Simulation_with_Python_experiment_data

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Preparing the data

```
library(banditsCI)
setwd(dirname(rstudioapi::getSourceEditorContext()$path))
gammahat <- as.matrix(read.csv('scores.csv', header = FALSE))
probs_array <- as.matrix(read.csv('probs.csv', header = FALSE))

set.seed(123)

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)), rep(1, nrow(gammahat)-1)), rep(1, nrow(gammahat))),
    nrow = nrow(gammahat)))</pre>
```

Running the simulation

```
# main effects
output estimates <- output estimates(policy1 = policy1 main,
                 gammahat = gammahat,
                 probs_array = probs_array,
                 floor_decay = 0.7)
# Get estimates for treatment effects of policies as contrast to control
\# \det(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(</pre>
  policy0 = policy1_main[[1]],
  policy1 = list(policy1_main[[3]]),
  contrasts = "combined",
 gammahat = gammahat,
 probs_array = probs_array,
```

```
floor_decay = 0.7)
out_full_te1.2 <- output_estimates(</pre>
  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 \hat hat (w_1, w_2) = Q \hat hat (w_1) - Q \hat hat (w_2)
out_full_te2.1 <- output_estimates(</pre>
  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(</pre>
  policy0 = policy1_main[[2]],
  policy1 = list(policy1_main[[3]]),
  contrasts = "separate",
  gammahat = gammahat,
  probs_array = probs_array,
 floor_decay = 0.7)
```

Function to compare the results

```
# Compare the two approaches for uniform and non_contextual_two_point
compare_methods <- function(output_estimates,</pre>
                             out full te1.1,
                             out_full_te1.2,
                             out_full_te2.1,
                             out_full_te2.2) {
  # Initialize an empty data frame to hold the comparison data
  comparison_df <- data.frame(method = character(),</pre>
                               estimate = numeric(),
                               std_error = numeric(),
                               contrasts = character(),
                               policy = integer(),
                               from = character(),
                               stringsAsFactors = FALSE)
  # Function to process and append data
  process_data <- function(data, policy_num, contrasts, from) {</pre>
    for (method in c("uniform", "non_contextual_twopoint")) {
      if (method %in% rownames(data)) {
        row <- data.frame(
          method = method,
          estimate = data[method, "estimate"],
```

Comparing the results

	method	estimate	std_error	contrasts	policy	from
2	non_contextual_twopoint	0.8267759	0.1125030	main effect	0	output_estimates[[1]]
4	$non_contextual_twopoint$	0.9138038	0.0580545	main effect	1	$output_estimates[[2]]$
6	$non_contextual_twopoint$	1.1012259	0.0104059	main effect	2	$output_estimates[[3]]$
8	$non_contextual_twopoint$	0.3891761	0.2723742	combined	(0,1)	$\operatorname{out_full_te1.1}[[1]]$
10	$non_contextual_twopoint$	0.4351515	0.2386683	combined	(0,2)	$\operatorname{out_full_te1.2}[[1]]$
12	$non_contextual_twopoint$	0.2744500	0.1129833	separate	(0,1)	$\operatorname{out_full_te2.1}[[1]]$
14	$non_contextual_twopoint$	0.1874221	0.0589797	separate	(0,2)	$\operatorname{out_full_te2.2}[[1]]$
1	uniform	0.7198237	0.2557261	main effect	0	$output_estimates[[1]]$
3	uniform	0.7106815	0.2011189	main effect	1	$output_estimates[[2]]$
5	uniform	1.1055150	0.0106840	main effect	2	$output_estimates[[3]]$
7	uniform	0.3856913	0.2559502	combined	(0,1)	$\operatorname{out_full_te1.1}[[1]]$
9	uniform	0.3948335	0.2014011	combined	(0,2)	$\operatorname{out_full_te1.2}[[1]]$
11	uniform	0.3856913	0.2559491	separate	(0,1)	$\operatorname{out_full_te2.1}[[1]]$
13	uniform	0.3948335	0.2014024	separate	(0,2)	$out_full_te2.2[[1]]$