Understanding the Impact of the Frequency of Distractions on Cognitive Ability

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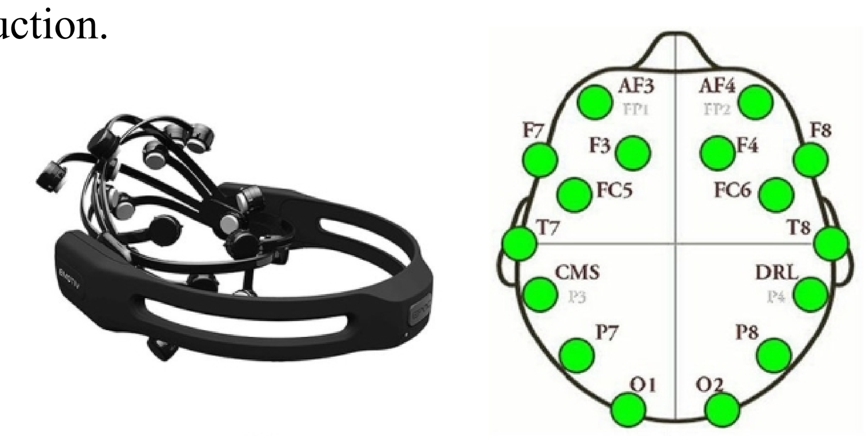
Objective

The objective of this research project is to utilize brain activity data collect through electroencephalograms (EEGs) to understand whether the frequency of auditive distractions has an impact on an individual's cognitive process. In this phase of the project, the goal was to use data in a study investigating the impact of different music on cognitive ability. Data from the subject's brain activity was used to create Linear Regression models that reflects the predicted behavior of test subjects in different circumstances based on collected data. These models are meant to prepare for future research that investigates the effect of patterned versus randomly timed audio distractions.

Introduction

Measuring human cognitive ability is an important aspect in research regarding education. Especially when researchers attempt to understand what might hinder one's ability to complete tasks. The basis for understanding how individuals process new information is present in the Cognitive Load Theory which claims that only a limited amount of information can be processed at a given time due to the extraneous cognitive load (Sweller, 2011). The research project attempts to understand whether the frequency of auditive distractions has the largest impact on this limited amount of information that humans can understand.

Recent developments in electroencephalography (EEG) technology have made it feasible to conduct research studies on students to improve current educational techniques. EEG signals are divided into five wavebands (α, β, θ, δ, and γ) that indicate different cognitive activity from various parts of the brain (Liu, 2013). The EEG headset readings utilize constructs of these wavebands to determine emotions like engagement and meditation. This makes our study more objective to the engagement and meditation conditions imposed on the test subject that cannot be detected from face-to-face instruction.



(a) (b)

a) EMOTIV EPOC EEG headset
b) Spatial mapping of the electrodes

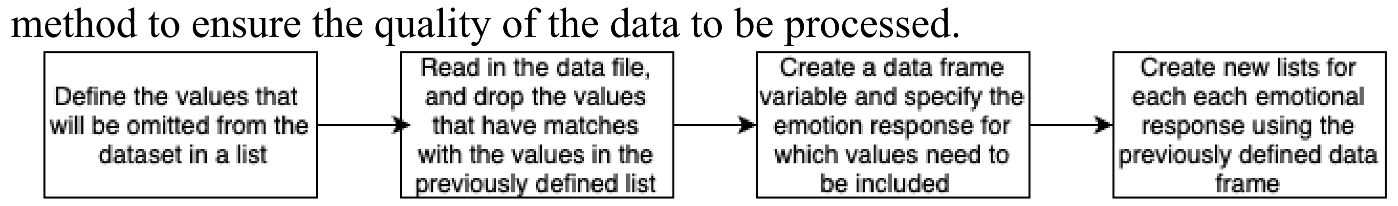
Research Question

What is the effect of patterned versus randomly timed distractions on a student's cognitive ability?

Method

In order to better understand the nature of EEG data and the use of different analysis techniques, data analysis was done utilizing data from a related study with audio stimuli (Paley, 2015). The following steps show the method followed to process and analyze the data.

1. *Collection of Data*
Sort through pre-existing datasets for these biometric sensors (e.g., Emotiv EPOC headset), by conducting a thorough review of past research (Paley, 2015) and other research online.
2. *Pre-processing of Data*
To prepare for different data mining techniques, it is vital to pre-process the data. This process was completed using a Python script that relies on the Pandas and NumPy libraries. The following flowchart shows the pre-processing method to ensure the quality of the data to be processed.



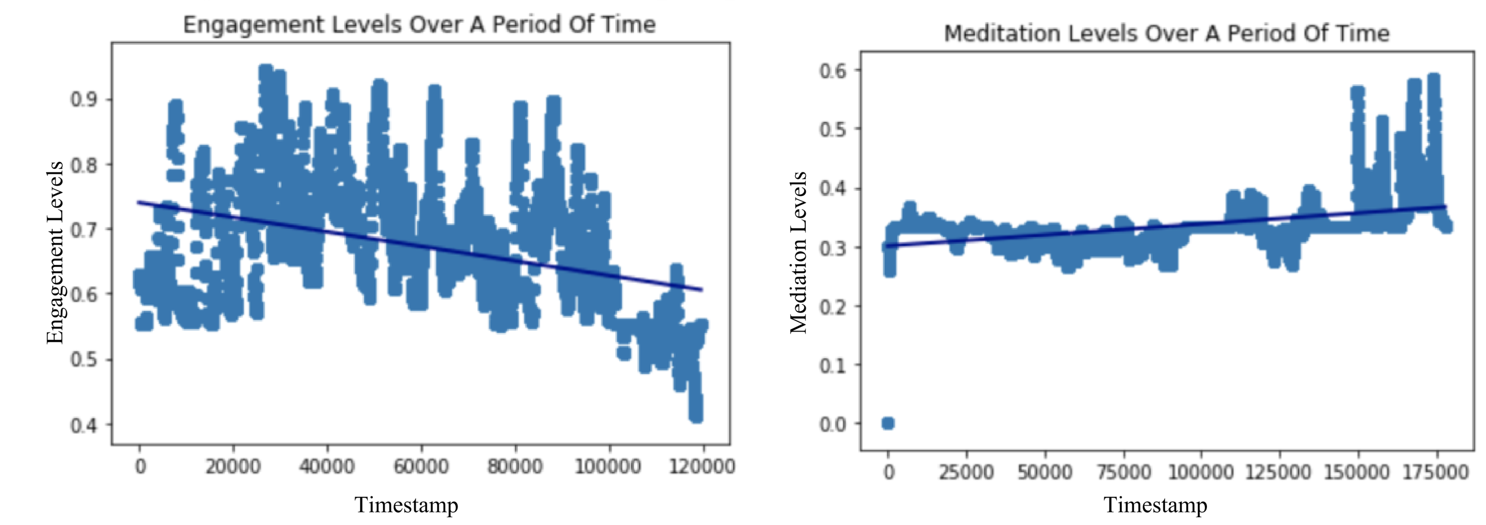
3. *Processing of Data*
After checking for data quality, data analysis was performed using linear regression. Data from the regression model like p-value, t-statistic, and R were used to determine linear correlation. The insight from this model showed whether the auditory stimuli affected the subject's emotional responses.

Results and Findings

The EEG headset automatically interpreted 5 emotional responses: Engagement, Excitement, Boredom, Frustration, Meditation. The likelihood of the user experiencing the emotional response is on a scale of 0 to 1, with the value of 1 implying that the user is experiencing that emotion. The objective in this phase of the experiment was to analyze the EEG data and construct linear regression models to better understand the data. It is also important to consider that the relationship between variables may not be linear. Thus a linear regression model may not be ideal to determine relationship between variables.

Engagement:
The values for engagement stayed stable with respect to time in the study. The value measuring engagement stayed relatively high, implying that the subjects were focused throughout their assessment. The data points, with a 95% confidence interval (**α** = 0.05), had an average p-value of 0 for engagement. Since the p-value conducted under a linear regression was significantly lower than **α**, the data suggests that engagement levels had a linear relationship with time as the subject was introduced to different auditory stimuli. The results from the linear regression model were different from the original study from which this data was extracted (Paley, 2015). The conclusion differed from the original study as it determined there was a linear correspondence for engagement, while the original study determined that were was no linear correspondence through the implementation of a one-way ANOVA.
Meditation:
The values for meditation had a steady increase with respect to time. The data points, with a 95% confidence interval (**α** = 0.05), had an average p-value of 0.0080 for meditation. Since the p-value conducted under a linear regression was significantly lower than **α**, the data suggests that meditation levels had a linear relationship with time as the subject was introduced to different auditory stimuli. The results from the linear regression model were different from the original study from which this data was extracted (Paley, 2015) The conclusion differed from the original study as it determined there was a linear correspondence for meditation, while the original study determined that were was no linear correspondence through the implementation of a one-way ANOVA.

Linear Regression model analysis of pre-processed data set



Conclusion

The objective of this experiment was to investigate the effects of different frequencies of auditory stimuli on the user's cognitive ability. This phase of the research focused on completing pre-processing and statistical analysis on pre-existing data sets (Paley, 2015) dealing with auditory stimuli to understand the nature of the data, and the way its processed. Specifically, understanding the influence of different types of music on the subject's engagement and meditation levels. The data analysis was successful in determining the subject's meditative and engagement response to auditory stimuli. The subjects had a positive response to auditory stimuli like classical music as evidenced by the high levels of engagement and meditation throughout their assessment. This leads to the conclusion that classical music may have a positive impact on subject's cognitive ability in similar situations. One of the limitations with linear regression model is that there is not always a linear correlation between the data and as a result linear regression may not be an ideal fit. However, for the purposes of this research, the linear regression model was sufficient to understand the nature of the EEG data. The experience with some of the limitations with linear regression will prove to be insightful for data analysis in the next phase of the research. As a result, other models like k-means clustering may be used to gain a better understanding of the impacts that auditory stimuli have on subject's cognitive ability.

Acknowledgements and References

Alongside Dr. Maria Elena Chavez-Echeagaray, I worked with Anish Agarwal who assisted in the data analysis with Linear Regression. I would also like to acknowledge Benjamin Henry Paley, as his data collection in his Honors Thesis was invaluable to the success of this project.

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