# Assignment 10/1: K – Means Clustering (In – class)

**Colab file:** Week10_K-means_inclass_assignment.ipynb - Colab

**Dataset:** Mall Customer Segmentation Data

**Describe for each column**

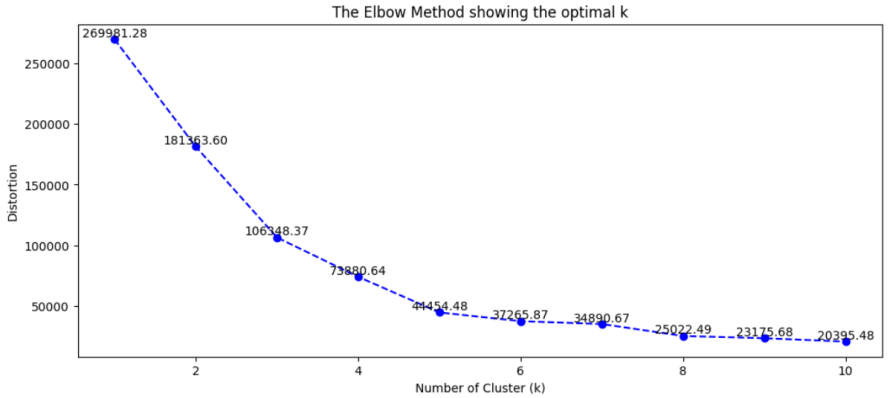
1. *CustomerID (INT)* – Unique ID assigned to the customer
2. *Gender (Category)* – Gender of customer (Female or Male)
3. *Age (INT)* – Age of customer
4. *Annual Income (k$) (INT)* – Annual Income of the customee
5. *Spending Score (INT)* – Score assigned by the mall (1 – 100) based on customer behavior and spending nature

**Objectives:**

To clustering of customers segmentation between Annual Income vs. Spending Score

**Summary Output:**

- Use **only** X **is Annual Income, and Spending Score** while Age, and Gender isn't used because of **same spreads between them.**
- From Elbow method, Select k = 5, which has the optimal clusters.




- After clustering, my dataset has 5 clusters.

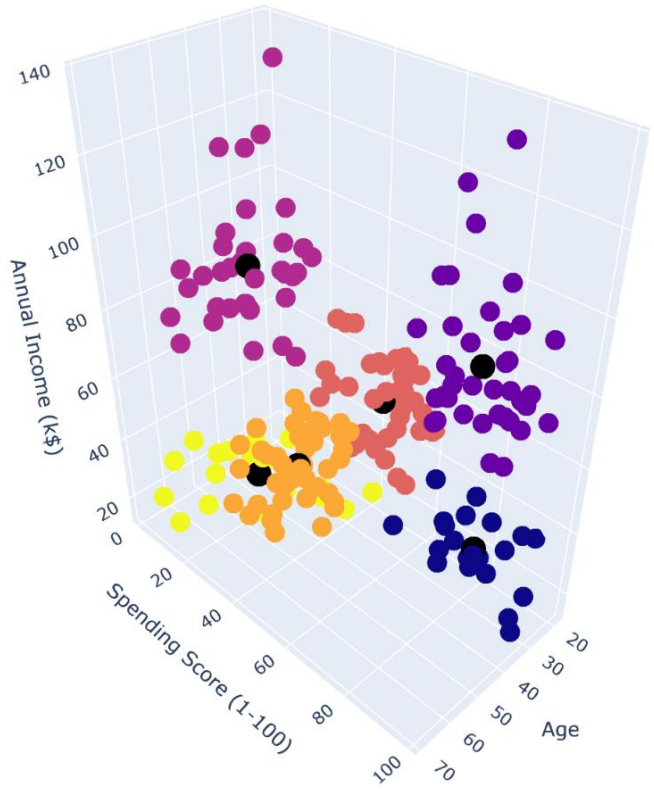

| Cluster | Zone | Interpret |
|---|---|---|
| 1 | Purple (Bottom left) | **low** annual income and **low** spending scores. |
| 2 | Green (Middle) | **moderate** annual income and spending scores. |
| 3 | Yellow (Top left) | **low** annual income but **high** spending scores. |
| 4 | Blue (Top right) | **high** annual income and **high** spending scores. |
| 5 | Teal (Bottom right) | **high** annual income but **low (to moderate)** spending scores. |

- Below table is describe some data.

| Cluster | Zone | Center | Size |
|---|---|---|---|
| 1 | Purple (Bottom left) | (26.30, 20.91) | 23 |
| 2 | Green (Middle) | (86.54, 82.13) | 81 |
| 3 | Yellow (Top left) | (55.30, 49.52) | 22 |
| 4 | Blue (Top right) | (88.20, 17.11) | 39 |
| 5 | Teal (Bottom right) | (25.73, 79.36) | 35 |

**Note:**

The center (or centroid) is calculated by the average of all data for each cluster.



**Overall Process:**

**1. Introduction and K-Means Overview**

- The notebook begins with a brief description of K-Means clustering, explaining its principles, how it works, and its common applications and limitations.
- It also mentions the dataset used, which contains customer information including gender, age, annual income, and spending score.
- Resource Dataset

**2. Data Preprocessing**

- Import Libraries and Dataset: Essential libraries like Pandas, NumPy, Matplotlib, Seaborn, Scikit-learn, and Plotly are imported.
- Exploratory Data Analysis (EDA):
    - The dataset is loaded and initial exploration is performed using df.head(), df.describe(), and df.isnull().sum().
    - The "CustomerID" column is removed as it is not relevant for clustering.
    - Box plots are generated to compare customer attributes (Age, Annual Income, Spending Score) by gender.
- Scatter plots and Pair plots:
    - Scatter plots examine the relationship between annual income and spending score. It suggests a potential structure for customer segmentation.
    - Pair plots show the relationships between all numerical variables and offer a more comprehensive view of the data.
- Correlation analysis:
    - A correlation matrix and heatmap are created to examine the linear relationships between the numerical variables in the dataset.

**3. Clustering with K-Means**

- Trial Clustering:
    - Initial K-Means clustering is performed with k=6. This is a trial attempt to understand the process.
    - The 'inertia' (within-cluster sum of squares) of the model is computed.
- Elbow Method:
    - The elbow method is used to determine the optimal number of clusters (k) for K-Means. This method calculates the inertia for various values of k,

helping find the point where adding more clusters doesn't significantly reduce the inertia.

- Clustering with Optimal K (k=5):
    - K-Means clustering is then performed using the optimal number of clusters found using the elbow method.
    - The model is fit to annual income and spending score.
    - Cluster labels are added to the df.
- Visualizing Clusters:
    - A scatter plot with cluster centers is created to visually show the identified customer segments.
    - The plots allows for the understanding of the customer segmentation into income and spending clusters.
    - A more beautiful plot is then created with a library *Plotly*, which allows the users to understand the customers clearly.

## Assignment 10/2: Hierarchical clustering (In – class)

**Colab file:** Week10_HierarchicalClustering_inclass_assignment - Colab

**Dataset:** Air Quality - UCI Machine Learning Repository

**Describe for each column**

| Column | Variable Name | Role | Type | Description | Units | Missing Values |
|---|---|---|---|---|---|---|
| 1 | Date | Feature | Date | | | no |
| 2 | Time | Feature | Categorical | | | no |
| 3 | CO(GT) | Feature | Integer | True hourly averaged concentration CO in mg/m^3 (reference analyzer) | mg/m^3 | no |
| 4 | PT08.S1(CO) | Feature | Categorical | hourly averaged sensor response (nominally CO targeted) | | no |
| 5 | NMHC(GT) | Feature | Integer | True hourly averaged overall Non Metanic Hydrocarbons concentration in microg/m^3 (reference analyzer) | microg/ m^3 | no |
| 6 | C6H6(GT) | Feature | Continuous | True hourly averaged Benzene concentration in microg/m^3 (reference analyzer) | microg/ m^3 | no |
| 7 | PT08.S2(NMHC) | Feature | Categorical | hourly averaged sensor response (nominally NMHC targeted) | | no |
| 8 | NOx(GT) | Feature | Integer | True hourly averaged NOx concentration in ppb (reference analyzer) | ppb | no |

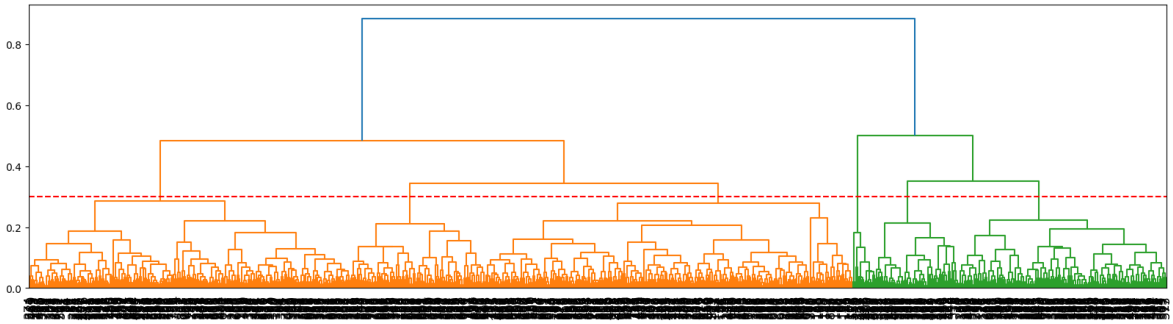
| | | | | | | |
|---|---|---|---|---|---|---|
| **9** | PT08.S3(NOx) | Feature | Categorical | hourly averaged sensor response (nominally NOx targeted) | | no |
| **10** | NO2(GT) | Feature | Integer | True hourly averaged NO2 concentration in microg/m^3 (reference analyzer) | microg/ m^3 | no |
| **11** | PT08.S4(NO2) | Feature | Categorical | hourly averaged sensor response (nominally NO2 targeted) | | no |
| **12** | PT08.S5(O3) | Feature | Categorical | hourly averaged sensor response (nominally O3 targeted) | | no |
| **13** | T | Feature | Continuous | Temperature | ℃ | no |
| **14** | RH | Feature | Continuous | Relative Humidity | % | no |
| **15** | AH | Feature | Continuous | Absolute Humidity | | no |

**Objectives:**

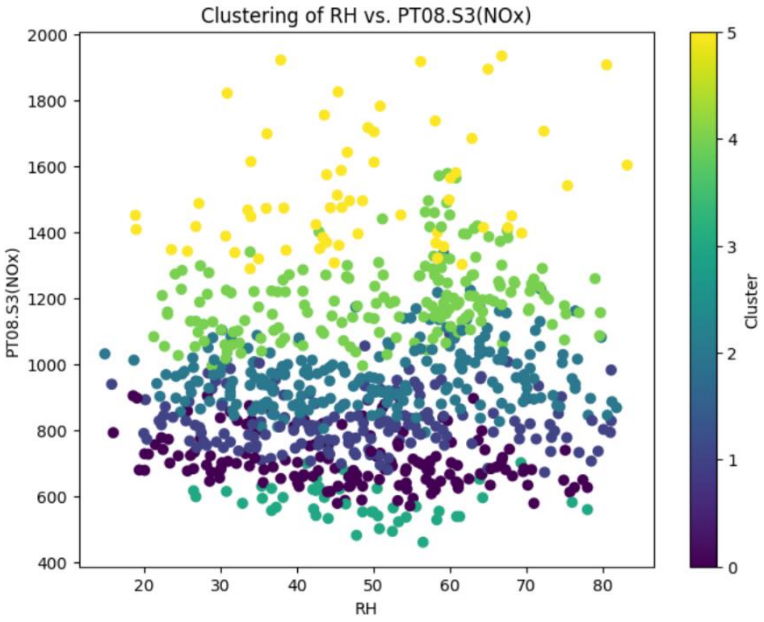
To clustering of data between Relative Humidity (RH) vs. Concentration of $NO_x$ PT08.S3(NOx)

**Summary Output:**

- Before data preprocessing, Use **X is dataframe, which drop "PT08.S3($NO_x$)" and "RH"**. It has only 827 rows, and 12 columns.
- After normalize the movement data, from distance_threshold at 0.30, I can split the relation with ***6*** clusters.



- I use linkage with ***"ward"***. Moreover, after the predicted model, the range of dataset for "PT08.S3($NO_x$)" and "RH" with 6 clusters are




Cluster 1 Summary:
RH range: [16.0, 78.0]
PT08.S3(NOx) range: [571.0, 905.0]

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Cluster 2 Summary:
RH range: [15.8, 81.1]
PT08.S3(NOx) range: [673.0, 1092.0]

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Cluster 3 Summary:
RH range: [14.9, 81.8]
PT08.S3(NOx) range: [794.0, 1337.0]

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Cluster 4 Summary:
RH range: [26.5, 78.0]
PT08.S3(NOx) range: [461.0, 702.0]

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Cluster 5 Summary:
RH range: [21.3, 79.7]
PT08.S3(NOx) range: [996.0, 1579.0]

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Cluster 6 Summary:
RH range: [18.9, 83.2]
PT08.S3(NOx) range: [1290.0, 1935.0]

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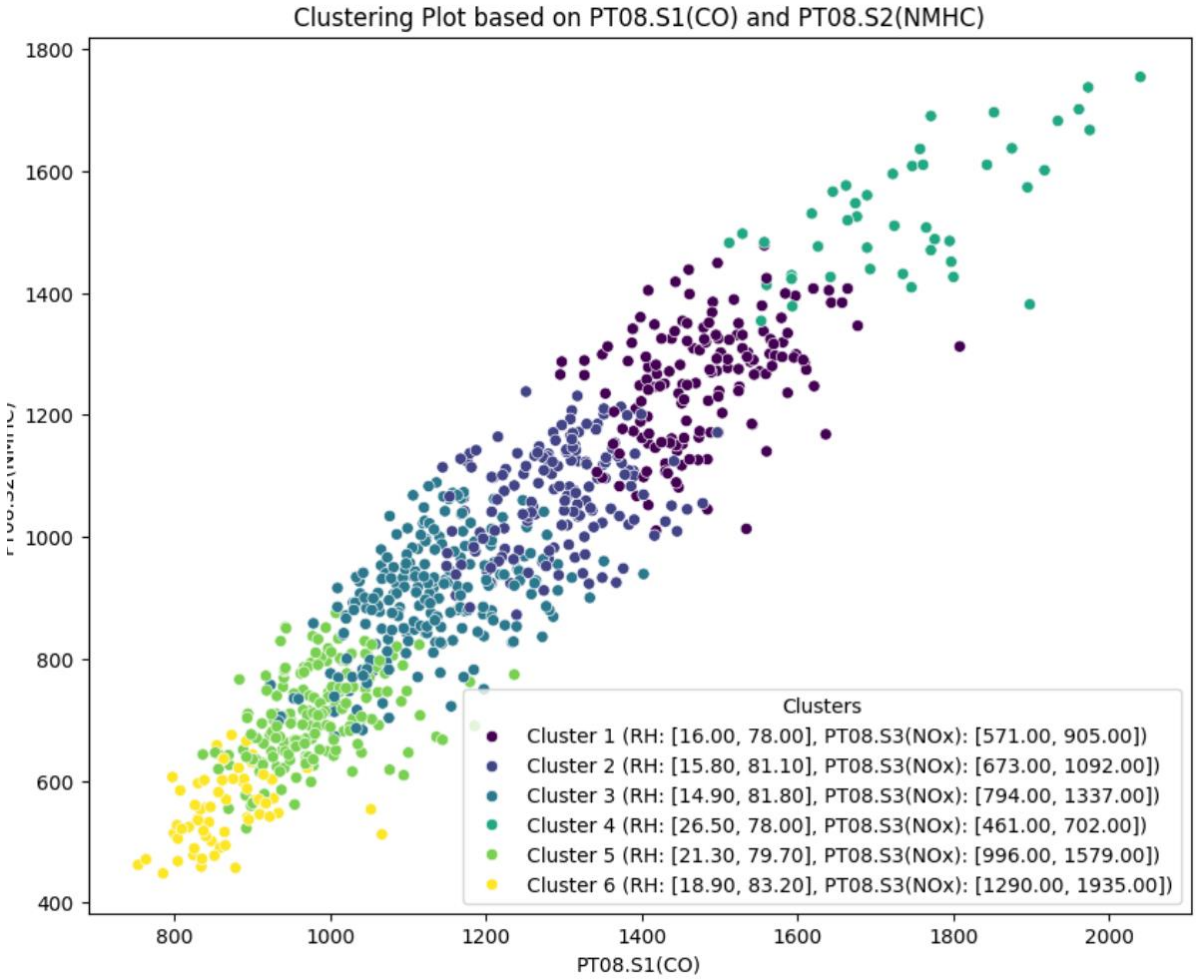
Clustering Plot based on PT08.S1(CO) and PT08.S2(NMHC)
1800
1600
1400
1200
1000
800
600
400
800
1000
1200
1400
1600
1800
2000
PT08.S1(CO)
Clusters
Cluster 1 (RH: [16.00, 78.00], PT08.S3(NOx): [571.00, 905.00])
Cluster 2 (RH: [15.80, 81.10], PT08.S3(NOx): [673.00, 1092.00])
Cluster 3 (RH: [14.90, 81.80], PT08.S3(NOx): [794.00, 1337.00])
Cluster 4 (RH: [26.50, 78.00], PT08.S3(NOx): [461.00, 702.00])
Cluster 5 (RH: [21.30, 79.70], PT08.S3(NOx): [996.00, 1579.00])
Cluster 6 (RH: [18.90, 83.20], PT08.S3(NOx): [1290.00, 1935.00])

**Overall Process:**

1. **Data Preparation:**
    - Imported the dataset from a provided URL.
    - Removed unnecessary columns (Date, Time).
    - Handled missing values by dropping rows with NaN.
    - Converted data types to float and replaced ',' with '.' for numerical consistency.
    - Removed rows with negative values, indicating potential errors.
2. **Exploratory Data Analysis (EDA):**
    - Visualized data distributions using histograms for each feature.
    - Created 3D and 2D scatter plots to understand relationships between variables like Relative Humidity (RH), NOx concentration, and Temperature (T).
3. **Hierarchical Clustering:**
    - Model Building: Used AgglomerativeClustering from scikit-learn to build the hierarchical model.
    - Dendrogram Visualization: Plotted a dendrogram to visualize the hierarchical structure of clusters.
    - Normalization: Normalized the data using normalize() to account for different scales among features, promoting a more equitable comparison.
    - Finding Optimal Number of Clusters (K): Used the dendrogram and a horizontal line to identify an appropriate number of clusters based on the distance at which the clusters naturally separate. The notebook shows an example using a threshold of 0.3, resulting in 6 clusters.
    - Linkage Method: 'ward' linkage was used for the final clustering model.
4. **Final Model and Results:**
    - Final Model: The final model was built with 6 clusters and 'ward' linkage.
    - Cluster Assignments: Each data point was assigned to a cluster based on the model's prediction.
    - Cluster Analysis: The notebook analyzed the characteristics of each cluster (e.g., the range of RH and NOx values).
    - Visualization: A scatter plot was used to visualize the clusters based on RH and NOx, showing the distinct groups identified by the clustering algorithm.