

```
library(ggplot2)
#install.packages('Rcpp')
#install.packages('dplyr')
library(dplyr)
library(randomForest)
library(Rcpp)
library(dplyr)
```

## Step 1: Load the data.

```
setwd("C:/Users/nwelpulw/Desktop/Udemy/Projects/Titanic")
train<-read.csv('train.csv',stringsAsFactors = FALSE)
test<-read.csv('test.csv',stringsAsFactors = FALSE)
```

train has 12 variables but test has 11 variables and to combine both datasets, number of column should be same.

So add Survived column with NA value in test dataset.

```
test$Survived<-NA
```

## Combine both datasets.

```
full<-rbind(train,test)
str(full)
```

```
## 'data.frame': 1309 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" ...
```

## Feature engineering with Name.

```
head(full$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"
```

Take out titles.

```
strsplit(full$Name,split = '[,.]')[[1]][2]
```

```
## [1] " Mr"
```

```
full$Title<-sapply(full$Name,FUN = function(x){strsplit(x,split = '[,.]')[[1]][2]})
```

There is blank space before title which needs to be removed.

```
full$Title<-sub(" ", "",full$Title)
```

```
table(full$Title,full$Sex)
```

```
##
##           female male
## Capt           0    1
## Col            0    4
## Don            0    1
## Dona           1    0
## Dr             1    7
## Jonkheer       0    1
## Lady           1    0
## Major          0    2
## Master         0   61
## Miss          260    0
## Mlle           2    0
## Mme            1    0
## Mr             0  757
## Mrs           197    0
## Ms             2    0
## Rev            0    8
## Sir            0    1
## the Countess   1    0
```

```
Rare_Title<-c('Capt','Col','Don','Dona','Dr','Jonkheer','Lady','Major','Rev','Sir','the Countess')
```

```
full$Title[full$Title=='Mlle' | full$Title=='Ms']<-'Miss'
```

```
full$Title[full$Title=='Mme']<-'Mrs'
```

```
full$Title[full$Title %in% Rare_Title]<-'Rare_Title'
```

```
table(full$Title,full$Sex)
```

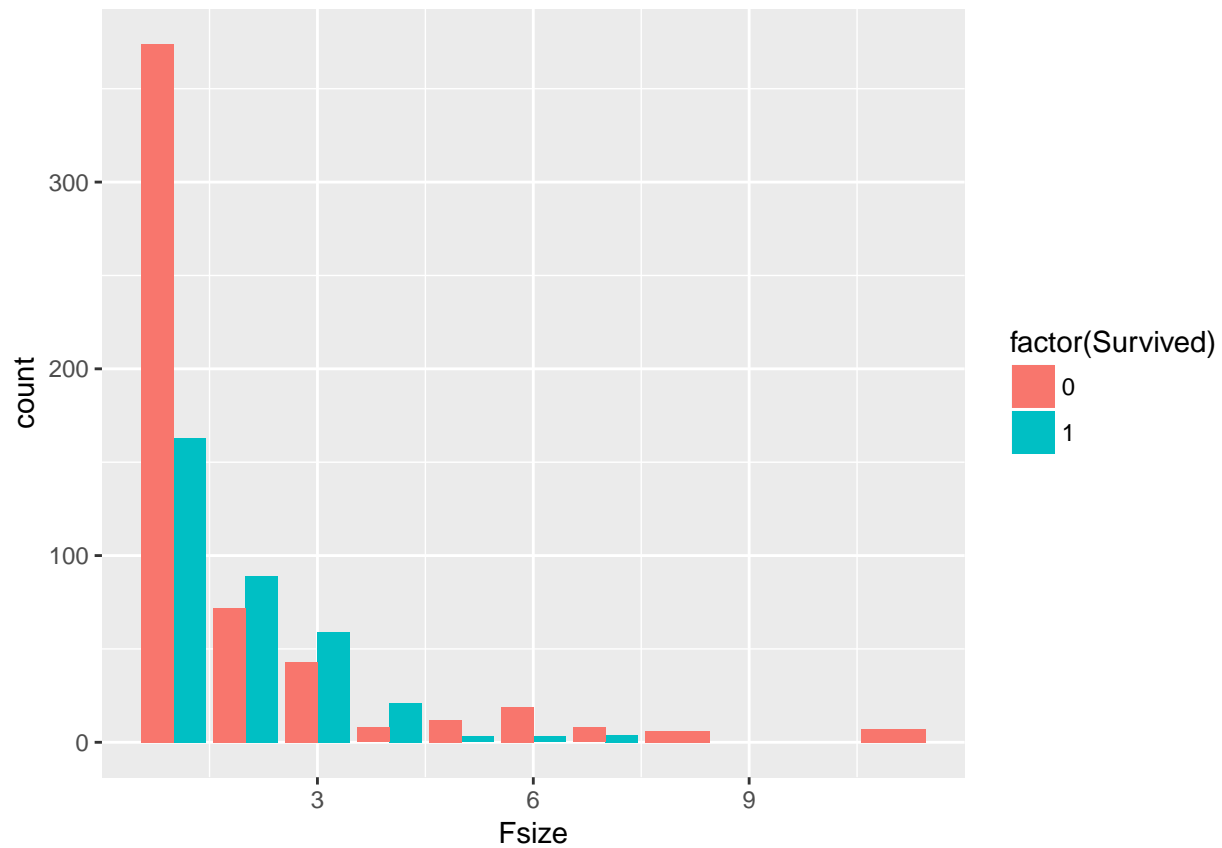
```
##
```

```
##           female male
## Master         0   61
## Miss          264   0
## Mr             0  757
## Mrs           198   0
## Rare_Title     4   25
```

\*\*\*\*\* Family Size \*\*\*\*\*

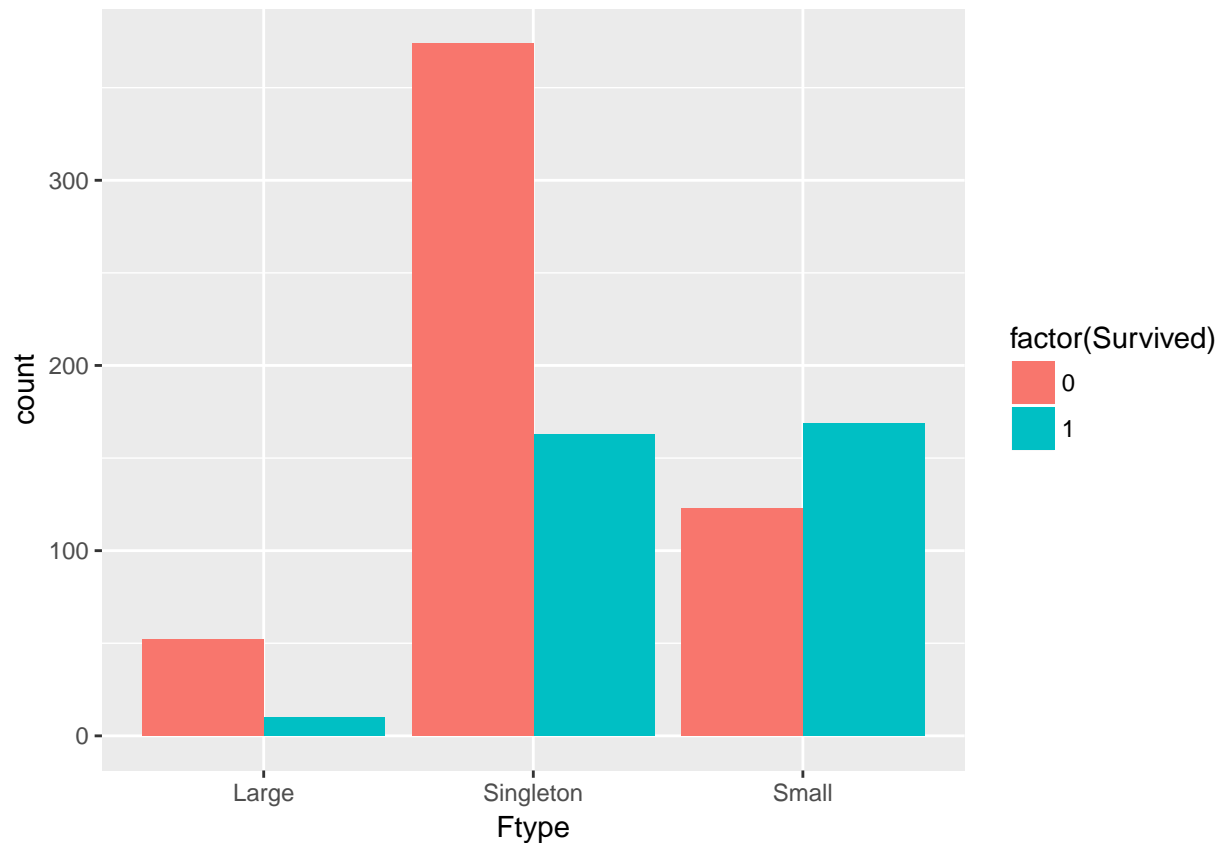
```
full$Fsize<-full$Parch+full$SibSp+1
```

```
ggplot()+geom_bar(data = full[1:891,],aes(x=Fsize,fill=factor(Survived)),position = 'dodge')
```



```
full$Ftype[full$Fsize==1]<- 'Singleton'
full$Ftype[full$Fsize>1 & full$Fsize<5]<- 'Small'
full$Ftype[full$Fsize>4]<- 'Large'
```

```
ggplot()+geom_bar(data = full[1:891,],aes(x=Ftype,fill=factor(Survived)),position = 'dodge')
```



#\*\*\*\*\* Cabin \*\*\*\*\*

```
head(full$Cabin[2])
```

```
## [1] "C85"
```

```
strsplit(full$Cabin,NULL)[[1]][1]
```

```
## [1] NA
```

```
full$deck<-sapply(full$Cabin,FUN = function(x){strsplit(x,NULL)[[1]][1]})
```

\*\*\*\*\* Missing Value : Embarked \*\*\*\*\*

```
head(full$Embarked)
```

```
## [1] "S" "C" "S" "S" "S" "Q"
```

```
which(full$Embarked=="")
```

```
## [1] 62 830
```

```
full[c(62,830),c(3,10,16)]
```

```
##      Pclass Fare deck
```

```
## 62      1    80    B
```

```
## 830      1    80    B
```

```
full[(full$Pclass==1 & full$deck=="B" & full$Embarked=="C"),c(3,10,16,12)]
```

##	Pclass	Fare	deck	Embarked
## NA	NA	NA	<NA>	<NA>
## 32	1	146.5208	B	C
## NA.1	NA	NA	<NA>	<NA>
## 55	1	61.9792	B	C
## NA.2	NA	NA	<NA>	<NA>
## 119	1	247.5208	B	C
## 140	1	79.2000	B	C
## NA.3	NA	NA	<NA>	<NA>
## 195	1	27.7208	B	C
## 196	1	146.5208	B	C
## NA.4	NA	NA	<NA>	<NA>
## NA.5	NA	NA	<NA>	<NA>
## 292	1	91.0792	B	C
## NA.6	NA	NA	<NA>	<NA>
## 300	1	247.5208	B	C
## NA.7	NA	NA	<NA>	<NA>
## 312	1	262.3750	B	C
## 330	1	57.9792	B	C
## 370	1	69.3000	B	C
## NA.8	NA	NA	<NA>	<NA>
## NA.9	NA	NA	<NA>	<NA>
## NA.10	NA	NA	<NA>	<NA>
## 485	1	91.0792	B	C
## 488	1	29.7000	B	C
## NA.11	NA	NA	<NA>	<NA>
## NA.12	NA	NA	<NA>	<NA>
## 524	1	57.9792	B	C
## NA.13	NA	NA	<NA>	<NA>
## 540	1	49.5000	B	C
## NA.14	NA	NA	<NA>	<NA>
## 588	1	79.2000	B	C
## NA.15	NA	NA	<NA>	<NA>
## 633	1	30.5000	B	C
## 642	1	69.3000	B	C
## 680	1	512.3292	B	C
## 738	1	512.3292	B	C
## 743	1	262.3750	B	C
## NA.16	NA	NA	<NA>	<NA>
## 790	1	79.2000	B	C
## NA.17	NA	NA	<NA>	<NA>
## NA.18	NA	NA	<NA>	<NA>
## NA.19	NA	NA	<NA>	<NA>
## NA.20	NA	NA	<NA>	<NA>
## 916	1	262.3750	B	C
## 918	1	61.9792	B	C
## 951	1	262.3750	B	C
## 956	1	262.3750	B	C
## NA.21	NA	NA	<NA>	<NA>
## 1034	1	262.3750	B	C
## 1058	1	50.4958	B	C
## NA.22	NA	NA	<NA>	<NA>

```
## 1076      1 247.5208    B      C
## NA.23     NA      NA <NA>    <NA>
## NA.24     NA      NA <NA>    <NA>
## NA.25     NA      NA <NA>    <NA>
## 1208      1 146.5208    B      C
## NA.26     NA      NA <NA>    <NA>
## 1235      1 512.3292    B      C
## NA.27     NA      NA <NA>    <NA>
## NA.28     NA      NA <NA>    <NA>
## 1289      1  79.2000    B      C
## NA.29     NA      NA <NA>    <NA>
```

```
#pclass<-train[train$Pclass==1 & train$Embarked!="",c(10,12) ]
```

```
#y_pred=lm(formula=Embarked ~ Fare,data =pclass)
```

```
full %>% filter(Pclass==1) %>%group_by(Pclass,Embarked)%>% summarise(mfare = median(Fare,na.rm=TRUE),n =
```

```
## # A tibble: 4 x 4
## # Groups:   Pclass [?]
##   Pclass Embarked  mfare     n
##   <int>    <chr>   <dbl> <int>
## 1      1      80.0000     2
## 2      1      C 76.7292    141
## 3      1      Q 90.0000     3
## 4      1      S 52.0000    177
```

```
full$Embarked[c(62,830)]<- 'C'
```

\*\*\*\*\* Missing Value : Fare \*\*\*\*\*

```
summary(full$Fare)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.   NA's
##    0.000  7.896 14.454 33.295 31.275 512.329     1
```

```
which(is.na(full$Fare))
```

```
## [1] 1044
```

```
full[1044,]
```

```
##      PassengerId Survived Pclass      Name Sex Age SibSp Parch
## 1044      1044      NA      3 Storey, Mr. Thomas male 60.5    0    0
##      Ticket Fare Cabin Embarked Title Fsize   Ftype deck
## 1044   3701   NA      S      Mr      1 Singleton <NA>
```

```
full %>% filter(Pclass=='3' & Embarked=='S') %>% summarise(median(Fare, na.rm = TRUE))
```

```
##      median(Fare, na.rm = TRUE)
## 1                      8.05
```

```
full$Fare[1044]<-8.05
```

\*\*\*\*\* Missing Value : Age \*\*\*\*\*

```
library(rpart)
```

```
summary(full$Age)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.     NA's
##      0.17  21.00   28.00   29.88   39.00   80.00     263
```

```
pred <- rpart(Age ~Pclass+SibSp+Embarked+Title,data = full[!is.na(full$Age),])
```

```
summary(pred)
```

```
## Call:
```

```
## rpart(formula = Age ~ Pclass + SibSp + Embarked + Title, data = full[!is.na(full$Age),
##      ])
```

```
##      n= 1046
```

```
##
```

```
##           CP nsplit rel error    xerror      xstd
## 1 0.21028409      0 1.0000000 1.0012796 0.04529407
## 2 0.10512853      1 0.7897159 0.7918756 0.03517463
## 3 0.05220533      2 0.6845874 0.6886374 0.03308297
## 4 0.02716919      3 0.6323821 0.6362894 0.03201778
## 5 0.01816094      4 0.6052129 0.6174335 0.03199064
## 6 0.01056208      5 0.5870519 0.5953919 0.03037402
## 7 0.01000000      6 0.5764899 0.5944076 0.03016726
```

```
##
```

```
## Variable importance
```

```
##      Title    Pclass    SibSp Embarked
##         55         29         10         5
```

```
##
```

```
## Node number 1: 1046 observations,      complexity param=0.2102841
```

```
##      mean=29.88114, MSE=207.5502
```

```
##      left son=2 (266 obs) right son=3 (780 obs)
```

```
##      Primary splits:
```

```
##          Title      splits as LLRRR,      improve=0.210284100, (0 missing)
```

```
##          Pclass    < 1.5 to the right, improve=0.154604900, (0 missing)
```

```
##          SibSp    < 2.5 to the right, improve=0.071073330, (0 missing)
```

```
##          Embarked splits as RLL,      improve=0.008481903, (0 missing)
```

```
##      Surrogate splits:
```

```
##          SibSp    < 2.5 to the right, agree=0.773, adj=0.109, (0 split)
```

```
##          Embarked splits as RLR,      agree=0.748, adj=0.008, (0 split)
```

```
##
```

```
## Node number 2: 266 observations,      complexity param=0.05220533
```

```
##      mean=18.56831, MSE=164.0627
```

```
##      left son=4 (53 obs) right son=5 (213 obs)
```

```
##      Primary splits:
```

```
##          Title      splits as LR---,      improve=0.25970370, (0 missing)
```

```
##          SibSp    < 0.5 to the right, improve=0.21272070, (0 missing)
```

```
##          Pclass    < 1.5 to the right, improve=0.19354290, (0 missing)
```

```
##          Embarked splits as RRL,      improve=0.02984813, (0 missing)
```

```
##      Surrogate splits:
```

```
##          SibSp    < 3.5 to the right, agree=0.831, adj=0.151, (0 split)
```

```
##
```

```

## Node number 3: 780 observations,      complexity param=0.1051285
##   mean=33.7391, MSE=163.8521
##   left son=6 (562 obs) right son=7 (218 obs)
##   Primary splits:
##       Pclass    < 1.5 to the right, improve=0.178578300, (0 missing)
##       Title     splits as  --LRR,    improve=0.039397110, (0 missing)
##       Embarked  splits as  RRL,      improve=0.011405030, (0 missing)
##       SibSp     < 2.5 to the right, improve=0.006958206, (0 missing)
##   Surrogate splits:
##       Embarked  splits as  RLL,      agree=0.767, adj=0.165, (0 split)
##       Title     splits as  --LRR,    agree=0.731, adj=0.037, (0 split)
##
## Node number 4: 53 observations
##   mean=5.482642, MSE=16.99177
##
## Node number 5: 213 observations,      complexity param=0.02716919
##   mean=21.82437, MSE=147.4482
##   left son=10 (152 obs) right son=11 (61 obs)
##   Primary splits:
##       Pclass    < 1.5 to the right, improve=0.18780720, (0 missing)
##       SibSp     < 0.5 to the right, improve=0.14555750, (0 missing)
##       Embarked  splits as  RRL,      improve=0.02453456, (0 missing)
##   Surrogate splits:
##       Embarked  splits as  RLL,      agree=0.775, adj=0.213, (0 split)
##
## Node number 6: 562 observations,      complexity param=0.01056208
##   mean=30.37011, MSE=116.7829
##   left son=12 (361 obs) right son=13 (201 obs)
##   Primary splits:
##       Pclass    < 2.5 to the right, improve=0.03493722, (0 missing)
##       Title     splits as  --LRR,    improve=0.02300209, (0 missing)
##       Embarked  splits as  LRL,      improve=0.01586441, (0 missing)
##       SibSp     < 1.5 to the right, improve=0.01297640, (0 missing)
##   Surrogate splits:
##       Title     splits as  --LRR,    agree=0.669, adj=0.075, (0 split)
##
## Node number 7: 218 observations
##   mean=42.42431, MSE=180.5023
##
## Node number 10: 152 observations,      complexity param=0.01816094
##   mean=18.49072, MSE=115.3497
##   left son=20 (53 obs) right son=21 (99 obs)
##   Primary splits:
##       SibSp     < 0.5 to the right, improve=0.22487070, (0 missing)
##       Embarked  splits as  LRR,      improve=0.06437730, (0 missing)
##       Pclass    < 2.5 to the right, improve=0.02326302, (0 missing)
##   Surrogate splits:
##       Embarked  splits as  LRR,      agree=0.678, adj=0.075, (0 split)
##
## Node number 11: 61 observations
##   mean=30.13115, MSE=130.7369
##
## Node number 12: 361 observations
##   mean=28.86288, MSE=100.2727

```



```
##
## Node number 13: 201 observations
##   mean=33.07711, MSE=135.0276
##
## Node number 20: 53 observations
##   mean=11.53, MSE=90.38458
##
## Node number 21: 99 observations
##   mean=22.21717, MSE=88.88971

y_pred<-predict(pred,newdata =full[is.na(full$Age),] )

summary(y_pred)
```

```
##   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   5.483  28.863  28.863  28.427  28.863  42.424
```

```
full$Age[is.na(full$Age)]<-predict(pred,newdata =full[is.na(full$Age),] )
```

## \*\*\*\*\* Random Forest Model \*\*\*\*\*

```
full$Sex<-factor(full$Sex)
full$Embarked<-factor(full$Embarked)
full$Title<-factor(full$Title)
full$Ftype<-factor(full$Ftype)

train <- full[1:891,]
test  <- full[892:1309,]

set.seed(123)
#train$Sex<-factor(train$Sex)
##train$Embarked<-factor(train$Embarked)
#train$Title<-factor(train$Title)
#train$Ftype<-factor(train$Ftype)

#test$Sex<-factor(test$Sex)
#test$Embarked<-factor(test$Embarked)
#test$Title<-factor(test$Title)
#test$Ftype<-factor(test$Ftype)

#rf_model<-randomForest(factor(Survived)~Pclass+Sex+Age+SibSp+Parch+Fare+Embarked+Title+Fsize+Ftype,data
rf_model<-randomForest(factor(Survived)~Pclass+Sex+Age+SibSp+Parch+Fare+Embarked+Title+Fsize+Ftype,data
rf_model  #740 right
```

```
##
## Call:
##   randomForest(formula = factor(Survived) ~ Pclass + Sex + Age + SibSp + Parch + Fare + Embarked
##               Type of random forest: classification
##               Number of trees: 500
## No. of variables tried at each split: 3
##
```

```
##          OOB estimate of  error rate: 17.06%
## Confusion matrix:
##      0   1 class.error
## 0 493  56   0.1020036
## 1   96 246   0.2807018

pred<-predict(rf_model,test)

#solution <- data.frame(PassengerID = test$PassengerId, Survived = pred)

# Write the solution to file
#write.csv(solution, file = 'titanic_2.csv', row.names = F)
```