

Revealing Feature Spaces Underlying Similarity Judgments of Natural Scenes

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Introduction

Elucidating the feature dimensions which form our perceptions is important in gaining insight into what drives our ability to understand the world around us. Hebart et al. (2020) developed a sparse positive similarity embeddings approach to reveal the semantic dimensions driving similarity judgements collected from an 'odd-one-out' stimulus triplet judgement task [1]. The triplet judgement task is limited in measuring similarity in individual participants, and the number of possible triplet combinations makes it hard to fully sample a large stimulus set.

An alternative to the triplet odd-one out task is the multiple arrangements (MA) task [2]. This task is efficient in capturing similarity judgments in individual participants with condition rich stimulus sets. Using representational similarity analysis [3], the results of the MA task can then be compared to model or brain representations. While capable of providing a fully sampled RDM, MA provides no insight into the dimensions driving these judgments.

Here we present a hybrid methodology which aims to combine the benefits of a fully sampled set of similarity judgements from MA with the deeper insights achieved by Hebart et al.

Methods

Perceived similarity judgments were measured from eight individual participants with a set of 100 diverse, condition-rich images of natural scenes taken from the Natural Scenes Dataset [4].

1) Similarity judgements measured using the MA task.

A) Stimuli are presented around a white circular arena.

B) On each trial, participants arrange the stimuli according to perceived similarity.

C) The resulting RDM is computed using an iterative weighted averaging procedure over the pairwise euclidean distances of the stimulus coordinates across all trials.

2) Computing odd-one-outs from MA coordinates

A) A random triplet of stimuli is selected and euclidean distance between them measured.

B) The pair with the smallest Euclidean distance is defined as the most similar pair.

$L_2 \left(\begin{matrix} \text{STOP} & \text{STOP} \\ \text{STOP} & \text{STOP} \\ \text{STOP} & \text{STOP} \end{matrix} \right)$

$\text{Min}(L_2)$

$\begin{matrix} 1 \\ 0 \\ 0 \end{matrix}$

C) For all possible triplet combinations, the index of the most similar pair is stored.

triplet batch

3) Learning sparse embeddings

Randomly initialised Sparse Feature Matrix

Identify odd-one-out using softmax of the dot-product

Model predicted most-similar pairs

Observed most-similar pairs

Backpropagation

Categorical Cross-Entropy

Results

The trained model is used to generate a representational dissimilarity matrix (RDM) for unseen pairwise combinations of stimuli. The average occurrence of two stimuli as the most similar pair is taken over all possible triplet combinations in which they occur. For a given pair of stimuli (S_i, S_j):

$$1 - \frac{\sum^n \Pr(S_i, S_j \mid S_i, S_j, \{S_1 \rightarrow S_n\} - \{S_i, S_j\})}{n}$$

This is repeated for all unseen pairs to generate an RDM from unseen test data. The final cross-validated RDM is then compared with the RDM obtained from traditional iterative weighted averaging (IWA).

	Subject 1	Subject 2	Subject 3	Subject 4	Subject 5	Subject 6	Subject 7	Subject 8
IWA								
Spearman Correlation	0.92	0.90	0.88	0.87	0.87	0.91	0.86	0.85
Model Generated								

Top 5 Stimuli for the resulting top 6 dimensions

← dimensions →

weight ↑

Results

The trained matrix can be used as the basis of an encoding model to predict recorded fMRI response patterns.

Spearman's Correlation Coefficients Between Model-Generated & Iteratively-Weighted RDMs With Increasing Dimensions

Spearman's Correlation Coefficients Between Model-Generated, Iteratively-Weighted, and Ground Truth RDMs for Simulated Subjects

Conclusions and Future Direction

Multiple arrangements can efficiently collect a fully sampled set of similarity judgements for a large set of stimuli. The information from MA can be used to train a model capable of accurately reconstructing unseen similarity judgements when compared with 'gold standard' IWA.

The dimensions recovered from this model provide an insight into the key semantic concepts driving the ability to identify and distinguish natural scenes in individual participants, and reveals the number of dimensions utilised in driving said judgements.

The resulting embedding can be used to predict fMRI response patterns using voxel-wise encoding modelling. Future efforts will aim to collect fully-sampled MA data for a much larger set of natural scenes to improve the activity pattern predictions.

References

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