Bakeoff Example

Paul Nguyen

2025-08-25

Bakeoff Example

To demonstrate one iteration of the bakeoff experiment, we will fit one instance of the cubic compositional model to one set of training/testing data. For this example, we'll run the simulation with fewer iterations (400) for faster compilation (normally 2000). The majority of the code is taken from study/study_bakeoff.R. You may need to run study/gen_bakeoff data_splits.R to produce the training and testing splits.

```
set.seed(2)
library(tidyverse)
library(readxl)
library(rstan)
library(rlist)
library(tidyselect)
library(forcats)

study = "../../decathlon_simulation"
data_dir = "../../decathlon_simulation/data/"
script_dir = "../../decathlon_simulation/study/"
stan_dir = "../../decathlon_simulation/stan_mods/"

source(paste0(script_dir, "decathlon_funs.R"))
source(paste0(script_dir, "settings_bakeoff.R"))
load(paste0(data_dir, "test_split_list_general.RData"))
```

In the study, we use a high performance computing cluster. We will manually set a job id for this example, which would typically determine the model type and data splits. In our experiments, we typically ran one model at a time. In this example, we will compare one instance of each cubic model (baseline, simple, and compositional).

Now, we can run each model.

```
baseline_sim <- get_baseline_cubic_sim(age_vec = age_vec,</pre>
                                     athlete_id = athlete_id,
                                     is_new_athlete = is_new_athlete,
                                     decathlon_data = train_df,
                                     stan_dir = stan_dir,
                                     iter = 400,
                                     return_all = F)
simple sim <- get simple cubic sim(age vec = age vec,
                                 athlete_id = athlete_id,
                                 is new athlete = is new athlete,
                                 decathlon_data = train_df,
                                 event_sums = event_sums,
                                 stan dir = stan dir,
                                 iter = 400.
                                 return_all = F)
comp_sim <- get_comp_cubic_sim(age_vec = age_vec,</pre>
                                athlete_id = athlete_id,
                                is_new_athlete = is_new_athlete,
                                decathlon_data = train_df,
                                event_sums = event_sums,
                                stan_dir = stan_dir,
                                iter = 400,
                                return_all = F)
```

Caculating SMSE's for each model. The SMSE of a model is its standardized mean squared error. This is calculated by taking the model's MSE and dividing it by the mean squared error if we had simply used the training mean as our test prediction for each observation. Lower SMSE's and MSE's are preferred.

```
group_by(athlete, age) %>%
    summarize(hundred_m = mean(hundred_m),
              long_jump = mean(long_jump),
              shot_put = mean(shot_put),
              high_jump = mean(high_jump),
              four_hundred_m = mean(four_hundred_m),
              hurdles = mean(hurdles),
              discus = mean(discus),
              pole_vault = mean(pole_vault),
              javelin = mean(javelin),
              fifteen_hundred_m = mean(fifteen_hundred_m),
              points = mean(calc_point, na.rm = T)
pred_df_simple$athlete_id <- test_df$athlete_id</pre>
pred_df_comp <- comp_sim$sim_events %>%
    group_by(athlete, age) %>%
    summarize(hundred_m = mean(hundred_m),
              long_jump = mean(long_jump),
              shot_put = mean(shot_put),
              high_jump = mean(high_jump),
              four_hundred_m = mean(four_hundred_m),
              hurdles = mean(hurdles),
              discus = mean(discus),
              pole_vault = mean(pole_vault),
              javelin = mean(javelin),
              fifteen_hundred_m = mean(fifteen_hundred_m),
              points = mean(calc_point, na.rm = T)
pred_df_comp$athlete_id <- test_df$athlete_id</pre>
mse_table <- data.frame(event = c(dec_events, "points"),</pre>
                        mse_simple = rep(NA, 11),
                        mse_comp = rep(NA, 11),
                        denom = rep(NA, 11),
                         smse_simple = rep(NA, 11),
                        smse\_comp = rep(NA, 11),
                        iter = iter)
# unstandardizing test df
for (event in dec_events) {
  event_mean <- event_sums %>%
    filter(event == !!event) %>%
    select(mean_score) %>%
    pull()
  event_sd <- event_sums %>%
    filter(event == !!event) %>%
    select(sd_score) %>%
    pull()
  test_df[event] <- (test_df[event] *event_sd ) + event_mean</pre>
  train_df[event] <- (train_df[event] *event_sd ) + event_mean</pre>
}
```

```
for (i in 1:11) {
  event = mse_table$event[i]
  mse_table$mse_simple[i] = mean((pred_df_simple[[event]] - test_df[[event]])^2,
                          na.rm = T)
  mse_table$mse_comp[i] = mean((pred_df_comp[[event]] - test_df[[event]])^2,
                          na.rm = T)
  mse_table$denom[i] = mean((mean(train_df[[event]]) - test_df[[event]])^2,
                            na.rm = T)
  mse_table$smse_simple[i] = mse_table$mse_simple[i] / mse_table$denom[i]
  mse_table$smse_comp[i] = mse_table$mse_comp[i] / mse_table$denom[i]
  mse_table$type = type
  mse_table$iter = iter
mse_table$smse_baseline <- c(rep(NA, 10), baseline_smse)</pre>
mse_table %>%
  select(event, smse_baseline, smse_simple, smse_comp) %>%
  mutate(smse_baseline = round(smse_baseline, 2),
         smse_simple = round(smse_simple, 2),
         smse_comp = round(smse_comp, 2))
```

##		event	${\tt smse_baseline}$	${\tt smse_simple}$	smse_comp
##	1	hundred_m	NA	0.31	0.31
##	2	long_jump	NA	0.44	0.44
##	3	shot_put	NA	0.18	0.18
##	4	high_jump	NA	0.34	0.33
##	5	four_hundred_m	NA	0.36	0.36
##	6	hurdles	NA	0.32	0.32
##	7	discus	NA	0.27	0.27
##	8	<pre>pole_vault</pre>	NA	0.27	0.27
##	9	javelin	NA	0.27	0.27
##	10	${\tt fifteen_hundred_m}$	NA	0.44	0.44
##	11	points	0.24	0.24	0.24

Above, we present the results for each model for this one training and testing data split. In our experiments, we repeat the above process 10 times for each model combination.