ALGONQUIN COLLEGE

CST8390 BUSINESS INTELLIGENCE & DATA ANALYTICS

Week 3

Classification – Decision Trees

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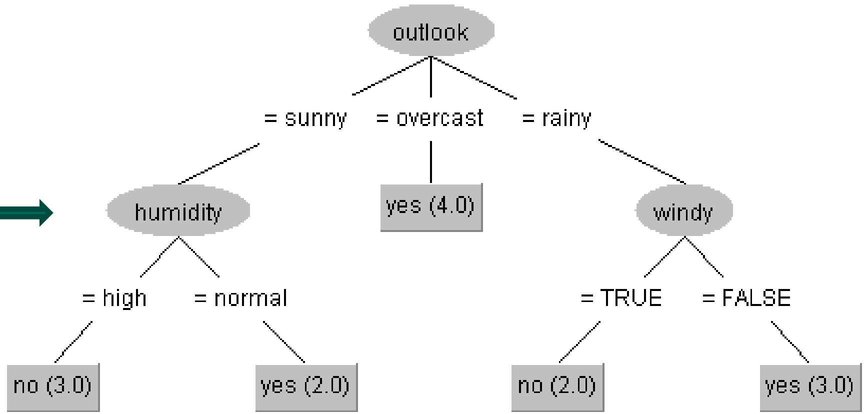
Decision Trees

Outlook	Temperature	Humidity	Windy	Play
sunny	hot	high	FALSE	no
sunny	hot	high	TRUE	no
overcast	hot	high	FALSE	yes
rainy	mild	high	FALSE	yes
rainy	cool	normal	FALSE	yes
rainy	cool	normal	TRUE	no
overcast	cool	normal	TRUE	yes
sunny	mild	high	FALSE	no
sunny	cool	normal	FALSE	yes
rainy	mild	normal	FALSE	yes
sunny	mild	normal	TRUE	yes
overcast	mild	high	TRUE	yes
overcast	hot	normal	FALSE	yes
rainy	mild	high	TRUE	no



Decision Trees

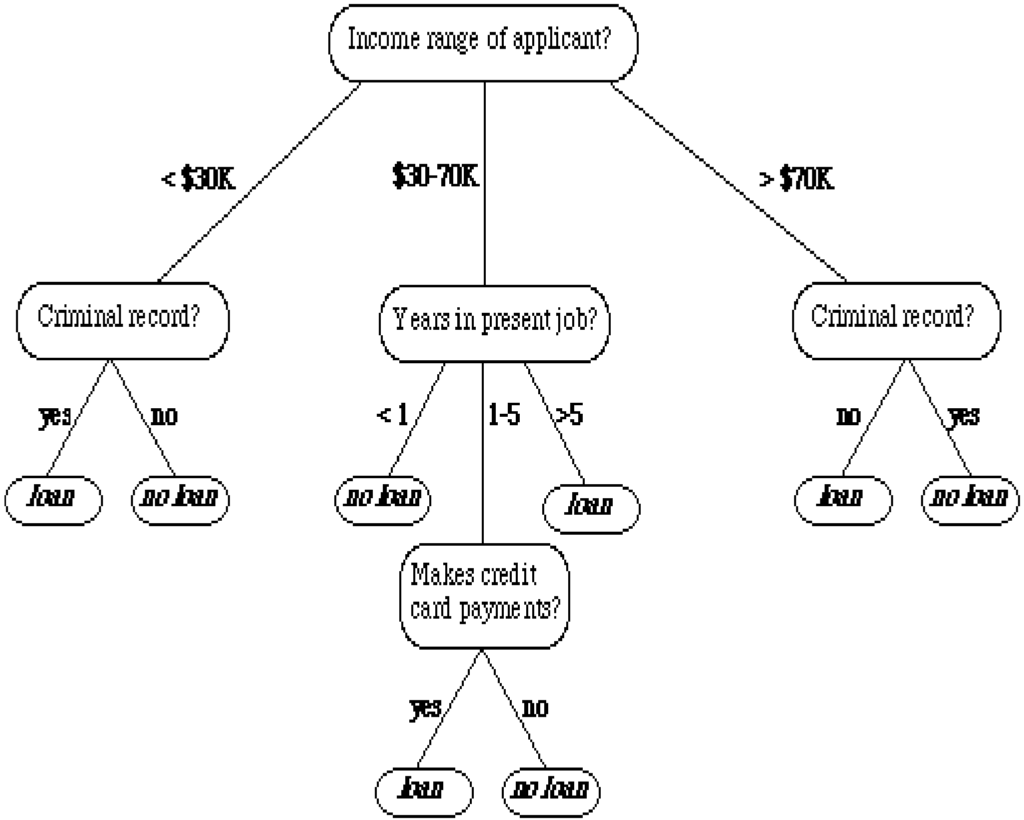
- How to construct decision trees?
- How to avoid overfitting?

Decision Trees

- Decision tree is a tree where:
  - each node represents a feature (attribute)
  - each branch represents a decision (rule)
  - each leaf represents an outcome (categorical or continuous values)

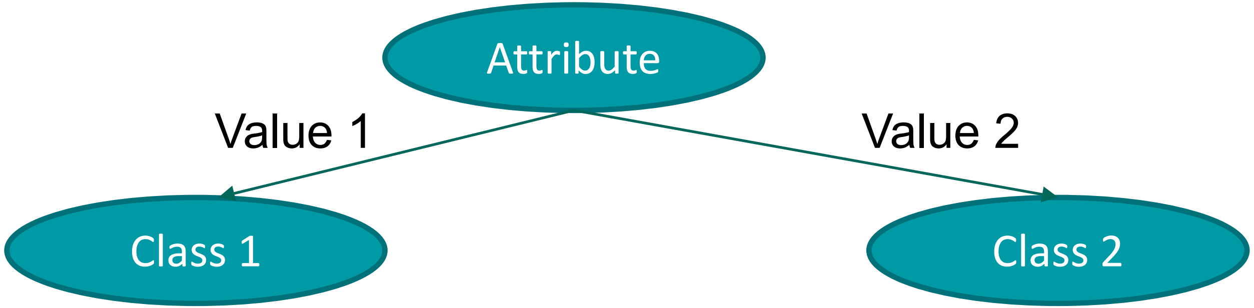
Decision Tree

- One of the most popular ML algorithms
- Used for both classification and regression
- You use data that you know is correct and the tree is created to repeat the decisions in the data.



Decision Tree Construction

- It is a method for approximating discrete-valued functions (Labels).
- It is a divide and conquer approach. Each leaf of the tree is the classification group. Each internal node tests an attribute, and a branch is the value.



How to build

- Start with the root of the tree. Pick an attribute to divide the instances into different groups. Then for each group, repeat the process until the groups are all the same.
- We want the smallest tree so that there are less things to compare. We will use the impurity criterion, or information gain (highest entropy)
- If an event is highly predictable, then it has low entropy or low uncertainty
- Random probabilities have higher entropy, or higher uncertainty.

$$\text{entropy}(p_1, p_2, p_3, \ldots, p_n) = -p_1\log(p_1) - p_2\log(p_2) - p_3\log(p_3) .. -p_n\log(p_n)$$

Decision Tree Algorithms

- ID3 (Iterative Dichotomiser 3)
  - Uses Entropy function and Information gain as metrics
- CART (Classification and Regression Trees)
  - Uses Gini Index as metric

Classification using ID3 Algorithm

Weather Dataset

Based on weather conditions, predict Y or N for "Play".

Outlook	Temperature	Humidity	Windy	Play
sunny	hot	high	FALSE	no
sunny	hot	high	TRUE	no
overcast	hot	high	FALSE	yes
rainy	mild	high	FALSE	yes
rainy	cool	normal	FALSE	yes
rainy	cool	normal	TRUE	no
overcast	cool	normal	TRUE	yes
sunny	mild	high	FALSE	no
sunny	cool	normal	FALSE	yes
rainy	mild	normal	FALSE	yes
sunny	mild	normal	TRUE	yes
overcast	mild	high	TRUE	yes
overcast	hot	normal	FALSE	yes
rainy	mild	high	TRUE	no

Entropy

- Measure of the amount of impurity or uncertainty in the dataset

$$H(S) = \sum_{c \in C} -p(c) \log_2 p(c)$$

Where S – current dataset for which entropy is being calculated

C – set of classes in S Example: $C = \{yes, no\}$

$p(c)$ – The proportion of the number of elements in class c to the number of elements in S

In ID3, entropy is calculated for each remaining attribute. The attribute with the smallest entropy is used to split the set S on the current iteration.

Information Gain

- Measure of the difference in entropy from before to after the set S is split on an attribute A.
- Measure on how much uncertainty in S was reduced after splitting S on attribute A

Information Gain

$$IG(A,S) = H(S) - \sum_{t \in T} p(t)H(t)$$

Where $H(S)$ - *Entropy of set S*

T– Subset created by splitting S by attribute A

$p(t)$– The proportion of the number of elements in t to the number of elements in S

$H(t)$ – Entropy of subset t

Metrics for Weather dataset

Steps

1. Compute the entropy for the dataset
2. For every attribute:
   i. Calculate entropy for all categorical values
   ii. Take average for the current attribute
   iii. Calculate gain for the current attribute
3. Pick the attribute with highest gain
4. Repeat until we get the tree we desired

Entropy for Weather dataset

$$H(S) = \sum_{c \in C} -p(c) \log_2 p(c)$$

Out of 14 instances, 9 are classified as Yes and 5 as No

$$P_{Yes} = -\frac{9}{14} * \log_2 \frac{9}{14} = 0.41$$

$$P_{No} = -\frac{5}{14} * \log_2 \frac{5}{14} = 0.53$$

$$H(S) = P_{Yes} + P_{No} = 0.94$$

Entropy of Outlook feature of Weather dataset

- $H(Outlook = Sunny) = -\frac{2}{5} * \log_2\frac{2}{5} - \frac{3}{5} * \log_2\frac{3}{5} = 0.5288 + 0.4422 = 0.971$
- $H(Outlook = Overcast) = -\frac{4}{4} * \log_2\frac{4}{4} - \frac{0}{4} * \log_2\frac{0}{4} = 0$
- $H(Outlook = Rainy) = -\frac{3}{5} * \log_2\frac{3}{5} - \frac{2}{5} * \log_2\frac{2}{5} = 0.4422 + 0.5288 = 0.971$
- $Average\ Entropy\ for\ Outlook$
- $M(Outlook) = \frac{5}{14} * 0.971 + \frac{4}{14} * 0 + \frac{5}{14} * 0.971 = 0.6936$

- Gain$(Outlook) = H(S) - M(Outlook) = 0.94 - 0.6936 = 0.2464$

Entropy of Windy feature of Weather dataset

- $H(Windy = False) = -\frac{6}{8} * \log_2\frac{6}{8} - \frac{2}{8} * \log_2\frac{2}{8} = 0.3113 + 0.5 = 0.8113$
- $H(Windy = True) = -\frac{3}{6} * \log_2\frac{3}{6} - \frac{3}{6} * \log_2\frac{3}{6} = 0.5+0.5=1$

- $Average\ Entropy\ for\ Windy$
- $M(Windy) = \frac{8}{14} * 0.8113 + \frac{6}{14} * 1 = 0.4636 + 0.4286 = 0.8922$

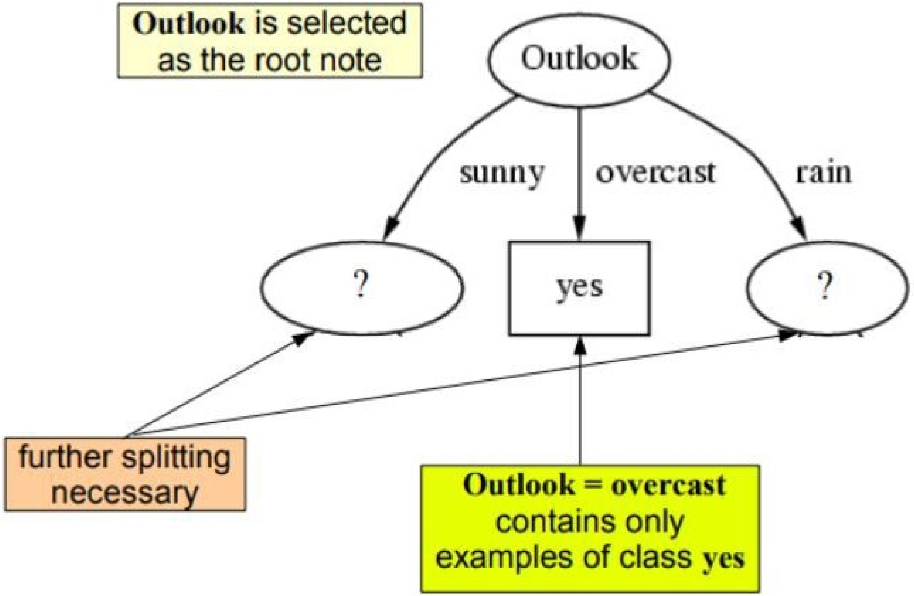
- Gain$(Windy) = H(S) - M(Windy) = 0.94 - 0.8922 = 0.0478$

Metrics Summary

Outlook	**Temperature**
Average Entropy: 0.693 Information Gain: **0.247**	Average Entropy: 0.911 Information Gain: 0.029
Humidity	Windy
Average Entropy: 0.788 Information Gain: 0.152	Average Entropy: 0.892 Information Gain: 0.048

As Outlook has the highest Information Gain, our root node is **Outlook**

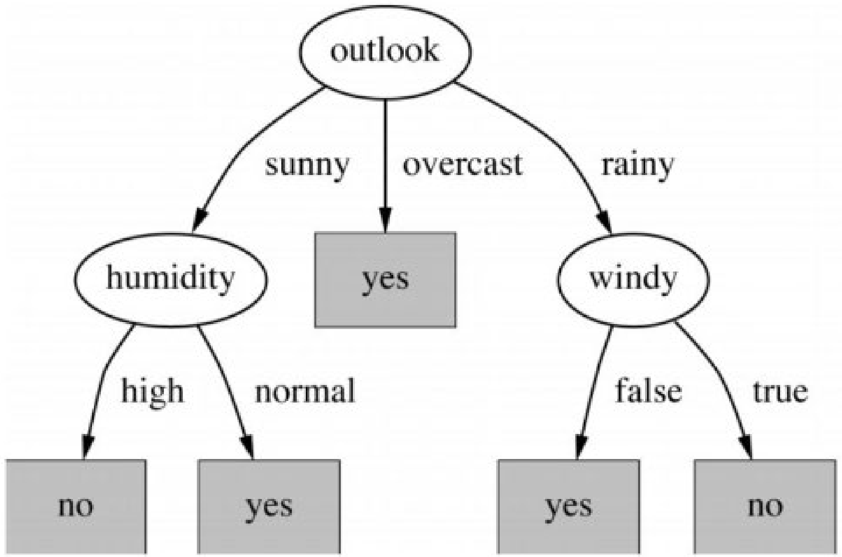
Initial Tree for Weather Dataset



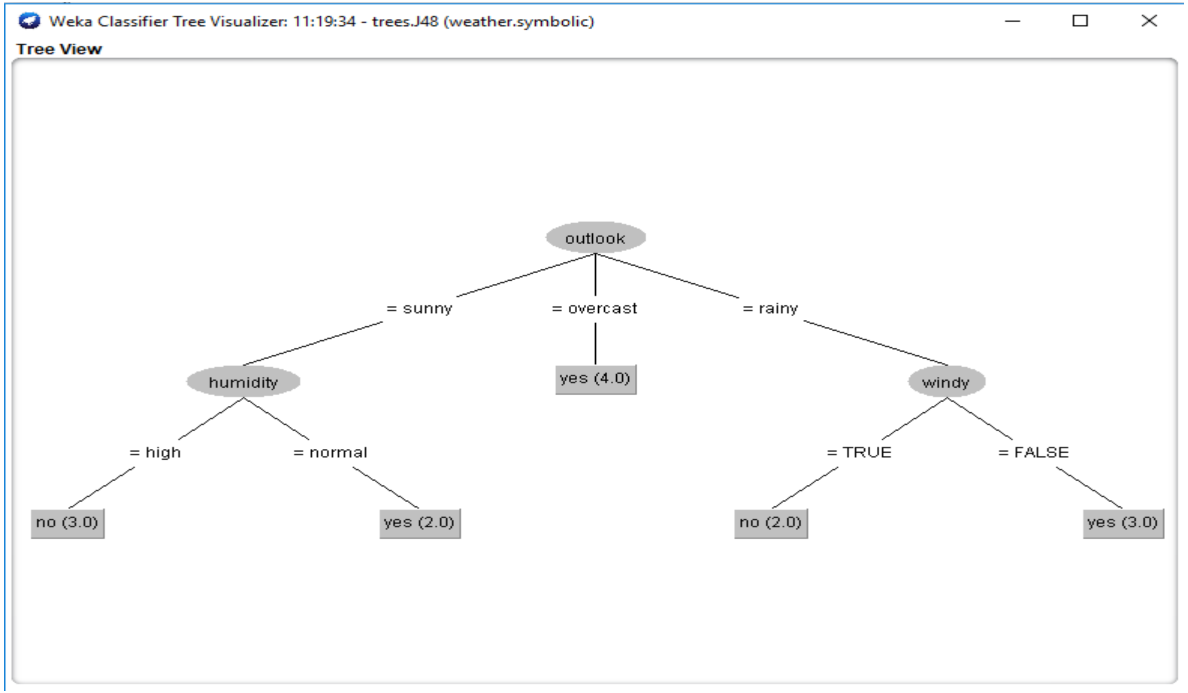
Developing Tree

- Repeat the same step for subtrees

Final decision tree



Weka Demo



Weka Classifier Tree Visualizer: 11:19:34 - trees.J48 (weather.symbolic)
Tree View
outlook
= sunny
= overcast
= rainy
humidity
yes (4.0)
windy
= high
= normal
= TRUE
= FALSE
no (3.0)
yes (2.0)
no (2.0)
yes (3.0)

References

Decision Tree:

- http://www.saedsayad.com/decision_tree.htm
- http://www.cs.waikato.ac.nz/ml/weka/mooc/dataminingwitheka/slides/Class3-DataMiningWithWeka-2013.pdf

Covariance and correlation:

- http://www.dummies.com/education/math/business-statistics/how-to-measure-the-covariance-and-correlation-of-data-samples/