Fit models, extract results

GS Verhoeven

Summary

This Notebook fits the models, extracts the results, and calculates the Ranked probability scores for the fitted models, as well as for three reference models, two based on (differing) Bookmaker odds, and one "random" model that predicts equal probabilities Win/Draw/Lose for each match. Finally, the Diebold-Mariano test statistic is used to statistically compare the prediction quality (as quantified with the Ranked probability Score) of the various models.

Load packages

```
library(data.table)
library(ggplot2)
library(rstan)
library(cowplot)
library(forecast)

rstan_options(auto_write = TRUE)
options(mc.cores = parallel::detectCores())
```

```
source("code/ppc_coverage_plot.R")
source("code/MakeTimeSeriesPlot.R")
source("code/Create_model_data_for_TS2.R")
source("code/addTeamIds.R")
source("code/create_league_table.R")
source("code/MakeEPLPlotAbility.R")
source("code/games_predicted_vs_actual_intervals.R")
source("code/ppc_coverage_plot.R")
source("code/calc_rps_scores.R")
source("code/odds_to_probability.R")
source("code/ReadfitsandCalculateRPS.R")
source("code/FitOneStepAhead.R")
source("code/ReadfitsandExtractCoefs.R")
```

Read & further prep Eredivisie dataset

`NL_ALL` contains all data for 2000-2018.

```
NL_ALL <- readRDS("data/NL Eredivisie 2000-2018.rds")

# set 2017/2018 season apart
NL_17 <- NL_ALL[Date > as.Date("2017-07-01")]

NL_ALL <- NL_ALL[Date < as.Date("2017-07-01")]
setkey(NL_ALL, Date)
```

```
# add round and season
nrounds <- nrow(NL_ALL)/9
nseasons <- nrow(NL_ALL)/(9*34)
NL_ALL <- NL_ALL[, round := rep(1:nrounds, each = 9)]
NL_ALL <- NL_ALL[, season := rep(1:nseasons, each = 34*9)]
```

```
# prep 2017/2018 separately
setkey(NL_17, Date)
nrounds <- ceiling(nrow(NL_17)/9)
start_nr_round <- max(NL_ALL$round)+1

round_vec <- rep(start_nr_round:(start_nr_round + nrounds), each = 9)
NL_17 <- NL_17[, round := round_vec[1:nrow(NL_17)]]
NL_17 <- NL_17[, season := 18]

# add to NL_ALL
NL_ALL <- rbind(NL_ALL, NL_17)

setkey(NL_ALL, Date)

NL_ALL <- NL_ALL[, row_id := 1:nrow(NL_ALL)]

saveRDS(NL_ALL, "output/NL_ALL.rds")
```

NL_ALL does not contain the betting odds of Bet365. We need these for the out-of-sample seasons 2015/2016 and 2016/2017 to compare our forecasts. So we create a separate dataset that includes these betting odds.

```
# read in raw data with betting odds
NL15 <- data.table(read.table(unz("data/data15.zip", "N1.csv"), header=T, quote="\"", sep=","))
NL16 <- data.table(read.table(unz("data/data16.zip", "N1.csv"), header=T, quote="\"", sep=","))

NLodds <- rbind(NL15, NL16)

NLodds <- NLodds[, Date := as.Date(Date, "%d/%m/%y")]
```

Forecasting approach: train / test choices

We pick two seasons as training set up to the first out-of-sample predictions, we then use an expanding window into the next two seasons.

For the first two out-of-sample weeks (home and away) we miss a prediction for the new team, which is not present in the in-sample dataset). This gives 304 predictions (17 * 9 -2). For the fourth season (Second out-of-sample season), the same situation occurs. Together, this makes for 608 out-of-sample match predictions where we can compare the predictive performance of the various models.

A technical issue is that we need to think carefully about new teams in t+1. They don't have parameters yet. Problem: team_ids in sample fitting don't match the prediction team ids. We solve this by generating matching id's during creation of model_Data.

Fit all models using Stan

This is the part where all the MCMC work gets done. Fit all models in `model_list` with fitting parameter settings fit_pars.

```
model_list <- data.table(read.csv2("models/model_list.csv"))

model_list
```

```
##     model_nr                              name
##  1:        1                   T-dist original
##  2:        2          T-dist with AT advantage
##  3:        3           Skellam offense/defense
##  4:        4                 T-dist no pooling
##  5:        5             Skellam single ability
##  6:        6                      T-dist no HA
##  7:        7 Skellam, no zif, offense/defense
##  8:        8    T-dist with AT advantage run2
##  9:        9                       T-dist run2
## 10:       10  Skellam offense/defense with AT
##                               stan_file        short_name
##  1:                      epl_model.stan              fitX
##  2:             epl_model_art_turf.stan        fit_epl_at
##  3:                skellam_dynamic.stan            fit_sd
##  4:            epl_model_no_pooling.stan        fit_epl_np
##  5: skellam_dynamic_single_ability.stan          fit_sd_sa
##  6:                epl_model_no_ha.stan fit_epl_xtra_no_ha
##  7:         skellam_dynamic_no_zif.stan       fit_sd_nozif
##  8:             epl_model_art_turf.stan    fit_epl_at_xtra
##  9:                      epl_model.stan       fit_epl_xtra
## 10:     skellam_dynamic_artificial.stan          fit_sd_at
##
##  1:                                                                                        goal_diff
##  2:                                                                          goal_difference_pred_rep, a
##  3:                 goal_difference_pred_rep, a_offense, a_defense, mixing_proportion, constant_mu,
##  4:                                                                                              goa
##  5:                                                                 goal_difference_pred_rep, a, mixing_
##  6:                                                                                                g
##  7:                                         goal_difference_pred_rep, a_offense, a_defense, constant_mu,
##  8:                                                                          goal_difference_pred_rep, a
##  9:                                                                                        goal_diff
## 10: goal_difference_pred_rep, a_offense, a_defense, mixing_proportion, constant_mu, home_advantage, 
##        dist ata ha part_pool n_ability zif
##  1:  T-dist   0  1         1         1   0
##  2:  T-dist   1  1         1         1   0
##  3: Skellam   0  1         1         2   1
##  4:  T-dist   0  1         0         1   0
##  5: Skellam   0  1         1         1   1
##  6:  T-dist   0  0         1         1   0
##  7: Skellam   0  1         1         2   0
##  8:  T-dist   1  1         1         1   0
##  9:  T-dist   0  1         1         1   0
## 10: Skellam   1  1         1         2   1
##                                                       extract_pars active
```

```
##  1:                                          b_home, b_prev, sigma_y      0
##  2:                       b_home, b_prev, sigma_y, art_turf_effect      0
##  3:                  constant_mu, home_advantage, mixing_proportion      0
##  4:                                          b_home, b_prev, sigma_y      0
##  5:                  constant_mu, home_advantage, mixing_proportion      0
##  6:                                              b_prev, sigma_y      0
##  7:                                 constant_mu, home_advantage      0
##  8:                       b_home, b_prev, sigma_y, art_turf_effect      0
##  9:                                          b_home, b_prev, sigma_y      0
## 10: constant_mu, home_advantage, mixing_proportion, art_turf_effect      0
```

For each model we specify which parameters should be saved (`include_pars`), this is to limit the amount of disk space used by the model fits (Currently 45 Gb for 68 weeks x 10 models = 680 model fits). In addition, we specify using `extract_pars` which parameters should be extracted from the fit models for analysis. `model_list` also contains metadata for each model: its full name, short name for saving files, various dimensions in which the models differ (artificial turf predictor yes/no, home advantage yes / no, partial pooling yes/no, one of two ability parameters for each team etc).

`fit_models` sets whether fitting should run or whether only saved fits are read and processed. `fullrun` sets whether saved fits should be processed or the saved result table should be read instead.

The One-step-ahead out-of-sample predictions are generated during sampling using the generated quantities{} block of Stan.

```
source("code/Create_model_data_for_TS2.R")
source("code/fitOneStepAhead.R")
source("code/ReadfitsandCalculateRPS.R")

fit_pars <- list(nsamples = 1000, # samples PER chain, including warmup
                 chains = 6,
                 warmup = 500,
                 nshifts_start = 0,
                 nshifts_end = 67,
                 init_r_val = 0.1,
                 start_round = 443,
                 end_round = 511,
                 prev_perf_season = 13,
                 target_folder = "c:/testversleutel/FITS/"
                 )
#saveRDS(fit_pars, "output/20180101 fitpars.rds")

fit_models <- 0
fullrun <- 0

if(fullrun){
  if(fit_models == 1) model_list <- model_list[active == 1,]
  # else extract predictions only
  osa_res <- list()
  for(i in 1:nrow(model_list)){

    split_string <- str_split(as.character(model_list[i, ]$include_pars), ", ")

    osa_res[[i]] <- fitOneStepAhead(toggle_dynamic = fit_models,
                                    sm_string = paste("models/", model_list$stan_file[i], sep = ''),
                                    model_short_name = model_list$short_name[i],
                                    model_long_name = model_list$name[i],
```

```
                                stanfit_include_pars = unlist(split_string),
                                fitpars = fit_pars)
  }
  saveRDS(osa_res, "output/20180405 osa_res.rds")
} else {osa_res <- readRDS("output/20180405 osa_res.rds")}

# re-read model_list to include non-active models as well
model_list <- data.table(read.csv2("models/model_list.csv"))
```

The no pooling model needs an increased adapt_delta to silence all warnings during sampling. All models are now "warning" free from Stan.

Extract coefficients from model fits

We're interested in all "global" (i.e. non-team specific) parameters. So constant_mu, home_advantage, artificial_turf_advantage etc. We want to extract this for all 68 weeks available for each model.

This allows us to see change in the coefficients over the two year period of data that we ADD to the years we start with (2013/2014 and 2014/2015). So the final model (last week of 2016/2017 season) is based on four seasons of match data.

```
read_fit_coefs <- 0

model_list_tmp <- model_list

coef_res <- c()

if(read_fit_coefs){
  for(i in 1:nrow(model_list_tmp)){

    split_string <- str_split(as.character(model_list_tmp[i, ]$extract_pars), ", ")

    coef_res[[i]] <- ReadFitsWrapper(sm_string = paste("models/", model_list_tmp$stan_file[i], sep = ''
                                     model_short_name = model_list_tmp$short_name[i],
                                     model_long_name = model_list_tmp$name[i],
                                     stanfit_extract_pars = unlist(split_string),
                                     fitpars = fit_pars)
  }
  #saveRDS(coef_res, "output/20180202 coef_res.rds")
  tidy_coef_res <- tidyCoefs(coef_res, model_list_tmp)
  # use this table in the manuscript
  saveRDS(tidy_coef_res, "output/tidy_coef_res.rds")

} else {tidy_coef_res <- readRDS("output/tidy_coef_res.rds")}
```

Extract Rhat and n_eff from fits

To check convergence and / or sampling problems, we extract all Rhat and n_eff from the fits for further inspection.

```
read_rhat_neff <- 0
```

```
model_list_tmp <- model_list

rhat_neff_res <- c()

if(read_rhat_neff){
  for(i in 1:nrow(model_list_tmp)){

    split_string <- str_split(as.character(model_list_tmp[i, ]$extract_pars), ", ")

    rhat_neff_res[[i]] <- ReadRhatNeffWrapper(sm_string = paste("models/", model_list_tmp$stan_file[i],
                                    model_short_name = model_list_tmp$short_name[i],
                                    model_long_name = model_list_tmp$name[i],
                                    stanfit_extract_pars = unlist(split_string),
                                    fitpars = fit_pars)
  }
  #saveRDS(rhat_neff_res, "output/20180323 rhat_neff_res.rds")
  tidy_rhat_neff_res <- tidyCoefs(rhat_neff_res, model_list_tmp)
  # use this table in the manuscript
  saveRDS(tidy_rhat_neff_res, "output/tidy_rhat_neff_res.rds")

} else {tidy_rhat_neff_res <- readRDS("output/tidy_rhat_neff_res.rds")}
```

Create dataset with all matches, and all predictions from each model

We use this dataset to identify strengths and weaknesses from the models (model checking).

We also add the bookmakers probabilities to calculate the average Ranked Probability Score (RPS).

We use basic normalization to convert betting odds to probabilities.

```
source("code/CombineDataWithPredictions.R")
fullrun <- 0

if(fullrun){
  for(i in 1:nrow(model_list)){
    if(i == 1){NL_ALL_PRED <- CombineDataWithPredictions(NL_ALL,
                                                         fit_pars,
                                                         osa_res,
                                                         model_nr = i)
    } else{NL_ALL_PRED <- rbind(NL_ALL_PRED,CombineDataWithPredictions(NL_ALL,
                                                         fit_pars,
                                                         osa_res,
                                                         model_nr = i))
    }
  }

  # abuse WH odds as sort key (also present in NL_ALL_PRED)
  setkey(NLodds, Date, WHH, WHD, WHA)

  # convert odds to probabilistic forecasts using basic normalization method
  bet365_probs <- odds_to_probability(NLodds[, .(B365H, B365D, B365A)])
  WH_probs <- odds_to_probability(NLodds[, .(WHH, WHD, WHA)])
```

```
  # Add equal probabilities (aka Equal_prob on typewriter) model
  Equal_prob_probz <- data.table(game_id = 1:nrow(NLodds),
                           prob_win = 1/3,
                           prob_draw = 1/3,
                           prob_loss = 1/3)

  # function to add the odds as model to NL_ALL_PRED table
  addOddsAsModel <- function(prediction_table, converted_odds){
    # we need a template
    prediction_table_new <- prediction_table[model_nr == 1,]
    # sort matches as in converted_odds
    setkey(prediction_table_new, Date,  WHH, WHD, WHA)

    new_model_nr <- max(prediction_table$model_nr) + 1
    prediction_table_new <- prediction_table_new[, model_nr := new_model_nr]
    dropcols <-  c("rps_vec", "p_win", "p_draw", "p_loss")
    prediction_table_new <- prediction_table_new[, !(colnames(prediction_table_new) %in% dropcols), wit

    prediction_table_new <- cbind(converted_odds[,.( prob_win, prob_draw, prob_loss)], prediction_table_

    actual_scorez <- Convert_actual_to_win_draw_loss_vector(NLodds$FTHG - NLodds$FTAG)
    # calculate RPS per game
    rps_vec <- calculate_rps(converted_odds[,.( prob_win, prob_draw, prob_loss)],
                             actual_scorez[,.(act_win, act_draw, act_loss)])

    prediction_table_new <- data.table(rps_vec, prediction_table_new)
    prediction_table_new <- prediction_table_new[is.na(act_win), rps_vec := NA]
    setnames(prediction_table_new, "prob_win", "p_win")
    setnames(prediction_table_new, "prob_draw", "p_draw")
    setnames(prediction_table_new, "prob_loss", "p_loss")
    prediction_table <- rbind(prediction_table_new, prediction_table)
    prediction_table
  }

  # add WH and Bet365 as models to NL_ALL_PRED
  NL_ALL_PRED <- addOddsAsModel(NL_ALL_PRED, WH_probs)
  NL_ALL_PRED <- addOddsAsModel(NL_ALL_PRED, bet365_probs)
  NL_ALL_PRED <- addOddsAsModel(NL_ALL_PRED, Equal_prob_probz)

  # remove the four matches without prediction also from betting odds "models"
  matches_wo_preds <- NL_ALL_PRED[is.na(rps_vec), .N, .(matchKey)]$matchKey

  NL_ALL_PRED <- NL_ALL_PRED[, has_pred := 1]
  NL_ALL_PRED <- NL_ALL_PRED[matchKey %in% matches_wo_preds, has_pred := 0]
saveRDS(NL_ALL_PRED, file = "Output/20180406 NL_ALL_PRED_w_odds.rds")
} else {NL_ALL_PRED <- readRDS("Output/20180406 NL_ALL_PRED_w_odds.rds")}
```

At this point, NL_ALL_PRED has rps scores for all 608 predicted matches for all models, including the betting odds of Bet365 and William Hill.

Create main result by model table

To compare the models, we calculate the average RPS for each model from the individual math dataset. From `model_list` , we add each models metadata to this table.

```
result <- NL_ALL_PRED[!(model_nr %in% c(11:13)),
                      .(aRPS = mean(rps_vec, na.rm = T),
                       N_pred = nrow(.SD[!is.na(rps_vec)])), .(model_nr)][order(aRPS)]

setkey(result, model_nr)
setkey(model_list, model_nr)
result <- model_list[result]
```

Add betting odds result to main result table

We append the betting odds RPS to the result table.

Use this table to present results in the manuscript.

```
actual_scorez <- Convert_actual_to_win_draw_loss_vector(NLodds$FTHG - NLodds$FTAG)

result_WH <- data.table(model_nr = 11, name = "William_hill odds", stan_file = NA,
                            short_name = "WH_odds", include_pars = NA, dist = "Benchmark", ata = NA,
                            ha = NA, part_pool = NA, n_ability = NA, zif = NA, extract_pars = NA,
                            active = 0, aRPS = NA, N_pred = NA)

result_WH$aRPS <- mean(NL_ALL_PRED[model_nr == 11 & !is.na(rps_vec),]$rps_vec)
result_WH$N_pred <- nrow(NL_ALL_PRED[model_nr == 11 & !is.na(rps_vec),])

result_Bet365 <- data.table(model_nr = 12, name = "Bet365 odds", stan_file = NA,
                            short_name = "B365_odds", include_pars = NA, dist = "Benchmark", ata = NA,
                            ha = NA, part_pool = NA, n_ability = NA, zif = NA, extract_pars = NA,
                            active = 0, aRPS = NA, N_pred = NA)

result_Bet365$aRPS <- mean(NL_ALL_PRED[model_nr == 12 & !is.na(rps_vec),]$rps_vec)
result_Bet365$N_pred <- nrow(NL_ALL_PRED[model_nr == 12 & !is.na(rps_vec),])

result_Equal_prob <- data.table(model_nr = 13, name = "Equal probability odds", stan_file = NA,
                            short_name = "Equal_prob_odds", include_pars = NA, dist = "Benchmark", ata
                            ha = NA, part_pool = NA, n_ability = NA, zif = NA, extract_pars = NA,
                            active = 0, aRPS = NA, N_pred = NA)

result_Equal_prob$aRPS <- mean(NL_ALL_PRED[model_nr == 13 & !is.na(rps_vec),]$rps_vec)
result_Equal_prob$N_pred <- nrow(NL_ALL_PRED[model_nr == 13 & !is.na(rps_vec),])


# unit test for calculate_arps(): expect rps of zero when using actual scores as predictions for acutal
#calculate_arps(actual_scorez[,.(act_win, act_draw, act_loss)], actual_scorez[,.(act_win, act_draw, act

result <- rbind(result, result_WH)
result <- rbind(result, result_Bet365)
result <- rbind(result, result_Equal_prob)
```

Add Diebold-Mariano test statistic

We also use the Diebold-Mariano test statistic to compare the predictive accuracy of the various models. We compare each model against three different reference models.

```
source("code/AddDMTest.R")
# bet365, beste odds
result <- AddDMtest(result, NL_ALL_PRED, ref_model_nr = 12) # Bet365 odds
# t-dist base model
result <- AddDMtest(result, NL_ALL_PRED, ref_model_nr = 1) # t-dist
# Skellam no zif is base model
result <- AddDMtest(result, NL_ALL_PRED, ref_model_nr = 7) # skellam no-zif

saveRDS(result, file = "output/20180406 average RPS by model.rds")
```

One of the assumptions when comparing two prediction error time series, is that there is no serial (auto) correlation. Since here the two vectors are Ranked probability scores of matches between different teams, we expect that this assumption holds. We test this for one of the models.

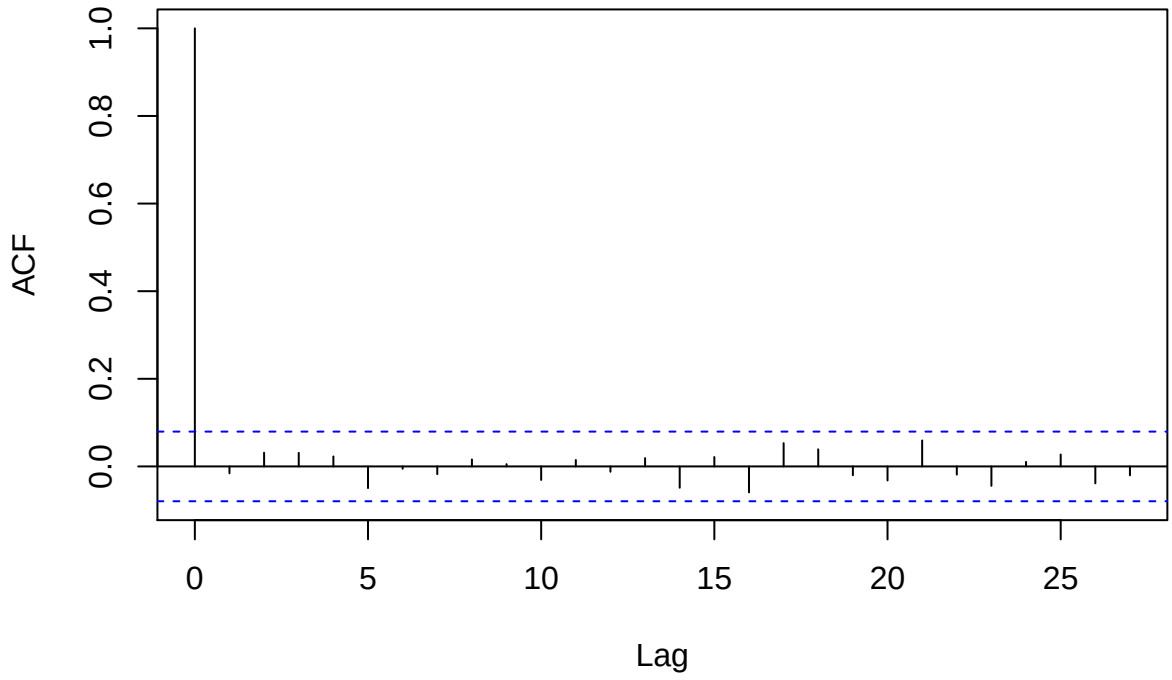
```
osa_res[[1]]$name
```

```
## [1] T-dist original
## 10 Levels: Skellam offense/defense ... T-dist with AT advantage run2
```

```
osa_res[[6]]$name
```

```
## [1] T-dist no HA
## 10 Levels: Skellam offense/defense ... T-dist with AT advantage run2
```

```
# check autocorrelation of time series (expect none since different teams)
e1 <- NL_ALL_PRED[model_nr == 6 & !is.na(rps_vec), ]$rps_vec
w <- acf(e1)
```




```
# Zero autocorrelation indeed
```

Check if we understand the Diebold-Mariano test statistic. We expect that this is basically a two sample t-test for equal sample means assuming equal variance. Thus, the DM-statistic p-value should be close / identical to the p-value of an OLS intercept only model for the difference of the two time series. This is indeed the case.

```
# partial pooling yes/no
delta <- osa_res[[1]]$rps_vec - osa_res[[6]]$rps_vec

# OLS intercept only
summary(lm(y ~ 1, data = data.frame(y = delta)))
```

```
##
## Call:
## lm(formula = y ~ 1, data = data.frame(y = delta))
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.13166 -0.05587 -0.01216  0.05283  0.15557
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.006036   0.002628  -2.297    0.022 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## Residual standard error: 0.06479 on 607 degrees of freedom
```

```
result[model_nr == 6,]$DMstat_1
```

```
## [1] -2.297
```

```
result[model_nr == 6,]$DMpval_1
```

```
## [1] 0.022
```

```
# identical
```

Display main result by model table

Finally, we list the result table for all models, including the betting odds and equal-probability reference models, but excluding the two reruns that we used to check for sampling stability / reproducability of our results.

```
# exclude reruns
knitr::kable(result[!(model_nr %in% c(8, 9)), .(name, N_pred, aRPS)][order(aRPS)])
```

name	N_pred	aRPS
Bet365 odds	608	0.1892859
William_hill odds	608	0.1901592
Skellam, no zif, offense/defense	608	0.1913812
Skellam offense/defense with AT	608	0.1916885
Skellam offense/defense	608	0.1917053
Skellam single ability	608	0.1920124
T-dist original	608	0.1920899
T-dist with AT advantage	608	0.1922611
T-dist no pooling	608	0.1957098
T-dist no HA	608	0.1981257
Equal probability odds	608	0.2374819