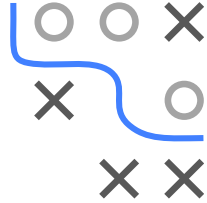
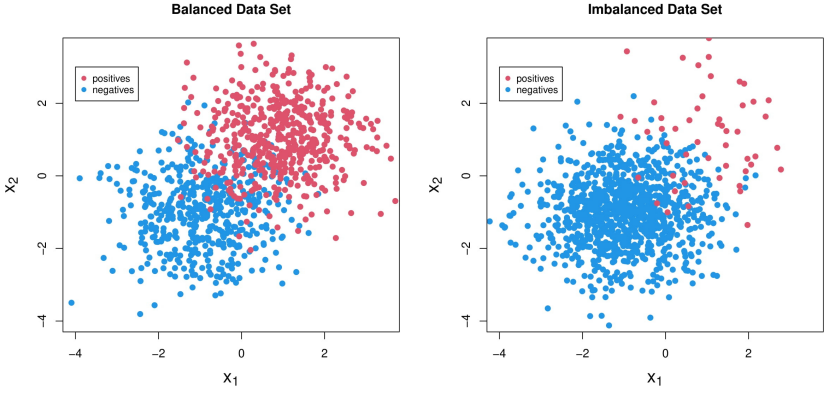
IMBALANCED DATA SETS

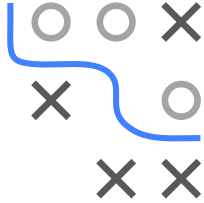
- Class imbalance: Ratio of classes is significantly different.
- Consequence: Undesirable predictive behavior for smaller class.
- Example: Sampling from two Gaussian distributions





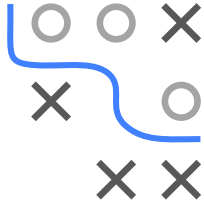
IMBALANCED DATA SETS: EXAMPLES

Domain	Task	Majority Class	Minor Class
Medicine	Predict tumor pathology	Benign	Malignant
Information retrieval	Find relevant items	Irrelevant items	Relevant items
Tracking criminals	Detect fraud emails	Non-fraud emails	Fraud emails
Weather prediction	Predict extreme weather	Normal weather	Tornado, hurricane



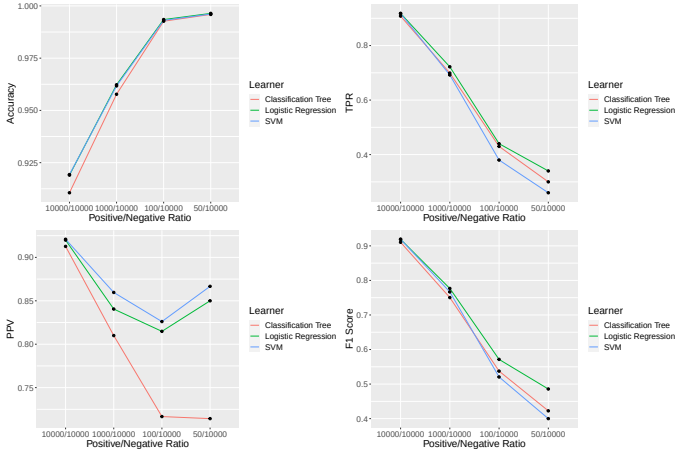
- Often, the minority class is the more important class.
- Imbalanced data can be a source of bias related to concept of fairness.

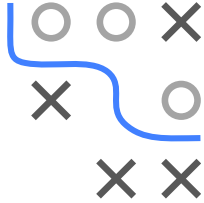
ISSUES WITH EVALUATING CLASSIFIERS



- Ideal case: correctly classify as many instances as possible
  $\Rightarrow$ High accuracy, preferably 100%.
- In practice, we often obtain on imbalanced data sets: **good** performance on the **majority** class(es), a **poor** performance on the **minority** class(es).
- Reason: the classifier is biased towards the **majority** class(es), as predicting the majority class pays off in terms of accuracy.
- Focusing only on accuracy can lead to bad performance on minority class.
- Example:
  - Assume that only 0.5% of the patients have a disease,
  - Always predicting “no disease” leads to accuracy of 99.5%

ISSUES WITH EVALUATING CLASSIFIERS

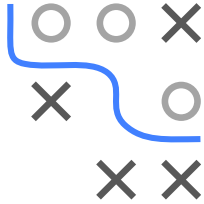




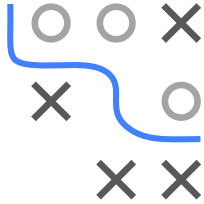
In each scenario, we have 10.000 obs in the negative class. Number of obs in positive class varies between 10.000, 1.000, 100, and 50. Train classifiers with 10-fold stratified cv. Evaluate via aggregated predictions on test set.

POSSIBLE SOLUTIONS

- Ideal performance metric: the learning is *properly* biased towards the minority class(es).
- Imbalance-aware performance metrics:
  - G-score
  - Balanced accuracy
  - Matthews Correlation Coefficient
  - Weighted macro F_1 score



POSSIBLE SOLUTIONS



Approach	Main idea	Remark
Algorithm-level	Bias classifiers towards minority	Special knowledge about classifiers is needed
Data-level	Rebalance classes by resampling	No modification of classifiers is needed
Cost-sensitive Learning	Introduce different costs for misclassification when learning	Between algorithm- and data-level approaches
Ensemble-based	Ensemble learning plus one of three techniques above	-