Decision Tree Algorithm

Comp328 tutorial 1

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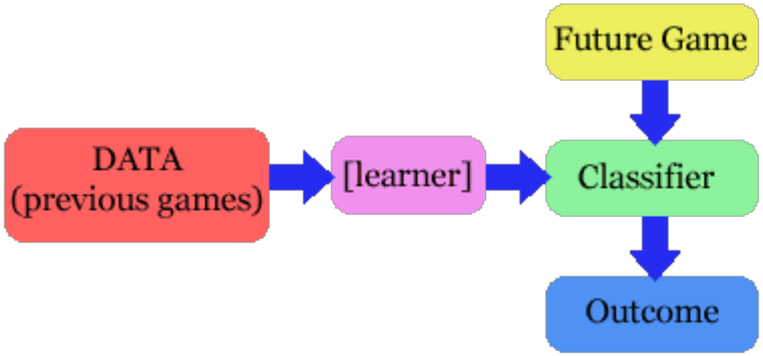
Outline

- Introduction
- Example
- Principles
  - Entropy
  - Information gain
- Evaluations
- Demo

The problem

- Given a set of training cases/objects and their attribute values, try to determine the target attribute value of new examples.
  - Classification
  - Prediction



Why decision tree?

- Decision trees are powerful and popular tools for classification and prediction.
- Decision trees represent *rules*, which can be understood by humans and used in knowledge system such as database.

key requirements

- **Attribute-value description:** object or case must be expressible in terms of a fixed collection of properties or attributes (e.g., hot, mild, cold).
- **Predefined classes (target values):** the target function has **discrete output values** (bollean or multiclass)
- **Sufficient data:** enough training cases should be provided to learn the model.

A simple example

- You want to guess the outcome of next week's game between the *MallRats* and the *Chinooks*.

- Available knowledge / Attribute
  - was the game at Home or Away
  - was the starting time 5pm, 7pm or 9pm.
  - Did Joe play center, or forward.
  - whether that opponent's center was tall or not.
  - …..

Basket ball data

Where	When	Fred Starts	Joe offense	Joe defense	Opp C	*OutCome*
Home	7pm	Yes	Center	Forward	Tall	*Won*
Home	7pm	Yes	Forward	Center	Short	*Won*
Away	7pm	Yes	Forward	Forward	Tall	*Won*
Home	5pm	No	Forward	Center	Tall	*Lost*
Away	9pm	Yes	Forward	Forward	Short	*Lost*
Away	7pm	No	Center	Forward	Tall	*Won*
Home	7pm	No	Forward	Center	Tall	*Lost*
Home	7pm	Yes	Center	Center	Talls	*Won*
Away	7pm	Yes	Center	Center	Short	*Won*
Home	9pm	No	Forward	Center	Short	*Lost*

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What we know

- The game will be away, at 9pm, and that Joe will play center on offense…

Where	When	Fred Starts	Joe offense	Joe defense	Opp C	*Outcome*
Away	9pm	No	Center	Forward	Tall	??

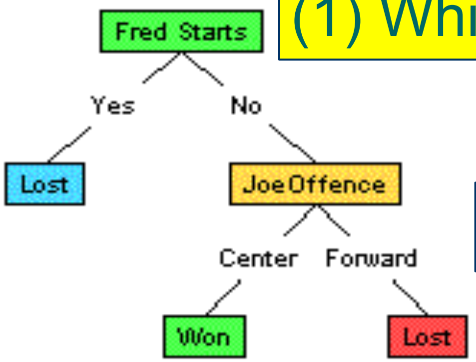
- A classification problem
- Generalizing the learned rule to new examples

Definition

- Decision tree is a classifier in the form of a tree structure
  - Decision node: specifies a test on a single attribute
  - Leaf node: indicates the value of the target attribute
  - Arc/edge: split of one attribute
  - Path: a disjunction of test to make the final decision

- Decision trees classify instances or examples by starting at the root of the tree and moving through it until a leaf node.

Illustration



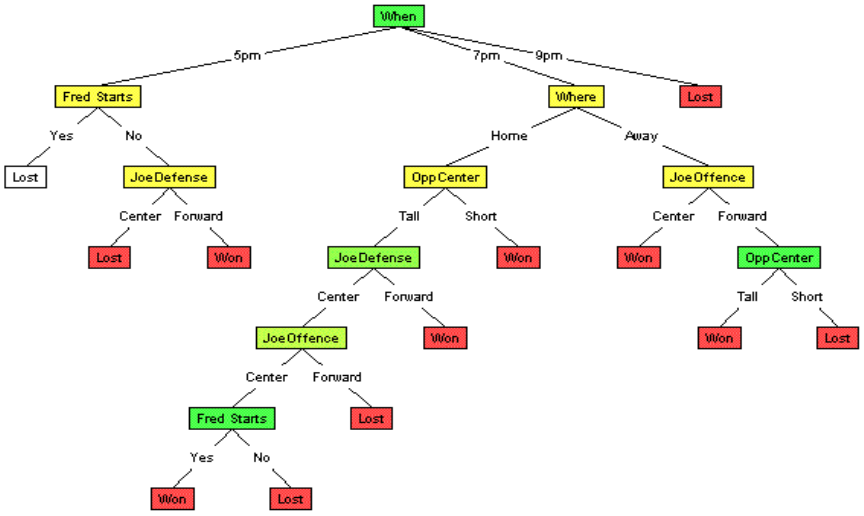
(1) Which to start? (root)

(2) Which node to proceed?

(3) When to stop/ come to conclusion?

Random split

- The tree can grow huge
- These trees are hard to understand.
- Larger trees are typically less accurate than smaller trees.



Principled Criterion

- Selection of an attribute to test at each node - choosing the most useful attribute for classifying examples.
- information gain
  - measures how well a given attribute separates the training examples according to their target classification
  - This measure is used to select among the candidate attributes at each step while growing the tree

Entropy

- A measure of homogeneity of the set of examples.
- Given a set S of positive and negative examples of some target concept (a 2-class problem), the entropy of set S relative to this binary classification is

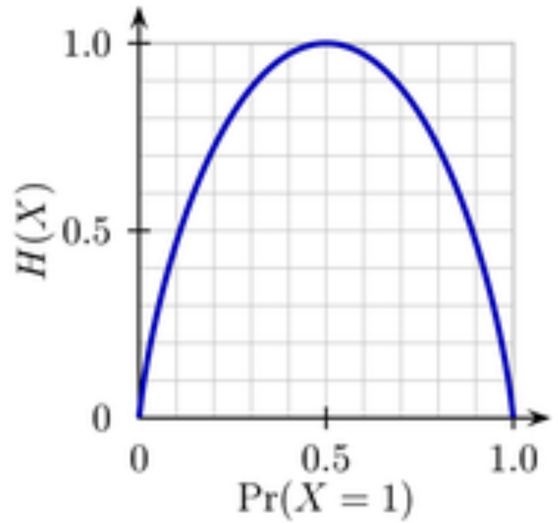
$$E(S) = - p(P)\log2\ p(P) – p(N)\log2\ p(N)$$

- Suppose S has 25 examples, 15 positive and 10 negatives [15+, 10-]. Then the entropy of S relative to this classification is

$$E(S)=-(15/25)\log_2(15/25) - (10/25)\log_2(10/25)$$

Some Intuitions

- The entropy is 0 if the outcome is ``certain''.
- The entropy is maximum if we have no knowledge of the system (or any outcome is equally possible).



Entropy of a 2-class problem with regard to the portion of one of the two groups

Information Gain

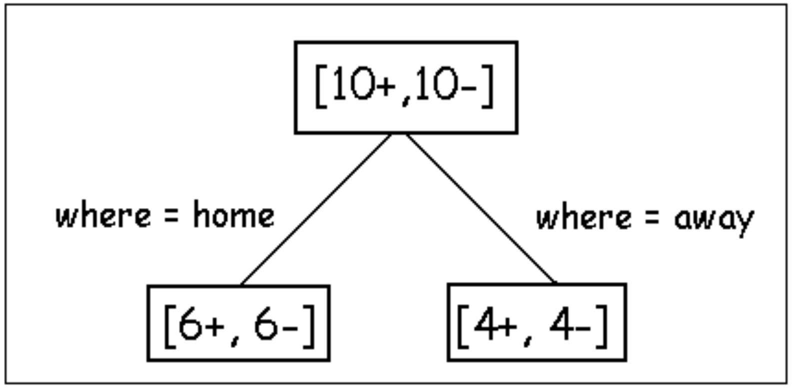
- Information gain measures the expected reduction in entropy, or uncertainty.

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

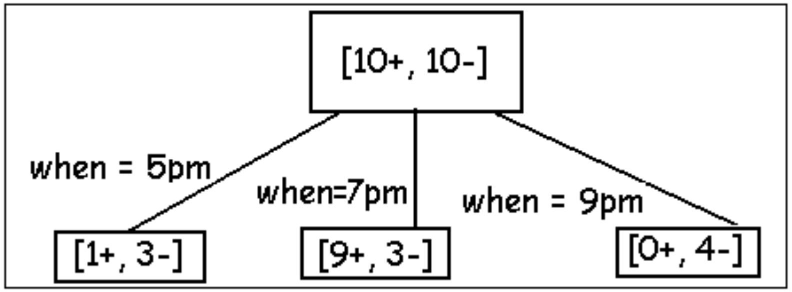
  - Values(A) is the set of all possible values for attribute A, and Sv the subset of S for which attribute A has value v Sv = {s in S | A(s) = v}.
  - the first term in the equation for *Gain* is just the entropy of the original collection *S*
  - the second term is the expected value of the entropy after S is partitioned using attribute A

- It is simply the expected reduction in entropy caused by partitioning the examples according to this attribute.
- It is the number of bits saved when encoding the target value of an arbitrary member of *S*, by knowing the value of attribute *A.*

Examples



- Before partitioning, the entropy is
  - *H(10/20, 10/20) = - 10/20 log(10/20) - 10/20 log(10/20) = 1*
- Using the ``where" attribute, divide into 2 subsets
  - Entropy of the first set H(home) = - 6/12 log(6/12) - 6/12 log(6/12) = 1
  - Entropy of the second set H(away) = - 4/8 log(6/8) - 4/8 log(4/8) = 1
- Expected entropy after partitioning
  - 12/20 * H(home) + 8/20 * H(away) = 1



- Using the ``when” attribute, divide into 3 subsets
  - Entropy of the first set H(5pm) = - 1/4 log(1/4) - 3/4 log(3/4);
  - Entropy of the second set H(7pm) = - 9/12 log(9/12) - 3/12 log(3/12);
  - Entropy of the second set H(9pm) = - 0/4 log(0/4) - 4/4 log(4/4) = 0
- Expected entropy after partitioning
  - 4/20 * H(1/4, 3/4) + 12/20 * H(9/12, 3/12) + 4/20 * H(0/4, 4/4) = 0.65
- Information gain 1-0.65 = 0.35

Decision

- Knowing the ``when'' attribute values provides larger information gain than ``where''.
- Therefore the ``when'' attribute should be chosen for testing prior to the ``where'' attribute.
- Similarly, we can compute the information gain for other attributes.
- At each node, choose the attribute with the largest information gain.

- Stopping rule
  - Every attribute has already been included along this path through the tree, or
  - The training examples associated with this leaf node all have the same target attribute value (i.e., their entropy is zero).

Demo

Continuous Attribute?

- Each non-leaf node is a test, its edge partitioning the attribute into subsets (easy for discrete attribute).
- For continuous attribute
  - Partition the continuous value of attribute A into a discrete set of intervals
  - Create a new boolean attribute A_c , looking for a threshold c,

$$A_c = \begin{cases} true & \text{if } A_c < c \\ false & \text{otherwise} \end{cases}$$

How to choose c ?

Evaluation

- Training accuracy
  - How many training instances can be correctly classify based on the available data?
  - Is high when the tree is deep/large, or when there is less confliction in the training instances.
  - however, higher training accuracy does not mean good generalization
- Testing accuracy
  - Given a number of new instances, how many of them can we correctly classify?
  - Cross validation

Strengths

- can generate understandable rules
- perform classification without much computation
- can handle continuous and categorical variables
- provide a clear indication of which fields are most important for prediction or classification

Weakness

- Not suitable for prediction of continuous attribute.
- Perform poorly with many class and small data.
- Computationally expensive to train.
  - At each node, each candidate splitting field must be sorted before its best split can be found.
  - In some algorithms, combinations of fields are used and a search must be made for optimal combining weights.
  - Pruning algorithms can also be expensive since many candidate sub-trees must be formed and compared.
- Do not treat well non-rectangular regions.