Unsupervised Machine Learning Algorithm

Title : Similar Car Recommendation (K-Means Clustering)

Import Libraries

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
from warnings import filterwarnings
filterwarnings("ignore")
```

Collecting Data

Reading in the Cars93.csv file into a pandas dataframe.

In [2]:
```
A = pd.read_csv("C:/Users/aksha/OneDrive/Desktop/Cars93.csv")
```

In [3]:
```
A.head()
```

Out[3]:

	id	Manufacturer	Model	Type	Min.Price	Price	Max.Price	MPG.city	MPG.highway	AirBags	...	Passengers	Length	Wheelbase	Width	Turn.circle	Rear.seat.room	Luggage.room	Weight	Origin	Make
0	1	Acura	Integra	Small	12.9	15.9	18.8	25	31	None	...	5	177	102	68	37	26.5	11.0	2705	non-USA	Acura Integra
1	2	Acura	Legend	Midsize	29.2	33.9	38.7	18	25	Driver & Passenger	...	5	195	115	71	38	30.0	15.0	3560	non-USA	Acura Legend
2	3	Audi	90	Compact	25.9	29.1	32.3	20	26	Driver only	...	5	180	102	67	37	28.0	14.0	3375	non-USA	Audi 90
3	4	Audi	100	Midsize	30.8	37.7	44.6	19	26	NaN	...	6	193	106	70	37	31.0	17.0	3405	non-USA	Audi 100
4	5	BMW	535i	Midsize	23.7	30.0	36.2	22	30	Driver only	...	4	186	109	69	39	27.0	13.0	3640	non-USA	BMW 535i

5 rows × 28 columns

In [4]:
```
#clustering done on the basis of these 2 columns
B = A[["Price","MPG.city"]]
```

Standardization of data using StandardScaler

Standardization is the process of normalizing values to bring all the data into nearly same values.StandardScaler transforms the data in such a way that it has mean as 0 and standard deviation as 1.

In [5]:
```
B = A[["Price","MPG.city"]]
from sklearn.preprocessing import StandardScaler
ss = StandardScaler()
C = pd.DataFrame(ss.fit_transform(B),columns=B.columns)
```

To see the clusters formed

In [6]:
```
from sklearn.cluster import KMeans
km = KMeans(n_clusters=4)
model = km.fit(C)
model.labels_
```

Out[6]:
```
array([2, 3, 0, 3, 0, 2, 0, 0, 0, 3, 3, 2, 2, 0, 2, 0, 0, 0, 3, 0, 2, 0,
       1, 2, 2, 0, 2, 0, 1, 0, 1, 2, 2, 2, 2, 0, 0, 0, 1, 1, 2, 1, 2, 1,
       2, 2, 2, 3, 0, 3, 3, 3, 1, 1, 2, 0, 3, 3, 3, 2, 0, 1, 0, 1, 2, 0,
       0, 2, 2, 0, 0, 2, 1, 2, 0, 0, 0, 0, 1, 1, 2, 2, 1, 1, 2, 2, 0, 2,
       0, 0, 0, 0, 0])
```

In [7]:
```
Q = pd.DataFrame(model.labels_,columns=["Cluster"])
Q.groupby(by="Cluster")['Cluster'].count()
```

Out[7]:
```
Cluster
0    35
1    16
2    30
3    12
Name: Cluster, dtype: int64
```

In [8]:
```
B['Cluster']=model.labels_
B["Make"] = A.Make   #type of car
B
```

Out[8]:

	Price	MPG.city	Cluster	Make
0	15.9	25	2	Acura Integra
1	33.9	18	3	Acura Legend
2	29.1	20	0	Audi 90
3	37.7	19	3	Audi 100
4	30.0	22	0	BMW 535i
...	...	...	...	...
88	19.7	17	0	Volkswagen Eurovan
89	20.0	21	0	Volkswagen Passat
90	23.3	18	0	Volkswagen Corrado
91	22.7	21	0	Volvo 240
92	26.7	20	0	Volvo 850

93 rows × 4 columns

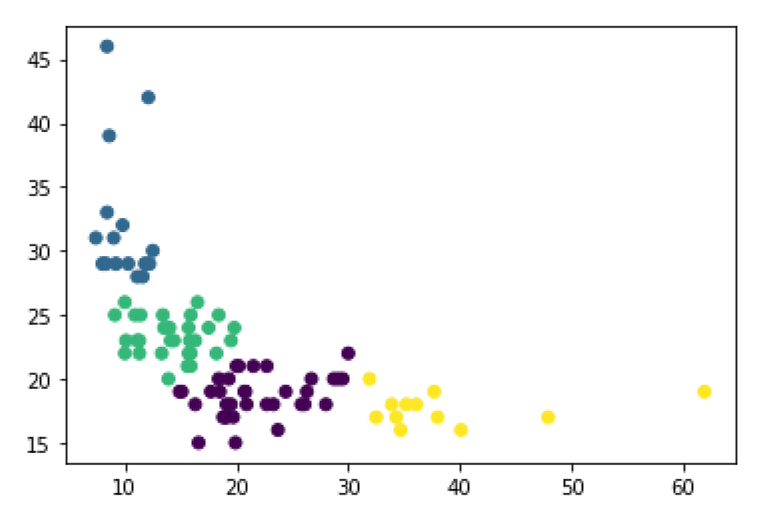
In [9]:
```
W = input("Enter a car to find similar cars: ")
cluster_no_of_given_car = B[B.Make == W][["Cluster"]].values[0][0]
print("These are cars similar to the one you like")
for i in B[B.Cluster == cluster_no_of_given_car].Make:
    print(i)
```

```
Enter a car to find similar cars: Audi 90
These are cars similar to the one you like
Audi 90
BMW 535i
Buick LeSabre
Buick Roadmaster
Buick Riviera
Chevrolet Camaro
Chevrolet Lumina_APV
Chevrolet Astro
Chevrolet Caprice
Chrylser Concorde
Chrysler Imperial
Dodge Caravan
Dodge Stealth
Eagle Vision
Ford Aerostar
Ford Taurus
Ford Crown_Victoria
Lexus ES300
Mazda MPV
Mercury Cougar
Mitsubishi Diamante
Nissan Quest
Nissan Maxima
Oldsmobile Silhouette
Oldsmobile Eighty-Eight
Pontiac Firebird
Pontiac Grand_Prix
Pontiac Bonneville
Saab 900
Toyota Previa
Volkswagen Eurovan
Volkswagen Passat
Volkswagen Corrado
Volvo 240
Volvo 850
```

Visual Representation of the clusters formed

In [10]:
```
plt.scatter(B.Price,B['MPG.city'],c=B.Cluster)
```

Out[10]:
```
<matplotlib.collections.PathCollection at 0x2a31f5b3bb0>
```



In [11]:
```
E = pd.DataFrame(ss.inverse_transform(model.cluster_centers_),columns=["X","Y"])
E
```

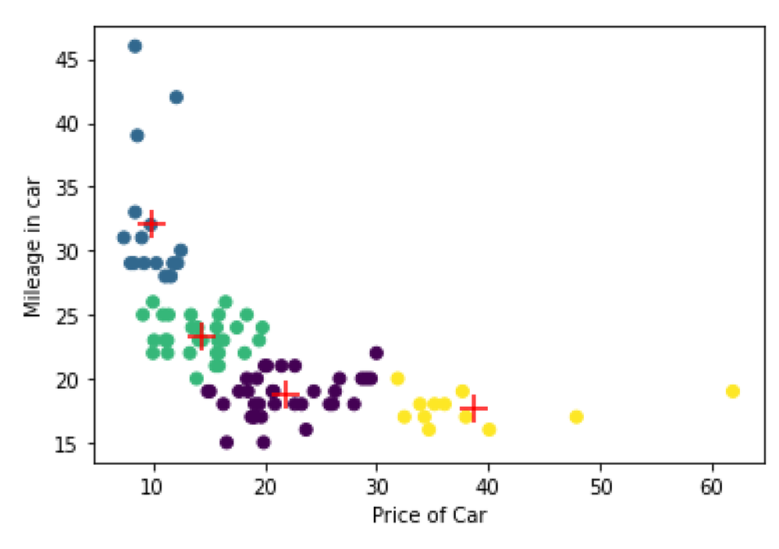
Out[11]:

	X	Y
0	21.800000	18.685714
1	9.918750	32.125000
2	14.283333	23.333333
3	38.683333	17.666667

To see the centroid of each cluster

In [12]:
```
plt.scatter(B.Price,B['MPG.city'],c=B.Cluster)
plt.scatter(E.X,E.Y,c="red",marker="+",s=200)
plt.xlabel("Price of Car")
plt.ylabel("Mileage in car")
```

Out[12]:
```
Text(0, 0.5, 'Mileage in car')
```



To decide the number of clusters to be created

Elbow Curve Method

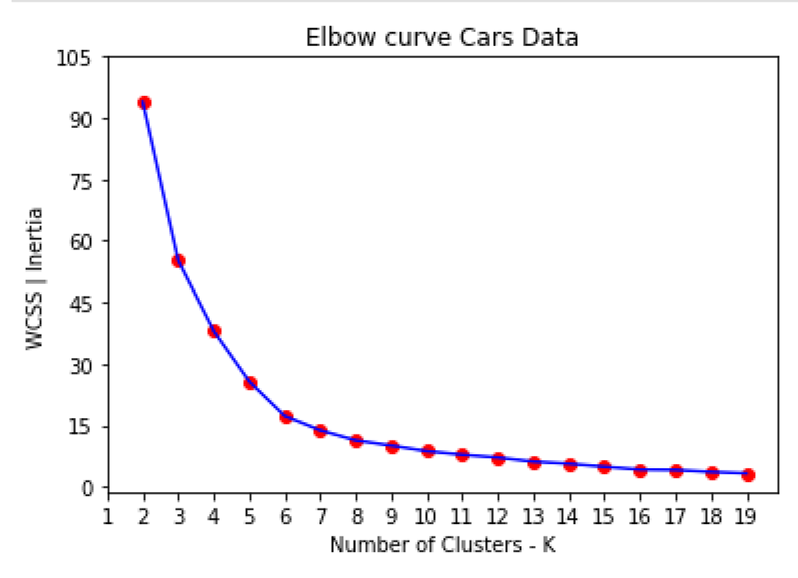
In this method, for each value of K, WCSS is calculated.WCSS is the sum of squared distance between each point and the centroid in a cluster. When we plot the WCSS with the K value,the plot looks like an elbow.

In [13]:
```
K = range(2,20,1)
WCSS = []
for i in K:
    km = KMeans(n_clusters=i)
    model = km.fit(C)
    WCSS.append(model.inertia_)
```

In [14]:
```
WCSS
```

Out[14]:
```
[93.92806219538846,
 55.24519288386834,
 38.06526065774016,
 25.743307121066692,
 17.313281420603605,
 13.8199333915689,
 11.361142402889634,
 10.089802614471116,
 8.726539830211355,
 7.863589957020757,
 7.1723793085871295,
 6.176582496719895,
 5.66564461097519,
 4.9334618052607855,
 4.233398764454621,
 4.145364761988652,
 3.6555558313918097,
 3.321945145881932]
```

In [15]:
```
plt.scatter(K,WCSS,c="red")
plt.plot(K,WCSS,c="blue")
plt.xlabel("Number of Clusters - K")
plt.ylabel("WCSS | Inertia")
plt.xticks(range(1,20,1))
plt.yticks(range(0,110,15))
plt.title("Elbow curve Cars Data")
plt.savefig("C:/Users/aksha/OneDrive/Desktop/ELBOW_CURVE.png")
```



K = 6 is the best value of K because from from 1 to 6,the distance is drastically reducing. But after 6, the distance is gradually reducing.

Hierarchical Clustering

.Algorithm that groups similar objects into groups called clusters. It creates Dendrogram

Agglomerative Clustering

It starts with individual data atoms. It follows the bottom to top approach. It is called as Dendrogram.

In [16]:
```
from sklearn.cluster import AgglomerativeClustering
agc = AgglomerativeClustering(n_clusters=5,linkage="single")
model = agc.fit(C)
model.labels_
```

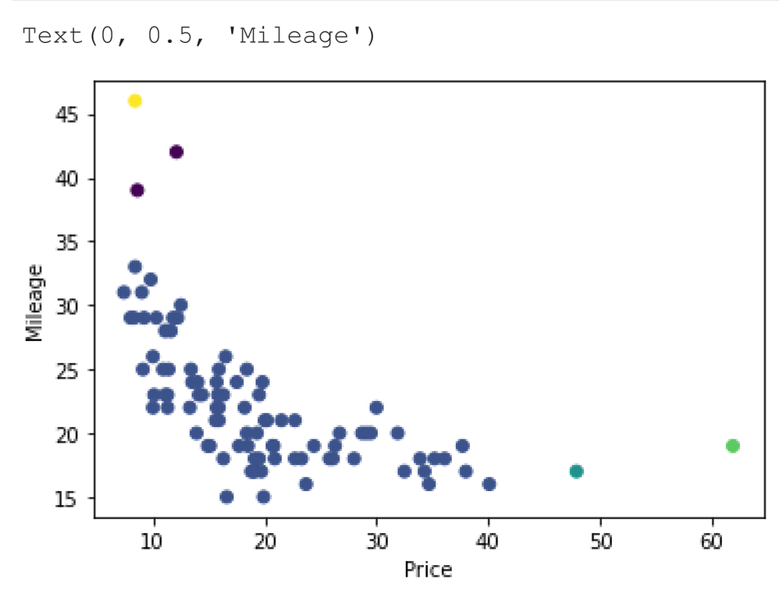
Out[16]:
```
array([1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 4, 1, 1, 0, 1, 1,
       1, 1, 1, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 3, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1], dtype=int64)
```

In [17]:
```
Q = pd.DataFrame(model.labels_,columns=["Cluster"])
Q.groupby(by="Cluster")['Cluster'].count()
```

Out[17]:
```
Cluster
0     2
1    88
2     1
3     1
4     1
Name: Cluster, dtype: int64
```

In [18]:
```
plt.scatter(B.Price,B['MPG.city'],c=model.labels_)
plt.xlabel("Price")
plt.ylabel("Mileage")
```

Out[18]:
```
Text(0, 0.5, 'Mileage')
```



In [19]:
```
#point to point distance
from scipy.spatial import distance_matrix
distance_matrix(C,C)
```

Out[19]:
```
array([[0.        , 2.25357714, 1.63948708, ..., 1.47025216, 1.00652265,
        1.43661919],
       [2.25357714, 0.        , 0.61453009, ..., 1.10332116, 1.28339191,
        0.83046302],
       [1.63948708, 0.61453009, 0.        , ..., 0.70177526, 0.68976194,
        0.24980856],
       ...,
       [1.47025216, 1.10332116, 0.70177526, ..., 0.        , 0.54034034,
        0.50326133],
       [1.00652265, 1.28339191, 0.68976194, ..., 0.54034034, 0.        ,
        0.45315871],
       [1.43661919, 0.83046302, 0.24980856, ..., 0.50326133, 0.45315871,
        0.        ]])
```

In [20]:
```
from scipy.cluster.hierarchy import dendrogram, linkage
```

point to cluster distance/cluster to cluster distance - Linkage

In [21]:
```
dendrogram(linkage(distance_matrix(C,C)))
plt.show()
```