Differentiating between broad & local context cues using surprisal: An fMRI study

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Context guides comprehenders' expectations during language processing. This study examines the roles of local context and broad context during natural language comprehension. Information-theoretic surprisal (Hale, 2001; Levy, 2008) can be utilized to capture both types of contextual cues. Surprisal can be interpreted as "the degree to which the actually perceived word deviates from expectation" (Lopopolo et al., 2017) and the expectation can be based on information from the immediately preceding words or previous sentences and paragraphs.

In this study, we use surprisal to look at how use of local and broader context are reflected in processing using an analysis of fMRI time courses collected during naturalistic listening. Lexical surprisal estimated using an LSTM (long short-term memory) language model is used to represent local context (van Schijndel & Linzen, 2018). For broader topical context, we use a new metric, topical surprisal (Bhattasali & Resnik, 2020). It is defined using the weighted average of a word's probability given a topic, where weights are the (posterior) probability that the context is about that topic; topics can be defined and probabilities estimated using a topic model (LDA; Blei et al., 2003).

Participants (n=51) listened to *The Little Prince*'s audiobook for 1 hour 38 minutes. Participants' comprehension was confirmed through multiple-choice questions. (90% accuracy, SD = 3.7%). The LSTM language model was trained on 90 million words of English Wikipedia (Gulordava et al., 2018). Using the wrapper for Mallet LDA (McCallum, 2002) in the Gensim toolkit (Rehurek & Sojka, 2010), we estimated a 100-topic model using the Brown corpus (Francis & Kučera, 1964). We compute topical surprisal for each of the 6,243 non-function words in the audio sample using the paragraph containing the word as its context (see Fig. 2). Additionally, we entered four regressors of non-interest into the GLM analysis (SPM12): word-offset, word frequency, pitch, intensity.

The whole-brain main effects were FWE-corrected (T-score > 5.3). Regression analyses localized the activation patterns for local and broad context to different areas. The peak activation for lexical surprisal (instantiating local context) was observed in bilateral ATL, along with a small cluster in left STG. Significant clusters for topical surprisal (instantiating broad context) were seen in the right Precuneus and right MTG (Fig. 1).
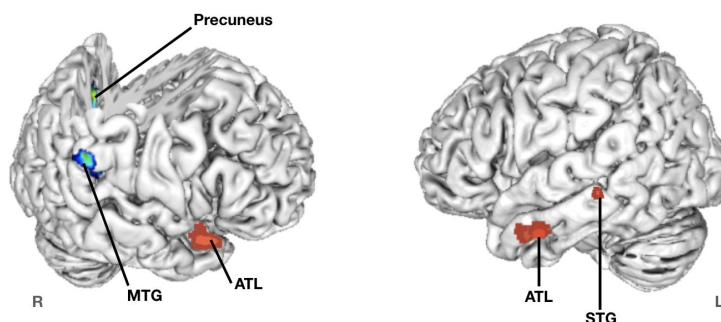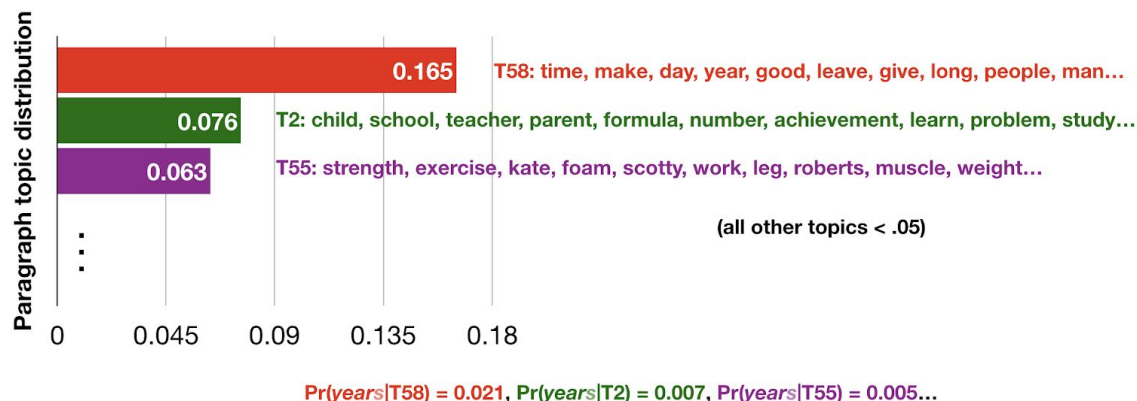

Fig. 1: Whole brain contrast image with significant clusters for lexical surprisal (in blue) & topical surprisal (in orange) after FWE voxel correction with p < 0.05

Our lexical surprisal results corroborate previous findings by Willems et al., (2015), Brennan et al., (2016), Shain et al., (2020) for bilateral ATL and by Willems et al. (2015), Lopopolo et al. (2016), Shain et al. (2020) for STG. Our topical surprisal results are supported by prior work on context and discourse-level phenomena (Bhattasali & Resnik, 2020; Maguire et al. 1999; Raposo et al., 2013; Whitney et al., 2009; Xu et al., 2005) and further supports this measure as a cognitively plausible metric with distinct neural substrates from lexical surprisal. Our novel approach to investigating contextual fit beyond the sentence level is also broadly consistent with the argument that smaller versus larger temporal receptive windows implicate regions associated with lower-level and higher-level tasks respectively (Lerner et al., 2011), a connection we plan to explore further. Overall the neurocognitive correlates for lexical surprisal and topical surprisal suggest that utilizing local and broad contextual cues during language processing recruit different brain regions and illustrate that various regions of the language network functionally contribute to processing different dimensions of contextual information.

During the fifty-four years that I've lived on this planet, I've only been disturbed three times. The first time was twenty-two years ago, by some scatterbrain who fell from god knows where. He made the most dreadful noise, and I made four mistakes in a sum. The second time was eleven [years] ago, by an attack of rheumatism. I don't get enough exercise. I don't have time to stroll about. I am a man of consequence. The third time—well, this is it! I was saying, then, five-hundred-and-one million—

Paragraph topic distribution

- 0.165 — T58: time, make, day, year, good, leave, give, long, people, man…
- 0.076 — T2: child, school, teacher, parent, formula, number, achievement, learn, problem, study…
- 0.063 — T55: strength, exercise, kate, foam, scotty, work, leg, roberts, muscle, weight…

(all other topics < .05)

Axis: 0 0.045 0.09 0.135 0.18

Pr(*years*|T58) = 0.021, Pr(*years*|T2) = 0.007, Pr(*years*|T55) = 0.005…

$$\text{surprisal}_c(\textit{years}) = -\log \sum_{\text{topic in Topics}} P(\textit{years} \mid \text{topic})\, P(\text{topic} \mid \text{context } c)$$

Fig. 2: Sample excerpt with topical surprisal example

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