hw_6

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Exercise 1:

```
# clean data
pokemon <- janitor::clean_names(data)
#pokemon <- pokemon_clean %>% filter(type_1 == "Bug"|type_1 == "Fire"|
                                     #type_1 == "Grass"|type_1 == "Normal"|
                                     #type_1 == "Water"|type_1 == "Psychic")
pokemon <- pokemon[pokemon$type_1 %in% c("Bug", "Fire", "Grass", "Normal", "Water", "Psychic"),]
pokemon$type_1 <- as.factor(pokemon$type_1)
pokemon$legendary <- as.factor(pokemon$legendary)
#split
set.seed(1027)
pokemon_split <- initial_split(pokemon, prop= 0.8, strata = "type_1")

pokemon_train <- training(pokemon_split)
pokemon_test <- testing(pokemon_split)
# folds
pokemon_folds <- vfold_cv(pokemon_train, strata = "type_1", v = 5)
# recipe
pokemon_recipe <- recipe(type_1 ~ legendary + generation + sp_atk +
                           attack + speed + defense +
                           hp + sp_def, pokemon_train) %>%
  step_dummy(all_nominal_predictors()) %>%
  step_center(all_predictors()) %>%
  step_scale(all_predictors())
```

Exercise 2:

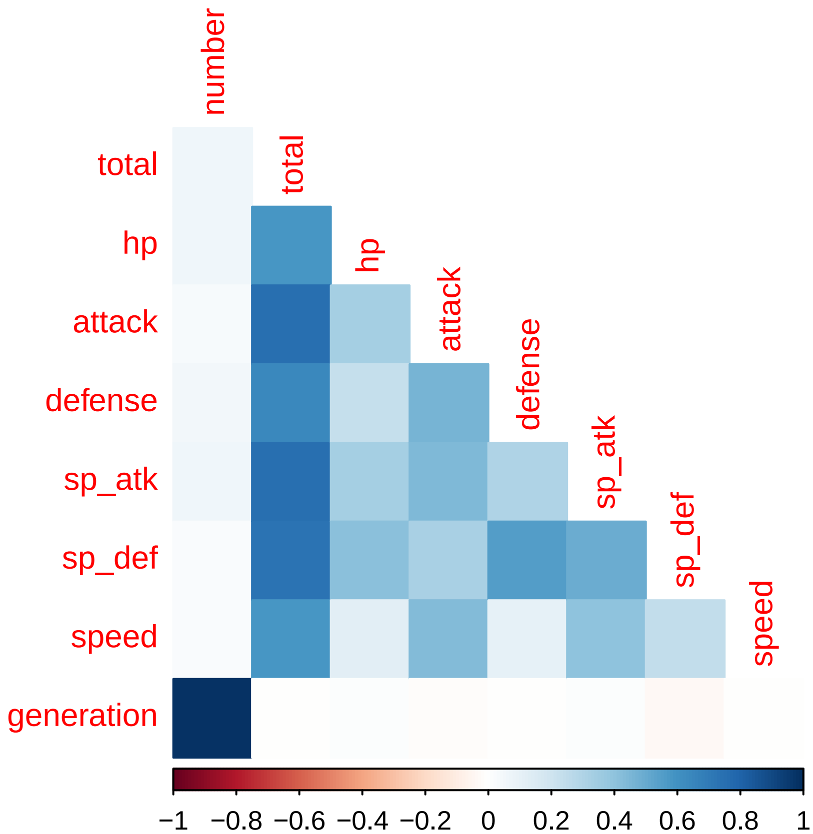
```
library(corrplot)
```

```
## corrplot 0.92 loaded
```

```
pokemon %>%
  select(is.numeric) %>%
  cor() %>%
  corrplot(type="lower", diag= FALSE, method = 'color')
```

```
## Warning: Predicate functions must be wrapped in `where()`.
##
##   # Bad
```

```
##   data %>% select(is.numeric)
##
##   # Good
##   data %>% select(where(is.numeric))
##
## i Please update your code.
## This message is displayed once per session.
```

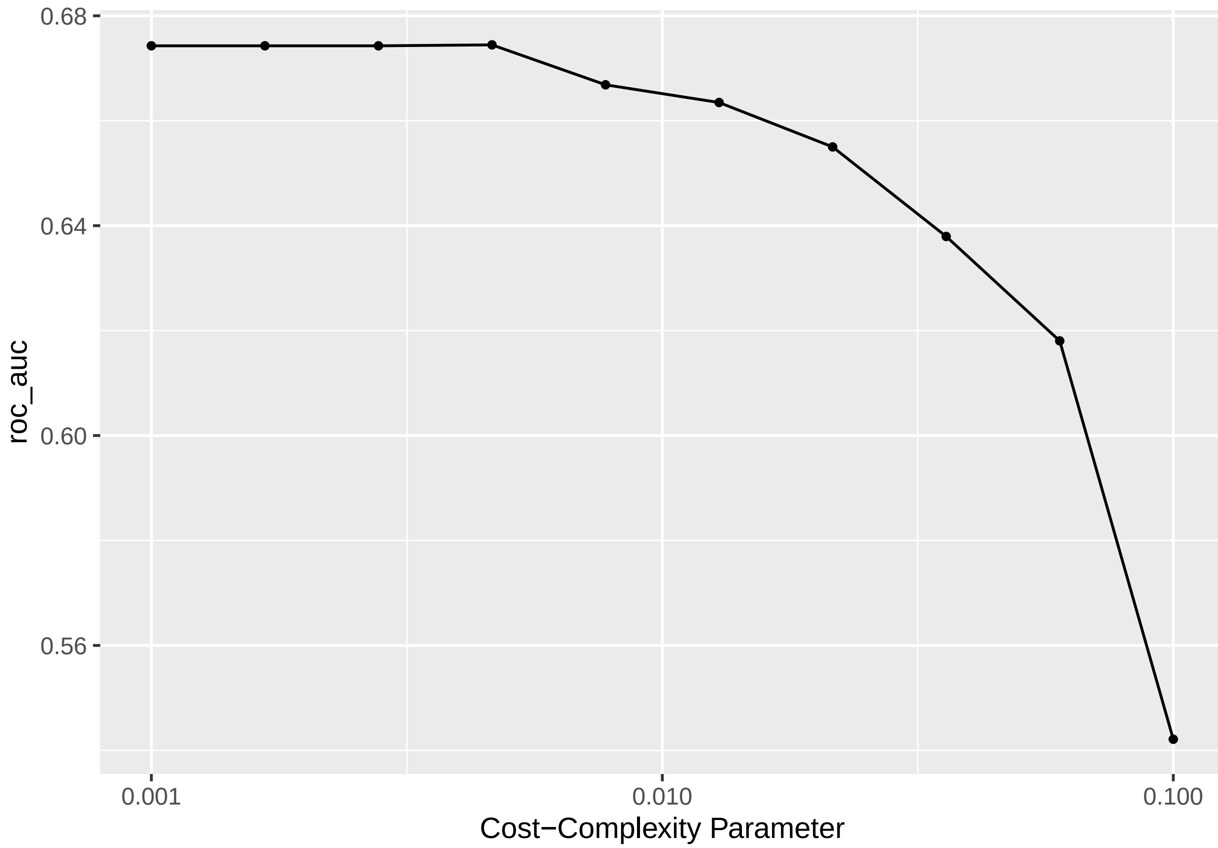


Total is strongly positively correlated with all other variables. In general most variables are positively correlated with each other. These relationships makes sense because a Pokemon with a higher level of defense or attack will most likely have a higher level of speed or defense. In other words a better quality Pokemon will have overall relatively higher levels to their characteristics.

Exercise 3:

```
tree_spec <- decision_tree() %>%
  set_engine("rpart")
class_tree_spec <- tree_spec %>%
  set_mode("classification")
class_tree_wf <- workflow() %>%
  add_model(class_tree_spec %>% set_args(cost_complexity = tune())) %>%
  add_recipe(pokemon_recipe)

param_grid <- grid_regular(cost_complexity(range = c(-3, -1)), levels = 10)

tune_res <- tune_grid(
  class_tree_wf,
```

```
  resamples = pokemon_folds,
  grid = param_grid,
  metrics = metric_set(roc_auc)
)
autoplot(tune_res)
```



After .008 the curve takes a downward trend in roc-auc value. The curve continues hyperbolically fall as cost-complexity increases. A single decision tree has a better performance with a lower cost-complexity parameter. Exercise 4:

```
best_compl <- select_best(tune_res)
best_compl
```

```
## # A tibble: 1 x 2
##   cost_complexity .config
##             <dbl> <chr>
## 1         0.00464 Preprocessor1_Model04
```

```
arrange(collect_metrics(tune_res), cost_complexity)
```

```
## # A tibble: 10 x 7
##    cost_complexity .metric .estimator  mean     n std_err .config
##              <dbl> <chr>   <chr>      <dbl> <int>   <dbl> <chr>
##  1         0.001   roc_auc hand_till  0.674     5  0.0112 Preprocessor1_Model01
##  2         0.00167 roc_auc hand_till  0.674     5  0.0112 Preprocessor1_Model02
```

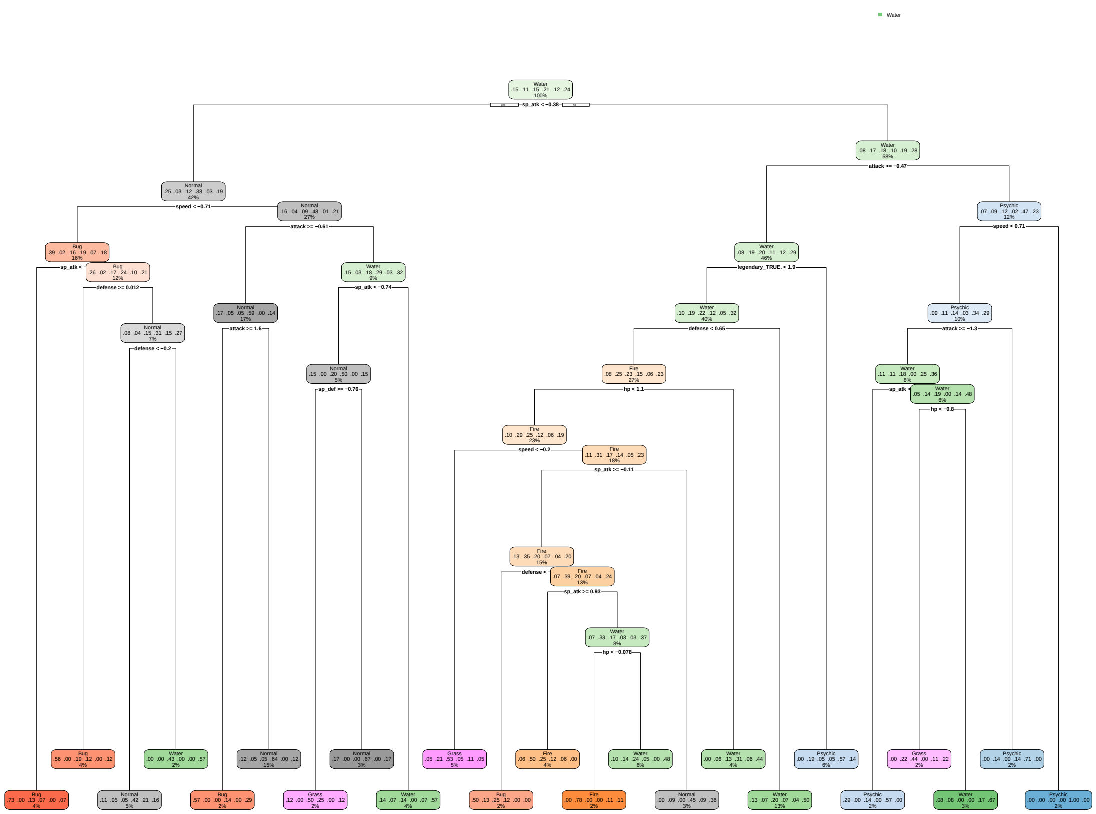
```
## 3          0.00278 roc_auc hand_till  0.674     5  0.0112 Preprocessor1_Model03
## 4          0.00464 roc_auc hand_till  0.674     5  0.0123 Preprocessor1_Model04
## 5          0.00774 roc_auc hand_till  0.667     5  0.0178 Preprocessor1_Model05
## 6          0.0129  roc_auc hand_till  0.663     5  0.0126 Preprocessor1_Model06
## 7          0.0215  roc_auc hand_till  0.655     5  0.0224 Preprocessor1_Model07
## 8          0.0359  roc_auc hand_till  0.638     5  0.0177 Preprocessor1_Model08
## 9          0.0599  roc_auc hand_till  0.618     5  0.0134 Preprocessor1_Model09
## 10         0.1     roc_auc hand_till  0.542     5  0.0261 Preprocessor1_Model10
```

The ROC-AUC of the best performing pruned decision tree is 0.6744568.

Exercise 5:

```r
class_tree_final <- finalize_workflow(class_tree_wf, best_compl)
class_tree_final_fit <- fit(class_tree_final, data = pokemon_train)

class_tree_final_fit %>%
  extract_fit_engine() %>%
  rpart.plot(roundint = FALSE)
```

```
## Warning: labs do not fit even at cex 0.15, there may be some overplotting
```



Exercise 5b:

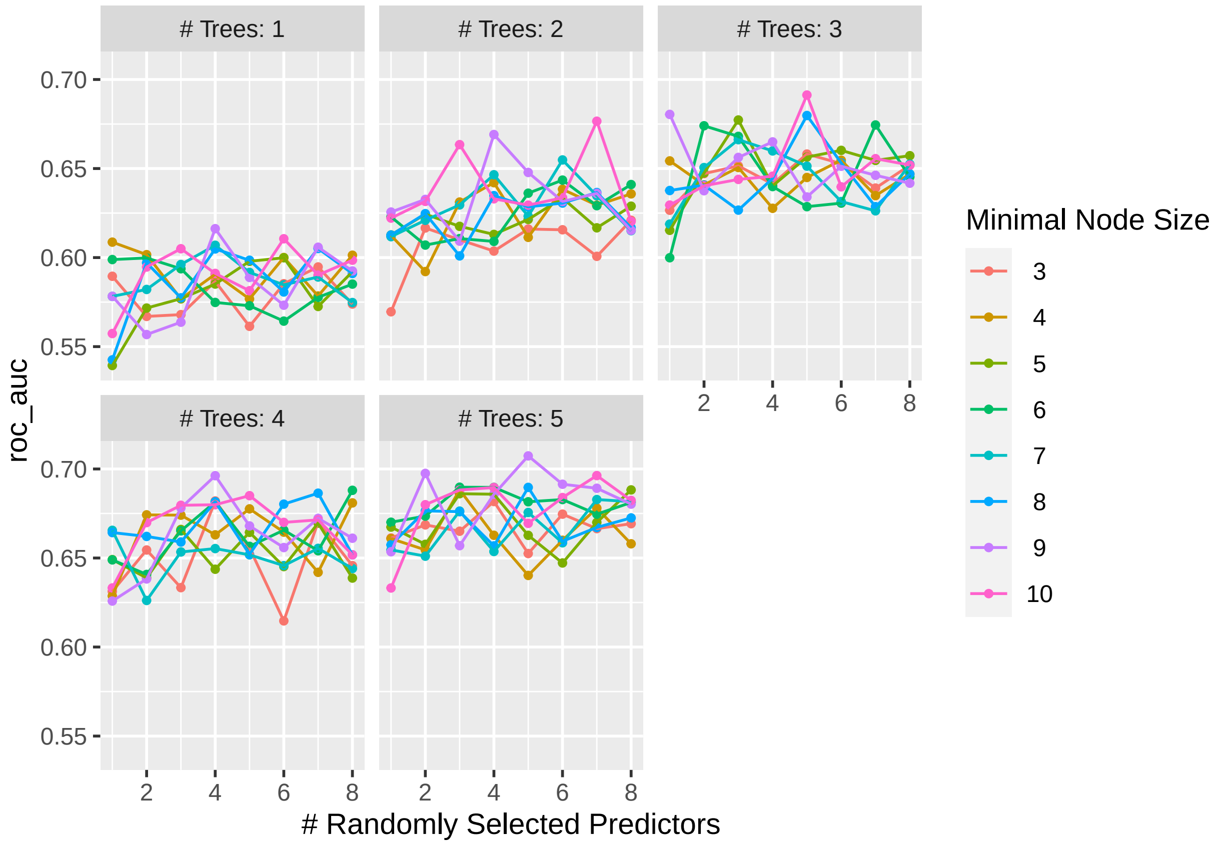
```r
class_for_spec <- rand_forest() %>%
  set_engine("ranger", importance = "impurity") %>%
  set_mode("classification")
class_for_wf <- workflow() %>%
  add_model(class_for_spec %>%
              set_args(mtry = tune(), trees = tune(),min_n = tune())) %>%
  add_recipe(pokemon_recipe)


param_grid_for <- grid_regular(mtry(range = c(1,8)), trees(range= c(1,5)),
                               min_n(range = c(3,10)), levels = 8)
```

mtry is number of variables to possibly split at in each node.
trees is number of trees in the model.
min_n is the minimal node size.

mtry should be between 1 and 8 because there are only 8 predictor variables in our recipe. mtry 8 would be a model that uses all 8 of our predictor variables.

Exercise 6:

```r
tune_res_for <- tune_grid(
  class_for_wf,
  resamples = pokemon_folds,
  grid = param_grid_for,
  metrics = metric_set(roc_auc))

autoplot(tune_res_for)
```



Exercise 7:

```
best_for <- select_best(tune_res_for)
best_for
```

```
## # A tibble: 1 x 4
##    mtry trees min_n .config
##   <int> <int> <int> <chr>
## 1     5     5     9 Preprocessor1_Model277
```

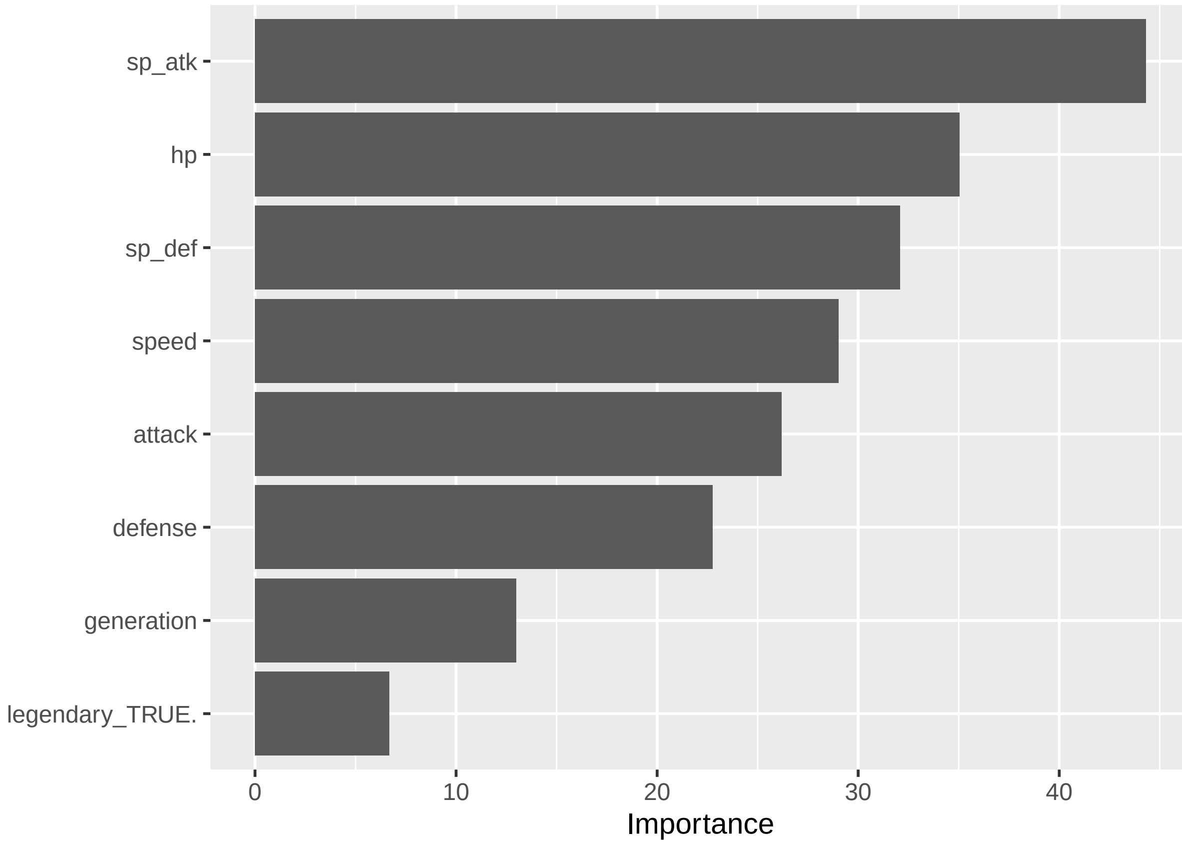
```
arrange(collect_metrics(tune_res_for), mtry, trees, min_n)
```

```
## # A tibble: 320 x 9
##     mtry trees min_n .metric .estimator  mean     n std_err .config
##    <int> <int> <int> <chr>   <chr>      <dbl> <int>   <dbl> <chr>
##  1     1     1     3 roc_auc hand_till  0.589     5 0.0150  Preprocessor1_Model~
##  2     1     1     4 roc_auc hand_till  0.609     5 0.0139  Preprocessor1_Model~
##  3     1     1     5 roc_auc hand_till  0.539     5 0.00782 Preprocessor1_Model~
##  4     1     1     6 roc_auc hand_till  0.599     5 0.0170  Preprocessor1_Model~
##  5     1     1     7 roc_auc hand_till  0.578     5 0.0237  Preprocessor1_Model~
##  6     1     1     8 roc_auc hand_till  0.543     5 0.00932 Preprocessor1_Model~
##  7     1     1     9 roc_auc hand_till  0.578     5 0.0235  Preprocessor1_Model~
##  8     1     1    10 roc_auc hand_till  0.557     5 0.0104  Preprocessor1_Model~
##  9     1     2     3 roc_auc hand_till  0.570     5 0.0158  Preprocessor1_Model~
## 10     1     2     4 roc_auc hand_till  0.612     5 0.0130  Preprocessor1_Model~
## # ... with 310 more rows
```

The ROC AUC is 0.7073355

Exercise 8:

```
class_for_final <- finalize_workflow(class_for_wf, best_for)
class_for_final_fit <- fit(class_for_final, data = pokemon_train)
class_for_final_fit%>%
  extract_fit_parsnip()%>%
  vip()
```

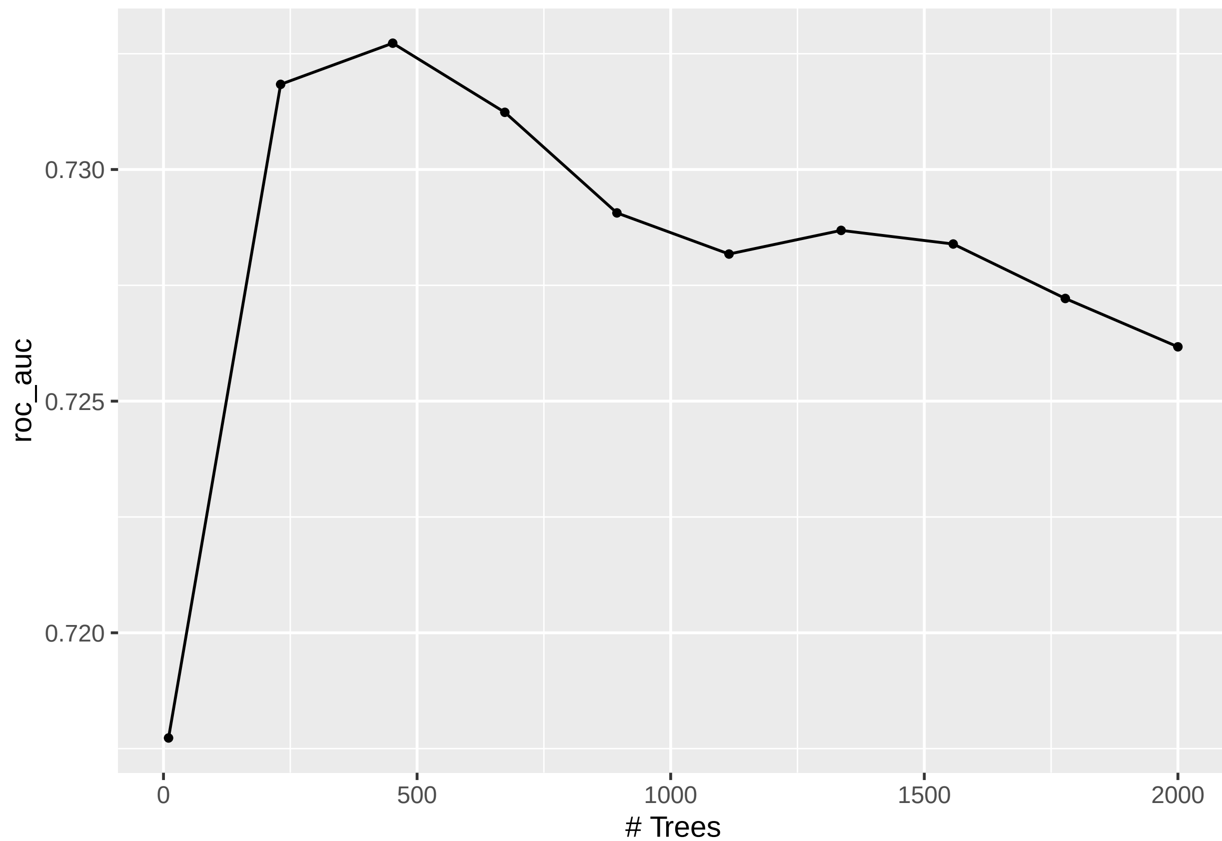


sp_attack and hp were the most useful, while generation and legendary were the least useful. Yes, I assume that you need to have successful sp_attack and hp make for the 'best' Pokemon.

Exercise 9:

```
boost_spec <- boost_tree() %>%
  set_engine("xgboost") %>%
  set_mode("classification")
boost_wf <- workflow() %>%
  add_model(boost_spec %>%
              set_args(trees = tune())) %>%
  add_recipe(pokemon_recipe)
param_grid_boost <- grid_regular(trees(range = c(10,2000)), levels = 10)

tune_res_boost <- tune_grid(
  boost_wf,
```

```r
  resamples = pokemon_folds,
  grid = param_grid_boost,
  metrics = metric_set(roc_auc))

autoplot(tune_res_boost)
```




```r
best_boost <- select_best(tune_res_boost)
best_boost
```

```
## # A tibble: 1 x 2
##   trees .config
##   <int> <chr>
## 1   452 Preprocessor1_Model03
```

```r
arrange(collect_metrics(tune_res_boost),trees)
```

```
## # A tibble: 10 x 7
##    trees .metric .estimator  mean     n std_err .config
##    <int> <chr>   <chr>      <dbl> <int>   <dbl> <chr>
##  1    10 roc_auc hand_till  0.718     5 0.00725 Preprocessor1_Model01
##  2   231 roc_auc hand_till  0.732     5 0.00802 Preprocessor1_Model02
##  3   452 roc_auc hand_till  0.733     5 0.00728 Preprocessor1_Model03
##  4   673 roc_auc hand_till  0.731     5 0.00779 Preprocessor1_Model04
##  5   894 roc_auc hand_till  0.729     5 0.00856 Preprocessor1_Model05
```

```
## 6  1115 roc_auc hand_till  0.728     5 0.00889 Preprocessor1_Model06
## 7  1336 roc_auc hand_till  0.729     5 0.00929 Preprocessor1_Model07
## 8  1557 roc_auc hand_till  0.728     5 0.00913 Preprocessor1_Model08
## 9  1778 roc_auc hand_till  0.727     5 0.00877 Preprocessor1_Model09
## 10 2000 roc_auc hand_till  0.726     5 0.00860 Preprocessor1_Model10
```

The ROC-AUC of the best model is 0.7327269

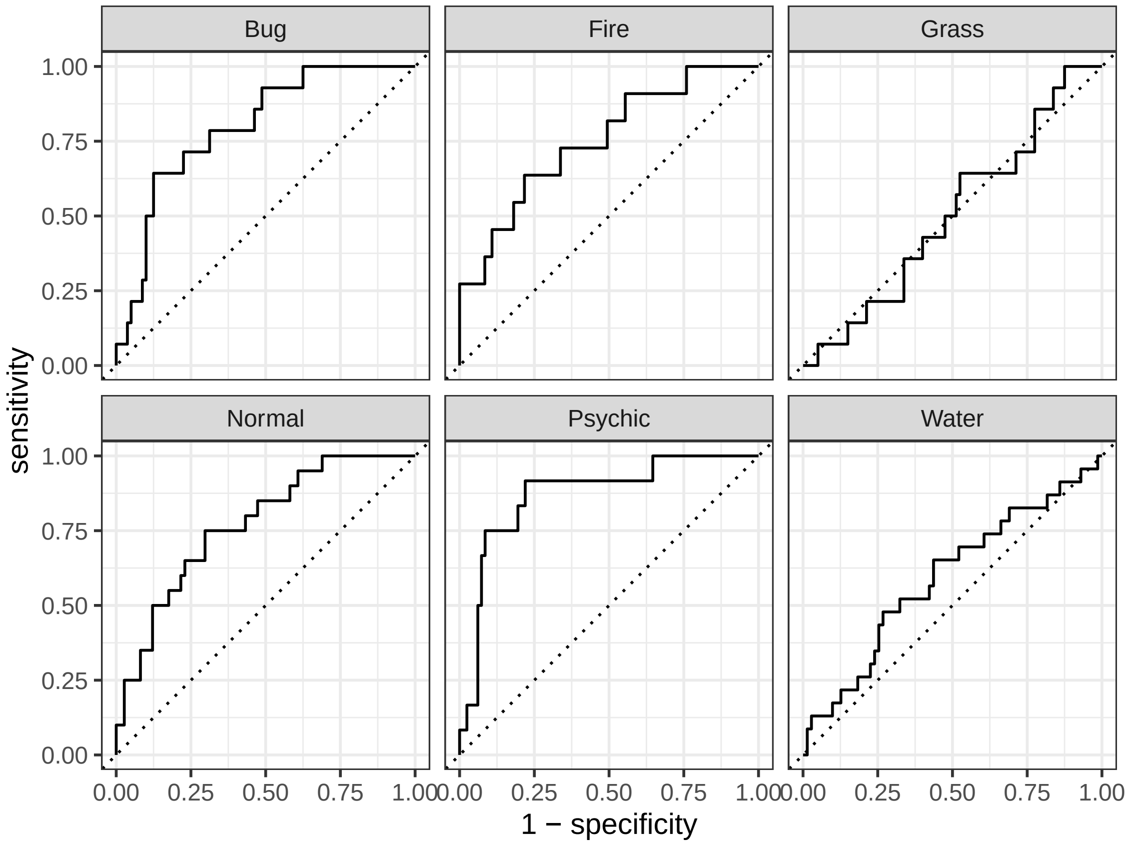
```
compl <- collect_metrics(tune_res)
roc_compl <- subset(compl, .config=='Preprocessor1_Model08')[,4]
roc_compl$type <- c('pruned tree')

forest <- collect_metrics(tune_res_for)
roc_forest <- subset(forest, .config =='Preprocessor1_Model118')[,6]
roc_forest$type <- c('random forest')


boost <- collect_metrics(tune_res_boost)
roc_boost <-subset(boost, .config == 'Preprocessor1_Model01')[,4]
roc_boost$type <- c('boosted tree')


x<-rbind(roc_compl, roc_forest, roc_boost )
table <-  x[,c(2,1)] %>% rename(roc_auc = mean)
table
```

```
## # A tibble: 3 x 2
##   type          roc_auc
##   <chr>           <dbl>
## 1 pruned tree     0.638
## 2 random forest   0.647
## 3 boosted tree    0.718
```

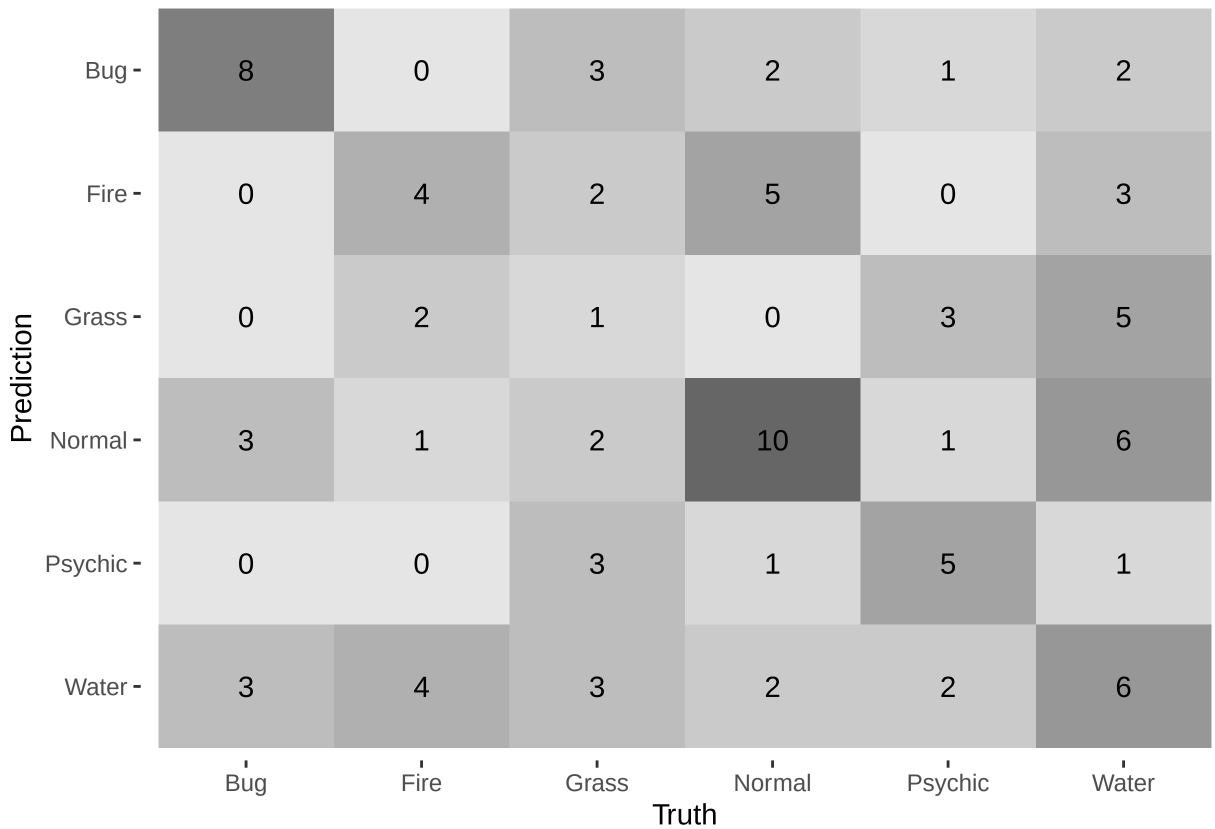
```
best_final <- select_best(tune_res_boost)
final_wf <- finalize_workflow(boost_wf, best_final)
final_fit <- fit(final_wf, data = pokemon_train)

augm <- augment(final_fit, new_data = pokemon_test)
augm %>% roc_auc(truth = type_1, estimate =c(
  .pred_Bug, .pred_Fire, .pred_Grass, .pred_Normal,
  .pred_Psychic, .pred_Water))
```

```
## # A tibble: 1 x 3
##   .metric .estimator .estimate
##   <chr>   <chr>          <dbl>
## 1 roc_auc hand_till      0.715
```

```
augm %>% roc_curve(truth = type_1, estimate =c(
  .pred_Bug, .pred_Fire, .pred_Grass, .pred_Normal,
  .pred_Psychic, .pred_Water)) %>%
  autoplot()
```




```
augm %>% conf_mat(truth = type_1, estimate =.pred_class) %>%
  autoplot(type = "heatmap")
```



Bug and Normal were the best and Grass and Fire were the worst.