HW 1

Q. 1.1)

a) TPT :

$$P(X, Y \mid E) = P(X \mid Y, E)\, P(Y \mid E)$$

Using LHS:-

$$P(x, y \mid e) = \frac{P(x, y, e)}{P(e)}$$

$$= \frac{P(x \mid y, e) \times P(y, e)}{P(e)} \quad \because P(x, y, e) = P(x \mid y, e)\, P(y, e)$$

$$= \frac{P(x \mid y, e) \times P(y \mid e)\, \cancel{P(e)}}{\cancel{P(e)}}$$

$$= P(x \mid y, e)\, P(y \mid e)$$

$\boxed{LHS = RHS}$ HP

b) TPT $P(X \mid Y, E) = \dfrac{P(Y \mid X, E)\, P(X \mid E)}{P(Y \mid E)}$

b) TPT:- $P(X|Y,E) = \frac{P(Y|X,E)\ P(X|E)}{P(Y|E)}$

LHS

$$P(X|Y,E) = \frac{P(X,Y|E)}{P(Y|E)}$$

$$= \frac{P(X,Y,E)}{P(Y|E)\ P(E)}$$

$$= \frac{P(Y|X,E) \times P(X|E) \times \cancel{P(E)}}{P(Y|E)\ \cancel{P(E)}}$$

$$= \frac{P(Y|X,E) \times P(X|E)}{P(Y|E)}$$

LHS = RHS HP //

c) TPT:- $P(X|E) = \sum_y P(X, Y=y|E)$

Now, $P(X|E) = \frac{P(X,E)}{P(E)}$

Using product rule,

$$= \frac{\sum_y P(X, Y=y, E)}{P(E)}$$ $\because$ Sum $\sum_y = 1$ for Y.

$$= \sum_y P(X, Y=y|E)$$

$= RHS$

HP //

HW 1 cont.

Q.1.2

1) Given : $P(X, Y|E) = P(X|E)\,P(Y|E)$ — ①

Now wkt,

$$P(X, Y|E) = P(X|Y,E)\cdot P(Y|E) \quad \text{— I}$$

So ① implies that

$$P(X|Y,E) = P(X|E) \quad \text{— ②}$$

Also, $P(X, Y|E) = \dfrac{P(X,Y,E)}{P(E)} = \dfrac{P(X,Y,E)}{P(E)} \times \dfrac{P(X,E)}{P(X,E)}$

$$= \frac{P(X,Y,E)}{P(X,E)} \times \frac{P(X,E)}{P(E)}$$

$$= P(Y|X,E) \times P(X|E) \quad \text{— IV}$$

Using ②, $= P(Y|X,E) \times P(X|Y,E)$ — II

From ~~Using~~ I : We get that :

$$P(Y|E) = P(Y|X,E) \quad \text{— ③}$$

Hence given ① we can get ② & ③

~~2) Given:~~ $\cancel{P(X,Y|E) = P(X|E)\,P(Y|E)}$

~~wkt,~~

2) Given: $P(X|Y,E) = P(X|E)$ — ②

wkt,

$$P(X,Y|E) = P(X|Y,E)\,P(Y|E) \quad \text{— I}$$

Using ② :-

$$P(X,Y|E) = P(X|E)\,P(Y|E) \quad \text{— ①}$$

Now from II,

wkt:

$$P(X,Y|E) = P(Y|X,E) \times P(X|E)$$

$$\therefore P(Y|(X,E)) = \frac{P(X,Y|E)}{P(X|E)} \quad \text{— III}$$

Using III in ①,

$$P(Y|E) = \frac{P(X,Y|E)}{P(X|E)} = P(Y|X,E) \quad \text{— ③}$$

Hence from ② we can get ① & ③.

3) Given that $P(Y \mid X, E) = P(Y|E)$

From (II):

$$P(X, Y|E) = P(X \mid Y, E)\, P(Y \mid X, E)$$

Using (3),

$$P(X, Y|E) = P(X \mid Y, E) \times P(Y \mid E)$$

& Using (IV):

$$P(X, Y \mid E) = P(X \mid E)\, P(Y \mid E) \quad -(1)$$

this also gives us,

$$P(X \mid Y, E) = P(X \mid E) \quad -(2)$$

Hence given (3) we can get (1) & (2).

Hence giving any one of (1), (2) or (3) we can derive the others.

HP //

Q. 1.3)

a) Set:

X : ~~A~~ Has Covid or not.
(1 : has covid 0 : not)

Y : Has cough or not
(1 : has cough 0 : not)

Z : Has sense of ~~smell~~ taste or not.
(1 : No taste 0 : taste)

$\therefore P(X=1) < P(X=1 \mid Y=1) < P(X=1 \mid Y=1, Z=1)$

has covid < has covid given cough < has covid given cough & no taste

b) Using same X, Y as (a),

Z : Has lost sense of taste
(0 : lost taste, 1 : has taste)

$\therefore P(X=1 \mid Y=1) > P(X=1)$

P(covid given cough) > P(covid)

& $P(X=1 \mid Y=1, Z=1) < P(X=1 \mid Y=1)$

P(covid given cough but has taste) < P(covid given cough)

P.T.O.

Q) 1.3)

c)

X : John studies regularly.

($X = 0$: No $X = 1$: Yes)

Y : Mary studies regularly.

(0 : No 1 : Yes)

Z : There is an exam upcoming.

($Z = 1$: Yes) ($Z = 0$: No)

$\Rightarrow P(X=1, Y=1) \neq P(X=1)\, P(Y=1)$

If John & Mary are both good students, this holds true.

$\Rightarrow P(X=1, Y=1 \mid Z=1) = P(X=1 \mid Z=1)\, P(Y=1 \mid Z=1)$

If there's an exam coming up, both will study no matter if good students or not.

HP

Q.1.4)

Given $P(D)$ is doping or not.

1 : doping, 0 : not doping.

$P(T)$: test result.

1 : +ve , 0 : -ve

a)

BN:-

$$\begin{array}{c} \textcircled{D} \\ \downarrow \\ \textcircled{T} \end{array}$$

CPT:- Given 1% chance of doping, $\therefore P(D=1) = 0.01$

$P(D=0) = 0.99$

P.T.O.

False Neg = 10% = 0.1   True Neg = 0.9   False Pos. = 5% = 0.05   True Neg = 0.95

CPT:-

D	T	P(T|D)
0	0	0.95
1	0	0.1
0	1	0.05
1	1	0.9

b) $P(ND \mid -ve) = P(D=0 \mid T=0)$

By Bayes,

$$= \frac{P(T=0 \mid D=0) \times P(D=0)}{P(T=0)}$$

$$= \frac{0.95 \times 0.99}{\sum_i P(T=0, D_i)} \quad \because \text{Marginalization}$$

$$= \frac{0.95 \times 0.99}{P(T=0, D=1) + P(T=0, D=0)}$$

$$= \frac{0.9405}{P(T=0 \mid D=1)\, P(D=1) + P(T=0 \mid D=0)\, P(D=0)}$$

$$= \frac{0.9405}{0.1 \times 0.01 + 0.95 \times 0.99}$$

$$= \frac{0.9405}{0.9415} = 0.99898$$

c) $P(D \mid +ve) = P(D=1 \mid T=1)$

$$= \frac{P(T=1 \mid D=1) \times P(D=1)}{P(T=1)} \quad \because \text{Bayes}$$

$$= \frac{0.9 \times 0.01}{0.01 \times 0.9 + 0.05 \times 0.99} \quad \because \text{Marginalization}$$

$$= 0.1538$$

Q1.5) Entropy $= H[x] = -\sum_{i=1}^{n} P_i \times \log(p_i)$.

a) Now, $\nabla f = \frac{d}{dp} - \sum_{i=1} P_i \times \log(p_i)$

uv rules

$$= \sum_i -\left[\log p_i + \frac{1}{p_i} \times p_i\right]$$

$$= \sum_i -\left[1 + \log p_i\right]$$

$$= \sum_i -(1 + \log p_i) \quad — (1)$$

$g(x) = \sum_i p_i \quad \nabla g = \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix}$ n time $— (2)$

$\therefore$ By Lagrange multipliers :-

$\nabla f = \lambda \nabla g$

$\therefore$ Using (1) & (2), $-(1 + \log p_i) = \lambda(1)$

$\lambda = -(1 + \log p_2)$ $\therefore p_1 = p_2 = p_3 = p_n$ to remain constant

Now, $\sum_i p_i = 1 \therefore P_i = \frac{1}{}$ (HP)

DATE / /

PAGE No.

b) RHS :-

$$-\sum_{x_1}\sum_{x_2}\cdots\sum_{x_n}\prod_{i=1}^{n} P(x_i)\log\left(\prod_{i=1}^{n} P(x_i)\right)$$

Sets loop at nth element.

$$\therefore -\sum_{x_1}\sum_{x_2}\cdots\sum_{x_{n-1}}\prod_{i=1}^{n-1} P(x_i)\sum_{x_n} P(x_n)\left[\sum_{i=1}^{n-1}\log P(x_i)+\log P(x_n)\right]$$

$\cancel{\therefore -\sum_{x_1}\sum_{x_2}}$

$$\therefore -\sum_{x_1} P(x_1) \sum_{x_2} P(x_2) \cdots \sum_{x_{n-1}} P(x_{n-1}) \left[\sum_{x_n} P(x_n)\cdot\left(\sum_{i=1}^{n-1}\log P(x_i)\right) + \sum_{x_n} P(x_n)\cdot\log P(x_n)\right]$$

Now, $\sum_{x_n} P(x_n) = 1$ & $H(X_i) = -\sum_{x_i} P(x_i)\log P(x_i)$

$$\therefore -\sum_{x_1} P_{x_1} \sum_{x_2} P_{x_2} \cdots \sum_{x_{n-1}} P(x_{n-1})\cdot\left[\sum_{i=1}^{n-1}\log P(x_i) - H(X_n)\right]$$

$$= -\sum_{x_1} P(x_1) \times \cdots \times \sum_{x_{(n-1)}} P(x_{(n-1)})\cdot\left[-H(X_n) + \log P(X_{n-1}) + \sum_{i=1}^{n-2}\log(P(x_i))\right]$$

P.T.O.

$$= -\sum_{x_1} P(x_1) \cdots \sum_{x_{n-2}} P(x_{n-2}) \times \Big[-H(X_n) - H(X_{n-1}) + \sum_{x_{n-1}} P(x_{n-1}) \cdot \sum_{i=1}^{n-2} \log(P(x_i)) \Big]$$

$$= -\sum_{x_1} P(x_1) \times \cdots \sum_{x_{n-2}} P(x_{n-2}) \Big[-H(X_n) - H(X_{n-1}) + \sum_{i=1}^{n-2} \log P(x_i) \Big]$$

Similarly, following the trend till $n=2$:-

$$= -\sum_{x_1} P(x_1) \Big[-\sum_{i=2}^{n} H(X_i) + \log P(x_1) \Big]$$

$$= -\Big[-\sum_{x_1} P(x_1) \sum_{i=2}^{n} H(X_i) + \sum_{x_1} P(x_1) \log P(x_1) \Big]$$

$$= -\Big[-\sum_{i=2}^{n} H(X_i) + (-H(X_1)) \Big]$$

$$= \sum_{i=2}^{n} H(X_i) + H(X_1)$$

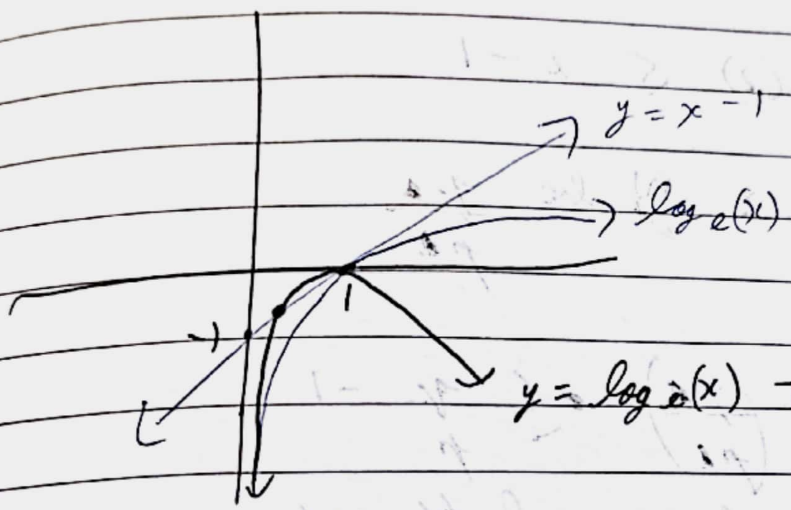
$$= \sum_{i=1}^{n} H(X_i)$$ //

HP //

1.6)
a) $\Rightarrow \frac{d}{dx} \log x - (x-1) = \frac{1}{x} - 1 - 0$

$= \frac{1}{x} - 1$

$\Rightarrow$ Graph of $x-1$ & $\log e(x)$:-



~~$\Rightarrow$ When x is betw^n ... 0,~~

~~Please regarding $\frac{1}{x} - 1$~~

~~omit. $f(x)$ ranges from negative to indeterminate.~~

$\Rightarrow$ When x is betw^n 0 & 1

$f(x) \in$ indeterminate to negative to 0 at $f(1)$.

@ $x=0$ $\quad x \in [0^+ ; 1[$

$\Rightarrow$ When $x > 1$,

$f(x)$ is again < 0.

$\therefore \log(x) \leq x - 1$,

. They are only equal when $x = 1$.

b) Given,

$$KL(p,q) = \sum_i p_i \log\left(\frac{p_i}{q_i}\right) \quad \text{--- (1)}$$

TPT, $KL(p,q) \geq 0$.

Now,

Consider the eq^n (a) :-

$$\log(x) \leq x - 1$$

Let x be $\frac{q}{p}$

$$\therefore \log\left(\frac{q}{p}\right) \leq \frac{q}{p} - 1$$

$\times$ by p on both sides.

$$\therefore p \log \frac{q}{p} \leq p\left(\frac{q}{p} - 1\right)$$

Taking $\sum$ on both side wrt i.

$$\therefore \sum_i p_i \log \frac{q_i}{p_i} \leq \sum_i (q_i - p_i)$$

$\times$ by $-$ve on both side,

$$\sum_i p_i \log \frac{p_i}{q_i} \geq \sum_i (p_i - q_i)$$

Now $\sum_i p_i - q_i = 0$ for all i.

$$\therefore \sum_i p_i \log \frac{p_i}{q_i} \geq 0$$

$\therefore KL(p,q) \geq 0$ from (1)

HP

// will only be equal when $p_i = q_i$ //

DATE	/ /
PAGE NO.	

c) TPT:- $KL(p,q) \geq \sum_i \left(\sqrt{p_i} - \sqrt{q_i}\right)^2$

Consider (a):-

$$\log(x) \leq x - 1$$

Set $x = \dfrac{\sqrt{q}}{\sqrt{p}}$

$\therefore$

$$\log \frac{\sqrt{q}}{\sqrt{p}} <= \frac{\sqrt{q}}{\sqrt{p}} - 1$$

p on both side:-

$$p \log \frac{\sqrt{q}}{\sqrt{p}} <= \frac{p}{\sqrt{p}} \sqrt{q} - p$$

$$\therefore \; p \log \frac{\sqrt{q}}{\sqrt{p}} < \sqrt{p}\sqrt{q} - p$$

Taking −ve common:-

$$p \log \frac{\sqrt{p}}{\sqrt{q}} \geq p - \sqrt{p}\sqrt{q}$$

~~i.e. KL~~ Taking summation:-

$$\sum_i \frac{1}{2} p_i \log \frac{p}{q} \geq \sum_i p_i - \sqrt{p_i}\sqrt{q_i}$$

i.e.

$$\frac{1}{2} KL(p,q) \geq \sum_i p_i - \sqrt{p_i}\sqrt{q_i}$$

$\times$ by 2 on both side,

$$\therefore \; KL(p,q) \geq \sum_i 2p_i - 2\sqrt{p_i}\sqrt{q_i}$$

Now, $\sum_i p_i = \sum_i q_i$

$$\therefore KL(p,q) \geq \sum_i p_i + p_i - 2\sqrt{p_i}\sqrt{q_i}$$

$$\geq \sum_i p_i + q_i - 2\sqrt{p_i}\sqrt{q_i}$$

$$K(p,q) \geq \sum_i \left(\sqrt{p_i} - \sqrt{q_i}\right)^2$$

HP //

d) Let X be a fair coin toss:-

$$P(X=0) = 0.5$$
$$P(X=1) = 0.5$$

Let Y be an unfair coin toss:-

$$P(Y=0) = 0.2$$
$$P(Y=1) = 0.8$$

TPT:- $KL(p,q) \neq KL(q,p)$

$$\therefore \sum_i p_i \log\left(\frac{p_i}{q_i}\right) \; ? \; \sum_i q_i \log\left(\frac{q_i}{p_i}\right)$$

$$\therefore 0.5 \log \frac{0.5}{0.2} + 0.5 \log \frac{0.5}{0.8} \; ? \; 0.2 \log \frac{0.2}{0.5} + 0.8 \log \frac{0.8}{0.5}$$

$$\therefore 0.5 \times 0.9163 + 0.5 \times -0.47 \; ? \; 0.2 \times -0.9163 + 0.8 \times 0.47$$

$$= 0.45815 + (-0.235) \; ? \; -0.18326 + 0.376$$

$$= 0.22315 \; ? \; 0.19434$$

$$0.22315 \neq 0.19434$$

$$\therefore KL(p,q) \neq KL(q,p)$$

HP //

Q) 1.7)

a) Tpt :-

$$I(X,Y) \geq 0$$

Now,

$$I(X,Y) = \sum_x \sum_y P(x,y) \log\left[\frac{P(x,y)}{P(x)P(y)}\right]$$

from 1.6, $\log(x) \geq x-1$

Using this,

$$\boxed{\cancel{= \sum_x \sum_y P(x,y) \left(\frac{P(x,y)}{P(x)P(y)} - 1\right)}}$$

$$= -1 \sum_x \sum_y P(x,y) \log\left(\frac{P(x)P(y)}{P(x,y)}\right)$$

$$\geq -1 \sum_x \sum_y P(x,y) \frac{P(x)P(y)}{P(x,y)} - 1$$

$$\geq -1 \sum_x \sum_y \cancel{P(x,y)} \frac{P(x)P(y) - P(x,y)}{\cancel{P(x,y)}}$$

$$\geq -1 \sum_x \sum_y P(x)P(y) - P(x,y)$$

$$-1\left[\sum_x P(x) \sum_y P(y) - \sum_x \sum_y P(x,y)\right]$$

$$-1\left[(1)(1) - 1\right]$$ $\because$ Marginalizaⁿ & $\sum P_i = 1$

$$= 0$$

$$\therefore I(x,y) \geq 0$$

HP Non-negative

b) TPT $I(X, Y) = 0$ only when X & Y are independent variables.

Let X, Y be independent vars,

$$I(X,Y) = \sum_x \sum_y P(x,y) \log\left[\frac{P(x,y)}{P(x)P(y)}\right]$$

$$= \sum_x \sum_y P(x,y) \log\left[\frac{P(x)P(y)}{P(x)P(y)}\right]$$

$\because$ X & Y are independent

$\therefore P(x,y) = P(x)P(y)$

$$= \sum_x \sum_y P(x,y) \log(1)$$

$$= 0$$

Also $\because \sum_x \sum_y P(x,y)$ can never be 0,

Only the log term can be 0, to make the whole eq^n $I(X,Y) = 0$

log term will only be 0 when numerator is equal to denominator,

i.e. $P(x,y) = P(x)P(y)$

This only occurs when X & Y are independent.

HP

Q.1.8)

a) Yes, the first BN implies a conditional independence between Y & Z while the second one does not.

~~b) No, there is no conditional independence in BN 2 or BN 3~~

c)

b) No, BN 2 & BN 3 both shows the same cond independence of X & Z.

2) Yes in BN 3, X & Z are shown as cond ind. while in BN 1 Y & Z are shown.

1.9)

A)

Reading dataset

```
with open("hw1_word_counts_05.txt") as ln:
  dataset = ln.readlines()
```

```
dataset[0:10]
```

```
['AARON 413\n',
 'ABABA 199\n',
 'ABACK 64\n',
 'ABATE 69\n',
 'ABBAS 290\n',
 'ABBEY 213\n',
 'ABBIE 42\n',
 'ABBOT 20\n',
 'ABDEL 337\n',
 'ABDOU 16\n']
```

Preprocessing

```
dataset[0].split()
```

```
['AARON', '413']
```

```
dataDic = {}
for i in range(len(dataset)):
  tmp = dataset[i].split()
  dataDic[tmp[0]] = int(tmp[1])
```

```
print(dataDic["FABRI"])
```

```
7
```

Sorting data

```
sorted_data = sorted(dataDic.items(), key=lambda kv: kv[1], reverse=True)

sorted_data[0]
```

```
('THREE', 273077)
```

```
sorted_data[1]
```

```
('SEVEN', 178842)
```

First 15 MOST common

```
print(sorted_data[:15])
```

```
[('THREE', 273077), ('SEVEN', 178842), ('EIGHT', 165764), ('WOULD', 159875), ('ABOUT
```

First 14 LEAST common

```
print(sorted_data[:-15:-1])
```

```
[('TROUP', 6), ('OTTIS', 6), ('MAPCO', 6), ('CAIXA', 6), ('BOSAK', 6), ('YALOM', 7),
```

Calculating the probability

```
sumi = 0
for i in sorted_data:
  sumi+=i[1]
```

```
# !pip3 install copy
# import copy
# probWord = copy.deepcopy(sorted_data)
probWord = {}
for i in sorted_data:
  probWord[i[0]] = i[1]/sumi
```

```
print(probWord)
```

```
{'THREE': 0.03562714868653127, 'SEVEN': 0.023332724928853858, 'EIGHT': 0.02162649609
```

Yup these results make sense according to the given dataset

B)

Function to cutshort by correct words and positions

```
def normalize(cg1):
  cg1.sort()
  tmp = []
  for i in range(ord('A'),ord('Z')+1):
    tmp.append(chr(i))
  for i in cg1:
    try:
      tmp.remove(i[0])
    except:
      continue
  for i in range(5):
    # print(i)
    try:
      if cg1[i][1] != i:
        cg1.insert(i, [tmp,i])
    except:
      cg1.insert(i, [tmp,i])
  return cg1


print(normalize([["D",0],["I",3]]))

  # return cg
def reduceByCorr(w1,cg1):
  if cg1 == [[]]:
    return w1
  cg1 = normalize(cg1)
  tmp = {}
  for keys in w1:
    f = 0
    for i in range(5):
      if type(cg1[i][0]) == str:
        if keys[i] == cg1[i][0]:
          continue
        else:
          f = 1
          break
      else:
        if keys[i] in cg1[i][0]:
          continue
        else:
          f = 1
          break
      # print(keys[i],cg[i][0],f)
```

```
    if f==0:
      tmp[keys] = w1[keys]
  return tmp
```

```
[['D', 0], [['A', 'B', 'C', 'E', 'F', 'G', 'H', 'J', 'K', 'L', 'M', 'N', 'O', 'P', '(
```

Function to cutshort by wrong guessed

```
def reduceByWrng(w1,wg1):
  # cg = normalize(cg)
  if wg1 == []:
    return w1
  tmp = {}
  for keys in w1:
    f = 0
    tmpp = list(keys)
    for i in wg1:
      if i in tmpp:
        f = 1
        break
    if f==0:
      tmp[keys] = w1[keys]
  return tmp
```

Find the total sum of cutshorted values

```
def totalSum(w1):
  sumi = 0
  for key in w1:
    sumi+=w1[key]
  return sumi
```

Func to define a Done list

```
def noNoList(cg,wg):
  tmp = []
  if cg!=[[]]:
    for i in cg:
      tmp.append(i[0])
  if wg!=[]:
    for i in wg:
      tmp.append(i)
  return tmp
```

Finding the next best character and it's probability

```
def nextBestChar(w1,sumi,done):
  dick = {}
  for key in w1:
    tmp = list(key)
    for i in range(ord('A'),ord('Z')+1):
      if chr(i) not in done:
        if chr(i) in tmp:
          if chr(i) not in dick:
            dick[chr(i)] = w1[key]
          else:
            dick[chr(i)] += w1[key]
  # print(dick)
  char = max(dick, key=dick.get)
  cnt = dick[char]
  prob = cnt/sumi
  return char,prob
```

To run it using input

```
# Change input here
cg = [["U",1]]
wg = ["A","E","I","O","S"]

done = noNoList(cg,wg)
newDic = reduceByCorr(dataDic,cg)
newDic = reduceByWrng(newDic,wg)
sumi = totalSum(newDic)
bestChar,prob = nextBestChar(newDic,sumi,done)
print(bestChar,prob)
```

```
Y 0.626965110163053
```

Debugging (ignore)

```
cg = [["D",0],["I",3]]
wg = ["A"]
```

```
done = noNoList(cg,wg)
print(done)
```

```
['D', 'I', 'A']
```

```
newDic = reduceByCorr(dataDic,cg)
print(newDic)
```

```
{'DAKIN': 17, 'DALIS': 15, 'DARIN': 37, 'DARIO': 28, 'DAVIE': 12, 'DAVIS': 3604, 'DEE
```

```
newDic = reduceByWrng(newDic,wg)
print(newDic)
```

```
{'DEBIT': 82, 'DENIM': 96, 'DENIS': 165, 'DEVIL': 362, 'DEVIN': 20, 'DJPIR': 37, 'DOF
```

```
sumi = totalSum(newDic)
print(sumi)
```

```
964
```

```
bestChar,prob = nextBestChar(newDic,sumi,done)
```

```
print(bestChar,prob)
```

```
E 0.7520746887966805
```

Final Table output

```
print("best next guess l\t Probability")
# Change input here
cg = [[[]],[[]],[["A",0],["S",4]],[["A",0],["S",4]],[["O",2]],[[]],[["D",0],["I",3]],[["D"
wg = [[],["E","A"],[],["I"],["A","E","M","N","T"],["E","O"],[],["A"],["A","E","I","O","S"]

for i in range(len(cg)):
  done = noNoList(cg[i],wg[i])
  newDic = reduceByCorr(dataDic,cg[i])
  newDic = reduceByWrng(newDic,wg[i])
  sumi = totalSum(newDic)
  bestChar,prob = nextBestChar(newDic,sumi,done)
  print(bestChar,prob,sep="\t\t\t")
```

```
best next guess l        Probability
E                       0.5394172389647974
O                       0.5340315651557658
E                       0.7715371621621622
E                       0.7127008416220352
R                       0.7453866259829712
I                       0.6365554141009611
A                       0.8206845238095238
E                       0.7520746887966805
Y                       0.626965110163053
```

+ Code + Text