CS 2750 Machine Learning
Lecture 19

Decision trees

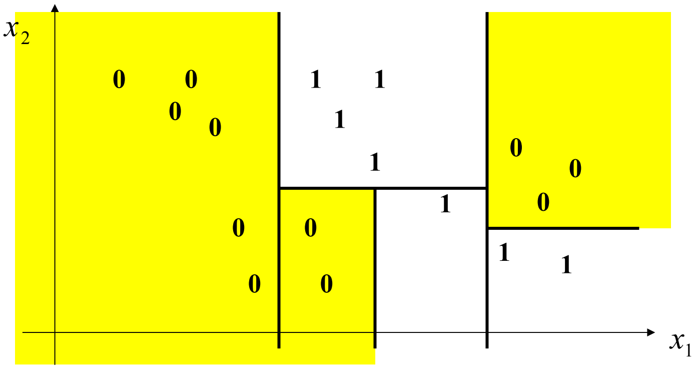
Milos Hauskrecht
milos@cs.pitt.edu
5329 Sennott Square

Announcement

- **Term project:**
  - **Reports** due on Wednesday, April 23 at 2pm
  - **Project presentations**:
    - When: Friday, April 25, 2003 at 1pm
    - Where: 5313 Sennott Square
    - 10 minutes ppt presentations
  - Example project reports are on the course web site.

Decision trees

- Back to the supervised learning
- An alternative approach to what we have seen so far:
  - **Partition the input space to regions**
  - **Regress or classify independently in every region**



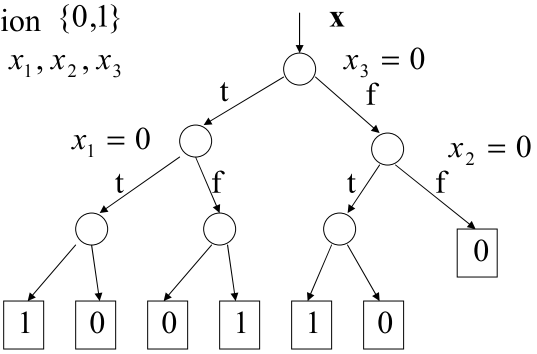
Decision trees

- The partitioning idea is used in the **decision tree model**:
  - Split the space recursively according to inputs in **x**
  - Regress or classify at the bottom of the tree

Example:

Binary classification $\{0,1\}$

Binary attributes x_1, x_2, x_3



Decision trees

How to construct the decision tree?

- **Top-bottom algorithm**:
  - Find the best split condition (quantified based on the impurity measure)
  - Stops when no improvement possible
- **Impurity measure**:
  - Measures how well are the two classes separated
  - Ideally we would like to separate all 0s and 1

- Splits of **finite vs. continuous value attributes**

  Continuous value attributes conditions: $x_3 \leq 0.5$

Impurity measure

Let $|D|$ - Total number of data entries

$|D_i|$ - Number of data entries classified as *i*

$p_i = \frac{|D_i|}{|D|}$ - ratio of instances classified as *i*

- **Impurity measure** defines how well e classes are separated
- In general the impurity measure should satisfy:
  - Largest when data are split evenly for attribute values

    $$p_i = \frac{1}{\text{number of classes}}$$

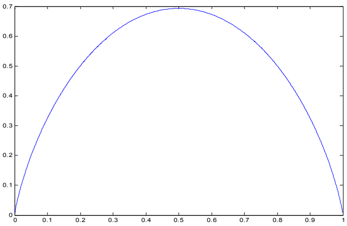
  - Should be 0 when all data belong to the same class

Impurity measures

- There are various impurity measures used in the literature
  - **Entropy based measure (Quinlan, C4.5)**

$$I(D) = Entropy\ (D) = -\sum_{i=1}^{k} p_i \log\ p_i$$

Example for k=2



  - **Gini measure (Breiman, CART)**

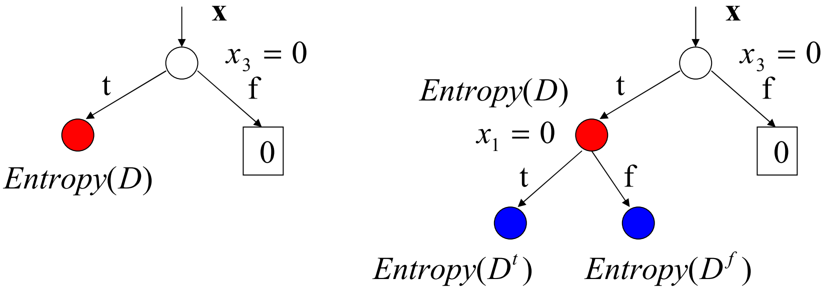
$$I(D) = Gini\ (D) = 1 - \sum_{i=1}^{k} p_i^{\ 2}$$

Impurity measures

- **Gain due to split** – expected reduction in the impurity measure (entropy example)

$$Gain\ (D, A) = Entropy\ (D) - \sum_{v \in Values\ (A)} \frac{|D^v|}{|D|} Entropy\ (D^v)$$

$|D^v|$ - a partition of D with the value of attribute A = v



Decision tree learning

- **Greedy learning algorithm:**

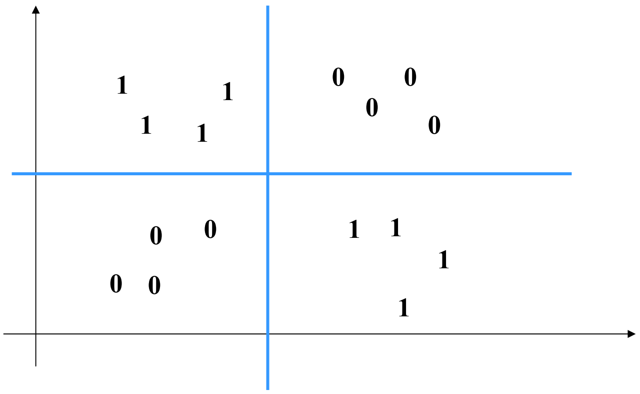
  Repeat until no or small improvement in the purity
  - Find the attribute with the highest gain
  - Add the attribute to the tree and split the set accordingly

- Builds the tree in the top-down fashion
  - Gradually expands the leaves of the partially built tree
- The method is greedy
  - It looks at a single attribute and gain in each step
  - May fail when the combination of attributes is needed to improve the purity (parity functions)

Decision tree learning

- **Limitations of greedy methods**

  Cases in which a combination of two or more attributes improves the impurity



Decision tree learning

By reducing the impurity measure we can grow **very large trees**

Problem: Overfitting

- We may split and classify very well the training set, but we may do worse in terms of the generalization error

Solutions to the overfitting problem:

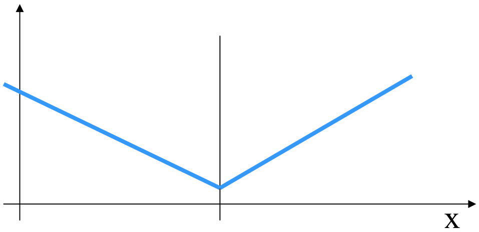
- **Solution 1.**
  - Prune branches of the tree built in the first phase
  - Use validation set to test for the overfit
- **Solution 2**.
  - Test for the overfit in the tree building phase
  - Stop building the tree when performance on the validation set deteriorates

Mixture of experts

- **Clustering before classification /regression:**
  - The reduction is not tuned towards the prediction task
  - Two or more clusters may be covered by a simple predictor
- **Solution**:
  - Cover different input regions with many (simple) networks
  - A kind of predictive clustering with regard to the prediction accuracy
- **Mixture of experts**

  Expert

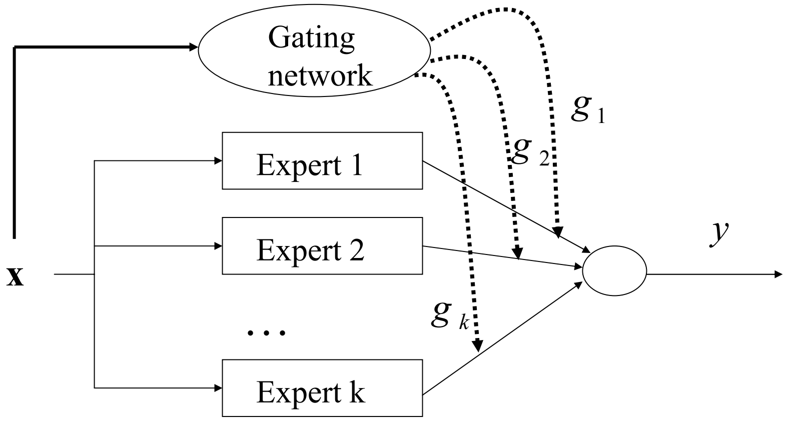
  = network learner



Mixture of experts

- **Gating network** : decides what expert to use

  $g_1, g_2, \ldots g_k$ - gating functions


Gating network
g_1
g_2
g_k
Expert 1
Expert 2
…
Expert k
$\mathbf{x}$
y