(Working Title): Gaze-Based Mind Windering Detection using Deep Learning

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Abstract

Mind wandering (MW) is a phenomenon where a person shifts their attention from task related to task-unrelated information. MW is potentially disruptive for any task that people perform, and systems that can detect and correct MW instances can be of great benefit to users. In this research, we investigated an existing gaze-based mind wandering dataset (Faber et al., 2018) consisting of 62 eye gaze features collected during a reading comprehension task. The dataset used 135 participants, who self reported instances of mind wandering during a computerized reading task. Eye gaze data were recorded during these trials. In this presented research, original MW detection using standard ML techniques, such as k-NN, SVM, random forests, and others, were first replicated on the data. Performance of the trained classifiers was measured using AUC-ROC scores and accuracy. The original ML performance on this data was matched in the reported reserach. We then applied deep learning classifiers to the mind wandering dataset, using combinations of deep, convolutional and recurrent layers. Where past and replicated classifiers achieved a best AUC-ROC score of about 0.6595, our best deep classifier using a 1D convolution achieved an AUC-ROC score of 0.8025, with a mean overall accuracy of 0.7278. In this research we report the results of the replication and the extension using deep learning to improve on the detectors performance, and we discuss how the deep learning classifiers may be working to improve the classification performance over traditional ML approaches.

1 Introduction

This is the introduction to this article. (Bixler & D'Mello, 2015; Faber et al., 2018).

2 Methods

3 Results

Figure 1 shows the resulting histogram of AUCROC performance seen from the grid search over model parameters trying to optimize AUCROC performance.

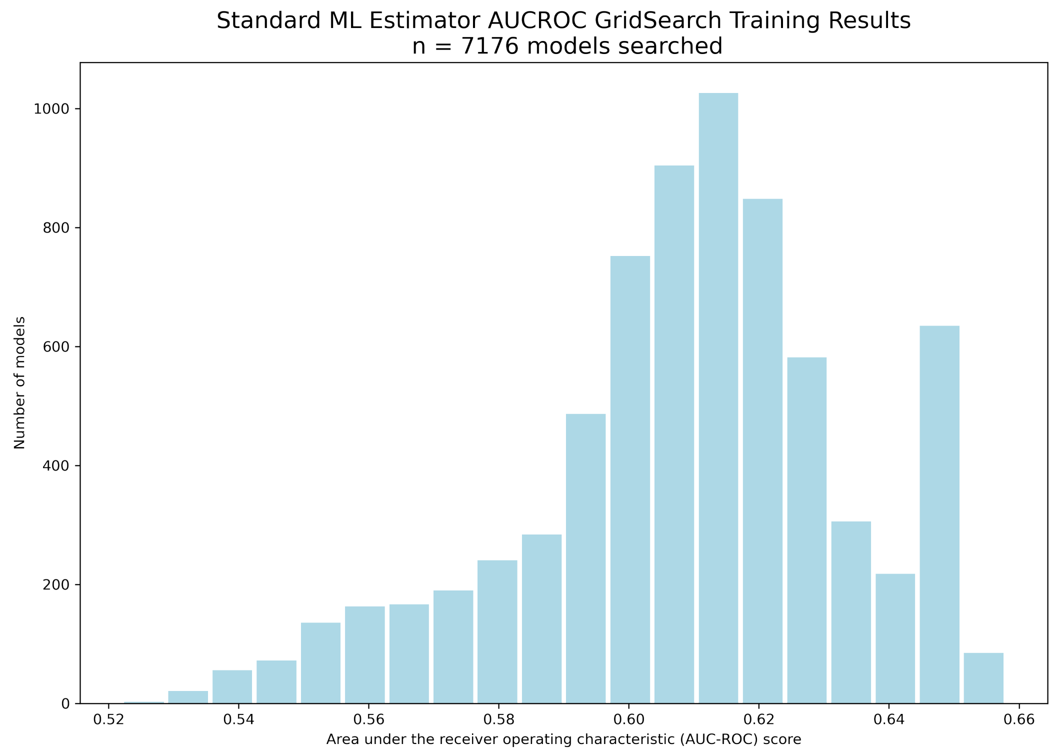

Figure 1: Histogram of AUCROC performance for parameter search of all trained models

Table 1 summarizes the performance of the best estimators we found for each estimator type. The best estimator shown was the one with the highest average aucroc score over the 5-fold cross validation, that is it was the estimator with the highest average aucroc score on the held back fold after training with the other folds. The table shows a final aucroc score obtained using the estimator to predict all of the mindwandering data. We also show the final accuracy scores, and precision and recall measures.

Table 1: Comparison of performance for best standard ML estimator found for each type by parameter grid search.

Model name	k-fold aucroc	final aucroc	accuracy	recall	precision
LogisticRegression	0.6258	0.5660	0.4485	0.8248	0.3090
kNN	0.6337	0.8304	0.7983	0.9012	0.5848

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Table 1: Comparison of performance for best standard ML estimator found for each type by parameter grid search.

Model name	k-fold aucroc	final aucroc	accuracy	recall	precision
SVM	0.6580	0.6272	0.5999	0.6873	0.3735
DecisionTree	0.6428	0.6157	0.5559	0.7475	0.3524
RandomForest	0.6535	0.6273	0.5773	0.7376	0.3646
NaiveBayes	0.6565	0.6165	0.6349	0.5759	0.3868

Figure 2 gives a comparison of the best estimator found for each of the standard machine learning estimators searched. The average score represents the average auc-roc score over the 5-fold cross validation obtained when performing the grid search. The final score is the auc-roc score of the best estimator using the full data set all together.

4 Discussion

5 Conclusion

References

Bixler, R., & D'Mello, S. K. (2015). Automatic gaze-based detection of mind wandering with metacognitive awareness. In F. Ricci, K. Bontcheva, O. Conlan, & S. Lawless (Eds.), *User modeling, adaptation and personalization* (pp. 31–43). Springer International Publishing. https://doi.org/10.1007/978-3-319-20267-9_3

Faber, M., Bixler, R., & D'Mello, S. K. (2018). An automated behavioral measure of mind wandering during computerized reading. *Behavior Research Methods*, *50*(1), 134–150. https://doi.org/10.3758/s13428-017-0857-y

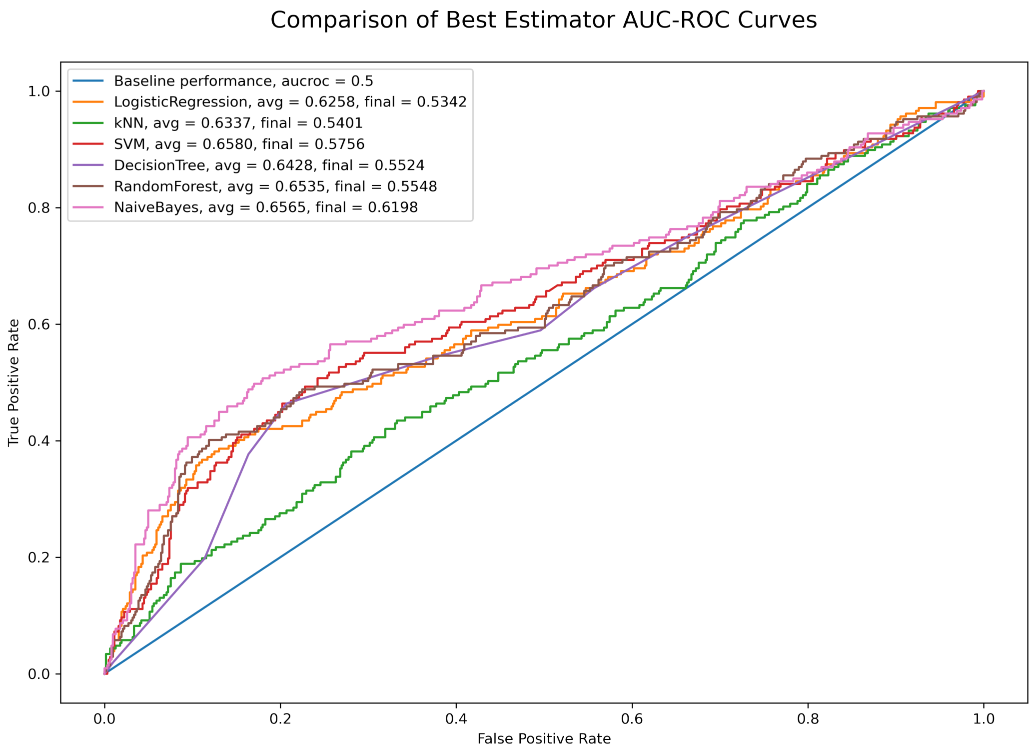

Figure 2: Comparison of AUCROC scores achieved by best standard ML models in each type of estimator that was explored.