CS-F415: Data Mining

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Classification KNN
Decision Tree

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Sept 04, 2024 M/T/W - 9/8/9 am 6108 @ BITS-Pilani [Jan-May 2024]

http://ktiwari.in/dm

Classification

Finding the right label

What feature (attributes) would you choose?

Color, texture, weight, density, hardness .....

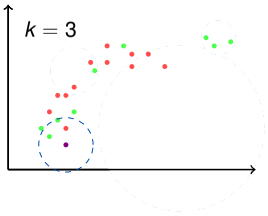
How to deal with multiple classes

- Multi-class: There are more than two labels - one of them to be assigned to an individual item
  1. One vs All: train multiple classifiers, one for each class, learning whether item belongs to that class or not.
  2. One vs One (all pairs): train classifier for every possible pair of classes $c * (c-1)/2$. Classification is obtained by majority voting
  3. Error correction codes
  4. Hierarchical methods
  5. One-class classification
- Multi-label: There are more than two labels - an individual item will be assigned more than one label

K Nearest Neighbor (KNN)

You are most likely as your friends (Bias)

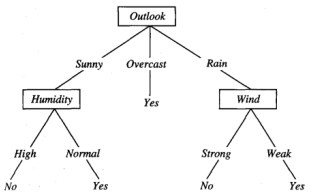
- Two step algorithm
  1. Search k other datum points (most difficult part)
  2. Apply majority voting
- A lazy learner, non-parametric model
- To avoid ties, k should NOT be a multiple of number of classes
- Small k is sensitive to noise and large one has high bias



Decision Tree

Decision Tree

A method to approximate discrete-valued functions. It is robust to noisy data and capable of learning disjunctive expressions. Primarily useful for classification.



- Each node in the tree specifies a test for some attribute
- Each branch descending from the node corresponds to one of the possible value
- Decision trees represent a disjunction of conjunctions

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

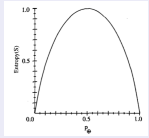
DT is Appropriate When ...

- Instances are represented by attribute-value pairs
- The target function has discrete output values
- Disjunctive descriptions may be required
- The training data may contain errors
- The training data may contains attributes with missing value

Entropy (Shannon's)

Characterizes the impurity of an arbitrary collection of examples

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



Range is 0 to 1, *i.e.* $0 \leq Entropy(S) \leq 1$

0 – when all members are of same class.

1 – if equal number of positive and negative

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

$$\begin{aligned} Entropy([9+,5-]) &= -(9/14)\log_2(9/14) \\ &\quad -(5/14)\log_2(5/14) \\ &= 0.94 \end{aligned}$$

Information Gain

Information Gain of an attribute, A[1] is the expected reduction in entropy caused by partitioning the dataset S according to that attribute

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

here S_v is a subset of S where value of the attribute A is v

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

For example

$$\begin{aligned} S_{Sunny} &= \{D1, D2, D8, D9, D11\} \\ S_{Overcast} &= \{D3, D7, D12, D13\} \\ S_{Rainy} &= \{D4, D5, D6, D10, D14\} \\ S_{Cool} &= \{D5, D6, D7, D9\} \\ S_{Hot} &= \{D1, D2, D3, D13\} \\ S_{Normal} &= \{D5, D6, D7, D9, D10, D11, D13\} \\ S_{High} &= \{D1, D2, D3, D4, D8, D12, D14\} \end{aligned}$$

And so on....

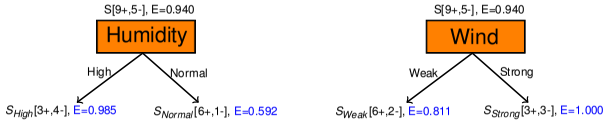
[1] Outlook, Temperature, Humidity, Wind

Information Gain

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

$S_{High} = \{D1, D2, D3, D4, D8, D12, D14\}$
$S_{Normal} = \{D5, D6, D7, D9, D10, D11, D13\}$

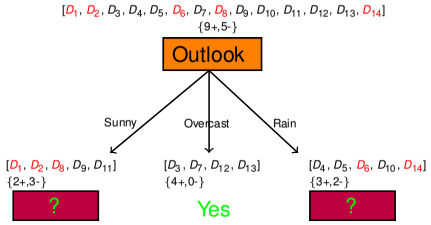
$S_{Weak} = \{D1, D3, D4, D5, D8, D9, D10, D13\}$
$S_{Strong} = \{D2, D6, D7, D11, D12, D14\}$



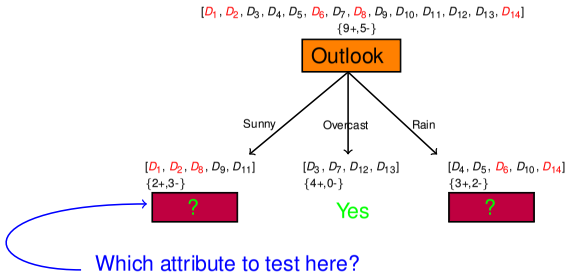
$$\text{Gain(S,Humidity)} = 0.940 - (7/14)0.985 - (7/14)0.592 = 0.151$$
$$\text{Gain(S,Wind)} = 0.940 - (8/14)0.811 - (6/14)1.000 = 0.048$$

Information Gain and Decision Tree

$$\begin{aligned} Gain(S, Humidity) &= 0.151 \\ Gain(S, Wind) &= 0.048 \\ Gain(S, Outlook) &= 0.246 \\ Gain(S, Temperature) &= 0.029 \end{aligned}$$



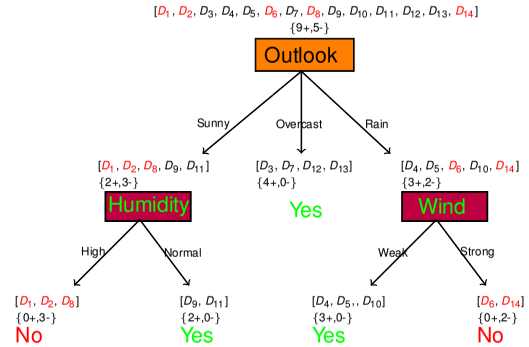
Recursively apply the same



$S_{sunny} = [D_1, D_2, D_8, D_9, D_{11}]$

$Gain(S_{sunny}, Humidity) = 0.970 - (3/5)0.0 - (2/5)0.0 = 0.970$
$Gain(S_{sunny}, Temperature) = 0.970 - (2/5)0.0 - (2/5)1.0 - (1/5)0.0 = 0.57$
$Gain(S_{sunny}, Wind) = 0.970 - (2/5)1.0 - (3/5)1.0 = 0.019$

Recursively apply the same



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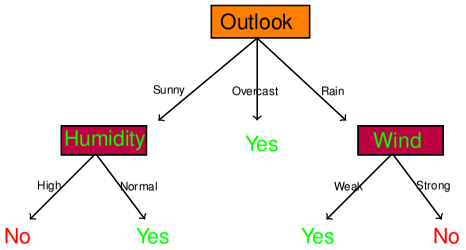
What is classification for
($Outlook = Rain, Humidity = High, Wind = Weak$)

ALERT: (missing value) what is Temperature?

Example



Classification for ($Outlook = Rain, Humidity = High, Wind = Weak$) is

YES

Iterative-Dichotomiser-3 (ID3) Algorithm By: John Ross Quinlan

Algorithm 1: ID3(Examples,Target_attribute,Attributes)

Examples are the training data, *Target_attribute* is the attribute whose value is to be predicted by the tree. *Attributes* is a list of other attributes that may be tested by the learned decision tree. Algorithm returns a decision tree that correctly classify the given example.

Create a single-node tree *Root*
IF all *Examples* are +ve **THEN return** *Root* with label +ve
IF all *Examples* are -ve **THEN return** *Root* with label -ve
IF *Attributes* $= \phi$ **THEN return** *Root* with most common *Target_attribute*
A $\leftarrow$ attribute from *Attributes* that best classifies *Examples*
Decision attribute for *Root* $\leftarrow$ A
foreach *value* v_i *of A* **do**
    Add a new tree branch below Root, to test A=v_i
    Examples$_{v_i}$ $\leftarrow$ subset of *Examples* having value v_i for A
    IF Examples$_{v_i} = \phi$ **THEN** below this branch add a leaf with label = most common value of *Target_attribute* in *Examples*
    ELSE below this branch add subtree
    ID3(Examples$_{v_i}$,*Target_attribute*,*Attributes*-{*A*})
return *Root*

Issues with Decision Tree

Given a collection of training examples, there could be many decision trees could be consistent with the examples

- ID3 search strategy
  - Selects in favor of shorter trees over longer ones, and
  - Selects trees that place the attributes with highest information gain closest to the root
- Issues in decision trees include
  1. How deeply to grow?
  2. Handling continuous attributes
  3. Choosing an appropriate attribute selection measure
  4. Missing attribute values
  5. Attributes with differing costs, and
  6. Improving computational efficiency

Thank You!

Thank you very much for your attention!

Queries ?