The role of oscillations for the predictions of *When* and *What* during language comprehension

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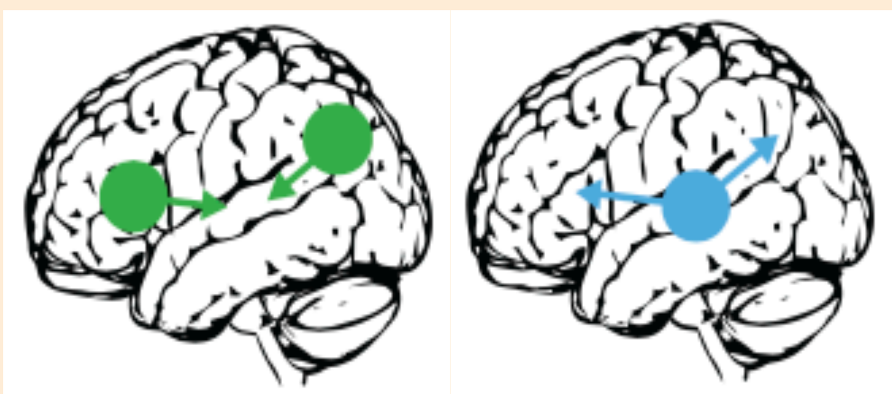
Introduction

Oscillations in language

- *Neural oscillations* = rhythmic cycles of neural activity
- *Entrainment* = neural inheritance of contextual rhythms:
  1. Drives temporal—***when***—predictions
  2. Is *passively* subserved by oscillations via bottom-up
- *Internal language model* = set of linguistic knowledge:
  1. Drives linguistic—***what***—predictions
  2. *Actively* tunes neural excitability via top-down

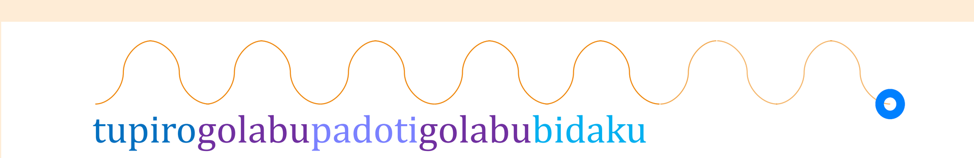


- Oscillations support language processing:
  1. By tracking exogenous signals (e.g., syllables)
  2. By endogenously predicting the *when* and the *what*

Q: *How do oscillations help to predict target events?*

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 word learning
- This process is subserved by neural oscillations
- Learning an artificial lexicon adds linguistic knowledge to the internal language model
- This knowledge allows for new top-down predictions on target identity



Q: *Does statistical learning empower **when** and **what** linguistic predictions through neural oscillations?*

Methods

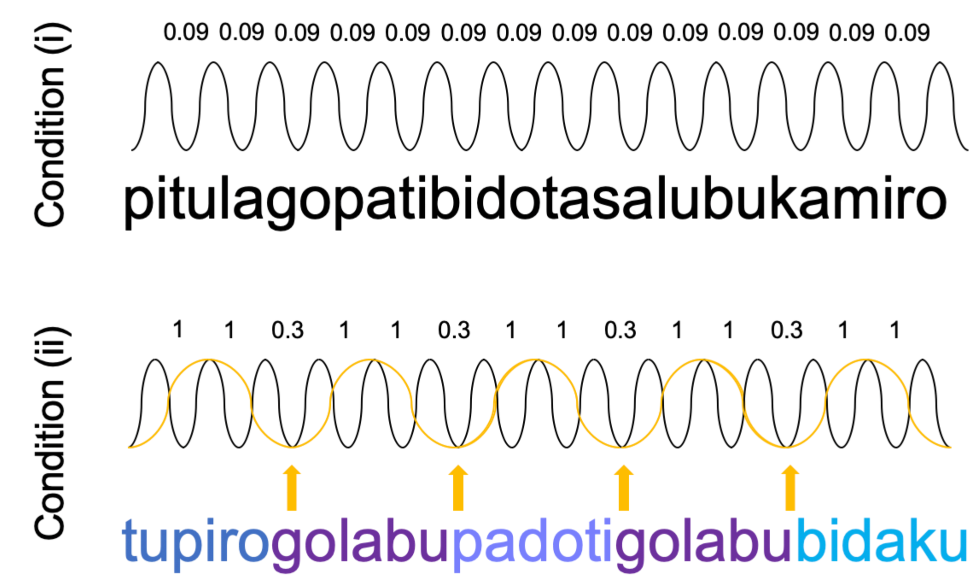
2×2 Experimental design

- Statistical learning paradigm:
  i. TP-random syllable stream
  ii. TP-structured syllable stream
- Downstream target violations:
  A. Prediction of ***when*** (Timing)
  B. Prediction of ***what*** (Content)

Data acquisition & analyses

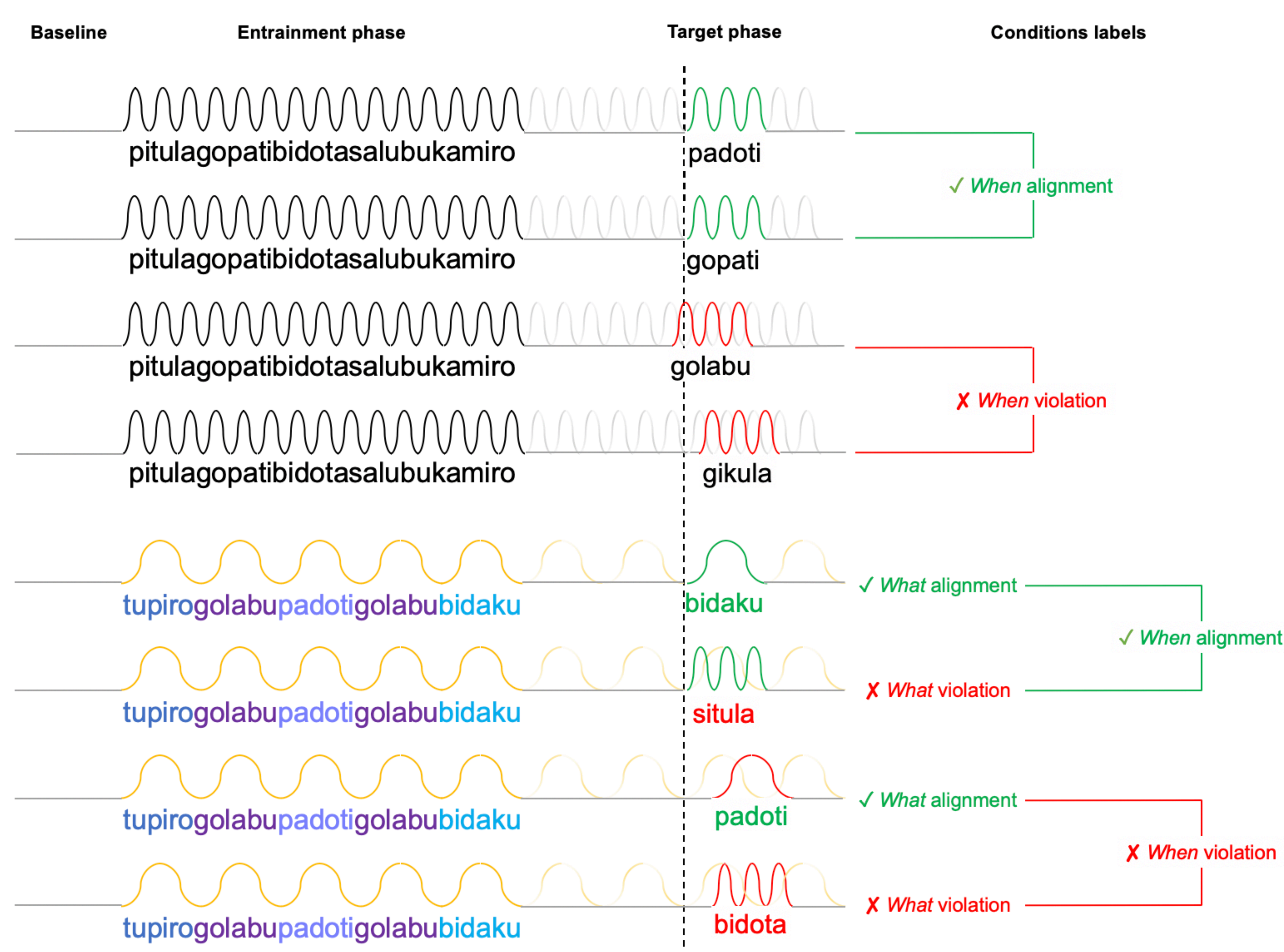
- Magnetoencephalography
- Neural Frequency Tagging
- Oscillatory power dynamics
- Inter-trial phase coherence
- Event-related fields (ERFs)
- 2-AFC recognition task:
  - Accuracy and RTs

1 Exposure phase (Paradigm)



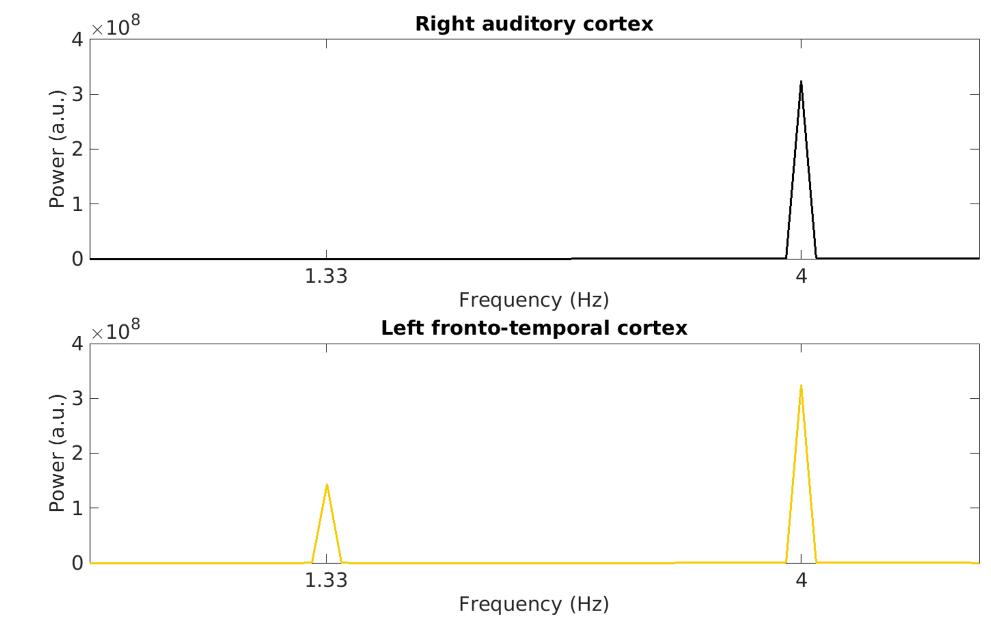
i. Random TPs = no learning of the artificial lexicon
ii. Structured TPs = learning of the artificial lexicon

2 Testing phase (Paradigm)



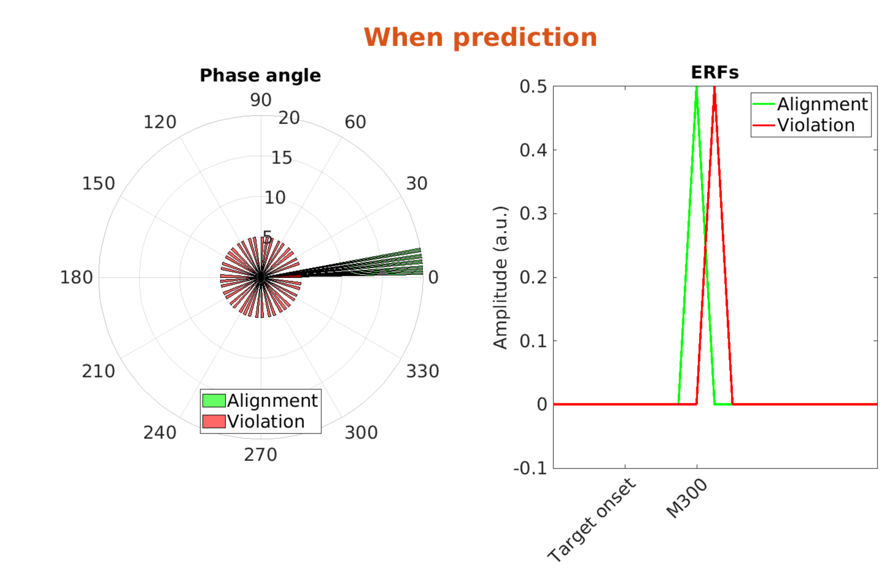
Hypotheses

3 Exposure phase (Expected results)

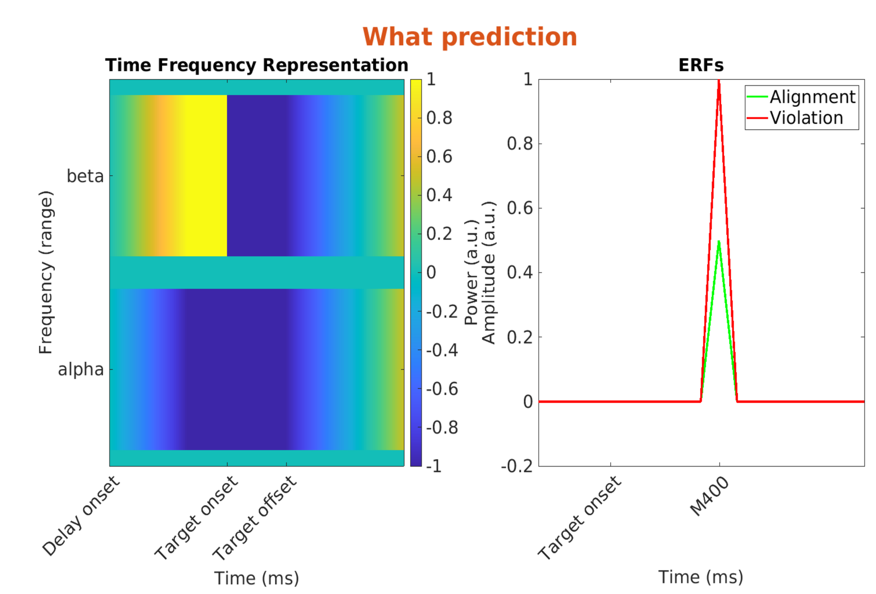


- ➢ Random TPs = neural tracking at the syllables rate
- ➢ Structured TPs = neural tracking at the word rate

4 Testing phase (Expected results)



- ➢ ***When*** prediction violations:
  - ➢ Pre-target phase clustering ↓
  - ➢ Post-target M300 latency ↑



- ➢ ***What*** prediction violations:
  - ➢ On-target beta power desynchronization ↑
  - ➢ Post-target M400 amplitude ↑

Discussion

Summary

- Oscillations carry predictions of both ***when*** and ***what***
  - ***When***: contextual rhythms drive neural entrainment, carrying prediction of *when* the target will occur
  - ***What***: internal language models (i.e. artificial lexicon) drive top-down linguistic prediction on target identity
- Exposure to a random stream of syllables (i) generates no internal model of the artificial lexicon
  1. Without a language model, only *when* predictions at the syllable level are triggered, due to entrainment
  2. Entrainment biases phase at the syllable rate
- Exposure to a structured stream of syllables (ii) generates an internal model of the artificial lexicon
  1. An internal language model triggers *when* and *what* linguistic predictions at the word level
  2. Linguistic predictions bias phase at the word rate
- *When* and *what* predictions should facilitate processing of a target that is aligned to an expected time point and to the linguistic knowledge of the artificial lexicon

Limitations

- 2×2 design: lack of parametric investigation of a gradient of model predictions (larger difference in predictability ↔ larger phase shifts relative to isochronous)
- In natural speech, the expected time—*when*—of the next linguistic unit may vary depending on *what* predictions

Conclusions

- Depending on ***when*** and ***what*** predictions, we predict:
  - Modulations of pre-target oscillatory phase
  - Changes in pre/post-target oscillatory power
  - Downstream effects on ERFs (M300/M400)
  - Differences in behavioral performance

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