HIERARCHIC SYNTAX IMPROVES READING TIME PREDICTION

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OVERVIEW

Previous studies have debated whether humans use hierarchic syntax

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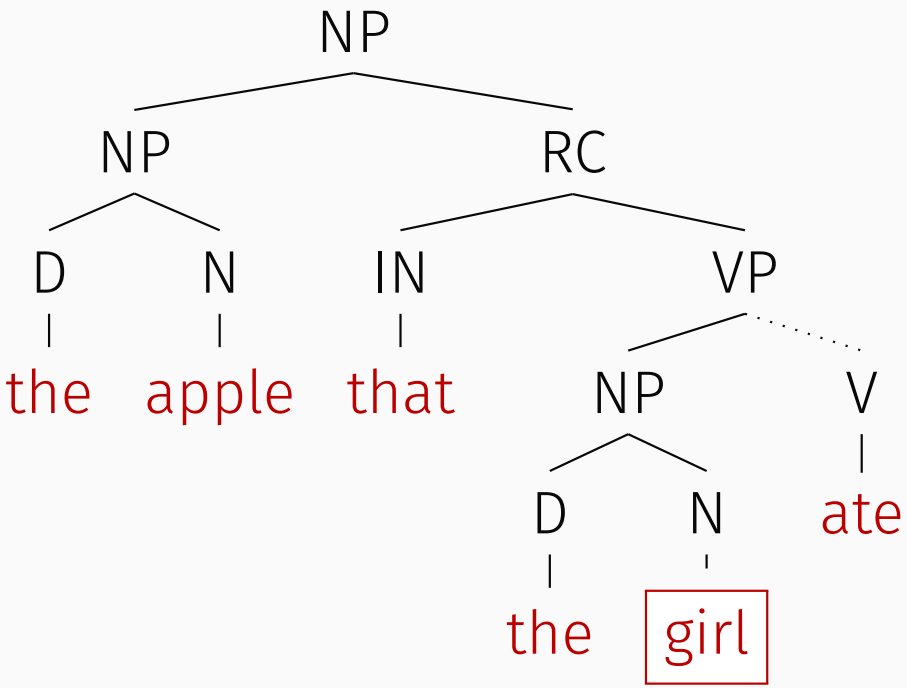

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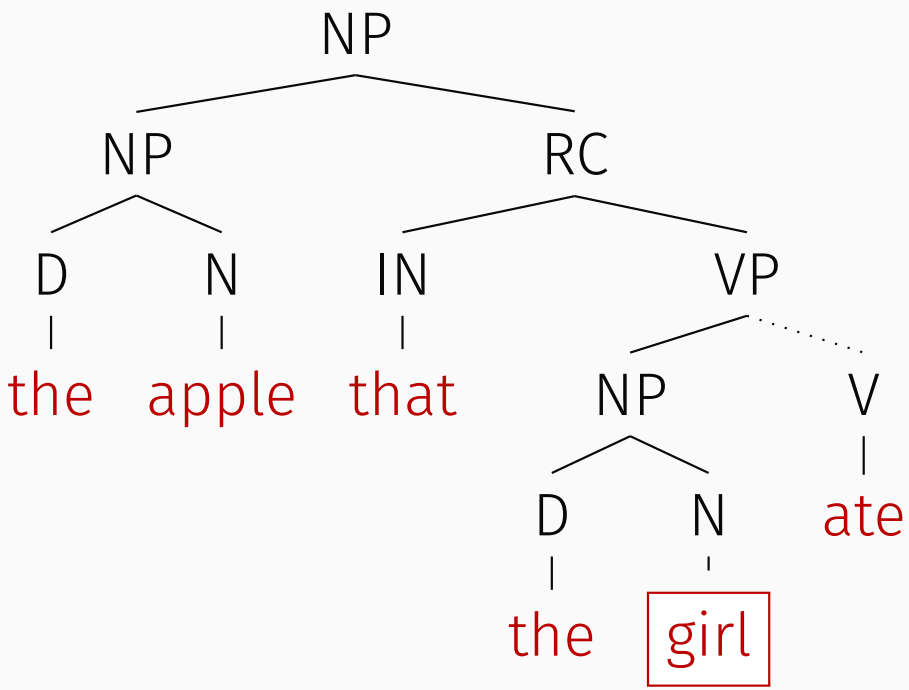

But standard baseline predictors may be deficient

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Hierarchic syntax not improved by accumulation

Long distance dependencies independently improve model

Hierarchic syntax in reading?

The red[1] apple that the girl[2] ate ...

Frank & Bod (2011)

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Baseline:

- Sentence Position
- Word length
- *N*-grams (Unigram, bigram)

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The red apple that the girl ate ...
w_1 w_2 w_3 w_4 w_5 w_6

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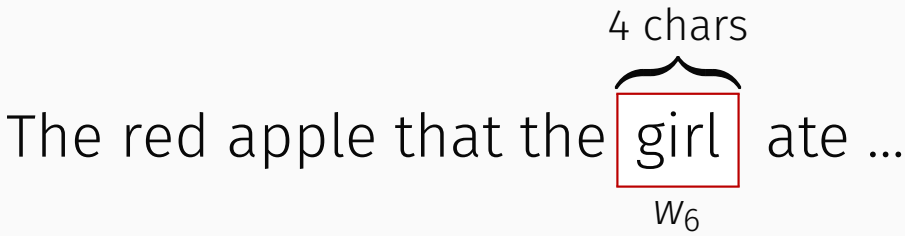

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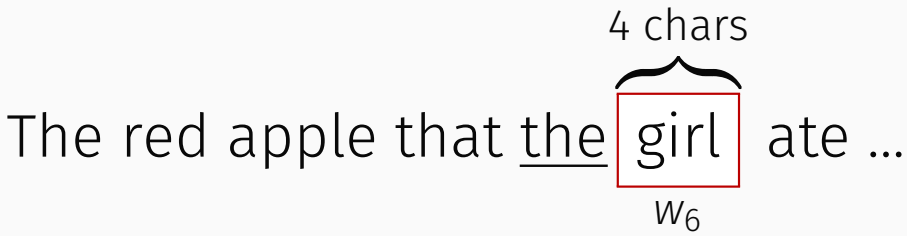

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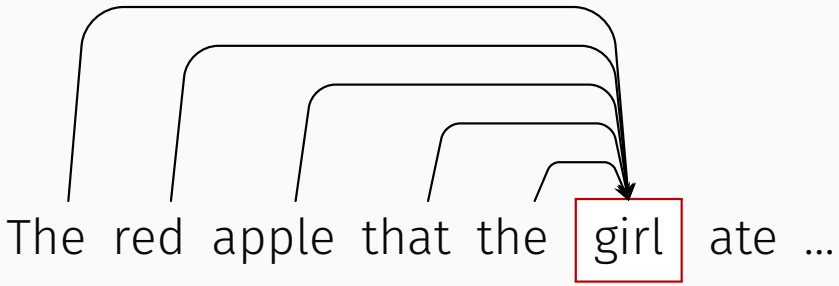

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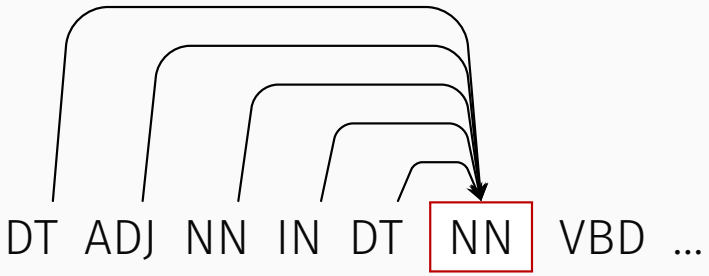

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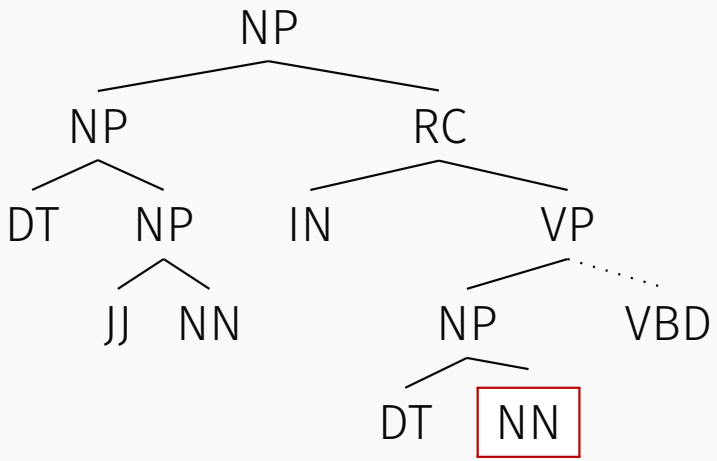

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PSG $<$ ESN + PSG

ESN $=$ ESN + PSG

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Outcome:

PSG $<$ ESN + PSG

ESN $=$ ESN + PSG Hierarchic doesn't help over sequential

Fossum & Levy (2012)

Replicated Frank & Bod (2011):

PSG $<$ ESN + PSG

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ESN $=$ ESN + PSG

Also: lexicalized syntax improves PSG fit

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Previous reading time studies:

- Unigrams/Bigrams/Trigrams
  Trained on WSJ, Dundee, BNC

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BIGRAM EXAMPLE

Reading time of *girl* after *red*

The red apple that the girl ate ...

region

X: bigram target X: bigram condition

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X: bigram target X: bigram condition

- Fails to capture entire sequence;
- Conditions never generated;

BIGRAM EXAMPLE

Reading time of *girl* after *red*

The red apple that the girl ate ...

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X: bigram target X: bigram condition

- Fails to capture entire sequence;
- Conditions never generated;
- Probability of sequence is deficient

CUMULATIVE BIGRAM EXAMPLE

Reading time of *girl* after *red*:

The $\overset{1}{\underline{\text{red}}}$ $\boxed{\underline{\text{apple}}}$ $\boxed{\underline{\text{that}}}$ $\boxed{\underline{\text{the}}}$ $\overset{2}{\boxed{\text{girl}}}$ ate ...

$\boxed{\text{X}}$: bigram targets $\underline{\text{X}}$: bigram conditions

CUMULATIVE BIGRAM EXAMPLE

Reading time of *girl* after *red*:

The ^{1}red apple that the ^{2}girl ate ...

X: bigram targets X: bigram conditions

- Captures entire sequence;
- Well-formed sequence probability;
- Reflects processing that must be done by humans

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Previous reading time studies:

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This study:

- 5-grams (w/ backoff)
- Trained on Gigaword 4.0
- Cumulative and Non-cumulative

EVALUATION

Dundee Corpus (Kennedy et al., 2003)

- 10 subjects
- 2,388 sentences
- 58,439 words
- 194,882 first pass durations
- 193,709 go-past durations

Exclusions:

- Unknown words (5 tokens)
- First and last of a line
- Regions larger than 4 words (track loss)

CUMU-n-GRAMS PREDICT READING TIMES

Baseline:

Fixed Effects

- Sentence Position
- Word length
- Region Length
- Preceding word fixated?

Random Effects

- Item/Subject Intercepts
- By Subject Slopes:
  - All Fixed Effects
  - N-grams (5-grams)
  - N-grams (Cumu-5-grams)

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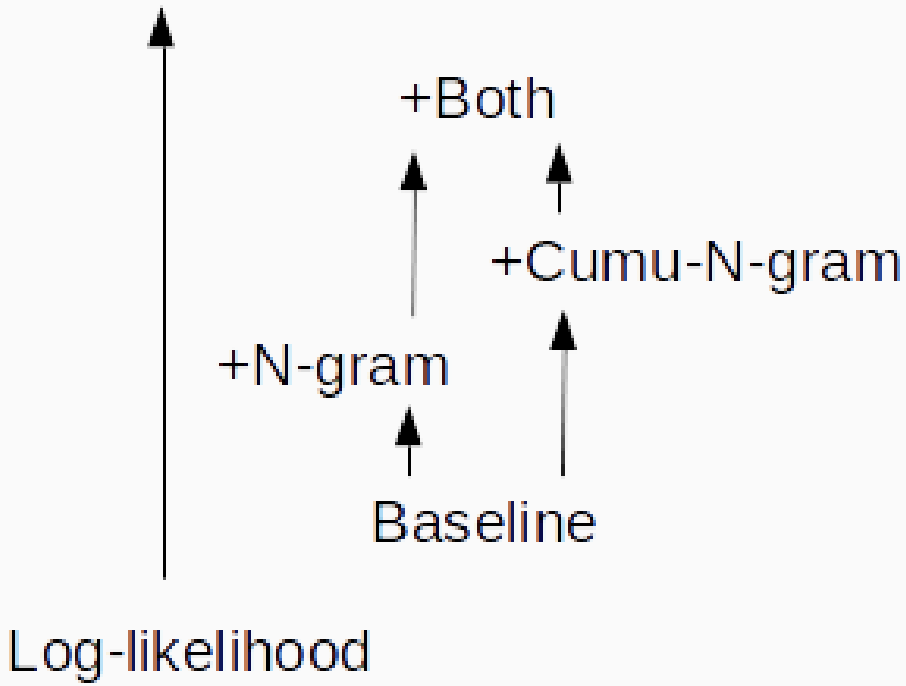

First Pass

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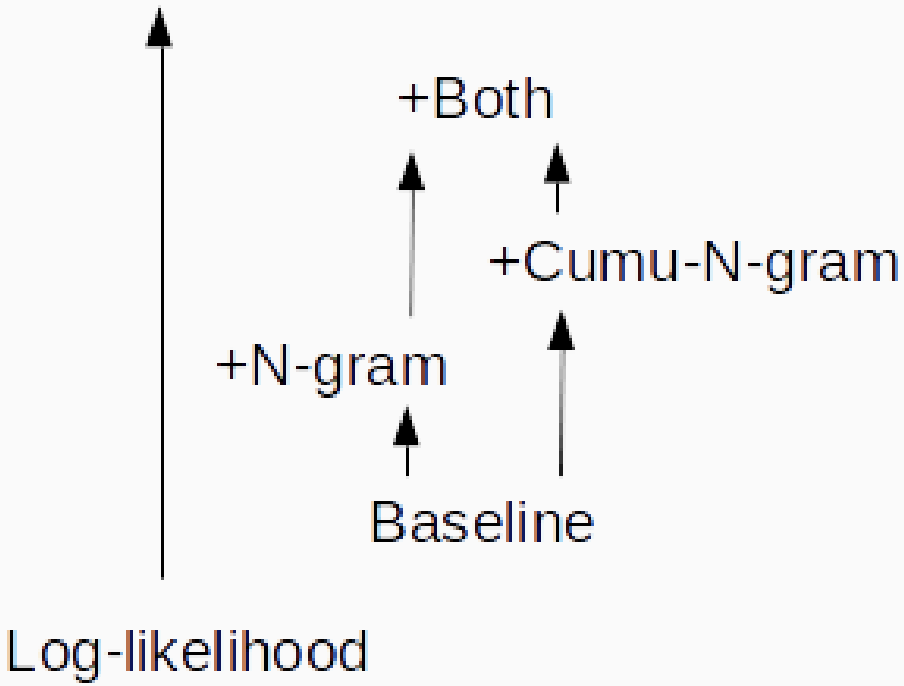

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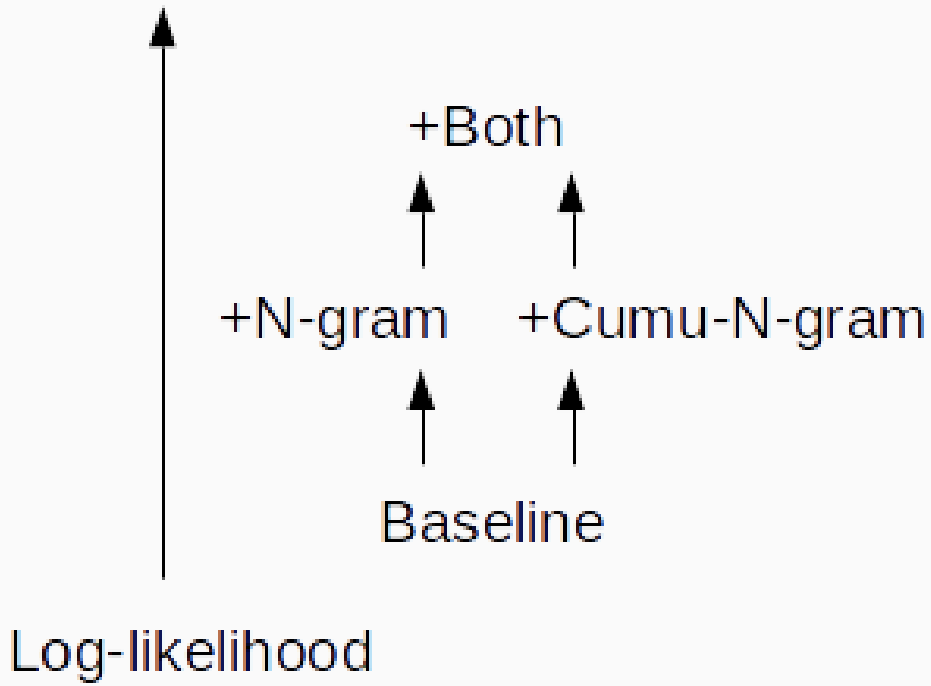

Go-Past

FOLLOW-UP QUESTIONS

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- If so, can it be similarly improved through accumulation?
  van Schijndel & Schuler (2013) found it could over weaker baselines

Grammar:
Berkeley parser, WSJ, 5 split-merge cycles (Petrov & Klein 2007)

Hierarchic surprisal predicts reading times

Baseline:

Fixed Effects

- Same as before
- *N*-grams (5-grams)
- *N*-grams (Cumu-5-grams)

HIERARCHIC SURPRISAL PREDICTS READING TIMES

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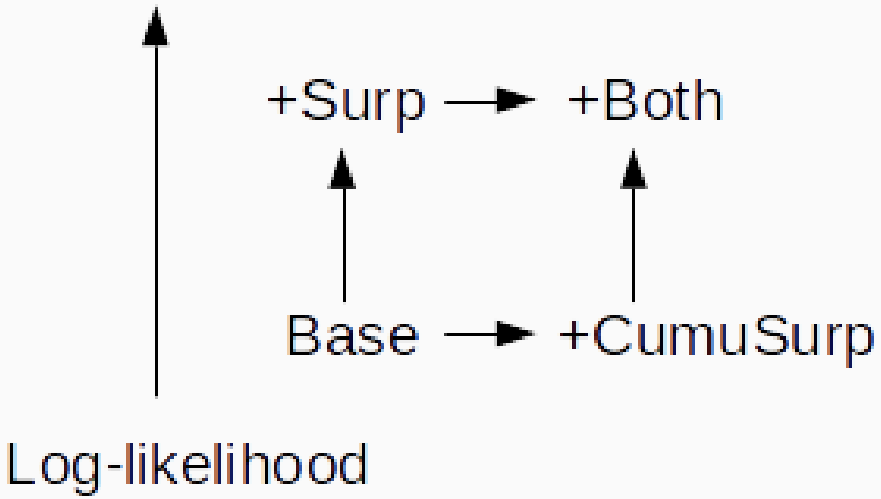

First Pass and Go-Past

Cumulative surprisal doesn't help?!

- Suggests previous findings were due to weaker *n*-gram baseline

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But... long-distance dependencies should affect reading times!

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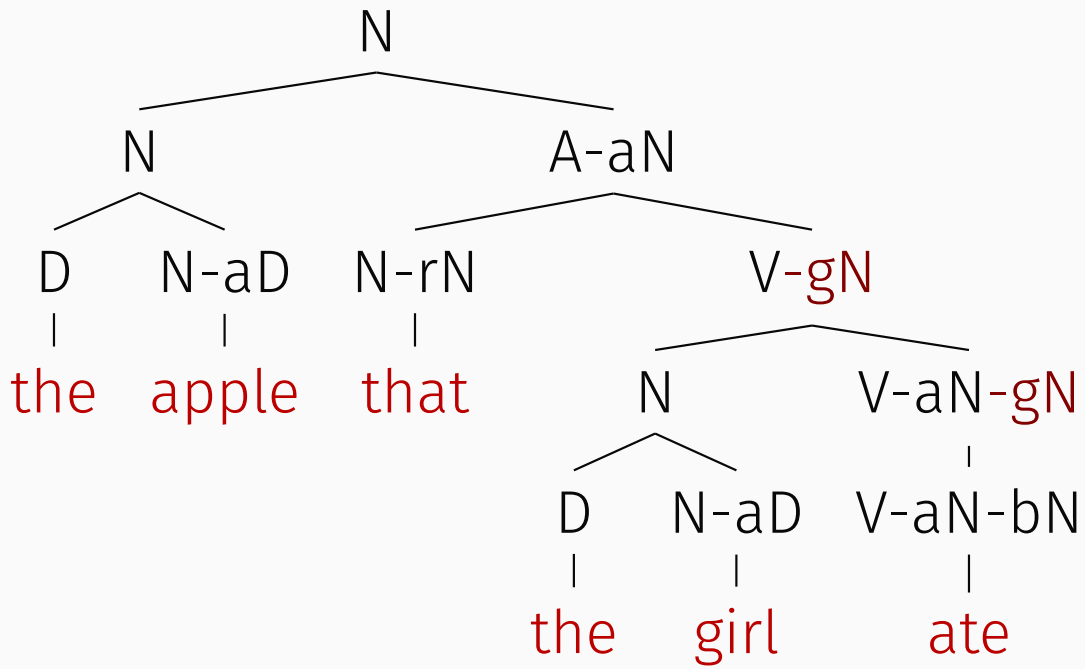
But... long-distance dependencies should affect reading times!

Let's try a PCFG that tracks long-distance deps

GENERALIZED CATEGORIAL GRAMMAR (GCG)

Nguyen et al. (2012)



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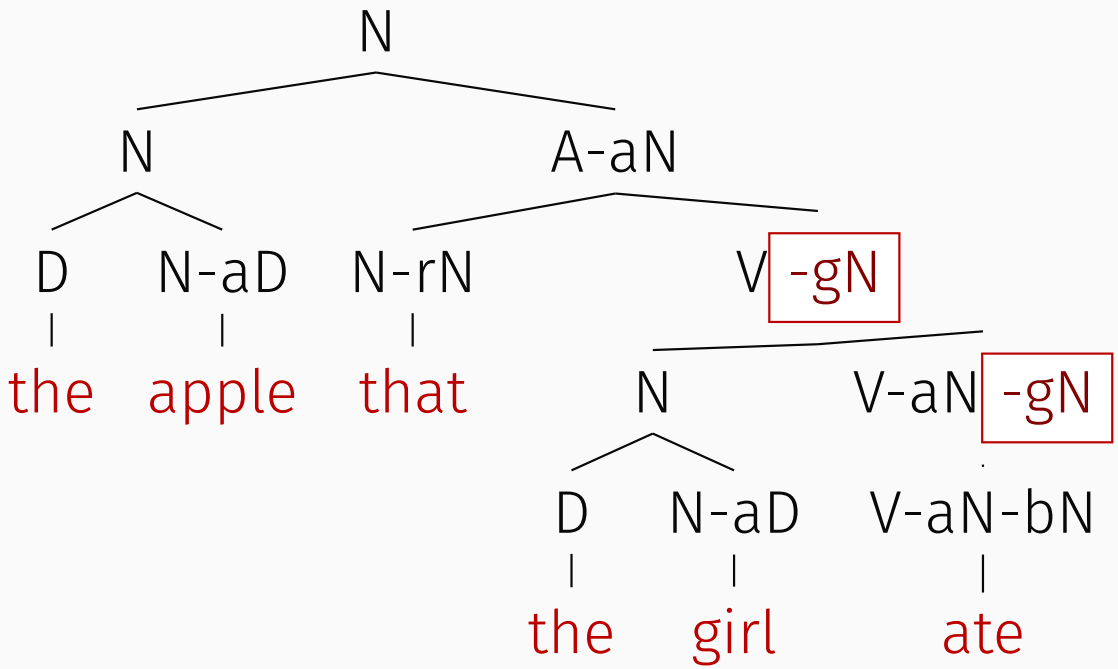

Long-distance surprisal predicts reading times

Baseline:

Fixed Effects

- Same as before

Random Effects

- Same as before
- By Subject Slopes:
  - Hierarchic PTB surprisal
  - Hierarchic GCG surprisal

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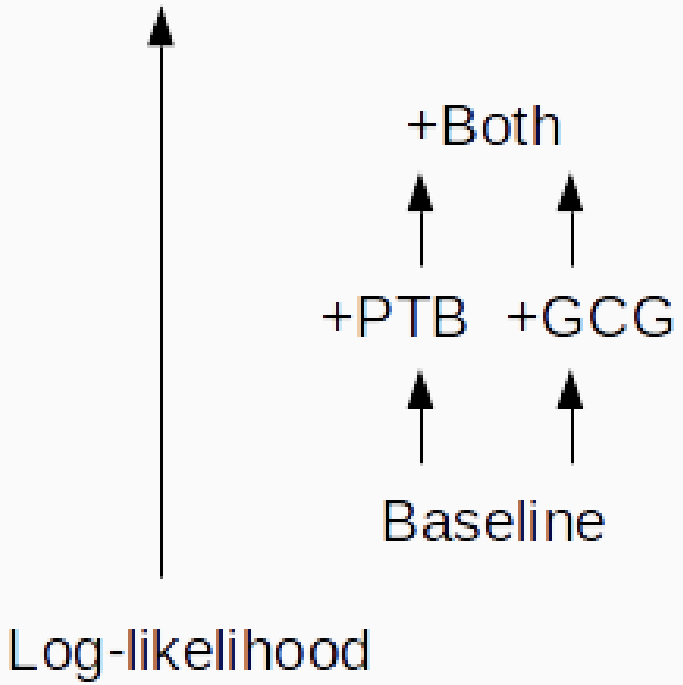
LONG-DISTANCE SURPRISAL PREDICTS READING TIMES



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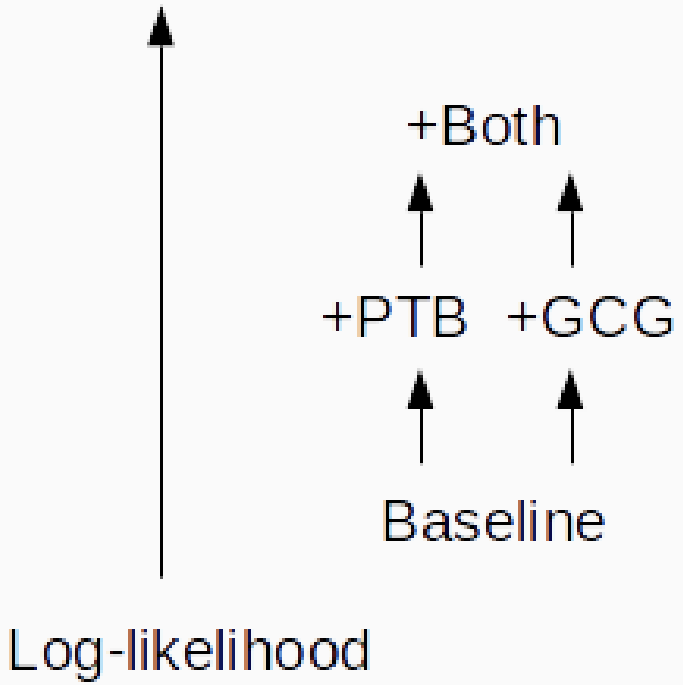

First Pass and Go-Past

Both help independently

Hierarchic syntax predicts reading times over strong linear baseline

DISCUSSION AND CONCLUSIONS

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Long-distance dependencies *do* affect reading times

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Hierarchic syntax predicts reading times over strong linear baseline

Long-distance dependencies *do* affect reading times

Studies should use cumu-*n*-grams in their baselines

Compare to Echo State Networks

FUTURE WORK

Compare to Echo State Networks

Test anticipatory accumulation

QUESTIONS?

Thanks to:

- Stefan Frank
- Attendees of CUNY 2015
- National Science Foundation (DGE-1343012)

CUMU-n-GRAMS PREDICT READING TIMES

First Pass Evaluation (Log-Likelihood):

Base -1212399	
Base+N-gram -1212396 ($p < 0.05$)	**Base+Cumu-n-gram** -1212392 ($p < 0.01$)
Base+Both -1212387 ($p < 0.01$)	**Base+Both** -1212387 ($p < 0.01$)

Comparable with go-past durations

Go-Past Evaluation (Log-Likelihood):

Base -1261582	
Base+*N*-gram -1261577 ($p < 0.01$)	**Base+Cumu-*n*-gram** -1261576 ($p < 0.01$)
Base+Both -1261570 ($p < 0.01$)	**Base+Both** -1261570 ($p < 0.01$)

HIERARCHIC SURPRISAL PREDICTS READING TIMES

First Pass Evaluation (Log-Likelihood):

Base −1212260	
Base+Surp −1212253 ($p < 0.01$)	Base+CumuSurp −1212259
Base+Both −1212253	**Base+Both** −1212253 ($p < 0.01$)

Comparable with go-past durations

Go-Past Evaluation (Log-Likelihood):

Base −1261488	
Base+Surp −1261481 ($p < 0.01$)	Base+CumuSurp −1261487
Base+Both −1261481	**Base+Both** −1261481 ($p < 0.01$)

Long-distance surprisal predicts reading times

First Pass Evaluation (Log-Likelihood):

Base -1212242	
Base+PTB -1212239 ($p < 0.01$)	**Base+GCG** -1212239 ($p < 0.05$)
Base+Both -1212235 ($p < 0.05$)	**Base+Both** -1212235 ($p < 0.01$)

Both help independently

PCFG surprisal helps more with go-past durations

Go-Past Evaluation (Log-Likelihood):

Base -1261474	
Base+PTB -1261468 ($p < 0.01$)	**Base+GCG** -1261470 ($p < 0.01$)
Base+Both -1261465 ($p < 0.01$)	**Base+Both** -1261465 ($p < 0.01$)

Again, both help independently.

FIXED EFFECT COEFFICIENTS FOR BASE+PTB+GCG

Predictor	First Pass		Go-Past	
	coef	t value	coef	t value
sentpos	−2.47	−3.59	−2.82	−3.38
wlen	25.90	8.67	28.98	9.97
prevfix	−30.16	−7.81	−37.42	−11.49
n-gram	−2.39	−1.81	−6.70	−3.36
cumu-*n*-gram	−14.69	−7.36	−11.68	−5.01
rlen	−5.67	−1.31	−12.51	−2.59
surp-GCG	4.97	2.87	5.74	2.73
surp-PTB	4.20	3.23	4.85	3.29