Lab Task 4

Name: Tazmeen Afroz
Roll No: 22p-9252
Section: BAI-5A

Basic Insights

In [23]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn.preprocessing



df = pd.read_csv('auto-mpg.csv')
df.head()
```

Out[23]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model year	origin	car na
0	18.0	8	307.0	130	3504	12.0	70	1	chevr chev ma
1	15.0	8	350.0	165	3693	11.5	70	1	b sky
2	18.0	8	318.0	150	3436	11.0	70	1	plymo sate
3	16.0	8	304.0	150	3433	12.0	70	1	rebe
4	17.0	8	302.0	140	3449	10.5	70	1	l to

Column Name	Description	Data Type	Range/Units	Notes
mpg	Miles per gallon	Continuous	9.0 - 46.6	Target variable; measure of fuel efficiency
cylinders	Number of cylinders in the engine	Discrete	3 - 8	Categorical, but represented as integers
displacement	Engine displacement	Continuous	68 - 455	Measured in cubic inches
horsepower	Engine horsepower	Continuous	46 - 230	Contains some missing values (denoted as '?')
weight	Vehicle weight	Continuous	1613 - 5140	Measured in pounds

Column Name	Description	Data Type	Range/Units	Notes
acceleration	Time to accelerate from 0 to 60 mph	Continuous	8.0 - 24.8	Measured in seconds
model year	Model year of the vehicle	Discrete	70 - 82	Represents model years 1970 to 1982
origin	Origin of the vehicle	Categorical	1, 2, 3	1 = USA, 2 = Europe, 3 = Japan
car name	Name of the vehicle	String	N/A	Unique for each instance

Notes:

1. The dataset contains **398 instances** (rows) and **9 attributes** (columns).
2. **'mpg'** is the target variable, typically used for prediction tasks in machine learning models.
3. **'horsepower'** is the only column with missing values, which may require handling in data preprocessing.
4. **'origin'** is encoded as numbers but represents categorical data and might need to be treated as such in analyses.
5. **'car name'** provides additional context but is typically not used as a feature in predictive modeling.
6. The dataset spans car models from **1970 to 1982**, capturing a significant period in automotive history.
7. There's a mix of continuous and categorical variables, which may require different preprocessing techniques.
8. Some variables (like **'weight'** and **'horsepower'**) may have strong correlations with the target variable **'mpg'**.

In [24]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 398 entries, 0 to 397
Data columns (total 9 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   mpg           398 non-null    float64
 1   cylinders     398 non-null    int64  
 2   displacement  398 non-null    float64
 3   horsepower    398 non-null    object 
 4   weight        398 non-null    int64  
 5   acceleration  398 non-null    float64
 6   model year    398 non-null    int64  
 7   origin        398 non-null    int64  
 8   car name      398 non-null    object 
dtypes: float64(3), int64(4), object(2)
memory usage: 28.1+ KB
```

In [25]:
```
df.describe(include="all").T.round(2)
```

Out[25]:

	count	unique	top	freq	mean	std	min	25%	5(
mpg	398.0	NaN	NaN	NaN	23.514573	7.815984	9.0	17.5	2:
cylinders	398.0	NaN	NaN	NaN	5.454774	1.701004	3.0	4.0	4
displacement	398.0	NaN	NaN	NaN	193.425879	104.269838	68.0	104.25	14!
horsepower	398	94	150	22	NaN	NaN	NaN	NaN	N
weight	398.0	NaN	NaN	NaN	2970.424623	846.841774	1613.0	2223.75	280:
acceleration	398.0	NaN	NaN	NaN	15.56809	2.757689	8.0	13.825	1:
model year	398.0	NaN	NaN	NaN	76.01005	3.697627	70.0	73.0	7(
origin	398.0	NaN	NaN	NaN	1.572864	0.802055	1.0	1.0	'
car name	398	305	ford pinto	6	NaN	NaN	NaN	NaN	N

In [26]:
```python
numerical_vars = df.select_dtypes(include=['int64', 'float64']).columns.toli
categorical_vars = df.select_dtypes(include=['object']).columns.tolist()
print('Numerical variables:', numerical_vars)
print('Categorical variables:', categorical_vars)
```

```
Numerical variables: ['mpg', 'cylinders', 'displacement', 'weight', 'acceler
ation', 'model year', 'origin']
Categorical variables: ['horsepower', 'car name']
```

In [27]:
```python
non_numeric = df['horsepower'][pd.to_numeric(df['horsepower'], errors='coerc
print(non_numeric.unique())
```

```
['?']
```

In [28]:
```python
# Replace '?' with NaN
df['horsepower'] = df['horsepower'].replace('?', np.nan)

df['horsepower'] = pd.to_numeric(df['horsepower'])
```

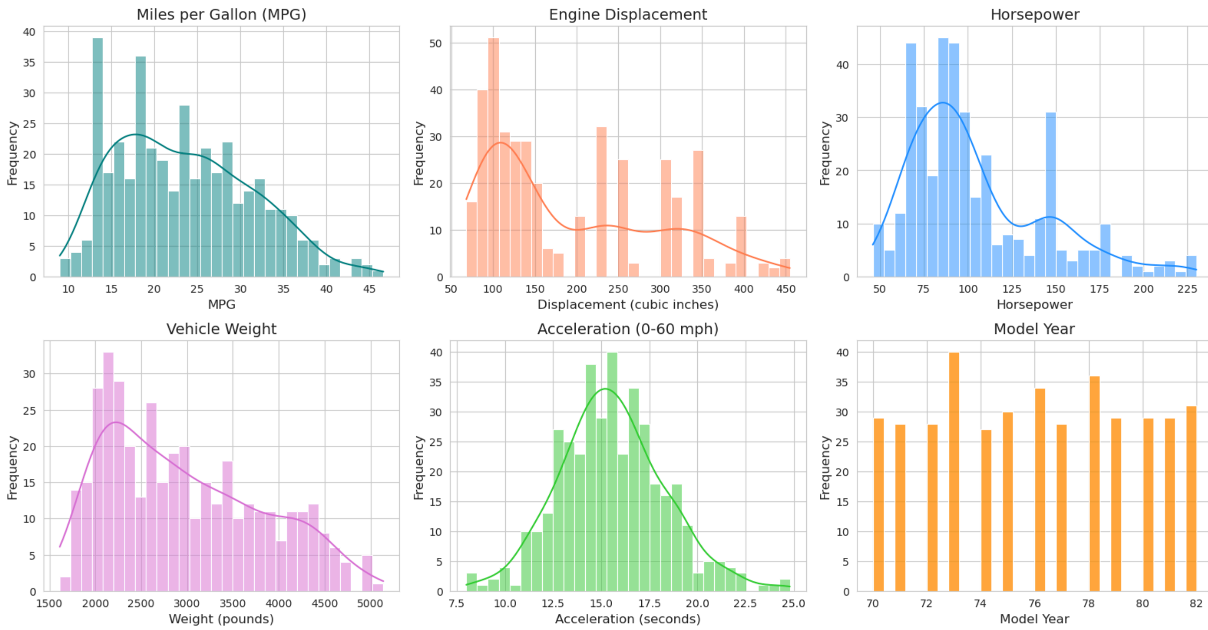
In [29]:
```python
categorical_count = df.select_dtypes(include='object').shape[1]
numerical_count = df.select_dtypes(exclude='object').shape[1]

print(f"Number of categorical variables: {categorical_count}")
print(f"Number of numerical variables: {numerical_count}")
```

```
Number of categorical variables: 1
Number of numerical variables: 8
```

Visualization

In [30]:
```python
import seaborn as sns
import matplotlib.pyplot as plt

sns.set_style("whitegrid")

plt.figure(figsize=(16, 12))
```

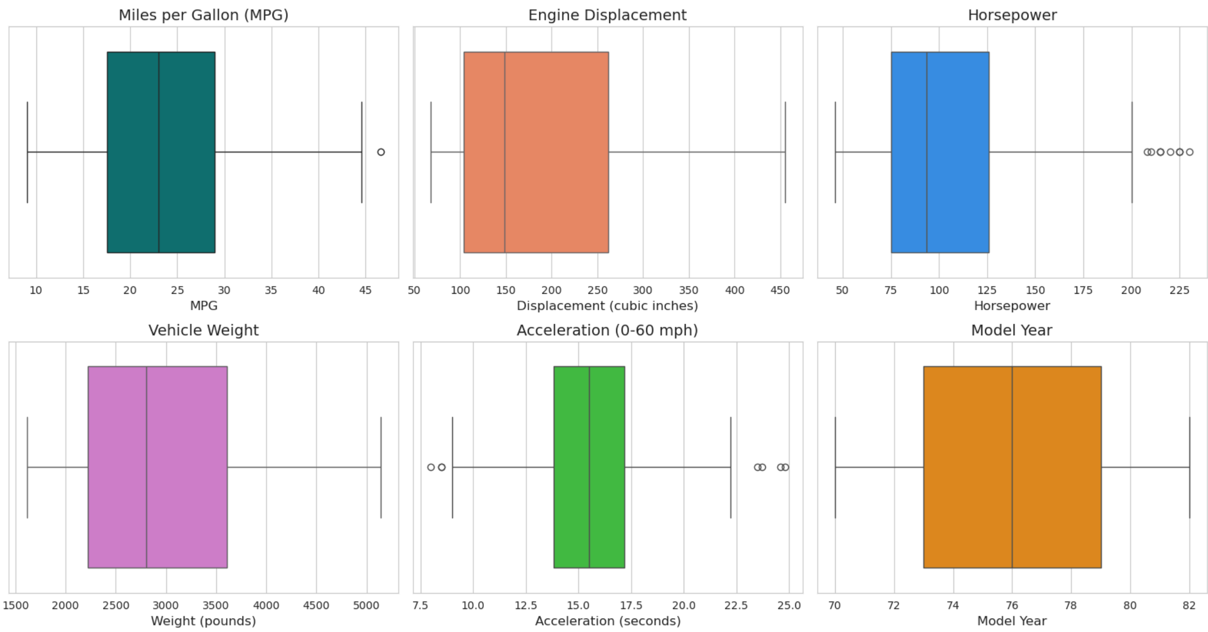
```
# Subplot 1 - MPG (Miles per Gallon)
plt.subplot(3, 3, 1)
sns.histplot(df['mpg'], bins=30, kde=True, color='teal')
plt.title('Miles per Gallon (MPG)', fontsize=14)
plt.xlabel('MPG', fontsize=12)
plt.ylabel('Frequency', fontsize=12)

# Subplot 2 - Displacement
plt.subplot(3, 3, 2)
sns.histplot(df['displacement'], bins=30, kde=True, color='coral')
plt.title('Engine Displacement', fontsize=14)
plt.xlabel('Displacement (cubic inches)', fontsize=12)
plt.ylabel('Frequency', fontsize=12)

# Subplot 3 - Horsepower
plt.subplot(3, 3, 3)
sns.histplot(df['horsepower'], bins=30, kde=True, color='dodgerblue')
plt.title('Horsepower', fontsize=14)
plt.xlabel('Horsepower', fontsize=12)
plt.ylabel('Frequency', fontsize=12)

# Subplot 4 - Vehicle Weight
plt.subplot(3, 3, 4)
sns.histplot(df['weight'], bins=30, kde=True, color='orchid')
plt.title('Vehicle Weight', fontsize=14)
plt.xlabel('Weight (pounds)', fontsize=12)
plt.ylabel('Frequency', fontsize=12)

# Subplot 5 - Acceleration
plt.subplot(3, 3, 5)
sns.histplot(df['acceleration'], bins=30, kde=True, color='limegreen')
plt.title('Acceleration (0-60 mph)', fontsize=14)
plt.xlabel('Acceleration (seconds)', fontsize=12)
plt.ylabel('Frequency', fontsize=12)

# Subplot 6 - Model Year
plt.subplot(3, 3, 6)
sns.histplot(df['model year'], bins=30, kde=False, color='darkorange')
plt.title('Model Year', fontsize=14)
plt.xlabel('Model Year', fontsize=12)
plt.ylabel('Frequency', fontsize=12)


plt.tight_layout()

plt.show()
```



In [31]:

```python
import seaborn as sns
import matplotlib.pyplot as plt

sns.set_style("whitegrid")

plt.figure(figsize=(16, 12))

# Subplot 1 - Boxplot for MPG (Miles per Gallon)
plt.subplot(3, 3, 1)
sns.boxplot(x=df['mpg'], color='teal')
plt.title('Miles per Gallon (MPG)', fontsize=14)
plt.xlabel('MPG', fontsize=12)

# Subplot 2 - Boxplot for Displacement
plt.subplot(3, 3, 2)
sns.boxplot(x=df['displacement'], color='coral')
plt.title('Engine Displacement', fontsize=14)
plt.xlabel('Displacement (cubic inches)', fontsize=12)

# Subplot 3 - Boxplot for Horsepower
plt.subplot(3, 3, 3)
sns.boxplot(x=df['horsepower'], color='dodgerblue')
plt.title('Horsepower', fontsize=14)
plt.xlabel('Horsepower', fontsize=12)

# Subplot 4 - Boxplot for Vehicle Weight
plt.subplot(3, 3, 4)
sns.boxplot(x=df['weight'], color='orchid')
plt.title('Vehicle Weight', fontsize=14)
plt.xlabel('Weight (pounds)', fontsize=12)

# Subplot 5 - Boxplot for Acceleration
plt.subplot(3, 3, 5)
sns.boxplot(x=df['acceleration'], color='limegreen')
plt.title('Acceleration (0-60 mph)', fontsize=14)
plt.xlabel('Acceleration (seconds)', fontsize=12)
```

```
# Subplot 6 - Boxplot for Model Year
plt.subplot(3, 3, 6)
sns.boxplot(x=df['model year'], color='darkorange')
plt.title('Model Year', fontsize=14)
plt.xlabel('Model Year', fontsize=12)


plt.tight_layout()


plt.show()
```



Cleaning

In [32]:
```
missing_values = df.isnull().sum()
print(missing_values)
```

```
mpg             0
cylinders       0
displacement    0
horsepower      6
weight          0
acceleration    0
model year      0
origin          0
car name        0
dtype: int64
```

In [33]:
```
duplicate_rows = df.duplicated().sum()
print(f"Number of duplicate rows: {duplicate_rows}")
```

```
Number of duplicate rows: 0
```

In [34]:
```
from sklearn.impute import SimpleImputer

imputer = SimpleImputer(strategy='mean')
```

```
df['horsepower'] = imputer.fit_transform(df[['horsepower']])
```

In [35]:
```
print(df.shape)
```

(398, 9)

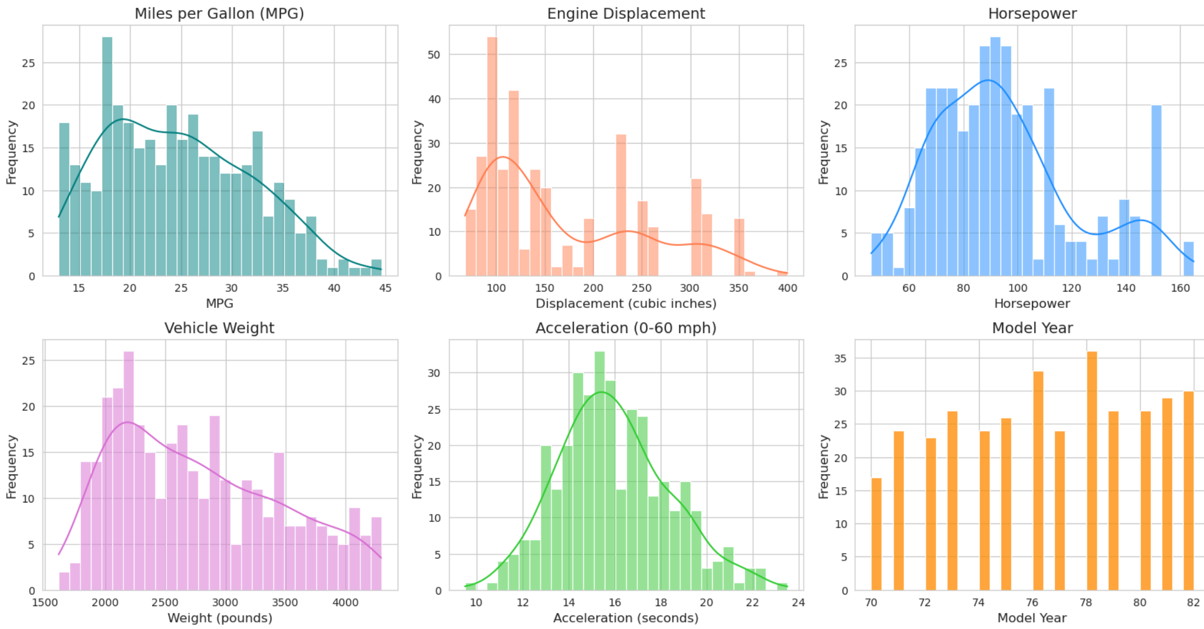
In [36]:
```
# IQR: Miles per Gallon (MPG), Engine Displacement, Horsepower , Vehicle Wei
# Z-Score: Acceleration (0-60 mph)
# Not Applicable: Model Year (categorical).

#first find the no of outliers in each column

from scipy.stats import zscore
from scipy.stats import skew
from scipy import stats
Iqr_columns = ['mpg', 'displacement', 'horsepower', 'weight']
Zscore_columns = ['acceleration']
def calculate_skewness(data):
    return stats.skew(data)

for column in Iqr_columns:
    skewness = calculate_skewness(df[column])
    print(f"Skewness of {column}: {skewness}")


Q1 = df[Iqr_columns].quantile(0.25)
Q3 = df[Iqr_columns].quantile(0.75)
IQR = Q3 - Q1

lower_bound = {}
upper_bound = {}

multipliers = {'mpg': 1.5, 'displacement': 1, 'horsepower': 0.9, 'weight': 0
for column in Iqr_columns:
    lower_bound[column] = Q1[column] - multipliers[column] * IQR[column]
    upper_bound[column] = Q3[column] + multipliers[column] * IQR[column]

    outliers = df[(df[column] < lower_bound[column]) | (df[column] > upper_b
    print(f"Number of outliers in {column}: {outliers}")

    df = df[(df[column] >= lower_bound[column]) & (df[column] <= upper_bounc

# Calculate the Z-Score for the 'acceleration' column
df['acceleration_zscore'] = zscore(df['acceleration'])

# Find the number of outliers
outliers = df[(df['acceleration_zscore'] > 3) | (df['acceleration_zscore'] <

print(f"Number of outliers in 'acceleration': {outliers}")

# Remove the outliers
df = df[(df['acceleration_zscore'] <= 3) & (df['acceleration_zscore'] >= -3)

df = df.drop('acceleration_zscore', axis=1)
```

```
Skewness of mpg: 0.45534192556309266
Skewness of displacement: 0.716930089340474
Skewness of horsepower: 1.0914191838332945
Skewness of weight: 0.5290589216608383
Number of outliers in mpg: 1
Number of outliers in displacement: 9
Number of outliers in horsepower: 23
Number of outliers in weight: 14
Number of outliers in 'acceleration': 4
```

In [37]:

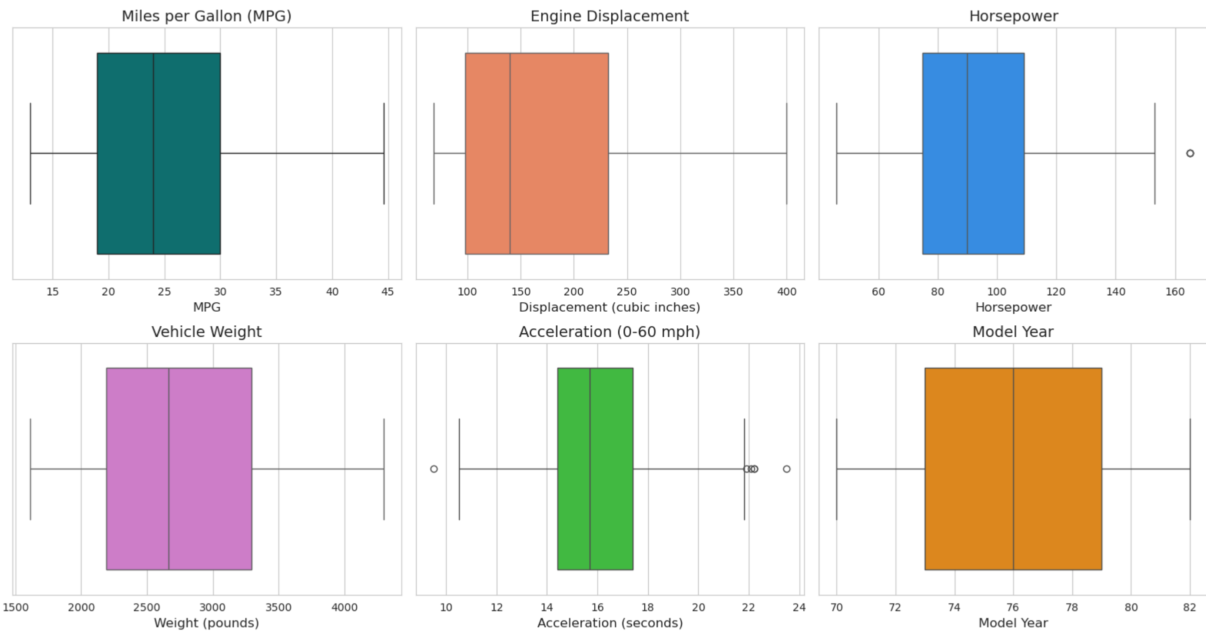
```
import seaborn as sns
import matplotlib.pyplot as plt

sns.set_style("whitegrid")

plt.figure(figsize=(16, 12))

# Subplot 1 - MPG (Miles per Gallon)
plt.subplot(3, 3, 1)
sns.histplot(df['mpg'], bins=30, kde=True, color='teal')
plt.title('Miles per Gallon (MPG)', fontsize=14)
plt.xlabel('MPG', fontsize=12)
plt.ylabel('Frequency', fontsize=12)

# Subplot 2 - Displacement
plt.subplot(3, 3, 2)
sns.histplot(df['displacement'], bins=30, kde=True, color='coral')
plt.title('Engine Displacement', fontsize=14)
plt.xlabel('Displacement (cubic inches)', fontsize=12)
plt.ylabel('Frequency', fontsize=12)

# Subplot 3 - Horsepower
plt.subplot(3, 3, 3)
sns.histplot(df['horsepower'], bins=30, kde=True, color='dodgerblue')
plt.title('Horsepower', fontsize=14)
plt.xlabel('Horsepower', fontsize=12)
plt.ylabel('Frequency', fontsize=12)

# Subplot 4 - Vehicle Weight
plt.subplot(3, 3, 4)
sns.histplot(df['weight'], bins=30, kde=True, color='orchid')
plt.title('Vehicle Weight', fontsize=14)
plt.xlabel('Weight (pounds)', fontsize=12)
plt.ylabel('Frequency', fontsize=12)

# Subplot 5 - Acceleration
plt.subplot(3, 3, 5)
sns.histplot(df['acceleration'], bins=30, kde=True, color='limegreen')
plt.title('Acceleration (0-60 mph)', fontsize=14)
plt.xlabel('Acceleration (seconds)', fontsize=12)
plt.ylabel('Frequency', fontsize=12)

# Subplot 6 - Model Year
plt.subplot(3, 3, 6)
sns.histplot(df['model year'], bins=30, kde=False, color='darkorange')
plt.title('Model Year', fontsize=14)
```

```
plt.xlabel('Model Year', fontsize=12)
plt.ylabel('Frequency', fontsize=12)


plt.tight_layout()

plt.show()
```



In [38]:
```
import seaborn as sns
import matplotlib.pyplot as plt

sns.set_style("whitegrid")

plt.figure(figsize=(16, 12))

# Subplot 1 - Boxplot for MPG (Miles per Gallon)
plt.subplot(3, 3, 1)
sns.boxplot(x=df['mpg'], color='teal')
plt.title('Miles per Gallon (MPG)', fontsize=14)
plt.xlabel('MPG', fontsize=12)

# Subplot 2 - Boxplot for Displacement
plt.subplot(3, 3, 2)
sns.boxplot(x=df['displacement'], color='coral')
plt.title('Engine Displacement', fontsize=14)
plt.xlabel('Displacement (cubic inches)', fontsize=12)

# Subplot 3 - Boxplot for Horsepower
plt.subplot(3, 3, 3)
sns.boxplot(x=df['horsepower'], color='dodgerblue')
plt.title('Horsepower', fontsize=14)
plt.xlabel('Horsepower', fontsize=12)

# Subplot 4 - Boxplot for Vehicle Weight
plt.subplot(3, 3, 4)
sns.boxplot(x=df['weight'], color='orchid')
plt.title('Vehicle Weight', fontsize=14)
```

```
plt.xlabel('Weight (pounds)', fontsize=12)

# Subplot 5 - Boxplot for Acceleration
plt.subplot(3, 3, 5)
sns.boxplot(x=df['acceleration'], color='limegreen')
plt.title('Acceleration (0-60 mph)', fontsize=14)
plt.xlabel('Acceleration (seconds)', fontsize=12)

# Subplot 6 - Boxplot for Model Year
plt.subplot(3, 3, 6)
sns.boxplot(x=df['model year'], color='darkorange')
plt.title('Model Year', fontsize=14)
plt.xlabel('Model Year', fontsize=12)


plt.tight_layout()


plt.show()
```

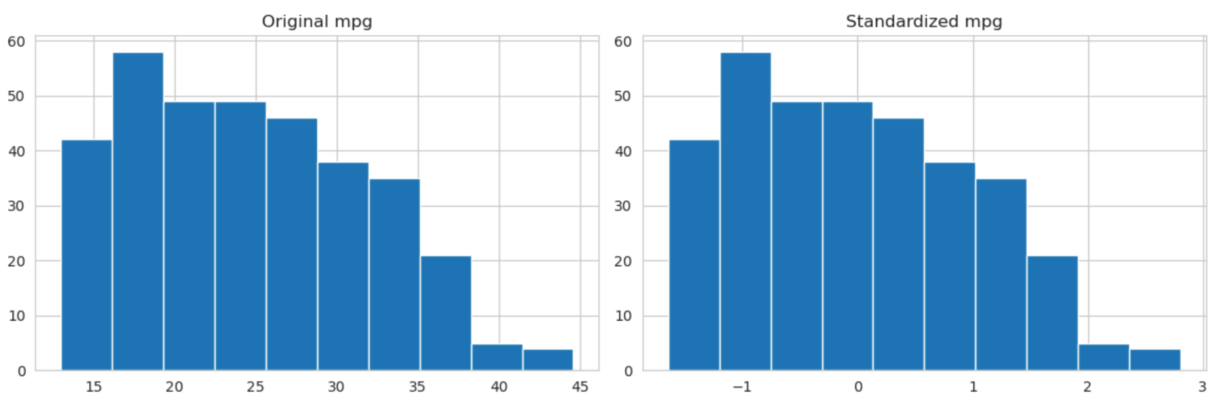


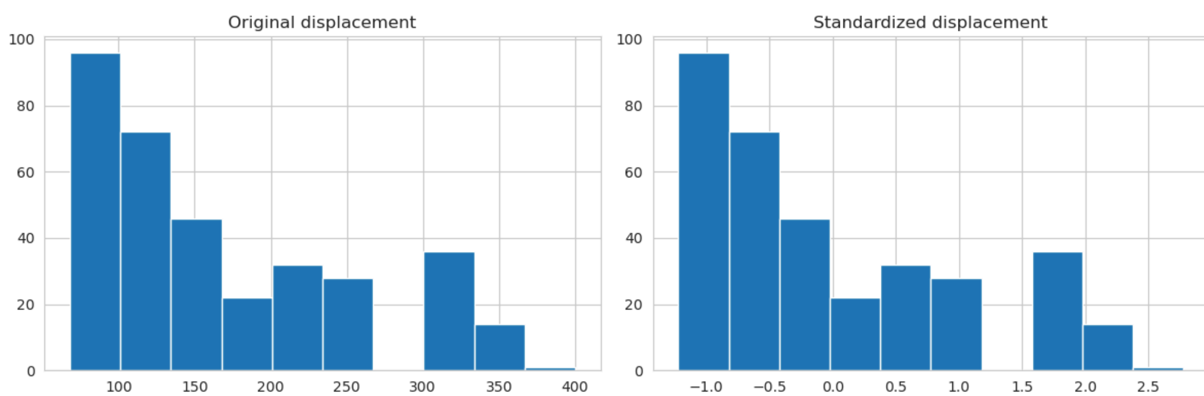
Encoding

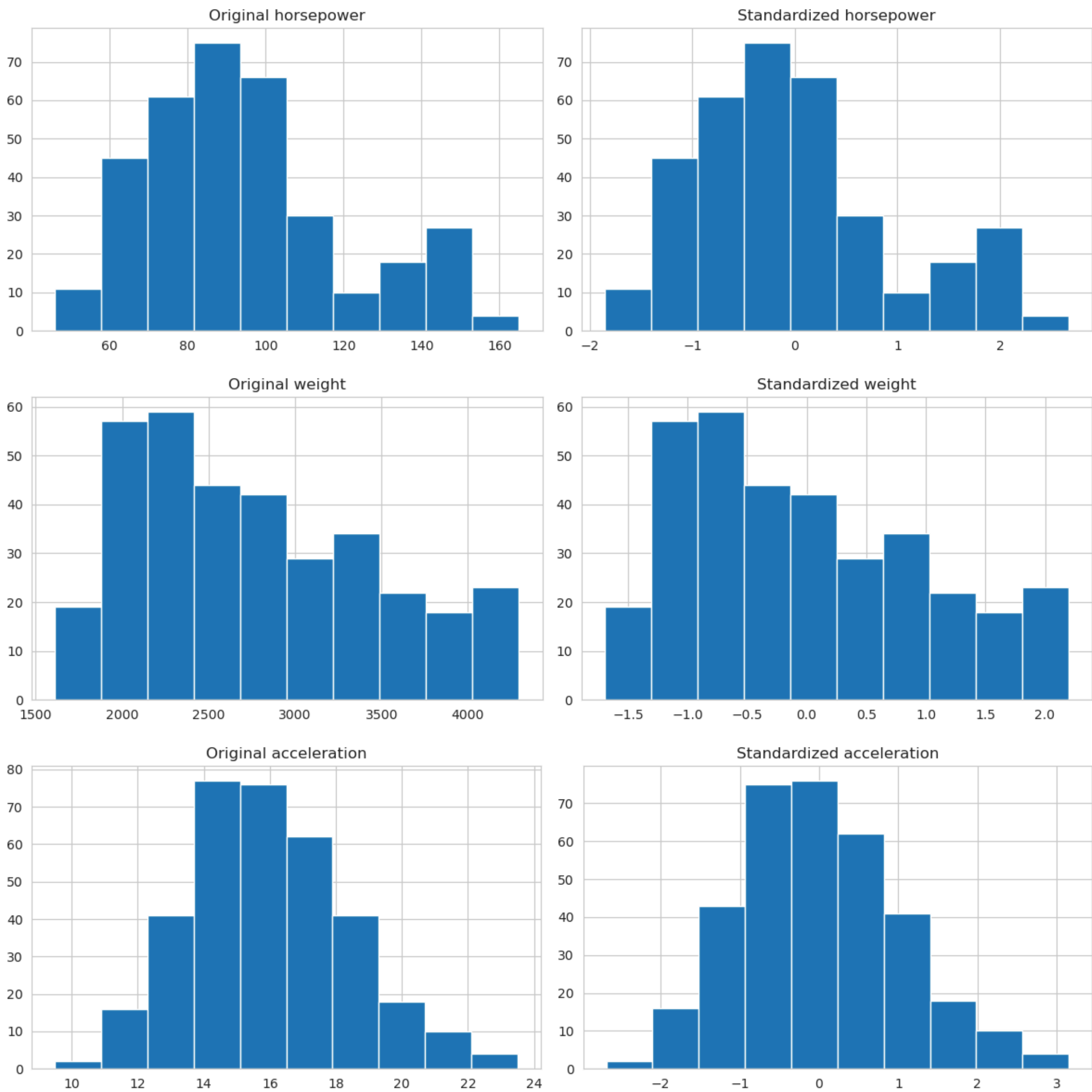
In [39]:
```
from sklearn.preprocessing import OneHotEncoder

import pandas as pd

encoder = OneHotEncoder(sparse_output=False)

encoded_cols = pd.DataFrame(encoder.fit_transform(df[['car name']]), columns

df = df.drop('car name', axis=1)

df = pd.concat([df, encoded_cols], axis=1)
```

In [43]:
```
from sklearn.preprocessing import StandardScaler
features_to_scale = ['mpg', 'displacement', 'horsepower', 'weight', 'acceler
```

```python
scaler = StandardScaler()
df_scaled = df.copy()
df_scaled[features_to_scale] = scaler.fit_transform(df[features_to_scale])

# Compare original and scaled data
for feature in features_to_scale:
    fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(12, 4))

    # Original data
    df[feature].hist(ax=ax1)
    ax1.set_title(f'Original {feature}')


    # Scaled data
    df_scaled[feature].hist(ax=ax2)
    ax2.set_title(f'Standardized {feature}')


    plt.tight_layout()
    plt.show()

print("Original data statistics:")
print(df[features_to_scale].describe())
print("\nStandardized data statistics:")
print(df_scaled[features_to_scale].describe())
```



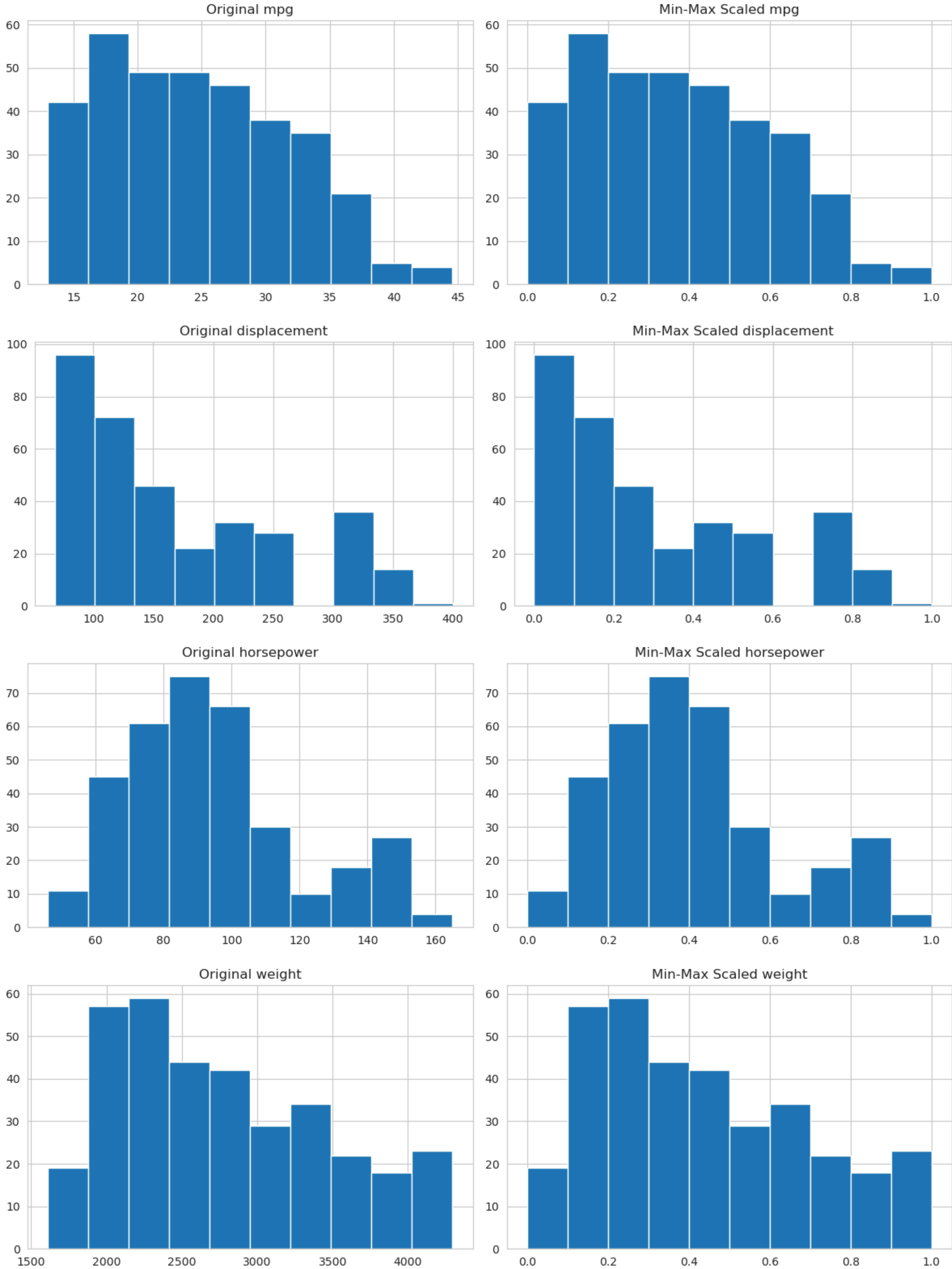


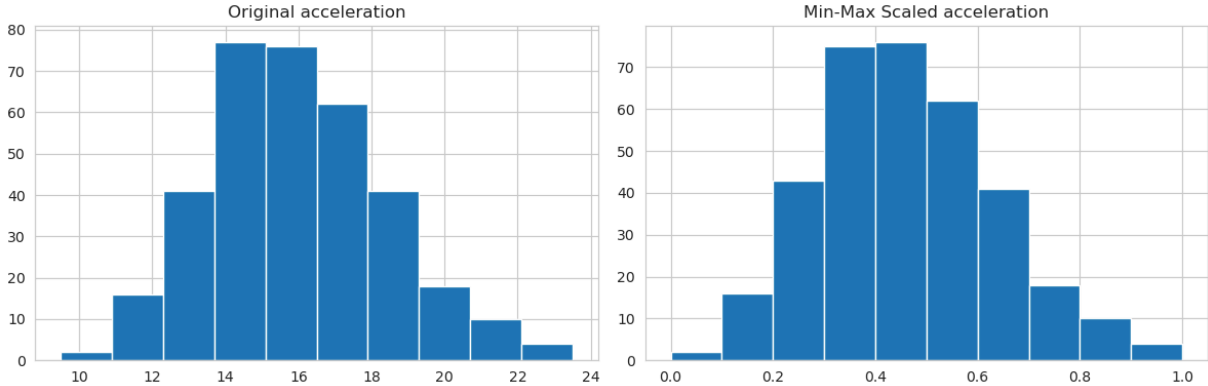

Original horsepower
0
10
20
30
40
50
60
70
60
80
100
120
140
160
Standardized horsepower
0
10
20
30
40
50
60
70
−2
−1
0
1
2
Original weight
0
10
20
30
40
50
60
1500
2000
2500
3000
3500
4000
Standardized weight
0
10
20
30
40
50
60
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0
Original acceleration
0
10
20
30
40
50
60
70
80
10
12
14
16
18
20
22
24
Standardized acceleration
0
10
20
30
40
50
60
70
−2
−1
0
1
2
3

```
Original data statistics:
              mpg  displacement  horsepower       weight  acceleration
count  347.000000    347.000000  347.000000   347.000000    347.000000
mean    24.683573    169.416427   94.766041  2780.662824     15.942075
std      7.112575     83.116223   26.355453   689.889343      2.403710
min     13.000000     68.000000   46.000000  1613.000000      9.500000
25%     19.000000     98.000000   75.000000  2189.500000     14.400000
50%     24.000000    140.000000   90.000000  2665.000000     15.700000
75%     30.000000    232.000000  109.000000  3295.000000     17.400000
max     44.600000    400.000000  165.000000  4295.000000     23.500000

Standardized data statistics:
                mpg  displacement    horsepower        weight  acceleration
count  3.470000e+02  3.470000e+02  3.470000e+02  3.470000e+02  3.470000e+02
mean  -1.228604e-16  1.638139e-16  5.221568e-16  3.276278e-16  3.634621e-16
std    1.001444e+00  1.001444e+00  1.001444e+00  1.001444e+00  1.001444e+00
min   -1.645037e+00 -1.221938e+00 -1.852993e+00 -1.694980e+00 -2.683926e+00
25%   -8.002420e-01 -8.604765e-01 -7.510622e-01 -8.581325e-01 -6.424660e-01
50%   -9.624653e-02 -3.544303e-01 -1.810981e-01 -1.678963e-01 -1.008543e-01
75%    7.485480e-01  7.540519e-01  5.408563e-01  7.466123e-01  6.074071e-01
max    2.804215e+00  2.778237e+00  2.668722e+00  2.198213e+00  3.148816e+00
```

In [44]:

```python
from sklearn.preprocessing import MinMaxScaler
min_max_scaler = MinMaxScaler()
df_minmax = df.copy()
df_minmax[features_to_scale] = min_max_scaler.fit_transform(df[features_to_s

# Compare original and min-max scaled data
for feature in features_to_scale:
    fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(12, 4))

    # Original data
    df[feature].hist(ax=ax1)
    ax1.set_title(f'Original {feature}')


    # Min-Max scaled data
    df_minmax[feature].hist(ax=ax2)
    ax2.set_title(f'Min-Max Scaled {feature}')


    plt.tight_layout()
    plt.show()

print("Original data statistics:")
print(df[features_to_scale].describe())
print("\nMin-Max scaled data statistics:")
print(df_minmax[features_to_scale].describe())
```


Original mpg
60
50
40
30
20
10
0
15 20 25 30 35 40 45
Min-Max Scaled mpg
60
50
40
30
20
10
0
0.0 0.2 0.4 0.6 0.8 1.0
Original displacement
100
80
60
40
20
0
100 150 200 250 300 350 400
Min-Max Scaled displacement
100
80
60
40
20
0
0.0 0.2 0.4 0.6 0.8 1.0
Original horsepower
70
60
50
40
30
20
10
0
60 80 100 120 140 160
Min-Max Scaled horsepower
70
60
50
40
30
20
10
0
0.0 0.2 0.4 0.6 0.8 1.0
Original weight
60
50
40
30
20
10
0
1500 2000 2500 3000 3500 4000
Min-Max Scaled weight
60
50
40
30
20
10
0
0.0 0.2 0.4 0.6 0.8 1.0




```
Original data statistics:
             mpg  displacement  horsepower       weight  acceleration
count  347.000000    347.000000  347.000000   347.000000    347.000000
mean    24.683573    169.416427   94.766041  2780.662824     15.942075
std      7.112575     83.116223   26.355453   689.889343      2.403710
min     13.000000     68.000000   46.000000  1613.000000      9.500000
25%     19.000000     98.000000   75.000000  2189.500000     14.400000
50%     24.000000    140.000000   90.000000  2665.000000     15.700000
75%     30.000000    232.000000  109.000000  3295.000000     17.400000
max     44.600000    400.000000  165.000000  4295.000000     23.500000

Min-Max scaled data statistics:
             mpg  displacement  horsepower      weight  acceleration
count  347.000000    347.000000  347.000000  347.000000    347.000000
mean     0.369733      0.305471    0.409799    0.435370      0.460148
std      0.225081      0.250350    0.221474    0.257229      0.171694
min      0.000000      0.000000    0.000000    0.000000      0.000000
25%      0.189873      0.090361    0.243697    0.214952      0.350000
50%      0.348101      0.216867    0.369748    0.392245      0.442857
75%      0.537975      0.493976    0.529412    0.627144      0.564286
max      1.000000      1.000000    1.000000    1.000000      1.000000
```

In [ ]: