Who Would Survive the Titanic Diaster

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Who Would Survive the Titanic Disaster?

This project is from https://www.kaggle.com/c/titanic

"The sinking of the RMS Titanic is one of the most infamous shipwrecks in history. On April 15, 1912, during her maiden voyage, the Titanic sank after colliding with an iceberg, killing 1502 out of 2224 passengers and crew. This sensational tragedy shocked the international community and led to better safety regulations for ships.

One of the reasons that the shipwreck led to such loss of life was that there were not enough lifeboats for the passengers and crew. Although there was some element of luck involved in surviving the sinking, some groups of people were more likely to survive than others, such as women, children, and the upper-class.

In this challenge, we ask you to complete the analysis of what sorts of people were likely to survive. In particular, we ask you to apply the tools of machine learning to predict which passengers survived the tragedy."

Step 1 - Collecting data —-

The data is from https://www.kaggle.com/c/titanic/data

The data has been split into two groups: training set (train.csv) test set (test.csv) Traing set includes 891 examples, 12 variables: a label variable, survival indicating whether or not survival, and 11 features.Test set includes 418 examples, 11 features. The 12 variables are discribed as following:

Variable Definition Key survival Survival 0 = No, 1 = Yes pclass Ticket class 1 = 1st, 2 = 2nd, 3 = 3rd sex Sex Age Age in years
sibsp # of siblings / spouses aboard the Titanic
parch # of parents / children aboard the Titanic
ticket Ticket number
fare Passenger fare
cabin Cabin number
embarked Port of Embarkation C = Cherbourg, Q = Queenstown, S = Southampton Variable Notes

pclass: A proxy for socio-economic status (SES) 1st = Upper 2nd = Middle 3rd = Lower

age: Age is fractional if less than 1. If the age is estimated, is it in the form of xx.5

sibsp: The dataset defines family relations in this way… Sibling = brother, sister, stepbrother, stepsister Spouse = husband, wife (mistresses and fiancés were ignored)

parch: The dataset defines family relations in this way… Parent = mother, father Child = daughter, son, stepdaughter, stepson Some children travelled only with a nanny, therefore parch=0 for them.

Step 2: Exploring and preparing the data—-

Explore the data to understand data, to clean data, to create new festures, to obtain insights, to find predictive features, and prepare the data for modeling.

Import data

Import the data into R

```r
# load R packages
library(plyr)  # data manipulation
library(dplyr)  # data manipulation
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:plyr':
##
##     arrange, count, desc, failwith, id, mutate, rename, summarise,
##     summarize

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```r
library(ggplot2) # data visiualization
library(scales) # data visiualization
library(gmodels) # crosstable
library(stringr) # String manipulation
library(caret) # tune parameters
```

```
## Loading required package: lattice
```

```r
library(rpart) # Decision tree utils
library(randomForest) # Random Forest
```

```
## randomForest 4.6-12

## Type rfNews() to see new features/changes/bug fixes.

##
## Attaching package: 'randomForest'

## The following object is masked from 'package:ggplot2':
##
##     margin

## The following object is masked from 'package:dplyr':
##
##     combine
```

```r
library(kernlab) # SVM
```

```
##
## Attaching package: 'kernlab'

## The following object is masked from 'package:scales':
##
##     alpha

## The following object is masked from 'package:ggplot2':
##
```

```
##     alpha
```

```r
library(party) # Conditional inference trees
```

```
## Loading required package: grid

## Loading required package: mvtnorm

## Loading required package: modeltools

## Loading required package: stats4

##
## Attaching package: 'modeltools'

## The following object is masked from 'package:kernlab':
##
##     prior

## The following object is masked from 'package:plyr':
##
##     empty

## Loading required package: strucchange

## Loading required package: zoo

##
## Attaching package: 'zoo'

## The following objects are masked from 'package:base':
##
##     as.Date, as.Date.numeric

## Loading required package: sandwich

##
## Attaching package: 'strucchange'

## The following object is masked from 'package:stringr':
##
##     boundary
```

```r
library(gbm) # gbm
```

```
## Loading required package: survival

##
## Attaching package: 'survival'

## The following object is masked from 'package:caret':
##
##     cluster

## Loading required package: splines

## Loading required package: parallel

## Loaded gbm 2.1.3
```

```r
library(MASS) # glm
```

```
##
## Attaching package: 'MASS'
```

```
## The following object is masked from 'package:dplyr':
##
##     select
```

```r
library(fastAdaboost) # AdaBoost
library(xgboost) #xgboost
```

```
##
## Attaching package: 'xgboost'
## The following object is masked from 'package:dplyr':
##
##     slice
```

```r
#Import the CSV file.
train <- read.csv("train.csv", header = TRUE, stringsAsFactors =FALSE)
test <- read.csv("test.csv", header = TRUE,stringsAsFactors =FALSE)
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)"
##  $ 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
str(test)
```

```
## 'data.frame':    418 obs. of  11 variables:
##  $ PassengerId: int  892 893 894 895 896 897 898 899 900 901 ...
##  $ Pclass     : int  3 3 2 3 3 3 3 2 3 3 ...
##  $ Name       : chr  "Kelly, Mr. James" "Wilkes, Mrs. James (Ellen Needs)" "Myles, Mr. Thomas Franci
##  $ Sex        : chr  "male" "female" "male" "male" ...
##  $ Age        : num  34.5 47 62 27 22 14 30 26 18 21 ...
##  $ SibSp      : int  0 1 0 0 1 0 0 1 0 2 ...
##  $ Parch      : int  0 0 0 0 1 0 0 1 0 0 ...
##  $ Ticket     : chr  "330911" "363272" "240276" "315154" ...
##  $ Fare       : num  7.83 7 9.69 8.66 12.29 ...
##  $ Cabin      : chr  "" "" "" "" ...
##  $ Embarked   : chr  "Q" "S" "Q" "S" ...
```

Combine data sets and convert data type

```r
# Add a "Survived" variable to the test set to allow for combining data sets
test$Survived <- NA

# Combine data sets
data <- rbind(train, test)
```

```r
# Convert data type to factor
data$Survived <- as.factor(data$Survived)
data$Pclass <- as.factor(data$Pclass)
data$Sex <- as.factor(data$Sex)
data$Embarked <- as.factor(data$Embarked)
```

Data understanding

Age has a lot of missing values. Fare and Embarked have a few missing values.There seem no outliers for all features.

```r
summary(data)
```

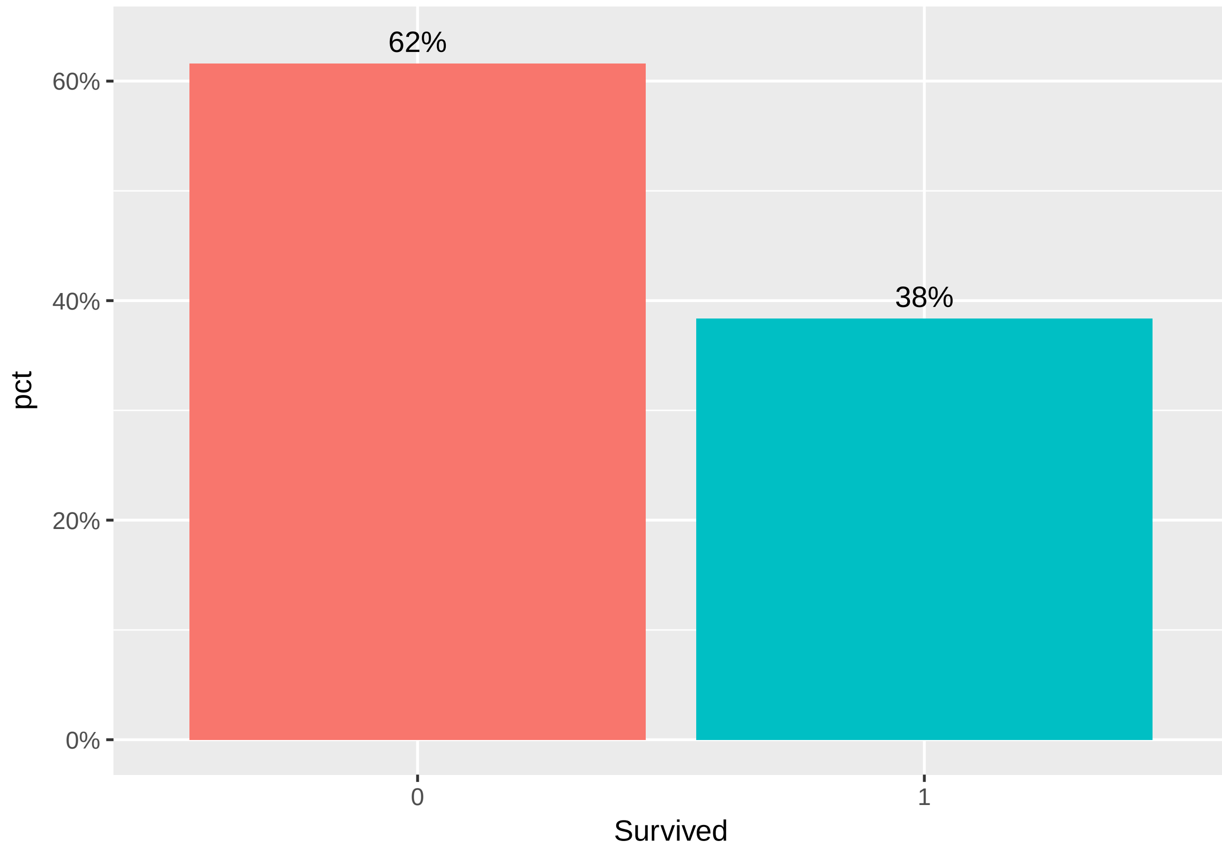
```
##   PassengerId   Survived   Pclass      Name               Sex
##  Min.   :   1   0   :549   1:323   Length:1309        female:466
##  1st Qu.: 328   1   :342   2:277   Class :character   male  :843
##  Median : 655   NA's:418   3:709   Mode  :character
##  Mean   : 655
##  3rd Qu.: 982
##  Max.   :1309
##
##       Age            SibSp            Parch          Ticket
##  Min.   : 0.17   Min.   :0.0000   Min.   :0.000   Length:1309
##  1st Qu.:21.00   1st Qu.:0.0000   1st Qu.:0.000   Class :character
##  Median :28.00   Median :0.0000   Median :0.000   Mode  :character
##  Mean   :29.88   Mean   :0.4989   Mean   :0.385
##  3rd Qu.:39.00   3rd Qu.:1.0000   3rd Qu.:0.000
##  Max.   :80.00   Max.   :8.0000   Max.   :9.000
##  NA's   :263
##       Fare            Cabin            Embarked
##  Min.   :  0.000   Length:1309         :  2
##  1st Qu.:  7.896   Class :character   C:270
##  Median : 14.454   Mode  :character   Q:123
##  Mean   : 33.295                      S:914
##  3rd Qu.: 31.275
##  Max.   :512.329
##  NA's   :1
```

Data exploration, data cleaning, data manipulation, and feature engineering

Survived: the survival rate was 38.4%.

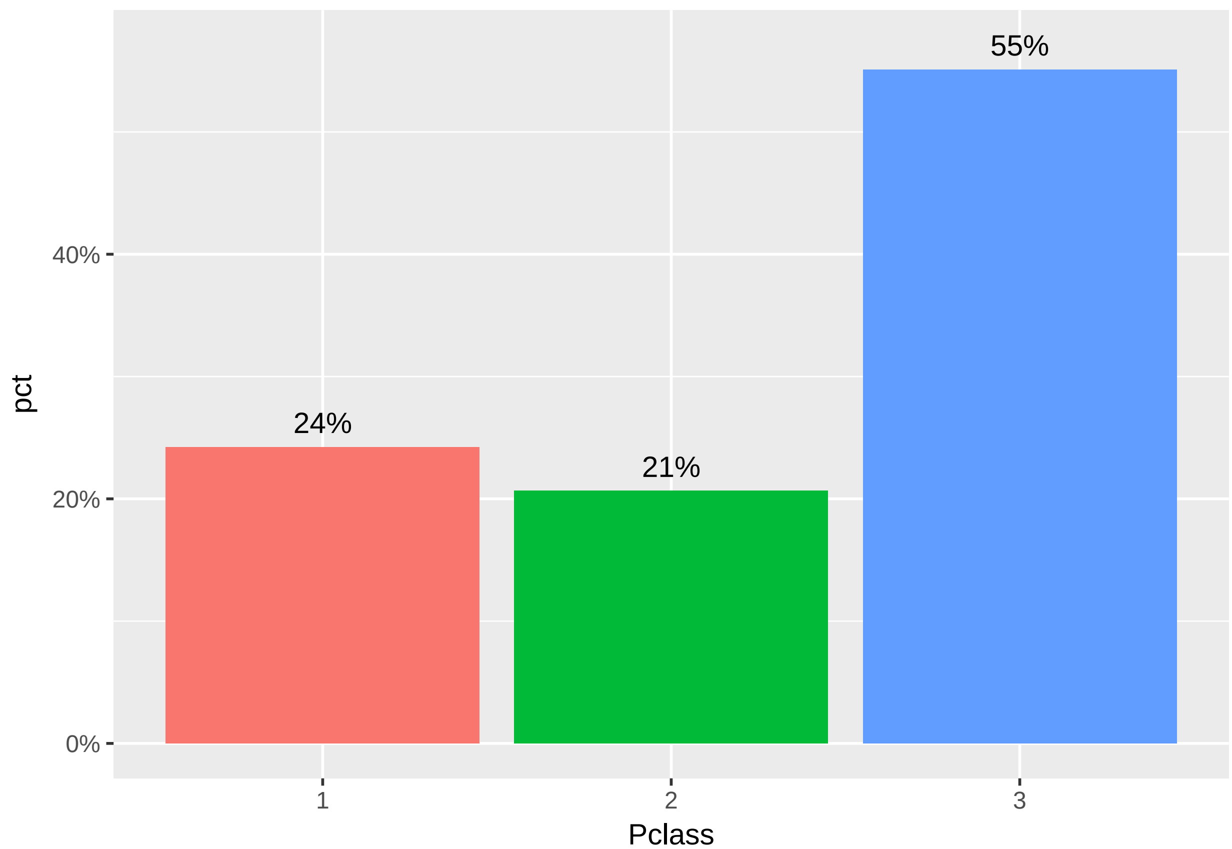
```r
# Survival rate
data[1:891,] %>%
  group_by(Survived) %>%
  summarise(count=n()) %>%
  mutate(pct=count/sum(count))  %>%
  ggplot(aes(x=Survived, y=pct, fill=Survived)) +
  geom_bar(stat="identity") +
  scale_y_continuous(labels=percent) +
```

```
  geom_text(aes(label=paste0(round(pct*100,0),"%"), y=pct+0.02), size=4, colour= "black")+
  theme(legend.position = "NULL")
```

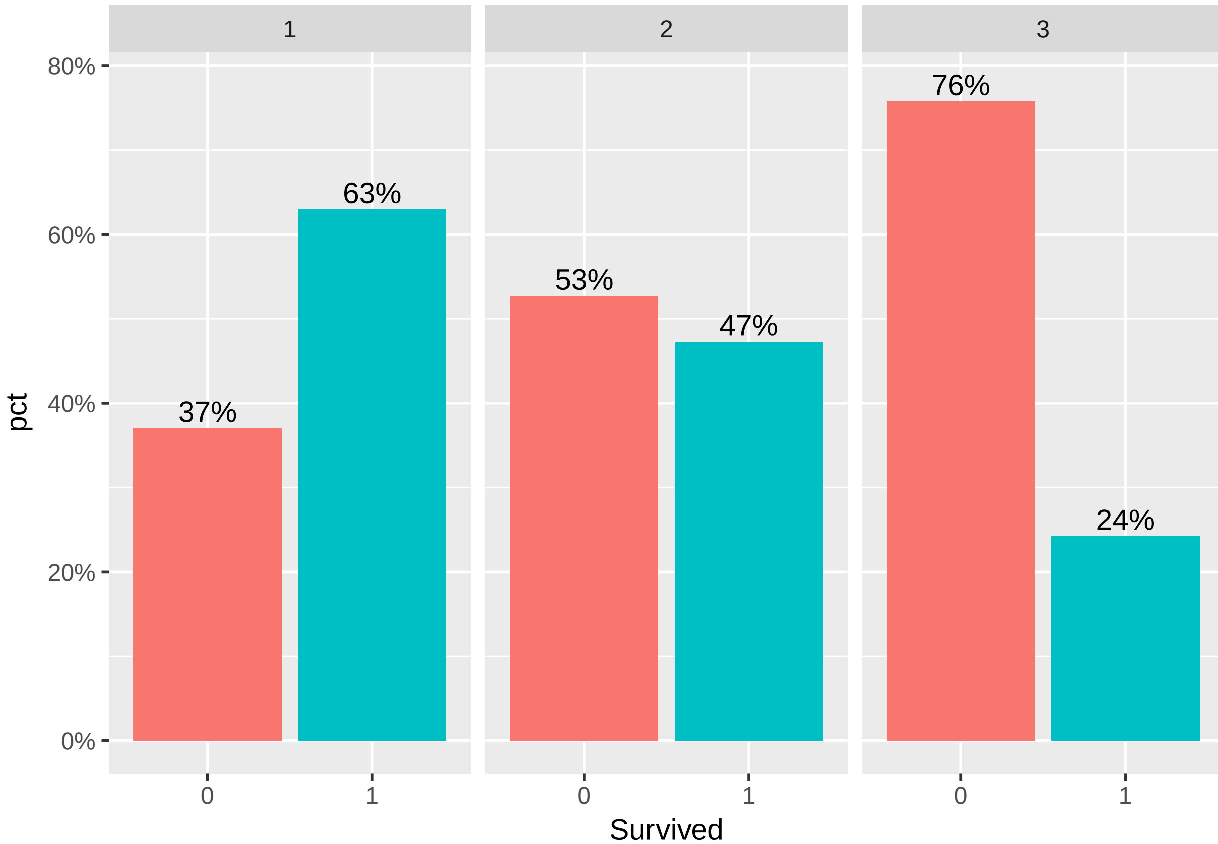


Pcalss: There are much more passengers in first class. 24% of passengers were in first class, 21% in second class, 55% in third class. Rich people survived at a higer rate. The survival rate is 63%, 47%, and 24% for first, second, and third class respectively.

```
# Pclass
data[1:891,] %>%
  group_by(Pclass) %>%
  summarise(count=n()) %>%
  mutate(pct=count/sum(count))  %>%
  ggplot(aes(x=Pclass, y=pct, fill=Pclass)) +
  geom_bar(stat="identity") +
  scale_y_continuous(labels=percent) +
  geom_text(aes(label=paste0(round(pct*100,0),"%"), y=pct+0.02), size=4, colour= "black")+
  theme(legend.position = "none")
```




```
#Pclass VS Survival Rate
data[1:891,] %>% group_by(Pclass, Survived) %>%
  summarise(count=n()) %>%
  mutate(pct=count/sum(count))  %>%
ggplot(aes(x=Survived, y=pct, fill=Survived)) +
  geom_bar(stat="identity") +
  facet_grid(. ~ Pclass) +
  scale_y_continuous(labels=percent) +
  geom_text(aes(label=paste0(round(pct*100,0),"%"), y=pct+0.02), size=4, colour= "black")+
  theme(legend.position = "none")
```



Name: contains formal titles, which can be extracted as a potentially useful feature. Ttile, new variable derived by Name. Baesd on the plots, 60% off passengers were Mr; "Women and children first" is true in Tatanic diaster. Women and children had more than 3 times that men had to survive;It's obvious that Title and Pclass play important roles in predicting who would survive. Passengers having title of Master, Miss, and Mrs had more than 90% chance to survive in first and second class, but those in third class had less han 50% chance. Mr even had less than 40% chance to survive in first class and about 10% in second and third class.

```
#Name: new variable Title derived by Name is predictive
# Look at the first few names
data$Name[1:20]
```

```
##  [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"
##  [7] "McCarthy, Mr. Timothy J"
##  [8] "Palsson, Master. Gosta Leonard"
##  [9] "Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)"
## [10] "Nasser, Mrs. Nicholas (Adele Achem)"
## [11] "Sandstrom, Miss. Marguerite Rut"
## [12] "Bonnell, Miss. Elizabeth"
## [13] "Saundercock, Mr. William Henry"
## [14] "Andersson, Mr. Anders Johan"
## [15] "Vestrom, Miss. Hulda Amanda Adolfina"
## [16] "Hewlett, Mrs. (Mary D Kingcome) "
```

```
## [17] "Rice, Master. Eugene"
## [18] "Williams, Mr. Charles Eugene"
## [19] "Vander Planke, Mrs. Julius (Emelia Maria Vandemoortele)"
## [20] "Masselmani, Mrs. Fatima"
```

```r
#extract title
data$Title = sapply(data$Name, FUN=function(x) { strsplit(x, split="[,.]")[[1]][2]})
data$Title = sub(' ', '', data$Title)
table(data$Title)
```

```
##
##          Capt           Col           Don          Dona            Dr
##             1             4             1             1             8
##      Jonkheer          Lady         Major        Master          Miss
##             1             1             2            61           260
##          Mlle           Mme            Mr           Mrs            Ms
##             2             1           757           197             2
##           Rev           Sir the Countess
##             8             1             1
```

```r
# combine special, rare titles
data$Title[data$Title %in% c('Capt', 'Col', 'Don', 'Major', 'Sir', 'Dr', 'Rev')] <- 'Mr'
data$Title[data$Title %in% c('Mme', 'Mlle', 'Ms','Dona', 'Lady', 'the Countess', 'Jonkheer')] <- 'Miss'
table(data$Title)
```

```
##
## Master   Miss     Mr    Mrs
##     61    269    782    197
```

```r
# convert to factor
data$Title = factor(data$Title)

# explore Title
# Title=Master,boys with age of 0.33-14.5,median= 4.0
table(data$Sex[data$Title=="Master"]) # they are male
```

```
##
## female   male
##      0     61
```

```r
summary(data$Age[data$Title=="Master"])# 0.33-14.5, median= 4.0
```

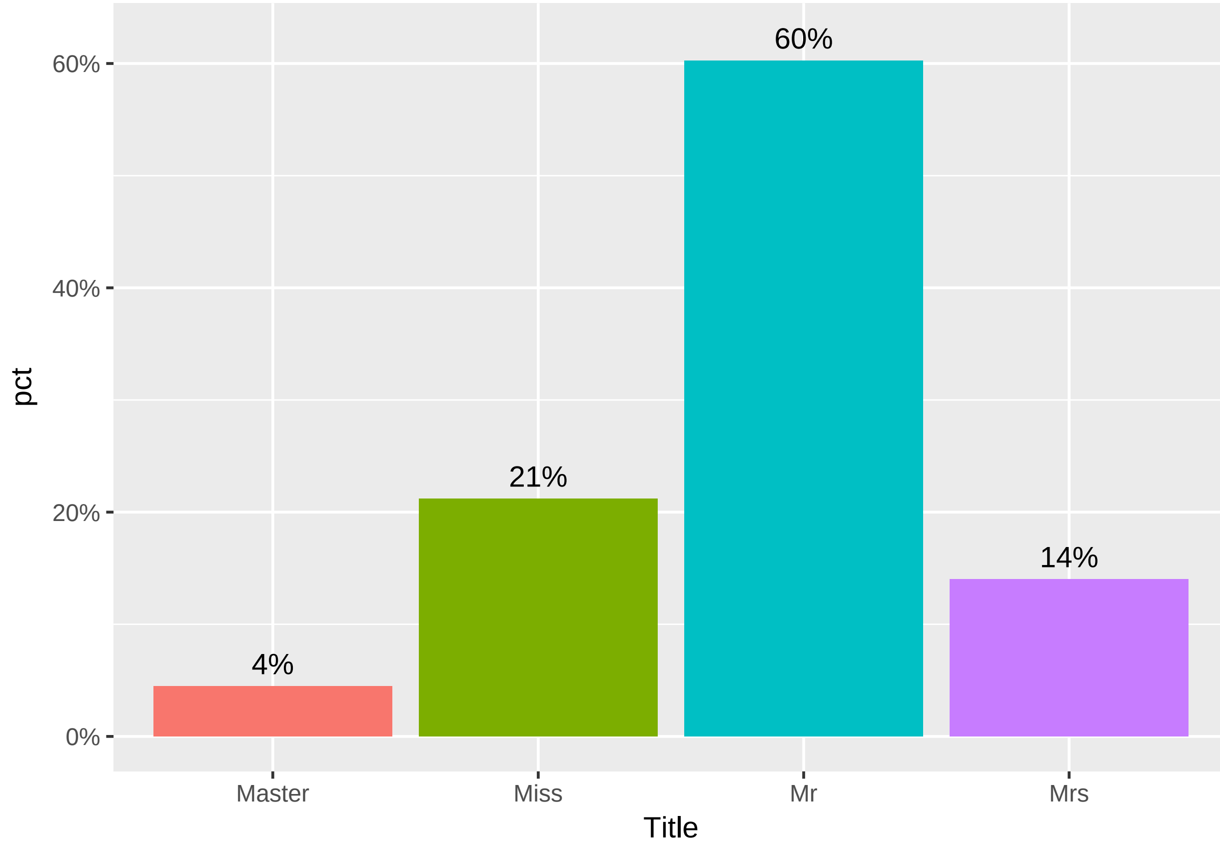
```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##   0.330   2.000   4.000   5.483   9.000  14.500       8
```

```r
# Title=Miss, age of 0.17-63.0
summary(data$Age[data$Title=="Miss"])# 0.17-63.0, median= 22.00, mean=22.16
```

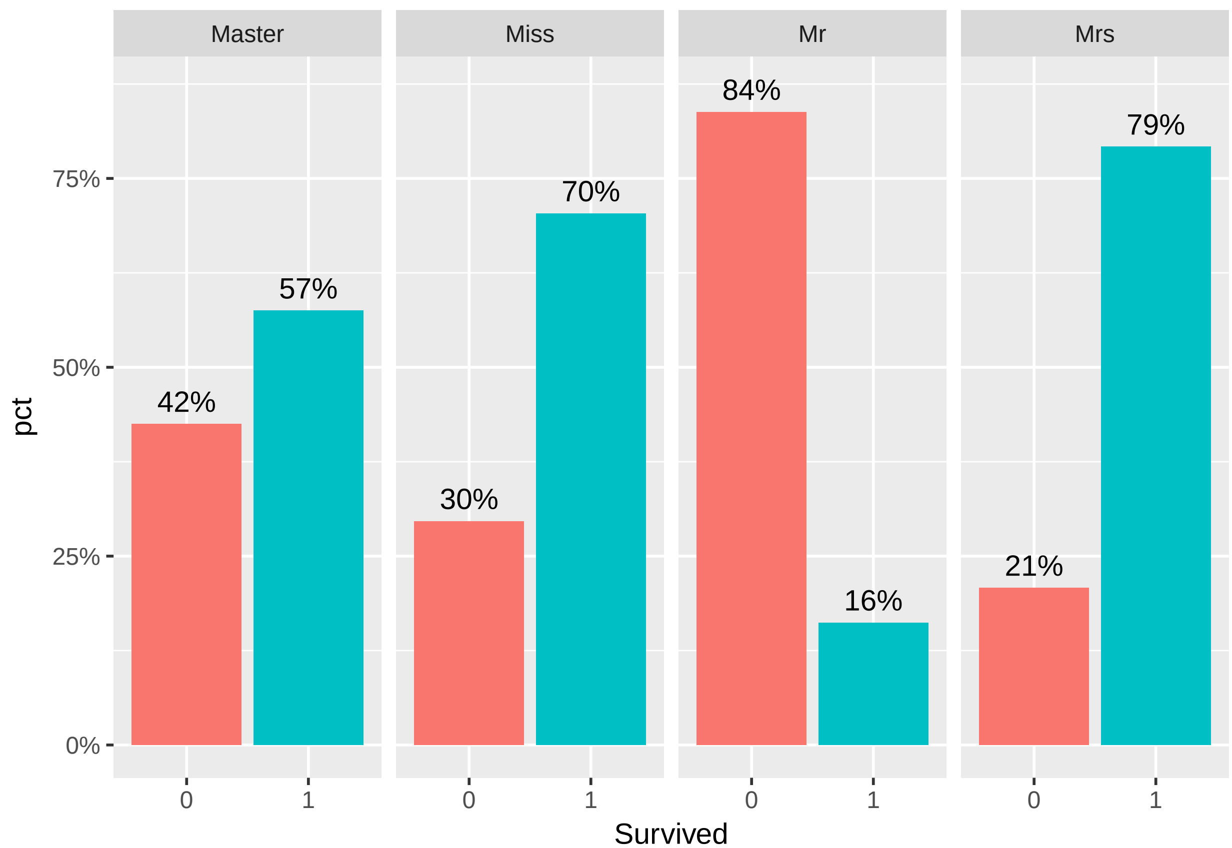
```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##    0.17   16.00   22.00   22.16   30.00   63.00      51
```

```r
# Title
data[1:891,] %>% group_by(Title) %>%
  summarise(count=n()) %>%
  mutate(pct=count/sum(count))  %>%
ggplot(aes(x=Title, y=pct, fill=Title)) +
  geom_bar(stat="identity") +
  scale_y_continuous(labels=percent) +
  geom_text(aes(label=paste0(round(pct*100,0),"%"), y=pct+0.02), size=4, colour= "black")+
```

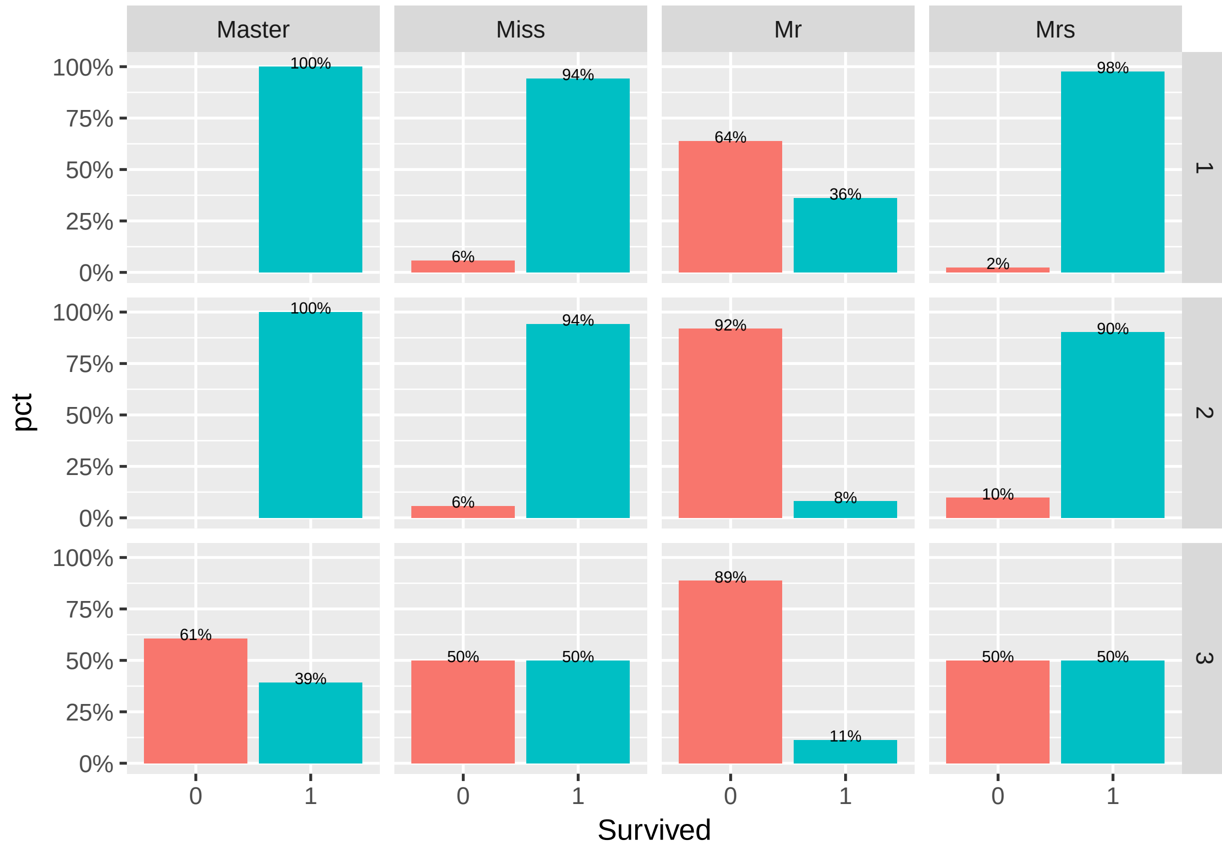
```r
  theme(legend.position = "none")
```




```r
# Title vs Survival
data[1:891,] %>% group_by(Title, Survived) %>%
  summarise(count=n()) %>%
  mutate(pct=count/sum(count))  %>%
ggplot(aes(x=Survived, y=pct, fill=Survived)) +
  geom_bar(stat="identity") +
  facet_grid(. ~ Title) +
  scale_y_continuous(labels=percent) +
  geom_text(aes(label=paste0(round(pct*100,0),"%"), y=pct+0.03), size=4, colour= "black")+
  theme(legend.position = "none")
```

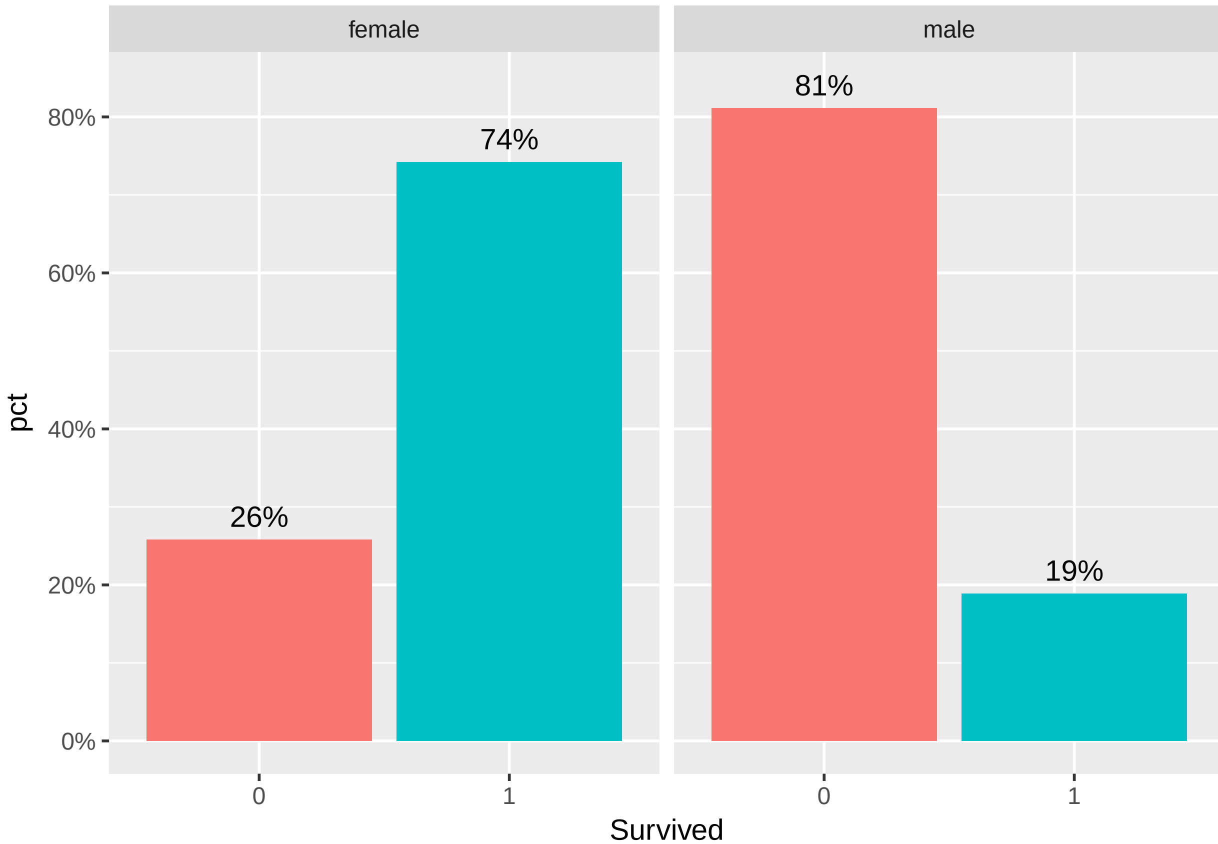



```r
# Title Vs vs survial under class
data[1:891,] %>% group_by(Pclass, Title, Survived) %>%
  summarise(count=n()) %>%
  mutate(pct=count/sum(count))  %>%
ggplot(aes(x=Survived, y=pct, fill=Survived)) +
  geom_bar(stat="identity") +
  facet_grid(Pclass ~ Title) +
  scale_y_continuous(labels=percent) +
  geom_text(aes(label=paste0(round(pct*100,0),"%"), y=pct+0.02), size=2, colour= "black")+
  theme(legend.position = "none")
```



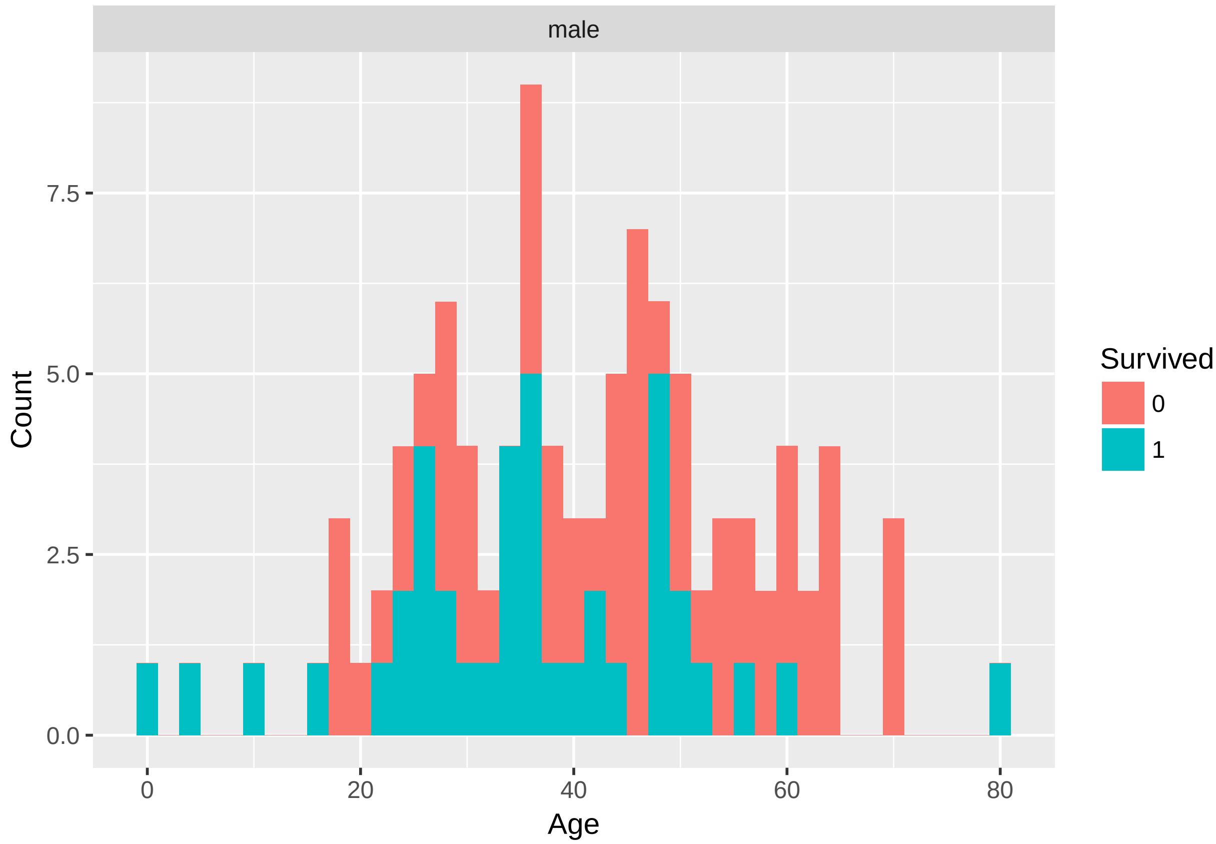
Sex: It is clearly obvious that female have much more chance, 74%, to survive than male, 19%.

```
#Sex
data[1:891,] %>% group_by(Sex, Survived) %>%
  summarise(count=n()) %>%
  mutate(pct=count/sum(count))  %>%
ggplot(aes(x=Survived, y=pct, fill=Survived)) +
  geom_bar(stat="identity") +
  facet_grid(. ~ Sex) +
  scale_y_continuous(labels=percent) +
  geom_text(aes(label=paste0(round(pct*100,0),"%"), y=pct+0.03), size=4, colour= "black")+
  theme(legend.position = "none")
```

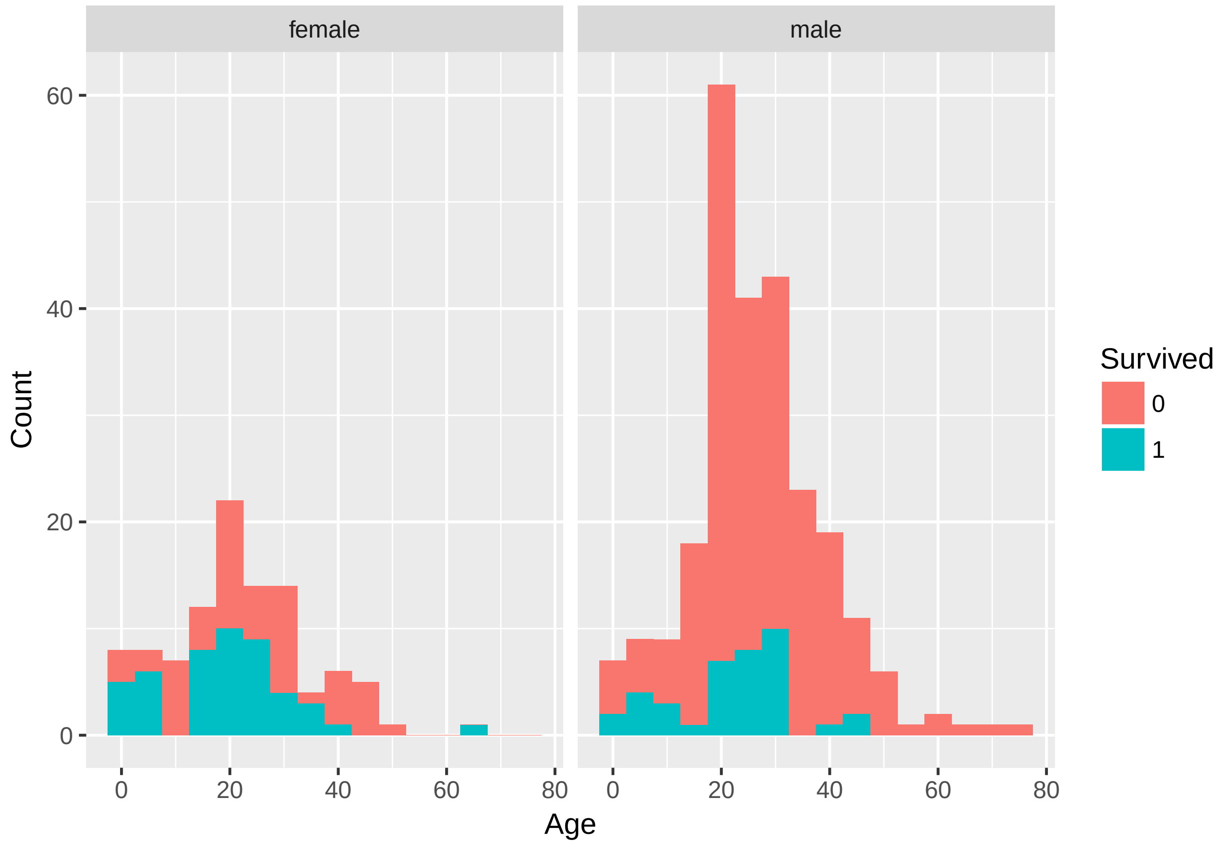


Age Based on the plot of Title above, Mr in first class and Master, Miss, and Mrs in third class are difficult to predict if they would survive, so I focus on these passengers. From the plot, Age is associated with survival rate. Then it is preferable to keep the age feature and to impute the missing values.

```
#Age vs Survival under Sex
ggplot( subset(data[1:891,],!is.na(Age) & Pclass=="1" & Sex=="male") , aes(x = Age, fill=Survived)) +
  geom_histogram( binwidth=2)  +
  facet_wrap(~ Sex) +
  labs( x = "Age", y = "Count")
```




```
ggplot( subset(data[1:891,],!is.na(Age) & Pclass=="3") , aes(x = Age, fill=Survived)) +
  geom_histogram( binwidth=5)  +
  facet_wrap(~ Sex) +
  labs( x = "Age", y = "Count")
```



how to impute missing values? method: Age1, impute Age by Title

```
#method1: Age1, impute Age by Title
#create Age1
data$Age1=data$Age
#Title=Master
summary(data$Age[data$Title=="Master"])# 0.33-14.5, boys with median= 4.0
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##   0.330   2.000   4.000   5.483   9.000  14.500       8
```

```
masterAge <- data$Title == "Master" & is.na(data$Age)
data[masterAge, "Age1"] <- 4.0

# Title=Miss
summary(data$Age[data$Title=="Miss"]) # 0.17-63.0, median= 22.00, mean=22.16
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##    0.17   16.00   22.00   22.16   30.00   63.00      51
```

```
missAlone <- data$Title == "Miss" & data$Parch==0 & data$SibSp==0
summary(data[missAlone, "Age"]) # mean=27
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##    5.00   21.00   26.00   27.38   33.00   58.00      34
```

```
missAloneAge <- missAlone & is.na(data$Age)
data[missAloneAge, "Age1"] <- 27
```

```
missNot <- data$Title == "Miss" & (data$Parch + data$SibSp >0 )
summary(data[missNot, "Age"]) # mean=15
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##    0.17    4.25   15.00   15.27   22.00   63.00      17
```

```
missNotAge <- missNot & is.na(data$Age)
data[missNotAge, "Age1"] <- 15

#Title=Mrs
summary(data$Age[data$Title =="Mrs"]) # mean=37
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##   14.00   27.00   35.50   36.99   46.50   76.00      27
```

```
mrsAge <- data$Title == "Mrs" & is.na(data$Age)
data[mrsAge, "Age1"] <- 37

#Title=Mr
summary(data$Age[data$Title =="Mr"]) # mean=33
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##    11.0    23.0    30.0    32.8    40.0    80.0     177
```

```
mrAge <- data$Title == "Mr" & is.na(data$Age)
data[mrAge, "Age1"] <- 33

summary(data$Age1)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    0.17   22.00   30.00   30.02   36.00   80.00
```

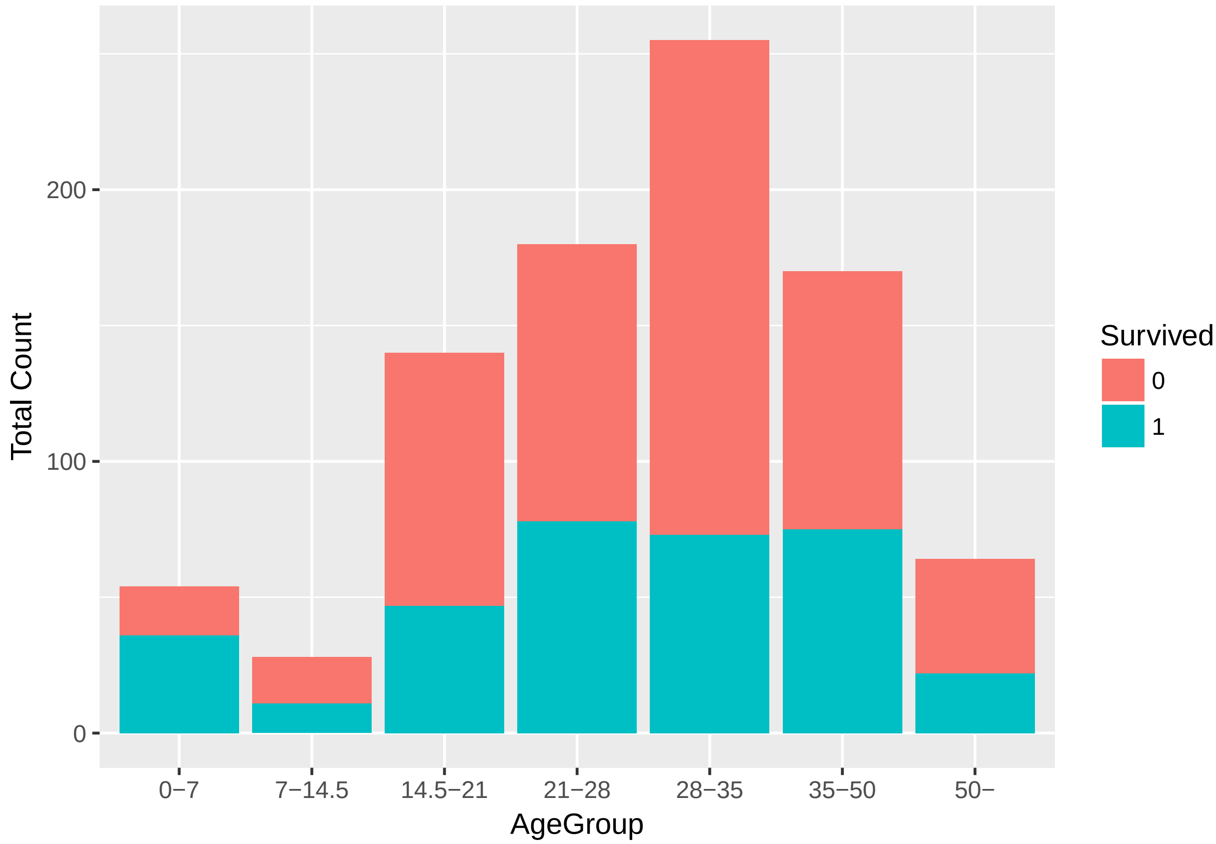
AgeGroup Based on the above Age plot, different Age group passengers had different chance to survive, so I group Age1. From the plot, the group of less than 7 years had the highest chance to survive, but the group of 28-35 had the least chance.Under pclass and Title, AgeGroup seems predictive.

```
# group Age1 to AgeGroup
AgeGroup= cut(data$Age1, breaks = c(0,7,14.5 ,21,28,35,50,80), labels = c("0-7", "7-14.5","14.5-21","21
table(AgeGroup)
```

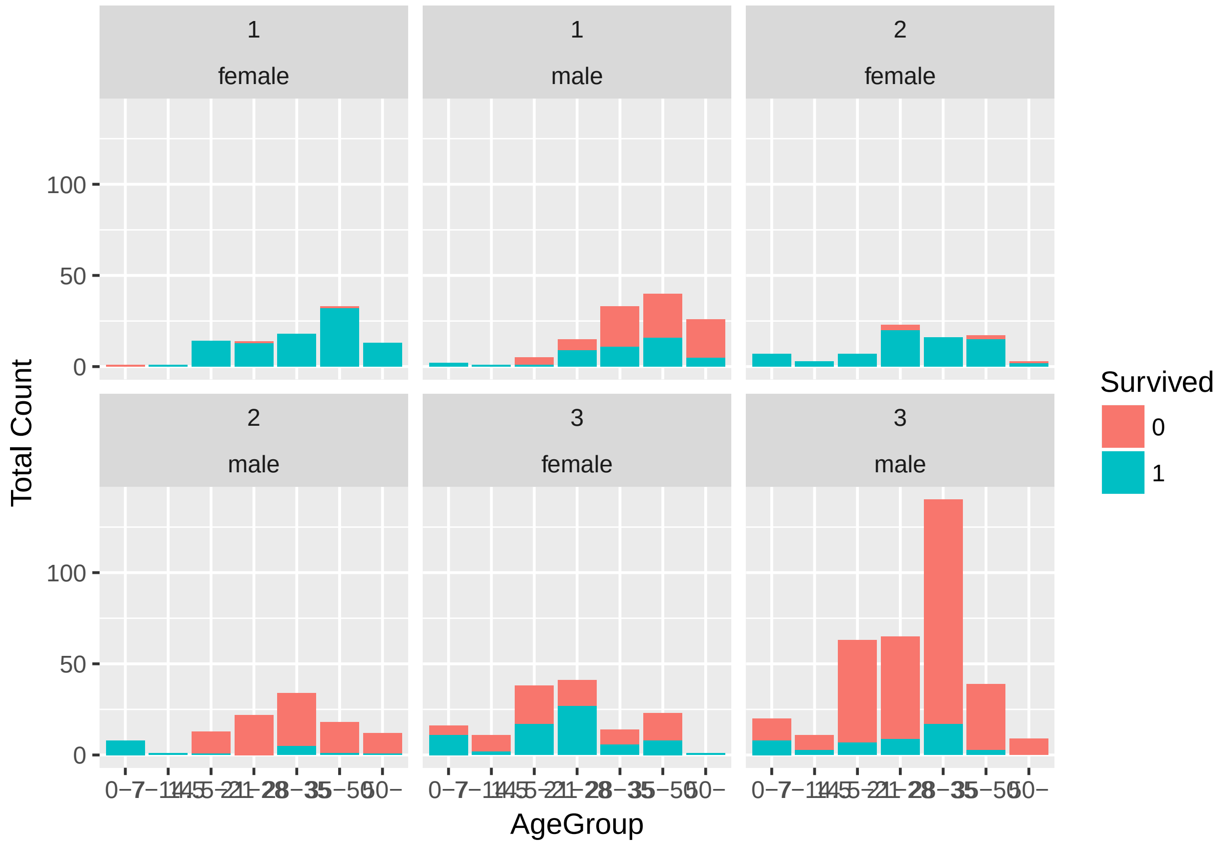
```
## AgeGroup
##     0-7  7-14.5 14.5-21   21-28   28-35   35-50     50-
##      74      43     198     280     365     254      95
```

```
data$AgeGroup=AgeGroup

#AgeGroup Vs Survival
ggplot(data[1:891,], aes(x = AgeGroup, fill=Survived)) +
  geom_bar() +
  xlab("AgeGroup") +
  ylab("Total Count") +
  labs(fill = "Survived")
```




```r
# AgeGroup Vs Title, under Pclass, Survival
ggplot(data[1:891,], aes(x = AgeGroup, fill=Survived)) +
  geom_bar() +
  facet_wrap(Pclass~Sex)+
  xlab("AgeGroup") +
  ylab("Total Count") +
  labs(fill = "Survived")
```

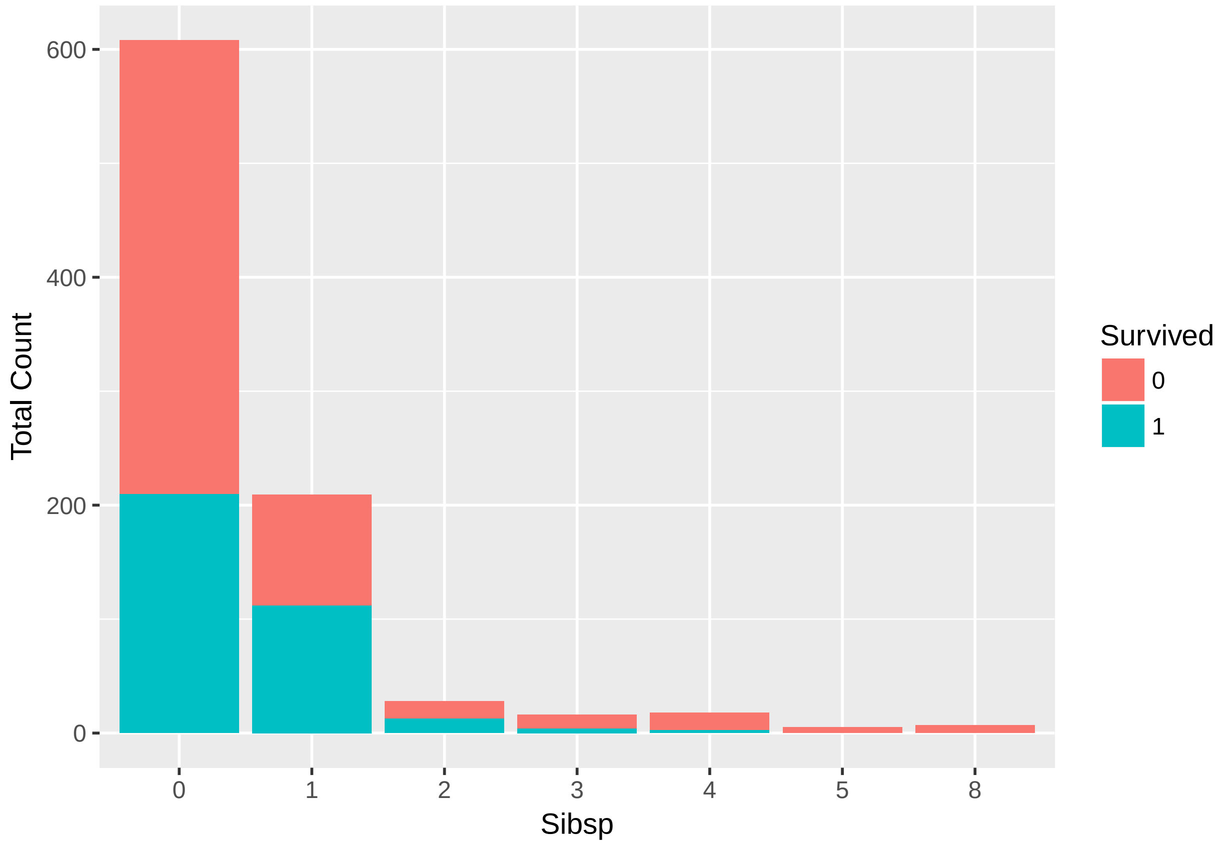


Sibsp: It seems that passengers having more than 2 siblings/spouses had very little chance to survive. Then I group it to SibGroup.

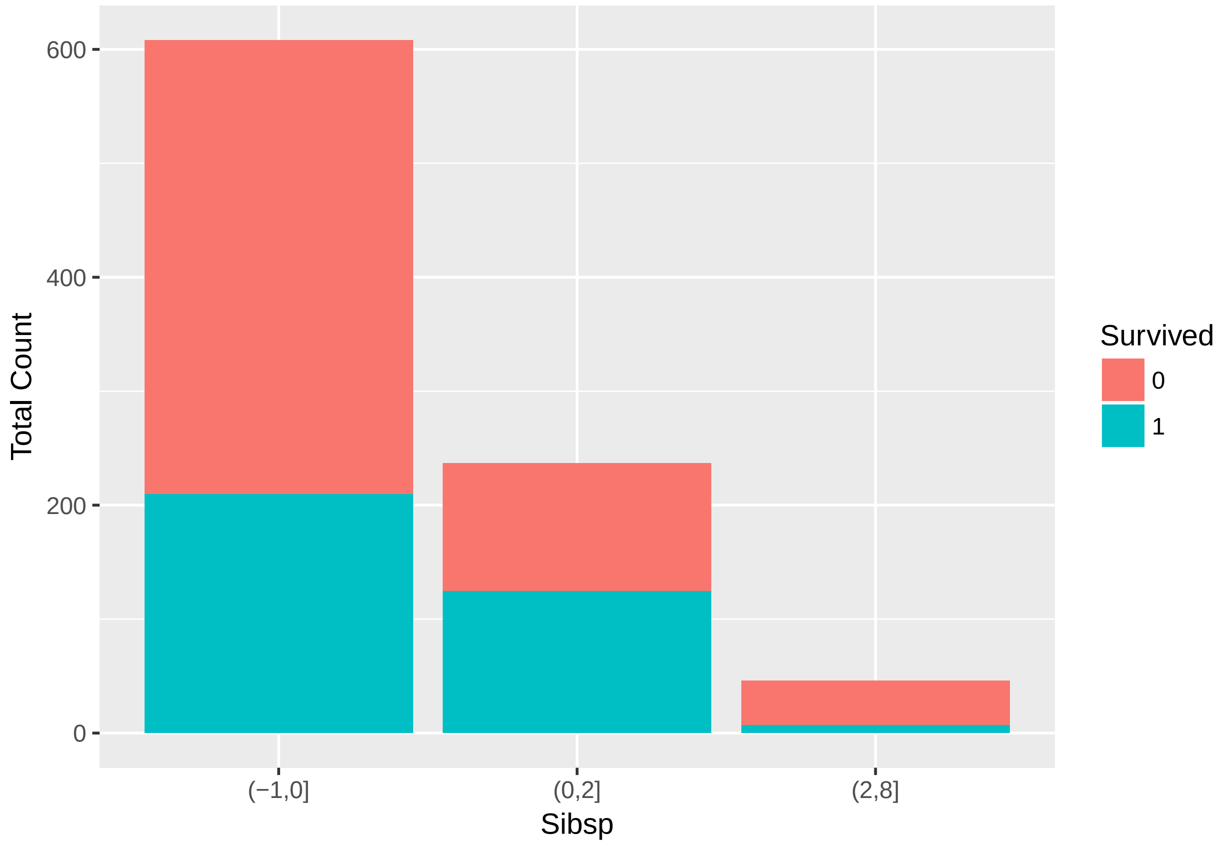
```
#Sibsp
summary(data$SibSp)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.0000  0.0000  0.0000  0.4989  1.0000  8.0000
```

```
ggplot(data[1:891,], aes(x = as.factor(SibSp), fill = Survived)) +
  geom_bar() +
  xlab("Sibsp") +
  ylab("Total Count") +
  labs(fill = "Survived")
```




```r
# SibGroup
data$SibGroup <- cut(data$SibSp, breaks=c(-1,0,2,8),levels=c("0","1-2","3-"))
# SibGroup vs Survival under pclass and title
ggplot(data[1:891,], aes(x = SibGroup, fill = Survived)) +
  geom_bar() +
    xlab("Sibsp") +
  ylab("Total Count") +
  labs(fill = "Survived")
```

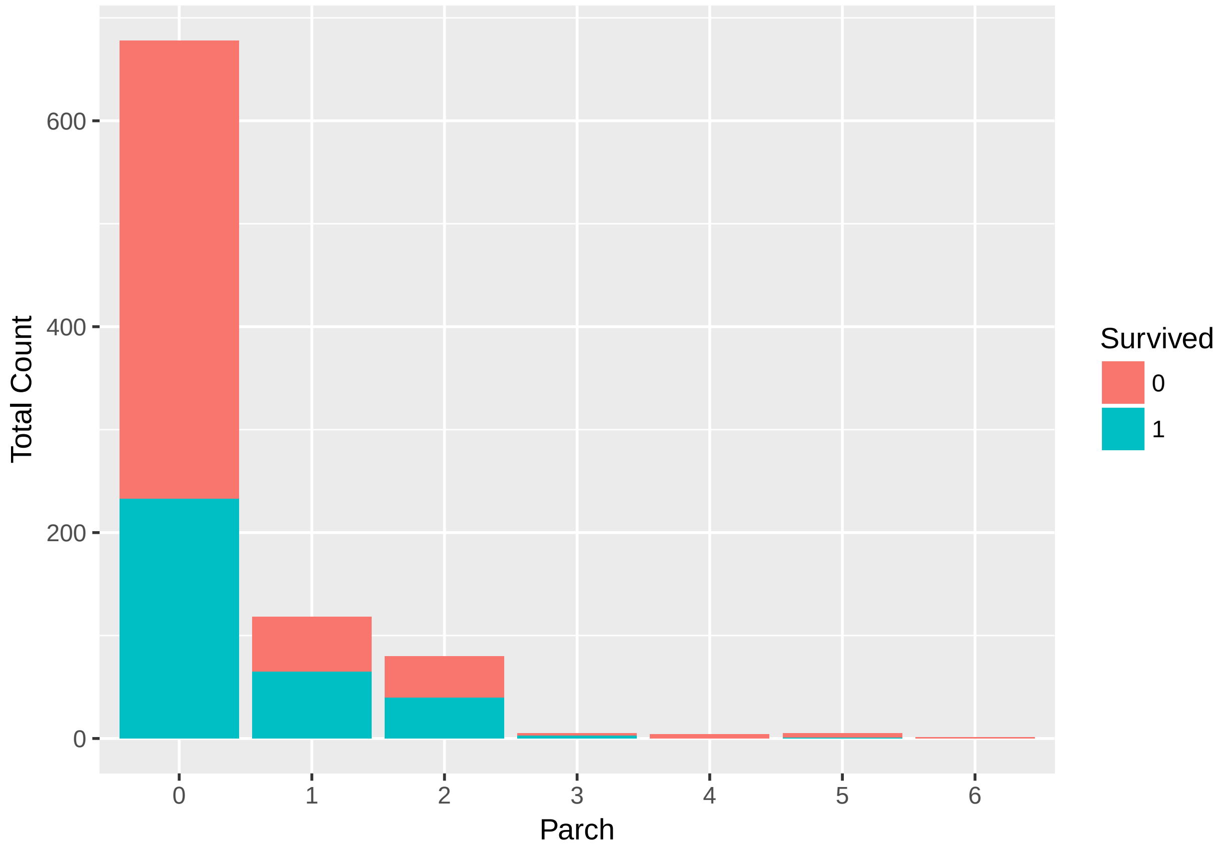


Parch: Similar with SibSp, passengers having 0 or more than 3 parents/children have less chance to survive. Then I group it to ParGroup.Under Pclass and Title, ParGroup is litte predictive for third class.

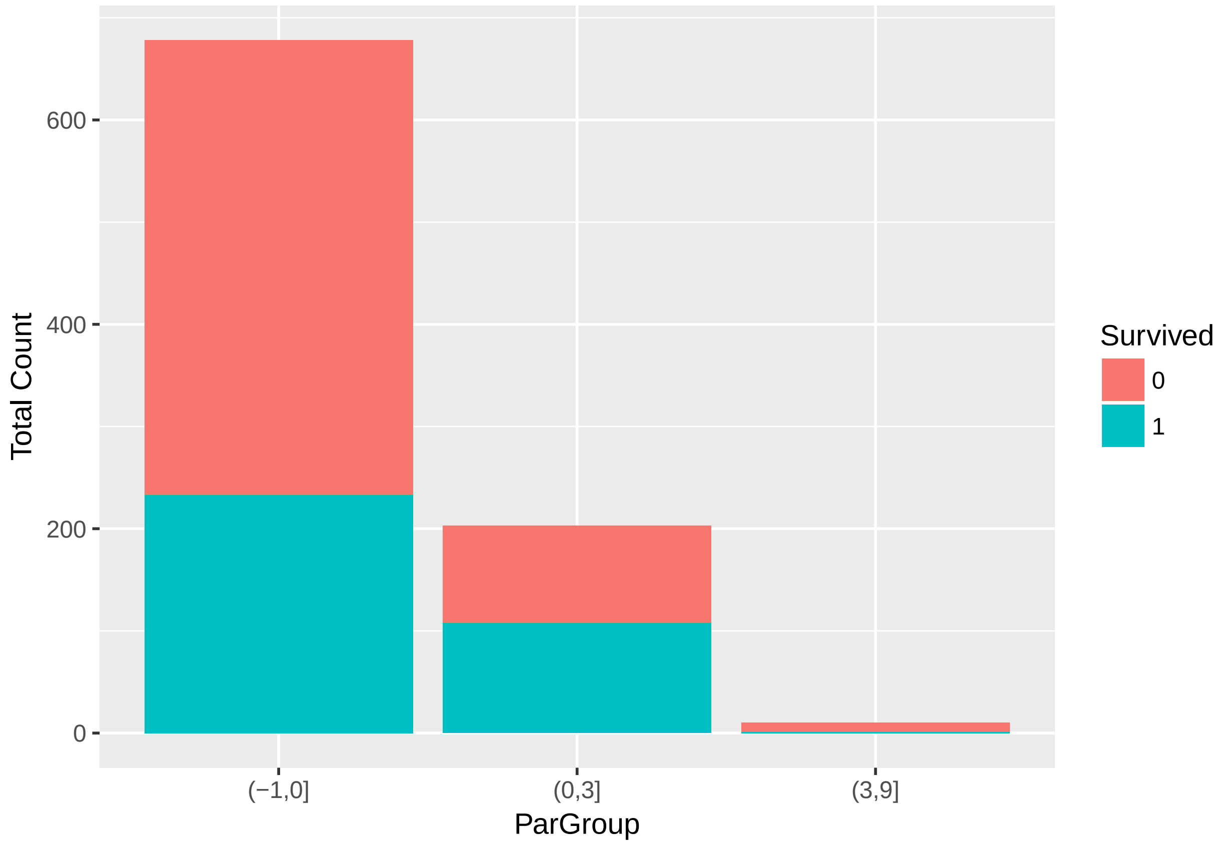
```
#Parch
summary(data$Parch)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.000   0.000   0.000   0.385   0.000   9.000
```

```
ggplot(data[1:891,], aes(x = as.factor(Parch), fill = Survived)) +
  geom_bar() +
  xlab("Parch") +
  ylab("Total Count") +
  labs(fill = "Survived")
```

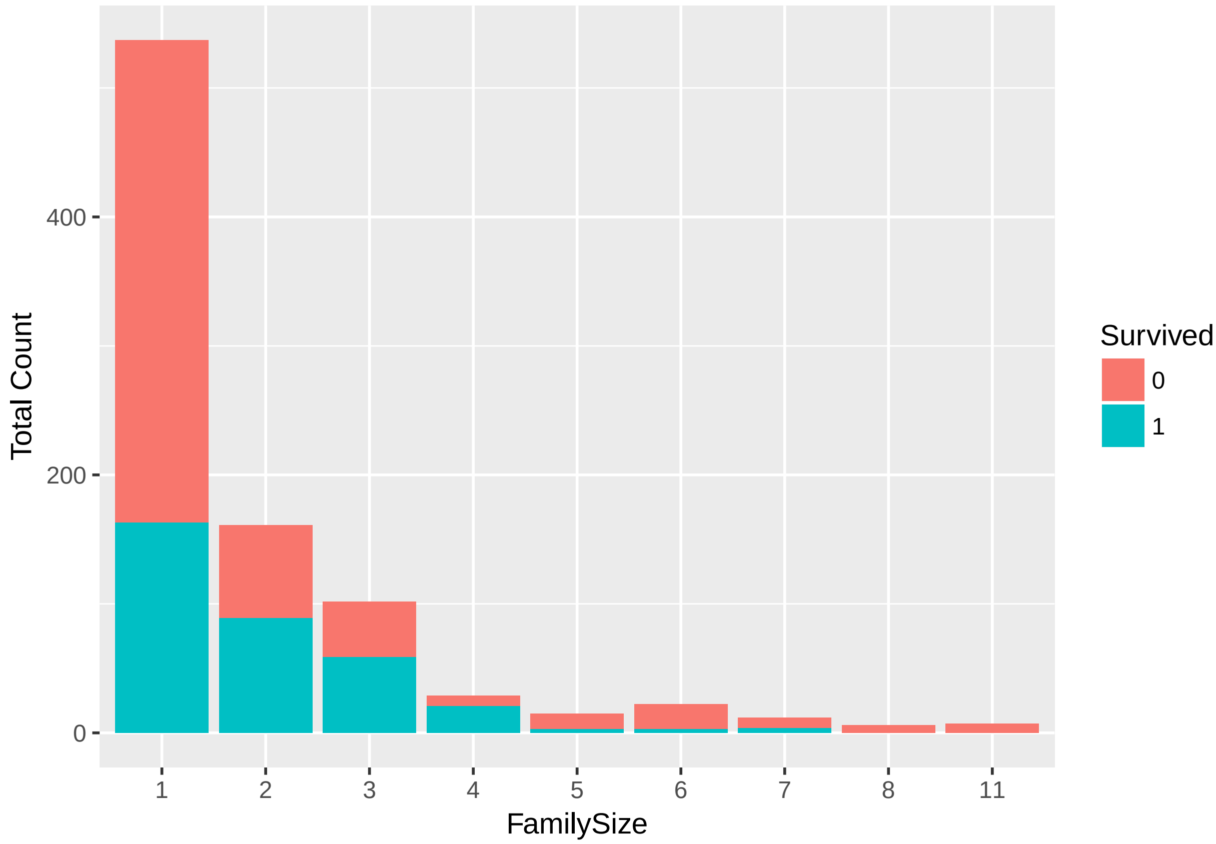



```
# ParGroup
data$ParGroup <- cut(data$Parch, breaks=c(-1,0,3,9), levels=c("0","1-3","4-"))
# ParGroup vs Survival under pclass and title
ggplot(data[1:891,], aes(x = ParGroup, fill = Survived)) +
  geom_bar() +
  xlab("ParGroup") +
  ylab("Total Count") +
  labs(fill = "Survived")
```



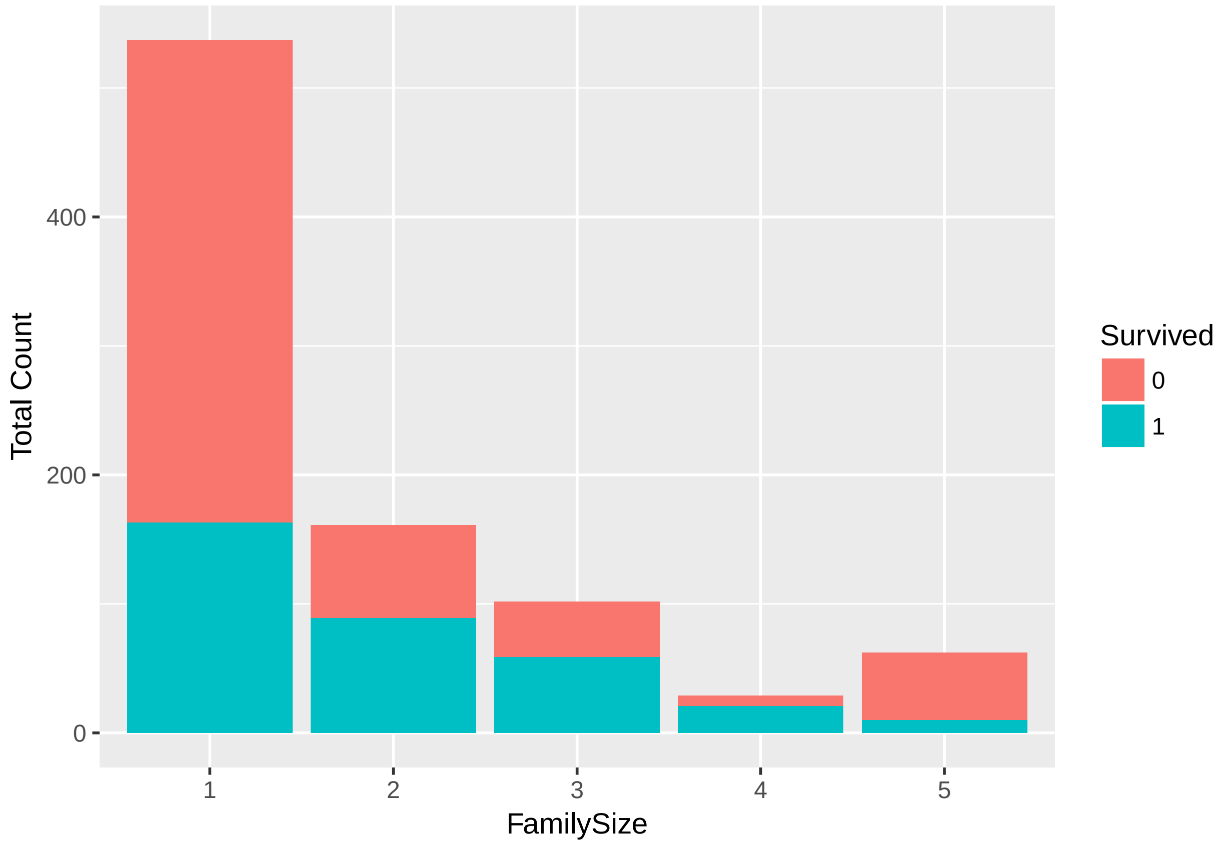
FamilySize FamilySize=SibSp+Parch+1. From the plots, about 60% of passengers were traveling alone, and passengers traveling alone and having a big family size had less chance to survive.

```
# Create FamilySize
data$FamilySize <- with(data,SibSp+Parch+1 )
# FamilySize and survived are associated? Yes
ggplot(data[1:891,], aes(x = as.factor(FamilySize), fill = Survived)) +
  geom_bar() +
  xlab("FamilySize") +
  ylab("Total Count") +
  labs(fill = "Survived")
```




```
# recode FamilySize since there are few examples for FamilySize>4
data$FamilySize[data$FamilySize>4] <- 5

# FamilySize vs survival
ggplot(data[1:891,], aes(x = as.factor(FamilySize), fill = Survived)) +
  geom_bar() +
  xlab("FamilySize") +
  ylab("Total Count") +
  labs(fill = "Survived")
```



Role * Parents, who needed to take care of their children have more chance to survive? Especially, when there were more than 1 kid, fathers were needed to help have more chance to survive? Refine Title varibale to look at. The result is surprising, parents have more chance to die.However, the differences between father and Mr, mother and Mrs are not much, so I will keep Title in modeling.

```
# derive Role variable
Role <- as.character(data$Title)
#Father role
#Familysize>=4,
# father, 2 more kids
Father2 <- data$Title=="Mr" & data$SibSp==1 & data$FamilySize>3
Role[Father2 & (data$Age>20 | is.na(data$Age))]="father2"
# FamilySize==3,
# Father, one kid
Father1 <- data$Title=="Mr" & data$SibSp==1 & data$FamilySize==3
Role[Father1 & (data$Age>20 | is.na(data$Age))]="father1" # exclude cases of mother with two kids
#father, 2kids
Father2 <- data$Title=="Mr" & data$SibSp==0 & data$FamilySize==3
Role[Father2 & (data$Age>20 | is.na(data$Age))]="father2"
# FamilySize==2
#father, 1 kid
Father1 <- data$Title=="Mr" & data$SibSp==0 & data$FamilySize==2
Role[Father1 & (data$Age>25 | is.na(data$Age))]="father1" # exclude adult son

# Mother role
Mother <- data$Title=="Mrs" & data$Parch>0
Role[Mother]="mother"
```

```r
# Role
table(Role)
```

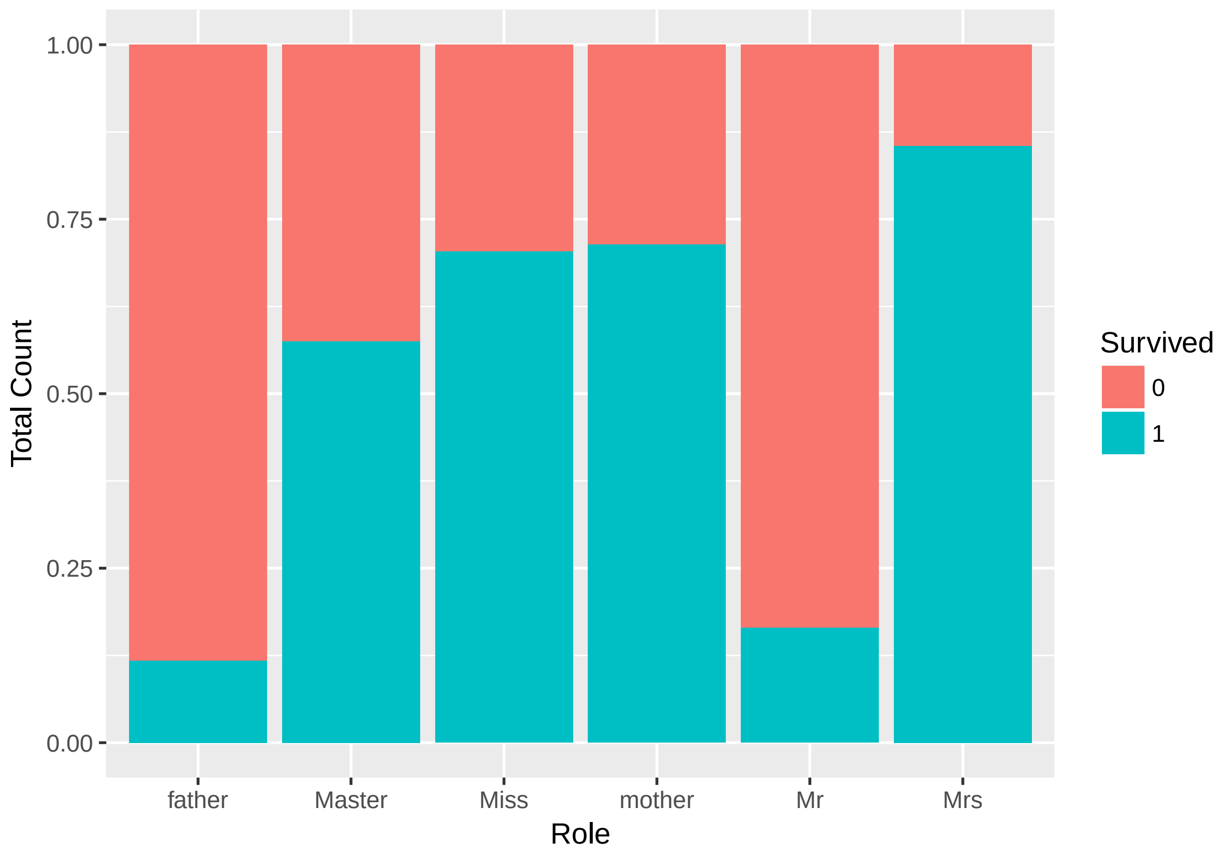
```
## Role
## father1 father2  Master    Miss  mother      Mr     Mrs
##      33      19      61     269      87     730     110
```

```r
data$Role <- Role

# combine father1 and father2 into father since there are only a few examples.
data$Role[data$Role=="father1" | data$Role=="father2" ]<- "father"

# convert to factor
data$Role<- as.factor(data$Role)

# Role Vs Survival
ggplot(data[1:891,], aes(x = Role, fill = Survived)) +
  geom_bar(position = 'fill') +
  xlab("Role") +
  ylab("Total Count") +
  labs(fill = "Survived")
```




```r
# convert type
data$FamilySize <- as.factor(data$FamilySize)
```

Ticket PartySize, the number of a group of people bought a joint ticket, so the fare for each person should be recalculated. PartySize, is like FamilySize, equals 1 or above 4 have high chance to die. Since the observations are limited when PartySize>4, I will combine them into 5 after I calculate the Fare for each passenger.

```
# derive PartySize, the number of passengers sharing a ticket
arrange(filter(data,FamilySize=="5"),Ticket) # a group  share a ticket
```

```
##    PassengerId Survived Pclass
## 1           28        0      1
## 2           89        1      1
## 3          342        1      1
## 4          439        0      1
## 5          945     <NA>      1
## 6          961     <NA>      1
## 7          775        1      2
## 8          438        1      2
## 9           69        1      3
## 10          51        0      3
## 11         165        0      3
## 12         267        0      3
## 13         639        0      3
## 14         687        0      3
## 15         825        0      3
## 16        1286     <NA>      3
## 17          26        1      3
## 18         183        0      3
## 19         234        1      3
## 20         262        1      3
## 21        1046     <NA>      3
## 22        1066     <NA>      3
## 23        1271     <NA>      3
## 24          14        0      3
## 25         120        0      3
## 26         542        0      3
## 27         543        0      3
## 28         611        0      3
## 29         814        0      3
## 30         851        0      3
## 31          64        0      3
## 32         168        0      3
## 33         361        0      3
## 34         635        0      3
## 35         643        0      3
## 36         820        0      3
## 37        1106     <NA>      3
## 38           8        0      3
## 39          25        0      3
## 40         375        0      3
## 41         568        0      3
## 42        1281     <NA>      3
## 43          17        0      3
## 44         172        0      3
## 45         279        0      3
## 46         788        0      3
## 47         886        0      3
## 48         947     <NA>      3
## 49         177        0      3
```

```
## 50         230        0      3
## 51         410        0      3
## 52         486        0      3
## 53        1024     <NA>      3
## 54          60        0      3
## 55          72        0      3
## 56         387        0      3
## 57         481        0      3
## 58         679        0      3
## 59         684        0      3
## 60        1031     <NA>      3
## 61        1032     <NA>      3
## 62         160        0      3
## 63         181        0      3
## 64         202        0      3
## 65         325        0      3
## 66         793        0      3
## 67         847        0      3
## 68         864        0      3
## 69        1080     <NA>      3
## 70        1234     <NA>      3
## 71        1252     <NA>      3
## 72        1257     <NA>      3
## 73         312        1      1
## 74         743        1      1
## 75         916     <NA>      1
## 76         956     <NA>      1
## 77        1034     <NA>      1
## 78          87        0      3
## 79         148        0      3
## 80         437        0      3
## 81         737        0      3
## 82        1059     <NA>      3
##                                                        Name    Sex  Age
## 1                             Fortune, Mr. Charles Alexander   male 19.0
## 2                                 Fortune, Miss. Mabel Helen female 23.0
## 3                             Fortune, Miss. Alice Elizabeth female 24.0
## 4                                          Fortune, Mr. Mark   male 64.0
## 5                                 Fortune, Miss. Ethel Flora female 28.0
## 6                        Fortune, Mrs. Mark (Mary McDougald) female 60.0
## 7                      Hocking, Mrs. Elizabeth (Eliza Needs) female 54.0
## 8                      Richards, Mrs. Sidney (Emily Hocking) female 24.0
## 9                           Andersson, Miss. Erna Alexandra female 17.0
## 10                                Panula, Master. Juha Niilo   male  7.0
## 11                              Panula, Master. Eino Viljami   male  1.0
## 12                                 Panula, Mr. Ernesti Arvid   male 16.0
## 13                    Panula, Mrs. Juha (Maria Emilia Ojala) female 41.0
## 14                                  Panula, Mr. Jaako Arnold   male 14.0
## 15                              Panula, Master. Urho Abraham   male  2.0
## 16                                  Kink-Heilmann, Mr. Anton   male 29.0
## 17 Asplund, Mrs. Carl Oscar (Selma Augusta Emilia Johansson) female 38.0
## 18                     Asplund, Master. Clarence Gustaf Hugo   male  9.0
## 19                           Asplund, Miss. Lillian Gertrud female  5.0
## 20                              Asplund, Master. Edvin Rojj Felix   male  3.0
```

```
## 21                                   Asplund, Master. Filip Oscar   male 13.0
## 22                 Asplund, Mr. Carl Oscar Vilhelm Gustafsson   male 40.0
## 23                                    Asplund, Master. Carl Edgar   male  5.0
## 24                                    Andersson, Mr. Anders Johan   male 39.0
## 25                              Andersson, Miss. Ellis Anna Maria female  2.0
## 26                           Andersson, Miss. Ingeborg Constanzia female  9.0
## 27                              Andersson, Miss. Sigrid Elisabeth female 11.0
## 28 Andersson, Mrs. Anders Johan (Alfrida Konstantia Brogren) female 39.0
## 29                             Andersson, Miss. Ebba Iris Alfrida female  6.0
## 30                        Andersson, Master. Sigvard Harald Elias   male  4.0
## 31                                         Skoog, Master. Harald   male  4.0
## 32           Skoog, Mrs. William (Anna Bernhardina Karlsson) female 45.0
## 33                                            Skoog, Mr. Wilhelm   male 40.0
## 34                                            Skoog, Miss. Mabel female  9.0
## 35                                Skoog, Miss. Margit Elizabeth female  2.0
## 36                                   Skoog, Master. Karl Thorsten   male 10.0
## 37                        Andersson, Miss. Ida Augusta Margareta female 38.0
## 38                                  Palsson, Master. Gosta Leonard   male  2.0
## 39                                 Palsson, Miss. Torborg Danira female  8.0
## 40                                    Palsson, Miss. Stina Viola female  3.0
## 41                  Palsson, Mrs. Nils (Alma Cornelia Berglund) female 29.0
## 42                                    Palsson, Master. Paul Folke   male  6.0
## 43                                          Rice, Master. Eugene   male  2.0
## 44                                          Rice, Master. Arthur   male  4.0
## 45                                            Rice, Master. Eric   male  7.0
## 46                                      Rice, Master. George Hugh   male  8.0
## 47                          Rice, Mrs. William (Margaret Norton) female 39.0
## 48                                          Rice, Master. Albert   male 10.0
## 49                                 Lefebre, Master. Henry Forbes   male   NA
## 50                                      Lefebre, Miss. Mathilde female   NA
## 51                                           Lefebre, Miss. Ida female   NA
## 52                                       Lefebre, Miss. Jeannie female   NA
## 53                                 Lefebre, Mrs. Frank (Frances) female   NA
## 54                             Goodwin, Master. William Frederick   male 11.0
## 55                                    Goodwin, Miss. Lillian Amy female 16.0
## 56                                Goodwin, Master. Sidney Leonard   male  1.0
## 57                                 Goodwin, Master. Harold Victor   male  9.0
## 58                       Goodwin, Mrs. Frederick (Augusta Tyler) female 43.0
## 59                                   Goodwin, Mr. Charles Edward   male 14.0
## 60                                 Goodwin, Mr. Charles Frederick   male 40.0
## 61                                   Goodwin, Miss. Jessie Allis female 10.0
## 62                                    Sage, Master. Thomas Henry   male   NA
## 63                                  Sage, Miss. Constance Gladys female   NA
## 64                                           Sage, Mr. Frederick   male   NA
## 65                                        Sage, Mr. George John Jr   male   NA
## 66                                        Sage, Miss. Stella Anna female   NA
## 67                                       Sage, Mr. Douglas Bullen   male   NA
## 68                           Sage, Miss. Dorothy Edith "Dolly" female   NA
## 69                                              Sage, Miss. Ada female   NA
## 70                                          Sage, Mr. John George   male   NA
## 71                                  Sage, Master. William Henry   male 14.5
## 72                                Sage, Mrs. John (Annie Bullen) female   NA
## 73                                   Ryerson, Miss. Emily Borie female 18.0
## 74                            Ryerson, Miss. Susan Parker "Suzette" female 21.0
```

```
## 75          Ryerson, Mrs. Arthur Larned (Emily Maria Borie) female 48.0
## 76                              Ryerson, Master. John Borie   male 13.0
## 77                               Ryerson, Mr. Arthur Larned   male 61.0
## 78                                   Ford, Mr. William Neal   male 16.0
## 79                         Ford, Miss. Robina Maggie "Ruby" female  9.0
## 80                     Ford, Miss. Doolina Margaret "Daisy" female 21.0
## 81                  Ford, Mrs. Edward (Margaret Ann Watson) female 48.0
## 82                                  Ford, Mr. Edward Watson   male 18.0
##    SibSp Parch    Ticket     Fare           Cabin Embarked  Title Age1
## 1      3     2     19950 263.0000     C23 C25 C27        S     Mr 19.0
## 2      3     2     19950 263.0000     C23 C25 C27        S   Miss 23.0
## 3      3     2     19950 263.0000     C23 C25 C27        S   Miss 24.0
## 4      1     4     19950 263.0000     C23 C25 C27        S     Mr 64.0
## 5      3     2     19950 263.0000     C23 C25 C27        S   Miss 28.0
## 6      1     4     19950 263.0000     C23 C25 C27        S    Mrs 60.0
## 7      1     3     29105  23.0000                        S    Mrs 54.0
## 8      2     3     29106  18.7500                        S    Mrs 24.0
## 9      4     2   3101281   7.9250                        S   Miss 17.0
## 10     4     1   3101295  39.6875                        S Master  7.0
## 11     4     1   3101295  39.6875                        S Master  1.0
## 12     4     1   3101295  39.6875                        S     Mr 16.0
## 13     0     5   3101295  39.6875                        S    Mrs 41.0
## 14     4     1   3101295  39.6875                        S     Mr 14.0
## 15     4     1   3101295  39.6875                        S Master  2.0
## 16     3     1    315153  22.0250                        S     Mr 29.0
## 17     1     5    347077  31.3875                        S    Mrs 38.0
## 18     4     2    347077  31.3875                        S Master  9.0
## 19     4     2    347077  31.3875                        S   Miss  5.0
## 20     4     2    347077  31.3875                        S Master  3.0
## 21     4     2    347077  31.3875                        S Master 13.0
## 22     1     5    347077  31.3875                        S     Mr 40.0
## 23     4     2    347077  31.3875                        S Master  5.0
## 24     1     5    347082  31.2750                        S     Mr 39.0
## 25     4     2    347082  31.2750                        S   Miss  2.0
## 26     4     2    347082  31.2750                        S   Miss  9.0
## 27     4     2    347082  31.2750                        S   Miss 11.0
## 28     1     5    347082  31.2750                        S    Mrs 39.0
## 29     4     2    347082  31.2750                        S   Miss  6.0
## 30     4     2    347082  31.2750                        S Master  4.0
## 31     3     2    347088  27.9000                        S Master  4.0
## 32     1     4    347088  27.9000                        S    Mrs 45.0
## 33     1     4    347088  27.9000                        S     Mr 40.0
## 34     3     2    347088  27.9000                        S   Miss  9.0
## 35     3     2    347088  27.9000                        S   Miss  2.0
## 36     3     2    347088  27.9000                        S Master 10.0
## 37     4     2    347091   7.7750                        S   Miss 38.0
## 38     3     1    349909  21.0750                        S Master  2.0
## 39     3     1    349909  21.0750                        S   Miss  8.0
## 40     3     1    349909  21.0750                        S   Miss  3.0
## 41     0     4    349909  21.0750                        S    Mrs 29.0
## 42     3     1    349909  21.0750                        S Master  6.0
## 43     4     1    382652  29.1250                        Q Master  2.0
## 44     4     1    382652  29.1250                        Q Master  4.0
## 45     4     1    382652  29.1250                        Q Master  7.0
```

```
## 46     4     1     382652  29.1250                         Q Master  8.0
## 47     0     5     382652  29.1250                         Q    Mrs 39.0
## 48     4     1     382652  29.1250                         Q Master 10.0
## 49     3     1       4133  25.4667                         S Master  4.0
## 50     3     1       4133  25.4667                         S   Miss 15.0
## 51     3     1       4133  25.4667                         S   Miss 15.0
## 52     3     1       4133  25.4667                         S   Miss 15.0
## 53     0     4       4133  25.4667                         S    Mrs 37.0
## 54     5     2    CA 2144  46.9000                         S Master 11.0
## 55     5     2    CA 2144  46.9000                         S   Miss 16.0
## 56     5     2    CA 2144  46.9000                         S Master  1.0
## 57     5     2    CA 2144  46.9000                         S Master  9.0
## 58     1     6    CA 2144  46.9000                         S    Mrs 43.0
## 59     5     2    CA 2144  46.9000                         S     Mr 14.0
## 60     1     6    CA 2144  46.9000                         S     Mr 40.0
## 61     5     2    CA 2144  46.9000                         S   Miss 10.0
## 62     8     2   CA. 2343  69.5500                         S Master  4.0
## 63     8     2   CA. 2343  69.5500                         S   Miss 15.0
## 64     8     2   CA. 2343  69.5500                         S     Mr 33.0
## 65     8     2   CA. 2343  69.5500                         S     Mr 33.0
## 66     8     2   CA. 2343  69.5500                         S   Miss 15.0
## 67     8     2   CA. 2343  69.5500                         S     Mr 33.0
## 68     8     2   CA. 2343  69.5500                         S   Miss 15.0
## 69     8     2   CA. 2343  69.5500                         S   Miss 15.0
## 70     1     9   CA. 2343  69.5500                         S     Mr 33.0
## 71     8     2   CA. 2343  69.5500                         S Master 14.5
## 72     1     9   CA. 2343  69.5500                         S    Mrs 37.0
## 73     2     2   PC 17608 262.3750 B57 B59 B63 B66         C   Miss 18.0
## 74     2     2   PC 17608 262.3750 B57 B59 B63 B66         C   Miss 21.0
## 75     1     3   PC 17608 262.3750 B57 B59 B63 B66         C    Mrs 48.0
## 76     2     2   PC 17608 262.3750 B57 B59 B63 B66         C Master 13.0
## 77     1     3   PC 17608 262.3750 B57 B59 B63 B66         C     Mr 61.0
## 78     1     3 W./C. 6608  34.3750                         S     Mr 16.0
## 79     2     2 W./C. 6608  34.3750                         S   Miss  9.0
## 80     2     2 W./C. 6608  34.3750                         S   Miss 21.0
## 81     1     3 W./C. 6608  34.3750                         S    Mrs 48.0
## 82     2     2 W./C. 6608  34.3750                         S     Mr 18.0
##    AgeGroup SibGroup ParGroup FamilySize   Role
## 1   14.5-21    (2,8]    (0,3]          5     Mr
## 2     21-28    (2,8]    (0,3]          5   Miss
## 3     21-28    (2,8]    (0,3]          5   Miss
## 4       50-    (0,2]    (3,9]          5 father
## 5     21-28    (2,8]    (0,3]          5   Miss
## 6       50-    (0,2]    (3,9]          5 mother
## 7       50-    (0,2]    (0,3]          5 mother
## 8     21-28    (0,2]    (0,3]          5 mother
## 9   14.5-21    (2,8]    (0,3]          5   Miss
## 10      0-7    (2,8]    (0,3]          5 Master
## 11      0-7    (2,8]    (0,3]          5 Master
## 12  14.5-21    (2,8]    (0,3]          5     Mr
## 13    35-50   (-1,0]    (3,9]          5 mother
## 14   7-14.5    (2,8]    (0,3]          5     Mr
## 15      0-7    (2,8]    (0,3]          5 Master
## 16    28-35    (2,8]    (0,3]          5     Mr
```

```
## 17    35-50    (0,2]    (3,9]           5 mother
## 18   7-14.5    (2,8]    (0,3]           5 Master
## 19      0-7    (2,8]    (0,3]           5   Miss
## 20      0-7    (2,8]    (0,3]           5 Master
## 21   7-14.5    (2,8]    (0,3]           5 Master
## 22    35-50    (0,2]    (3,9]           5 father
## 23      0-7    (2,8]    (0,3]           5 Master
## 24    35-50    (0,2]    (3,9]           5 father
## 25      0-7    (2,8]    (0,3]           5   Miss
## 26   7-14.5    (2,8]    (0,3]           5   Miss
## 27   7-14.5    (2,8]    (0,3]           5   Miss
## 28    35-50    (0,2]    (3,9]           5 mother
## 29      0-7    (2,8]    (0,3]           5   Miss
## 30      0-7    (2,8]    (0,3]           5 Master
## 31      0-7    (2,8]    (0,3]           5 Master
## 32    35-50    (0,2]    (3,9]           5 mother
## 33    35-50    (0,2]    (3,9]           5 father
## 34   7-14.5    (2,8]    (0,3]           5   Miss
## 35      0-7    (2,8]    (0,3]           5   Miss
## 36   7-14.5    (2,8]    (0,3]           5 Master
## 37    35-50    (2,8]    (0,3]           5   Miss
## 38      0-7    (2,8]    (0,3]           5 Master
## 39   7-14.5    (2,8]    (0,3]           5   Miss
## 40      0-7    (2,8]    (0,3]           5   Miss
## 41    28-35   (-1,0]    (3,9]           5 mother
## 42      0-7    (2,8]    (0,3]           5 Master
## 43      0-7    (2,8]    (0,3]           5 Master
## 44      0-7    (2,8]    (0,3]           5 Master
## 45      0-7    (2,8]    (0,3]           5 Master
## 46   7-14.5    (2,8]    (0,3]           5 Master
## 47    35-50   (-1,0]    (3,9]           5 mother
## 48   7-14.5    (2,8]    (0,3]           5 Master
## 49      0-7    (2,8]    (0,3]           5 Master
## 50  14.5-21    (2,8]    (0,3]           5   Miss
## 51  14.5-21    (2,8]    (0,3]           5   Miss
## 52  14.5-21    (2,8]    (0,3]           5   Miss
## 53    35-50   (-1,0]    (3,9]           5 mother
## 54   7-14.5    (2,8]    (0,3]           5 Master
## 55  14.5-21    (2,8]    (0,3]           5   Miss
## 56      0-7    (2,8]    (0,3]           5 Master
## 57   7-14.5    (2,8]    (0,3]           5 Master
## 58    35-50    (0,2]    (3,9]           5 mother
## 59   7-14.5    (2,8]    (0,3]           5     Mr
## 60    35-50    (0,2]    (3,9]           5 father
## 61   7-14.5    (2,8]    (0,3]           5   Miss
## 62      0-7    (2,8]    (0,3]           5 Master
## 63  14.5-21    (2,8]    (0,3]           5   Miss
## 64    28-35    (2,8]    (0,3]           5     Mr
## 65    28-35    (2,8]    (0,3]           5     Mr
## 66  14.5-21    (2,8]    (0,3]           5   Miss
## 67    28-35    (2,8]    (0,3]           5     Mr
## 68  14.5-21    (2,8]    (0,3]           5   Miss
## 69  14.5-21    (2,8]    (0,3]           5   Miss
## 70    28-35    (0,2]    (3,9]           5 father
```

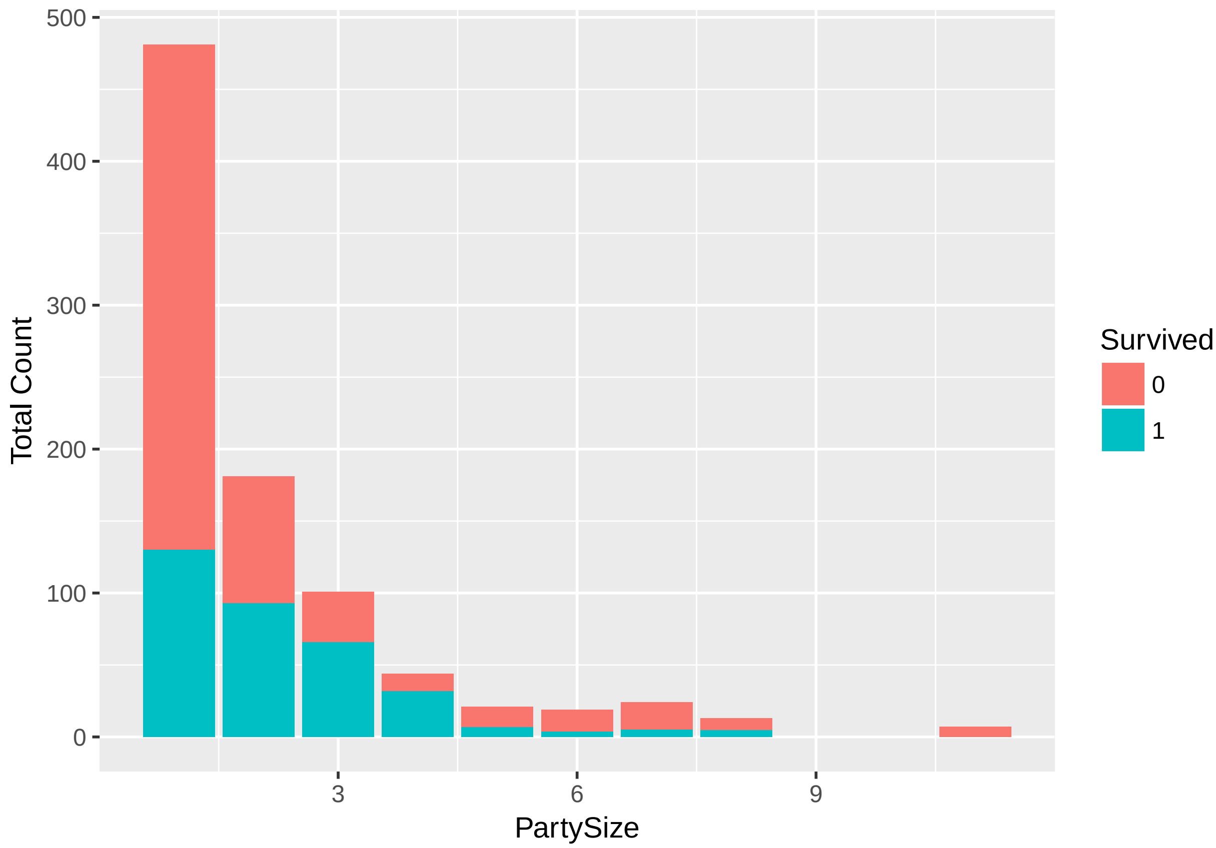
```
## 71   7-14.5    (2,8]     (0,3]          5 Master
## 72    35-50    (0,2]     (3,9]          5 mother
## 73  14.5-21    (0,2]     (0,3]          5   Miss
## 74  14.5-21    (0,2]     (0,3]          5   Miss
## 75    35-50    (0,2]     (0,3]          5 mother
## 76   7-14.5    (0,2]     (0,3]          5 Master
## 77      50-    (0,2]     (0,3]          5 father
## 78  14.5-21    (0,2]     (0,3]          5     Mr
## 79   7-14.5    (0,2]     (0,3]          5   Miss
## 80  14.5-21    (0,2]     (0,3]          5   Miss
## 81    35-50    (0,2]     (0,3]          5 mother
## 82  14.5-21    (0,2]     (0,3]          5     Mr
```

```
ticket.party <- data %>%
             group_by(Ticket) %>%
             summarise(PartySize=n())
# merge PartySize to data
data <- left_join(data,ticket.party,by="Ticket")

# look at PartySize
table(data$PartySize)
```

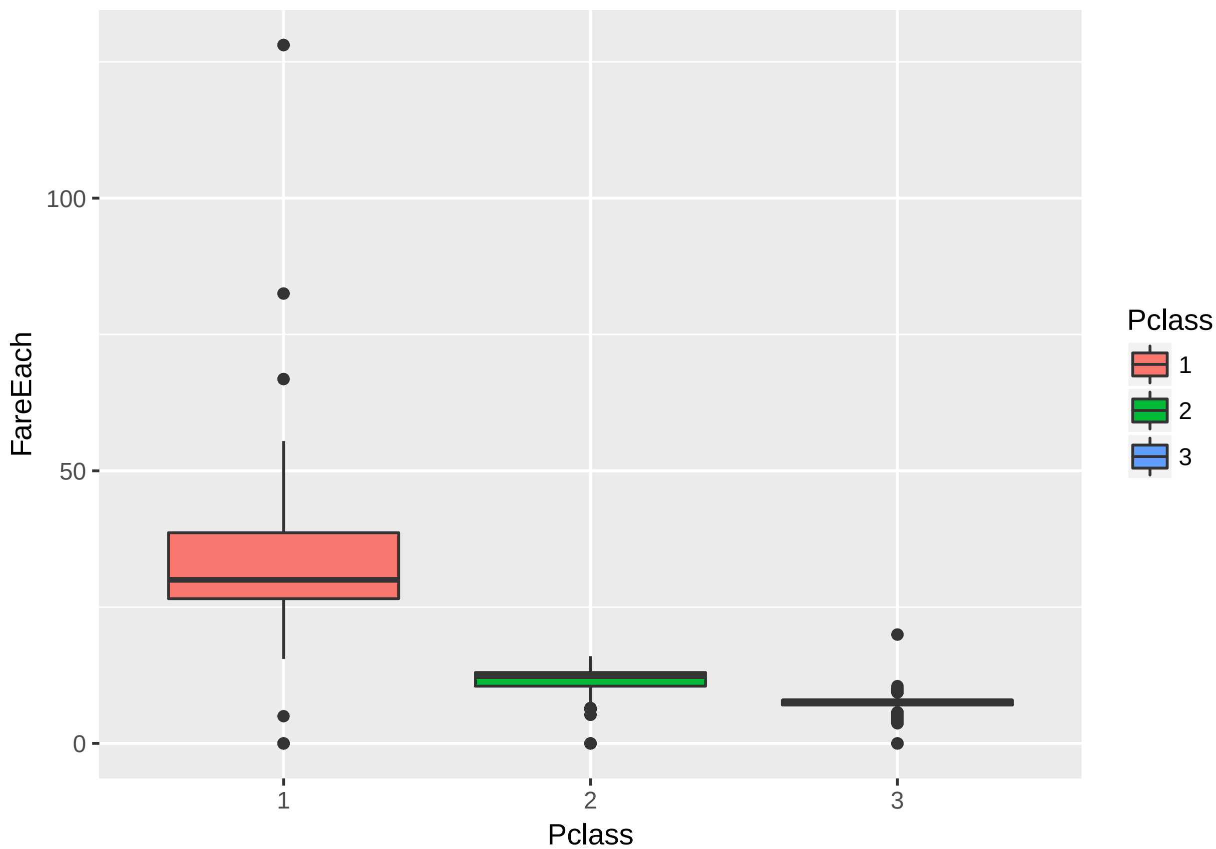
```
##
##   1   2   3   4   5   6   7   8  11
## 713 264 147  64  35  24  35  16  11
```

```
# Partysize vs survival
ggplot(data[1:891,], aes(x = PartySize, fill = Survived)) +
  geom_bar() +
  xlab("PartySize") +
  ylab("Total Count") +
  labs(fill = "Survived")
```



Fare FareEach,Fare for each passenger. FareGroup, group FareEach, the more a passenger paid, the more chance of survival they had.

```
# recalculate fare for each passenger
data$FareEach <- with(data, Fare/PartySize)
# impute missing values
#Intuitively, FareEach should be associated with Pclass, the boxplot proves this.
# disributions of FareEach for Pclass
ggplot(data[1:891,], aes(x = Pclass, y = FareEach, fill = Pclass)) +
  geom_boxplot() +
  xlab("Pclass") +
  ylab("FareEach")
```




```
summary(data$Fare)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##   0.000   7.896  14.450  33.300  31.280 512.300       1
```

```
filter(data, is.na(Fare))
```

```
##   PassengerId Survived Pclass               Name  Sex  Age SibSp Parch
## 1        1044     <NA>      3 Storey, Mr. Thomas male 60.5     0     0
##   Ticket Fare Cabin Embarked Title Age1 AgeGroup SibGroup ParGroup
## 1   3701   NA              S    Mr 60.5      50-   (-1,0]   (-1,0]
##   FamilySize Role PartySize FareEach
## 1          1   Mr         1       NA
```

```
summary(data[which(data$Pclass==3),"FareEach"]) # mean=7.329
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##   0.000   7.060   7.750   7.329   7.925  19.970       1
```

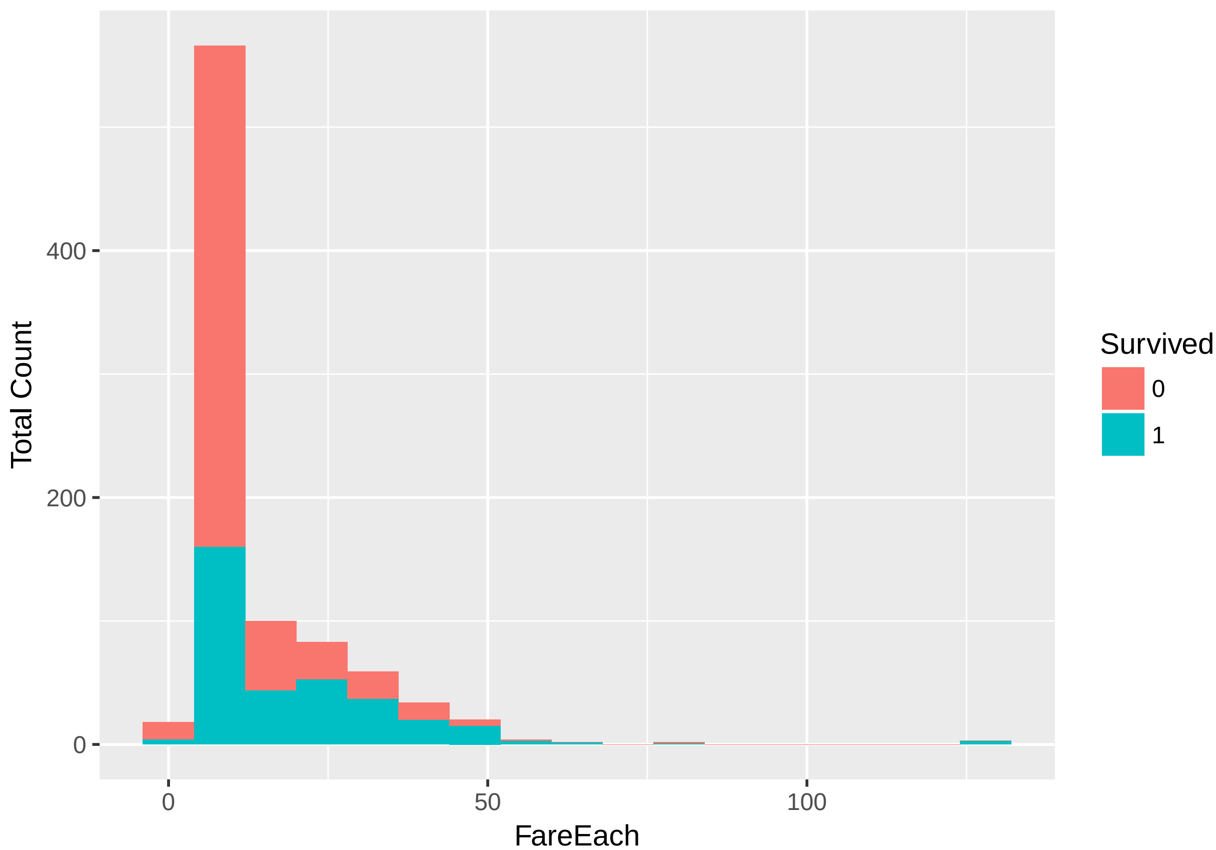
```
data$FareEach[which(is.na(data$Fare))] <- 7.329

# Fare is associated with Suvival?
summary(data$FareEach)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    0.00    7.55    8.05   14.75   15.00  128.10
```

```
ggplot(data[1:891,], aes(x = FareEach, fill = Survived)) +
  geom_histogram(binwidth = 8) +
```

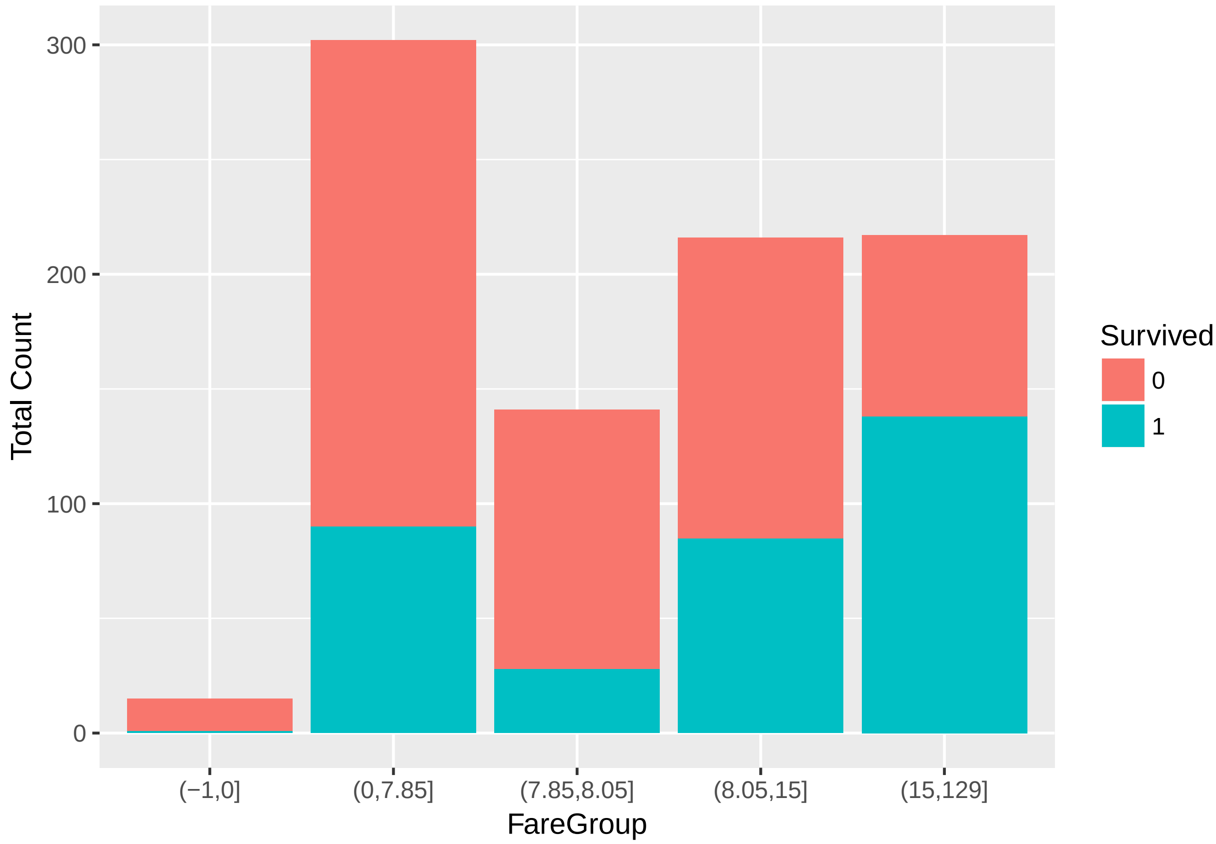
```
  xlab("FareEach") +
  ylab("Total Count") +
  labs(fill = "Survived")
```




```
# group FareEach by quantile
summary(data$FareEach)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    0.00    7.55    8.05   14.75   15.00  128.10
```

```
data$FareGroup <- cut(data$FareEach, breaks=c(-1,0,7.85,8.05,15.00,129))
# FareGroup vs Survival
ggplot(data[1:891,], aes(x = FareGroup, fill = Survived)) +
geom_bar()+
xlab("FareGroup") +
ylab("Total Count") +
labs(fill = "Survived")
```




```
# recode PartySize since there are few examples for PartySize>4
data$PartySize[data$PartySize>5] <- 5
data$PartySize <- as.factor(data$PartySize)
```

Cabin CabinFirst, the first letter of Cabin, may represent different position of the ship, so it may associated with survival rate. The plot proves it. Passengers whose Cabins' first letters are B,C,D,E,F had more chance to survive. However, most passengers didn't have a cabin, and these had much less chance to survive than those having a cabin. I will create a feature, HaveCabin, indicate if a passenger had a cabin, and use it in modeling.

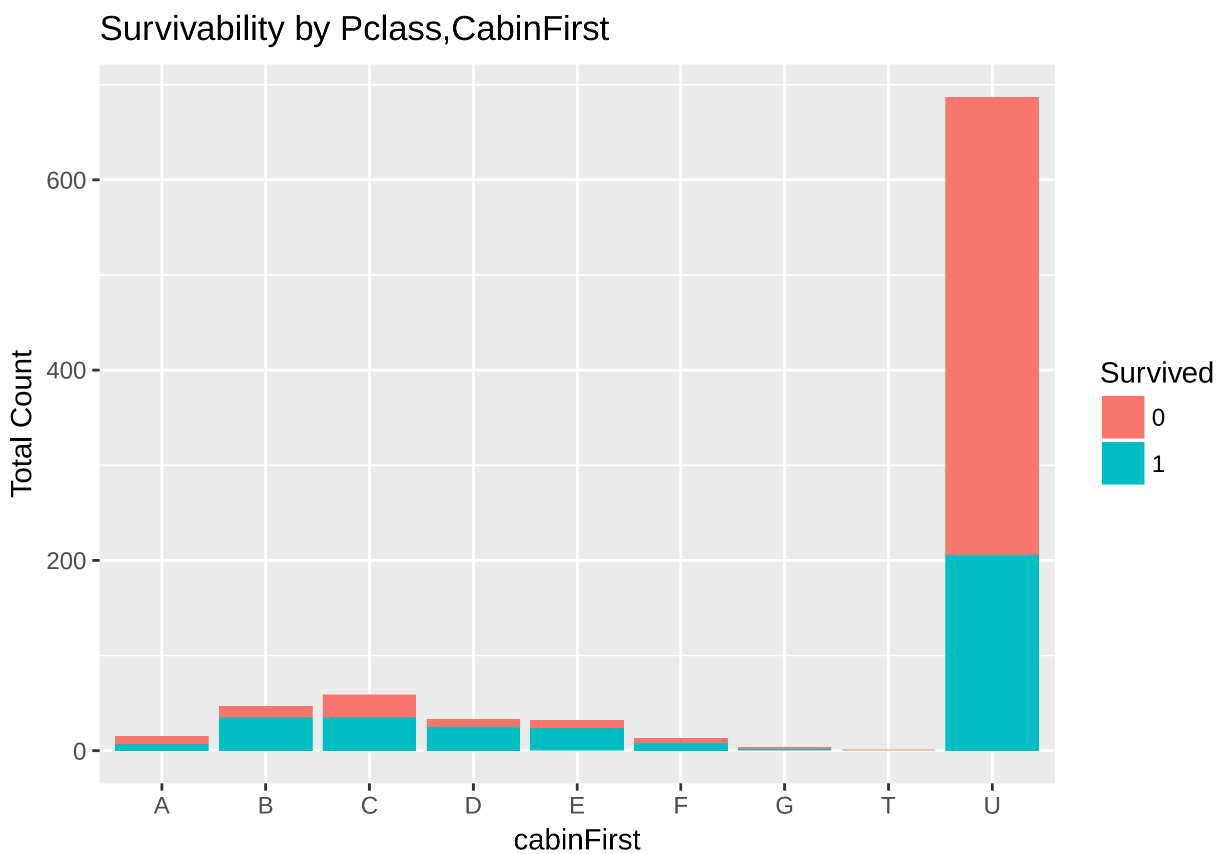
```
# Replace empty cabins with a "U"
length(unique(data$Cabin))
```

```
## [1] 187
```

```
data$Cabin[data$Cabin == ""] <- "U"

# Take a look at just the first letter as a factor
data$CabinFirst <- as.factor(substr(data$Cabin, 1, 1))

# Plot
# Cabin is associated with survival rate? Yes
ggplot(data[1:891,], aes(x = CabinFirst, fill = Survived)) +
  geom_bar() +
  ggtitle("Survivability by Pclass,CabinFirst") +
  xlab("cabinFirst") +
  ylab("Total Count") +
  labs(fill = "Survived")
```




```
data$HaveCabin <- as.factor(ifelse(data$Cabin=="U","0","1"))
```

Side: Since the ship was hitted on the left side, maybe side is a good predictor. Maybe Cabin's last number, like house/room number, can have the information. The plot shows passengers having cabins on the left side of the ship had slightly less chance to survive than those on the right side.

```
CabinLast <- str_sub(data$Cabin, -1, -1)
table(CabinLast)
```

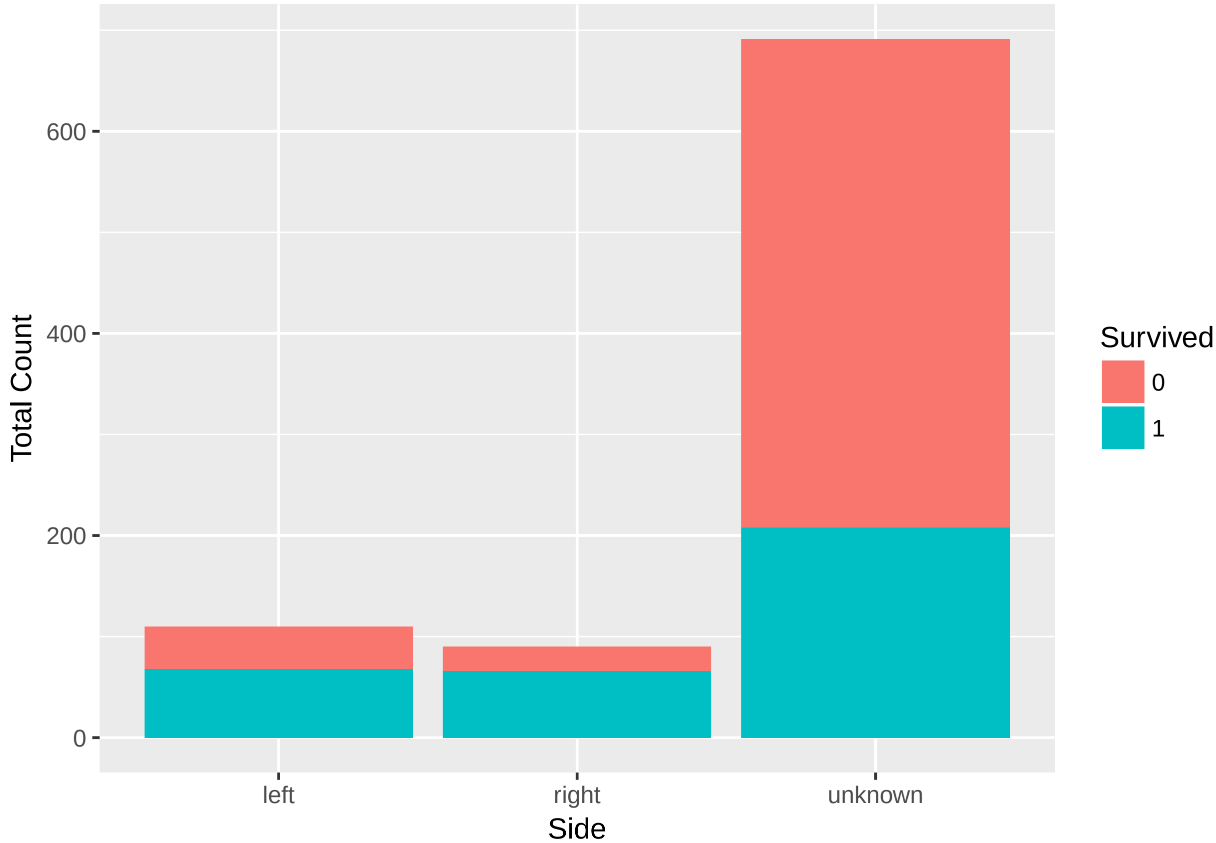
```
## CabinLast
##    0    1    2    3    4    5    6    7    8    9    D    F    T    U
##   30   29   24   25   28   27   45   28   32   21    4    1    1 1014
```

```
Side <- rep("unknown",length(CabinLast))
Side[CabinLast %in% c("0","2","4","6", "8")] <- "left"
Side[CabinLast %in% c("1","3","5","7", "9")] <- "right"
# convert into factor
table(Side)
```

```
## Side
##    left   right unknown
##     159     130    1020
```

```
data$Side <- factor(Side)
# Side Vs Survival
ggplot(data[1:891,], aes(x = Side, fill = Survived)) +
  geom_bar() +
  xlab("Side") +
  ylab("Total Count") +
```

```r
  labs(fill = "Survived")
```

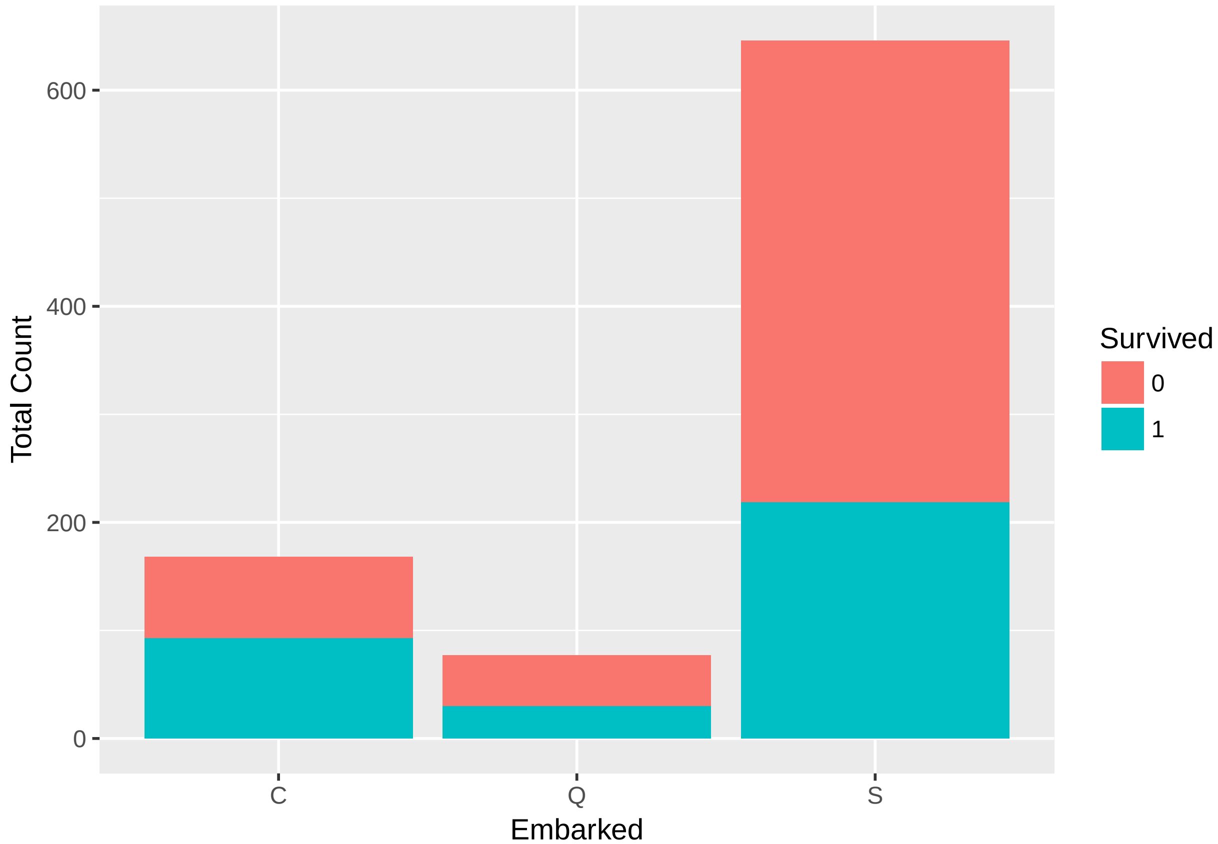


Embarked: It seems that passenger coming from Cherbourg (C) had more chance to survive. Maybe the proportion of first class passengers was higher for those from Cherbourg than those from Queenstown (Q), Southampton (S).The plot proves it. The passengers from Queenstown (Q) are almost third class, but the survival rate is much higher than that of the third class. From the table, there are more children and women, 53%, in those from Queenstown (Q).

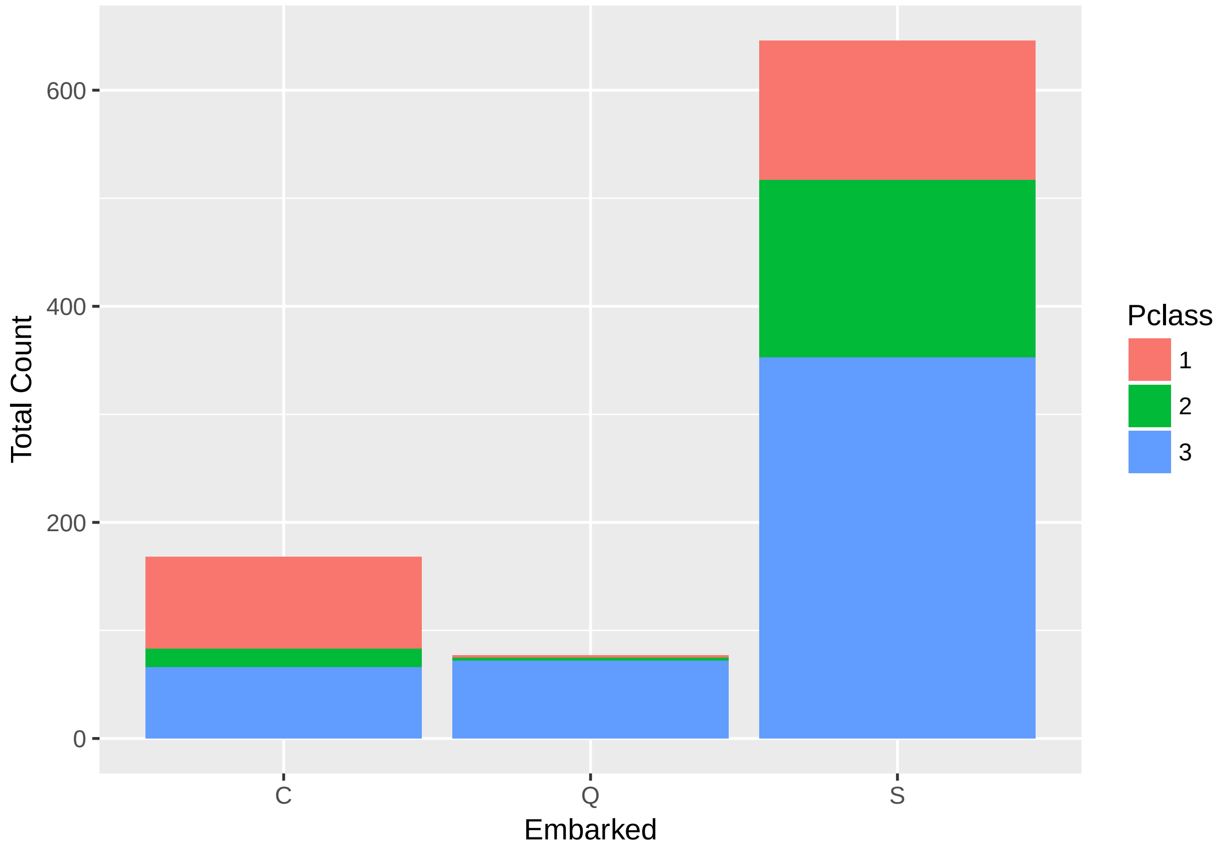
```r
# understand Embarked
table(data$Embarked)
```

```
##
##       C   Q   S
##   2 270 123 914
```

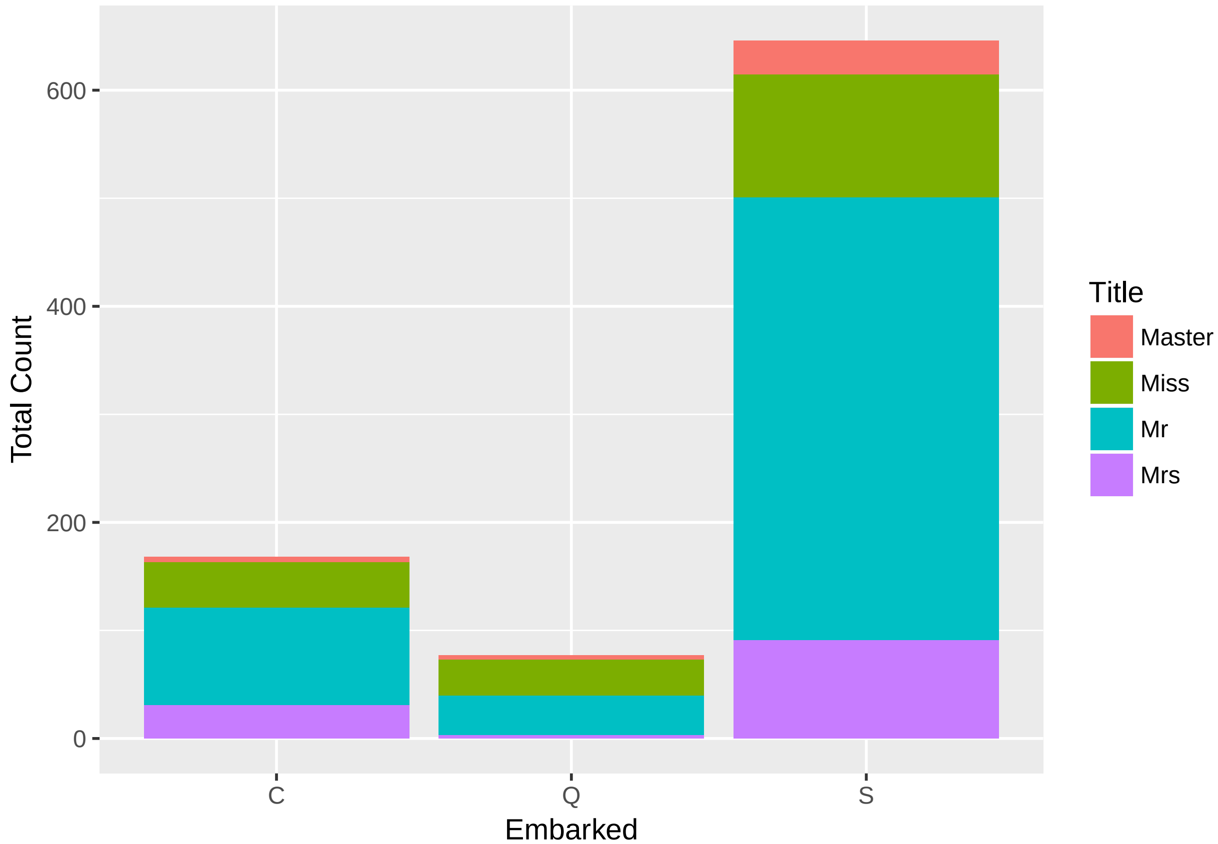
```r
# replace missing values with mode
data[which(data$Embarked==""),"Embarked"]<-"S"
# drop missing values level
data$Embarked<-factor(data$Embarked, levels=c("C","Q","S"))
# the survival rate is associated with where the passengers are from?
ggplot(data[1:891,], aes(x = Embarked, fill = Survived)) +
  geom_bar() +
  xlab("Embarked") +
  ylab("Total Count") +
  labs(fill = "Survived")
```




```r
# the proportion of first class passengers is higher for those from Cherbourg? Yes
ggplot(data[1:891,], aes(x = Embarked, fill = Pclass)) +
  geom_bar() +
  xlab("Embarked") +
  ylab("Total Count") +
  labs(fill = "Pclass")
```




```r
# there are more children and women in those from Queenstown (Q)? Yes
ggplot(data[1:891,], aes(x = Embarked, fill = Title)) +
  geom_bar() +
  xlab("Embarked") +
  ylab("Total Count") +
  labs(fill = "Title")
```




```
prop.table(table(data$Embarked, data$Title),1)
```

```
##
##          Master       Miss         Mr        Mrs
##   C 0.04074074 0.20000000 0.54074074 0.21851852
##   Q 0.04065041 0.45528455 0.47154472 0.03252033
##   S 0.04912664 0.17358079 0.63100437 0.14628821
```

Data preparation - creating training and test datasets

Create training dataset to build models and test dataset to make predictions.

```
# split the data frames to training and test datasets
train.df <- data[1:891, c( "Survived", "Pclass", "Sex", "Embarked", "Title", "AgeGroup", "SibGroup", "Pa
train.df$Survived <- factor(train.df$Survived, levels = c("0","1"))

test.df <- data[892:1309, c( "Pclass", "Sex", "Embarked", "Title", "AgeGroup", "SibGroup", "ParGroup",
```

check type of features

```
str(train.df)
```

```
## 'data.frame':    891 obs. of  12 variables:
```

```
##  $ Survived  : Factor w/ 2 levels "0","1": 1 2 2 2 1 1 1 1 2 2 ...
##  $ Pclass    : Factor w/ 3 levels "1","2","3": 3 1 3 1 3 3 1 3 3 2 ...
##  $ Sex       : Factor w/ 2 levels "female","male": 2 1 1 1 2 2 2 2 1 1 ...
##  $ Embarked  : Factor w/ 3 levels "C","Q","S": 3 1 3 3 3 2 3 3 3 1 ...
##  $ Title     : Factor w/ 4 levels "Master","Miss",..: 3 4 2 4 3 3 3 1 4 4 ...
##  $ AgeGroup  : Factor w/ 7 levels "0-7","7-14.5",..: 4 6 4 5 5 5 7 1 4 2 ...
##  $ SibGroup  : Factor w/ 3 levels "(-1,0]","(0,2]",..: 2 2 1 2 1 1 1 3 1 2 ...
##  $ ParGroup  : Factor w/ 3 levels "(-1,0]","(0,3]",..: 1 1 1 1 1 1 1 2 2 1 ...
##  $ FamilySize: Factor w/ 5 levels "1","2","3","4",..: 2 2 1 2 1 1 1 5 3 2 ...
##  $ PartySize : Factor w/ 5 levels "1","2","3","4",..: 1 2 1 2 1 1 2 5 3 2 ...
##  $ FareGroup : Factor w/ 5 levels "(-1,0]","(0,7.85]",..: 2 5 3 5 3 4 5 2 2 5 ...
##  $ HaveCabin : Factor w/ 2 levels "0","1": 1 2 1 2 1 1 2 1 1 1 ...
```

Step 3: Training and evaluating models on the training dataset —-

Since the training dataset is small, I will use cross validation to tune parameters for every algorithm and evaluate models. Based on the values of Cross validaion accuracy of the models, the gbm model, whose CV accuracy is 0.8417, is the best. Therefore, I will use the gbm model as the final model to make predictions on the test dataset.

store fitted accuracy and cross validation accuracy.

```
train.acc <- numeric(5)
cv.acc <- numeric(5)
```

build a gbm model

```
# tune parameters
ctrl <- trainControl(method = "cv",
                     number = 10 )
grid_gbm <-  expand.grid(interaction.depth = c(5, 7, 9),
                        n.trees = (1:4)*50,
                        shrinkage = 0.01,
                        n.minobsinnode = c(12, 14, 16, 18))

set.seed(1234)
m_gbm1 <- train(Survived ~ ., data = train.df,
                method = "gbm",
                trControl = ctrl,
                verbose = FALSE,
                tuneGrid = grid_gbm,
                metric = "Accuracy")
m_gbm1$bestTune
```

```
##    n.trees interaction.depth shrinkage n.minobsinnode
## 22     100                 7      0.01             14
```

```
# Evaluate model performance by cross validation
set.seed(1234)
m_gbm <- train(Survived ~ ., data = train.df,
```

```r
                 method = "gbm",
                 trControl = ctrl,
                 verbose = FALSE,
                 tuneGrid = m_gbm1$bestTune,
                 metric = "Accuracy")

#accuracy
train.acc[1] <- mean(predict(m_gbm,train.df)== train.df$Survived)
train.acc[1]
```

```
## [1] 0.8439955
```

```r
cv.acc[1] <- m_gbm$results$Accuracy
cv.acc[1]
```

```
## [1] 0.839508
```

```r
# look at feature importance
imp.gbm <- varImp(m_gbm, scale = FALSE)
imp.gbm
```

```
## gbm variable importance
##
##   only 20 most important variables shown (out of 31)
##
##                     Overall
## TitleMr            1272.918
## Pclass3             370.200
## Sexmale             191.694
## PartySize5          143.111
## FamilySize5          86.155
## FareGroup(15,129]    81.265
## HaveCabin1           76.702
## EmbarkedS            41.661
## FareGroup(0,7.85]    37.984
## SibGroup(2,8]        24.552
## AgeGroup21-28        11.836
## PartySize2           11.090
## SibGroup(0,2]        10.631
## AgeGroup35-50        10.037
## ParGroup(0,3]         9.452
## AgeGroup50-           9.179
## TitleMiss             8.718
## EmbarkedQ             7.754
## TitleMrs              6.433
## FamilySize2           6.410
```

build a random forest model

```r
# tune parameters
grid_rf <- expand.grid( .mtry = c(2, 3, 4, 5))
set.seed(1234)
m_rf1 <- train(Survived ~ .,  data=train.df,
```

```r
              method = "rf",
              metric = "Accuracy",
              trControl = ctrl,
              tuneGrid = grid_rf)
m_rf1$bestTune
```

```
##   mtry
## 2    3
```

```r
# Evaluate model performance by cross validation
set.seed(1234)
m_rf <- train(Survived ~ ., data = train.df,
                 method = "rf",
                 metric = "Accuracy",
                 trControl = ctrl,
                 tuneGrid = m_rf1$bestTune
                 )

#accuracy
train.acc[2] <- mean(predict(m_rf,train.df)== train.df$Survived)
train.acc[2]
```

```
## [1] 0.8664422
```

```r
cv.acc[2] <- m_rf$results$Accuracy
cv.acc[2]
```

```
## [1] 0.8294337
```

```r
# look at feature importance
imp.rf <- varImp(m_rf, scale = FALSE)
imp.rf
```

```
## rf variable importance
##
##   only 20 most important variables shown (out of 31)
##
##                      Overall
## TitleMr               46.703
## Sexmale               35.384
## TitleMiss             17.111
## TitleMrs              16.272
## Pclass3               13.988
## HaveCabin1            11.808
## FareGroup(15,129]     10.567
## PartySize5             6.659
## PartySize3             5.121
## FareGroup(0,7.85]      5.054
## FamilySize5            4.941
## EmbarkedS              4.845
## ParGroup(0,3]          4.765
## Pclass2                4.714
## SibGroup(0,2]          4.444
## AgeGroup21-28          3.756
## FareGroup(8.05,15]     3.656
## FamilySize3            3.544
```

```
## PartySize2           3.525
## FamilySize2          3.457
```

build a xgboost model

```
# tune parameters
grid_xg <- expand.grid( nrounds= (1:4)*50,
                        max_depth= c(7, 9, 11),
                        eta= 0.3,
                        gamma=0,
                        min_child_weight=c(6,8,10),
                        colsample_bytree= c(0.6, 0.8, 1),
                        subsample=1)
set.seed(1234)
m_xg1 <- train(Survived ~ .,  data=train.df,
               method = "xgbTree",
               metric = "Accuracy",
               trControl = ctrl,
               tuneGrid = grid_xg)
m_xg1$bestTune
```

```
##    nrounds max_depth eta gamma colsample_bytree min_child_weight subsample
## 62     100         9 0.3     0                1                6         1
```

```
# Evaluate model performance by cross validation
set.seed(1234)
m_xg <- train(Survived ~ ., data = train.df,
                 method = "xgbTree",
                 metric = "Accuracy",
                 trControl = ctrl,
                 tuneGrid = m_xg1$bestTune
                 )

#accuracy
train.acc[3] <- mean(predict(m_xg,train.df)== train.df$Survived)
train.acc[3]
```

```
## [1] 0.8799102
```

```
cv.acc[3] <- m_xg$results$Accuracy
cv.acc[3]
```

```
## [1] 0.8338268
```

```
# look at feature importance
imp.xg <- varImp(m_xg, scale = FALSE)
imp.xg
```

```
## xgbTree variable importance
##
##   only 20 most important variables shown (out of 31)
##
##                       Overall
## TitleMr              0.471658
## Pclass3              0.153248
```

```
## PartySize5           0.075372
## FareGroup(15,129]    0.039956
## HaveCabin1           0.037084
## FareGroup(0,7.85]    0.030441
## EmbarkedS            0.022529
## FareGroup(7.85,8.05] 0.019584
## AgeGroup21-28        0.017209
## AgeGroup35-50        0.014784
## FareGroup(8.05,15]   0.012722
## SibGroup(0,2]        0.011996
## AgeGroup28-35        0.011380
## TitleMiss            0.011131
## PartySize2           0.011126
## ParGroup(0,3]        0.009285
## AgeGroup14.5-21      0.008611
## Sexmale              0.007275
## PartySize3           0.006151
## EmbarkedQ            0.006010
```

build a logistic regression model

The fit accuracy is 0.8507, Cv accuracy is 0.8385.

```r
# select features
# fit a logistic regression model with all features
model.glm1=glm(Survived ~ ., data=train.df,
              family= "binomial" )
# significnat test
anova(model.glm1, test="Chisq")
```

```
## Analysis of Deviance Table
##
## Model: binomial, link: logit
##
## Response: Survived
##
## Terms added sequentially (first to last)
##
##
##             Df Deviance Resid. Df Resid. Dev  Pr(>Chi)
## NULL                          890    1186.66
## Pclass       2  103.547       888    1083.11 < 2.2e-16 ***
## Sex          1  256.220       887     826.89 < 2.2e-16 ***
## Embarked     2    7.863       885     819.03   0.01962 *
## Title        3   49.215       882     769.81 1.174e-10 ***
## AgeGroup     6   13.217       876     756.59   0.03972 *
## SibGroup     2   35.077       874     721.52 2.416e-08 ***
## ParGroup     2    8.711       872     712.81   0.01284 *
## FamilySize   4    4.704       868     708.10   0.31909
## PartySize    4    4.220       864     703.88   0.37706
## FareGroup    4    5.844       860     698.04   0.21108
## HaveCabin    1    4.268       859     693.77   0.03883 *
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
# drop insignificant features and  fit a  model
model.glm2=glm(Survived ~ Pclass + Sex + Embarked + Title + AgeGroup + SibGroup + ParGroup + HaveCabin,
               data=train.df,
               family = "binomial" )

# goodness of fit test
library(ResourceSelection)
```

```
## ResourceSelection 0.3-2   2017-02-28
```

```r
hl <- hoslem.test(model.glm2$y, fitted(model.glm2), g=10)
hl # p-value=0.08, poor fit
```

```
##
##  Hosmer and Lemeshow goodness of fit (GOF) test
##
## data:  model.glm2$y, fitted(model.glm2)
## X-squared = 14.139, df = 8, p-value = 0.07821
```

```r
# add interation effects and use sepwise to select features
step.glm <- step(model.glm2,
                 scope = list(upper = as.formula(Survived ~ .^2),
                              lower = as.formula(Survived ~ .)),
                 direction = "both")
```

```
## Start:  AIC=748
## Survived ~ Pclass + Sex + Embarked + Title + AgeGroup + SibGroup +
##     ParGroup + HaveCabin
```

```
## Warning: glm.fit: algorithm did not converge
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
##                      Df Deviance    AIC
## + Pclass:Sex          2   685.99 729.99
## + Pclass:Title        6   681.38 733.38
## + Sex:SibGroup        2   691.57 735.57
## + Title:SibGroup      6   687.92 739.92
## + Pclass:ParGroup     3   698.77 744.77
## + Embarked:ParGroup   3   699.35 745.35
## + SibGroup:ParGroup   3   699.50 745.50
## + Pclass:SibGroup     4   698.34 746.34
## + AgeGroup:SibGroup  10   686.85 746.85
## + SibGroup:HaveCabin  2   703.64 747.64
## <none>                    708.00 748.00
## + Embarked:SibGroup   3   702.72 748.72
## + Sex:HaveCabin       1   707.71 749.71
## + Sex:Embarked        2   705.82 749.82
## + Sex:Title           1   708.00 750.00
## + Embarked:HaveCabin  2   706.75 750.75
## + Sex:ParGroup        2   707.48 751.48
## + Pclass:HaveCabin    2   707.62 751.62
## + ParGroup:HaveCabin  2   707.94 751.94
## + Title:HaveCabin     3   706.34 752.34
## + Embarked:Title      6   700.83 752.83
## + AgeGroup:HaveCabin  6   701.45 753.45
```

```
## + Title:ParGroup      4   706.13 754.13
## + Pclass:AgeGroup    12   690.13 754.13
## + Pclass:Embarked     4   707.14 755.14
## + Sex:AgeGroup        6   703.66 755.66
## + Embarked:AgeGroup  12   695.94 759.94
## + AgeGroup:ParGroup   8   706.56 762.56
## + Title:AgeGroup     12   701.42 765.42
##
## Step:  AIC=729.99
## Survived ~ Pclass + Sex + Embarked + Title + AgeGroup + SibGroup +
##     ParGroup + HaveCabin + Pclass:Sex

## Warning: glm.fit: algorithm did not converge

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

##                     Df Deviance    AIC
## + Sex:SibGroup        2   665.81 713.81
## + Title:SibGroup      6   661.49 717.49
## + SibGroup:ParGroup   3   676.62 726.62
## + Sex:Embarked        2   679.23 727.23
## + Embarked:ParGroup   3   677.46 727.46
## + AgeGroup:SibGroup  10   664.40 728.40
## + Sex:HaveCabin       1   683.80 729.80
## <none>                    685.99 729.99
## + Embarked:SibGroup   3   680.53 730.53
## + Embarked:Title      6   674.68 730.68
## + SibGroup:HaveCabin  2   683.09 731.09
## + Sex:Title           1   685.99 731.99
## + Embarked:HaveCabin  2   684.25 732.25
## + Pclass:SibGroup     4   680.34 732.34
## + Pclass:ParGroup     3   682.92 732.92
## + Title:HaveCabin     3   682.95 732.95
## + Pclass:Title        4   681.38 733.38
## + Pclass:AgeGroup    12   665.45 733.45
## + Pclass:HaveCabin    2   685.78 733.78
## + Sex:ParGroup        2   685.82 733.82
## + ParGroup:HaveCabin  2   685.92 733.92
## + AgeGroup:HaveCabin  6   680.65 736.65
## + Pclass:Embarked     4   684.94 736.94
## + Title:ParGroup      4   685.06 737.06
## + Sex:AgeGroup        6   681.36 737.36
## + Embarked:AgeGroup  12   669.90 737.90
## + Title:AgeGroup     12   676.46 744.46
## + AgeGroup:ParGroup   8   684.59 744.59
## - Pclass:Sex          2   708.00 748.00
##
## Step:  AIC=713.81
## Survived ~ Pclass + Sex + Embarked + Title + AgeGroup + SibGroup +
##     ParGroup + HaveCabin + Pclass:Sex + Sex:SibGroup

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: algorithm did not converge

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## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

##                      Df Deviance     AIC
## + Sex:Embarked        2    658.8   710.8
## <none>                     665.8   713.8
## + Embarked:ParGroup   3    660.0   714.0
## + Sex:HaveCabin       1    664.0   714.0
## + SibGroup:ParGroup   3    660.6   714.6
## + Embarked:HaveCabin  2    663.7   715.7
## + Sex:Title           1    665.8   715.8
## + Embarked:SibGroup   3    662.3   716.3
## + SibGroup:HaveCabin  2    664.5   716.5
## + Pclass:AgeGroup    12    645.2   717.2
## + Embarked:Title      6    657.2   717.2
## + Pclass:HaveCabin    2    665.6   717.6
## + Pclass:ParGroup     3    663.7   717.7
## + Sex:ParGroup        2    665.7   717.7
## + ParGroup:HaveCabin  2    665.7   717.7
## + AgeGroup:HaveCabin  6    657.8   717.8
## + Title:HaveCabin     3    663.8   717.8
## + Pclass:SibGroup     4    663.4   719.4
## + Title:SibGroup      5    661.5   719.5
## + Pclass:Embarked     4    664.6   720.6
## + Pclass:Title        4    665.2   721.2
## + Title:ParGroup      4    665.6   721.6
## + AgeGroup:SibGroup  10    654.5   722.5
## + Embarked:AgeGroup  12    651.2   723.2
## + Sex:AgeGroup        6    663.6   723.6
## - Sex:SibGroup        2    686.0   730.0
## + AgeGroup:ParGroup   9    666.0   732.0
## - Pclass:Sex          2    691.6   735.6
## + Title:AgeGroup     11  11173.5 11243.5
##
## Step:  AIC=710.82
## Survived ~ Pclass + Sex + Embarked + Title + AgeGroup + SibGroup +
##     ParGroup + HaveCabin + Pclass:Sex + Sex:SibGroup + Sex:Embarked

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: algorithm did not converge

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## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

##                      Df Deviance     AIC
## + Embarked:ParGroup   3    651.6   709.6
## <none>                     658.8   710.8
## + Sex:HaveCabin       1    657.2   711.2
## + SibGroup:ParGroup   3    653.5   711.5
## + Embarked:HaveCabin  2    656.4   712.4
## + Sex:Title           1    658.8   712.8
## + SibGroup:HaveCabin  2    657.6   713.6
## - Sex:Embarked        2    665.8   713.8
## + Embarked:SibGroup   3    656.0   714.0
## + Pclass:AgeGroup    12    638.5   714.5
## + Pclass:ParGroup     3    656.6   714.6
## + Sex:ParGroup        2    658.7   714.7
## + ParGroup:HaveCabin  2    658.7   714.7
## + Pclass:HaveCabin    2    658.7   714.7
## + AgeGroup:HaveCabin  6    650.7   714.7
## + Title:HaveCabin     3    657.1   715.1
## + Pclass:SibGroup     4    656.4   716.4
## + Title:SibGroup      5    654.9   716.9
## + Embarked:Title      4    657.2   717.2
## + Pclass:Title        4    657.9   717.9
## + Pclass:Embarked     4    658.4   718.4
## + Title:ParGroup      4    658.7   718.7
## + AgeGroup:SibGroup  10    647.8   719.8
## + Sex:AgeGroup        6    656.7   720.7
## + AgeGroup:ParGroup   8    657.4   725.4
## + Embarked:AgeGroup  12    650.4   726.4
## - Sex:SibGroup        2    679.2   727.2
## - Pclass:Sex          2    689.5   737.5
## + Title:AgeGroup     11  13047.8 13121.8
##
## Step:  AIC=709.56
## Survived ~ Pclass + Sex + Embarked + Title + AgeGroup + SibGroup +
##     ParGroup + HaveCabin + Pclass:Sex + Sex:SibGroup + Sex:Embarked +
##     Embarked:ParGroup
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

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## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: algorithm did not converge
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: algorithm did not converge
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
##                      Df Deviance     AIC
## <none>                     651.6   709.6
## + Sex:HaveCabin       1    650.0   710.0
## - Embarked:ParGroup   3    658.8   710.8
## + Embarked:HaveCabin  2    649.4   711.4
## + SibGroup:ParGroup   3    647.5   711.5
## + Sex:Title           1    651.6   711.6
## + Embarked:SibGroup   3    647.7   711.7
## + SibGroup:HaveCabin  2    650.3   712.3
## + Sex:ParGroup        2    651.2   713.2
## + ParGroup:HaveCabin  2    651.3   713.3
## + Pclass:HaveCabin    2    651.5   713.5
## + Pclass:AgeGroup    12    631.6   713.6
## + AgeGroup:HaveCabin  6    643.7   713.7
## + Title:HaveCabin     3    649.8   713.8
## + Pclass:ParGroup     3    649.9   713.9
## - Sex:Embarked        2    660.0   714.0
## + Pclass:SibGroup     4    649.0   715.0
## + Pclass:Title        4    650.3   716.3
## + Pclass:Embarked     4    651.1   717.1
## + Embarked:Title      4    651.1   717.1
## + Title:ParGroup      4    651.2   717.2
## + Sex:AgeGroup        6    648.9   718.9
## + AgeGroup:SibGroup  10    641.7   719.7
## + AgeGroup:ParGroup   8    649.1   723.1
## - Sex:SibGroup        2    670.5   724.5
## + Embarked:AgeGroup  12    645.6   727.6
## - Pclass:Sex          2    682.4   736.4
## + Title:SibGroup      4  12182.8 12248.8
## + Title:AgeGroup     12  22563.3 22645.3
```

```r
# train a model with the features stepwise selected
model.glm <- glm(Survived ~ Pclass + Sex + Embarked + Title + AgeGroup + SibGroup +
```

```r
    ParGroup + HaveCabin + Pclass:Sex + Sex:SibGroup + Sex:Embarked + Embarked:ParGroup,
                 data=train.df,
                 family ="binomial")
summary(model.glm)
```

```
##
## Call:
## glm(formula = Survived ~ Pclass + Sex + Embarked + Title + AgeGroup +
##     SibGroup + ParGroup + HaveCabin + Pclass:Sex + Sex:SibGroup +
##     Sex:Embarked + Embarked:ParGroup, family = "binomial", data = train.df)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.8768  -0.5156  -0.4121   0.3137   2.5778
##
## Coefficients: (1 not defined because of singularities)
##                          Estimate Std. Error z value Pr(>|z|)
## (Intercept)               39.2872  2730.4427   0.014  0.98852
## Pclass2                   -0.4702     0.8212  -0.573  0.56692
## Pclass3                   -3.1542     0.7219  -4.369 1.25e-05 ***
## Sexmale                  -19.8254  2664.3652  -0.007  0.99406
## EmbarkedQ                  1.0162     0.7317   1.389  0.16489
## EmbarkedS                 -0.7530     0.5774  -1.304  0.19220
## TitleMiss                -34.0362  2730.4426  -0.012  0.99005
## TitleMr                  -18.4822   597.0554  -0.031  0.97530
## TitleMrs                 -33.0352  2730.4426  -0.012  0.99035
## AgeGroup7-14.5            -2.1368     0.8796  -2.429  0.01512 *
## AgeGroup14.5-21           -1.6789     0.6998  -2.399  0.01644 *
## AgeGroup21-28             -1.6126     0.7246  -2.225  0.02605 *
## AgeGroup28-35             -1.6244     0.7435  -2.185  0.02891 *
## AgeGroup35-50             -2.0853     0.7639  -2.730  0.00634 **
## AgeGroup50-               -2.5923     0.8418  -3.080  0.00207 **
## SibGroup(0,2]             -0.5442     0.3995  -1.362  0.17319
## SibGroup(2,8]             -1.2339     0.7350  -1.679  0.09322 .
## ParGroup(0,3]             -0.1330     0.5264  -0.253  0.80053
## ParGroup(3,9]             -1.7556     1.1481  -1.529  0.12621
## HaveCabin1                 0.7601     0.3916   1.941  0.05226 .
## Pclass2:Sexmale           -0.9340     0.8691  -1.075  0.28251
## Pclass3:Sexmale            2.1054     0.7069   2.978  0.00290 **
## Sexmale:SibGroup(0,2]      0.6762     0.5109   1.323  0.18568
## Sexmale:SibGroup(2,8]    -18.5710   597.0567  -0.031  0.97519
## Sexmale:EmbarkedQ         -1.7711     0.9883  -1.792  0.07313 .
## Sexmale:EmbarkedS          0.4840     0.6198   0.781  0.43488
## EmbarkedQ:ParGroup(0,3]  -17.4531  1172.2527  -0.015  0.98812
## EmbarkedS:ParGroup(0,3]   -0.4591     0.6517  -0.704  0.48113
## EmbarkedQ:ParGroup(3,9]  -17.8393  3956.1805  -0.005  0.99640
## EmbarkedS:ParGroup(3,9]        NA         NA      NA       NA
## ---
## 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:  651.56  on 862  degrees of freedom
```

```
## AIC: 709.56
##
## Number of Fisher Scoring iterations: 16
```

```r
# goodness of fit test
hl <- hoslem.test(model.glm$y, fitted(model.glm), g=10)
hl # p-value=0.94, good fit
```

```
##
##  Hosmer and Lemeshow goodness of fit (GOF) test
##
## data:  model.glm$y, fitted(model.glm)
## X-squared = 2.8692, df = 8, p-value = 0.9423
```

```r
# evaluate model by cross validation
m_glm <- train(Survived ~ Pclass + Sex + Embarked + Title + AgeGroup + SibGroup +
    ParGroup + HaveCabin + Pclass:Sex + Sex:SibGroup + Sex:Embarked + Embarked:ParGroup,  data=train.df
               method = "glm",
               family = "binomial",
               metric = "Accuracy",
               trControl = ctrl,
               tuneLength = 5)
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning in predict.lm(object, newdata, se.fit, scale = 1, type =
## ifelse(type == : prediction from a rank-deficient fit may be misleading

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## Warning in predict.lm(object, newdata, se.fit, scale = 1, type =
## ifelse(type == : prediction from a rank-deficient fit may be misleading
```

```r
m_glm
```

```
## Generalized Linear Model
##
## 891 samples
##   8 predictor
##   2 classes: '0', '1'
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 801, 803, 802, 802, 802, 802, ...
## Resampling results:
##
##   Accuracy   Kappa
##   0.8385362  0.6441233
```

```r
# look at feature importance
imp.glm <- varImp(m_glm, scale = FALSE)
imp.glm
```

```
## glm variable importance
##
##   only 20 most important variables shown (out of 28)
##
##                           Overall
## Pclass3                    4.3692
## `AgeGroup50-`              3.0796
## `Pclass3:Sexmale`          2.9785
## `AgeGroup35-50`            2.7296
## `AgeGroup7-14.5`           2.4294
## `AgeGroup14.5-21`          2.3991
## `AgeGroup21-28`            2.2255
## `AgeGroup28-35`            2.1848
## HaveCabin1                 1.9410
## `Sexmale:EmbarkedQ`        1.7920
## `SibGroup(2,8]`            1.6787
## `ParGroup(3,9]`            1.5292
## EmbarkedQ                  1.3888
## `SibGroup(0,2]`            1.3620
## `Sexmale:SibGroup(0,2]`    1.3235
## EmbarkedS                  1.3041
## `Pclass2:Sexmale`          1.0747
## `Sexmale:EmbarkedS`        0.7809
## `EmbarkedS:ParGroup(0,3]`  0.7045
## Pclass2                    0.5726
```

```r
# accuracy
train.acc[4] <- mean(predict(m_glm,train.df)==train.df$Survived)
```

```
## Warning in predict.lm(object, newdata, se.fit, scale = 1, type =
## ifelse(type == : prediction from a rank-deficient fit may be misleading
```

```r
train.acc[4]
```

```
## [1] 0.8507295
```

```r
cv.acc[4] <-  m_glm$results$Accuracy
cv.acc[4]
```

```
## [1] 0.8385362
```

build a svm model

```r
# tune parameters
grid_svm <- expand.grid(sigma = c(.01, .015, 0.2),
                        C= c(0.7, 0.8, 0.9, 1, 1.1))
set.seed(1234)
m_svm1 <- train(Survived ~ .,  data=train.df,
               method = "svmRadial",
               metric = "Accuracy",
               trControl = ctrl,
               tuneGrid = grid_svm)
m_svm1$bestTune
```

```
##   sigma   C
## 8 0.015 0.9
```

```r
# Evaluate model performance by cross validation
set.seed(1234)
m_svm <- train(Survived ~ .,  data=train.df,
               method = "svmRadial",
               metric = "Accuracy",
               trControl = ctrl,
               tuneGrid = m_svm1$bestTune)

# look at feature importance
imp.svm <- varImp(m_svm, scale = FALSE)
imp.svm
```

```
## ROC curve variable importance
##
##              Importance
## Sex              0.7669
## Pclass           0.6814
## FareGroup        0.6573
## HaveCabin        0.6369
## PartySize        0.6173
## FamilySize       0.5866
## Embarked         0.5744
## ParGroup         0.5623
## Title            0.5464
## SibGroup         0.5446
## AgeGroup         0.5317
```

```r
# accuracy
train.acc[5] <- mean(predict(m_svm,train.df)==train.df$Survived)
train.acc[5]
```

```
## [1] 0.8338945
```

```
cv.acc[5] <-  m_svm$results$Accuracy
cv.acc[5]
```

```
## [1] 0.8316553
```

Summarize the performance of the 5 models

```
model.name<- c("gbm", "randomForest", "xgboost","GLM","SVM")
result <- data.frame(model.name, train.acc, cv.acc)
result
```

```
##     model.name train.acc    cv.acc
## 1          gbm 0.8439955 0.8395080
## 2 randomForest 0.8664422 0.8294337
## 3      xgboost 0.8799102 0.8338268
## 4          GLM 0.8507295 0.8385362
## 5          SVM 0.8338945 0.8316553
```

Step 4: Making prediction —-

The accuracy on test dataset is 0.80861, which gets me in the top 10% teams in the Tatanic competition using only one model.

Use the gbm model to make predictions

```
# use the gbm model to make predictions
prediction.gbm <- predict(m_gbm, test.df)
table(prediction.gbm)
```

```
## prediction.gbm
##   0   1
## 271 147
```

```
# Write out a CSV file for submission to Kaggle
submit.gbm <- data.frame(PassengerId = 892:1309, Survived = prediction.gbm)
write.csv(submit.gbm, file = "titanic_zlqgbm.csv", row.names = FALSE) #0.80861
```