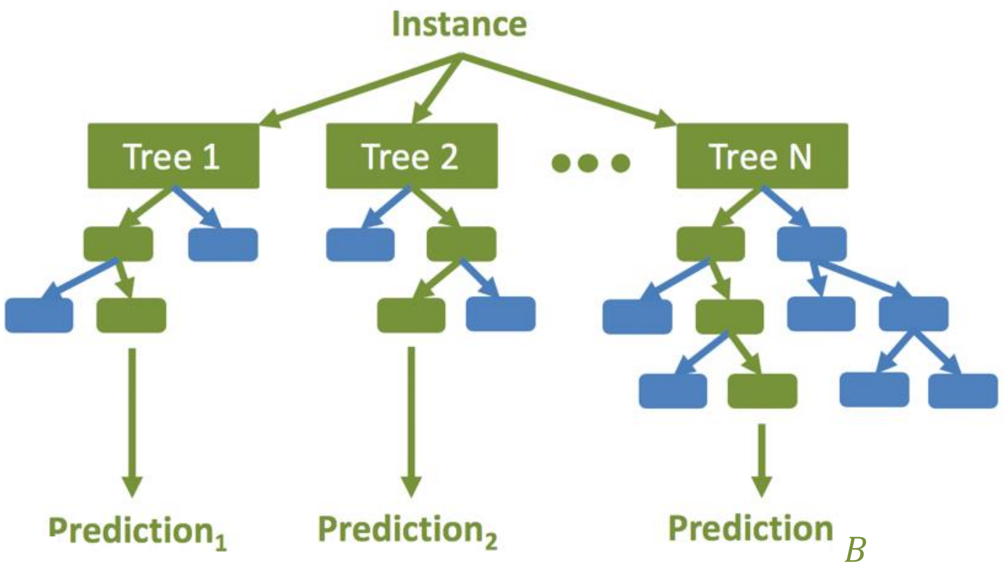
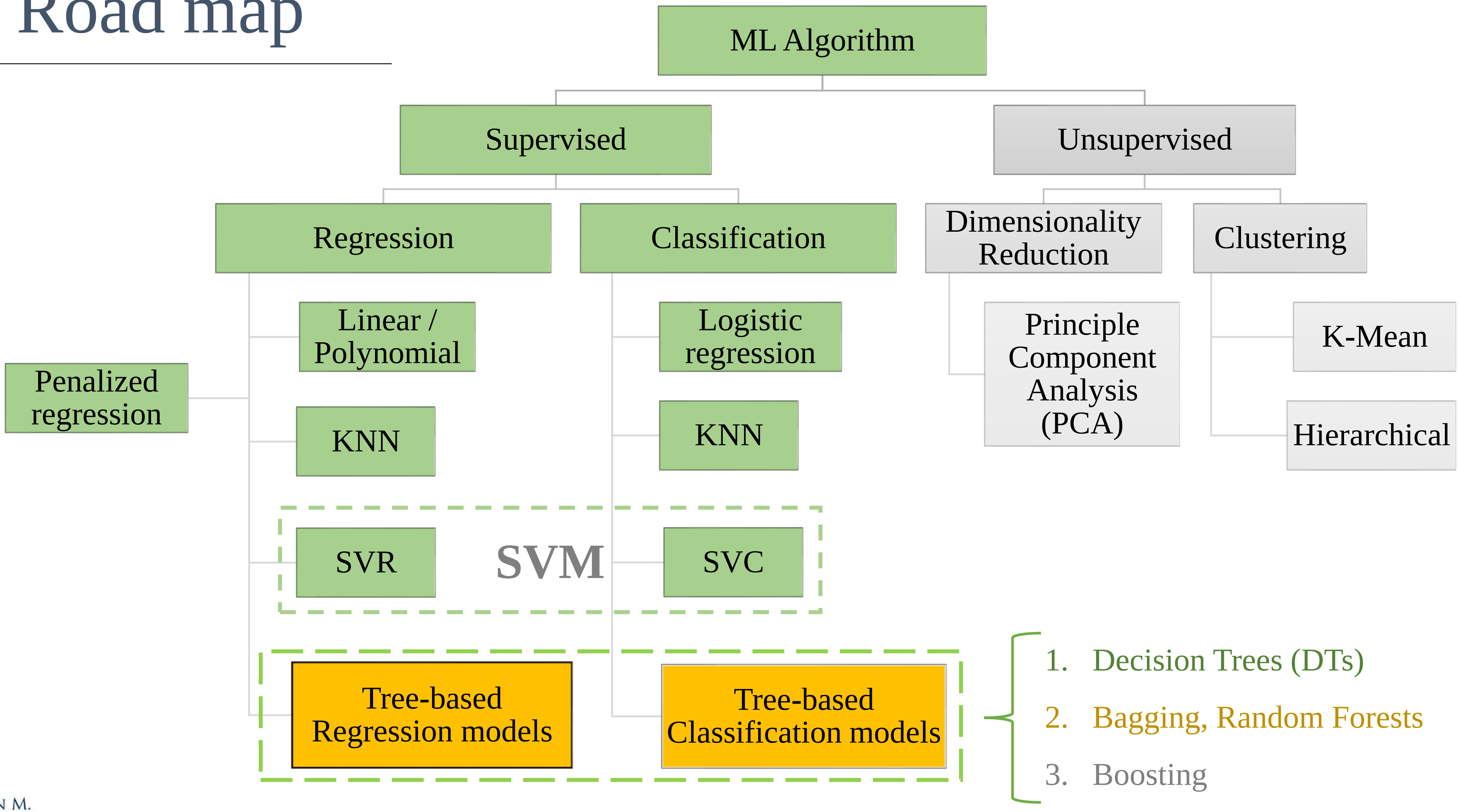
Class -20
Bagging and Random Forests

Prof. Pedram Jahangiry



Road map



ML Algorithm
Supervised
Unsupervised
Regression
Classification
Dimensionality Reduction
Clustering
Linear / Polynomial
Logistic regression
Principle Component Analysis (PCA)
K-Mean
Penalized regression
KNN
KNN
Hierarchical
SVR
SVM
SVC
Tree-based Regression models
Tree-based Classification models
1. Decision Trees (DTs)
2. Bagging, Random Forests
3. Boosting

Topics

Part I

1. Why not a simple tree?
2. Ensemble Learning

Part II

1. Bootstrap Aggregation (Bagging)
2. Random Forests

Part III

1. Hyperparameters
2. Feature importance

Part IV

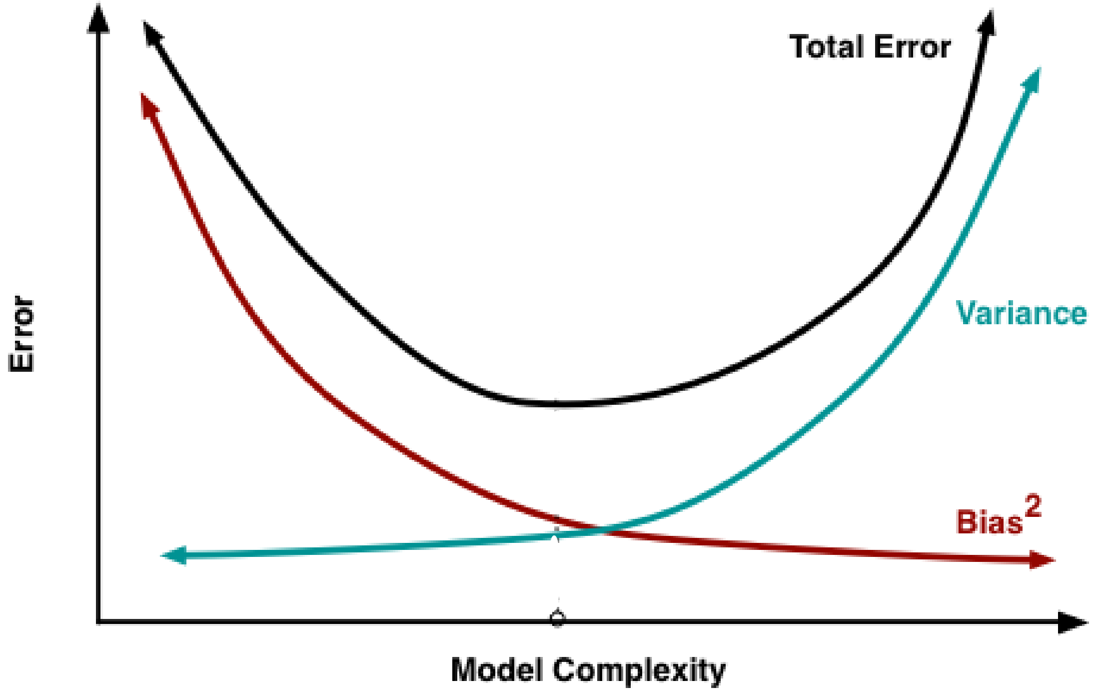
1. Pros and Cons
2. Applications in Finance

Part I

Motivation

Why not a simple tree?

- Goal: Reduce the bias and variance at the same time?!

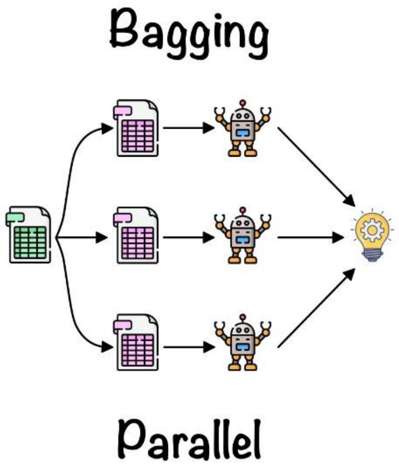


Ensemble Learning

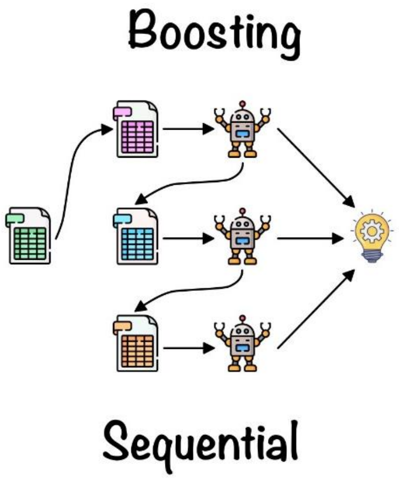
- Why not use the predictions of a group (an ensemble) of models?
- Ensemble Learning: Combining the predictions from a collection of models
- Idea: instead of trying to learn one super-accurate model, focusing on training many low-accuracy models and then combining the predictions given by those weak models.
- Ensemble learning typically produces more accurate and more stable predictions than the best single model.
- Ensemble learning methods are based on:
  1. Aggregation of heterogeneous learners (voting classifiers / average predictions)
  2. Aggregation of homogeneous learners (**bagging** and **boosting**)

Bagging vs Boosting

- Bagging consists of creating many “copies” of the training data (each copy is slightly different from another) and then apply the weak learner to each copy to obtain multiple weak models and then combine them.



- Boosting consists of using the “original” training data and iteratively creating multiple models by using a weak learner. Each new model would be different from the previous ones in the sense that the weak learner, by building each new model tries to “fix” the errors which previous models make.



Part II

Bagging and Random Forest

Bootstrap Aggregation (Bagging)

Training set

n	X_1	X_2	X_3	X_4	y
1	a_1	b_1	c_1	d_1	y_1
2	a_2	b_2	c_2	d_2	y_2
3	a_3	b_3	c_3	d_3	y_3
4	a_4	b_4	c_4	d_4	y_4
5	a_5	b_5	c_5	d_5	y_5

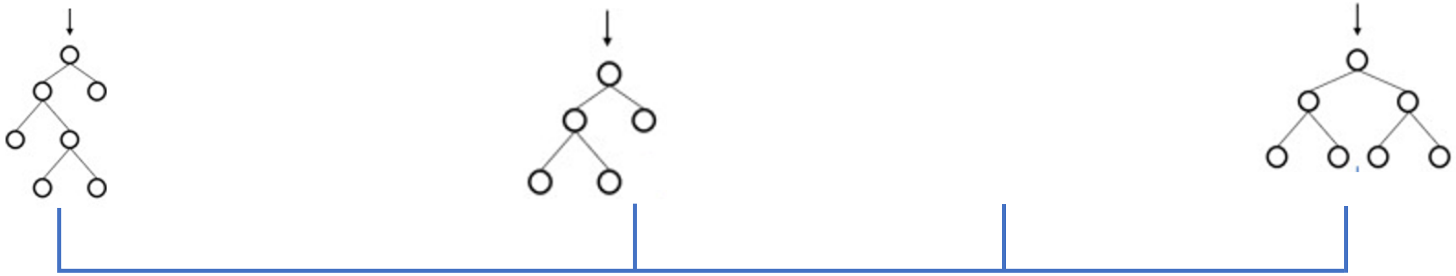
Bootstrapping

n	X_1	X_2	X_3	X_4	y
1	a_1	b_1	c_1	d_1	y_1
1	a_1	b_1	c_1	d_1	y_1
3	a_3	b_3	c_3	d_3	y_3
4	a_4	b_4	c_4	d_4	y_4
3	a_3	b_3	c_3	d_3	y_3

n	X_1	X_2	X_3	X_4	y
5	a_5	b_5	c_5	d_5	y_5
2	a_2	b_2	c_2	d_2	y_2
3	a_3	b_3	c_3	d_3	y_3
2	a_2	b_2	c_2	d_2	y_2
5	a_5	b_5	c_5	d_5	y_5

....

n	X_1	X_2	X_3	X_4	y
4	a_4	b_4	c_4	d_4	y_4
2	a_2	b_2	c_2	d_2	y_2
3	a_3	b_3	c_3	d_3	y_3
4	a_4	b_4	c_4	d_4	y_4
3	a_3	b_3	c_3	d_3	y_3



Ensemble of trees

Aggregation

Bagging procedure

- Bootstrap aggregating (or bagging) is a general-purpose procedure for reducing the variance of a learning method.
- Given a training set, first we create B random samples (with replacement) of the training set.
- For each sample $\boldsymbol{b}$, build a decision tree model $\boldsymbol{f_b}$
- After training, we have B decision trees. The predictions for a new test observation x is obtained as the **average** of B predictions (for regression) or a **majority vote** (for classification).

$$y \leftarrow \hat{f}(\mathbf{x}) \stackrel{\text{def}}{=} \frac{1}{B}\sum_{b=1}^{B} f_b(\mathbf{x}) \qquad or \qquad most\ frequent\ f_b(X)$$

- Bagging is a very useful technique because it helps to improve the stability of predictions and protects against overfitting the model. (why?)

Random Forests

- Random forests provide an improvement over The "vanilla" bagging algorithm by using a small trick that **decorrelates** the trees.
- RF uses a modified tree learning algorithm that at each split, inspects a **random subset of the features** (instead of inspecting the entire feature space!)
- The reason for doing this is to avoid the correlation of the trees in our forest:

"Suppose there is one very strong feature in the data set. When using bagged trees, most of the trees will use that feature as the top split, resulting in an ensemble of similar trees that are highly correlated"

Random Forests

n	X_1	X_2	X_3	X_4	y
1	a_1	b_1	c_1	d_1	y_1
2	a_2	b_2	c_2	d_2	y_2
3	a_3	b_3	c_3	d_3	y_3
4	a_4	b_4	c_4	d_4	y_4
5	a_5	b_5	c_5	d_5	y_5

Training set

Random subset of features happens at each split!

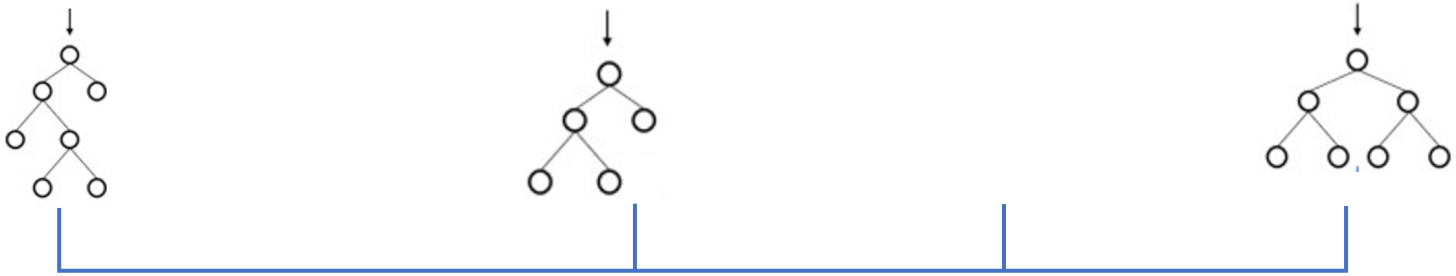
n	X_1	X_4	y
1	a_1	d_1	y_1
1	a_1	d_1	y_1
3	a_3	d_3	y_3
4	a_4	d_4	y_4
3	a_3	d_3	y_3

n	X_2	X_3	y
5	b_5	c_5	y_5
2	b_2	c_2	y_2
3	b_3	c_3	y_3
2	b_2	c_2	y_2
5	b_5	c_5	y_5

....

n	X_1	X_3	y
4	a_4	c_4	y_4
2	a_2	c_2	y_2
3	a_3	c_3	y_3
4	a_4	c_4	y_4
3	a_3	c_3	y_3

Bootstrapping



Ensemble of trees

Aggregation

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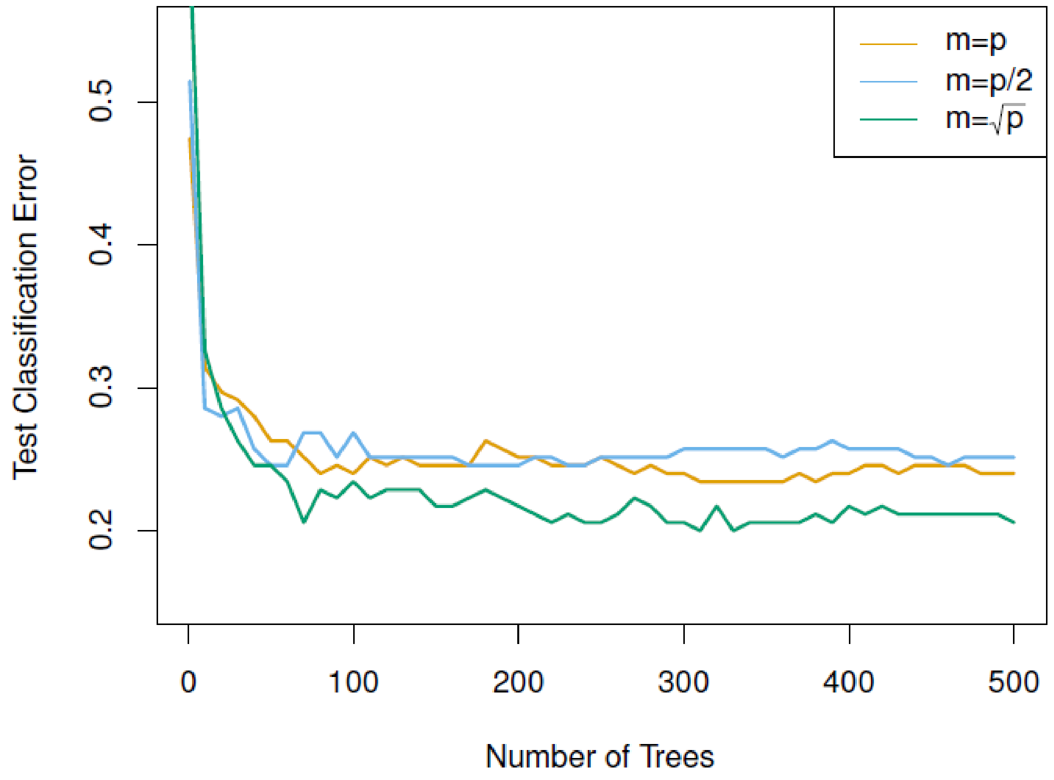
Random Forests vs Bagging

- A random subset $\boldsymbol{m}$, can be any subset of $\boldsymbol{p}$ features like $\frac{p}{2}$ or $\sqrt{p}$ or $\log(p)$ $etc.$



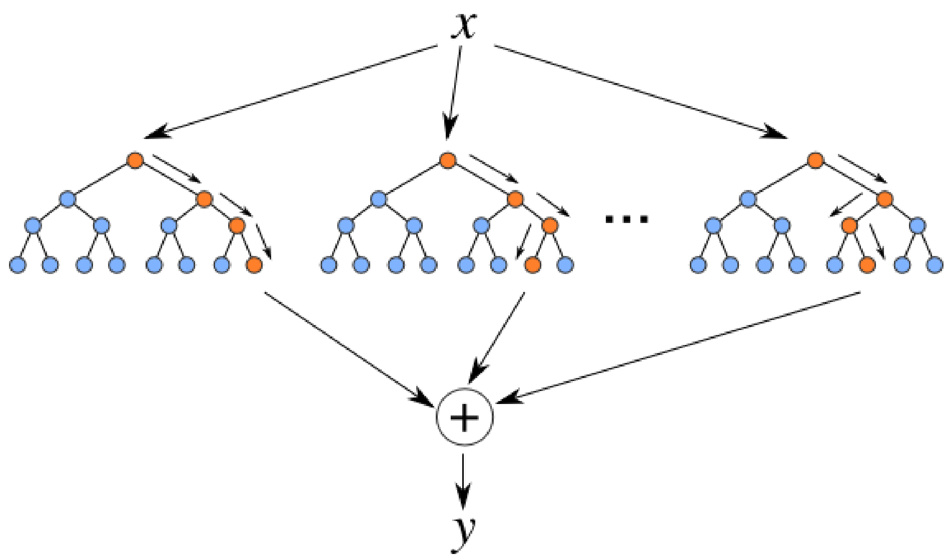
Part III

Hyper parameters

Feature importance

Hyperparameters

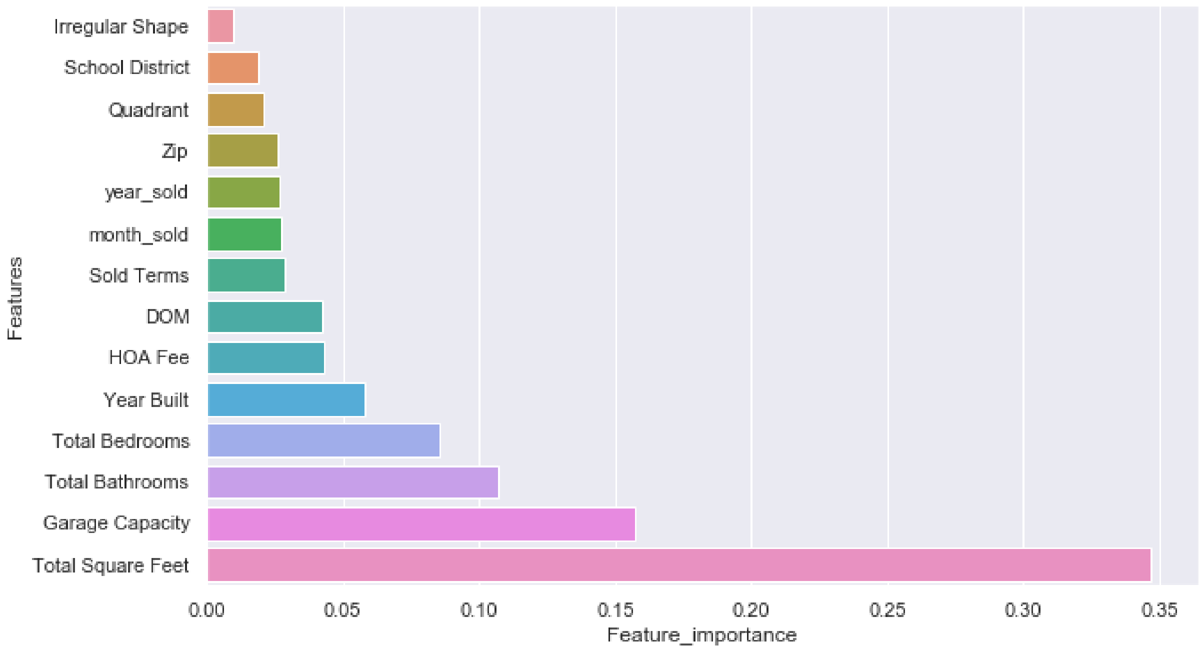
- The most important hyper parameters are:
  - ✓ The number of subset features (m)
  - ✓ The number of trees to use (B)
  - ✓ The minimum size of each node (or leaf)
  - ✓ The maximum number of leaf nodes
  - ✓ The maximum depth of each tree
  - ✓ Criterion: gini, entropy



- Grid search CV could be used to tune a combination of hyper parameters.

Feature importance

- Feature importance refers to techniques that assign a score to input features based on how useful they are at predicting a target variable.
- For RF , the total amount that the RSS is decreased / Gini index or entropy is decreased due to splits over a given predictor, averaged over all *B* trees. A **large** value indicates an **important** predictor.



Part IV

Pros and Cons

Applications in finance

Random Forests’ Pros and Cons

Pros:

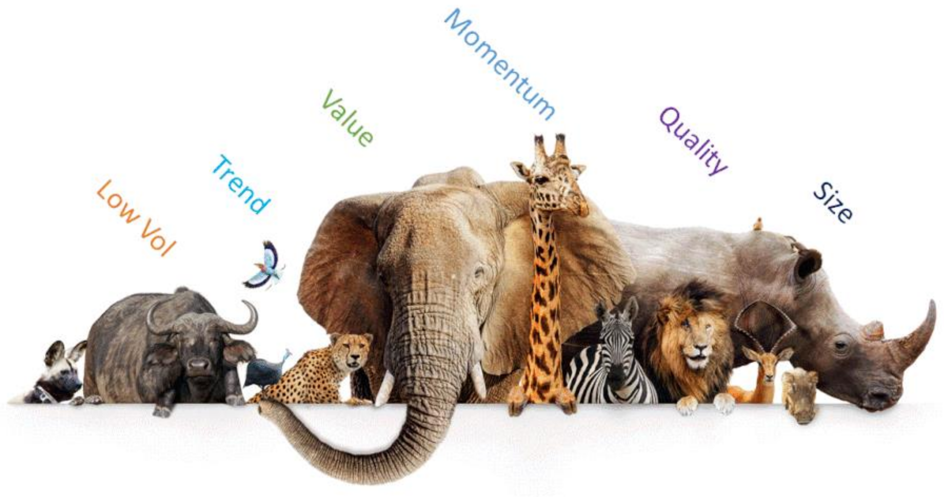
- One of the most widely used ensemble learning algorithms. Because on top of all the advantages of a Decision Tree model (handling categorical data, learning nonlinear patterns, no preprocessing needed, nonparametric), it can:
- Avoid overfitting by reducing the model variance.
- Parallelizable!
- Great with high dimensionality
- Quick training and prediction speed (why?)

Cons:

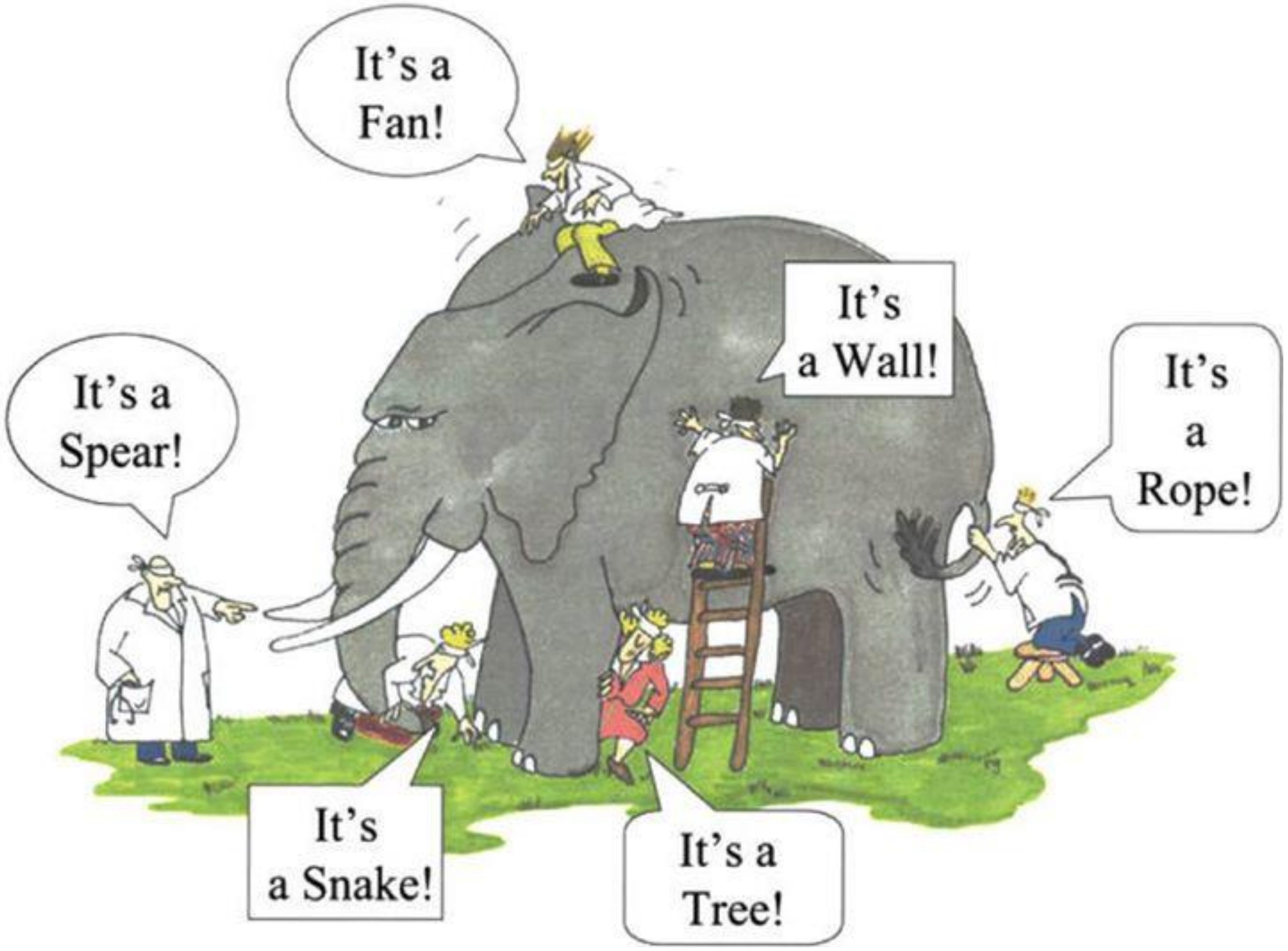
- Lacks the ease of interpretability of individual trees! Relatively black box type of algorithm.
- Can overfit without tuning the hyperparameters.

Random Forests’ Applications in finance

- Factor based investment strategies for asset allocation or investment selection
- Predicting whether an IPO will be successful based on some ranked factors including:
    - Percent oversubscribed,
    - First trading day close price
    - First trading day volume
    - …
- Fundamental factor modeling!
    - P/E, EV/EBITDA, P/S, P/B, …



Question of the day: Wisdom of Crowds



Students’ questions

1. I've heard the term bootstrapping in an econometric context before. Are the two concepts the same?
2. Are random forest trees allowed to be deeper with little cost to over-fitting when compared to decision trees?
3. I didn't really get what the disadvantages of random forest. I also don't really understand what bootstrapping does and how it works.
4. I don't know when you would use decision trees over random forest.
5. I don't get what's meant by a 'weaker learner' that's being applied to the copies of the training data.
6. When making a random forest, does the code make ALL possible decision trees with the data? If not, how do we decide which, and if yes, would that not take too long with large data sets?
7. Do we set the number of nodes for the tree or is this truly a "black box" that we just look at the output?
8. Is bootstrapping attempting to accomplish the same thing as splitting the data into test sets?