Homework 6 [20pt]

Introduction to Data Science

Spring 2023

In this assignment, you will analyze the Baltimore crime data collected by Baltimore Police Department using clustering method. You will apply the K-Means algorithm from scratch, train the model on the train dataset, evaluate your model using validation dataset, and visualize the clustering results on your test dataset.

In [1]:

```
import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
```

In [2]:

```
df = pd.read_csv("BPD_2012_2017.csv")
print(len(df))

# Drop missing values
df = df.dropna(subset=['Longitude', 'Latitude'])

# Show first 3 rows
df.head(3)
```

```
276529
```

Out[2]:

	CrimeDate	CrimeTime	CrimeCode	Location	Description	Inside/Outside	Weapon	Post
0	09/02/2017	23:30:00	3JK	4200 AUDREY AVE	ROBBERY - RESIDENCE	I	KNIFE	913.0
1	09/02/2017	23:00:00	7A	800 NEWINGTON AVE	AUTO THEFT	O	NaN	133.0
2	09/02/2017	22:53:00	9S	600 RADNOR AV	SHOOTING	Outside	FIREARM	524.0

In [3]:

```
# Select two features from dataframe as dataset
X = df[['Longitude', 'Latitude']].to_numpy()

print(X.shape)
```

```
(274325, 2)
```

where variable X is the whole dataset we will use for clustering

Problem 1 Train-Validation-Test Split [3pt]

Use function `train_test_split` in module `sklearn.model_selection` with a `random_state` of `3407` to split the whole dataset X into train, validation and test dataset, with ratio 0.6, 0.2, 0.2.

FYI: To verify your code correctness, the shape of your train, validation and test dataset should exactly be as follows:

- shape of train dataset: (164595, 2)
- shape of validation dataset: (54865, 2)
- shape of test dataset: (54865, 2)

Comment: Usually we don't do train-validation-test split in unsupervised learning. This is just for coding practice.

In [4]:

```
from sklearn.model_selection import train_test_split

random_state = 3407
X_train, X_test = train_test_split( X,
                                    test_size=0.2,
                                    train_size=0.8,
                                    random_state=random_state,
                                    shuffle=True,
                                    stratify=None
                                   )
X_train, X_valid = train_test_split( X_train,
                                    test_size=0.25,
                                    train_size=0.75,
                                    random_state=random_state,
                                    shuffle=True,
                                    stratify=None
                                   ) #  0.75 * 0.8 = 0.6
```

In [5]:

```
X_train.shape, X_test.shape, X_valid.shape
```

Out[5]:

```
((164595, 2), (54865, 2), (54865, 2))
```

Problem 2 K-Means Fitting and Model Evaluation

Follow the instruction below and finish the three tasks in this problem

1. Write a function computing the validation inertias, given the trained K-Means Model and the validation dataset. [3pt]

2. Fit KMeans clusters to the training set for K in [2, 14] using a `random_state` of `3407`. [5pt]

3. Plot the training inertias as a function of K. In a separate figure, plot the validation inertias as a function of K, where validation inertias should be obtained by the function in step 1. [2pt]

In [6]:

```
def validation(kmeans, X_val):
    '''
    Input: kmeans - your trained K-Means model using sklearn.cluster.KMeans
            X_val - validation dataset

    Output: validation inertias
    '''
    preds = kmeans.fit_predict(X_val)
    K = np.max(preds) + 1
    print(f"K is {K}")
    iner = np.sum([np.sum(np.sum((X_valid[preds == i] - kmeans.cluster_centers_[i])*
        range(0,K)])
    print(iner)
    return iner
```

In [7]:

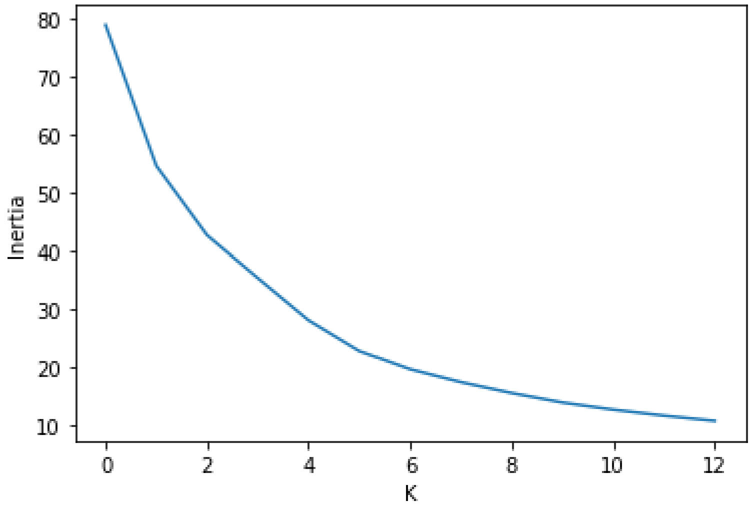
```
from sklearn.cluster import KMeans

inertias = []
for k in range(2,15):
    model = KMeans(n_clusters=k, random_state=random_state)
    model.fit(X_train)
    inertias.append(validation(model, X_valid))
```

```
K is 2
78.99244997556735
K is 3
54.66806765259908
K is 4
42.699985996752275
K is 5
35.317731004442415
K is 6
28.042457977440915
K is 7
22.72184467473326
K is 8
19.57639976228317
K is 9
17.348384973500607
K is 10
15.467501594354855
K is 11
13.831459458252922
K is 12
12.603210771825575
K is 13
11.570887811855394
K is 14
10.664998117729654
```

In [8]:

```
plt.figure()
plt.plot(inertias)
plt.xlabel("K")
plt.ylabel("Inertia")
plt.show()
```



Based on validation plot, is there a clear "elbow" in the plot? If so, choose the K value using the elbow method. If not, propose an alternative quantitative method, and specify the K value chosen by your method. Provide a detailed explanation. [2pt]

Your answer: There was not a clear evidence or breakpoint in the inertia plot. By visually assessing the inertia plot, as we are increasing the # of clusters (k) we can't see any point that shows a convergence for inetria. So for a better assessment, I will use the silhouette method for this purpose.

Silhouette analysis can be used to study the separation distance between the resulting clusters. The silhouette plot displays a measure of how close each point in one cluster is to points in the neighboring clusters and thus provides a way to assess parameters like number of clusters visually. This measure has a range of [-1, 1].

Based on this plot (shown bellow), we can conclude that the number K=8,9 are the best, because we reach an almost stable value for the sil. index after this #.

In [9]:

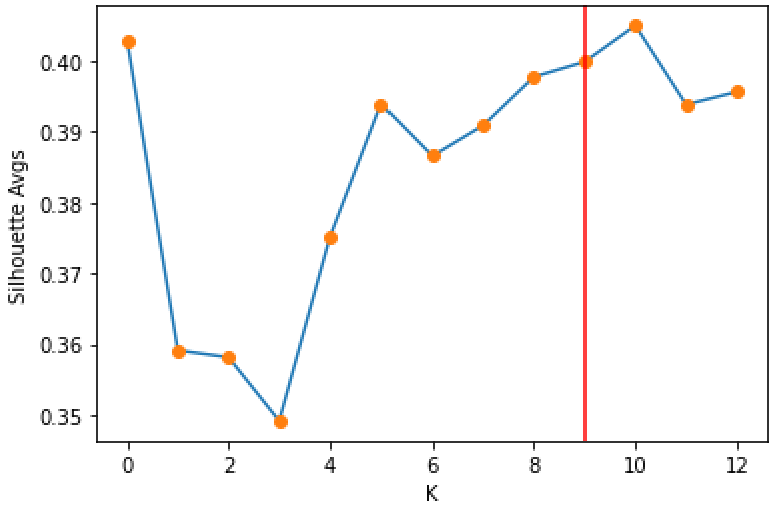
```
from sklearn.metrics import silhouette_score

silhouette_avgs = []
for k in range(2,15):
    clusterer = KMeans(n_clusters=k, random_state=random_state)
    cluster_labels = clusterer.fit_predict(X_valid)
    # The silhouette_score gives the average value for all the samples.
    # This gives a perspective into the density and separation of the formed
    # clusters
    silhouette_avg = silhouette_score(X_valid, cluster_labels)
    silhouette_avgs.append(silhouette_avg)
    print(
        "For n_clusters =",
        k,
        "The average silhouette_score is :",
        silhouette_avg,
    )
```

```
For n_clusters = 2 The average silhouette_score is : 0.402934754662347
7
For n_clusters = 3 The average silhouette_score is : 0.359120999320700
3
For n_clusters = 4 The average silhouette_score is : 0.358152740800608
7
For n_clusters = 5 The average silhouette_score is : 0.349171245804525
47
For n_clusters = 6 The average silhouette_score is : 0.375137183935968
95
For n_clusters = 7 The average silhouette_score is : 0.393864595535821
For n_clusters = 8 The average silhouette_score is : 0.386586471878228
64
For n_clusters = 9 The average silhouette_score is : 0.390887112172053
2
For n_clusters = 10 The average silhouette_score is : 0.39774411096572
226
For n_clusters = 11 The average silhouette_score is : 0.39986490820171
383
For n_clusters = 12 The average silhouette_score is : 0.40499162663199
84
For n_clusters = 13 The average silhouette_score is : 0.39382900688029
937
For n_clusters = 14 The average silhouette_score is : 0.39562528905932
6
```

In [10]:

```
plt.figure()
plt.plot(silhouette_avgs)
plt.plot(silhouette_avgs,'o')
plt.xlabel("K")
plt.ylabel("Silhouette Avgs")
plt.axvline(9,c='r')
plt.show()
```



Problem 3 Result Visualization

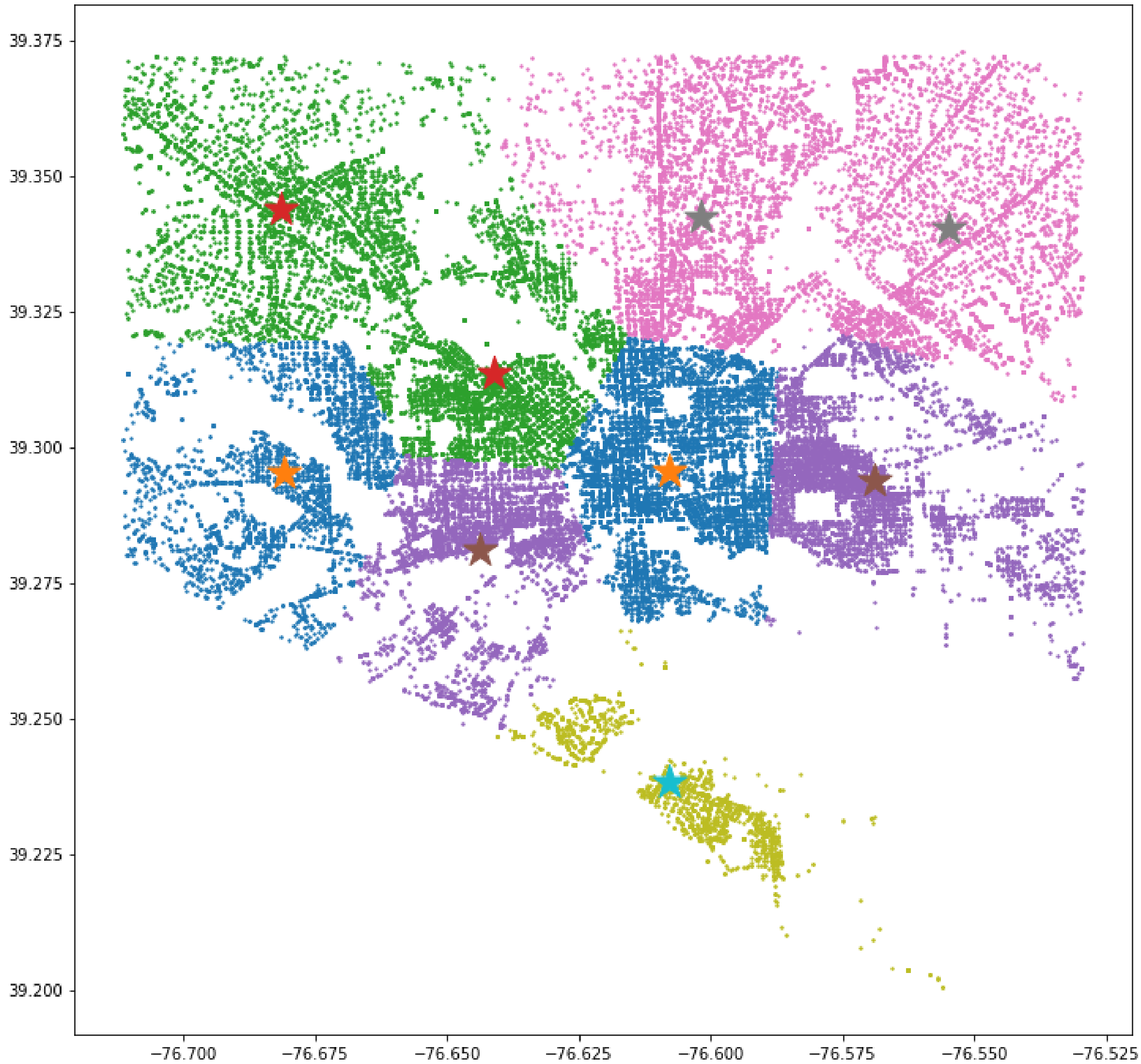
Train your model with the selected number of clusters in problem 2 and plot the cluster assignments on the test dataset using the *plot_clusters* function. [3pt]

In [11]:

```
def plot_clusters(kmeans, X_test):
    '''
    Input: kmeans - your trained K-Means model using sklearn.cluster.KMeans
           X_val - test dataset
    *** DO NOT MODIFY THIS CODE BLOCK ***
    '''
    test_labels = kmeans.predict(X_test)
    plt.figure(figsize=(12,12))
    for i in range(np.max(test_labels)+1):
        plt.scatter(X_test[test_labels == i, 0] , X_test[test_labels == i, 1] , s=2,
        plt.scatter(kmeans.cluster_centers_[i,0], kmeans.cluster_centers_[i, 1], lab
    plt.show()

K = 9
model = KMeans(n_clusters=K, random_state=random_state)
model.fit(X_train)

plot_clusters(model, X_test)
```



[2pt] Do these clusters show a different pattern than what you would expect from uniformly distributed locations? Optionally, you can repeat your evaluation on the pseudo-random uniformly distributed longitudes and lattitudes below to support your answer. But a verbal explanation of your analysis and prediction is also fine.

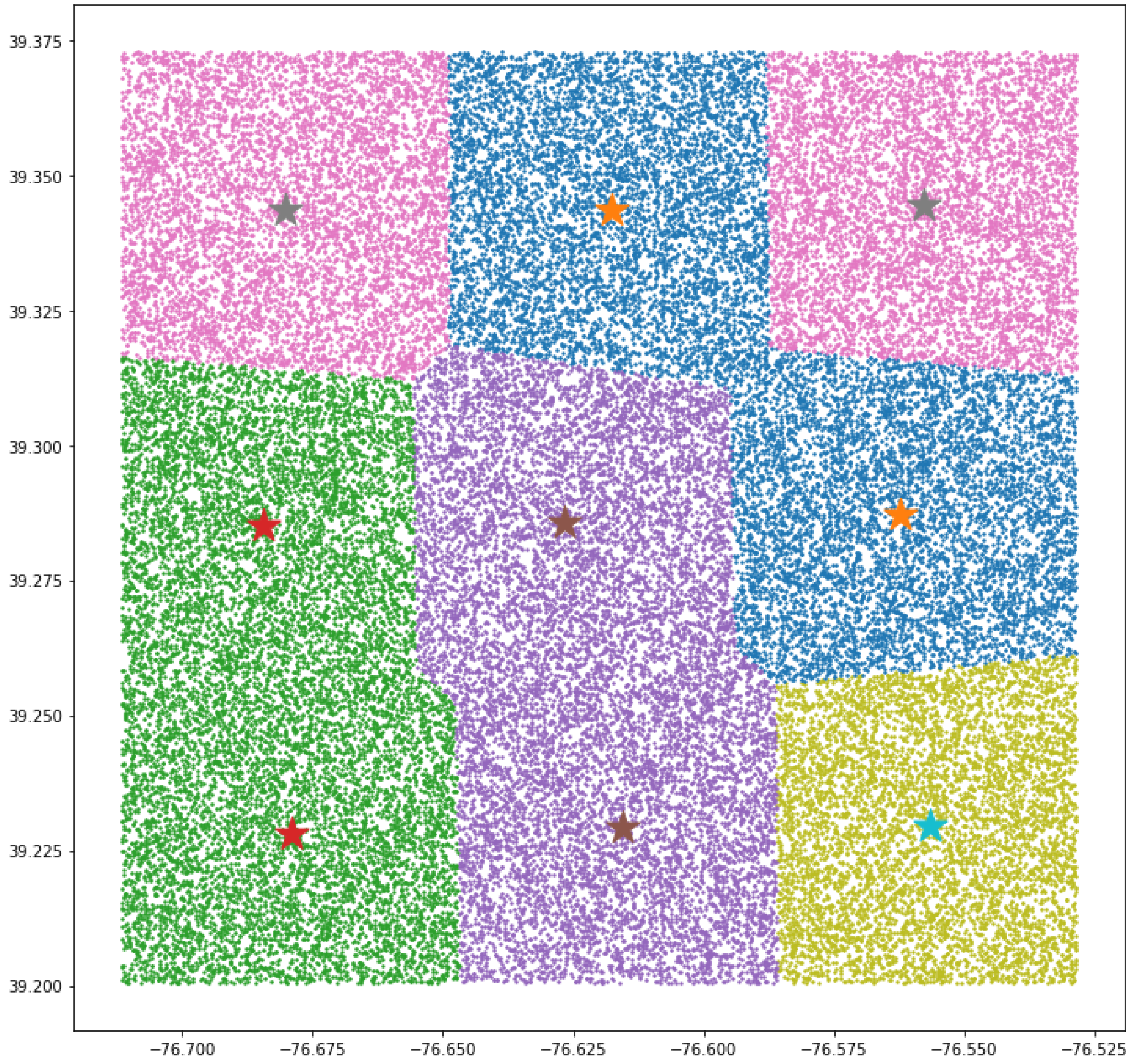
In [12]:

```
min_longitude = X[:,0].min()
max_longitude = X[:,0].max()
min_latitude = X[:,1].min()
max_latitude = X[:,1].max()

X_uniform = np.random.uniform(low=[min_longitude, min_latitude], high=[max_longitude
X_uniform_train, X_uniform_test = train_test_split(X_uniform, test_size=0.2, random_

K = 9
model = KMeans(n_clusters=K, random_state=random_state)
model.fit(X_uniform_train)

plot_clusters(model, X_uniform_test)
```



It is evident that our pattern is not very distinct from an uniform distribution. The

made clutsters are well seperated and it reflect the uniform distribution that we were expecting.

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