

```

import numpy as np

def problem_1a (A, B):
    return A + B

def problem_1b (A, B, C):
    return (A @ B) - C

def problem_1c (A, B, C):
    return (A * B) + C.T

def problem_1d (x, y):
    return np.dot(x,y)

def problem_1e (A, x):
    return np.linalg.solve(np.linalg.inv(A),x)

def problem_1f (A, x):
    return np.linalg.solve(A.T, x.T).T

def problem_1g (A, j):
    return np.sum(A[list(filter(lambda x: x%2==0,np.arange(A.shape[0]+1))),j])

def problem_1h (A, c, d):
    A = A[np.nonzero(A > c-1)]
    A = A[np.nonzero(A < d+1)]
    return np.mean(A)

def problem_1i (A, k):
    e_vals,e_vctr = np.linalg.eig(A)
    if k==0:
        return np.array([0.])
    elif k>A.shape[0]:
        return np.zeros(k)
    else:
        e_vals.sort()
        e_vals = e_vals[::-1][:k]
    return e_vals

def problem_1j (x, k, m, s):
    z = np.ones(x.shape[0])[::np.newaxis]
    I = np.identity(x.shape[0])
    return np.random.multivariate_normal(mean=(x+(m*z)).flatten(),cov=(s*I),size=(x.shape[0],k))[0].T

def problem_1k (A):
    return np.random.shuffle(A)

def problem_1l (x):
    return np.divide(np.subtract(A,np.mean(A)),np.std(A))

def problem_1m (x, k):
    return np.repeat(x,k,axis=0).reshape(x.shape[0],k)

```

```
def problem_2a()->None:
    X = np.arange(9).reshape(3,3)
    row_min = X.min(axis=1)[: ,np.newaxis]
    '''
    Previously it was a row vector so it was subtracting element wise but after reshaping
    it in column vector we are able to get the desired results
    '''

    print(X-row_min)
    return None
```

```
def problem_2b()->None:
    X = np.arange(9).reshape(3,3)
    row_min = X.min(axis=1).reshape(-1,1)
    '''
    to get to this solution I didn't use chatgpt or anything else just tried by hand and then replicated it on google colab
    '''

    print(
        np.subtract(
            np.multiply(
                X,np.ones(shape=(3,3))
            ),
            np.vstack(
                tup=(
                    np.multiply(
                        np.array([row_min[0]]),np.ones(shape=(3,3))
                    ),
                    np.multiply(
                        np.array([row_min[1]]),np.ones(shape=(3,3))
                    ),
                    np.multiply(np.array([row_min[2]]),np.ones(shape=(3,3))),
                )
            ).reshape(3,3,3)
        )
    )
```

```

def linear_regression (X_tr, y_tr):
    return np.linalg.inv(X_tr.T.dot(X_tr)).dot(X_tr.T).dot(y_tr)

def train_age_regressor ()->None:
    # Load data
    X_tr = np.reshape(np.load("age_regression_Xtr.npy"), (-1, 48*48))
    y_tr = np.load("age_regression_ytr.npy")
    X_te = np.reshape(np.load("age_regression_Xte.npy"), (-1, 48*48))
    y_te = np.load("age_regression_yte.npy")

    w = linear_regression(X_tr, ytr)

    # Report fMSE cost on the training and testing data (separately)
    mse_tr = ((1 / (2 * X_tr.shape[0])) * np.sum(np.square(np.dot(X_tr,w)-y_tr)))
    print('Mean squared error for Training Set is {:.2f}'.format(mse_tr))

    mse_te = ((1 / (2 * X_te.shape[0])) * np.sum(np.square(np.dot(X_te,w)-y_te)))
    print('Mean squared error for Test Set is {:.2f}'.format(mse_te))
    ...

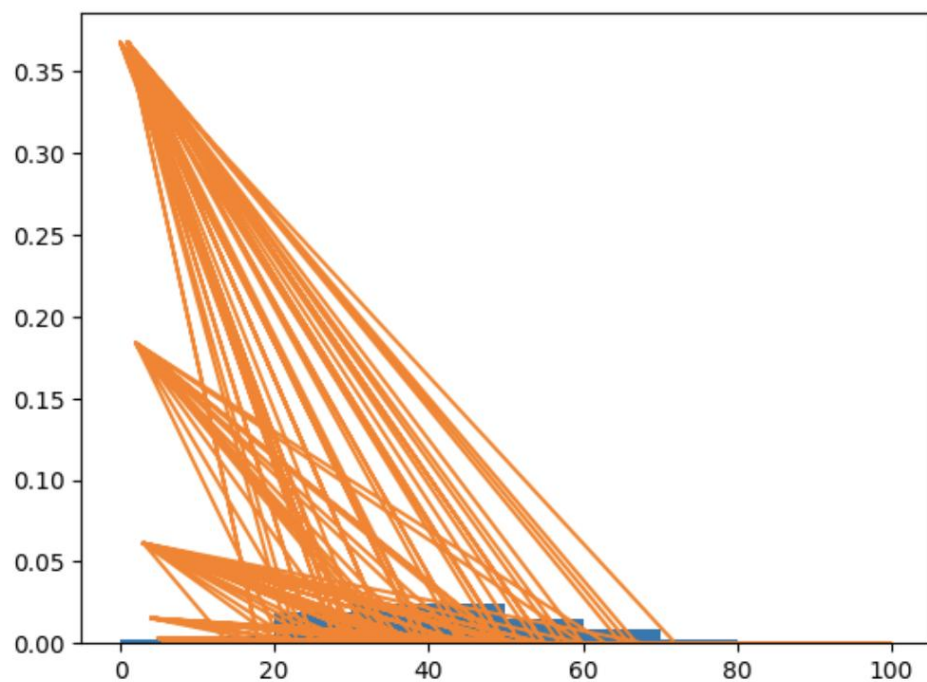
    Mean squared error for Training Set is 40.43
    Mean squared error for Test Set is 373.09
    ...

    return None

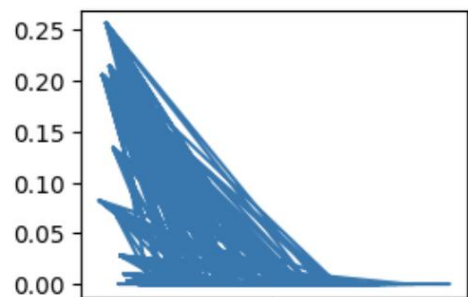
```

```
1  import numpy as np
2  import matplotlib.pyplot as plt
3  %matplotlib inline
4  import scipy
5
6  problem_4a = np.load("age_regression_ytr.npy")
7
8  plt.hist(x=problem_4a,density=True)
9
10 print(
11     np.mean(problem_4a),
12     np.median(problem_4a),
13     np.min(problem_4a),
14     np.max(problem_4a),
15     sorted(problem_4a)[40:60],
16 )
17
18 plt.plot(problem_4a,scipy.stats.poisson.pmf(problem_4a,1))
19 plt.show()
20
21 rate_of_occurence_mu = [2.5,3.1,3.7,4.3]
22
23 figure, axis = plt.subplots(nrows=2,ncols=2,sharex=True,sharey=True,)
24
25 axis[0, 0].plot(problem_4a,scipy.stats.poisson.pmf(problem_4a,rate_of_occurence_mu[0]))
26 axis[0, 0].set_title(f"Rate of Occurence {rate_of_occurence_mu[0]}")
27
28 axis[0, 1].plot(problem_4a,scipy.stats.poisson.pmf(problem_4a,rate_of_occurence_mu[1]))
29 axis[0, 1].set_title(f"Rate of Occurence {rate_of_occurence_mu[1]}")
30
31 axis[1, 0].plot(problem_4a,scipy.stats.poisson.pmf(problem_4a,rate_of_occurence_mu[2]))
32 axis[1, 0].set_title(f"Rate of Occurence {rate_of_occurence_mu[2]}")
33
34 axis[1, 1].plot(problem_4a,scipy.stats.poisson.pmf(problem_4a,rate_of_occurence_mu[3]))
35 axis[1, 1].set_title(f"Rate of Occurence {rate_of_occurence_mu[3]}")
36
37 plt.show()
```

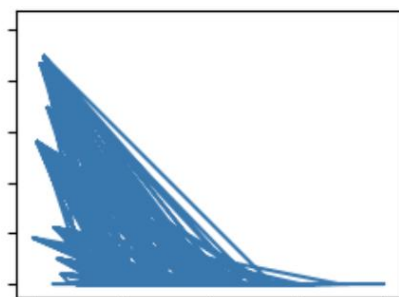

39.57944735 40.0 0.0 100.0 [3.0, 3.0, 3.0, 3.0, 4.0, 4.0, 4.0, 4.0, 4.0, 5.0, 5.0, 5.0, 5.0, 5.0, 5.0, 5.5, 6.0, 6.0, 6.0]



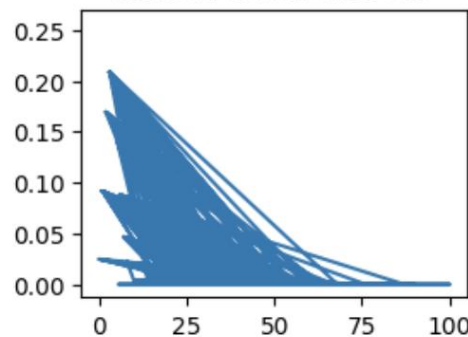
Rate of Occurrence 2.5



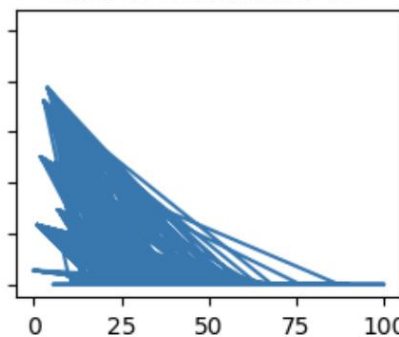
Rate of Occurrence 3.1



Rate of Occurrence 3.7



Rate of Occurrence 4.3



```

1 def get_mu_sigma(x:float)->tuple:
2     return np.power(x,2), (2 - (1 / (1 + np.exp(-np.power(x,2)))))
3 mu_val,sigma_val = get_mu_sigma(x=1)
4 random_value_score = 0
5 z_score_val = ((random_value_score - mu_val) / sigma_val)
6 prob = scipy.stats.norm.cdf(z_score_val)
7 comute_percent = (1-prob) * 100 # more than random_value_score
8 print('Proba : {:.2f}%'.format(comute_percent))

```

Proba : 78.47%

```

1 # for problem 4b
2 # 1. when value of x is large in magnitute the value of y tends to be larger
3 # 2. when value of x is small in magnitute the uncertainty in the corresponding value of y tend to be larger
4 # 3. The probability that a r.v. Y sampled from that distribution is positive - Proba : 78.47%

```

5(a)

Two column vectors x & a .

$$x \rightarrow \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \quad a \rightarrow \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{bmatrix}$$

$$x^T a = [x_1, x_2, \dots, x_n] \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{bmatrix}$$

$$= x_1 a_1 + x_2 a_2 + \dots + x_n a_n \rightarrow \textcircled{1}$$

$$a^T x = [a_1, a_2, \dots, a_n] \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$$

$$= a_1 x_1 + a_2 x_2 + \dots + a_n x_n \rightarrow \textcircled{2}$$

$$\nabla_x (x^T a) = \sum_{p=1}^n a_p \hat{x}_p = a \text{ (vector)}$$

$$\text{Similarly } \nabla_x (a^T x) = \sum_{p=1}^n a_p \hat{x}_p = a \text{ (vector)}$$

$$\boxed{\therefore \nabla_x (x^T a) = \nabla_x (a^T x) = a.}$$

5(b)

To prove $\nabla_x (x^T A x) = (A + A^T) x$

$x \in \mathbb{R}^n$ & $A \rightarrow$ any $(n \times n)$ matrix

$x \rightarrow$ column vector

$$x \rightarrow \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \quad A \rightarrow \begin{bmatrix} a_{11} & \dots & a_{1n} \\ \vdots & & \vdots \\ a_{n1} & \dots & a_{nn} \end{bmatrix}$$

$$x^T \cdot A = [x_1, \dots, x_n] \begin{bmatrix} a_{11} & \dots & a_{1n} \\ \vdots & & \vdots \\ a_{n1} & \dots & a_{nn} \end{bmatrix}$$

$$= [x_1 \times a_{11} + x_2 \times a_{21} + x_3 \times a_{31} + \dots] \rightarrow \textcircled{1}$$

(will give a vector)

$$\therefore \nabla_n (X^T A X) = (X^T A)_{\text{vector}} \cdot (X)_{\text{vector}}$$

$$\Rightarrow \nabla_n (X^T A X) = (X^T A) + (X^T \cdot A)^T$$

$$\Rightarrow \text{To simplify } (X^T A)^T = (A^T X)$$

$$\therefore \nabla_n (X^T A X) = (X^T A)^T + (A^T \cdot X)$$

$$= (X A^T) + (A^T \cdot X)$$

$$= X (A^T + A) \quad \dots \quad (2)$$

$$\boxed{\therefore \nabla_n (X^T A X) = (A + A^T) X}$$

5(c) To prove $\nabla_n (X^T A X) = 2AX$

$X \rightarrow$ Column vector

$A \rightarrow$ any symmetric $n \times n$ matrix

Since we know that

$$\nabla_n (X^T A X) = (A + A^T) X$$

(from eq (2))

Also, since A is symmetric matrix

$$A^T = A \quad \therefore A + A^T = 2A$$

$$\boxed{\therefore \nabla_n (X^T A X) = 2AX}$$

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(2) to prove $\nabla_x [(Ax+b)^T (Ax+b)]$
 $= 2A^T (Ax+b)$

$x \rightarrow$ column vector

$A \rightarrow$ symmetric $n \times n$ matrix (i.e. $A^T = A$)

$b \rightarrow$ constant column vector.

$$(Ax+b)^T \cdot (Ax+b) = [(Ax^T + b^T) \cdot (Ax+b)]$$

$$\frac{d}{dx} (Ax)^T = A \quad \& \quad \frac{d}{dx} b^T = 0 \quad (\text{Constant})$$

$$\therefore \frac{d}{dx} [(Ax+b)^T \cdot (Ax+b)]$$

$$= (Ax+b) \cdot 2A^T$$

$$\therefore \nabla_x [(Ax+b)^T \cdot (Ax+b)] = 2A^T (Ax+b)$$