Re-modeling incremental and holistic processing in multi-word comprehension

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Incremental processing vs. holistic processing

**Incremental processing (IP):**
- Comprehenders weigh target multi-word string (MWS) against all representations compatible with accruing evidence from unfolding input (e.g. Levy 2008);
- MWS frequency is not meaningful on its own, only when weighted against partial input of MWS.

**Holistic processing (HP):**
- Comprehenders process MWS independently of representations compatible with partial input (Arnon & Snider 2010 et seq., Christiansen & Chater 2016);
- MWS frequency is meaningful on its own, above & beyond MWS internal distributional information.

**Research question:** can incremental & holistic processing both non-redundantly constrain MWS comprehension?

Towards a complete characterization of IP: syntagmatic & paradigmatic competition

- Various incremental measures proposed (e.g. conditional probability, surprisal, logit, informativity, mutual information).
- Lack of unified characterization of IP precludes direct comparison of IP & HP.
- I propose a two-dimensional competitive characterization of IP.
- Along syntagmatic axis, the target competes with its subcomponents.
- Along paradigmatic axis, it competes with partially overlapping MWS.

Generalizing processing measures: dense & sparse competition

**Syntagmatic competition:**
- dense: Syntagmatic Competition Index
  - $\text{SEC}(\text{the cat slept}) = \frac{P(M|\text{the cat slept})}{P(M|\text{the cat)})}$
- sparse: Negative Mutual Information
  - $\text{Neg. M}(\text{the cat slept}) = -\log_2 P(M|\text{the cat slept})$

**Paradigmatic competition:**
- dense: Paradigmatic Competition Index
  - $\text{PCI}(\text{the cat slept}) = P(\text{the cat}) + P(\text{the cat}) - P(\text{the cat}) P(\text{the cat slept})$
- sparse: Negative Conditional Probability
  - $\text{Neg. CP}(\text{the cat slept}) = -P(\text{the cat}) P(\text{the cat slept})$

Building hypothesis-driven conjunctive models using multi-model inference & bagging

**Model rankings by bagged AIC (B=1000)**

<table>
<thead>
<tr>
<th>Model</th>
<th>Pred. log-likelihood</th>
<th>Conc. log-likelihood</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tremblay &amp; Tucker</td>
<td>171.4</td>
<td>171.0</td>
</tr>
<tr>
<td>Arnon &amp; Snider</td>
<td>169.9</td>
<td>169.5</td>
</tr>
</tbody>
</table>

*Whiskers indicate 95% confidence intervals. Note that confidence intervals are used here for visualization purposes only. Hypothesis testing tools used in frequentist statistics are not interpretable in multi-model inference.

Take-away points

- Multi-word comprehension non-redundantly integrates offline holistic exemplars and incremental hypotheses weighted online.
- Findings support multilevel exemplar models of sentence comprehension: chunking yields exemplar clouds of different complexity (Walsh et. al 2010).
- Unified account of incremental processing: established incremental processing measures, mutual information & conditional probability, can be treated as special (i.e. sparse) cases of more general processing streams, syntagmatic & paradigmatic competition respectively.
- Incremental competition density: sparse competition measures are on average preferred to their dense counterparts; may be due to behavioral tasks used (i.e. MWS presented all at once rather than incrementally).

Re-modeling two existing MWS datasets

**Arnon & Snider (2010)**
- Stimuli: 90 four-grams from Switchboard & Fisher
- Conditions: 4 non-discrete frequency bins (stimuli continuous across frequency spectrum)
- Task: phrasal-decision (phrases vs. word scramble)
- Participants: 49 native American English speakers

**Tremblay & Tucker (2011)**
- Stimuli: 432 four-grams from BNC (112 most frequent + 320 randomly selected)
- Stimuli continuous across frequency spectrum
- Task: unprepared production task (comprehension approximated by RTs)
- Participants: 17 native American English speakers

Acknowledgements & selected references

**Acknowledgements:**
I thank Arnon, Neal Snider, and Antoine Tremblay for sharing their data with me and answering related questions. I thank Joan Bresnan, Meghan Sumner, and Tom Wasow for their sustained advice on this project. All errors are mine.

**Selected references:**

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