# Introduction to Data Science

DSA1101

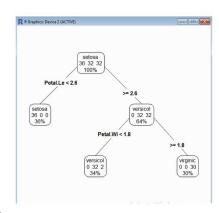
Semester 1, 2018/2019 Week 6

- Classification is widely used for prediction purposes.
- For example, by building a classifier on the transcripts of United States Congressional floor debates, it can be determined whether the speeches represent support or opposition to proposed legislation.
- Classification can help health care professionals diagnose heart disease patients.
- Based on an e-mail's content, e-mail providers also use classification to decide whether the incoming e-mail messages are spam.

- A decision tree (also called prediction tree) uses a tree structure to specify sequences of decisions and consequences.
- Given a set of features  $X = (x_1, x_2, ..., x_n)$ , the goal is to predict a response or output variable Y
- Each member of the set  $(x_1, x_2, ..., x_n)$  is called an input variable or feature. label y/attribute x



Decision Tree
Classification in R

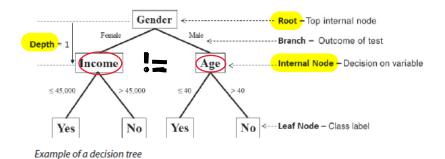


- Prediction can be achieved by constructing a decision tree with test points and branches.
- At each test point, a decision is made to pick a specific branch and traverse down the tree.
- Eventually, a final point is reached, and a prediction can be made.

- Each test point in a decision tree involves testing a particular input variable (or attribute), and each branch represents the decision being made.
- Due to its flexibility and easy visualization, decision trees are commonly deployed in data mining applications for classification purposes.

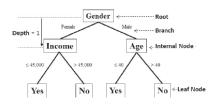
- The input values of a decision tree can be categorical or continuous.
- A decision tree employs a structure of test points (called nodes) and branches, which represent the decision being made.
- A node without further branches is called a leaf node.
- The leaf nodes return class labels and, in some implementations, they return the probability scores.

- Classification trees usually apply to output variables that are categorical (often binary) in nature, such as yes or no, purchase or not purchase, and so on.
- They can be easily represented in a visual way, and the corresponding decision rules are quite straightforward.
- We will start with an example with predicting whether customers will buy a product

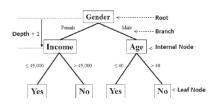


Example of a decision tree. Source: Data Science & Big Data Analytics

- 'Branch' refers to the outcome of a decision and is visualized as a line connecting two nodes.
- If a decision is numerical, the "greater than" branch is usually placed on the right, and the "less than" branch is placed on the left.
- Depending on the nature of the variable, one of the branches may need to include an "equal to" component.

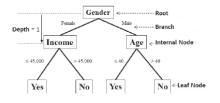


- Internal nodes are the decision or test points.
- Each internal node refers to an input variable or an attribute.
- The top internal node is called the root.

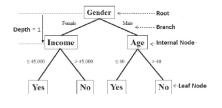


- The decision tree on the left is a binary tree in that each internal node has no more than two branches.
- The branching of a node is referred to as a split.
- The top internal node is called the root.

- Sometimes decision trees may have more than two branches stemming from a node.
- For example, suppose an input variable Weather is categorical and has three choices: Sunny, Rainy, and Snowy
- Then the corresponding node Weather in the decision tree may have three branches labeled as Sunny, Rainy, and Snowy, respectively.



- The depth of a node is the minimum number of steps required to reach the node from the root.
- In the decision tree on the left, nodes Income and Age have a depth of one, and the four nodes on the bottom of the tree have a depth of two.



- Leaf nodes are at the end of the last branches on the tree.
- They represent class labels: the outcome of all the prior decisions.
- The path from the root to a leaf node contains a series of decisions made at various internal nodes.

- Decision trees are widely used in practice.
- For example, to classify animals, questions (like cold-blooded or warm-blooded, mammal or not mammal) are answered to arrive at a certain classification.
- Another example is a checklist of symptoms during medical evaluation of a patient.
- The artificial intelligence engine of a video game commonly uses decision trees to control the autonomous actions of a character in response to various scenarios.

- Retailers can use decision trees to segment customers or predict response rates to marketing and promotions.
- Financial institutions can use decision trees to help decide if a loan application should be approved or denied. In the case of loan approval, computers can use the logical if-then statements to predict whether the customer will default on the loan.
- For customers with a clear (strong) outcome, no human interaction is required; for observations that may not generate a clear response, a human is needed for the decision.

- Our first example of decision trees in in R concerns a bank that wants to market its term deposit products (such as Certificates of Deposit) to the appropriate customers.
- Given the demographics of clients and their reactions to previous campaign phone calls, the bank's goal is to predict which clients would subscribe to a term deposit.

- The dataset 'bank-sample.csv' which has been posted to IVLE contains records of 2000 customers
- The variables include (1) job, (2) marital status, (3) education level, (4) if the credit is in default, (5) if there is a housing loan, (6) if the customer currently has a personal loan, (7) contact type, (8) result of the previous marketing campaign contact (poutcome), and finally (9) if the client actually subscribed to the term deposit.

- Attributes (1) through (8) are the input variables or features
- (9) is considered the (binary) outcome: The outcome subscribed is either yes (meaning the customer will subscribe to the term deposit) or no (meaning the customer won't subscribe).
- All the variables listed earlier are categorical

#### Preliminary look at the dataset

```
> bankdata = read.csv("bank-sample.csv", header=TRUE)
   head(bankdata)
                     marital education default balance
    age
     31
          management single tertiary
                                            no
     45 entrepreneur married tertiary
                                                  1752
                                            nο
6 3 46
            services divorced secondary
                                                  4329
                                            no
 4 35
         management married tertiary
                                                  1108
                                            no
     39
         management married secondary
                                                 1410
                                            no
     31
          management
                     single tertiary
                                            no
                                                   499
```

#### Preliminary look at the dataset

```
contact day month duration campaign
     housing loan
         ves
                no cellular
                                   apr
                                             185
         yes
               yes cellular
                                   nov
                                              56
                no cellular
                                             534
         no
                                   nov
5
6
7
         yes
                no cellular
                                   nov
                                              52
                                              55
         yes
                                   may
                no
                                             122
         ves
                    unknown
                                   jun
                nο
8
     pdays previous poutcome subscribed
                      unknown
10 2
                     unknown
                                        nο
11 3
                   0 unknown
                                       yes
12 4
                   0 unknown
                                        no
13 5
                   0 unknown
        -1
                                        nο
14 6
        -1
                     unknown
                                        no
```

- In R, the package rpart contains functions for modeling decision trees
- The optional package rpart.plot enables the plotting of a tree.
- We will show how to use decision trees in R to predict which clients would subscribe to a term deposit.

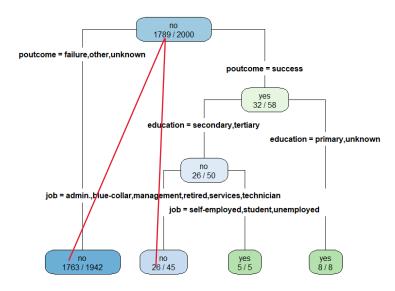
```
install.packages("rpart")
install.packages("rpart.plot")
library("rpart")
library("rpart.plot")
```

- We will build a decision tree to predict subscribed based on the features: job, marital, education, default, housing, loan, contact and poutcome.
- We will study how the decision tree is fitted in more detail after the recess week

```
fit <- rpart(subscribed ~job + marital + education
2 + default + housing + loan + contact + poutcome,
3 method="class",
4 data=bankdata,
5 control=rpart.control(minsplit=1),
6 parms=list(split='information'))</pre>
```

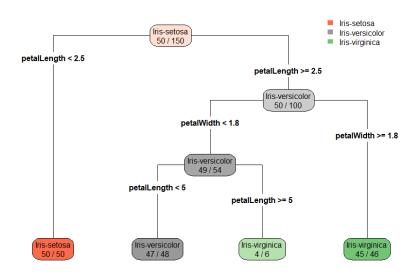
We can visualize the resulting fitted decision tree using rpart.plot:

```
rpart.plot(fit, type=4, extra=2, clip.right.labs=
FALSE, varlen=0, faclen=0)
```



 We will illustrate decision trees using another example: Iris classification dataset

 The task is to predict Iris species based on sepal length / width as well as petal length/width:



• Compare the fitted decision tree with visual plots:

```
library(ggplot2)
library(magrittr)

# sepal width vs. sepal length
ggplot(iris, aes(x=X1, y=X2, color=Y)) +
geom_point()+
labs(x = "sepal length")+ labs(y = "sepal width")

# petal width vs. petal length
ggplot(iris, aes(x=X3, y=X4, color=Y)) +
geom_point()+
labs(x = "petal length")+ labs(y = "petal width")
```

