Week 10 Lab (K Means)

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About The Data

We'll be using the Customer Dataset from kaggle for this lab, but feel free to follow along with your own dataset. The dataset contains the following attributes:

- CustomerID
- Genre
- Age
- Annual*Income*(k$)
- Spending_Score

Our goal is to group/cluster these customers.

About K Means

K Means Clustering is an unsupervised learning algorithm that tries to cluster data based on their similarity. Unsupervised learning means that there is no outcome to be predicted, and the algorithm just tries to find patterns in the data. In k means clustering, we have the specify the number of clusters we want the data to be grouped into. The algorithm randomly assigns each observation to a cluster, and finds the centroid of each cluster. Then, the algorithm iterates through two steps: Reassign data points to the cluster whose centroid is closest. Calculate new centroid of each cluster. These two steps are repeated till the within cluster variation cannot be reduced any further. The within cluster variation is calculated as the sum of the euclidean distance between the data points and their respective cluster centroids. Refer back to the lecture video or slides for more detail on K Means.

Implementation

Because K Means is used more for finding patterns in our data, we'll skip the data exploration portion, but you're welcome to explore this data or your own if working with a different dataset.

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
from matplotlib import rcParams
rcParams['figure.figsize'] = 15, 5
sns.set_style('darkgrid')
```

Let's first load the data into a pandas DataFrame. We'll use the CustomerID column as our index_col for this DataFrame.

In [3]:
```
customer_df = pd.read_csv('customers.csv', index_col='CustomerID')
customer_df.head()
```

Out[3]:

CustomerID	Genre	Age	Annual_Income_(k$)	Spending_Score
1	Male	19	15	39
2	Male	21	15	81
3	Female	20	16	6
4	Female	23	16	77
5	Female	31	17	40

calling ***.info()*** we see that there are no missing values in this dataset since there are 200 entries in total and 200 non-null entries in each column.

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

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 200 entries, 1 to 200
Data columns (total 4 columns):
 #   Column              Non-Null Count  Dtype 
---  ------              --------------  ----- 
 0   Genre               200 non-null    object
 1   Age                 200 non-null    int64 
 2   Annual_Income_(k$)  200 non-null    int64 
 3   Spending_Score      200 non-null    int64 
dtypes: int64(3), object(1)
memory usage: 7.8+ KB
```

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

Out[5]:

	Age	Annual_Income_(k$)	Spending_Score
count	200.000000	200.000000	200.000000
mean	38.850000	60.560000	50.200000
std	13.969007	26.264721	25.823522
min	18.000000	15.000000	1.000000
25%	28.750000	41.500000	34.750000
50%	36.000000	61.500000	50.000000
75%	49.000000	78.000000	73.000000
max	70.000000	137.000000	99.000000

To ensure that we don't have any duplicates, we can call ***.drop_duplicates(inplace=True)*** on our DataFrame.

In [6]:
```
customer_df.drop_duplicates(inplace=True)
```

Just so that we can visualize our clusters in the end of this lab, we'll go ahead and only work with 2 variables (spending score and income). However, you're free to use more than 2 variables if you're working with your own dataset.

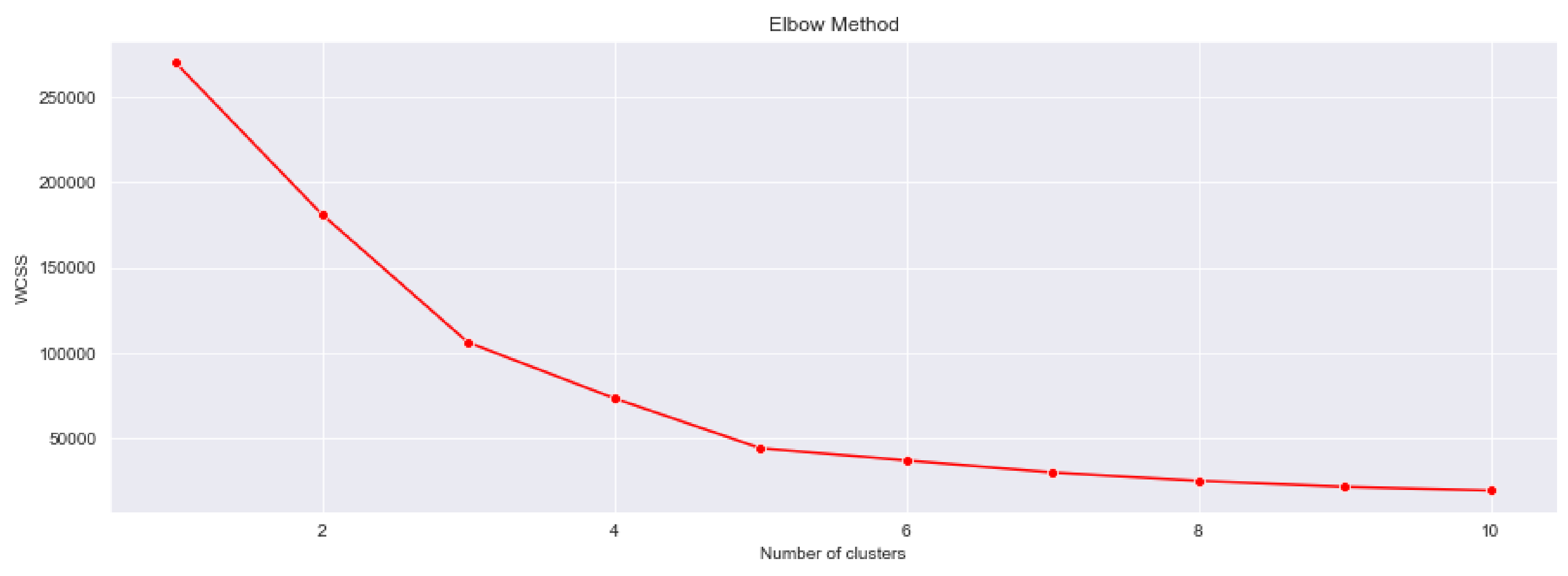
In [12]:
```
# Saving only Spending_Score and income values into X.
X = customer_df.iloc[:, [2, 3]].values
```

We'll now use the elbow method to find the optimal number of clusters.

In [15]:
```
from sklearn.cluster import KMeans

# where we'll store all of the wcss values for plotting later.
wcss = []
for i in range(1, 11):
    # random_state just to ensure we get the same values in the end.
    kmeans = KMeans(n_clusters = i, random_state = 42)
    kmeans.fit(X)
    # inertia method returns wcss for that model.
    wcss.append(kmeans.inertia_)

# creating lineplot to visualize wcss and find optimal number of clusters
sns.lineplot(x=range(1, 11), y=wcss,marker='o',color='red')
plt.title('Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()
```



We're now ready to create our KMeans model and run our predictions on the X vector we created earlier with spending score and income.

In [16]:
```
kmeans = KMeans(n_clusters = 5, init = 'k-means++', random_state = 42)
y_pred = kmeans.fit_predict(X)
```

Note: You won't typically be plotting the clusters to visualize since you'll usually have more than 2 variables, but since we only worked with 2 variables, let's go ahead and visualize our clusters.

In [19]:
```
sns.scatterplot(x=X[y_pred == 0, 0], y=X[y_pred == 0, 1], color = 'yellow', label = 'Cluster 1',s=50)
sns.scatterplot(x=X[y_pred == 1, 0], y=X[y_pred == 1, 1], color = 'blue', label = 'Cluster 2',s=50)
sns.scatterplot(x=X[y_pred == 2, 0], y=X[y_pred == 2, 1], color = 'green', label = 'Cluster 3',s=50)
sns.scatterplot(x=X[y_pred == 3, 0], y=X[y_pred == 3, 1], color = 'grey', label = 'Cluster 4',s=50)
sns.scatterplot(x=X[y_pred == 4, 0], y=X[y_pred == 4, 1], color = 'orange', label = 'Cluster 5',s=50)
sns.scatterplot(x=kmeans.cluster_centers_[:, 0], y=kmeans.cluster_centers_[:, 1], color = 'red',
                label = 'Centroids',s=100,marker=',')
plt.title('Clusters of customers')
plt.xlabel('Annual Income')
plt.ylabel('Spending Score')
plt.legend()
plt.show()
```

Congrats! 😊 You know know how to use KMeans in sklearn. Try repeating the lab steps on your own data for practice. Since we don't have the ground truth (unsupervised) to compare and evaulate performance, there's not much more we can do here to evaluate our model like we're used to doing. You'll later learn about Silhouette analysis, which will come in handy.