Deep Image Reconstruction From Brain Activity

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Abstract

Introduction

The goal of this project is to reconstruct images from brain activity. Specifically, the project will use fMRI data to reconstruct images. The project will use a deep neural network to reconstruct images, using differentiable programming and geometric deep learning.

Being able to decode images from brain activity has many applications. For example, it could be used to help people with locked-in syndrome communicate with the outside world. Pursuing this goal is also interesting from a scientific perspective, as it could help us understand how the brain processes visual information.

Literature Review

Decoding images from brain activity is a well studied problem in the field of neuroscience. The first successful decoding of images from brain activity was done by Haxby et al. (2001). Like the current project, Haxby et al. used fMRI data. Most recently Lin, Sprague, and Singh (2022) used a deep neural network to decode images from brain activity. Also Thomas, Ré, and Poldrack (2023) merits mention, focusing on developing a mapping between brain activity and mental states more broadly.

Data

The data used in this project is derived from the Natural Scenes Dataset Allen et al. (2022). The dataset consists of 73,000 images of natural scences and various assoicated responses, collected over the course of one year from 8 subjects. Specifically, the data used in this project is from the Algonauts Project Gifford et al. (2023). Associated with each subject are region of interest (ROI) masks. These masks are used to extract the fMRI data from the images, at specific locations in the brain.

Methods

The project will use a deep neural network to reconstruct images from brain activity. The steup is that of a supervised learning problem, where the input is the fMRI data, and the output is the image. The network will be trained using gradient descent. The network will be implemented using JAX Frostig, Johnson, and Leary (n.d.), a library for differentiable programming.

The network will be a graph neural network (GNN) Bronstein et al. (2021).

Results

Discussion

Conclusion

References

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Appendix