# B.TECH. (2020-24)
## Artificial Intelligence

# Open Ended
**LAB File**
on
# FUNDAMENTALS OF MACHINE LEARNING [CSE313]

Submitted To
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# OPEN ENDED EXPERIMENT

## Aim

To implement k means clustering algorithm over a dataset

## Software Used

Google Colab

## Theory

K-Means Clustering is an Unsupervised Learning algorithm, which groups the unlabeled dataset into different clusters. Here K defines the number of pre-defined clusters that need to be created in the process, as if K=2, there will be two clusters, and for K=3, there will be three clusters, and so on. It is a centroid-based algorithm, where each cluster is associated with a centroid. The main aim of this algorithm is to minimize the sum of distances between the data point and their corresponding clusters. The performance of the K-means clustering algorithm depends upon highly efficient clusters that it forms. But choosing the optimal number of clusters is a big task.

## Elbow Method

The Elbow method is one of the most popular ways to find the optimal number of clusters. This method uses the concept of WCSS value. **WCSS** stands for **Within Cluster Sum of Squares**, which defines the total variations within a cluster.

To find the optimal value of clusters, the elbow method follows the below steps:

- It executes the K-means clustering on a given dataset for different K values (ranges from 1-10).
- For each value of K, calculates the WCSS value.
- Plots a curve between calculated WCSS values and the number of clusters K.
- The sharp point of bend or a point of the plot looks like an arm, then that point is considered as the best value of K.

## Program Code and Output

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt # for data visualization
import seaborn as sns # for statistical data visualization
%matplotlib inline
```

```
data = 'Live.csv'

df = pd.read_csv(data)
```

```
df.shape
```

```
(7050, 16)
```

```
df.head()
```

| status_type | status_published | num_reactions | num_comments | num_shares | num_likes | num_loves | num_wows | num_hahas | num_sads | num_angrys | Column1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| video | 4/22/2018 6:00 | 529 | 512 | 262 | 432 | 92 | 3 | 1 | 1 | 0 | NaN |
| photo | 4/21/2018 22:45 | 150 | 0 | 0 | 150 | 0 | 0 | 0 | 0 | 0 | NaN |
| video | 4/21/2018 6:17 | 227 | 236 | 57 | 204 | 21 | 1 | 1 | 0 | 0 | NaN |
| photo | 4/21/2018 2:29 | 111 | 0 | 0 | 111 | 0 | 0 | 0 | 0 | 0 | NaN |
| photo | 4/18/2018 3:22 | 213 | 0 | 0 | 204 | 9 | 0 | 0 | 0 | 0 | NaN |

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7050 entries, 0 to 7049
Data columns (total 16 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   status_id         7050 non-null   object
 1   status_type       7050 non-null   object
 2   status_published  7050 non-null   object
 3   num_reactions     7050 non-null   int64
 4   num_comments      7050 non-null   int64
 5   num_shares        7050 non-null   int64
 6   num_likes         7050 non-null   int64
 7   num_loves         7050 non-null   int64
 8   num_wows          7050 non-null   int64
 9   num_hahas         7050 non-null   int64
 10  num_sads          7050 non-null   int64
 11  num_angrys        7050 non-null   int64
 12  Column1           0 non-null      float64
 13  Column2           0 non-null      float64
 14  Column3           0 non-null      float64
 15  Column4           0 non-null      float64
dtypes: float64(4), int64(9), object(3)
memory usage: 881.4+ KB
```

```
df.isnull().sum()
```

```
status_id              0
status_type            0
status_published       0
num_reactions          0
num_comments           0
num_shares             0
num_likes              0
num_loves              0
num_wows               0
num_hahas              0
num_sads               0
num_angrys             0
Column1             7050
Column2             7050
Column3             7050
Column4             7050
dtype: int64
```

```
df.drop(['Column1', 'Column2', 'Column3', 'Column4'], axis=1, inplace=True)
```

```
df.describe()
```

| | num_reactions | num_comments | num_shares | num_likes | num_loves | num_wows | num_hahas | num_sads | num_angrys |
|---|---|---|---|---|---|---|---|---|---|
| **count** | 7050.000000 | 7050.000000 | 7050.000000 | 7050.000000 | 7050.000000 | 7050.000000 | 7050.000000 | 7050.000000 | 7050.000000 |
| **mean** | 230.117163 | 224.356028 | 40.022553 | 215.043121 | 12.728652 | 1.289362 | 0.696454 | 0.243688 | 0.113191 |
| **std** | 462.625309 | 889.636820 | 131.599965 | 449.472357 | 39.972930 | 8.719650 | 3.957183 | 1.597156 | 0.726812 |
| **min** | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 |
| **25%** | 17.000000 | 0.000000 | 0.000000 | 17.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 |
| **50%** | 59.500000 | 4.000000 | 0.000000 | 58.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 |
| **75%** | 219.000000 | 23.000000 | 4.000000 | 184.750000 | 3.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 |
| **max** | 4710.000000 | 20990.000000 | 3424.000000 | 4710.000000 | 657.000000 | 278.000000 | 157.000000 | 51.000000 | 31.000000 |

```
df.corr()
```

| | status_type | num_reactions | num_comments | num_shares | num_likes | num_loves | num_wows | num_hahas | num_sads | num_angrys |
|---|---|---|---|---|---|---|---|---|---|---|
| **status_type** | 1.000000 | 0.102860 | 0.320975 | 0.390910 | 0.067423 | 0.388612 | 0.093844 | 0.177903 | 0.081233 | 0.130989 |
| **num_reactions** | 0.102860 | 1.000000 | 0.150843 | 0.250723 | 0.994923 | 0.305003 | 0.267752 | 0.176028 | 0.075138 | 0.124326 |
| **num_comments** | 0.320975 | 0.150843 | 1.000000 | 0.640637 | 0.101687 | 0.521223 | 0.162394 | 0.325048 | 0.236453 | 0.225184 |
| **num_shares** | 0.390910 | 0.250723 | 0.640637 | 1.000000 | 0.172492 | 0.820000 | 0.407628 | 0.399826 | 0.199970 | 0.312513 |
| **num_likes** | 0.067423 | 0.994923 | 0.101687 | 0.172492 | 1.000000 | 0.209308 | 0.207800 | 0.120784 | 0.052169 | 0.087431 |
| **num_loves** | 0.388612 | 0.305003 | 0.521223 | 0.820000 | 0.209308 | 1.000000 | 0.508798 | 0.507830 | 0.207600 | 0.371001 |
| **num_wows** | 0.093844 | 0.267752 | 0.162394 | 0.407628 | 0.207800 | 0.508798 | 1.000000 | 0.287756 | 0.086503 | 0.183087 |
| **num_hahas** | 0.177903 | 0.176028 | 0.325048 | 0.399826 | 0.120784 | 0.507830 | 0.287756 | 1.000000 | 0.141421 | 0.211910 |
| **num_sads** | 0.081233 | 0.075138 | 0.236453 | 0.199970 | 0.052169 | 0.207600 | 0.086503 | 0.141421 | 1.000000 | 0.142072 |
| **num_angrys** | 0.130989 | 0.124326 | 0.225184 | 0.312513 | 0.087431 | 0.371001 | 0.183087 | 0.211910 | 0.142072 | 1.000000 |

```
df['status_id'].unique()
```

```
array(['246675545449582_1649696485147474',
       '246675545449582_1649426988507757',
       '246675545449582_1648730588577397', ...,
       '1050855161656896_1060126464063099',
       '1050855161656896_1058663487542730',
       '1050855161656896_1050858841656528'], dtype=object)
```

```
len(df['status_id'].unique())
```

```
6997
```

```
df['status_published'].unique()
```

```
array(['4/22/2018 6:00', '4/21/2018 22:45', '4/21/2018 6:17', ...,
       '9/21/2016 23:03', '9/20/2016 0:43', '9/10/2016 10:30'],
      dtype=object)
```

```
len(df['status_published'].unique())
```

```
6913
```

```
df.drop(['status_id', 'status_published'], axis=1, inplace=True)
```

```
df.head()
```

| | status_type | num_reactions | num_comments | num_shares | num_likes | num_loves | num_wows | num_hahas | num_sads | num_angrys |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | video | 529 | 512 | 262 | 432 | 92 | 3 | 1 | 1 | 0 |
| **1** | photo | 150 | 0 | 0 | 150 | 0 | 0 | 0 | 0 | 0 |
| **2** | video | 227 | 236 | 57 | 204 | 21 | 1 | 1 | 0 | 0 |
| **3** | photo | 111 | 0 | 0 | 111 | 0 | 0 | 0 | 0 | 0 |
| **4** | photo | 213 | 0 | 0 | 204 | 9 | 0 | 0 | 0 | 0 |

```
X = df

y = df['status_type']
```

```
from sklearn.preprocessing import LabelEncoder

le = LabelEncoder()

X['status_type'] = le.fit_transform(X['status_type'])

y = le.transform(y)
```

```
cols = X.columns
```

```
from sklearn.preprocessing import MinMaxScaler

ms = MinMaxScaler()

X = ms.fit_transform(X)
```

```
X = pd.DataFrame(X, columns=[cols])
```

```
from sklearn.cluster import KMeans

kmeans = KMeans(n_clusters=2, random_state=0)

kmeans.fit(X)
```

```
KMeans(n_clusters=2, random_state=0)
```

```
kmeans.cluster_centers_
```

```
array([[3.28506857e-01, 3.90710874e-02, 7.54854864e-04, 7.53667113e-04,
        3.85438884e-02, 2.17448568e-03, 2.43721364e-03, 1.20039760e-03,
        2.75348016e-03, 1.45313276e-03],
       [9.54921576e-01, 6.46330441e-02, 2.67028654e-02, 2.93171709e-02,
        5.71231462e-02, 4.71007076e-02, 8.18581889e-03, 9.65207685e-03,
        8.04219428e-03, 7.19501847e-03]])
```

```
kmeans.inertia_
```

```
237.7572640441955
```

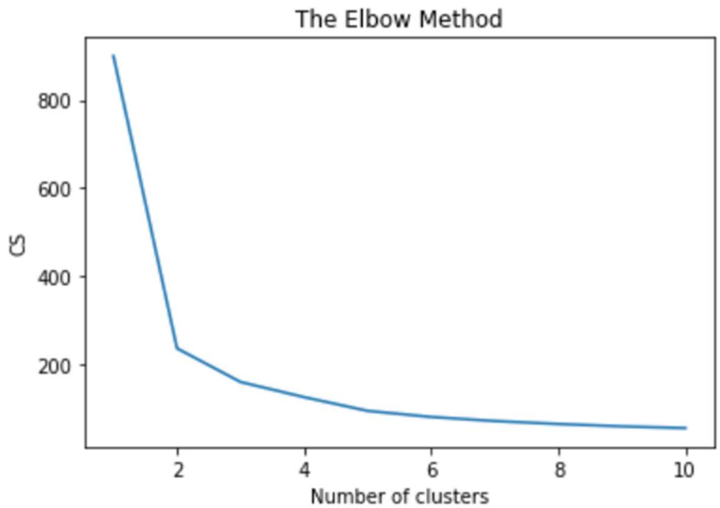
```
labels = kmeans.labels_

# check how many of the samples were correctly labeled
correct_labels = sum(y == labels)

print("Result: %d out of %d samples were correctly labeled." % (correct_labels, y.size))
```

```
Result: 63 out of 7050 samples were correctly labeled.
```

```
print('Accuracy score: {0:0.2f}'. format(correct_labels/float(y.size)))
```

```
Accuracy score: 0.01
```

```python
from sklearn.cluster import KMeans
cs = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters = i, init = 'k-means++', max_iter = 300, n_init = 10, random_state = 0)
    kmeans.fit(X)
    cs.append(kmeans.inertia_)
plt.plot(range(1, 11), cs)
plt.title('The Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('CS')
plt.show()
```




```python
from sklearn.cluster import KMeans

kmeans = KMeans(n_clusters=2,random_state=0)

kmeans.fit(X)

labels = kmeans.labels_

# check how many of the samples were correctly labeled

correct_labels = sum(y == labels)

print("Result: %d out of %d samples were correctly labeled." % (correct_labels, y.size))

print('Accuracy score: {0:0.2f}'. format(correct_labels/float(y.size)))
```

```
Result: 63 out of 7050 samples were correctly labeled.
Accuracy score: 0.01
```

```python
kmeans = KMeans(n_clusters=3, random_state=0)

kmeans.fit(X)

# check how many of the samples were correctly labeled
labels = kmeans.labels_

correct_labels = sum(y == labels)
print("Result: %d out of %d samples were correctly labeled." % (correct_labels, y.size))
print('Accuracy score: {0:0.2f}'. format(correct_labels/float(y.size)))
```

```
Result: 138 out of 7050 samples were correctly labeled.
Accuracy score: 0.02
```

```python
kmeans = KMeans(n_clusters=4, random_state=0)

kmeans.fit(X)

# check how many of the samples were correctly labeled
labels = kmeans.labels_

correct_labels = sum(y == labels)
print("Result: %d out of %d samples were correctly labeled." % (correct_labels, y.size))
print('Accuracy score: {0:0.2f}'. format(correct_labels/float(y.size)))
```

```
Result: 4340 out of 7050 samples were correctly labeled.
Accuracy score: 0.62
```

```python
kmeans = KMeans(n_clusters=5, random_state=0)

kmeans.fit(X)

# check how many of the samples were correctly labeled
labels = kmeans.labels_

correct_labels = sum(y == labels)
print("Result: %d out of %d samples were correctly labeled." % (correct_labels, y.size))
print('Accuracy score: {0:0.2f}'. format(correct_labels/float(y.size)))
```

```
Result: 82 out of 7050 samples were correctly labeled.
Accuracy score: 0.01
```

## Discussion and Conclusion

The lesser the model inertia, the better the model fit. So, we use the elbow method to find optimal number of clusters. There is a kink at k=2.Hence k=2 can be considered a good number of the cluster to cluster this data. So, we have changed the value of k and found relatively higher classification accuracy of 62% with k=4. Hence, we can conclude that k=4 being the optimal number of clusters.

| CRITERIA | TOTAL MARKS | MARKS OBTAINED | COMMENTS |
|---|---|---|---|
| Concept (A) | 2 | | |
| Implementation (B) | 2 | | |
| Performance (C) | 2 | | |
| Total | 6 | | |