

Homework 5

```
library(tidymodels)

## -- Attaching packages ----- tidymodels 0.2.0 --

## v broom      0.8.0    v recipes     0.2.0
## v dials      0.1.1    v rsample     0.1.1
## v dplyr      1.0.9    v tibble      3.1.7
## v ggplot2    3.3.6    v tidyverse   1.2.0
## v infer       1.0.0    v tune        0.2.0
## v modeldata   0.1.1    v workflows   0.2.6
## v parsnip     0.2.1    v workflowsets 0.2.1
## v purrr       0.3.4    v yardstick   0.0.9

## -- Conflicts ----- tidyverse_conflicts() --
## x purrr::discard() masks scales::discard()
## x dplyr::filter()  masks stats::filter()
## x dplyr::lag()    masks stats::lag()
## x recipes::step() masks stats::step()
## * Learn how to get started at https://www.tidymodels.org/start/

library(ISLR)
library(ISLR2)

##
## Attaching package: 'ISLR2'

## The following objects are masked from 'package:ISLR':
## 
##     Auto, Credit

library(tidyverse)

## -- Attaching packages ----- tidyverse 1.3.1 --

## v readr      2.1.2    vforcats 0.5.1
## v stringr    1.4.0

## -- Conflicts ----- tidyverse_conflicts() --
## x readr::col_factor() masks scales::col_factor()
## x purrr::discard()   masks scales::discard()
## x dplyr::filter()    masks stats::filter()
## x stringr::fixed()   masks recipes::fixed()
## x dplyr::lag()       masks stats::lag()
## x readr::spec()      masks yardstick::spec()
```

```

library(glmnet)

## Loading required package: Matrix

## 
## Attaching package: 'Matrix'

## The following objects are masked from 'package:tidyverse':
## 
##     expand, pack, unpack

## Loaded glmnet 4.1-4

library(janitor)

## 
## Attaching package: 'janitor'

## The following objects are masked from 'package:stats':
## 
##     chisq.test, fisher.test

tidymodels_prefer()

poke <- read.csv('Pokemon.csv')

pokemon <- clean_names(poke)

```

Clean names made all the predictor names lowercase and replaced periods with underscores. This is useful because it allows us to write code to access these predictors, such as `pokemon$type_1` without the periods and spaces confusing R.

```

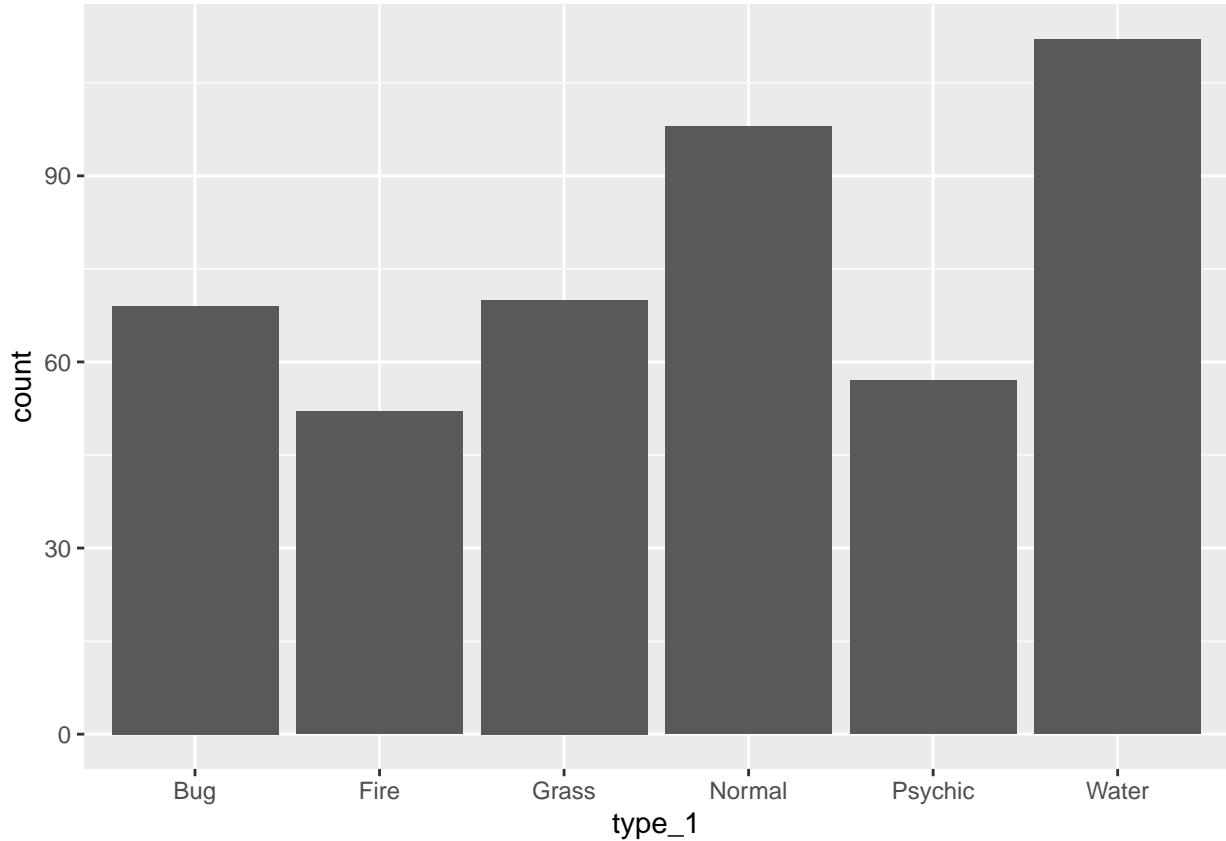
pokemon <- pokemon%>%filter(type_1 == 'Bug' | type_1== 'Fire' | type_1== 'Grass' | type_1== 'Normal' | 

pokemon$legendary <- as.factor(pokemon$legendary)

pokemon$type_1 <- as.factor(pokemon$type_1)
pokemon$generation <- as.factor(pokemon$generation)

ggplot(pokemon, aes(x=type_1)) + geom_bar()

```



```
set.seed(608)
pokeSplit <- initial_split(pokemon, prop = 0.80,
                           strata = type_1)
poke_train <- training(pokeSplit)
poke_test <- testing(pokeSplit)
```

Training set has 364, Test had 94.

```
poke_fold <- vfold_cv(poke_train, v = 5, strata = type_1)
```

We want to stratify the folds so that we don't end up with folds consisting mostly of one type or having very little of one type.

```
pokeRecipe <- recipe(type_1 ~ legendary + generation + sp_atk + attack + speed + defense + hp + sp_def
summary(pokeRecipe)
```

```
## # A tibble: 9 x 4
##   variable  type    role     source
##   <chr>      <chr>   <chr>    <chr>
## 1 legendary nominal predictor original
## 2 generation nominal predictor original
## 3 sp_atk    numeric predictor original
## 4 attack     numeric predictor original
## 5 speed      numeric predictor original
```

```

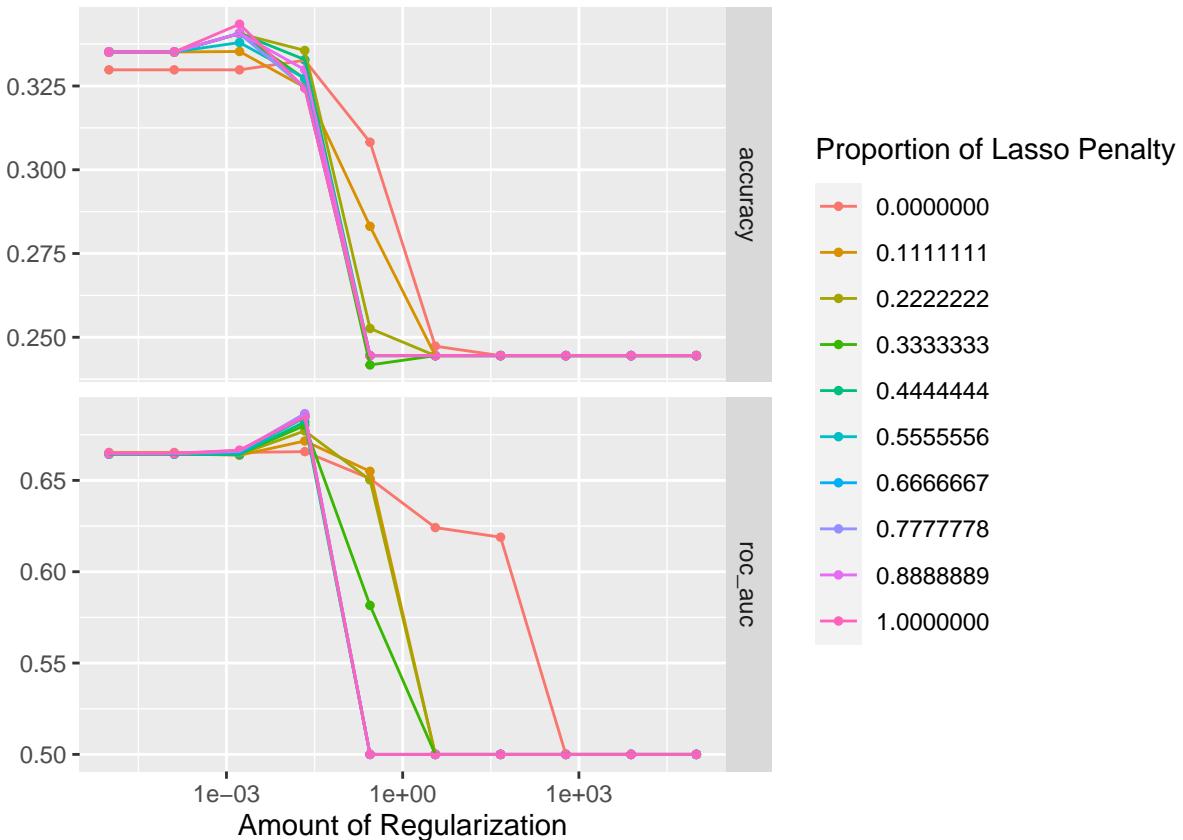
## 6 defense      numeric predictor original
## 7 hp           numeric predictor original
## 8 sp_def       numeric predictor original
## 9 type_1        nominal outcome   original

penMix <- grid_regular(penalty(range=c(-5,5)), mixture(range= c(0,1)), levels = 10)
mReg <- multinom_reg(penalty = tune(), mixture = tune()) %>% set_engine('glmnet') %>% set_mode('classification')
mWkflow <- workflow() %>% add_model(mReg) %>% add_recipe(pokeRecipe)

```

I will be fitting 50 models total

```
tuneFit <- tune_grid(mWkflow, resamples = poke_fold, grid = penMix)
autplot(tuneFit)
```



smaller values of mixture and penalty produce better AUC and accuracy.

```

selected <- select_best(tuneFit, metric = 'roc_auc')
finalwkflw <- finalize_workflow(mWkflow, selected)

final_fit <- fit(finalwkflw, data = poke_train)

augment(final_fit, new_data = poke_test) %>% accuracy(truth = type_1, estimate = .pred_class)

## # A tibble: 1 x 3
##   .metric  .estimator .estimate
##   <chr>    <chr>        <dbl>
## 1 accuracy  multiclass  0.404

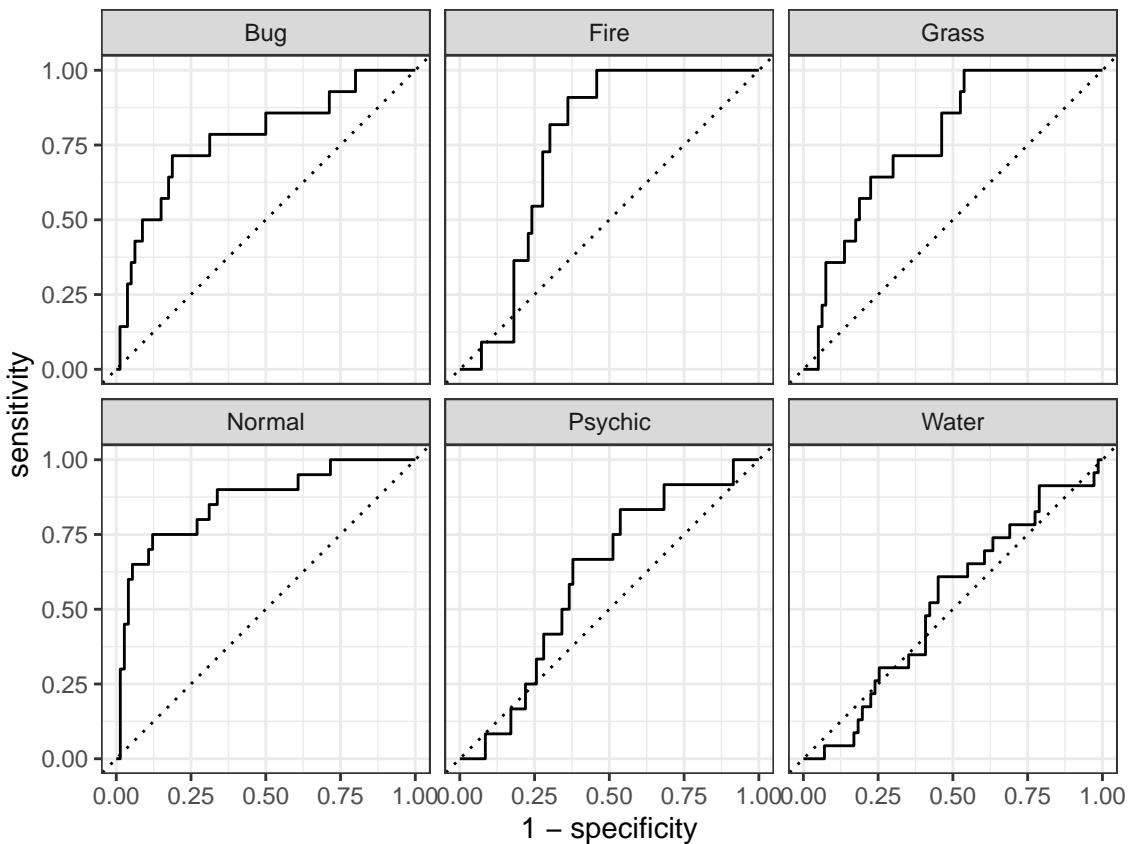
```

low accuracy: 0.4042553

```
augment(final_fit, new_data = poke_test) %>% roc_auc(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     0.705
```

AUC = 0.7050415

```
augment(final_fit, new_data = poke_test) %>% roc_curve(type_1, estimate = c(.pred_Bug, .pred_Fire, .pred_Grass, .pred_Normal, .pred_Psychic, .pred_Water))
```



```
augment(final_fit, new_data = poke_test) %>% conf_mat(truth = type_1, estimate = .pred_class) %>% autoplot
```

	Bug	Fire	Grass	Normal	Psychic	Water
Bug -	4	0	2	1	0	1
Fire -	0	0	0	0	0	0
Grass -	0	0	0	0	0	0
Normal -	4	1	1	14	0	7
Psychic -	0	3	1	0	6	1
Water -	6	7	10	5	6	14
Truth	Bug	Fire	Grass	Normal	Psychic	Water