1. Analiza braków danych
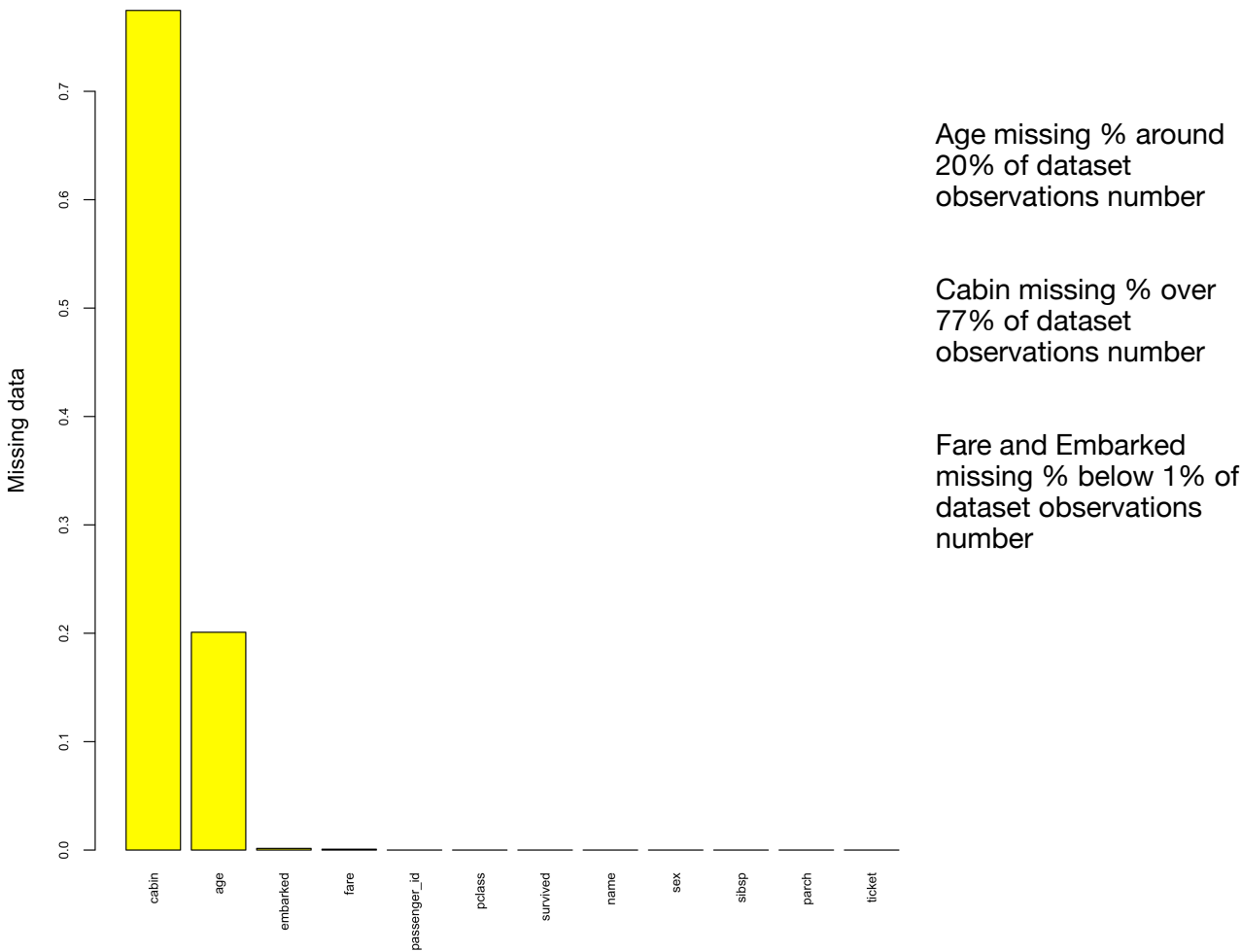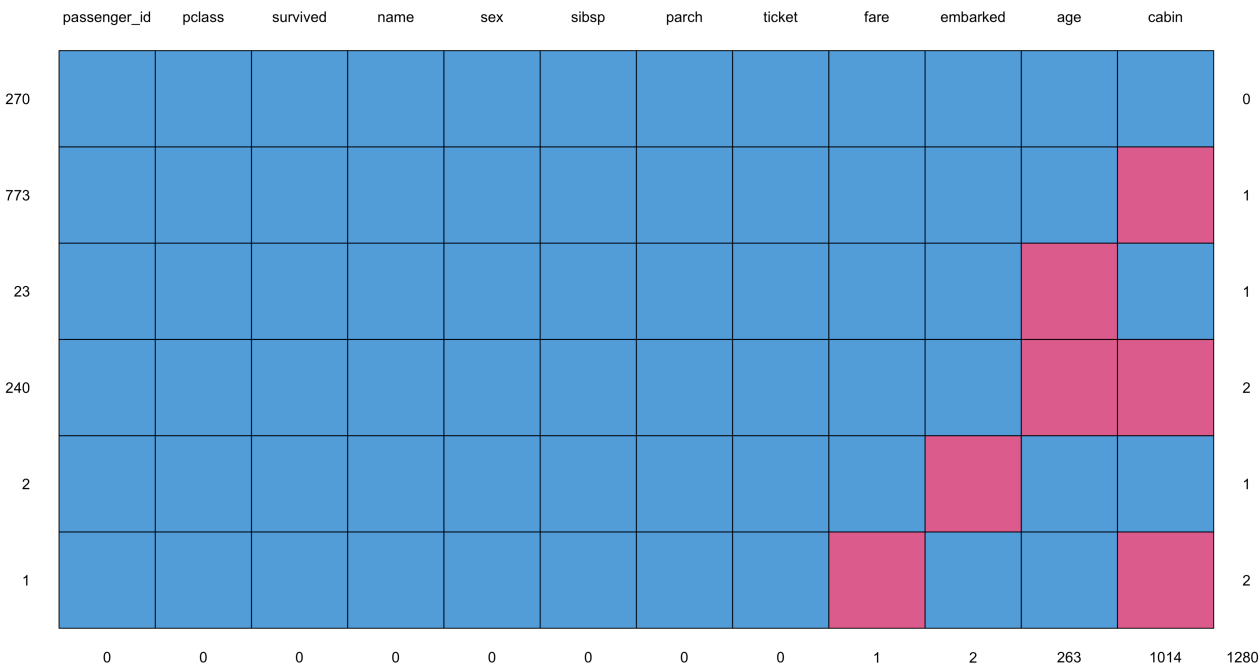
#age missing 263 times
#fare missing once
#cabin missing 1014 times
#embarked missing twice

Age missing % around 20% of dataset observations number

Cabin missing % over 77% of dataset observations number

Fare and Embarked missing % below 1% of dataset observations number

1.2 Analiza struktury dla zmiennych: sex, pclass, embarked

SEX

- no missing values
- Male : 843 | 64,4 %
- Female : 466 | 35,6 %

PCLASS

- no missing values
- 1st class : 709 people | 54,16%
- 2nd class : 277 people | 21,16%
- 3rd class : 323 people | 24,68%

EMBARKED

- 2 values missing
- Southampton : 914 | 69,82%
- Queenstown : 123 | 9,4%
- Cherbourg : 270 | 20,63%
- NA - Unspecified : 2 | 0,15%

2. Częstości dla zmiennej objaśnianej survived

SURVIVED: 500 | 38,2%
NOT SURVIVED: 809 | 61,8%

3. Braki danych w poszczególnych kolumnach

- w punkcie 1

4. Statystyki opisowe dla zmiennych age i fare

AGE

#not applying imputations -> 263 values missing
#min - 0.1667 -> Youngest person was a baby younger than a year
#max - 80.00 -> Oldest person was 80 years old
#avg - 29.88 -> The average of age among titanic passengers was 29.88 years
#med - 28.00 -> The median of age among titanic passengers was 28.00 years
#Q1 - 21.00 -> 25% of titanic passengers were in the age <= 21.00 years and 75% of passengers were in the age >= 21.00
#Q3 - 39.00 -> 75% of titanic passengers were in the age <= 39.00 years and 25% of passengers were in the age >= 39.00

Histogram of titanic passengers' age
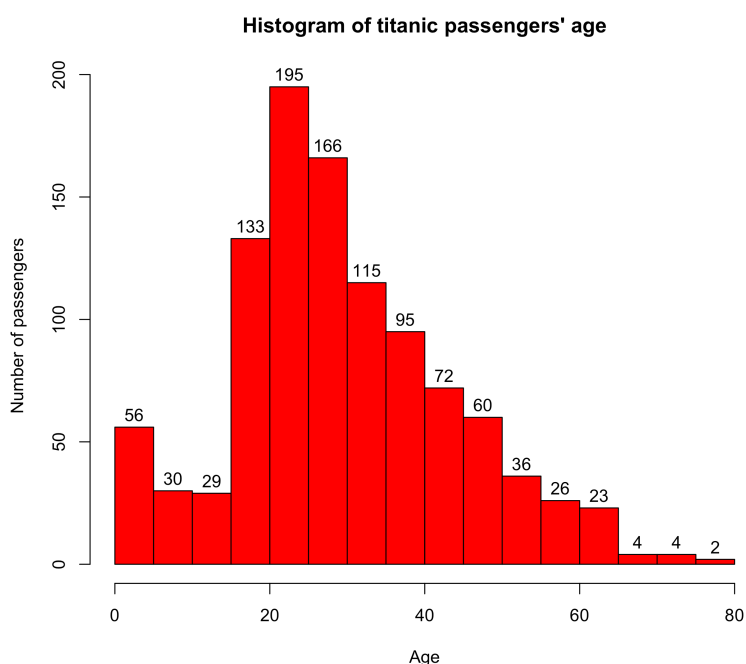
FARE

#not applying imputations -> 1 value missing
#min - 0.000 -> We can quess -> some people were traveling for free (invitation, reward etc.)
#max - 512.329 -> Value of most expensive ticket was 512.32 in unspecified currency
#avg - 33.295 -> The average of ticket prices paid by the passengers was 33.29 in uspecified currency
#med - 14.454 -> The median value of ticket price paid by the passengers was 14.45 in unspecified currency
#Q1 - 7.896 -> 25% of titanic passengers had to pay a price <= 7.89 and 75% of them had to pay >= 7.89
#Q3 - 31.275 -> 75% of titanic passengers had to pay a price <= 31.27 and 25% of them had to pay >= 31.27

Histogram of titanic ticket prices
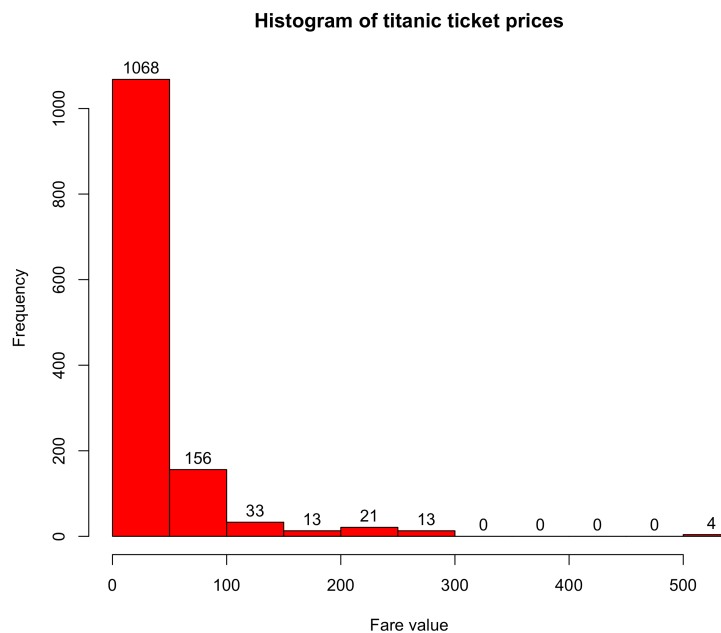
5. Wykres rozrzutu age vs fare + badanie korelacji

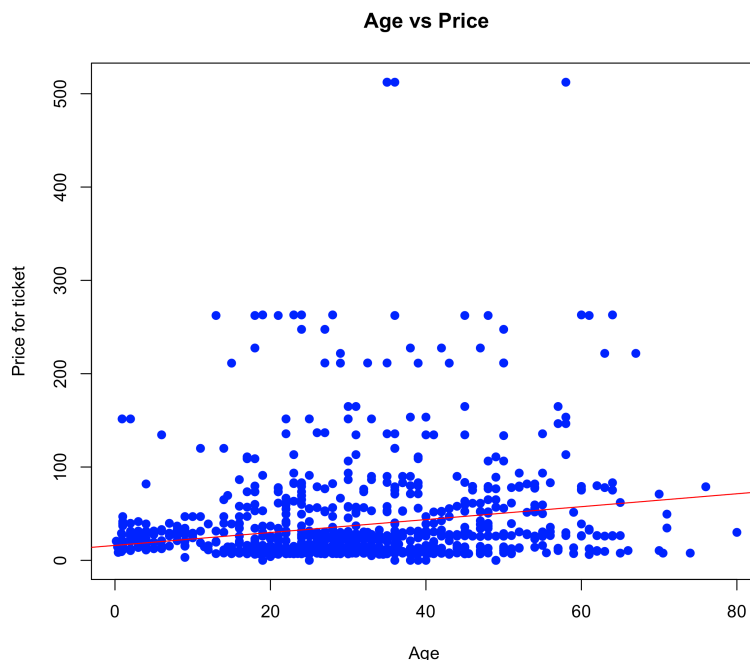#H0: correlation = 0
#H1: correlation != 0
#p-val -> <0.05
#=> H1 -> cor = 0.1787394 -> weak positive correlation.
#Indicates a weak linear relationship between the variables -> the age does not define the price of the ticket

Age vs Price

6. Podział na training/test set => w kodzie

7. Porównanie struktury survived w obu zbiorach

TRAINING SET:
#0 - not survived - 55 people | 30,56%
#1 - survived - 125 people | 69,44%

TEST SET:
#0 - not survived - 35 people | 38,89%
#1 - survived - 55 people | 61,11%

8. Zastąpienie braków dla zmiennej objaśniającej embarked => w kodzie

9 i 10. Braki danych dla zmiennej objaśniającej age => w kodzie

A -> uzupełniono wartością średnią całego zbioru
B -> Wykorzystanie metody imputacji HMISC z opcją median

11 & 12 Oszacowanie modelu regresji logistycznej GLM z funkcją wiążącą logit

Według współczynnika istotności -> zmienne age, sex, pclass są istotne do dalszej analizy

#model formula
#hasSurvived = 3.496 - 0.03(age) - 2.44(the patient is male) - 1.0596(travelingBy2ndClass) -
1.879115(travelingBy3rdClass) - 0.595(GotOnBoarnInPortQ) -0.4122(GotOnBoardInPortS)

#Along with increase of age by 1 year the chances of survival are decreasing by 4.101 times
ceteris paribus
#Changes of survival for men were 13.512 times smaller than for female ceteris paribus
#Chances of survival for passengers traveling in the second class were 3.930 times smaller than
for passengers traveling in first class ceteris paribus
#Chances of survival for passengers traveling in third class were 7,603 times smaller than for
passengers traveling first class ceteris paribus

13. Oszacować random forest => w kodzie

#results
#OOB estimate of error rate: 20.62%
#Confusion matrix:
0   1 class.error
#0 482 45 0.08538899
#1 135 211 0.39017341

14. Interpretacja Random Forest

//Potrzebuję nauczyć się w jaki sposób wyciągać wartość AUC => przyda się do obliczania
współczynnika Ginniego mówiącego o idealności konkretnego modelu

#error misclasified to total observations - 19.72%
#accuracy = 1-OOB => 80,28% => it's quite ok
#sensitivity => TP/(TP+FN) => 0.7811 ~ 78% success in predicting the real survived cases ->
Quite good
SENS_RandomForest <- 482/(482+135)
SENS_RandomForest
#specificity => TN/(FP+TN) => 0.82421 ~ 82% -> success in predicting real not survived cases =>
Quite good
SPEC_RandomForest <- 211/(45+211)
SPEC_RandomForest

Model jest dość dobry

15. Porównanie modelu GLM + Random Forest

#Będę mógł przejść do tego dopiero w momencie, kiedy uda mi się dokończyć pełne statystyki
dla GLM i Random Forest