Assignment 2

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Data context

This dataset contains information about customers. Demographic data,

Data exploration

```
dim(df)
```

```
## [1] 7043   21
```

```
names(df)
```

```
##  [1] "customerID"       "gender"           "SeniorCitizen"    "Partner"
##  [5] "Dependents"       "tenure"           "PhoneService"     "MultipleLines"
##  [9] "InternetService"  "OnlineSecurity"   "OnlineBackup"     "DeviceProtection"
## [13] "TechSupport"      "StreamingTV"      "StreamingMovies"  "Contract"
## [17] "PaperlessBilling" "PaymentMethod"    "MonthlyCharges"   "TotalCharges"
## [21] "Churn"
```

```
#str(df)
#summary(df)
```

Variable Description

In total, we have 21 variables related to demographic, services, and accountant data. One is the ID, three are numerical variables, and 17 are categorical (? binary) variables. We will conduct a descriptive analysis and a data quality report for each variable, considering aspects such as the number of missing values, errors, and the distribution or balance of the variable…

1. customerID

Demographic data

2. gender Is a binary variable (female/male).

```
sum(is.na(df$gender))
```

```
## [1] 0
```

```
table(df$gender)
```

```
##
## Female   Male
##   3488   3555
```

3. SeniorCitizen It is a binary variable. Levels: 1(=yes)/0(=no).

```
sum(is.na(df$SeniorCitizen))
```

```
## [1] 0
```

```
table(df$SeniorCitizen)
```

```
##
##    0    1
## 5901 1142
```

4. Partner It is a binary variable. Levels: Yes/No.

```
sum(is.na(df$Partner))
```

```
## [1] 0
```

```
table(df$Partner)
```

```
##
##   No  Yes
## 3641 3402
```

5. Dependents It is a binary variable. Levels: Yes/No.

```
sum(is.na(df$Dependents))
```

```
## [1] 0
```

```
table(df$Dependents)
```

```
##
##   No  Yes
## 4933 2110
```

```
#plots
par(mfrow = c(2, 2))
barplot(table(df$gender), main = "Distribution of gender",xlab = "Gender",col = "skyblue")
barplot(table(df$SeniorCitizen), main = "Distribution of SeniorCitizen",xlab = "SeniorCitizen",col = "sl
barplot(table(df$Partner), main = "Distribution of Partner",xlab = "Partner",col = "skyblue")
barplot(table(df$Dependents), main = "Distribution of Dependents",xlab = "Dependents",col = "skyblue")
```

Services of the costumer data

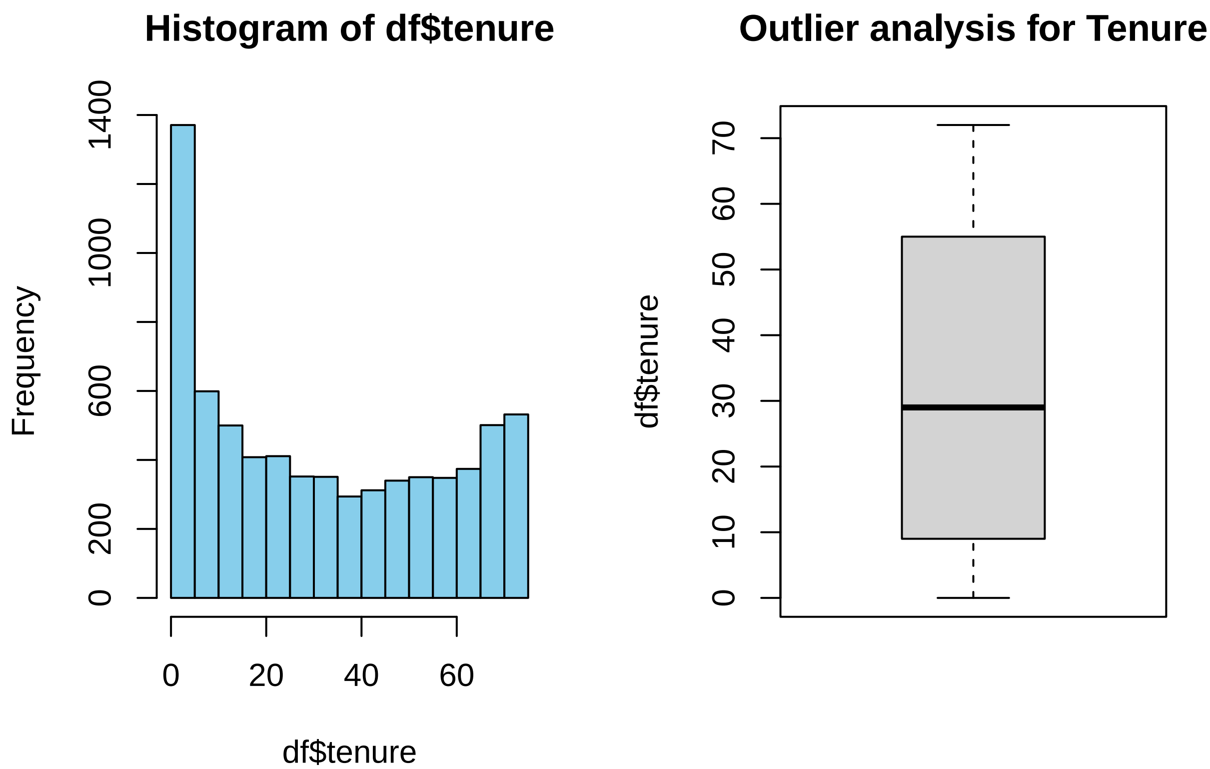
Services that each customer has signed up for:

6. tenure It is a numerical variable that indicates the duration, in months, that the customer has stayed with the company. We shall explore the statistics of the variable and look for the *outliers*

```
summary(df$tenure)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    0.00    9.00   29.00   32.37   55.00   72.00
```

```
par(mfrow = c(1, 2))
hist(df$tenure,breaks=20, col="skyblue")
Boxplot(df$tenure, main="Outlier analysis for Tenure")
```




```
par(mfrow = c(1, 1))
sm_t <- summary(df$tenure)
iqr_t <- sm_t["3rd Qu."] - sm_t["1st Qu."]
# Mild Outliers
mild_ub_t <- sm_t["3rd Qu."] + 1.5 * iqr_t
mild_lb_t <- sm_t["1st Qu."] - 1.5 * iqr_t
length(which(df$tenure > mild_ub_t | df$tenure < mild_lb_t)) # number of mild outliers
```

```
## [1] 0
```

```
# Severe Outliers
severe_ub_t <- sm_t["3rd Qu."] + 3 * iqr_t
severe_lb_t <- sm_t["1st Qu."] - 3 * iqr_t
length(which(df$tenure > severe_ub_t | df$tenure < severe_lb_t)) # number of severe outliers
```

```
## [1] 0
```

There are *no mild nor severe outliers* in Tenure.

7. PhoneService It is a binary variable. Levels: Yes/No.

```
sum(is.na(df$PhoneService))
```

```
## [1] 0
```

```
table(df$PhoneService)
```

```
##
##   No  Yes
##  682 6361
```

8. MultipleLines Categorical variable with 3 levels, No/No phone service/Yes.

```
sum(is.na(df$MultipleLines))
```

```
## [1] 0
```

```
table(df$MultipleLines)
```

```
##
##               No No phone service              Yes
##             3390              682             2971
```

Check inconsistencies: - Cannot happen that a costumer has not phoneservice and multiplelines.

```
subset(df, MultipleLines == "Yes" & PhoneService == "No")
```

```
##  [1] customerID       gender           SeniorCitizen    Partner
##  [5] Dependents       tenure           PhoneService     MultipleLines
##  [9] InternetService  OnlineSecurity   OnlineBackup     DeviceProtection
## [13] TechSupport      StreamingTV      StreamingMovies  Contract
## [17] PaperlessBilling PaymentMethod    MonthlyCharges   TotalCharges
## [21] Churn
## <0 rows> (or 0-length row.names)
```

9. InternetService

Categorical variable with 3 levels: DSL/Fiber optic/No.

```
table(df$InternetService)
```

```
##
##         DSL Fiber optic          No
##        2421        3096        1526
```

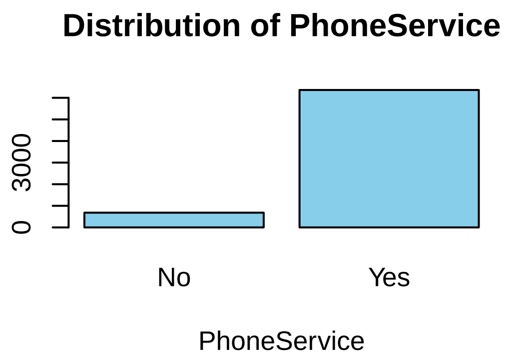
10. OnlineSecurity

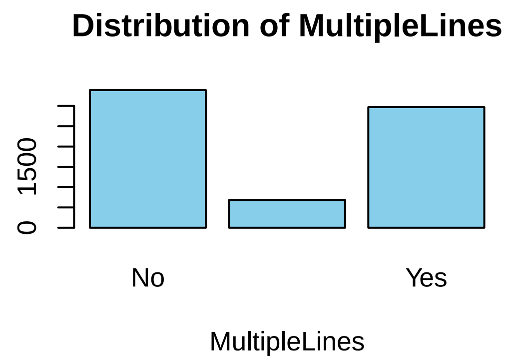
Categorical variable with 3 levels: No/No internet service/Yes

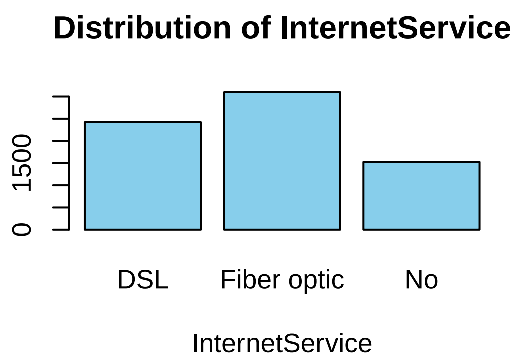
```
table(df$OnlineSecurity)
```

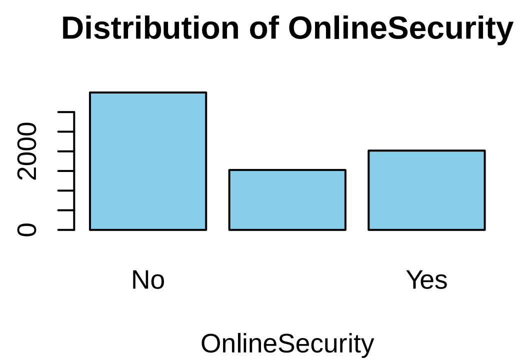
```
##
##                  No No internet service                 Yes
##                3498                1526                2019
```

```
#plots:
par(mfrow = c(2, 2))
barplot(table(df$PhoneService), main = "Distribution of PhoneService",xlab = "PhoneService",col = "skybl
barplot(table(df$MultipleLines), main = "Distribution of MultipleLines",xlab = "MultipleLines",col = "sk
barplot(table(df$InternetService), main = "Distribution of InternetService",xlab = "InternetService",col
barplot(table(df$OnlineSecurity), main = "Distribution of OnlineSecurity",xlab = "OnlineSecurity",col =
```









Check consistency

```
sum(df$InternetService == "No")
```

```
## [1] 1526
```

```
sum(df$OnlineSecurity == "No internet service")
```

```
## [1] 1526
```

```
nrow(subset(df, InternetService == "No" & OnlineSecurity == "No internet service"))
```

```
## [1] 1526
```

11. OnlineBackup Categorical variable with 3 levels: No/No internet service/Yes

```
table(df$OnlineBackup)
```

```
##
##                  No No internet service                 Yes
##                3088                1526                2429
```

```
# Check concistency
sum(df$OnlineBackup == "No internet service") #1526
```

```
## [1] 1526
```

```
sum(df$OnlineSecurity == "No internet service") #1526
```

```
## [1] 1526
```

12. DeviceProtection Categorical variable with 3 levels: No/No internet service/Yes

```r
table(df$DeviceProtection)
```

```
##
##                  No No internet service                 Yes
##                3095                1526                2422
```

```r
# Check concistency
sum(df$OnlineSecurity == "No internet service") #1526
```

```
## [1] 1526
```

```r
sum(df$DeviceProtection == "No internet service") #1526
```

```
## [1] 1526
```

13. TechSupport Categorical variable with 3 levels: No/No internet service/Yes

```r
table(df$TechSupport)
```

```
##
##                  No No internet service                 Yes
##                3473                1526                2044
```

```r
#Check consistency
sum(df$DeviceProtection == "No internet service") #1526
```

```
## [1] 1526
```

```r
sum(df$TechSupport == "No internet service") #1526
```

```
## [1] 1526
```

14. StreamingTV Categorical variable with 3 levels: No/No internet service/Yes

```r
table(df$StreamingTV)
```

```
##
##                  No No internet service                 Yes
##                2810                1526                2707
```

```r
#Check consistency
sum(df$TechSupport == "No internet service") #1526
```

```
## [1] 1526
```

```r
sum(df$StreamingTV == "No internet service") #1526
```

```
## [1] 1526
```

15. StreamingMovies Categorical variable with 3 levels: No/No internet service/Yes

```r
table(df$StreamingMovies)
```

```
##
##                  No No internet service                 Yes
##                2785                1526                2732
```

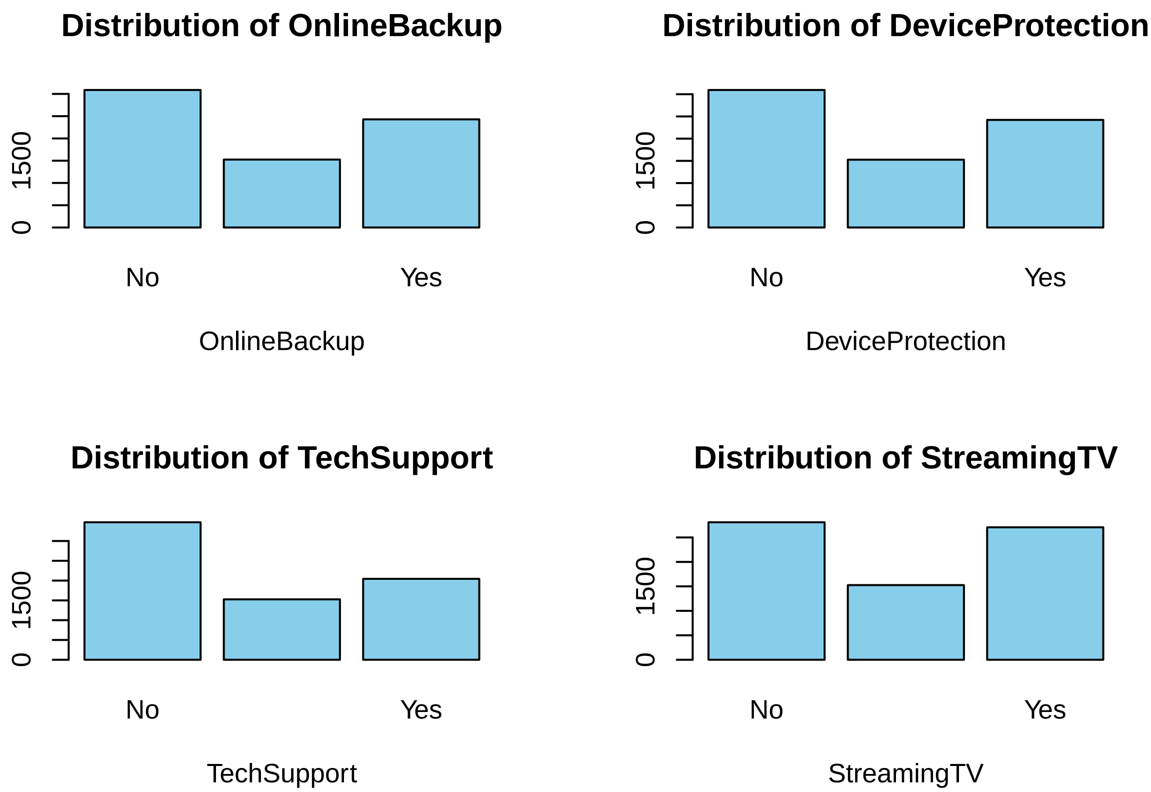
```r
#Check consistency
sum(df$StreamingTV == "No internet service") #1526
```

```
## [1] 1526
```

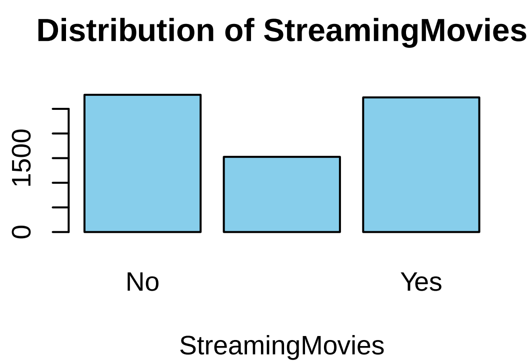
```r
sum(df$StreamingMovies == "No internet service") #1526
```

```
## [1] 1526
```

```r
#plots:
par(mfrow = c(2, 2))
barplot(table(df$OnlineBackup), main = "Distribution of OnlineBackup",xlab = "OnlineBackup",col = "skybl
barplot(table(df$DeviceProtection), main = "Distribution of DeviceProtection",xlab = "DeviceProtection"
barplot(table(df$TechSupport), main = "Distribution of TechSupport",xlab = "TechSupport",col = "skyblue
barplot(table(df$StreamingTV), main = "Distribution of StreamingTV",xlab = "StreamingTV",col = "skyblue
```




```r
barplot(table(df$StreamingMovies), main = "Distribution of StreamingMovies",xlab = "StreamingMovies",col
```



Customer account data

16. Contract Categorical variable with 3 levels: Month-to-month/One year/Two year

```r
table(df$Contract)
```

```
##
## Month-to-month       One year       Two year
##           3875           1473           1695
```

17. PaperlessBilling It is a binary variable. Levels: No/Yes

```r
table(df$PaperlessBilling)
```

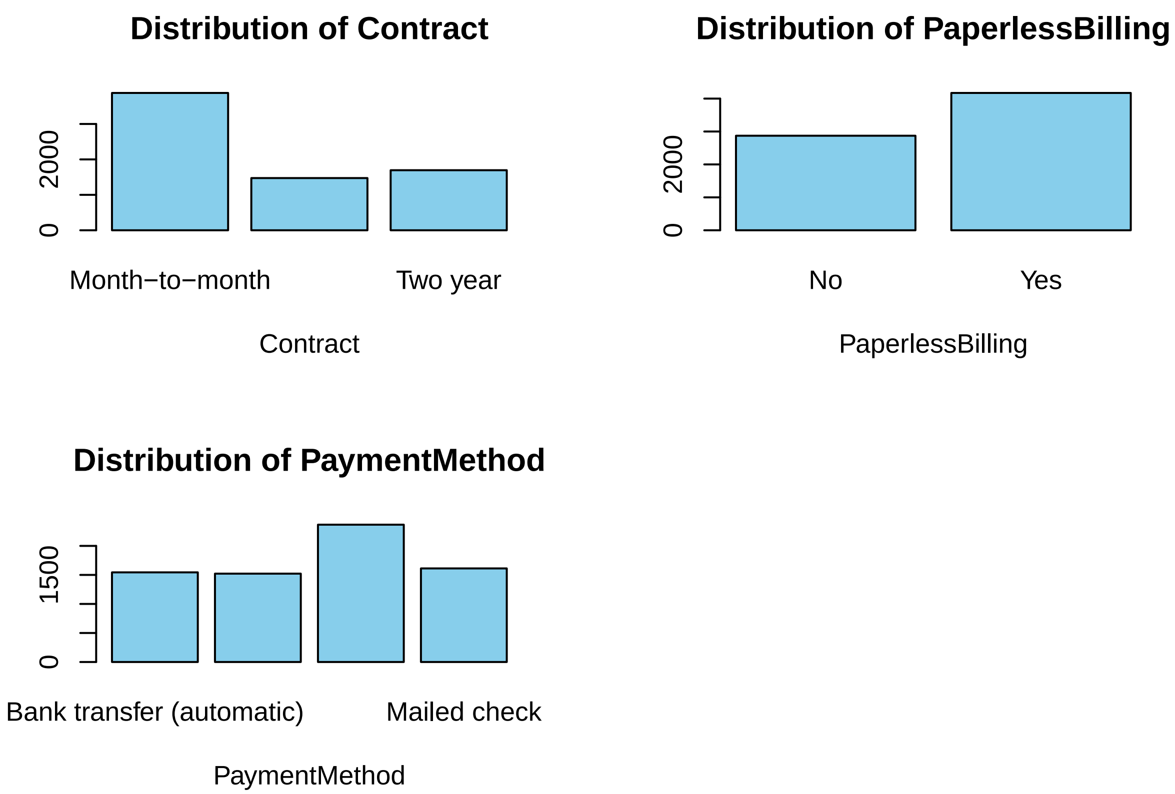
```
##
##   No  Yes
## 2872 4171
```

18. PaymentMethod Categorical variable with 4 levels: Bank transfer (automatic)/Credit card (automatic)/Electronic check/Mailed check

```r
table(df$PaymentMethod)
```

```
##
## Bank transfer (automatic)   Credit card (automatic)          Electronic check
##                      1544                      1522                      2365
##              Mailed check
##                      1612
```

```r
#plots
par(mfrow = c(2, 2))
barplot(table(df$Contract), main = "Distribution of Contract",xlab = "Contract",col = "skyblue")
barplot(table(df$PaperlessBilling), main = "Distribution of PaperlessBilling",xlab = "PaperlessBilling"
barplot(table(df$PaymentMethod), main = "Distribution of PaymentMethod",xlab = "PaymentMethod",col = "sk
```

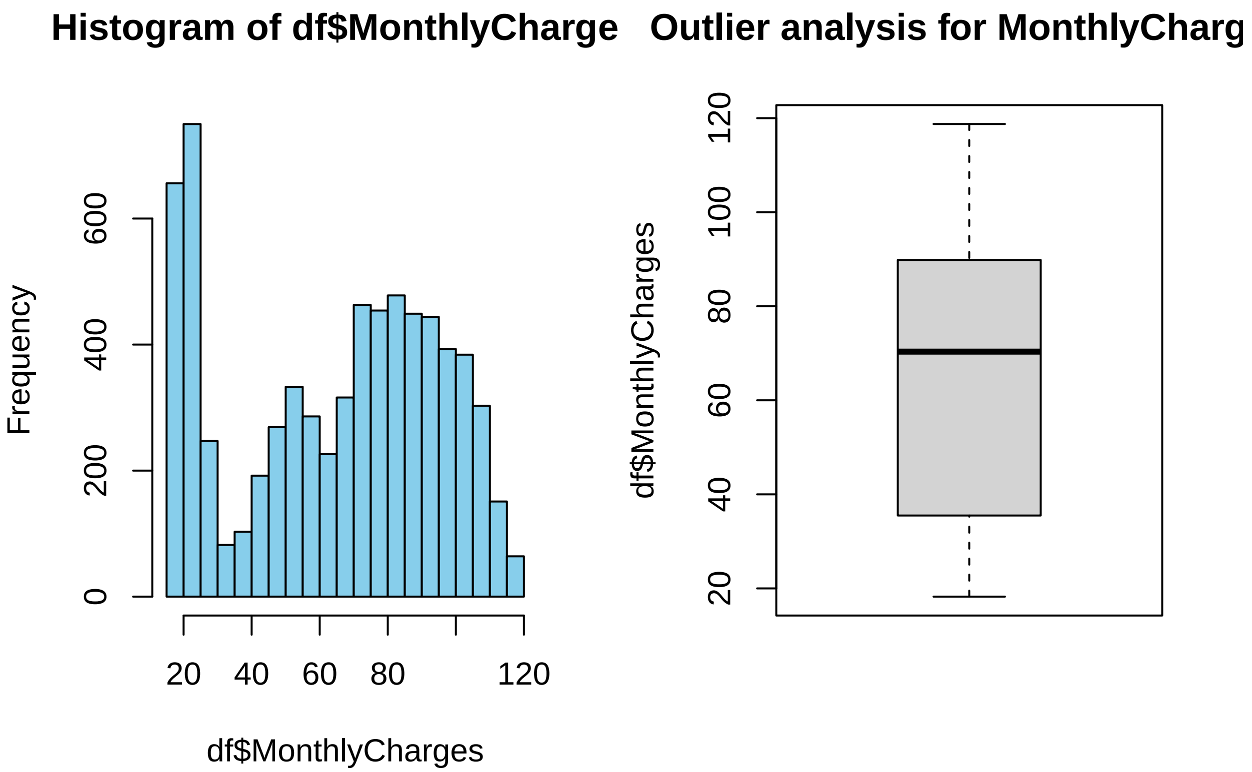


19. MonthlyCharges It is a numerical variable.

```
summary(df$MonthlyCharges)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   18.25   35.50   70.35   64.76   89.85  118.75
```

```
par(mfrow = c(1,2 ))
hist(df$MonthlyCharges,breaks=20,col="skyblue")
Boxplot(df$MonthlyCharges, main="Outlier analysis for MonthlyCharges")
```



Let's look for *outliers*.

```
sm <- summary(df$MonthlyCharges)
iqr <- sm["3rd Qu."] - sm["1st Qu."]
# Mild Outliers
mild_ub <- sm["3rd Qu."] + 1.5 * iqr
mild_lb <- sm["1st Qu."] - 1.5 * iqr
length(which(df$MonthlyCharges > mild_ub | df$MonthlyCharges < mild_lb)) # number of mild outliers
```

```
## [1] 0
```

```
# Severe Outliers
severe_ub <- sm["3rd Qu."] + 3 * iqr
severe_lb <- sm["1st Qu."] - 3 * iqr
length(which(df$MonthlyCharges > severe_ub | df$MonthlyCharges < severe_lb)) # number of severe outlier
```

```
## [1] 0
```

There are no mild nor severe outliers in MonthlyCharges.

20. TotalCharges (numeric) It is a numerical variable.

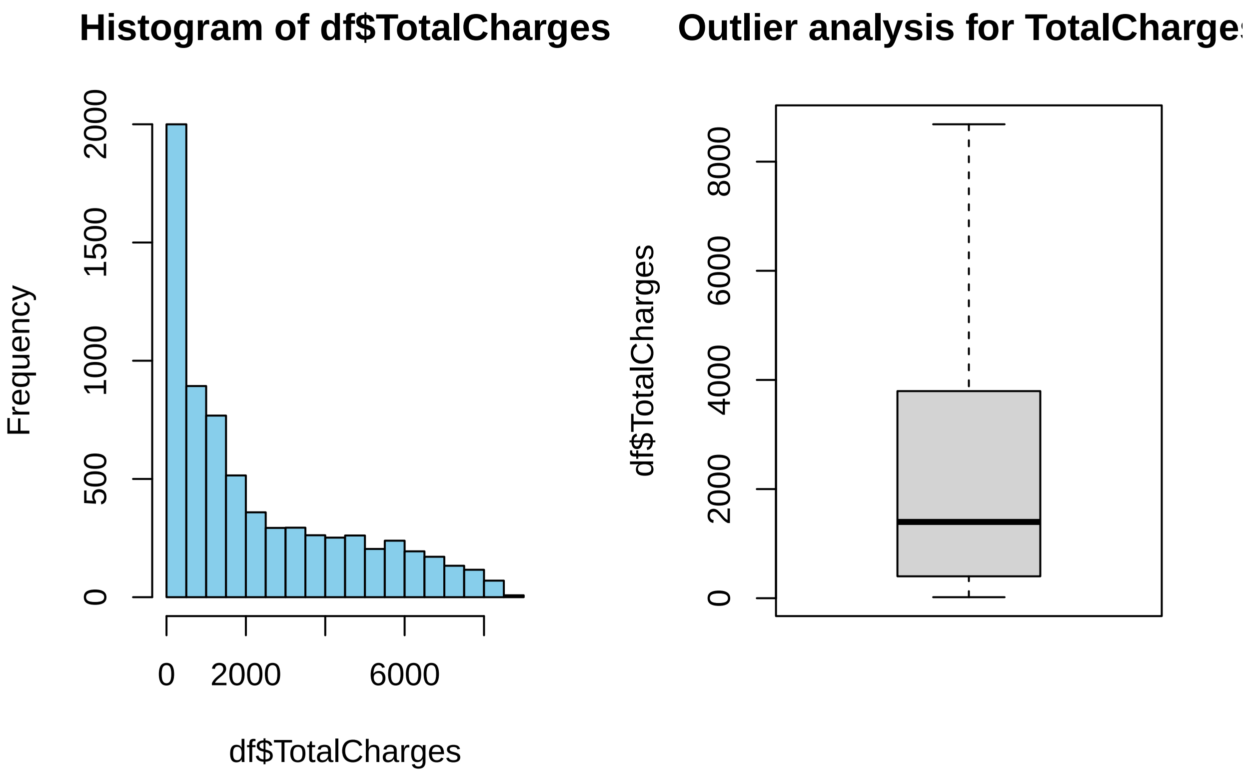
```r
summary(df$TotalCharges)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    18.8   401.4  1397.5  2283.3  3794.7  8684.8      11
```

```r
sum(is.na(df$TotalCharges))
```

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

```r
par(mfrow = c(1, 2))
hist(df$TotalCharges,breaks=20,col="skyblue")
Boxplot(df$TotalCharges, main="Outlier analysis for TotalCharges")
```



Let's look for *outliers*.

```r
sm <- summary(df$TotalCharges)
iqr <- sm["3rd Qu."] - sm["1st Qu."]
# Mild Outliers
mild_ub <- sm["3rd Qu."] + 1.5 * iqr
mild_lb <- sm["1st Qu."] - 1.5 * iqr
length(which(df$TotalCharges > mild_ub | df$TotalCharges < mild_lb)) # number of mild outliers
```

```
## [1] 0
```

```r
# Severe Outliers
severe_ub <- sm["3rd Qu."] + 3 * iqr
severe_lb <- sm["1st Qu."] - 3 * iqr
length(which(df$TotalCharges > severe_ub | df$TotalCharges < severe_lb)) # number of severe outliers
```

```
## [1] 0
```

There are no mild nor severe outliers.

Target:

21. Churn It is the target variable. It is binary, describes whether the customer churned or not (Yes or No).

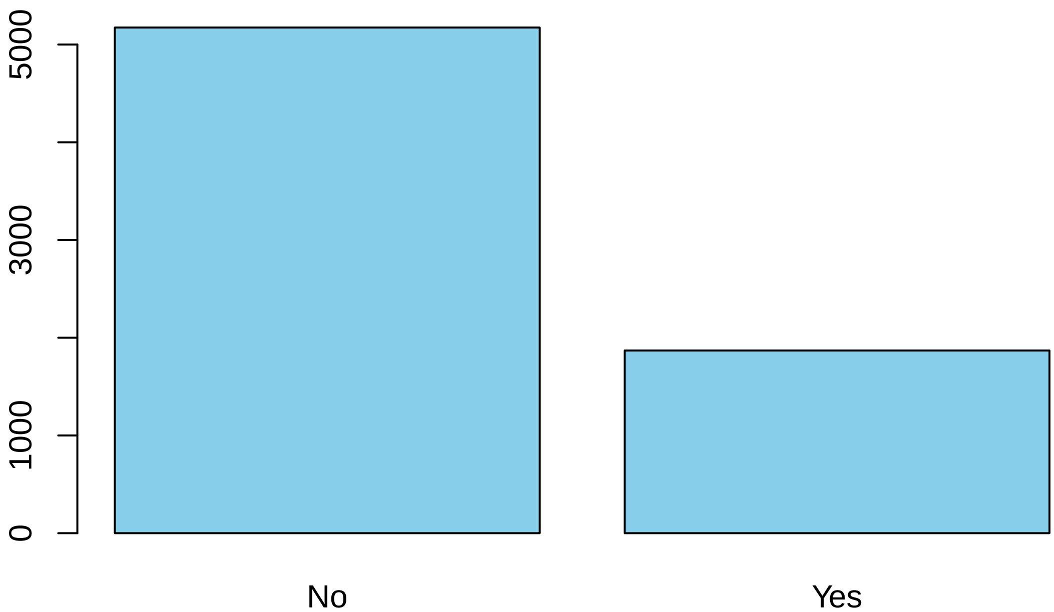
```
table(df$Churn)
```

```
##
##   No  Yes
## 5174 1869
```

```
prop.table(table(df$Churn))
```

```
##
##        No       Yes
## 0.7346301 0.2653699
```

```
barplot(table(df$Churn), col="skyblue")
```



Data preprocessing

Recode variables into correct type

We shall reconvert the type of certain variables that are encoded with wrong type. First, we convert the character variables (except the ID) into factors.

```
char_cols <- which(sapply(df, is.character))
df[, char_cols[-1]]<- lapply(df[, char_cols[-1]], as.factor)
```

Also, we convert the numerical variable SeniorCitizen into a factor.

```
df$SeniorCitizen<- factor(df$SeniorCitizen)
```

Data imputation

```
summary(is.na(df))
```

```
##  customerID         gender         SeniorCitizen    Partner
```

```
##  Mode :logical   Mode :logical   Mode :logical   Mode :logical
##  FALSE:7043      FALSE:7043      FALSE:7043      FALSE:7043
##
##  Dependents        tenure        PhoneService    MultipleLines
##  Mode :logical   Mode :logical   Mode :logical   Mode :logical
##  FALSE:7043      FALSE:7043      FALSE:7043      FALSE:7043
##
##  InternetService OnlineSecurity  OnlineBackup    DeviceProtection
##  Mode :logical   Mode :logical   Mode :logical   Mode :logical
##  FALSE:7043      FALSE:7043      FALSE:7043      FALSE:7043
##
##  TechSupport     StreamingTV     StreamingMovies  Contract
##  Mode :logical   Mode :logical   Mode :logical   Mode :logical
##  FALSE:7043      FALSE:7043      FALSE:7043      FALSE:7043
##
##  PaperlessBilling PaymentMethod   MonthlyCharges  TotalCharges
##  Mode :logical    Mode :logical   Mode :logical   Mode :logical
##  FALSE:7043       FALSE:7043      FALSE:7043      FALSE:7032
##                                                   TRUE :11
##    Churn
##  Mode :logical
##  FALSE:7043
##
```

Only the variable TotalCharges has NA's.

The missing data corresponds to the individuals that have not payed yet the charges of the current month, we can guess that are new clients of the company.

Duplicate values: no

```
dim(df)
```

```
## [1] 7043   21
```

```
length(unique(df$customerID))
```

```
## [1] 7043
```

These NA exist because the costumer hasn't payed yet that month (tenure is 0). We convert these NA to 0.

```
ll <- which(is.na(df$TotalCharges))
df[ll,"TotalCharges"] <- 0
summary(is.na(df$TotalCharges))
```

```
##    Mode   FALSE
## logical    7043
```

Correlation between categorical

The categorical variables MultipleLines and PhoneService are 100% correlated. We might have multicollinearity between these two variables.

```
contingency_table<-table(df$MultipleLines,df$PhoneService)
sqrt(chisq.test(contingency_table)$statistic / (sum(contingency_table) * (min(dim(contingency_table)) -
```

```
## X-squared
##         1
```

Profiling

```r
res.cat=catdes(df, 21)
res.cat$test.chi2
```

```
##                       p.value df
## Contract         5.863038e-258  2
## OnlineSecurity   2.661150e-185  2
## TechSupport      1.443084e-180  2
## InternetService  9.571788e-160  2
## PaymentMethod    3.682355e-140  3
## OnlineBackup     2.079759e-131  2
## DeviceProtection 5.505219e-122  2
## StreamingMovies   2.667757e-82  2
## StreamingTV       5.528994e-82  2
## PaperlessBilling  2.614597e-58  1
## Dependents        3.276083e-43  1
## SeniorCitizen     9.477904e-37  1
## Partner           1.519037e-36  1
## MultipleLines     3.464383e-03  2
```

```r
lapply(res.cat$category, head, n = 5)
```

```
## $No
##                                      Cla/Mod  Mod/Cla   Global       p.value
## Contract=Two year                   97.16814 31.83224 24.06645 3.588830e-187
## StreamingMovies=No internet service  92.59502 27.30963 21.66690  6.584621e-98
## StreamingTV=No internet service      92.59502 27.30963 21.66690  6.584621e-98
## TechSupport=No internet service      92.59502 27.30963 21.66690  6.584621e-98
## DeviceProtection=No internet service 92.59502 27.30963 21.66690  6.584621e-98
##                                        v.test
## Contract=Two year                   29.17894
## StreamingMovies=No internet service  20.99981
## StreamingTV=No internet service      20.99981
## TechSupport=No internet service      20.99981
## DeviceProtection=No internet service 20.99981
##
## $Yes
##                                Cla/Mod  Mod/Cla   Global       p.value
## Contract=Month-to-month        42.70968 88.55003 55.01917 3.620915e-283
## OnlineSecurity=No              41.76672 78.17014 49.66634 6.171504e-190
## TechSupport=No                 41.63547 77.36758 49.31137 1.899538e-183
## InternetService=Fiber optic    41.89276 69.39540 43.95854 2.289126e-148
## PaymentMethod=Electronic check 45.28541 57.30337 33.57944 1.790860e-136
##                                  v.test
## Contract=Month-to-month        35.95931
## OnlineSecurity=No              29.39603
## TechSupport=No                 28.88395
## InternetService=Fiber optic    25.94114
## PaymentMethod=Electronic check 24.86476
```

```r
lapply(res.cat$category, tail, n = 5)
```

```
## $No
##                                Cla/Mod  Mod/Cla   Global       p.value
## PaymentMethod=Electronic check 54.71459 25.00966 33.57944 1.790860e-136
```

```
## InternetService=Fiber optic    58.10724 34.77000 43.95854 2.289126e-148
## TechSupport=No                 58.36453 39.17665 49.31137 1.899538e-183
## OnlineSecurity=No              58.23328 39.36993 49.66634 6.171504e-190
## Contract=Month-to-month        57.29032 42.90684 55.01917 3.620915e-283
##                                  v.test
## PaymentMethod=Electronic check -24.86476
## InternetService=Fiber optic    -25.94114
## TechSupport=No                 -28.88395
## OnlineSecurity=No              -29.39603
## Contract=Month-to-month        -35.95931
##
## $Yes
##                                    Cla/Mod  Mod/Cla   Global       p.value
## DeviceProtection=No internet service 7.404980 6.046014 21.66690  6.584621e-98
## OnlineBackup=No internet service     7.404980 6.046014 21.66690  6.584621e-98
## OnlineSecurity=No internet service   7.404980 6.046014 21.66690  6.584621e-98
## InternetService=No                   7.404980 6.046014 21.66690  6.584621e-98
## Contract=Two year                    2.831858 2.568218 24.06645 3.588830e-187
##                                        v.test
## DeviceProtection=No internet service -20.99981
## OnlineBackup=No internet service     -20.99981
## OnlineSecurity=No internet service   -20.99981
## InternetService=No                   -20.99981
## Contract=Two year                    -29.17894
```

```
res.cat$quanti.var
```

```
##                      Eta2       P-value
## tenure         0.12406504 7.999058e-205
## TotalCharges   0.03933251  2.127212e-63
## MonthlyCharges 0.03738671  2.706646e-60
```

```
res.cat$quanti
```

```
## $No
##                   v.test Mean in category Overall mean sd in category
## tenure          29.55784         37.56997     32.37115       24.11145
## TotalCharges    16.64270       2549.91144   2279.73430     2329.72904
## MonthlyCharges -16.22582         61.26512     64.76169       31.08964
##                Overall sd       p.value
## tenure           24.55774 5.207314e-192
## TotalCharges   2266.63354  3.418341e-62
## MonthlyCharges   30.08791  3.312724e-59
##
## $Yes
##                   v.test Mean in category Overall mean sd in category
## MonthlyCharges  16.22582         74.44133     64.76169       24.65945
## TotalCharges   -16.64270       1531.79609   2279.73430     1890.31709
## tenure         -29.55784         17.97913     32.37115       19.52590
##                Overall sd       p.value
## MonthlyCharges   30.08791  3.312724e-59
## TotalCharges   2266.63354  3.418341e-62
## tenure           24.55774 5.207314e-192
```

Regarding to the results of the test Chi^2 all correlations with the variables are significant since the $p-value$ is less than 0,05. Since the response variable is binary, we have different results for each answer and also for all outcomes of the categorical parameters.

For example, we can analyse in detail the variable "Contract". For the customers that haven't churned, the correlation between the ones that have a contract of two year is directly proportional and it's the highest relation. However, we can see that is the costumer has churned the ones that have a two-year contract have an strong negative correlation. The ones that have a month-to-month contract are the opposite of the previous answer; they have the highest positive correlation with the costumers that have churned and the negative with the ones that haven't.

Besides the latter variable, we can observe the parameter that have a higher positive correlation with the costumers that churn is the parameter "OnlineSecurity" and "TechSupport" when the answer is "No". The parameters that have a negative relation with the costumers that churn are when they haven't hired an Internet Service. We can see that all parameters that have an answer that is "No internet service" have also a negative relation with the response variable "Yes". We can deduce that they might have multicollinearity with the parameter Internet Service, but we will check it later.

The parameters that have a higher positive relation with the costumers that don't churn are the ones that have a negative relation when the response variable is "Yes", that we have analysed before. In the same vein, we can observe that the parameters that have a negative relation with the costumers that churn are "OnlineSecurity" and "TechSupport" when the answer is "No", the same parameters that have a positive relation when the costumers churn. We can see that the target answer "Yes" and "No" have an approximate opposite correlations with the explanatory variables.

Modelling

Data transformations:

Recall that the following variables:

- OnlineSecurity
- OnlineBackup
- DeviceProtection
- TechSupport
- StreamingTV
- StreamingMovies

are categorical variables with 3 levels: No/No internet service/Yes.

We observe that they contain "No internet service" as a response. We have a variable called *InternetService* that is a categorical variable with 3 levels: DSL/Fiber optic/No. Whenever *InternetService*="No" implies -> var="No internet service". Therefore we decided to transform the level "No internet service" into "No" in the 6 variables above since this variable will specify.

```
df$OnlineSecurity[df$OnlineSecurity=="No internet service"] <- "No"
df$OnlineBackup[df$OnlineBackup=="No internet service"] <- "No"
df$DeviceProtection[df$DeviceProtection=="No internet service"] <- "No"
df$TechSupport[df$TechSupport=="No internet service"] <- "No"
df$StreamingTV[df$StreamingTV=="No internet service"] <- "No"
df$StreamingMovies[df$StreamingMovies=="No internet service"] <- "No"
```

We saw that *MultipleLines* is 100% related with *PhoneService*. The reason is similar as the previous parameters: one answer of *MultipleLines* is "No phone service". We set this answer to "No" since we don't lose the information because it is contained inside the parameter *PhoneService*.

```
df$MultipleLines[df$MultipleLines=="No phone service"] <- "No"
```

Modelling:

```
set.seed(1234)
m <- floor(0.7*nrow(df))
train_d <- sample(seq_len(nrow(df)),size = m)

train <- df[train_d,]
test <- df[-train_d,]
```

Recall that the target variable is *Churn*.

Numerical Variables

We start the modelling by the null model.

```
mod0 <- glm(Churn ~ 1, data=train, family=binomial)
mod0$deviance
```

```
## [1] 5694.218
```

We continue by adding the numerical variables and assessing the model.

```
which(sapply(df, is.numeric))
```

```
##         tenure MonthlyCharges   TotalCharges
##              6             19             20
```

We start by *tenure*

```
mod1 <- glm(Churn ~ tenure, data=train, family=binomial)
mod1$deviance;AIC(mod0,mod1) #summary(mod1)
```

```
## [1] 5040.677
```

```
##      df      AIC
## mod0  1 5696.218
## mod1  2 5044.677
```

```
anova( mod0, mod1,  test="Chisq")
```

```
## Analysis of Deviance Table
##
## Model 1: Churn ~ 1
## Model 2: Churn ~ tenure
##   Resid. Df Resid. Dev Df Deviance  Pr(>Chi)
## 1      4929     5694.2
## 2      4928     5040.7  1   653.54 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Add MonthlyCharges

```
mod2 <- glm(Churn ~ tenure + MonthlyCharges, data=train, family=binomial)
mod2$deviance
```

```
## [1] 4467.45
```

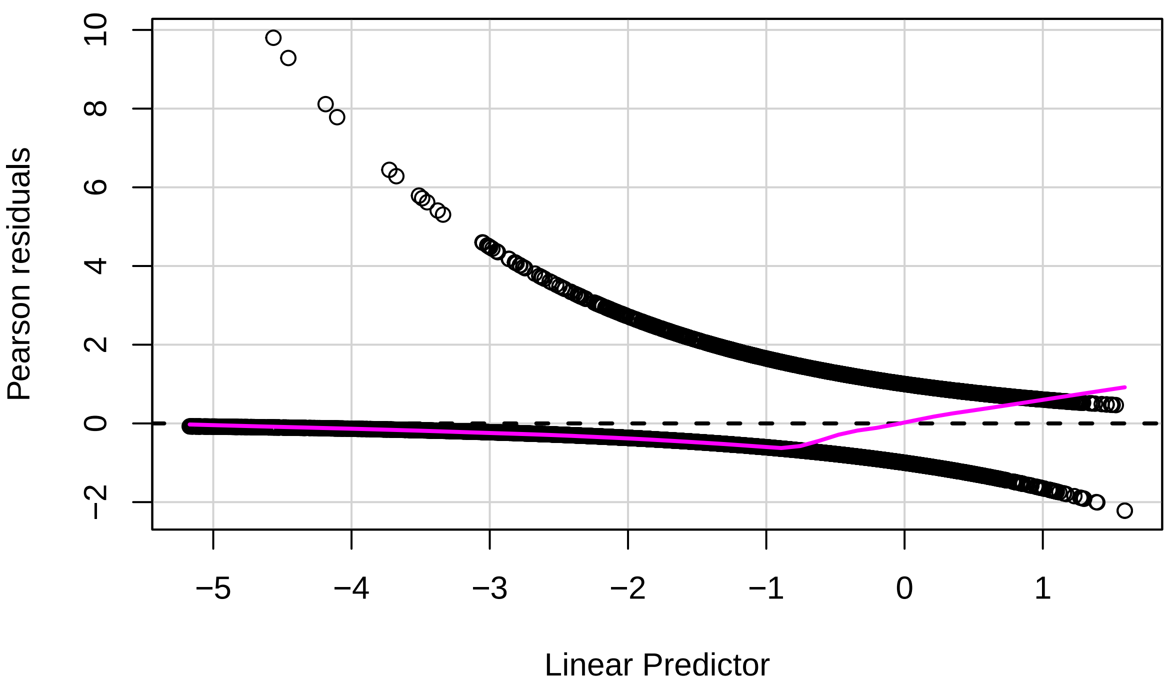
```
AIC(mod2) #4473.45
```

```
## [1] 4473.45
```

```r
anova( mod1, mod2,  test="Chisq")
```

```
## Analysis of Deviance Table
##
## Model 1: Churn ~ tenure
## Model 2: Churn ~ tenure + MonthlyCharges
##   Resid. Df Resid. Dev Df Deviance  Pr(>Chi)
## 1      4928     5040.7
## 2      4927     4467.5  1   573.23 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
residualPlot(mod2)
```



Add TotalCharges

```r
mod3 <- glm(Churn ~ tenure + MonthlyCharges + TotalCharges, data=train, family=binomial)
mod3$deviance
```

```
## [1] 4460.555
```

```r
anova( mod2, mod3,  test="Chisq") #significant
```

```
## Analysis of Deviance Table
##
## Model 1: Churn ~ tenure + MonthlyCharges
## Model 2: Churn ~ tenure + MonthlyCharges + TotalCharges
##   Resid. Df Resid. Dev Df Deviance Pr(>Chi)
## 1      4927     4467.5
## 2      4926     4460.6  1   6.8951 0.008643 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
AIC(mod3) #4468.55
```

```
## [1] 4468.555
```

```r
vif(mod3)
```

```
##          tenure MonthlyCharges   TotalCharges
##       14.730657       2.271293      18.869079
```

It is significant enough but we can also see that *TotalCHarges* has a high VIF, so it has high multicollinearity. We decide to not include it in the model.

Inlfuential data

```r
infl <- influence.measures(mod3)

sum(residuals(mod3,'deviance')^2)
```

```
## [1] 4460.555
```

```r
sum(residuals(mod3,'pearson')^2)
```

```
## [1] 5196.056
```

```r
influential_indices <- which(infl$is.inf == TRUE)
length(influential_indices)
```

```
## [1] 209
```

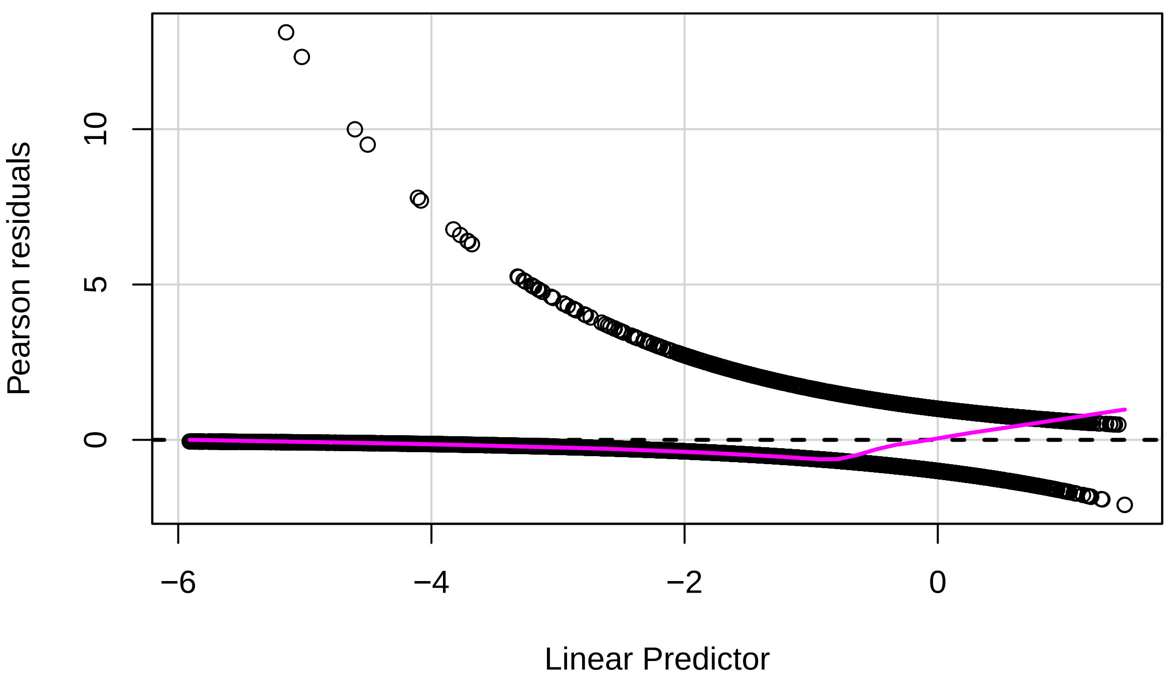
```r
length(train$customerID)
```

```
## [1] 4930
```

We have 209 influential points out of 4930.

Residuals

```r
residualPlot(mod3)
```



The residuals need to be nearer to the 0.

Categorical Variables

Now, we shall add the categorical variables. The order of addition is significant, therefore we start by adding the most correlated variables with the target.

Contract InternetService StreamingMovies StreamingTV TechSupport DeviceProtection OnlineBackup OnlineSecurity PaperlessBilling Dependents MultipleLines SeniorCitizen Partner PaymentMethod PhoneService

Contract

We start with *Contract* variable.

```
mod4 <- glm(Churn ~ tenure + MonthlyCharges + Contract, data=train, family=binomial)
AIC(mod4) #4302.2 better
```

```
## [1] 4302.234
```

```
anova( mod3, mod4,  test="Chisq") #significant
```

```
## Analysis of Deviance Table
##
## Model 1: Churn ~ tenure + MonthlyCharges + TotalCharges
## Model 2: Churn ~ tenure + MonthlyCharges + Contract
##   Resid. Df Resid. Dev Df Deviance  Pr(>Chi)
## 1      4926     4460.6
## 2      4925     4292.2  1   168.32 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
vif(mod4)
```

```
##                    GVIF Df GVIF^(1/(2*Df))
## tenure         1.707900  1        1.306867
## MonthlyCharges 1.300967  1        1.140599
## Contract       1.361428  2        1.080186
```

We add the parameter because it improves the model.

InternetService

```
mod5 <- glm(Churn ~ tenure + MonthlyCharges + Contract + InternetService, data=train, family=binomial)
AIC(mod5) #4254.1 better
```

```
## [1] 4254.114
```

```
anova( mod4, mod5,  test="Chisq") #significant
```

```
## Analysis of Deviance Table
##
## Model 1: Churn ~ tenure + MonthlyCharges + Contract
## Model 2: Churn ~ tenure + MonthlyCharges + Contract + InternetService
##   Resid. Df Resid. Dev Df Deviance  Pr(>Chi)
## 1      4925     4292.2
## 2      4923     4240.1  2    52.12 4.811e-12 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
vif(mod5)
```

```
##                     GVIF Df GVIF^(1/(2*Df))
## tenure          1.738643  1        1.318576
## MonthlyCharges  6.009378  1        2.451403
## Contract        1.450931  2        1.097518
## InternetService 5.338238  2        1.520021
```

StreamingMovies

```r
mod6 <- glm(Churn ~ tenure + MonthlyCharges + Contract + InternetService + StreamingMovies, data=train,
AIC(mod6) #4238.6 better
```

```
## [1] 4238.552
```

```r
anova( mod5, mod6,  test="Chisq") #significant
```

```
## Analysis of Deviance Table
##
## Model 1: Churn ~ tenure + MonthlyCharges + Contract + InternetService
## Model 2: Churn ~ tenure + MonthlyCharges + Contract + InternetService +
##     StreamingMovies
##   Resid. Df Resid. Dev Df Deviance Pr(>Chi)
## 1      4923     4240.1
## 2      4922     4222.6  1   17.563 2.78e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
vif(mod6)
```

```
##                     GVIF Df GVIF^(1/(2*Df))
## tenure          1.734387  1        1.316961
## MonthlyCharges  9.114445  1        3.019014
## Contract        1.447519  2        1.096872
## InternetService 6.680296  2        1.607677
## StreamingMovies 1.878425  1        1.370556
```

The model has improved but the VIF is becoming higher.

StreamingTV

```r
mod7 <- glm(Churn ~ tenure + MonthlyCharges + Contract + InternetService + StreamingMovies + StreamingT
AIC(mod7) #4213.5 better
```

```
## [1] 4213.55
```

```r
anova( mod6, mod7,  test="Chisq") #significant
```

```
## Analysis of Deviance Table
##
## Model 1: Churn ~ tenure + MonthlyCharges + Contract + InternetService +
##     StreamingMovies
## Model 2: Churn ~ tenure + MonthlyCharges + Contract + InternetService +
##     StreamingMovies + StreamingTV
##   Resid. Df Resid. Dev Df Deviance  Pr(>Chi)
## 1      4922     4222.6
```

```
## 2      4921     4195.5  1   27.002 2.033e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
vif(mod7)
```

```
##                      GVIF Df GVIF^(1/(2*Df))
## tenure           1.732269  1        1.316157
## MonthlyCharges  12.166459  1        3.488045
## Contract         1.443988  2        1.096203
## InternetService  7.954251  2        1.679383
## StreamingMovies  1.860165  1        1.363878
## StreamingTV      1.906895  1        1.380904
```

MonthlyCharges has a high VIF. We'll may need to add transformations or maybe discard this variable For now, we will keep the parameters that we have been adding.

TechSupport

```
mod8 <- glm(Churn ~ tenure + MonthlyCharges + Contract + InternetService + StreamingMovies + StreamingT
#summary(mod8) #4208.3 better
AIC(mod8)
```

```
## [1] 4208.273
```

```
anova( mod7, mod8,  test="Chisq") #significant
```

```
## Analysis of Deviance Table
##
## Model 1: Churn ~ tenure + MonthlyCharges + Contract + InternetService +
##     StreamingMovies + StreamingTV
## Model 2: Churn ~ tenure + MonthlyCharges + Contract + InternetService +
##     StreamingMovies + StreamingTV + TechSupport
##   Resid. Df Resid. Dev Df Deviance Pr(>Chi)
## 1      4921     4195.5
## 2      4920     4188.3  1   7.2764 0.006987 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
vif(mod8)
```

```
##                      GVIF Df GVIF^(1/(2*Df))
## tenure           1.732344  1        1.316185
## MonthlyCharges  13.838376  1        3.719997
## Contract         1.475851  2        1.102201
## InternetService  9.342986  2        1.748322
## StreamingMovies  1.893830  1        1.376165
## StreamingTV      1.943568  1        1.394119
## TechSupport      1.294163  1        1.137613
```

Including *TechSupport* improves the model.

DeviceProtection

```
mod9 <- glm(Churn ~ tenure + MonthlyCharges + Contract + InternetService + StreamingMovies + StreamingT
summary(mod9) #4209.3 worse
```

```
##
## Call:
## glm(formula = Churn ~ tenure + MonthlyCharges + Contract + InternetService +
##     StreamingMovies + StreamingTV + TechSupport + DeviceProtection,
##     family = binomial, data = train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.7717  -0.6683  -0.2984   0.7723   3.1679
##
## Coefficients:
##                             Estimate Std. Error z value Pr(>|z|)
## (Intercept)                  0.20725    0.24332   0.852 0.394345
## tenure                      -0.03217    0.00250 -12.868  < 2e-16 ***
## MonthlyCharges              -0.01417    0.00558  -2.539 0.011129 *
## ContractOne year            -0.84846    0.12453  -6.813 9.54e-12 ***
## ContractTwo year            -1.71130    0.21068  -8.123 4.55e-16 ***
## InternetServiceFiber optic  1.49636    0.20259   7.386 1.51e-13 ***
## InternetServiceNo           -1.33473    0.19328  -6.906 5.00e-12 ***
## StreamingMoviesYes           0.41040    0.10661   3.850 0.000118 ***
## StreamingTVYes               0.51843    0.10817   4.793 1.64e-06 ***
## TechSupportYes              -0.27817    0.10447  -2.663 0.007751 **
## DeviceProtectionYes          0.09141    0.09477   0.965 0.334789
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 5694.2  on 4929  degrees of freedom
## Residual deviance: 4187.3  on 4919  degrees of freedom
## AIC: 4209.3
##
## Number of Fisher Scoring iterations: 6
```

```r
AIC(mod9)
```

```
## [1] 4209.343
```

```r
anova( mod8, mod9,  test="Chisq") #not significant
```

```
## Analysis of Deviance Table
##
## Model 1: Churn ~ tenure + MonthlyCharges + Contract + InternetService +
##     StreamingMovies + StreamingTV + TechSupport
## Model 2: Churn ~ tenure + MonthlyCharges + Contract + InternetService +
##     StreamingMovies + StreamingTV + TechSupport + DeviceProtection
##   Resid. Df Resid. Dev Df Deviance Pr(>Chi)
## 1      4920     4188.3
## 2      4919     4187.3  1  0.93092   0.3346
```

We don't add the variable to the model. It does not improve it.

OnlineBackup

```r
mod10 <- glm(Churn ~ tenure + MonthlyCharges + Contract + InternetService + StreamingMovies + Streaming
AIC(mod10) #4209.6 worse
```

```
## [1] 4209.632
```

```r
anova( mod8, mod10,  test="Chisq") #not significant
```

```
## Analysis of Deviance Table
##
## Model 1: Churn ~ tenure + MonthlyCharges + Contract + InternetService +
##     StreamingMovies + StreamingTV + TechSupport
## Model 2: Churn ~ tenure + MonthlyCharges + Contract + InternetService +
##     StreamingMovies + StreamingTV + TechSupport + OnlineBackup
##   Resid. Df Resid. Dev Df Deviance Pr(>Chi)
## 1      4920     4188.3
## 2      4919     4187.6  1  0.64158   0.4231
```

We don't add the variable to the model. It does not improve it.

OnlineSecurity

```r
mod11 <- glm(Churn ~ tenure + MonthlyCharges + Contract + InternetService + StreamingMovies + Streaming
AIC(mod11) #4199 better
```

```
## [1] 4198.953
```

```r
anova( mod8, mod11,  test="Chisq") #significant
```

```
## Analysis of Deviance Table
##
## Model 1: Churn ~ tenure + MonthlyCharges + Contract + InternetService +
##     StreamingMovies + StreamingTV + TechSupport
## Model 2: Churn ~ tenure + MonthlyCharges + Contract + InternetService +
##     StreamingMovies + StreamingTV + TechSupport + OnlineSecurity
##   Resid. Df Resid. Dev Df Deviance  Pr(>Chi)
## 1      4920     4188.3
## 2      4919     4177.0  1   11.321 0.0007665 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

We keep the variable

PaperlessBilling

```r
mod12 <- glm(Churn ~ tenure + MonthlyCharges + Contract + InternetService + StreamingMovies + Streaming
summary(mod12) #4184.5 better
```

```
##
## Call:
## glm(formula = Churn ~ tenure + MonthlyCharges + Contract + InternetService +
##     StreamingMovies + StreamingTV + TechSupport + OnlineSecurity +
##     PaperlessBilling, family = binomial, data = train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.8020  -0.6855  -0.2930   0.7658   3.1924
##
## Coefficients:
```

```
##                              Estimate Std. Error z value Pr(>|z|)
## (Intercept)                 -0.206715   0.251517  -0.822 0.411150
## tenure                      -0.031980   0.002512 -12.730  < 2e-16 ***
## MonthlyCharges              -0.006893   0.005737  -1.202 0.229554
## ContractOne year            -0.774511   0.125366  -6.178 6.49e-10 ***
## ContractTwo year            -1.575801   0.211901  -7.436 1.03e-13 ***
## InternetServiceFiber optic   1.162390   0.211629   5.493 3.96e-08 ***
## InternetServiceNo           -1.216241   0.195326  -6.227 4.76e-10 ***
## StreamingMoviesYes           0.328093   0.109142   3.006 0.002646 **
## StreamingTVYes               0.412453   0.111023   3.715 0.000203 ***
## TechSupportYes              -0.293252   0.105072  -2.791 0.005255 **
## OnlineSecurityYes           -0.325252   0.105781  -3.075 0.002107 **
## PaperlessBillingYes          0.354796   0.087670   4.047 5.19e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 5694.2  on 4929  degrees of freedom
## Residual deviance: 4160.5  on 4918  degrees of freedom
## AIC: 4184.5
##
## Number of Fisher Scoring iterations: 6
```

```
AIC(mod12)
```

```
## [1] 4184.475
```

```
anova( mod11, mod12,  test="Chisq") #significant
```

```
## Analysis of Deviance Table
##
## Model 1: Churn ~ tenure + MonthlyCharges + Contract + InternetService +
##     StreamingMovies + StreamingTV + TechSupport + OnlineSecurity
## Model 2: Churn ~ tenure + MonthlyCharges + Contract + InternetService +
##     StreamingMovies + StreamingTV + TechSupport + OnlineSecurity +
##     PaperlessBilling
##   Resid. Df Resid. Dev Df Deviance  Pr(>Chi)
## 1      4919     4177.0
## 2      4918     4160.5  1   16.478 4.923e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
vif(mod12)
```

```
##                      GVIF Df GVIF^(1/(2*Df))
## tenure           1.760119  1        1.326695
## MonthlyCharges  15.519259  1        3.939449
## Contract         1.507661  2        1.108092
## InternetService 10.973792  2        1.820075
## StreamingMovies  1.970408  1        1.403712
## StreamingTV      2.035605  1        1.426746
## TechSupport      1.298079  1        1.139333
## OnlineSecurity   1.247294  1        1.116823
## PaperlessBilling 1.111928  1        1.054480
```

We keep the variable

Dependents

```r
mod13 <- glm(Churn ~ tenure + MonthlyCharges + Contract + InternetService + StreamingMovies + Streaming
summary(mod13) #4177.2 better
```

```
##
## Call:
## glm(formula = Churn ~ tenure + MonthlyCharges + Contract + InternetService +
##     StreamingMovies + StreamingTV + TechSupport + OnlineSecurity +
##     PaperlessBilling + Dependents, family = binomial, data = train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.8158  -0.6832  -0.2973   0.7559   3.1478
##
## Coefficients:
##                             Estimate Std. Error z value Pr(>|z|)
## (Intercept)                -0.160331   0.252462  -0.635  0.52538
## tenure                     -0.031654   0.002520 -12.559  < 2e-16 ***
## MonthlyCharges             -0.006595   0.005749  -1.147  0.25137
## ContractOne year           -0.746604   0.125870  -5.932 3.00e-09 ***
## ContractTwo year           -1.536143   0.212595  -7.226 4.99e-13 ***
## InternetServiceFiber optic  1.133942   0.212173   5.344 9.07e-08 ***
## InternetServiceNo          -1.193933   0.195766  -6.099 1.07e-09 ***
## StreamingMoviesYes          0.317729   0.109348   2.906  0.00366 **
## StreamingTVYes              0.412210   0.111213   3.706  0.00021 ***
## TechSupportYes             -0.287327   0.105193  -2.731  0.00631 **
## OnlineSecurityYes          -0.317077   0.105920  -2.994  0.00276 **
## PaperlessBillingYes         0.351625   0.087803   4.005 6.21e-05 ***
## DependentsYes              -0.291003   0.096298  -3.022  0.00251 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 5694.2  on 4929  degrees of freedom
## Residual deviance: 4151.2  on 4917  degrees of freedom
## AIC: 4177.2
##
## Number of Fisher Scoring iterations: 6
```

```r
AIC(mod13)
```

```
## [1] 4177.206
```

```r
anova( mod12, mod13,  test="Chisq") #significant
```

```
## Analysis of Deviance Table
##
## Model 1: Churn ~ tenure + MonthlyCharges + Contract + InternetService +
##     StreamingMovies + StreamingTV + TechSupport + OnlineSecurity +
##     PaperlessBilling
## Model 2: Churn ~ tenure + MonthlyCharges + Contract + InternetService +
##     StreamingMovies + StreamingTV + TechSupport + OnlineSecurity +
##     PaperlessBilling + Dependents
##   Resid. Df Resid. Dev Df Deviance Pr(>Chi)
```

```
## 1      4918     4160.5
## 2      4917     4151.2  1   9.2692  0.00233 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
vif(mod13)
```

```
##                       GVIF Df GVIF^(1/(2*Df))
## tenure            1.773404  1        1.331692
## MonthlyCharges   15.562560  1        3.944941
## Contract          1.522708  2        1.110847
## InternetService  10.992492  2        1.820849
## StreamingMovies   1.973305  1        1.404744
## StreamingTV       2.037770  1        1.427505
## TechSupport       1.299374  1        1.139901
## OnlineSecurity    1.247956  1        1.117120
## PaperlessBilling  1.112626  1        1.054811
## Dependents        1.027601  1        1.013706
```

We keep the variable

MultipleLines

```r
mod14 <- glm(Churn ~ tenure + MonthlyCharges + Contract + InternetService + StreamingMovies + Streaming
AIC(mod14) #4162.2 better
```

```
## [1] 4162.18
```

```r
anova( mod13, mod14,  test="Chisq") #significant
```

```
## Analysis of Deviance Table
##
## Model 1: Churn ~ tenure + MonthlyCharges + Contract + InternetService +
##     StreamingMovies + StreamingTV + TechSupport + OnlineSecurity +
##     PaperlessBilling + Dependents
## Model 2: Churn ~ tenure + MonthlyCharges + Contract + InternetService +
##     StreamingMovies + StreamingTV + TechSupport + OnlineSecurity +
##     PaperlessBilling + Dependents + MultipleLines
##   Resid. Df Resid. Dev Df Deviance  Pr(>Chi)
## 1      4917     4151.2
## 2      4916     4134.2  1   17.026 3.688e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
vif(mod14)
```

```
##                       GVIF Df GVIF^(1/(2*Df))
## tenure            1.860860  1        1.364133
## MonthlyCharges   19.785122  1        4.448047
## Contract          1.529039  2        1.112000
## InternetService  12.562934  2        1.882664
## StreamingMovies   2.104685  1        1.450753
## StreamingTV       2.150829  1        1.466570
## TechSupport       1.346109  1        1.160219
## OnlineSecurity    1.283323  1        1.132838
## PaperlessBilling  1.113149  1        1.055059
## Dependents        1.028391  1        1.014096
```

```
## MultipleLines     1.749163  1        1.322559
```

We keep the variable

SeniorCitizen

```
mod15 <- glm(Churn ~ tenure + MonthlyCharges + Contract + InternetService + StreamingMovies + Streaming
AIC(mod15) #4155.7 better
```

```
## [1] 4155.702
```

```
anova( mod14, mod15,  test="Chisq") #significant
```

```
## Analysis of Deviance Table
##
## Model 1: Churn ~ tenure + MonthlyCharges + Contract + InternetService +
##     StreamingMovies + StreamingTV + TechSupport + OnlineSecurity +
##     PaperlessBilling + Dependents + MultipleLines
## Model 2: Churn ~ tenure + MonthlyCharges + Contract + InternetService +
##     StreamingMovies + StreamingTV + TechSupport + OnlineSecurity +
##     PaperlessBilling + Dependents + MultipleLines + SeniorCitizen
##   Resid. Df Resid. Dev Df Deviance Pr(>Chi)
## 1      4916     4134.2
## 2      4915     4125.7  1   8.4782 0.003594 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
vif(mod15)
```

```
##                       GVIF Df GVIF^(1/(2*Df))
## tenure            1.889241  1        1.374497
## MonthlyCharges   19.790331  1        4.448632
## Contract          1.536772  2        1.113403
## InternetService  12.635139  2        1.885363
## StreamingMovies   2.104216  1        1.450592
## StreamingTV       2.148543  1        1.465791
## TechSupport       1.353673  1        1.163474
## OnlineSecurity    1.286526  1        1.134251
## PaperlessBilling  1.114284  1        1.055597
## Dependents        1.056349  1        1.027789
## MultipleLines     1.752169  1        1.323695
## SeniorCitizen     1.113813  1        1.055374
```

We keep the variable

Partner

```
mod16 <- glm(Churn ~ tenure + MonthlyCharges + Contract + InternetService + StreamingMovies + Streaming
AIC(mod16) #4157.7 worse
```

```
## [1] 4157.677
```

```
anova( mod15, mod16,  test="Chisq") #not significant
```

```
## Analysis of Deviance Table
##
## Model 1: Churn ~ tenure + MonthlyCharges + Contract + InternetService +
```

```
##     StreamingMovies + StreamingTV + TechSupport + OnlineSecurity +
##     PaperlessBilling + Dependents + MultipleLines + SeniorCitizen
## Model 2: Churn ~ tenure + MonthlyCharges + Contract + InternetService +
##     StreamingMovies + StreamingTV + TechSupport + OnlineSecurity +
##     PaperlessBilling + Dependents + MultipleLines + SeniorCitizen +
##     Partner
##   Resid. Df Resid. Dev Df Deviance Pr(>Chi)
## 1      4915     4125.7
## 2      4914     4125.7  1 0.024971   0.8744
```

We don't keep the variable

PaymentMethod

```
mod17 <- glm(Churn ~ tenure + MonthlyCharges + Contract + InternetService + StreamingMovies + Streaming
AIC(mod17) #4139.4 better
```

```
## [1] 4139.434
```

```
anova( mod15, mod17,  test="Chisq") #significant
```

```
## Analysis of Deviance Table
##
## Model 1: Churn ~ tenure + MonthlyCharges + Contract + InternetService +
##     StreamingMovies + StreamingTV + TechSupport + OnlineSecurity +
##     PaperlessBilling + Dependents + MultipleLines + SeniorCitizen
## Model 2: Churn ~ tenure + MonthlyCharges + Contract + InternetService +
##     StreamingMovies + StreamingTV + TechSupport + OnlineSecurity +
##     PaperlessBilling + Dependents + MultipleLines + SeniorCitizen +
##     PaymentMethod
##   Resid. Df Resid. Dev Df Deviance  Pr(>Chi)
## 1      4915     4125.7
## 2      4912     4103.4  3   22.269 5.735e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
vif(mod17)
```

```
##                       GVIF Df GVIF^(1/(2*Df))
## tenure            1.963626  1        1.401295
## MonthlyCharges   19.895259  1        4.460410
## Contract          1.543913  2        1.114694
## InternetService  13.046889  2        1.900539
## StreamingMovies   2.110866  1        1.452882
## StreamingTV       2.164001  1        1.471054
## TechSupport       1.357356  1        1.165056
## OnlineSecurity    1.291867  1        1.136603
## PaperlessBilling  1.120742  1        1.058651
## Dependents        1.057502  1        1.028349
## MultipleLines     1.753352  1        1.324142
## SeniorCitizen     1.116591  1        1.056689
## PaymentMethod     1.332467  3        1.049001
```

PhoneService

```
mod18 <- glm(Churn ~ tenure + MonthlyCharges + Contract + InternetService + StreamingMovies + Streaming
AIC(mod18)#4139.4 it does not change anything
```

```
## [1] 4139.379
```

```
anova( mod17, mod18,  test="Chisq") #not significant
```

```
## Analysis of Deviance Table
##
## Model 1: Churn ~ tenure + MonthlyCharges + Contract + InternetService +
##     StreamingMovies + StreamingTV + TechSupport + OnlineSecurity +
##     PaperlessBilling + Dependents + MultipleLines + SeniorCitizen +
##     PaymentMethod
## Model 2: Churn ~ tenure + MonthlyCharges + Contract + InternetService +
##     StreamingMovies + StreamingTV + TechSupport + OnlineSecurity +
##     PaperlessBilling + Dependents + MultipleLines + SeniorCitizen +
##     PaymentMethod + PhoneService
##   Resid. Df Resid. Dev Df Deviance Pr(>Chi)
## 1      4912     4103.4
## 2      4911     4101.4  1    2.055   0.1517
```

We don't include the parameter

Inlfuential data

We check the influential data after including the categorical variables

```
infl_2 <- influence.measures(mod17)

sum(residuals(mod17,'deviance')^2)
```

```
## [1] 4103.434
```

```
sum(residuals(mod17,'pearson')^2)
```

```
## [1] 4919.679
```

```
influential_indices_2 <- which(infl_2$is.inf == TRUE)
length(influential_indices_2)
```

```
## [1] 98
```

```
length(train$customerID)
```

```
## [1] 4930
```

The influential data has reduced until 98 tuples.

Interactions

We need to search for interactions. Possible interactions:

- Dependents and Multiple Lines

```
mod19 <- glm(Churn ~ tenure + MonthlyCharges + Contract + InternetService + StreamingMovies + Streaming
 #4140.4 worse
AIC(mod19)
```

```
## [1] 4140.355
```

```r
anova( mod17, mod19,  test="Chisq") #not significant
```

```
## Analysis of Deviance Table
##
## Model 1: Churn ~ tenure + MonthlyCharges + Contract + InternetService +
##     StreamingMovies + StreamingTV + TechSupport + OnlineSecurity +
##     PaperlessBilling + Dependents + MultipleLines + SeniorCitizen +
##     PaymentMethod
## Model 2: Churn ~ tenure + MonthlyCharges + Contract + InternetService +
##     StreamingMovies + StreamingTV + TechSupport + OnlineSecurity +
##     PaperlessBilling + Dependents * MultipleLines + SeniorCitizen +
##     PaymentMethod
##   Resid. Df Resid. Dev Df Deviance Pr(>Chi)
## 1      4912     4103.4
## 2      4911     4102.4  1   1.0787    0.299
```

We don't include the interaction since it is not significative

- MonthlyCharges and InternetService

```r
mod20 <- glm(Churn ~ tenure + InternetService * MonthlyCharges + Contract + StreamingMovies + Streaming
AIC(mod20) #4133.7 better
```

```
## [1] 4133.664
```

```r
anova( mod17, mod20,  test="Chisq") #significant
```

```
## Analysis of Deviance Table
##
## Model 1: Churn ~ tenure + MonthlyCharges + Contract + InternetService +
##     StreamingMovies + StreamingTV + TechSupport + OnlineSecurity +
##     PaperlessBilling + Dependents + MultipleLines + SeniorCitizen +
##     PaymentMethod
## Model 2: Churn ~ tenure + InternetService * MonthlyCharges + Contract +
##     StreamingMovies + StreamingTV + TechSupport + OnlineSecurity +
##     PaperlessBilling + Dependents + MultipleLines + SeniorCitizen +
##     PaymentMethod
##   Resid. Df Resid. Dev Df Deviance Pr(>Chi)
## 1      4912     4103.4
## 2      4910     4093.7  2   9.7694 0.007561 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
vif(mod20)
```

```
## there are higher-order terms (interactions) in this model
## consider setting type = 'predictor'; see ?vif
```

```
##                                       GVIF Df GVIF^(1/(2*Df))
## tenure                            2.079881  1        1.442179
## InternetService                9738.807709  2        9.934052
## MonthlyCharges                   21.386127  1        4.624514
## Contract                          1.550405  2        1.115864
## StreamingMovies                   2.374759  1        1.541025
## StreamingTV                       2.416906  1        1.554640
## TechSupport                       1.374225  1        1.172273
## OnlineSecurity                    1.300790  1        1.140522
```

```
## PaperlessBilling                        1.124965  1        1.060644
## Dependents                              1.056690  1        1.027954
## MultipleLines                           1.897486  1        1.377493
## SeniorCitizen                           1.115802  1        1.056315
## PaymentMethod                           1.346214  3        1.050797
## InternetService:MonthlyCharges 11466.767397  2       10.348091
```

- SeniorCitizen and PaymentMethod

```
mod21 <- glm(Churn ~ tenure + InternetService + MonthlyCharges + Contract + StreamingMovies + Streaming
AIC(mod21) #4133 better and also better than mod20
```

```
## [1] 4133.038
```

```
anova( mod17, mod21,  test="Chisq") #significant
```

```
## Analysis of Deviance Table
##
## Model 1: Churn ~ tenure + MonthlyCharges + Contract + InternetService +
##     StreamingMovies + StreamingTV + TechSupport + OnlineSecurity +
##     PaperlessBilling + Dependents + MultipleLines + SeniorCitizen +
##     PaymentMethod
## Model 2: Churn ~ tenure + InternetService + MonthlyCharges + Contract +
##     StreamingMovies + StreamingTV + TechSupport + OnlineSecurity +
##     PaperlessBilling + Dependents + MultipleLines + SeniorCitizen *
##     PaymentMethod
##   Resid. Df Resid. Dev Df Deviance Pr(>Chi)
## 1      4912     4103.4
## 2      4909     4091.0  3   12.396 0.006144 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
anova( mod20, mod21,  test="Chisq") #not significant
```

```
## Analysis of Deviance Table
##
## Model 1: Churn ~ tenure + InternetService * MonthlyCharges + Contract +
##     StreamingMovies + StreamingTV + TechSupport + OnlineSecurity +
##     PaperlessBilling + Dependents + MultipleLines + SeniorCitizen +
##     PaymentMethod
## Model 2: Churn ~ tenure + InternetService + MonthlyCharges + Contract +
##     StreamingMovies + StreamingTV + TechSupport + OnlineSecurity +
##     PaperlessBilling + Dependents + MultipleLines + SeniorCitizen *
##     PaymentMethod
##   Resid. Df Resid. Dev Df Deviance Pr(>Chi)
## 1      4910     4093.7
## 2      4909     4091.0  1   2.6261   0.1051
```

```
vif(mod21) #better multicollinearity
```

```
## there are higher-order terms (interactions) in this model
## consider setting type = 'predictor'; see ?vif
```

```
##                                 GVIF Df GVIF^(1/(2*Df))
## tenure                      1.973899  1        1.404955
## InternetService            13.127210  2        1.903457
## MonthlyCharges             19.972402  1        4.469049
## Contract                    1.548154  2        1.115459
```

```
## StreamingMovies              2.114568  1        1.454155
## StreamingTV                  2.168544  1        1.472598
## TechSupport                  1.359278  1        1.165881
## OnlineSecurity               1.292280  1        1.136785
## PaperlessBilling             1.120630  1        1.058598
## Dependents                   1.058287  1        1.028731
## MultipleLines                1.759302  1        1.326387
## SeniorCitizen                6.564344  1        2.562098
## PaymentMethod                2.413718  3        1.158193
## SeniorCitizen:PaymentMethod 10.225907  3        1.473274
```

```r
mod22 <- glm(Churn ~ tenure + InternetService * MonthlyCharges + Contract + StreamingMovies + Streaming
AIC(mod22) #4126.8 better
```

```
## [1] 4126.835
```

```r
anova( mod21, mod22,  test="Chisq") #significant
```

```
## Analysis of Deviance Table
##
## Model 1: Churn ~ tenure + InternetService + MonthlyCharges + Contract +
##     StreamingMovies + StreamingTV + TechSupport + OnlineSecurity +
##     PaperlessBilling + Dependents + MultipleLines + SeniorCitizen *
##     PaymentMethod
## Model 2: Churn ~ tenure + InternetService * MonthlyCharges + Contract +
##     StreamingMovies + StreamingTV + TechSupport + OnlineSecurity +
##     PaperlessBilling + Dependents + MultipleLines + SeniorCitizen *
##     PaymentMethod
##   Resid. Df Resid. Dev Df Deviance Pr(>Chi)
## 1      4909     4091.0
## 2      4907     4080.8  2   10.203 0.006088 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
anova( mod20, mod22,  test="Chisq") #significant
```

```
## Analysis of Deviance Table
##
## Model 1: Churn ~ tenure + InternetService * MonthlyCharges + Contract +
##     StreamingMovies + StreamingTV + TechSupport + OnlineSecurity +
##     PaperlessBilling + Dependents + MultipleLines + SeniorCitizen +
##     PaymentMethod
## Model 2: Churn ~ tenure + InternetService * MonthlyCharges + Contract +
##     StreamingMovies + StreamingTV + TechSupport + OnlineSecurity +
##     PaperlessBilling + Dependents + MultipleLines + SeniorCitizen *
##     PaymentMethod
##   Resid. Df Resid. Dev Df Deviance Pr(>Chi)
## 1      4910     4093.7
## 2      4907     4080.8  3   12.829 0.005021 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
vif(mod22)
```

```
## there are higher-order terms (interactions) in this model
## consider setting type = 'predictor'; see ?vif
```

```
##                                      GVIF Df GVIF^(1/(2*Df))
## tenure                          2.092433  1        1.446525
## InternetService              9747.368394  2        9.936235
## MonthlyCharges                 21.496711  1        4.636455
## Contract                        1.554570  2        1.116613
## StreamingMovies                 2.379677  1        1.542620
## StreamingTV                     2.420865  1        1.555913
## TechSupport                     1.375906  1        1.172990
## OnlineSecurity                  1.300799  1        1.140526
## PaperlessBilling                1.124887  1        1.060607
## Dependents                      1.057390  1        1.028295
## MultipleLines                   1.905667  1        1.380459
## SeniorCitizen                   6.580622  1        2.565272
## PaymentMethod                   2.445976  3        1.160759
## InternetService:MonthlyCharges 11487.448457  2       10.352754
## SeniorCitizen:PaymentMethod    10.277317  3        1.474506
```

Having both interactions improves the model but VIF gets worse. The best model is with SeniorCitizen and PaymentMethod interaction (mod21)

###Second Order variable

```
mod23 <- glm(Churn ~ tenure + I(tenure^2) + InternetService + MonthlyCharges + Contract + StreamingMovi
AIC(mod23) #4088.4 better
```

```
## [1] 4088.366
```

```
anova( mod21, mod23,  test="Chisq") #significant
```

```
## Analysis of Deviance Table
##
## Model 1: Churn ~ tenure + InternetService + MonthlyCharges + Contract +
##     StreamingMovies + StreamingTV + TechSupport + OnlineSecurity +
##     PaperlessBilling + Dependents + MultipleLines + SeniorCitizen *
##     PaymentMethod
## Model 2: Churn ~ tenure + I(tenure^2) + InternetService + MonthlyCharges +
##     Contract + StreamingMovies + StreamingTV + TechSupport +
##     OnlineSecurity + PaperlessBilling + Dependents + MultipleLines +
##     SeniorCitizen * PaymentMethod
##   Resid. Df Resid. Dev Df Deviance  Pr(>Chi)
## 1      4909     4091.0
## 2      4908     4044.4  1   46.672 8.392e-12 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
vif(mod23)
```

```
## there are higher-order terms (interactions) in this model
## consider setting type = 'predictor'; see ?vif
```

```
##                                GVIF Df GVIF^(1/(2*Df))
## tenure                    15.110913  1        3.887276
## I(tenure^2)               14.413478  1        3.796509
## InternetService           13.143356  2        1.904042
## MonthlyCharges            20.658589  1        4.545172
## Contract                   1.830861  2        1.163225
## StreamingMovies            2.155609  1        1.468199
## StreamingTV                2.220993  1        1.490300
```

```
## TechSupport                  1.373947  1        1.172155
## OnlineSecurity               1.306102  1        1.142848
## PaperlessBilling             1.124076  1        1.060225
## Dependents                   1.060211  1        1.029666
## MultipleLines                1.824384  1        1.350697
## SeniorCitizen                6.421969  1        2.534160
## PaymentMethod                2.503172  3        1.165239
## SeniorCitizen:PaymentMethod 10.118072  3        1.470674
```

```
mod23.1 <- glm(Churn ~ tenure + I(tenure^2) + InternetService + Contract + StreamingMovies + StreamingT
AIC(mod23.1) #4093.9 worse
```

```
## [1] 4093.873
```

```
anova( mod23, mod23.1,  test="Chisq") #significant
```

```
## Analysis of Deviance Table
##
## Model 1: Churn ~ tenure + I(tenure^2) + InternetService + MonthlyCharges +
##     Contract + StreamingMovies + StreamingTV + TechSupport +
##     OnlineSecurity + PaperlessBilling + Dependents + MultipleLines +
##     SeniorCitizen * PaymentMethod
## Model 2: Churn ~ tenure + I(tenure^2) + InternetService + Contract + StreamingMovies +
##     StreamingTV + TechSupport + OnlineSecurity + PaperlessBilling +
##     Dependents + MultipleLines + SeniorCitizen * PaymentMethod
##   Resid. Df Resid. Dev Df Deviance Pr(>Chi)
## 1      4908     4044.4
## 2      4909     4051.9 -1  -7.5068 0.006147 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
vif(mod23.1) #better vif
```

```
## there are higher-order terms (interactions) in this model
## consider setting type = 'predictor'; see ?vif
```

```
##                                  GVIF Df GVIF^(1/(2*Df))
## tenure                      15.094283  1        3.885136
## I(tenure^2)                 14.395726  1        3.794170
## InternetService              1.753349  2        1.150713
## Contract                     1.832458  2        1.163479
## StreamingMovies              1.439408  1        1.199753
## StreamingTV                  1.476549  1        1.215133
## TechSupport                  1.176693  1        1.084755
## OnlineSecurity               1.145979  1        1.070504
## PaperlessBilling             1.123469  1        1.059938
## Dependents                   1.059050  1        1.029102
## MultipleLines                1.406194  1        1.185831
## SeniorCitizen                6.416355  1        2.533052
## PaymentMethod                2.500773  3        1.165053
## SeniorCitizen:PaymentMethod 10.110887  3        1.470499
```

Removing *MonthlyCharges* from the model is getting a bit worse the AIC but the change is significant and it improves the VIF.

For improving the multicollinearity we add log in *tenure*

```r
mod23.4 <- glm(Churn ~ log(tenure + 0.01) + I(tenure^2) + InternetService + Contract + StreamingMovies +
AIC(mod23.4) #4059.53
```

```
## [1] 4059.531
```

```r
vif(mod23.4)
```

```
## there are higher-order terms (interactions) in this model
## consider setting type = 'predictor'; see ?vif
```

```
##                                   GVIF Df GVIF^(1/(2*Df))
## log(tenure + 0.01)            2.500964  1        1.581444
## I(tenure^2)                   2.794150  1        1.671571
## InternetService               1.770563  2        1.153527
## Contract                      1.731667  2        1.147139
## StreamingMovies               1.429558  1        1.195641
## StreamingTV                   1.458661  1        1.207750
## TechSupport                   1.172948  1        1.083027
## OnlineSecurity                1.140765  1        1.068066
## PaperlessBilling              1.125341  1        1.060821
## Dependents                    1.057858  1        1.028522
## MultipleLines                 1.385364  1        1.177015
## SeniorCitizen                 6.404190  1        2.530650
## PaymentMethod                 2.532835  3        1.167529
## SeniorCitizen:PaymentMethod  10.154436  3        1.471553
```

We keep this last model.

Inlfuential data

We check the influential data after including the interactions and the second order variables.

```r
infl_3 <- influence.measures(mod23.4)

sum(residuals(mod23.4,'deviance')^2)
```

```
## [1] 4017.531
```

```r
sum(residuals(mod23.4,'pearson')^2)
```

```
## [1] 4952.141
```

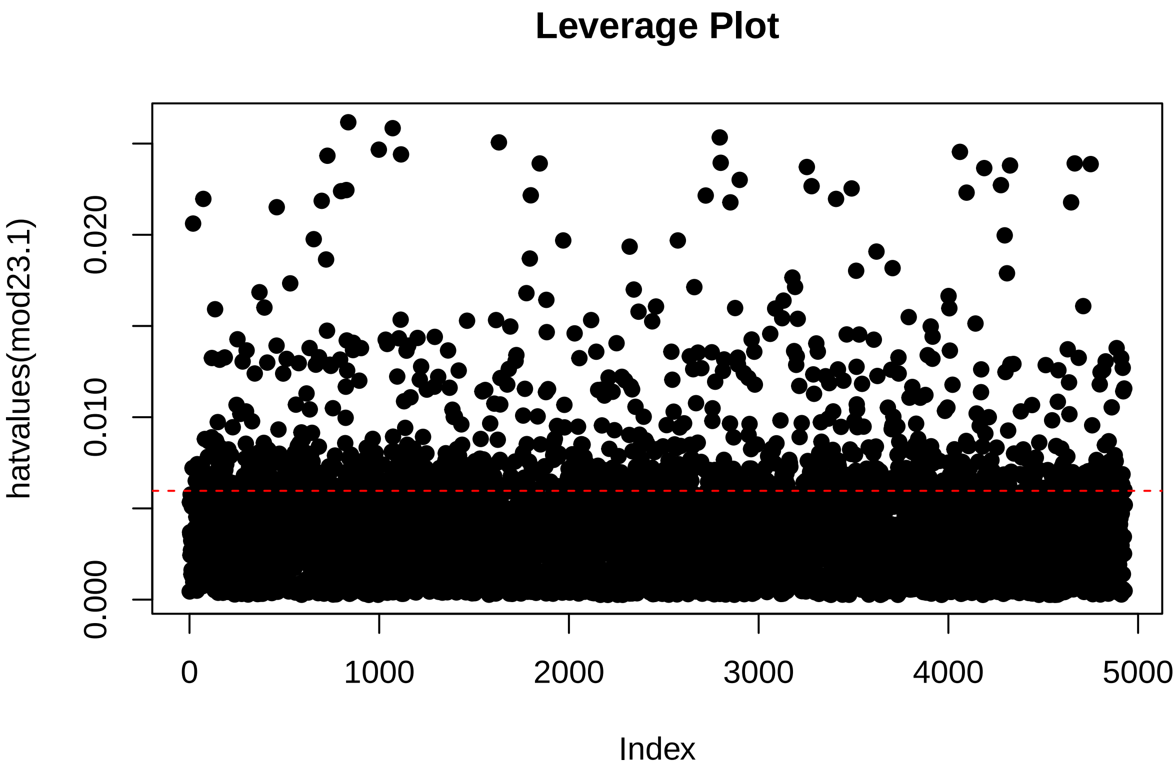
```r
influential_indices_3 <- which(infl_3$is.inf == TRUE)
length(influential_indices_3)
```

```
## [1] 399
```

```r
length(train$customerID)
```

```
## [1] 4930
```

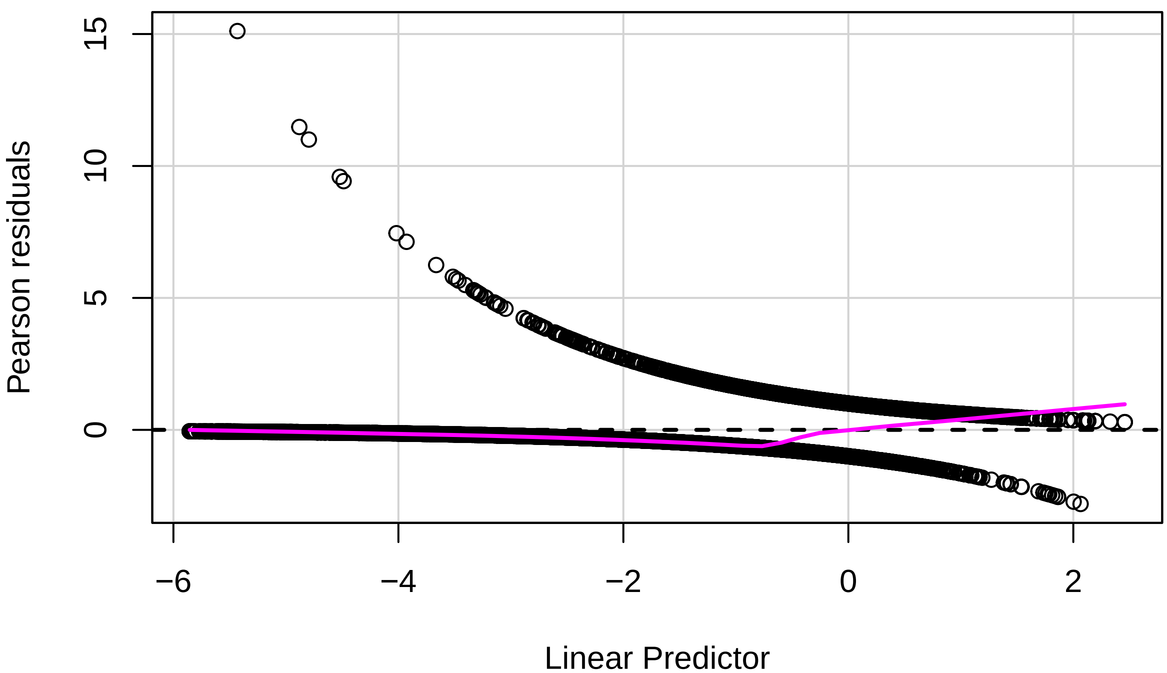
```r
#Leverage values
plot(hatvalues(mod23.1), pch = 19, main = "Leverage Plot")
abline(h = 2 * ncol(model.matrix(mod23.1))/length(df$customerID), col = "red", lty = 2)
```



We have more influential data than before, 399 tuples. We see that they are distributed randomly. We consider to not delete this data because it gives us important information for the model.

Residuals

```
residualPlot(mod23.4)
```



We see that we have improved the residuals.

Predictions

```
rmse <- function(fitted, actual){
  sqrt(mean((fitted - actual)^2))
}

RSQUARE <- function(predictions, actual_values) {
  ss_residual <- sum((actual_values - predictions)^2)
  ss_total <- sum((actual_values - mean(actual_values))^2)
  rsquare <- 1 - (ss_residual / ss_total)
  return(rsquare)
}
```

```
#selecting the parameters that we have in the model

test_data <- test[c(3,5,6,8,9,10,13,14,15,16,17,18)]

pred_prob <- predict(mod23.4, newdata = test_data, type="response")

churn_pred<- ifelse(pred_prob>0.5,"Yes","No")

table(churn_pred)
```

```
## churn_pred
##   No  Yes
## 1677  436
```

```
table(test$Churn)
```

```
##
##   No  Yes
## 1547  566
```

```
#Confusion table

tt <- table(churn_pred, test$Churn);tt
```

```
##
## churn_pred   No  Yes
##        No  1409  268
##        Yes  138  298
```

```
100*sum(diag(tt))/sum(tt) #80.79
```

```
## [1] 80.78561
```

The accuracy of our model is good, it is 80.79.

```
roc_curve <- roc(test$Churn, pred_prob)
```

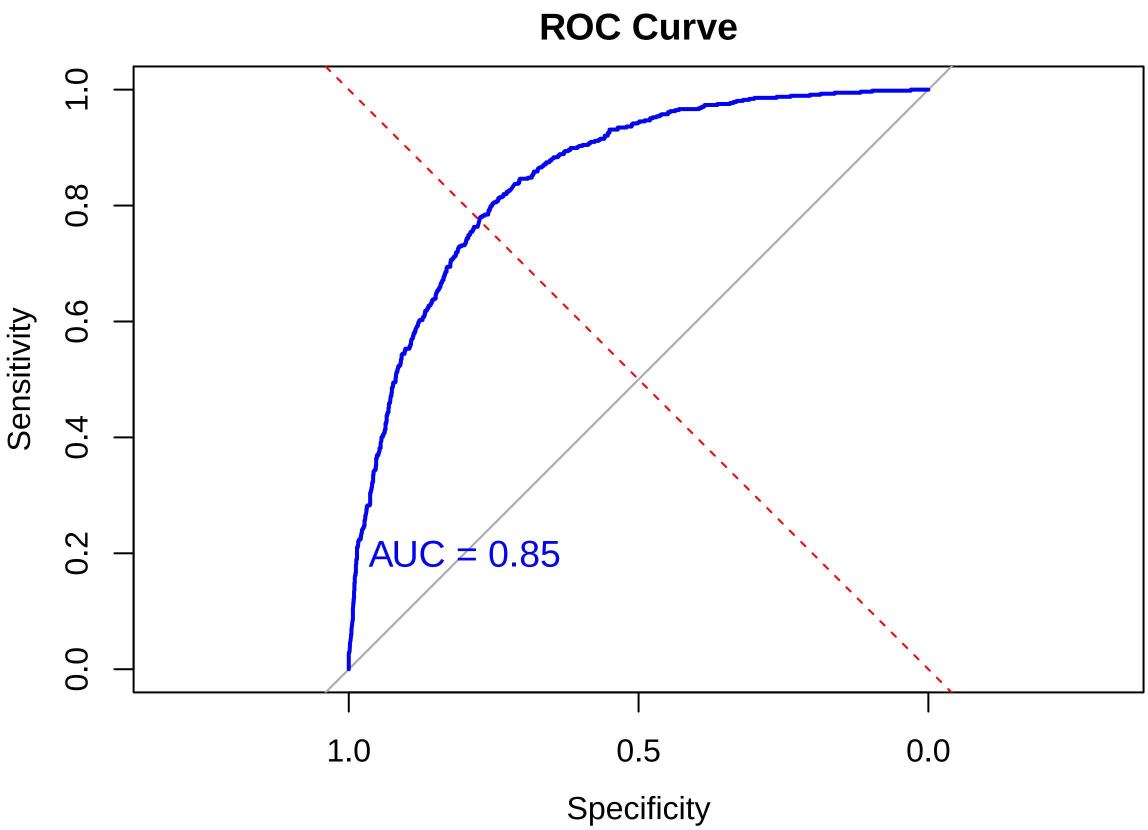
```
## Setting levels: control = No, case = Yes
```

```
## Setting direction: controls < cases
```

```
# Plot the ROC curve
plot(roc_curve, main = "ROC Curve", col = "blue", lwd = 2)

# Add diagonal reference line for comparison
abline(a = 0, b = 1, lty = 2, col = "red")
```

```r
# Add AUC (Area Under the Curve) value to the plot
text(0.8, 0.2, paste("AUC =", round(auc(roc_curve), 2)), col = "blue", cex = 1.2)
```



Our Area Under the Curve for ROC curve is 0.85 so it is high.

Our final model is

```r
coef(mod23.4)
```

```
##                                         (Intercept)
##                                        5.747068e-02
##                                 log(tenure + 0.01)
##                                       -5.438358e-01
##                                        I(tenure^2)
##                                       -4.494426e-05
##                        InternetServiceFiber optic
##                                        7.544949e-01
##                                  InternetServiceNo
##                                       -9.744106e-01
##                                   ContractOne year
##                                       -7.534039e-01
##                                   ContractTwo year
##                                       -1.895286e+00
##                                 StreamingMoviesYes
##                                        2.624637e-01
##                                     StreamingTVYes
##                                        3.305712e-01
##                                     TechSupportYes
```

```
##                                             -2.174029e-01
##                                         OnlineSecurityYes
##                                             -2.801188e-01
##                                       PaperlessBillingYes
##                                              3.294340e-01
##                                             DependentsYes
##                                             -2.300625e-01
##                                          MultipleLinesYes
##                                              3.244615e-01
##                                            SeniorCitizen1
##                                             -1.540301e-01
##                PaymentMethodCredit card (automatic)
##                                             -2.543356e-01
##                       PaymentMethodElectronic check
##                                              2.736901e-01
##                           PaymentMethodMailed check
##                                             -2.447431e-01
## SeniorCitizen1:PaymentMethodCredit card (automatic)
##                                              8.653999e-01
##       SeniorCitizen1:PaymentMethodElectronic check
##                                              2.843971e-01
##           SeniorCitizen1:PaymentMethodMailed check
##                                              1.101151e+00
```

$Y = -0.58 - 0.08 tenure + 0.0007 tenure^2 + 0.75 InternetServiceFiberoptic - 0.92 InternetServiceNo - 0.72 ContractOneyear - 1$

\

Annex

Univariate

```r
names(train)
```

```
##  [1] "customerID"       "gender"           "SeniorCitizen"    "Partner"
##  [5] "Dependents"       "tenure"           "PhoneService"     "MultipleLines"
##  [9] "InternetService"  "OnlineSecurity"   "OnlineBackup"     "DeviceProtection"
## [13] "TechSupport"      "StreamingTV"      "StreamingMovies"  "Contract"
## [17] "PaperlessBilling" "PaymentMethod"    "MonthlyCharges"   "TotalCharges"
## [21] "Churn"
```

```r
mod <- glm(Churn ~ gender, data=train, family=binomial)
summary(mod)
```

```
##
## Call:
## glm(formula = Churn ~ gender, family = binomial, data = train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -0.7894  -0.7894  -0.7776   1.6235   1.6393
##
## Coefficients:
```

```
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -1.00637    0.04542 -22.158   <2e-16 ***
## genderMale  -0.03499    0.06460  -0.542    0.588
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 5694.2  on 4929  degrees of freedom
## Residual deviance: 5693.9  on 4928  degrees of freedom
## AIC: 5697.9
##
## Number of Fisher Scoring iterations: 4
```

```
mod2 <- glm(Churn ~ SeniorCitizen, data=train, family=binomial)
summary(mod2)
```

```
##
## Call:
## glm(formula = Churn ~ SeniorCitizen, family = binomial, data = train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.0497  -0.7288  -0.7288   1.3107   1.7064
##
## Coefficients:
##                Estimate Std. Error z value Pr(>|z|)
## (Intercept)    -1.19026    0.03682  -32.33   <2e-16 ***
## SeniorCitizen1  0.88226    0.08027   10.99   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 5694.2  on 4929  degrees of freedom
## Residual deviance: 5577.9  on 4928  degrees of freedom
## AIC: 5581.9
##
## Number of Fisher Scoring iterations: 4
```

```
mod3 <- glm(Churn ~ Partner, data=train, family=binomial)
summary(mod3)
```

```
##
## Call:
## glm(formula = Churn ~ Partner, family = binomial, data = train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -0.8946  -0.8946  -0.6573   1.4895   1.8102
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -0.70909    0.04215  -16.82   <2e-16 ***
## PartnerYes  -0.71326    0.06676  -10.68   <2e-16 ***
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 5694.2  on 4929  degrees of freedom
## Residual deviance: 5576.5  on 4928  degrees of freedom
## AIC: 5580.5
##
## Number of Fisher Scoring iterations: 4
```

```
mod4 <- glm(Churn ~ Dependents, data=train, family=binomial)
summary(mod4)
```

```
##
## Call:
## glm(formula = Churn ~ Dependents, family = binomial, data = train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -0.8682  -0.8682  -0.5642   1.5221   1.9577
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept)   -0.78158    0.03662  -21.34   <2e-16 ***
## DependentsYes -0.97564    0.08228  -11.86   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 5694.2  on 4929  degrees of freedom
## Residual deviance: 5534.9  on 4928  degrees of freedom
## AIC: 5538.9
##
## Number of Fisher Scoring iterations: 4
```

```
mod5 <- glm(Churn ~ tenure, data=train, family=binomial)
summary(mod5)
```

```
##
## Call:
## glm(formula = Churn ~ tenure, family = binomial, data = train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.1818  -0.8360  -0.4898   1.1893   2.3715
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.010348   0.050517   0.205    0.838
## tenure      -0.038339   0.001679 -22.837   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 5694.2  on 4929  degrees of freedom
## Residual deviance: 5040.7  on 4928  degrees of freedom
## AIC: 5044.7
##
## Number of Fisher Scoring iterations: 4
```

```r
mod6 <- glm(Churn ~ PhoneService, data=train, family=binomial)
summary(mod6)
```

```
##
## Call:
## glm(formula = Churn ~ PhoneService, family = binomial, data = train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -0.7876  -0.7876  -0.7876   1.6259   1.6844
##
## Coefficients:
##                  Estimate Std. Error z value Pr(>|z|)
## (Intercept)       -1.1415     0.1076 -10.611   <2e-16 ***
## PhoneServiceYes    0.1299     0.1128   1.151     0.25
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 5694.2  on 4929  degrees of freedom
## Residual deviance: 5692.9  on 4928  degrees of freedom
## AIC: 5696.9
##
## Number of Fisher Scoring iterations: 4
```

```r
mod7 <- glm(Churn ~ MultipleLines, data=train, family=binomial)
summary(mod7)
```

```
##
## Call:
## glm(formula = Churn ~ MultipleLines, family = binomial, data = train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -0.8283  -0.8283  -0.7504   1.5726   1.6763
##
## Coefficients:
##                   Estimate Std. Error z value Pr(>|z|)
## (Intercept)       -1.12350    0.04348 -25.841  < 2e-16 ***
## MultipleLinesYes   0.23006    0.06505   3.537 0.000405 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 5694.2  on 4929  degrees of freedom
```

```
## Residual deviance: 5681.7  on 4928  degrees of freedom
## AIC: 5685.7
##
## Number of Fisher Scoring iterations: 4
```

```r
mod8 <- glm(Churn ~ InternetService, data=train, family=binomial)
summary(mod8)
```

```
##
## Call:
## glm(formula = Churn ~ InternetService, family = binomial, data = train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.0398  -1.0398  -0.6431   1.3215   2.3065
##
## Coefficients:
##                            Estimate Std. Error z value Pr(>|z|)
## (Intercept)                -1.47098    0.06258 -23.506   <2e-16 ***
## InternetServiceFiber optic  1.13842    0.07611  14.957   <2e-16 ***
## InternetServiceNo          -1.11658    0.13582  -8.221   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 5694.2  on 4929  degrees of freedom
## Residual deviance: 5132.9  on 4927  degrees of freedom
## AIC: 5138.9
##
## Number of Fisher Scoring iterations: 5
```

```r
mod9 <- glm(Churn ~ OnlineSecurity, data=train, family=binomial)
summary(mod9)
```

```
##
## Call:
## glm(formula = Churn ~ OnlineSecurity, family = binomial, data = train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -0.8625  -0.8625  -0.5630   1.5292   1.9598
##
## Coefficients:
##                   Estimate Std. Error z value Pr(>|z|)
## (Intercept)       -0.79719    0.03633  -21.94   <2e-16 ***
## OnlineSecurityYes -0.96472    0.08405  -11.48   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 5694.2  on 4929  degrees of freedom
## Residual deviance: 5544.3  on 4928  degrees of freedom
## AIC: 5548.3
```

```
##
## Number of Fisher Scoring iterations: 4
```

```r
mod10 <- glm(Churn ~ OnlineBackup, data=train, family=binomial)
summary(mod10)
```

```
##
## Call:
## glm(formula = Churn ~ OnlineBackup, family = binomial, data = train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -0.8221  -0.8221  -0.7079   1.5805   1.7359
##
## Coefficients:
##                 Estimate Std. Error z value Pr(>|z|)
## (Intercept)     -0.91109    0.03891 -23.414  < 2e-16 ***
## OnlineBackupYes -0.34507    0.07016  -4.919 8.72e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 5694.2  on 4929  degrees of freedom
## Residual deviance: 5669.4  on 4928  degrees of freedom
## AIC: 5673.4
##
## Number of Fisher Scoring iterations: 4
```

```r
mod11 <- glm(Churn ~ DeviceProtection, data=train, family=binomial)
summary(mod11)
```

```
##
## Call:
## glm(formula = Churn ~ DeviceProtection, family = binomial, data = train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -0.8147  -0.8147  -0.7228   1.5901   1.7148
##
## Coefficients:
##                     Estimate Std. Error z value Pr(>|z|)
## (Intercept)         -0.93239    0.03909 -23.852  < 2e-16 ***
## DeviceProtectionYes -0.27669    0.06963  -3.973 7.09e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 5694.2  on 4929  degrees of freedom
## Residual deviance: 5678.1  on 4928  degrees of freedom
## AIC: 5682.1
##
## Number of Fisher Scoring iterations: 4
```

```r
mod12 <- glm(Churn ~ TechSupport, data=train, family=binomial)
summary(mod12)
```

```
##
## Call:
## glm(formula = Churn ~ TechSupport, family = binomial, data = train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -0.8594  -0.8594  -0.5874   1.5331   1.9196
##
## Coefficients:
##                Estimate Std. Error z value Pr(>|z|)
## (Intercept)    -0.80594    0.03674  -21.94   <2e-16 ***
## TechSupportYes -0.86397    0.08058  -10.72   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 5694.2  on 4929  degrees of freedom
## Residual deviance: 5566.6  on 4928  degrees of freedom
## AIC: 5570.6
##
## Number of Fisher Scoring iterations: 4
```

```r
mod13 <- glm(Churn ~ StreamingTV, data=train, family=binomial)
summary(mod13)
```

```
##
## Call:
## glm(formula = Churn ~ StreamingTV, family = binomial, data = train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -0.8464  -0.8464  -0.7424   1.5495   1.6873
##
## Coefficients:
##                Estimate Std. Error z value Pr(>|z|)
## (Intercept)    -1.14795    0.04263 -26.931  < 2e-16 ***
## StreamingTVYes  0.30561    0.06551   4.665 3.09e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 5694.2  on 4929  degrees of freedom
## Residual deviance: 5672.6  on 4928  degrees of freedom
## AIC: 5676.6
##
## Number of Fisher Scoring iterations: 4
```

```r
mod14 <- glm(Churn ~ StreamingMovies, data=train, family=binomial)
summary(mod14)
```

```
##
## Call:
## glm(formula = Churn ~ StreamingMovies, family = binomial, data = train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -0.8342  -0.8342  -0.7498   1.5650   1.6770
##
## Coefficients:
##                    Estimate Std. Error z value Pr(>|z|)
## (Intercept)        -1.12512    0.04254 -26.449  < 2e-16 ***
## StreamingMoviesYes  0.24849    0.06550   3.794 0.000148 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 5694.2  on 4929  degrees of freedom
## Residual deviance: 5679.9  on 4928  degrees of freedom
## AIC: 5683.9
##
## Number of Fisher Scoring iterations: 4
```

```
mod15 <- glm(Churn ~ Contract, data=train, family=binomial)
summary(mod15)
```

```
##
## Call:
## glm(formula = Churn ~ Contract, family = binomial, data = train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.0490  -1.0490  -0.4923   1.3115   2.6944
##
## Coefficients:
##                  Estimate Std. Error z value Pr(>|z|)
## (Intercept)      -0.30975    0.03876  -7.992 1.33e-15 ***
## ContractOne year -1.73958    0.10521 -16.535  < 2e-16 ***
## ContractTwo year -3.29329    0.18611 -17.695  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 5694.2  on 4929  degrees of freedom
## Residual deviance: 4736.2  on 4927  degrees of freedom
## AIC: 4742.2
##
## Number of Fisher Scoring iterations: 6
```

```
mod16 <- glm(Churn ~ PaperlessBilling, data=train, family=binomial)
summary(mod16)
```

```
##
## Call:
```

```
## glm(formula = Churn ~ PaperlessBilling, family = binomial, data = train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -0.9003  -0.9003  -0.5994   1.4825   1.9001
##
## Coefficients:
##                     Estimate Std. Error z value Pr(>|z|)
## (Intercept)         -1.62562    0.06013  -27.04   <2e-16 ***
## PaperlessBillingYes  0.93196    0.07182   12.98   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 5694.2  on 4929  degrees of freedom
## Residual deviance: 5512.4  on 4928  degrees of freedom
## AIC: 5516.4
##
## Number of Fisher Scoring iterations: 4
```

```
mod17 <- glm(Churn ~ PaymentMethod, data=train, family=binomial)
summary(mod17)
```

```
##
## Call:
## glm(formula = Churn ~ PaymentMethod, family = binomial, data = train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.0988  -0.6466  -0.6073   1.2581   1.9537
##
## Coefficients:
##                                      Estimate Std. Error z value Pr(>|z|)
## (Intercept)                          -1.59686    0.08266 -19.319   <2e-16 ***
## PaymentMethodCredit card (automatic) -0.15101    0.11847  -1.275    0.202
## PaymentMethodElectronic check         1.40923    0.09627  14.638   <2e-16 ***
## PaymentMethodMailed check             0.13813    0.11233   1.230    0.219
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 5694.2  on 4929  degrees of freedom
## Residual deviance: 5246.3  on 4926  degrees of freedom
## AIC: 5254.3
##
## Number of Fisher Scoring iterations: 4
```

```
mod18 <- glm(Churn ~ MonthlyCharges, data=train, family=binomial)
summary(mod18)
```

```
##
## Call:
## glm(formula = Churn ~ MonthlyCharges, family = binomial, data = train)
```

```
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.0858  -0.8479  -0.6574   1.3652   1.9844
##
## Coefficients:
##                 Estimate Std. Error z value Pr(>|z|)
## (Intercept)    -2.120267   0.090047  -23.55   <2e-16 ***
## MonthlyCharges  0.016008   0.001166   13.73   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 5694.2  on 4929  degrees of freedom
## Residual deviance: 5491.4  on 4928  degrees of freedom
## AIC: 5495.4
##
## Number of Fisher Scoring iterations: 4
```

```
mod19 <- glm(Churn ~ TotalCharges, data=train, family=binomial)
summary(mod19)
```

```
##
## Call:
## glm(formula = Churn ~ TotalCharges, family = binomial, data = train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -0.9463  -0.8675  -0.6810   1.4321   2.2323
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -5.713e-01  4.451e-02  -12.84   <2e-16 ***
## TotalCharges -2.257e-04  1.726e-05  -13.07   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 5694.2  on 4929  degrees of freedom
## Residual deviance: 5494.9  on 4928  degrees of freedom
## AIC: 5498.9
##
## Number of Fisher Scoring iterations: 4
```

```
AIC(mod, mod1,mod2,mod3,mod4,mod5,mod6,mod7,mod8,mod9,mod10,mod11,mod12, mod13,mod14)
```

```
##       df      AIC
## mod    2 5697.925
## mod1   2 5044.677
## mod2   2 5581.910
## mod3   2 5580.505
## mod4   2 5538.857
## mod5   2 5044.677
```

```
## mod6   2 5696.868
## mod7   2 5685.746
## mod8   3 5138.946
## mod9   2 5548.342
## mod10  2 5673.442
## mod11  2 5682.144
## mod12  2 5570.586
## mod13  2 5676.581
## mod14  2 5683.895
```