# Task 3: Customer Segmentation / Clustering

## Perform customer segmentation using clustering techniques. Use both profile information

## (from Customers.csv) and transaction information (from Transactions.csv).

#### ● You have the flexibility to choose any clustering algorithm and any number of clusters in

#### between(2 and 10)

#### ● Calculate clustering metrics, including the DB Index(Evaluation will be done on this).

#### ● Visualise your clusters using relevant plots.

### Deliverables:

#### ● A report on your clustering results, including:

#### ○ *The number of clusters formed.*

#### ○ *DB Index value.*

#### ○ *Other relevant clustering metrics.*

#### ● A Jupyter Notebook/Python script containing your clustering code.

### Evaluation Criteria:

#### ● Clustering logic and metrics.

#### ● Visual representation of clusters

In [ ]:
```

```

In [ ]:
```

```

# Importing Libraries

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.cluster import KMeans
from sklearn.metrics import davies_bouldin_score, silhouette_score
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import LabelEncoder
from kneed import KneeLocator
from sklearn.metrics import calinski_harabasz_score
```

# Loading Data

In [2]:
```
transaction_df=pd.read_csv('transaction_data.csv')
```

In [3]:
```
transaction_df.sample(5) #merged customer.csv and product.csv in transact
```

Out[3]:

| | TransactionID | CustomerID | ProductID | TransactionDate | Quantity | TotalValue | Price | Cate |
|---|---|---|---|---|---|---|---|---|
| **808** | T00266 | C0125 | P099 | 2024-02-27 18:25:58 | 2 | 708.58 | 354.29 | B |
| **786** | T00935 | C0109 | P029 | 2024-09-21 09:44:39 | 1 | 433.64 | 433.64 | Electr |
| **896** | T00736 | C0195 | P028 | 2024-03-05 10:46:53 | 4 | 942.32 | 235.58 | H D |
| **706** | T00689 | C0024 | P090 | 2024-05-30 00:00:01 | 2 | 330.60 | 165.30 | B |
| **79** | T00501 | C0158 | P023 | 2024-09-04 16:19:42 | 3 | 1363.59 | 454.53 | H D |

# EDA

In [4]:
```
transaction_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 11 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   TransactionID    1000 non-null   object 
 1   CustomerID       1000 non-null   object 
 2   ProductID        1000 non-null   object 
 3   TransactionDate  1000 non-null   object 
 4   Quantity         1000 non-null   int64  
 5   TotalValue       1000 non-null   float64
 6   Price            1000 non-null   float64
 7   Category         1000 non-null   object 
 8   ProductName      1000 non-null   object 
 9   Region           1000 non-null   object 
 10  SignupDate       1000 non-null   object 
dtypes: float64(2), int64(1), object(8)
memory usage: 86.1+ KB
```

In [5]:
```
transaction_df.describe()
```

Out[5]:

| | Quantity | TotalValue | Price |
|---|---|---|---|
| **count** | 1000.000000 | 1000.000000 | 1000.00000 |
| **mean** | 2.537000 | 689.995560 | 272.55407 |
| **std** | 1.117981 | 493.144478 | 140.73639 |
| **min** | 1.000000 | 16.080000 | 16.08000 |
| **25%** | 2.000000 | 295.295000 | 147.95000 |
| **50%** | 3.000000 | 588.880000 | 299.93000 |
| **75%** | 4.000000 | 1011.660000 | 404.40000 |
| **max** | 4.000000 | 1991.040000 | 497.76000 |

In [6]:
```
transaction_df.columns
```

Out[6]:
```
Index(['TransactionID', 'CustomerID', 'ProductID', 'TransactionDate',
       'Quantity', 'TotalValue', 'Price', 'Category', 'ProductName', 'Regio
n',
       'SignupDate'],
      dtype='object')
```

In [7]:
```
transaction_df["ProductName"].unique().tolist()
```

Out[7]:
```
['ComfortLiving Bluetooth Speaker',
 'HomeSense T-Shirt',
 'ActiveWear Smartphone',
 'TechPro Textbook',
 'TechPro Running Shoes',
 'TechPro Rug',
 'ActiveWear Cookware Set',
 'BookWorld Biography',
 'BookWorld Cookware Set',
 'HomeSense Novel',
 'ComfortLiving Smartphone',
 'SoundWave Cookbook',
 'ComfortLiving Smartwatch',
 'SoundWave Mystery Book',
 'TechPro Vase',
 'HomeSense Desk Lamp',
 'ActiveWear Wall Art',
 'ComfortLiving Biography',
 'ComfortLiving Desk Lamp',
 'SoundWave Novel',
 'ComfortLiving Cookware Set',
 'TechPro Novel',
 'BookWorld Running Shoes',
 'ActiveWear Jeans',
 'BookWorld Jacket',
 'BookWorld Smartwatch',
 'ActiveWear Textbook',
 'ActiveWear Smartwatch',
 'ActiveWear Cookbook',
 'SoundWave Headphones',
 'HomeSense Rug',
 'HomeSense Sweater',
 'TechPro Smartwatch',
 'ActiveWear Running Shoes',
 'HomeSense Wall Art',
 'SoundWave Rug',
 'ActiveWear Headphones',
 'SoundWave Jeans',
 'SoundWave Desk Lamp',
 'BookWorld Cookbook',
 'BookWorld Wall Art',
 'TechPro Cookbook',
 'SoundWave Jacket',
 'BookWorld Sweater',
 'HomeSense Bluetooth Speaker',
 'SoundWave Textbook',
 'HomeSense Headphones',
 'ActiveWear Biography',
 'ComfortLiving Laptop',
 'ActiveWear Rug',
 'HomeSense Running Shoes',
 'ComfortLiving Mystery Book',
 'ActiveWear T-Shirt',
 'TechPro T-Shirt',
 'ActiveWear Jacket',
 'BookWorld Rug',
 'TechPro Headphones',
```

```
'ComfortLiving Sweater',
'SoundWave Smartwatch',
'ComfortLiving Rug',
'ComfortLiving Headphones',
'HomeSense Cookware Set',
'BookWorld Bluetooth Speaker',
'SoundWave Laptop',
'SoundWave Bluetooth Speaker',
'SoundWave T-Shirt']
```

In [8]:
```
transaction_df.drop(columns=['ProductName'])
```

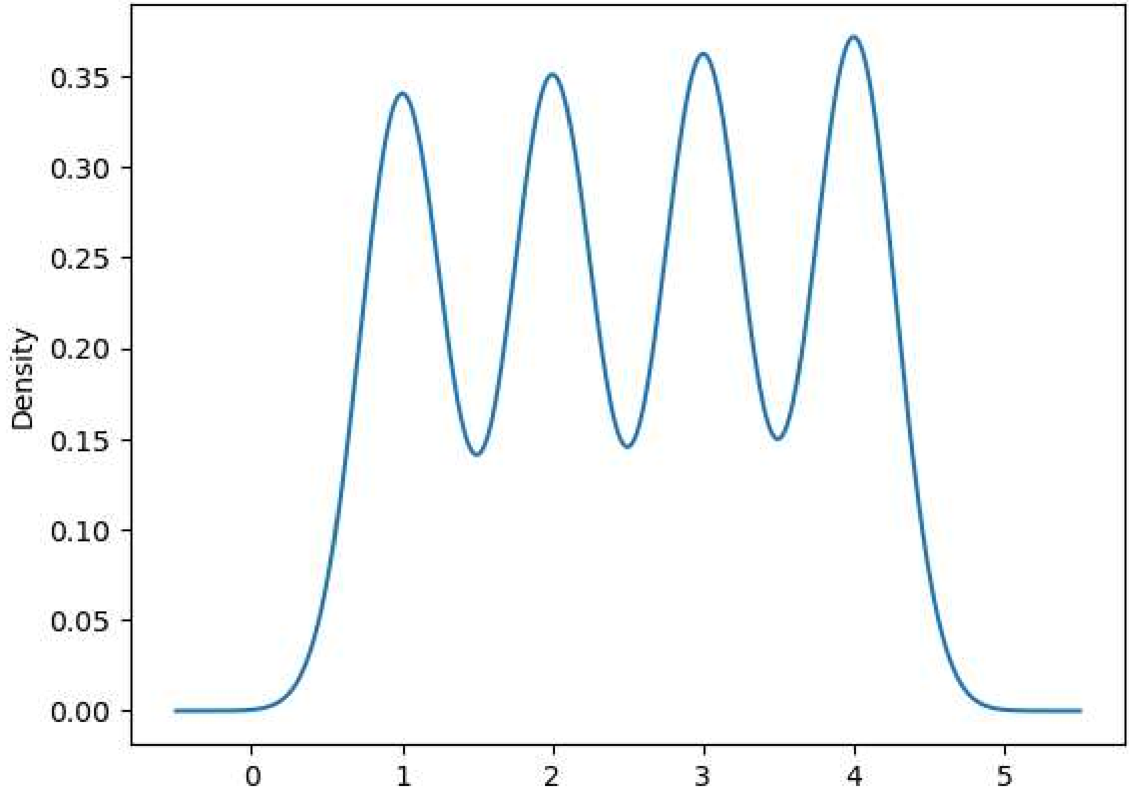
Out[8]:

| | TransactionID | CustomerID | ProductID | TransactionDate | Quantity | TotalValue | Price | Cate |
|---|---|---|---|---|---|---|---|---|
| **0** | T00001 | C0199 | P067 | 2024-08-25 12:38:23 | 1 | 300.68 | 300.68 | Electr |
| **1** | T00112 | C0146 | P067 | 2024-05-27 22:23:54 | 1 | 300.68 | 300.68 | Electr |
| **2** | T00166 | C0127 | P067 | 2024-04-25 07:38:55 | 1 | 300.68 | 300.68 | Electr |
| **3** | T00272 | C0087 | P067 | 2024-03-26 22:55:37 | 2 | 601.36 | 300.68 | Electr |
| **4** | T00363 | C0070 | P067 | 2024-03-21 15:10:10 | 3 | 902.04 | 300.68 | Electr |
| **...** | ... | ... | ... | ... | ... | ... | ... | |
| **995** | T00496 | C0118 | P037 | 2024-10-24 08:30:27 | 1 | 459.86 | 459.86 | Electr |
| **996** | T00759 | C0059 | P037 | 2024-06-04 02:15:24 | 3 | 1379.58 | 459.86 | Electr |
| **997** | T00922 | C0018 | P037 | 2024-04-05 13:05:32 | 4 | 1839.44 | 459.86 | Electr |
| **998** | T00959 | C0115 | P037 | 2024-09-29 10:16:02 | 2 | 919.72 | 459.86 | Electr |
| **999** | T00992 | C0024 | P037 | 2024-04-21 10:52:24 | 1 | 459.86 | 459.86 | Electr |

1000 rows × 10 columns

In [9]:
```
transaction_df["Quantity"].plot.kde()
```

Out[9]: <Axes: ylabel='Density'>




In [10]:
```
transaction_df.dtypes

```

Out[10]:
```
TransactionID       object
CustomerID          object
ProductID           object
TransactionDate     object
Quantity             int64
TotalValue         float64
Price              float64
Category            object
ProductName         object
Region              object
SignupDate          object
dtype: object
```

In [11]:
```
transaction_df.nunique()
```

Out[11]:
```
TransactionID      1000
CustomerID          199
ProductID           100
TransactionDate    1000
Quantity              4
TotalValue          369
Price               100
Category              4
ProductName          66
Region                4
SignupDate          178
dtype: int64
```

# One Hot Encoding for nominal values

In [12]:
```
encoded_df = pd.get_dummies(transaction_df, columns=["Category", "Region"]
encoded_df.head(5)
```

Out[12]:

| | TransactionID | CustomerID | ProductID | TransactionDate | Quantity | TotalValue | Price | ProductI |
|---|---|---|---|---|---|---|---|---|
| **0** | T00001 | C0199 | P067 | 2024-08-25 12:38:23 | 1 | 300.68 | 300.68 | Comfort Blue Sp |
| **1** | T00112 | C0146 | P067 | 2024-05-27 22:23:54 | 1 | 300.68 | 300.68 | Comfort Blue Sp |
| **2** | T00166 | C0127 | P067 | 2024-04-25 07:38:55 | 1 | 300.68 | 300.68 | Comfort Blue Sp |
| **3** | T00272 | C0087 | P067 | 2024-03-26 22:55:37 | 2 | 601.36 | 300.68 | Comfort Blue Sp |
| **4** | T00363 | C0070 | P067 | 2024-03-21 15:10:10 | 3 | 902.04 | 300.68 | Comfort Blue Sp |

In [13]:
```
encoded_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 15 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   TransactionID         1000 non-null   object 
 1   CustomerID            1000 non-null   object 
 2   ProductID             1000 non-null   object 
 3   TransactionDate       1000 non-null   object 
 4   Quantity              1000 non-null   int64  
 5   TotalValue            1000 non-null   float64
 6   Price                 1000 non-null   float64
 7   ProductName           1000 non-null   object 
 8   SignupDate            1000 non-null   object 
 9   Category_Clothing     1000 non-null   bool   
 10  Category_Electronics  1000 non-null   bool   
 11  Category_Home Decor   1000 non-null   bool   
 12  Region_Europe         1000 non-null   bool   
 13  Region_North America  1000 non-null   bool   
 14  Region_South America  1000 non-null   bool   
dtypes: bool(6), float64(2), int64(1), object(6)
memory usage: 76.3+ KB
```

# Scaling

In [14]:
```
scaler = StandardScaler()
scaled_data = scaler.fit_transform(encoded_df[["Quantity", "TotalValue", '

```

In [15]:
```
scaled_data[0]
```

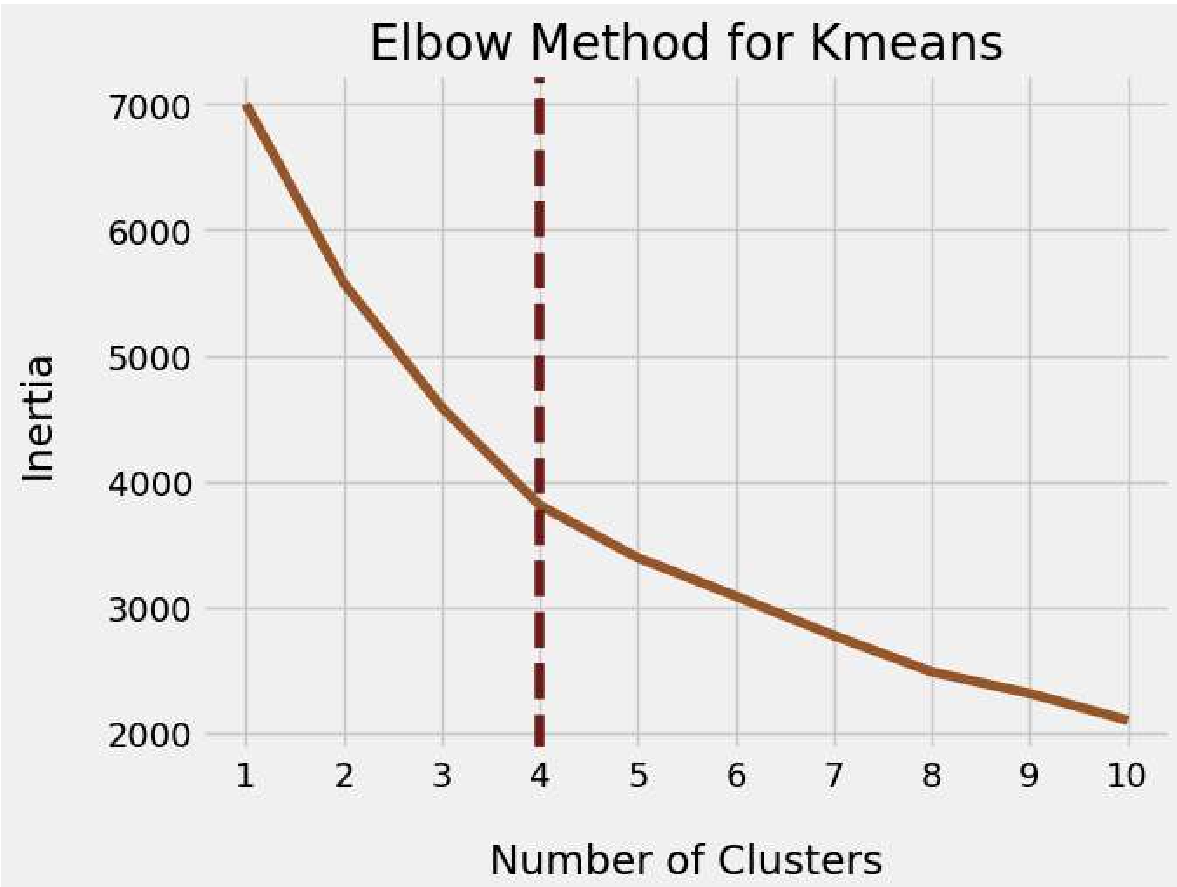
Out[15]:
```
array([-1.37548802, -0.7898504 ,  0.19994831, -0.57427105,  1.80928281,
       -0.56811207, -0.66089455])
```

## Training K-Means Clustering Model

In [16]:
```
kmeans_set = {"init":"k-means++", "n_init":10, "max_iter":300, "random_sta
inertias = [] # inertia for k cluster
for k in range(1,11):
    kmeans = KMeans(n_clusters=k, **kmeans_set)
    kmeans.fit(scaled_data)
    inertias.append(kmeans.inertia_)
```

# Elbow Method for finding optimal Value of Clusters

In [17]:
```
def elbow_optimizer(inertias,i):
    kl = KneeLocator(range(1,11), inertias, curve='convex', direction="de
    plt.style.use("fivethirtyeight")
    sns.lineplot(x=range(1,11), y=inertias, color='#99582a')
    plt.xticks(range(1,11))
    plt.xlabel("Number of Clusters", labelpad=20)
    plt.ylabel("Inertia", labelpad=20)
    plt.title(f"Elbow Method for {i}", y=1)
    plt.axvline(x=kl.elbow, color='#6f1d1b', label='axvline-fullheight', l
    plt.show()
elbow_optimizer(inertias, 'Kmeans')
```




***Here kneeLocator gives the optimal value of k =4***

# Evaluation Metrics through Silhouette Calinski Harabasz Davies Bouldin Scores

In [18]:
```
silhouette = []
calinski_harabasz =[]
davies_bouldin =[]

for k in range(2,11):
    kmeans=KMeans(n_clusters=k, **kmeans_set)
    kmeans.fit(scaled_data)
    sil_score = silhouette_score(scaled_data, kmeans.labels_)
    silhouette.append(sil_score)
for k in range(2,11):
    kmeans=KMeans(n_clusters=k, **kmeans_set)
    kmeans.fit(scaled_data)
    cal_score=calinski_harabasz_score(scaled_data, kmeans.labels_)
    calinski_harabasz.append(cal_score)
for k in range(2,11):
    kmeans=KMeans(n_clusters=k, **kmeans_set)
    kmeans.fit(scaled_data)
    dav_score=davies_bouldin_score(scaled_data, kmeans.labels_)
    davies_bouldin.append(dav_score)

print(f"Length of Silhouette List: {len(silhouette)}")
print(f"Length of Calinski-Harabasz List: {len(calinski_harabasz)}")
print(f"Length of Davies-Bouldin List: {len(davies_bouldin)}")
```

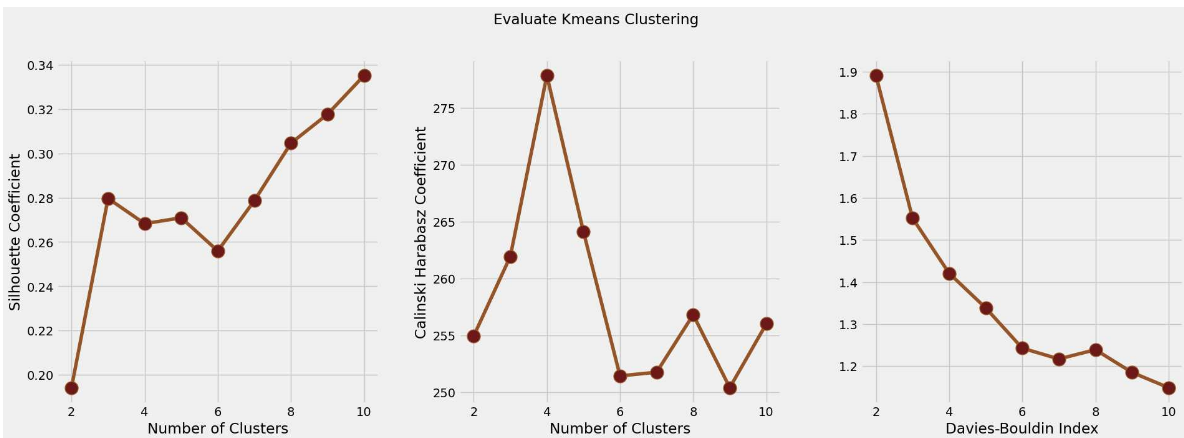
```
Length of Silhouette List: 9
Length of Calinski-Harabasz List: 9
Length of Davies-Bouldin List: 9
```

In [19]:

```python
for k in range(2, 11):
    print(f"Clusters: {k}")
    print(f"Silhouette Score: {silhouette[k-2]}")
    print(f"Calinski-Harabasz Score: {calinski_harabasz[k-2]}")
    print(f"Davies-Bouldin Index: {davies_bouldin[k-2]}")
    print("-" * 30)
```

```
Clusters: 2
Silhouette Score: 0.19425679797236556
Calinski-Harabasz Score: 254.94942265955044
Davies-Bouldin Index: 1.8911469337293945
------------------------------
Clusters: 3
Silhouette Score: 0.2796641782512556
Calinski-Harabasz Score: 261.9422993448456
Davies-Bouldin Index: 1.551790632606875
------------------------------
Clusters: 4
Silhouette Score: 0.2682631228175757
Calinski-Harabasz Score: 277.8726185450916
Davies-Bouldin Index: 1.420816441648777
------------------------------
Clusters: 5
Silhouette Score: 0.2709113897521873
Calinski-Harabasz Score: 264.1231759798257
Davies-Bouldin Index: 1.3383959306293445
------------------------------
Clusters: 6
Silhouette Score: 0.2559554590520348
Calinski-Harabasz Score: 251.43038909359421
Davies-Bouldin Index: 1.242717488362681
------------------------------
Clusters: 7
Silhouette Score: 0.278660249219073
Calinski-Harabasz Score: 251.75357811517796
Davies-Bouldin Index: 1.2170529106387602
------------------------------
Clusters: 8
Silhouette Score: 0.30457306469337186
Calinski-Harabasz Score: 256.81073054264147
Davies-Bouldin Index: 1.2390302703233114
------------------------------
Clusters: 9
Silhouette Score: 0.3176515473205272
Calinski-Harabasz Score: 250.39602347702296
Davies-Bouldin Index: 1.1850435430060366
------------------------------
Clusters: 10
Silhouette Score: 0.3351360312803388
Calinski-Harabasz Score: 256.01281996960296
Davies-Bouldin Index: 1.1488506340000295
------------------------------
```

In [20]:
```
def plot_evaluation(sil, cal, dav, name, x=range(2,11)):
    fig, ax = plt.subplots(1,3, figsize=(20,8), dpi=100)
    ax[0].plot(x, sil, color='#99582a', marker='o', ms=15, mfc='#6f1d1b')
    ax[1].plot(x, cal, color='#99582a', marker='o', ms=15, mfc='#6f1d1b')
    ax[2].plot(x, dav, color='#99582a', marker='o', ms=15, mfc='#6f1d1b')
    ax[0].set_xlabel("Number of Clusters")
    ax[0].set_ylabel("Silhouette Coefficient")
    ax[1].set_xlabel("Number of Clusters")
    ax[1].set_ylabel("Calinski Harabasz Coefficient")
    ax[2].set_xlabel("Number of Clusters")
    ax[2].set_xlabel("Davies-Bouldin Index")
    plt.suptitle(f'Evaluate {name} Clustering',y=0.92)
    plt.tight_layout(pad=3)
    plt.show()
# checking the correctness of the elbow method's result
plot_evaluation(silhouette, calinski_harabasz, davies_bouldin, 'Kmeans')
```




**Here the optimum score comes from cluster 4 i.e Clusters: 4**

**Silhouette Score: 0.2682631228175757**

**Calinski-Harabasz Score: 277.8726185450916**

**Davies-Bouldin Index: 1.420816441648777**

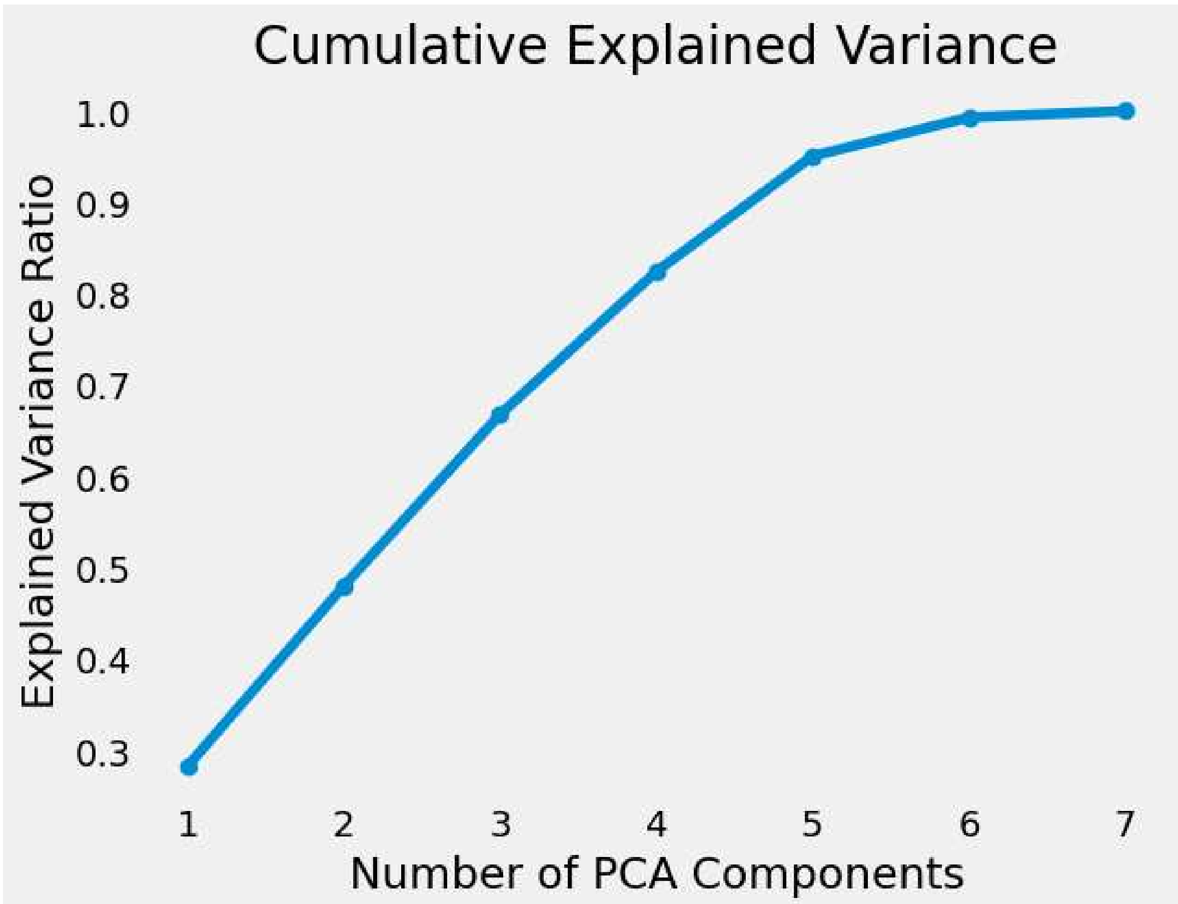
# Dimentionslity Reduction through PCA for better Performance

In [21]:
```
from sklearn.decomposition import PCA
```

In [44]:
```
# 1. Dimensionality Reduction using PCA (if applicable)
pca = PCA(n_components=2)  # Reducing to 2 components for visualization
scaled_data_pca = pca.fit_transform(scaled_data)
```

In [55]:

```
pca = PCA()
scaled_data_pca=pca.fit(scaled_data)
plt.plot(range(1, len(pca.explained_variance_ratio_) + 1), np.cumsum(pca.e
plt.title('Cumulative Explained Variance')
plt.xlabel('Number of PCA Components')
plt.ylabel('Explained Variance Ratio')
plt.grid()
plt.show()

```



In [45]:

```
silhouette = []
calinski_harabasz =[]
davies_bouldin =[]

for k in range(2,11):
    kmeans=KMeans(n_clusters=k, **kmeans_set)
    kmeans.fit(scaled_data_pca)
    sil_score = silhouette_score(scaled_data_pca, kmeans.labels_)
    silhouette.append(sil_score)
for k in range(2,11):
    kmeans=KMeans(n_clusters=k, **kmeans_set)
    kmeans.fit(scaled_data_pca)
    cal_score=calinski_harabasz_score(scaled_data_pca, kmeans.labels_)
    calinski_harabasz.append(cal_score)
for k in range(2,11):
    kmeans=KMeans(n_clusters=k, **kmeans_set)
    kmeans.fit(scaled_data_pca)
    dav_score=davies_bouldin_score(scaled_data_pca, kmeans.labels_)
    davies_bouldin.append(dav_score)

print(f"Length of Silhouette List: {len(silhouette)}")
print(f"Length of Calinski-Harabasz List: {len(calinski_harabasz)}")
print(f"Length of Davies-Bouldin List: {len(davies_bouldin)}")
```

```
Length of Silhouette List: 9
Length of Calinski-Harabasz List: 9
Length of Davies-Bouldin List: 9
```

In [46]:
```
for k in range(2, 11):
    print(f"Clusters: {k}")
    print(f"Silhouette Score: {silhouette[k-2]}")
    print(f"Calinski-Harabasz Score: {calinski_harabasz[k-2]}")
    print(f"Davies-Bouldin Index: {davies_bouldin[k-2]}")
    print("-" * 30)
```

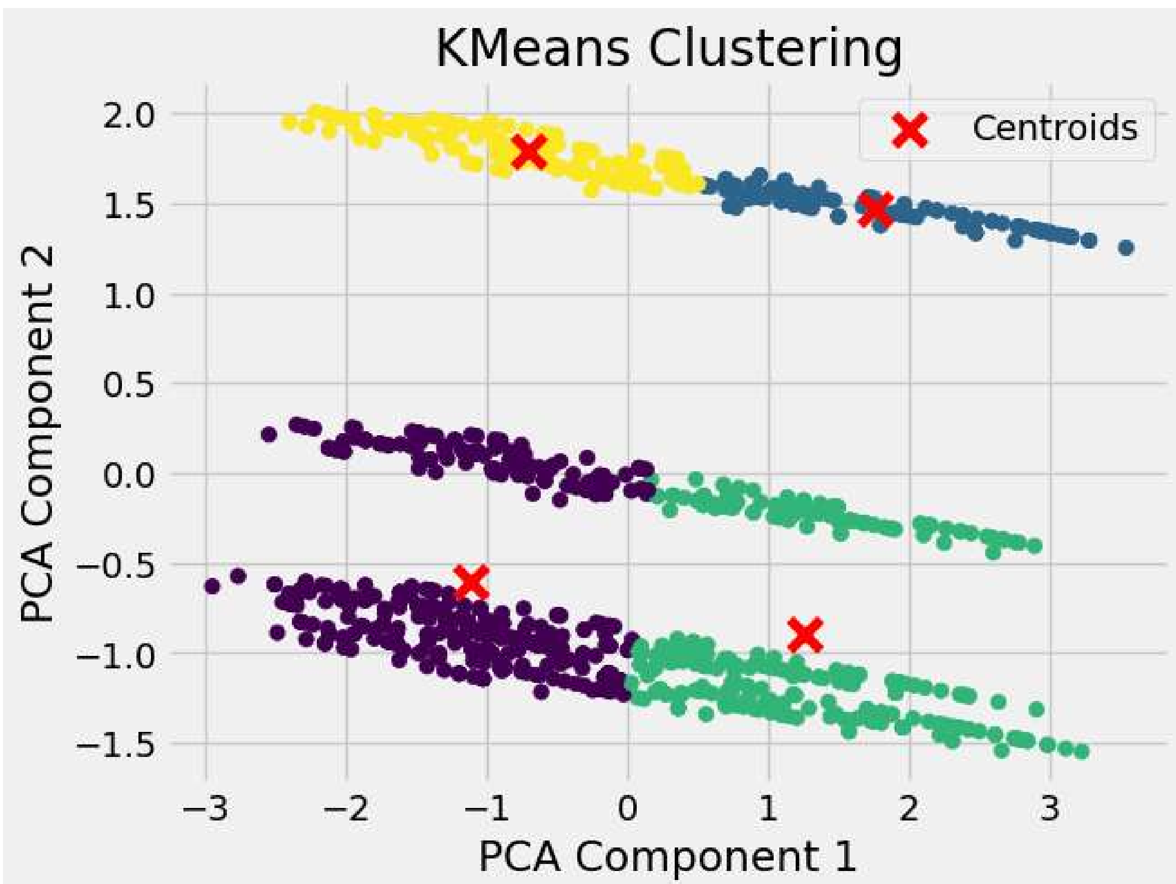
```
Clusters: 2
Silhouette Score: 0.3924995590848138
Calinski-Harabasz Score: 727.860367843966
Davies-Bouldin Index: 1.070674264082367
------------------------------
Clusters: 3
Silhouette Score: 0.47804643795522705
Calinski-Harabasz Score: 997.2394143442125
Davies-Bouldin Index: 0.7390275528184649
------------------------------
Clusters: 4
Silhouette Score: 0.5137425248227989
Calinski-Harabasz Score: 1252.9925199463207
Davies-Bouldin Index: 0.6433556604363969
------------------------------
Clusters: 5
Silhouette Score: 0.4710014808338019
Calinski-Harabasz Score: 1362.2600452701959
Davies-Bouldin Index: 0.7089534540045808
------------------------------
Clusters: 6
Silhouette Score: 0.4676135077429991
Calinski-Harabasz Score: 1391.0210951470133
Davies-Bouldin Index: 0.6721531147988794
------------------------------
Clusters: 7
Silhouette Score: 0.4351358645556148
Calinski-Harabasz Score: 1458.4634265601107
Davies-Bouldin Index: 0.7601694916720022
------------------------------
Clusters: 8
Silhouette Score: 0.472673687329367
Calinski-Harabasz Score: 1515.7356912181378
Davies-Bouldin Index: 0.6944700387292625
------------------------------
Clusters: 9
Silhouette Score: 0.49995742402426524
Calinski-Harabasz Score: 1593.5771174752017
Davies-Bouldin Index: 0.6614712006035178
------------------------------
Clusters: 10
Silhouette Score: 0.4935953987008554
Calinski-Harabasz Score: 1670.143932549534
Davies-Bouldin Index: 0.6473667985337891
------------------------------
```

In [47]:
```
optimal_k = 4
kmeans = KMeans(n_clusters=optimal_k, **kmeans_set)
clusters = kmeans.fit(scaled_data_pca)
```

In [48]:
```
clusters
```

Out[48]:
```
KMeans
KMeans(n_clusters=4, n_init=10, random_state=42)
```

In [49]:
```python

# Fit the KMeans model
kmeans = KMeans(n_clusters=optimal_k, **kmeans_set)
clusters = kmeans.fit(scaled_data_pca)

# Get cluster labels
cluster_labels = kmeans.labels_

# Get the centroids of the clusters
centroids = kmeans.cluster_centers_

# Plot the data points and centroids
plt.scatter(scaled_data_pca[:, 0], scaled_data_pca[:, 1], c=cluster_label
plt.scatter(centroids[:, 0], centroids[:, 1], marker='x', s=150, c='red',

# Add labels and title
plt.xlabel('PCA Component 1')
plt.ylabel('PCA Component 2')
plt.title('KMeans Clustering')
plt.legend()

# Show the plot
plt.show()
```




In [ ]:
```python

```

# CONCLUSION

***Silhouette Score: Higher is better. A score closer to 1 indicates well-separated clusters.***

***Calinski-Harabasz Score: Higher is better. It measures the ratio of the sum of between-cluster dispersion to within-cluster dispersion.***

***Davies-Bouldin Index: Lower is better. It measures the average similarity ratio of each cluster with the one it’s most similar to.***

## Observations:

### Clusters = 4:

#### Highest Silhouette Score: 0.5137

#### Relatively high Calinski-Harabasz Score: 1252.99

#### Low Davies-Bouldin Index: 0.643

### This is the best balance across all metrics.

### Clusters = 3:

#### Slightly lower Silhouette Score than 4: 0.478

#### Lower Davies-Bouldin Index than 4: 0.739

### Clusters > 4:

#### The Silhouette Score starts to decrease.

#### The Calinski-Harabasz Score improves as clusters increase, but this is expected because more clusters always improve dispersion metrics.

#### The Davies-Bouldin Index fluctuates but doesn’t improve significantly.

In [ ]:
```
1
```

In [ ]:
```
1
```

In [ ]:
```
1
```

In [ ]:
```
1
```