Titanic

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Introduction

This is the second part of programming assignment 1.

Data Cleaning

Load required R libraries and read data

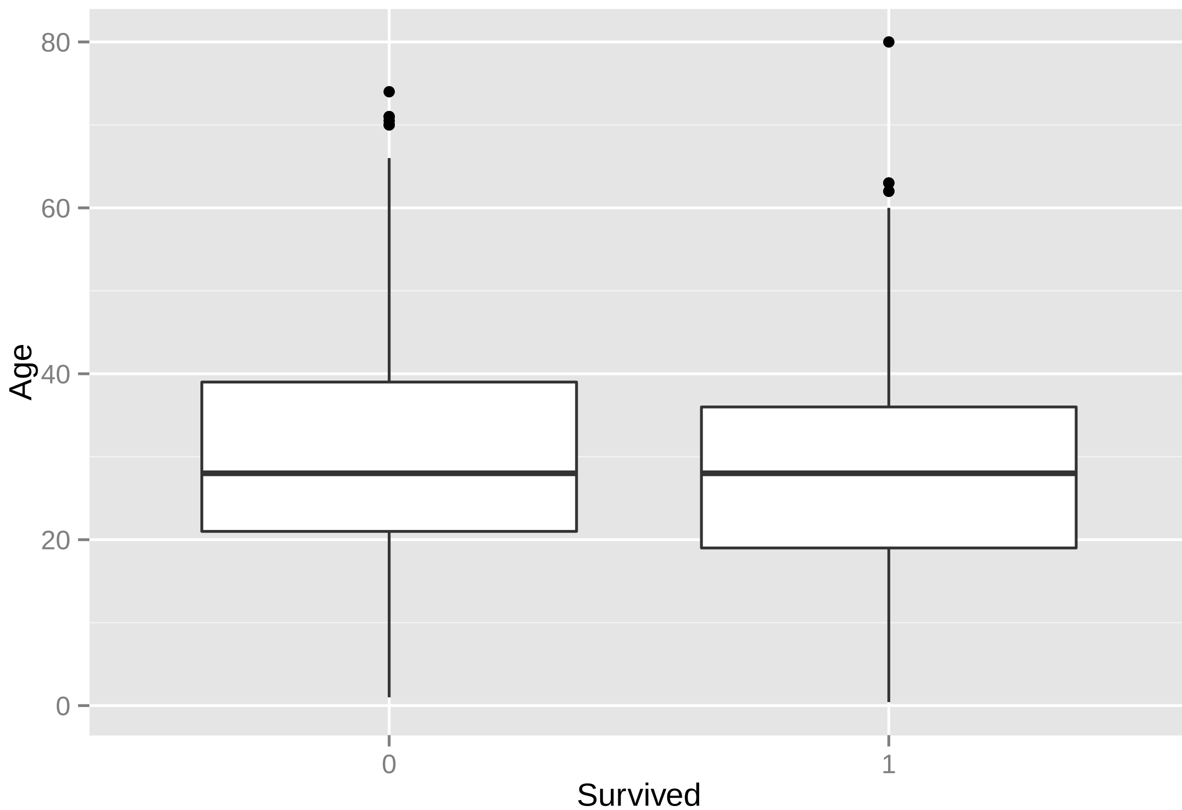
```
require(plyr)
require(ggplot2)
set.seed(35)
readData <- function(fileName) {
    data <- read.csv(file = fileName, header = T, na.strings=c("","NA"))
    data$PassengerId <- as.integer(data$PassengerId)
    data$Pclass <- as.factor(data$Pclass)
    data$Ticket <- as.character(data$Ticket)
    data$Name <- as.character(data$Name)
    data$Cabin <- as.character(data$Cabin)
    data
}
train <- readData(fileName = "./train.csv")
train$Survived <- as.factor(train$Survived)
summary(train)
```

```
##   PassengerId  Survived Pclass      Name                Sex
##  Min.   :  1   0:549    1:216   Length:891         female:314
##  1st Qu.:224   1:342    2:184   Class :character   male  :577
##  Median :446            3:491   Mode  :character
##  Mean   :446
##  3rd Qu.:668
##  Max.   :891
##
##       Age            SibSp           Parch           Ticket
##  Min.   : 0.42   Min.   :0.000   Min.   :0.000   Length:891
##  1st Qu.:20.12   1st Qu.:0.000   1st Qu.:0.000   Class :character
##  Median :28.00   Median :0.000   Median :0.000   Mode  :character
##  Mean   :29.70   Mean   :0.523   Mean   :0.382
##  3rd Qu.:38.00   3rd Qu.:1.000   3rd Qu.:0.000
##  Max.   :80.00   Max.   :8.000   Max.   :6.000
##  NA's   :177
##       Fare          Cabin           Embarked
##  Min.   :  0.0   Length:891         C   :168
##  1st Qu.:  7.9   Class :character   Q   : 77
##  Median : 14.5   Mode  :character   S   :644
##  Mean   : 32.2                      NA's:  2
```

```
##   3rd Qu.: 31.0
##   Max.   :512.3
##
```

Data Visulization and Feature Engineering

Age and Survived rate



Pclass is a good indicator

Using the plot method suggested by this article, I managed to plot the relationship between survived and Pclass.

```
mosaicplot(train$Pclass ~ train$Survived, main="Passenger Survival by Class",
           color=c("#8dd3c7", "#fb8072"), shade=FALSE,  xlab="", ylab="",
           off=c(0), cex.axis=1.4)
```

Ignore Cabin feature

```
require(Hmisc)
describe(train$Cabin)
```

```
## train$Cabin
##       n missing  unique
##     204     687     147
##
## lowest : A10 A14 A16 A19 A20, highest: F33 F38 F4  G6  T
```

The missing data in **Cabin** is too much to interpolate, thus we will not use it as a feature in training model.

Extracting titles from Name

```
head(train$Name)
```

```
## [1] "Braund, Mr. Owen Harris"
## [2] "Cumings, Mrs. John Bradley (Florence Briggs Thayer)"
## [3] "Heikkinen, Miss. Laina"
## [4] "Futrelle, Mrs. Jacques Heath (Lily May Peel)"
## [5] "Allen, Mr. William Henry"
## [6] "Moran, Mr. James"
```

According to one tutorial on this challenge, the Wikipedia entry for the English honorific "Master" explains that,

```
By the late 19th century, etiquette dictated that men be addressed as Mister,
and boys as Master.
```

So I extracted the title feature from **Name**. And group 'same' titles together according to the rules suggested by this article

```
extractTitle <- function(data) {
    title <- sapply(data$Name, FUN = function(x) {strsplit(x, split="[.,]")[[1]][2]
                                                  })
    title <- gsub("^\\s+|\\s+$", "", title)
    title
}
groupTitle <- function(data, oldTitles, newTitle) {
    for (title in oldTitles) {
        data[data$Title == title, "Title"] <- newTitle
    }
    data$Title
}

train$Title <- extractTitle(train)
train$Title <- groupTitle(train, c("Capt", "Col", "Don",
                                   "Dr", "Jonkheer", "Lady",
                                   "Major", "Rev", "Sir"), "Upper Class")
train$Title <- groupTitle(train, c("the Countess", "Ms"), "Mrs")
train$Title <- groupTitle(train, c("Mlle", "Mme"), "Miss")
train$Title <- as.factor(train$Title)
```

Impute null values in Age field and Embarked Field

```
summary(train$Age)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##    0.42   20.10   28.00   29.70   38.00   80.00     177
```

If we look at the **Age** field, there are a lot of missing values. I interpolate on a **per-title** basis, and used **impute** method from **Hmisc** package.

```
imputeAge <- function(data) {
    age <- data$Age
    for (title in unique(data$Title)) {
        age[data$Title == title] <- impute(age[data$Title == title], fun = median)
    }
    age
}
train$Age <- imputeAge(train)
```

There is only two field missing in **Embarked**, I impute them with 'S', since 'S' is the most common element.

```r
train[is.na(train$Embarked),]$Embarked <- 'S'
```

Women and children first policy

Also I added a new feature indicating whether a person is a female or under age 12.

```r
extractPolicy <- function(data) {
    plc <- rep(0, length(data$Sex))
    plc[data$Sex == 'female' | data$Age < 12] <- 1
    factor(plc)
}
train$Plc <- extractPolicy(train)
chisq.test(table(train$Plc, train$Survived))
```

```
##
##  Pearson's Chi-squared test with Yates' continuity correction
##
## data:  table(train$Plc, train$Survived)
## X-squared = 278.9, df = 1, p-value < 2.2e-16
```

I conducted the chi-square test on the new feature, since p-value is smaller than **.05**, we can reject the null hypothesis that the policy feature is independent of the survive rate.

Family feature

I added **SibSp** and **Parch** together to form a new feature indicating the number of family members.

```r
extractFamily <- function(data) {
    data$SibSp + data$Parch
}
train$Family <- extractFamily(train)
```

Model Fitting and tuning

fit model

First, I will use all the variable(except **SipSp** and **Parch**, instead I used the **Family** feature to represent) to train a logistic regression model.

```r
train.model <- glm(Survived ~ Pclass + Sex + Age + Title +
                       Plc + Fare + Embarked + Family, data = train,
                   family = binomial(link=logit))
summary(train.model)
```

```
##
## Call:
## glm(formula = Survived ~ Pclass + Sex + Age + Title + Plc + Fare +
##     Embarked + Family, family = binomial(link = logit), data = train)
##
```

```
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.365  -0.565  -0.381   0.551   2.516
##
## Coefficients:
##                    Estimate Std. Error z value Pr(>|z|)
## (Intercept)        4.59e+01   1.38e+03    0.03  0.97353
## Pclass2           -1.07e+00   3.22e-01   -3.32  0.00089 ***
## Pclass3           -2.16e+00   3.19e-01   -6.78  1.2e-11 ***
## Sexmale           -2.85e+01   8.78e+02   -0.03  0.97406
## Age               -2.91e-02   9.62e-03   -3.02  0.00249 **
## TitleMiss         -2.89e+01   8.78e+02   -0.03  0.97371
## TitleMr           -1.65e+01   6.17e+02   -0.03  0.97874
## TitleMrs          -2.80e+01   8.78e+02   -0.03  0.97454
## TitleUpper Class -1.64e+01   6.17e+02   -0.03  0.97876
## Plc1              -1.32e+01   6.17e+02   -0.02  0.98299
## Fare               3.61e-03   2.66e-03    1.36  0.17358
## EmbarkedQ         -1.59e-01   3.96e-01   -0.40  0.68829
## EmbarkedS         -4.31e-01   2.52e-01   -1.71  0.08662 .
## Family            -4.62e-01   8.45e-02   -5.46  4.7e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1186.66  on 890  degrees of freedom
## Residual deviance:  724.34  on 877  degrees of freedom
## AIC: 752.3
##
## Number of Fisher Scoring iterations: 13
```

From the summary we can see, only a few of variables has passed the **z-test**, which are **Pclass**, **SibSp** and **Parch**. For others, we can not reject the null hypothesis that the corresponding coefficient being zero.

Model Selection based on AIC

So next I conducted feature selection based on AIC.

```r
step(train.model, trace = 0)
```

```
##
## Call:  glm(formula = Survived ~ Pclass + Sex + Age + Title + Fare +
##     Family, family = binomial(link = logit), data = train)
##
## Coefficients:
##      (Intercept)            Pclass2            Pclass3            Sexmale
##         19.39894           -1.16663           -2.17861          -15.42092
##              Age          TitleMiss            TitleMr           TitleMrs
##         -0.02977          -15.83491           -3.36616          -14.93213
## TitleUpper Class               Fare             Family
##         -3.27790            0.00434           -0.48189
##
## Degrees of Freedom: 890 Total (i.e. Null);  880 Residual
```

```
## Null Deviance:       1190
## Residual Deviance: 729   AIC: 751
```

Ok, so I trained next model based on AIC suggestion.

```
train.model <- glm(formula = Survived ~ Pclass + Sex + Age +
                Title + Fare + Family, family = binomial(link = logit),
                   data = train)
summary(train.model)
```

```
##
## Call:
## glm(formula = Survived ~ Pclass + Sex + Age + Title + Fare +
##     Family, family = binomial(link = logit), data = train)
##
## Deviance Residuals:
##    Min      1Q  Median      3Q     Max
## -2.444  -0.555  -0.389   0.541   2.592
##
## Coefficients:
##                    Estimate Std. Error z value Pr(>|z|)
## (Intercept)        19.39894  622.00349    0.03  0.97512
## Pclass2            -1.16663    0.31795   -3.67  0.00024 ***
## Pclass3            -2.17861    0.31173   -6.99  2.8e-12 ***
## Sexmale           -15.42092  622.00323   -0.02  0.98022
## Age                -0.02977    0.00957   -3.11  0.00186 **
## TitleMiss         -15.83491  622.00342   -0.03  0.97969
## TitleMr            -3.36616    0.52734   -6.38  1.7e-10 ***
## TitleMrs          -14.93213  622.00347   -0.02  0.98085
## TitleUpper Class   -3.27790    0.77688   -4.22  2.5e-05 ***
## Fare                0.00434    0.00264    1.64  0.10001
## Family             -0.48189    0.08317   -5.79  6.9e-09 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1186.66  on 890  degrees of freedom
## Residual deviance:  728.51  on 880  degrees of freedom
## AIC: 750.5
##
## Number of Fisher Scoring iterations: 13
```

From the summary we can see, Title **Mr** and **Upper Class** seem to be a good indicator, but other titles are not. So I am going to drop **Miss** and **Mrs**. Also, **fare** and **Sex** can be dropped.

```
train.model <- glm(formula = Survived ~ Pclass + Age +
                       I(Title=="Mr") + I(Title=="Upper Class") +
                       Family, family = binomial(link = logit),
                   data = train)
summary(train.model)
```

```
##
```

```
## Call:
## glm(formula = Survived ~ Pclass + Age + I(Title == "Mr") + I(Title ==
##     "Upper Class") + Family, family = binomial(link = logit),
##     data = train)
##
## Deviance Residuals:
##    Min      1Q  Median      3Q     Max
## -2.402  -0.591  -0.389   0.561   2.574
##
## Coefficients:
##                              Estimate Std. Error z value Pr(>|z|)
## (Intercept)                   3.88201    0.40082    9.69  < 2e-16 ***
## Pclass2                      -1.29825    0.27466   -4.73  2.3e-06 ***
## Pclass3                      -2.41402    0.25871   -9.33  < 2e-16 ***
## Age                          -0.02111    0.00799   -2.64   0.0083 **
## I(Title == "Mr")TRUE         -3.31258    0.22748  -14.56  < 2e-16 ***
## I(Title == "Upper Class")TRUE -3.08798    0.53498   -5.77  7.8e-09 ***
## Family                       -0.39884    0.07065   -5.65  1.6e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1186.66  on 890  degrees of freedom
## Residual deviance:  742.66  on 884  degrees of freedom
## AIC: 756.7
##
## Number of Fisher Scoring iterations: 5
```

Confusion Matrix

Finally I build a confusion matrix.

```r
Survived <- predict(train.model, newdata = train, type="response")
predictions <- as.data.frame(Survived)
predictions$Survived <- sapply(predictions$Survived,
                               function(x) {ifelse(x >= 0.5,
                                                   "Predicted Survived",
                                                   "Predicted Not Survived")})
predictions$Truth <- train$Survived
prop.table(table(predictions$Truth, predictions$Survived), 2)
```

```
##
##     Predicted Not Survived Predicted Survived
##   0                 0.8387             0.1821
##   1                 0.1613             0.8179
```

Submit Result

The following script does the same processing procedures on test dataset, and save the prediction to csv file.

```r
test <- readData('./test.csv')
test$Title <- extractTitle(test)
test$Title <- groupTitle(test, c("Capt", "Col", "Don",
                                 "Dr", "Jonkheer", "Lady",
                                 "Major", "Rev", "Sir"), "Upper Class")
test$Title <- groupTitle(test, c("the Countess", "Ms"), "Mrs")
test$Title <- groupTitle(test, c("Mlle", "Mme"), "Miss")
test$Age <- imputeAge(test)
test$Family <- extractFamily(test)
# use probability 0.5 as a threshold.
Survived <- predict(train.model, newdata = test, type="response")
predictions <- as.data.frame(Survived)
predictions$PassengerId <- test[,1]
predictions$Survived <- sapply(predictions$Survived, function(x) {ifelse(x >= 0.5, 1, 0)})

write.csv(predictions, file='result.csv', row.names=F, quote=F)
```

I achieved **0.78947** accurancy rate on kaggle's data.