

# Analyst Price Target Analysis using Random Forest 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)]
```

```
finaldf[names(finaldf)] <- lapply(finaldf[names(finaldf)], factor)
```

```
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(417)
#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,]
```

```
h2o.init(
  nthreads=-1,          ## -1: use all available threads
  max_mem_size = "2G")  ## specify the memory size for the H2O cloud
```

```
##
## H2O is not running yet, starting it now...
##
## Note: In case of errors look at the following log files:
##   /var/folders/0c/5jjqfkcj5qz84mm0xwqgh_zr0000gn/T//Rtmp4JPVad/h2o_virajbhalala_sta
rted_from_r.out
##   /var/folders/0c/5jjqfkcj5qz84mm0xwqgh_zr0000gn/T//Rtmp4JPVad/h2o_virajbhalala_sta
rted_from_r.err
##
##
## Starting H2O JVM and connecting: ... Connection successful!
##
## R is connected to the H2O cluster:
##   H2O cluster uptime:      4 seconds 199 milliseconds
##   H2O cluster version:    3.10.4.6
##   H2O cluster version age: 1 month and 16 days
##   H2O cluster name:       H2O_started_from_R_virajbhalala_ybo673
##   H2O cluster total nodes: 1
##   H2O cluster total memory: 1.78 GB
##   H2O cluster total cores: 4
##   H2O cluster allowed cores: 4
##   H2O cluster healthy:    TRUE
##   H2O Connection ip:      localhost
##   H2O Connection port:    54321
##   H2O Connection proxy:   NA
##   H2O Internal Security:  FALSE
##   R Version:              R version 3.3.2 (2016-10-31)
```

```
h2o.removeAll()           # Clean slate - just in case the cluster was already running
```

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

```
system.time({  
  training <- as.h2o(training, destination_frame="training")  
  testing <- as.h2o(testing, destination_frame="testing")  
  
  ## assign the first result the R variable train and the H2O name train.hex  
  train <- h2o.assign(training, "train.hex")  
  test <- h2o.assign(testing, "test.hex")    ## R test, H2O test.hex  
})
```

```
##  
|  
|  
|  
|=====| 100%  
##  
|  
|  
|  
|=====| 100%
```

```
##   user  system elapsed  
##  1.181   0.054   3.503
```

```
#delete headers  
train <- train[-1, ]  
test <- test[-1, ]
```



```

#system.time({
## run our first predictive model
## FOR EACH MODEL, NEED TO CHANGE PREDICTOR AND TARGET COLUMN!
rfl <- h2o.randomForest(      ## h2o.randomForest function
  training_frame = train,    ## the H2O frame for training
  #validation_frame = valid,  ## the H2O frame for validation (not required)
  # x=-3,                    ## the predictor columns, by column index - if x is missing, then all columns except y are used
  y=1,                       ## the target index (what we are predicting)
  model_id = "rf_covType_v1", ## name the model in H2O
                                ## not required, but helps use Flow
  ntrees = 50,               ## use a maximum of 200 trees to create the
                                ## random forest model. The default is 50.
                                ## I have increased it because I will let
                                ## the early stopping criteria decide when
                                ## the random forest is sufficiently accurate
  stopping_rounds = 2,       ## Stop fitting new trees when the 2-tree
                                ## average is within 0.001 (default) of
                                ## the prior two 2-tree averages.
                                ## Can be thought of as a convergence setting
  score_each_iteration = T,  ## Predict against training and validation for
                                ## each tree. Default will skip several.
  seed = 1000000)           ## Set the random seed so that this can be

```

```

##
|
|
|
|=====| 10%
|
|=====| 30%
|
|=====| 46%
|
|=====| 100%

```

```

## reproduced.
#})

```

```

system.time(rf.probs <- as.data.frame(h2o.predict(rfl, test)$p1))

```

```

##
|
|
|
|=====| 100%

```

```

## user system elapsed
## 0.144 0.011 2.158

```

```
nrow(rf.probs) == nrow(test) # verify that this is equivalent to nrow(testing)
```

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

```
# set cutoff value (selection is detailed in the Analysis section)
```

```
rf.pred <- as.numeric(rf.probs > 0.65)
# set positive class as "1"
# use precision/recall mode
```

```
#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
```

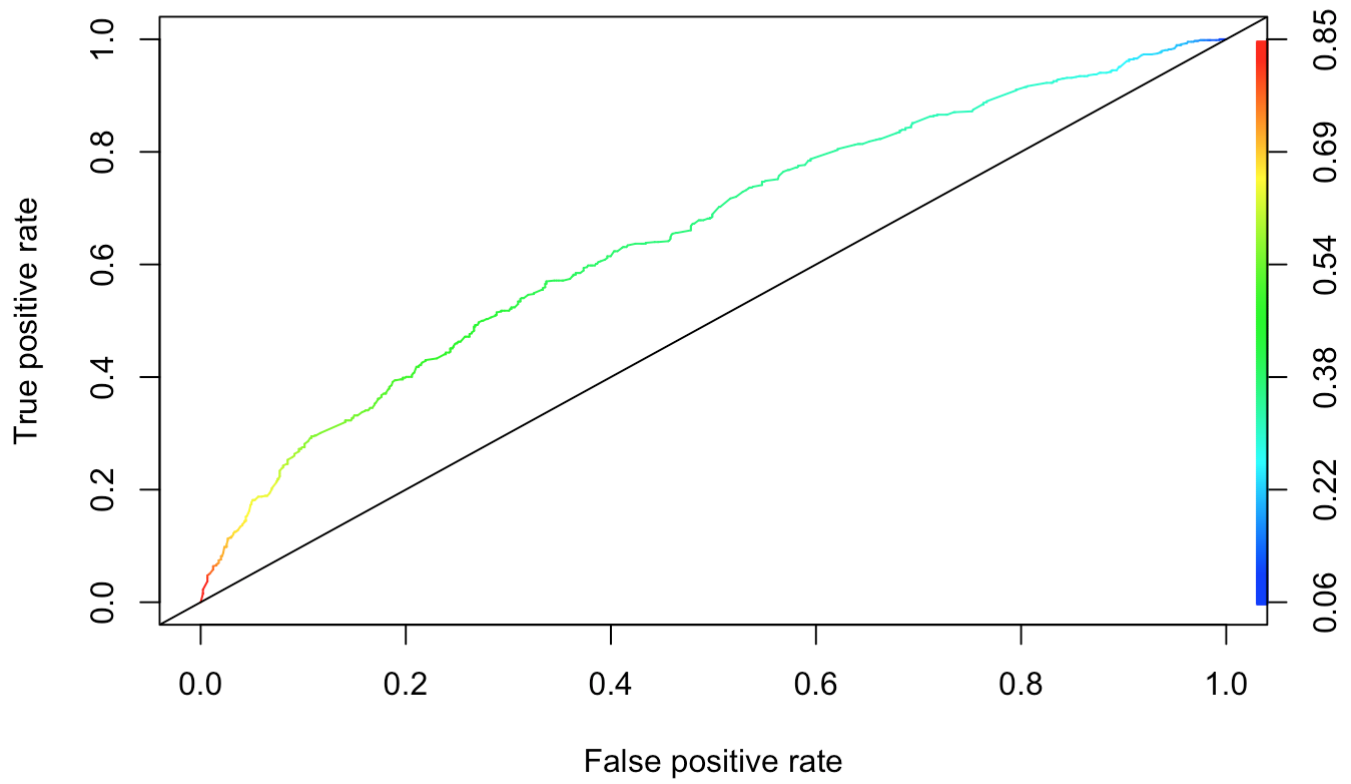
```
 #and it is actually true. (ignored that rating and that rating was correct)
```

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

```
output_vector_testing <- as.data.frame(test)$TargetAchieved
confusionMatrix(rf.pred, output_vector_testing, positive="1", mode="prec_recall")
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##           0 865 563
##           1  43 109
##
##           Accuracy : 0.6165
##           95% CI : (0.592, 0.6405)
##           No Information Rate : 0.5747
##           P-Value [Acc > NIR] : 0.0004072
##
##           Kappa : 0.1277
##           Mcnemar's Test P-Value : < 2.2e-16
##
##           Precision : 0.71711
##           Recall : 0.16220
##           F1 : 0.26456
##           Prevalence : 0.42532
##           Detection Rate : 0.06899
##           Detection Prevalence : 0.09620
##           Balanced Accuracy : 0.55742
##
##           'Positive' Class : 1
##
```

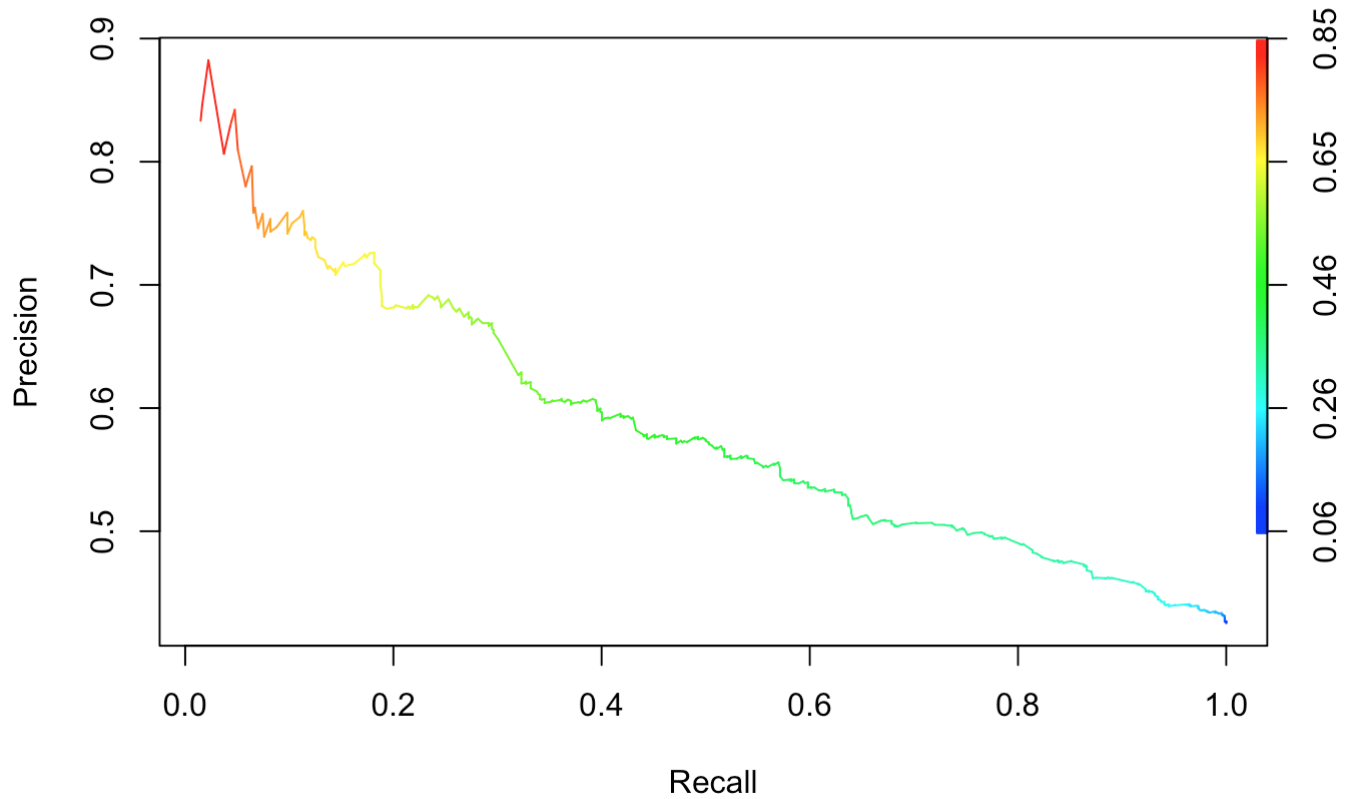
```
pred<- prediction(rf.probs, output_vector_testing)
perf <- performance(pred,"tpr","fpr")
plot(perf, colorize=TRUE)
abline(a=0, b=1)
```



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

```
## [[1]]  
## [1] 0.6536917
```

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



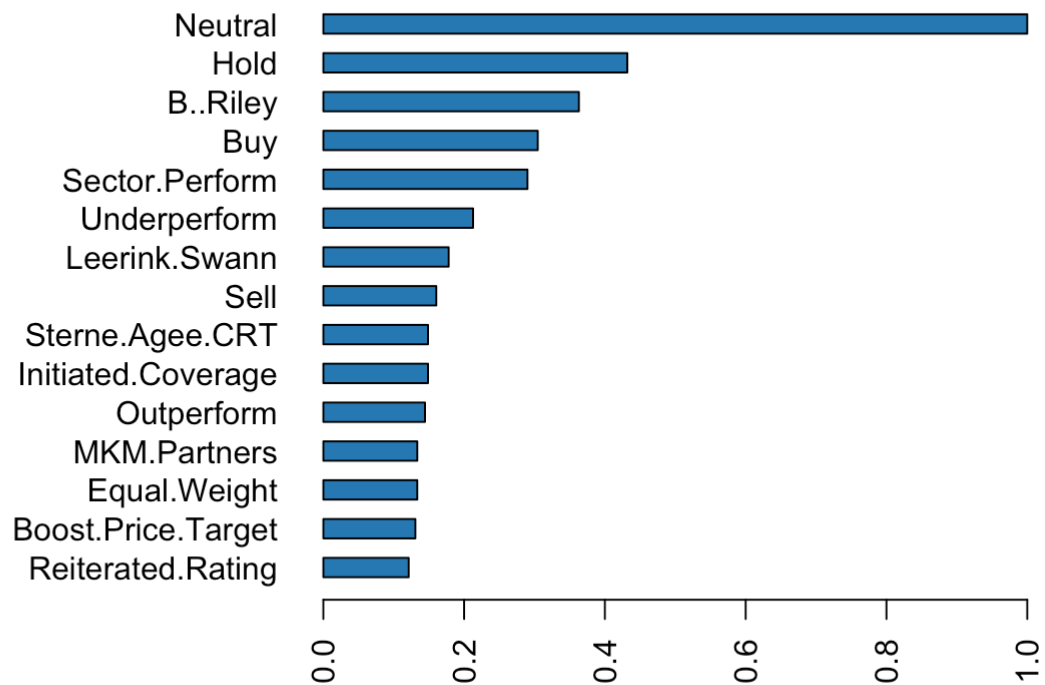
```
importance <- h2o.varimp(rf1)
head(importance, 25)
```

```
## Variable Importances:
```

```
##      variable relative_importance scaled_importance percentage
## 1      Neutral      340.788849          1.000000    0.149966
## 2         Hold      147.175522          0.431867    0.064765
## 3      B..Riley      123.742058          0.363105    0.054453
## 4         Buy      103.824883          0.304660    0.045689
## 5 Sector.Perform       98.848679          0.290058    0.043499
##
## ---
##      variable relative_importance scaled_importance percentage
## 20  Deutsche.Bank.AG       27.070045          0.079433    0.011912
## 21         Upgrade       25.804388          0.075720    0.011355
## 22 Royal.Bank.Of.Canada       23.935081          0.070234    0.010533
## 23         Downgrade       23.807281          0.069859    0.010477
## 24   Robert.W..Baird       23.783762          0.069790    0.010466
## 25         FBR...Co       23.212437          0.068114    0.010215
```

```
h2o.varimp_plot(rf1, num_of_features = 15)
```

## Variable Importance: DRF



```
# All done, shutdown H2O  
h2o.shutdown(prompt=FALSE)
```

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