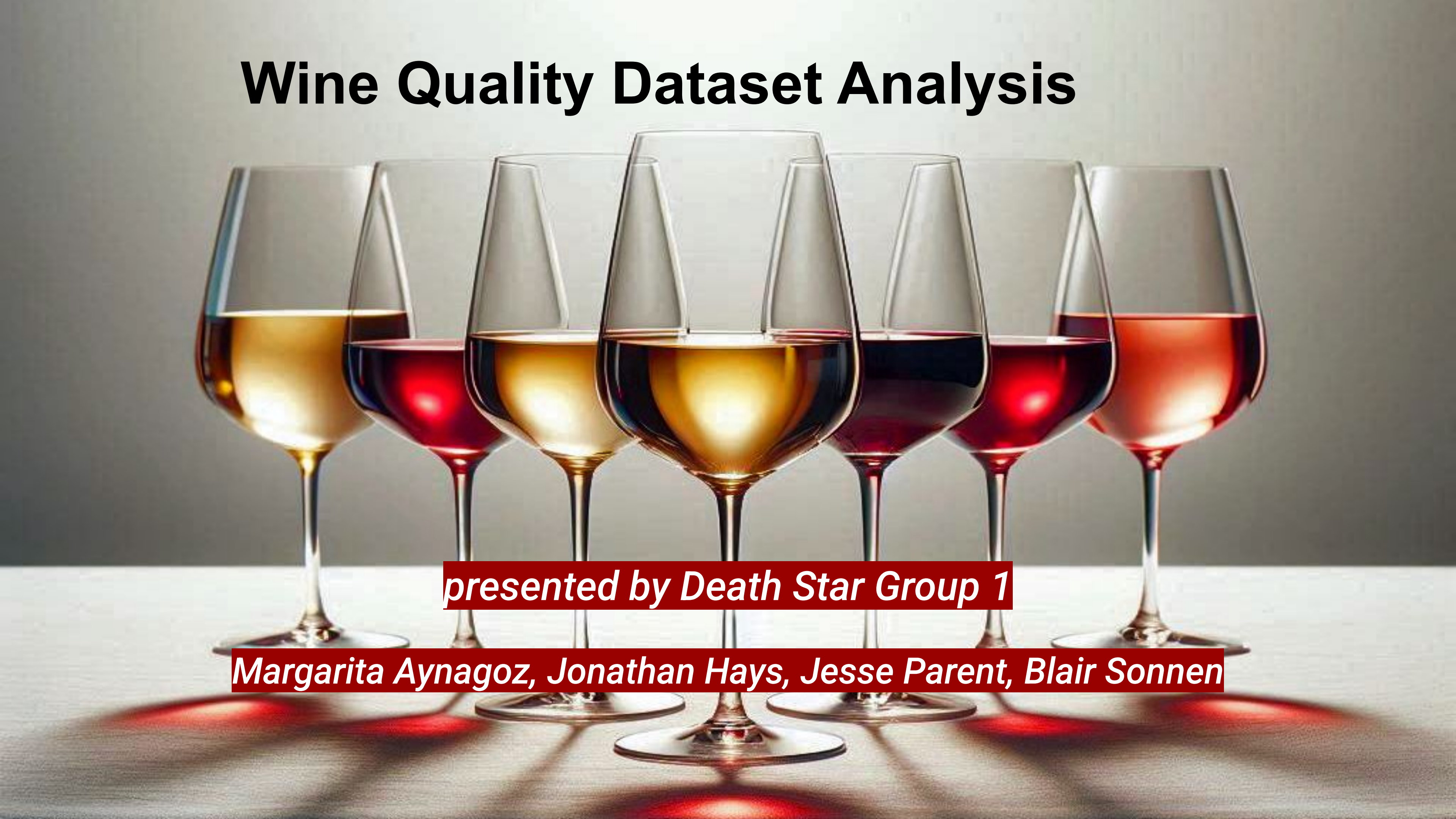
Wine Quality Dataset Analysis



presented by Death Star Group 1

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Wine Quality is Subjective.

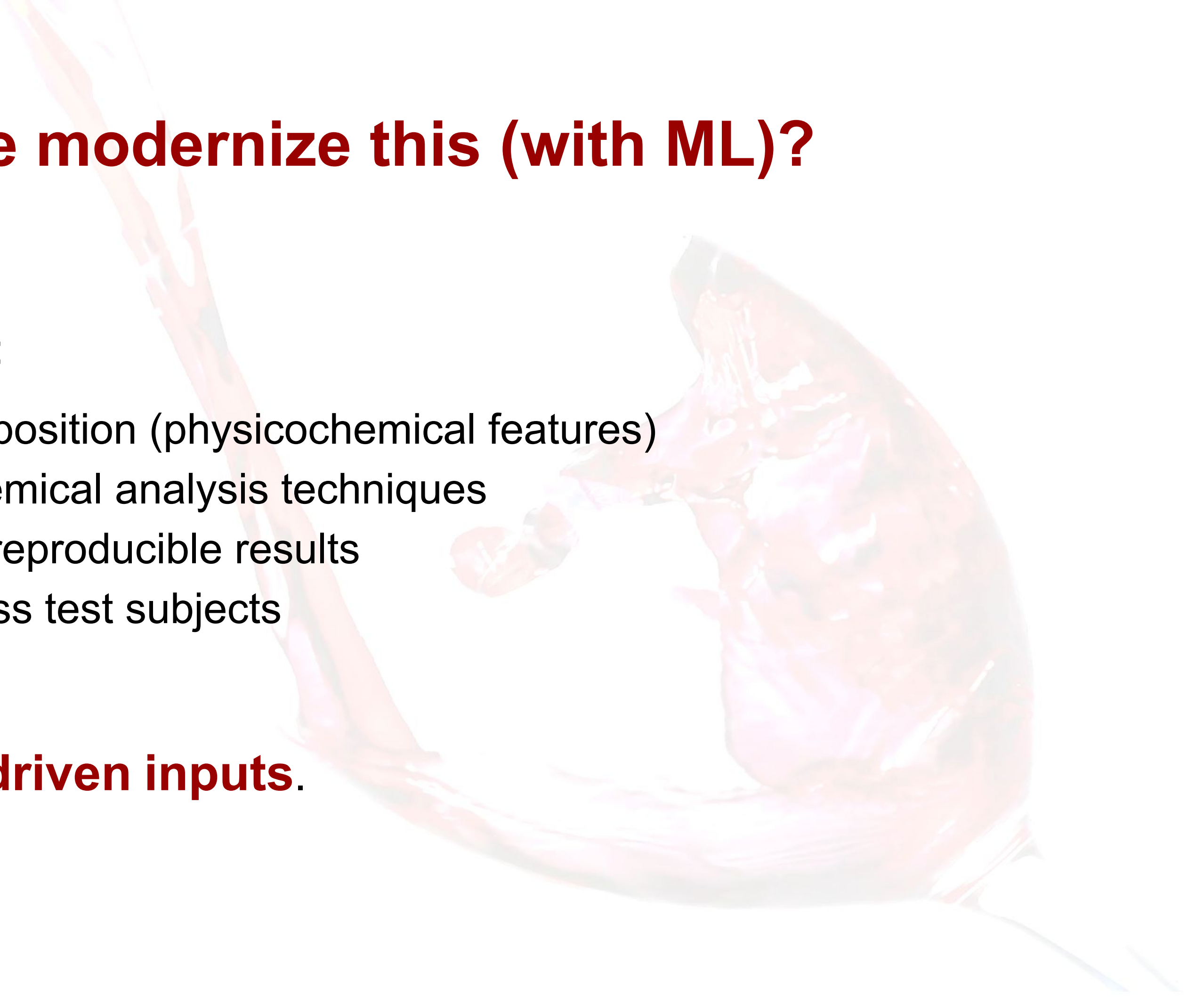
Right?

Problem: quality perception is often driven by

- ***Vintner heritage***
- ***Sensory analysis***
- ***Subjective opinions of sommeliers, etc.***
- ***Brand presence***

These are not data-driven inputs.

Can we modernize this (with ML)?



Our solution says yes:

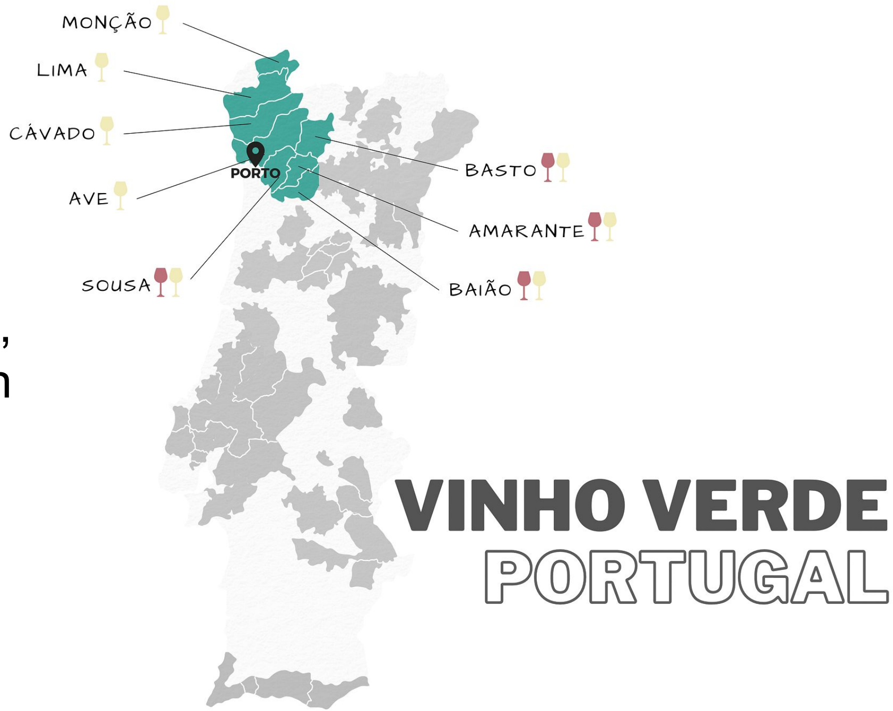
- Measurable composition (physicochemical features)
- Availability of chemical analysis techniques
- Repeatable and reproducible results
- Seemingly endless test subjects

These ARE data-driven inputs.

Good Data Can Provide Proof.

We can prove this using ML analysis:

- 6500-row dataset
- Red and White wine
- chemical properties and quality rating,
- sourced from a region in northwestern Portugal called Vinho Verde.
- Uses oenologist wine evaluations

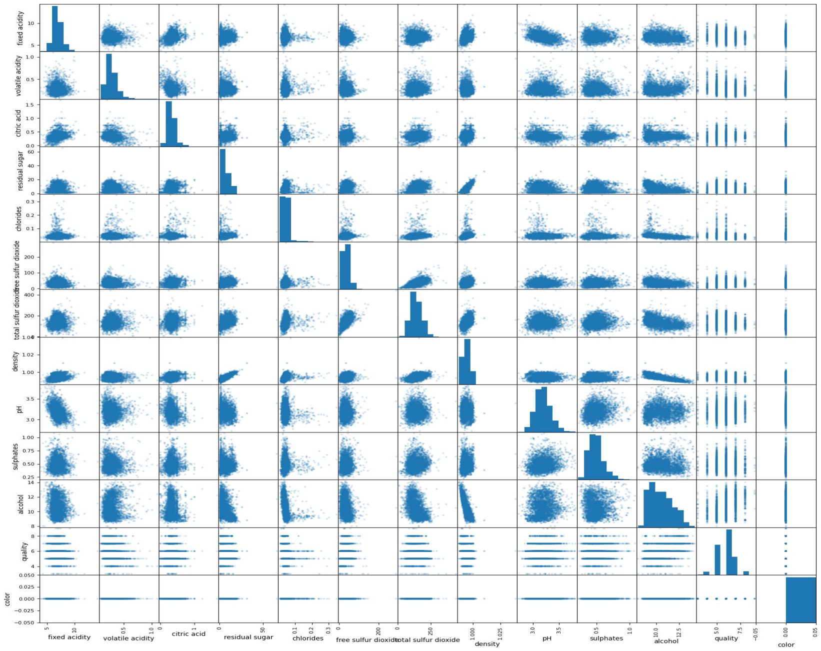


Wine Quality Dataset from the UCI Machine Learning Repository

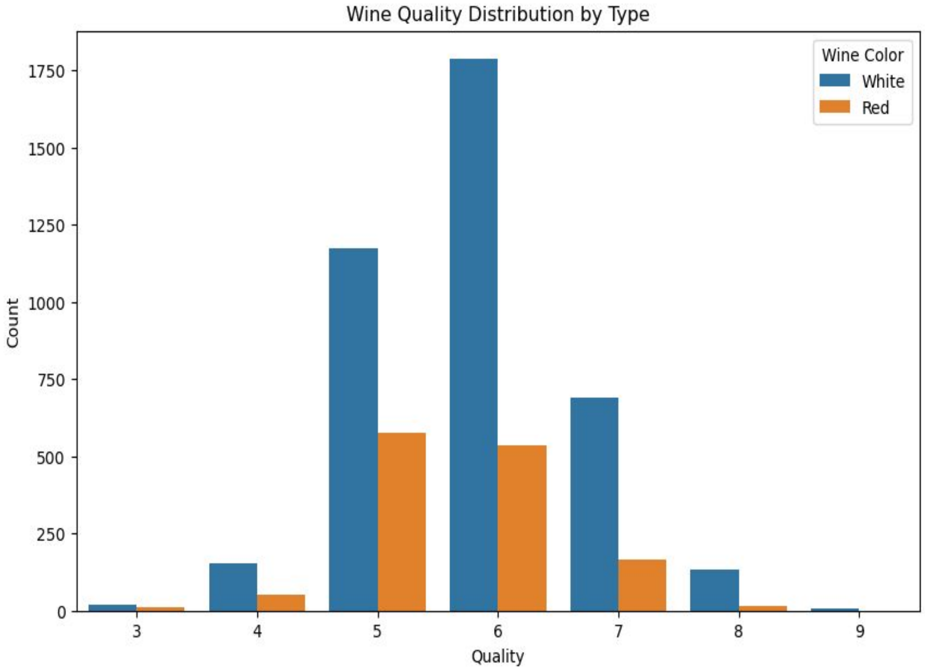
We envision a future where producers can adapt their methods based on analytical findings, resulting in improved wine quality and greater customer satisfaction.

Wine - A Symbol of Celebration

- A beverage that brings people together.
- Elevates ordinary moments to extraordinary experiences.



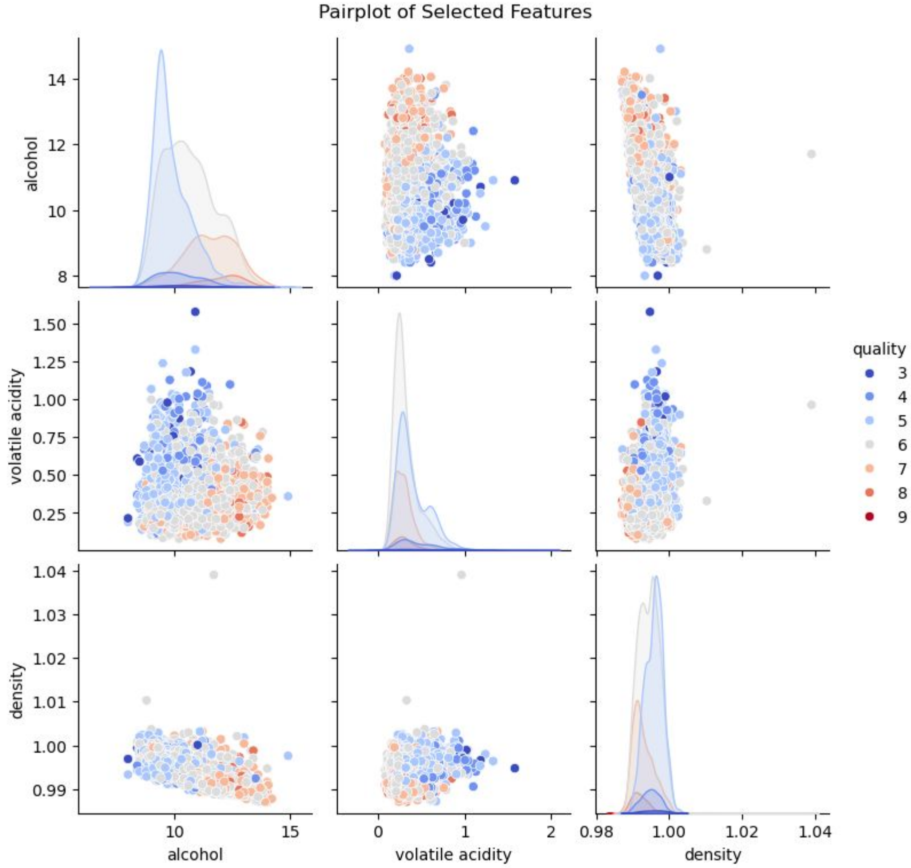
Visualizations of features and their relationships with the target variable **quality**.



- Histograms and boxplots to visualize feature distributions.

- Correlation matrices to identify relationships between features and overall quality.

- Create bins for the quality column.



Data Cleanup and Feature Selection:

- Drop the **“color”** column due to it not being relevant to quality.
- Drop the **“free sulfur dioxide”** column due to it being highly correlated with **“total sulfur dioxide”** column.
- Drop the **“chlorides”**, **“citric acid”**, **“fixed acidity“** columns because of the P-value did not significantly influence quality predictions.

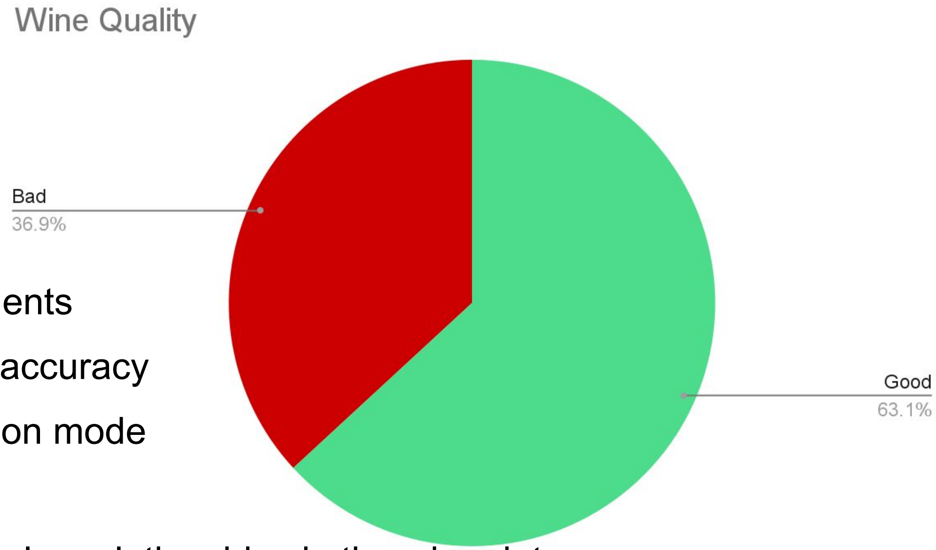
Allow us to focus on the most impactful variables that truly contribute to the quality of wine.

○Approach: Jesse

- Combine the white and red wine datasets with a new color column
- Clean the data (drop nulls, de-duplicate)
- Visually analyze the data and look for relationships and shape of data
  - Notice relationships
  - Detect imbalanced output
- Use Binning for quality into 0 (bad) and 1 (good)
  - Avoids heavily imbalanced data
  - Higher accuracy

- Analyze feature importance (p-values - Binary Logistic Regression) and drop less important features
  - P-Values greater than 0.05 were dropped
  - We did not find a benefit from dropping features in model analysis
- Scale Data
  - Not necessary for all models but benefits Logistic Regression (no benefit found)
  - RandomForest handles unscaled data well, but is not adversely impacted by scaling

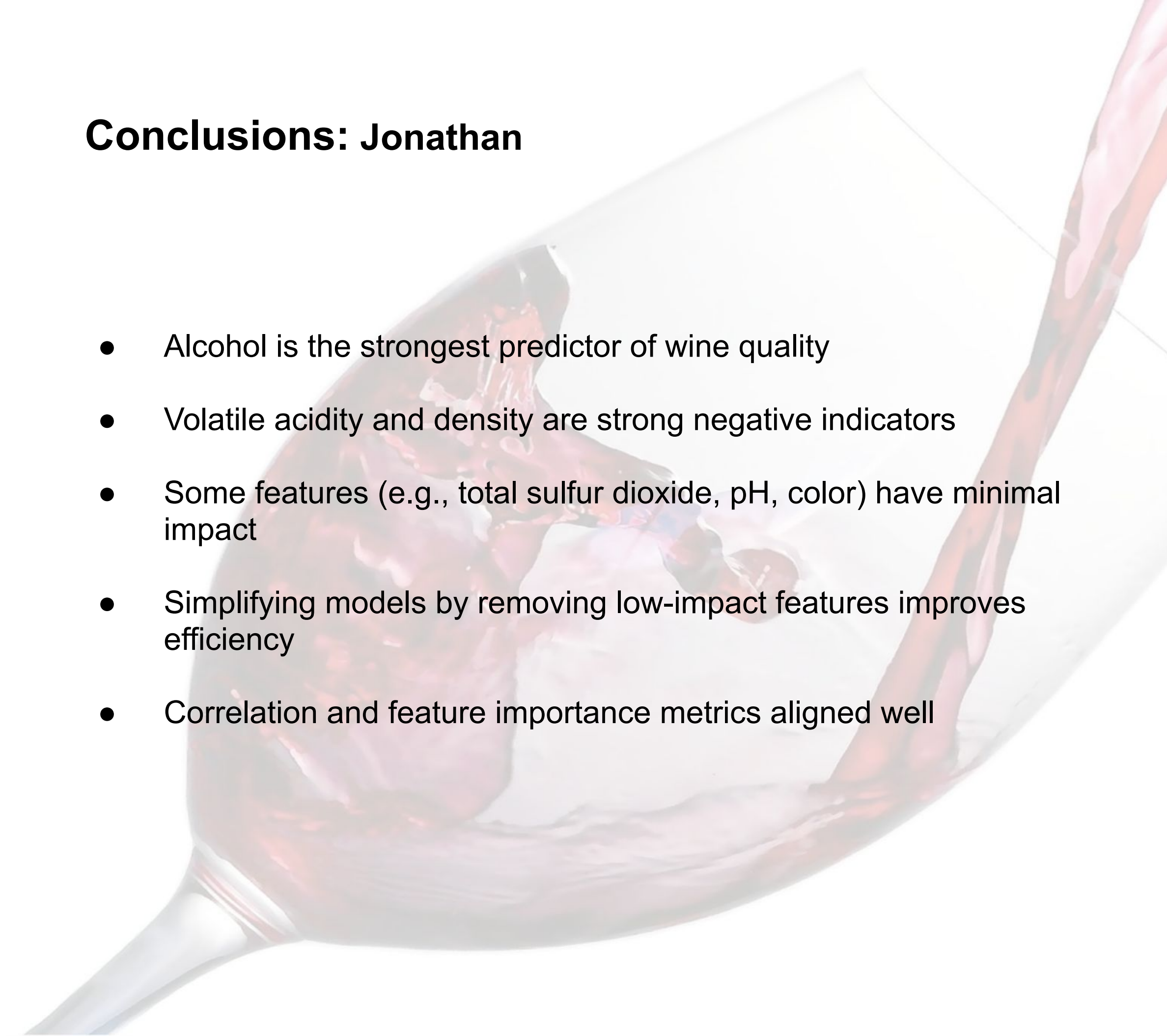
○Approach: Jesse

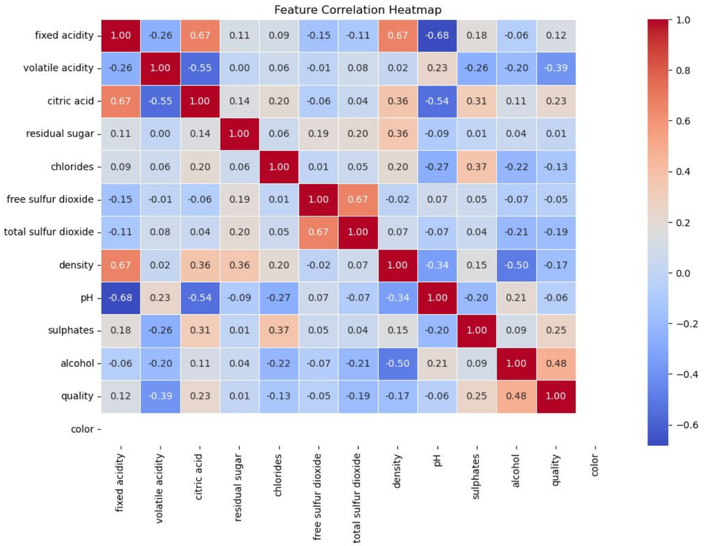


- Rebalance data using SMOTE and SMOTEENN
  - More good quality wine results than bad
  - Random Forest showed no accuracy improvements
  - Logistic Regression showed negative effect on accuracy
- Model Selection - Binary output (quality) = classification mode
  - Random Forest
    - Best for high accuracy and capturing complex relationships in the wine data
  - Logistic Regression
    - Best for understanding which factors (e.g., acidity, alcohol) strongly impact wine quality
- Hyperparameter Optimization
  - Random Forest showed 1% additional accuracy increase (78%)
  - Logistic Regression showed no significant improvement

Conclusions: Jonathan

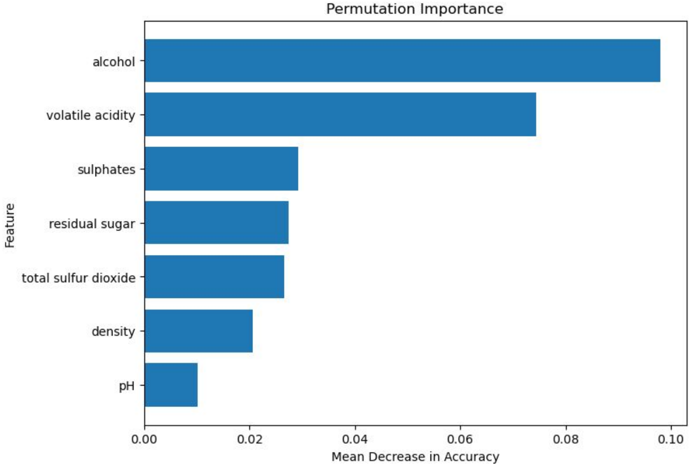
- Alcohol is the strongest predictor of wine quality
- Volatile acidity and density are strong negative indicators
- Some features (e.g., total sulfur dioxide, pH, color) have minimal impact
- Simplifying models by removing low-impact features improves efficiency
- Correlation and feature importance metrics aligned well





Feature Correlation Heatmap

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality	color
fixed acidity	1.00	-0.26	0.67	0.11	0.09	-0.15	-0.11	0.67	-0.68	0.18	-0.06	0.12	
volatile acidity	-0.26	1.00	-0.55	0.00	0.06	-0.01	0.08	0.02	0.23	-0.26	-0.20	-0.39	
citric acid	0.67	-0.55	1.00	0.14	0.20	-0.06	0.04	0.36	-0.54	0.31	0.11	0.23	
residual sugar	0.11	0.00	0.14	1.00	0.06	0.19	0.20	0.36	-0.09	0.01	0.04	0.01	
chlorides	0.09	0.06	0.20	0.06	1.00	0.01	0.05	0.20	-0.27	0.37	-0.22	-0.13	
free sulfur dioxide	-0.15	-0.01	-0.06	0.19	0.01	1.00	0.67	-0.02	0.07	0.05	-0.07	-0.05	
total sulfur dioxide	-0.11	0.08	0.04	0.20	0.05	0.67	1.00	0.07	-0.07	0.04	-0.21	-0.19	
density	0.67	0.02	0.36	0.36	0.20	-0.02	0.07	1.00	-0.34	0.15	-0.50	-0.17	
pH	-0.68	0.23	-0.54	-0.09	-0.27	0.07	-0.07	-0.34	1.00	-0.20	0.21	-0.06	
sulphates	0.18	-0.26	0.31	0.01	0.37	0.05	0.04	0.15	-0.20	1.00	0.09	0.25	
alcohol	-0.06	-0.20	0.11	0.04	-0.22	-0.07	-0.21	-0.50	0.21	0.09	1.00	0.48	
quality	0.12	-0.39	0.23	0.01	-0.13	-0.05	-0.19	-0.17	-0.06	0.25	0.48	1.00	
color													



What could have been next?

- Analyzing our results as compared to the 2009 paper from Cortez et al.
- Performing additional model runs on SVM with hyperparameter tuning.
- Running these models on Red and White datasets separately.
- Finding more recent data from another region
    - Or a large volume vintner
- Possibly merging crowdsourced ratings into dataset if possible