Final Project

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```
training_data <- training_data %>%
  janitor::clean_names() %>%
  dplyr::select(-id) %>%
  mutate(severity = case_match(as.numeric(severity),
                                1 ~ "Not Severe",
                                2 ~ "Severe"),
         severity = factor(severity),
         gender = case_match(gender,
                              1 ~ "Male",
                             0 ~ "Female"),
         race = case_match(as.numeric(race),
                           1 ~ "White",
                           2 ~ "Asian",
                           3 ~ "Black",
                           4 ~ "Hispanic"),
         smoking = case_match(as.numeric(smoking),
                               1 ~ "Never",
                               2 ~ "Former",
                               3 ~ "Current"),
         hypertension = case_match(hypertension,
                                    0 ~ "No",
                                    1 ~ "Yes"),
         diabetes = case_match(diabetes,
                                0 ~ "No",
                                1 ~ "Yes"),
         vaccine = case_match(vaccine,
                               0 ~ "Not Vaccinated",
                               1 ~ "Vaccinated")
```

```
2 ~ "Asian",
                  3 ~ "Black",
                  4 ~ "Hispanic"),
smoking = case match(as.numeric(smoking),
                     1 ~ "Never",
                     2 ~ "Former",
                     3 ~ "Current"),
hypertension = case_match(hypertension,
                          0 ~ "No",
                           1 ~ "Yes"),
diabetes = case_match(diabetes,
                      0 ~ "No",
                       1 ~ "Yes"),
vaccine = case_match(vaccine,
                     0 ~ "Not Vaccinated",
                     1 ~ "Vaccinated")
```

Exploratory analysis and data visualization

We will create box plots for continuous predictors such as Age, Height, Weight, BMI, Systolic blood pressure (SBP), LDL cholesterol (LDL), and Depression. These plots will show how these metrics vary with the severity of COVID-19.

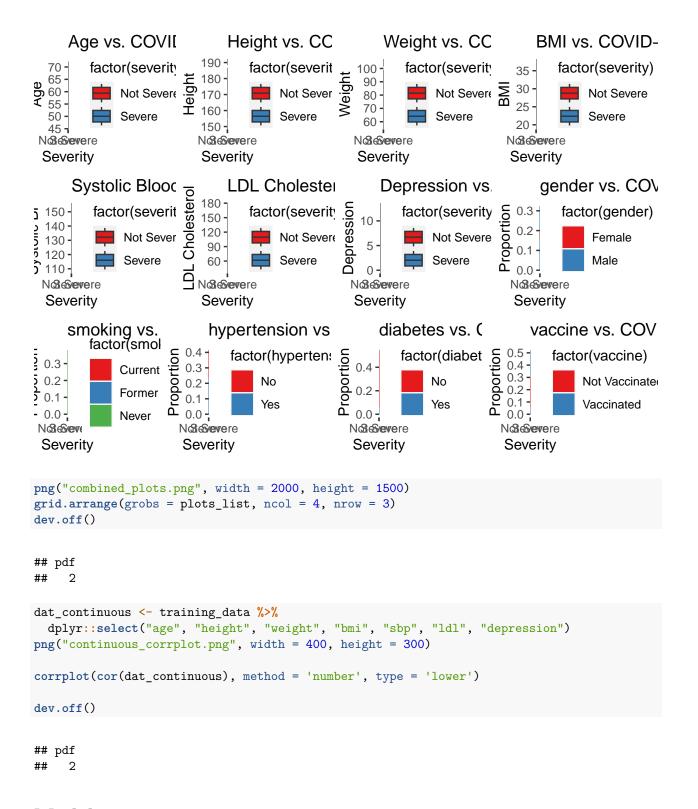
```
# Boxplot for Age vs. Severity
p1 <- ggplot(training_data, aes(x = factor(severity), y = age, fill = factor(severity))) +
  geom_boxplot() +
  labs(title = "Age vs. COVID-19 Severity", x = "Severity", y = "Age") +
  scale_fill_brewer(palette = "Set1")
# Boxplot for Height vs. Severity
p2 <- ggplot(training_data, aes(x = factor(severity), y = height, fill = factor(severity))) +
  geom_boxplot() +
  labs(title = "Height vs. COVID-19 Severity", x = "Severity", y = "Height") +
  scale fill brewer(palette = "Set1")
# Boxplot for Weight vs. Severity
p3 <- ggplot(training_data, aes(x = factor(severity), y = weight, fill = factor(severity))) +
  geom_boxplot() +
  labs(title = "Weight vs. COVID-19 Severity", x = "Severity", y = "Weight") +
  scale_fill_brewer(palette = "Set1")
# Boxplot for BMI vs. Severity
p4 <- ggplot(training_data, aes(x = factor(severity), y = bmi, fill = factor(severity))) +
  geom_boxplot() +
  labs(title = "BMI vs. COVID-19 Severity", x = "Severity", y = "BMI") +
  scale_fill_brewer(palette = "Set1")
# Boxplot for SBP vs. Severity
p5 <- ggplot(training_data, aes(x = factor(severity)), y = sbp, fill = factor(severity))) +
  geom boxplot() +
  labs(title = "Systolic Blood Pressure vs. COVID-19 Severity", x = "Severity", y = "Systolic BP") +
```

```
# Boxplot for LDL vs. Severity
p6 <- ggplot(training_data, aes(x = factor(severity), y = ldl, fill = factor(severity))) +
geom_boxplot() +
labs(title = "LDL Cholesterol vs. COVID-19 Severity", x = "Severity", y = "LDL Cholesterol") +
scale_fill_brewer(palette = "Set1")

# Boxplot for Depression vs. Severity
p7 <- ggplot(training_data, aes(x = factor(severity), y = depression, fill = factor(severity))) +
geom_boxplot() +
labs(title = "Depression vs. COVID-19 Severity", x = "Severity", y = "Depression") +
scale_fill_brewer(palette = "Set1")</pre>
```

We will visualize the relationship between categorical predictors and severity. We will focus on gender, smoking status, hypertension, diabetes, and vaccination status. We will use bar plots showing the proportion within each severity category.

```
# Function to create proportion bar plots
create_prop_plot <- function(data, varname) {</pre>
  plot <- data %>%
    group_by(severity, !!rlang::sym(varname)) %>%
    summarise(Count = n(), .groups = 'drop') %>%
    mutate(Prop = Count / sum(Count)) %>%
    ggplot(aes(x = factor(severity), y = Prop, fill = factor(!!rlang::sym(varname)))) +
    geom_bar(stat = "identity", position = position_dodge()) +
    labs(title = paste(varname, "vs. COVID-19 Severity"), x = "Severity", y = "Proportion") +
    scale_fill_brewer(palette = "Set1")
  return(plot)
}
# Proportion Bar Plots
p8 <- create_prop_plot(training_data, "gender")</pre>
p9 <- create_prop_plot(training_data, "smoking")
p10 <- create_prop_plot(training_data, "hypertension")
p11 <- create_prop_plot(training_data, "diabetes")</pre>
p12 <- create_prop_plot(training_data, "vaccine")</pre>
plots_list <- list(p1, p2, p3, p4, p5, p6, p7, p8, p9, p10, p11, p12)
combined_plot <- grid.arrange(grobs = plots_list, ncol = 4, nrow = 3)</pre>
```

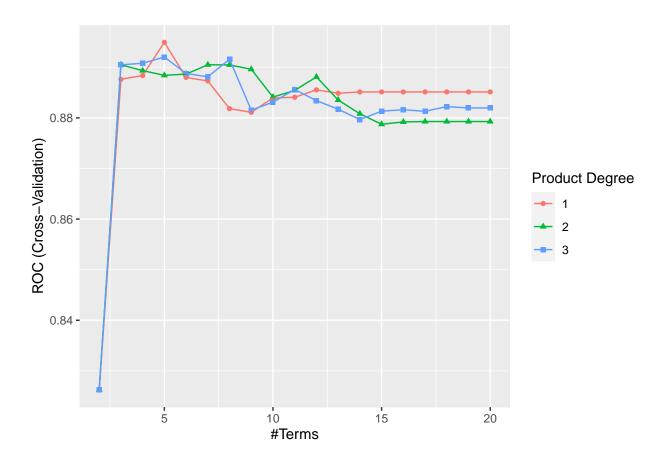


Model Training

MARS

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
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## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

ggplot(mars.fit)



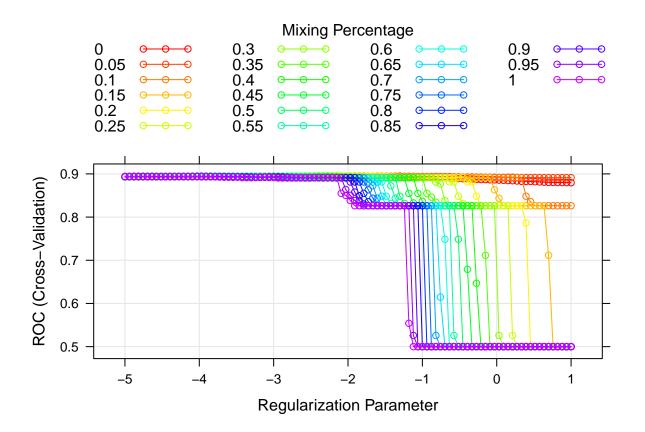
mars.fit\$bestTune

```
## nprune degree
## 4 5 1
```

coef(mars.fit\$finalModel)

```
## (Intercept) vaccineVaccinated h(sbp-139) h(139-sbp)
## 1.98341761 -3.50798169 -0.01515556 -0.13557595
## h(bmi-27)
## 0.24293455
```

Penalized Logistic Regression

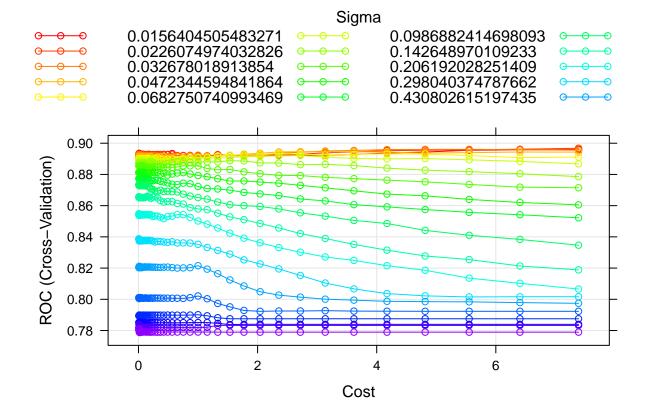


```
glmn.fit$bestTune
```

```
## alpha lambda
## 441 0.2 0.07609615
```

SVM

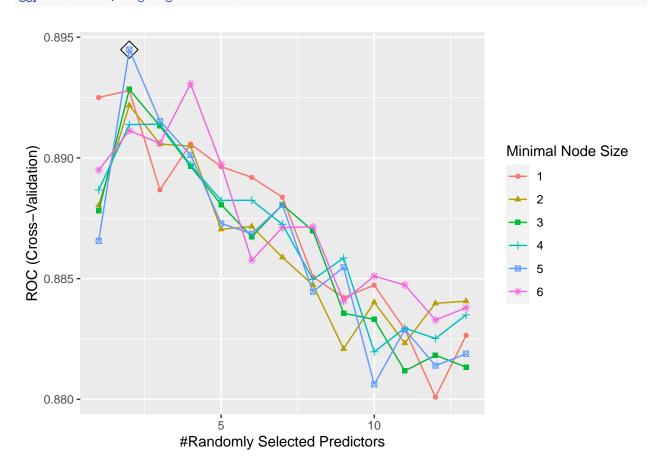
maximum number of iterations reached 9.44953e-05 9.418661e-05maximum number of iterations reached 1.



Random Forest

mtry splitrule min.node.size
11 2 gini 5

```
ggplot(rf.fit, highlight = TRUE)
```



LDA

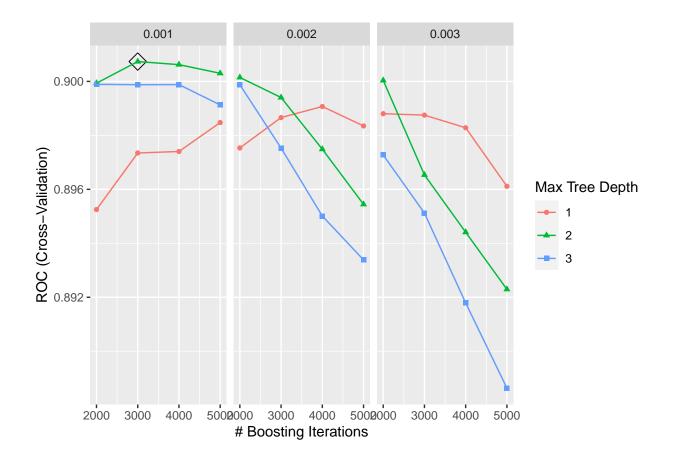
```
set.seed(1)
ctrl <- trainControl(method = "cv",</pre>
                     number = 10,
                     summaryFunction = twoClassSummary,
                     classProbs = TRUE)
lda.fit <- train(make.names(severity) ~.,</pre>
                 data = training_data,
                 method = "lda",
                 metric = "ROC",
                 trControl = ctrl)
lda.fit$finalModel
## Call:
## lda(x, grouping = y)
## Prior probabilities of groups:
## Not.Severe
                  Severe
                  0.3575
       0.6425
##
##
## Group means:
                   age genderMale raceBlack raceHispanic raceWhite smokingFormer
## Not.Severe 59.46887 0.5038911 0.2003891
                                              0.09533074 0.6381323
                                                                         0.3054475
## Severe
              61.04545 0.4580420 0.1608392
                                               0.10839161 0.6748252
                                                                         0.3181818
##
              smokingNever
                             height
                                      weight
                                                   bmi diabetesYes hypertensionYes
## Not.Severe
                 0.5914397 170.1516 79.04125 27.35331
                                                         0.1498054
                                                                          0.3540856
## Severe
                 0.5699301 169.7269 80.10245 27.86993
                                                         0.1538462
                                                                          0.6503497
##
                   sbp
                            ldl vaccineVaccinated depression
## Not.Severe 128.0272 108.4689
                                        0.8132296
                                                     6.912451
## Severe
             133.1224 113.4580
                                                     6.902098
                                        0.1608392
## Coefficients of linear discriminants:
                              LD1
## age
                      0.034385337
## genderMale
                     -0.236369596
## raceBlack
                      0.133771275
## raceHispanic
                      0.011221117
## raceWhite
                      0.126074229
## smokingFormer
                     -0.220509810
## smokingNever
                     -0.248324764
## height
                      0.067561771
## weight
                     -0.077322293
## bmi
                      0.301287096
## diabetesYes
                      0.144018177
## hypertensionYes
                      0.215120572
## sbp
                      0.036100853
## ldl
                      0.004588793
## vaccineVaccinated -2.478676582
## depression
                     -0.010600382
```

AdaBoost

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ggplot(gbmA.fit, highlight = TRUE)

```
set.seed(1)
gbmA.grid <- expand.grid(n.trees = c(2000,3000,4000,5000),
                         interaction.depth = 1:3,
                         shrinkage = c(0.001, 0.002, 0.003),
                         n.minobsinnode = 1)
ctrl <- trainControl(method = "cv",</pre>
                     number = 10,
                     summaryFunction = twoClassSummary,
                     classProbs = TRUE)
gbmA.fit <- train(make.names(severity) ~ .,</pre>
                  data = training_data,
                  method = "gbm",
                  tuneGrid = gbmA.grid,
                  metric = "ROC",
                  trControl = ctrl,
                  distribution = "adaboost",
                  verbose = FALSE)
gbmA.fit$bestTune
##
    n.trees interaction.depth shrinkage n.minobsinnode
        3000
                                    0.001
```

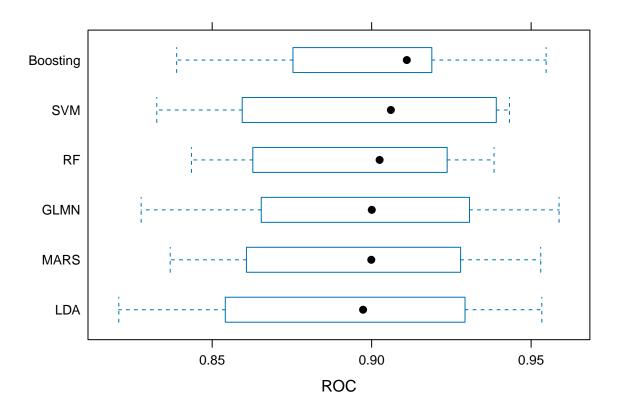


Compare all models

```
resamp <- resamples(list(MARS = mars.fit,</pre>
                          GLMN = glmn.fit,
                          SVM = svmr.fit,
                          RF = rf.fit,
                          LDA = lda.fit,
                          Boosting = gbmA.fit))
summary(resamp)
##
## Call:
## summary.resamples(object = resamp)
##
## Models: MARS, GLMN, SVM, RF, LDA, Boosting
## Number of resamples: 10
##
## ROC
##
                 Min.
                         1st Qu.
                                    Median
                                                 Mean
                                                        3rd Qu.
## MARS
            0.8368347 0.8617374 0.8998836 0.8949289 0.9242048 0.9530088
## GLMN
            0.8277311 0.8667531 0.9000364 0.8953483 0.9279149 0.9587559
                                                                              0
## SVM
            0.8326331\ 0.8639673\ 0.9060241\ 0.8967610\ 0.9359244\ 0.9432049
                                                                              0
## RF
            0.8435013 0.8629141 0.9024939 0.8944851 0.9221477 0.9383754
                                                                              0
            0.8207283 0.8569460 0.8973124 0.8924337 0.9280664 0.9533469
                                                                              0
## LDA
```

```
## Boosting 0.8388594 0.8755656 0.9110222 0.9007355 0.9184898 0.9546991
##
##
  Sens
##
               Min.
                     1st Qu.
                               Median
                                                 3rd Qu.
                                                             Max. NA's
                                          Mean
## MARS
          0.8461538 0.8634050 0.8823529 0.8970965 0.9226998 0.9803922
                                                                    0
## GLMN
## SVM
          0.7692308 0.8125000 0.8448341 0.8505279 0.8823529 0.9411765
          0.8653846 0.9082768 0.9411765 0.9360106 0.9754902 0.9807692
## RF
## LDA
          0.7500000 0.8076923 0.8350302 0.8407994 0.8725490 0.9411765
  Boosting 0.8653846 0.8829186 0.9019608 0.9164781 0.9558824 0.9807692
##
##
  Spec
                               Median
##
               Min.
                     1st Qu.
                                          Mean
                                                 3rd Qu.
                                                             Max. NA's
          0.6785714 0.7327586 0.7721675 0.7758621 0.8143473 0.8620690
## MARS
## GLMN
          0.6428571 0.7521552 0.7586207 0.7656404 0.8143473 0.8620690
## SVM
          ## RF
          0.5714286 0.6813424 0.7413793 0.7270936 0.7789409 0.8275862
          0.7142857  0.8017241  0.8571429  0.8352217  0.8620690  0.8965517
## LDA
## Boosting 0.6428571 0.6982759 0.7413793 0.7480296 0.7912562 0.8620690
                                                                    0
```

bwplot(resamp, metric = "ROC")



```
resamp_summary <- summary(resamp)
roc_summary <- as.data.frame(resamp_summary$statistics$ROC)</pre>
```

```
roc_summary$Model <- rownames(roc_summary)</pre>
write.csv(roc_summary, "Roc_summary.csv", row.names = FALSE)
png("Roc_boxplot.png", width = 400, height = 300)
bwplot(resamp, metric = "ROC")
dev.off()
## pdf
##
     2
boosting.pred <- predict(gbmA.fit, newdata = test_data, type = "prob")</pre>
boosting.pred
##
       Not.Severe
                      Severe
       0.89630340 0.10369660
## 1
## 2
      0.43313344 0.56686656
## 3
       0.48536884 0.51463116
      0.09701847 0.90298153
## 4
## 5
       0.90786982 0.09213018
## 6
       0.16864968 0.83135032
## 7
       0.29994593 0.70005407
## 8
       0.21075008 0.78924992
## 9
       0.13076766 0.86923234
## 10 0.82659319 0.17340681
## 11 0.88841781 0.11158219
## 12 0.13667853 0.86332147
## 13 0.80671339 0.19328661
## 14 0.87902215 0.12097785
## 15 0.90451779 0.09548221
## 16 0.76508389 0.23491611
## 17
      0.43040267 0.56959733
## 18 0.85820468 0.14179532
## 19 0.83302007 0.16697993
## 20 0.90749853 0.09250147
## 21
      0.93204529 0.06795471
     0.66431513 0.33568487
## 23
      0.90224590 0.09775410
## 24
       0.63228775 0.36771225
      0.46271132 0.53728868
## 25
## 26 0.36734190 0.63265810
## 27
     0.59463071 0.40536929
## 28
       0.81730975 0.18269025
## 29 0.88712291 0.11287709
## 30
     0.86823897 0.13176103
## 31 0.90730277 0.09269723
## 32 0.39872172 0.60127828
## 33 0.38333235 0.61666765
## 34 0.92901686 0.07098314
## 35 0.92442802 0.07557198
## 36
     0.82882768 0.17117232
## 37
      0.92975988 0.07024012
## 38 0.89737049 0.10262951
```

```
0.92412334 0.07587666
       0.90447153 0.09552847
## 40
       0.80911791 0.19088209
##
  42
       0.89197911 0.10802089
   43
       0.16119579 0.83880421
       0.86505699 0.13494301
##
   44
       0.90463468 0.09536532
   45
## 46
       0.25120471 0.74879529
##
  47
       0.83158037 0.16841963
##
  48
       0.86855693 0.13144307
   49
       0.89904276 0.10095724
##
       0.16234205 0.83765795
  50
##
   51
       0.91067025 0.08932975
## 52
       0.89465317 0.10534683
## 53
       0.37343253 0.62656747
## 54
       0.90610908 0.09389092
       0.12278553 0.87721447
##
  55
##
       0.82262376 0.17737624
##
       0.15771395 0.84228605
  57
##
   58
       0.88992615 0.11007385
##
   59
       0.82794851 0.17205149
       0.41472213 0.58527787
   60
       0.47594334 0.52405666
## 61
       0.93578565 0.06421435
##
   62
  63
##
       0.59317092 0.40682908
   64
       0.83680774 0.16319226
##
   65
       0.83380199 0.16619801
##
   66
       0.83583076 0.16416924
##
       0.84462906 0.15537094
   67
##
   68
       0.82533962 0.17466038
## 69
       0.82769313 0.17230687
##
   70
       0.33682737 0.66317263
##
   71
       0.28624634 0.71375366
       0.15022671 0.84977329
##
  72
##
   73
       0.09694790 0.90305210
##
       0.83721026 0.16278974
   74
  75
       0.84263824 0.15736176
## 76
       0.92562460 0.07437540
##
   77
       0.82965066 0.17034934
       0.84491196 0.15508804
##
  78
       0.16538680 0.83461320
##
  80
       0.79523000 0.20477000
##
   81
       0.91967321 0.08032679
##
   82
       0.91734443 0.08265557
  83
       0.89476862 0.10523138
## 84
       0.89444763 0.10555237
##
   85
       0.82213997 0.17786003
##
   86
       0.33064473 0.66935527
##
   87
       0.29481632 0.70518368
##
   88
       0.16952340 0.83047660
       0.56554200 0.43445800
##
   89
## 90
       0.84461564 0.15538436
## 91
      0.16653051 0.83346949
## 92 0.29974965 0.70025035
```

```
## 93 0.08620767 0.91379233
## 94 0.08550628 0.91449372
      0.70556311 0.29443689
## 96
      0.91067020 0.08932980
## 97
       0.79940976 0.20059024
## 98 0.52096980 0.47903020
## 99 0.52738486 0.47261514
## 100 0.87533982 0.12466018
## 101 0.45085086 0.54914914
## 102 0.12700413 0.87299587
## 103 0.83689636 0.16310364
## 104 0.86151238 0.13848762
## 105 0.91107545 0.08892455
## 106 0.29365365 0.70634635
## 107 0.57086494 0.42913506
## 108 0.79878612 0.20121388
## 109 0.92424837 0.07575163
## 110 0.86046557 0.13953443
## 111 0.08615355 0.91384645
## 112 0.85219908 0.14780092
## 113 0.08603372 0.91396628
## 114 0.91194087 0.08805913
## 115 0.21730042 0.78269958
## 116 0.33543170 0.66456830
## 117 0.88932934 0.11067066
## 118 0.92045660 0.07954340
## 119 0.82824881 0.17175119
## 120 0.92836296 0.07163704
## 121 0.91000058 0.08999942
## 122 0.10885632 0.89114368
## 123 0.92837357 0.07162643
## 124 0.92734810 0.07265190
## 125 0.28608311 0.71391689
## 126 0.86104339 0.13895661
## 127 0.90264339 0.09735661
## 128 0.90530990 0.09469010
## 129 0.33398536 0.66601464
## 130 0.91513714 0.08486286
## 131 0.90832988 0.09167012
## 132 0.92321434 0.07678566
## 133 0.23457417 0.76542583
## 134 0.82805458 0.17194542
## 135 0.90947823 0.09052177
## 136 0.63393663 0.36606337
## 137 0.93141038 0.06858962
## 138 0.87155771 0.12844229
## 139 0.89921140 0.10078860
## 140 0.91955694 0.08044306
## 141 0.80501464 0.19498536
## 142 0.80820967 0.19179033
## 143 0.85839121 0.14160879
## 144 0.91764995 0.08235005
## 145 0.81786168 0.18213832
## 146 0.92854100 0.07145900
```

```
## 147 0.33320542 0.66679458
## 148 0.80193426 0.19806574
## 149 0.91545423 0.08454577
## 150 0.89709530 0.10290470
## 151 0.92254355 0.07745645
## 152 0.89502023 0.10497977
## 153 0.83439419 0.16560581
## 154 0.28949786 0.71050214
## 155 0.18781695 0.81218305
## 156 0.92054712 0.07945288
## 157 0.92957568 0.07042432
## 158 0.82460084 0.17539916
## 159 0.56796791 0.43203209
## 160 0.30046659 0.69953341
## 161 0.90844882 0.09155118
## 162 0.93377849 0.06622151
## 163 0.25026066 0.74973934
## 164 0.53685511 0.46314489
## 165 0.34890735 0.65109265
## 166 0.54557646 0.45442354
## 167 0.92047548 0.07952452
## 168 0.25322062 0.74677938
## 169 0.91998302 0.08001698
## 170 0.85804436 0.14195564
## 171 0.93023826 0.06976174
## 172 0.93159371 0.06840629
## 173 0.90705164 0.09294836
## 174 0.78445812 0.21554188
## 175 0.87013877 0.12986123
## 176 0.91727599 0.08272401
## 177 0.92543856 0.07456144
## 178 0.89979656 0.10020344
## 179 0.80527319 0.19472681
## 180 0.64309591 0.35690409
## 181 0.89487274 0.10512726
## 182 0.84814624 0.15185376
## 183 0.82740004 0.17259996
## 184 0.62368353 0.37631647
## 185 0.34434075 0.65565925
## 186 0.83839183 0.16160817
## 187 0.83510160 0.16489840
## 188 0.77502233 0.22497767
## 189 0.53967743 0.46032257
## 190 0.80847454 0.19152546
## 191 0.23514521 0.76485479
## 192 0.20449541 0.79550459
## 193 0.21511544 0.78488456
## 194 0.33885739 0.66114261
## 195 0.92400030 0.07599970
## 196 0.83279144 0.16720856
## 197 0.92323815 0.07676185
## 198 0.89392083 0.10607917
## 199 0.86127466 0.13872534
## 200 0.40622057 0.59377943
```