Assignment 8: Dynamic Game

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Simulate data

Suppose that there are $m = 1, \cdots, M$ markets and in each market there are $i = 1, \cdots, N$ firms and each firm makes decisions for $t = 1, \cdots, \infty$. In the following, I suppress the index of market, m. We solve the model under the infinite-horizon assumption, but generate data only for $t = 1, \cdots, T$. There are $L = 3$ state $\{1, 2, 3\}$ states for each firm. Each firm can choose $K + 1 = 2$ actions $\{0, 1\}$. Thus, $m_a := (K + 1)^N$ and $m_s = L^N$. Let a_i and s_i be firm i's action and state and a and s are vectors of individual actions and states.

The mean period payoff to firm i is:

$$\pi_i(a, s) := \tilde{\pi}(a_i, s_i, \overline{s}) := \alpha \ln s_i - \eta \ln s_i \sum_{j \neq i} \ln s_j - \beta a_i,$$

where $\alpha, \beta, \eta > 0$, and $\alpha > \eta$. The term η means that the returns to investment decreases as rival's average state profile improves. The period payoff is:

$$\tilde{\pi}(a_i, s_i, \overline{s}) + \epsilon_i(a_i),$$

and $\epsilon_i(a_i)$ is an i.i.d. type-I extreme random variable that is independent of all the other variables.

At the beginning of each period, the state s is realized and publicly observed. Then choice-specific shocks $\epsilon_i(a_i), a_i = 0, 1$ are realized and privately observed by firm $i = 1, \cdots, N$. Then each firm simultaneously chooses her action. Then, the game moves to next period.

State transition is independent across firms conditional on individual state and action.

Suppose that $s_i > 1$ and $s_i < L$. If $a_i = 0$, the state stays at the same state with probability $1 - \kappa$ and moves down by 1 with probability κ. If $a = 1$, the state moves up by 1 with probability γ, moves down by 1 with probability κ, and stays at the same with probability $1 - \kappa - \gamma$.

Suppose that $s_i = 1$. If $a_i = 0$, the state stays at the same state with probability 1. If $a_i = 1$, the state moves up by 1 with probability γ and stays at the same with probability $1 - \gamma$.

Suppose that $s_i = L$. If $a_i = 0$, the state stays at the same state with probability $1 - \kappa$ and moves down by 1 with probability κ. If $a = 1$, the state moves down by 1 with probability κ, and stays at the same with probability $1 - \kappa$.

The mean period profit is summarized in Π as:

$$\Pi := \begin{pmatrix} \pi(1,1) \\ \vdots \\ \pi(m_a, 1) \\ \vdots \\ \pi(1, m_s) \\ \vdots \\ \pi(m_a, m_s) \end{pmatrix}$$

The transition law is summarized in G as:

$$g(a, s, s') := \mathbb{P}\{s_{t+1} = s' | s_t = s, a_t = a\},$$

$$G := \begin{pmatrix} g(1,1,1) & \cdots & g(1,1,m_s) \\ \vdots & & \vdots \\ g(m_a,1,1) & \cdots & g(m_a,1,m_s) \\ & \vdots & \\ g(1,m_s,1) & \cdots & g(1,m_s,m_s) \\ \vdots & & \vdots \\ g(m_a,m_s,1) & \cdots & g(m_a,m_s,m_s) \end{pmatrix}.$$

The discount factor is denoted by δ. We simulate data for M markets with N firms for T periods.

1. Set constants and parameters as follows:

```
# set seed
set.seed(1)
# set constants
L <- 5
K <- 1
T <- 100
N <- 3
M <- 1000
lambda <- 1e-10
# set parameters
alpha <- 1
eta <- 0.3
beta <- 2
kappa <- 0.1
gamma <- 0.6
delta <- 0.95
```

2. Write a function `compute_action_state_space(K, L, N)` that returns a data frame for action and state space. Returned objects are list of data frame `A` and `S`. In `A`, column `k` is the index of an action profile, `i` is the index of a firm, and `a` is the action of the firm. In `S`, column `l` is the index of an state profile, `i` is the index of a firm, and `s` is the state of the firm.

```
output <- compute_action_state_space(L, K, N)
A <- output$A
head(A)
```

```
## # A tibble: 6 x 3
##       k     i     a
##   <int> <int> <int>
## 1     1     1     0
## 2     1     2     0
## 3     1     3     0
## 4     2     1     1
## 5     2     2     0
## 6     2     3     0
```

```r
tail(A)
```

```
## # A tibble: 6 x 3
##       k     i     a
##   <int> <int> <int>
## 1     7     1     0
## 2     7     2     1
## 3     7     3     1
## 4     8     1     1
## 5     8     2     1
## 6     8     3     1
```

```r
S <- output$S
head(S)
```

```
## # A tibble: 6 x 3
##       l     i     s
##   <int> <int> <int>
## 1     1     1     1
## 2     1     2     1
## 3     1     3     1
## 4     2     1     2
## 5     2     2     1
## 6     2     3     1
```

```r
tail(S)
```

```
## # A tibble: 6 x 3
##       l     i     s
##   <int> <int> <int>
## 1   124     1     4
## 2   124     2     5
## 3   124     3     5
## 4   125     1     5
## 5   125     2     5
## 6   125     3     5
```

```r
# dimension
m_a <- max(A$k); m_a
```

```
## [1] 8
```

```r
m_s <- max(S$l); m_s
```

```
## [1] 125
```

3. Write function `compute_PI_game(alpha, beta, eta, L, K, N)` that returns a list of Π_i.

```r
PI <- compute_PI_game(alpha, beta, eta, A, S)
head(PI[[N]])
```

```
##      [,1]
## [1,]    0
## [2,]    0
## [3,]    0
## [4,]    0
## [5,]   -2
## [6,]   -2
```

```r
dim(PI[[N]])[1] == m_s * m_a
```

```
## [1] TRUE
```

4. Write function `compute_G_game(g, A, S)` that converts an individual transition probability matrix into a joint transition probability matrix G.

```r
G_marginal <- compute_G(kappa, gamma, L, K)
G <- compute_G_game(G_marginal, A, S)
head(G)
```

```
##         1    2 3 4 5    6    7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
## [1,] 1.00 0.00 0 0 0 0.00 0.00 0 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
## [2,] 0.40 0.60 0 0 0 0.00 0.00 0 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
## [3,] 0.40 0.00 0 0 0 0.60 0.00 0 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
## [4,] 0.16 0.24 0 0 0 0.24 0.36 0 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
## [5,] 0.40 0.00 0 0 0 0.00 0.00 0 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
## [6,] 0.16 0.24 0 0 0 0.00 0.00 0 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
##      25   26   27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47
## [1,]  0 0.00 0.00  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
## [2,]  0 0.00 0.00  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
## [3,]  0 0.00 0.00  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
## [4,]  0 0.00 0.00  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
## [5,]  0 0.60 0.00  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
## [6,]  0 0.24 0.36  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
##      48 49 50 51 52 53 54 55 56 57 58 59 60 61 62 63 64 65 66 67 68 69 70 71 72
## [1,]  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
## [2,]  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
## [3,]  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
## [4,]  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
## [5,]  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
## [6,]  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
##      73 74 75 76 77 78 79 80 81 82 83 84 85 86 87 88 89 90 91 92 93 94 95 96 97
## [1,]  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
## [2,]  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
## [3,]  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
## [4,]  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
## [5,]  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
## [6,]  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
##      98 99 100 101 102 103 104 105 106 107 108 109 110 111 112 113 114 115 116
```

```
## [1,]  0  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
## [2,]  0  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
## [3,]  0  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
## [4,]  0  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
## [5,]  0  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
## [6,]  0  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
##      117 118 119 120 121 122 123 124 125
## [1,]   0   0   0   0   0   0   0   0   0
## [2,]   0   0   0   0   0   0   0   0   0
## [3,]   0   0   0   0   0   0   0   0   0
## [4,]   0   0   0   0   0   0   0   0   0
## [5,]   0   0   0   0   0   0   0   0   0
## [6,]   0   0   0   0   0   0   0   0   0
```

```
dim(G)[1] == m_s * m_a
```

```
## [1] TRUE
```

```
dim(G)[2] == m_s
```

```
## [1] TRUE
```

The ex-ante-value function for a firm is written as a function of a conditional choice probability as follows:

$$\varphi_i^{(\theta_1,\theta_2)}(p) := [I - \delta\Sigma(p)G]^{-1}[\Sigma(p)\Pi_i + D_i(p)],$$

where $\theta_1 = (\alpha, \beta, \eta)$ and $\theta_2 = (\kappa, \gamma)$, $p_i(a_i|s)$ is the probability that firm i choose action a_i when the state profile is s, and:

$$p(a|s) = \prod_{i=1}^N p_i(a_i|s),$$

$$p(s) = \begin{pmatrix} p(1|s) \\ \vdots \\ p(m_a|s) \end{pmatrix},$$

$$p = \begin{pmatrix} p(1) \\ \vdots \\ p(m_s) \end{pmatrix},$$

$$\Sigma(p) = \begin{pmatrix} p(1)' & & \\ & \ddots & \\ & & p(L)' \end{pmatrix}$$

and:

$$D_i(p) = \begin{pmatrix} \sum_{k=0}^K \mathbb{E}\{\epsilon_i^k|a_i = k, 1\} p_i(a_i = k|1) \\ \vdots \\ \sum_{k=0}^K \mathbb{E}\{\epsilon_i^k|a_i = k, m_s\} p_i(a_i = k|m_s) \end{pmatrix}.$$

5. Write a function `initialize_p_marginal(A, S)` that defines an initial marginal condition choice probability. In the output `p_marginal`, `p` is the probability for firm `i` to take action `a` conditional on the state profile being `l`. Next, write a function `compute_p_joint(p_marginal, A, S)` that computes a corresponding joint conditional choice probability from a marginal conditional choice probability. In the output `p_joint`, `p` is the joint probability that firms take action profile `k` condition on the state profile being `l`. Finally, write a function `compute_p_marginal(p_joint, A, S)` that compute a corresponding marginal conditional choice probability from a joint conditional choice probability.

```
# define a conditional choice probability for each firm
p_marginal <- initialize_p_marginal(A, S)
p_marginal
```

```
## # A tibble: 750 x 4
##        i     l     a     p
##    <int> <int> <int> <dbl>
##  1     1     1     0   0.5
##  2     1     1     1   0.5
##  3     1     2     0   0.5
##  4     1     2     1   0.5
##  5     1     3     0   0.5
##  6     1     3     1   0.5
##  7     1     4     0   0.5
##  8     1     4     1   0.5
##  9     1     5     0   0.5
## 10     1     5     1   0.5
## # ... with 740 more rows
```

```
dim(p_marginal)[1] == N * m_s * (K + 1)
```

```
## [1] TRUE
```

```
# compute joint conitional choice probability from marginal probability
p_joint <- compute_p_joint(p_marginal, A, S)
p_joint
```

```
## # A tibble: 1,000 x 3
##        l     k     p
##    <int> <int> <dbl>
##  1     1     1 0.125
##  2     1     2 0.125
##  3     1     3 0.125
##  4     1     4 0.125
##  5     1     5 0.125
##  6     1     6 0.125
##  7     1     7 0.125
##  8     1     8 0.125
##  9     2     1 0.125
## 10     2     2 0.125
## # ... with 990 more rows
```

```r
dim(p_joint)[1] == m_s * m_a
```

```
## [1] TRUE
```

```r
# compute marginal conditional chocie probability from joint probability
p_marginal_2 <- compute_p_marginal(p_joint, A, S)
max(abs(p_marginal - p_marginal_2))
```

```
## [1] 0
```

6. Write a function `compute_Sigma(p_marginal, A, S)` that computes $\Sigma(p)$ given a joint conditional choice probability. Then, write a function `compute_D(p_marginal)` that returns a list of $D_i(p)$.

```r
# compute Sigma for ex-ante value function calculation
Sigma <- compute_Sigma(p_marginal, A, S)
head(Sigma)
```

```
## [1] 0.125 0.000 0.000 0.000 0.000 0.000
```

```r
dim(Sigma)[1] == m_s
```

```
## [1] TRUE
```

```r
dim(Sigma)[2] == m_s * m_a
```

```
## [1] TRUE
```

```r
# compute D for ex-ante value function calculation
D <- compute_D(p_marginal)
head(D[[N]])
```

```
##          [,1]
## [1,] 1.270363
## [2,] 1.270363
## [3,] 1.270363
## [4,] 1.270363
## [5,] 1.270363
## [6,] 1.270363
```

```r
dim(D[[N]])[1] == m_s
```

```
## [1] TRUE
```

7. Write a function `compute_exante_value_game(p_marginal, A, S, PI, G, delta)` that returns a list of matrices whose i-th element represents the ex-ante value function given a conditional choice probability for firm i.

```r
# compute ex-ante value funciton for each firm
V <- compute_exante_value_game(p_marginal, A, S, PI, G, delta)
head(V[[N]])
```

```
## [1] 10.786330 10.175982  9.606812  9.255459  9.115332 10.175982
```

```r
dim(V[[N]])[1] == m_s
```

```
## [1] TRUE
```

The optimal conditional choice probability is written as a function of an ex-ante value function and a conditional choice probability of others as follows:

$$\Lambda_i^{(\theta_1,\theta_2)}(V_i, p_{-i})(a_i, s) := \frac{\exp\{\sum_{a_{-i}} p_{-i}(a_{-i}|s)[\pi_i(a_i, a_{-i}, s) + \delta \sum_{s'} V_i(s')g(a_i, a_{-i}, s, s')]\}}{\sum_{a_i'} \exp\{\sum_{a_{-i}} p_{-i}(a_{-i}|s)[\pi_i(a_i', a_{-i}, s) + \delta \sum_{s'} V_i(s')g(a_i', a_{-i}, s, s')]\}},$$

where V is an ex-ante value function.

8. Write a function `compute_profile_value_game(V, PI, G, delta, S, A)` that returns a data frame that contains information on value function at a state and action profile for each firm. In the output `value`, `i` is the index of a firm, `l` is the index of a state profile, `k` is the index of an action profile, and `value` is the value for the firm at the state and action profile.

```r
# compute state-action-profile value function
value <- compute_profile_value_game(V, PI, G, delta, S, A)
value
```

```
## # A tibble: 3,000 x 4
##        i     l     k value
##    <int> <int> <int> <dbl>
##  1     1     1     1 10.2
##  2     1     1     2  9.63
##  3     1     1     3  9.90
##  4     1     1     4  9.13
##  5     1     1     5  9.90
##  6     1     1     6  9.13
##  7     1     1     7  9.55
##  8     1     1     8  8.64
##  9     1     2     1 13.0
## 10     1     2     2 12.1
## # ... with 2,990 more rows
```

```r
dim(value)[1] == N * m_s * m_a
```

```
## [1] TRUE
```

9. Write a function `compute_choice_value_game(p_marginal, V, PI, G, delta, A, S)` that computes a data frame that contains information on a choice-specific value function given an ex-ante value function and a conditional choice probability of others.

compute choice-specific value function
```
# compute choice-specific value function
value <- compute_choice_value_game(p_marginal, V, PI, G, delta, A, S)
value
```

```
## # A tibble: 750 x 4
##        i     l     a value
##    <int> <int> <int> <dbl>
##  1     1     1     0  9.90
##  2     1     1     1  9.13
##  3     1     2     0 12.4
##  4     1     2     1 11.4
##  5     1     3     0 14.5
##  6     1     3     1 13.2
##  7     1     4     0 16.0
##  8     1     4     1 14.3
##  9     1     5     0 16.8
## 10     1     5     1 14.8
## # ... with 740 more rows
```

10. Write a function `compute_ccp_game(p_marginal, V, PI, G, delta, A, S)` that computes a data frame that contains information on a conditional choice probability given an ex-ante value function and a conditional choice probability of others.

```
# compute conditional choice probability
p_marginal <- compute_ccp_game(p_marginal, V, PI, G, delta, A, S)
p_marginal
```

```
## # A tibble: 750 x 4
##        i     l     a     p
##    <int> <int> <int> <dbl>
##  1     1     1     0 0.683
##  2     1     1     1 0.317
##  3     1     2     0 0.734
##  4     1     2     1 0.266
##  5     1     3     0 0.794
##  6     1     3     1 0.206
##  7     1     4     0 0.840
##  8     1     4     1 0.160
##  9     1     5     0 0.881
## 10     1     5     1 0.119
## # ... with 740 more rows
```

11. Write a function `solve_dynamic_game(PI, G, L, K, delta, lambda, A, S)` that find the equilibrium conditional choice probability and ex-ante value function by iterating the update of an ex-ante value function and a best-response conditional choice probability. The iteration should stop when $\max_s |V^{(r+1)}(s) - V^{(r)}(s)| < \lambda$ with $\lambda = 10^{-10}$. There is no theoretical guarantee for the convergence.

```
# solve the dynamic game model
output <-
  solve_dynamic_game(PI, G, L, K, delta, lambda, A, S)
save(output, file = "data/A8_equilibrium.RData")
```

```r
load(file = "data/A8_equilibrium.RData")
p_marginal <- output$p_marginal; head(p_marginal)
```

```
## # A tibble: 6 x 4
##       i     l     a     p
##   <int> <int> <int> <dbl>
## 1     1     1     0 0.534
## 2     1     1     1 0.466
## 3     1     2     0 0.545
## 4     1     2     1 0.455
## 5     1     3     0 0.629
## 6     1     3     1 0.371
```

```r
V <- output$V[[N]]; head(V)
```

```
## [1] 18.98883 18.51236 18.08141 17.77417 17.59426 18.51236
```

```r
# compute joint conitional choice probability
p_joint <- compute_p_joint(p_marginal, A, S); head(p_joint)
```

```
## # A tibble: 6 x 3
##       l     k     p
##   <int> <int> <dbl>
## 1     1     1 0.152
## 2     1     2 0.133
## 3     1     3 0.133
## 4     1     4 0.116
## 5     1     5 0.133
## 6     1     6 0.116
```

12. Write a function `simulate_dynamic_game(p_joint, l, G, N, T, S, A, seed)` that simulate the data for a market starting from an initial state for T periods. The function should accept a value of seed and set the seed at the beginning of the procedure inside the function, because the process is stochastic.

```r
# simulate a dynamic game
# set initial state profile
l <- 1
# draw simulation for a firm
seed <- 1
df <- simulate_dynamic_game(p_joint, l, G, N, T, S, A, seed)
df
```

```
## # A tibble: 300 x 6
##        t     i     l     k     s     a
##    <int> <int> <dbl> <dbl> <int> <int>
##  1     1     1     1     5     1     0
##  2     1     2     1     5     1     0
##  3     1     3     1     5     1     1
##  4     2     1    26     2     1     1
##  5     2     2    26     2     1     0
```

```
## 6      2     3    26     2     2     0
## 7      3     1    26     8     1     1
## 8      3     2    26     8     1     1
## 9      3     3    26     8     2     1
## 10     4     1    52     8     2     1
## # ... with 290 more rows
```

13. Write a function `simulate_dynamic_decision_across_firms(p_joint, l, G, N, T, M, S, A, seed)` that returns simulation data for N firm. For firm i, set the seed at i

```r
# simulate data across markets
df <- simulate_dynamic_decision_across_markets(p_joint, l, G, N, T, M, S, A)
save(df, file = "data/A8_df.RData")
```

```r
load(file = "data/A8_df.RData")
df
```

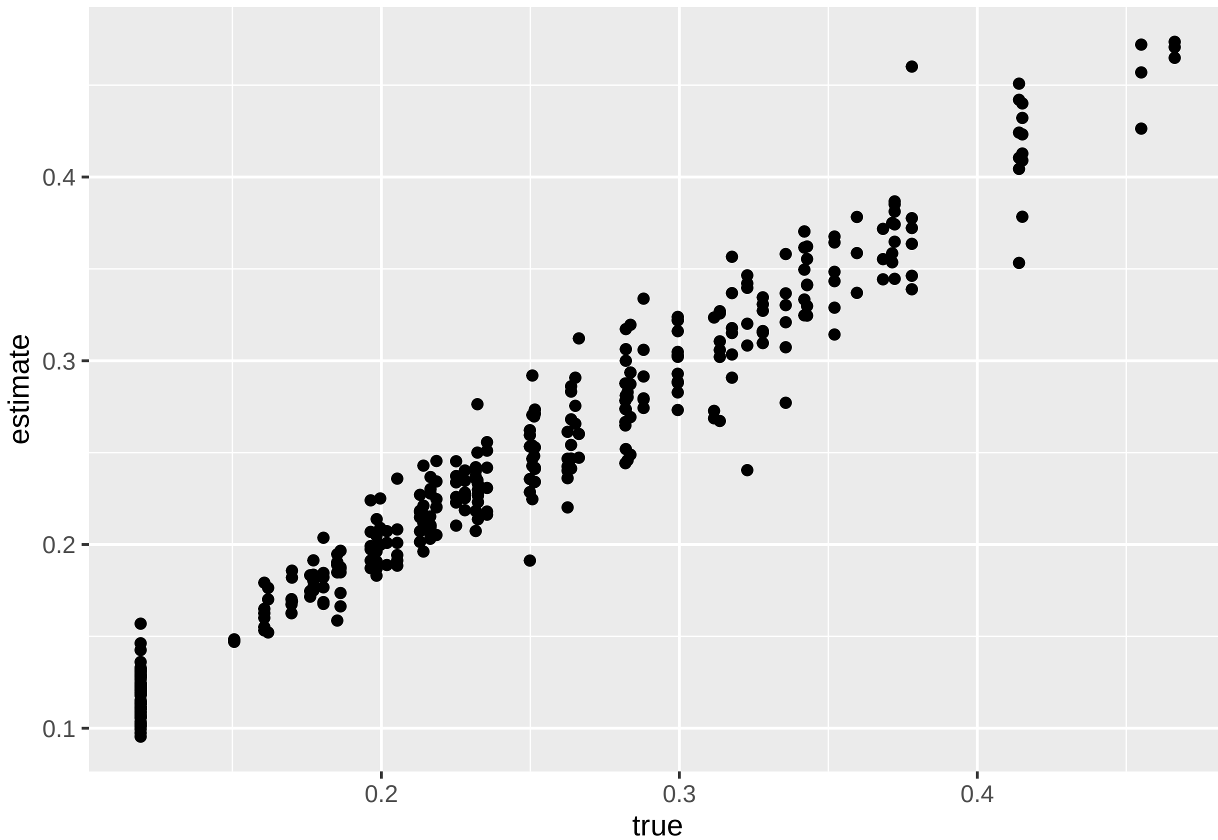
```
## # A tibble: 300,000 x 7
##         m     t     i     l     k     s     a
##     <int> <int> <int> <dbl> <dbl> <int> <int>
##  1      1     1     1     1     5     1     0
##  2      1     1     2     1     5     1     0
##  3      1     1     3     1     5     1     1
##  4      1     2     1    26     2     1     1
##  5      1     2     2    26     2     1     0
##  6      1     2     3    26     2     2     0
##  7      1     3     1    26     8     1     1
##  8      1     3     2    26     8     1     1
##  9      1     3     3    26     8     2     1
## 10      1     4     1    52     8     2     1
## # ... with 299,990 more rows
```

```r
summary(df)
```

```
##        m                t                 i           l                 k        
##  Min.   :   1.0   Min.   :  1.00   Min.   :1   Min.   :  1.00   Min.   :1.000  
##  1st Qu.: 250.8   1st Qu.: 25.75   1st Qu.:1   1st Qu.: 43.00   1st Qu.:1.000  
##  Median : 500.5   Median : 50.50   Median :2   Median : 74.00   Median :2.000  
##  Mean   : 500.5   Mean   : 50.50   Mean   :2   Mean   : 71.02   Mean   :2.497  
##  3rd Qu.: 750.2   3rd Qu.: 75.25   3rd Qu.:3   3rd Qu.:100.00   3rd Qu.:4.000  
##  Max.   :1000.0   Max.   :100.00   Max.   :3   Max.   :125.00   Max.   :8.000  
##        s               a         
##  Min.   :1.000   Min.   :0.0000  
##  1st Qu.:2.000   1st Qu.:0.0000  
##  Median :3.000   Median :0.0000  
##  Mean   :3.273   Mean   :0.2141  
##  3rd Qu.:5.000   3rd Qu.:0.0000  
##  Max.   :5.000   Max.   :1.0000
```

14. Write a function `estimate_ccp_marginal_game(df)` that returns a non-parametric estimate of the marginal conditional choice probability for each firm in the data. Compare the estimated conditional choice probability and the true conditional choice probability by a bar plot.

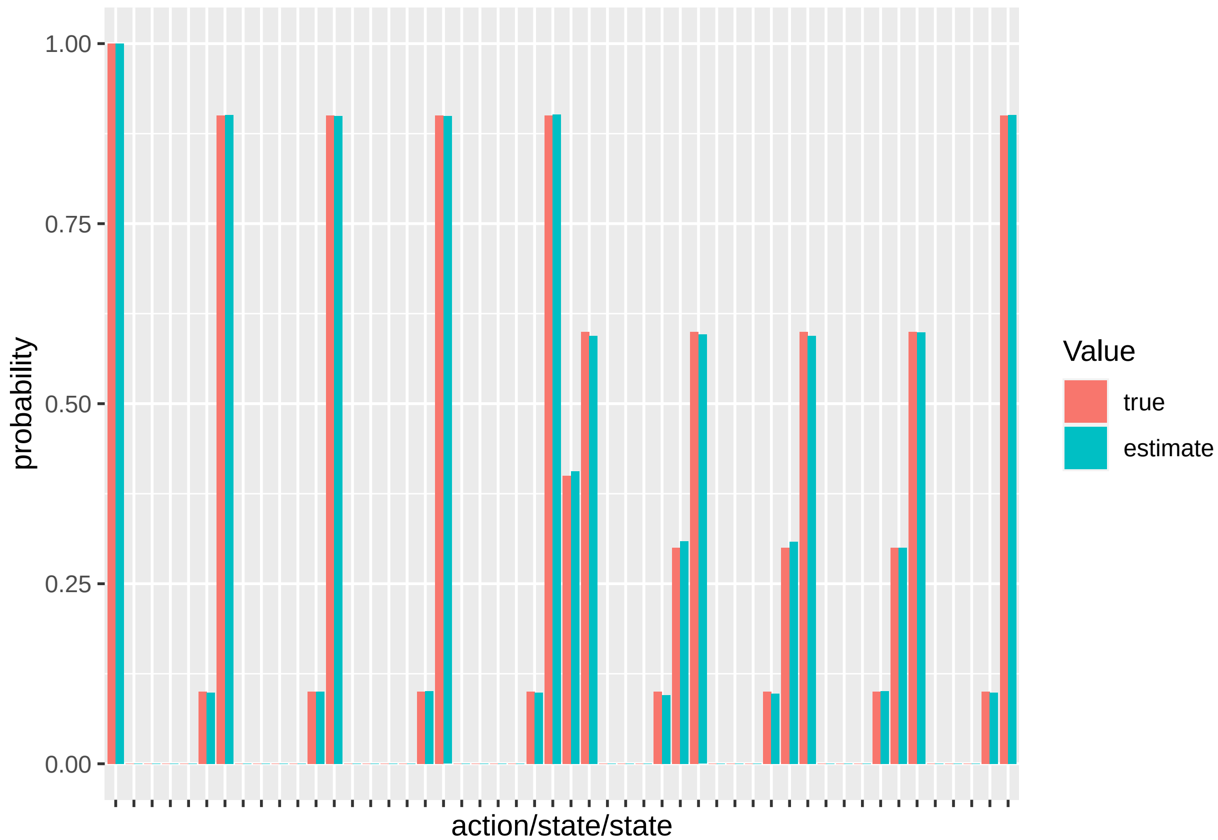
```r
# non-parametrically estimate the conditional choice probability
p_marginal_est <- estimate_ccp_marginal_game(df)
check_ccp <- p_marginal_est %>%
  dplyr::rename(estimate = p) %>%
  dplyr::left_join(p_marginal, by = c("i", "l", "a")) %>%
  dplyr::rename(true = p) %>%
  dplyr::filter(a == 1)
ggplot(data = check_ccp, aes(x = true, y = estimate)) +
  geom_point() +
  labs(fill = "Value") + xlab("true") + ylab("estimate")
```



15. Write a function `estimate_G_marginal(df)` that returns a non-parametric estimate of the marginal transition probability matrix. Compare the estimated transition matrix and the true transition matrix by a bar plot.

```r
# non-parametrically estimate individual transition probability
G_marginal_est <- estimate_G_marginal(df)
check_G <- data.frame(type = "true", reshape2::melt(G_marginal))
check_G_est <- data.frame(type = "estimate", reshape2::melt(G_marginal_est))
check_G <- rbind(check_G, check_G_est)
check_G$variable = paste(check_G$Var1, check_G$Var2, sep = "_")
ggplot(data = check_G, aes(x = variable, y = value,
                           fill = type)) +
    geom_bar(stat = "identity", position = "dodge") +
```

```
labs(fill = "Value") + xlab("action/state/state") + ylab("probability") +
theme(axis.text.x = element_blank())
```



Estimate parameters

1. Vectorize the parameters as follows:

```
theta_1 <- c(alpha, beta, eta)
theta_2 <- c(kappa, gamma)
theta <- c(theta_1, theta_2)
```

We estimate the parameters by a CCP approach.

1. Write a function `estimate_theta_2_game(df)` that returns the estimates of κ and γ directly from data by counting relevant events.

```
# estimate theta_2
theta_2_est <- estimate_theta_2_game(df); theta_2_est
```

```
## [1] 0.09929994 0.59579550
```

The objective function of the minimum distance estimator based on the conditional choice probability approach is:

$$\frac{1}{NKm_s}\sum_{i=1}^{N}\sum_{l=1}^{m_s}\sum_{k=1}^{K}\{\hat{p}_i(a_k|s_l) - p_i^{(\theta_1,\theta_2)}(a_k|s_l)\}^2,$$

where $\hat{p}_i$ is the non-parametric estimate of the marginal conditional choice probability and $p_i^{(\theta_1,\theta_2)}$ is the marginal conditional choice probability under parameters θ_1 and θ_2 given $\hat{p}_i$. a_k is k-th action for a firm and s_l is l-th state profile.

2. Write a function `compute_CCP_objective_game(theta_1, theta_2, p_est, L, K, delta)` that returns the objective function of the above minimum distance estimator given a non-parametric estimate of the conditional choice probability and θ_1 and θ_2.

```
# compute the objective function of the minimum distance estimator based on the CCP approach
objective <- compute_CCP_objective_game(theta_1, theta_2, p_marginal_est, A, S, delta, lambda)
save(objective, file = "data/A8_objective.RData")
```

```
load(file = "data/A8_objective.RData")
objective
```

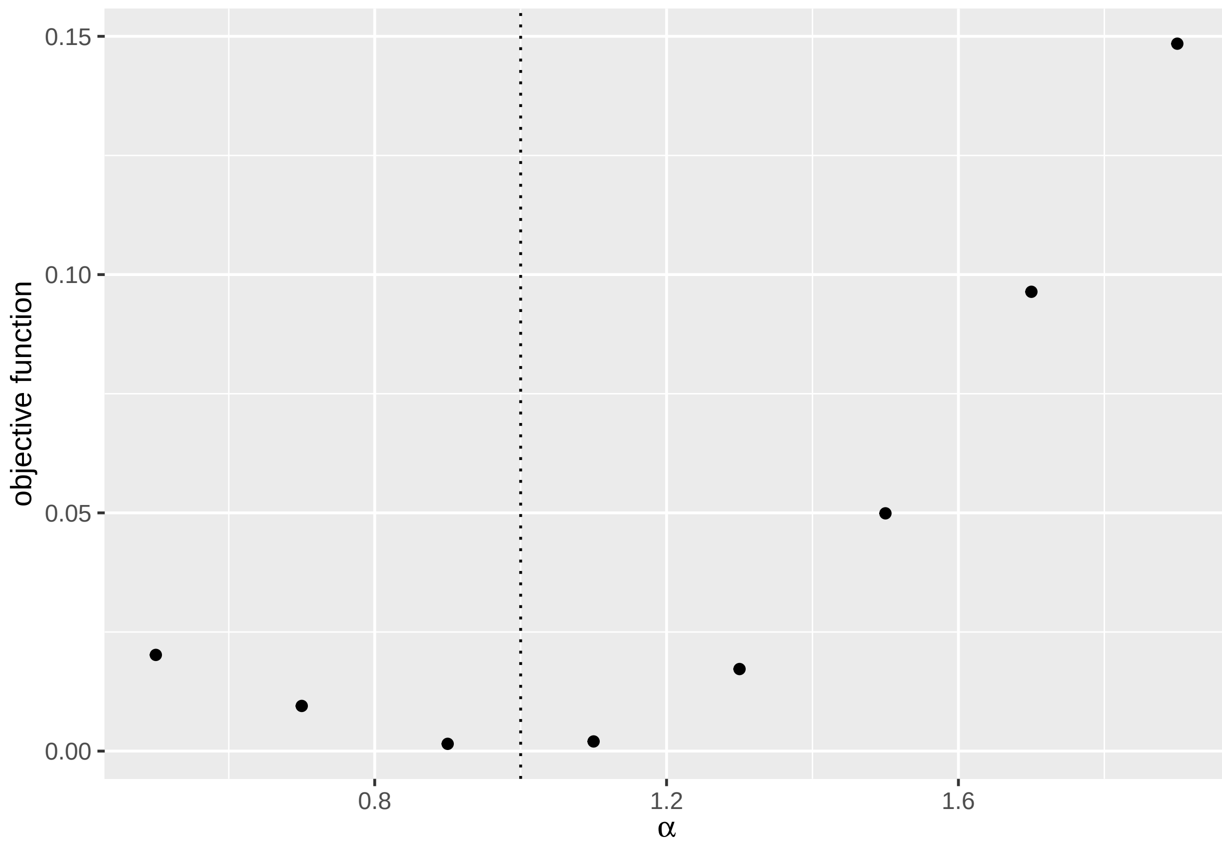
```
## [1] 0.0003059688
```

3. Check the value of the objective function around the true parameter.

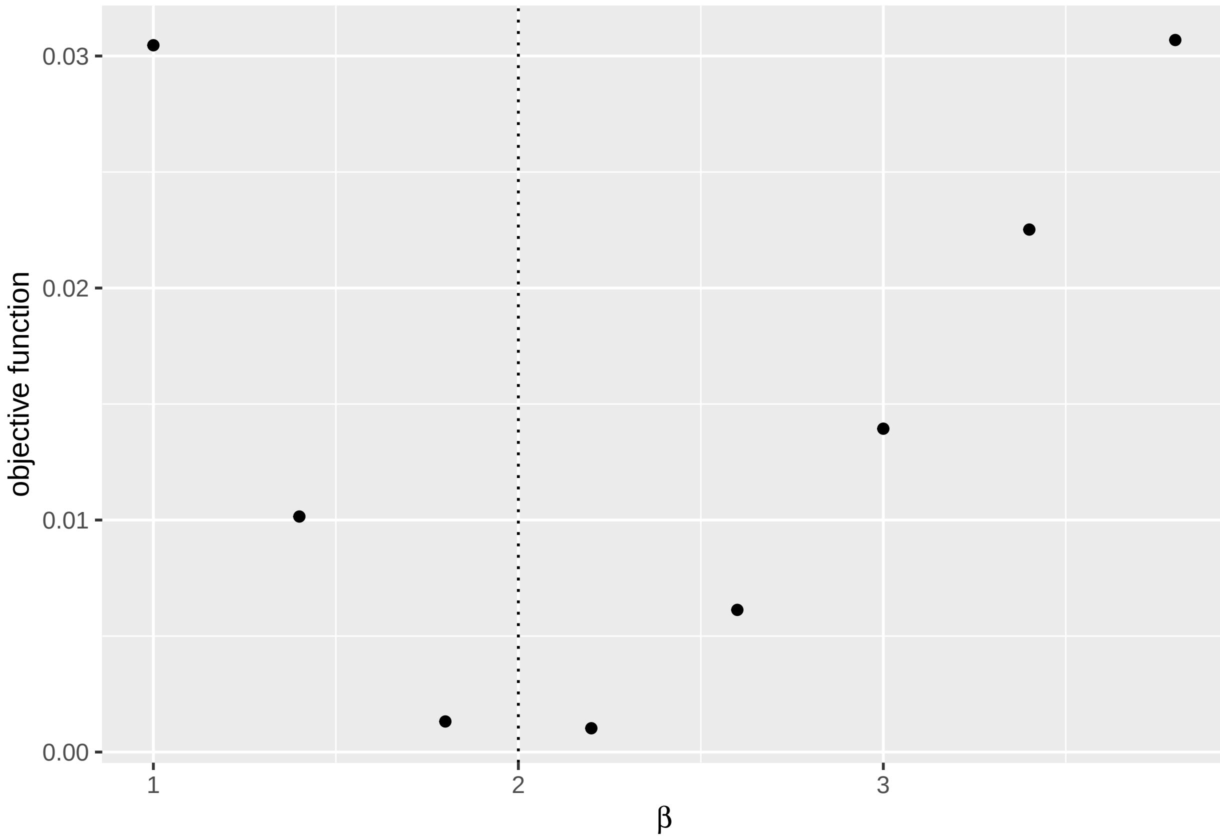
```
# label
label <- c("\\alpha", "\\beta", "\\eta")
label <- paste("$", label, "$", sep = "")
# compute the graph
graph <- foreach (i = 1:length(theta_1)) %do% {
  theta_i <- theta_1[i]
  theta_i_list <- theta_i * seq(0.5, 2, by = 0.2)
  objective_i <-
    foreach (j = 1:length(theta_i_list),
             .combine = "rbind") %dopar% {
               theta_ij <- theta_i_list[j]
               theta_j <- theta_1
               theta_j[i] <- theta_ij
               objective_ij <-
                 compute_CCP_objective_game(theta_j, theta_2, p_marginal_est, A, S, delta, lambda)
               return(objective_ij)
             }
  df_graph <- data.frame(x = theta_i_list, y = objective_i)
  g <- ggplot(data = df_graph, aes(x = x, y = y)) +
    geom_point() +
    geom_vline(xintercept = theta_i, linetype = "dotted") +
    ylab("objective function") + xlab(TeX(label[i]))
  return(g)
}
save(graph, file = "data/A8_CCP_graph.RData")
```

```r
load(file = "data/A8_CCP_graph.RData")
graph
```

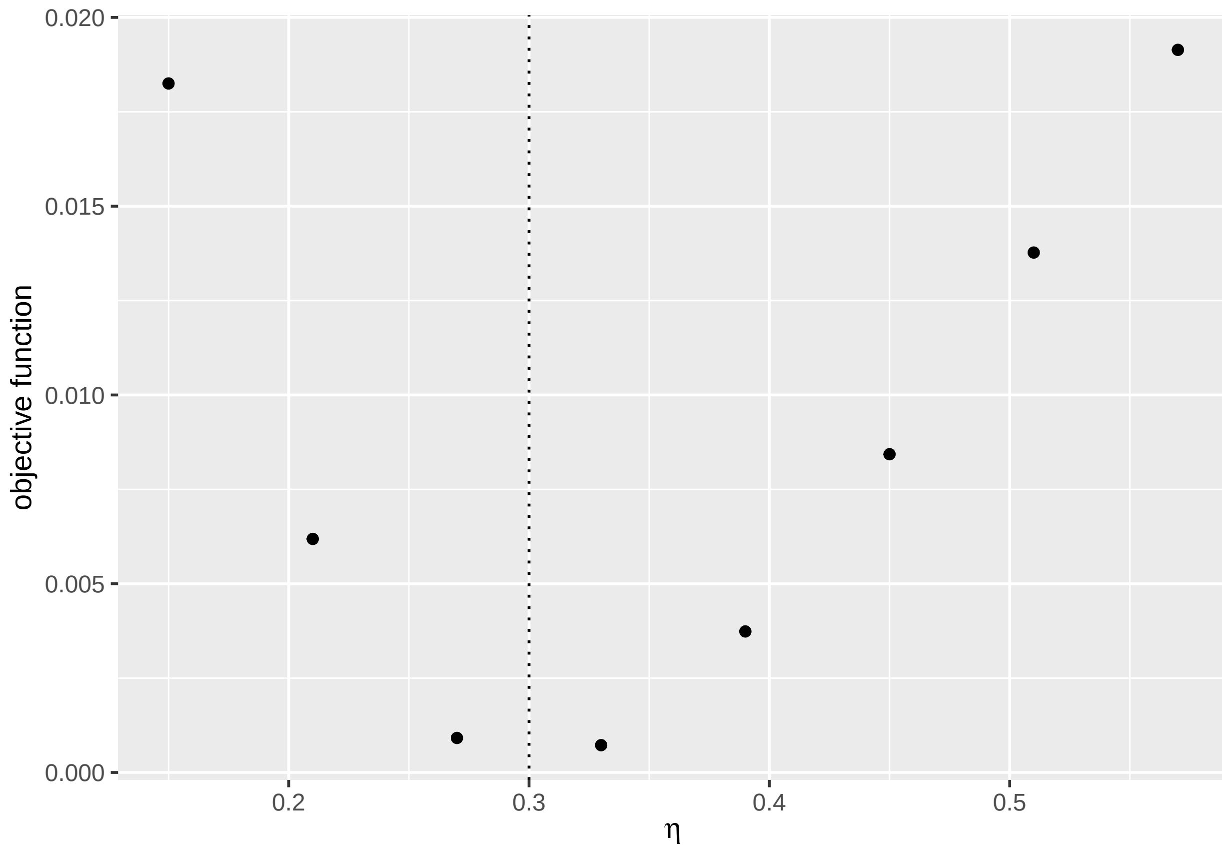
```
## [[1]]
```




```
##
## [[2]]
```




```
##
## [[3]]
```



4. Estimate the parameters by minimizing the objective function. To keep the model to be well-defined, impose an ad hoc lower and upper bounds such that $\alpha \in [0, 1], \beta \in [0, 5], \delta \in [0, 1]$.

```
lower <- rep(0, length(theta_1))
upper <- c(1, 5, 0.3)
CCP_result <-
  optim(par = theta_1,
        fn = compute_CCP_objective_game,
        method = "L-BFGS-B",
        lower = lower,
        upper = upper,
        theta_2 = theta_2_est,
        p_marginal_est = p_marginal_est,
        A = A,
        S = S,
        delta = delta,
        lambda = lambda)
save(CCP_result, file = "data/A8_CCP_result.RData")
```

```
load(file = "data/A8_CCP_result.RData")
CCP_result
```

```
## $par
## [1] 0.998164 2.000860 0.300000
##
```

```
## $value
## [1] 0.000303798
##
## $counts
## function gradient
##        5        5
##
## $convergence
## [1] 0
##
## $message
## [1] "CONVERGENCE: REL_REDUCTION_OF_F <= FACTR*EPSMCH"
```

```r
compare <-
  data.frame(
    true = theta_1,
    estimate = CCP_result$par
  ); compare
```

```
##   true estimate
## 1  1.0 0.998164
## 2  2.0 2.000860
## 3  0.3 0.300000
```