$$QI. P(\pi_{3} = 'R' \mid X) = P(x_{1}x_{1}x_{2}, A, \pi_{3} = x_{2}) \cdot P(x_{1}x_{2}, \pi_{3} = x_{2}) \cdot g_{2}(t) \cdot g_{2}(t)$$

$$F(x) \qquad f_{1}(x) \cdot f_{1}(x) \cdot f_{2}(x) \cdot f_{3}(x) \cdot f_{3}(x) \cdot g_{3}(t) \cdot g_{3}($$

```
f_{1}(4) = .91 \cdot [.01875.90 + 6.857e^{-3} \cdot .25] = 0.01692
 f_{v}(4) = .25 \cdot [.01875 \cdot .10 + 6.857e^{-3} \cdot .75] = 1.754 \cdot 10^{-3}
 fr(5) = .91.[.01692.90+1.754e-3.25] = 0.01426
 Fr (5) .25 01.754 -10+
fu(5)=.25[.01692.10+1.754=1.75]=7.519.10-4
                    - REVERSE
9 (4) = ( E (A) 9 (F) + 90.
gr(4) = tpaen(A)gr(5) + tpuev(A)gv(5) = .90..91./+.10.25./=0.844
9,(4)=type,(A)g,(s) + type,(A)g,(5)=.25.91.1+.75.25.1=0.415
9 (3) = t pr e (A) g (4) + t e v e v (A) g v (4) = .90. 91.0.844 + .10.25.415 = 0.7016
9v(3)=tvae(A)g,(4)+tvvev(A)gv(4)=.25.91.0.844+75.25.415=0.2698
```

```
QZ: 24, 33, 42, 30, 44, 58, 27, 39, 47, 51
          FOR ISMONIAL PICTRIBUTION:
          E(x) = np
P(x = k | \mathbf{G}) = \binom{n}{k} \Theta^{k} (1 - \Theta)^{n-k}
                                                                                                                                                                                              WE COULD ALSO USE
         1. METHOD OF MOMENTS:
                                                                                                                                                                                      - 0= np(1-p)
But we won'T ...
                  \mathcal{J} = \frac{\mu_{\chi}}{n} = \frac{(24+37+42+30+44+38+27+39+47+51)}{10} \cdot \frac{1}{1000} = 0.0375
          2. LEAST SQUARES
           SS = (24 - n\theta)^{2} + (33 - n\theta)^{2} + (42 - n\theta)^{2} + \dots + (51 - n\theta)^{2}
           \frac{dSS}{d\theta} = -2n(24-0) - 2n(33-0) - 2n(42-n\theta) + ... + 2n(51-n\theta) = 0 \qquad P - 2n
= 24 - n\theta + 33 - n\theta + ... + S1 - n\theta \implies \theta = \frac{24+33+...+51}{10n} = \frac{375}{(0.000)} = \frac{375}{0.000}
3. Maximum [IKEZIHOZO]

P(D|B) = \theta^{24} (1-\theta)^{976} \cdot \theta^{35} (1-\theta)^{467}
= \theta^{100} (1-\theta)^{9625} (000) \text{ (1000)} \text{ (244) Community: } (k) = \frac{N!}{k! (n-k)!}
P(D|B) = \frac{1000!}{24! 976!} \cdot \theta^{24} (1-\theta)^{976} \cdot \frac{1000!}{33! 967!} \theta^{33} (1-\theta)^{967}
P(D|B) = \begin{pmatrix} \text{Super} \\ \text{MESSY Constant} \end{pmatrix} \cdot \theta^{375} (1-\theta)^{9625}
P(D|B) = \begin{pmatrix} \text{Super} \\ \text{MESSY Constant} \end{pmatrix} \cdot \theta^{375} (1-\theta)^{9625}
P(D|B) = \begin{pmatrix} \text{Super} \\ \text{MESSY Constant} \end{pmatrix} \cdot \theta^{375} (1-\theta)^{9625}
P(D|B) = \begin{pmatrix} \text{Super} \\ \text{MESSY Constant} \end{pmatrix} \cdot \theta^{375} (1-\theta)^{9625}

\ln \left[ P(D(\Theta)) \right] = \ln C + 375 \ln \Theta + 9625 \ln (1-\Theta)

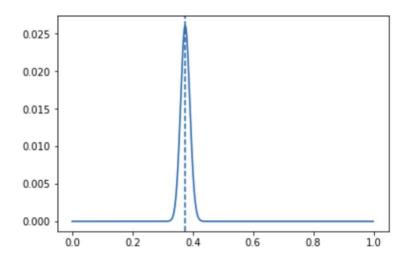
\frac{d}{d\theta} \ln \left[ L(x) \right] = \frac{1}{4} \frac{375}{6} + \frac{9625}{1-6} \frac{375 - 3750 - 96250}{6(1-\Theta)} = 0

= \frac{575(1-\Theta)}{6(1-\Theta)} + \frac{-9625\Theta}{6(1-\Theta)} = \frac{375 - 3750 - 96250}{6(1-\Theta)} = 0

                                                                                                                                                                                                   SET dL=0
                                                                                                          - 100000 = - 375
                                                                                                                   G = 375 = [.0375]
```

Bayesian method probability distribution:

0.375



```
#! /usr/bin/env python
\#\# Code for generating plot above and MAP estimate:
import numpy as np
from matplotlib import pyplot as plt
def theta likelihood(thet):
    likel\overline{i}hood = np.power(thet, 375) * np.power(1-thet, 625)
    return likelihood
thet_values = np.arange(0,1,.001)
pdf_values = np.zeros_like(thet_values)
for n in range(len(thet values)):
    thet = thet_values[n]
    pdf values[n] = theta likelihood(thet)
pdf_values = pdf_values / sum(pdf_values)
map_estimate = thet_values[np.argmax(pdf_values)]
print(map_estimate)
#print(pdf_values)
plt.plot(thet values, pdf values)
plt.axvline(map_estimate,linestyle='dashed')
plt.show()
```

	4. BAYESIAN METHOD
	ASSUME WIFORM DISTRIBUTED [
	$P(\theta D) = \frac{P(D \theta)P(\theta)}{P(D \theta)P(\theta)D(\theta)}$
	= SP(DlO)P(O)do P(DlO) LET C = SP(DlO)P(O)do
	$=C \cdot P(D G)$
	= C2 · O 375 (1-0) 9625 LET C2 = SP(DIO) PRO) do)
	P(0)= 1 EVENTUMENE
	Q3.
	SI-AGCTA A CGT ANCESTAL PROSS
	52-ACCGA A .85 .05 .05 P(A)=P(C)=P(G)=P(T)=0.25
	K=2 F. C .05 .85 .05 .05
	9 .05 .05 .85 .05 4 PROBABILITIES FOR SUSSTIRMON
	T .05 .05 05 -85 AFTER 1 THA ASIFTON (GENERATION)
	1: P(Anal An) · P(An) + P(Anala) · P(C) · P(Anal Ga) · P(Ga) + P(Anal Ta) - P(E)
i	$P(A \cap A \mid A_a) = P(A_{s_1} \mid A_a) \cdot P(A_{s_2} \mid A_a)$
was a spanning to the same of	, T, O O O
	P(A2 Aa) = P(A2 A,). P(A,)+ P(A2 (C,). P(C,)
	P(A,) = P(A, 1A,) P(A,) + P(A, 1Ca) 1(Ca)
	T ² .09 .73 .09 .09
	RATHER THAN B RECURSION, WE .09 .09 .09 .09
	(A- USE MATRIX MULTIPLICATION - 09.09.73]
D	
	P(AnA Q) = .73.77.25 + .09.09.25 + .09.09.25 + .09.09.25

and the state of the

And Pos 1 = .73-.73. 25 + 3 (.09.09.25) = 0.1393 Gnc pos 2 = P(Gnc / A) P.(Aa) + ... = (.09..09..25)-2 + (.73..09..25) - 2 = 0.036 pos 3 = pos 1 = 0.1893 pos 4 = pos 2 = 0.0369 pos 5 = pos 1 = 0.1393 Pros (S, 152 /a) = pos1. pos2. pos3- p=4. pos5 = 0.1393 · 0.0369 · 0.1393 · 0.0369 · 0.1393 = 3.68 · 10 -6

Calculating T2, probabilities:

```
In [15]: import numpy as np
         T = np.ones([4,4]) / 20
         for n in range(4):
             T[n,n] = .85
         print(T) # Gen 1, looking great
         print(T*T) # That's not right...we need dot product
         print(np.dot(T,T)) # That looks better.
         [[0.85 0.05 0.05 0.05]
          [0.05 0.85 0.05 0.05]
          [0.05 0.05 0.85 0.05]
          [0.05 0.05 0.05 0.85]]
         [[0.7225 0.0025 0.0025 0.0025]
          [0.0025 0.7225 0.0025 0.0025]
          [0.0025 0.0025 0.7225 0.0025]
          [0.0025 0.0025 0.0025 0.7225]]
         [[0.73 0.09 0.09 0.09]
          [0.09 0.73 0.09 0.09]
          [0.09 0.09 0.73 0.09]
          [0.09 0.09 0.09 0.73]]
In [14]: pos1 = .73 * .73 * .25 + 3 * (.09 * .09 * .25)
         pos2 = 2 * (.09 * .09 * .25) + 2 * (.73 * .09 * .25)
         print(pos1 * pos2 * pos1 * pos2 * pos1)
Out[14]: 3.680493724705767e-06
```