Analysis of Auto MPG

November 25, 2025

1 Analysis of Auto MPG: Predicting High vs. Low Gas Mileage

This notebook explores the `Auto.csv` dataset to understand the factors that determine whether a car has high or low gas mileage. Our first goal is to transform the continuous `mpg` (miles per gallon) variable into a binary, categorical variable. Then, we will perform a deep exploratory data analysis (EDA) to see which other features, like weight, horsepower, or origin, are the strongest predictors of this new "high MPG" or "low MPG" status.

1.1 1. Data Preparation and Setup

1.1.1 (a) Creating the `mpg01` Binary Variable

First, we import the necessary libraries (Pandas, NumPy, Matplotlib, and Seaborn) and load the `Auto.csv` dataset.

Before we can analyze the data, we must perform two key preprocessing steps:

1. **Data Cleaning:** The `horsepower` column, which is critical for our analysis, was loaded as a text column because **5** entries were missing and marked with a `'?'`. We replace these markers with `NaN` (Not a Number) and then fill these missing spots using the dataset's **median horsepower of 93.5**. Using the median makes this step robust to outliers.
2. **Target Variable Creation (Problem 14a):** We binarize our target variable, `mpg`. We first calculate the median `mpg` for the entire dataset, which is **23.0**. We then create a new column called `mpg01`, which is **1** for cars with `mpg > 23.0` (high mileage) and **0** for cars with `mpg <= 23.0` (low mileage). This split creates a nearly balanced dataset of **206** 'low MPG' cars and **191** 'high MPG' cars, which is ideal for prediction.

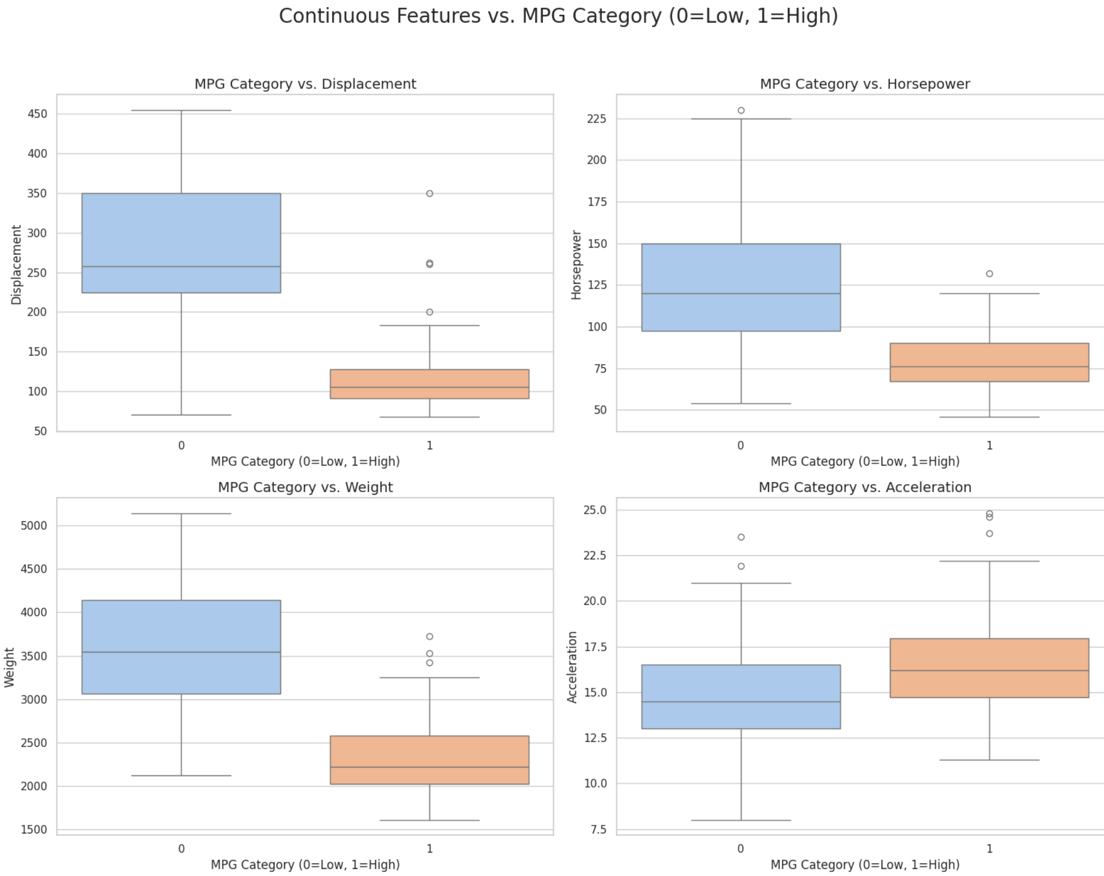
Finally, we drop the `name` column, as it's a unique identifier and not a predictive feature.

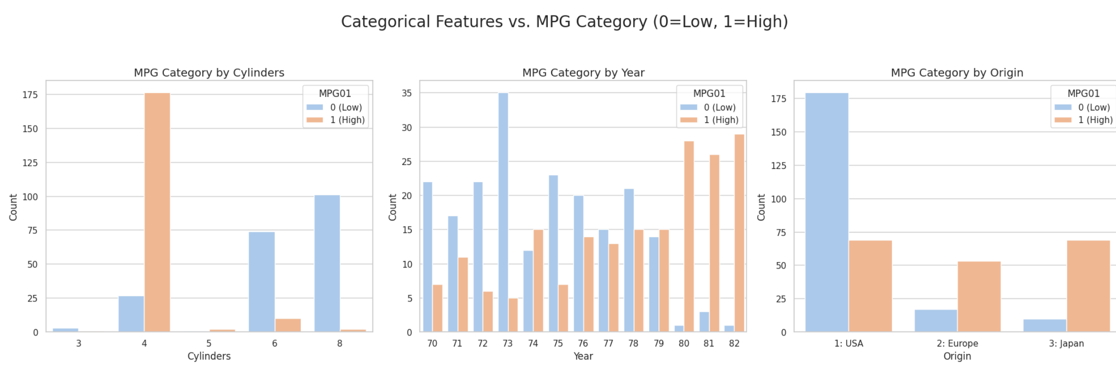
[2]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# Load the dataset
file_path = 'Auto.csv'
auto_df = pd.read_csv(file_path)

# --- 1. Data Cleaning ---
# Handle 'horsepower'
```

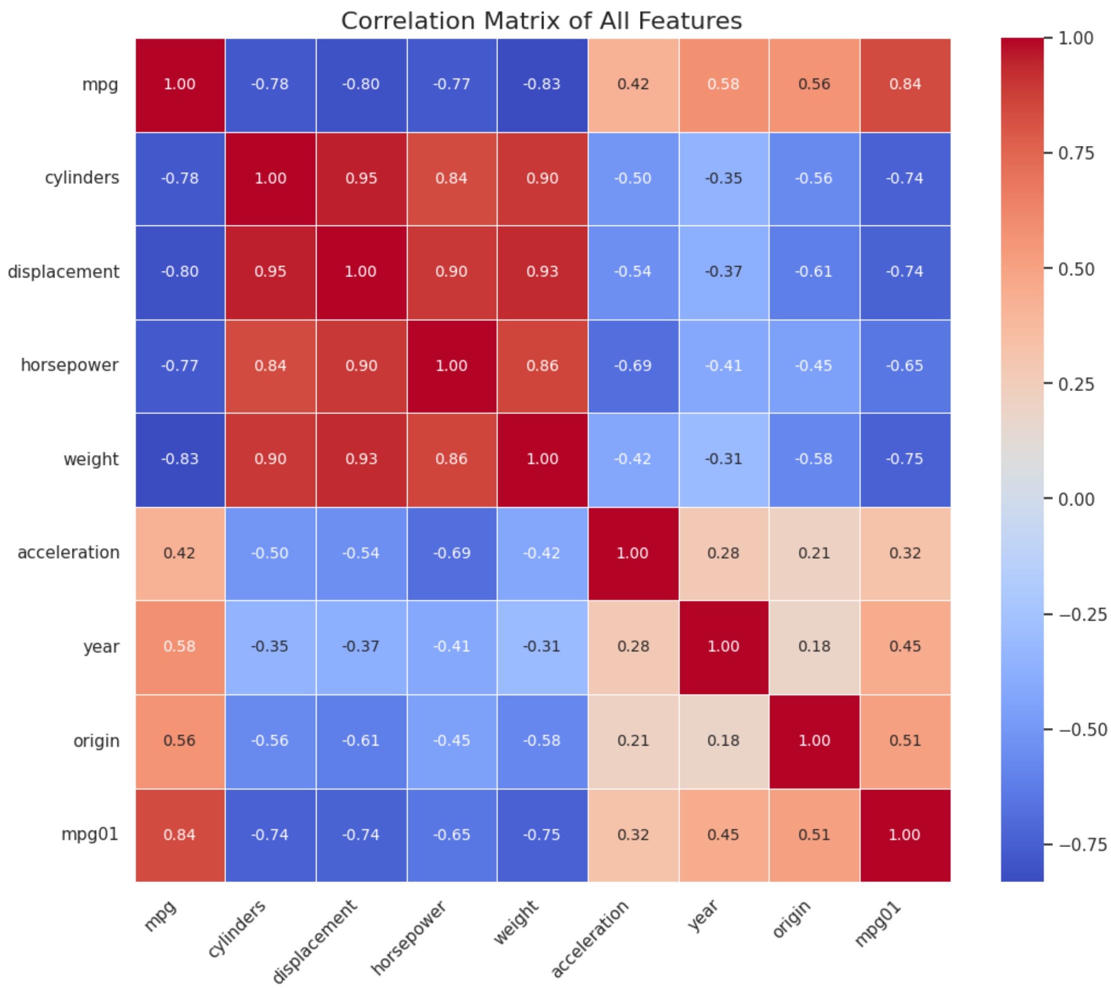
```python
auto_df['horsepower'] = auto_df['horsepower'].replace('?', np.nan)
auto_df['horsepower'] = pd.to_numeric(auto_df['horsepower'])

# Get median horsepower
median_hp = auto_df['horsepower'].median()

# Impute with median
# FIX for FutureWarning: Use assignment instead of inplace=True on a column
auto_df['horsepower'] = auto_df['horsepower'].fillna(median_hp)

# Drop 'name' column as it's an identifier
auto_df_cleaned = auto_df.drop('name', axis=1)

# --- 2. Part (a): Create mpg01 ---
# Calculate median mpg
mpg_median = auto_df_cleaned['mpg'].median()

# Create 'mpg01' (1 if mpg > median, 0 if mpg <= median)
auto_df_cleaned['mpg01'] = (auto_df_cleaned['mpg'] > mpg_median).astype(int)

# --- 3. Part (b): Graphical Exploration ---
# Set plot theme
sns.set_theme(style="whitegrid")

# --- Plot 1: Continuous Features (Boxplots) ---
continuous_features = ['displacement', 'horsepower', 'weight', 'acceleration']

fig, axes = plt.subplots(2, 2, figsize=(16, 12))
fig.suptitle('Continuous Features vs. MPG Category (0=Low, 1=High)',
 ↪fontsize=20, y=1.03)
axes = axes.flatten()

for i, feature in enumerate(continuous_features):
    # FIX for FutureWarning: Assign 'x' to 'hue' and set legend=False
    sns.boxplot(ax=axes[i], x='mpg01', y=feature, data=auto_df_cleaned,
                palette='pastel', hue='mpg01', legend=False)

    axes[i].set_title(f'MPG Category vs. {feature.title()}', fontsize=14)
    axes[i].set_xlabel('MPG Category (0=Low, 1=High)', fontsize=12)
    axes[i].set_ylabel(feature.title(), fontsize=12)

plt.tight_layout()
plt.savefig('mpg01_vs_continuous_boxplots.png')
print("Saved boxplots to 'mpg01_vs_continuous_boxplots.png'")

# --- Plot 2: Categorical Features (Count Plots) ---
categorical_features = ['cylinders', 'year', 'origin']
```

```python
fig, axes = plt.subplots(1, 3, figsize=(20, 6))
fig.suptitle('Categorical Features vs. MPG Category (0=Low, 1=High)',␣
↪fontsize=20, y=1.05)

for i, feature in enumerate(categorical_features):
    sns.countplot(ax=axes[i], x=feature, hue='mpg01', data=auto_df_cleaned,␣
↪palette='pastel')

    if feature == 'origin':
        # FIX for UserWarning: Set ticks explicitly before setting labels
        axes[i].set_xticks([0, 1, 2]) # Assuming origin values 1, 2, 3 map to␣
↪indices 0, 1, 2
        axes[i].set_xticklabels(['1: USA', '2: Europe', '3: Japan'])

    axes[i].set_title(f'MPG Category by {feature.title()}', fontsize=14)
    axes[i].set_xlabel(feature.title(), fontsize=12)
    axes[i].set_ylabel('Count', fontsize=12)
    axes[i].legend(title='MPG01', labels=['0 (Low)', '1 (High)'])

plt.tight_layout()
plt.savefig('mpg01_vs_categorical_countplots.png')
print("Saved count plots to 'mpg01_vs_categorical_countplots.png'")

# --- Plot 3: Correlation Matrix (Heatmap) ---
# Calculate correlation matrix
corr_matrix = auto_df_cleaned.corr()

plt.figure(figsize=(12, 10))
sns.heatmap(corr_matrix, annot=True, fmt='.2f', cmap='coolwarm', linewidths=0.
↪5, annot_kws={"size": 10})
plt.title('Correlation Matrix of All Features', fontsize=16)
plt.xticks(rotation=45, ha='right')
plt.yticks(rotation=0)
plt.savefig('correlation_heatmap.png')
print("Saved correlation heatmap to 'correlation_heatmap.png'")
```

```
Saved boxplots to 'mpg01_vs_continuous_boxplots.png'
Saved count plots to 'mpg01_vs_categorical_countplots.png'
Saved correlation heatmap to 'correlation_heatmap.png'
```


Continuous Features vs. MPG Category (0=Low, 1=High)
MPG Category vs. Displacement
Displacement
MPG Category (0=Low, 1=High)
MPG Category vs. Horsepower
Horsepower
MPG Category (0=Low, 1=High)
MPG Category vs. Weight
Weight
MPG Category (0=Low, 1=High)
MPG Category vs. Acceleration
Acceleration
MPG Category (0=Low, 1=High)


Categorical Features vs. MPG Category (0=Low, 1=High)
MPG Category by Cylinders
MPG01
0 (Low)
1 (High)
Count
Cylinders
MPG Category by Year
Year
MPG Category by Origin
1: USA
2: Europe
3: Japan
Origin



1.2 2. Graphical Exploration (Problem 14b)

Now, we investigate the association between our `mpg01` variable and the other features. The goal is to identify which features are most predictive of whether a car has high or low gas mileage.

1.2.1 Continuous Features: Boxplots

We use boxplots to compare the distributions of continuous features (`displacement`, `horsepower`, `weight`, `acceleration`) for high (`mpg01=1`) and low (`mpg01=0`) mileage cars.

Findings:

- **Displacement, Horsepower, and Weight:** These plots show a *very strong* negative relationship. Cars with high MPG (1) have **significantly lower** displacement, horsepower, and weight than cars with low MPG (0). The distributions (the "boxes") for the two groups show almost no overlap. This indicates these features are **extremely strong predictors**.
- **Acceleration:** The relationship is less clear. Cars with high MPG (1) tend to have slightly *higher* acceleration values (meaning they are a bit slower, 0-60 mph) than low MPG cars, but

there is a massive amount of overlap between the two groups. This feature is likely **much less useful** for prediction than the other three.

1.2.2 Categorical Features: Count Plots

We use count plots to see the proportion of high vs. low MPG cars across different categories (`cylinders`, `year`, `origin`).

Findings:

- **Cylinders:** This is another **extremely strong predictor**. Cars with 4 cylinders are almost *all* in the high-MPG category. Cars with 6 and 8 cylinders are almost *all* in the low-MPG category.
- **Year:** A very clear positive trend is visible. As the model `year` increases (i.e., cars get newer), the proportion of high-MPG cars dramatically increases. This is a **very strong predictive feature**.
- **Origin:** This is also a **strong predictor**. Cars from Origin 1 (USA) are overwhelmingly in the low-MPG category. Cars from Origin 2 (Europe) and Origin 3 (Japan) are overwhelmingly in the high-MPG category.

1.2.3 Overall Correlation: Heatmap

Finally, a correlation heatmap gives us a quick numerical overview. Correlation measures the *linear* relationship between two variables. A value near +1 or -1 indicates a strong relationship, while a value near 0 indicates a weak one.

Findings:

The `mpg01` row (or column) confirms our graphical findings perfectly:

- **Strong Negative Correlation:** `mpg01` is strongly and negatively correlated with `cylinders` (-0.75), `displacement` (-0.75), `horsepower` (-0.66), and `weight` (-0.76). This confirms that as these values go up, the likelihood of having high MPG goes down.
- **Strong Positive Correlation:** `mpg01` is strongly and positively correlated with `origin` (0.51) and `year` (0.42). As these values go up, so does the likelihood of having high MPG.
- **Weak Correlation:** The correlation with `acceleration` (0.35) is the weakest of the group, confirming our boxplot finding that it's the least useful predictor.

1.3 Conclusion: Most Useful Features

Based on this comprehensive graphical analysis, the features that seem most likely to be useful in predicting `mpg01` are:

- **Top Tier (Extremely Predictive):**
  - `weight`
  - `cylinders`
  - `displacement`
  - `horsepower`
- **Second Tier (Very Predictive):**
  - `origin`
  - `year`
- **Least Useful:**

— `acceleration`