Understanding Consumer Preferences for Movie Trailers from EEG using Machine Learning

Pankaj Pandey  
Computer Science and Engineering  
Indian Institute of Technology Gandhinagar  
Gujarat, India  
pankaj.p@iitgn.ac.in

Raunak Swarnkar  
Centre for Cognitive & Brain Sciences  
Indian Institute of Technology Gandhinagar  
Gujarat, India  
raunak.swarnkar@iitgn.ac.in

Shobhit Kakaria  
Centre for Cognitive and Brain Sciences  
Indian Institute of Technology Gandhinagar  
Gujarat, India  
shobhit.kakaria@iitgn.ac.in

Krishna Prasad Miyapuram  
Centre for Cognitive and Brain Sciences  
Computer Science and Engineering  
Indian Institute of Technology Gandhinagar  
Gujarat, India  
kprasad@iitgn.ac.in

Abstract—Neuromarketing aims to understand consumer behavior using neuroscience. Brain imaging tools such as EEG have been used to better understand consumer behavior that goes beyond self-report measures which can be a more accurate measure to understand how and why consumers prefer choosing one product over another. Previous studies have shown that consumer preferences can be effectively predicted by understanding changes in evoked responses as captured by EEG. However, understanding ordered preference of choices was not studied earlier. In this study, we try to decipher the evoked responses using EEG while participants were presented with naturalistic stimuli i.e. movie trailers. Using Machine Learning techniques to mine the patterns in EEG signals, we predicted the movie rating with more than above-chance, 72% accuracy. Our research shows that neural correlates can be an effective predictor of consumer choices and can significantly enhance our understanding of consumer behavior.

Index Terms—Neuromarketing, EEG, Machine Learning, Discrete Wavelet Decomposition

INTRODUCTION

Consumer neuroscience systematically aims to understand consumer behavior and underlying preferences through the lens of psychology, neuroscience, marketing and economics [1]. Currently, consumer research relies on the stimulus-response model to capture the underlying brain processes. The development of human neuroscience tools to understand the latent mechanisms gave rise to progress of using neuroscience to effectively understand what the consumer prefers going beyond the traditional subjective scores [2]. [3]. Understanding what contributes to the observed behavior by complex, naturalistic stimuli has immense importance in marketing research [4]–[6]. Preferences of consumers have been widely studied using other modes than self-reported measures. The idea of ‘preference’ has been historically approached differently in psychology, economics, marketing and neuroscience. One neuroscience study has shown that behavior preferences can be attributed to brain activity in the ventromedial prefrontal (vmPFC) cortex and ventral striatum [7].

Electroencephalography (EEG) is being recently used as a tool to understand the neural correlates of consumer behavior due to its advantage of providing temporal resolution of stimulus-response. Previous research suggests using EEG to understand the patterns of brain activity of participants watching advertisements to understand their buying preferences [8]. The main motivation behind this current study is to understand consumer neuroeconomics from a machine learning perspective, primarily to understand movie preferences, which is a line of research that has not received much attention. For instance, the US movie box office revenue is above $10 Billion per year. However, investing in such projects is risky. It has been found that only 36% of movies achieve a break-even over the production cost, in terms of profits. Movie producers spend huge amounts on movie trailers and use different marketing techniques to gauge consumer reactions, and eventually, box-office earnings. Study used EEG for predicting brain responses to movie trailers based on individual consumer preferences, where brainwave signals in the beta frequency oscillation range were found to be a good predictor for like/dislike of a movie trailer [9]. In another work, EEG was used to study consumer behavior where it was found that future choices in terms of which product a consumer will prefer buying, was predicted using EEG [10].

In this study, we study consumer behavior in terms of movie trailer preferences using both neural and behavioral measures, with the main aim to use pattern recognition techniques to understand evoked responses in EEG. The present study tries to systematically investigate whether neural correlates can be a valuable predictor of individual choice preferences.

MATERIALS AND METHODS

A. Experiment Design

The dataset was collected using a 128 channel Net Station Electroencephalography (EEG) device from 18 healthy individuals (13 were men, and 5 were women) at Indian Institute...
of Technology, Gandhinagar. The mean age of participants was 22.4 years within the range of 18-26 years. No participant reported any history of neurological or psychiatric disorder. Fifteen participants were right-handed, and three were left-handed. Data acquisition was done using EGI Netstation 5.2. The experiment consisted of 12 trial blocks. In the experiment, every subject was asked to watch 12 trailers of upcoming movies, and after each trailer, there were four questions to be answered on a likert scale of 1-5:
1) Rating
2) Familiarity
3) Purchase Intent
4) Willigness to Spend
Lastly, participants were asked to report an ordered preference to arrange the movies in descending order, the movie trailers they liked the most to least preferred. Experiment Design is shown in fig. 1.

This step consisted of removal of data points in the dataset that were erroneous. Those samples where the electrodes were not in proper location, or not in contact with the scalp, were excluded from the dataset before further processing. EEG signal is susceptible to noise or artefacts and has to be corrected as part of the signal pre-processing step as mentioned in the below. All the pre-processing was performed using EEGLab Package in MATLAB [11]. Further, bad channels were rejected using Artifact Subspace Reconstruction using Makato’s Pre-processing pipeline [12]. Re-referencing was performed across all channels. The following artefacts were identified and removed.

1) Physiological Artefacts: Electrooculogram (EOG): This is the electrical noise generated by eye blink and cornea movement that is captured in the EEG signal and has to be removed. It can be estimated as the change of potential in electrodes near the eyes at Fp1- Fp2 (Fronto Parietal). Fluttering of the eyelids appears as a 3Hz –10Hz signal, and hence was removed using Band Pass filters.
Electromyogram (EMG): This is the electrical “noise” generated by muscle activity. Facial Muscle movement; swallowing, grimacing, chewing can be captured in EEG and has to be removed. This noise commonly appears in the frontal and temporal electrodes.

2) External Artefacts: Physical movement: This can lead to lose contact of electrode due to abrupt physical movement of subjects and is captured as a high amplitude, low frequency noise. Electrode Contact: Poor electrode contact gives rise to low frequency artifacts and all such trials were removed which had lost any electrode contacts.

B. Feature Extraction
In order to extract features from EEG signals, a well-established method is to decompose the mother wavelet into sub-frequency bands. There are primarily 5 types of frequency bands as shown in table I.

A general method for decomposition is to use Fast Fourier Transform. But since EEG electrode signal is non-stationary, FFT might not be the best alternative [13]–[15]. Instead, we used Discrete Wavelet Transform (DWT) Method (db-8 wavelet) using Matlab Wavelet Toolbox to extract two features, Power and Entropy for all 5 frequency sub-bands in range of 0-60 Hz, across all 128 channels.

| Frequency Band | Frequency Range(Hz) |
|----------------|---------------------|
| Delta          | 0-3.5               |
| Theta          | 4-7                 |
| Alpha          | 8-13                |
| Beta           | 14-30               |
| Gamma          | 30-60               |

C. Feature Elimination
Since the feature set had a large number of features consisting of 5 DWT features for both Power and Entropy, two feature elimination techniques were used:
1) Recursive Feature Elimination: This algorithm ranks the features by associating the weights with features and prune the features as per the weights. It forms the smaller set after each iteration and terminate until the given (k) number of features is achieved.
2) Sequential Backward Selection (SBS): A greedy search technique to reduce dimensions of the feature vector from a d space to lower dimensional k space.

These two methods were used to select features which were further trained with the set of classifiers.

D. Machine Learning Classifiers
Choosing the correct set of Machine Learning models is a crucial step for classification. 9 Machine Learning classifiers were used to predict the labelled class using the extracted feature set, which includes: k Nearest Neighbors, Random Forest, Quadratic Discriminant Analysis, Decision Tree, Multilayer Perceptron, Gaussian Naive Bayes, Gaussian Process Classifier, Ridge Classifier, Support Vector Classifier. Every classifier was trained with a Cross-Validation set and test for performance using the test set. The hyper-parameters of the classifiers were tuned iteratively. We trained the models using python. [16], [17].
TABLE II

| Classifier         | Feature Elimination | Test Accuracy |
|--------------------|---------------------|---------------|
| LNN                | RFE                 | 0.7237        |
| Random Forest      | SBS                 | 0.7189        |
| LNN                | SBS                 | 0.6923        |
| Multi-layer Perceptron | SBS              | 0.6769        |

E. Results

The total sample size of 216 data points was divided into train set with 151 and test set with 65 samples. All the 4 bands were found to have discriminating information for the classifier. Machine learning classifiers were then used to train and were tested accordingly, with the top 5 classifiers using 10 Fold Cross-Validation with their results as shown in table II.

I. DISCUSSION

The use of EEG in Neuromarketing to understand consumer behavior is an important area of research given its wide implications. Machine learning techniques have aided immensely in this regard, to decode the information in EEG signals. In this study, we attempted to find whether consumer preferences can be predicted using EEG signals and achieved high accuracy to predict ratings. The main aim to predict ordered preference of movie trailer still needs to be studied, which is the primary goal of this study. However, using EEG for consumer research has its own challenges. EEG signals have a low Signal-to-Noise ratio and hence, it becomes a challenge to accurately process the signal. Sensitivity to various artefacts also poses problems in the data cleaning process. Better signal processing techniques could further improve the Signal-to-Noise ratio and could improve classification performance which needs to be explored. However, the most significant challenge faced was the small n-large-p problem i.e. large number of features as compared to number of samples. One limitation of our work is that we had averaged the feature values across channels, which may have led to loss of information. One way to resolve this would be to use dimensionality reduction techniques. We made a preliminary attempt to use PCA but did not get any significant improvements. Using non-linear dimensionality reduction techniques such as t-SNE and UMAP which are considered to be the state-of-the-art techniques need to be further explored. Deep Learning techniques have been found to be quite powerful when learning internal representations of features, which could be significant as a dimensionality reduction step, which can be further explored.

REFERENCES

[1] D. Ariely and G. S. Berns, “Neuromarketing: the hope and hype of neuroimaging in business,” Nature reviews neuroscience, vol. 11, no. 4, pp. 284–292, 2010.
[2] M. Hsu and C. Yoon, “The neuroscience of consumer choice,” Current opinion in behavioral sciences, vol. 5, pp. 116–121, 2015.
[3] R. B. Silberstein and G. E. Nield, “Brain activity correlates of consumer brand choice shift associated with television advertising,” International Journal of Advertising, vol. 27, no. 3, pp. 359–380, 2008.
[4] M. Hubert and P. Kenning, “A current overview of consumer neuroscience,” Journal of Consumer Behaviour: An International Research Review, vol. 7, no. 4-5, pp. 272–292, 2008.
[5] J. P. Dmochowski, M. A. Bezdek, B. P. Abelson, J. S. Johnson, E. H. Schumacher, and L. C. Parra, “Audience preferences are predicted by temporal reliability of neural processing,” Nature communications, vol. 5, no. 1, pp. 1–9, 2014.
[6] H. Plassmann, T. Ambler, S. Braeutigam, and P. Kenning, “What can advertisers learn from neuroscience?” International Journal of Advertising, vol. 26, no. 2, pp. 151–175, 2007.
[7] S. M. McClure, J. Li, D. Tomlin, K. S. Cypert, L. M. Montague, and P. R. Montague, “Neural correlates of behavioral preference for culturally familiar drinks,” Neuron, vol. 44, no. 2, pp. 379–387, 2004.
[8] Y. J. Wang and M. S. Minor, “Validity, reliability, and applicability of psychophysiological techniques in marketing research,” Psychology & Marketing, vol. 25, no. 2, pp. 197–232, 2008.
[9] M. A. Boksem and A. Smidts, “Brain responses to movie trailers predict individual preferences for movies and their population-wide commercial success,” Journal of Marketing Research, vol. 52, no. 4, pp. 482–492, 2015.
[10] D. Kang, J. Kim, D.-P. Jung, Y. S. Cho, and S.-P. Kim, “Investigation of engagement of viewers in movie trailers using electroencephalography,” Brain-Computer Interfaces, vol. 2, no. 4, pp. 193–201, 2015.
[11] A. Delorme and S. Makeig, “EEGLab: an open source toolbox for analysis of single-trial eeg dynamics including independent component analysis,” Journal of neuroscience methods, vol. 134, no. 1, pp. 9–21, 2004.
[12] Makoto. Makoto’s preprocessing pipeline. [Online]. Available: https://sccn.ucsd.edu/wiki/Makoto’s_preprocess_pipeline
[13] J. Gross, “Analytical methods and experimental approaches for electrophysiological studies of brain oscillations,” Journal of neuroscience methods, vol. 228, pp. 57–66, 2014.
[14] M. R. Azim, M. S. Amin, S. A. Haque, M. N. Ambia, and M. A. Shoeb, “Feature extraction of human sleep eeg signals using wavelet transform and fourier transform,” in 2010 2nd International Conference on Signal Processing Systems, vol. 3. IEEE, 2010, pp. V3–701.
[15] A. Hamad, E. H. Houssine, A. E. Hassanien, and A. A. Fahmy, “Feature extraction of epilepsy eeg using discrete wavelet transform,” in 2016 12th international computer engineering conference (ICENCO). IEEE, 2016, pp. 190–195.
[16] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg et al., “Scikit-learn: Machine learning in python,” the Journal of machine Learning research, vol. 12, pp. 2825–2830, 2011.
[17] S. Raschka, “Mixextend: Providing machine learning and data science utilities and extensions to python’s scientific computing stack,” The Journal of Open Source Software, vol. 3, no. 24, Apr. 2018. [Online]. Available: http://joss.theoj.org/papers/10.21105/joss.00638