ALMA MATER STUDIORUM
UNIVERSITÀ DI BOLOGNA

Predicting Red Wine Quality

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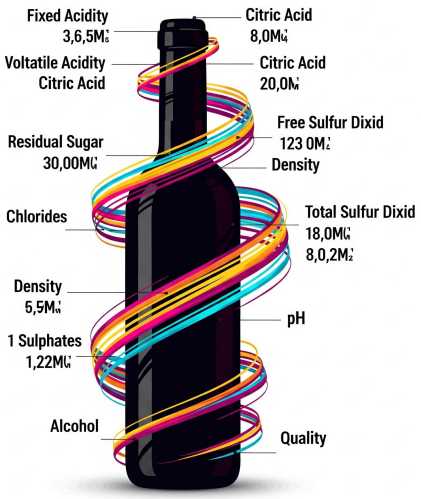
Course: Matteo Francia - Machine Learning and Data Mining (Module 2) - A.Y. 2024/25

Machine Learning Course Project

PROJECT OVERVIEW



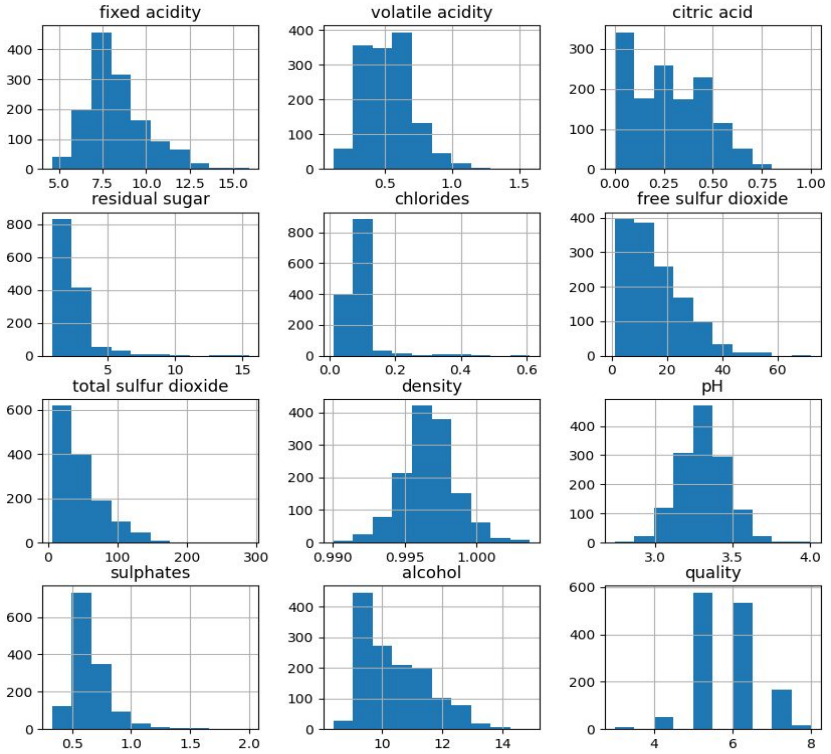
- Dataset: Red Wine Quality (Cortez et al., 2009)
- Features: 11 physicochemical attributes of wine
- Target: Quality score from 1 to 10 - dataset 3 to 8
- Class Imbalance: majority of the wines are in the range of 5 - 6

Problem: Can we develop a machine learning model to classify red wines as "good" or "bad" based on their physicochemical properties?

Exploratory Data Analysis (EDA)

- **No Null values**
- **240 duplicates removed**

❖ Histogram of Features to check distribution
  - ❖ Target Class imbalance (majority 5/6) - SMOTE
  - ❖ Skewed distribution



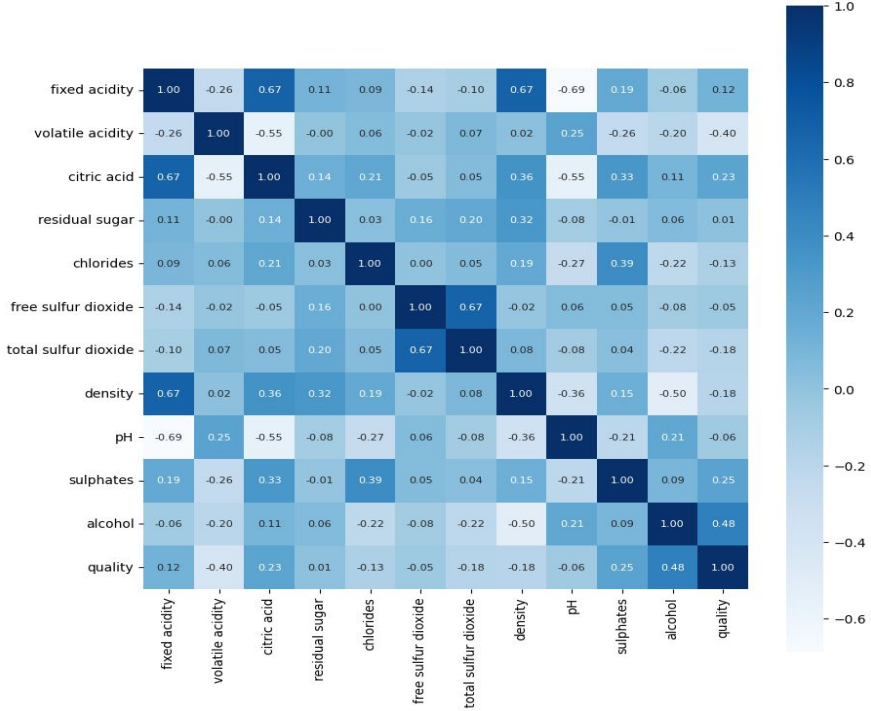
Pearson Correlation: Heatmap

With target:

- Alcohol -> 0.48
- Volatile Acidity -> 0.4 (-ve)
- Weak - sulphates/ citric acid -0.25/0.23
- No relation - residual sugar, pH

Amongst Feature:

- Fixed acidity & Citric Acid - 0.67
- Free Sulphur Dioxide & Total Sulphur Dioxide - 0.67

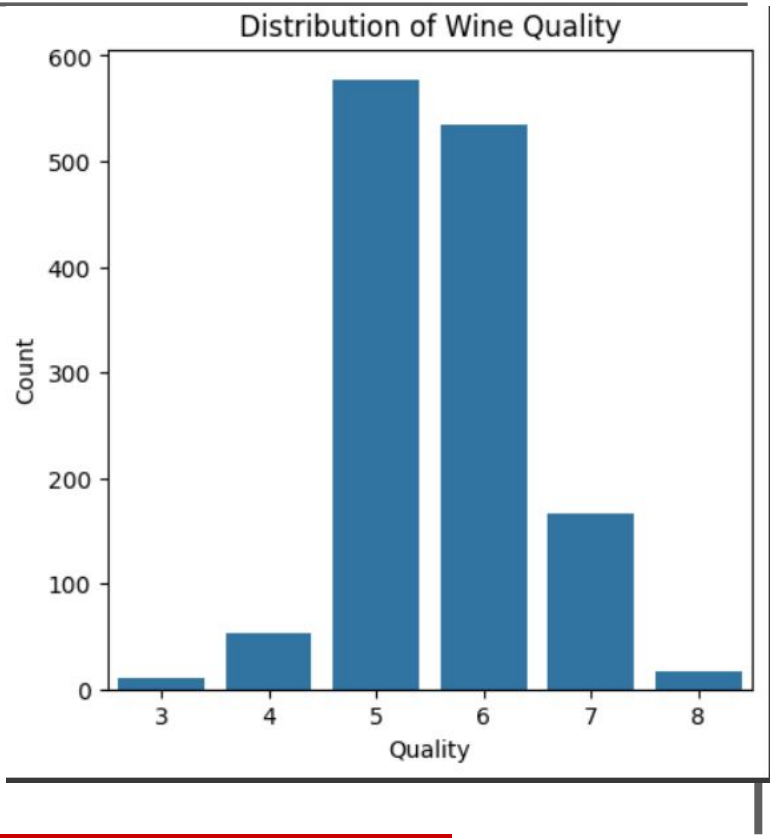


Target Binarization

Quality >=7 is “Good” else bad

Imbalanced dataset ~13% good samples -SMOTE

Pros: Meaningful segregation, identifies truly good wines



Data Preparation

Train-Test split:
- No information leak during training

Log Transformation:
- To address the right skew of features

Standardization:
- Learn the scaling rules from training set
- Transform both the sets using the same

Smote: Synthetic Minority Over-sampling technique
- Generate Synthetic samples for minority Class
- Avoid Bias by models

Model Training - Tree based Classifiers

Reasoning for Tree-Based Models:

- These models are generally robust to multicollinearity and skewed feature distributions and are effective at capturing non-linear relationships.
- The most popular when it comes to classification problems

Models Trained:

1. **Decision Tree:** A baseline model to understand the basic feature splits.
2. **Random Forest :** An ensemble method to reduce overfitting and improve generalization.
3. **AdaBoost :** A boosting algorithm that iteratively focuses on misclassified samples.
4. **Gradient Boosting:** Another powerful boosting method that builds trees sequentially to correct errors.

Evaluation Metric:
F1-Score was the primary metric due to the class imbalance. It provides a better measure of success than accuracy by balancing precision and recall.

Modelling phase 2 - Non Parametric

Potential Problems:

- The performance of Distance based models might be hindered by **high dimensionality** and **correlated features.**
- Note that we handled skew during log transformation.

Principal Component Analysis (PCA):

- PCA was applied to the standardized training data - **Dimensionality reduction** and to combine correlated features into new, **uncorrelated components**.
- Components were retained to explain **90% of the variance**.

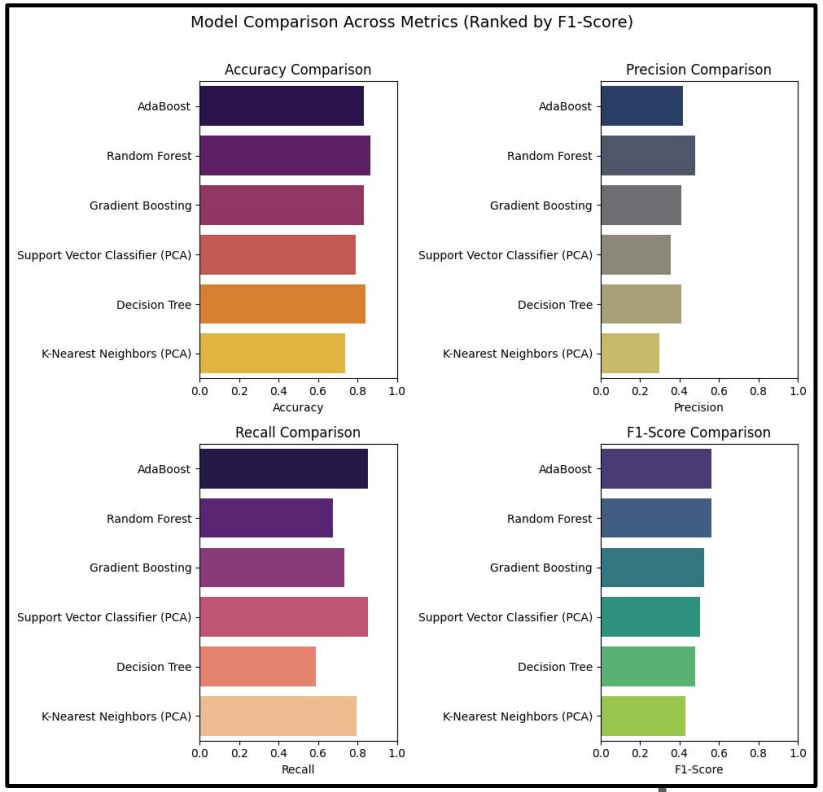
Models Trained on PCA-transformed data:

1. **k-Nearest Neighbors (KNN):** A distance-based algorithm that often benefits from a reduced and less noisy feature space.
2. **Support Vector Machine (SVM):** Also sensitive to feature scale and dimensionality, making it a good candidate for PCA transformed data.

Combined results

PERFORMANCE ON TEST SET

Model	Accuracy	Precision	Recall	F1-Score
AdaBoost	0.8346	0.4203	0.8529	0.5631
Rand. Forest	0.8676	0.4792	0.6765	0.5610
Grad. Boost.	0.8346	0.4098	0.7353	0.5263
SVC (PCA)	0.7904	0.3580	0.8529	0.5043
Dec. Tree	0.8419	0.4082	0.5882	0.4819
KNN (PCA)	0.7390	0.2967	0.7941	0.4320



- **Ranked by F1-Score:** Primary metric for imbalanced data.
- **High Accuracy:** Masks Precision/Recall trade-off for the minority class.
- **Ensemble Methods Dominated:** AdaBoost strongest overall; Random Forest achieved best Precision.
- **Distance-Based Classifiers:** Mixed results and inferior to ensembles.


BEST MODEL?

Conclusions

- The main learning from the dataset was how to handle class imbalance
- Ensemble models provided the **most balanced performance** for this classification task when evaluated on F1 Scores
- SMOTE Likely enabled **higher Recall**, but potentially contributed to lower Precision by broadening decision boundaries.
- A consistent Precision/Recall tradeoff was observed, suggesting inherent dataset challenges.
- This suggests that while the physicochemical features are informative, they do not provide a perfectly clear boundary to separate "good" from "bad" wines, reflecting the subjective nature of wine tasting.

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THANK YOU!