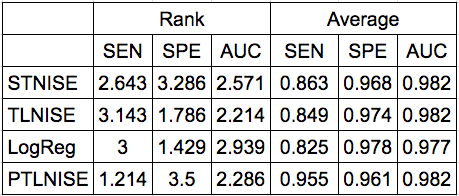
**Multi-objective transfer learning for epileptic seizure detection**

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**Introduction:** Due to the scarcity of well labeled epileptic seizure data and the usual rarity of seizure events of an average patient, it becomes relevant to develop methods capable of using data from multiple patients aiming at improving classification performance on a specific patient. With this purpose in mind, we propose a method that uses a multi-objective optimization method to share data and learning parameters from a source patient to a target patient.

**Materials and Methods:** The data consisted of EEG recordings of 14 selected patients with labeled seizures, available at [1, 2]. Features were extracted from properties of a graph formed by the correlations between electrodes, as in [3]. In this work, the methodology consists of generating multiple models using NISE [4] (a versatile multi-objective optimizer), considering two objective functions, and selecting a classifier, among the generated efficient candidate solutions, using a harmonic mean between sensitivity and specificity. Each classifier adopts a two-phases synthesis approach: the first phase involves training the source task model, and the second phase is devoted to transferring parameters and data from a source to a target model. The generated model is denoted TLNISE (transfer learning NISE).

**Results:** The comparison benchmarks presented in Table 1 were: a regularized Logistic Regression (LogReg) as well as a single-task NISE (STNISE) formulation, which considers only target patients’ data. Additionally, to illustrate the best achievable performance of TLNISE, it is also considered a best *a posteriori* model (PTLNISE), supported by the classifier’s performance in the real test case (which violates any fair design principle, thus serving just as a reference). TLNISE and the benchmarks were evaluated using sensitivity (SEN), specificity (SPE) and the area under the curve (AUC) of the ROC curve. The first three columns of Table 1 present the average Friedman rank among all patients for each metric, while the last three columns present the average values across all patients.

Table 1: Friedman rank (the lower the better) and average values (the higher the better) for SEN, SPE and AUC metrics.

**Discussion:** Table 1 shows that TLNISE has the best ranking for AUC, a middle performance on SPE, while PTLNISE, exhibits a better ranking for SEN. This suggests that TLNISE struggles particularly in its last stage of model selection. The first position in AUC ranking suggests that this transfer learning scheme has a potential to simultaneously benefit the performance on both SEN and SPE metrics, while the single-task methods STNISE and LogReg tend to favor single metrics.

**Conclusion:** This work reveals a good performance of transfer learning for seizure detection, based on a multi-objective approach (TLNISE). The results indicate that further improvements in model selection are welcome, and the next research step will be the usage of ensemble approaches, since TLNISE generates multiple diverse models.

**References:** [1] Goldberger, A.L. et al. Circulation 101(23): e215-e220, 2000. [2] Shoeb, A. Ph.D. Thesis, MIT, 2009. [3] Dhulekar et al. Machine Learning and Data Mining in Pattern Recognition 11th ed. 9166:32-52, 2015. [4] Cohon, J. L. Multiobjective programming and planning:127-140, 1978.

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