Decision Tree Example

MSE 2400 EaLiCaRA

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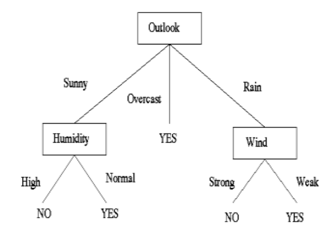
Decision Tree Learning (1)

- Decision tree induction is a simple but powerful learning paradigm. In this method a set of training examples is broken down into smaller and smaller subsets while at the same time an associated decision tree get incrementally developed. At the end of the learning process, a decision tree covering the training set is returned.
- The decision tree can be thought of as a set sentences (in Disjunctive Normal Form) written propositional logic.

Decision Tree Learning (2)

- Some characteristics of problems that are well suited to Decision Tree Learning are:
  - Attribute-value paired elements
  - Discrete target function
  - Disjunctive descriptions (of target function)
  - Works well with missing or erroneous training data

Decision Tree (goal?)



(Outlook = Sunny $\wedge$ Humidity = Normal) $\vee$ (Outlook = Overcast) $\vee$ (Outlook = Rain $\wedge$ Wind = Weak)

[See: Tom M. Mitchell, *Machine Learning*, McGraw-Hill, 1997]

Play Tennis Data

Day	Outlook	Temperature	Humidity	Wind	PlayTennis
D1	Sunny	Hot	High	Weak	No
D2	Sunny	Hot	High	Strong	No
D3	Overcast	Hot	High	Weak	Yes
D4	Rain	Mild	High	Weak	Yes
D5	Rain	Cool	Normal	Weak	Yes
D6	Rain	Cool	Normal	Strong	No
D7	Overcast	Cool	Normal	Strong	Yes
D8	Sunny	Mild	High	Weak	No
D9	Sunny	Cool	Normal	Weak	Yes
D10	Rain	Mild	Normal	Weak	Yes
D11	Sunny	Mild	Normal	Strong	Yes
D12	Overcast	Mild	High	Strong	Yes
D13	Overcast	Hot	Normal	Weak	Yes
D14	Rain	Mild	High	Strong	No

Building a Decision Tree

- **Building a Decision Tree**

1. First test all attributes and select the one that would function as the best root;
2. Break-up the training set into subsets based on the branches of the root node;
3. Test the remaining attributes to see which ones fit best underneath the branches of the root node;
4. Continue this process for all other branches until
   a. all examples of a subset are of one type
   b. there are no examples left (return majority classification of the parent)
   c. there are no more attributes left (default value should be majority classification)

Finding Best Attribute

- Determining which attribute is best (Entropy & Gain)
- Entropy (E) is the minimum number of bits needed in order to classify an arbitrary example as yes or no
- $E(S) = \Sigma^{c}_{i=1} -p_i \log_2 p_i$,
  - Where S is a set of training examples,
  - c is the number of classes, and
  - p_i is the proportion of the training set that is of class i
- For our entropy equation $0 \log_2 0 = 0$
- The information gain G(S,A) where A is an attribute
- $G(S,A) \equiv E(S) - \Sigma_{v \text{ in Values}(A)} \quad (|S_v| \ / \ |S|) \ * E(Sv)$

Example (1)

- Let's Try an Example!
- Let
  - E([X+,Y-]) represent that there are X positive training elements and Y negative elements.
- Therefore the Entropy for the training data, E(S), can be represented as E([9+,5-]) because of the 14 training examples 9 of them are **yes** and 5 of them are **no**.

Example (2)

- Let's start off by calculating the Entropy of the Training Set.
- $E(S) = E([9+,5-]) = (-9/14 \log_2 9/14) + (-5/14 \log_2 5/14)$
- = 0.94

Example (3)

- Next we will need to calculate the information gain G(S,A) for each attribute A where A is taken from the set {Outlook, Temperature, Humidity, Wind}.

Example (4)

- The information gain for Outlook is:
  - G(S,Outlook) = E(S) – [5/14 * E(Outlook=sunny) + 4/14 * E(Outlook = overcast) + 5/14 * E(Outlook=rain)]
  - G(S,Outlook) = E([9+,5-]) – [5/14*E(2+,3-) + 4/14*E([4+,0-]) + 5/14*E([3+,2-])]
  - G(S,Outlook) = 0.94 – [5/14*0.971 + 4/14*0.0 + 5/14*0.971]
  - **G(S,Outlook) = 0.246**

Example (5)

- G(S,Temperature) = 0.94 – [4/14*E(Temperature=hot) + 6/14*E(Temperature=mild) + 4/14*E(Temperature=cool)]
- G(S,Temperature) = 0.94 – [4/14*E([2+,2-]) + 6/14*E([4+,2-]) + 4/14*E([3+,1-])]
- G(S,Temperature) = 0.94 – [4/14 + 6/14*0.918 + 4/14*0.811]
- **G(S,Temperature) = 0.029**

Example (6)

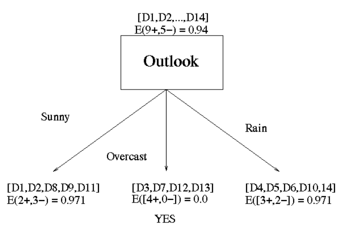
- G(S,Humidity) = 0.94 – [7/14*E(Humidity=high) + 7/14*E(Humidity=normal)]
- G(S,Humidity = 0.94 – [7/14*E([3+,4-]) + 7/14*E([6+,1-])]
- G(S,Humidity = 0.94 – [7/14*0.985 + 7/14*0.592]
- **G(S,Humidity) = 0.1515**

Example (7)

- G(S,Wind) = 0.94 – [8/14*0.811 + 6/14*1.00]
- **G(S,Wind) = 0.048**

Example (8)

- Outlook is our winner!



Next Level (1)

- Now that we have discovered the root of our decision tree we must now recursively find the nodes that should go below Sunny, Overcast, and Rain.

Next Level (2)

- G(Outlook=Rain, Humidity) = 0.971 – [2/5*E(Outlook=Rain ^ Humidity=high) + 3/5*E(Outlook=Rain ^Humidity=normal]
- **G(Outlook=Rain, Humidity) = 0.02**
- G(Outlook=Rain,Wind) = 0.971- [3/5*0 + 2/5*0]
- **G(Outlook=Rain,Wind) = 0.971**

Next Level (3)

- Now our decision tree looks like: