Classification

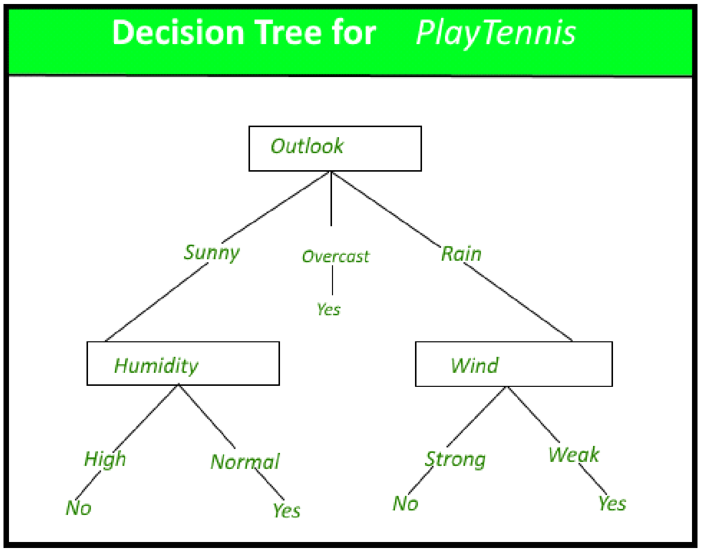
Tuesday, October 12, 2021 4:32 PM

Given a training set where data is labeled with a special attribute called a class (discrete value)
We want to find a model for the class attribute as a function of the values of the other attributes
- Seems similar to arrhythmia dataset with class in **y**

Classification Techniques

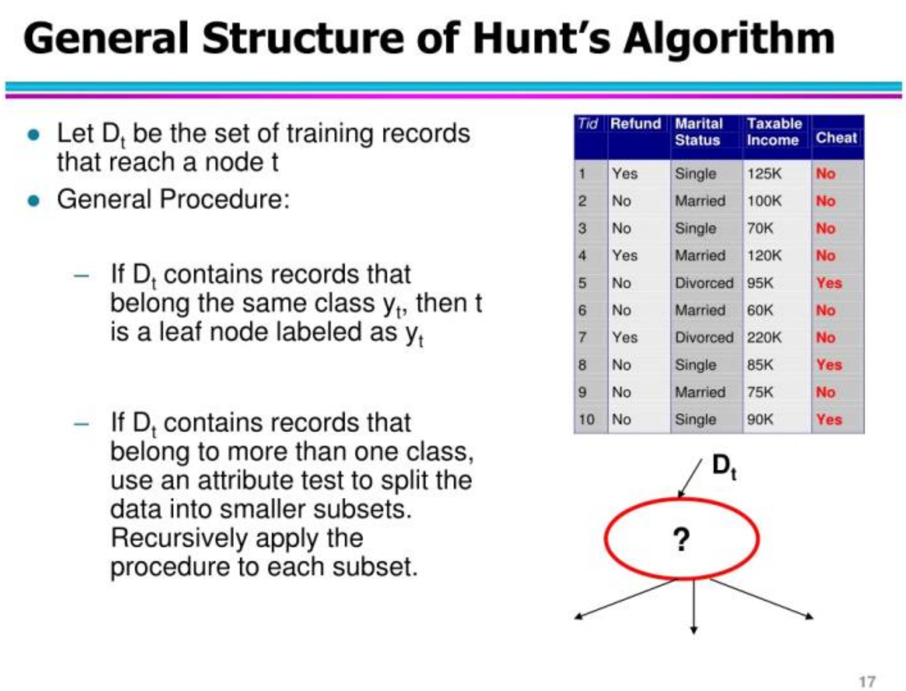
- Instance based classifiers
  - Keep a record of attributes which we can use to predict the class label of unseen classes
  - If we have an old record that matches the new record, we can label it the same
  - Rote-learners:
    - Perform classification only if the attributes of the unseen record exactly match a record in our training set
  - Nearest Neighbor:
    - Use the **k** closest records to perform classification
    - Requires a large training set, distance function, and a value for **k**
    - Classifying an unseen record:
      1. Compute distance of unseen record to all training records
      2. Identify the k nearest neighbors
      3. Aggregate the labels of these k neighbors to predict the label of the unseen record
    - Aggregation methods:
      - Majority rule
      - Weighted majority based on distance (w=1/d^2)
    - Scaling issues:
      - Attributes should be scaled to prevent distance measures from being dominated by one attribute
      - Example
        - Height: 1m ---> 2m
        - Income: 10k ---> 1million
    - Choosing the value of k:
      - If k is too small -> sensitive to noise points + overfitting (doesn't generalize well)
      - If k is too big -> neighborhood may include points from other classes
    - Pros:
      - Sime to understand why a given unseen record was given a particular class
      - Adapts to new attributes
    - Cons:
      - Expensive to classify new points
      - KNN can be problematic in high dimensions

- Decision trees
  - Classify records by traversing the decision tree until we reach a class attribute



Algorithms:

Hunt's Algorithm



Tid	Refund	Marital Status	Taxable Income	Cheat
1	Yes	Single	125K	No
2	No	Married	100K	No
3	No	Single	70K	No
4	Yes	Married	120K	No
5	No	Divorced	95K	Yes
6	No	Married	60K	No
7	Yes	Divorced	220K	No
8	No	Single	85K	Yes
9	No	Married	75K	No
10	No	Single	90K	Yes

If D_t is an empty set, then t is a leaf node labeled by the default class, y_d

Attribute types:

- Nominal
- Ordinal
- Continuous

Nominal Attribute Splitting:

- Multiway split: Use as many partitions as distinct values
- Binary split: Divide values into two subsets, requires optimal partitioning

- Continuous Attribute Splitting:
  - Discretization: form an ordinal categorical attribute
    - Static - discretize once at the beginning
    - Dynamic - ranges can be found by equal interval bucketing, equal frequency bucketing (percentiles), or clustering
  - Binary Decision: (A < v) or (A >= v)
    - Find best possible value for an optimal cut

- Determining the best split:
  - Greedy Approach:
    - Nodes with homogeneous class distribution are preferred
    - Need a measure of node impurity

CO: 5	C1: 5

Non-homogeneous, high impurity

C0: 9	C1: 1

Homegeneous, low impurity

- Compare loss of impurity between two different splits
  - Methods of measuring node impurity:
    - Gini Index
    - Entropy

Impurity Criterion

Gini Index

$$I_G = 1 - \sum_{j=1}^{c} p_j^2$$

p_j: proportion of the samples that belongs to class c for a particular node

Entropy

$$I_H = - \sum_{j=1}^{c} p_j log_2(p_j)$$

p_j: proportion of the samples that belongs to class c for a particular node.

*This is the the definition of entropy for all non-empty classes (p ≠ 0). The entropy is 0 if all samples at a node belong to the same class.

- Misclassification
  - Similar to Gini but with linear growth/decay

- CART
- ID3, C4.5
- SLIQ, SPRINT

- Stopping Criteria for tree induction:
  - Stop expanding a node when all the records belong to the same class
  - Stop expanding when all the records have similar attribute values
  - Early termination
- Creating too large of a tree will result in overfitting and higher error percentage
  - Might happen because of noise points or insufficient examples

Naïve Bayes

Support Vector Machines
Neural Networks