MEG Representational Similarity Analysis Implicates Hierarchical Integration in Sentence Processing

Presented During: Posters - Thursday Even Numbers
Thursday, June 21, 2018: 12:45 PM - 01:45 PM

Presented During: Posters - Tuesday Even Numbers
Tuesday, June 19, 2018: 12:45 PM - 01:45 PM

Presented During: Posters - Wednesday Even Numbers
Wednesday, June 20, 2018: 12:45 PM - 01:45 PM

Submission No:

2078

Submission Type:

Abstract Submission

Authors:

Nicole Rafidi[1], Daniel Schwartz[1], Mariya Toneva[1], Sharmistha Jat[2], Tom Mitchell[1]

Institutions:

[1]Carnegie Mellon University, Pittsburgh, PA, [2]Indian Institute of Science, Bangalore, India

E-Poster

Introduction:

Multiple hypotheses exist for how the brain constructs sentence meaning. Most fall into two groups based on their assumptions about the processing order of the words within the sentence [Armeni et al. 2017, Ding et al. 2017]. The first considers a sequential processing order, while the second uses hierarchical syntactic rules. We test which hypothesis best explains MEG data recorded during reading of sentences with active and passive voice. Under the sequential hypothesis, the voice of a sentence should change its neural signature because word order changes. Under the hierarchical hypothesis, active and passive sentences corresponding to the same proposition should exhibit similar neural signatures.

Methods:

We test how well three language models explain MEG data collected during noun-verb-noun sentence reading. The models we test are bag of words (BoW), sequential word order, and hierarchical.

In the BoW model, a sentence is represented by averaging the GloVe vectors (Pennington et al 2014) corresponding to all content words (the nouns and verb) in the sentence. By computing the pairwise distances between these vectors, we form a representational dissimilarity matrix (RDM) (Kriegeskorte et al. 2008).

For the other two models, the distance between a pair of sentences is the normalized sum of the distances between pairs of content words in WordNet (Miller 1995). In the sequential model, the content words are paired by their position in the sentence (i.e. first nouns; main verbs; last nouns). In the hierarchical model, the content words are paired by their semantic role (i.e. agents; main verbs; patients).

As their neural activity was recorded with the Elekta Neuromag scanner, 18 participants read 16 noun-verb-noun sentences. 8 propositions were presented in both active and passive voice 10 times and an average of these was used for analysis. Each word was presented for 300ms with 200ms rest, and 2s between sentences. The data were spatially filtered using temporal signal space separation (tSSS), low-pass filtered to 150Hz with notch filters at 60 and 120Hz, and downsampled to 500Hz. Artifacts from tSSS-filtered same-day empty room data, ocular and cardiac artifacts were removed via signal space projection (SSP).

We created a separate MEG RDM at each timepoint, aligning sentences to main verb presentation. For a timepoint, the sensor values form the vector representation of that sentence stimulus and the pairwise Euclidean distance between each of the 16 sentences was computed. One RDM was computed per participant, and the resulting RDMs were averaged across participants, generating a timeseries of participant-averaged MEG RDMs.

To compare a language model to the brain data, we measure the correlation between the model RDM and the MEG RDMs.To estimate the significance of the correlation between two RDMs, we use the Mantel test for distance matrices (Mantel 1967). See Figure 1 for a schematic of the analysis methods.

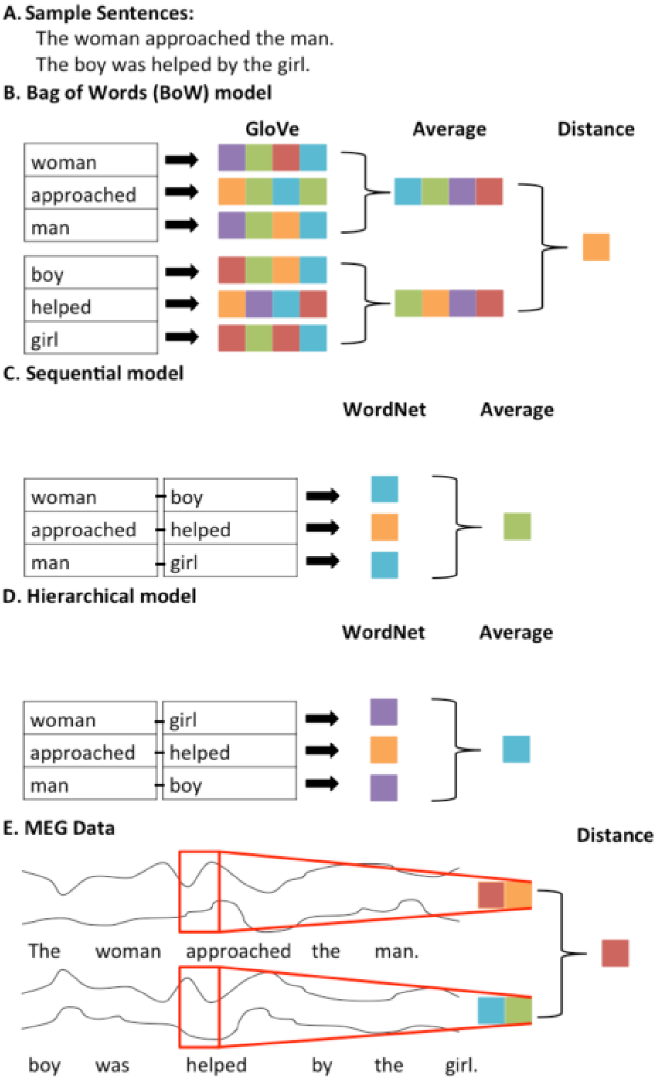

Figure 1: Methods schematic for two sample sentences, illustrating how each element of the RDM is computed under each model and for the MEG data. A. Sample sentences from experiment. B. Example computation of pairwise distance between two sample sentences under BoW model. To generate the sentence-level vector, the GloVe vectors for each of the content words are averaged. Then the pairwise distance of these sentence-level vectors are computed. C. Example computation under the sequential model. Sentence content words are aligned by sequential order. The distance between sentences is the normalized average WordNet distance between content word pairs. D. Example computation under the hierarchical model. Sentence content words are aligned by semantic role in sentence. The distance between sentences is the normalized average WordNet distance between content word pairs. E. Example computation for a single timepoint of MEG data. The sensor activations at that timepoint are treated as a vector. The distance between sentences is the distance between those vectors. This computation is repeated at each timepoint, creating a timeseries of RDMs.

Results:

All three models correlate with the MEG data for some timepoints, after verb presentation and briefly post sentence. However, the hierarchical model correlates significantly for more timepoints and is often the best correlated model even if that correlation is not significant. See Figure 2 for a detailed explanation of these results.

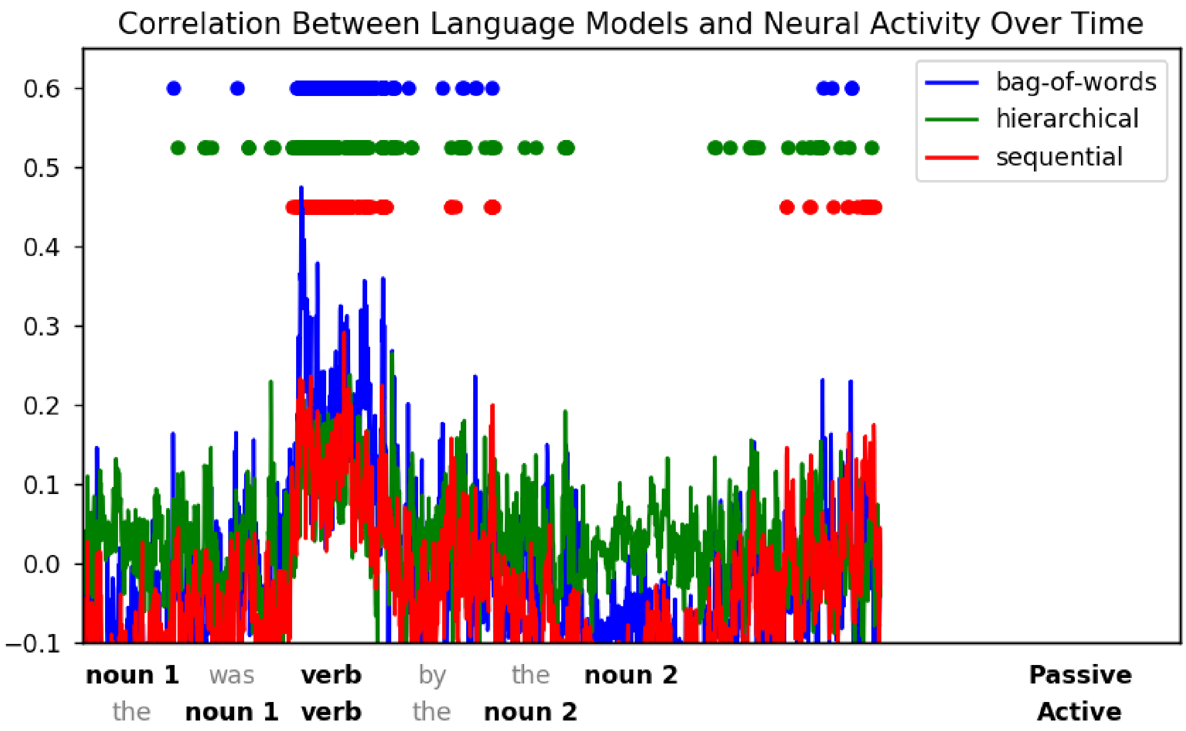

Figure 2: Correlation between language models and neural activity over time. MEG recordings are aligned to the presentation of the verb in each sentence. Each colored dot at the top of the plot signifies a single timepoint where the correlation between the MEG recordings and the corresponding language model is statistically significant at the 0.05 level (Mantel test, corrected for multiple comparisons across time using the Benjamini-Hochberg-Yekutieli procedure for positively correlated tests). In this figure, we see that the hierarchical language model timeseries significantly correlates with the brain activity RDM for a longer duration than the other language models. There is also an intriguing period just after the verb presentation where the correlation between the hierarchical language model and the brain activity is stronger than the correlation between the other models and the brain activity.

Conclusions:

Our analysis shows that a hierarchical model of meaning correlates with neural activity for a longer duration than models which use a bag of words meaning representation or sequential meaning construction. Additionally, just after verb presentation the hierarchical model is the model best correlated with the MEG data. Next we plan to source localize the data and test which regions underlie these correlations. Our method enables the study of language processing hypotheses in the brain at a fine time scale and can be applied to a wide variety of language models.

The first three authors contributed equally to this abstract.

Imaging Methods:

MEG

Language:

Language Comprehension and Semantics [1]
Reading and Writing

Modeling and Analysis Methods:

EEG/MEG Modeling and Analysis [2]
Multivariate modeling

Keywords:

Data analysis
Language
Machine Learning
MEG

[1|2]Indicates the priority used for review