Distinct neural circuits for tracking prosodic and statistical regularities in speech?

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Introduction

Statistical learning

- Word **learning** relies on statistical **regularities** in speech
- These regularities are shaped by transitional probabilities (**TPs**) between syllables
- The extraction of TPs enables **chunking** and **learning**
- **Prosodic** marking at chunk boundaries facilitates learning

RQ: *Do brain oscillations support statistical learning?*

Oscillations in language

- *Neural oscillations* = **rhythmic cycles** of neural activity
- Neural oscillations support language processing by phase alignment to:
  1. Exogenous acoustic units in speech (syllables)
  2. Higher order acoustic marking (**prosody**)
  3. Endogenous abstract cues (**TP patterns**)

RQ: *Are TPs and prosodic cues concurrently tracked by distinct neural circuits for learning and chunking?*

RQ: *Does statistical learning of artificial words rely on top-down modulations from high-order cortical areas?*

Methods

Stimuli

- Controlled for frequency of use of syllables (L1: **German**)
- Controlled for overlap and periodicity of phonetic features

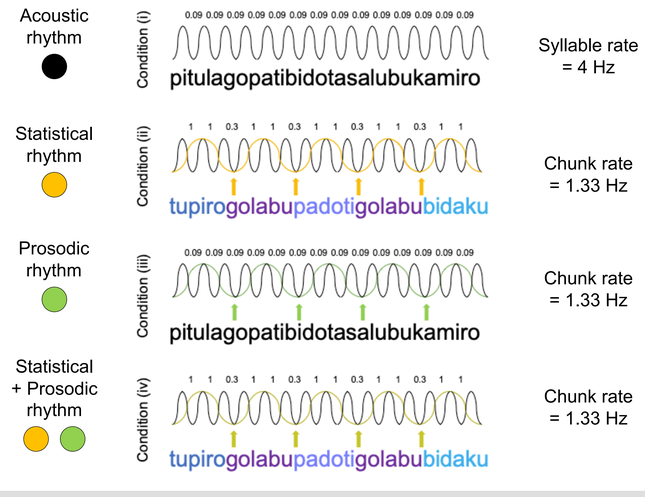
Data acquisition & analyses

Magnetoencephalography:
Neural frequency tagging (NFT)
Inter-trial phase coherence
Event related fields (ERFs)

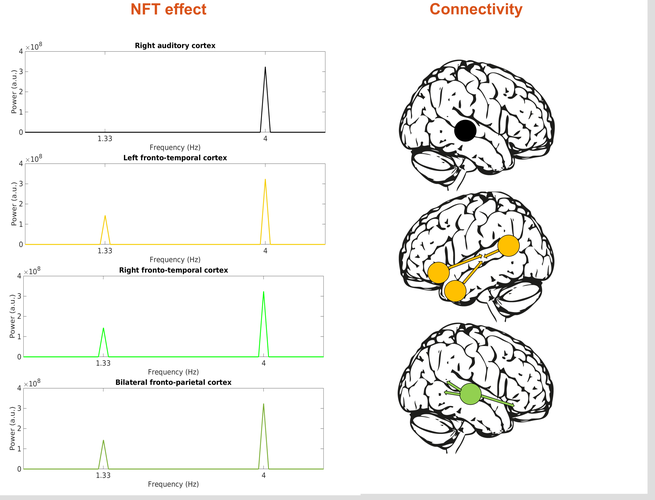
Behavioral performance:
Explicit learning:
- Word Recognition
- Confidence Rating

Exposure Phase

1 Conditions

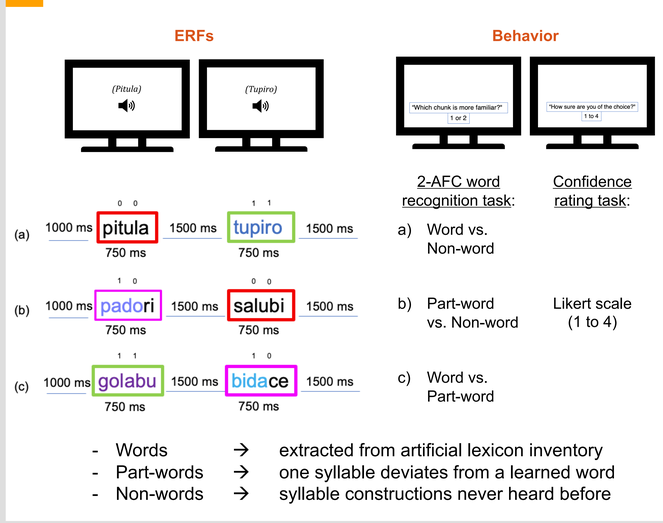


2 Expected Results



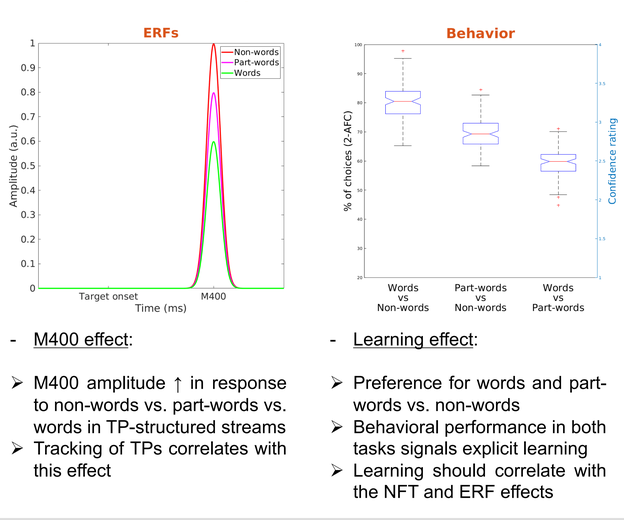
Testing Phase

3 Conditions



- Words → extracted from artificial lexicon inventory
- Part-words → one syllable deviates from a learned word
- Non-words → syllable constructions never heard before

4 Expected Results



- M400 effect:
  - ➢ M400 amplitude ↑ in response to non-words vs. part-words vs. words in TP-structured streams
  - ➢ Tracking of TPs correlates with this effect
- Learning effect:
  - ➢ Preference for words and part-words vs. non-words
  - ➢ Behavioral performance in both tasks signals explicit learning
  - ➢ Learning should correlate with the NFT and ERF effects

Discussion

Summary

- Distinct MEG-source reconstructed neural circuits should exhibit **periodic activity** at the chunk rate when TPs and prosodic cues are regularly presented in a syllable stream
- Neural **tracking** of coherent statistical and prosodic cues is expected to be associated with learning enhancement
- **Evoked** responses (e.g., M400) to test chunks should be larger for non-words compared to words (− familiarity)
- Neural tracking at the chunk rate in cortical regions that are sensitive to TP should **correlate** with neural (evoked) responses and behavioral performance (learning)
- **Connectivity** from high-order regions (e.g., sensorimotor network) feedbacks temporal predictions to sensory areas and t**op-down** modulate neural tracking at the chunk rate
- Acoustic and prosodic cues might instead be processed **bottom-up**, thus showing a reversed **connectivity** profile

Conclusion

- Our study could show that **rhythmic processing** of **TPs** and **prosodic** cues embedded in a syllable stream:
  1. Is neurally dissociable
  2. Relies on feedback and feedforward connectivity
  3. Jointly impacts statistical learning of artificial words

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