IMPORT PACKAGES

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

LOAD DATASET

```
df = pd.read_csv("Live.csv")
df.head()
```

```
   status_id status_type status_published  num_reactions  num_comments  \
0          1       video   4/22/2018 6:00            529           512

1          2       photo  4/21/2018 22:45            150             0

2          3       video   4/21/2018 6:17            227           236

3          4       photo   4/21/2018 2:29            111             0

4          5       photo   4/18/2018 3:22            213             0


   num_shares  num_likes  num_loves  num_wows  num_hahas  num_sads  \
0         262        432         92         3          1         1
1           0        150          0         0          0         0
2          57        204         21         1          1         0
3           0        111          0         0          0         0
4           0        204          9         0          0         0

   num_angrys  Column1  Column2  Column3  Column4
0           0      NaN      NaN      NaN      NaN
1           0      NaN      NaN      NaN      NaN
2           0      NaN      NaN      NaN      NaN
3           0      NaN      NaN      NaN      NaN
4           0      NaN      NaN      NaN      NaN
```

DATA PREPROCESSING

```
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   int64
```

```
 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(10), object(2)
memory usage: 881.4+ KB
```

Cols 12 to 15 are of no meaning so we drop it

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

These 2 cols have unique values for most of the data so they will carry no meaning so they are dropped

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

df.head()

  status_type  num_reactions  num_comments  num_shares  num_likes
num_loves  \
0       video            529           512         262        432
92
1       photo            150             0           0        150
0
2       video            227           236          57        204
21
3       photo            111             0           0        111
0
4       photo            213             0           0        204
9

   num_wows  num_hahas  num_sads  num_angrys
0         3          1         1           0
1         0          0         0           0
2         1          1         0           0
3         0          0         0           0
4         0          0         0           0
```

```
df.describe()
```

```
       num_reactions  num_comments   num_shares    num_likes
num_loves  \
count    7050.000000   7050.000000  7050.000000  7050.000000
7050.000000
mean      230.117163    224.356028    40.022553   215.043121
12.728652
std       462.625309    889.636820   131.599965   449.472357
39.972930
min         0.000000      0.000000     0.000000     0.000000
0.000000
25%        17.000000      0.000000     0.000000    17.000000
0.000000
50%        59.500000      4.000000     0.000000    58.000000
0.000000
75%       219.000000     23.000000     4.000000   184.750000
3.000000
max      4710.000000  20990.000000  3424.000000  4710.000000
657.000000

          num_wows    num_hahas     num_sads   num_angrys
count  7050.000000  7050.000000  7050.000000  7050.000000
mean      1.289362     0.696454     0.243688     0.113191
std       8.719650     3.957183     1.597156     0.726812
min       0.000000     0.000000     0.000000     0.000000
25%       0.000000     0.000000     0.000000     0.000000
50%       0.000000     0.000000     0.000000     0.000000
75%       0.000000     0.000000     0.000000     0.000000
max     278.000000   157.000000    51.000000    31.000000
```

We are encoding the catagorical data (Only the status type variale) and then scaling the whole dataset using MinMaxScaling method

```
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import LabelEncoder

le = LabelEncoder()

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

ms = MinMaxScaler()
df = ms.fit_transform(df)

df
```

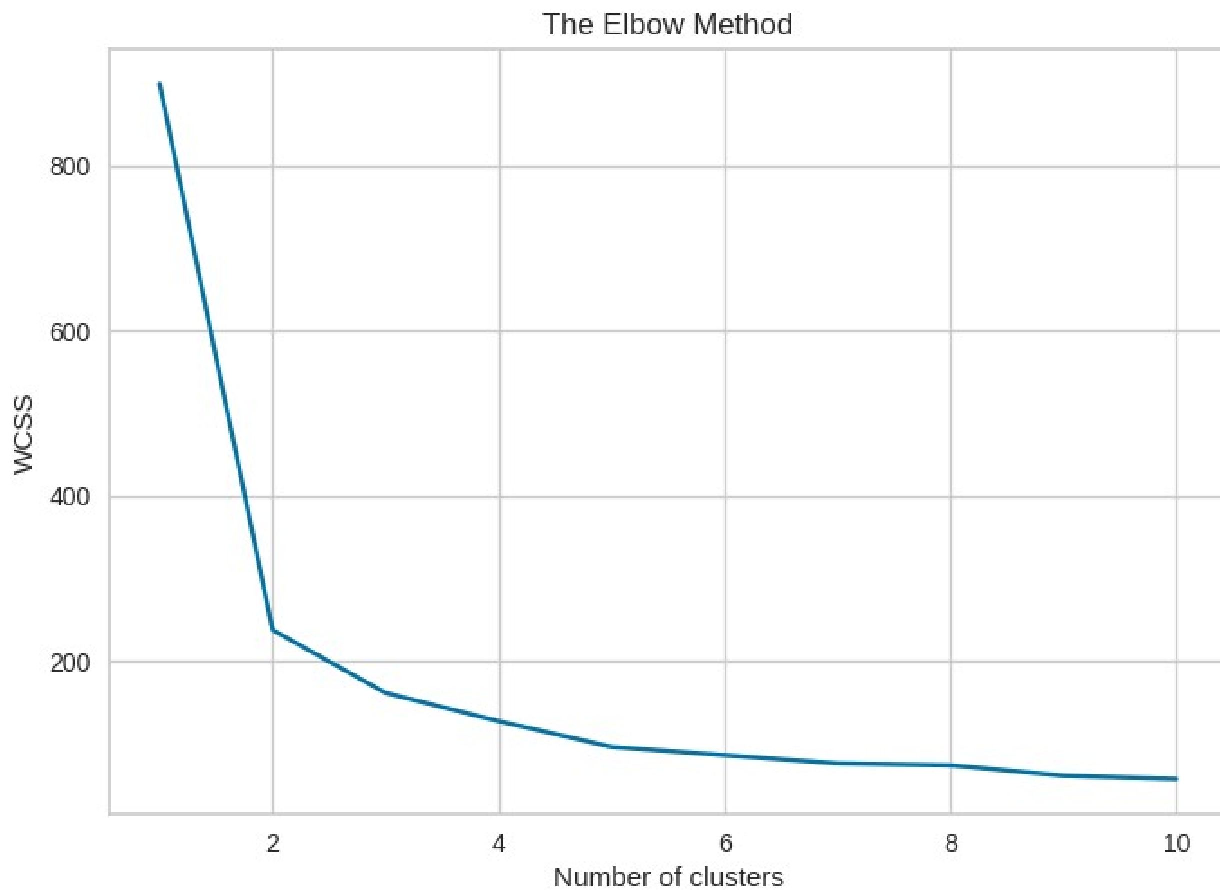
```
array([[1.00000000e+00, 1.12314225e-01, 2.43925679e-02, ...,
        6.36942675e-03, 1.96078431e-02, 0.00000000e+00],
       [3.33333333e-01, 3.18471338e-02, 0.00000000e+00, ...,
        0.00000000e+00, 0.00000000e+00, 0.00000000e+00],
```

```
       [1.00000000e+00, 4.81953291e-02, 1.12434493e-02, ...,
        6.36942675e-03, 0.00000000e+00, 0.00000000e+00],
       ...,
       [3.33333333e-01, 4.24628450e-04, 0.00000000e+00, ...,
        0.00000000e+00, 0.00000000e+00, 0.00000000e+00],
       [3.33333333e-01, 7.45222930e-02, 5.71700810e-04, ...,
        0.00000000e+00, 0.00000000e+00, 0.00000000e+00],
       [3.33333333e-01, 3.60934183e-03, 0.00000000e+00, ...,
        0.00000000e+00, 0.00000000e+00, 0.00000000e+00]])
```

FINDING THE OPTIMAL K

Elbow method is used to plot the WCSS (Within cluster sum of square) vs the no of clusters which ranges from 1 t 10

```
from sklearn.cluster import KMeans
wcss = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters = i, init = 'random', max_iter = 1000,
n_init = 10, random_state = 0)
    kmeans.fit(df)
    wcss.append(kmeans.inertia_)
plt.plot(range(1, 11), wcss)
plt.title('The Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()
```



Here we can see that the drop in intertia or WCSS value is very flat after k is 3 so we can go for that value

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

kmeans.fit(df)

/home/ex5/.local/lib/python3.8/site-packages/sklearn/cluster/
_kmeans.py:1416: FutureWarning: The default value of `n_init` will
change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly
to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)

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

Prnting the 3 cluster centroids

```
kmeans.cluster_centers_

array([[9.63495146e-01, 4.95849772e-02, 2.78226802e-02, 3.05676663e-
02,
        4.17542514e-02, 4.92500480e-02, 8.18188168e-03, 1.01094552e-
```

```
02,
         8.39139539e-03, 7.52896962e-03],
        [3.28742853e-01, 1.99588196e-02, 6.50282622e-04, 5.37894046e-
04,
         1.94880247e-02, 1.93982105e-03, 2.03104006e-03, 1.16647149e-
03,
         2.84240297e-03, 1.51976868e-03],
        [4.91071429e-01, 3.99261955e-01, 3.03716055e-03, 4.36954133e-
03,
         3.97921722e-01, 5.17322606e-03, 9.59232614e-03, 1.23218077e-
03,
         9.33706816e-04, 1.92012289e-04]])
```

Viewing the inertia or WCSS when k=3

```
kmeans.inertia_
```

```
161.60463573139072
```