Overview of Imbalanced Classification

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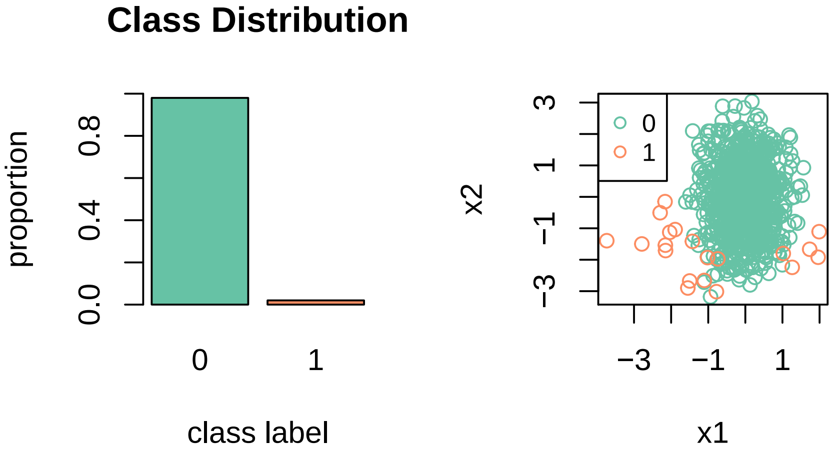
Classifying under the setting that the number of samples in different classes are very different.



Many Real-World Situations

Imbalanced data is very common in various real-world situations. And the problem becomes more challenging (overfitting) in the presence of *rare events*, below are some of the examples:

- Cancer diagnosis
- Spam detection
- Fraud credit card transaction detection
- Natural disasters prediction

What Could Go Wrong With Usual Metric?

- If we're using "accuracy" as the performance measure...
- Dummy classifier that classifies everything to the majority could still maintain high accuracy.
- Not useful?

Confusion Matrix

It seems that "accuracy" isn't giving us the whole picture, since our primary goal is to correctly identify the minority class.

A simple but effective evaluation criterion for skewed class distribution is the confusion matrix.

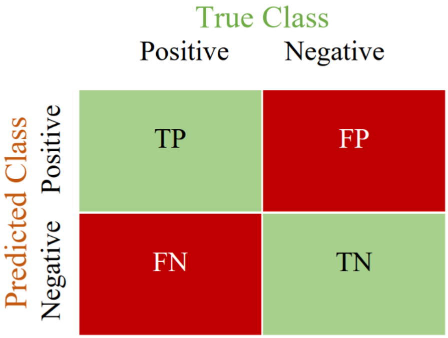


Figure 1: Confusion Matrix

Accuracy, Precision, Sensitivity, Specificity

Accuracy: (TP+TN)/(TP+FP+TN+FN), how many samples are correctly predicted out of all samples.

Precision: TP/(TP+FP), how many samples are truly positive out of all positive predictions.

Sensitivity (Recall): TP/(TP+FN), how many samples are predicted positive out of all true positive samples. A.k.a True Positive Rate.

Specificity: TN/(TN+FP), how many samples are predicted negative out of all true negative samples. A.k.a. True Negative Rate.

For the ideal case, where FN and FP are 0, the above 4 metrics would be 1.

ROC Curve

- receiver operating characteristic curve
- illustrate the diagnostic ability of a binary classifier as its discrimination threshold is varied
- access the tradeoff between sensitivity (TPR) and specificity (1-FPR)

Area Under the ROC Curve (AUC)

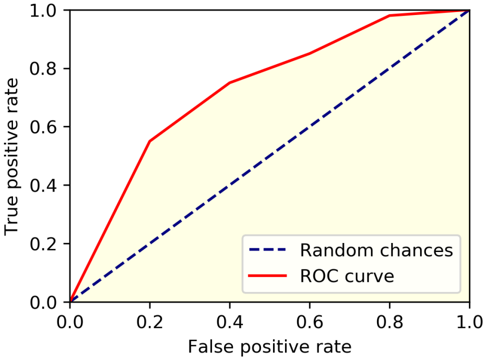


Figure 2: ROC curve

- Want a classifier with a large Area Under the ROC Curve (AUC).

Image source: Huy Bui

ROC curves for multi-class classification?

One vs all method.

If you have three classes named A, B and C, you can have one ROC for each of the following cases:

- A vs. B and C
- B vs. A and C
- C vs. A and B

Common Re-sampling Methods

- Undersampling: random undersample the majority class
- Oversampling : random oversample the minority class
  - SMOTE(Synthetic Minority Over-Sampling Technique): interpolate between nearby minority samples to avoid overfitting (Chawla et al. (2002), image source: He and Garcia (2009))

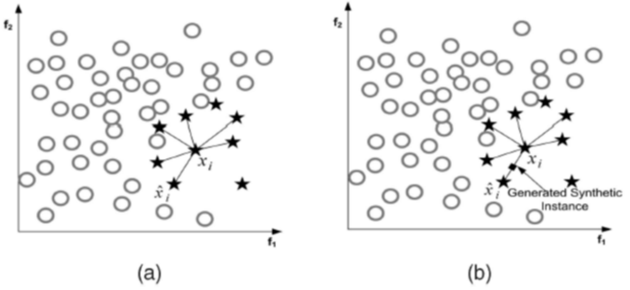


Fig. 3. (a) Example of the K-nearest neighbors for the x_i example under consideration ($K = 6$). (b) Data creation based on euclidian distance.

- Place more weights on the minority class (or larger penalty constant), forcing the classifier to correctly classify on the minority samples. Ex: Cost-Sensitive Support Vector Machines (SVM) (Veropoulos et al. (1999) and Wu and Chang (2003)), Label-Distribution-Aware Margin Loss (Cao et al. (2019))

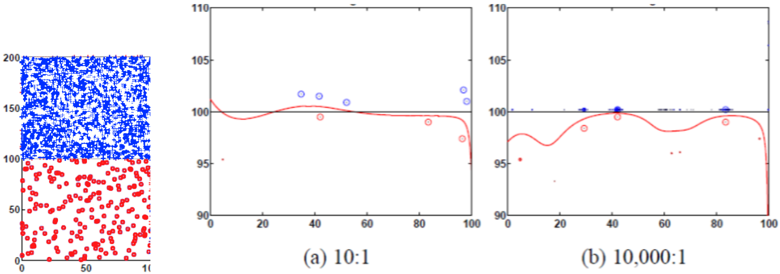


Figure 3: SVM with Different Imbalanced Ratio

Common Ensemble Methods

- MetaCost: bagging + Cost Matrix (Domingos (1999))
- SMOTEBagging: SMOTE + bagging (Wang and Yao (2009))
- UnderBagging: random undersampling + bagging (Barandela, Valdovinos, and Sánchez (2003))
- SMOTE-Boost: SMOTE + boosting (Chawla et al. (2003))
- RUSBoost: random undersampling + boosting (Seiffert et al. (2009))

Deep Learning Methods

- Focal Loss: similar to re-weighting scheme. It changes the loss function by giving less weights on the samples that are classified correctly (Lin et al. (2017))
- Data Generation through conditional generative adversarial networks (cGAN): similar to oversampling, but uses cGAN to generate more minority samples. (Douzas and Bacao (2018))

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