Optimizing ROC Curves with a Sort-Based Surrogate Loss for Binary Classification and Changepoint Detection

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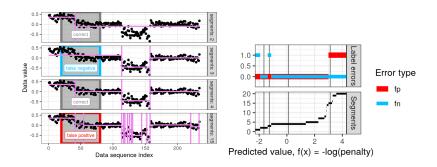
Problem Setting and Related Work

Results

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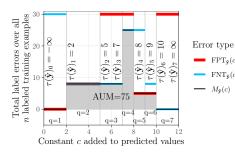
Real data example with non-monotonic label error

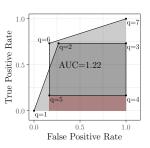


Looping ROC curve, simple synthetic example

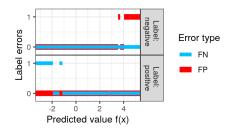
 $FPT_{\hat{y}}(c)$

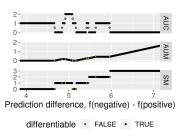
 $\text{FNT}_{\hat{\mathbf{y}}}(c)$ $M_{\hat{y}}(c)$



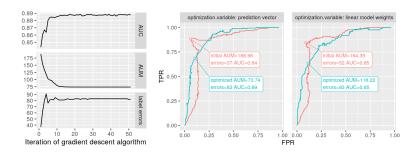


Real data example with AUC greater than one

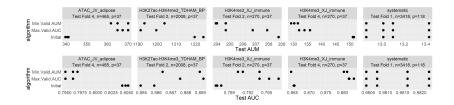




Train set ROC curves for a real changepoint problem

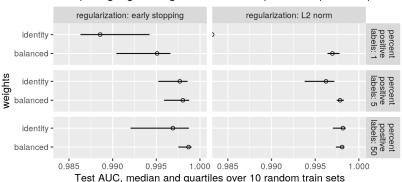


Learning algorithm results in better test AUC/AUM for changepoint problems

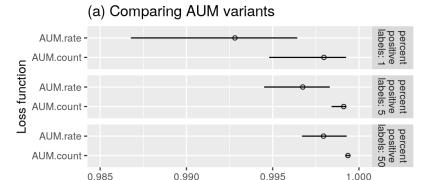


Standard logistic loss fails for highly imbalanced labels

Comparing logistic regression models (control experiment)



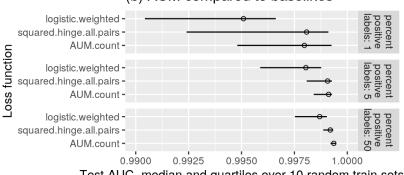
Error rate loss is not as useful as error count loss



Test AUC, median and quartiles over 10 random train sets

Learning algorithm competitive for unbalanced binary classification

(b) AUM compared to baselines



Test AUC, median and quartiles over 10 random train sets

Comparable computation time to other loss functions

