Cluster Analysis of Car Performance

Objective:

The objective of this analysis is to group cars based on their performance metrics using hierarchical clustering techniques.

Step 1:

Data Description:

The dataset includes information about cars, including:

- name: Car model name
- mpg: Miles per gallon (fuel efficiency)
- cyl: Number of cylinders
- disp: Displacement (cubic inches)
- hp: Gross horsepower
- drat: Rear axle ratio
- wt: Weight (1000 lbs)
- qsec: 1/4 mile time
- vs: Engine type (0 = V-shaped, 1 = straight)
- am: Transmission (0 = automatic, 1 = manual)
- gear: Number of forward gears
- carb: Number of carburetors

Step 2:

Data Preprocessing:

- Checked for missing values and confirmed data completeness.
- Selected all numerical columns (excluding the car name, categorical variables) for analysis.
- Standardized the data using Z-score normalization to ensure each variable contributes equally.

$$\text{std\_value} = \frac{\text{value} - \text{mean}}{\text{standard deviation}}$$

Key Code Snippet (Data Preprocessing):

```
stdz_mpg    = (df1['mpg'] - df1['mpg'].mean() )/ df1['mpg'].std()
stdz_disp   = (df1['disp'] - df1['disp'].mean() )/ df1['disp'].std()
stdz_hp     = (df1['hp'] - df1['hp'].mean() )/ df1['hp'].std()
stdz_drat    = (df1['drat'] - df1['drat'].mean() )/ df1['drat'].std()
stdz_wt     = (df1['wt'] - df1['wt'].mean() )/ df1['wt'].std()
stdz_qsec   = (df1['qsec'] - df1['qsec'].mean() )/ df1['qsec'].std()
```

Step 3:

Distance Calculation:

- Calculated pairwise distances between car's standardized features using the Euclidean, Mankowski (P=3), Mankowski(P=4) and Manhattan distance metric.
- Constructed a distance matrix to represent the dissimilarity between cars.

Key Code Snippet (Distance Calculation):

```
from scipy.spatial.distance import pdist, squareform
from scipy.spatial.distance import euclidean, minkowski, cityblock

euclidean_dist = pd.DataFrame(squareform(pdist(df2, metric='euclidean')))
minkowski_3_dist = pd.DataFrame(squareform(pdist(df2, metric='minkowski', p = 3)))
minkowski_4_dist = pd.DataFrame(squareform(pdist(df2, metric='minkowski', p = 4)))
cityblock_dist = pd.DataFrame(squareform(pdist(df2, metric='cityblock')))
```

Step 4:

Clustering Technique:

- Applied hierarchical clustering using the Average method to minimize variance within clusters.
- Visualized clusters using dendrograms to determine optimal clusters.

Key Code Snippet (Clustering):

```
from scipy.cluster.hierarchy import linkage
from scipy.cluster.hierarchy import dendrogram

avc_link = linkage(Car_Types[['Min_Distance']].fillna(0), method='average')
dend = dendrogram(avc_link)
```

Step 5:

Cluster Assignment:

- Divided cars into clusters using the fcluster method based on dendrogram analysis.
- Assigned each car to a cluster and counted the number of cars in each cluster.

Key Code Snippet (f cluster):

```
from scipy.cluster.hierarchy import fcluster

clusters = fcluster(avc_link, 3, criterion="maxclust")
df3["clusters"] = clusters
```

	Car 1	Min_Distance	clusters	Car Model	Car Name
0	1	0.345555	1	Mini	Mazda RX4
1	2	0.576897	1	Mini	Mazda RX4 Wag
2	3	0.716444	1	Mini	Datsun 710
3	4	0.448726	1	Mini	Hornet 4 Drive
4	5	0.716444	1	Mini	Hornet Sportabout

Step 6:

Car Cluster Assignment:

- Listed each car along with its assigned cluster.
- Provided the count of cars in each cluster.

Key Code Snippet (Cluster Assignment):

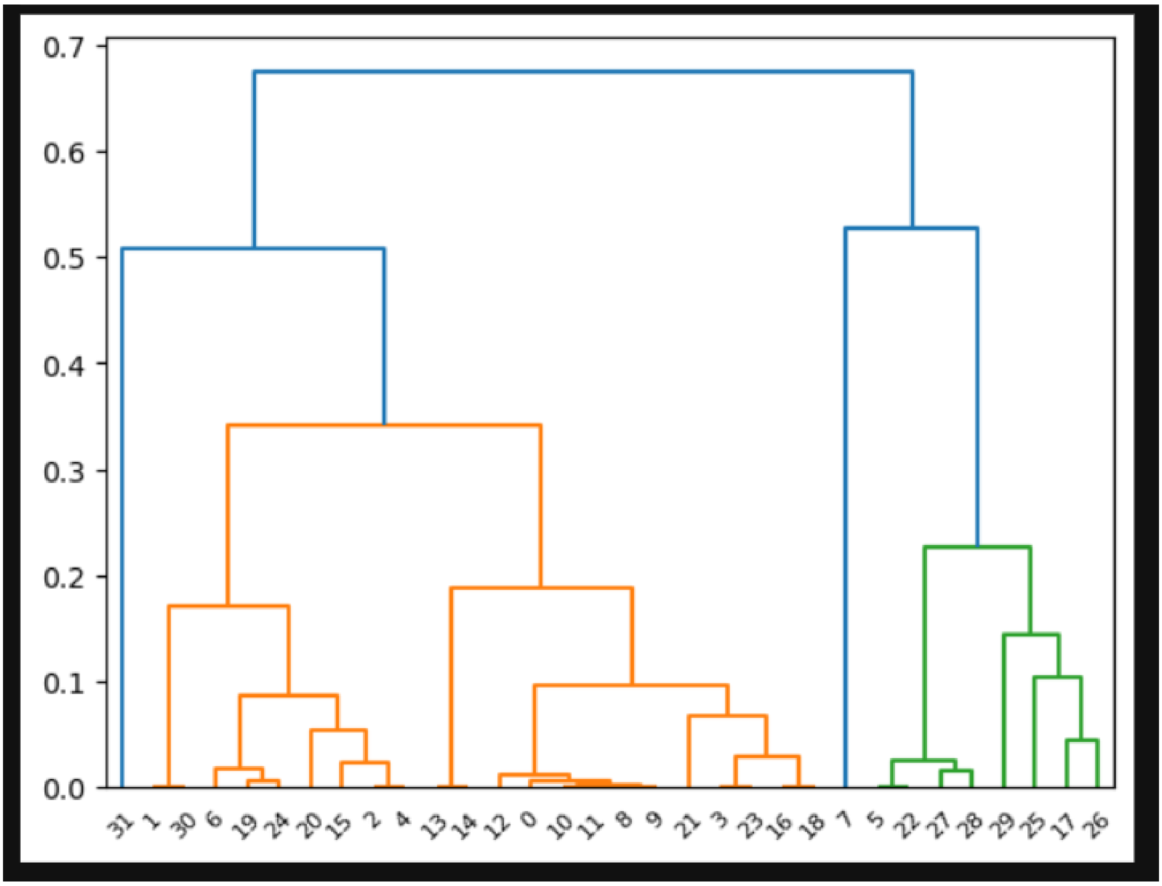
```
freq_table=pd.crosstab(F_Data['Car Type'],'count')
freq_table
```

col_0	count
Car Type	
Mini	12
Prime	10
Sedan	9

Step 7:

Visualization:

- Generated dendrograms to visualize hierarchical clustering results.



Results:

1. **Cluster Distribution:**
    - The clustering revealed that cars were grouped into distinct clusters based on their mechanical and performance attributes.
    - The clusters showed meaningful groupings, such as low-power, fuel-efficient cars vs. high-performance, heavier cars.
2. **Cluster-Wise Distribution:**
    - The cars were divided into three clusters:
        - Cluster 1: Contains economy/fuel-efficient vehicles. **(Mini = 12)**
        - Cluster 2: Contains mid-range performance cars. **(Prime = 10)**
        - Cluster 3: Includes high horsepower, heavy vehicles. **(Sedan = 9)**

- The distribution showed a logical segmentation of cars based on common performance traits.

3. **Dendrogram Interpretation:**
   - The dendrogram helped determine that 3 clusters are appropriate based on visible separation in the tree.
   - The vertical height where clusters merge indicates the dissimilarity — the greater the height, the more different the clusters.
   - Cars that merge at lower heights are more similar in features.

Conclusion:

Hierarchical clustering of the mtcars dataset provided valuable insights into the natural groupings of vehicles. These insights can support automotive marketing strategies, segment analysis, and consumer targeting based on car characteristics.

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import itertools
from scipy.spatial.distance import pdist, squareform
from scipy.cluster.hierarchy import linkage, fcluster, dendrogram
from sklearn.cluster import AgglomerativeClustering
from itertools import combinations
from scipy.spatial.distance import euclidean, minkowski, cityblock
```

[2]:
```
df = pd.read_csv("D:/mtcars.csv")
df.head()
```

[2]:

	name	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
0	Mazda RX4	21.0	6	160.0	110	3.90	2.620	16.46	0	1	4	4
1	Mazda RX4 Wag	21.0	6	160.0	110	3.90	2.875	17.02	0	1	4	4
2	Datsun 710	22.8	4	108.0	93	3.85	2.320	18.61	1	1	4	1
3	Hornet 4 Drive	21.4	6	258.0	110	3.08	3.215	19.44	1	0	3	1
4	Hornet Sportabout	18.7	8	360.0	175	3.15	3.440	17.02	0	0	3	2

mpg - Miles per Gallon, cyl - no. of cylinders, disp - displacement, in cubic inches, hp - horsepower, drat - driveshaft ratio, wt - weight, qsec - 1/4 mile time; a measure of acceleration, vs - 'V' or straight - engine shape, am - transmission; auto or manual, gear - no. of gears, carb - np. of carburetors.

[3]:
```
df.isnull().sum()
```

[3]:
```
name    0
mpg     0
cyl     0
disp    0
hp      0
drat    0
wt      0
qsec    0
vs      0
am      0
gear    0
```

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32 entries, 0 to 31
Data columns (total 12 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   name    32 non-null     object
 1   mpg     32 non-null     float64
 2   cyl     32 non-null     int64
 3   disp    32 non-null     float64
 4   hp      32 non-null     int64
 5   drat    32 non-null     float64
 6   wt      32 non-null     float64
 7   qsec    32 non-null     float64
 8   vs      32 non-null     int64
 9   am      32 non-null     int64
 10  gear    32 non-null     int64
 11  carb    32 non-null     int64
dtypes: float64(5), int64(6), object(1)
memory usage: 3.1+ KB
```

[5]:
```
df.shape  # checking the number of rows and columns
```

[5]: (32, 12)

[6]:
```
df1 = df.iloc[:, 1:]
df1.tail(2)
```

[6]:

	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
30	15.0	8	301.0	335	3.54	3.57	14.6	0	1	5	8
31	21.4	4	121.0	109	4.11	2.78	18.6	1	1	4	2

[7]:
```
stdz_mpg    = (df1['mpg'] - df1['mpg'].mean() )/ df1['mpg'].std()
stdz_disp   = (df1['disp'] - df1['disp'].mean() )/ df1['disp'].std()
stdz_hp     = (df1['hp'] - df1['hp'].mean() )/ df1['hp'].std()
stdz_drat    = (df1['drat'] - df1['drat'].mean() )/ df1['drat'].std()
stdz_wt     = (df1['wt'] - df1['wt'].mean() )/ df1['wt'].std()
stdz_qsec   = (df1['qsec'] - df1['qsec'].mean() )/ df1['qsec'].std()
```

[8]:
```
dict = {
    'std_mpg'   : stdz_mpg,
    'std_disp'  : stdz_disp,
    'std_hp'    : stdz_hp,
    'std_drat'   : stdz_drat,
    'std_wt'    : stdz_wt,
    'std_qsec'  : stdz_qsec

}
df2 = pd.DataFrame(dict)
df2.tail(2)
```

[8]:

	std_mpg	std_disp	std_hp	std_drat	std_wt	std_qsec
30	-0.844644	0.567039	2.746567	-0.105788	0.360516	-1.818049
31	0.217253	-0.885292	-0.549678	0.960273	-0.446877	0.420411

[9]:
```
euclidean_dist = pd.DataFrame(squareform(pdist(df2, metric='euclidean')))
euclidean_dist.head(2)
```

[9]:

	0	1	2	3	4	5	6	7	8	9	...	22	23	24	25	26	27	
0	0.00000	0.40759	1.370066	2.476390	2.533097	3.197234	3.231908	2.288671	3.666620	1.375829	...	2.344945	3.140120	2.960784	2.097512	1.452212	2.026922	3.16
1	0.40759	0.00000	1.203708	2.221811	2.439154	2.936349	3.212904	1.964396	3.327022	0.988352	...	2.221736	3.121677	2.841279	2.018604	1.564150	2.170234	3.25

2 rows × 32 columns

[10]:

```
# Extract all unique combinations of indices (i, j) where i < j
index_pairs = list(itertools.combinations(range(len(euclidean_dist)), 2))

# Convert combinations to DataFrame
distances = [{"Car Pair": (i, j), "Distance": euclidean_dist.iloc[i, j]} for i, j in index_pairs]
distance_df = pd.DataFrame(distances)

# Find the pair with the smallest distance
min_distance_pair = distance_df.loc[distance_df["Distance"].idxmin()]

# Display all combinations and the smallest one
print(distance_df)  # Displays pairs
print("\nSmallest Distance Pair:\n", min_distance_pair)
```

```
     Car Pair  Distance
0      (0, 1)  0.407590
1      (0, 2)  1.370066
2      (0, 3)  2.476390
3      (0, 4)  2.533097
4      (0, 5)  3.197234
..        ...       ...
491  (28, 30)  1.743684
492  (28, 31)  3.857913
493  (29, 30)  2.929638
494  (29, 31)  2.212061
495  (30, 31)  4.571782

[496 rows x 2 columns]

Smallest Distance Pair:
 Car Pair    (14, 15)
Distance    0.295682
Name: 343, dtype: object
```

[11]:

```
minkowski_3_dist = pd.DataFrame(squareform(pdist(df2, metric='minkowski', p = 3)))
minkowski_3_dist.head(2)
```

[11]:

	0	1	2	3	4	5	6	7	8	9	...	22	23	24	25	26	27	
0	0.000000	0.364627	1.235757	2.077347	2.039956	2.709764	2.536314	2.045361	3.609040	1.196769	...	1.827158	2.493064	2.395448	1.664640	1.198048	1.756042	2.
1	0.364627	0.000000	1.001171	1.878384	2.005177	2.514844	2.520111	1.738642	3.292476	0.840523	...	1.776815	2.468658	2.334417	1.557052	1.265923	1.880450	2.

[12]:

```
# Extract all unique combinations of indices (i, j) where i < j
index_pairs_3 = list(itertools.combinations(range(len(minkowski_3_dist)), 2))

# Convert combinations to DataFrame
distances_3 = [{"Car Pair": (i, j), "Distance": minkowski_3_dist.iloc[i, j]} for i, j in index_pairs_3]
distance_df_3 = pd.DataFrame(distances_3)

# Find the pair with the smallest distance
min_distance_pair_3 = distance_df_3.loc[distance_df_3["Distance"].idxmin()]

# Display all combinations and the smallest one
print(distance_df_3)  # Displays pairs
print("\nSmallest Distance Pair:\n", min_distance_pair_3)
```

```
     Car Pair  Distance
0      (0, 1)  0.364627
1      (0, 2)  1.235757
2      (0, 3)  2.077347
3      (0, 4)  2.039956
4      (0, 5)  2.709764
..        ...       ...
491  (28, 30)  1.489412
492  (28, 31)  3.137921
493  (29, 30)  2.512181
494  (29, 31)  1.904915
495  (30, 31)  3.756980

[496 rows x 2 columns]

Smallest Distance Pair:
 Car Pair    (14, 15)
Distance    0.232671
Name: 343, dtype: object
```

[13]:

```
minkowski_4_dist = pd.DataFrame(squareform(pdist(df2, metric='minkowski', p = 4)))
minkowski_4_dist.head(2)
```

[13]:

	0	1	2	3	4	5	6	7	8	9	...	22	23	24	25	26	27	
0	0.000000	0.345555	1.210516	1.927182	1.860602	2.529520	2.279835	1.996313	3.604437	1.129345	...	1.637928	2.252970	2.187017	1.515521	1.109220	1.662438	2.
1	0.345555	0.000000	0.937701	1.746366	1.845208	2.363531	2.270101	1.687570	3.290655	0.787048	...	1.613356	2.232333	2.150180	1.380858	1.154249	1.767077	2.

[14]:
```python
# Extract all unique combinations of indices (i, j) where i < j
index_pairs_4 = list(itertools.combinations(range(len(minkowski_4_dist)), 2))

# Convert combinations to DataFrame
distances_4 = [{"Car Pair": (i, j), "Distance": minkowski_4_dist.iloc[i, j]} for i, j in index_pairs_4]
distance_df_4 = pd.DataFrame(distances_4)

# Find the pair with the smallest distance
min_distance_pair_4 = distance_df_4.loc[distance_df_4["Distance"].idxmin()]

# Display all combinations and the smallest one
print(distance_df_4)  # Displays pairs
print("\nSmallest Distance Pair:\n", min_distance_pair_4)
```

```
     Car Pair  Distance
0      (0, 1)  0.345555
1      (0, 2)  1.210516
2      (0, 3)  1.927182
3      (0, 4)  1.860602
4      (0, 5)  2.529520
..        ...       ...
491  (28, 30)  1.398105
492  (28, 31)  2.855285
493  (29, 30)  2.397659
494  (29, 31)  1.805613
495  (30, 31)  3.503115

[496 rows x 2 columns]

Smallest Distance Pair:
 Car Pair    (14, 15)
Distance    0.208739
Name: 343, dtype: object
```

[15]:
```python
cityblock_dist = pd.DataFrame(squareform(pdist(df2, metric='cityblock')))
cityblock_dist.head(2)
```

[15]:

	0	1	2	3	4	5	6	7	8	9	...	22	23	24	25	26	27	
0	0.000000	0.573999	2.56946	4.666466	5.497505	6.173318	7.302742	4.327877	4.855346	2.454737	...	5.413347	6.932011	6.298910	4.742793	3.043170	3.747803	6.9
1	0.573999	0.000000	2.51669	4.092467	4.923506	5.599320	7.355512	3.753878	4.281347	1.880738	...	4.839348	6.984781	5.724911	4.690023	3.348553	3.829341	6.9

[16]:
```python
# Extract all unique combinations of indices (i, j) where i < j
index_pairs_CB = list(itertools.combinations(range(len(cityblock_dist)), 2))

# Convert combinations to DataFrame
distances_CB = [{"Car Pair":(i, j), "Distance": cityblock_dist.iloc[i, j]} for i, j in index_pairs_CB]
distance_df_CB = pd.DataFrame(distances_CB)

# Find the pair with the smallest distance
min_distance_pair_CB = distance_df_CB.loc[distance_df_CB["Distance"].idxmin()]

# Display all combinations and the smallest one
print(distance_df_CB)  # Displays pairs
print("\nSmallest Distance Pair:\n", min_distance_pair_CB)
```

```
     Car Pair  Distance
0      (0, 1)  0.573999
1      (0, 2)  2.569460
2      (0, 3)  4.666466
3      (0, 4)  5.497505
4      (0, 5)  6.173318
..        ...       ...
491  (28, 30)  3.308268
492  (28, 31)  7.944354
493  (29, 30)  5.843032
494  (29, 31)  4.099795
495  (30, 31)  9.922387

[496 rows x 2 columns]

Smallest Distance Pair:
 Car Pair     (9, 10)
Distance    0.568059
Name: 243, dtype: object
```

[17]:
```python
np.random.seed(42)  # For reproducibility
d = np.random.rand(32, 6)  # Simulating 32 Cars with 6 feature attributes

# Sample section mapping (Assigning random sections: Mini, Prime, Sedan)
Car_type = {i: np.random.choice(['Mini', 'Prime', 'Sedan']) for i in range(len(d))}
```

[19]:
```python
# Creating a distance Matrix DataFrame from a Dictionary
dist_matrix = {
    "Car Pair" : distance_df["Car Pair"],
    "Car 1": [i for i, j in distance_df["Car Pair"]],
    "Car 2": [j for i, j in distance_df["Car Pair"]],
    "Car_Type 1": [Car_type[i] for i, j in distance_df["Car Pair"]],
    "Car_Type 2": [Car_type[j] for i, j in distance_df["Car Pair"]],
    "Euclidean" : distance_df["Distance"],
    "Minkowiski (p=3)" : distance_df_3["Distance"],
    "Minkowiski (p=4)" : distance_df_4["Distance"],
    "Manhattan/Cityblock" : distance_df_CB["Distance"]
                            }
data = pd.DataFrame(dist_matrix)
data.head(2)
```

[19]:

	Car Pair	Car 1	Car 2	Car_Type 1	Car_Type 2	Euclidean	Minkowiski (p=3)	Minkowiski (p=4)	Manhattan/Cityblock
0	(0, 1)	0	1	Mini	Sedan	0.407590	0.364627	0.345555	0.573999
1	(0, 2)	0	2	Mini	Sedan	1.370066	1.235757	1.210516	2.569460

[20]:
```python
# Define Distance Columns
distance_columns = ["Euclidean", "Minkowiski (p=3)", "Minkowiski (p=4)", "Manhattan/Cityblock"]

# Find Minimum Distance for Each Row
data["Min_Distance"] = data[distance_columns].min(axis=1)

# Find Which Distance Metric is the Minimum
data["Min_Distance_Type"] = data[distance_columns].idxmin(axis=1)

# Display Results
print(data[["Car Pair", "Car 1", "Car 2", "Min_Distance", "Min_Distance_Type"]].head())
```

```
  Car Pair  Car 1  Car 2  Min_Distance Min_Distance_Type
0   (0, 1)      0      1      0.345555  Minkowiski (p=4)
1   (0, 2)      0      2      1.210516  Minkowiski (p=4)
2   (0, 3)      0      3      1.927182  Minkowiski (p=4)
3   (0, 4)      0      4      1.860602  Minkowiski (p=4)
4   (0, 5)      0      5      2.529520  Minkowiski (p=4)
```

[28]:
```python
# Extract student IDs and their sections
Car_Types = pd.concat([
    data[['Car 1', 'Car_Type 1', 'Min_Distance', 'Min_Distance_Type']],
    data[['Car 2', 'Car_Type 2', 'Min_Distance', 'Min_Distance_Type']].rename(columns={'Car 2': 'Car 1',
                                                                                       'Car_Type 2': 'Car_Type 1'})
], ignore_index=True)
```

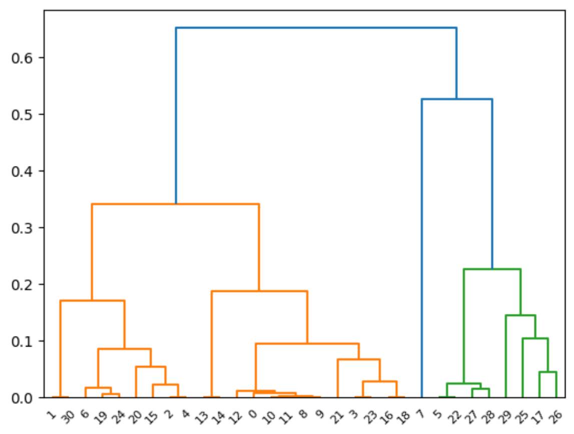
[29]:
```python
# Remove duplicates and keep only the minimum distance per student
Car_Types = Car_Types.groupby('Car 1', as_index=False).agg({'Car_Type 1': 'first', 'Min_Distance': 'min',
                                                            'Min_Distance_Type': 'first'})

# Ensure student IDs remain 1-200
Car_Types = Car_Types[Car_Types['Car 1'].between(1, 200)].sort_values(by='Car 1').reset_index(drop=True)
Car_Types.head(2)
```

[29]:

	Car 1	Car_Type 1	Min_Distance	Min_Distance_Type
0	1	Sedan	0.345555	Minkowiski (p=4)
1	2	Sedan	0.576897	Minkowiski (p=4)

[30]:
```python
avc_link = linkage(Car_Types[['Min_Distance']].fillna(0), method='average')
dend = dendrogram(avc_link)
```



[34]:
```python
clusters = fcluster(avc_link, 3, criterion="maxclust")
Car_Types["clusters"] = clusters

Car_Types["Car Name"] = df["name"]
Car_Types.head()
```

[34]:

	Car 1	Car_Type 1	Min_Distance	Min_Distance_Type	clusters	Car Name
0	1	Sedan	0.345555	Minkowiski (p=4)	1	Mazda RX4
1	2	Sedan	0.576897	Minkowiski (p=4)	1	Mazda RX4 Wag
2	3	Mini	0.716444	Minkowiski (p=4)	1	Datsun 710
3	4	Mini	0.448726	Minkowiski (p=4)	1	Hornet 4 Drive
4	5	Sedan	0.716444	Minkowiski (p=4)	1	Hornet Sportabout

[36]:
```python
# Create a DataFrame for each Car and type of car

Final_data = {
    "Car Name" : Car_Types["Car Name"],
    "Car ID" : Car_Types["Car 1"],
    "Car Type" : Car_Types["Car_Type 1"]
                }
F_Data = pd.DataFrame(Final_data)
F_Data.tail()
```

[36]:

	Car Name	Car ID	Car Type
26	Porsche 914-2	27	Mini
27	Lotus Europa	28	Mini
28	Ford Pantera L	29	Mini
29	Ferrari Dino	30	Prime
30	Maserati Bora	31	Mini

[37]:
```python
freq_table=pd.crosstab(F_Data['Car Type'],'count')
freq_table
```

[37]:

col_0	count
Car Type	
Mini	12
Prime	10
Sedan	9