Simulation with Python Experiment Data

2024-10-20

1. Preparing the data

```
library(banditsCI)

# Read in data generated in python notebook
gammahat <- as.matrix(read.csv('scores.csv', header = FALSE))
probs_array <- as.matrix(read.csv('probs.csv', header = FALSE))

# Define the policies we want to evaluate
policy1_main <- list(
  # includes all matrices in policy1 and policy0
  matrix(
    c(rep(1, nrow(gammahat)), rep(0, nrow(gammahat)), rep(0, nrow(gammahat))),
    nrow = nrow(gammahat)),
  matrix(
    c(rep(0, nrow(gammahat)), rep(1, nrow(gammahat)), rep(0, nrow(gammahat))),
    nrow = nrow(gammahat)),
  matrix(
    c(rep(0, nrow(gammahat)*(ncol(gammahat)-1)), rep(1, nrow(gammahat))),
    nrow = nrow(gammahat)))
```

2. Estimation

2.1 Main Effects

```
output_estimates <- output_estimates(policy1 = policy1_main,
                                     gammahat = gammahat,
                                     probs_array = probs_array,
                                     floor_decay = 0.7)
```

2.2 Treatment effects in contrast to control

$\delta(w_1, w_2) = E[Y_t(w_1) - Y_t(w_2)]$.

In Hadad et al. (2021) there are two approaches. The first approach: use the difference in AIPW scores as the unbiased scoring rule for $\delta(w_1, w_2)$.

The following function implements the first approach by subtracting policy0, the control arm, from all the arms in policy1, except for the control arm itself.

```
out_full_te1.1 <- output_estimates(
  policy0 = policy1_main[[1]],
  policy1 = list(policy1_main[[3]]),
  contrasts = "combined",
```

```r
  gammahat = gammahat,
  probs_array = probs_array,
  floor_decay = 0.7)

out_full_te1.2 <- output_estimates(
  policy0 = policy1_main[[2]],
  policy1 = list(policy1_main[[3]]),
  contrasts = "combined",
  gammahat = gammahat,
  probs_array = probs_array,
  floor_decay = 0.7)
```

The second approach takes asymptotically normal inference about $\delta(w_1, w_2) : \delta^h at(w_1, w_2) = Q^h at(w_1) - Q^h at(w_2)$

```r
out_full_te2.1 <- output_estimates(
  policy0 = policy1_main[[1]],
  policy1 = list(policy1_main[[3]]),
  contrasts = "separate",
  gammahat = gammahat,
  probs_array = probs_array,
  floor_decay = 0.7)

out_full_te2.2 <- output_estimates(
  policy0 = policy1_main[[2]],
  policy1 = list(policy1_main[[3]]),
  contrasts = "separate",
  gammahat = gammahat,
  probs_array = probs_array,
  floor_decay = 0.7)
```

3. Compare the results

```r
# Compare the two approaches for uniform and non_contextual_two_point
comparison_df <- data.frame(method = character(),
                            estimate = numeric(),
                            std_error = numeric(),
                            contrasts = character(),
                            policy = integer(),
                            stringsAsFactors = FALSE)

# Function to process and append data
process_data <- function(data, policy_num, contrasts) {
  for (method in c("uniform", "non_contextual_twopoint")) {
    if (method %in% rownames(data)) {
      row <- data.frame(
        method = method,
        estimate = data[method, "estimate"],
        std_error = data[method, "std.error"],
        contrasts = contrasts,
        policy = policy_num,
        stringsAsFactors = FALSE
      )
```

```r
      comparison_df <<- rbind(comparison_df, row)
    }
  }
}

# Process and append data for each subset and condition
process_data(output_estimates[[1]], "0", "main effect")
process_data(output_estimates[[2]], "1", "main effect")
process_data(output_estimates[[3]], "2", "main effect")
process_data(out_full_te1.1[[1]], "(0,1)", "combined")
process_data(out_full_te1.2[[1]], "(0,2)", "combined")
process_data(out_full_te2.1[[1]], "(0,1)", "separate")
process_data(out_full_te2.2[[1]], "(0,2)", "separate")


# print the comparison data frame as a table
knitr::kable(comparison_df)
```

method	estimate	std_error	contrasts	policy
uniform	0.7198237	0.2557261	main effect	0
non_contextual_twopoint	0.8267759	0.1125030	main effect	0
uniform	0.7106815	0.2011189	main effect	1
non_contextual_twopoint	0.9138038	0.0580545	main effect	1
uniform	1.1055150	0.0106840	main effect	2
non_contextual_twopoint	1.1012259	0.0104059	main effect	2
uniform	0.3856913	0.2559502	combined	(0,1)
non_contextual_twopoint	0.3891761	0.2723742	combined	(0,1)
uniform	0.3948335	0.2014011	combined	(0,2)
non_contextual_twopoint	0.4351515	0.2386683	combined	(0,2)
uniform	0.3856913	0.2559491	separate	(0,1)
non_contextual_twopoint	0.2744500	0.1129833	separate	(0,1)
uniform	0.3948335	0.2014024	separate	(0,2)
non_contextual_twopoint	0.1874221	0.0589797	separate	(0,2)