# HIERARCHIC SYNTAX IMPROVES READING TIME PREDICTION

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Previous studies have debated whether humans use hierarchic syntax

## OVERVIEW

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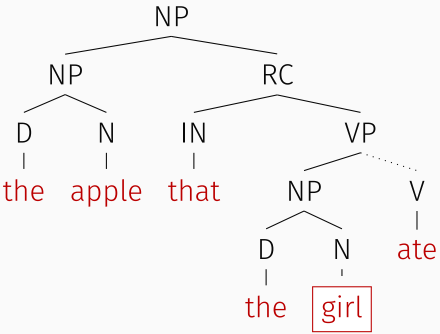

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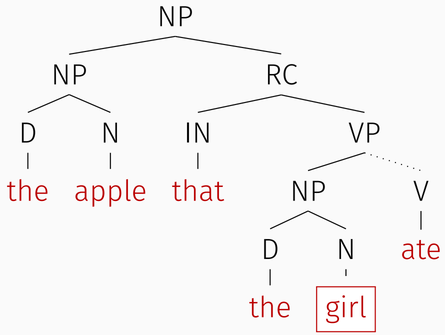


But standard baseline predictors may be deficient

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Baselines can be greatly improved (accumulation)

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Long distance dependencies independently improve model

1 2

The red apple that the $\boxed{\text{girl}}$ ate ...

## Frank & Bod (2011)

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

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Baseline:

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

The red apple that the $\boxed{\text{girl}}$ ate …

$w_1$ $w_2$ $w_3$ $w_4$ $w_5$ $w_6$

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$$\text{The red apple that the } \overbrace{\boxed{\text{girl}}}^{\text{4 chars}}_{w_6} \text{ ate ...}$$

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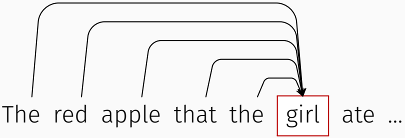


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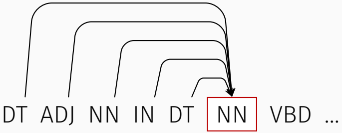


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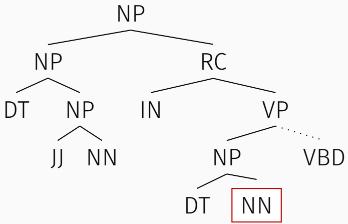


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ESN $=$ ESN + PSG

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

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Also: lexicalized syntax improves PSG fit

# IMPROVED $n$-GRAM BASELINE

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Reading time of *girl* after *red*

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$\boxed{X}$: bigram target $\underline{X}$: bigram condition

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

## Cumulative Bigram Example

Reading time of *girl* after *red*:

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

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

## Cumulative Bigram Example

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

$\boxed{\text{X}}$: 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

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)

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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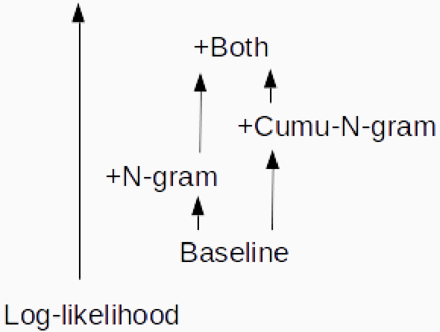
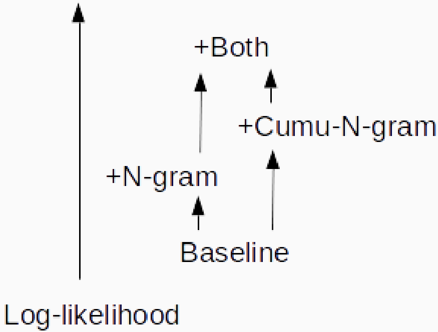
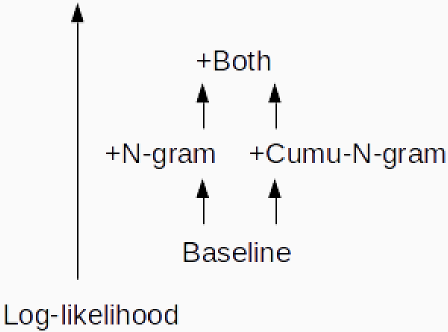



First Pass

# CUMU-$n$-GRAMS PREDICT READING TIMES




First Pass




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)

Baseline:

Fixed Effects

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

# HIERARCHIC SURPRISAL PREDICTS READING TIMES

Baseline:

Fixed Effects

- Same as before
- *N*-grams (5-grams)
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Random Effects

- Same as before
- By Subject Slopes:
  - Hierarchic surprisal
  - Cumu-Hierarchic surprisal

Baseline:

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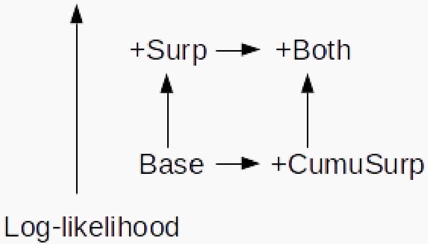


First Pass and Go-Past

## CUMULATIVE SURPRISAL DOESN'T HELP?!

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But… long-distance dependencies should affect reading times!

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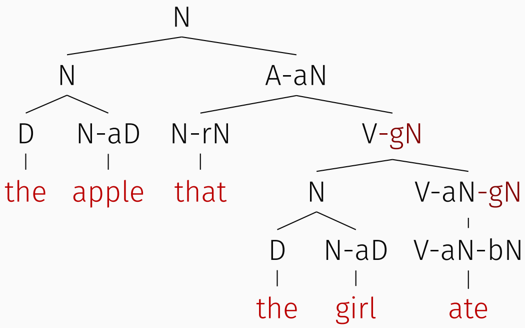
But... long-distance dependencies should affect reading times!

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

Nguyen et al. (2012)



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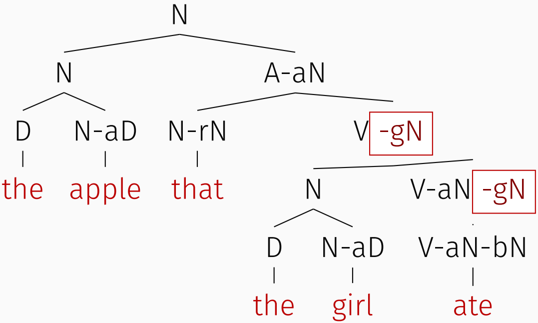

Baseline:

Fixed Effects

- Same as before

Random Effects

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

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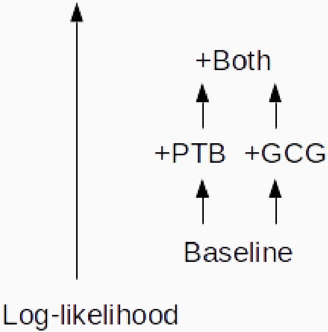


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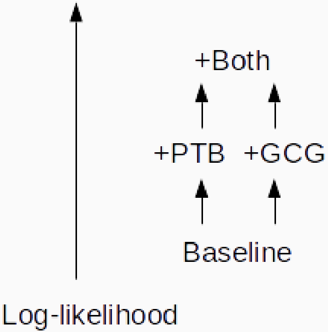


First Pass and Go-Past

Both help independently

Hierarchic syntax predicts reading times over strong linear baseline

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Long-distance dependencies *do* affect reading times

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

# FUTURE WORK

Compare to Echo State Networks

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Test anticipatory accumulation

## QUESTIONS?

Thanks to:

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

First Pass Evaluation (Log-Likelihood):

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

Comparable with go-past durations

Go-Past Evaluation (Log-Likelihood):

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

First Pass Evaluation (Log-Likelihood):

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

Comparable with go-past durations

Go-Past Evaluation (Log-Likelihood):

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

First Pass Evaluation (Log-Likelihood):

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

Both help independently

PCFG surprisal helps more with go-past durations

Go-Past Evaluation (Log-Likelihood):

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

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 |