Machine Learning

Learning with Decision Tree – Classification

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Outline

- Learning with Regression and Trees
  - Learning with Regression
    - Simple Linear Regression
    - Multiple Linear Regression
    - Logistic Regression
  - Learning with Trees
    - Decision Trees
    - Constructing Decision Trees using Gini Index
    - Classification and Regression Trees (CART)

Learning with Decision Tree – Classification

- Categorical Dataset

Outlook	Temp	Humidity	Windy	Play Golf
Rainy	Hot	High	False	No
Rainy	Hot	High	True	No
Overcast	Hot	High	False	Yes
Sunny	Mild	High	False	Yes
Sunny	Cool	Normal	False	Yes
Sunny	Cool	Normal	True	No
Overcast	Cool	Normal	True	Yes
Rainy	Mild	High	False	No
Rainy	Cool	Normal	False	Yes
Sunny	Mild	Normal	False	Yes
Rainy	Mild	Normal	True	Yes
Overcast	Mild	High	True	Yes
Overcast	Hot	Normal	False	Yes
Sunny	Mild	High	True	No

Learning with Decision Tree – Classification

- Decision tree learning
- ID3 (Iterative Dichotomiser 3) is an algorithm
    - Invented by Ross Quinlan used to generate a decision tree from a dataset.
    - ID3 is the precursor to the C4.5 algorithm
    - It is typically used in the machine learning and natural language processing domains.
- Decision tree builds classification or regression models in the form of a tree structure.
- It breaks down a dataset into smaller and smaller subsets
    - while at the same time an associated decision tree is incrementally developed.

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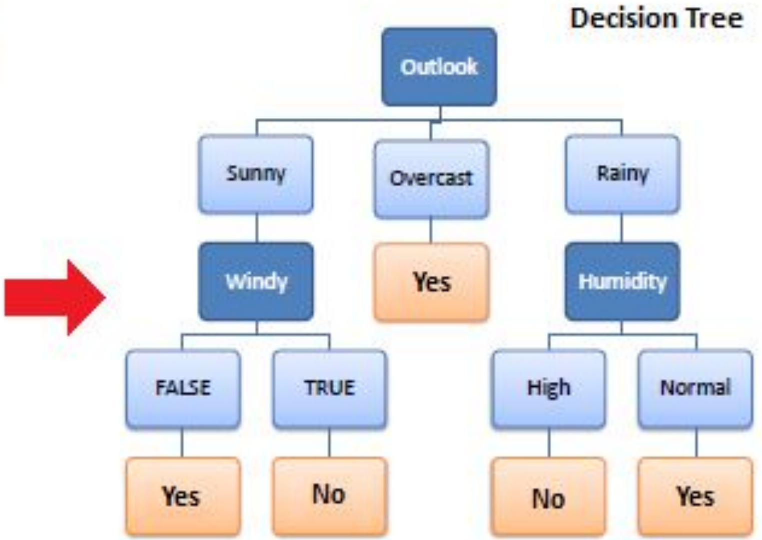
- Algorithm
  - The core algorithm for building decision trees called ID3 by J. R. Quinlan
  - It employs a top-down, greedy search through the space of possible branches with no backtracking.
  - ID3 uses Entropy and Information Gain to construct a decision tree.
- Entropy
- A decision tree is built top-down from a root node and
  - Involves partitioning the data into subsets that contain instances with similar values (homogenous).
- ID3 algorithm uses entropy to calculate the homogeneity of a sample.
  - If the sample is completely homogeneous the entropy is zero and
  - If the sample is an equally divided it has entropy of one.

Learning with Decision Tree – Classification

- Example
- The final result is a tree with decision nodes and leaf nodes.
- A decision node (e.g., Outlook) has two or more branches (e.g., Sunny, Overcast and Rainy).
- Leaf node (e.g., Play) represents a classification or decision.
- The topmost decision node in a tree which corresponds to the best predictor called root node.
- Decision trees can handle both categorical and numerical data.

Predictors				Target
Outlook	**Temp.**	**Humidity**	**Windy**	**Play Golf**
Rainy	Hot	High	False	No
Rainy	Hot	High	True	No
Overcast	Hot	High	False	Yes
Sunny	Mild	High	False	Yes
Sunny	Cool	Normal	False	Yes
Sunny	Cool	Normal	True	No
Overcast	Cool	Normal	True	Yes
Rainy	Mild	High	False	No
Rainy	Cool	Normal	False	Yes
Sunny	Mild	Normal	False	Yes
Rainy	Mild	Normal	True	Yes
Overcast	Mild	High	True	Yes
Overcast	Hot	Normal	False	Yes
Sunny	Mild	High	True	No



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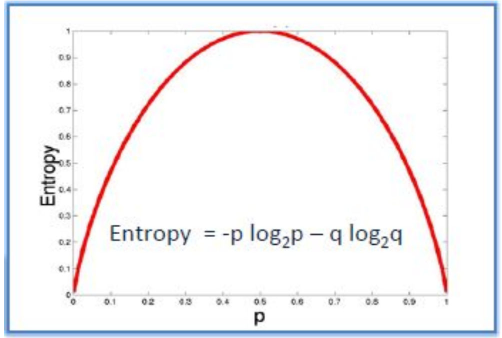
- To build a decision tree, we need to calculate two types of entropy using frequency tables as follows:
- a) Entropy using the frequency table of one attribute:

$$E(S) = \sum_{i=1}^{c} - p_i \log_2 p_i$$

Play Golf	
Yes	No
9	5

Entropy(PlayGolf) = Entropy (5,9)
= Entropy (0.36, 0.64)
= - ($0.36 \log_2 0.36$) - ($0.64 \log_2 0.64$)
= 0.94



Entropy = -0.5 $\log_2$0.5 – 0.5 $\log_2$0.5 = 1

- b) Entropy using the frequency table of two attributes:

$$E(T, X) = \sum_{c \in X} P(c) E(c)$$

		Play Golf		
		Yes	No	
Outlook	Sunny	3	2	5
	Overcast	4	0	4
	Rainy	2	3	5
				14

E(PlayGolf, Outlook) = **P**(Sunny)***E**(3,2) + **P**(Overcast)***E**(4,0) + **P**(Rainy)***E**(2,3)

= (5/14)*0.971 + (4/14)*0.0 + (5/14)*0.971

= 0.693

Learning with Decision Tree – Classification

- Information Gain
- The information gain is based on the decrease in entropy after a dataset is split on an attribute.
- Constructing a decision tree is all about finding attribute that returns the highest information gain
  - (i.e., the most homogeneous branches).
- Step 1: Calculate entropy of the target.

$$\begin{aligned} \textbf{Entropy(PlayGolf)} &= \text{Entropy}(5,9) \\ &= \text{Entropy}(0.36, 0.64) \\ &= -(0.36 \log_2 0.36) - (0.64 \log_2 0.64) \\ &= 0.94 \end{aligned}$$

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- Step 2: The dataset is then split on the different attributes.
- The entropy for each branch is calculated.
- Then it is added proportionally, to get total entropy for the split.
- Resulting entropy is subtracted from the entropy before the split.
- The result is the Information Gain, or decrease in entropy.

$$Gain(T,X) = Entropy(T) - Entropy(T,X)$$

G(PlayGolf, Outlook) = **E**(PlayGolf) – **E**(PlayGolf, Outlook)

= 0.940 – 0.693 = 0.247

		Play Golf	
		Yes	No
Outlook	Sunny	3	2
	Overcast	4	0
	Rainy	2	3
Gain = 0.247			

		Play Golf	
		Yes	No
Temp.	Hot	2	2
	Mild	4	2
	Cool	3	1
Gain = 0.029			

		Play Golf	
		Yes	No
Humidity	High	3	4
	Normal	6	1
Gain = 0.152			

		Play Golf	
		Yes	No
Windy	False	6	2
	True	3	3
Gain = 0.048			

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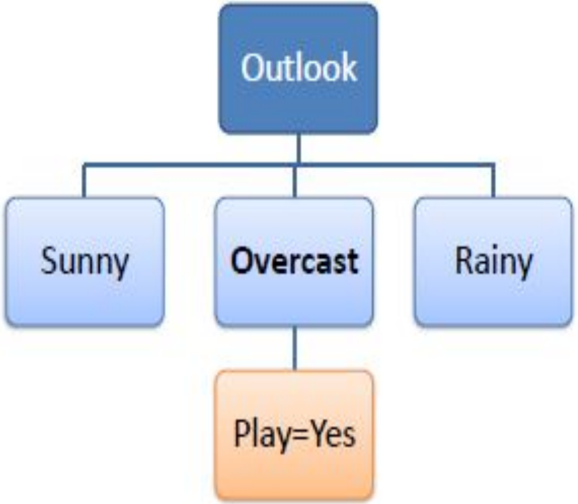
- Step 3: Choose attribute with the largest information gain as the decision node.

		Play Golf	
		Yes	No
Outlook	Sunny	3	2
	Overcast	4	0
	Rainy	2	3
Gain = 0.247			

- Step 4a: A branch with entropy of 0 is a leaf node.

Temp	Humidity	Windy	Play Golf
Hot	High	FALSE	Yes
Cool	Normal	TRUE	Yes
Mild	High	TRUE	Yes
Hot	Normal	FALSE	Yes
Hot	High	FALSE	Yes



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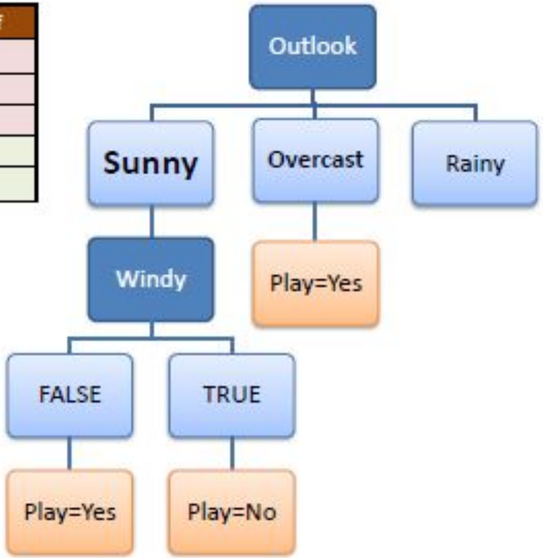
- Step 4b: A branch with entropy more than 0 needs further splitting.

Temp	Humidity	Windy	Play Golf
Mild	High	FALSE	Yes
Cool	Normal	FALSE	Yes
Mild	Normal	FALSE	Yes
Cool	Normal	TRUE	No
Mild	High	TRUE	No



- Step 5: The ID3 algorithm is run recursively on the non-leaf branches, until all data is classified.

Learning with Decision Tree – Classification

- Decision Tree to Decision Rules
  - A decision tree can easily be transformed to a set of rules
    - by mapping from the root node to the leaf nodes one by one.

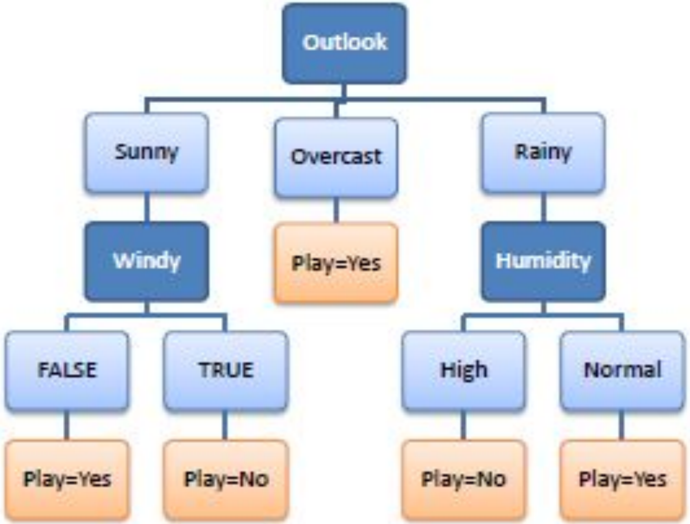
R_1: IF (Outlook=Sunny) AND (Windy=FALSE) THEN Play=Yes

R_2: IF (Outlook=Sunny) AND (Windy=TRUE) THEN Play=No

R_3: IF (Outlook=Overcast) THEN Play=Yes

R_4: IF (Outlook=Rainy) AND (Humidity=High) THEN Play=No

R_5: IF (Outlook=Rain) AND (Humidity=Normal) THEN Play=Yes



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Thank You.