3050571 Practical Clin Data Sci

Session 10: Machine learning framework

February 15, 2024

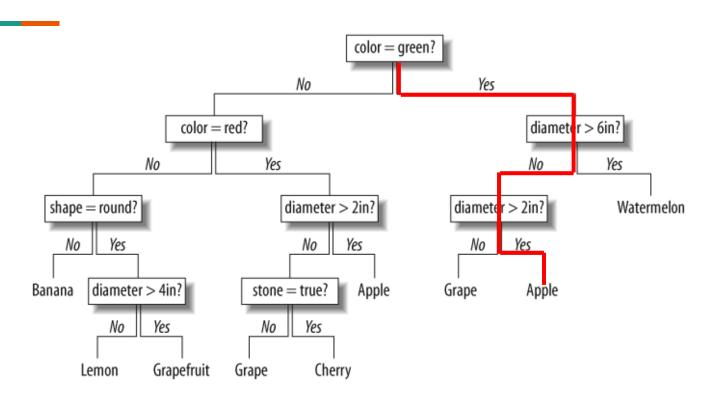


Sira Sriswasdi, PhD

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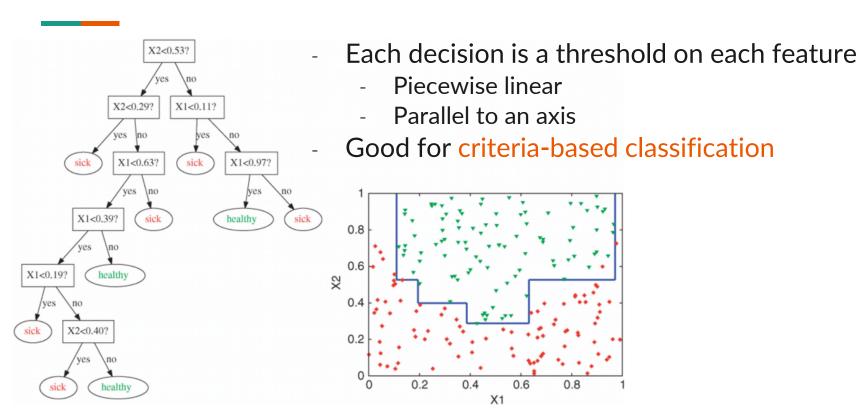
Decision tree

Decision tree



Source: Programming collective intelligence by Toby Segaran

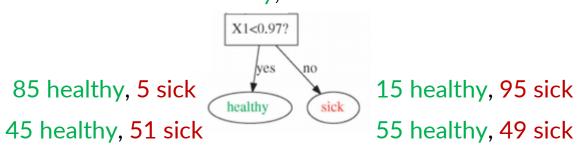
Decision tree behaviors



Miller, C. "Screening meter data: Characterization of temporal energy data from large groups of non-residential buildings"

Splitting quality

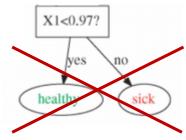




- Gini impurity: $\sum p(1-p)$
- Entropy: $-\sum p \ln(p)$
 - Minimal at p = 0 or 1 → Perfect split
 - Maximal at p = $0.5 \rightarrow 50-50$ split
- Search for feature and cutoff that yield lowest impurity or entropy

Control mechanisms for tree building

1. Too few samples to make a split

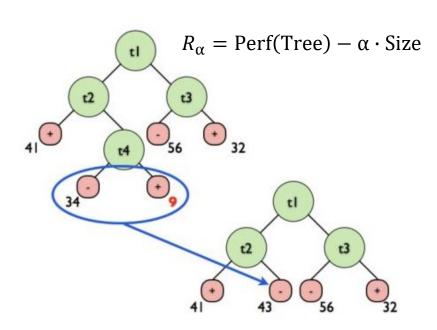


3. Impurity or entropy does not change much after the split

2. Too few samples on either branch

- Limit the tree size
- Limit the improvement in quality
- Limit the number of samples that support a split

Tree pruning (post-processing)



Patel, N. and Upadhyay, S. "Study of Various Decision Tree Pruning Methods with their Empirical Comparison in WEKA" IJCA 2012

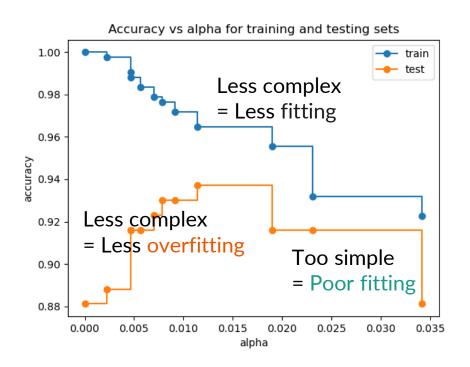
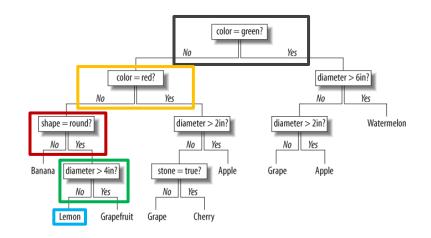


Image from scikit-learn,org

Regularization on features

- Linear model: $\widehat{y}_i = b_0 + b_1 x_{i,1} + \cdots + b_n x_{i,n}$
 - LASSO
- Tree model:
 - Repeatedly using the same feature
 - Early decision affects the rest
- Feature bagging
 - Look at only *N* features at each step
 - Force model to use diverse features



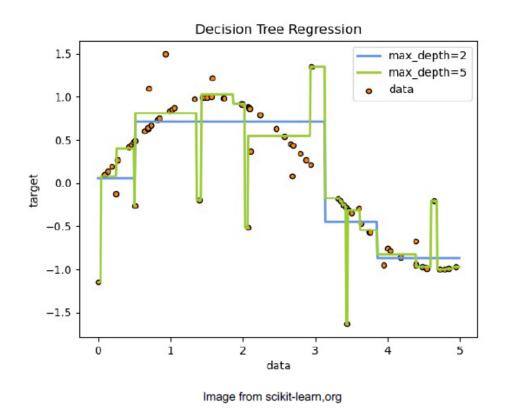
Decision tree for regression



Image from saedsayad.com

- Predict an average of samples in the same branch

Decision tree is a piecewise constant function



Linear-Tree model

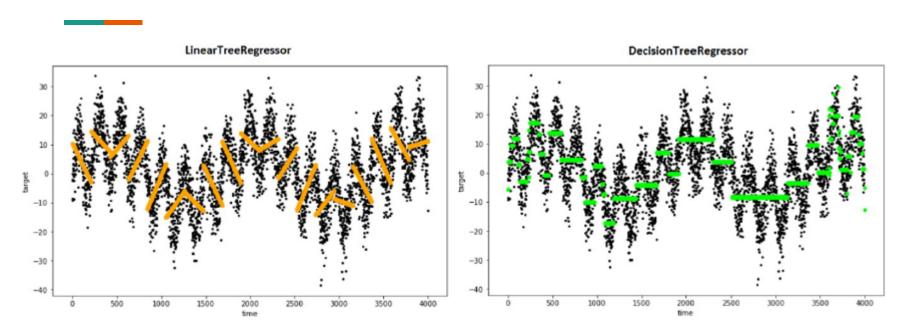
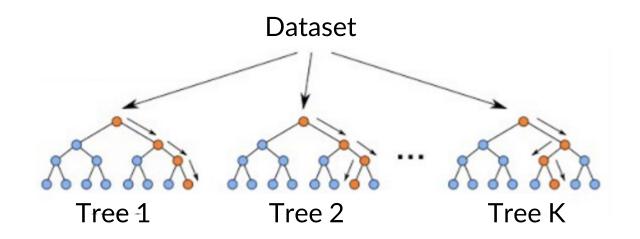


Image from towarddatascience.com

- Fit a different linear model in each branch

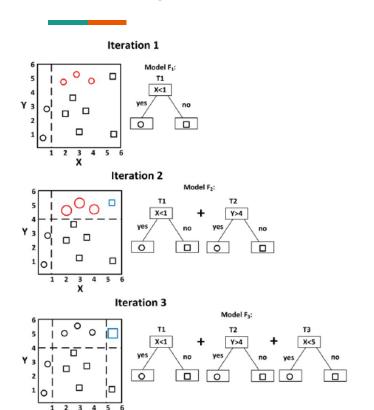
Ensemble approaches

Bagging: Random forest



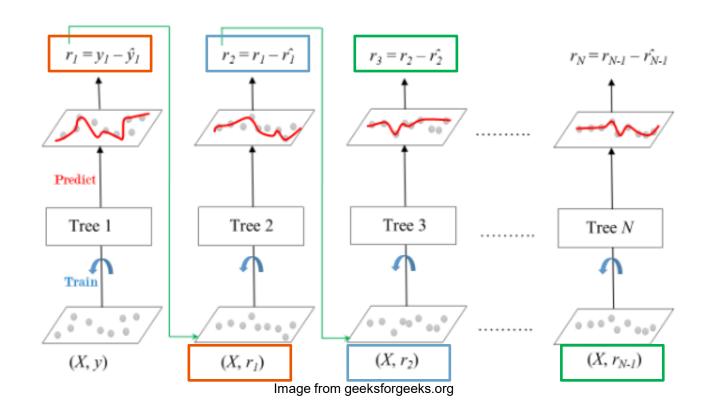
- Sample 80% of the dataset to train each decision tree
- Each tree may overfit to different part of the dataset
- But the consensus should be correct

Boosting for classification

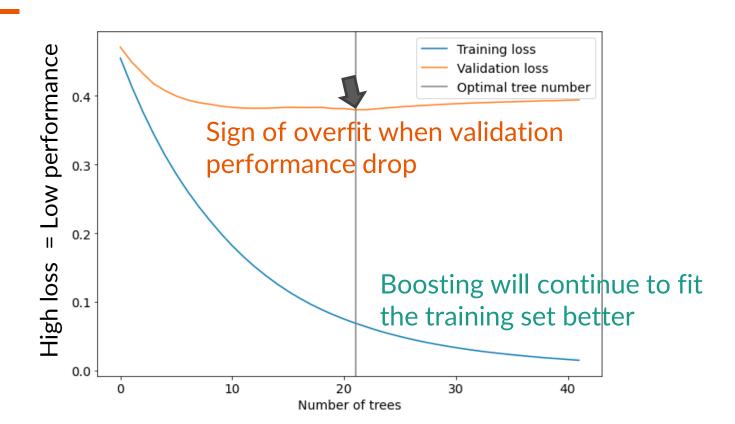


- The first model made some mistakes
- The mistakes were assigned higher weights for the subsequent models
- As more models are added, the ensemble should make less errors
- Ensemble = $\mathbf{w_1} f_1(x) + \cdots + \mathbf{w_n} f_n(x)$

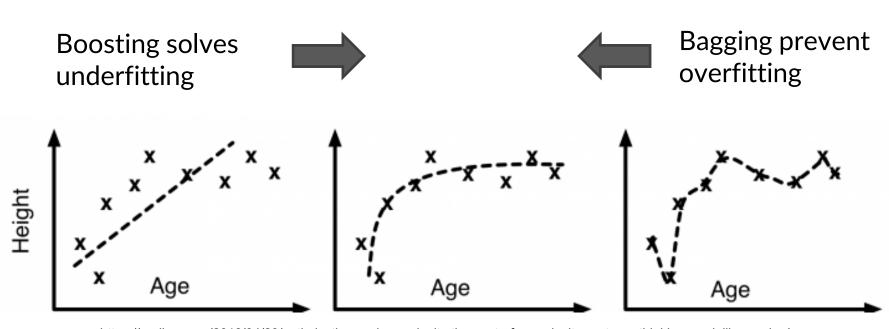
Boosting for regression



Controlling boosting with learning rate



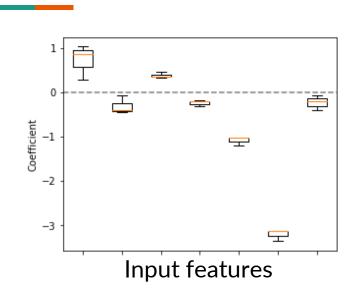
Impact of ensemble

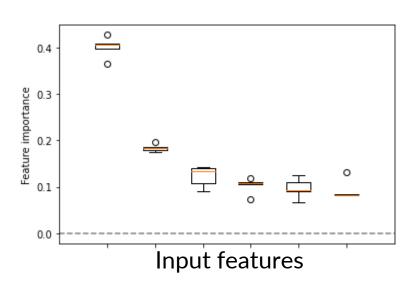


https://realkm.com/2018/04/23/optimization-and-complexity-the-cost-of-complexity-systems-thinking-modelling-series/

Explainability

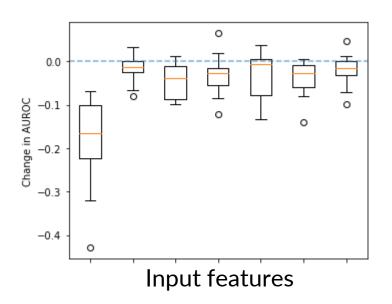
Feature importance





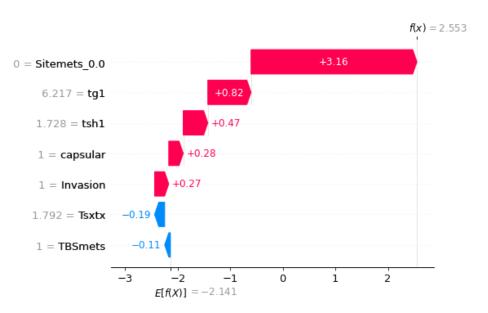
- Coefficients of linear, logistic, and SVM models
- Average improvement in impurity or entropy in tree models
- Model-level explanation

Change in performance after dropping a feature



- Compare performance with and without each input feature
- Big drop = important

Shapley value



Change in predicted value due to the addition of a feature i

$$- \varphi_{i}(v) = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(n-|S|-1)!}{n!} [v(S \cup \{i\}) - v(S)]$$

Sample-level explanation

Any questions?

See you on February 23rd