Day60_Clustering

August 9, 2025

1 Clustering

1. What is Clustering?

Clustering is an **unsupervised learning** technique that groups data points based on similarity. Unlike regression or classification, **there is no dependent variable** — the algorithm itself finds the groups.

2. Regression vs Classification vs Clustering

- **Regression**: DV is continuous (e.g., predicting salary).
- **Classification**: DV is categorical/binary (e.g., spam or not spam).
- **Clustering**: No DV — only features, and we find groups (clusters) from them.

3. Types of Clustering

1. **PCA** — Dimensionality reduction, often used before clustering.
2. **K-Means** — Centroid-based, fast, requires `K`.
3. **Hierarchical Clustering** — Tree/dendrogram approach.
4. **DBSCAN** — Density-based, detects noise and arbitrary-shaped clusters.

In this notebook: - PCA already completed earlier. - We now focus on **K-Means** (with manual math + code).

4. K-Means — Manual Math Example

Dataset: Student Heights & Weights

Student	Height (cm)	Weight (kg)
$S1$	185	72
$S2$	170	56
$S3$	168	60
$S4$	179	68

Step 1 — Initialization Choose first 2 points as initial centroids:

$$\mu_1 = (185, 72), \quad \mu_2 = (170, 56)$$

Step 2 — Assignment

For each point, compute Euclidean distance to both centroids:

$$d((h_1, w_1), (h_2, w_2)) = \sqrt{(h_1 - h_2)^2 + (w_1 - w_2)^2}$$

Assign point to nearest centroid.

Step 3 — Update

Recalculate centroids as mean of points in each cluster:

$$\mu_k = \frac{1}{|C_k|} \sum_{x_i \in C_k} x_i$$

Step 4 — Repeat

Continue **Assignment** $\rightarrow$ **Update** until centroids stop changing (convergence).

2 Manual Example in Python

[1]:
```python
import numpy as np

# Heights & weights dataset
data = np.array([[185, 72], [170, 56], [168, 60], [179, 68]])

# Initial centroids (first two points)
centroids = np.array([data[0], data[1]])
print("Initial centroids:\n", centroids)

# Compute distances and assign clusters
distances = np.linalg.norm(data[:, np.newaxis] - centroids, axis=2)
clusters = np.argmin(distances, axis=1)
print("Cluster assignments:", clusters)

# Update centroids
for k in range(2):
    centroids[k] = data[clusters == k].mean(axis=0)
print("Updated centroids:\n", centroids)
```

```
Initial centroids:
 [[185  72]
 [170  56]]
Cluster assignments: [0 1 1 0]
Updated centroids:
 [[182  70]
 [169  58]]
```

2.1 Manual K-Means Example — Output Explanation

Initial Centroids
We chose the first 2 points as starting centers:

$$\mu_1 = (185, 72), \quad \mu_2 = (170, 56)$$

Cluster Assignment
For each student, we calculate the Euclidean distance:

$$d((h_1, w_1), (h_2, w_2)) = \sqrt{(h_1 - h_2)^2 + (w_1 - w_2)^2}$$

Points are assigned to the nearest centroid:
- Cluster 0 → S1, S4
- Cluster 1 → S2, S3

Centroid Update
New centroids = mean of each cluster's points:

$$\mu_1 = (182, 70), \quad \mu_2 = (169, 58)$$

After 1 iteration: centroids moved closer to the center of their assigned points.
Repeat **assign → update** until no change (**convergence**).

Elbow Method Theory

5. Elbow Method — Choosing Optimal K

We want the number of clusters `K` where adding more clusters **doesn't significantly reduce** the **WCSS** (Within-Cluster Sum of Squares).

Formula for WCSS:

$$WCSS = \sum_{k=1}^{K} \sum_{x_i \in C_k} \|x_i - \mu_k\|^2$$

How to interpret the Elbow graph:

- **X-axis**: Number of clusters (K)
- **Y-axis**: WCSS
- The **"elbow point"** is where the curve bends — after this point, adding more clusters gives little gain.

This is our **optimal K**.

3 Applying K-Means on Real Data

Now, let's apply K-Means to a real dataset (**Mall_Customers.csv**) to find out
which customers belong to which group based on their **annual income** and **spending score**.
This will help identify different customer segments for targeted marketing.

3.1 Load CSV & Prepare Data

[3]:
```python
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
import warnings
warnings.filterwarnings("ignore", message="KMeans is known to have a memory␣
↪leak")

# Load dataset
df = pd.read_csv(r"C:\Users\Lenovo\Downloads\Mall_Customers.csv")
df.head()
```

[3]:

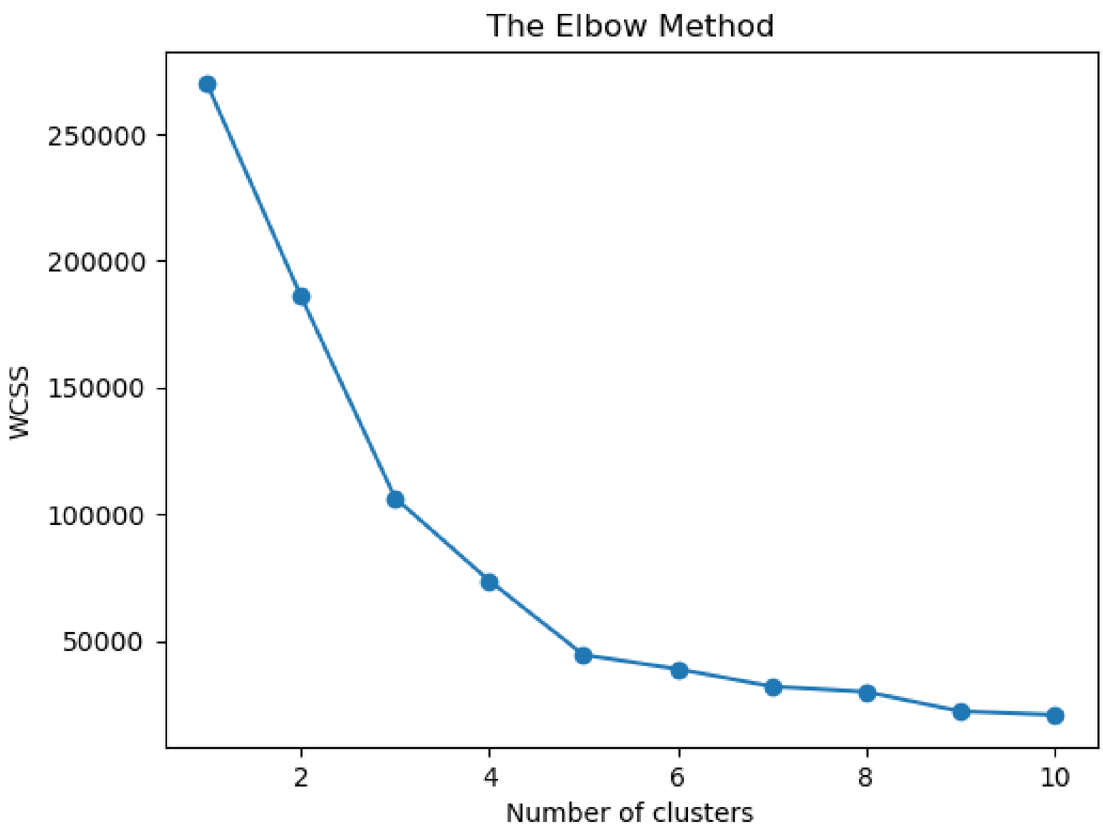
	CustomerID	Genre	Age	Annual Income (k$)	Spending Score (1-100)
0	1	Male	19	15	39
1	2	Male	21	15	81
2	3	Female	20	16	6
3	4	Female	23	16	77
4	5	Female	31	17	40

[4]:
```python
# We'll use Annual Income (3rd col) and Spending Score (4th col)
X = df.iloc[:, [3, 4]].values
```

3.2 Elbow Method

[5]:
```python
# Elbow Method to find optimal K
#Loop through \(K = 1\) to \(10\), fit K-Means, store **WCSS**, and
#plot it to visually find the "elbow point" - the optimal number of clusters.
wcss = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters=i, init="k-means++", random_state=0)
    kmeans.fit(X)
    wcss.append(kmeans.inertia_)

plt.plot(range(1, 11), wcss, marker='o')
plt.title("The Elbow Method")
plt.xlabel("Number of clusters")
plt.ylabel("WCSS")
plt.show()
```



How to Read the Elbow Method Graph

- **X-axis** → Number of clusters ((K)) we try.
- **Y-axis** → WCSS (Within-Cluster Sum of Squares), which measures how spread out points are within each cluster.

Steps to read:

1. Start at (K=1): WCSS is **highest** because all points are in one cluster → very spread out.
2. As (K) increases: WCSS **drops quickly** because clusters get smaller and points are closer to their centroids.
3. Look for the **"elbow point"**: where the sharp drop flattens into a gentle slope.
4. The elbow point means **adding more clusters beyond this gives little improvement**.

In this graph, the bend is around **(K=5)** → this is the **optimal number of clusters**.

3.3 Choosing K

From the Elbow graph, we select **K=5** as it gives the best balance — beyond this, WCSS reduction is minimal.

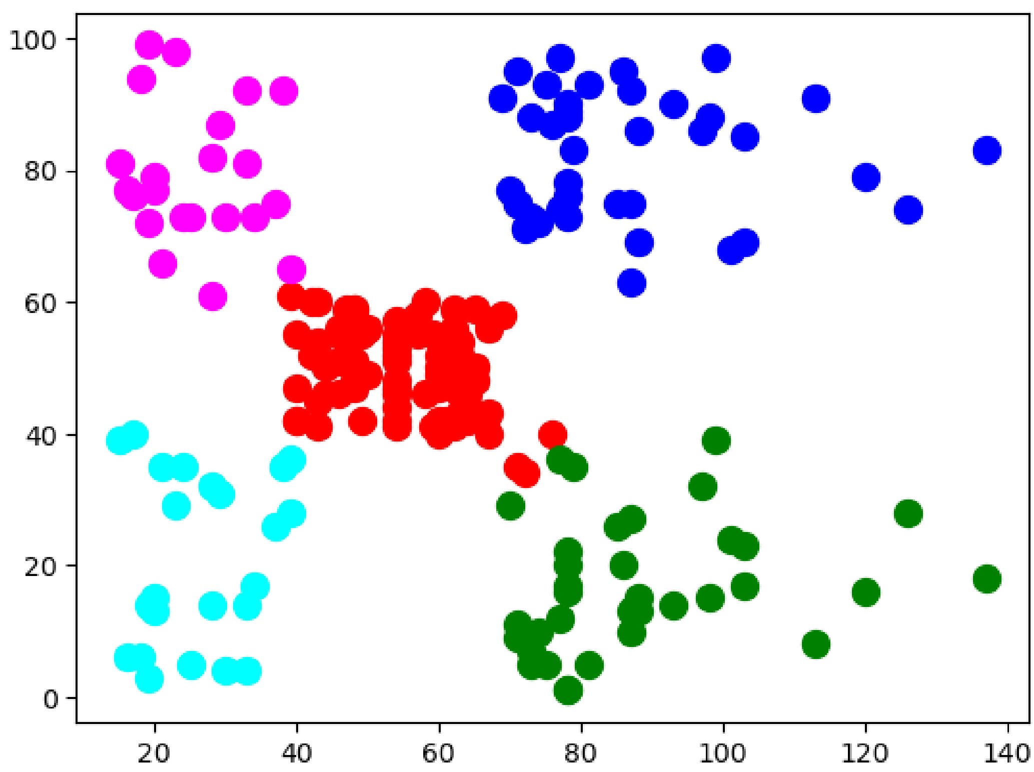
3.4 Fit K-Means & Predict

[6]:
```
kmeans = KMeans(n_clusters=5, init="k-means++", random_state=0)
y_kmeans = kmeans.fit_predict(X)
```

3.5 Plot Clusters

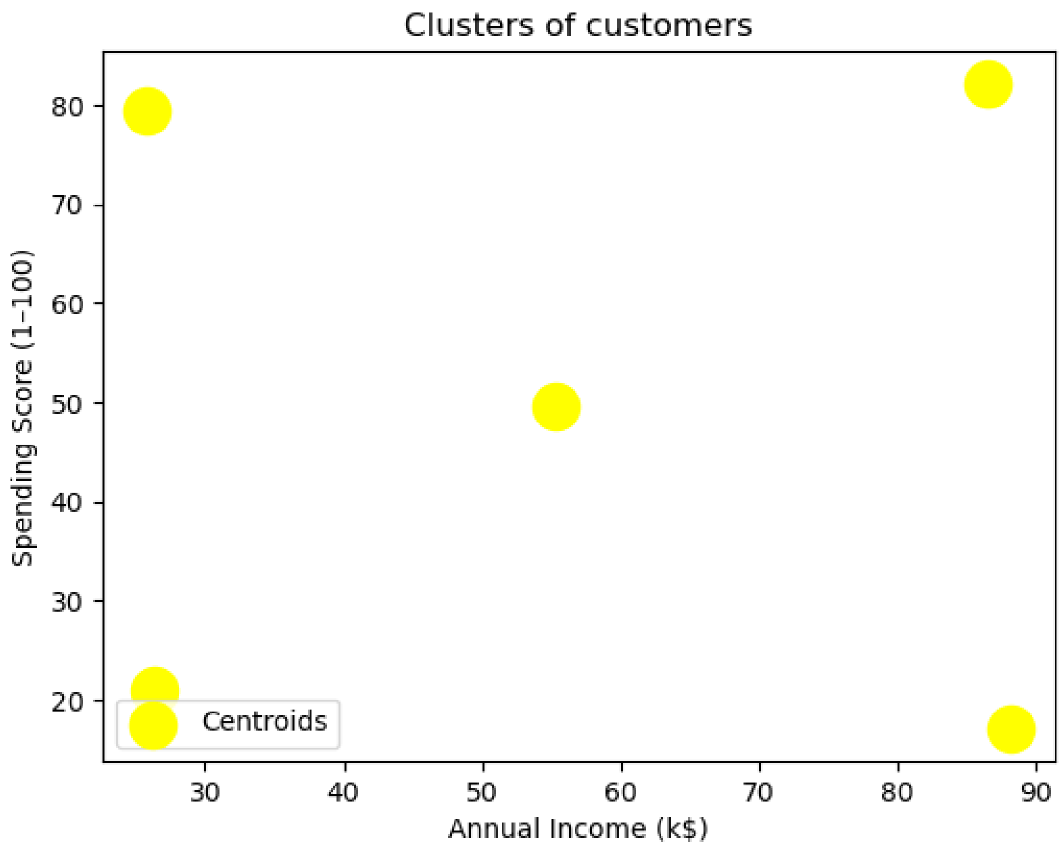
[7]:
```
# Plot each cluster
plt.scatter(X[y_kmeans == 0, 0], X[y_kmeans == 0, 1], s=100, c='red', label='Cluster 1')
plt.scatter(X[y_kmeans == 1, 0], X[y_kmeans == 1, 1], s=100, c='blue', label='Cluster 2')
plt.scatter(X[y_kmeans == 2, 0], X[y_kmeans == 2, 1], s=100, c='green', label='Cluster 3')
plt.scatter(X[y_kmeans == 3, 0], X[y_kmeans == 3, 1], s=100, c='cyan', label='Cluster 4')
plt.scatter(X[y_kmeans == 4, 0], X[y_kmeans == 4, 1], s=100, c='magenta', label='Cluster 5')
```

[7]: <matplotlib.collections.PathCollection at 0x193b06bf890>



[8]:
```
# Plot centroids
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1],
            s=300, c='yellow', label='Centroids')

plt.title('Clusters of customers')
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.legend()
plt.show()
```



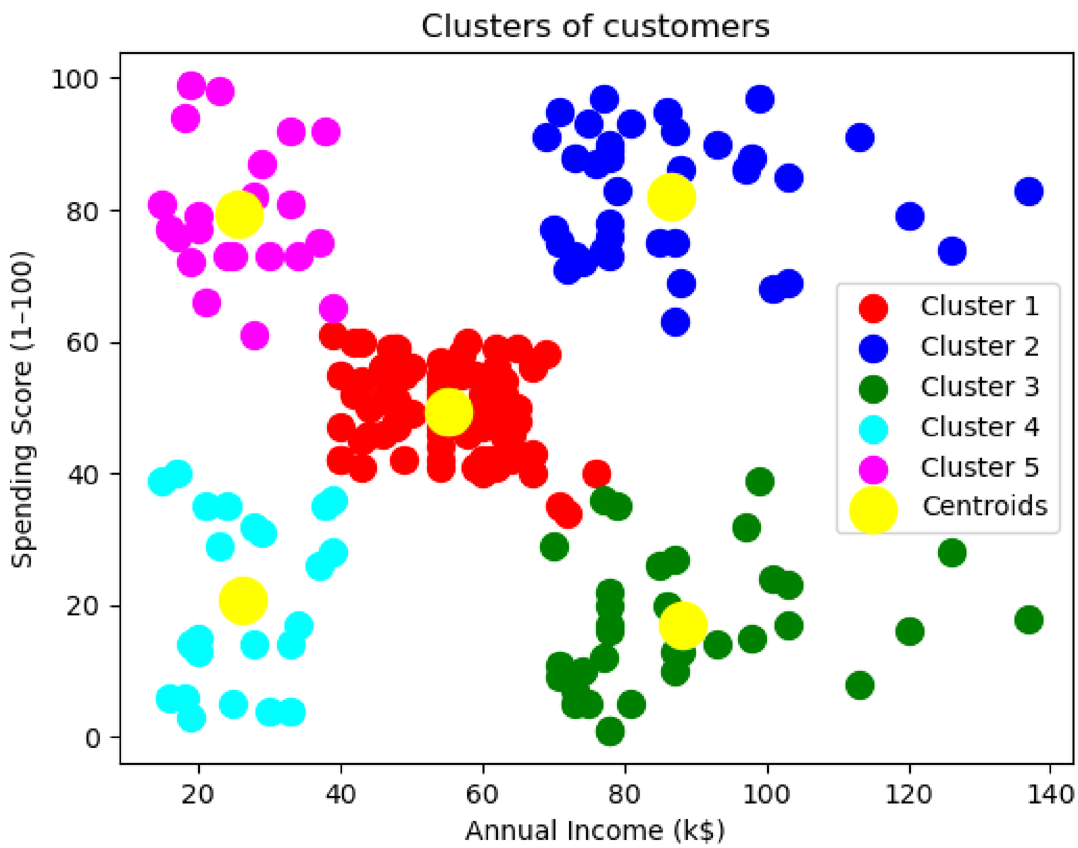
3.6 Plot Clusters with centroids

[9]:
```
# Plot each cluster
plt.scatter(X[y_kmeans == 0, 0], X[y_kmeans == 0, 1], s=100, c='red',␣
 ↪label='Cluster 1')
plt.scatter(X[y_kmeans == 1, 0], X[y_kmeans == 1, 1], s=100, c='blue',␣
 ↪label='Cluster 2')
plt.scatter(X[y_kmeans == 2, 0], X[y_kmeans == 2, 1], s=100, c='green',␣
 ↪label='Cluster 3')
```

```
plt.scatter(X[y_kmeans == 3, 0], X[y_kmeans == 3, 1], s=100, c='cyan',␣
↪label='Cluster 4')
plt.scatter(X[y_kmeans == 4, 0], X[y_kmeans == 4, 1], s=100, c='magenta',␣
↪label='Cluster 5')

# Plot centroids
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1],
            s=300, c='yellow', label='Centroids')

plt.title('Clusters of customers')
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.legend()
plt.show()
```



Customer Segmentation Output

The scatter plot shows **5 customer clusters** formed using K-Means based on **Annual Income (X-axis)** and **Spending Score (Y-axis)**.

- **Colors** represent different customer groups with similar spending & income patterns.

- **Yellow dots** = Centroids (center points of each cluster).
- Customers in the same cluster are **more similar** to each other than to customers in other clusters.

Example:

- **Pink cluster** → Low income, high spending.
- **Green cluster** → High income, low spending.
- **Blue cluster** → High income, high spending.

3.7 Save Clustered Data

[10]:
```
df['Cluster'] = y_kmeans
df.to_csv("clustered_data.csv", index=False)
print("Clustered data saved.")
```

```
Clustered data saved.
```

3.8 Load Saved Data

[11]:
```
import os
print("Saved at:", os.getcwd())

df1 = pd.read_csv(r"C:\Users\Lenovo\OneDrive\Desktop\Python Everyday␣
↪work\Github work\clustered_data.csv")
df1.head()
```

```
Saved at: C:\Users\Lenovo\OneDrive\Desktop\Python Everyday work\Github work
```

[11]:
```
   CustomerID   Genre  Age  Annual Income (k$)  Spending Score (1-100)  \
0           1    Male   19                  15                      39
1           2    Male   21                  15                      81
2           3  Female   20                  16                       6
3           4  Female   23                  16                      77
4           5  Female   31                  17                      40

   Cluster
0        3
1        4
2        3
3        4
4        3
```

3.9 Summary

- Understood difference between regression, classification, and clustering.

- Learned K-Means math and manual working.

- Applied Elbow Method to select optimal K.
- Built and visualized customer clusters from Mall_Customers dataset.
- Saved final results for further use.