Breakthrough Experience Prediction Using Machine Learning Based on EEG Spectral Activity

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Abstract

When under the influence of N,N-Dimethyltryptamine (DMT), subjects often report having experienced breakthrough, an altered state characterized by contact with entities leading to profound insights. The article tries to predict the occurrence of such episodes using Machine Learning models based on EEG spectral data recorded while under the influence, alongside subsequent questionnaires and interviews.

Keywords: DMT; neuroscience; breakthrough; EEG; Machine Learning

Introduction

To this day, little is understood about the states of altered consciousness individuals can experience either via intense meditation, drug use, or other means. A specific sensation reported by people who have inhaled N, N-Dimethyltryptamine (DMT) is known as breakthrough (Michael, Luke, & Robinson, 2023) or hyperspace (St John, 2018): they defined it as being characterized by entry to an immersive space and rating high subjective intensity, and discovered that these experiences are marked by disembodiment, extravagant visual effects, transforming the core of the sense of self and generally desirable emotional effects. Tagliazucchi et al. (2021) made available a dataset of EEG data recorded before and after healthy subjects (N=35, of which 6 were not used due to noisy data, as per their work) had inhaled DMT, alongside questionnaires compiled before and after and the transcription of an interview concerning the experience. This paper builds upon their findings, specifically the post-experience questionnaires and spectral data associated with the ninety brain areas indicated in the Automated Anatomical Labeling (AAL-90). While subjects were not directly asked about the breakthrough phenomenon, it is correlated with items from questionnaires, including but not limited to: ratings for "Gateway" and "Harmony/Unity" from the Near-Death Experience (Greyson, 1983) (NDE) questionnaire; ratings for "I experienced boundless pleasure", "I felt I was being transformed forever in a miraculous way" and "Everything seemed to unify into a oneness" from the 5-Dimensional Altered States of Consciousness (Studerus, Gamma, & Vollenweider, 2010) (5D-ASC) questionnaire; the interviews also gave clues that helped determine which subjects had entered this mental state.

Methods

The first requirement was to determine whether a robust evaluation, to indicate whether the subjects had experienced a breakthrough or not, could be established. Each author independently reviewed the questionnaires and selected questions that correlated with the breakthrough phenomenon according to the relevant literature: scores from each subject for those questions were then normalized and summed up, resulting in a high degree of overlap (>90%). In addition, an independent Spanish-speaking domain expert reviewed the interviews, and their findings were concordant with the classification established by the authors. For the few discordant results, this review was used as a deciding factor. A threshold was then established at the 6.5 landmark for the summed questionnaire score, based on the median. Any individual with a score higher than this value is considered to have experienced a breakthrough; those with a lower score are considered not to have experienced one. This scoring was made publicly available, see the Technology Statement to access it.

Establishing Statistical Significance via Permutation Testing

Given the limited number of subjects available and a degree of uncertainty in the initial classification, whether a statistically significant difference between the two groups of subjects existed had to be established before trying to train any predictive model. A permutation test was run to validate this intuition (Table 1): for each frequency band data, a Logistic Regression was trained on 80% and validated on 20% of the set using accuracy as a metric ("Non-shuffled Mean Accuracy"), and another Logistic Regression was trained using the same split, but randomly shuffling the labels of the training set, making it effectively random ("Shuffled Mean Accuracy"). This procedure was repeated 1000 times, and the results were then compared using Welch's t-test with Bonferroni correction to establish statistical significance ("Adjusted p-value"). Being a binary classification, absolute distance from the shuffled scores is the most important factor, as a consistently very negative performance can be corrected by switching labels; hyperparameters were not optimized, as this procedure's goal was to establish whether significant differences between groups existed, and by performing hyperparameter search at this stage we ran was the risk of overfitting on the dataset, given its small dimensions.

Logistic Regression Results

Band	Shuffled Mean Accuracy	Non-Shuffled Mean Accuracy	Adjusted p-value
Alpha	0.41	0.39	.029
Beta	0.39	0.36	<.001
Delta	0.44	0.56	<.001
Gamma1	0.38	0.35	<.001
Gamma2	0.37	0.35	.004
Theta	0.43	0.71	<.001
All Bands	0.45	0.64	<.001

Table 1: Permutation Test Results on different bands

Text-Based Classification

Due to the small available Dataset, an approach to establish whether a breakthrough had occured using self-reports from the Erowid website (*Erowid*, n.d.) on subjective DMT experiences was also attempted. The self-reports were labeled as breakthrough experiences if they contained specific hand-picked n-grams (1, 2, or 3 words) strongly associated with such experiences, as established by the authors. 20% of the dataset was reserved for testing purposes, and the resulting training split consisted of 45 self-reports. The hand-picked n-grams were removed before training to mitigate classification bias, and a pipeline of Tfidf-Vectorizer followed by a Random Forest Classifier resulted in the best performing model. Different models were compared over 1000 iterations of different random train-test-split's to overcome bias. The findings suggest that the model does perform well with a mean accuracy of 0.73425 and an F1-score of 0.52 and is able to generalize on new data, hence a Random Forest Classifier which performs closely to the mean was chosen to be used to predict breakthrough experiences on the data from Tagliazucchi et al. (2021). Unfortunately, the findings from these predictions do not support our previous conclusions, which we hypothesize may be caused by the difference between the self-report and interview formats, the timing since the experience, or other data shifts between the datasets. Regardless, the Erowid reports offer valuable insights into subjective DMT experiences through the feature importances identified by the Random Forest Classifier (Figure 1).

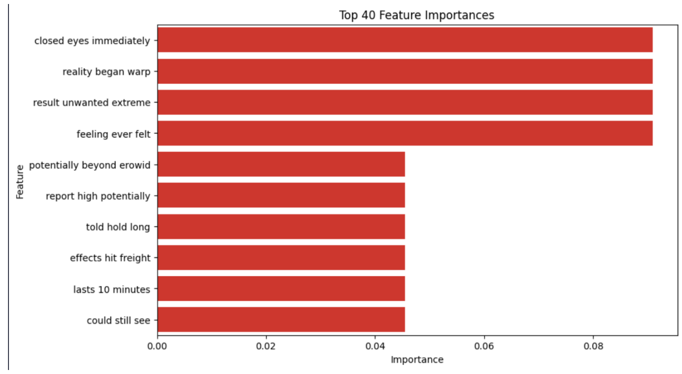

Figure 1: Feature Importance of Forest Classifier on Erowid Dataset

Machine Learning Predictions

Having established a significant difference between subjects that had been assigned different labels existed, we opted for an AutoML procedure using the TPOT library (Le, Fu, & Moore, 2020) to find the best model that could learn data patterns from EEG recordings of different bands, using a Regressor model to predict the questionnaire score associated with each subject (the chosen hyperparameters were: 10 generations, population size of 30, and random state of 42). 23 subjects were used as Train set, performing cross-validation established a Ridge Regressor as the best performing model. When applied to the test set and converting its predictions into labels with the previously established threshold of 6.5, it correctly categorized 5 out of 6 subjects (accuracy = 83.3%, precision = 100%).

Results

Our Permutation Testing pointed towards a strong correlation between Theta Band activity (and, to a lesser degree, Delta) and breakthrough experience, which is in line with what has already been reported by both Timmermann et al. (2019) and Michael et al. (2023). We extracted the most significant features from our permutation testing models (by taking the average) and our AutoML model, and they pointed to the same four brain regions (labeled according to the AAL-90): the right side of the middle frontal gyrus, the left rectus gyrus, the right side of the inferior frontal gyrus (opercular part), and the right side of the middle frontal gyrus (orbital part), represented in red in figures 2 and 3.

Tagliazucchi et al. (2021) also reported correlations between Theta band activity, the "Trascendental" component of the MEQ30 questionnaire (Barrett, Johnson, & Griffiths,

2015) and the "Unity" component of the 5D-ASC questionnaire, and activations in the most influential brain regions in our findings, underscoring a significant overlap between those components of the questionnaires and breakthrough experience.

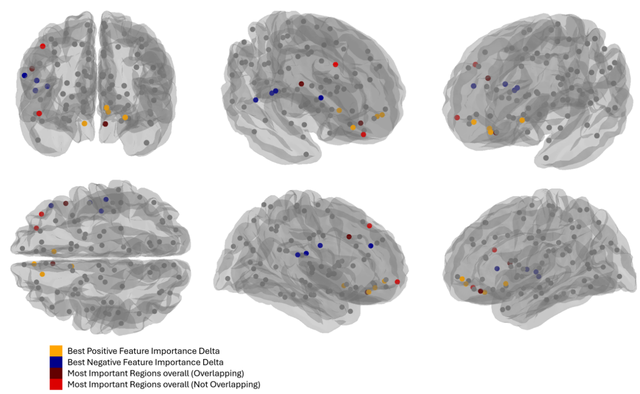

Figure 2: Brain Model of Important Brain Regions for Machine Learning Models' Training (Delta Band)

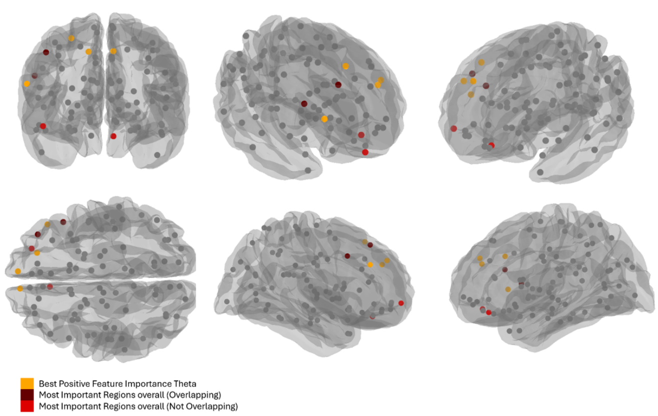

Figure 3: Brain Model of Important Brain Regions for Machine Learning Models' Training (Theta Band)

Note. Top row: anterior view, right and left anterolateral superior views. Bottom row: superior view, right and left lateral hemisphere views. Red regions (bright and dark) are the four areas identified as most relevant across all frequency bands. Orange regions indicate relevance during a breakthrough for high electrical activity in the area. Blue regions show relevance when activity in the area is low. Images generated using Plotly and nilearn libraries (Plotly, 2024; Nilearn, 2024)

The absence of blue regions in figure 3 is due to Theta band showing no low-activity regions as being relevant to identify a breakthrough. The presence of many overlapping regions (dark red color) confirm Delta and Theta's prominence on the overall classification of breakthrough experience by models, highlighting their particular importance for breakthroughs compared to other frequencies.

Discussion

Our findings are in line with the literature concerning this phenomenon, and expand our understanding of the brain regions most likely to be involved in it. The limited number of datasets available for studies focusing on altered states of consciousness and illegal substances poses at the time of writing a limitation to conducting more rigorous studies and adopting data hungry methodologies (such as using Deep Learning techniques), yet the authors believe plenty of benefits may come from a more thorough understanding of the inner workings of altered states of mind. The identification of relevant brain regions as mentioned in the previous paragraph could be used in a future work to compare this phenomenon with other states of altered consciousness, from intense meditation to sleep, to identify key similarities and differences, and perhaps find different ways to induce the transformative and positive valence a breakthrough is characterized by. The methodology used to determine whether a breakthrough was experienced by the subjects within the dataset could be objected to, and the model we have trained should not be used blindly in following studies concerning the topic, yet hopefully it will prove itself useful to expand the study of the breakthrough experience to all DMT-related EEG datasets.

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Technology Statement

The EEG dataset was made publicly available by Tagliazucchi et al. (2021). The obtained data is anonymised. Work on this paper did not involve collecting data from human participants or animals. The original owner of the data and code used in this paper retains ownership of the data and code during and after the completion of this paper.

The code, and associated Docker container, used for the permutation testing section of this paper can be accessed by running:

```
git clone https://FumaNet:github_pat_11APMPOU
Y0hPufXpKMgULV_7GQTa3ZL2g8OeJbI3Chx9NaxBEFygb
CB0j6eZAii1LSE7D5LPEWrMAKCNG1@github.com/Fuma
Net/Breakthrough_DMT.git
```

The repository includes a csv file named ”LabelsAllSubjects.csv”, which contains columns indicating the subject numbers (”n”) and the associated breakthrough scores (”Average with interview”).

The code to run the TPOT AutoML procedure and obtain the predictive model can be accessed at:

```
https://colab.research.google.com/drive/1_Br1tqb
9Fb46wK0I0f5NA1CYm1Jlcqx-?usp=sharing
```

CRediT Author Statement

Francesco Fumagalli: Data Cleaning, Permutation Testing, Original Draft Preparation, Writing **Merve Şafak:** Review, Ground Truth Labelling **Paula Šego:** Initial Idea Proposal, Literature Review, Machine Learning Model **Kai Speidel:** Text-Based Classification **Lucia Welther:** Brain Visualizations, Supervision