STAT6011/7611/6111/3317 COMPUTATIONAL STATISTICS (2016 Fall)

Assignment 4

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1

The code is below. I denote the 'Fair' by 0 and 'Loaded' by 1 in this code.

Listing 1: problem 1

```
import numpy as np
            def vitervi(transition):
                           tosses = "251326344212463366565535614566523665561326345621443235213263461435421"
                           \begin{array}{l} \text{prob loaded} = \{ \text{"1": 1/12, "2": 1/12, "3": 1/12, "4": 1/12, "5":1/3, "6":1/3} \} \\ \text{prob fair} = \{ \text{"1": 1/6, "2": 1/6, "3": 1/6, "4": 1/6, "5": 1/6, "6": 1/6} \} \end{array}
    5
    6
                           score\_loaded = np.ones(len(tosses))
                           score\_fair = np.ones(len(tosses))
    8
                           score\_loaded[0] = 0.5 * prob\_loaded[tosses[0]]
   9
                           score_fair[0] = 0.5 * prob_fair[tosses[0]]
10
11
                           for i in range(1,len(tosses)):
12
                                         score\_loaded[i] = max(score\_loaded[i-1] * transition[1,1], score\_fair[i-1] * transition[1,0]) * prob\_loaded[tosses[i-1] * transition[1,0] * trans
13
                                         score\_fair[i] = max(score\_loaded[i-1] * transition[0,1], score\_fair[i-1] * transition[0,0]) * prob\_fair[tosses[i]]
14
15
                           state\_estimation = np.ones(len(tosses))
16
17
                           for n, j in enumerate(score_loaded - score_fair):
                                         if j < 0:
18
19
                                                       state\_estimation[n] = 0
20
21
                           return(state_estimation)
23 transition1 = np.array([[0.8, 0.3], [0.2, 0.7]])
24 transition2 = np.array([[0.9, 0.15], [0.1, 0.85]])
25 transition3 = np.array([[0.95, 0.05], [0.6, 0.4]])
26 transition4 = np.array([[0.5, 0.5], [0.5, 0.5]])
           vitervi(transition1)
            vitervi(transition2)
           vitervi(transition3)
            vitervi(transition4)
```

And the results are as follows.

Listing 2: problem 2

```
1 import numpy as np
 2 from scipy.special import eval_hermite
3 from scipy.special import hermite
 4 from scipy.special import h_roots
 5 from scipy.special import he_roots
   from scipy.stats import norm
   def GH(m):
       points = h\_roots(m)[0]
9
        weights = h\_roots(m)[1]
10
       return sum([weights[i] * np.exp(points[i] **2) * norm.pdf(points[i]) for i in range(len(points))])
11
13
   def GH_weights(m):
       points = h\_roots(m)[0]
       weights = h_{roots(m)}[1]
15
16
       return [weights[i] * np.exp(points[i]**2) for i in range(len(points))]
17
   a = [5, 10, 20, 30]
18
19
   # approximation result
   for m in a:
21
       \mathbf{print}(\mathrm{GH(m)})
22
23
   # weights
24
25
   for m in a:
       print(GH_weights(m))
26
    # points
28
29
   for m in a:
       print(h_roots(m)[0])
```

In the below question, I mean the weights by the values multiplied by weight functions.

2.1

I prove the integral of standard normal probability distribution function is equal to 1.

2.2

```
I use the above code to compute the approximation of the integral.
```

```
When the number of nodes is 5,
```

the approximation result is 0.99684628222456162,

the nodes are [-2.02018287, -0.95857246, 0., 0.95857246, 2.02018287],

the weights are [1.1814886255359833, 0.98658099675142807, 0.94530872048294179, 0.98658099675142807, 1.1814886255359833]

When the number of nodes is 10,

the approximation result is 0.99998763906433263

the nodes are [-3.43615912, -2.53273167, -1.75668365, -1.03661083, -0.34290133, 0.34290133, 1.03661083, 1.75668365, 2.53273167, 3.43615912],

and the weights are [1.0254516913657519, 0.82066612640481784, 0.74144193194356545, 0.70329632310490586, 0.6870818539512733, 0.6870818539512733, 0.70329632310490586, 0.74144193194356545, 0.82066612640481784, 1.0254516913657519]

When the number of nodes is 20,

the approximation result is 0.999999999979803234,

the nodes are [-5.38748089, -4.60368245, -3.94476404, -3.34785457, -2.78880606, -2.254974, -1.73853771, -1.23407622, -0.73747373, -0.24534071, 0.24534071, 0.73747373, 1.23407622, 1.73853771, 2.254974, 2.78880606, 3.34785457, 3.94476404, 4.60368245, 5.38748089],

 $\begin{array}{l} 0.49092150066674595,\ 0.49092150066674595,\ 0.4938433852720529,\ 0.49992087133628998,\ 0.50967902711745705,\ 0.52408035094855054,\ 0.54485174236452072,\ 0.57526244285250083,\ 0.62227869619138665,\ 0.70433296117692357,\ 0.89859196145317 \end{array}$

3

Listing 3: problem 3

```
import numpy as np
   from scipy.special import p_roots
   from scipy.special import u_roots
   from scipy.special import t_roots
   \mathbf{def}\ f(\mathbf{x}):
       return (x**9) / np.sqrt(x**2 + 1)
 7
 8
9
   \mathbf{def} \, \mathrm{GL}(\mathrm{m, a, b}):
       points = p\_roots(m)[0]
10
11
        weights = p_roots(m)[1]
        return (b-a)*sum([weights[i]*f((b-a)*points[i]/2 + (b+a)/2) for i in range(len(points))])/2
12
13
   def Cheby1(m, a, b):
14
        points = t\_roots(m)[0]
15
16
        weights = t\_roots(m)[1]
        return (b-a)*sum([weights[i]*np.sqrt(1-(points[i])**2)*f((b-a)*points[i]/2+(b+a)/2) for i in range(len(points
17
             ))])/2
18
   def Cheby2(m, a, b):
19
        points = u\_roots(m)[0]
20
        weights = u_roots(m)[1]
21
        return (b-a)*sum([(weights[i]/np.sqrt(1-(points[i])**2)) * f((b-a)*points[i]/2 + (b+a)/2) for i in range(len(
22
             points))))/2
23
a = [5, 10]
25
   for m in a:
26
27
        # approximation results
       print(GL(m))
28
       print(Cheby1(m))
29
30
        print(Cheby2(m))
31
        \# nodes
32
33
       print(p_roots(m)[0])
        print(t_roots(m)[0])
34
        print(u_roots(m)[0])
35
36
        # weights
37
        print(p_roots(m)[1])
38
39
        print(t_roots(m)[1])
        print(u_roots(m)[1])
```

In the below questions, I mean the weights by the values not multiplied by the weight functions.

3.1

```
When I use Legendre polynomial as orthogonal polynomial,
   the approximation result is -49.506283813990549,
   the nodes are [-0.90617985, -0.53846931, 0., 0.53846931, 0.90617985],
   the weights are [0.23692689, 0.47862867, 0.56888889, 0.47862867, 0.23692689].
   When I use Chebyshev type 1 polynomial as orthogonal polynomial,
   the approximation result is -57.161045874594777,
   the nodes are [-9.51056516e-01, -5.87785252e-01, 6.12323400e-17, 5.87785252e-01, 9.51056516e-01,]
   the weights are [0.62831853, 0.62831853, 0.62831853, 0.62831853].
   When I use Chebyshev type 2 polynomial as orthogonal polynomial,
   the approximation result is -40.789633611622008,
   the nodes are [-8.66025404e-01, -5.00000000e-01, 6.12323400e-17, 5.00000000e-01, 8.66025404e-01]
   the weights are [0.13089969, 0.39269908, 0.52359878, 0.39269908, 0.13089969].
```

3.2

When I use Legendre polynomial as orthogonal polynomial,

the approximation result is -49.493963006199031,

0.86506337, 0.97390653,

the weights are [0.06667134, 0.14945135, 0.21908636, 0.26926672, 0.29552422, 0.29552422, 0.26926672, 0.21908636,0.14945135, 0.06667134].

When I use Chebyshev type 1 polynomial as orthogonal polynomial,

the approximation result is -50.987455239343021,

the nodes are [-0.98768834, -0.89100652, -0.70710678, -0.4539905, -0.15643447, 0.15643447, 0.4539905, 0.70710678,0.89100652, 0.98768834

the weights are [0.31415927, 0.31415927,0.31415927, 0.31415927].

When I use Chebyshev type 2 polynomial as orthogonal polynomial,

the approximation result is -47.101342989695162,

the nodes are [-0.95949297, -0.84125353, -0.65486073, -0.41541501, -0.14231484, 0.14231484, 0.41541501, 0.65486073,0.84125353, 0.95949297

the weights are [0.02266894, 0.08347854, 0.16312218, 0.23631356, 0.27981494, 0.27981494, 0.23631356, 0.16312218,0.08347854, 0.02266894].

4

Listing 4: problem 4

```
import numpy as np
        from scipy.stats import binom
  4 n = 25
  6 	ext{ iteration} = 100
        values = np.ones((iteration, 3))
      initial_value = [1/3, 1/3, 1/3]
        values[0, :] = initial_value
  9
10
       for ite in range(1, iteration):
11
                 \begin{array}{l} \text{q.a} = (2*\text{values}[\text{ite-1}, 2]) \ / \ (2*\text{values}[\text{ite-1}, 2] + \text{values}[\text{ite-1}, 0]) \\ \text{q.b} = (2*\text{values}[\text{ite-1}, 2]) \ / \ (2*\text{values}[\text{ite-1}, 2] + \text{values}[\text{ite-1}, 1]) \\ \text{under} = \text{sum}([\text{binom.pmf(i, n, q.a)} * \text{binom.pmf(j, n, q.b)} * (3*n - i) \text{ for } i \text{ in } \text{range(n+1)} \text{ for } j \text{ in } \text{range(n+1)}]) \\ \text{upper} = \text{sum}([\text{binom.pmf(i, n, q.a)} * \text{binom.pmf(j, n, q.b)} * (2*n + i + j) \text{ for } i \text{ in } \text{range(n+1)} \text{ for } j \text{ in } \text{range(n+1)}) \\ \end{array}
12
13
14
15
                  values[ite, 0] = 1/(2+(upper/under))
16
                  values[ite, 1] = 1/(2+(upper/under))
17
```

4.1

4.2

By using the above code, I get the estimation result after 100 iterations. The result is $[p_a, p_b, p_o] = [0.28021178, 0.28021178, 0.43957643].$

5

Listing 5: problem 5

```
# data generate
   import numpy as np
 4 I = 100
 5 J = 2
 6 beta_0 = -1
   beta_1 = 1
   sigma_u = 0.5
   sigma_eps = 1
10
11 np.random.seed(12345)
12
value_x = np.random.normal(0, 1, (I, J))
u = \text{np.random.normal}(0, \text{sigma\_u}, I)
15 value_u = np.ones((I, J))
   value_u[:, 0] = u
16
   value_u[:, 1] = u
17
   value\_eps = np.random.normal(0, sigma\_eps, (I, J))
   value_y = beta_0 + beta_1 * value_x + value_u + value_eps
19
20
21
   \# implement EM algorithm
22
    \# para = (beta_0, beta_1, sigma_eps, sigma_u)
23
    # sigma is variance
25 iteration = 500
   XY = sum(sum(value_y * value_x))
   X = sum(sum(value_x))
   Y = sum(sum(value_y))
   X_2 = sum(sum(value_x * value_x))
30
   \mathbf{def} \ \mathrm{xE}(\mathrm{E}_{-}\mathrm{t}):
31
        return sum(sum(value_x * np.array([E_t, E_t]).T))
32
33
   def eps_right(E_t, beta0, beta1):
34
        return (sum(sum((value_y - beta0-beta1*value_x)**2)) + J * sum(E_t**2) - 2*sum(sum((value_y - beta0 - beta0-beta1*value_x)**2)))
35
              beta1*value_x) * np.array([E_t, E_t]).T)))/(I*J)
36
37 initial = [0, 0, 5, 5]
   E_t = np.ones(I)
   estimation = np.ones((iteration, 4))
   estimation[0, :] = initial
40
41
   for ite in range(1,iteration):
42
43
        u = estimation[ite-1, 3]
        eps = estimation[ite-1, 2]
44
45
        beta0 = estimation[ite-1, 0]
        beta1 = estimation[ite-1, 1]
46
47
        for i in range(I):
             E_{-}t[i] = u*sum([value\_y[i, j] - beta0 - beta1*value\_x[i, j] \textbf{ for } j \textbf{ in } range(J)]) \ / \ (J*u + eps)
48
49
        V_t = eps*u/(J*u + eps)
        estimation[ite, 1] = (I*J*XY - Y*X - J*(I*xE(E_t) - sum(E_t)*X))/(I*J*X_2 - X**2)
50
        estimation[ite, 0] = (Y-beta1*X - J*sum(E_t))/(I*J)
estimation[ite, 2] = V_t + eps_right(E_t, estimation[ite-1, 0], estimation[ite-1, 1])
estimation[ite, 3] = V_t + sum(E_t*2)/I
51
52
53
54
   # change the last variance into standard deviation
55
   estimation[:, 2] = np.sqrt(estimation[:, 2])
```

```
stimation[:, 3] = np.sqrt(estimation[:, 3])

# compute the bias and std
bias = np.average(estimation, axis = 0) - [-1, 1, 1, 0.5]

std = np.std(estimation, axis = 0)

print("bias<sub>□</sub>:", bias)
print("std<sub>□</sub>:", std)
```