Ensemble Learning
[RN2] Sec 18.4
[RN3] Sec 18.10

CS 486/686

University of Waterloo

Lecture 18: July 2, 2015

Outline

- Ensemble Learning
  - Bagging
  - Boosting

Supervised Learning

- So far…
  - Decision trees
  - Statistical learning
    - Bayesian Learning
    - Maximum a posteriori
    - Maximum likelihood

- Which technique should we pick?

Ensemble Learning

- Sometimes each learning technique yields a different hypothesis
- But no perfect hypothesis…
- Could we combine several imperfect hypotheses into a better hypothesis?

Ensemble Learning

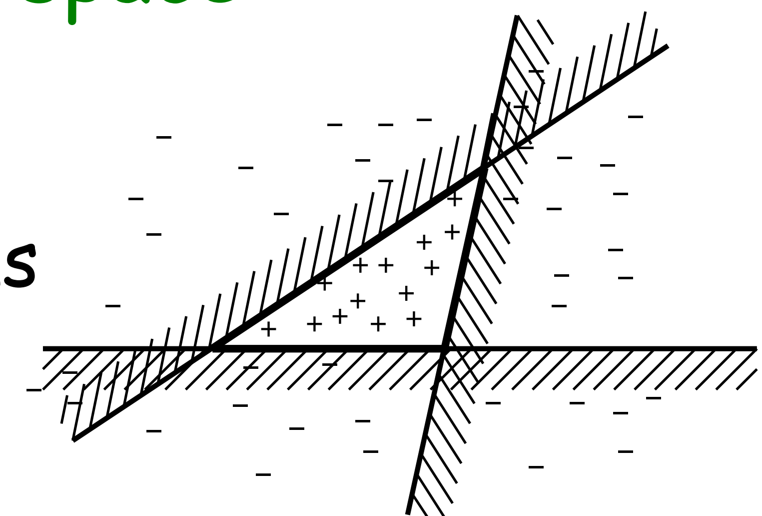
- Analogies:
  - Elections combine voters' choices to pick a good candidate
  - Committees combine experts' opinions to make better decisions

- Intuitions:
  - Individuals often make mistakes, but the "majority" is less likely to make mistakes.
  - Individuals often have partial knowledge, but a committee can pool expertise to make better decisions.

Ensemble Learning

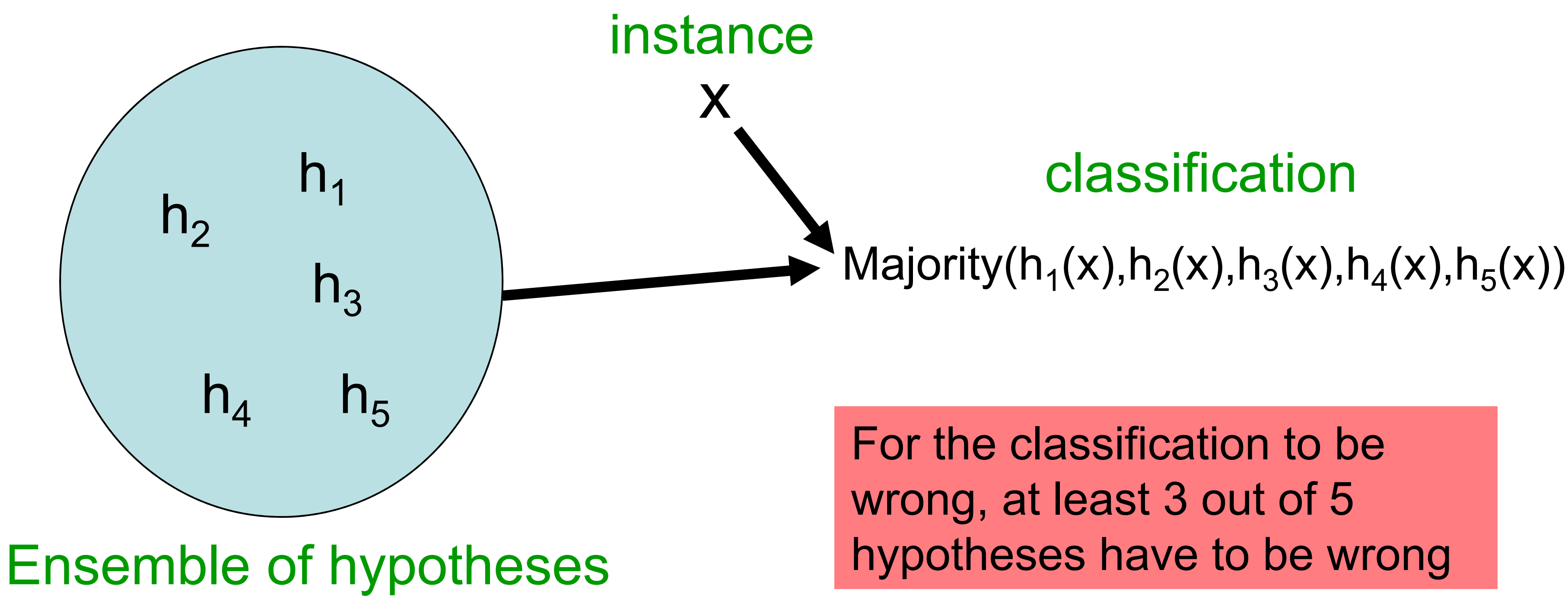
- Definition: method to select and combine an ensemble of hypotheses into a (hopefully) better hypothesis

- Can enlarge hypothesis space
  - Perceptrons
    - linear separators
  - Ensemble of perceptrons
    - polytope



Bagging

- Majority Voting



Bagging

- Assumptions:
  - Each h_i makes error with probability p
  - The hypotheses are independent
- Majority voting of n hypotheses:
  - k hypotheses make an error: $\binom{n}{k} p^k(1-p)^{n-k}$
  - Majority makes an error: $\Sigma_{k>n/2} \binom{n}{k} p^k(1-p)^{n-k}$
  - With n=5, p=0.1 ➔ err(majority) < 0.01

Weighted Majority

- In practice
  - Hypotheses rarely independent
  - Some hypotheses have less errors than others

- Let's take a weighted majority
- Intuition:
  - Decrease weight of correlated hypotheses
  - Increase weight of good hypotheses

Boosting

- Very popular ensemble technique
- Computes a weighted majority
- Can “boost” a “weak learner“
- Operates on a weighted training set

Weighted Training Set

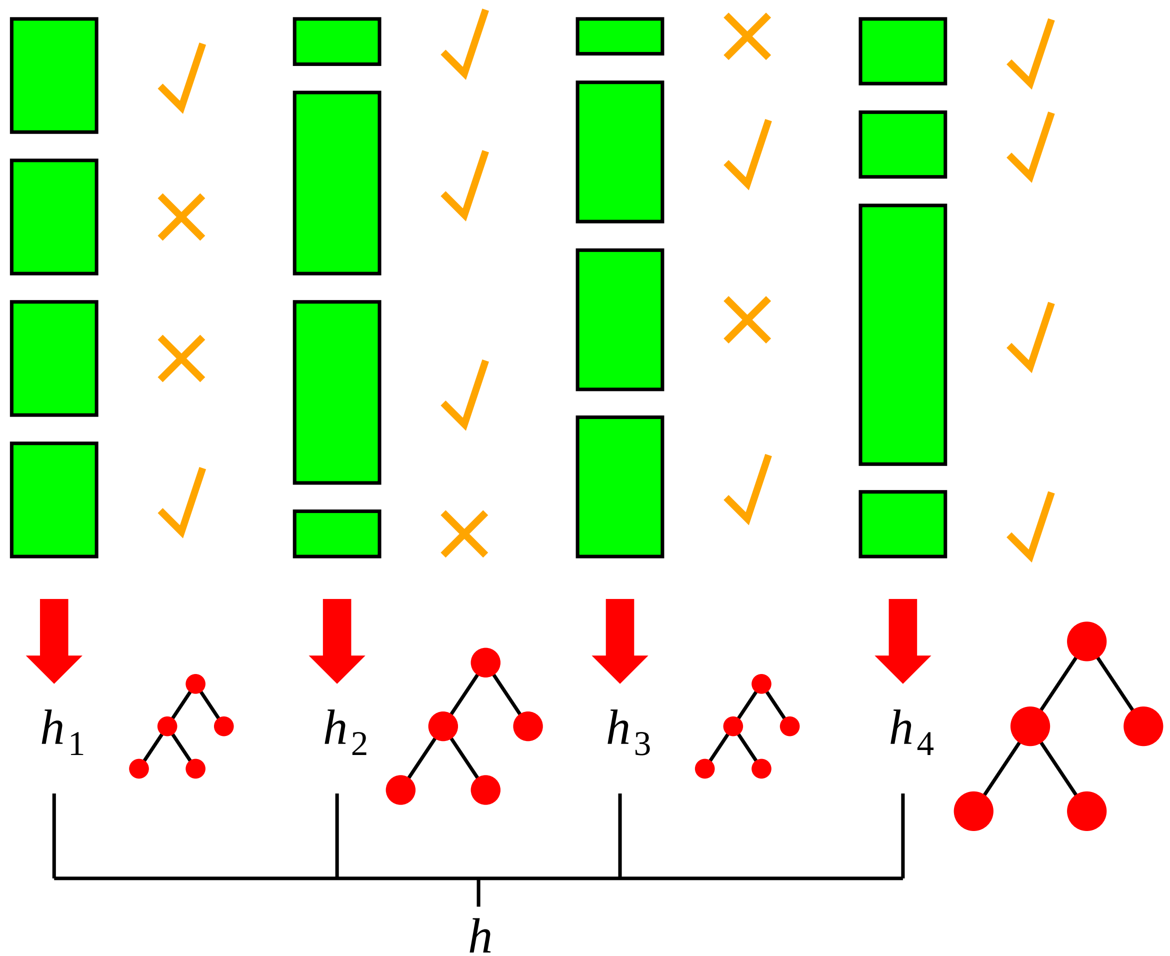
- Learning with a weighted training set
  - Supervised learning → minimize train. error
  - Bias algorithm to learn correctly instances with high weights

- Idea: when an instance is misclassified by a hypothesis, increase its weight so that the next hypothesis is more likely to classify it correctly

Boosting Framework

- Set all instance weights w_x to 1
- Repeat
  - $h_i \leftarrow$ learn(dataset, weights)
  - Increase w_x of misclassified instances x
- Until sufficient number of hypotheses
- Ensemble hypothesis is the weighted majority of h_i's with weights w_i proportional to the accuracy of h_i

Boosting Framework



AdaBoost (Adaptive Boosting)

w: vector of N instance weights
z: vector of M hypoth. weights

- $w_j \leftarrow 1/N \quad \forall_j$
- For m=1 to M do
  - $h_m \leftarrow$ learn(dataset,w)
  - err $\leftarrow 0$
  - For each (x_j, y_j) in dataset do
    - If $h_m(x_j) \neq y_j$ then err $\leftarrow$ err + w_j
  - For each (x_j, y_j) in dataset do
    - If $h_m(x_j) = y_j$ then $w_j \leftarrow w_j$ err / (1-err)
  - w $\leftarrow$ normalize(w)
  - $z_m \leftarrow \log[(1\text{-err}) / \text{err}]$
- Return *weighted-majority(h,z)*

What can we boost?

- Weak learner: produces hypotheses at least as good as random classifier.
- Examples:
  - Rules of thumb
  - Decision stumps (decision trees of one node)
  - Perceptrons
  - Naïve Bayes models

Boosting Paradigm

- Advantages
  - No need to learn a perfect hypothesis
  - Can boost any weak learning algorithm
  - Boosting is very simple to program
  - Good generalization

- Paradigm shift
  - Don't try to learn a perfect hypothesis
  - Just learn simple rules of thumbs and boost them

Boosting Paradigm

- When we already have a bunch of hypotheses, boosting provides a principled approach to combine them

- Useful for
  - Sensor fusion
  - Combining experts

Applications

- Any supervised learning task
  - Collaborative filtering (Netflix challenge)
  - Body part recognition (Kinect)
  - Spam filtering
  - Speech recognition/natural language processing
  - Data mining
  - Etc.

Netflix Challenge

- Problem: predict movie ratings based on database of ratings by previous users

- Launch: 2006
  - Goal: improve Netflix predictions by 10%
  - Grand Prize: 1 million $

Progress

- 2007: BellKor 8.43% improvement
- 2008:
  - No individual algorithm improves by > 9.43%
  - Top two teams BellKor and BigChaos unite
    - Start of ensemble learning
    - Jointly improve by > 9.43%
- June 26, 2009:
  - Top 3 teams BellKor, BigChaos and Pragmatic unite
  - Jointly improve > 10%
  - 30 days left for anyone to beat them

The Ensemble

- Formation of "Grand Prize Team":
  - Anyone could join
  - Share of $1 million grand prize proportional to improvement in team score
  - Improvement: 9.46%
- 5 days to the deadline
  - "The Ensemble" team is born
    - Union of Grand Prize team and Vanderlay Industries
    - Ensemble of many researchers

Finale

- Last Day: July 26, 2009

- 6:18 pm:
  - BellKor's Pragmatic Chaos: 10.06% improv.
- 6:38 pm:
  - The Ensemble: 10.06% improvement

- Tie breaker: time of submission

Xbox 360 Kinect

- Microsoft Cambridge
- Body part recognition: supervised learning

Depth camera

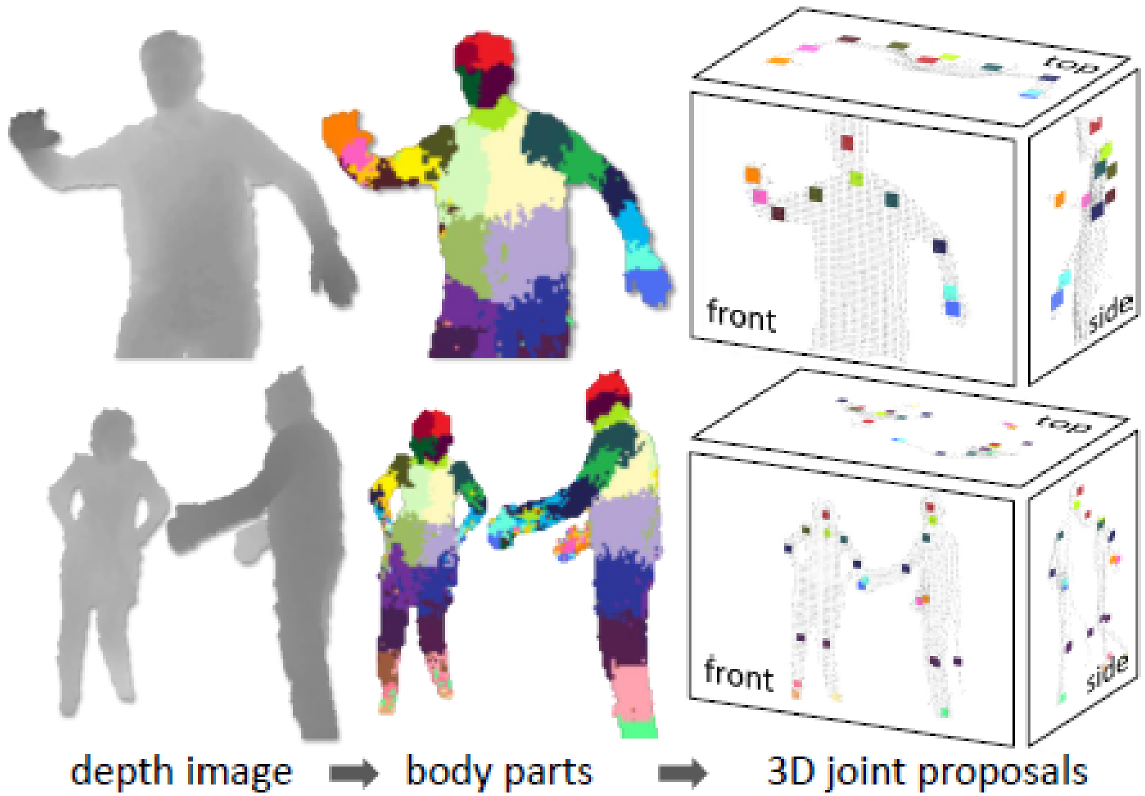
- Kinect

Infrared image

Gray scale depth map

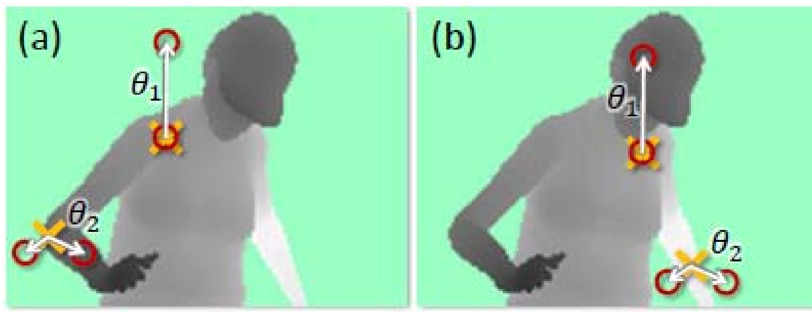
Kinect Body Part Recognition

- Problem: label each pixel with a body part



Kinect Body Part Recognition

- Features: depth differences between pairs of pixels



- Classification: forest of decision trees