HW6

Stats 506 Homework 6

Margaret Miles

Problem #1: Rcpp

In the notes, we defined a C_mean function. Using this as a template, implement a C_moment function that returns the kth central moment. Generate a vector of moderate length and show that you are able to replicate the results of e1071::moment.

Notes & Hints: Be cognizant of your scaling factor. Be sure to look at the arguments of e1071::moment.

```r
library(Rcpp)
#' C_moment function
#'
#' Takes in a vector and returns the kth central moment
#' central moment is defined as m = E[(x-mu)^k] =
#' m = 1/n*sum(xi - mean)^k
#'
#' @params v = vector
#' @params k = number in central moment
#' @returns moment = kth central moment
cppFunction("
            double C_moment(NumericVector v, int k){
            double sum = 0;
            double n = v.length();
            double mean = 0;

            for (int j = 0; j < v.length(); ++j){
                mean += v[j];
            }
            double m = mean / v.length();

            for (int i = 0; i < v.length(); ++i){
                double x = v[i] - m;
                sum += std::pow(x, k);
            }
            return(sum/n);
            }")
```

Generate a vector of moderate length and show that you are able to replicate the results of e1071::moment.

```r
library(e1071)

set.seed(123)
v <- rnorm(1000)

# test several moments
C_moment(v, 2)       # variance (not sample variance!)
```

```
[1] 0.9824755
```

```r
moment(v, order=2, center=TRUE)
```

```
[1] 0.9824755
```

```r
C_moment(v, 3)       # third central moment
```

```
[1] 0.06358509
```

```r
moment(v, order=3, center=TRUE)
```

```
[1] 0.06358509
```

```r
C_moment(v, 4)       # fourth central moment
```

```
[1] 2.8241
```

```r
moment(v, order=4, center=TRUE)
```

```
[1] 2.8241
```

Problem #2: Expanding on waldCI

a. Write a class bootstrapWaldCI that produces a CI using bootstrap, similar to waldCI. It should inherit from waldCI using either the version from the solutions or your version - in either case, include the relevant code in this homework by using source() on a file containing the waldCI code.

The booststrapWaldCI constructor should take in a data set and a function that returns a scalar. E.g.

makeBootstrapCI(function(x) mean(x$myvar), data = mydata, reps = 100)

Add an optional level argument and an optional compute argument that accepts either “serial” (using no parallel processing), “parallel” (using either forks or sockets from parallel).

The constructor should carry out the bootstrap using the requested compute approach. Most functions can be inherited from waldCI, but add the additional function rebootstrap that performs a new bootstrap. rebootstrap should only take in one argument of a bootstrapWaldCI object.

Note: Be careful with inheritance and S4:

The @.Data slot only applies if the child class contains an S3 class; if it contains S4, it simply adds the childs slots alongside the parent slots. Slot names should not be re-used unless you're explicltly overwriting existing slots.

```r
source("waldCI.R")
library(parallel)

#create a new bootstrapWaldCI object based on waldCI
setClass(
  "bootstrapWaldCI",
  contains = "waldCI",   # inherit level, mean, sterr and methods
  slots = c(
    bootStats = "numeric",   # bootstrap statistics
    reps      = "integer",   # number of resamples
    compute   = "character", # "serial" or "parallel"
    statFun   = "function",  # function used to compute stat
    data      = "ANY"        # original data
  )
)

# serial bootstrap method
.bootstrap_serial <- function(statFun, data, reps) {
  n <- NROW(data)
  out <- numeric(reps)

  for (i in seq_len(reps)) {
    idx <- sample.int(n, size = n, replace = TRUE)
    out[i] <- statFun(data[idx, , drop = FALSE])
  }

  out
}

# parallel bootstrap method
.bootstrap_parallel <- function(statFun, data, reps) {
  if (!requireNamespace("parallel", quietly = TRUE)) {
    stop("Package 'parallel' is required for compute = 'parallel'.")
  }

  n  <- NROW(data)
  cl <- parallel::makeCluster(parallel::detectCores())
  on.exit(parallel::stopCluster(cl), add = TRUE)

  parallel::clusterExport(
    cl,
    varlist = c("data", "statFun", "n"),
    envir   = environment()
  )

  res <- parallel::parLapply(
    cl,
    X = seq_len(reps),
    fun = function(i) {
      idx <- sample.int(n, size = n, replace = TRUE)
      statFun(data[idx, , drop = FALSE])
    }
  )

  unlist(res, use.names = FALSE)
}

# constructor
makeBootstrapCI <- function(statFun,
                            data,
                            reps    = 100L,
                            level   = 0.95,
                            compute = c("serial", "parallel")) {
  stopifnot(is.function(statFun))
  compute <- match.arg(compute)
  reps    <- as.integer(reps)

  ## original estimate on full data
  est <- statFun(data)

  ## bootstrap
  bootStats <- switch(
    compute,
    serial   = .bootstrap_serial(statFun, data, reps),
    parallel = .bootstrap_parallel(statFun, data, reps)
  )

  se_boot <- sd(bootStats)

  ## build child object
  obj <- new("bootstrapWaldCI",
             level    = level,
             mean     = est,
             sterr    = se_boot,
             bootStats = bootStats,
             reps      = reps,
             compute   = compute,
             statFun   = statFun,
             data      = data)

  validObject(obj)
  obj
}
```

```r
# show method for bootstrapWaldCI
setMethod(
  "show",
  "bootstrapWaldCI",
  function(object) {
    ## parent show: prints "X% CI: (lb, ub)"
    callNextMethod()

    cat("Bootstrap reps:", object@reps, "\n")
    cat("Compute mode:  ", object@compute, "\n", sep = "")
    invisible(object)
  }
)

setGeneric(
  "rebootstrap",
  function(object) standardGeneric("rebootstrap")
)
```

```
[1] "rebootstrap"
```

```r
## define method for bootstrapWaldCI
setMethod(
  "rebootstrap",
  "bootstrapWaldCI",
  function(object) {
    statFun <- object@statFun
    data    <- object@data
    reps    <- object@reps
    compute <- object@compute
    level   <- object@level

    ## recompute original estimate on full data
    est <- statFun(data)

    ## new bootstrap run
    bootStats <- switch(
      compute,
      serial   = .bootstrap_serial(statFun, data, reps),
      parallel = .bootstrap_parallel(statFun, data, reps)
    )

    se_boot <- sd(bootStats)

    ## update *parent* slots (waldCI)
    object@mean  <- est
    object@sterr <- se_boot
    object@level <- level
    ## update *child* slots
    object@bootStats <- bootStats

    validObject(object)
    object
  }
)
```

b. Show your code works by executing the following:

ci1 <- makeBootstrapCI(function(x) mean(x$y), ggplot2::diamonds, reps = 1000) ci1 rebootstrap(ci1)

```
ci1 <- makeBootstrapCI(function(x) mean(x$y),
                       ggplot2::diamonds,
                       reps = 1000)
ci1
```

```
95% CI: (5.724792, 5.74426)
Bootstrap reps: 1000
Compute mode:  serial
```

```
rebootstrap(ci1)
```

```
95% CI: (5.724774, 5.744278)
Bootstrap reps: 1000
Compute mode:  serial
```

Compare and comment on the performance of the two compute methods.

```
## Serial
system.time(
  ci1_serial <- makeBootstrapCI(
    function(x) mean(x$y),
    data    = ggplot2::diamonds,
    reps    = 1000,
    compute = "serial"
  )
)
```

```
   user  system elapsed 
  1.921   0.149   2.071 
```

```
## Parallel
system.time(
  ci1_parallel <- makeBootstrapCI(
    function(x) mean(x$y),
    data    = ggplot2::diamonds,
    reps    = 1000,
    compute = "parallel"
  )
)
```

```
   user  system elapsed 
  0.058   0.024   4.478 
```

Since this is just a mean and only 1000 reps, the serial is faster because it doesn't need that extra time to set up the parrallel processing.

c. Write a function called dispCoef that takes in data (based upon mtcars; it must take in a generic data for the bootstrap) and fits the model: mpg ~ cyl + disp + wt. It should return the coefficient associated with disp.

```r
dispCoef <- function(data) {
  fit <- lm(mpg ~ cyl + disp + wt, data = data)
  coef(fit)[["disp"]]
}
```

Execute the following:

ci2 <- makeBootstrapCI(dispCoef, mtcars, reps = 1000) ci2 rebootstrap(ci2)

```r
ci2 <- makeBootstrapCI(dispCoef,
                       mtcars,
                       reps = 1000)
ci2
```

```
95% CI: (-0.01089334, 0.02583919)
Bootstrap reps: 1000
Compute mode:  serial
```

```r
rebootstrap(ci2)
```

```
95% CI: (-0.01103191, 0.02597776)
Bootstrap reps: 1000
Compute mode:  serial
```

Compare and comment on the performance of the two compute methods.

```r
## Serial
system.time(
  ci2_serial <- makeBootstrapCI(
    dispCoef,
    data    = mtcars,
    reps    = 100000,
    compute = "serial"
  )
)
```

```
   user  system elapsed 
 24.372   0.091  24.510 
```

```
## Parallel
system.time(
  ci2_parallel <- makeBootstrapCI(
    dispCoef,
    data    = mtcars,
    reps    = 100000,
    compute = "parallel"
  )
)
```

```
   user  system elapsed 
  0.022   0.010   4.468 
```

When it was only 1,000 reps the series and parrallel were comprable but similar because the regression just takes longer than a mean. But when I upped the process to 100,000 runs you can see that parrallel is just significantly faster than series.

Problem #3: Large data

Generate artificial data by running the code in this script. Do not include this script in your submitted PDF; either use source() or save/load to get the data into R.

```
# Load data-generating script
source("Problem3data.R")
```

```
Data.frame `df` is 251.8 Mb
```

```
# Assuming the script creates an object called 'bigdat' or similar
str(df)
```

```
'data.frame':	3000000 obs. of  15 variables:
 $ age              : num  25.5 28.2 42.5 30.6 31 ...
 $ country          : Factor w/ 6 levels "Germany","India",..: 6 5 5 2 6 1 6 2 6 2 ...
 $ device_type      : Factor w/ 4 levels "desktop","laptop",..: 3 4 1 3 1 2 3 2 3 1 ...
 $ employment_status : Factor w/ 4 levels "full_time","part_time",..: 3 3 3 1 2 1 1 2 1 1
...
 $ course_difficulty : Ord.factor w/ 3 levels "advanced"<"intermediate"<..: 3 2 3 3 3 2 2
3 3 2 ...
 $ prior_gpa        : num  3.01 2.72 3.86 2.71 2.52 ...
 $ weekly_study_hours: num  5.33 8.46 9.81 5.6 6.71 ...
 $ forum_posts      : int  1 3 3 0 1 0 0 1 0 1 ...
 $ quiz_attempts    : int  3 2 1 7 1 2 1 1 0 2 ...
 $ session_minutes  : num  256 395 447 268 470 ...
 $ paid_subscription : int  0 1 0 0 1 1 0 1 1 0 ...
 $ final_score      : num  55.5 53.6 75.1 63.9 71.4 ...
 $ completed_course  : int  0 1 0 1 0 0 1 0 1 1 ...
 $ early_dropout     : num  1 0 0 0 0 0 0 1 0 0 ...
 $ time_to_dropout   : num  5.95 NA NA NA NA ...
```

a. Fit one model per country. Fit a mixed effects logistic regression model, predicting course completion based upon prior GPA, number of forum posts, number of quiz attempts, and a random effect for device type. Standardize the predictors within each country. Generate some sort of visualization of the estimated coefficients for number of forum posts in each country.

```r
library(dplyr)
```

```

Attaching package: 'dplyr'

The following object is masked _by_ '.GlobalEnv':

    contains

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

    filter, lag

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

    intersect, setdiff, setequal, union
```

```r
library(lme4)
```

```
Loading required package: Matrix
```

```r
library(purrr)
library(tidyr)
```

```

Attaching package: 'tidyr'

The following object is masked _by_ '.GlobalEnv':

    contains

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

    expand, pack, unpack
```

```r
library(ggplot2)
```

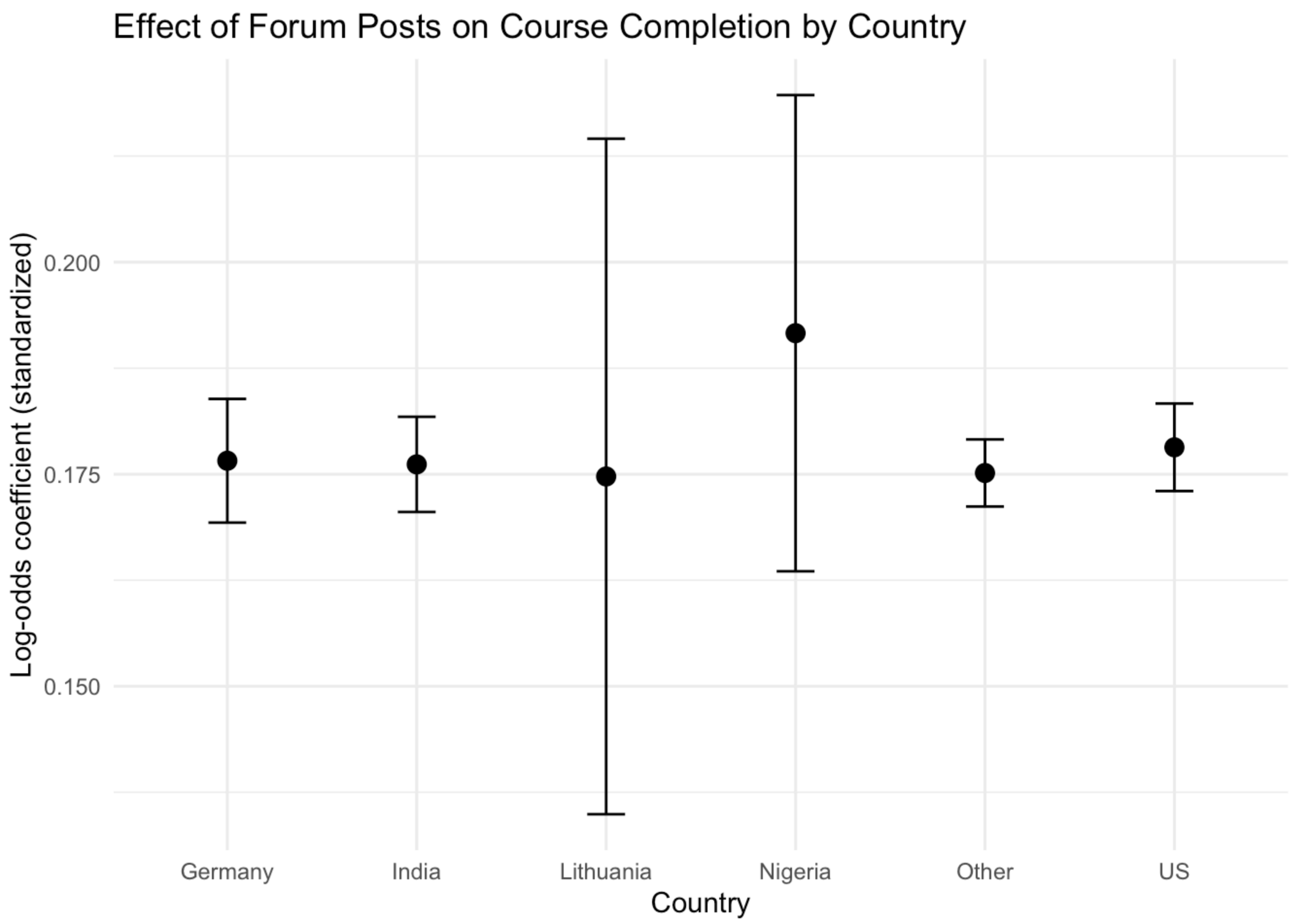
```

Attaching package: 'ggplot2'
```

```
The following object is masked from 'package:e1071':

    element
```

```
# fit one model per country
data_list <- split(df, df$country)

# fit mixed effects logistic regression model
# predicting course completion based upon prior GPA, number of forum posts, number of qui
model_country <- function(dat) {
  # standardize each variable
  dat <- dat %>%
    mutate(
      #prior gpa
      std_gpa = scale(prior_gpa),
      #number of forum posts
      std_posts = scale(forum_posts),
      #number of quiz attempts
      std_attempt = scale(quiz_attempts)
    )

  # logistic regression with device time random effect
  glmer(
    completed_course ~ std_gpa + std_posts + std_attempt + (1 | device_type),
    data = dat,
    family = binomial(link = "logit")
  )
}

model1 <- model_country(data_list[[1]])
model2 <- model_country(data_list[[2]])
model3 <- model_country(data_list[[3]])
model4 <- model_country(data_list[[4]])
model5 <- model_country(data_list[[5]])
model6 <- model_country(data_list[[6]])

#plot estimated coefficients for number of forum posts in each country

# extract std_posts coefficient and std error
models <- list(model1, model2, model3, model4, model5, model6)
posts_coef <- data.frame(
  country = c("Germany","India","Lithuania","Nigeria","Other",
              "US"),
  coef = numeric(6),
  se = numeric(6)
)

for(i in 1:6){
  posts_coef$coef[i] <- fixef(models[[i]])["std_posts"]
  posts_coef$se[i] <- sqrt(diag(vcov(models[[i]])))["std_posts"]
}
posts_coef
```

```
    country      coef          se
1   Germany 0.1765868 0.003646498
2     India 0.1761593 0.002804818
3 Lithuania 0.1747323 0.019908599
4   Nigeria 0.1916268 0.014035955
5     Other 0.1751442 0.001978480
6        US 0.1781707 0.002580410
```

```
library(ggplot2)

ggplot(posts_coef, aes(x = country, y = coef)) +
  geom_point(size = 3) +
  geom_errorbar(aes(ymin = coef - 2*se, ymax = coef + 2*se), width = 0.2) +
  theme_minimal() +
  labs(
    title = "Effect of Forum Posts on Course Completion by Country",
    y = "Log-odds coefficient (standardized)",
    x = "Country"
  )
```



Report the running time (from system.time) for each of the 6 models.

```r
# fit models with run times
run1 <- system.time({
  model1 <- model_country(data_list[[1]])
})
run2 <- system.time({
  model2 <- model_country(data_list[[2]])
})
run3 <- system.time({
  model3 <- model_country(data_list[[3]])
})
run4 <- system.time({
  model4 <- model_country(data_list[[4]])
})
run5 <- system.time({
  model5 <- model_country(data_list[[5]])
})
run6 <- system.time({
  model6 <- model_country(data_list[[6]])
})
print(as.character(data_list[[1]]$country[1]))
```

```
[1] "Germany"
```

```r
run1
```

```
   user  system elapsed 
 18.688   0.958  19.660 
```

```r
print(as.character(data_list[[2]]$country[1]))
```

```
[1] "India"
```

```r
run2
```

```
   user  system elapsed 
 29.065   1.885  30.956 
```

```r
print(as.character(data_list[[3]]$country[1]))
```

```
[1] "Lithuania"
```

```r
run3
```

```
   user  system elapsed 
  0.542   0.111   0.654 
```

```r
print(as.character(data_list[[4]]$country[1]))
```

```
[1] "Nigeria"
```

```r
run4
```

```
   user  system elapsed 
  1.220   0.168   1.387 
```

```r
print(as.character(data_list[[5]]$country[1]))
```

```
[1] "Other"
```

```r
run5
```

```
   user  system elapsed 
 60.448   8.979  69.527 
```

```r
print(as.character(data_list[[6]]$country[1]))
```

```
[1] "US"
```

```r
run6
```

```
   user  system elapsed 
 36.804   2.464  39.382 
```

b. Devise an approach that minimizes the running time of your script. Report the running time of your entire script (running models and estimating coefficients; no need for a new plot). Do not use a different package for the models. Show that the results match those from part a).

```r
library(dplyr)
library(lme4)
library(purrr)

# Split data by country
data_list <- split(df, df$country)

fit_country <- function(dat) {
  dat <- dat %>%
    mutate(
      std_gpa = scale(prior_gpa),
      std_posts = scale(forum_posts),
      std_attempt = scale(quiz_attempts)
    )

  glmer(
    completed_course ~ std_gpa + std_posts + std_attempt + (1 | device_type),
    data = dat,
    family = binomial(link = "logit")
  )
}

time2 <- system.time({
  # Fit all 6 models in one line using map
  models <- map(data_list, fit_country)

  # Extract std_posts coefficient and SE
  coef_df <- map_df(
    names(models),
    ~ tibble(
        country = .x,
        std_posts_coef = fixef(models[[.x]])["std_posts"],
        std_posts_se   = sqrt(diag(vcov(models[[.x]])))["std_posts"]
    )
  )
  coef_df
})

# time of faster version
print("Time of faster version: ")
```

```
[1] "Time of faster version: "
```

```
time2
```

```
   user  system elapsed
148.172  13.641 162.565
```

Problem #4: **data.table**

Repeat problem set 4, question 2, using data.table.

You can make the same or different decision as you did last time. You can also use or ignore the decisions I made in the solutions. As before, there is no “correct” answer (including those in the problem set 4 solutions).

Use the tidyverse for this problem. In particular, use piping and dplyr as much as you are able. Note: Use of any deprecated functions will result in a point loss.

Use the “ATP Matches” data from 2019 available at https://raw.githubusercontent.com/JeffSackmann/tennis_atp/refs/heads/master/atp_matches_2019.csv. This data tracks all Tennis matches. This data does not have documentation, so you’ll have to explore the data yourself to figure out it’s structure. Use it to answer the following questions. Your answers should show both the output from R that allows you to answer it, as well as a written answer.

```r
tennis_matches <- read.csv("atp_matches_2019.csv")
library(skimr)
skim(tennis_matches)
```

Data summary

Name	tennis_matches
Number of rows	2806
Number of columns	49
_______________________	
Column type frequency:	
character	14
numeric	35
________________________	
Group variables	None

Variable type: character

skim_variable	n_missing	complete_rate	min	max	empty	n_unique	whitespace
tourney_id	0	1	8	34	0	128	0
tourney_name	0	1	4	31	0	128	0
surface	0	1	4	5	0	3	0
tourney_level	0	1	1	1	0	5	0
winner_entry	0	1	0	3	2373	7	0
winner_name	0	1	5	27	0	242	0
winner_hand	0	1	1	1	0	3	0
winner_ioc	0	1	3	3	0	69	0
loser_entry	0	1	0	3	2152	7	0
loser_name	0	1	5	31	0	345	0
loser_hand	0	1	0	1	1	4	0
loser_ioc	0	1	3	3	0	74	0
score	0	1	3	30	0	1153	0
round	0	1	1	4	0	8	0

Variable type: numeric

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50
draw_size	0	1.00	59.74	42.06	4.0	32.00	32.0
tourney_date	0	1.00	20190305.49	1630.01	20181231.0	20190304.00	20190610.0

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50
match_num	0	1.00	288.28	217.74	1.0	247.00	279.0
winner_id	0	1.00	114844.34	23183.37	100644.0	104926.00	105732.0
winner_seed	1680	0.40	7.82	7.13	1.0	3.00	6.0
winner_ht	5	1.00	187.52	7.39	170.0	183.00	188.0
winner_age	1	1.00	27.60	4.92	16.3	23.30	27.9
loser_id	0	1.00	115522.87	24151.38	100644.0	105138.00	105815.0
loser_seed	2096	0.25	8.66	7.39	1.0	4.00	6.0
loser_ht	23	0.99	186.96	7.11	170.0	183.00	188.0
loser_age	0	1.00	27.47	4.72	15.2	23.42	27.6
best_of	0	1.00	3.36	0.77	3.0	3.00	3.0
minutes	116	0.96	110.78	40.86	18.0	80.00	104.0
w_ace	112	0.96	7.50	6.07	0.0	3.00	6.0
w_df	112	0.96	2.76	2.43	0.0	1.00	2.0
w_svpt	112	0.96	79.27	29.43	8.0	58.00	74.0
w_1stIn	112	0.96	49.77	19.01	2.0	36.00	46.0
w_1stWon	112	0.96	37.99	13.78	2.0	28.00	35.0
w_2ndWon	112	0.96	16.37	6.85	1.0	12.00	15.0
w_SvGms	112	0.96	12.80	4.24	1.0	10.00	12.0
w_bpSaved	112	0.96	3.33	3.04	0.0	1.00	3.0
w_bpFaced	112	0.96	4.81	3.95	0.0	2.00	4.0
l_ace	112	0.96	5.79	5.63	0.0	2.00	4.0
l_df	112	0.96	3.27	2.47	0.0	2.00	3.0
l_svpt	112	0.96	82.45	28.95	11.0	61.00	77.0
l_1stIn	112	0.96	50.65	19.29	3.0	37.00	47.0
l_1stWon	112	0.96	34.26	14.57	1.0	24.00	32.0
l_2ndWon	112	0.96	14.88	6.88	0.0	10.00	14.0
l_SvGms	112	0.96	12.57	4.22	1.0	9.00	12.0
l_bpSaved	112	0.96	4.77	3.30	0.0	2.00	4.0
l_bpFaced	112	0.96	8.43	4.16	0.0	5.00	8.0
winner_rank	8	1.00	63.88	81.71	1.0	19.00	47.0
winner_rank_points	8	1.00	1754.97	2065.67	6.0	698.50	1011.0
loser_rank	41	0.99	85.83	103.00	1.0	34.00	62.0
loser_rank_points	41	0.99	1131.61	1179.62	2.0	573.00	860.0

```
library(data.table)
```

```
Attaching package: 'data.table'

The following object is masked from 'package:purrr':

    transpose

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

    between, first, last
```

```
# Convert to data.table
setDT(tennis_matches)
```

a. How many tournaments took place in 2019?

```
# Convert date and extract year
tennis_matches[, tourney_date := as.character(tourney_date)]
tennis_matches[, year := as.numeric(substr(tourney_date, 1, 4))]

table(tennis_matches[,year])
```

```
2018 2019 
  85 2721 
```

```
# there are a lot of davis cups, combine them into one
tourney_2019_davis <- tennis_matches[year == 2019 & grepl("Davis", tourney_name, ignore.c
davis_tourneys <- uniqueN(tourney_2019_davis$tourney_id)  # n_distinct equivalent

# now tournaments took place in 2019
tourn_2019 <- tennis_matches[year == 2019]
tot_tourneys <- uniqueN(tourn_2019$tourney_id)

# remove all but one davis tourney ID
total_2019 <- tot_tourneys - davis_tourneys + 1

print(total_2019)
```

```
[1] 66
```

Based on my R code, there were 66 tourneys in 2019.

b. Did any player win more than one tournament? If so, how many players won more than one tournament, and how many tournaments did the most winning player(s) win?

```
# pull final round
finals <- tennis_matches[round == "F"]

# Count number of tournaments won per player
winner_counts <- finals[, .(tournaments_won = uniqueN(tourney_id)), by = winner_name]

# number of players that won 1< tournaments
multi_winners <- nrow(winner_counts[tournaments_won > 1])

# most winning player
top_winners <- winner_counts[tournaments_won == max(winner_counts$tournaments_won)]
```

Assuming that every tourney has only one winner which is the winner of round "F" for final, and all tourneys have a distinct ID, there were 41 winners of tournaments, there were 12 winners with more than 1 win, and Dominic Thiem and Novak Djokovic won the most with 5.

c. Is there any evidence that winners have more aces than losers? (If you address this with a hypothesis test, do not use base R functionality - continue to remain in the Tidyverse.)

```
# pull win aces
win_aces <- tennis_matches[, .(total_aces = sum(w_ace, na.rm = TRUE)),
                           by = winner_name]
win_aces[, role := "Winner"]
lose_aces <- tennis_matches[, .(total_aces = sum(l_ace, na.rm = TRUE)),
                           by = loser_name]
lose_aces[, role := "Loser"]

# Rename player columns to match
setnames(win_aces, "winner_name", "player")
setnames(lose_aces, "loser_name", "player")


# Combine winners and losers
aces_combined <- rbindlist(list(win_aces, lose_aces))

aces_combined
```

```
                player total_aces   role
                <char>      <int> <char>
  1:      Kei Nishikori        102 Winner
  2:     Daniil Medvedev       511 Winner
  3: Jo-Wilfried Tsonga        373 Winner
  4:      Jeremy Chardy        252 Winner
  5:     Alex De Minaur        179 Winner
 ---
583:      Zsombor Piros          4  Loser
584:         Peter Nagy          0  Loser
585:       Gabor Borsos          3  Loser
```

```
586:      David Szintai          7  Loser
587:          Yibing Wu          5  Loser
```

```
# hypothesis test
t.test(total_aces ~ role, data = aces_combined)
```

```

	Welch Two Sample t-test

data:  total_aces by role
t = -4.5303, df = 352.82, p-value = 8.07e-06
alternative hypothesis: true difference in means between group Loser and group Winner is
not equal to 0
95 percent confidence interval:
 -54.82773 -21.63412
sample estimates:
 mean in group Loser mean in group Winner
            45.23188             83.46281
```

The mean number of aces for winners was higher than for losers. The two-sample t-test gives a p-value of p = 8.07e-6, suggesting that there is significant evidence that winners serve more aces than losers.

d. Identify the player(s) with the highest win-rate. (Note that this is NOT asking for the highest number of wins.) Restrict to players with at least 5 matches.

```
# find total wins for each person
total_wins <- tennis_matches[, .(wins = .N), by = winner_name]

# total losses
total_losses <- tennis_matches[, .(losses = .N), by = loser_name]


# Aggregate wins losses to find matches per player
setnames(total_wins, "winner_name", "player")
setnames(total_losses, "loser_name", "player")
player_stats <- merge(total_wins, total_losses, by = "player", all = TRUE)
player_stats[, matches_played := wins + losses]

# now find rate
player_stats[, win_rate := wins / matches_played]

# Restrict to players with at least 5 matches
player_stats_5 <- player_stats[matches_played >= 5]

# find players with highest win rates
top_players <- player_stats_5[win_rate == max(win_rate)]

top_players
```

```
Key: <player>
         player  wins losses matches_played  win_rate
         <char> <int>  <int>          <int>     <num>
1: Rafael Nadal    60      9             69 0.8695652
```