

# Homework 6

PSTAT 131/231

## Contents

### Exercise 1

Read in the data and set things up as in Homework 5:

- Use `clean_names()`
- Filter out the rarer Pokémon types
- Convert `type_1` and `legendary` to factors

```
pokemon <- pokemon <- read.csv("C:/Users/rocke/Downloads/homework-5/homework-5/data/Pokemon.csv")
pokemon <- clean_names(pokemon)
target <- c("Bug", "Fire", "Grass", "Normal", "Water", "Psychic")
pokemon <- pokemon %>%
  filter(type_1 %in% target)
pokemon$type_1 <- factor(pokemon$type_1)
pokemon$legendary <- factor(pokemon$legendary)
pokemon$generation <- factor(pokemon$generation)
```

Do an initial split of the data; you can choose the percentage for splitting. Stratify on the outcome variable.

```
set.seed(1234)
pokemon_split <- initial_split(pokemon, prop = 0.7, strata = type_1)
pokemon_train <- training(pokemon_split)
pokemon_test <- testing(pokemon_split)
dim(pokemon_split) # verifying training and testing sets have the desired number of observations

##   analysis assessment          n          p
##       318         140        458        13
```

Fold the training set using  $v$ -fold cross-validation, with  $v = 5$ . Stratify on the outcome variable.

```
pokemon_folds <- vfold_cv(pokemon_train, v = 5, strata = type_1)
```

Set up a recipe to predict `type_1` with `legendary`, `generation`, `sp_atk`, `attack`, `speed`, `defense`, `hp`, and `sp_def`:

- Dummy-code `legendary` and `generation`;
- Center and scale all predictors.

```

pokemon_recipe <- recipe(type_1 ~ legendary + generation + sp_atk + attack + speed + defense + hp + sp_
  step_dummy(legendary) %>%
  step_dummy(generation) %>%
  step_normalize(all_predictors())

```

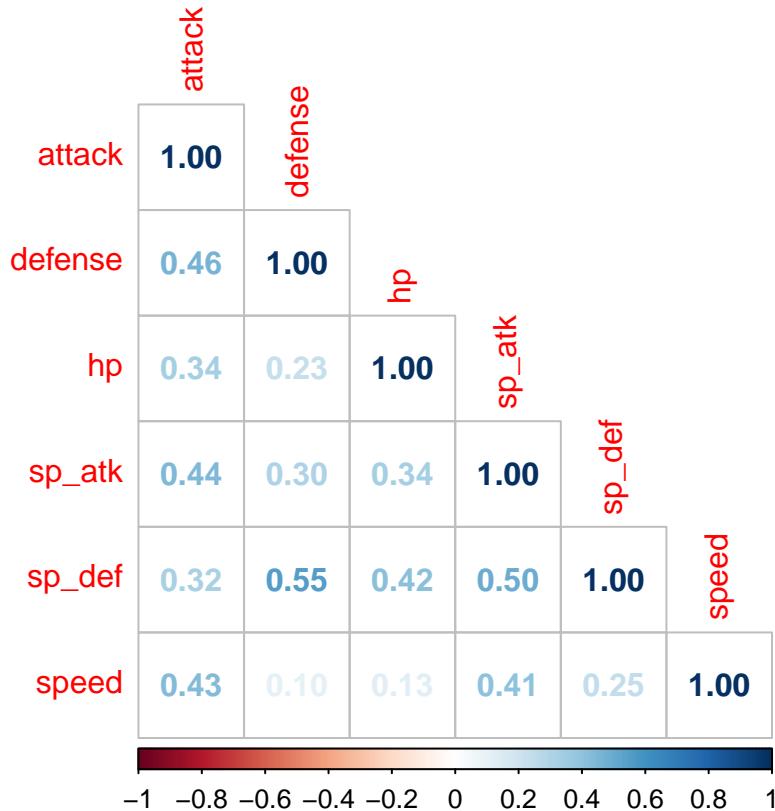
## Exercise 2

Create a correlation matrix of the training set, using the `corrplot` package. *Note: You can choose how to handle the continuous variables for this plot; justify your decision(s).*

```

pokemon_continuous <- pokemon[, c(6, 7, 8, 9, 10, 11)]
pokemon_cor <- cor(pokemon_continuous)
corrplot(pokemon_cor, method = "number", order = "alphabet", type = "lower")

```



I kept only the variables that were continuous in nature, so I did not include legendary or generation. I opted not to include the variables that were not in our recipe as well.

What relationships, if any, do you notice? Do these relationships make sense to you?

I notice that attack and defense, sp\_atk and attack, speed and attack, sp\_def and defense, hp and sp\_def, sp\_atk and sp\_def, and speed and sp\_atk were moderately (positively) correlated. I agree with most of the relationships, except for attack and defense. I would have thought that attack and defense would be negatively correlated to balance out the pokemon stats, but their positive association is quite strong!

### Exercise 3

First, set up a decision tree model and workflow. Tune the `cost_complexity` hyperparameter. Use the same levels we used in Lab 7 – that is, `range = c(-3, -1)`. Specify that the metric we want to optimize is `roc_auc`.

```
tree_spec <- decision_tree() %>%
  set_engine("rpart")

class_tree_spec <- tree_spec %>%
  set_mode("classification")

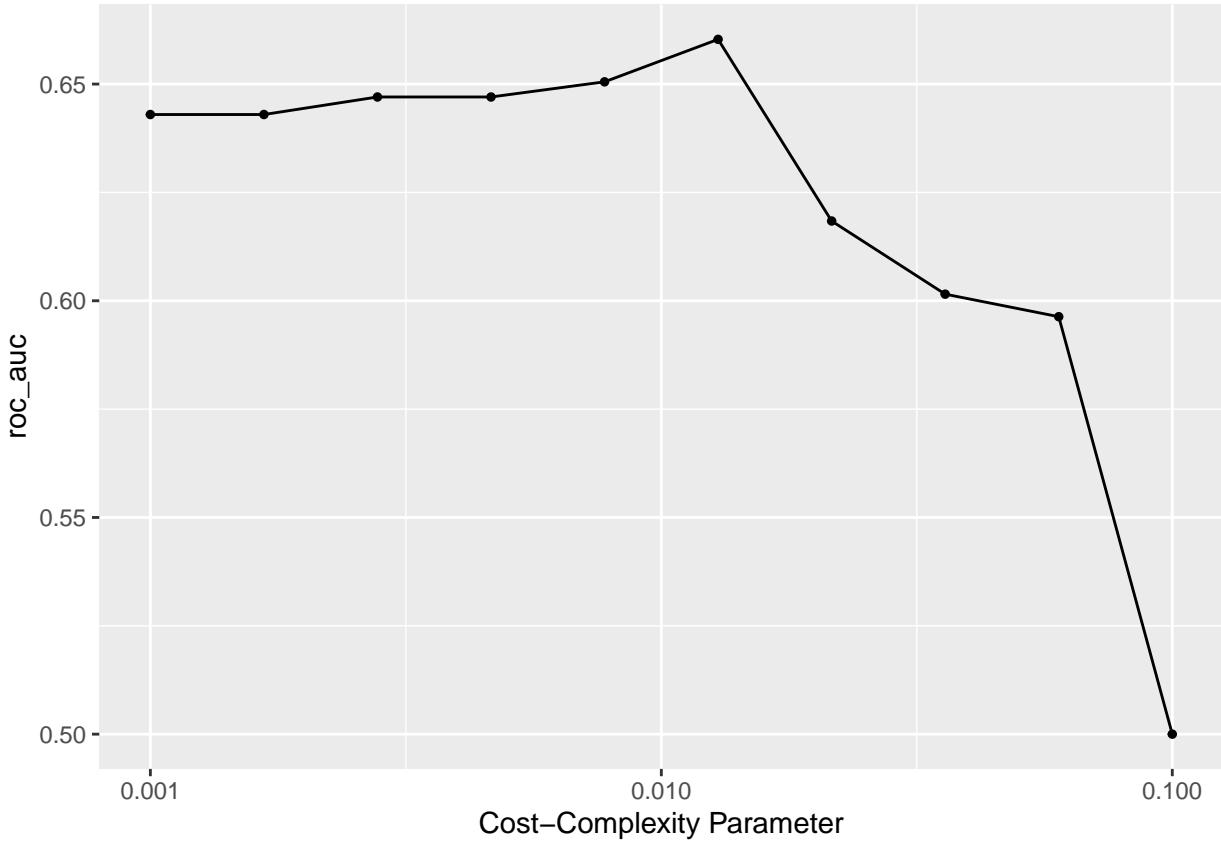
class_tree_wf <- workflow() %>%
  add_model(class_tree_spec %>% set_args(cost_complexity = tune())) %>%
  add_recipe(pokemon_recipe)

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

tune_result <- tune_grid(
  class_tree_wf,
  resamples = pokemon_folds,
  grid = param_grid,
  metrics = metric_set(roc_auc)
)
```

Print an `autoplot()` of the results. What do you observe? Does a single decision tree perform better with a smaller or larger complexity penalty?

```
autoplot(tune_result)
```



I observe that our model starts off well and improves until a complexity parameter of about 0.013, then drops significantly. For the most part, a single decision tree performs better with a smaller complexity penalty.

#### Exercise 4

What is the `roc_auc` of your best-performing pruned decision tree on the folds? *Hint: Use `collect_metrics()` and `arrange()`.*

```
decision_tree <- collect_metrics(tune_result) %>%
  arrange(desc(mean))
decision_tree

## # A tibble: 10 x 7
##   cost_complexity .metric .estimator  mean     n std_err .config
##             <dbl> <chr>    <chr>     <dbl> <int>   <dbl> <chr>
## 1        0.0129  roc_auc hand_till  0.660     5 0.0141 Preprocessor1_Model06
## 2        0.00774  roc_auc hand_till  0.651     5 0.0163 Preprocessor1_Model05
## 3        0.00278  roc_auc hand_till  0.647     5 0.0186 Preprocessor1_Model03
## 4        0.00464  roc_auc hand_till  0.647     5 0.0186 Preprocessor1_Model04
## 5        0.001    roc_auc hand_till  0.643     5 0.0183 Preprocessor1_Model01
## 6        0.00167  roc_auc hand_till  0.643     5 0.0183 Preprocessor1_Model02
## 7        0.0215   roc_auc hand_till  0.618     5 0.00683 Preprocessor1_Model07
## 8        0.0359   roc_auc hand_till  0.602     5 0.0132 Preprocessor1_Model08
## 9        0.0599   roc_auc hand_till  0.596     5 0.0146 Preprocessor1_Model09
## 10       0.1      roc_auc hand_till  0.5       5 0    Preprocessor1_Model10
```

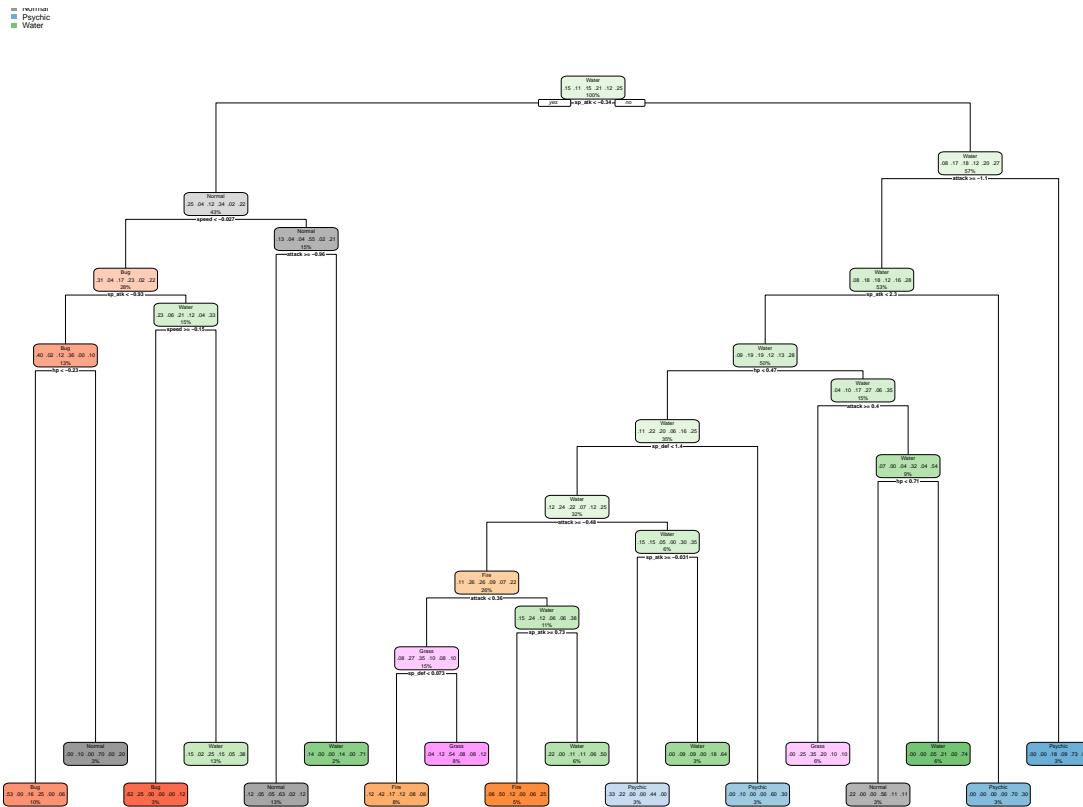
The roc\_auc of the best performing pruned decision tree is 0.6603222.

### Exercise 5

Using `rpart.plot`, fit and visualize your best-performing pruned decision tree with the *training* set.

```
best_complexity <- select_best(tune_result)
class_tree_final <- finalize_workflow(class_tree_wf, best_complexity)
class_tree_final_fit <- fit(class_tree_final, data = pokemon_train)

class_tree_final_fit %>%
  extract_fit_engine() %>%
  rpart.plot()
```



### Exercise 5

Now set up a random forest model and workflow. Use the `ranger` engine and set `importance = "impurity"`. Tune `mtry`, `trees`, and `min_n`. Using the documentation for `rand_forest()`, explain in your own words what each of these hyperparameters represent.

```
rf_spec <- rand_forest(mtry = tune(), trees = tune(), min_n = tune()) %>%
  set_engine("ranger", importance = "impurity") %>%
  set_mode("classification")
```

```
rf_wf <- workflow() %>%
  add_model(rf_spec) %>%
  add_recipe(pokemon_recipe)
```

Mtry is used to tune the number of predictors that will be sampled randomly at each split– this will aid in lowering the bias from the greedy approach.

Trees is used to tune the number of trees used in each ensemble.

Min\_n is used to tune the minimum required number of data points in a node before it is split further.

Create a regular grid with 8 levels each. You can choose plausible ranges for each hyperparameter. Note that `mtry` should not be smaller than 1 or larger than 8. **Explain why not. What type of model would `mtry = 8` represent?**

```
parameter_grid <- grid_regular(mtry(range = c(1, 8)), trees(range = c(50, 150)), min_n(range = c(1, 15)))
```

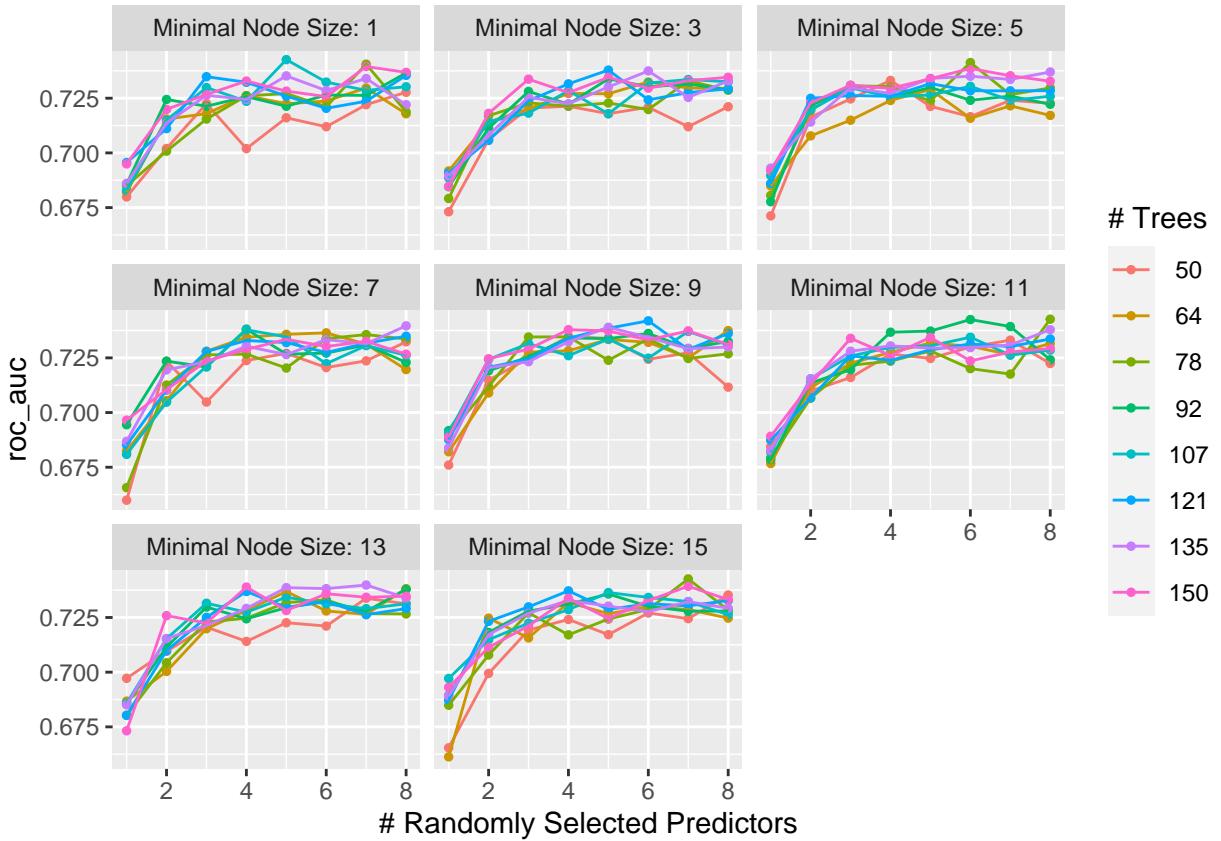
Due to our data, we cannot use mtry values that are less than 1 because then that would mean we will use 0 predictors to split, and we cannot use mtry values that are larger than 8 because we only have 8 predictors to choose from. An mtry value = 8 would represent a bagging model.

## Exercise 6

Specify `roc_auc` as a metric. Tune the model and print an `autoplot()` of the results. What do you observe? What values of the hyperparameters seem to yield the best performance?

```
tune_res <- tune_grid(
  rf_wf,
  resamples = pokemon_folds,
  grid = parameter_grid,
  metrics = metric_set(roc_auc)
)

autoplot(tune_res)
```



I observe that less trees tends to yield worse results, the results get better as the mtry values increase, and that a higher minimal node size tends to get better results. Though it really depends on the combination of value for the three hyperparameters.

### Exercise 7

What is the `roc_auc` of your best-performing random forest model on the folds? Hint: Use `collect_metrics()` and `arrange()`.

```
random_forest <- collect_metrics(tune_res) %>%
  arrange(desc(mean))
random_forest
```

```
## # A tibble: 512 x 9
##       mtry   trees min_n .metric .estimator  mean     n std_err .config
##       <int>  <int> <int> <chr>    <chr>    <dbl> <int>   <dbl> <chr>
## 1       8      78     11 roc_auc hand_till 0.743     5 0.0126 Preprocessor1_Model-
## 2       5     107      1 roc_auc hand_till 0.743     5 0.00970 Preprocessor1_Model-
## 3       7      78     15 roc_auc hand_till 0.743     5 0.0198 Preprocessor1_Model-
## 4       6      92     11 roc_auc hand_till 0.743     5 0.0126 Preprocessor1_Model-
## 5       6     121      9 roc_auc hand_till 0.742     5 0.0168 Preprocessor1_Model-
## 6       6      78      5 roc_auc hand_till 0.741     5 0.0133 Preprocessor1_Model-
## 7       7      78      1 roc_auc hand_till 0.741     5 0.0127 Preprocessor1_Model-
## 8       7     135     13 roc_auc hand_till 0.740     5 0.0144 Preprocessor1_Model-
## 9       8     135      7 roc_auc hand_till 0.740     5 0.00726 Preprocessor1_Model-
## 10      7     150      1 roc_auc hand_till 0.739     5 0.00548 Preprocessor1_Model-
```

```
## # ... with 502 more rows
```

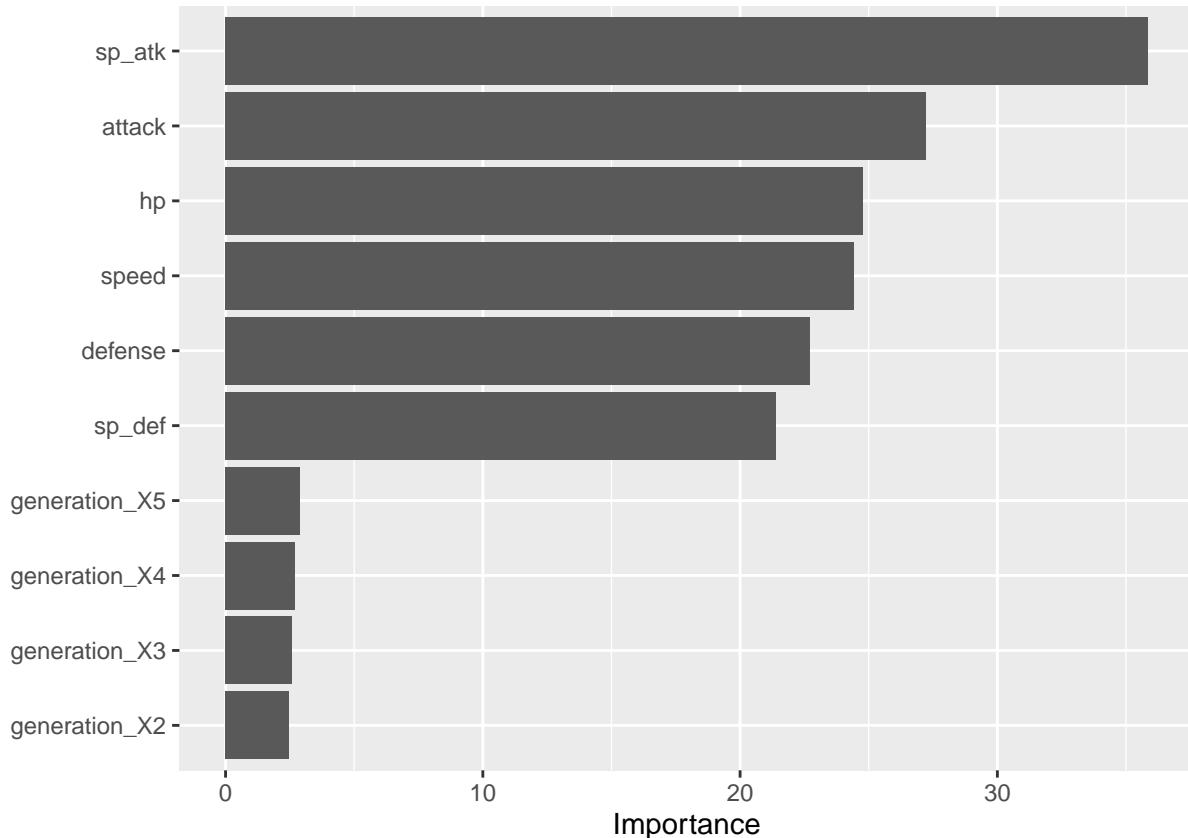
The roc\_auc of the best-performing random forest model is 0.7426766.

### Exercise 8

Create a variable importance plot, using `vip()`, with your best-performing random forest model fit on the *training* set.

```
best_complexity <- select_best(tune_res)
rf_final <- finalize_workflow(rf_wf, best_complexity)
rf_final_fit <- fit(rf_final, data = pokemon_train)

rf_final_fit %>%
  extract_fit_parsnip() %>%
  vip()
```



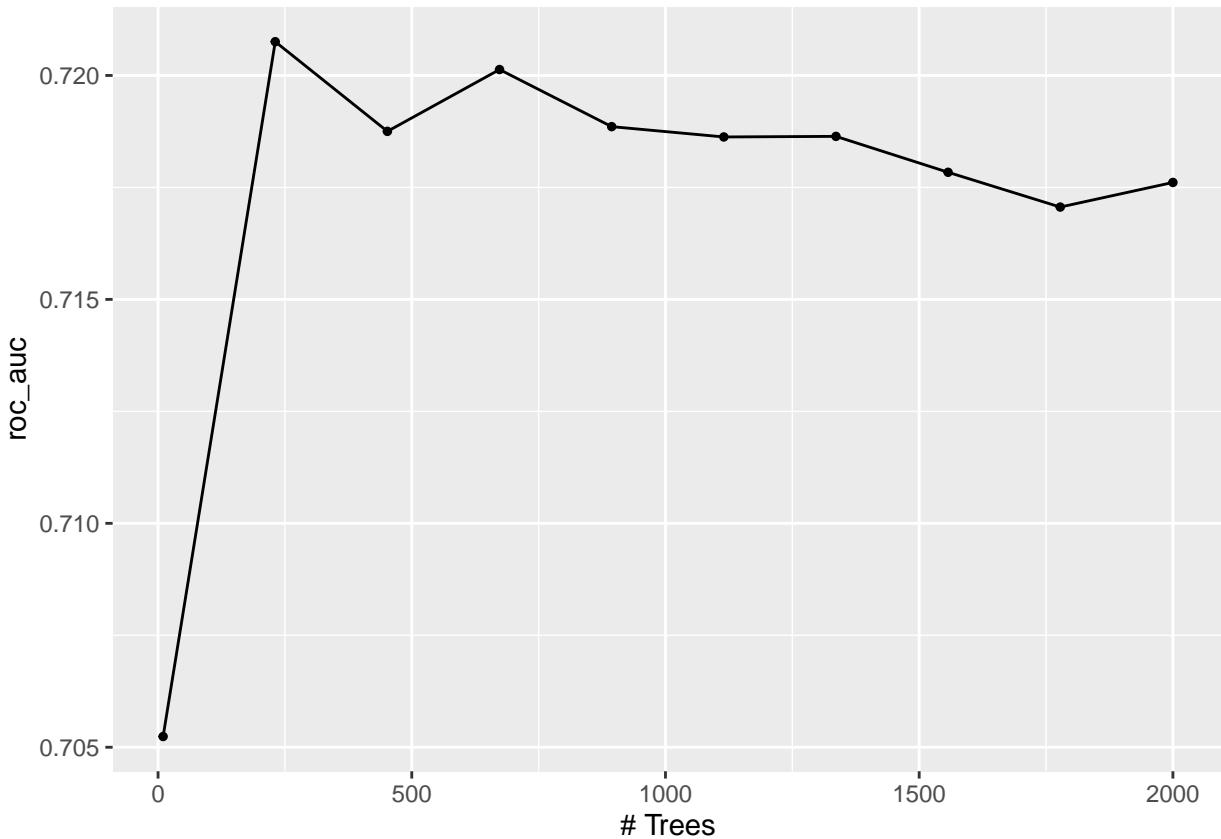
Which variables were most useful? Which were least useful? Are these results what you expected, or not?

The most useful variable was sp\_atk, followed by attack, hp, and speed. The least useful were the generation\_x variables. I think these results are expected because certain types may be better predicted by their attributes (ex. fire type maybe has higher attack on average). Additionally, the generation that a pokémon was from isn't very telling for the pokémon type.

### Exercise 9

Finally, set up a boosted tree model and workflow. Use the `xgboost` engine. Tune `trees`. Create a regular grid with 10 levels; let `trees` range from 10 to 2000. Specify `roc_auc` and again print an `autoplot()` of the results.

```
boost_spec <- boost_tree(trees = tune()) %>%  
  set_engine("xgboost") %>%  
  set_mode("classification")  
  
boost_wf <- workflow() %>%  
  add_model(boost_spec) %>%  
  add_recipe(pokemon_recipe)  
  
tree_grid <- grid_regular(trees(range = c(10, 2000)), levels = 10)  
  
tuning_res <- tune_grid(  
  boost_wf,  
  resamples = pokemon_folds,  
  grid = tree_grid,  
  metrics = metric_set(roc_auc)  
)  
  
autoplot(tuning_res)
```



What do you observe?

I observe that a higher number of trees was greatly improving the model until around 250, then gradually performed worse.

What is the `roc_auc` of your best-performing boosted tree model on the folds? Hint: Use `collect_metrics()` and `arrange()`.

```
boosted_tree <- collect_metrics(tuning_res) %>%
  arrange(desc(mean))
boosted_tree

## # A tibble: 10 x 7
##   trees .metric .estimator  mean    n std_err .config
##   <int> <chr>   <chr>     <dbl> <int>   <dbl> <chr>
## 1    1 roc_auc hand_till 0.721     5 0.0105 Preprocessor1_Model02
## 2    2 673 roc_auc hand_till 0.720     5 0.00939 Preprocessor1_Model04
## 3    3 894 roc_auc hand_till 0.719     5 0.00971 Preprocessor1_Model05
## 4    4 452 roc_auc hand_till 0.719     5 0.00940 Preprocessor1_Model03
## 5   1336 roc_auc hand_till 0.719     5 0.00961 Preprocessor1_Model07
## 6   1115 roc_auc hand_till 0.719     5 0.00991 Preprocessor1_Model06
## 7   1557 roc_auc hand_till 0.718     5 0.00942 Preprocessor1_Model08
## 8   2000 roc_auc hand_till 0.718     5 0.00929 Preprocessor1_Model10
## 9   1778 roc_auc hand_till 0.717     5 0.00934 Preprocessor1_Model09
## 10    10 roc_auc hand_till 0.705     5 0.0137 Preprocessor1_Model01
```

The `roc_auc` of the best performing boosted tree is 0.7207540.

## Exercise 10

Display a table of the three ROC AUC values for your best-performing pruned tree, random forest, and boosted tree models. Which performed best on the folds? Select the best of the three and use `select_best()`, `finalize_workflow()`, and `fit()` to fit it to the *testing* set.

```
models <- data.frame(decision_tree[1,4])
models[2,] <- random_forest[1,6]
models[3,] <- boosted_tree[1,4]

rownames(models) <- c("Decision Tree", "Random Forest", "Boosted Tree")
models %>%
  arrange(desc(mean))

##               mean
## Random Forest 0.7426766
## Boosted Tree  0.7207540
## Decision Tree 0.6603222

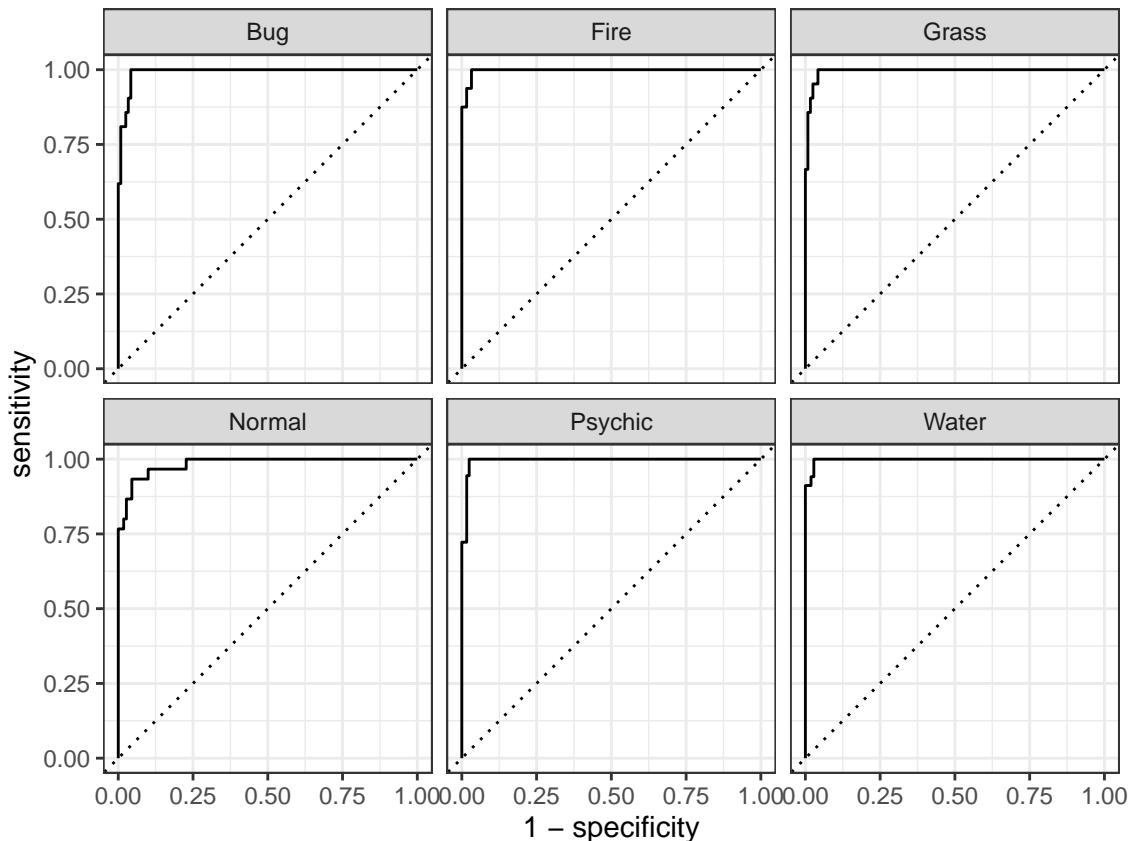
best_metrics <- select_best(tune_res)
rf_final <- finalize_workflow(rf_wf, best_metrics)
rf_final_fit_testdata <- fit(rf_final, data = pokemon_test) # use it on the testing or training data?
```

Print the AUC value of your best-performing model on the testing set. Print the ROC curves. Finally, create and visualize a confusion matrix heat map.

```
augment(rf_final_fittestdata, new_data = pokemon_test) %>%
  roc_auc(truth = type_1, .pred_Bug:.pred_Water)
```

```
## # A tibble: 1 x 3
##   .metric .estimator .estimate
##   <chr>   <chr>        <dbl>
## 1 roc_auc hand_till     0.993
```

```
augment(rf_final_fittestdata, new_data = pokemon_test) %>%
  roc_curve(truth = type_1, .pred_Bug:.pred_Water) %>%
  autoplot()
```



```
augment(rf_final_fittestdata, new_data = pokemon_test) %>%
  conf_mat(truth = type_1, .pred_class) %>%
  autoplot(type = "heatmap")
```

	Bug	Fire	Grass	Normal	Psychic	Water
Bug -	18	0	0	1	0	0
Fire -	0	14	0	0	0	0
Grass -	0	1	18	0	0	0
Normal -	1	1	2	26	0	1
Psychic -	0	0	1	1	18	0
Water -	2	0	0	2	0	33
Truth	Bug	Fire	Grass	Normal	Psychic	Water

Which classes was your model most accurate at predicting? Which was it worst at?

My model was most accurate at predicting Water, Fire, and Grass. It was the worst at predicting Psychic, Normal, and Bug.