Automated Word Timing from Speech Audio for Brain Signal Analysis

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Introduction

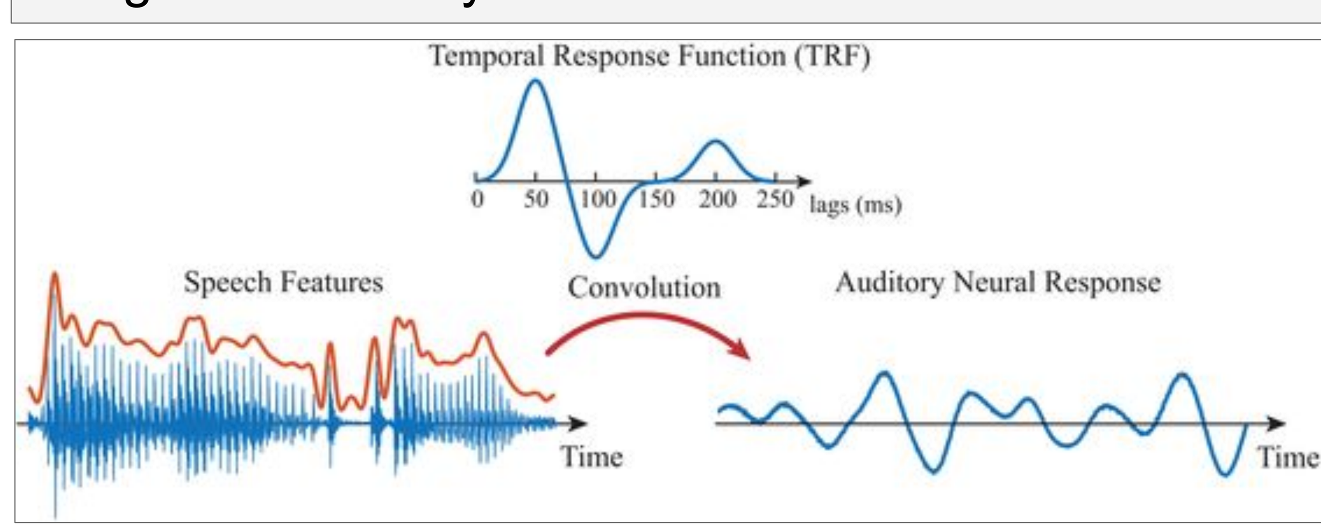
- When the brain processes speech, it actively identifies and interprets words.
- During speech listening, the brain imaging technique magnetoencephalography (MEG) measures magnetic signals generated by brain electrical activity
  - Including signals identifying and interpreting words.
- In a typical experiment, subjects listen to speech recordings, and MEG shows neural responses elicited by the start of each word.
  - To see this, the times at which each word is spoken must be known.

Gap: Several speech-to-text alignment tools have been designed to generate word-level timestamps from audio files, however researchers often have to manually adjust the results. With large amounts of data, this essential task becomes especially time-consuming.

Question: How can a variety of speech alignment models collaborate to automate the process of extracting word timings and improve timing accuracy?

Methods

- Extracted word-level timestamps from speech processing systems
- Twelve ~1-minute-long speech recordings from single-speaker passages of an audiobook
- Recorded MEG data from five participants
- Implemented Python algorithm to standardize the output from all models with the original transcript as reference
- Analyzed how closely the combination of four systems would estimate the human annotated timings using the scikit-learn linear regression library



Impulse response framework to predict auditory neural response

- To visualize the quality of the automated timings, Temporal Response Functions (TRFs) were constructed to map word onsets to neural responses

Evaluation

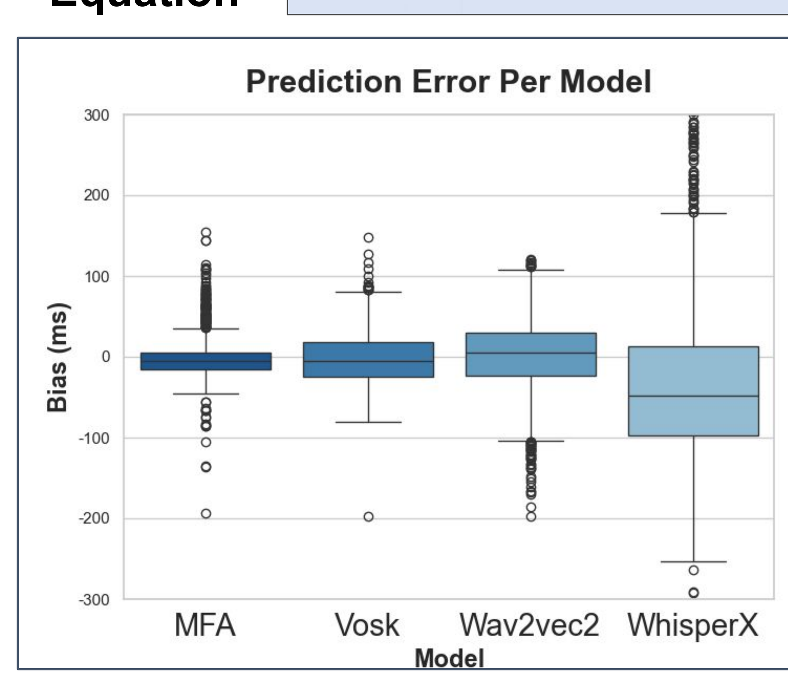
Four approaches were utilized that combine a list of classical and modern speech alignment systems.

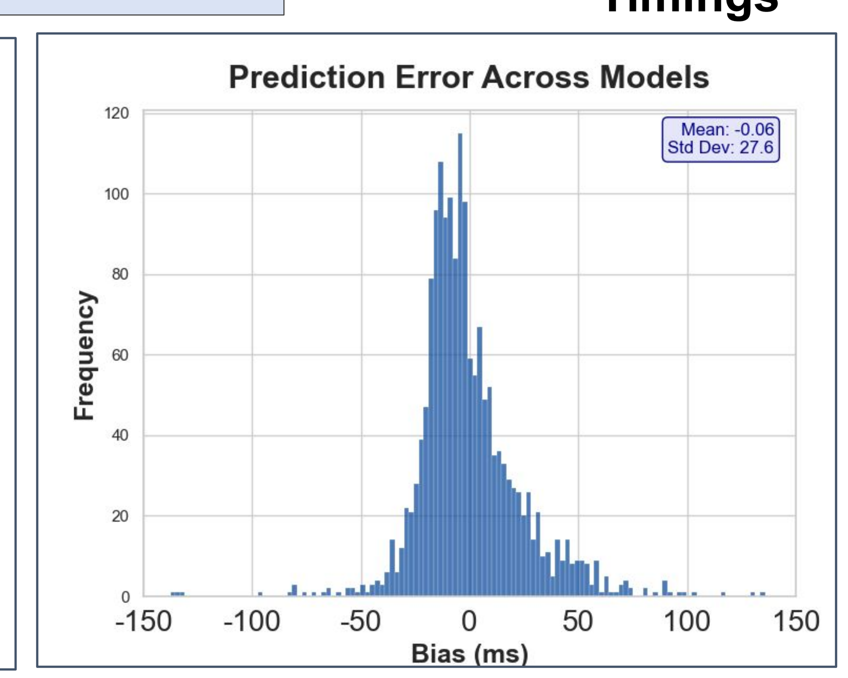
Model Type	System	Functionality
Montreal Forced Aligner (3.3.0)	Kaldi Gaussian Mixture Model – Classical Machine Learning	Time-aligns a transcript with audio using a pronunciation dictionary and acoustic model.
WhisperX (Large –v2)	Open AI Whisper with Wav2vec2 – Deep Neural Network	Transcribes 30s audio chunks; estimate word timings via phoneme recognition
Wav2vec2 (Large-960h -lv60-self)	Transformer model – Deep Neural Network	Converts audio into feature vectors; aligns transcribed text to signal
Vosk (en-us-0.22)	Kaldi Model – Deep Neural Network	Processes audio in small frames with real time text and timing prediction

Results

- Each model's regression was evaluated based on how closely it matched the human annotated timings
  - MFA (Least Variability □ Consistent Predictions)
  - Vosk (Median closest to zero □ More accurate)
  - Wav2Vec2(More errors with delayed predictions)
  - WhisperX (Greatest variability, significant outliers)

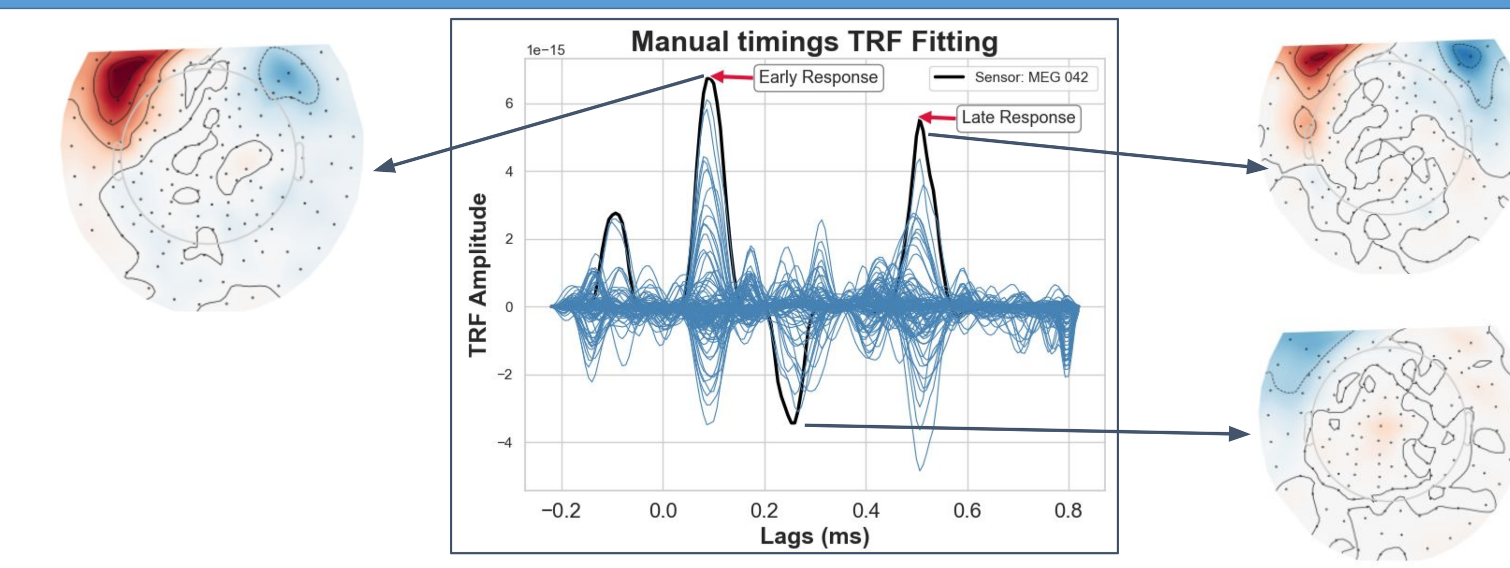
Regression Equation $\hat{y} = \beta_0 + \beta_1 X + \varepsilon$ Predicted Timings

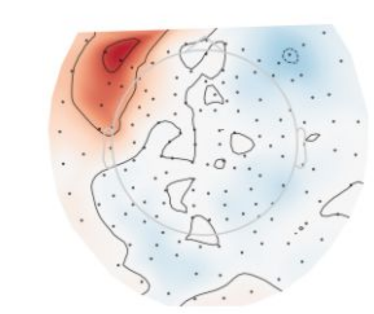


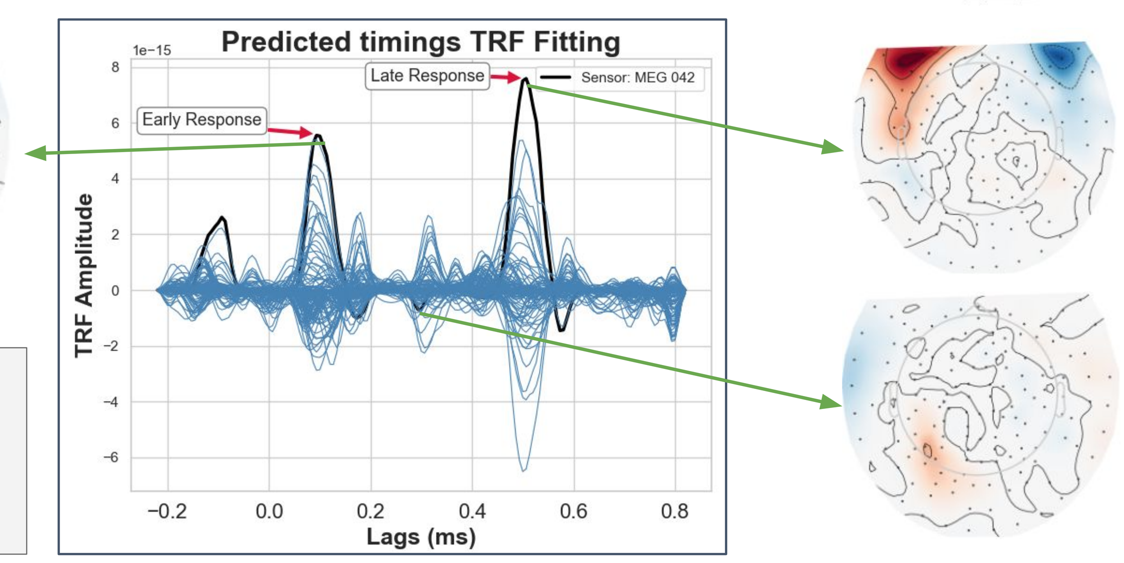


- Difference between predicted times across all models and the manually annotated timings lay between -25 to 25 ms
  - Ideally, this would be 0 confirming perfect predictions
- Right skewness indicate tendency of the models to systematically delay timings

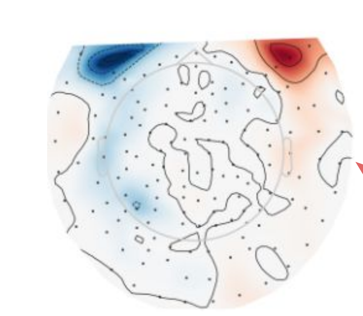
TRF Analysis

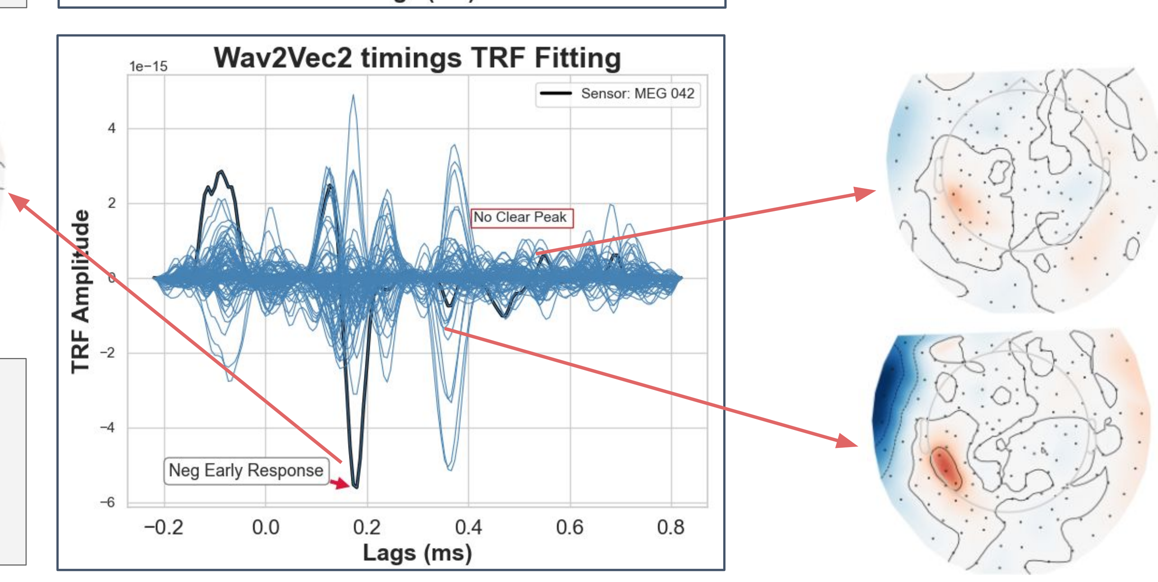






Comparable peak latencies in same direction





Opposite direction with no distinct late response

Discussion

- Predictions from the combined model aligned more closely to the manual timings compared to the state-of-the-art model, Wav2vec2
  - Topographic maps demonstrate that magnetic field amplitudes mirrors that from the manual timings
- Regression-derived timings provide a reliable level of precision suitable for many analyses
- Rapid and consistent extraction of acoustic features offers clear advantage over manual timings
  - Scalability over large datasets will save time in preprocessing
- Future work will focus on better ways of combining the models to improve accuracy

Acknowledgements & References