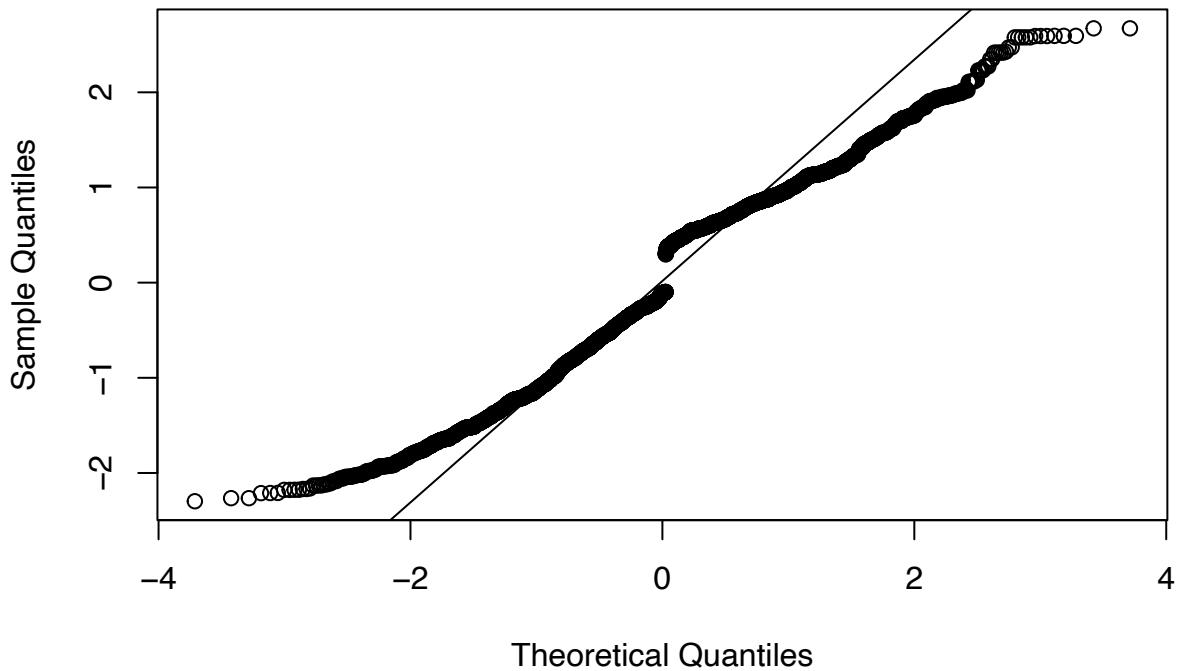
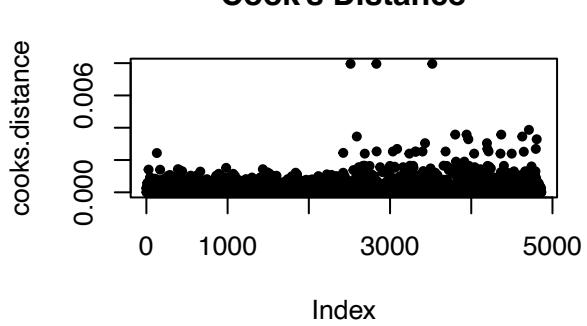
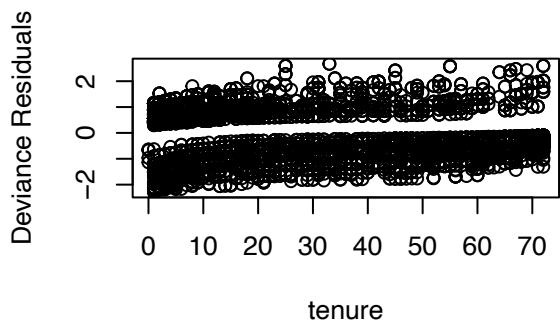
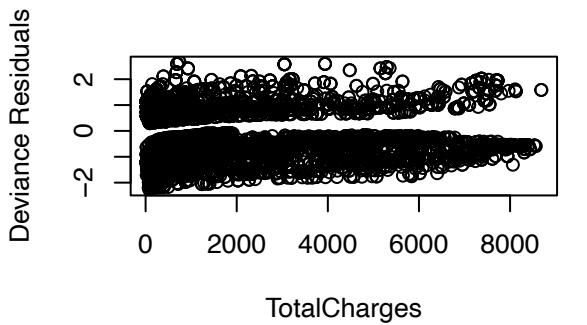
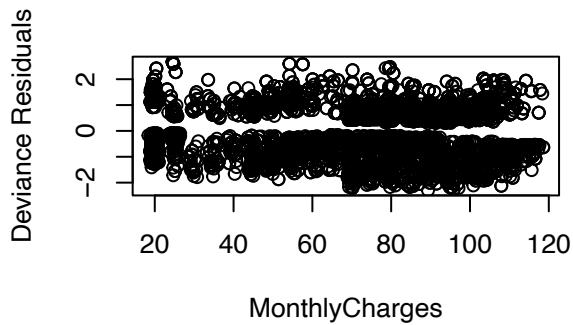


```
qqnorm(residuals2)
qqline(residuals2)
```

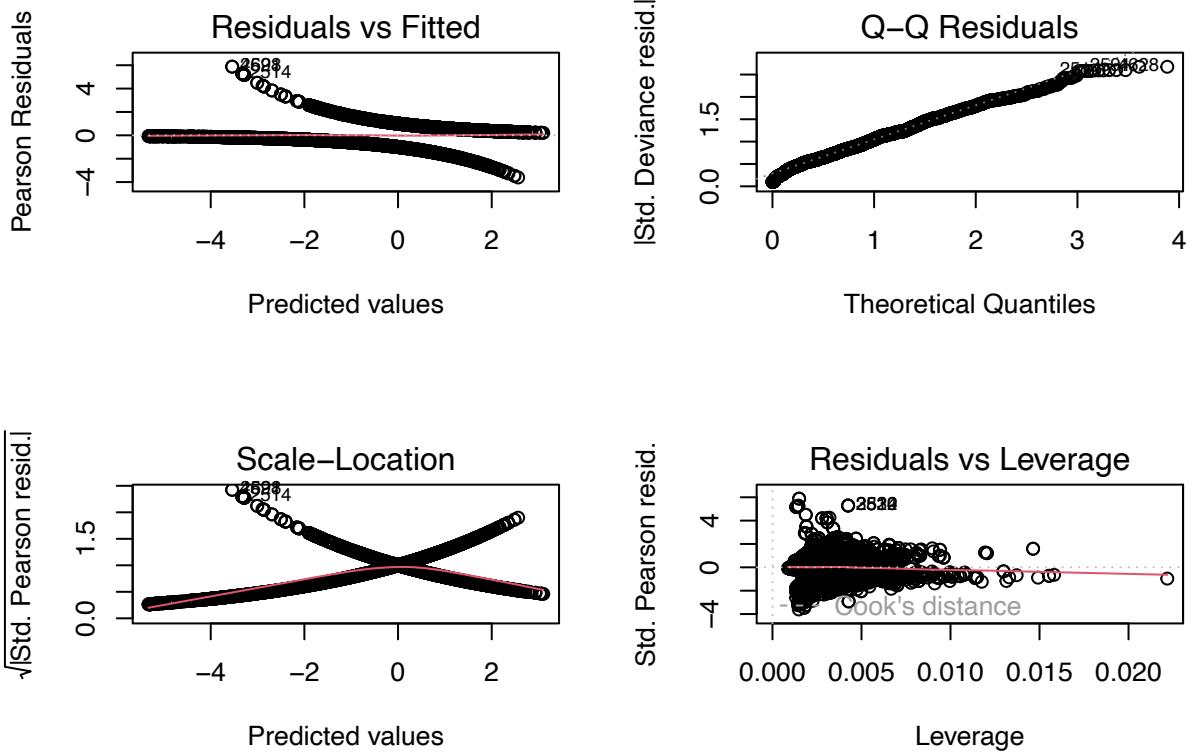
## Normal Q-Q Plot



```
par(mfrow = c(2, 2))
plot(train$MonthlyCharges, residuals2, ylab = "Deviance Residuals", xlab = "MonthlyCharges")
plot(train$TotalCharges, residuals2, ylab = "Deviance Residuals", xlab = "TotalCharges")
plot(train$tenure, residuals2, ylab = "Deviance Residuals", xlab = "tenure")
cooks.distance <- cooks.distance(f_model)
plot(cooks.distance, pch = 20, main = "Cook's Distance")
```



```
plot(f_model)
```



```
# Now the normal Q-Q Plot does not follow such a linear pattern
```

Remove data points with a Cook's Distance greater than .001

```
cooks2 <- cooks.distance(f_model)
outliers2 <- which(cooks2 > 0.002)
train_clean2 <- train[-outliers2, ]

# Create model without outliers
# f_model_cleaned <- glm(Churn ~ poly(MonthlyCharges, 2) + poly(TotalCharges, 2) + poly(tenure, 3) +
f_model_cleaned <- glm(Churn ~ poly(MonthlyCharges, 2) + poly(TotalCharges, 2) + poly(tenure, 3) + S

#Test it only the train_clean2:
print(f_model_cleaned)

##
## Call: glm(formula = Churn ~ poly(MonthlyCharges, 2) + poly(TotalCharges,
##           2) + poly(tenure, 3) + SeniorCitizen + InternetService +
##           StreamingTV + StreamingMovies + Contract, family = "binomial",
##           data = train_clean2)
##
## Coefficients:
```

```

##          (Intercept)      poly(MonthlyCharges, 2)1
##                  -1.0135      -41.4221
##      poly(MonthlyCharges, 2)2      poly(TotalCharges, 2)1
##                      3.6818      44.6777
##      poly(TotalCharges, 2)2      poly(tenure, 3)1
##                      10.8576     -101.2892
##      poly(tenure, 3)2      poly(tenure, 3)3
##                      -3.8141     -16.5357
##      SeniorCitizen1      InternetServiceFiber optic
##                      0.4880      1.6222
##      InternetServiceNo      StreamingTVNo internet service
##                      -1.3513      NA
##      StreamingTVYes      StreamingMoviesNo internet service
##                      0.5719      NA
##      StreamingMoviesYes      ContractOne year
##                      0.5015     -0.8105
##      ContractTwo year
##                      -2.0572
##
## Degrees of Freedom: 4830 Total (i.e. Null); 4816 Residual
## Null Deviance: 6694
## Residual Deviance: 4540 AIC: 4570

evaluation(f_model_cleaned, train_clean2)

## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from rank-deficient fit; attr(*, "non-estim") has doubtful cases

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

## Setting direction: controls < cases

## Training Set Metrics:
## AUC: 0.8511899
## [1] "Confusion Matrix:"
##           Predicted
##   Actual    No    Yes
##   No     1768   712
##   Yes     405 1946
## Recall: 0.8277329
## F1-score: 0.7770014

## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from rank-deficient fit; attr(*, "non-estim") has doubtful cases

## Setting levels: control = No, case = Yes
## Setting direction: controls < cases

## Test Set Metrics:
## AUC: 0.8454064
## [1] "Confusion Matrix:"
##           Predicted

```

```

## Actual No Yes
##   No 1127 457
##   Yes 87 499
## Recall: 0.8515358
## F1-score: 0.6472114

#Trying the step function
step_model <- step( f_model_cleaned, k= log(nrow(df)))

## Start: AIC=4672.74
## Churn ~ poly(MonthlyCharges, 2) + poly(TotalCharges, 2) + poly(tenure,
##      3) + SeniorCitizen + InternetService + StreamingTV + StreamingMovies +
##      Contract
##
##                                Df Deviance    AIC
## - poly(TotalCharges, 2)    2  4552.5 4667.7
## - poly(MonthlyCharges, 2)  2  4553.4 4668.6
## <none>                      4539.8 4672.7
## - StreamingMovies          1  4561.0 4685.0
## - SeniorCitizen            1  4565.6 4689.7
## - StreamingTV              1  4566.9 4690.9
## - poly(tenure, 3)          3  4633.9 4740.2
## - InternetService          1  4618.3 4742.3
## - Contract                 2  4678.1 4793.3
##
## Step: AIC=4667.66
## Churn ~ poly(MonthlyCharges, 2) + poly(tenure, 3) + SeniorCitizen +
##       InternetService + StreamingTV + StreamingMovies + Contract
##
##                                Df Deviance    AIC
## <none>                      4552.5 4667.7
## - poly(MonthlyCharges, 2)    2  4570.8 4668.3
## - StreamingMovies           1  4569.5 4675.8
## - StreamingTV               1  4574.3 4680.6
## - SeniorCitizen             1  4577.9 4684.2
## - InternetService           1  4622.6 4728.9
## - Contract                  2  4698.6 4796.1
## - poly(tenure, 3)           3  4862.2 4950.8

summary(step_model)

##
## Call:
## glm(formula = Churn ~ poly(MonthlyCharges, 2) + poly(tenure,
##      3) + SeniorCitizen + InternetService + StreamingTV + StreamingMovies +
##      Contract, family = "binomial", data = train_clean2)
##
## Coefficients: (2 not defined because of singularities)
##                               Estimate Std. Error z value Pr(>|z|)
## (Intercept)                -0.78140   0.14733 -5.304 1.13e-07 ***
## poly(MonthlyCharges, 2)1    -26.67568   9.88197 -2.699 0.006946 **
## poly(MonthlyCharges, 2)2     15.37508   4.42251  3.477 0.000508 ***
## poly(tenure, 3)1             -62.98780   4.46284 -14.114 < 2e-16 ***

```

```

## poly(tenure, 3)2          11.02733   3.13907   3.513  0.000443 ***
## poly(tenure, 3)3         -14.49748   2.81922  -5.142  2.71e-07 ***
## SeniorCitizen1           0.48386   0.09713   4.982  6.30e-07 ***
## InternetServiceFiber optic    1.49500   0.18075   8.271  < 2e-16 ***
## InternetServiceNo        -1.50771   0.23938  -6.298  3.01e-10 ***
## StreamingTVNo internet service      NA       NA       NA       NA
## StreamingTVYes            0.50482   0.10870   4.644  3.41e-06 ***
## StreamingMoviesNo internet service      NA       NA       NA       NA
## StreamingMoviesYes          0.44339   0.10802   4.105  4.05e-05 ***
## ContractOne year          -0.79932   0.11091  -7.207  5.73e-13 ***
## ContractTwo year          -2.08310   0.20009  -10.411 < 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: 6693.7 on 4830 degrees of freedom
## Residual deviance: 4552.5 on 4818 degrees of freedom
## AIC: 4578.5
##
## Number of Fisher Scoring iterations: 5

evaluation(step_model, train_clean2)

## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from rank-deficient fit; attr(*, "non-estim") has doubtful cases

## Setting levels: control = No, case = Yes
## Setting direction: controls < cases

## Training Set Metrics:
## AUC: 0.8510832
## [1] "Confusion Matrix:"
##     Predicted
## Actual  No  Yes
##   No 1806 674
##   Yes 458 1893
## Recall: 0.8051893
## F1-score: 0.7698251

## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from rank-deficient fit; attr(*, "non-estim") has doubtful cases

## Setting levels: control = No, case = Yes
## Setting direction: controls < cases

## Test Set Metrics:
## AUC: 0.8474828
## [1] "Confusion Matrix:"
##     Predicted
## Actual  No  Yes
##   No 1148 441

```

```

##      Yes    98   488
## Recall: 0.8327645
## F1-score: 0.6442244

#This lowers the AIC, but also lowers the recall
#So we'll leave the previous model as best

```

Idea: what if we have a separate model for categorizing points that have a high cooks distance? Maybe there is something unique to outliers that gives away whether or not they will churn.

Building the best model with the interactions

```

# Builds a model using a formula and data, returns the model and its F1-score on the training data
build_model_formula <- function(formula, data) {
  # Fit the logistic regression model
  model <- glm(formula, data = data, family = "binomial")

  # Make predictions on the training set
  predictions <- predict(model, newdata = data, type = "response")

  # Convert probabilities to binary predictions
  binary_predictions <- ifelse(predictions > 0.5, 1, 0)

  # Calculate confusion matrix
  confusion_matrix <- table(data$Churn, binary_predictions)

  # Calculate precision, recall, and F-score
  precision <- confusion_matrix[2, 2] / sum(confusion_matrix[, 2])
  recall <- confusion_matrix[2, 2] / sum(confusion_matrix[2, ])
  f_score <- 2 * (precision * recall) / (precision + recall)

  return(list(model = model, f_score = f_score))
}

#Finds the best interactions to fit into the model
find_best_model2 <- function(data) {
  # List of factors to consider
  covariates <- c("poly(MonthlyCharges,2)", "poly(TotalCharges,2)", "poly(tenure,3)")
  selected_factors <- c("SeniorCitizen", "InternetService", "StreamingTV", "StreamingMovies", "Contract")
  factors <- c("SeniorCitizen", "Partner", "MultipleLines", "InternetService", "OnlineBackup", "StreamingTV", "StreamingMovies", "Contract", "PaymentMethod", "Churn")

  # Initialize variables to store the best model and F-score
  best_global_model <- NULL
  best_global_f_score <- 0

  # Choose best interactions starting at 1 interaction
 flen <- length(factors)
  chosen_interactions <- c()
  while(TRUE) {

    best_model <- NULL
    best_f_score <- 0
    # Add a dummy interaction to increase the number of interactions for the next for loop
    chosen_interactions <- c(chosen_interactions, "Contract")
  }
}

```

```

for (i in 1:flen^2) {

  # Remove the previously added interaction
  chosen_interactions <- chosen_interactions[-length(chosen_interactions)]

  # Create the formula with the chosen interactions
  if(i %% flen == (i-1) %% flen) next
  chosen_interactions <- c(chosen_interactions, paste(factors[i %% flen + 1], factors[(i-1) %% flen], reformulate(c(covariates, selected_factors, chosen_interactions), response = "Churn")
  # print(formula)

  # Build the model
  result <- build_model_formula(formula, data)
  model <- result$model
  f_score <- result$f_score

  # Update the best model if the F-score is higher
  if (f_score > best_f_score) {
    best_model <- model
    best_f_score <- f_score
  }
}
if (best_f_score > best_global_f_score) {
  best_global_model <- best_model
  best_global_f_score <- best_f_score
} else break
}

# Return the best model and its F-score
return(list(model = best_model, f_score = best_f_score))
}

# Call the function with your training data
result <- find_best_model2(train_clean2)

## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from rank-deficient fit; attr(*, "non-estim") has doubtful cases

## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from rank-deficient fit; attr(*, "non-estim") has doubtful cases

## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from rank-deficient fit; attr(*, "non-estim") has doubtful cases

## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from rank-deficient fit; attr(*, "non-estim") has doubtful cases

## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from rank-deficient fit; attr(*, "non-estim") has doubtful cases

## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from rank-deficient fit; attr(*, "non-estim") has doubtful cases

```





















```

##                               (Intercept)
##                               -1.0659
##             poly(MonthlyCharges, 2)1
##                               -40.5207
##             poly(MonthlyCharges, 2)2
##                               2.4183
##             poly(TotalCharges, 2)1
##                               49.4840
##             poly(TotalCharges, 2)2
##                               11.0555
##             poly(tenure, 3)1
##                               -105.8805
##             poly(tenure, 3)2
##                               -4.5028
##             poly(tenure, 3)3
##                               -16.4412
##             SeniorCitizen1
##                               0.9283
##             InternetServiceFiber optic
##                               1.6829
##             InternetServiceNo
##                               -1.2524
##             StreamingTVNo internet service
##                               NA
##             StreamingTVYes
##                               0.5654
##             StreamingMoviesNo internet service
##                               NA
##             StreamingMoviesYes
##                               0.5030
##             ContractOne year
##                               -0.8128
##             ContractTwo year
##                               -2.0624
##             SeniorCitizen1:InternetServiceFiber optic
##                               -0.5666
##             SeniorCitizen1:InternetServiceNo
##                               -0.2769
##
## Degrees of Freedom: 4830 Total (i.e. Null); 4814 Residual
## Null Deviance:      6694
## Residual Deviance: 4534 AIC: 4568

```

```
evaluation(best_model_Winte, train_clean2)
```

```

## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from rank-deficient fit; attr(*, "non-estim") has doubtful cases

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

## Setting direction: controls < cases

## Training Set Metrics:

```

```

## AUC: 0.8517806
## [1] "Confusion Matrix:"
##           Predicted
## Actual    No  Yes
##   No    1774 706
##   Yes   395 1956
## Recall: 0.8319864
## F1-score: 0.780371

## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from rank-deficient fit; attr(*, "non-estim") has doubtful cases

## Setting levels: control = No, case = Yes
## Setting direction: controls < cases

## Test Set Metrics:
## AUC: 0.845624
## [1] "Confusion Matrix:"
##           Predicted
## Actual    No  Yes
##   No    1117 467
##   Yes   84 502
## Recall: 0.8566553
## F1-score: 0.6456592

#Best model with interactions

f_model <- glm(Churn ~ poly(MonthlyCharges, 2) + poly(TotalCharges, 2) + poly(tenure, 3) + InternetS
print(f_model)

## 
## Call: glm(formula = Churn ~ poly(MonthlyCharges, 2) + poly(TotalCharges,
##       2) + poly(tenure, 3) + InternetService + StreamingTV + StreamingMovies +
##       Contract + SeniorCitizen * PaymentMethod + Contract * SeniorCitizen,
##       family = "binomial", data = train_clean2)
##
## Coefficients:
##                               (Intercept)
##                               -1.02420
## poly(MonthlyCharges, 2)1
##                           -40.36063
## poly(MonthlyCharges, 2)2
##                           3.83958
## poly(TotalCharges, 2)1
##                           51.61468
## poly(TotalCharges, 2)2
##                           9.17601
## poly(tenure, 3)1
##                          -107.61070
## poly(tenure, 3)2
##                          -2.68595
## poly(tenure, 3)3
##                          -16.36771

```

```

##          InternetServiceFiber optic
##                                1.51021
##          InternetServiceNo
##                                -1.24303
##          StreamingTVNo internet service
##                                NA
##          StreamingTVYes
##                                0.55438
##          StreamingMoviesNo internet service
##                                NA
##          StreamingMoviesYes
##                                0.44684
##          ContractOne year
##                                -0.72956
##          ContractTwo year
##                                -1.91322
##          SeniorCitizen1
##                                0.17070
##          PaymentMethodCredit card (automatic)
##                                -0.02012
##          PaymentMethodElectronic check
##                                0.22597
##          PaymentMethodMailed check
##                                -0.16058
## SeniorCitizen1:PaymentMethodCredit card (automatic)
##                                0.77175
## SeniorCitizen1:PaymentMethodElectronic check
##                                0.30561
## SeniorCitizen1:PaymentMethodMailed check
##                                0.49719
## ContractOne year:SeniorCitizen1
##                                -0.27793
## ContractTwo year:SeniorCitizen1
##                                -0.42190
##
## Degrees of Freedom: 4830 Total (i.e. Null); 4808 Residual
## Null Deviance: 6694
## Residual Deviance: 4519 AIC: 4565

```

```
evaluation(f_model, train_clean2)
```

```

## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from rank-deficient fit; attr(*, "non-estim") has doubtful cases

## Setting levels: control = No, case = Yes
## Setting direction: controls < cases

## Training Set Metrics:
## AUC: 0.8527371
## [1] "Confusion Matrix:"
##      Predicted
## Actual   No  Yes
##     No 1808 672

```

```

##      Yes 455 1896
## Recall: 0.8064653
## F1-score: 0.7708884

## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from rank-deficient fit; attr(*, "non-estim") has doubtful cases

## Setting levels: control = No, case = Yes
## Setting direction: controls < cases

## Test Set Metrics:
## AUC: 0.8472944
## [1] "Confusion Matrix:"
##          Predicted
## Actual    No  Yes
##   No    1156 428
##   Yes    104  482
## Recall: 0.8225256
## F1-score: 0.644385

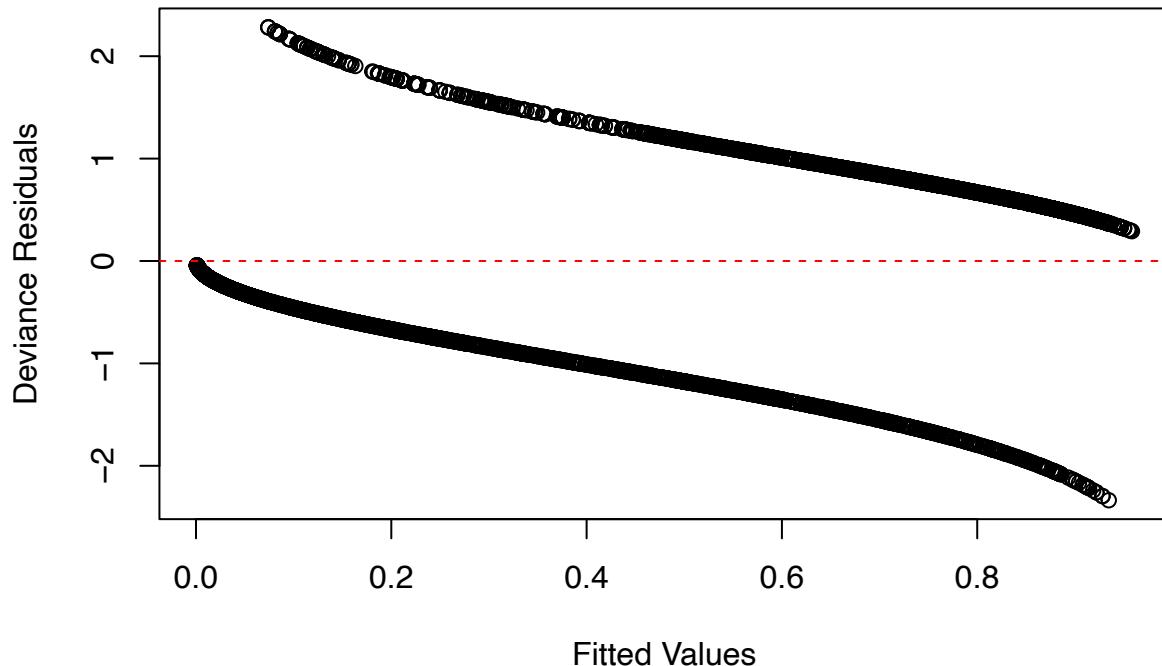
```

Residual Analysis of Numeric + Factor + Interactions Model

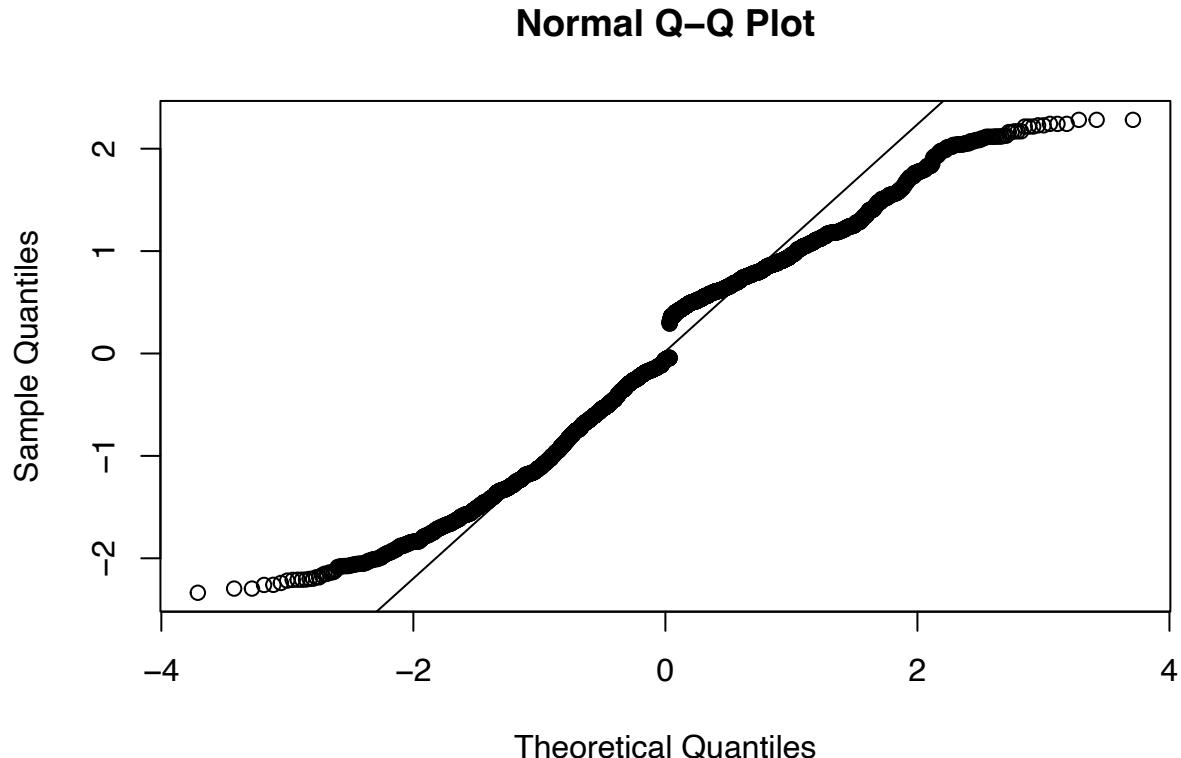
```

residuals2 <- residuals(f_model, type = "deviance")
#For checking heteroscedasticity
plot(fitted(f_model), residuals2, ylab = "Deviance Residuals", xlab = "Fitted Values")
abline(h = 0, col = "red", lty = 2)

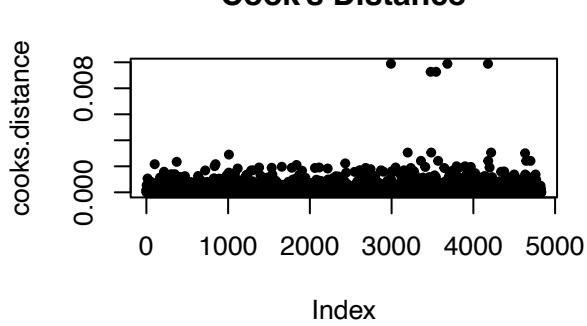
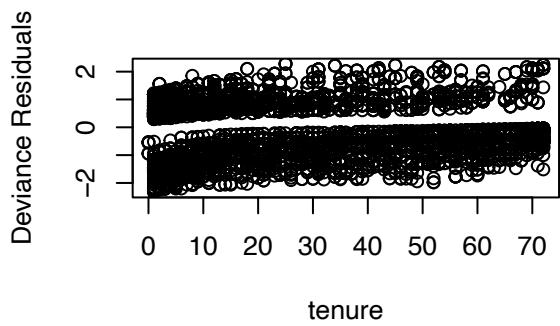
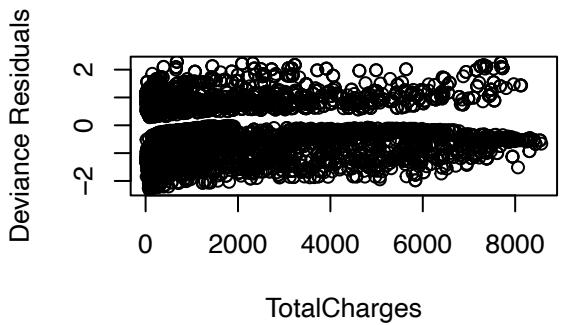
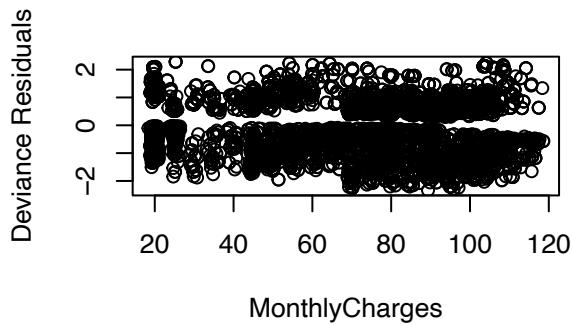
```



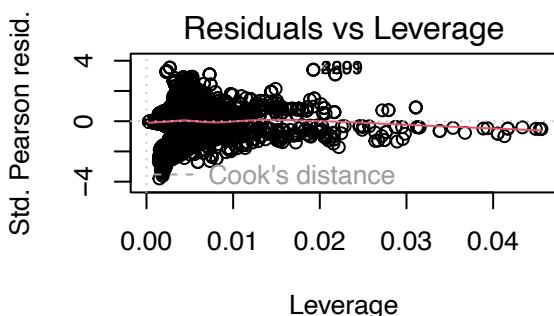
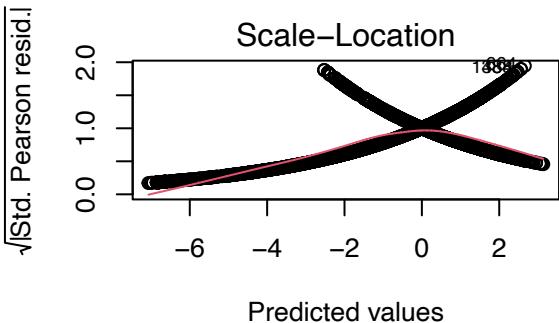
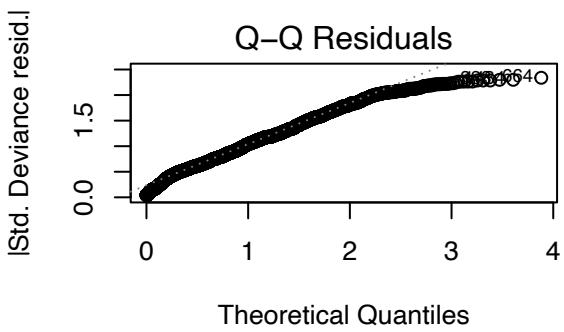
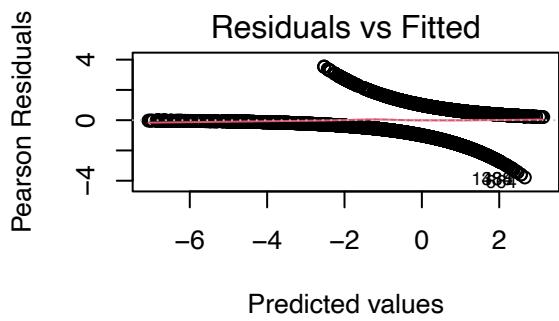
```
qqnorm(residuals2)
qqline(residuals2)
```



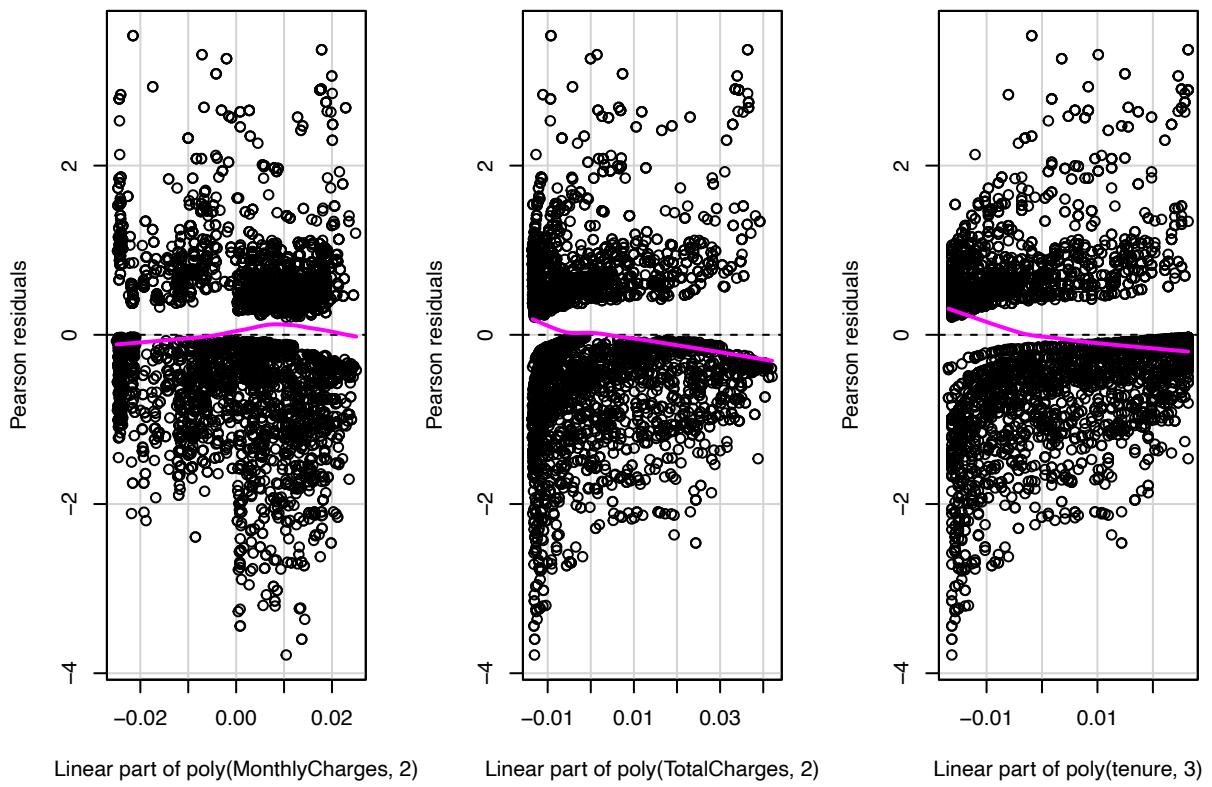
```
par(mfrow = c(2, 2))
plot(train_clean2$MonthlyCharges, residuals2, ylab = "Deviance Residuals", xlab = "MonthlyCharges")
plot(train_clean2$TotalCharges, residuals2, ylab = "Deviance Residuals", xlab = "TotalCharges")
plot(train_clean2$tenure, residuals2, ylab = "Deviance Residuals", xlab = "tenure")
cooks.distance <- cooks.distance(f_model)
plot(cooks.distance, pch = 20, main = "Cook's Distance")
```

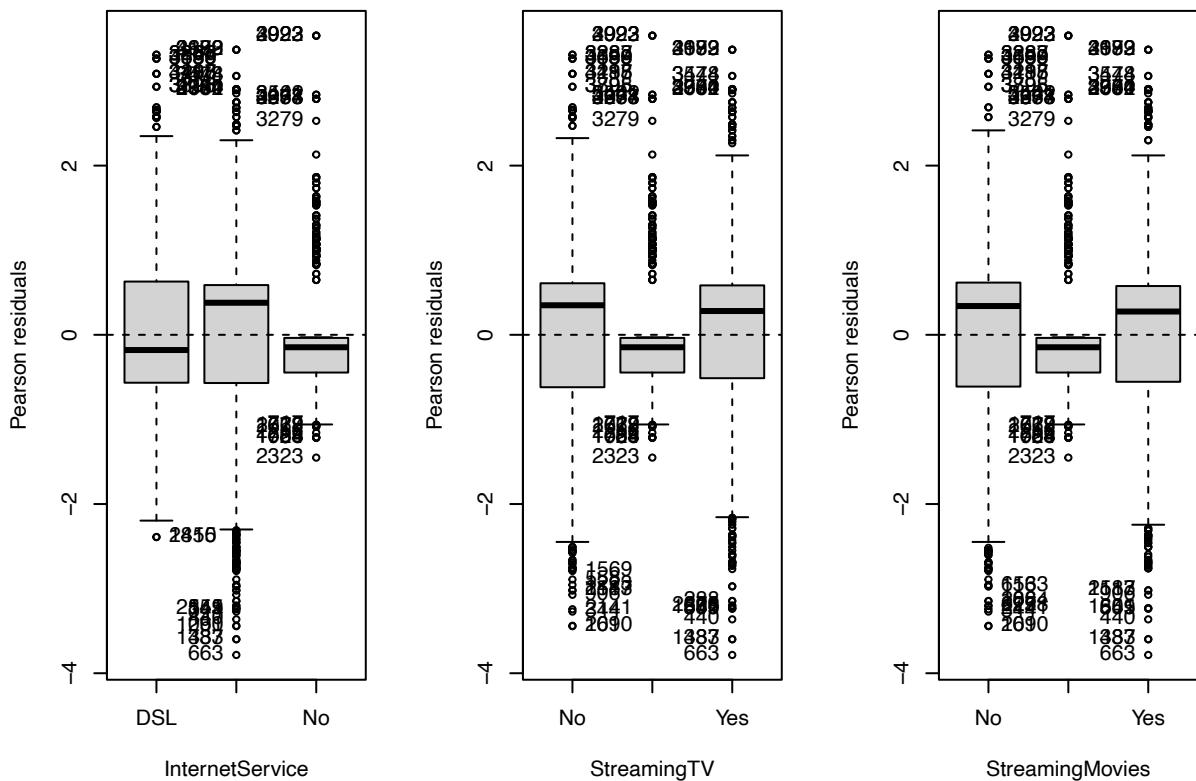


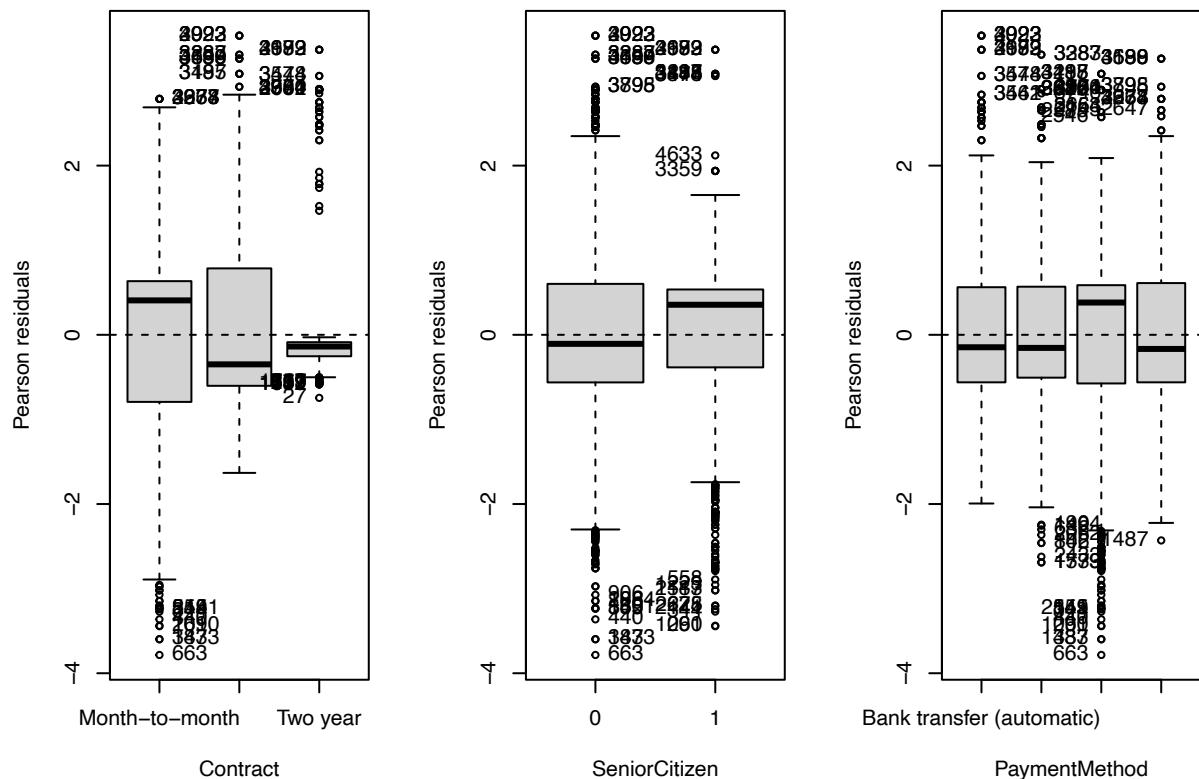
```
plot(f_model)
```



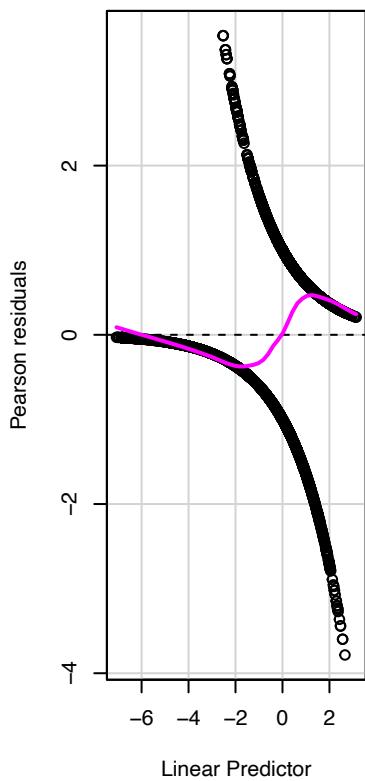
```
#Added  
residualPlots(f_model, layout=c(1, 3))
```



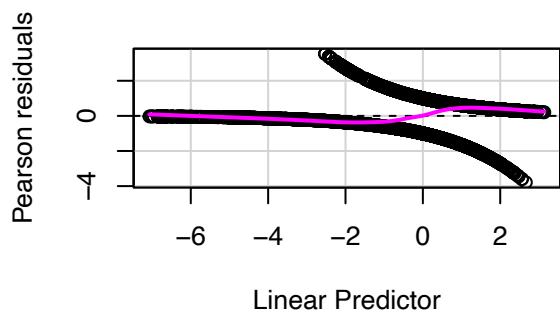




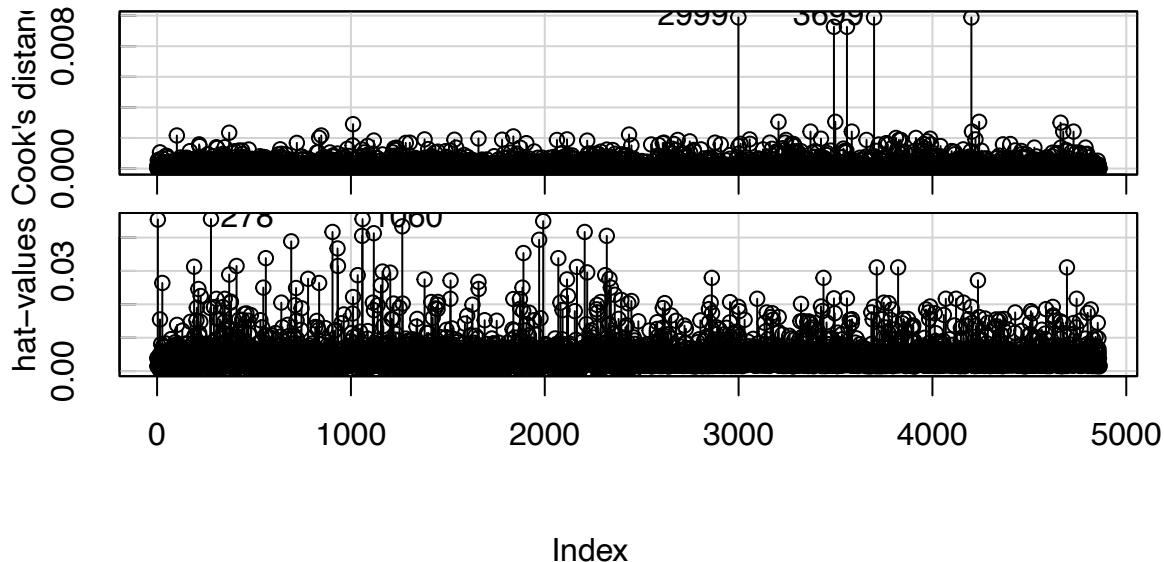
```
## Warning in residualPlots.default(model, ...): No possible lack-of-fit tests
```



```
residualPlot(f_model)
?residualPlots
influenceIndexPlot(f_model, vars=c("Cook", "hat"))
```



## Diagnostic Plots



```
# Now the normal Q-Q Plot does not follow such a linear pattern
```

Remove influential points

```
cooksdist2 <- cooks.distance(f_model)
outliers3 <- which(cooksdist2 > 0.002)
train_clean3 <- train_clean2[-outliers3, ]

# Create model without outliers
f_model_cleaned3 <- glm(Churn ~ poly(MonthlyCharges, 2) + poly(TotalCharges, 2) + poly(tenure, 3) +
print(f_model_cleaned3)

##
## Call: glm(formula = Churn ~ poly(MonthlyCharges, 2) + poly(TotalCharges,
##          2) + poly(tenure, 3) + InternetService + StreamingTV + StreamingMovies +
##          Contract + SeniorCitizen * PaymentMethod + Contract * SeniorCitizen,
##          family = "binomial", data = train_clean3)
##
## Coefficients:
##                               (Intercept)
##                               -1.03445
## poly(MonthlyCharges, 2)1
##                           -40.53821
## poly(MonthlyCharges, 2)2
```

```

##                                     4.46690
##      poly(TotalCharges, 2)1          61.76584
##      poly(TotalCharges, 2)2         10.08875
##      poly(tenure, 3)1           -117.90566
##      poly(tenure, 3)2           -4.41398
##      poly(tenure, 3)3          -16.29033
##      InternetServiceFiber optic     1.50846
##      InternetServiceNo          -1.22906
##      StreamingTVNo internet service    NA
##      StreamingTVYes            0.58171
##      StreamingMoviesNo internet service   NA
##      StreamingMoviesYes          0.41474
##      ContractOne year           -0.75806
##      ContractTwo year           -1.94601
##      SeniorCitizen1             0.08858
##      PaymentMethodCredit card (automatic) -0.02116
##      PaymentMethodElectronic check  0.22261
##      PaymentMethodMailed check       -0.17435
##      SeniorCitizen1:PaymentMethodCredit card (automatic) 1.06508
##      SeniorCitizen1:PaymentMethodElectronic check  0.40381
##      SeniorCitizen1:PaymentMethodMailed check  0.92579
##      ContractOne year:SeniorCitizen1        -0.76121
##      ContractTwo year:SeniorCitizen1       -14.42896
##
## Degrees of Freedom: 4807 Total (i.e. Null);  4785 Residual
## Null Deviance:      6661
## Residual Deviance: 4415  AIC: 4461

evaluation(f_model_cleaned3, train_clean3)

## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from rank-deficient fit; attr(*, "non-estim") has doubtful cases

```

```

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

## Setting direction: controls < cases

## Training Set Metrics:
## AUC: 0.8571402
## [1] "Confusion Matrix:"
##           Predicted
## Actual    No   Yes
##   No    1796  677
##   Yes    418 1917
## Recall: 0.820985
## F1-score: 0.7778454

## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from rank-deficient fit; attr(*, "non-estim") has doubtful cases

## Setting levels: control = No, case = Yes
## Setting direction: controls < cases

## Test Set Metrics:
## AUC: 0.8467934
## [1] "Confusion Matrix:"
##           Predicted
## Actual    No   Yes
##   No    1149  435
##   Yes     95  491
## Recall: 0.837884
## F1-score: 0.6494709

# Model has better AIC and F1score than the previous, so we reiterate to get it even better

result <- find_best_model2(train_clean3)

## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from rank-deficient fit; attr(*, "non-estim") has doubtful cases

## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from rank-deficient fit; attr(*, "non-estim") has doubtful cases

## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from rank-deficient fit; attr(*, "non-estim") has doubtful cases

## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from rank-deficient fit; attr(*, "non-estim") has doubtful cases

## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from rank-deficient fit; attr(*, "non-estim") has doubtful cases

## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from rank-deficient fit; attr(*, "non-estim") has doubtful cases

```





















```

##          poly(MonthlyCharges, 2)1      -45.8149
##          poly(MonthlyCharges, 2)2       4.0706
##          poly(TotalCharges, 2)1        59.4328
##          poly(TotalCharges, 2)2       11.6779
##          poly(tenure, 3)1      -115.0405
##          poly(tenure, 3)2       -5.5501
##          poly(tenure, 3)3      -16.1588
##          SeniorCitizen1        0.4043
##          InternetServiceFiber optic     1.7680
##          InternetServiceNo           -0.6624
##          StreamingTVNo internet service NA
##          StreamingTVYes            0.6050
##          StreamingMoviesNo internet service NA
##          StreamingMoviesYes         0.4485
##          ContractOne year          -0.8888
##          ContractTwo year          -2.1547
##          PaymentMethodCredit card (automatic) 0.6361
##          PaymentMethodElectronic check    0.2607
##          PaymentMethodMailed check      0.2112
##          InternetServiceFiber optic:PaymentMethodCredit card (automatic) -0.5829
##          InternetServiceNo:PaymentMethodCredit card (automatic)      -1.4639
##          InternetServiceFiber optic:PaymentMethodElectronic check    0.1092
##          InternetServiceNo:PaymentMethodElectronic check      -0.7566
##          InternetServiceFiber optic:PaymentMethodMailed check      -0.5876
##          InternetServiceNo:PaymentMethodMailed check      -0.7180
##
## Degrees of Freedom: 4807 Total (i.e. Null);  4784 Residual
## Null Deviance:      6661
## Residual Deviance: 4424  AIC: 4472

```

```

evaluation(best_model_Winte2, train_clean3)

## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from rank-deficient fit; attr(*, "non-estim") has doubtful cases

## Setting levels: control = No, case = Yes
## Setting direction: controls < cases

## Training Set Metrics:
## AUC: 0.8574414
## [1] "Confusion Matrix:"
##          Predicted
## Actual    No   Yes
##   No    1807  666
##   Yes    400 1935
## Recall: 0.8286938
## F1-score: 0.7840357

## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from rank-deficient fit; attr(*, "non-estim") has doubtful cases

## Setting levels: control = No, case = Yes
## Setting direction: controls < cases

## Test Set Metrics:
## AUC: 0.8454629
## [1] "Confusion Matrix:"
##          Predicted
## Actual    No   Yes
##   No    1146  438
##   Yes     93  493
## Recall: 0.8412969
## F1-score: 0.649967

```

```

Anova(best_model_Winte2)

## Analysis of Deviance Table (Type II tests)
##
## Response: Churn
##              LR Chisq Df Pr(>Chisq)
## poly(MonthlyCharges, 2)      15.927  2  0.0003480 ***
## poly(TotalCharges, 2)        17.923  2  0.0001283 ***
## poly(tenure, 3)              95.360  3 < 2.2e-16 ***
## SeniorCitizen                16.779  1  4.201e-05 ***
## InternetService               69.715  1 < 2.2e-16 ***
## StreamingTV                   28.855  1  7.799e-08 ***
## StreamingMovies                 16.171  1  5.787e-05 ***
## Contract                      142.970  2 < 2.2e-16 ***
## PaymentMethod                  13.257  3  0.0041131 **
## InternetService:PaymentMethod 20.813  6  0.0019821 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```

# This reiteration has given us the same model as before

# Print the best model and its F-score
print(best_model_Winte2)

## 
## Call: glm(formula = formula, family = "binomial", data = data)
##
## Coefficients:
##                               (Intercept) 
##                                     -1.2993  
## poly(MonthlyCharges, 2)1 
##                                     -45.8149 
## poly(MonthlyCharges, 2)2 
##                                     4.0706  
## poly(TotalCharges, 2)1 
##                                     59.4328 
## poly(TotalCharges, 2)2 
##                                     11.6779 
## poly(tenure, 3)1 
##                                     -115.0405 
## poly(tenure, 3)2 
##                                     -5.5501 
## poly(tenure, 3)3 
##                                     -16.1588 
## SeniorCitizen1 
##                                     0.4043  
## InternetServiceFiber optic 
##                                     1.7680  
## InternetServiceNo 
##                                     -0.6624 
## StreamingTVNo internet service 
##                                     NA      
## StreamingTVYes 
##                                     0.6050  
## StreamingMoviesNo internet service 
##                                     NA      
## StreamingMoviesYes 
##                                     0.4485  
## ContractOne year 
##                                     -0.8888 
## ContractTwo year 
##                                     -2.1547 
## PaymentMethodCredit card (automatic) 
##                                     0.6361  
## PaymentMethodElectronic check 
##                                     0.2607  
## PaymentMethodMailed check 
##                                     0.2112 
## InternetServiceFiber optic:PaymentMethodCredit card (automatic) 
##                                     -0.5829 
## InternetServiceNo:PaymentMethodCredit card (automatic) 
##                                     -1.4639
## 
```

```

##          InternetServiceFiber optic:PaymentMethodElectronic check
##                                         0.1092
##          InternetServiceNo:PaymentMethodElectronic check
##                                         -0.7566
##          InternetServiceFiber optic:PaymentMethodMailed check
##                                         -0.5876
##          InternetServiceNo:PaymentMethodMailed check
##                                         -0.7180
##
## Degrees of Freedom: 4807 Total (i.e. Null);  4784 Residual
## Null Deviance:      6661
## Residual Deviance: 4424  AIC: 4472

evaluation(best_model_Winte2, train_clean3)

## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from rank-deficient fit; attr(*, "non-estim") has doubtful cases

## Setting levels: control = No, case = Yes
## Setting direction: controls < cases

## Training Set Metrics:
## AUC: 0.8574414
## [1] "Confusion Matrix:"
##       Predicted
## Actual   No   Yes
##   No    1807  666
##   Yes    400 1935
## Recall: 0.8286938
## F1-score: 0.7840357

## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from rank-deficient fit; attr(*, "non-estim") has doubtful cases

## Setting levels: control = No, case = Yes
## Setting direction: controls < cases

## Test Set Metrics:
## AUC: 0.8454629
## [1] "Confusion Matrix:"
##       Predicted
## Actual   No   Yes
##   No    1146  438
##   Yes     93  493
## Recall: 0.8412969
## F1-score: 0.649967

print(paste("Best F-score:", best_f_score2))

## [1] "Best F-score: 0.784035656401945"

```

```
Anova(best_model_Winte2)
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: Churn
## LR Chisq Df Pr(>Chisq)
## poly(MonthlyCharges, 2) 15.927 2 0.0003480 ***
## poly(TotalCharges, 2) 17.923 2 0.0001283 ***
## poly(tenure, 3) 95.360 3 < 2.2e-16 ***
## SeniorCitizen 16.779 1 4.201e-05 ***
## InternetService 69.715 1 < 2.2e-16 ***
## StreamingTV 28.855 1 7.799e-08 ***
## StreamingMovies 16.171 1 5.787e-05 ***
## Contract 142.970 2 < 2.2e-16 ***
## PaymentMethod 13.257 3 0.0041131 **
## InternetService:PaymentMethod 20.813 6 0.0019821 **
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ',' 1
```

```
step(best_model_Winte2)
```

```
## Start: AIC=4472.49
## Churn ~ poly(MonthlyCharges, 2) + poly(TotalCharges, 2) + poly(tenure,
##           3) + SeniorCitizen + InternetService + StreamingTV + StreamingMovies +
##           Contract + PaymentMethod * InternetService
##
##                               Df Deviance     AIC
## <none>                      4424.5 4472.5
## - InternetService:PaymentMethod 6  4445.3 4481.3
## - poly(MonthlyCharges, 2)        2  4440.4 4484.4
## - poly(TotalCharges, 2)         2  4442.4 4486.4
## - StreamingMovies               1  4440.7 4486.7
## - SeniorCitizen                 1  4441.3 4487.3
## - StreamingTV                   1  4453.3 4499.3
## - poly(tenure, 3)                3  4519.9 4561.9
## - Contract                      2  4567.5 4611.5
##
## Call: glm(formula = Churn ~ poly(MonthlyCharges, 2) + poly(TotalCharges,
##           2) + poly(tenure, 3) + SeniorCitizen + InternetService +
##           StreamingTV + StreamingMovies + Contract + PaymentMethod *
##           InternetService, family = "binomial", data = data)
##
## Coefficients:
##                               (Intercept)
##                                         -1.2993
## poly(MonthlyCharges, 2)1
##                                         -45.8149
## poly(MonthlyCharges, 2)2
##                                         4.0706
## poly(TotalCharges, 2)1
##                                         59.4328
```

```

##          poly(TotalCharges, 2)2
##                                11.6779
##          poly(tenure, 3)1
##                                -115.0405
##          poly(tenure, 3)2
##                                -5.5501
##          poly(tenure, 3)3
##                                -16.1588
##          SeniorCitizen1
##                                0.4043
##          InternetServiceFiber optic
##                                1.7680
##          InternetServiceNo
##                                -0.6624
##          StreamingTVNo internet service
##                                NA
##          StreamingTVYes
##                                0.6050
##          StreamingMoviesNo internet service
##                                NA
##          StreamingMoviesYes
##                                0.4485
##          ContractOne year
##                                -0.8888
##          ContractTwo year
##                                -2.1547
##          PaymentMethodCredit card (automatic)
##                                0.6361
##          PaymentMethodElectronic check
##                                0.2607
##          PaymentMethodMailed check
##                                0.2112
##          InternetServiceFiber optic:PaymentMethodCredit card (automatic)
##                                -0.5829
##          InternetServiceNo:PaymentMethodCredit card (automatic)
##                                -1.4639
##          InternetServiceFiber optic:PaymentMethodElectronic check
##                                0.1092
##          InternetServiceNo:PaymentMethodElectronic check
##                                -0.7566
##          InternetServiceFiber optic:PaymentMethodMailed check
##                                -0.5876
##          InternetServiceNo:PaymentMethodMailed check
##                                -0.7180
##
## Degrees of Freedom: 4807 Total (i.e. Null);  4784 Residual
## Null Deviance:      6661
## Residual Deviance: 4424  AIC: 4472

evaluation(best_model_Winte2, train_clean3)

## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from rank-deficient fit; attr(*, "non-estim") has doubtful cases

```

```

## Setting levels: control = No, case = Yes
## Setting direction: controls < cases

## Training Set Metrics:
## AUC: 0.8574414
## [1] "Confusion Matrix:"
##          Predicted
## Actual    No  Yes
##   No    1807 666
##   Yes    400 1935
## Recall: 0.8286938
## F1-score: 0.7840357

## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from rank-deficient fit; attr(*, "non-estim") has doubtful cases

## Setting levels: control = No, case = Yes
## Setting direction: controls < cases

## Test Set Metrics:
## AUC: 0.8454629
## [1] "Confusion Matrix:"
##          Predicted
## Actual    No  Yes
##   No    1146 438
##   Yes    93 493
## Recall: 0.8412969
## F1-score: 0.649967

f_model <- glm(Churn ~ poly(MonthlyCharges, 2) + poly(TotalCharges, 2) + poly(tenure, 3) + InternetS
evaluation(f_model, train_clean3)

## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from rank-deficient fit; attr(*, "non-estim") has doubtful cases

## Setting levels: control = No, case = Yes
## Setting direction: controls < cases

## Training Set Metrics:
## AUC: 0.8555873
## [1] "Confusion Matrix:"
##          Predicted
## Actual    No  Yes
##   No    1777 696
##   Yes    384 1951
## Recall: 0.835546
## F1-score: 0.7832196

## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from rank-deficient fit; attr(*, "non-estim") has doubtful cases

```

```

## Setting levels: control = No, case = Yes
## Setting direction: controls < cases

## Test Set Metrics:
## AUC: 0.8451845
## [1] "Confusion Matrix:"
##          Predicted
## Actual    No   Yes
##   No    1126  458
##   Yes     88  498
## Recall: 0.8498294
## F1-score: 0.6459144

print(f_model)

## Call: glm(formula = Churn ~ poly(MonthlyCharges, 2) + poly(TotalCharges,
##                                2) + poly(tenure, 3) + InternetService + StreamingTV + StreamingMovies +
##                                Contract + Contract * SeniorCitizen, family = "binomial",
##                                data = train_clean2)
##
## Coefficients:
##                               (Intercept)      poly(MonthlyCharges, 2)1
##                                         -1.0189                  -41.1922
## poly(MonthlyCharges, 2)2      poly(TotalCharges, 2)1
##                                         3.6265                   45.3095
## poly(TotalCharges, 2)2      poly(tenure, 3)1
##                                         11.0865                 -101.5759
## poly(tenure, 3)2      poly(tenure, 3)3
##                                         -3.5985                  -16.5038
## InternetServiceFiber optic InternetServiceNo
##                                         1.6155                  -1.3464
## StreamingTVNo internet service StreamingTVYes
##                                         NA                      0.5705
## StreamingMoviesNo internet service StreamingMoviesYes
##                                         NA                      0.4973
## ContractOne year           ContractTwo year
##                                         -0.7731                 -2.0024
## SeniorCitizen1           ContractOne year:SeniorCitizen1
##                                         0.5471                  -0.2474
## ContractTwo year:SeniorCitizen1
##                                         -0.4968
##
## Degrees of Freedom: 4830 Total (i.e. Null);  4814 Residual
## Null Deviance:       6694
## Residual Deviance: 4538  AIC: 4572

# We get the same model as before, meaning we cannot get a better model with our method
# Let us try step
step(f_model_cleaned3)

```

## Start: AIC=4460.96

```

## Churn ~ poly(MonthlyCharges, 2) + poly(TotalCharges, 2) + poly(tenure,
##      3) + InternetService + StreamingTV + StreamingMovies + Contract +
##      SeniorCitizen * PaymentMethod + Contract * SeniorCitizen
##
##                                     Df Deviance    AIC
## <none>                           4415.0 4461.0
## - SeniorCitizen:PaymentMethod  3   4426.5 4466.5
## - poly(MonthlyCharges, 2)       2   4427.9 4469.9
## - StreamingMovies              1   4428.7 4472.7
## - poly(TotalCharges, 2)         2   4433.1 4475.1
## - Contract:SeniorCitizen      2   4434.3 4476.3
## - StreamingTV                  1   4441.8 4485.8
## - InternetService              1   4478.5 4522.5
## - poly(tenure, 3)               3   4517.0 4557.0

##
## Call: glm(formula = Churn ~ poly(MonthlyCharges, 2) + poly(TotalCharges,
##      2) + poly(tenure, 3) + InternetService + StreamingTV + StreamingMovies +
##      Contract + SeniorCitizen * PaymentMethod + Contract * SeniorCitizen,
##      family = "binomial", data = train_clean3)
##
## Coefficients:
##                               (Intercept)
##                               -1.03445
## poly(MonthlyCharges, 2)1
##                               -40.53821
## poly(MonthlyCharges, 2)2
##                               4.46690
## poly(TotalCharges, 2)1
##                               61.76584
## poly(TotalCharges, 2)2
##                               10.08875
## poly(tenure, 3)1
##                               -117.90566
## poly(tenure, 3)2
##                               -4.41398
## poly(tenure, 3)3
##                               -16.29033
## InternetServiceFiber optic
##                               1.50846
## InternetServiceNo
##                               -1.22906
## StreamingTVNo internet service
##                               NA
## StreamingTVYes
##                               0.58171
## StreamingMoviesNo internet service
##                               NA
## StreamingMoviesYes
##                               0.41474
## ContractOne year
##                               -0.75806
## ContractTwo year
##                               -1.94601

```

```

##                               SeniorCitizen1
##                               0.08858
## PaymentMethodCredit card (automatic)
##                               -0.02116
## PaymentMethodElectronic check
##                               0.22261
## PaymentMethodMailed check
##                               -0.17435
## SeniorCitizen1:PaymentMethodCredit card (automatic)
##                               1.06508
## SeniorCitizen1:PaymentMethodElectronic check
##                               0.40381
## SeniorCitizen1:PaymentMethodMailed check
##                               0.92579
## ContractOne year:SeniorCitizen1
##                               -0.76121
## ContractTwo year:SeniorCitizen1
##                               -14.42896
##
## Degrees of Freedom: 4807 Total (i.e. Null); 4785 Residual
## Null Deviance: 6661
## Residual Deviance: 4415 AIC: 4461

```

*# It shows that this is indeed the best model*

Final analysis Goodness of fit and Model Interpretation. Train and Test datasets.

```

#Assessment metric: area under the ROC curve score and confusion table prediction capability analysis

#Comparing to the previous model using anova
f_model_cleaned2 <- glm(Churn ~ poly(MonthlyCharges, 2) + poly(TotalCharges, 2) + poly(tenure, 3) +
anova(f_model_cleaned2, f_model_cleaned3)

```

```

## Analysis of Deviance Table
##
## Model 1: Churn ~ poly(MonthlyCharges, 2) + poly(TotalCharges, 2) + poly(tenure,
##           3) + InternetService + StreamingTV + StreamingMovies + Contract
## Model 2: Churn ~ poly(MonthlyCharges, 2) + poly(TotalCharges, 2) + poly(tenure,
##           3) + InternetService + StreamingTV + StreamingMovies + Contract +
##           SeniorCitizen * PaymentMethod + Contract * SeniorCitizen
##   Resid. Df Resid. Dev Df Deviance
## 1      4794    4478.2
## 2      4785    4415.0  9    63.233

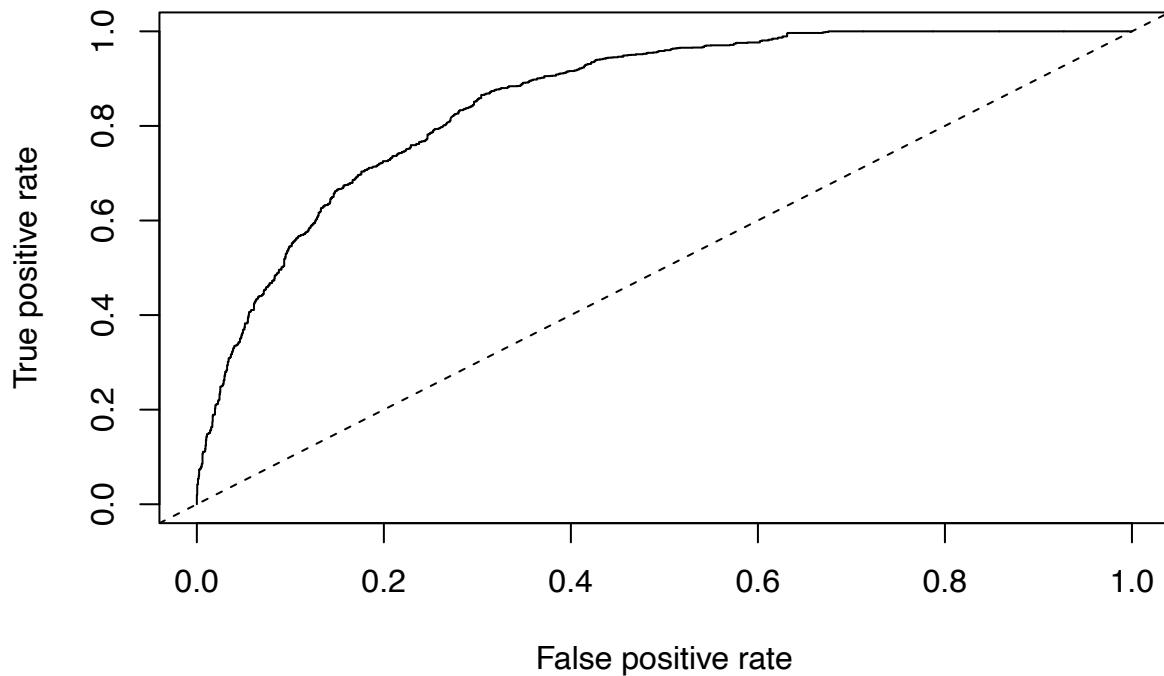
```

*# Compare residual deviance, AIC and F1-score with the model without interactions*

```

# ROC curve
library(ROCR)
roc_data<-prediction(predict(f_model_cleaned3, type="response"), train_clean3$Churn)
par(mfrow=c(1,1))
plot(performance(roc_data,"tpr","fpr"))
abline(0,1,lty=2)

```



```

# Area under ROC curve, Recall, F1-score, Anova
evaluation(f_model_cleaned3, train_clean3)

## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from rank-deficient fit; attr(*, "non-estim") has doubtful cases

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

## Setting direction: controls < cases

## Training Set Metrics:
## AUC: 0.8571402
## [1] "Confusion Matrix:"
##          Predicted
## Actual    No  Yes
##   No  1796  677
##   Yes  418  1917
## Recall: 0.820985
## F1-score: 0.7778454

## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from rank-deficient fit; attr(*, "non-estim") has doubtful cases

## Setting levels: control = No, case = Yes
## Setting direction: controls < cases

```

```

## Test Set Metrics:
## AUC: 0.8467934
## [1] "Confusion Matrix:"
##           Predicted
##   Actual    No  Yes
##   No     1149 435
##   Yes      95 491
## Recall: 0.837884
## F1-score: 0.6494709

f_model_cleaned3$formula

```

```

## Churn ~ poly(MonthlyCharges, 2) + poly(TotalCharges, 2) + poly(tenure,
##          3) + InternetService + StreamingTV + StreamingMovies + Contract +
##          SeniorCitizen * PaymentMethod + Contract * SeniorCitizen

```

```
Anova(f_model_cleaned3)
```

```

## Analysis of Deviance Table (Type II tests)
##
## Response: Churn
##                         LR Chisq Df Pr(>Chisq)
## poly(MonthlyCharges, 2)      12.901  2  0.0015796 **
## poly(TotalCharges, 2)        18.110  2  0.0001168 ***
## poly(tenure, 3)              102.002  3 < 2.2e-16 ***
## InternetService              63.491  1  1.611e-15 ***
## StreamingTV                  26.822  1  2.231e-07 ***
## StreamingMovies               13.724  1  0.0002117 ***
## Contract                      136.125  2 < 2.2e-16 ***
## SeniorCitizen                 16.513  1  4.831e-05 ***
## PaymentMethod                  12.472  3  0.0059287 **
## SeniorCitizen:PaymentMethod   11.494  3  0.0093320 **
## Contract:SeniorCitizen        19.359  2  6.254e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

*#Anova says that StreamingMovies is not significant, but if we take it out all metrics worsen somewhat*

```
f_model_cleaned_no_movies <- glm(Churn ~ poly(MonthlyCharges, 2) + poly(TotalCharges, 2) + poly(tenure, 3) + InternetService + StreamingTV + Contract + SeniorCitizen * PaymentMethod + Contract * SeniorCitizen, family = "binomial", data = train_clean3)
```

```

## Call:  glm(formula = Churn ~ poly(MonthlyCharges, 2) + poly(TotalCharges,
##          2) + poly(tenure, 3) + InternetService + StreamingTV + Contract +
##          SeniorCitizen * PaymentMethod + Contract * SeniorCitizen,
##          family = "binomial", data = train_clean3)
##
## Coefficients:
##                               (Intercept)
##                               -0.70653
## poly(MonthlyCharges, 2)1
##                           -21.81133
## poly(MonthlyCharges, 2)2

```

```

##          10.60518
##      poly(TotalCharges, 2)1
##          54.81777
##      poly(TotalCharges, 2)2
##          8.14292
##      poly(tenure, 3)1
##          -113.21962
##      poly(tenure, 3)2
##          -2.56972
##      poly(tenure, 3)3
##          -16.00634
##  InternetServiceFiber optic
##          1.21369
##  InternetServiceNo
##          -1.23604
##  StreamingTVNo internet service
##          NA
##  StreamingTVYes
##          0.55936
##  ContractOne year
##          -0.74382
##  ContractTwo year
##          -1.94845
##  SeniorCitizen1
##          0.09644
##  PaymentMethodCredit card (automatic)
##          -0.01766
##  PaymentMethodElectronic check
##          0.24971
##  PaymentMethodMailed check
##          -0.18303
## SeniorCitizen1:PaymentMethodCredit card (automatic)
##          1.12830
## SeniorCitizen1:PaymentMethodElectronic check
##          0.41546
## SeniorCitizen1:PaymentMethodMailed check
##          0.94635
## ContractOne year:SeniorCitizen1
##          -0.79758
## ContractTwo year:SeniorCitizen1
##          -14.49383
##
## Degrees of Freedom: 4807 Total (i.e. Null);  4786 Residual
## Null Deviance:      6661
## Residual Deviance: 4429  AIC: 4473

evaluation(f_model_cleaned_no_movies, train_clean3)

```

```

## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from rank-deficient fit; attr(*, "non-estim") has doubtful cases

## Setting levels: control = No, case = Yes
## Setting direction: controls < cases

```

```

## Training Set Metrics:
## AUC: 0.8563685
## [1] "Confusion Matrix:"
##           Predicted
##   Actual    No  Yes
##   No     1795 678
##   Yes     437 1898
## Recall: 0.812848
## F1-score: 0.7729587

```

```

## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from rank-deficient fit; attr(*, "non-estim") has doubtful cases

```

```

## Setting levels: control = No, case = Yes
## Setting direction: controls < cases

```

```

## Test Set Metrics:
## AUC: 0.8452162
## [1] "Confusion Matrix:"
##           Predicted
##   Actual    No  Yes
##   No     1152 432
##   Yes      98 488
## Recall: 0.8327645
## F1-score: 0.6480744

```

```
Anova(f_model_cleaned_no_movies)
```

```

## Analysis of Deviance Table (Type II tests)
##
## Response: Churn
##                         LR Chisq Df Pr(>Chisq)
## poly(MonthlyCharges, 2)    7.872  2  0.019527 *
## poly(TotalCharges, 2)     14.279  2  0.000793 ***
## poly(tenure, 3)            98.913  3 < 2.2e-16 ***
## InternetService          49.912  1  1.608e-12 ***
## StreamingTV                24.840  1  6.228e-07 ***
## Contract                  136.301  2 < 2.2e-16 ***
## SeniorCitizen              18.506  1  1.693e-05 ***
## PaymentMethod               15.408  3  0.001499 **
## SeniorCitizen:PaymentMethod 12.881  3  0.004900 **
## Contract:SeniorCitizen      20.662  2  3.261e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ',' 1

```

```
#get the coef() and coef(exp())
coef(f_model_cleaned3)
```

```

##                                         (Intercept)
##                                         -1.03444516
## poly(MonthlyCharges, 2)1
##                                         -40.53820853

```

```

##          poly(MonthlyCharges, 2)2
##                                4.46690344
##          poly(TotalCharges, 2)1
##                                61.76584281
##          poly(TotalCharges, 2)2
##                                10.08875029
##          poly(tenure, 3)1
##                                -117.90566228
##          poly(tenure, 3)2
##                                -4.41398136
##          poly(tenure, 3)3
##                                -16.29033171
##          InternetServiceFiber optic
##                                1.50846066
##          InternetServiceNo
##                                -1.22906404
##          StreamingTVNo internet service
##                                NA
##          StreamingTVYes
##                                0.58170643
##          StreamingMoviesNo internet service
##                                NA
##          StreamingMoviesYes
##                                0.41473813
##          ContractOne year
##                                -0.75806323
##          ContractTwo year
##                                -1.94600764
##          SeniorCitizen1
##                                0.08858450
##          PaymentMethodCredit card (automatic)
##                                -0.02115969
##          PaymentMethodElectronic check
##                                0.22260509
##          PaymentMethodMailed check
##                                -0.17435030
##          SeniorCitizen1:PaymentMethodCredit card (automatic)
##                                1.06507626
##          SeniorCitizen1:PaymentMethodElectronic check
##                                0.40381404
##          SeniorCitizen1:PaymentMethodMailed check
##                                0.92578765
##          ContractOne year:SeniorCitizen1
##                                -0.76121425
##          ContractTwo year:SeniorCitizen1
##                                -14.42895675

##### Use this one to interpret how each variable predicts whether the customer leaves
exp(coef(f_model_cleaned3))

```

```

##          (Intercept)
##                                3.554235e-01
##          poly(MonthlyCharges, 2)1
##                                2.480160e-18

```

```

##          poly(MonthlyCharges, 2)2
##                                8.708664e+01
##          poly(TotalCharges, 2)1
##                                6.676744e+26
##          poly(TotalCharges, 2)2
##                                2.407069e+04
##          poly(tenure, 3)1
##                                6.226177e-52
##          poly(tenure, 3)2
##                                1.210688e-02
##          poly(tenure, 3)3
##                                8.417804e-08
##          InternetServiceFiber optic
##                                4.519768e+00
##          InternetServiceNo
##                                2.925663e-01
##          StreamingTVNo internet service
##                                NA
##          StreamingTVYes
##                                1.789089e+00
##          StreamingMoviesNo internet service
##                                NA
##          StreamingMoviesYes
##                                1.513974e+00
##          ContractOne year
##                                4.685731e-01
##          ContractTwo year
##                                1.428432e-01
##          SeniorCitizen1
##                                1.092627e+00
##          PaymentMethodCredit card (automatic)
##                                9.790626e-01
##          PaymentMethodElectronic check
##                                1.249327e+00
##          PaymentMethodMailed check
##                                8.400026e-01
##          SeniorCitizen1:PaymentMethodCredit card (automatic)
##                                2.901060e+00
##          SeniorCitizen1:PaymentMethodElectronic check
##                                1.497525e+00
##          SeniorCitizen1:PaymentMethodMailed check
##                                2.523855e+00
##          ContractOne year:SeniorCitizen1
##                                4.670989e-01
##          ContractTwo year:SeniorCitizen1
##                                5.414816e-07

```

```
#0.5*(1-0.5)*(coef(f_model_cleaned3))
```