

# Prosocial Analysis

## Prosocial Parent + Child, All Attributes

```
library(caret)
```

```
## Warning: package 'caret' was built under R version 3.6.2
```

```
## Loading required package: lattice
```

```
## Loading required package: ggplot2
```

```
df <- read.csv('cleandata.csv')
df<- df[(df$prosocial_parent <= (3)) | (df$prosocial_parent == 6), ]
df<- df[(df$prosocial_child <= (3)) | (df$prosocial_child == 6), ]
df$prosocial_sum <- df$prosocial_parent+df$prosocial_child
df <- df[df$prosocial_sum != 9, ]
df <- df[df$prosocial_sum != 8, ]
df <- df[df$prosocial_sum != 7, ]
cut <- df[df$prosocial_sum == 6, ]
cut <- cut[cut$prosocial_child != 3, ]
df <- subset(df, !(subjectkey %in% cut$subjectkey))

df$y <- ifelse(df$prosocial_sum <= (6), 0, 1)
df <- subset(df, select=-c(X,aggressive_sumscore , prosocial_child, prosocial_parent,
interview_date, interview_age, subjectkey, prosocial_sum))
```

```

library('miscTools')
cm_tb <- data.frame(matrix(ncol = 11, nrow = 0))
colnames(cm_tb) <- c("Sensitivity", "Specificity", "Pos Pred Value", "Neg Pred Value",
, "Precision", "Recall", "F1", "Prevalence", "Detection Rate", "Detection Prevalence"
, "Balanced Accuracy")

truedf <- df[df$y==1,]
truedf <- truedf[sample(1:nrow(truedf), 200, replace = TRUE), ]
falsedf <- df[df$y==0,]
falsedf <- falsedf[sample(1:nrow(falsedf), 200, replace = TRUE), ]

finaldf <- rbind(truedf, falsedf)
glm.fit <- glm(y ~ ., data = finaldf, family = binomial)

summary(glm.fit)

```

```

##
## Call:
## glm(formula = y ~ ., family = binomial, data = finaldf)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -2.46203  -0.47470   0.00792   0.42255   2.54893
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)    -20.59969     7.79488  -2.643 0.008224 **
## asr_scr_perstr_t     0.06403     0.02290   2.796 0.005167 **
## asr_scr_anxdep_t    -0.10873     0.08617  -1.262 0.207019
## asr_scr_withdrawn_t -0.02139     0.07689  -0.278 0.780911
## asr_scr_somatic_t   -0.28039     0.12327  -2.275 0.022932 *
## asr_scr_thought_t    0.10438     0.05715   1.826 0.067778 .
## asr_scr_attention_t -0.09900     0.11034  -0.897 0.369573
## asr_scr_aggressive_t  0.11435     0.09477   1.207 0.227614
## asr_scr_rulebreak_t   0.07050     0.07312   0.964 0.334969
## asr_scr_intrusive_t   0.15219     0.06488   2.346 0.018990 *
## asr_scr_internal_t    0.08195     0.07938   1.032 0.301876
## asr_scr_external_t   -0.15935     0.07027  -2.268 0.023350 *
## asr_scr_totprob_t    -0.03393     0.11146  -0.304 0.760790
## asr_scr_depress_t     0.09531     0.08788   1.085 0.278141
## asr_scr_anxdisord_t   0.04146     0.06641   0.624 0.532421
## asr_scr_somaticpr_t   0.16956     0.10021   1.692 0.090655 .
## asr_scr_avoidant_t   -0.06946     0.06137  -1.132 0.257675
## asr_scr_adhd_t       -0.06132     0.21170  -0.290 0.772085
## asr_scr_antisocial_t  0.09308     0.08079   1.152 0.249233

```

```
## asr_scr_inattention_t      0.07709      0.14200      0.543 0.587176
## asr_scr_hyperactive_t      0.02589      0.13883      0.186 0.852076
## crpbi_bothcare             0.01846      0.02798      0.660 0.509444
## parent_monitor_y           1.06934      0.36280      2.947 0.003204 **
## kbi_p_conflict             -1.42586      0.41956     -3.398 0.000678 ***
## kbi_p_c_best_friend        -0.23850      0.20310     -1.174 0.240256
## kbi_p_c_reg_friend_group   -0.87584      0.44689     -1.960 0.050013 .
## kbi_p_c_bully              -0.36163      0.52446     -0.690 0.490485
## kbi_p_c_mh_sa              -1.21295      0.47741     -2.541 0.011064 *
## fes_youth                  -0.04578      0.09560     -0.479 0.632045
## fes_p_ss_fc_pr             -0.03826      0.09960     -0.384 0.700894
## macv_p_ss_fs               1.61283      0.45860      3.517 0.000437 ***
## macv_p_ss_fo              -0.78363      0.43374     -1.807 0.070811 .
## macv_p_ss_isr             -0.78134      0.33933     -2.303 0.021300 *
## macv_p_ss_fr               0.15248      0.34296      0.445 0.656612
## macv_p_ss_r               -0.86698      0.26310     -3.295 0.000983 ***
## demo_prnt_age_v2           0.05382      0.03202      1.681 0.092811 .
## demo_prnt_marital_v2       0.36297      0.14030      2.587 0.009680 **
## demo_comb_income_v2        0.13934      0.11311      1.232 0.217967
## demo_fam_exp               1.81122      0.66476      2.725 0.006437 **
## demo_yrs_1                 -0.44784      0.21837     -2.051 0.040284 *
## demo_yrs_2                 1.47077      0.33609      4.376 1.21e-05 ***
## parent_rules_q1            -0.06633      0.31508     -0.211 0.833260
## parent_rules_q4            -0.28319      0.41349     -0.685 0.493422
## parent_rules_q7            -0.08896      0.35081     -0.254 0.799823
## su_risk_p_1                -0.02480      0.15498     -0.160 0.872866
## su_risk_p_2_3              -0.25335      0.25313     -1.001 0.316889
## su_risk_p_4_5              0.01015      0.28731      0.035 0.971807
## neighborhood1_2_3_p        -0.23022      0.22623     -1.018 0.308842
## neighborhood_crime_y        0.47101      0.18954      2.485 0.012955 *
## sexM                       -2.31467      0.41698     -5.551 2.84e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 554.52  on 399  degrees of freedom
## Residual deviance: 268.69  on 350  degrees of freedom
## AIC: 368.69
##
## Number of Fisher Scoring iterations: 6
```

```
cm <- confusionMatrix(table(as.numeric(glm.fit$fitted.values>0.5), finaldf$y))
print(cm$byClass)
```

##	Sensitivity	Specificity	Pos Pred Value
##	0.8750000	0.8300000	0.8373206
##	Neg Pred Value	Precision	Recall
##	0.8691099	0.8373206	0.8750000
##	F1	Prevalence	Detection Rate
##	0.8557457	0.5000000	0.4375000
##	Detection Prevalence	Balanced Accuracy	
##	0.5225000	0.8525000	

```

for (t in 1:5000){
  truedf <- df[df$y==1,]
  truedf <- truedf[sample(1:nrow(truedf), 200, replace = TRUE), ]
  falsedf <- df[df$y==0,]
  falsedf <- falsedf[sample(1:nrow(falsedf), 200, replace = TRUE), ]

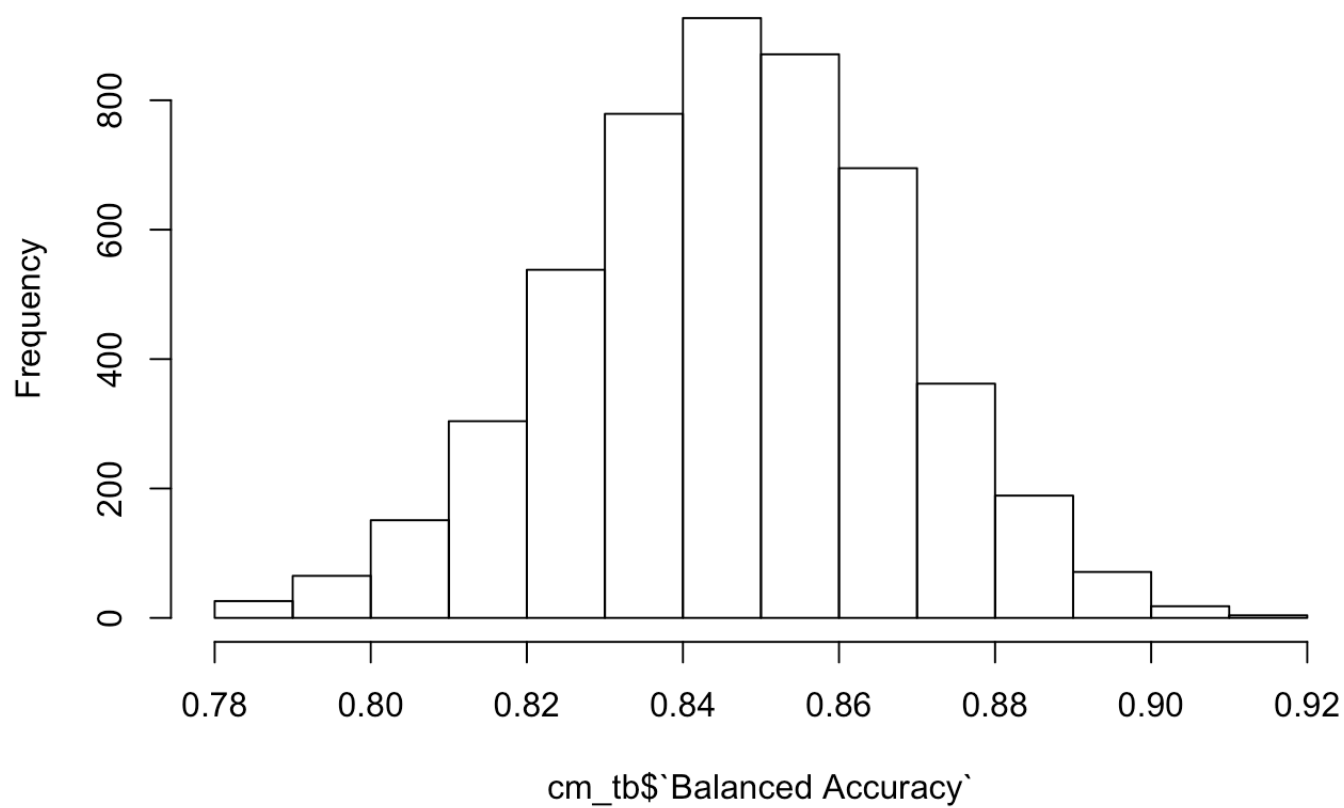
  finaldf <- rbind(truedf, falsedf)
  glm.fit <- glm(y ~ ., data = finaldf, family = binomial)

  cm <- confusionMatrix(table(as.numeric(glm.fit$fitted.values>0.5), finaldf$y))
  cm_tb <- rbind(cm_tb, as.data.frame(t(cm$byClass)))
}

```

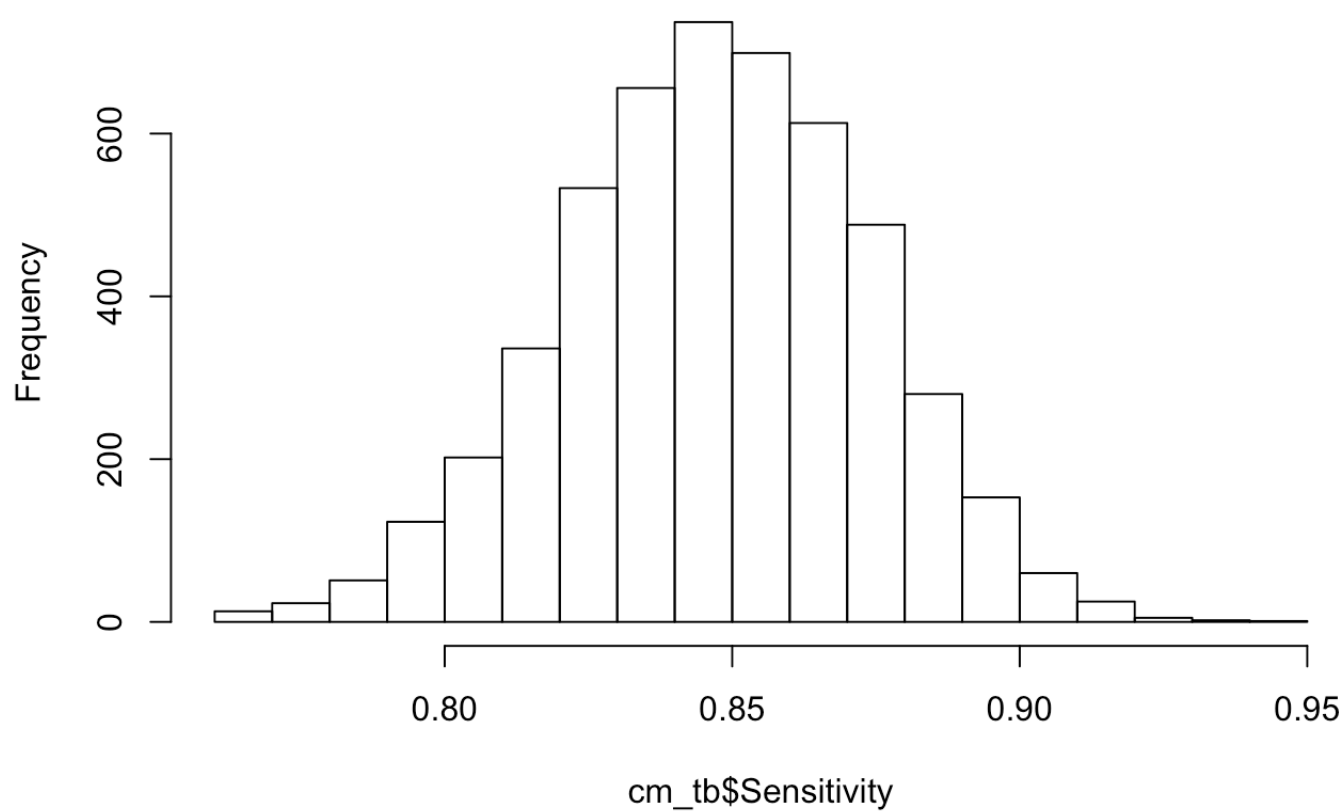
```
hist(cm_tb$`Balanced Accuracy`)
```

## Histogram of cm\_tb\$`Balanced Accuracy`



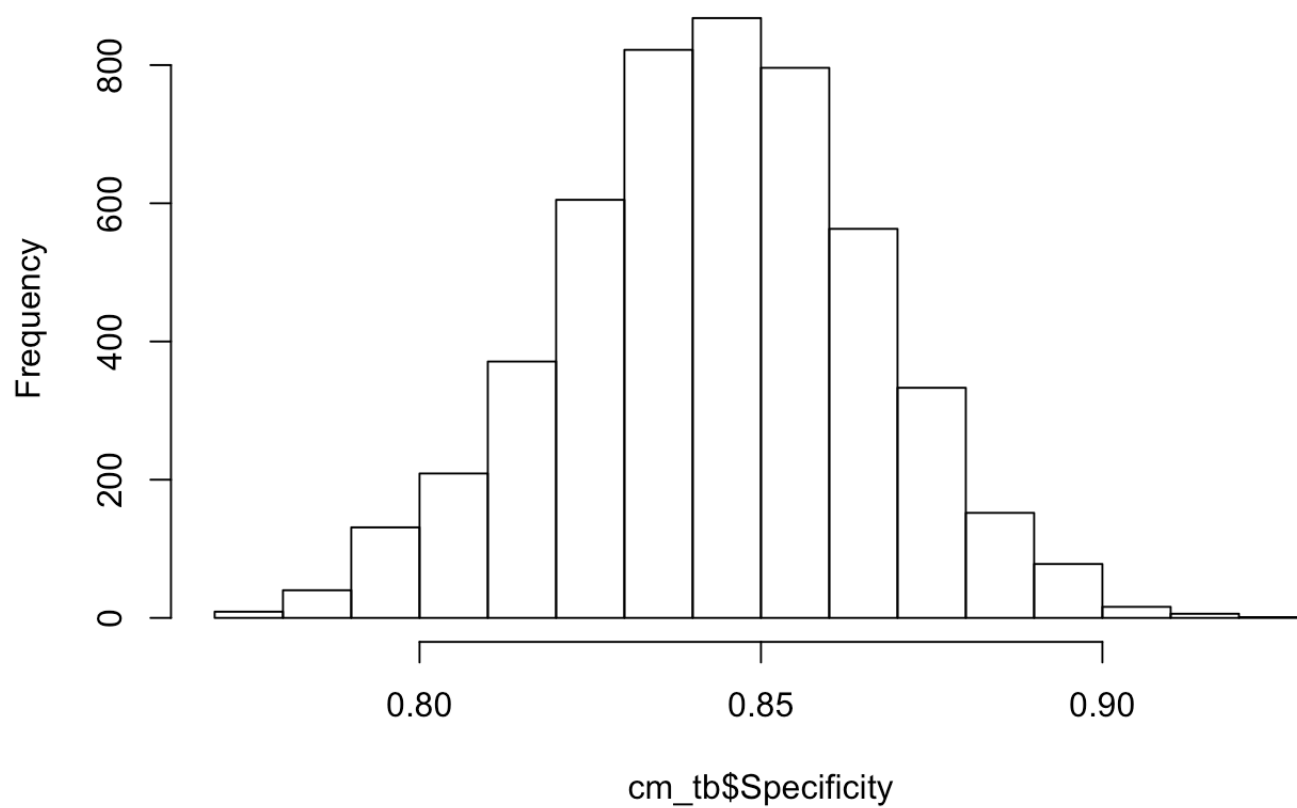
```
hist(cm_tb$Sensitivity)
```

## Histogram of cm\_tb\$Sensitivity



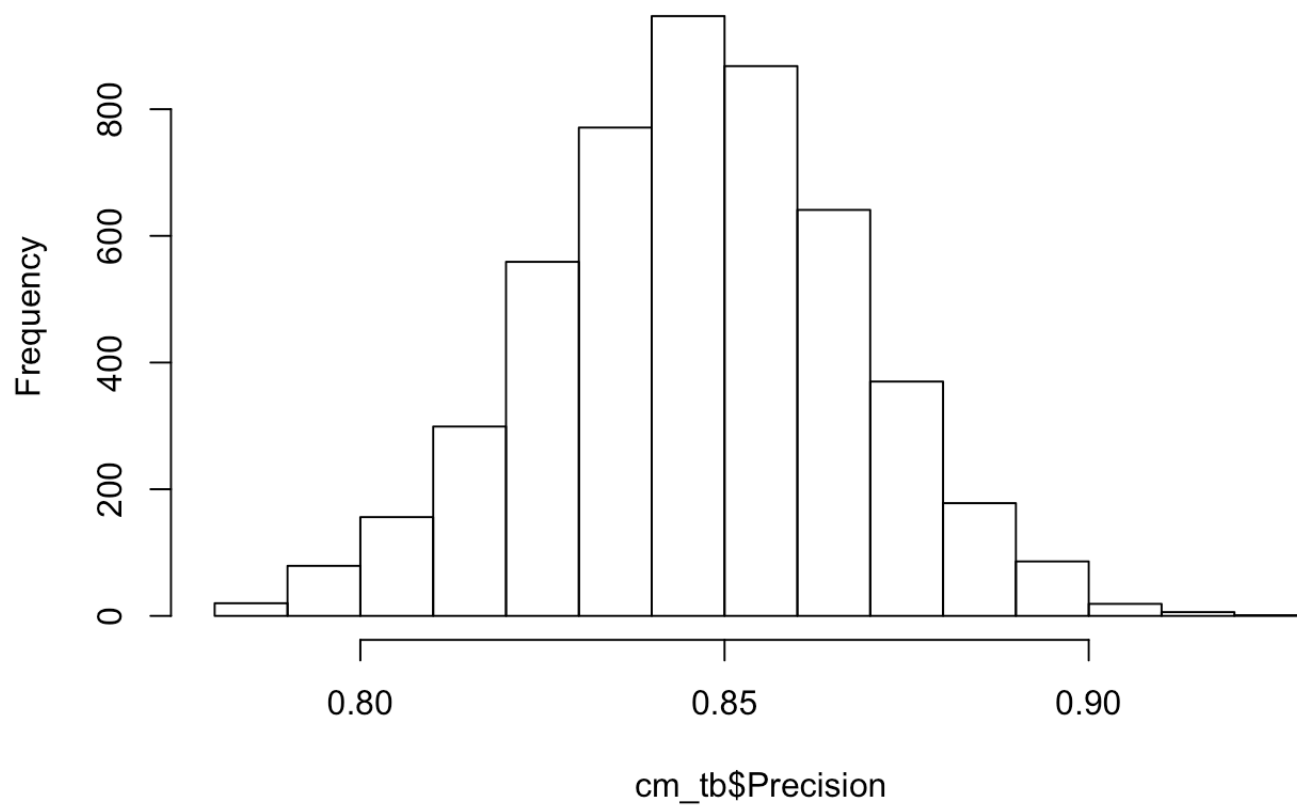
```
hist(cm_tb$Specificity)
```

## Histogram of cm\_tb\$Specificity



```
hist(cm_tb$Precision)
```

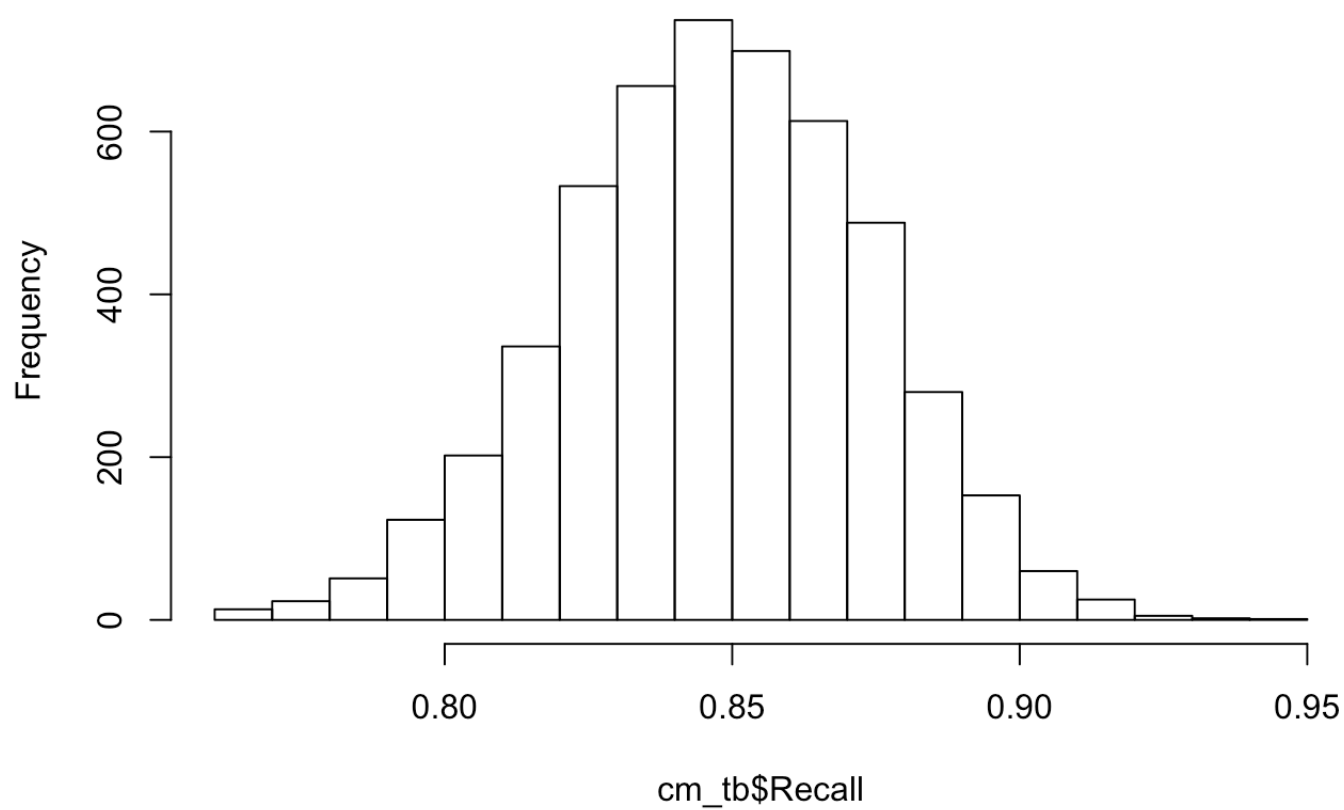
## Histogram of cm\_tb\$Precision



```
hist(cm_tb$Recall)
```

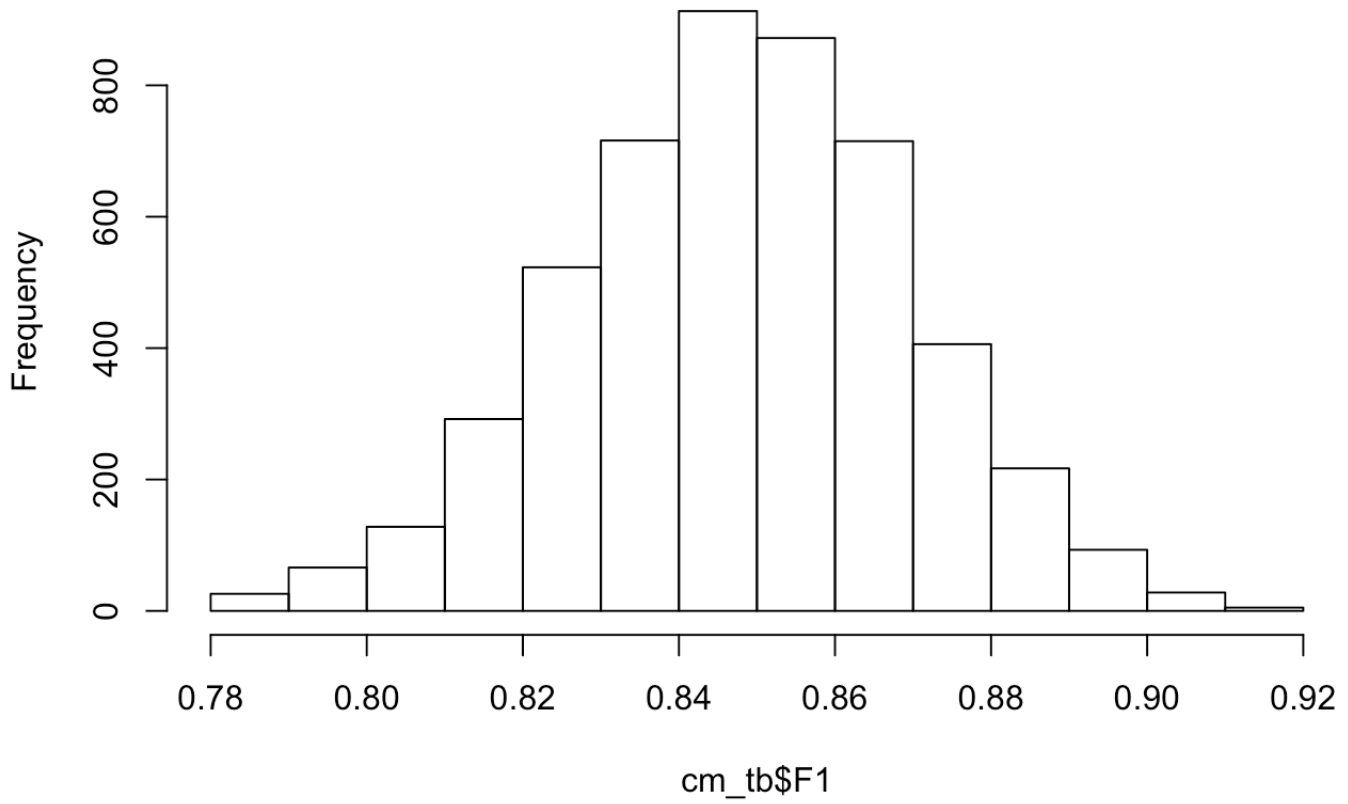


## Histogram of cm\_tb\$Recall



```
hist(cm_tb$F1)
```

**Histogram of cm\_tb\$F1**



## Prosocial Child, brain

Attribute selection

```
df <- read.csv('./brain_cb.csv')
df <- df[complete.cases(df), ]

df<- df[(df$prosocial_parent <= (3)) | (df$prosocial_parent == 6), ]
df<- df[(df$prosocial_child <= (3)) | (df$prosocial_child == 6), ]
df$prosocial_sum <- df$prosocial_parent+df$prosocial_child
df <- df[df$prosocial_sum != 9, ]
df <- df[df$prosocial_sum != 8, ]
df <- df[df$prosocial_sum != 7, ]
cut <- df[df$prosocial_sum == 6, ]
cut <- cut[cut$prosocial_child != 3, ]
df <- subset(df, !(subjectkey %in% cut$subjectkey))

df$y <- ifelse(df$prosocial_sum <= (6), 0, 1)
df <- subset(df, select=-c(aggressive_sumscore, prosocial_child, prosocial_parent, subjectkey, prosocial_sum))
```

```
cm_tb <- data.frame(matrix(ncol = 11, nrow = 0))
colnames(cm_tb) <- c("Sensitivity", "Specificity", "Pos Pred Value", "Neg Pred Value",
, "Precision", "Recall", "F1", "Prevalence", "Detection Rate", "Detection Prevalence",
, "Balanced Accuracy")

truedf <- df[df$y==1,]
truedf <- truedf[sample(1:nrow(truedf), 200, replace = TRUE), ]
falsedf <- df[df$y==0,]
falsedf <- falsedf[sample(1:nrow(falsedf), 200, replace = TRUE), ]

finaldf <- rbind(truedf, falsedf)
glm.fit <- glm(y ~ ., data = finaldf, family = binomial)

summary(glm.fit)
```

```
##
## Call:
## glm(formula = y ~ ., family = binomial, data = finaldf)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -2.08730  -1.05714   0.06183   1.01431   2.72349
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)    -0.02652    0.33057  -0.080  0.93605
## rsfmri_cor_ngd_cerc_scs_thp -0.54567    1.06612  -0.512  0.60877
```

```

## rsfmri_cor_ngd_cerc_scs_cde -2.30741    1.42031   -1.625    0.10425
## rsfmri_cor_ngd_cerc_scs_pt    3.57546    1.22387    2.921    0.00348 **
## rsfmri_cor_ngd_cerc_scs_hp  -1.89931    1.28600   -1.477    0.13970
## rsfmri_cor_ngd_cerc_scs_ag    1.02585    0.85389    1.201    0.22960
## rsfmri_cor_ngd_cerc_scs_aa    0.03424    0.83223    0.041    0.96718
## rsfmri_cor_ngd_cerc_scs_bs  -0.99262    0.90384   -1.098    0.27211
## rsfmri_cor_ngd_df_scs_thp   -0.58832    1.51702   -0.388    0.69816
## rsfmri_cor_ngd_df_scs_cde   -2.16270    1.12590   -1.921    0.05475 .
## rsfmri_cor_ngd_df_scs_pt   -0.62134    1.28794   -0.482    0.62950
## rsfmri_cor_ngd_df_scs_hp     0.21545    0.91573    0.235    0.81400
## rsfmri_cor_ngd_df_scs_ag     2.51557    1.33588    1.883    0.05969 .
## rsfmri_cor_ngd_df_scs_aa     0.12558    0.77297    0.162    0.87094
## rsfmri_cor_ngd_df_scs_bs   -0.05538    0.63796   -0.087    0.93083
## rsfmri_cor_ngd_dsa_scs_thp  -3.04228    1.04373   -2.915    0.00356 **
## rsfmri_cor_ngd_dsa_scs_cde  -0.36941    1.00900   -0.366    0.71428
## rsfmri_cor_ngd_dsa_scs_pt   -1.30430    1.30096   -1.003    0.31607
## rsfmri_cor_ngd_dsa_scs_hp    1.78239    1.55883    1.143    0.25286
## rsfmri_cor_ngd_dsa_scs_ag   -2.70473    1.67357   -1.616    0.10606
## rsfmri_cor_ngd_dsa_scs_aa   -0.06285    1.11981   -0.056    0.95524
## rsfmri_cor_ngd_dsa_scs_bs    2.82898    1.06666    2.652    0.00800 **
## rsfmri_cor_ngd_fopa_scs_thp  0.69106    0.89831    0.769    0.44172
## rsfmri_cor_ngd_fopa_scs_cde -3.56373    1.78703   -1.994    0.04613 *
## rsfmri_cor_ngd_fopa_scs_pt  -2.17060    1.09186   -1.988    0.04681 *
## rsfmri_cor_ngd_fopa_scs_hp  -0.84753    1.03024   -0.823    0.41071
## rsfmri_cor_ngd_fopa_scs_ag    0.06168    1.00645    0.061    0.95113
## rsfmri_cor_ngd_fopa_scs_aa  -1.14919    1.35387   -0.849    0.39598
## rsfmri_cor_ngd_fopa_scs_bs    1.03553    0.70233    1.474    0.14036
## rsfmri_cor_ngd_sa_scs_thp     1.16960    1.07106    1.092    0.27483
## rsfmri_cor_ngd_sa_scs_cde   -1.00591    0.89002   -1.130    0.25839
## rsfmri_cor_ngd_sa_scs_pt     1.63495    1.38240    1.183    0.23693
## rsfmri_cor_ngd_sa_scs_hp     1.27627    1.05554    1.209    0.22662
## rsfmri_cor_ngd_sa_scs_ag     0.82689    1.11242    0.743    0.45729
## rsfmri_cor_ngd_sa_scs_aa     2.56698    1.84823    1.389    0.16487
## rsfmri_cor_ngd_sa_scs_bs   -0.24077    0.84449   -0.285    0.77557
## rsfmri_cor_ngd_vta_scs_thp    1.58686    1.02339    1.551    0.12100
## rsfmri_cor_ngd_vta_scs_cde  -0.95752    1.35063   -0.709    0.47836
## rsfmri_cor_ngd_vta_scs_pt   -1.81284    1.54868   -1.171    0.24177
## rsfmri_cor_ngd_vta_scs_hp     2.54633    1.18001    2.158    0.03094 *
## rsfmri_cor_ngd_vta_scs_ag     1.43461    1.51570    0.946    0.34389
## rsfmri_cor_ngd_vta_scs_aa     0.14835    1.11851    0.133    0.89448
## rsfmri_cor_ngd_vta_scs_bs   -3.33302    1.40120   -2.379    0.01737 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
## Null deviance: 554.52  on 399  degrees of freedom

```

```
## Residual deviance: 484.86 on 357 degrees of freedom
## AIC: 570.86
##
## Number of Fisher Scoring iterations: 5
```

```
cm <- confusionMatrix(table(as.numeric(glm.fit$fitted.values>0.5), finaldf$y))
print(cm$byClass)
```

##	Sensitivity	Specificity	Pos Pred Value
##	0.6600000	0.7250000	0.7058824
##	Neg Pred Value	Precision	Recall
##	0.6807512	0.7058824	0.6600000
##	F1	Prevalence	Detection Rate
##	0.6821705	0.5000000	0.3300000
##	Detection Prevalence	Balanced Accuracy	
##	0.4675000	0.6925000	

```
for (t in 1:5000){
  truedf <- df[df$y==1,]
  truedf <- truedf[sample(1:nrow(truedf), 200, replace = TRUE), ]
  falsedf <- df[df$y==0,]
  falsedf <- falsedf[sample(1:nrow(falsedf), 200, replace = TRUE), ]

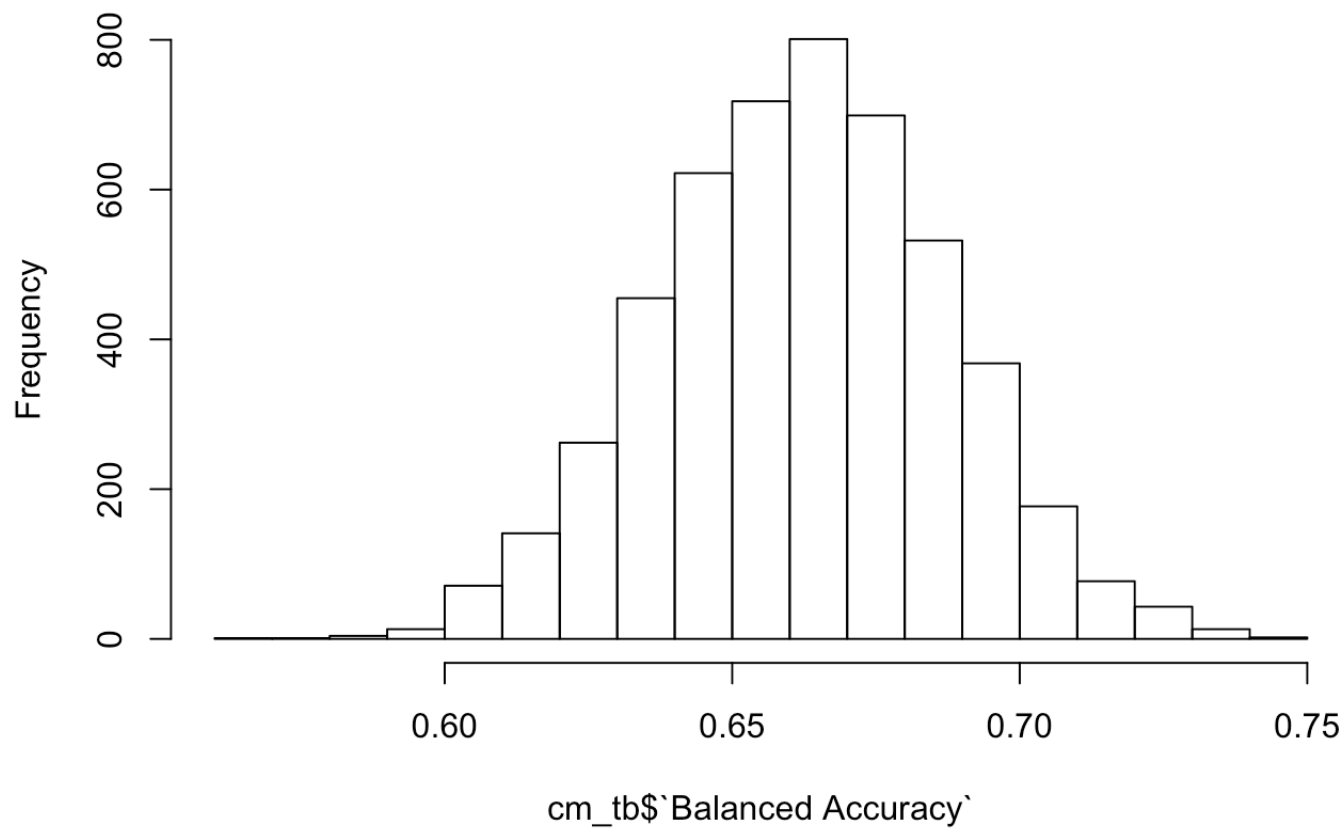
  finaldf <- rbind(truedf, falsedf)
  glm.fit <- glm(y ~ ., data = finaldf, family = binomial)

  summary(glm.fit)

  cm <- confusionMatrix(table(as.numeric(glm.fit$fitted.values>0.5), finaldf$y))
  cm_tb <- rbind(cm_tb, as.data.frame(t(cm$byClass)))
}
```

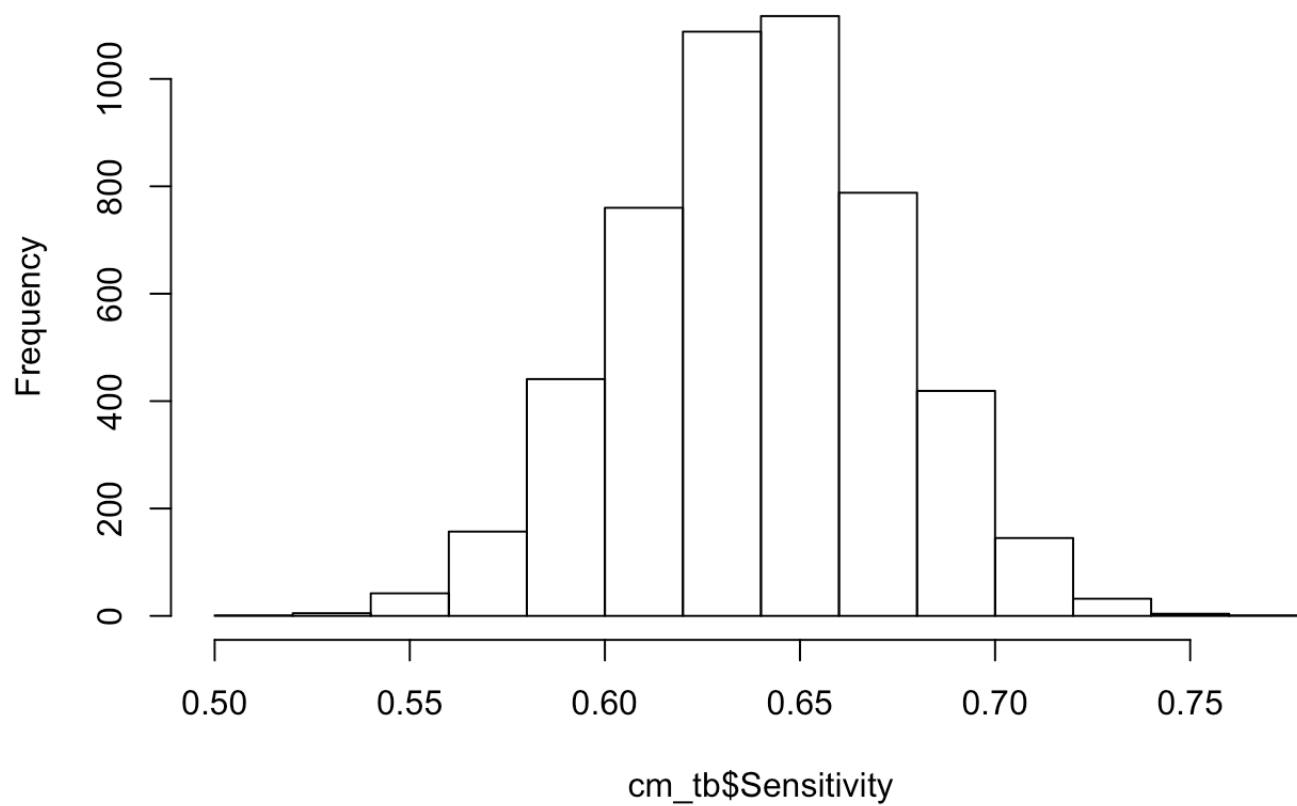
```
hist(cm_tb$`Balanced Accuracy`)
```

## Histogram of cm\_tb\$`Balanced Accuracy`



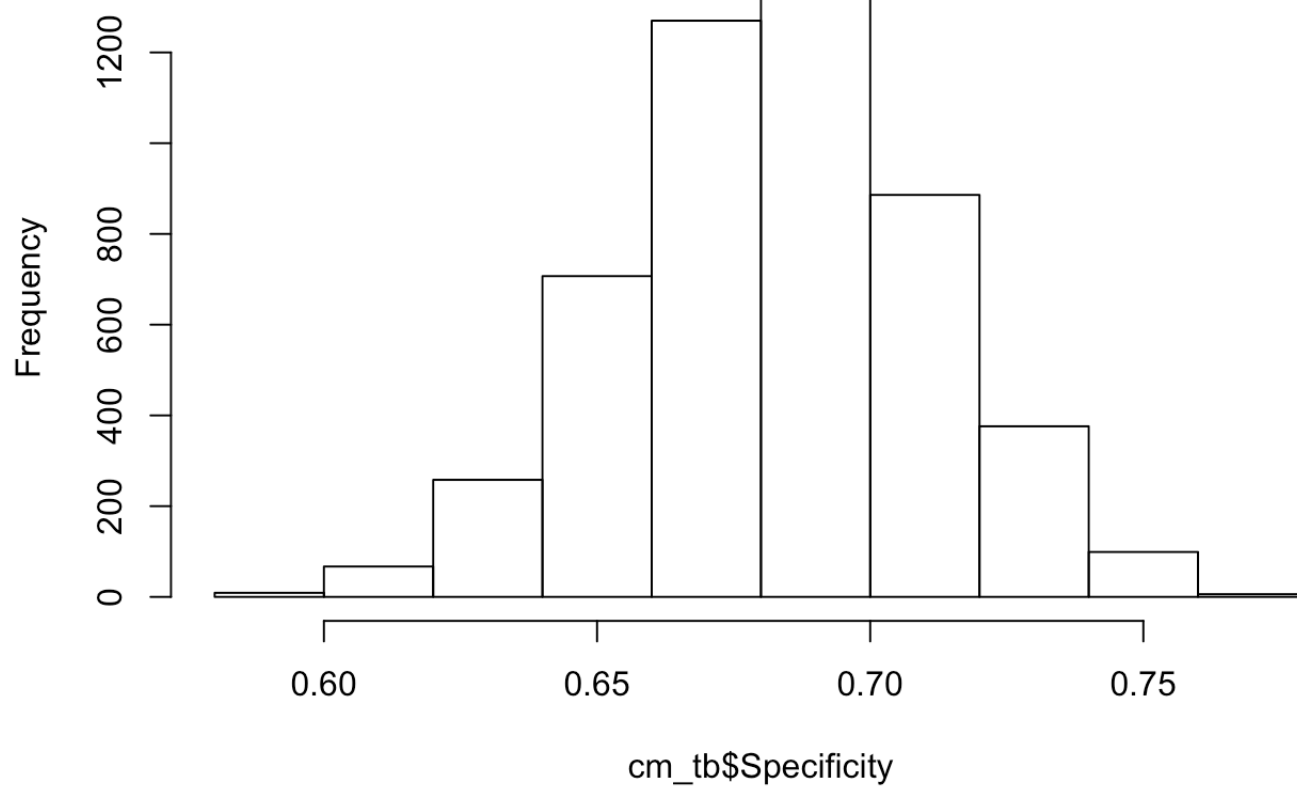
```
hist(cm_tb$Sensitivity)
```

## Histogram of cm\_tb\$Sensitivity



```
hist(cm_tb$Specificity)
```

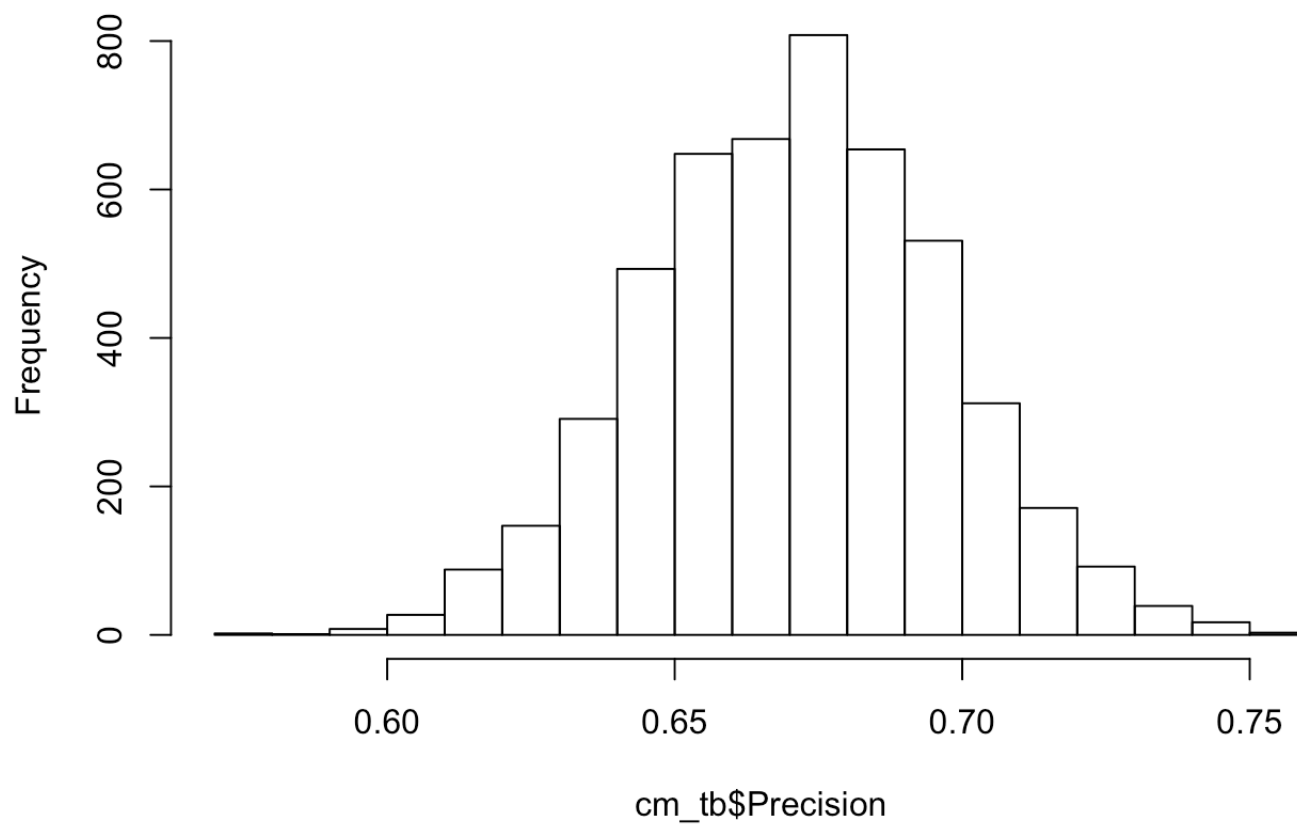
## Histogram of cm\_tb\$Specificity



```
hist(cm_tb$Precision)
```

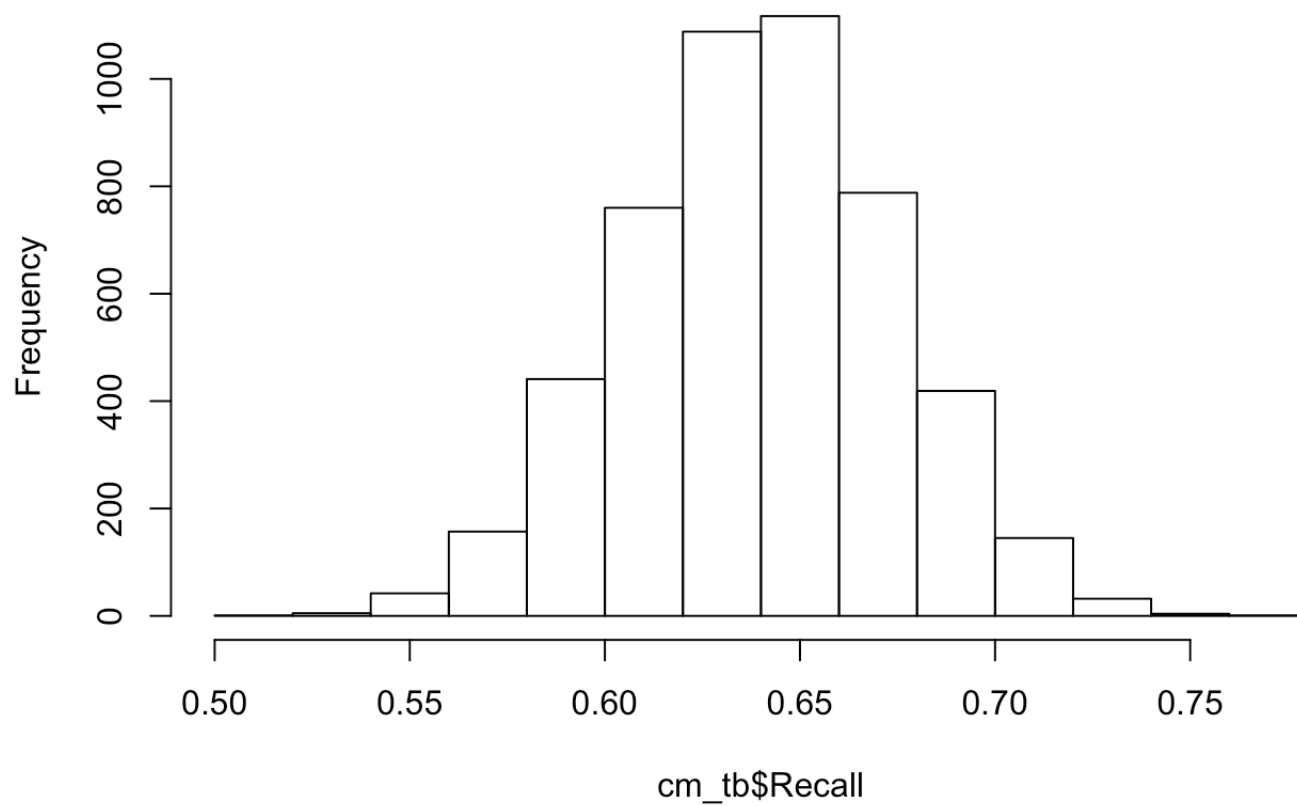


## Histogram of cm\_tb\$Precision



```
hist(cm_tb$Recall)
```

## Histogram of cm\_tb\$Recall



```
hist(cm_tb$F1)
```

# Histogram of cm\_tb\$F1

