

P1.

i) I think step 3 is more efficient than step 2, because with $\sigma_0 = 1$, the $p(x, y)$ is very small when $\pi(x, y)$ is large. So It is hard for step 2 to get sample with more useful information.

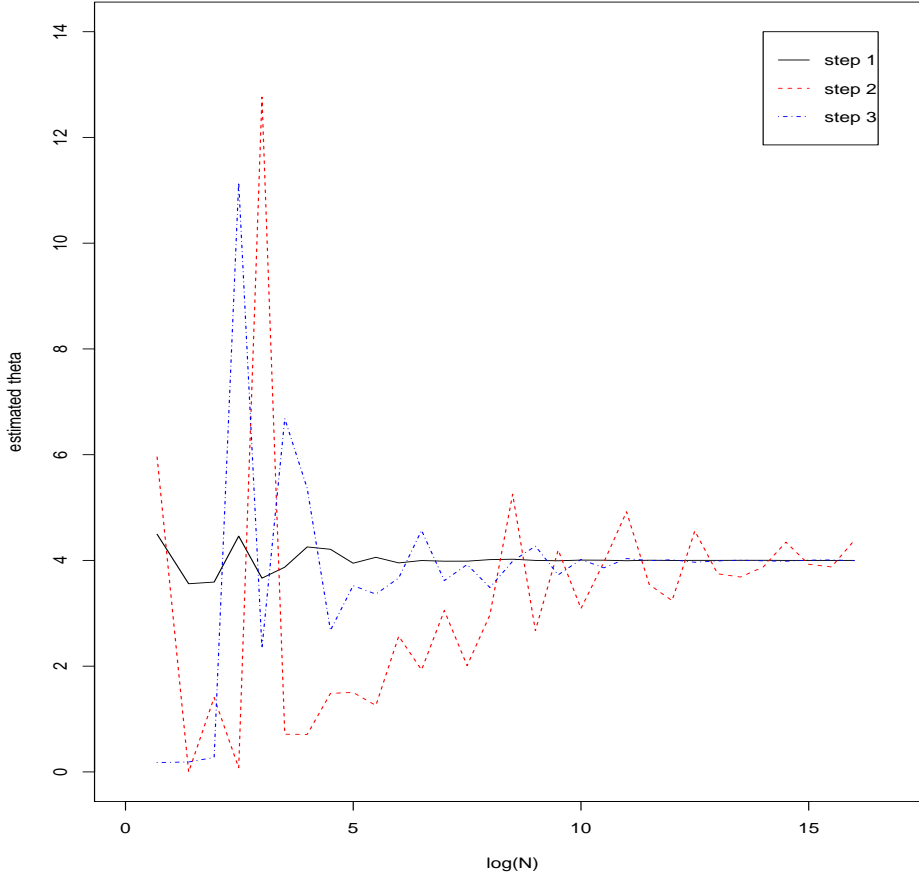


Figure 1: $\hat{\theta}$ against n

From Figure 1, we can see $\hat{\theta}_1$ of step 1 quickly converges to 4 after sampling amount increase to 10^5 . For step 2, $\hat{\theta}_2$ are prone to converge to 4, but the estimated values are not stable even when $N = 10^{15}$. For step 3, $\hat{\theta}_3$ converges to 4 after the amount increases to 10^{10} . So step 1 is the best method and step 3 is better than step 2.

ii)

First calculate the $ess(n)$ for step 2 and step 3.

$$\begin{aligned}
\omega &= \frac{\pi(x, y)}{p(x, y)} \\
E[\omega] &= E\left[\frac{\pi(x, y)}{p(x, y)}\right] = \int \frac{\pi(x, y)}{p(x, y)} p(x, y) dx dy = 1 \\
E[\omega^2] &= E\left[\frac{\pi(x, y)^2}{p(x, y)^2}\right] = \int \frac{\pi(x, y)^2}{p(x, y)} dx dy = \int \frac{\sigma_0^2}{2\pi} e^{-\left[(x-2)^2 + (y-2)^2 - \frac{1}{2\sigma_0^2}(x^2 + y^2)\right]} dx dy \\
&= \int \frac{\sigma_0^2}{2\pi} e^{-\left[\left(1 - \frac{1}{2\sigma_0^2}\right)x^2 - 4x + \left(1 - \frac{1}{2\sigma_0^2}\right)y^2 - 4y + 8\right]} dx dy \\
&= \int \frac{\sigma_0^2}{2\pi} e^{-(1 - \frac{1}{2\sigma_0^2})\left[x - \frac{4\sigma_0^2}{2\sigma_0^2 - 1}\right]^2 + \frac{8\sigma_0^2}{2\sigma_0^2 - 1}} e^{-(1 - \frac{1}{2\sigma_0^2})\left[y - \frac{4\sigma_0^2}{2\sigma_0^2 - 1}\right]^2 + \frac{8\sigma_0^2}{2\sigma_0^2 - 1}} e^{-8} dx dy \\
&= \frac{\sigma_0^2}{2\pi} \left(\sqrt{\frac{\pi}{\frac{2\sigma_0^2 - 1}{2\sigma_0^2}}}\right)^2 e^{\frac{16\sigma_0^2}{2\sigma_0^2 - 1}} e^{-8} \\
&= \frac{\sigma_0^4}{2\sigma_0^2 - 1} e^{\frac{8}{2\sigma_0^2 - 1}} \\
\Rightarrow ess(n) &= \frac{n}{1 + Var[\omega]} = \frac{n}{E[\omega^2]} = \frac{2\sigma_0^2 - 1}{\sigma_0^4} e^{\frac{-8}{2\sigma_0^2 - 1}} n
\end{aligned}$$

For step 2, $\sigma_0 = 1 \Rightarrow ess(n) = e^{-8}n = 0.000335n$. For step 3, $\sigma_0 = 4 \Rightarrow ess(n) = 0.09355n$. For ess^* , calculating one $\hat{\theta}$ is not enough to estimate errors, so calculate $\hat{\theta}$ at least 500 times for each step and then calculate the standard deviation of each estimate. If 2 steps have a similar standard deviation, the estimated errors could be regarded as same. For example, if $n_1 = 5$, the standard deviation of step 1 is 0.6282757. For step 2, $n_2 = 210000$, the standard deviation of step 2 is 0.5757558. So we can think $ess^*(n_1) = ess^*(n_2)$ and theoretical value $n_2 = 5 * e^8 = 14904$.

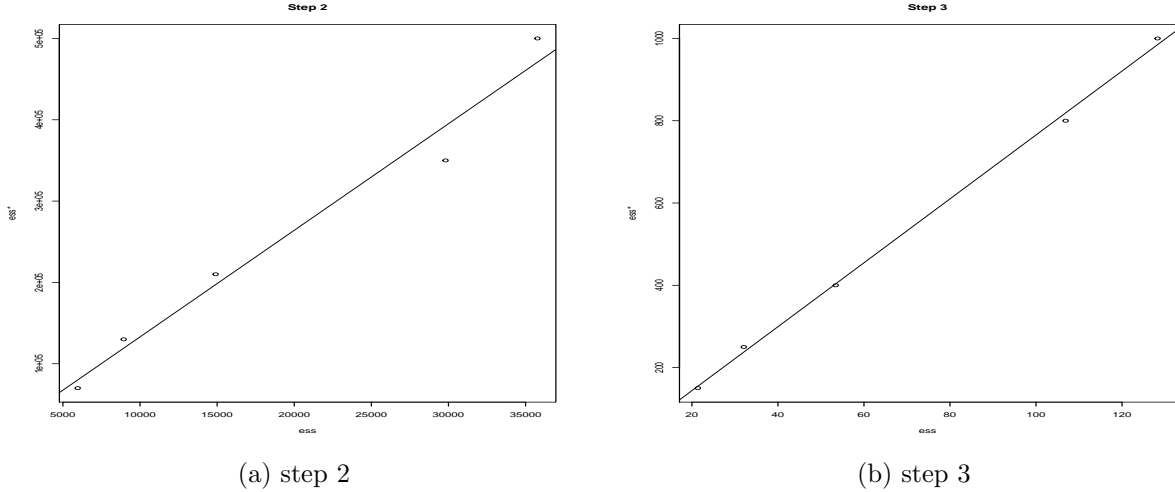


Figure 2

We can see ess and ess^* are proportional for both step 2 and step 3. From Figure 2a and Figure 2b, if we want step 2 and step 3 have the same effective sample size, step 2 requires much more

samples.

The following is R code.

P2.

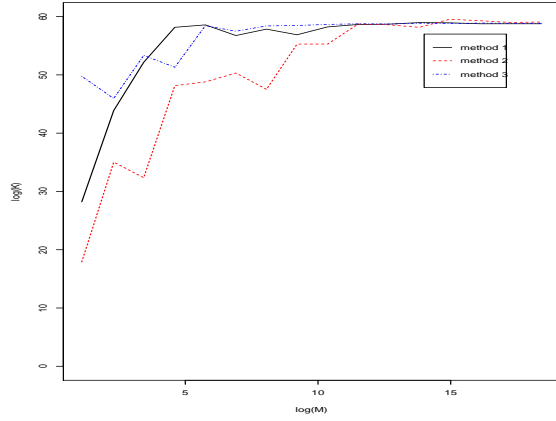
Method 1: I use probability $g_1(x) = \prod_{j=1}^m \frac{1}{k_j}$, where m is the total length of the path, and k_j is the number of possible choices at j -th step.

Method 2: I introduce an early termination rate $\epsilon = 0.05$ at each step (while in textbook, $\epsilon = 0.1$).

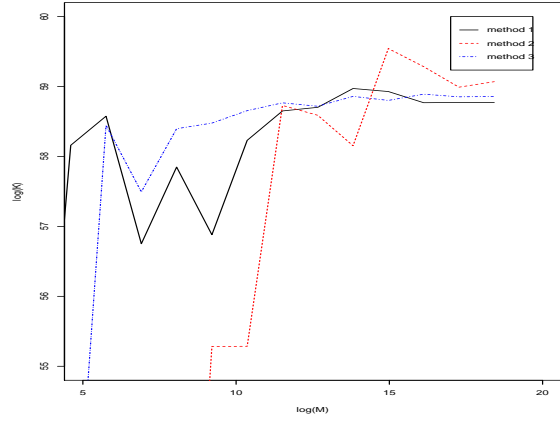
So $g_2(x) = \prod_{j=1}^m \frac{1}{k_j * 0.95}$.

Method 3: For any walk that longer than 50, $u = 5$ more children based on it are generated and are reweighed by $\omega_0 = \frac{\omega}{u}$.

i)



(a) Global log-log plot of K against M



(b) Local log-log plot of K against M

Figure 3

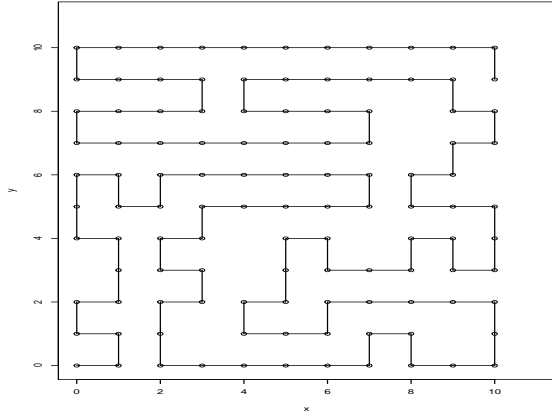
From Figure 3a, we can see that SIS processes of all 3 methods are converging with M increasing. Figure 3b demonstrates that Method 3 converges the fastest and Method 2 converges the most slowly. The limit values of Method 2 and Method 3 are higher than Method 1, which means the bias cannot be neglected. The following are the estimated value of K s when $M = 10^8$ for the 3 methods respectively: $3.316744 * 10^{25}$, $4.512596 * 10^{25}$, $3.649155 * 10^{25}$.

ii)

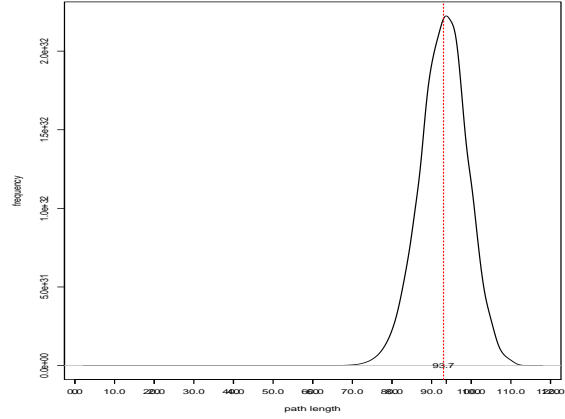
I applied the method mentioned in textbook.

$1.501552 * 10^{24}$

iii)



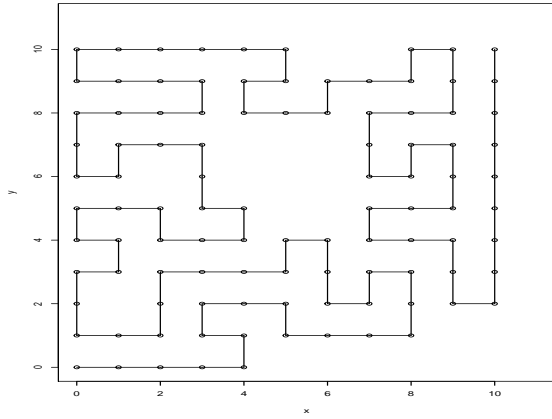
(a) Longest path



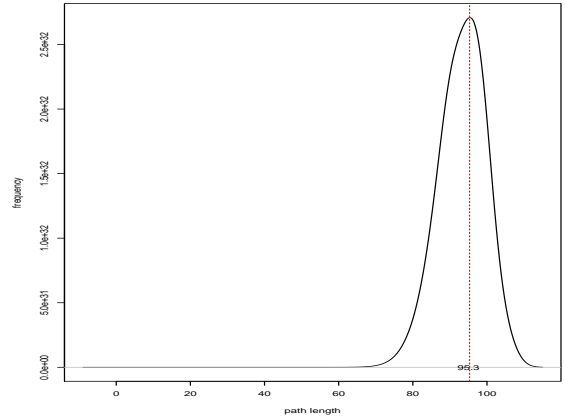
(b) Density function of paths

Figure 4: Method 1

For Method 1, Figure 4a has length 111.



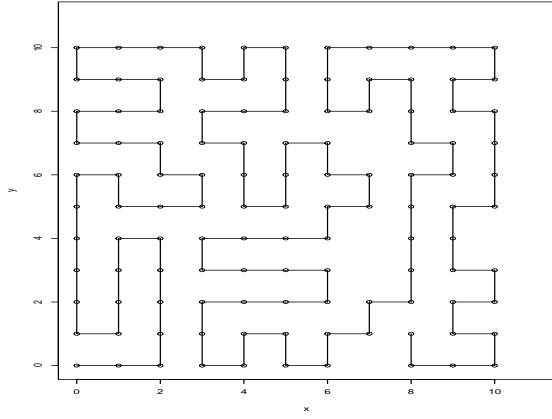
(a) Longest path



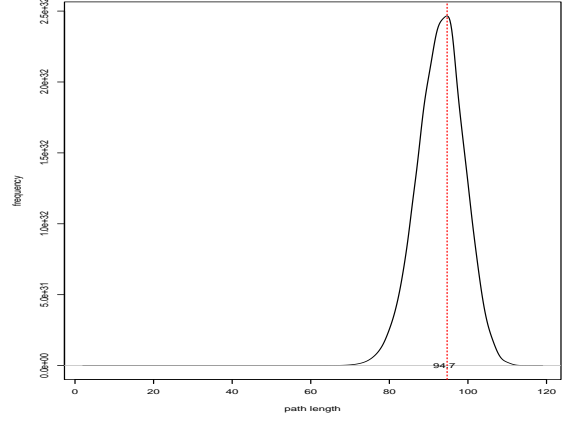
(b) Density function of paths

Figure 5: Method 2

For Method 2, Figure 5a has length 100. Figure 5b is against intuition. The most dense point is 95.3 while the length of the longest path for Method 2 is 100. But it's reasonable, because $\frac{1}{\epsilon}^m$ makes longer paths' weight much more larger.



(a) Longest path



(b) Density function of paths

Figure 6: Method 3

For Method 3, Figure 6a has length 115. The most dense point is 94.7 which is a little higher than the one of Method 1, because there are more paths, having length more than 50 and some of which are adapted to new weights.

The following are C++ codes for all questions.