Decision Trees

Decision tree is a type of supervised learning algorithm with a pre-defined target variable used for classifcation problems.

There are two types:

- Categorical Variable Decision tree + Student will play baseball: Y or N
- Continous Variable Decision Tree

Advantages

- Easy
- Used in data exploration
- Less data cleaning required
- Data type is not a contstraint
- Non parametric method

Disadvantages

- Overfitting
- Not fit for continous variables

Node splits based on algorithms

1. Gini Index
- Works well with categorical target: 1 or 0 +Binary Split
- CART uses Gini method to create binary splits
- For sub-nodes, uses sum of squares: P^2 + Q^2
2. Chi-Square
- Uses Chi Square
- Generates tree call CHAID
- To find out the statistical significance between the differences between sub-nodes and parent node
3. Information Gain
4. Reduction in Variance

Key Parameters

1. Min_samples_split
- Defines the minimum number of samples (or observations) which are required in a node to be considered for splitting.

- Used to control over-fitting. Higher values prevent a model from learning relations which might be highly specific to the particular sample selected for a tree.
- Too high values can lead to under-fitting hence, it should be tuned using CV.

2. Min_sample_leaf

- Defines the minimum samples (or observations) required in a terminal node or leaf.
- Used to control over-fitting similar to min_samples_split.
- Generally lower values should be chosen for imbalanced class problems because the regions in which the minority class will be in majority will be very small
- The maximum depth of a tree.
- Used to control over-fitting as higher depth will allow model to learn relations very specific to a particular sample.
- Should be tuned using CV.

4. Max_features

- The maximum number of terminal nodes or leaves in a tree.
- Can be defined in place of max_depth. Since binary trees are created, a depth of 'n' would produce a maximum of 2^n leaves.

Need to prune tree

- We first make the decision tree to a large depth.
- Then we start at the bottom and start removing leaves which are giving us negative returns when compared from the top.
- Suppose a split is giving us a gain of say -10 (loss of 10) and then the next split on that gives us a gain of 20. A simple decision tree will stop at step 1 but in pruning, we will see that the overall gain is +10 and keep both leaves.

Quick Examples of Decision Trees

Example 1: Titanic Data Set From Kaggle

```
#Data Set Up
train <- read.csv("train.csv", stringsAsFactors=FALSE)
test <- read.csv("test.csv", stringsAsFactors=FALSE)
attach(test)
attach(train)

## The following objects are masked from test:
##
##     Age, Cabin, Embarked, Fare, Name, Parch, PassengerId, Pclass,
##     Sex, SibSp, Ticket

#Look at data
head(train)

##   PassengerId Survived Pclass
## 1           1        0      3
```

```
## 2           2        1      1
## 3           3        1      3
## 4           4        1      1
## 5           5        0      3
## 6           6        0      3
##                                                     Name    Sex Age SibSp
## 1                                Braund, Mr. Owen Harris   male  22     1
## 2 Cumings, Mrs. John Bradley (Florence Briggs Thayer) female  38     1
## 3                                 Heikkinen, Miss. Laina female  26     0
## 4        Futrelle, Mrs. Jacques Heath (Lily May Peel) female  35     1
## 5                               Allen, Mr. William Henry   male  35     0
## 6                                       Moran, Mr. James   male  NA     0
##   Parch           Ticket    Fare Cabin Embarked
## 1     0        A/5 21171  7.2500              S
## 2     0         PC 17599 71.2833   C85        C
## 3     0 STON/O2. 3101282  7.9250              S
## 4     0           113803 53.1000  C123        S
## 5     0           373450  8.0500              S
## 6     0           330877  8.4583              Q
```

```r
str(train)
```

```
## 'data.frame':    891 obs. of  12 variables:
##  $ PassengerId: int  1 2 3 4 5 6 7 8 9 10 ...
##  $ Survived   : int  0 1 1 1 0 0 0 0 1 1 ...
##  $ Pclass     : int  3 1 3 1 3 3 1 3 3 2 ...
##  $ Name       : chr  "Braund, Mr. Owen Harris" "Cumings, Mrs. John Bradley
(Florence Briggs Thayer)" "Heikkinen, Miss. Laina" "Futrelle, Mrs. Jacques He
ath (Lily May Peel)" ...
##  $ Sex        : chr  "male" "female" "female" "female" ...
##  $ Age        : num  22 38 26 35 35 NA 54 2 27 14 ...
##  $ SibSp      : int  1 1 0 1 0 0 0 3 0 1 ...
##  $ Parch      : int  0 0 0 0 0 0 0 1 2 0 ...
##  $ Ticket     : chr  "A/5 21171" "PC 17599" "STON/O2. 3101282" "113803" ..
.
##  $ Fare       : num  7.25 71.28 7.92 53.1 8.05 ...
##  $ Cabin      : chr  "" "C85" "" "C123" ...
##  $ Embarked   : chr  "S" "C" "S" "S" ...
```

```r
#Percent of those who survived
table(train$Survived)
```

```
## 
##   0   1 
## 549 342
```

```r
prop.table(table(train$Survived)) ###38% Survived
```

```
## 
##         0         1 
## 0.6161616 0.3838384
```

```r
#Everyone dies prediction
test$Survived <- rep(0,418)
### rep function will create the survived column in data frame and repeat
###'0' prediction 418
### very simple prediction

#Create new data frame with Pass ID and survival
submit <- data.frame(PassengerId = test$PassengerId, Survived = test$Survived
)
write.csv(submit, file = "theyallperish.csv", row.names = FALSE)


#Sex and Survival
summary(train$Sex)
```

```
##    Length     Class      Mode
##       891 character character
```

```r
table(train$Sex)
```

```
##
## female   male
##    314    577
```

```r
prop.table(table(train$Sex,train$Survived)) #divides by total num of passenge
r not within groups
```

```
##
##                   0          1
##   female 0.09090909 0.26150393
##   male   0.52525253 0.12233446
```

```r
prop.table(table(train$Sex,train$Survived),1) #denominator with gender ##most
women survived
```

```
##
##                  0         1
##   female 0.2579618 0.7420382
##   male   0.8110919 0.1889081
```

```r
##New variable for model
test$Survived <- 0
test$Survived[test$Sex == 'female'] <- 1

#Age and survival
summary(train$Age)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##    0.42   20.12   28.00   29.70   38.00   80.00     177
```

```r
##Categorical assigments to Age
train$Child <- 0
```

```r
train$Child[train$Age < 18] <- 1

#Find the number of survivors for the Age and Gender Subsets
aggregate(Survived ~ Child + Sex, data=train, FUN=sum)
```

```
##   Child    Sex Survived
## 1     0 female      195
## 2     1 female       38
## 3     0   male       86
## 4     1   male       23
```

```r
##For percent
aggregate(Survived ~ Child + Sex, data=train, FUN=function(x) {sum(x)/length(
x)})
```

```
##   Child    Sex  Survived
## 1     0 female 0.7528958
## 2     1 female 0.6909091
## 3     0   male 0.1657033
## 4     1   male 0.3965517
```

```r
#Fare paid + Survival
train$Fare2 <- '30+'
train$Fare2[train$Fare < 30 & train$Fare >= 20] <- '20-30'
train$Fare2[train$Fare < 20 & train$Fare >= 10] <- '10-20'
train$Fare2[train$Fare < 10] <- '<10'

#Class/Fare/Sex affects
aggregate(Survived ~ Fare2 + Pclass + Sex, data=train, FUN=function(x) {sum(x
)/length(x)})
```

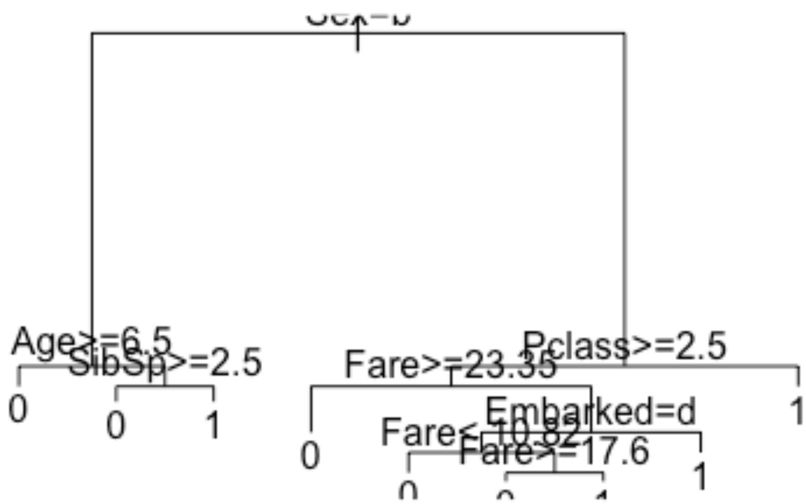
```
##    Fare2 Pclass    Sex  Survived
## 1  20-30      1 female 0.8333333
## 2    30+      1 female 0.9772727
## 3  10-20      2 female 0.9142857
## 4  20-30      2 female 0.9000000
## 5    30+      2 female 1.0000000
## 6    <10      3 female 0.5937500
## 7  10-20      3 female 0.5813953
## 8  20-30      3 female 0.3333333
## 9    30+      3 female 0.1250000
## 10   <10      1   male 0.0000000
## 11 20-30      1   male 0.4000000
## 12   30+      1   male 0.3837209
## 13   <10      2   male 0.0000000
## 14 10-20      2   male 0.1587302
## 15 20-30      2   male 0.1600000
## 16   30+      2   male 0.2142857
## 17   <10      3   male 0.1115385
## 18 10-20      3   male 0.2368421
```

```
## 19 20-30       3    male 0.1250000
## 20   30+       3    male 0.2400000
```

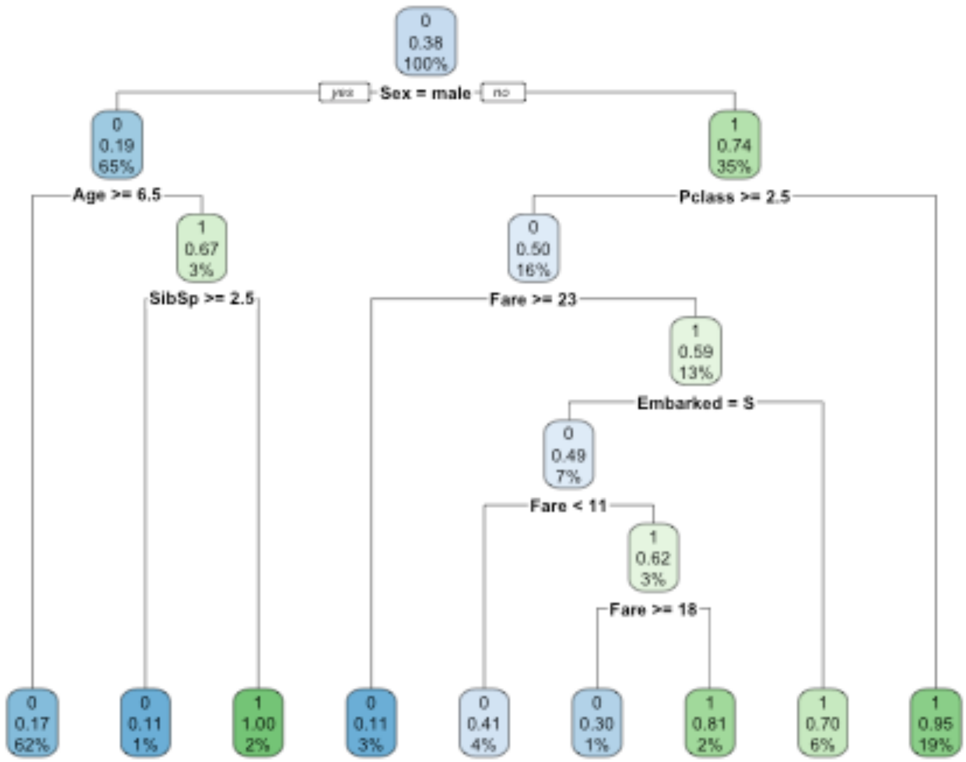
```
## Why would someone in third class with an expensive ticket be worse off?
test$Survived <- 0
test$Survived[test$Sex == 'female'] <- 1
test$Survived[test$Sex == 'female' & test$Pclass == 3 & test$Fare >= 20] <- 0

#Recursive Partitioning and Regression Trees
library(rpart)
```

```
## Warning: package 'rpart' was built under R version 3.4.3
```

```
## to predict a continous variable  use method = "anova"
fit <- rpart(Survived ~ Pclass + Sex + Age + SibSp + Parch + Fare + Embarked,
data=train,method="class")
plot(fit)
text(fit)
```




```
#For prettier tree
library(rpart.plot)
library(RColorBrewer)
rpart.plot(fit)
```



Random Forest gives more accurate predictions.