Analysis of EEG characteristics in Identifying Congruent Modal/Lexical Stimuli

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ABSTRACT

There are millions of neurons in the human brain that act as important roles for controlling human behaviors reacting to different stimuli. Nowadays, understanding behaviors and patterns of brain is one of the major tasks neuroscientists are working on. One of the methods that they used is by analyzing the signals from the brain. EEG is one of the most significant tools for acquiring brains signals. Neuroscientists often use EEG signals to study brain-behavior relations. EEG is important because it allows the neuroscientists to detect activity of various actions within the brain, for example, EEG can help to determine interference on the brain, reading the color red wriiten in blue color causes interference since we are receiving two non-congruent stimuli from a sensory(visual) point and a (word) point. For this project, we use machine learning system to discover characteristics of EEG that help identify where in the brain modality, lexicality, semantically congruent stimuli are recognize. The EEG data that we use is recorded when the subjects are observing a series of stimuli.

INTRODUCTION

Interference or inhibition have been largely studied since early as 1890 and has been a large part of scientific research. The famous "Stroop Effect" named after researcher J. Ridley Stroop attributed the powerful effects of interference of color word stimuli upon visually seeing colors. Reading the color red written in blue color causes interference. We are receiving two non-congruent stimuli from a sensory (visual) point and reading a word (lexical). Picture-word analogue of the stroop effect has also been researched. In the picture-word interference (PWI) task, subjects name objects in picture while having a distractor word written on the picture. The distractor can be the name of the picture (pictured cat, word cat), categorically related word (pictured cat, word dog) or categorically unrelated word (pictured cat, word pen). Research findings on PWI is similar to the findings of the stroop effect. Trials with categorically related distractors such as a picture of a cat and word dog(category: animal) slow down response times opposed to semantically congruent picture and word such as picture of cat and word car. This finding is analogous to that in the colour word Stroop task. The different color word and font color slowed response times(category:color) opposed to color words all written in black.

Recent research has introduced ways to reduce or even reverse the effects of an incongruent word. Dave Britton from the graduate center of City University of New York documented brain neural activity using EEG, response times, and accuracy of selecting correct target stimuli. The flanker selective paradigm used 20 different combinations of visual/auditory modalities with word/nonword lexicalities as both flankers (distractors) and as targets to manipulate attention with phonological congruent and non-congruent trials. This project will use machine learning to help discover characteristics of EEG that help identify where in the brain Audio/Visual(modality) , Language/Non-Language(lexicality) and semantically congruent are recognized. We learn where and how modality, lexicality and semantic content are stored in the brain. Thus, once we discover the parts of the brain that work together we can investigate the signal outputs of the part of the brain given, therefore, to help the neuroscientists to identify when and where the brain is the most active when the subjects are experiencing modality , lexicality or semantic stimuli.

BACKGROUND

Integrated information from different modalities are crucial for information processing [1]. The convergence of information from multisensory input enhances behavioral performance (e.g, speed and accuracy) due to the increase of certain neurons activating (firing) together. The firing rate of cells of multisensory inputs far exceeds firing rate of unisensory inputs. This means that humans are capable of realizing kind of input and storing information when we have more than one sensory organ being used(such as seeing and hearing)Semantic Congruence refers to the combination of multisensory stimuli that are presented in terms of the same meaning. The impact of multisensory input has been investigated in several studies [2,3] and significantly faster times were found in semantically congruent audio-visual pairings compared with unisensory input. Significant longer times were found for mismatched incongruent audio-visual pairings. Thus, semantic congruence has an significant impact on the integration of information across different modalities.

Two visual-audio bimodal stimulus (VABS) systems were conducted on a study[4]. The study was comparing congruent and non-congruent VABS based model. The paper aimed to see if semantically congruent stimuli can get the same performance as incongruent stimuli in Brain computer interface (BCI) systems. The results showed higher amplitude of the Event Related Potential (ERP) of semantically incongruent non-target and target stimuli. The acquired raw EEG data was preprocessed for artifact removal through Independent component analysis(ICA). ICA is a dimension reduction method aims to extract new features from original features to reduce the dimensions of feature space and therefore yielding a better classification performance[6]. ICA has the capabilities to extract new features that are independent from each other as possible and also convey the output information faithfully. Data was than filtered through Band pass of 0.5-40Hz and down sampled to 200Hz. The event related potentials of three channels (target ERPs and distractor ERPs) were calculated and averaged for each condition (congruent and incongruent). They plotted the ERP of each channel (CZ, FC5 and CPz) for each condition (congruent and incongruent) with two colors representing the target stimuli and distractor stimuli. The spatial temporal distribution of class discrimination (target and distractor) were shown for both conditions. The scalp map was shown depicting the average sign value for three specific time intervals. A Positive value represents that target ERPs have larger amplitude than distractor ERPs. Whereas a negative value represents the opposite. Support Vector Machine (SVM) was used to do binary classification of target and non-target. The illustration of Fig 1 demonstrates that higher class discrimination values are lying at channels around FCz, Cz, CPz, and Pz with the time interval from 200ms to 500ms approximately.

From this research we can learn to visualize the patterns associated with each target ERPs and distracters ERPs so that we can find evidence to differentiate characteristics of EEG. This will help us classify the type of information contained in the EEG (e.g visual, audio, language, non-language), and find sufficient evidence in the EEG that shows brain has understood semantic congruent stimuli was seen. We can see from figure 1 that there is no significant evidence to classify congruent and incongruent from the results because results are similar. The research explains that they might not have had enough data to get better results. We aim to make sure that our data is sufficient enough and replicate this experiment to acquire better results.

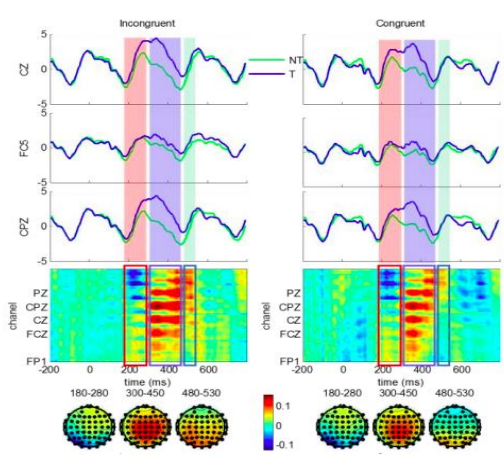


Figure 1: Readings shown between 200 ms and 500 ms where the highest class discrimination was noticed. The radical change in color from neutral green shows that either ERP target amplitude was higher than ERP distractor or vice versa.

MEATHOD

Our first step in this project is to preprocess the data to filter out noise. Furthermore we link each event from trg. file with the EEG data files. This entails multiple levels of bandwidth filtering and ICA (Independent Component Analysis) to strengthen the desired signals. We also work with Dave Britton, who provided us with the data, to verify the results of preprocessing.

After removing the artifact, the raw data was then converted into 500ms epochs, as

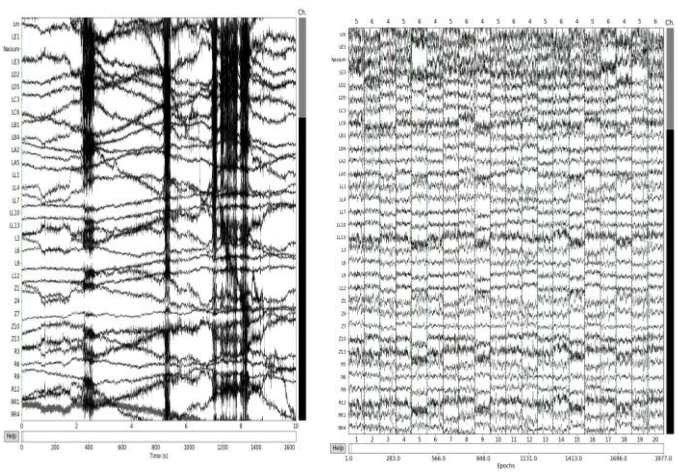


Figure 2 The Raw EEG data before(left) and after(right) ICA filtering

defined in the experimental setup where the raw data came from [6]. The experiment was set up when the subjects were exposed to stimuli for 500 ms, after the 500 ms, another stimuli was presented. One entire trial consists of three 500 ms. Each stimuli has its own event IDs, the trigger files provided to us included the event IDs that describe each trial, including the configuration of modality and lexicality. Therefore, combination of three event IDs make up one trial. , Then in order to fit our data into the binary classifier, we have to re-label our data into binary, since that is the nature of our research problem [5]. Because three event IDs make up of the content of one trial, therefore, the labels can be generated for each trial based on the pattern of events ID. For example, in the case of modality problem, event IDs combinations that are greater than 700 are visual signals, less than 700 will be audio signals. In the case of lexicality problem, when the first digit is odd, it’s language signals, when it’s even, it’s non-language signals.

Once we have preprocess and label our data correct, we aimed to analyze our machine learning algorithms to identify deciding factors that affect the final classification result, and based on the deciding factors we predict that they will correlate with the parts of the brain that are responsible for making such decisions.

We use machine learning to work on and answer the following research problems with a set of EEG data.

1. Identify the modality of the given stimuli (audio vs. visual stimulus)

2. Identify the lexicality of the given stimuli (language vs. non-language stimuli)
3. Identify the semantic content of the stimuli (e.g dog, baby, etc.)
4. Identify the parts of the brain that are being used on problem 1-3

For each of these problems, we explore the factors that the algorithms choose to base its decisions on and map them to the human brain, which allows psychologists to understand the part of the brain is working The classifiers that we are using for doing machine learning classification are Logistical Regression and Random Forest. The main reason why we choose to use Logistical Regression is because it provides us with the coefficients that are the same shape as our features array. From the coefficients we are able to determine what are the best or worst performing features for our classification.

For my own individual task I choose to use Random Forest because Random Forest is considered as a highly accurate and robust method and we can get the relative features importance, which helps in selecting the most contributing features for the classifiers. Once I have collected the most important features, I can then map those features back to the brain to determine when and where the brain contributes the most when classifying modality, lexicality or congruency problems. It's also very important to choose the best parameters when doing classification so that we can optimize our results. The parameters that I tune for Random Forest are the following:

- **max_depth**: The maximum splits for all trees in the forest.
- **bootstrap**: An indicator of whether or not to use bootstrap samples when building trees.
- **max_features**: The maximum number of features that will be used in node splitting
- **criterion:** This is the metric used to asses the stopping criteria for the decision trees.

In order to select the best parameters, I utilized a functionality called GridSearchCV. The GridSeachCV evaluates all combinations that I defined for the parameters and then choose the best one for our training data that gives the best result. After using GridSeachCV, the Best parameters I get are:

- **max_depth**: 4
- **bootstrap:** False
- **max_features:** Auto
- **criterion:** entropy

Besides the parameters described above, there are also one more important parameter for Random Forest that we have to optimize to get the best result, this parameter is the N-estimators. In order to find the best N-estimators, the concept of out-of-bag (OOB Error) rate for Random Forest is a very useful.

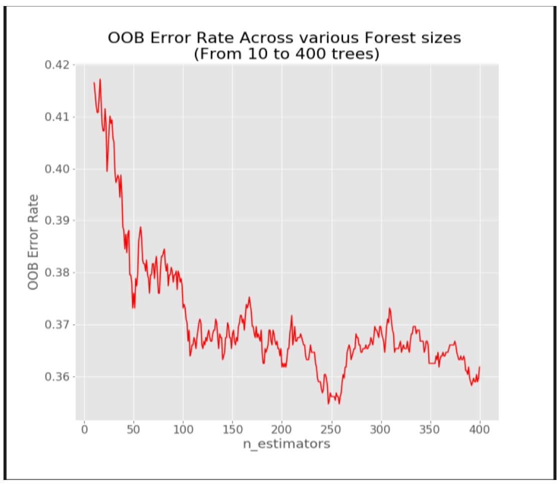


Figure 3 Example of Out-of-bag Error rate across various forest sizes

Figure 2 above shows how the Out-Of-Bag Error rate can be measured at the addition of each new tree during the training process. The plot allows us to find a suitable value for N-estimators at which the error stabilizes. It's obvious from the plot that starting from N-estimators equal to 110 is when the Out-Of-Bag Error rate begins to stabilizes, so for our classification experiment, we set the N-estimators equal to 110 for best results.

Vectorizer is used to transform the shape of our input data from 3 dimensions(number of epoch * number of channels * number f sample) to 2 dimensions(number of epoch * number of features) Once we have train the model using Random Forest with the best parameters selected, we can access feature importance. Feature importance is an extra variable with the model provided by Scikit-learn, it shows the relative importance or contribution of each features in the prediction. It automatically computes the relevance score of each feature in the training phase. Then it scales the relevance down so that the sum of all scores is 1. The score can help us to choose the most important features and drop the least important ones. By ranking the features, it can give us an insight into the mind by showing what variables played an important part in the prediction generated by the model, in our case, we can see the top channels that contribute the most when the classifier is doing classification, knowing this information would help the neuroscientist focus on the top channels and their relationships with modality, lexicality and congruency problems.

Result

In the method section I was able to optimize the random forest classifier and executing a complete pipeline for classifying modality and lexicality problems. Table 1 shown below give us a clear idea of the average accuracy score compared between Random Forests and Logistical Regression when classify modality and lexicality problems.

Classifier	Accuracy for modality	Accuracy for lexicality
Random Forest	69%	60%
Logistic Regression	63%	55%

Table 1. The average classification scores for both Random Forest and Logistical Regression for modality and lexicality.

As expected, random forest performed better than Logistical Regression in terms of accuracy since Random Forest is considered as a more complicated classifier that has the capacity to handle large space features better. It should work better for our data compare to Logistical Regression because it's a highly accurate and robust method that combined decision trees that are independent of the size of the feature space. It doesn't suffer from the overfitting problem because it takes the average of all prediction which cancels out the bias [8].

As mention in the method section, Scikit-Learn provides the feature importance methods that allow us to see the relevance score of each feature in the training phase.

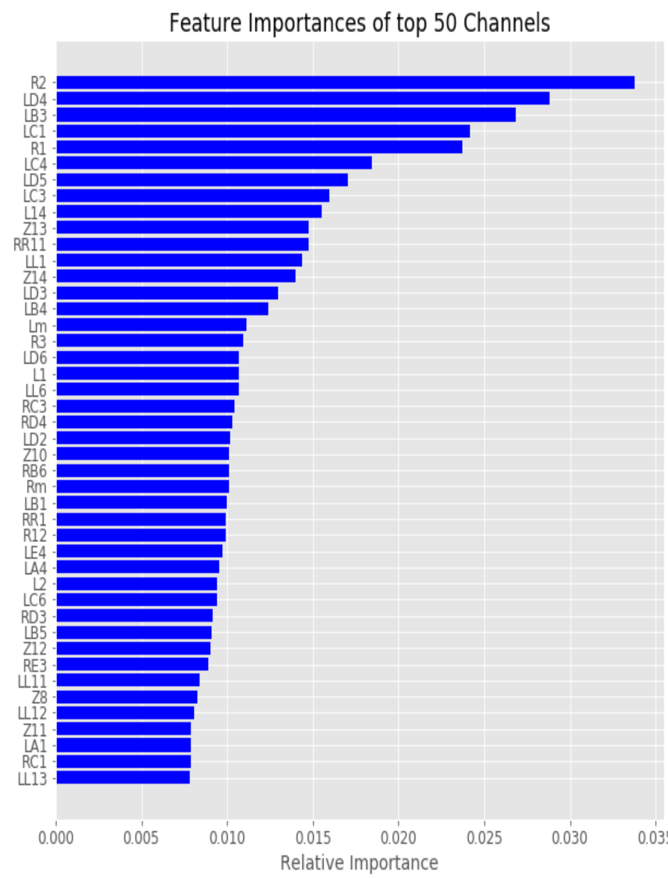
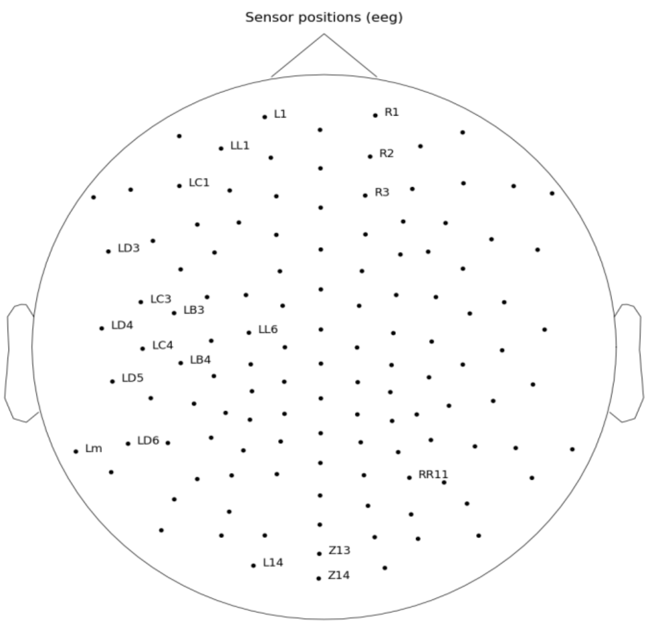


Figure 4 List of top 50 channels sorted by relative importance in descending order

Figure 4 above illustrate the relative importance of each channels contribute to the classifier, for the lexicality problem. If we plot the top 20 channels above on the brain map, we get the picture shown below on figure 5 that identify the positions on the brain that contribute the most to the Random Forest classifier. Those are the deciding channels that affect the final classification result, and based on the deciding channels we predict that they will correlate with the parts of the brain that are responsible for making lexicality decision.

Figure 5 Position on the brain of the deciding channels for Random Forest Classifier.



Besides ranking the feature importance by channels, we also rank them by time points in space just to compare the results . Figure 6 illustrate the MNE topographic plot of the patter of feature importance for the lexicality problem. It's clearly shown from the figure that one of the spikes occurs at around t=130ms, the position on the brain for higher importance points are very similar when compare it with the plotting of highest ranking of the channels shown in figure 5. It's mainly located at the back and the left of the brain. Therefore, this shows that the plot in figure 5 and 6 is consistent since they all shows the similar regions on the brain that are believed to have the highest contribution for lexicality problem.

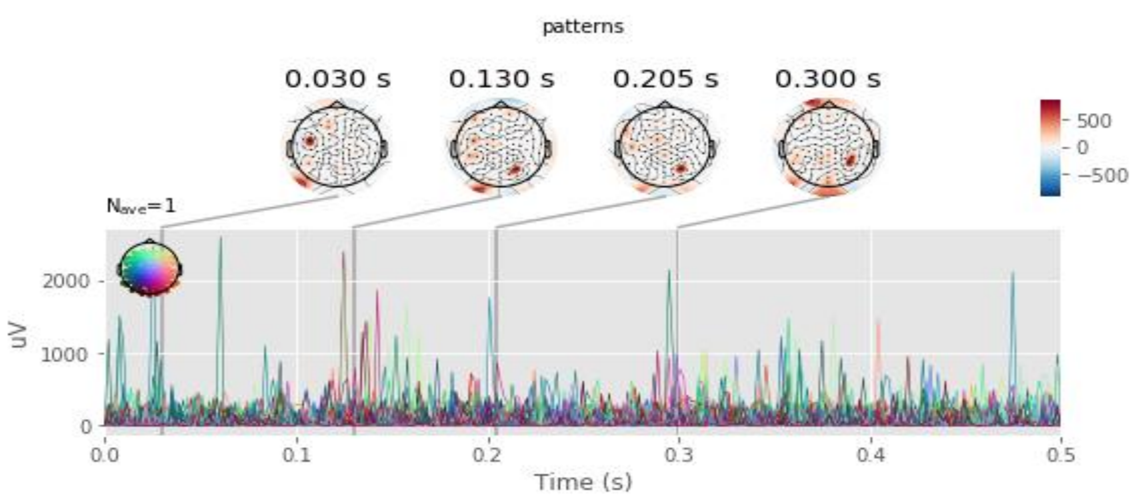


Figure 6 The feature importance plot over time for Language VS. Non Language using Random Forest

We perform classification again by selecting on the top 20 most important channels, the result are shown in table 2 below.

	All Data	Reduced Data
Score	60%	64%

Table 2. Comparison of Accuracy between All Data and top channels.

Since we believe that those top channels are the deciding channels for lexicality problem, it will be reasonable if we select only those channels and do classification again, it will yield for better classification.

Table 2 above shows that when classifying only the top 20 most-important channels, it will give us better score. Therefore, this shows that those channels with high important do contribute more to classification and from that we can predict those part of the brain are responsible for making lexicality decision.

Modality problem are considered to be easier to classify and identity the most used channels in the brain. Table 1 shows that the classification scores were higher in both classifier. It's believed the reason for that is because more decisions being made in the brain for lexicality compare to modality.

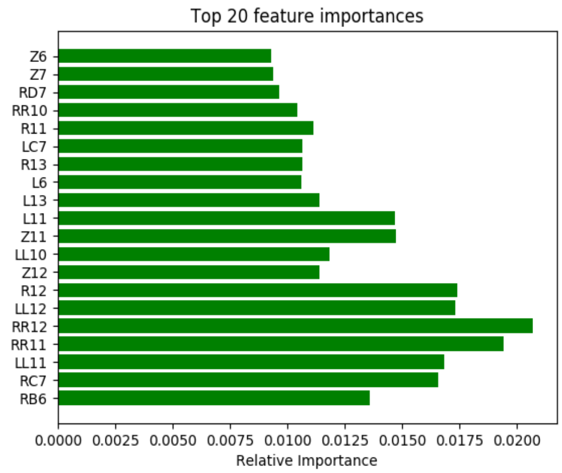


Figure 7 . The top 20 most important channels for Audio vs Visual

Professor Dave observed that between 120 ms to 230 ms are the most active time segment in the data from his original experiment, figure 8 confirm with the results since the highest importance appear to be locate at around t=125 and t=175. During those time is when the Random Forest classifier use the most for classification of modality.

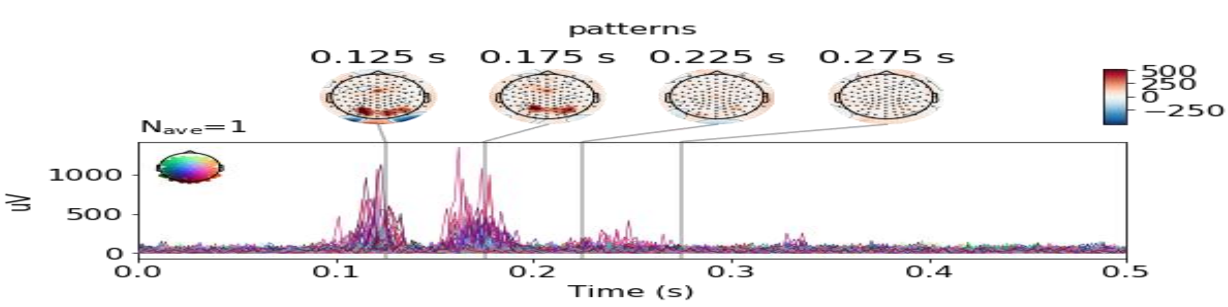


Figure 8 The feature importance plot over time for Audio vs. Visual using Random Forest

Conclusion

Our team was able to build a classification and visualization pipeline to tackle the classsfication problems regarding modality and lexicality successfully. Random Forest is consider to be the more accurate in its classification which can be shown in the result section. It gives a sets of channels that are consider to be important during the training phase for both modality and lexicality problem. We learn where and how modality, lexicality and semantic content are stored in the brain. Thus, once we discover the parts of the brain that work together we can investigate the signal outputs of the part of the brain given, therefore, to help the neuroscientists to identify when and where the brain is the most active when the subjects are experiencing modality , lexicality or semantic stimuli. With the method stated in the paper, neuroscientist can find out exactly where and when the algorithm is learning its most useful features. Knowing those will be able to help the neuroscientist to better understand where and when and how the brain make decisions when dealing with modality, lexicality and congruent stimuli.

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