

Analyst Price Target Analysis using XGBoost model

```
#Drop Cols that will not be used in model
finaldf <- read.csv("AnalystRatingData/ratings.csv", check.names = TRUE)
drops <- c("Date", "Firm", "Action", "Rating", "Ticker", "", "Price.After.One.Year", "Price.T
arget")
finaldf <- finaldf[ , !(names(finaldf) %in% drops)]
```

```
#convert everything to numeric as XGBoost only recognize numeric data
finaldf[names(finaldf)] <- lapply(finaldf[names(finaldf)], as.numeric)
```

```
nzv <- nearZeroVar(finaldf, saveMetrics = TRUE)
sorted <- nzv[order(nzv$freqRatio), ]
print(sorted)
```

##	freqRatio	percentUnique	zeroVar
## Reiterated.Rating	1.081721	0.03792907	FALSE
## TargetAchieved	1.348775	0.03792907	FALSE
## Buy	1.465171	0.03792907	FALSE
## Lower.Price.Target	4.813671	0.03792907	FALSE
## Boost.Price.Target	4.845898	0.03792907	FALSE
## Outperform	5.383777	0.03792907	FALSE
## Neutral	8.466786	0.03792907	FALSE
## Hold	10.929864	0.03792907	FALSE
## Overweight	11.584726	0.03792907	FALSE
## Initiated.Coverage	12.731771	0.03792907	FALSE
## Royal.Bank.Of.Canada	17.566901	0.03792907	FALSE
## Deutsche.Bank.AG	18.675373	0.03792907	FALSE
## Upgrade	18.749064	0.03792907	FALSE
## Jefferies.Group.LLC	20.610656	0.03792907	FALSE
## Piper.Jaffray.Companies	21.438298	0.03792907	FALSE
## Downgrade	22.026201	0.03792907	FALSE
## Barclays.PLC	24.597087	0.03792907	FALSE
## Credit.Suisse.Group	26.041026	0.03792907	FALSE
## B..Riley	27.502703	0.03792907	FALSE
## Cowen.and.Company	27.657609	0.03792907	FALSE
## Morgan.Stanley	28.294444	0.03792907	FALSE
## X	28.960227	0.03792907	FALSE
## Goldman.Sachs.Group..Inc...The.	31.549383	0.03792907	FALSE
## Market.Perform	31.956250	0.03792907	FALSE
## J.P.Morgan.Chase...Co	32.163522	0.03792907	FALSE
## Citigroup.Inc.	37.772059	0.03792907	FALSE
## Equal.Weight	38.059259	0.03792907	FALSE
## Robert.W..Baird	39.561538	0.03792907	FALSE
## Canaccord.Genuity	42.221311	0.03792907	FALSE
## Nomura	45.663717	0.03792907	FALSE
## Stifel.Nicolaus	46.080357	0.03792907	FALSE
## Oppenheimer.Holdings..Inc.	46.504505	0.03792907	FALSE
## Bank.of.America.Corporation	46.936364	0.03792907	FALSE
## BMO.Capital.Markets	48.745283	0.03792907	FALSE
## Susquehanna.Bancshares.Inc	51.730000	0.03792907	FALSE
## Wedbush	52.806122	0.03792907	FALSE
## Mizuho	53.360825	0.03792907	FALSE
## Sell	55.095745	0.03792907	FALSE
## Leerink.Swann	56.945055	0.03792907	FALSE
## MKM.Partners	57.588889	0.03792907	FALSE
## Pacific.Crest	58.247191	0.03792907	FALSE
## Sector.Perform	58.247191	0.03792907	FALSE
## FBR...Co	58.920455	0.03792907	FALSE
## Macquarie	68.381579	0.03792907	FALSE
## Cantor.Fitzgerald	70.256757	0.03792907	FALSE
## Brean.Capital	72.236111	0.03792907	FALSE
## Sanford.C..Bernstein	73.267606	0.03792907	FALSE
## Evercore.ISI	75.420290	0.03792907	FALSE
## SunTrust.Banks..Inc.	75.420290	0.03792907	FALSE
## Sterne.Agee.CRT	82.698413	0.03792907	FALSE
## Topeka.Capital.Markets	85.442623	0.03792907	FALSE
## Positive	85.442623	0.03792907	FALSE

## Argus	91.508772	0.03792907	FALSE
## Needham...Company.LLC	91.508772	0.03792907	FALSE
## Set.Price.Target	102.392157	0.03792907	FALSE
## Raymond.James.Financial..Inc.	111.191489	0.03792907	FALSE
## Underperform	113.630435	0.03792907	FALSE
## BTIG.Research	116.177778	0.03792907	FALSE
## Pivotal.Research	124.547619	0.03792907	FALSE
## Underweight	130.825000	0.03792907	FALSE
## Strong.Buy	145.472222	0.03792907	FALSE
## Axiom.Securities	174.766667	0.03792907	FALSE
## JMP.Securities	174.766667	0.03792907	FALSE
## Telsey.Advisory.Group	174.766667	0.03792907	FALSE
## Summit.Research	201.807692	0.03792907	FALSE
## Maxim.Group	218.708333	0.03792907	FALSE
## Wunderlich	228.260870	0.03792907	FALSE
## Benchmark.Co.	238.681818	0.03792907	FALSE
## Drexel.Hamilton	238.681818	0.03792907	FALSE
## Rosenblatt.Securities	262.650000	0.03792907	FALSE
## Buckingham.Research	276.526316	0.03792907	FALSE
## Craig.Hallum	276.526316	0.03792907	FALSE
## S.P.Equity.Research	291.944444	0.03792907	FALSE
## Global.Equities.Research	328.562500	0.03792907	FALSE
## KeyCorp	350.533333	0.03792907	FALSE
## Roth.Capital	375.642857	0.03792907	FALSE
## Moffett.Nathanson	404.615385	0.03792907	FALSE
## Standpoint.Research	404.615385	0.03792907	FALSE
## Wells.Fargo...Co	404.615385	0.03792907	FALSE
## Market.Outperform	404.615385	0.03792907	FALSE
## Monness.Crespi...Hardt	438.416667	0.03792907	FALSE
## Top.Pick	438.416667	0.03792907	FALSE
## Chardan.Capital	478.363636	0.03792907	FALSE
## FBN.Securities	478.363636	0.03792907	FALSE
## HC.Wainwright	478.363636	0.03792907	FALSE
## Conviction.Buy	526.300000	0.03792907	FALSE
## Atlantic.Securities	584.888889	0.03792907	FALSE
## BNP.Paribas	584.888889	0.03792907	FALSE
## Stephens	584.888889	0.03792907	FALSE
## Avondale.Partners	658.125000	0.03792907	FALSE
## Gabelli	658.125000	0.03792907	FALSE
## William.Blair	658.125000	0.03792907	FALSE
## Compass.Point	752.285714	0.03792907	FALSE
## Dougherty...Co	752.285714	0.03792907	FALSE
## HSBC.Holdings.plc	752.285714	0.03792907	FALSE
## Reduce	752.285714	0.03792907	FALSE
## Barrington.Research	877.833333	0.03792907	FALSE
## Wolfe.Research	877.833333	0.03792907	FALSE
## Berenberg.Bank	1053.600000	0.03792907	FALSE
## Janney.Montgomery.Scott	1053.600000	0.03792907	FALSE
## Northland.Securities	1053.600000	0.03792907	FALSE
## Societe.Generale	1053.600000	0.03792907	FALSE
## Ascendant.Capital.Markets	1317.250000	0.03792907	FALSE
## BB.T.Corporation	1317.250000	0.03792907	FALSE
## DA.Davidson	1317.250000	0.03792907	FALSE
## Guggenheim	1317.250000	0.03792907	FALSE

## Jyske.Bank	1317.250000	0.03792907	FALSE
## Keefe..Bruyette...Woods	1317.250000	0.03792907	FALSE
## Longbow.Research	1317.250000	0.03792907	FALSE
## Scotiabank	1317.250000	0.03792907	FALSE
## Independent.Research.GmbH	1756.666667	0.03792907	FALSE
## UBS.Group.AG	1756.666667	0.03792907	FALSE
## In.Line	1756.666667	0.03792907	FALSE
## Mkt.Perform	1756.666667	0.03792907	FALSE
## Boenning.Scattergood	2635.500000	0.03792907	FALSE
## Evercore.Partners.Inc	2635.500000	0.03792907	FALSE
## Hilliard.Lyons	2635.500000	0.03792907	FALSE
## Imperial.Capital	2635.500000	0.03792907	FALSE
## T.H..Capital	2635.500000	0.03792907	FALSE
## BGC.Financial	5272.000000	0.03792907	FALSE
## CRT.Capital	5272.000000	0.03792907	FALSE
## Feltl...Co.	5272.000000	0.03792907	FALSE
## First.Analysis	5272.000000	0.03792907	FALSE
## Hovde.Group	5272.000000	0.03792907	FALSE
## Mitsubishi.UFJ.Financial.Group	5272.000000	0.03792907	FALSE
## MLV...Co.	5272.000000	0.03792907	FALSE
## National.Bank.Financial	5272.000000	0.03792907	FALSE
## Sidoti	5272.000000	0.03792907	FALSE
## Taglich.Brothers	5272.000000	0.03792907	FALSE
## Williams.Capital	5272.000000	0.03792907	FALSE
## But.Estimates.Debate.As.Orders.Slow	5272.000000	0.03792907	FALSE
## Focus.List	5272.000000	0.03792907	FALSE
## Overweight.Rating.	5272.000000	0.03792907	FALSE
## Sector.Outperform	5272.000000	0.03792907	FALSE
## Weight	5272.000000	0.03792907	FALSE
##	nzv		
## Reiterated.Rating	FALSE		
## TargetAchieved	FALSE		
## Buy	FALSE		
## Lower.Price.Target	FALSE		
## Boost.Price.Target	FALSE		
## Outperform	FALSE		
## Neutral	FALSE		
## Hold	FALSE		
## Overweight	FALSE		
## Initiated.Coverage	FALSE		
## Royal.Bank.Of.Canada	FALSE		
## Deutsche.Bank.AG	FALSE		
## Upgrade	FALSE		
## Jefferies.Group.LLC	TRUE		
## Piper.Jaffray.Companies	TRUE		
## Downgrade	TRUE		
## Barclays.PLC	TRUE		
## Credit.Suisse.Group	TRUE		
## B..Riley	TRUE		
## Cowen.and.Company	TRUE		
## Morgan.Stanley	TRUE		
## X	TRUE		
## Goldman.Sachs.Group..Inc...The.	TRUE		
## Market.Perform	TRUE		

## J.P.Morgan.Chase...Co	TRUE
## Citigroup.Inc.	TRUE
## Equal.Weight	TRUE
## Robert.W..Baird	TRUE
## Canaccord.Genuity	TRUE
## Nomura	TRUE
## Stifel.Nicolaus	TRUE
## Oppenheimer.Holdings..Inc.	TRUE
## Bank.of.America.Corporation	TRUE
## BMO.Capital.Markets	TRUE
## Susquehanna.Bancshares.Inc	TRUE
## Wedbush	TRUE
## Mizuho	TRUE
## Sell	TRUE
## Leerink.Swann	TRUE
## MKM.Partners	TRUE
## Pacific.Crest	TRUE
## Sector.Perform	TRUE
## FBR...Co	TRUE
## Macquarie	TRUE
## Cantor.Fitzgerald	TRUE
## Brean.Capital	TRUE
## Sanford.C..Bernstein	TRUE
## Evercore.ISI	TRUE
## SunTrust.Banks..Inc.	TRUE
## Sterne.Agee.CRT	TRUE
## Topeka.Capital.Markets	TRUE
## Positive	TRUE
## Argus	TRUE
## Needham...Company.LLC	TRUE
## Set.Price.Target	TRUE
## Raymond.James.Financial..Inc.	TRUE
## Underperform	TRUE
## BTIG.Research	TRUE
## Pivotal.Research	TRUE
## Underweight	TRUE
## Strong.Buy	TRUE
## Axiom.Securities	TRUE
## JMP.Securities	TRUE
## Telsey.Advisory.Group	TRUE
## Summit.Research	TRUE
## Maxim.Group	TRUE
## Wunderlich	TRUE
## Benchmark.Co.	TRUE
## Drexel.Hamilton	TRUE
## Rosenblatt.Securities	TRUE
## Buckingham.Research	TRUE
## Craig.Hallum	TRUE
## S.P.Equity.Research	TRUE
## Global.Equities.Research	TRUE
## KeyCorp	TRUE
## Roth.Capital	TRUE
## Moffett.Nathanson	TRUE
## Standpoint.Research	TRUE

## Wells.Fargo...Co	TRUE
## Market.Outperform	TRUE
## Monness.Crespi...Hardt	TRUE
## Top.Pick	TRUE
## Chardan.Capital	TRUE
## FBN.Securities	TRUE
## HC.Wainwright	TRUE
## Conviction.Buy	TRUE
## Atlantic.Securities	TRUE
## BNP.Paribas	TRUE
## Stephens	TRUE
## Avondale.Partners	TRUE
## Gabelli	TRUE
## William.Blair	TRUE
## Compass.Point	TRUE
## Dougherty...Co	TRUE
## HSBC.Holdings.plc	TRUE
## Reduce	TRUE
## Barrington.Research	TRUE
## Wolfe.Research	TRUE
## Berenberg.Bank	TRUE
## Janney.Montgomery.Scott	TRUE
## Northland.Securities	TRUE
## Societe.Generale	TRUE
## Ascendant.Capital.Markets	TRUE
## BB.T.Corporation	TRUE
## DA.Davidson	TRUE
## Guggenheim	TRUE
## Jyske.Bank	TRUE
## Keefe..Bruyette...Woods	TRUE
## Longbow.Research	TRUE
## Scotiabank	TRUE
## Independent.Research.GmbH	TRUE
## UBS.Group.AG	TRUE
## In.Line	TRUE
## Mkt.Perform	TRUE
## Boenning.Scattergood	TRUE
## Evercore.Partners.Inc	TRUE
## Hilliard.Lyons	TRUE
## Imperial.Capital	TRUE
## T.H..Capital	TRUE
## BGC.Financial	TRUE
## CRT.Capital	TRUE
## Feltl...Co.	TRUE
## First.Analysis	TRUE
## Hovde.Group	TRUE
## Mitsubishi.UFJ.Financial.Group	TRUE
## MLV...Co.	TRUE
## National.Bank.Financial	TRUE
## Sidoti	TRUE
## Taglich.Brothers	TRUE
## Williams.Capital	TRUE
## But.Estimates.Debate.As.Orders.Slow	TRUE
## Focus.List	TRUE

```
## Overweight.Rating.          TRUE
## Sector.Outperform          TRUE
## Weight                     TRUE
```

```
#remove features that with high freq ratio (which appears less frequently). freqRatio o
f 700 means it appears once in 700 times. This
#helped us to remove some of analyst/banks that are less known and
remove_features <- rownames(nzv[nzv$freqRatio > 700, ])
#this reduced number of columns from 137 to 94
finaldf <- finaldf[,!names(finaldf)%in% remove_features]
```

```
set.seed(410)
#make.name will replace space with dot in column names
names(finaldf)<-make.names(names(finaldf),unique=TRUE)
finaldf<-x<-na.omit(finaldf)
inTrain <- createDataPartition(y=finaldf$"TargetAchieved",p = 0.7, list=FALSE)
training <- finaldf[inTrain,]
testing <- finaldf[-inTrain,]
output_vector_training <- training$TargetAchieved
output_vector_testing <- testing$TargetAchieved

#drop independent variable form training and testing set as xgboost will understand it a
s a feature
training <- training[ , !names(training) %in% c("TargetAchieved")]
testing <- testing[ , !names(testing) %in% c("TargetAchieved")]
```

```
dtrain <- xgb.DMatrix(as.matrix(training), label = output_vector_training)
dtest <- xgb.DMatrix(as.matrix(testing), label = output_vector_testing)
#just to check if we have either 0 or 1
sumwpos <- sum(output_vector_training == 1)
sumwneg <- sum(output_vector_training == 0)
nrow(training) == sumwpos + sumwneg
```

```
## [1] TRUE
```

```

xgb_params_1 = list(
  objective = "binary:logistic", # binary classification
  eta = 0.1, # learning rate
  max.depth = 4, # maxtree depth
  eval_metric = "auc", # evaluation metric
  scale_pos_weight = sumwneg / sumwpos
)

system.time(
  bst <- xgboost(data = dtrain,
    params = xgb_params_1,
    nrounds = 250,
    verbose = 1,
    print_every_n = 10,
    early_stopping_rounds = 50) # stop if no improvement within n trees)
)

```

```

## [1] train-auc:0.614044
## Will train until train_auc hasn't improved in 50 rounds.
##
## [11] train-auc:0.646063
## [21] train-auc:0.678651
## [31] train-auc:0.687306
## [41] train-auc:0.697653
## [51] train-auc:0.701955
## [61] train-auc:0.706757
## [71] train-auc:0.712065
## [81] train-auc:0.716154
## [91] train-auc:0.721212
## [101] train-auc:0.724315
## [111] train-auc:0.726147
## [121] train-auc:0.728632
## [131] train-auc:0.730410
## [141] train-auc:0.731798
## [151] train-auc:0.733245
## [161] train-auc:0.734244
## [171] train-auc:0.734893
## [181] train-auc:0.735968
## [191] train-auc:0.736963
## [201] train-auc:0.737952
## [211] train-auc:0.738404
## [221] train-auc:0.738973
## [231] train-auc:0.739307
## [241] train-auc:0.739862
## [250] train-auc:0.740617

```

```

## user system elapsed
## 2.550 0.067 2.764

```



```
xgb.probs <- predict(bst, as.matrix(testing))
length(xgb.probs) == nrow(testing) # verify that this is equivalent to nrow(testing)
```

```
## [1] TRUE
```

```
#this creates a list with all 0 with same size as testing
xgb.predict <- rep( 0 ,nrow(testing))
```

```
#In our case having higher precission is more important as getting False Positive rate i
s costly
#(When you predict True but its actually false thus you loose money! or cant get your gu
ranteed
#return by following analyst) and False Negative is not important because what you predi
cted false
#and it is actually true. (ignored that rating and that rating was correct)
```

```
#Check the threshold graph to see relation between precission and recall in our case
```

```
xgb.pred <- as.numeric(xgb.probs > 0.65)
confusionMatrix(xgb.pred, output_vector_testing, positive="1", mode="prec_recall")
```

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

```
##
```

```
##           Reference
```

```
## Prediction    0    1
```

```
##           0 811 483
```

```
##           1  97 190
```

```
##
```

```
##           Accuracy : 0.6331
```

```
##           95% CI : (0.6088, 0.657)
```

```
## No Information Rate : 0.5743
```

```
## P-Value [Acc > NIR] : 1.082e-06
```

```
##
```

```
##           Kappa : 0.1896
```

```
## McNemar's Test P-Value : < 2.2e-16
```

```
##
```

```
##           Precision : 0.6620
```

```
##           Recall : 0.2823
```

```
##           F1 : 0.3958
```

```
##           Prevalence : 0.4257
```

```
##           Detection Rate : 0.1202
```

```
## Detection Prevalence : 0.1815
```

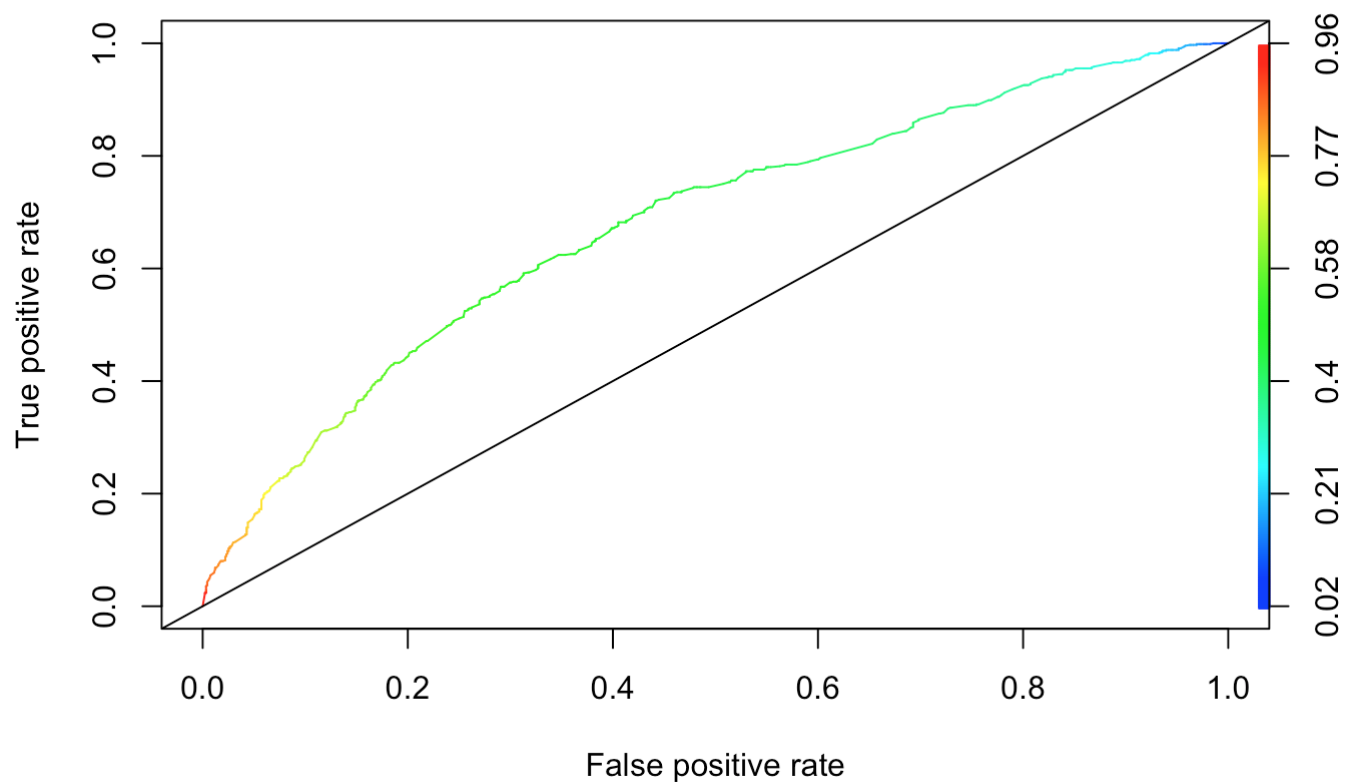
```
## Balanced Accuracy : 0.5877
```

```
##
```

```
## 'Positive' Class : 1
```

```
##
```

```
pred<- prediction(xgb.probs, output_vector_testing)
perf <- performance(pred,"tpr","fpr")
plot(perf, colorize=TRUE)
abline(a=0, b=1)
```



```
#AUC or C-Stats
performance(pred, measure = "auc")@y.values
```

```
## [[1]]
## [1] 0.679864
```

```

dfLength <- length(seq(0.00,0.999,0.001))
thresholdDF <- data.frame(percent = numeric(dfLength),threshold = numeric(dfLength),
precision = numeric(dfLength), recall = numeric(dfLength), f1 = numeric(dfLength))
dfListIndex <-0
for (i in seq(0.00, 0.999, 0.001)){
  dfListIndex = dfListIndex +1
  #get minimum value from the sorted list which will be our cutoff value
  threshold = min(head(sort(xgb.probs,decreasing=TRUE), n = (length(xgb.probs)*(1-i))
  ))
  thresholdDF$percent[dfListIndex] = (1-i)*100
  thresholdDF$threshold[dfListIndex] = threshold
  # set to 1 if probability is above threshold otehr wise 0
  xgb.pred = rep(0, nrow(testing))
  xgb.pred[xgb.probs >= threshold] = 1
  #create confustion matrix and get pos pred value from the confusion matrix
  cm = confusionMatrix(xgb.pred, output_vector_testing, positive="1",
mode="prec_recall")
  byClass = cm$byClass
  precision = byClass[5]
  recall = byClass[6]
  f1 = byClass[7]
  thresholdDF$precision[dfListIndex] = precision
  thresholdDF$recall[dfListIndex] = recall
  thresholdDF$f1[dfListIndex] = f1
}

```

```

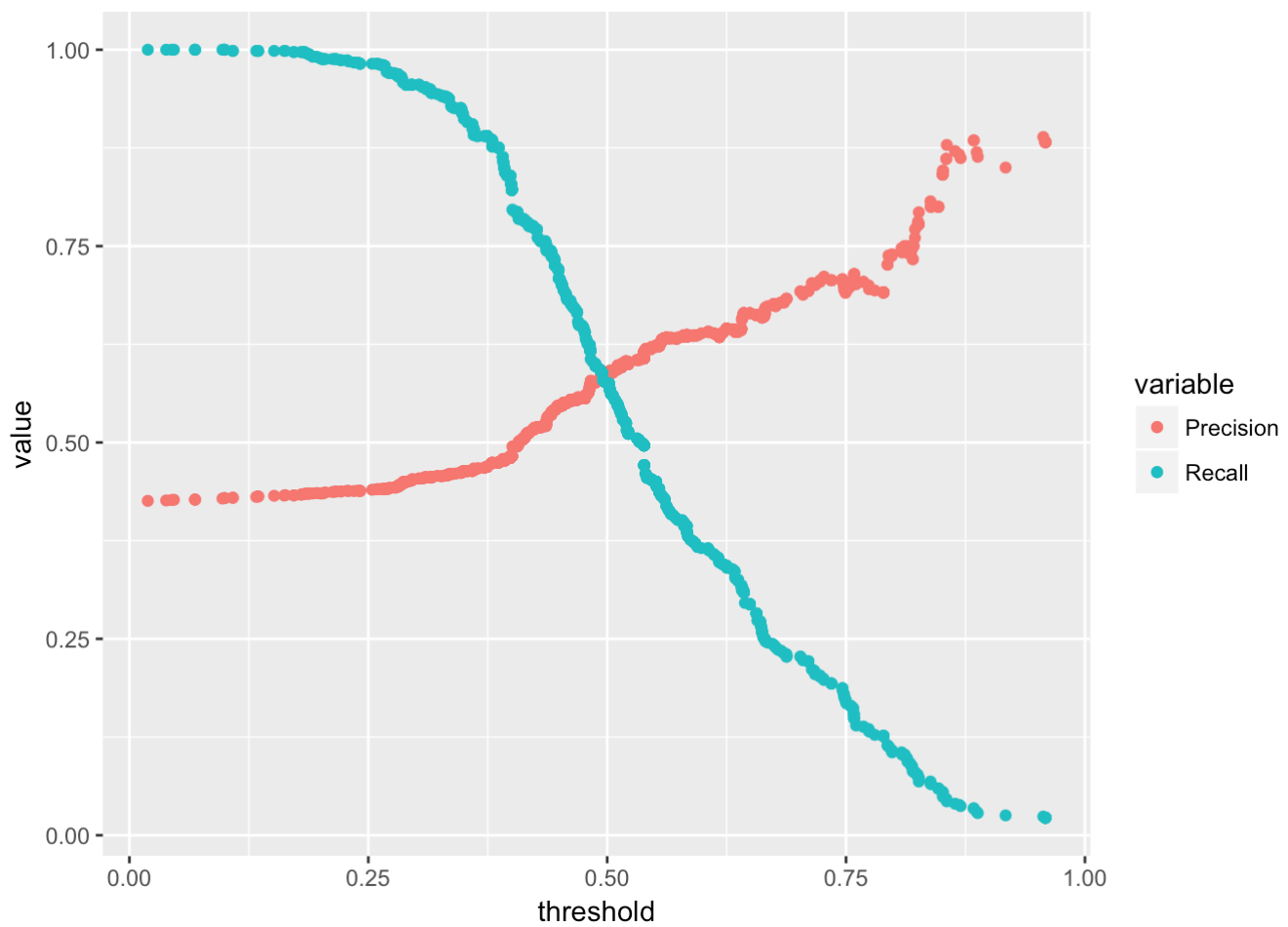
## Warning in confusionMatrix.default(xgb.pred, output_vector_testing,
## positive = "1", : Levels are not in the same order for reference and data.
## Refactoring data to match.

```

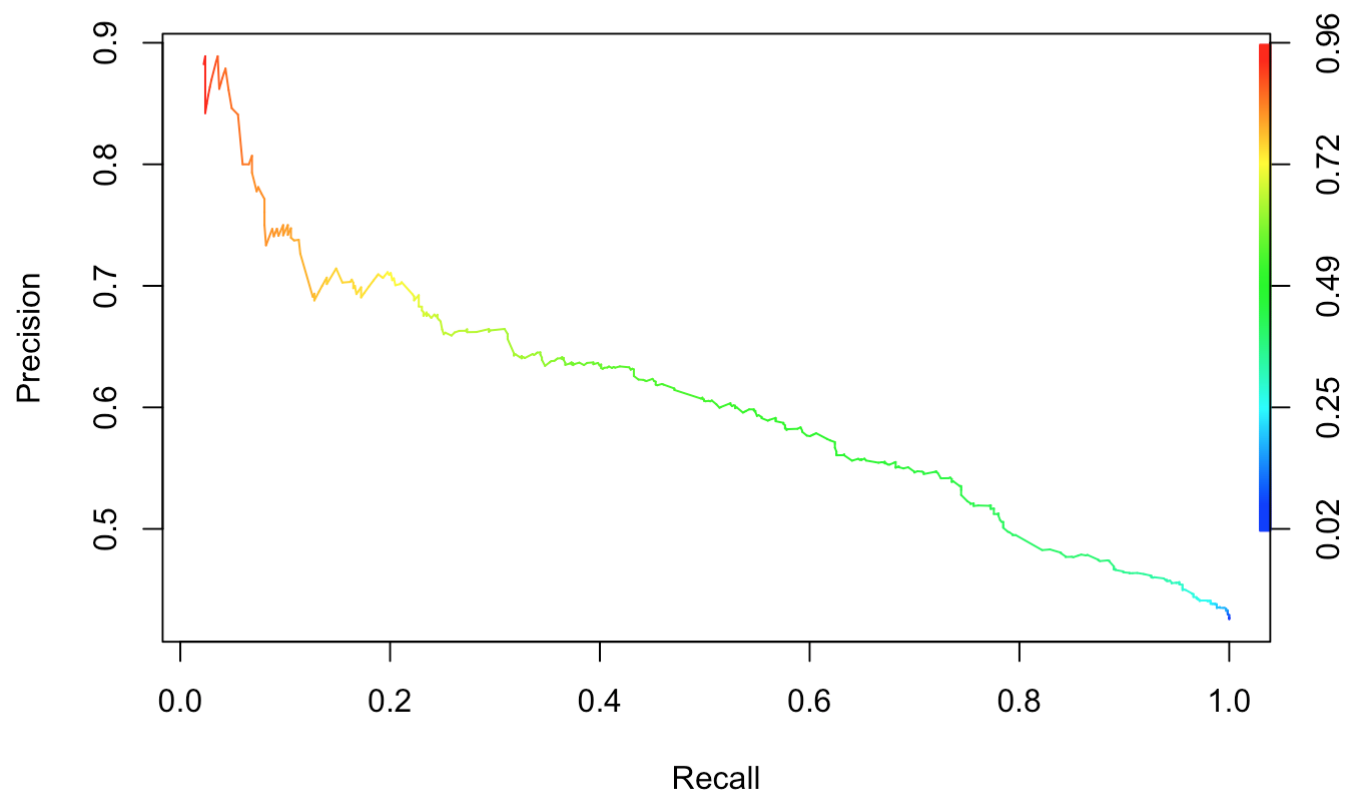
```

# Plot
ggplot(data=thresholdDF,aes(threshold, y=value,color =variable))+ geom_point(aes(y=preci
sion , col = "Precision"))+ geom_point(aes(y=recall , col = "Recall"))

```



```
perf <- performance(pred,"prec","rec")  
plot(perf, colorize=TRUE)
```



```
importance <- xgb.importance(feature_names = colnames(dtrain), model = bst)
head(importance, 25)
```

##	Feature	Gain	Cover	Frequency
## 1:	Neutral	0.163744211	0.026622026	0.034059946
## 2:	Hold	0.096002070	0.036820422	0.029064487
## 3:	Sector.Perform	0.061171462	0.029537314	0.014078111
## 4:	Reiterated.Rating	0.054640240	0.016993371	0.108537693
## 5:	Underperform	0.035581780	0.035729617	0.016802906
## 6:	B..Riley	0.035015884	0.034335775	0.020890100
## 7:	Initiated.Coverage	0.031881785	0.020718009	0.042234332
## 8:	Boost.Price.Target	0.031208389	0.009183818	0.060399637
## 9:	Equal.Weight	0.030039546	0.022822314	0.012261580
## 10:	Leerink.Swann	0.029723777	0.027152911	0.012715713
## 11:	Buy	0.028614989	0.017330933	0.071752952
## 12:	Sell	0.024005013	0.029979371	0.014532243
## 13:	Downgrade	0.021791320	0.023348469	0.039509537
## 14:	Lower.Price.Target	0.021686147	0.002262820	0.033151680
## 15:	Market.Perform	0.019955851	0.028596782	0.015894641
## 16:	Upgrade	0.017998923	0.004226613	0.030881017
## 17:	Bank.of.America.Corporation	0.016158312	0.011965734	0.021344233
## 18:	Outperform	0.015315279	0.007284579	0.024069028
## 19:	Citigroup.Inc.	0.015147563	0.012615295	0.015894641
## 20:	SunTrust.Banks..Inc.	0.014014662	0.023551335	0.011353315
## 21:	Sanford.C..Bernstein	0.012654713	0.012989764	0.014986376
## 22:	MKM.Partners	0.012178455	0.023849788	0.010899183
## 23:	Macquarie	0.010213151	0.019716325	0.009082652
## 24:	Underweight	0.010030488	0.020872581	0.009536785
## 25:	Cantor.Fitzgerald	0.009972372	0.006453986	0.008628520
##	Feature	Gain	Cover	Frequency

```
xgb.plot.importance(importance_matrix = importance, top_n = 15)
```

