

House Pricing

```
import pandas as pd
```

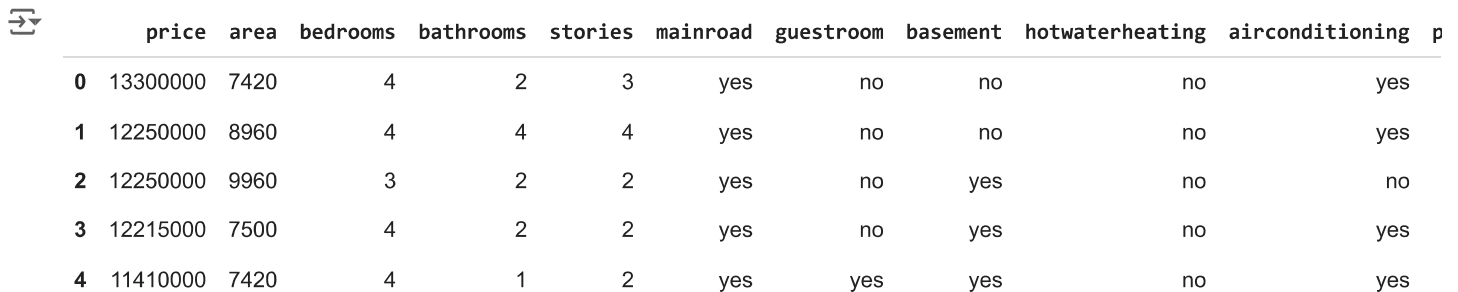
```
df=pd.read_csv('/content/Housing_Price (1).csv')
```

```
df.describe()
```



| | price | area | bedrooms | bathrooms | stories | parking |
|--------------|--------------|--------------|------------|------------|------------|------------|
| count | 5.450000e+02 | 545.000000 | 545.000000 | 545.000000 | 545.000000 | 545.000000 |
| mean | 4.766729e+06 | 5150.541284 | 2.965138 | 1.286239 | 1.805505 | 0.693578 |
| std | 1.870440e+06 | 2170.141023 | 0.738064 | 0.502470 | 0.867492 | 0.861586 |
| min | 1.750000e+06 | 1650.000000 | 1.000000 | 1.000000 | 1.000000 | 0.000000 |
| 25% | 3.430000e+06 | 3600.000000 | 2.000000 | 1.000000 | 1.000000 | 0.000000 |
| 50% | 4.340000e+06 | 4600.000000 | 3.000000 | 1.000000 | 2.000000 | 0.000000 |
| 75% | 5.740000e+06 | 6360.000000 | 3.000000 | 2.000000 | 2.000000 | 1.000000 |
| max | 1.330000e+07 | 16200.000000 | 6.000000 | 4.000000 | 4.000000 | 3.000000 |

```
df.head(5)
```



| | price | area | bedrooms | bathrooms | stories | mainroad | guestroom | basement | hotwaterheating | airconditioning | p |
|----------|----------|------|----------|-----------|---------|----------|-----------|----------|-----------------|-----------------|---|
| 0 | 13300000 | 7420 | 4 | 2 | 3 | yes | no | no | no | yes | |
| 1 | 12250000 | 8960 | 4 | 4 | 4 | yes | no | no | no | yes | |
| 2 | 12250000 | 9960 | 3 | 2 | 2 | yes | no | yes | no | no | |
| 3 | 12215000 | 7500 | 4 | 2 | 2 | yes | no | yes | no | yes | |
| 4 | 11410000 | 7420 | 4 | 1 | 2 | yes | yes | yes | no | yes | |

Next steps:

[Generate code with df](#)
[View recommended plots](#)
[New interactive sheet](#)

```
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.cluster import KMeans
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
import matplotlib.pyplot as plt
```

```
# Identify numerical and categorical columns
numerical_features = ['price', 'area', 'bedrooms', 'bathrooms', 'stories', 'parking']
categorical_features = ['mainroad', 'guestroom', 'basement', 'hotwaterheating', 'airconditioning', 'prefarea', 'furnis
```

```
# Preprocessing: Standardizing numerical features and encoding categorical features
```

```
preprocessor = ColumnTransformer(
    transformers=[
        ('num', StandardScaler(), numerical_features),
        ('cat', OneHotEncoder(drop='first'), categorical_features)
    ])
```

```
# Apply KMeans clustering with a guessed range for clusters (e.g., k=3 for simplicity)
```

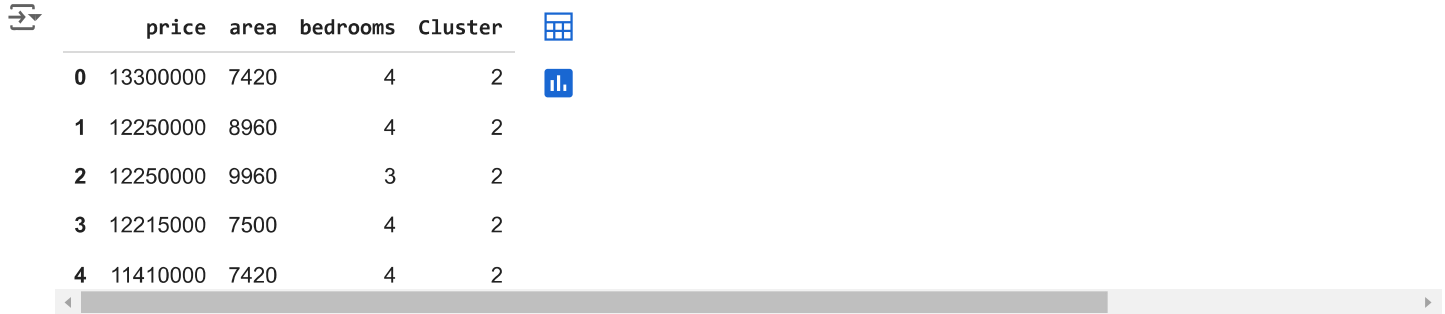
```
kmeans_pipeline = Pipeline(steps=[('preprocessor', preprocessor),
```

```
(['kmeans', KMeans(n_clusters=3, random_state=0)])])
```

```
# Fit the model to the data
kmeans_pipeline.fit(df)

# Add cluster labels to the original dataframe
df['Cluster'] = kmeans_pipeline['kmeans'].labels_

# Display the clustered data sample
df[['price', 'area', 'bedrooms', 'Cluster']].head()
```



| | price | area | bedrooms | Cluster |
|---|----------|------|----------|---------|
| 0 | 13300000 | 7420 | 4 | 2 |
| 1 | 12250000 | 8960 | 4 | 2 |
| 2 | 12250000 | 9960 | 3 | 2 |
| 3 | 12215000 | 7500 | 4 | 2 |
| 4 | 11410000 | 7420 | 4 | 2 |

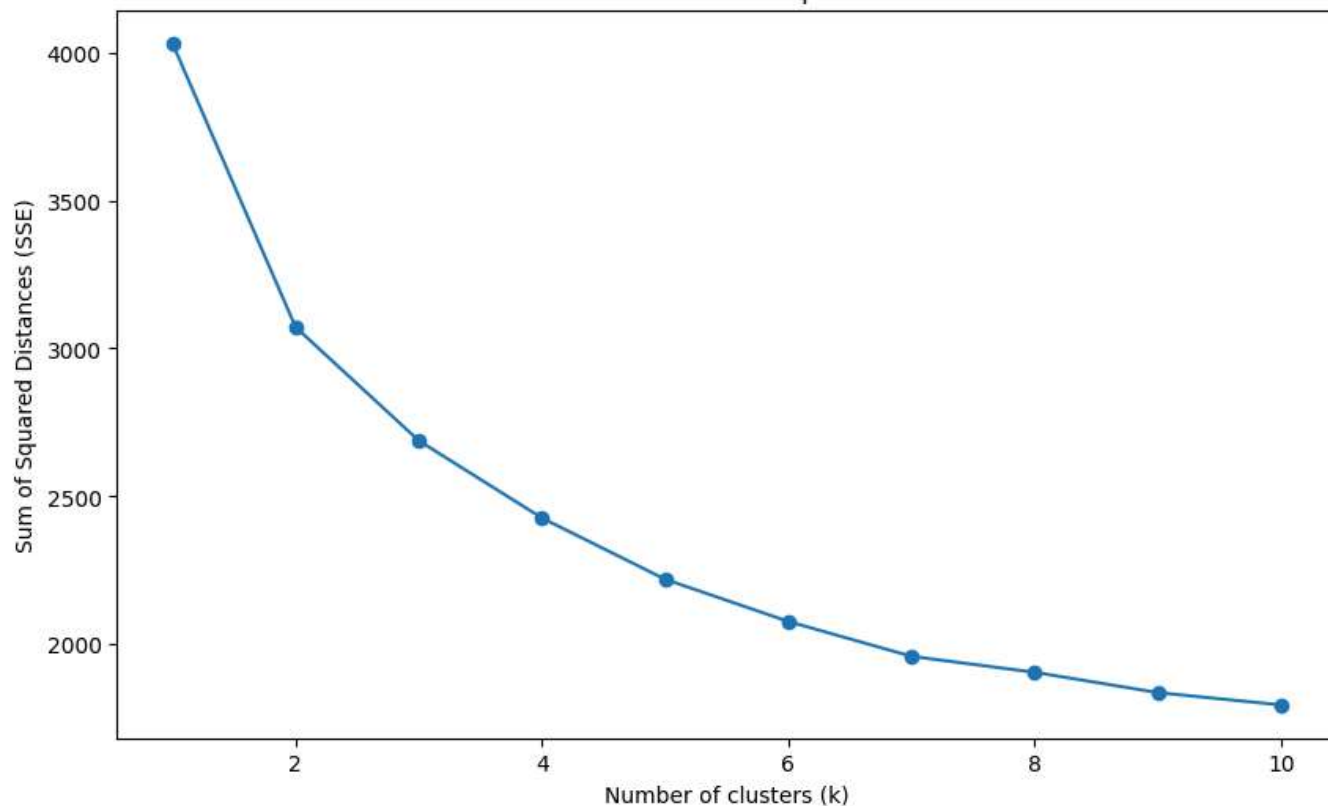
```
# Elbow method to find the optimal number of clusters (k)
sse = [] # Sum of squared distances for each k
k_range = range(1, 11)

# Calculate SSE for each k
for k in k_range:
    kmeans = KMeans(n_clusters=k, random_state=0)
    kmeans.fit(preprocessor.fit_transform(df))
    sse.append(kmeans.inertia_)

# Plotting the elbow graph
plt.figure(figsize=(10, 6))
plt.plot(k_range, sse, marker='o')
plt.xlabel('Number of clusters (k)')
plt.ylabel('Sum of Squared Distances (SSE)')
plt.title('Elbow Method for Optimal k')
plt.show()
```



Elbow Method for Optimal k



```

from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
import matplotlib.pyplot as plt

# Define the relevant features in the dataset
numerical_features = ['price', 'area', 'bedrooms', 'bathrooms', 'stories', 'parking']
categorical_features = ['mainroad', 'guestroom', 'basement', 'hotwaterheating', 'airconditioning', 'prefarea', 'furnish']

# Preprocessing step
preprocessor = ColumnTransformer(
    transformers=[
        ('num', StandardScaler(), numerical_features),
        ('cat', OneHotEncoder(drop='first'), categorical_features)
    ])

# Initialize an empty list to store the sum of squared distances for each k
sse = []
k_values = range(1, 11)

# Calculate SSE for each k value
for k in k_values:
    kmeans = KMeans(n_clusters=k, random_state=0)
    transformed_data = preprocessor.fit_transform(df) # Preprocess data
    kmeans.fit(transformed_data)
    sse.append(kmeans.inertia_)

# Plot the elbow curve with annotations
plt.figure(figsize=(10, 6))
plt.plot(k_values, sse, marker='o', color='b')
plt.xlabel('Number of clusters (k)')
plt.ylabel('Sum of Squared Distances (SSE)')
plt.title('Elbow Method for Optimal k')

# Annotate each point with its SSE value

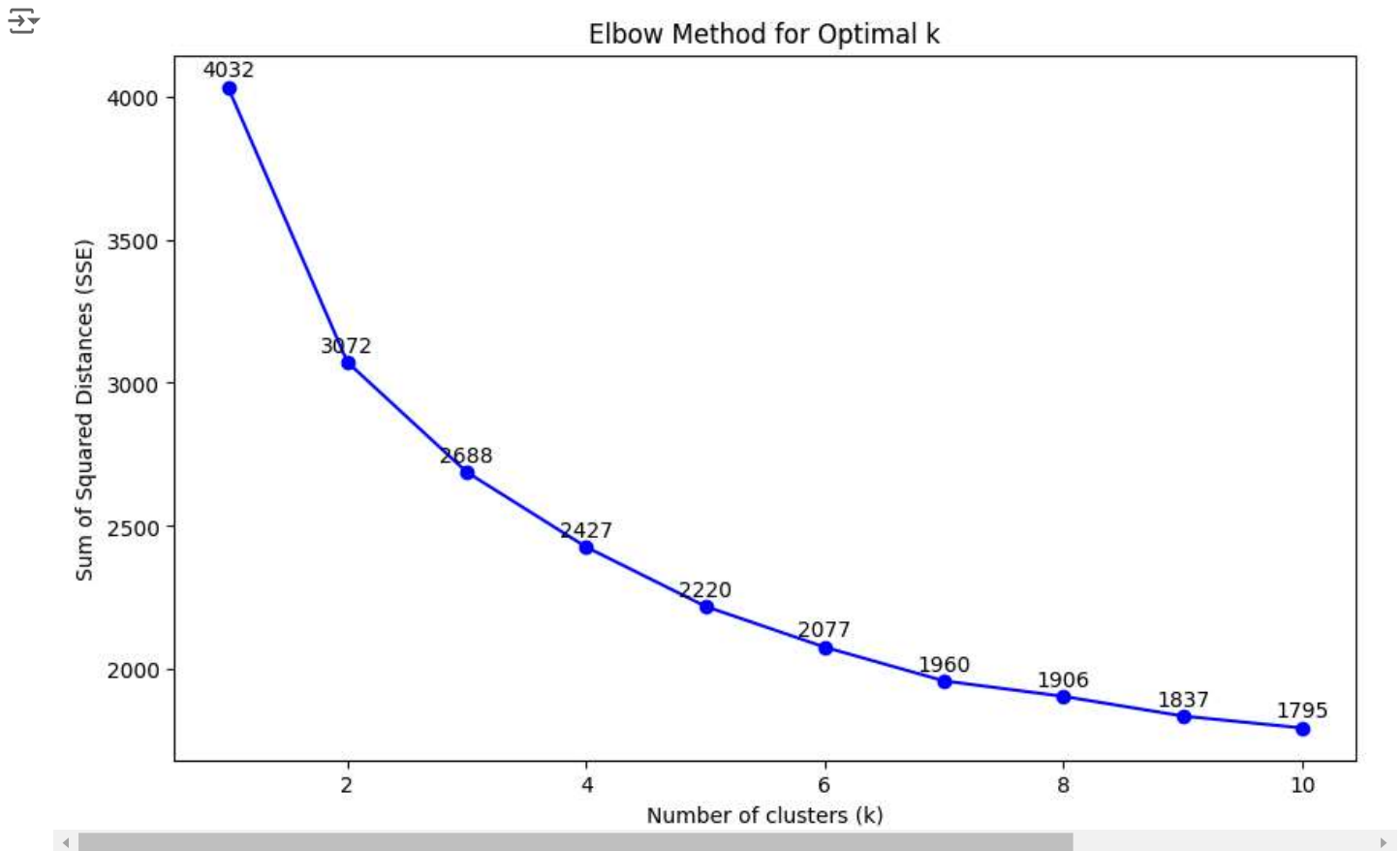
```

```

for i, txt in enumerate(sse):
    plt.annotate(f'{txt:.0f}', (k_values[i], sse[i]), textcoords="offset points", xytext=(0,5), ha='center')

plt.show()

```



```

# Fit KMeans with k = 4
kmeans = KMeans(n_clusters=4, random_state=0)
transformed_data = preprocessor.fit_transform(df)
df['Cluster'] = kmeans.fit_predict(transformed_data)

# Plotting clusters based on 'area' and 'price'
plt.figure(figsize=(10, 6))
plt.scatter(df['area'], df['price'], c=df['Cluster'], cmap='viridis', marker='o')
plt.colorbar(label='Cluster')
plt.xlabel('Area (sq ft)')
plt.ylabel('Price')
plt.title('Housing Clusters with k=5 Based on Area and Price')
plt.show()

```



```
# Retrieve the centroids for the 5 clusters
centroids = kmeans.cluster_centers_

# Inverse transform to get the original scale for interpretability
# Only applies to numerical features, as categorical are one-hot encoded
centroids_original_scale = preprocessor.named_transformers_['num'].inverse_transform(centroids[:, :len(numerical_features)])

# Convert to a DataFrame for better readability
centroid_df = pd.DataFrame(centroids_original_scale, columns=numerical_features)
print("Centroids of each cluster:\n", centroid_df)
```

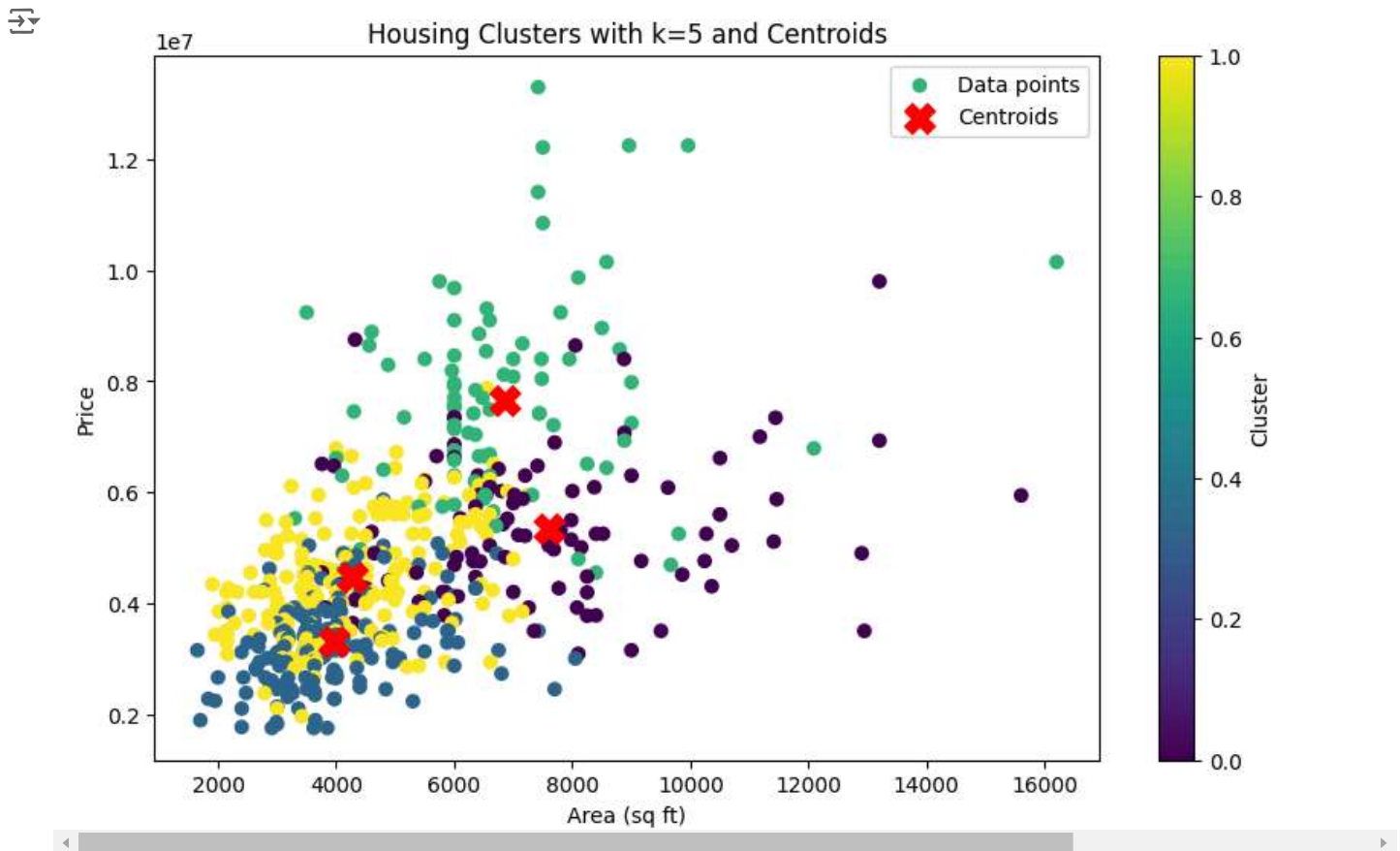
```
Centroids of each cluster:
   price      area  bedrooms  bathrooms  stories  parking
0  5.351989e+06  7589.860215   2.774194    1.086022   1.236559   1.569892
1  3.305531e+06  3949.863636   2.340909    1.034091   1.244318   0.267045
2  7.665741e+06  6845.550562   3.483146    2.000000   2.887640   1.202247
3  4.471166e+06  4260.737968   3.401070    1.283422   2.101604   0.417112
```

```
# Fit KMeans with k = 4
kmeans = KMeans(n_clusters=4, random_state=0)
transformed_data = preprocessor.fit_transform(df)
df['Cluster'] = kmeans.fit_predict(transformed_data)

# Retrieve and inverse transform centroids for visualization
centroids = preprocessor.named_transformers_['num'].inverse_transform(kmeans.cluster_centers_[ :, :len(numerical_features)])
centroids_df = pd.DataFrame(centroids, columns=numerical_features)

# Plot clusters and centroids based on 'area' and 'price'
plt.figure(figsize=(10, 6))
plt.scatter(df['area'], df['price'], c=df['Cluster'], cmap='viridis', marker='o', label="Data points")
plt.scatter(centroids_df['area'], centroids_df['price'], c='red', marker='x', s=200, label="Centroids")
plt.colorbar(label='Cluster')
plt.xlabel('Area (sq ft)')
plt.ylabel('Price')
```

```
plt.title('Housing Clusters with k=5 and Centroids')
plt.legend()
plt.show()
```



```
# Retrieve centroid values and inverse transform for better interpretability
centroids_original_scale = preprocessor.named_transformers_['num'].inverse_transform(kmeans.cluster_centers_[0:5, :])
centroid_df = pd.DataFrame(centroids_original_scale, columns=numerical_features)
print("Centroids of each cluster:\n", centroid_df)
```

```
Centroids of each cluster:
```

| | price | area | bedrooms | bathrooms | stories | parking |
|---|--------------|-------------|----------|-----------|----------|----------|
| 0 | 5.351989e+06 | 7589.860215 | 2.774194 | 1.086022 | 1.236559 | 1.569892 |
| 1 | 3.305531e+06 | 3949.863636 | 2.340909 | 1.034091 | 1.244318 | 0.267045 |
| 2 | 7.665741e+06 | 6845.550562 | 3.483146 | 2.000000 | 2.887640 | 1.202247 |
| 3 | 4.471166e+06 | 4260.737968 | 3.401070 | 1.283422 | 2.101604 | 0.417112 |

▼ Breast Cancer

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.datasets import load_breast_cancer
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
```

```
# Load the breast cancer dataset
data = load_breast_cancer()
df = pd.DataFrame(data.data, columns=data.feature_names)
```

```
df['target'] = data.target # This includes the labels (malignant/benign)
```

```
# Standardize the features
```

```
scaler = StandardScaler()
```

```
X_scaled = scaler.fit_transform(df.drop('target', axis=1))
```

```
# Elbow method to find optimal number of clusters
```

```
inertia = []
```

```
range_n_clusters = range(1, 11)
```

```
for n_clusters in range_n_clusters:
```

```
    kmeans = KMeans(n_clusters=n_clusters, random_state=42)
```

```
    kmeans.fit(X_scaled)
```

```
    inertia.append(kmeans.inertia_)
```

```
# Plot inertia
```

```
plt.figure(figsize=(12, 5))
```

```
plt.subplot(1, 2, 1)
```

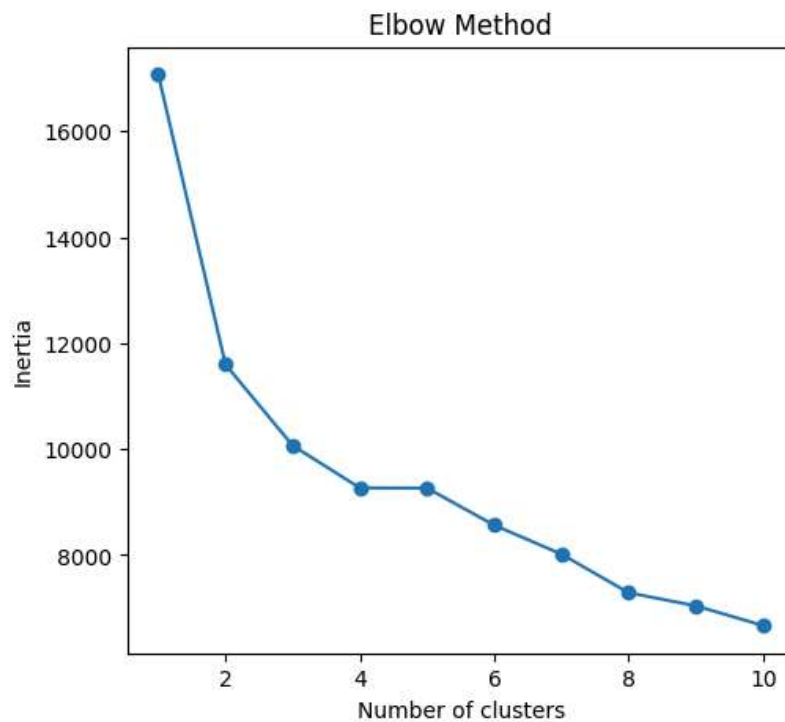
```
plt.plot(range_n_clusters, inertia, marker='o')
```

```
plt.title('Elbow Method')
```

```
plt.xlabel('Number of clusters')
```

```
plt.ylabel('Inertia')
```

```
Text(0, 0.5, 'Inertia')
```



Wine Quality

```
import pandas as pd
```

```
# Load the dataset
data = pd.read_csv("/content/Wine_Quality.csv")
```

```
# Check for missing values
print(data.isnull().sum())
```

```

type          0
fixed acidity  10
volatile acidity  8
citric acid    3
residual sugar  2
chlorides      2
free sulfur dioxide  0
total sulfur dioxide  0
density        0
pH             9
sulphates      4
alcohol        0
quality        0
dtype: int64

```

```
data_clean = data.dropna()
```

```
from sklearn.preprocessing import StandardScaler, LabelEncoder
```

```
# Encode 'type' column (if categorical)
data_clean['type'] = LabelEncoder().fit_transform(data_clean['type'])
```

```
# Drop 'quality' (if clustering without it) and scale features
features = data_clean.drop('quality', axis=1)
scaler = StandardScaler()
scaled_features = scaler.fit_transform(features)
```

```

<ipython-input-30-1d3208d25c52>:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

```

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#return

```
data_clean['type'] = LabelEncoder().fit_transform(data_clean['type'])
```

```
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
```

```

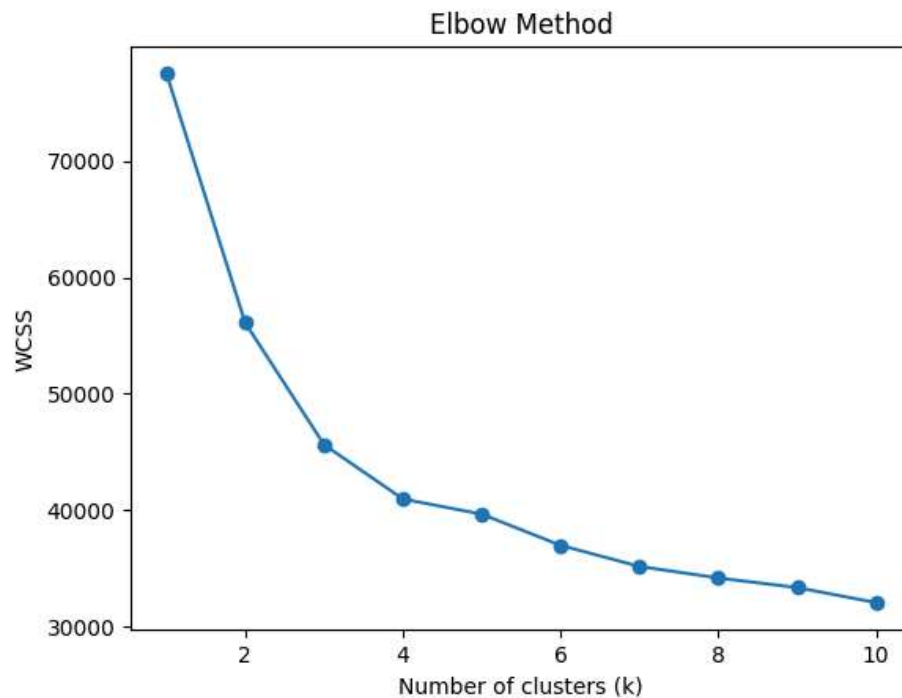
wcss = []
for k in range(1, 11):
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(scaled_features)
    wcss.append(kmeans.inertia_)

```

```

# Plot the Elbow curve
plt.plot(range(1, 11), wcss, marker='o')
plt.title('Elbow Method')
plt.xlabel('Number of clusters (k)')
plt.ylabel('WCSS')
plt.show()

```

```
# Perform K-Means with the chosen k (e.g., k=3)
kmeans = KMeans(n_clusters=3, random_state=42)
clusters = kmeans.fit_predict(scaled_features)
```

```
# Add cluster labels to the original data
data_clean['Cluster'] = clusters
print(data_clean.head())
```



```
type  fixed acidity  volatile acidity  citric acid  residual sugar \
0      1           7.0             0.27         0.36         20.7
1      1           6.3             0.30         0.34          1.6
2      1           8.1             0.28         0.40          6.9
3      1           7.2             0.23         0.32          8.5
4      1           7.2             0.23         0.32          8.5
```

```
chlorides  free sulfur dioxide  total sulfur dioxide  density  pH \
0      0.045             45.0             170.0    1.0010  3.00
1      0.049             14.0             132.0    0.9940  3.30
2      0.050             30.0             97.0     0.9951  3.26
3      0.058             47.0             186.0    0.9956  3.19
4      0.058             47.0             186.0    0.9956  3.19
```

```
sulphates  alcohol  quality  Cluster
0      0.45      8.8      6        0
1      0.49      9.5      6        2
2      0.44     10.1      6        2
3      0.40      9.9      6        0
4      0.40      9.9      6        0
```

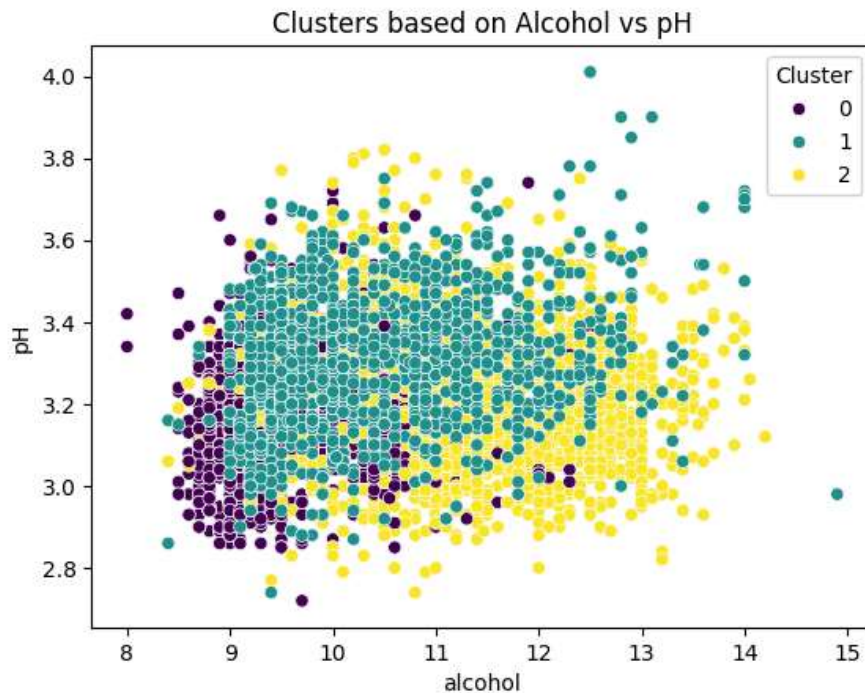
```
<ipython-input-55-d39c6c220705>:6: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

```
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user\_guide/indexing.html#return
data_clean['Cluster'] = clusters
```

```
import seaborn as sns
```

```
# Example visualization (if using 2 features)
sns.scatterplot(data=data_clean, x='alcohol', y='pH', hue='Cluster', palette='viridis')
plt.title('Clusters based on Alcohol vs pH')
```

```
plt.title('Clusters based on Alcohol vs pH')
plt.show()
```



```
from sklearn.cluster import KMeans
```

```
# Apply K-Means with your optimal k value (e.g., k=3)
kmeans = KMeans(n_clusters=3, random_state=42)
clusters = kmeans.fit_predict(scaled_features)
```

```
# Add the cluster labels to the original DataFrame
data_clean['Cluster'] = clusters
```



```
<ipython-input-57-9229bad41349>:8: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

```
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user\_guide/indexing.html#return
data_clean['Cluster'] = clusters
```

```
# Calculate the mean of each feature for each cluster
centroids = data_clean.groupby('Cluster').mean()
print("Cluster Centroids:")
print(centroids)
```



```
Cluster Centroids:
      type  fixed acidity  volatile acidity  citric acid \
Cluster
0      0.997873      6.974322      0.283075      0.358634
1      0.004419      8.343497      0.530780      0.270612
2      0.995997      6.775700      0.274031      0.319176

      residual sugar  chlorides  free sulfur dioxide  total sulfur dioxide \
Cluster
0      11.189952      0.053310      45.535354      169.863105
1       2.507355      0.087919      15.704861      45.986742
2       3.390377      0.040944      28.919947      118.538359
```

| | density | pH | sulphates | alcohol | quality |
|---------|----------|----------|-----------|-----------|----------|
| Cluster | | | | | |
| 0 | 0.996988 | 3.156582 | 0.493530 | 9.541946 | 5.619883 |
| 1 | 0.996783 | 3.310764 | 0.659230 | 10.404956 | 5.627525 |
| 2 | 0.992159 | 3.208239 | 0.487081 | 11.135851 | 6.044029 |

```
import matplotlib.pyplot as plt
import seaborn as sns

# Plot clusters (example using 'alcohol' vs 'pH')
sns.scatterplot(data=data_clean, x='alcohol', y='pH', hue='Cluster', palette='viridis', legend='full')

# Plot centroids (cluster means)
plt.scatter(centroids['alcohol'], centroids['pH'], s=200, c='red', marker='X', label='Centroids')

# Add title and legend
plt.title('Clusters with Centroids (Alcohol vs pH)')
plt.legend()
plt.show()
```

