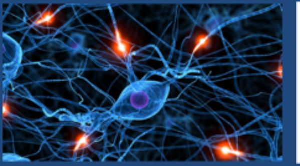
MSc in Computational Cognitive Neuroscience



Goldsmiths
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Connectivity Based Model For Creative Evaluation

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Aim:

To predict creative evaluation using machine learning techniques trained on EEG signal data, to support a neurobiological connectivity-based model of creative cognition.

Introduction:

According to the neuroeconomics perspective of decision making, evaluating creative ideas requires deriving a single value out of the sum of one or more of its associated attributes. These attributes can be generalised into two broad categories: the functional role (utility, relevance, risk) and the uniqueness (novelty, originality). Each of these attributes can be given a subjective value, dependent on individual preferences and the context, that will contribute to the individuals overall creative evaluation. This necessitates a decision to be made by an agent about the quality of the work. Hence, creative evaluation is value driven process (Lin, Vartanian, 2018).

The neuroeconomic framework for creative cognition proposes that the overall satisfaction derived from a product or idea is the weighted sum of all attributes, in the context of an idea, which provides the overall strength of the creative evaluation (Lin, Vartanian, 2018). This can be formulated as: (Berkman, Hutcherson, Livingston, Kahn, & Inzlicht, 2017).

Hypotheses:

It is hypothesised that Bhattacharya's et al EEG data (2018) will support the assumption that there is a consistent internalized model of creative cognition, in line with Lin and Vartanian's framework of a value-driven decision-making process (2018). From a connectivity view, we expect the behavioural responses to correlate positively with alpha activity in the mPFC, OFC and PCC. Furthermore, it is hypothesized that an artificial neural network (ANN) will be able to predict the creative evaluations ratings, from the behavioural data, using extracted EEG signal features.

Methodology:

Participants:

For the behavioural data, the critical between-subject factor in the experiment was expertise: there is a non-expert condition and two expert conditions. For the non-expert condition, a total of 80 healthy participants (60 females, age: M±SD = 20.18±2 years) were recruited from Queen Mary University of London, UK. All participants gave written informed consent and were compensated between £5-13 (the exact amount depended on performance).

For the expert conditions, the type of expertise was divided in two: domain-general, domain-specific. Domain-general experts (N=16) were recruited with a snowball methodology from junior and senior science staff at Queen Mary, University of London. As for the domain-specific experts, N=10 domain-specific experts were recruited, from which two judges had to be discarded due to providing incomplete data, resulting in a final data set of N=8 experts with M±SD = 20.38±10.37 years of relevant expertise. The experts were aged M±SD =47.38±12.22 years, 3 of them are males. Domain-specific experts were selected based on the following criteria: (1) they must be UK residents and proficient English speakers, (2) they must have at least 10 years of expertise in their domain, (3) their domain must be related to cities, e.g., urban planning, architecture, civil engineering, policy making to cities, etc., and (4) they also must have some understanding of creativity, e.g., writing poems or publishing novels, composing music, coding programs, etc.

For the EEG sampling, only the non-expert participants where present for the recordings (N=29). All participants gave their written informed consent before the beginning of the experiment. Experimental protocols set according to the Helsinki declaration.
The study protocol was approved by the Local Ethics Committee at the Queen Mary, University of London (reference number: QMREC1566a)

Procedure:

All non-expert participants were asked to provide demographic information (age, gender, highest education), as well as potentially relevant experience related to the task domain, their current motivational levels, and their subjective interpretation of creativity. Once completed, all non-expert participants were presented with two tasks: Feature rating task and Investment task. In the Feature rating task, participants were first familiarized with the four features of creativity. After this, each project proposal (N=15) was presented for 60s, and for each, participants rated the project according to each of the four features; rating responses were provided on a visual analogue scale (VAS) from 0 (not at all) to 100 (most). In the Investment task, participants were presented with the same 15 projects, but this time they were instructed to indicate their willingness to invest in each project; they indicated their response on a scale between 0 (no investment) to 100 (maximum investment). Participants were explicitly instructed to make their investment judgment solely based on their subjective interpretation of creativity. In principle, the investment responses can be considered as a reasonable proxy for overall creativity; thus, hereafter we refer to these responses as creativity ratings.
The reward schedule for each non-expert participant was the same. In order to extrinsically motivate participants, they were informed that the amount of they could earn (between £5 and £13) was dependent on their performance; this was assessed based on a normative rating as provided by the domain-general experts (N=16). Total earnings were presented to participants after completing the feature rating task and the investment task. In order to assess the extent to which participants were sufficiently motivated by the investment task, at the end of the experiment participants were asked the following: 1) Did you imagine yourself as an investor? (10-point Likert scale from "I stayed completely outside of the game" to "I was fully immersed, felt as an investor", measuring intrinsic motivation) (2) "How much did the potential earning in the experiment motivate you?" (5-point Likert scale from "I did not care" to "I tried to earn as much money as possible", measuring extrinsic motivation).

Data Acquisition:

EEG signals were recorded from 64 electrodes by using a BioSemi Active Two® amplifier. The vertical and horizontal eye movements were recorded by four additional electrodes. The sampling frequency was 512 Hz. The EEG data were algebraically re-referenced to the average of two earlobes.

Pre-processing:

The first part of the analysis is pre-processing the EEG signal data. This involves acquisition of signal, removal of artefacts, signal averaging, thresholding of the output, enhancement of the resulting signal, and finally, edge detection. Pre-processing was done during the analysis using MATLAB-based toolboxes, EEGLAB and Fieldtrip and by custom-made MATLAB scripts. A notch filter at 50Hz will be applied to reduce power line interferences. Artefacts will be corrected by using a ICA analysis.

Feature Extraction:

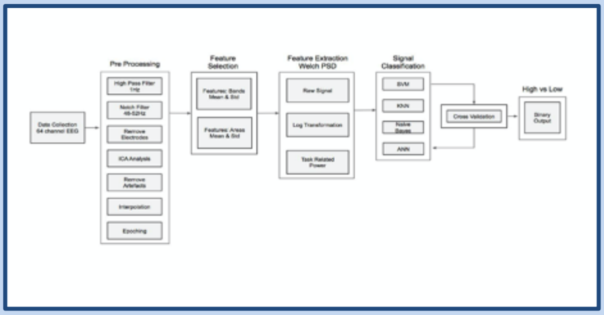
The next step is the feature extraction scheme which determines a feature vector from a regular vector. A feature is defined as a distinctive characteristic measurement component, extracted from a segment of a pattern. The subdivisions of the feature extraction modalities are the statistical characteristics and syntactic descriptions. Feature extraction scheme chooses the most significant information for classification. First, we will look for features according to the changes of spectral power based on different standard oscillations from the low frequency to high frequency range. This will be done on the feature rating task, selecting features important to an individual attribute and identifying their regional connections.
We will also analyse the connectivity by measuring the activity in the different brain regions using phase synchronisation analysis to see if the activity correlates with the theoretical assumptions. According to Lin and Vartanian's framework we should expect to find stronger alpha activity synchronised in the mPFC, OFC and PCC.

Prediction/ Results:

The final step is the signal classification which will be solved by applying an custom ANN that will discriminate amongst significant features to predict the creative value of a proposal. The training will take a small sample of pre-processed brain signal features as the input with the output corresponding to the participants ratings. The features present in the individual attribute evaluations will be correlated to the ratings given.

This will be evaluated in two stages corresponding to the two tasks.
The first part will be applying a network to the feature rating task whereby participants rated individual attributes; utility, riskiness, originality and scalability. We will see if the algorithm can correctly predict, with a >75% accuracy, the average ratings on each attribute.

The final part will be to apply the trained network to predict the overall investment scores.



Methodology Pipeline:

First step is to run a high pass filter (1Hz) and a notch pass filter (50Hz). Second, run an Independent Component Analysis (ICA) to reject eye blink components. Third, extract epochs from the response time. Fourth, select and extract features using the Welch method to obtain the power spectral densities (PSD) of the signals. Fifth, classify the attributes using a variety of classification algorithms, with the PSD as input features .

Independent Components:

Fig 1 shows Independent component (IC1) power spectral activity, extracted using ICA. This component corresponded to a blink artefact and so was rejected.Fig 2 shows the electrode locations.

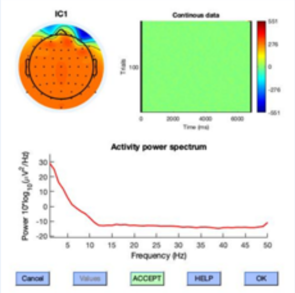


Fig 1. Power Spectrum

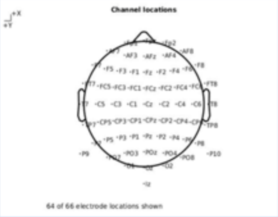


Fig 2. Channel Locations

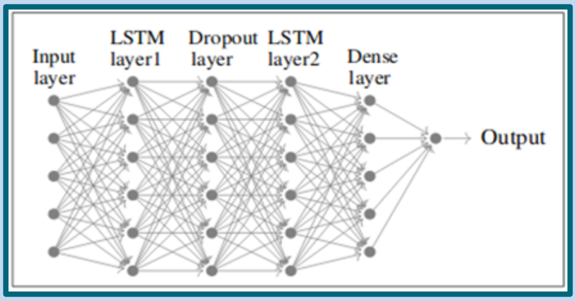


Fig 3. LSTM Network

LSTM networks are Deep Learning Networks. They consist of two fully connected LSTM layers, with a Dropout layer mediating between, and a Dense layer to flatten the output for classification. The first layer takes the PSD as input features. The Dropout layer reduces overfitting by preventing units from co-adapting.

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