

Deep Transfer learning for Cross-Experiment Prediction of Rapid Serial Visual Presentation Events

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Introduction: Designing classifiers for robust cross-subject and cross-experiment prediction of brain activities in responses to cognitive events is a significant challenge in brain-computer interface (BCI) applications. We have developed previously a new EEG-tailored deep convolution neural network(CNN) model called CNN4EEG and showed its robust and superior performance than existing shallow algorithms including XDAWN for predicting Rapid Serial Visual Presentation (RSVP) target events. In this work, we investigate transfer learning (TL) [1-2] based on CNN4EEG for cross-experiment prediction.

Material, Methods and Results: We used the data from three different RSVP experiments (CT2WS and Static Motion, and Expertise RSVP [3-4]). For each, we extracted 1s EEG epochs with sampling rate 512 Hz obtained from RSVP experiments. First we trained a CNN4EEG with a data set containing 17000 training epochs obtained from combined epochs from CT2WS and Static Motion. A new RSVP dataset with 256 training and 1044 testing samples comes from Expertise data set. A CNN4EEG with seven hidden layers is trained. The input epoch size is 64×128 and the output of the deep convolutional neural network has 2 nodes for two class classification. The hidden layers characteristics are listed in the Table 1 (layers are defined as kernel width \times kernel height / number of feature maps).

Table 1: Deep convolutional neural network hidden layers

Feature-maps	Max Pooling	Feature-maps	Max Pooling	Dropout	Fully-connected	Fully-connected	Fully-connected	Dropout
64 \times 4/10	1 \times 2	1 \times 8/20	1 \times 2	50%	400 nodes	200 nodes	100 nodes	50%

When we use the trained CNN for the classification of the new data set without any fine-tuning, AUC score for the classification of the 1044 testing samples is 68.84%. On the other hand, when the weights of the trained model is used as initialization weight and a fine tuning is conducted afterwards, with 256 training samples, the AUC score of the classification of the 1044 testing samples reaches to 78.57%. Apparently the fine tuning of the deep convolutional neural network causes a ten percent increase in classification performance. It is notable that TL with XDAWN result in 63.98% AUC score.

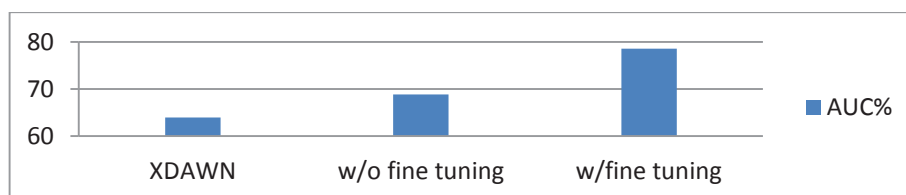


Figure 1: AUC of transfer learning for XDAWN and with and without fine tuning

Discussion: Our experimental results on EEG RSVP data are performed in two cases, using a pertained deep convolutional neural network as a feature extractor and also using its weights just as initialization weights and doing a fine tuning. The results clearly show that the TL with our deep model CNN4EEG can significantly improve the cross-experiment classification performance.

Significance: In this paper, we investigated the transfer learning for cross-experiment prediction of RSVP target events. We show that TL can reduce the over-fitting phenomenon when we implement DL algorithms on a target RSVP dataset; finally, we provided this CNN model trained from a large source RSVP dataset as a transferable model for other RSVP BCI tasks to use.

References

- [1] Yosinski, Jason, et al. "How transferable are features in deep neural networks?." Advances in Neural Information Processing Systems. 2014.
- [2] Donahue, Jeff, et al. "Decaf: A deep convolutional activation feature for generic visual recognition." arXiv preprint arXiv:1310.1531 (2013).
- [3] "U.S Department of Defense Office of the Secretary of Defense," Code of federal regulations, protection of human subjects. 32 CFR 219, 1999.
- [4] "U.S. Department of the Army. Use of volunteers as subjects of research. AR 70-25," Washington, DC: Government Printing Office, 1990.