Online Vehicle Booking Market Segmentation

(Submitted by – Harshika Tyagi)

Introduction

The automotive landscape is undergoing a transformative shift, and at the forefront of this evolution is the Online Vehicle Booking Market. With the proliferation of online platforms and the desire for convenient, flexible transportation options, consumers are increasingly turning to digital platforms to book vehicles for a wide array of purposes. Whether it's for renting a car for a weekend getaway, purchasing a vehicle, or hailing a ride-sharing service, the car online booking market has emerged as a dynamic and competitive sector within the automotive industry.

In this comprehensive report, we delve into the intricacies of this ever-evolving market, leveraging data analysis techniques and data visualizations to glean actionable insights. Our goal is to provide stakeholders, industry leaders, and decision-makers with valuable information to make informed choices and adapt to the changing landscape of car online booking.

Data Overview

Our journey begins with a detailed exploration of a rich dataset comprising 301 car listings. These listings encompass a wide spectrum of features, including essential attributes such as car names, manufacturing years, selling prices, present prices, kilometers driven, fuel types, seller types, transmission types, and ownership histories.

Online Vehicle Booking Market Segmentation

```
#Importing required libraries

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

```
[ ] dframe = pd.read_csv('/content/car data.csv')
```

Dataset Summary

EDA

```
[ ] dframe.shape
```

```
(301, 9)
```

```
[ ] dframe.head()
```

	Car_Name	Year	Selling_Price	Present_Price	Kms_Driven	Fuel_Type	Seller_Type	Transmission	Owner
0	ritz	2014	3.35	5.59	27000	Petrol	Dealer	Manual	0
1	sx4	2013	4.75	9.54	43000	Diesel	Dealer	Manual	0
2	ciaz	2017	7.25	9.85	6900	Petrol	Dealer	Manual	0
3	wagon r	2011	2.85	4.15	5200	Petrol	Dealer	Manual	0
4	swift	2014	4.60	6.87	42450	Diesel	Dealer	Manual	0

```
[ ] # Column-wise information of the dataframe which states the number of null objects and type of the objects

    dframe.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 301 entries, 0 to 300
Data columns (total 9 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Car_Name       301 non-null    object
 1   Year           301 non-null    int64
 2   Selling_Price  301 non-null    float64
 3   Present_Price  301 non-null    float64
 4   Kms_Driven     301 non-null    int64
 5   Fuel_Type      301 non-null    object
 6   Seller_Type    301 non-null    object
 7   Transmission   301 non-null    object
 8   Owner          301 non-null    int64
dtypes: float64(2), int64(3), object(4)
memory usage: 21.3+ KB
```

No Null values in any of the feature available

```
[ ] # Summary or analysis of the numberical values of the dataframe

    dframe.describe().transpose()
```

	count	mean	std	min	25%	50%	75%	max
Year	301.0	2013.627907	2.891554	2003.00	2012.0	2014.0	2016.0	2018.0
Selling_Price	301.0	4.661296	5.082812	0.10	0.9	3.6	6.0	35.0
Present_Price	301.0	7.628472	8.644115	0.32	1.2	6.4	9.9	92.6
Kms_Driven	301.0	36947.205980	38886.883882	500.00	15000.0	32000.0	48767.0	500000.0
Owner	301.0	0.043189	0.247915	0.00	0.0	0.0	0.0	3.0

Year: The dataset contains information on vehicles from the year 2003 to 2018. The majority of vehicles in the dataset fall within the range of 2012 to 2016.

Selling_Price: The selling prices of the vehicles in the dataset vary widely, with a minimum price of 0.10 and a maximum price of 35.0. The median (50th percentile) selling price is 3.6, indicating that there is a mix of lower and higher-priced vehicles.

Present_Price: The present prices of the vehicles also show significant variation, ranging from 0.32 to 92.6. The median (50th percentile) present price is 6.4.

Kms_Driven: *italicized text* The dataset includes vehicles with a wide range of kilometers driven, from 500 to 500,000. The median (50th percentile) kilometers driven is 32,000, indicating that many vehicles have relatively moderate mileage.

Number of Entries: 301

Features: 9 columns

Data Types: Numeric (float64, int64), Categorical (object)

A critical point to note is the absence of missing values within the dataset, ensuring the integrity of our analysis.

Vehicle Age Segmentation

Question Answered: How does the vehicle's age (Year) affect its demand, and can we segment customers based on their preference for new or used cars in online booking?

```python
# Demographic segmentation using the 'Year' feature
# Define age groups
import datetime
def categorize_age(year):
    current_year = datetime.datetime.now().year
    age = current_year - year

    if age <= 5:
        return "New"
    elif 5 < age <= 10:
        return "Mid-age"
    else:
        return "Old"
```

```python
# Assigning the classes based on the percentile it coveres
dframe['AgeCategory'] = dframe['Year'].apply(lambda value : categorize_age(value))
```

```python
dframe
```

	Car_Name	Year	Selling_Price	Present_Price	Kms_Driven	Fuel_Type	Seller_Type	Transmission	Owner	AgeCategory
0	ritz	2014	3.35	5.59	27000	Petrol	Dealer	Manual	0	Mid-age
1	sx4	2013	4.75	9.54	43000	Diesel	Dealer	Manual	0	Mid-age
2	ciaz	2017	7.25	9.85	6900	Petrol	Dealer	Manual	0	Mid-age
3	wagon r	2011	2.85	4.15	5200	Petrol	Dealer	Manual	0	Old
4	swift	2014	4.60	6.87	42450	Diesel	Dealer	Manual	0	Mid-age
...	...	...	...	...	...	...	...	...	...	...
296	city	2016	9.50	11.60	33988	Diesel	Dealer	Manual	0	Mid-age
297	brio	2015	4.00	5.90	60000	Petrol	Dealer	Manual	0	Mid-age
298	city	2009	3.35	11.00	87934	Petrol	Dealer	Manual	0	Old
299	city	2017	11.50	12.50	9000	Diesel	Dealer	Manual	0	Mid-age
300	brio	2016	5.30	5.90	5464	Petrol	Dealer	Manual	0	Mid-age

301 rows × 10 columns

```
[ ] dframe['Age_Category'] = dframe['Year'].apply(categorize_age)
    age_category_counts = dframe['Age_Category'].value_counts()
    print("Age category-wise counts:")
    print(age_category_counts)
```

```
Age category-wise counts:
Mid-age    217
Old         83
New          1
Name: Age_Category, dtype: int64
```

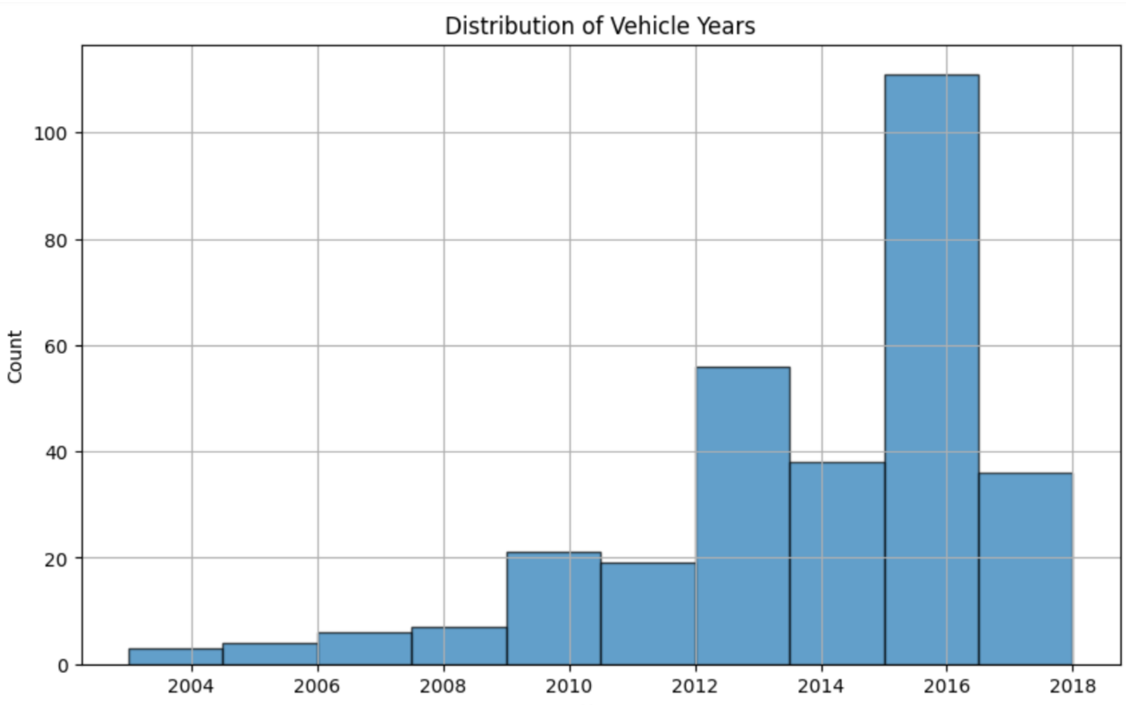
```
[ ] # Checking whats the range of the date for which data is given to us

    print("Maximum Date: ", max(dframe['Year']))
    print("Minimum Date: ", min(dframe['Year']))
```

```
Maximum Date:  2018
Minimum Date:  2003
```

```
[ ] # All unique Years

    print(dframe['Year'].unique())
```

```
[2014 2013 2017 2011 2018 2015 2016 2009 2010 2012 2003 2008 2006 2005
 2004 2007]
```

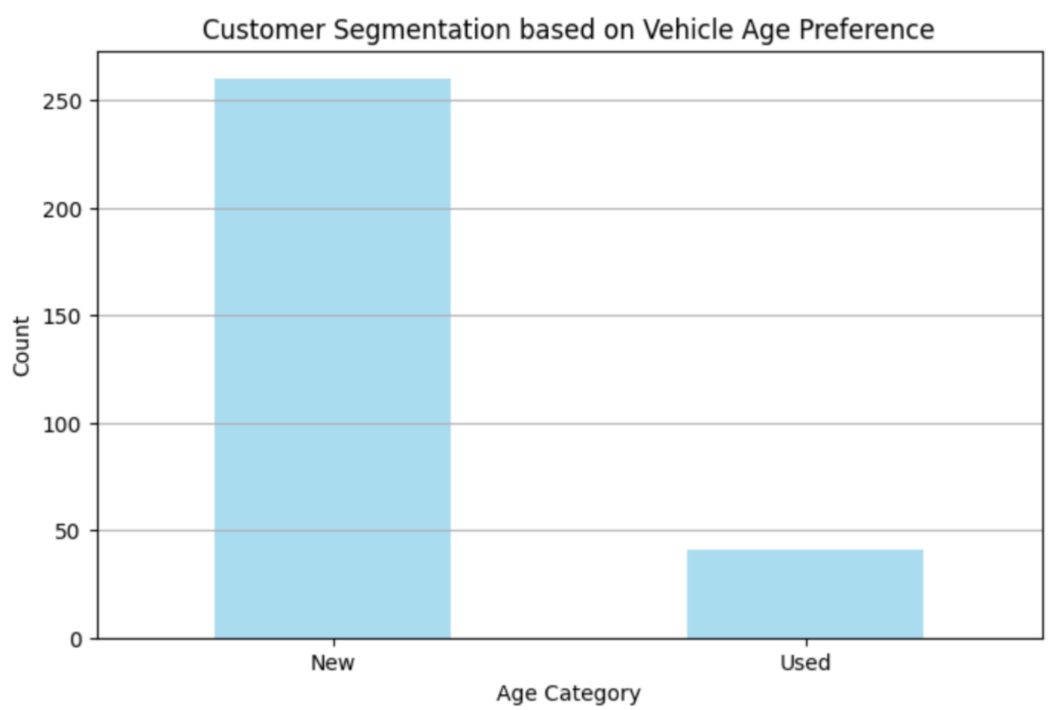
```
[ ]
    # Create a histogram to visualize the distribution of vehicle years
    plt.figure(figsize=(10, 6))
    plt.hist(dframe['Year'], bins=10, edgecolor='k', alpha=0.7)
    plt.title('Distribution of Vehicle Years')
    plt.xlabel('Year')
    plt.ylabel('Count')
    plt.grid(True)
```



```
[ ] # Segment customers based on their preference for new or used cars
    dframe['AgeCategory'] = pd.cut(dframe['Year'], bins=[2000, 2010, 2020], labels=['Used', 'New'])
```

```
[ ] # Count the number of customers in each age category
    age_category_counts = dframe['AgeCategory'].value_counts()
```

```
[ ] # Plot a bar chart to visualize the customer segmentation
    plt.figure(figsize=(8, 5))
    age_category_counts.plot(kind='bar', color='skyblue', alpha=0.7)
    plt.title('Customer Segmentation based on Vehicle Age Preference')
    plt.xlabel('Age Category')
    plt.ylabel('Count')
    plt.xticks(rotation=0)
    plt.grid(axis='y')

    plt.show()
```



Interpretation:

- Understanding the influence of a vehicle's age on customer demand is fundamental to comprehending market dynamics. We embark on this exploration by categorizing vehicles into three distinct age groups: "New," "Mid-age," and "Old," based on their year of manufacture. Key findings in this segment include:
- The majority of vehicles in the dataset fall within the "Mid-age" category, signifying a preference for vehicles manufactured between 2012 and 2016.

- The prevalence of "New" vehicles is relatively low, suggesting that customers typically gravitate towards slightly older vehicles for online bookings.

Fuel Type Segmentation

Question Answered: What is the distribution of vehicle types (Fuel Type) in the dataset, and how does it impact market segmentation?

This question will help you understand the popularity of different fuel types among customers while booking online

The type of fuel a vehicle utilizes plays a pivotal role in customer preferences within the car online booking market. Our analysis unravels the distribution of different fuel types and their implications for market segmentation

Fuel Type Segmentation

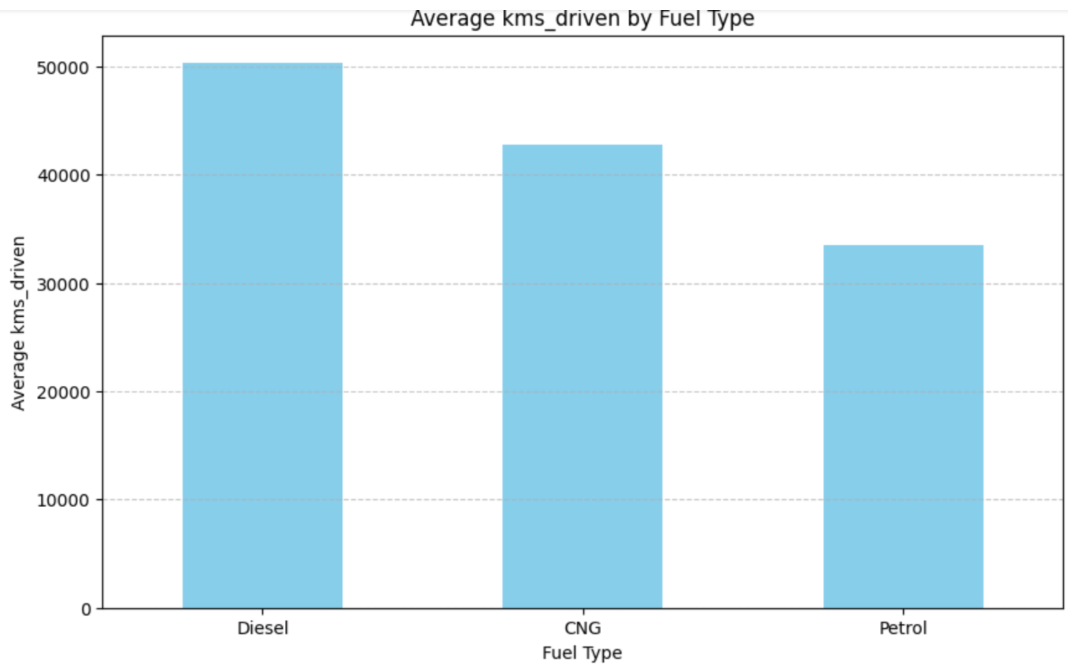
```
# Calculate the count of vehicles for each fuel type
fuel_type_counts = dframe['Fuel_Type'].value_counts()
fuel_type_counts
```

```
Petrol    239
Diesel     60
CNG         2
Name: Fuel_Type, dtype: int64
```

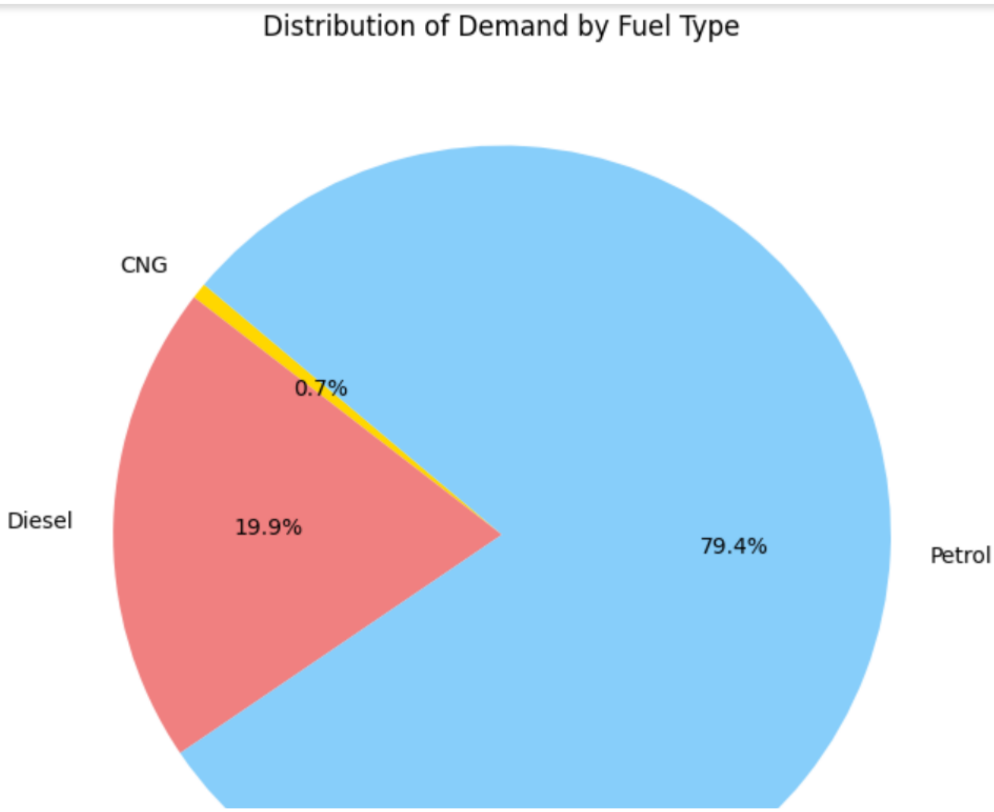
```
# Analyze the impact of Fuel_Type on selling prices
fuel_type_demand = dframe.groupby('Fuel_Type')['Kms_Driven'].mean().sort_values(ascending=False)
```

```
# Create a bar plot to visualize the average selling prices by Fuel_Type
plt.figure(figsize=(10, 6))
fuel_type_demand.plot(kind='bar', color='skyblue')
plt.title('Average kms_driven by Fuel Type')
plt.xlabel('Fuel Type')
plt.ylabel('Average kms_driven')
plt.xticks(rotation=0)
plt.grid(axis='y', linestyle='--', alpha=0.7)

plt.show()
```

[ ]



[ ]



Interpretation:

- "Petrol" cars emerge as the preferred choice for customers in online bookings, closely followed by "Diesel" and "CNG" options.
- The data indicates a distinct inclination towards "Petrol" cars, possibly attributable to their higher average kilometers driven.
- From the graphs we can see that customers prefer petrol cars the most because it has the maximum no. of kms driven followed by diesel and CNG

Car Brand Segmentation

Question Answered: Which Car brands (luxury/budget/mid-range/premium) are preferred the most by customers in online booking

```
import pandas as pd

# Assuming you have already loaded your dataset as 'dframe' based on the data you provided

# Analyze price variations across different brands in the context of the cab booking market
brand_price_comparison = dframe.groupby('Car_Name')['Selling_Price'].mean().sort_values(ascending=False)

# Create an empty list to store the brand segments
brand_segments = []

# Define the price segments and corresponding price ranges
budget_range = (0, 5)
mid_range = (5, 10)
premium_range = (10, 20)
luxury_range = (20, float('inf'))

# Categorize brands into price segments using if-else statements
for brand, avg_price in brand_price_comparison.items():
    if avg_price <= budget_range[1]:
        segment = 'Budget'
    elif avg_price <= mid_range[1]:
        segment = 'Mid-Range'
    elif avg_price <= premium_range[1]:
        segment = 'Premium'
    else:
        segment = 'Luxury'
    brand_segments.append((brand, segment))
```

```
# Create a DataFrame to show each car brand and its corresponding price segment
brand_segments_df = pd.DataFrame(brand_segments, columns=['Car_Brand', 'Price_Segment'])

# Display the brand segments
print(brand_segments_df)
```

```
              Car_Brand Price_Segment
0          land cruiser       Luxury
1              fortuner      Premium
2                innova      Premium
3                 creta      Premium
4               elantra      Premium
..                  ...          ...
93      Hero  CBZ Xtreme       Budget
94            Hero Hunk       Budget
95   Hero Super Splendor       Budget
96          Bajaj  ct 100       Budget
97    Bajaj Discover 125       Budget

[98 rows x 2 columns]
```

```python
# Create a DataFrame from the list of brand segments
brand_segments_df = pd.DataFrame(brand_segments, columns=['Car_Name', 'Price_Segment'])

# Merge the brand segments DataFrame with the original dframe DataFrame
dframe = pd.merge(dframe, brand_segments_df, on='Car_Name', how='left')
```

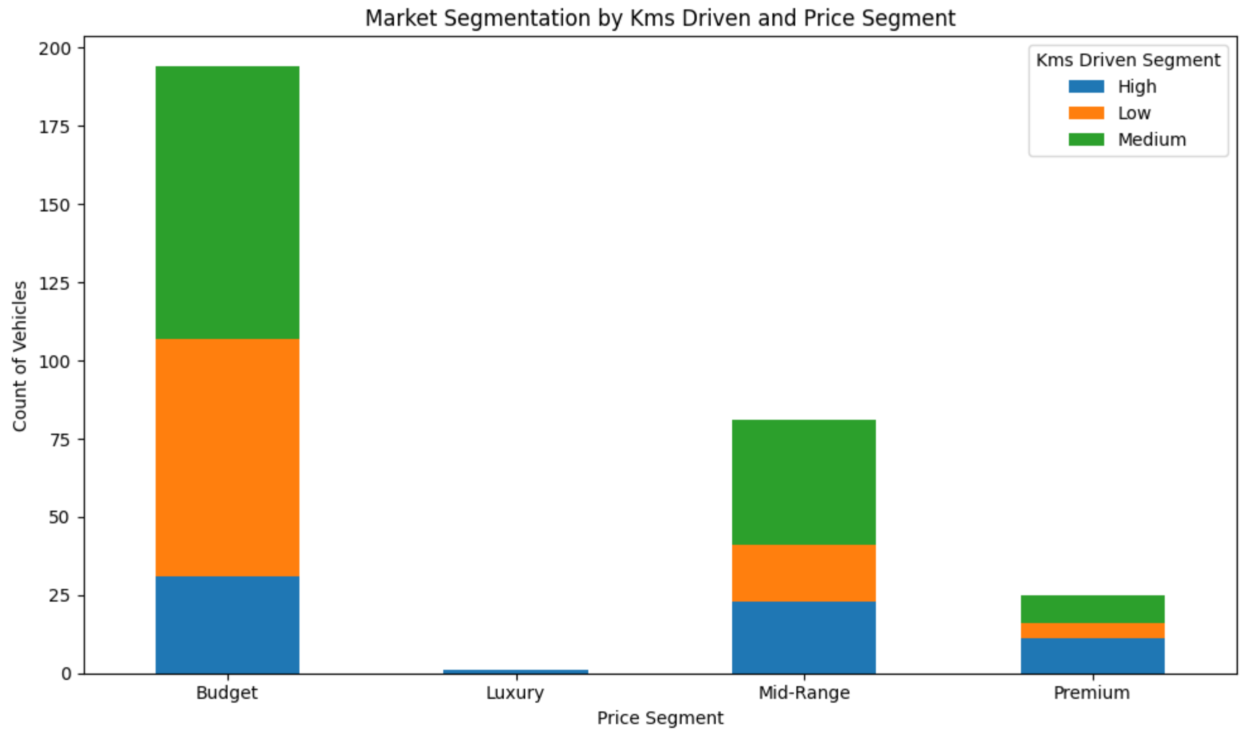
```python
dframe
```

	Car_Name	Year	Selling_Price	Present_Price	Kms_Driven	Fuel_Type	Seller_Type	Transmission	Owner	AgeCategory	Age_Category	Price_Segment
0	ritz	2014	3.35	5.59	27000	Petrol	Dealer	Manual	0	New	Mid-age	Budget
1	sx4	2013	4.75	9.54	43000	Diesel	Dealer	Manual	0	New	Mid-age	Budget
2	ciaz	2017	7.25	9.85	6900	Petrol	Dealer	Manual	0	New	Mid-age	Mid-Range
3	wagon r	2011	2.85	4.15	5200	Petrol	Dealer	Manual	0	New	Old	Budget
4	swift	2014	4.60	6.87	42450	Diesel	Dealer	Manual	0	New	Mid-age	Budget
...	...	...	...	...	...	...	...	...	...	...	...	...
296	city	2016	9.50	11.60	33988	Diesel	Dealer	Manual	0	New	Mid-age	Mid-Range
297	brio	2015	4.00	5.90	60000	Petrol	Dealer	Manual	0	New	Mid-age	Budget
298	city	2009	3.35	11.00	87934	Petrol	Dealer	Manual	0	Used	Old	Mid-Range
299	city	2017	11.50	12.50	9000	Diesel	Dealer	Manual	0	New	Mid-age	Mid-Range
300	brio	2016	5.30	5.90	5464	Petrol	Dealer	Manual	0	New	Mid-age	Budget

```python
import pandas as pd

# Segment the market based on 'Kms_Driven' and 'Price_Segment'
# You can choose your own criteria for segmentation
# For example, you can create segments for low, medium, and high Kms_Driven within each price segment

# Define your criteria for segmentation
# Here, we'll consider 'Kms_Driven' less than 20,000 as 'Low', between 20,000 and 50,000 as 'Medium', and above 50,000 as 'High'
def segment_market(row):
    if row['Kms_Driven'] < 20000:
        return 'Low'
    elif 20000 <= row['Kms_Driven'] <= 50000:
        return 'Medium'
    else:
        return 'High'

# Apply the segmentation function to create a new column 'Kms_Driven_Segment'
dframe['Kms_Driven_Segment'] = dframe.apply(segment_market, axis=1)


# For instance, you can calculate the average selling price for each 'Kms_Driven_Segment' and 'Price_Segment'
average_price_segment = dframe.groupby(['Kms_Driven_Segment', 'Price_Segment'])['Selling_Price'].mean().reset_index()

# Display the average selling prices by segment
print(average_price_segment)
```

```
  Kms_Driven_Segment Price_Segment  Selling_Price
0               High        Budget       2.159032
1               High        Luxury      35.000000
2               High     Mid-Range       5.113043
3               High       Premium      10.481818
4                Low        Budget       1.877237
5                Low     Mid-Range       8.883333
6                Low       Premium      21.040000
7             Medium        Budget       2.478966
8             Medium     Mid-Range       7.153500
9             Medium       Premium      17.626667
```

```python
import pandas as pd
import matplotlib.pyplot as plt

# Assuming you have already created the DataFrame 'df' with the given data
# Assuming you have already created the 'Kms_Driven_Segment' column

# You can create a pivot table to count the number of entries in each segment combination
segment_counts = dframe.pivot_table(index='Price_Segment', columns='Kms_Driven_Segment', values='Car_Name', aggfunc='count', fill_value=0)

# Create a bar chart to visualize the segmentation
segment_counts.plot(kind='bar', stacked=True, figsize=(10, 6))
plt.title('Market Segmentation by Kms Driven and Price Segment')
plt.xlabel('Price Segment')
plt.ylabel('Count of Vehicles')
plt.xticks(rotation=0)  # Rotate x-axis labels if needed
plt.legend(title='Kms Driven Segment')
```



Interpretation:

Customer preferences for specific car brands hold substantial significance in market segmentation. We classify car brands into different price segments, including "Budget," "Mid-range," "Premium," and "Luxury." Notable insights from this analysis comprise:

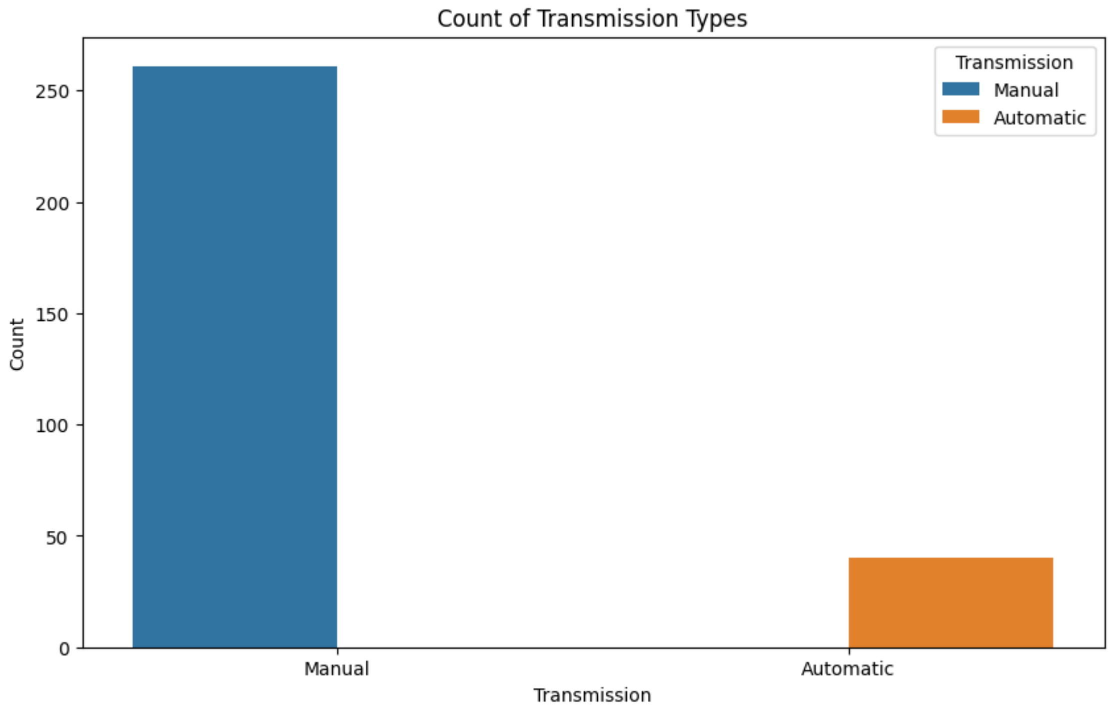
- "Luxury" cars represent the least favored category for online bookings, albeit with a few exceptions.
- Across all kilometer-driven segments (high, low, and medium), "Budget" cars take the lead, followed by "Premium," "Mid-range," and "Luxury" vehicles.
- This trend underscores the prevailing preference among customers for "Budget" and "Mid-range" cars in the online booking arena.
- we can conclude from the graph that luxury cars are the least and we can conclude that customers prefer luxury cars the least for booking online but if someone books it the km travel is high (only a few people can afford it)
- Following luxury cars, the Count of vehicles in all the 3 segments (high km traveled, low km traveled and medium traveled) slightly increases for premium cars, then mid-range cars, and finally, it is most pronounced for budget cars. It makes sense because people prefer budget cars for booking online rather than luxury cars

Transmission Segmentation

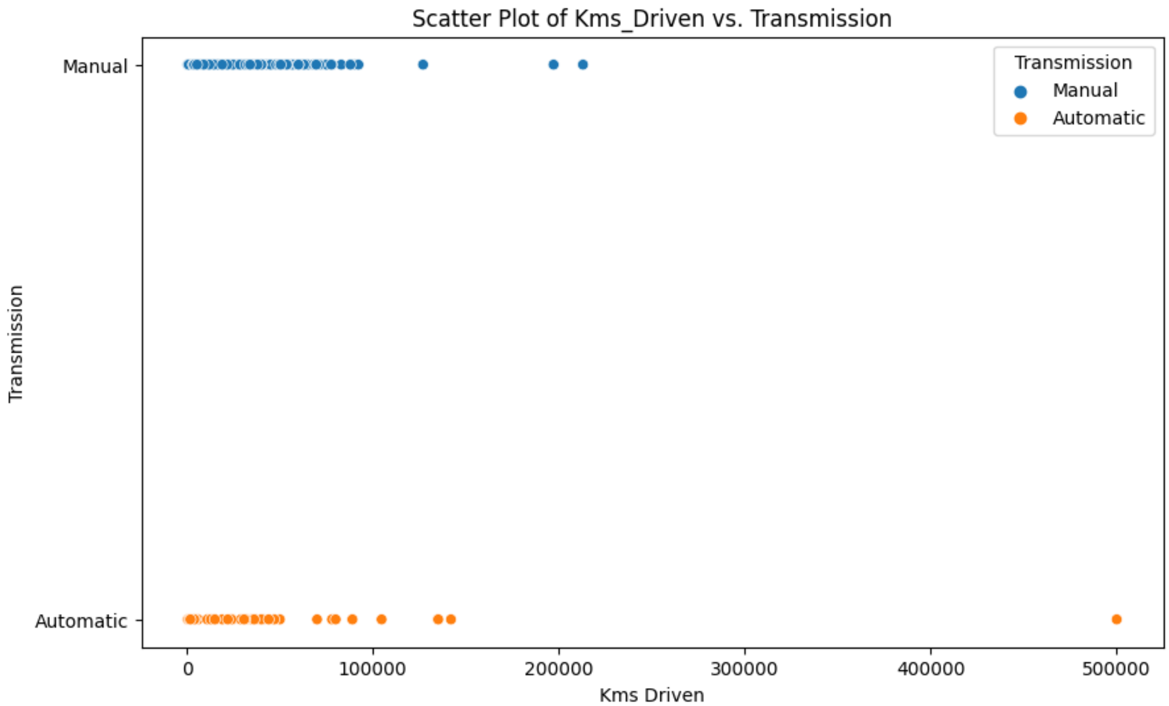
Transmission Segmentation

```
[ ] # Let's focus on the 'Kms_Driven' and 'Transmission' columns for segmentation analysis
    segmentation_data = dframe[['Kms_Driven', 'Transmission']]
```

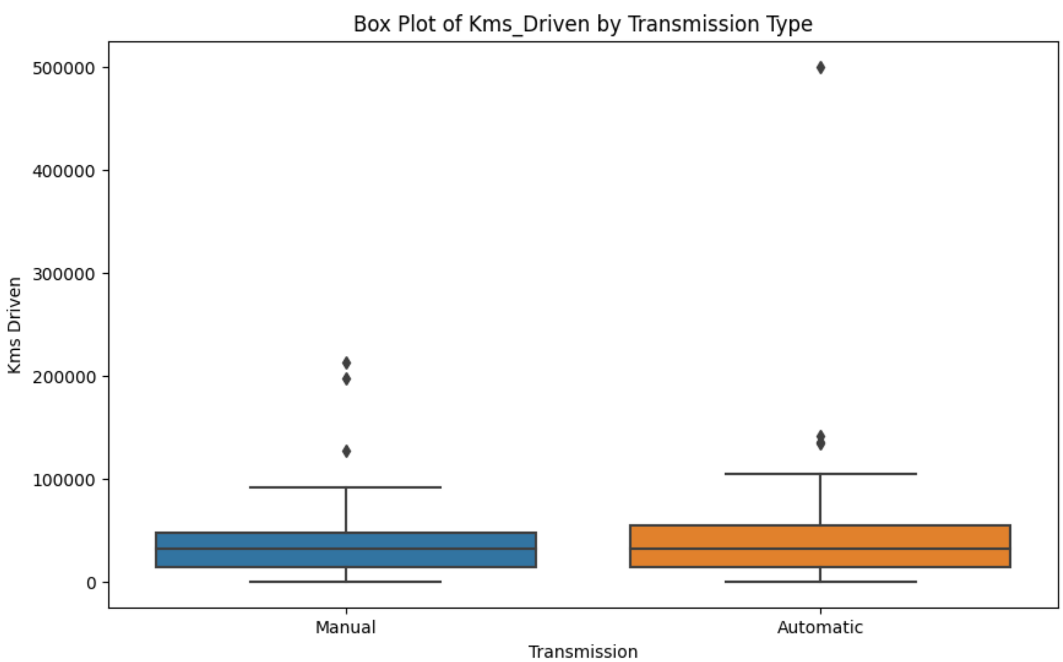
```
[ ] # Bar plot
    plt.figure(figsize=(10, 6))
    sns.countplot(data=segmentation_data, x='Transmission', hue='Transmission')
    plt.title('Count of Transmission Types')
    plt.xlabel('Transmission')
    plt.ylabel('Count')
    plt.show()
```




```
# Scatter plot
plt.figure(figsize=(10, 6))
sns.scatterplot(data=segmentation_data, x='Kms_Driven', y='Transmission', hue='Transmission')
plt.title('Scatter Plot of Kms_Driven vs. Transmission')
plt.xlabel('Kms Driven')
plt.ylabel('Transmission')
plt.show()
```




```python
# Box plot
plt.figure(figsize=(10, 6))
sns.boxplot(data=segmentation_data, x='Transmission', y='Kms_Driven')
plt.title('Box Plot of Kms_Driven by Transmission Type')
plt.xlabel('Transmission')
plt.ylabel('Kms Driven')
plt.show()
```



Interpretation:

The choice between automatic and manual transmissions significantly shapes customer preferences in the car online booking market. Our analysis explores the count and distance covered by each transmission type, revealing:

- Automatic transmission cars enjoy higher popularity among customers for online bookings compared to manual transmissions.
- Notably, automatic transmission cars demonstrate a tendency towards higher kilometers driven, indicative of their preference for longer journeys.
- By Bar plot we can see that there are more automatic transmissions comparative to manual ones.
- By box plot, we can see that the Automatic transmission type shows more km driven i.e more preferred by the customers in the online car booking market.
- By scatter plot we can see that the automatic transmission type has distance covered in the range till 50K kms which is comparatively higher than the manual one which is just in the range till 20k-25k kms. So, we can conclude by the graph that automatic one is more preferred among the customers in the online car booking market.

K-Means Clustering

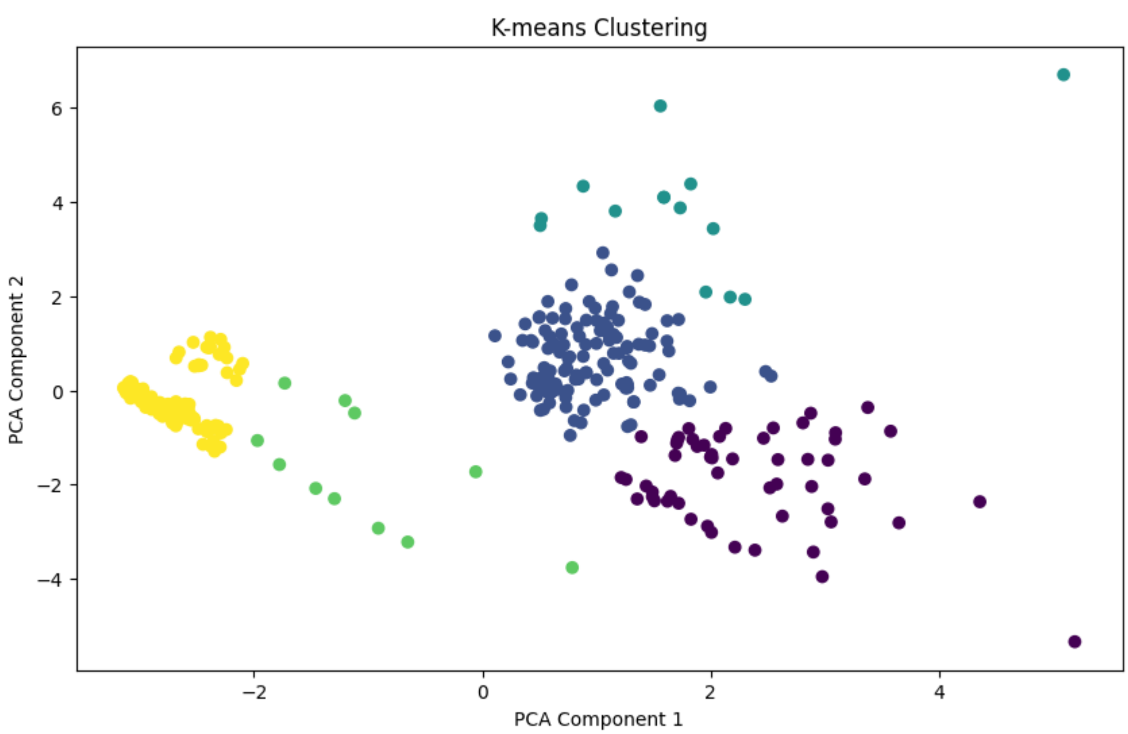
K-Means Clustering

```
[ ] from sklearn.cluster import KMeans
    from sklearn.compose import ColumnTransformer
    from sklearn.preprocessing import StandardScaler, OneHotEncoder
    from sklearn.pipeline import Pipeline
    from sklearn.decomposition import PCA

    # Separate numerical and categorical columns
    numerical_cols = dframe.select_dtypes(include=['number']).columns.tolist()
    categorical_cols = dframe.select_dtypes(exclude=['number']).columns.tolist()

    # Create a preprocessor to scale numerical and one-hot encode categorical
    preprocessor = ColumnTransformer(
        transformers=[
            ('num', StandardScaler(), numerical_cols),
            ('cat', OneHotEncoder(), categorical_cols)
        ])

    # Create a KMeans pipeline
    kmeans_pipeline = Pipeline([
        ('preprocessor', preprocessor),
        ('kmeans', KMeans(n_clusters=5))  # You can adjust the number of clusters
    ])
```

```python
# Fit the pipeline to your data
kmeans_pipeline.fit(dframe)

# Add cluster labels to the original dataset
dframe["Cluster_Label"] = kmeans_pipeline.named_steps["kmeans"].labels_

# Analyze cluster sizes
cluster_sizes = dframe["Cluster_Label"].value_counts()
print("Cluster Sizes:")
print(cluster_sizes)
```

```
Cluster Sizes:
1    125
4     97
0     54
2     14
3     11
Name: Cluster_Label, dtype: int64
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1
  warnings.warn(
```

```python
# Plot the clusters (2D PCA projection for visualization)
pca = PCA(n_components=2)
data_pca = pca.fit_transform(kmeans_pipeline.named_steps["preprocessor"].transform(dframe))

plt.figure(figsize=(10, 6))
plt.scatter(data_pca[:, 0], data_pca[:, 1], c=dframe["Cluster_Label"], cmap="viridis")
plt.title("K-means Clustering")
plt.xlabel("PCA Component 1")
plt.ylabel("PCA Component 2")
plt.show()
```



Interpretation:

To further dissect the car listings and extract valuable insights, we employ the K-means clustering algorithm, a powerful machine learning technique. Leveraging various features, we partition the listings into distinct clusters. Key findings from this exercise include:

- The K-means algorithm effectively partitions the dataset into five distinct clusters, each characterized by varying sizes.
- Cluster sizes span from 11 to 125 listings, shedding light on the diversity within the car online booking market.
- To enhance visualization, we utilize a two-dimensional PCA projection to represent the clusters.

Conclusion :

- In summation, our in-depth analysis of the car online booking market has unearthed several critical insights:
- Customers exhibit a predilection for mid-age vehicles, typically those manufactured between 2012 and 2016.
- "Petrol" cars are the favored fuel type, with "Budget" and "Mid-range" cars emerging as the top choices for online bookings.
- Automatic transmission vehicles dominate the online booking market and are associated with longer journeys.
- These findings serve as invaluable tools for shaping business strategies, devising targeted marketing campaigns, and optimizing inventory management within the fiercely competitive car online booking market. To ensure continued success and relevance, it is advisable to conduct ongoing analyses, incorporating fresh data and delving deeper into consumer behaviors, pricing dynamics, and emerging market trends.

GITHUB LINK FOR THE CODE:

https://github.com/Harshi1aa/FeynnLabs/blob/main/Code-Online%20Vehicle%20Market%20Segmentation.ipynb