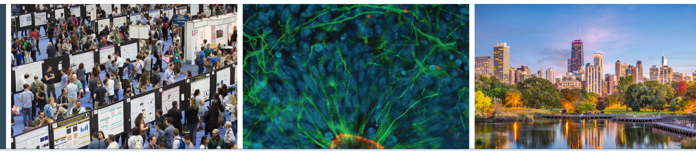

Session 339 - Language Acquisition and Coding

Add to Itinerary

339.11 / CC40 - Sparse experimental design for encoding models

October 21, 2019, 8:00 AM - 12:00 PM | Hall A

Presenter at Poster
Mon, Oct. 21, 2019 10:00 AM - 11:00 AM

Session Type
Poster

Authors

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Disclosures

L. Xu: None. **A. Lebel:** None. **A.G. Huth:** None.

Abstract

Encoding models predict neural or fMRI responses from natural stimuli but have high requirements on both data quality and quantity. This makes it difficult to scale such experiments to very large numbers of subjects or stimuli. Here we aim to solve this issue by using a sparse experimental design, in which each subject is exposed to a different small fraction of the total stimulus set. This sparse dataset is used to fit a spatio-temporal shared response model (SRM) for the whole brain, which assumes that the same stimuli evoke synchronic and localized responses across subjects. The SRM learns brain response patterns from responses of same subject to different stimuli, and learns stimulus features from the responses of different subjects to the same stimuli. These response patterns and stimulus features are then used to reconstruct data for all the stimuli that were not played for each subject. The original and reconstructed data are then concatenated and used to fit separate encoding models for each subject with standard regression techniques. In a test experiment, 3 subjects listened to all 60 auditory stimuli (12 hours in total) and 6 other subjects listened to a small fraction (around 20/60) of the same auditory stimuli, while undergoing fMRI scanning. With SRM, the concatenated datasets improve encoding model performance by 47.3% (± 18.6) for 3 good subjects, and by 268.8% (± 120.8) for the other 3 poor subjects. In simulations, we tested our model on 40 subjects and 10 to 100 stimuli with the same total data collection budget (each subject sees 10 random stimuli), and found that the concatenated dataset with SRM performs much better than the baseline. Finally, we show how to optimize the design of these sparse experiments by treating the connections between stimuli and subjects as a bipartite graph, and then showing that certain graph properties (such as the eigenvalue gap and mean path length) are closely linked to model performance. In conclusion, our SRM model suggests the sparse experimental design for encoding models with lower cost of time and money on data collection, and also shows the potential to denoise noisy datasets. Further, the response patterns and stimulus features learned by SRM could also be interpreted to gain insight into stimulus features that are represented similarly across subjects.

Abstract Citation