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| **Reading the Readers: Using fMRI to Predict Noun Meaning Recognition** |
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**Abstract**

The Abstract paragraph should be indented ½ inch (3 picas) on both left and right-hand margins. Use 10 point type, with a vertical spacing of 11 points. **Abstract** must be centered, bold and in point size 12. Two line spaces precede the Abstract. The Abstract must be limited to one paragraph.

**1 Introduction**

Functional magnetic resonance imaging in conjunction with machine learning has been used to predict cognitive events, specifically noun recognition in readers, via machine learning on activity in the brain [3]. Increasing the accuracy and efficiency of the algorithms involved with this learning offers the chance to improve brain computer interfaces, such as those that could assist people who have suffered from brain injuries or have cognitive defects. Alternatively, there also exist possibilities for applications to criminal investigation and more accurate lie detection systems.

Since the brain is a complex system with high dimensionality, overfitting and complexity management can be an issue for any given machine learning algorithm. The goal of our experiment was to determine the parameters and conditions that optimize accuracy of noun prediction while keeping memory usage and runtime reasonable. The goal of this project as a whole is to enable the prediction of the noun that a given person reads based on their brain’s fMRI signature in response to that noun.

**1.1 Background**

Functional magnetic resonance imaging, or fMRI, uses a powerful magnetic field around a subject’s brain to detect changes in blood flow to various parts of the brain, since increased blood floor is closely correlated to increases in neuronal activity in the brain, and deoxygenated versus oxygenated hemoglobin in blood has different and observable magnetic properties.

The data set we used was produced by an experiment by Carnegie Mellon University in which nine adult participants were shown line drawings and noun labels of sixty different nouns. Participants were asked to assign 218 semantic features (properties) to each word shown; for example, a single semantic feature might represent the questions, “Is it an animal?” The noun “ant” has a value of 4 for this feature while the noun “airplane” has a value of 1. Note that although the semantic features are meant to be simple yes-no questions, no attempt was made to ensure consistency among participants’ responses to the semantic feature questions in regards to their target noun.

When participants were shown a particular word, the fMRI records activity in the brain as a 21,764-dimension vector. Each dimension represents a voxel, a “cube” of brain in the third dimension. Thus, a 3d map of the brain can be established for a single person’s reading of any particular word. Using this map to predict words not in the training set that have their own, unique semantic feature vector and fMRI response requires machine learning on a training “dictionary” of words, as the algorithm must learn to correlate brain activity in certain areas to semantic features of a word.

The data set contained 360 trials. For our experiments we used 300 trials as the training set and 60 trials as the test set. This was done so as not to perform testing on the training data.

In terms of applicability, fMRI is not practical for day-to-day consumer use. fMRI machines are massive, expensive, and require lots of energy to keep the superconducting magnets responsible for generating the magnetic field at extremely cold temperatures, often through the use of liquid helium. However, the implications of this study could be used with less involved brain-computer interfaces such as non-invasive EEG, which consists of a skullcap with electrodes which can measure electrical activity in the brain, or even commercial electrode headsets. This would require better noise-reduction and signal-processing capabilities, as these platforms would be less likely to record brain activity at the resolution and spatial/temporal integrity that fMRI is able to.

The use of fMRI in lie detection has been discussed; in this case, fMRI machines might still be usable, as the participant would most likely be involved in a setting where portability is not an issue. However, further efforts are needed to refine prediction algorithms as well as address the possibility of people fooling the algorithm through careful training.

On a fundamental level, our learning objective was to perform 218 sparse, linear regression models, each consisting of mapping an fMRI reading consisting of 21,764 voxel values to a semantic feature vector that represented a particular word in the training set. Once established, word prediction between two possible word choices could proceed by choosing the least L2 distance between the regression model and the two semantic feature vectors for the possible words.

**2 Methods**

Our regression model used least absolute shrinkage and selection operator (LASSO) as its regularization algorithm.

LASSO penalizes large coefficients in the regression polynomial to address the issue of overfitting and produce a sparse solution to this learning objective.

Leave one out cross validation (LOOCV) was used to choose the optimal LASSO weighting factor λ.

To optimize the LASSO objective, stochastic coordinate descent (SCD) was used.

Because the fMRI reading contains so many dimensions, lack of memory was an important consideration and a frequent limitation when implementing these algorithms. Two strategies of dimensionality reduction were used. Initially, we used a very simple method of dimensionality reduction by establishing an arbitrary variance threshold and eliminating all dimensions whose variance was below that value.

We also implemented principal component analysis (PCA).

However, it is suggested that this strategy may not be the best approach for reducing dimensionality for data sets with more dimensions than data points []-[].

**3 Headings: first level**

First level headings are lower case (except for first word and proper nouns), flush left, bold and in point size 12. One line space before the first level heading and ½ line space after the first level heading.

**3.1 Headings: second level**

Second level headings are lower case (except for first word and proper nouns), flush left, bold and in point size 10. One line space before the second level heading and ½ line space after the second level heading.

**3.1.1 Headings: third level**

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**4 Citations, figures, tables, references**

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As submission is double blind, refer to your own published work in the third person. That is, use "In the previous work of Jones et al. [4]", not "In our previous work [4]". If you cite your other papers that are not widely available (e.g. a journal paper under review), use anonymous author names in the citation, e.g. an author of the form "A.Anonymous".

**4.2 Footnotes**

Indicate footnotes with a number in the text. Place the footnotes at the bottom of the page on which they appear. Precede the footnote with a horizontal rule of 2 inches (12 picas).

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Figure 1: Sample Figure Caption

**4.4 Tables**

All tables must be centered, neat, clean and legible. Do not use hand drawn tables. The table number and title always appear before the table. See Table 1.

Place one line space before the table title, one line space after the table title, and one line space after the table. The table title must be lower case (except for first word and proper nouns); tables are numbered consecutively.

Table 1: Sample table title

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| **Part**  **Description** |  |
| Dendrite | Input terminal |
| Axon | Output terminal |
| Soma | Cell Body (contains cell nucleus) |

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**6 Conclusion**

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**References**

[1] Friedman, Roberta. “Predicting brain response to nouns.” *Biomedical Computation Review* (2008).

[2] Jelodar, Ahmad. et al. “WordNet based features for predicting brain activity associated with meanings of nouns.” *Proceedings of the NAACL HLT 2010 First Workshop on Computational Neurolinguistics* (2010), 18-26.

[3] Mitchell, Tom. et al. “Predicting human brain activity associated with the meanings of nouns. *Science* 320.5880 (2008), 1191-1195.

[4] Tian, Siva T. “Dimensionality reduction for classification with high-dimensional data.” Dissertation, University of Southern California. Los Angeles: Proquest/UMI, 2009 (Publication No. 3368663).

[5] Wang, Z. et al. “Strategies for reducing large fMRI data sets for independent component analysis.” *Magnetic Resonance Imaging* 24.5 (2006), 591-596. PubMed.gov. 24 May 2013. <http://www.ncbi.nlm.nih.gov/pubmed/16735180>