Surprising Linkages

Marten van Schijndel
Department of Linguistics, Cornell University
April 3, 2023

Background

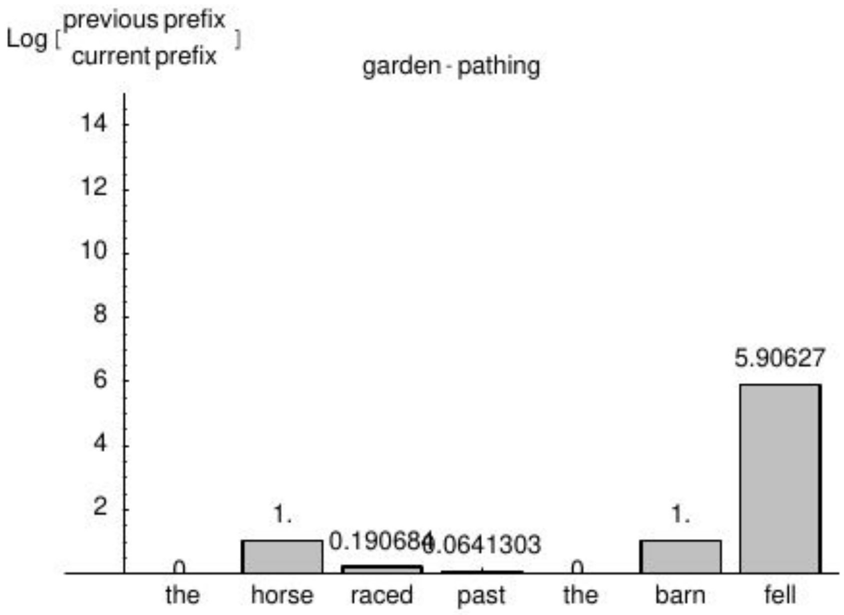
$$\text{Surprisal}(w_t) = -\log \mathrm{P}(w_t \mid w_1 \ldots w_{t-1})$$

Surprisal reflects the contextual (im)probability of an event

Terminology: Surprisal = information content = information load = (un)predictability

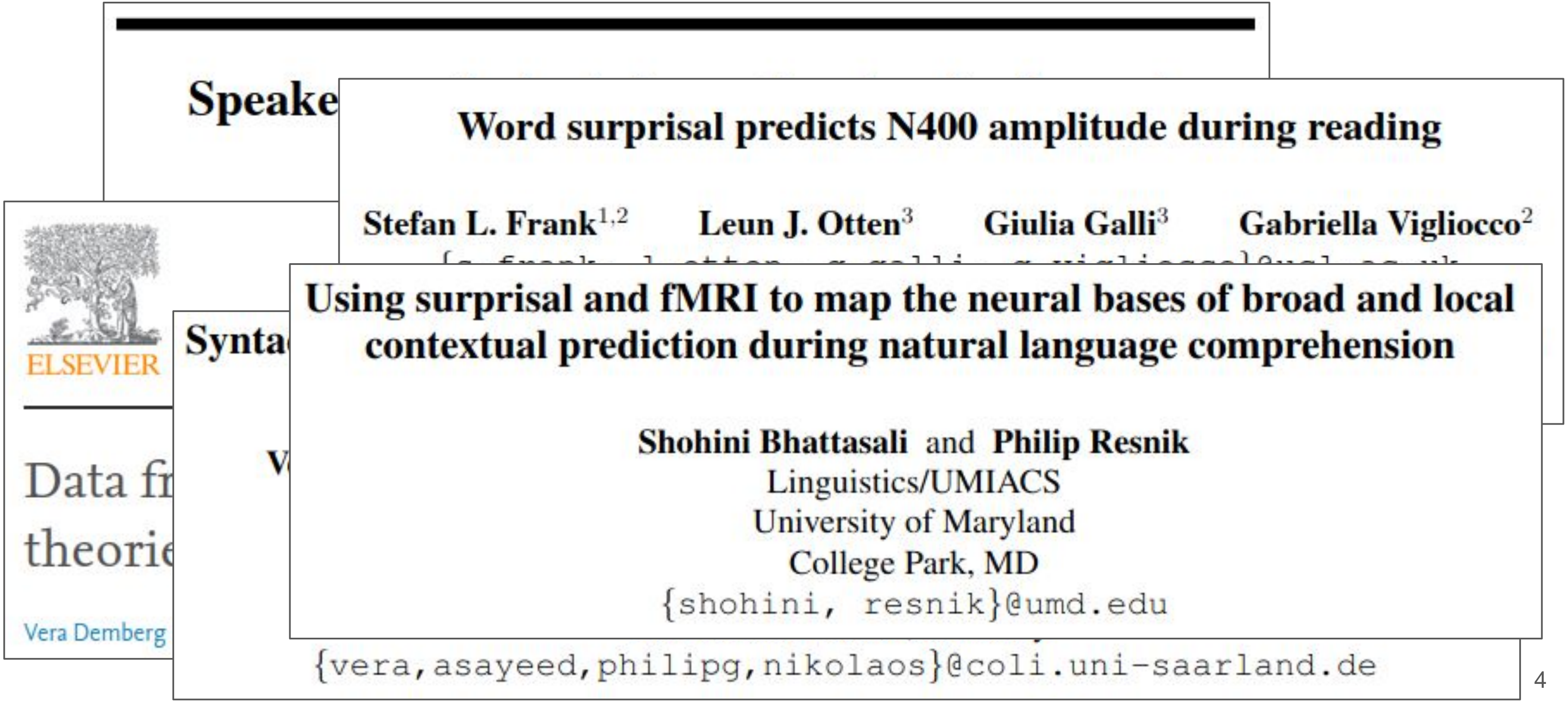
Surprisal predicts linguistic disambiguation

1.0	S	→	NP VP .
0.876404494831	NP	→	DT NN
0.123595505169	NP	→	NP VP
1.0	PP	→	IN NP
0.171428571172	VP	→	VBD PP
0.752380952552	VP	→	VBN PP
0.0761904762759	VP	→	VBD
1.0	DT	→	*the*
0.5	NN	→	*horse*
0.5	NN	→	*barn*
0.5	VBD	→	*fell*
0.5	VBD	→	*raced*
1.0	VBN	→	*raced*
1.0	IN	→	*past*



Hale, 2001, *NAACL*

Surprisal predicts human behavior



But *how* does surprisal influence behavior?

Tal Linzen

COGNITIVE SCIENCE
A Multidisciplinary Journal

Cognitive Science 45 (2021) e12988

ISSN: 1551-6709 online
DOI: 10.1111/cogs.12988

Single-Stage Prediction Models Do Not Explain the Magnitude of Syntactic Disambiguation Difficulty

Marten van Schijndel, PhD,[a] Tal Linzen, PhD[b]

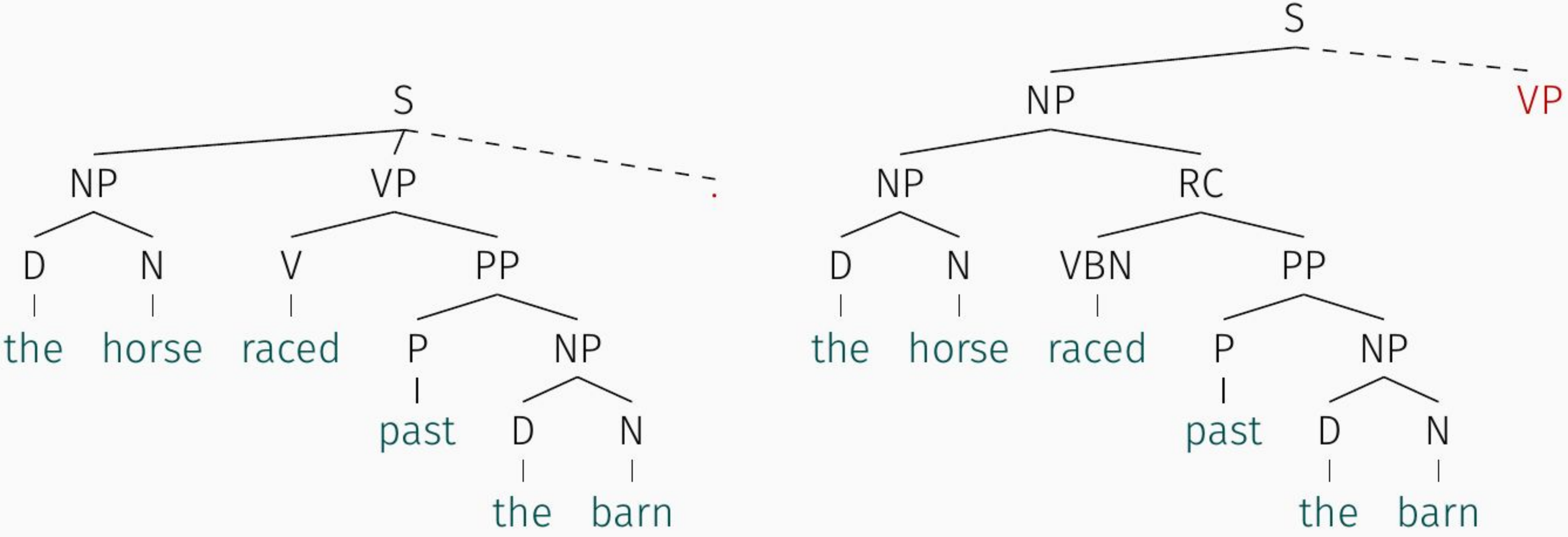
[a]*Department of Linguistics, Cornell University*
[b]*Department of Linguistics and Center for Data Science, New York University*

The horse raced past the barn fell

Bever, 1970, *Cognition and the Development of Language*

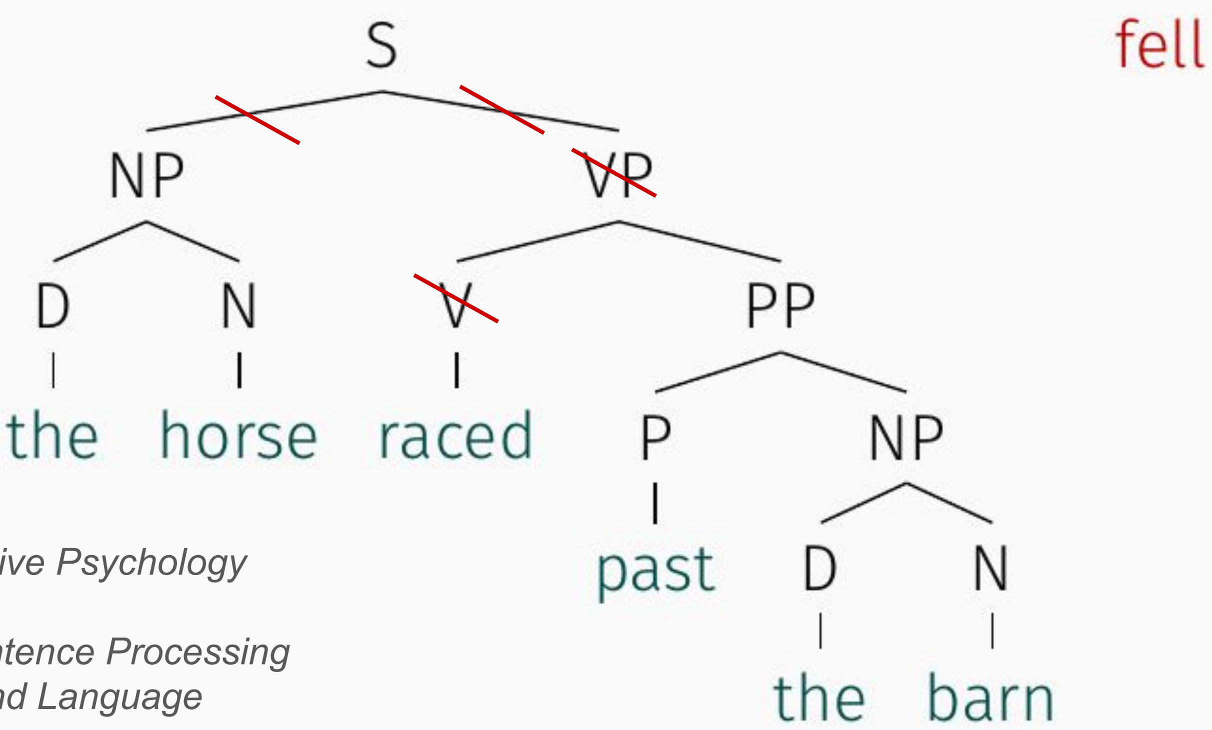
The horse which was raced past the barn fell

Bever, 1970, *Cognition and the Development of Language*


S
NP
VP
D
N
V
PP
the
horse
raced
P
NP
past
D
N
the
barn
.
S
NP
VP
NP
RC
D
N
VBN
PP
the
horse
raced
P
NP
past
D
N
the
barn

Theorized disambiguation mechanisms

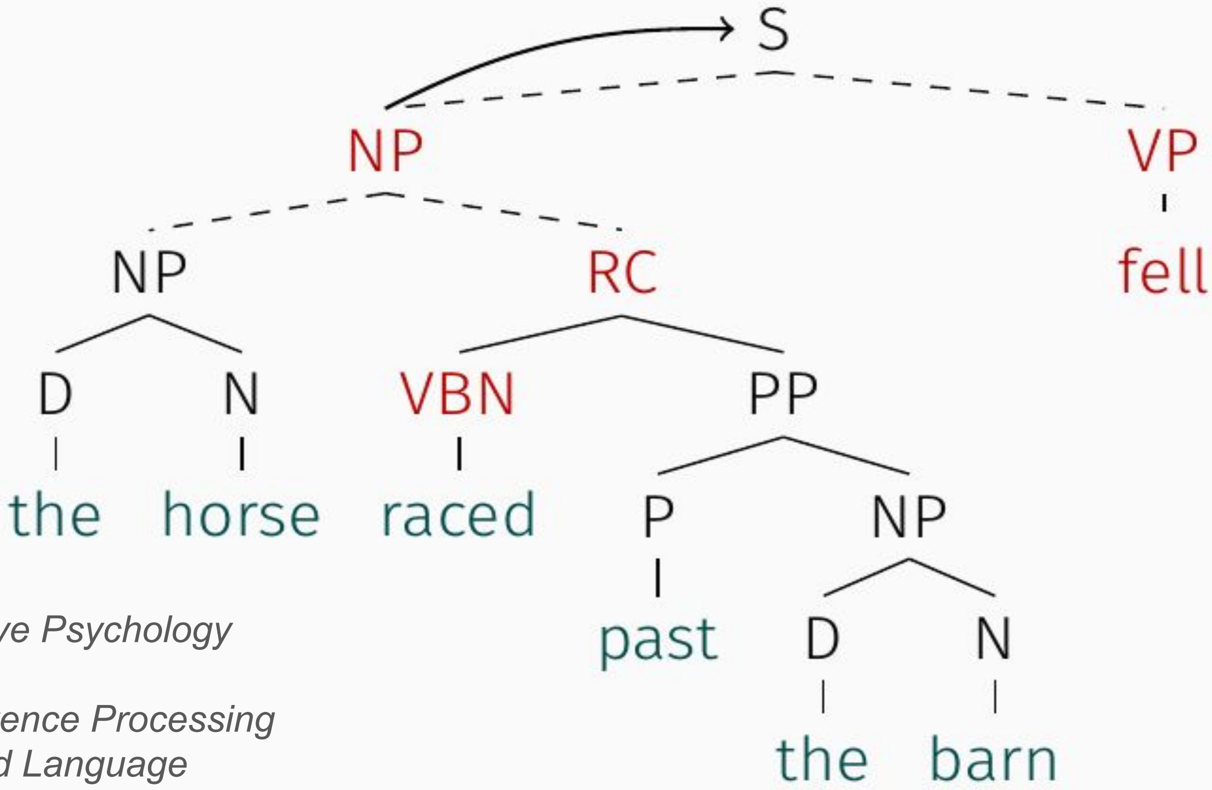
H1: Serial tree surgery



Frazier & Rayner, 1982, *Cognitive Psychology*
Pritchett, 1988, *Language*
Lewis, 1998, *Reanalysis in Sentence Processing*
Sturt et al., 1999, *J. Memory and Language*

Theorized disambiguation mechanisms

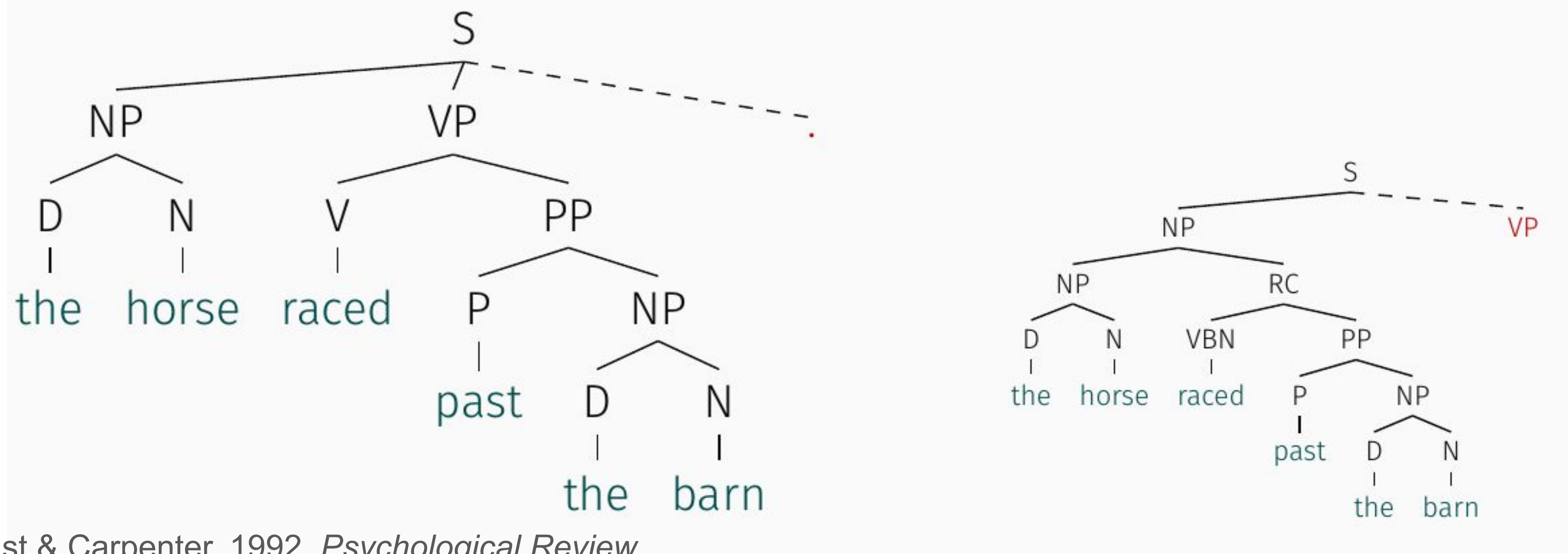
H1: Serial tree surgery



Frazier & Rayner, 1982, *Cognitive Psychology*
Pritchett, 1988, *Language*
Lewis, 1998, *Reanalysis in Sentence Processing*
Sturt et al., 1999, *J. Memory and Language*

Theorized disambiguation mechanisms

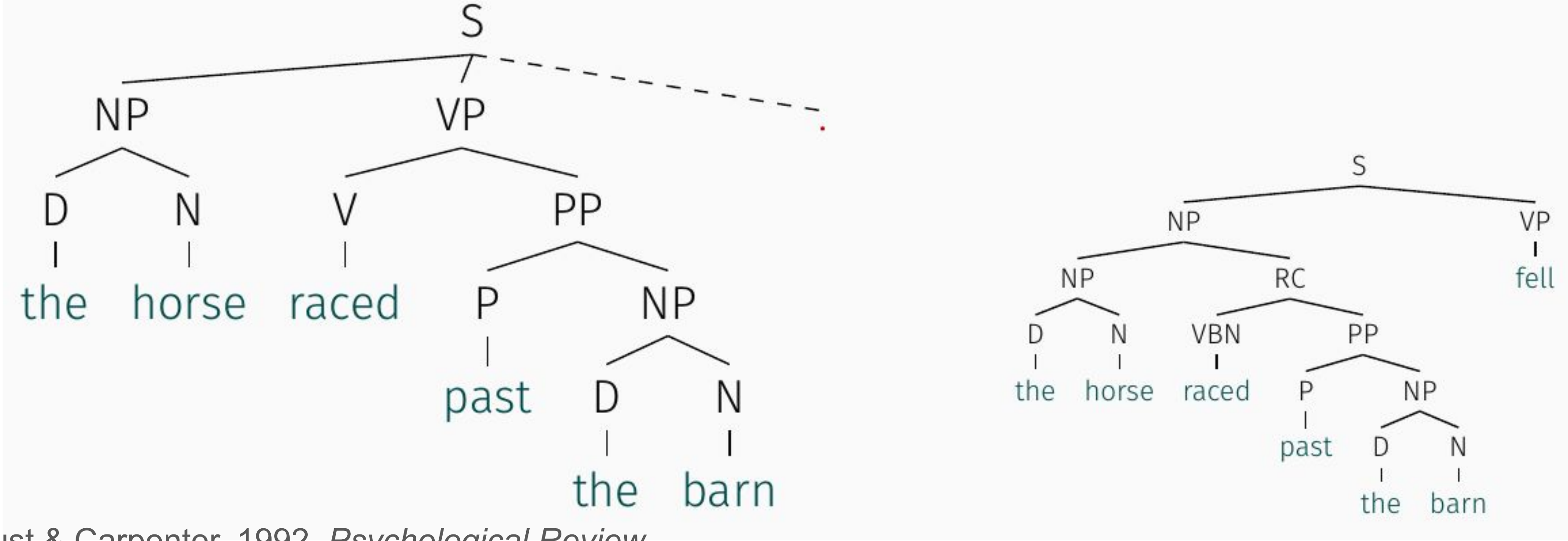
H2: Parallel reranking



Just & Carpenter, 1992, *Psychological Review*
Hale, 2001, *NAACL*
Levy, 2013, *Sentence Processing*

Theorized disambiguation mechanisms

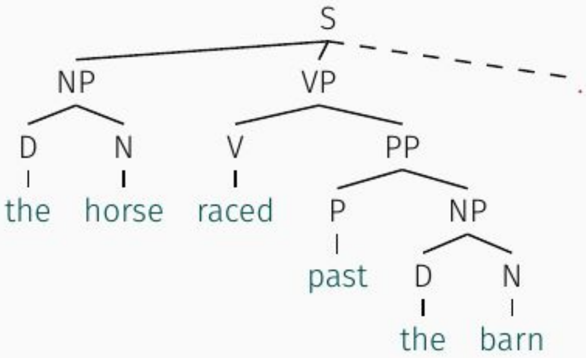
H2: Parallel reranking

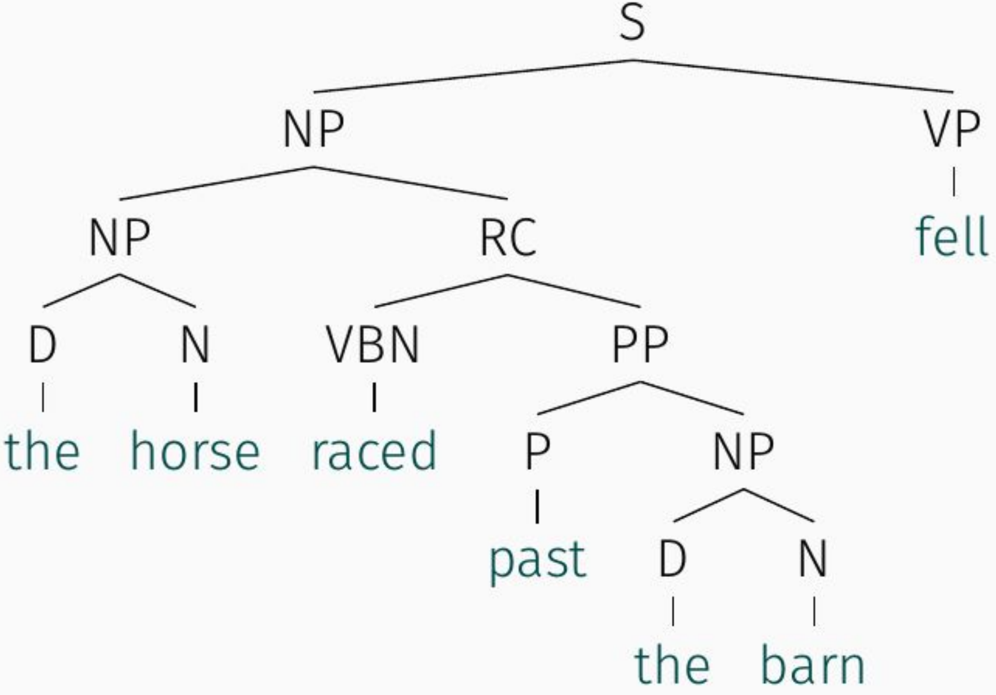


Just & Carpenter, 1992, *Psychological Review*
Hale, 2001, *NAACL*
Levy, 2013, *Sentence Processing*

Theorized disambiguation mechanisms

H2: Parallel reranking





Just & Carpenter, 1992, *Psychological Review*
Hale, 2001, *NAACL*
Levy, 2013, *Sentence Processing*

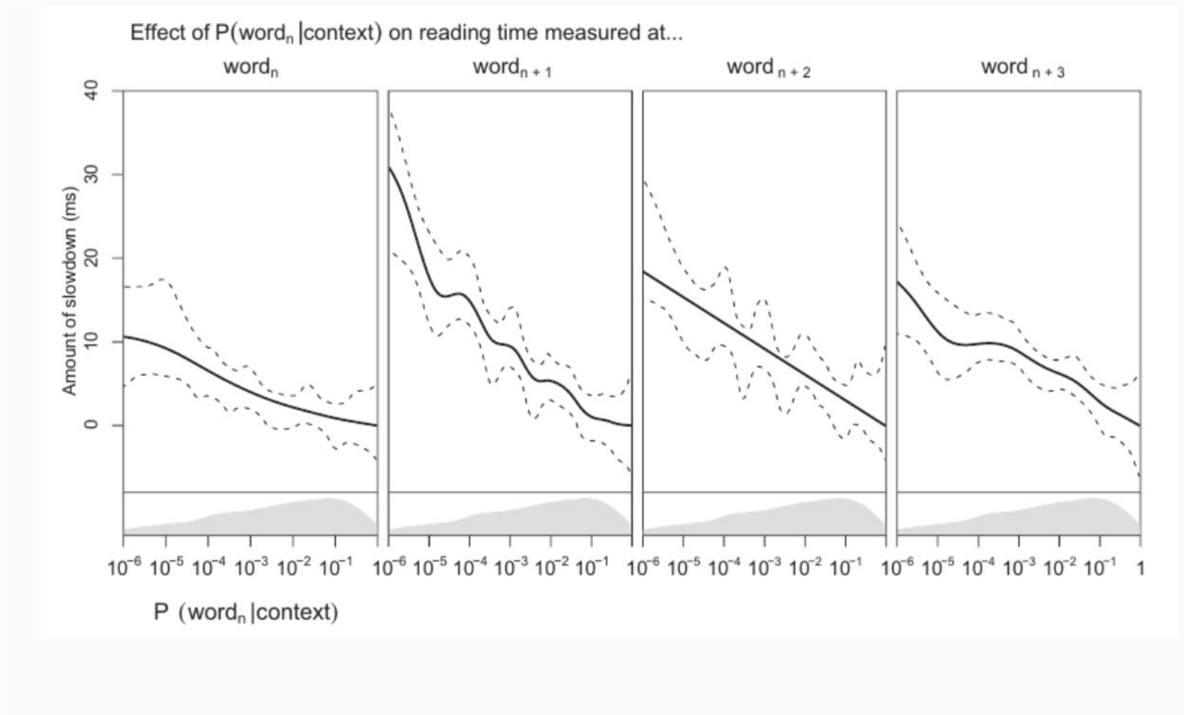
NNs can predict garden path *existence*

van Schijndel & Linzen, 2018, *Proc CogSci*
Futrell et al., 2019, *Proc NAACL*
Frank & Hoeks, 2019, *Proc CogSci*
Davis & van Schijndel, 2020, *Proc CogSci*

NNs can predict garden path *existence*

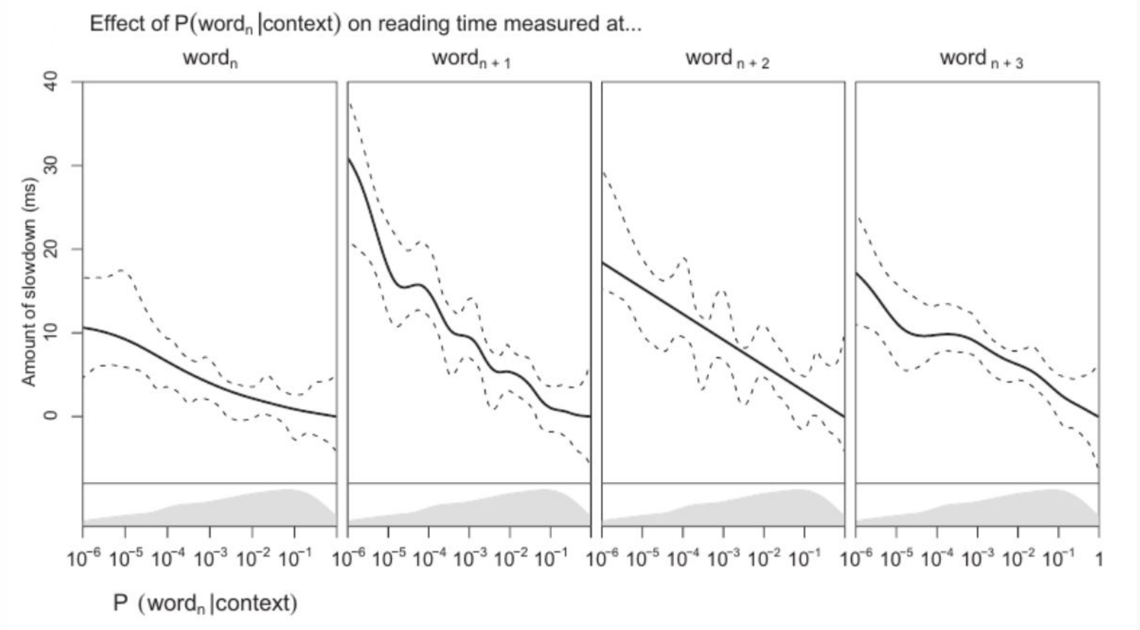
Look beyond garden path *existence* to garden path *magnitude*

Surprisal is linearly related to reading times!



Smith and Levy, 2013, *Cognition*

Surprisal is linearly related to reading times!



$$RT(w_i) = \delta_0 S(w_i) + \delta_{-1} S(w_{i-1}) + \delta_{-2} S(w_{i-2}) + \delta_{-3} S(w_{i-3})$$

Smith and Levy, 2013, *Cognition*

WikiRNN:

Gulordava et al. (2018) LSTM

Data: Wikipedia (80M words)

SoapRNN:

2-layer LSTM (Same parameters as WikiRNN)

Data: Corpus of American Soap Operas (80M words; Davies, 2011)

Mapping probs to reading times

Reading Time Data (SPR; Prasad and Linzen, 2019)

- 80 simple sentences (fillers)
- 224 participants
- 1000 words / participant

Linear Mixed Regression

time ~ text position + word length x frequency + … + predictability_t

Smith & Levy, 2013:

$\delta_0 = 0.53\ \delta_{-1} = 1.53\ \delta_{-2} = 0.92\ \delta_{-3} = 0.84$

WikiRNN using Prasad & Linzen, 2019:

$(\delta_0 = 0.04)\ \delta_{-1} = 1.10\ \delta_{-2} = 0.37\ \delta_{-3} = 0.39$

SoapRNN using Prasad & Linzen, 2019:

$(\delta_0 = -0.04)\ \delta_{-1} = 0.83\ \delta_{-2} = 0.91\ \delta_{-3} = 0.44$

Three Garden Paths

NP/S: The woman saw
- the doctor wore a hat.
- that the doctor wore a hat.

Three Garden Paths

NP/S: The woman saw
- the doctor wore a hat.
- that the doctor wore a hat.

NP/Z: When the woman
- visited her nephew laughed loudly.
- visited, her nephew laughed loudly.

MV/RR: The horse
- raced past the barn fell.
- which was raced past the barn fell.

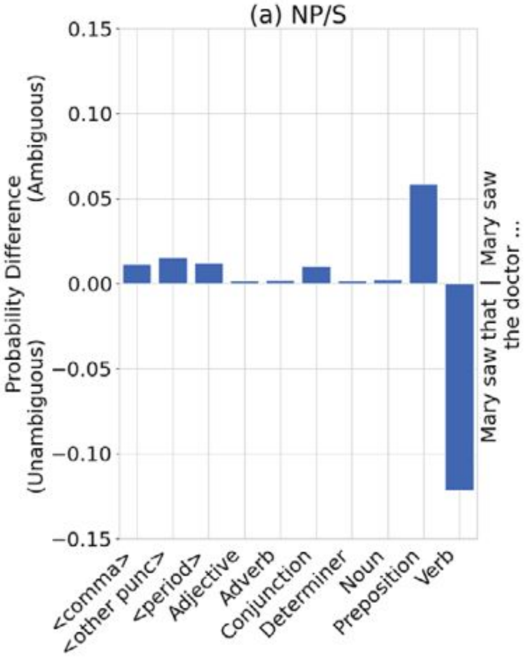
The horse raced past the barn fell

The horse which was raced past the barn fell

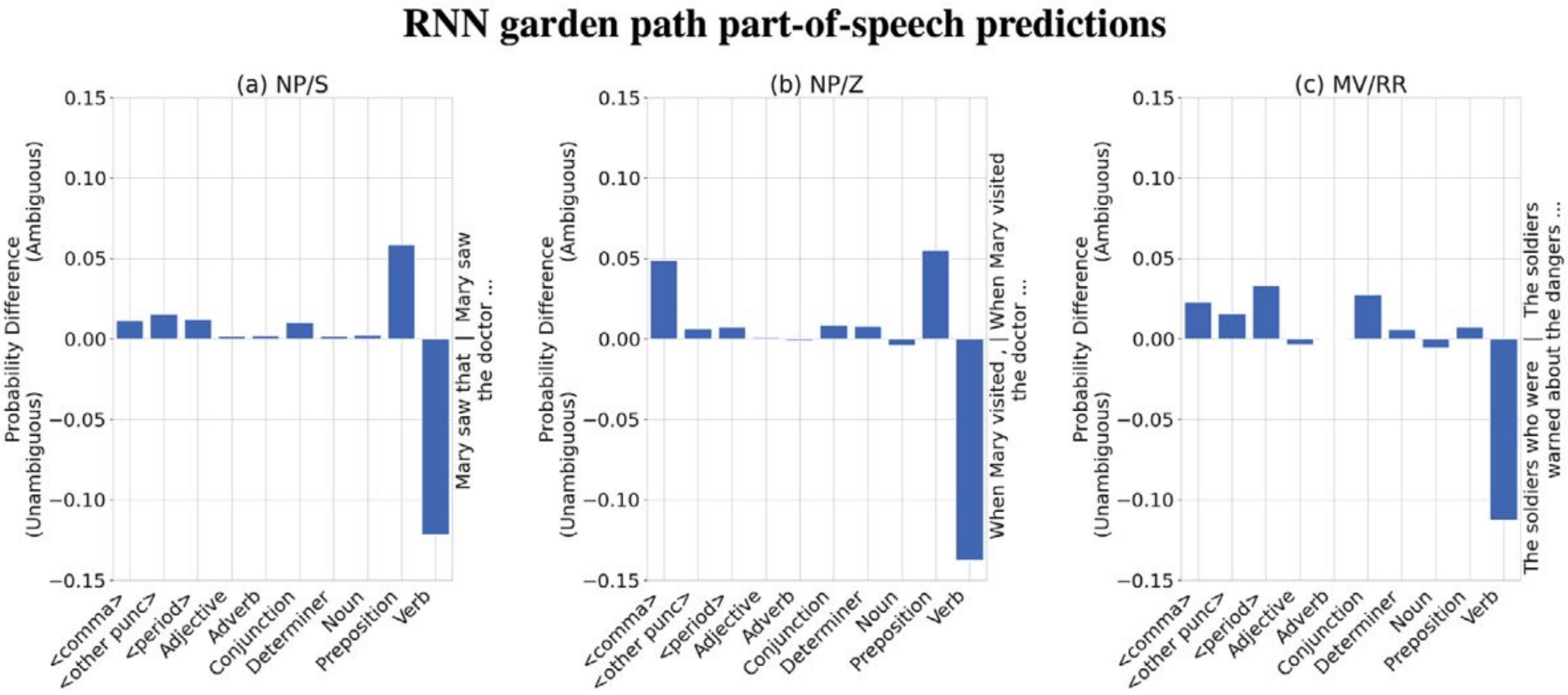
Bever, 1970, *Cognition and the Development of Language*

NNs have human-like garden path interpretations

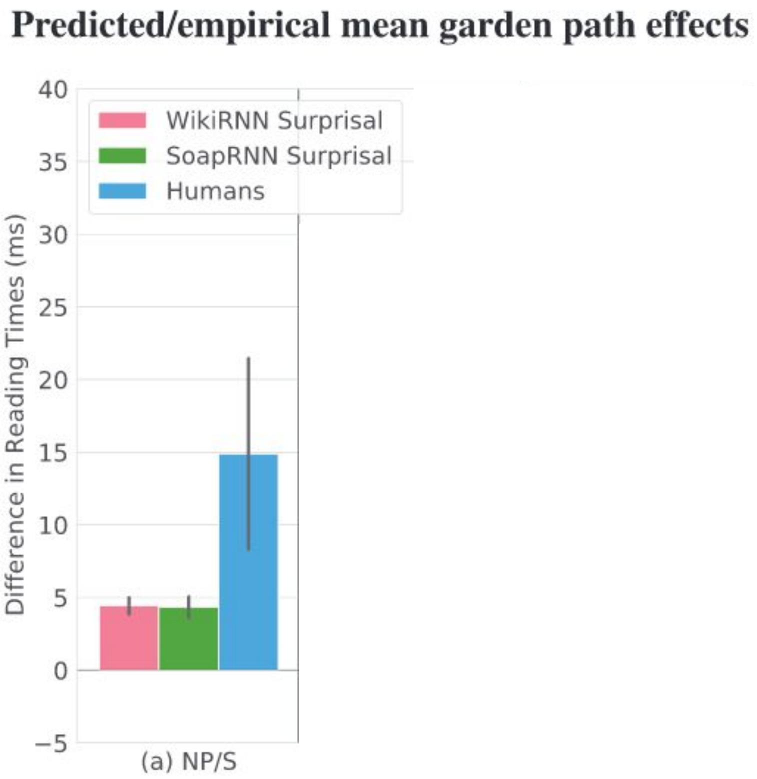
RNN garden path part-of-speech predictions



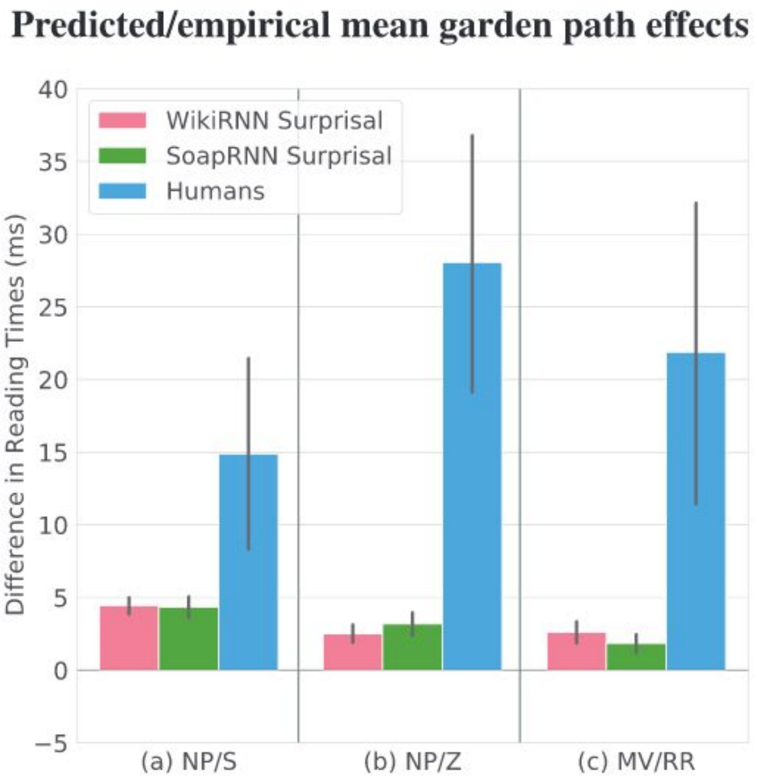
NNs have human-like garden path interpretations



Surprisal is unable to predict effect magnitude

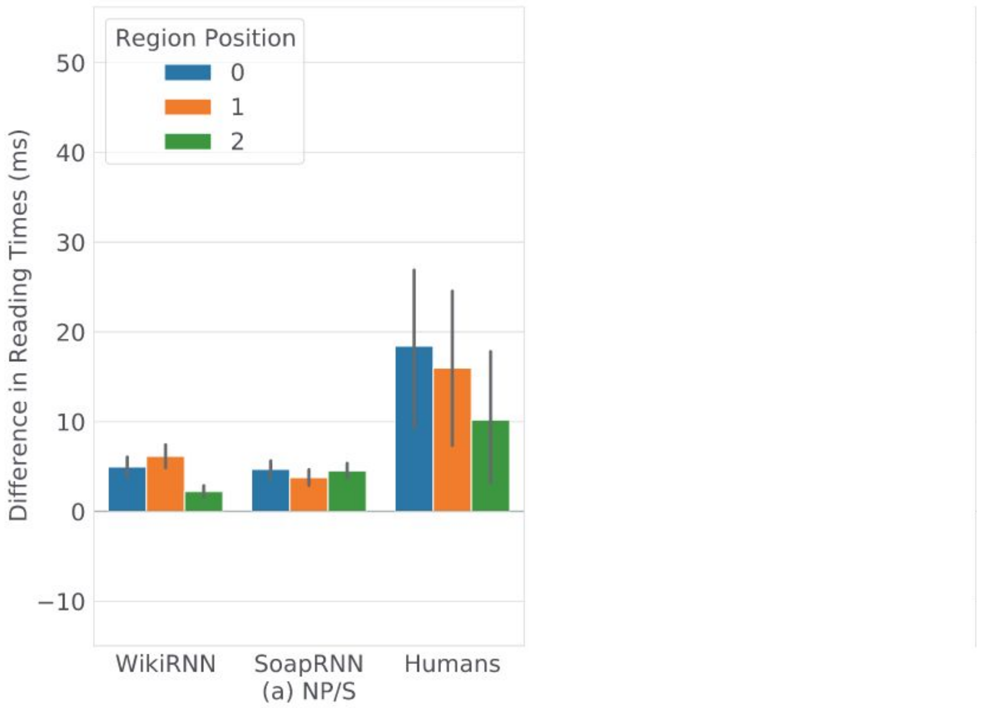


Surprisal is unable to predict effect magnitude

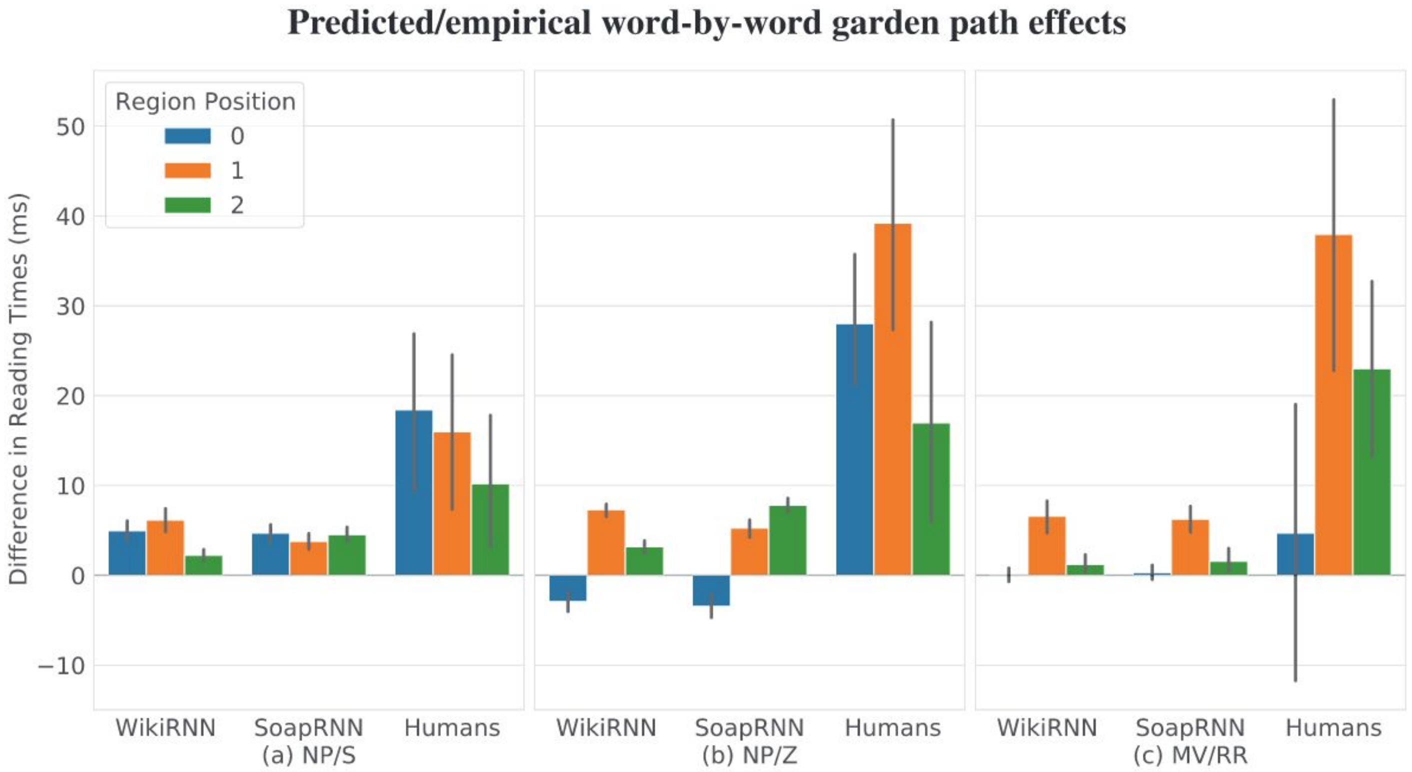


Each construction produces different behavior

Predicted/empirical word-by-word garden path effects



Each construction produces different behavior



Paper Conclusions

- Neural networks capture expected garden path interpretations
- Conversion rates are fairly similar, but all underestimate human responses
- Different garden paths exhibit different timecourses
- Suggests human responses influenced by factors beyond predictability

Deb Bhattacharya

Code-switching in online posts reveals evidence for audience design

Debasmita Bhattacharya
Department of Computer Science
Columbia University
db3526@columbia.edu

Marten van Schijndel
Department of Linguistics
Cornell University
mv443@cornell.edu

Under Review

What is code-switching

Matrix Language Embedded Language

暑期 短租 还 available 哦。

summer short-rental still available *excl.*

The summer rental is still available.

Surprisal influences code-switching

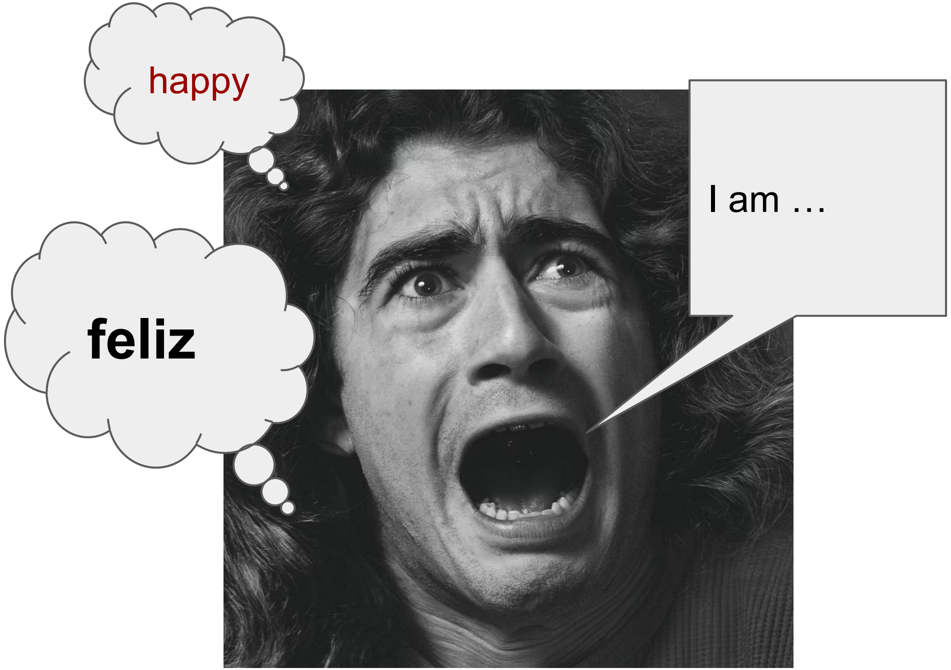
Surprising continuations are more likely to be code-switched

Why would this be?

MyslÍn and Levy, 2015, *Language*
Calvillo et al., 2020, *EMNLP*

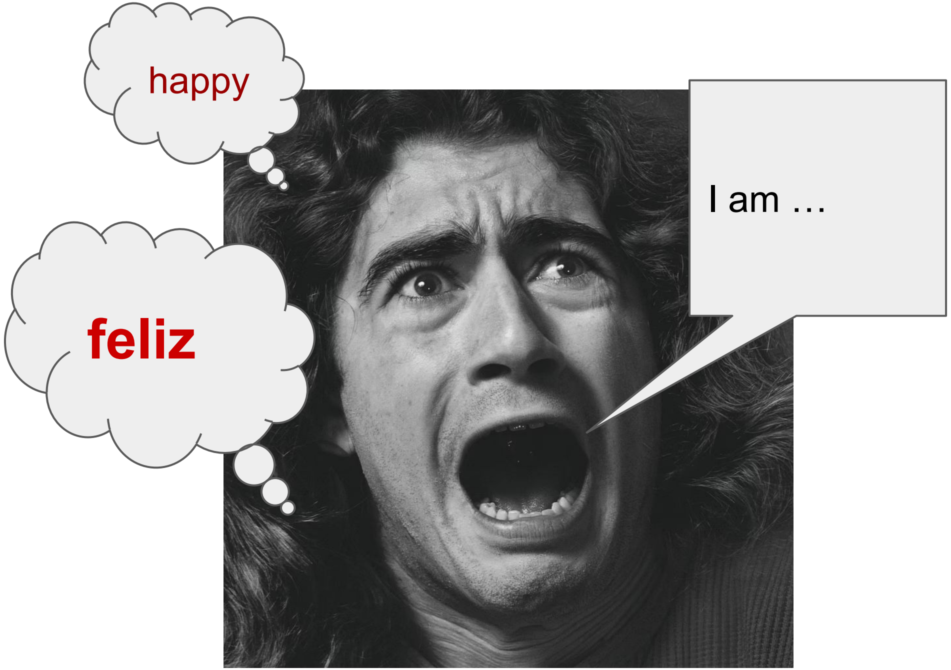
Hypothesized mechanisms for surprisal influence

H1: Speaker-driven code-switching



Hypothesized mechanisms for surprisal influence

H2: Audience-driven code-switching



Hypothesized mechanisms for surprisal influence

H1: Speaker-driven code-switching

Prediction: Embedded surprisal < Matrix surprisal

H2: Audience-driven code-switching

Prediction: Matrix surprisal ≤ Embedded surprisal

Code-switching data

暑期 短租 还 available 哦。
summer short-rental still available *excl.*
The summer rental is still available.

Code-switching data

(1) CS:

暑期 短租 还 available 哦。
summer short-rental still available *excl.*
The summer rental is still available.

Key:
CS-1

(2) CS:

暑期 短租 还 有空的 哦。
summer short-rental still available *excl.*
The summer rental is still available.

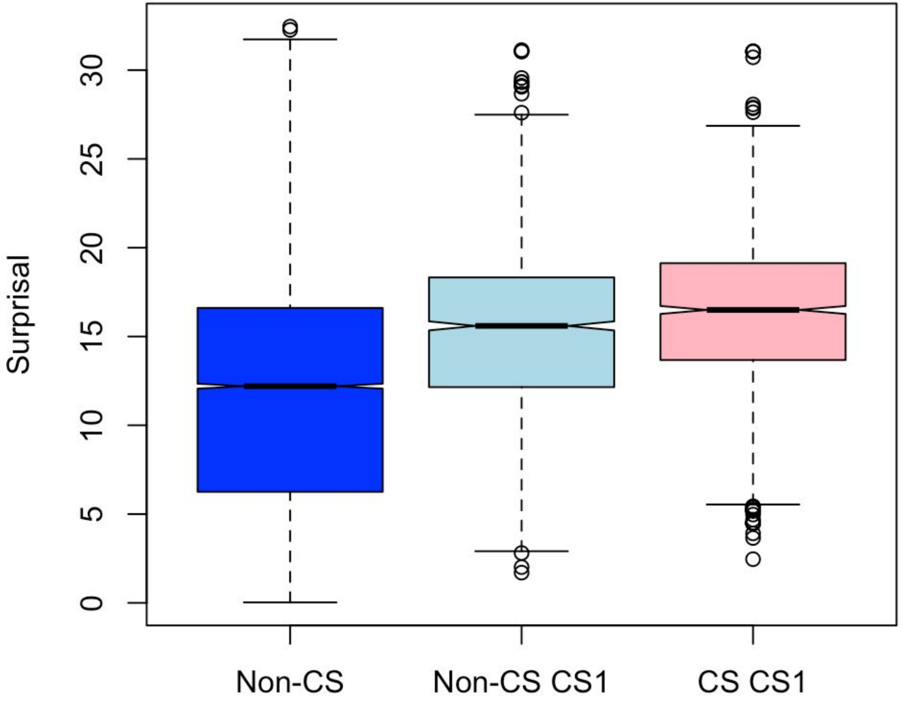
(3) Non-CS:

附近 有 很多 餐馆。
nearby has many restaurant.
There are many restaurants nearby.

Key:
CS-1
Non-CS

Replication: Surprisal is correlated with code-switching

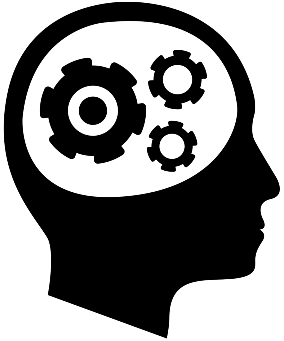
Unigram surprisal (frequency), 5-gram surprisal: Chinese Wikipedia (35 million tokens)



Factor	coef	std err	t
Intercept	0.5223	0.006	94.419
POS=verb	0.0048	0.010	0.481
POS=other	**-0.0609**	0.009	**-6.852**
Frequency	**0.8935**	0.007	**119.696**
Word length	**-0.0431**	0.008	**-5.716**
Sentence length	**0.0460**	0.007	**6.660**
Surprisal	**0.0605**	0.008	**7.251**

Table 1: Summary of the logistic regression model for CS1 (coded 1) versus random Non-CS1 (coded 0).

Code-switching model to test our hypotheses



	w1	w2	w3	w4	w5
zh:	暑期	短租	还	有空的	哦
en:	The summer	rental	is still	available	oh!

Corpus expansion

We generated English machine translations

(1) CS: 暑期 短租 还 available 哦。
summer short-rental still available *excl.*
The summer rental is still available.

(2) CS: 暑期 短租 还 有空的 哦。
summer short-rental still available *excl.*
The summer rental is still available.

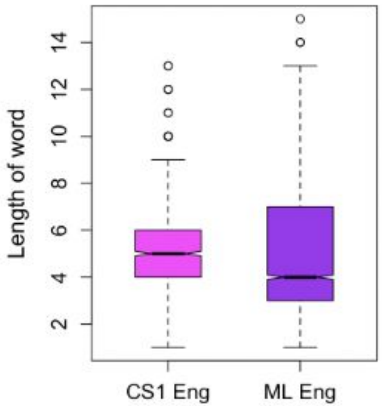
Key:
CS-1

---

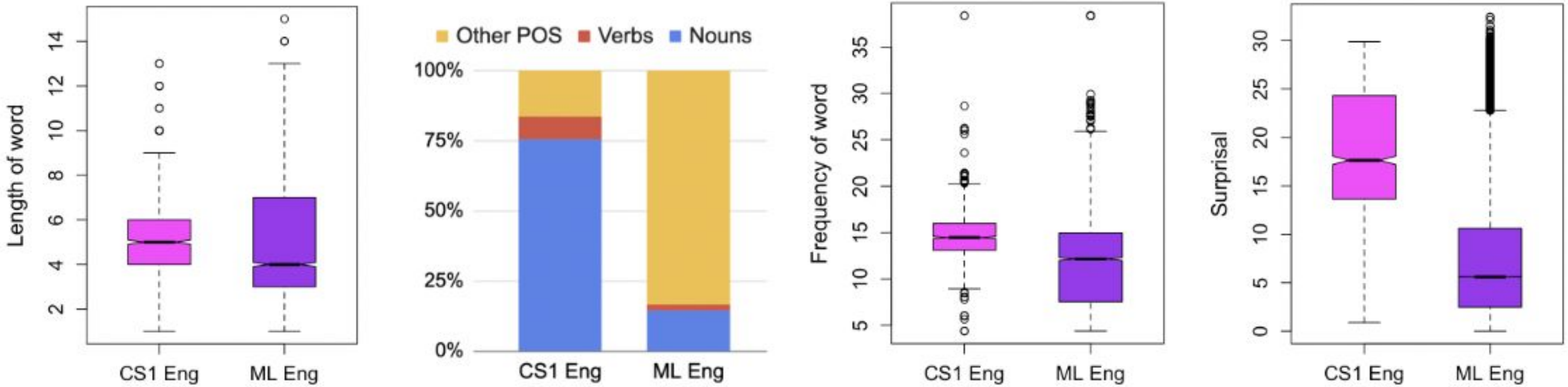
(3) Non-CS: 附近 有 很多 餐馆。
nearby has many restaurant.
There are many restaurants nearby.

Key:
CS-1
Non-CS

CS1 English is more complex than monolingual English

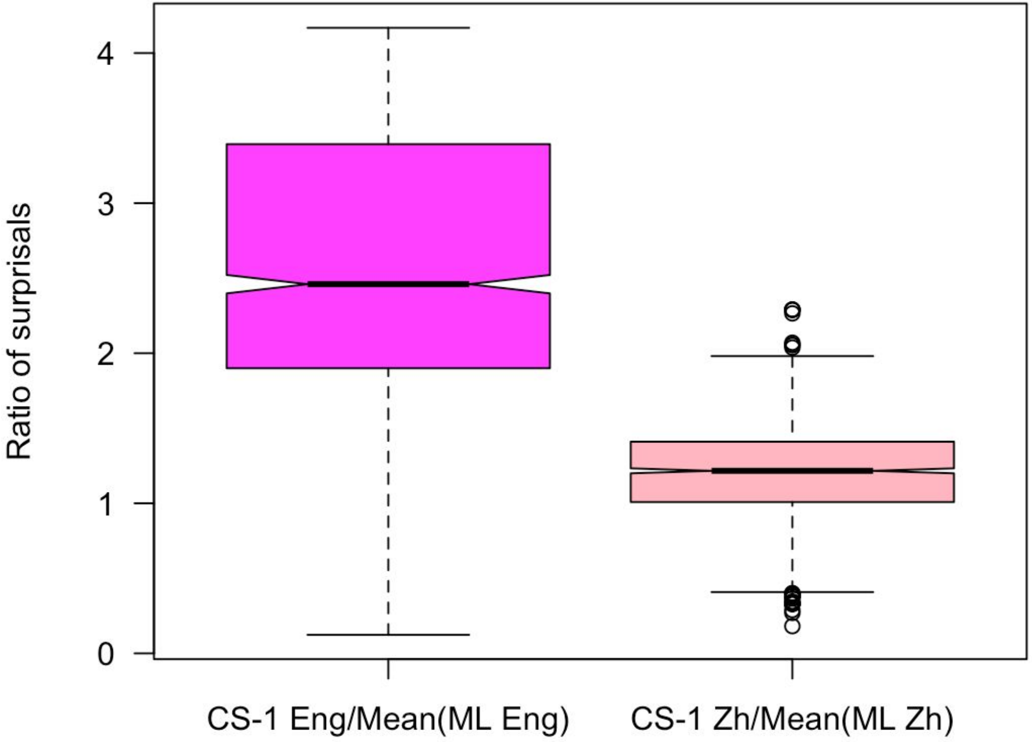


CS1 English is more complex than monolingual English



What is the relative complexity of CS1 English compared with CS1 Chinese?

CS1 English is more complex than CS1 Chinese



Paper Conclusions

Surprisal has an audience-driven influence on code-switching

- Code-switching is correlated with high surprisal,
  but code-switches tend to be more complex than monolingual speech

- Suggests speakers use code-switching to signal complexity for listeners,
  rather than necessarily finding it more salient for themselves

Talk conclusions

- Surprisal underestimates human behavioral responses
- There are additional repair mechanisms beyond re-ranking
- At areas of high surprisal, code-switching is used to signal to the audience about the area of high complexity

Thanks!

Tal Linzen

Deb Bhattacharya

C.Psyd

Cornell NLP