Data Assessment – 1

Tasks:

Day 2: Data Processing and Analysis

- 1. **Data Processing**
- o Use Pandas to:
- § Clean the dataset (handle missing values, format dates)
- § Create derived features relevant to the chosen dataset
- § Aggregate data for meaningful analysis
- 2. **Exploratory Analysis**
- o Use Jupyter Notebooks to:
- § Generate descriptive statistics
- § Create visualizations using Matplotlib
- § Document key findings and insights
- § Explore relationships between variables

Solution:

1. Import required packages:

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

[2] ✓ 7.2s

2. Import the dataset

```
df = pd.read_csv('Toyota.csv')
df
```

[3] ✓ 0.0s

	Unnamed: 0	Price	Age	KM	FuelType	HP	MetColor	Automatic	CC	Doors	Weight
0	0	13500	23.0	46986	Diesel	90	1.0	0	2000	three	1165
1	1	13750	23.0	72937	Diesel	90	1.0	0	2000	3	1165
2	2	13950	24.0	41711	Diesel	90	NaN	0	2000	3	1165
3	3	14950	26.0	48000	Diesel	90	0.0	0	2000	3	1165
4	4	13750	30.0	38500	Diesel	90	0.0	0	2000	3	1170
...	...	...	...	...	...	...	...	...	...	...	...
1431	1431	7500	NaN	20544	Petrol	86	1.0	0	1300	3	1025
1432	1432	10845	72.0	??	Petrol	86	0.0	0	1300	3	1015
1433	1433	8500	NaN	17016	Petrol	86	0.0	0	1300	3	1015
1434	1434	7250	70.0	??	NaN	86	1.0	0	1300	3	1015
1435	1435	6950	76.0	1	Petrol	110	0.0	0	1600	5	1114

1436 rows × 11 columns

3. Get information about the dataset

```
df.info()
```

[4] ✓ 0.0s

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1436 entries, 0 to 1435
Data columns (total 11 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   Unnamed: 0  1436 non-null   int64  
 1   Price       1436 non-null   int64  
 2   Age         1336 non-null   float64
 3   KM          1436 non-null   object 
 4   FuelType    1336 non-null   object 
 5   HP          1436 non-null   object 
 6   MetColor    1286 non-null   float64
 7   Automatic   1436 non-null   int64  
 8   CC          1436 non-null   int64  
 9   Doors       1436 non-null   object 
 10  Weight      1436 non-null   int64  
dtypes: float64(2), int64(5), object(4)
memory usage: 123.5+ KB
```

4. Dropping the unwanted column named 'unnamed'

```
df.drop(columns=['Unnamed: 0'], inplace=True, errors='ignore')
[5] ✓ 0.0s

df.columns
[6] ✓ 0.0s
... Index(['Price', 'Age', 'KM', 'FuelType', 'HP', 'MetColor', 'Automatic', 'CC',
       'Doors', 'Weight'],
      dtype='object')
```

5. Check for null values

```
df.isnull().sum()
[7] ✓ 0.0s
... Price          0
    Age          100
    KM             0
    FuelType     100
    HP             0
    MetColor     150
    Automatic      0
    CC             0
    Doors          0
    Weight         0
    dtype: int64
```

6. Clean the data (missing values, wrong data types and question mark)

```
# Replace ?? with NaN
df.replace("??", np.nan, inplace=True)

# Convert data types
df['KM'] = df['KM'].str.replace(',', '').astype(float)
df['HP'] = pd.to_numeric(df['HP'], errors='coerce')
df['Doors'] = df['Doors'].replace({'three': 3, 'four': 4, 'five': 5}).astype(float)

#  missing values
df.fillna({
    'Age': df['Age'].median(),
    'KM': df['KM'].median(),
    'HP': df['HP'].median(),
    'FuelType': df['FuelType'].mode()[0],
    'MetColor': df['MetColor'].mode()[0],
    'Doors': df['Doors'].mode()[0]
}, inplace=True)
```

[8] ✓ 0.0s

```
df.isnull().sum()
```

[9] ✓ 0.0s

```
Price        0
Age          0
KM           0
FuelType     0
HP           0
MetColor     0
Automatic    0
CC           0
Doors        0
Weight       0
dtype: int64
```

7. Plot graphs of clean data

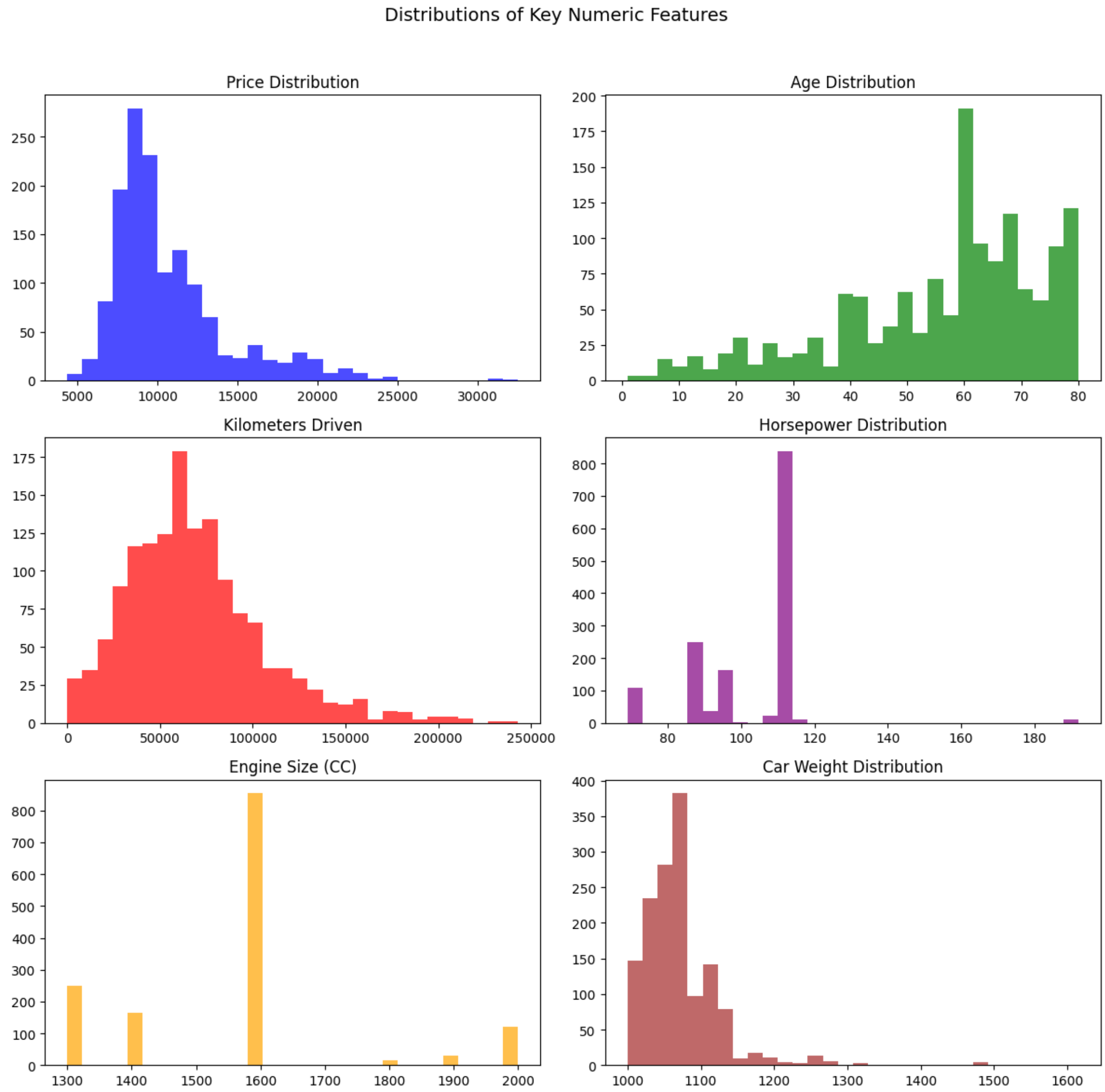
```
# Plot distributions of numeric features
fig, axes = plt.subplots(3, 2, figsize=(12, 12))
fig.suptitle("Distributions of Key Numeric Features", fontsize=14)

axes[0, 0].hist(df['Price'], bins=30, color='blue', alpha=0.7)
axes[0, 0].set_title("Price Distribution")
axes[0, 1].hist(df['Age'], bins=30, color='green', alpha=0.7)
axes[0, 1].set_title("Age Distribution")
axes[1, 0].hist(df['KM'], bins=30, color='red', alpha=0.7)
axes[1, 0].set_title("Kilometers Driven")
axes[1, 1].hist(df['HP'], bins=30, color='purple', alpha=0.7)
axes[1, 1].set_title("Horsepower Distribution")
axes[2, 0].hist(df['CC'], bins=30, color='orange', alpha=0.7)
axes[2, 0].set_title("Engine Size (CC)")
axes[2, 1].hist(df['Weight'], bins=30, color='brown', alpha=0.7)
axes[2, 1].set_title("Car Weight Distribution")

plt.tight_layout(rect=[0, 0, 1, 0.96])
plt.show()
```

[11] ✓ 1.4s

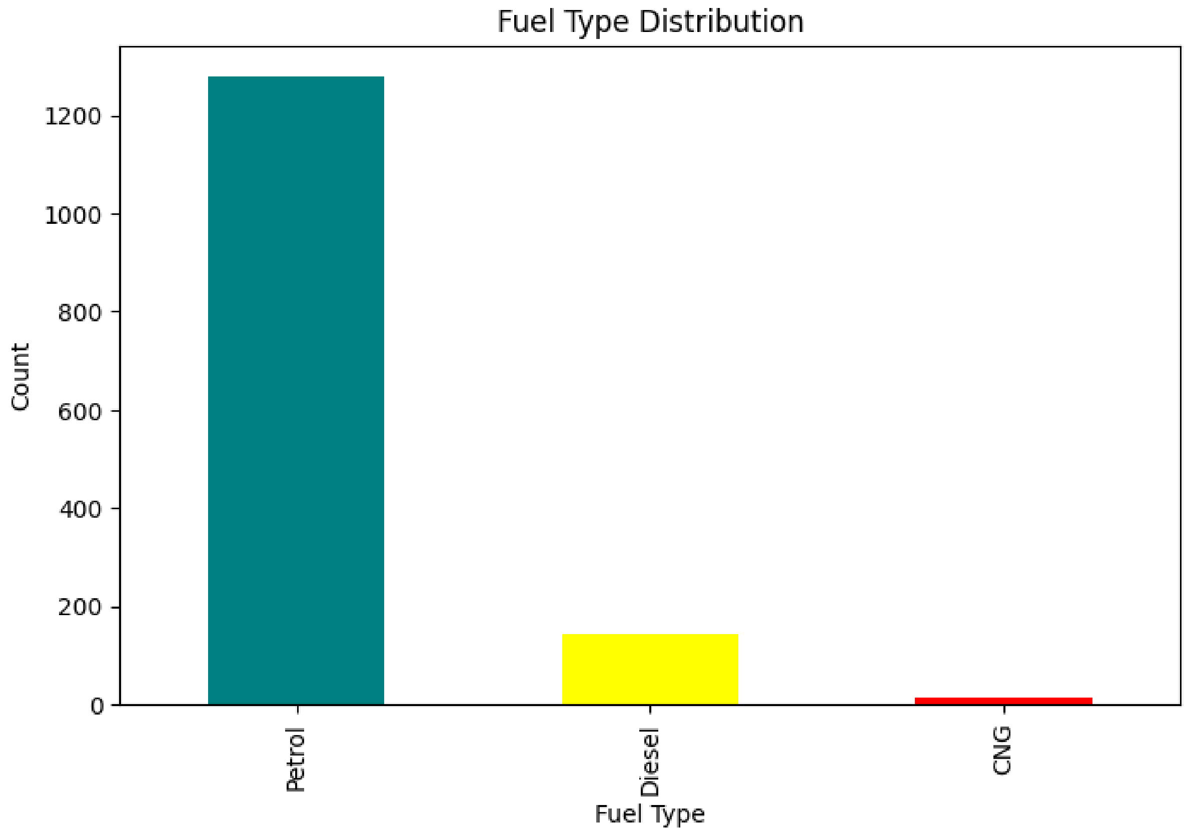
8. Plots of numeric features



9. Fuel type distribution

```
# Fuel Type Distribution
plt.figure(figsize=(8, 5))
df['FuelType'].value_counts().plot(kind='bar', color=['teal', 'yellow', 'red'])
plt.title("Fuel Type Distribution")
plt.xlabel("Fuel Type")
plt.ylabel("Count")
plt.show()
```

[15] ✓ 0.1s



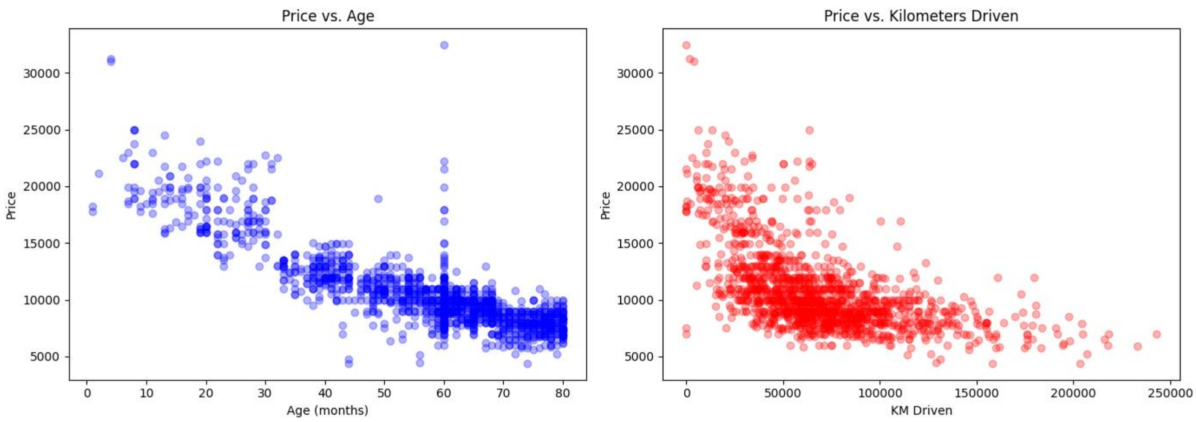
10. Plots for relationships between features

```
# Scatter plots for relationships between key variables
fig, axes = plt.subplots(1, 2, figsize=(14, 5))

axes[0].scatter(df["Age"], df["Price"], alpha=0.3, color='blue')
axes[0].set_title("Price vs. Age")
axes[0].set_xlabel("Age (months)")
axes[0].set_ylabel("Price")

axes[1].scatter(df["KM"], df["Price"], alpha=0.3, color='red')
axes[1].set_title("Price vs. Kilometers Driven")
axes[1].set_xlabel("KM Driven")
axes[1].set_ylabel("Price")

plt.tight_layout()
plt.show()
```
[17] ✓ 0.3s



11. Insights

- **Price vs. Age**: Older cars have lower prices
- **Price vs. KM Driven**: Cars with higher kilometers driven have lower prices.
- **Fuel Type Popularity**: Petrol cars are the most common, followed by diesel, with very few LPG cars in the dataset.
- **Horsepower & Price**: Cars with higher horsepower have higher prices.