Retrieving structures from memory causes difficulty during incremental processing

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Based on Shain et al. 2016

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**Hypothesis:** Memory access in incremental parsing causes reading time delays.

- Predicted by a number of theories of sentence processing (e.g. Gibson 2000; Johnson-Laird 1983).
- Supported by numerous previous studies (e.g. Grodner and Gibson 2005; Boston et al. 2011; von der Malsburg, Kliegl, and Vasishth 2015).
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Conclusion

- Memory retrieval effects exist in human sentence processing.
This work was supported by grants from the National Science Foundation: Graduate Research Fellowship Program Award DGE-1343012 to MvS; Doctoral Dissertation Research Improvement Award 1551543 to RF; Linguistics Program Award 1534318 to EG.
So why are we still working on this?
Introduction

- **Previous findings:** Mixed.
  - **Constructed stimuli:** Strong effects
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Potential weaknesses in each type of stimulus

**Constructed:**
- Limited domain (e.g. relative clauses)
- Confounds from lack of context or semantic strangeness
- Lack of information theoretic controls (e.g. surprisal)

**Naturally-occurring:**
- Limited number of subjects (10 in Dundee)
- 'Easy' stimuli


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- The Dependency Locality Theory (DLT): Cost as function of dependency length.
- Left-corner parsing: Cost as function of parser operations that involve memory retrieval.
- Many plausible implementations of the cost function
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Experimental setup: The Natural Stories corpus

- Experiments used Natural Stories corpus (Futrell et al. in prep):
  - Constructed-natural stimuli:
    - Fluent narrative text
    - Memory-intensive constructions
  - SPR data collected
  - 10 texts, 10257 words, 181 subjects, 848,207 events
- Partitioned into exploratory (1/3) and confirmatory (2/3) corpora
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- DLT (Gibson 2000): Difficulty by dependency length (# discourse referents (DR))
- Intuition: Older things are harder to access in memory
- For simplicity, DR = nouns and finite verbs
- Integration cost is sum of:
  - Discourse cost: 1 for nouns/verbs, 0 otherwise
  - Dependency length: Length in DR of all dependencies with preceding words
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The Dependency Locality Theory: Example

Yesterday, the **person supervisors** and **co-workers caught** stealing **millions fled**.

Dependency length = 4 (4 intervening DR (bold))
The Dependency Locality Theory: Results
## The Dependency Locality Theory: Results

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Reliable broad-coverage DLT effect
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Popular model of sentence processing

Left-corner parsing

- Popular model of sentence processing
Maintains a store of derivation fragments $a/b, a'/b', \ldots$, each consisting of active category $a$ lacking awaited category $b$.

Incrementally assembles trees by forking/joining fragments.
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Left-corner parsing: Example

NP

the
Left-corner parsing: Example

NP

N

the dog
Left-corner parsing: Example

NP

N

the
dog
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NP

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- Many plausible predictor implementations (see Shain et al. 2016)
- Best predictor on exploratory: “no fork”
  - Top sign must be recalled from memory
  - Flags right edges of constituents
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<td><strong>Left corner (no-fork)</strong></td>
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**Reliable broad-coverage left corner effect**
No-fork estimate (3.88ms) is entire effect.

DLT effect has a large range (12) but is usually small (95th percentile = 2).

No-fork effect estimate larger for most events, smaller for large DLT.
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The DLT vs. left-corner

+ We seem to have effects from both processing models.
+ These models are often taken to be competing.
+ Maybe they’re measuring the same thing...
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+ DLT and left-corner effects are independent via ‘diamond’ LRT.
+ Both effects improve significantly over baseline and over each other.
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How general are these effects?

Are these effects widespread, or are they driven by particular contexts?
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+ Left corner effect survives even when nouns and verbs are filtered out.
+ DLT effect does not.
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- **Main contribution:** First strong evidence of broad-coverage memory effects in sentence processing.
- Supports psychological validity of dependency/constituency.
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- Significant independent contributions from both DLT and left corner
- Possibly semantics vs. syntax?
  - DLT has access to semantic information like head/dependent, referential status, etc. Left corner does not.
  - DLT effect driven by N/V, which introduces discourse referents.
- Separate contributions might indicate separate mechanisms for (semantic) dependency construction vs. retrieval of syntactic derivations.
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Futrell, Richard et al. (in prep). “Natural stories corpus”.


References II


Appendix: Experimental setup

+ Filtered out sentence starts/ends (leaving 768,023 events)
+ Models evaluated via likelihood ratio test (LRT)
+ Reading times transformed by Box and Cox (1964) ($\lambda \approx 0.63$)
+ **Baseline:**
  
  $\text{boxcox(readingTime)} \sim \text{sentencePosition} + \text{wordLength} + \text{5GramSurp} + \text{pcfgSurp} + (1 + \text{sentenceID} + \text{sentencePosition} + \text{wordLength} + \text{5GramSurp} + \text{pcfgSurp} + \text{mainEffect} \mid \text{subject}) + (1 \mid \text{word}) + (1 \mid \text{sentenceID})$

+ All predictors z-score normalized prior to evaluation
+ $\beta$ values above are divided by standard deviation and backtransformed into ms, only valid at mean

+ Predictors computed over trees in Generalized Categorial Grammar (GCG) (Nguyen, van Schijndel, and Schuler 2012)
  + Automatically reannotated from Penn Treebank-style gold and hand-corrected
  + Contains implicit dependency and memory store representations, can be used to calculate all predictors from single source
In this study, we consider 3 additional broad-coverage modifications of the DLT:

- **DLT-V**: Verbs are more expensive. Non-finite verbs receive a cost of 1 (instead of 0) and finite verbs receive a cost of 2 (instead of 1).
- **DLT-C**: Coordination is less expensive. Dependencies out of coordinate structures skip preceding conjuncts. Dependencies with intervening coordinations just use heaviest conjunct.
- **DLT-M**: Exclude modifier dependencies. Dependencies to preceding modifiers are ignored.

Modifications can be applied in any combination, yielding 8 implementation variants of the DLT for this study.

Best variant was DLT-C and DLT-M together.
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Modifications can be applied in any combination, yielding 8 implementation variants of the DLT for this study.

Best variant was DLT-C and DLT-M together.
No-fork (shift + match): Word satisfies $b$. $a$ is complete.

$$\frac{a/b}{a} \ x_t \ b \rightarrow x_t.$$
Yes-fork (shift): Word does not satisfy $b$, fork off new complete category $c$.

\[
\frac{a/b}{a/b} \xrightarrow{x_t} \frac{c}{b} \xrightarrow{+} c \ldots ; \quad c \rightarrow x_t.
\]
**Yes-join (predict + match):** Complete category $c$ satisfies $b$ while predicting $b'$. Store updates from $⟨\ldots, a/b, c⟩$ to $⟨\ldots, a/b'⟩$.

\[
\frac{a/b \quad c}{a/b'} \quad b \rightarrow c \quad b'.
\]  

(+J)
No-join (predict): Complete category c does not satisfy b. Predict new $a'$ and $b'$ from c. Store updates from $\langle \ldots, a/b, c \rangle$ to $\langle \ldots, a/b, a'/b' \rangle$.

\[
\frac{a/b \quad c}{a/b \quad a'/b'} \quad b \xrightarrow{+} a' \ldots \quad ; \quad a' \rightarrow c \ b'.
\]
Appendix: Left-corner predictors

- Memory effects are predicted when signs must be recalled by left-corner parser, but implementation details matter.
- We implemented 3 families of left-corner predictors:
  - EMBD: End of embedded region. True if \(-F+J\) or end of carrier, false otherwise.
  - NoF: No fork \((-F)\) operation. True if \(F\) decision was negative.
  - REINST: Reinforcement operation. Union of EMBD and NoF.
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Appendix: Left-corner predictors

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Appendix: Left-corner predictors

+ Also included distance-weighted variants of each of these (since last recall event) by:
  + Number of words
  + Number of DLT discourse referents
  + Number of verb-modified DLT discourse referents

+ $3 \times 4 = 12$ total left-corner predictors.
Appendix: Left-corner predictors

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## Appendix: Full results

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<th>Best</th>
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<th>Confirmatory corpus</th>
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<td>( \beta ) \hspace{1cm} ( \beta)-ms \hspace{1cm} t-value \hspace{1cm} p-value</td>
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