CONTROLLING FOR CONFOUNDS IN ONLINE MEASURES OF SENTENCE COMPLEXITY

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PREACHING TO THE CHOIR

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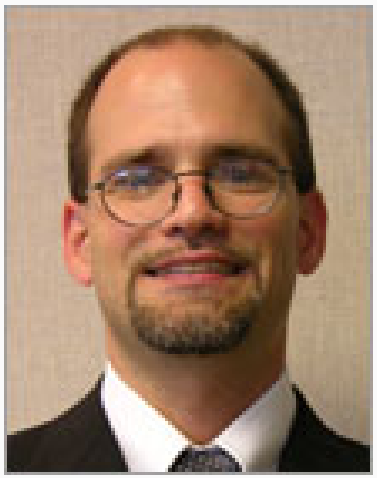
How do people try to account for frequencies?

Case Study 1: Cloze Probabilities
van Schijndel, Culicover, & Schuler (2014)





Pertains to: Pickering & Traxler (2003), inter alia

Ask subjects to generate distribution

Generation/cloze probabilities

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Sentence generation norming:
Write sentences with these words

landed, sneezed, laughed, ...

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Cloze norming:
Complete this sentence

The pilot landed _____

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> The pilot landed the plane.

Generation/cloze probabilities

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Sentence generation norming:
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landed, sneezed, laughed, ...

Cloze norming:
Complete this sentence

The pilot landed the plane. The pilot landed in the field.

Generation/cloze probabilities

Ask subjects to generate distribution

Sentence generation norming:
Write sentences with these words

landed, sneezed, laughed, ...

Cloze norming:
Complete this sentence

NP:The pilot landed the plane. PP: The pilot landed in the field.

25% 40%

Pickering & Traxler (2003) used 6 cloze tasks to determine frequencies

Pickering & Traxler (2003)

Stimuli

(1) That's the plane that the pilot landed behind in the fog.
(2) That's the truck that the pilot landed behind in the fog.

Readers slow down at *landed* in (2)

Pickering & Traxler (2003)

Stimuli

(1) That's the plane that the pilot landed behind in the fog.
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Readers slow down at *landed* in (2)

Suggests they try to link *truck* as the object of *landed* despite:

- *landed* biased for PP complement
  - 40% PP complement
  - 25% NP complement

Pickering & Traxler (2003)

Readers initially adopt a transitive interpretation despite subcat bias

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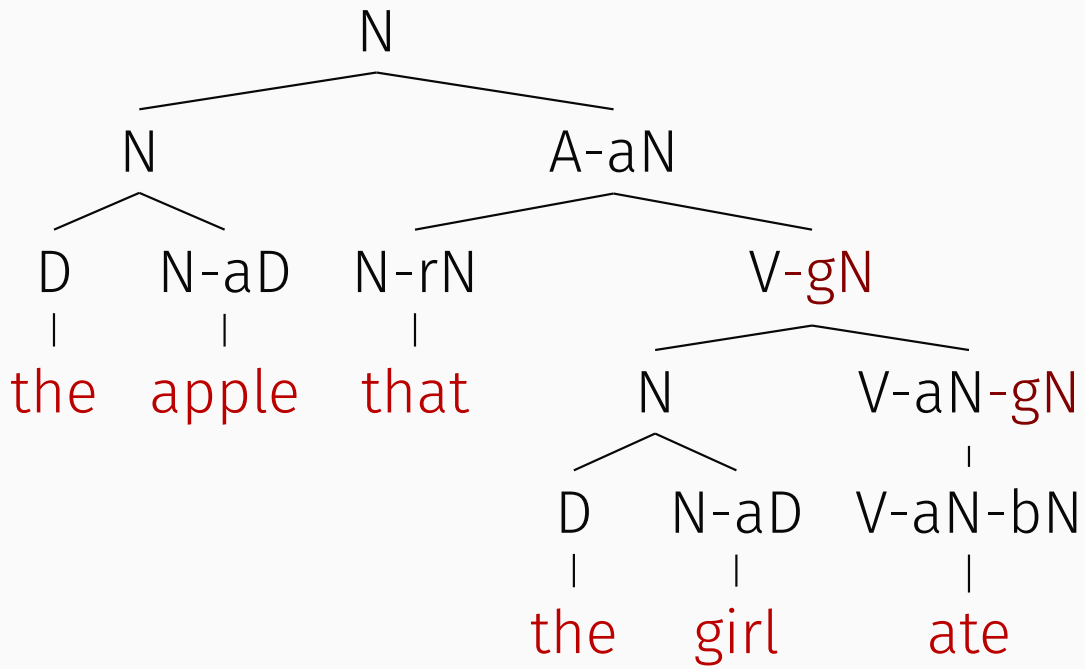
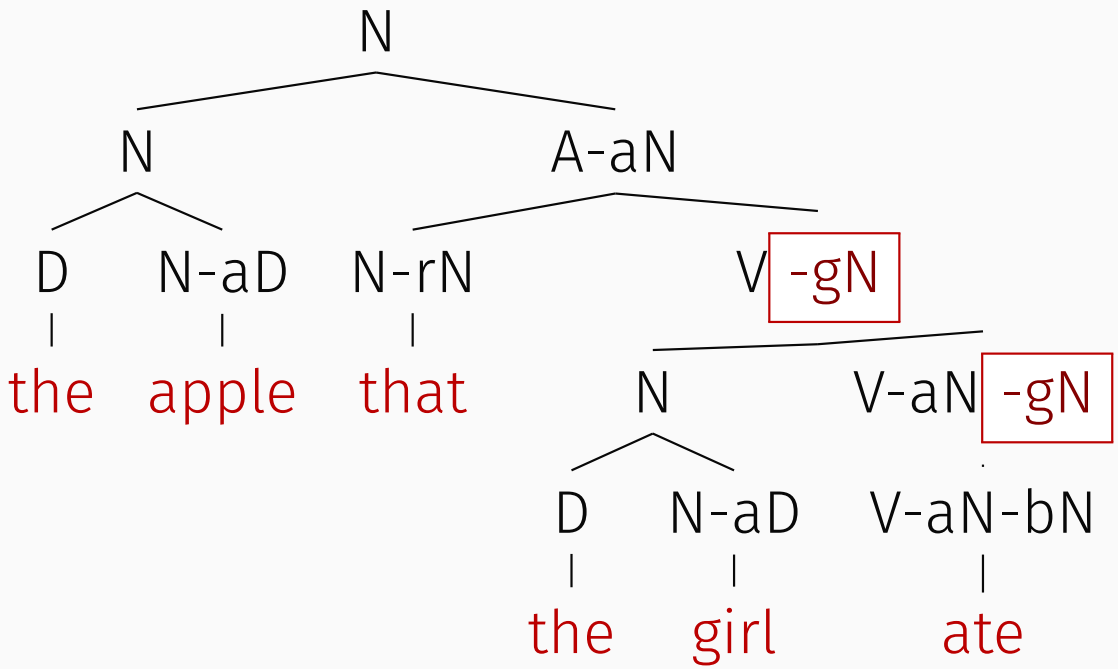
But what about syntactic frequencies?

Nguyen et al. (2012)



GENERALIZED CATEGORIAL GRAMMAR (GCG)

Nguyen et al. (2012)



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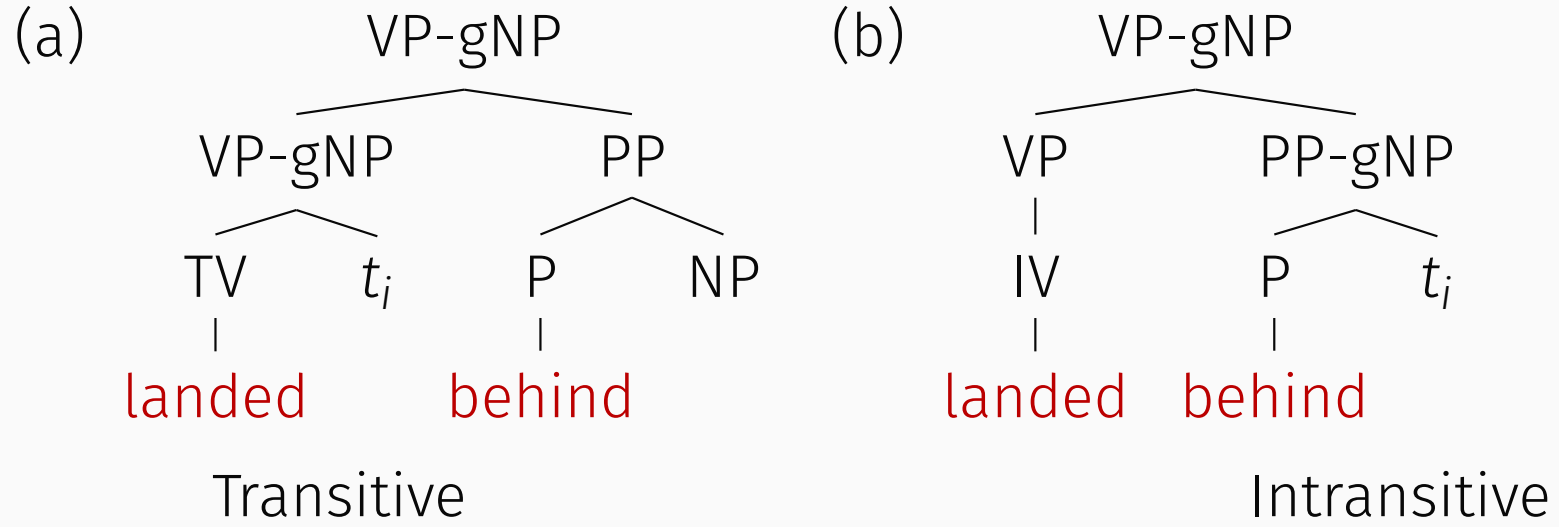

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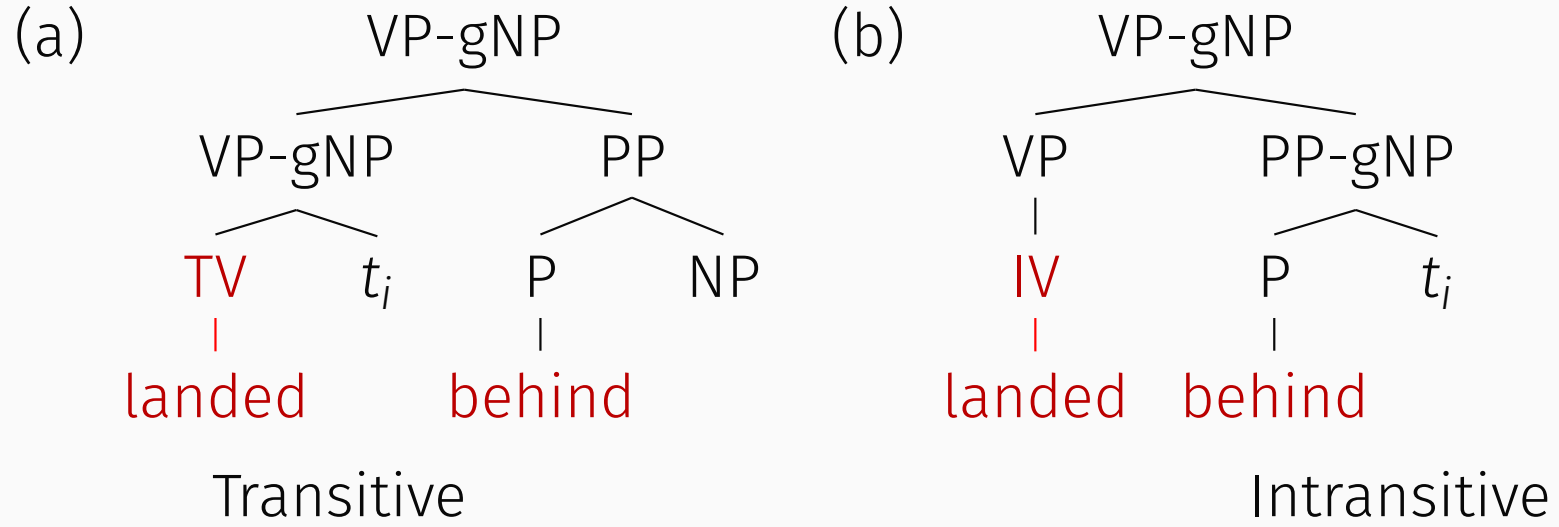

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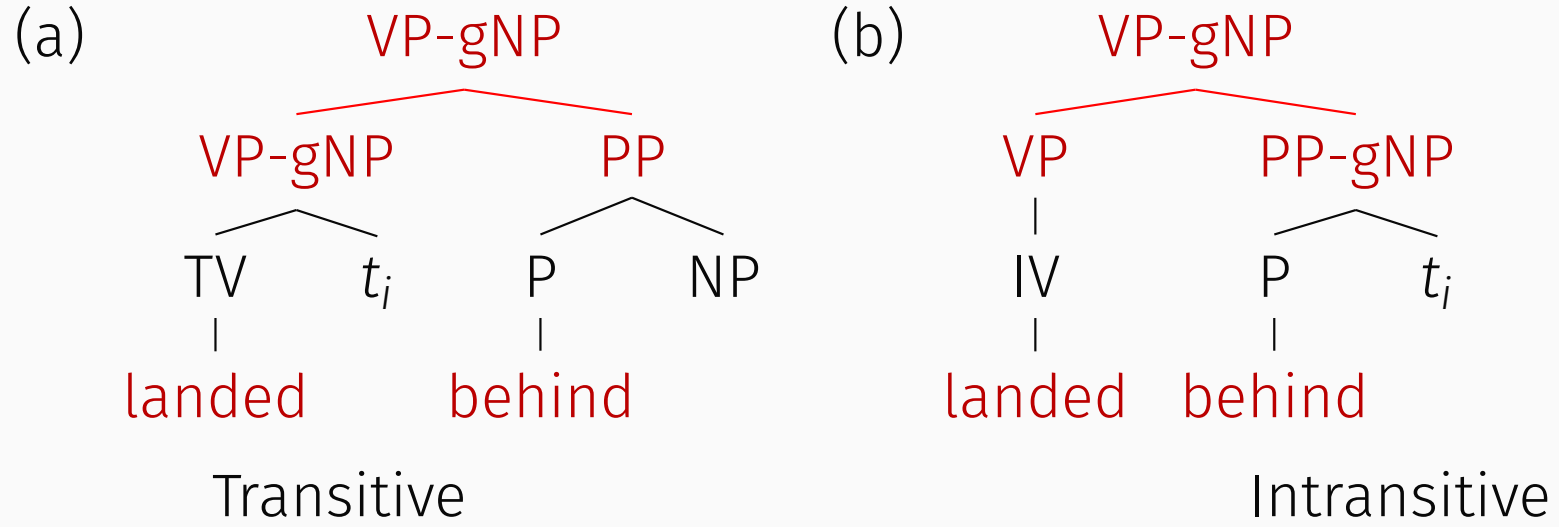

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Transitive interpretation is 300% more likely!

RESULTS: CASE STUDY 1

Subcat processing accounted for by hierarchic syntactic frequencies

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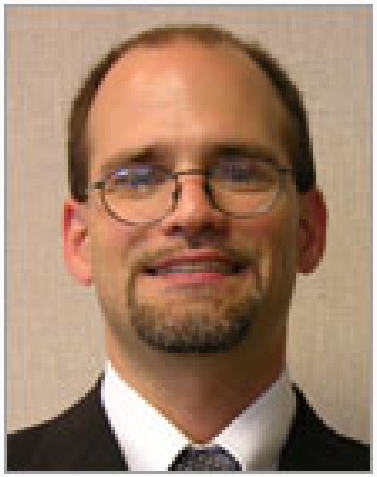
Also applies to heavy-NP shift heuristics (Staub, 2006), unaccusative processing (Staub et al., 2007), etc.

Suggests cloze probabilities are insufficient as a frequency control

But do people use hierarchic syntactic probabilities?

Case Study 2: *N*-grams and Syntactic Probabilities
van Schijndel & Schuler (2015)



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Previous studies have debated whether humans use hierarchic syntax

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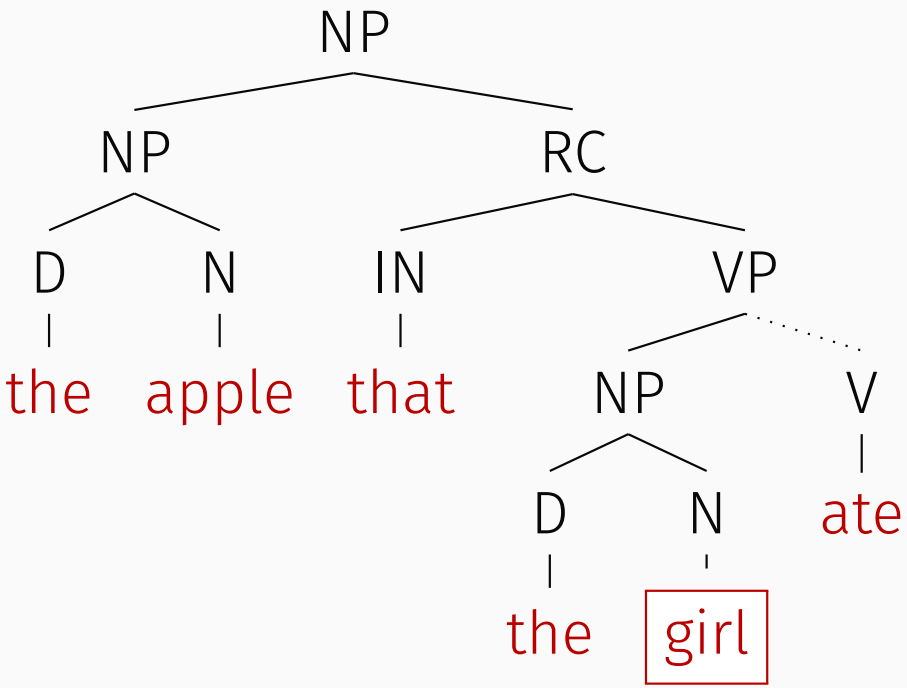

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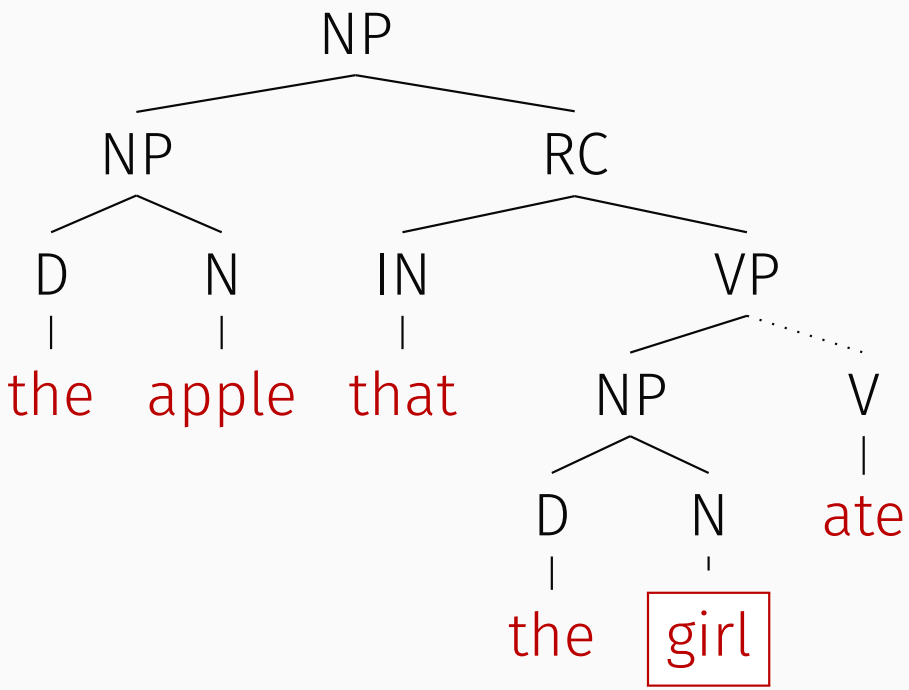

But how robust were their models?

Case study 2: overview

This work shows that:

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N-gram models can be greatly improved (accumulation)

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Hierarchic syntax is still predictive over stronger baseline

Hierarchic syntax not improved by accumulation

Hierarchic syntax in reading?

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

Frank & Bod (2011)

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

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Baseline:

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

Hierarchic syntax in reading?

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

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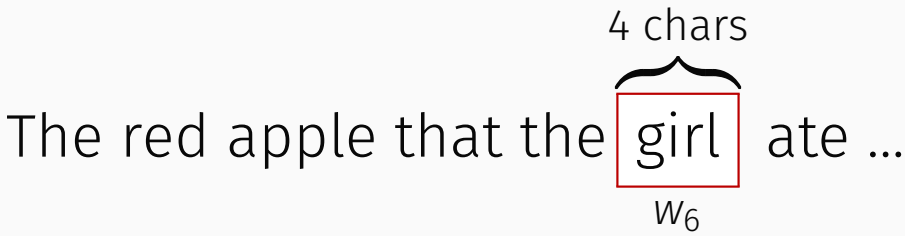

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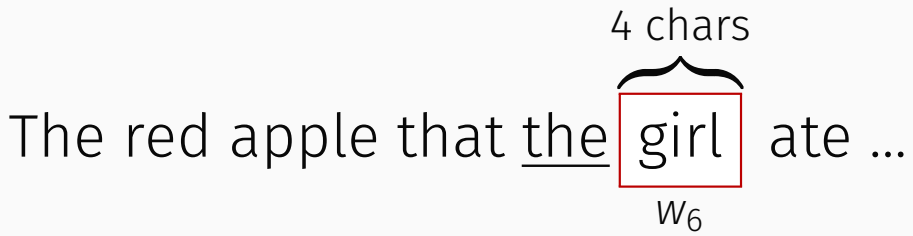

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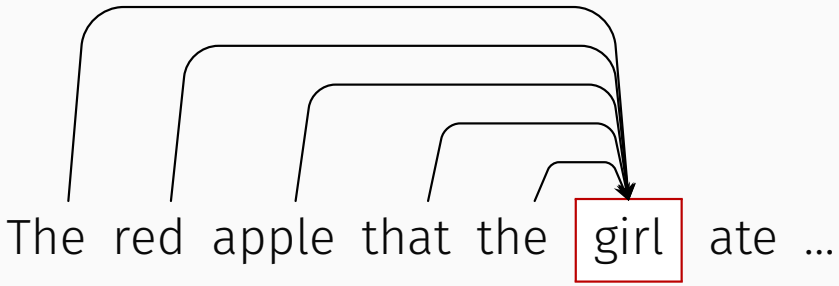

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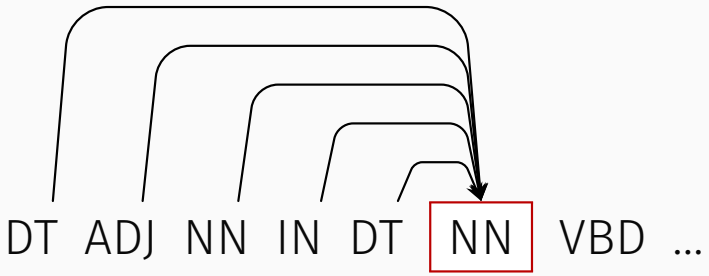

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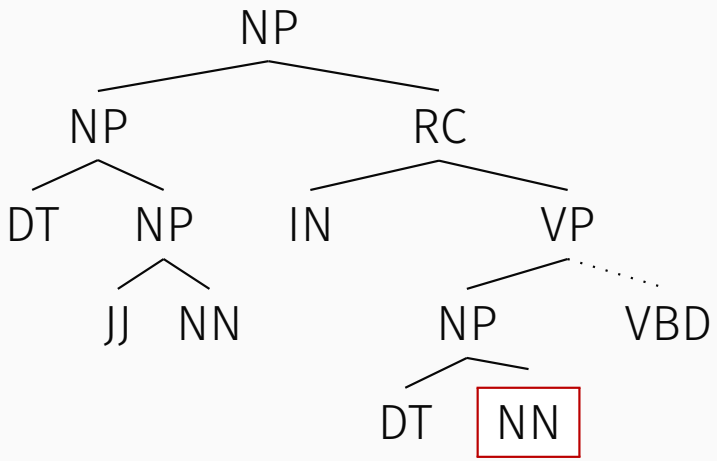

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PSG $<$ ESN + PSG

ESN $=$ ESN + PSG

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

FOSSUM & LEVY (2012)

Replicated Frank & Bod (2011):

PSG $<$ ESN + PSG

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Also: lexicalized syntax improves PSG fit

IMPROVED n-GRAM BASELINE

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

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- Fails to capture entire sequence;

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Reading time of *girl* after *red*

X: bigram target X: bigram condition

- Fails to capture entire sequence;
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- 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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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)

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:
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  - N-grams (5-grams)
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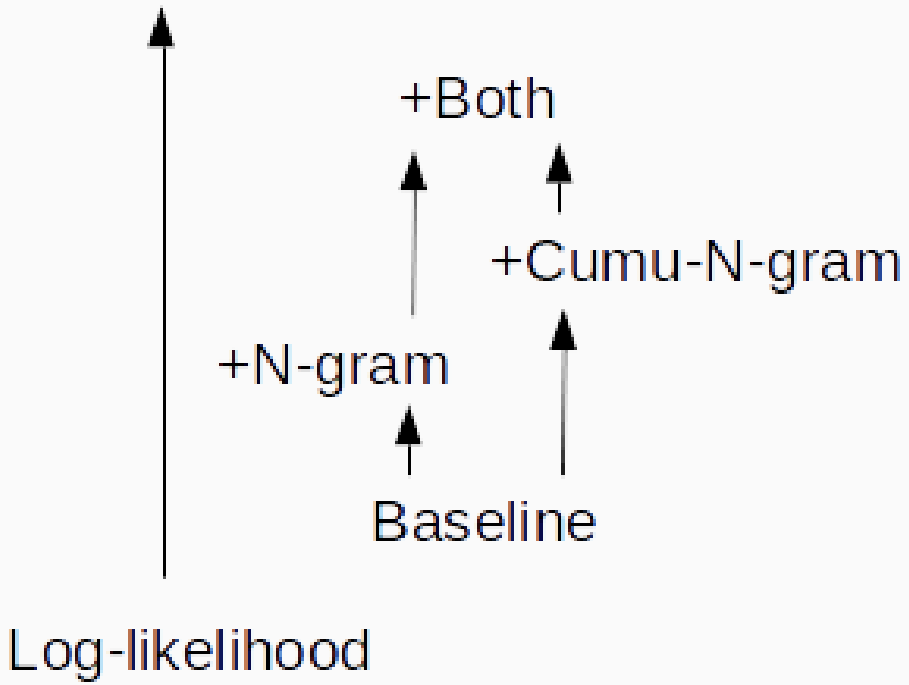

First Pass and Go-Past

Follow-up questions

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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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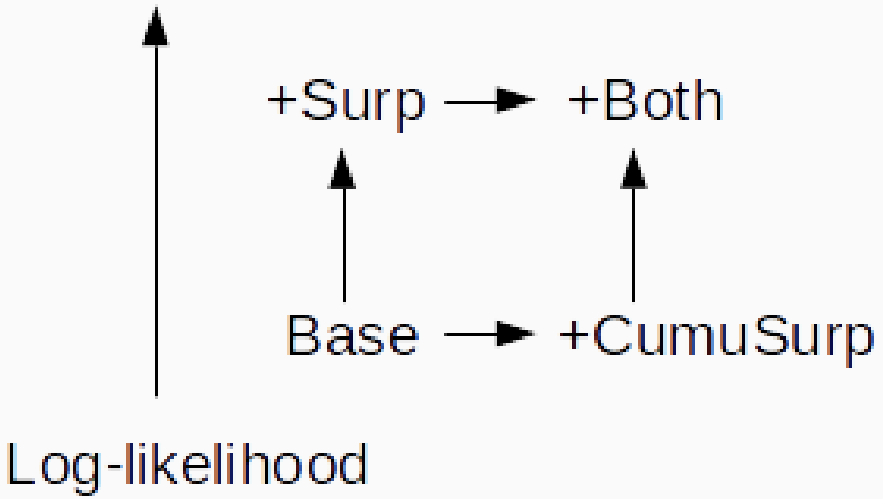

First Pass and Go-Past

Cumulative surprisal doesn't help?!

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Follow-up work shows long distance dependencies independently influence reading times

RESULTS: CASE STUDY 2

Hierarchic syntax predicts reading times over strong linear baseline

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

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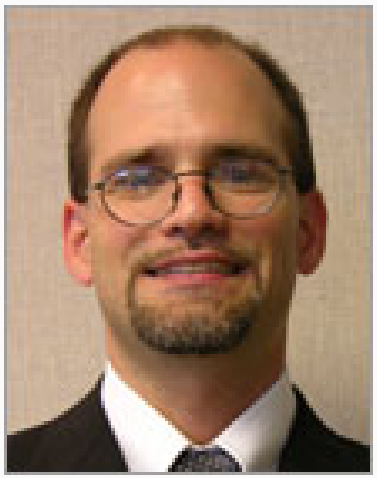
- Cloze probabilities
- *N*-gram frequencies (local and cumulative)
- Hierarchic syntactic frequencies
- Long distance dependency frequencies
- ...(discourse, etc.)

Then we can try to interpret experimental results.

What do we do about convergence?
Is there a way to avoid this explosion of control predictors?

Case Study 3: Evading Frequency Confounds
van Schijndel, Murphy, & Schuler (2015)





MOTIVATING QUESTION

Can we measure memory load without controlling for frequency effects?

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Let's try using MEG.

WHAT IS MEG?

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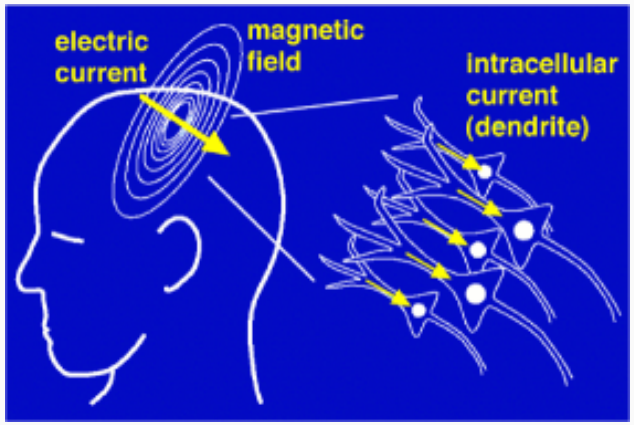
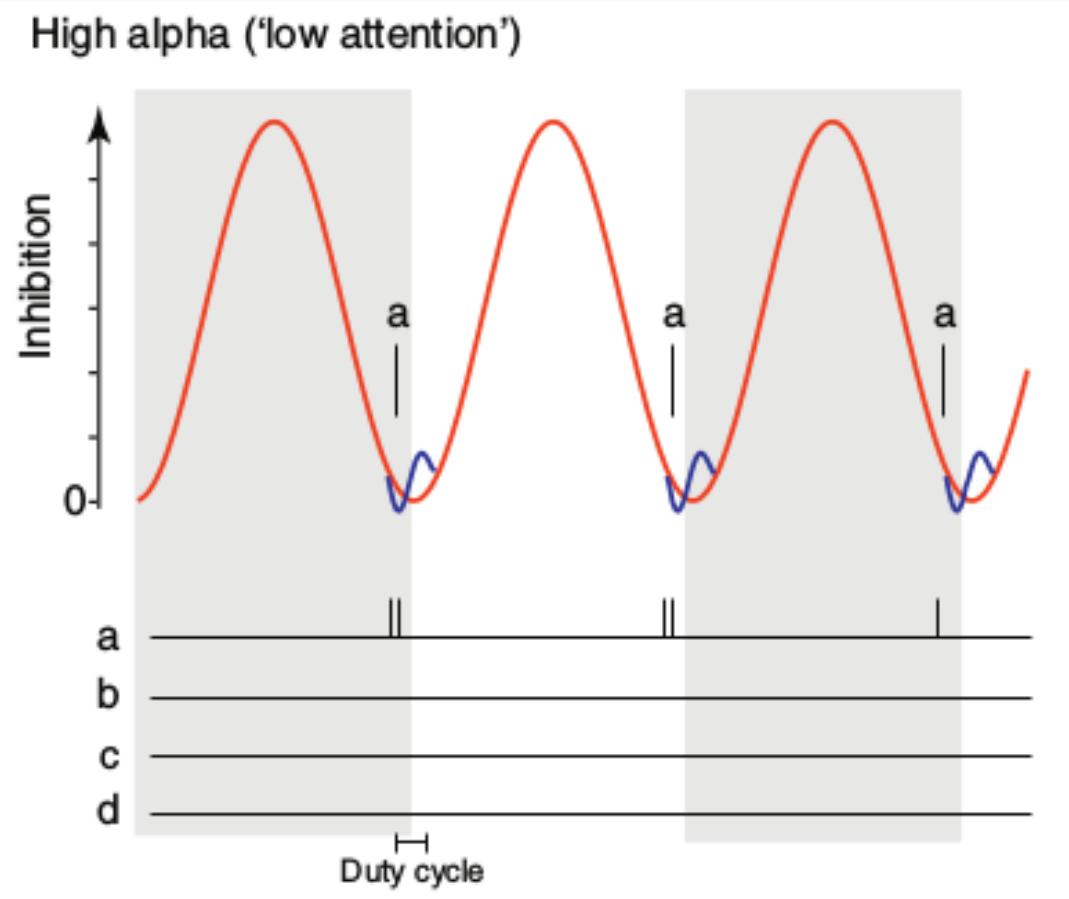


102 locations

HOW MIGHT MEG REFLECT LOAD?



Jensen et al., (2012)

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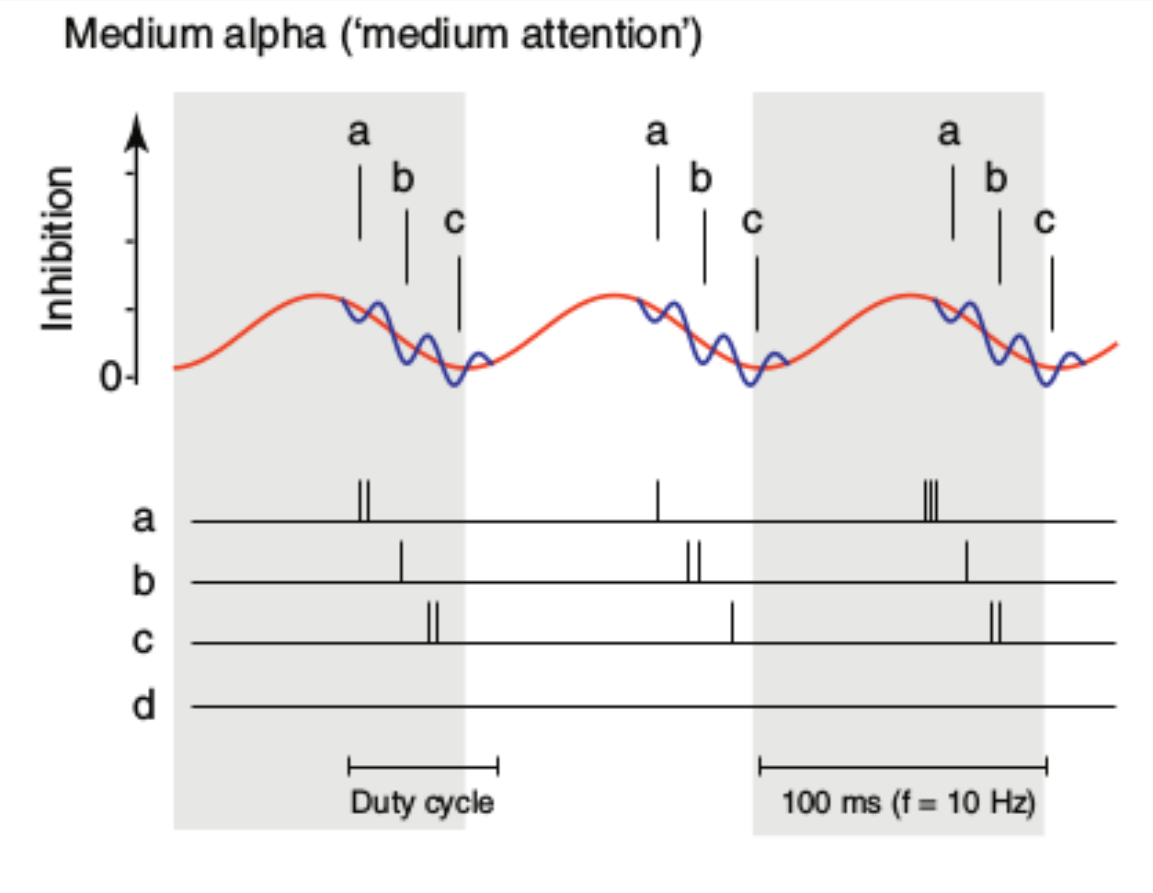

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Look for synchronized firing between sensors (brain regions)

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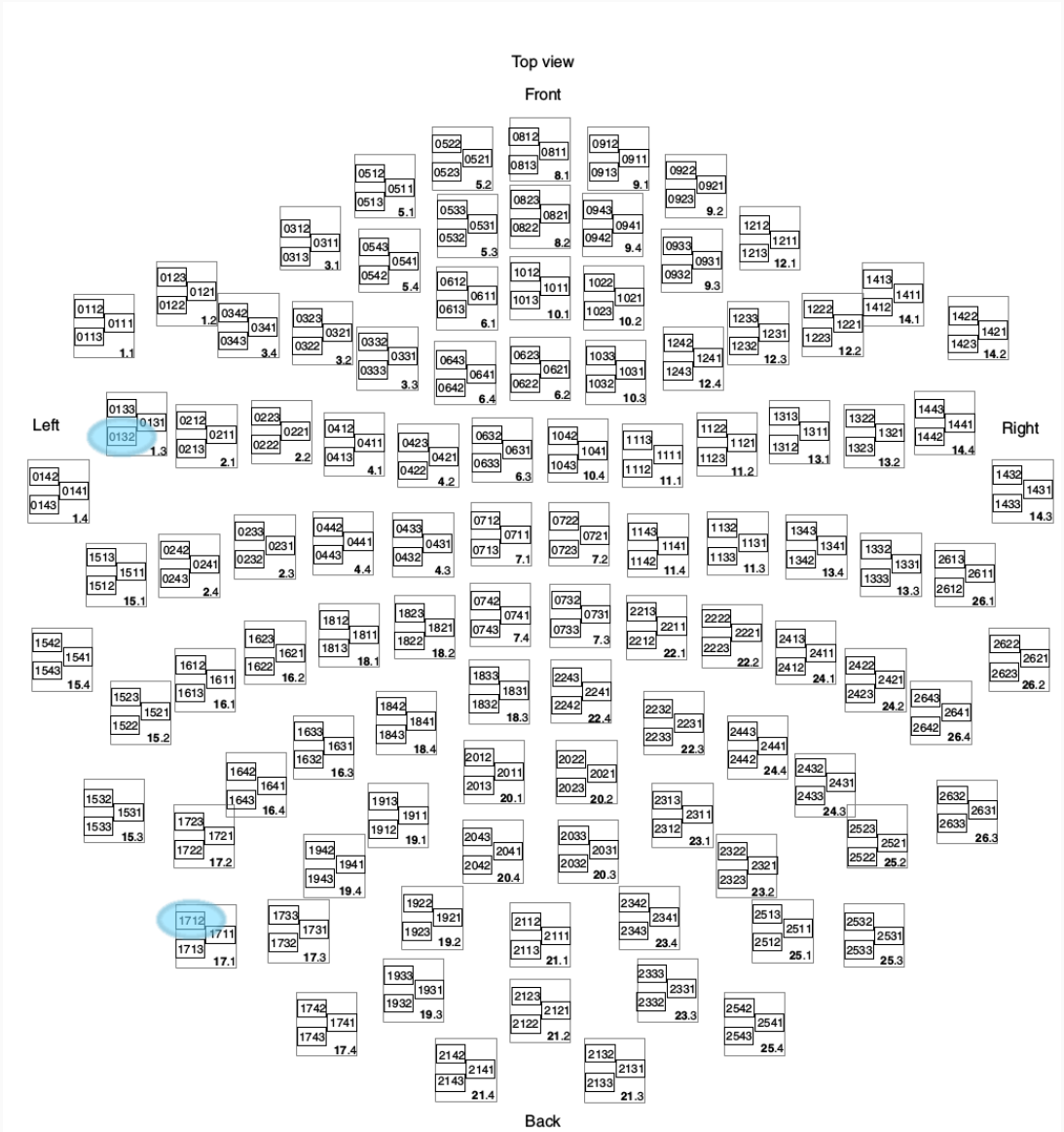

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This study uses *spectral coherence* measurements.

SPECTRAL COHERENCE

$$\text{coherence}(x, y) = \frac{\mathrm{E}[S_{xy}]}{\sqrt{\mathrm{E}[S_{xx}] \cdot \mathrm{E}[S_{yy}]}}$$

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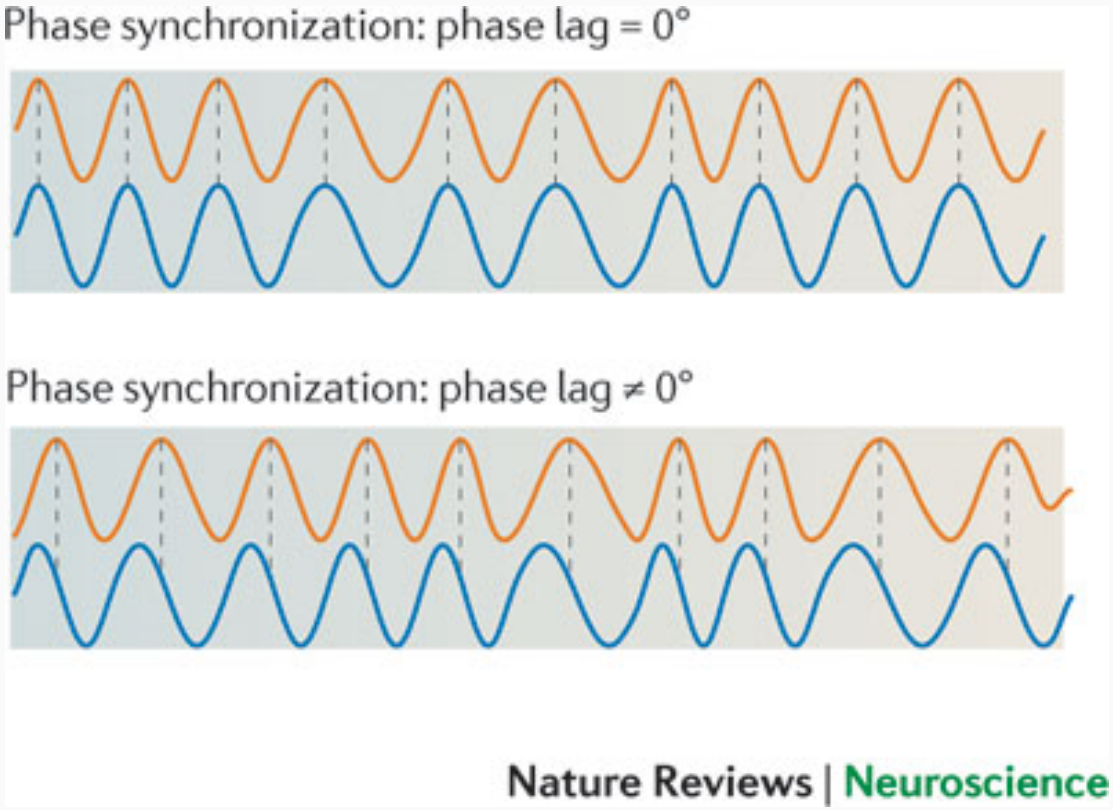
SPECTRAL COHERENCE

$$\text{coherence}(x, y) = \frac{\mathrm{E}[S_{xy}]}{\sqrt{\mathrm{E}[S_{xx}] \cdot \mathrm{E}[S_{yy}]}} \quad \begin{array}{l} \leftarrow \text{cross-correlation} \\ \leftarrow \text{autocorrelations} \end{array}$$

Amount of connectivity (synchronization) not caused by chance

SPECTRAL COHERENCE: PHASE SYNCHRONY



Fell & Axmacher (2011)

AUDIOBOOK MEG CORPUS

Collected 2 years ago at CMU

AUDIOBOOK MEG CORPUS

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3 subjects

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Heart of Darkness, ch. 2
12,342 words
80 (8 x 10) minutes
Synched with parallel audio recording
and forced alignment

AUDIOBOOK MEG CORPUS

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Heart of Darkness, ch. 2
12,342 words
80 (8 x 10) minutes
Synched with parallel audio recording
and forced alignment

306-channel Elekta Neuromag, CMU
Movement/noise correction: SSP, SSS, tSSS
Band-pass filtered 0.01–50 Hz
Downsampled to 125 Hz
Visually scanned for muscle artifacts; none found

MEMORY LOAD VIA CENTER EMBEDDING

*d*1 The cart broke.
*d*2 that the man bought

MEMORY LOAD VIA CENTER EMBEDDING

*d*1 The cart broke.
*d*2 that the man bought

Depth annotations:
van Schijndel et al., (2013) parser
Nguyen et al., (2012) Generalized Categorial Grammar (GCG)

DATA FILTERING

Remove words:

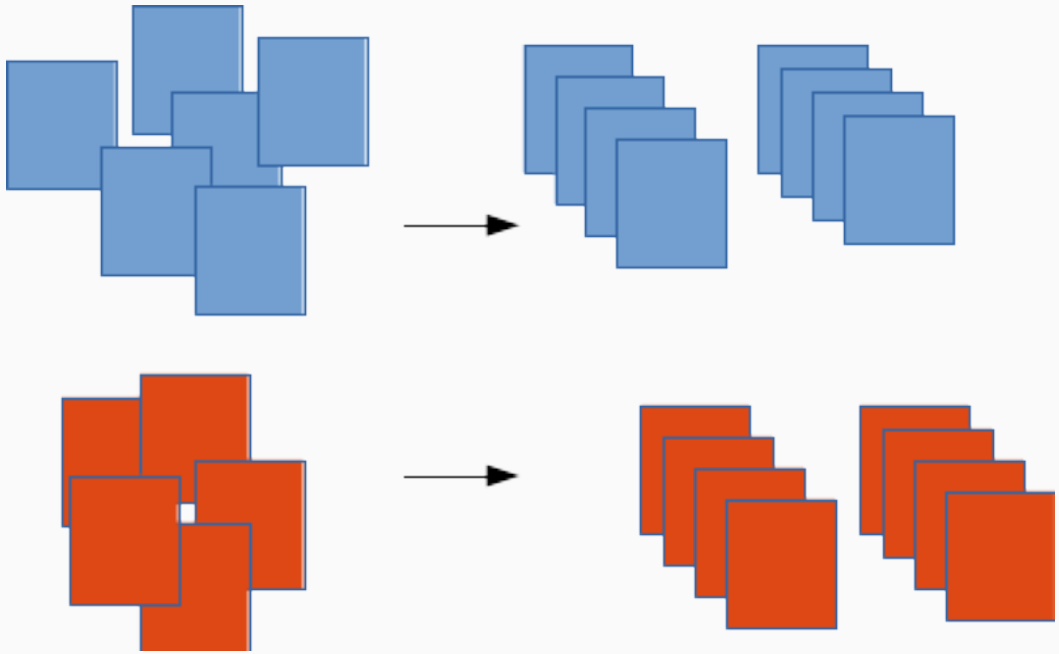
- in short or long sentences (<4 or >50 words)
- that follow a word at another depth
- that fail to parse

Partition data:

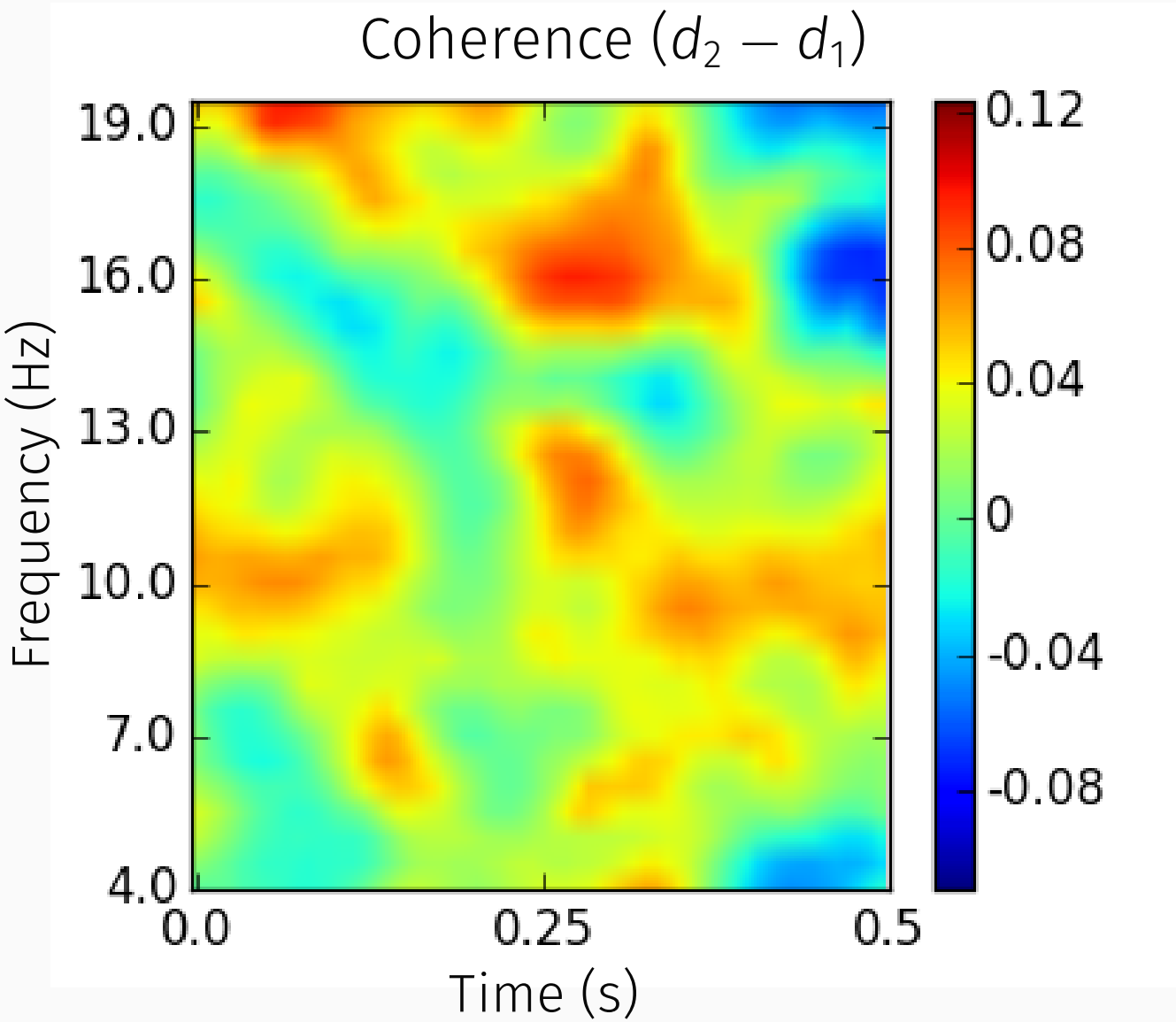
- Dev set: One third of corpus
- Test set: Two thirds of corpus

COMPUTE COHERENCE

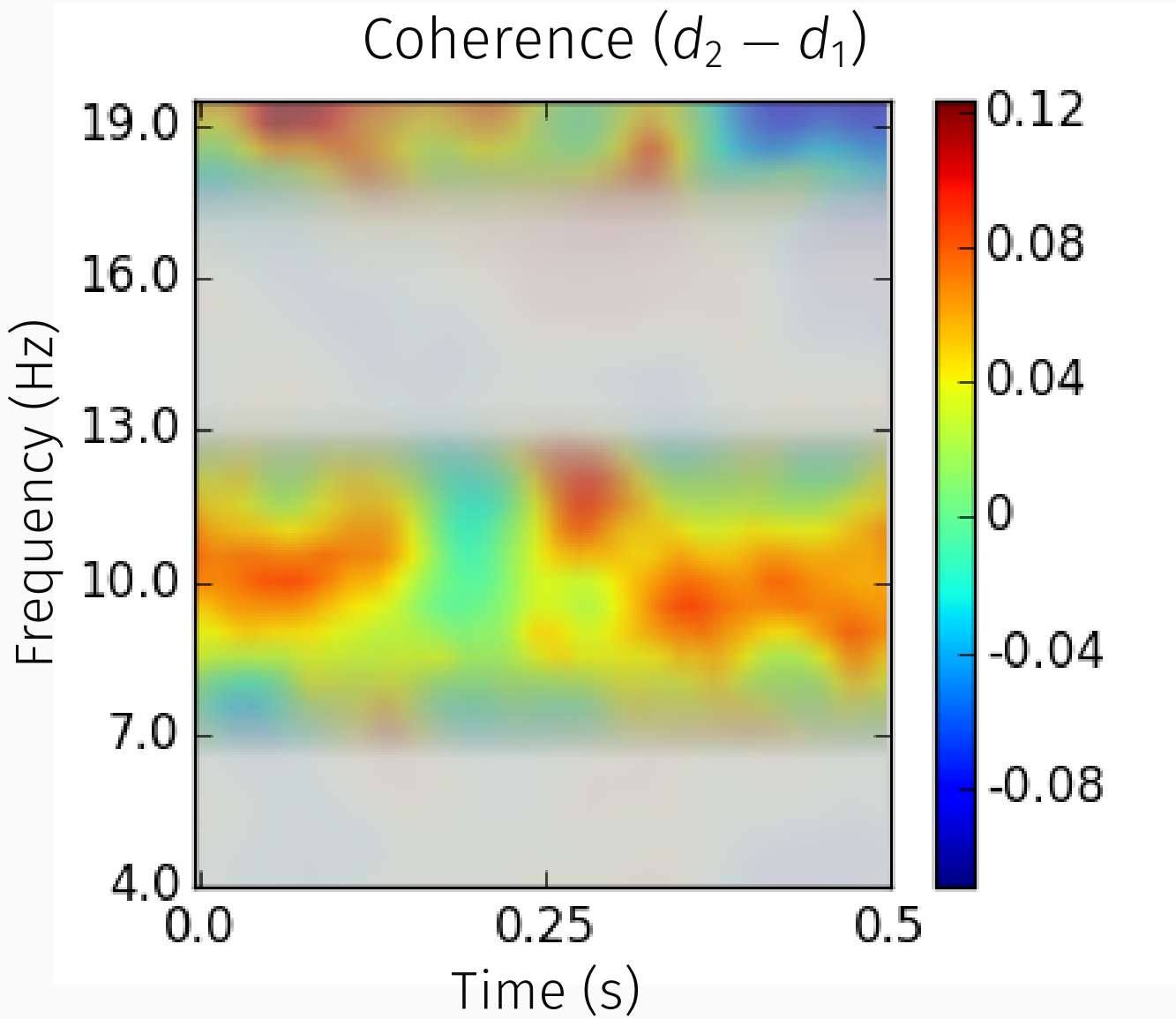
- Group by factor
- Compute coherence over subsets of 4 epochs



DEV COHERENCE



DEV COHERENCE +VARIANCE



POSSIBLE CONFOUNDS?

Sentence position

Unigram, Bigram, Trigram: COCA logprobs

PCFG surprisal: parser output

DEV RESULTS

Factor	p-value
Unigram	0.941
Bigram	0.257
Trigram	0.073
PCFG Surprisal	0.482
Sentence Position	0.031
Depth	0.005

Depth 1 (40 items) Depth 2 (1118 items)

TEST RESULTS

Factor	p-value
Unigram	0.6480
Bigram	0.7762
Trigram	0.0264
PCFG Surprisal	0.3295
Sentence Position	0.4628
Depth	0.00002

Depth 1 (86 items) Depth 2 (2142 items)

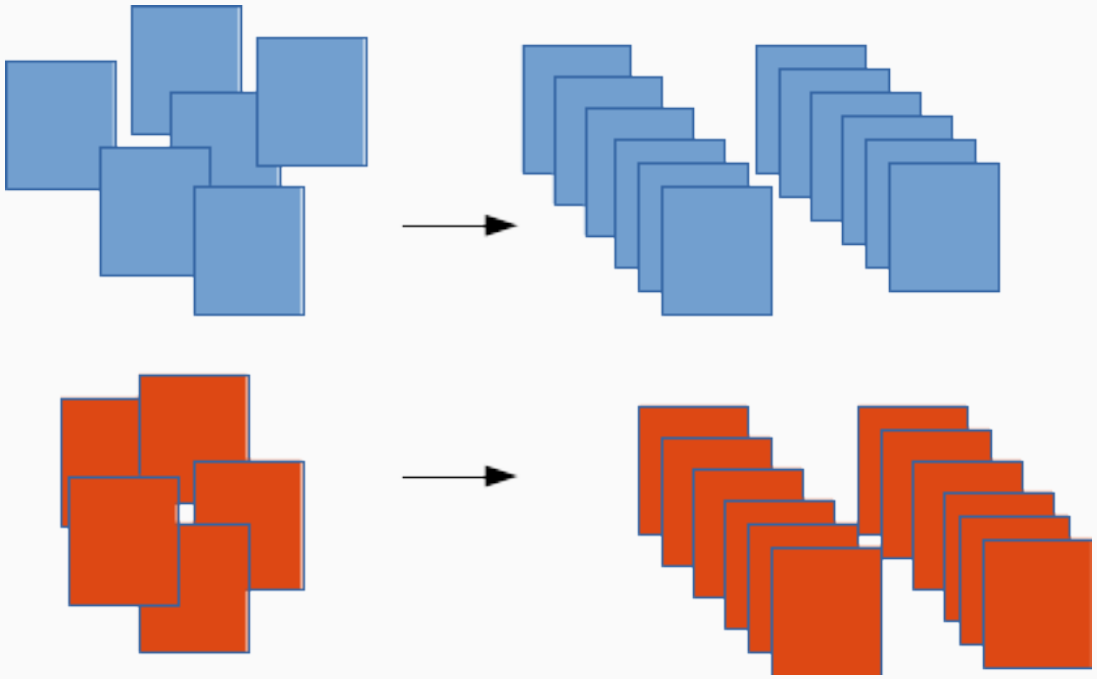
TEST RESULTS

Factor	p-value
Unigram	0.6480
Bigram	0.7762
Trigram	0.0264
PCFG Surprisal	0.3295
Sentence Position	0.4628
Depth	0.00002

Bonferroni correction removes trigrams, but ...

COMPUTE COHERENCE: INCREASED RESOLUTION

- Group by factor
- Compute coherence over subsets of 6 epochs



TEST RESULTS: INCREASED RESOLUTION

Factor	p-value
Trigram	0.3817
Depth	0.0046

Depth 1 (57 items) Depth 2 (1428 items)

RESULTS: CASE STUDY 3

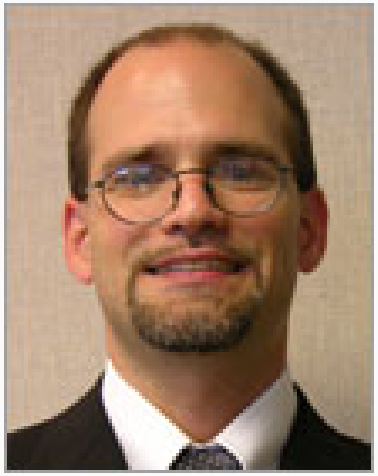
- Memory load is reflected in MEG connectivity
- Common confounds do not pose problems for oscillatory measures

CONCLUSIONS

- Cloze probabilities are insufficient as frequency control
- Hierarchic syntactic frequencies strongly influence processing
- Reading time studies need to use local *and* cumulative *n*-grams
- Oscillatory analyses could avoid control predictor explosion

ACKNOWLEDGEMENTS





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THANKS! QUESTIONS?

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- Reading time studies need to use local *and* cumulative *n*-grams
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