Week 3 - Decision Tree - R

September 19, 2018

1 Data Warehousing and Data Mining

1.1 Labs

1.1.1 Prepared by Gilroy Gordon

Contact Information SCIT ext. 3643
ggordonutech@gmail.com
gilroy.gordon@utech.edu.jm

1.1.2 Week 3 - Decision Trees in R

Additional Reference Resources:
Decision Trees: https://www.statmethods.net/advstats/cart.html
Importing Different Types of Data: http://www.milanor.net/blog/read-excel-files-from-r/
Party package (Partitioning Recursively) : https://cran.r-project.org/web/packages/party/party.pdf
xlsx packages requires rJava : https://github.com/hannarud/r-best-practices/wiki/Installing-RJava-(Ubuntu)

1.2 Objectives

```
> Data Selection
> Data Preprocessing
    > Noisy Data - Invalid Attribute Values
    > Casewise Deletion
> Data Transformation
    > Dummy Encoding
> Data Mining
     > Decision Trees
> Model Evaluation and Prediction
     > Train/Test Split - 70/30
> Presentation
     > Tree Chart
     > Tree Rules
     > Confusion Matrix
```

1.3 Import required libraries and acquire data

NB. The data required was retrieved from the required text for this course. This should assist you in following the concepts from the book better

```
In [1]: #library("gdata")
```

```
In [2]: data_path = './data/Creditcardprom.xls' # Path to data file
        my.data =  read.csv('./data/Creditcardprom.csv',header=TRUE,check.names=FALSE) # read da
```

```
In [3]: #view the data
        my.data
```

Income Range	Magazine Promo	Watch Promo	Life Ins Promo	Credit Card Ins.	Sex	Age
40-50,000	Yes	No	No	No	Male	45
30-40,000	Yes	Yes	Yes	No	Female	40
40-50,000	No	No	No	No	Male	42
30-40,000	Yes	Yes	Yes	Yes	Male	43
50-60,000	Yes	No	Yes	No	Female	38
20-30,000	No	No	No	No	Female	55
30-40,000	Yes	No	Yes	Yes	Male	35
20-30,000	No	Yes	No	No	Male	27
30-40,000	Yes	No	No	No	Male	43
30-40,000	Yes	Yes	Yes	No	Female	41
40-50,000	No	Yes	Yes	No	Female	43
20-30,000	No	Yes	Yes	No	Male	29
50-60,000	Yes	Yes	Yes	No	Female	39
40-50,000	No	Yes	No	No	Male	55
20-30,000	No	No	Yes	Yes	Female	19

```
In [4]: # What columns are in the data set ? Do they have spaces that I should consider
        colnames(my.data)
```

1. 'Income Range' 2. 'Magazine Promo' 3. 'Watch Promo' 4. 'Life Ins Promo' 5. 'Credit Card Ins.' 6. 'Sex' 7. 'Age'

```
In [5]: # The first two(2) rows have invalid data. Let us perform casewise deletion to remove th
        my.data = my.data[-c(0,1), ] # dropping items 0 and 1 from axis 0 or the x axis (rows)
        # NB. The "-" sign used to request the complement of the data
        my.data #viewing data
```

	Income Range	Magazine Promo	Watch Promo	Life Ins Promo	Credit Card Ins.	Sex	Age
2	30-40,000	Yes	Yes	Yes	No	Female	40
3	40-50,000	No	No	No	No	Male	42
4	30-40,000	Yes	Yes	Yes	Yes	Male	43
5	50-60,000	Yes	No	Yes	No	Female	38
6	20-30,000	No	No	No	No	Female	55
7	30-40,000	Yes	No	Yes	Yes	Male	35
8	20-30,000	No	Yes	No	No	Male	27
9	30-40,000	Yes	No	No	No	Male	43
10	30-40,000	Yes	Yes	Yes	No	Female	41
11	40-50,000	No	Yes	Yes	No	Female	43
12	20-30,000	No	Yes	Yes	No	Male	29
13	50-60,000	Yes	Yes	Yes	No	Female	39
14	40-50,000	No	Yes	No	No	Male	55
15	20-30,000	No	No	Yes	Yes	Female	19

In [6]:
```
# We are only interested in a few columns
# extracting only sex, age and income,range, watch promo and life insurance promo
data2 = my.data[c('Income Range','Sex','Age', 'Watch Promo', 'Life Ins Promo')]
data2
```

	Income Range	Sex	Age	Watch Promo	Life Ins Promo
2	30-40,000	Female	40	Yes	Yes
3	40-50,000	Male	42	No	No
4	30-40,000	Male	43	Yes	Yes
5	50-60,000	Female	38	No	Yes
6	20-30,000	Female	55	No	No
7	30-40,000	Male	35	No	Yes
8	20-30,000	Male	27	Yes	No
9	30-40,000	Male	43	No	No
10	30-40,000	Female	41	Yes	Yes
11	40-50,000	Female	43	Yes	Yes
12	20-30,000	Male	29	Yes	Yes
13	50-60,000	Female	39	Yes	Yes
14	40-50,000	Male	55	Yes	No
15	20-30,000	Female	19	No	Yes

1.4 Aim : Use a decision tree to identify suitable rules for a Life Ins Promo

In [7]:
```
# separate our data into dependent (Y) and independent(X) variables
X_data = data2[c('Income Range','Sex','Age', 'Watch Promo')]
Y_data = data2[c('Life Ins Promo')]
```

1.5 70/30 Train Test Split

We will split the data using a 70/30 split. i.e. 70% of the data will be randomly chosen to train the model and 30% will be used to evaluate the model

In [8]:
```
require(caTools)  # loading caTools library
```

```
Loading required package: caTools
```

```
In [9]: set.seed(400)   #  set seed to ensure you always have same random numbers generated
        # splits the data in the ratio mentioned in SplitRatio. After splitting marks these rows
        sample = sample.split(X_data,SplitRatio = 0.70)
        # creates a training dataset named train1 with rows which are marked as TRUE
        X_train=subset(X_data,sample ==TRUE)
        X_test =subset(X_data, sample==FALSE)
        y_train=subset(Y_data,sample ==TRUE)
        y_test =subset(Y_data, sample==FALSE)

        # The package we will use in R will not require that we split the independent and depend

        train = subset(data2,sample=TRUE)
        test = subset(data2,sample=FALSE)
```

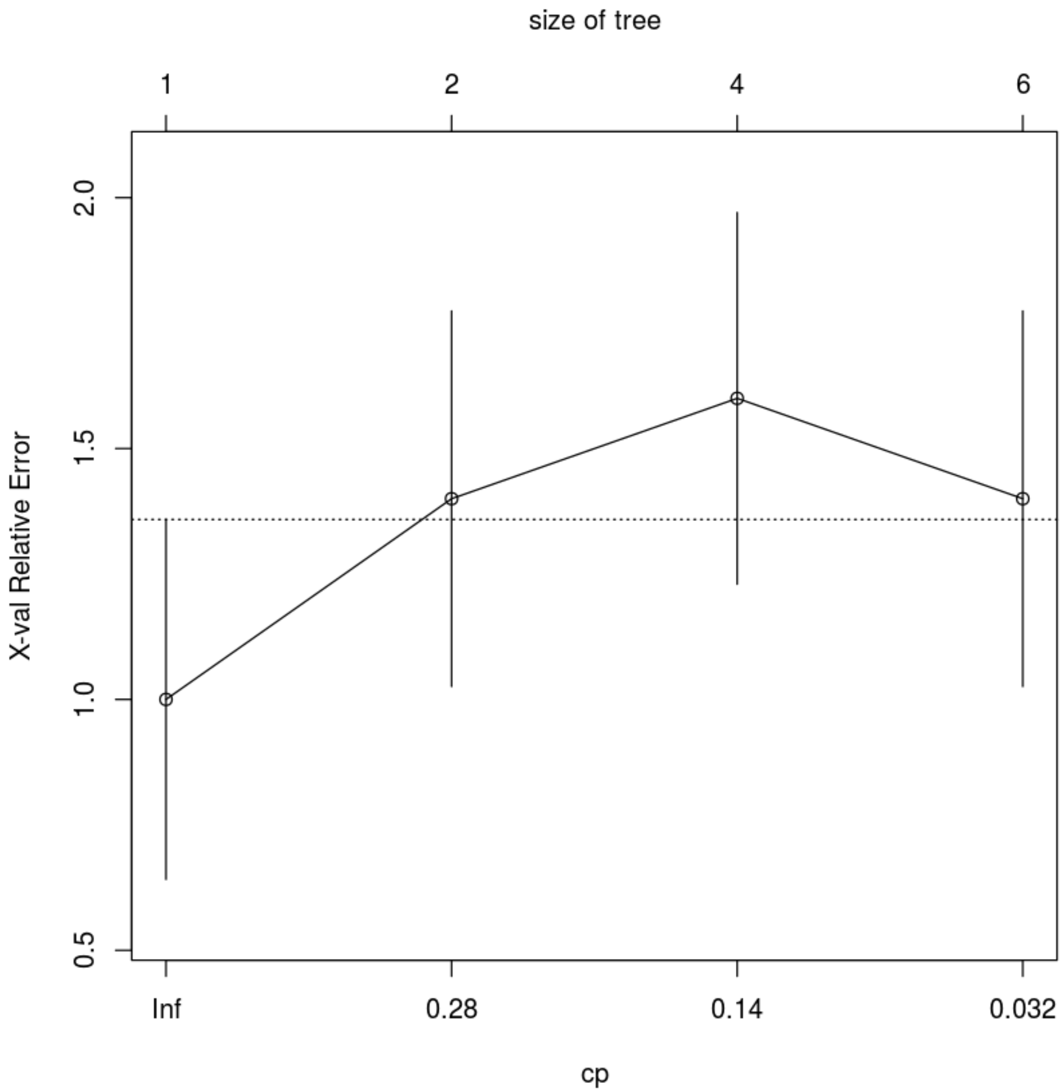
1.6 Building the Decision Tree

```
In [10]: library(rpart)
```

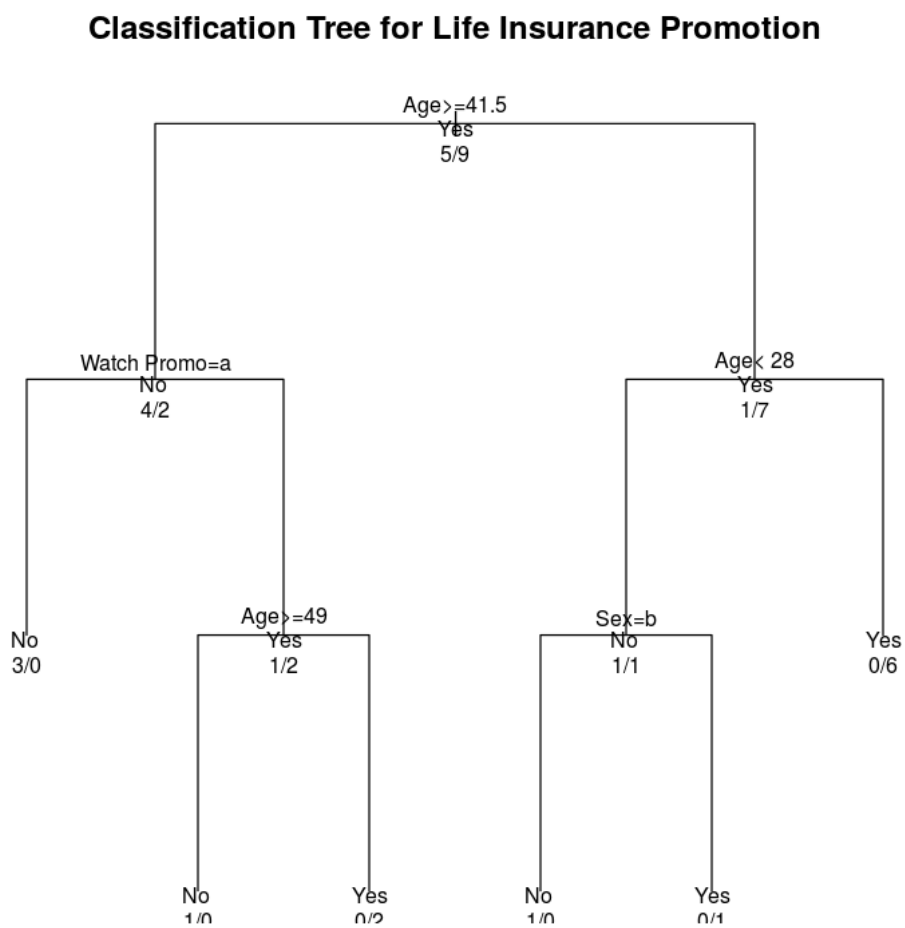
```
In [11]: # Build the classifier  by training it on all the data, rpart has cross validation buil
         clf <- rpart("`Life Ins Promo` ~ `Income Range` + `Sex` + `Age` + `Watch Promo`",
            method="class",data=train,control=rpart.control(minsplit=2)) # method class is used
```

1.7 Describing the tree and visualizations

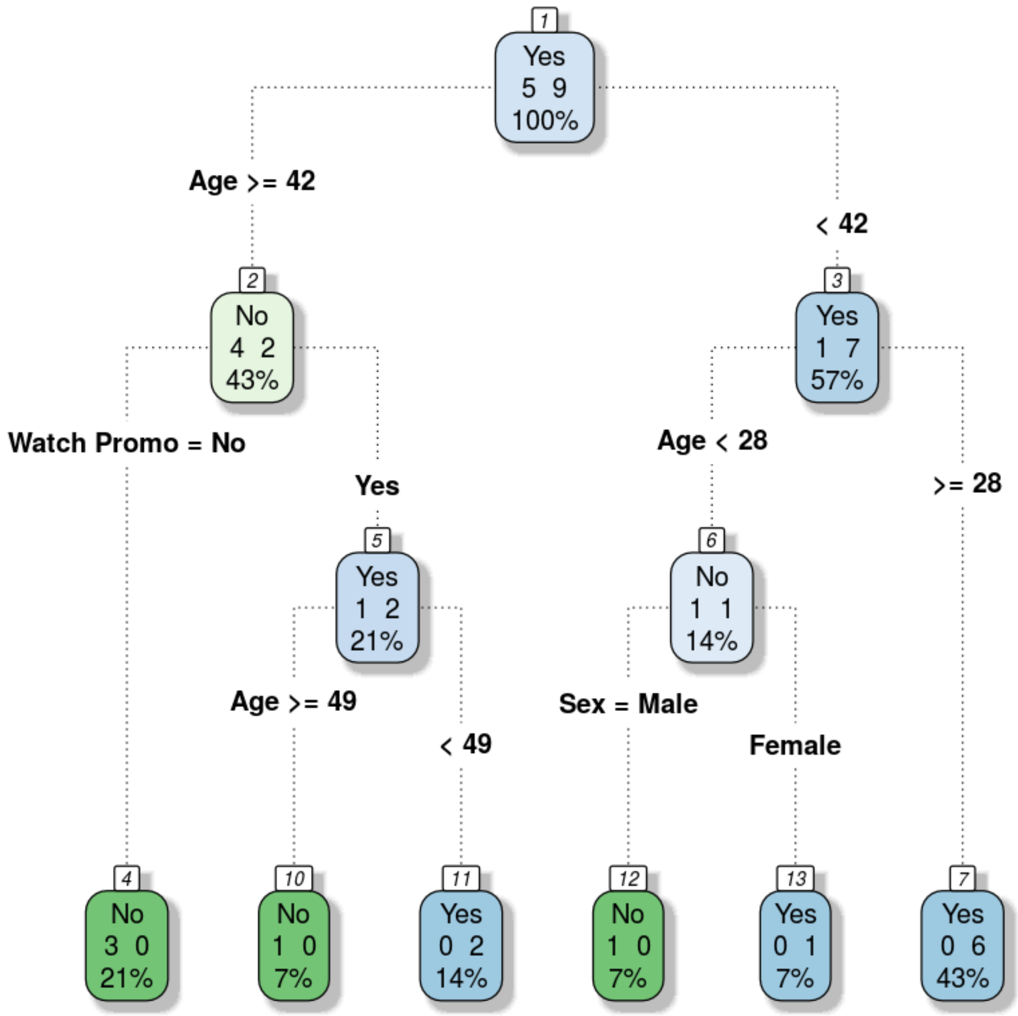
```
In [12]: plotcp(clf) # visualize cross-validation results
```




```
In [13]: # plot tree
         plot(clf, uniform=TRUE,
            main="Classification Tree for Life Insurance Promotion")
         text(clf, use.n=TRUE, all=TRUE, cex=.8)
```




```
In [14]: library(rpart)
         library(rpart.plot)
         rpart.plot(clf, # please see help(rpart.plot)
         type=4,
         extra=101,
         box.palette="GnBu",
         branch.lty=3,
         shadow.col="gray",
         nn=TRUE
         )
```




```
In [15]: help(rpart.plot)

In [16]: summary(clf) # display the results

Call:
rpart(formula = "`Life Ins Promo` ~ `Income Range` + `Sex` + `Age` + `Watch Promo`",
    data = train, method = "class", control = rpart.control(minsplit = 2))
  n= 14

    CP nsplit rel error xerror      xstd
1 0.40      0       1.0    1.0 0.3585686
2 0.20      1       0.6    1.4 0.3741657
3 0.10      3       0.2    1.6 0.3703280
```

```
4 0.01      5       0.0    1.4 0.3741657

Variable importance
         Age Income Range          Sex  Watch Promo
          50           18           16           16

Node number 1: 14 observations,    complexity param=0.4
  predicted class=Yes  expected loss=0.3571429  P(node) =1
    class counts:     5     9
   probabilities: 0.357 0.643
  left son=2 (6 obs) right son=3 (8 obs)
  Primary splits:
      Age          < 41.5 to the right, improve=2.0119050, (0 missing)
      Income Range splits as  LRLR,     improve=1.2857140, (0 missing)
      Sex          splits as  RL,       improve=1.2857140, (0 missing)
      Watch Promo  splits as  LR,       improve=0.4285714, (0 missing)
  Surrogate splits:
      Income Range splits as  RRLR, agree=0.786, adj=0.500, (0 split)
      Sex          splits as  RL,   agree=0.643, adj=0.167, (0 split)

Node number 2: 6 observations,    complexity param=0.2
  predicted class=No   expected loss=0.3333333  P(node) =0.4285714
    class counts:     4     2
   probabilities: 0.667 0.333
  left son=4 (3 obs) right son=5 (3 obs)
  Primary splits:
      Watch Promo  splits as  LR,       improve=1.3333330, (0 missing)
      Age          < 49   to the right, improve=0.6666667, (0 missing)
      Income Range splits as  LRR-,     improve=0.2666667, (0 missing)
      Sex          splits as  RL,       improve=0.1666667, (0 missing)
  Surrogate splits:
      Income Range splits as  LRR-, agree=0.667, adj=0.333, (0 split)

Node number 3: 8 observations,    complexity param=0.1
  predicted class=Yes  expected loss=0.125  P(node) =0.5714286
    class counts:     1     7
   probabilities: 0.125 0.875
  left son=6 (2 obs) right son=7 (6 obs)
  Primary splits:
      Age          < 28   to the left,  improve=0.7500000, (0 missing)
      Income Range splits as  LR-R,     improve=0.4166667, (0 missing)
      Sex          splits as  RL,       improve=0.4166667, (0 missing)
      Watch Promo  splits as  RL,       improve=0.1500000, (0 missing)

Node number 4: 3 observations
  predicted class=No   expected loss=0  P(node) =0.2142857
    class counts:     3     0
   probabilities: 1.000 0.000
```

```
Node number 5: 3 observations,    complexity param=0.2
  predicted class=Yes  expected loss=0.3333333  P(node) =0.2142857
    class counts:     1     2
   probabilities: 0.333 0.667
  left son=10 (1 obs) right son=11 (2 obs)
  Primary splits:
      Age          < 49   to the right, improve=1.3333330, (0 missing)
      Income Range splits as  -RL-,     improve=0.3333333, (0 missing)
      Sex          splits as  RL,       improve=0.3333333, (0 missing)

Node number 6: 2 observations,    complexity param=0.1
  predicted class=No   expected loss=0.5  P(node) =0.1428571
    class counts:     1     1
   probabilities: 0.500 0.500
  left son=12 (1 obs) right son=13 (1 obs)
  Primary splits:
      Sex         splits as  RL,       improve=1, (0 missing)
      Age         < 23   to the right, improve=1, (0 missing)
      Watch Promo splits as  RL,       improve=1, (0 missing)

Node number 7: 6 observations
  predicted class=Yes  expected loss=0  P(node) =0.4285714
    class counts:     0     6
   probabilities: 0.000 1.000

Node number 10: 1 observations
  predicted class=No   expected loss=0  P(node) =0.07142857
    class counts:     1     0
   probabilities: 1.000 0.000

Node number 11: 2 observations
  predicted class=Yes  expected loss=0  P(node) =0.1428571
    class counts:     0     2
   probabilities: 0.000 1.000

Node number 12: 1 observations
  predicted class=No   expected loss=0  P(node) =0.07142857
    class counts:     1     0
   probabilities: 1.000 0.000

Node number 13: 1 observations
  predicted class=Yes  expected loss=0  P(node) =0.07142857
    class counts:     0     1
   probabilities: 0.000 1.000
```