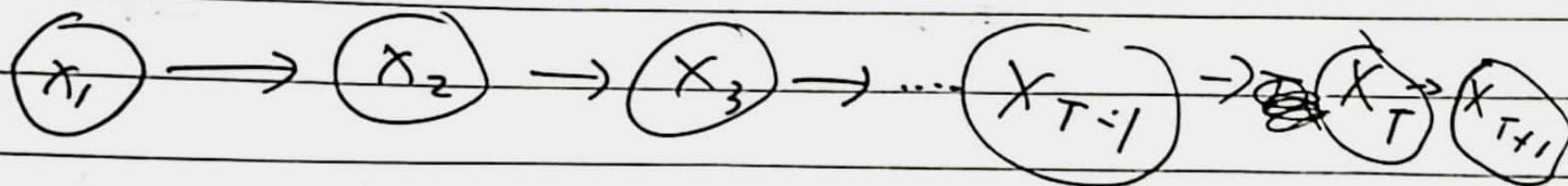


PAGE NO.	
DATE	/ /

250A H.W. 3

(Q.3.1) $A_{ij} = P(x_{t+1}=j \mid x_t=i)$



$$P(x_{t+1}=j \mid x_{t_1}=i) = [A^t]_{i,j}$$

j) Given $[A]_{ij} = P(x_{t+1} = j | x_t = i)$

If $t=1$,

$$P(x_2 = j | x_1 = i) = [A]_{ij}$$

Now, Assuming when $t=t$,

$$P(x_{t+1} = j | x_t = i) = [A^t]_{ij}$$

We should prove that, at $t=t+1$,

$$P(x_{t+2} = j | x_1 = i) = [A^{t+1}]_{ij}$$

LHS

$$P(X_{t+2} = j | X_1 = i) \quad \text{Ansatz}$$

$$= \sum_a P(X_{t+2} = j, X_{t+1} = a | X_1 = i)$$

∴ Marginalizaⁿ

$$= \sum_a P(X_{t+1} = a | X_1 = i) \cdot P(X_{t+2} = j | X_{t+1} = a, X_1 = i)$$

∴ Prod. rule

Now $X_1 = i \perp X_{t+2}$

given X_{t+1}

of d(i).

$$\therefore \sum_a P(X_{t+1} = a | X_1 = i) \cdot P(X_{t+2} = j | X_{t+1} = a)$$

$$= \sum_a [A^t]_{ia} \times [A]_{aj}$$

$$\left[[A]^t_{i1}, [A]^t_{i2}, [A]^t_{i3}, \dots, [A]^t_{in} \right]$$

$$[A]^t_{ij}$$

$$\begin{bmatrix} [A]_{1j} \\ [A]_{2j} \\ \vdots \\ [A]_{nj} \end{bmatrix}$$

$$= [A]^t_{ij} \times [A]_{ij} \rightarrow (A)^t_{ij}$$

$$= [A^{t+1}]_{ij} = RHS$$

(HP)

(Q 3.1)

b) We need to find $[A^\pm]_{ij}$.

which is a single element of the Matrix A^\pm .

\therefore Consider,

Step 1:-

i th

$$\begin{bmatrix} & & \end{bmatrix} \begin{bmatrix} & & \end{bmatrix} \begin{bmatrix} & & \end{bmatrix}$$

A_0

\times

$A \times A$

~~\dots~~

$t-1$ times.

We multiply the i th row $t-2$ times with matrix
 $\overset{\text{"A."}}{A}$.

$$TC = n^2(t-2) = n^2 t$$

Step 2:-

$$[\quad] \times \left[\begin{array}{c} [] \\ [] \\ [] \end{array} \right]$$

result of
step 1

j th row.

Now we multiply the result of step 1 into the *j* th ~~row~~ column of $M \times A$.

$$TC = n^2$$

* This will result in the one of a single element that will be $[A^T]_{i,j}$

\Rightarrow To summarize :

$$(A_i \times A \text{ (t-2) times}) \times A_j = [A^T]_{i,j}$$

$$\begin{aligned} TC &= n^2 t + n \\ &= n^2 t \\ &= n^2 t \end{aligned}$$

Q) 3.1 c)

We know that,

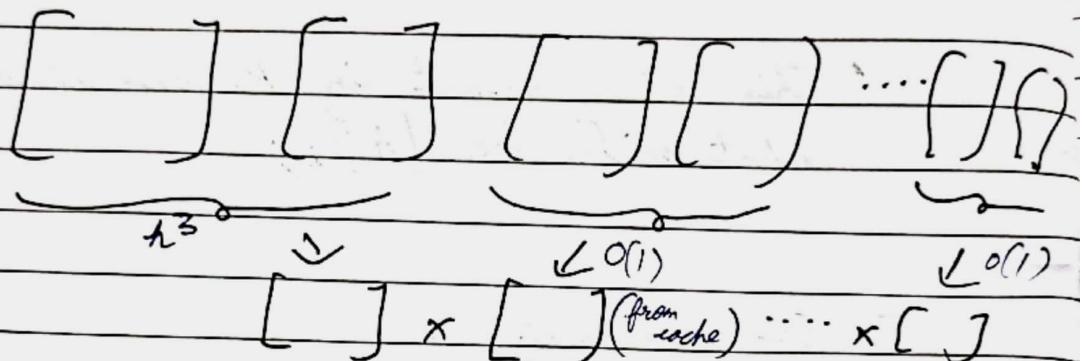
Matrix \times Matrix

$$TC = n^3$$

Now we have to multiply t matrices.

We can use a cache based system to drop the TC from $n^3 t$ to $n^3 \log_2 t$.

iP.



Base Case:-

$$\begin{matrix} [] & \times & [] \\ & & n^3 \end{matrix}$$

\therefore we took $\log_2(t)$ times instead t .

$$\begin{aligned} \therefore TC &= n^3 \log_2 t \\ &= m^3 \log_2 t \end{aligned}$$

d) we get from 3.1 b)

TC to find $(A^T)_{i,j} = m^2 t$.

~~In b)'s step 1~~

In b)'s step 1 while multiplying the i^{th} row we can skip all the 0's columns while multiplying with the matrix.

$$\text{Hence } TC = t(m \times 2 + m \times 0(1))$$

$$= mat + ma \\ = mat$$

\curvearrowleft skipping

Following the step 2 as is,

we get the total,

$$TC = mat$$

$$= smt //$$

HP

e)

$$P(x_1 = i \mid x_{T+1} = j)$$

$$= \frac{P(x_{T+1} = j \mid x_1 = i) P(x_1 = i)}{P(x_{T+1} = j)}$$

 \therefore Bayes Rule

$$= \frac{[A^T]_{ij} \times P(x_1 = i)}{\sum_x P(x_{T+1} = j, x_1 = x)}$$

 \therefore Marginalizing

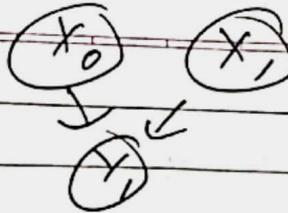
$$= \frac{[A^T]_{ij} \times P(x_1 = i)}{\sum_x P(x_{T+1} = j \mid x_1 = x) \times P(x_1 = x)}$$

 \therefore Prod-rule

$$= \frac{[A^T]_{ij} P(x_1 = i)}{\sum_x [A^T]_{xj} P(x_1 = x)}$$

//

3.2



~~a)~~ In the CPT we would have $P(Y, | X_0, X_1)$
to find,

$$P(Y, | X_1)$$

$$= \sum_{X_0} P(Y, | X_0 = x_0, X_1) \quad \because \text{Marginaliz?}$$

$$= \sum_{x_0} P(X_0 = x_0 | X_1) P(Y, | X_0 = x_0, X_1) \quad \because \text{Prod rule}$$

$$= \sum_{x_0} P(X_0 = x_0) P(Y, | X_0 = x_0, X_1) \quad \because \text{Marginally ind.}$$

b) To find $P(Y_1)$,

$$= \sum_{x_0} \sum_{x_1} P(X_0 = x_0, X_1 = x_1, Y_1) \quad \because \text{Marginaliz?}$$

$$= \sum_{x_0} \sum_{x_1} P(X_0 = x_0) P(X_1 = x_1) P(Y_1, | X_0 = x_0, X_1 = x_1) \quad \because \text{Prod rule.} \quad \because \text{Marginally ind.}$$

c) To find $P(X_0 | Y_1, Y_2, \dots, Y_{n-1})$

$$= P(X_0) \quad \because \text{Given } E = \{Y_1, Y_2, \dots, Y_{n-1}\},$$

it is ~~II~~ at Y_n by
d (iii),

$$d) P(Y_n | X_0, Y_1, Y_2, \dots, Y_{n-1})$$

$$= \sum_x P(Y_n, X_{n-1}=x | X_0, Y_1, Y_2, \dots, Y_{n-1})$$

: Marginaliz^

$$= \sum_x P(X_{n-1}=x | X_0, Y_1, \dots, Y_{n-1}) P(P(Y_n | X_{n-1}=x, X_0, Y_1, \dots, Y_{n-1}))$$

: Prod. rule

$$= \sum_x P(X_{n-1}=x | Y_1, \dots, Y_{n-1}) \times P(Y_n | X_{n-1}=x, X_n)$$

: Given $\{Y_1, \dots, Y_{n-1}\}$,

$$X_{n-1}=x \perp\!\!\!\perp X_n$$

By d(iii)

: Given X_{n-1} ,

$$Y_n \perp\!\!\!\perp Y_1, \dots, Y_{n-1}$$

By d(ii)

(Q. 3-2) e)

$$P(Y_n | Y_1, Y_2 \dots Y_{n-1})$$

$$= \sum_{x_1} \sum_{x_n} P(Y_n, X_{n-1}=x_1, X_n=x_n | Y_1 \dots Y_{n-1})$$

∴ Marginalize

$$\cancel{= \sum_{x_1} \sum_{x_n} P(X_n=x_1 | Y_1 \dots Y_{n-1}) P(Y_n | X_{n-1}=x_1, Y_1 \dots Y_{n-1})} \\ \times \cancel{P(X_{n-1}=x_1 | X_n=x_n, Y_1 \dots Y_{n-1})}$$

$$= \sum_{x_1} \sum_{x_n} P(X_n=x_1)$$

By Prod. rule :-

$$= \sum_{x_1} \sum_{x_n} P(X_n=x_1 | Y_1 \dots Y_{n-1}) P(X_{n-1}=x_1 | X_n=x_n, Y_1 \dots Y_{n-1}) \\ \times P(Y_n | X_n=x_n, X_{n-1}=x_1, Y_1 \dots Y_{n-1})$$

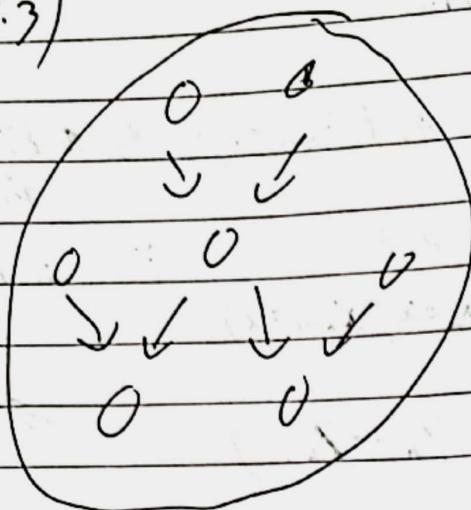
$$= \sum_{x_1} \sum_{x_n} P(X_n=x_1) P(X_{n-1}=x_1 | Y_1 \dots Y_{n-1}) \\ \times P(Y_n | X_n=x_1, X_{n-1}=x_1)$$

↓
∴ d(iii)

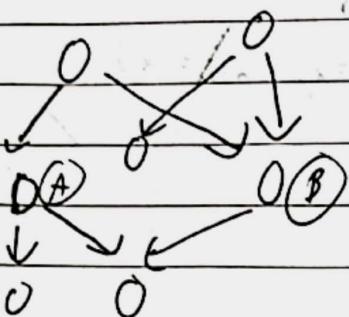
↓
d(ii)

↑
d(i)
//

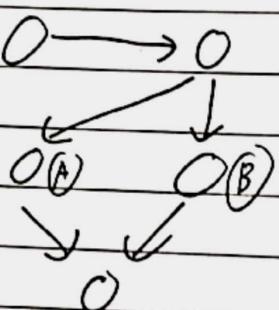
3.3)



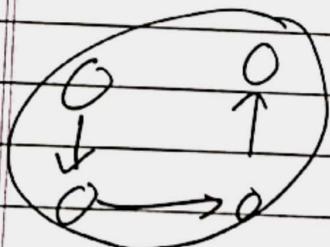
polytree ✓



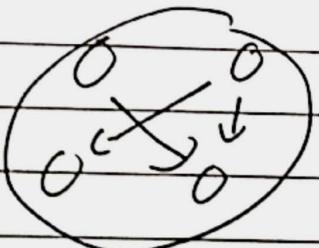
Node A & B can be clustered
to make polytree.



Node A & B can be clustered
to make PT.



polytree ✓

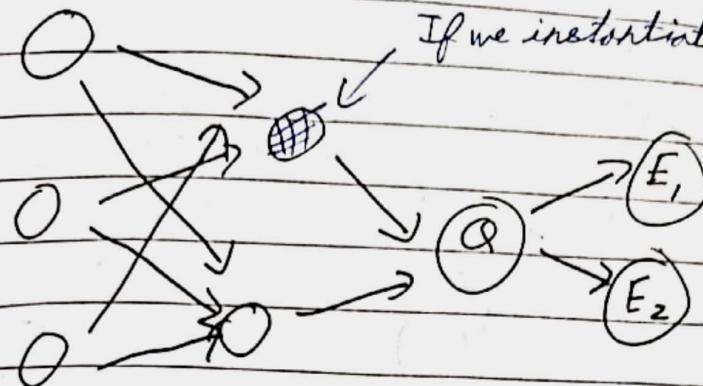


polytree ✓

11

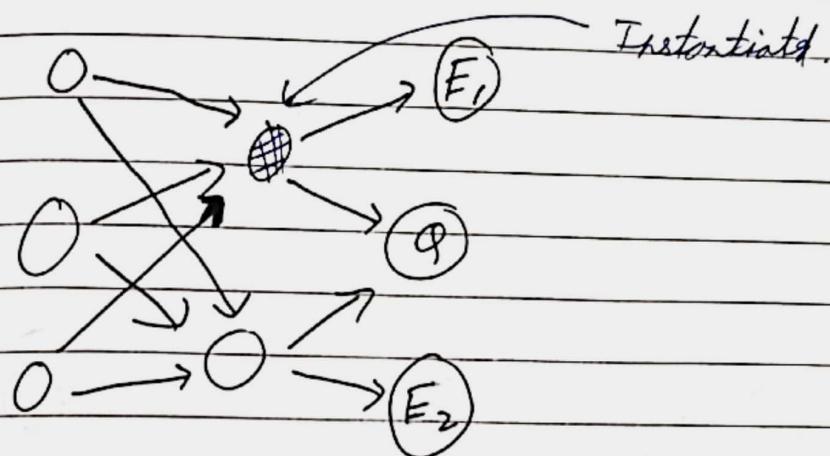
Q. 3.4)

1)



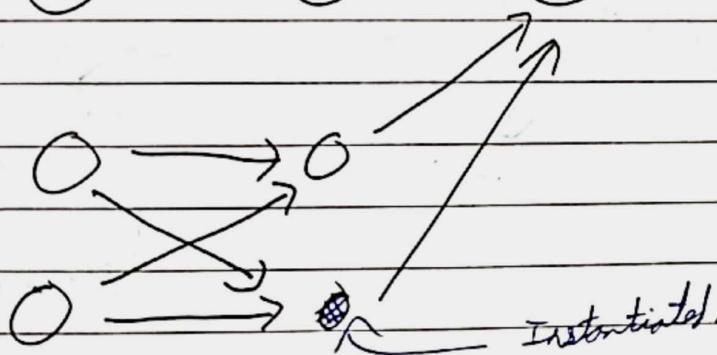
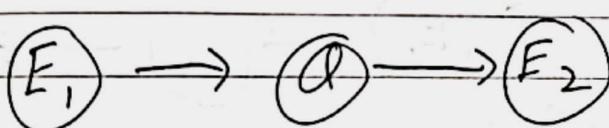
If we instantiate this, we get a polyglot.

2)



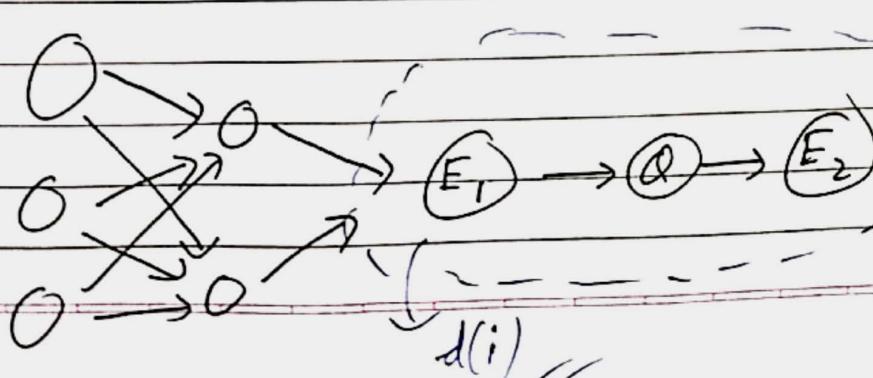
Instantiated.

3)



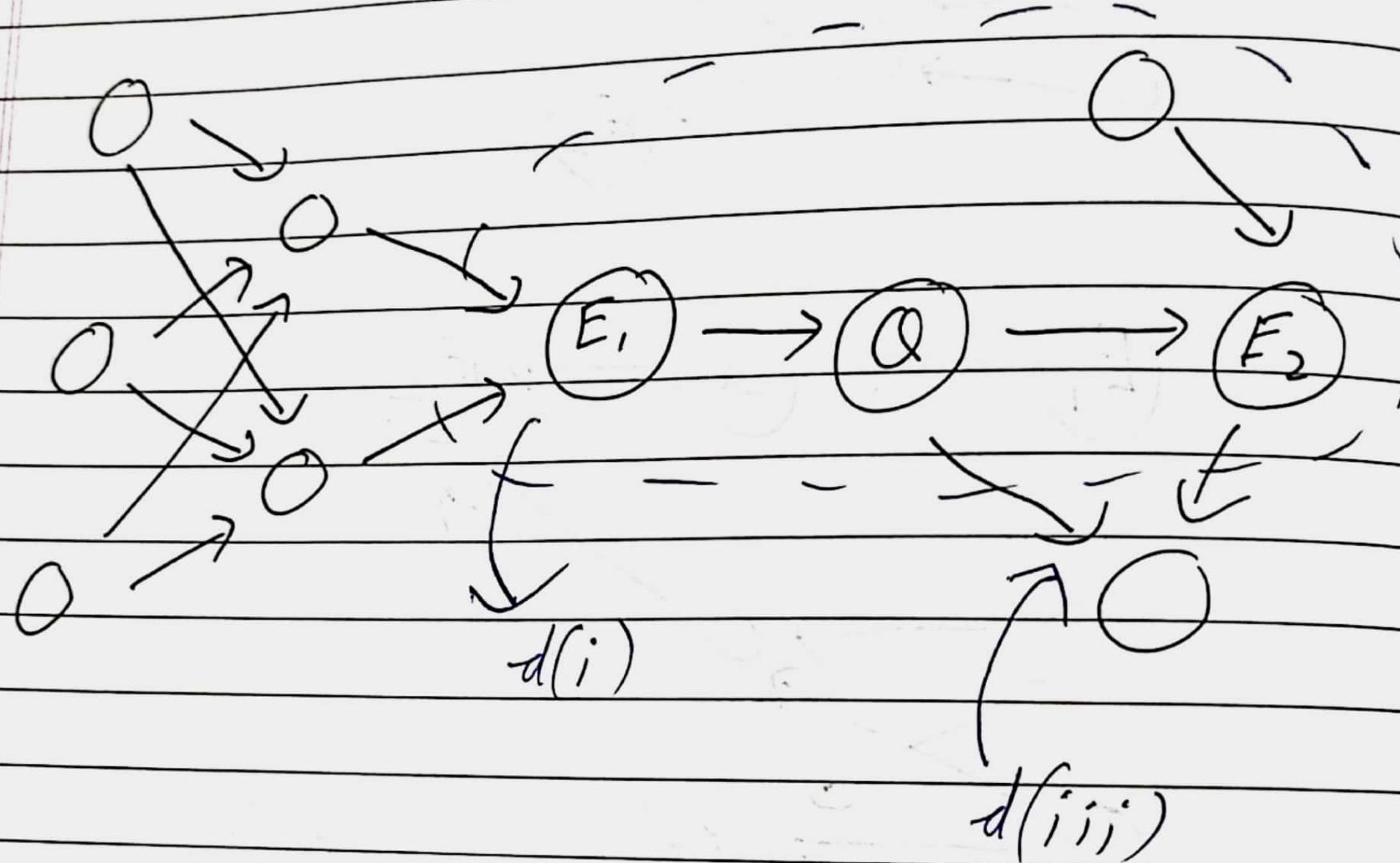
Instantiated.

4)



$d(i)$

s)



(2.3.5)

$$P(Z | B_1, B_2, \dots, B_n) = \left(\frac{1-\alpha}{1+\alpha} \right)^\alpha \quad | Z = f(B)$$

$$P(B_i = 1) = \frac{1}{2}$$

$$f(B) = \sum_{i=1}^n 2^{i-1} B_i$$

1)

$$\sum_{z=-\infty}^{\infty} P(Z=z | B_1, B_2, \dots, B_n) = 1$$

$$= \sum_{z=-\infty}^{\infty} \left(\frac{1-\alpha}{1+\alpha} \right)^\alpha \alpha^{|Z=z-f(B)|}$$

$$K = Z = z - f(B)$$

$$\text{When } 1) Z = -\infty$$

$$K \rightarrow -\infty$$

$$2) Z = \infty$$

$$\therefore = \sum_{K=0}^{\infty} \left(\frac{1-\alpha}{1+\alpha} \right)^\alpha \alpha^{|K|} \quad K \rightarrow +\infty$$

$$= \frac{1-\alpha}{1+\alpha} \left(\alpha^{|K=0|} + 2 \sum_{k=1}^{\infty} \alpha^k \right)$$

$$= \frac{1-\alpha}{1+\alpha} \left(1 + 2 \left(\frac{1}{1-\alpha} - \alpha^{|K=0|} \right) \right)$$

$$\therefore \sum_{i=0}^{\infty} \alpha^i = \frac{1}{1-\alpha}$$

$$= \frac{1-\alpha}{1+\alpha} \left(1 + \frac{2}{1-\alpha} - 2 \right)$$

$$= \cancel{\frac{1-\alpha}{1+\alpha}} \left(\cancel{1-\alpha} + \cancel{2} - \cancel{2} + \cancel{\frac{2\alpha}{1-\alpha}} \right)$$

$$= \frac{1+\alpha}{1-\alpha} = 1$$

//

HP

3.5)

$$\text{a)} \quad n = 10 \quad I = [2, 5, 8, 10] \\ \alpha = 0.1$$

For K samples,

$$P(B_{i,t} = 1 | Z = 128)$$

$$\approx \sum_{t=1}^K I(b_{i,t}, 1) P(Z = 128 | B_1 = b_{1,t}, \dots, B_{10} = b_{10,t})$$

$$\frac{\sum_{t=1}^K P(Z = 128 | B_1 = b_{1,t}, \dots, B_{10} = b_{10,t})}{\sum_{t=1}^K}$$

$$= \sum_{t=1}^K I(b_{i,t}, 1) \left(\frac{1-\alpha}{1+\alpha} \right)^{128 - \sum_{n=1}^{10} 2^{n-1} B_{n,t}}$$

$$\frac{\sum_{t=1}^K \left(\frac{1-\alpha}{1+\alpha} \right)^{128 - \sum_{n=1}^{10} 2^{n-1} B_{n,t}}}{\sum_{t=1}^K}$$

$$= \sum_{t=1}^K I(b_{i,t}, 1) \times 0.1 \frac{|128 - \sum_{n=1}^{10} 2^{n-1} B_{n,t}|}{\sum_{t=1}^K 0.1 |128 - \sum_{n=1}^{10} 2^{n-1} B_{n,t}|}$$

//
P.T.O

DATE

///



Ans from code:-

Bit# prob.

"2": 0.10408707182850167

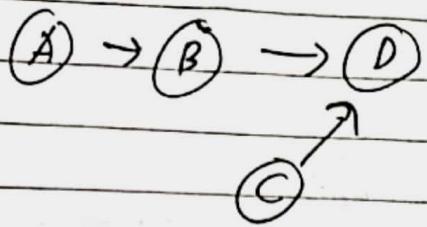
"5": 0.0895519134875286

"8": 0.9109719376915066

"10": 0.0

//

Q) 3.6) a)



$$P(B|A, C, D)$$

$$= \frac{P(A, B, C, D)}{P(A) P(B|A) P(C|B, A) P(D|C)}$$

$$= \frac{P(A, B, C, D)}{P(A) P(C|A) P(D|A, C)} \quad : \text{Prod. Rule}$$

$$= \frac{P(A) P(B|A) P(C|A, B) P(D|A, B, C)}{P(A) P(C|A) P(D|A, C)} \quad : P(C|AB) \& P(A) = P(C)$$

$$= \frac{P(B|A) P(C) P(D|B, C)}{P(C) P(D|A, C)} \quad \text{By d(iii)}$$

$$\therefore P(D|ABC) = P(D|BC)$$

By d(i)

$$= \frac{P(B|A) P(D|B, C)}{\sum_b P(B=b|A, C)} \quad : \text{Marginaliz.}$$

$$= \frac{P(B|A) P(D|B, C)}{\sum_b P(B=b|AC) P(D|A, B=b, C)} \quad : \text{Prod. Rule}$$

$$= \frac{P(B|A) P(D|B, C)}{\sum_b P(B=b|A) P(D|B=b, C)}$$

$$\therefore P(D|A, B=b, C) = P(D|B, C)$$

By d(i)

$$\& P(B=b|AC) = P(B=b|A)$$

By d(iii)

$$b) P(B | A, C, D, E, F)$$

$$= P(B | A, C, D, E) \quad \begin{matrix} CDE \\ \therefore P(B | A, F) = P(B | A) \\ \text{by d(ii)} \end{matrix}$$

$$= P(B | A, C, D) \quad \begin{matrix} CDE \\ \therefore P(B | A, C, D) = P(B | A, C, D) \\ \text{by d(ii)} \end{matrix}$$

= Ans of (a)

//

$$c) P(B, E, F | A, C, D)$$

$$= P(E, F | A, C, D) P(B | A, B, C, D, E, F) \quad \begin{matrix} \downarrow \\ \text{in (b)} \end{matrix} \quad \begin{matrix} \text{Prod rule} \\ \therefore \text{by d(iii)} \end{matrix}$$

$$= P(E, F | A, C) \times (b)$$

$$= P(F | A, C) P(E | F, A, C) \times (b)$$

\therefore Prod rule.

$$= P(F | A) P(E | C) (b)$$

\therefore by d(ii)

//

//

3.7) More likelihood weighting:-

a) Single node of evidence.

$$P(\alpha = q_1 \mid E = e)$$

$$= \sum_{i=1}^n I(\alpha, q_i) P(E = e \mid Y = y_i, Z = z_i)$$

$$\sum_{i=1}^n P(E = e \mid Y = y_i, Z = z_i)$$

; from Likelihood formula.

b)

~~I(\alpha, q_i)~~

$$h) \sum_{t=1}^n P(E_1 = e_1 | Q_1 = q_1 t, X = xt) \\ \times P(E_2 = e_2 | E_1 = e_1, Z = zt)$$

$$\hat{\sum}_{t=1}^n P(E_1 = e_1 | Q_1 = q_1 t, X = xt) \\ \times P(E_2 = e_2 | E_1 = e_1, Z = zt)$$

\therefore from likelihood formula for multiple nodes.

```

from random import randint
import numpy as np
import math
from matplotlib import pyplot as plt

N = 10 # number of bits
alpha = 0.1
I = [2,5,8,10]
S = 1000000 # samples

probForEachSample = np.zeros((len(I),S))
# probForEachSample=[]

for i in range(len(I)):
    tmpNum = 0.0
    tmpDen = 0.0
    for s in range(1,S+1):
        B = []
        for b in range(1,N+1): # random bits for this sample
            B.append(randint(0,1))
        Indicator = int(B[I[i]-1] == 1)

        tmp = 0
        for b in range(1,N+1):
            tmp+=((pow(2,(b-1)))*B[b-1])
        # print(s,tmp)
        tmp = 128 - tmp
        # print(s,tmp)
        # print("abs",abs(tmp))
        secondTerm = pow(alpha,abs(tmp))
        # print(s,"secondTerm",secondTerm)
        tmpNum += (Indicator*secondTerm)
        tmpDen += secondTerm
        # print(tmpNum,tmpDen)
        if tmpDen == 0:
            if s==1:
                probForEachSample[i,s-1] = 0
            else:
                probForEachSample[i,s-1] = probForEachSample[i,s-2]
        else:
            probForEachSample[i,s-1] = tmpNum/tmpDen
    # probForEachSample.append(tmpNum/tmpDen)

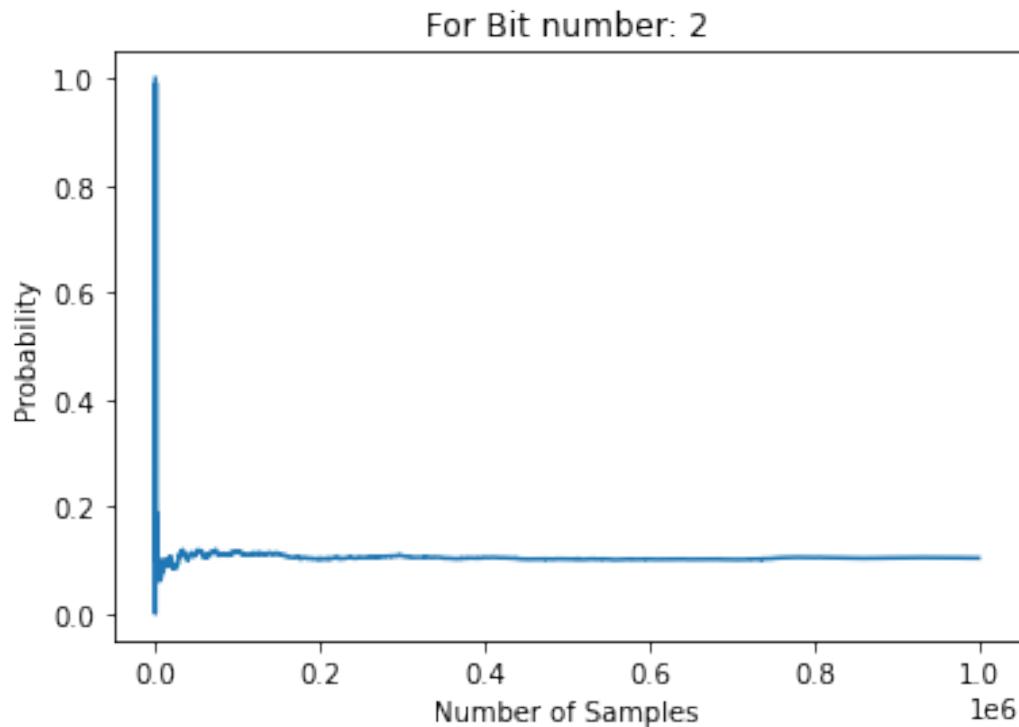
print("Finals Answers:")
for i in range(len(I)):
    print(I[i]," : ",probForEachSample[i,S-1])

Finals Answers:
2 : 0.10408707182850167
5 : 0.0895519134875286

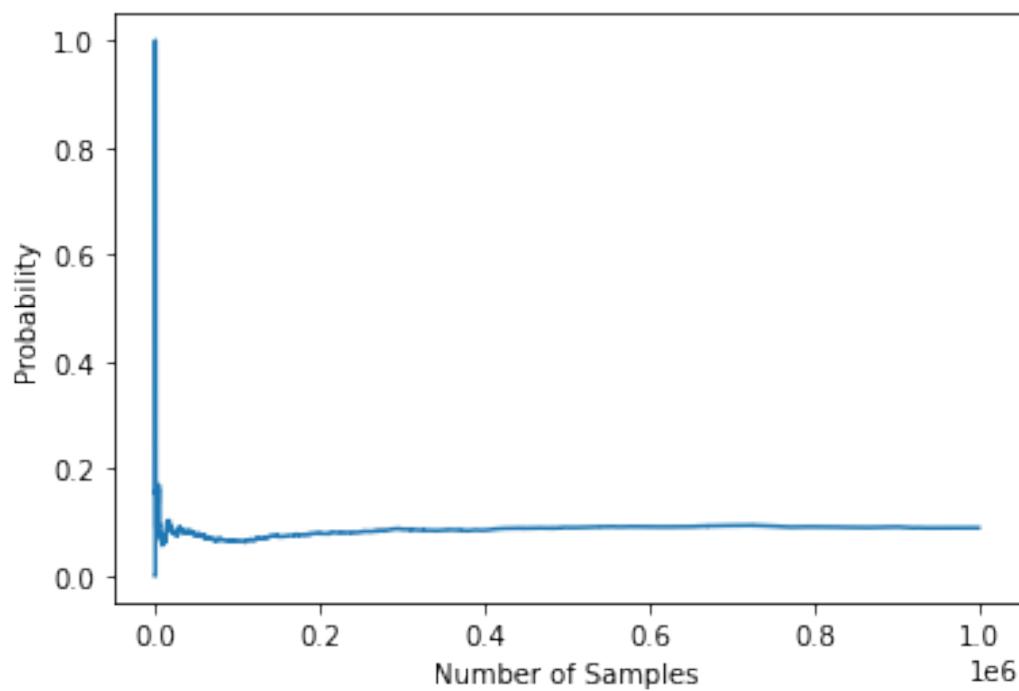
```

```
8 : 0.9109719376915066
10 : 0.0

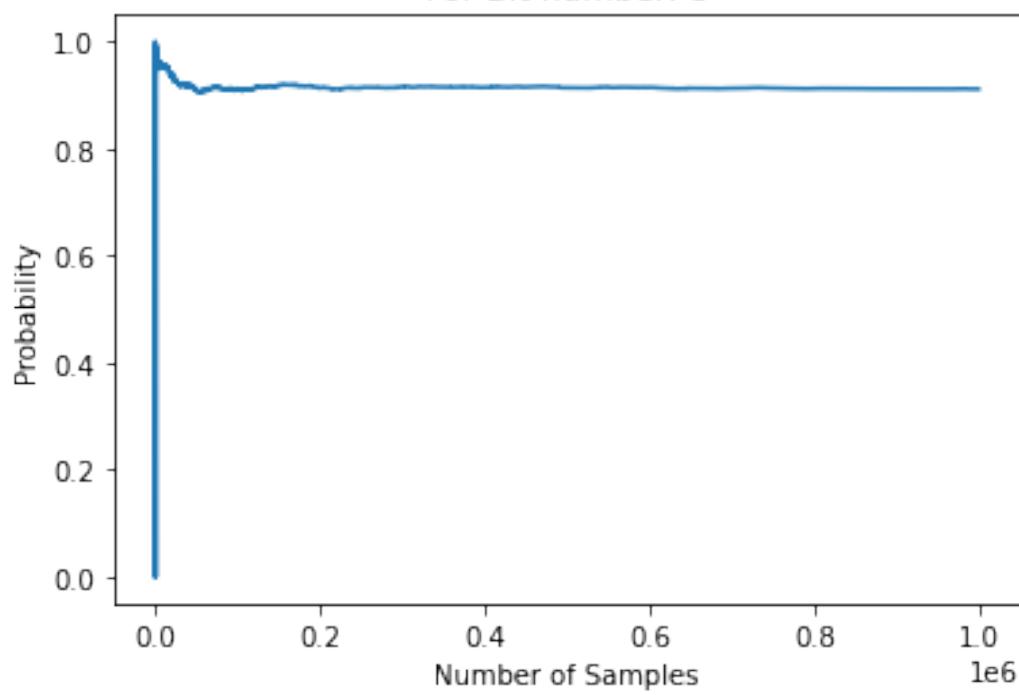
# Printing graph
for i in range(len(I)):
    plt.plot(range(1,S+1),probForEachSample[i])
    plt.title("For Bit number: "+str(I[i]))
    plt.xlabel('Number of Samples')
    plt.ylabel('Probability')
    plt.show()
```



For Bit number: 5



For Bit number: 8



For Bit number: 10

