Imbalanced Data

1. What is imbalanced data
2. Preprocessing methods
3. Examples of classification algorithms

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What is imbalanced data

Imbalanced datasets are those in which examples from some classes occur much more often than from other classes.

- fraud detection
- medical diagnosis
- product categorization
- network intrusion detection

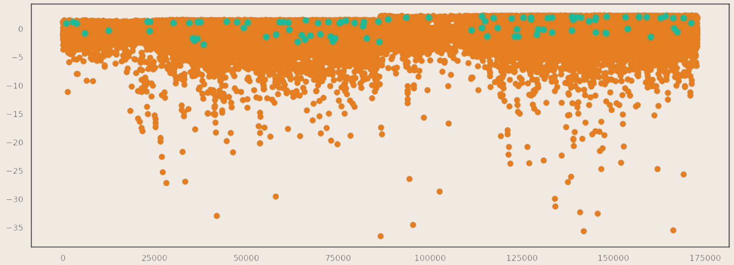
Preprocessing methods

- Oversampling methods
  - Random
  - SMOTE
  - Borderline1-SMOTE
  - Borderline2-SMOTE
- Undersampling methods
  - Random
  - Near Miss1-3
  - CNN
  - ENN
  - RENN
  - Tomek Link Removal

Introduction

- Markings:
  - L (large) - majority class
  - S (small) - minority class
  - r (ratio) = |S|/|L|
  - T - training set

> *Credit Fraudulent Detection*
> *|L| = 284315*
> *|S| = 492*
> *r = 0.17%*

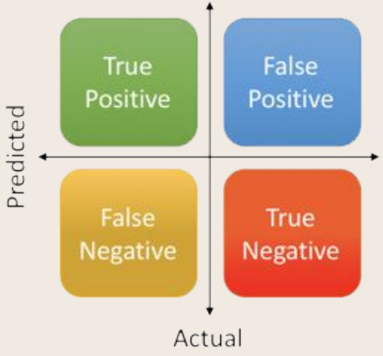


$$\textbf{Precision} = \frac{\text{True Positive}}{\text{Actual Results}} \quad \text{or} \quad \frac{\text{True Positive}}{\text{True Positive + False Positive}}$$

$$\textbf{Recall} = \frac{\text{True Positive}}{\text{Predicted Results}} \quad \text{or} \quad \frac{\text{True Positive}}{\text{True Positive + False Negative}}$$

$$\textbf{Accuracy} = \frac{\text{True Positive + True Negative}}{\text{Total}}$$

$$\textbf{F1 Score} = 2 * \frac{\text{Precision * Recall}}{\text{Precision + Recall}}$$



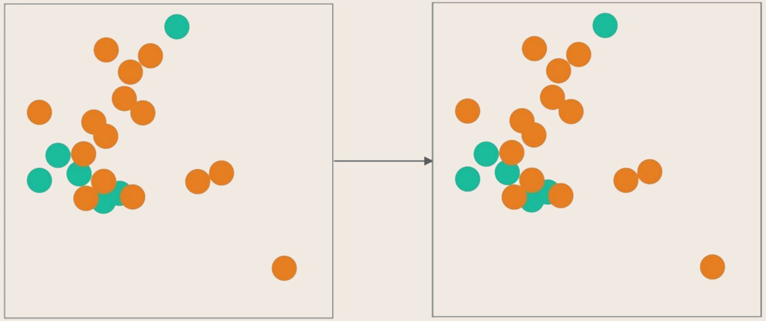
https://www.kaggle.com/mlg-ulb/creditcardfraud/home
https://github.com/Nexer8/Imbalanced_Data

Oversampling methods

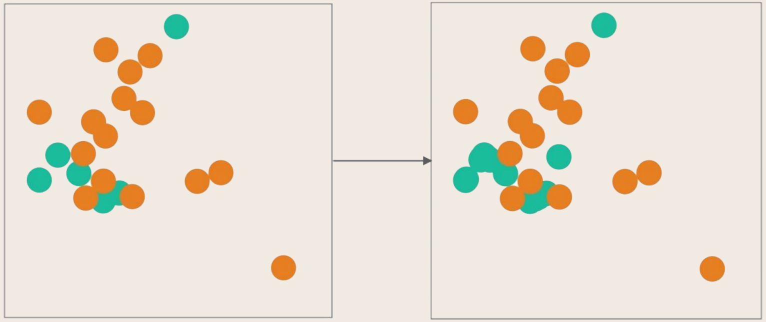
- *ROS - Random Oversampling*
  - duplication of randomly selected points from the minority class
- *SMOTE* (*Synthetic Minority Oversampling Technique*)
  1. Calculate the *k* nearest neighbors from *S*.
  2. Randomly select $r \leq k$ neighbors (with swap).
  3. Pick a random point along the lines connecting *p* and each of the *r* neighbors.
  4. Add these designated points to the *S* class dataset.

\> *Random Oversampling (|L| = |S| = 213245)*
  - *Precision = 0.08*
  - *Recall = 0.87*
  - *f1 = 0.14*

\> *SMOTE (|L| = |S| = 213245)*
  - *Precision = 0.1*
  - *Recall = 0.86*
  - *f1 = 0.18*



Random oversampling



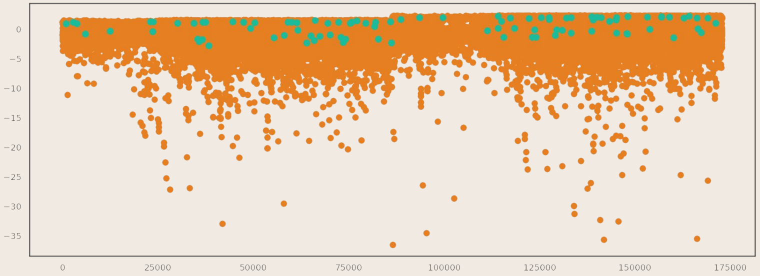
Synthetic Minority Oversampling Technique

Oversampling methods

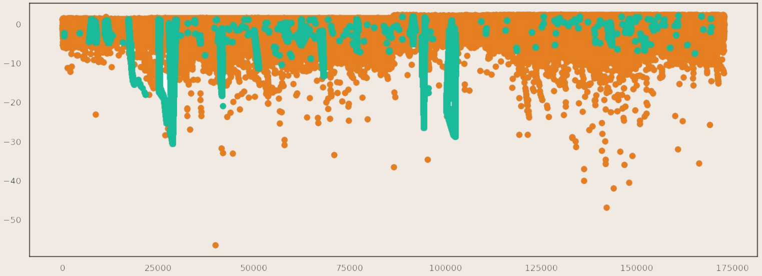
- *Borderline1-SMOTE* - for each p from S:
    1. Designate its m nearest neighbors from T. Name this set Mp, $m` = |Mp \cap L|$
    2. If $m` = m$, then p is “polluted” example. Ignore p
    3. If $0 \le m` \le m/2$, then p is “safe”. Ignore p
    4. If $m/2 \le m`$, add p to set called *DANGER*
    - For each point d from *DANGER* use the *SMOTE algorithm*
- *Bordeline2-SMOTE*
    - New points are created along lines connecting them to their closest neighbors from S or L.

\> *Borderline1-SMOTE* ($|L| = |S| = 213245$)
- *Precision = 0.25*
- *Recall = 0.73*
- *f1 = 0.37*

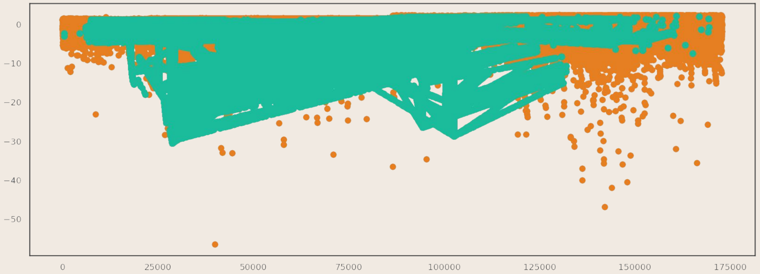
\> *Borderline2-SMOTE* ($|L| = 213245$, $|S| = 213244$)
- *Precision = 0.17*
- *Recall = 0.79*
- *f1 = 0.28*



Base dataset



Borderline1-SMOTE



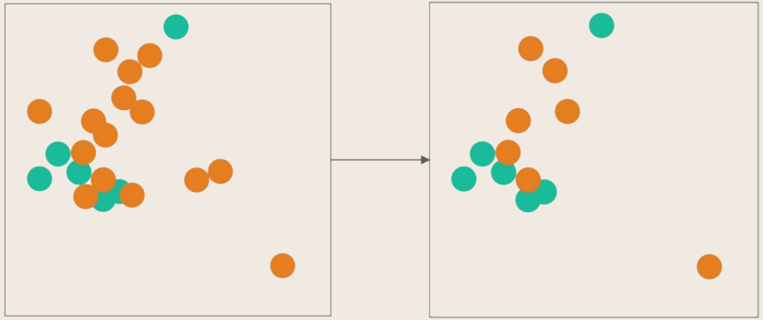
Borderline2-SMOTE

Undersampling methods

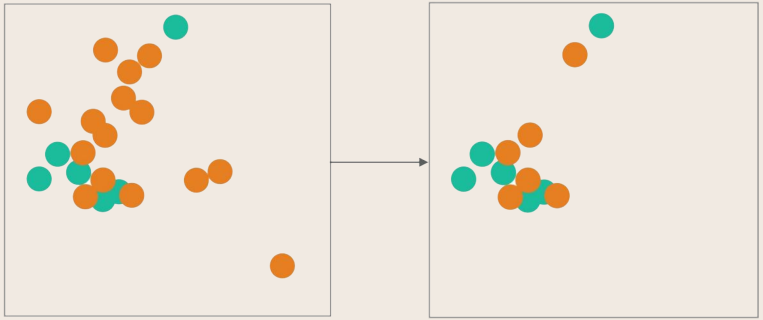
- *RUS (Random Undersampling)*
  - removal of randomly selected points from the majority class
- *Near Miss-1*
  - leaves the points from *L*, whose average distance to the *k* closest neighbors from *S* is the smallest

\> *Random Undersampling (|L| = |S| = 360)*
  - *Precision = 0.06*
  - *Recall = 0.86*
  - *f1 = 0.12*

\> *Near Miss-1 (|L| = |S| = 360)*
  - *Precision = 0.01*
  - *Recall = 0.9*
  - *f1 = 0.02*



Random undersampling



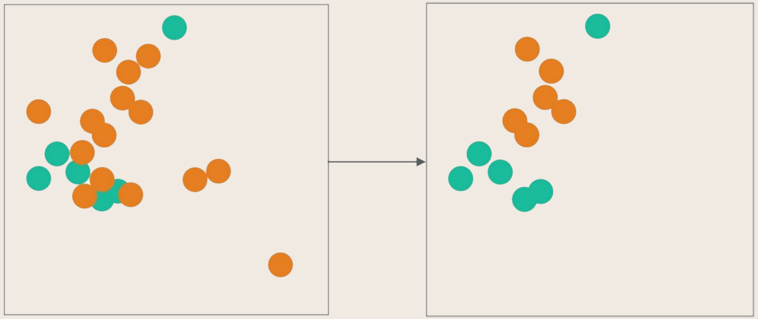
Near Miss-1, k = 3

Undersampling methods

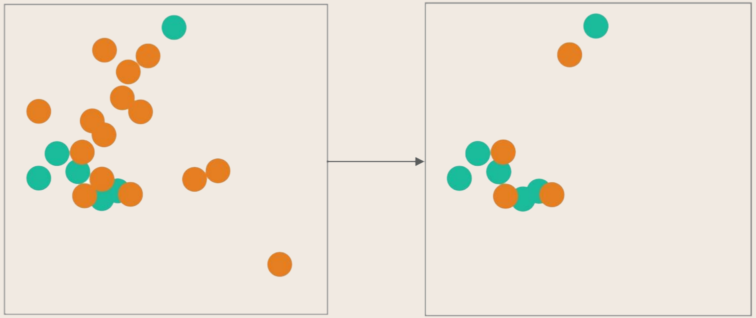
- *Near Miss-2*
  - leaves the points from *L*, whose average distance to the *k* farthest neighbors from *S* is the smallest
- *Near Miss-3*
  - chooses the *k* nearest neighbors from *L* for each point from *S*

> *Near Miss-2 (|L| = |S| = 360)*
  - *Precision = 0.02*
  - *Recall = 0.91*
  - *f1 = 0.04*

> *Near Miss-3 (|L| = |S| = 360)*
  - *Precision = 0.09*
  - *Recall = 0.88*
  - *f1 = 0.16*



Near Miss-2, k = 3



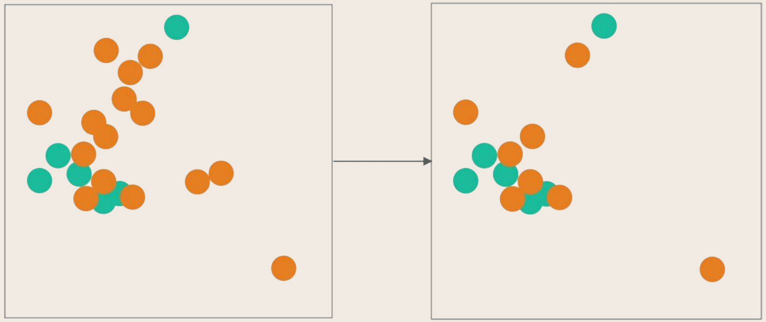
Near Miss-3, k = 3

Undersampling methods

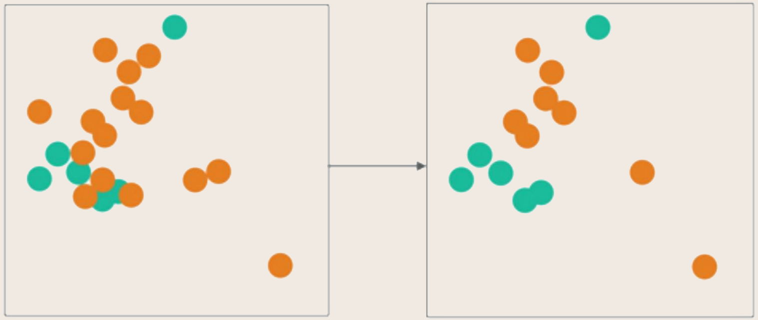
- *CNN (Condensed Nearest Neighbor)*
    1. Pick a random point *p* from *T* and set *U* = *{p}*
    2. Search *T* - *U* and add to *U* the first point you find, whose closest neighbor from *U* is of a different class
    3. Repeat step *2.* until *U* reaches its maximum
- *ENN (Edited Nearest Neighbor)*
    - remove points whose class is different from that of the majority from the *k* nearest neighbors

> *CNN (|L| = 1072, |S| = 360)*
- *Precision = 0.26*
- *Recall = 0.8*
- *f1 = 0.39*

> *ENN (|L| = 212926, |S| = 360)*
- *Precision = 0.76*
- *Recall = 0.56*
- *f1 = 0.65*



Condensed Nearest Neighbor, k = 3



Edited Nearest Neighbor

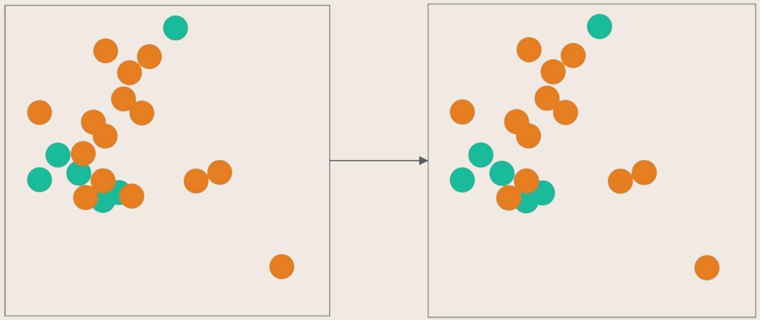
Undersampling methods

- *RENN (Repeated Edited Nearest Neighbor)*
  - repeat *ENN* until the remaining dataset is minimal
- *TLR (Tomek Link Removal)*
  - removal of all *Tomek links* from *L*

> *RENN (|L| = 212728, |S| = 360)*
  - *Precision = 0.74*
  - *Recall = 0.53*
  - *f1 = 0.62*

> *TLR (|L| = 213186, |S| =360)*
  - *Precision = 0.78*
  - *Recall = 0.58*
  - *f1 = 0.66*

Repeated Edited Nearest Neighbor



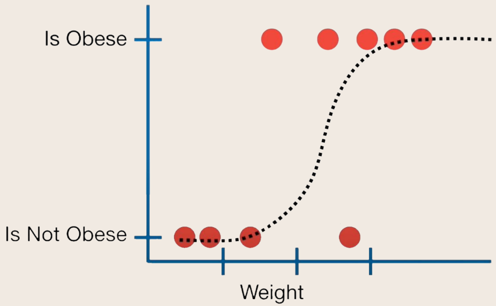
Tomek Link Removal

Examples of imbalanced data classification algorithms

- Logistic Regression
- Random Forest
- EasyEnsemble
- Support Vector Machines

Examples of imbalanced data classification algorithms

- *Logistic Regression*
  - a special case of the generalized linear model
  - the dependent variable is on a dichotomous scale (takes only two values)
  - the probability of an event occurring
- *Random Forest*
  - built on decision trees
  - uses the general bootstrap aggregation technique
  - *Weighted Random Forest*



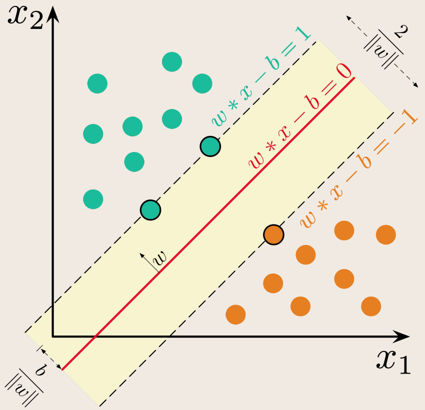
Logistic Regression

> *Logistic Regression (|L| = 71108, |S| = 94)*
  - *Precision = 0.9*
  - *Recall = 0.64*
  - *f1 = 0.75*

> *Random Forest (|L| = 71108, |S| = 94)*
  - *Precision = 0.96*
  - *Recall = 0.8*
  - *f1 = 0.87*

Examples of imbalanced data classification algorithms

- *SVM (Support Vector Machines)*
  - finds optimal hyperplanes separating extreme points
  - *maximum margin strategy*
- *EasyEnsemble* - for *i = 1, …, N:*
  1. Randomly select a subset *Li* from L such that |*Li*| = |S|
  2. Use *AdaBoost* with *Li* and *S*
  3. Combine the above classifiers into one



Support Vector Machines

> *SVM (|L| = 213245, |S| = 360)*
> - *Precision = 0.69*
> - *Recall = 0.33*
> - *f1 = 0.45*

> *EasyEnsemble (|L| = 213245, |S| = 360)*
> - *Precision = 0.05*
> - *Recall = 0.89*
> - *f1 = 0.09*