CODE for paper "Dynamic conditional quantile treatment effects evaluation with applications to ridesharing"

This folder contains the code for the simulation studies and real data analysis. The folder "real data temporal code" contains code for the temporal data analysis in section 6, "real data spatiotemporal code" contains code for the spatiotemporal data analysis in section 6. The folder "simulation code" contains code for the simulation studies in Section 7.

1 Code for generating table and figures in Section 6

1.1 Temporal data analysis

- The folder "real data temporal code" contains the estimation code and plot code for the temporal data analysis
- Demo_data.csv: the columns correspond to the i-th day, the t-th time interval, the reward $y_{i,t}$, and the two state variables $S_{1,i,t}, S_{2,i,t}$, the treatment $A_{i,t}$.

date	time	y	S1	S2	A
0	0	-0.427338143	0.373650112	-0.42395057	0
0	1	0.60151949	-0.081270133	-0.092235335	1
0	2	0.118222279	0.033649472	-0.27381817	1
0	3	1.181598657	0.131022353	0.723841073	0
0	4	0.164371915	0.447087103	0.443484031	1
0	5	0.529181754	0.100320653	-0.142520552	0
0	6	1.902987239	1.188521412	0.045743955	1
0	7	0.828756835	0.537623416	0.535206058	1
0	8	2.380526064	1.409321766	0.248349533	0
0	9	1.876077224	1.338307049	0.295507529	1
0	10	2.132645869	0.912941976	-0.504833826	1

- settings_multiple_S_simu.py: the estimation and testing function for the conditional quantile treatment effect.
- Quantile_RealData.py: estimate the conditional quantile treatment effects given data
  - ♦ Input: the temporal dataset formulized similar to the Demo_data.csv.
  - ♦ For $\tau \in \{0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9\}$, estimate the quantile treatment effect.
  - ♦ Output: for each τ, testing results for DE and IE ("Testing_τ.csv"); Fitted values and residuals for the outcome ("y_tau_τ.csv"); Fitted values and residuals for the state variables ("S_tau_τ.csv"); Estimation results for the state variables model ("Est_tau_τ.csv").
- linear_multiple_S.py: the estimation and testing function for the average

treatment effect.

- Linear_RealData.py: estimate the average treatment effects given data.
  - ♦ Input: the temporal dataset formulized similar to the Demo_data.csv.
  - ♦ Output: Testing results for DE and IE ("Testing_linear.csv"); Fitted values and residuals for the outcome ("y_tau_linear.csv"); Fitted values and residuals for the state variables ("S_tau_linear.csv"); Estimation results for the state variables model ("Est_tau_linear.csv").
- Table 1: results summarize from "Testing_linear.csv" for the average effect, and "Testing_τ.csv" for each τ for the AA dataset and the AB dataset.
- Figures 3-4: Figures3_4.R based on the obtained "y_tau_τ.csv" and "Testing_τ.csv" files, the first part is generating Figure 3, and the second part is for Figure 4.

1.2 Spatiotemporal code data analysis

- The folder "real data temporal code" contains the estimation code and plot code for the temporal data analysis
- Spatial_S_without_barA.py: the estimation and testing function for spatiotemporal conditional quantile treatment effect.
- RealData_Analysis_QTE.py: estimate quantile treatment effects given data:
  - ♦ Input: the spatiotemporal dataset formulized similar to the Demo_data.csv, one with additional column "region" indicating the region information
  - ♦ For $\tau \in \{0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9\}$, estimate the quantile treatment effect.
  - ♦ Output: for each τ, estimation and testing results for DE and IE ("Est_testing_τ.csv"); Fitted values and residuals for the outcome ("y_tau_τ.csv"); Fitted values and residuals for the state variables ("S1_tau_τ.csv").
- Spatial_linear_without_barA.py: the estimation and testing function for spatiotemporal average treatment effect.
- RealData_Linear.py: estimate the average treatment effects given data
  - ♦ Input: the spatiotemporal dataset formulized similar to the Demo_data.csv, with one additional column "region" indicating the region information.
  - ♦ Output: Estimation and testing results for DE and IE ("Est_testing_linear.csv"); Fitted values and residuals for the outcome ("y_tau_linear.csv"); Fitted values and residuals for the state variables ("S_tau_linear.csv"); Estimation results for the state variables model ("Est_tau_linear.csv").
- Table 2: results summarize from "Est_testing_linear.csv" for the average effect, and "Est_testing_τ.csv" for each τ.
- Figures 5: Figure5.R based on the obtained "Est_testing_τ.csv".

2 Code for generating figures in Section 7

2.1 Generate simulation results for quantile treatment effects

- settings_multiple_S_simu.py: the main estimation and testing function
- simu_demo_data.csv: an data example to generate the simulation data, which is generated by the generate_temporalData function in settings_multiple_S_simu.py by simu_data= generate_temporalData(40, 24, 1, 1, 0.5, 1, 0,0)

date	time	y	S1	S2
0	0	-0.427338143	0.373650112	-0.42395057
0	1	0.60151949	-0.081270133	-0.092235335
0	2	0.118222279	0.033649472	-0.27381817
0	3	1.181598657	0.131022353	0.723841073
0	4	0.164371915	0.447087103	0.443484031
0	5	0.529181754	0.100320653	-0.142520552
0	6	1.902987239	1.188521412	0.045743955
0	7	0.828756835	0.537623416	0.535206058
0	8	2.380526064	1.409321766	0.248349533
0	9	1.876077224	1.338307049	0.295507529
0	10	2.132645869	0.912941976	-0.504833826

This dataset contains the reward function, two state variables: $\{y_{i,t}, S_{1,i,t}, S_{2,i,t}, i = 0, \ldots, 23, t = 0, \ldots, 23\}$. The first column "data" indicated the i-th day, the second column "time" is the t-th time interval, the third column if the reward $y_{i,t}$, and the last two columns correspond to the two state variables $S_{1,i,t}, S_{2,i,t}$.

- settings_multiple.py: a simulation demo for the setting $(NN = 40, TI = 1, \tau = 0.5, \delta = 0)$ including generating data, estimation of QDE, QIE and the corresponding testing results. The generated data are based on the above simu_demo_data.csv
- Output of "settings_multiple.py": estimation and testing results for each setting
- All settings: the combinations of $NN \in \{20,40\}, TI \in \{1,3\}, \tau \in \{0.2, 0.5, 0.8\}, \delta \in \{0, 0.01, 0.025, 0.05, 0.075, 0.1\}$.

2.2 Generate simulation results for competing methods

- noInterference_compare.py.py: the main estimation and testing function for the "NoInterference" method
- settings_noInterference_compare: a simulation demo for the setting $(NN = 40, TI = 1, \tau = 0.5, \delta = 0)$ for the "NoInterference" method
- Output of "settings_compare.py": estimation and testing results for each setting

- Linear_multiple_S.py: the main estimation and testing function for the "ATE" method
- settings_linear.py: a simulation demo for the setting $(NN = 40, TI = 1, \tau = 0.5, \delta = 0)$ for the "ATE" method
- Output of "settings_linear.py": estimation and testing results for each setting
- All settings: the combinations of $NN \in \{20,40\}, TI \in \{1,3\}, \tau \in \{0.2, 0.5, 0.8\}, \delta \in \{0, 0.01, 0.025, 0.05, 0.075, 0.1\}$.

2.3 Generate the table and figures for simulation studies

- ResidMultiple_NN_40_TI_1: this folder contains a simulation output sample for the setting $(NN = 40, TI = 1, \tau = 0.5, \delta = 0)$, delta_IE_0_deltaIE_0_tau_0.5_h_0.csv. We use the variables 'QTE_indicator_RightSide', 'QDE_indicator_RightSide', 'QIE_indicator_RightSide' to calculate the empirical rejection rates of quantile treatment effect, the direct quantile treatment effect and the indirect quantile treatment effect.
- Figures 6-7: Figures6_7.R based on the results of all the methods under all the settings, the results has been summarize to the following form

NN	TI	method	tau	X0.0	X0.01	X0.025	X0.05	X0.075	X0.1
20	1	Quantile	0.8	0.042	0.14	0.484	0.704	0.702	0.566
20	1	Linear	0.8	0.042	0.06	0.196	0.258	0.176	0.118
20	1	adhoc	0.8	0.046	0.056	0.044	0.044	0.066	0.07
20	3	Quantile	0.8	0.042	0.12	0.382	0.678	0.67	0.58
20	3	Linear	0.8	0.03	0.07	0.152	0.196	0.178	0.114
20	3	adhoc	0.8	0.064	0.07	0.06	0.054	0.074	0.058
40	1	Quantile	0.8	0.024	0.31	0.816	0.96	0.954	0.914
40	1	Linear	0.8	0.044	0.136	0.364	0.424	0.31	0.152
40	1	adhoc	0.8	0.052	0.064	0.056	0.062	0.08	0.082
40	3	Quantile	0.8	0.05	0.268	0.728	0.966	0.952	0.936
40	3	Linear	0.8	0.036	0.124	0.294	0.402	0.28	0.162
40	3	adhoc	0.8	0.062	0.054	0.062	0.06	0.068	0.074