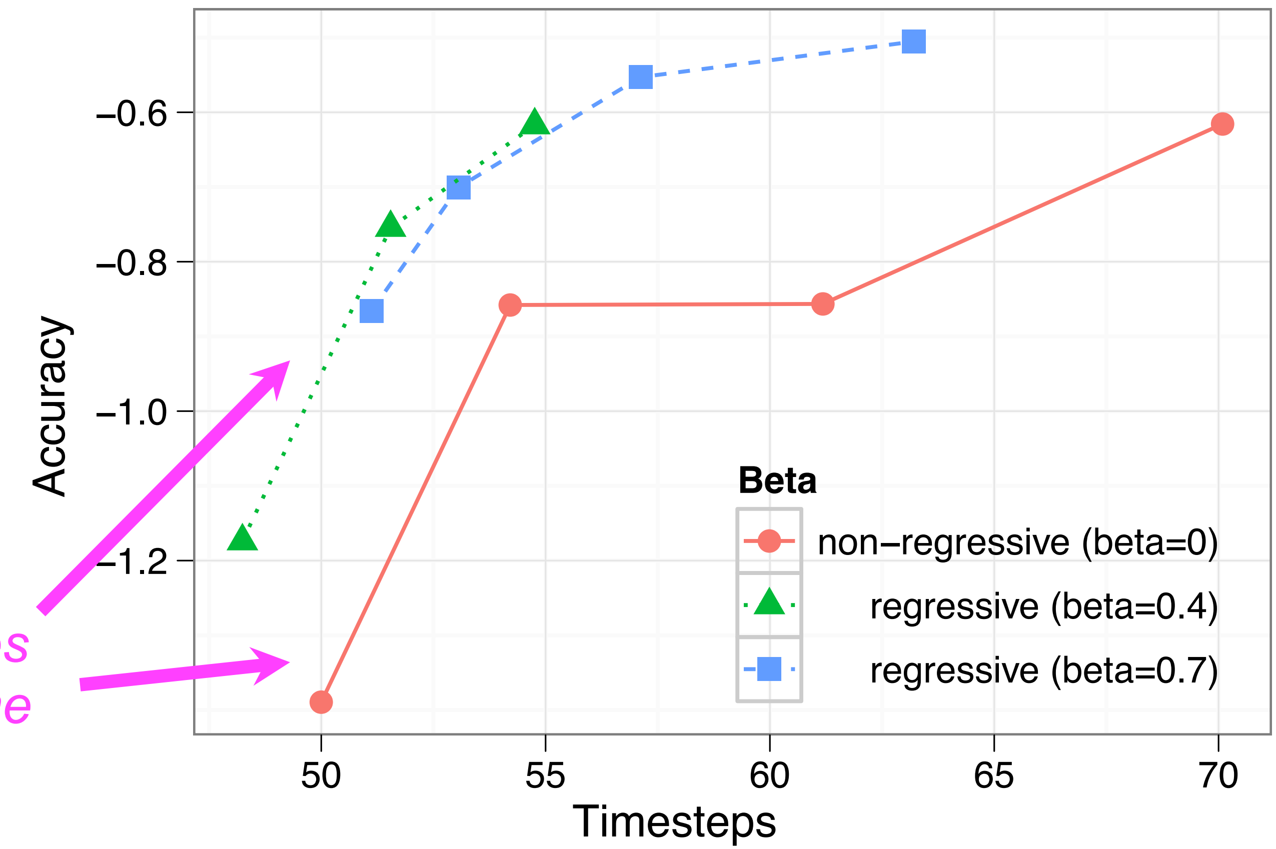


*Non-regressive policies always beaten by some regressive policy*

# 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 $\gamma$ 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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| $\gamma$ | $\alpha$ | $\beta$ |
|---|---|---|
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| $\gamma$ | $\alpha$ | $\beta$ |
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| 0.1 | 0.36 | 0.80 |
| 0.4 | 0.18 | 0.38 |

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|---|---|---|---|---|
| 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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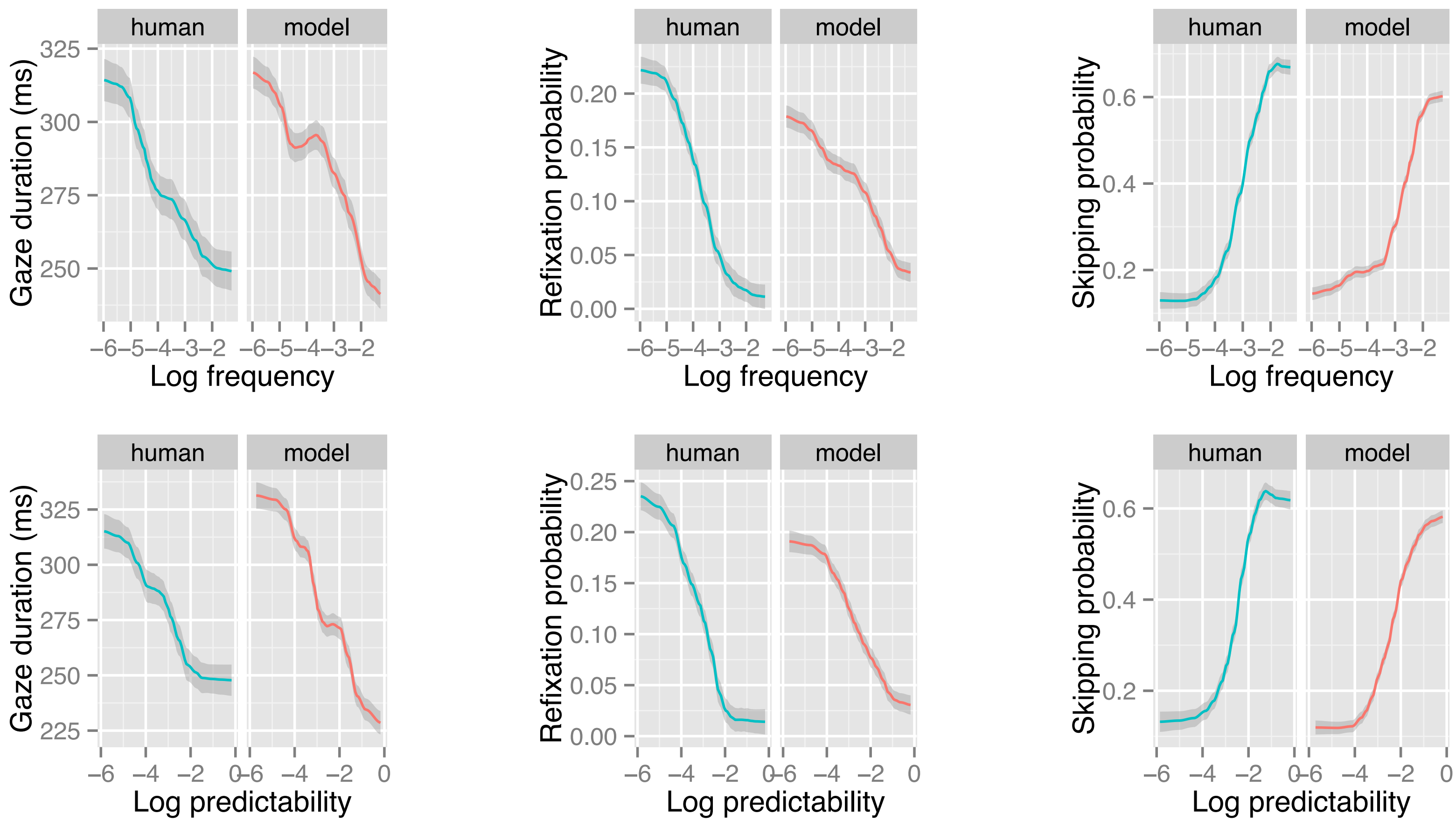
- The method works, and gives intuitive results

*(Bicknell & Levy, 2010)*

# Empirical match with human reading

- Benchmark measures in eye-movement modeling:

**frequency**




**predictability**

predicts size and shape of all effects

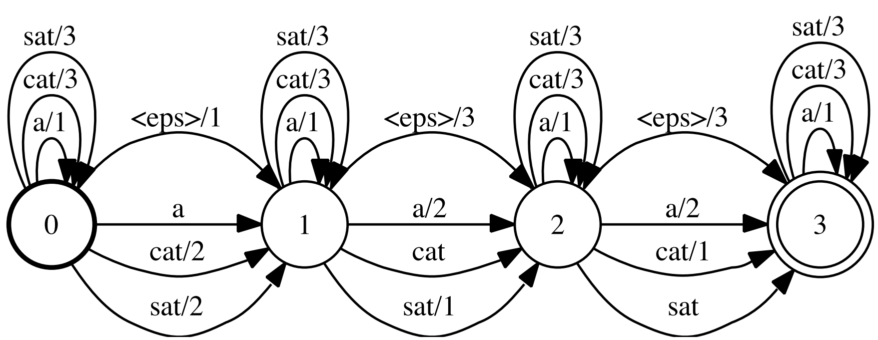
Bicknell & Levy (2012)

# 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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