AUTOMOBILE CUSTOMER SEGMENTATION

DATA SCIENCE AND MACHINE LEARNING PROJECT

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Introduction

- Businesses in the automotive industry face the challenge of meeting diverse consumer demands in a rapidly evolving market.
- Our innovative approach: Comprehensive Automobile Customer Segmentation.
- Rooted in the CRISP-DM framework, emphasizing clustering methods for precise segmentation.
- CRISP-DM ensures alignment with business goals throughout the process.
- Clustering uncovers hidden trends and distinct buyer personas for tailored strategies.
- Personalization drives customer satisfaction, loyalty, and competitiveness.
- We're pioneering a customer-focused transformation in the automotive sector.

PROBLEM STATEMENT

Objective

Identify and segment diverse customer groups within the automotive industry using powerful data analysis techniques.

Factors for Segmentation

Behavioural patterns, personal demographics, past purchases, vehicle preferences, and more.

Goals

- Enhanced Customization
- Efficient Targeting (Segmentation)
- Production Optimization
- Elevated Customer Satisfaction
- Improved Competitiveness

DATA UNDERSTANDING

Dataset Information:

- Total Columns: 27
- Total Data Entries: 205
  - Observation: Missing data present in the dataset

NUMERIC AND CATEGORICAL DATA IN DATA SET

Categorical data: 10

- Make
- Fuel Type,
- Num-of-Doors
- Body Style
- Drive wheels
- Engine Location
- Engine-type
- Num-of-cylinders
- Fuel-system

Numerical columns: 17

- ID
- Symbolling
- Normalized Losses
- Wheelbase
- Length
- Width
- Height
- Curb Weight
- Engine-size
- Bore
- Stroke
- Compression-ratio
- Horsepower
- Peak-rpm
- City-mpg
- Highway-mpg
- Price.

DATA PREPARATION

(i) Dropping the "ID" Column and Checking for Missing Values:

- Removed the "ID" column as it's for indexing.
- Checked for missing values in each attribute.

```
#Dropping ID which is not required for the analysis
df.drop('ID', axis=1, inplace=True)
```

Missing values:

normalized-losses: 41, num-of-doors: 2, bore: 4, stroke: 4, horsepower: 2, peak-rpm: 2, price: 4

(ii) Proportion of Missing Values:

- Examined the proportion of missing values in the dataset.

Missing values:

normalized-losses: 41, num-of-doors: 2, bore: 4, stroke: 4, horsepower: 2, peak-rpm: 2, price: 4

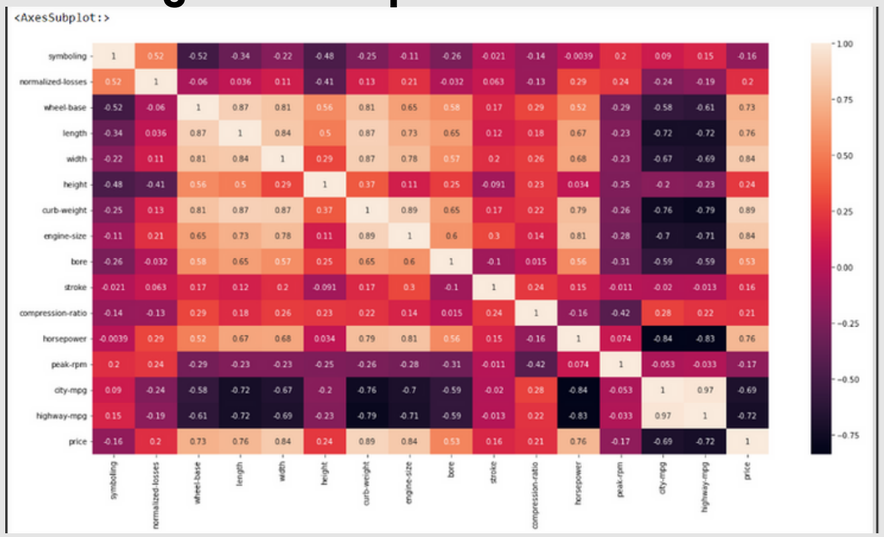
(iii) Missing Value Analysis with Complete Case Approach:

- Utilized a "complete case approach" to handle missing values.

```
Original data: (204, 26)
After removing cases with missing values: (159, 26)
```

(iv) Data Visualization Using a Heat Map:

- Visualized the reduced dataset using a heat map to gain insights.

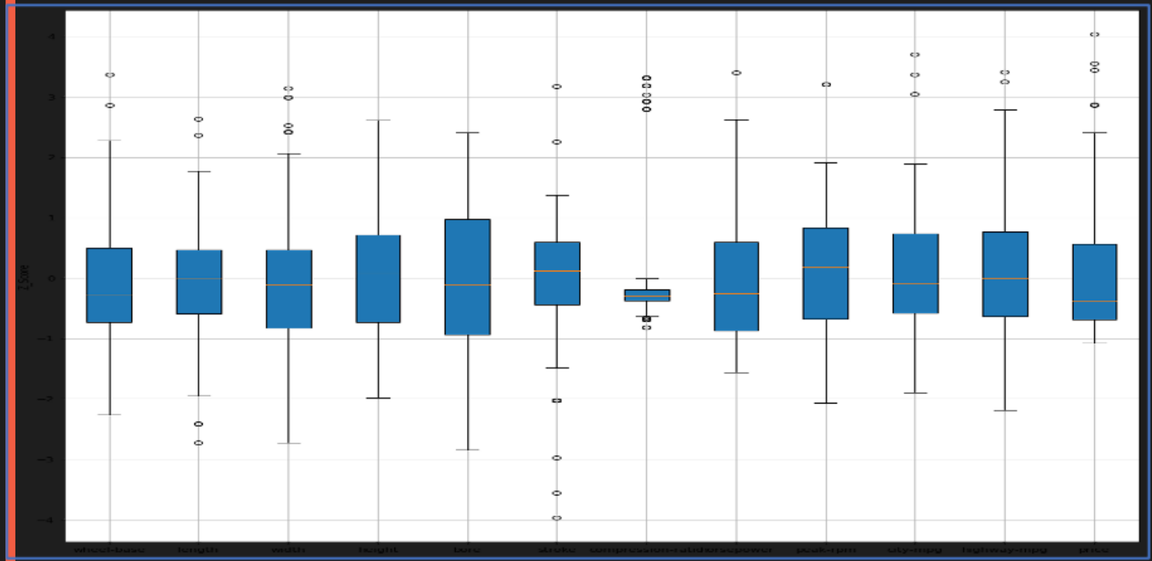


Continuing.....

DATA PREPARATION

(v) Detecting and Removing Outliers with a Box Plot:

- Identified outliers in the dataset, with special focus on variables like 'wheelbase', 'length', 'width', 'stroke', and 'compression-ratio'.
- Removed outliers to enhance data quality.



```
df_cc = df_cc.drop([46,69,71])
df_cc = df_cc.drop(['z_score_tc'],axis=1)
df_cc.shape
```

```
(156, 26)
```

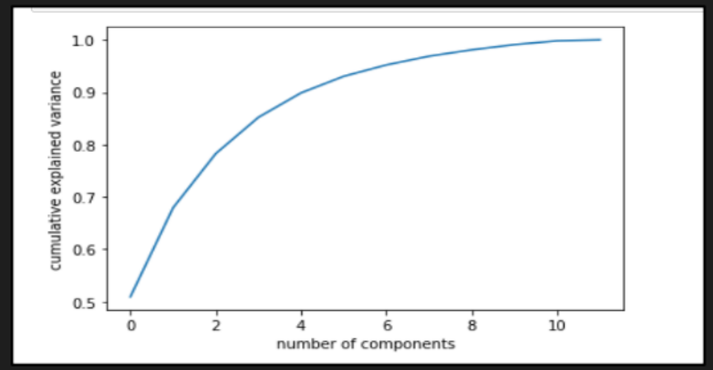
(vi) Standardization of Variables:

- Standardized all variables to ensure they are on the same scale.

	wheel-base	length	width	height	bore	stroke	compression-ratio	horsepower	peak-rpm	
count	1.590000e+02	1.590000e+02	1.590000e+02	1.590000e+02	1.590000e+02	1.590000e+02	1.590000e+02	1.590000e+02	1.590000e+02	1
mean	3.910219e-17	1.592018e-16	-9.216946e-17	7.680788e-17	1.578053e-16	-1.431420e-17	-1.024687e-16	-7.820439e-17	7.122185e-17	-6
std	1.003160e+00	1.003160e+00	1.003160e+00	1.003160e+00	1.003160e+00	1.003160e+00	1.003160e+00	1.003160e+00	1.003160e+00	1
min	-2.264382e+00	-2.726052e+00	-2.733387e+00	-1.989450e+00	-2.852323e+00	-3.967739e+00	-8.153080e-01	-1.562169e+00	-2.075946e+00	-1
25%	-7.307413e-01	-5.888313e-01	-8.278868e-01	-7.292889e-01	-9.385807e-01	-4.468386e-01	-3.768500e-01	-8.763838e-01	-6.759523e-01	-5
50%	-2.648250e-01	-1.204546e-03	-1.068868e-01	8.871045e-02	-1.130451e-01	1.144643e-01	-2.994751e-01	-2.559115e-01	1.855821e-01	-8
75%	4.922888e-01	4.688969e-01	4.596132e-01	7.077369e-01	9.751611e-01	5.907213e-01	-1.963085e-01	5.931560e-01	8.317329e-01	7
max	3.365439e+00	2.627881e+00	3.137613e+00	2.609033e+00	2.401086e+00	3.176117e+00	3.311356e+00	3.401610e+00	3.200952e+00	3

(vii) Principal Component Analysis (PCA):

- Employed PCA to reduce dimensionality and identify features with maximum variance.



DATA PREPARATION

- Determined that N_components = 7 captures 95% of the variance in the data.

```
df_scaled_PCA.describe()
```

	PC1	PC2	PC3	PC4	PC5	PC6	PC7
count	1.590000e+02	1.590000e+02	1.590000e+02	1.590000e+02	1.590000e+02	1.590000e+02	1.590000e+02
mean	-6.703233e-17	3.281791e-17	2.548625e-17	-3.980045e-17	1.605983e-17	-3.491267e-18	-2.374062e-17
std	2.480103e+00	1.432203e+00	1.117914e+00	9.150836e-01	7.506872e-01	6.180477e-01	5.122136e-01
min	-6.419292e+00	-2.946859e+00	-3.027363e+00	-2.133965e+00	-1.774734e+00	-1.409866e+00	-1.234456e+00
25%	-2.023323e+00	-8.097650e-01	-7.632839e-01	-6.371174e-01	-3.998593e-01	-3.064365e-01	-3.904681e-01
50%	-2.524995e-01	-2.202330e-01	-1.108700e-01	2.133919e-02	-1.054212e-01	-2.551090e-02	4.156915e-03
75%	1.801396e+00	2.519642e-01	6.867493e-01	5.576630e-01	5.209028e-01	3.333498e-01	3.394876e-01
max	6.628805e+00	4.018251e+00	3.435482e+00	2.902558e+00	2.765473e+00	2.975714e+00	1.510192e+00

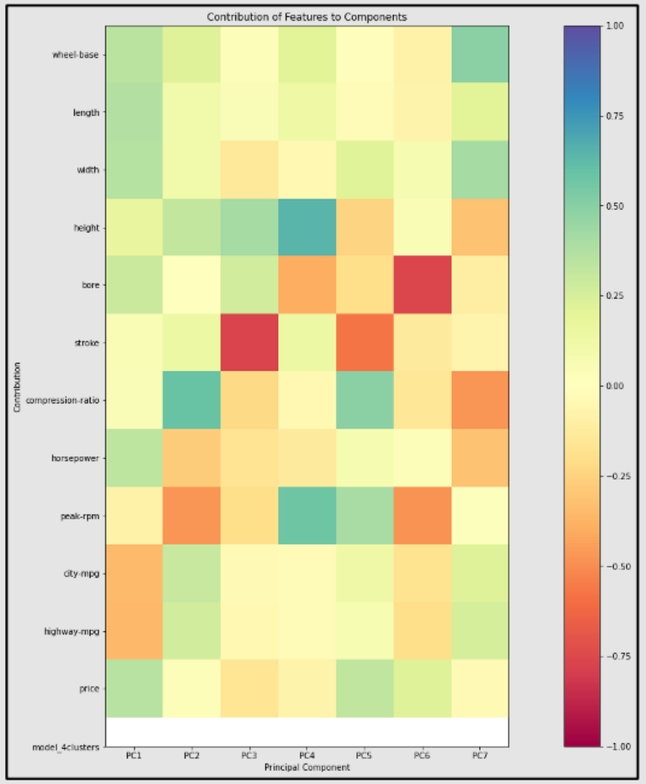
(viii) Understanding Principal Components:

- Described the seven principal components and their contributions to the variance.
- Analyzed features like "mean," "std dev," "min," "max," and "quartile" for each component.

(ix) Identifying Features Contributing to PCA:

- Visualized the relationship between principal components and their contribution to the dataset using a heat map.

Principal components vs Contribution

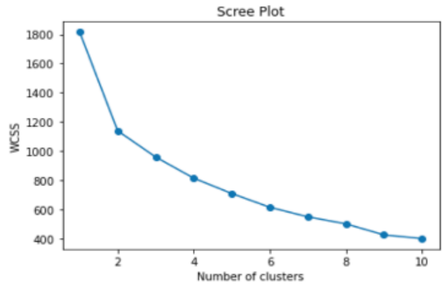


MODELING

(i) Building K-Means Cluster Model:

- Grouped data into clusters.
- Utilized the elbow method (Scree plot) to determine the optimal number of clusters.
- Found that a 3-cluster solution performed best.

```
Counter({0: 159})
Counter({1: 86, 0: 73})
Counter({1: 62, 2: 58, 0: 39})
Counter({2: 57, 1: 53, 3: 40, 0: 9})
Counter({4: 52, 2: 51, 0: 40, 3: 9, 1: 7})
Counter({3: 56, 2: 38, 4: 35, 1: 14, 5: 9, 0: 7})
Counter({0: 50, 2: 43, 4: 27, 1: 15, 6: 9, 5: 8, 3: 7})
Counter({4: 41, 5: 34, 7: 21, 3: 19, 0: 16, 1: 13, 6: 8, 2: 7})
Counter({6: 27, 7: 26, 4: 24, 1: 22, 2: 20, 8: 13, 3: 12, 5: 8, 0: 7})
Counter({2: 31, 9: 26, 0: 23, 7: 20, 1: 19, 6: 13, 3: 8, 8: 7, 5: 7, 4: 5})
cluster_errors: [1816.542520172245, 1139.6459091783045, 959.7125550517167, 815.1460899726046, 709.9943260722448, 615.7755570
505301, 550.4112198297769, 502.4802804332869, 426.64900832966225, 401.5449734180206]
```



Measuring the performance-

```
Silhouette Coefficient for 3 clusters: 0.236
Silhouette Coefficient for 4 clusters: 0.267
```

```
Calinski-Harabasz index of 3 clusters: 69.633
Calinski-Harabasz index of 4 clusters: 63.248
```

Examining Characteristics with 3 cluster Solutions

```
model_3clusters
0    63
1    44
2    52
dtype: int64
```

model_3clusters	length	wheel-base	width	cluster_size
0	-0.02	-0.16	-0.16	63
1	1.18	1.17	1.23	44
2	-0.98	-0.80	-0.85	52

model_3clusters	bore	height	stroke	cluster_size
0	0.16	-0.11	0.02	63
1	0.86	0.57	0.08	44
2	-0.92	-0.34	-0.09	52

model_3clusters	compression-ratio	horsepower	peak-rpm	cluster_size
0	-0.31	-0.02	-0.04	63
1	0.24	1.15	-0.15	44
2	0.17	-0.95	0.17	52

model_3clusters	city-mpg	highway-mpg	price	cluster_size
0	-0.20	-0.18	-0.25	97
1	-1.02	-1.04	1.29	39
2	1.10	1.09	-0.79	23

INSIGHTS (K-MEANS CLUSTER MODEL)

- Classification on the basis of cluster size, cluster 0 is the larger cluster containing 63 data points followed by cluster 2 with 52 data points and the last is cluster 1 with 44 data points.
- We can notice that cluster 0 & 2 has lowest length, width & wheel base of the automobile model whereas cluster 1 has all the three features higher than other two.

- Cluster 1 has models with highest diameter of each wheel in the automobile (bore), with highest height and highest number of phases in engine's cycle(stroke).
- Cluster 2 has models with lowest diameter of each wheel(bore), lowest height of the model and low number of phases in engine's cycle(stroke).
- Cluster 0 has models with less height but medium diameter of each wheel and number of phases in engine's cycle of the model.

- Cluster 1 has models with highest volume of cylinder and chamber (compression-ratio) in the engine with highest power automobile (horsepower) but low revolutions per minute (peak-rpm)
- Cluster 0 has models with lowest volume of cylinder and chamber in the engine (compression-ratio), low power automobile (horsepower) and low revolutions per minute ((peak-rpm)Car
- Cluster 2 has models with lowest power automobile (horsepower) but medium volume of cylinder and chamber of the enginMeo (dceolsmpression-ratio with medium revolutions per minute (peak-rpm)

- Cluster 2 has cheapest automobile models (price) with highest scoring car in an average city (city-mpg) & highway (highway-mpg)
- Cluster 1 are the most expensive automobile models with lowest scoring car in an average city or highway as it is pretty obviuos that in an average city or highway the number of expensive cars would be less due to affordability of the citizens and road infrastructure
- Cluster 0 has average price automobile model with medium score in city & highway and highest number of data points

MODELING

(ii) Building Hierarchical Clustering Model:

- Performed hierarchical clustering with various cluster sizes.
- Identified that a 9-cluster solution yielded good results.

```
clusterid3
0    97
1    39
2    23
dtype: int64

clusterid4
0    59
1    39
2    23
3    38
dtype: int64

clusterid5
0    39
1    38
2    23
3    29
4    30
dtype: int64

clusterid6
0    30
1    38
2    23
3    29
4    30
5     9
dtype: int64

clusterid7
0    23
1    38
2     9
3    29
4    30
5    18
6    12
dtype: int64
clusterid8
0    38
1    29
2     9
3    17
4    30
5    18
6    12
7     6
dtype: int64
```

Performed Hierarchical clustering with 3,4,5,6,7,8,9,10 clusters.

Measuring the performance-

```
Silhouette Coefficient of 3 clusters: 0.301
Silhouette Coefficient of 4 clusters: 0.483
Silhouette Coefficient of 5 clusters: 0.569
Silhouette Coefficient of 6 clusters: 0.633
Silhouette Coefficient of 7 clusters: 0.622
Silhouette Coefficient of 8 clusters: 0.660
Silhouette Coefficient of 9 clusters: 0.622
Silhouette Coefficient of 10 clusters: 0.598
```

```
Calinski-Harabasz index of 3 clusters: 35.890
Calinski-Harabasz index of 4 clusters: 85.549
Calinski-Harabasz index of 5 clusters: 117.445
Calinski-Harabasz index of 6 clusters: 188.320
Calinski-Harabasz index of 7 clusters: 180.083
Calinski-Harabasz index of 8 clusters: 226.160
Calinski-Harabasz index of 9 clusters: 240.381
Calinski-Harabasz index of 10 clusters: 233.249
```

```
clusterid9
0    29
1    10
2     9
3    28
4    30
5    18
6    12
7     6
8    17
dtype: int64
```

Examining Characteristics

clusterid9	length	wheel-base	width	cluster_size
0	-0.57	-0.57	-0.83	29
1	0.84	0.40	1.76	10
2	1.40	2.01	1.87	9
3	1.15	1.04	0.78	28
4	-0.45	-0.50	-0.42	30
5	0.35	0.25	0.20	18
6	-0.31	-0.41	-0.34	12
7	-0.31	-0.38	-0.39	6
8	-1.40	-1.01	-0.99	17

clusterid9	bore	height	stroke	cluster_size
0	-0.63	0.36	-0.26	29
1	0.44	-0.91	0.45	10
2	0.83	1.07	1.04	9
3	0.89	0.86	-0.59	28
4	-0.58	-0.41	0.67	30
5	0.57	-0.17	0.78	18
6	1.20	-0.07	-2.11	12
7	-0.78	0.30	0.54	6
8	-1.25	-1.22	-0.11	17

clusterid9	compression-ratio	horsepower	peak-rpm	cluster_size
0	-0.28	-0.88	-0.30	29
1	-0.37	1.98	0.19	10
2	2.95	0.34	-1.65	9
3	-0.35	1.00	0.44	28
4	-0.37	-0.07	1.07	30
5	-0.35	0.26	-1.07	18
6	-0.35	-0.31	-0.73	12
7	3.22	-1.28	-1.00	6
8	-0.17	-0.97	0.67	17

clusterid9	city-mpg	highway-mpg	price	cluster_size
0	0.60	0.64	-0.70	29
1	-1.40	-1.41	1.78	10
2	-0.20	-0.51	1.74	9
3	-1.07	-1.01	0.83	28
4	-0.06	-0.01	-0.44	30
5	-0.30	-0.24	0.08	18
6	-0.03	-0.21	-0.50	12
7	1.89	1.93	-0.59	6
8	1.44	1.41	-0.88	17

INSIGHTS (HIERARCHICAL CLUSTERING MODEL)

- Cluster 2 & 3 have automobile models of highest length while Cluster 1 & 5 have medium length models whereas cluster 0,4,6,7,8 have lowest length automobile models
- It can be observed that clusters with highest length have highest type of wheel base as well (cluster 2 & 3), cluster 1 & 5 have medium wheel base model whereas cluster 0,4,6,7,8 have low type of wheel base
- Cluster 1 & 2 have highest width of the automobile model while cluster 3 & 5 have medium width models wheras cluster 0,4,6,7,8 have lowest width automobile models

- Cluster 6 & 3 have the models with highest diameter of each wheel, whereas cluster 8 and 7 have models with lowest diameter of each wheel
- Cluster 2 & 3 have models with highest height, whereas cluster 8 & 1 have lowest height models
- Cluster 2 & 5 have models with more number of phases in engine's cycle than cluster 6 & 3 have models with least number of phases in engine's cycle

- Cluster 3 & 2 have models with highest volume of cylinder and chamber in the engine whereas cluster 1 & 4 have models with lowest volume of cylinder and chamber in the engine
- It can be observed that Cluster 1 & 3 have models with highest power of engine despite having low volume of chamber of theC aenrgine, also cluster 7 having haighest volume of cylinder and chamber in the engine have lowest power engineModels
- Also Cluster 4 have lowest volume of chamber in the engine but have highest revolutiuons per minute

- Cluster 7 & 8 have lowest price and highest score in number of car in an average city and on a highway whereas cluster 1 & 2 have the models with the most expensive cars and the lowest in number in an average city and on a highway

- Inference : The more expensive car is the least is the number of car in an average city or on a highway

MODELING

(iii) Executing Clustering

- Prepared initial centres using the k-means++ method.
- Developed a Gower metric for clustering.
- Executed k-means clustering using a specific distance metric.
- Obtained cluster results and assigned labels.

```
initial_centers = kmeans_plusplus_initializer(df_scaled_PCA, 4).initialize()
```

```
gower_metric = distance_metric(type_metric.GOWER,data=df_scaled_PCA)
```

```
kmeans_instance = kmeans(df_scaled_PCA, initial_centers, metric=gower_metric)
```

```
kmeans_instance.process()
clusters = kmeans_instance.get_clusters()
```

Printing the allocated clusters

```
print(clusters)
```

```
[[0, 6, 7, 13, 18, 20, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 38, 39, 40, 41, 42, 52, 53, 54, 55, 56, 57, 58, 69, 70, 85, 9
7, 98, 99, 100, 101, 102, 103, 104, 105, 106, 107, 108, 124, 125, 126, 127, 128, 129, 130, 131, 132, 134, 135, 136, 141, 14
3, 144, 146, 147], [1, 2, 3, 4, 5, 32, 43, 44, 45, 46, 47, 48, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 90, 91, 9
2, 93, 94, 95, 96, 133, 137, 138, 139, 148, 149, 150, 151, 152, 153, 154, 155, 156, 157, 158], [8, 9, 10, 11, 12, 14, 15, 1
6, 19, 21, 49, 50, 51, 60, 84, 86, 87, 88, 117, 118, 140, 142, 145], [17, 33, 34, 35, 36, 37, 59, 61, 62, 63, 64, 65, 66, 6
7, 68, 89, 109, 110, 111, 112, 113, 114, 115, 116, 119, 120, 121, 122, 123]]
```

Adding the cluster labels to data frame df for analysis:

```
cluster_size = df.groupby(['clusterid']).size()
print(cluster_size)
```

```
clusterid
0    60
1    47
2    23
3    29
dtype: int64
```

Examining Characteristics

clusterid	length	wheel-base	width	cluster_size
0	-0.18	-0.25	-0.22	60
1	1.13	1.09	1.20	47
2	-1.11	-0.85	-0.83	23
3	-0.57	-0.57	-0.83	29

clusterid	bore	height	stroke	cluster_size
0	0.12	-0.27	0.15	60
1	0.78	0.52	-0.06	47
2	-1.13	-0.82	0.06	23
3	-0.63	0.36	-0.26	29

clusterid	compression-ratio	horsepower	peak-rpm	cluster_size
0	-0.36	-0.02	0.07	60
1	0.28	1.08	-0.01	47
2	0.71	-1.06	0.23	23
3	-0.28	-0.88	-0.30	29

clusterid	city-mpg	highway-mpg	price	cluster_size
0	-0.12	-0.12	-0.3	60
1	-0.98	-1.00	1.2	47
2	1.56	1.55	-0.8	23
3	0.60	0.64	-0.7	29

INSIGHTS (EXECUTING CLUSTERING)

- Classification on the basis of cluster size, cluster 0 is the larger cluster containing 60 data points followed by cluster 1 with 47 data points then cluster 3 with 29 data points and the last is cluster 2 with 23 data points
- We can notice that cluster 2 & 3 has lowest length, width & wheel base of the automobile model whereas cluster 1 has all the three features higher than other two.

- Cluster 1 has models with highest diameter of each wheel in the automobile (bore), with highest height but low number of phases in engine's cycle(stroke).
- Cluster 2 has models with lowest diameter of each wheel(bore), lowest height of the model but moderate number of phases in engine's cycle(stroke).
- Cluster 0 has models with less height but moderate diameter of each wheel and highest number of phases in engine's cycle of the model.
- Cluster 3 has models with moderate height but lowest diameter of each wheel in the automobile

- Cluster 2 has models with highest volume of cylinder and chamber (compression-ratio) in the engine and low revolutions per minute (peak-rpm) but lowest power automobile (horsepower)
- Cluster 1 has models with moderate volume of cylinder and chamber (compression-ratio) in the engine and low revolutions per minute (peak-rpm) but have highest power automobile (horsepower)
- Cluster 0 has models with lowest volume of cylinder and chamber in the engine (compression-ratio), low power automobileC (ahrorsepower) but moderate revolutions per minute ((peak-rpm)Models
- Cluster 3 has models with low power automobile (horsepower),low volume of cylinder and chamber of the engine (compression-ratio) with lowest revolutions per minute (peak-rpm)

- Cluster 2 has cheapest automobile models (price) with highest scoring car in an average city (city-mpg) & highway (highway-mpg)
- Cluster 1 are the most expensive automobile models with lowest scoring car in an average city or highway as it is pretty obviuos that in an average city or highway the number of expensive cars would be less due to affordability of the citizens and road infrastructure
- Cluster 3 has moderate number of cars in average city and highway with moerate pricing
- Cluster 0 has low price automobile model with low score in city & highway and highest number of data points

CONCLUSION

The K-Means and Hierarchical Clustering methods yielded similar results in terms of the number of optimal clusters.

Cluster 1 consistently appeared to represent higher-end automobile models with larger wheels, higher-power engines, and higher prices.

Cluster 2 tended to represent more economical models with smaller dimensions and lower power.

Cluster 0 (K-Means) and Cluster 3 (Hierarchical) had somewhat intermediate characteristics.