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Machine Learning

Session 22 - T

Data Imbalance in Machine Learning

Degree in Applied Data Science

2024/2025

Data Imbalance

- **Common issue** in machine learning where class distribution in a dataset is highly skewed;

- **One class significantly outnumbers the others;**

- Real-world scenarios:
  - Fraud detection;
  - Medical diagnosis;
  - Text classification;
  - Image recognition;

Data Imbalance

- Consequences of data imbalance:
  - Data imbalance can have a **huge impact on model performance**;
  - **Poor generalization for the minority class**.

- **Why?**

  - Machine learning models are typically designed to **optimize overall accuracy**, which means they tend to favor the majority class.

Data Imbalance

- Model Performance on Imbalanced Datasets:
  - **High accuracy rate**, but **ineffective at minority class** identification and classification;

- Practical Implications:
  - In applications like fraud detection or medical diagnosis, may lead to:
    - **Undetected fraudulent transactions**
    - **Missed critical diagnoses**

- Adressing data imbalance:
  - **Rebalance dataset**;
  - **Adjust the model learning process**;
  - **Use specialized evaluation metrics** for imbalanced data performance.

Approaches to Adress Data Imbalance

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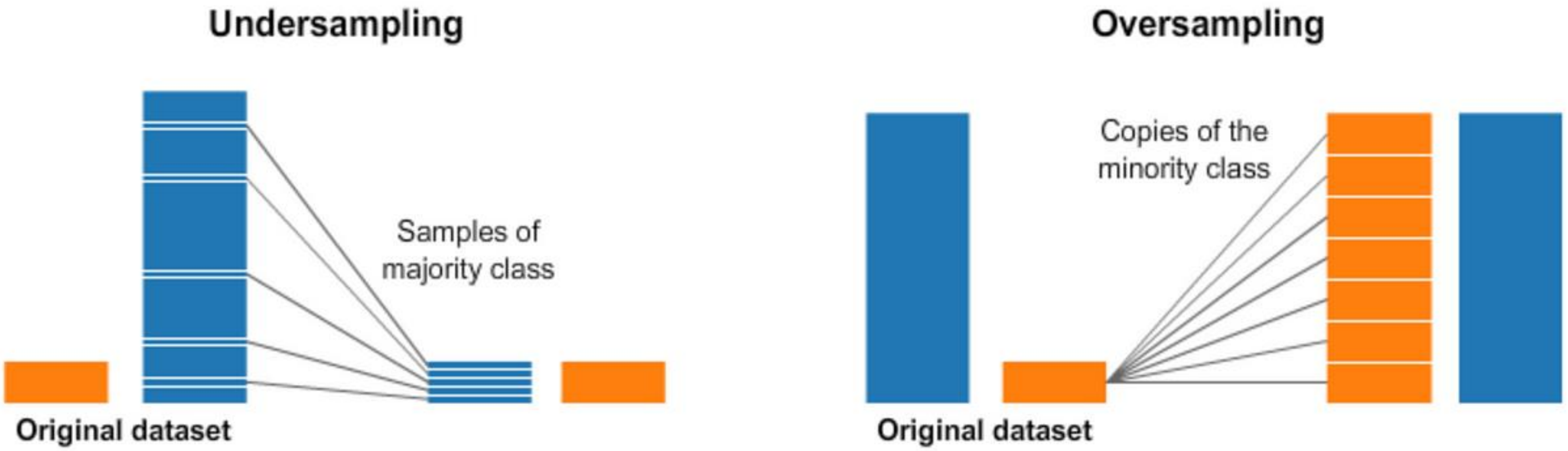
- Data-level methods:
  - **Oversampling**;
  - **Undersampling**;
  - Combined over and undersampling.



Data-Level Methods

- **Resampling techniques** are a commonly used for adressing data imbalance;

- They modify the data by:
  - **Increasing the minority class** samples (oversampling);
  - **Decreasing the majority class** samples (undersampling).

Oversampling Techniques

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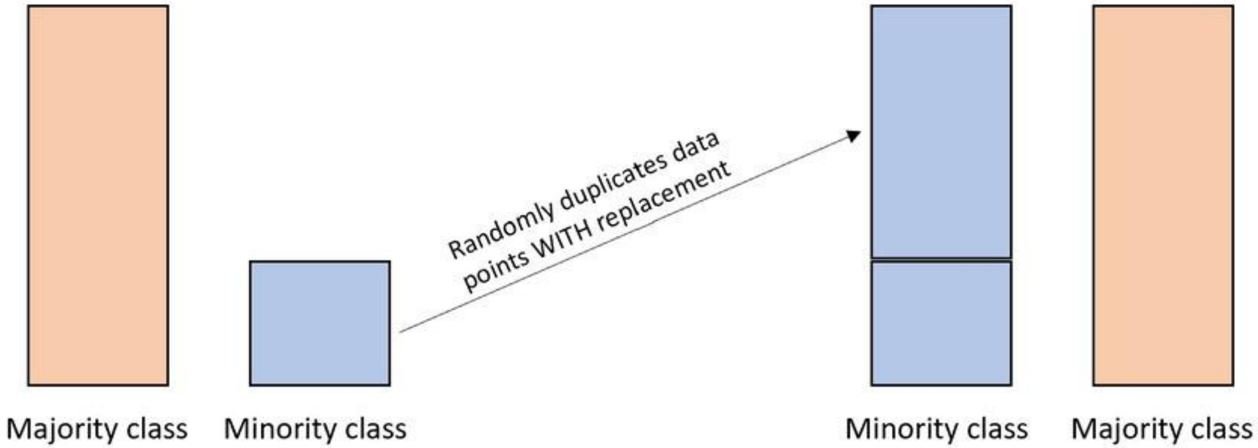
- **Random oversampling**:
  - Increases the number of minority class samples by **randomly duplicating existinting minority class samples**;
  - Can **improve model performance on minority class**, but increases the risk of **overfitting** due to the repeated samples.



Oversampling Techniques

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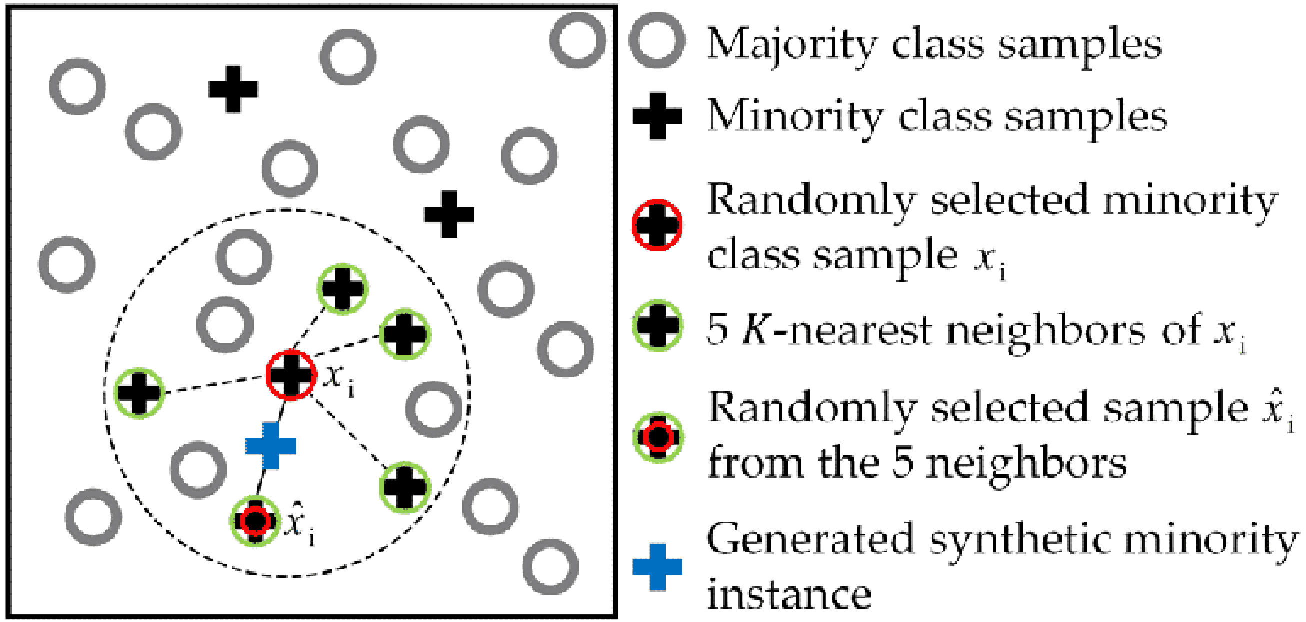
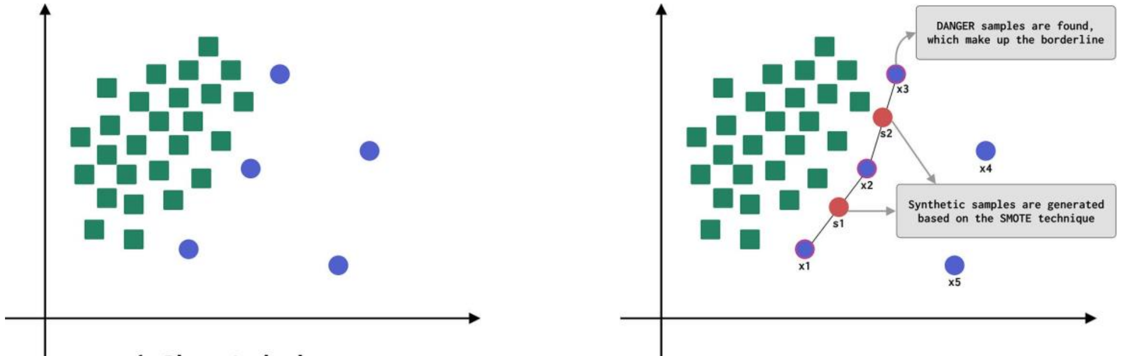
- **SMOTE** (Synthetic Minority Oversampling Technique):
  - Increases minority class samples by creating **synthetic examples** (no duplicates);
  - New samples are generated by **interpolating between existing minority class** examples;
  - **Reduces risk of overfitting** (compared to random oversampling).



Oversampling Techniques

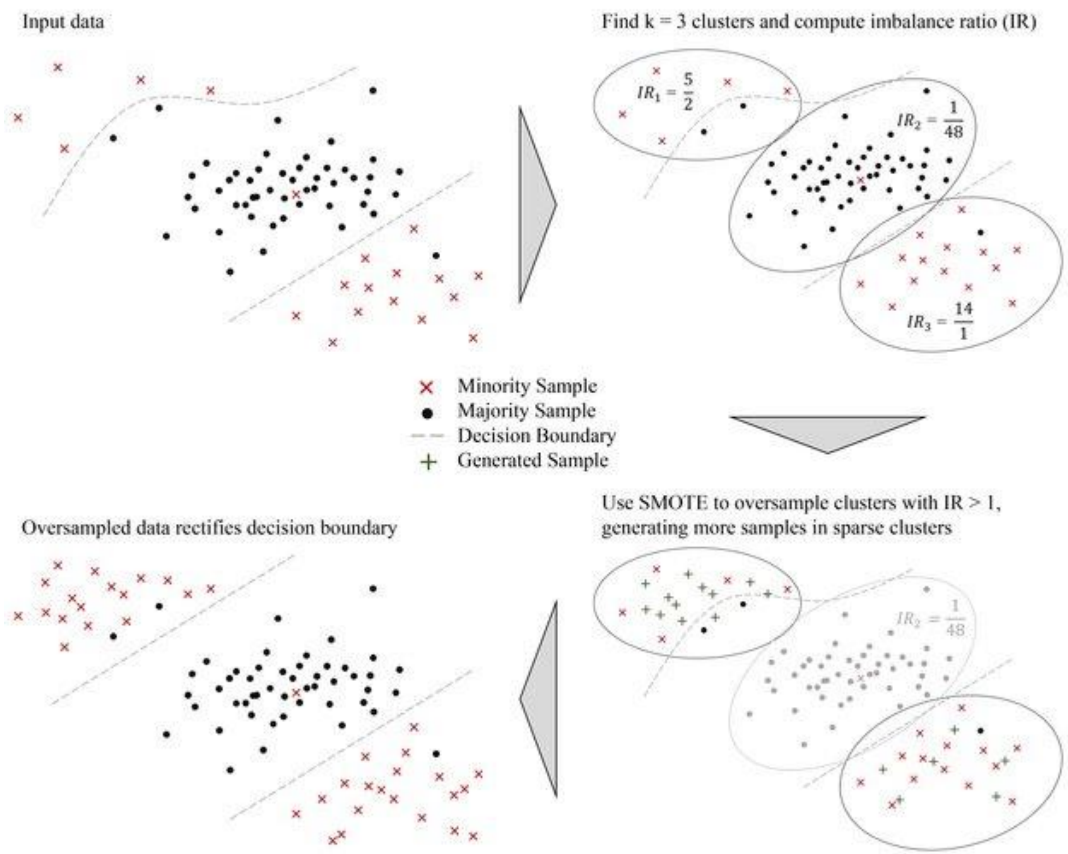
- SMOTE variations:
  - **SMOTEN**:
    - SMOTE for **nominal** (categorical) data.
  - **SMOTENC**:
    - SMOTE for **nominal and continuous** data.
  - **Borderline-SMOTE**:
    - Focus on **samples near the decision boundary**;
    - Aims to improve classification of difficult, borderline cases.



a) Class Imbalance
b) Borderline-SMOTE

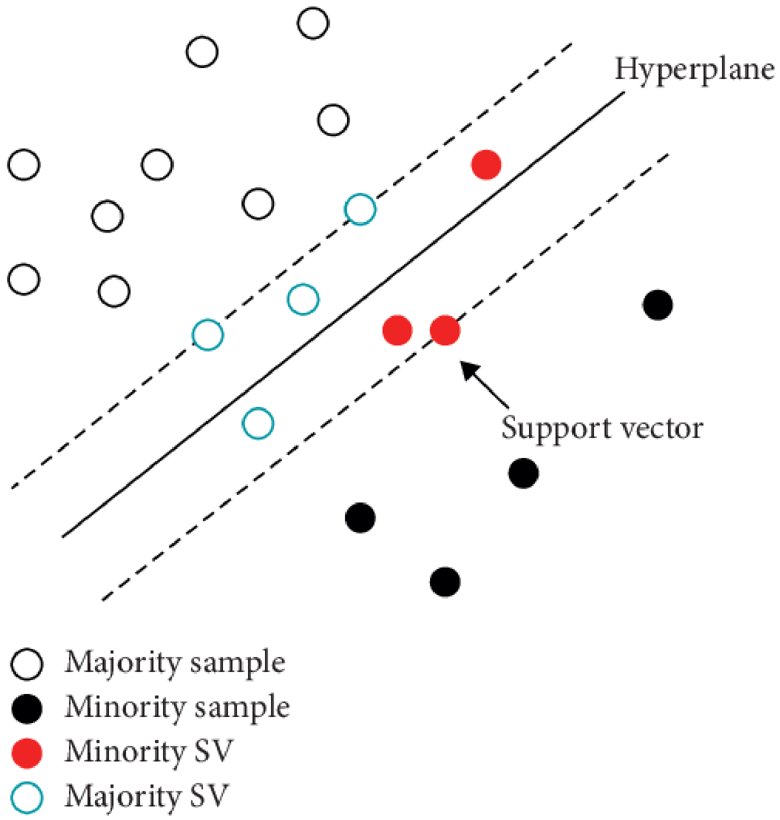
Oversampling Techniques

- SMOTE variations:
  - **Kmeans-SMOTE**:
    - Combines k-means with SMOTE;
    - **Clusters the dataset** into K clusters using K-Means;
    - Applies SMOTE within each cluster to generate synthetic minority class samples;
    - Aims to create more **diverse and representative synthetic samples**.



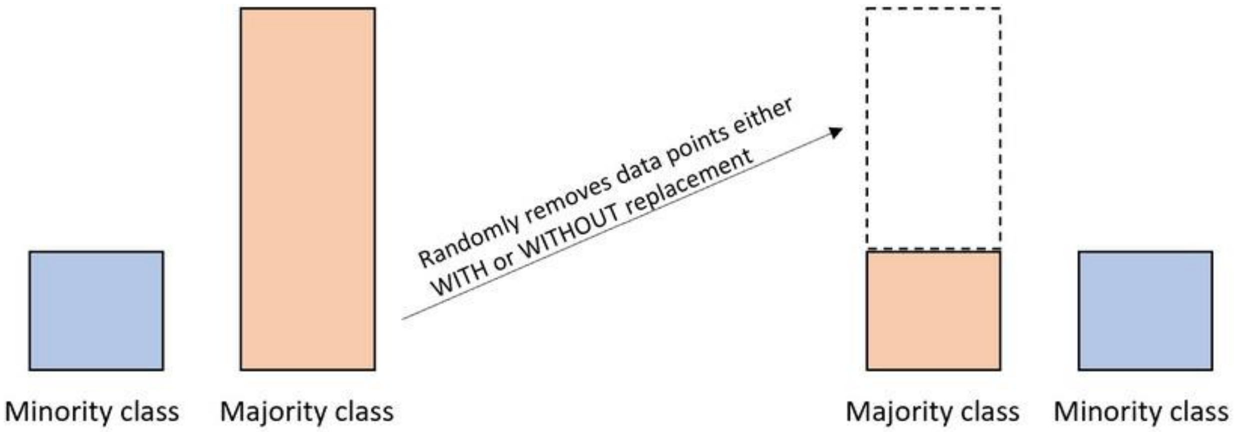
Oversampling Techniques

- SMOTE variations:
  - **svm-SMOTE**:
    - Combines **SVMs** with **SMOTE**;
    - Uses SVM to identify the **decision boundary** between classes;
    - Generates **synthetic minority class samples near the SVM decision boundary**;
    - Focuses on **difficult-to-classify samples**.



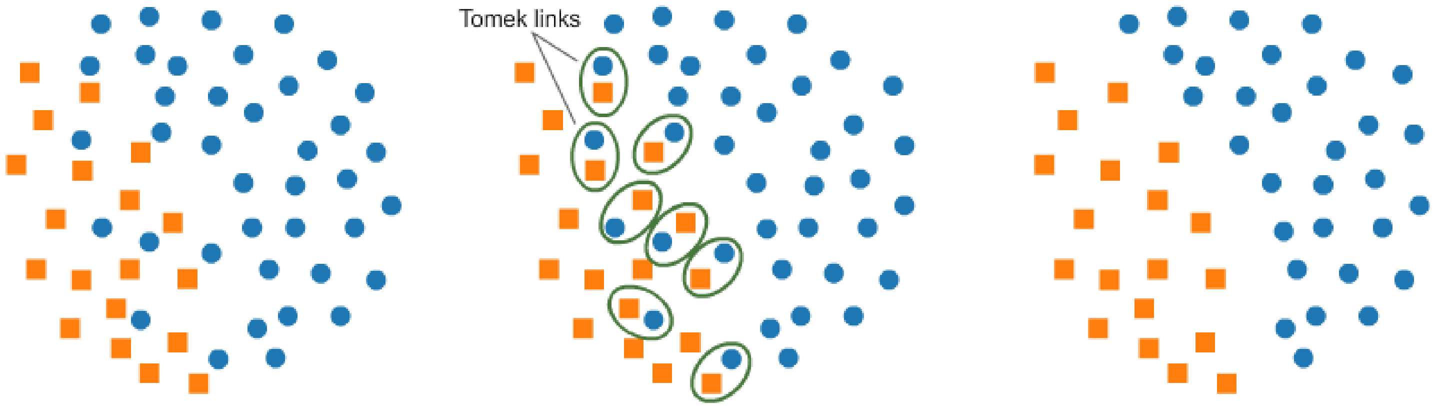
Undersampling Techniques

- **Random undersampling:**
  - Balances data by **randomly removing samples from the majority class**;
  - **Simple and quick**;
  - Risk of **losing important information** from the data.



Undersampling Techniques

- **Tomek Links**:
  - Identifies and removes **Tomek links**, which are **pairs of nearest neighbors from different classes**;
  - Aims to **remove borderline examples** to clarify class boundaries;
  - Helps to **reduce class overlap** and improve classifier performance.



Undersampling Techniques

- **Cluster Centroids Undersampling**:
  - Replaces majority class with **cluster centroids**;
  - Aims to **retain important information** while reducing majority class size;
  - Balances class distribution and **minimizes information loss**.

- **Condensed Nearest Neighbor Undersampling:**
  - Undersampling technique based on **nearest neighbor classification**;
  - Iteratively **selects samples that correctly classify others**;
  - **Retains representative samples** while **removing redundant ones**;
  - Helps reduce dataset size while preserving classification accuracy.

Undersampling Techniques

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- Others:
  - Edited Nearest Neighbours
  - AllKNN
  - NearMiss
  - One Sided Selection
  - Etc...

Combining Under and Oversampling Techniques

- Using both under and oversampling may help mitigate the drawbacks of each technique while leveraging their advantages.

- **SMOTEENN** - SMOTE with Edited Nearest Neighbors (ENN):
  - Generates synthetic minority class samples (SMOTE) and removes majority class examples misclassified by a KNN classifier (Edited Nearest Neighbors).

- **SMOTETomek**- SMOTE with Tomek Links:
  - Generates synthetic minority class samples (SMOTE) and removes Tomek links.

Approaches to Adress Data Imbalance

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- **Algorithm-level techniques**:
  - Some models can inherently better deal with class imbalance (e.g. RandomForests, AdaBoost, etc.);
  - Building ensembles of multiple models;

Approaches to Adress Data Imbalance

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- **Algorithm-level techniques**:
  - Some models can inherently better deal with class imbalance (e.g. **RandomForests**, **AdaBoost**, etc.);
  - Building **ensembles** of multiple models;
  - Assigning **different misclassification costs to classes** can encourage the model to focus on the minority class;
  - **Threshold adjustment** to control the trade-off between precision and recall.

- **Evaluation metrics**:
  - When working with imblanced data, it is important to use appropriate evaluation metrics (e.g. **imbalanced accuracy, precision, recall, f1-score, AUC-ROC, Matthew's correlation coefficient**).

Resources

- He, H., & Ma, Y. (2013). Imbalanced Learning: Foundations, algorithms, and applications (H. He & Y. Ma, Eds.; 1st ed.). Wiley-IEEE Press.

- Fernández, A., García, S., Galar, M., Prati, R. C., Krawczyk, B., & Herrera, F. (2018). Learning from imbalanced data sets (1st ed.). Springer.

- https://imbalanced-learn.org/stable/