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**Classifying Creativity: Applying Machine Learning Techniques to Divergent Thinking
EEG Data**

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Abstract

Prior research has shown that greater EEG alpha power (8-13 Hz) is characteristic of more creative individuals, and more creative task conditions. The present study investigated the potential for machine learning to classify more and less creative brain states. Participants completed an Alternate Uses Task, in which they thought of Normal or Uncommon (more creative) uses for everyday objects (e.g., brick). We hypothesized that alpha power would be greater for Uncommon (vs. Common) uses, and that a machine learning (ML) approach would enable the reliable classification data from the two conditions. Further, we expected that ML would be successful at classifying more (vs. less) creative individuals. As expected, alpha power was significantly greater for the Uncommon than for the Normal condition. Using spectrally weighted common spatial patterns to extract EEG features, and quadratic discriminant analysis, we found that classification accuracy for the two conditions varied widely among individuals, with a mean of 63.9%. For more vs. less creative individuals, 82.3% classification accuracy was attained. These findings indicate the potential for broader adoption of machine learning in creativity research.

Keywords: Alpha, Classification, EEG, Creativity, AUT

Classifying Creativity: Applying Machine Learning Techniques to Divergent Thinking

EEG Data

Barring a few early exceptions, (Martindale & Mines, 1975; Martindale & Hasenfus, 1978), the use of electroencephalography (EEG) has only recently become common in creativity research. The increased interest and utilization of EEG to assess creative cognition – the ability to generate novel and useful ideas (Sternberg & Lubart, 1996) – is largely attributable to the EEG's excellent temporal resolution, which allows investigations of event-related potentials (ERPs), as well as transient network coherence and phase-locked activity. EEG-based research has been well-suited for highlighting the complex dynamics of creative cognition, bringing valuable insights to the field (for review, Stevens & Zabelina, 2019).

EEG and Divergent Thinking

Divergent thinking (DT) tasks are a common and long-standing method for examining creative idea generation (Guilford, 1967). One standard way to assess DT is with an Alternate Uses Task (AUT). On the AUT, participants are asked to generate novel uses for common objects, such as a brick, and their responses are typically scored for fluency (i.e., number of uses generated) and originality (i.e., uniqueness of responses).

EEG-based work most consistently suggests that better performance on the AUT tasks is linked with increased alpha-band (8-13 Hz) activity (Benedek, 2018; Fink & Benedek, 2014). Higher task-related power (TRP) in the alpha range, for example, has been found in the frontal and parietal regions when greater creative demands are imposed during the AUT (Jauk, Benedek, & Neubauer, 2012). A positive association between alpha power and creativity has also been found in other tasks that have novel and normal response conditions (Zhou, Chen, Wang, Zhao, Zhou, & Lu, 2018). Alpha power was reported to be primarily increased at the beginning of

creative idea generation (when participants were asked to think of creative uses for common objects), dip, then increase again just prior to participants' responses (Schwab, Benedek, Papousek, Weiss, & Fink, 2014). This U-shaped alpha effect was found to be particularly true of more creative individuals (Rominger et al., 2019). Furthermore, alpha power was found to decrease over time in an open-ended task involving a change from more strongly divergent, to more strongly convergent, thinking (Zhou et al., 2018). When participants were asked to provide novel uses for the same object in four distinct, sequential response phases, both alpha and creativity ratings increased from the first to the later phases, possibly reflecting the greater creative demand involved in generating the additional responses (Agnoli, Zanon, Mastria, Avenanti, & Corazza, in press).

Individual differences have also been reported at the trial level: More creative people have demonstrated higher alpha-band power than less creative individuals on the AUT (Fink & Neubauer 2008). Additionally, those who perform better on the AUT have demonstrated greater duration of increased frontal and parietal alpha power (Camarda, et al., 2018), and show greater between-condition differences in frontal alpha TRP, compared to less creative individuals (Jauk et al., 2012).

The relationship between alpha-band power and creativity is thought to be at least partially attributable to reduced attention to external stimuli in favor of more internally oriented attention (Benedek, 2018). Specifically, participants might demonstrate greater creativity and alpha power on the AUT because they successfully inhibit information that is not relevant to the task at hand. Indeed, when attention is externally (vs. internally) oriented, alpha has been found to decrease (Benedek, Bergner, Könen, Fink, & Neubauer, 2011). Visual processing can be

demanding, and it is perhaps unsurprising that the simple act of closing one's eyes has been found to increase AUT performance (Ritter, Abbing, & Van Schie, 2018).

Alpha, however, is not the only frequency band that has been shown to relate to successful AUT performance. Changes in delta- and theta-band activity have also been reported (Boot, Baas, Mühlfeld, de Dreu, & van Gaal, 2017; Wokke, Ridderinkhof, & Padding, 2018). Theta in particular appears to have an interesting relationship with DT, as evidenced by increased theta fronto-occipital functional connectivity in more (vs. less) creative individuals (Wokke et al., 2018). Previously, frontal theta was found to be associated with greater cognitive control (Cavanaugh & Frank, 2014). Given the role of attention (internal vs. external) in DT (Benedek, 2018), this finding may point to the theta-dependent suppression of visual functions by frontal executive areas. In other words, theta activity may be an indication of top-down processing in the service of creative cognition. This view is supported by the implication of the lower end of the EEG spectrum (i.e., theta) in long-range communication between brain regions (Clayton, Yeung, & Kadosh, 2015). In light of these findings, it is clear that the relationship between oscillatory neural activity and creativity is not confined to the alpha frequency band, though alpha's relationship to creativity is the most well-supported by current empirical investigations.

The practice of using machine learning (ML) techniques to understand the nature of EEG signals has grown substantially in recent years. In creativity research, however, this is a technique that is novel and ripe for implementation, with unexplored territory extending in every direction. The purpose of the present study was thus to move into this literature gap and investigate the extent to which more and less creative brain states can be reliably discerned according to their EEG characteristics, allowing for unbiased detection of creative thinking.

EEG and Machine Learning

The growing use of machine learning in EEG research is at least partially attributable to the increased availability of code and software packages, as well as the ever-increasing computational capacity of modern computers, without the need to purchase a machine that can fill a small room. The purposes of studies of this nature have varied widely, and include attempts to detect disease (Orrù, Pettersson-Yeo, Marquand, Sartori, & Mechelli, 2012), recognize emotional states (Giannakaki, Giannakakis, Farmaki, & Sakkalis 2017), and even classify individuals by learning style (Jawed, Amin, Malik, & Faye, 2019). In the case of brain-computer interface (BCI) applications, motor cortical patterns have been classified and used to control virtual and even physical objects (Abiri, Borhani, Sellers, Jiang, & Zhao, 2018). This approach is of particular interest in fields of research such as stroke, paralysis, and other areas in which mobility is compromised.

ML is an attractive approach in the field of creativity research for several reasons. An important one is that, while certain EEG features that are known to be related to creativity can be specifically targeted in an ML paradigm (e.g., specific frequency band or channels), the “hands-off” nature of the algorithmic process, once it is set in motion, does afford researchers the possibility of discovering new features that are not expected. In other words, if the information that is used as ML input is broader in content than what would be assumed to be essential, a machine would be more likely to detect a previously unknown pattern. Further, while some features of the creative process are understood, based on the replication of results in studies from various laboratories (e.g., Benedek, Schickel, Jauk, Fink, & Neubauer, 2014; Jauk et al., 2012; Schwab et al., 2014), it is still not obvious to assume that, at the individual level, everyone is creative in precisely the same way. In other words, people may utilize disparate strategies and

resources to arrive at analogous creative ideas. Variability among individuals can cause difficulties for researchers when attempting to determine common functional or anatomical features among individuals. ML, however, makes it possible to detect EEG features that are subject-specific under certain experimental conditions, and make predictions about the nature of new information obtained from that same individual.

ML Types and Procedures

In order to classify EEG data, feature extraction is used to reduce data dimensionality and select the EEG features that are relevant for classification. Common algorithms include estimates of power spectral density (PSD), wavelet transform, and common spatial pattern (CSP) analysis. Once useful features are determined, a decision-making algorithm is used to classify the data. There are various types of algorithms, including the support vector machine (SVM), k-nearest neighbors (k-NN), artificial neural networks (ANN), and linear discriminant analysis (LDA) (Christensen & Abdullah, 2018). Once the decision-making algorithm has made some determination regarding the nature of the EEG signal, this determination is output for the user.

The success of ML techniques in the classification of brain states can be assessed by accuracy during training, and by how accurately a trained model can categorize new data, if real-time feedback is desired. Training accuracy is typically assessed using a cross-validation procedure. Datasets are frequently divided into 10 parts, 9 of which are used for training, while the one remaining part is used to test the model's accuracy. This specific process is referred to as "10-fold cross-validation". Validation outputs frequently include false-positive, false-negative, true-positive, and true-negative rates, and/or an overall accuracy rate.

Accuracy can vary considerably across studies, which is not surprising, given the diverse nature of the questions that are addressed in the literature, and the wide variety of tasks and

analytical methodologies that are employed. There are many examples of ML's ability to classify mental state EEG data. For example, using an SVM on data from 12 bilateral pairs of electrodes, 4 different musically elicited emotions were correctly classified at an average rate of 82.29% across participants (Lin, Wang, Jung, Wu, Jeng, Duann, & Chen, 2010). This was slightly better than the 81.52% accuracy they achieved using a multilayer perceptron. SVM, k-NN, and a least-squares (LS) classifier were used to classify EEG responses to exciting and relaxing music, recorded from 27 pairs of bilateral electrodes (Duan, Wang, & Lu, 2012). SVM performed best in this study, with an average rate of 80.08% accuracy across participants. It is noteworthy that classification accuracy can vary between individuals. In this study, for example, the lowest observed rate was 67.47%, while the highest rate was 98.97%.

It is possible to use very few EEG channels and achieve satisfactory results, as was demonstrated recently (Avinash, Dikshant, & Seema, 2018). Using data from 3 bilateral pairs of electrodes and only from the theta band, LDA was 90% accurate in the classification of positive and negative responses to musical stimuli, while k-NN was 100% accurate when using 3 neighbors (k). The potential to classify whether participants liked or disliked music was investigated using a 14-channel EEG headset (Emotiv EPOC) and 4 different classification algorithms (SVM, k-NN, and 2 types of discriminant analyses; Hadjidimitriou & Hadjileontiadis, 2012). The best-performing algorithm in this study was found to be k-NN, which achieved an accuracy rate of 86.52% using the complete dataset from all participants. Somewhat surprisingly, using only a single EEG channel (Pz-Oz) and a random-forest classifier, 5 sleep stages were correctly classified at a rate of 88.66% in healthy subjects, though accuracy dropped to 66.96% in a group with REM behavioral disorder (Boostani, Karimzadeh, & Nami, 2017).

ML/EEG has also been used with success in more strictly cognitive studies. In a schizophrenia study on working memory, task performance (correct or incorrect) was classified by SVM using five frequency components (high theta, low theta, alpha, beta, and gamma) taken from four different time periods (during baseline, encoding, retention, and retrieval stages) at three electrode sites (Fz, Cz, and Oz; Johannesen, Bi, Jiang, Kenney, & Chi-Ming, 2016). The model successfully classified performance with 84% accuracy in healthy controls, with frontal gamma during the encoding stage and central theta during retention as the most heavily weighted features. In the same study, a second model was able to classify healthy controls and schizophrenia patients with 87% accuracy, with frontal theta during baseline and frontal alpha during retrieval as the most heavily weighted features. Cognitive load has also been predicted from EEG features that were extracted from data collected while participants completed the Raven's APM Set II, which uses 36 increasingly difficult manipulations of shapes to assess general intelligence (Friedman, Fekete, Gal, & Shriki, 2019). The approach taken in this study involved extracting features from band power in delta, theta, alpha, beta, and gamma bands for each of 62 EEG channels, in addition to measures of neural complexity and connectivity. An XGB algorithm, which is decision tree-based, was used. Predictably, decreasing the number of categories by increasing the bin size of difficulty levels (fewer bins, more individual levels in each) increased prediction results. Interestingly, when considering all channels, the addition of complexity features did not improve results, while the addition of connectivity features did. Perhaps more interestingly, prediction quality improved when the number of channels included in the analysis was restricted between 12 and 30 (r^2 peaks of 0.7 for 12 and 26 electrodes, in the case of spectral features only), and the inclusion of only 8 channels still yielded 95% of peak

performance. In short, the best results were obtained when the number of bins and channels were limited.

To our knowledge, there is no empirical work in which DT was investigated using EEG/ML techniques. One study, however, reported in conference proceedings that moments of intense in-the-moment creativity (ITMC) were accurately discerned from less creative periods at a rate of 82.98% by an SVM algorithm (Carrol & Latulipe, 2012). These ITMC moments were determined by external judges who watched participants sketch over the course of 30 minutes via video. Data analysis was restricted to the alpha and beta bands, and the limited-channel EPOC headset was used for acquisition. While this is only one study, when considered in combination with the broader field of EEG/ML research, it does point to the potential of similar methodologies in the pursuit of new perspectives on creative cognition. This potential is made more appealing by the results of a human-computer interface study, in which internal and external attentional states were classified using LDA (Putze, Scherer, & Schultz, 2016). Researchers used a visual oddball task to heighten external attention, and several different tasks that require internal attention (mental math, word generation, and episodic memory). Classification accuracy using only band power features reached 80.4%, and when ERP features were included, accuracy increased to 81.2%. As previously mentioned, the direction in which one's attention is focused can be an indicator of changes in both creativity and alpha power, further demonstrating the potential for EEG/ML in the creativity field. Recognition of this potential was the primary motivation for the current study.

Present Study

The present study utilized a computerized version of an Alternate Uses Task (AUT) (adapted from Jauk et al., 2012). During the task, participants were presented with a common

object, such as a “brick,” and were asked to think of an “Uncommon”, or unusual use for each object (experimental condition), or a “Normal”, or common use for the object (control condition). Each trial consisted of four phases: 1) a reference phase , which presented participants with a “jittered” fixation cross; 2) a preparation phase, where participants saw a cue indicating the kind of use (normal or uncommon) that was required for the current trial; 3) an idea generation phase, where the name of the object was displayed until participants indicated they had thought of a response; and 4) a response phase, where participants typed their response.

Prior research on creativity has consistently found between-condition and between-subject differences in the alpha range and beyond (for review, Stevens Jr. & Zabelina, 2019). It was predicted that the use of ML would enable the reliable classification of multi-band EEG data from more and less creative task conditions, and from more and less creative individuals. In addition to the manipulation of various ML parameters, a priori-based channel selection (reduction) was explored for the purpose of mitigating computational strain.

Methods

Participants

Thirty healthy individuals participated in the present study (8 males, 21 females, mean age = 19.55, $SD = 1.99$). One participant was excluded from all data analyses because the task instructions were not followed correctly, resulting in a final sample of 29 participants. Most participants self-identified as White/Caucasian (86.2%). All participants had normal or corrected-to-normal vision. They were not diagnosed with any psychiatric disorders at the time and were fluent English speakers. They were not under the influence of excessive caffeine, unprescribed medication, or alcohol. The study was approved by the local institutional review

board. All participants gave written informed consent prior to their sessions and were compensated with research credits.

Experimental task and procedures

The AUT was used as a measure of creative idea generation. In this task, participants were presented with 30 different common objects (see Appendix for a list of objects used in this study). Each object was presented twice – once in the Normal condition, and once in the Uncommon condition. Order of object presentation, and the order of condition for each object was computer-randomized for each session. Specifically, each of the 30 items was presented first in one of the two conditions, then all 30 were presented again, but in the opposite condition to their first appearance. In the Normal condition, participants were instructed to think of ordinary, common ways to use the objects. In the Uncommon condition, they were instructed to think of unusual, creative ways to use the objects. Participants were told they had up to 30 seconds to respond for each object, at which point the trial would time out. Participants were instructed to remain as still as possible, and limit eye movement and blinking except in between trials. All instructions were presented visually, on a computer screen, and verbally, by a researcher.

Each of the 60 trials in the AUT began with the presentation of a fixation cross for a duration that was randomized between 2 and 5 seconds in 25 millisecond increments (~3.5s). Next, a cue word, either “Normal” or “Uncommon”, was displayed for 5 seconds. This was followed by the name of an object, which remained on the screen for up to 30 seconds. To respond, participants hit the ‘Enter’ key on the computer keyboard. This interrupted the object presentation and brought up a white text box in which to type. Participants typed their responses, then hit ‘Enter’ again to record the answer and move on to the next trial (Figure 1). Participants were told it was okay to move their eyes freely while typing, but to keep them still again once the

next fixation cross appeared. Trials were presented in 4 blocks of 15 trials, with a user-defined break period between blocks. The task typically took about 35 minutes to complete.

Figure 1. Alternate Uses Task (AUT) phases and timing.

The task was custom coded using Presentation® software (Version 20.2, Neurobehavioral Systems, Inc., Berkeley, CA, www.neurobs.com). Port codes appearing in the EEG time series files were programmed to identify the occurrence of experimental elements. These included unique codes to distinguish the presentation of Normal and Uncommon condition cue words and object names. This allowed models to be trained to classify epochs during which 2 different kinds of thinking occurred.

In order to examine individual differences in creativity, and conduct score-based creativity classification analysis, 5 independent judges blind to the conditions and the purpose of the study (all undergraduate psychology students, 1 male, 4 female, M age = 20.2, SD = 1.17) rated all responses for creativity (“How creative is this response?”). Ratings were made on a Likert-type scale from 1 (least creative) to 10 (most creative). Raters achieved good inter-rater reliability (Cronbach’s α s > .80). Two groups (High- and Low-creative) were formed by selecting the top and bottom 9 participants (middle excluded), based on the ratings.

EEG recording and equipment

EEG signals were acquired using the Biosemi ActiveTwo system, with 32 scalp and 4 EOG AG/AgCl electrodes positioned according to the 10/20 system. Linked mastoid electrodes were used for reference. EEG data were recorded at 2048 Hz using the BioSemi ActiveTwo biopotential measurement system (BioSemi, Amsterdam, The Netherlands) and ActiView software (BioSemi). During recording, signals were high-pass filtered at 0.16 Hz. Recordings were monitored continuously during experimental sessions, and all potentially artifact-producing events (coughing, sneezing, obvious muscle-based or other noise) were recorded by a researcher. No subjects had out-of-the-ordinary artifact-producing issues (sneezing or coughing spells, etc.). Both raw and cleaned data (process described below) were used separately in analyses (i.e., transitory events like blinks, muscle twitches, etc, were not removed prior to raw data feature extraction and classification). This was done with the intent of determining the accuracy that could be attained with minimal processing.

General Analysis Strategy

ML classification analyses of condition types (Normal and Uncommon) and creative types (High and Low) were the focus of this study. Between-condition spectral analyses focusing on the 8-30 Hz frequency range were also performed using cleaned data (see Spectral Analyses section for details). This was done to provide insight into the effectiveness of the task design to elicit condition-related changes in brain activity. Classification was performed on EEG data in two forms – raw and cleaned. This was done to allow a comparison of ML results derived through a normal offline EEG processing pipeline, and those that might be obtained through real-time processing. In both cases, variations in the following aspects of EEG data selection were examined: electrode locations/channels, time windows, frequency ranges (see Machine Learning

Analyses section). The variations that were tested were predetermined, and those that are reported here were chosen based on classification performance; although, reporting on the 1-2.5 second window that comprises most results was predetermined (see Machine Learning Analyses section). Additional analyses were performed to assess the possible influence of artifacts on classification (see A Smaller, Earlier Analysis Time Window section, and Assessing the Potential Impact of Artifacts on Classification section).

Data processing

All signal processing occurred in MATLAB R2018b (The MathWorks, Inc., Natick, Massachusetts, United States) using the EEGLAB (version 14.2.1; Delorme and Makeig, 2004) and BCILAB toolboxes (developer version; <https://github.com/sccn/BCILAB>) (Kothe & Makeig, 2013), which are made freely available by the Schwartz Center for Computational Neuroscience. Additional statistical analyses were carried out using IBM SPSS Statistics for Windows, version 25.

Spectral analyses

EEG signals were high-pass filtered at 1 Hz and low-pass filtered at 58 Hz. Fifty-eight Hz was above the frequency range of interest, based on the literature, and setting the cutoff at this point filtered out frequencies in the range of line noise. Channel locations were assigned, and signals were referenced to the averaged mastoids (M1 and M2). Artifact Subspace Reconstruction (developed by Christian Kothe as part of BCILAB's online cleaning, now available for offline use) was used to identify and reject artifactual principle components. ASR uses a sliding window (0.5 seconds, 50% overlap) to remove transient, high-amplitude artifacts (e.g., eyeblinks, muscle twitches, etc.), after which rejected component activity is reconstructed from surviving components. Infomax ICA (Bell & Sejnowski, 1995) was performed. Multiple

Artifact Rejection Algorithm (MARA) (Winkler, Brandl, Horn, Waldburger, Allefeld, & Tangermann., 2014; Gabard-Durnam, Mendez Leal, Wilkinson, & Levin, 2018), which extracts 6 features from the temporal (1. mean local skewness), spatial (2. range within pattern, 3. current density norm), and spectral (4. log alpha power, 5. lambda, and 6. fit error) domains, was used to identify and remove “bad” independent components (ICs). MARA’s default component rejection threshold of 50% probability – that a component is artifactual – was altered in MATLAB to a more conservative 80%. Statistical comparisons were carried out using EEGLAB.

Machine learning analyses

Unfiltered EEG data (raw .bdf files), as well as datasets that were processed as noted in the previous section (cleaned data), were loaded in BCILAB. The continuous data were analyzed at both the individual and group levels. Data epochs of interest were selected in BCILAB using EEGLAB functions (BCILAB is designed primarily for real-time processing and will not process non-continuous, pre-epoch data as the program stands). These were defined as the periods from 1 to 2.5 seconds after stimulus onset, i.e., the appearances of object names. Additional latencies during the AUT task were also tested: an earlier, shorter interval immediately following the beginning of creative ideation (0.75 to 1.75 seconds); from -4 to -1 seconds, in relation to the onset of ideation (during the 5-second Normal or Uncommon preparation phase); and from -2 to -0.5 seconds, in relation to response (button press). These other intervals, however, yielded inferior classification accuracy. Additionally, prior to testing of these other intervals, the 1-2.5 second time period was selected based on a previous AUT study (Schwab et al., 2014), in which it was found that alpha band task-related power changes at dorsal frontal (F3/F4) and parietal (P3/P4) sites were greatest in the first of three evenly divided intervals beginning at the onset of idea generation (from 1-9 seconds post-onset, 2.67 seconds per interval), with no difference in

TRP between hemispheres. Port codes sent from Presentation created event markers in the datasets to indicate these timepoints, as well as the occurrences of other task events. The 2 condition types (Normal and Uncommon) were distinctly identified by these markers.

Channel combinations of different quantities and from different locations on the scalp were systematically tested in order to find the best possible classification accuracy. These included a full-scalp combination (all 32 cortical channels), and P4 alone. In all cases, combinations included P4 (right parietal), given the consensus among studies regarding this region's involvement in creative ideation (Benedek, 2018). The locations of other individual channels that were combined with P4 were Fz, F3, F7, Cz, C3, Pz, P3, P7, T7 and the matching contralateral channels of each non-midline (z) channel. Channel combinations that were combined with P4 were as follows: (2 additional channels) F3/F7 (left frontal), F3/C3 (left frontocentral), C3/P3 (left centroparietal) C3/T7 (left centrotemporal), and the matching contralateral pairs of each; (3 additional channels) C3/C4/P3 (bilateral centroparietal), and P3/P7/P8 (bilateral parietal); (4 additional channels) F3/F4/F7/F8 (bilateral frontal), F3/F4/C3/C4 (bilateral frontocentral). These channel combinations were chosen to provide good coverage of cortical regions that have either been observed to be differentially responsive to the demands of the Normal and Uncommon AUT conditions (Jauk et al., 2012), or responsive in the early stages of creative ideation (Rominger et al., 2019; Schwab et al., 2014). The primary motivation for attempting classification using mainly smaller channel groups was twofold: 1) to reduce computational expense, and 2) to potentially enhance the performance of the feature extraction and classification algorithms by not including data that were unlikely to be helpful for classification.

EEG features were extracted using 3 iterations of a Spectrally Weighted Common Spatial Patterns (SpecCSP) algorithm (Ramoser, Muller-Gerking, & Pfurtscheller, 2000). Initial frequency bands of interest were theta (4-8 Hz), low alpha (8-10 Hz), high alpha (10-13 Hz), beta (13-30 Hz), and gamma (30-42 Hz), though theta and gamma were later excluded to enhance classification performance. Results therefore are restricted to data from the low-alpha, high-alpha, and beta bands. The minimum-phase filter frequency specification was set at 6 Hz at the low end, and 44 Hz at the high end. The number of SpecCSP patterns was set to no greater than the number of channels selected for a given dataset, i.e., 2 channels = 2 CSP patterns (errors occur otherwise). To reduce computational load, data were downsampled to 100 Hz at this stage, in accordance with the Nyquist Theorem (digital sample rate must be $\geq 2 \times$ the highest analog frequency under analysis).

The types of supervised classification algorithms used were quadratic discriminant analysis (QDA) and Support Vector Machine (SVM). QDA differs from LDA in that it can learn quadratic boundaries, as opposed to linear boundaries, and is therefore more flexible. This is important when data classes are not linearly separable. Also, in contrast to LDA, QDA does not require that different classes have identical covariance matrices (Bhattacharyya, Khasnobish, Konar, Tibarewala, & Naga, 2011). The quadratic discriminant function is $\delta k(x) = -1/2 \log |\Sigma_k| - 1/2(x - \mu_k)^T \Sigma_k^{-1} (x - \mu_k) + \log \pi_k$. SVMs are discriminative classifiers that are very commonly used in neurophysiological data classification. The purpose of this algorithm is to find a linearly separable hyperplane, or decision boundary, by which to differentiate classes (Rossi & Villa, 2007). The margin between the plane and the nearest data points on either side, which are known as support vectors, is maximized. If a decision boundary cannot be found, SVM will search after transforming the data to a higher dimension. Because of its ubiquity in biosignal classification

analyses, it was deemed important to include SVM in testing on the current dataset. As noted in the results section, however, QDA consistently outperformed SVM in the current study, so the reported results are restricted to QDA.

For both classifier types, predictive models were trained on SpecCSP-derived features using a leave-one-out 10-fold cross-validation performance estimation procedure (1 section held out for testing, 9 sections used for training, repeated for each section; 5 trials around any test trial excluded from the training set). During the task, distinct event codes marking the onset of Normal and Uncommon ideation periods were added to the data stream by Presentation. These were used as target markers (classifiers). For the classification of High- and Low-creative participants, in-house code was used to modify Uncommon condition event codes for the High-creative group. This differentiated the intervals of interest for the High- and Low-creative groups from one another. Performance estimates at the group and individual levels are described in terms of classification accuracy, as determined by true/false positive and negative rates.

Results

Participants responded faster in the Normal condition ($M = 1.99s$, $SD = 0.83$) than in the Uncommon condition ($M = 9.23s$, $SD = 2.58$), $t(28) = 16.95$, $p < 0.001$, $d = 3.14$. This result was not surprising, given that the Normal responses were obvious in nature, and were expected to be easier to generate.

Paired t -tests were used to examine between-condition log-transformed power spectral density (PSD) in EEGLAB. All subjects' cleaned data were included. For the Uncommon condition, power was significantly greater than in the Normal condition in a number of frequency ranges at F4 (Figure 2). This included a continuous range spanning the low- and high-alpha bands (8.6-10Hz and 10-11.5Hz), $t(28) = 2.35$, $p = 0.013$, and $t(28) = 1.96$, $p = 0.03$,

respectively. Power was also greater in the Uncommon (vs. Normal) condition in numerous ranges of the beta band between 17.5 and 27.6 Hz ($p < 0.05$). Power was also greater at P4 for the Uncommon (vs. Normal) condition, including much of the low- (8.6-10 Hz) and high-alpha bands (10.3-11.8 Hz), $t(28) = 1.75$, $p = 0.04$, and $t(28) = 1.74$, $p = 0.05$, respectively). Much like F4, though over a greater portion of the frequency band, power at P4 was greater in numerous ranges of the beta band between 12.9 and 20.1 Hz, and at 28 Hz ($p < 0.05$) (Figure 2).

Figure 2. Between-condition (Normal versus Uncommon) comparison of spectral power density at F4 and P4 electrode sites. Black bars along the x-axis indicate frequencies where differences between conditions are significant at the level of $p < 0.05$. The topographic map (all channels) at bottom shows power at 10 Hz (alpha) for the two conditions separately.

Though the difference was typically minor, QDA classification in BCILAB outperformed that of SVM in all cases, so QDA results are reported. Classification accuracy generally maintained an inverse relationship with the number of channels that were included. Accuracy was indeed found to be highest when restricting the number of channels to right frontal (F4) and right parietal (P4). In addition to a reduced number of features and increased accuracy, this restriction provided the benefit of reduced computational expense. The EEG classification results reported below are therefore restricted to the F4/P4 channel combination.

Condition Classification Results: Individual Level, All Participants

Ten-fold cross-validation of QDA condition classification for individual participants was assessed using both raw signals and cleaned data separately. For raw data, individual accuracy rates ranged from 36.7% to 93.3%, with a mean of 63.9% ($SD = 0.15$). For cleaned data, individual accuracy ranged from 39% to 95% with a mean of 62.7% ($SD = 0.15$).

Condition Classification Results: Whole-Group Level

For whole-group condition classification, all participants' data were concatenated and used for model training. Raw and cleaned data were used separately to train and evaluate models. Score-based (AUT task ratings) classification of more and less creative individuals was also performed using both raw and cleaned data from the Uncommon condition only, thus minimizing the impact of fast responses, which were common in the Normal condition. Due to the extremes in classification accuracy among individuals, whole-group classification accuracy was generally poorer than individual classification.

Using all participants' raw data, the condition classification accuracy for QDA was 59.7% (Figure 3). Additionally, when a QDA-derived model was trained on all participants' raw

data, and the model was then applied to individuals, classification accuracy ranged from 40% to 85%, with a mean of 59.2% ($SD = 0.12$).

Classification of High- and Low-creative Individuals

Condition Classification

Figure 3. Spectrally weighted common spatial patterns (Spec-CSP) found in High- and Low-creative groups (top), and in whole-group condition classification analyses (bottom). Two EEG channels (black dots) were used for classification: F4 (right frontal) and P4 (right parietal). Spectral patterns are shown beneath the topographic maps. Relative to the rest of the spectrum, frontal patterns (upper and lower left side) exhibit heavily weighted beta (13-30 Hz), and parietal patterns (upper and lower right side) exhibit heavily weighted alpha (8-13 Hz).

Accuracy using all participants' cleaned data was slightly lower than for raw data. Condition classification accuracy for QDA was 57.5% (+/-11.8%; folds = 10), and when a QDA-derived model that was trained on all participants' cleaned data was applied to each individual, predictive accuracy ranged from 47.4% to 88.3%, with a mean of 58.5% ($SD = 0.13$).

Condition Classification Results: High- and Low-Creative Groups Separately

For raw data classification, High-creative group accuracy was 56.3% (+/-11.7%; folds = 10). Increasing the number of folds decreased accuracy slightly, to 56.1% (+/-13%; folds = 25). Low-creative group accuracy was slightly better, at 58.1% (+/-11.2%; folds = 10), and 59.2% (+/-13.7%; folds = 25).

QDA condition classification accuracy was 54.9% for cleaned High-creative group data ($n=9$). Increasing the number of folds increased accuracy to 56% (+/-14.8%; folds = 25). Condition classification accuracy for cleaned Low-creative group data ($n=9$) was slightly better, at 56.9% (+/-13.4%; folds = 10). Increasing the number of folds increased accuracy to 58.5% (+/-14.9%; folds = 25).

Group Classification Results: High- and Low-Creatives

For raw data, between-group creativity classification was 82.3% (+/-12.7%; folds = 10). For 5 folds, accuracy was 80.6% (+/-11.3%). As was the case for cleaned data, raising the number of folds to 25 reduced accuracy, compared to using 10 (81.2%, +/-15.7%).

For cleaned data, classification of the High-and Low-creative groups) was 81.3% (+/-13.2%; folds = 10) (Figure 3). At only 5 folds, accuracy was 79.6% (+/-10.7%). Raising the number of folds to 25 did not improve accuracy, but rather reduced it, relative to using 10 folds (80.7%, +/-16.4%).

A Smaller, Earlier Analysis Time Window

There was initial concern on the part of researchers that a time window starting at 0.5 seconds could include stimulus response features that would be non-specific to either condition, thereby hampering classification. This early period was therefore not included in the original analysis plan. This thinking is somewhat in line with the earliest analysis window of 1-3.67 seconds used by Schwab et al. (2014). Because of the typically fast reaction times observed in the Normal condition in this study, however, a window from 0.5 to 1.75 seconds was added to the analyses. This avoided the mean Normal condition RT of 1.99 seconds, though some responses are still unavoidably present in this window. For condition classification, accuracy was lower in the 0.5-1.75s window than in the 1-2.5s window that has been described for raw data (-5.5%) and for cleaned data (-5.69%). For creativity-based classification, accuracy was higher in the 0.5-1.75s window than in the 1-2.5s window for raw data (+5.8%) and for cleaned data (+3.1%).

Assessing the Potential Impact of Artifacts on Classification

Due to RT-related concerns that response artifacts might have influenced classification using the 1-2.5s window, additional analyses were conducted to assess their possible influence. For all subjects, the mean number of Normal epochs (30 total) containing responses was 23.66, $SD = 5.81$. Uncommon trials (also 30) contained 4.62 responses on average, $SD = 5.08$. This between-condition difference was significant, $t(28) = 13.3$, $p < 0.01$. Response-containing epochs for High-creative ($M = 18.89$, $SD = 7.36$) and Low-creative ($M = 19$, $SD = 8.29$) groups were also assessed. When the between-condition difference scores for each group were compared, no between-group difference was found, $t(16) = -0.03$, $p = 0.49$.

Further testing of EEG data for the presence of artifacts was conducted. Using automated thresholding, cleaned data were tested for abnormal voltage values ($\pm 75 \mu\text{V}$) and abnormal spectra (for eye movements, $\pm 50 \text{ dB}$ in the 0-2 Hz window; for muscle, +25 or -100 dB in the 20-40 Hz window) in EEGLAB. For all subjects, the number of trials that were exceeded these thresholds in the Normal condition was 32 ($M = 1.1$, $SD = 3.55$); in the Uncommon condition, 45 trials exceeded thresholds ($M = 1.55$, $SD = 4.52$). There was not a significant between-condition difference, $t(28) = -1.61$, $p = 0.12$. A further test of between-group (High/Low creativity) differences in the number of threshold-exceeding trials also revealed no significant difference, $t(16) = 0.61$, $p = 0.55$. Visual inspection of cleaned data also did not reveal typical blink or lateral eye movement artifacts.

Discussion

The present study utilized an Alternate Uses Task (AUT) on which participants were presented with a common object and were asked to either think of Uncommon (creative) or Normal (not creative) ways to use these objects. Participants' responses were judged by independent raters for creativity, and two groups (High- and Low-creative) were formed based on their responses. Prior research found EEG differences between more and less creative conditions, and between more and less creative individuals (Benedek, 2018), thus we predicted that a machine learning approach would be able to classify the two task conditions, and the two groups.

Classification of Uncommon and Normal Responses

Overall, as predicted, the study was successful at classifying the creative states, as well as creative groups. EEG Spectral comparisons revealed the expected between-condition differences for the group as a whole. Specifically, right frontal and parietal alpha-band power was greater in

the Uncommon, compared to the Normal condition at the beginning of creative ideation. Other studies have observed greater alpha TRP in Uncommon, compared to Normal conditions (Jauk et al., 2012), and increased alpha TRP during creative ideation (Benedek et al., 2014), highlighting the importance of alpha in creativity. Response times in the Uncommon condition were significantly slower than in the Normal condition. This finding is similar to those of other studies (Jauk et al., 2012), and provides external validity that participants were more likely to provide responses that came to mind quickly in the Normal condition. In the Uncommon condition, participants took longer, likely because they rejected obvious, typical ideas about object use in favor of less obvious, and thus more creative, ideas.

The most relevant channel combination for accurate classification was right frontal and parietal electrodes, F4 and P4. This restricted selection was beneficial not only in terms of classification accuracy, but it also reduced computational expense. This finding bodes especially well for future studies involving real-time data processing and neurofeedback.

In addition to the main period of 1-2.5 seconds that is reported in results, the general analysis strategy (subsection in Methods) included testing of several other latencies during the AUT task. These periods included the 0.75-1.75 second post-stimulus window, a period during the preparation phase, in which participants were shown the cue word indicating which type of thinking they were about to do (Normal or Uncommon), and in the period just before responding. No other time period, however, yielded the accuracy found by selecting the period just after the name of each object appeared, barring the initial period to process the stimulus. Indeed, numerous periods just after stimulus onset were also tested, and the period reported here (1-2.5 seconds) yielded the greatest classification accuracy. This finding is corroborated by the results of a previous study where alpha power increased at the beginning of the creative ideation phase

of a trial, then decreased (Rominger et al., 2019; Schwab et al., 2014). Although this previous work also found alpha increases just prior to responding, classification of data from this period was not as successful in the current study as data from the beginning of the creative ideation period.

In terms of classification accuracy, individual models generally worked better than group models, which is expected, given the individual difference variability in processing styles, task focus, and other variables. Participants whose models achieved the highest accuracy rates also demonstrated greater power in the alpha and beta bands at both electrode sites (F4/P4) than those whose models were less accurate. The most notable differences between High- and Low-accuracy groups at right frontal and parietal regions resided in both the low- and high-alpha ranges – primarily 9-12 Hz – though power was generally greater for the High-accuracy group from about 25 Hz down to the low end of the frequency spectrum. The reason for this difference is somewhat unclear, though a trend was found for the link between higher creativity scores and increased classification accuracy. This leaves some ambiguity as to the reason(s) for the observed differences between High- and Low-accuracy groups, though the decreased signal power across much of the analyzed spectrum (8-30 Hz) introduces the possibility of a difference in overall signal quality for Low-accuracy data.

Classification of More and Less Creative Individuals

Prior research has pointed to the differences in the EEG characteristics of more, compared to less creative people (Beaty, Seli, & Schacter, 2019; Benedek, 2018). In the current study, more versus less creative participants were successfully classified at a rate of just over 82%, in the case of raw data. This level of between-group classification accuracy is encouraging, in terms of continued research in this vein. Specifically, there is the possibility of using models

derived from highly creative individuals to provide real-time feedback to other participants in a training paradigm. Given the outperformance of individualized classification, however, expectations of this nature should be temperate. It is possible that a model derived from highly creative individuals will simply not provide helpful feedback to those whose EEG features match it poorly. A more likely benefit of continued research in this area is a richer understanding of creative thinking through the use of data-driven, ML analyses.

To our knowledge, this is the first ML-based EEG study on divergent thinking, thus variations in AUT parameters, the use of different types of DT tasks, and the adoption of ever-emerging and improving ML methods are all potential candidates to be used in this pursuit. Lastly, the observation that the classification of raw data resulted in accuracy rates that were essentially equivalent to the rates achieved using cleaned data highlights the possibility of successfully classifying EEG data in real time without the need for ultra-high-performance equipment. In other words, if computationally expensive data processing, like ICA, is not necessary to achieve good results, then research of this kind is not restricted to labs that possess machines that can perform such computations at break-neck speeds.

Limitations

One potential limitation is unbalanced male/female ration (8 males, 21 females). While it is possible that sex differences in EEG patterns could be an issue for classification in some circumstances, it is unclear that such is the case in this study. It was recently found that a deep learning network was able to classify males and females with 80% accuracy (Putten, Olbrich, & Arns, 2018), however, researchers used a deep convolutional neural network applied to raw EEG. Thus, their analysis method differed substantially from that of the current study, so it is not possible to infer from their results that the current approach would be sensitive to sex

differences. As a precaution, a 2-tailed t-test comparing male and female classification accuracy was performed, but no sex differences were found.

Another limitation is the use of a 1-2.5 second time period used for classification, given the 1.99-second mean response time in the Normal condition. This complication was not anticipated. Given the self-paced task design, it raised the possibility that response-related factors might have played a role in the observed accuracy rates. The additional analysis of an earlier interval (0.5-1.75 seconds) that did not contain the mean response time, however, yielded higher accuracy rates, despite prior concerns that features related to stimulus onset, *not* condition type, could muddy the waters for classification. Additional analyses also revealed that while there was a highly significant between-condition difference in the number of Normal and Uncommon trials that contained responses, this difference was the same for both High- and Low-creative groups. Thus, it seems unlikely that fast response times affected group classification results. Additional analyses to assess the general influence of artifacts, including on condition classification, showed a low rate of artifacts in the 1-2.5 second window (4.4%) for all trials, and no difference between conditions. Altogether, these additional findings seem to indicate that response-related activity likely had a negligible effect on classification accuracy. This line of thinking is perhaps most heavily bolstered by the finding that changing the epoch window to 0.5-1.75, which ends 0.24 seconds before mean RT, actually improved accuracy, in the case of between-group classification. If response-related features had been the driver of this classification, then including this period would have presumably resulted in superior model performance. That being said, it is interesting that when the analysis window was changed from 1-2.5s to 0.5-1.75s, condition classification accuracy decreased. One possible reason for changes in the opposite direction for condition classification vs. creativity-based classification is that an earlier window

somehow favors creativity-based classification, while a later window somehow favors condition classification. One possible explanation for this is that individual differences that are present before creative ideation begins in earnest can be discerned algorithmically. In contrast, condition-based differences are more readily discerned after ideation is well underway. There is also still the matter of condition differences based on response-related, late-window features, but the likelihood that such features affected condition classification results in a meaningful way in this study seems low.

Future Directions

Future research could employ a timed ideation period for both AUT conditions, thereby avoiding response-related EEG data. The period just prior to response could also be a focus of analysis, given the changes that occur toward the end of creative ideation (Rominger et al., 2019; Schwab et al., 2014). Fast responses in the Normal condition in the present study left a very narrow window between stimulus onset and task response. This meant that many response-locked epochs of interest would contain both stimulus onset and the pre-stimulus period. All things considered, a longer “forced thinking” period, as used by Schwab et al. (2014) would be of benefit in future studies.

Further use of ML in creativity research has the potential to identify classification features that have previously been overlooked, potentially stimulating new lines of research. Future EEG/ML creativity studies could include measures such as functional connectivity, event-related potentials, and others. Real-time ML-based neurofeedback is also an enticing option. This study is a step in these directions.

Conclusions

In conclusion, the potential value of ML in creativity research is a virtually untapped resource, and the applications could extend well outside of EEG-focused studies. For example, future studies could examine if natural language processing can be used to perform consistent, objective assessments of written or verbal creative task responses, or if image processing ML could do the same for drawings. Certainly, there are other physiological measures to which ML could be applied. Indeed, ML has been used to make predictions based on fMRI data, and even gene-brain interactions, both of which are relevant to investigations of creativity (Ren, Yang, & Qiu, 2019). Considering the growing ubiquity of ML and its successful implementation in numerous branches of scientific research, it is likely that the field of creativity research would be well-served by a broader adoption of its use.

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Appendix

List of objects used in the present study in the Alternate Uses Task (AUT)

1. Brick
2. Plate
3. Rope
4. Toothbrush
5. Broom
6. Fork
7. Flowerpot
8. Tire
9. Shovel
10. Coffee Cup
11. Chair
12. Book
13. Doormat
14. Ruler
15. Belt
16. Garbage Can
17. Rake
18. Curtain
19. Spoon
20. Comb
21. Garden Hose
22. Pillow
23. Umbrella
24. Boots
25. Magazine
26. Dustpan
27. Purse
28. Hammer
29. Pencil
30. Scissors