

Ensemble_Learning_MU3D

2022-11-03

load packages

```
library(reshape2)
```

```
## Warning: package 'reshape2' was built under R version 4.2.2
```

```
library(tidyverse)
```

```
## Warning: package 'tidyverse' was built under R version 4.2.2
```

```
## -- Attaching packages ----- tidyverse 1.3.2 --
```

```
## v ggplot2 3.4.0      v purrr   0.3.5
## v tibble  3.1.8      v dplyr  1.0.10
## v tidyr   1.2.1      v stringr 1.4.1
## v readr   2.1.3      v forcats 0.5.2
```

```
## Warning: package 'ggplot2' was built under R version 4.2.2
```

```
## Warning: package 'stringr' was built under R version 4.2.2
```

```
## Warning: package 'forcats' was built under R version 4.2.2
```

```
## -- Conflicts ----- tidyverse_conflicts() --
```

```
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()     masks stats::lag()
```

```
library(factoextra)
```

```
## Warning: package 'factoextra' was built under R version 4.2.2
```

```
## Welcome! Want to learn more? See two factoextra-related books at https://goo.gl/ve3WBa
```

```
library(psych)
```

```
## Warning: package 'psych' was built under R version 4.2.2
```

```
##
```

```
## Attaching package: 'psych'
```

```
##
```

```
## The following objects are masked from 'package:ggplot2':
```

```
##
```

```
##    %+%, alpha
```

```
library(corrplot)
```

```
## Warning: package 'corrplot' was built under R version 4.2.2
```

```
## corrplot 0.92 loaded
```

```
library(FactoMineR)
```

```
## Warning: package 'FactoMineR' was built under R version 4.2.2
```

```
library(devtools)
```

```
## Warning: package 'devtools' was built under R version 4.2.2
```

```
## Loading required package: usethis
```

```
## Warning: package 'usethis' was built under R version 4.2.2
```

```
install_github('sinhrks/ggfortify',force = TRUE)
```

```
## WARNING: Rtools is required to build R packages, but is not currently installed.
```

```
##
```

```
## Please download and install Rtools 4.2 from https://cran.r-project.org/bin/windows/Rtools/ or https://cran.r-project.org/bin/windows/Rtools/
```

```
## Downloading GitHub repo sinhrks/ggfortify@HEAD
```

```
## WARNING: Rtools is required to build R packages, but is not currently installed.
```

```
##
```

```
## Please download and install Rtools 4.2 from https://cran.r-project.org/bin/windows/Rtools/ or https://cran.r-project.org/bin/windows/Rtools/
```

```
##      checking for file 'C:\Users\kunbu\AppData\Local\Temp\RtmpaQeabl\remotes216c62736c34\sinhrks\
```

```
##      - preparing 'ggfortify':
```

```
##      checking DESCRIPTION meta-information ...      checking DESCRIPTION meta-information ... v check
```

```
##      - checking for LF line-endings in source and make files and shell scripts
```

```
##      - checking for empty or unneeded directories
```

```
##      - building 'ggfortify_0.4.15.tar.gz'
```

```
##
```

```
##
```

```
library(ggfortify)
```

```
library(e1071)
```

```
## Warning: package 'e1071' was built under R version 4.2.2
```

```
library(caret)
```

```
## Warning: package 'caret' was built under R version 4.2.2
```

```
## Loading required package: lattice
##
## Attaching package: 'caret'
##
## The following object is masked from 'package:purrr':
##
##     lift
```

```
library(randomForest)
```

```
## Warning: package 'randomForest' was built under R version 4.2.2
```

```
## randomForest 4.7-1.1
## Type rfNews() to see new features/changes/bug fixes.
##
## Attaching package: 'randomForest'
##
## The following object is masked from 'package:psych':
##
##     outlier
##
## The following object is masked from 'package:dplyr':
##
##     combine
##
## The following object is masked from 'package:ggplot2':
##
##     margin
```

import video level dataset

Boxplot for variables

```
#remove veracity first
MU3D_Video_Level_Data <- MU3D_Video_Level_Data0[,-grep("Veracity",colnames(MU3D_Video_Level_Data0))]
str(MU3D_Video_Level_Data)
```

```
## 'data.frame':   320 obs. of  13 variables:
## $ VideoID      : chr  "BF001_1PT" "BF001_2NL" "BF001_3NT" "BF001_4PL" ...
## $ Valence      : int   1 0 0 1 1 0 0 1 1 0 ...
## $ Sex          : int   0 0 0 0 0 0 0 0 0 0 ...
## $ Race         : int   0 0 0 0 0 0 0 0 0 0 ...
## $ VidLength_ms : int  38783 37120 38484 38026 36351 36650 29141 36480 36960 29610 ...
## $ VidLength_sec: num   38.8 37.1 38.5 38 36.4 ...
## $ WordCount    : int  110 88 120 124 91 73 95 104 91 114 ...
## $ Accuracy     : num   0.77 0.4 0.77 0.58 0.59 0.33 0.6 0.64 0.64 0.27 ...
## $ TruthProp    : num   0.77 0.6 0.77 0.42 0.59 0.67 0.6 0.36 0.64 0.73 ...
## $ Attractive   : num   4.55 3.55 3.27 4.05 4.86 5.05 4.4 4.27 3.09 3 ...
## $ Trustworthy  : num   4.32 3.75 3.95 4.05 4.36 4.62 4.5 3.73 4.27 4.55 ...
## $ Anxious      : num   3.18 3.05 2.82 3.11 3.32 2.33 3.15 2.91 2.64 2.73 ...
## $ Transcription: chr    "My best friend is a really nice person. Um. She's always kind to everyone. S"
```

```

#scaled
colnames(MU3D_Video_Level_Data)

## [1] "VideoID"      "Valence"      "Sex"          "Race"
## [5] "VidLength_ms" "VidLength_sec" "WordCount"    "Accuracy"
## [9] "TruthProp"    "Attractive"    "Trustworthy"  "Anxious"
## [13] "Transcription"

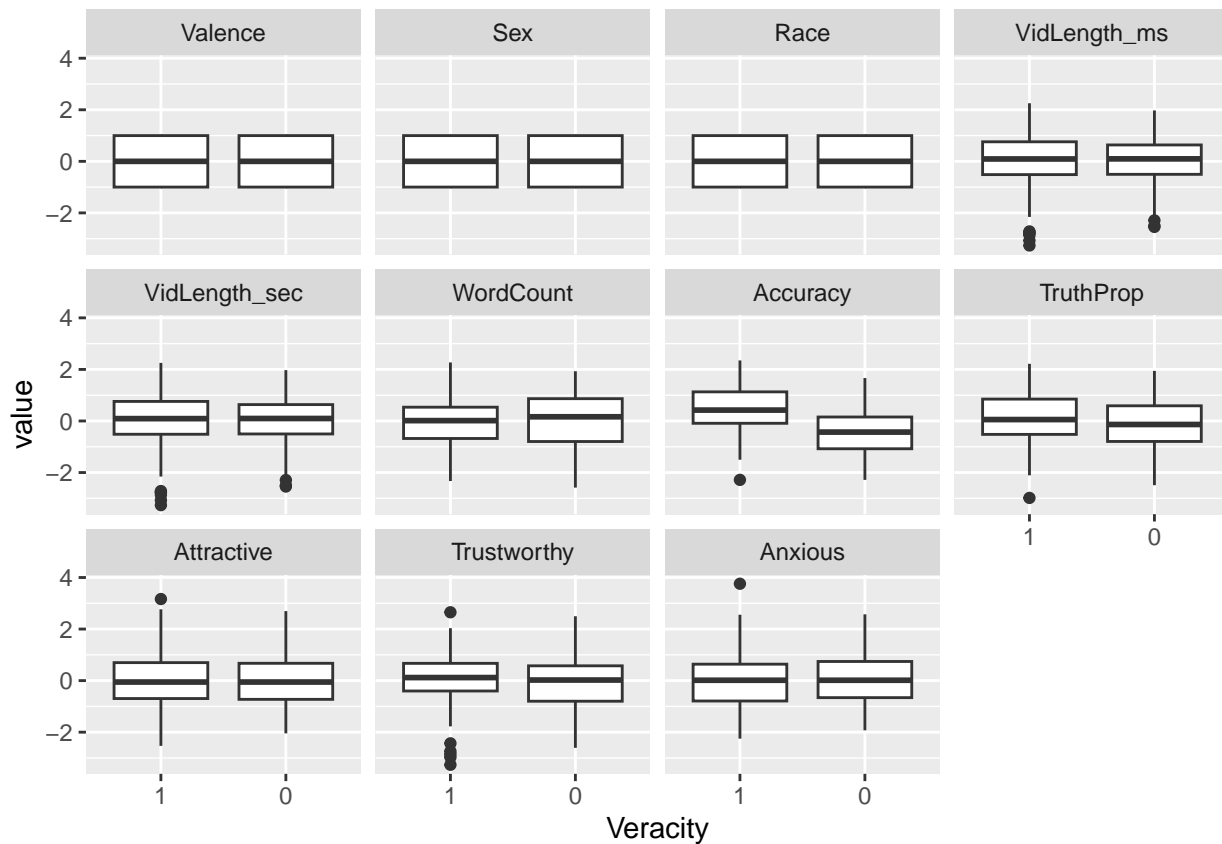
MU3D_Video_Level_Data.scaled <- data.frame(scale(MU3D_Video_Level_Data[, -grep("VideoID|Transcription", c

#level veractiy
levels0 <- unique(c(MU3D_Video_Level_Data0$Veracity, MU3D_Video_Level_Data0$Veracity))
#add veracity back
MU3D_Video_Level_Data.scaled$Veracity <- factor(MU3D_Video_Level_Data0$Veracity, levels = levels0)

#melt data for boxplot
MU3D_Video_Level_Data.scaled.melt <- melt(MU3D_Video_Level_Data.scaled, id.var = "Veracity")

#plot boxplot
ggplot(data = MU3D_Video_Level_Data.scaled.melt, aes(x=Veracity, y = value))+
  geom_boxplot() +
  facet_wrap(~variable, ncol=4)

```



Feature Selection

```
# ensure results are repeatable
set.seed(7)
# load the library
library(mlbench)
```

```
## Warning: package 'mlbench' was built under R version 4.2.2
```

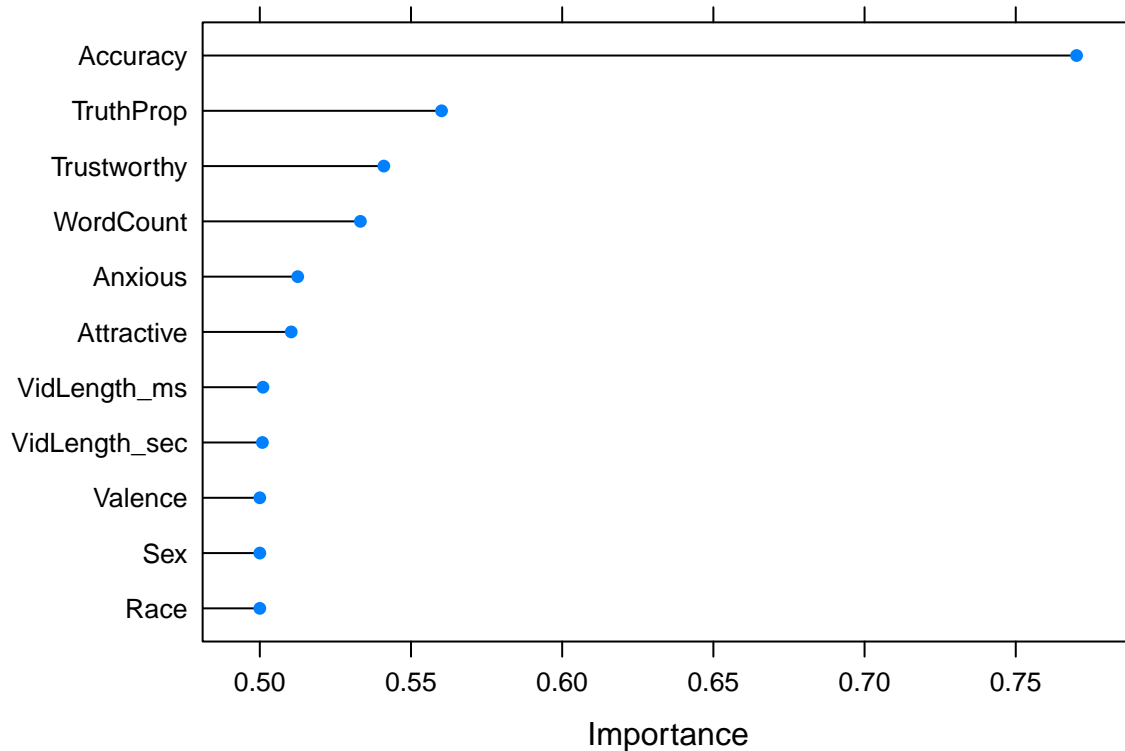
```
library(caret)

# prepare training scheme
control <- trainControl(method="repeatedcv", number=10, repeats=3)
# train the model
model <- train(Veracity~., data=MU3D_Video_Level_Data.scaled, method="lvq", preProcess="scale", trControl=control)
# estimate variable importance
importance <- varImp(model, scale=FALSE)
# summarize importance
print(importance)
```

```
## ROC curve variable importance
```

```
##
##              Importance
## Accuracy      0.7701
## TruthProp     0.5601
## Trustworthy   0.5410
## WordCount     0.5333
## Anxious       0.5125
## Attractive    0.5104
## VidLength_ms  0.5011
## VidLength_sec 0.5009
## Sex           0.5000
## Valence       0.5000
## Race          0.5000
```

```
# plot importance
plot(importance)
```



```
features <- colnames(MU3D_Video_Level_Data.scaled[,importance$importance[X0]>=0.51])
```

Individual learning classifier

Splitting data set into training and test datasets using 80/20 cretira.

```
#split train and test 80/20
set.seed(123)
smp_size_raw <- floor(0.80 * nrow(MU3D_Video_Level_Data.scaled))
train_ind_raw <- sample(nrow(MU3D_Video_Level_Data.scaled), size = smp_size_raw)
train_raw.df <- as.data.frame(MU3D_Video_Level_Data.scaled[train_ind_raw, importance$importance[X0]>=0.51])
test_raw.df <- as.data.frame(MU3D_Video_Level_Data.scaled[-train_ind_raw, importance$importance[X0]>=0.51])
train_raw.df$Veracity <- MU3D_Video_Level_Data.scaled[train_ind_raw, 12]
test_raw.df$Veracity <- MU3D_Video_Level_Data.scaled[-train_ind_raw, 12]
```

SVM

```
poly.tune <- tune.svm(Veracity ~ ., data = train_raw.df,
                      kernel = "polynomial",
                      degree = c(2, 3, 4, 5, 6),
                      coef0 = c(0.1, 0.5, 1, 2, 3, 4))
summary(poly.tune) #best degree is 4,coef0 = 2, misclassification rate no larger than 12.87%
```

```

##
## Parameter tuning of 'svm':
##
## - sampling method: 10-fold cross validation
##
## - best parameters:
##   degree coef0
##       4      4
##
## - best performance: 0.1212308
##
## - Detailed performance results:
##   degree coef0      error dispersion
## 1      2    0.1 0.2187692 0.08477778
## 2      3    0.1 0.2190769 0.07740091
## 3      4    0.1 0.2809231 0.08762541
## 4      5    0.1 0.3198462 0.09631050
## 5      6    0.1 0.3393846 0.09094493
## 6      2    0.5 0.2153846 0.08745958
## 7      3    0.5 0.1923077 0.08548889
## 8      4    0.5 0.1924615 0.08580960
## 9      5    0.5 0.1884615 0.08634975
## 10     6    0.5 0.1884615 0.09945611
## 11     2    1.0 0.2153846 0.09278226
## 12     3    1.0 0.1607692 0.06875716
## 13     4    1.0 0.1804615 0.08473511
## 14     5    1.0 0.1607692 0.07611974
## 15     6    1.0 0.1524615 0.09130639
## 16     2    2.0 0.2153846 0.10125316
## 17     3    2.0 0.1569231 0.07513827
## 18     4    2.0 0.1333846 0.08342141
## 19     5    2.0 0.1444615 0.08240134
## 20     6    2.0 0.1447692 0.08342267
## 21     2    3.0 0.2113846 0.08681432
## 22     3    3.0 0.1607692 0.07319963
## 23     4    3.0 0.1252308 0.08762841
## 24     5    3.0 0.1567692 0.10907886
## 25     6    3.0 0.1413846 0.10289805
## 26     2    4.0 0.2152308 0.08481081
## 27     3    4.0 0.1489231 0.06117328
## 28     4    4.0 0.1212308 0.09574182
## 29     5    4.0 0.1449231 0.10847530
## 30     6    4.0 0.1295385 0.10254051

best.poly <- poly.tune$best.model
poly.test <- predict(best.poly, newdata = test_raw.df)
table(poly.test, test_raw.df$Veracity)

##
## poly.test  1  0
##           1 27  8
##           0  2 27

```

```
confusionMatrix(poly.test, test_raw.df$Veracity, dnn = c("Prediction", "Reference"))
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  1  0
##           1 27  8
##           0  2 27
##
##           Accuracy : 0.8438
##           95% CI : (0.7314, 0.9224)
##       No Information Rate : 0.5469
##       P-Value [Acc > NIR] : 4.925e-07
##
##           Kappa : 0.6902
##
##  Mcnemar's Test P-Value : 0.1138
##
##           Sensitivity : 0.9310
##           Specificity : 0.7714
##       Pos Pred Value : 0.7714
##       Neg Pred Value : 0.9310
##           Prevalence : 0.4531
##       Detection Rate : 0.4219
##   Detection Prevalence : 0.5469
##       Balanced Accuracy : 0.8512
##
##       'Positive' Class : 1
##
```

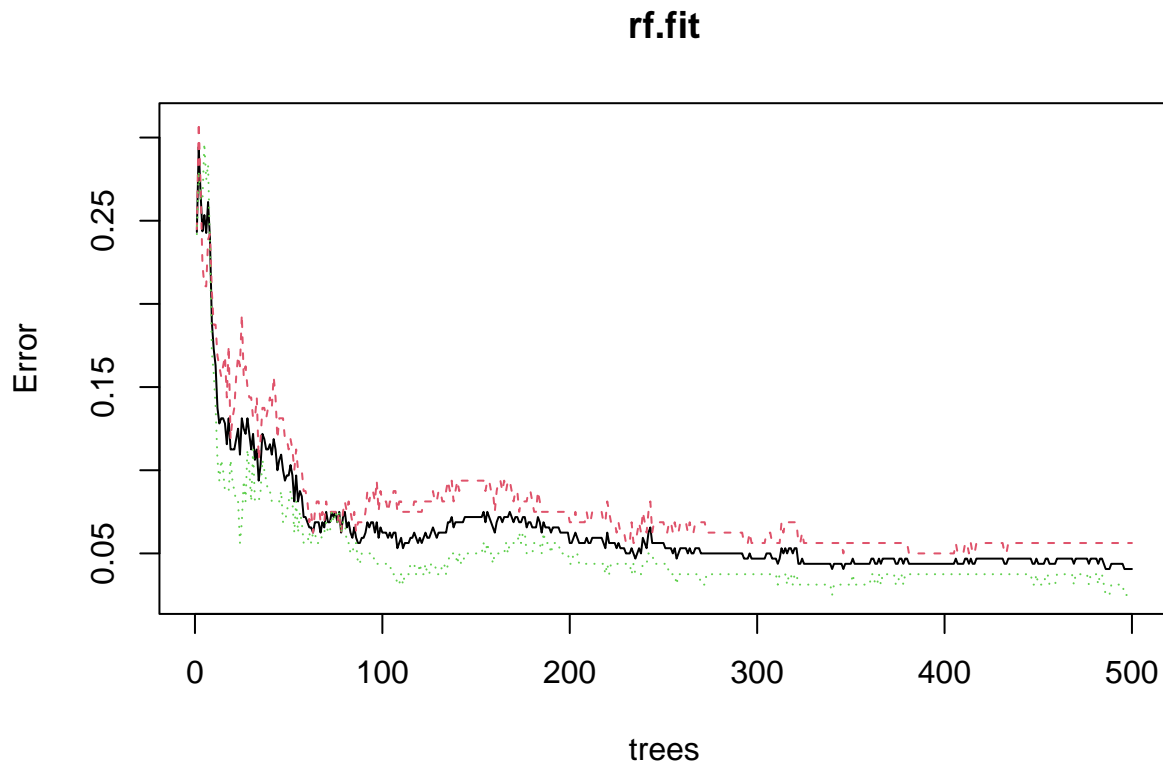
Random Forest

```
set.seed(123)
rf.fit <- randomForest(Veracity~., data= MU3D_Video_Level_Data.scaled)
rf.fit

##
## Call:
## randomForest(formula = Veracity ~ ., data = MU3D_Video_Level_Data.scaled)
##           Type of random forest: classification
##           Number of trees: 500
## No. of variables tried at each split: 3
##
##           OOB estimate of  error rate: 4.06%
## Confusion matrix:
##      1   0 class.error
## 1 151   9      0.05625
## 0   4 156      0.02500
```



```
plot(rf.fit)
```

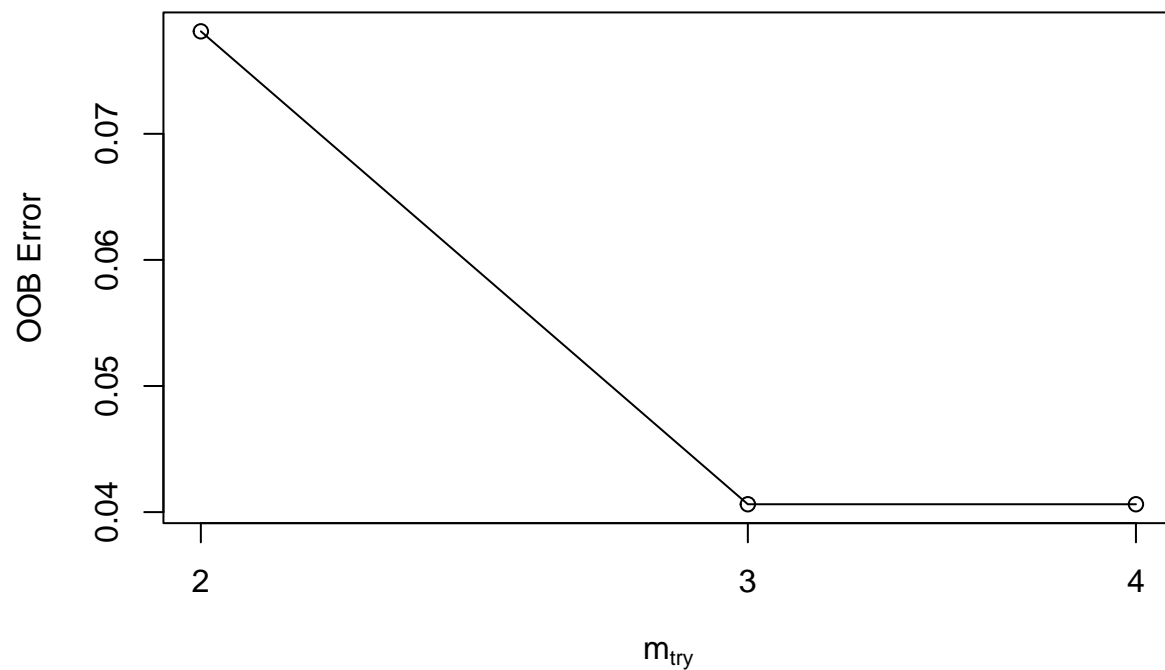


```
which.min(rf.fit$err.rate[,1])
```

```
## [1] 340
```

```
set.seed(123)
mtry <- tuneRF(MU3D_Video_Level_Data.scaled[, -12], MU3D_Video_Level_Data.scaled$Veracity, ntreeTry=1000,
               stepFactor=1.5, improve=0.01, trace=TRUE, plot=TRUE)
```

```
## mtry = 3  OOB error = 4.06%
## Searching left ...
## mtry = 2    OOB error = 7.81%
## -0.9230769 0.01
## Searching right ...
## mtry = 4    OOB error = 4.06%
## 0 0.01
```



```
best.m <- mtry[mtry[,2] == min(mtry[,2]), 1]
print(mtry)
```

```
##      mtry OOBError
## 2.00B    2 0.078125
## 3.00B    3 0.040625
## 4.00B    4 0.040625
```

```
print(best.m)
```

```
## 3.00B 4.00B
##      3      4
```

```
set.seed(123)
rf.fit1 <- randomForest(Veracity~., data=train_raw.df[, -3], mtry=best.m, importance=TRUE, ntree=334)
```

```
## Warning in mtry < 1 || mtry > p: 'length(x) = 2 > 1' in coercion to 'logical(1)'
```

```
## Warning in mtry < 1 || mtry > p: 'length(x) = 2 > 1' in coercion to 'logical(1)'
```

```
print(rf.fit1)
```

```
##
```

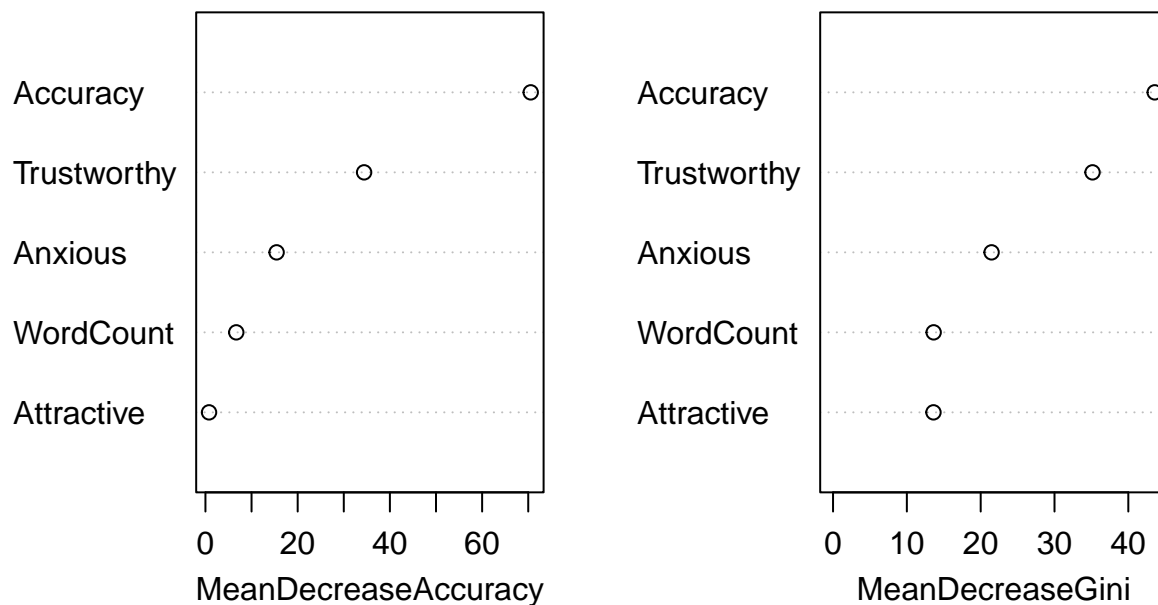
```
## Call:
## randomForest(formula = Veracity ~ ., data = train_raw.df[, -3], mtry = best.m, importance = TRUE)
##              Type of random forest: classification
##              Number of trees: 334
## No. of variables tried at each split: 3
##
##              OOB estimate of  error rate: 23.05%
## Confusion matrix:
##      1  0 class.error
## 1 98 33  0.2519084
## 0 26 99  0.2080000
```

```
#Evaluate variable importance
importance(rf.fit1)
```

```
##              1              0 MeanDecreaseAccuracy MeanDecreaseGini
## WordCount    5.469427  4.019675          6.6861805          13.62865
## Accuracy    51.273047 55.159668          70.5412102          43.57648
## Attractive   -1.342833  2.496349           0.7810218          13.60494
## Trustworthy  24.495995 27.475946          34.4083459          35.15233
## Anxious       6.050911 14.959367          15.4323272          21.47542
```

```
varImpPlot(rf.fit1)
```

rf.fit1



```
rf.pred <- predict(rf.fit1, test_raw.df)
confusionMatrix(rf.pred, test_raw.df$Veracity)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  1  0
##           1 22  7
##           0  7 28
##
##           Accuracy : 0.7812
##           95% CI : (0.6603, 0.8749)
##       No Information Rate : 0.5469
##       P-Value [Acc > NIR] : 8.469e-05
##
##           Kappa : 0.5586
##
##  Mcnemar's Test P-Value : 1
##
##           Sensitivity : 0.7586
##           Specificity : 0.8000
##       Pos Pred Value : 0.7586
##       Neg Pred Value : 0.8000
##           Prevalence : 0.4531
##       Detection Rate : 0.3438
##       Detection Prevalence : 0.4531
##       Balanced Accuracy : 0.7793
##
##       'Positive' Class : 1
##
```

```
set.seed(123)
pred1=predict(rf.fit1, test_raw.df, type = "prob")
library(ROCR)
```

plot AUC

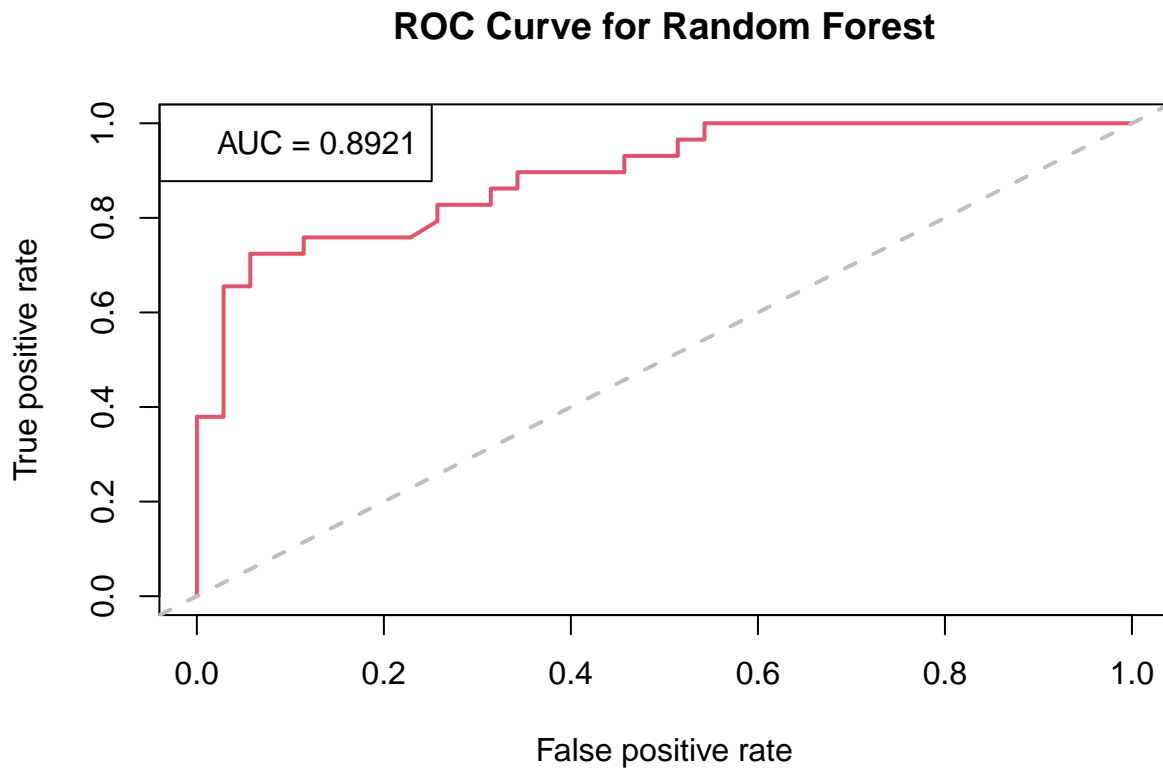
```
## Warning: package 'ROCR' was built under R version 4.2.2
```

```
perf = prediction(pred1[,1], test_raw.df$Veracity)
# 1. Area under curve
auc = performance(perf, "auc")
auc@y.values[[1]]
```

```
## [1] 0.8921182
```

```
# 2. True Positive and Negative Rate
pred3 = performance(perf, "tpr","fpr")
# 3. Plot the ROC curve
```

```
plot(pred3,main="ROC Curve for Random Forest",col=2,lwd=2)
abline(a=0,b=1,lwd=2,lty=2,col="gray")
legend("topleft", c(paste0("AUC = ", round(auc@y.values[[1]],4))))
```



KNN

```
library(class)

target_category <- train_raw.df$Veracity
test_category <- test_raw.df$Veracity
k=sqrt(dim(MU3D_Video_Level_Data)[1])
##run knn function
knn.fit <- knn(train_raw.df,test_raw.df,cl=target_category,k=k)

##create confusion matrix
confusionMatrix(knn.fit, test_raw.df$Veracity, dnn = c("Prediction", "Reference"))

## Confusion Matrix and Statistics
##
##           Reference
## Prediction  1    0
##           1 29   0
##           0  0 35
```

```
##
##           Accuracy : 1
##           95% CI : (0.944, 1)
##      No Information Rate : 0.5469
##      P-Value [Acc > NIR] : < 2.2e-16
##
##           Kappa : 1
##
##      McNemar's Test P-Value : NA
##
##           Sensitivity : 1.0000
##           Specificity : 1.0000
##      Pos Pred Value : 1.0000
##      Neg Pred Value : 1.0000
##           Prevalence : 0.4531
##      Detection Rate : 0.4531
##      Detection Prevalence : 0.4531
##      Balanced Accuracy : 1.0000
##
##      'Positive' Class : 1
##
```

GLM

```
##run glm function
glm.fit <- glm(Veracity~. ,family = binomial(link = "logit"), train_raw.df,)
outcome <- predict(glm.fit, newdata = test_raw.df, type = 'response')
outcome1 <- as.factor(ifelse(outcome > 0.5, 1, 0))
##create confusion matrix
confusionMatrix(data = outcome1, test_raw.df$Veracity, dnn = c("Prediction", "Reference"))
```

```
## Warning in confusionMatrix.default(data = outcome1, test_raw.df$Veracity, :
## Levels are not in the same order for reference and data. Refactoring data to
## match.
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  1  0
##           1  9 23
##           0 20 12
##
##           Accuracy : 0.3281
##           95% CI : (0.2159, 0.4569)
##      No Information Rate : 0.5469
##      P-Value [Acc > NIR] : 0.9999
##
##           Kappa : -0.3438
##
##      McNemar's Test P-Value : 0.7604
##
```

```
##           Sensitivity : 0.3103
##           Specificity : 0.3429
##           Pos Pred Value : 0.2812
##           Neg Pred Value : 0.3750
##           Prevalence : 0.4531
##           Detection Rate : 0.1406
##           Detection Prevalence : 0.5000
##           Balanced Accuracy : 0.3266
##
##           'Positive' Class : 1
##
```

WSRF

```
#install.packages("wsrf")
library(wsrf)
```

```
## Warning: package 'wsrf' was built under R version 4.2.2

## Loading required package: parallel

## Loading required package: Rcpp

## wsrf: An R Package for Scalable Weighted Subspace Random Forests.

## Version 1.7.27

## Use C++ standard thread library for parallel computing

##
## Attaching package: 'wsrf'

## The following objects are masked from 'package:randomForest':
##
##   combine, importance

## The following object is masked from 'package:dplyr':
##
##   combine
```

```
target <- "Veracity"
ds <- MU3D_Video_Level_Data.scaled
vars <- names(ds)

if (sum(is.na(ds[vars]))) ds[vars] <- na.roughfix(ds[vars])
ds[target] <- as.factor(ds[[target]])
(tt <- table(ds[target]))
```

```
## Veracity
##   1   0
## 160 160
```

```

form <- as.formula(paste(target, "~ ."))

model.wsrfl.1 <- wsrfl(form, data=train_raw.df, parallel=FALSE)
print(model.wsrfl.1)

## A Weighted Subspace Random Forest model with 500 trees.
##
##   No. of variables tried at each split: 3
##       Minimum size of terminal nodes: 2
##           Out-of-Bag Error Rate: 0.05
##               Strength: 0.77
##                   Correlation: 0.07
##
## Confusion matrix:
##      1   0 class.error
## 1 125   6         0.05
## 0   7 118         0.06

wdrfl.fit <- predict(model.wsrfl.1, newdata=test_raw.df, type="class")$class

##create confusion matrix
confusionMatrix(wdrfl.fit, test_raw.df$Veracity, dnn = c("Prediction", "Reference"))

## Confusion Matrix and Statistics
##
##           Reference
## Prediction  1   0
##           1 29  3
##           0  0 32
##
##           Accuracy : 0.9531
##           95% CI : (0.8691, 0.9902)
##       No Information Rate : 0.5469
##       P-Value [Acc > NIR] : 4.219e-13
##
##           Kappa : 0.9062
##
##  Mcnemar's Test P-Value : 0.2482
##
##           Sensitivity : 1.0000
##           Specificity : 0.9143
##       Pos Pred Value : 0.9062
##       Neg Pred Value : 1.0000
##           Prevalence : 0.4531
##       Detection Rate : 0.4531
##       Detection Prevalence : 0.5000
##       Balanced Accuracy : 0.9571
##
##       'Positive' Class : 1
##

```


GBM

```
#install.packages("gbm")
library(gbm)
```

```
## Warning: package 'gbm' was built under R version 4.2.2
```

```
## Loaded gbm 2.1.8.1
```

```
fit.gbm <- gbm(Veracity~. , data= train_raw.df,
               distribution = 'multinomial',
               cv.folds = 10,
               shrinkage = .01,
               n.minobsinnode = 10,
               n.trees = 200)
```

```
## Warning: Setting 'distribution = "multinomial"' is ill-advised as it is
## currently broken. It exists only for backwards compatibility. Use at your own
## risk.
```

```
pred <- predict.gbm(object = fit.gbm,
                    newdata = test_raw.df,
                    n.trees = 200,
                    type = "response")
```

```
##create confusion matrix
```

```
pred.labels = colnames(pred)[apply(pred, 1, which.max)]
result = data.frame(test_raw.df$Veracity, pred.labels)
caret::confusionMatrix(test_raw.df$Veracity, as.factor(pred.labels))
```

```
## Warning in confusionMatrix.default(test_raw.df$Veracity,
## as.factor(pred.labels)): Levels are not in the same order for reference and
## data. Refactoring data to match.
```

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

```
##
```

```
##           Reference
```

```
## Prediction 0  1
```

```
##           0 19 16
```

```
##           1  7 22
```

```
##
```

```
##           Accuracy : 0.6406
```

```
##           95% CI : (0.511, 0.7568)
```

```
## No Information Rate : 0.5938
```

```
## P-Value [Acc > NIR] : 0.26403
```

```
##
```

```
##           Kappa : 0.2937
```

```
##
```

```
## McNemar's Test P-Value : 0.09529
```

```
##
```

```
##           Sensitivity : 0.7308
##           Specificity : 0.5789
##           Pos Pred Value : 0.5429
##           Neg Pred Value : 0.7586
##           Prevalence : 0.4062
##           Detection Rate : 0.2969
##           Detection Prevalence : 0.5469
##           Balanced Accuracy : 0.6549
##
##           'Positive' Class : 0
##
```

Ensemble Learning

```
library(caretEnsemble)
```

```
## Warning: package 'caretEnsemble' was built under R version 4.2.2
```

```
##
## Attaching package: 'caretEnsemble'
```

```
## The following object is masked from 'package:ggplot2':
##
## autoplot
```

```
set.seed(100)
```

```
control_stacking <- caret::trainControl(method="repeatedcv", number=5, repeats=2, savePredictions=TRUE,
algorithms_to_use <- c( 'glm', 'knn', 'svmPoly', 'svmLinear', 'wsrf', 'gbm')
stacked_models <- caretList(make.names(Veracity) ~., data=MU3D_Video_Level_Data.scaled, trControl=contr
```

```
## Warning in trControlCheck(x = trControl, y = target): x$savePredictions == TRUE
## is deprecated. Setting to 'final' instead.
```

```
## Warning in trControlCheck(x = trControl, y = target): indexes not defined in
## trControl. Attempting to set them ourselves, so each model in the ensemble will
## have the same resampling indexes.
```

## Iter	TrainDeviance	ValidDeviance	StepSize	Improve
## 1	1.3583	nan	0.1000	0.0133
## 2	1.3382	nan	0.1000	0.0078
## 3	1.3199	nan	0.1000	0.0074
## 4	1.2949	nan	0.1000	0.0115
## 5	1.2803	nan	0.1000	0.0065
## 6	1.2638	nan	0.1000	0.0080
## 7	1.2515	nan	0.1000	0.0048
## 8	1.2403	nan	0.1000	0.0020
## 9	1.2342	nan	0.1000	0.0000
## 10	1.2277	nan	0.1000	0.0008
## 20	1.1541	nan	0.1000	-0.0007

##	40	1.0918	nan	0.1000	-0.0013
##	60	1.0528	nan	0.1000	-0.0017
##	80	1.0171	nan	0.1000	-0.0025
##	100	0.9827	nan	0.1000	-0.0034
##	120	0.9603	nan	0.1000	-0.0005
##	140	0.9401	nan	0.1000	-0.0003
##	150	0.9265	nan	0.1000	-0.0029
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.2937	nan	0.1000	0.0447
##	2	1.2243	nan	0.1000	0.0341
##	3	1.1633	nan	0.1000	0.0268
##	4	1.1163	nan	0.1000	0.0191
##	5	1.0525	nan	0.1000	0.0248
##	6	1.0281	nan	0.1000	0.0088
##	7	1.0090	nan	0.1000	0.0054
##	8	0.9547	nan	0.1000	0.0265
##	9	0.9201	nan	0.1000	0.0133
##	10	0.8915	nan	0.1000	0.0108
##	20	0.8319	nan	0.1000	-0.0020
##	40	0.6226	nan	0.1000	-0.0008
##	60	0.4704	nan	0.1000	0.0066
##	80	0.3438	nan	0.1000	0.0006
##	100	0.2657	nan	0.1000	0.0056
##	120	0.2219	nan	0.1000	-0.0007
##	140	0.1809	nan	0.1000	-0.0012
##	150	0.1484	nan	0.1000	-0.0007
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.2769	nan	0.1000	0.0499
##	2	1.1186	nan	0.1000	0.0781
##	3	1.0262	nan	0.1000	0.0450
##	4	0.9424	nan	0.1000	0.0384
##	5	0.9132	nan	0.1000	0.0090
##	6	0.8140	nan	0.1000	0.0500
##	7	0.7505	nan	0.1000	0.0312
##	8	0.6727	nan	0.1000	0.0387
##	9	0.6577	nan	0.1000	0.0059
##	10	0.6146	nan	0.1000	0.0198
##	20	0.3466	nan	0.1000	0.0153
##	40	0.2001	nan	0.1000	-0.0009
##	60	0.1530	nan	0.1000	-0.0011
##	80	0.1145	nan	0.1000	-0.0008
##	100	0.0866	nan	0.1000	-0.0004
##	120	0.0640	nan	0.1000	0.0003
##	140	0.0498	nan	0.1000	-0.0006
##	150	0.0427	nan	0.1000	-0.0001
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3562	nan	0.1000	0.0160
##	2	1.3223	nan	0.1000	0.0134
##	3	1.3044	nan	0.1000	0.0067
##	4	1.2859	nan	0.1000	0.0090
##	5	1.2711	nan	0.1000	0.0072

##	6	1.2507	nan	0.1000	0.0076
##	7	1.2345	nan	0.1000	0.0052
##	8	1.2265	nan	0.1000	0.0018
##	9	1.2143	nan	0.1000	0.0047
##	10	1.2049	nan	0.1000	0.0032
##	20	1.1338	nan	0.1000	0.0015
##	40	1.0737	nan	0.1000	-0.0015
##	60	1.0487	nan	0.1000	-0.0040
##	80	1.0207	nan	0.1000	-0.0019
##	100	0.9995	nan	0.1000	-0.0027
##	120	0.9691	nan	0.1000	-0.0012
##	140	0.9453	nan	0.1000	-0.0031
##	150	0.9358	nan	0.1000	-0.0040
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.2910	nan	0.1000	0.0431
##	2	1.2202	nan	0.1000	0.0330
##	3	1.1317	nan	0.1000	0.0425
##	4	1.0814	nan	0.1000	0.0226
##	5	0.9961	nan	0.1000	0.0384
##	6	0.9359	nan	0.1000	0.0270
##	7	0.8857	nan	0.1000	0.0238
##	8	0.8759	nan	0.1000	0.0028
##	9	0.8480	nan	0.1000	0.0111
##	10	0.7955	nan	0.1000	0.0239
##	20	0.5915	nan	0.1000	-0.0015
##	40	0.4659	nan	0.1000	-0.0015
##	60	0.3820	nan	0.1000	-0.0015
##	80	0.2680	nan	0.1000	0.0038
##	100	0.1881	nan	0.1000	-0.0008
##	120	0.1379	nan	0.1000	0.0006
##	140	0.1184	nan	0.1000	-0.0004
##	150	0.1120	nan	0.1000	-0.0011
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.2731	nan	0.1000	0.0528
##	2	1.1796	nan	0.1000	0.0390
##	3	1.0329	nan	0.1000	0.0719
##	4	0.9220	nan	0.1000	0.0520
##	5	0.8683	nan	0.1000	0.0213
##	6	0.7985	nan	0.1000	0.0302
##	7	0.7104	nan	0.1000	0.0424
##	8	0.6358	nan	0.1000	0.0373
##	9	0.5989	nan	0.1000	0.0147
##	10	0.5428	nan	0.1000	0.0271
##	20	0.2595	nan	0.1000	0.0104
##	40	0.1033	nan	0.1000	0.0001
##	60	0.0669	nan	0.1000	0.0006
##	80	0.0438	nan	0.1000	0.0005
##	100	0.0322	nan	0.1000	-0.0002
##	120	0.0261	nan	0.1000	-0.0001
##	140	0.0194	nan	0.1000	-0.0001
##	150	0.0165	nan	0.1000	-0.0001
##					

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3539	nan	0.1000	0.0154
##	2	1.3272	nan	0.1000	0.0115
##	3	1.3051	nan	0.1000	0.0097
##	4	1.2835	nan	0.1000	0.0088
##	5	1.2661	nan	0.1000	0.0071
##	6	1.2490	nan	0.1000	0.0059
##	7	1.2337	nan	0.1000	0.0044
##	8	1.2229	nan	0.1000	0.0013
##	9	1.2141	nan	0.1000	-0.0006
##	10	1.2030	nan	0.1000	0.0022
##	20	1.1416	nan	0.1000	0.0029
##	40	1.0702	nan	0.1000	-0.0015
##	60	1.0323	nan	0.1000	-0.0004
##	80	1.0069	nan	0.1000	-0.0053
##	100	0.9787	nan	0.1000	-0.0023
##	120	0.9597	nan	0.1000	-0.0026
##	140	0.9397	nan	0.1000	-0.0023
##	150	0.9311	nan	0.1000	-0.0011
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.2951	nan	0.1000	0.0406
##	2	1.2121	nan	0.1000	0.0339
##	3	1.1778	nan	0.1000	0.0131
##	4	1.0954	nan	0.1000	0.0386
##	5	1.0538	nan	0.1000	0.0161
##	6	0.9830	nan	0.1000	0.0338
##	7	0.9289	nan	0.1000	0.0223
##	8	0.8704	nan	0.1000	0.0283
##	9	0.8325	nan	0.1000	0.0180
##	10	0.7839	nan	0.1000	0.0236
##	20	0.6163	nan	0.1000	-0.0021
##	40	0.4384	nan	0.1000	-0.0001
##	60	0.3764	nan	0.1000	-0.0018
##	80	0.2848	nan	0.1000	-0.0009
##	100	0.2170	nan	0.1000	-0.0016
##	120	0.1841	nan	0.1000	-0.0004
##	140	0.1608	nan	0.1000	-0.0005
##	150	0.1460	nan	0.1000	-0.0009
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.2663	nan	0.1000	0.0547
##	2	1.1160	nan	0.1000	0.0761
##	3	1.0325	nan	0.1000	0.0399
##	4	0.9214	nan	0.1000	0.0551
##	5	0.8226	nan	0.1000	0.0494
##	6	0.7612	nan	0.1000	0.0278
##	7	0.7159	nan	0.1000	0.0212
##	8	0.6507	nan	0.1000	0.0314
##	9	0.6098	nan	0.1000	0.0185
##	10	0.5527	nan	0.1000	0.0279
##	20	0.2811	nan	0.1000	0.0035
##	40	0.1553	nan	0.1000	-0.0007
##	60	0.1123	nan	0.1000	-0.0009

##	80	0.0891	nan	0.1000	-0.0009
##	100	0.0698	nan	0.1000	-0.0007
##	120	0.0595	nan	0.1000	-0.0003
##	140	0.0443	nan	0.1000	0.0009
##	150	0.0384	nan	0.1000	-0.0003
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3519	nan	0.1000	0.0167
##	2	1.3199	nan	0.1000	0.0136
##	3	1.2876	nan	0.1000	0.0131
##	4	1.2569	nan	0.1000	0.0082
##	5	1.2359	nan	0.1000	0.0083
##	6	1.2204	nan	0.1000	0.0058
##	7	1.2083	nan	0.1000	0.0066
##	8	1.1980	nan	0.1000	0.0033
##	9	1.1847	nan	0.1000	0.0038
##	10	1.1766	nan	0.1000	0.0025
##	20	1.1266	nan	0.1000	-0.0070
##	40	1.0782	nan	0.1000	-0.0053
##	60	1.0272	nan	0.1000	-0.0012
##	80	1.0032	nan	0.1000	-0.0026
##	100	0.9713	nan	0.1000	-0.0044
##	120	0.9513	nan	0.1000	-0.0022
##	140	0.9266	nan	0.1000	-0.0020
##	150	0.9199	nan	0.1000	-0.0012
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.2985	nan	0.1000	0.0440
##	2	1.2191	nan	0.1000	0.0368
##	3	1.1532	nan	0.1000	0.0313
##	4	1.0831	nan	0.1000	0.0316
##	5	1.0175	nan	0.1000	0.0286
##	6	0.9506	nan	0.1000	0.0333
##	7	0.9005	nan	0.1000	0.0238
##	8	0.8686	nan	0.1000	0.0129
##	9	0.8166	nan	0.1000	0.0248
##	10	0.7902	nan	0.1000	0.0104
##	20	0.5823	nan	0.1000	0.0007
##	40	0.4651	nan	0.1000	-0.0009
##	60	0.4138	nan	0.1000	-0.0007
##	80	0.3336	nan	0.1000	0.0044
##	100	0.2688	nan	0.1000	-0.0020
##	120	0.2221	nan	0.1000	-0.0010
##	140	0.1734	nan	0.1000	-0.0004
##	150	0.1640	nan	0.1000	-0.0011
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.2105	nan	0.1000	0.0892
##	2	1.0937	nan	0.1000	0.0554
##	3	0.9982	nan	0.1000	0.0455
##	4	0.9201	nan	0.1000	0.0348
##	5	0.8556	nan	0.1000	0.0310
##	6	0.7615	nan	0.1000	0.0445
##	7	0.7230	nan	0.1000	0.0181

##	8	0.6524	nan	0.1000	0.0358
##	9	0.6075	nan	0.1000	0.0214
##	10	0.5494	nan	0.1000	0.0280
##	20	0.2620	nan	0.1000	0.0087
##	40	0.1381	nan	0.1000	0.0000
##	60	0.1029	nan	0.1000	-0.0004
##	80	0.0834	nan	0.1000	-0.0002
##	100	0.0629	nan	0.1000	-0.0006
##	120	0.0487	nan	0.1000	-0.0002
##	140	0.0396	nan	0.1000	-0.0002
##	150	0.0339	nan	0.1000	-0.0000

##

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3533	nan	0.1000	0.0181
##	2	1.3196	nan	0.1000	0.0145
##	3	1.2960	nan	0.1000	0.0111
##	4	1.2695	nan	0.1000	0.0111
##	5	1.2514	nan	0.1000	0.0052
##	6	1.2395	nan	0.1000	0.0044
##	7	1.2220	nan	0.1000	0.0065
##	8	1.2106	nan	0.1000	0.0048
##	9	1.1974	nan	0.1000	0.0033
##	10	1.1862	nan	0.1000	0.0031
##	20	1.1321	nan	0.1000	-0.0031
##	40	1.0673	nan	0.1000	-0.0022
##	60	1.0225	nan	0.1000	-0.0030
##	80	0.9930	nan	0.1000	-0.0064
##	100	0.9647	nan	0.1000	-0.0009
##	120	0.9449	nan	0.1000	-0.0018
##	140	0.9193	nan	0.1000	-0.0027
##	150	0.9068	nan	0.1000	-0.0013

##

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.2663	nan	0.1000	0.0547
##	2	1.1833	nan	0.1000	0.0408
##	3	1.1114	nan	0.1000	0.0367
##	4	1.0585	nan	0.1000	0.0229
##	5	0.9853	nan	0.1000	0.0383
##	6	0.9274	nan	0.1000	0.0285
##	7	0.9037	nan	0.1000	0.0104
##	8	0.8494	nan	0.1000	0.0241
##	9	0.7968	nan	0.1000	0.0248
##	10	0.7710	nan	0.1000	0.0083
##	20	0.5931	nan	0.1000	0.0055
##	40	0.4628	nan	0.1000	0.0006
##	60	0.3454	nan	0.1000	0.0004
##	80	0.2582	nan	0.1000	-0.0005
##	100	0.1920	nan	0.1000	-0.0006
##	120	0.1675	nan	0.1000	-0.0010
##	140	0.1295	nan	0.1000	0.0007
##	150	0.1189	nan	0.1000	0.0002

##

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.2165	nan	0.1000	0.0833

##	2	1.1405	nan	0.1000	0.0342
##	3	1.0471	nan	0.1000	0.0415
##	4	0.9261	nan	0.1000	0.0592
##	5	0.8543	nan	0.1000	0.0304
##	6	0.7629	nan	0.1000	0.0449
##	7	0.6850	nan	0.1000	0.0393
##	8	0.6170	nan	0.1000	0.0332
##	9	0.5570	nan	0.1000	0.0285
##	10	0.5063	nan	0.1000	0.0247
##	20	0.2631	nan	0.1000	0.0096
##	40	0.1302	nan	0.1000	-0.0005
##	60	0.0995	nan	0.1000	0.0003
##	80	0.0703	nan	0.1000	-0.0005
##	100	0.0529	nan	0.1000	-0.0008
##	120	0.0404	nan	0.1000	-0.0002
##	140	0.0314	nan	0.1000	0.0002
##	150	0.0293	nan	0.1000	-0.0002

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3554	nan	0.1000	0.0161
##	2	1.3251	nan	0.1000	0.0116
##	3	1.3094	nan	0.1000	0.0047
##	4	1.2825	nan	0.1000	0.0033
##	5	1.2652	nan	0.1000	0.0070
##	6	1.2549	nan	0.1000	0.0015
##	7	1.2338	nan	0.1000	0.0082
##	8	1.2217	nan	0.1000	0.0067
##	9	1.2157	nan	0.1000	-0.0003
##	10	1.2039	nan	0.1000	0.0024
##	20	1.1335	nan	0.1000	0.0014
##	40	1.0678	nan	0.1000	-0.0011
##	60	1.0319	nan	0.1000	-0.0002
##	80	0.9962	nan	0.1000	-0.0034
##	100	0.9724	nan	0.1000	-0.0012
##	120	0.9456	nan	0.1000	-0.0045
##	140	0.9231	nan	0.1000	-0.0008
##	150	0.9179	nan	0.1000	-0.0026

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.2862	nan	0.1000	0.0480
##	2	1.2128	nan	0.1000	0.0334
##	3	1.1442	nan	0.1000	0.0327
##	4	1.0929	nan	0.1000	0.0247
##	5	1.0390	nan	0.1000	0.0289
##	6	1.0000	nan	0.1000	0.0188
##	7	0.9630	nan	0.1000	0.0168
##	8	0.9177	nan	0.1000	0.0192
##	9	0.8574	nan	0.1000	0.0289
##	10	0.8144	nan	0.1000	0.0197
##	20	0.5949	nan	0.1000	-0.0005
##	40	0.4647	nan	0.1000	0.0084
##	60	0.3544	nan	0.1000	-0.0007
##	80	0.2892	nan	0.1000	0.0001
##	100	0.2296	nan	0.1000	0.0005

##	120	0.1639	nan	0.1000	-0.0017
##	140	0.1344	nan	0.1000	-0.0007
##	150	0.1224	nan	0.1000	-0.0005
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.2835	nan	0.1000	0.0474
##	2	1.1702	nan	0.1000	0.0514
##	3	1.0360	nan	0.1000	0.0657
##	4	0.9537	nan	0.1000	0.0377
##	5	0.8822	nan	0.1000	0.0344
##	6	0.8260	nan	0.1000	0.0247
##	7	0.8054	nan	0.1000	0.0043
##	8	0.7506	nan	0.1000	0.0241
##	9	0.6953	nan	0.1000	0.0287
##	10	0.6232	nan	0.1000	0.0355
##	20	0.2917	nan	0.1000	0.0063
##	40	0.1268	nan	0.1000	-0.0011
##	60	0.0898	nan	0.1000	-0.0007
##	80	0.0735	nan	0.1000	-0.0007
##	100	0.0577	nan	0.1000	-0.0003
##	120	0.0435	nan	0.1000	0.0014
##	140	0.0342	nan	0.1000	-0.0001
##	150	0.0323	nan	0.1000	-0.0004
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3515	nan	0.1000	0.0143
##	2	1.3225	nan	0.1000	0.0145
##	3	1.3060	nan	0.1000	0.0110
##	4	1.2858	nan	0.1000	0.0053
##	5	1.2649	nan	0.1000	0.0044
##	6	1.2506	nan	0.1000	0.0060
##	7	1.2338	nan	0.1000	0.0058
##	8	1.2236	nan	0.1000	0.0037
##	9	1.2130	nan	0.1000	0.0049
##	10	1.2088	nan	0.1000	-0.0035
##	20	1.1515	nan	0.1000	-0.0029
##	40	1.0930	nan	0.1000	-0.0025
##	60	1.0591	nan	0.1000	-0.0026
##	80	1.0306	nan	0.1000	-0.0017
##	100	1.0109	nan	0.1000	-0.0021
##	120	0.9929	nan	0.1000	-0.0043
##	140	0.9641	nan	0.1000	-0.0012
##	150	0.9541	nan	0.1000	-0.0021
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.2783	nan	0.1000	0.0506
##	2	1.1842	nan	0.1000	0.0446
##	3	1.1201	nan	0.1000	0.0235
##	4	1.0644	nan	0.1000	0.0242
##	5	0.9842	nan	0.1000	0.0412
##	6	0.9231	nan	0.1000	0.0282
##	7	0.9061	nan	0.1000	0.0050
##	8	0.8839	nan	0.1000	0.0115
##	9	0.8320	nan	0.1000	0.0222

##	10	0.8203	nan	0.1000	0.0045
##	20	0.6347	nan	0.1000	0.0223
##	40	0.5379	nan	0.1000	-0.0015
##	60	0.4212	nan	0.1000	-0.0008
##	80	0.3151	nan	0.1000	0.0001
##	100	0.2510	nan	0.1000	-0.0012
##	120	0.2000	nan	0.1000	0.0013
##	140	0.1468	nan	0.1000	0.0021
##	150	0.1223	nan	0.1000	-0.0005
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3321	nan	0.1000	0.0151
##	2	1.1716	nan	0.1000	0.0777
##	3	1.0262	nan	0.1000	0.0722
##	4	0.9617	nan	0.1000	0.0245
##	5	0.8523	nan	0.1000	0.0554
##	6	0.7961	nan	0.1000	0.0309
##	7	0.7104	nan	0.1000	0.0430
##	8	0.6331	nan	0.1000	0.0370
##	9	0.5697	nan	0.1000	0.0321
##	10	0.5218	nan	0.1000	0.0229
##	20	0.2631	nan	0.1000	0.0031
##	40	0.0963	nan	0.1000	-0.0003
##	60	0.0623	nan	0.1000	0.0004
##	80	0.0397	nan	0.1000	-0.0001
##	100	0.0287	nan	0.1000	0.0001
##	120	0.0219	nan	0.1000	-0.0003
##	140	0.0176	nan	0.1000	0.0003
##	150	0.0158	nan	0.1000	-0.0001
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3510	nan	0.1000	0.0164
##	2	1.3199	nan	0.1000	0.0155
##	3	1.3048	nan	0.1000	0.0044
##	4	1.2789	nan	0.1000	0.0111
##	5	1.2602	nan	0.1000	0.0084
##	6	1.2452	nan	0.1000	0.0082
##	7	1.2326	nan	0.1000	0.0053
##	8	1.2158	nan	0.1000	0.0052
##	9	1.2114	nan	0.1000	-0.0006
##	10	1.2016	nan	0.1000	0.0038
##	20	1.1399	nan	0.1000	-0.0034
##	40	1.0943	nan	0.1000	-0.0038
##	60	1.0531	nan	0.1000	-0.0018
##	80	1.0243	nan	0.1000	-0.0026
##	100	1.0018	nan	0.1000	-0.0036
##	120	0.9730	nan	0.1000	-0.0008
##	140	0.9511	nan	0.1000	-0.0016
##	150	0.9423	nan	0.1000	-0.0051
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.2926	nan	0.1000	0.0406
##	2	1.1940	nan	0.1000	0.0411
##	3	1.1254	nan	0.1000	0.0322

##	4	1.0547	nan	0.1000	0.0315
##	5	0.9893	nan	0.1000	0.0299
##	6	0.9453	nan	0.1000	0.0204
##	7	0.8863	nan	0.1000	0.0278
##	8	0.8487	nan	0.1000	0.0189
##	9	0.8064	nan	0.1000	0.0198
##	10	0.7643	nan	0.1000	0.0195
##	20	0.5916	nan	0.1000	0.0097
##	40	0.4255	nan	0.1000	0.0029
##	60	0.3512	nan	0.1000	-0.0011
##	80	0.3044	nan	0.1000	-0.0010
##	100	0.2415	nan	0.1000	-0.0005
##	120	0.2136	nan	0.1000	-0.0016
##	140	0.1718	nan	0.1000	-0.0002
##	150	0.1588	nan	0.1000	0.0020
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.2078	nan	0.1000	0.0864
##	2	1.0797	nan	0.1000	0.0624
##	3	0.9563	nan	0.1000	0.0605
##	4	0.8547	nan	0.1000	0.0504
##	5	0.7947	nan	0.1000	0.0304
##	6	0.7243	nan	0.1000	0.0354
##	7	0.6772	nan	0.1000	0.0209
##	8	0.6293	nan	0.1000	0.0240
##	9	0.5716	nan	0.1000	0.0277
##	10	0.5182	nan	0.1000	0.0244
##	20	0.2589	nan	0.1000	0.0087
##	40	0.1297	nan	0.1000	0.0002
##	60	0.0956	nan	0.1000	-0.0004
##	80	0.0765	nan	0.1000	-0.0004
##	100	0.0640	nan	0.1000	-0.0003
##	120	0.0501	nan	0.1000	-0.0004
##	140	0.0419	nan	0.1000	-0.0008
##	150	0.0373	nan	0.1000	-0.0004
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3475	nan	0.1000	0.0179
##	2	1.3175	nan	0.1000	0.0128
##	3	1.2842	nan	0.1000	0.0124
##	4	1.2637	nan	0.1000	0.0108
##	5	1.2463	nan	0.1000	0.0075
##	6	1.2243	nan	0.1000	0.0057
##	7	1.2111	nan	0.1000	0.0060
##	8	1.1992	nan	0.1000	0.0062
##	9	1.1875	nan	0.1000	0.0036
##	10	1.1781	nan	0.1000	0.0021
##	20	1.1086	nan	0.1000	-0.0018
##	40	1.0456	nan	0.1000	-0.0013
##	60	1.0124	nan	0.1000	-0.0024
##	80	0.9821	nan	0.1000	-0.0036
##	100	0.9524	nan	0.1000	-0.0020
##	120	0.9287	nan	0.1000	-0.0044
##	140	0.9075	nan	0.1000	-0.0034

```

##      150      0.9045      nan      0.1000     -0.0003
##
## Iter   TrainDeviance   ValidDeviance   StepSize   Improve
##      1      1.2775      nan      0.1000      0.0583
##      2      1.1865      nan      0.1000      0.0385
##      3      1.1085      nan      0.1000      0.0370
##      4      1.0617      nan      0.1000      0.0200
##      5      1.0070      nan      0.1000      0.0258
##      6      0.9678      nan      0.1000      0.0138
##      7      0.9335      nan      0.1000      0.0160
##      8      0.8985      nan      0.1000      0.0145
##      9      0.8576      nan      0.1000      0.0152
##     10      0.8420      nan      0.1000      0.0049
##     20      0.6234      nan      0.1000     -0.0001
##     40      0.4655      nan      0.1000      0.0021
##     60      0.3536      nan      0.1000      0.0007
##     80      0.2844      nan      0.1000     -0.0012
##    100      0.2451      nan      0.1000     -0.0003
##    120      0.2098      nan      0.1000     -0.0010
##    140      0.1717      nan      0.1000     -0.0007
##    150      0.1674      nan      0.1000     -0.0009
##
## Iter   TrainDeviance   ValidDeviance   StepSize   Improve
##      1      1.2646      nan      0.1000      0.0614
##      2      1.2187      nan      0.1000      0.0174
##      3      1.0767      nan      0.1000      0.0728
##      4      1.0486      nan      0.1000      0.0122
##      5      0.9441      nan      0.1000      0.0509
##      6      0.8712      nan      0.1000      0.0343
##      7      0.8386      nan      0.1000      0.0144
##      8      0.7800      nan      0.1000      0.0257
##      9      0.7374      nan      0.1000      0.0186
##     10      0.6923      nan      0.1000      0.0204
##     20      0.3854      nan      0.1000      0.0176
##     40      0.1881      nan      0.1000      0.0059
##     60      0.1368      nan      0.1000      0.0011
##     80      0.1115      nan      0.1000     -0.0002
##    100      0.0886      nan      0.1000     -0.0010
##    120      0.0703      nan      0.1000     -0.0002
##    140      0.0524      nan      0.1000     -0.0001
##    150      0.0473      nan      0.1000     -0.0006
##
## Iter   TrainDeviance   ValidDeviance   StepSize   Improve
##      1      1.3540      nan      0.1000      0.0108
##      2      1.3228      nan      0.1000      0.0121
##      3      1.2968      nan      0.1000      0.0111
##      4      1.2808      nan      0.1000      0.0096
##      5      1.2635      nan      0.1000      0.0070
##      6      1.2617      nan      0.1000     -0.0023
##      7      1.2472      nan      0.1000      0.0052
##      8      1.2317      nan      0.1000      0.0072
##      9      1.2241      nan      0.1000     -0.0008
##     10      1.2115      nan      0.1000      0.0025
##     20      1.1355      nan      0.1000     -0.0017

```

##	40	1.0758	nan	0.1000	-0.0034
##	60	1.0409	nan	0.1000	-0.0043
##	80	1.0110	nan	0.1000	-0.0020
##	100	0.9871	nan	0.1000	-0.0008
##	120	0.9617	nan	0.1000	-0.0051
##	140	0.9384	nan	0.1000	-0.0019
##	150	0.9329	nan	0.1000	-0.0050
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.2972	nan	0.1000	0.0405
##	2	1.2183	nan	0.1000	0.0378
##	3	1.1504	nan	0.1000	0.0340
##	4	1.0883	nan	0.1000	0.0246
##	5	1.0674	nan	0.1000	0.0096
##	6	1.0445	nan	0.1000	0.0076
##	7	0.9990	nan	0.1000	0.0199
##	8	0.9224	nan	0.1000	0.0338
##	9	0.9044	nan	0.1000	0.0045
##	10	0.8782	nan	0.1000	0.0088
##	20	0.6760	nan	0.1000	-0.0009
##	40	0.5285	nan	0.1000	0.0001
##	60	0.4527	nan	0.1000	-0.0016
##	80	0.3832	nan	0.1000	-0.0011
##	100	0.3165	nan	0.1000	-0.0008
##	120	0.2496	nan	0.1000	0.0040
##	140	0.2136	nan	0.1000	0.0003
##	150	0.1925	nan	0.1000	-0.0007
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.2326	nan	0.1000	0.0748
##	2	1.1773	nan	0.1000	0.0265
##	3	1.0755	nan	0.1000	0.0483
##	4	1.0347	nan	0.1000	0.0162
##	5	0.9491	nan	0.1000	0.0416
##	6	0.9037	nan	0.1000	0.0191
##	7	0.8115	nan	0.1000	0.0442
##	8	0.7350	nan	0.1000	0.0377
##	9	0.7111	nan	0.1000	0.0094
##	10	0.6389	nan	0.1000	0.0368
##	20	0.4444	nan	0.1000	0.0010
##	40	0.2072	nan	0.1000	-0.0002
##	60	0.1496	nan	0.1000	-0.0007
##	80	0.1227	nan	0.1000	-0.0010
##	100	0.1009	nan	0.1000	0.0004
##	120	0.0758	nan	0.1000	-0.0005
##	140	0.0601	nan	0.1000	-0.0002
##	150	0.0541	nan	0.1000	-0.0005
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	1.3345	nan	0.1000	0.0165
##	2	1.2072	nan	0.1000	0.0638
##	3	1.1068	nan	0.1000	0.0478
##	4	0.9793	nan	0.1000	0.0644
##	5	0.9074	nan	0.1000	0.0343

```
##      6      0.8415      nan      0.1000      0.0262
##      7      0.7672      nan      0.1000      0.0359
##      8      0.6904      nan      0.1000      0.0393
##      9      0.6456      nan      0.1000      0.0225
##     10      0.5947      nan      0.1000      0.0253
##     20      0.3133      nan      0.1000      0.0073
##     40      0.1374      nan      0.1000      0.0003
##     50      0.1235      nan      0.1000     -0.0015
```

```
stacking_results <- resamples(stacked_models)

stacking_summary<- summary(stacking_results)
stacking_summary
```

```
##
## Call:
## summary.resamples(object = stacking_results)
##
## Models: glm, knn, svmPoly, svmLinear, wsrfl, gbm
## Number of resamples: 10
##
## Accuracy
##           Min.   1st Qu.   Median     Mean   3rd Qu.   Max. NA's
## glm         0.609375 0.6757812 0.7031250 0.7093750 0.7500000 0.812500  0
## knn         0.640625 0.6914062 0.7421875 0.7375000 0.7656250 0.828125  0
## svmPoly     0.765625 0.7851562 0.8125000 0.8031250 0.8125000 0.843750  0
## svmLinear   0.765625 0.7851562 0.7968750 0.8015625 0.8125000 0.843750  0
## wsrfl       0.906250 0.9375000 0.9453125 0.9531250 0.9648438 1.000000  0
## gbm         0.953125 0.9570312 0.9843750 0.9765625 0.9843750 1.000000  0
##
## Kappa
##           Min.   1st Qu.   Median     Mean   3rd Qu.   Max. NA's
## glm         0.21875 0.3515625 0.406250 0.418750 0.5000000 0.62500  0
## knn         0.28125 0.3828125 0.484375 0.475000 0.5312500 0.65625  0
## svmPoly     0.53125 0.5703125 0.625000 0.606250 0.6250000 0.68750  0
## svmLinear   0.53125 0.5703125 0.593750 0.603125 0.6250000 0.68750  0
## wsrfl       0.81250 0.8750000 0.890625 0.906250 0.9296875 1.00000  0
## gbm         0.90625 0.9140625 0.968750 0.953125 0.9687500 1.00000  0
```

Plot results

```
glm_cm<- confusionMatrix(stacked_models$glm$pred$pred, stacked_models$glm$pred$obs)
knn_cm<- confusionMatrix(stacked_models$knn$pred$pred, stacked_models$knn$pred$obs)
svmPoly_cm<- confusionMatrix(stacked_models$svmPoly$pred$pred, stacked_models$svmPoly$pred$obs)
svmLinear_cm<- confusionMatrix(stacked_models$svmLinear$pred$pred, stacked_models$svmLinear$pred$obs)
wsrfl_cm<- confusionMatrix(stacked_models$wsrfl$pred$pred, stacked_models$wsrfl$pred$obs)
gbm_cm<- confusionMatrix(stacked_models$gbm$pred$pred, stacked_models$gbm$pred$obs)

data <- data.frame(matrix(c(0.7109, 0.7422, 0.7969, 0.7953, 0.9578, 0.9734,
                           0.7344, 0.7562, 0.9938, 1.0000, 0.9625, 0.9812,
                           0.6875, 0.7281, 0.6000, 0.5906, 0.9531, 0.9656,
```

```

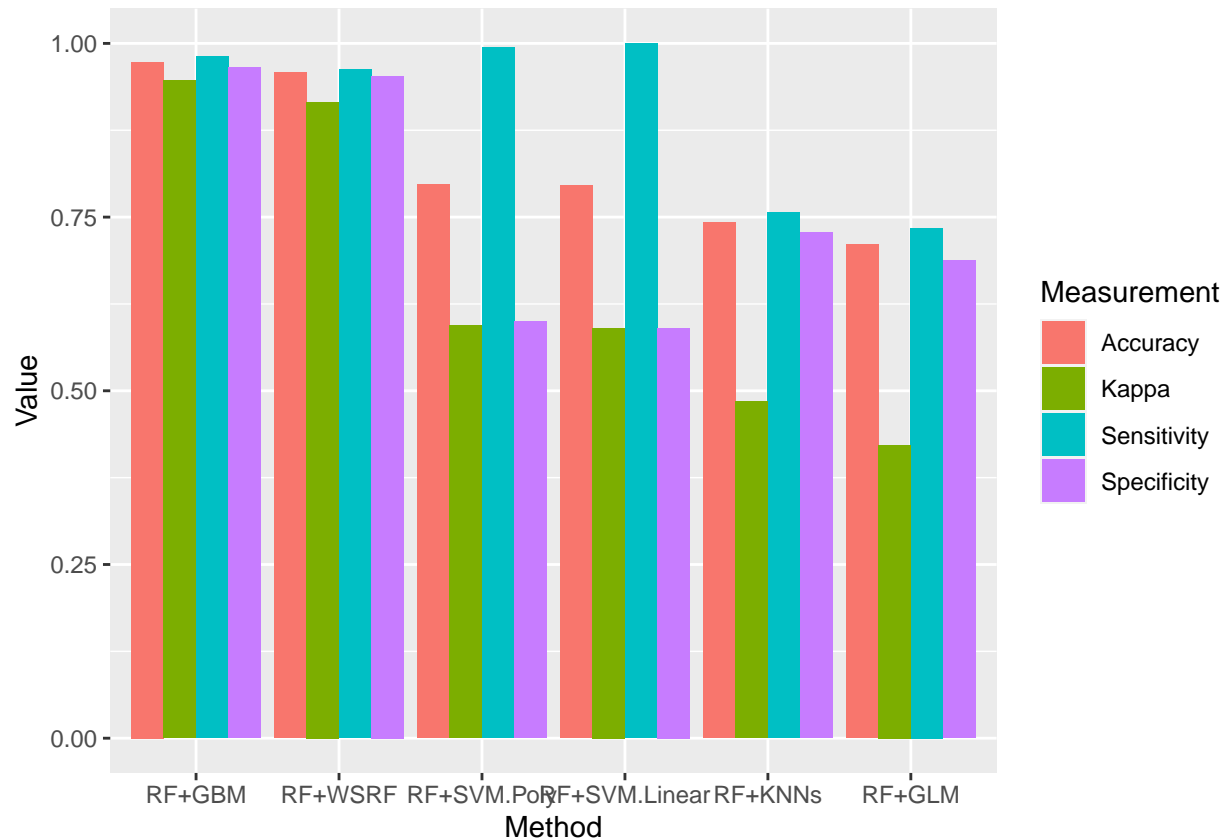
                                0.4219, 0.4844, 0.5938, 0.5906, 0.9156, 0.9469),6,4))
row <- c("RF+GLM", "RF+KNNs", "RF+SVM.Poly", "RF+SVM.Linear", "RF+WSRF", "RF+GBM")
col <- c("Accuracy", "Sensitivity", "Specificity", "Kappa")
colnames(data) <- col
data$Method <- row
rownames(data) <- c(1:6)
data1<- data[,c(5,1,2,3,4)]

#write.csv(data, "ensemble_result.csv")
#plotting
library(ggplot2)

data2 <- tidyr::gather(data1, key="Measurement", value="Value", 2:5)

# Grouped
ggplot(data2, aes(fill=Measurement, y=Value, x=reorder(Method, -Value))) +
  geom_bar(position="dodge", stat="identity")+
  xlab("Method")

```



NLP in Transcription

document summarize

```
# write summerizer function  
library(textmineR)
```

```
## Warning: package 'textmineR' was built under R version 4.2.2
```

```
## Loading required package: Matrix
```

```
## Warning: package 'Matrix' was built under R version 4.2.2
```

```
##
```

```
## Attaching package: 'Matrix'
```

```
## The following objects are masked from 'package:tidyr':
```

```
##
```

```
##      expand, pack, unpack
```

```
##
```

```
## Attaching package: 'textmineR'
```

```
## The following object is masked from 'package:Matrix':
```

```
##
```

```
##      update
```

```
## The following object is masked from 'package:stats':
```

```
##
```

```
##      update
```

```
library(igraph)
```

```
## Warning: package 'igraph' was built under R version 4.2.2
```

```
##
```

```
## Attaching package: 'igraph'
```

```
## The following object is masked from 'package:wsrf':
```

```
##
```

```
##      strength
```

```
## The following object is masked from 'package:class':
```

```
##
```

```
##      knn
```

```
## The following objects are masked from 'package:dplyr':
```

```
##
```

```
##      as_data_frame, groups, union
```



```
## The following objects are masked from 'package:purrr':
##
##   compose, simplify
```

```
## The following object is masked from 'package:tidyr':
##
##   crossing
```

```
## The following object is masked from 'package:tibble':
##
##   as_data_frame
```

```
## The following objects are masked from 'package:stats':
##
##   decompose, spectrum
```

```
## The following object is masked from 'package:base':
##
##   union
```

```
tcm <- CreateTcm(doc_vec = MU3D_Video_Level_Data$Transcription,
                 skipgram_window = 10,
                 verbose = FALSE,
                 cpus = 2)
```

as(<dgTMatrix>, "dgCMatrix") is deprecated since Matrix 1.5-0; do as(., "CsparseMatrix") instead

```
# use LDA to get embeddings into probability space
# This will take considerably longer as the TCM matrix has many more rows
# than a DTM
```

```
embeddings <- FitLdaModel(dtm = tcm,
                          k = 50,
                          iterations = 200,
                          burnin = 180,
                          alpha = 0.1,
                          beta = 0.05,
                          optimize_alpha = TRUE,
                          calc_likelihood = FALSE,
                          calc_coherence = FALSE,
                          calc_r2 = FALSE,
                          cpus = 2)
```

```
summarizer <- function(doc, gamma) {
```

```
  # recursive fanciness to handle multiple docs at once
  if (length(doc) > 1 )
    # use a try statement to catch any weirdness that may arise
    return(sapply(doc, function(d) try(summarizer(d, gamma))))
```

```
  # parse it into sentences
```

```
  sent <- stringi::stri_split_boundaries(doc, type = "sentence")[[ 1 ]]
```

```

names(sent) <- seq_along(sent) # so we know index and order

# embed the sentences in the model
e <- CreateDtm(sent, ngram_window = c(1,1), verbose = FALSE, cpus = 2)

# remove any documents with 2 or fewer words
e <- e[ rowSums(e) > 2 , ]

vocab <- intersect(colnames(e), colnames(gamma))

e <- e / rowSums(e)

e <- e[ , vocab ] %*% t(gamma[ , vocab ])

e <- as.matrix(e)

# get the pairwise distances between each embedded sentence
e_dist <- CalcHellingerDist(e)

# turn into a similarity matrix
g <- (1 - e_dist) * 100

# we don't need sentences connected to themselves
diag(g) <- 0

# turn into a nearest-neighbor graph
g <- apply(g, 1, function(x){
  x[ x < sort(x, decreasing = TRUE)[ 3 ] ] <- 0
  x
})

# by taking pointwise max, we'll make the matrix symmetric again
g <- pmax(g, t(g))

g <- graph.adjacency(g, mode = "undirected", weighted = TRUE)

# calculate eigenvector centrality
ev <- evcent(g)

# format the result
result <- sent[ names(ev$vector)[ order(ev$vector, decreasing = TRUE)[ 1:3 ] ] ]

result <- result[ order(as.numeric(names(result))) ]

paste(result, collapse = " ")
}

```

Summarize text

```

docs <- MU3D_Video_Level_Data$Transcription[1]
sums <- summarizer(docs, gamma = embeddings$gamma)
docs

```

```
## [1] "My best friend is a really nice person. Um. She's always kind to everyone. She continues to just  
sums
```

```
## [1] "She has taught me so much throughout, like I've known her maybe a year and a half and she's taught
```