Supervised

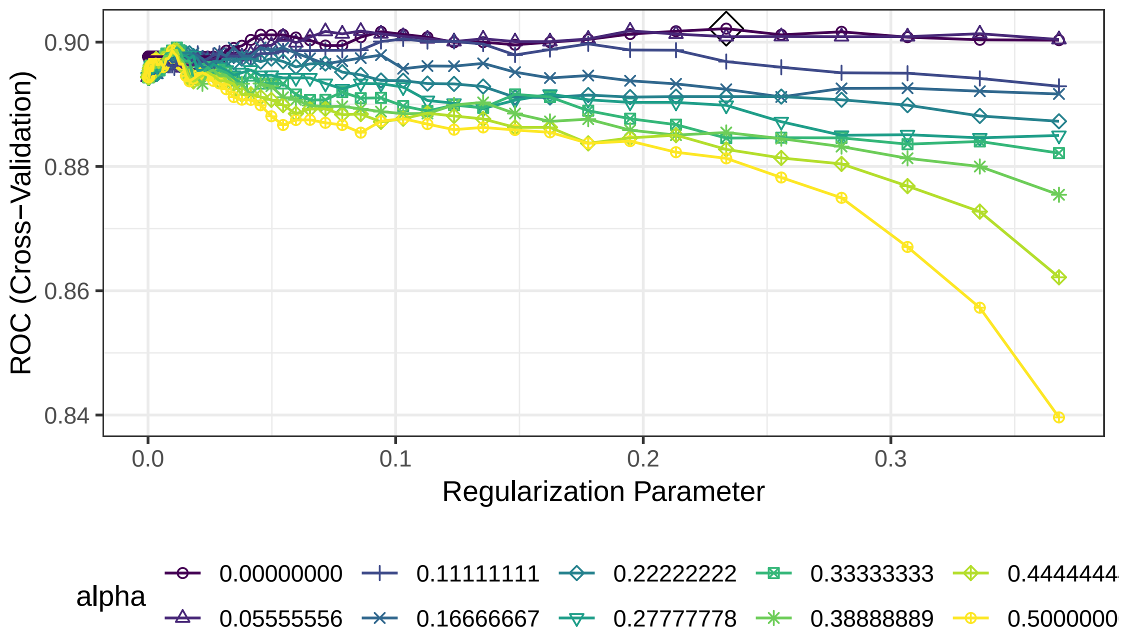
2019-5-15

```r
heart_disease = read_csv("./heart.csv") %>%
    mutate(target = ifelse(target==1, 0, 1)) %>%
    mutate(target=as.factor(target)) %>%
    mutate(target=as.factor(ifelse(target==0, "absence", "presence")))%>%
    mutate(target = relevel(target, "presence"))

heart_disease = heart_disease %>%
    filter(thal != 0) %>%
    mutate(sex=as.factor(sex),
           cp=as.factor(cp),
           fbs=as.factor(fbs),
           restecg=as.factor(restecg),
           exang=as.factor(exang),
           slope=as.factor(slope),
           thal=factor(thal))

model.x <- model.matrix(target~.,heart_disease)[,-1]
model.y <- heart_disease$target
```

Regularized logistic

```r
ctrl = trainControl(method = "cv",
                    classProbs = TRUE,
                    summaryFunction = twoClassSummary)


glmnGrid <- expand.grid(.alpha = seq(0, 0.5, length = 10),
                        .lambda = exp(seq(-10,-1, length = 100)))
set.seed(1)
model.glm <- train(x = model.x,
                   y = model.y,
                   method = "glmnet",
                   tuneGrid = glmnGrid,
                   metric = "ROC",
                   trControl = ctrl)

ggplot(model.glm, highlight = T)  +
    viridis::scale_color_viridis(discrete = TRUE) +
    scale_shape_manual(values = seq(1,10))
```

```
## Scale for 'colour' is already present. Adding another scale for
## 'colour', which will replace the existing scale.

## Scale for 'shape' is already present. Adding another scale for 'shape',
## which will replace the existing scale.
```




```r
model.glm$bestTune
```

```
##    alpha    lambda
## 95     0 0.2335065
```

```r
glmnet = glmnet(x = model.x, y = model.y,
       family = "binomial",
       alpha = 0,
       lambda = 0.1946867)
broom::tidy(glmnet)
```

```
## # A tibble: 19 x 5
##    term         step estimate lambda dev.ratio
##    <chr>       <dbl>    <dbl>  <dbl>     <dbl>
##  1 (Intercept)     1  0.624    0.195     0.431
##  2 age             1 -0.00885  0.195     0.431
##  3 sex1            1 -0.462    0.195     0.431
##  4 cp1             1  0.385    0.195     0.431
##  5 cp2             1  0.586    0.195     0.431
##  6 cp3             1  0.524    0.195     0.431
##  7 trestbps        1 -0.00476  0.195     0.431
##  8 chol            1 -0.00120  0.195     0.431
##  9 fbs1            1  0.0693   0.195     0.431
## 10 restecg1        1  0.246    0.195     0.431
## 11 restecg2        1 -0.198    0.195     0.431
## 12 thalach         1  0.00952  0.195     0.431
## 13 exang1          1 -0.522    0.195     0.431
## 14 oldpeak         1 -0.199    0.195     0.431
## 15 slope1          1 -0.293    0.195     0.431
## 16 slope2          1  0.290    0.195     0.431
## 17 ca              1 -0.306    0.195     0.431
## 18 thal2           1  0.527    0.195     0.431
## 19 thal3           1 -0.526    0.195     0.431
```

LDA

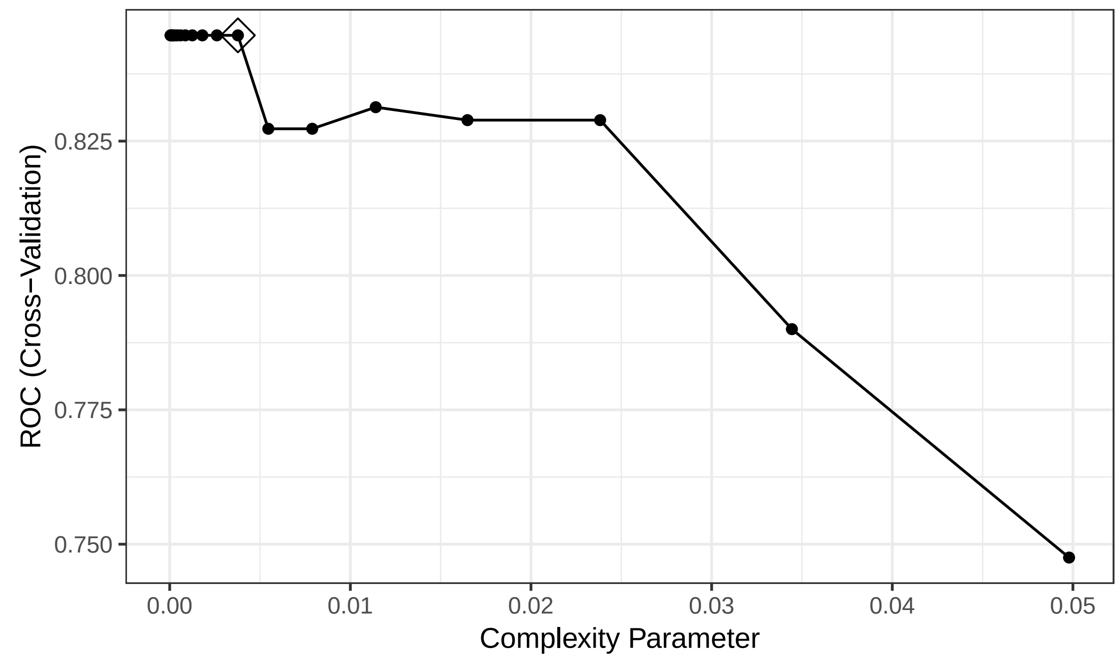
```r
set.seed(1)
model.lda = train(x = model.x,
                   y = model.y,
                  method = "lda",
                  metric = "ROC",
                  trControl = ctrl)
```

Naive bayes

```r
set.seed(1)
nbGrid = expand.grid(usekernel = c(FALSE,TRUE),
                     fL = 1, adjust = seq(0, 4, length = 20))
model.bayes = train(x = model.x,
                    y = model.y,
                    method = "nb",
                    tuneGrid = nbGrid,
                    metric = "ROC",
                    trControl = ctrl)

ggplot(model.bayes, highlight = T)

model.bayes$bestTune
```

##Tree

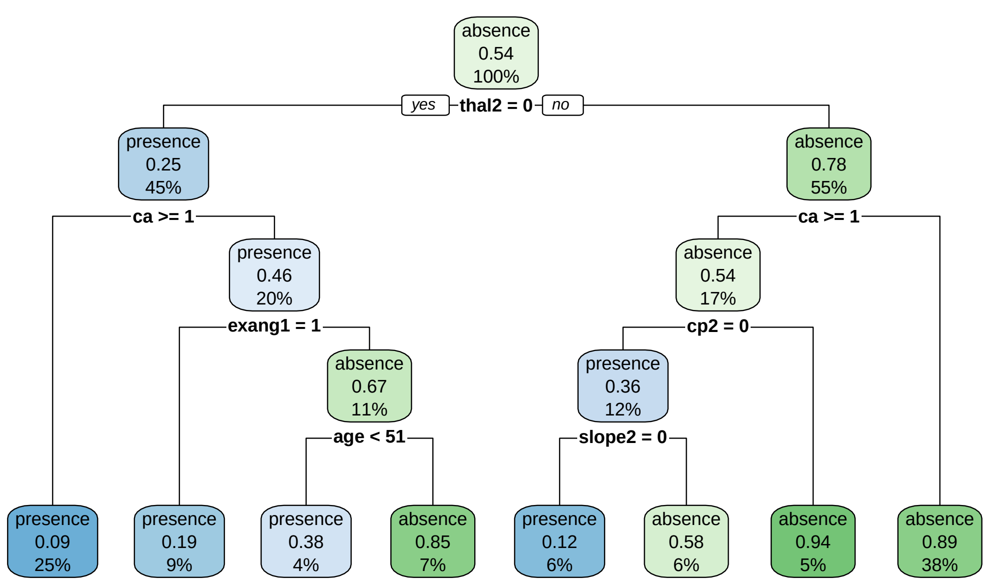
```r
set.seed(1)
tree.class <- train(model.x, model.y,
                    method = "rpart",
                    tuneGrid = data.frame(cp = exp(seq(-10,-3, len = 20))),
                    trControl = ctrl,
                    metric = "ROC")
ggplot(tree.class, highlight = TRUE)
```




```
tree.class$bestTune
```

```
##            cp
## 13 0.003776539
```

```
rpart.plot(tree.class$finalModel)
```



##Bagging

```
bagging.grid <- expand.grid(mtry = 18,
                            splitrule = "gini",
                            min.node.size = 10:50)
```

```r
set.seed(1)
bagging.class <- train(model.x, model.y,
                method = "ranger",
                tuneGrid = bagging.grid,
                metric = "ROC",
                trControl = ctrl,
                importance = "impurity")

ggplot(bagging.class, highlight = TRUE)
bagging.class$bestTune

barplot(sort(ranger::importance(bagging.class$finalModel),
             decreasing = FALSE),
las = 2, horiz = TRUE, cex.names = 0.7,
col = colorRampPalette(colors = c("darkred","white","darkblue"))(18))
```

##Random Forest

```r
rf.grid <- expand.grid(mtry = 1:6,
                       splitrule = "gini",
                       min.node.size = seq(1,191, by = 2))

set.seed(1)
rf.class <- train(model.x, model.y,
                  method = "ranger",
                  tuneGrid = rf.grid,
                  metric = "ROC",
                  trControl = ctrl,
                  importance = "impurity")

rf.class$bestTune

ggplot(rf.class, highlight = TRUE) +
    viridis::scale_color_viridis(discrete = TRUE) +
    scale_shape_manual(values = seq(1,7))

barplot(sort(ranger::importance(rf.class$finalModel), decreasing = FALSE),
las = 2, horiz = TRUE, cex.names = 0.7,
col = colorRampPalette(colors = c("darkred","white","darkblue"))(18))
```

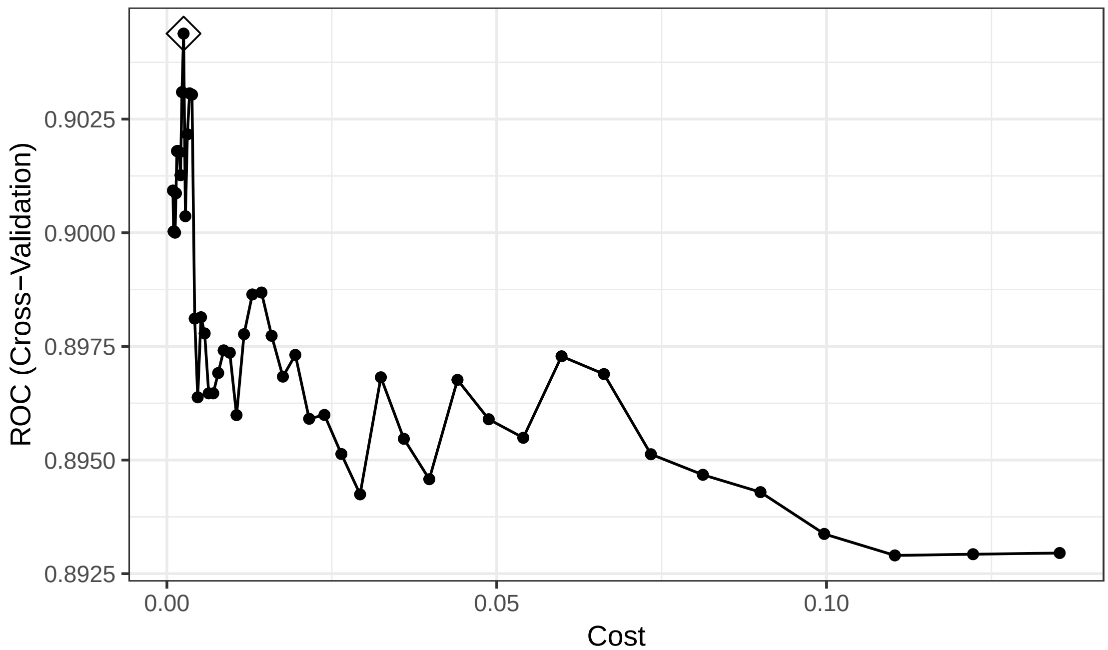
##Boosting

```r
boost.grid <- expand.grid(n.trees = seq(20, 1700, by = 25),
                          interaction.depth = 1:6,
                          shrinkage =  seq(0.005, 0.06, by = 0.005),
                          n.minobsinnode = 1)

set.seed(1)
# Adaboost loss function
boost.class = train(model.x, model.y,
                    tuneGrid = boost.grid,
                    trControl = ctrl,
                    method = "gbm",
                    distribution = "adaboost",
```

```r
                    metric = "ROC",
                    verbose = FALSE)

boost.class$bestTune

ggplot(boost.class, highlight = TRUE) +
    viridis::scale_color_viridis(discrete = TRUE) +
    scale_shape_manual(values = seq(0,11))

summary(boost.class$finalModel, las = 2, cBars = 19, cex.names = 0.6)
```

SVM ROC

```r
## linear boundary
set.seed(1)
svml.fit <- train(target~.,
                  data = heart_disease,
                  method = "svmLinear2",
                  preProcess = c("center", "scale"),
                  tuneGrid = data.frame(cost = exp(seq(-7,-2,len=50))),
                  trControl = ctrl,
                  metric = "ROC")

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




```r
svml.fit$bestTune
```

```
##            cost
## 11 0.002529859
```

```r
## radial kernel
svmr.grid <- expand.grid(C = exp(seq(-4,5,len=50)),
```

```
                          sigma = exp(seq(-5,-2,len=10)))
set.seed(1)
svmr.fit <- train(target~.,
                  data = heart_disease,
                  method = "svmRadial",
                  preProcess = c("center", "scale"),
                  tuneGrid = svmr.grid,
                  trControl = ctrl,
                  metric = "ROC")

ggplot(svmr.fit, highlight = TRUE) +
    viridis::scale_color_viridis(discrete = TRUE) +
    scale_shape_manual(values = seq(1,10))
svmr.fit$bestTune
```

Neural network

```
nnetGrid <- expand.grid(size = seq(from = 16, to = 30, by = 2),
                        decay = seq(from = 5, to = 8, length = 30))

set.seed(1)
cnnet.fit <- train(target~.,
                   heart_disease,
                   method = "nnet",
                   tuneGrid = nnetGrid,
                   preProcess = c("center","scale"),
                   trControl = ctrl,
                   metric = "ROC",
                   trace = FALSE)

ggplot(cnnet.fit, highlight = TRUE) +
    viridis::scale_color_viridis(discrete = TRUE) +
    scale_shape_manual(values = seq(1,13))

cnnet.fit$bestTune
```

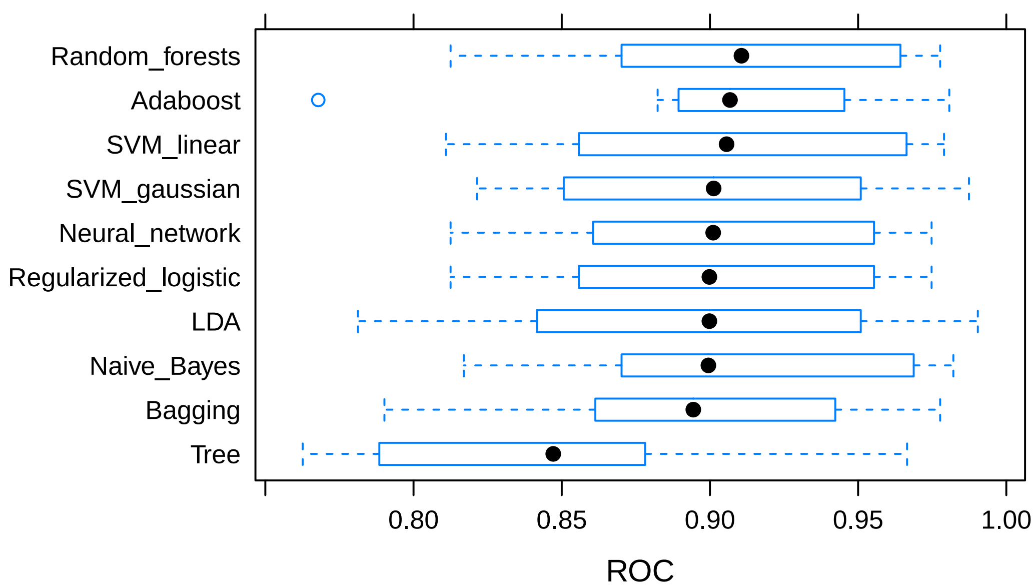
```
load(file = "./saved_results/cnnet.rda")
load(file = "./saved_results/boost.rda")
load(file = "./saved_results/rf.rda")
load(file = "./saved_results/bagging.rda")
load(file = "./saved_results/bayes.rda")
load(file = "./saved_results/svmr.rda")

resamp = resamples(list(
                        Regularized_logistic = model.glm,
                        LDA = model.lda,
                        Naive_Bayes = model.bayes,
                        Adaboost = boost.class,
                        Random_forests = rf.class,
                        Bagging = bagging.class,
                        Tree = tree.class,
                        Neural_network = cnnet.fit,
                        SVM_linear = svml.fit,
```

```r
                         SVM_gaussian = svmr.fit
                         ))
summary(resamp)
```

```
##
## Call:
## summary.resamples(object = resamp)
##
## Models: Regularized_logistic, LDA, Naive_Bayes, Adaboost, Random_forests, Bagging, Tree, Neural_netwo
## Number of resamples: 10
##
## ROC
##                           Min.   1st Qu.    Median      Mean   3rd Qu.
## Regularized_logistic 0.8125000 0.8612839 0.8998162 0.9021715 0.9553571
## LDA                  0.7812500 0.8463660 0.8998162 0.8981719 0.9497768
## Naive_Bayes          0.8169643 0.8725103 0.8994829 0.9097952 0.9681490
## Adaboost             0.7678571 0.8918572 0.9067752 0.9062419 0.9434086
## Random_forests       0.8125000 0.8747424 0.9106335 0.9091185 0.9637605
## Bagging              0.7901786 0.8613445 0.8943924 0.8934995 0.9357224
## Tree                 0.7626050 0.7968750 0.8471386 0.8446792 0.8771008
## Neural_network       0.8125000 0.8641827 0.9010989 0.9026261 0.9553571
## SVM_linear           0.8109244 0.8605769 0.9056238 0.9043815 0.9658310
## SVM_gaussian         0.8214286 0.8567590 0.9012605 0.9027614 0.9497768
##                           Max. NA's
## Regularized_logistic 0.9747899    0
## LDA                  0.9903846    0
## Naive_Bayes          0.9821429    0
## Adaboost             0.9807692    0
## Random_forests       0.9776786    0
## Bagging              0.9776786    0
## Tree                 0.9665179    0
## Neural_network       0.9747899    0
## SVM_linear           0.9789916    0
## SVM_gaussian         0.9873950    0
##
## Sens
##                           Min.   1st Qu.    Median      Mean   3rd Qu.
## Regularized_logistic 0.5714286 0.6923077 0.7857143 0.7950549 0.9065934
## LDA                  0.5714286 0.6978022 0.7857143 0.7725275 0.8310440
## Naive_Bayes          0.6428571 0.7857143 0.8159341 0.8258242 0.9038462
## Adaboost             0.6153846 0.6978022 0.7857143 0.7879121 0.8571429
## Random_forests       0.6428571 0.6923077 0.7142857 0.7659341 0.8310440
## Bagging              0.6428571 0.6978022 0.7500000 0.7659341 0.8310440
## Tree                 0.6153846 0.7280220 0.7774725 0.7725275 0.8392857
## Neural_network       0.5714286 0.6923077 0.7857143 0.7950549 0.9065934
## SVM_linear           0.5714286 0.6552198 0.7500000 0.7653846 0.8543956
## SVM_gaussian         0.5384615 0.6401099 0.7857143 0.7653846 0.8571429
##                           Max. NA's
## Regularized_logistic 1.0000000    0
## LDA                  1.0000000    0
## Naive_Bayes          1.0000000    0
## Adaboost             1.0000000    0
## Random_forests       1.0000000    0
## Bagging              0.9285714    0
```

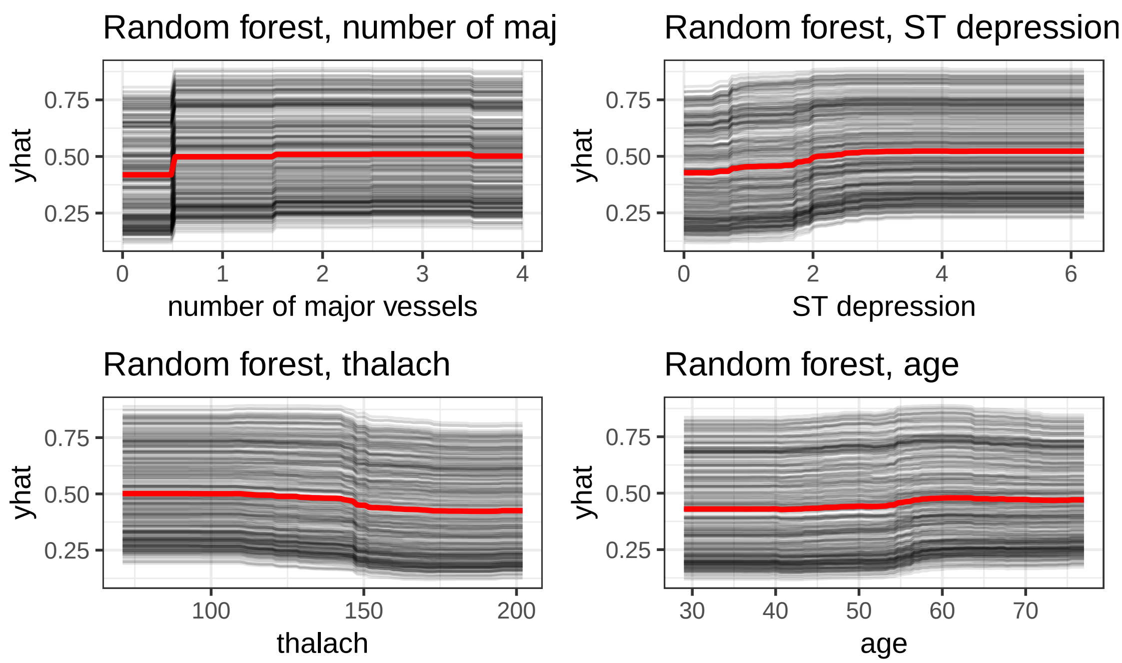
```
## Tree                  0.9285714    0
## Neural_network        1.0000000    0
## SVM_linear            1.0000000    0
## SVM_gaussian          1.0000000    0
##
## Spec
##                           Min.   1st Qu.    Median      Mean   3rd Qu.
## Regularized_logistic 0.7500000 0.8152574 0.8786765 0.8838235 0.9411765
## LDA                  0.7500000 0.8152574 0.9099265 0.8838235 0.9411765
## Naive_Bayes          0.7500000 0.7500000 0.8235294 0.8470588 0.9264706
## Adaboost             0.6875000 0.8281250 0.9375000 0.8775735 0.9402574
## Random_forests       0.7058824 0.7812500 0.8786765 0.8658088 0.9402574
## Bagging              0.6875000 0.7766544 0.8235294 0.8297794 0.8621324
## Tree                 0.5625000 0.8152574 0.8492647 0.8349265 0.8823529
## Neural_network       0.7500000 0.8152574 0.8786765 0.8838235 0.9411765
## SVM_linear           0.7500000 0.7766544 0.8786765 0.8658088 0.9264706
## SVM_gaussian         0.7500000 0.8125000 0.8492647 0.8536765 0.9237132
##                           Max. NA's
## Regularized_logistic 1.0000000    0
## LDA                  1.0000000    0
## Naive_Bayes          1.0000000    0
## Adaboost             0.9411765    0
## Random_forests       1.0000000    0
## Bagging              1.0000000    0
## Tree                 0.9375000    0
## Neural_network       1.0000000    0
## SVM_linear           1.0000000    0
## SVM_gaussian         0.9411765    0
```

```
bwplot(resamp, metric = "ROC")
```



###centered ICE

```r
ice_thalach.rf = rf.class %>%
    pdp::partial(pred.var = "thalach",
            grid.resolution = 100,
            ice = TRUE,
            prob = TRUE) %>%
    autoplot(train = heart_disease, alpha = .1) +
    ggtitle("Random forest, thalach")

ice_ca.rf = rf.class %>%
    pdp::partial(pred.var = "ca",
            grid.resolution = 100,
            ice = TRUE,
            prob = TRUE) %>%
    autoplot(train = heart_disease, alpha = .1,
             xlab = "number of major vessels") +
    ggtitle("Random forest, number of major vessels")

ice_oldpeak.rf =  rf.class %>%
    partial(pred.var = "oldpeak",
            grid.resolution = 100,
            ice = TRUE,
            prob = TRUE) %>%
    autoplot(train = heart_disease, alpha = .1,
             xlab = "ST depression") +
    ggtitle("Random forest, ST depression")

ice_age.rf = rf.class %>%
    pdp::partial(pred.var = "age",
            grid.resolution = 100,
            ice = TRUE,
            prob = TRUE) %>%
    autoplot(train = heart_disease, alpha = .1) +
    ggtitle("Random forest, age")

grid.arrange(ice_ca.rf, ice_oldpeak.rf,
             ice_thalach.rf, ice_age.rf, nrow = 2)
```



Variable importance

```r
library(gbm)
```

```
## Loaded gbm 2.1.5
```

```r
varImp(model.glm)
```

```
## glmnet variable importance
##
##            Overall
## cp2       100.0000
## thal2      94.8188
## thal3      93.4880
## exang1     92.3686
## cp3        87.3424
## sex1       79.4864
## cp1        66.9913
## slope2     52.7207
## slope1     52.7011
## ca         52.4277
## restecg1   42.4609
## restecg2   36.5417
## oldpeak    34.8283
## fbs1       10.6763
## thalach     1.4898
## age         1.4370
## trestbps    0.6164
## chol        0.0000
```

```r
varImp(model.lda)
```

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

```
##
##          Importance
## thal2      100.0000
## thalach     95.2812
## thal3       90.1317
## oldpeak     89.9165
## ca          89.7356
## exang1      76.2594
## slope2      73.0991
## slope1      66.7700
## cp2         52.2776
## age         51.1237
## sex1        47.3435
## cp1         33.1353
## restecg1    33.0578
## chol        25.1356
## trestbps    24.9634
## cp3          6.4669
## restecg2     0.5339
## fbs1         0.0000
```

```r
varImp(model.bayes)
```

```
## ROC curve variable importance
##
##          Importance
## thal2      100.0000
## thalach     95.2812
## thal3       90.1317
## oldpeak     89.9165
## ca          89.7356
## exang1      76.2594
## slope2      73.0991
## slope1      66.7700
## cp2         52.2776
## age         51.1237
## sex1        47.3435
## cp1         33.1353
## restecg1    33.0578
## chol        25.1356
## trestbps    24.9634
## cp3          6.4669
## restecg2     0.5339
## fbs1         0.0000
```

```r
varImp(boost.class)
```

```
## gbm variable importance
##
##           Overall
## ca       100.0000
## oldpeak   79.6457
## thal2     77.0270
## thalach   61.2231
## chol      52.8994
```

```
## trestbps  50.8206
## age       42.3494
## exang1    40.8228
## cp2       28.2991
## thal3     28.0742
## sex1      19.9508
## cp3       19.4944
## slope2    17.4076
## slope1     9.4854
## restecg1   8.0607
## cp1        7.8021
## fbs1       0.9966
## restecg2   0.0000
```

```r
varImp(rf.class)
```

```
## ranger variable importance
##
##          Overall
## thal2    100.000
## ca        94.184
## thal3     78.793
## oldpeak   77.081
## thalach   71.046
## exang1    59.586
## slope2    49.347
## age       48.026
## cp2       34.566
## chol      33.949
## sex1      32.134
## slope1    31.905
## trestbps  30.498
## cp1       15.616
## restecg1  10.725
## cp3        8.663
## fbs1       2.118
## restecg2   0.000
```

```r
varImp(bagging.class)
```

```
## ranger variable importance
##
##            Overall
## thal2    100.00000
## ca        47.18886
## oldpeak   32.70738
## thalach   27.53944
## age       14.77607
## exang1    13.43368
## trestbps  10.65010
## cp2       10.41997
## thal3      9.60369
## chol       8.71625
## cp3        5.61067
## slope2     3.96182
```

```
## sex1       3.24090
## restecg1   1.96555
## slope1     1.74960
## cp1        0.74229
## fbs1       0.04796
## restecg2   0.00000
```

```r
varImp(tree.class)
```

```
## rpart variable importance
##
##          Overall
## thalach  100.000
## ca        96.684
## exang1    87.087
## thal2     80.067
## thal3     68.075
## oldpeak   37.514
## age       25.951
## slope2    17.578
## cp2       15.249
## sex1      14.902
## slope1    13.928
## cp3        8.264
## chol       7.543
## cp1        4.269
## fbs1       0.000
## restecg1   0.000
## restecg2   0.000
## trestbps   0.000
```

```r
varImp(cnnet.fit)
```

```
## nnet variable importance
##
##          Overall
## ca       100.000
## thal2     85.381
## thal3     82.923
## cp2       82.012
## exang1    77.280
## oldpeak   71.835
## thalach   68.244
## sex1      65.485
## slope2    44.568
## slope1    44.370
## cp1       40.316
## cp3       38.814
## restecg1  32.957
## trestbps  21.097
## age       21.068
## chol      12.338
## fbs1       1.239
## restecg2   0.000
```

#Comparing accuracy

##Regularized logistic

```
ctrl2 <- trainControl(method = "cv")

glmnGrid <- expand.grid(.alpha = 0,
                        .lambda = 0.2335065)

set.seed(1)
model.glm.2 <- train(x = model.x,
                   y = model.y,
                   tuneGrid = glmnGrid,
                   method = "glmnet",
                   metric = "Accuracy",
                   trControl = ctrl2)
```

##LDA

```
set.seed(1)
model.lda.2 = train(x = model.x,
                  y = model.y,
                  method = "lda",
                  metric = "Accuracy",
                  trControl = ctrl2)
```

##Naive bayes

```
set.seed(1)
nbGrid = expand.grid(usekernel = TRUE,
                     fL = 1, adjust = 1.473684)
model.bayes.2 = train(x = model.x,
                    y = model.y,
                    method = "nb",
                    tuneGrid = nbGrid,
                    metric = "Accuracy",
                    trControl = ctrl2)
```

##Tree

```
set.seed(1)
tree.class.2 <- train(model.x, model.y,
                    method = "rpart",
                    tuneGrid = data.frame(cp = 0.003776539),
                    trControl = ctrl2,
                    metric = "Accuracy")
```

##Bagging

```
bagging.grid <- expand.grid(mtry = 18,
                            splitrule = "gini",
                            min.node.size = 40)

set.seed(1)
bagging.class.2 <- train(model.x, model.y,
                method = "ranger",
                tuneGrid = bagging.grid,
                metric = "Accuracy",
                trControl = ctrl2,
                importance = "impurity")
```

##Random Forest

```r
rf.grid <- expand.grid(mtry = 1,
                       splitrule = "gini",
                       min.node.size = 25)

set.seed(1)
rf.class.2 <- train(model.x, model.y,
                    method = "ranger",
                    tuneGrid = rf.grid,
                    metric = "Accuracy",
                    trControl = ctrl2,
                    importance = "impurity")
```

##Boosting

```r
boost.grid <- expand.grid(n.trees = 1370,
                          interaction.depth = 1,
                          shrinkage = 0.015,
                          n.minobsinnode = 1)

set.seed(1)
# Adaboost loss function
boost.class.2 = train(model.x, model.y,
                      tuneGrid = boost.grid,
                      trControl = ctrl2,
                      method = "gbm",
                      distribution = "adaboost",
                      metric = "Accuracy",
                      verbose = FALSE)
```

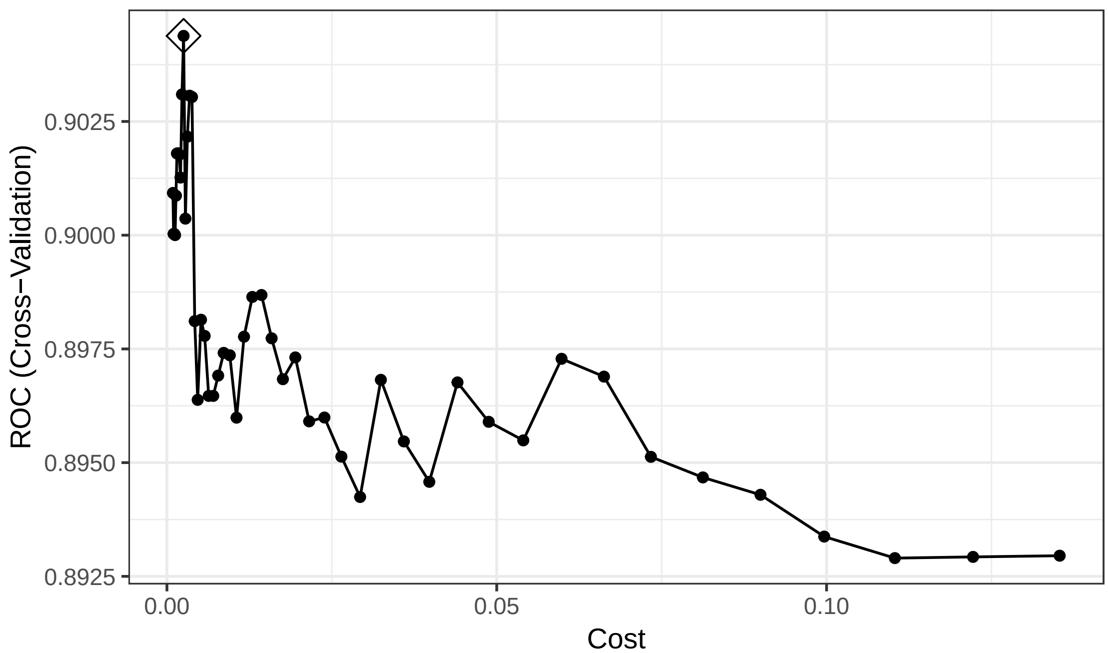
Neural network

```r
nnetGrid <- expand.grid(size = 18,
                        decay = 6.448276)

set.seed(1)
cnnet.fit.2 <- train(target~.,
                     heart_disease,
                     method = "nnet",
                     tuneGrid = nnetGrid,
                     preProcess = c("center","scale"),
                     trControl = ctrl2,
                     metric = "Accuracy",
                     trace = FALSE)
```

SVM

```r
## linear boundary
set.seed(1)
svml.fit.2 <- train(target~.,
                    data = heart_disease,
                    method = "svmLinear2",
```

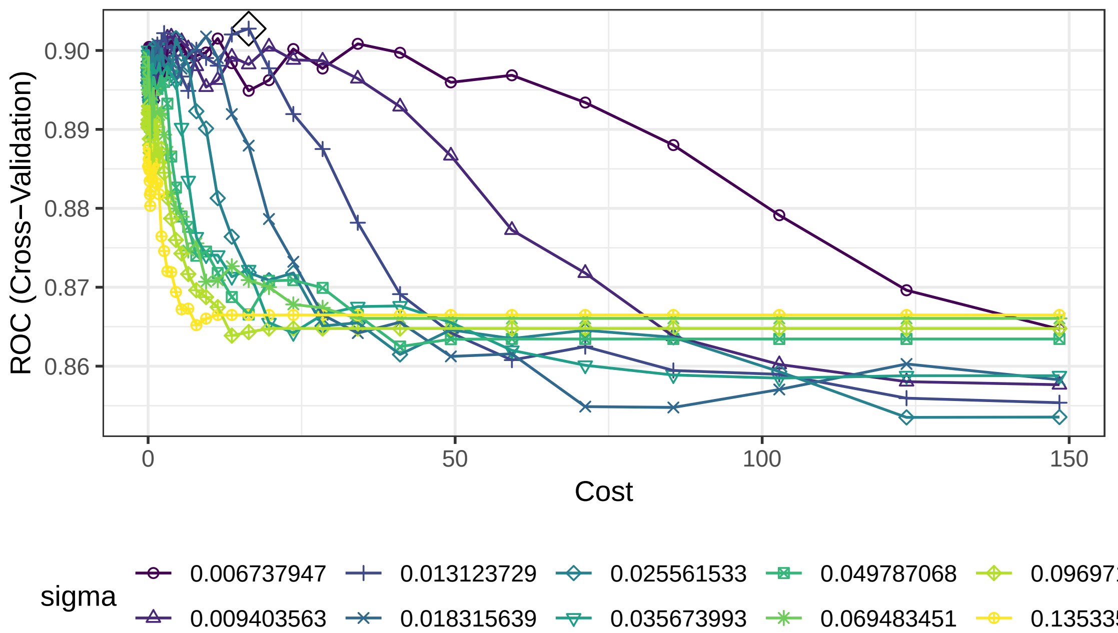
```r
                  preProcess = c("center", "scale"),
                  tuneGrid = data.frame(cost = exp(seq(-7,-2,len=50))),
                  trControl = ctrl2)

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




```r
svml.fit$bestTune
```

```
##           cost
## 11 0.002529859
```

```r
## radial kernel
svmr.grid <- expand.grid(C = exp(seq(-4,5,len=50)),
                         sigma = exp(seq(-5,-2,len=10)))
set.seed(1)
svmr.fit.2 <- train(target~.,
                  data = heart_disease,
                  method = "svmRadial",
                  preProcess = c("center", "scale"),
                  tuneGrid = svmr.grid,
                  trControl = ctrl2)

ggplot(svmr.fit, highlight = TRUE) +
    viridis::scale_color_viridis(discrete = TRUE) +
    scale_shape_manual(values = seq(1,10))
```




```r
svmr.fit$bestTune
```

```
##          sigma        C
## 373 0.01312373 16.37766
```

```r
resamp = resamples(list(
                        glm.fit = model.glm.2,
                        lda.fit = model.lda.2,
                        bayes.fit = model.bayes.2,
                        boost = boost.class.2,
                        rf = rf.class.2,
                        bagging = bagging.class.2,
                        tree = tree.class.2,
                        cnnet.fit = cnnet.fit.2,
                        svml.fit = svml.fit.2,
                        svmr.fit = svmr.fit.2
                        ))
summary(resamp)
```

```
##
## Call:
## summary.resamples(object = resamp)
##
## Models: glm.fit, lda.fit, bayes.fit, boost, rf, bagging, tree, cnnet.fit, svml.fit, svmr.fit
## Number of resamples: 10
##
## Accuracy
##                Min.   1st Qu.    Median      Mean   3rd Qu.      Max. NA's
## glm.fit   0.7000000 0.8031609 0.8360215 0.8441416 0.9000000 0.9677419    0
## lda.fit   0.7096774 0.7732759 0.8333333 0.8340267 0.8846774 0.9677419    0
## bayes.fit 0.7000000 0.7732759 0.8526882 0.8374750 0.8916667 0.9677419    0
## boost     0.7096774 0.7482759 0.8500000 0.8341416 0.8927419 0.9655172    0
## rf        0.6774194 0.7606322 0.8032258 0.8175677 0.9066092 0.9354839    0
```

```
## bagging   0.6666667 0.7806452 0.8331479 0.8141268 0.8562291 0.9000000    0
## tree      0.6666667 0.7789210 0.8166667 0.8066704 0.8666667 0.8709677    0
## cnnet.fit 0.7000000 0.8031609 0.8360215 0.8441416 0.9000000 0.9677419    0
## svml.fit  0.6774194 0.8000000 0.8360215 0.8378124 0.9155172 0.9677419    0
## svmr.fit  0.7419355 0.8068966 0.8500000 0.8473674 0.8927419 0.9354839    0
##
## Kappa
##                Min.   1st Qu.    Median      Mean   3rd Qu.      Max. NA's
## glm.fit   0.3946188 0.5944980 0.6694856 0.6826138 0.8004166 0.9352818    0
## lda.fit   0.4025696 0.5423267 0.6603832 0.6617627 0.7653612 0.9352818    0
## bayes.fit 0.3946188 0.5469194 0.7004056 0.6724875 0.7814956 0.9352818    0
## boost     0.4101480 0.4940966 0.6916528 0.6626159 0.7826973 0.9307876    0
## rf        0.3404255 0.5082084 0.6012348 0.6283910 0.8082234 0.8697479    0
## bagging   0.3303571 0.5478123 0.6580195 0.6220325 0.7099677 0.7963801    0
## tree      0.3421053 0.5469316 0.6266968 0.6090815 0.7315396 0.7427386    0
## cnnet.fit 0.3946188 0.5944980 0.6694856 0.6826138 0.8004166 0.9352818    0
## svml.fit  0.3404255 0.5893826 0.6709540 0.6710978 0.8279169 0.9352818    0
## svmr.fit  0.4655172 0.6095944 0.6904463 0.6889089 0.7861955 0.8697479    0
```

```r
bwplot(resamp)
```