Report

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Representational Similarity Analysis

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Introduction

Systems neuroscience is the study of how different regions of the brain interact to produce behavior and cognition and is a complex and challenging field. One of the main challenges is understanding the neural mechanisms underlying complex cognitive processes, as well as identifying how different brain regions interact and communicate with each other, and relating neural activity to behavior (Kriegeskorte, 2015). Representational Similarity Analysis (RSA) is a statistical method used to compare patterns of neural activity across different brain regions or conditions and is a powerful tool for systems neuroscience (Kriegeskorte and Kievit, 2013).

RSA can be used to overcome some of the limitations of other techniques used in systems neuroscience. For example, functional Magnetic Resonance Imaging (fMRI) allows for the non-invasive study of brain activity by measuring blood flow, but it has a low temporal resolution, meaning it is not able to track rapid changes in neural activity (Logothetis, 2008). Electroencephalography (EEG) has a high temporal resolution, but low spatial resolution, meaning it can track rapid changes in neural activity, but it's not able to identify the specific location of the activity in the brain (Nunez and Srinivasan, 2006). Single-cell recordings provide high spatial and temporal resolution, but it is an invasive technique and can only be performed on animals (Ecker et al., 2010). RSA can help to overcome some of these limitations by combining information from different techniques.

Why use RSA?

RSA is a widely used analytical method in cognitive neuroscience that aims to investigate the neural representations of stimuli in the brain (Kriegeskorte, 2008; Kriegeskorte et al., 2008). The core assumption of RSA is that stimuli that are perceived or semantically similar should elicit similar patterns of neural activity across different brain regions or conditions. RSA enables the quantification of this similarity and the examination of how it relates to the similarity of the stimuli themselves, or other cognitive or behavioral measures (Kriegeskorte et al., 2008).

The procedure for RSA includes measuring neural activity, typically via fMRI or EEG, in response to a set of stimuli and comparing the similarity of the activity patterns across different stimuli, conditions, or brain regions (Kriegeskorte et al., 2008). This similarity can be computed using various metrics such as correlation, cosine similarity, or Euclidean distance (Kriegeskorte et al., 2008).

Procedure of RSA

The basic procedure of RSA includes the following steps as shown in figure 1:

1. Data Collection

   Data on neural activity is first gathered using neuroimaging methods like fMRI or EEG (Poldrack, 2011). This data is typically arranged in a "design matrix" that details the conditions or tasks assigned to the participants during the experiment.

2. Representation of Neural Activity

   The neural activity data is represented in a way that can be compared across conditions or tasks (Kriegeskorte, 2008). This is typically done by creating a "representation" of the activity in each brain region, such as the mean activity during a particular task or the pattern of activity across multiple time points.

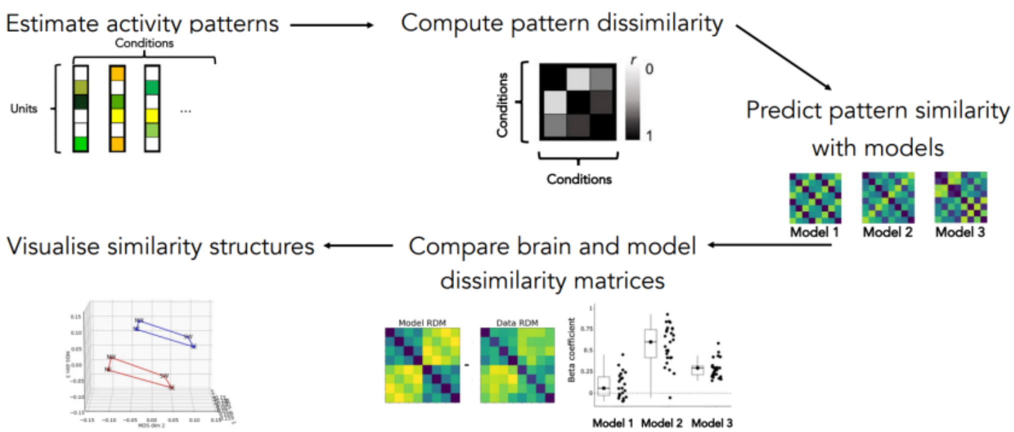

Fig 1. Steps involved in RSA

3. Similarity Computation

   After the neural activity is represented, the similarity between the representations can be computed (Kriegeskorte, Mur, & Bandettini, 2008). This is typically done by comparing the representations using a mathematical measure of similarity or dissimilarity, such as correlation or Euclidean distance.

4. Statistical Analysis

   These similarity values are analyzed statistically to identify and predict patterns of neural activity that are related to the experimental conditions or tasks (Kriegeskorte, Mur, & Bandettini, 2008). This can be done using techniques such as multivariate regression or pattern classification. Dissimilarity matrices are computed by comparing the predicted patterns against the brain activity. Next, these matrices are used to graphically represent the data such as a box plot. By using graphical representations, it becomes simpler to understand and interpret the meaning of the data.

Analysis

RSA is a versatile method that can be applied to a wide range of research questions in cognitive neuroscience, for example, the study of how the brain encodes visual, auditory, or somatosensory information, the identification of neural representations of different features of stimuli, the examination of the neural mechanisms underlying memory consolidation and retrieval, language processing and acquisition and different types of decision making (Kriegeskorte et al., 2008). Additionally, RSA can be used to investigate the neural mechanisms of cognitive disorders such as schizophrenia, autism, and Alzheimer's disease by comparing the similarity of neural activity patterns across different groups of individuals (Kriegeskorte et al., 2008).

Strengths

Some of the strengths of RSA are that it is a method used to quantify neural representations of stimuli in the brain. The method relies on comparing the similarity of neural activity patterns across different stimuli, conditions, or brain regions. RSA can be used to relate these neural representations to other cognitive or behavioral measures, providing insights into how the brain encodes and processes different types of information. This method can be applied to a wide range of research questions in cognitive neuroscience, such as perception, memory, language, and decision-making. Additionally, RSA can also be used to examine the neural mechanisms underlying cognitive disorders, such as schizophrenia, autism, and Alzheimer's disease. RSA is a flexible method that can be applied using various imaging modalities, such as fMRI, EEG, and MEG. Furthermore, RSA is a data-driven method, which means it doesn't require any prior assumptions about the neural representations of stimuli.

Limitations

RSA is a technique used to establish neural representations of stimuli by presenting a large number of stimuli to participants. The method is based on the assumption that stimuli that are perceptually or semantically similar will elicit similar neural activity patterns. However, this assumption may not always hold true, and RSA only provides information about the correlation between neural activity patterns, not about the direction of causality. Additionally, RSA is limited by the resolution of the imaging modality used and can't provide information about neural activity at the single-neuron level. Furthermore, RSA is computationally expensive, and it is limited by the number of brain regions that can be analyzed. RSA also relies on the assumption that neural activity patterns are stationary, which may not be the case in dynamic systems such as the brain.

Alternatives

With the aforementioned limitations, there are some alternative techniques to use. Multivariate pattern analysis (MVPA) and decoding analysis are both techniques that can be used to study neural representations of stimuli in the brain. These techniques are similar to Representational Similarity Analysis (RSA) in that they both use machine learning algorithms to classify patterns of neural activity across different stimuli, conditions, or brain regions. However, MVPA and decoding analysis can provide more specific information about the features of the stimuli that are encoded by the brain, whereas RSA is more focused on comparing the similarity of neural activity patterns across different stimuli, conditions, or brain regions (Norman et al., 2006; Peelen & Downing, 2005). Dynamic Causal Modeling (DCM) is another technique that allows inferring the causal interactions between brain regions. DCM is a powerful tool for studying neural mechanisms underlying different cognitive processes and disorders, such as perception, action, and decision-making (Friston et al., 2003). Unlike RSA, DCM is focused on identifying causal interactions between different regions of the brain and how they work together to produce behavior and cognition. In the end, while RSA, MVPA, decoding analysis, and DCM are all techniques that can be used to study neural representations of stimuli in the brain, each of them has its own strengths and limitations.

Summary

In summary, RSA is a powerful analytical method, that helps researchers understand how different regions of the brain interact to produce behavior and cognition. It can be used to complement other techniques in systems neuroscience by providing a quantitative way to compare neural activity across different regions, conditions, and techniques, and by revealing patterns of neural activity that are shared across different regions, conditions, and techniques.

Practical report

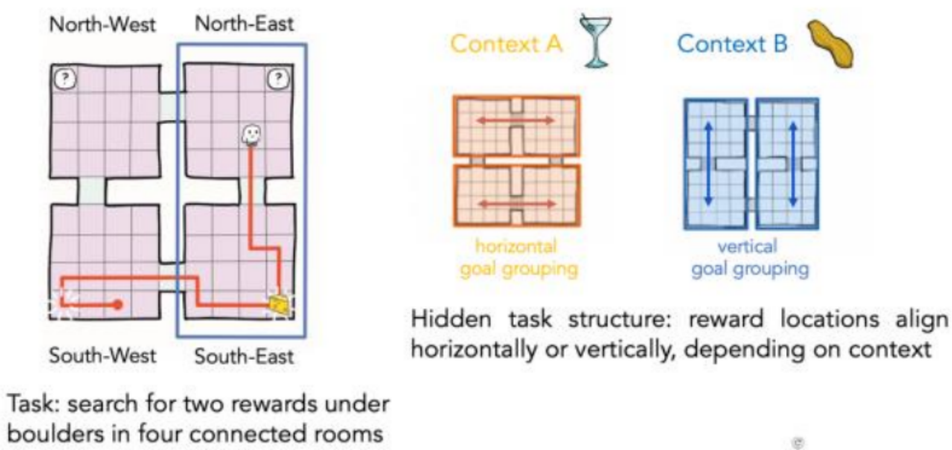

Fig 2. Illustration of the spatial layout of the navigation task (left) and the latent task structure with horizontal and vertical goal grouping (right).

Task

The practical is based on a study that used functional magnetic resonance imaging (fMRI) to investigate neural activity related to context-dependent navigation. The participants were presented with a task in which they had to search for two rewards located under boulders in four interconnected rooms. The task contained a hidden structure, with the location of the second reward varying depending on the identity of the cued reward stimulus. The study used a 3T Siemens Trio fMRI scanner, which is a high-field magnetic resonance imaging device that is capable of producing detailed images of the brain. Participants received a monetary bonus that decreased with the time taken to find the rewards, providing an incentive for them to find the rewards quickly. The study aims to investigate the neural processes involved in learning a hidden task structure that enables participants to quickly infer the location of the second reward and maximize their payoff.

Objective

The primary objective is to perform RSA and evaluate how specific regions in the brain encode spatial information, particularly with regard to the geometry of four distinct rooms, and how these representations change over time.

Experiment

We performed RSA on a dataset of 27 participants with respect to the visual and parietal regions of the brain. The visual part represents the occipital lobe and the parietal part represents the parietal lobe. According to the aforementioned steps of RSA, these are steps one and two for data collection and representation of neural activity respectively. Next, to compute the similarity we spilt the data of each participant and calculate the Euclidean distance by subtracting the mean from each data point. After merging the normalized data back together we receive our similarity and dissimilarity matrices. These matrices are cross-validated to ensure that the errors are generalized and that observed matrices are true representations of the original data. Further to analyze the data, we test these matrices with 3 different models (with respect to room direction, room distance, and context). Next, we compare the regressed models against the beta coefficients that were estimated using the similarity matrices. And plot the results of the similarity structures against the three dimensions that represent the three models used.

In the practical, we applied RSA to a dataset of 27 participants in order to investigate the neural activity in the visual (occipital region) and parietal regions of the brain. First, we used the collected data for each participant to represent information about their neural activity. Next, we used RSA to represent the neural activity data by splitting the data for each participant, calculating the Euclidean distance by subtracting the mean from each data point and merging the normalized data back together to generate similarity and dissimilarity matrices. We cross-validated these matrices to ensure that they were valid representations of the original data. We then tested the similarity and dissimilarity matrices using three different models: one that was based on the direction of the room, one that was based on the distance of the room, and one that was based on the context of the room. Next, we compared the results of the regressed models to the beta coefficients that were estimated using the similarity matrices. Finally, we plotted the results of the similarity structures against the three dimensions that represent the three models used to further analyze the data.

Results

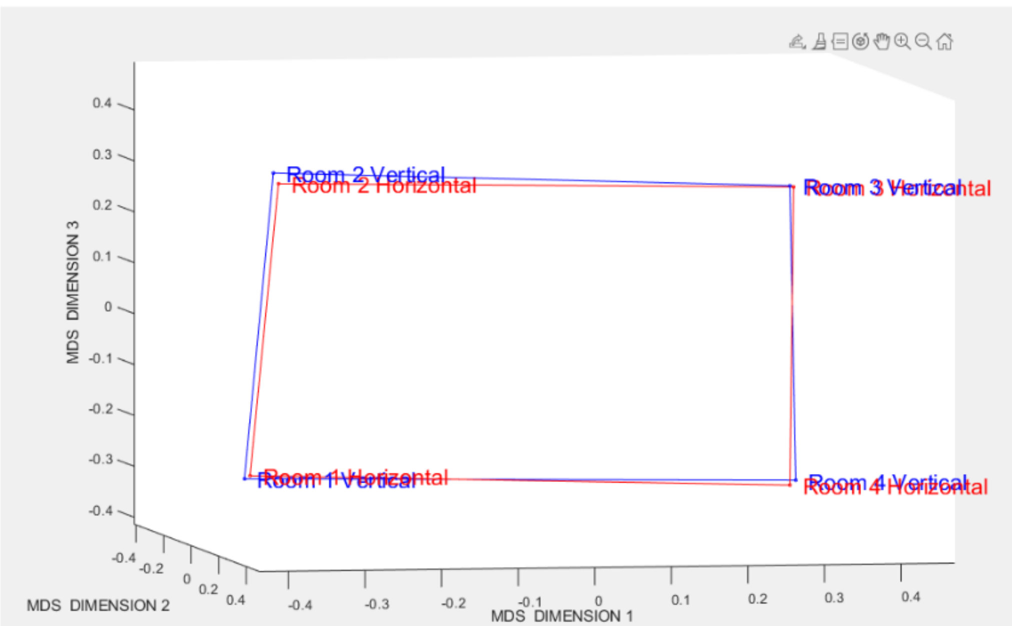

Fig 3. Box plot of the data from a Visual perspective.

The results showed that when visual cues were present, there was no correlation between the room identified and the direction of movement, but there was a correlation between the spatial position of each room, as indicated in Figure 3. In contrast, when visual cues were not available and participants had to rely on their parietal senses, a correlation was observed between the direction of movement, but there was no correlation between the spatial configuration of the room, as depicted in Figure 4.

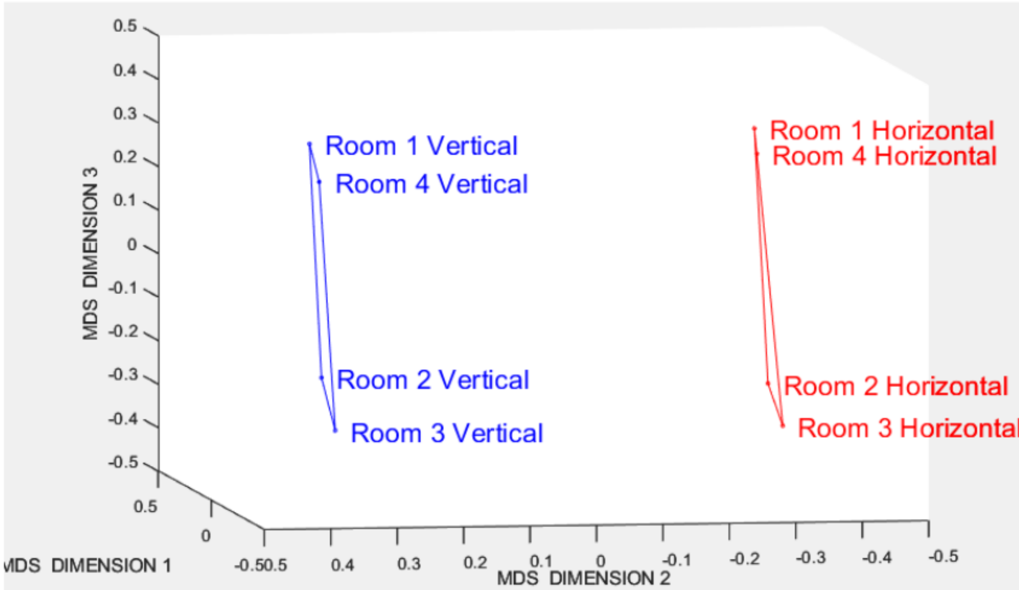

Fig 4. Box plot of the data from a Parietal perspective.

Discussion and Conclusion

We can infer that the position and orientation of a room have a greater influence on the visual region of the brain, as represented by the occipital lobe, than the direction of movement. This is supported by the fact that participants in the study treated each room as a distinct entity and made decisions about movement based on their perception of the room. Conversely, when the parietal region of the brain is activated, the direction of movement appears to have a greater influence on decision-making. This is supported by the role of the parietal lobe in processing information from the other senses and the observation that participants based their movement decisions on the direction of the rooms.

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