

Project Report

Saniya Bekova

2024-12-04

```
library(tidymodels)
```

```
-- Attaching packages ----- tidymodels 1.2.0 --
```

v broom	1.0.6	v recipes	1.1.0
v dials	1.3.0	v rsample	1.2.1
v dplyr	1.1.4	v tibble	3.2.1
v ggplot2	3.5.1	v tidyr	1.3.1
v infer	1.0.7	v tune	1.2.1
v modeldata	1.4.0	v workflows	1.1.4
v parsnip	1.2.1	v workflowsets	1.1.0
v purrr	1.0.2	v yardstick	1.3.1

```
-- Conflicts ----- tidymodels_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(tidyverse)
```

```
-- Attaching core tidyverse packages ----- tidyverse 2.0.0 --
```

v forcats	1.0.0	v readr	2.1.5
v lubridate	1.9.3	v stringr	1.5.1

```
-- 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()
i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become
```

```
library(bonsai)
library(themis)
```

```
#-country, -p7, -leader, -deputy_leader, -`Country Code`, -Region, -`Income Group`, -medal_Efficiency
#year, team_size_all, team_size_male, Value_gross_enr_ratio_for_tertirary_edu, Value_gov_expense
combined_educ_data <-read_csv("data/combined_educ_data.csv")
```

```
Rows: 1142 Columns: 38
```

```
-- Column specification -----
Delimiter: ","
chr  (6): country, leader, deputy_leader, Country Code, Region, Income Group
dbl (31): year, team_size_all, team_size_male, team_size_female, p1, p2, p3,...
lg1  (1): p7
```

```
i Use `spec()` to retrieve the full column specification for this data.
i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
str(combined_educ_data)
```

```
spc_tbl_ [1,142 x 38] (S3: spec_tbl_df/tbl_df/tbl/data.frame)
 $ year                : num [1:1142] 2019 2019 2019 2019 2019 ...
 $ country              : chr [1:1142] "People's Republic of China" "United States of America" ...
 $ team_size_all        : num [1:1142] 6 6 6 6 6 6 6 6 6 6 ...
 $ team_size_male       : num [1:1142] 6 6 6 6 6 6 6 6 5 5 ...
 $ team_size_female     : num [1:1142] NA NA NA NA NA NA NA NA 1 1 ...
 $ p1                   : num [1:1142] 40 42 42 41 42 39 39 42 42 42 ...
 $ p2                   : num [1:1142] 41 40 39 41 35 40 31 30 26 28 ...
 $ p3                   : num [1:1142] 27 26 31 17 5 17 10 13 19 9 ...
 $ p4                   : num [1:1142] 41 42 42 42 42 35 40 40 31 40 ...
 $ p5                   : num [1:1142] 42 42 42 42 40 42 42 42 37 42 ...
```

```

$ p6 : num [1:1142] 36 35 30 4 21 6 15 7 16 7 ...
$ p7 : logi [1:1142] NA NA NA NA NA NA ...
$ awards_gold : num [1:1142] 6 6 6 3 3 2 2 2 3 1 ...
$ awards_silver : num [1:1142] 0 0 0 3 3 4 4 4 1 3 ...
$ awards_bronze : num [1:1142] 0 0 0 0 0 0 0 0 2 2 ...
$ awards_honorable_mentions : num [1:1142] 0 0 0 0 0 0 0 0 0 0 ...
$ leader : chr [1:1142] "Bin Xiong" "Po-Shen Loh" "Yongjin S
$ deputy_leader : chr [1:1142] "Yijie He" "Yang Liu" "Suyoung Choi
$ total_score : num [1:1142] 227 227 226 187 185 179 177 174 171
$ average_score_per_contestant : num [1:1142] 37.8 37.8 37.7 31.2 30.8 ...
$ medal_Efficiency : num [1:1142] 1 1 1 1 1 1 1 1 1 1 ...
$ Country Code : chr [1:1142] NA NA NA NA ...
$ Value_gross_enr_ratio_for_tertirary_edu : num [1:1142] NA 87.9 94 NA 45.4 ...
$ Value_gov_expen_as_perc_of_GPP : num [1:1142] NA 4.96 4.68 NA 3.02 3.7 NA 2.73 3.6
$ Value_literacy_rate : num [1:1142] NA NA 98.7 NA 98.5 ...
$ Region : chr [1:1142] NA "North America" "East Asia & Pac
$ Income Group : chr [1:1142] NA "High income: OECD" "High income
$ Gov_Investment_Per_Medal : num [1:1142] NA 0.827 0.78 NA 0.503 ...
$ Lit_Performance_Ratio : num [1:1142] NA NA 2.62 NA 3.2 ...
$ SE.TER.GRAD.SC.ZS : num [1:1142] NA NA NA NA NA ...
$ IT.NET.USER.P2 : num [1:1142] NA NA NA NA NA NA NA NA NA NA NA ...
$ SL.TLF.ADVN.ZS : num [1:1142] NA NA NA NA NA NA NA NA NA NA NA ...
$ UIS.X.US.FSGOV : num [1:1142] NA NA NA NA NA NA NA NA NA NA NA ...
$ UIS.X.USCONST.FSGOV : num [1:1142] NA NA NA NA NA NA NA NA NA NA NA ...
$ NY.GDP.PCAP.CD : num [1:1142] NA NA NA NA NA NA NA NA NA NA NA ...
$ SE.XPD.TOTL.GB.ZS : num [1:1142] NA NA NA NA NA NA NA NA NA NA NA ...
$ SE.XPD.CUR.TOTL.ZS : num [1:1142] NA NA NA NA NA NA NA NA NA NA NA ...
$ OECD.TSAL.1.E10 : num [1:1142] NA NA NA NA NA ...
- attr(*, "spec")=
.. cols(
..   year = col_double(),
..   country = col_character(),
..   team_size_all = col_double(),
..   team_size_male = col_double(),
..   team_size_female = col_double(),
..   p1 = col_double(),
..   p2 = col_double(),
..   p3 = col_double(),
..   p4 = col_double(),
..   p5 = col_double(),
..   p6 = col_double(),
..   p7 = col_logical(),
..   awards_gold = col_double(),

```

```

..   awards_silver = col_double(),
..   awards_bronze = col_double(),
..   awards_honorable_mentions = col_double(),
..   leader = col_character(),
..   deputy_leader = col_character(),
..   total_score = col_double(),
..   average_score_per_contestant = col_double(),
..   medal_Efficiency = col_double(),
..   `Country Code` = col_character(),
..   Value_gross_enr_ratio_for_tertirary_edu = col_double(),
..   Value_gov_expen_as_perc_of_GPP = col_double(),
..   Value_literacy_rate = col_double(),
..   Region = col_character(),
..   `Income Group` = col_character(),
..   Gov_Investment_Per_Medal = col_double(),
..   Lit_Performance_Ratio = col_double(),
..   SE.TER.GRAD.SC.ZS = col_double(),
..   IT.NET.USER.P2 = col_double(),
..   SL.TLF.ADVN.ZS = col_double(),
..   UIS.X.US.FSGOV = col_double(),
..   UIS.X.USCONST.FSGOV = col_double(),
..   NY.GDP.PCAP.CD = col_double(),
..   SE.XPD.TOTL.GB.ZS = col_double(),
..   SE.XPD.CUR.TOTL.ZS = col_double(),
..   OECD.TSAL.1.E10 = col_double()
.. )
- attr(*, "problems")=<externalptr>

```

```

education_numeric_data <- combined_educ_data |>
  select(-country, -p7, -leader, -deputy_leader, -`Country Code`, -Region, -`Income Group`, -)

```

```

set.seed(1234)
educ_data_split <- initial_split(education_numeric_data, prop = 3/4, strata = Value_gov_exper)
train_data <- training(educ_data_split)
test_data <- testing(educ_data_split)

edu_recipe <- recipe(average_score_per_contestant ~ ., data = train_data) |>
  step_nzv(all_predictors()) |> # Remove near-zero variance predictors
  step_impute_mean(all_numeric(), -all_outcomes()) |> # Impute missing values for numeric pr
  step_impute_mode(all_nominal()) |>
  step_unknown(all_nominal(), -all_outcomes()) |>
  step_normalize(all_numeric_predictors()) # Normalize numeric predictors

```

```
library(tidymodels)
library(glmnet)
```

Loading required package: Matrix

Attaching package: 'Matrix'

The following objects are masked from 'package:tidyr':

expand, pack, unpack

Loaded glmnet 4.1-8

```
library(dplyr)

lasso_spec_tune <- linear_reg() |>
  set_engine("glmnet") |>
  set_args(mixture = 1, penalty = tune()) |>
  set_mode("regression")

lasso_recipe <- recipe(average_score_per_contestant ~ ., data = train_data) |>
  step_nzv(all_predictors()) |>
  step_impute_mean(all_numeric(), -all_outcomes()) |>
  step_normalize(all_numeric_predictors())

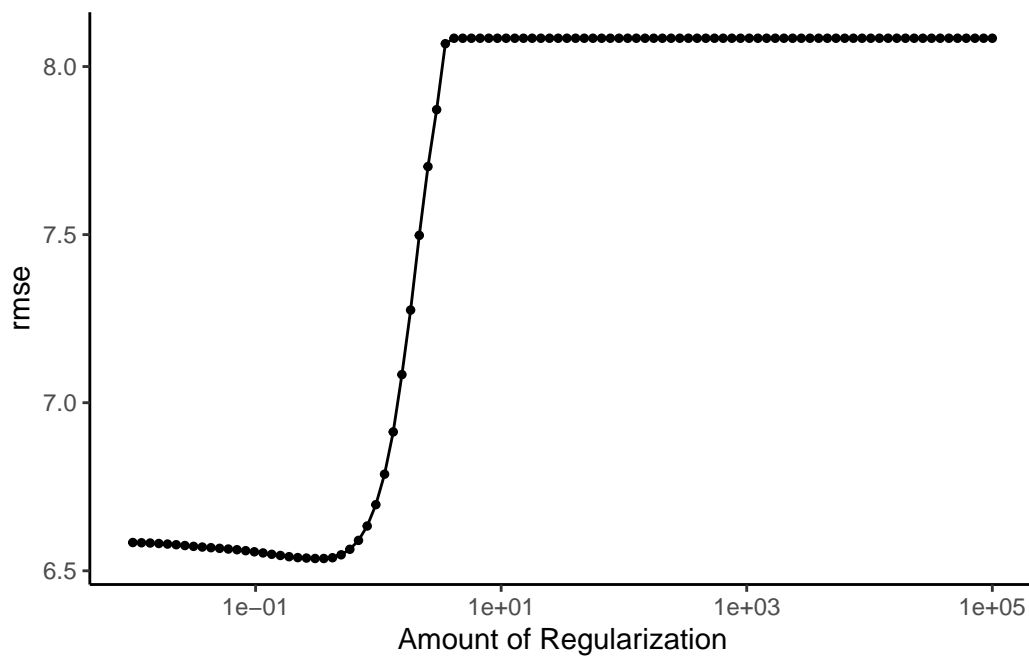
lasso_wf <- workflow() |>
  add_recipe(lasso_recipe) |>
  add_model(lasso_spec_tune)

penalty_grid <- grid_regular(
  penalty(range = c(-2, 5)),
  levels = 100
)
```

```
data_cv5 <- vfold_cv(train_data, v = 5)

tune_output <- tune_grid(
  lasso_wf,
  resamples = data_cv5,
  metrics = metric_set(yardstick::rmse),
  grid = penalty_grid
)

autoplot(tune_output) + theme_classic()
```



```
collect_metrics(tune_output) |>
  filter(.metric == "rmse") |>
  select(penalty, mean_rmse = mean)
```

```
# A tibble: 100 x 2
  penalty mean_rmse
  <dbl>     <dbl>
1  0.01      6.58
2  0.0118    6.58
```

```

3  0.0138      6.58
4  0.0163      6.58
5  0.0192      6.58
6  0.0226      6.58
7  0.0266      6.58
8  0.0313      6.57
9  0.0368      6.57
10 0.0433      6.57
# i 90 more rows

```

```
best_pen_lasso <- select_best(tune_output, metric = "rmse")
```

```

lasso_final_fit <- lasso_wf |>
  finalize_workflow(best_pen_lasso) |>
  fit(data = train_data)

```

```

lasso_coefs <- coef(
  lasso_final_fit |>
    extract_fit_engine(),
  s = best_pen_lasso$penalty
)

```

```

tibble(
  Predictor = rownames(lasso_coefs),
  Coefficient = as.vector(lasso_coefs)
)

```

```
# A tibble: 19 x 2
```

	Predictor	Coefficient
	<chr>	<dbl>
1	(Intercept)	14.5
2	year	0
3	team_size_all	0
4	team_size_male	2.53
5	team_size_female	-0.0789
6	Value_gross_enr_ratio_for_tertirary_edu	0.788
7	Value_gov_expen_as_perc_of_GPP	0
8	Value_literacy_rate	0.334
9	Gov_Investment_Per_Medal	-1.87

10	Lit_Performance_Ratio	-1.22
11	SE.TER.GRAD.SC.ZS	0
12	IT.NET.USER.P2	0
13	SL.TLF.ADVN.ZS	0
14	UIS.X.US.FSGOV	0.919
15	UIS.X.USCONST.FSGOV	0
16	NY.GDP.PCAP.CD	0.00193
17	SE.XPD.TOTL.GB.ZS	0
18	SE.XPD.CUR.TOTL.ZS	0
19	OECD.TSAL.1.E10	0

Linear Regression

```
library(tidymodels)
library(Metrics)
```

Attaching package: 'Metrics'

The following objects are masked from 'package:yardstick':

accuracy, mae, mape, mase, precision, recall, rmse, smape

```
library(dplyr)

# Create a linear regression model specification
lm_spec <- linear_reg() |>
  set_engine("lm")

# Create a workflow to combine preprocessing and modeling
lm_workflow <- workflow() |>
  add_recipe(edu_recipe) |>
  add_model(lm_spec)

# Fit the model to the training data
lm_fit <- fit(lm_workflow, data = train_data)

# View model summary using the new function
summary_model <- extract_fit_parsnip(lm_fit) |>
```



```
tidy()
print(summary_model)
```

```
# A tibble: 19 x 5
```

	term	estimate	std.error	statistic	p.value
	<chr>	<dbl>	<dbl>	<dbl>	<dbl>
1	(Intercept)	14.5	0.221	65.8	0
2	year	-0.292	0.244	-1.19	2.33e- 1
3	team_size_all	0.250	0.385	0.650	5.16e- 1
4	team_size_male	2.62	0.389	6.73	3.06e-11
5	team_size_female	-0.389	0.233	-1.67	9.56e- 2
6	Value_gross_enr_ratio_for_tertirary_edu	0.992	0.268	3.70	2.27e- 4
7	Value_gov_expen_as_perc_of_GPP	-0.266	0.274	-0.973	3.31e- 1
8	Value_literacy_rate	0.485	0.279	1.74	8.29e- 2
9	Gov_Investment_Per_Medal	-2.15	0.257	-8.38	2.29e-16
10	Lit_Performance_Ratio	-1.44	0.244	-5.91	5.07e- 9
11	SE.TER.GRAD.SC.ZS	-0.176	0.233	-0.757	4.50e- 1
12	IT.NET.USER.P2	-0.103	0.361	-0.286	7.75e- 1
13	SL.TLF.ADVN.ZS	-0.290	0.234	-1.24	2.14e- 1
14	UIS.X.US.FSGOV	3.28	1.56	2.10	3.58e- 2
15	UIS.X.USCONST.FSGOV	-2.14	1.57	-1.37	1.72e- 1
16	NY.GDP.PCAP.CD	0.511	0.355	1.44	1.51e- 1
17	SE.XPD.TOTL.GB.ZS	0.368	0.243	1.52	1.30e- 1
18	SE.XPD.CUR.TOTL.ZS	0.310	0.228	1.36	1.75e- 1
19	OECD.TSAL.1.E10	-0.0988	0.250	-0.395	6.93e- 1

```
# Preprocess and predict on the test data
```

```
y_pred <- predict(lm_fit, new_data = test_data) |>
  pull(.pred)
```

```
# Replace negative predictions with a small positive value to avoid NaNs in log
```

```
y_pred <- ifelse(y_pred < 0, 1e-6, y_pred)
```

```
# Evaluate performance metrics
```

```
mse_train <- mean((train_data$average_score_per_contestant - predict(lm_fit, new_data = train_data) |>
  pull(.pred))^2)
```

```
r2_train <- caret::R2(predict(lm_fit, new_data = train_data) |> pull(.pred), train_data$average_score_per_contestant)
```

```
mse_test <- mean((test_data$average_score_per_contestant - y_pred)^2)
```

```
r2_test <- caret::R2(y_pred, test_data$average_score_per_contestant)
```

```
# Calculate additional error metrics
msle_test <- msle(test_data$average_score_per_contestant, y_pred)
rmsle_test <- sqrt(msle_test)

# Print results
cat("Training MSE:", mse_train, "\n")
```

Training MSE: 40.69752

```
cat("Training R-squared:", r2_train, "\n")
```

Training R-squared: 0.3768742

```
cat("Test MSE:", mse_test, "\n")
```

Test MSE: 41.71663

```
cat("Test R-squared:", r2_test, "\n")
```

Test R-squared: 0.3984548

```
cat("Mean Squared Log Error (MSLE):", msle_test, "\n")
```

Mean Squared Log Error (MSLE): 0.399063

```
cat("Root Mean Squared Log Error (RMSLE):", rmsle_test, "\n")
```

Root Mean Squared Log Error (RMSLE): 0.6317143

Gradient Boosting

```
boost_edu <- boost_tree(mode = "regression",
                        engine = "lightgbm",
                        # B
                        trees = tune(),
                        # d
                        tree_depth = tune(),
                        # lambda
                        learn_rate = tune())
```

```
boost_wf <- workflow() |>
  add_recipe(edu_recipe) |>
  add_model(boost_edu)
```

```
```{r cv-bayes-r}
#| eval: false

folds <- vfold_cv(train_data,
 v = 6)

boost_grid <- crossing(
 trees = seq(500, 3000, by = 500),
 tree_depth = 1:5,
 learn_rate = c(0.01, 0.05, 0.1)
)

boost_cv_edu <- tune_grid(boost_wf,
 resamples = folds,
 grid = boost_grid,
 metrics = metric_set(yardstick::rmse)
)

boost_params <- extract_parameter_set_dials(boost_wf)

boost_params <- boost_params |>
 update(trees = trees(range = c(1000, 3000)))

set.seed(756)
boost_cv_bayes_edu <- boost_wf |>
 tune_bayes(
```

```

 resamples = folds,
 param_info = boost_params,
 initial = boost_cv_edu,
 iter = 50,
 metrics = metric_set(yardstick::rmse),
 control = control_bayes(no_improve = 15)
)

save(boost_cv_bayes_edu, file = "data/boost_cv_bayes_edu.RData")
```

```

```
load(file = "data/boost_cv_bayes_edu.RData")
```

```
collect_metrics(boost_cv_bayes_edu) |>
  arrange(desc(mean))
```

```

# A tibble: 131 x 10
   trees tree_depth learn_rate .metric .estimator  mean     n std_err .config
   <dbl>      <int>      <dbl> <chr>   <chr>      <dbl> <int>  <dbl> <chr>
1    500         1      0.01 rmse    standard    5.81     6   0.203 Preproces~
2   1000         1      0.01 rmse    standard    5.57     6   0.201 Preproces~
3   1500         1      0.01 rmse    standard    5.47     6   0.193 Preproces~
4   2000         1      0.01 rmse    standard    5.43     6   0.187 Preproces~
5   2500         1      0.01 rmse    standard    5.40     6   0.182 Preproces~
6    500         1      0.05 rmse    standard    5.40     6   0.181 Preproces~
7   3000         1      0.01 rmse    standard    5.39     6   0.177 Preproces~
8    500         1      0.1  rmse    standard    5.36     6   0.167 Preproces~
9   1000         1      0.05 rmse    standard    5.36     6   0.166 Preproces~
10  1500         1      0.05 rmse    standard    5.34     6   0.161 Preproces~
# i 121 more rows
# i 1 more variable: .iter <int>

```

```

```{r eval-bayes-r}
#| eval: true

boost_wf_best_bayes <- boost_wf |>
 finalize_workflow(select_best(boost_cv_bayes_edu,
 metric = "rmse")) |>
 fit(train_data)

edu_aug_bayes <- boost_wf_best_bayes |>

```

```

augment(new_data = test_data)

Calculate RMSE and R^2
boost_metrics <- metrics(
 edu_aug_bayes,
 truth = average_score_per_contestant,
 estimate = .pred
)

print(boost_metrics) # Displays RMSE and R^2
```

```

```

# A tibble: 3 x 3
  .metric .estimator .estimate
  <chr>    <chr>         <dbl>
1 rmse    standard         4.72
2 rsq     standard         0.684
3 mae     standard         3.09

```