Enhanced Boosting-based Transfer Learning for Modeling Ecological Momentary Assessment Data

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1 Introduction [5]

In the domain of psychopathology, the use of Ecological Momentary Assessment (EMA) allows for real-time data collection, providing valuable insights into the temporal dynamics and variability across multiple individuals [6,7]. Such rich EMA information can be used to build personalized models that predict the future of EMA symptomatology. However, a challenge in building personalized models is the limited amount of data available for each individual [3,4]. To address this, transfer learning can be applied to improve predictions for a specific individual (target domain) by incorporating data from other individuals (source domain).

Among the existing transfer learning approaches, Transfer Adaptive Boosting (TrAdaBoost) is further explored and enhanced to adapt to the EMA context [2]. According to the boosting concept, the goal is to build an ensemble of models, each time adjusting the weights of an instance on its misclassification rate, and whether they belong to a target or source individual. For instances in the source domain, weight updating is based on the similarity to the target individual, whereas instances in the target domain should be more influential. Thus, the impact of different re-weighting strategies and the number of similar individuals in the source are thoroughly investigated to ultimately improve individual 1-lag classification performance.

2 Methodology

During the TrAdaBoost modeling process, various important steps are involved and need to be enhanced and adapted to the EMA context, including training a weak classifier, calculating the training error, re-weighting all the instances in the target and source domain, and normalizing the weights [1]. Among the proposed enhancements, one of the most important once is the training error, since it is involved in all weight updating and prediction aggregation strategies. Although typically the weighted average of the absolute error is used, a modified training error metric is proposed based on the F1 score, providing a more representative measure of both majority and minority classes.

Moving to the core of the boosting concept, the original re-weighting strategy ensures that the model focuses on the harder instances in the next training iterations. Although misclassified instances receive higher weights in the target, assuming these are useful instances, this concept is not always applicable to the source. The misclassified source instances generally indicate that they may not be valuable for the target, but potentially could be also challenging and valuable instances. Thus, in our approach, we first explore updating strategies that initially increase and then decrease the weights of the misclassified source data. Following, the source weights are updated not only based on the F1-based errors but also considering the relevance and similarity to the target domain. If a misclassified source is highly similar to the target, there is a high probability that this is relevant despite the misclassification. Therefore, data from different sources should be updated differently based on their similarity level to the target.

3 Experimental Results - Discussion

Different experimental choices are assessed in a multivariate binary classification task [5]. First, we examine the impact of varying the number of similar source domains (individuals) as well as the method of updating the source weights on the overall performance. Among the re-weighting strategies, the performance of the increasing-decreasing approach started rising after incorporating more than 4 similar sources, with the average value converging to 0.53. This shows that more sources can provide valuable information and improve performance.

After identifying the optimal experimental setting for TrAdaBoost, we compare this with some baseline approaches, including personalized models without any transfer learning components (Decision Tree, AdaBoost) and original TrAdaBoost (using 1 and 10 sources). According to the results of Figure 1, the proposed enhancements in TrAdaBoost provide the highest F1 scores, outperforming the original TrAdaBoost but only marginally the personalized models. Further statistical analysis revealed that 132 out of 187 individuals achieved an improved F1 score (average increase of 5.1%) compared to trees. This suggests further exploration of the specific ineffective cases.

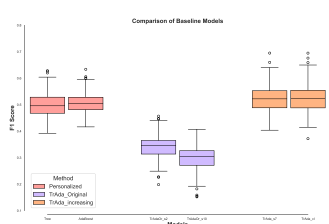

Fig. 1: F1 distributions across all 187 individuals.

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