Classification

Classification vs. Regression vs. Clustering

Classification – model (can also be called a classifier) predicts a categorical label

Ex: You are given an image. You have to predict whether it is a cat image or a dog image.

Regression – model predicts continuous-valued function, or ordered value

Ex: Prediction or forecasting of sales data.

Clustering – Unsupervised learning

Grouping of things based on similarity or dissimilarity of attributes.

Ex: Creation of severity clusters and hot spots during the Covid-19 pandemic.

Based on high and low footfall in the areas with patients for sneezing, coughing and fever.

Classification and Clustering

Let’s take the example of T-shirt store.

Problem 1:

Salesman gets to know height and weight of the customer who comes in.
And he has to classify this customer for a t-shirt size.

(height, weight, age) --> (t-shirt size as in small, medium, large)

Problem 2:

You open a new store in some part of the world. And you collect data about people’s age, height and weight.
As a store owner, you would like to know how many groups of t-shirts sizes should be there and what are those t-shirt sizes.
As in: xs, s, m, l, xl (so on, so forth)

General Architecture of Classification Model

Classification:

training data + testing data --> classifier <-- predictions (labels)

Training – training set

Testing – test set (validation)

Accuracy measurement of classification

Steps involved in building a classifier:
Step 1: Collect the data.
As in from the client. Or through a survey or study.

Step 2: Split the data into training set and test set.

Step 3: As part of training: You do data preprocessing and model selection.

Step 4: Model Evaluation on Test data set.

Decision Tree Induction

Decision tree induction is the learning of decision trees from class-labeled training tuples. A **decision tree** is a flowchart-like tree structure, where each **internal node** (nonleaf node) denotes a test on an attribute, each **branch** represents an outcome of the test, and each **leaf node** (or *terminal node*) holds a class label. The topmost node in a tree is the **root** node.

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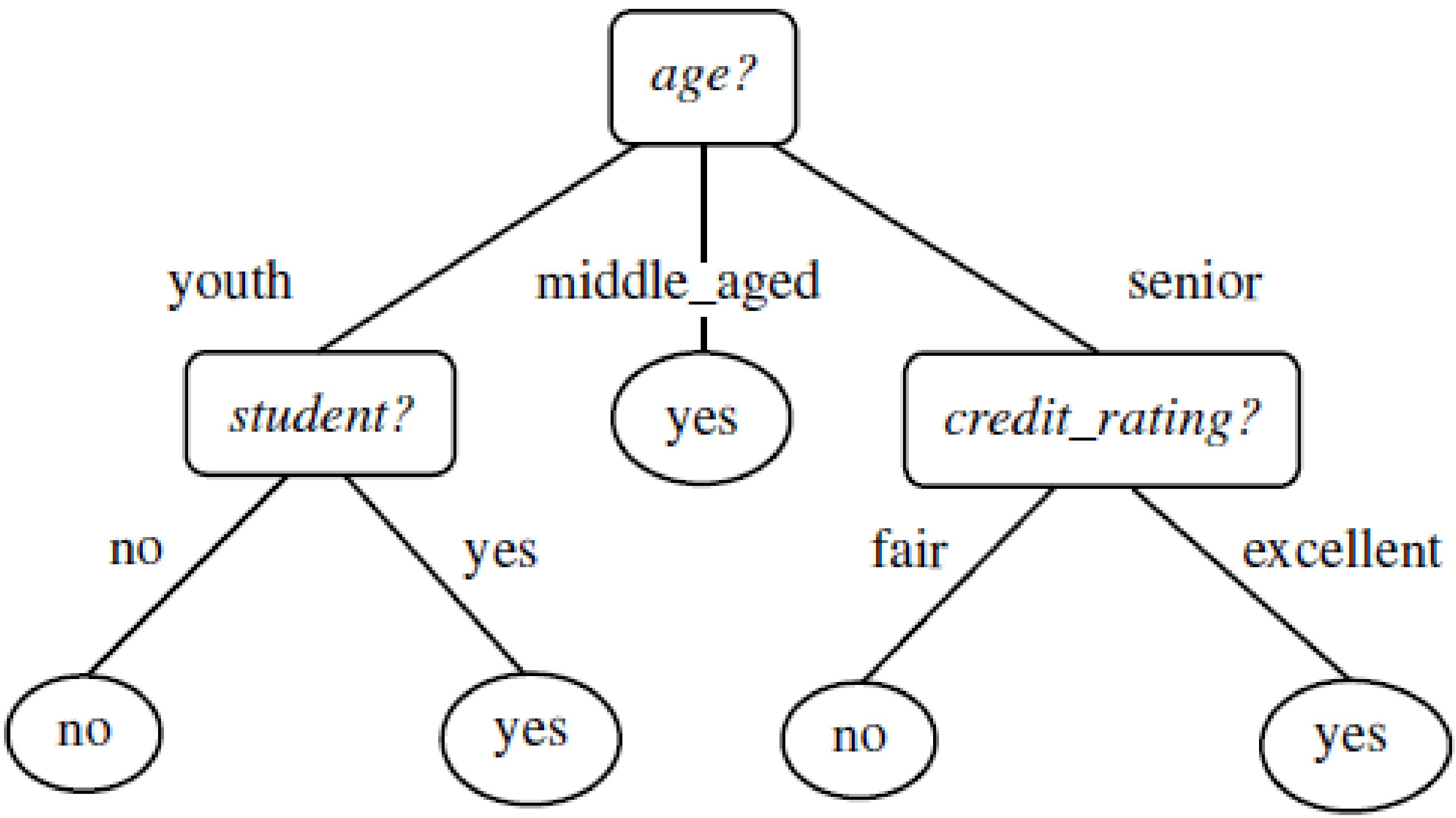

Decision Tree Induction

Attribute Selection Measures (or Splitting Rules)

- Information gain (entropy)
- Gain ratio
- Gini Index

Attribute Selection Measures

Information Gain

Expected information needed to classify a tuple in D:

$$Info(D) = -\sum_{i=1}^{m} p_i \log_2(p_i)$$

where p_i is the probability that an arbitrary tuple in D belongs to class C_i

$|C_{i,D}|/|D|$

If we select attribute A for partition, then the information we still need for classification is given by:

$$Info_A(D) = \sum_{j=1}^{v} \frac{|D_j|}{|D|} \times Info(D_j)$$

Attribute A can be used to split D into v partitions or subsets

$$Gain(A) = Info(D) - Info_A(D)$$

Attribute Selection Measures

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$$Info(D) = -\frac{9}{14}\log_2\left(\frac{9}{14}\right) - \frac{5}{14}\log_2\left(\frac{5}{14}\right)$$

$$Info(D) = -\sum_{i=1}^{m} p_i \log_2(p_i)$$

Attribute Selection Measures

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$$Info(D) = -\frac{9}{14}\log_2\left(\frac{9}{14}\right) - \frac{5}{14}\log_2\left(\frac{5}{14}\right) = 0.940 \text{ bits.}$$

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$$Info(D) = -\frac{9}{14}\log_2\left(\frac{9}{14}\right) - \frac{5}{14}\log_2\left(\frac{5}{14}\right) = 0.940 \text{ bits.}$$

$$\begin{aligned} Info_{age}(D) &= \frac{5}{14} \times \left(-\frac{2}{5}\log_2\frac{2}{5} - \frac{3}{5}\log_2\frac{3}{5}\right) \\ &\quad + \frac{4}{14} \times \left(-\frac{4}{4}\log_2\frac{4}{4} - \frac{0}{4}\log_2\frac{0}{4}\right) \\ &\quad + \frac{5}{14} \times \left(-\frac{3}{5}\log_2\frac{3}{5} - \frac{2}{5}\log_2\frac{2}{5}\right) \\ &= 0.694 \text{ bits.} \end{aligned}$$

$$Info_A(D) = \sum_{j=1}^{v} \frac{|D_j|}{|D|} \times Info(D_j)$$

Attribute Selection Measures

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$$Gain(age) = Info(D) - Info_{age}(D) = 0.940 - 0.694 = 0.246 \text{ bits}$$

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$$Gain(age) = Info(D) - Info_{age}(D) = 0.940 - 0.694 = 0.246 \text{ bits}$$

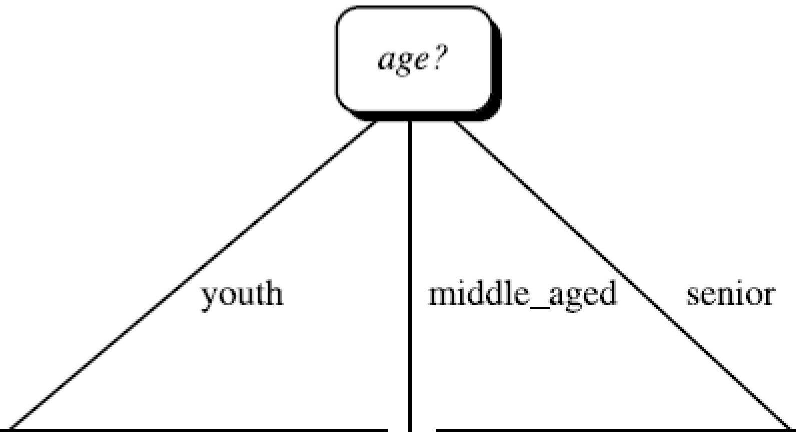
$$Gain(income) = 0.029 \text{ bits}$$

$$Gain(student) = 0.151 \text{ bits}$$

$$Gain(credit\_rating) = 0.048 \text{ bits}$$

$$Info_A(D) = \sum_{j=1}^{v} \frac{|D_j|}{|D|} \times Info(D_j)$$

Attribute Selection Measures



income	*student*	*credit_rating*	*class*
high	no	fair	no
high	no	excellent	no
medium	no	fair	no
low	yes	fair	yes
medium	yes	excellent	yes

income	*student*	*credit_rating*	*class*
high	no	fair	yes
low	yes	excellent	yes
medium	no	excellent	yes
high	yes	fair	yes

income	*student*	*credit_rating*	*class*
medium	no	fair	yes
low	yes	fair	yes
low	yes	excellent	no
medium	yes	fair	yes
medium	no	excellent	no

Attribute Selection Measures

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$$GainRatio(A) = \frac{Gain(A)}{SplitInfo(A)}$$

$$SplitInfo_A(D) = -\sum_{j=1}^{v} \frac{|D_j|}{|D|} \times \log_2\left(\frac{|D_j|}{|D|}\right)$$

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Computation of gain ratio for the attribute *income*.

$$SplitInfo_A(D) = -\frac{4}{14} \times \log_2\left(\frac{4}{14}\right) - \frac{6}{14} \times \log_2\left(\frac{6}{14}\right) - \frac{4}{14} \times \log_2\left(\frac{4}{14}\right)$$

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Computation of gain ratio for the attribute *income*.

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= 0.468 (?)

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The Gini index measures the impurity of D, a data partition or set of training tuples

$$Gini(D) = 1 - \sum_{i=1}^{m} p_i^2$$

where p_i is the probability that a tuple in D belongs to class C_i and is estimated by $|C_{i,D}|/|D|$. The sum is computed over m classes.

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if a binary split on A partitions D into D_1 and D_2,

gini index of D given that partitioning is

$$Gini_A(D) = \frac{|D_1|}{|D|}Gini(D_1) + \frac{|D_2|}{|D|}Gini(D_2)$$

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Consider each attribute and all possible split. Ex. Let's consider attribute income. Find Gini index of the split into subset {low, medium} and {high}

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$$Gini(D) = 1 - \sum_{i=1}^{m} p_i^2$$

Fill correct values here:

$$\begin{aligned}
&Gini_{income \in \{low,medium\}}(D) \\
&= \frac{10}{14} Gini(D_1) + \frac{4}{14} Gini(D_2) \\
&= \frac{10}{14}\left(1 - \left(\frac{6}{10}\right)^2 - \left(\frac{4}{10}\right)^2\right) + \frac{4}{14}\left(1 - \left(\frac{1}{4}\right)^2 - \left(\frac{3}{4}\right)^2\right) \\
&= 0.450 \\
&= Gini_{income \in \{high\}}(D).
\end{aligned}$$

Thank You!