Clustering algorithms for customer segmentation

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Context

In today's competitive world, it is crucial to understand customer behavior and categorize customers based on their demography and buying behavior. This is a critical

aspect of customer segmentation that allows marketers to better tailor their marketing efforts to various audience subsets in terms of promotional, marketing and product development strategies.

Objective

This article demonstrates the concept of segmentation of a customer data set from an e-commerce site using k-means clustering in python. The data set contains the ***annual income*** of ~300 customers and their ***annual spend*** on an e-commerce site. We will use the k-means clustering algorithm to derive the optimum number of clusters and understand the underlying customer segments based on the data provided.

About the data set

The dataset consists of Annual income (in $000) of 303 customers and their total spend (in $000) on an e-commerce site for a period of one year. Let us explore the data using *numpy* and *pandas* libraries in python.

```
#Load the required packages
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

#Plot styling
import seaborn as sns; sns.set()  # for plot styling
%matplotlib inline

plt.rcParams['figure.figsize'] = (16, 9)
plt.style.use('ggplot')

#Read the csv file
dataset=pd.read_csv('CLV.csv')

#Explore the dataset
dataset.head()#top 5 columns
len(dataset) # of rows

#descriptive statistics of the dataset
dataset.describe().transpose()
```

	INCOME	SPEND
0	233	150

1	250	187
2	204	172
3	236	178
4	354	163

dataset.head()

	count	mean	std	min	25%	50%	75%	max
INCOME	303.0	245.273927	48.499412	126.0	211.0	240.0	274.0	417.0
SPEND	303.0	149.646865	22.905161	71.0	133.5	153.0	166.0	202.0

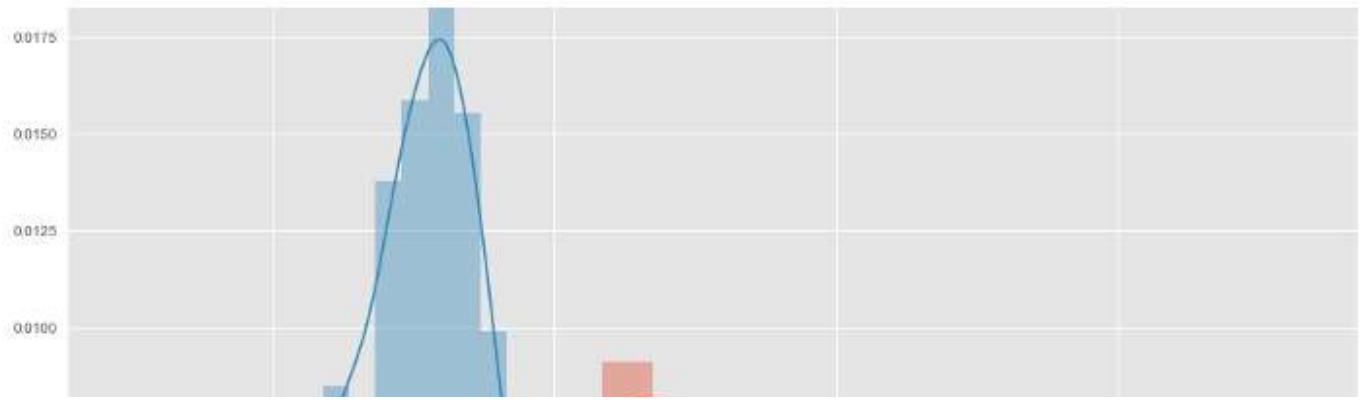
dataset.describe().transpose()

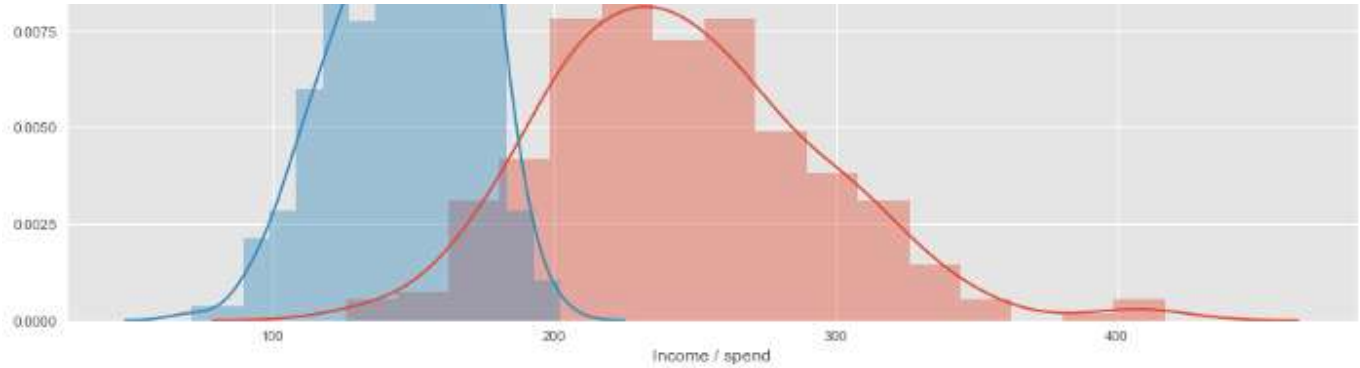
The dataset consists of 303 rows. The mean annual income is 245000 and the mean annual spend is 149000. The distribution of the annual income and annual spend has been illustrated with a *distplot* and *violinplot*.

Visualizing the data

The displot and violinplot give an indication of the data distribution of Income and Spend.

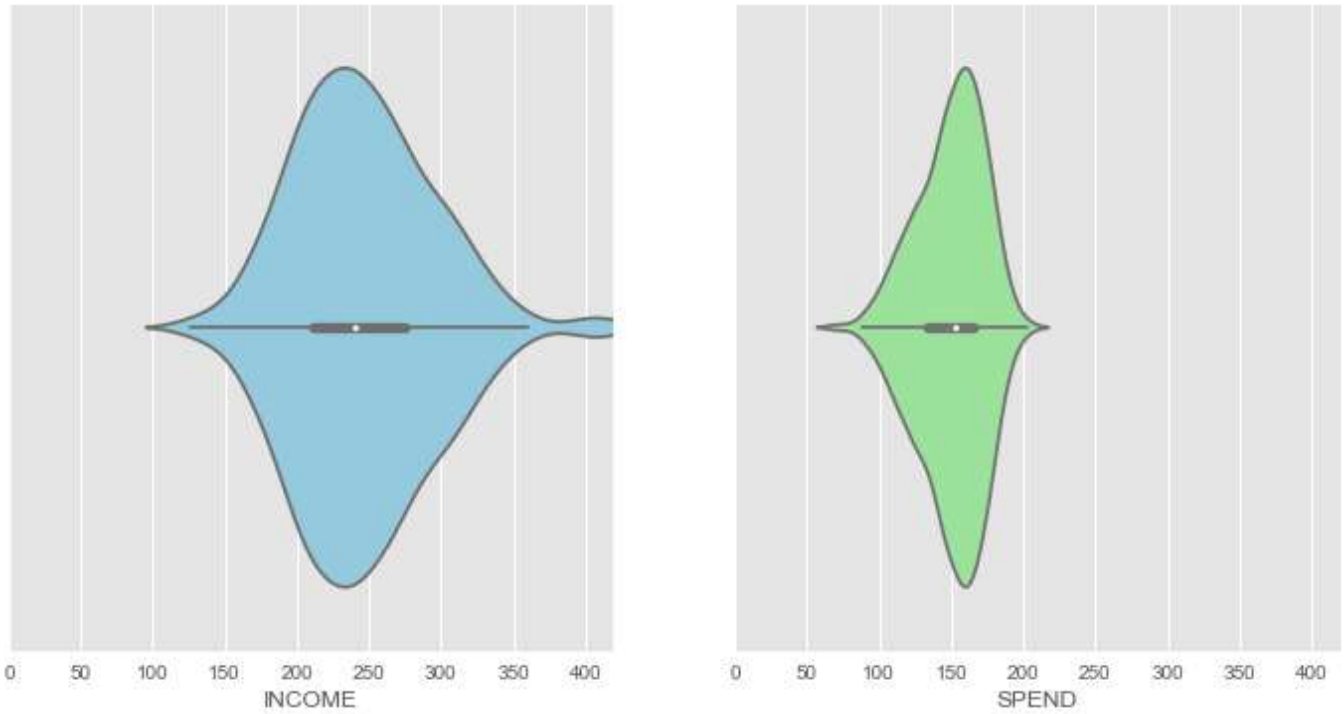
```
#Visualizing the data - displot
plot_income = sns.distplot(dataset["INCOME"])
plot_spend = sns.distplot(dataset["SPEND"])
plt.xlabel('Income / spend')
```





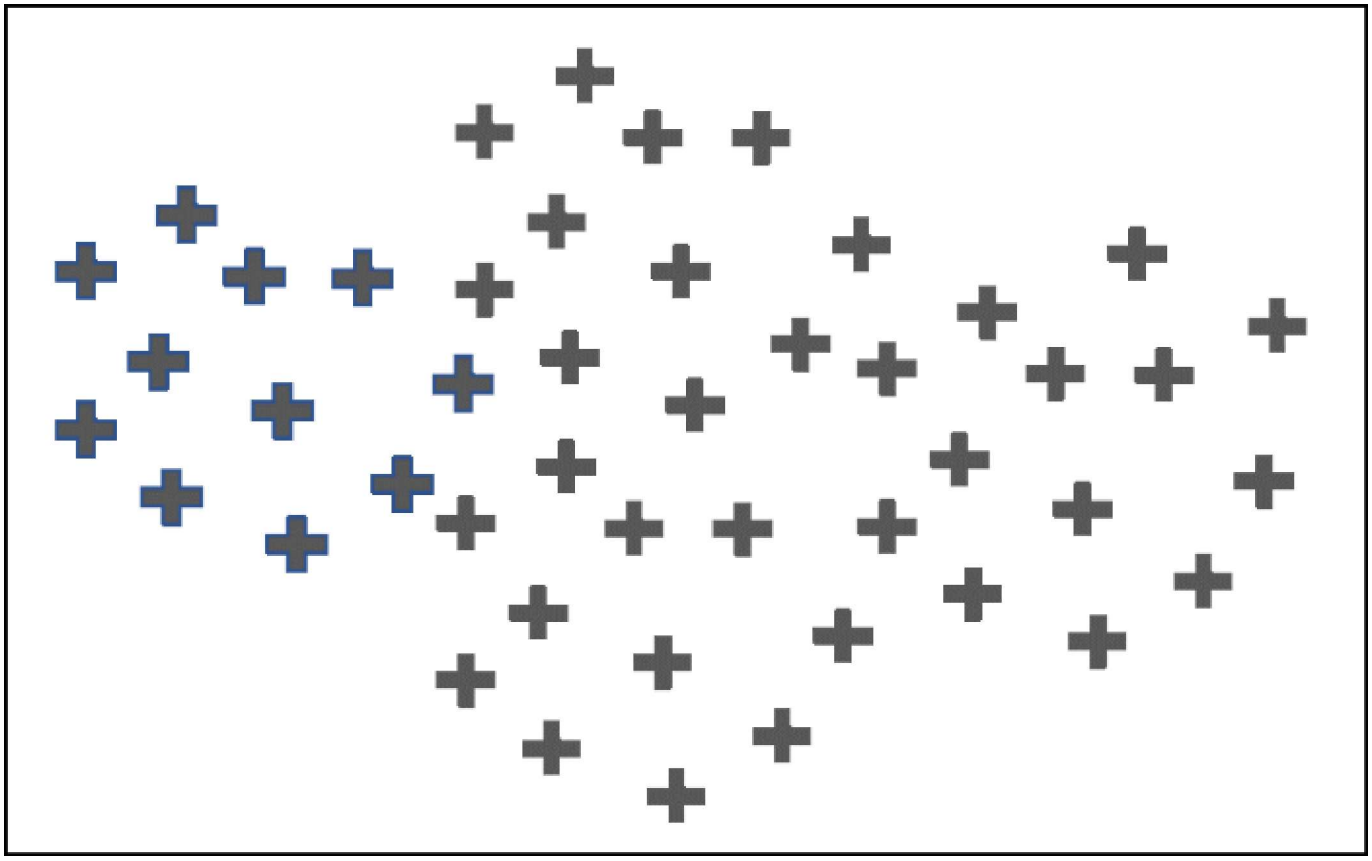
Distribution plot of Income & Spend

```
#Violin plot of Income and Spend
f, axes = plt.subplots(1,2, figsize=(12,6), sharex=True, sharey=True)
v1 = sns.violinplot(data=dataset, x='INCOME',
color="skyblue",ax=axes[0])
v2 = sns.violinplot(data=dataset, x='SPEND',color="lightgreen",
ax=axes[1])
v1.set(xlim=(0,420))
```

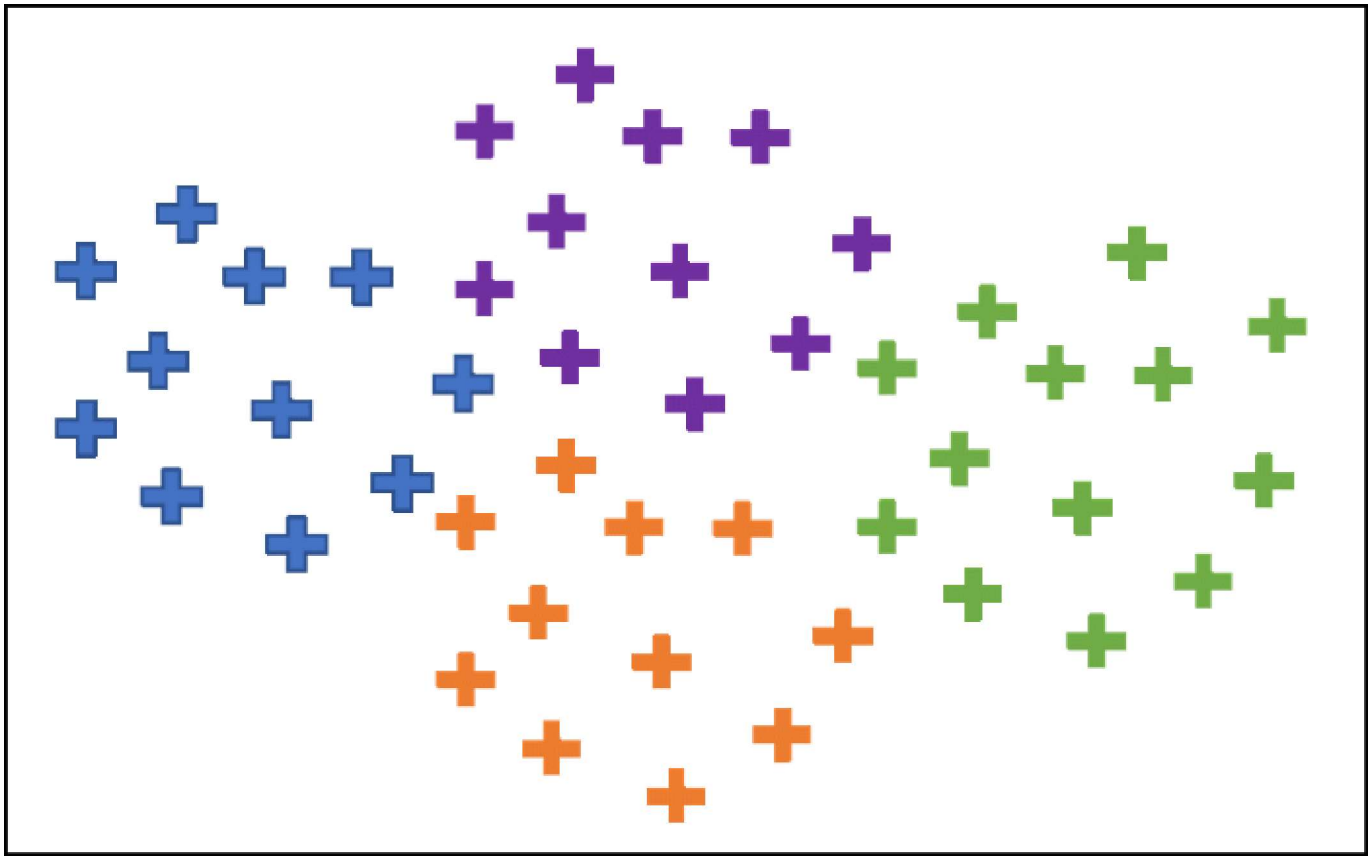


Clustering fundamentals

Clustering is an unsupervised machine learning technique, where there are no defined dependent and independent variables. The patterns in the data are used to identify / group similar observations.



Original Dataset



After Clustering

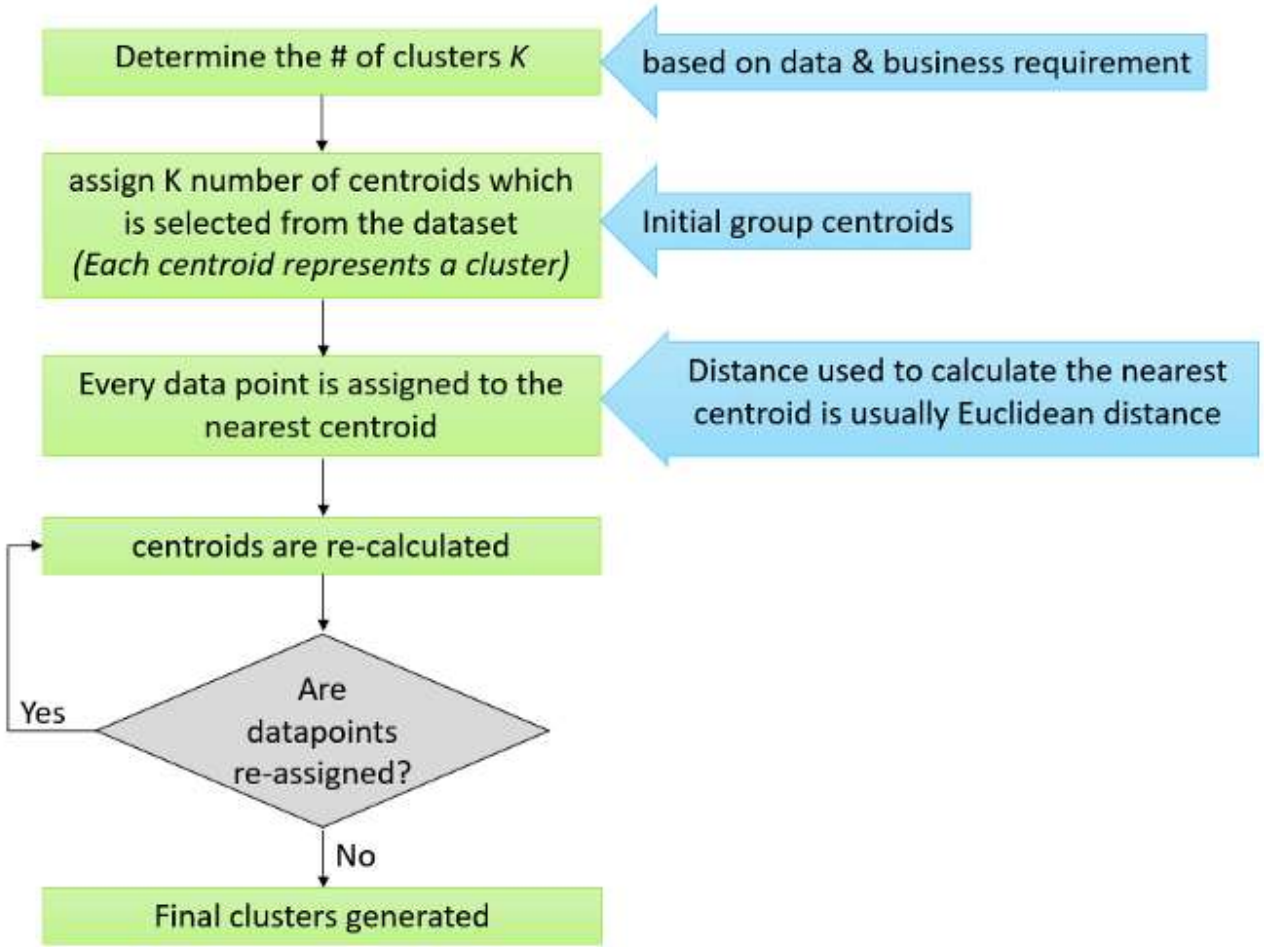
The objective of any clustering algorithm is to ensure that the distance between datapoints in a cluster is very low compared to the distance between 2 clusters. In other words, members of a group are very similar, and members of different groups are extremely dissimilar.

We will use are k-means clustering for creating customer segments based on their income and spend data.

K-Means clustering

K-means clustering is an iterative clustering algorithm where the number of clusters K is predetermined and the algorithm iteratively assigns each data point to one of the K clusters based on the feature similarity.

Broad steps of the k-means algorithm



The mathematics of clustering

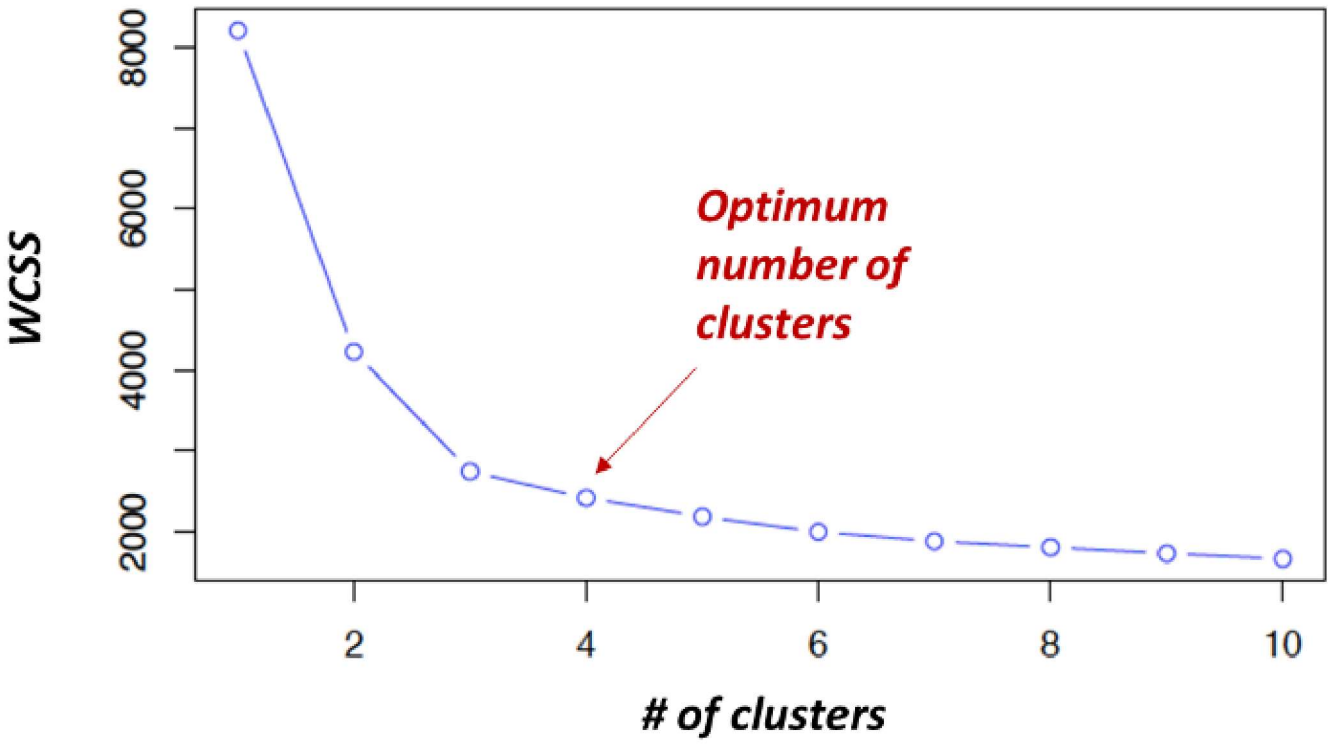
The mathematics behind clustering, in very simple terms involves minimizing the sum of square of distances between the cluster centroid and its associated data points:

$$Minimize \sum_{j=1}^{k} \sum_{i=1}^{n} (x_{ij} - c_j)^2$$

- K = number of clusters
- N= number of data points
- C=centroid of cluster j
- $(xij — cj)$– Distance between data point and centroid to which it is assigned

Deciding on the optimum number of clusters 'K'

The main input for k-means clustering is the number of clusters. This is derived using the concept of ***minimizing within cluster sum of square (WCSS)***. A scree plot is created which plots the number of clusters in the X axis and the WCSS for each cluster number in the y-axis.

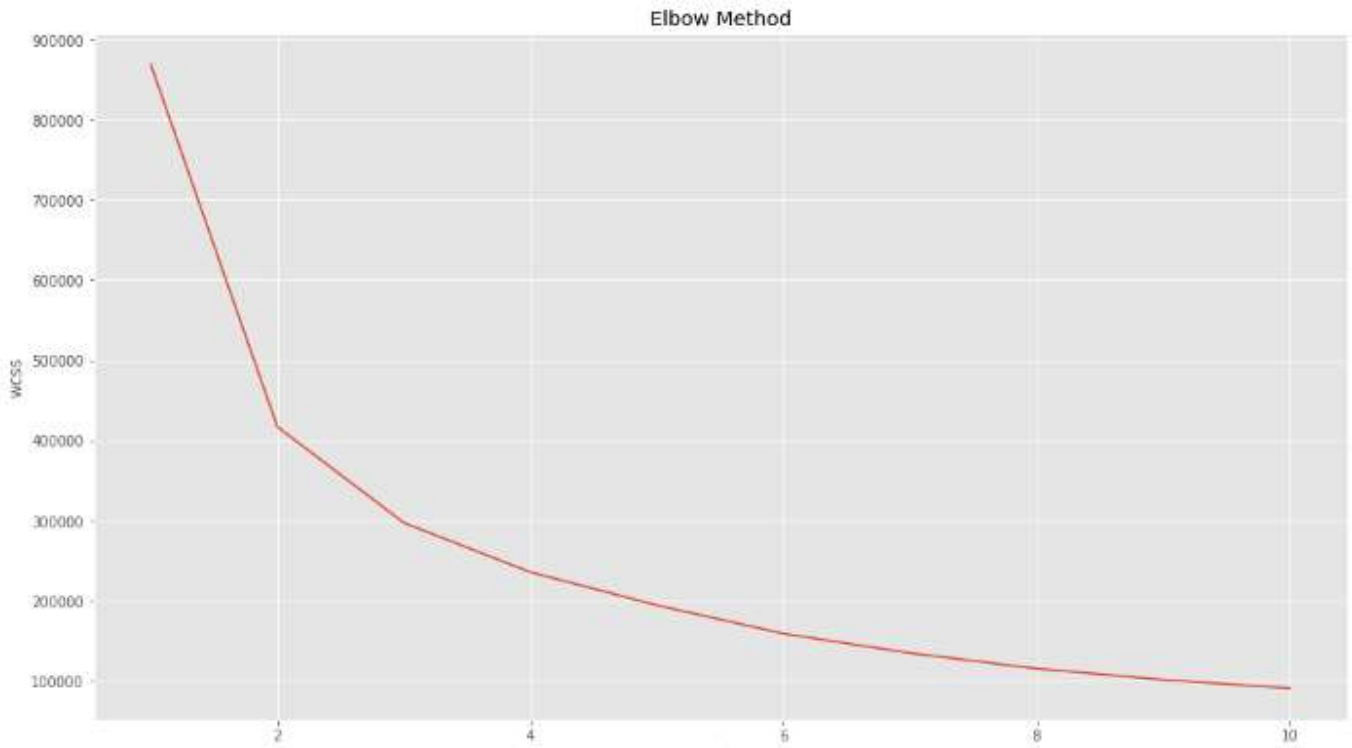


Scree plot / Elbow method to determine optimum number of clusters

As the number of clusters increase, the WCSS keeps decreasing. The decrease of WCSS is initially steep and then the rate of decrease slows down resulting in an elbow plot. The number of clusters at the elbow formation usually gives an indication on the optimum number of clusters. This combined with specific knowledge of the business requirement should be used to decide on the optimum number of clusters.

For our dataset, we will arrive at the optimum number of clusters using the elbow method:

```
#Using the elbow method to find the optimum number of clusters
from sklearn.cluster import KMeans
wcss = []
for i in range(1,11):
    km=KMeans(n_clusters=i,init='k-means++', max_iter=300, n_init=10,
random_state=0)
    km.fit(X)
    wcss.append(km.inertia_)
plt.plot(range(1,11),wcss)
plt.title('Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('wcss')
plt.show()
```



Scree plot of given datatset on customer Income & Spend

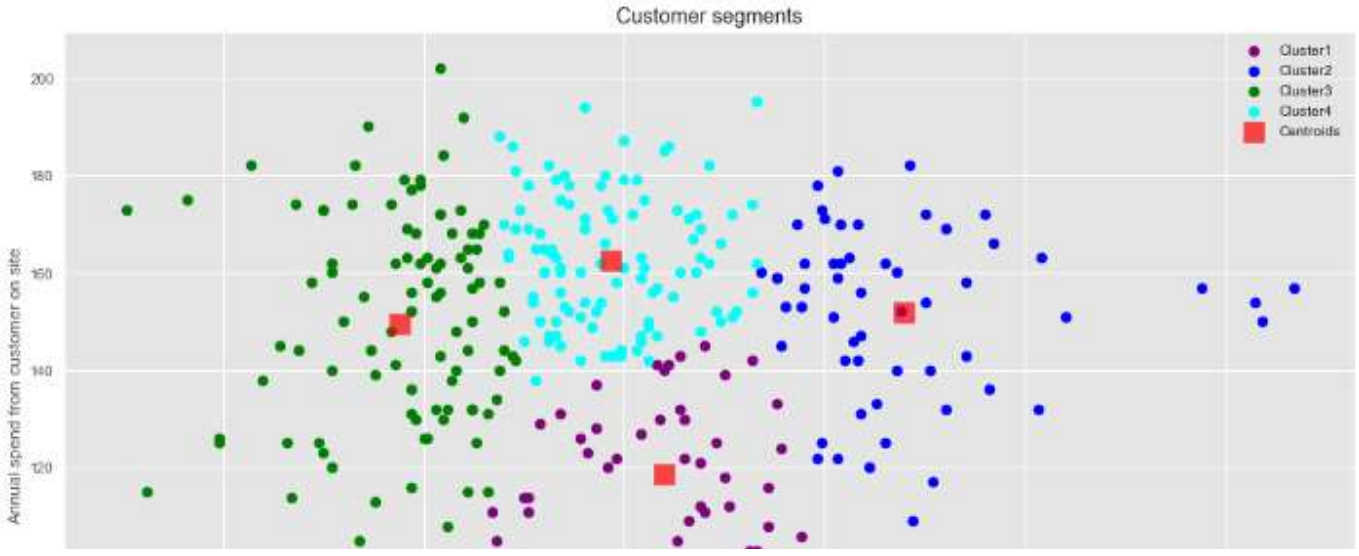
Based on the elbow plot, we could choose 4,5 or 6 clusters. Let us try both the number of clusters and visualize the clusters to decide on the final number of clusters.

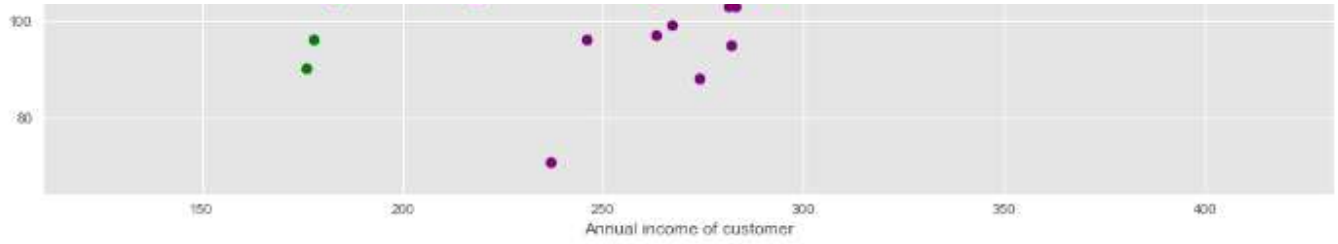
Fitting the k-means to the dataset with k=4

```
##Fitting kmeans to the dataset with k=4
km4=KMeans(n_clusters=4,init='k-means++', max_iter=300, n_init=10,
random_state=0)
y_means = km4.fit_predict(X)

#Visualizing the clusters for k=4
plt.scatter(X[y_means==0,0],X[y_means==0,1],s=50,
c='purple',label='Cluster1')
plt.scatter(X[y_means==1,0],X[y_means==1,1],s=50,
c='blue',label='Cluster2')
plt.scatter(X[y_means==2,0],X[y_means==2,1],s=50,
c='green',label='Cluster3')
plt.scatter(X[y_means==3,0],X[y_means==3,1],s=50,
c='cyan',label='Cluster4')

plt.scatter(km4.cluster_centers_[:,0],
km4.cluster_centers_[:,1],s=200,marker='s', c='red', alpha=0.7,
label='Centroids')
plt.title('Customer segments')
plt.xlabel('Annual income of customer')
plt.ylabel('Annual spend from customer on site')
plt.legend()
plt.show()
```





Cluster plot : k=4

The plot shows the distribution of the 4 clusters. We could interpret them as the following customer segments:

1. Cluster 1: Customers with medium annual income and low annual spend
2. Cluster 2: Customers with high annual income and medium to high annual spend
3. Cluster 3: Customers with low annual income
4. Cluster 4: Customers with medium annual income but high annual spend

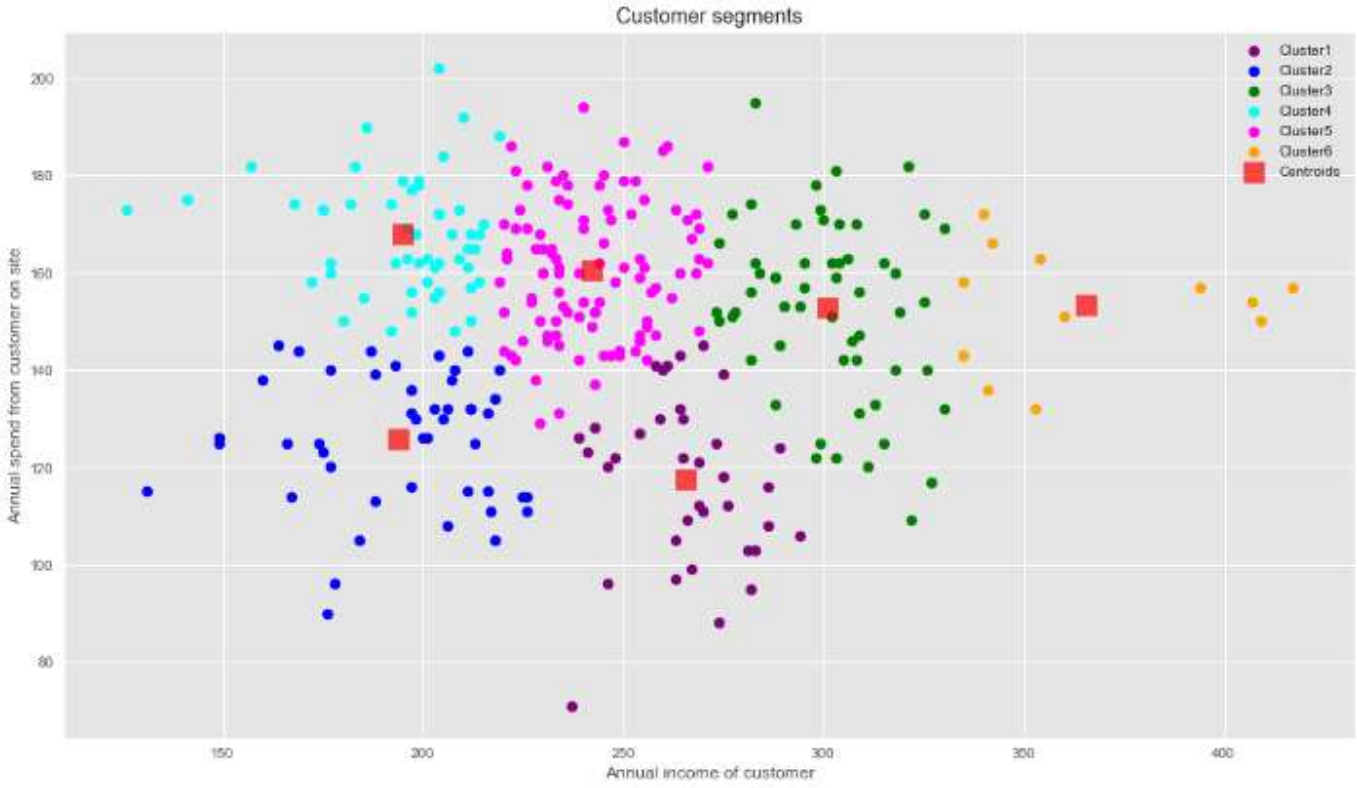
Cluster 4 straight away is one potential customer segment. However, Cluster 2 and 3 can be segmented further to arrive at a more specific target customer group. Let us now look at how the clusters are created when k=6:

```
##Fitting kmeans to the dataset - k=6
km4=KMeans(n_clusters=6,init='k-means++', max_iter=300, n_init=10,
random_state=0)
y_means = km4.fit_predict(X)

#Visualizing the clusters
plt.scatter(X[y_means==0,0],X[y_means==0,1],s=50,
c='purple',label='Cluster1')
plt.scatter(X[y_means==1,0],X[y_means==1,1],s=50,
c='blue',label='Cluster2')
plt.scatter(X[y_means==2,0],X[y_means==2,1],s=50,
c='green',label='Cluster3')
plt.scatter(X[y_means==3,0],X[y_means==3,1],s=50,
c='cyan',label='Cluster4')
plt.scatter(X[y_means==4,0],X[y_means==4,1],s=50,
c='magenta',label='Cluster5')
plt.scatter(X[y_means==5,0],X[y_means==5,1],s=50,
c='orange',label='Cluster6')

plt.scatter(km.cluster_centers_[:,0],
km.cluster_centers_[:,1],s=200,marker='s', c='red', alpha=0.7,
label='Centroids')
```

```
plt.title('Customer segments')
plt.xlabel('Annual income of customer')
plt.ylabel('Annual spend from customer on site')
plt.legend()
plt.show()
```



Cluster plot : k=6

Setting the number of clusters to 6 seems to provide a more meaningful customer segmentation.

1. Cluster 1: Medium income, low annual spend
2. Cluster 2: Low income, low annual spend
3. Cluster 3: High income, high annual spend
4. Cluster 4: Low income, high annual spend
5. Cluster 5: Medium income, low annual spend
6. Cluster 6: Very high income, high annual spend

Thus it is evident that 6 clusters provides a more meaningful segmentation of the customers.

Marketing strategies for the customer segments

Based on the 6 clusters, we could formulate marketing strategies relevant to each cluster:

- A typical strategy would focus certain promotional efforts for the high value customers of Cluster 6 & Cluster 3.
- Cluster 4 is a unique customer segment, where in spite of their relatively lower annual income, these customers tend to spend more on the site, indicating their loyalty. There could be some discounted pricing based promotional campaigns for this group so as to retain them.
- For Cluster 2 where both the income and annual spend are low, further analysis could be needed to find the reasons for the lower spend and price-sensitive strategies could be introduced to increase the spend from this segment.
- Customers in clusters 1 and 5 are not spending enough on the site in spite of a good annual income — further analysis of these segments could lead to insights on the satisfaction / dissatisfaction of these customers or lesser visibility of the e-commerce site to these customers. Strategies could be evolved accordingly.

We have thus seen, how we could arrive at meaningful insights and recommendations by using clustering algorithms to generate customer segments. For the sake of simplicity, the dataset used only 2 variables — income and spend. In a typical business scenario, there could be several variables which could possibly generate much more realistic and business-specific insights.