assignment-4

November 16, 2021

0.1 Required Libraries

[ ]:
```
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
from sklearn.cluster import KMeans
from sklearn.metrics import mean_squared_error, rand_score
from sklearn.metrics.pairwise import cosine_similarity

np.set_printoptions(precision=3)
```

1 Question 1

In this exercise, you will perform k-means clustering on the seed data at the following link: https://archive.ics.uci.edu/ml/datasets/seeds

You will perform clustering using the following values of k: 2,3, 4, and 5. In each case you will determine the SSE value and calculate the value of Rand index and tabulate your results.

[ ]:
```
columns = ["Area", "Perrimeter", "Compactness", "Kernel Length", "Kernel␣
↪Width", "Asymmetry Coefficient", "Kernel Groove Length", "Variant"]
data = pd.read_csv("seeds_dataset.txt", delim_whitespace=True, names=columns)
X = data.to_numpy()[:,:-1]
Y = data.to_numpy()[:,-1]

data.describe()
```

[ ]:
```
              Area  Perrimeter  Compactness  Kernel Length  Kernel Width  \
count   210.000000  210.000000   210.000000     210.000000    210.000000
mean     14.847524   14.559286     0.870999       5.628533      3.258605
std       2.909699    1.305959     0.023629       0.443063      0.377714
min      10.590000   12.410000     0.808100       4.899000      2.630000
25%      12.270000   13.450000     0.856900       5.262250      2.944000
50%      14.355000   14.320000     0.873450       5.523500      3.237000
75%      17.305000   15.715000     0.887775       5.979750      3.561750
max      21.180000   17.250000     0.918300       6.675000      4.033000
```

```
       Asymmetry Coefficient  Kernel Groove Length     Variant
count             210.000000            210.000000  210.000000
mean                3.700201              5.408071    2.000000
std                 1.503557              0.491480    0.818448
min                 0.765100              4.519000    1.000000
25%                 2.561500              5.045000    1.000000
50%                 3.599000              5.223000    2.000000
75%                 4.768750              5.877000    3.000000
max                 8.456000              6.550000    3.000000
```

[ ]:
```python
for k in [2, 3, 4, 5]:
    kmeans = KMeans(n_clusters=k)
    kmeans.fit(X)
    predicted = kmeans.predict(X)
    sse = mean_squared_error(Y, predicted)
    rand = rand_score(Y, predicted)
    print(f"KMeans clustering for K={k}:\n\tSSE = {sse}\n\tRand index = {rand}")
```

```
KMeans clustering for K=2:
        SSE = 3.6095238095238096
        Rand index = 0.7309637730690363
KMeans clustering for K=3:
        SSE = 2.738095238095238
        Rand index = 0.8743677375256322
KMeans clustering for K=4:
        SSE = 2.361904761904762
        Rand index = 0.8359990886306676
KMeans clustering for K=5:
        SSE = 2.1952380952380954
        Rand index = 0.8062884483937115
```

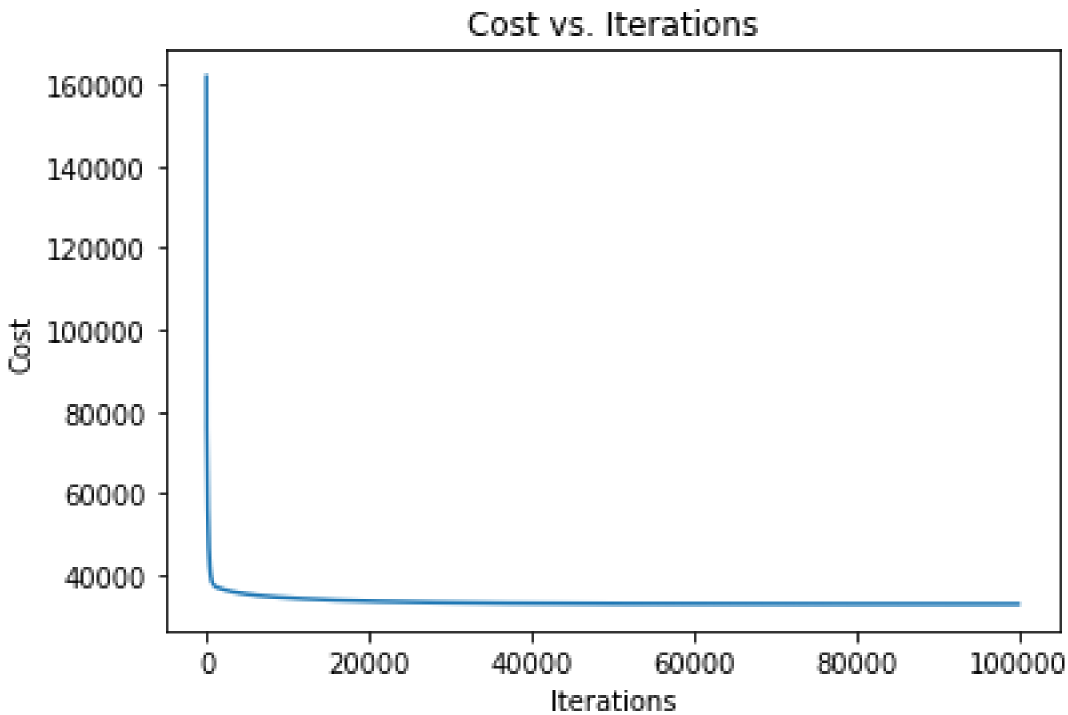
2 Question 2

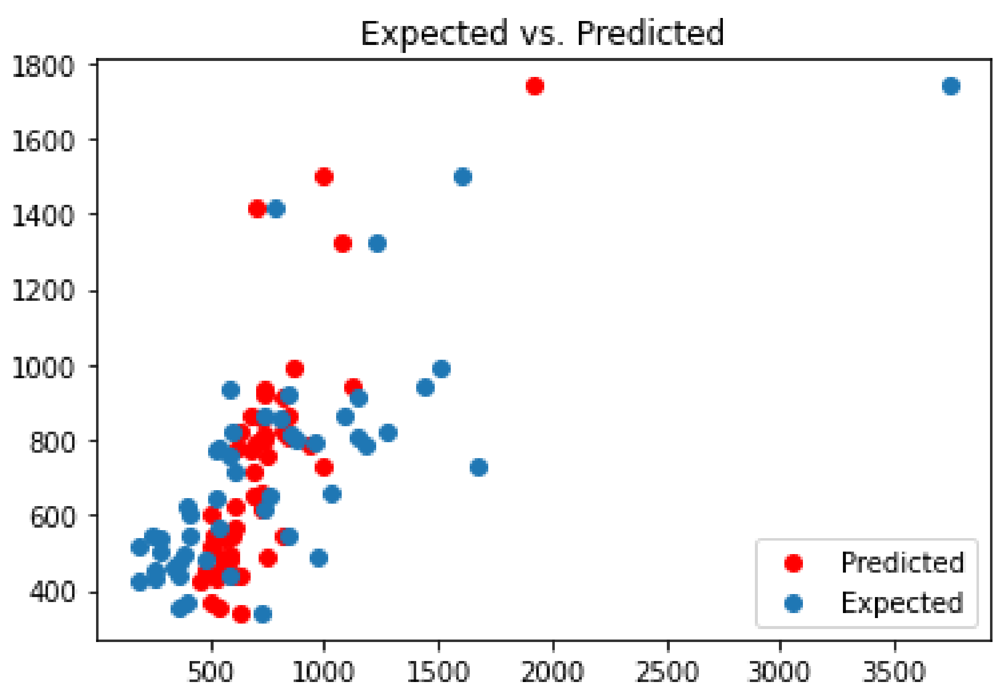
In this exercise, you will build a linear predictive model to predict crime rate based on a number of factors. The data is in the "crime-rate" file. You will build the model by writing your own script for gradient search. Experiment with 2-3 learning rates to see the effect of learning rate on the search.

[ ]:
```python
data = pd.read_csv("CrimeRate.csv")
X = data.to_numpy().astype(np.float64)[:,1:7]
Y = data.to_numpy().astype(np.float64)[:,0]
rates = [0.000001, 0.0000025]
epochs = 100000

beta = np.ones(6)
```

```
expected = np.dot(X, beta)

def gradientDescent(X, Y, beta, rate, m=50):
    cost = []
    for _ in range (epochs):
        predicted = np.dot(X, beta)
        loss = predicted - Y
        mse = np.sum(loss ** 2) / m
        cost.append(mse)
        gradient = np.dot(X.T, loss) / m
        beta = beta - (rate * gradient)
    return beta, cost

for alpha in rates:
    beta_, cost = gradientDescent(X, Y, beta, alpha)

    print(f"Alpha: {alpha}")
    plt.plot(range(epochs), cost)
    plt.title("Cost vs. Iterations")
    plt.xlabel("Iterations")
    plt.ylabel("Cost")
    plt.show()

    y = np.dot(X, beta_)

    plt.scatter(y, Y, color="red", label="Predicted")
    plt.scatter(expected, Y, label="Expected")
    plt.legend(loc="lower right")
    plt.title("Expected vs. Predicted")
    plt.show()

    print("Beta: " + str(beta_))
```

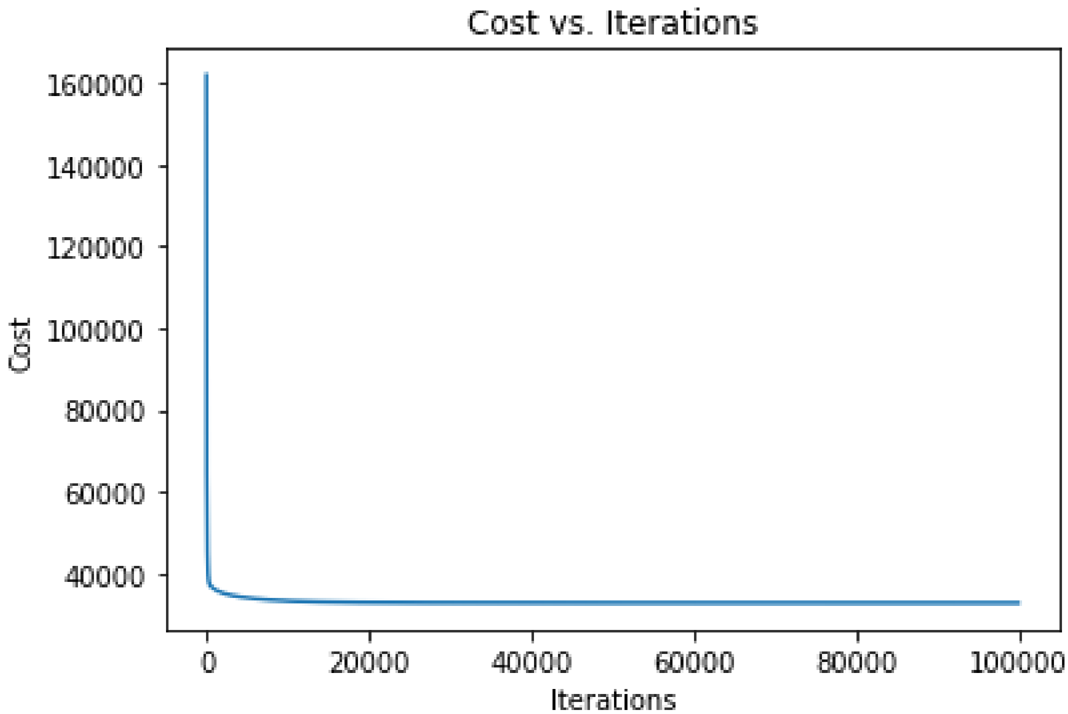
```
Alpha: 1e-06
```



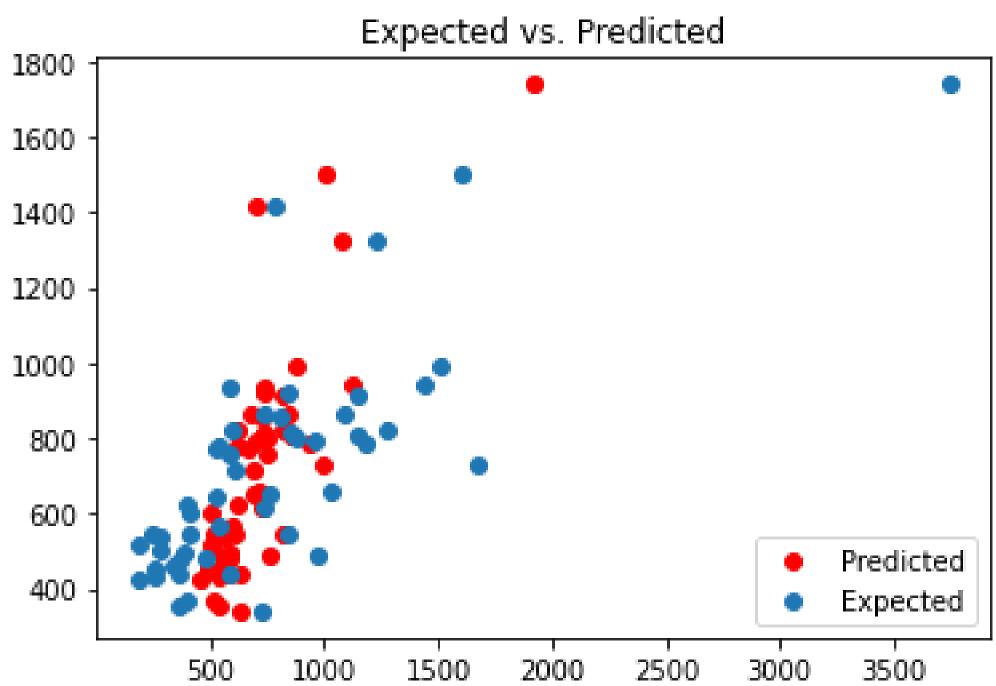



```
Beta: [ 0.335   3.884   2.8     9.765   2.95   -2.827]
```

Alpha: 2.5e-06



Cost vs. Iterations
Cost
Iterations
160000
140000
120000
100000
80000
60000
40000
0
20000
40000
60000
80000
100000



Expected vs. Predicted
1800
1600
1400
1200
1000
800
600
400
500
1000
1500
2000
2500
3000
3500
Predicted
Expected

```
Beta: [ 0.335  3.937  3.007  9.635  3.153 -4.145]
```

3 Question 3

A transaction database is given below. Using the A-priori algorithm, determine all frequent itemsets with minimum support of 30%. **Show results at each step of the algorithm.**

TID#	Items Bought
1	A, B, D, E
2	B, C, D
3	A, B, D, E
4	A, C, D, E
5	B, C, D, E
6	B, D, E
7	C, D
8	A, B, C
9	A, D, E
10	B, D

[ ]:
```
data = pd.read_csv("TransactionDatabase.csv")
print(data)

C1 = {}
for letter in data.columns:
    C1[letter] = np.sum(data[letter])

Lvalue = len(data) * 0.3
L1 = {x:y for x, y in C1.items() if y >= Lvalue}
print("L1: ", L1)

def occurrences(items):
    count = 0

    for i in range(len(data)):
        hasOccurrence = True
        for letter in items:
            if data.iloc[i][letter] == 0:
                hasOccurrence = False

        if hasOccurrence:
            count += 1

    return count

def printL(L):
```

```
    for x, y in L.items():
        print("\t(" + ", ".join(x) + "): " + str(y))

C2 = set([frozenset([x, y]) for x in C1 for y in C1 if x != y])
L2 = {x:occurrences(x) for x in C2 if occurrences(x) >= 3}
print("L2:")
printL(L2)

C3 = set([frozenset([x, y, z]) for x in C1 for y in C1 for z in C1 if x != y␣
 ↪and x != z and y != z])
L3 = {x:occurrences(x) for x in C3 if occurrences(x) >= 3}
print("L3:")
printL(L3)

print("No elements in L4")
```

```
   A  B  C  D  E
0  1  1  0  1  1
1  0  1  1  1  0
2  1  1  0  1  1
3  1  0  1  1  1
4  0  1  1  1  1
5  0  1  0  1  1
6  0  0  1  1  0
7  1  1  1  0  0
8  1  0  0  1  1
9  0  1  0  1  0
L1:  {'A': 5, 'B': 7, 'C': 5, 'D': 9, 'E': 6}
L2:
        (E, B): 4
        (E, D): 6
        (E, A): 4
        (C, B): 3
        (D, A): 4
        (A, B): 3
        (C, D): 4
        (D, B): 6
L3:
        (E, D, A): 4
        (E, D, B): 4
No elements in L4
```

4 Question 4

Consider the following simple IR situation. We have five keywords and six documents. The term-document matrix is given by the following matrix F.

	D1	D2	D3	D4	D5	D6
K1	1	0	1	0	0	0
K2	0	1	0	0	0	0
K3	1	1	0	0	0	0
K4	1	0	0	1	1	0
K5	0	0	0	1	0	1

1. Obtain the singular value decomposition of F.
2. Reconstruct F using only the top two singular values.
3. Show the representation of the documents and the keywords in the 2-D space after SVD application.
4. Using the cosine similarity measure in the LSI space, calculate the document similarity matrix.

[ ]:
```python
F = np.array([
    [1, 0, 1, 0, 0, 0],
    [0, 1, 0, 0, 0, 0],
    [1, 1, 0, 0, 0, 0],
    [1, 0, 0, 1, 1, 0],
    [0, 0, 0, 1, 0, 1]
])

u, s, v = np.linalg.svd(F)
print(f"1.\nU:\n{u}\nS:{s}\nV:\n{v}")
```

```
1.
U:
[[ 4.403e-01 -2.962e-01 -5.695e-01  5.774e-01 -2.464e-01]
 [ 1.293e-01 -3.315e-01  5.870e-01  7.216e-16 -7.272e-01]
 [ 4.755e-01 -5.111e-01  3.677e-01  4.978e-16  6.144e-01]
 [ 7.030e-01  3.506e-01 -1.549e-01 -5.774e-01 -1.598e-01]
 [ 2.627e-01  6.467e-01  4.146e-01  5.774e-01  8.661e-02]]
S:[2.163 1.594 1.275 1.    0.394]
V:
[[ 7.486e-01  2.797e-01  2.036e-01  4.466e-01  3.251e-01  1.215e-01]
 [-2.865e-01 -5.285e-01 -1.858e-01  6.255e-01  2.199e-01  4.056e-01]
 [-2.797e-01  7.486e-01 -4.466e-01  2.036e-01 -1.215e-01  3.251e-01]
 [-4.718e-16  1.017e-15  5.774e-01  2.163e-16 -5.774e-01  5.774e-01]
 [ 5.285e-01 -2.865e-01 -6.255e-01 -1.858e-01 -4.056e-01  2.199e-01]
 [-3.578e-17 -9.252e-18  3.578e-17 -5.774e-01  5.774e-01  5.774e-01]]
```

[ ]:
```python
sigma = np.zeros((5, 6))

for i in range(2):
    sigma[i, i] = s[i]

reconstructed = np.round(np.dot(u, np.dot(sigma, v)))
```

```python
print(f"2. Reconstructed F:\n{reconstructed}")
```

```
2. Reconstructed F:
[[ 1.  1.  0.  0.  0. -0.]
 [ 0.  0.  0. -0. -0. -0.]
 [ 1.  1.  0. -0.  0. -0.]
 [ 1.  0.  0.  1.  1.  0.]
 [ 0. -0. -0.  1.  0.  0.]]
```

[ ]:
```python
u2 = np.array([u[:, 0]*s[0], u[:, 1]*s[1]]).T
v2 = np.array([v[:, 0]*s[0], v[:, 1]*s[1]]).T

print("3.")
print("Terms:\n", u2)
print("Documents:\n", v2)
```

```
3.
Terms:
 [[ 0.952 -0.472]
 [ 0.28  -0.528]
 [ 1.028 -0.815]
 [ 1.52   0.559]
 [ 0.568  1.031]]
Documents:
 [[ 1.619e+00  4.460e-01]
 [-6.195e-01 -8.426e-01]
 [-6.049e-01  1.194e+00]
 [-1.020e-15  1.622e-15]
 [ 1.143e+00 -4.567e-01]
 [-7.738e-17 -1.475e-17]]
```

[ ]:
```python
print("4.\n", cosine_similarity(F))
```

```
4.
 [[1.    0.    0.5   0.408 0.   ]
 [0.    1.    0.707 0.    0.   ]
 [0.5   0.707 1.    0.408 0.   ]
 [0.408 0.    0.408 1.    0.408]
 [0.    0.    0.    0.408 1.   ]]
```