ADS 503 Final Project

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The Data

Our target variable "Risk Performance" along with the first 13 predictor columns

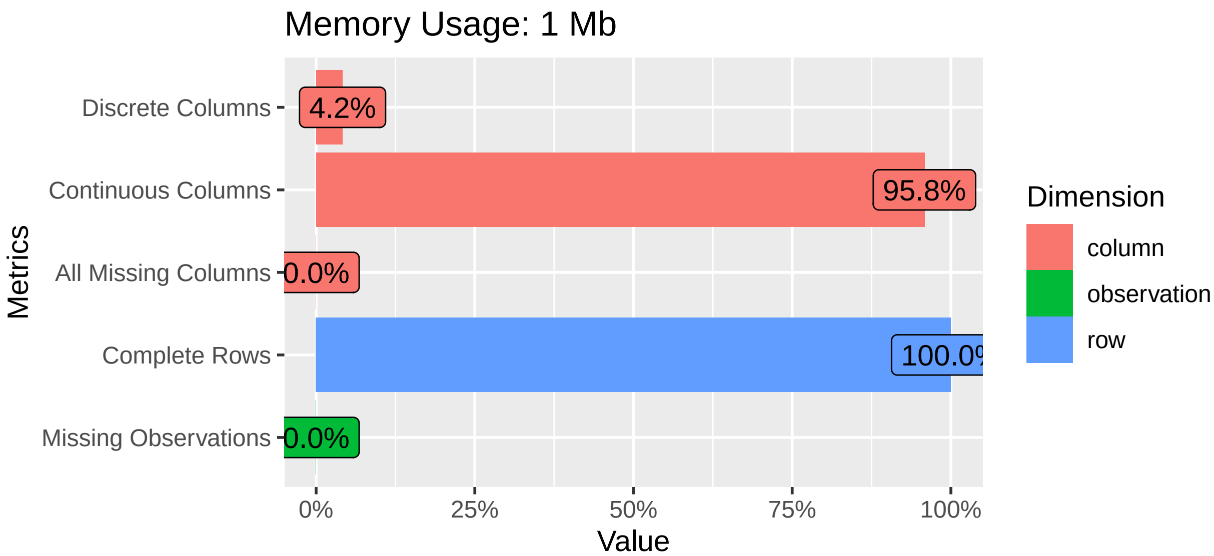
```
file_loc <- '/Volumes/GoogleDrive/My Drive/503/Project 503/Fico Data/heloc_dataset_v1.csv'
heloc <- read.csv(file_loc)

# sort col names for readability purposes
heloc <- heloc[ , order(names(heloc))]

knitr::kable(heloc[1:4,c(24,1:13)]) %>%
  kableExtra::kable_styling("striped", full_width = F) %>%
  kableExtra::row_spec(0, angle = -90)
```

Predictor columns 14 to 23

```
knitr::kable(heloc[1:4,c(24,14:23)]) %>%
  kableExtra::kable_styling("striped", full_width = F) %>%
  kableExtra::row_spec(0, angle = -90)
```

Data Pre-Processing

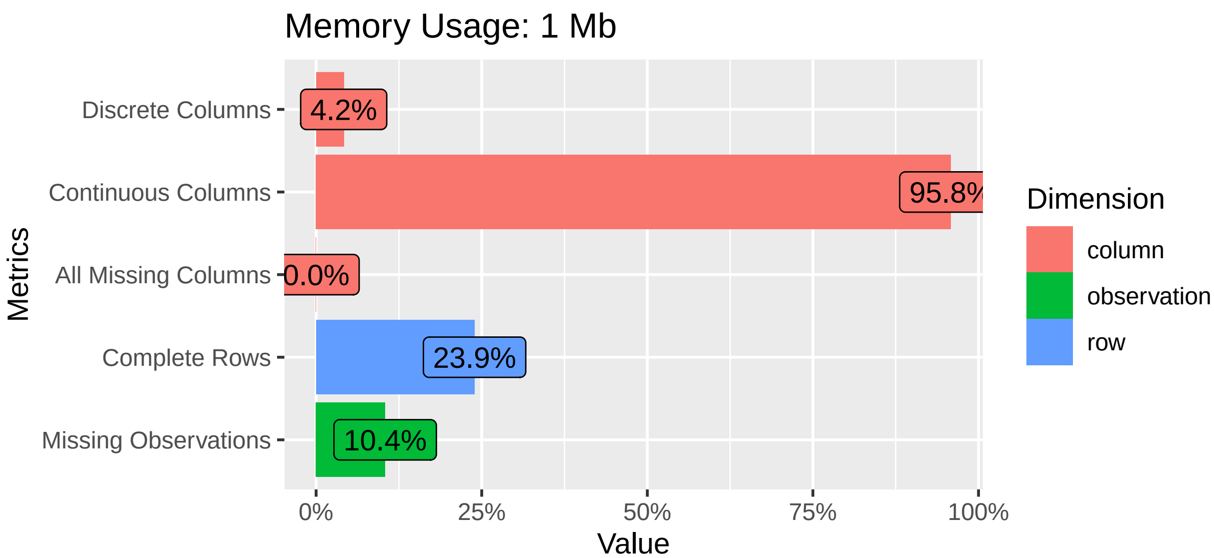
```
DataExplorer::plot_intro(heloc)
```



RiskPerformance	AverageMInFile	ExternalRiskEstimate	MaxDelq2PublicRecLast12M	MaxDelqEver	MSinceMostRecentDelq	MSinceMostRecentInqexcl7days	MSinceMostRecentTradeOpen	MSinceOldestTradeOpen	NetFractionInstallBurden	NetFractionRevolvingBurden	NumBank2NatlTradesWHighUtilization	NumInqLast6M	NumInqLast6Mexcl7days
Bad	84	55	3	5	2	0	4	144	-8	33	1	0	0
Bad	41	61	0	8	-7	0	15	58	-8	0	-8	0	0
Bad	24	67	7	8	-7	0	5	66	66	53	1	4	4
Bad	73	66	6	6	76	0	1	169	83	72	3	5	4

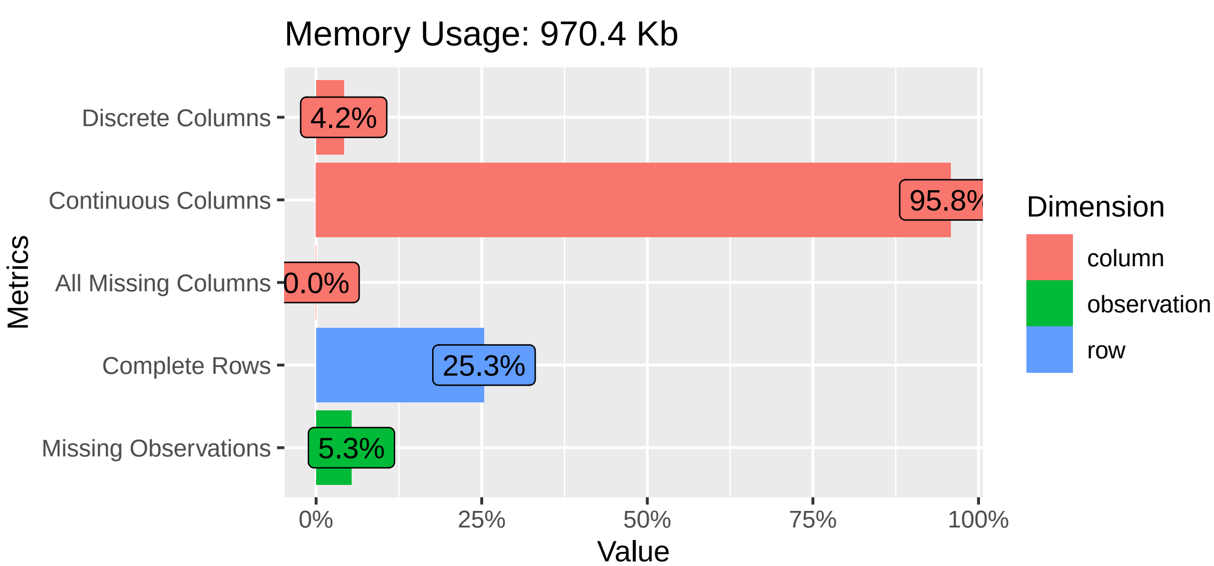
RiskPerformance	NumInstallTradesWBalance	NumRevolvingTradesWBalance	NumSatisfactoryTrades	NumTotalTrades	NumTrades60Ever2DerogPubRec	NumTrades90Ever2DerogPubRec	NumTradesOpeninLast12M	PercentInstallTrades	PercentTradesNeverDelq	PercentTradesWBalance
Bad	1	8	20	23	3	0	1	43	83	69
Bad	-8	0	2	7	4	4	0	67	100	0
Bad	2	4	9	9	0	0	4	44	100	86
Bad	4	6	28	30	1	1	3	57	93	91

```r
# -9 = No Credit History
# -8 and -7 = No recent activity
heloc[heloc == -9] <- NA
heloc[heloc == -8] <- NA
heloc[heloc == -7] <- NA
DataExplorer::plot_intro(heloc)
```

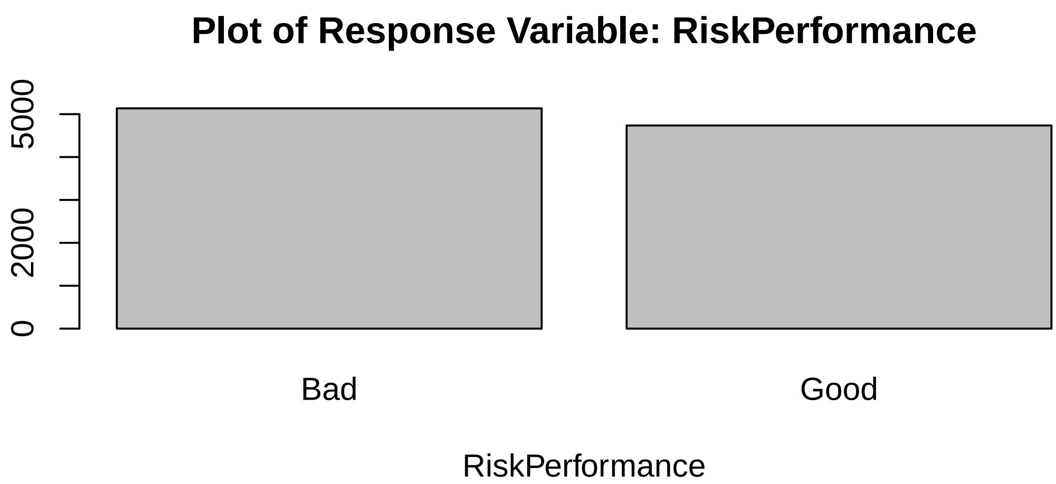


It appears that roughly 76.1% of our data had one or more predictors had a -9,-8,-7.

```r
# removing missing values from rows that span across all columns (588 values)
heloc_No_NA <- heloc %>% dplyr::filter_at(vars(-RiskPerformance),
                                          any_vars(!is.na(.)))
DataExplorer::plot_intro(heloc_No_NA)
```




```r
# bar plot of response variable; RiskPerformance
barplot(table(heloc_No_NA$RiskPerformance),
        main="Plot of Response Variable: RiskPerformance",
        xlab="RiskPerformance")
```




```
table(heloc_No_NA$RiskPerformance)
```

```
##
##  Bad Good
## 5136 4735
```

A 51:47 split! Nearly a 50:50 balance!

```
# create training indices
set.seed(3)
heloc_training <- caret::createDataPartition(heloc_No_NA$RiskPerformance,
                                             p=0.8,
                                             list=FALSE)

# training/set sets
heloc_train <- heloc_No_NA[heloc_training, ]
heloc_test <- heloc_No_NA[-heloc_training, ]

# knn imputation
heloc_impute <- caret::preProcess(heloc_train,
                                  method = 'knnImpute')

heloc_train <- stats::predict(heloc_impute,
                              newdata=heloc_train)

heloc_test <- stats::predict(heloc_impute,
                             newdata=heloc_test)

# remove highly correlated predictors
high_corr <- caret::findCorrelation(stats::cor(heloc_train[, -24]),
                                    0.85)

# removal of high cor predictors
heloc_train <- heloc_train[, -(high_corr)]
heloc_test <- heloc_test[, -(high_corr)]
names(heloc_test[high_corr])
```

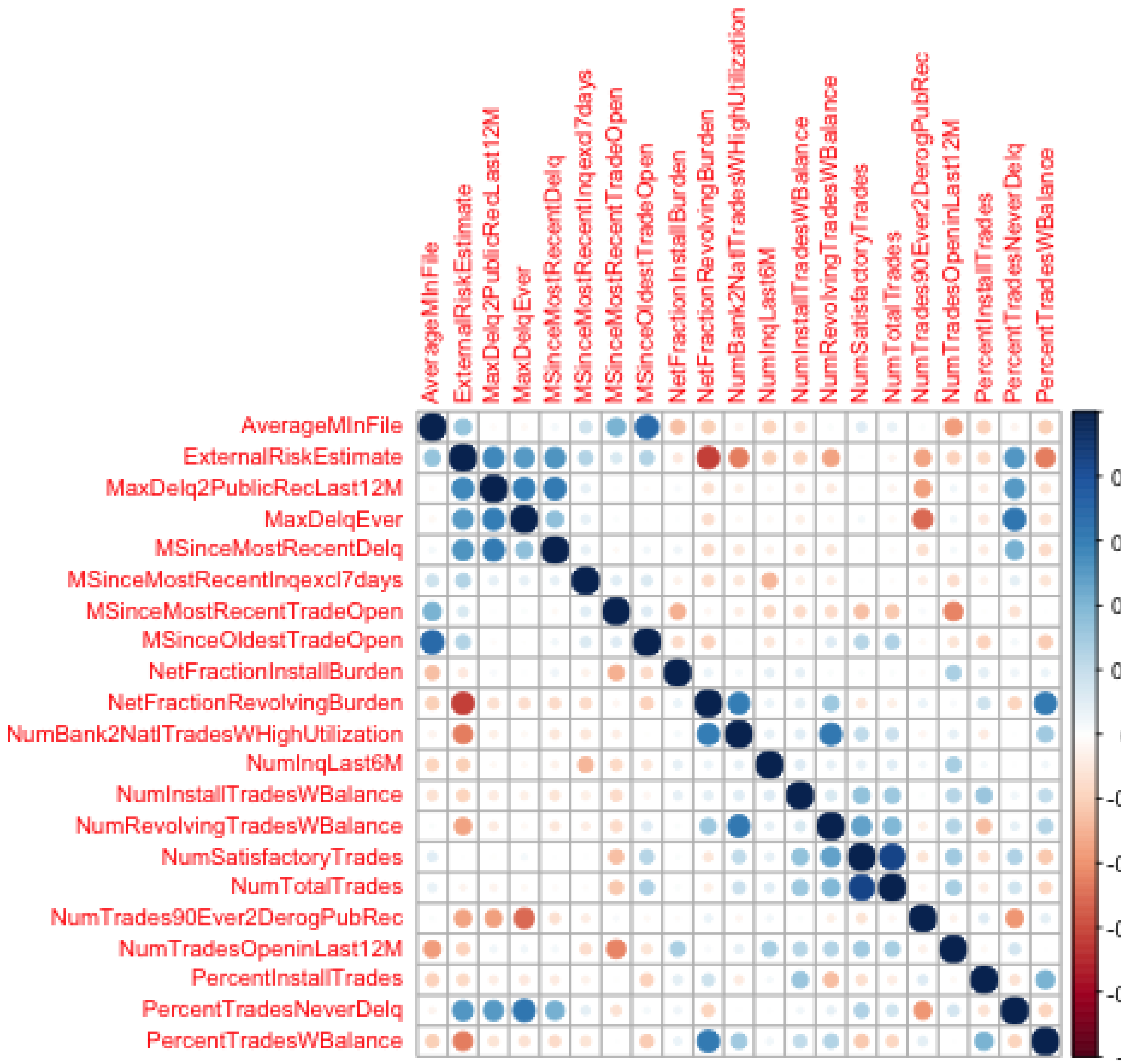
```
## [1] "NumTradesOpeninLast12M"   "NumInstallTradesWBalance"
```

We keep the heloc_train/test dataframes for formula based functions.

```r
no_risk_bool <- names(heloc_train) != 'RiskPerformance'

# x = predictors
heloc_train_x <- heloc_train[,no_risk_bool]
heloc_test_x <- heloc_test[,no_risk_bool]

# y = response/target
heloc_train_y <- heloc_train[,'RiskPerformance']
heloc_test_y <- heloc_test[,'RiskPerformance']
```

EDA

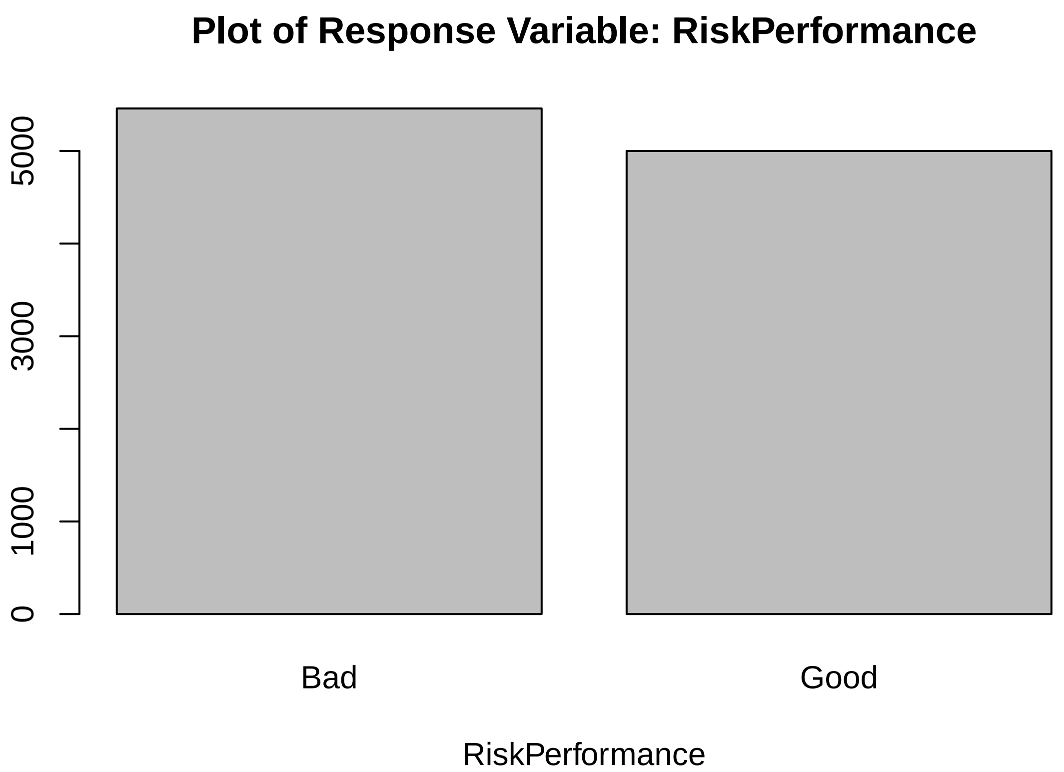
```r
# correlations
png(file="Corr_Plot.png")
# correlations
corrplot::corrplot(stats::cor(heloc_train),
                   number.cex = 0.5,
                   tl.cex = 0.8)
dev.off()
```



Correlation Plot

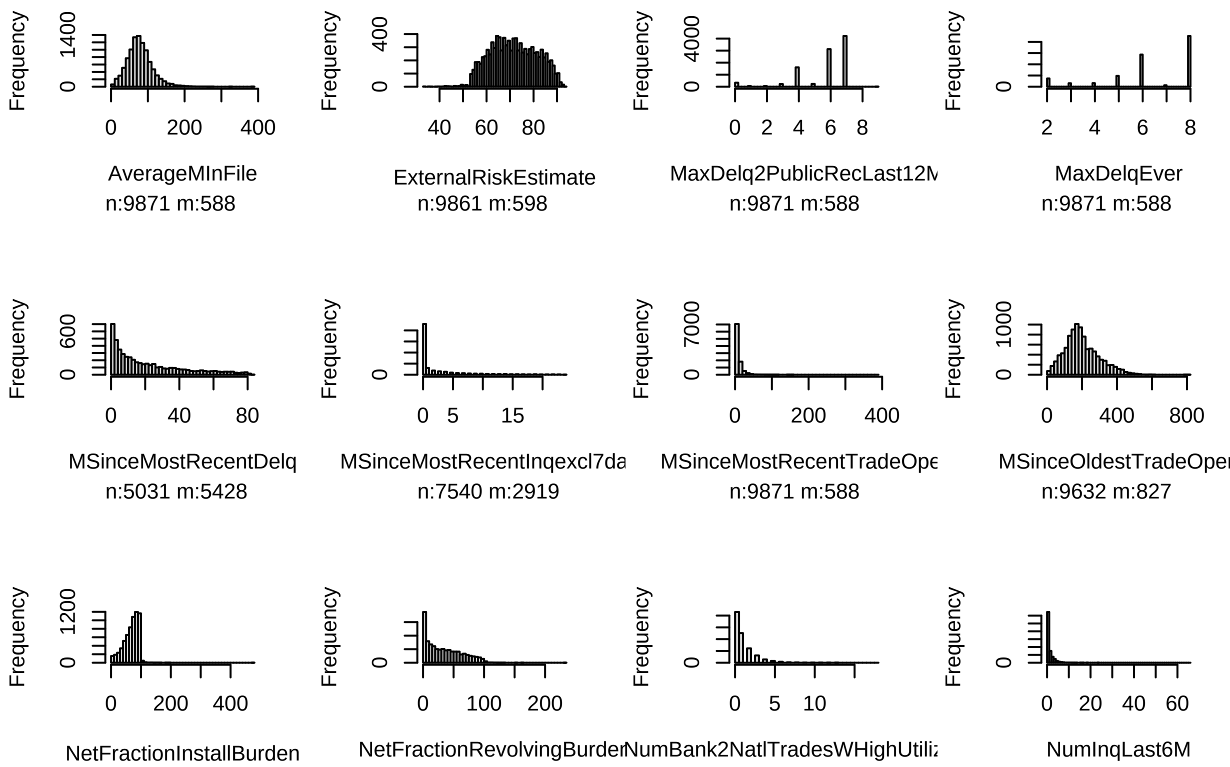
Outcome Bar Plot

```
# bar plot of response variable; RiskPerformance
barplot(table(heloc$RiskPerformance), main="Plot of Response Variable: RiskPerformance", xlab="RiskPerf
```

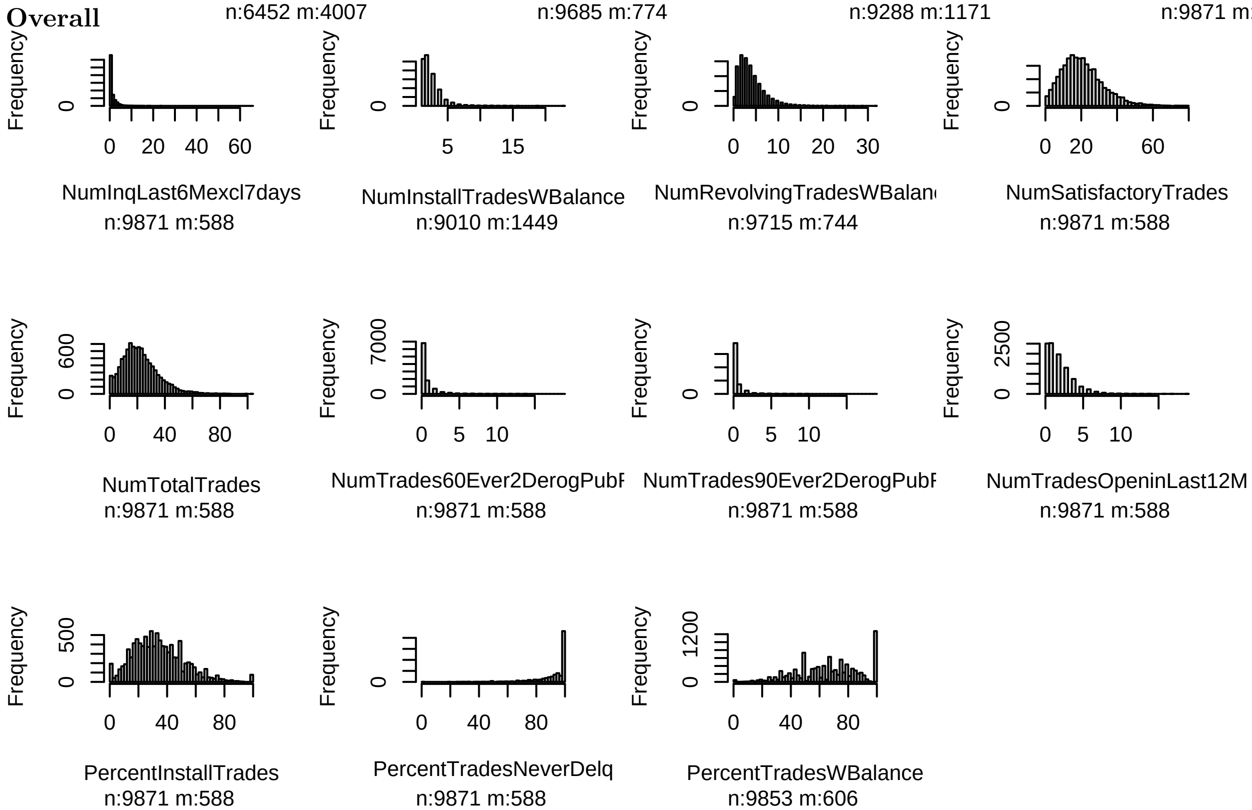


Histograms

```
# histograms to view predictor variable frequencies
par(mfrow=c(3,4))
Hmisc::hist.data.frame(heloc[,1:23])
```



Overall



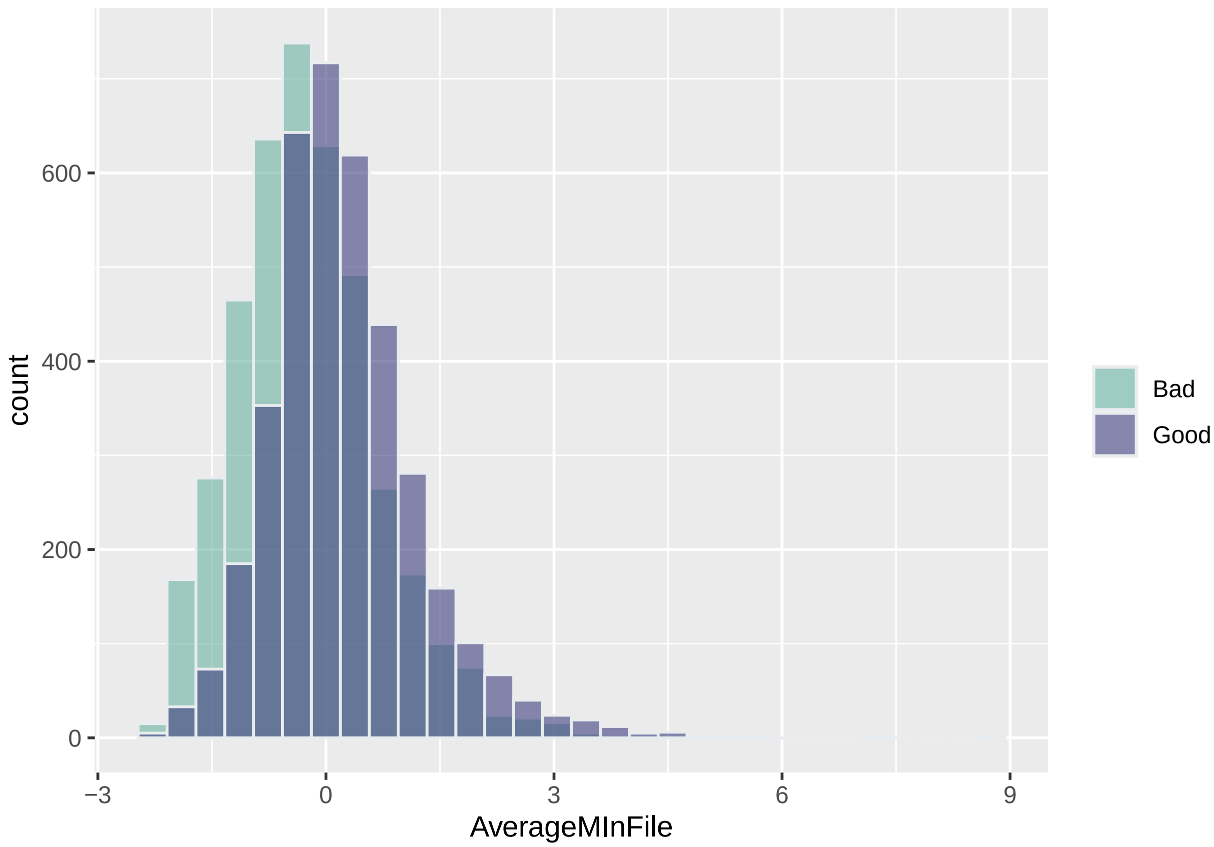
By Outcome

```r
# Deselect Bool Outcome/Response/Target variable
no_risk_bool <- names(heloc_train) != 'RiskPerformance'
```

```r
# heloc_imputed_full_set <- dplyr::as_tibble(heloc_imputed_full_set)
heloc_ifs_names <- colnames(heloc_train[,no_risk_bool])

# empty list to gather all
plot_list <- list()
for (name in heloc_ifs_names){
  p <- heloc_train %>%
    ggplot( aes(x=heloc_train[,name], fill=RiskPerformance)) +
      geom_histogram( color="#e9ecef", alpha=0.6, position = 'identity') +
      scale_fill_manual(values=c("#69b3a2", "#404080")) +
      xlab(name) +
      labs(fill="")
  print(p)
}
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

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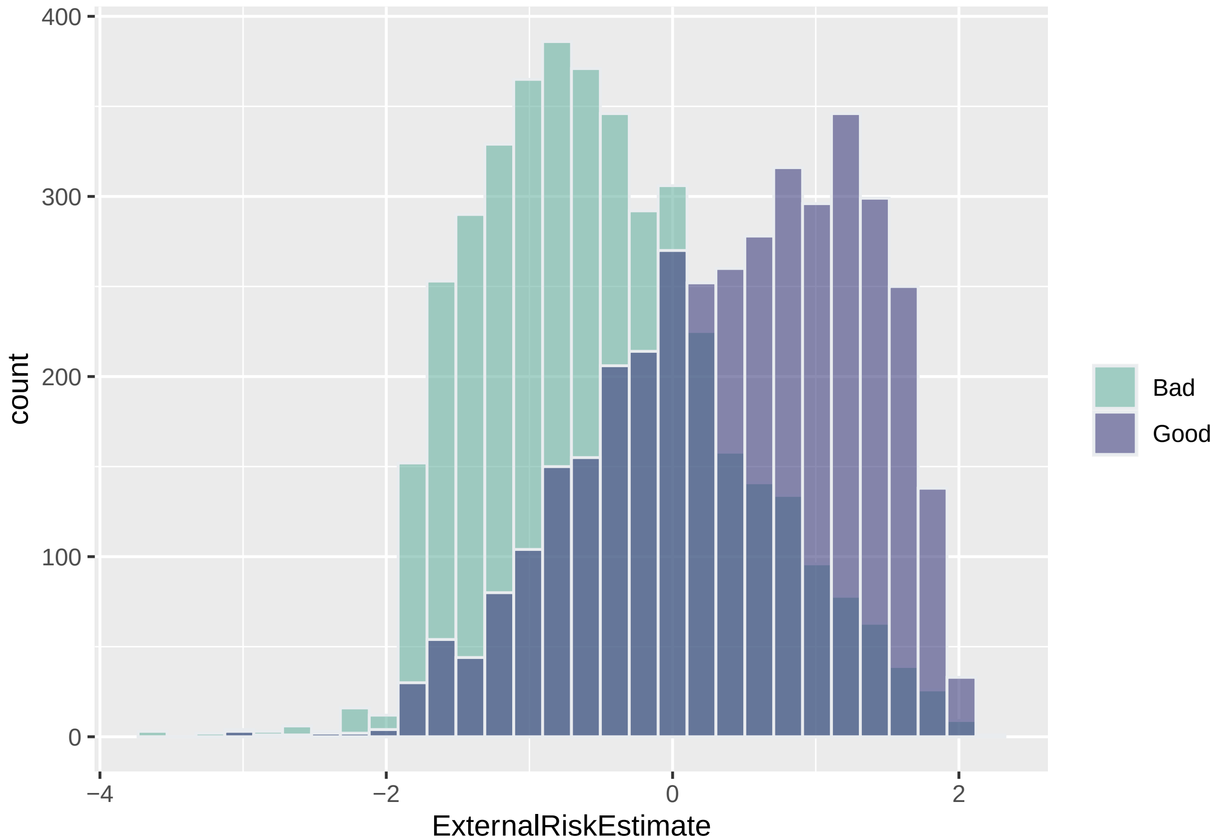


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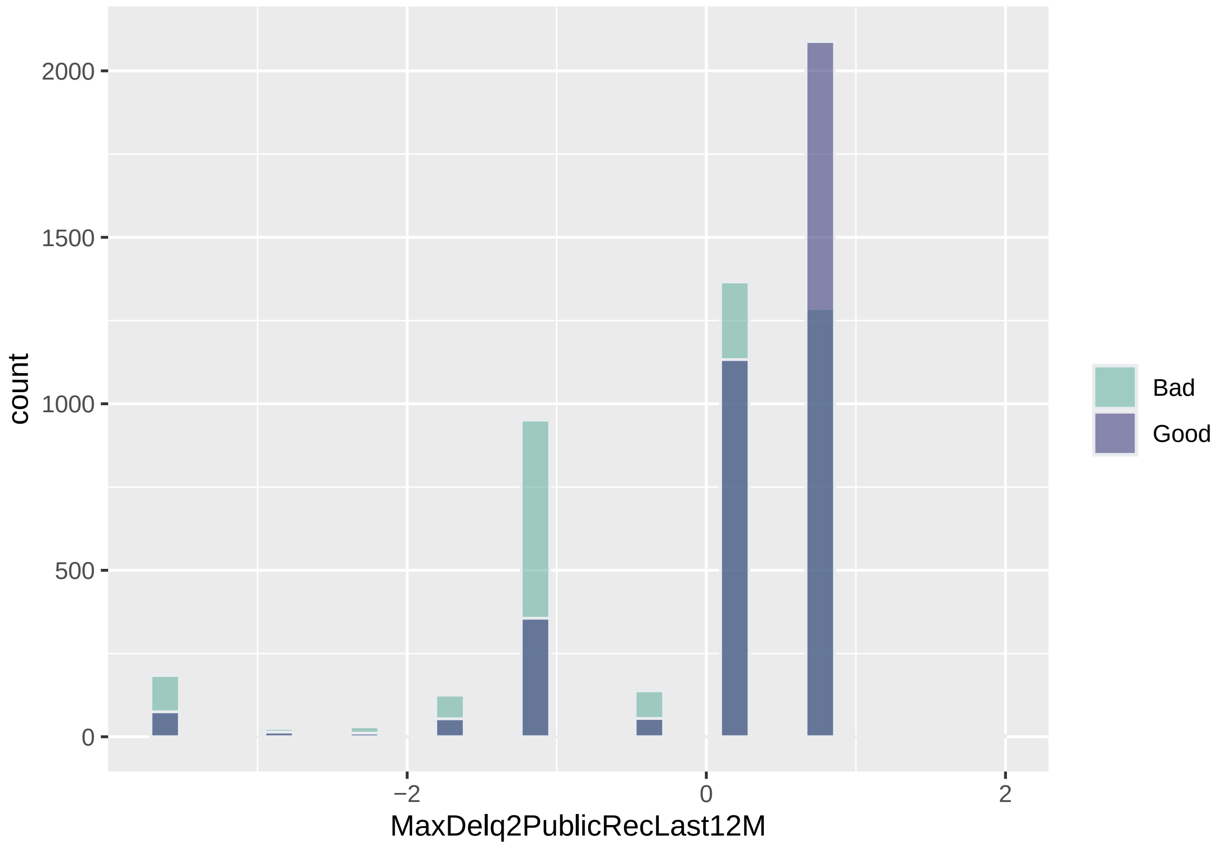


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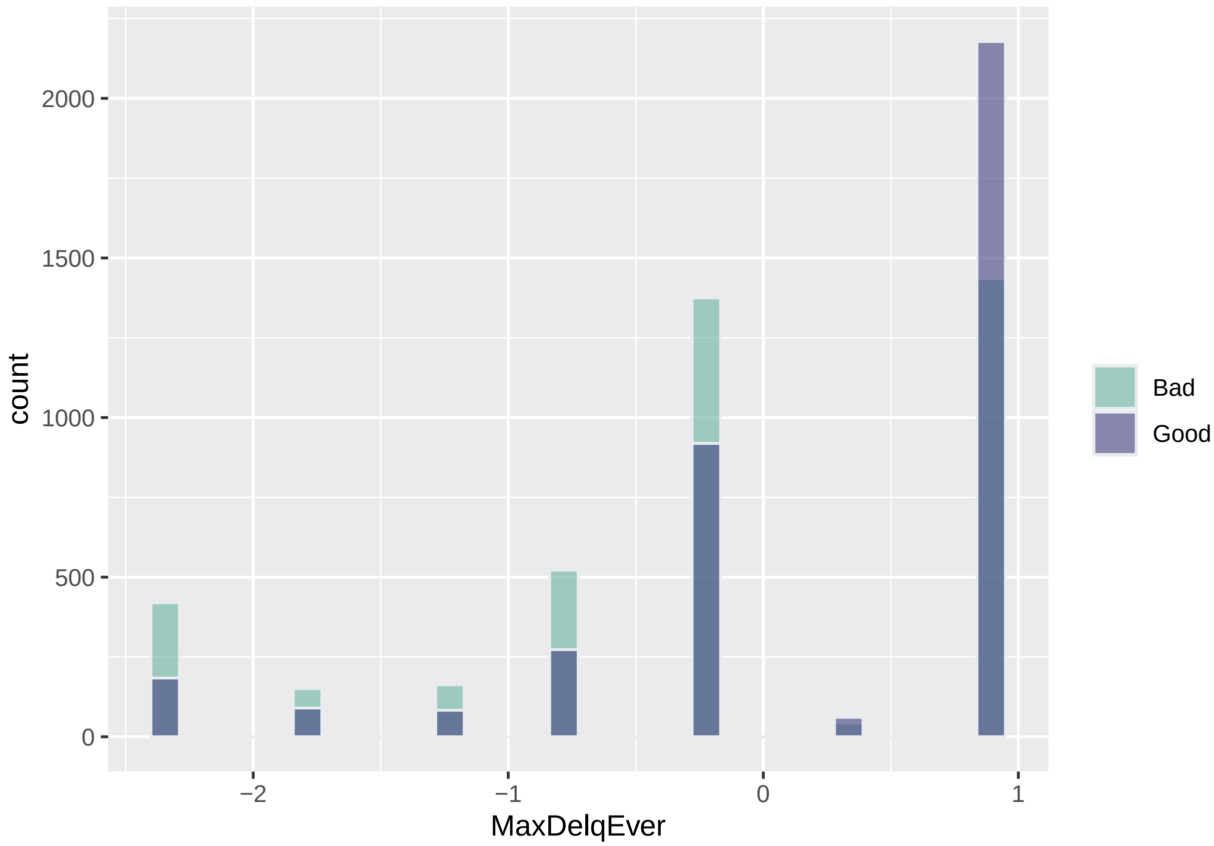


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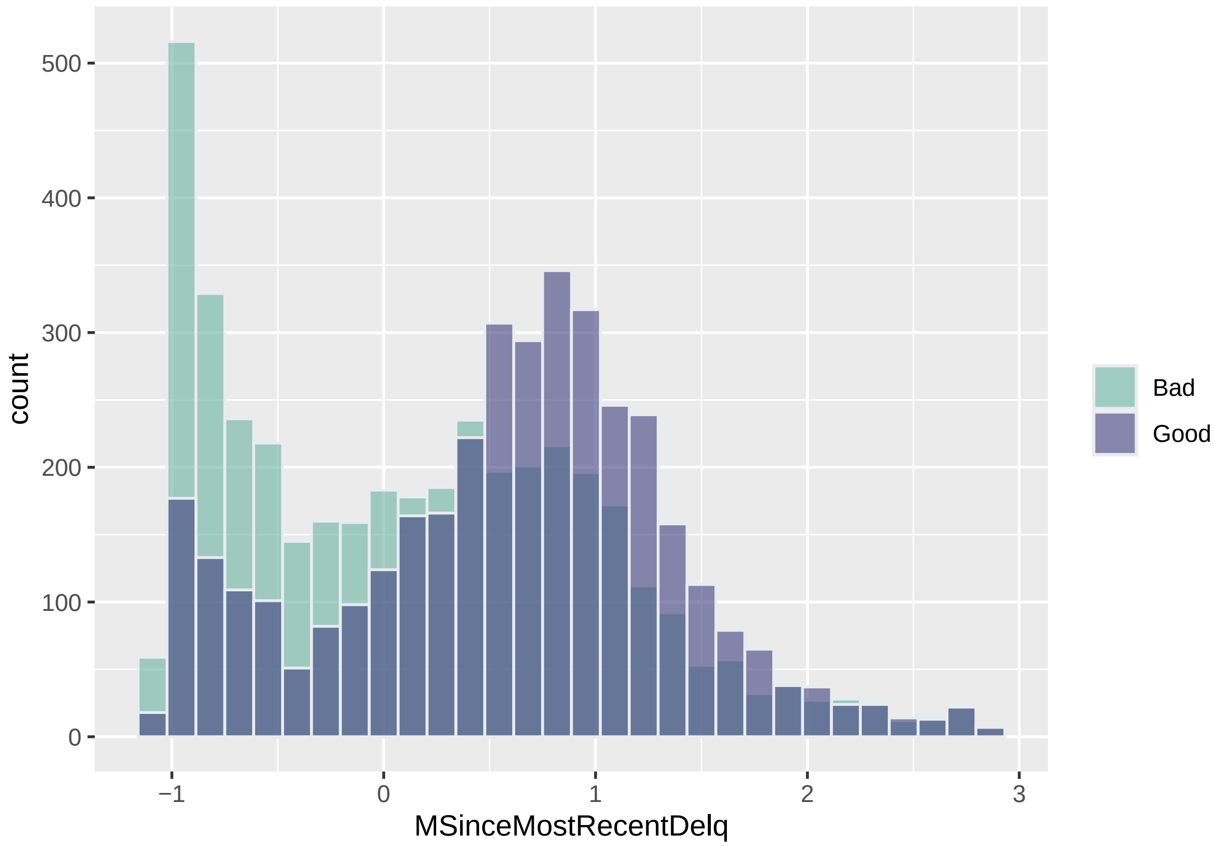


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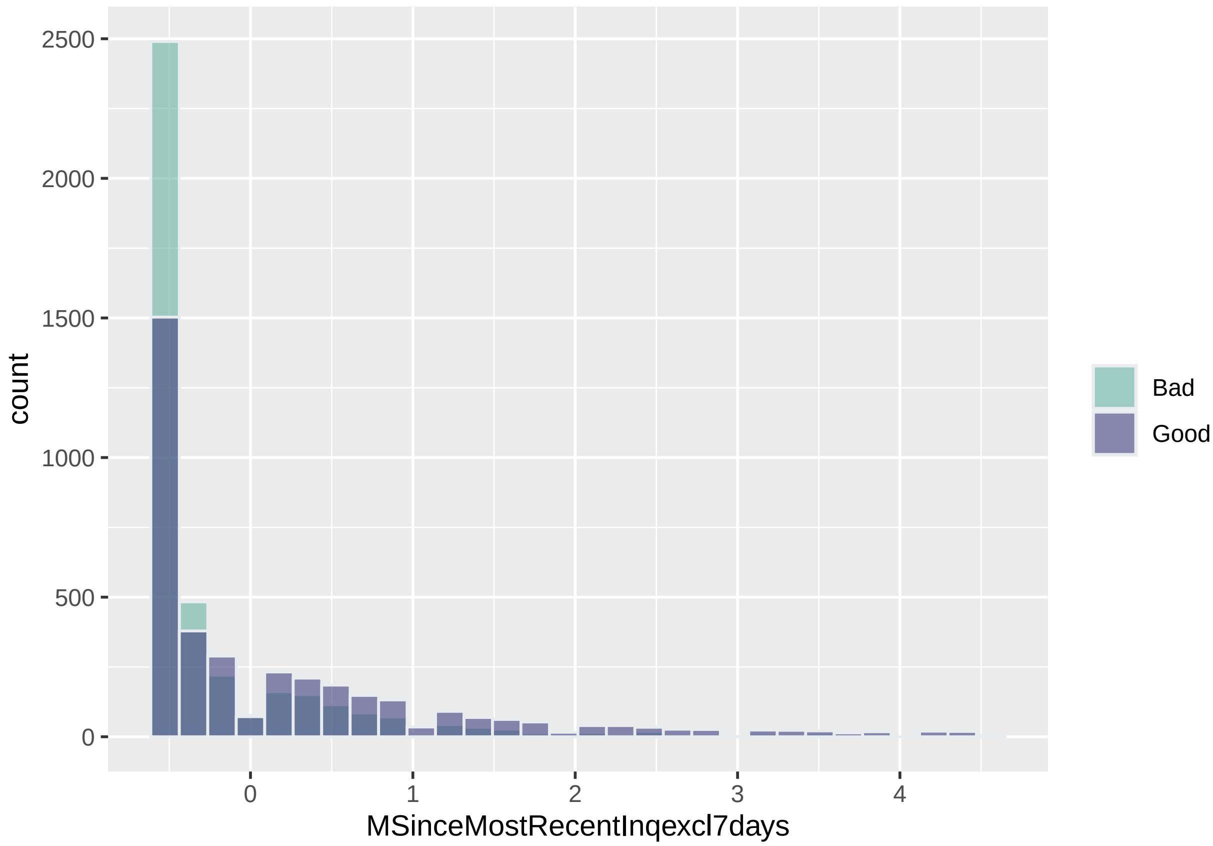


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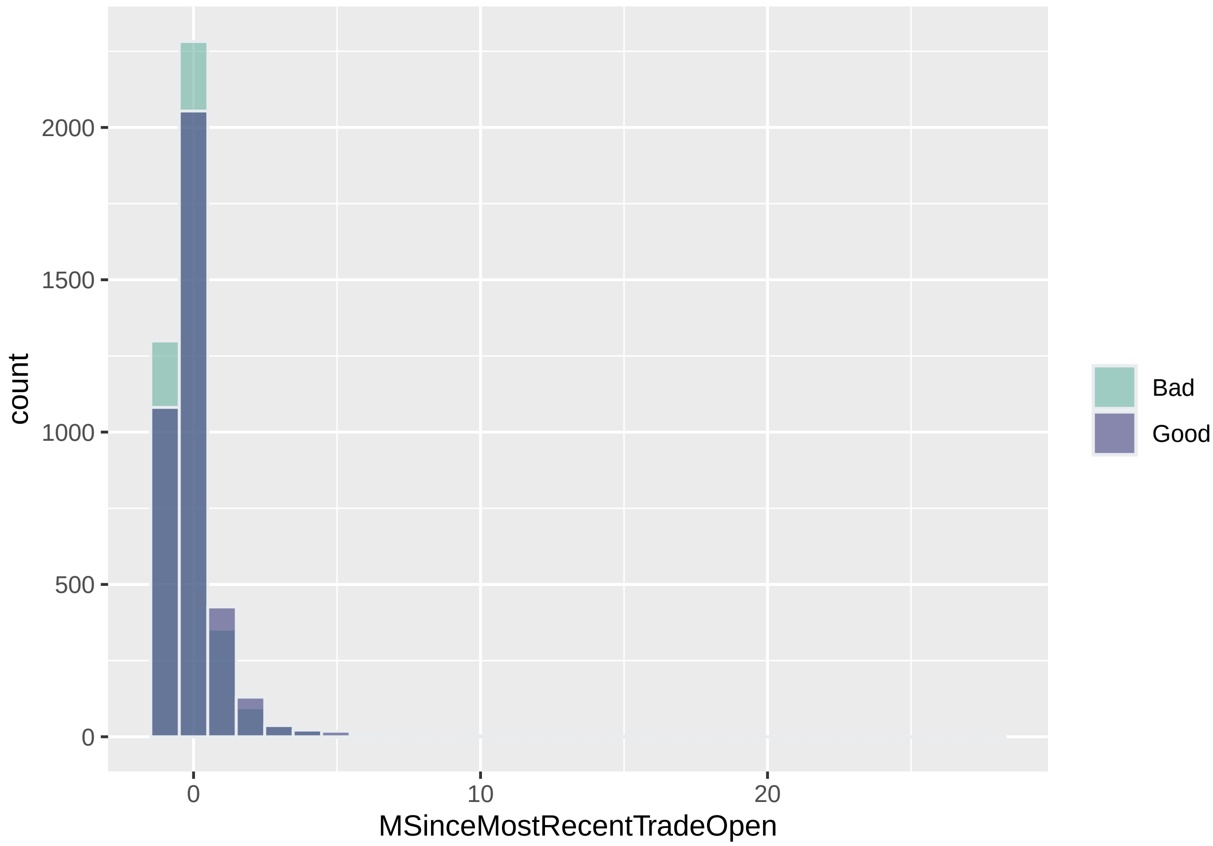
```




```
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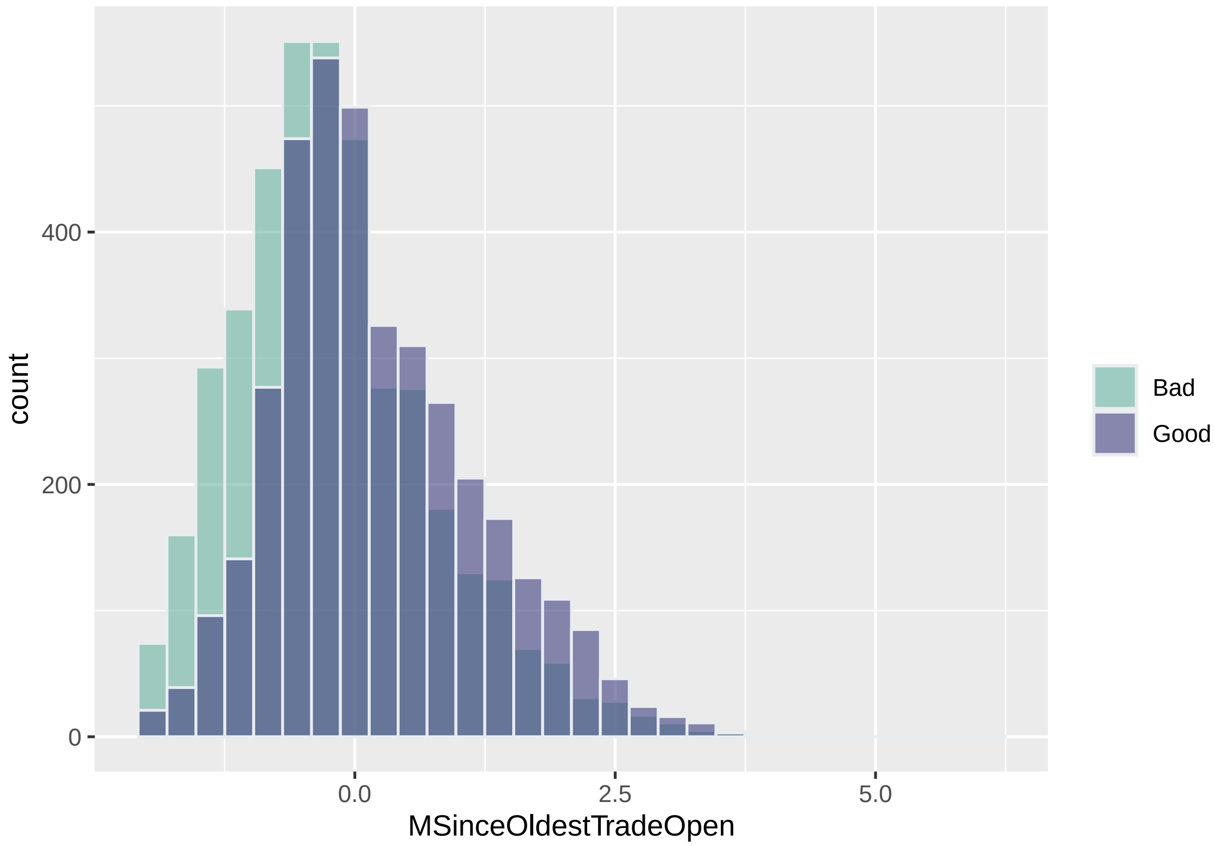
```




```
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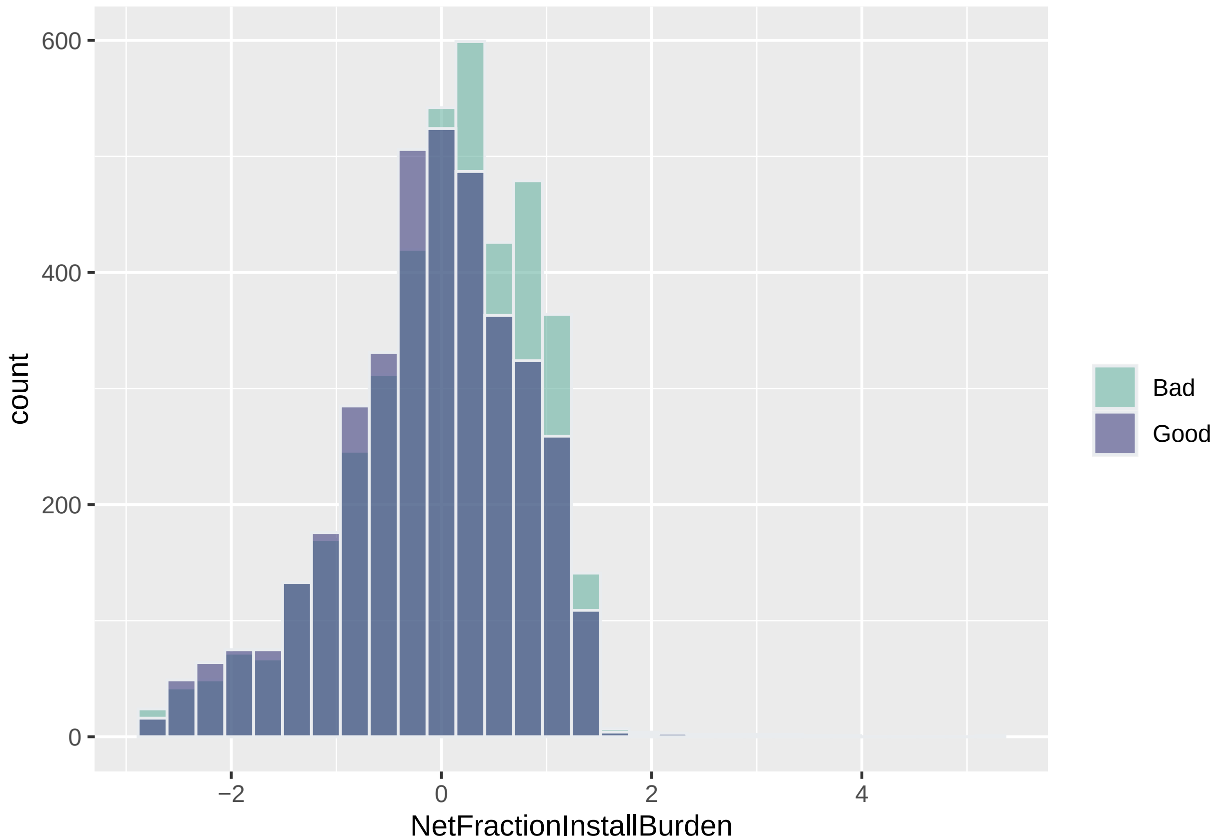
```




```
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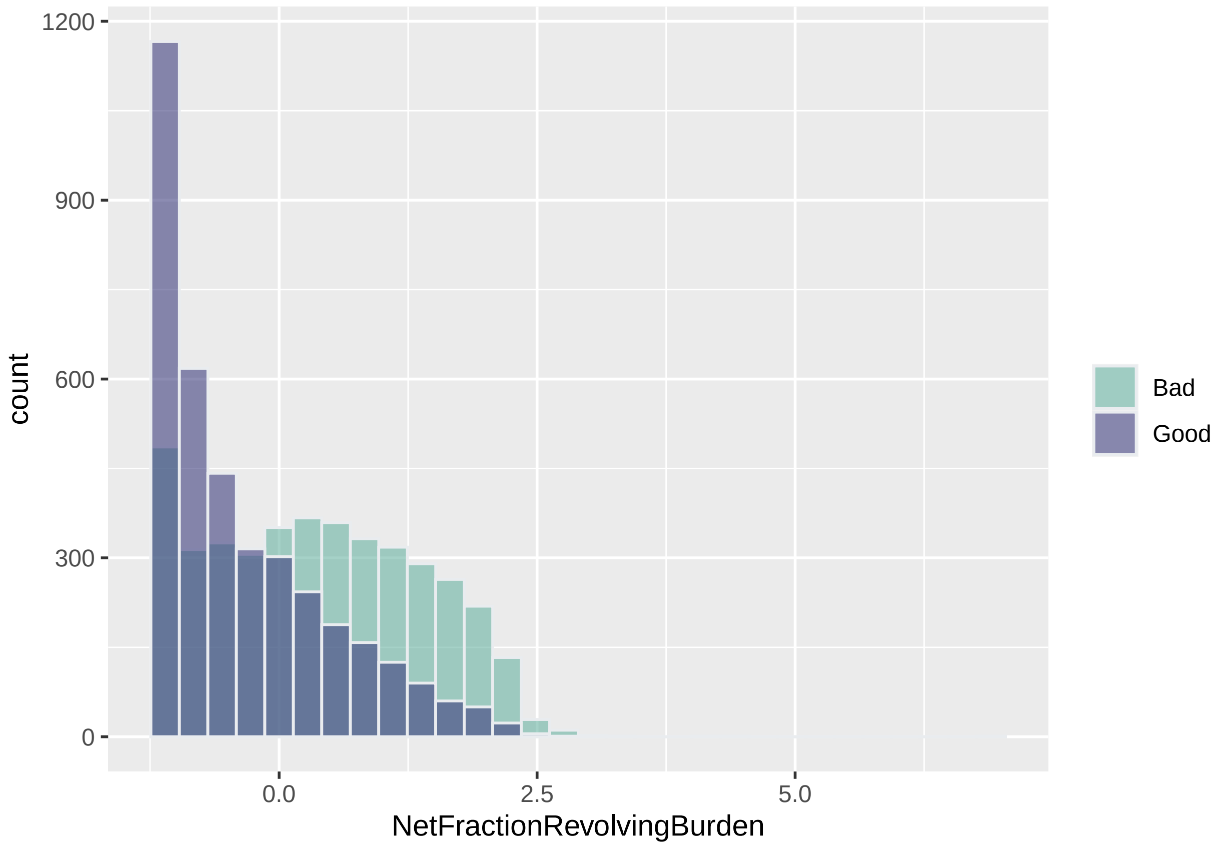
```




```
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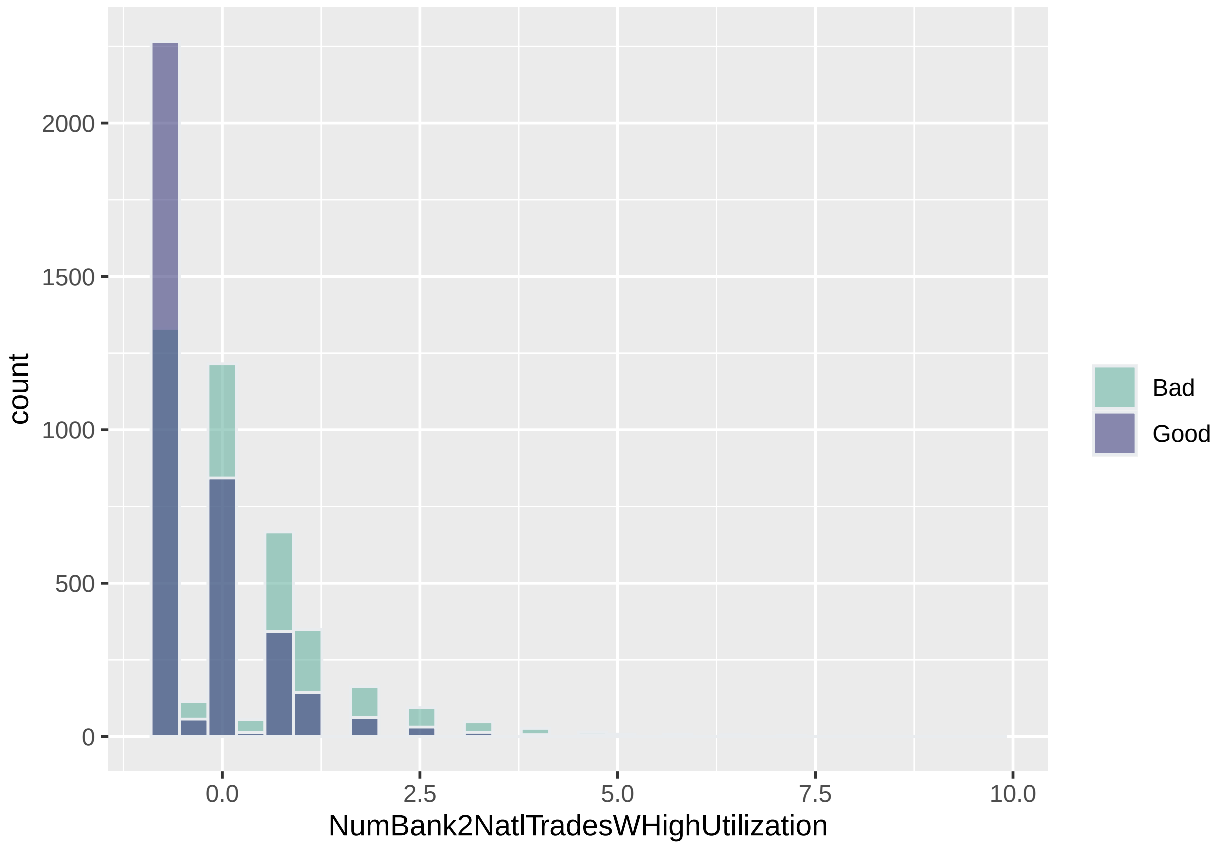
```




```
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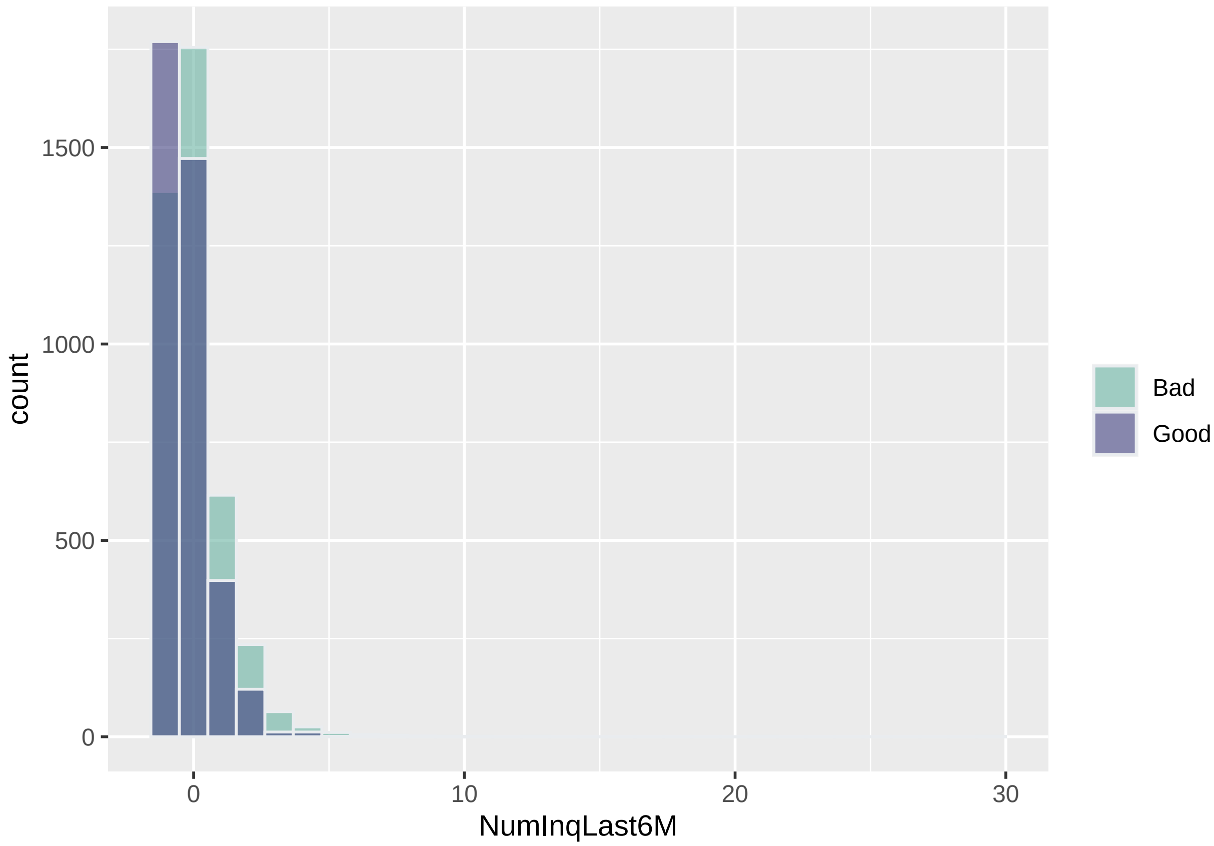
```




```
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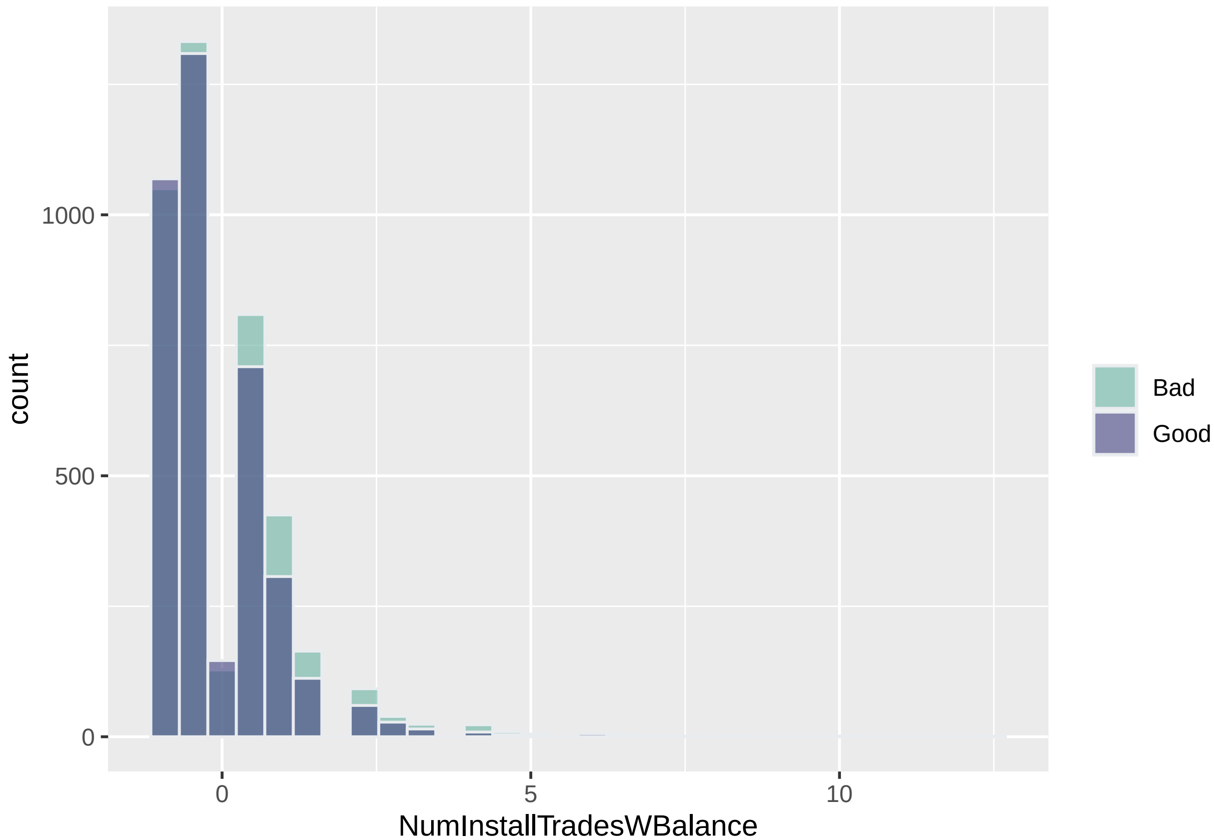
```




```
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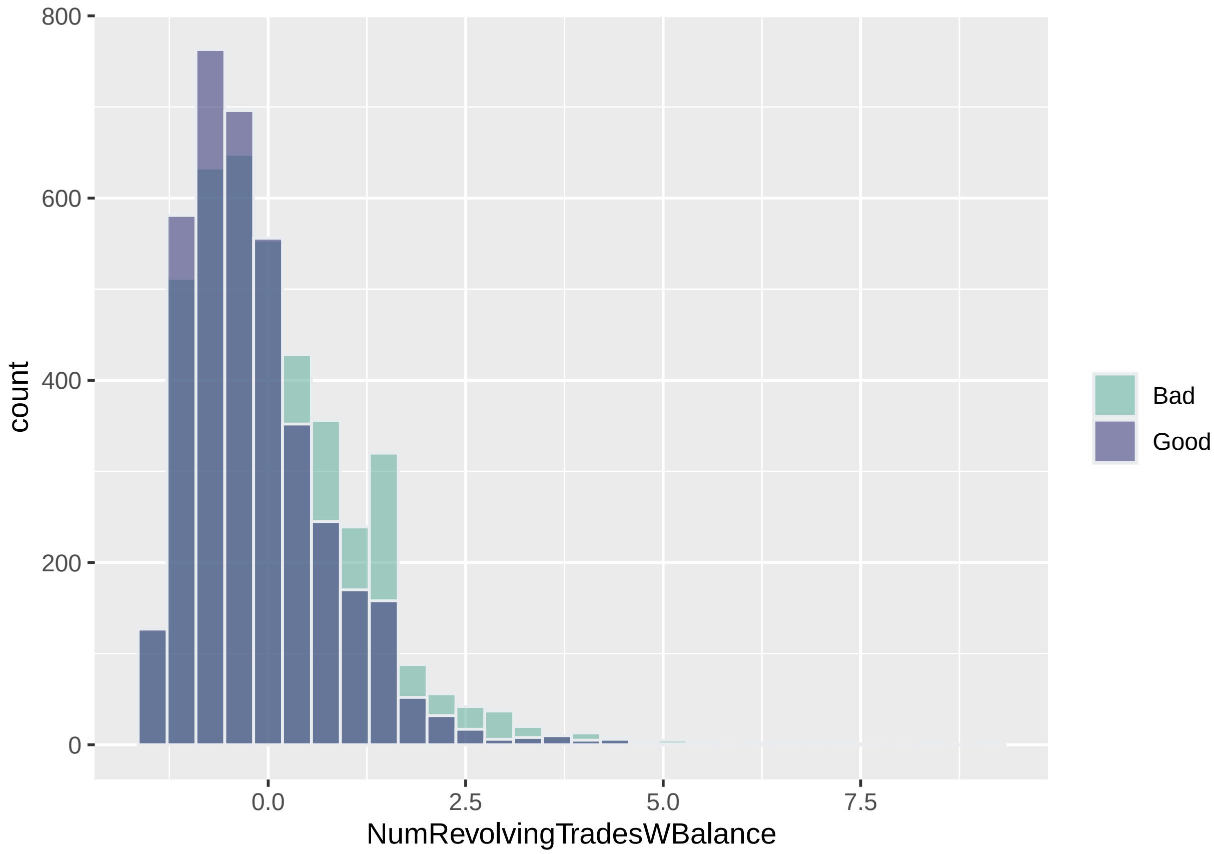
```




```
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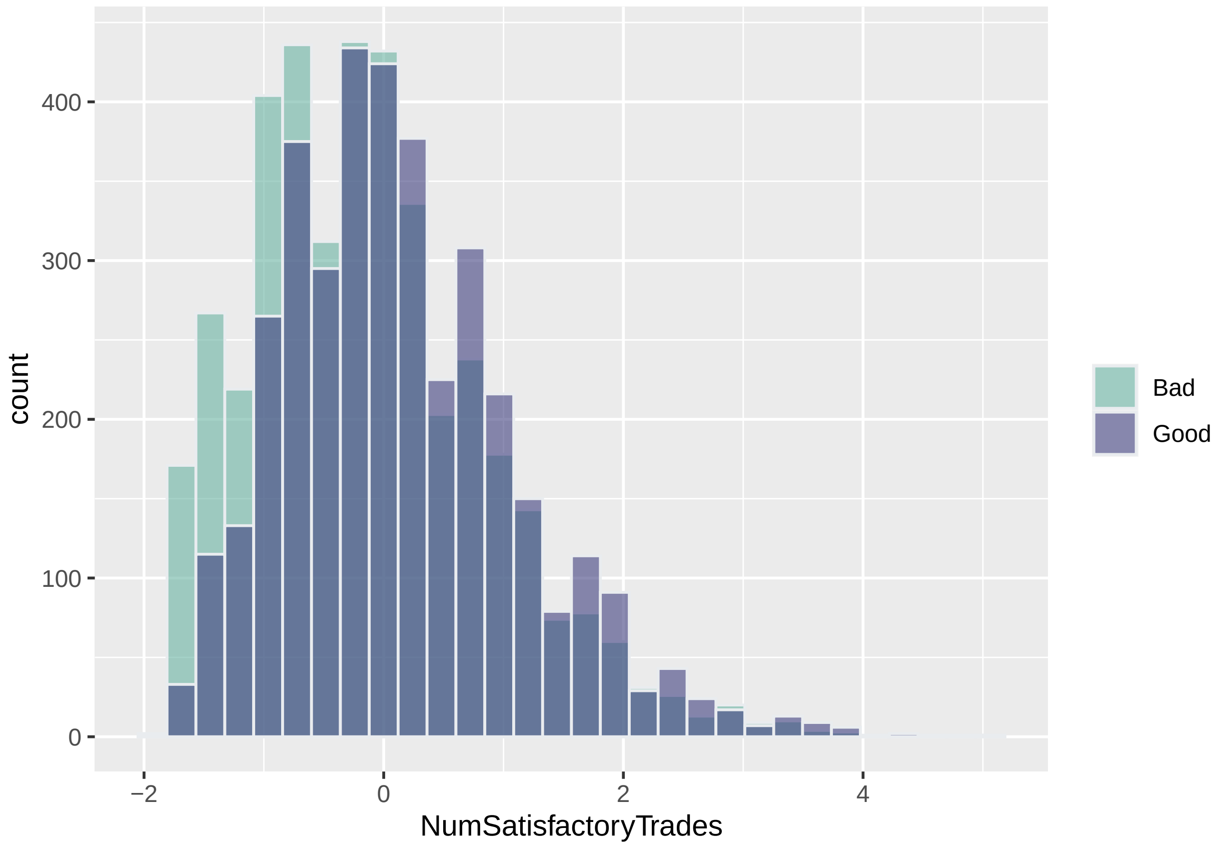
```




```
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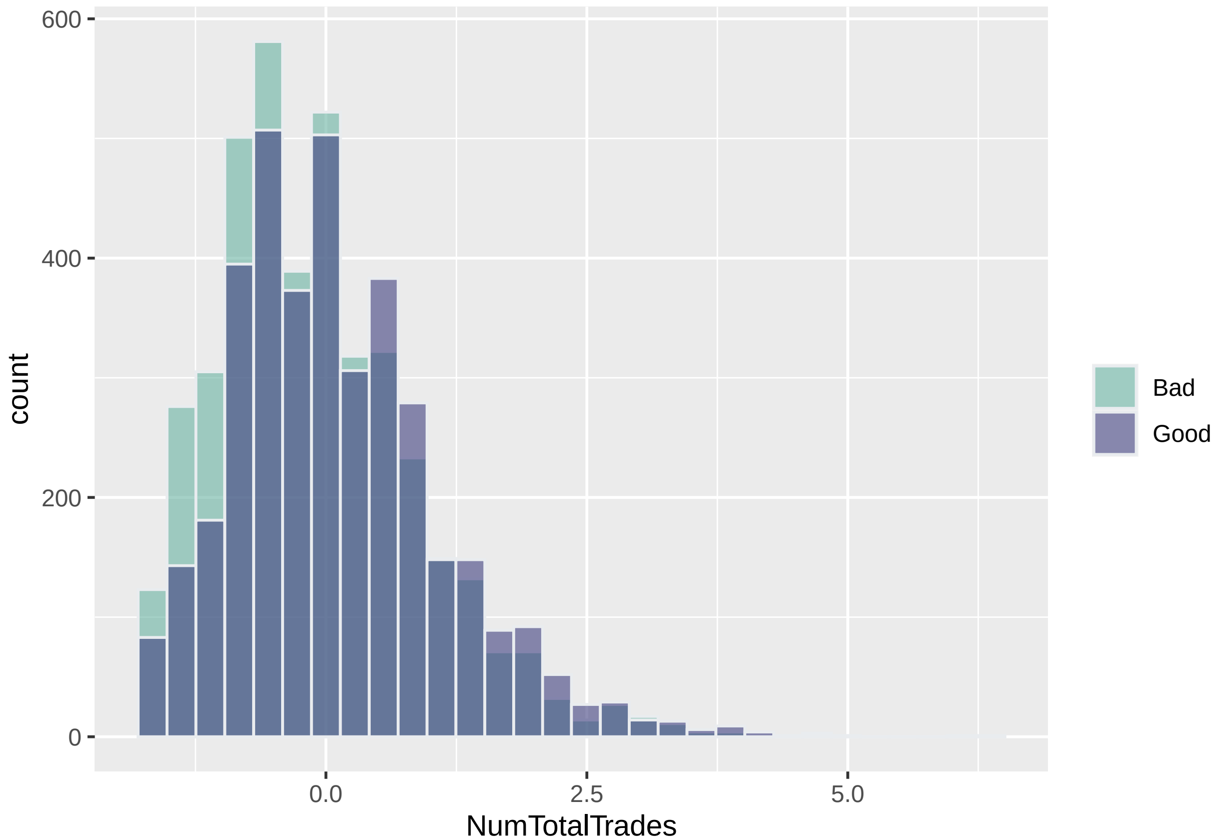
```




```
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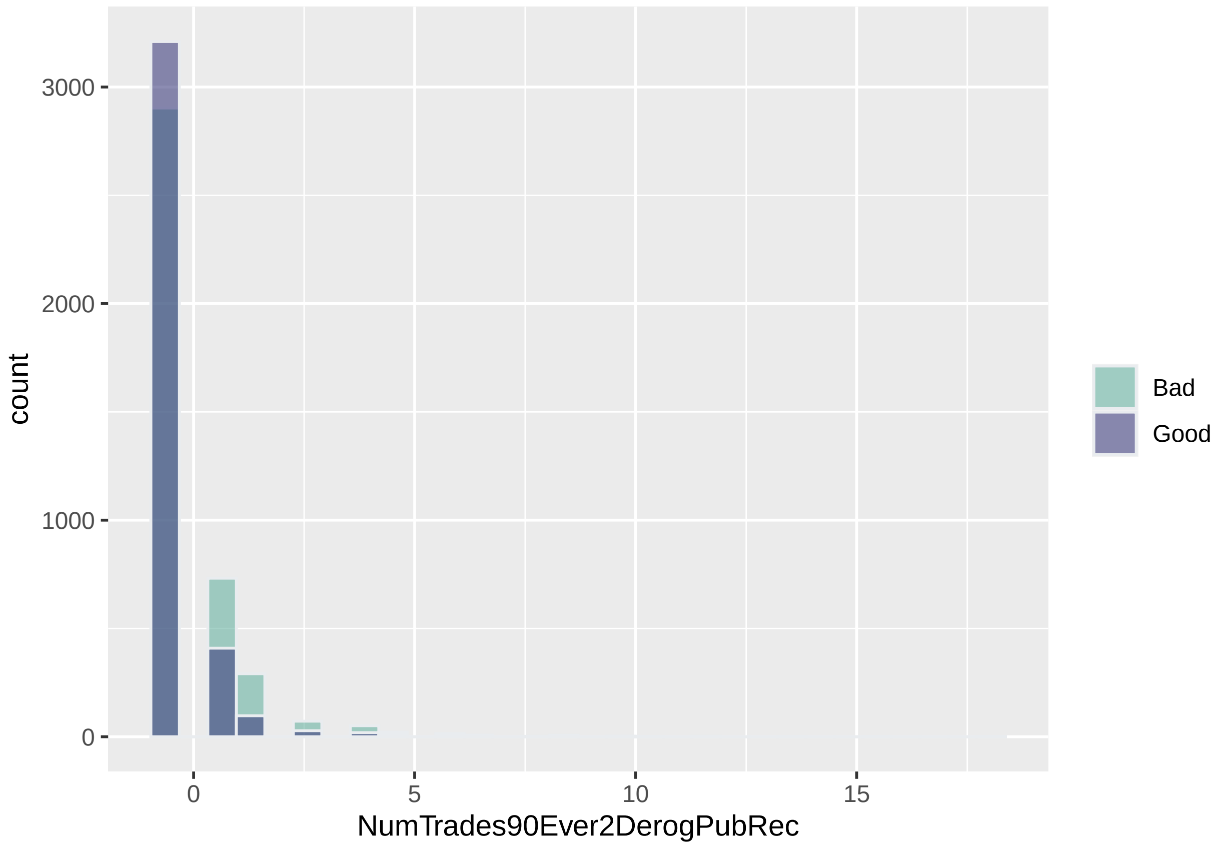
```




```
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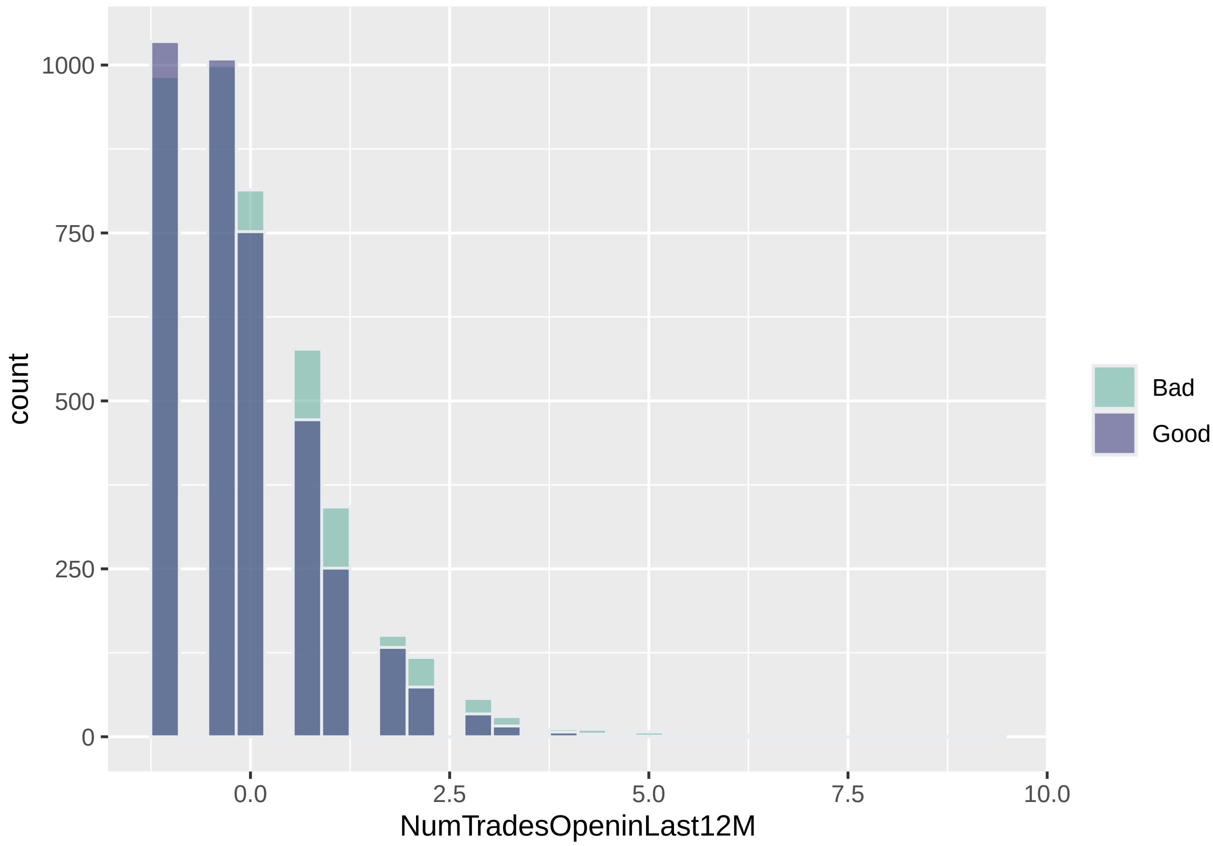
```




```
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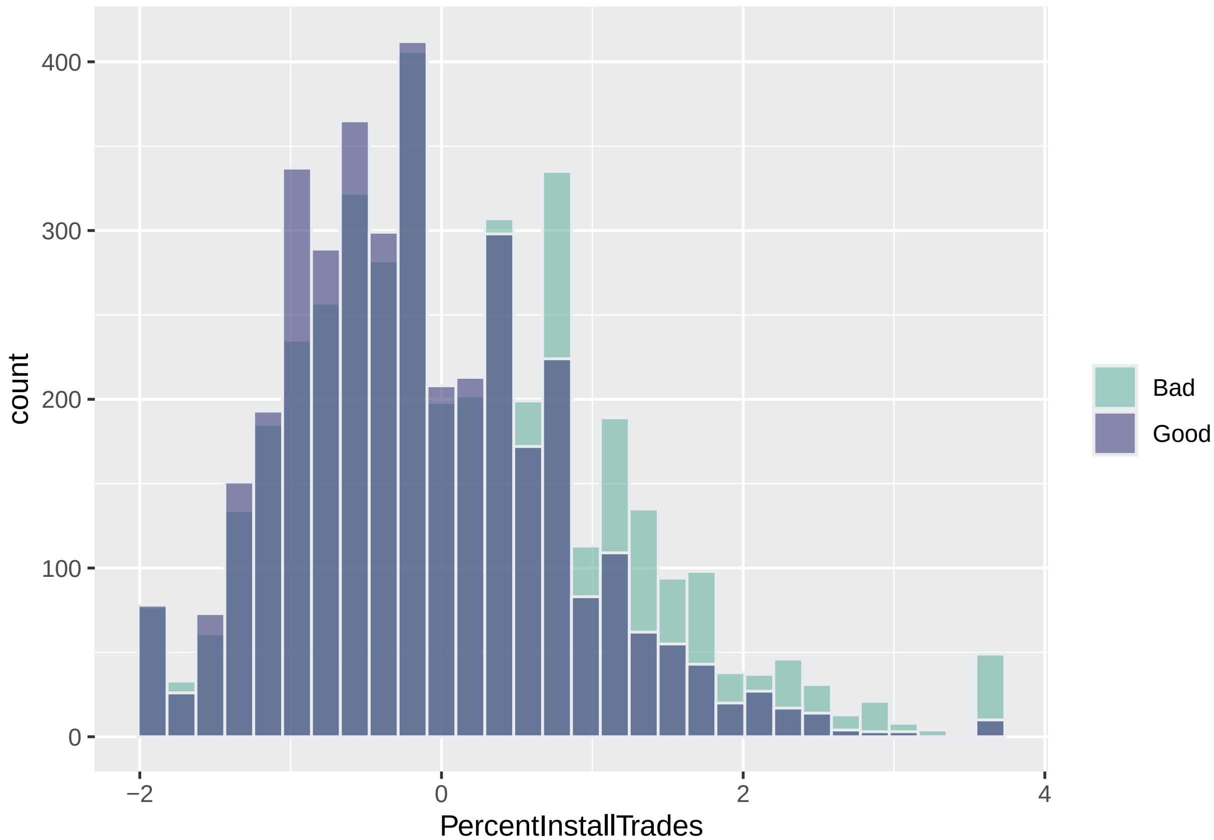
```




```
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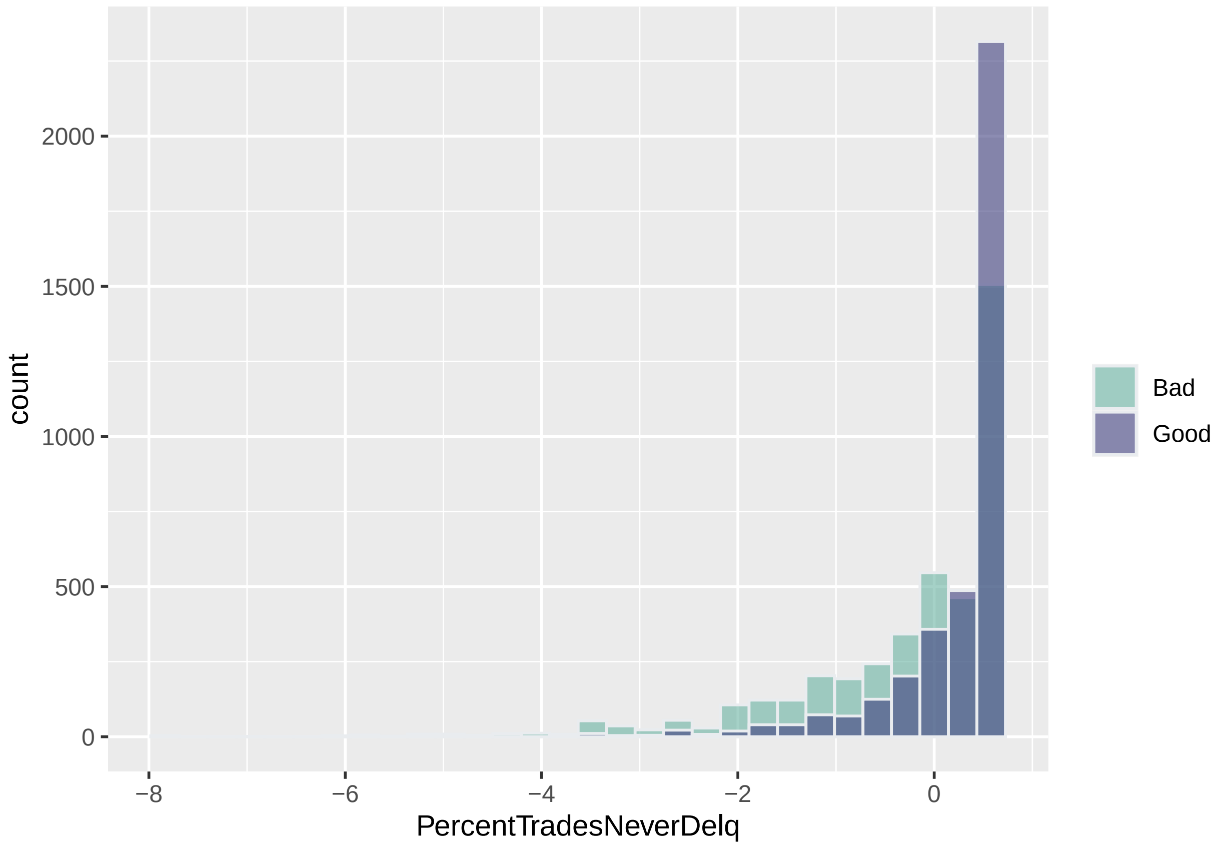
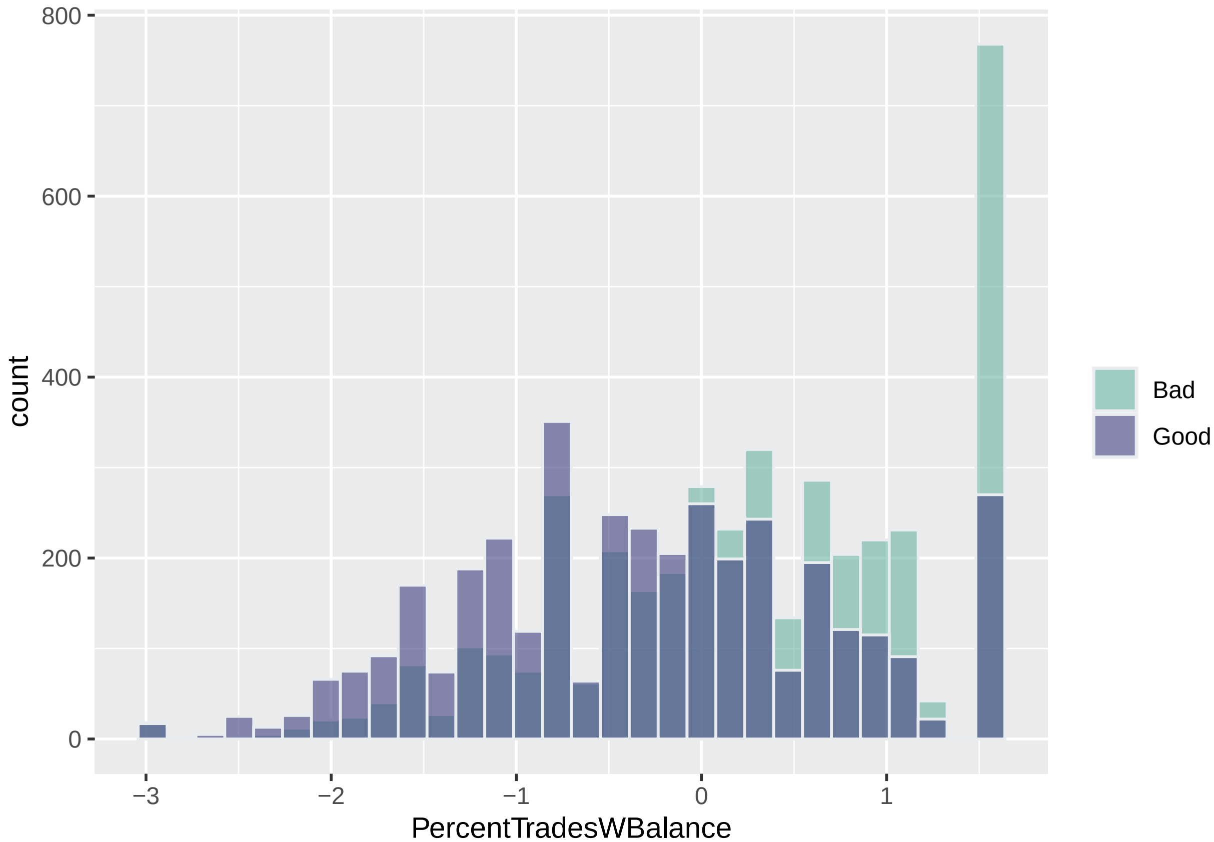
```

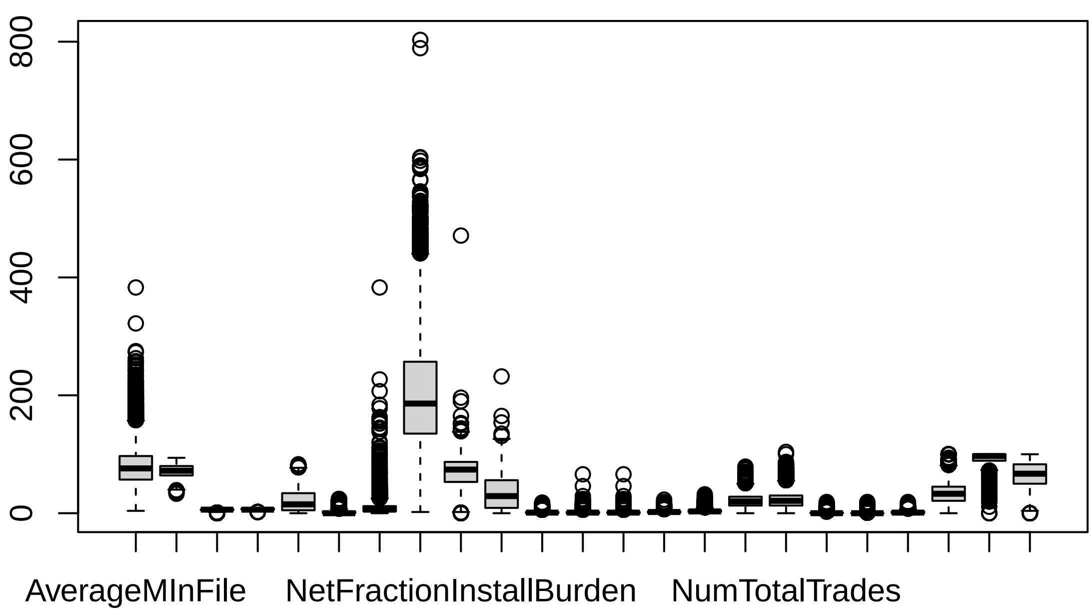



```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



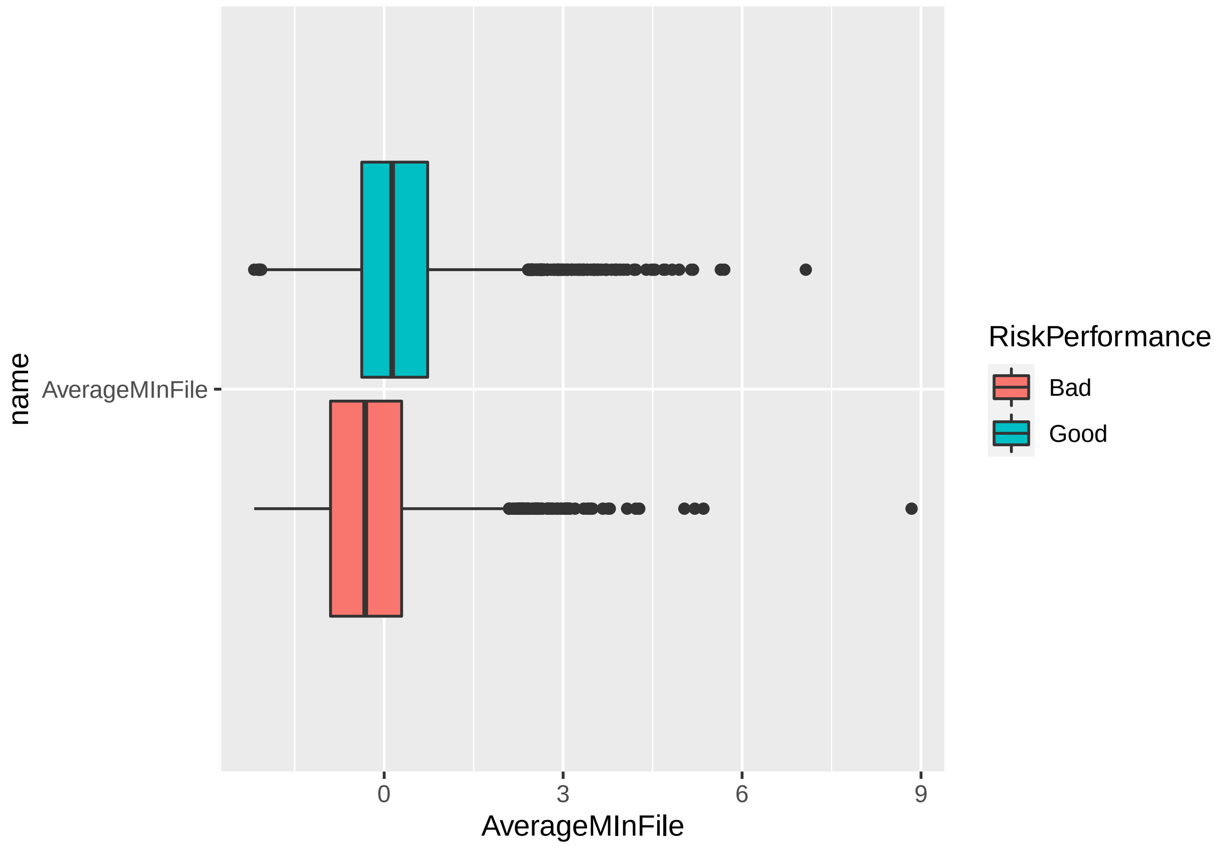
BoxPlots

```r
# boxplot to view outliers
boxplot(heloc[, 1:23])
```



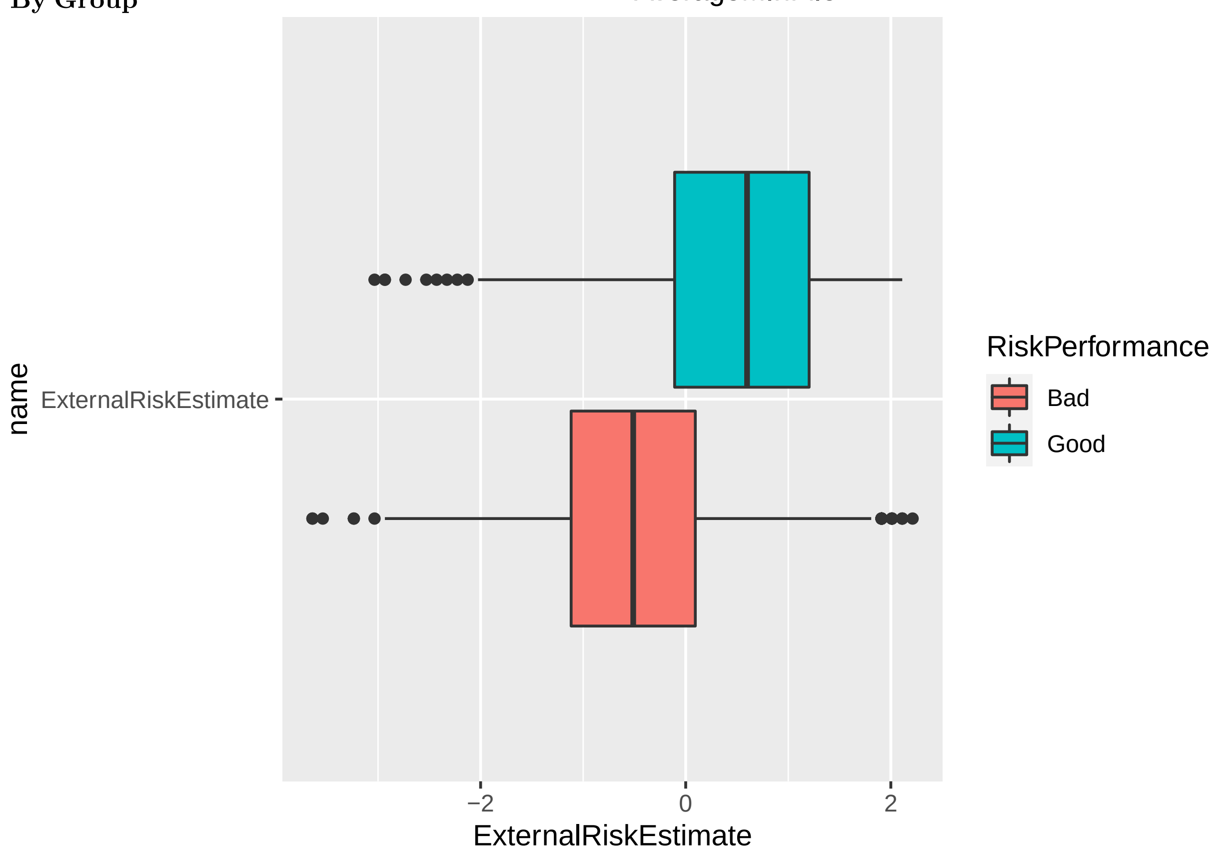
Overall

```r
for (name in heloc_ifs_names){
  # boxplot to view outliers
  p <- heloc_train %>%
          ggplot( aes(x=heloc_train[,name], y=name, fill=RiskPerformance)) +
          geom_boxplot() +
          xlab(name)
  print(p)
}
```

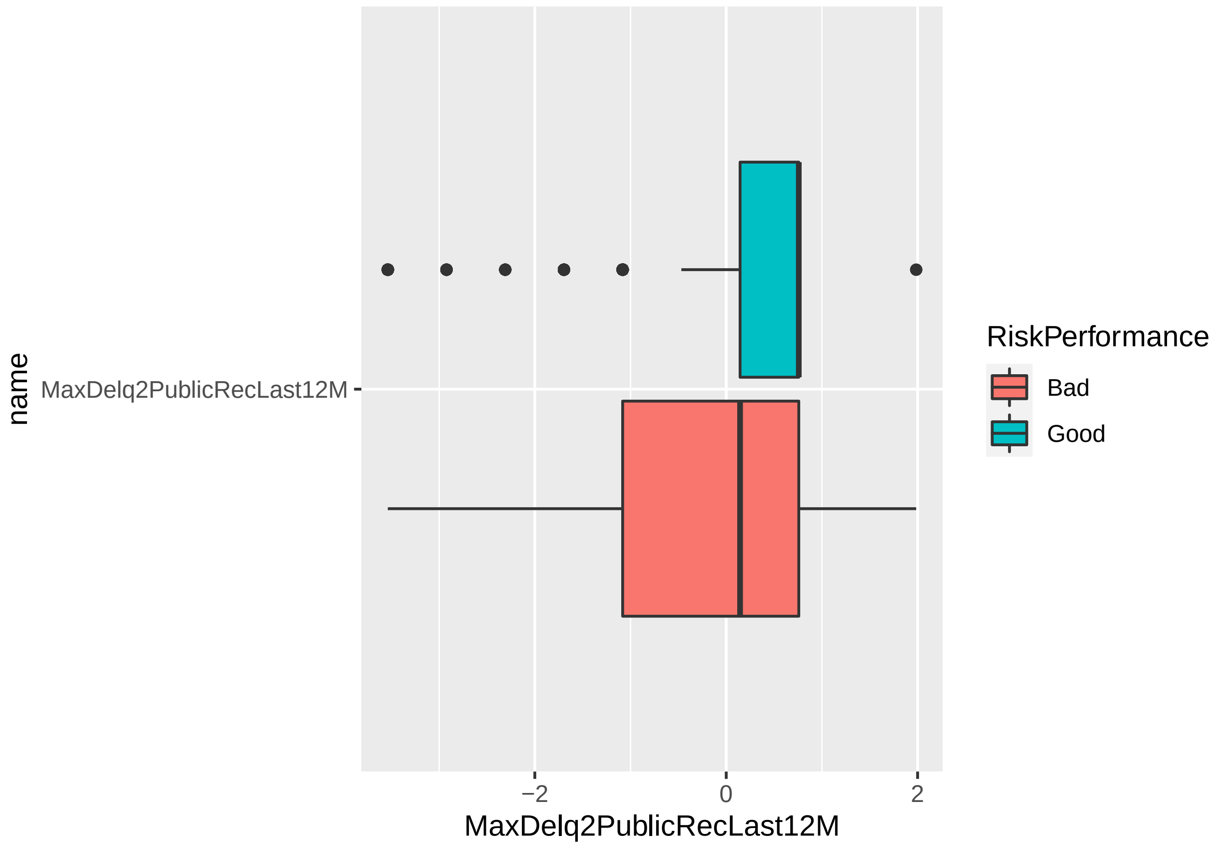


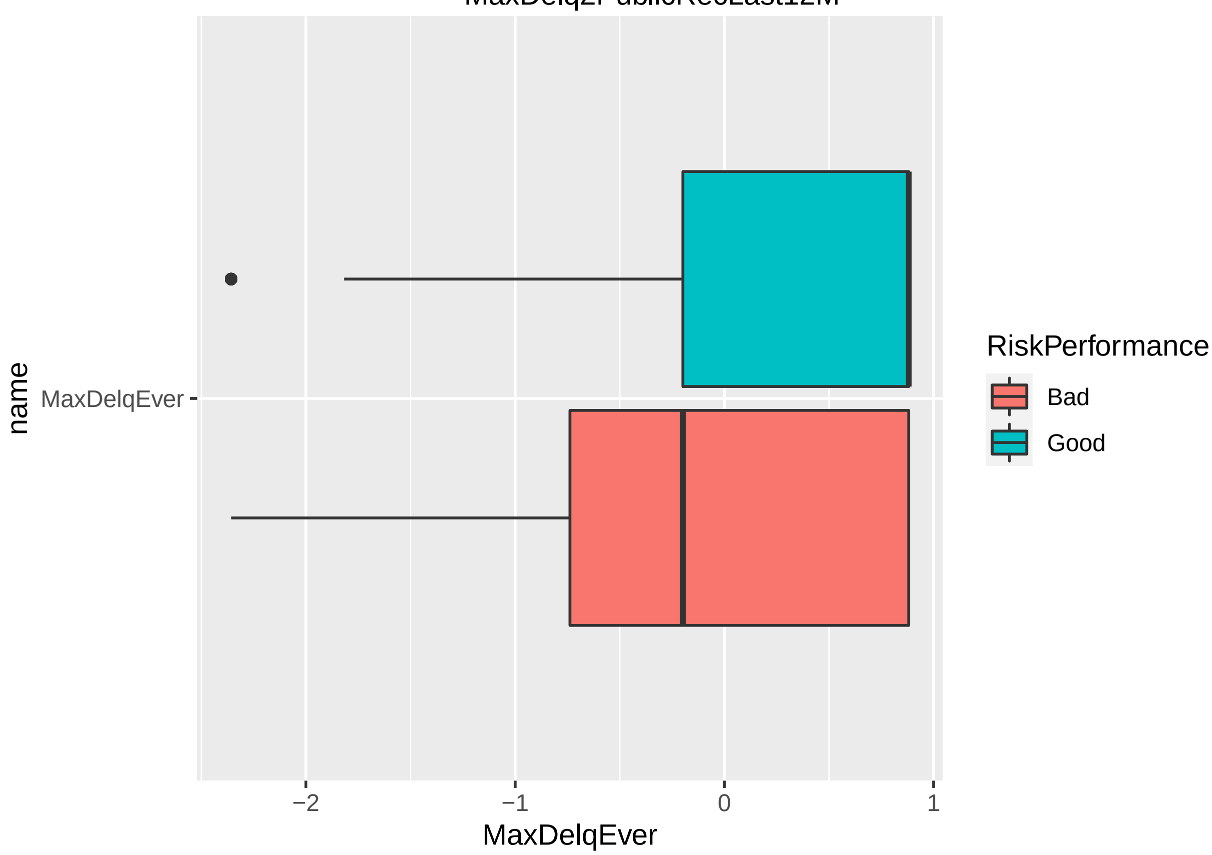
name
AverageMInFile
0
3
6
9
AverageMInFile
RiskPerformance
Bad
Good

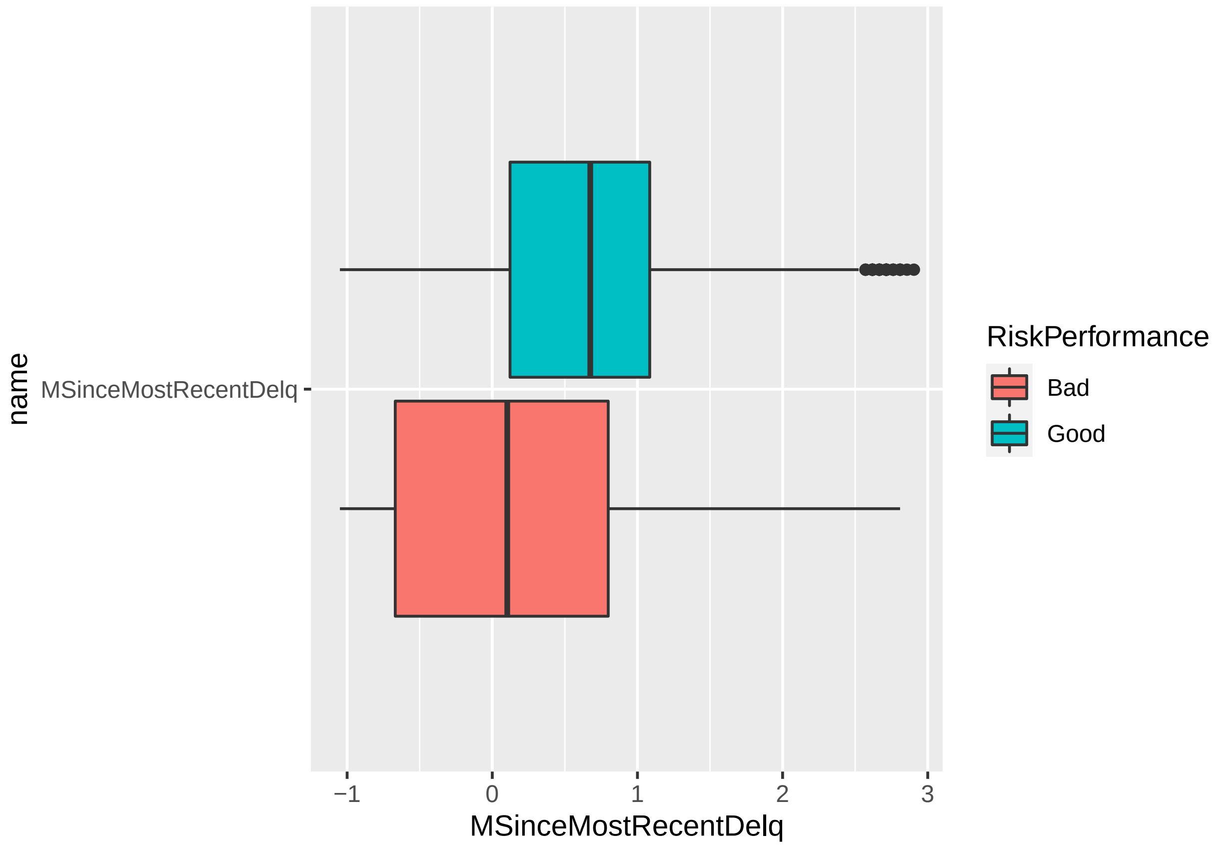
By Group

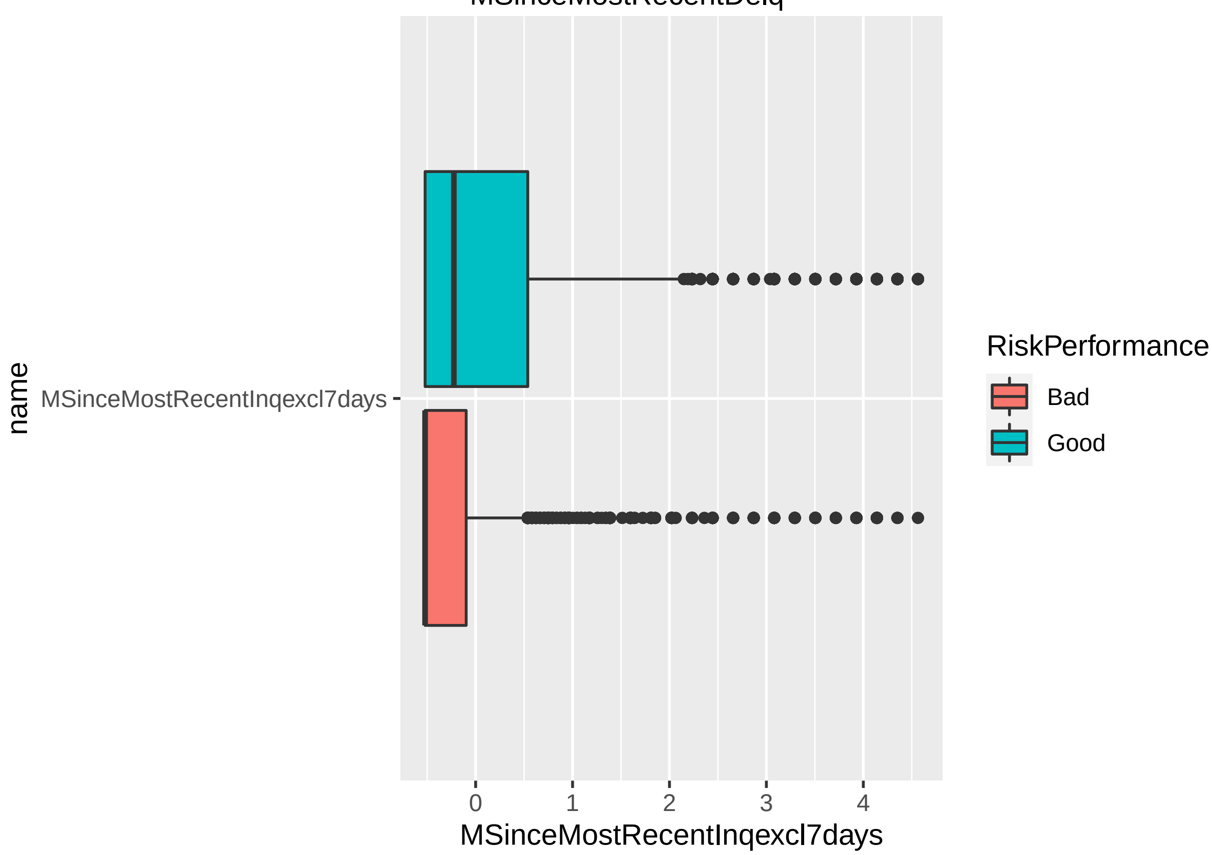


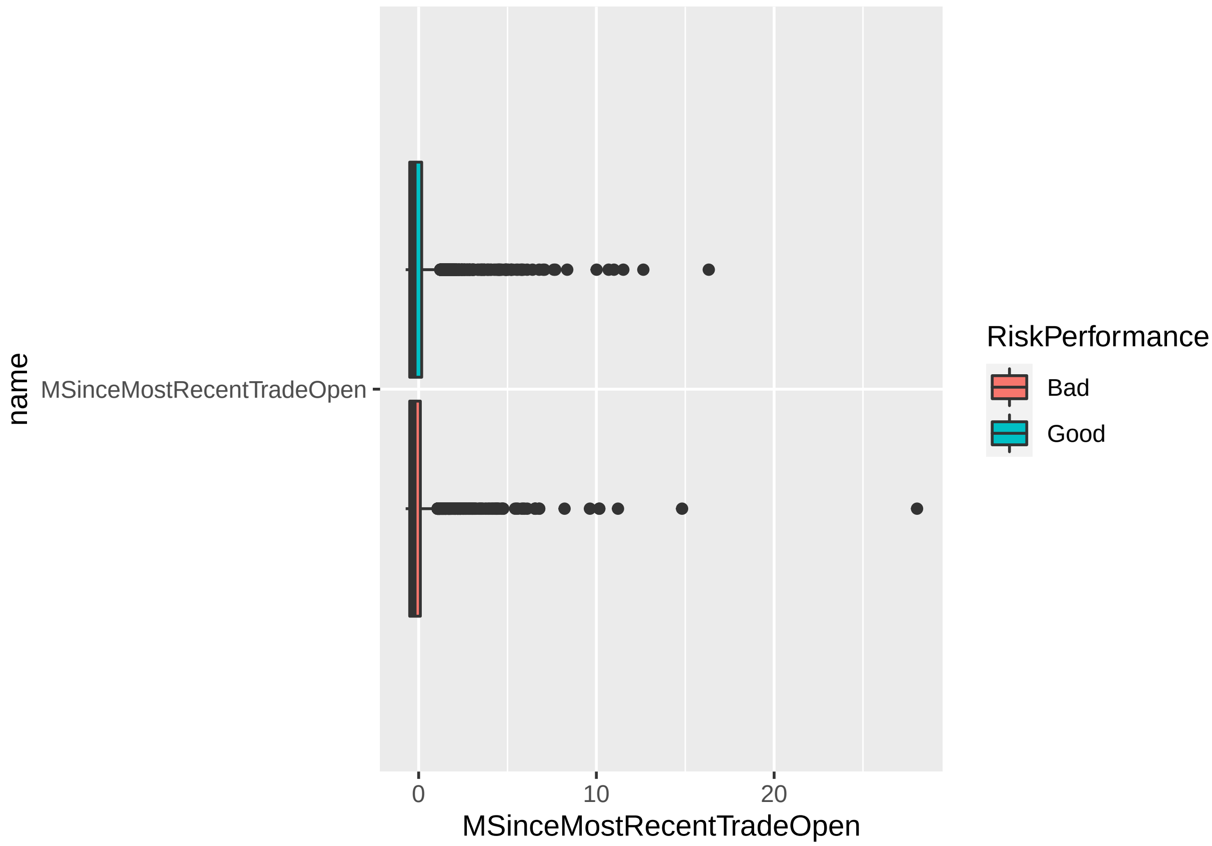
name
ExternalRiskEstimate
−2
0
2
ExternalRiskEstimate
RiskPerformance
Bad
Good

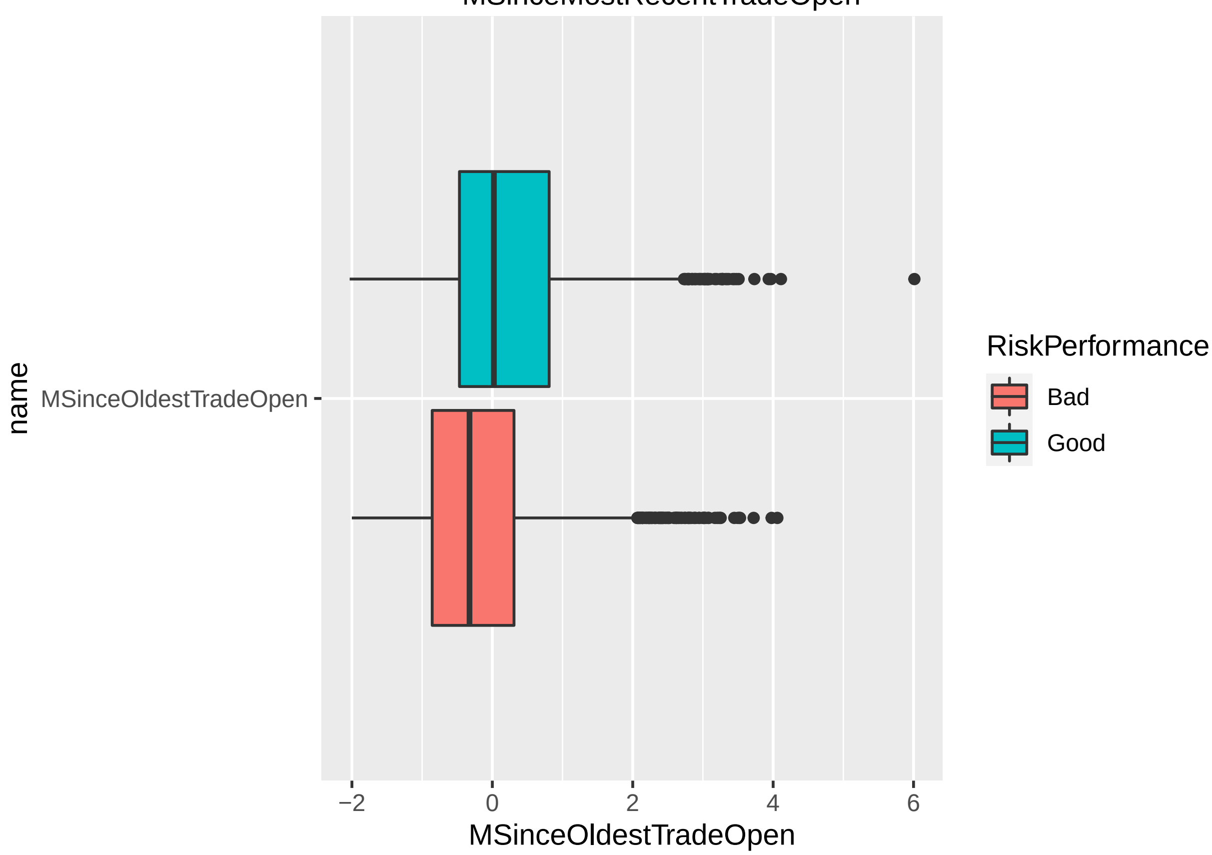

name
MaxDelq2PublicRecLast12M
−2
0
2
MaxDelq2PublicRecLast12M
RiskPerformance
Bad
Good

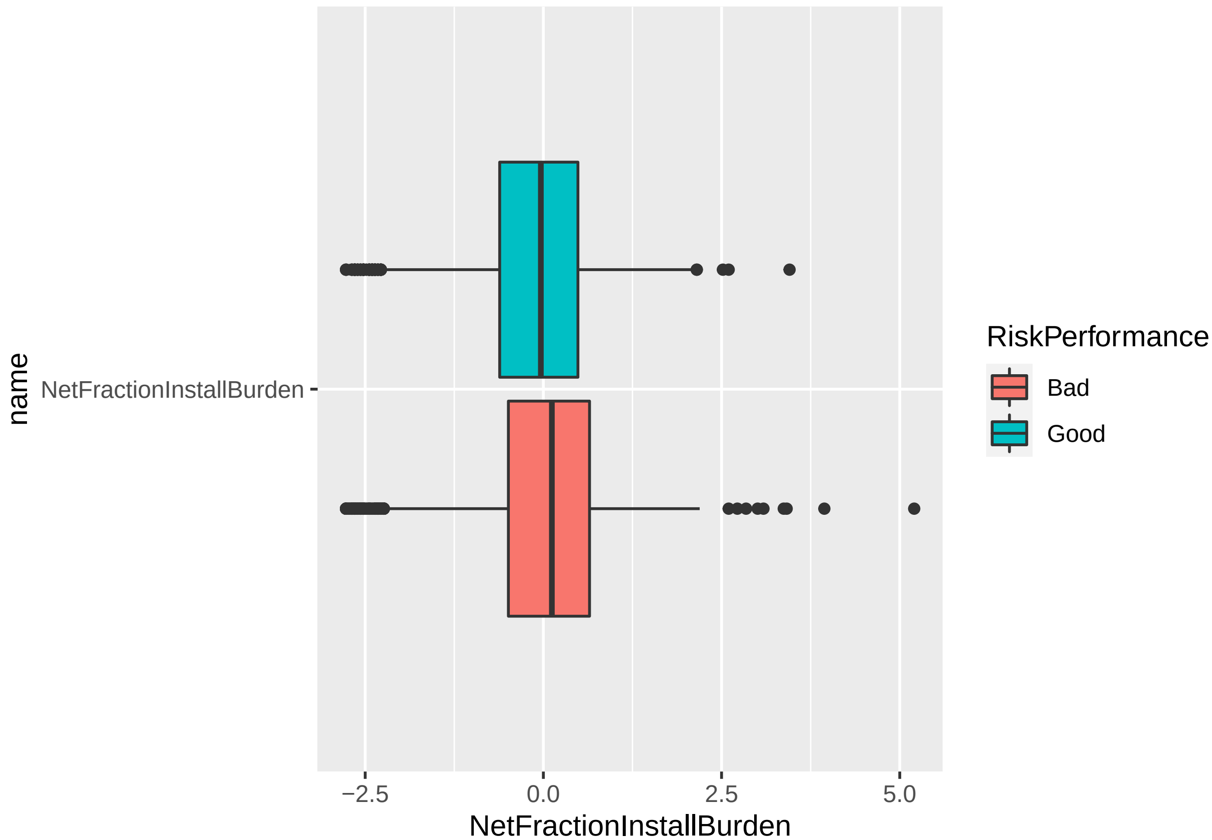

name
MaxDelqEver
−2
−1
0
1
MaxDelqEver
RiskPerformance
Bad
Good

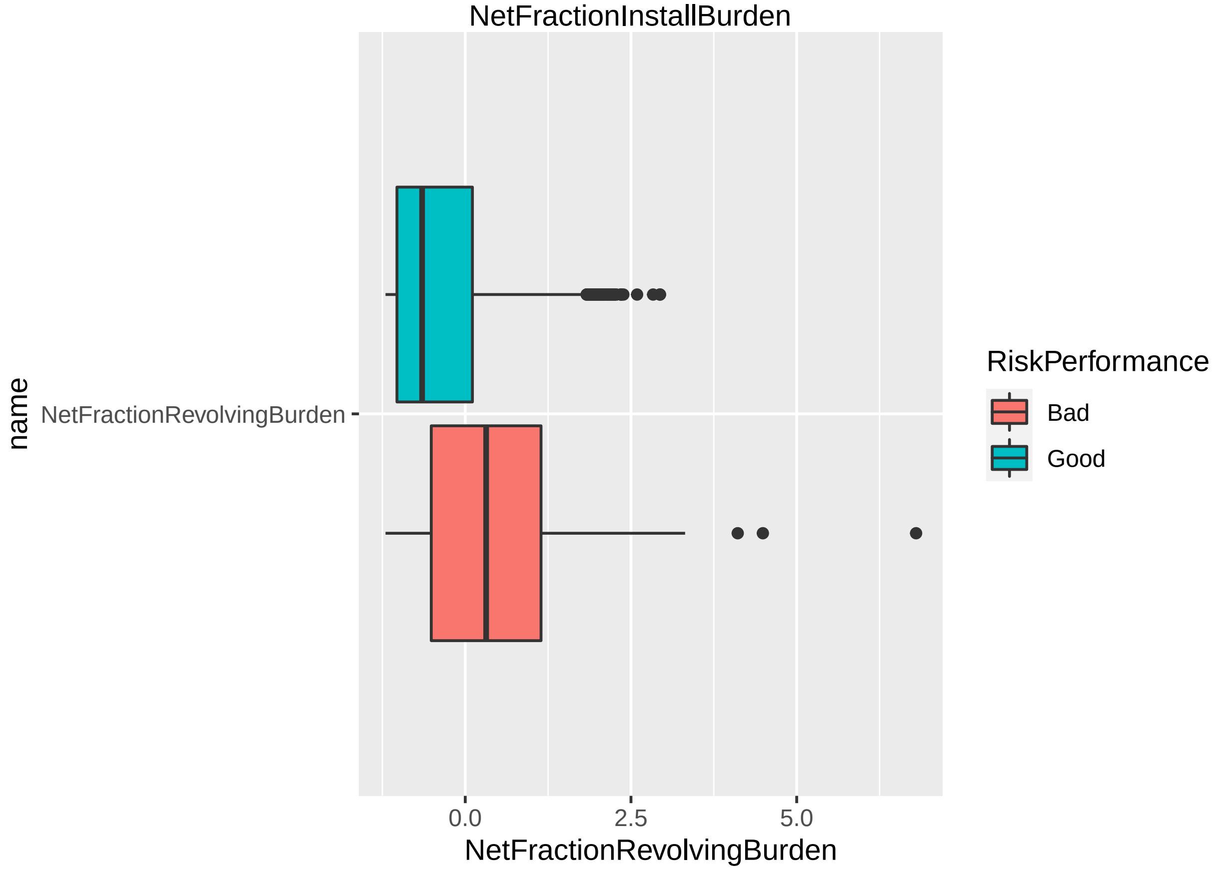

name
MSinceMostRecentDelq
−1
0
1
2
3
MSinceMostRecentDelq
RiskPerformance
Bad
Good

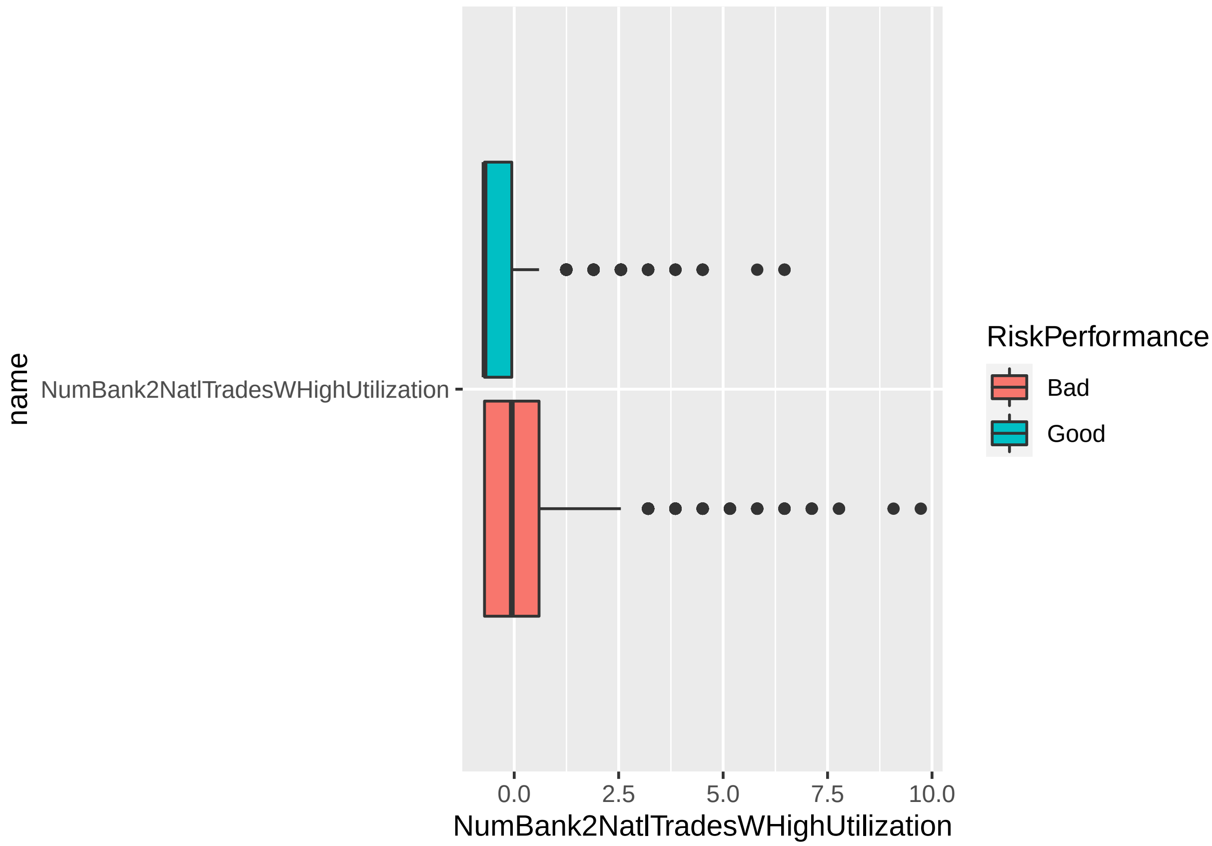

name
MSinceMostRecentInqexcl7days
0
1
2
3
4
MSinceMostRecentInqexcl7days
RiskPerformance
Bad
Good


name
MSinceMostRecentTradeOpen
0
10
20
MSinceMostRecentTradeOpen
RiskPerformance
Bad
Good

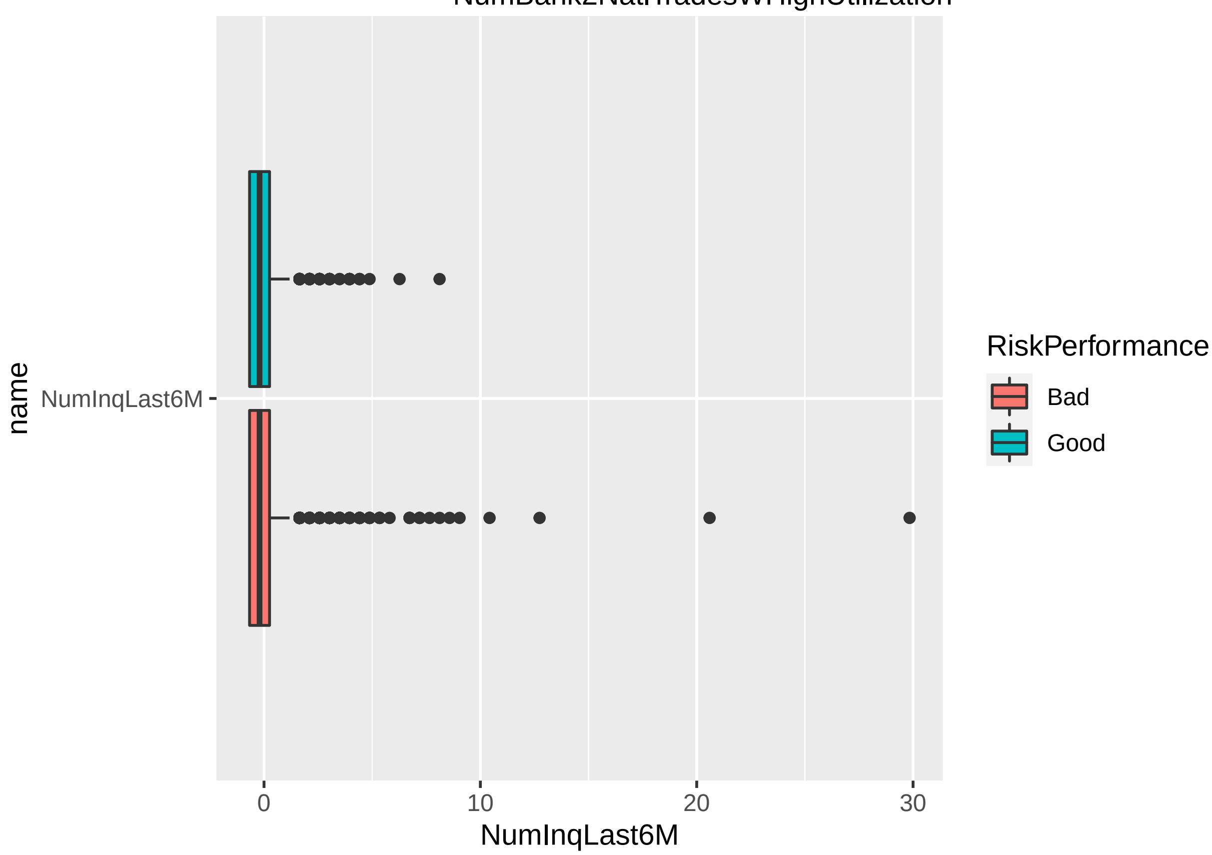

name
MSinceOldestTradeOpen
−2
0
2
4
6
MSinceOldestTradeOpen
RiskPerformance
Bad
Good


name
NetFractionInstallBurden
−2.5
0.0
2.5
5.0
NetFractionInstallBurden
RiskPerformance
Bad
Good

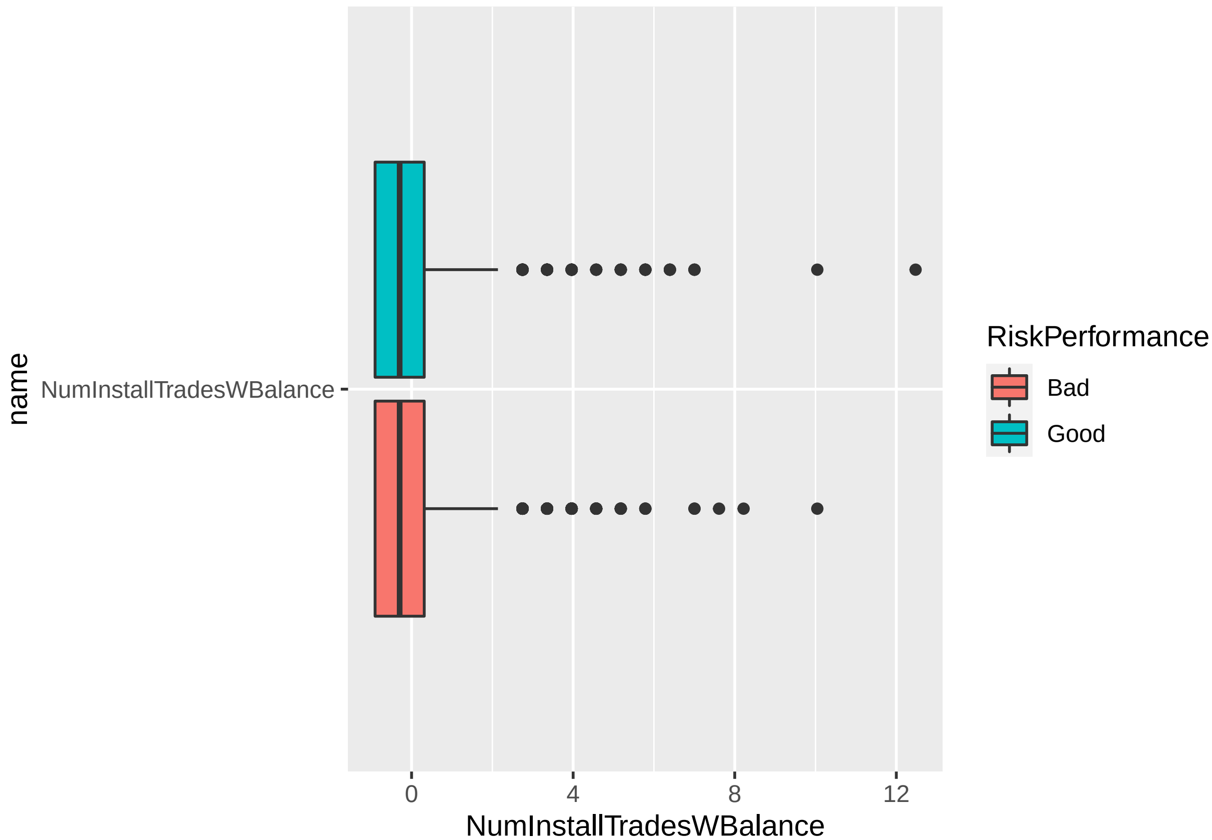

name
NetFractionRevolvingBurden
0.0
2.5
5.0
NetFractionRevolvingBurden
RiskPerformance
Bad
Good

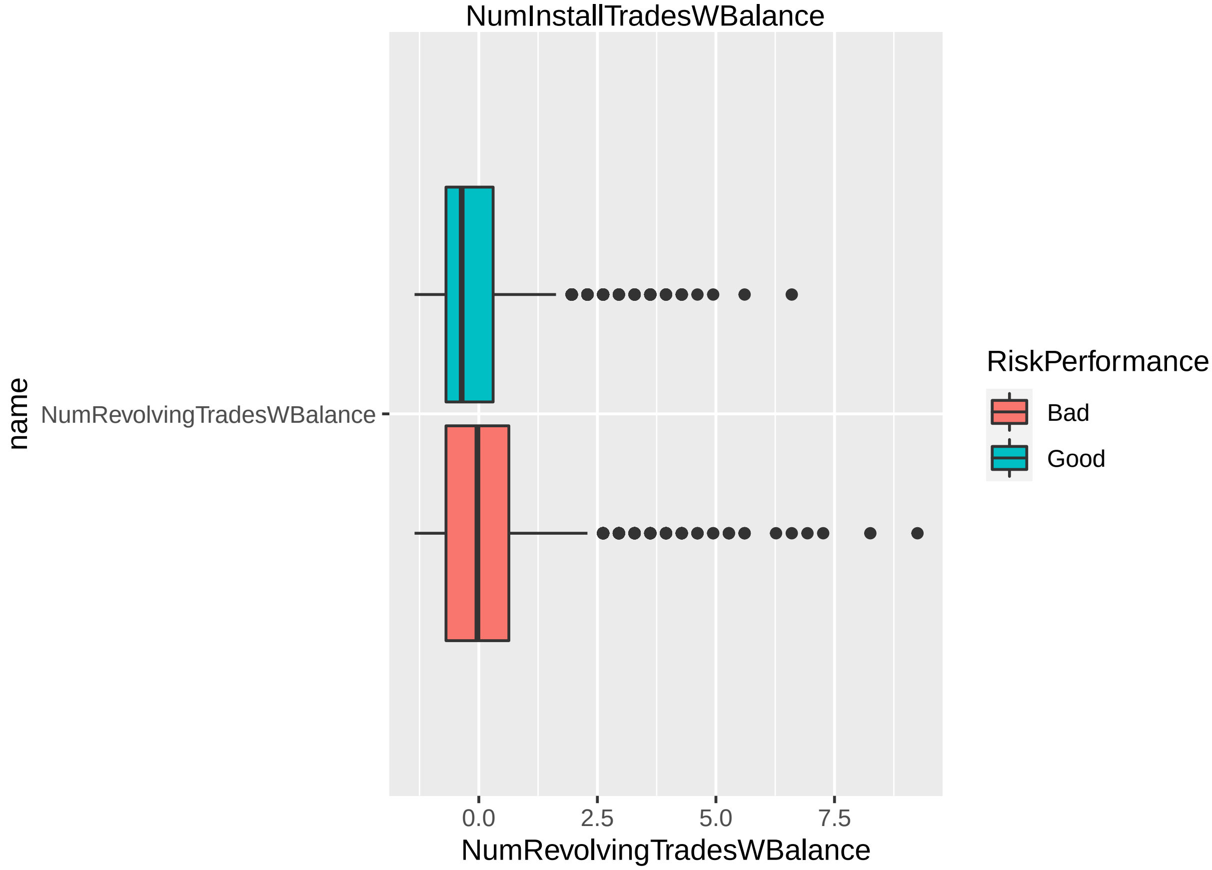


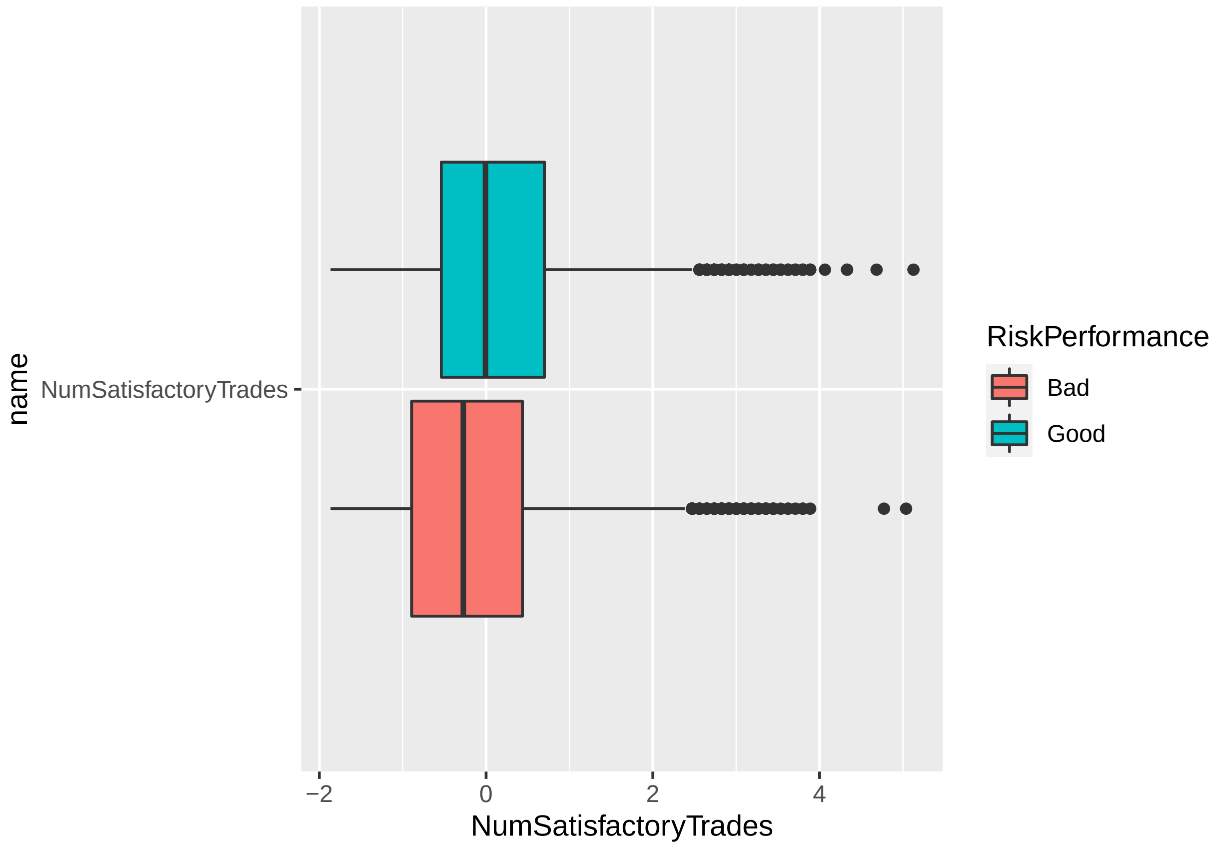
name
NumBank2NatlTradesWHighUtilization
0.0
2.5
5.0
7.5
10.0
NumBank2NatlTradesWHighUtilization
RiskPerformance
Bad
Good

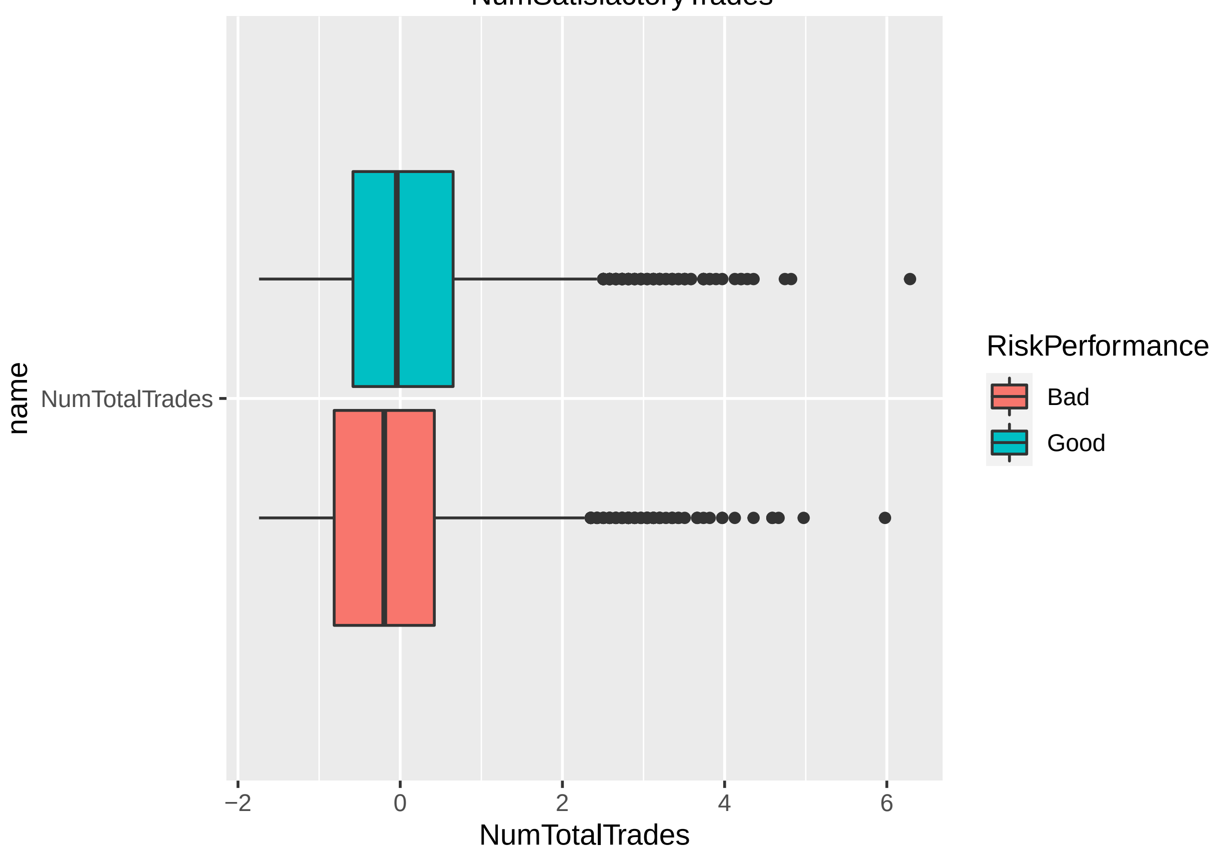


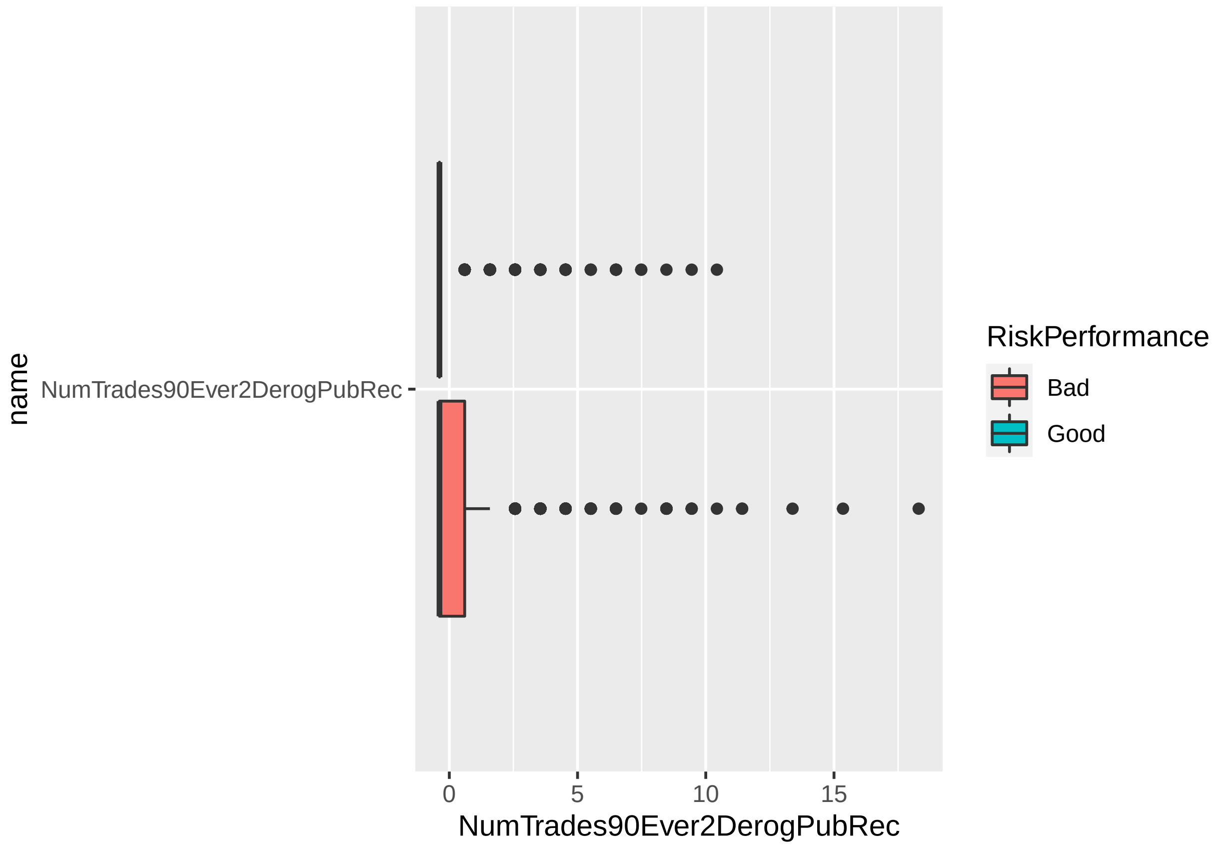
name
NumInqLast6M
0
10
20
30
NumInqLast6M
RiskPerformance
Bad
Good

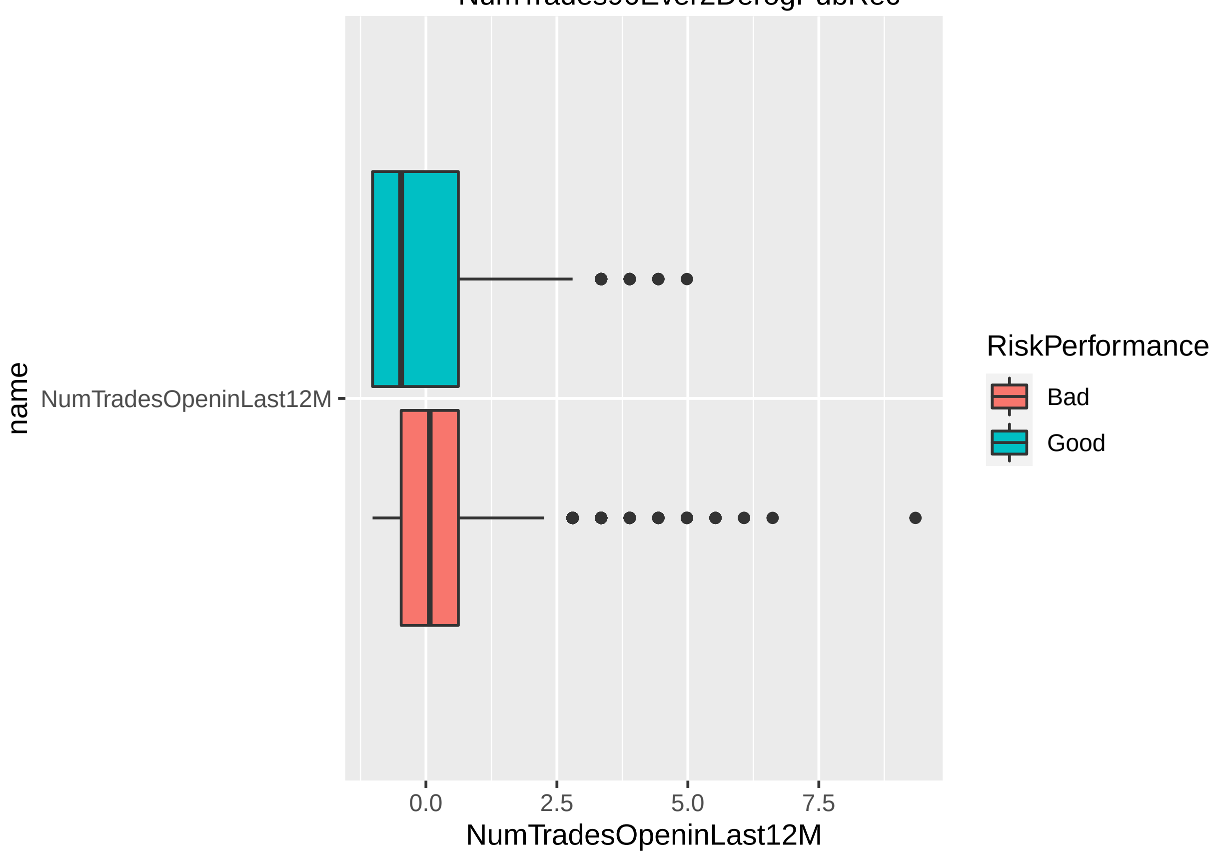

name
NumInstallTradesWBalance
0
4
8
12
NumInstallTradesWBalance
RiskPerformance
Bad
Good

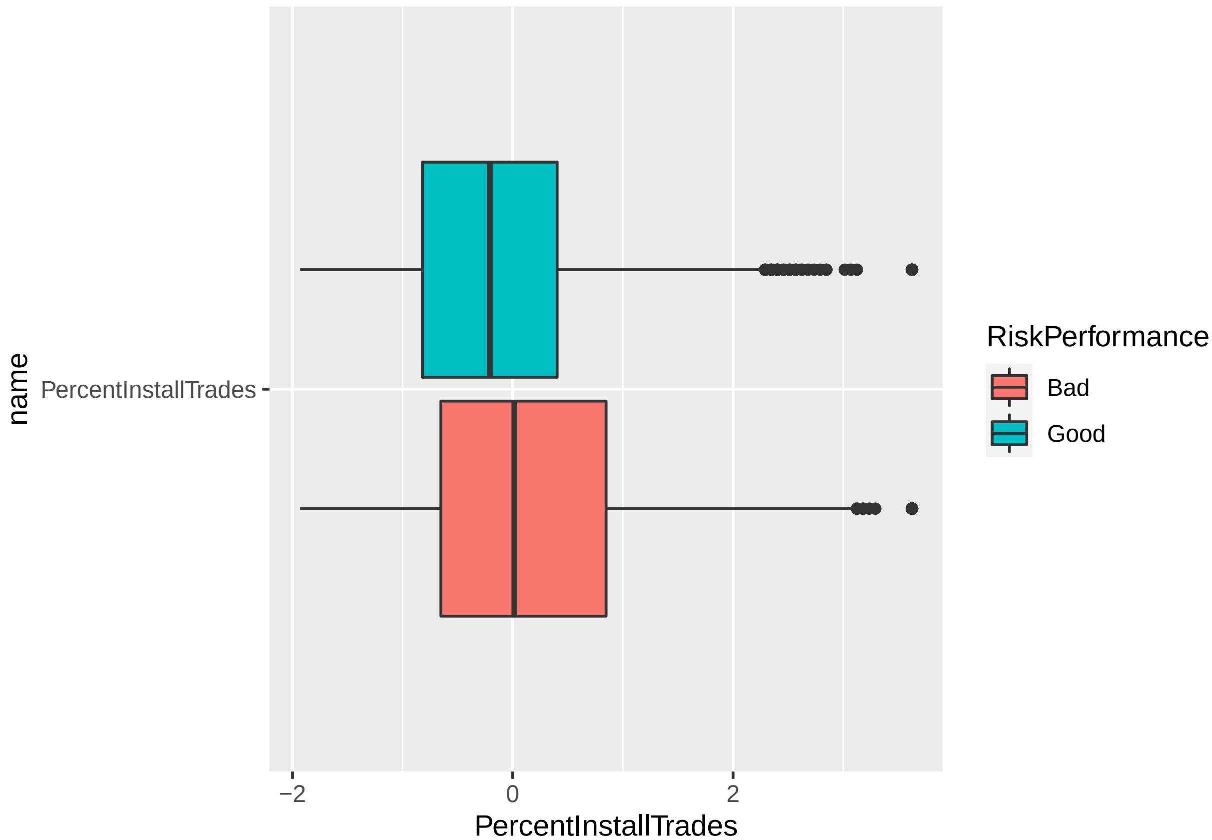

name
NumRevolvingTradesWBalance
0.0
2.5
5.0
7.5
NumRevolvingTradesWBalance
RiskPerformance
Bad
Good


name
NumSatisfactoryTrades
−2
0
2
4
NumSatisfactoryTrades
RiskPerformance
Bad
Good

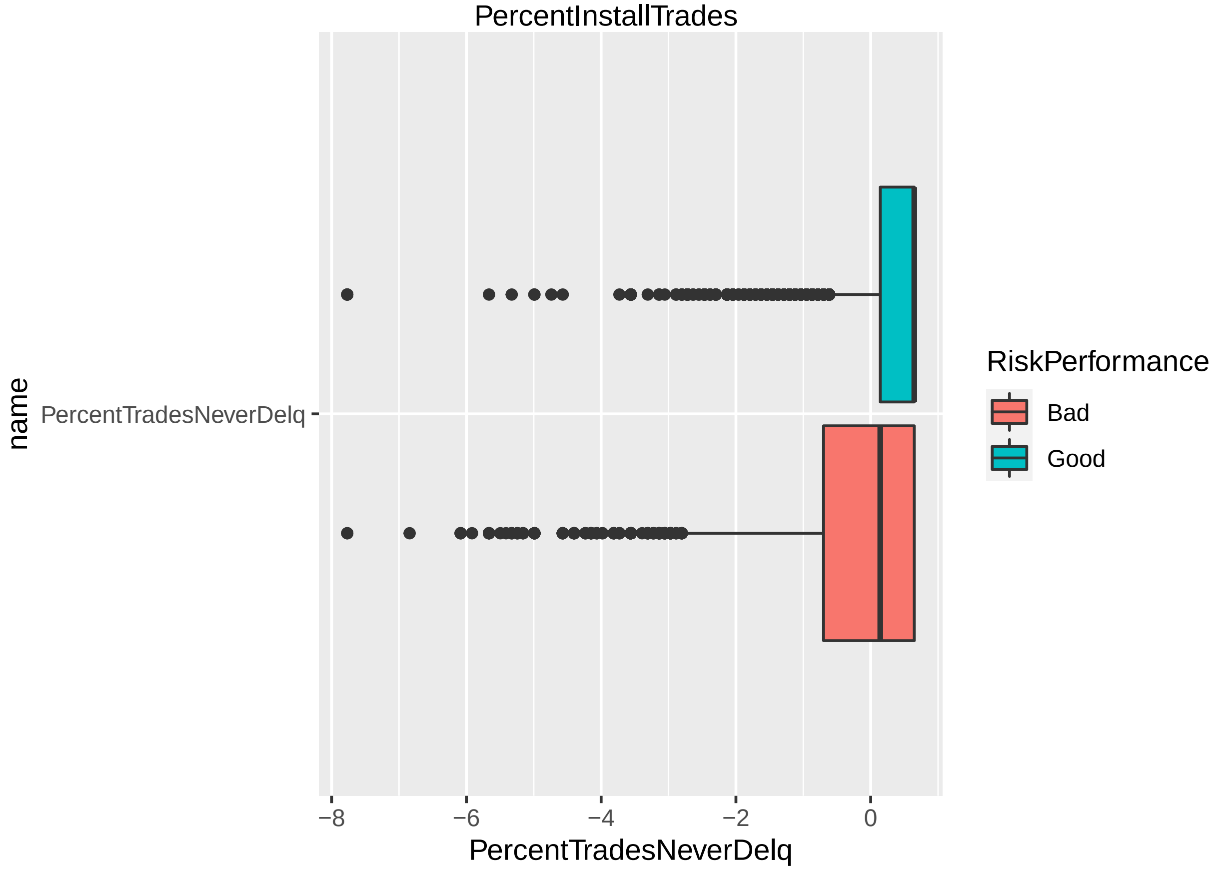

name
NumTotalTrades
−2
0
2
4
6
NumTotalTrades
RiskPerformance
Bad
Good


name
NumTrades90Ever2DerogPubRec
0
5
10
15
NumTrades90Ever2DerogPubRec
RiskPerformance
Bad
Good

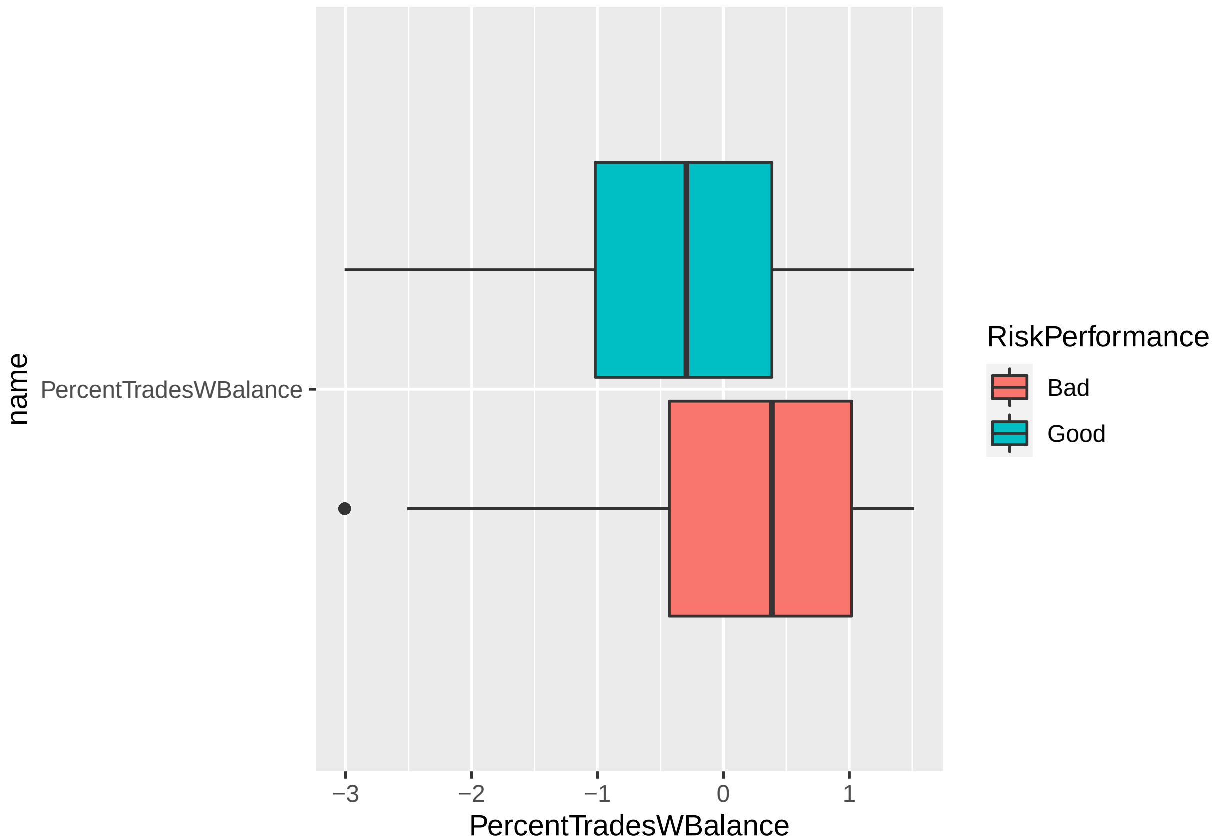

name
NumTradesOpeninLast12M
0.0
2.5
5.0
7.5
NumTradesOpeninLast12M
RiskPerformance
Bad
Good



name
PercentInstallTrades
−2
0
2
PercentInstallTrades
RiskPerformance
Bad
Good



name
PercentTradesNeverDelq
−8
−6
−4
−2
0
PercentTradesNeverDelq
RiskPerformance
Bad
Good




```
control <- caret::trainControl(method="cv",
                               classProbs=TRUE,
                               savePredictions=TRUE,
                               summaryFunction=twoClassSummary)
```

Models

With the following models, we are trying to maximize the SPECIFICITY of the models to prevent any non-qualified loanees being presented with a HELOC loan.

Specificity is defined as: "The specificity is defined as the rate that nonevent samples are predicted as nonevents" (Kuhn & Johnson, 2013)

```
bestIndex <- function(model){
  # returns top ROC value and surrounding indices from model
  highest_score <- max(model$results$ROC)

  # get row index and convert to type Int
  best_index <- rownames(model$results[model$results$ROC == highest_score,])
  best_index <- as.integer(best_index)

  return(best_index)
}

confusionMatrix <- function(testResults.model){
  caret::confusionMatrix(testResults.model,
                         as.factor(testResults$obs),
```

```r
                       positive="Good")
}

modelScoreBoard <- function(testResults){
  # feed in testResults dataframe and out comes a model scoreboard!
  scoreboard <- data.frame()

  bool <- names(testResults) != 'obs'
  col_names <- colnames(testResults[,bool])

  for (colname in col_names){

    testResults.model <- testResults[,colname]
    cf <- caret::confusionMatrix(testResults.model,
                                 as.factor(testResults$obs),
                                 positive="Good")

    # gather testResults
    acc <- data.frame(metric=cf$overall[1])
    # gather Precision, Sensitivity, Specificity, & F1
    metrics <- list(cf$byClass[c(5,1,2,7)])
    metrics <- data.frame(Metrics=metrics)
    names(metrics) <- 'metric'
    # gather all metrics in 1 df
    metrics <- rbind(acc,metrics)
    names(metrics) <- colname

    metrics <- t(metrics)
    scoreboard <- rbind(scoreboard, metrics)
  }
  return(scoreboard)
}

# helper function for roc
roc_build <- function(model) {
  THE_ROC <- roc(response = model$pred$obs,
                 predictor = model$pred$Bad,
                 levels = rev(levels(model$pred$obs)))
  return(THE_ROC)
}
```

Discriminant Classification Models

LDA

```r
set.seed(100)
lda_model <- caret::train(x=heloc_train_x,
                          y=heloc_train_y,
                          method="lda",
                          metric="ROC",
                          trControl=control)

lda_modelRoc <- roc_build(lda_model)
```

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

```r
lda_model
```

```
## Linear Discriminant Analysis
##
## 7897 samples
##   21 predictor
##    2 classes: 'Bad', 'Good'
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 7107, 7107, 7107, 7108, 7107, 7108, ...
## Resampling results:
##
##   ROC        Sens       Spec
##   0.7998689  0.7527435  0.7114538
```

```r
lda_predictions <- stats::predict(lda_model, heloc_test_x)

# create dataframe to store
testResults <- data.frame(obs=heloc_test_y,
                          lda_model=lda_predictions)

# confusion matrix
confusionMatrix(testResults$lda_model)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction Bad Good
##       Bad  768  288
##       Good 259  659
##
##                Accuracy : 0.7229
##                  95% CI : (0.7026, 0.7426)
##     No Information Rate : 0.5203
##     P-Value [Acc > NIR] : <2e-16
##
##                   Kappa : 0.4442
##
##  Mcnemar's Test P-Value : 0.2312
##
##             Sensitivity : 0.6959
##             Specificity : 0.7478
##          Pos Pred Value : 0.7179
##          Neg Pred Value : 0.7273
##              Prevalence : 0.4797
##          Detection Rate : 0.3338
##    Detection Prevalence : 0.4650
##       Balanced Accuracy : 0.7218
##
##        'Positive' Class : Good
##
```

Logistic Regression

```
set.seed(100)
logreg_model <- caret::train(x=heloc_train_x,
                             y=heloc_train_y,
                             method="glm",
                             metric="ROC",
                             trControl=control)

testResults$log_reg_model <- stats::predict(logreg_model, heloc_test_x)
logreg_modelRoc <- roc_build(logreg_model)
```

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

```
logreg_model
```

```
## Generalized Linear Model
##
## 7897 samples
##   21 predictor
##    2 classes: 'Bad', 'Good'
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 7107, 7107, 7107, 7108, 7107, 7108, ...
## Resampling results:
##
##   ROC        Sens       Spec
##   0.8000842  0.7554216  0.7130383
```

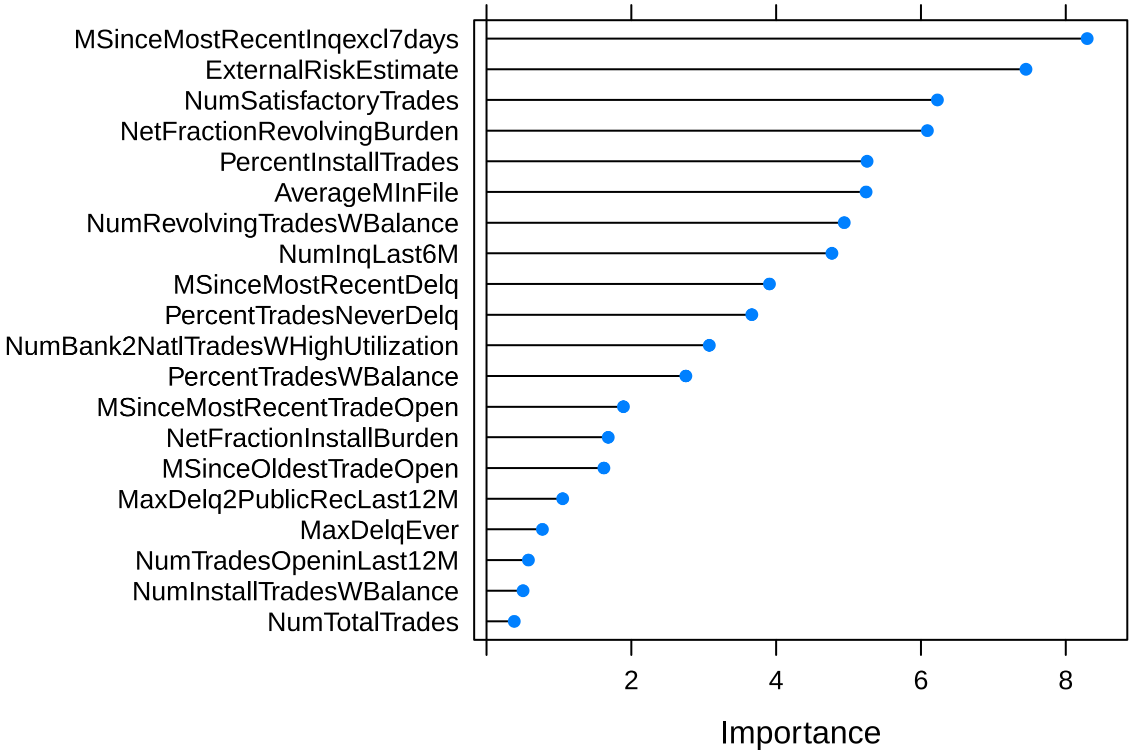
```
logreg_model$finalModel$coefficients
```

```
##                  (Intercept)                     AverageMInFile
##                -0.1803777116                       0.2470129097
##         ExternalRiskEstimate              MaxDelq2PublicRecLast12M
##                 0.4763324385                       0.0454362796
##                  MaxDelqEver                 MSinceMostRecentDelq
##                 0.0320452303                       0.1630765084
##     MSinceMostRecentInqexcl7days          MSinceMostRecentTradeOpen
##                 0.2726958674                      -0.0650335190
##          MSinceOldestTradeOpen              NetFractionInstallBurden
##                 0.0649987498                      -0.0543543815
##       NetFractionRevolvingBurden NumBank2NatlTradesWHighUtilization
##                -0.2929249411                      -0.1376246387
##                  NumInqLast6M              NumInstallTradesWBalance
##                -0.1638154810                       0.0167061783
##       NumRevolvingTradesWBalance                NumSatisfactoryTrades
##                -0.2278121804                       0.3689635005
##                NumTotalTrades           NumTrades90Ever2DerogPubRec
##                 0.0194119014                       0.0001783062
##          NumTradesOpeninLast12M                PercentInstallTrades
##                -0.0196622137                      -0.1878716750
##          PercentTradesNeverDelq                PercentTradesWBalance
##                 0.1716749452                       0.1173618900
```

```r
confusionMatrix(testResults$log_reg_model)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction Bad Good
##       Bad  766  288
##       Good 261  659
##
##                Accuracy : 0.7219
##                  95% CI : (0.7015, 0.7416)
##     No Information Rate : 0.5203
##     P-Value [Acc > NIR] : <2e-16
##
##                   Kappa : 0.4422
##
##  Mcnemar's Test P-Value : 0.2671
##
##             Sensitivity : 0.6959
##             Specificity : 0.7459
##          Pos Pred Value : 0.7163
##          Neg Pred Value : 0.7268
##              Prevalence : 0.4797
##          Detection Rate : 0.3338
##    Detection Prevalence : 0.4661
##       Balanced Accuracy : 0.7209
##
##        'Positive' Class : Good
##
```

```r
lr_varImp <- caret::varImp(logreg_model, scale=FALSE)
plot(lr_varImp, top=20)
```



Cost Matrix Threshold Analysis

```
#get raw probs from model
predictions <- predict(logreg_model, heloc_test_x, type = 'prob')
predictions$OBS <- as.factor(heloc_test$RiskPerformance)
predictions <- predictions %>%
  mutate(lr10 = as.factor(if_else(Bad > 0.1, 'Bad', 'Good')))
predictions <- predictions %>%
  mutate(lr20 = as.factor(if_else(Bad > 0.2, 'Bad', 'Good')))
predictions <- predictions %>%
  mutate(lr30 = as.factor(if_else(Bad > 0.3, 'Bad', 'Good')))
predictions <- predictions %>%
  mutate(lr40 = as.factor(if_else(Bad > 0.4, 'Bad', 'Good')))
predictions <- predictions %>%
  mutate(lr50 = as.factor(if_else(Bad > 0.5, 'Bad', 'Good')))
predictions <- predictions %>%
  mutate(lr60 = as.factor(if_else(Bad > 0.6, 'Bad', 'Good')))
predictions <- predictions %>%
  mutate(lr70 = as.factor(if_else(Bad > 0.7, 'Bad', 'Good')))
predictions <- predictions %>%
  mutate(lr80 = as.factor(if_else(Bad > 0.8, 'Bad', 'Good')))
predictions <- predictions %>%
  mutate(lr90 = as.factor(if_else(Bad > 0.9, 'Bad', 'Good')))

# cf function
cost_confusionMatrix <- function(prediction.rate){
  cm <- caret::confusionMatrix(prediction.rate,
                               predictions$OBS,
                               positive = "Bad")
  return(cm)
}
```

```r
CF10 <- cost_confusionMatrix(predictions$lr10)
CF20 <- cost_confusionMatrix(predictions$lr20)
CF30 <- cost_confusionMatrix(predictions$lr30)
CF40 <- cost_confusionMatrix(predictions$lr40)
CF50 <- cost_confusionMatrix(predictions$lr50)
CF60 <- cost_confusionMatrix(predictions$lr60)
CF70 <- cost_confusionMatrix(predictions$lr70)
CF80 <- cost_confusionMatrix(predictions$lr80)
CF90 <- cost_confusionMatrix(predictions$lr90)

Costs = matrix(c(0,-1000*.85,-60,60), ncol=2, nrow=2)

Prev = matrix(c(9.6/50,9.6/50,2,2), ncol=2, nrow=2)

CF10$table
```

```
##             Reference
## Prediction   Bad Good
##        Bad  1023  895
##        Good    4   52
```

```r
sum(CF10$table*Costs*Prev)
```

```
## [1] -101812.8
```

```r
CF20$table
```

```
##             Reference
## Prediction Bad Good
##        Bad  993  730
##        Good  34  217
```

```r
sum(CF20$table*Costs*Prev)
```

```
## [1] -67108.8
```

```r
CF30$table
```

```
##             Reference
## Prediction Bad Good
##        Bad  934  531
##        Good  93  416
```

```r
sum(CF30$table*Costs*Prev)
```

```
## [1] -28977.6
```

```r
CF40$table
```

```
##             Reference
## Prediction Bad Good
##        Bad  859  378
##        Good 168  569
```

```r
sum(CF40$table*Costs*Prev)
```

```
## [1] -4497.6
```

```r
CF50$table
```

```
##            Reference
## Prediction Bad Good
##        Bad  766  288
##        Good 261  659
```

```r
sum(CF50$table*Costs*Prev)
```

```
## [1] 1924.8
```

```r
CF60$table
```

```
##            Reference
## Prediction Bad Good
##        Bad  652  180
##        Good 375  767
```

```r
sum(CF60$table*Costs*Prev)
```

```
## [1] 9240
```

```r
CF70$table
```

```
##            Reference
## Prediction Bad Good
##        Bad  510  103
##        Good 517  844
```

```r
sum(CF70$table*Costs*Prev)
```

```
## [1] 4545.6
```

```r
CF80$table
```

```
##            Reference
## Prediction Bad Good
##        Bad  318   36
##        Good 709  911
```

```r
sum(CF80$table*Costs*Prev)
```

```
## [1] -10708.8
```

```r
CF90$table
```

```
##            Reference
## Prediction Bad Good
##        Bad   85    6
##        Good 942  941
```

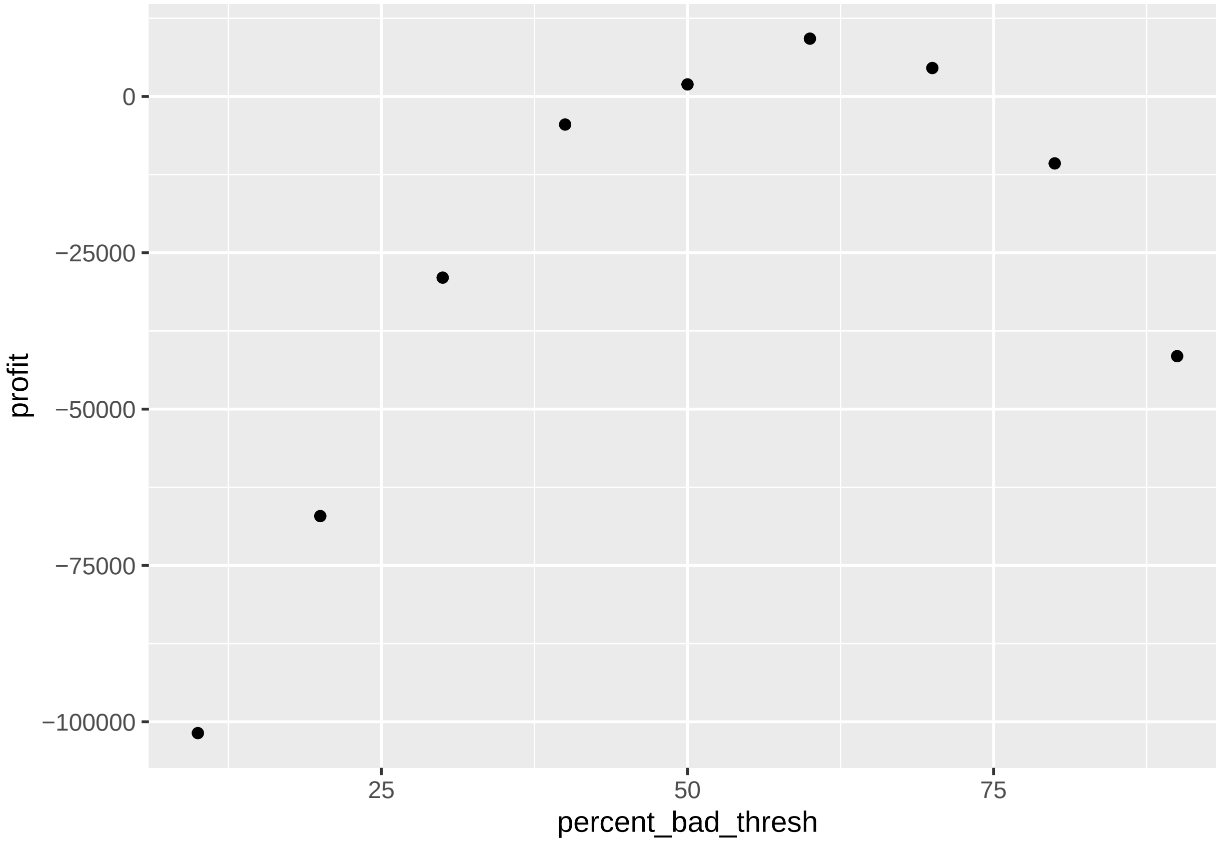
```r
sum(CF90$table*Costs*Prev)
```

```
## [1] -41534.4
```

```r
PlotProf<-data.frame(percent_bad_thresh = c(10,20,30,40,50,60,70,80,90),
                     profit = c(sum(CF10$table*Costs*Prev),
                                sum(CF20$table*Costs*Prev),
                                sum(CF30$table*Costs*Prev),
                                sum(CF40$table*Costs*Prev),
                                sum(CF50$table*Costs*Prev),
                                sum(CF60$table*Costs*Prev),
                                sum(CF70$table*Costs*Prev),
                                sum(CF80$table*Costs*Prev),
```

```
                                    sum(CF90$table*Costs*Prev)))

ggplot(PlotProf, aes(y=profit, x=percent_bad_thresh)) +
    geom_point()
```



Penalized Logistic Regression

```
set.seed(100)
glmnGrid <- expand.grid(alpha=c(0, 0.1, 0.2, 0.4, 0.6, 0.8, 1),
                        lambda=seq(0.01, 0.2, length=5))

logreg_penalized_model <- caret::train(x=heloc_train_x,
                                       y=heloc_train_y,
                                       method="glmnet",
                                       metric="ROC",
                                       tuneGrid=glmnGrid,
                                       trControl=control)

# bestIndex(logreg_penalized_model)
logreg_penalized_model$results[3:7,1:5]
```

```
##   alpha lambda       ROC      Sens      Spec
## 3   0.0 0.1050 0.7987157 0.7583402 0.7043291
## 4   0.0 0.1525 0.7981792 0.7607732 0.7024836
## 5   0.0 0.2000 0.7976588 0.7619904 0.7011636
## 6   0.1 0.0100 0.8001371 0.7551771 0.7114524
```

```
## 7   0.1 0.0575 0.7992612 0.7551777 0.7043277
```

```r
logreg_penalized_modelRoc <- roc_build(logreg_penalized_model)
```

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

Based on the best ROC, has the best specificity, our main metric. This enables us to insure that we only accept best qualified candidates, thus reducing the risk of a loanee defaulting on a $100,000 loan.

```r
# Utilizing Best Model
testResults$logreg_penalized_model <- stats::predict(logreg_penalized_model,
                                                     heloc_test_x)
# confusion matrix
confusionMatrix(testResults$logreg_penalized_model)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction Bad Good
##       Bad  773  282
##       Good 254  665
##
##                Accuracy : 0.7285
##                  95% CI : (0.7083, 0.748)
##     No Information Rate : 0.5203
##     P-Value [Acc > NIR] : <2e-16
##
##                   Kappa : 0.4554
##
##  Mcnemar's Test P-Value : 0.2435
##
##             Sensitivity : 0.7022
##             Specificity : 0.7527
##          Pos Pred Value : 0.7236
##          Neg Pred Value : 0.7327
##              Prevalence : 0.4797
##          Detection Rate : 0.3369
##    Detection Prevalence : 0.4656
##       Balanced Accuracy : 0.7274
##
##        'Positive' Class : Good
##
```

Nonlinear Classification Models

Flexibble Discriminant Analysis

```r
# set.seed(100)
# fdaGrid <- expand.grid(degree=c(1,2),
#                        nprune=seq(14, 20, 1))
#
# set.seed(100)
# fdaModel <- caret::train(x = heloc_train_x,
#                          y = heloc_train_y,
#                          method = "fda",
#                          metric = "ROC",
```

```r
#                             trControl=control,
#                             tuneGrid=fdaGrid)
# # bestIndex(fdaModel)
# fdaModel$results[1:18,1:5]
```

As we see, the best is that of nprune 16 with a specificity of 72.15% (index = 15).

```r
fdaGrid <- expand.grid(degree=1,
                       nprune=16)

set.seed(100)
fdaModel <- caret::train(x = heloc_train_x,
                         y = heloc_train_y,
                         method = "fda",
                         metric = "ROC",
                         trControl=control,
                         tuneGrid=fdaGrid)
```

```
## Loading required package: earth
## Loading required package: Formula
## Loading required package: plotmo
## Loading required package: plotrix
## Loading required package: TeachingDemos
```

```r
fda_modelRoc <- roc_build(fdaModel)
```

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

```r
testResults$fda_model <- predict(fdaModel,
                                 heloc_test_x)
# confusion matrix
confusionMatrix(testResults$fda_model)
```

```
## Confusion Matrix and Statistics
##
##             Reference
## Prediction Bad Good
##       Bad   762  265
##       Good 265  682
##
##                Accuracy : 0.7315
##                  95% CI : (0.7114, 0.751)
##     No Information Rate : 0.5203
##     P-Value [Acc > NIR] : <2e-16
##
##                   Kappa : 0.4621
##
##  Mcnemar's Test P-Value : 1
##
##             Sensitivity : 0.7202
##             Specificity : 0.7420
##          Pos Pred Value : 0.7202
##          Neg Pred Value : 0.7420
##              Prevalence : 0.4797
```

```
##          Detection Rate : 0.3455
##    Detection Prevalence : 0.4797
##       Balanced Accuracy : 0.7311
##
##        'Positive' Class : Good
##
```

Neural Network

```r
# set.seed(100)
# nnetGrid <- expand.grid(size = 1:2,
#                         decay = c(0, 0.1, 0.25, 0.5, 0.75, 1))
#
# nnetModel <- caret::train(x = heloc_train_x,
#                           y = heloc_train_y,
#                           method = "nnet",
#                           tuneGrid = nnetGrid,
#                           metric = "ROC",
#                           trace = FALSE,
#                           maxit = 2000,
#                           trControl = control)
# nnetModel$bestTune$results[1:6,1:5]
```

It appears that the model starts to over fit once the decay goes to 0.1. The nnet model chose size=2 with decay of 2, with nearly identical ROC, Sensitivity, and Specificity scores and thus size 1 with decay 0 is our choice.

```r
set.seed(100)
nnetGrid <- expand.grid(size = 1,
                        decay = 0)

nnetModel <- caret::train(x = heloc_train_x,
                   y = heloc_train_y,
                   method = "nnet",
                   tuneGrid = nnetGrid,
                   metric = "ROC",
                   trace = FALSE,
                   maxit = 2000,
                   trControl = control)

nnet_modelRoc <- roc_build(nnetModel)
```

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

```r
testResults$nnet_model <- predict(nnetModel,
                                  heloc_test_x)
# confusion matrix
confusionMatrix(testResults$nnet_model)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction Bad Good
##       Bad  769  291
##       Good 258  656
##
```

```
##                Accuracy : 0.7219
##                  95% CI : (0.7015, 0.7416)
##     No Information Rate : 0.5203
##     P-Value [Acc > NIR] : <2e-16
##
##                   Kappa : 0.4421
##
##  Mcnemar's Test P-Value : 0.172
##
##             Sensitivity : 0.6927
##             Specificity : 0.7488
##          Pos Pred Value : 0.7177
##          Neg Pred Value : 0.7255
##              Prevalence : 0.4797
##          Detection Rate : 0.3323
##    Detection Prevalence : 0.4630
##       Balanced Accuracy : 0.7207
##
##        'Positive' Class : Good
##
```

Classification Trees

Boosted Tree

```
# gbmGrid <- expand.grid(interaction.depth =  c(2,3),
#                        n.trees = c(1000,2000,3000,4000), #default val = 1000
#                        shrinkage = c(0.01, 0.1),
#                        n.minobsinnode = c(5,10)) # default val = 10
# set.seed(100)
# gbmModel <- caret::train(x = heloc_train_x,
#                          y = heloc_train_y,
#                          method = "gbm",
#                          tuneGrid = gbmGrid,
#                          verbose = FALSE,
#                          metric = "ROC",
#                          trControl= control)
# gbmModel$results
```

```
gbmGrid <- expand.grid(interaction.depth = 2,
                       n.trees = 1000,
                       shrinkage = 0.01,
                       n.minobsinnode = 5)
set.seed(100)
gbmModel <- caret::train(x = heloc_train_x,
                         y = heloc_train_y,
                         method = "gbm",
                         tuneGrid = gbmGrid,
                         verbose = FALSE,
                         metric = "ROC",
                         trControl= control)

gbm_modelRoc <- roc_build(gbmModel)
```

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

```r
testResults$gbm_model <- predict(gbmModel,
                                heloc_test_x)
# confusion matrix
confusionMatrix(testResults$gbm_model)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction Bad Good
##       Bad  775  285
##       Good 252  662
##
##                Accuracy : 0.728
##                  95% CI : (0.7078, 0.7475)
##     No Information Rate : 0.5203
##     P-Value [Acc > NIR] : <2e-16
##
##                   Kappa : 0.4543
##
##  Mcnemar's Test P-Value : 0.1673
##
##             Sensitivity : 0.6990
##             Specificity : 0.7546
##          Pos Pred Value : 0.7243
##          Neg Pred Value : 0.7311
##              Prevalence : 0.4797
##          Detection Rate : 0.3354
##    Detection Prevalence : 0.4630
##       Balanced Accuracy : 0.7268
##
##        'Positive' Class : Good
##
```

```r
# gbmGrid <- expand.grid(interaction.depth = c(2,3),
#                        n.trees = c(1000,2000),
#                        shrinkage = c(0.01, 0.1),
#                        n.minobsinnode = c(5,10))
# set.seed(100)
# gbmMono_model <- caret::train(x = heloc_train_x,
#                               y = heloc_train_y,
#                               method = "gbm",
#                               var.monotone = c(-1,-1,-1,-1,-1,-1,-1,-1,
#                                                1,1,1,1,0,0,-1,0,-1,1,
#                                                0,-1,1),
#                               tuneGrid = gbmGrid,
#                               verbose = FALSE,
#                               metric = "ROC",
#                               trControl= control)
# gbmMono_model$results
```

```r
gbmGrid <- expand.grid(interaction.depth = 2,
                       n.trees = 1000,
```

```r
                       shrinkage = 0.01,
                       n.minobsinnode = 5)
set.seed(100)
gbmMono_model <- caret::train(x = heloc_train_x,
                         y = heloc_train_y,
                         var.monotone = c(-1,-1,-1,-1,-1,-1,-1,-1,
                                          1,1,1,1,0,0,-1,0,-1,1,
                                          0,-1,1),
                         method = "gbm",
                         tuneGrid = gbmGrid,
                         verbose = FALSE,
                         metric = "ROC",
                         trControl= control)

gbmMono_modelRoc <- roc_build(gbmMono_model)
```

GBM with monotonic constraints

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

```r
testResults$gbmMono_model <- predict(gbmMono_model,
                                     heloc_test_x)
confusionMatrix(testResults$gbmMono_model)
```

```
## Confusion Matrix and Statistics
##
##             Reference
## Prediction  Bad Good
##       Bad   772  281
##       Good  255  666
##
##                Accuracy : 0.7285
##                  95% CI : (0.7083, 0.748)
##     No Information Rate : 0.5203
##     P-Value [Acc > NIR] : <2e-16
##
##                   Kappa : 0.4555
##
##  Mcnemar's Test P-Value : 0.2802
##
##             Sensitivity : 0.7033
##             Specificity : 0.7517
##          Pos Pred Value : 0.7231
##          Neg Pred Value : 0.7331
##              Prevalence : 0.4797
##          Detection Rate : 0.3374
##    Detection Prevalence : 0.4666
##       Balanced Accuracy : 0.7275
##
##        'Positive' Class : Good
##
```

CART

```
# set.seed(100)
# rpart_grid <- expand.grid(cp=c(0.0005, 0.001250, 0.0015, 0.00175, 0.002))
#
# rpart_model <- caret::train(x=heloc_train_x,
#                             y=heloc_train_y,
#                             method="rpart",
#                             metric="ROC",
#                             trControl=control,
#                             tuneGrid = rpart_grid)
#
# testResults$rpart_model <- predict(rpart_model, heloc_test_x)
#
# rpart_model
```

As we see, specificity for this model is one of the worst out of all the models we have.

```
set.seed(100)
rpart_grid <- expand.grid(cp=0.00175)

rpart_model <- caret::train(x=heloc_train_x,
                            y=heloc_train_y,
                            method="rpart",
                            metric="ROC",
                            trControl=control,
                            tuneGrid = rpart_grid)

rpart_modelRoc <- roc_build(rpart_model)
```

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

```
rpart_model
```

```
## CART
##
## 7897 samples
##   21 predictor
##    2 classes: 'Bad', 'Good'
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 7107, 7107, 7107, 7108, 7107, 7108, ...
## Resampling results:
##
##   ROC        Sens       Spec
##   0.7558931  0.7551742  0.671846
##
## Tuning parameter 'cp' was held constant at a value of 0.00175
```

```
testResults$rpart_model <- predict(rpart_model, heloc_test_x)

confusionMatrix(testResults$rpart_model)
```

```
## Confusion Matrix and Statistics
##
```

```
##           Reference
## Prediction Bad Good
##       Bad  748  282
##       Good 279  665
##
##                Accuracy : 0.7158
##                  95% CI : (0.6953, 0.7356)
##     No Information Rate : 0.5203
##     P-Value [Acc > NIR] : <2e-16
##
##                   Kappa : 0.4306
##
##  Mcnemar's Test P-Value : 0.9327
##
##             Sensitivity : 0.7022
##             Specificity : 0.7283
##          Pos Pred Value : 0.7044
##          Neg Pred Value : 0.7262
##              Prevalence : 0.4797
##          Detection Rate : 0.3369
##    Detection Prevalence : 0.4782
##       Balanced Accuracy : 0.7153
##
##        'Positive' Class : Good
##
```

Random Forest

```r
# set.seed(100)
# rf_grid <- expand.grid(mtry=c(5,10,15))
#
# randomForest_model <- caret::train(x=heloc_train_x,
#                             y=heloc_train_y,
#                             method="rf",
#                             metric="ROC",
#                             trControl=control,
#                             tuneGrid = rf_grid)
#
# randomForest_model
```

```r
set.seed(100)
rf_grid <- expand.grid(mtry=5)

randomForest_model <- caret::train(x=heloc_train_x,
                                   y=heloc_train_y,
                                   method="rf",
                                   metric="ROC",
                                   trControl=control,
                                   tuneGrid = rf_grid)

randomForest_modelRoc <- roc_build(randomForest_model)
```

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

```r
randomForest_model
```

```
## Random Forest
##
## 7897 samples
##   21 predictor
##    2 classes: 'Bad', 'Good'
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 7107, 7107, 7107, 7108, 7107, 7108, ...
## Resampling results:
##
##   ROC        Sens       Spec
##   0.7951729  0.7736746  0.6847978
##
## Tuning parameter 'mtry' was held constant at a value of 5
```

```r
testResults$randomForest_model <- predict(randomForest_model, heloc_test_x)

confusionMatrix(testResults$randomForest_model)
```

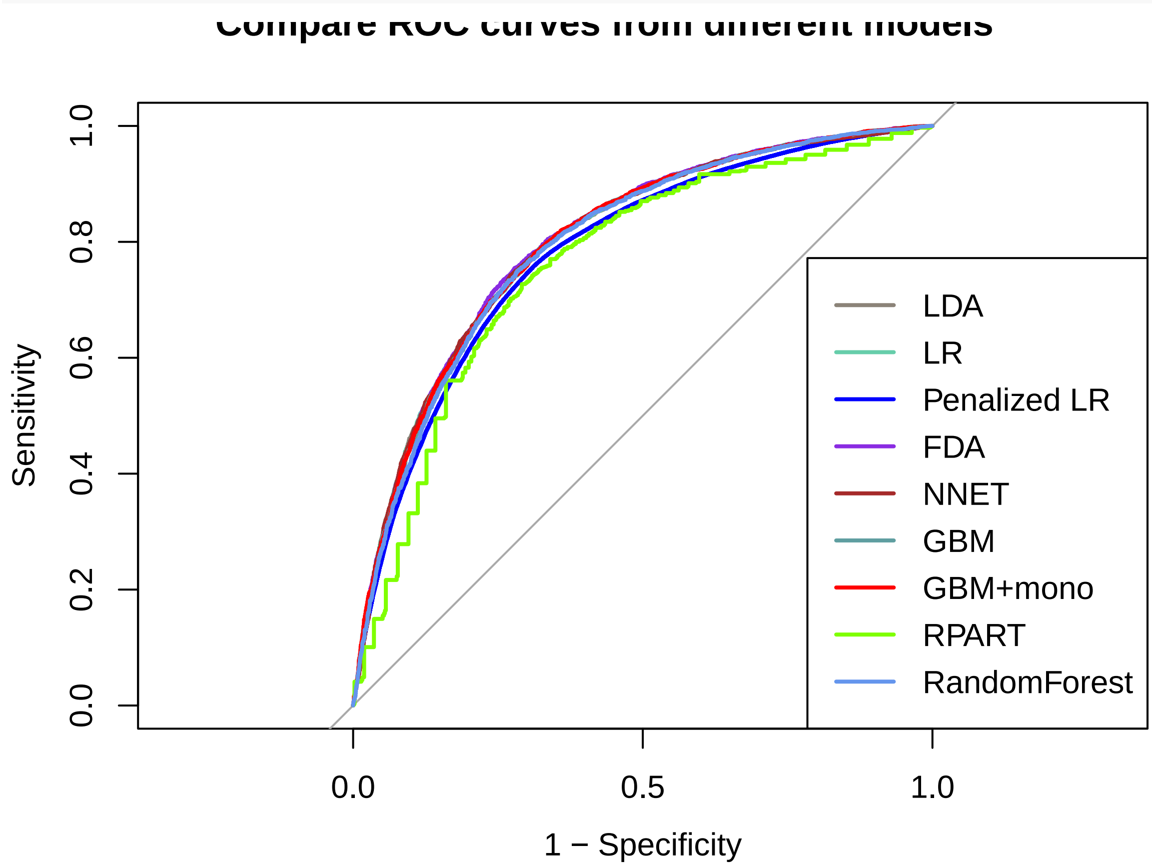
```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction Bad Good
##       Bad  790  291
##       Good 237  656
##
##                Accuracy : 0.7325
##                  95% CI : (0.7124, 0.7519)
##     No Information Rate : 0.5203
##     P-Value [Acc > NIR] : < 2e-16
##
##                   Kappa : 0.463
##
##  Mcnemar's Test P-Value : 0.02108
##
##             Sensitivity : 0.6927
##             Specificity : 0.7692
##          Pos Pred Value : 0.7346
##          Neg Pred Value : 0.7308
##              Prevalence : 0.4797
##          Detection Rate : 0.3323
##    Detection Prevalence : 0.4524
##       Balanced Accuracy : 0.7310
##
##        'Positive' Class : Good
##
```

Result Discussion

```r
plot(lda_modelRoc, type='s', col='antiquewhite4', legacy.axes=TRUE)
plot(logreg_modelRoc, type='s', col='aquamarine3', legacy.axes=TRUE, add=TRUE)
```

```r
plot(logreg_penalized_modelRoc, type='s', col='blue', legacy.axes=TRUE, add=TRUE)
plot(fda_modelRoc, type='s', col='blueviolet', legacy.axes=TRUE, add=TRUE)
plot(nnet_modelRoc, type='s', col='brown', legacy.axes=TRUE, add=TRUE)
plot(gbm_modelRoc, type='s', col='cadetblue', legacy.axes=TRUE, add=TRUE)
plot(gbmMono_modelRoc, type='s', col='red', legacy.axes=TRUE, add=TRUE)
plot(rpart_modelRoc, type='s', col='chartreuse', legacy.axes=TRUE, add=TRUE)
plot(randomForest_modelRoc, type='s', col='cornflowerblue', legacy.axes=TRUE, add=TRUE)

legend_ <- c('LDA', 'LR', 'Penalized LR','FDA', 'NNET','GBM','GBM+mono', 'RPART','RandomForest')
colors_ <-c('antiquewhite4',
            'aquamarine3',
            'blue',
            'blueviolet',
            'brown',
            'cadetblue',
            'red',
            'chartreuse',
            'cornflowerblue')
legend('bottomright', legend=legend_,
       col=colors_, lwd=2)
title(main = 'Compare ROC curves from different models', outer = TRUE)
```




```r
# gather all model AUCs in 1 list
aucs <- c(lda_modelRoc$auc,
          logreg_modelRoc$auc,
          logreg_penalized_modelRoc$auc,
          fda_modelRoc$auc,
```

```r
         nnet_modelRoc$auc,
         gbm_modelRoc$auc,
         gbmMono_modelRoc$auc,
         rpart_modelRoc$auc,
         randomForest_modelRoc$auc)

scoreboard <- modelScoreBoard(testResults)
# add AUC list as a column
scoreboard$AUC <- aucs
scoreboard
```

```
##                         Accuracy Precision Sensitivity Specificity        F1
## lda_model              0.7228977 0.7178649   0.6958817   0.7478092 0.7067024
## log_reg_model          0.7218845 0.7163043   0.6958817   0.7458617 0.7059454
## logreg_penalized_model 0.7284701 0.7236126   0.7022175   0.7526777 0.7127546
## fda_model              0.7315096 0.7201690   0.7201690   0.7419669 0.7201690
## nnet_model             0.7218845 0.7177243   0.6927138   0.7487829 0.7049973
## gbm_model              0.7279635 0.7242888   0.6990496   0.7546251 0.7114455
## gbmMono_model          0.7284701 0.7231270   0.7032735   0.7517040 0.7130621
## rpart_model            0.7158055 0.7044492   0.7022175   0.7283350 0.7033316
## randomForest_model     0.7325228 0.7346025   0.6927138   0.7692308 0.7130435
##                              AUC
## lda_model              0.7998810
## log_reg_model          0.8002390
## logreg_penalized_model 0.7820838
## fda_model              0.8032575
## nnet_model             0.8001313
## gbm_model              0.7998948
## gbmMono_model          0.8003082
## rpart_model            0.7554376
## randomForest_model     0.7950744
```

REFERENCES:

Kuhn, M., & Johnson, K. (2013). Applied Predictive Modeling. New York: Springer.