Table 1: (Mean) Squared Error in the dart-throwing setting

# of draws (or quadrature points)	Psuedo-MC (Mean Squared Error)	Quasi-MC	Newton-Cortes
100	0.0234	0.0200	1.0e-05 *0.1458
1,000	0.0027	0.0011	1.0e-05 *0.0007
10,000	0.0003	0.0000	1.0e-05 *0.0000

1: The First Problem

I drew 100² points from the 2-dimensional Halton sequence, and counted the ratio of the points whose squared Euclidean norm is weakly less than 1. The estimated π is 3.1448.

2: The Second Problem

I have 100^2 quadrature points in $[0,1] \times [0,1]$, and use a Newton-Cortes method to get an approximation of π , which is 3.1016. The weights are 1/N, where N denotes the number of quadrature points.

3: The Third Problem

Now I use the implicit function $y = \sqrt{1-x^2}$ for the upper-right part of the unit circle. I have 100^2 points in [0,1] from a Halton sequence, and approximate π . The estimate is 3.1422.

4: The Fourth Problem

I have 10,000 quadrature points in [0,1], and use a Newton-Cortes method. The weights are again 1/N, where N denotes the number of quadrature points. This time I use the implicit function to get an approximation of π . The estimate is 3.1414.

5: The Fifth Question

- (1) First we compare the results from a psuedo-MC with those from a Newton-Cortes and a quasi-MC in the two-dimensional, dart-throwing setting. Table 1 compares them. A Newton-Cortes gets the most accurate estimates. But it's not a fair comparison because a Newton-Cortes has 100, 1,000 or 10,000 quadrature points, which means actually 100^2 , $1,000^2$, $10,000^2$ draws in $[0,1] \times [0,1]$. But the others have 100, 1,000 or 10,000 draws there. So I should say a quasi-MC does a fairly good job for its unfairly small number of draws. The second column shows the mean squared errors from a psuedo-MC, and the third and fourth column show the squared columns from a quasi-MC and a Newton-Cortes. For a psuedo-MC, I get 200 simulations and calculate the mean squared error.
- (2) Next we compare the results in the one-dimensional setting using the implicit function. Table 2 shows the result. Again, in this setting that favors a Newton-Cortes and a psuedo-MC, A quasi-MC makes a comparable performance, although the other two get more accurate estimates.

6: Code

[%] Motoaki Takahashi % HW4 for Econ 512 Empirical Method

Table 2: (Mean) Squared Error in the implicit function setting

```
Psuedo-MC
# of draws (quadrature points)
                                              Quasi-MC
                                                               Newton-Cortes
                                     0.0090
                                              1.0e-04 *0.1989
                                                               1.0e-06 *0.1185
                          100
                         1,000
                                     0.0007
                                              1.0e-04 *0.0015
                                                               1.0e-06 *0.0001
                                              1.0e-04 *0.0000
                        10,000
                                     0.0001
                                                               1.0e-06 *0.0000
```

```
clear
diary hw4.out
%% Question 1
 \mbox{\ensuremath{\mbox{\%}}} I draw 100^2 points in the unit square from Halton sequence.
n = 100^2;
h = haltonseq(n, 2);
hsq = h.^2;
hsq = sum(hsq, 2);
hsq = sum(hsq<=1);
pi1=4*length(hsq)/n
  clear h hsq
%% Question 2
% weights are 1/100^2 where 100^2 is the # of draws (points)
x = transpose(0.01:0.01:1); % 100 by 1 vector running from 0.01 to 1
y = transpose(0.01:0.01:1); % 100 by 1 vector running from 0.01 to 1
grid = [kron(x, ones(100,1)), kron(ones(100,1), y)];
grid = grid - 2;
grid = sum(grid, 2);
grid = grid(grid<-1);
prid = grid(grid<-1);
 clear grid
h = haltonseq(n, 1);
h = sqrt(1-h.^2);
pi3 = 4*sum(h)/n
%% Question 4
grid = 0.0001:0.0001:1; % 10000 vector
grid = sqrt(1-grid.^2);
  pi4 = 4*sum(grid)/length(grid)
  clear grid
%% Question 5
 % We have two methods: (1) two-dimensional random draws (2) one-dimensional
% implicit function
% (1) two dimendional
% quasi-MC
% simulated pi's from 100, 1000, 10000 draws from a quasi-MC method
% Here I use the built-in function haltonset to get a Halton sequence.
% https://www.mathworks.com/help/stats/generating-quasi-random-numbers.html
% Following the above web page, get a sequence that skips the first 1000 values of the Halton sequence and then retains every 101st point p = haltonser(2, 'Skip', 163, 'Leap', 162);

% Apply reverse-radix scrambling
p = scramble(p, 'RR2');
p = scramble(p,'RR2');
quasi_100 = sim_pi(p(1:100,:))
quasi_1000 = sim_pi(p(1:1000,:))
quasi_10000 = sim_pi(p(1:10000,:))
se_quasi='([quasi_100; quasi_1000; quasi_10000]-pi*ones(3,1)).^2
 % Newton-Coates
% Newton-Coates
x = (0.005:0.01:0.995).'; % 100-vector
y = (0.005:0.01:0.995).'; % 100-vector
grid = [kron(x, ones(100,1)), kron(ones(100,1), y)];
nc_100 = sim_pi(grid)
x = (0.0005:0.001:0.9995).'; % 1000-vector
y = (0.0005:0.001:0.9995).'; % 1000-vector
grid = [kron(x, ones(1000,1)), kron(ones(1000,1), y)];
nc_1000 = sim_pi(grid)
x = (0.00005:0.0001:0.99995).'; % 10000-vector
y = (0.00005:0.0001:0.99995).'; % 10000-vector
grid =[kron(x, ones(10000,1)), kron(ones(10000,1), y)];
 nc_10000 = sim_pi(grid)
 se_nc=([nc_100; nc_1000; nc_10000]-pi*ones(3,1)).^2
% psuedo-MC
k = 100;
sim_pis = ones(200,1);
for i=1:200
               h = rand(k,2);
sim_pis(i,1) = sim_pi(h);
mse100 = mean((sim_pis-pi*ones(200,1)).^2);
k = 1000;
sim_pis = ones(200,1);
for i=1:200
   h = rand(k,2);
   sim_pis(i,1) = sim_pi(h);
and
```

```
mse1000 = mean((sim_pis-pi*ones(200,1)).^2);
k = 10000;
sim_pis = ones(200,1);
for i=1:200
h = rand(k,2);
sim_pis(i,1) = sim_pi(h);
end
mse10000 = mean((sim_pis-pi*ones(200,1)).^2);
mse_psuedo = [mse100; mse1000; mse10000]
clear k i
\% (2) one-dimensional, implicit function
% (2) One-timensiving, amplify, % quasi-MC clear p p = haltonset(1,'Skip',1e3,'Leap',1e2); p = scramble(p,'RR2');
 \begin{array}{ll} quasi\_oned\_pi = \\ [sim\_pi2(p(1:100)); \\ sim\_pi2(p(101:1100)); \\ sim\_pi2(p(1101:11100))] \\ se\_quasi\_oned = \\ (quasi\_oned\_pi-pi*ones(3,1)).^2 \\ \end{array} 
% Newton-Cortes
nc_oned_pi = [sim_pi2(0.005:0.01:0.995); sim_pi2(0.0005:0.001:0.9995); sim_pi2(0.00005:0.0001:0.99995)]
se_nc_oned = (nc_oned_pi-pi*ones(3,1)).^2
% psuedo-MC
k = 100;
pi_oned = 6*ones(200,1);
for i=1:200
h = rand(k,1);
pi_oned(i) = sim_pi2(h);
end
mse100_2 = mean((pi_oned-pi*ones(200,1)).^2)
k = 1000;
pi_oned = 6*ones(200,1);
for i=1:200
    h = rand(k,1);
    pi_oned(i) = sim_pi2(h);
end
mse1000_2 = mean((pi_oned-pi*ones(200,1)).^2)
h = 10000;
pi_oned = 6*ones(200,1);
for i=1:200
    h = rand(k,1);
    pi_oned(i) = sim_pi2(h);
end
mse10000_2 = mean((pi_oned-pi*ones(200,1)).^2)
mse_psuedo_2 = [mse100_2; mse1000_2; mse10000_2]
diary off
```

7: Output

```
pi1 =
    3.1448

pi2 =
    3.1016

pi3 =
    3.1422

pi4 =
    3.1414
```

 $quasi_100 =$

3

quasi_1000 =

3.1080

quasi_10000 =

3.1408

se_quasi =

0.0200

0.0011

0.0000

nc_100 =

3.1428

nc_1000 =

3.1417

nc_10000 =

3.1416

se_nc =

1.0e-05 *

0.1458

0.0007

0.0000

mse_psuedo =

0.0234

0.0027

0.0003

quasi_oned_pi =

3.1371

3.1412

3.1416

- se_quasi_oned =
 - 1.0e-04 *
 - 0.1989
 - 0.0015
 - 0.0000
- nc_oned_pi =
 - 3.1419
 - 3.1416
 - 3.1416
- se_nc_oned =
 - 1.0e-06 *
 - 0.1185
 - 0.0001
 - 0.0000
- $mse100_2 =$
 - 0.0090
- $mse1000_2 =$
 - 7.2973e-04
- $mse10000_2 =$
 - 7.7822e-05
- mse_psuedo_2 =
 - 0.0090
 - 0.0007
 - 0.0001