# Untitled7

August 20, 2021

The data science methodology followed for this project has been outlined by John Rollins, IBM

Business Understanding

Analytical Approach

Data requirements

Data collection

Data Understanding

Data Preparation

Modeling

Evaluation

1. Business Understanding

Customer segmentation is the practice of dividing a company's customers into groups that reflect similarity among customers in each group. The goal of this project is to divide customers into groups based on common characteristics in order to maximize the value of each customer to the business.

2. Analytical Approach

Clustering of Customers based on similar characteristics is an Unsupervised Learning as for each observation we do not have any target variable. For this project I will use two Machine Learning models

I will use KMeans Clustering Algorithm which aims to partition n observations into k clusters in which each observation belongs to the cluster with the nearest mean I will also use Hierarchical clustering which is an algorithm that groups similar objects into groups called clusters. The end-point is a set of clusters, where each cluster is distinct from each other cluster, and the objects within each cluster are broadly similar to each other. 3,4. Data Requirements and Data Collection We would require a dataset which gives us information regarding customers from a market. For this project, the dataset has been provided to us on Kaggle. This data set is created only for the learning purpose of the customer segmentation concepts , also known as market basket analysis

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

```python
from sklearn.cluster import KMeans
from sklearn.cluster import AgglomerativeClustering
```

[2]:
```python
df = pd.read_csv("Mall_Customers.csv")
```

[3]:
```python
df.head()
```

[3]:
```
   CustomerID  Gender  Age  Annual Income (k$)  Spending Score (1-100)
0           1    Male   19                  15                      39
1           2    Male   21                  15                      81
2           3  Female   20                  16                       6
3           4  Female   23                  16                      77
4           5  Female   31                  17                      40
```

[4]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 5 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   CustomerID              200 non-null    int64
 1   Gender                  200 non-null    object
 2   Age                     200 non-null    int64
 3   Annual Income (k$)      200 non-null    int64
 4   Spending Score (1-100)  200 non-null    int64
dtypes: int64(4), object(1)
memory usage: 7.9+ KB
```

[5]:
```python
df.columns
```

[5]:
```
Index(['CustomerID', 'Gender', 'Age', 'Annual Income (k$)',
       'Spending Score (1-100)'],
      dtype='object')
```

[6]:
```python
df.isnull().sum()
```

[6]:
```
CustomerID                0
Gender                    0
Age                       0
Annual Income (k$)        0
Spending Score (1-100)    0
dtype: int64
```

Dataset Understanding:

There are total of 200 observations with each having 5 variables. The column of the dataset include CustomerID, Gender, Age, Annual Income, Spending Score. There are no missing values (Good day for us XD) There is one categorical variable - Gender

[7]:
```
df.describe()
```

[7]:

| | CustomerID | Age | Annual Income (k$) | Spending Score (1-100) |
|---|---|---|---|---|
| count | 200.000000 | 200.000000 | 200.000000 | 200.000000 |
| mean | 100.500000 | 38.850000 | 60.560000 | 50.200000 |
| std | 57.879185 | 13.969007 | 26.264721 | 25.823522 |
| min | 1.000000 | 18.000000 | 15.000000 | 1.000000 |
| 25% | 50.750000 | 28.750000 | 41.500000 | 34.750000 |
| 50% | 100.500000 | 36.000000 | 61.500000 | 50.000000 |
| 75% | 150.250000 | 49.000000 | 78.000000 | 73.000000 |
| max | 200.000000 | 70.000000 | 137.000000 | 99.000000 |

[8]:
```
df.describe(include=['O']).T
```

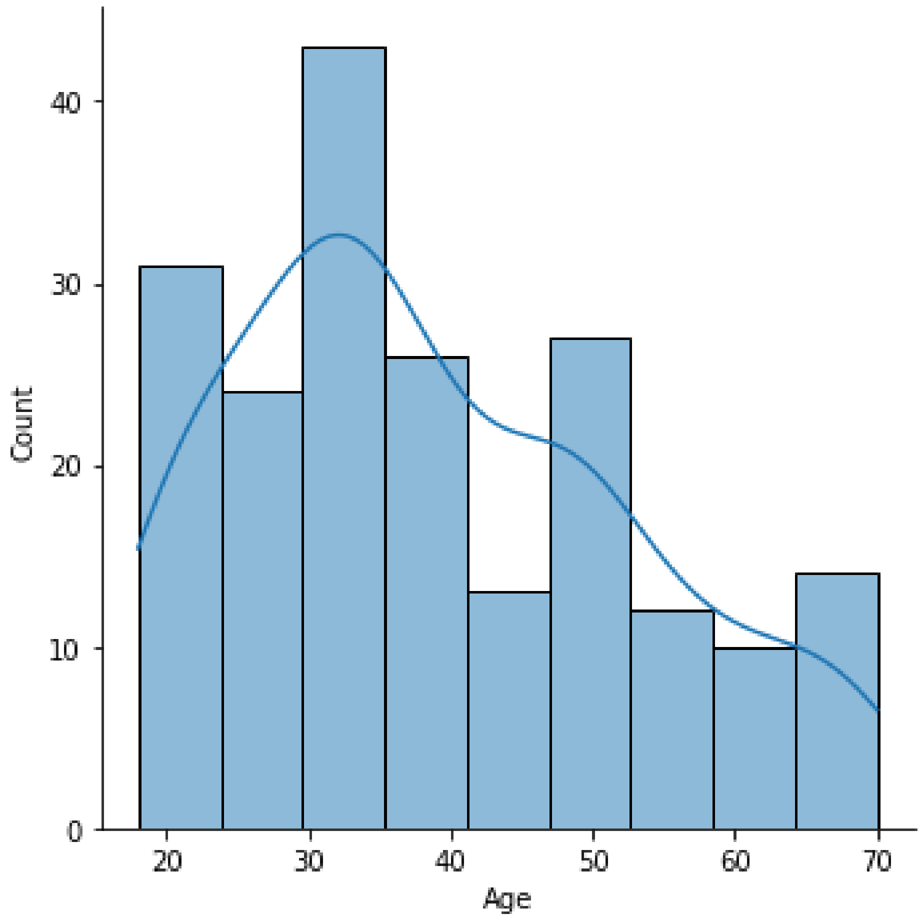
[8]:

| | count | unique | top | freq |
|---|---|---|---|---|
| Gender | 200 | 2 | Female | 112 |

[9]:
```
df.rename(columns={"Annual Income (k$)": "Income", "Spending Score (1-100)":␣
↪"Score"}, inplace=True)
```

[10]:
```
sns.displot(x='Age', data=df, kde=True)
```

[10]: <seaborn.axisgrid.FacetGrid at 0x2520f147850>

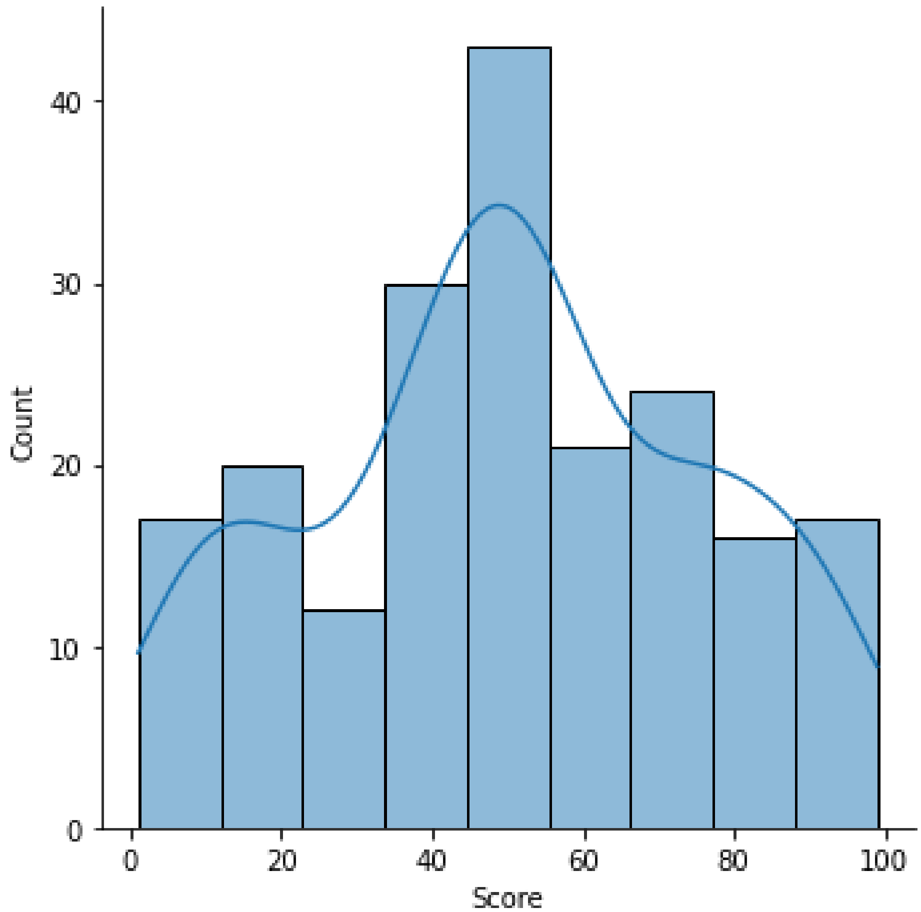



```
[11]: df['Score'].unique()
```

```
[11]: array([39, 81,  6, 77, 40, 76, 94,  3, 72, 14, 99, 15, 13, 79, 35, 66, 29,
             98, 73,  5, 82, 32, 61, 31, 87,  4, 92, 17, 26, 75, 36, 28, 65, 55,
             47, 42, 52, 60, 54, 45, 41, 50, 46, 51, 56, 59, 48, 49, 53, 44, 57,
             58, 43, 91, 95, 11,  9, 34, 71, 88,  7, 10, 93, 12, 97, 74, 22, 90,
             20, 16, 89,  1, 78, 83, 27, 63, 86, 69, 24, 68, 85, 23,  8, 18],
            dtype=int64)
```

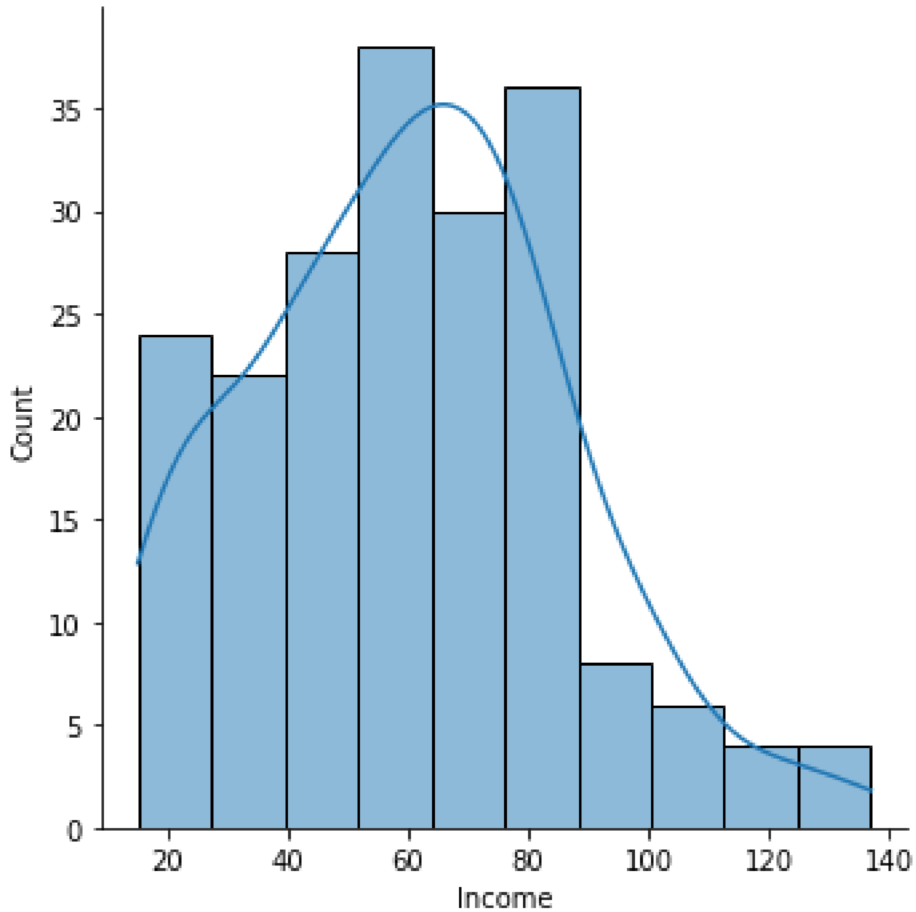
```
[12]: sns.displot(x='Score', data=df, kde=True)
```

```
[12]: <seaborn.axisgrid.FacetGrid at 0x2520f4b2fa0>
```



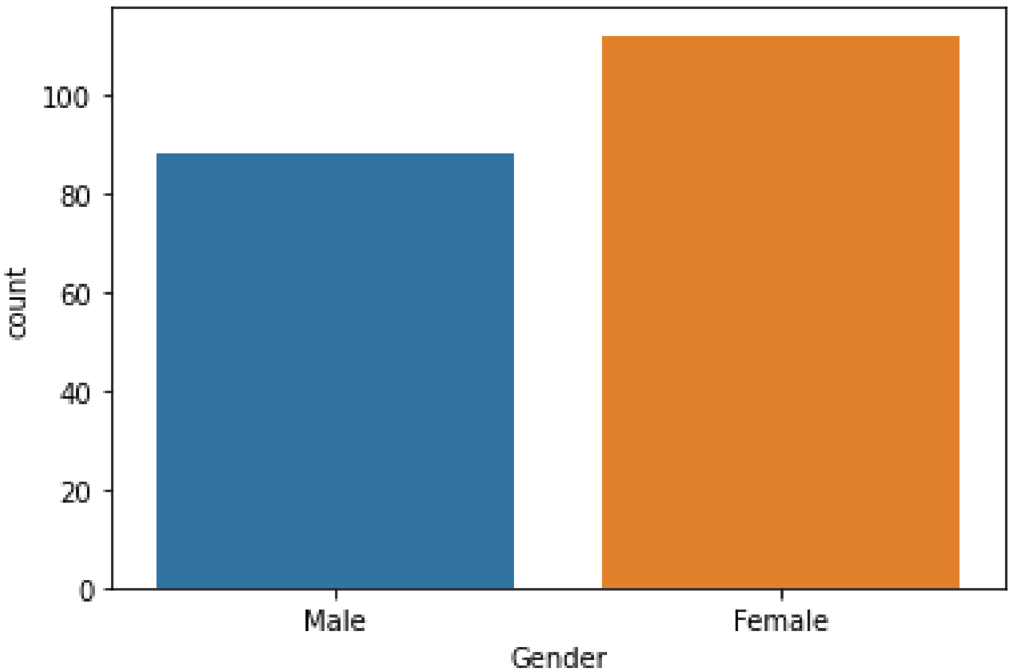

```
[13]: sns.displot(x='Income', data=df, kde=True)
```

```
[13]: <seaborn.axisgrid.FacetGrid at 0x2520f5ac550>
```




[14]:
```
sns.countplot(x='Gender', data=df)
```

[14]: <AxesSubplot:xlabel='Gender', ylabel='count'>




[15]:
```
df['Gender'].value_counts()
```

[15]:
```
Female    112
Male       88
Name: Gender, dtype: int64
```

[16]:
```
sns.heatmap(df.corr(), annot=True)
```

[16]:
```
<AxesSubplot:>
```


[17]:
```
df.drop('CustomerID', axis=1, inplace=True)
```

[18]:
```
df.head()
```

[18]:

| | Gender | Age | Income | Score |
|---|---|---|---|---|
| 0 | Male | 19 | 15 | 39 |
| 1 | Male | 21 | 15 | 81 |
| 2 | Female | 20 | 16 | 6 |
| 3 | Female | 23 | 16 | 77 |
| 4 | Female | 31 | 17 | 40 |

[19]:
```
df = pd.get_dummies(df).reset_index(drop=True)
```

[20]:
```
df.head()
```

[20]:

| | Age | Income | Score | Gender_Female | Gender_Male |
|---|---|---|---|---|---|
| 0 | 19 | 15 | 39 | 0 | 1 |
| 1 | 21 | 15 | 81 | 0 | 1 |
| 2 | 20 | 16 | 6 | 1 | 0 |
| 3 | 23 | 16 | 77 | 1 | 0 |
| 4 | 31 | 17 | 40 | 1 | 0 |

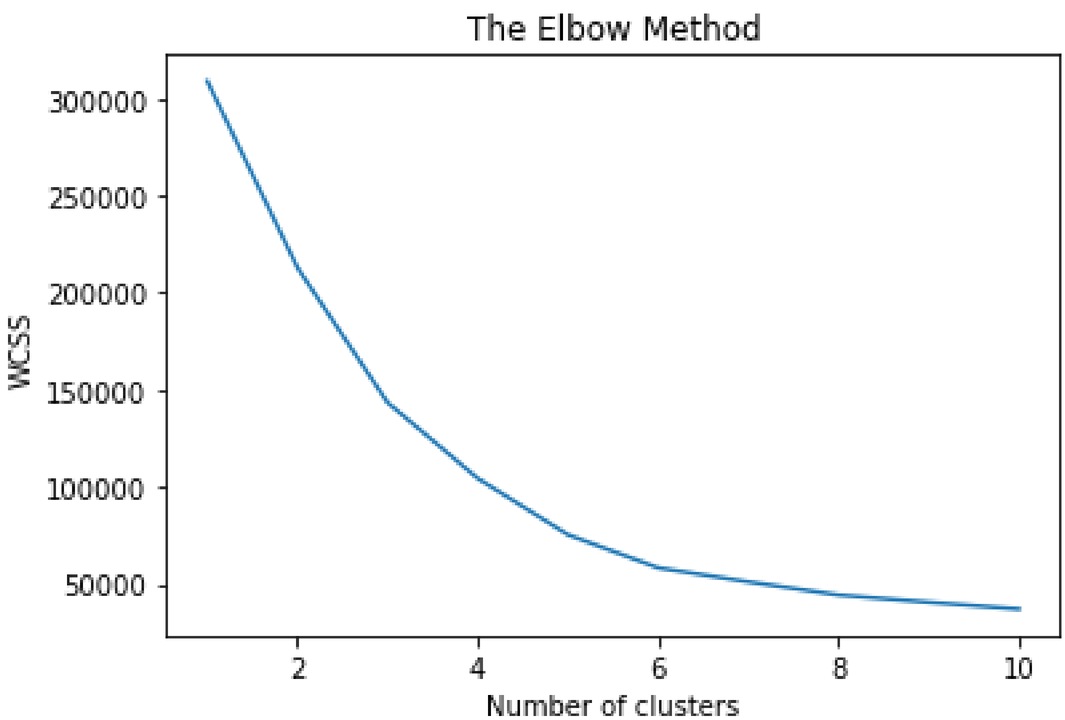
K Means Clustering In K-means, objects are assigned to a cluster based on the Euclidean distance between the object and the center of the cluster, also referred to as the cluster centroid.

But we do not know in advance how many clusters there are, and we do not know what the clusters will look like. That is why we work in two steps.

First, we determine the optimal number of clusters, and then We determine starting values for each cluster.

[21]:
```
X = df.iloc[:,].values
```

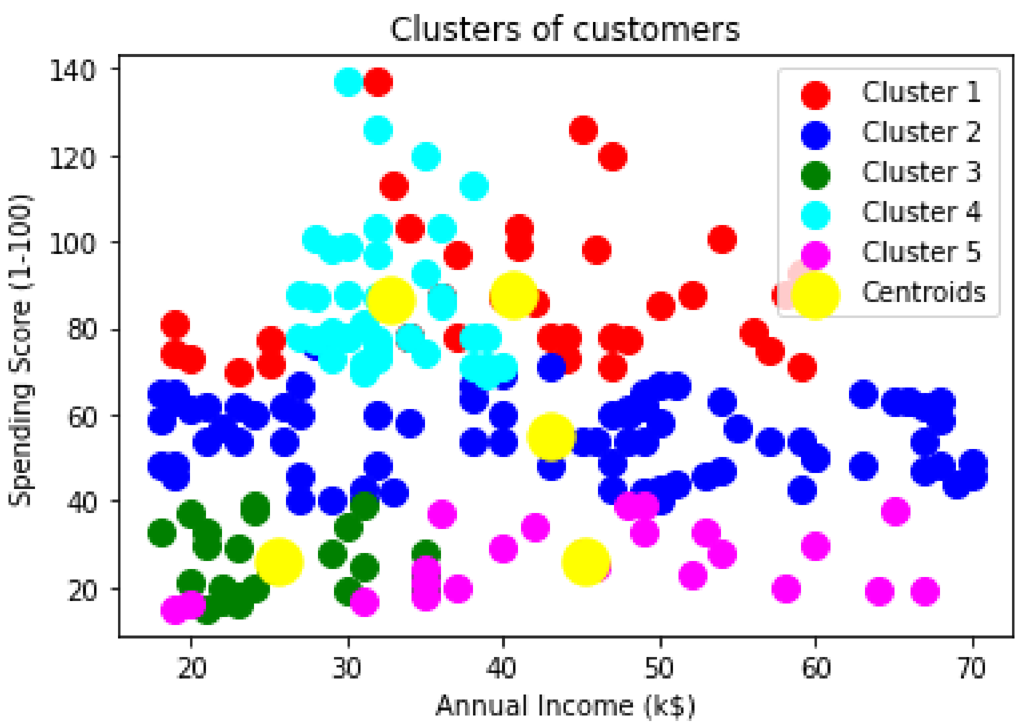
[22]:
```
# Using the elbow method to find the optimal number of clusters
wcss = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters = i, init = 'k-means++', random_state = 42)
    kmeans.fit(X)
    wcss.append(kmeans.inertia_)
plt.plot(range(1, 11), wcss)
plt.title('The Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()
```




[23]:
```
# Fitting K-Means to the dataset
kmeans = KMeans(n_clusters = 5, init = 'k-means++', random_state = 42)
y_kmeans = kmeans.fit_predict(X)
```

[24]:
```
# Visualising the clusters
plt.scatter(X[y_kmeans == 0, 0], X[y_kmeans == 0, 1], s = 100, c = 'red', label␣
↪= 'Cluster 1')
```

```
plt.scatter(X[y_kmeans == 1, 0], X[y_kmeans == 1, 1], s = 100, c = 'blue',␣
 ↪label = 'Cluster 2')
plt.scatter(X[y_kmeans == 2, 0], X[y_kmeans == 2, 1], s = 100, c = 'green',␣
 ↪label = 'Cluster 3')
plt.scatter(X[y_kmeans == 3, 0], X[y_kmeans == 3, 1], s = 100, c = 'cyan',␣
 ↪label = 'Cluster 4')
plt.scatter(X[y_kmeans == 4, 0], X[y_kmeans == 4, 1], s = 100, c = 'magenta',␣
 ↪label = 'Cluster 5')
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1], s =␣
 ↪300, c = 'yellow', label = 'Centroids')
plt.title('Clusters of customers')
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.legend()
plt.show()
```



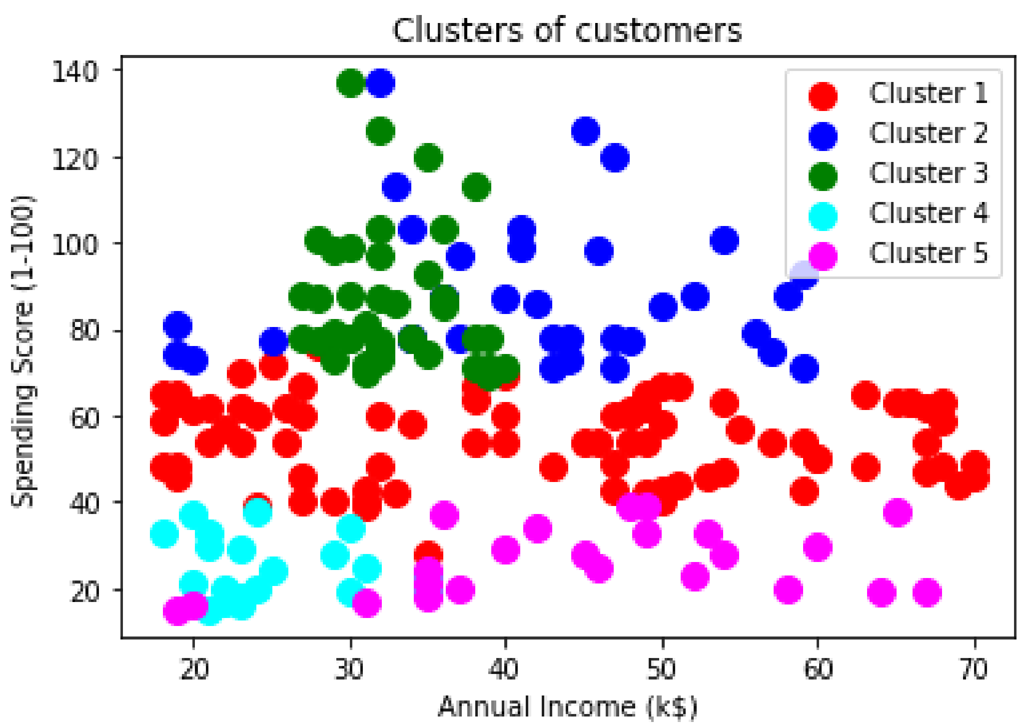

Hierarchical clustering Hierarchical clustering, also known as hierarchical cluster analysis, is an algorithm that groups similar objects into groups called clusters. The endpoint is a set of clusters, where each cluster is distinct from each other cluster, and the objects within each cluster are broadly similar to each other.

[25]:
```
hc = AgglomerativeClustering(n_clusters = 5, affinity = 'euclidean', linkage =␣
 ↪'ward')
```

```
y_hc = hc.fit_predict(X)
```

[26]:

```
# Visualising the clusters
plt.scatter(X[y_hc == 0, 0], X[y_hc == 0, 1], s = 100, c = 'red', label =␣
↪'Cluster 1')
plt.scatter(X[y_hc == 1, 0], X[y_hc == 1, 1], s = 100, c = 'blue', label =␣
↪'Cluster 2')
plt.scatter(X[y_hc == 2, 0], X[y_hc == 2, 1], s = 100, c = 'green', label =␣
↪'Cluster 3')
plt.scatter(X[y_hc == 3, 0], X[y_hc == 3, 1], s = 100, c = 'cyan', label =␣
↪'Cluster 4')
plt.scatter(X[y_hc == 4, 0], X[y_hc == 4, 1], s = 100, c = 'magenta', label =␣
↪'Cluster 5')
plt.title('Clusters of customers')
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.legend()
plt.show()
```




[ ]: