MA3227 : Assignment #3

Due on Wednsday, 4 Apr 2014

Chen Yu A0077976E Engineering Science Programme

Homework Part I

(1)

Case 1:

$$\hat{V}_{B1} = \frac{\text{\#hits in B}}{\text{\#hits in A}} V_A$$

Let $\hat{\theta}_1 = \frac{\text{\#hits in B}}{\text{\#hits in A}}$, which follows a binomial distribution with $N = n, p = \frac{V_B}{V_A}$. Then

$$\sigma_1 = \frac{\theta_1(1 - \theta_1)}{n} V_A^2 = \frac{V_A V_B (V_A - V_B)}{n}$$

Case 2:

$$\hat{V}_{B2} = \frac{\text{#hits in } B \setminus D}{\text{#hits in } A \setminus D} (V_A - V_D) + V_{B \setminus D}$$

Let $\hat{\theta}_2 = \frac{\text{\#hits in BD}}{\text{\#hits in}A \setminus D}$, which follows a binomial distribution with $N = n, p = \frac{V_{B \setminus D}}{V_{A \setminus D}}$. Then

$$\sigma_{2} = \frac{\theta_{2}(1 - \theta_{2})}{n} (V_{A} - V_{D})^{2}$$

$$= \frac{(V_{A} - V_{D})V_{B \setminus D}(V_{A} - V_{B \setminus D} - V_{D})}{n}$$

$$= \frac{(V_{A} - V_{D})(V_{B} - V_{B \cap D})(V_{A} - V_{D \setminus B} - V_{B})}{n}$$

Since

$$V_A > V_A - V_D$$

$$V_B > V_B - V_{B_{B \cap D}}$$

$$V_A - V_B > V_A - V_B - V_{D \setminus B}$$

we get $\sigma_1 > \sigma_2$

(2)

a) In this method, the estimator follows a binomial distribution with n=N and $p=\frac{I}{1}=I$ Hence the variance is

$$\frac{1}{N}I(1-I) = \frac{1}{N}(I-I^2)$$

b) The variance of this Monte Carlo Integration is

$$\operatorname{Var}\left[\frac{1}{N}\sum_{i=1}^{n}f(U_{i})\right] = \frac{1}{N^{2}}N\operatorname{Var}\left[f(U_{i})\right]$$
$$= \frac{1}{N}\left(\operatorname{E}\left[f(U_{i})^{2}\right] - I^{2}\right)$$

Since

$$\forall x \in [0, 1], f(x) \in (0, 1)$$

we have

$$f(x)^2 < f(x)$$

, thus

$$E[f(U_i)^2] < E[f(U_i)]$$

Therefore the method in b) has a smaller variance.

Chen Yu

(3)

$$(n-1)S_n^2 = \sum_{i=1}^n (X_i - \bar{X})^2$$

$$= \sum_{i=1}^n (X_i^2 - 2\bar{X}X_i + \bar{x}^2)$$

$$= \sum_{i=1}^n X_i^2 - 2\bar{X}\sum_{i=1}^n X_i + n\bar{x}^2$$

$$= \sum_{i=1}^n X_i^2 - 2n\bar{X}^2 + n\bar{x}^2$$

$$= \sum_{i=1}^n X_i^2 - n\bar{X}^2$$

$$E[S_n^2] = \frac{1}{n-1} E[\sum_{i=1}^n X_i^2 - n\bar{X}^2]$$

$$= \frac{1}{n-1} (nE[X_i^2] - nE[\bar{X}^2])$$

$$= \frac{n}{n-1} (E[X_i^2] - E[\bar{X}^2])$$

$$E[X_i^2] = (E[X_i])^2 + Var[X_i]$$

$$\begin{split} \mathbf{E}[\bar{X}^2] &= (\mathbf{E}[\bar{X}])^2 + \mathrm{Var}[\bar{X}] \\ &= (\mathbf{E}[\frac{1}{n}\sum_{i=1}^n X_i])^2 + \mathrm{Var}[\frac{1}{n}\sum_{i=1}^n X_i] \\ &= (\mathbf{E}[X_i])^2 + \frac{1}{n}\mathrm{Var}[X_i] \end{split} \tag{i.i.d}$$

Therefore,

$$E[S_n^2] = \frac{n}{n-1} ((E[X_i])^2 + Var[X_i] - (E[X_i])^2 - \frac{1}{n} Var[X_i])$$

= $Var[X_i]$

Chen Yu Homework Part I

Homework Part II(1)

Let $P_{x,y}$ be the transition probability function. The transition probability function generated by the new Metropolis algorithm is

$$Q_{x,y} = \min\{1, \frac{P_{y,x}f(y)}{P_{x,y}f(x)}\}P_{x,y}$$

$$f(x)Q_{x,y} = f(x)\min\{1, \frac{P_{y,x}f(y)}{P_{x,y}f(x)}\}P_{x,y}$$
$$= \min\{f(x)P_{y,x}, f(y)P_{y,x}\}$$

$$\begin{split} f(y)Q_{y,x} &= f(y)\min\{1, \frac{P_{x,y}f(x)}{P_{y,x}f(y)}\}P_{y,x} \\ &= \min\{f(x)P_{y,x}, f(y)P_{y,x}\} \end{split}$$

$$\implies f(x)Q_{x,y} = f(y)Q_{y,x}$$

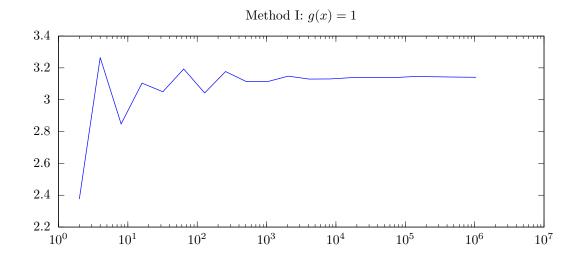
, thus satisfying the detailed balance, which ensures that the Metropolis-Hasting chain generated has invariant distribution.

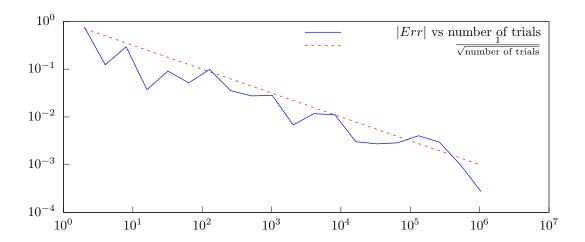
Computer Project Part I

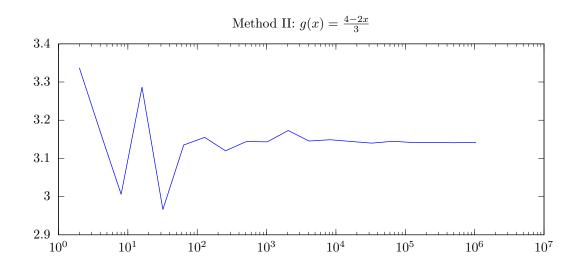
Code

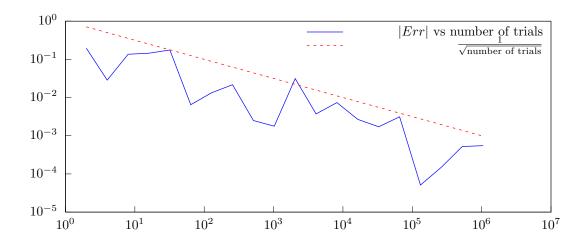
```
clear;
close all;
graphics_toolkit("gnuplot");
function I = repI(i)
     I = [];
     for j = 1:i
                I = [I,'I'];
     end
end
nTrials=2. (1:20); m=length (nTrials);
vEst = cell(3,1);
for i = 1:3
     vEst{i} = zeros(1,m);
end
rand('state',0);
for i=1:m
     n=nTrials(i);
     x = rand(1, n);
     vEst{1}(i) = sum(4*sqrt(1-x.^2))/n;
     x = -sqrt(4 - 3*rand(1,n)) + 2;
     vEst{2}(i) = sum(12*sqrt(1-x.^2)./(4-2*x))/n;
     x = -sqrt(1 - rand(1,n)) + 1;
     vEst{3}(i) = sum(4*sqrt(1-x.^2)./(2-2*x))/n;
end
err = cell(3,1);
for i = 1:3
     err{i} = abs(vEst{i} - pi);
end
equation = cell(3,1);
equation{1} = '$g(x) = 1$';
equation{2} = ' $g(x) = \\ frac{4-2x}{3}$';
equation{3} = '$g(x) = 2-2x$';
for i = 1:3
     the_plot = figure(i);
     subplot (2, 1, 1);
     semilogx(nTrials, vEst{i}, 'LineWidth', 2);
     title(['Method ',repI(i),': ', equation{i}]);
     subplot (2, 1, 2);
     hold on;
     loglog(nTrials, err{i}, 'LineWidth', 2);
     loglog(nTrials, 1./sqrt(nTrials),'r:','LineWidth', 2);
     \operatorname{legend}('\$\abs{Err}) vs number of trials',
```

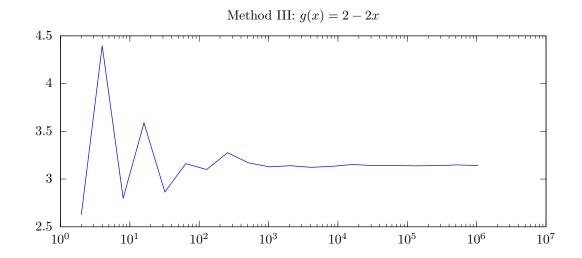
Figures

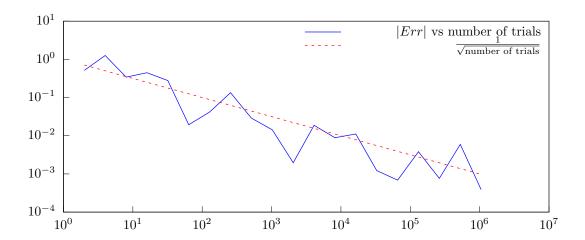


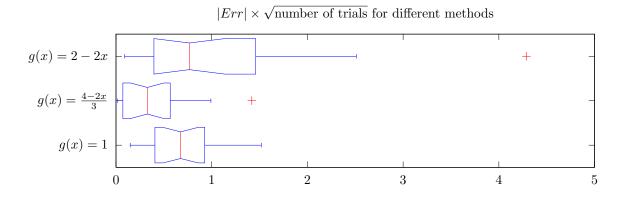












Computer Project Part II

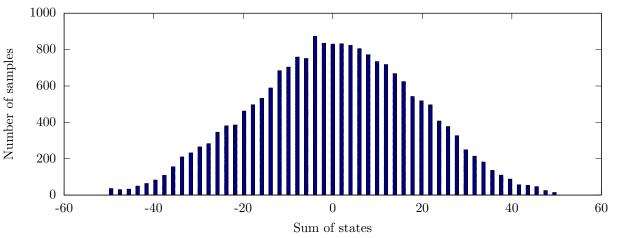
Code

```
clear; close all;
   graphics_toolkit("gnuplot");
   N_bins = 101;
   function M = Metro_Ising(mu, N_steps, sample_rate, N)
        x = ones(N, 1);
        M = zeros(0, N_steps/sample_rate);
        for i = 1:N_steps
             j = ceil(N*rand);
10
             if j == 1
                  h = \exp(-2*mu*x(1)*(x(2)));
             elseif j == N
                  h = \exp(-2*mu*x(N)*(x(N-1)));
             else
                  h = \exp(-2*mu*x(j)*(x(j-1)+x(j+1)));
             end
             U = rand;
             if U <= h
                  x(j) = -x(j);
             end
             if \mod(i, 50) == 0
                  M(i/50) = sum(x);
             end
        end
   end
   N_steps = 1e6;
   sample_rate = 50;
  N = 50;
   %mesh = -N:floor(2*N/(N_bins - 1)):N;
   %[n, h] = hist(M, mesh);
   the_plot = figure();
   M_h = Metro_Ising(1, N_steps, sample_rate, N);
   M_l = Metro_Ising(2, N_steps, sample_rate, N);
   h_{plot} = subplot(2,1,1);
   hist (M_h, 101);
   title(['Histogram of sum of states of high temperature ($\mu = 1$)',
          '1D Ising model with $20,000$ from $1,000,000$ states']);
   xlabel('Sum of states');
   ylabel('Number of samples');
   l_plot = subplot(2,1,2);
  hist (M_1, 101);
   title(['Histogram of sum of states of low temperature (<math>mu = 2)',
          '1D Ising model with $20,000$ from $1,000,000$ states']);
   xlabel('Sum of states');
   ylabel('Number of samples');
```

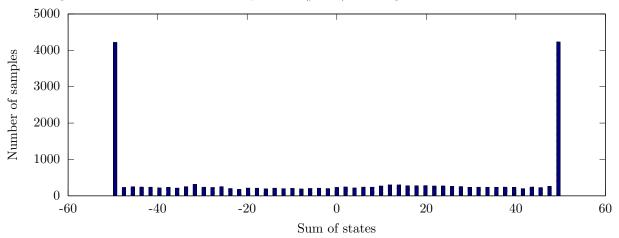
print(the_plot, ['MetropolisIsing','.tex'],'-S520,400','-dtex')

Figures

Histogram of sum of states of high temperature ($\mu = 1$) 1D Ising model with 20,000 from 1,000,000 states



Histogram of sum of states of low temperature ($\mu = 2$) 1D Ising model with 20,000 from 1,000,000 states



Homework Part II(2)

f is the distribution of all microstates in the state space of 2^N possible micro states of $(x_1, x_2, ..., x_N)$, where $x_i = -1$ or 1.

 $P_{x,y} = \frac{1}{N}$ if $x_i = y_i$ for all but one component; which results in a proposed state y where only the spin of one particle is reversed.