Data preparation and feature engineering on Titanic data set

For this Lab, we will use the Titanic data set, available from Kaggle.com:
http://www.kaggle.com/c/titanic-gettingStarted/data

Load the data (training and test sets)

```
titanic.train <- read.csv("data/titanic/train.csv", stringsAsFactors = F)
titanic.test <- read.csv("data/titanic/test.csv", stringsAsFactors = F)
```

Let's start by examining the structure of the data sets Note: description of all the varibles is available at the Kaggle website

```
str(titanic.train)
```

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

```
str(titanic.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 Francis" "Wirz, Mr. Albert" ...
##  $ 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" ...
```

The structure of the training and test sets is almost exactly the same (as expected). In fact, the only difference is the Survived column that is present in the training, but absent in the test set - it is the response (outcome) variable, that is, the variable with the class values.

Detecting missing values

Let's start by checking if the data is complete, that is, if there are some missing values. One way to do that is through the summary f. which will let us know if a variable has NA values

```
summary(titanic.train)

##   PassengerId      Survived         Pclass          Name
##  Min.   :  1.0   Min.   :0.0000   Min.   :1.000   Length:891
##  1st Qu.:223.5   1st Qu.:0.0000   1st Qu.:2.000   Class :character
##  Median :446.0   Median :0.0000   Median :3.000   Mode  :character
##  Mean   :446.0   Mean   :0.3838   Mean   :2.309
##  3rd Qu.:668.5   3rd Qu.:1.0000   3rd Qu.:3.000
##  Max.   :891.0   Max.   :1.0000   Max.   :3.000
##
##      Sex                  Age            SibSp           Parch
##  Length:891         Min.   : 0.42   Min.   :0.000   Min.   :0.0000
##  Class :character   1st Qu.:20.12   1st Qu.:0.000   1st Qu.:0.0000
##  Mode  :character   Median :28.00   Median :0.000   Median :0.0000
##                     Mean   :29.70   Mean   :0.523   Mean   :0.3816
##                     3rd Qu.:38.00   3rd Qu.:1.000   3rd Qu.:0.0000
##                     Max.   :80.00   Max.   :8.000   Max.   :6.0000
##                     NA's   :177
##     Ticket               Fare            Cabin             Embarked
##  Length:891         Min.   :  0.00   Length:891         Length:891
##  Class :character   1st Qu.:  7.91   Class :character   Class :character
##  Mode  :character   Median : 14.45   Mode  :character   Mode  :character
##                     Mean   : 32.20
##                     3rd Qu.: 31.00
##                     Max.   :512.33
##
```

It seems that in the training set only Age has missing values, and quite a number of them (177).

```
summary(titanic.test)

##   PassengerId         Pclass          Name                Sex
##  Min.   : 892.0   Min.   :1.000   Length:418         Length:418
##  1st Qu.: 996.2   1st Qu.:1.000   Class :character   Class :character
##  Median :1100.5   Median :3.000   Mode  :character   Mode  :character
##  Mean   :1100.5   Mean   :2.266
##  3rd Qu.:1204.8   3rd Qu.:3.000
##  Max.   :1309.0   Max.   :3.000
##
##       Age            SibSp            Parch            Ticket
##  Min.   : 0.17   Min.   :0.0000   Min.   :0.0000   Length:418
```

```
##  1st Qu.:21.00   1st Qu.:0.0000   1st Qu.:0.0000   Class :character
##  Median :27.00   Median :0.0000   Median :0.0000   Mode  :character
##  Mean   :30.27   Mean   :0.4474   Mean   :0.3923
##  3rd Qu.:39.00   3rd Qu.:1.0000   3rd Qu.:0.0000
##  Max.   :76.00   Max.   :8.0000   Max.   :9.0000
##  NA's   :86
##       Fare              Cabin              Embarked
##  Min.   :  0.000   Length:418         Length:418
##  1st Qu.:  7.896   Class :character   Class :character
##  Median : 14.454   Mode  :character   Mode  :character
##  Mean   : 35.627
##  3rd Qu.: 31.500
##  Max.   :512.329
##  NA's   :1
```

In the test set, in addition to the 86 NAs for Age, there is also one missing value for the Fare variable.

So, based on the NA values, it seems that only Age variable has a serious issue with missing values.

However, if you take a closer look at the output of the str() f., you'll notice that for some observations (passengers) the value for Cabin seems to be missing, that is, Cabin value is equal to empty string (""). Let's inspect this more closely by checking how many "" values we have for the Cabin variable in both datasets:

```
length(which(titanic.train$Cabin==""))

## [1] 687

length(which(titanic.test$Cabin==""))

## [1] 327
```

So, for 687 passengers in the training set and 327 passanges in the test, we have "" as the Cabin value. Should we consider these as missing values?

Recall that on Titanic, there were three classes of passengers, and only those from the 1st class were offered a cabin. So, some of the empty string values we have observed are due to the fact that passengers were from the 2nd or the 3rd class, meaning that they really didn't have a cabin. In those cases empty string is not a missing value, but "not applicable" value. However, passengers from the 1st class should have had a cabin; so, an empty string for the Cabin value of a 1st class passenger is a 'real' missing value. Let's check how many such values we have in the training set:

```
train.class1.no.cabin <- which(titanic.train$Pclass==1 &
titanic.train$Cabin=="")
length(train.class1.no.cabin)

## [1] 40
```

Also, on the test set:

```
test.class1.no.cabin <- which(titanic.test$Pclass==1 &
titanic.test$Cabin=="")
length(test.class1.no.cabin)

## [1] 27
```

So, for 40 1st class passengers in the training set and 27 1st class passengers in the test set, the Cabin value is missing. To make this explicit, let's replace the missing Cabin values for 1st class passengers with NAs:

```
titanic.train$Cabin[train.class1.no.cabin] <- NA
titanic.test$Cabin[test.class1.no.cabin] <- NA
```

We can check the results of this transformation:

```
length(which(is.na(titanic.train$Cabin)))

## [1] 40

length(which(is.na(titanic.test$Cabin)))

## [1] 27
```

Note that we have discovered missing values of the Cabin variable by spotting a few empty strings in the output of the str() f. However, if those values were not amongst the first couple of values listed by str(), they would have passed unnoticed. So, let's check other string variables for missing values 'hidden' as empty strings:

```
apply(X = titanic.train[,c("Name","Sex","Ticket","Embarked")],
      MARGIN = 2,
      FUN = function(x) length(which(x=="")))

##      Name       Sex    Ticket  Embarked
##         0         0         0         2
```

In the training set, only for the Embarked variable, we have 2 missing values.

```
apply(X = titanic.test[,c("Name","Sex","Ticket","Embarked")],
      MARGIN = 2,
      FUN = function(x) length(which(x=="")))

##      Name       Sex    Ticket  Embarked
##         0         0         0         0
```

In the test set, none of the examined variables has missing values.

We'll set the two missing values of Embarked to NA, as we did with the Cabin.

```
titanic.train$Embarked[titanic.train$Embarked==""] <- NA
```

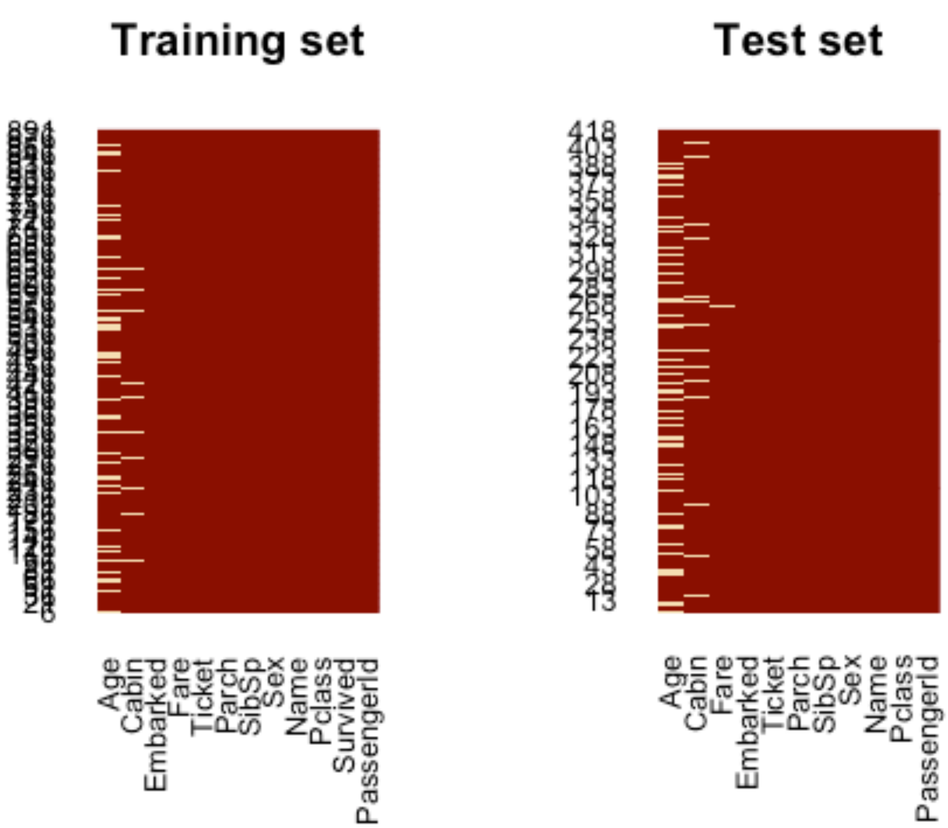
We have now examined all the variables for the missing values. Before proceeding with 'fixing' the missing values, let's see how we can make use of visualizations to more easily spot missing values.

An easy way to get a high level view on the data completeness is to visualize the data using some functions from the **Amelia** R package

```r
#install.packages('Amelia')
library(Amelia)

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

We will use the missmap() f. to plot the missing data from the traning and test sets

```r
par(mfrow=c(1,2)) # structure the display area to show two plots in the same row
missmap(obj = titanic.train, main = "Training set", legend = FALSE)
missmap(obj = titanic.test, main = "Test set", legend = FALSE)
```




```r
par(mfrow=c(1,1)) # reverting plotting area to the default (one plot per row)
```

Note: the detection of missing values in the missmap() f. is based on the NA values; so, if we hadn't transformed those empty strings (for Cabin and Embarked) into NAs, they wouldn't be visualized as missing.

Handling missing values

Let's now see how to deal with missing values. We'll start with those cases that are easier to deal with, that is, variables where we have just a few missing values.

Categorical variables with a small number of missing values

In our datasets, Embarked variables falls into this category:

```
unique(titanic.train$Embarked)
```

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

```
unique(titanic.test$Embarked)
```

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

So, as we see, Embarked is essentially a nominal (categorical) variable with 3 possible values ('S', 'C', and 'Q'). And, we have seen that it has 2 missing values (in the train set).

In a situation like this, the missing values are replaced by the 'majority class', that is, the most dominant value

```
xtabs(~Embarked, data = titanic.train)
```

```
## Embarked
##   C   Q   S
## 168  77 644
```

So, "S" is the dominant value, and it will be used as a replacement for NAs

```
titanic.train$Embarked[is.na(titanic.train$Embarked)] <- 'S'
xtabs(~Embarked, data = titanic.train)
```

```
## Embarked
##   C   Q   S
## 168  77 646
```

Let's also make Embarked a 'true' categorical variable by transforming it into a factor variable:

```
titanic.train$Embarked <- factor(titanic.train$Embarked)
titanic.test$Embarked <- factor(titanic.test$Embarked)
```

Numerical variables with a small number of missing values

In our data set, Fare variable belongs to this category - it is a numerical variable with 1 missing value (in the test set)

A typical way to deal with missing values in situations like this is to replace them with the average value of the variable on a subset of observations that are the closest (most similar) to the observation(s) with the missing value. One way to do this is to apply the **kNN** method. However, we can opt for a simpler approach: we will replace the missing Fare value with the average Fare value for the passengers of the same class (Pclass).

First, we need to check the distribution of the Fare variable, to decide if we should use mean or median as the average value

```
shapiro.test(titanic.test$Fare)

##
##  Shapiro-Wilk normality test
##
## data:  titanic.test$Fare
## W = 0.5393, p-value < 2.2e-16
```

The variable is not normaly distributed -> use median

Now, identify the passenger class (Pclass) of the passenger whose Fare is missing

```
missing.fare.pclass <- titanic.test$Pclass[is.na(titanic.test$Fare)]
```

Compute median Fare for the other passengers of the same class

```
median.fare <- median(x = titanic.test$Fare[titanic.test$Pclass ==
missing.fare.pclass],
                      na.rm = T) # we have to set this to true as Fare has
one NA value
```

Set the missing Fare value to the computed median value

```
titanic.test$Fare[is.na(titanic.test$Fare)] <- median.fare
```

Check if the NA value was really replaced

```
summary(titanic.test$Fare)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.000   7.896  14.454  35.561  31.472 512.329
```

Variables with many missing values and/or missing values that are difficult to replace

The Age variable is an example of the first type: variable with many missing value; Cabin is an example of the second type, as it is a categorical variable with many different values (~150)

For such variables we apply the process known as *imputation* - the process of replacing missing values with substituted (predicted) values. It is, in fact, the task of predicting (good substitutes for) the missing values. R has several packages for imputation: MICE, Amelia, HMisc,...

We are not going to do imputation (out of scope of this course), but will instead create new variables (features) that will, in a way, serve as substitutes or proxies for Age and Cabin.

Feature selection

To select features to be used for creating a prediction model, we have to examine if and to what extent they are associated with the response (outcome) variable.

If we are familiar with the domain of the problem (prediction task), we can start from the knowledge and/or intuition about the predictors. Otherwise, that is, if the domain is unknown to us (such as would be prediction of the outcome of some chemical reactions) or the real names (labels) of the variables are withdrawn (e.g. for privacy reasons), we have to rely on some well establish general methods for feature selection (such as forward or backward selection).

Since the Titanic data set is associated with a familiar domain, we can start from some intuition about potential predictors.

Examining the predictive power of variables from the data set

It's well-known that in disasters woman and children are often the first to be rescued. Let's check if that was the case in the Titanic disaster.

We'll start by looking at the survival based on the gender. First, let's see the proportion of males and females in the dataset

```
titanic.train$Sex <- factor(titanic.train$Sex)
summary( titanic.train$Sex )

## female   male
##    314    577

prop.table(summary( titanic.train$Sex ))

##   female     male
## 0.352413 0.647587
```

Now, examine the survival counts based on the gender

```
xtabs(~Sex + Survived, data = titanic.train)

##         Survived
## Sex        0   1
##   female  81 233
##   male   468 109
```

and the proportions

```
sex.surv.tbl <- prop.table(xtabs(~Sex + Survived,
                                 data = titanic.train),
                           margin = 1) # proportions are computed at the row
level (each row sums to 1)
sex.surv.tbl
```

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

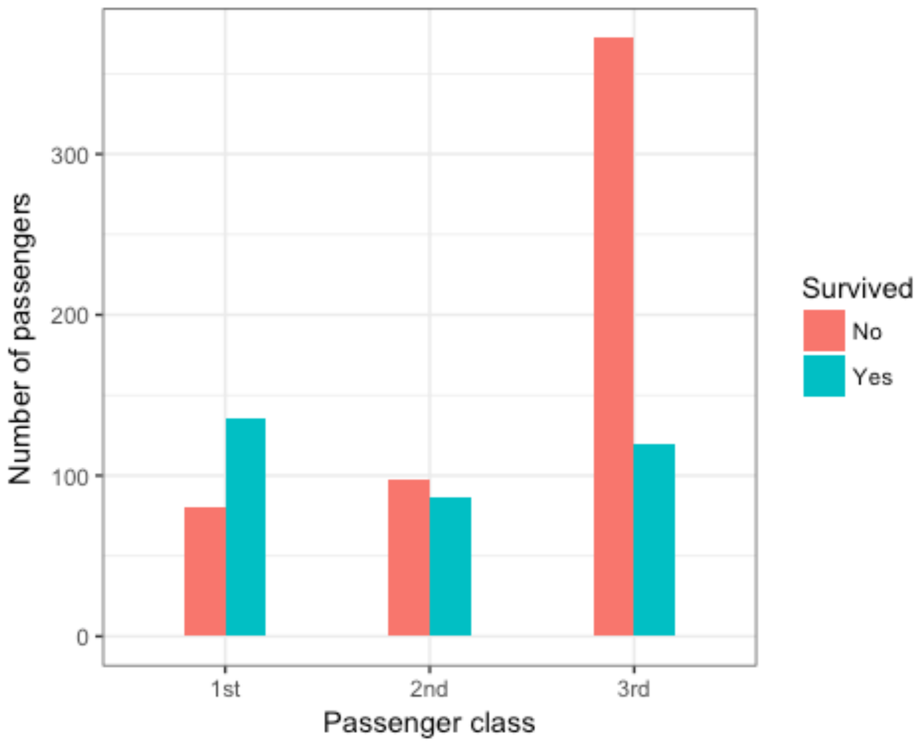
Obviously, gender is highly associated with the survival.

Before inspecting if/how age group has affected the chances for survival, let's quickly take a look at the potential impact of the passenger class (1st, 2nd or 3rd), as it is reasonable to expect that those from a higher class would have had higher chances of survival. We can do that again using tables, but it might be more effective to examine it visually, using the ggplot2 package:

```
library(ggplot2)
```

For plotting the survival against the passenger class, we need to transform both variables into factor variables (they are given as variables of type int)

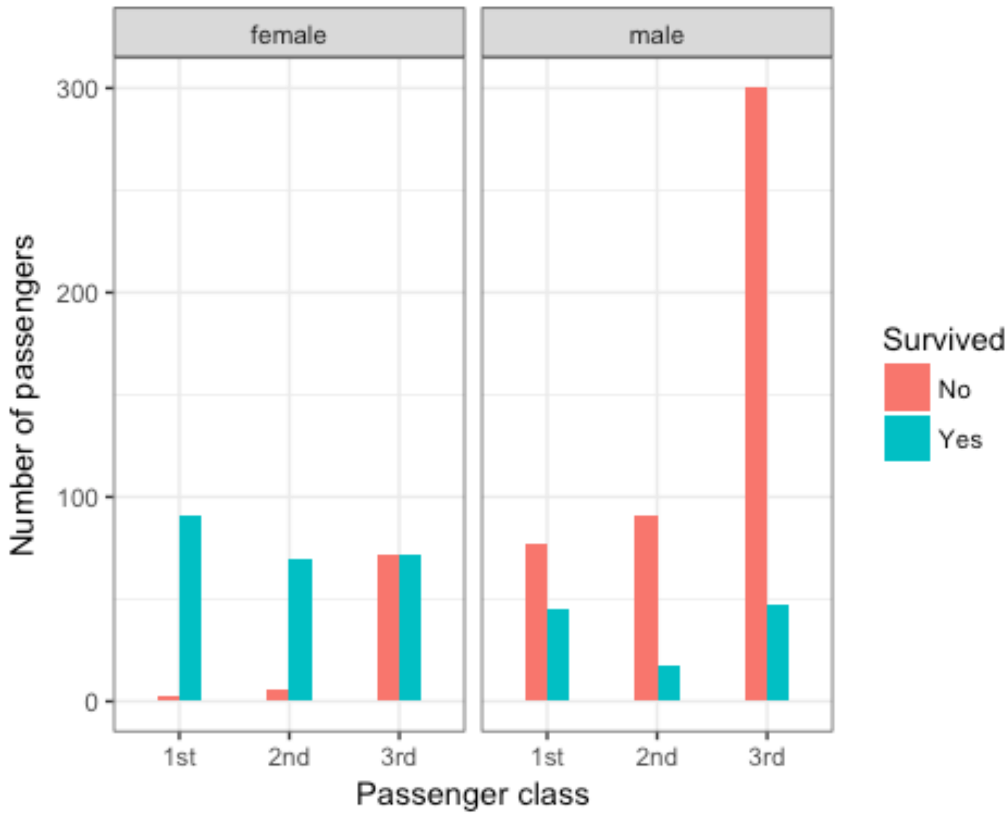
```
titanic.train$Survived <- factor(titanic.train$Survived,
                                 levels = c(0,1), labels = c('No','Yes'))

titanic.train$Pclass <- factor(titanic.train$Pclass,
                               levels = c(1,2,3),
                               labels = c("1st", "2nd", "3rd"))

gp1 <- ggplot(data = titanic.train,
              mapping = aes(x = Pclass, fill=Survived)) +
        geom_bar(position = "dodge", width = 0.4) +
        ylab("Number of passengers") + xlab("Passenger class") +
        theme_bw()
gp1
```



The chart suggests that passenger class is another relevant predictor.

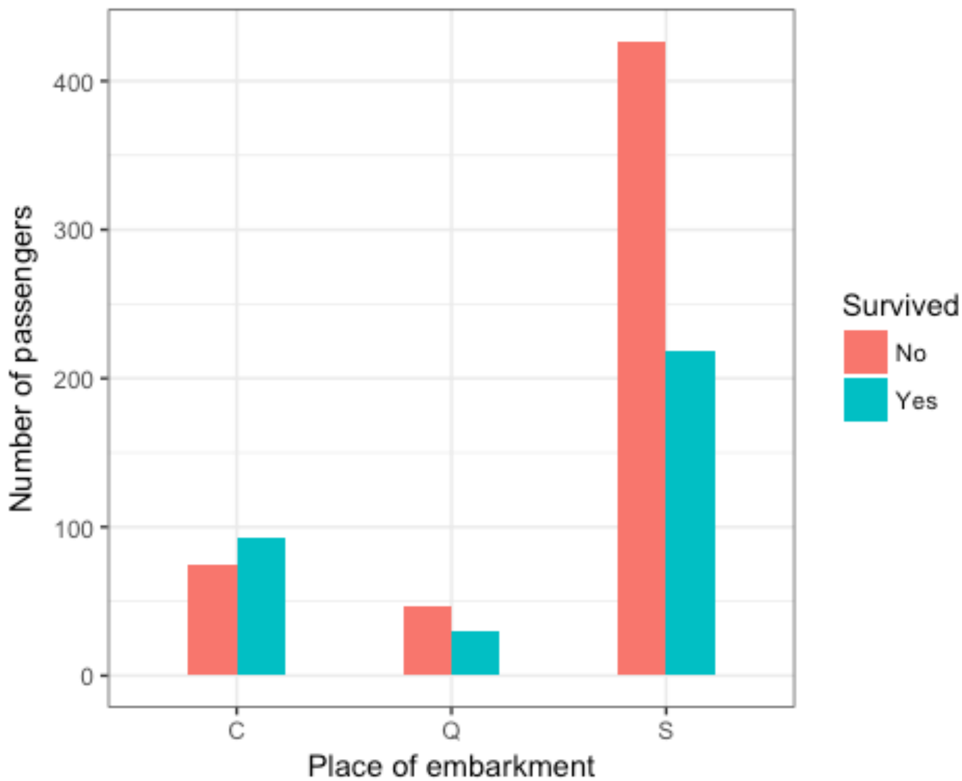
Let's examine passenger class and gender together

```
gp2 <- gp1 + facet_wrap(~Sex)
gp2
```



Let's also inspect if the place of embarkment (the Embarked variable) affected the survival

```
gp3 <- ggplot(data = titanic.train,
              mapping = aes(x = Embarked, fill = Survived)) +
        geom_bar(position = "dodge", width = 0.45) +
        ylab("Number of passengers") + xlab("Place of embarkment") +
        theme_bw()
gp3
```



It seems that those who embarked in Cherbourg had higher chance of surviving than the passengers who embarked in the other two ports. Though not as strong as Sex and Pclass, this variable seems to be a viable candidate for a predictor.

Feature engineering

When creating new features (attributes) to be used for prediction purposes, we need to base those features on the data from both the training and the test sets, so that the features are available both for training the prediction model, and making predictions on the unseen test data.

Hence, we should merge the training and the test sets and develop new features on the merged data. But before we do that, we need to assure that the training and the test sets have exactly the same structure. To that end, we will first add the Survived column to the test data, as a factor variable with the same levels as in the training set:

```
titanic.test$Survived <- factor(NA, levels = levels(titanic.train$Survived))
```

Next, we need to transform the Pclass, Sex, and Embarked variables in the test set into factors, since we've done that in the training set (the structure should be exactly the same)

```
titanic.test$Pclass <- factor(x = titanic.test$Pclass,
                              levels = c(1,2,3),
                              labels = levels(titanic.train$Pclass))
titanic.test$Sex <- factor(x = titanic.test$Sex,
                           levels = c("female", "male"),
```

```
                        labels = levels(titanic.train$Sex))
titanic.test$Embarked <- factor(x = titanic.test$Embarked,
                                levels = c("S", "C", "Q"),
                                labels = levels(titanic.test$Embarked))
```

Make the order of the columns in the test set the same as in the train set:

```
titanic.test <- titanic.test[,names(titanic.train)]
```

Now, we can merge the two datasets

```
titanic.all <- rbind(titanic.train, titanic.test)
```

Creating an age proxy variable

Recall that the Age variable has a lot of missing values, and simple imputation methods we considered cannot be used in such cases. So, we will create a new variable that approximates the passengers' age group. We'll do that by making use of the Name variable.

To start, let's first inspect the values of this variable

```
titanic.all$Name[1:10]
```

```
##  [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)"
```

We can observe that the Name variable consists of surname, title, first name, and in some cases additional name (maiden name of married woman).

The idea is to use the title of a person as a rough proxy for his/her age.

First, we need to extract title from the Name variable; to that end, we'll split the Name string using "," or "." as delimiters; lets' try it first:

```
strsplit(x = titanic.all$Name[1], split = "[,|.]")
```

```
## [[1]]
## [1] "Braund"       " Mr"           " Owen Harris"
```

We get a list of vectors, where each vector consists of pieces of a person's name. To extract the title, we need to simplify the output, so that instead of a list, we get a vector (with the elements of a person's name)

```
unlist(strsplit(x = titanic.all$Name[1], split = "[,|.]"))
```

```
## [1] "Braund"       " Mr"          " Owen Harris"
```

and then, take the second element of that vector:

```
unlist(strsplit(x = titanic.all$Name[1], split = "[,|.]"))[2]

## [1] " Mr"
```

You might have noticed a space before the title, we'll remove that quickly, but before that, we'll apply this procedure to all the rows in the titanic.all dataset to create a new feature:

```
titanic.all$Title <- sapply(titanic.all$Name,
                            FUN = function(x) unlist(strsplit(x, split =
"[,|.]"))[2] )
```

Now, let's remove that leading blank space

```
titanic.all$Title <- trimws(titanic.all$Title, which = "left")
```

Note: if trimws() f. is not working on your computer, use str_trim() f. from the *stringr* R package.

We can now inspect different kinds of titles we have in the dataset

```
table(titanic.all$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
```

There are some rarely occuring titles that won't be much usefull for creating a model; so, we'll aggregate those titles into broader categories that represent some basic age-gender groups:

```
adult.women <- c("Dona", "Lady", "Mme", "Mrs", "the Countess")
girls <- c("Ms", "Mlle", "Miss")
adult.men <- c("Capt", "Col", "Don", "Dr", "Major", "Mr", "Rev", "Sir")
boys <- c("Master", "Jonkheer")
```

First, we'll introduce a new variable (feature) to represent the age-gender group

```
titanic.all$AgeGender <- vector(mode = "character", length =
nrow(titanic.all))
```

and, now define each age-gender group using the Title groupings we defined above

```r
titanic.all$AgeGender[ titanic.all$Title %in% adult.women ] <- "AdultWomen"
titanic.all$AgeGender[ titanic.all$Title %in% adult.men ] <- "AdultMen"
titanic.all$AgeGender[ titanic.all$Title %in% girls ] <- "Girls"
titanic.all$AgeGender[ titanic.all$Title %in% boys ] <- "Boys"
```

Note: the %in% operator checks to see if a value is an element of the given vector

Let's see how passengers are distributed across our age-gender groups:

```r
table(titanic.all$AgeGender)
```

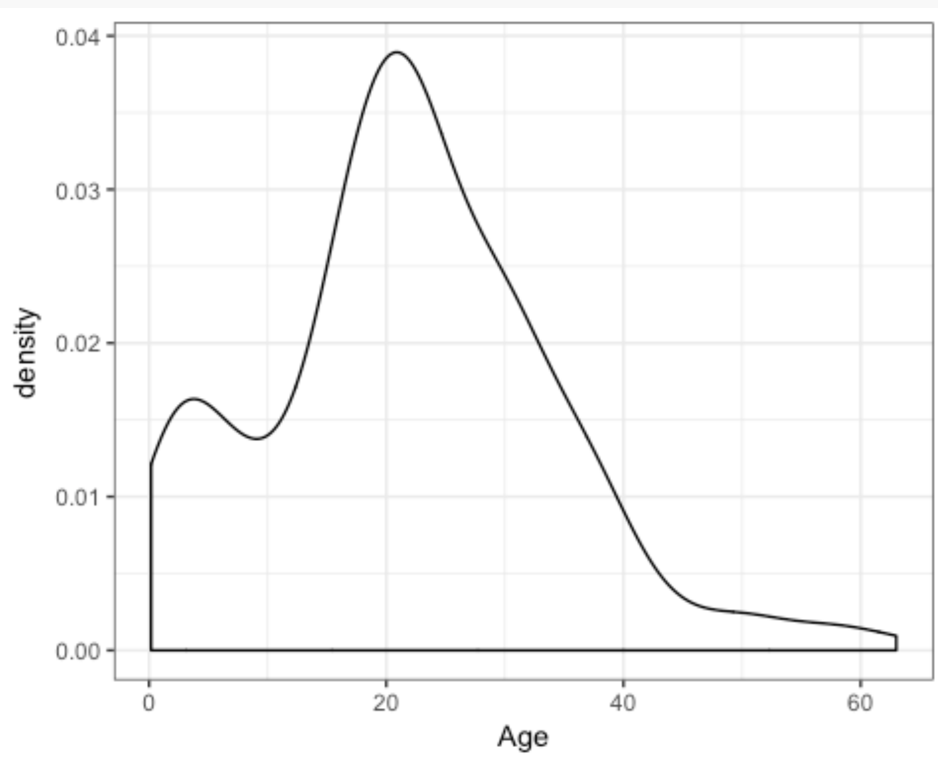
```
##
##   AdultMen AdultWomen       Boys      Girls
##        782        201         62        264
```

We observe a high disproportion in the number of boys and girls, and man and woman. Let's take a closer look at the groups with unexpectedly high number of passengers, namely Girls and AdultMen groups.

We'll make use of the available values of the Age variable to see how our Girls group is distributed with respect age.

```r
ggplot(data = titanic.all[titanic.all$AgeGender=="Girls",],
       mapping = aes(x = Age)) +
  geom_density() +
  theme_bw()
```

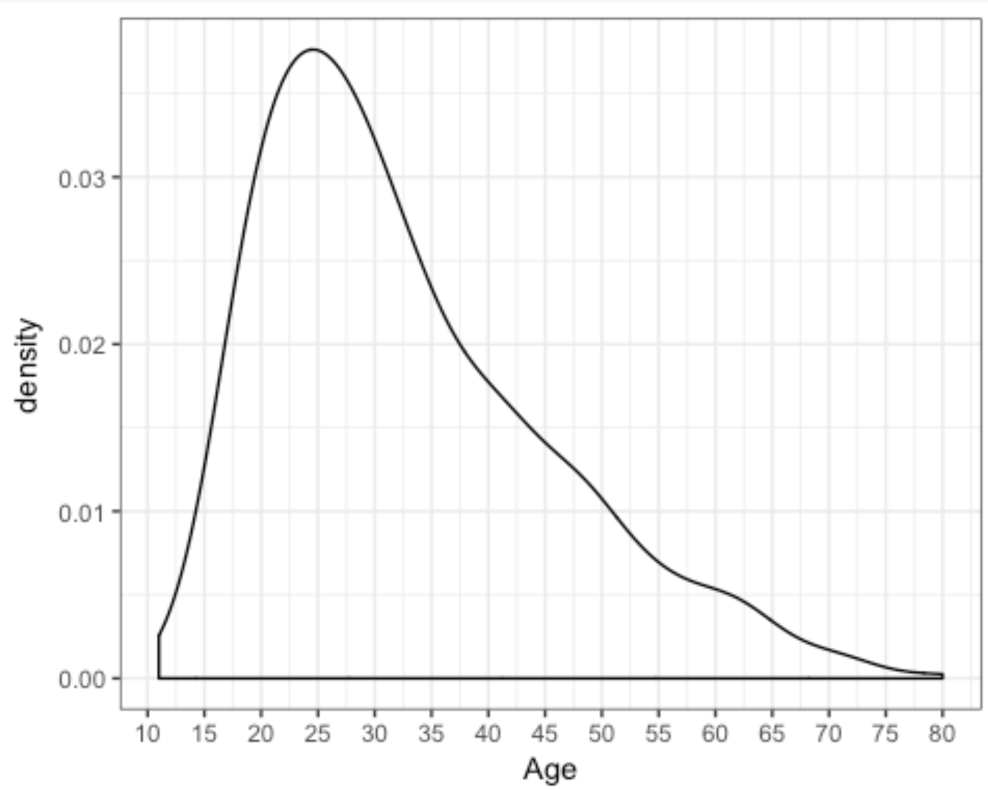
```
## Warning: Removed 51 rows containing non-finite values (stat_density).
```



It is obvious from the graph that the Girls group includes a considerable number of adult women. We'll need to fix this. But before that, let's also inspect the AdultMen group.

```
ggplot(data = titanic.all[titanic.all$AgeGender=="AdultMen", ],
       mapping = aes(x = Age)) +
  geom_density() +
  scale_x_continuous(breaks = seq(5,80,5)) +
  theme_bw()
```

```
## Warning: Removed 177 rows containing non-finite values (stat_density).
```



From this plot we can see that the AdultMen group also includes some males who cannot be qualified as adults.

We will try to fix both problems using the available values of the Age variable.

First, let's check for how many passengers in the 'Girls' group the Age value is available:

```
nrow(titanic.all[titanic.all$AgeGender=="Girls" & !is.na(titanic.all$Age),])
```

```
## [1] 213
```

So, we have Age value for 213 out of 264 Girls, which is not bad at all (80%). We'll make use of these available Age values to move some Girls to AdultWomen group, using 18 years of age as the threshold:

```
titanic.all$AgeGender[titanic.all$AgeGender=="Girls" &
                        !is.na(titanic.all$Age) &
                        titanic.all$Age >= 18] <- "AdultWomen"
```

We'll do a similar thing for the AdultMen group. First, check the number of AdultMen passengers for whom age is available:

```
nrow(titanic.all[titanic.all$AgeGender=="AdultMen" &
!is.na(titanic.all$Age),])

## [1] 605
```

We have Age value for 605 out of 782 AdultMen passengers (77%). Let's make use of those values to move some passengers from AdultMen to Boys group using, again, the 18 year threshold

```
titanic.all$AgeGender[titanic.all$AgeGender=="AdultMen" &
                        !is.na(titanic.all$Age) &
                        titanic.all$Age < 18] <- "Boys"
```

Let's check the AgeGender proportions after these modifications

```
table(titanic.all$AgeGender)

##
##   AdultMen AdultWomen       Boys      Girls
##        753        347         91        118

round(prop.table(table(titanic.all$AgeGender)), digits = 2)

##
##   AdultMen AdultWomen       Boys      Girls
##       0.58       0.27       0.07       0.09
```

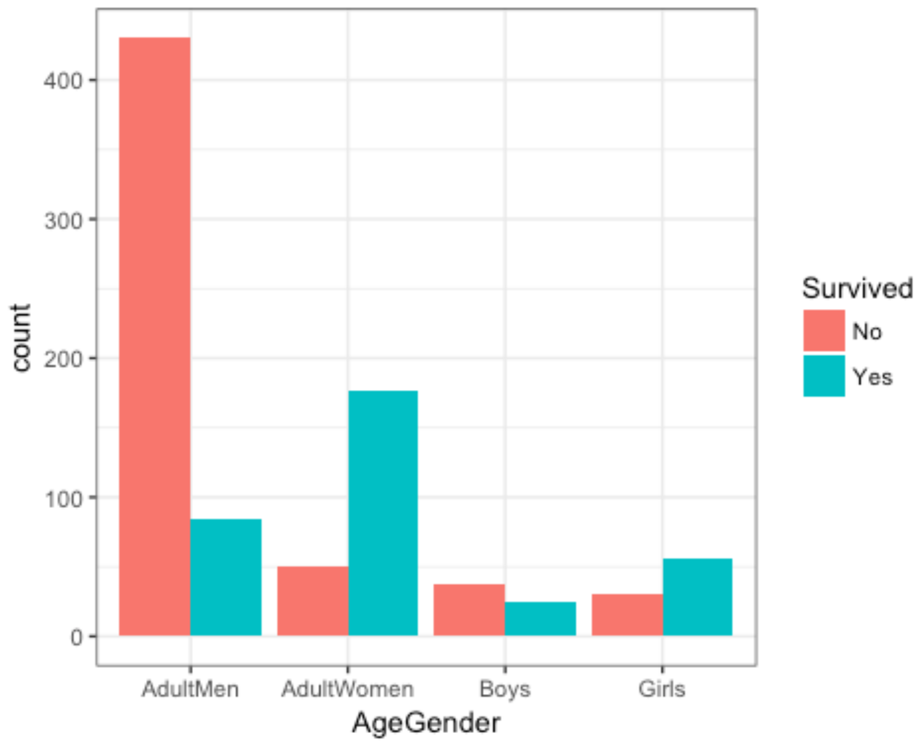
This looks far more realistic.

Finally, we'll transform AgeGender into a factor variable, so that it can be better used for data exploration and prediction purposes

```
titanic.all$AgeGender <- factor(titanic.all$AgeGender)
summary(titanic.all$AgeGender)

##   AdultMen AdultWomen       Boys      Girls
##        753        347         91        118
```

Let's see if our efforts in creating the AgeGender variable were worthwhile, that is, if AgeGender is likely to be a significant predictor. To that end, we will plot the AgeGender groups against the Survival variable.

```
ggplot(data = titanic.all[1:891,],
       mapping = aes(x = AgeGender, fill=Survived)) +
  geom_bar(position = "dodge") +
  theme_bw()
```



Note: we are using only the first 891 observations in the merged dataset as these are observations from the training set for which we know the outcome (i.e., survival).

Let's examine this also as percentages. First, we need to compute the percentages

```
age.gen.surv.tbl <- prop.table(table(AgeGender =
titanic.all$AgeGender[1:891],
                                     Survived = titanic.all$Survived[1:891]),
                               margin = 1)
age.gen.surv.tbl

##             Survived
## AgeGender           No       Yes
##   AdultMen   0.8349515 0.1650485
##   AdultWomen 0.2212389 0.7787611
##   Boys       0.6031746 0.3968254
##   Girls      0.3563218 0.6436782
```

Note that we are setting the margin parameter to 1 as we want to have percentages of survived and not-survived (column values) computed for each AgeGender group (row) individually. Try setting margin to 2 and not setting it at all to observe the effect.

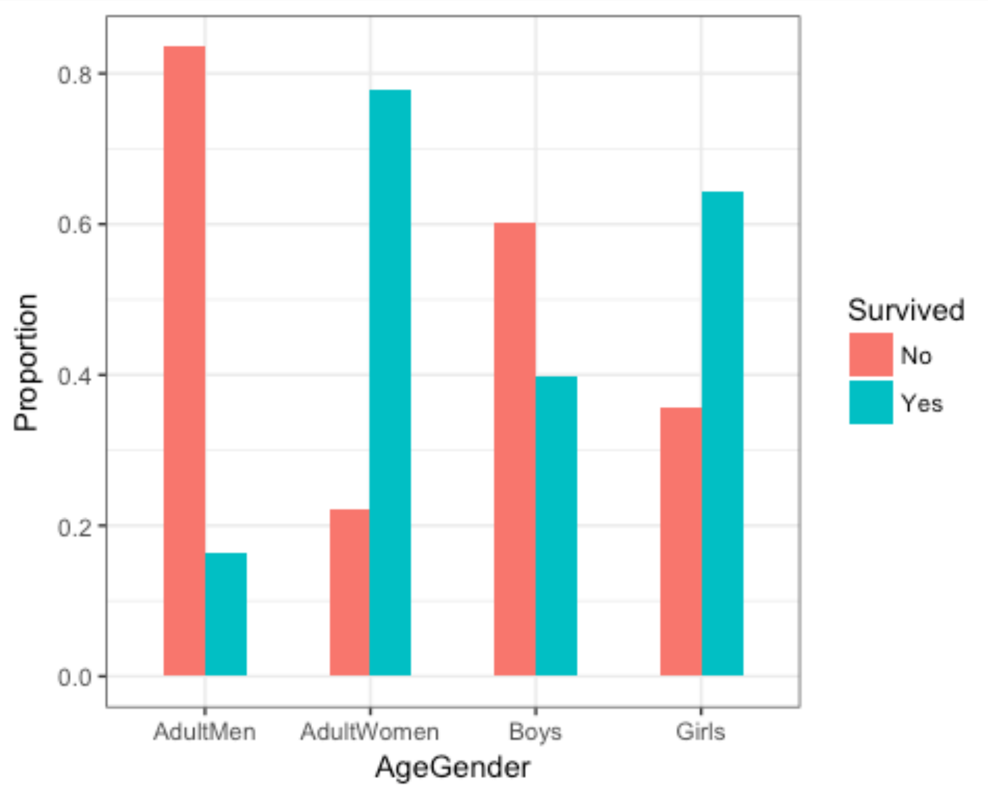
For plotting, we'll transform the table into a data frame

```
age.gen.surv.df <- as.data.frame(age.gen.surv.tbl)
age.gen.surv.df
```

```
##     AgeGender Survived      Freq
## 1    AdultMen       No 0.8349515
## 2  AdultWomen       No 0.2212389
## 3        Boys       No 0.6031746
## 4       Girls       No 0.3563218
## 5    AdultMen      Yes 0.1650485
## 6  AdultWomen      Yes 0.7787611
## 7        Boys      Yes 0.3968254
## 8       Girls      Yes 0.6436782
```

Note the difference in the structure of the table and the data frame

```
ggplot(data = age.gen.surv.df,
       mapping = aes(x = AgeGender, y = Freq, fill=Survived)) +
  geom_col(position = "dodge", width = 0.5) +
  ylab("Proportion") +
  theme_bw()
```



Obviously, the age/gender group affects survival.

Creating FamilySize variable

Recall that we have two variable related to the number of family members one is travelling with:

- SibSp - the number of siblings and spouses a passenger is travelling with
- Parch - the number of parents and children one is travelling with

```
summary(titanic.all$SibSp)
```

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

```
summary(titanic.all$Parch)
```

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

To get a better insight into the number of family members passengers were travelling with, we'll create a new variable FamilySize by simply adding the value of the SibSp and Parch variables:

```
titanic.all$FamilySize <- titanic.all$SibSp + titanic.all$Parch
summary(titanic.all$FamilySize)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.0000  0.0000  0.0000  0.8839  1.0000 10.0000
```

We can observe that large majority of passengers didn't travel with family members.

```
table(titanic.all$FamilySize)
```

```
##
##   0   1   2   3   4   5   6   7  10
## 790 235 159  43  22  25  16   8  11
```

It can be also observed that those who travelled with 3+ family members were not that numerous

```
length(which(titanic.all$FamilySize>=3))/length(titanic.all$FamilySize)
```

```
## [1] 0.09549274
```

Only 10% of passengers travelled with 3+ family members. In situations like this - several values of a variable spread across a small proportion of the observations - it is recommended to aggregate those values. We'll apply that practice to the FamilySize variable and aggregate observations with 3+ family members:

```
titanic.all$FamilySize[titanic.all$FamilySize > 3] <- 3
```

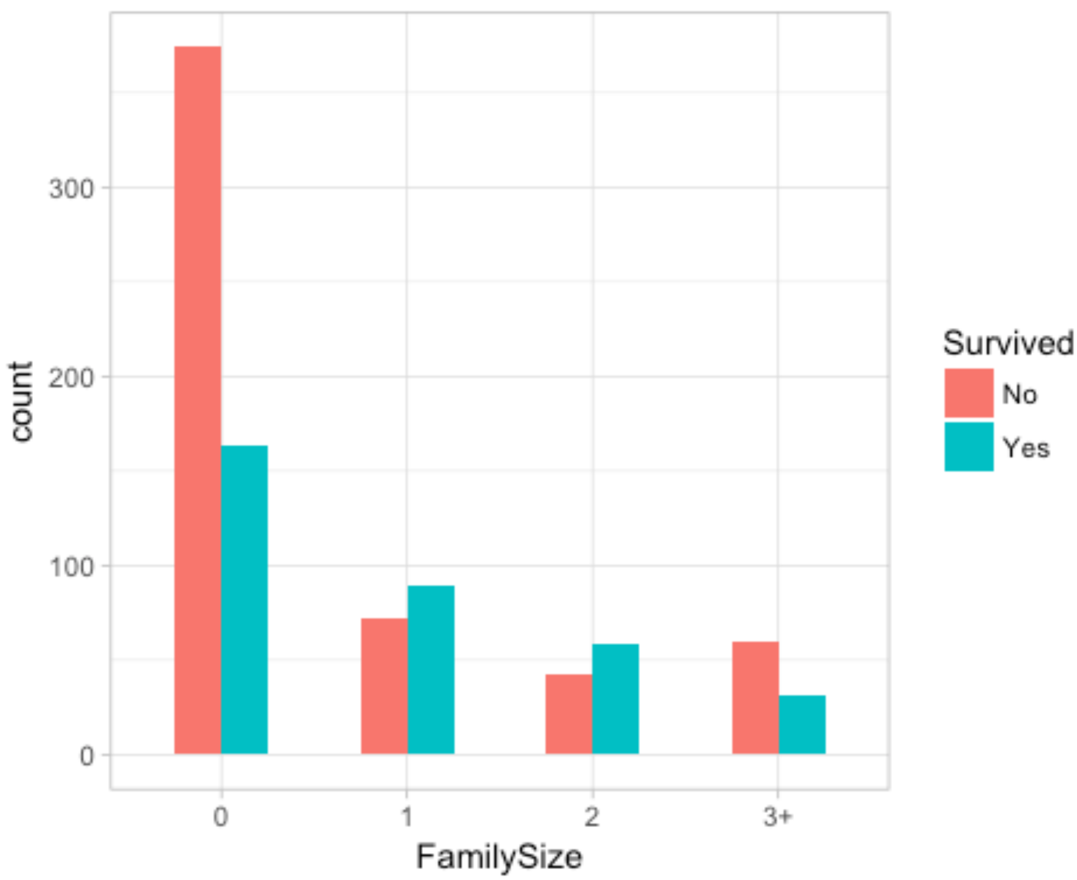
and turn FamilySize into a factor:

```
titanic.all$FamilySize <- factor(titanic.all$FamilySize,
                                 levels = c(0,1,2,3), labels = c("0", "1",
"2", "3+"))
table(titanic.all$FamilySize)
```

```
##
##   0   1   2  3+
## 790 235 159 125
```

Let's see how this new feature affects the survival prospects

```
ggplot(data = titanic.all[1:891,],
       mapping = aes(x = FamilySize, fill = Survived)) +
  geom_bar(position = "dodge", width = 0.5) +
  theme_light()
```



We can see that those who travelled with 1 or 2 family members had better prospects than those who travelled without family members or with 3+ family members.

Making use of the Ticket variable

Let's examine the Ticket variable and see if we can make some use of it

```
titanic.all$Ticket[1:20]
```

```
##  [1] "A/5 21171"          "PC 17599"           "STON/O2. 3101282"
##  [4] "113803"             "373450"             "330877"
##  [7] "17463"              "349909"             "347742"
## [10] "237736"             "PP 9549"            "113783"
## [13] "A/5. 2151"          "347082"             "350406"
## [16] "248706"             "382652"             "244373"
## [19] "345763"             "2649"
```

We can observe that some tickets start with letters, while others consist of digits only.

```
length(unique(titanic.all$Ticket))

## [1] 929
```

929 unique ticket values for 1309 passengers suggests that some passengers were travelling on the same ticket. Let's examine this further as a shared ticket is an indicator that a passenger was not travelling alone, and we saw that the number of people one was travelling with might have had affected their survival prospects.

```
# tapply, as applied here, computes the number of occurrences of each unique
Ticket value
ticket.count <- tapply(titanic.all$Ticket,
                       INDEX = titanic.all$Ticket,
                       FUN = function(x) sum( !is.na(x) ))
ticket.count.df <- data.frame(ticket=names(ticket.count),
                              count=as.integer(ticket.count))
head(ticket.count.df)

##   ticket count
## 1 110152     3
## 2 110413     3
## 3 110465     2
## 4 110469     1
## 5 110489     1
## 6 110564     1
```

Let's examine the number of passengers per single and shared tickets:

```
table(ticket.count.df$count)

## 
##   1   2   3   4   5   6   7   8  11 
## 713 132  49  16   7   4   5   2   1
```

We can see that majority of passengers travelled on a single person ticket, a considerable number of them shared a ticket with one person, and a small number shared their ticket with 3+ people.

We'll add ticket count to each passenger by merging titanic.all dataset with the ticket.count.df based on the ticket value:

```
titanic.all <- merge(x = titanic.all, y = ticket.count.df,
                     by.x = "Ticket", by.y = "ticket",
                     all.x = TRUE, all.y = TRUE)

# change the name of the newly added column:
colnames(titanic.all)[16] <- "PersonPerTicket"
```

As we did with FamilySize, we'll aggregate infrequent values of PersonPerTicket and transform the variable into a factor

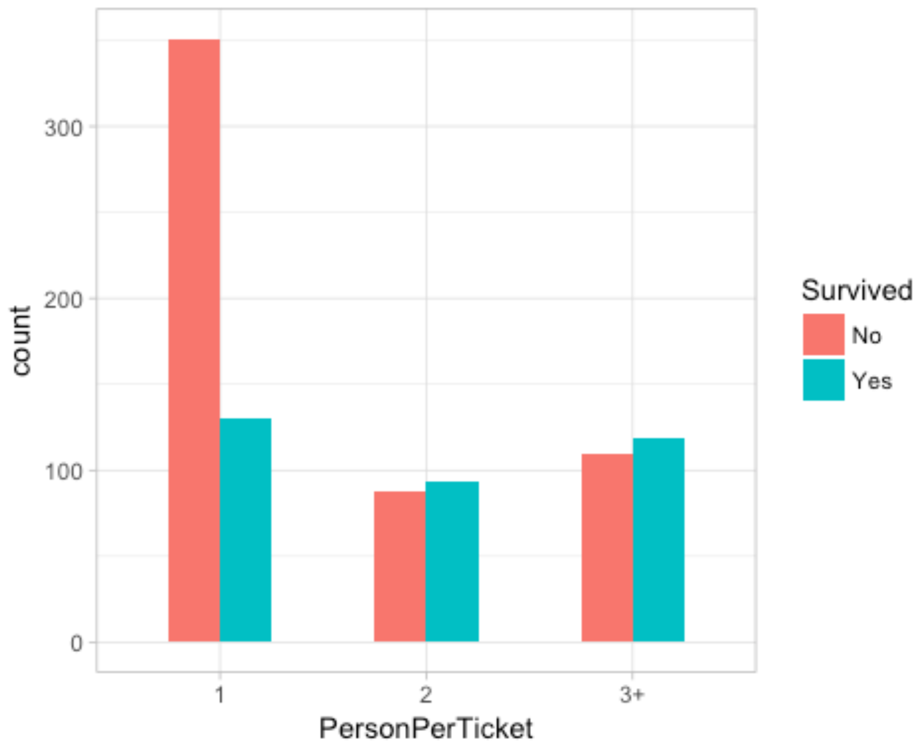
```
titanic.all$PersonPerTicket[titanic.all$PersonPerTicket > 3] <- 3
titanic.all$PersonPerTicket <- factor(titanic.all$PersonPerTicket,
                                      levels = c(1,2,3), labels = c("1", "2",
"3+"))
table(titanic.all$PersonPerTicket)

##
##   1   2  3+
## 713 264 332
```

Out of curiosity, we can crosstab this variable with FamilySize to see if there were some passengers who were not travelling with family members but still had company, as well as those who really travelled alone

```
xtabs(~ PersonPerTicket + FamilySize, data = titanic.all)

##                FamilySize
## PersonPerTicket   0   1   2  3+
##              1  663  31  16   3
##              2   62 170  25   7
##              3+  65  34 118 115
```

Let's examine the PersonPerTicket feature from the perspective of its relevance for a passenger's survival

```
ggplot(data = titanic.all[!is.na(titanic.all$Survived),],
                    mapping = aes(x = PersonPerTicket, fill=Survived)) +
  geom_bar(position = "dodge", width = 0.5) +
  theme_light()
```



It seems that this feature could be a useful predictor. Note that when we merged the titanic.all and ticket.count.df data frames, the order of rows in the titanic.all changed, so it is not the case any more that the first 891 observations are those taken from the training set and the rest are from the test set. Therefore, in the data argument (of ggplot()) we had to select observations based on having value for the Survived attribute.

Let's also check what a plot based on percentages would look like.

Compute first the percentages of survived and not survived for each PersonPerTicket value:

```
tcount.surv.tbl <- prop.table(table(PersonPerTicket =
titanic.all$PersonPerTicket,
                                    Survived = titanic.all$Survived,
                                    useNA = "no"),
                               margin = 1)
tcount.surv.tbl
```

```
##                Survived
## PersonPerTicket        No       Yes
##              1  0.7297297 0.2702703
##              2  0.4861878 0.5138122
##              3+ 0.4803493 0.5196507
```

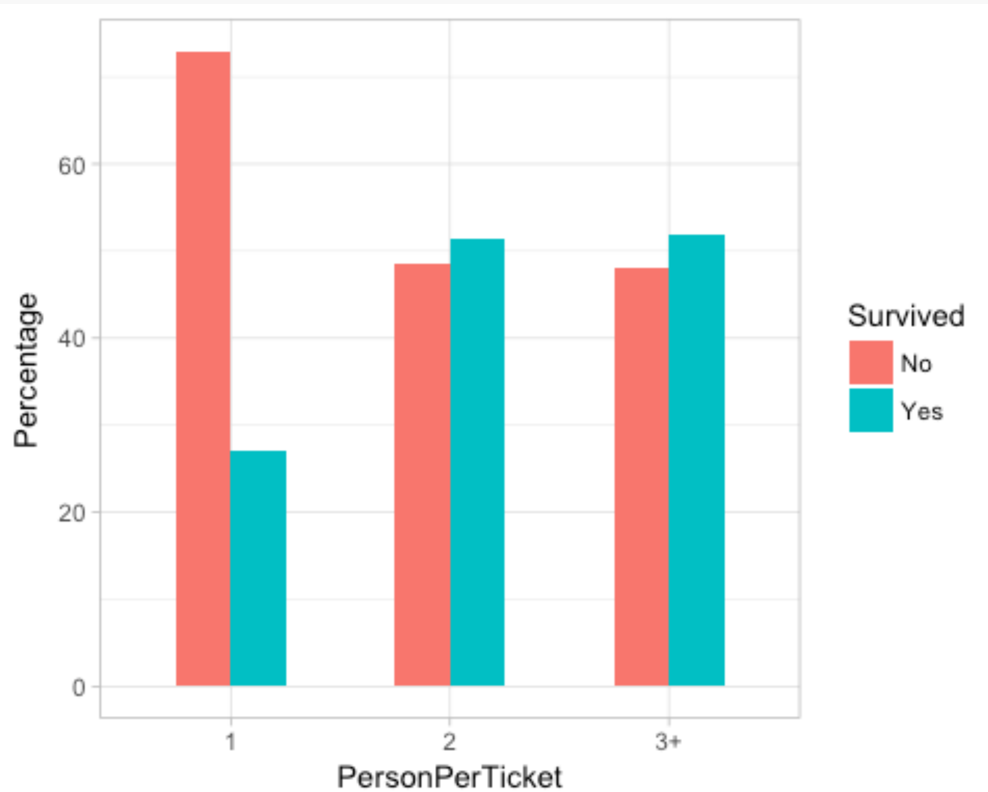
In the table() f. we used the useNA argument to restrict the computations to only those observations where the Survived variable is not NA (that is, observations are from the training set).

Transform the table into a data frame (required for plotting):

```r
tcount.surv.df <- as.data.frame(tcount.surv.tbl)
tcount.surv.df
```

```
##   PersonPerTicket Survived      Freq
## 1               1       No 0.7297297
## 2               2       No 0.4861878
## 3              3+       No 0.4803493
## 4               1      Yes 0.2702703
## 5               2      Yes 0.5138122
## 6              3+      Yes 0.5196507
```

```r
ggplot(data = tcount.surv.df,
       mapping = aes(x = PersonPerTicket, y = Freq*100, fill=Survived)) +
  geom_col(width = 0.5, position = "dodge") +
  theme_light() +
  ylab("Percentage")
```



It seems that this variable can, indeed, be worth including in a prediction model.

Save the augmented data set

Finally, let's split the augmented data set again into training and test parts and save them. Training observations are those that have the Survived value set; test observations have NA value for the Survived attribute

```r
ttrain.new <- titanic.all[!is.na(titanic.all$Survived),]
ttest.new <- titanic.all[is.na(titanic.all$Survived),]
```

```
saveRDS(ttrain.new, file = "data/titanic/train_new.RData")
saveRDS(ttest.new, file = "data/titanic/test_new.RData")
```