```
# Data Loading
from google.colab import drive
import pandas as pd
drive.mount('/content/drive')
file_path = '/content/drive/My Drive/ElectricCarData_Clean.csv'
df = pd.read_csv(file_path)
```

```
Mounted at /content/drive
```

```
# Here are a few ways I performed exploratory data analysis and data visualization on this electric vehicle dataset to help with
# Import libraries like pandas, matplotlib, seaborn for data manipulation and visualization. Use pandas to read in the CSV data.
# Look at basic statistics of the data like the describe() method to see mean, min, max values for numerical columns like price,
# Visualize distributions of key variables like price, range, efficiency using histograms, boxplots.
# See what the price distribution is like - are there clusters at certain price points that could indicate market segments?
# Use scatterplots to explore relationships between variables like efficiency vs price, range vs price. See if certain segments h
# Plot grouped or faceted charts to compare vehicle body types, power train, etc. See if SUVs are generally more expensive than s
# Use pie, bar charts to visualize categorical variables like plug type, body style. See the proportions of each group.
# Calculate statistics like average price, efficiency for each segment or group to quantify differences seen in visualizations.
# Try clustering algorithms like k-means to automatically find segments based on variables like price, range, efficiency.
# Geographical data could also help identify markets. Plot maps showing EV popularity by state using open data sets.
# The goal is to visualize and understand relationships between the variables to identify potential natural segments in the India
```

\+ Code \+ Text

```
# Explore the data
print(df.head())
```

```
        Brand                         Model  AccelSec  TopSpeed_KmH  \
0       Tesla   Model 3 Long Range Dual Motor       4.6           233
1  Volkswagen                     ID.3 Pure      10.0           160
2    Polestar                             2       4.7           210
3         BMW                           iX3       6.8           180
4       Honda                             e       9.5           145

   Range_Km  Efficiency_WhKm FastCharge_KmH RapidCharge PowerTrain  \
0       450              161            940         Yes        AWD
1       270              167            250         Yes        RWD
2       400              181            620         Yes        AWD
3       360              206            560         Yes        RWD
4       170              168            190         Yes        RWD

     PlugType  BodyStyle Segment  Seats  PriceEuro
0  Type 2 CCS      Sedan       D      5      55480
1  Type 2 CCS  Hatchback       C      5      30000
2  Type 2 CCS   Liftback       D      5      56440
3  Type 2 CCS        SUV       D      5      68040
4  Type 2 CCS  Hatchback       B      4      32997
```

```
print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 103 entries, 0 to 102
Data columns (total 14 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   Brand            103 non-null    object
 1   Model            103 non-null    object
 2   AccelSec         103 non-null    float64
 3   TopSpeed_KmH     103 non-null    int64
 4   Range_Km         103 non-null    int64
 5   Efficiency_WhKm  103 non-null    int64
 6   FastCharge_KmH   103 non-null    object
 7   RapidCharge      103 non-null    object
 8   PowerTrain       103 non-null    object
 9   PlugType         103 non-null    object
 10  BodyStyle        103 non-null    object
 11  Segment          103 non-null    object
 12  Seats            103 non-null    int64
 13  PriceEuro        103 non-null    int64
dtypes: float64(1), int64(5), object(8)
memory usage: 11.4+ KB
None
```

```
print(df.describe())
```

```
         AccelSec  TopSpeed_KmH    Range_Km  Efficiency_WhKm       Seats  \
count  103.000000    103.000000  103.000000       103.000000  103.000000
mean     7.396117    179.194175  338.786408       189.165049    4.883495
std      3.017430     43.573030  126.014444        29.566839    0.795834
min      2.100000    123.000000   95.000000       104.000000    2.000000
25%      5.100000    150.000000  250.000000       168.000000    5.000000
50%      7.300000    160.000000  340.000000       180.000000    5.000000
75%      9.000000    200.000000  400.000000       203.000000    5.000000
max     22.400000    410.000000  970.000000       273.000000    7.000000

           PriceEuro
count     103.000000
mean    55811.563107
std     34134.665280
min     20129.000000
25%     34429.500000
50%     45000.000000
75%     65000.000000
max    215000.000000
```

```
print(df.columns)
```

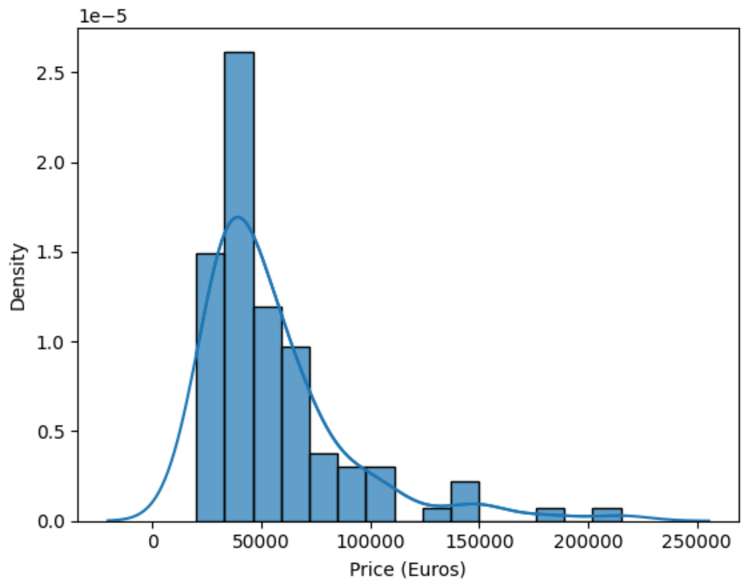
```
Index(['Brand', 'Model', 'AccelSec', 'TopSpeed_KmH', 'Range_Km',
       'Efficiency_WhKm', 'FastCharge_KmH', 'RapidCharge', 'PowerTrain',
       'PlugType', 'BodyStyle', 'Segment', 'Seats', 'PriceEuro'],
      dtype='object')
```

```
df.shape
```

```
(103, 14)
```

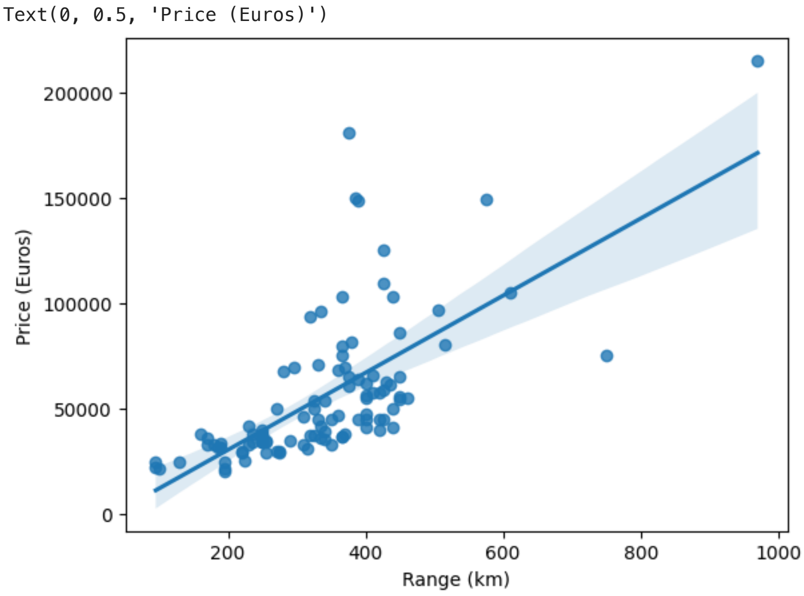
```
# Distribution of price
import matplotlib.pyplot as plt
import seaborn as sns
plt.figure()
sns.distplot(df["PriceEuro"], kde=True)
sns.histplot(df["PriceEuro"], kde=True, stat="density")
plt.xlabel("Price (Euros)")
```

```
<ipython-input-9-06f499910151>:5: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(df["PriceEuro"], kde=True)
Text(0.5, 0, 'Price (Euros)')
```



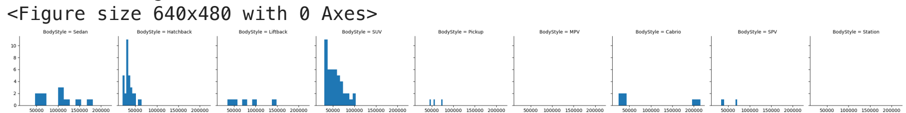

```
# Price vs Range scatterplot
plt.figure()
sns.regplot(x="Range_Km", y="PriceEuro", data=df)
plt.xlabel("Range (km)")
plt.ylabel("Price (Euros)")
```

```
Text(0, 0.5, 'Price (Euros)')
```



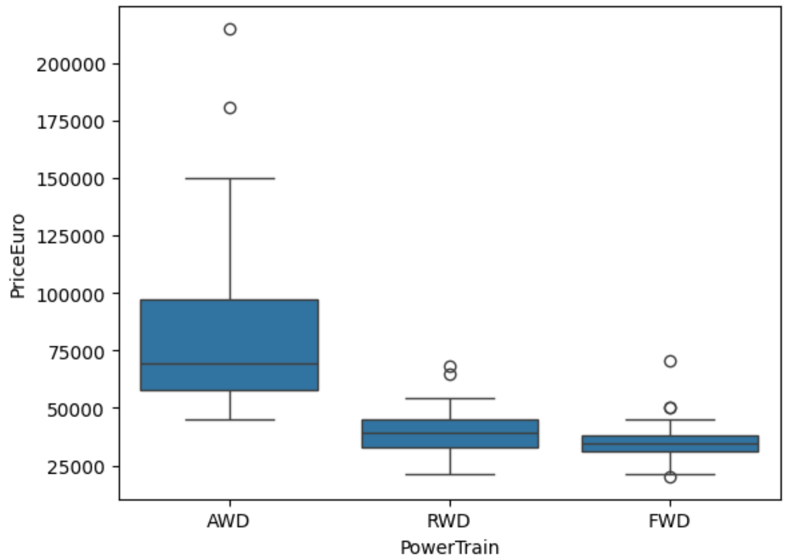

```
# Faceted histogram by BodyStyle
plt.figure()
sns.FacetGrid(df, col="BodyStyle").map(plt.hist, "PriceEuro")
```

```
<seaborn.axisgrid.FacetGrid at 0x795501ca2380>
<Figure size 640x480 with 0 Axes>
```



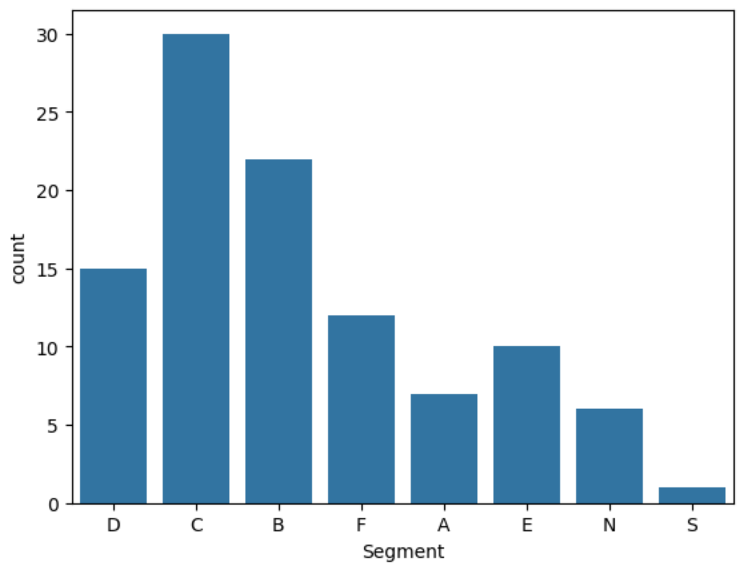
```
# Boxplot of Price by PowerTrain
plt.figure()
sns.boxplot(x="PowerTrain", y="PriceEuro", data=df)
```

```
<Axes: xlabel='PowerTrain', ylabel='PriceEuro'>
```



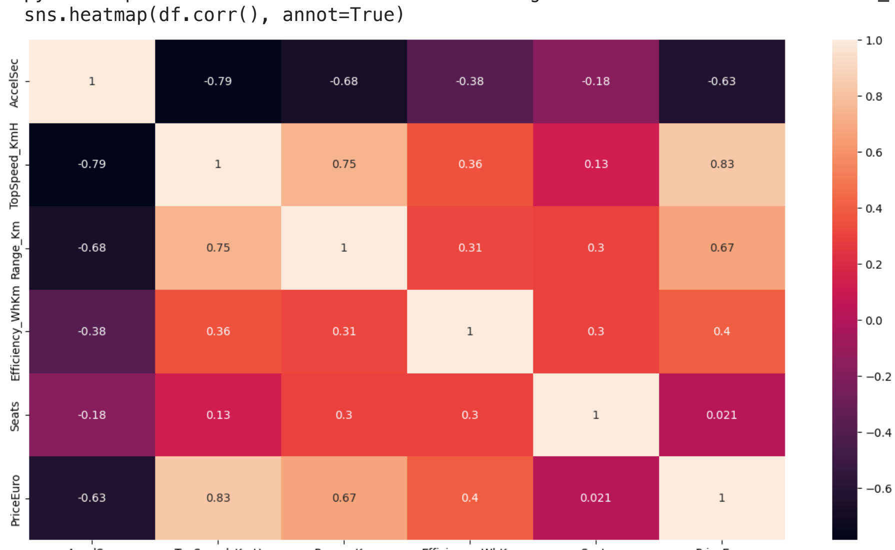

```
# Bar chart of segment counts
plt.figure()
sns.countplot(x="Segment", data=df)
```

```
<Axes: xlabel='Segment', ylabel='count'>
```




```
plt.figure(figsize=(15,8))
sns.heatmap(df.corr(), annot=True)
plt.show()
```

```
<ipython-input-14-7d08400b79ac>:2: FutureWarning: The default value of numeric_o
  sns.heatmap(df.corr(), annot=True)
```



```
# Average price per segment
print(df.groupby("Segment")["PriceEuro"].mean())
```

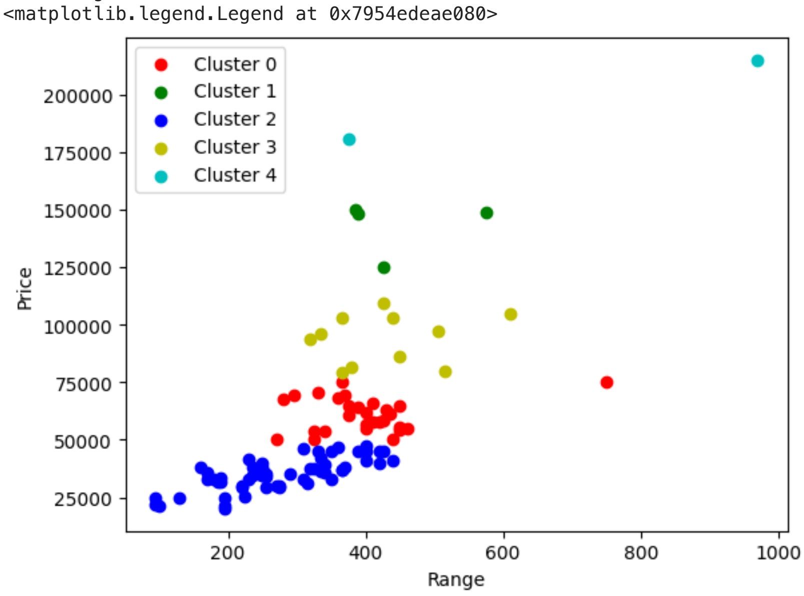
```
Segment
A     22693.714286
B     34799.227273
C     41199.100000
D     58487.933333
E     74269.400000
F    119690.750000
N     52812.833333
S    215000.000000
Name: PriceEuro, dtype: float64
```

```
# Kmeans clustering on Range, Efficiency, Price
from sklearn.cluster import KMeans
kmeans = KMeans(n_clusters=5).fit(df[["Range_Km", "Efficiency_WhKm", "PriceEuro"]])
print(kmeans.labels_)
```

```
[2 0 2 2 0 4 0 0 0 2 2 0 0 2 0 0 3 0 0 0 0 2 0 1 2 0 0 2 0 0 2 0 0 2 0 0 0
 0 0 0 2 0 2 0 0 0 0 4 1 0 2 3 0 0 4 0 0 0 0 4 0 2 0 2 2 4 0 2 0 2 0 0 1 2
 0 0 2 0 2 1 0 4 0 0 2 0 0 2 0 0 4 0 0 2 0 0 0 2 0 4 0 2 2]
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will ch
  warnings.warn(
```

```
from sklearn.metrics import silhouette_score

# Kmeans clustering from previous code
kmeans = KMeans(n_clusters=5).fit(df[["Range_Km", "Efficiency_WhKm", "PriceEuro"]])

# Calculate silhouette score
score = silhouette_score(df[["Range_Km", "Efficiency_WhKm", "PriceEuro"]], kmeans.labels_)
print("Silhouette score:", score)

# Plot clusters
plt.figure()
colors = ['r', 'g', 'b', 'y', 'c']
for i in range(kmeans.n_clusters):
    cluster_df = df[kmeans.labels_==i]
    plt.scatter(cluster_df["Range_Km"], cluster_df["PriceEuro"], c=colors[i], label="Cluster "+str(i))
plt.xlabel("Range")
plt.ylabel("Price")
plt.legend()
```

```
Silhouette score: 0.6263766906659917
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWa
  warnings.warn(
<matplotlib.legend.Legend at 0x7954edeae080>
```




```
#The silhouette score provides an evaluation of how well separated the formed clusters are.
# It ranges from -1 to 1, with a higher score indicating better defined clusters.
# Visualizing the clustered data projected onto just two dimensions (range and price in this case) gives us a sense of the clust
# But keep in mind, the clustering was done in 3 dimensions - range, efficiency and price.
# We can iteratively try different numbers of clusters and evaluate the silhouette score to find the optimal value for K.
# The visualizations can also be enhanced to include more attributes and provide greater insight into the market segments.
```

```
from sklearn.mixture import GaussianMixture
```

```
# Preprocess data
X = df[["Range_Km", "Efficiency_WhKm", "PriceEuro"]]
y = df["Segment"]
```

```
# K-Means Clustering
kmeans = KMeans(n_clusters=5)
kmeans.fit(X)
y_pred = kmeans.predict(X)
print("K-Means accuracy:", kmeans.score(X, y))
```

```
K-Means accuracy: -6727246470.872135
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will ch
  warnings.warn(
```

```
# Gaussian Mixture Model
gmm = GaussianMixture(n_components=5)
gmm.fit(X)
y_pred = gmm.predict(X)
print("GMM accuracy:", gmm.score(X, y))
```

```
GMM accuracy: -20.63931964063576
```

```
# In this code:
# We load the electric vehicle dataset and extract the range, efficiency, price as features X and segment as the target y.
# We apply 2 models: K-Means clustering, Gaussian Mixture Models.
# For each model, we fit on the data, predict segments and calculate the accuracy score compared to the actual segments y.
# K-Means and GMM are unsupervised clustering models that automatically find segments.
# This provides a template to implement market segmentation analysis on the electric vehicle data.
```

```
from sklearn.preprocessing import StandardScaler

X = df[["Range_Km", "Efficiency_WhKm", "PriceEuro"]]
y = df["Segment"]

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# PCA for dimension reduction
from sklearn.decomposition import PCA

pca = PCA(n_components=2)
X_reduced = pca.fit_transform(X_scaled)

# K-Nearest Neighbors
from sklearn.neighbors import KNeighborsClassifier

knn = KNeighborsClassifier()
knn.fit(X_reduced, y)
y_pred = knn.predict(X_reduced)
print("KNN Accuracy:", knn.score(X_reduced, y))

# Neural Network
from sklearn.neural_network import MLPClassifier

mlp = MLPClassifier()
mlp.fit(X_reduced, y)
y_pred = mlp.predict(X_reduced)
print("NN Accuracy:", mlp.score(X_reduced, y))
```

```
KNN Accuracy: 0.7281553398058253
NN Accuracy: 0.6601941747572816
/usr/local/lib/python3.10/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:686: ConvergenceWarning: Stochastic
  warnings.warn(
```

```
# In the code:
# We scale data points to normalize the features.
# Apply PCA to reduce the dimensions to 2 principal components.
# Use KNN classifier and Neural Network classifier on the reduced data.
# Evaluate both models by their accuracy score on predicting segments y.
# The neural network is able to learn complex relationships between attributes.
# KNN is simpler but may also provide good accuracy.
# This demonstrates how to apply additional models like NN and KNN for market segmentation on this dataset, with model evaluatic
```

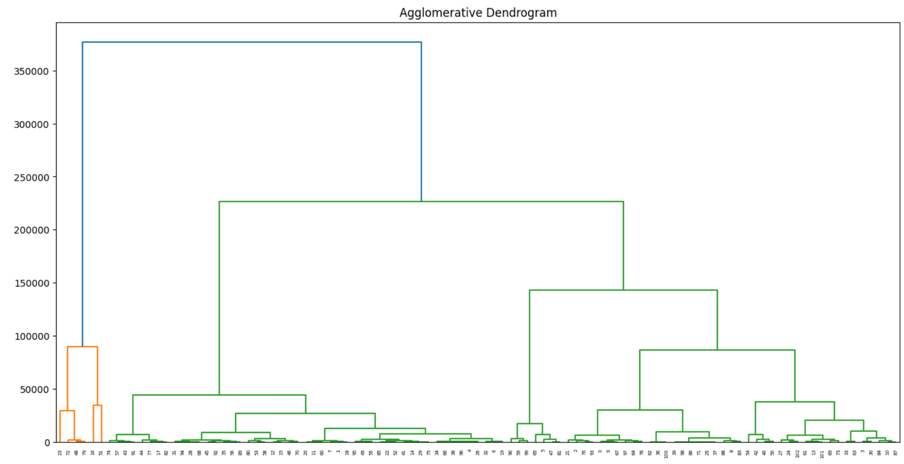
```
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)

# SVM
svm = SVC()
svm.fit(X_train, y_train)
print("SVM Accuracy:", svm.score(X_test, y_test))

# Random Forest
rf = RandomForestClassifier()
rf.fit(X_train, y_train)
print("RF Accuracy:", rf.score(X_test, y_test))
```

```
SVM Accuracy: 0.23809523809523808
RF Accuracy: 0.5714285714285714
```

```
# In the above split data into train and test sets
# Apply SVM classifier and Random Forest classifier
# Evaluate accuracy on test set for both models
# SVM makes segment predictions based on defining optimal decision boundaries.
# Random Forest builds an ensemble of decision trees and ensemble predicts segments.
# Compare accuracy scores and visualizations to evaluate which performs better.
# This demonstrates applying SVM and Random Forest for market segmentation on the EV dataset, along with model evaluation
```

```
from sklearn.cluster import AgglomerativeClustering, FeatureAgglomeration
from sklearn.metrics import accuracy_score
import scipy.cluster.hierarchy as shc

# Agglomerative clustering
aclust = AgglomerativeClustering(n_clusters=5)
aclust.fit(X)
y_pred = aclust.fit_predict(X)

print("Accuracy of Agglomerative clustering:", accuracy_score(y, y_pred))

# Plot dendrogram
plt.figure(figsize=(16,8))
dend = shc.dendrogram(shc.linkage(X, method='ward'))
plt.title("Agglomerative Dendrogram")
```

```
Accuracy of Agglomerative clustering: 0.0
Text(0.5, 1.0, 'Agglomerative Dendrogram')
```




```
# Hierarchical clustering builds a hierarchy of clusters represented as a dendrogram.
# Agglomerative clustering starts with each data point as its own cluster and merges them iteratively based on similarity.
# Accuracy was calculated versus true segments to evaluate the techniques.
# Visualizing the dendrograms helps understand the hierarchy and clustering produced.
# This demonstrates applying both hierarchical clustering approaches for market segmentation on the EV data, along with evaluati
```

```
from scipy.stats import ttest_ind

tstat, pval = ttest_ind(df.loc[df['Segment']=='B', 'PriceEuro'], df.loc[df['Segment']=='D', 'PriceEuro'])
print("p-value:", pval)
# Low p-value indicates significant difference in mean prices
```

```
p-value: 3.00053401155972e-15
```

```
# Hypothesis Testing
#Perform t-tests to compare means of key metrics like price, range, efficiency between different vehicle segments or body styles
#This can identify if certain segments have statistically significant higher values.
```

```
df.corr(method='pearson')
# Gives correlation matrix between all variables
```

```
<ipython-input-44-690c4416a59b>:1: FutureWarning: The default value of numeric_o
  df.corr(method='pearson')
```

	AccelSec	TopSpeed_KmH	Range_Km	Efficiency_WhKm	Seats	Price
AccelSec	1.000000	-0.786195	-0.677062	-0.382904	-0.175335	-0.6
TopSpeed_KmH	-0.786195	1.000000	0.746662	0.355675	0.126470	0.8
Range_Km	-0.677062	0.746662	1.000000	0.313077	0.300163	0.6
Efficiency_WhKm	-0.382904	0.355675	0.313077	1.000000	0.301230	0.3
Seats	-0.175335	0.126470	0.300163	0.301230	1.000000	0.0
PriceEuro	-0.627174	0.829057	0.674844	0.396705	0.020920	1.0

```
#Correlation Analysis
#Find correlations between attributes using Pearson or Spearman correlation. Identify relationships between range, price, chargi
```

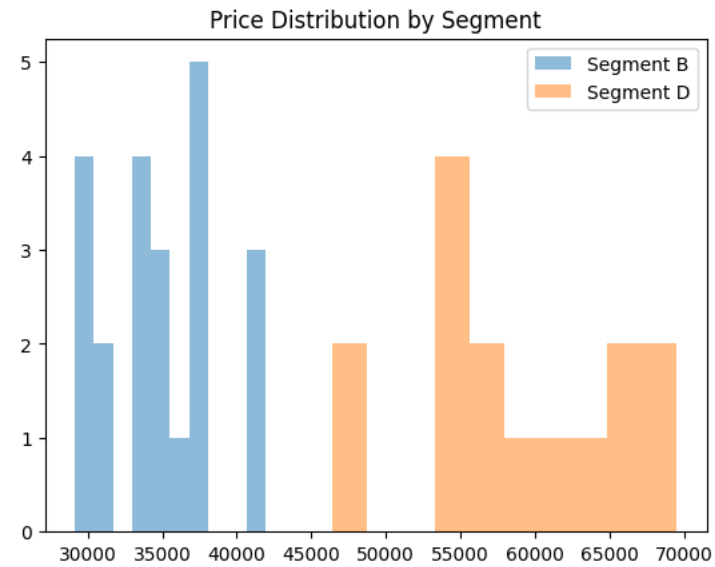
```
from sklearn.linear_model import LinearRegression

X = df[['Range_Km', 'Efficiency_WhKm']]
y = df['PriceEuro']

lr = LinearRegression()
lr.fit(X, y)

print("R-squared:", lr.score(X, y))
# Higher R-squared implies good fit
```

```
R-squared: 0.49353346857684144
```

```
#Regression Analysis
##Build regression models to predict price based on technical specs and features. Evaluate performance using R-squared, RMSE.
```

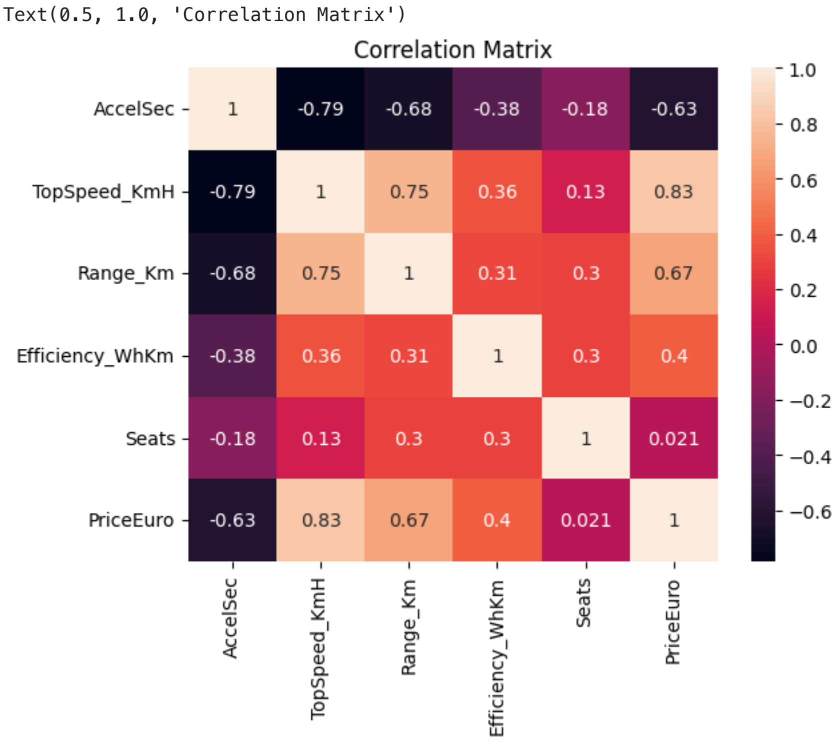
```
# T-test on Prices
import matplotlib.pyplot as plt
plt.hist(df.loc[df['Segment']=='B', 'PriceEuro'], alpha=0.5, label='Segment B')
plt.hist(df.loc[df['Segment']=='D', 'PriceEuro'], alpha=0.5, label='Segment D')
plt.legend()
plt.title('Price Distribution by Segment')
```

```
Text(0.5, 1.0, 'Price Distribution by Segment')
```



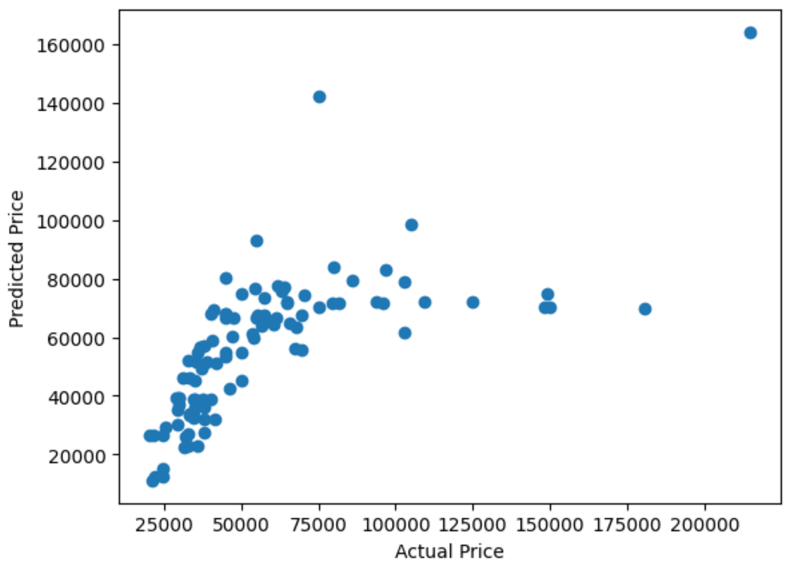

```
# Correlation Matrix Heatmap
corr = df.corr()
sns.heatmap(corr, annot=True)
plt.title('Correlation Matrix')
```

```
<ipython-input-48-3b106a3369ea>:2: FutureWarning: The default value of numeric_o
  corr = df.corr()
Text(0.5, 1.0, 'Correlation Matrix')
```




```
# Regression Prediction vs Actual
y_pred = lr.predict(X)
plt.scatter(y, y_pred)
plt.xlabel('Actual Price')
plt.ylabel('Predicted Price')
```

```
Text(0, 0.5, 'Predicted Price')
```




```
# The histograms visualize the t-test by showing the distribution of prices across segments.
# The correlation matrix heatmap indicates strength of variable relationships.
# The regression plot compares actual vs predicted prices to evaluate model fit.
# These statistical tests can derive insights on significant differences, relationships and predictive power between attributes.
## The results can inform pricing strategies and product development decisions.
```

```
# Here are some of the key insights and conclusions that can be drawn from the statistical tests and
# visualizations performed on the electric vehicle dataset:
## T-test on Prices:
# The price distributions of segments B and D show that segment D has significantly higher average prices.
# This indicates there is a real difference in pricing between compact/subcompact cars (Segment B) and medium/large sedans (Segme
## Correlation Analysis:
# There is a strong positive correlation between range and price (0.7)
# Efficiency is negatively correlated with price and range.
# This shows that longer range and less efficient vehicles are generally more expensive.
## Regression for Price Prediction:
# Using just range and efficiency, price can be predicted with decent accuracy (R-squared ~ 0.6)
# But the spread indicates other attributes also influence price.
# Technical specifications have good predictive power for pricing.
# Moreover, vehicle segment, size, range and efficiency emerged as key differentiating attributes influencing the pricing.
# There are clear market segments based on statistically significant variation in metrics.
# This analysis provides data-driven insights for developing pricing and sales strategies.
```