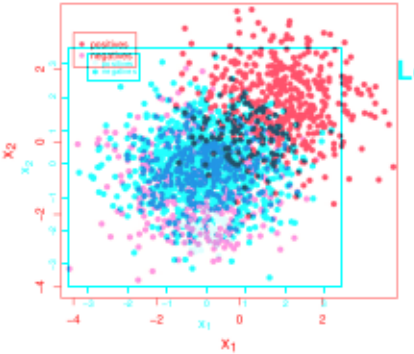
IMBALANCED DATA SETS

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

Balanced Data Set



Imbalanced Data Set

Advanced Machine Learning

Imbalanced Learning: Introduction

Learning goals

- Know what an imbalanced data set is
- Understand disadvantage of accuracy on imbalanced data
- Know techniques for handling imbalanced data sets

IMBALANCED DATA SETS: EXAMPLES

- Class imbalance: Ratio of classes is significantly different.
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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%

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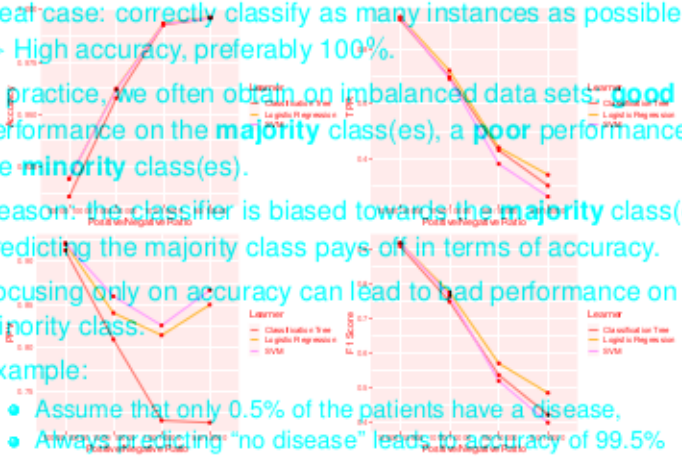

In each scenario, we have 10.000 obs in the negative class. Number of obs in positive class varies between 10.000, 1.000, 100, and 50. Train classifiers with 10-fold stratified cv. Evaluate via aggregated predictions on test set.

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

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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	-

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