CS109 – Data Science

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Announcements

- HW2 is due today!
- Please execute your notebooks, but without test output.

- Help with lecture material

Books

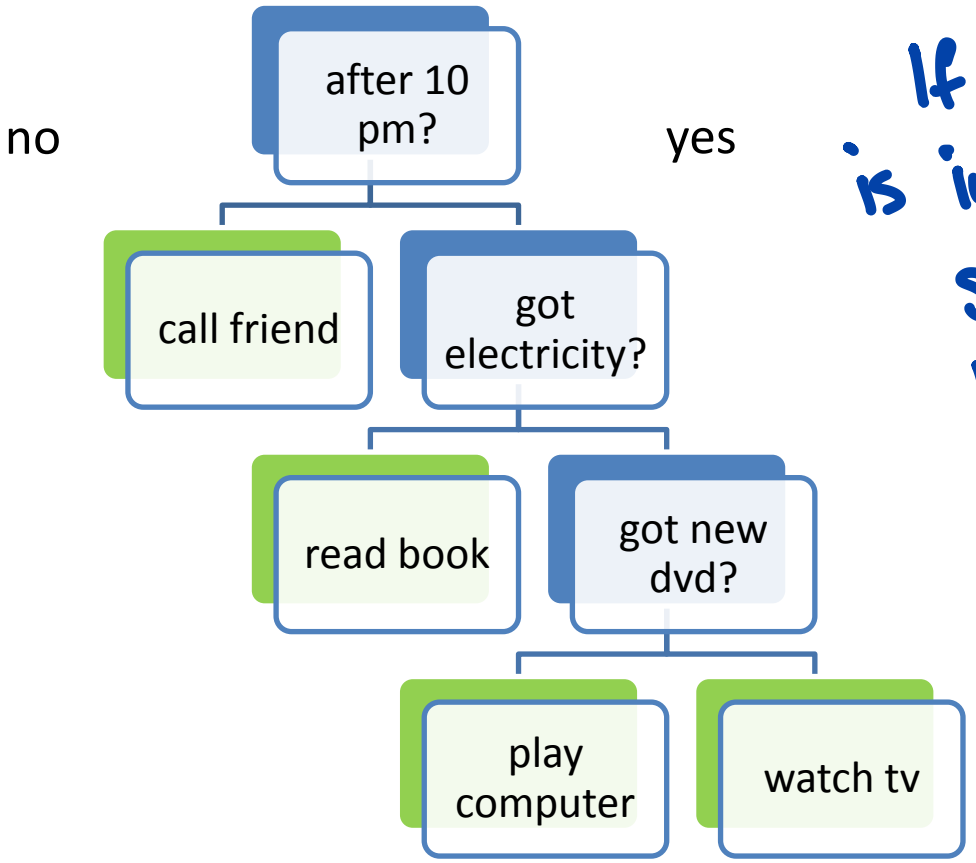
- “Elements of Statistical Learning”
- http://statweb.stanford.edu/~tibs/ElemStatLearn/

- “Pattern Recognition and Machine Learning”
- http://research.microsoft.com/en-us/um/people/cmbishop/PRML/

Next Topics

- Tree classifier
- Bagging
- Random Forest

Decision Tree



If small, it is interpretable.

Simple.

Intuitive.

Do not the case with support vector machines (SVM)

Decision Trees

Not predictive.

- Fast training
- Fast prediciton

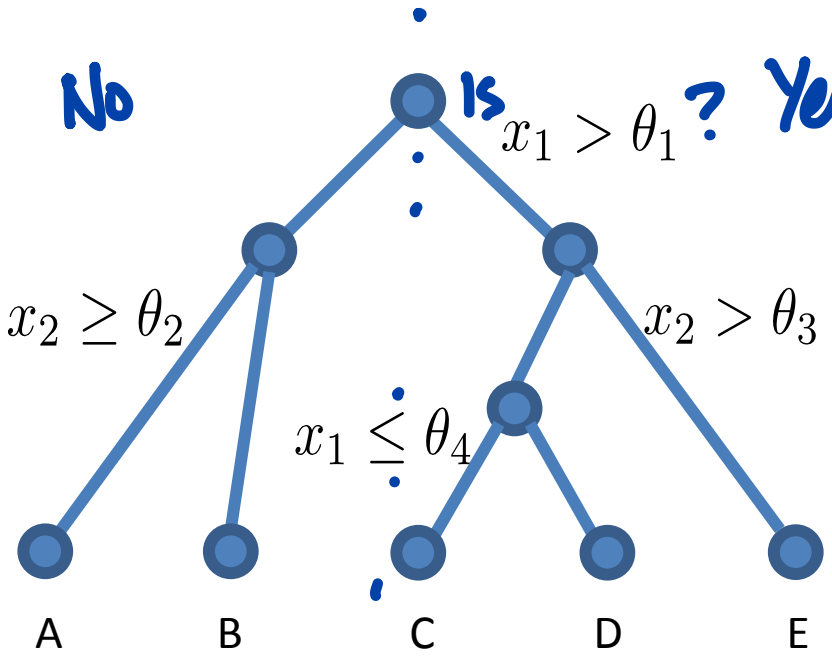
leads to

- Easy to understand
- Easy to interpret

http://en.akinator.com/personnages/jeu

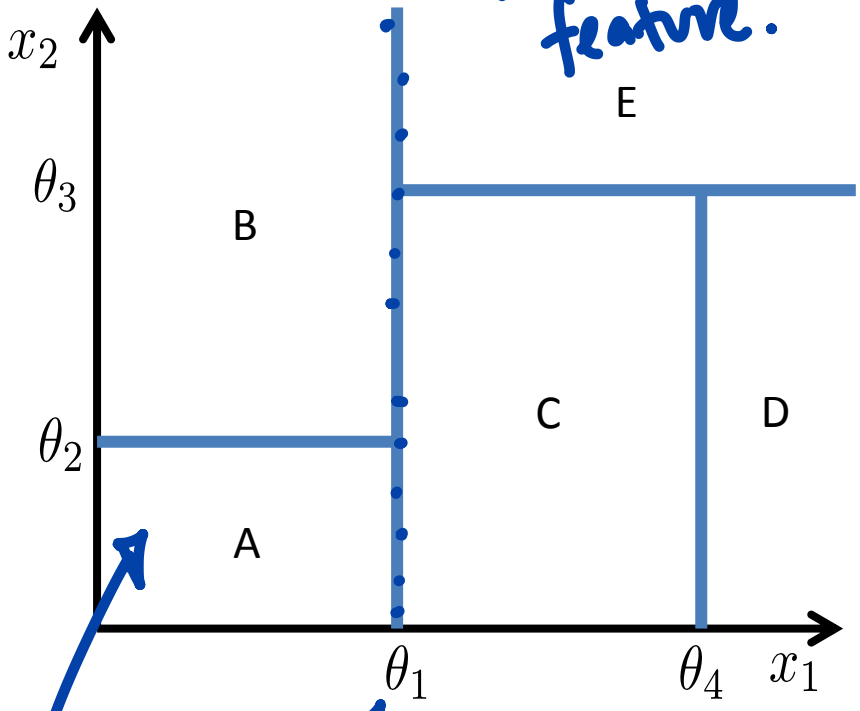
Decision Tree - Idea

Log single decision rules.



• Uses thresholds.

straight lines from 1 feature.



Cells / Classes

Splits in half.

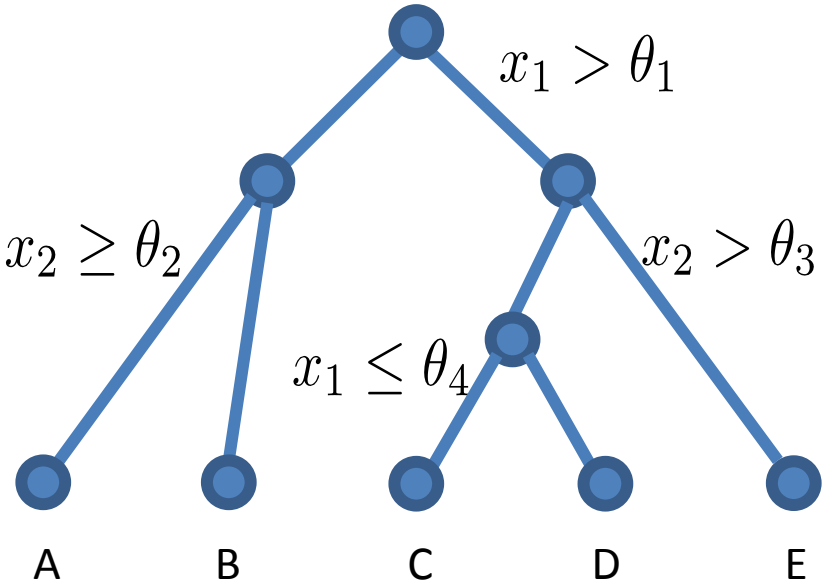
Bishop, "Pattern Recognition and Machine Learning", Springer, 2006

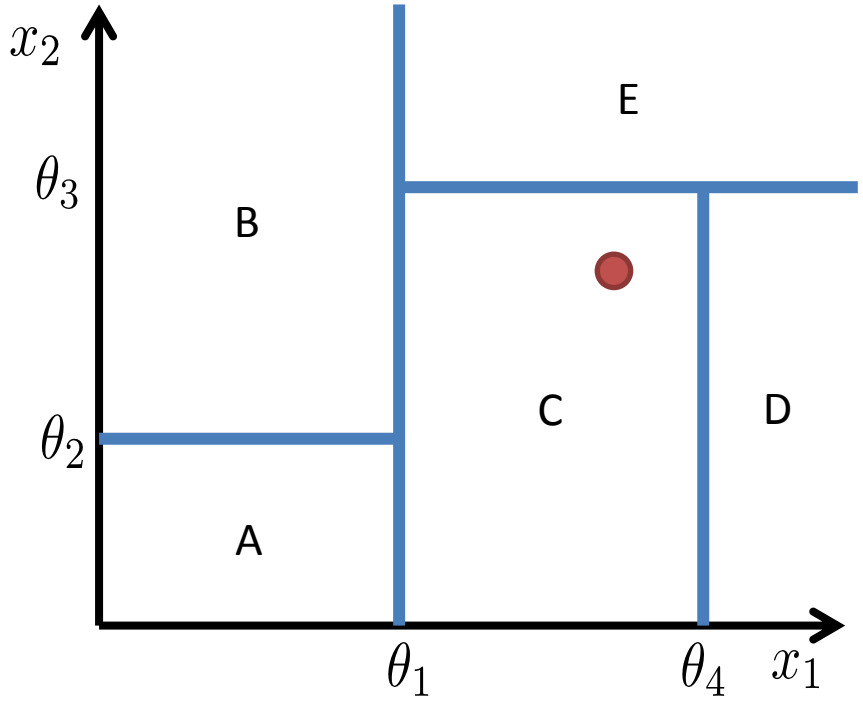
Decision Tree - Idea

- What is a the benefit of using only one feature at a time? Fast performance. Only need to look @ 1 feature. Binary search w/ lots of splits. Also interpretable. Sequential process w/ categorys.
- What is the drawback? Straight lines, would need to have a lot of splits → big tree

↓
SVM requires # conversion

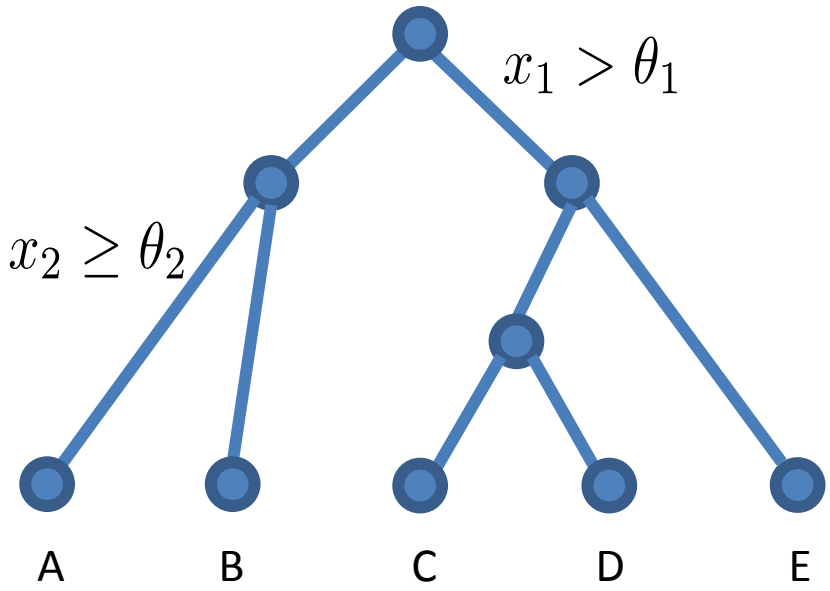
Decision Tree - Prediction



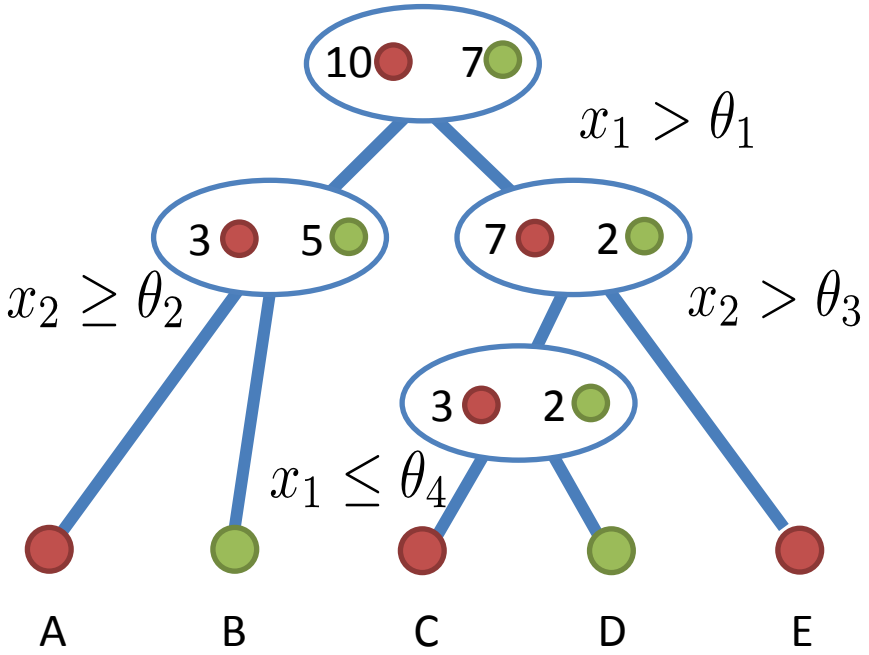


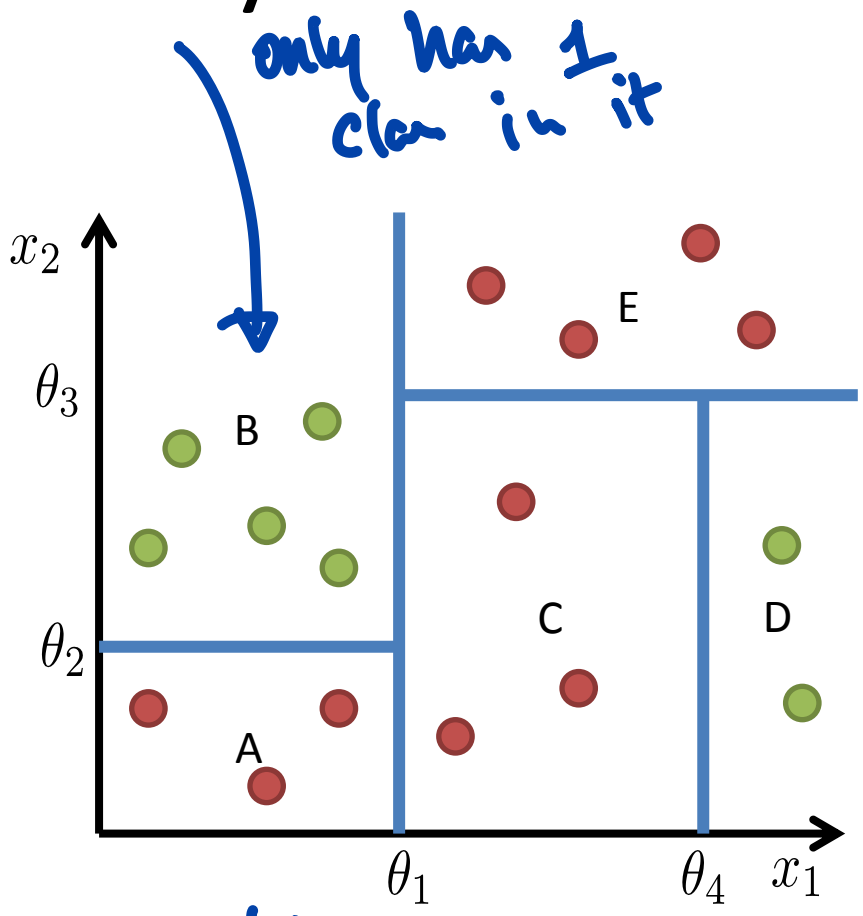
Decision Tree -Training

- Learn the tree structure:
  - which feature to query x_1, x_2
  - which threshold to choose θ_1, θ_2



Node Purity

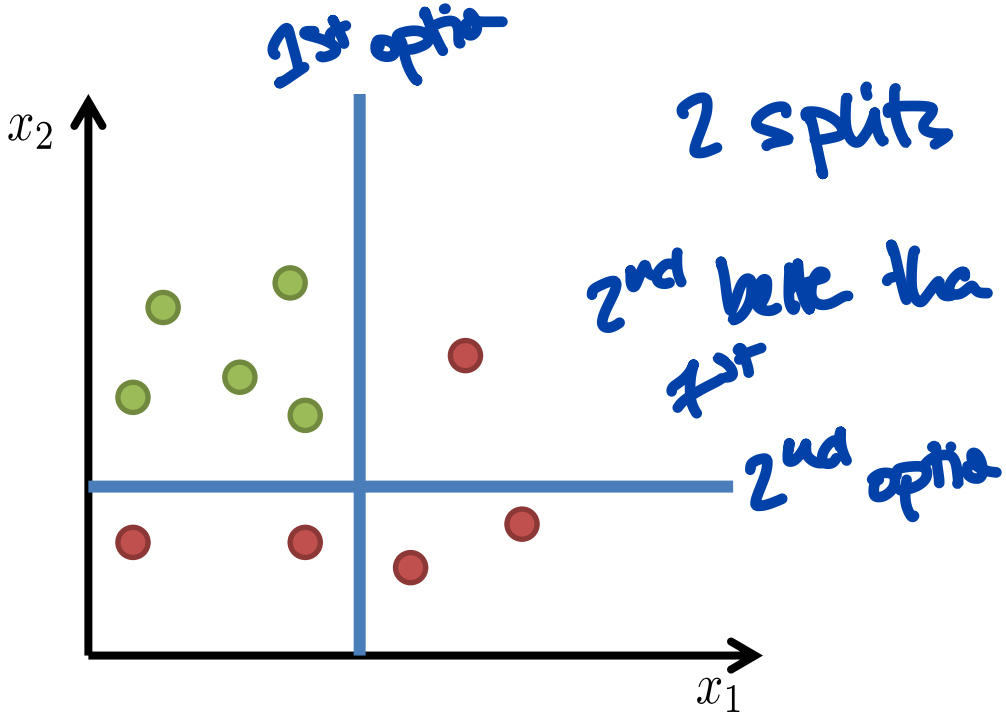




Extreme would be a cell/class for each node

Gini Impurity (default in sklearn)

- Expected error
- if you randomly choose a sample
- and predict the class of the entire node based on it.



Gini Impurity

Example:

4 **red**, 3 **green**, 3 **blue** data points

- Class probabilities:
  - red: 4/10 green: 3/10 blue: 3/10
- misclassification:
  - red: 4/10 * (3/10 + 3/10)

Picking red

Making an error

Gini Impurity

- misclassification:
  - **red**:

    4/10 * (3/10 + 3/10) = 0.24

  - **green** and **blue**:

    3/10 * (4/10 + 3/10) = 0.21

- gini impurity: **0.24** + **0.21** + **0.21** = 0.66

Gini Impurity

- Number of classes: C
- Number of data points: N
- Number of data points of class i: N_i

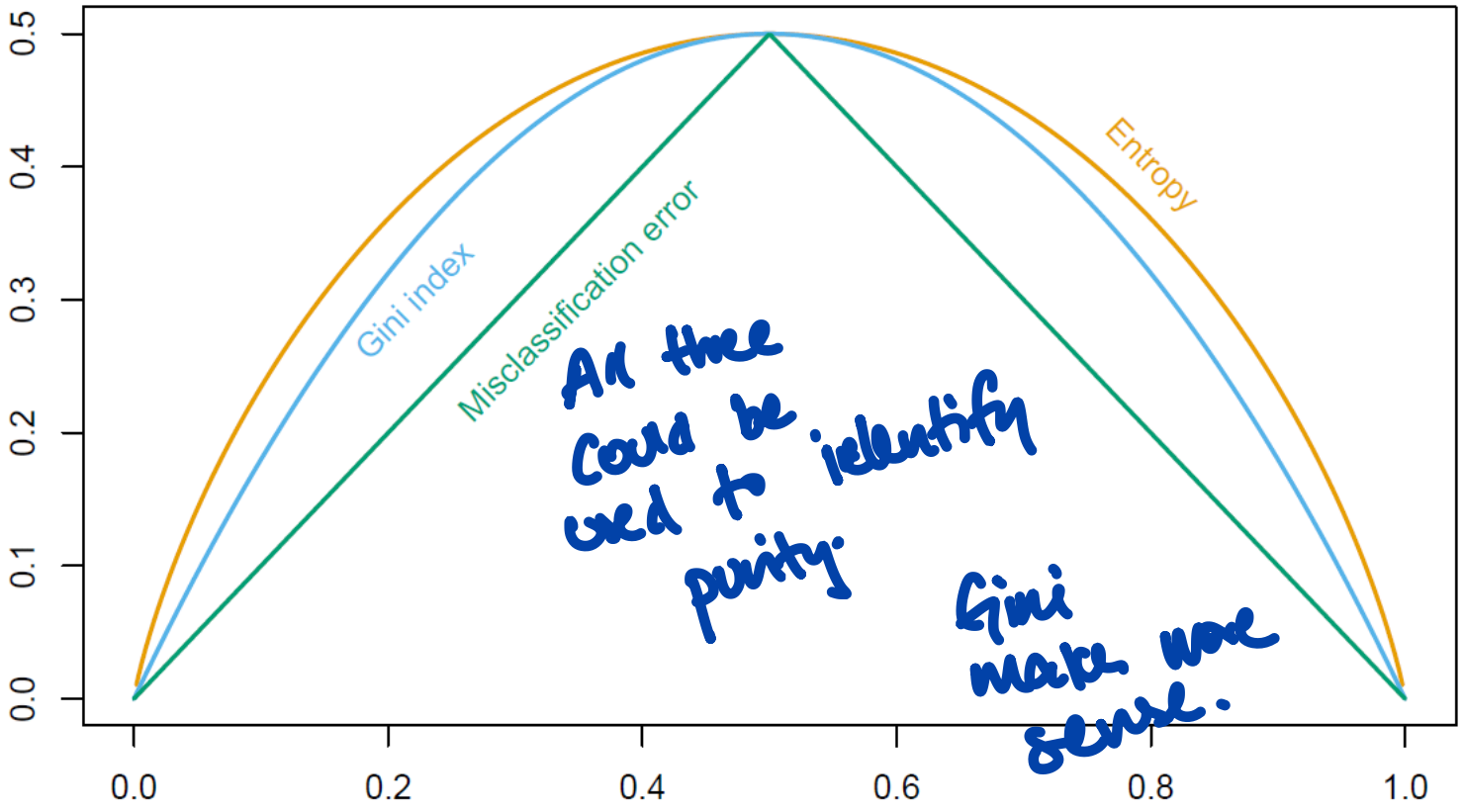
red, green, blue from above.

$$I_G = \sum_{i=1}^{C} \frac{N_i}{N} \left(1 - \frac{N_i}{N}\right)$$

true class

wrong prediction

Gini Impurity

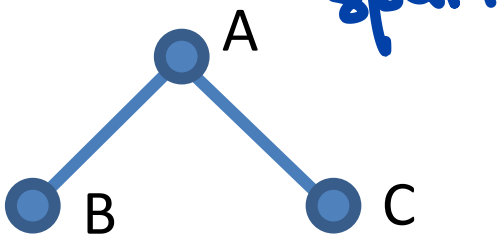


Hastie et al.,"The Elements of Statistical Learning: Data Mining, Inference, and Prediction", Springer (2009)

Node Purity Gain

↳ Want to judge the split not just the node after it split.

- Compare:
  - Gini impurity of parent node
  - Gini impurity of child nodes



$$\Delta I_G = I_G(A) - \frac{N(B)}{N(A)} I_G(B) - \frac{N(C)}{N(A)} I_G(C)$$

Misclassification

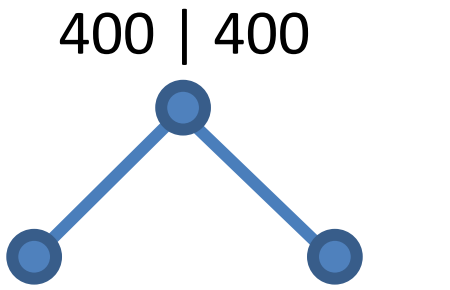
- $\frac{1}{N} \sum_i^N \mathbf{1}(\hat{y}_i \neq y_i)$

  ↳ is the predicted label the same as the actual label?

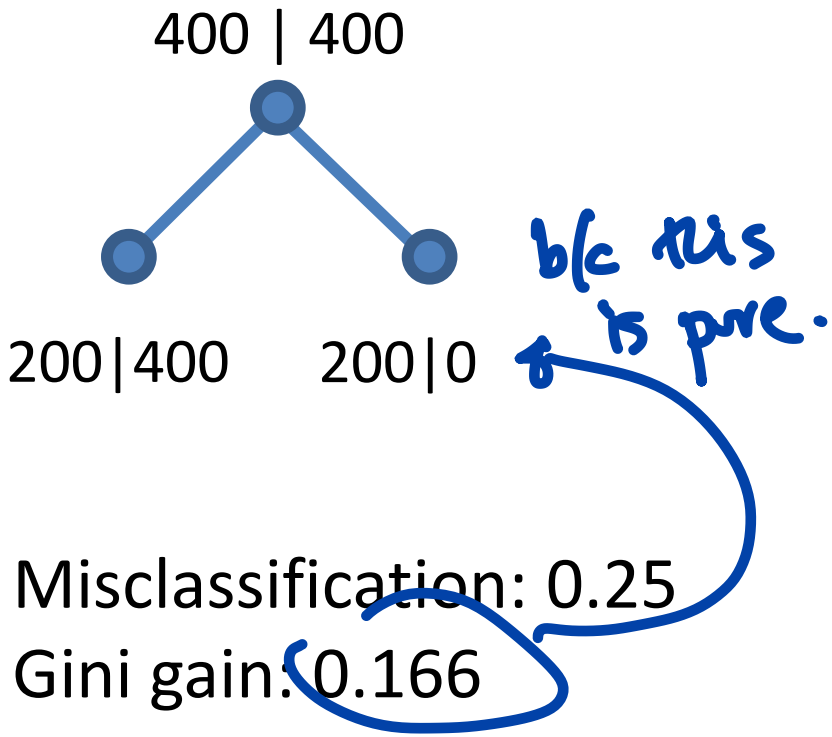
- not differentiable

Comparison Gini vs Misclassification

- Binary problem: 400 samples per class



Misclassification: 0.25
Gini gain: 0.125



Misclassification: 0.25
Gini gain: 0.166

Pseudocode

- Check if already finished – if leaf node is pure.
- For each feature x_i
  - Calculate the gain from splitting on x_i
  - Let x_{best} be the feature with highest gain
- Create a decision *node* that splits on x_{best}
- Repeat on the sub-nodes

→ Take at best next step, doesn't look ahead.

- Does this produce an optimal tree?
- What does optimal tree mean?

↳ Not easy to define → purity? interpretable?

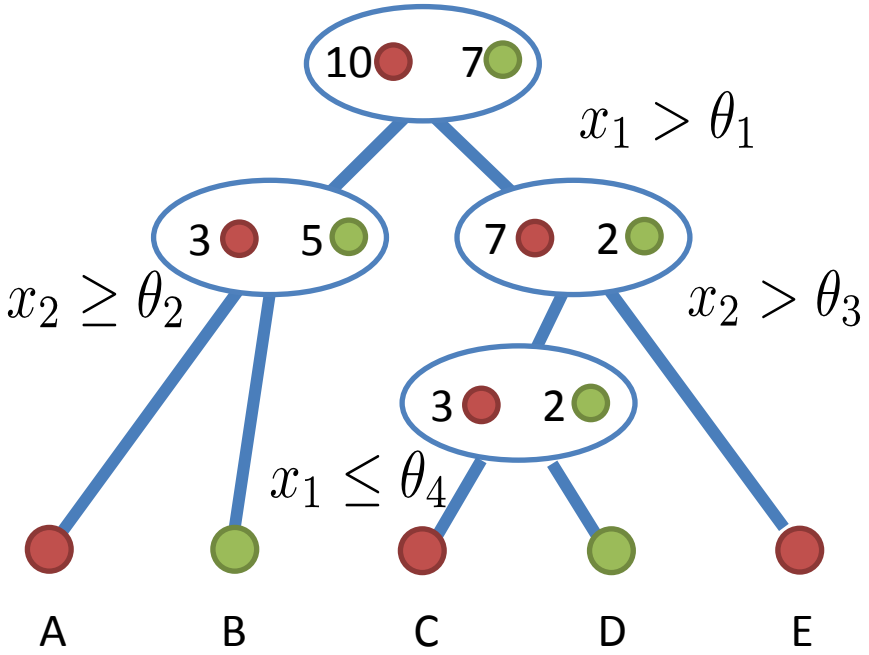
http://en.wikipedia.org/wiki/C4.5_algorithm

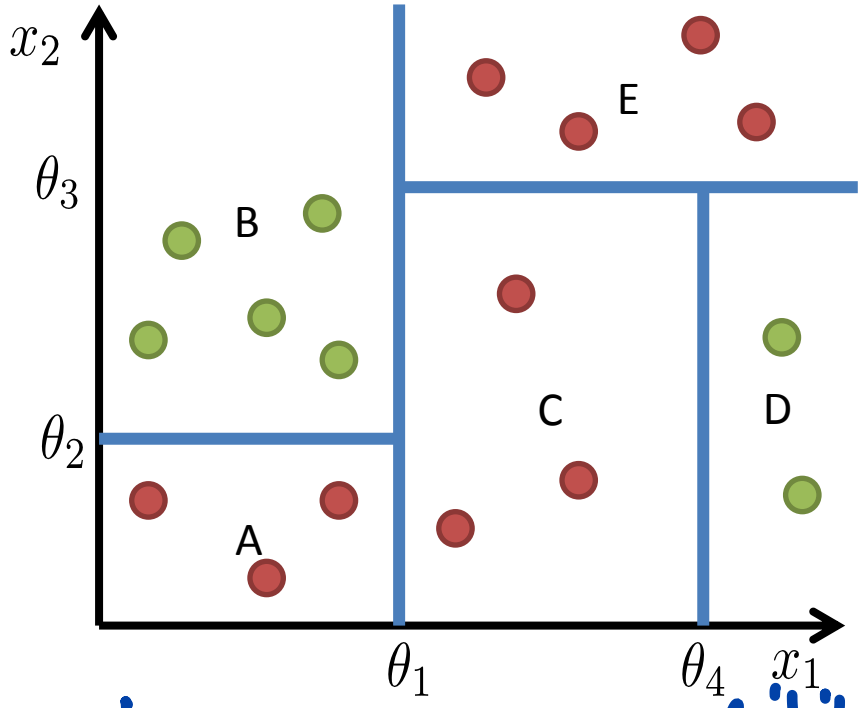
When to Stop

- node contains only one class
- node contains less than x data points
- max depth is reached → limits time to compute.
- node purity is sufficient → not completely pure
- you start to overfit => cross-validation
  - Computationally intense but w/ current computer can do.
  - DT them to overfit.

Tree Pruning

Grow the whole tree then remove leaves.

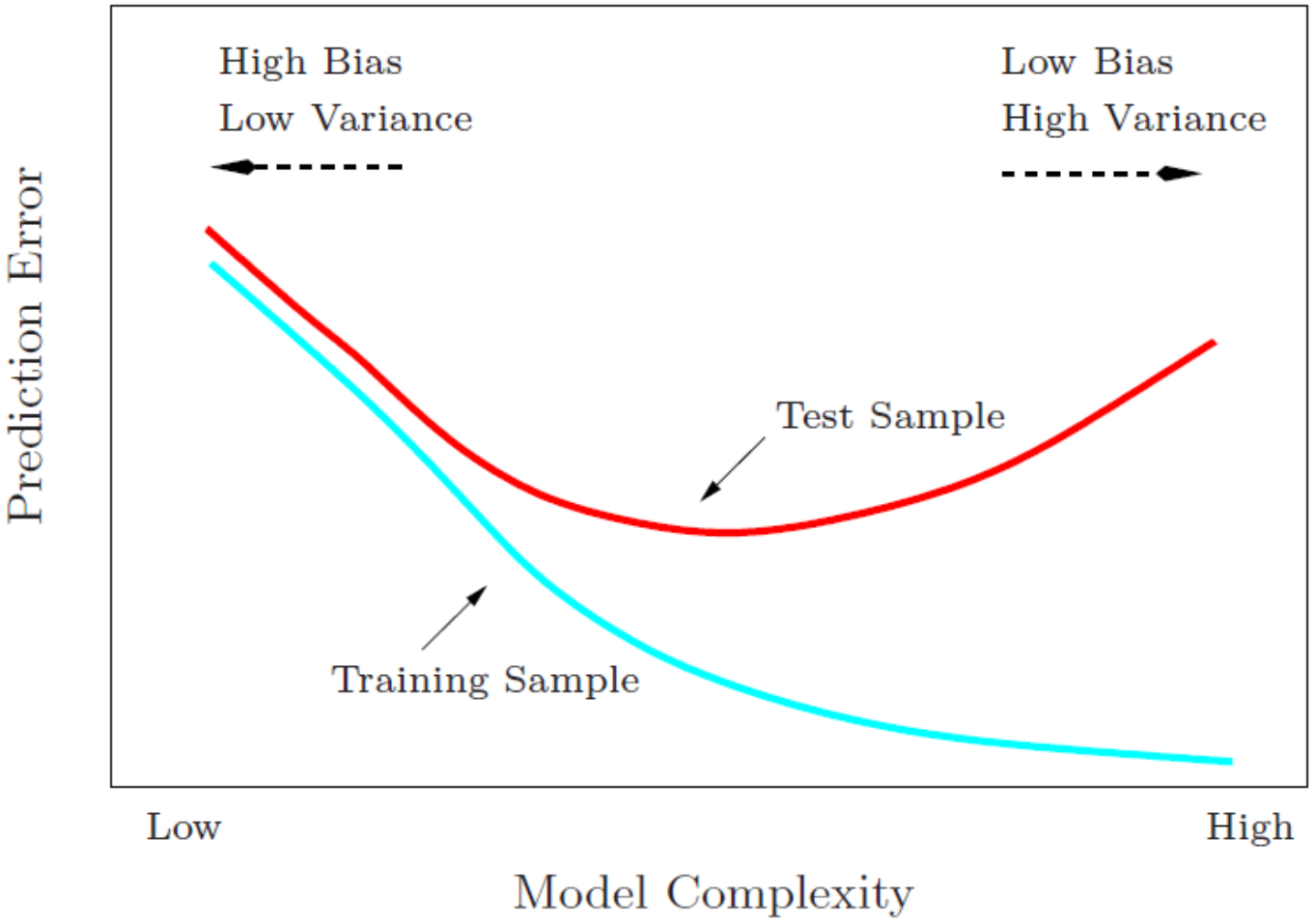




If impure, take the majority. Or use probability ratio?

How do you make a prediction for the merged cell?

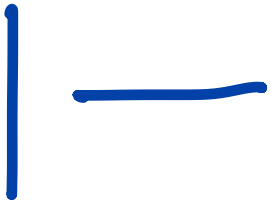
Pruning and Complexity



Hastie et al.,"The Elements of Statistical Learning: Data Mining, Inference, and Prediction", Springer (2009)

Decision Trees - Disadvantages

- Sensitive to small changes in the data
- Overfitting
- Only axis aligned splits



high variance. leads to overfitting.

Decision Trees vs SVM

Characteristic	SVM	Trees
Natural handling of data of "mixed" type	▼	▲
Handling of missing values	▼	▲
Robustness to outliers in input space	▼	▲
Insensitive to monotone transformations of inputs	▼	▲
Computational scalability (large N)	▼	▲
Ability to deal with irrelevant inputs	▼	▲
Ability to extract linear combinations of features	▲	▼
Interpretability	▼	◆
Predictive power	▲	▼

Needs #s.

b/c 1 feature @ a time.

has to care about dot products.
↳ mean computation expensive.

if small.

doesn't generalize well.

Hastie et al.,"The Elements of Statistical Learning: Data Mining, Inference, and Prediction", Springer (2009)

Wisdom of Crowds

The collective knowledge of a diverse and independent body of people typically exceeds the knowledge of any single individual, and can be harnessed by voting.

James Surowiecki

http://socialmedia4srm.wordpress.com/

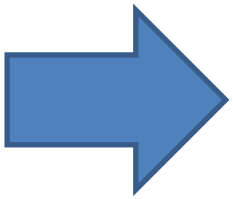

Netflix Prize

Netflix Prize

- Take home messages:
  - Early gains are easy. (8%).
  - Gains through an ensemble approach. (avg. of 800 models)

Ensemble Methods

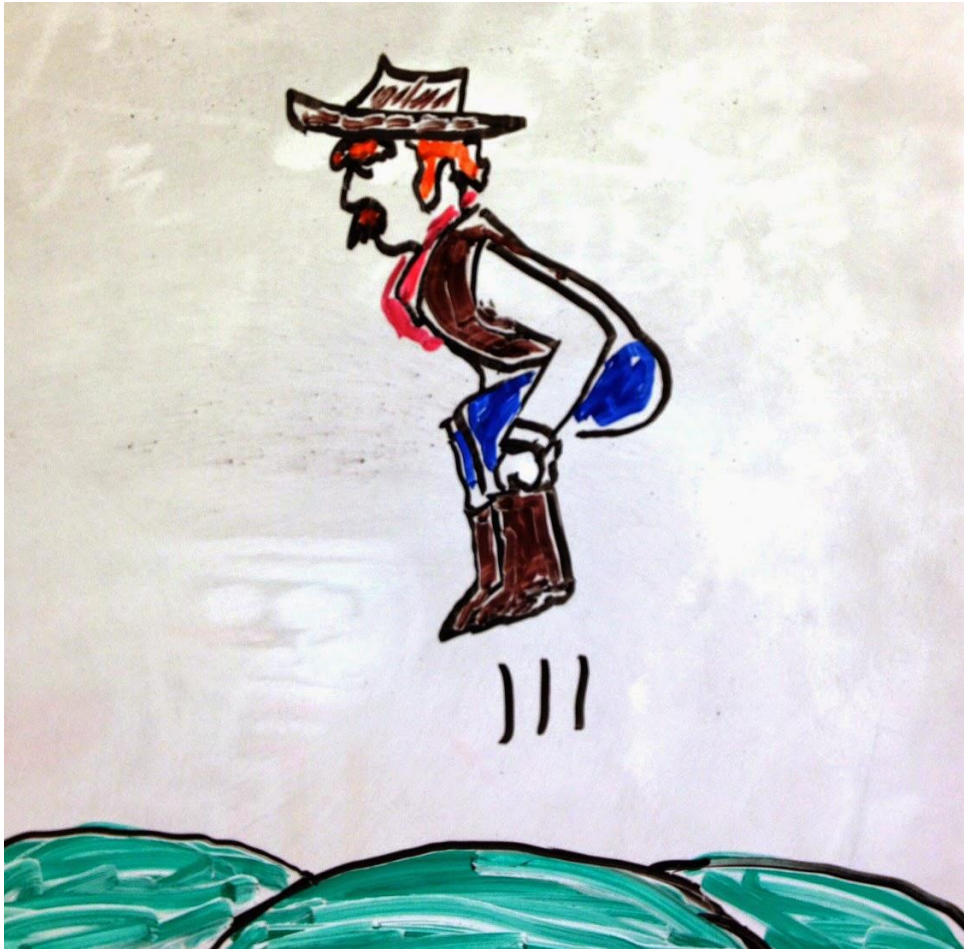
- A single decision tree does not perform well
- But, it is super fast (training + testing)
- What if we learn multiple trees?



We need to make sure they do not all just learn the same.

Can't just run it 100 times.

Bootstrap



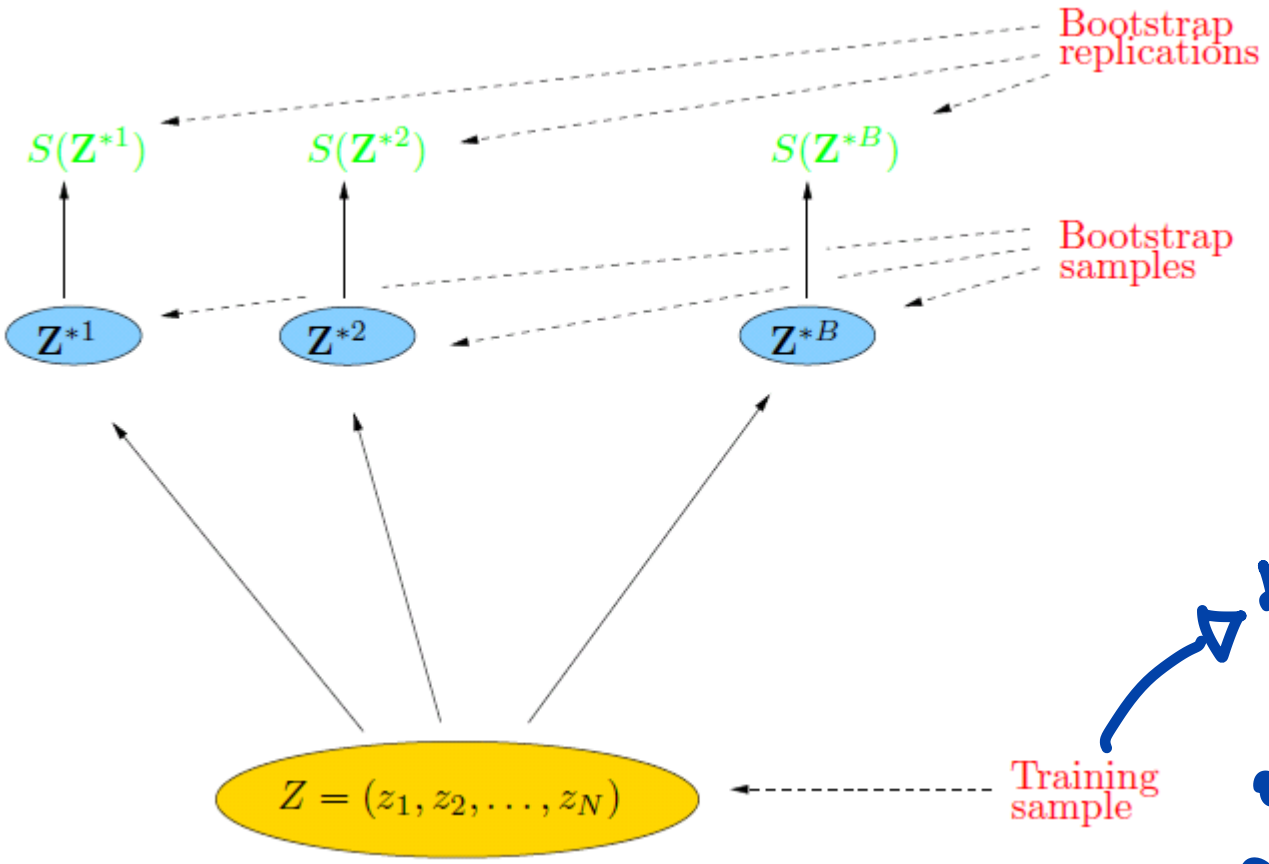
Bootstrap

- Resampling method from statistics
- Useful to get error bars on estimates

- Take N data points
- Draw N times with replacement

- Get estimate from each bootstrapped sample

Bootstrap



How the same number of points as original set (some duplicated)

Hastie et al.,"The Elements of Statistical Learning: Data Mining, Inference, and Prediction", Springer (2009)

Bootstrap

- I can generate more data!
- Can I do cross validation on this?

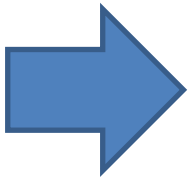
No. B/c same data points.

↳ Bootstrap sets will have overlap.

↳ Okay for DT

Bootstrap vs Cross-validation

- Bootstrap has overlap in data sets



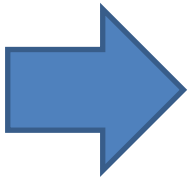
Do not use simple bootstrap to generate train and test data from same data set.

$$p(n \in Z^{*i}) = \frac{1}{N}$$

Probability of choosing n

Bootstrap vs Cross-validation

- Bootstrap has overlap in data sets



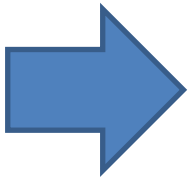
Do not use simple bootstrap to generate train and test data from same data set.

$$p(n \in Z^{*i}) = \qquad 1 - \frac{1}{N}$$

Probability of not choosing n

Bootstrap vs Cross-validation

- Bootstrap has overlap in data sets



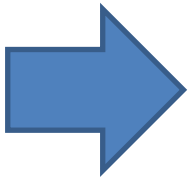
Do not use simple bootstrap to generate train and test data from same data set.

$$p(n \in Z^{*i}) = \qquad (1 - \frac{1}{N})^N$$

Probability of not choosing n in N draws

Bootstrap vs Cross-validation

- Bootstrap has overlap in data sets



Do not use simple bootstrap to generate train and test data from same data set.

$$p(n \in Z^{*i}) = 1 - (1 - \frac{1}{N})^N$$

Probability of (not not) choosing n in N draws

Bootstrap vs Cross-validation

- Bootstrap has overlap in data sets

Do not use simple bootstrap to generate train and test data from same data set.

$$p(n \in Z^{*i}) = 1 - e^{-1}$$

$$\approx 0.632$$

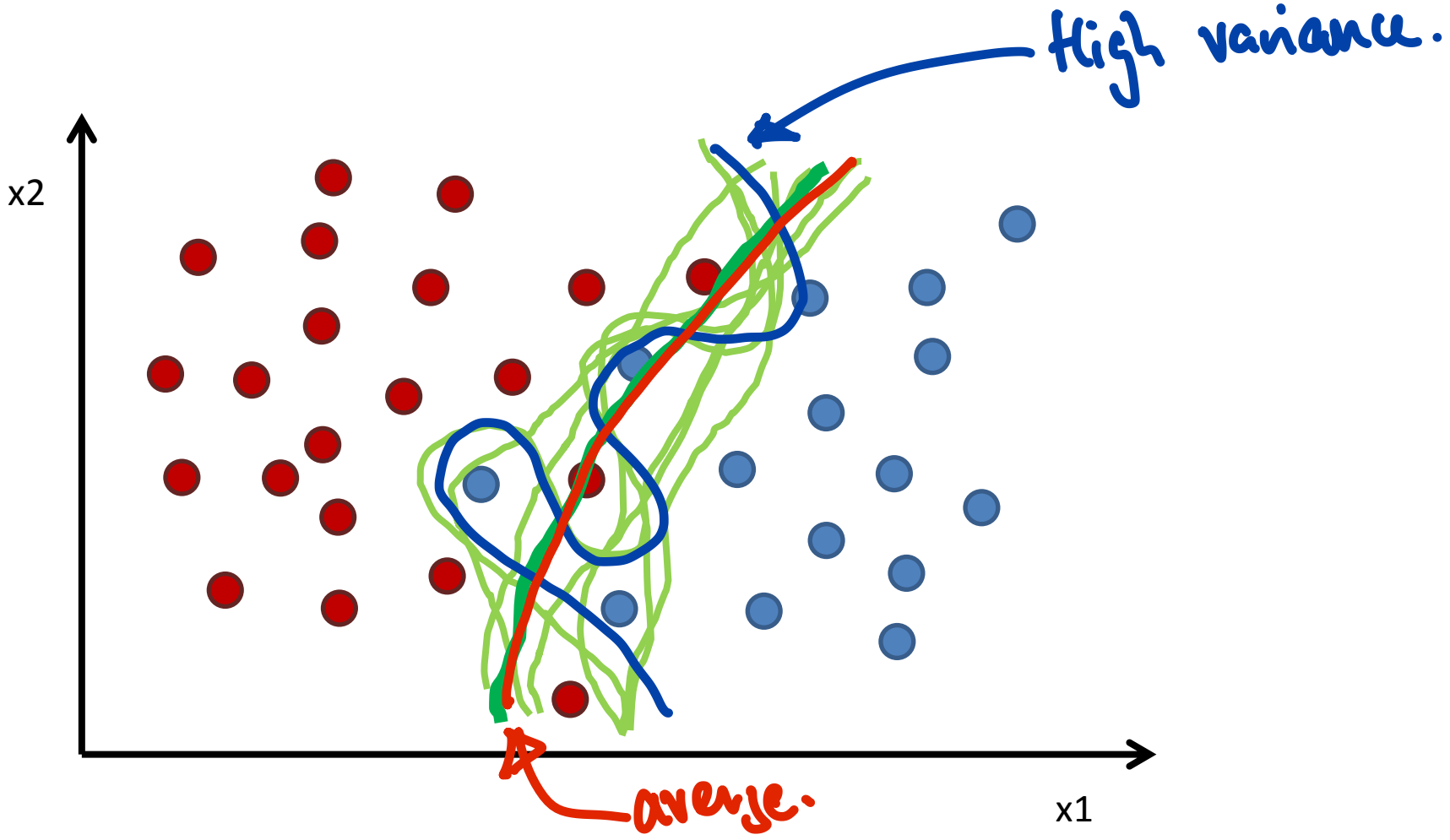
This number is important later

Bagging

- Bootstrap aggregating

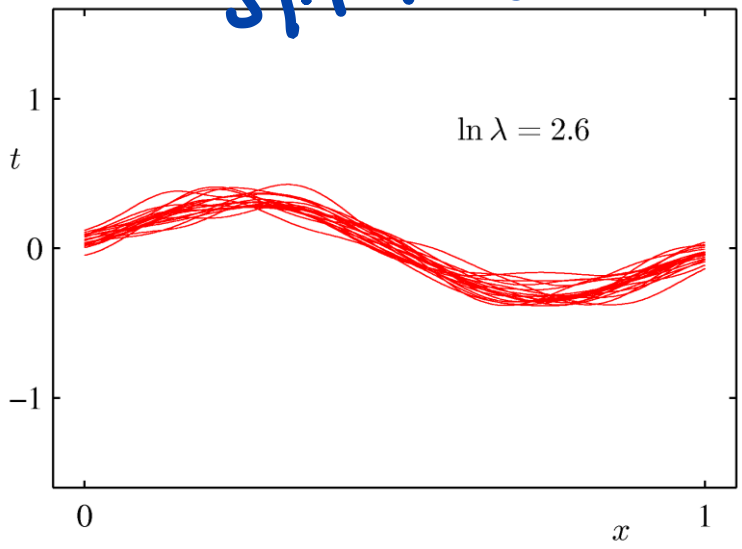
- Sample with replacement from your data set
- Learn a classifier for each bootstrap sample
- Average the results

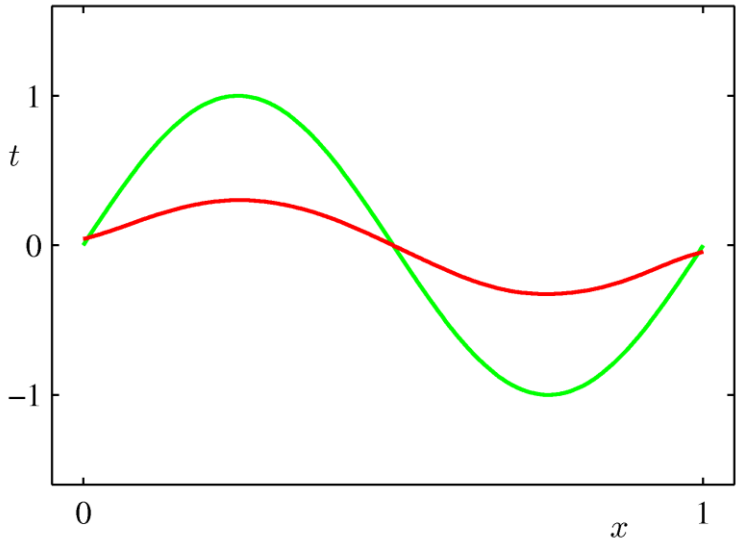
Bagging Example

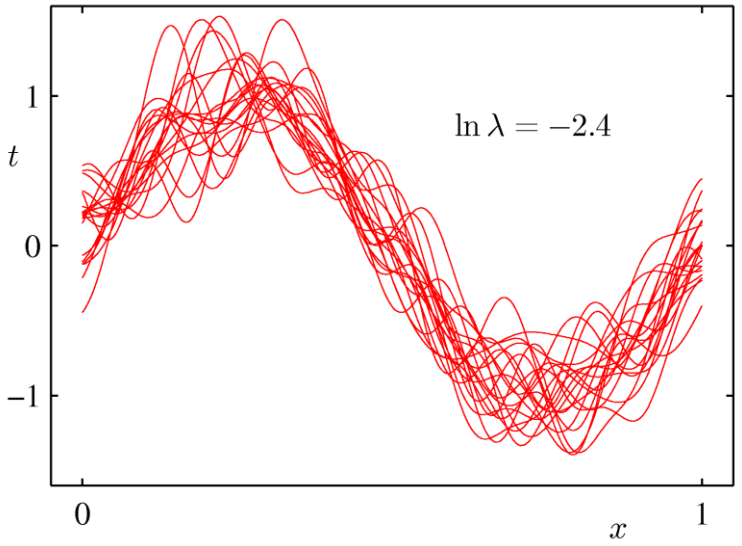


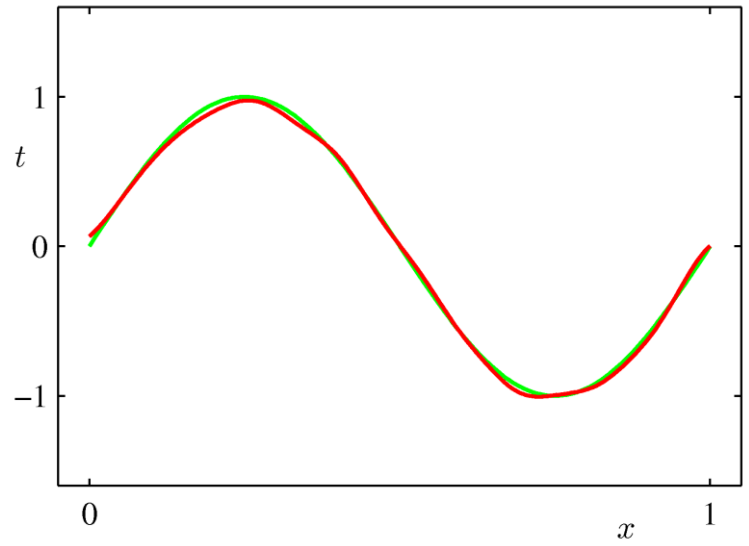
Bias-Variance Trade-off

Let Bagging reduce variance w/o increasing bias too much.



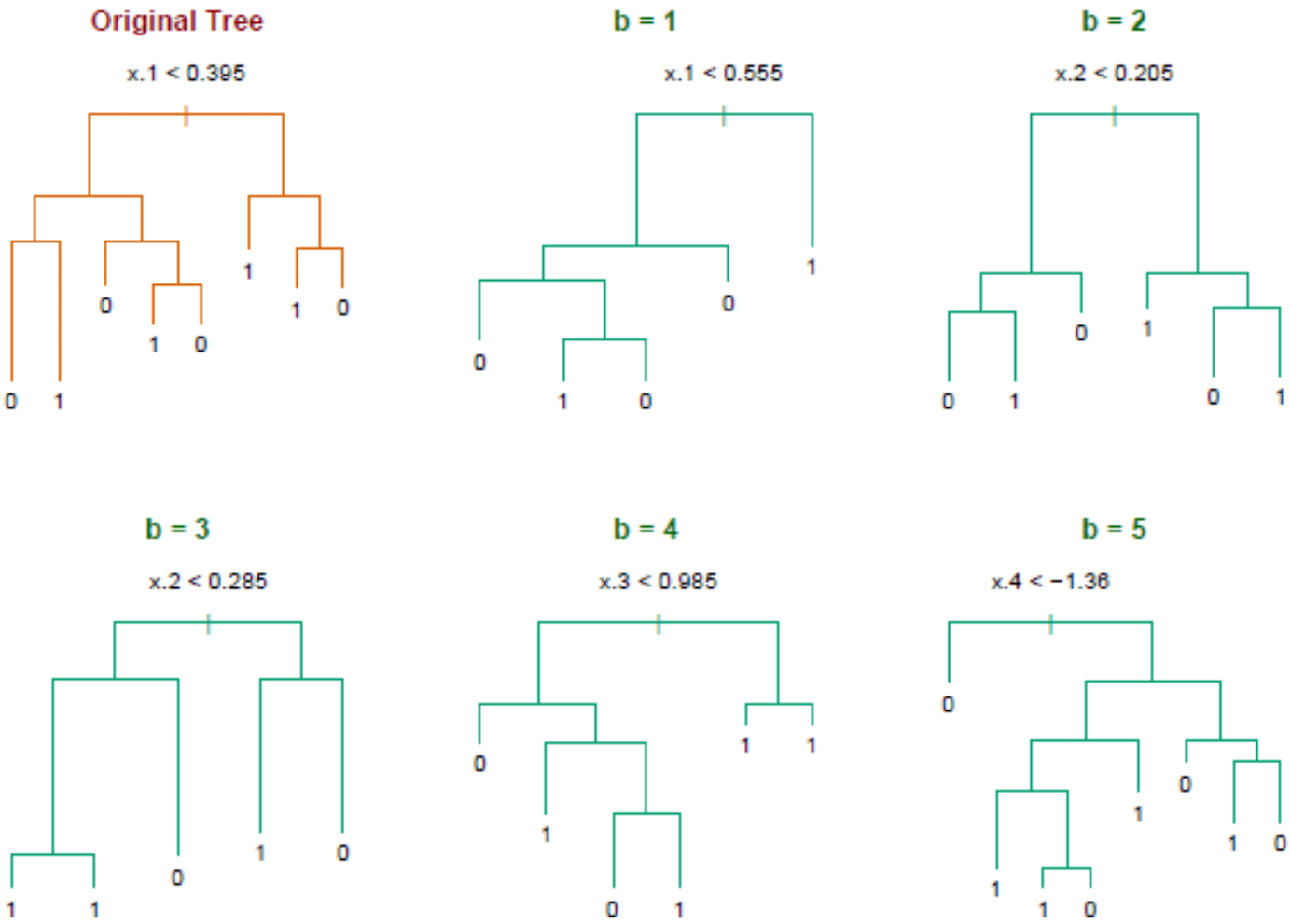






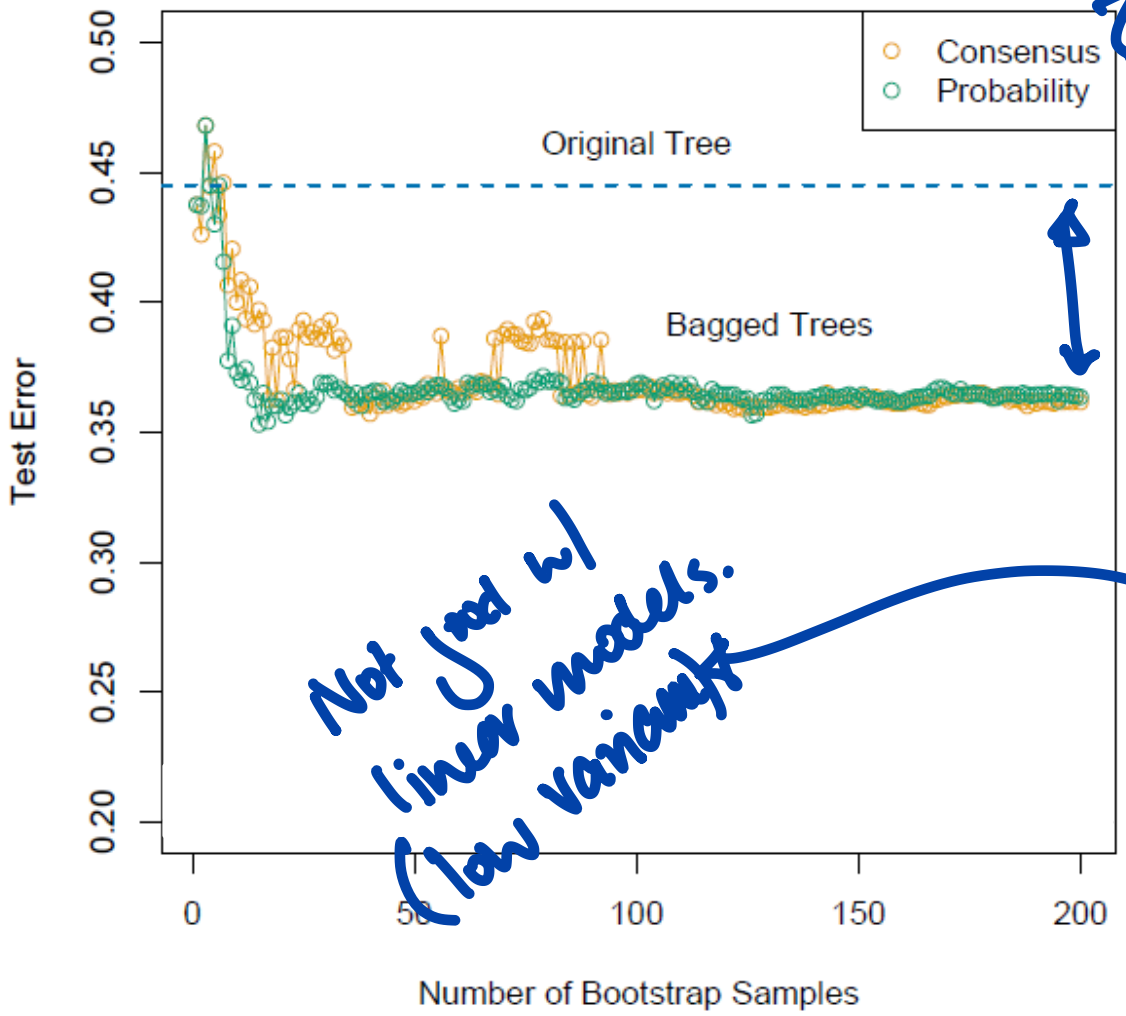
Bagging Decision Trees

→ randomness is introduced.



Hastie et al.,"The Elements of Statistical Learning: Data Mining, Inference, and Prediction", Springer (2009)

Bagging Decision Trees



Two options. Consensus is majority approach.

Reduction due to bagging

Not good w/ linear models. (low variance)

Bagging can be done w/ ANY approach that have high variance + are fast.

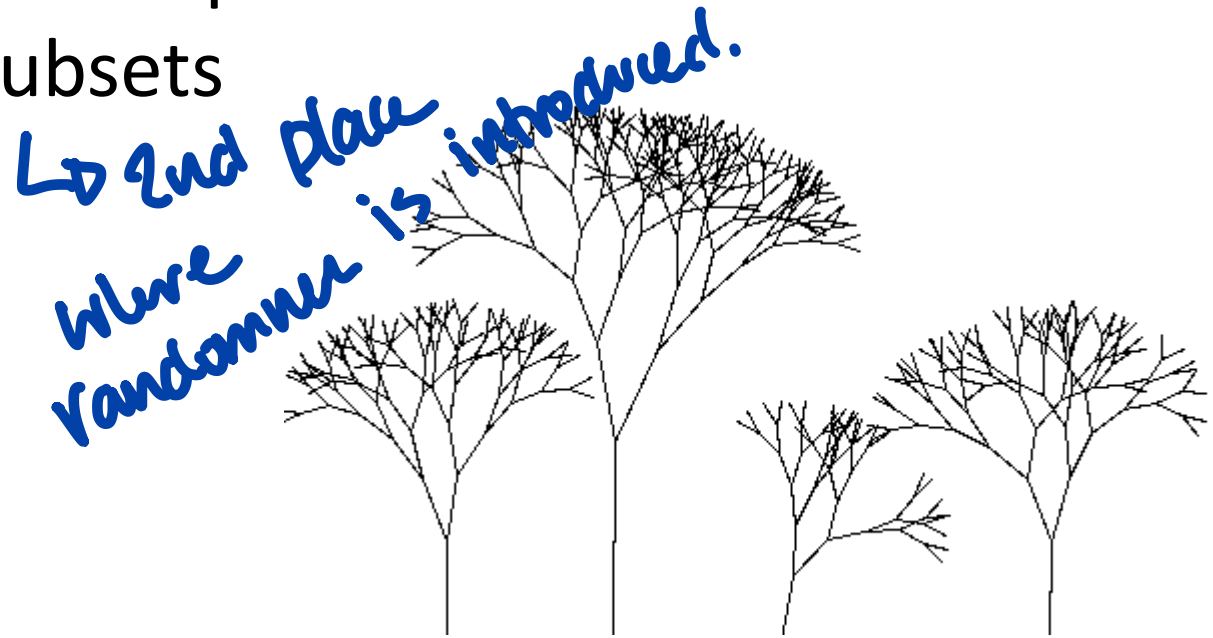
Hastie et al.,"The Elements of Statistical Learning: Data Mining, Inference, and Prediction", Springer (2009)

Bagging

- Reduces overfitting (variance)
- Normally uses one type of classifier
- Decision trees are popular
- Not helping with linear models
- Easy to parallelize

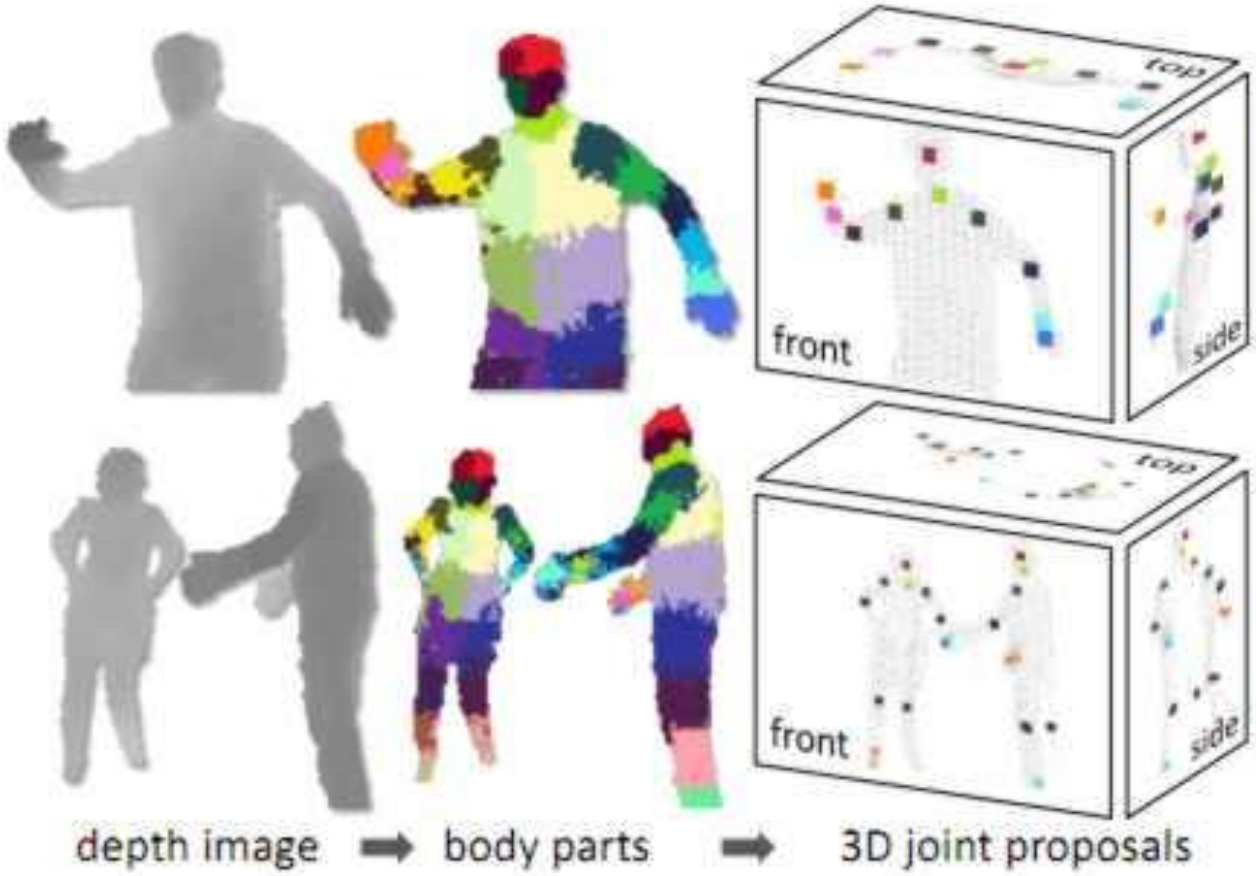
Random Forest

- Builds upon the idea of bagging
- Each tree build from bootstrap sample
- Node splits calculated from random feature subsets



http://www.andrewbuntine.com/articles/about/fun

Random Forest – Fun Fact



hand_tracking_kinect.mp4

http://research.microsoft.com/en-us/projects/handpose/

Random Forest

- All trees are fully grown
- No pruning

- Two parameters
  - Number of trees
  - Number of features

Random Forest Error Rate

- Error depends on:
  - Correlation between trees (higher is worse)
  - Strength of single trees (higher is better)

- Increasing number of features for each split:
  - Increases correlation
  - Increases strength of single trees

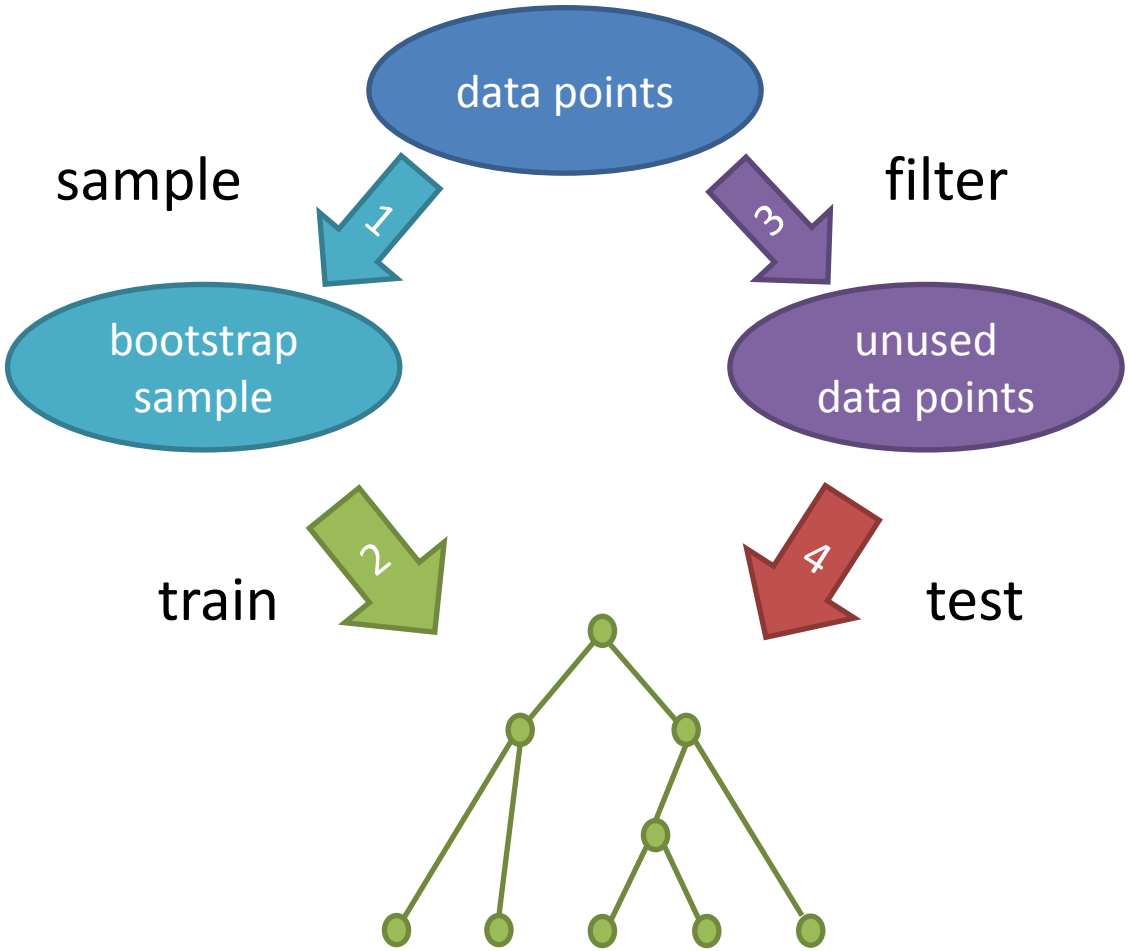
Out of Bag Error

- Each tree is trained on a bootstrapped sample
- About 1/3 of data points not used for training

- Predict unseen points with each tree
- Measure error

Out of Bag Error

≈ 0.632



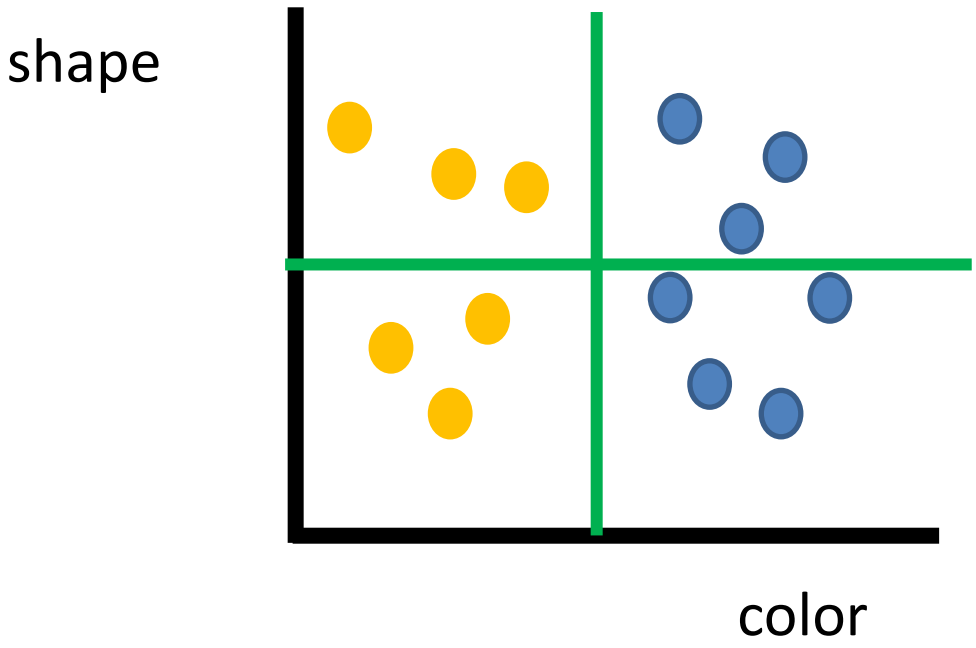
Out of Bag Error

- Very similar to cross-validation
- Measured during training
- Can be too optimistic

Variable Importance - 1

- Again use out of bag samples
- Predict class for these samples
- Randomly permute values of one feature
- Predict classes again
- Measure decrease in accuracy

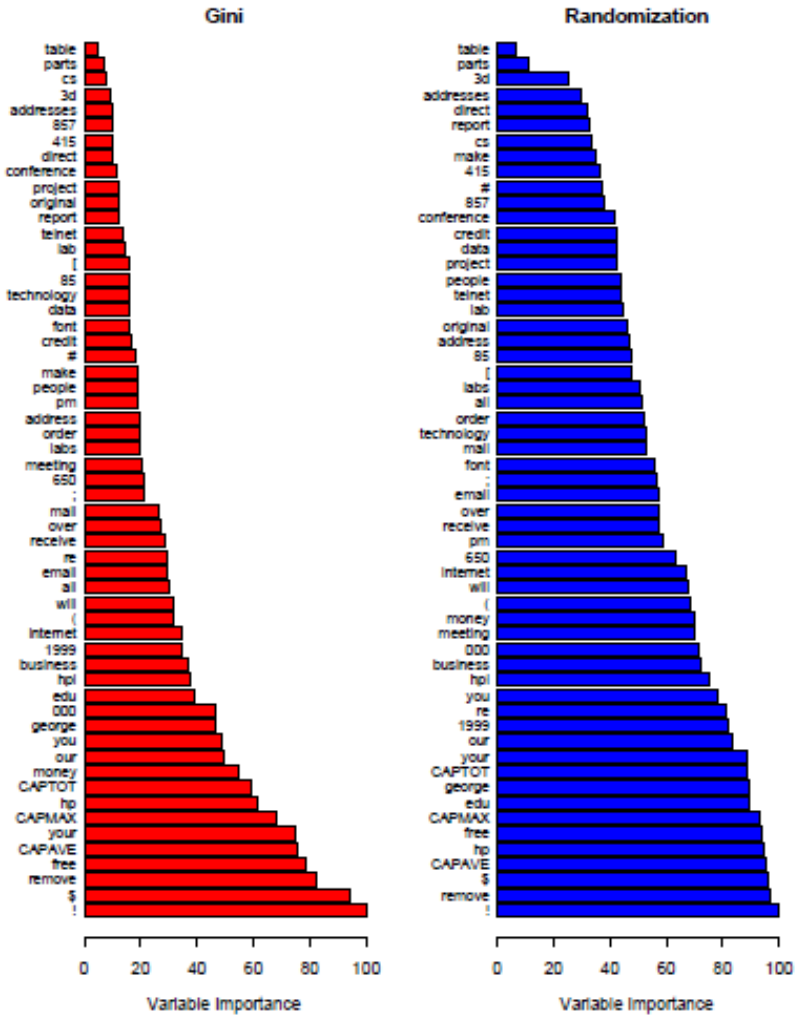
Variable Importance - 1



Variable Importance - 2

- Measure split criterion improvement
- Record improvements for each feature
- Accumulate over whole ensemble

Example: Spam classification

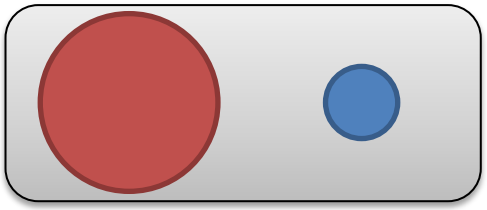


Randomization tends to spread out the variable importance more uniformly.

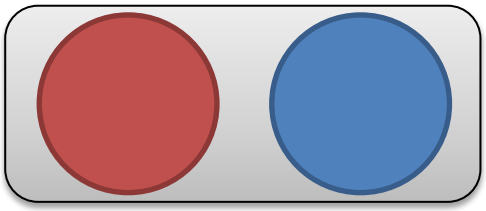
Hastie et al.,"The Elements of Statistical Learning: Data Mining, Inference, and Prediction", Springer (2009)

Unbalanced Classes

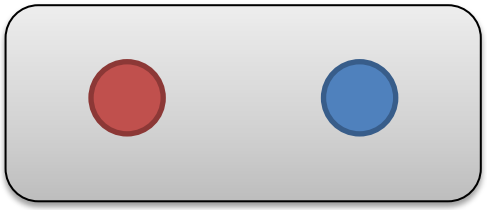
- The Problem:



- Oversample:

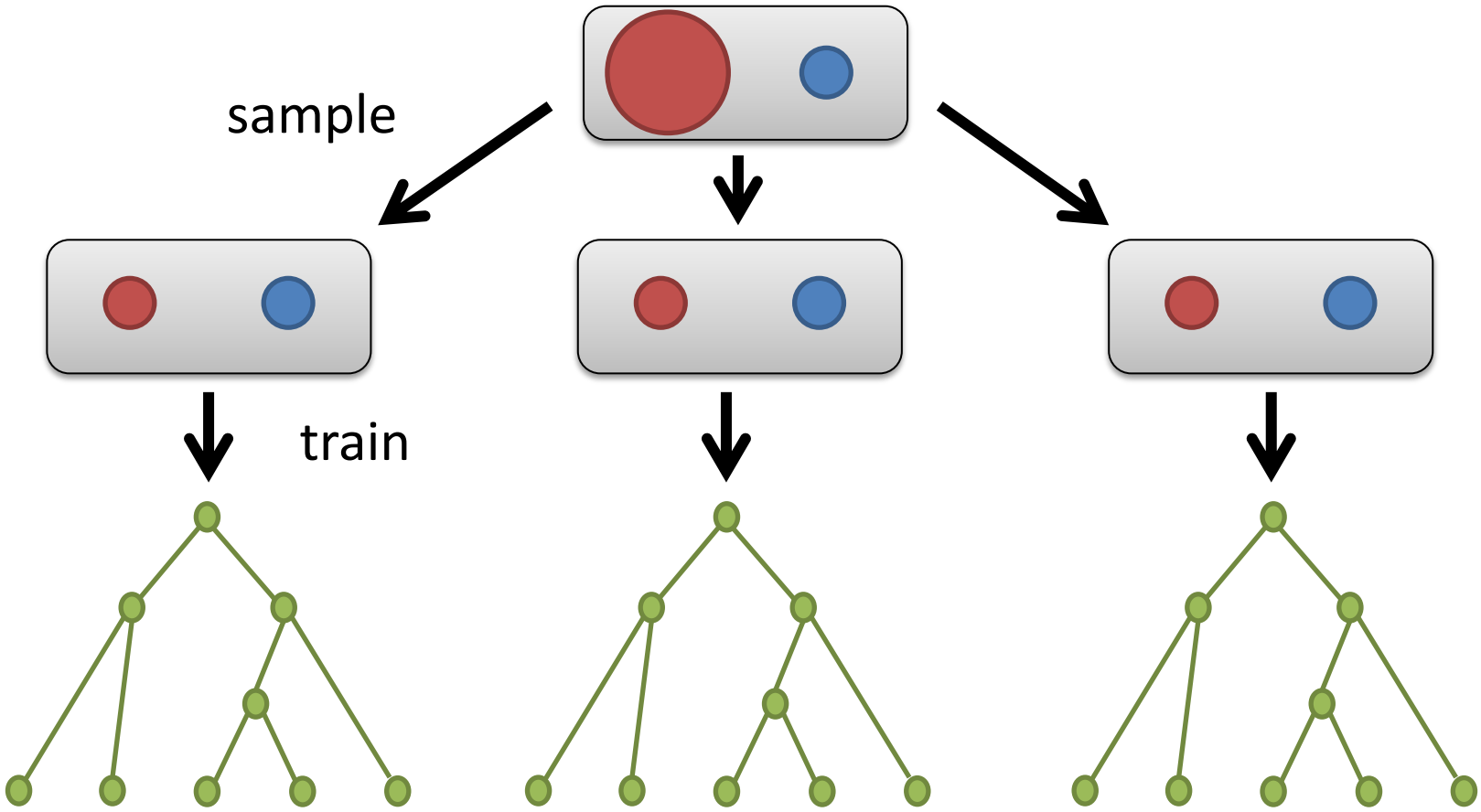


- Subsample:



- Subsample for each tree!

Random Forest Subsampling



Random Forest

- Similar to Bagging
- Easy to parallelize
- Packaged with some neat functions:
  - Out of bag error
  - Feature importance measure
  - Proximity estimation