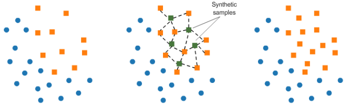
Advanced Machine Learning

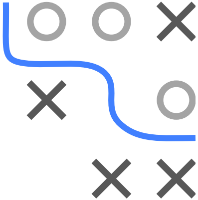
Imbalanced Learning: Sampling Methods Part 1



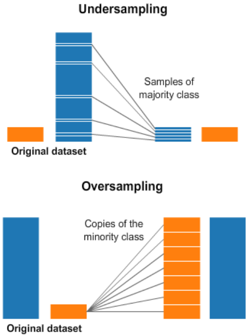
Learning goals

- Know the idea of sampling methods for coping with imbalanced data
- Understand the different undersampling techniques

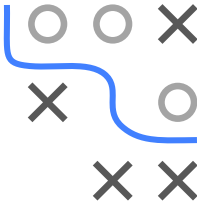
SAMPLING METHODS: OVERVIEW



- Balance training data distribution to perform better on minority classes.
- Independent of classifier $\rightsquigarrow$ very flexible and general.
- Three groups:
  - Undersampling — Removing instances of majority class(es).
  - Oversampling — Adding/Creating new instances of minority class(es).
  - Oversampling is slower, but usually works better.
  - Hybrid — Combining both sampling.

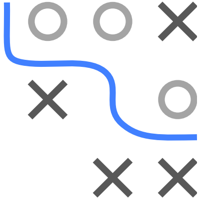


RANDOM UNDERSAMPLING/OVERSAMPLING



- Random oversampling (ROS):
  - Randomly **replicate minority** instances until a desired imbalance ratio.
  - Prone to overfitting due to multiple tied instances!
- Random undersampling (RUS):
  - Randomly **eliminate majority** instances until a desired imbalance ratio.
  - Might remove informative instances and destroy important concepts in data!
- Better: Introduce heuristics in removal process (RUS) and do not create exact copies (ROS).

UNDERSAMPLING: TOMEK LINKS



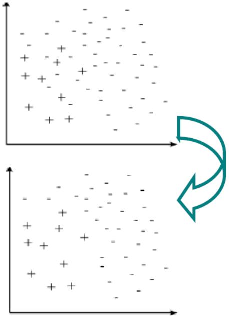
- Remove only noisy borderline examples of majority class(es).
- Noisy borderline examples:
  - From different classes.
  - “Very close” to each other.

- Let $E^{(i)} = (\mathbf{x}^{(i)}, y^{(i)})$ and $E^{(j)} = (\mathbf{x}^{(j)}, y^{(j)})$ be two data points in $\mathcal{D}$ with $y^{(i)} \neq y^{(j)}$.

- A pair $(E^{(i)}, E^{(j)})$ is called *Tomek link* iff there is no other data point $E^{(k)} = (\mathbf{x}^{(k)}, y^{(k)})$ such that

  $d(\mathbf{x}^{(i)}, \mathbf{x}^{(k)}) < d(\mathbf{x}^{(i)}, \mathbf{x}^{(j)})$
  or $d(\mathbf{x}^{(j)}, \mathbf{x}^{(k)}) < d(\mathbf{x}^{(i)}, \mathbf{x}^{(j)})$ holds,

  where d is some distance on $\mathcal{X}$.



Francisco Herrera (2013), Imbalanced Classification: Common Approaches and Open Problems (URL).

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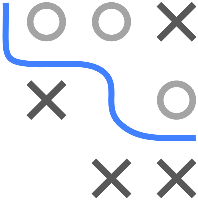
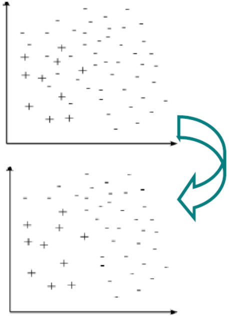


- A pair $(E^{(i)}, E^{(j)})$ is called *Tomek link* iff there is no other data point $E^{(k)} = (\mathbf{x}^{(k)}, y^{(k)})$ such that $d(\mathbf{x}^{(i)}, \mathbf{x}^{(k)}) < d(\mathbf{x}^{(i)}, \mathbf{x}^{(j)})$ or $d(\mathbf{x}^{(j)}, \mathbf{x}^{(k)}) < d(\mathbf{x}^{(i)}, \mathbf{x}^{(j)})$ holds.
- $E^{(i)}$ and $E^{(j)}$ have different y's $\rightsquigarrow$ a bordeline case.
- Remove majority instance in each data pair in a Tomek link.
- No sampling here, but it can be combined with RUS.



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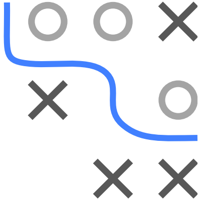
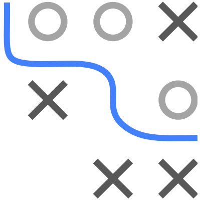
UNDERSAMPLING: CONDENSED NEAREST NEIGHBOR (CNN)



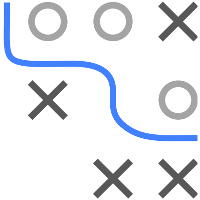
- Remove majority instances far away from decision boundary.
- Constructing a consistent subset $\tilde{\mathcal{D}}$ of $\mathcal{D}$ in terms of the 1-NN classifier.
- A subset $\tilde{\mathcal{D}}$ of $\mathcal{D}$ is called consistent if using a 1-NN classifier on $\tilde{\mathcal{D}}$ classifies each instance in $\mathcal{D}$ correctly.

UNDERSAMPLING: CONDENSED NEAREST NEIGHBOR (CNN)



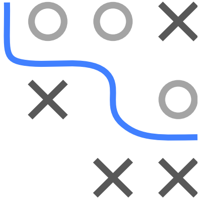
- Creates a consistent subset:
  1. Initialize $\tilde{\mathcal{D}}$ by selecting **all minority** instances and randomly picking **one majority** instance.
  2. Classify each instance in $\mathcal{D}$ with the 1-NN classifier based on $\tilde{\mathcal{D}}$.
  3. Remove all misclassified instances from $\mathcal{D}$.

UNDERSAMPLING: OTHER APPROACHES



- Neighborhood cleaning rule (NCL):
  1. Find 3 nearest neighbors for each $(\mathbf{x}^{(i)}, y^{(i)})$ in $\mathcal{D}$.
  2. If $y^{(i)}$ is majority class *and* 3-NN classifies it as minority $\rightsquigarrow$ Remove $(\mathbf{x}^{(i)}, y^{(i)})$ from $\mathcal{D}$.
  3. If $y^{(i)}$ is minority class *and* 3-NN classifies it as majority $\rightsquigarrow$ Remove 3 nearest neighbors from $\mathcal{D}$.
- One-sided selection (OSS): Tomek link + CNN
- CNN + Tomek link: to reduce computation of finding Tomek links $\rightsquigarrow$ first use CNN and then remove the Tomek links.
- Clustering approaches: Class Purity Maximization (CPM) and Undersampling based on Clustering (SBC).

OVERSAMPLING: SMOTE



- The Synthetic Minority Oversampling Technique (SMOTE) operates by creating **new synthetic examples** of minority class.
- Interpolate between neighboring minority examples.
- Examples are created in $\mathcal{X}$ rather than in $\mathcal{X} \times \mathcal{Y}$.
- Algorithm: For each minority instance:
  - Find *k* nearest minority neighbors.
  - Randomly select *j* of these neighbors.
  - Randomly generate new instances along the lines connecting the minority instance and its *j* neighbors.