Name: Ishan Prabhune

A20538828

In [1]:
```
#K-Means Clustering

import warnings
warnings.filterwarnings('ignore')

#Importing the Python Libraries

import pandas as pd
from sklearn import preprocessing
from IPython.display import display, HTML

DataFrame=pd.read_csv('C:/Users/ishan/Downloads/Malware Data/malware_MultiClass.

# Shape of the DataFrame
print(DataFrame.shape)

# Striping the column names
DataFrame=DataFrame.rename(columns=lambda x: x.strip())

# Cleaning the Data
cols=DataFrame.columns

# print out and display DataFrameframe as tables in HTML
display(HTML(DataFrame.head(5).to_html()))
```

```
(100000, 36)
```

	hash	millisecond	classi
0	42fb5e2ec009a05ff5143227297074f1e9c6c3ebb9c914e223349672eca79ad0	0	r
1	42fb5e2ec009a05ff5143227297074f1e9c6c3ebb9c914e223349672eca79ad0	1	r
2	42fb5e2ec009a05ff5143227297074f1e9c6c3ebb9c914e223349672eca79ad0	2	r
3	42fb5e2ec009a05ff5143227297074f1e9c6c3ebb9c914e223349672eca79ad0	3	r
4	42fb5e2ec009a05ff5143227297074f1e9c6c3ebb9c914e223349672eca79ad0	4	r

In [2]:
```
# Checking for missing values in DataFrame
print('ColumnName, DataType, MissingValues')
for i in cols:
    print(i, ',', DataFrame[i].dtype,',', DataFrame[i].isnull().any())
```

```
ColumnName, DataType, MissingValues
hash , object , False
millisecond , int64 , False
classification , object , False
os , object , False
state , int64 , False
usage_counter , int64 , False
prio , int64 , False
static_prio , int64 , False
normal_prio , int64 , False
policy , int64 , False
vm_pgoff , int64 , False
vm_truncate_count , int64 , False
task_size , int64 , False
cached_hole_size , int64 , False
free_area_cache , int64 , False
mm_users , int64 , False
map_count , int64 , False
hiwater_rss , int64 , False
total_vm , int64 , False
shared_vm , int64 , False
exec_vm , int64 , False
reserved_vm , int64 , False
nr_ptes , int64 , False
end_data , int64 , False
last_interval , int64 , False
nvcsw , int64 , False
nivcsw , int64 , False
min_flt , int64 , False
maj_flt , int64 , False
fs_excl_counter , int64 , False
lock , int64 , False
utime , int64 , False
stime , int64 , False
gtime , int64 , False
cgtime , int64 , False
signal_nvcsw , int64 , False
```

In [3]:

```
# Selecting the Required Columns
SelectedColumns = ['classification','os','usage_counter','prio','static_prio','n

# Extracting selected columns
DataFrame = DataFrame[SelectedColumns]

# Displaying the selected DataFrame
DataFrame.head(5)
```

Out[3]:

	classification	os	usage_counter	prio	static_prio	normal_prio	vm_pgo
0	malware	CentOS	0	3069378560	14274	0	
1	malware	Windows	0	3069378560	14274	0	
2	malware	Mac	0	3069378560	14274	0	
3	malware	Ubuntu	0	3069378560	14274	0	
4	malware	Mac	0	3069378560	14274	0	

In [4]:
```
# Excluding the label, for the clustering task
DataFrame=DataFrame.drop('classification', axis=1)

print('Column DataFrametypes:\n',DataFrame.dtypes)
DataFrame.head(5)
```

```
Column DataFrametypes:
 os                    object
usage_counter         int64
prio                  int64
static_prio           int64
normal_prio           int64
vm_pgoff              int64
vm_truncate_count     int64
task_size             int64
map_count             int64
hiwater_rss           int64
total_vm              int64
shared_vm             int64
exec_vm               int64
reserved_vm           int64
nr_ptes               int64
nvcsw                 int64
nivcsw                int64
signal_nvcsw          int64
dtype: object
```

Out[4]:

	os	usage_counter	prio	static_prio	normal_prio	vm_pgoff	vm_trunca
0	CentOS	0	3069378560	14274	0	0	
1	Windows	0	3069378560	14274	0	0	
2	Mac	0	3069378560	14274	0	0	
3	Ubuntu	0	3069378560	14274	0	0	
4	Mac	0	3069378560	14274	0	0	

In [5]:
```
# Removing the columns which has all 0 values
DataFrame_zero = DataFrame.columns[(DataFrame == 0).all()]
DataFrame = DataFrame.drop(columns=DataFrame_zero)
DataFrame.head(5)
```

Out[5]:

	os	prio	static_prio	vm_truncate_count	map_count	total_vm	shared_
0	CentOS	3069378560	14274	13173	6850	150	1
1	Windows	3069378560	14274	13173	6850	150	1
2	Mac	3069378560	14274	13173	6850	150	1
3	Ubuntu	3069378560	14274	13173	6850	150	1
4	Mac	3069378560	14274	13173	6850	150	1

In [6]:
```
# Converting all nominal variables to binary variables
DataFrame_num=DataFrame.copy(deep=True)
```

```
# Creating the new binary columns
DataFrame_dummies=pd.get_dummies(DataFrame_num[['os']],dtype=float)

# Add them to DataFrame
DataFrame_num=DataFrame_num.join(DataFrame_dummies)

# Dropping original columns
DataFrame_num=DataFrame_num.drop('os',axis=1)

DataFrame_num.head(5)
```

Out[6]:

	prio	static_prio	vm_truncate_count	map_count	total_vm	shared_vm	exec_\
0	3069378560	14274	13173	6850	150	120	1
1	3069378560	14274	13173	6850	150	120	1
2	3069378560	14274	13173	6850	150	120	1
3	3069378560	14274	13173	6850	150	120	1
4	3069378560	14274	13173	6850	150	120	1

In [7]:

```
# Dropping the extra binary columns, since we only need N-1 binary columns
DataFrame_num=DataFrame_num.drop('os_Windows', axis=1)

display('DataFrame_num:',HTML(DataFrame_num.head(10).to_html()))
```

'DataFrame_num:'

	prio	static_prio	vm_truncate_count	map_count	total_vm	shared_vm	exec_vm
0	3069378560	14274	13173	6850	150	120	124
1	3069378560	14274	13173	6850	150	120	124
2	3069378560	14274	13173	6850	150	120	124
3	3069378560	14274	13173	6850	150	120	124
4	3069378560	14274	13173	6850	150	120	124
5	3069378560	14274	13173	6850	150	120	124
6	3069378560	14274	13173	6850	150	120	124
7	3069378560	14274	13173	6850	150	120	124
8	3069378560	14274	13173	6850	150	120	124
9	3069378560	14274	13173	6852	150	120	124

In [8]:

```
# Normalized all numerical features
# min-max normalization to scale [0, 1]
cols_to_norm = DataFrame_num.columns.to_list()
DataFrame_num[cols_to_norm] = DataFrame_num[cols_to_norm].apply(lambda x: (x - x

# We ignore the label column
DataFrame_knn=DataFrame_num.copy(deep=True)
```

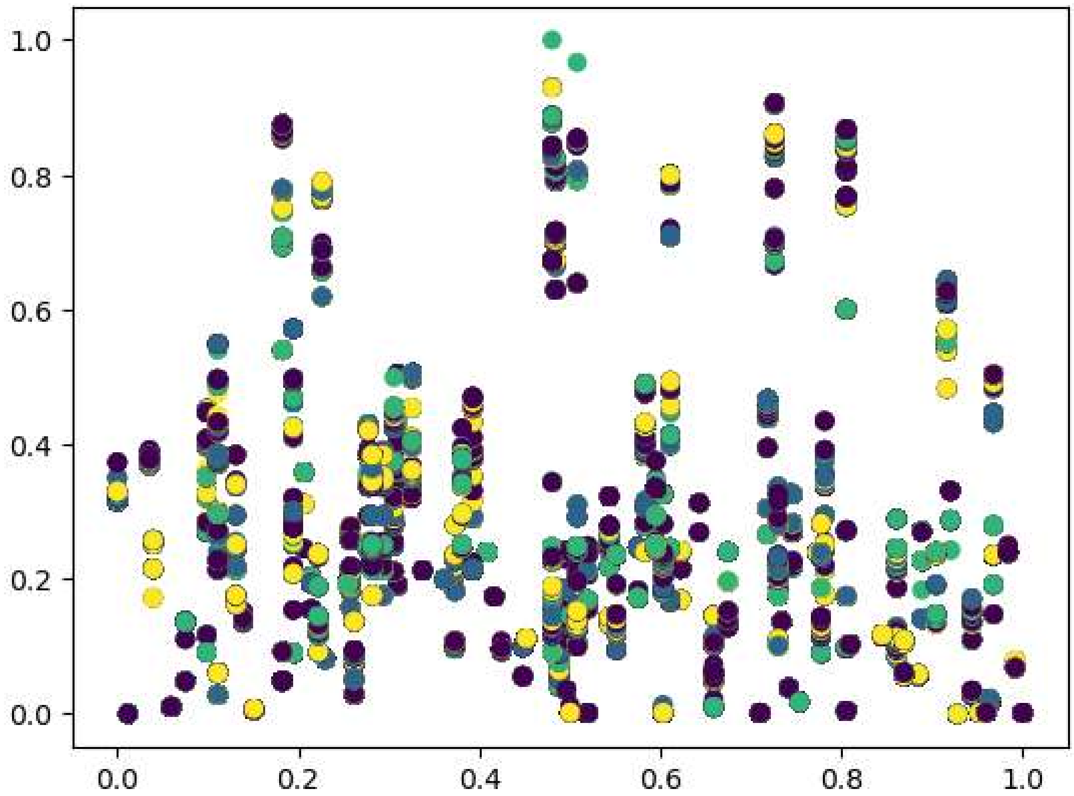
```
DataFrame_kmeans=DataFrame_num.copy(deep=True)
display(HTML(DataFrame_kmeans.head(10).to_html()))
```

	prio	static_prio	vm_truncate_count	map_count	total_vm	shared_vm	exec_vm	re
0	0.18254	0.016007	0.199175	0.166510	0.052031	1.0	0.307692	
1	0.18254	0.016007	0.199175	0.166510	0.052031	1.0	0.307692	
2	0.18254	0.016007	0.199175	0.166510	0.052031	1.0	0.307692	
3	0.18254	0.016007	0.199175	0.166510	0.052031	1.0	0.307692	
4	0.18254	0.016007	0.199175	0.166510	0.052031	1.0	0.307692	
5	0.18254	0.016007	0.199175	0.166510	0.052031	1.0	0.307692	
6	0.18254	0.016007	0.199175	0.166510	0.052031	1.0	0.307692	
7	0.18254	0.016007	0.199175	0.166510	0.052031	1.0	0.307692	
8	0.18254	0.016007	0.199175	0.166510	0.052031	1.0	0.307692	
9	0.18254	0.016007	0.199175	0.166589	0.052031	1.0	0.307692	

In [9]:

```
# By K-Means

import matplotlib.pyplot as plt
from matplotlib.colors import ListedColormap
from sklearn.cluster import KMeans

# API, https://scikit-learn.org/stable/modules/generated/sklearn.cluster.KMeans.

kmeans=KMeans(n_clusters=4, random_state=1,max_iter=500)
kmeans.fit(DataFrame_kmeans)
y_pred=kmeans.predict(DataFrame_kmeans)

plt.scatter(DataFrame_kmeans['prio'],DataFrame_kmeans['nvcsw'],c=y_pred,cmap='vi
```

Out[9]: <matplotlib.collections.PathCollection at 0x1e41ae680d0>



In [10]:
```
# Getting the cluster labels and then adding it back to the original DataFrame
opt=kmeans.labels_
DataFrame_knn['Cluster']=opt
display('DataFrame:',HTML(DataFrame_knn.head(10).to_html()))
```

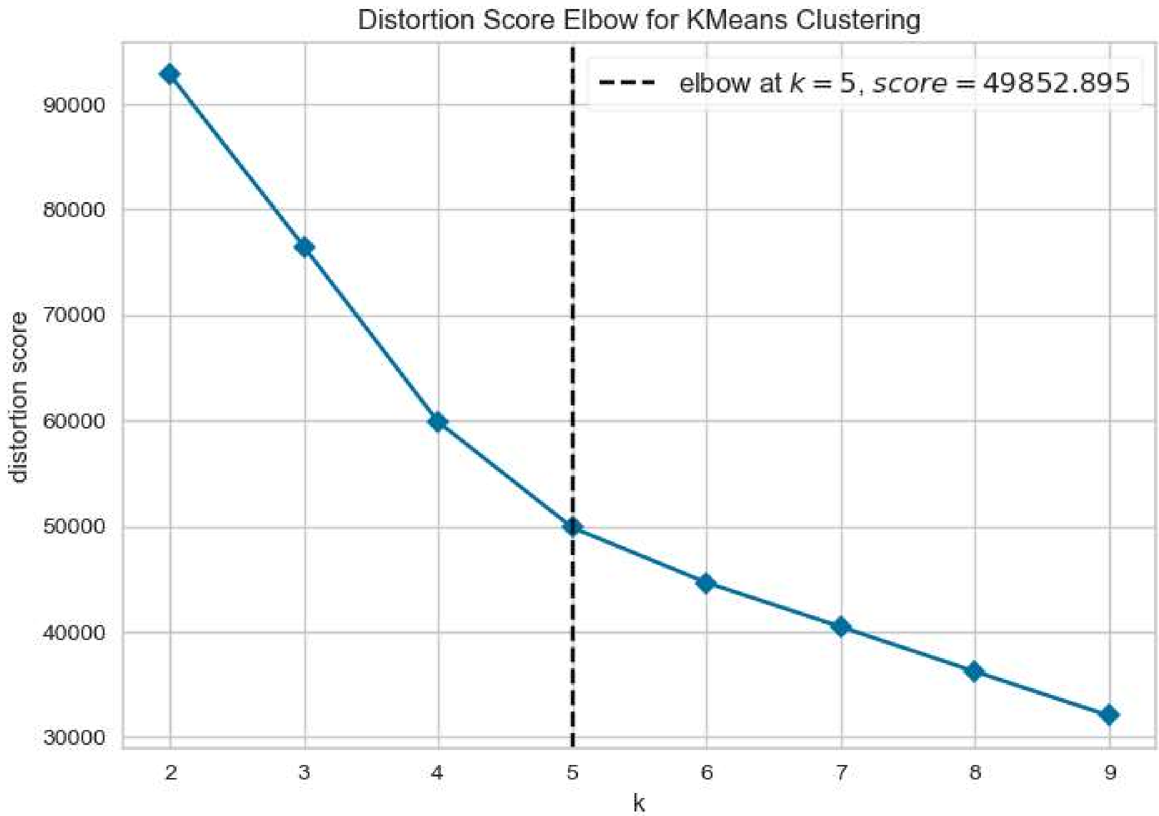
'DataFrame:'

	prio	static_prio	vm_truncate_count	map_count	total_vm	shared_vm	exec_vm	re
0	0.18254	0.016007	0.199175	0.166510	0.052031	1.0	0.307692	
1	0.18254	0.016007	0.199175	0.166510	0.052031	1.0	0.307692	
2	0.18254	0.016007	0.199175	0.166510	0.052031	1.0	0.307692	
3	0.18254	0.016007	0.199175	0.166510	0.052031	1.0	0.307692	
4	0.18254	0.016007	0.199175	0.166510	0.052031	1.0	0.307692	
5	0.18254	0.016007	0.199175	0.166510	0.052031	1.0	0.307692	
6	0.18254	0.016007	0.199175	0.166510	0.052031	1.0	0.307692	
7	0.18254	0.016007	0.199175	0.166510	0.052031	1.0	0.307692	
8	0.18254	0.016007	0.199175	0.166510	0.052031	1.0	0.307692	
9	0.18254	0.016007	0.199175	0.166589	0.052031	1.0	0.307692	

In [12]:
```
# try different K value and find the best K for KMeans by using Elbow method

import yellowbrick
from yellowbrick.cluster import KElbowVisualizer
# API, https://www.scikit-yb.org/en/latest/api/cluster/elbow.html
print(yellowbrick.__version__)
```

```
km = KMeans(random_state=42,max_iter=500, algorithm='elkan')
visualizer = KElbowVisualizer(km, k=(2,10), timings=False, distance_metric='eucl

# Fitting the DataFrame to the visualizer
visualizer.fit(DataFrame_kmeans)

# Finalize and render the figure
visualizer.show()

# find the best K value
km = KMeans(n_clusters=3)
km = km.fit(DataFrame_kmeans)

# Clustering the labels to each data point based on the clustering results
opt=km.labels_
DataFrame_knn['Cluster']=opt
display('DataFrame:',HTML(DataFrame_knn.tail(10).to_html()))
```

1.5



'DataFrame:'

	prio	static_prio	vm_truncate_count	map_count	total_vm	shared_vm	exec_\
99990	0.928571	0.0	0.040717	0.04153	0.01283	1.0	0.0480
99991	0.928571	0.0	0.040717	0.04153	0.01283	1.0	0.0480
99992	0.928571	0.0	0.040717	0.04153	0.01283	1.0	0.0480
99993	0.928571	0.0	0.040717	0.04153	0.01283	1.0	0.0480
99994	0.928571	0.0	0.040717	0.04153	0.01283	1.0	0.0480
99995	0.928571	0.0	0.040717	0.04153	0.01283	1.0	0.0480
99996	0.928571	0.0	0.040717	0.04153	0.01283	1.0	0.0480
99997	0.928571	0.0	0.040717	0.04153	0.01283	1.0	0.0480
99998	0.928571	0.0	0.040717	0.04153	0.01283	1.0	0.0480
99999	0.928571	0.0	0.040717	0.04153	0.01283	1.0	0.0480

In [15]:

```
#Evaluating the K-Means results by using at least two methods

# Silhouette Score
from sklearn.metrics import silhouette_score
from sklearn.cluster import KMeans


kmeans = KMeans(n_clusters = 4 , max_iter=500, random_state=42, algorithm='elkan
kmeans.fit(DataFrame_kmeans)
SilhouetteScore = silhouette_score(DataFrame_kmeans, kmeans.labels_)
print('K = 4 Silhouette score is', SilhouetteScore)


kmeans = KMeans(n_clusters = 5 , max_iter=500, random_state=42, algorithm='elkan
kmeans.fit(DataFrame_kmeans)
SilhouetteScore = silhouette_score(DataFrame_kmeans, kmeans.labels_)
print('K = 5 Silhouette score is', SilhouetteScore)
```

```
K = 4 Silhouette score is 0.346678081334281
K = 5 Silhouette score is 0.3423073806476197
```

Conclusion:

KMeans clustering with Yellowbrick determined **K=5** as the optimal number of clusters, with a distortion score of **49852.895**. Re-running with **K=3**, cluster labels were assigned. The Elbow method graph visually displayed the significant decrease in distortion up to **K=5**, aiding in effective data segmentation-

Two evaluation methods were applied to the K-Means clustering results:

1. **Silhouette Score**:
   - For K=4, the Silhouette score is **0.3467**.
   - For K=5, the Silhouette score is **0.3423**.

These scores indicate the quality of clustering, where a higher Silhouette score implies better-defined clusters. The results suggest that K=4 provides slightly better clustering results based on Silhouettedataset.

In [ ]: