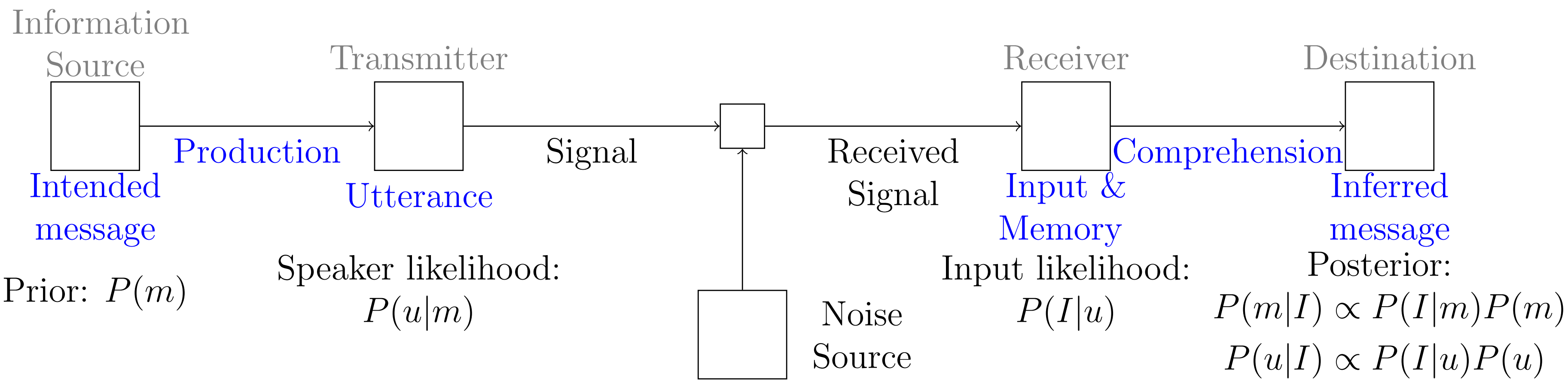
Noisy-channel sentence comprehension theory II



Roger Levy

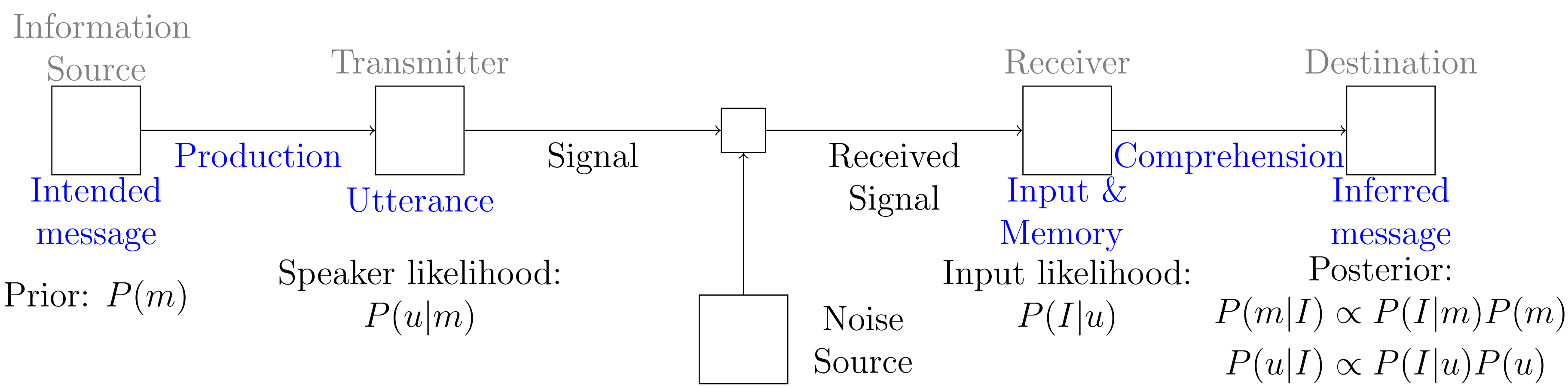
9.19: Computational Psycholinguistics

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

`The woman lost the diamond.`

Did the woman lose something? **Yes**

`The ball kicked the girl.`

Did the girl kick something? **No**

`The businessman benefited from the tax law.`

Did the tax law benefit from anything? **No**

`The cook baked a cake Lucy.`

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

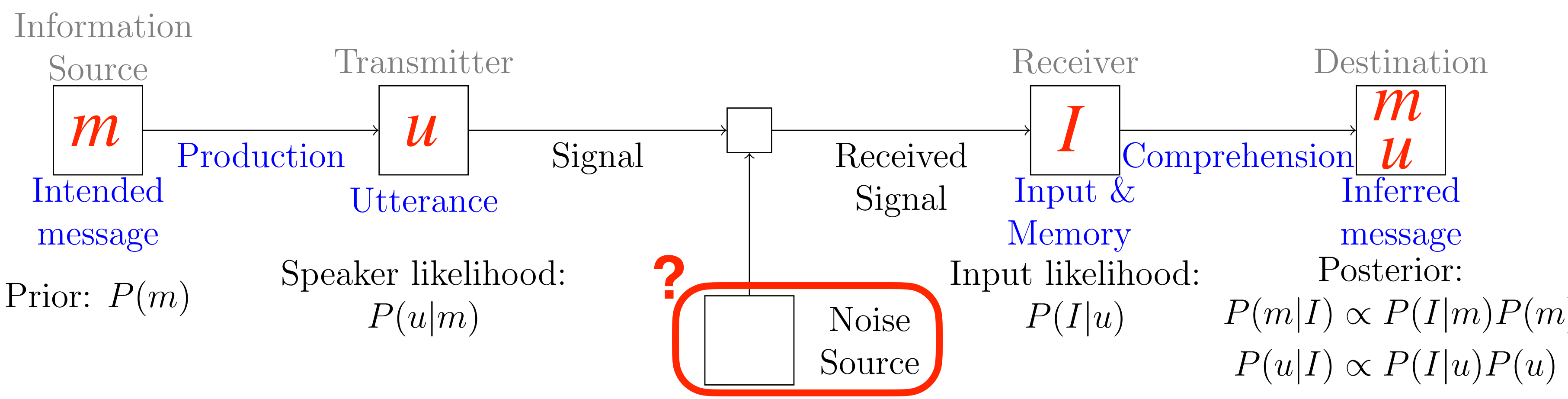
Over 2/3 of answers!

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

Noisy-channel semantic interpretation?

I ← **The cook baked a cake Lucy.**

m? *Was something baked for Lucy?*



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

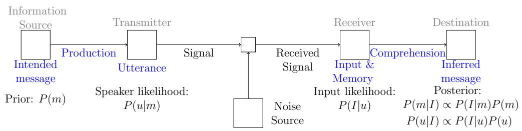
The cook baked a cake Lucy.

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

The cook baked a cake Lucy.

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

Predictions for implausible sentences



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

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

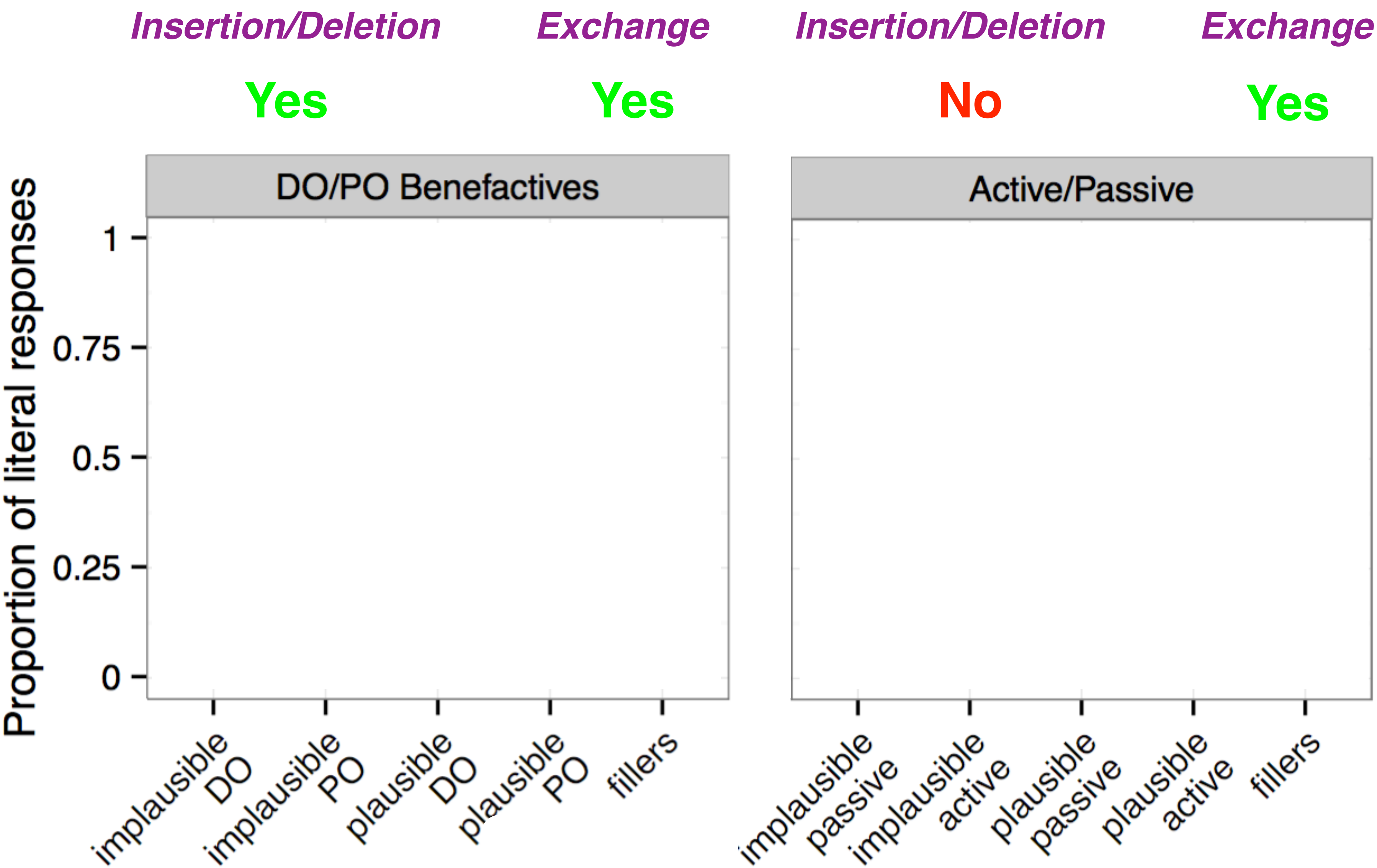
Active/Passive alternation

		Deletion/ insertion	***Exchange***
Implausible	**`The ball kicked the girl.`**	No	Yes
	`The girl was kicked by the ball.`	No	Yes
Plausible	**`The girl kicked the ball.`**	No	Yes
	`The ball was kicked by the girl.`	No	Yes

(Gibson et al., 2013)

Literal vs. non-literal interpretation rates

Non-literal interpretations for implausible sentences?



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

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

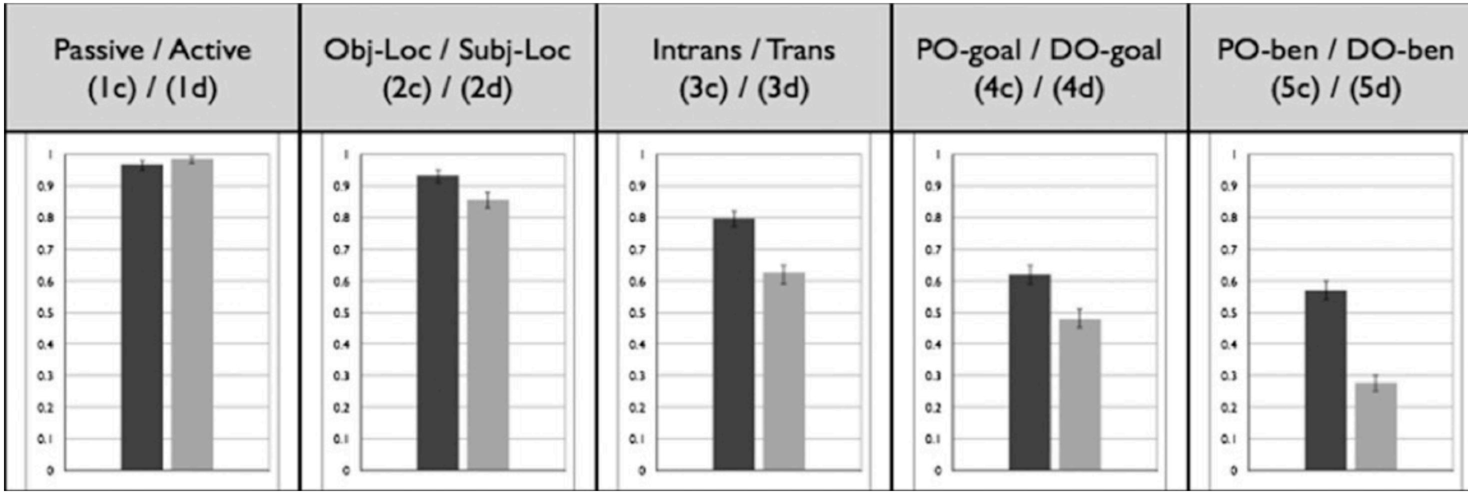
(Gibson et al., 2013; plausible versions not shown here)

Five alternations in an insertion/deletion model

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

Noise operation

Plausibility



Base experiment

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

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"

Many implausible trials

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

(Gibson et al., 2013)

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

2 Choose insertion location

The cook baked Lucy a cake.

3 Choose what to insert

for

↓

The cook baked Lucy for a cake.

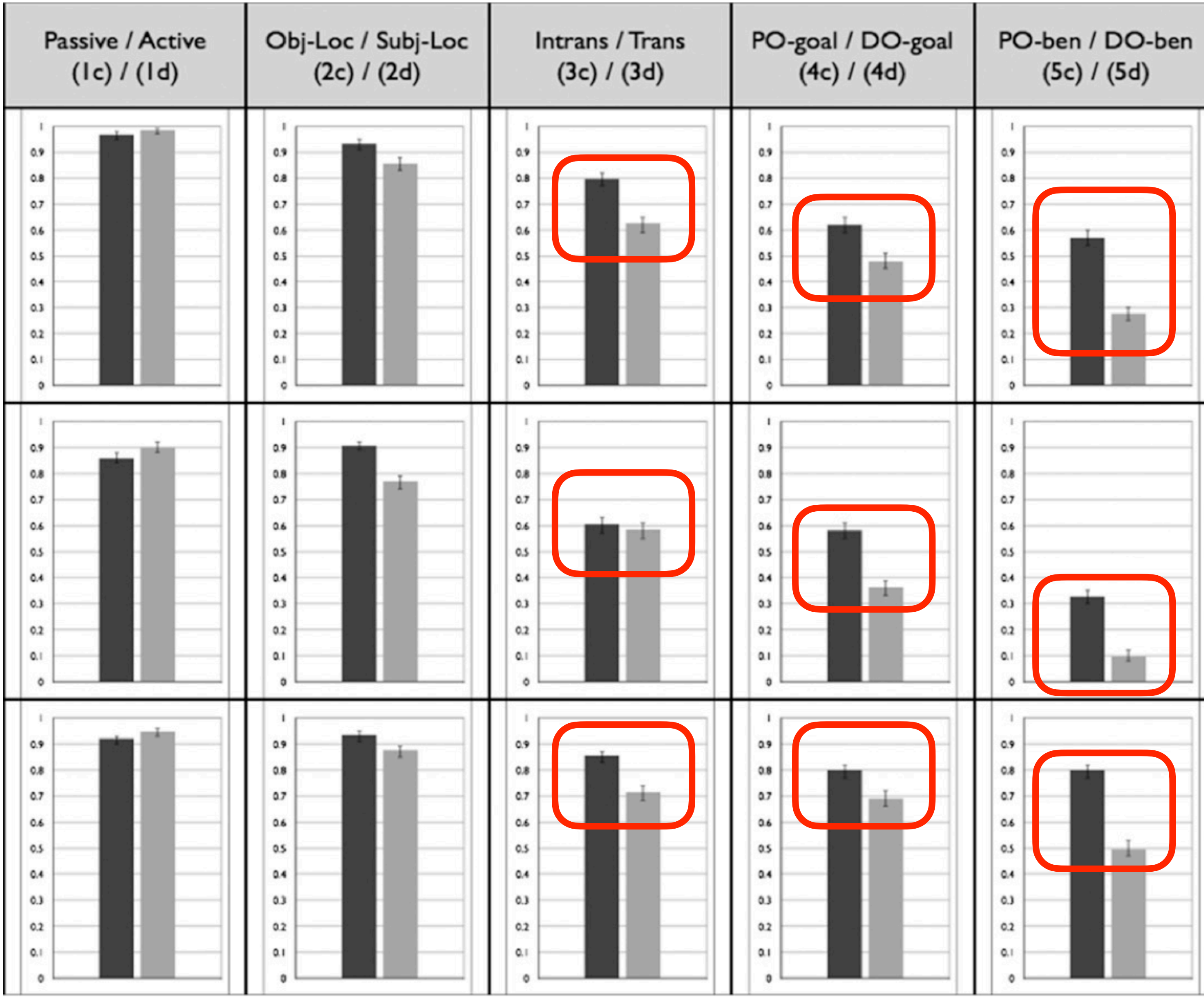
Noisy-channel prediction: inferring deletions should be intrinsically easier than inferring insertions!

Five alternations in an insertion/deletion model

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

Noise operation

Plausibility



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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)

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.

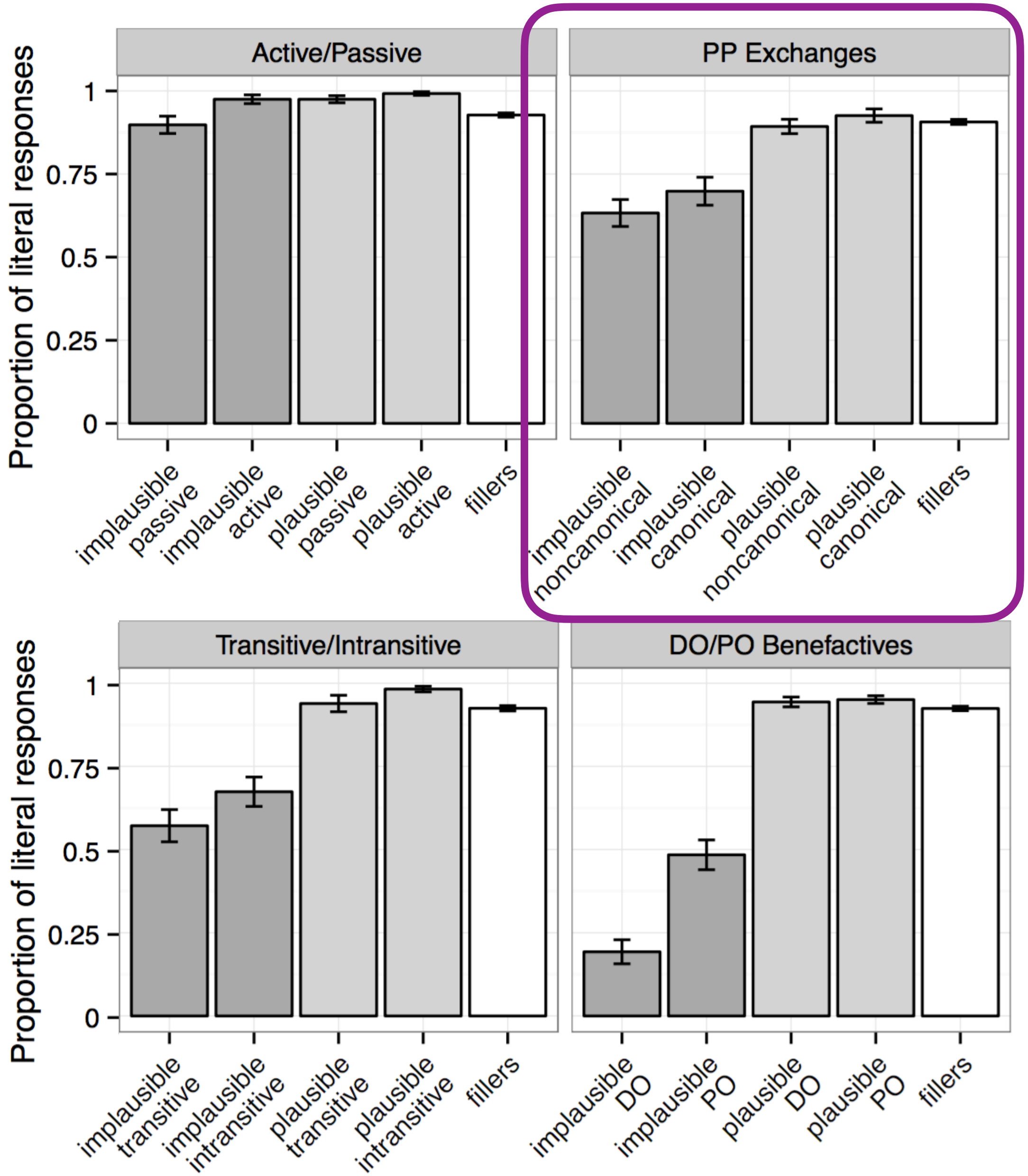
- An occasional speech error of mine that I've noticed for years, but that no one ever notices me make
- Extraordinarily unlikely under an insertions/deletions noise model
- But reasonably likely if word ***exchanges*** are admitted

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]

Did something fall to the floor?

(Poppels & Levy 2016)

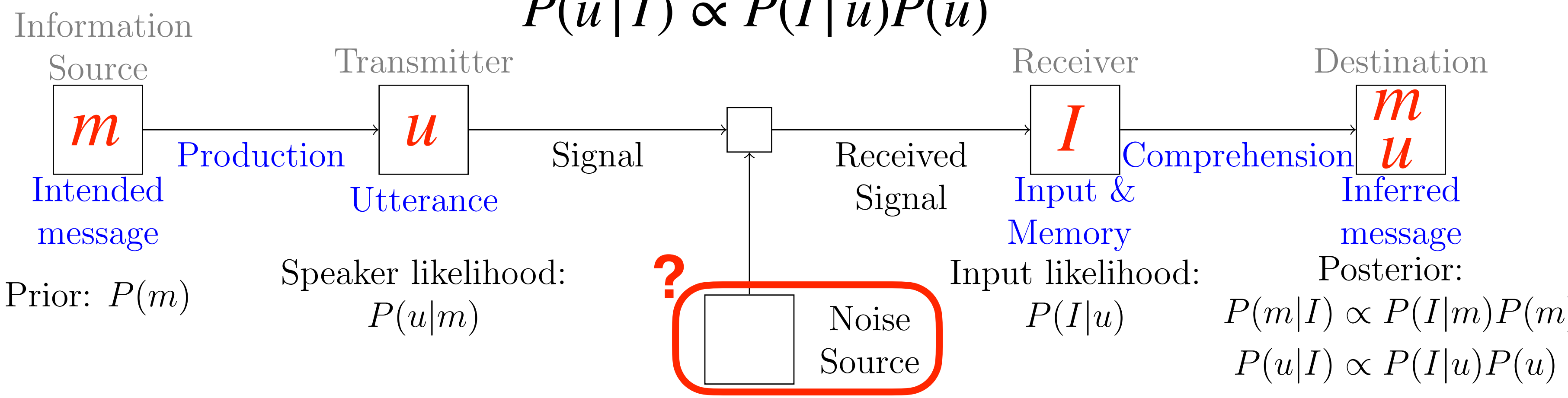
Exchanges in the noise model



(Poppels & Levy 2016)

Probing inferred intended utterances

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



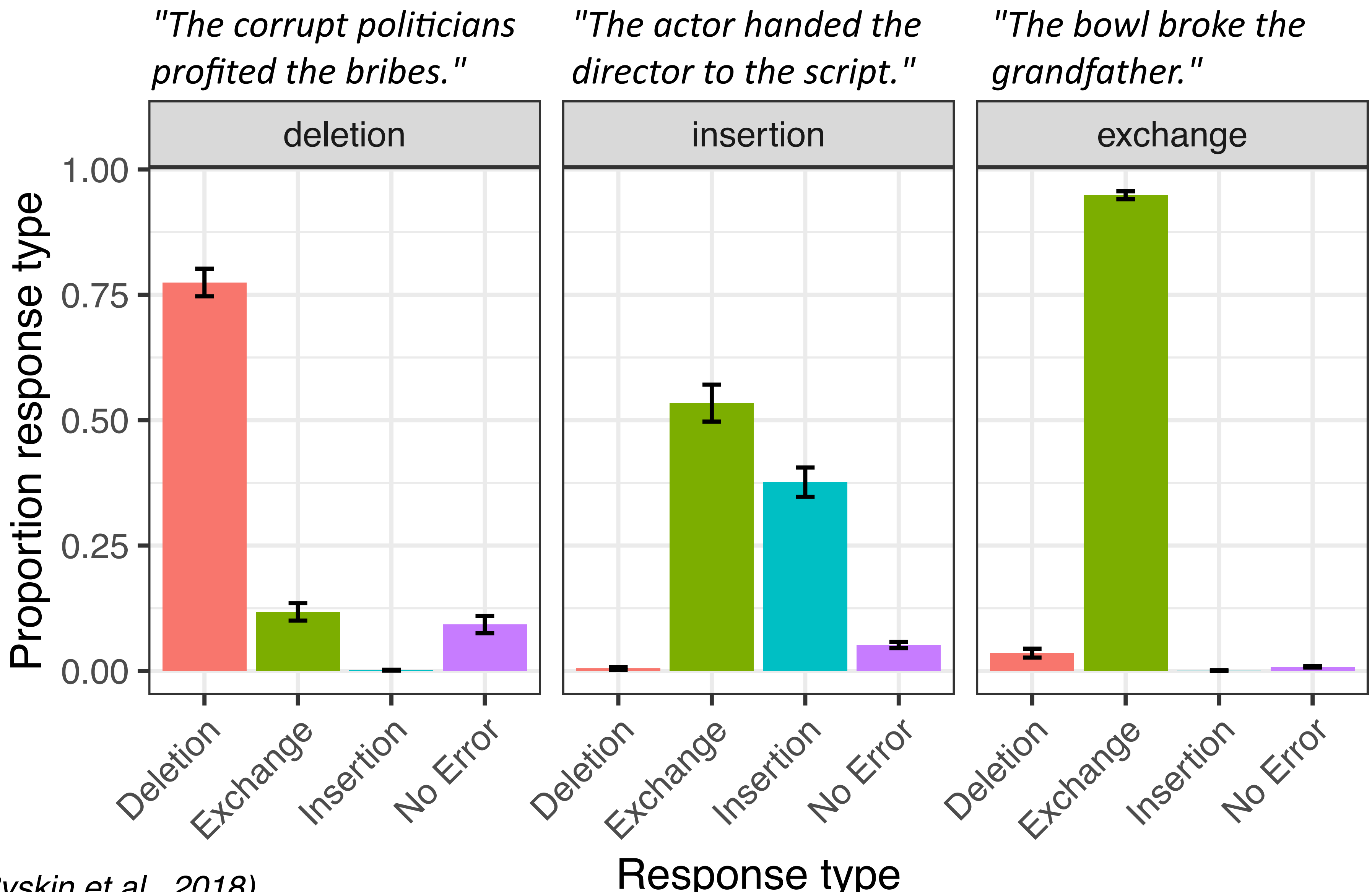
Experiment "cover story": read transcriptions of speech that might have errors, retype with edits if they think the speaker might have meant something else

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

`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



(Ryskin et al., 2018)

Noisy-channel interpretation summary

- The noisy-channel framework suggests investigating global interpretations as well as incremental processing
- "Non-literal" interpretations can be very frequent for the right stimuli
- Interpretations broadly follow Bayesian principle of trade-off between prior and likelihood
  - Deletions easier to infer than insertions
  - Higher grammatical error rate in environment→more non-literal inference
  - 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

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

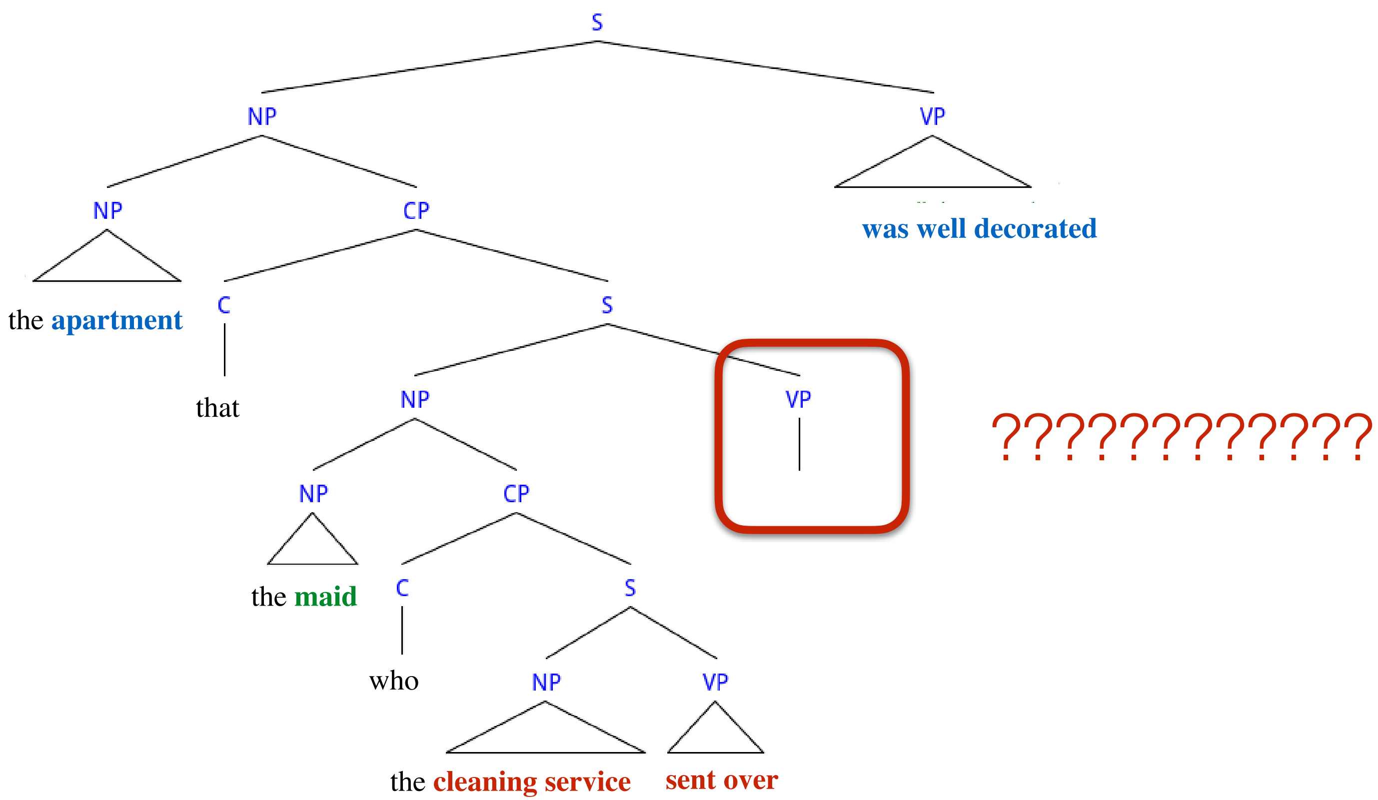
(Futrell & Levy, 2017; Futrell et al., 2020)

(Slide courtesy Richard Futrell)

Structural Forgetting

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

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



(Slide courtesy Richard Futrell)

Structural Forgetting

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

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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?

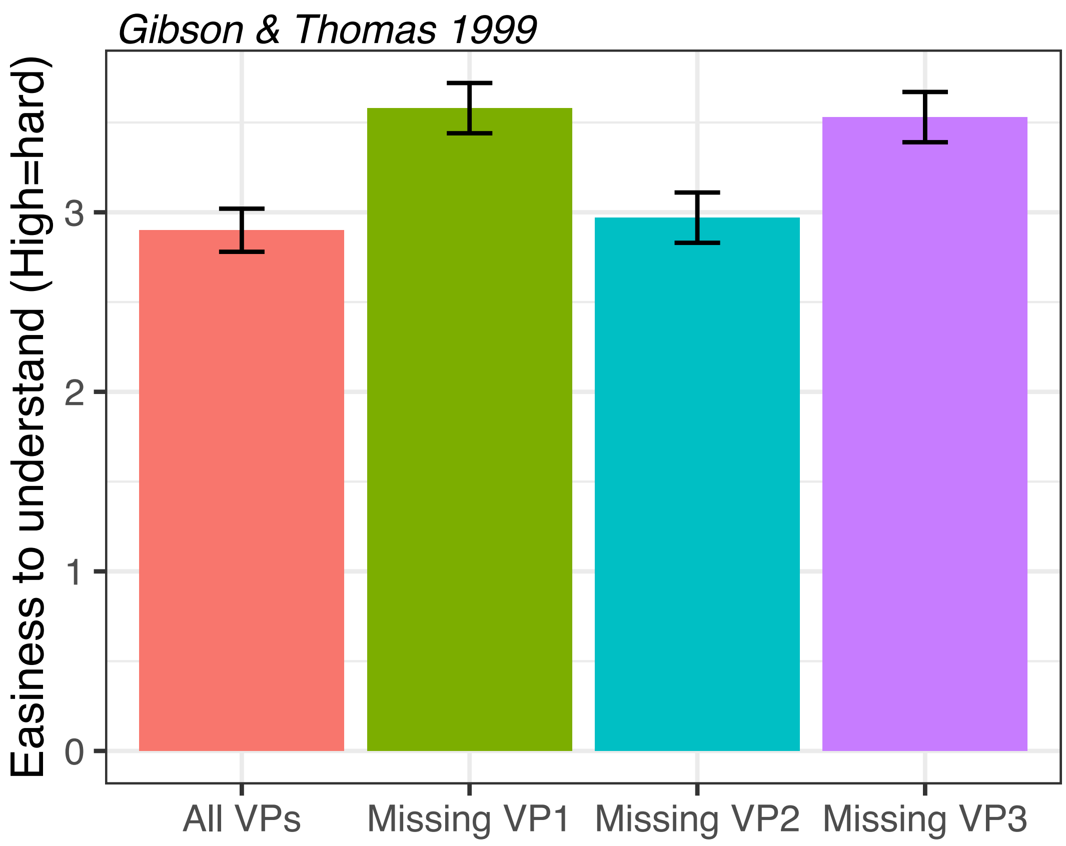
(Slide courtesy Richard Futrell)

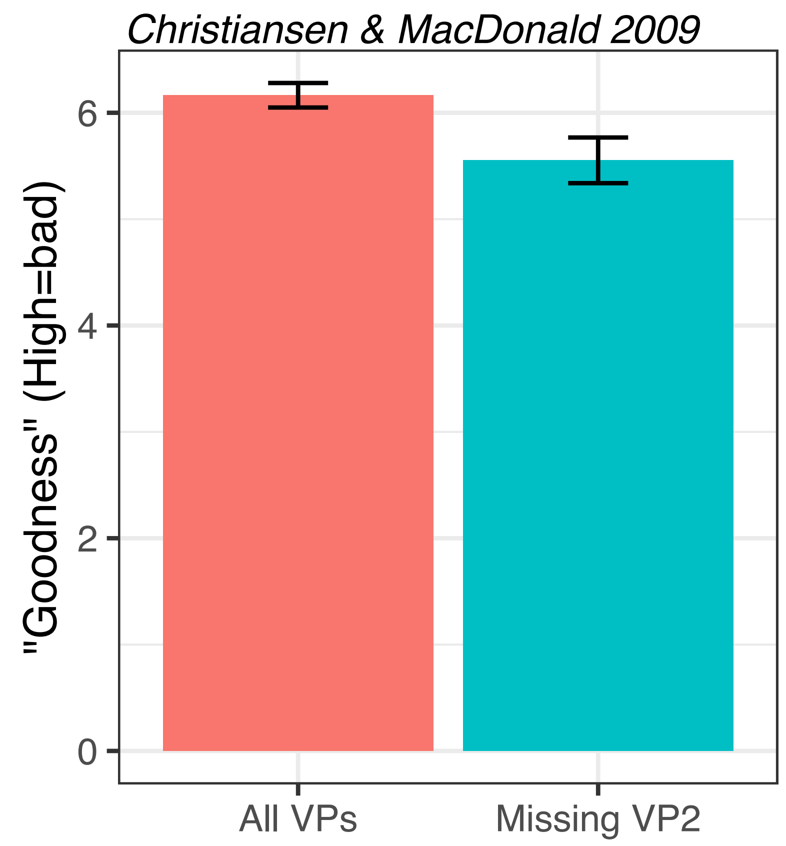
Gibson & Thomas 1999: whole-sentence reading

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.





Structural Forgetting

1. *The apartment that the maid who the cleaning service was well-decorated. 👍
   *Die Wohnung, die das Zimmermädchen, das der Reinigungsdienst übersandte, war gut eingerichtet. 👎

2. The apartment that the maid who the cleaning service cleaned was well-decorated. 👎
   Die Wohnung, die das Zimmermädchen, das der Reinigungsdienst übersandte, reinigte, war gut eingerichtet. 👍

- But the effect is **language-dependent** (Vasishth et al., 2010; Frank et al., 2016).
  - In German (and Dutch), people prefer 2 over 1.
- What is the difference between English and German?
- Frank et al. (2016) show that at recurrent neural network gives higher probability to (1) in English, but (2) in German.
  - But why?

(Slide courtesy Richard Futrell)

Structural Forgetting

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

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

- These contexts are more common in German than English (Roland et al., 2007).
  - English: the maid [that cleaned the apartment] **80%**
    the apartment [that the maid cleaned] **20%**
  - German: das Dienstmädchen, [das die Wohnung reinigte]
    die Wohnung, [die das Dienstmädchen reinigte]

(Slide courtesy Richard Futrell)

Noisy-Context Surprisal Account of Structural Forgetting

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

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

C(NOUN THAT NOUN THAT NOUN VERB VERB) <
C(NOUN THAT NOUN THAT NOUN VERB VERB VERB)

C(2 VERBS) < C(3 VERBS)

(Slide courtesy Richard Futrell)

Noisy-Context Surprisal Account of Structural Forgetting

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

- 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)

Noisy-Context Surprisal Account of Structural Forgetting

- Futrell & Levy (2017) demonstrate that this works for toy grammars of English and German.

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*
RC -> THAT NP VERB	1-*s*

NOUN VERB

NOUN PREP NOUN VERB

NOUN THAT VERB NOUN VERB

NOUN THAT NOUN VERB VERB

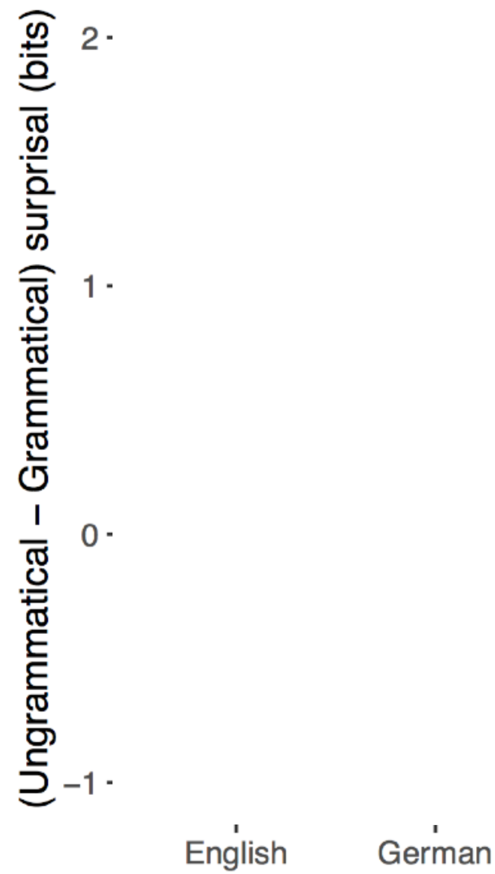
NOUN THAT NOUN THAT NOUN...

Plus **deletion noise**: every token in the context is forgotten (deleted) with probability d

(Slide courtesy Richard Futrell)

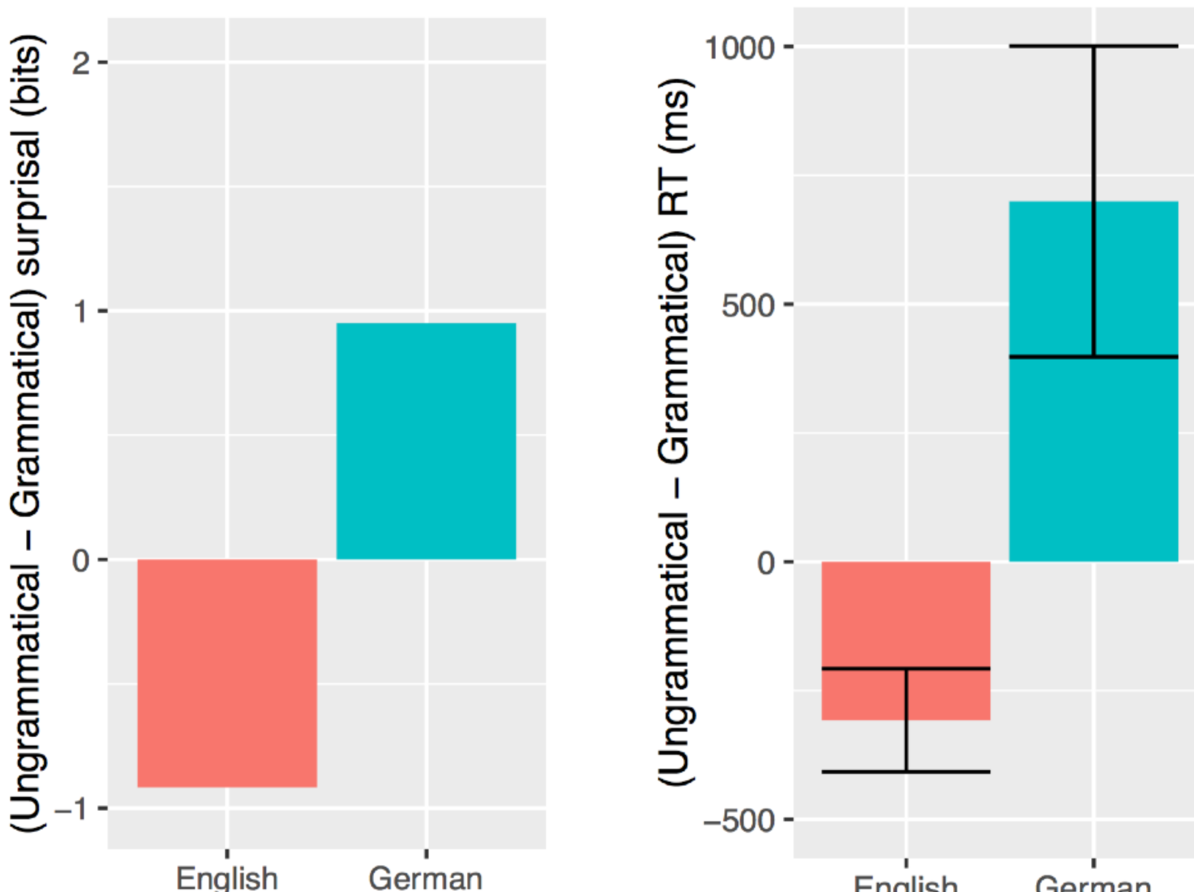
Noisy-Context Surprisal Account of Structural Forgetting

- Setting the verb-final RC rate to 100% for German and 20% for English (Roland et al., 2007),
- we find surprisal differences matching the forgetting effect:



(Slide courtesy Richard Futrell)

Noisy-Context Surprisal Account of Structural Forgetting



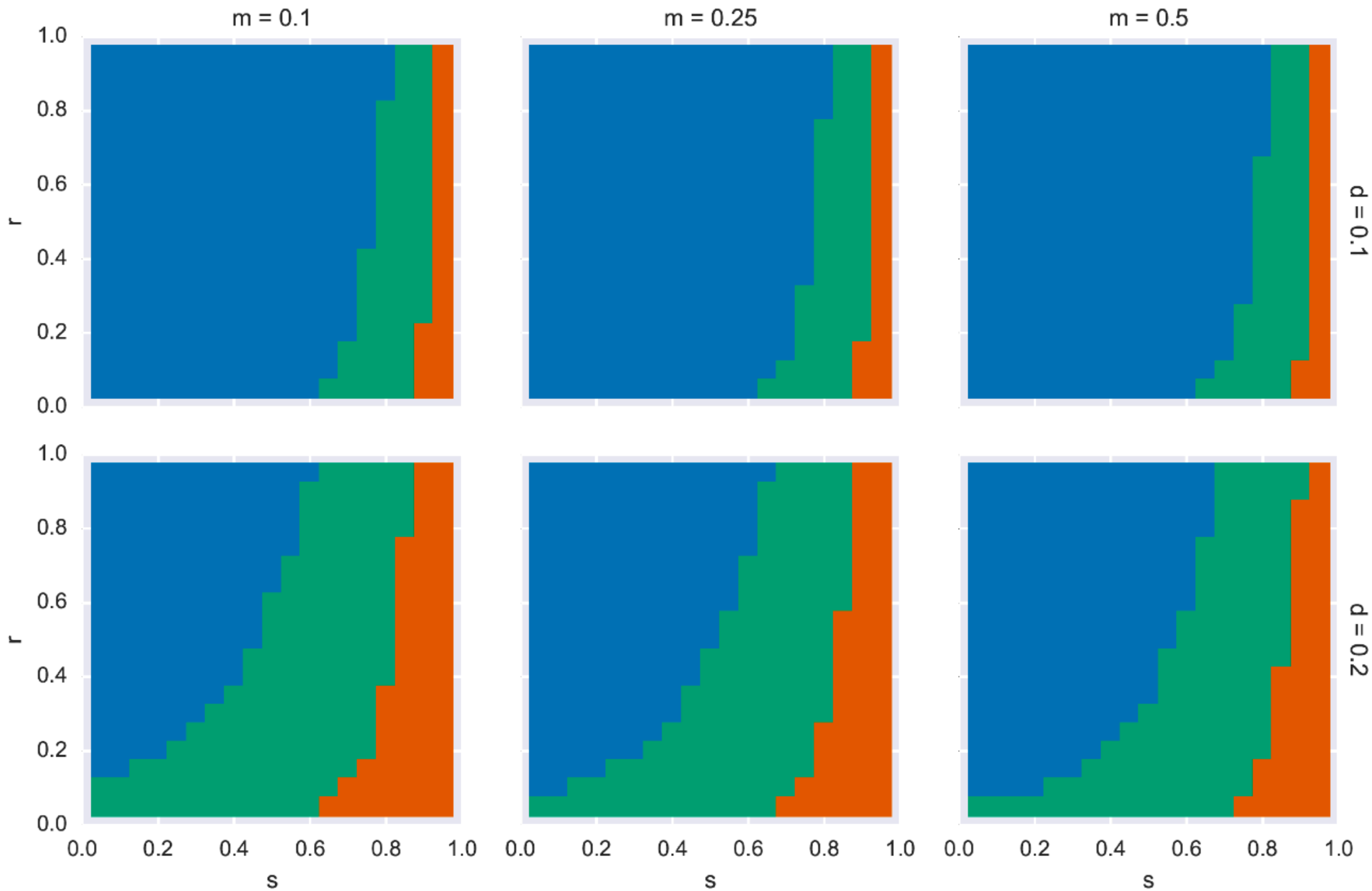
Vasishth et al. (2010)

(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)

Noisy-Context Surprisal Account of Structural Forgetting

- 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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Prediction 2: hallucinated garden paths

- Try reading the sentence below:

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

- 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

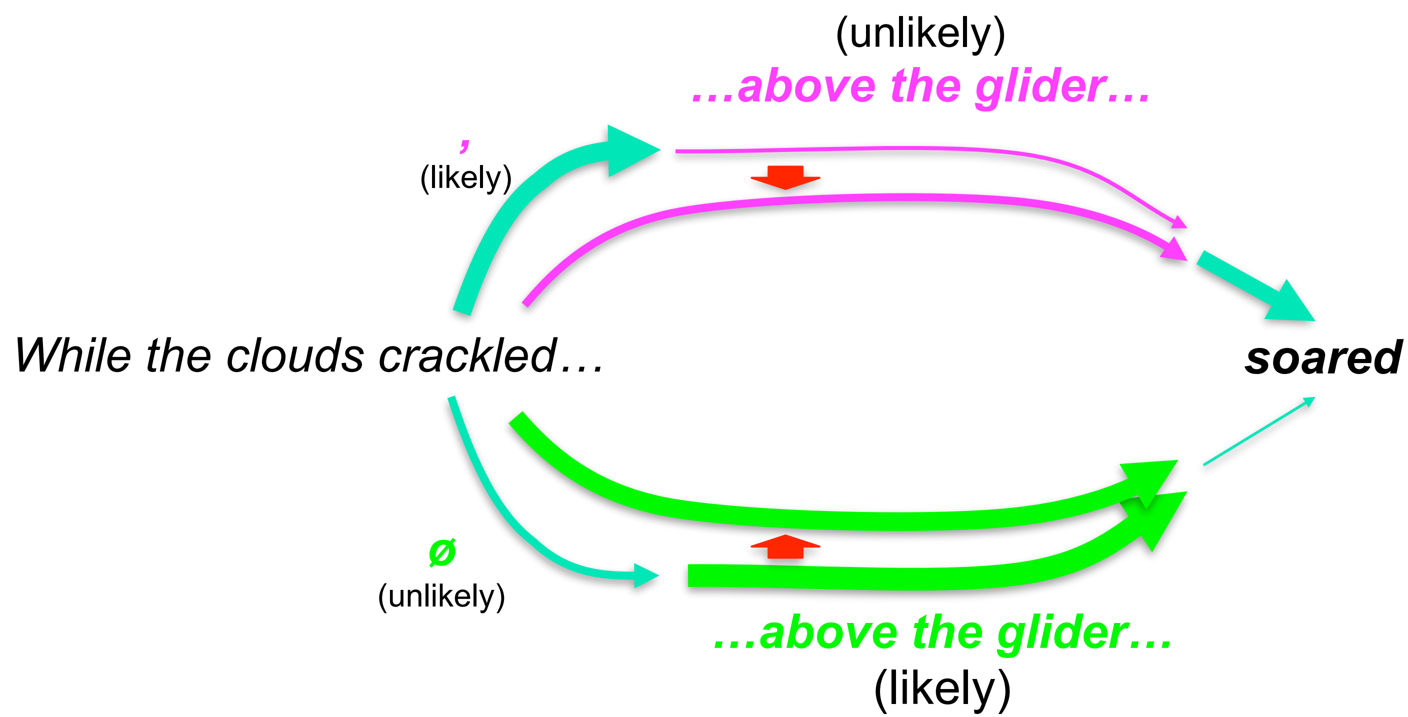
  - "With a comma after *mending* there would be no syntactic garden path left to be studied." (Fodor, 2002)
- We'll see that the story is slightly more complicated.

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`)
- Crucially, the main clause's initial PP would make a great dependent of the subordinate verb…
- …but doing that *would require the comma to be ignored.*
- Inferences through *…glider* should thus involve a tradeoff between perceptual input and prior expectations



- Inferences as probabilistic paths through the sentence:
  - Perceptual cost of ignoring the comma
  - Unlikeliness of main-clause continuation after comma
  - Likeliness of postverbal continuation without comma
- These inferences together make *soared* very surprising!

$$P(w_i|\text{Context}) = \sum_{\text{Path}} P(w_i|\text{Path}, \text{Context})P(\text{Path}|\text{Context})$$

Prediction 2: hallucinated garden paths

- Two properties come together to create "hallucinated garden path"
  1. Subordinate clause into which the main-clause inverted phrase would fit well
  2. Main clause with locative inversion
- Experimental design: cross (1) and (2)

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

- The phrase *in the distance* fulfills a similar thematic role as above the glider for crackled
- Should reduce hallucinated garden-path effect

Prediction 2: Hallucinated garden paths

- 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

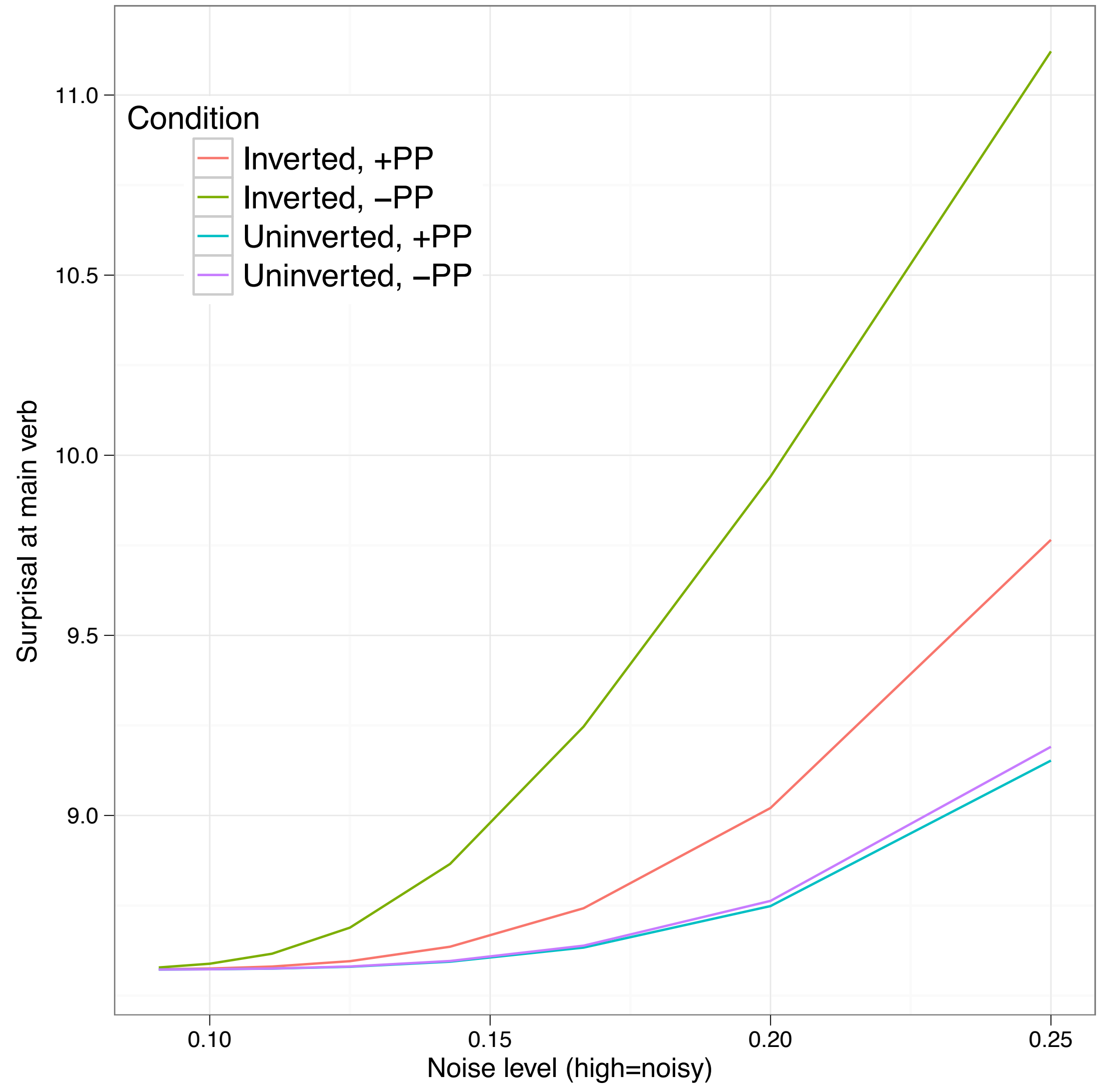
Model predictions

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

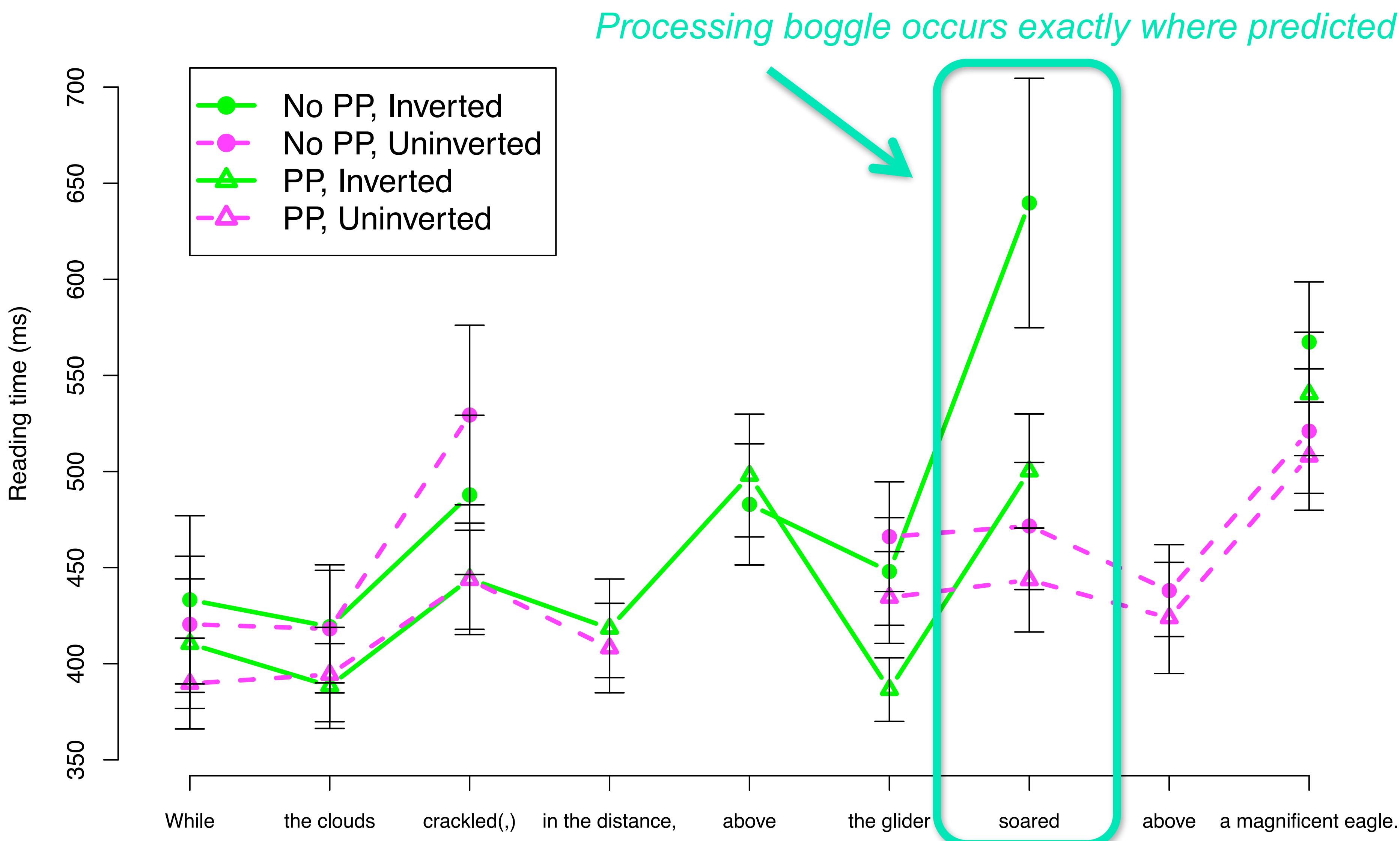
While the clouds crackled in the distance, above the glider soared a magnificent eagle.

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



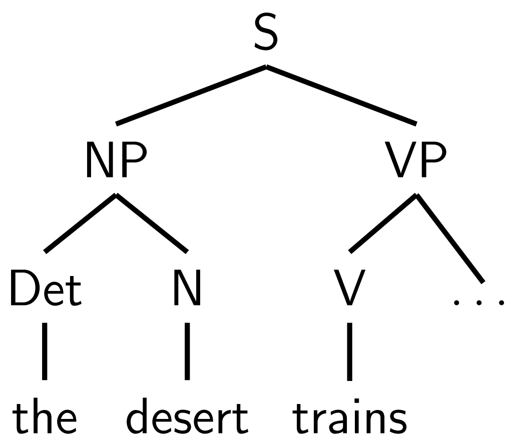
Hallucinated garden-path summary

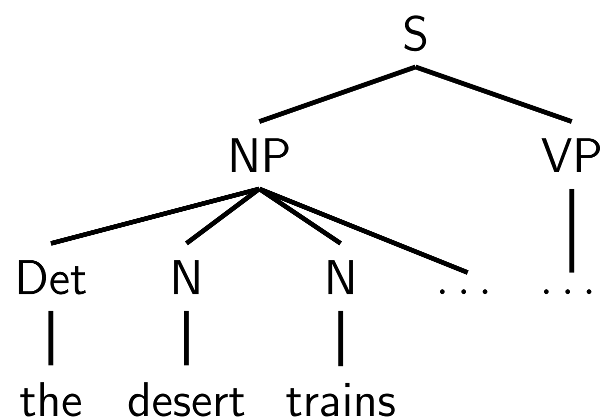
- The *at/toward* study showed that comprehenders *note the possibility of* alternative strings and *act on it*
- This study showed that comprehenders can actually *devote resources to* grammatical analyses inconsistent with the surface string

Hallucinated garden paths cont'd

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

I know that the desert trains could resupply the camp.





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

(Frazier & Rayner, 1987; Macdonald, 1993)

Hallucinated GPs with words

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

Could be "intern chauffeured"

The intern chauffeur for the governor hoped for more interesting work.
[NN, "dense" neighborhood]

The intern chauffeured for the governor but hoped for more interesting work.
[NV, "dense" neighborhood]

Could NOT be "inexperienced chauffeured"

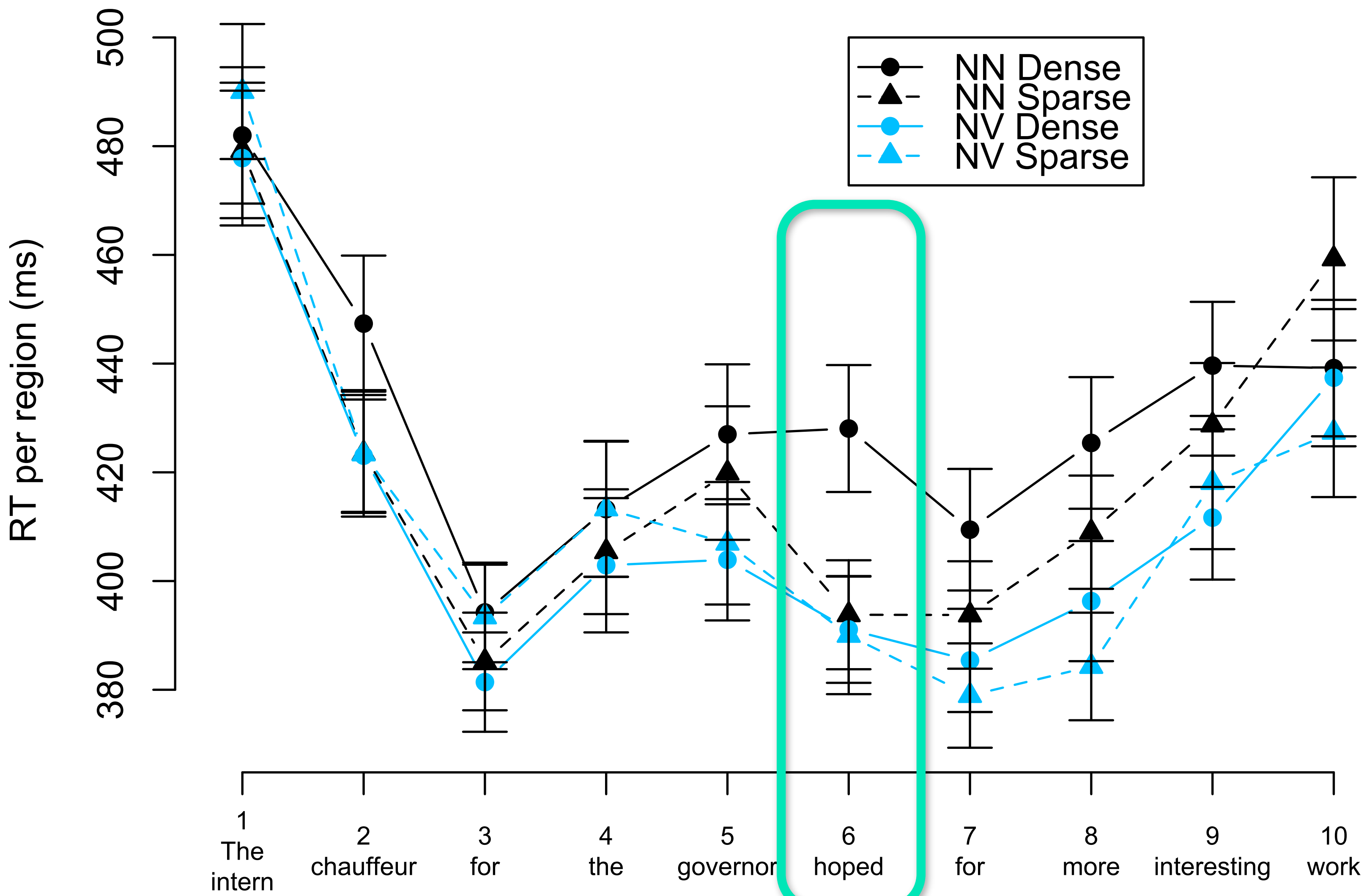
The inexperienced chauffeur for the governor hoped for more interesting work.
[NN, "sparse" neighborhood]

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



(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 <u>for</u> a cake.	Implausible	1	0
The cook baked a cake <u>for</u> Lucy.	Plausible	1	0
The cook baked a cake Lucy.	Implausible	0	1

Structure of the noise model

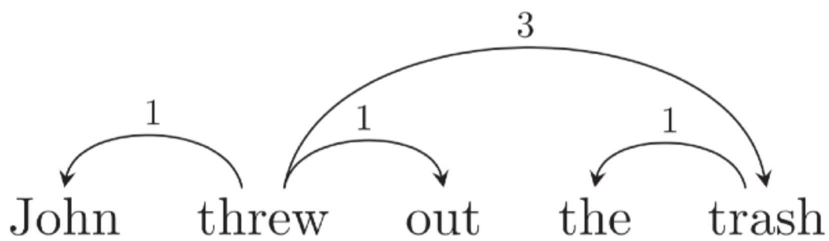
Consistently given literal interpretation

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

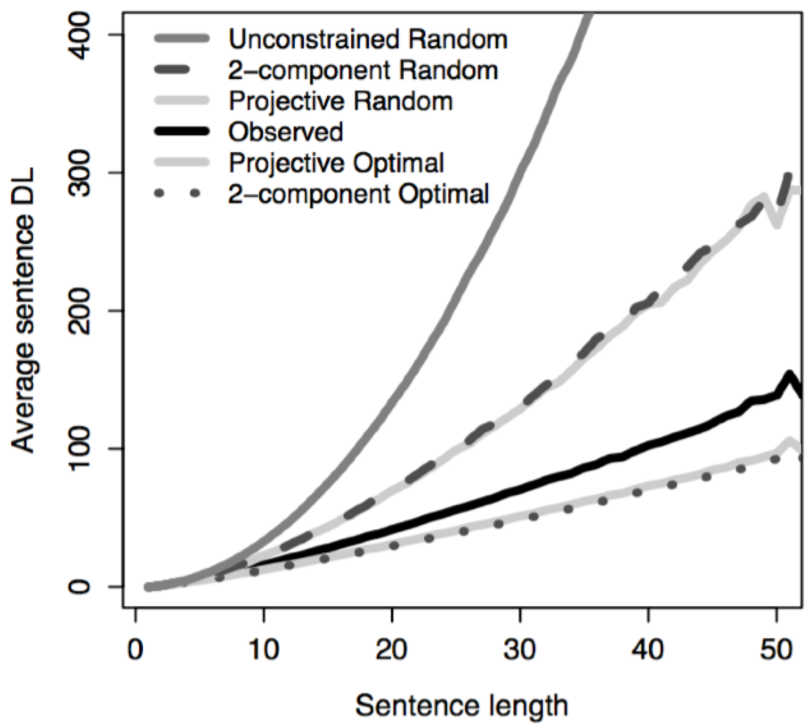
Often "corrected" to plausible interpretation inconsistent with literal meaning

Dependency length and noisy-channel surprisal

- Syntactic dependencies vary in linear distance



- Idea with long history: short dependencies preferred



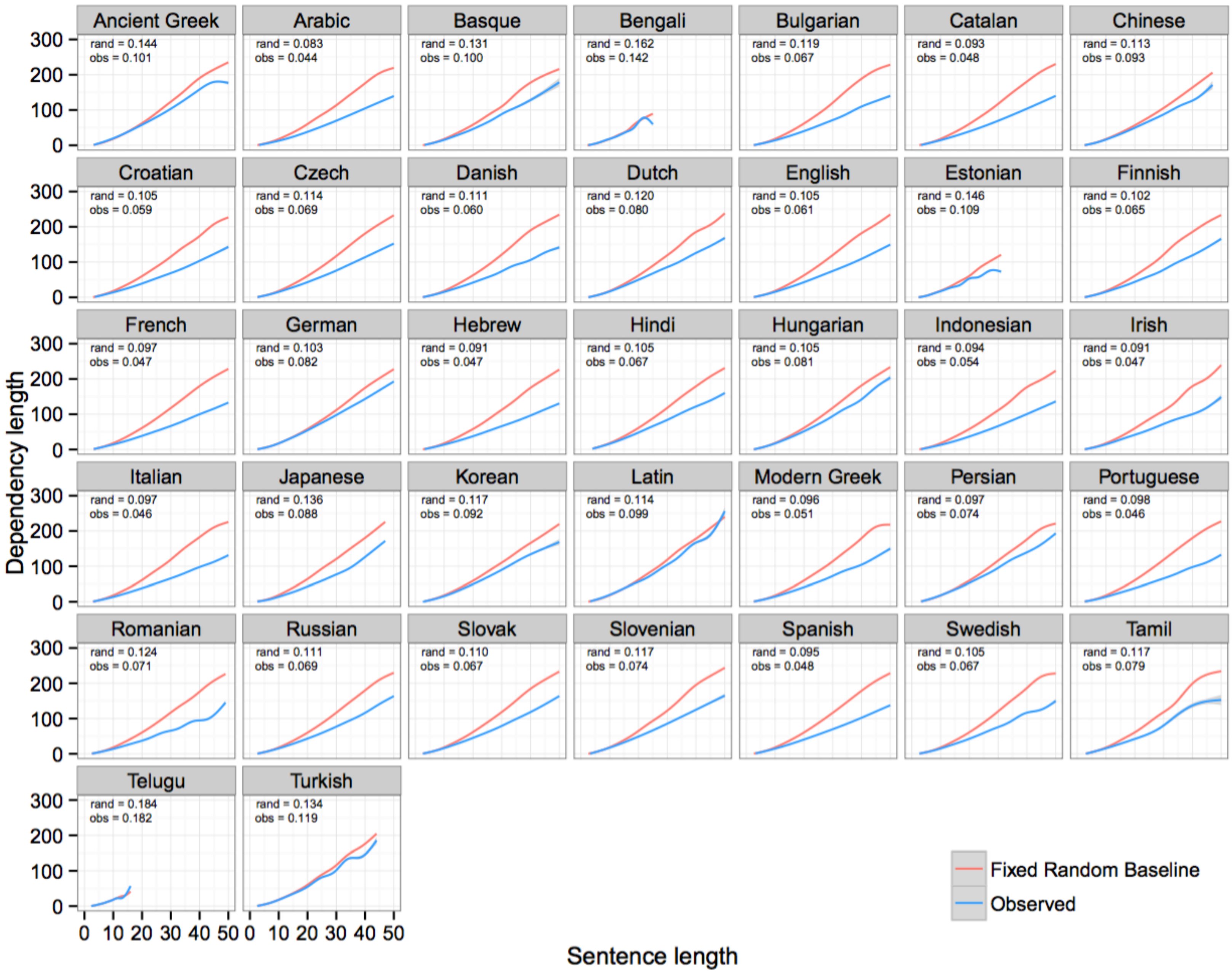
Random-linearization dependency lengths

Observed dependency lengths

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

Dependency lengths are short across languages!

(Futrell et al., 2015)



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

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

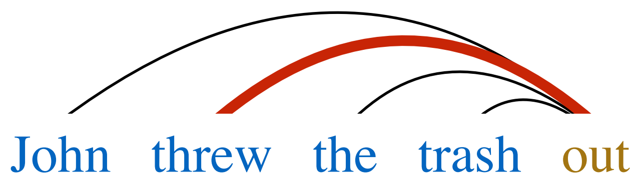
(Futrell & Levy, 2017)

(Slide courtesy Richard Futrell)

Derivation of Information Locality

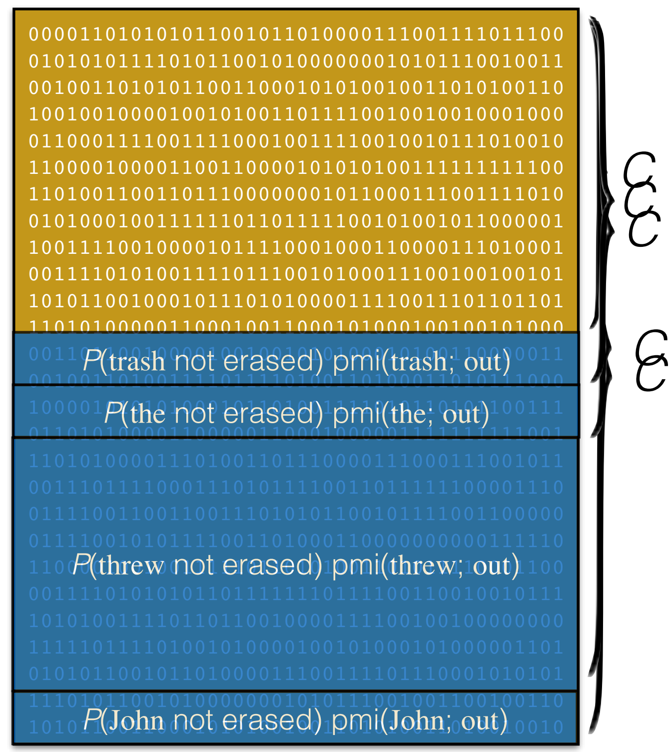
- Erasure noise decreases the influence of context:

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



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

- P(threw not erased) pmi(threw; out)
- P(the not erased) pmi(the; out)
- P(trash not erased) pmi(trash; out)



(Futrell & Levy, 2017)

(Slide courtesy Richard Futrell)

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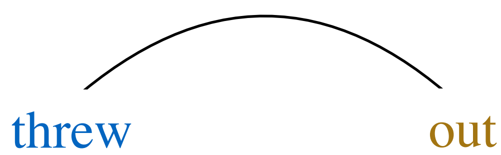

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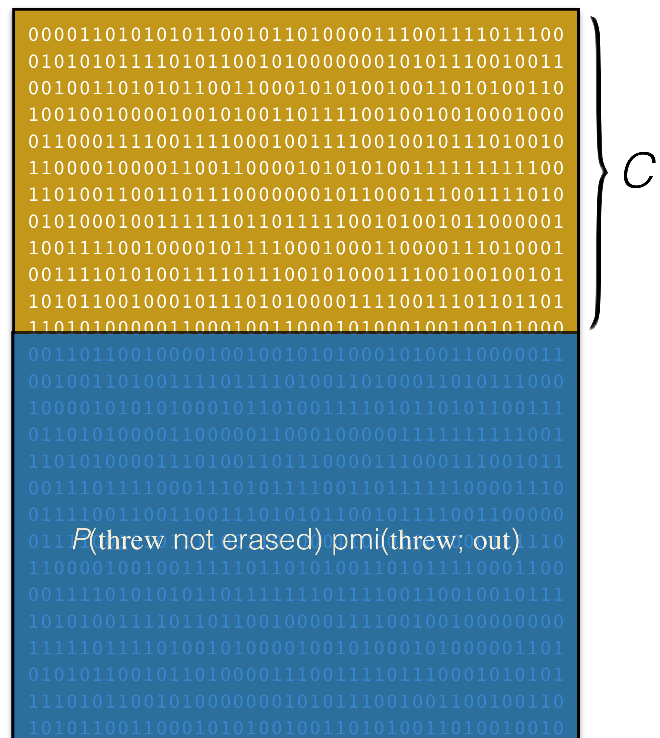

(Futrell & Levy, 2017)

(Slide courtesy Richard Futrell)

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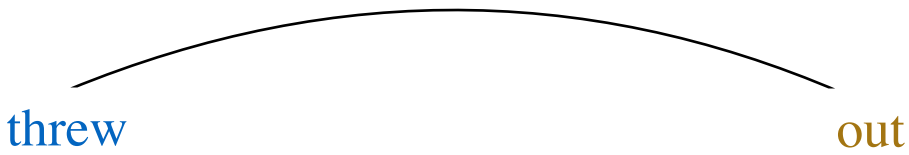
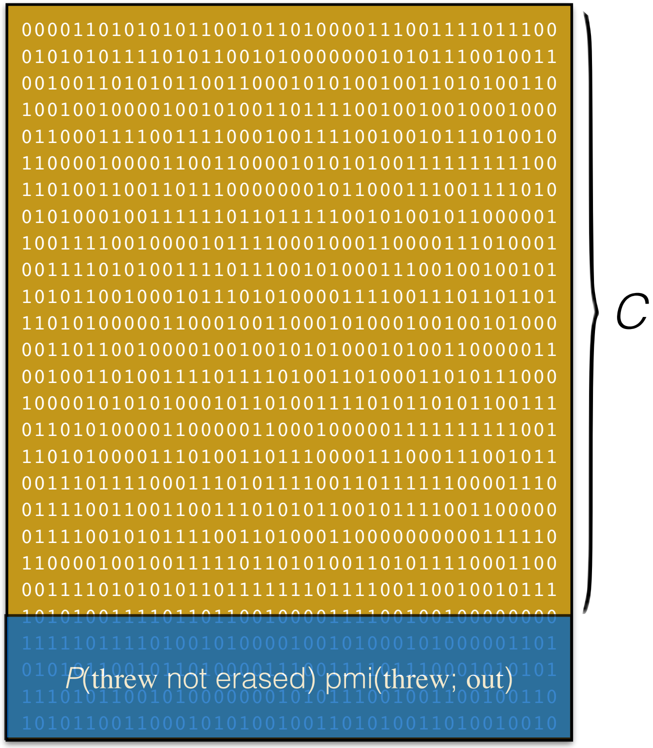




h(out) - P(threw not erased) pmi(threw; out)

- 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)

(Slide courtesy Richard Futrell)

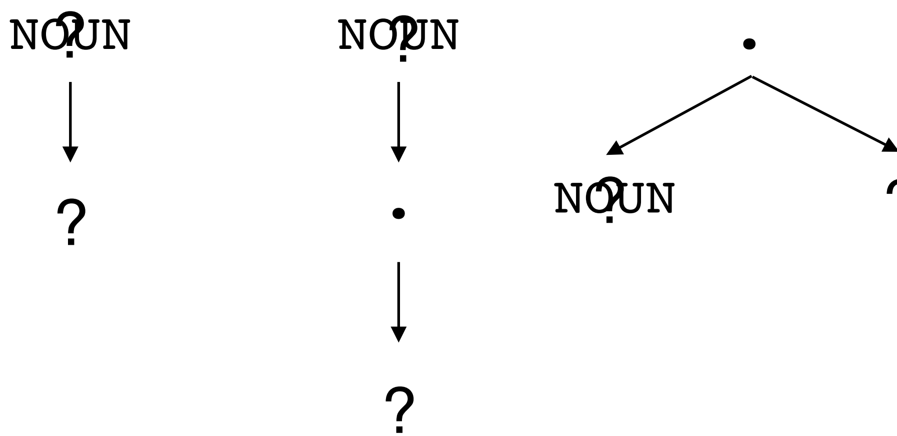
Information Locality

- **Information locality:** prediction of processing difficulty when words that predict each other (have high mutual information) are far apart.
- How does this relate to **dependency locality**?
- Hypothesis: **Words in syntactic dependencies have high mutual information**.
  - If this is true, then we can see dependency locality effects as a subset of information locality effects.
- We will show that the hypothesis is true in dependency corpora.

(Futrell & Levy, 2017)

(Slide courtesy Richard Futrell)

Do Dependencies Have High Mutual Information?

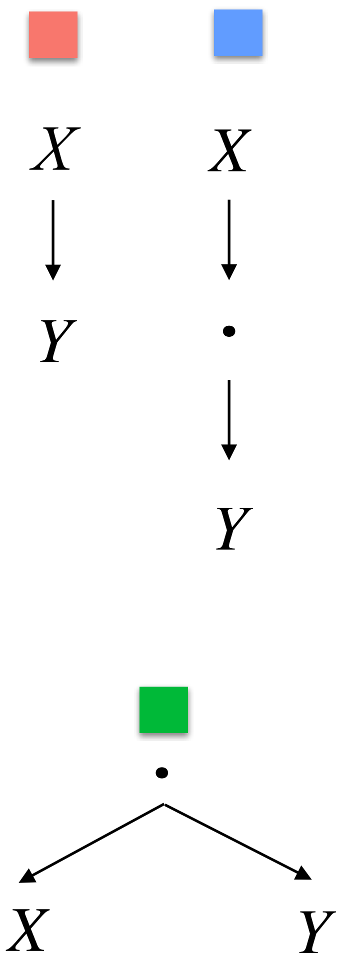


- We calculated mutual information values over part-of-speech tags for pairs of words in the UD corpora.

(Futrell & Levy, 2017)

(Slide courtesy Richard Futrell)

Do Dependencies Have High Mutual Information?



(Futrell & Levy, 2017)

(Slide courtesy Richard Futrell)

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

- 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

*From the closet, she pulled out a *acket for the upcoming game*

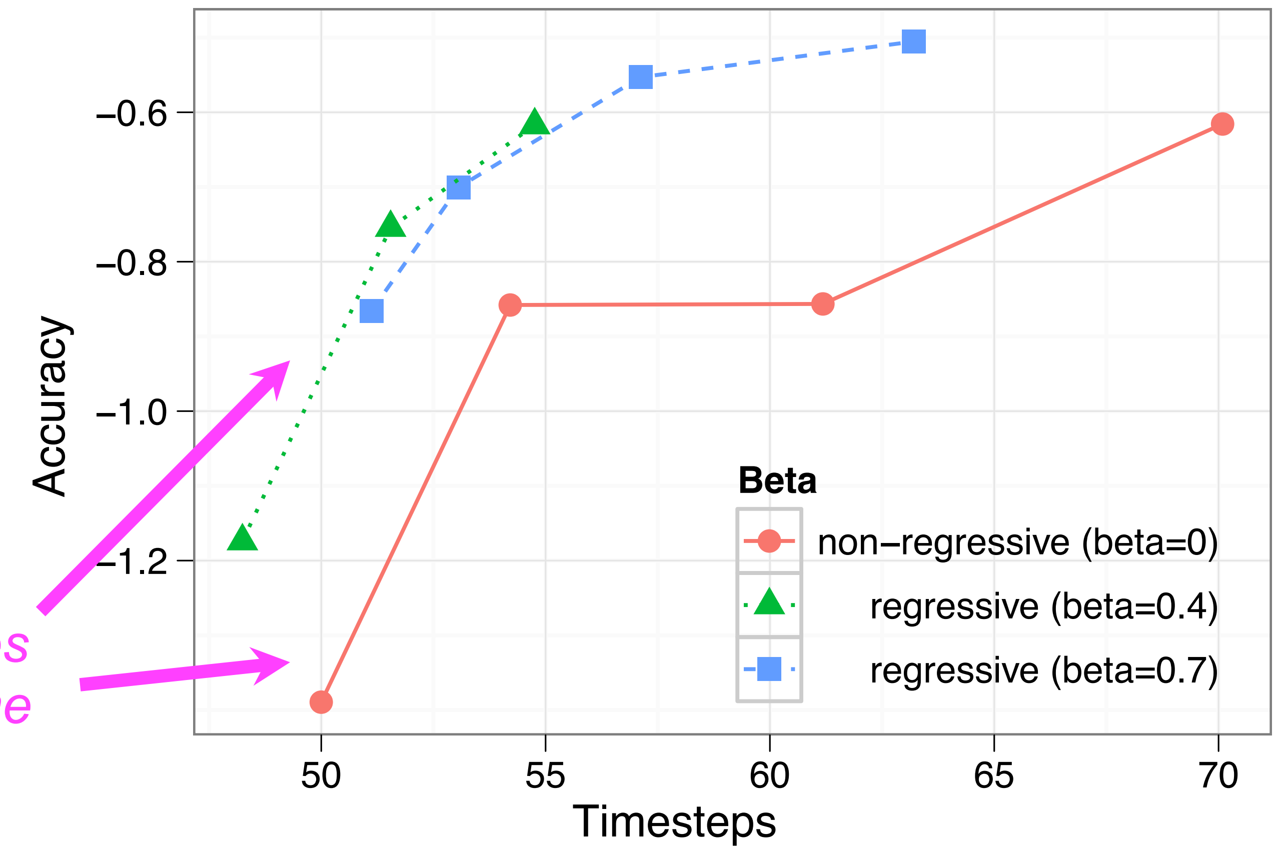
Confidence=0.59

```
P(jacket)=0.38
P(racket)=0.59
P(packet)=0.02
...
```

- 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



Non-regressive policies always beaten by some regressive policy

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)

γ	α	β
0.025		
0.1		
0.4		

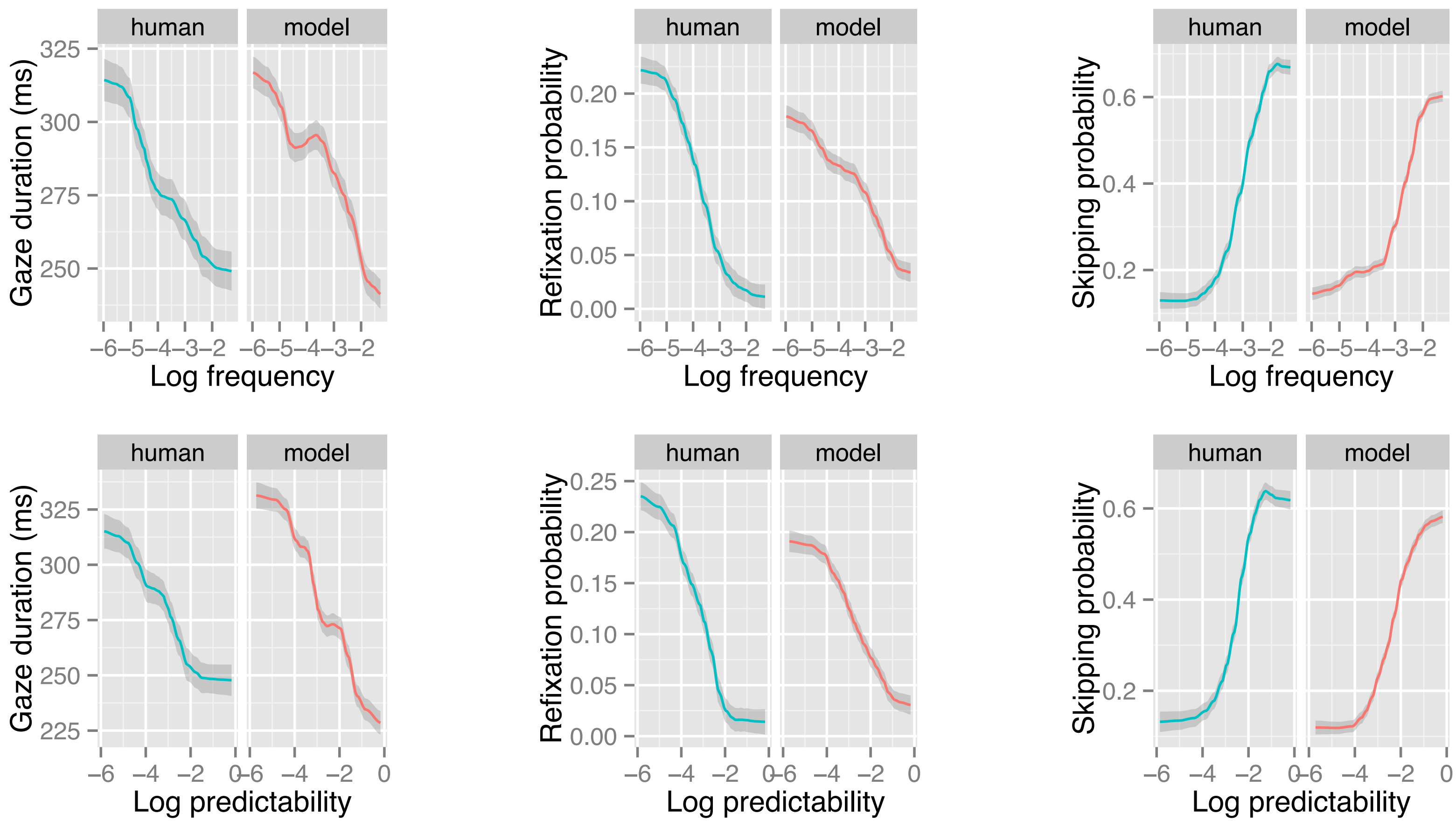
- The method works, and gives intuitive results

(Bicknell & Levy, 2010)

Empirical match with human reading

- Benchmark measures in eye-movement modeling:

frequency



predicts size and shape of all effects

predictability

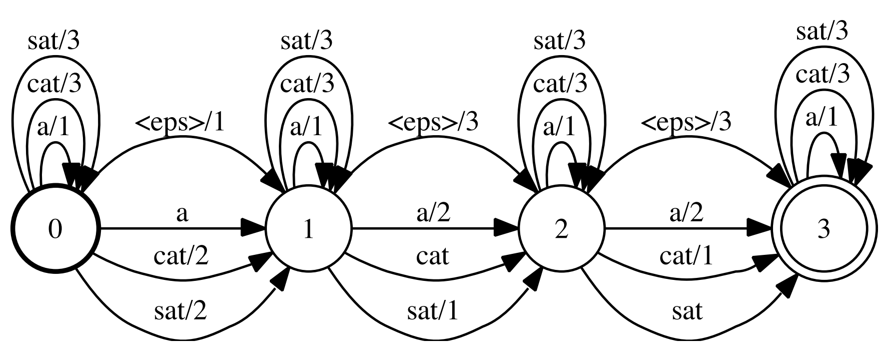
Bicknell & Levy (2012)

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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