Data Mining Workflow

Set Up the R Notebook for Analysis

```
# Load necessary packages
library('swat')
```

```
## SWAT 1.0.0
```

```
options(cas.print.messages = FALSE)
library('ggplot2')
library('reshape2')


# Hide credentials
login <- read.csv('login.csv')
hostname <- paste(login[1,])
username <- paste(login[2,])
password <- paste(login[3,])

# Data name
indata <- 'hmeq'

# Hostname, port, username, password
conn <- CAS(hostname, 8777, username, password, protocol = 'http')
```

```
## NOTE: Connecting to CAS and generating CAS action functions for loaded

##       action sets...

## NOTE: To generate the functions with signatures (for tab completion), set

##       options(cas.gen.function.sig=TRUE).
```

```
# Read in the dataset
castbl <- cas.read.csv(conn, 'http://support.sas.com/documentation/onlinedoc/viya/exampledatasets/hmeq.
```

View Data

```
# Print the first few rows
head(castbl)
```

```
##   BAD LOAN MORTDUE  VALUE  REASON    JOB  YOJ DEROG DELINQ     CLAGE NINQ
## 1   1 1100   25860  39025 HomeImp  Other 10.5     0      0  94.36667    1
## 2   1 1300   70053  68400 HomeImp  Other  7.0     0      2 121.83333    0
## 3   1 1500   13500  16700 HomeImp  Other  4.0     0      0 149.46667    1
## 4   1 1500     NaN    NaN                NaN   NaN    NaN       NaN  NaN
## 5   0 1700   97800 112000 HomeImp Office  3.0     0      0  93.33333    0
## 6   1 1700   30548  40320 HomeImp  Other  9.0     0      0 101.46600    1
##   CLNO  DEBTINC
## 1    9      NaN
## 2   14      NaN
## 3   10      NaN
```

```
## 4  NaN      NaN
## 5   14      NaN
## 6    8 37.11361
```

Get Summary Statistics

```
# Use summary function to get variable summary
summary(castbl)
```

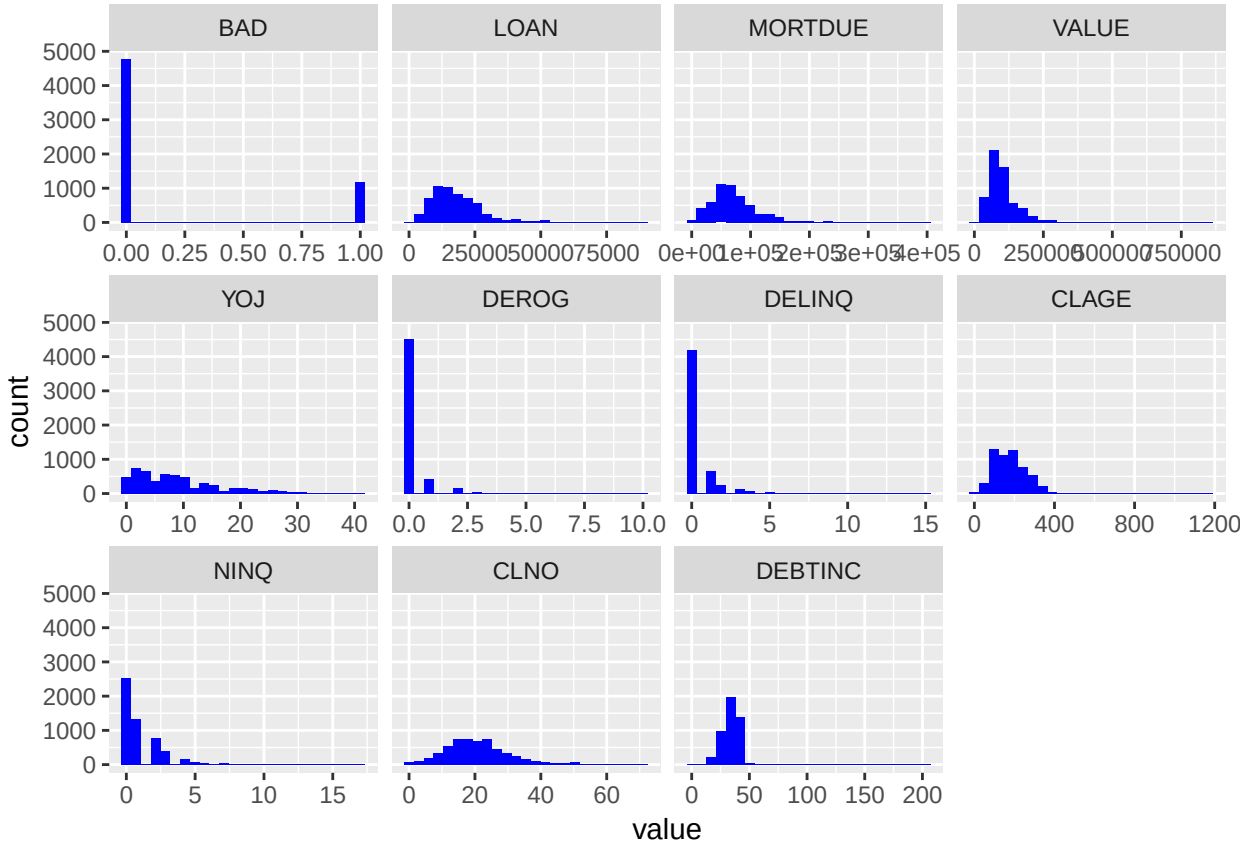
```
##       BAD              LOAN          MORTDUE
##  Min.   :0.0000   Min.   : 1100   Min.   :2063
##  1st Qu.:0.0000   1st Qu.:11100   1st Qu.:46268
##  Median :0.0000   Median :16300   Median :65019
##  Mean   :0.1995   Mean   :18608   Mean   :73760.8171995589
##  3rd Qu.:0.0000   3rd Qu.:23300   3rd Qu.:91491
##  Max.   :1.0000   Max.   :89900   Max.   :399550
##                                   NA's   :518
##      VALUE                     REASON          JOB
##  Min.   :8000              DebtCon:3928   Mgr    : 767
##  1st Qu.:66069             HomeImp:1780   Office : 948
##  Median :89235.5           NA's   : 252   Other  :2388
##  Mean   :101776.04874145                  ProfExe:1276
##  3rd Qu.:119831.5                         Sales  : 109
##  Max.   :855909                           Self   : 193
##  NA's   :112                              NA's   : 279
##       YOJ                      DEROG
##  Min.   :0                 Min.   :0
##  1st Qu.:3                 1st Qu.:0
##  Median :7                 Median :0
##  Mean   :8.9222681359045   Mean   :0.254569687738
##  3rd Qu.:13                3rd Qu.:0
##  Max.   :41                Max.   :10
##  NA's   :515               NA's   :708
##      DELINQ                     CLAGE
##  Min.   :0                  Min.   :0
##  1st Qu.:0                  1st Qu.:115.103196832924
##  Median :0                  Median :173.466666666667
##  Mean   :0.44944237918215   Mean   :179.766275186577
##  3rd Qu.:0                  3rd Qu.:231.574833599946
##  Max.   :15                 Max.   :1168.23356094464
##  NA's   :580                NA's   :308
##       NINQ                       CLNO
##  Min.   :0                  Min.   :0
##  1st Qu.:0                  1st Qu.:15
##  Median :1                  Median :20
##  Mean   :1.18605504587155   Mean   :21.2960962007668
##  3rd Qu.:2                  3rd Qu.:26
##  Max.   :17                 Max.   :71
##  NA's   :510                NA's   :222
##     DEBTINC
##  Min.   :0.52449921542988
##  1st Qu.:29.1400313718617
##  Median :34.818261818587
```

```
##  Mean   :33.7799153487192
##  3rd Qu.:39.0031406283719
##  Max.   :203.312148691165
##  NA's   :1267
```

Visualize Numeric Variables

```
# Bring data locally
df <- to.casDataFrame(castbl, obs = nrow(castbl))

# Use reshape2's melt to help with data formatting
d <- melt(df[sapply(df, is.numeric)], id.vars=NULL)
ggplot(d, aes(x = value)) +
    facet_wrap(~variable,scales = 'free_x') +
    geom_histogram(fill = 'blue', bins = 25)
```



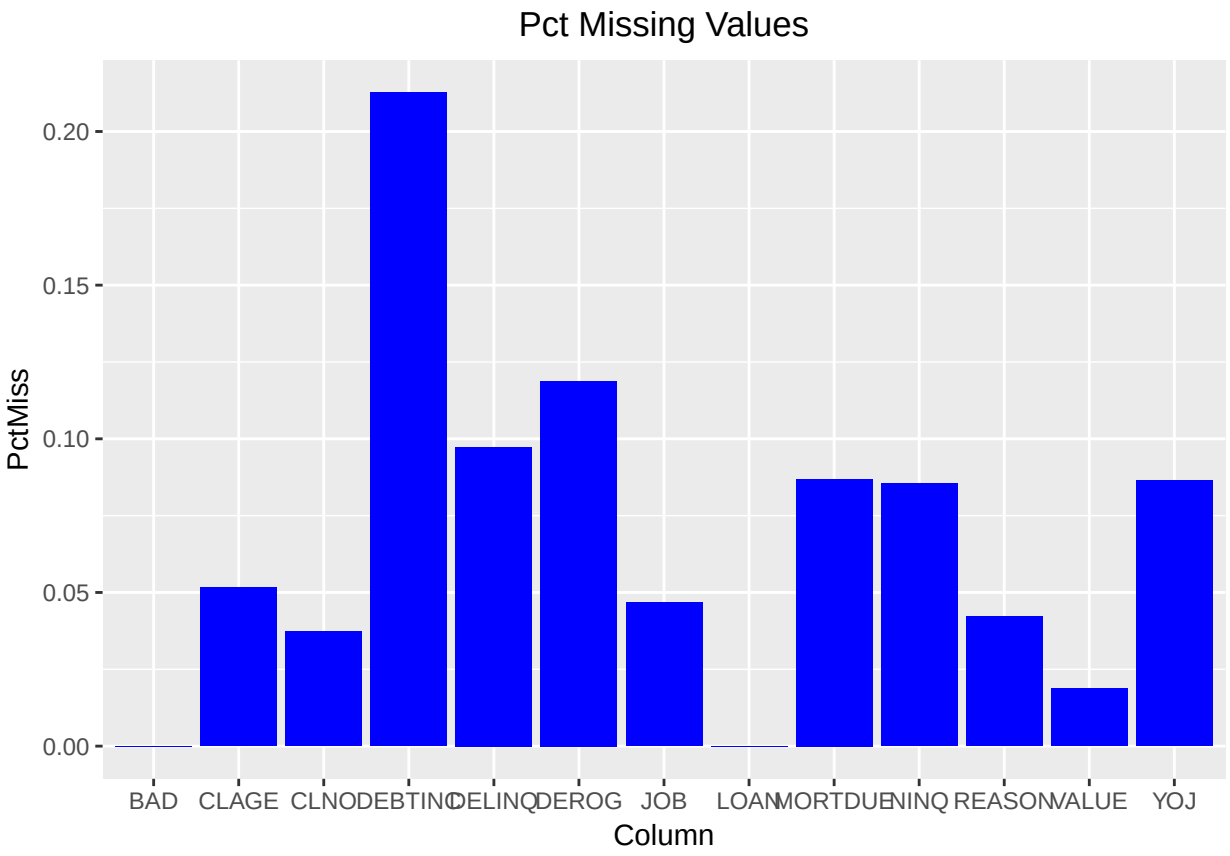
Check for Missingness

```
tbl <- cas.simple.distinct(castbl)$Distinct[,c('Column', 'NMiss')]
tbl
```

```
##     Column NMiss
## 1      BAD     0
## 2     LOAN     0
```

```
## 3  MORTDUE   518
## 4    VALUE   112
## 5   REASON   252
## 6      JOB   279
## 7      YOJ   515
## 8    DEROG   708
## 9   DELINQ   580
## 10   CLAGE   308
## 11    NINQ   510
## 12    CLNO   222
## 13 DEBTINC  1267
```

```
tbl$PctMiss <- tbl$NMiss/nrow(castbl)
ggplot(tbl, aes(Column, PctMiss)) + geom_col(fill = 'blue') + ggtitle('Pct Missing Values') + theme(plo
```



Impute Missing Values

```
# Impute missing values, median for continuous variables, most frequent for nominal
cas.dataPreprocess.impute(castbl,
    methodContinuous = 'MEDIAN',
    methodNominal    = 'MODE',
    inputs           = colnames(castbl)[-1],
    copyAllVars      = TRUE,
    casOut           = list(name = indata, replace = TRUE)
)
```

```
## $ImputeInfo
##    Variable ImputeTech   ResultVar    N NMiss ImputedValueContinuous
## 1      LOAN     Median    IMP_LOAN 5960     0             16300.00000
## 2   MORTDUE     Median IMP_MORTDUE 5442   518             65019.00000
## 3     VALUE     Median   IMP_VALUE 5848   112             89235.50000
## 4    REASON       Mode  IMP_REASON 5708   252                     NaN
## 5       JOB       Mode     IMP_JOB 5681   279                     NaN
## 6       YOJ     Median     IMP_YOJ 5445   515                 7.00000
## 7     DEROG     Median   IMP_DEROG 5252   708                 0.00000
## 8    DELINQ     Median  IMP_DELINQ 5380   580                 0.00000
## 9     CLAGE     Median   IMP_CLAGE 5652   308               173.46667
## 10     NINQ     Median    IMP_NINQ 5450   510                 1.00000
## 11     CLNO     Median    IMP_CLNO 5738   222                20.00000
## 12  DEBTINC     Median IMP_DEBTINC 4693  1267                34.81826
##    ImputedValueNominal
## 1
## 2
## 3
## 4              DebtCon
## 5                Other
## 6
## 7
## 8
## 9
## 10
## 11
## 12
##
## $OutputCasTables
##                casLib Name Rows Columns
## 1 CASUSERHDFS(jelueb) hmeq 5960      25
```

Split the Data into Training and Validation

```
# Load the sampling actionset
loadActionSet(conn, 'sampling')

# Partition the data
cas.sampling.srs(conn,
    table   = indata,
    samppct = 30,
    partind = TRUE,
    output  = list(casOut = list(name = indata, replace = T), copyVars = 'ALL')
)
```

```
# Load the fedsql actionset
loadActionSet(conn, 'fedsql')

# Make sure the partition worked correctly using SQL
cas.fedsql.execDirect(conn, query = paste0("
    SELECT
        CASE WHEN _PartInd_ = 0 THEN 'Training' ELSE 'Validation' END AS name,
        _PartInd_,
```

```
        COUNT(*) AS obs
    FROM ", indata, "
    GROUP BY
        CASE WHEN _PartInd_ = 0 THEN 'Training' ELSE 'Validation' END,
        _PartInd_;
"))$`Result Set`
```

```
##         NAME _PartInd_  OBS
## 1   Training         0 4172
## 2 Validation         1 1788
```

Variable Shortcuts

Note: I do not want to hard code any of my variable names.

```
# Get variable info and types
colinfo <- head(cas.table.columnInfo(conn, table = indata)$ColumnInfo, -1)

# My target variable is the first column
target <- colinfo$Column[1]

# For models that can inherently handle missing values (ex: Decision Tree)
inputs <- colinfo$Column[-1]
nominals <- c(target, subset(colinfo, Type == 'varchar')$Column)

# For models that cannot handle missing values (ex: Neural Network)
imp.inputs <- grep('IMP_', inputs, value = T)
imp.nominals <- c(target, grep('IMP_', nominals, value = T))
```

Model Building

Decision Tree

```
# Load the decsion tree actionset
loadActionSet(conn, 'decisionTree')

# Train the decision tree model
cas.decisionTree.dtreeTrain(conn,
    table    = list(name = indata, where = '_PartInd_ = 0'),
    target   = target,
    inputs   = inputs,
    nominals = nominals,
    varImp   = TRUE,
    casOut   = list(name = 'dt_model', replace = TRUE)
)
```

```
## $DTreeVarImpInfo
##   Variable Importance        Std Count
## 1  DEBTINC  407.30031 160.880450     2
## 2   DELINQ   47.33167   0.000000     1
## 3    DEROG   16.21110   0.000000     1
```

```
## 4     CLNO   10.43390   3.486067     2
##
## $ModelInfo
##                             Descr      Value
## 1          Number of Tree Nodes   13.00000
## 2        Max Number of Branches    2.00000
## 3             Number of Levels    6.00000
## 4             Number of Leaves    7.00000
## 5               Number of Bins   20.00000
## 6        Minimum Size of Leaves    5.00000
## 7        Maximum Size of Leaves 3224.00000
## 8           Number of Variables   24.00000
## 9  Confidence Level for Pruning    0.25000
## 10  Number of Observations Used 4172.00000
## 11  Misclassification Error (%)   13.71045
##
## $OutputCasTables
##                 casLib     Name Rows Columns
## 1 CASUSERHDFS(jelueb) dt_model   13      27
```

Random Forest

```
# Train the random forest model
cas.decisionTree.forestTrain(conn,
    table    = list(name = indata, where = '_PartInd_ = 0'),
    target   = target,
    inputs   = inputs,
    nominals = nominals,
    casOut   = list(name = 'rf_model', replace = TRUE)
)
```

```
## $ModelInfo
##                                Descr      Value
## 1                    Number of Trees   50.00000
## 2  Number of Selected Variables (M)    5.00000
## 3                Random Number Seed    0.00000
## 4          Bootstrap Percentage (%)   63.21206
## 5                    Number of Bins   20.00000
## 6               Number of Variables   24.00000
## 7      Confidence Level for Pruning    0.25000
## 8          Max Number of Tree Nodes   27.00000
## 9          Min Number of Tree Nodes   11.00000
## 10           Max Number of Branches    2.00000
## 11           Min Number of Branches    2.00000
## 12             Max Number of Levels    6.00000
## 13             Min Number of Levels    6.00000
## 14             Max Number of Leaves   14.00000
## 15             Min Number of Leaves    6.00000
## 16           Maximum Size of Leaves 2579.00000
## 17           Minimum Size of Leaves    5.00000
## 18               Out-of-Bag MCR (%)        NaN
##
## $OutputCasTables
```

```
##                casLib     Name Rows Columns
## 1 CASUSERHDFS(jelueb) rf_model  724      39
```

Gradient Boosting

```
# Train the gradient boosting model
cas.decisionTree.gbtreeTrain(conn,
    table    = list(name = indata, where = '_PartInd_ = 0'),
    target   = target,
    inputs   = inputs,
    nominals = nominals,
    casOut   = list(name = 'gbt_model', replace = TRUE)
)
```

```
## $ModelInfo
##                                Descr  Value
## 1                   Number of Trees   50.0
## 2                      Distribution    2.0
## 3                     Learning Rate    0.1
## 4                  Subsampling Rate    0.5
## 5  Number of Selected Variables (M)   24.0
## 6                     Number of Bins   20.0
## 7                Number of Variables   24.0
## 8          Max Number of Tree Nodes   61.0
## 9          Min Number of Tree Nodes   21.0
## 10           Max Number of Branches    2.0
## 11           Min Number of Branches    2.0
## 12             Max Number of Levels    6.0
## 13             Min Number of Levels    6.0
## 14             Max Number of Leaves   31.0
## 15             Min Number of Leaves   11.0
## 16           Maximum Size of Leaves 1430.0
## 17           Minimum Size of Leaves    5.0
## 18               Random Number Seed    0.0
##
## $OutputCasTables
##                casLib      Name Rows Columns
## 1 CASUSERHDFS(jelueb) gbt_model 2446      31
```

Neural Network

```
# Load the neuralNet actionset
loadActionSet(conn, 'neuralNet')

# Build a neural network model
cas.neuralNet.annTrain(conn,
    table    = list(name = indata, where = '_PartInd_ = 0'),
    target   = target,
    inputs   = imp.inputs,
    nominals = imp.nominals,
    casOut   = list(name = 'nn_model', replace = TRUE)
)
```

```
## $ConvergenceStatus
##                                          Reason
## 1 The optimization exited on maximum iterations.
##
## $ModelInfo
##                          Descr        Value
## 1                        Model   Neural Net
## 2  Number of Observations Used         4172
## 3  Number of Observations Read         4172
## 4     Target/Response Variable          BAD
## 5               Number of Nodes           20
## 6         Number of Input Nodes           18
## 7        Number of Output Nodes            2
## 8        Number of Hidden Nodes            0
## 9  Number of Weight Parameters           18
## 10   Number of Bias Parameters            2
## 11                Architecture         GLIM
## 12       Number of Neural Nets            1
## 13             Objective Value 1.5113809425
##
## $OptIterHistory
##    Progress Objective     Loss
## 1         1  4.025347 4.025347
## 2         2  2.441133 2.441133
## 3         3  1.615989 1.615989
## 4         4  1.577615 1.577615
## 5         5  1.541579 1.541579
## 6         6  1.528510 1.528510
## 7         7  1.515959 1.515959
## 8         8  1.513655 1.513655
## 9         9  1.512013 1.512013
## 10       10  1.511381 1.511381
##
## $OutputCasTables
##                casLib     Name Rows Columns
## 1 CASUSERHDFS(jelueb) nn_model   20      15
```

Score the Models

```
# Score the models
models <- c('dt','rf','gbt','nn')
scores <- c(cas.decisionTree.dtreeScore, cas.decisionTree.forestScore, cas.decisionTree.gbtreeScore, cas
names(scores) <- models

# Function to help automate prediction process on new data
score.params <- function(model){return(list(
    object       = defCasTable(conn, indata),
    modelTable   = list(name = paste0(model, '_model')),
    copyVars     = list(target, '_PartInd_'),
    assessonerow = TRUE,
    casOut       = list(name = paste0(model, '_scored'), replace = T)
))}
lapply(models, function(x) {do.call(scores[[x]], score.params(x))})
```

Compare Confusion Matrix

```
# Load the percentile actionset for scoring
loadActionSet(conn, 'percentile')

# Useful function for model assessment
assess.model <- function(model){
    cas.percentile.assess(conn,
        table    = list(name = paste0(model,'_scored'), where = '_PartInd_ = 1'),
        inputs   = paste0('_', model, '_P_           1'),
        response = target,
        event    = '1')
}

model.names <- c('Decision Tree', 'Random Forest', 'Gradient Boosting', 'Neural Network')
roc.df <- data.frame()
for (i in 1:length(models)){
    tmp <- (assess.model(models[i]))$ROCInfo
    tmp$Model <- model.names[i]
    roc.df <- rbind(roc.df, tmp)
}

# Manipulate the dataframe
compare <- subset(roc.df, CutOff == 0.5)
rownames(compare) <- NULL
compare[,c('Model','TP','FP','FN','TN')]
```

```
##               Model  TP  FP  FN   TN
## 1     Decision Tree 274 143 111 1260
## 2     Random Forest  46   1 339 1402
## 3 Gradient Boosting 253  43 132 1360
## 4    Neural Network 124  41 261 1362
```

Compare Misclassification

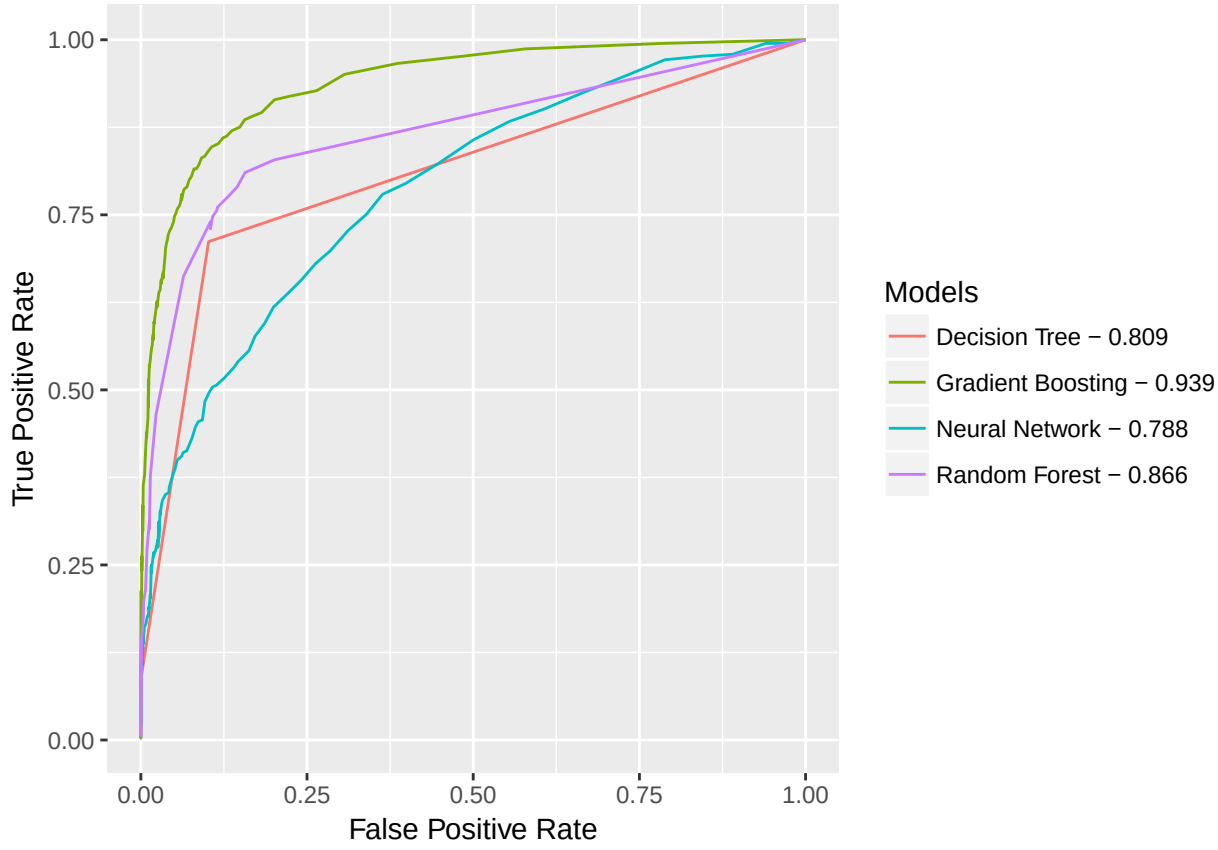
```
# Build a dataframe to compare the misclassification rates
compare$Misclassification <- 1 - compare$ACC
miss <- compare[order(compare$Misclassification), c('Model','Misclassification')]
rownames(miss) <- NULL
miss
```

```
##               Model Misclassification
## 1 Gradient Boosting        0.09787472
## 2     Decision Tree        0.14205817
## 3    Neural Network        0.16890380
## 4     Random Forest        0.19015660
```

Compare ROC Curve

```
# Add a new column to be used as the ROC curve label
roc.df$Models <- paste(roc.df$Model, round(roc.df$C, 3), sep = ' - ')

# Create the ROC curve
ggplot(data = roc.df[c('FPR', 'Sensitivity', 'Models')],
       aes(x = as.numeric(FPR), y = as.numeric(Sensitivity), colour = Models)) + geom_line() +
       labs(x = 'False Positive Rate', y = 'True Positive Rate')
```



Compare XGBoost Model

```
# Load additional packages
library('xgboost')
suppressPackageStartupMessages(library('caret'))

# Bring data locally and make sure it's in the right format
df <- to.casDataFrame(defCasTable(conn, indata), obs = nrow(castbl))
df <- df[,c(target, inputs, '_PartInd_')]

# Create dummy variables through one-hot encoding
df.dum <- df[,nominals[-1]]
dummies <- dummyVars('~ .', data = df.dum)
df.ohe <- as.data.frame(predict(dummies, newdata = df))
```

```r
df.all.combined <- cbind(df[,-c(which(colnames(df) %in% nominals[-1]))], df.ohe)

# Split into training and validation
train <- df.all.combined[df.all.combined['_PartInd_'] == 0,]
valid <- df.all.combined[df.all.combined['_PartInd_'] == 1,]

# Train the XGBoost model
bst <- xgboost(
    data = data.matrix(train[,-1]),
    label = data.matrix(train[,1]),
    missing = 'NAN',
    nround = 50,
    objective = 'binary:logistic',
    eta = 0.1,
    max_depth = 6,
    subsample = 0.5,
    colsample_bytree = 0.5
)
```

```
## [1]  train-error:0.107383
## [2]  train-error:0.112176
## [3]  train-error:0.120086
## [4]  train-error:0.107383
## [5]  train-error:0.100192
## [6]  train-error:0.101151
## [7]  train-error:0.096596
## [8]  train-error:0.093241
## [9]  train-error:0.089885
## [10] train-error:0.084612
## [11] train-error:0.086290
## [12] train-error:0.084132
## [13] train-error:0.083174
## [14] train-error:0.083893
## [15] train-error:0.082215
## [16] train-error:0.080537
## [17] train-error:0.079338
## [18] train-error:0.079818
## [19] train-error:0.078859
## [20] train-error:0.077421
## [21] train-error:0.074784
## [22] train-error:0.073586
## [23] train-error:0.074545
## [24] train-error:0.070709
## [25] train-error:0.071908
## [26] train-error:0.071429
## [27] train-error:0.071668
## [28] train-error:0.071189
## [29] train-error:0.070470
## [30] train-error:0.067354
## [31] train-error:0.067593
## [32] train-error:0.068792
## [33] train-error:0.066874
## [34] train-error:0.066395
## [35] train-error:0.064957
```

```
## [36] train-error:0.064957
## [37] train-error:0.064957
## [38] train-error:0.064717
## [39] train-error:0.062560
## [40] train-error:0.061122
## [41] train-error:0.061122
## [42] train-error:0.060403
## [43] train-error:0.059923
## [44] train-error:0.059444
## [45] train-error:0.058245
## [46] train-error:0.058965
## [47] train-error:0.057766
## [48] train-error:0.057047
## [49] train-error:0.056568
## [50] train-error:0.056568
```

Score and Assess XGBoost on Validation Data

```
# Create a dataframe with the misclassification rate for XGBoost
pred <- as.numeric(predict(bst, data.matrix(valid[,-1]), missing = 'NAN') > 0.5)
Misclassification <- mean(as.numeric(pred > 0.5) != valid[,1])
xgb <- data.frame(cbind(Model = 'R - XGBoost', Misclassification))
xgb
```

```
##         Model  Misclassification
## 1 R - XGBoost 0.0995525727069351
```

Final Assessment with CAS and R Models

```
# Combine the assessments and order by most accurate on validation data
err <- data.frame(rbind(miss, xgb))
err[,-1] <- round(as.numeric(as.character(err[,-1])),7)
err <- err[order(err[,-1]),]
rownames(err) <- NULL
err
```

```
##               Model Misclassification
## 1 Gradient Boosting         0.0978747
## 2       R - XGBoost         0.0995526
## 3     Decision Tree         0.1420582
## 4    Neural Network         0.1689038
## 5     Random Forest         0.1901566
```

Save the CAS Gradient Boosting Model

```
# Save the champion model for later use
cas.table.save(conn, table = list(name = 'gbt_model'), name = 'Jesse_SAS_gbt', replace = T)
```

```
## $caslib
## [1] "CASUSERHDFS(jelueb)"
##
```

```
## $name
## [1] "Jesse_SAS_gbt.sashdat"
```

End the Session

```
# End the session
cas.session.endSession(conn)
```