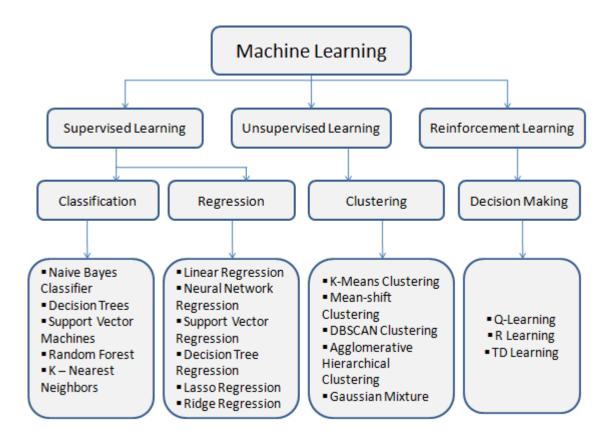
## Al Algorithms – 1: Intro to Al Algorithms

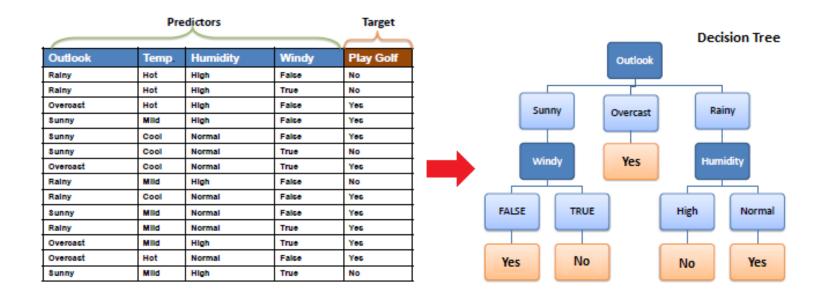
- Sayed Ahmed
- PhD Studies in Electrical and Computer Eng. (McMaster University) (Partially Complete)
- Master of Engineering in Electrical and Computer Engineering (McMaster University)
- MSc in Data Science and Analytics (Toronto Metropolitan University/Ryerson)
- MSc in Computer Science (U of Manitoba)
- BSc. Engineering in Computer Science and Engineering (BUET)
- Extensive experience in Software Development and Engineering (primarily in Canada)
- · Significant experience in Teaching
- Taught in Universities, Colleges, and Training Institutes

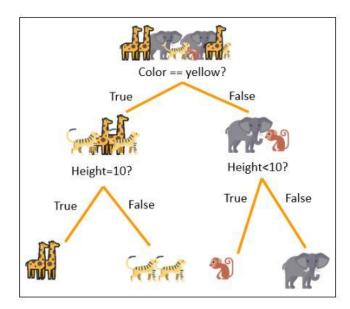


## Machine Learning Algorithms

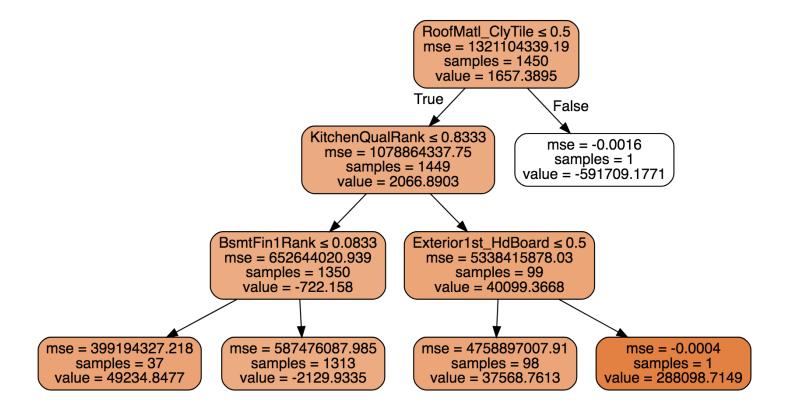


#### Decision Tree and Classification

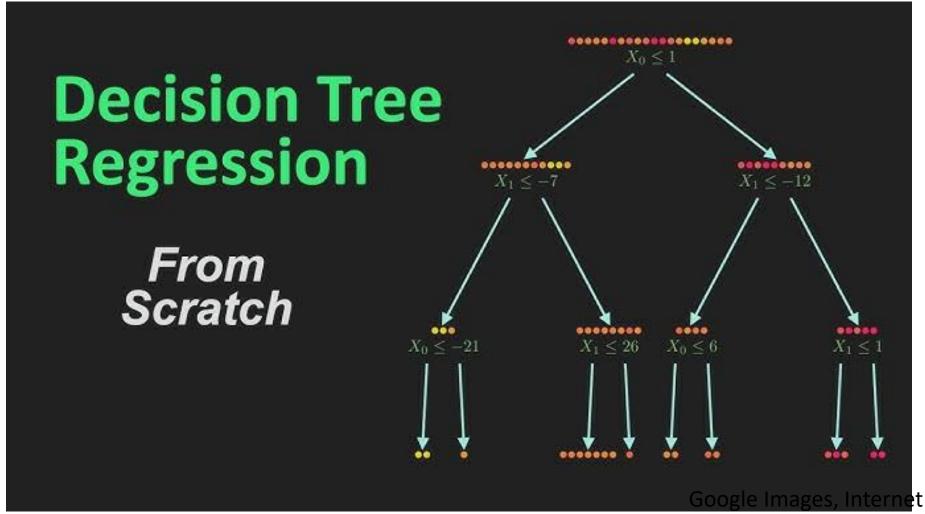




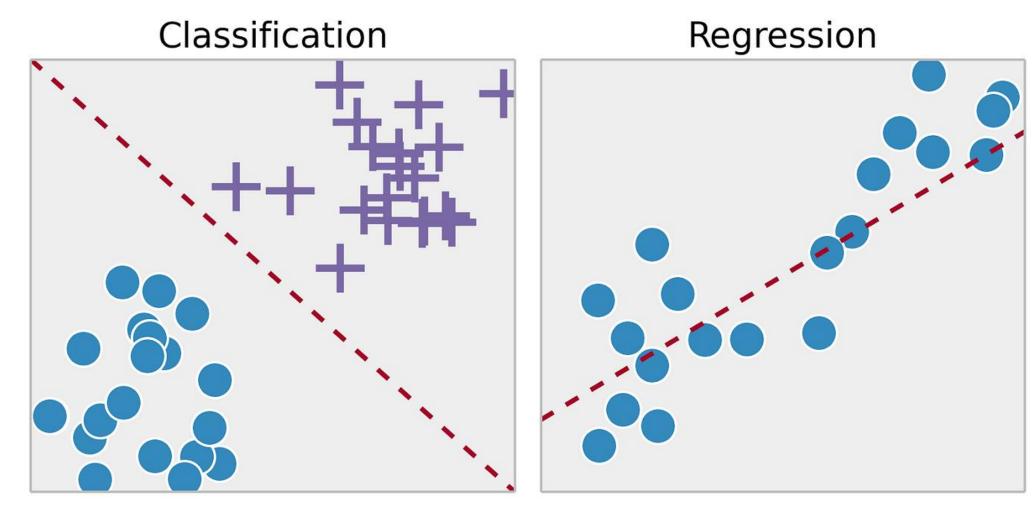
#### Decision Tree and Regression



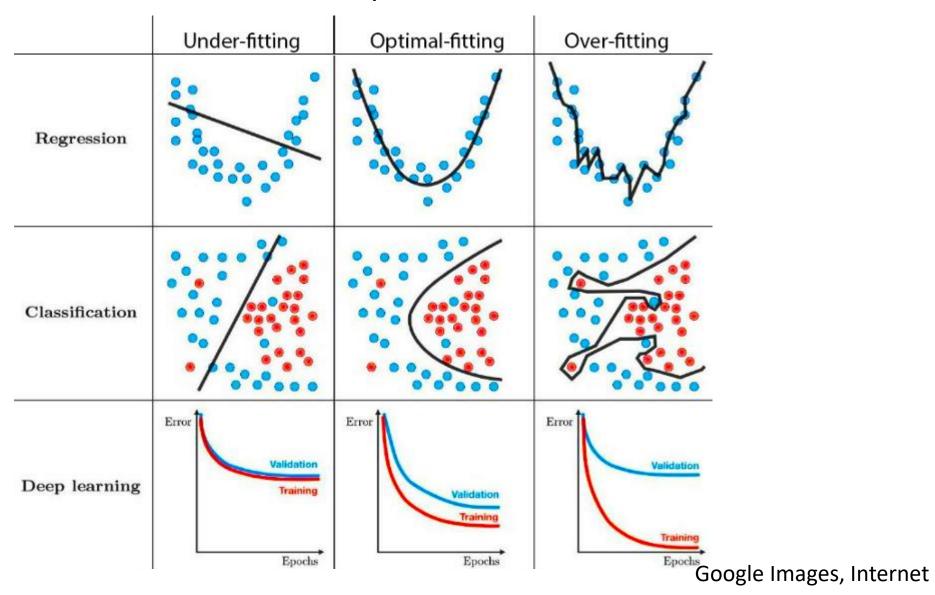
#### Regression and Decision Trees



## Supervised Learning



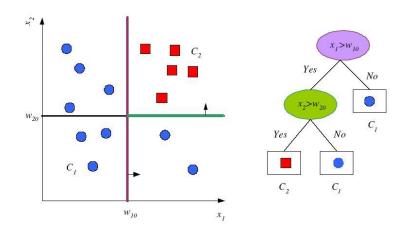
#### Underfit, Overfit, Optimal Fit



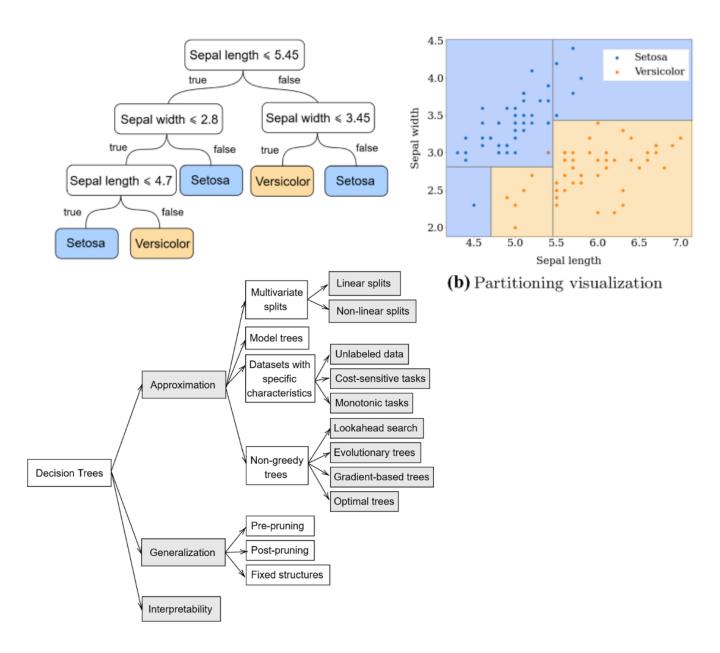
## Decision Tree Approaches



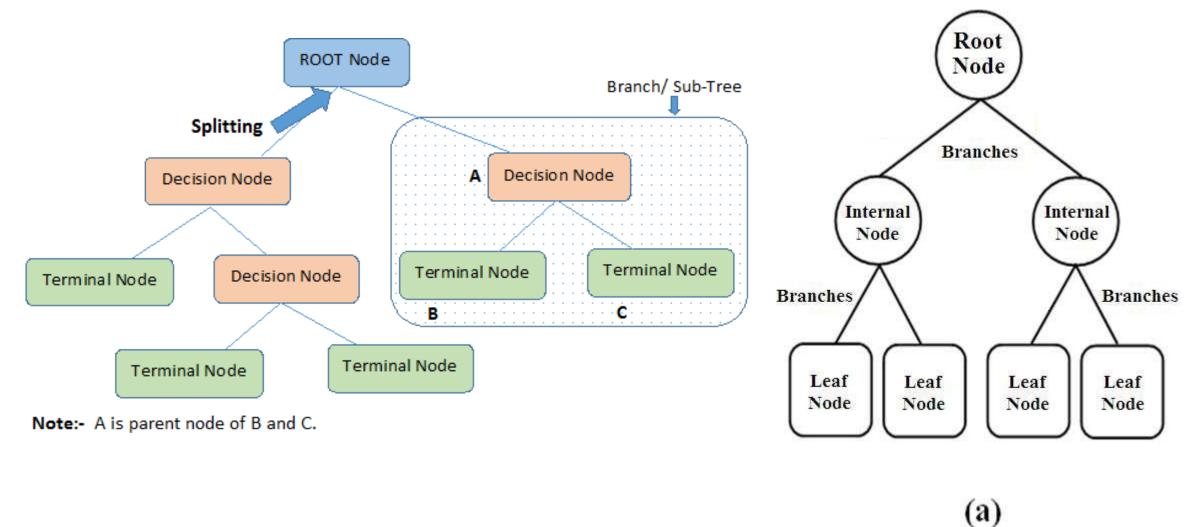
#### Tree Uses Nodes, and Leaves



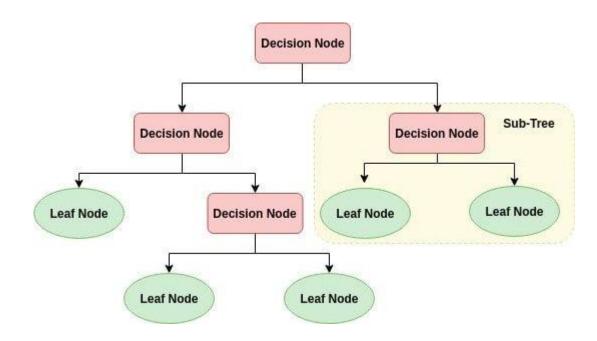
Lecture Notes for E Alpaydin 2004 Introduction to Machine Learning © The MIT Press (V1.1)



#### Decision Tree, Node Types



## Node Types



#### Pros and Cons: Decision Trees

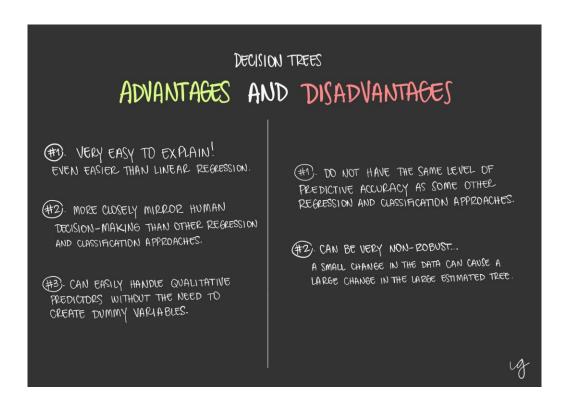
#### Decision Tree Pros and Cons

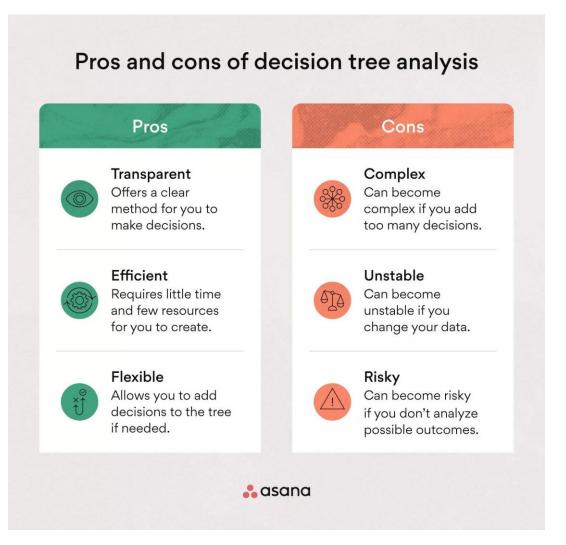
#### Pros

- No data assumptions
- Non-linear
- Discontinuous

#### Cons

- No extrapolation
- Need substantial amount of data
- Not descriptive

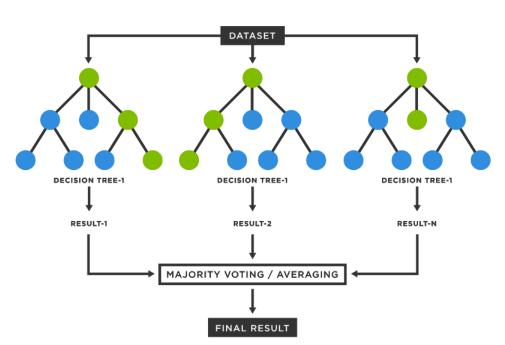


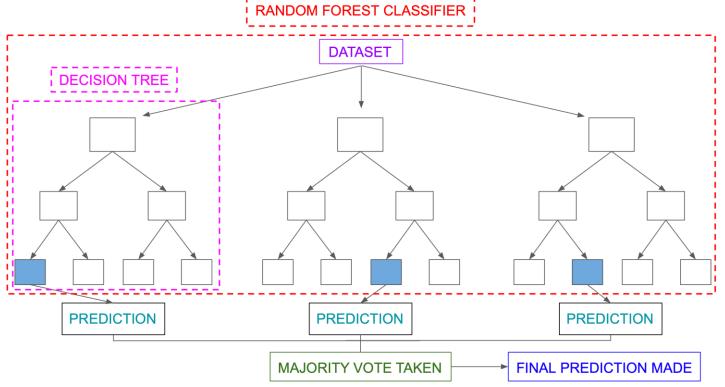


#### Decision Trees vs Random Forest

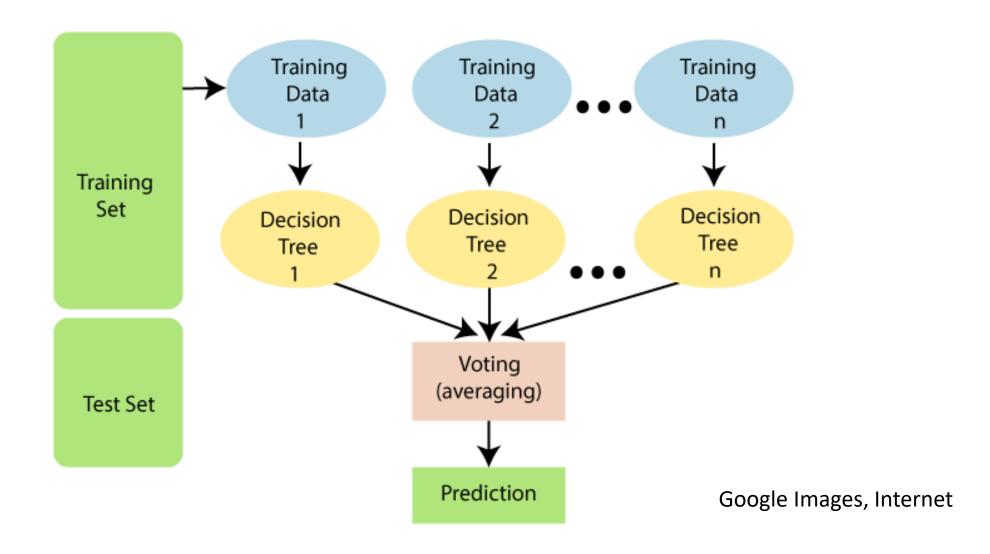
	Decision Tree	Random Forest	
Interpretability	Easy to interpret	Hard to interpret	
Accuracy	Accuracy can vary	Highly accurate	
Overfitting	Likely to overfit data	Unlikely to overfit data	
Outliers	Can be highly affected by outliers	Robust against outliers	
Computation	Quick to build	Slow to build (computationally intensive)	

#### Random Forest

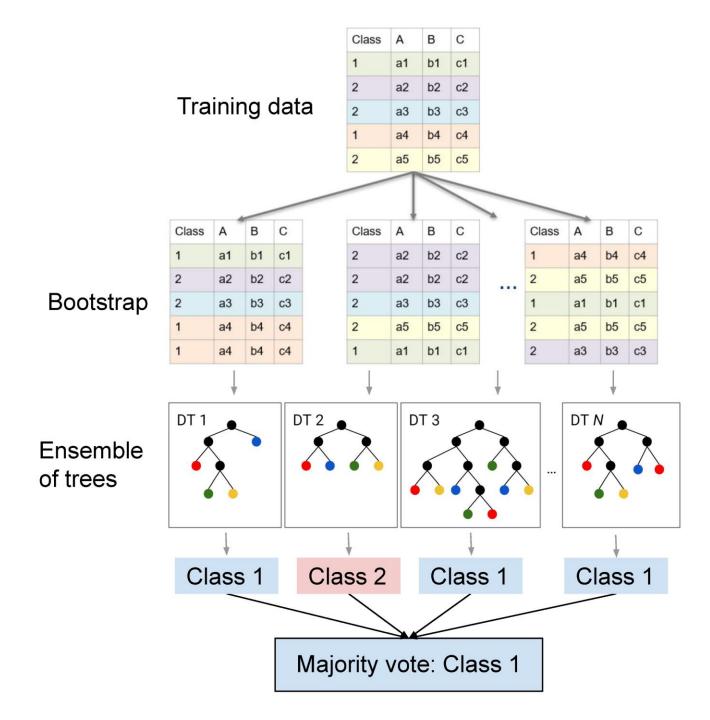




#### Random Forest



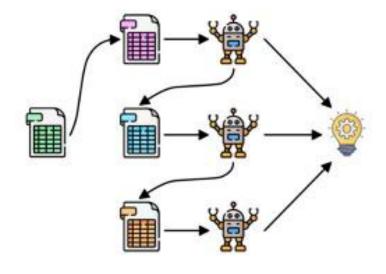
#### Random Forest



#### Random Forest Algorithms

# Bagging Parallel

## Boosting

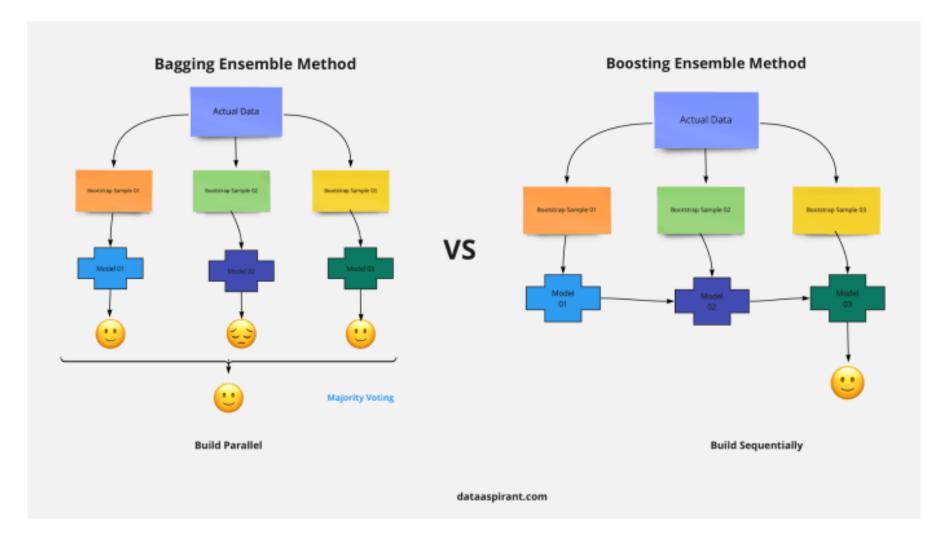


Sequential

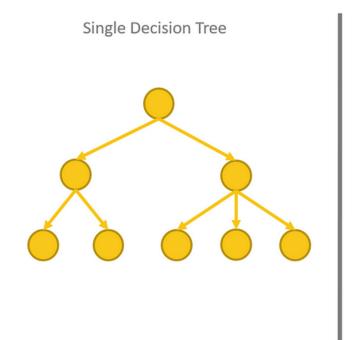
## Bagging, Boosting, Stacking

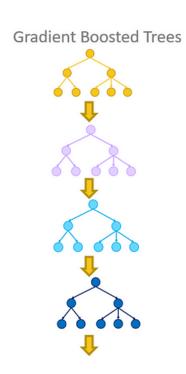
	Bagging	Boosting	Stacking
Purpose	Reduce Variance	Reduce Bias	Improve Accuracy
Base Learner Types	Homogeneous	Homogeneous	Heterogeneous
Base Learner Training	Parallel	Sequential	Meta Model
Aggregation	Max Voting, Averaging	Weighted Averaging	Weighted Averaging

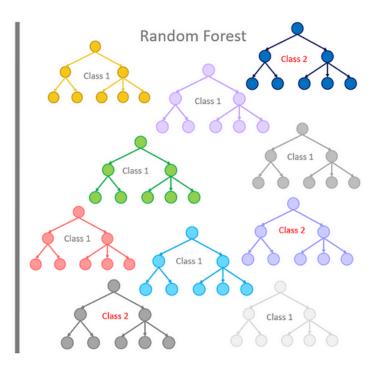
#### Ensemble Methods



#### **Gradient Boosted Trees**



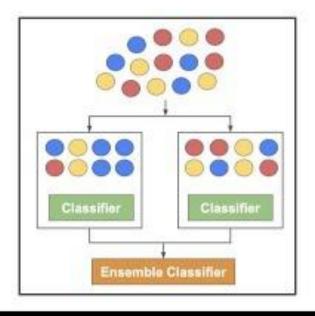


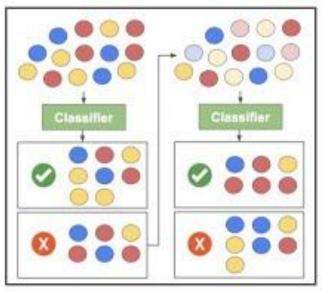


#### Bagging vs Boosting

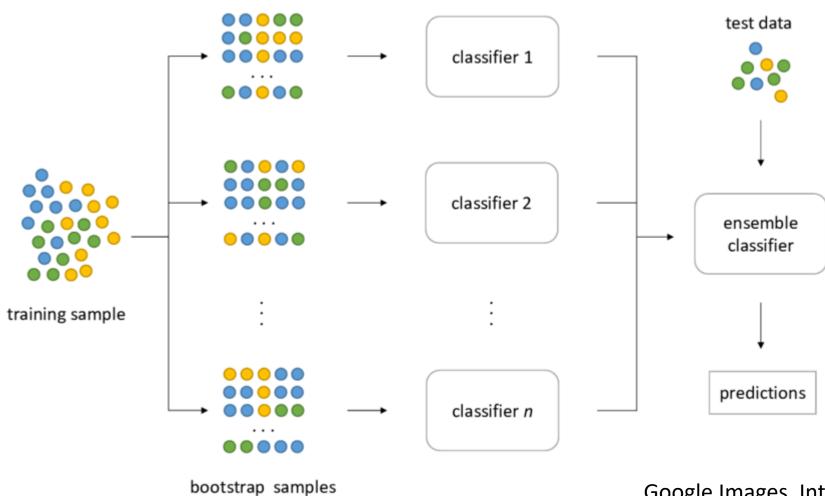
## **Bagging vs Boosting**







#### Bootstrapping

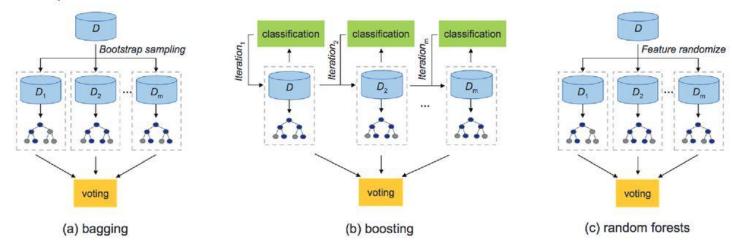


#### Ensemble Learning

#### **Ensemble learning**

Aggregating a group of classifiers ("base classifiers") as an ensemble committee and making the prediction by consensus.

Weak learner ensembles (each base learner has high EPE, but is easy to train):

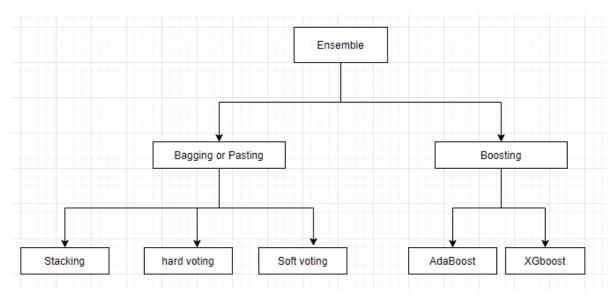


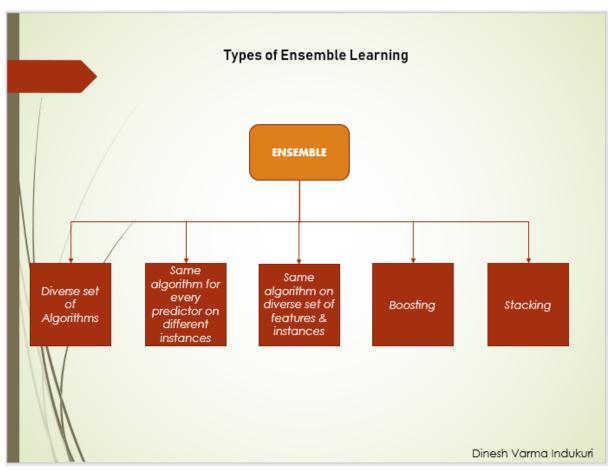
Google Images, Internet

Fig. 1: Schematic illustration of the three popular ensemble methods.

Current Bioinformatics, 5, (4):296-308, 2010.

#### Types of Ensemble Learning





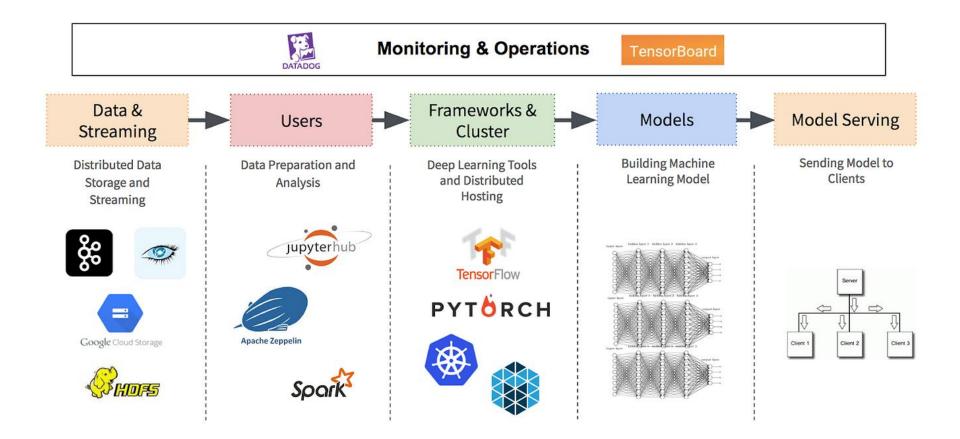
#### Machine Learning Frameworks





#### Machine Learning Frameworks

#### Deep Learning Pipeline



#### Machine Learning Frameworks

