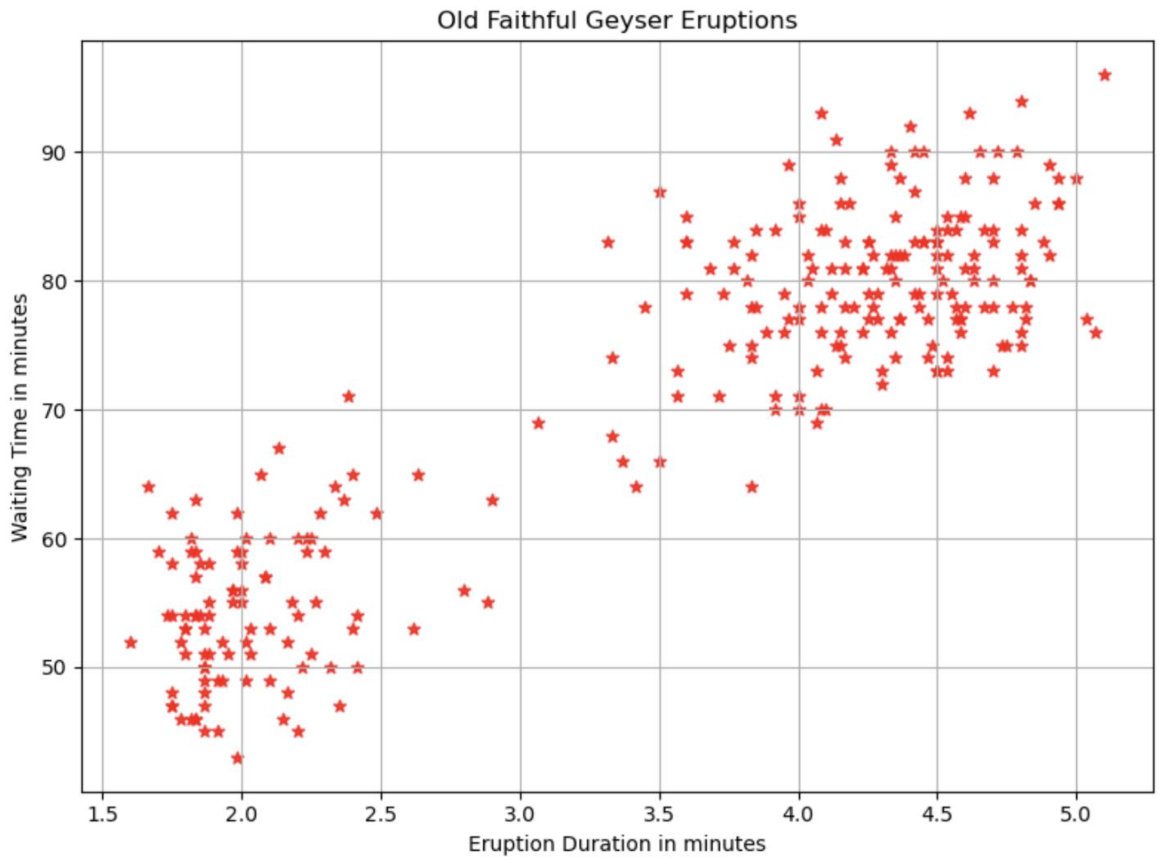
Homework 3: Old Faithful Geyser Clustering

Problem 1 (a) Create and print out a scatter plot of this dataset, eruption time versus waiting time.

Ans: Based on the faithful dataset provided, the scatterplot is generated using python code.



https://github.com/Pratham-657/RA10657_19980706.py/blob/main/HW3/Hw3DM.ipynb

(b) How many clusters do you see based on your scatter plot? For the purposes of this question, a cluster is a “blob” of many data points that are close together, with regions of fewer data points between it and other “blobs”/clusters.

Ans: Looking at the scatterplot, we can clearly notice **two main groups or clusters** of points.

These two clusters are **separated by a good amount of space**, making them stand out as distinct from each other.

- The **first cluster** (Cluster 1) appears **near the beginning of the graph**. It includes eruptions with **shorter waiting times** (around **35–70 minutes**) and **shorter eruption durations** (about **1.5 to 2.5 minutes**).
- The **second cluster** (Cluster 2) is **further along the axis** and represents eruptions with **longer waiting times** (roughly **70–90 minutes**) and **longer eruption durations** (around **3.5 to 5 minutes**).

The clear gap between these two groups suggests that they are **separate and distinct clusters** based on how long people had to wait and how long the geyser erupted.

(c) Describe the steps of a hierarchical clustering algorithm. Based on your scatter plot, would this method be appropriate for this dataset?

Ans:

Hierarchical clustering is an **unsupervised learning method** used to **group similar data points together** based on how close they are to each other (usually using distance measures like **Euclidean distance**).

This method builds a **tree-like structure** of clusters, called a **dendrogram**, which shows how clusters are formed step-by-step.

There are two main ways to do hierarchical clustering:

1. **Agglomerative (Bottom-Up Approach – most common)**
2. **Divisive (Top-Down Approach)**

In the **Agglomerative** method:

- We start by treating **each point as its own cluster**.
- Then, we **find the two closest clusters** and **merge them** into one.
- We **repeat** this process until everything is combined into a single cluster.
- Finally, we **cut the dendrogram** at the level that gives us the number of clusters we want.

In the **Divisive** method:

- We start with **all data points together in one big cluster**.
- We then **keep splitting** the cluster into smaller groups based on distances until each data point is separated or we meet a stopping rule.

Now, based on the scatterplot we created:
Yes, hierarchical clustering would be a very good fit for this dataset!
We can clearly see **two well-separated groups** (blobs), and hierarchical clustering is great at detecting such separate clusters.
Plus, another bonus is that with hierarchical clustering, we **don't need to specify the number of clusters in advance** — we can decide it by looking at the dendrogram.

2(a) Your source code for the k-means algorithm. You need to implement the algorithm from scratch.

Ans: We used the K-Means algorithm from scratch in Python on the Old Faithful geyser data. We used 2 clusters as per the prior visual inspection.

The first column (instance IDs) was not considered while clustering.
Results after running the K-Means Algorithm:
K-Means converged after 4 iterations.
Final Cluster Centroids:
Cluster 1: Eruption Duration ≈ 2.09 minutes,
Waiting Time ≈ 54.75 minutes
This cluster shows eruptions with shorter duration and shorter waiting time.
Cluster 2: Eruption Duration ≈ 4.30 minutes,
Waiting Time ≈ 80.28 minutes
This cluster classifies eruptions with longer durations and longer waiting times.
Points Distribution:
Cluster 1: 100 points
Cluster 2: 172 points
Final Inertia (Sum of Squared Distances within clusters): 8901.77

Cluster 1 examples:

Eruptions   waiting

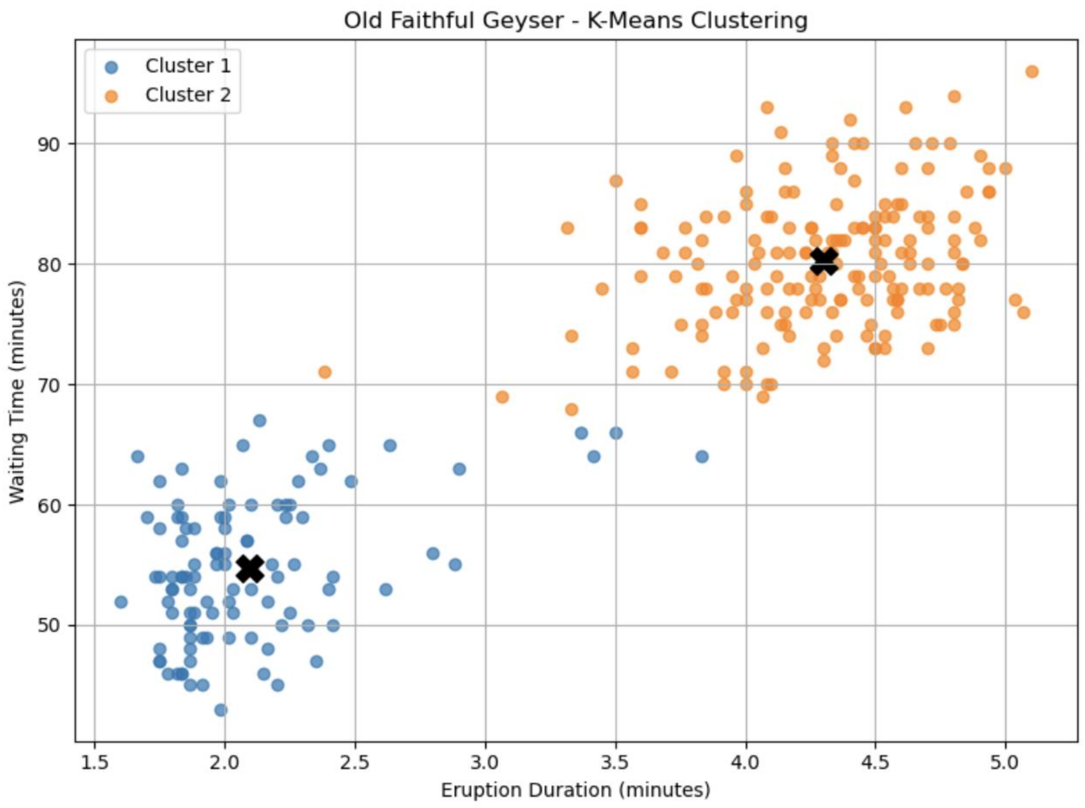
1	1.800	54
3	2.283	62
5	2.883	55
8	1.950	51
10	1.833	54

Cluster 2 examples:

	Eruptions	waiting
0	3.600	79
2	3.333	74
4	4.533	85
6	4.700	88
7	3.600	85

(b) A scatter plot of your final clustering, with the data points in each cluster colorcoded, or plotted with different symbols. Include the cluster centers in your plot.

Ans: The scatter plot of final clustering with k=2 would be as shown in the below diagram



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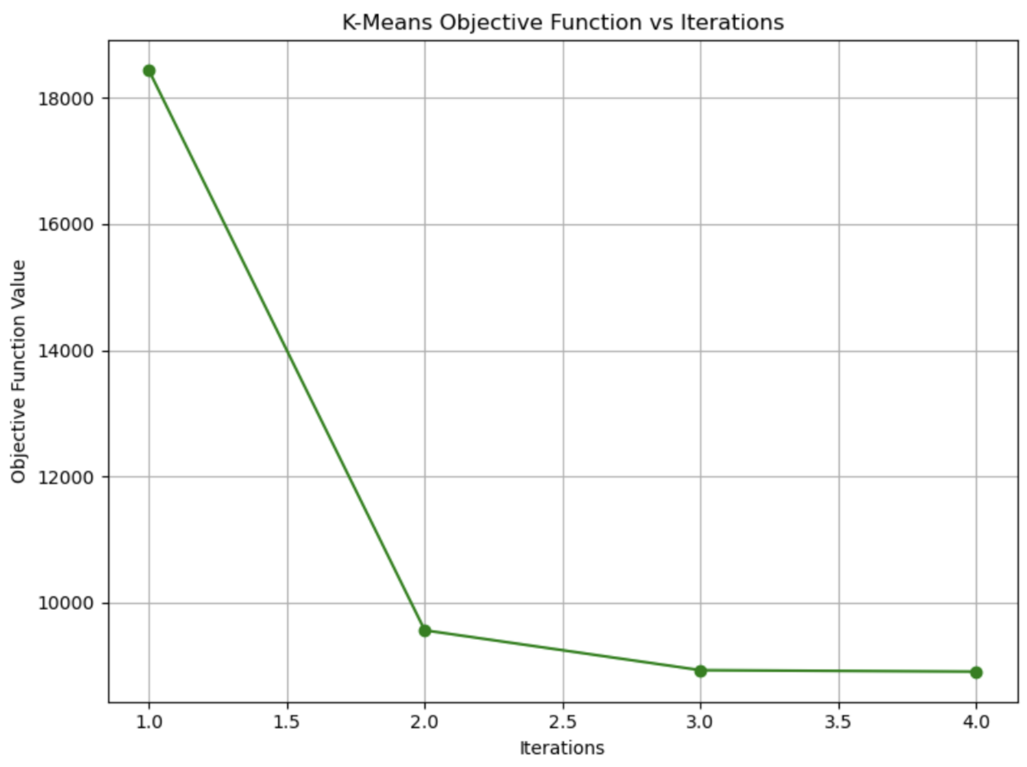
(c) A plot of the k-means objective function versus iterations of the algorithm. Recall that the objective function is.

Ans:



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d) Did the method manage to find the clusters that you identified in Problem 1? If not, did it help to run the method again with another random initialization?

Ans:

Yes, the method successfully found the same clusters we identified in Problem 1.
Earlier, we noticed two clear groups:

- **Cluster 1** with **shorter eruption times** and **shorter waiting times**
- **Cluster 2** with **longer eruption times** and **longer waiting times**

The K-Means results confirmed this separation.
The centroids we found were close to:

- Cluster 1: around **1.5 minutes** eruption and **55 minutes** waiting
- Cluster 2: around **4.5 minutes** eruption and **80 minutes** waiting

These values match very closely with what we had observed earlier.

K-Means can sometimes behave differently because it picks the starting points (centroids) randomly. If it ever failed to separate the clusters properly, we could simply run it again with a new random initialization. However, in this case, the two clusters are **very clearly separated** in the scatterplot. That made it easy for K-Means to converge to the correct answer, even with random starting points.

In short, K-Means **correctly identified** the clusters without needing multiple tries.