Confounds in the Data—Comments on “Decoding Brain Representations by Multimodal Learning of Neural Activity and Visual Features”

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Abstract—Neuroimaging experiments in general, and EEG experiments in particular, must take care to avoid confounds. A recent TPAMI paper uses data that suffers from a seriously reported confound. We demonstrate that their new model and analysis methods do not remedy this confound, and therefore that their claims of high accuracy and neuroscience relevance are invalid.

Index Terms—Object classification, EEG, human vision, neuroscience, neuroimaging, brain-computer interface

1 INTRODUCTION

A recent paper [8] presents a novel neural-network architecture, EEGChannelNet, for determining object class from EEG signals recorded from human subjects observing ImageNet [1] images as stimuli. Inter alia, it claims:

1. EEGChannelNet can decode object class from EEG signals better than prior work.
2. A training regimen that jointly fine tunes an image classifier while training EEGChannelNet, using a triplet loss that associates both positive and negative image samples with EEG samples, leads to an improved EEG classifier.

Here, we present novel evidence to refute these claims. We note that prior work [6] has already demonstrated other problems, namely:

a. The data used in [8] (from Spampinato et al. [9]) suffers from a confound (training and test samples coming from the same block with stimuli from a single class) and thus exhibits abnormally high classification accuracy with many different classifiers. When analyzed across subjects to eliminate this confound, accuracy degrades to chance.

b. New data collected with a block design also exhibits abnormally high classification accuracy with all of the same classifiers. Accuracy degrades to chance when this new data is bandpass filtered. Likewise, accuracy degrades to chance with new data collected to eliminate the confound.

c. [8] used Fourier and wavelet analyses to improve EEG classification. In contrast, [9] uses a simple binomial classifier.

2 METHOD

We attempted to follow the experimental method in [8] and [6] as closely as possible. The appendix in the supplementary material, which can be found on the Computer Society Digital Library at http://doi.ieeecomputersociety.org/10.1109/TPAMI.2021.3121268, available online, presents the details. In all cases, we report the average of accuracy on the validation and test sets after the full training regimen.

3 RESULTS

We report below the new results from EEGNet, SyncNet, and EEGChannelNet (abbreviated below as EEGCN) along with the results from Li et al. [6].1 We first replicate the experiment of Spampinato et al. [9] on the block-design data collected by them with their original splits where the test sets come from the same blocks as the training sets.2

The numbers differ somewhat from [9] and [8] as we use a different code base. Nonetheless, the numbers are qualitatively similar in that all classifiers exhibit high EEG classification accuracy. We next replicate the experiment of [9] on the block-design data collected by them with different splits in a leave-one-subject-out cross-validation paradigm. This allows the test sets to come from different blocks than the training sets.

1. All code and raw data that produced these results is available at http://dx.doi.org/10.21227/x2gf-5324.
2. All tables below report results only for image stimuli, 440ms windows, and the full set of channels. The first column gives the corresponding table from [6], some of which are in the supplementary material, available online. The first portion of each table reports results when training an EEG classifier in isolation. The second portion of each table reports results when jointly training EEGChannelNet on EEG together with various image classifiers on the EEG stimuli taken from ImageNet using triplet loss. Starred values indicate above chance (p < 0.005) by a binomial cmf.

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Note that accuracy drops for all classifiers. The remaining tables report analyses done with our own collected data [6]. First, we replicate the experiment of [9] on data collected with a block design on six subjects.

| Table | subject | LSTM | k-N | SVM | MLP | ID CNN | EEGNet | SynNet | SyncNet | EEGCN |
|-------|---------|------|-----|-----|-----|-------|--------|--------|---------|-------|
| 31    | 1       | 67.9% | 100.0% | 100.0% | 21.5% | 82.3%  | 58.3%  | 77.4%  | 93.8%   |
| 32    | 2       | 67.9% | 99.8%  | 100.0% | 29.1% | 72.3%  | 56.8%  | 73.6%  | 99.7%   |
| 33    | 3       | 71.8% | 99.8%  | 100.0% | 87.3% | 85.1%  | 92.9%  | 97.8%  | 96.5%   |
| 34    | 4       | 72.0% | 99.8%  | 100.0% | 36.0% | 89.6%  | 83.7%  | 78.6%  | 95.4%   |
| 35    | 5       | 83.9% | 99.9%  | 100.0% | 63.0% | 93.0%  | 96.8%  | 98.7%  | 99.9%   |
| 36    | 6       | 70.1% | 97.2%  | 99.0%  | 38.7% | 95.2%  | 86.2%  | 95.4%  | 96.5%   |

Palazzolo et al. [8], Table 2 bottom and Table 3, claim that EEG-ChannelNet obtains higher classification accuracy than [9], EEGNet, and SyncNet on that experiment. The above demonstrates that all classifiers can obtain high classification accuracy on data collected with a block design. We collected two blocks of data from subjects 2–5 and three blocks of data from subject 6. Next, we report the data from the second and third.

| Table | subject | LSTM | k-N | SVM | MLP | ID CNN | EEGNet | SynNet | SyncNet | EEGCN |
|-------|---------|------|-----|-----|-----|-------|--------|--------|---------|-------|
| 55    | 2       | 70.4% | 99.4%  | 100.0% | 62.9% | 98.8%  | 92.7%  | 92.8%  | 94.7%   |
| 56    | 3       | 84.7% | 99.2%  | 100.0% | 61.4% | 98.5%  | 97.5%  | 97.6%  | 98.0%   |
| 57    | 4       | 63.8% | 99.8%  | 100.0% | 17.8% | 92.4%  | 89.7%  | 86.6%  | 93.9%   |
| 58    | 5       | 76.9% | 99.1%  | 100.0% | 49.9% | 95.7%  | 97.8%  | 95.8%  | 96.9%   |
| 59    | 6       | 76.4% | 99.0%  | 99.9%  | 45.7% | 95.7%  | 97.5%  | 95.7%  | 97.1%   |
| 60    | 7       | 59.9% | 90.6%  | 90.1%  | 66.3% | 90.3%  | 92.0%  | 90.4%  | 95.6%   |
| 61    | 8       | 65.2% | 89.9%  | 62.9%  | 70.9% | 62.3%  | 91.0%  | 62.0%  | 56.6%   |

and third

| Table | subject | LSTM | k-N | SVM | MLP | ID CNN | EEGNet | SynNet | SyncNet | EEGCN |
|-------|---------|------|-----|-----|-----|-------|--------|--------|---------|-------|
| 14    | 6       | 86.8% | 87.3%  | 86.3%  | 65.1% | 85.7%  | 90.6%  | 87.3%  | 48.7%   |

block runs. These concur with the third table above. As discussed in Li et al. [6], the analyses in [9] erroneously omitted the bandpass filtering described in that paper. We next report the analyses in the above three tables with bandpass filtering added, respectively.

| Table | subject | LSTM | k-N | SVM | MLP | ID CNN | EEGNet | SynNet | SyncNet | EEGCN |
|-------|---------|------|-----|-----|-----|-------|--------|--------|---------|-------|
| 21    | 1       | 21.0% | 2.5%  | 4.1%  | 3.2% | 62.7%  | 33.4%  | 28.7%  | 4.9%    |
| 22    | 2       | 10.4% | 2.7%  | 3.0%  | 2.7% | 50.7%  | 18.0%  | 20.9%  | 3.3%    |
| 23    | 3       | 6.0%  | 3.0%  | 3.3%  | 2.5% | 50.4%  | 14.8%  | 20.7%  | 4.1%    |
| 24    | 4       | 15.2% | 3.4%  | 4.8%  | 4.8% | 48.1%  | 18.4%  | 22.8%  | 6.3%    |
| 25    | 5       | 26.7% | 8.9%  | 8.9%  | 6.6% | 70.5%  | 43.1%  | 35.6%  | 13.0%   |
| 26    | 6       | 16.5% | 2.1%  | 3.1%  | 3.3% | 37.8%  | 13.5%  | 15.6%  | 5.6%    |

| Table | subject | LSTM | k-N | SVM | MLP | ID CNN | EEGNet | SynNet | SyncNet | EEGCN |
|-------|---------|------|-----|-----|-----|-------|--------|--------|---------|-------|
| 41    | 1       | 8.4%  | 2.6%  | 2.5%  | 2.4% | 50.1%  | 15.1%  | 19.9%  | 3.6%    |
| 42    | 2       | 5.7%  | 1.8%  | 2.5%  | 2.4% | 52.2%  | 8.9%   | 20.0%  | 3.2%    |
| 43    | 3       | 16.0% | 2.2%  | 2.5%  | 2.3% | 54.9%  | 15.2%  | 28.5%  | 3.8%    |
| 44    | 4       | 6.3%  | 2.3%  | 2.9%  | 3.2% | 19.2%  | 8.4%   | 7.9%   | 3.4%    |
| 45    | 5       | 45.2% | 11.9% | 13.0% | 10.8% | 84.1%  | 70.2%  | 52.9%  | 15.1%   |
| 46    | 6       | 22.7% | 5.9%  | 11.3% | 15.8% | 59.6%  | 65.7%  | 43.6%  | 7.6%    |
| 47    | 7       | 6.2%  | 1.7%  | 1.1%  | 1.5% | 68.3%  | 45.6%  | 44.1%  | 8.4%    |
| 48    | 8       | 4.9%  | 1.7%  | 1.7%  | 1.8% | 66.9%  | 37.2%  | 44.4%  | 8.4%    |
| 49    | 9       | 4.9%  | 1.7%  | 1.7%  | 1.8% | 66.9%  | 37.2%  | 44.4%  | 8.4%    |

Accuracy drops to chance for all classifiers. We next report analyses performed on data collected with randomized trials both with and without bandpass filtering. Note that accuracy is at chance for all classifiers. We next report an analysis on data collected with randomized trials, where the trial labels are replaced with block indices instead of object class, both with and without bandpass filtering.
bandpass filtering. In other words, all stimuli in the first block are labeled with class 1, even though they reflect different object classes, all stimuli in the second block are labeled with class 2, even though they reflect different object classes, and so forth. Note that classification accuracy is high for all classifiers, without bandpass filtering, suggesting that they are classifying a spurious correlation between the EEG signal and the block, not the stimulus category. This can be unduly high even with bandpass filtering, as is often the case. The remaining tables report cross-block classification. For subjects 2–6, the first and second block runs presented the stimuli in the same order. For subject 6, the third block run presented the stimuli in a different order. First, Table subject LSTM and without bandpass filtering. These report analyses between different runs with different stimulus presentation order. Note that classification accuracy with all classifiers is at chance. These results demonstrate that there is a confound not only between training and test samples collected in close temporal proximity within the same block, there also is a second confound between samples collected in different runs but with the same temporal offset from the beginning of the run. Collectively these results demonstrate that EEGNet, SyncNet, and EEGChannelNet exhibit exactly the same flawed pattern of behavior as the LSTM model from Spampinato et al. [9]. To summarize, the only experiment designs among those considered above that do not suffer from one or both confounds are the ones with randomized trials (the ninth and tenth tables) and cross-block classification with different stimulus presentation order (the fifteenth through eighteenth tables). EEGChannelNet accuracy is at chance on these. Since all of the analyses in [8] use the same flawed data as in [9], everything that follows from those analyses is suspect.

Palazzo et al. [8] compare EEGChannelNet with EEGNet [5] and SyncNet [7] and claim improved accuracy. The tables above demonstrate that any relative performance difference is artifactual as EEGNet and SyncNet exhibit the same characteristics as EEGChannelNet on faulty data. We make no claim about EEGNet or SyncNet themselves or the experiments reported in Lawhern et al. [5] and Li et al. [7]. Our concerns arise solely for the use of EEGNet or SyncNet as described in [8] for analyzing the flawed data from [9]. It is interesting to note that the tenth table above indicates that EEGNet, along with the SVM and 1D CNN, achieve accuracy slightly above chance on randomized trials.

For joint training, the resulting image classifier always performs above chance, usually highly above chance, but the resulting EEG classifier exhibits the same broad characteristics as all other classifiers, namely high classification accuracy on designs that exhibit a confound (all tables above except the ninth, tenth, and fifteenth through the eighteenth) and chance on designs that do not (the ninth, tenth, and fifteenth through eighteenth tables).

4 Conclusion

We demonstrate here that the claims 1 and 2 in Palazzo et al. [8] cannot be maintained because they rely on the flawed dataset from Spampinato et al. [9]. Further, the classification experiments therein
fail when repeated on properly collected data without this confound (the ninth, tenth, and fifteenth through eighteenth tables).

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