# Assignment 9

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## Part 1: kNN

1.

Read in the heart.csv data file.

We remove the ST\_Slope column as instructed.

```
# Read in space-separated data using "read_csv()" function.
# Remove column ST_Slope, convert HeartDisease to a factor
heartData <- read.csv(file = "./heart.csv") %>% select(-ST_Slope)
```

### **2**.

Create dummy columns corresponding to the values of Sex, ChestPainType, and RestingECG for use in our kNN fit.

We can follow the example from section 3.1 in the provided caret vignette to create dummy variables. dummyVars ignores integers, so we specify the full set of variables with the formula  $\sim$  . and create a new data frame, newHeartData.

```
# Use dummyVars() and predict() to create new columns.
dummies <- dummyVars( ~ ., data = heartData)
newHeartData <- predict(dummies, newdata = heartData)
newHeartData <- as_data_frame(newHeartData)

## Warning: `as_data_frame()` was deprecated in tibble 2.0.0.
## Please use `as_tibble()` instead.
## The signature and semantics have changed, see `?as_tibble`.
## This warning is displayed once every 8 hours.
## Call `lifecycle::last_lifecycle_warnings()` to see where this warning was generated.</pre>
```

```
newHeartData$HeartDisease <- as.factor(newHeartData$HeartDisease)</pre>
```

#### 3.

Now split the data set you've created into a training and testing set. Use p = 0.8.

We can create train and test partitions with the createDataPartition function.

```
# p = 0.8 places 80% of observations in the training set
set.seed(50)
heartIndex <- createDataPartition(newHeartData$HeartDisease, p = 0.8, list = FALSE)
heartTrain <- newHeartData[heartIndex, ]
heartTest <- newHeartData[-heartIndex, ]</pre>
```

#### 4.

Finally, train the kNN model. Use repeated 10 fold cross-validation, with the number of repeats being 3. You should also preprocess the data by centering and scaling. Lastly, set the **tuneGrid** so that you are considering values of k of 1, 2, 3, ..., 40.

The caret package allows us to pre-process data, fit and tune models on the training set, and predict on the test set.

#### 5.

Check how well your model does on the test set using the confusionMatrix() function.

```
# See confusion matrix on test set (correct/incorrect predictions)
confusionMatrix(data = heartTest$HeartDisease, reference = predict(kNNFit, newdata = heartTest))
## Confusion Matrix and Statistics
##
##
             Reference
## Prediction 0 1
##
            0 60 22
            1 18 83
##
##
##
                  Accuracy : 0.7814
##
                    95% CI: (0.7145, 0.839)
       No Information Rate: 0.5738
##
##
       P-Value [Acc > NIR] : 2.949e-09
##
##
                     Kappa : 0.556
##
   Mcnemar's Test P-Value: 0.6353
##
##
##
               Sensitivity: 0.7692
##
               Specificity: 0.7905
##
            Pos Pred Value: 0.7317
```

```
## Neg Pred Value : 0.8218
## Prevalence : 0.4262
## Detection Rate : 0.3279
## Detection Prevalence : 0.4481
## Balanced Accuracy : 0.7799
##
## 'Positive' Class : 0
```

#### Part 2: Ensemble

We'll look at predicting the same heart disease variable in this section as well, just instead of using kNN we'll use the following methods:

#### 1.

##

A classification tree (use method = rpart: tuning parameter is cp, use values 0, 0.001, 0.002, ..., 0.1).

We use seq() to generate values from 0 to 0.1. With this method, we see an accuracy of approximately 80.33%.

```
# Create tuning parameter by generating regular sequence
rpartParam \leftarrow seq(from = 0, to = 0.1, by = 0.001)
# Classification tree fit
rpartFit <- train(HeartDisease ~ ., data = heartTrain,</pre>
               method = "rpart",
               preProcess = c("center", "scale"),
               trControl = trainControl(method = "repeatedcv",
                                         number = 10, repeats = 3),
               tuneGrid = data.frame(cp = rpartParam))
# See confusion matrix on test set (correct/incorrect predictions)
confusionMatrix(data = heartTest$HeartDisease, reference = predict(rpartFit, newdata = heartTest))
## Confusion Matrix and Statistics
##
             Reference
##
## Prediction 0 1
##
            0 57 25
            1 11 90
##
##
##
                  Accuracy: 0.8033
                    95% CI: (0.7382, 0.8583)
##
##
       No Information Rate: 0.6284
       P-Value [Acc > NIR] : 2.307e-07
##
##
##
                     Kappa: 0.5958
##
    Mcnemar's Test P-Value: 0.03026
##
##
##
               Sensitivity: 0.8382
               Specificity: 0.7826
##
            Pos Pred Value: 0.6951
##
            Neg Pred Value: 0.8911
##
```

Prevalence: 0.3716

```
##
            Detection Rate: 0.3115
##
      Detection Prevalence: 0.4481
##
         Balanced Accuracy: 0.8104
##
##
          'Positive' Class : 0
##
2.
A bagged tree (use method = treebag: no tuning parameter).
Here, we see a slightly lower accuracy of 79.23%.
# Bagged tree fit
baggedTreeFit <- train(HeartDisease ~ ., data = heartTrain,</pre>
               method = "treebag",
               preProcess = c("center", "scale"),
               trControl = trainControl(method = "repeatedcv",
                                         number = 10, repeats = 3))
# See confusion matrix on test set (correct/incorrect predictions)
confusionMatrix(data = heartTest$HeartDisease,
                reference = predict(baggedTreeFit, newdata = heartTest))
## Confusion Matrix and Statistics
##
##
             Reference
## Prediction 0 1
##
            0 57 25
##
            1 13 88
##
##
                  Accuracy : 0.7923
##
                    95% CI: (0.7263, 0.8487)
##
       No Information Rate: 0.6175
       P-Value [Acc > NIR] : 2.954e-07
##
##
##
                      Kappa: 0.5743
##
    Mcnemar's Test P-Value: 0.07435
##
##
##
               Sensitivity: 0.8143
               Specificity: 0.7788
##
##
            Pos Pred Value: 0.6951
##
            Neg Pred Value: 0.8713
                Prevalence: 0.3825
##
##
            Detection Rate: 0.3115
##
      Detection Prevalence: 0.4481
##
         Balanced Accuracy: 0.7965
##
          'Positive' Class : 0
##
##
3.
```

A random forest (use method = rf: tuning parameter is mtry, use vales of 1, 2, ..., 15).

Here, we see an accuracy of ~80.87%, on part with the classification tree method.

```
# Random forest fit
rfFit <- train(HeartDisease ~ ., data = heartTrain,</pre>
               method = "rf",
               preProcess = c("center", "scale"),
               trControl = trainControl(method = "repeatedcv",
                                         number = 10, repeats = 3),
               tuneGrid = data.frame(mtry = 1:15))
# See confusion matrix on test set (correct/incorrect predictions)
confusionMatrix(data = heartTest$HeartDisease,
                reference = predict(rfFit, newdata = heartTest))
## Confusion Matrix and Statistics
##
##
             Reference
## Prediction 0 1
##
            0 59 23
##
            1 13 88
##
##
                  Accuracy: 0.8033
                    95% CI: (0.7382, 0.8583)
##
##
       No Information Rate: 0.6066
##
       P-Value [Acc > NIR] : 9.382e-09
##
##
                     Kappa: 0.5977
##
##
   Mcnemar's Test P-Value: 0.1336
##
               Sensitivity: 0.8194
##
##
               Specificity: 0.7928
            Pos Pred Value: 0.7195
##
##
            Neg Pred Value: 0.8713
##
                Prevalence: 0.3934
##
            Detection Rate: 0.3224
##
      Detection Prevalence: 0.4481
##
         Balanced Accuracy: 0.8061
##
##
          'Positive' Class: 0
##
4.
```

A boosted tree (use method = gbm: tuning parameters are n.trees, interaction.depth, shrinkage, and n.minobsinnode, use all combinations of n.trees of 25, 50, 100, 150, and 200, interaction.depth of 1, 2, 3, 4, shrinkage = 0.1, and n.minobsinnode = 10; Hint: use expand.grid() to create your data frame for tuneGrid).

With this method, our accuracy with the test data set is ~79.78%. ß

## Confusion Matrix and Statistics

```
##
##
             Reference
## Prediction 0 1
##
            0 58 24
            1 15 86
##
##
                  Accuracy : 0.7869
##
                    95% CI : (0.7204, 0.8438)
##
       No Information Rate: 0.6011
##
##
       P-Value [Acc > NIR] : 7.088e-08
##
##
                     Kappa: 0.5646
##
   Mcnemar's Test P-Value : 0.2002
##
##
               Sensitivity: 0.7945
##
##
               Specificity: 0.7818
##
            Pos Pred Value: 0.7073
##
            Neg Pred Value : 0.8515
                Prevalence: 0.3989
##
##
            Detection Rate: 0.3169
##
      Detection Prevalence : 0.4481
##
         Balanced Accuracy: 0.7882
##
##
          'Positive' Class : 0
##
```