FREQUENCIES THAT MATTER IN SENTENCE PROCESSING

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FREQUENCIES ARE IMPORTANT

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Occurrence frequencies describe languages well

- Zipf
- Statistical NLP (esp. vector spaces)

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Occurrence frequencies have major influence on sentence processing

- Behavioral measures (e.g., reading times)
- Processing measures (e.g., ERPs)
- Uniform Information Density
- Saarland SFB-1102

Linguists must control for frequencies to do research

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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

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Sentence generation norming:
Write sentences with these words

landed, sneezed, laughed, …

generation/cloze probabilities

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Cloze norming:
Complete this sentence

The pilot landed _____

GENERATION/CLOZE PROBABILITIES

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

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

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

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Sentence generation norming:
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Cloze norming:
Complete this sentence

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

25%   40%

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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)

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)

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

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

Readers initially adopt a transitive interpretation despite subcat bias

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∴ Early-attachment processing heuristic

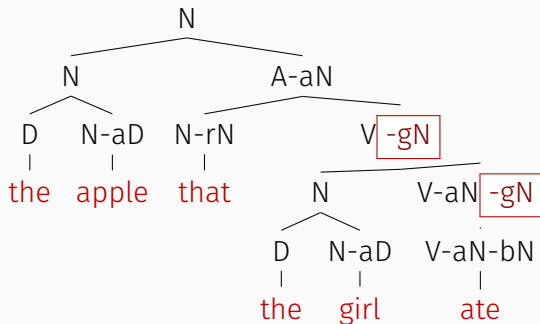Readers initially adopt a transitive interpretation despite subcat bias

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But what about syntactic frequencies?
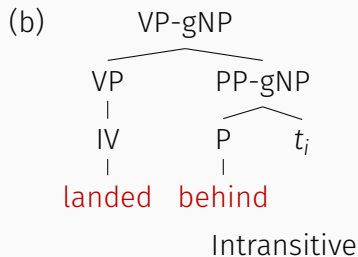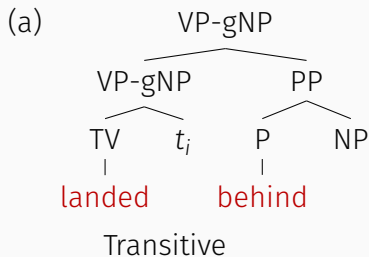
Nguyen et al. (2012)

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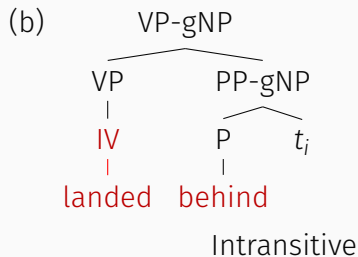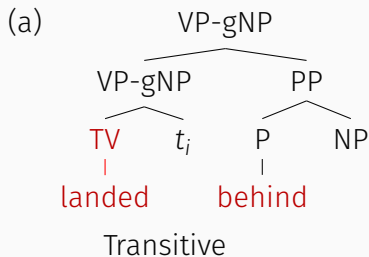## PICKERING & TRAXLER (2003)

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	(a) VP-gNP		(b) VP-gNP

Transitive

Intransitive

PICKERING & TRAXLER (2003)
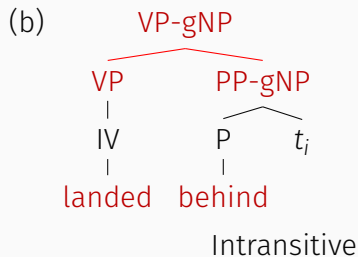
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(a)

VP-gNP
├── VP-gNP
│   ├── TV — landed
│   └── t_i
└── PP
    ├── P — behind
    └── NP

Transitive

(b)

VP-gNP
├── VP
│   └── IV — landed
└── PP-gNP
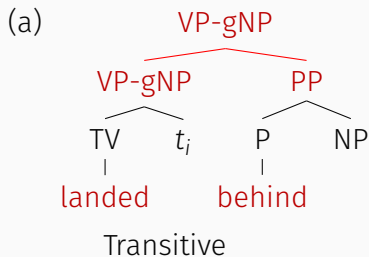   ├── P — behind
    └── t_i

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Transitive interpretation is 300% more likely!

Subcat processing accounted for by hierarchic syntactic frequencies
Early attachment heuristic unnecessary

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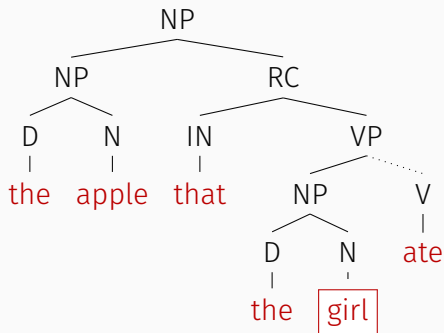But do people use hierarchic syntactic probabilities?

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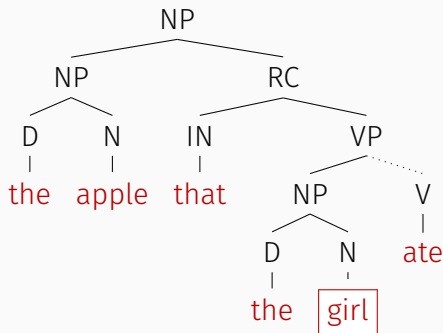van Schijndel & Schuler (2015)

Pertains to: Frank & Bod (2011), inter alia

Previous studies have debated whether humans use hierarchic syntax

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But how robust were their models?

This work shows that:

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Hierarchic syntax is still predictive over stronger baseline

(Long distance dependencies independently improve model)

The red apple that the girl ate ...

FRANK & BOD (2011)

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

FRANK & BOD (2011)

Baseline:

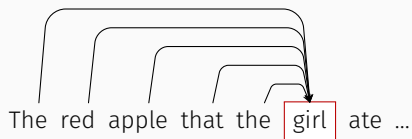- Sentence Position
- Word length
- *N*-grams (Unigram, bigram)

The red apple that the $\boxed{\text{girl}}$ ate ...
w_1 w_2 w_3 w_4 w_5 w_6

FRANK & BOD (2011)

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4 chars

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

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$$\overbrace{}^{\text{4 chars}}$$

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HIERARCHIC SYNTAX IN READING?

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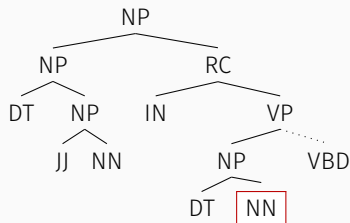
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Test POS Predictors:

- Echo State Network (ESN)
- Phrase Structure Grammar (PSG)

DT ADJ NN IN DT NN VBD ...

FRANK & BOD (2011)

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

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Replicated Frank & Bod (2011):
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Also: lexicalized syntax improves PSG fit

IMPROVED *n*-GRAM BASELINE

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- *N*-grams trained on WSJ, Dundee, BNC (or less)

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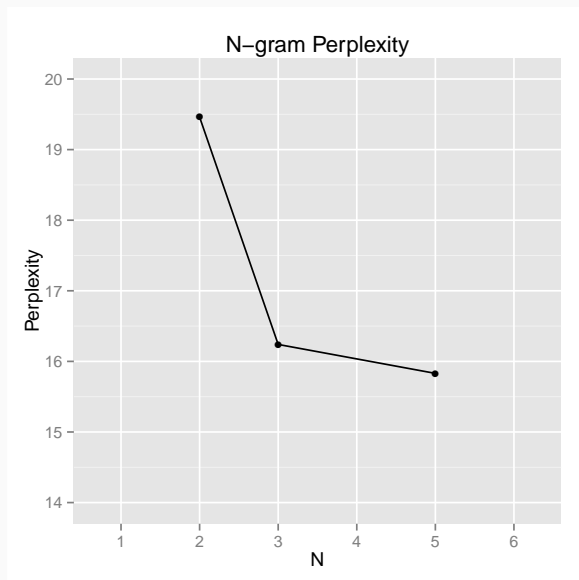
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BIGRAM EXAMPLE

Reading time of *girl* after *red*

The re̲d apple that the̲ girl ate ...

region

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

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1 2

region

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Reading time of *girl* after *red*

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$\underbrace{\qquad\qquad\qquad}_{\text{region}}$

X : bigram target   <u>X</u>: 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 <u>red</u> [apple] [that] [the] [girl] ate …

$\boxed{\text{X}}$: bigram targets   <u>X</u>: bigram conditions

Cumulative Bigram Example

Reading time of *girl* after *red*:

The <u>red</u> [apple] [that] [the] [girl] ate …

$\boxed{\text{X}}$: bigram targets   <u>X</u>: bigram conditions

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

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- Cumulative and Non-cumulative

EVALUATION

Dundee Corpus (Kennedy et al., 2003)

- 10 subjects
- 2,388 sentences
- First pass durations ($\sim$ 200,000)
- Go-past durations ($\sim$ 200,000)

Exclusions:

- Unknown words (<5 tokens)
- First and last of each 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)
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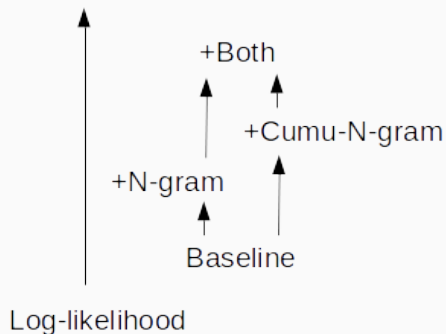
First Pass and Go-Past

- Is hierarchic surprisal useful over the better baseline?

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  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)

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

Hierarchic syntax predicts reading times over strong linear baseline

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Long-distance dependencies help over hierarchic syntax

Hierarchic syntax predicts reading times over strong linear baseline

Long-distance dependencies help over hierarchic syntax

Studies should use cumu-n-grams in their baselines

WHAT DOES THIS MEAN FOR OUR MODELS?

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- *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)

Can we measure memory load with fewer controls?

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Why do so many factors influence results?

Can we measure memory load with fewer controls?

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Do the factors become separable in another space?

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Why do so many factors influence results?
  Low dimensionality measures.

Do the factors become separable in another space?
  Let's try using MEG.
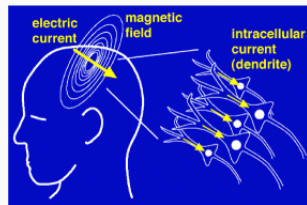
102 locations
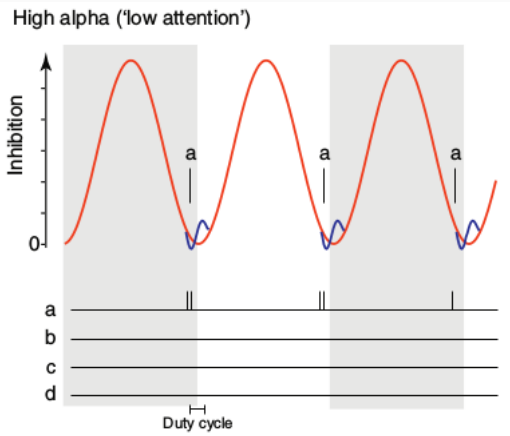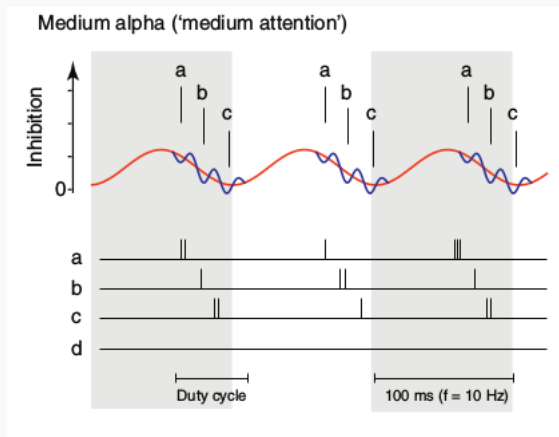
Jensen et al., (2012)

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Look for synchronized firing between sensors (brain regions)
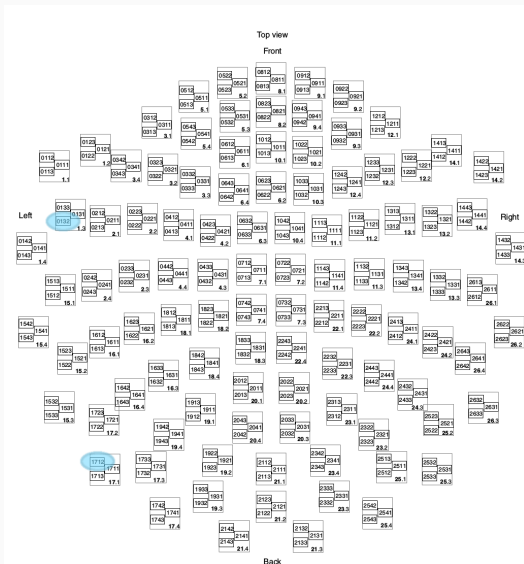
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This study uses *spectral coherence* measurements.

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

SPECTRAL COHERENCE

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

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Amount of connectivity (synchronization) not caused by chance
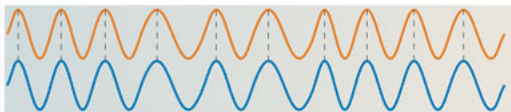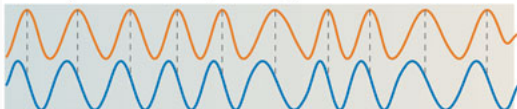
Fell & Axmacher (2011)

AUDIOBOOK MEG CORPUS

Collected 2 years ago at CMU

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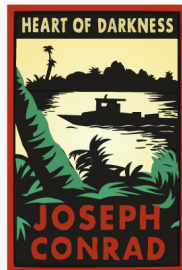
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306-channel Elekta Neuromag, CMU
Movement/noise correction: SSP, SSS, tSSS
Band-pass filtered 0.01–50 Hz
Downsampled to 125 Hz
Visually scanned for muscle artifacts; none found

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

MEMORY LOAD VIA CENTER EMBEDDING

*d*1 The cart   broke.
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Depth annotations:
van Schijndel et al., (2013) parser
Nguyen et al., (2012) Generalized Categorial Grammar (GCG)

DATA FILTERING
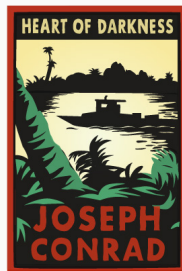
Remove words:

- 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

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

Coherence $(d_2 - d_1)$
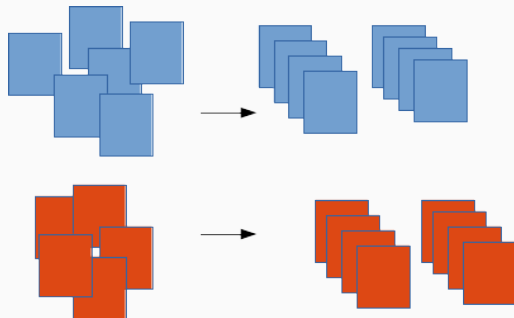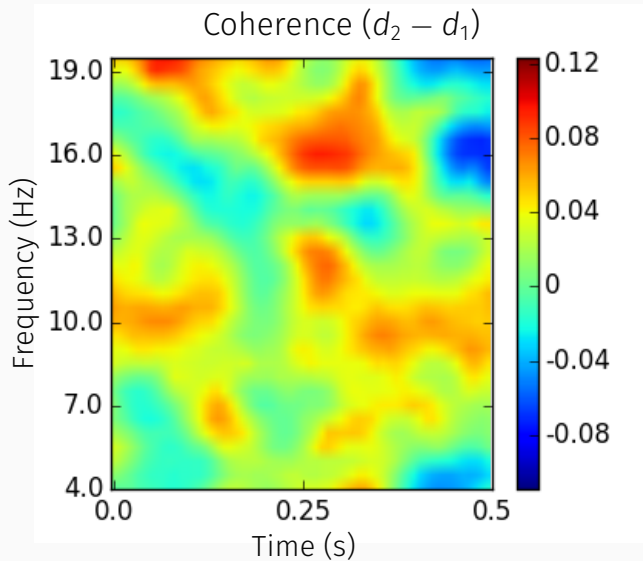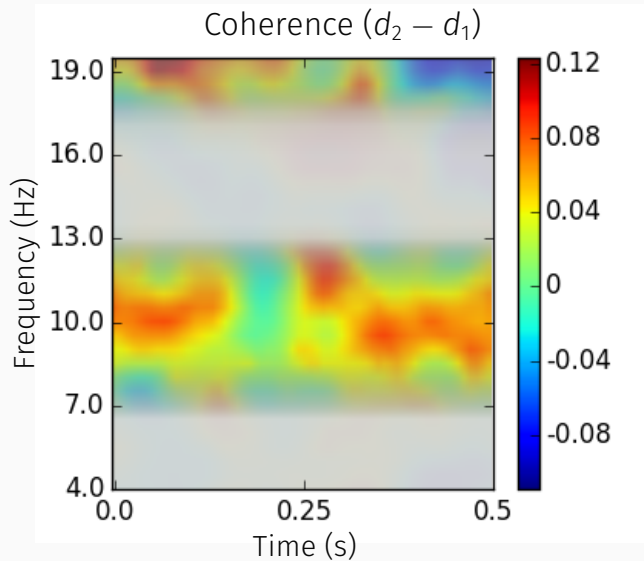
Sentence position

Unigram, Bigram, Trigram: COCA logprobs

PCFG surprisal: parser output

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)

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)

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 …

- Group by factor
- Compute coherence over subsets of 6 epochs
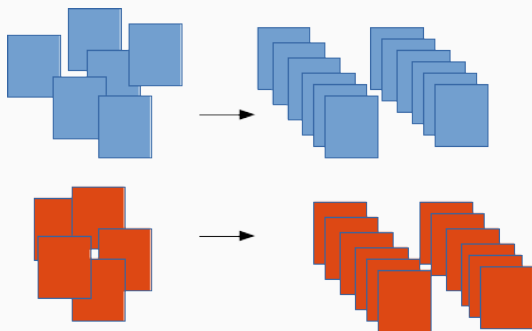
Factor	p-value
Trigram	0.3817
Depth	0.0046

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

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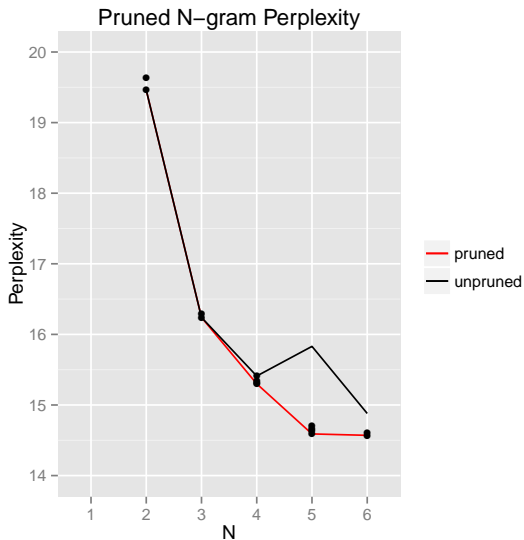- Common confounds do not pose problems for oscillatory measures

- 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

- Cloze probabilities are insufficient as frequency control
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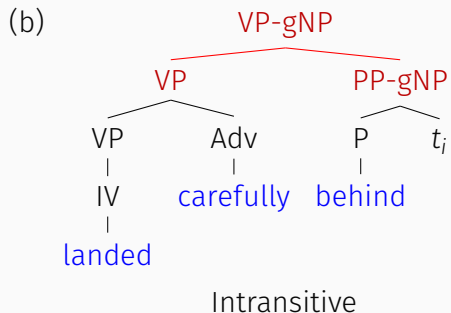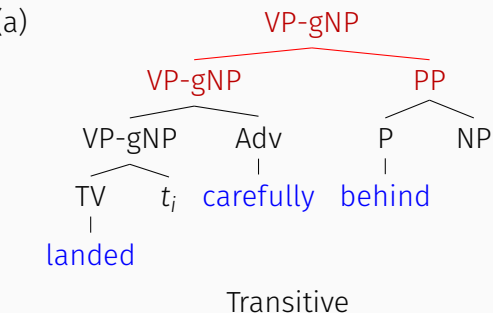- Oscillatory analyses could avoid control predictor explosion

How probable is each subtree?

Wall Street Journal (WSJ) section of the Penn Treebank:

(a) Transitive

(b) Intransitive

How probable is each subtree?
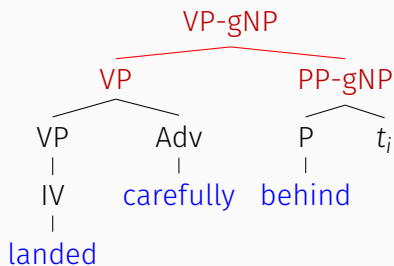
Wall Street Journal (WSJ) section of the Penn Treebank:

(a) Transitive — 0.17

(b) Intransitive — 0.01

What is the probability of each interpretation?

P(syntactic configuration)·P(generating the verb from that tree)

$$P(\text{Transitive}) = P(\text{VP-gNP}\rightarrow\text{VP-gNP PP}) \cdot P(verb \mid \text{TV}) \qquad (1)$$

$$P(\text{Intransitive}) = P(\text{VP-gNP}\rightarrow\text{VP PP-gNP}) \cdot P(verb \mid \text{IV}) \qquad (2)$$

What is the probability of each interpretation?

P(syntactic configuration)·P(~~generating the verb from that tree~~)

P(subcat bias)/P(preterminal prior)

$$P(\text{Transitive}) = P(\text{VP-gNP} \rightarrow \text{VP-gNP PP}) \cdot P(verb \mid \text{TV}) \qquad (1)$$

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MODEL

What is the probability of each interpretation?

P(syntactic configuration)·P(subcat bias)/P(preterminal prior)

$$P(\text{Transitive}) = P(\text{VP-gNP} \rightarrow \text{VP-gNP PP}) \cdot P(verb \mid \text{TV}) \qquad (1)$$

$$\propto P(\text{VP-gNP} \rightarrow \text{VP-gNP PP}) \cdot \frac{P(\text{TV} \mid verb)}{P(\text{TV})}$$

$$P(\text{Intransitive}) = P(\text{VP-gNP} \rightarrow \text{VP PP-gNP}) \cdot P(verb \mid \text{IV}) \qquad (2)$$

$$\propto P(\text{VP-gNP} \rightarrow \text{VP PP-gNP}) \cdot \frac{P(\text{IV} \mid verb)}{P(\text{IV})}$$

What are the preterminal priors?

Relative prior probability from the WSJ:

$$P(TV):P(IV) = 2.6:1$$

What is the probability of each interpretation?

P(syntactic configuration)·P(subcat bias)/P(preterminal prior)

$$P(\text{Transitive}) \propto P(\text{VP-gNP}\rightarrow\text{VP-gNP PP}) \cdot \frac{P(\text{TV} \mid verb)}{P(\text{TV})}$$

$$= 0.17 \cdot \frac{P(\text{TV} \mid verb)}{2.6} \tag{1}$$

$$P(\text{Intransitive}) \propto P(\text{VP-gNP}\rightarrow\text{VP PP-gNP}) \cdot \frac{P(\text{IV} \mid verb)}{P(\text{IV})}$$

$$= 0.01 \cdot \frac{P(\text{IV} \mid verb)}{1.0} \tag{2}$$

What is the probability of each interpretation?

P(syntactic configuration)·P(subcat bias)/P(preterminal prior)

$$P(\text{Transitive}) \propto P(\text{VP-gNP} \rightarrow \text{VP-gNP PP}) \cdot \frac{P(\text{TV} \mid verb)}{P(\text{TV})}$$

$$= 0.17 \cdot \frac{P(\text{TV} \mid verb)}{2.6} = 0.065 \cdot P(\text{TV} \mid verb) \tag{1}$$

$$P(\text{Intransitive}) \propto P(\text{VP-gNP} \rightarrow \text{VP PP-gNP}) \cdot \frac{P(\text{IV} \mid verb)}{P(\text{IV})}$$

$$= 0.01 \cdot \frac{P(\text{IV} \mid verb)}{1.0} = 0.01 \cdot P(\text{IV} \mid verb) \tag{2}$$

What is the probability of each interpretation?

P(syntactic configuration)·P(subcat bias)/P(preterminal prior)

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$$= 0.01 \cdot \frac{P(\text{IV} \mid verb)}{1.0} = 0.01 \cdot P(\text{IV} \mid verb) \qquad (2)$$

Pickering & Traxler (2003) experimentally determined subcat biases for a wide variety of verbs

PICKERING & TRAXLER (2003)

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

Using Pickering & Traxler's (2003) subcat bias data:

Pickering & Traxler (2003)

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

Using Pickering & Traxler's (2003) subcat bias data:

$$P(\text{Transitive} \mid \text{landed}) \propto 0.17 \cdot \frac{0.25}{2.6} = 0.016$$

$$P(\text{Intransitive} \mid \text{landed}) \propto 0.01 \cdot \frac{0.40}{1.0} = 0.004$$