

At: Q1

$$a) \text{ for } E[Z] = E_{x,y \in [0,1]}[(X-Y)^2] = E\left[\left(X - \frac{1}{2} + \frac{1}{2} - Y\right)^2\right]$$

$$= E\left[\left(X - \frac{1}{2} - (Y - \frac{1}{2})\right)^2\right]$$

$$= E\left[\left(X - \frac{1}{2}\right)^2\right] + E\left[\left(Y - \frac{1}{2}\right)^2\right] + 2E\left[\left(X - \frac{1}{2}\right)\left(Y - \frac{1}{2}\right)\right]$$

$$\text{Since } X, Y \text{ are Independent; } E\left[\left(X - \frac{1}{2}\right)\left(Y - \frac{1}{2}\right)\right] \\ = E\left(X - \frac{1}{2}\right) E\left(Y - \frac{1}{2}\right)$$

$$\text{Since } X, Y \text{ are uniformly distributed on } [0,1] \Rightarrow E(X) = E(Y)$$

$$\Rightarrow E\left(X - \frac{1}{2}\right) = E\left(Y - \frac{1}{2}\right) = 0$$

$$\Rightarrow E[Z] = E\left[\left(X - \frac{1}{2}\right)^2\right] + E\left[\left(Y - \frac{1}{2}\right)^2\right] \quad E\left[\left(X - \frac{1}{2}\right)^2\right] = E\left[\left(Y - \frac{1}{2}\right)^2\right]$$

$$= 2 E\left[\left(X - \frac{1}{2}\right)^2\right]$$

$$= 2 \int_0^1 \left(x - \frac{1}{2}\right)^2 dx = 2 \left[\frac{x^3}{3} - \frac{x^2}{2} + \frac{x}{4} \right]_0^1 = 2 \times \frac{1}{12} = \frac{1}{6} = E[Z]$$

Q1) a)
for the
Variance

$$\text{Var}(Z) = \text{Var}[(X-Y)^2] = E[(X-Y)^2]^2 - E[(X-Y)^2]^2$$

$$\text{We compute for } E[(X-Y)^4] = E[X^4 - 4X^3Y + 6X^2Y^2 - 4XY^3 + Y^4]$$

$$= E[X^4] - E[4X^3Y] + E[6X^2Y^2] - E[4XY^3] + E[Y^4]$$

$$= \frac{n^5}{5} \Big|_0^1 - 4 \frac{n^4}{4} \Big|_0^1 \frac{y^2}{2} \Big|_0^1 + 6 \frac{n^3}{3} \Big|_0^1 \frac{y^3}{3} \Big|_0^1 - 4 \frac{n^2}{2} \Big|_0^1 \frac{y^4}{4} \Big|_0^1 + \frac{y^5}{5} \Big|_0^1$$

$$= \frac{1}{5} - 4 \frac{1}{4} \frac{1}{2} + 6 \frac{1}{3} \frac{1}{3} - 4 \frac{1}{2} \frac{1}{4} + \frac{1}{5} = \frac{2}{5} + \frac{6}{9} - 1 = \frac{18-25}{45} =$$

$$\Rightarrow \text{Var}(Z) = \frac{1}{15} - \left[\frac{1}{6}\right]^2 = \frac{7}{180}$$

Q1) b) for expected values

$$\text{let us expand } E[R] = E[\|\vec{X} - \vec{Y}\|_2^2]$$

$$= E[(X_1 - Y_1)^2 + \dots + (X_d - Y_d)^2] = E(X_1 - Y_1)^2 + \dots + E(X_d - Y_d)^2$$

note that $(X_i - Y_i)^2 = (X_j - Y_j)^2 \quad \forall i, j \in [1, d]$

$\Rightarrow E[R] = d E[(X_1 - Y_1)^2]$ we know the ^{squared} deviation between two uniformly distributed variables is $\frac{1}{6}$ from part A

$$\Rightarrow E[R] = d \times \frac{1}{6} = \frac{d}{6}$$

for Variance(R) in the same manner we have

$$\text{Var}(R) = \text{Var}[(X_1 - Y_1)^2 + \dots + (X_d - Y_d)^2] \text{ since all variables are independent,}$$

$$\text{Var}(R) = d \text{Var}[(X_1 - Y_1)^2] = \frac{d}{5} \quad \text{from part a}$$

Q1) c) two points in a d -dim cube are furthest from each other if one is on corner $(0, \dots, 0)^d$ and the other $(1, \dots, 1)^d$ where the squared euclidean distance will be $\frac{1^2 + \dots + 1^2}{d} = d$

Now, from part b, we know the expected value and standard deviation of the S.E.D in d -dim is of $O(d)$, since the maximum distance is also of $O(d)$ we can conclude

that ^{points} ~~distance~~ in d dimensional space become further, with the same distance as d grows

Question 2)

a) ~~we~~ we have $H(X) = \sum_n P(x_n) \log_2 \left(\frac{1}{P(x_n)} \right)$ where $P(x_n)$ is a PDF

it is clear that $0 \leq P(x_n) \leq 1 \quad \forall x_n \in X$

$$\Rightarrow \forall n \quad \log_2 \left(\frac{1}{P(x_n)} \right) \geq 0 \quad (\text{since } \frac{1}{P(x_n)} \geq 1 \text{ since } P(x_n) \neq 0)$$

$$\Rightarrow P(x_n) \log_2 \left(\frac{1}{P(x_n)} \right) \geq 0 \quad \forall n$$

$$\Rightarrow \sum_n P(x_n) \log_2 \left(\frac{1}{P(x_n)} \right) \geq 0 \quad \square$$

b) $H(X, Y)$

since X, Y are independent, $P(X, Y) = P(X) \times P(Y)$

$$\Rightarrow H(X, Y) = \sum_n \sum_y P(x_n, y) \log_2 \left(\frac{1}{P(x_n, y)} \right)$$

$$= \sum_n \sum_y P(x_n) P(y) \log_2 \left(\frac{1}{P(x_n) P(y)} \right) = \sum_{n, y} P(x_n) P(y) \log_2 \left(\frac{1}{P(x_n)} \right) + \sum_{n, y} P(x_n) P(y) \log_2 \left(\frac{1}{P(y)} \right)$$

$$= \sum_n P(x_n) \log_2 \left(\frac{1}{P(x_n)} \right) + \sum_y P(y) \log_2 \left(\frac{1}{P(y)} \right) = H(X) + H(Y) \quad \square$$

Question 2, part c

Question 2)

Part c) we know that $P(X, Y) = P(X \cap Y) = P(Y \cap X) = P(X) \cdot P(Y|X)$

we have:

$$\begin{aligned}
 H(X, Y) &= \sum_{x, y} P(x, y) \log_2 \frac{1}{P(x, y)} = \sum_{x, y} P(x) \cdot P(y|x) \cdot \log_2 \left[\frac{1}{P(x) \cdot P(y|x)} \right] \\
 &= \sum_{m, y} P(m) \cdot P(y|m) \cdot \log_2 \frac{1}{P(m)} + \sum_{m, y} P(m) \cdot P(y|m) \cdot \log_2 \frac{1}{P(y|m)} \\
 &= \sum_m P(m) \cdot \log_2 \frac{1}{P(m)} + \sum_{m, y} P(m, y) \cdot \log_2 \frac{1}{P(y|m)} = H(X) + H(Y|X) \quad \square
 \end{aligned}$$

Question 2, Part d)

We know $\log_2(x)$ is concave; ~~that $\log_2(x)$ is concave~~

$$KL(P||q) = \sum_n P(n) \log_2 \frac{P(n)}{q(n)} \quad \text{if we show } -KL(P||q) \leq 0$$

$$\Rightarrow KL(P||q) \geq 0$$

$$-KL(P||q) = - \sum_n P(n) \log_2 \frac{P(n)}{q(n)} =$$

$$\sum_n P(n) \log_2 \frac{q(n)}{P(n)}$$

We know \log is concave

$$\Rightarrow \log[E(X)] \geq E(\log(X))$$

$$= E \left[\log_2 \left(\frac{q(n)}{P(n)} \right) \right]$$

$$\leq \log_2 E \left[\frac{q(n)}{P(n)} \right]$$

$$= \log_2 \sum_n P(n) \frac{q(n)}{P(n)}$$

$$= \log_2 1 = 0$$

$$\Rightarrow -KL \leq 0$$

$$\Rightarrow KL \geq 0 \quad \square$$

Question 2: Part e.

$$I(Y; X) = H(Y) - H(Y|X)$$

$$= - \sum_y P(y) \log P(y) + \sum_{n,y} P(n) P(y|x) \log P(y|x) \quad P(x) = P(y|x) = P(n,y)$$

$$= \sum_{n,y} P(n,y) \log_2 P(y|x) - \sum_y \left(\sum_n P(n,y) \right) \log_2 P(y) \quad P(y) = \sum_n P(n,y)$$

$$= \sum_{n,y} P(n,y) \log_2 P(y|x) - \sum_{n,y} P(n,y) \log_2 P(y)$$

$$= \sum_{n,y} P(n,y) \log_2 \frac{P(y|x)}{P(y)}$$

$$= \sum_{n,y} P(n,y) \log_2 \frac{P(y|x) P(n)}{P(y) P(n)}$$

$$= \sum_{n,y} P(n,y) \log_2 \frac{P(n,y)}{P(y) P(n)}$$

$$= KL(P(n,y) \parallel P(n) P(y)) \quad \square$$

Question 3:

Part a)

Please refer to the code and run function `load_data()`

Part b)

Please refer to the code and run function `select_tree_model()`

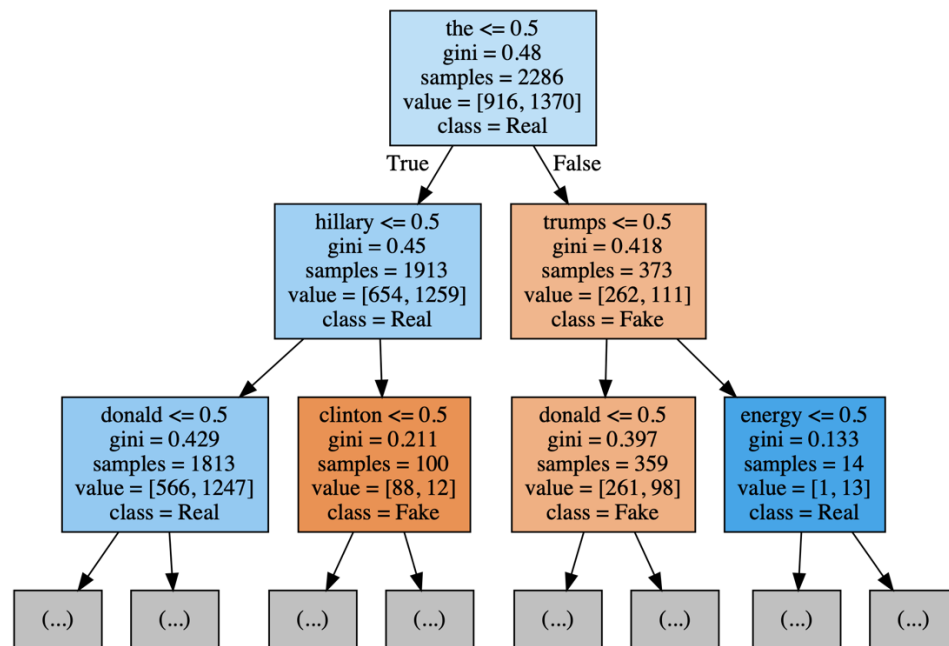
Please also check below for sample reports on the validation sets

Part c)

Reports:

```
(csc311) farazkhoshbakhtian@Farazs-MacBook-Pro 1 % python hw1_code.py
Results for gini index, max depth of 16 :
    Accuracy : 74.6938775510204
Results for gini index, max depth of 33 :
    Accuracy : 75.71428571428571
Results for gini index, max depth of 49 :
    Accuracy : 76.53061224489795
Results for gini index, max depth of 66 :
    Accuracy : 75.51020408163265
Results for entropy index, max depth of 16 :
    Accuracy : 72.85714285714285
Results for entropy index, max depth of 33 :
    Accuracy : 74.08163265306122
Results for entropy index, max depth of 49 :
    Accuracy : 74.89795918367346
Results for entropy index, max depth of 66 :
    Accuracy : 75.10204081632654
Max accuracy on validation sets: 76.53061224489795
-----
Best tree is based on: gini and gets this accuracy on the training set:
    Accuracy : 73.67346938775509
```

Graph:



Part d)

Please run `compute_information_gain()` and check below for the reports:

```

l = ['noneexistencword', 'the', 'hillary', 'trumps', 'trump', 'donald', 'blasts', 'war']
for word in l:
    ig = compute_information_gain(learning_data['X_train'], learning_data['y_train'], x=word)
    print("Information Gain for <{}> is: {}".format(word, ig))

```

```

(csc311) farazkhoshbakhtian@Farazs-MacBook-Pro 1 % python hw1_code.py
Information Gain for <noneexistencword> is: 0.0
Information Gain for <the> is: 0.052637477270443433
Information Gain for <hillary> is: 0.0443445873158429
Information Gain for <trumps> is: 0.045006363601046706
Information Gain for <trump> is: 0.034388047535468425
Information Gain for <donald> is: 0.049398847926479306
Information Gain for <blasts> is: 0.0003827842554411376
Information Gain for <war> is: 0.0036013172443748465
(csc311) farazkhoshbakhtian@Farazs-MacBook-Pro 1 %

```

As you can see, “noneexistencword” gets an information gain of 0 which is correct, and the word “the” gets the highest information gain of all, which justifies it being at the root of the decision tree.

Part e)

For the reports:

```
(csc311) farazkhoshbakhtian@Farazs-MacBook-Pro 1 % python hw1_code.py
Training Accuracy for 1 Nearest Neighbours --> Accuracy : 100.0
Validation Accuracy for 1 Nearest Neighbours --> Accuracy : 68.16326530612244
Training Accuracy for 2 Nearest Neighbours --> Accuracy : 91.86351706036746
Validation Accuracy for 2 Nearest Neighbours --> Accuracy : 62.44897959183674
Training Accuracy for 3 Nearest Neighbours --> Accuracy : 85.7830271216098
Validation Accuracy for 3 Nearest Neighbours --> Accuracy : 69.59183673469389
Training Accuracy for 4 Nearest Neighbours --> Accuracy : 83.90201224846894
Validation Accuracy for 4 Nearest Neighbours --> Accuracy : 66.3265306122449
Training Accuracy for 5 Nearest Neighbours --> Accuracy : 79.39632545931758
Validation Accuracy for 5 Nearest Neighbours --> Accuracy : 67.75510204081633
Training Accuracy for 6 Nearest Neighbours --> Accuracy : 80.31496062992126
Validation Accuracy for 6 Nearest Neighbours --> Accuracy : 65.91836734693878
Training Accuracy for 7 Nearest Neighbours --> Accuracy : 77.90901137357831
Validation Accuracy for 7 Nearest Neighbours --> Accuracy : 70.40816326530613
Training Accuracy for 8 Nearest Neighbours --> Accuracy : 79.04636920384952
Validation Accuracy for 8 Nearest Neighbours --> Accuracy : 68.36734693877551
Training Accuracy for 9 Nearest Neighbours --> Accuracy : 75.54680664916886
Validation Accuracy for 9 Nearest Neighbours --> Accuracy : 67.9591836734694
Training Accuracy for 10 Nearest Neighbours --> Accuracy : 77.95275590551181
Validation Accuracy for 10 Nearest Neighbours --> Accuracy : 69.79591836734694
Training Accuracy for 11 Nearest Neighbours --> Accuracy : 74.93438320209974
Validation Accuracy for 11 Nearest Neighbours --> Accuracy : 68.77551020408164
Training Accuracy for 12 Nearest Neighbours --> Accuracy : 77.07786526684166
Validation Accuracy for 12 Nearest Neighbours --> Accuracy : 70.20408163265306
Training Accuracy for 13 Nearest Neighbours --> Accuracy : 74.10323709536308
Validation Accuracy for 13 Nearest Neighbours --> Accuracy : 68.16326530612244
Training Accuracy for 14 Nearest Neighbours --> Accuracy : 76.42169728783902
Validation Accuracy for 14 Nearest Neighbours --> Accuracy : 69.79591836734694
Training Accuracy for 15 Nearest Neighbours --> Accuracy : 72.96587926509186
Validation Accuracy for 15 Nearest Neighbours --> Accuracy : 67.75510204081633
Training Accuracy for 16 Nearest Neighbours --> Accuracy : 74.71566054243219
Validation Accuracy for 16 Nearest Neighbours --> Accuracy : 70.0
Training Accuracy for 17 Nearest Neighbours --> Accuracy : 72.52843394575677
Validation Accuracy for 17 Nearest Neighbours --> Accuracy : 67.9591836734694
Training Accuracy for 18 Nearest Neighbours --> Accuracy : 73.53455818022748
Validation Accuracy for 18 Nearest Neighbours --> Accuracy : 67.75510204081633
Training Accuracy for 19 Nearest Neighbours --> Accuracy : 71.21609798775154
Validation Accuracy for 19 Nearest Neighbours --> Accuracy : 66.73469387755102
Training Accuracy for 20 Nearest Neighbours --> Accuracy : 72.52843394575677
Validation Accuracy for 20 Nearest Neighbours --> Accuracy : 68.16326530612244
-----
Best model on validation set is with 7 neighbours, with accuracy 70.40816326530613
Test Accuracy for 7 Nearest Neighbours --> Accuracy : 68.57142857142857
```

For the graph:

