An Analysis of Frequency- and Memory-Based Processing Costs

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Motivation

Observation isn't explanation

Many current metrics predict complexity with no cognitive explanation.

- Surprisal and entropy reduction reflect corpus statistics.

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Goal: An Explanation

- How do current theories of working memory fit with current theories of language processing?
- Do memory effects predict difficulty over frequency effects?
- Provide a rationale for *why* humans have certain difficulties

Overview

Hypothesis

Memory effects cause processing difficulty beyond frequency effects

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Memory effects cause processing difficulty beyond frequency effects

1. Working memory primer
2. Memory and language processing theories
3. Introduce connected component parser
4. Eye-tracking evaluation
5. Results

Working Memory

Temporal and Sequential Cueing

Temporal Context Model [Howard and Kahana, 2002]
Hierarchic Sequential Prediction [Botvinick, 2007]

- Learned *sequential* associations
- Contextual *temporal* associations

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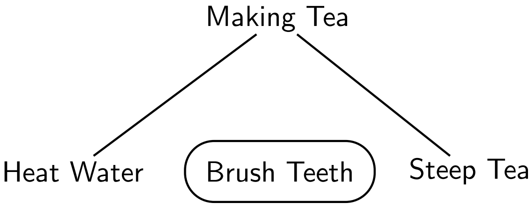

Temporal Cueing in the Morning

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Attended vs Passive States [McElree, 2006]

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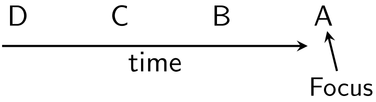

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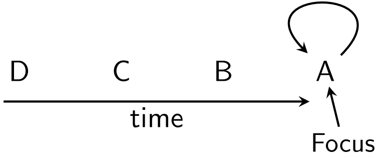

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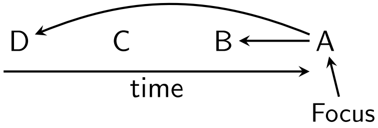

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Attended vs Passive States [McElree, 2006]

$$\textbf{Difficulty with}\begin{cases}\text{Temporal cueing}\\ \text{(Accessing non-focused information)}\end{cases}$$

$$\textbf{Temporal cueing}\begin{cases}\text{Resolving embedded dependencies}\end{cases}$$

Key: Inhibition Facilitation

Language Processing

Dependency Locality Theory [Gibson, 2000]

$$\textbf{Difficulty with} \begin{cases} \text{Unresolved dependencies} \end{cases}$$

$$\textcolor{red}{\textbf{Storage cost}} \begin{cases} \text{Beginning dependencies} \\ \text{Maintaining dependencies} \end{cases}$$

$$\textcolor{red}{\textbf{Integration cost}} \begin{cases} \text{Resolving dependencies} \end{cases}$$

Language Processing

ACT-R [Lewis et al., 2006]

$$\textbf{Difficulty with} \begin{cases} \text{Activation decay} \\ \text{Similarity interference} \end{cases}$$

$$\textbf{Encoding cost} \begin{cases} \text{Beginning a new dependency} \end{cases}$$

$$\textbf{Retrieval cost} \begin{cases} \text{Resolving a dependency} \end{cases}$$

Retrieval can be *facilitated* by re-activations.

Language Processing

Dynamic Recruitment [Just and Varma, 2007]
Difficult constructions → extra processing resources

Difficulty with { Center embeddings

Recruitment { Beginning embeddings

Release { Completing embeddings

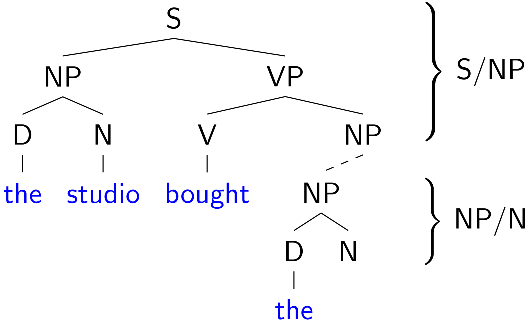
Language Processing

Embedding Difference [Wu et al., 2010]

Increased embedding depth $\Big\{$ Beginning embeddings

Reduced embedding depth $\Big\{$ Completing embeddings

Connected Components



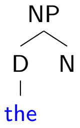
'S/NP' and 'NP/N' represent unresolved dependencies

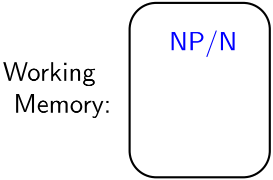
Predictions

Theory	Encoding	Integration
Hier. Sequential Prediction		**positive**
Dependency Locality Theory	**positive**	**positive**
ACT-R	**positive**	**positive**
Dynamic Recruitment	**positive**	**negative**
Embedding Difference	**positive**	**negative**

Predicted correlation of parse operations to reading times under each theory

Connected Component Parsing





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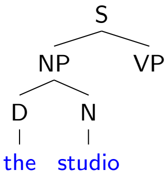
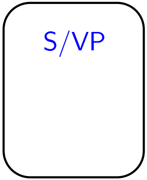


Working Memory:



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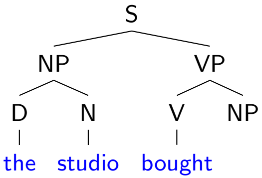

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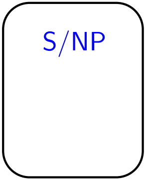

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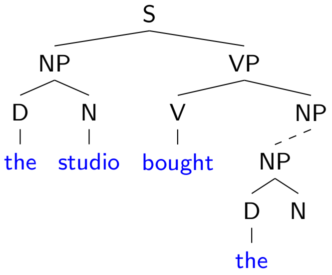

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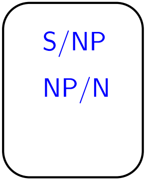

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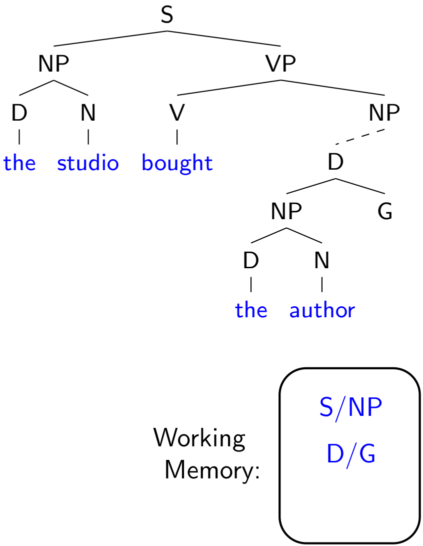

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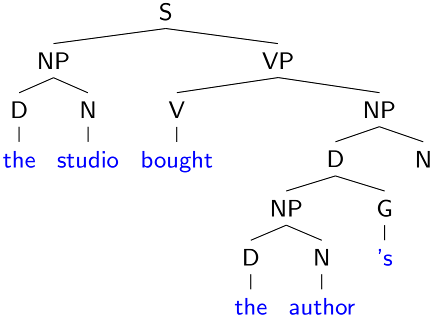
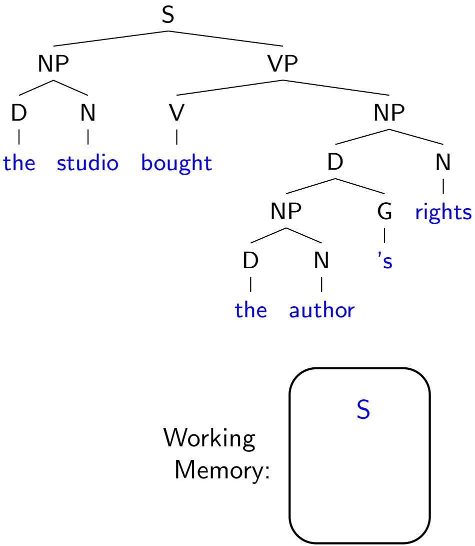


Working Memory:

S/N

Connected Component Parsing



Parser Operations

F and L binary decisions (+,–) made at each timestep

- **F(irst)**: Current word is the **first** element of a new embedding
- **L(ast)**: Current word is the **last** element of an embedding

Only one F, only one L [van Schijndel et al, 2013]

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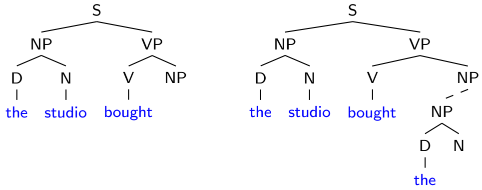
- F+L– (Encode): Create a new connected component



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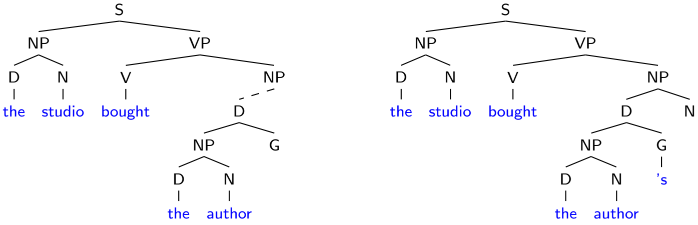
- F+L– (Encode): Create a new connected component
- F–L+ (Integrate): Combine two connected components



Integrate

Eye Tracking

- Assumption: Slower reading = difficulty
- How much can be processed up to a given point?
- Many different metrics (fixation duration, regression, etc)

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Measure of choice: Go-Past Duration [Clifton et al., 2007]

Eye Tracking

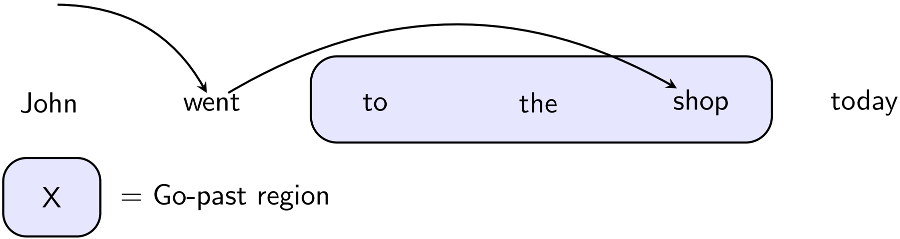
Go-past durations:

John went to the shop today

Cumulative factors are summed over the go-past region
Non-cumulative factors are based on the initial word in a region (shop)

Eye Tracking

Go-past durations:



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Training

Parser accuracy is comparable to Berkeley [van Schijndel et al., 2012]

- Parser and Lexicon: WSJ02-21 [Marcus et al., 1993]
  - 39,832 sentences
  - 950,028 words
- Ngrams: Brown [Francis and Kucera, 1979], WSJ02-21, BNC, Dundee[Kennedy et al., 2003]
  - 5,052,904 sentences
  - 87,302,312 words

Ngrams calculated using SRILM [Stolcke, 2002] with modified Kneser-Ney smoothing [Chen and Goodman, 1998]

Evaluation

- Dundee corpus [Kennedy et al., 2003]
  - 10 subjects
  - 2,388 sentences
  - 58,439 words
  - 260,124 go-past durations
- Filtered Dundee corpus
  - 154,168 go-past durations

Exclusions: UNK-threshold 5, first and last of a line, fixations skipping more than 4 words (track/attention loss)

Metric Calculations: Probability-weighted, parallel model

Baseline Metrics

Fitting a linear mixed effects model (*lmer* in R)

Fixed Effects

- Word length
- Sentence position
- Prev, Next word fixated?
- Unigram and bigram probs
- Surprisal
- Region length
- Cumulative surprisal
- Cumulative entropy reduction
- Joint interactions
- Spillover predictors

By-subject random slopes (Note: Not in paper)

- Effect of interest (e.g. Encode)
- Prev word fixated?
- Cumulative surprisal
- Region length

With Subject and Item random intercepts
Fit to log-transformed durations

Predictions - Revisited

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Results

Operation	Factor	Coeff	Std. Error	t-score	p-value
Encoding	F+L–	0.023	0.005	4.238	0.001
Integration	F–L+	-0.015	0.005	-3.215	0.007
Cue Active	F–L–	0.002	0.003	0.800	0.437
Cue Awaited	F+L+	-0.004	0.003	-1.298	0.22

Significance of Improvement over Baseline

Each FL factor is cumulative

Conclusion

- No positive integration cost with frequency

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- No positive integration cost with frequency
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- No evidence of DLT's maintenance cost
- Confounds assumption of Slow = Difficult
- Remaining inhibition suggests difficulty beyond frequency effects (perhaps a cause of frequency effects)

Fin

Thanks!

Thanks to Kodi Weatherholtz and Rory Turnbull for their assistance with R-wrangling and working with linear mixed effect models!

Thanks to Peter Culicover, Micha Elsner, and the OSU CompLing group for feedback on the project.

Questions?

Frequency Effects

Surprisal [Hale, 2001]

Predictability of a word given the context:

$$surprisal(x_t) = -\log_2 \left(\frac{\sum_{s \in S(x_1 \ldots x_t)} P(s)}{\sum_{s \in S(x_1 \ldots x_{t-1})} P(s)} \right) \tag{1}$$

Entropy Reduction [Hale, 2003]

Entropy is a measure of uncertainty:

$$H(x_{1 \ldots t}) = \sum_{s \in S(x_1 \ldots x_t)} -P(s) \cdot \log_2 P(s) \tag{2}$$

The reduction in uncertainty caused by observing x_t:

$$\Delta H(x_{1 \ldots t}) = \max(0, H(x_{1 \ldots t-1}) - H(x_{1 \ldots t})) \tag{3}$$

$S(x_1 \ldots x_t)$ = trees whose leaves have $x_1 \ldots x_t$ as a prefix

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John went to the shop today

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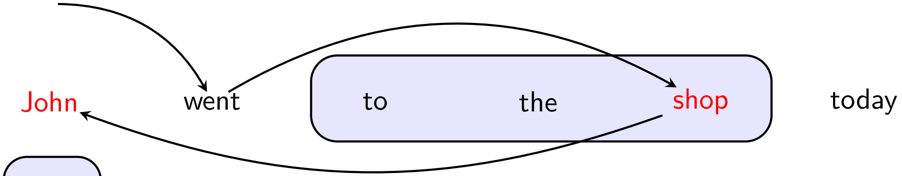

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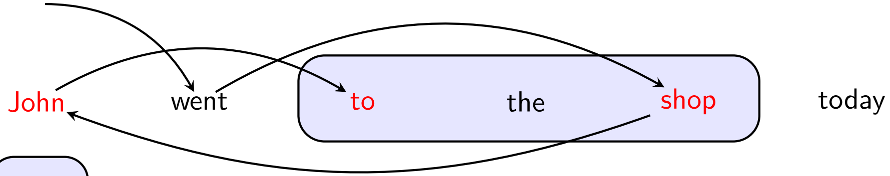

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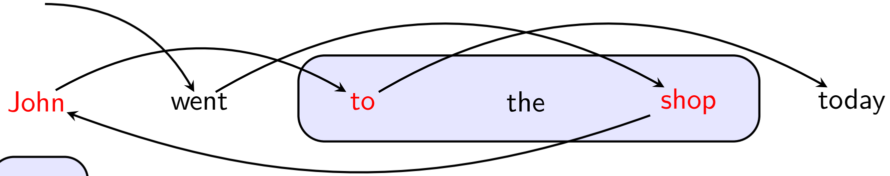

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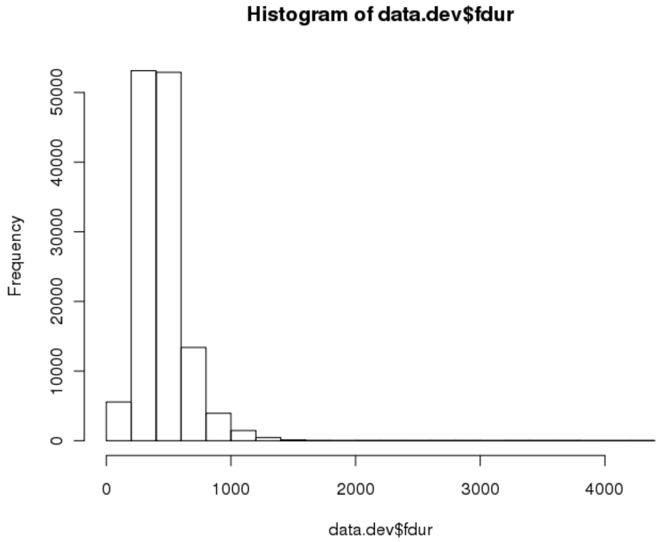
Transforming the response variable



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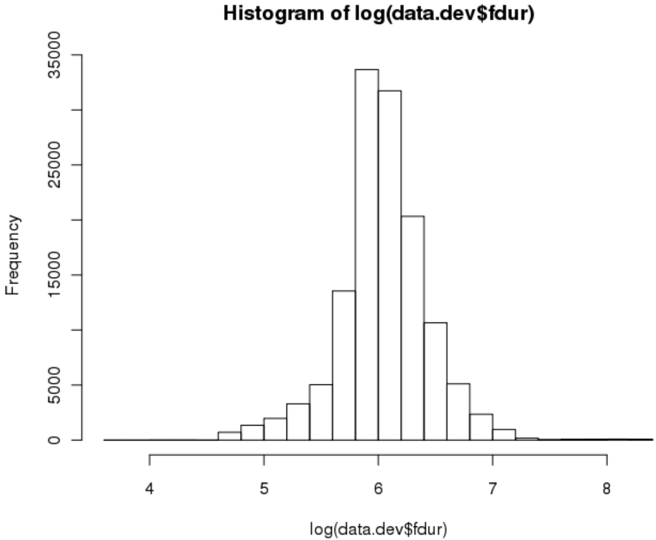

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