Assignment Code: DA-AG-009 EDA | Assignment

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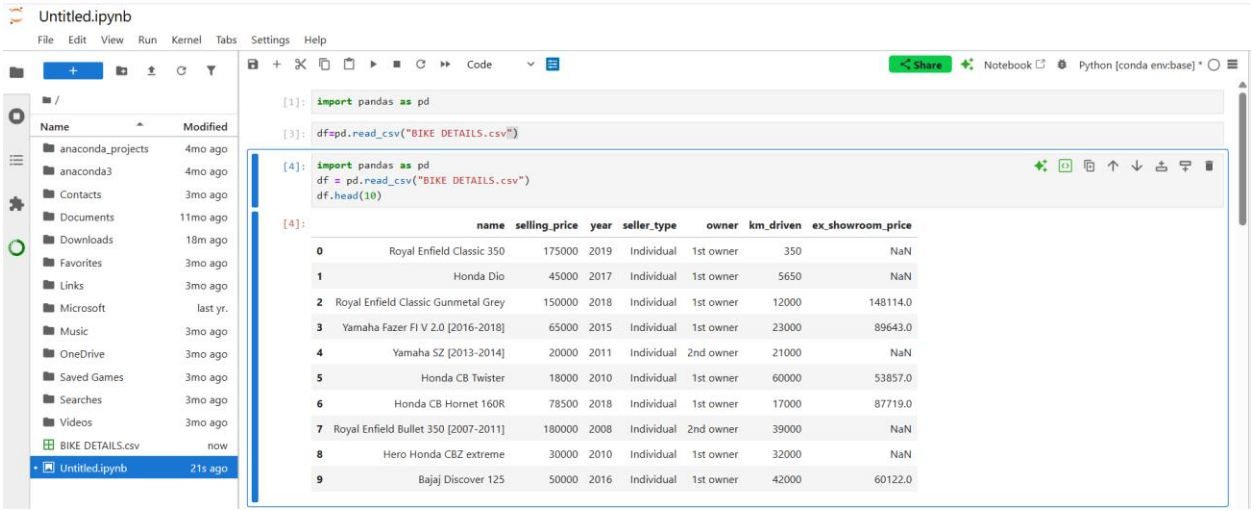
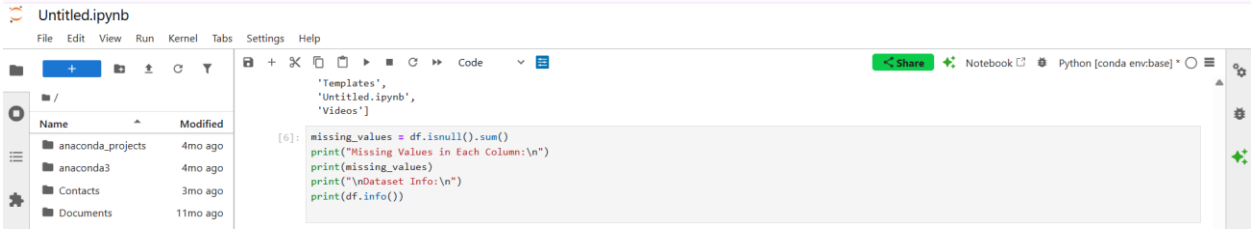
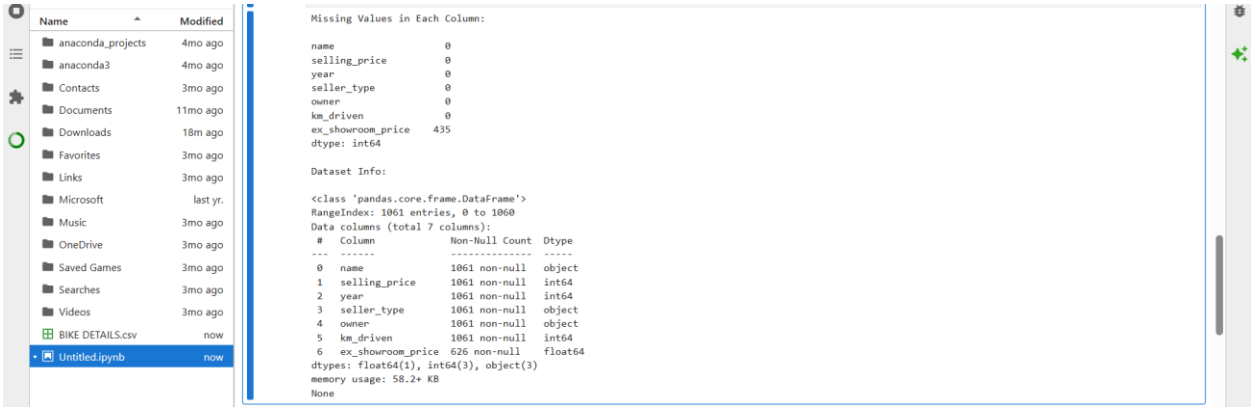
Question 1: Read the Bike Details dataset into a Pandas DataFrame and display its first 10 rows.



Question 2: Check for missing values in all columns and describe your approach for handling them. (Include your Python code and output in the code box below.)

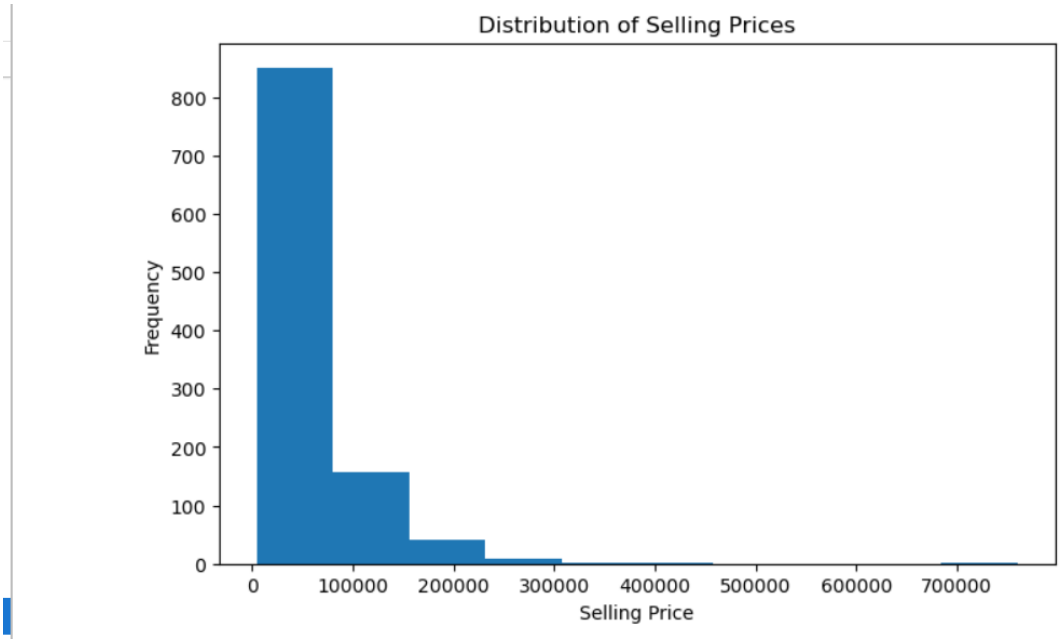




Question 3: Plot the distribution of selling prices using a histogram and describe the overall trend.

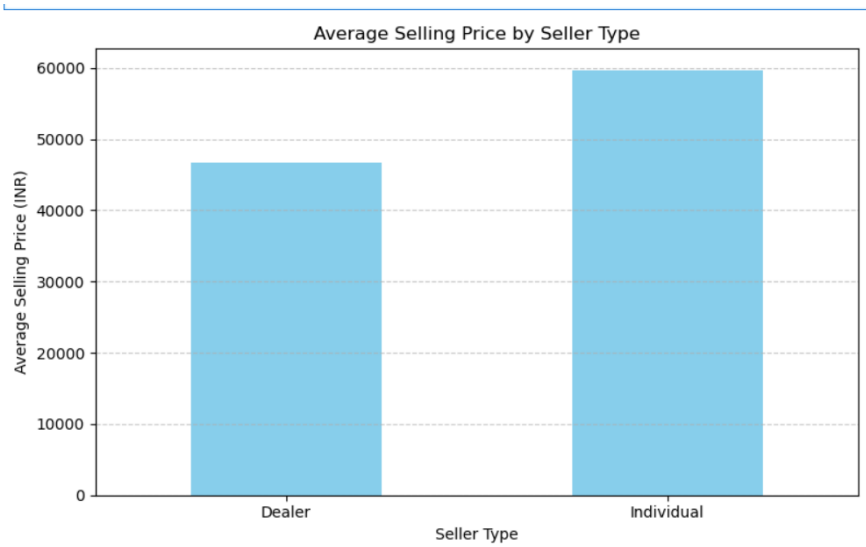
(Include your Python code and output in the code box below.)

```
[7]: import matplotlib.pyplot as plt
     plt.figure(figsize=(8,5))
     plt.hist(df['selling_price'].dropna())
     plt.xlabel("Selling Price")
     plt.ylabel("Frequency")
     plt.title("Distribution of Selling Prices")
     plt.show()
```



Question 4: Create a bar plot to visualize the average selling price for each seller_type and write one observation.

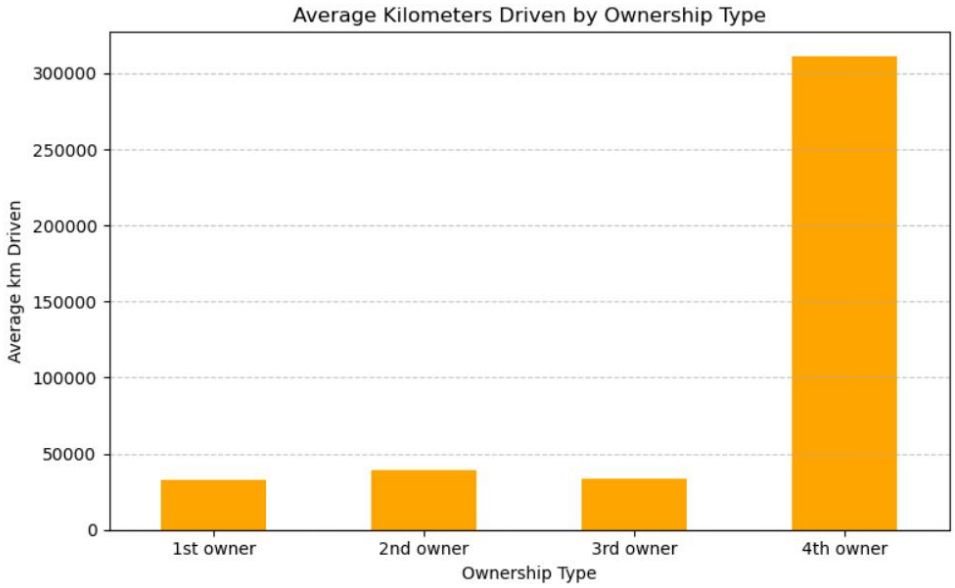
```
•[8]:
df = pd.read_csv("BIKE DETAILS.csv")

# NaN values hatao seller_type aur selling_price ke liye
df_clean = df.dropna(subset=["seller_type", "selling_price"])

# seller_type ke hisaab se average selling price nikaalo
avg_price = df_clean.groupby("seller_type")["selling_price"].mean()

# Bar plot banao
plt.figure(figsize=(8, 5))
avg_price.plot(kind="bar", color="skyblue")
plt.title("Average Selling Price by Seller Type")
plt.xlabel("Seller Type")
plt.ylabel("Average Selling Price (INR)")
plt.xticks(rotation=0)
plt.grid(axis="y", linestyle="--", alpha=0.7)
plt.tight_layout()
plt.show()
```



Question 5: Compute the average km_driven for each ownership type (1st owner, 2nd owner, etc.), and present the result as a bar plot.

[9]:

```
df = pd.read_csv("BIKE DETAILS.csv")

# NaN values hatao owner aur km_driven ke liye
df_clean = df.dropna(subset=["owner", "km_driven"])

# owner ke hisaab se average km_driven nikaalo
avg_km = df_clean.groupby("owner")["km_driven"].mean()

# Bar plot banao
plt.figure(figsize=(8, 5))
avg_km.plot(kind="bar", color="orange")
plt.title("Average Kilometers Driven by Ownership Type")
plt.xlabel("Ownership Type")
plt.ylabel("Average km Driven")
plt.xticks(rotation=0)
plt.grid(axis="y", linestyle="--", alpha=0.7)
plt.tight_layout()
plt.show()
```



Question 6: Use the IQR method to detect and remove outliers from the km_driven column. Show before-and-after summary statistics.

[10]:

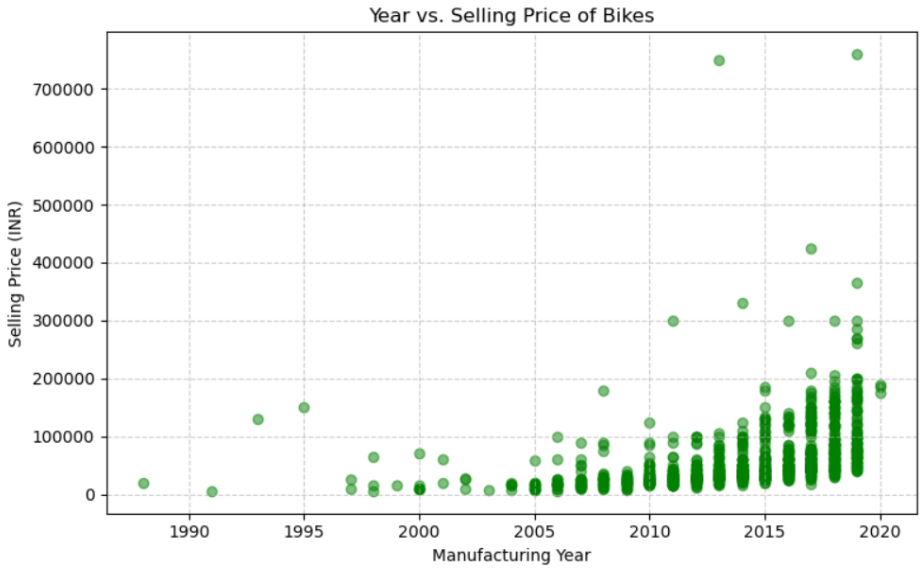
```
df = pd.read_csv("BIKE DETAILS.csv")


df_clean = df.dropna(subset=["km_driven"])


print("Before removing outliers:")
print(df_clean["km_driven"].describe())


Q1 = df_clean["km_driven"].quantile(0.25)
Q3 = df_clean["km_driven"].quantile(0.75)
IQR = Q3 - Q1


lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR


df_no_outliers = df_clean[(df_clean["km_driven"] >= lower_bound) & (df_clean["km_driven"] <= upper_bound)]


print("\nAfter removing outliers:")
print(df_no_outliers["km_driven"].describe())
```

```
Before removing outliers:
count      1061.000000
mean      34359.833176
std       51623.152702
min         350.000000
25%       13500.000000
50%       25000.000000
75%       43000.000000
max      880000.000000
Name: km_driven, dtype: float64

After removing outliers:
count     1022.000000
mean     28203.415851
std      19552.083583
min        350.000000
25%      13000.000000
50%      24000.000000
75%      40000.000000
max      86000.000000
Name: km_driven, dtype: float64
```

Question 7: Create a scatter plot of year vs. selling_price to explore the relationship between a bike's age and its price.

[11]:

```
df = pd.read_csv("BIKE DETAILS.csv")


df_clean = df.dropna(subset=["year", "selling_price"])


plt.figure(figsize=(8, 5))
plt.scatter(df_clean["year"], df_clean["selling_price"], alpha=0.5, color="green")
plt.title("Year vs. Selling Price of Bikes")
plt.xlabel("Manufacturing Year")
plt.ylabel("Selling Price (INR)")
plt.grid(True, linestyle="--", alpha=0.6)
plt.tight_layout()
plt.show()
```



Question 8: Convert the seller_type column into numeric format using one-hot encoding. Display the first 5 rows of the resulting DataFrame.

[12]:

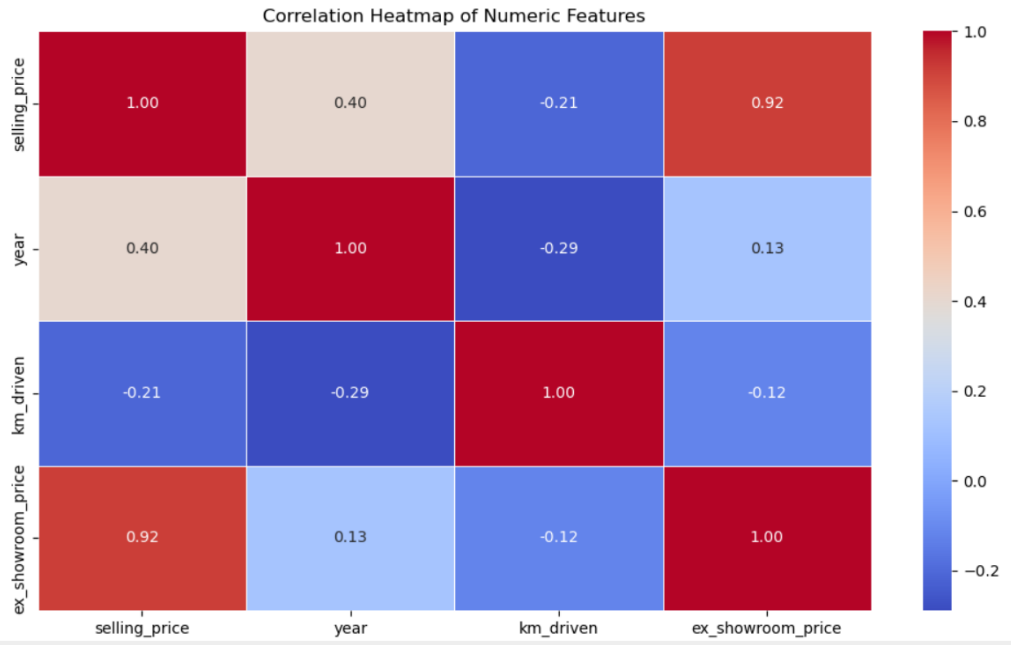
```
df = pd.read_csv("BIKE DETAILS.csv")

df_encoded = pd.get_dummies(df, columns=["seller_type"])


print(df_encoded.head())
```

```
                              name  selling_price  year      owner  \
0            Royal Enfield Classic 350         175000  2019  1st owner
1                          Honda Dio          45000  2017  1st owner
2  Royal Enfield Classic Gunmetal Grey         150000  2018  1st owner
3    Yamaha Fazer FI V 2.0 [2016-2018]          65000  2015  1st owner
4                Yamaha SZ [2013-2014]          20000  2011  2nd owner

   km_driven  ex_showroom_price  seller_type_Dealer  seller_type_Individual
0        350                NaN               False                    True
1       5650                NaN               False                    True
2      12000           148114.0               False                    True
3      23000            89643.0               False                    True
4      21000                NaN               False                    True
```

Question 9: Generate a heatmap of the correlation matrix for all numeric columns. What correlations stand out the most?

```
[14]:
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

df = pd.read_csv("BIKE DETAILS.csv")


numeric_df = df.select_dtypes(include=["number"])


corr_matrix = numeric_df.corr()

plt.figure(figsize=(10, 6))
sns.heatmap(corr_matrix, annot=True, cmap="coolwarm", fmt=".2f", linewidths=0.5)
plt.title("Correlation Heatmap of Numeric Features")
plt.tight_layout()
plt.show()
```

Code Share Notebook Python [conda env:b



Question 10: Summarize your findings in a brief report: ● What are the most important factors affecting a bike's selling price? ● Mention any data cleaning or feature engineering you performed.

Key Factors Affecting a Bike's Selling Price

- **Year of Manufacture**: Newer bikes tend to have higher selling prices due to lower depreciation.
- **Kilometers Driven:** Bikes with fewer kilometers driven usually sell for more, indicating less wear and tear.
- **Ownership History**: First-owner bikes are priced higher than second or third-owner bikes, as buyers prefer fewer previous owners.
- **Ex-Showroom Price:** There is a strong positive correlation between the original price and the resale value.
- **Seller Type**: Most listings are from individual sellers, which influences pricing trends in the dataset.

Data Cleaning and Feature Engineering

- **Missing Value Handling:** Removed rows with missing values in critical columns like selling_price, km_driven, and owner.
- **Outlier Removal**: Applied the IQR method to the km_driven column to eliminate extreme values.
- **One-Hot Encoding**: Converted the seller_type column into numeric format using one-hot encoding for modeling.
- **Correlation Analysis**: Generated a heatmap to identify strong relationships between numeric features.