

python_II

February 26, 2025

1 Data Manipulation and Visualization with Python

In this notebook, we will cover data manipulation and visualization using Python. We will use the pandas library for data manipulation and the matplotlib and seaborn libraries for data visualization.

```
[1]: # Import necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# Set seaborn style for plots
sns.set(style="whitegrid")
```

2 Reading in a Dataset and Gathering Basic Information

Let's start by reading in a CSV file and gathering basic information about the dataset.

```
[2]: # Read in the CSV file
df = pd.read_csv('mpg.csv')

# Display the first few rows of the dataframe
df.head()
```

```
[2]:  manufacturer model  displ  year  cyl      trans drv  cty  hwy fl  class
0      audi      a4    1.8  1999    4    auto(l5)  f   18   29  p  compact
1      audi      a4    1.8  1999    4  manual(m5)  f   21   29  p  compact
2      audi      a4    2.0  2008    4  manual(m6)  f   20   31  p  compact
3      audi      a4    2.0  2008    4    auto(av)  f   21   30  p  compact
4      audi      a4    2.8  1999    6    auto(l5)  f   16   26  p  compact
```

2.1 Basic Information about the DataFrame

Here are some good ways to get basic information about a dataframe in Python:

- `head()`: Displays the first few rows of the dataframe.
- `tail()`: Displays the last few rows of the dataframe.
- `shape`: Returns the dimensions of the dataframe (number of rows and columns).
- `columns`: Returns the column names of the dataframe.

- `info()`: Displays the structure of the dataframe, including data types and a preview of the data.
- `describe()`: Provides summary statistics for each column in the dataframe.

[3]: *# Display the first few rows of the dataframe*

```
df.head()
```

Get the dimensions of the dataframe

```
df.shape
```

Get the column names of the dataframe

```
df.columns
```

Display the structure of the dataframe

```
df.info()
```

Provide summary statistics for each column in the dataframe

```
df.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 234 entries, 0 to 233
```

```
Data columns (total 11 columns):
```

#	Column	Non-Null Count	Dtype
0	manufacturer	234 non-null	object
1	model	234 non-null	object
2	displ	234 non-null	float64
3	year	234 non-null	int64
4	cyl	234 non-null	int64
5	trans	234 non-null	object
6	drv	234 non-null	object
7	cty	234 non-null	int64
8	hwy	234 non-null	int64
9	fl	234 non-null	object
10	class	234 non-null	object

```
dtypes: float64(1), int64(4), object(6)
```

```
memory usage: 20.2+ KB
```

[3]:

	displ	year	cyl	cty	hwy
count	234.000000	234.000000	234.000000	234.000000	234.000000
mean	3.471795	2003.500000	5.888889	16.858974	23.440171
std	1.291959	4.509646	1.611534	4.255946	5.954643
min	1.600000	1999.000000	4.000000	9.000000	12.000000
25%	2.400000	1999.000000	4.000000	14.000000	18.000000
50%	3.300000	2003.500000	6.000000	17.000000	24.000000
75%	4.600000	2008.000000	8.000000	19.000000	27.000000
max	7.000000	2008.000000	8.000000	35.000000	44.000000

3 Data Manipulation with Pandas

We will now cover some basic data manipulation techniques using the pandas library.

```
[4]: # Create a sample "dictionary" object
data = {
    'name': ['Andie', 'Bridger', 'Scott'],
    'gender': ['Female', 'non-binary', 'Male'],
    'male': [False, False, True],
    'income_cat': ['middle', 'poor', 'rich'],
    'park_dist': [1.0, 0.5, 0.1]
}

data
```

```
[4]: {'name': ['Andie', 'Bridger', 'Scott'],
      'gender': ['Female', 'non-binary', 'Male'],
      'male': [False, False, True],
      'income_cat': ['middle', 'poor', 'rich'],
      'park_dist': [1.0, 0.5, 0.1]}
```

```
[5]: # turn the dictionary into a pandas dataframe
df_sample = pd.DataFrame(data)
df_sample
```

```
[5]:
```

	name	gender	male	income_cat	park_dist
0	Andie	Female	False	middle	1.0
1	Bridger	non-binary	False	poor	0.5
2	Scott	Male	True	rich	0.1

3.1 assign()

The `assign()` method can be used to add new columns or modify existing ones.

```
[6]: # Add 1 mile to park_dist
df_sample = df_sample.assign(park_dist=lambda x: x.park_dist + 1)
df_sample
```

```
[6]:
```

	name	gender	male	income_cat	park_dist
0	Andie	Female	False	middle	2.0
1	Bridger	non-binary	False	poor	1.5
2	Scott	Male	True	rich	1.1

3.2 np.where()

The `np.where()` function can be used to conditionally modify values in a dataframe.

```
[7]:
```

```
# Correct park_dist for non-male individuals
df_sample['park_dist_correct'] = np.where(df_sample['male'] == False,
    ↪df_sample['park_dist'] - 0.25, df_sample['park_dist'])
df_sample
```

```
[7]:
```

	name	gender	male	income_cat	park_dist	park_dist_correct
0	Andie	Female	False	middle	2.0	1.75
1	Bridger	non-binary	False	poor	1.5	1.25
2	Scott	Male	True	rich	1.1	1.10

3.3 filter with conditional statements

Filtering rows in a dataframe can be done using boolean indexing.

```
[8]: # Filter rows where pollution_level is 'Low'
df_env_data = pd.DataFrame({
    'ecosystem': ['Forest', 'Desert', 'Wetland', 'Grassland', 'Urban'],
    'species_richness': [120, 45, 80, 60, 30],
    'pollution_level': ['Low', 'High', 'Medium', 'Low', 'High']
})
low_pollution_data = df_env_data[df_env_data['pollution_level'] == 'Low']
low_pollution_data
```

```
[8]:
```

	ecosystem	species_richness	pollution_level
0	Forest	120	Low
3	Grassland	60	Low

3.4 dropna()

Dropping rows with missing values can be done using the `dropna()` method.

```
[9]: # Drop rows with missing values in the 'ecosystem' column
df_env_data_na = pd.DataFrame({
    'ecosystem': ['Forest', 'Desert', 'Wetland', np.nan, 'Urban'],
    'species_richness': [120, 45, 80, 60, 30],
    'pollution_level': ['Low', 'High', 'Medium', 'Low', 'High']
})
df_env_data_clean = df_env_data_na.dropna(subset=['ecosystem'])
df_env_data_clean
```

```
[9]:
```

	ecosystem	species_richness	pollution_level
0	Forest	120	Low
1	Desert	45	High
2	Wetland	80	Medium
4	Urban	30	High

3.5 select with []

Selecting specific columns can be done using square bracket notation

```
[10]: # Select only the 'ecosystem' and 'pollution_level' columns
pollution_data = df_env_data[['ecosystem', 'pollution_level']]
pollution_data
```

```
[10]:  ecosystem pollution_level
0    Forest                Low
1    Desert                High
2  Wetland                Medium
3  Grassland                Low
4    Urban                 High
```

3.6 groupby()

Grouping data and calculating aggregate statistics can be done using the `groupby()` method.

```
[11]: # Group by 'ecosystem' and calculate the mean species richness
df_env_long = pd.DataFrame({
    'ecosystem': ['Forest', 'Desert', 'Wetland', 'Grassland', 'Urban',
    ↪ 'Forest', 'Desert', 'Wetland', 'Grassland', 'Urban'],
    'species_richness': [120, 45, 80, 60, 30, 110, 50, 85, 65, 35],
    'pollution_level': ['Low', 'High', 'Medium', 'Low', 'High', 'Low', 'High',
    ↪ 'Medium', 'Low', 'High']
})
df_env_grouped = df_env_long.groupby('ecosystem').species_richness.mean().
    ↪ reset_index()
df_env_grouped
```

```
[11]:  ecosystem  species_richness
0    Desert                47.5
1    Forest               115.0
2  Grassland               62.5
3    Urban                 32.5
4  Wetland                 82.5
```

3.7 agg()

The `agg()` method can be used to apply multiple aggregation functions to grouped data.

```
[12]: # Group by 'ecosystem' and calculate the mean and total species richness
summary_table = df_env_long.groupby('ecosystem').species_richness.agg(['mean',
    ↪ 'sum']).reset_index()
summary_table.columns = ['ecosystem', 'mean_species_richness',
    ↪ 'total_species_richness']
summary_table
```

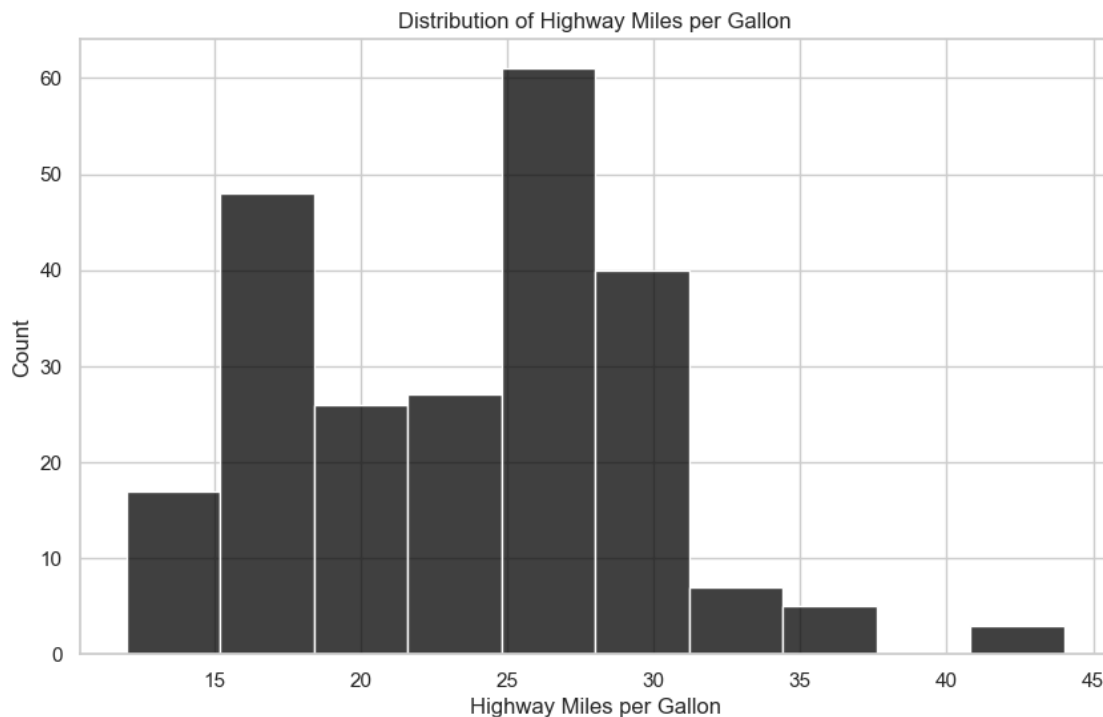
```
[12]:  ecosystem  mean_species_richness  total_species_richness
0    Desert                47.5                95
1    Forest               115.0               230
```

2	Grassland	62.5	125
3	Urban	32.5	65
4	Wetland	82.5	165

4 Basic Data Visualization

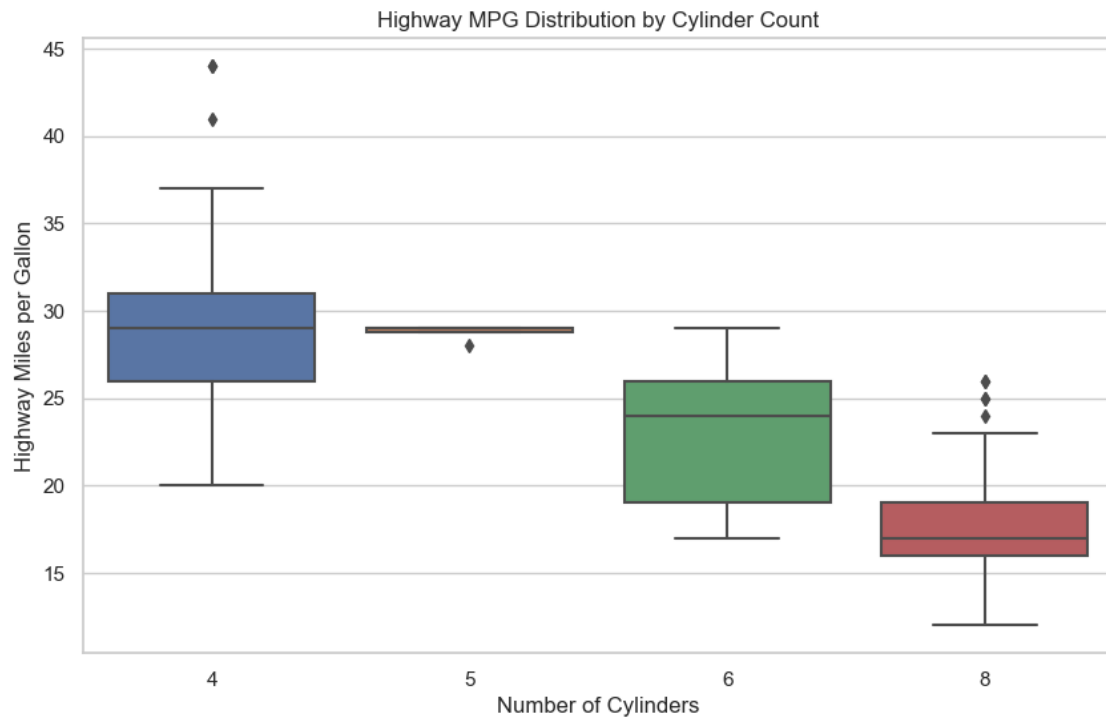
Unlike R where using the ggplot2 package has become the dominant way to make plots, Python has many ways to visualize data. Below, we go through one example. We will end the lecture here today, but the code is provided below so that you have an example. You should explore it on your own!

```
[13]: # Histogram
plt.figure(figsize=(10, 6))
sns.histplot(df['hwy'], bins=10, kde=False, color='black')
plt.title('Distribution of Highway Miles per Gallon')
plt.xlabel('Highway Miles per Gallon')
plt.ylabel('Count')
plt.show()
```

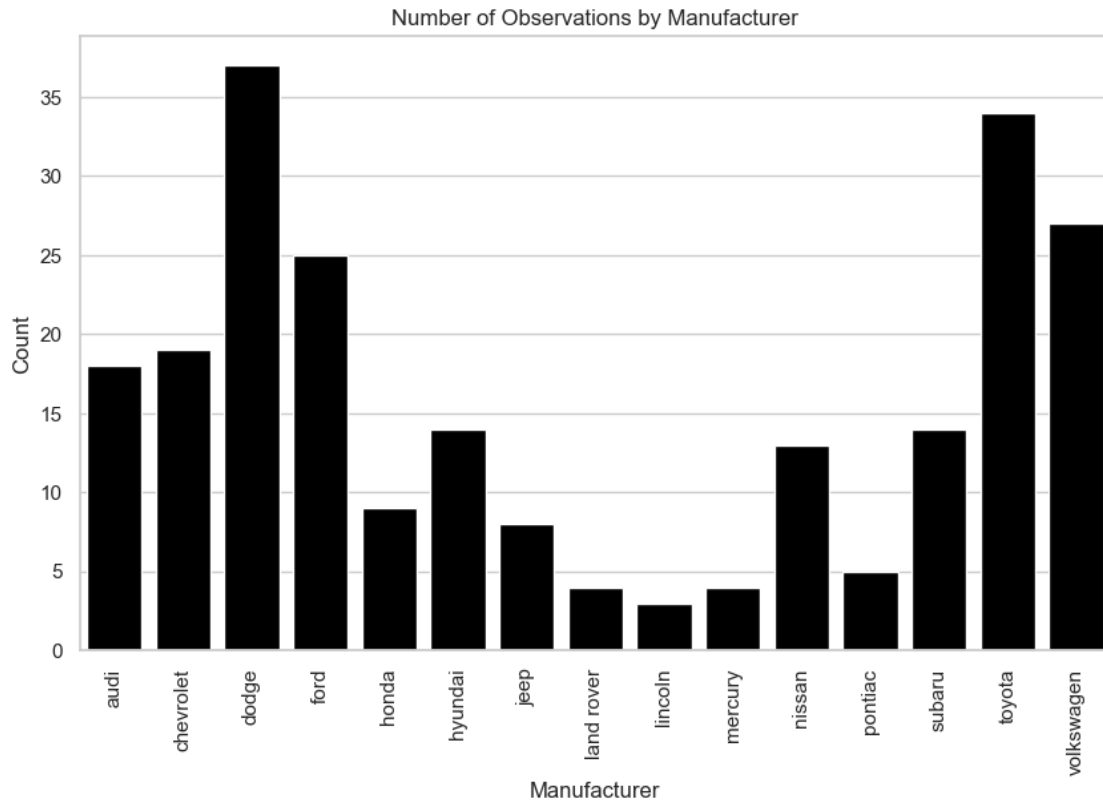


```
[14]: # Box plot
plt.figure(figsize=(10, 6))
sns.boxplot(x='cyl', y='hwy', data=df)
plt.title('Highway MPG Distribution by Cylinder Count')
```

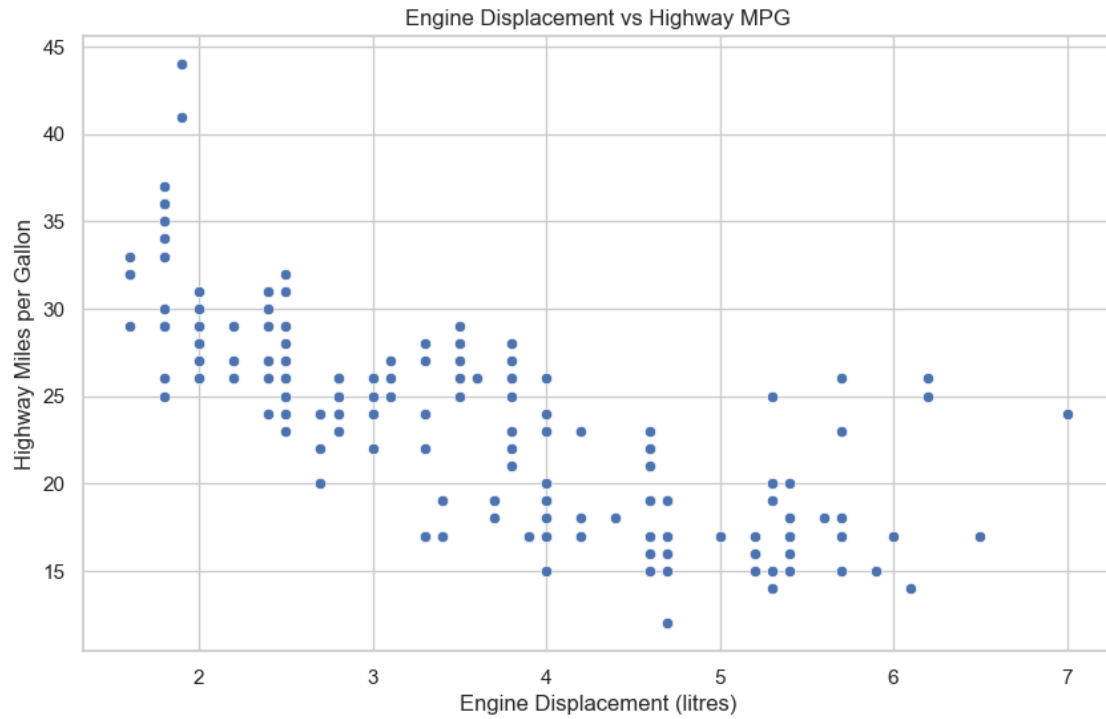
```
plt.xlabel('Number of Cylinders')
plt.ylabel('Highway Miles per Gallon')
plt.show()
```



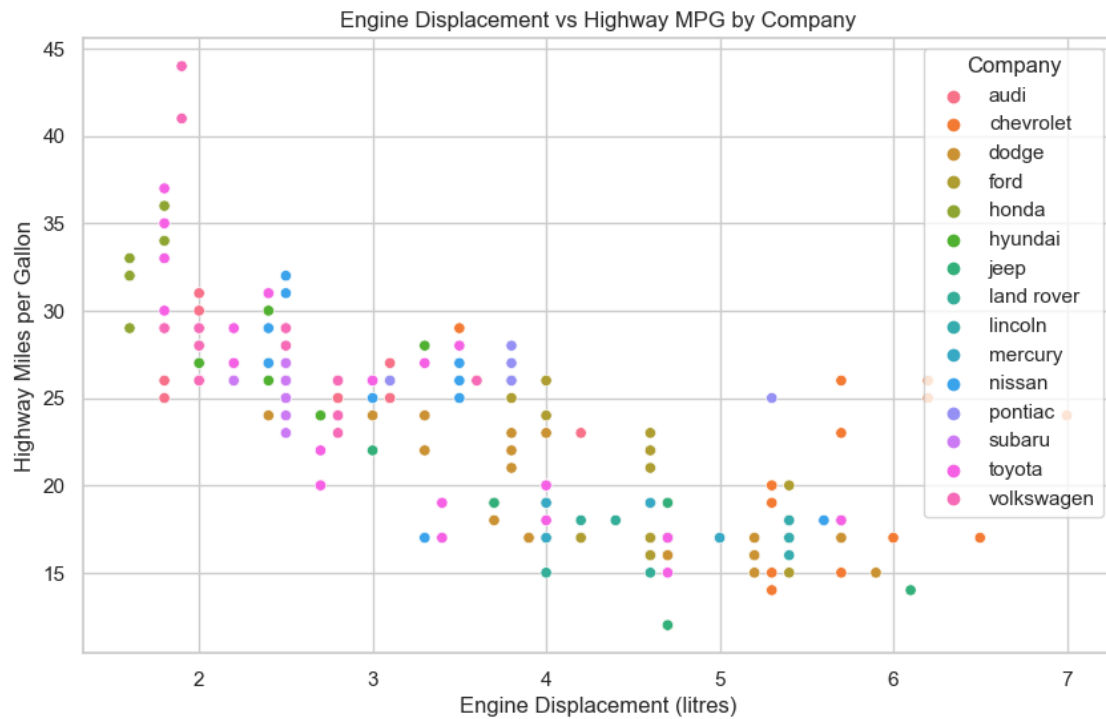
```
[15]: # Bar chart
plt.figure(figsize=(10, 6))
sns.countplot(x='manufacturer', data=df, color='black')
plt.title('Number of Observations by Manufacturer')
plt.xlabel('Manufacturer')
plt.ylabel('Count')
plt.xticks(rotation=90)
plt.show()
```



```
[16]: # Scatter plot
plt.figure(figsize=(10, 6))
sns.scatterplot(x='displ', y='hwy', data=df)
plt.title('Engine Displacement vs Highway MPG')
plt.xlabel('Engine Displacement (litres)')
plt.ylabel('Highway Miles per Gallon')
plt.show()
```

```
[17]: # Scatter plot with color grouping
plt.figure(figsize=(10, 6))
sns.scatterplot(x='displ', y='hwy', hue='manufacturer', data=df)
plt.title('Engine Displacement vs Highway MPG by Company')
plt.xlabel('Engine Displacement (litres)')
plt.ylabel('Highway Miles per Gallon')
plt.legend(title='Company')
plt.show()
```



```
[18]: # Facet plot
g = sns.FacetGrid(df, col='manufacturer', col_wrap=4, height=4)
g.map(sns.scatterplot, 'displ', 'hwy')
g.set_axis_labels('Engine Displacement (litres)', 'Highway Miles per Gallon')
g.fig.suptitle('Engine Displacement vs Highway MPG by Manufacturer', y=1.03)
plt.show()
```

```
/Users/a5creel/anaconda3/lib/python3.11/site-packages/seaborn/axisgrid.py:118:
UserWarning: The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```

Engine Displacement vs Highway MPG by Manufacturer

