Question 1

a.

```
i run python\ lwUmbrella.py\ 1000\ 10\ 11111100000
```

 $P(R_10 = T|u_1:10) = 0.0510$

 $P(R_10 = F|u_1:10) = 0.9490$

 $P(R_10 = T|u_1:10) = 0.0454$

 $P(R_10 = F|u_1:10) = 0.9546$

 $P(R_10 = T|u_1:10) = 0.0503$

 $P(R_10 = F|u_1:10) = 0.9497$

 $P(R_10 = T|u_1:10) = 0.0819$

 $P(R_10 = F|u_1:10) = 0.9181$

 $P(R_10 = T|u_1:10) = 0.0601$

 $P(R_10 = F|u_1:10) = 0.9399$

 $P(R_10 = T|u_1:10) = 0.0581$

 $P(R_10 = F|u_1:10) = 0.9419$

 $P(R_10 = T|u_1:10) = 0.0863$

 $P(R_10 = F|u_1:10) = 0.9137$

 $P(R_10 = T|u_1:10) = 0.0355$

 $P(R_10 = F|u_1:10) = 0.9645$

 $P(R_10 = T|u_1:10) = 0.0641$

 $P(R_10 = F|u_1:10) = 0.9359$

 $P(R_10 = T|u_1:10) = 0.0496$

 $P(R_10 = F|u_1:10) = 0.9504$

After running 10 time, the varience of estimates is 0.00023

ii run python lwUmbrella.py 1000 10 0000000111

 $P(R_10 = T|u_1:10) = 0.9148$

 $P(R_10 = F|u_1:10) = 0.0852$

 $P(R_10 = T|u_1:10) = 0.8302$

$$P(R_10 = T|u_1:10) = 0.9023$$

 $P(R_10 = F|u_1:10) = 0.0977$

 $P(R_10 = F|u_1:10) = 0.1144$

After running 10 time, the varience of estimates is 0.00117

iii run $python\ lwUmbrella.py\ 1000\ 10\ 0101010101$

$$P(R_10 = T|u_1:10) = 0.7453$$
 $P(R_10 = F|u_1:10) = 0.2547$
 $P(R_10 = T|u_1:10) = 0.6556$
 $P(R_10 = F|u_1:10) = 0.3444$
 $P(R_10 = T|u_1:10) = 0.5090$
 $P(R_10 = F|u_1:10) = 0.4910$
 $P(R_10 = T|u_1:10) = 0.6519$
 $P(R_10 = F|u_1:10) = 0.3481$
 $P(R_10 = T|u_1:10) = 0.6152$
 $P(R_10 = F|u_1:10) = 0.3848$
 $P(R_10 = T|u_1:10) = 0.3848$
 $P(R_10 = F|u_1:10) = 0.7164$
 $P(R_10 = F|u_1:10) = 0.2836$

$$P(R_{-}10 = T|u_{-}1:10) = 0.7323$$

 $P(R_{-}10 = F|u_{-}1:10) = 0.2677$
 $P(R_{-}10 = T|u_{-}1:10) = 0.7094$
 $P(R_{-}10 = F|u_{-}1:10) = 0.2906$
 $P(R_{-}10 = T|u_{-}1:10) = 0.7283$
 $P(R_{-}10 = F|u_{-}1:10) = 0.2717$
 $P(R_{-}10 = T|u_{-}1:10) = 0.6656$
 $P(R_{-}10 = F|u_{-}1:10) = 0.3344$

After running 10 time, the varience of estimates is 0.00461

b.

i run $python\ pfUmbrella.py\ 1000\ 10\ 11111100000$

$$P(R_{-}10 = T|u_{-}1:10) = 0.0580$$
 $P(R_{-}10 = F|u_{-}1:10) = 0.9420$
 $P(R_{-}10 = T|u_{-}1:10) = 0.0510$
 $P(R_{-}10 = F|u_{-}1:10) = 0.9490$
 $P(R_{-}10 = T|u_{-}1:10) = 0.0640$
 $P(R_{-}10 = F|u_{-}1:10) = 0.9360$
 $P(R_{-}10 = T|u_{-}1:10) = 0.0570$
 $P(R_{-}10 = F|u_{-}1:10) = 0.9430$
 $P(R_{-}10 = T|u_{-}1:10) = 0.9430$
 $P(R_{-}10 = T|u_{-}1:10) = 0.0570$
 $P(R_{-}10 = F|u_{-}1:10) = 0.9560$
 $P(R_{-}10 = T|u_{-}1:10) = 0.9570$
 $P(R_{-}10 = F|u_{-}1:10) = 0.9430$
 $P(R_{-}10 = T|u_{-}1:10) = 0.9430$
 $P(R_{-}10 = T|u_{-}1:10) = 0.9430$
 $P(R_{-}10 = T|u_{-}1:10) = 0.9530$
 $P(R_{-}10 = T|u_{-}1:10) = 0.9570$
 $P(R_{-}10 = F|u_{-}1:10) = 0.9300$
 $P(R_{-}10 = T|u_{-}1:10) = 0.9300$
 $P(R_{-}10 = T|u_{-}1:10) = 0.9430$
 $P(R_{-}10 = T|u_{-}1:10) = 0.9430$

```
P(R_10 = F|u_1:10) = 0.9330
```

After running 10 time, the varience of estimates is 0.00006 ii run python pfUmbrella.py 1000 10 0000000111

 $P(R_10 = T|u_1:10) = 0.8990$

 $P(R_10 = F|u_1:10) = 0.1010$

 $P(R_10 = T|u_1:10) = 0.8950$

 $P(R_10 = F|u_1:10) = 0.1050$

 $P(R_10 = T|u_1:10) = 0.8820$

 $P(R_10 = F|u_1:10) = 0.1180$

 $P(R_10 = T|u_1:10) = 0.8660$

 $P(R_10 = F|u_1:10) = 0.1340$

 $P(R_10 = T|u_1:10) = 0.8910$

 $P(R_10 = F|u_1:10) = 0.1090$

 $P(R_10 = T|u_1:10) = 0.8790$

 $P(R_10 = F|u_1:10) = 0.1210$

 $P(R_10 = T|u_1:10) = 0.8960$

 $P(R_10 = F|u_1:10) = 0.1040$

 $P(R_10 = T|u_1:10) = 0.9050$

 $P(R_10 = F|u_1:10) = 0.0950$

 $P(R_10 = T|u_1:10) = 0.9010$

 $P(R_10 = F|u_1:10) = 0.0990$

 $P(R_10 = T|u_1:10) = 0.8950$

 $P(R_10 = F|u_1:10) = 0.1050$

After running 10 time, the varience of estimates is 0.00013 iii run $python\ pfUmbrella.py\ 1000\ 10\ 0101010101$

 $P(R_10 = T|u_1:10) = 0.7540$

 $P(R_10 = F|u_1:10) = 0.2460$

 $P(R_10 = T|u_1:10) = 0.7160$

 $P(R_10 = F|u_1:10) = 0.2840$

 $P(R_10 = T|u_1:10) = 0.6940$

 $P(R_10 = F|u_1:10) = 0.3060$

```
P(R_{10} = T|u_{1}:10) = 0.6920
P(R_{10} = F|u_{1}:10) = 0.3080

P(R_{10} = T|u_{1}:10) = 0.7010
P(R_{10} = F|u_{1}:10) = 0.2990

P(R_{10} = T|u_{1}:10) = 0.7120
P(R_{10} = F|u_{1}:10) = 0.2880

P(R_{10} = T|u_{1}:10) = 0.6990
P(R_{10} = F|u_{1}:10) = 0.3010

P(R_{10} = T|u_{1}:10) = 0.7160
P(R_{10} = F|u_{1}:10) = 0.2840

P(R_{10} = T|u_{1}:10) = 0.7470
P(R_{10} = F|u_{1}:10) = 0.2530

P(R_{10} = T|u_{1}:10) = 0.7260
P(R_{10} = F|u_{1}:10) = 0.7260
P(R_{10} = F|u_{1}:10) = 0.7260
P(R_{10} = F|u_{1}:10) = 0.7260
```

After running 10 time, the varience of estimates is 0.00041

c. I have written a code to exactly calculate in DBN.

i run $python\ exactDBN.py\ 10\ 11111100000$

$$P(R_10 = T|u_1:10) = 0.0562$$

 $P(R_10 = F|u_1:10) = 0.9438$

ii run python exactDBN.py 10 0000000111

$$P(R_10 = T|u_1:10) = 0.8902$$

 $P(R_10 = F|u_1:10) = 0.1098$

iii run python exactDBN.py 10 0101010101

$$P(R_10 = T|u_1:10) = 0.7171$$

 $P(R_10 = F|u_1:10) = 0.2829$

compare the results with what we got in (a) and (b), it is safe to conclude that Particle Filtering is more accurate and stable than Likelihood Weight method, since it is more close to exact result and its variance is smaller.

Question 2

a.

• run python mdpVI.py -2

```
s = (1, 1) : U[s] = -10.8153, a = r

s = (1, 2) : U[s] = -9.5425, a = u

s = (1, 3) : U[s] = -7.0425, a = r
```

```
s = (2, 1) : U[s] = -8.4744, a = r
 s = (2, 3) : U[s] = -4.2300, a = r
 s = (3, 1) : U[s] = -5.9744, a = r
 s = (3, 2) : U[s] = -3.5704, a = r
 s = (3, 3) : U[s] = -1.7300, a = r
 s = (4, 1) : U[s] = -3.7749, a = u
 s = (4, 2) : U[s] = -1.0000, a = N
 s = (4, 3) : U[s] = 1.0000, a = N
• run python mdpVI.py -0.2
 s = (1, 1) : U[s] = -0.3273, a = u
 s = (1, 2) : U[s] = -0.0826, a = u
 s = (1, 3) : U[s] = 0.1674, a = r
 s = (2, 1) : U[s] = -0.2848, a = r
 s = (2, 3) : U[s] = 0.4486, a = r
 s = (3, 1) : U[s] = -0.0348, a = u
 s = (3, 2) : U[s] = 0.2877, a = u
 s = (3, 3) : U[s] = 0.6986, a = r
 s = (4, 1) : U[s] = -0.3642, a = 1
 s = (4, 2) : U[s] = -1.0000, a = N
 s = (4, 3) : U[s] = 1.0000, a = N
• run python mdpVI.py -0.01
 s = (1, 1) : U[s] = 0.9232, a = u
 s = (1, 2) : U[s] = 0.9372, a = u
 s = (1, 3) : U[s] = 0.9497, a = r
 s = (2, 1) : U[s] = 0.9107, a = 1
```

```
s = (1, 1) : U[s] = 0.9232 , a = u

s = (1, 2) : U[s] = 0.9372 , a = u

s = (1, 3) : U[s] = 0.9497 , a = r

s = (2, 1) : U[s] = 0.9107 , a = 1

s = (2, 3) : U[s] = 0.9638 , a = r

s = (3, 1) : U[s] = 0.8969 , a = 1

s = (3, 2) : U[s] = 0.8866 , a = 1

s = (3, 3) : U[s] = 0.9763 , a = r

s = (4, 1) : U[s] = 0.7969 , a = d

s = (4, 2) : U[s] = -1.0000 , a = N

s = (4, 3) : U[s] = 1.0000 , a = N
```

b.

• run python mdpPI.py -2

```
s = (1, 1) : U[s] = -10.8153 , a = r
s = (1, 2) : U[s] = -9.5425 , a = u
s = (1, 3) : U[s] = -7.0425 , a = r
s = (2, 1) : U[s] = -8.4744 , a = r
s = (2, 3) : U[s] = -4.2300 , a = r
s = (3, 1) : U[s] = -5.9744 , a = r
s = (3, 2) : U[s] = -3.5704 , a = r
s = (3, 3) : U[s] = -1.7300 , a = r
s = (4, 1) : U[s] = -3.7749 , a = u
s = (4, 2) : U[s] = -1.0000 , a = N
```

$$s = (4, 3) : U[s] = 1.0000$$
, $a = N$

• run python mdpPI.py -0.2

• run python mdpPI.py -0.01

```
s = (1, 1) : U[s] = 0.9232 , a = u

s = (1, 2) : U[s] = 0.9372 , a = u

s = (1, 3) : U[s] = 0.9497 , a = r

s = (2, 1) : U[s] = 0.9107 , a = 1

s = (2, 3) : U[s] = 0.9638 , a = r

s = (3, 1) : U[s] = 0.8969 , a = 1

s = (3, 2) : U[s] = 0.8866 , a = 1

s = (3, 3) : U[s] = 0.9763 , a = r

s = (4, 1) : U[s] = 0.7969 , a = d

s = (4, 2) : U[s] = -1.0000 , a = N

s = (4, 3) : U[s] = 1.0000 , a = N
```

It can be seen that mdpPI.py and mdpVI.py give exactly the same solution.

Question 3

Using the idea of Dynamical Programming, we can efficiently compute $argmax_{x_1,\dots,x_{100}}f(x)$ let

(1)
$$V(j, x_1, x_{j+1}, x_{j+2}) = \max_{x_2, x_3, \dots, x_j} \phi_1(x_1, x_2, x_3) \phi_1 \dots \phi_{j-1} \phi_j(x_j, x_{j+1}, x_{j+2})$$

then we have

(2)
$$V(j+1, x_1, x_{j+2}, x_{j+3}) = \max_{x_{j+1}} V(j, x_1, x_{j+1}, x_{j+2}) \phi_{j+1}(x_{j+1}, x_{j+2}, x_{j+3})$$

SO

(3)
$$f(x) = \max_{x_1, x_{99}, x_{100}} \phi_0(x_1, x_{100}) V(98, x_1, x_{99}, x_{100})$$

since we are asked to compute $argmax_{x_1,\dots,x_{100}}f(x)$, we just need to record where V comes from, to be concrete, let

(4)
$$record(j+1, x_1, x_{j+2}, x_{j+3}) = argmax_{x_{j+1}}V(j, x_1, x_{j+1}, x_{j+2})\phi_{j+1}(x_{j+1}, x_{j+2}, x_{j+3})$$

thus we can construct the set $\{x_1, x_2, \dots, x_{100}\}$ from the array record.

Anaysis:

(2) requires O(1), there are 100×2^3 states, thus total time complexity would be $O(100 \times 2^3)$

Question 4

a. proof:

We have

$$\sum_{k} P(E_j = e_{jk}|E)EU(\alpha|E, E_j = e_{jk}) = EU(\alpha|E)$$

By definition,

$$EU(\alpha_{e_{jk}}|E, E_j = e_{jk}) \ge EU(\alpha|E, E_j = e_{jk})$$

Combine those facts, we have

$$VPI_{E}(E_{j}) = \left(\sum_{k} P(E_{j} = e_{jk}|E)EU(\alpha_{e_{jk}}|E, E_{j} = e_{jk})\right) - EU(\alpha|E)$$

$$\geq \left(\sum_{k} P(E_{j} = e_{jk}|E)EU(\alpha|E, E_{j} = e_{jk})\right) - EU(\alpha|E)$$

$$= 0$$

b. To simplify the notation, denote $\text{VPI}_E(E_j) = V_E(E_j) - EU(\alpha|E)$, thus $V_E(E_j) = \sum_{e_{jn}} P(E_j = e_{jn}|E) EU(\alpha_{jn}|E, E_j = e_{jn})$, by this definition, $EU(\alpha|E) = V_E()$. Now,

(5)
$$VPI_E(E_j, E_k) = V_E(E_j, E_k) - V_E()$$

Note

$$V_E(E_j) = \sum_{e_{jn}} P(E_j = e_{jn}|E) EU(\alpha_{jn}|E, E_j = e_{jn}) = \sum_{e_{jn}} P(E_j = e_{jn}|E) V_{E, E_j = e_{jn}}()$$

similarly, we have

$$V_E(E_j, E_k) = \sum_{e_{jn}} P(E_j = e_{jn}|E) V_{E, E_j = e_{jn}}(E_k)$$

Note that

$$(5) = \left(V_{E}(E_{j}, E_{k}) - V_{E}(E_{j})\right) + \left(V_{E}(E_{j}) - V_{E}(t)\right)$$

$$= \sum_{e_{jn}} P(E_{j} = e_{jn}|E) \left(V_{E, E_{j} = e_{jn}}(E_{k}) - V_{E, E_{j} = e_{jn}}(t)\right) + \text{VPI}_{E}(E_{j})$$

$$= \sum_{e_{jn}} P(E_{j} = e_{jn}|E) \text{VPI}_{E, E_{j} = e_{jn}}(E_{k}) + \text{VPI}_{E}(E_{j})$$

$$= \text{VPI}_{E, E_{j}}(E_{k}) + \text{VPI}_{E}(E_{j})$$

since we have

$$(5) = \left(V_E(E_k, E_j) - V_E(E_k)\right) + \left(V_E(E_k) - V_E()\right)$$

We can similarly prove

$$(5) = VPI_{E,E_k}(E_j) + VPI_E(E_k)$$

Thus we have got what we want.