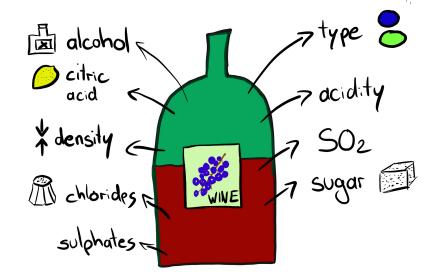
Explainable AI (XAI)

Christoph Molnar

13. Institutstag - July 05, 2019

Let's Predict Wine Quality



Disclaimer: I am NOT a wine expert!



How can we develop a wine quality prediction program?

Programing vs. Machine Learning

Machine Learning (supervised)



Machine Learning (supervised)



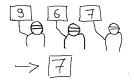
Machine Learning (supervised)



Step 1: Find data

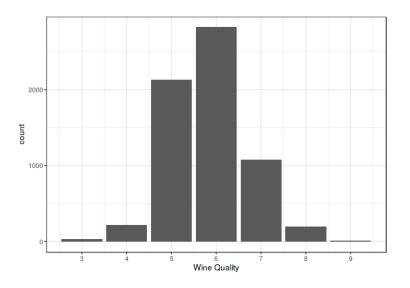
Wine Dataset

- ▶ 6500 red and white Portuguese "Vinho Verde" wines
- ► Features: Physicochemical properties
- Quality assessed by blind tasting, from 0 (very bad) to 10 (excellent)



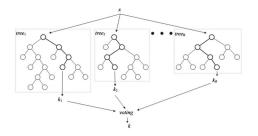
P. Cortez, A. Cerdeira, F. Almeida, T. Matos and J. Reis. Modeling wine preferences by data mining from physicochemical properties. In Decision Support Systems, Elsevier, 47(4):547-553, 2009.

Wine Quality Distribution



Step 2: Apply Machine Learning

Random Forest

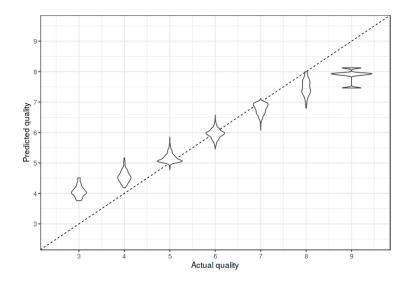


 $Image: \ http://www.hallwaymathlete.com/2016/05/introduction-to-machine-learning-with.html \\$

Train Random Forest to Predict Quality

Mean absolute error on test data (cross-validated): 0.44

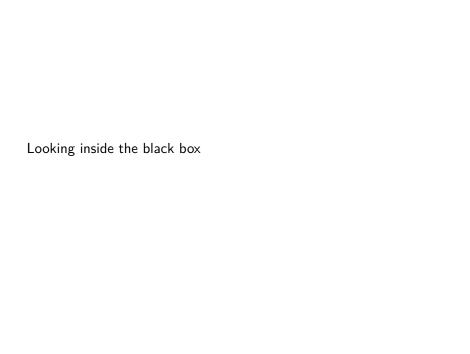
Prediction vs. Actual Quality



Step 3: Profit

We want to know:

- Which wine properties are the most predictive for quality?
- How does a property affect the predicted wine quality?
- Can we extract a "Rule of Thumb" from the black box?
- Why did a wine get a certain prediction?
- ► How do we have to change a wine to achieve a different prediction?





Permutation Feature Importance

original

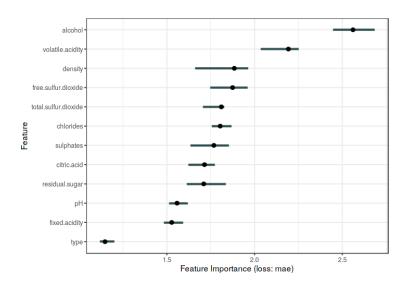
x_1	 x_j	 x_p
3	1.4	6.0
5	1.2	7.2
6	2.0	8.9

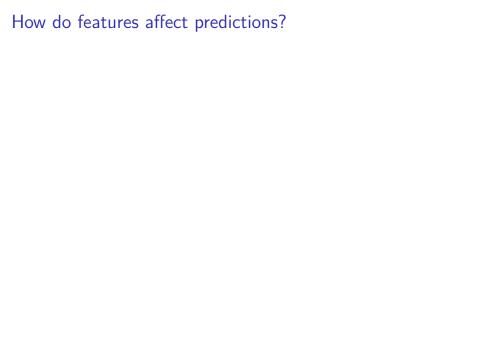
\rightarrow

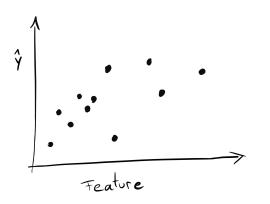
shuffled x_i

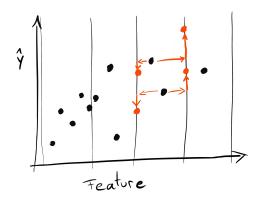
situitied wy				
x_1		x_j		x_p
3		2.0		6.0
5		1.4		7.2
6		1.2		8.9

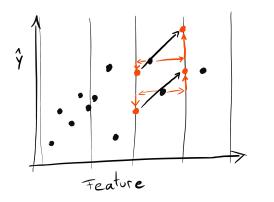
Which features are important?

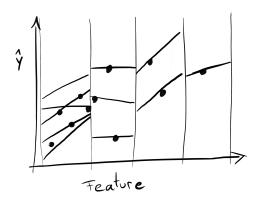


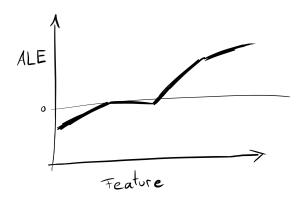




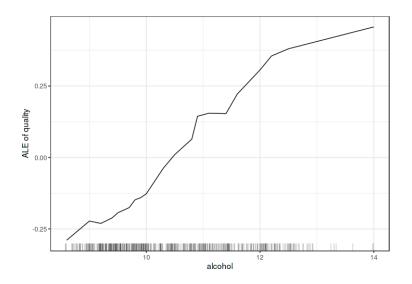




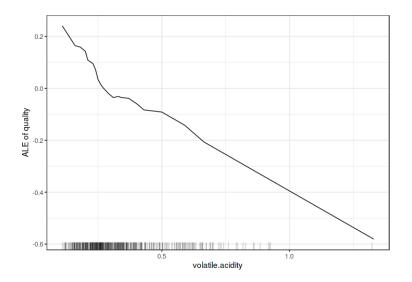




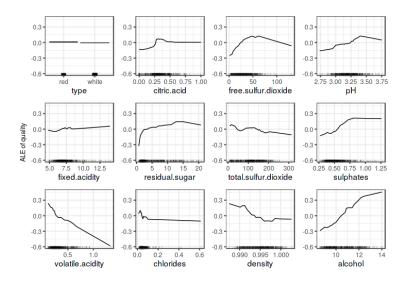
Effect of Alcohol

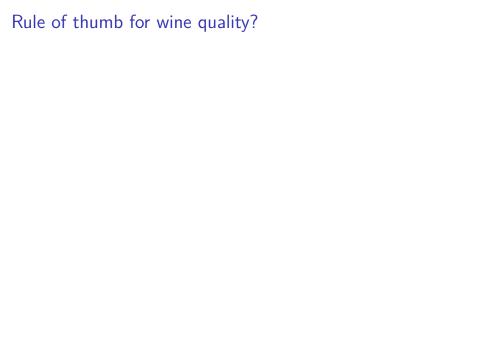


Effect of Volatile Acidity



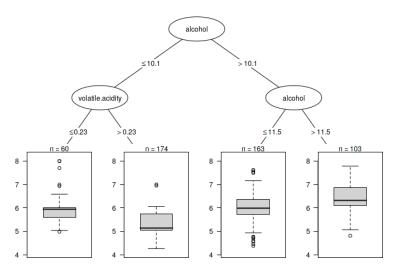
How do features affect predictions?





Surrogate Model

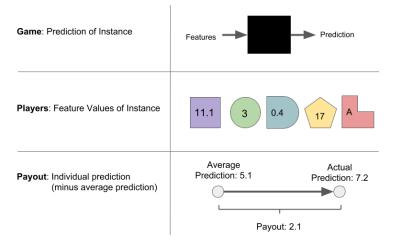
Surrogate Model



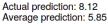
Tree explains 37.36% of black box prediction variance.

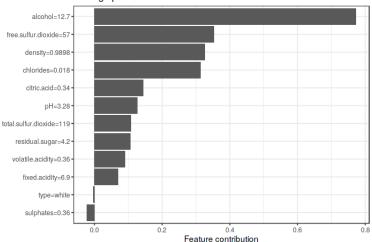
Explain individual predictions

Shapley Value

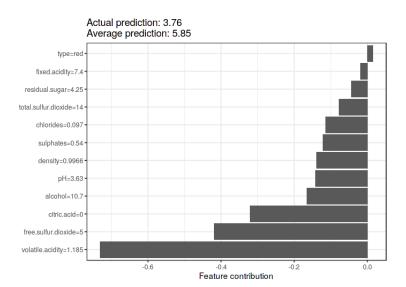


Explain best wine





Explain worst wine





Counterfactual Explanations

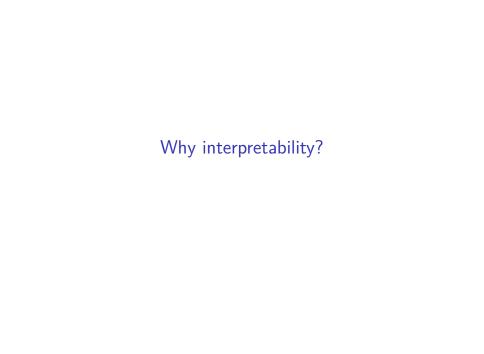
Counterfactual Explanations

Counterfactual Explanations

Improve worst wine?

How do we get the wine above predicted quality of 5?

- Decreasing volatile acidity to 0.2 yields predicted quality of 5.09
- ► Decreasing volatile acidity to 1.0 and increasing alcohol to 13% yields predicted quality of 5.01



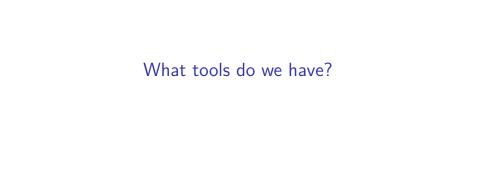
Interested in learning more?

More on interpretable machine learning in my book http://christophm.github.io/interpretable-ml-book/.

Backup

Units in Wine dataset

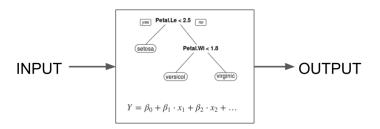
- fixed acidity g(tartaric acid)/dm³
- volatile acidity: g(acetric acid/dm³)
- ► citric acid: g/dm³
- ► residual sugar: g/dm³
- chlorides: g(sodium chloride)/dm³
- ► free sulfur dioxide: mg/dm³
- total sulfur dioxide: mg/dm³
- ▶ density> g/cm³
- ▶ pH
- sulphates: g(postassium sulphate) / dm³
- ► alcohol vol.%



Interpretable Models



Interpretable Models



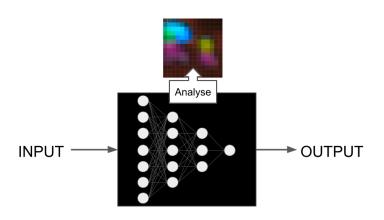
Intepretable Model: Linear Regression

Intepretable Model: Decision Tree

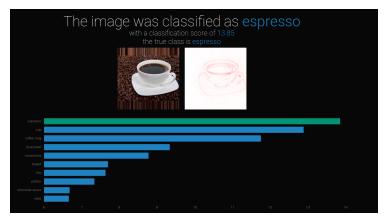
Interpretable Model: Decision Rules

IF $90m^2 \leq \text{size} < 110m^2$ AND location = "good" THEN rent is between 1540 and 1890 EUR

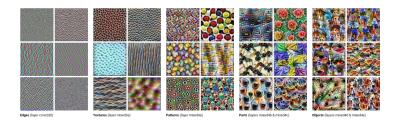




Layerwise Relevance Propagation (LRP)



Bach, Sebastian, et al. "On pixel-wise explanations for non-linear classifier decisions by layer-wise relevance propagation." PloS one 10.7 (2015): e0130140.

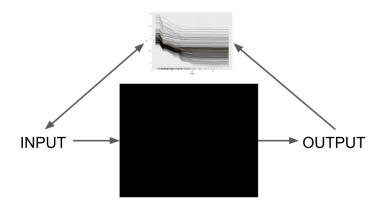


https://distill.pub/2017/feature-visualization/

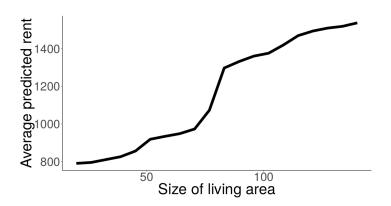
Model-agnostic Methods



Model-agnostic Methods



Model-agnostic Methods



Model-agnostic Methods: Global Surrogate

Model-agnostic Methods: Local Surrogate