Multi-class Imbalanced Learning

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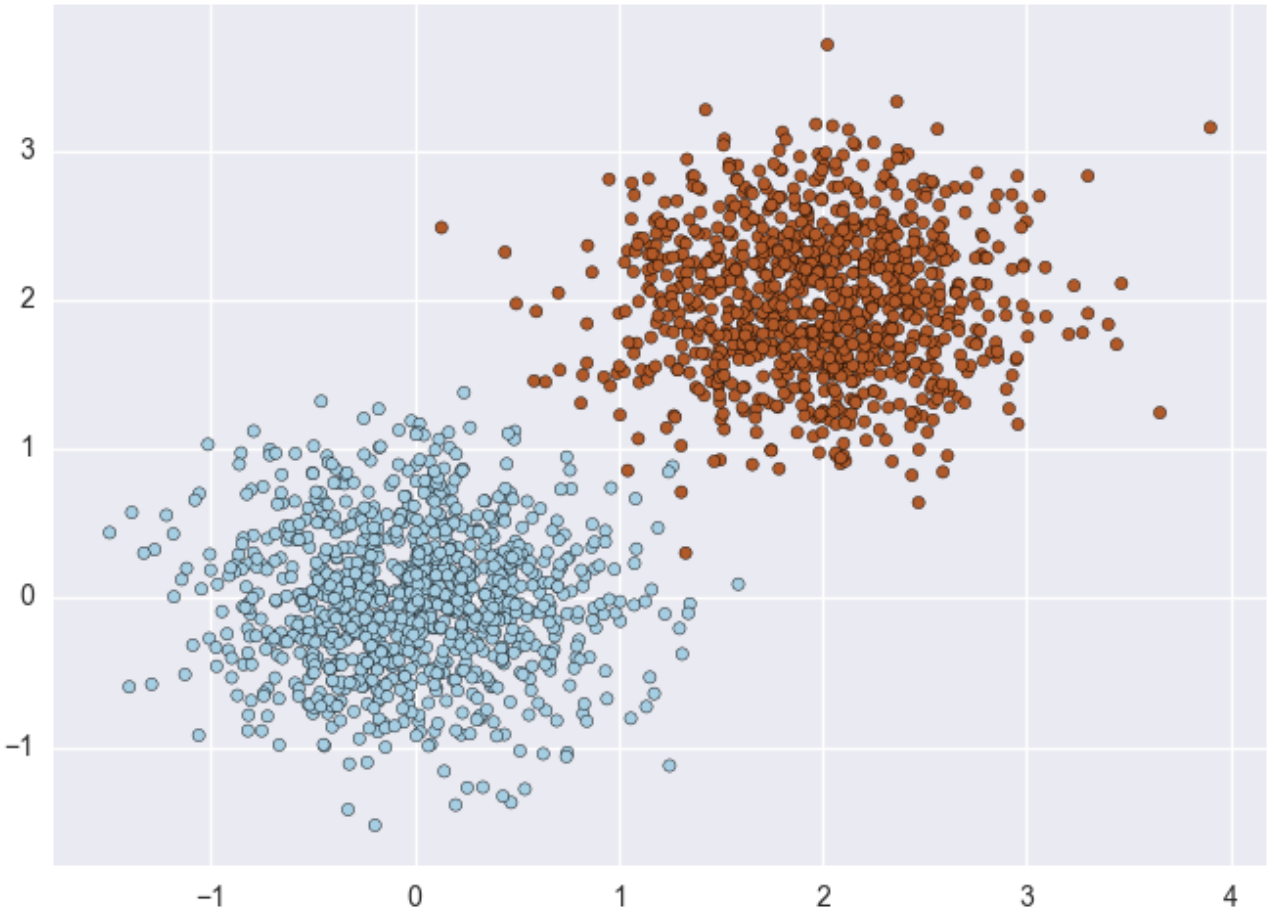
Classification Problem



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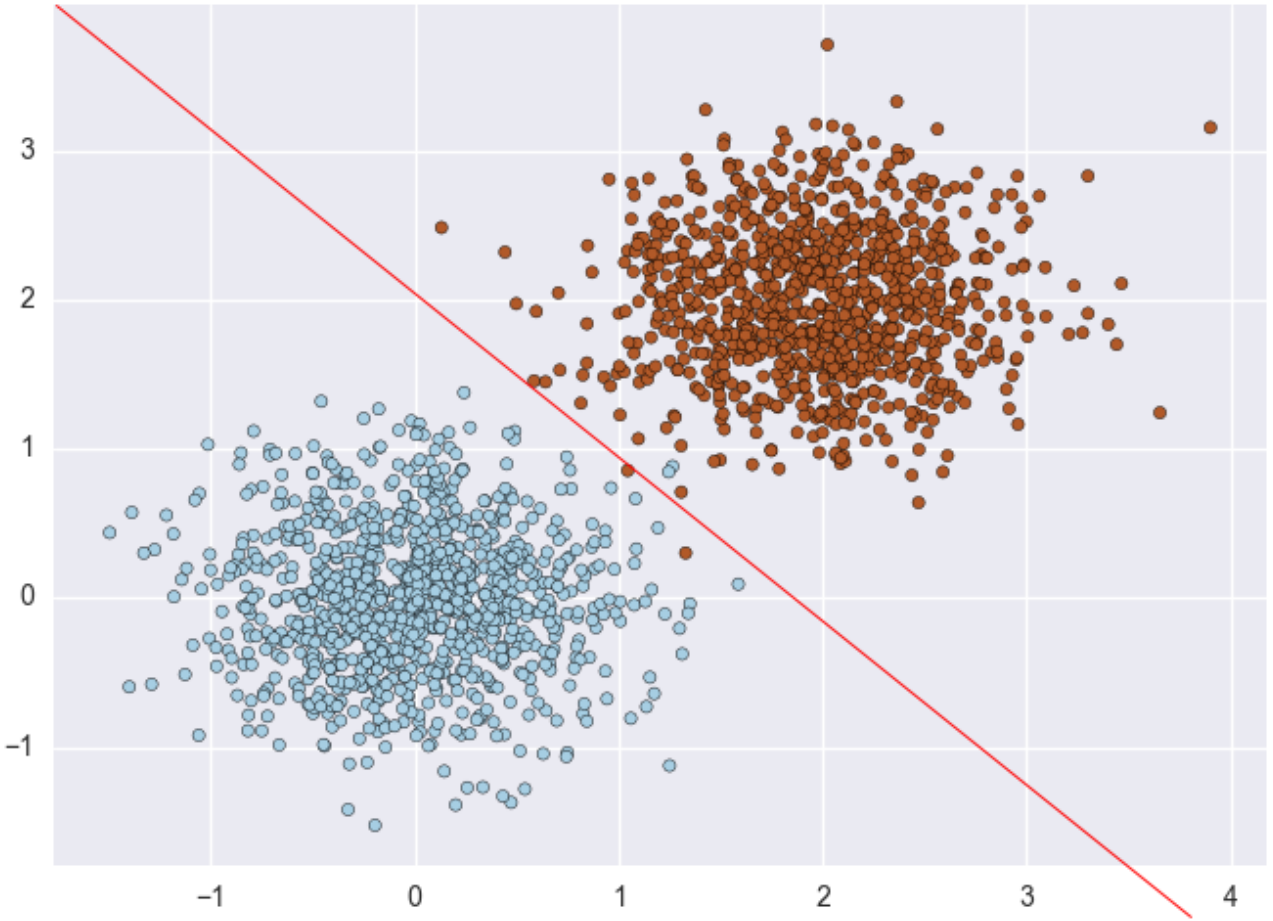
classifiers



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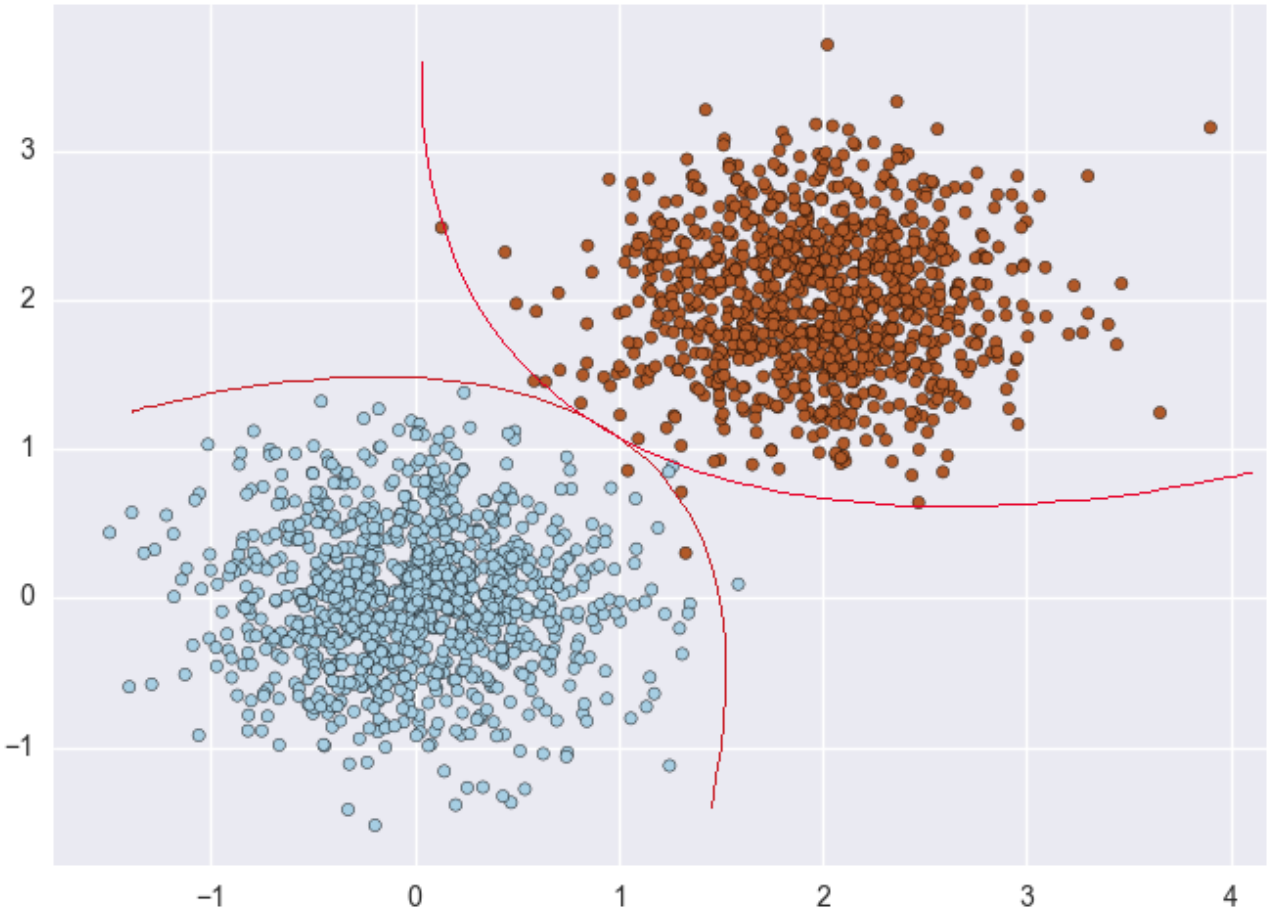

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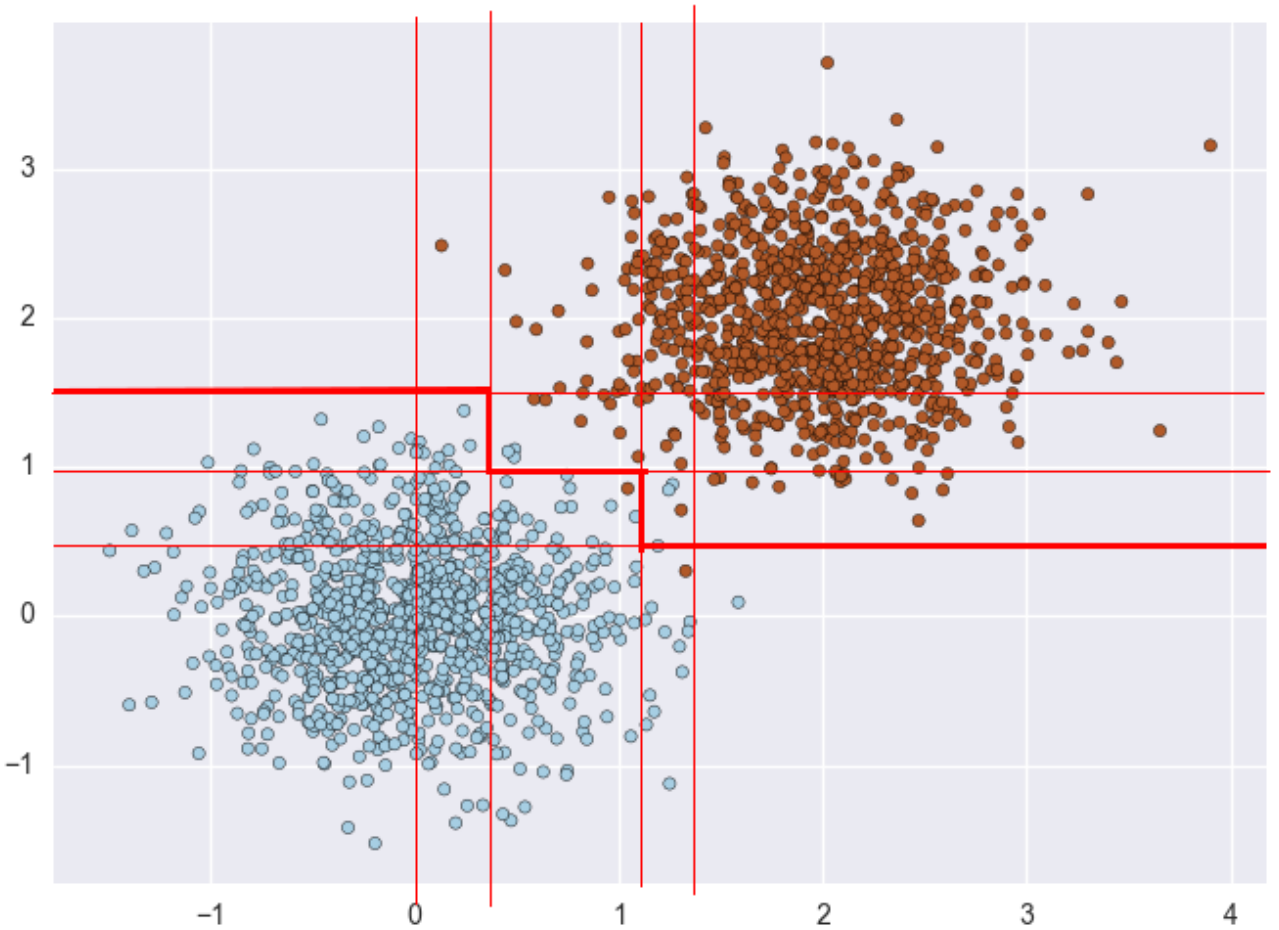
classifiers



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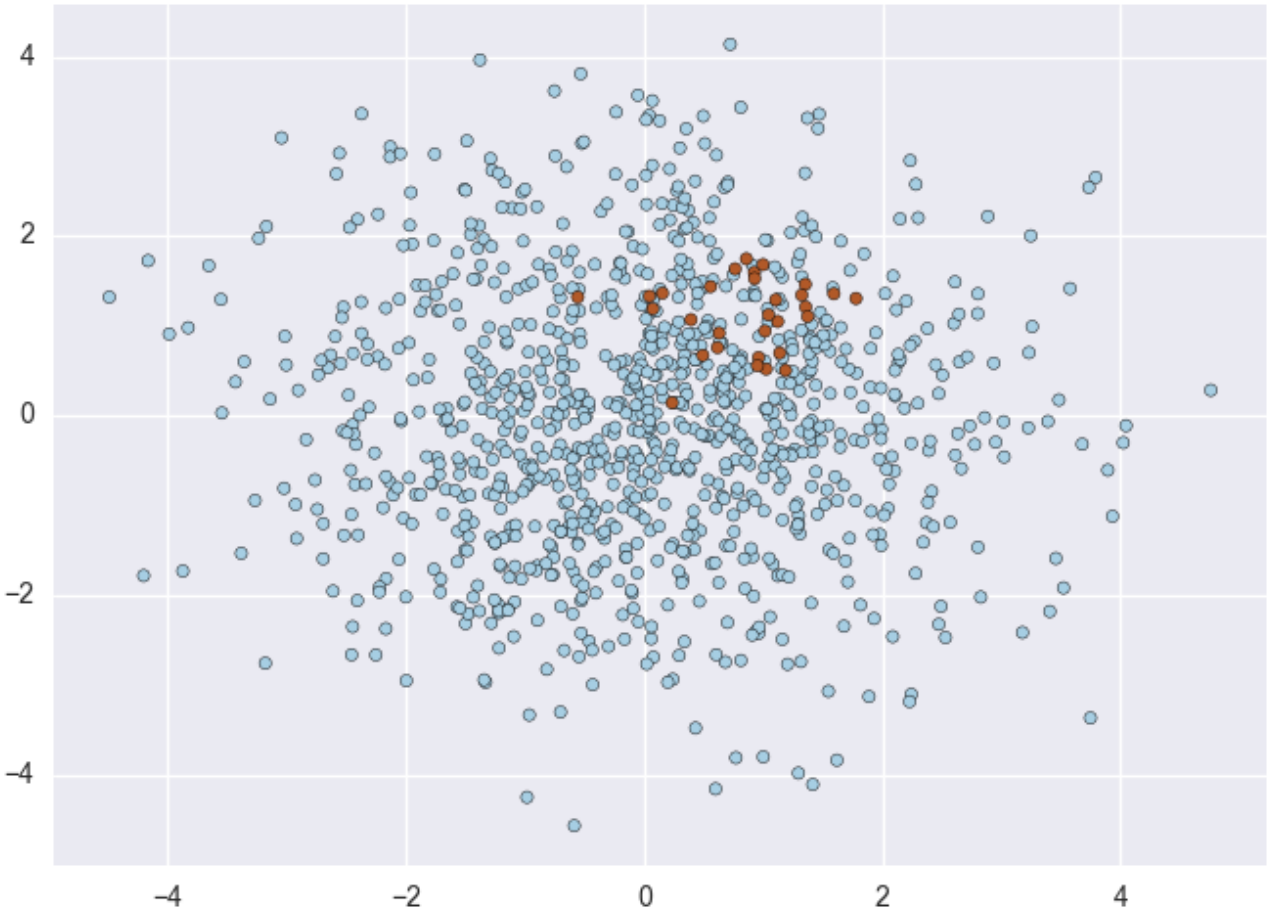
Real World



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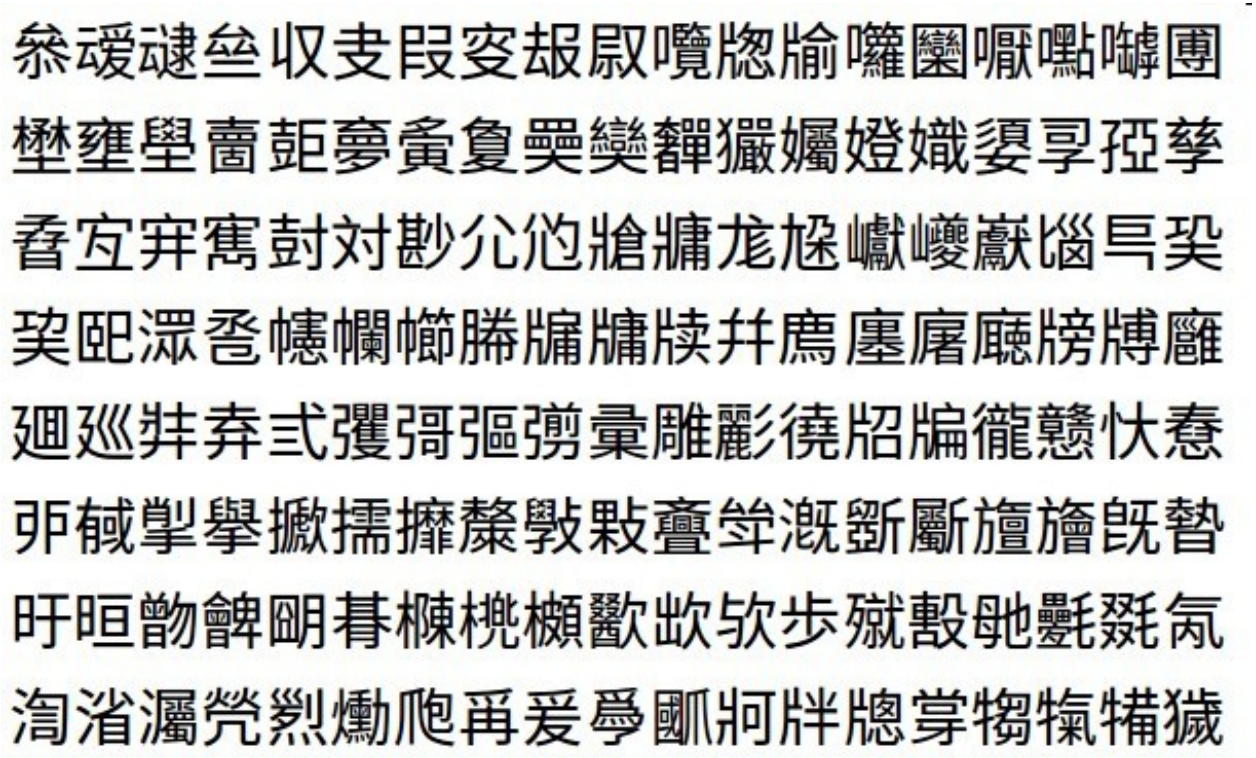
Doggy

Introduction

Rare Word



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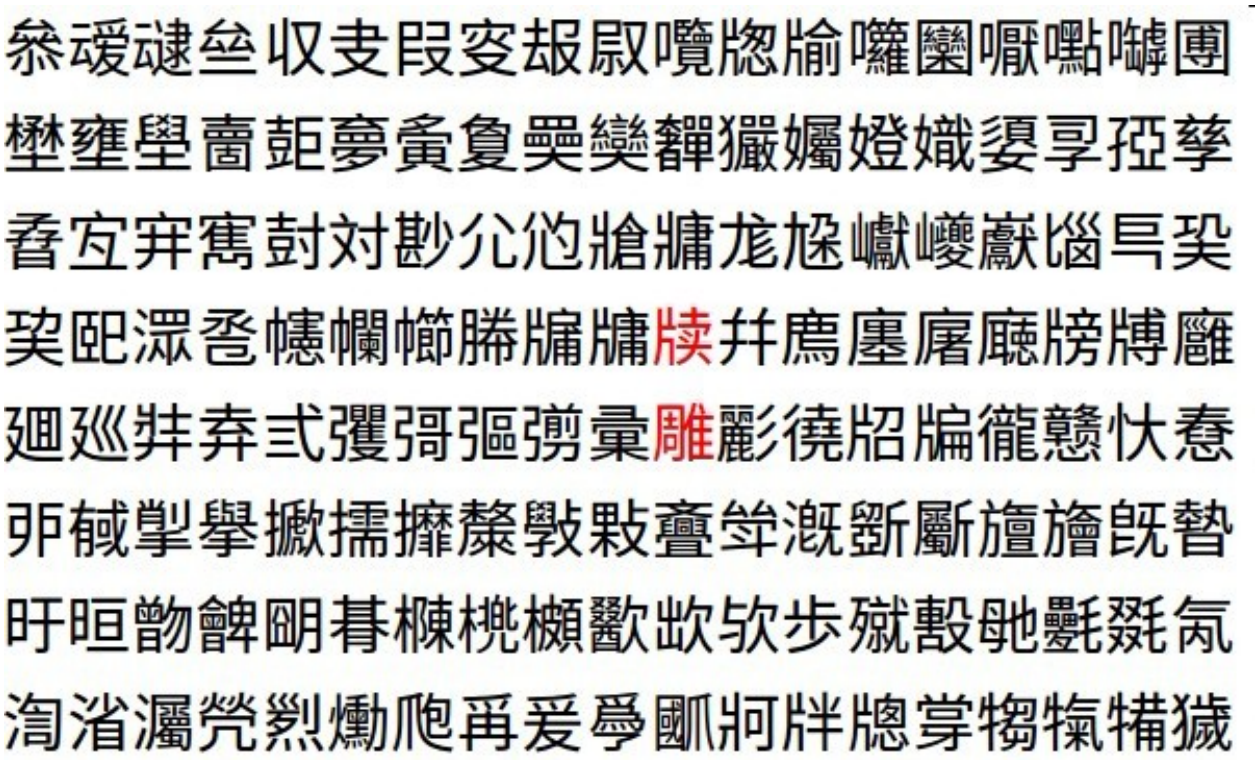
Rare Word



Introduction

Imbalanced Ratio

imbalanced ratio = majority class / minority class

ZooScan

427 / 28 = 15.25

Kaggle

1979 / 9 = 219.89

WHOI

2606720 / 4 = 651680

EVEN MORE THAN 10^8 !

WHY?

Evaluation Criteria

Name	Formula	Explanation
True Positive Rate (TP rate)	TP / (TP + FP)	The closer to 1, the better. TP rate = 1 when FP = 0. (No false positives)
True Negative Rate (TN rate)	TN / (TN + FN)	The closer to 1, the better. TN rate = 1 when FN = 0. (No false negatives)
False Positive Rate (FP rate)	FP / (FP + TN)	The closer to 0, the better. FP rate = 0 when FP = 0. (No false positives)
False Negative Rate (FN rate)	FN / (FN + TP)	The closer to 0, the better. FN rate = 0 when FN = 0. (No false negatives)

$$G - mean = \sqrt{TPr * TNr}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN} = TPr$$

$$F - measure = \frac{2 * Precision * Recall}{Precision + Recall}$$

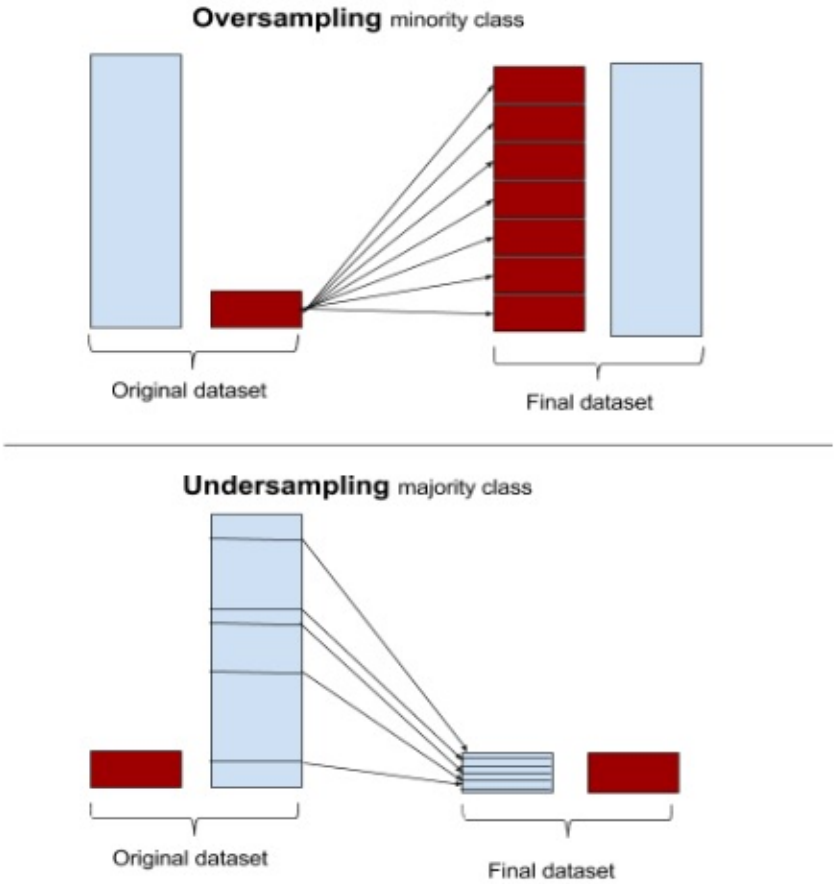
Approaches

Overview

- Sampling
  Under-sampling
  Over-samping
- Cost-sensitive learning
- Ensembled classifier
  EasyEnsemble
  BalanceCascade

Approaches

Sampling



Best approache: SMOTE

Approaches

Cost-sensitive

$$L(x, i) = \sum_j P(j|x)c(i, j)$$

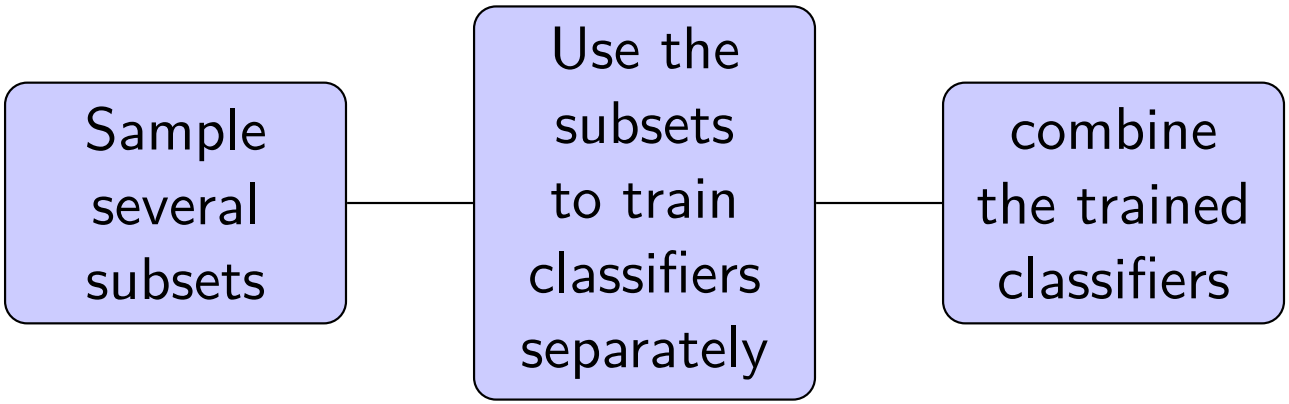
Minimize the overall cost.

- x : an example
- i : a class
- j : the jth class
- P : Probability
- c : cost matrix

Best approaches: AdaCost, AsymBoost

Approaches

Ensembled Classifier



Best approaches: EasyEnsemble, BalanceCascade, SMOTEBoost

Approaches

EasyEnsemble.M $\Rightarrow$ EasyEnsemble.D

1: Input:A set of minority class examples $\mathcal{P}$, k-1 sets of majority class examples $\mathcal{N}$, $|\mathcal{P}| < |\mathcal{N}_k|$, the number of subsets T to sample from $\mathcal{N}_k$, and s_i,the number of iterations to train an AdaBoost ensemble H_i

2: for i$\Leftarrow$ 1:T

3: $D_i = \mathcal{N}_1$

4: for t$\Leftarrow$ 1:k

5: Randomly sample a subset $\mathcal{N}_{it}$ from $\mathcal{N}_k$, N_{it},$|N_{it}| = |P| + \frac{C_1 * (|C_i - |P|)}{|C_k|}$ in the t^{th}

6: $D_i = D_i \bigcup \mathcal{N}_{it}$

7: $H_t(x) = sgn\left(\sum_{d=1}^{s_i} \alpha_{t,d} h_{t,d}(x) - \theta_i\right)$

8: $H(x) = sgn\left(\sum_{t=1}^{T} \sum_{d=1}^{s_i} \alpha_{t,d} h_{t,d}(x) - \sum_{t=1}^{T} \theta_i\right)$

Q.-Q.Li, and X.-Y.Liu. "EasyEnsemble.M for multiclass imbalance problem." In: Pattern Recognition and Artificial Int
27.2(2014):187-192.

Future Work

- Optimize the algorithm to cost less runtime
- Use Kaggle and WHOI datasets
- Increase the amount of time in each dataset


Q&A