

Dealing with Imbalanced Data 10-Oct-2018

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Outline

- The Imbalanced Classes Problem
- Loss Function Weighing
- Undersampling Methods
- Oversampling Methods
- Feature Learning
- Feature Engineering
- Anomaly Detection
- Resources

What is unbalanced Data?

• When the minority class, is much rarer than the other classes.



Why is this a Problem?

- ML Algorithms perform poor in unbalanced data.
- Classifiers designed to optimize accuracy
- Assuming uniformity of misclassification costs

Fraud Detection

- Assume Fraud is only 1% of all transaction
- Create model and has 99% Accuracy



Fraud Detection

- Assume Fraud is only 1% of all transaction
- Create model and has 99% Accuracy
- Model classifies everything as not fraud.



Evaluation

• Don't use Accuracy!

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

- use Confusion Matrix
- use ROC Curves
- multiple metrics if possible



Fraud Detection

• Misclassify Fraud comes at a high cost.





Loss Weighting

- Most ML Algorithms have loss functions
- increase the loss when misclassify the minority class

Loss =
$$\frac{1}{N} \sum_{i=1}^{N} (y_i - 1)h(x_i) + y_i(h(x_i) - 1)$$



Loss Weighting

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Loss =
$$\frac{1}{N} \sum_{i=1}^{N} (y_i - 1)h(x_i) + y_i(h(x_i) - 1)$$

Multiply with a value



Sampling Methods

- If our data is imbalanced, we will can make it balanced!
- Generate/Remove data to get it balanced

Random Undersampling

• Randomly Remove Data from Majority Class



Tomek Links

- Tomek links are pairs of opposite classes which are close
- Increases the separation between classes



NEARMISS-1

• NearMiss-1 selects samples from the majority class for which the average distance to K nearest neighbours is the smallest.



NEARMISS-2

• NearMiss-2 selects samples from the majority class for which the average distance to the K farthest neighbors is the smallest.



Nearmiss combined



Random Oversampling

• Oversample minority class by randomly "copying" points from the class



Synthetic Minority Oversampling Technique(SMOTE)

- Find "k-nearest neighbors" of an anchor point *x*, from minority class
- Randomly select one of the nearest neighbors and interpolate randomly between the two



Adaptive Synthetic Sampling (ADASYN)

- Generate minority data samples according to their distributions
- more synthetic data for minority class samples that are harder to learn
- less synthetic data for minority samples that are easier to learn.



Ensemble

- Ensemble multiple sampling methods
- Ex: SMOTE + Token Links



Ensemble

- Ensemble multiple sampling methods
- Ex: SMOTE + Token Links
- Bagging and Bootstrapping (Ex. Subset-SMOTE)



Imbalanced-learn

- Easy sklearn-like API
- Can be used in sklearn Pipelines
- Supports all major resampling methods

from sklearn.svm import LinearSVC
from imblearn.under_sampling import NearMiss
from imblearn.pipeline import make_pipeline

pipeline = make_pipeline(NearMiss(version=2), LinearSVC())

```
pipeline.fit(X_train, y_train)
```

Feature Learning

- Create generative model on the minority class
- If done well, it can outperforms resampling
- Generative model have more parameters to tune.
- May take longer due to training. (Neural Network)

Synthetic Minority Reconstruction Technique (SMRT)

- Train variational autoencoder on the data
- oversampling -> sampling the autoencoder
- Performs very well
- Requires lot of data and training epochs



Feature Engineering

• Create Features which help separation of the classes





Cosine Kernel PCA

Anomaly Detection

- Treat problem as a anomaly detection problem
- Use ML Algorithms and methods dedicated for such tasks



One Class SVM



Source:http://www.geocities.jp/mabonakai/sub/ex_oneCsvm.htm

Isolation Forest



Resources

- SMRT: <u>https://github.com/tgsmith61591/smrt</u>
- Imbalanced-learn: <u>http://imbalanced-learn.org/</u>

Kubat, Miroslav, Robert C. Holte, and Stan Matwin. "Machine learning for the detection of oil spills in satellite radar images." *Machine learning* 30.2-3 (1998): 195-215.

Thank you for your Attention

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https://goo.gl/v7wBso

