

The Cognitive Throttle of Language: Exploring the Limits of Information Processing

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Introduction

Temporal constraints

- Auditory short-term memory is limited to 2-3 seconds [1].
- For language, a proposed window of 2.4 seconds, including ~6 words when assuming a rate of 150 words per minute [2-3].
- Timing constraint may come from limited duration of underlying electrophysiological windows: cycles of low-frequency neural activity serve the formation of multi-word chunks.
 - Phase angles of oscillatory activity in the delta band (< 4 Hz) predict the offsets of multi-word chunks [4], in particular when chunks last for 2.7 seconds [5].
- Yet, time window is confounded with amount of information

Uniform Information Density Hypothesis

- Information density: the amount of information in a unit
- Uniform information density (UID): speakers prefer utterances that convey/distribute information uniformly across speech signals [6-7].
- Some psycholinguistic evidence for UID:
 - Similar information rates (~39 bits/s) for syllables across different languages [8-9].
 - Entropy rate increases with sentence number [10].

Main questions

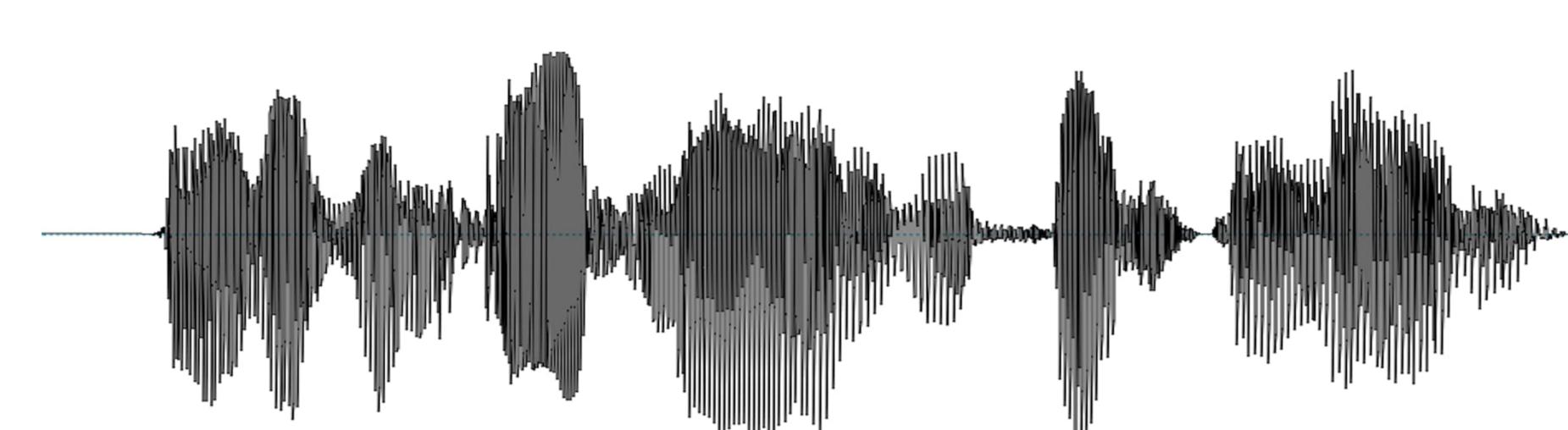
- According to UID, is there a limit to the amount of information that can determine how we define a chunk in continuous speech?
- In particular, does the chunk-related neural activity correlate with chunk boundaries defined by the summation of surprisals?

Methods

EEG preprocessing

- Analysis of openly available dataset [11]
- 18 native English speaking young adults (19–38 years old)
- Electroencephalography (EEG) recording during naturalistic story listening ("The Old Man and the Sea" by Ernest Hemingway)
- Automated EEG pre-processing (adjusted from HAPPE; [12])

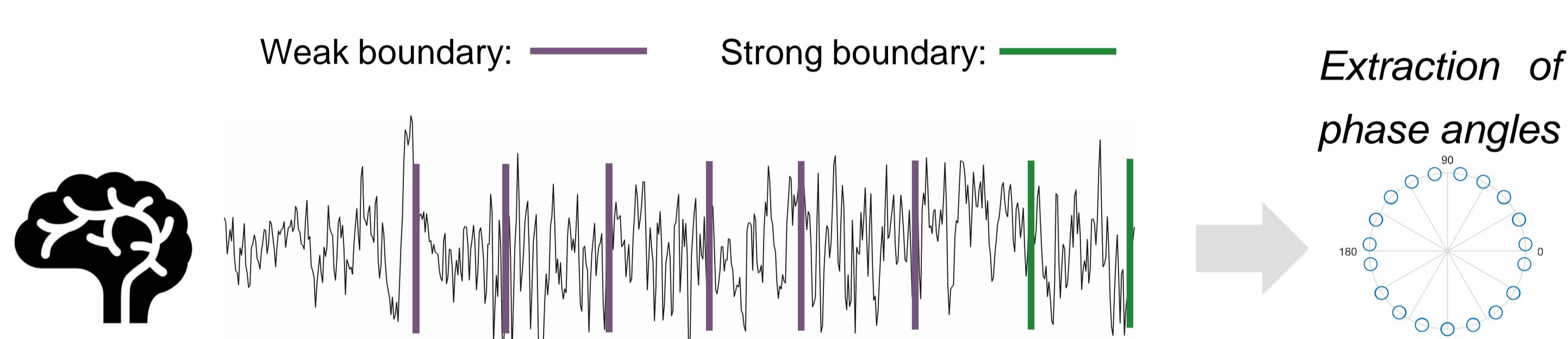
Information in a chunk



Text: He was an old man who fished alone...
GPT2 surprisal: 8.58 3.31 6.03 5.98 1.75 2.62 14.52 8.33...
Cut-off (5): 1 0 1 1 0 0 1 1...
Cut-off (10): 0 1 0 1 0 0 1 0...
...
Cut-off (50): 0 0 0 0 0 0 0 1...
SUM: 1 1 2 3 1 0 6 5...
Median split (SUM>3): to determine the most possible boundaries

EEG analysis

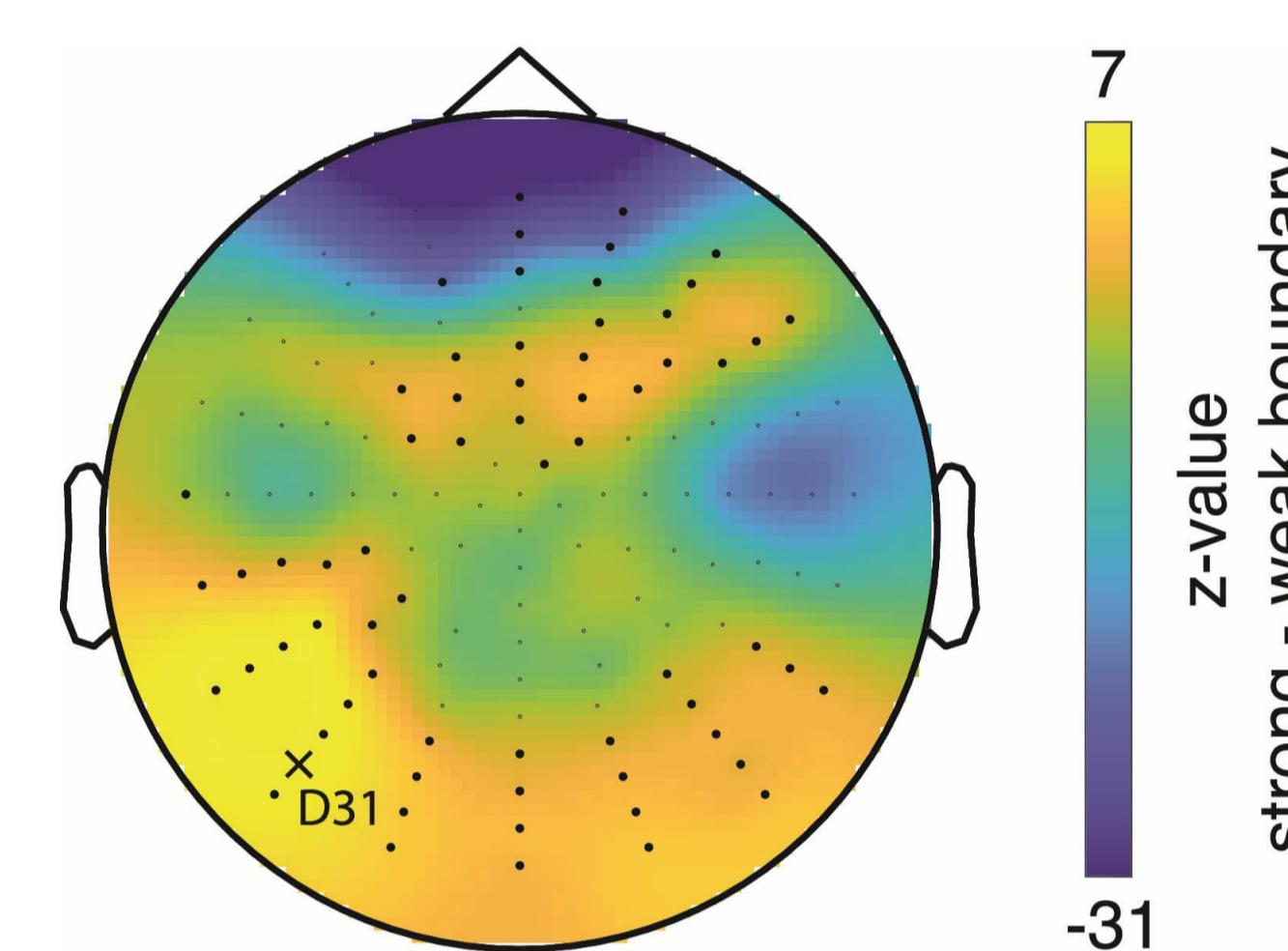
- Extraction of phase angles (< 2 Hz) at word-offsets



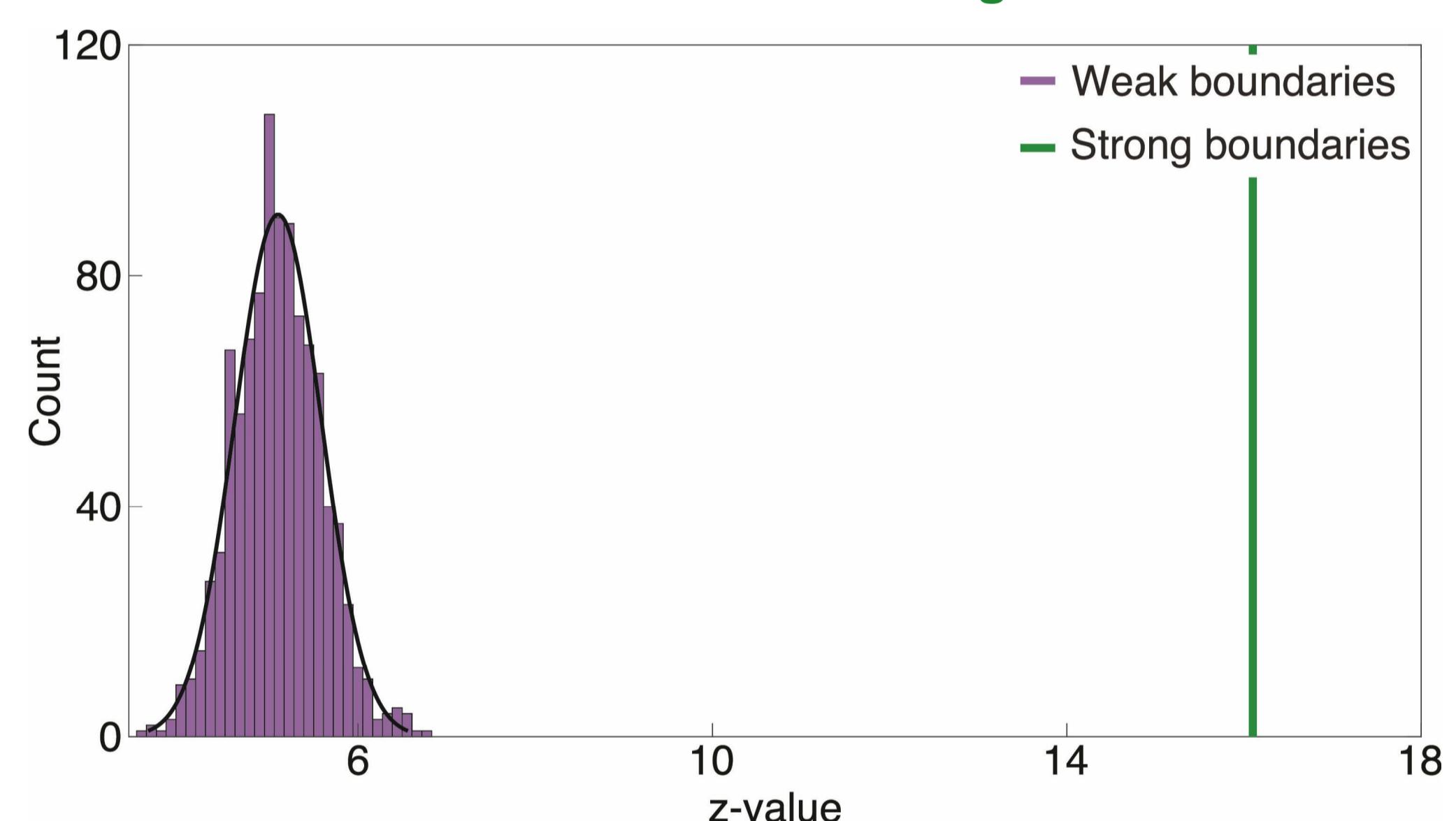
- Comparison of phase clustering at surprisal (strong) boundaries against a surrogate distribution based on word-offsets of weak boundaries

Results

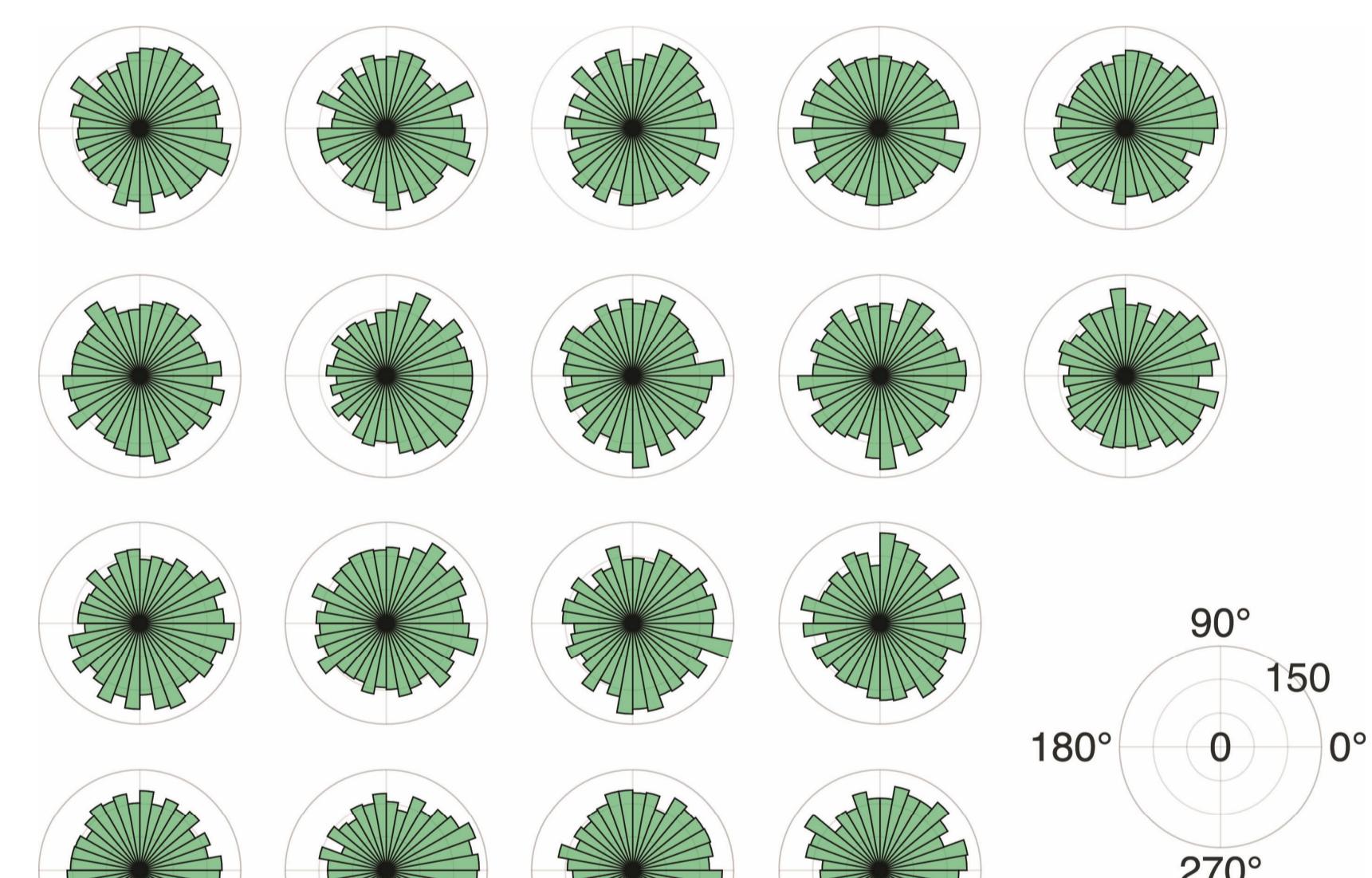
Topography of phase clustering difference between strong and weak boundaries (Median Split: SUM >3)



Histogram of the statistical values from the Rayleigh's test of the bootstrapped weak boundaries and value of the observed strong boundaries at electrode D31



Phase clustering of strong boundaries for each participant (at electrode D31)



Summary

- Phase clustering of the delta band (< 2 Hertz) is higher for the strong boundaries defined by the surprisal cut-offs, as compared to the weak boundaries.
- This suggests after accumulating enough information (i.e., surprisal values), participants insert a chunk boundary.
- Limitations of information processing indeed play a role in determining multi-word chunks and are reflected by neural processing windows.

Discussion

Future directions/open questions

- Different ways of quantifying information density in chunk (e.g. local vs. global, [13-15])
- How to tease apart timing constraints and information density in a chunk
- How to determine optimal surprisal value (i.e., which amount of information can be processed best)
- In addition to GPT-models, there are various ways of computing surprisal values (e.g., syntactic surprisal to account for linguistic structure, [16])
- If information is distributed uniformly, chunks should not have a pre-determined beginning or end (e.g., surprisal in chunks may be uniform within a moving window)

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