

Pattern Classification and Recognition:

# Ensemble Learning

ECE 681

Spring 2016

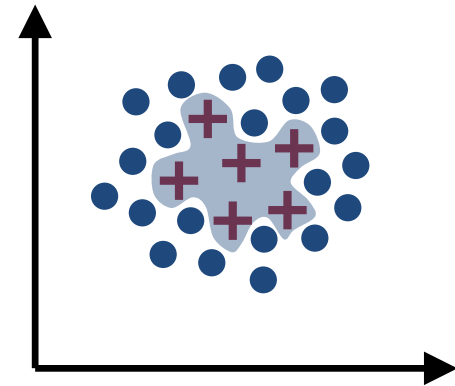
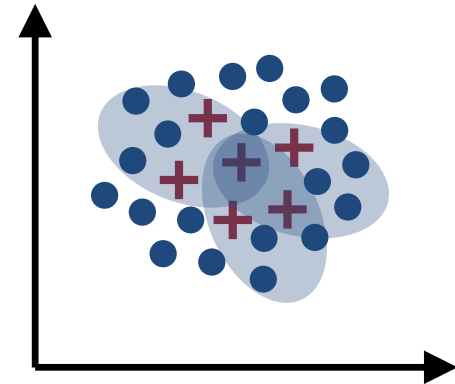
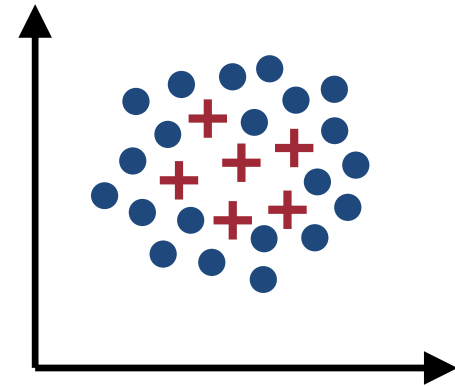
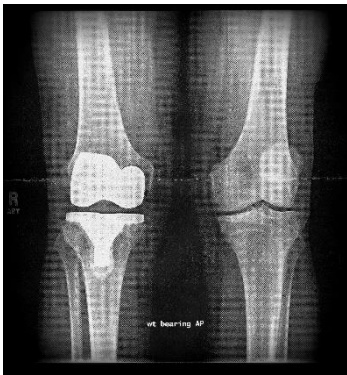
Stacy Tatum, Ph.D.

# Committees

“A camel is a horse designed by a committee.”



# Decisions by Committee

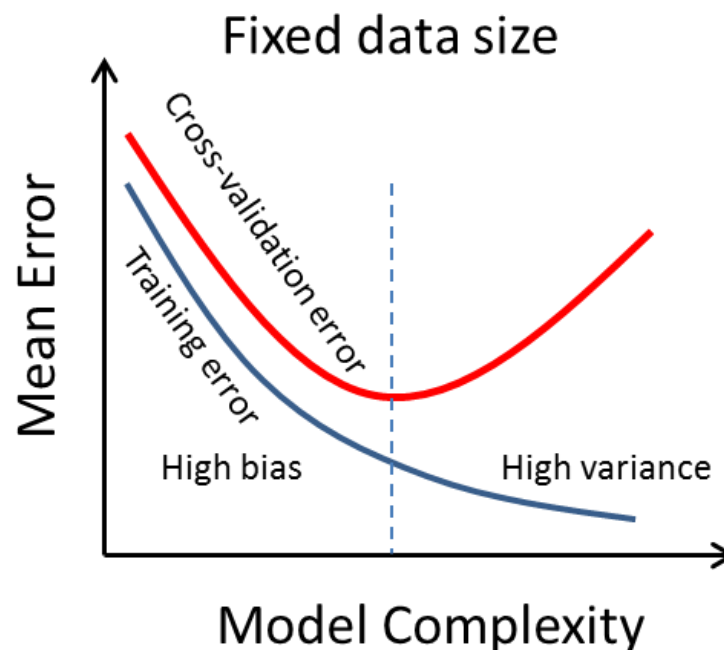


Which classifiers?  
How to make complementary?  
How to combine?

# Generalization Error

A lingering question...

- How to ensure performance on the training set fairly (accurately?) predicts performance on a test set?
- Average/ expected difference between training set and testing set performance



→ Ensemble learning, or committee machines

# Classifier (In)Stability

## UNSTABLE CLASSIFIERS

Small changes in data set  
→ major changes in classifier

High variance (from overfitting)

Low bias

Neural networks, Decision trees

## STABLE CLASSIFIERS

Small changes in data set  
→ small changes in data set

Low variance

(Possibly) high bias  
(from underfitting)

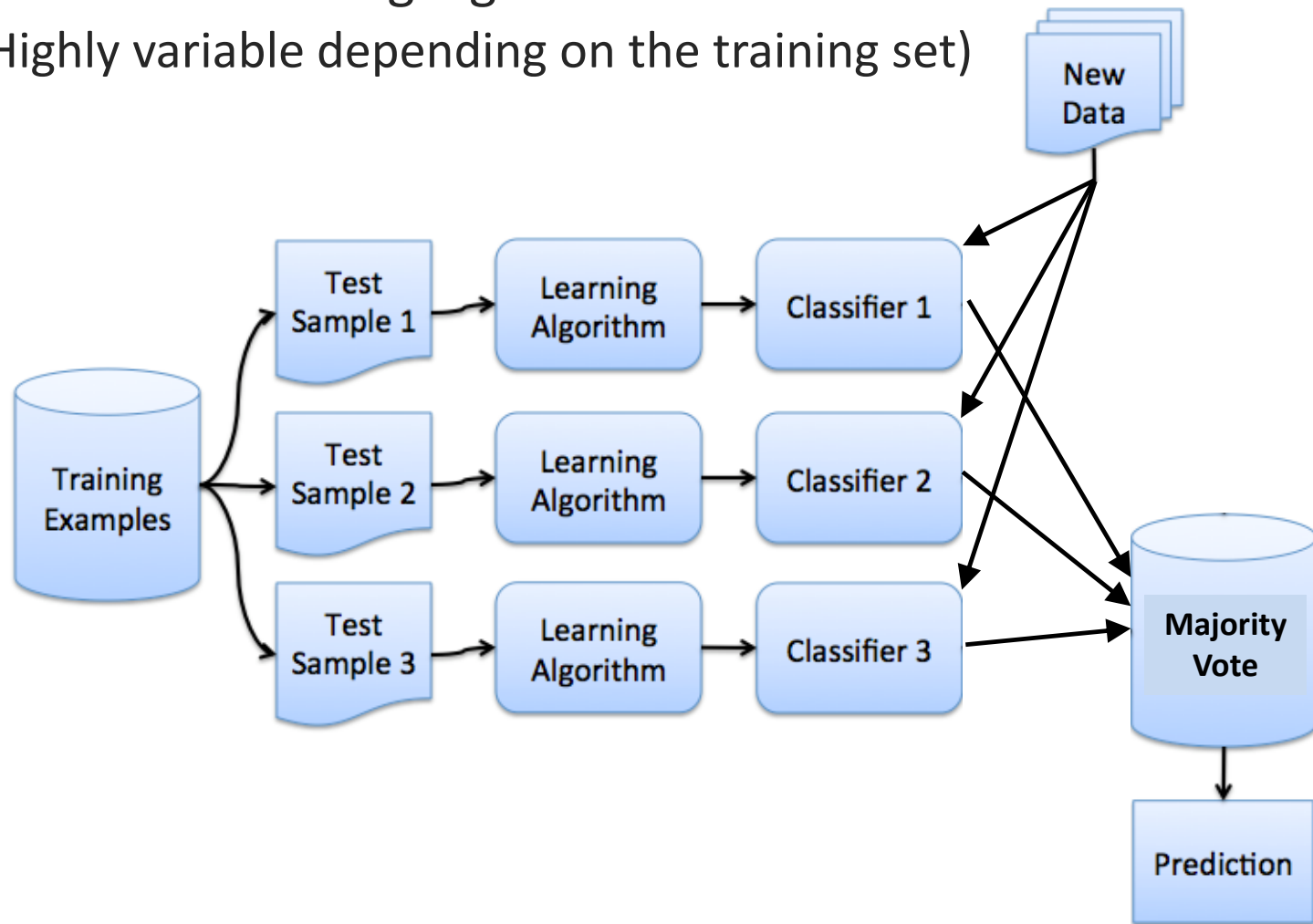
Linear discriminant analysis

Exploit classifier instability to create a diverse set of classifiers  
using subsets of the data

# Bagging (Bootstrap Aggregating)

Useful if the learning algorithm is unstable

- (Highly variable depending on the training set)



# Boosting

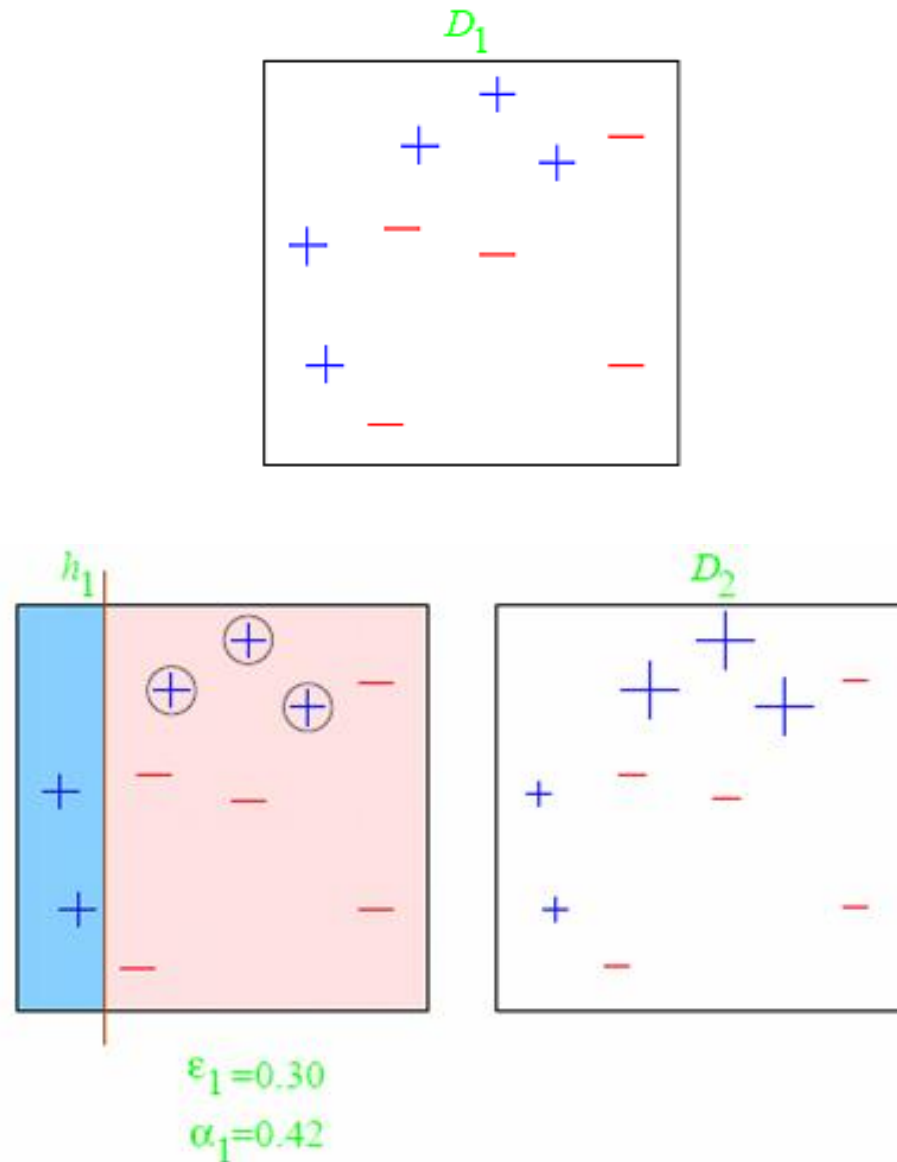
Useful if the learning algorithm is complex and unstable

- Highly variable depending on the training set

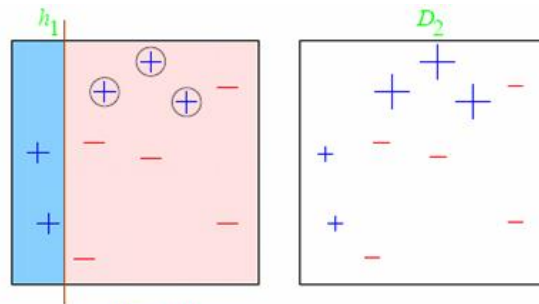
Combine weak classifiers to create a strong classifier

AdaBoost (adaptive boosting)

- Upweight training previously incorrectly classified training samples

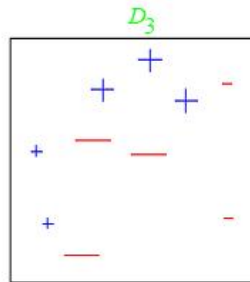
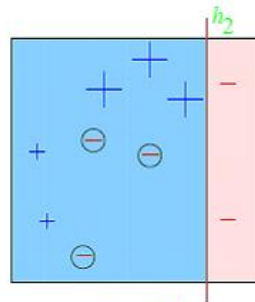
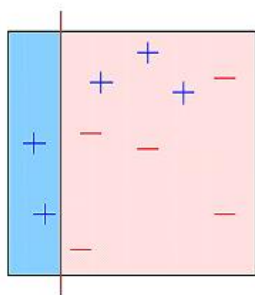


# Boosting



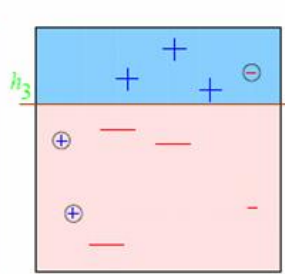
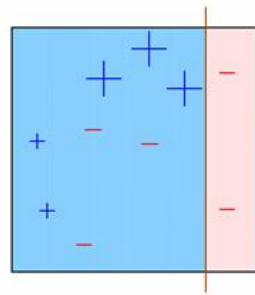
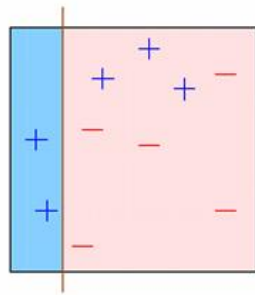
$$\epsilon_1=0.30$$

$$\alpha_1=0.42$$



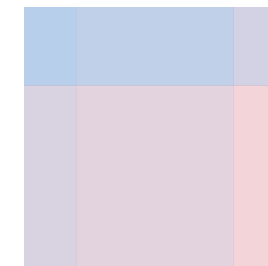
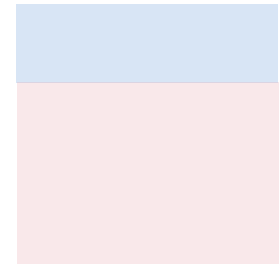
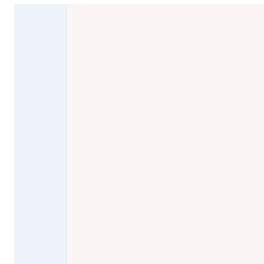
$$\epsilon_2=0.21$$

$$\alpha_2=0.65$$



$$\epsilon_3=0.14$$

$$\alpha_3=0.92$$





# Bagging vs. Boosting

## BAGGING

Different data samples for each classifier

Majority vote

## BOOSTING

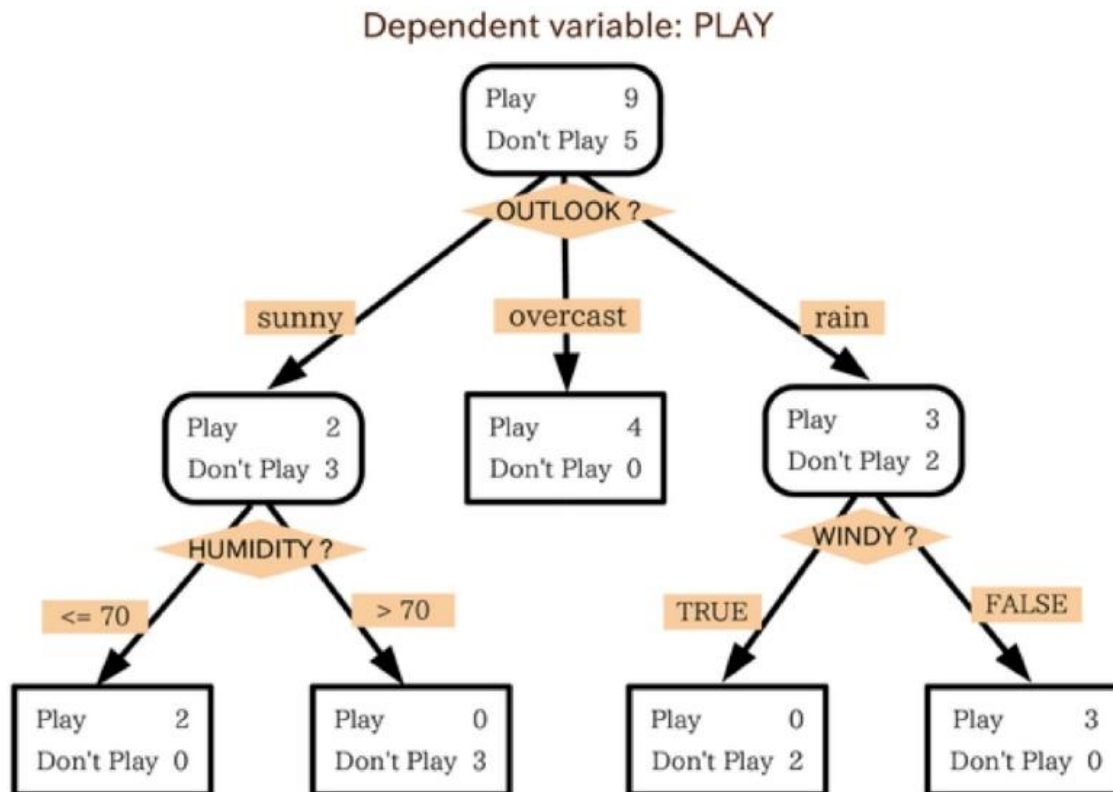
Different weighting of data for each classifier

Weighted vote

# Classification Trees

Sequence of (typically binary) decisions

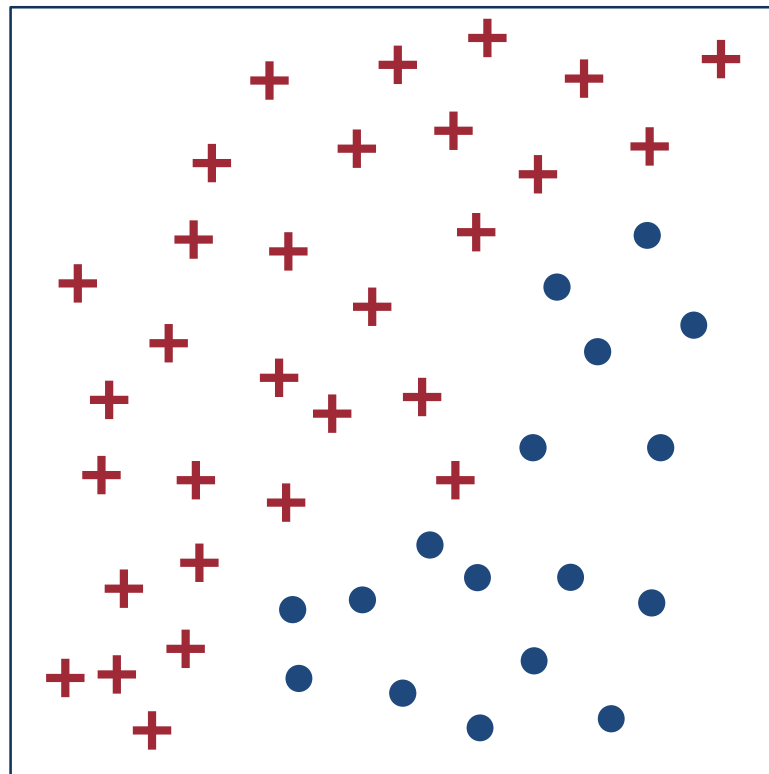
Continue until all data in the *terminal node* are a single class



# Classification Trees

Sequence of (typically binary) decisions

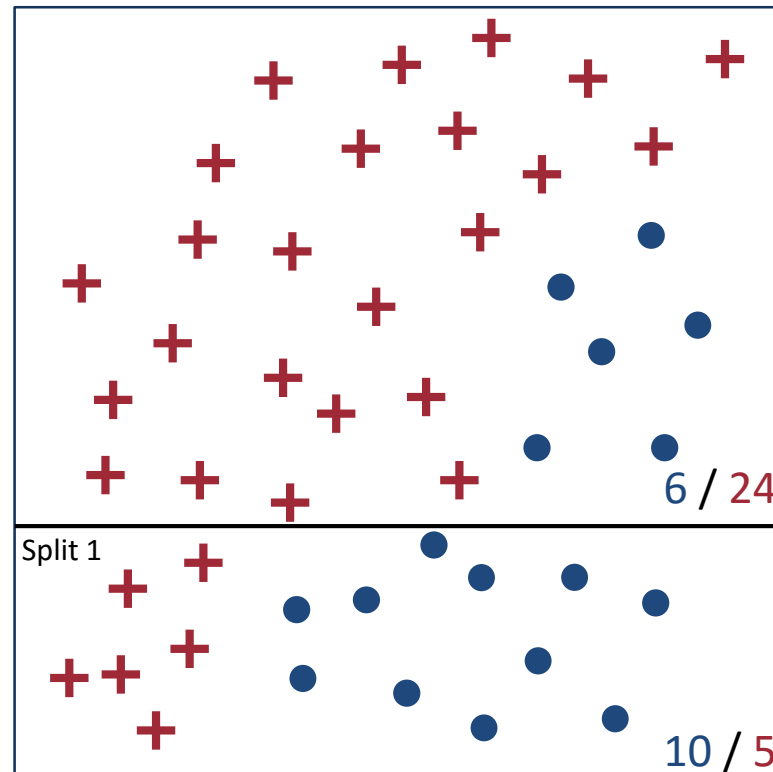
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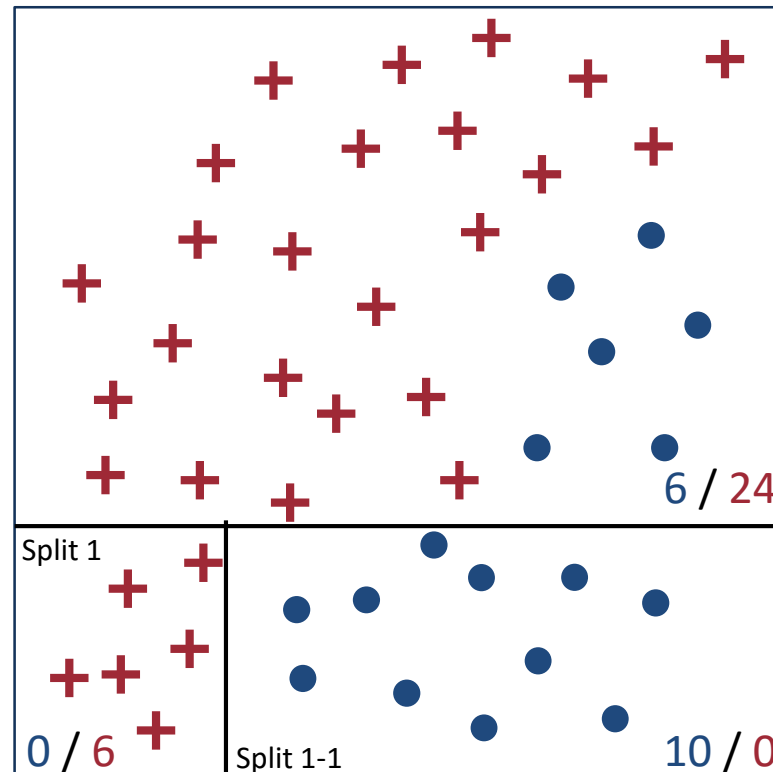
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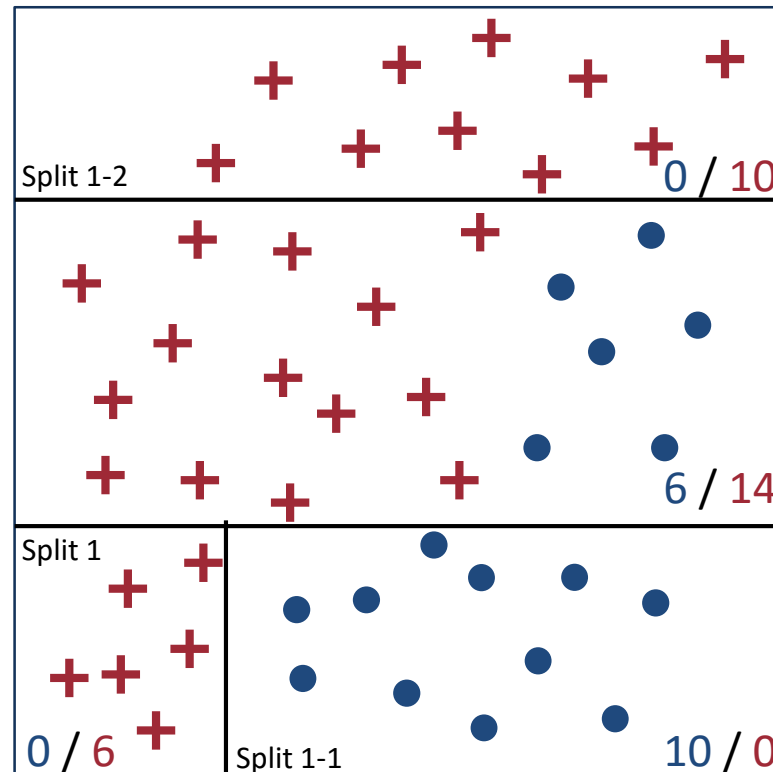
Continue until all data points in the *terminal node* are a single class



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Sequence of (typically binary) decisions

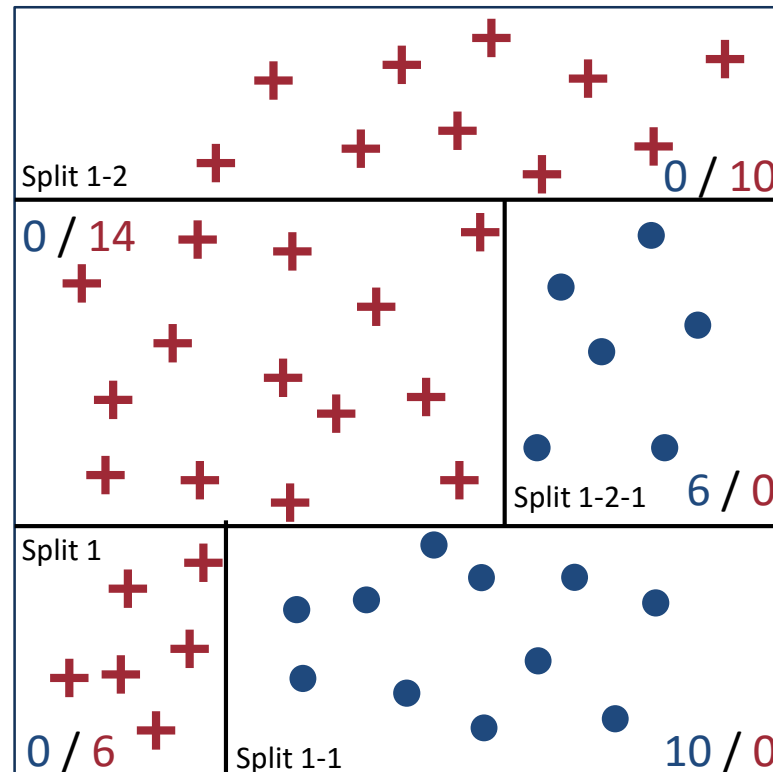
Continue until all data points in the *terminal node* are a single class



# Classification Trees

Sequence of (typically binary) decisions

Continue until all data points in the *terminal node* are a single class

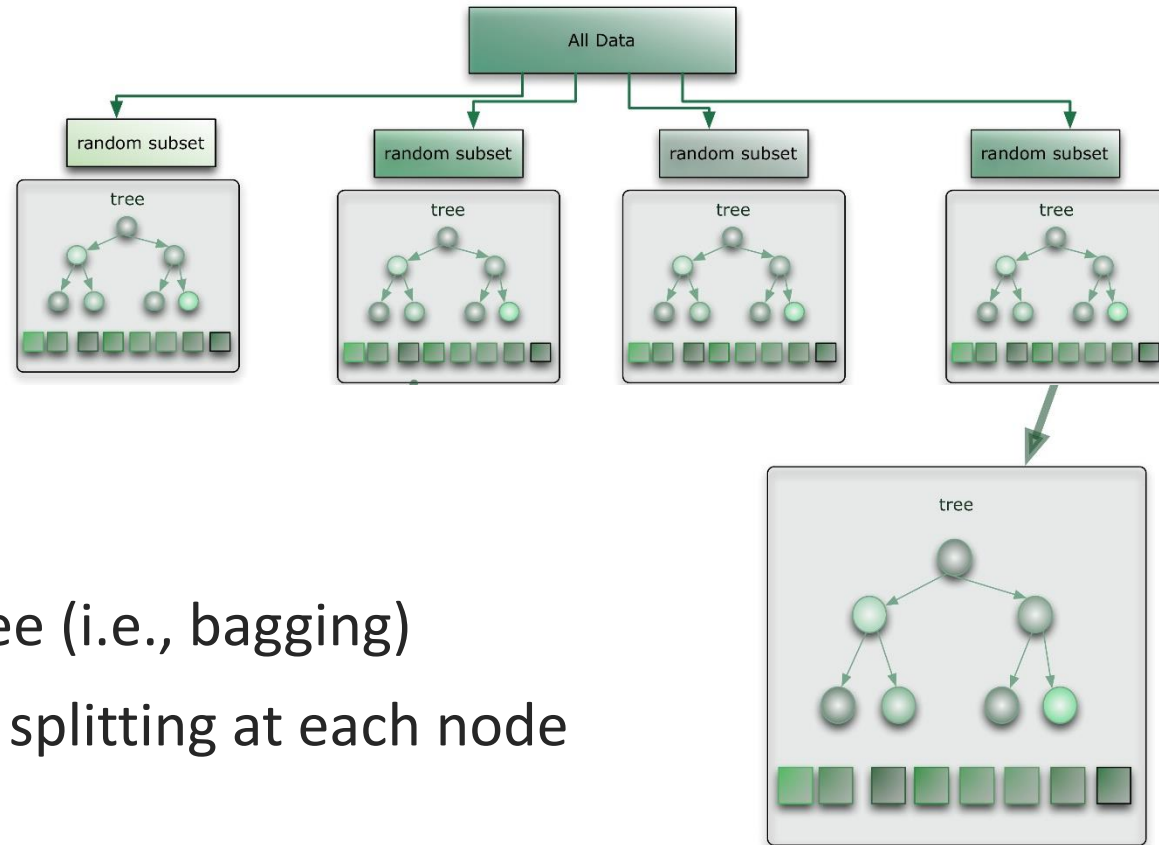


# Random Forests

## Collection of random trees

At each node:

choose some small subset of variables at random  
find a variable (and a value for that variable) which optimizes the split



## Randomize:

- Data used for each tree (i.e., bagging)
- Features available for splitting at each node