CS109 – Data Science

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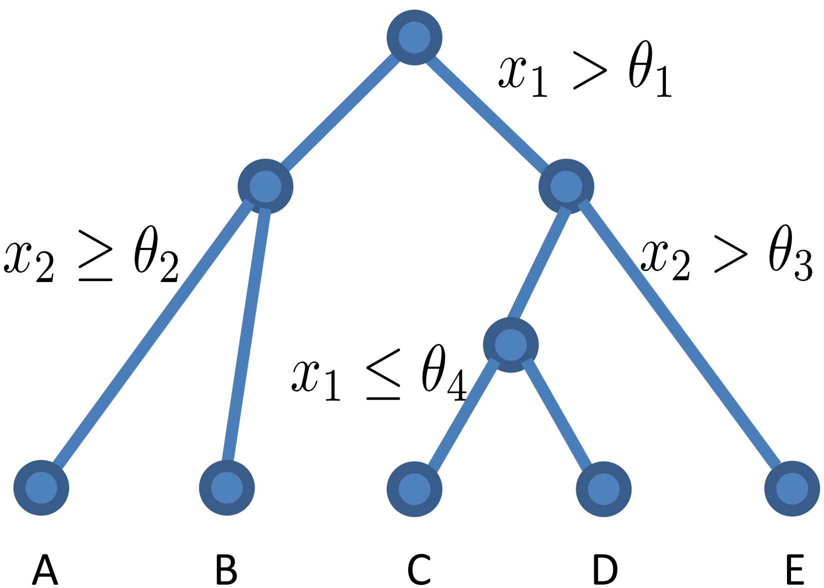
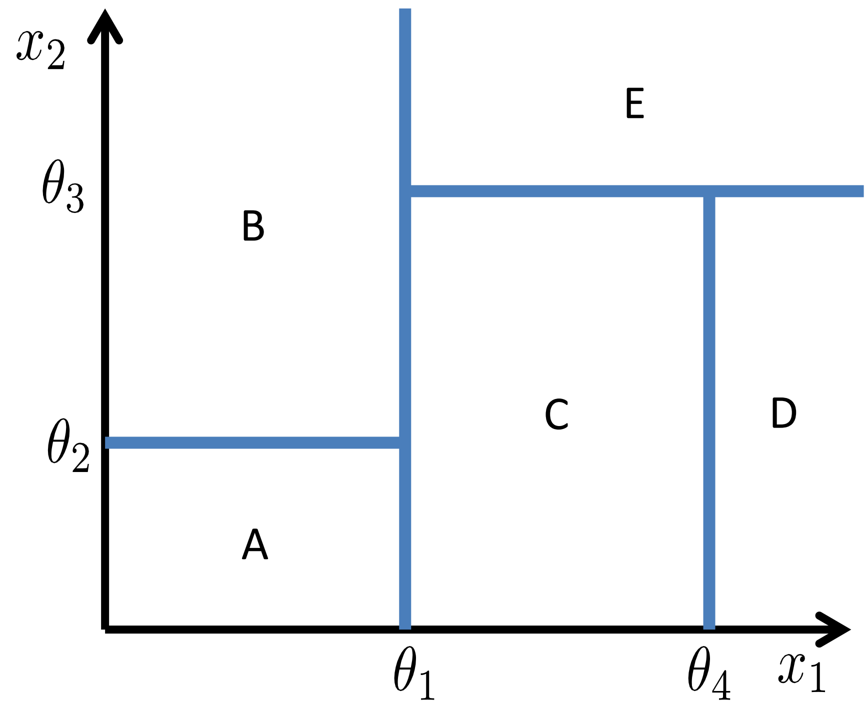
Announcements

- Don’t forget to register your final project group!
- HW4 is out
- Problem 2a post on piazza – have a look

Decision Tree - Idea





Bishop, “Pattern Recognition and Machine Learning”, Springer, 2006

DecisionTree in sklearn

- http://scikit-learn.org/stable/modules/generated/sklearn.tree.DecisionTreeClassifier.html

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	▲	▼

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

Abalone data

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

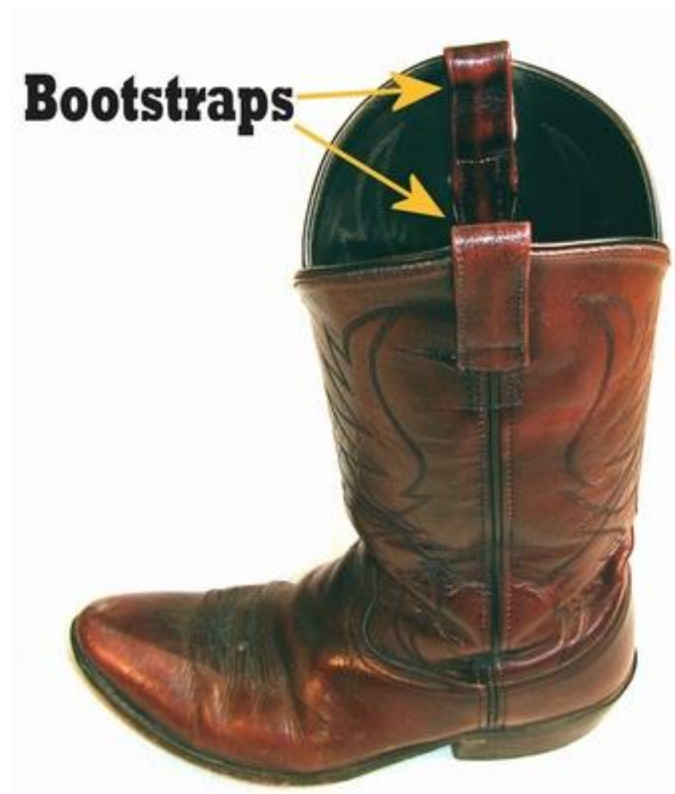
- Take home messages:
  - SVD rocks!
  - Initially great progress, then significantly slowed down
  - Ensembles were the method of choice
  - This was a surprise!
  - And a bit of a dissapointment

Ensemble Methods

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

For multiple trees we need even more data!

Bootstrap



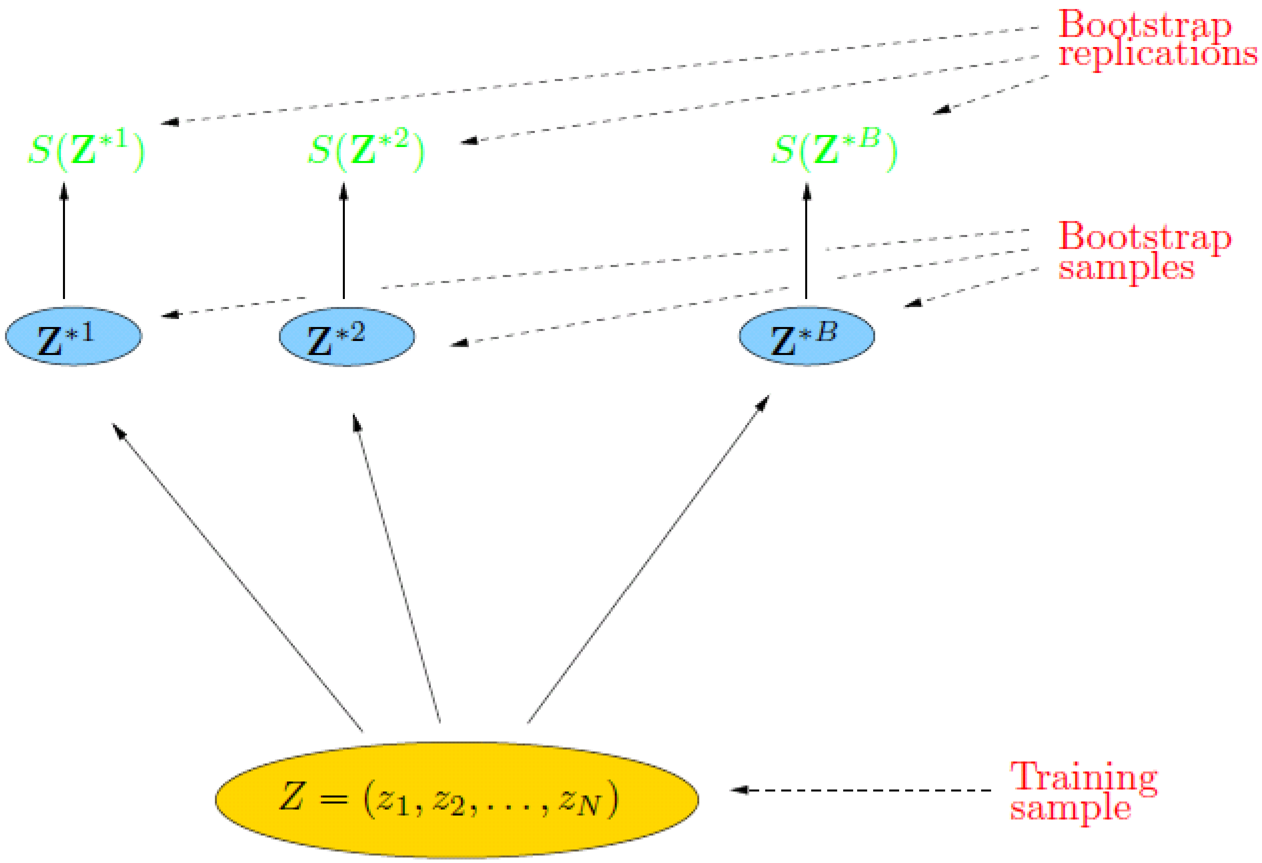
Bootstrap

- 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



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

This is neat!

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

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.

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

$$\approx 0.632$$

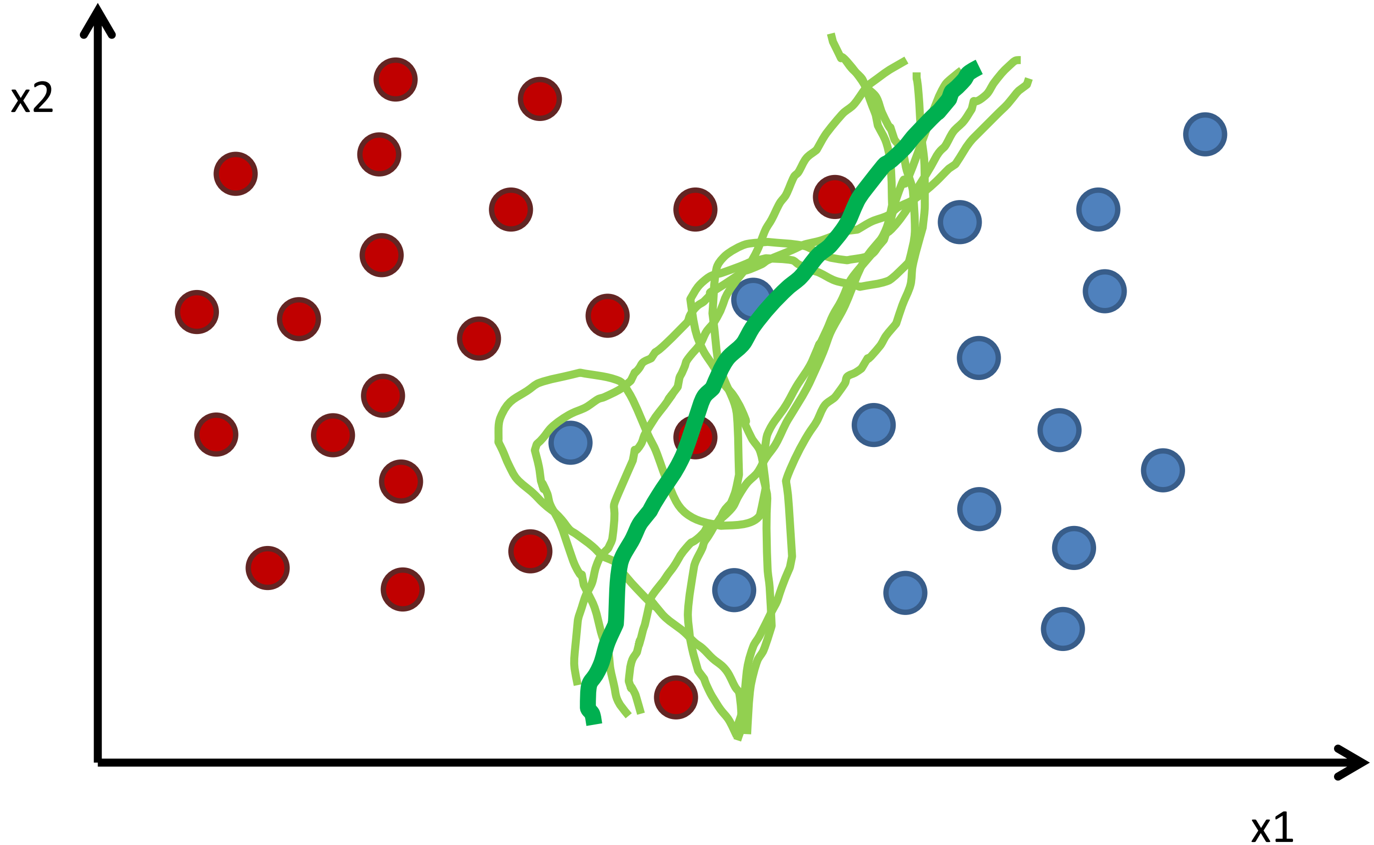
This number is important later

Bagging

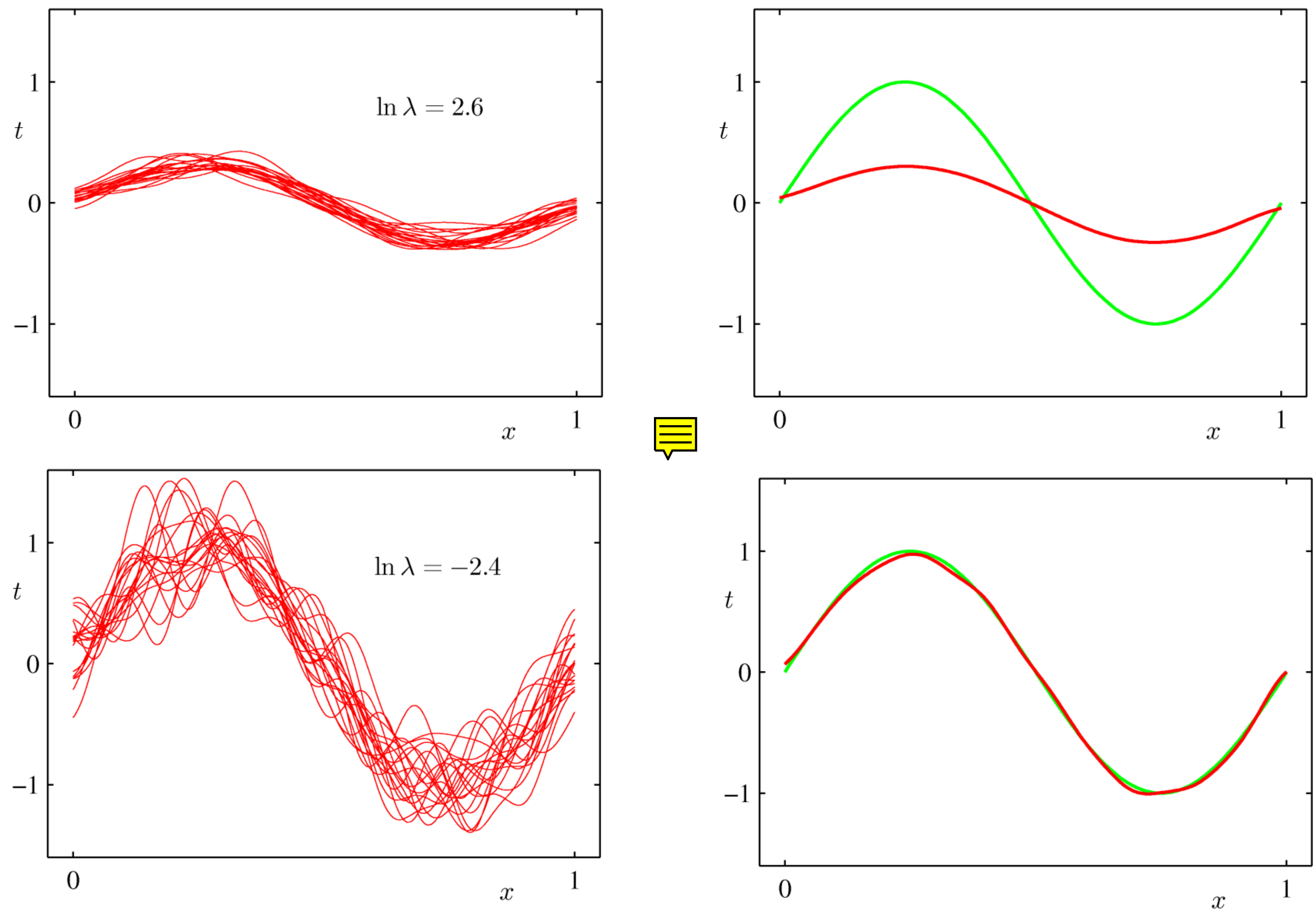
- Bootstrap aggregating

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

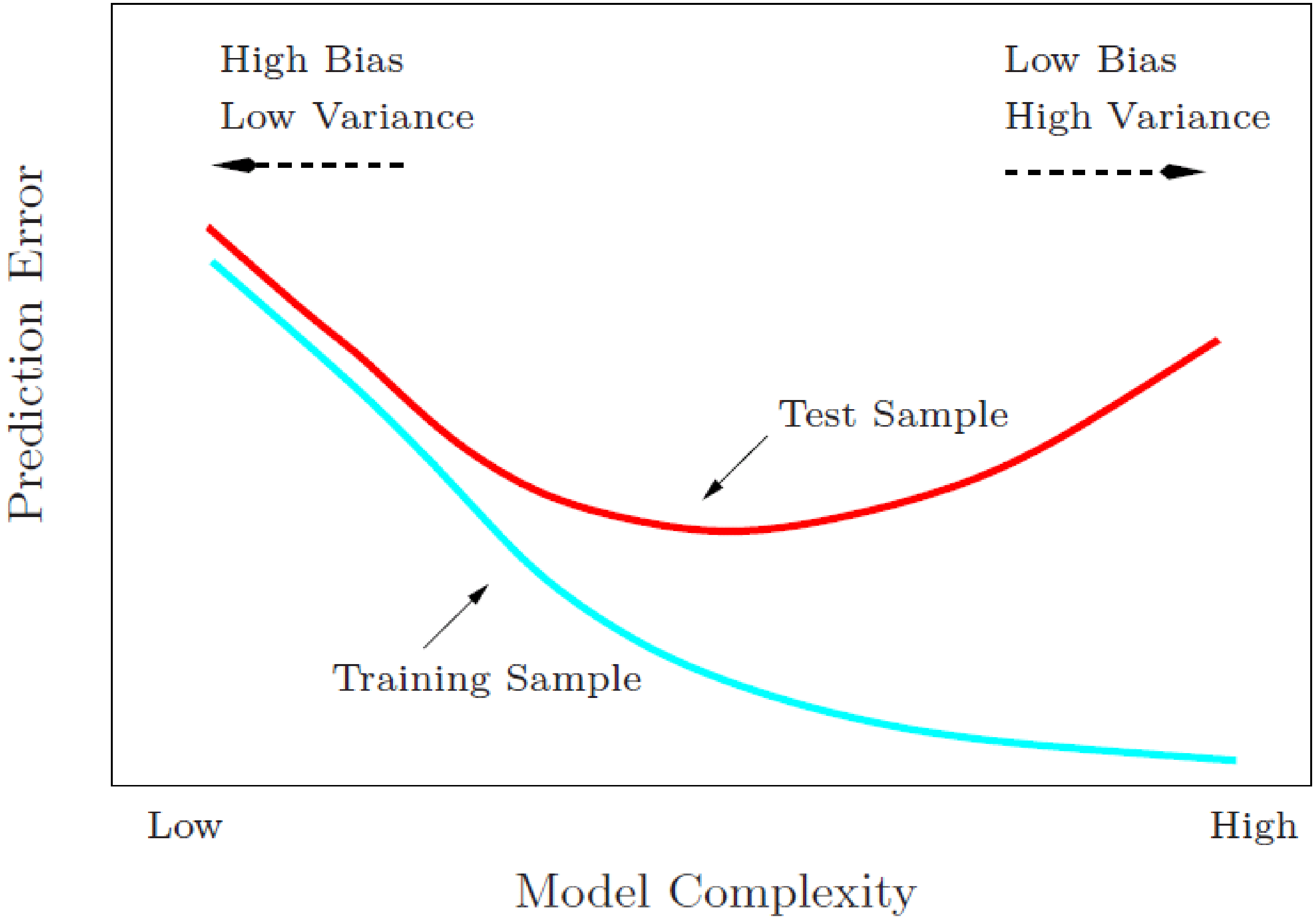
Bagging Example



Bias-Variance Trade-off

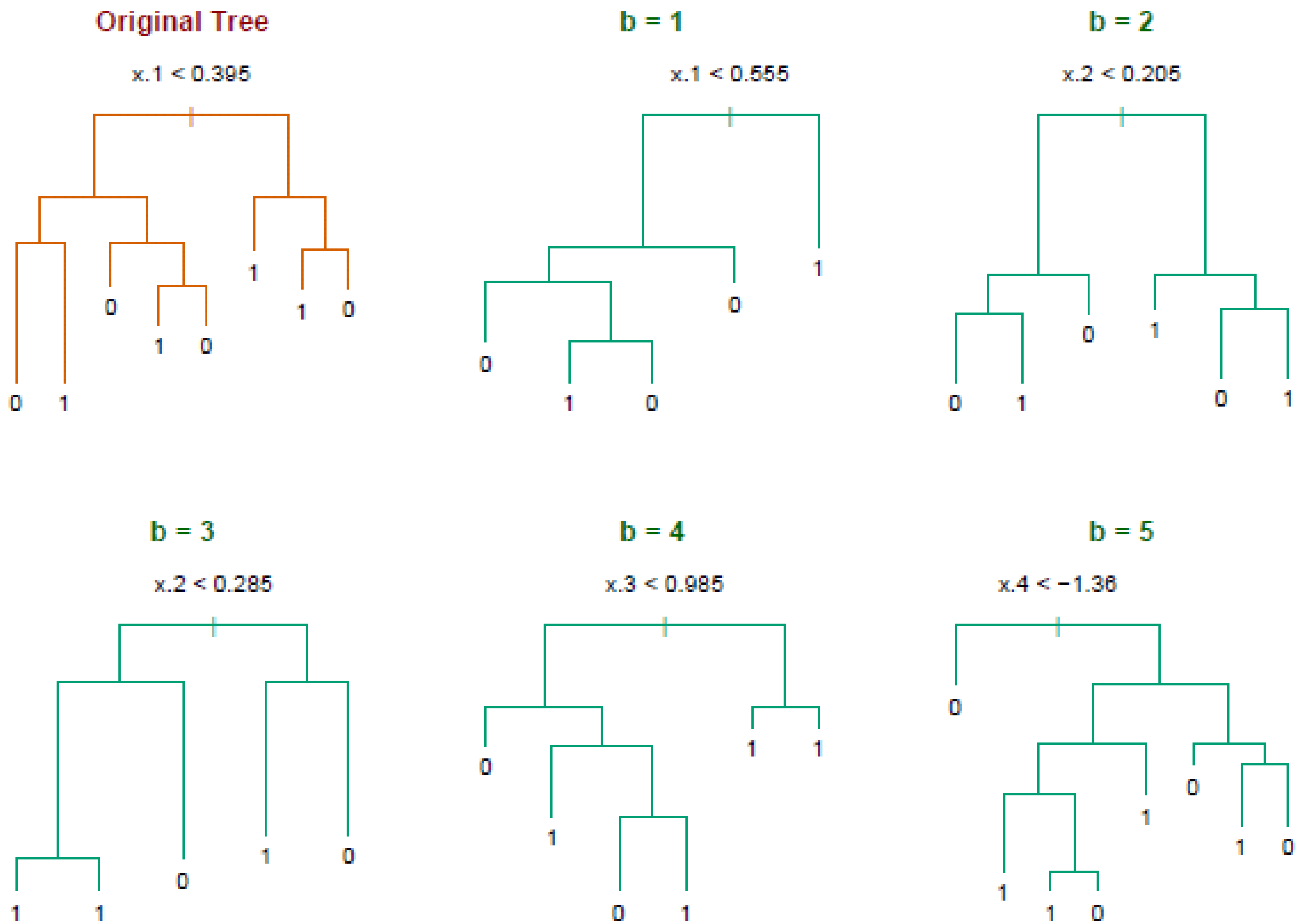


We Have Seen This Before



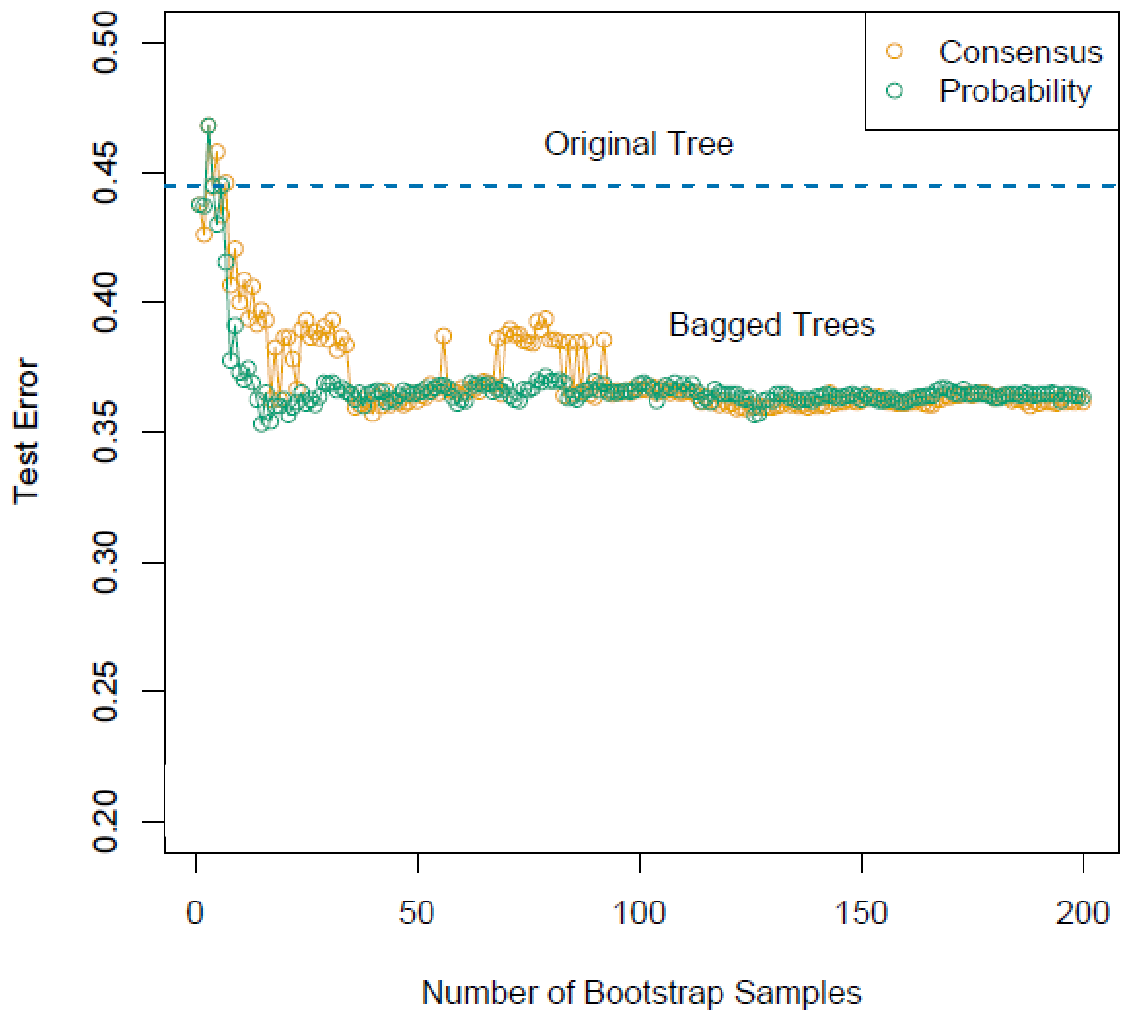
Hastie et al.,"The Elements of Statistical Learning: Data Mining, Inference, and Prediction", Springer (2009)

Bagging Decision Trees



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

Bagging Decision Trees

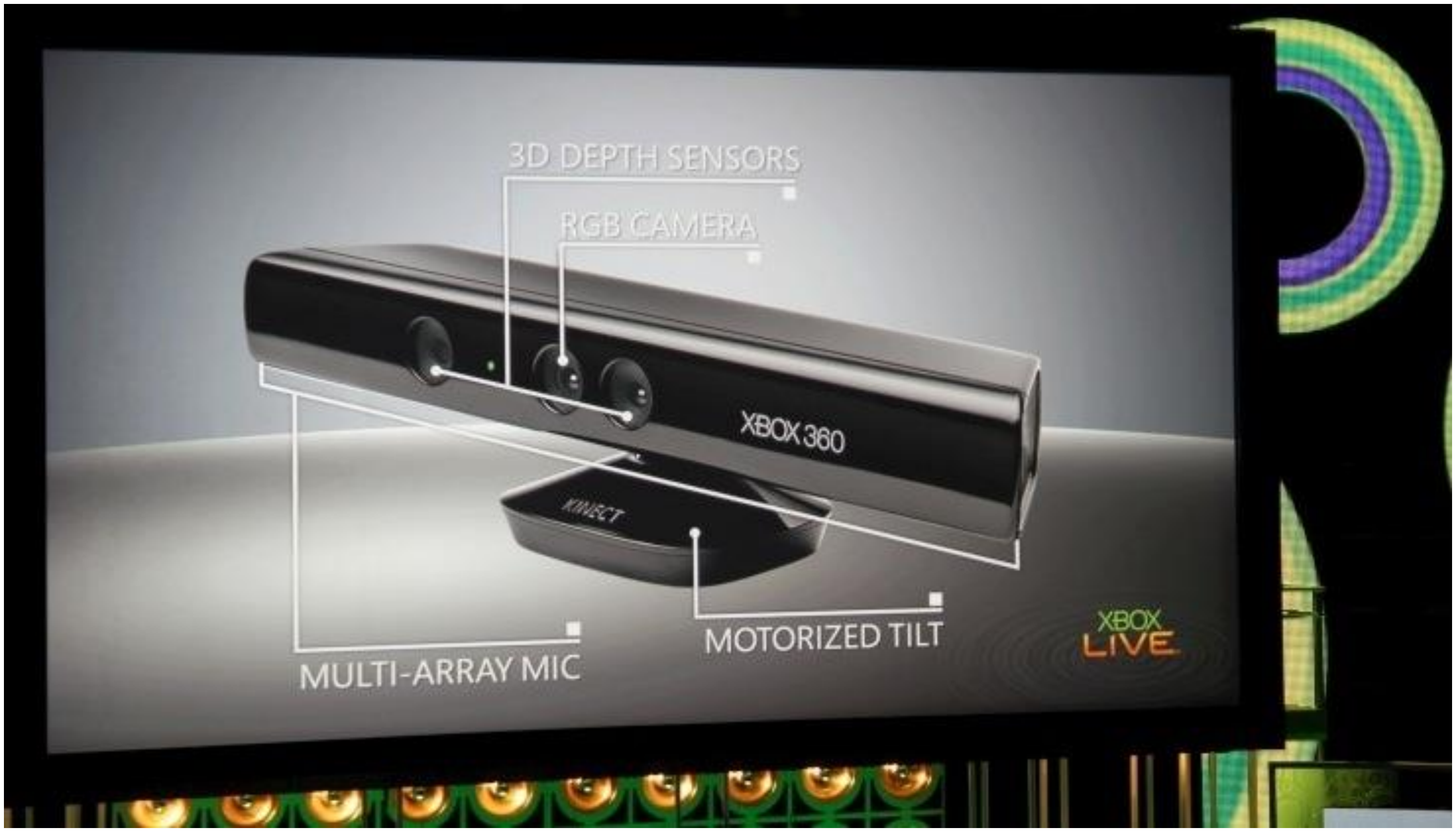


Hastie et al.,"The Elements of Statistical Learning: Data Mining, Inference, and Prediction", Springer (2009)

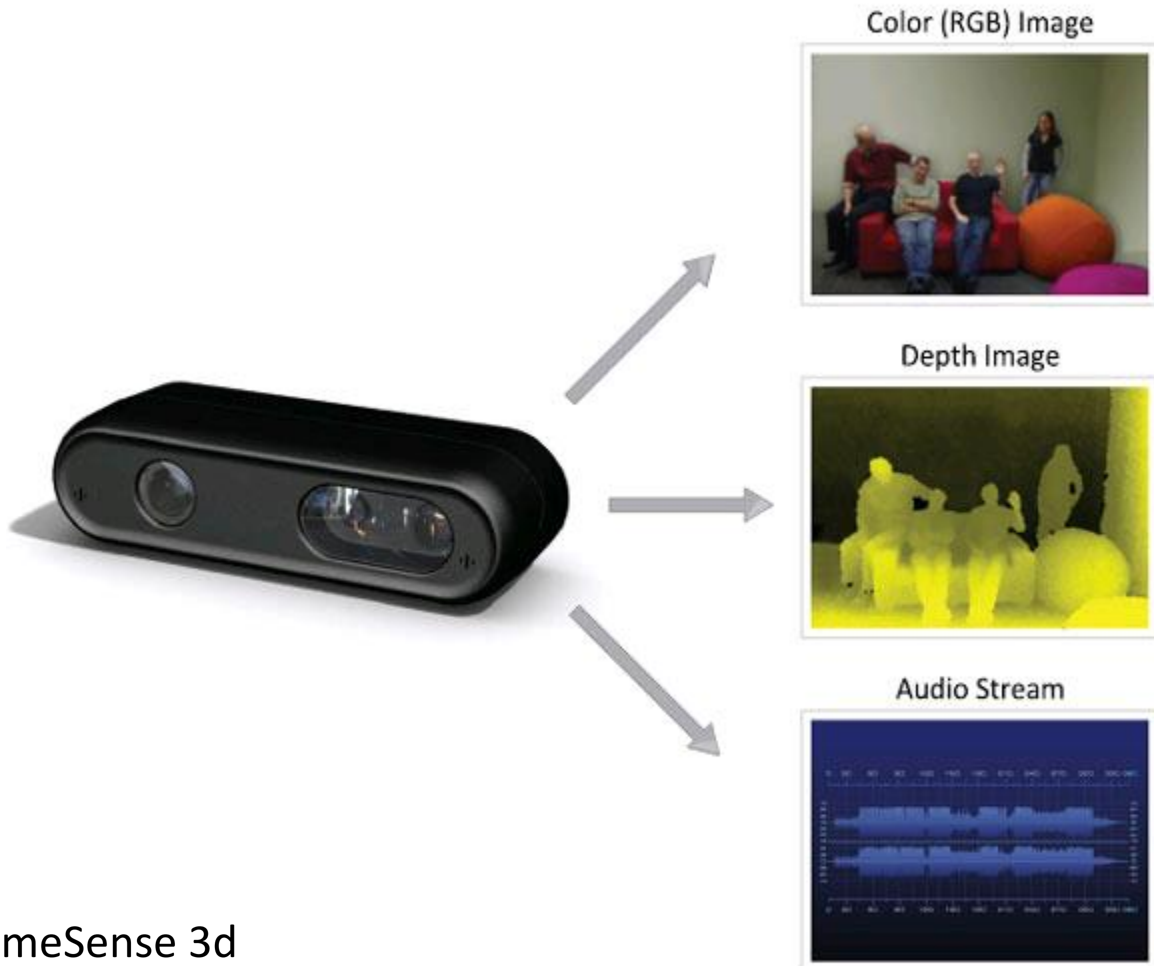
Bagging

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

Kinect

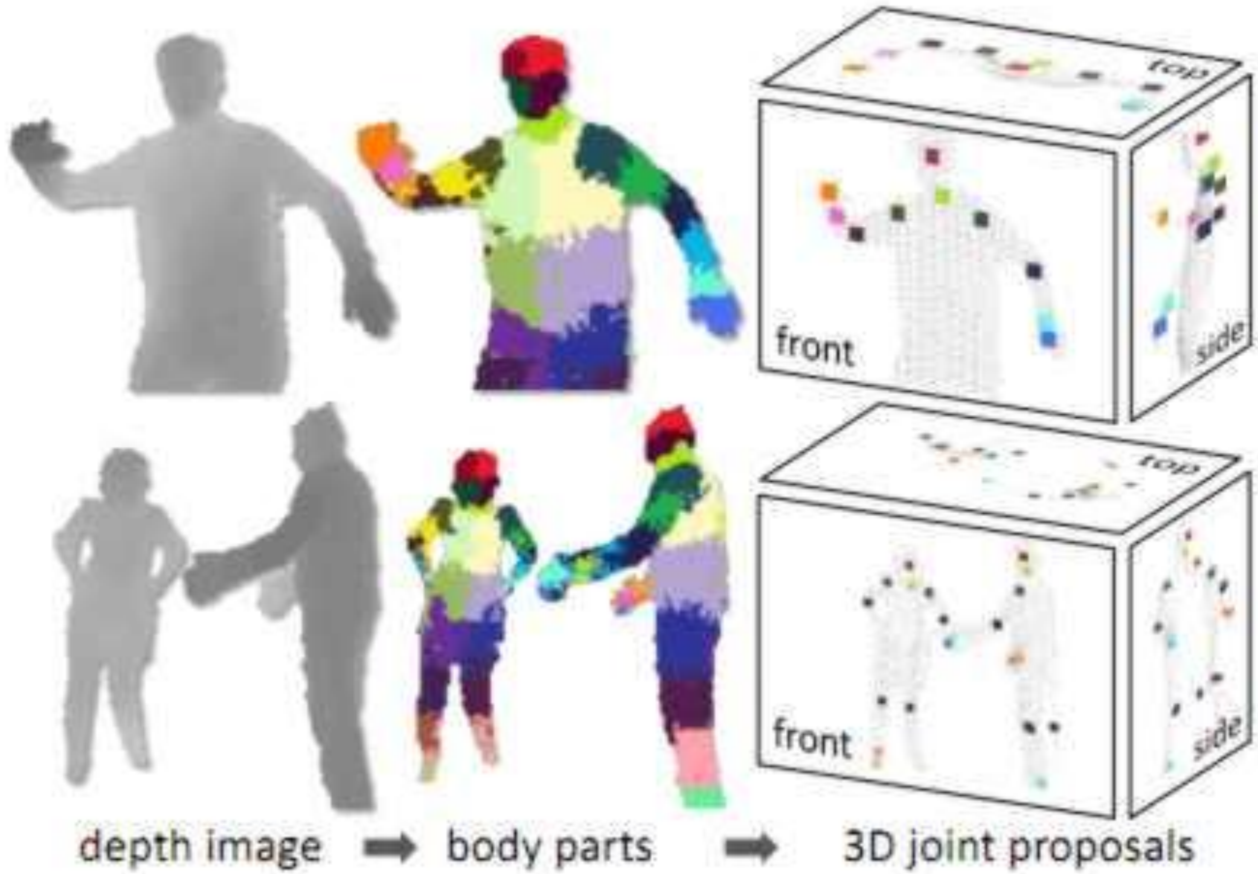

3D DEPTH SENSORS
RGB CAMERA
XBOX 360
KINECT
MULTI-ARRAY MIC
MOTORIZED TILT
XBOX
LIVE

Kinect Sensor



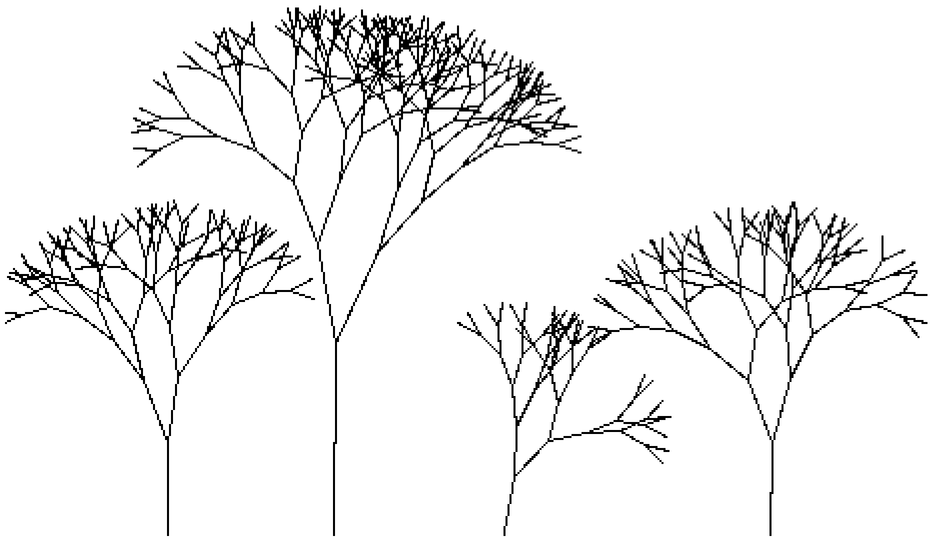
PrimeSense 3d

Random Forest – Body Part Recognition



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

- All trees are fully grown
- No pruning

- Two parameters
  - number of features
  - number of trees

Random Forest Error Rate

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

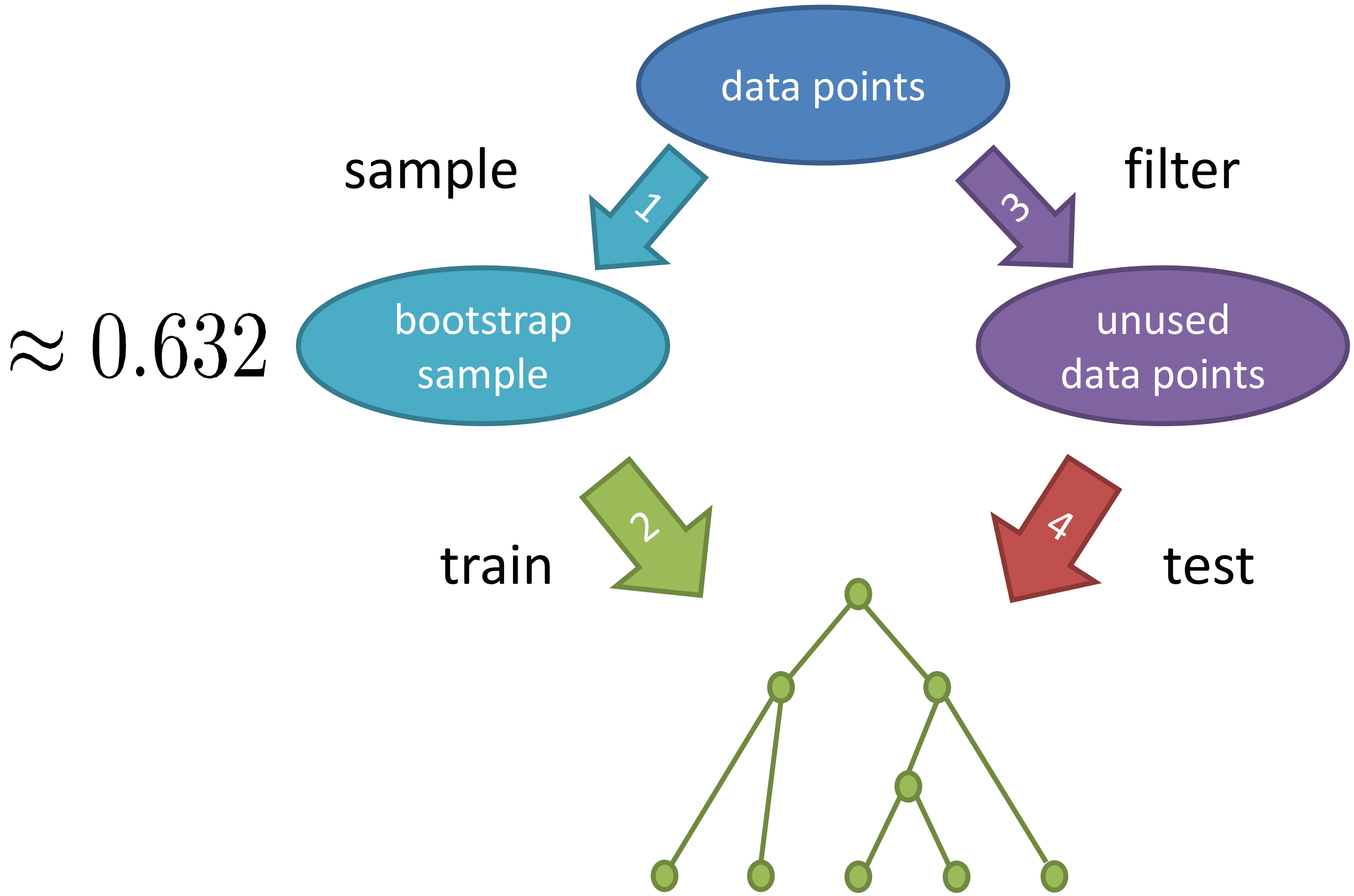
- Increasing number of features for each split:
  - Increases correlation
  - Increases strength of single trees

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



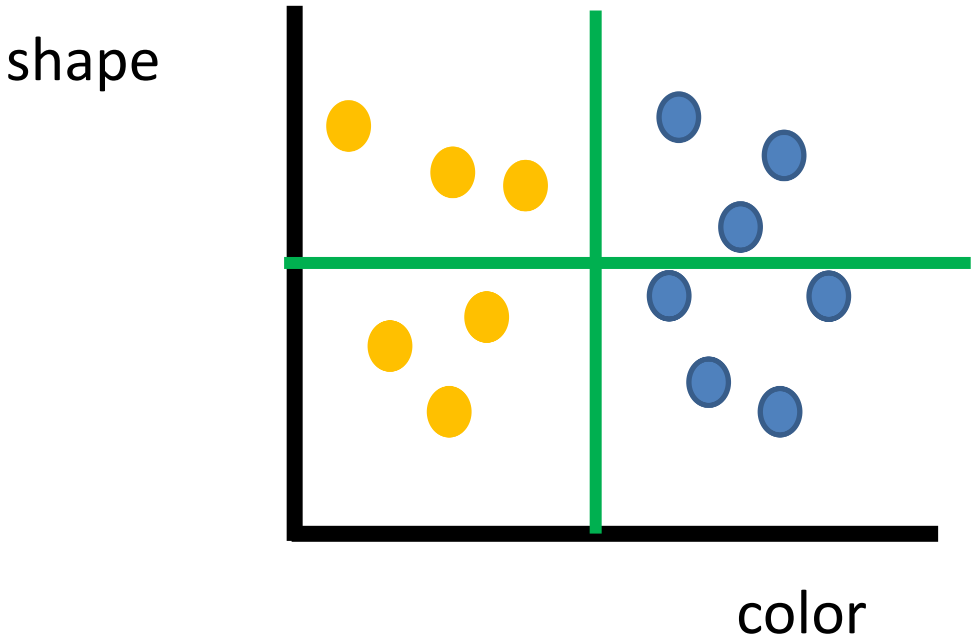
Out of Bag Error

- 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

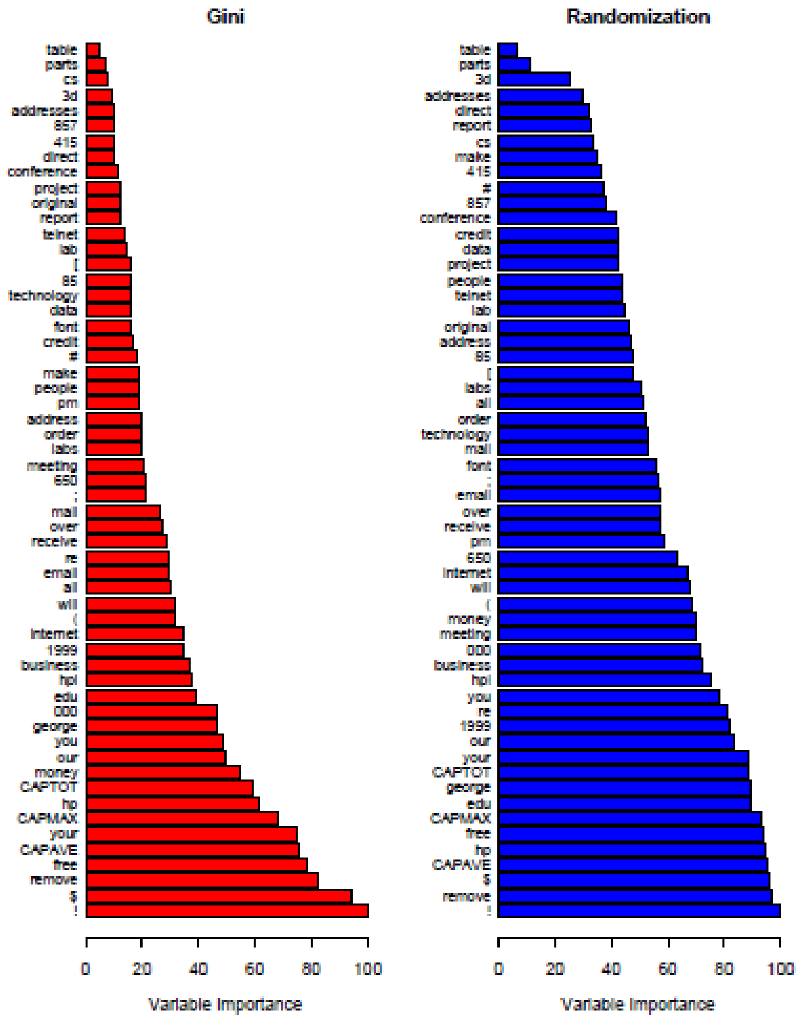
Variable Importance - 1



Variable Importance - 2

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

Example: Spam classification



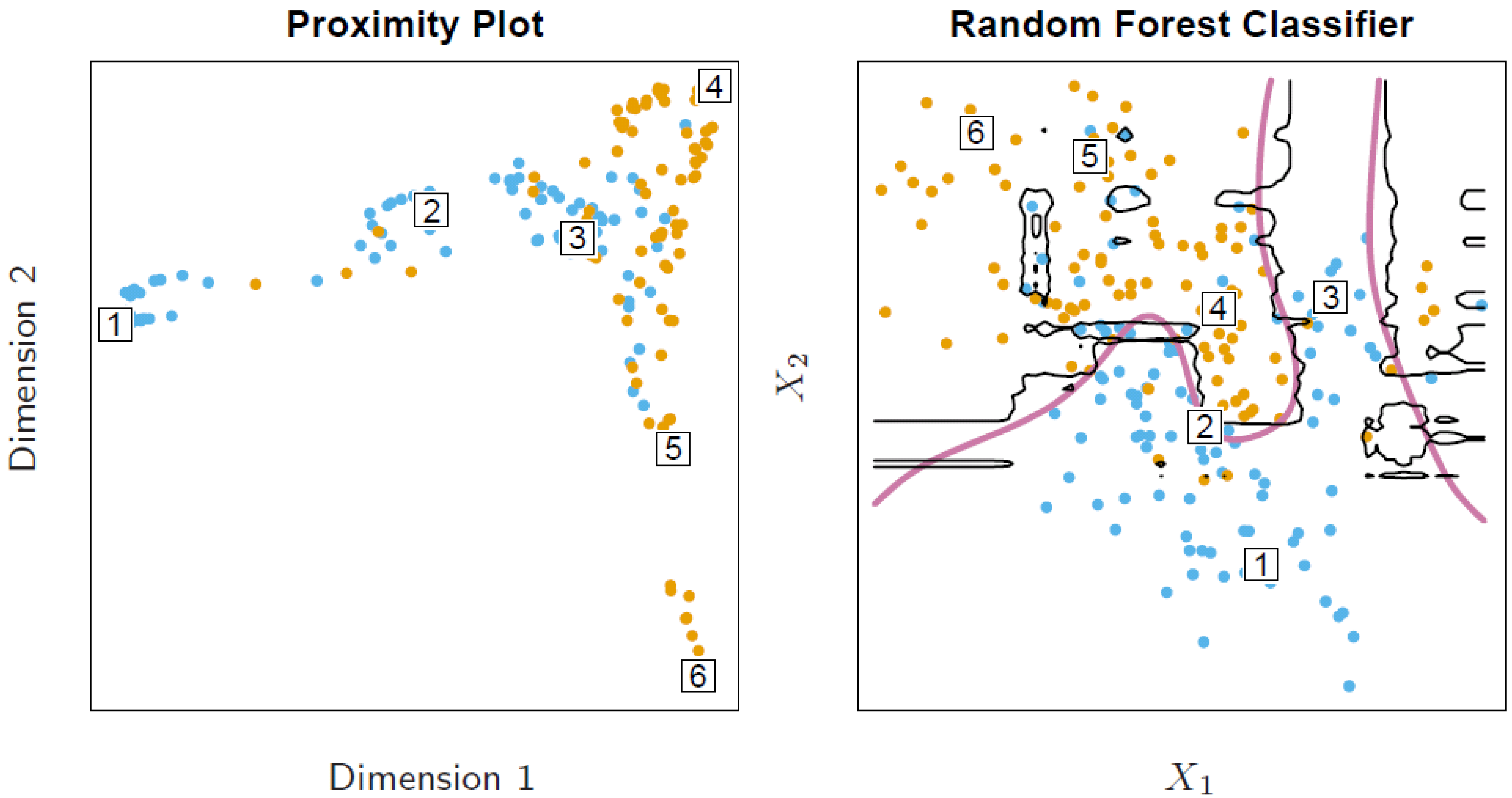
Randomization tends to spread out the variable importance more uniformly.

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

Proximity

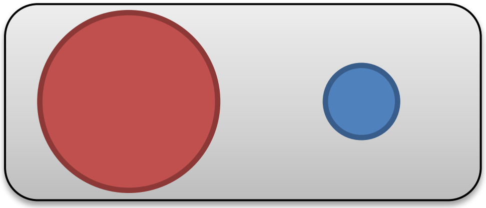
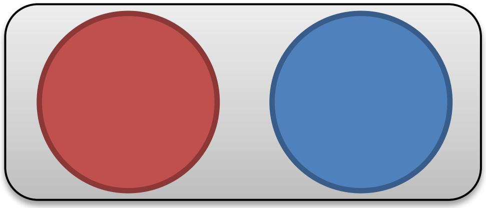
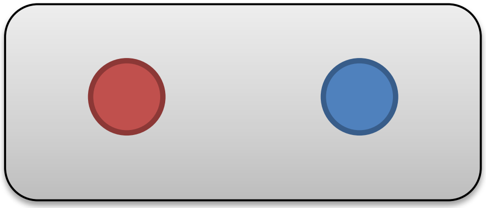
- Pairwise distance: NxN matrix
- Classify complete data set for each tree
- Same leaf => increase proximity
- Normalize by the number of trees

Proximity Visualization

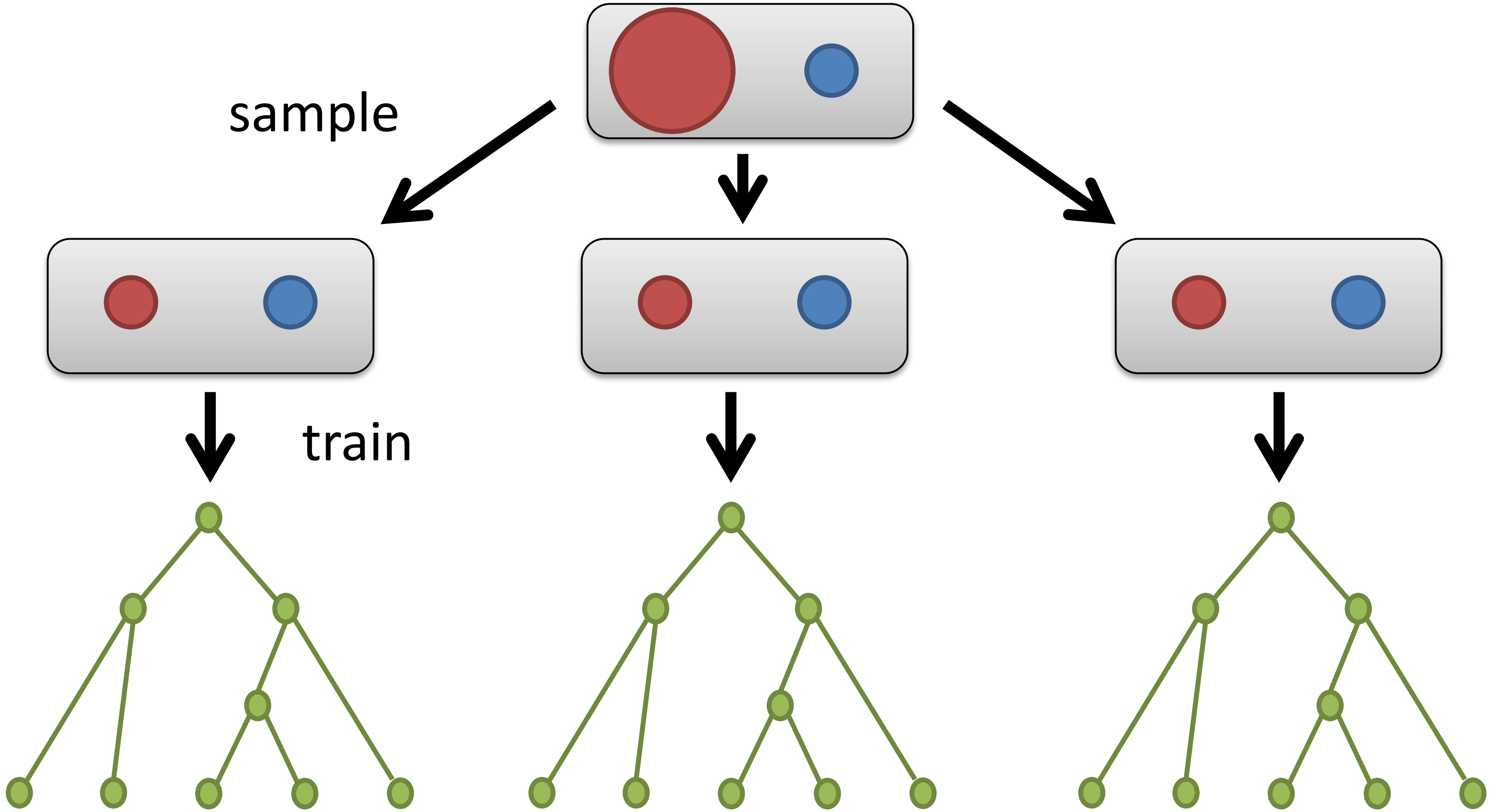


Hastie et al.,"The Elements of Statistical Learning: Data Mining, Inference, and Prediction", Springer (2009)

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

Error Measures

- True positive (tp)
- True negative (tn)
- False positive (fp)
- False negative (fn)

		predicted	
		1	-1
true	1	tp	fn
	-1	fp	tn

TPR and FPR

- True Positive Rate:

$$\frac{tp}{tp+fn}$$

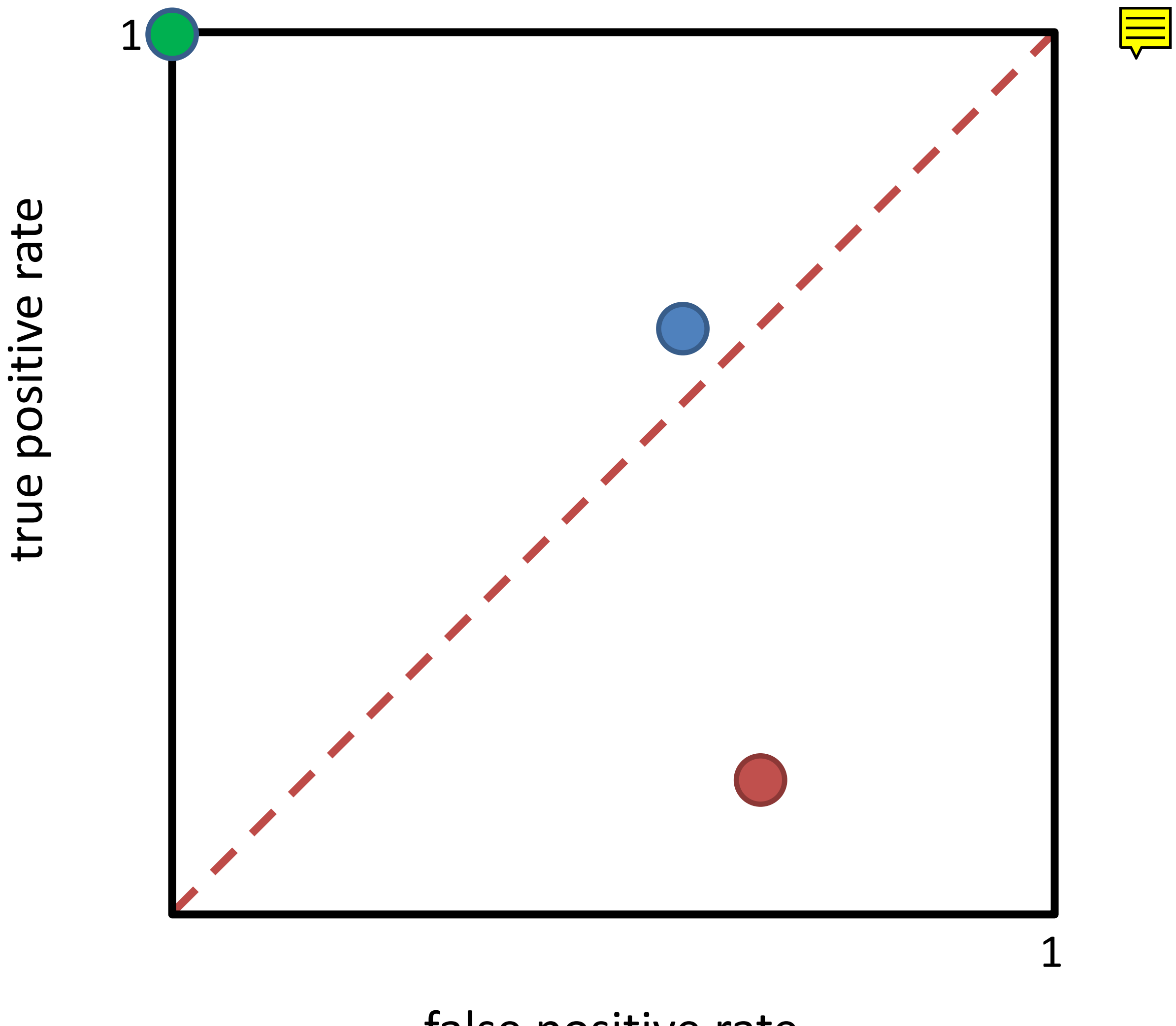
- False Positive Rate:

$$\frac{fp}{fp+tn}$$

predicted

		1	-1
true	1	tp	fn
	-1	fp	tn

Reciever Operating Characteristic



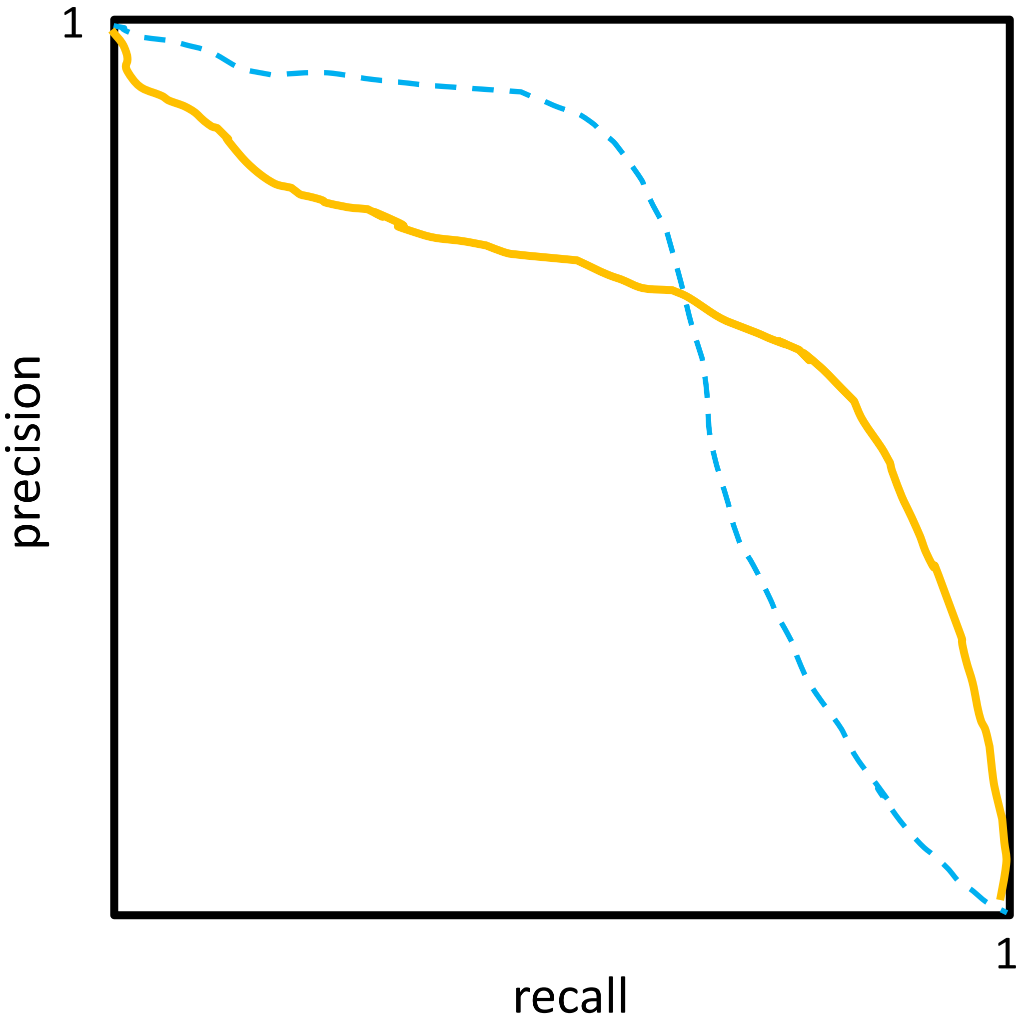
Precision Recall

- Recall: $\frac{tp}{tp+fn}$

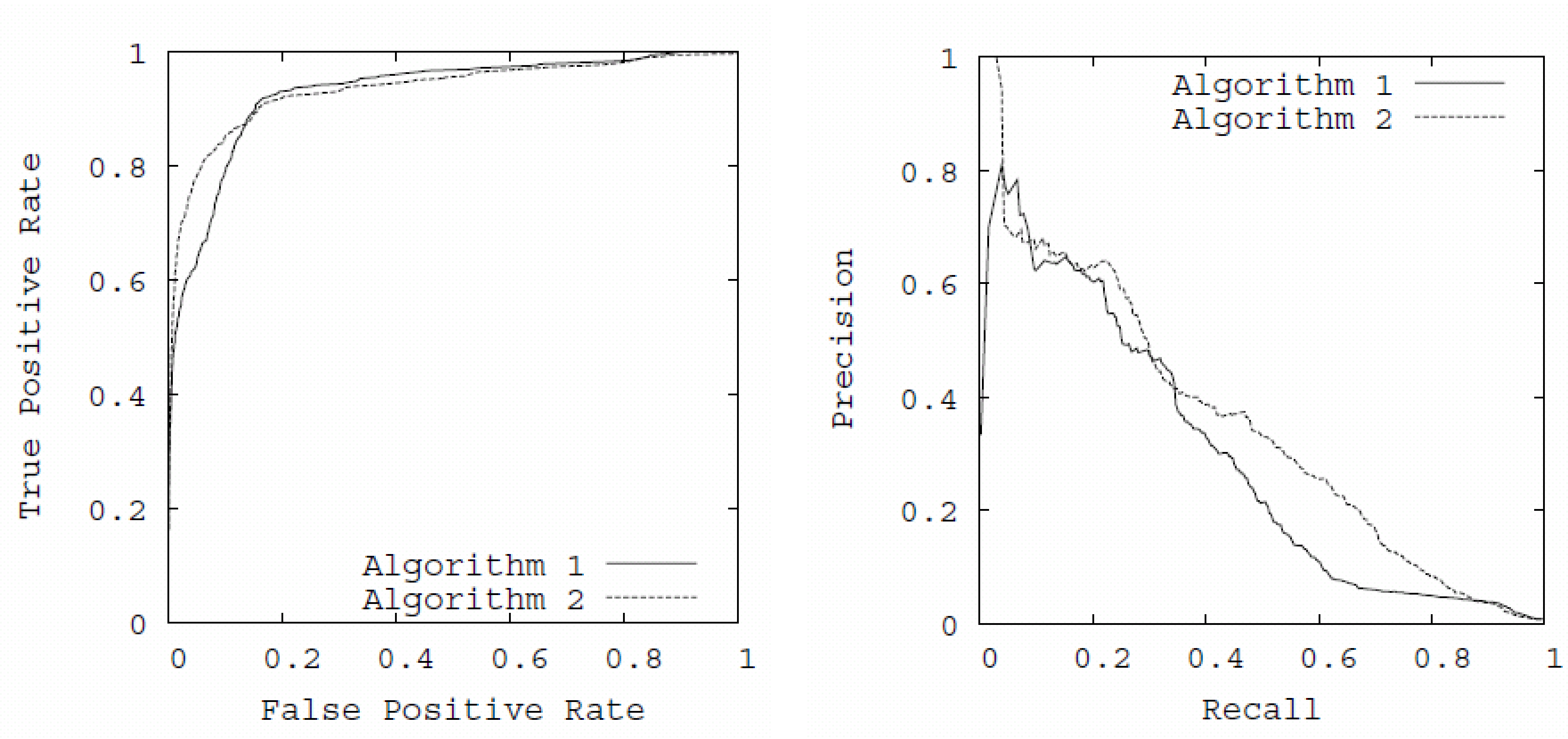
- Precision: $\frac{tp}{tp+fp}$

		predicted	
		1	-1
true	1	tp	fn
	-1	fp	tn

Precision Recall Curve



Comparison



J. Davis & M. Goadrich,
“The Relationship Between Precision-Recall and ROC Curves.”,
ICML (2006)

F-measure

- Weighted average of precision and recall

$$F_\beta = \frac{(\beta^2+1)\cdot P\cdot R}{\beta^2\cdot P+R}$$

- Usual case: $\beta = 1$
- Increasing β allocates weight to recall

Boosting

- Also ensemble method like Bagging
- But:
  - weak learners evolve over time
  - votes are weighted

- Better than Bagging for many applications

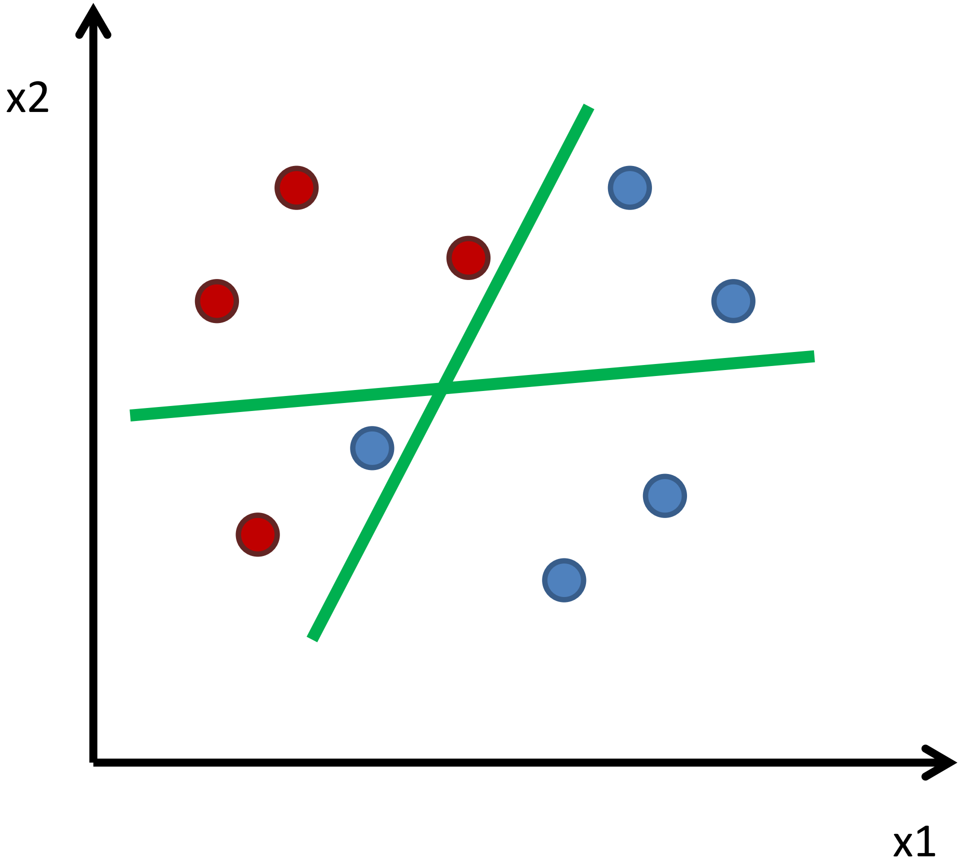
⇒ Very popular method

Boosting

“Boosting is one of the most powerful learning ideas introduced in the last twenty years.”

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

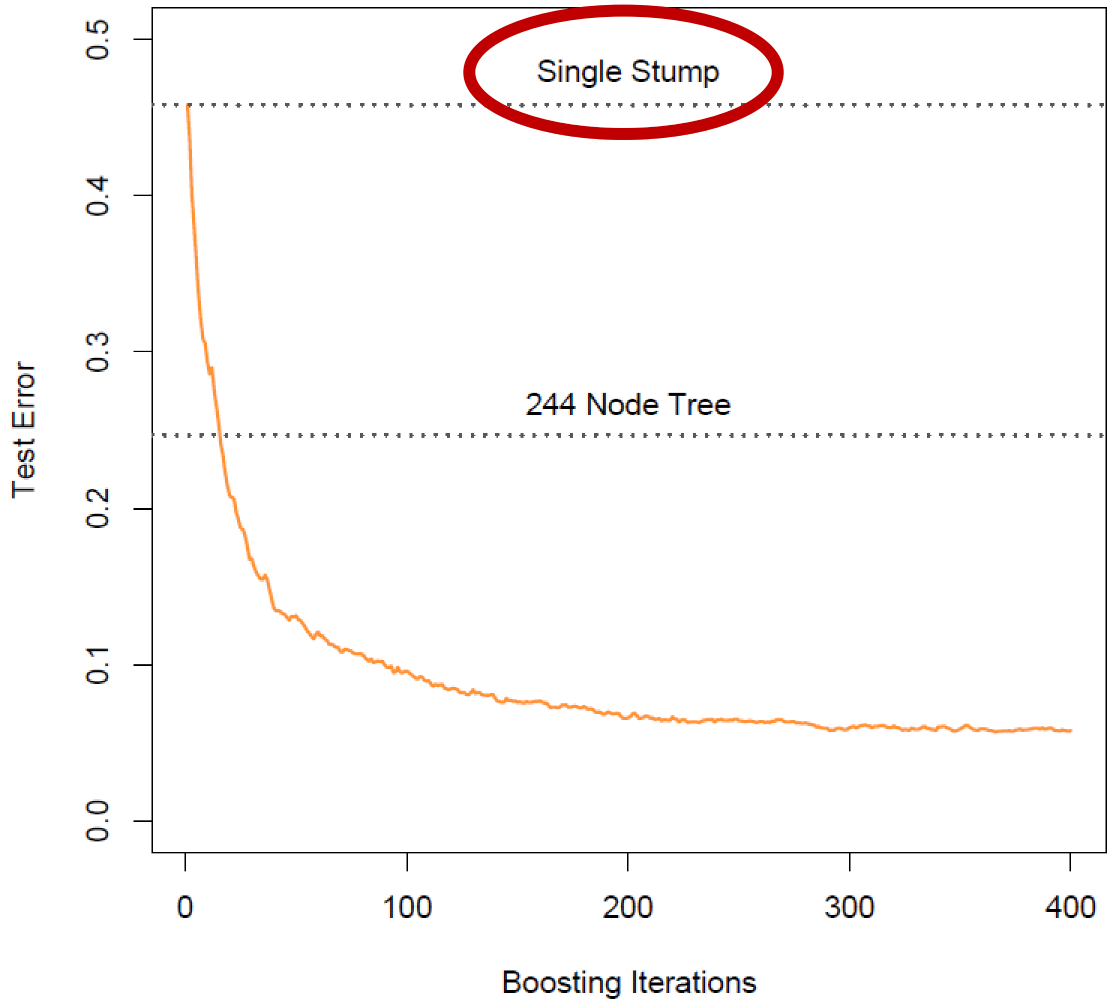
Adaboost



AdaBoost

- Initialize weights for data points
- For each iteration:
  - Fit classifier to training data
  - Compute weighted classification error
  - Compute weight for classifier from the error
  - Update weights for data points
- Final classifier is weighted sum of all single classifiers

AdaBoost



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

AdaBoost

AdaBoost in Action

Kai O. Arras
Social Robotics Lab, University of Freiburg

Nov 2009 Social Robotics Laboratory

AdaBoost

- Introduced by Freund and Schapire in 1995
- Worked great, nobody understood why!

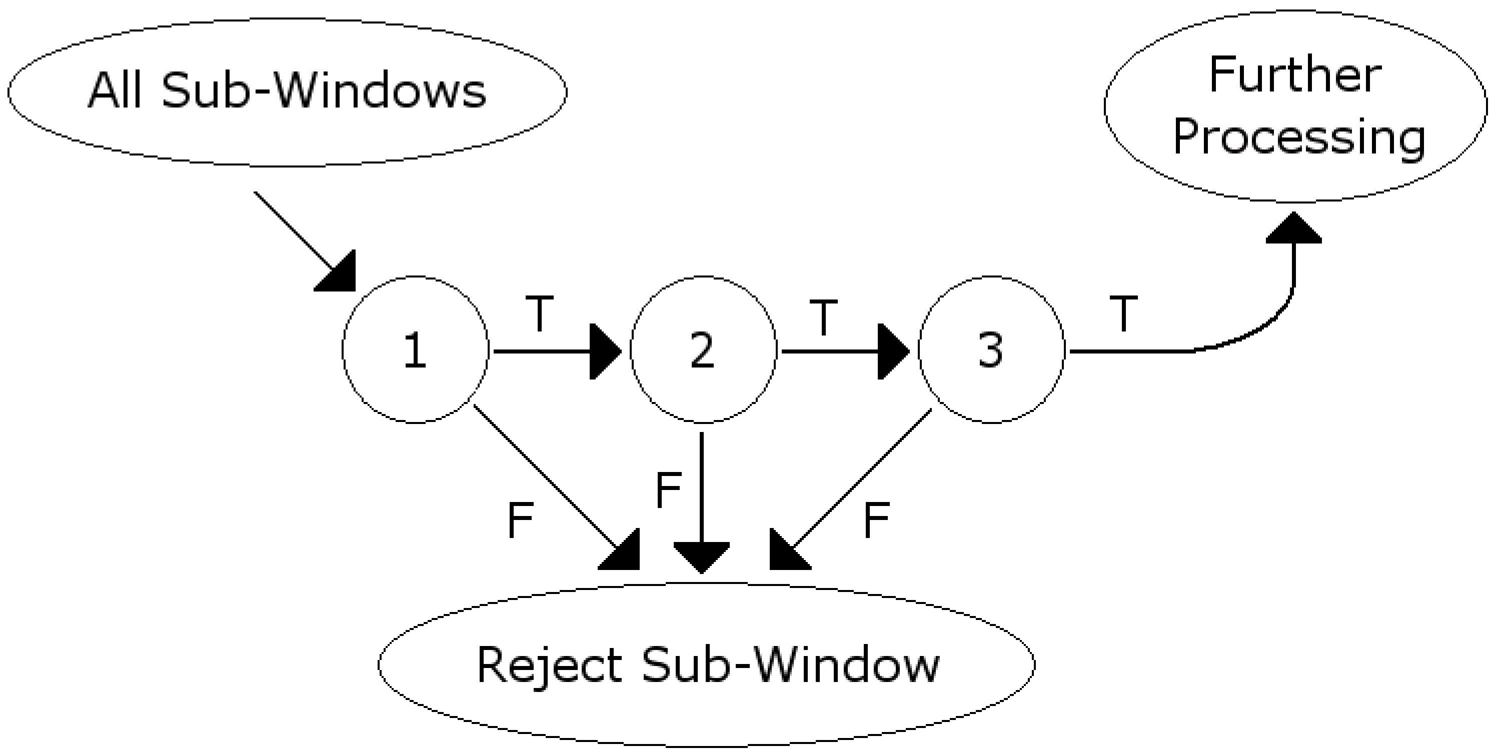
- Then five years later (Friedman et al. 2000):
  - Adaboost minimizes exponential loss function.
- There still are open questions.

Cascade Classifier

- Ensemble methods are strong
- But prediction is slow
- Solution: Make prediction faster

Idea: Build a cascade

Cascade Classifier



http://en.wikipedia.org/wiki/Viola%E2%80%93Jones_object_detection_framework

Cascade Classifier

- Developed for fast object recognition
- Each classifier depends on its predecessor
- False positive rate:

$$\mathrm{F} = \prod_{i=1}^{K} f_i$$

- Detection rate:

$$\mathrm{D} = \prod_{i=1}^{K} d_i$$

Performance Example

- 10 stage classifier
- Want: detection rate = 0.9
- Need: detection rate 0.99 per stage

- But: high false positive rate is ok

$$(0.3^{10} \approx 6 \times 10^{-6})$$

Viola Jones Face Detection

http://cvdazzle.com/

Viola Jones Face Detection

- Takes long to train
- Prediction in real time!

- Widely used today