Kaggle Titanic Data Analysis Report

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4/2/2020

Transforming the Kaggle data into data frames

The Kaggle API for command line was used to get the data to start this analysis.

After installing the Kaggle API (Kaggle API 1.5.6), from the comamnd line, following https://www.kaggle.com/docs/api:

```
$ kaggle competitions download -c titanic
    Downloading titanic.zip to /home/pablo/Documents/Winter 2020/ENSF 611/Project/titanic
    0%|                                                  | 0.00/34.1k [00:00<?, ?B/s]
    100%|
```

A new folder called `data/` was created under the project root directory and the file was moved there. The following R command inspects what's in the file without actually decompressing it.

```r
unzip("data/titanic.zip", list = TRUE)
```

```
##                    Name     Length                Date
## 1 gender_submission.csv 4294967295 2019-12-11 02:17:00
## 2              test.csv 4294967295 2019-12-11 02:17:00
## 3             train.csv 4294967295 2019-12-11 02:17:00
```

Then the `.csv` files were extracted, stored in R compressed data format, `.rds`, for back up as invidivual sets of train and test sets, as well as a sample of how data must be submitted for scoring. Data frames were then populated with this data and supplied in memory for the exploratory phase.

```r
create_files <- function (fname,...) {
    try(expr = read.csv(unzip(zipfile = ..., files = c(fname))),silent = TRUE);
}

extract_file_names <- function (names) {
    setNames((unlist(strsplit(apply(names, MARGIN = c(1), function(r) r[1]), " "))), NULL)
}



create_df_from_zip_file <- function(file_name) {
    if(file.exists(file_name)) {
        files_from_kaggle <- unzip(file_name, list = TRUE)
        names <- extract_file_names(files_from_kaggle)
        dfs <- lapply(names, create_files, file_name)
        dfs
    }
}
```

The create a list of three data frames with the Kaggle data for the Titanic data analysis project

```
dfs <- create_df_from_zip_file("data/titanic.zip")
```

```
## Warning in unzip(zipfile = ..., files = c(fname)): error -1 in extracting from
## zip file
```

```
if (dim(dfs[[1]])[2] == 2) { saveRDS(object = dfs[[3]], file = "data/sample_submission.rds")}
if (dim(dfs[[2]])[2] == 11) { saveRDS(object = dfs[[2]], file = "data/test.rds")}
if (dim(dfs[[3]])[2] == 12) { saveRDS(object = dfs[[3]], file = "data/train.rds")}

rm(dfs)
rm('create_files')
rm('extract_file_names')
rm('create_df_from_zip_file')
```

Now the data frames are generated from the backups.

```
titanic_train <- readRDS("data/train.rds")
titanic_test <- readRDS("data/test.rds")
out1<-paste0("Train data is ", dim(titanic_train)[1], " rows by ", dim(titanic_train)[2], " columns")
out2<-paste0("Test data is ", dim(titanic_test)[1], " rows by ", dim(titanic_test)[2], " columns")
print(out1)
```

```
## [1] "Train data is 596 rows by 12 columns"
```

```
print(out2)
```

```
## [1] "Test data is 418 rows by 11 columns"
```

This is the preallocated train/test split given by Kaggle.

Data cleaning

Clean up all rows with mising values.

```
titanic_train_clean <- titanic_train[complete.cases(titanic_train), ]
dim(titanic_train_clean)
```

```
## [1] 471  12
```

```
titanic_test_clean <- titanic_test[complete.cases(titanic_test), ]
dim(titanic_test_clean)
```

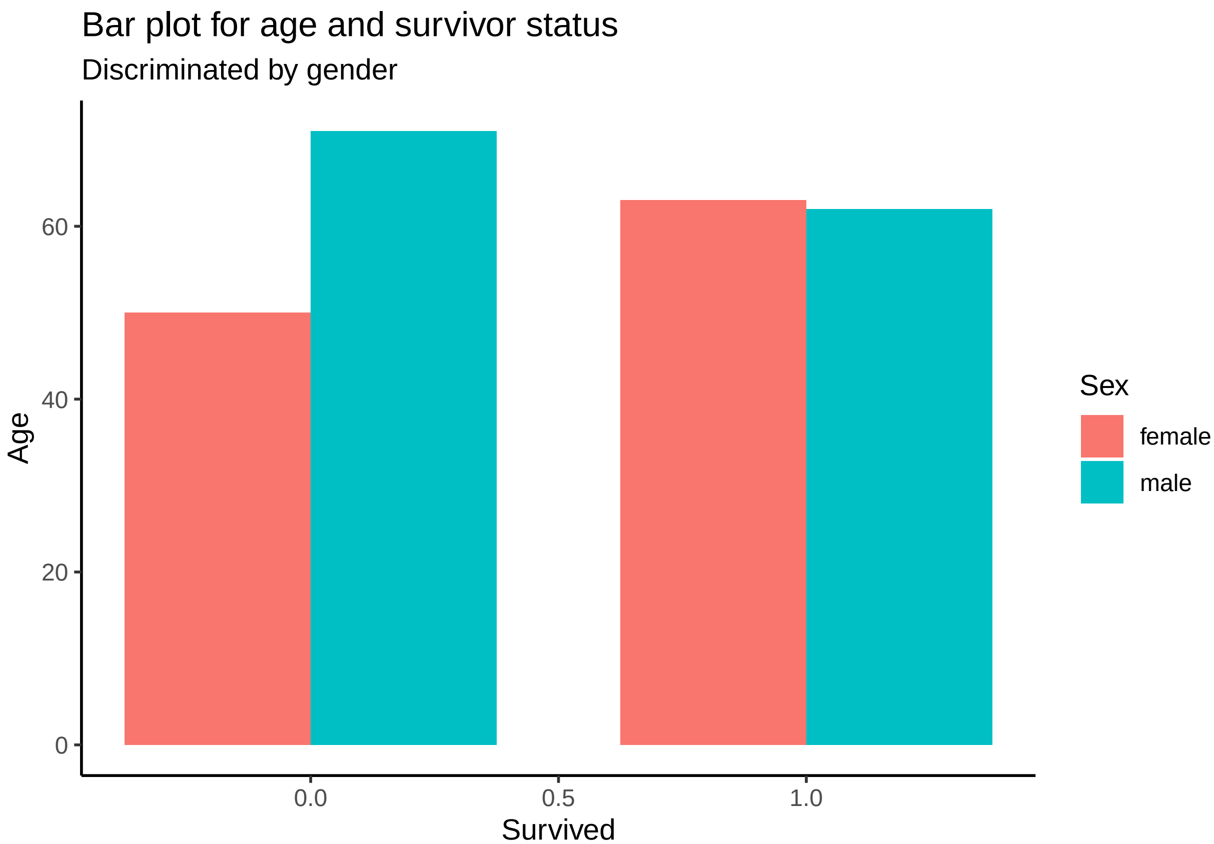
```
## [1] 331  11
```

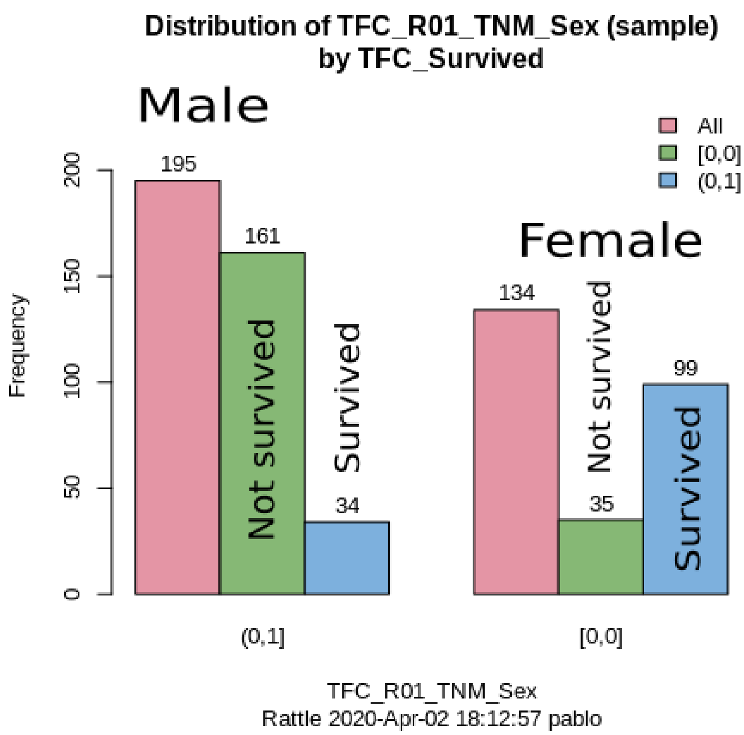
As a result of removing all records with any `NA` there was a reduction of 125 records in the train set. Similarly, 87 records were removed from the test data set.

Data exploration

Using the R package `rattle` (Williams 2011), some basic statistics were observed.

The actual proportion of passengers that died according to (Wikipedia contributors 2020) was 67.75, the training data has a casualty ratio of 59.57. The distribution by age and the fraction by gender can be seen int he two plots below.



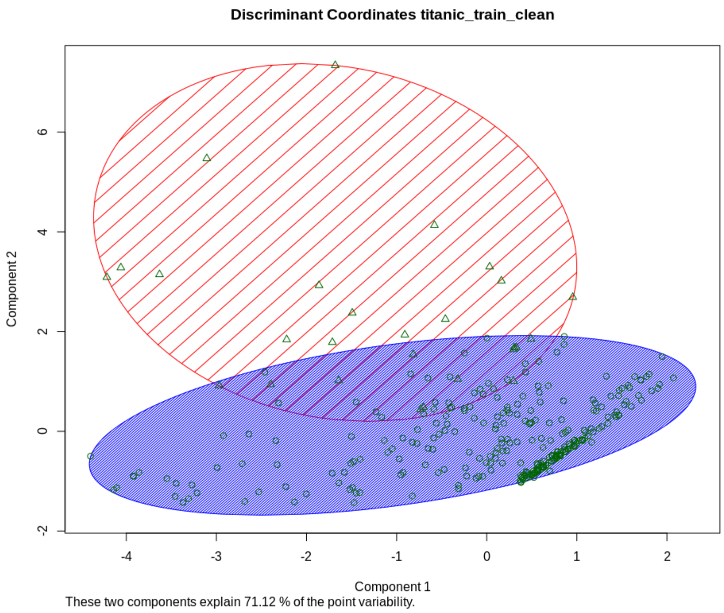


A clustering analysis with KMeans and two clusters, one with 302 passengers and a second one with 27. Between the two they explain 71.12% of the point variability of the data. The cluster centers are:

```
    Age      SibSp      Parch       Fare
```

1 30.11947 0.5430464 0.3874172 23.81876 2 33.10815 0.7037037 1.0740741 174.72669

Their plot appear below:



These clusters may indicate that there are data does naturally separate in two groups but the meaning of these clusters isn't very clear. Another analysis shows that the number of clusters stabilizes after approximately 5.

Exploration with a generalized linear model

Using the `rattle` package a quick generalize linear model with the `probit` function showed how the statistically significant coefficients were those of the variables:

```
1. `SibSp`: number of siblings and/or spouse
2. `Age`
3. `TFC_Pclass(1,2]`: first class passengers
4. `TFC_Pclass(2,3] : second class passengers
5. `TFC_R01_TNM_Sex(0,1]`: the gender of the passenger, 0 for female, 1 for male
```

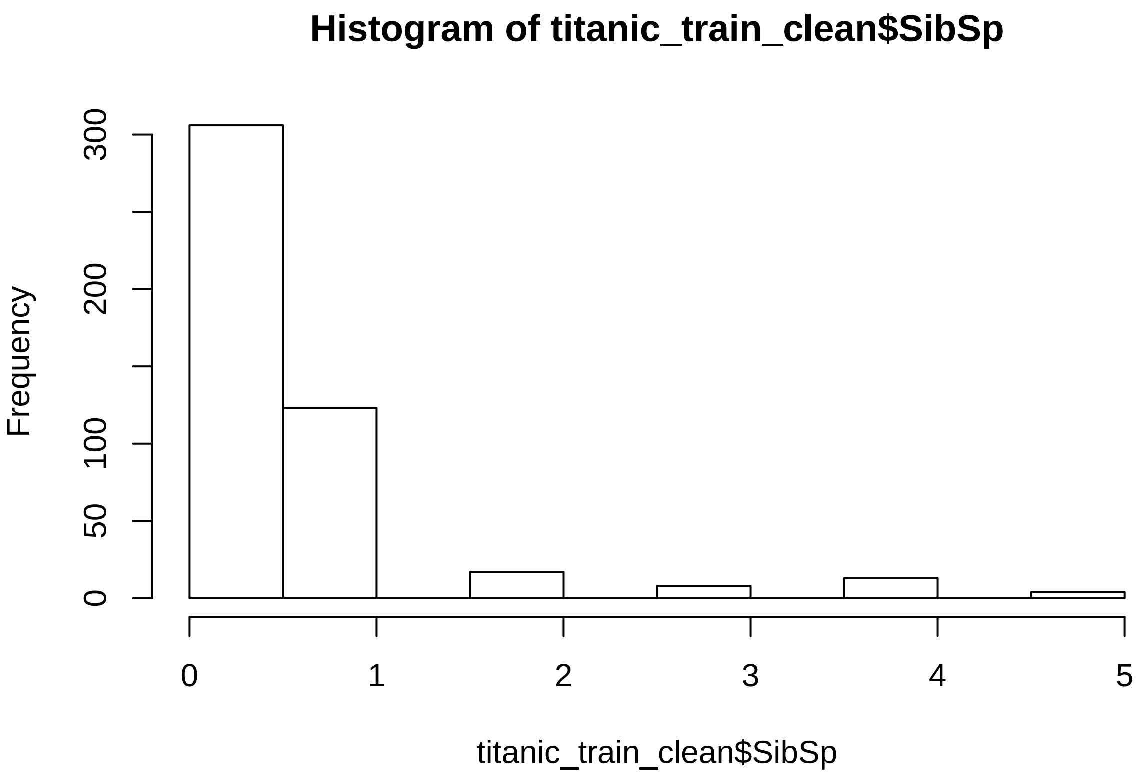
```
Summary of the Probit Regression model (built using glm):

Call:
glm(formula = TFC_Survived ~ ., family = binomial(link = "probit"),
    data = crs$dataset[crs$train, c(crs$input, crs$target)])

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.2590  -0.7393  -0.3666   0.5816   2.5985

Coefficients:
                        Estimate  Std. Error z value   Pr(>|z|)
(Intercept)            5.5917216 146.9544573   0.038    0.96965
Age                   -0.0199283   0.0067510  -2.952    0.00316 **
SibSp                 -0.2234184   0.1020782  -2.189    0.02862 *
Parch                 -0.0370586   0.1216786  -0.305    0.76070
```

```
Fare                   -0.0001906   0.0024013  -0.079    0.93672
EmbarkedC              -3.3562126 146.9542888  -0.023    0.98178
EmbarkedQ              -2.8990208 146.9549656  -0.020    0.98426
EmbarkedS              -3.3481248 146.9542837  -0.023    0.98182
TFC_Pclass(1,2]        -0.6508577   0.2950677  -2.206    0.02740 *
TFC_Pclass(2,3]        -1.3804582   0.3034635  -4.549 0.00000539 ***
TFC_R01_TNM_Sex(0,1]   -1.6522252   0.1792327  -9.218    < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Numerical variables

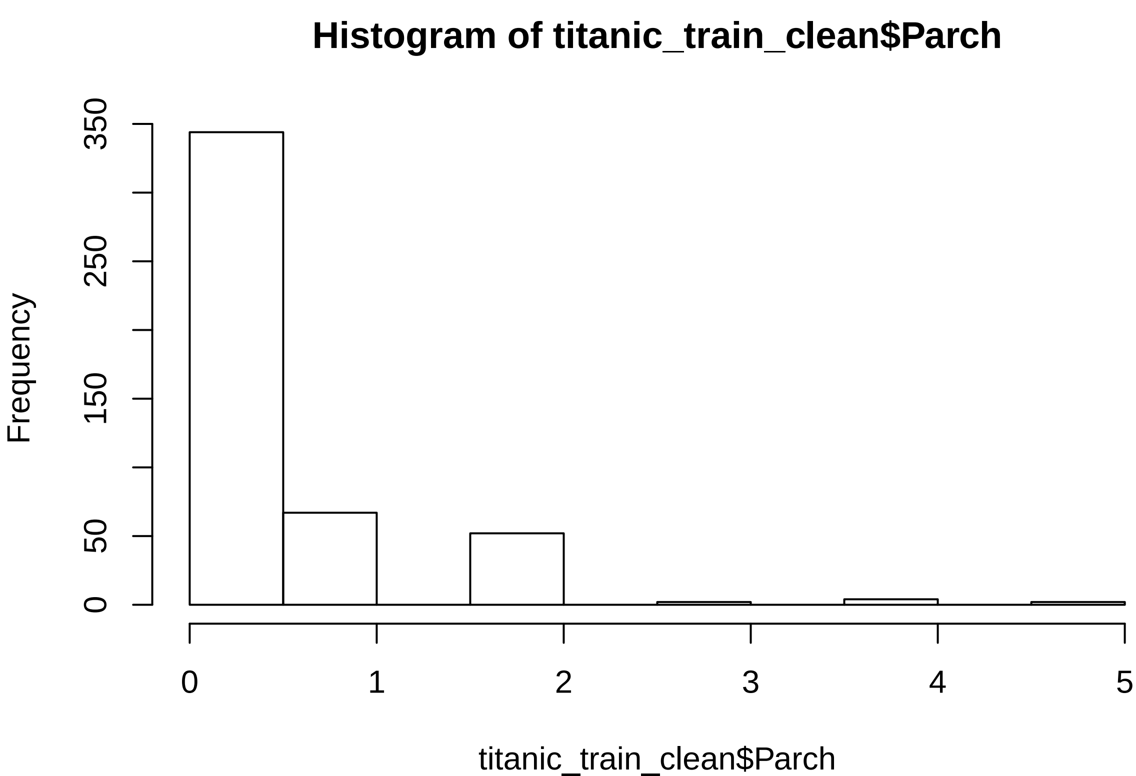
The input numerical variables are `Age`, `SibSp`, `Parch`, and `Fare`. The variables `SibSp`, the number od siblings and spouses, can be treated as acontinuous value between 0 and the max observed in the data, 5.

The variable `Age` has a distribution that is centered around central values so a min max scaler could be appropriate to aid some of the predictors deal with different scales among variables.



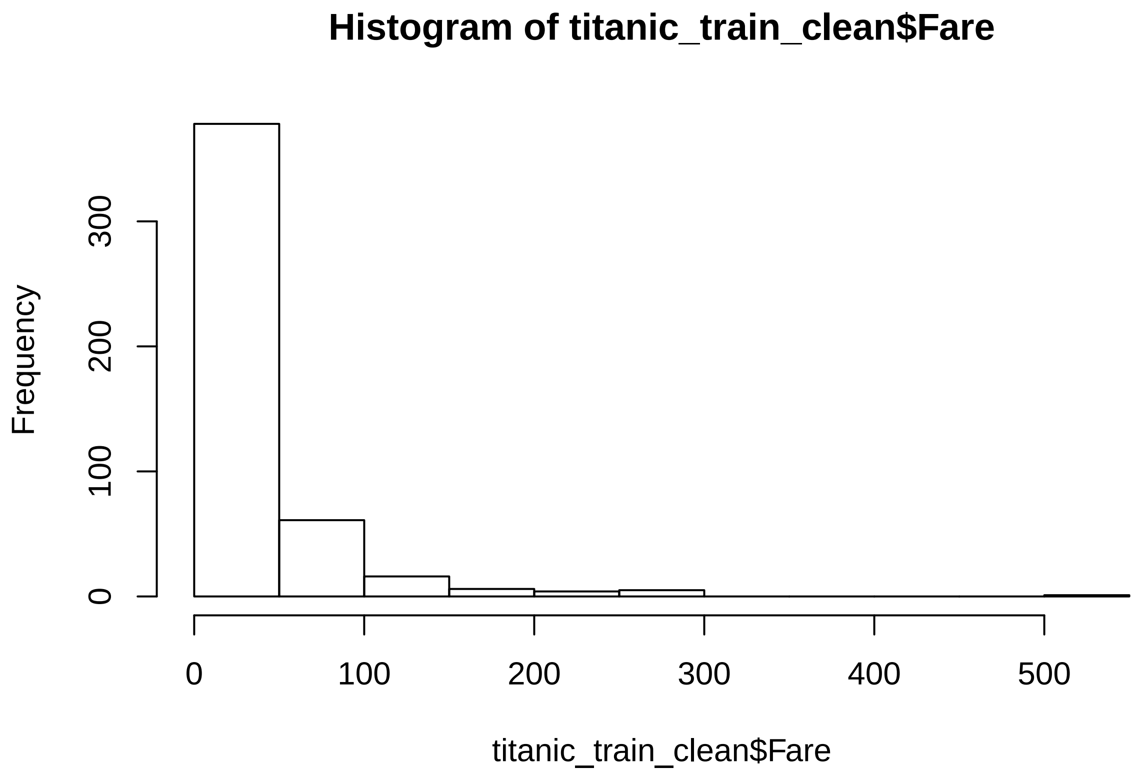
It also shows high values for skewness 2.265915 and kurtosis 5.217676. This indicates that this variable needs to be scaled with a standard scaler.

`Parch`, the number of parents and children accompanying the passenger, can also be treated as a continuous independent variable.



As the histogram shows and the values of skewness 1.836532 kurtosis 3.152783 indicate it should also be normalized with a standard scaler.

Finaly `Fare` shows a very skewed distribution towards the low values. This is confirmed by the statistics of the variable: a mean of 36.20, a median of 16.70, a standard deviation of 52.52, skeness 4.050455, and kurtosis 24.262948. Therefore a standard scaler is th recommended preprocessing.



Categorical variables

The input categorical variables are `Sex` for gender Female (0) or Male (1), `Pclass` for the passenger category assigned by the shipping company, 1st, 2nd, or 3rd, en encoded as 1, 2 or 3, and treated as a continuous variable here that will be normalized with min max.

The dependent or predicted variable is `Survived` that takes 196 (59.6%) negative outcomes represented as 0 and 133 (40.4%) positive results represented as 1.

Preprocessing

Only the numerical variables identified in the previous section were normalized. The `preObj` should be used to train and predict with the test data set for consistency.

```
library(caret)
```

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

```
preObj <- preProcess(titanic_train_clean[,c("Age","SibSp","Parch","Fare")], method = c("center","scale"
# sibsbstd <- predict(preObj, titanic_train_clean[,c(6,7,8,9)])$SibSp
titanic_train_transformed <- predict(preObj, titanic_train_clean[,c("Age","SibSp","Parch","Fare")])
titanic_train_scaled <- cbind(titanic_train_clean[,c("PassengerId","Pclass","Sex","Embarked", "Survived
titanic_train_scaled$Survived <- as.factor(titanic_train_scaled$Survived)
titanic_train_scaled$Pclass <- as.factor(titanic_train_scaled$Pclass)
```

The variables `Name` and `Cabin` were dropped from this data frame because they hold very little meaning for prediction.

Model building

Logistic regression

```
default_glm_mod = train(form = Survived ~ .,
                        data = titanic_train_scaled,
                        trControl = trainControl(method = "cv", number = 5),
                        method = "glm",
                        family = "binomial")
```

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

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

```
default_glm_mod
```

```
## Generalized Linear Model
##
## 471 samples
##   8 predictor
##   2 classes: '0', '1'
##
## No pre-processing
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 376, 377, 377, 377, 377
## Resampling results:
##
##   Accuracy   Kappa
##   0.7875924  0.5556794
```

Decision tree

Random forests

References

Wikipedia contributors. 2020. "Passengers of the Rms Titanic." April 1, 2020. https://en.wikipedia.org/wiki/Passengers_of_the_RMS_Titanic.

Williams, Graham. 2011. *Data Mining with Rattle and R: The Art of Excavating Data for Knowledge Discovery*. Use R. New York, NY: Springer New York.