Liam Creedon

Classification Analysis in FFA

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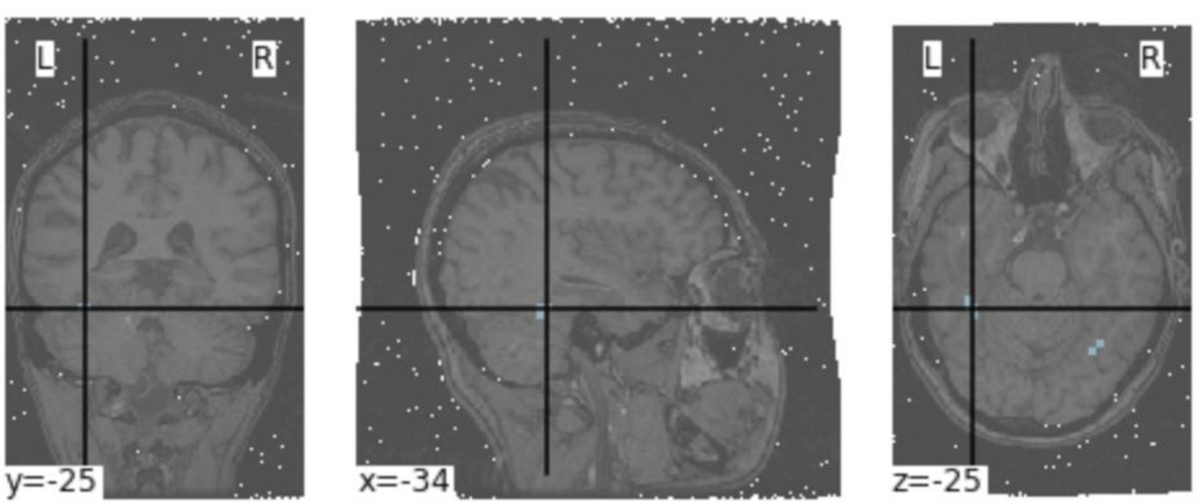
GOALS

1. This study seeks to determine whether the Fusiform Face Area (FFA) encodes representations for objects, as well as faces.
2. Use fMRI data from the Haxby et al. (2001) study, and a brain mask for the FFA to explore the neural activities for a patient when shown images belonging to predetermined categories. The results will be assessed to determine if the FFA is sensitive to object -stimuli. Studies have shown that the FFA excels in recognizing faces, but as posited by the distributional hypothesis, information is encoded in many different locations in the brain.
3. Use classification analysis, specifically K Nearest Neighbors, to differentiate neural activity patterns corresponding to each category of the images presented to the patient. Categories are as follows: bottle, cat, chair, face, house, scissors, shoe, and scrambled images. Determine one of the following:
    a. FFA strictly encodes faces
    b. FFA plays some role in object recognition
    c. FFA plays as much of a role in object recognition as it does face recognition

HYPOTHESIS

FFA plays little role in object recognition, and therefore primarily encodes for faces.



METHODS

- ➔ fMRI data from subject one from Haxby et al. (2001)
    - ◆ Data contains neural activity for the subject when shown images corresponding to each of the 8 object categories:
        - Bottle, cat, chair, face, house, scissors, shoe, scrambled pictures
    - ◆ Data for neural activity when the subject is at rest is removed prior to classification analysis
- ➔ Voxels from the FFA are isolated using a mask on the brain image
- ➔ To train the classifier, the model is provided the dataset along with the correct category labels
- ➔ The model is then tested using a within subject, leave one run out cross validation method
    - ◆ A 2 way test will look at classification of ‘face’ and ‘non-face’
    - ◆ Another 8 way test will look at classification of all categories individually
- ➔ Each test will be run with 3 different k values (1, 3, 10)
- ➔ The results from each test will be averaged for a mean accuracy of the classifier
- ➔ The accuracy will be tested for significance using the binomial test

PREDICTIONS

Face vs non-face

This test should yield a near 100% accuracy for classifying whether or not an object-stimulus is a face. We know that the FFA specializes in distinguishing faces from previous studies.

All categories

I expect that this test will see lower accuracies, but not 0% accuracy. I believe that the model will be able to classify a handful of images correctly based on the similarity. I believe that the trials with a lower k value will yield more correct classifications than the trials with a higher k value.

RESULTS

Mean accuracies	K = 1	K = 3	K = 10
2 way classifier	1.0000 +/- 0.0000	1.0000 +/- 0.0000	1.0000 +/- 0.0000
8 way classifier	0.1609 +/- 0.0662	0.1354 +/- 0.0541	0.1447 +/- 0.0740

Binomial test results	K = 1	K = 3	K = 10
2 way classifier	108 / 108 correct p = 0.0000	108 / 108 correct p = 0.0000	108 / 108 correct p = 0.0000
8 way classifier	139 / 864 correct p = 0.0019	117 / 864 correct p = 0.3544	125 / 864 p = 0.0893

The two tables above describe the mean accuracies and binomial test results from each of the different classifiers. As we can see from the charts, the two way classifier has 100% accuracy in classifying faces, and that the p value is 0. Therefore the results are insignificant, or this is the expected behavior of the 2 way classifier.

For the 8 way classifier, we see that the accuracy for the classifier with 3 neighbors was the lowest, and that the classifier with 1 neighbor was the highest on average; however, all of the classifiers were only about correct about 15% of the time. The binomial p values told us for the k=1 classifier, this was normal, but for the k=3 and k=10 classifiers, this was statistically significant, meaning that this result was likely skewed.

CONCLUSION

Through the results of this study we can conclude that the FFA primarily specializes in recognizing faces, and plays little to no role in object recognition. We can also conclude that smaller k values are noisy and that larger k values smooth the data, but provide more of a bias. This is seen in that the k value of 3 was not as effective as the k value of 10.

INNOVATION

In this study, we used classification analysis, more specifically a K Nearest Neighbors classifier, in order to classify the neural representations yielded from the FFA voxels of a subject. In this class, we have looked at the Haxby data using a Ventral Temporal brain mask for object classifying. We saw that the ventral temporal lobe plays an important role in object processing. This study allows us to examine a more specific area of the VT lobe, the FFA, to see what role this area plays in the object processing that occurs in the VT. Also, in looking at different sizes for k, we are analyzing the efficiencies of a KNN classifier with different k sizes.

SIGNIFICANCE

This study allows us to specify what role the FFA plays in object processing. If we can show that the FFA is particular towards face stimuli, we can use this knowledge to localize deficiencies in people. For example, if a person suffers a stroke, and they lose the ability to recognize faces, then we know where in the brain we need to look to treat this stroke.

I would be curious to see which categories (if any) the model can classify correctly, and if there can be any conclusions drawn from this.

> ex. if one of the categories was ‘car tail-lights’, whether or not the model would have better success in classifying this (example)).