PORTFOLIO

MPG DATASET ANALYSIS

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TETRIS BATCH IV: DATA ANALYTICS FAST TRACK BY DQLAB

EXERCISE LEARNING JOURNEY PYTHON :
DATA VISUALIZATION AND EDA (EXPLORATORY DATA ANALYSIS)
MPG DATASET ANALYSIS

LINK GITHUB : GITHUB.COM/RETNOWM/MPG-DATASET-ANALYSIS

TOOLS

STEP :

1. MOUNTING GOOGLE DRIVE
2. IMPORT LIBRARIES
3. IMPORT MPG DATASET
4. MISSING VALUE
5. EDA (EXPLORATORY DATA ANALYSIS)

1. MOUNTING GOOGLE DRIVE

```
[ ] from google.colab import drive
    drive.mount('/content/drive')

    Mounted at /content/drive
```

2. IMPORT LIBRARIES

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

3. IMPORT MPG DATASET

```
[ ] mpg = pd.read_csv("/content/drive/MyDrive/Colab Notebooks/tetris python/mpg.csv")
    mpg.head()
```

	mpg	cylinders	displacement	horsepower	weight	acceleration	model_year	origin	name
0	18.0	8	307.0	130.0	3504	12.0	70	usa	chevrolet chevelle malibu
1	15.0	8	350.0	165.0	3693	11.5	70	usa	buick skylark 320
2	18.0	8	318.0	150.0	3436	11.0	70	usa	plymouth satellite
3	16.0	8	304.0	150.0	3433	12.0	70	usa	amc rebel sst
4	17.0	8	302.0	140.0	3449	10.5	70	usa	ford torino

```
[ ] mpg.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    392 non-null    float64
 4   weight        398 non-null    int64
 5   acceleration  398 non-null    float64
 6   model_year    398 non-null    int64
 7   origin        398 non-null    object
 8   name          398 non-null    object
dtypes: float64(4), int64(3), object(2)
memory usage: 28.1+ KB
```

Observation :

1. The dataset has 9 columns, with a size of 398 rows
2. 7 numeric columns, 2 categorical columns
3. There are missing values in the horsepower column.

4. MISSING VALUE

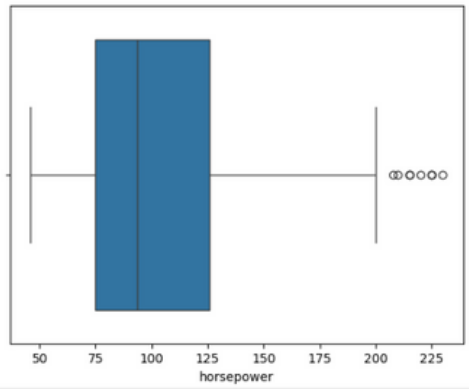
```
# Displays missing values
missing_values_horsepower = mpg[mpg["horsepower"].isnull()]
print(missing_values_horsepower)
```

```
      mpg  cylinders  displacement  horsepower  weight  acceleration  \
32   25.0          4          98.0         NaN    2046          19.0
126  21.0          6         200.0         NaN    2875          17.0
330  40.9          4          85.0         NaN    1835          17.3
336  23.6          4         140.0         NaN    2905          14.3
354  34.5          4         100.0         NaN    2320          15.8
374  23.0          4         151.0         NaN    3035          20.5

     model_year  origin                 name
32           71     usa            ford pinto
126          74     usa         ford maverick
330          80  europe  renault lecar deluxe
336          80     usa    ford mustang cobra
354          81  europe           renault 18i
374          82     usa       amc concord dl
```

```
[ ] # check for outliers in the horsepower variable
    sns.boxplot(data=mpg, x="horsepower")
    # There are outliers above Q3, therefore we will impute the middle value rather than the average value
```

```
<Axes: xlabel='horsepower'>
```

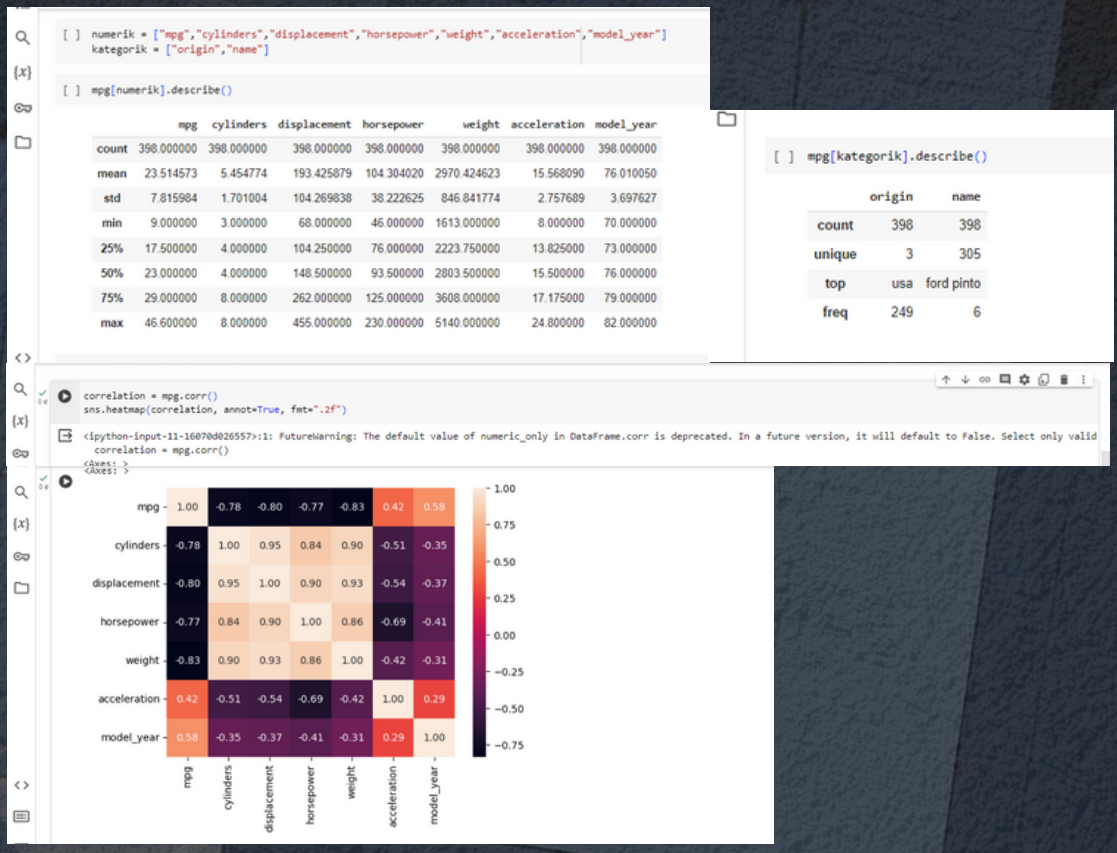



```
[ ] median_horsepower = mpg["horsepower"].median()
    mpg["horsepower"].fillna(median_horsepower, inplace=True)
    print(mpg)
```

```
      mpg  cylinders  displacement  horsepower  weight  acceleration  \
0    18.0          8         307.0       130.0    3504          12.0
1    15.0          8         350.0       165.0    3693          11.5
2    18.0          8         318.0       150.0    3436          11.0
3    16.0          8         304.0       150.0    3433          12.0
4    17.0          8         302.0       140.0    3449          10.5
..    ...        ...           ...         ...     ...           ...
393  27.0          4         140.0        86.0    2790          15.6
394  44.0          4          97.0        52.0    2130          24.6
395  32.0          4         135.0        84.0    2295          11.6
396  28.0          4         120.0        79.0    2625          18.6
397  31.0          4         119.0        82.0    2720          19.4

     model_year  origin                  name
0            70     usa  chevrolet chevelle malibu
1            70     usa          buick skylark 320
2            70     usa         plymouth satellite
3            70     usa              amc rebel sst
4            70     usa                ford torino
..          ...     ...                       ...
393          82     usa           ford mustang gl
394          82  europe                 vw pickup
395          82     usa             dodge rampage
396          82     usa               ford ranger
397          82     usa                chevy s-10
```

5. EDA (EXPLORATORY DATA ANALYSIS)



```
[ ] numerik = ["mpg","cylinders","displacement","horsepower","weight","acceleration","model_year"]
    kategorik = ["origin","name"]

[ ] mpg[numerik].describe()
```

	mpg	cylinders	displacement	horsepower	weight	acceleration	model_year
count	398.000000	398.000000	398.000000	398.000000	398.000000	398.000000	398.000000
mean	23.514573	5.454774	193.425879	104.304020	2970.424623	15.568090	76.010050
std	7.815984	1.701004	104.269838	38.222625	846.841774	2.757689	3.697627
min	9.000000	3.000000	68.000000	46.000000	1613.000000	8.000000	70.000000
25%	17.500000	4.000000	104.250000	76.000000	2223.750000	13.825000	73.000000
50%	23.000000	4.000000	148.500000	93.500000	2803.500000	15.500000	76.000000
75%	29.000000	8.000000	262.000000	125.000000	3608.000000	17.175000	79.000000
max	46.600000	8.000000	455.000000	230.000000	5140.000000	24.800000	82.000000

```
[ ] mpg[kategorik].describe()
```

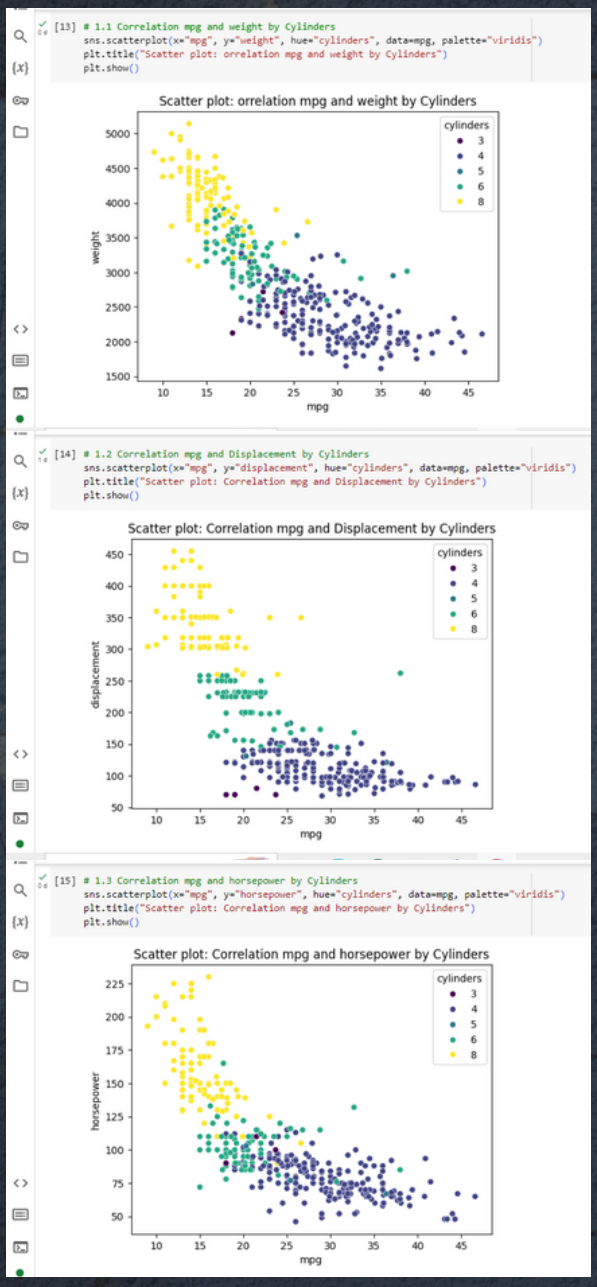
	origin	name
count	398	398
unique	3	305
top	usa	ford pinto
freq	249	6

```
correlation = mpg.corr()
sns.heatmap(correlation, annot=True, fmt=".2f")
```

```
<ipython-input-11-16070d026557>:1: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid
  correlation = mpg.corr()
<Axes: >
```

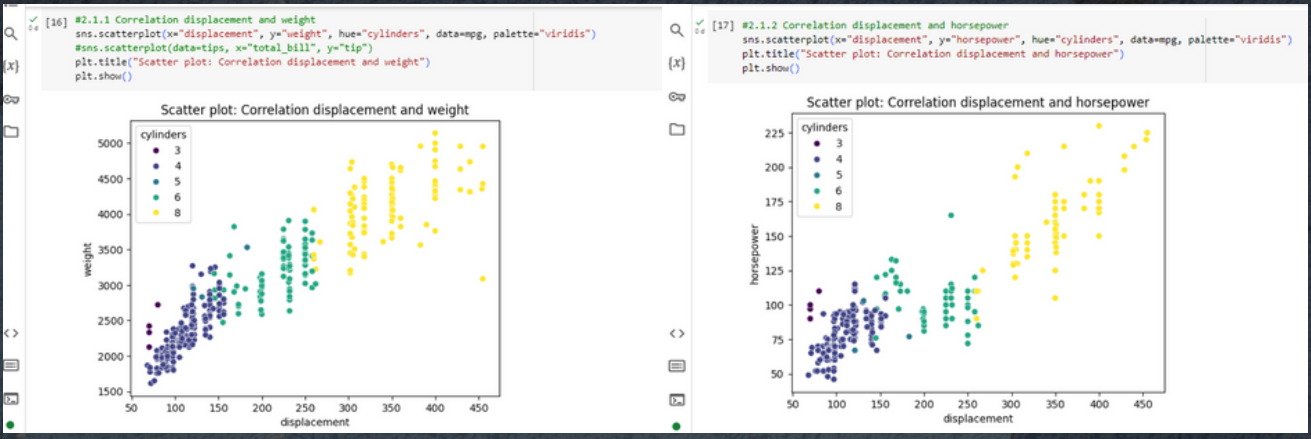

Based on numerical data correlation, among others:

- Which is negatively correlated with mpg :
  1. weight
  2. displacement
  3. cylinders
  4. horsepower
- Which is positively correlated : displacement with weight and horsepower



Conclusion :

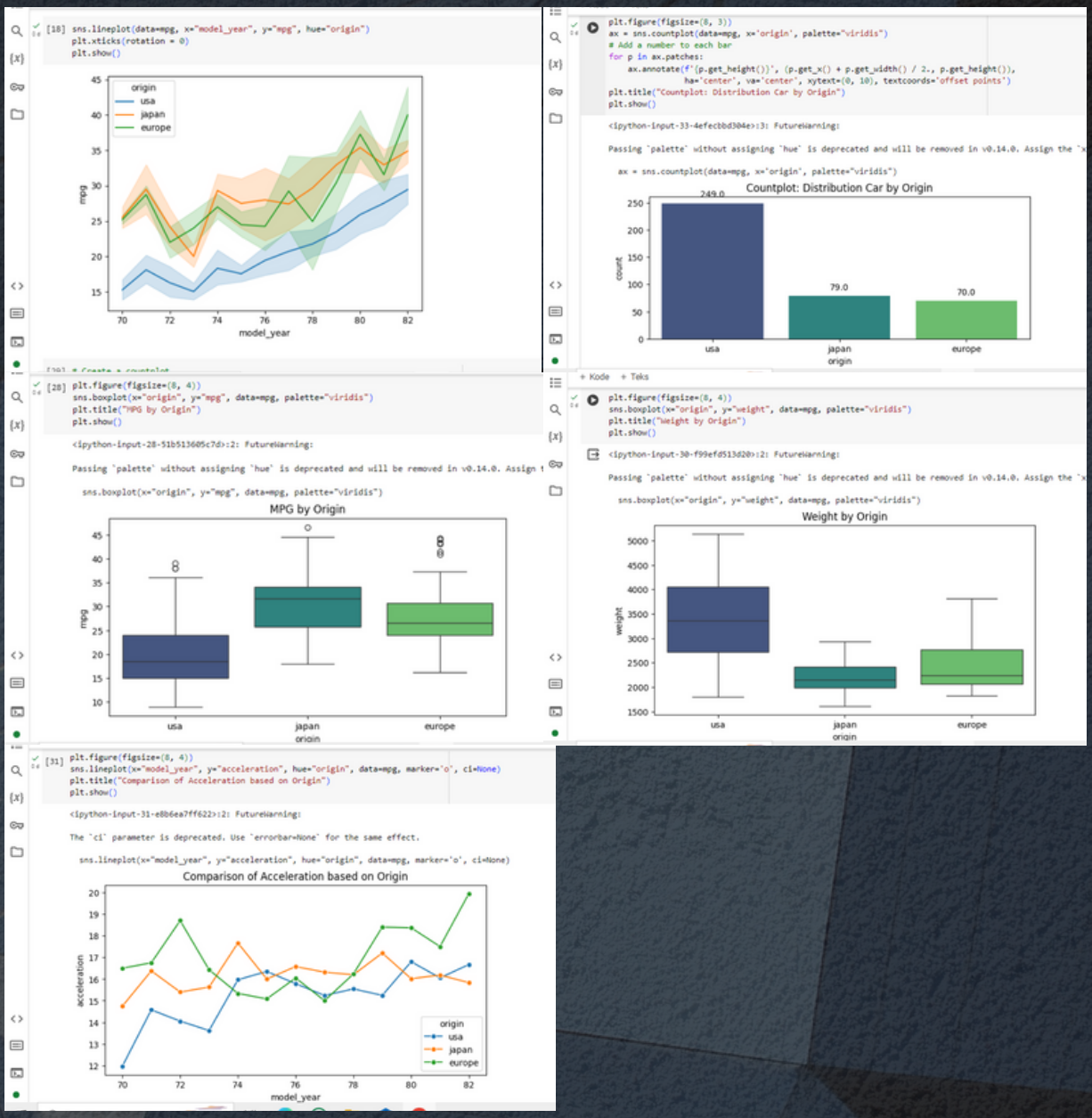
- Weight, displacement and horsepower have the same correlation results with respect to MPG, that is, the higher the weight, displacement and horsepower, the lower the MPG or the car tends to be less efficient in fuel use, which is reflected in a decrease in the “MPG“ value.
- Cars with a high number of cylinders tend to have low fuel efficiency (low MPG), and often cars with a high number of cylinders also have high weight, displacement and horsepower.



Conclusion :

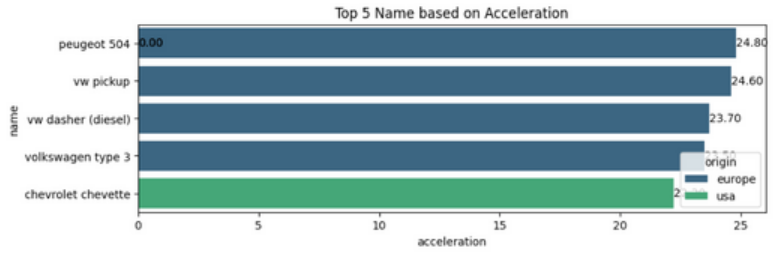
- The correlation between displacement and weight and horsepower has a positive relationship, namely the higher the displacement, the higher the weight and horsepower

1. Greater displacement often indicates a larger or more complex engine, which can result in an increase in vehicle weight.
2. Engines that have greater Displacement can usually burn more fuel and produce more power, which is reflected in a higher “horsepower“ value.

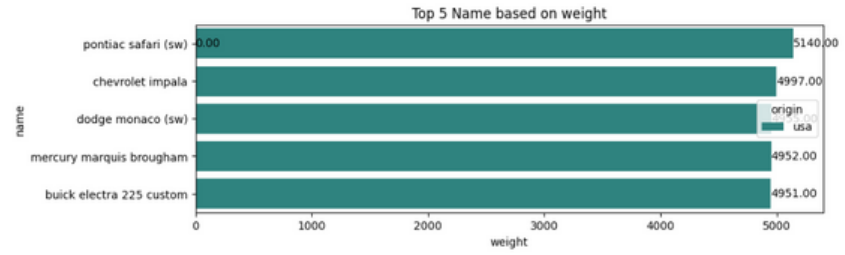


1. The largest number of cars comes from the USA (249) followed by Japan (79) and Europe (70)
2. Based on the model year, cars from the USA have a lower MPG value than cars from Japan and Europe
3. That cars from the USA tend to have lower fuel efficiency than Japan and Europe. In other words, cars from Japan and Europe have higher average “mpg“, indicating better fuel efficiency.
4. It can be seen from the comparison of weight and MPG for each origin, the USA has a heavier weight, followed by Europe and finally Japan. This can affect fuel efficiency (mpg), as heavier cars tend to require more energy to move, which can result in lower fuel efficiency.

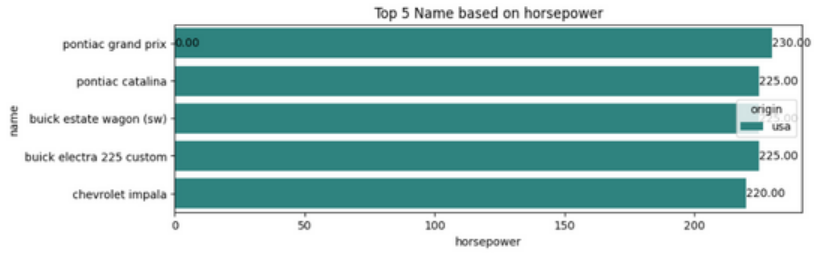
```
# Displays the top 5 car names based on acceleration
top5_acceleration = mpg.nlargest(5, 'acceleration')
# Create a horizontal bar chart with Seaborn and add numbers
plt.figure(figsize=(10, 3))
ax = sns.barplot(x=top5_acceleration['acceleration'], y=top5_acceleration['name'], hue=top5_acceleration['origin'], palette='viridis', orient='h')
# Add numbers to the diagram
for p in ax.patches:
    ax.annotate(f'{p.get_width():.2f}', (p.get_width(), p.get_y() + p.get_height()/2), ha='left', va='center')
plt.title("Top 5 Name based on Acceleration")
plt.show()
```



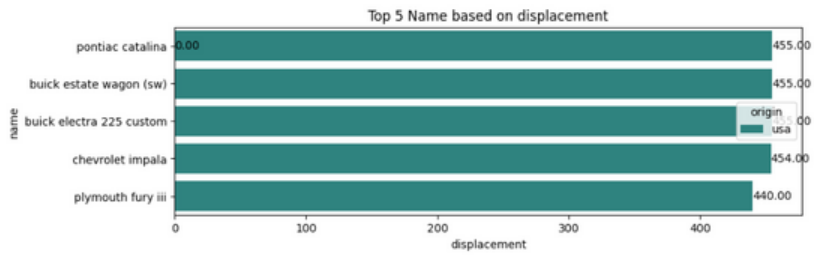

```
# Displays the top 5 car names based on weight
top5_acceleration = mpg.nlargest(5, 'weight')
# Create a horizontal bar chart with Seaborn and add numbers
plt.figure(figsize=(10, 3))
ax = sns.barplot(x=top5_acceleration['weight'], y=top5_acceleration['name'], hue=top5_acceleration['origin'], palette='viridis', orient='h')
# Add numbers to the diagram
for p in ax.patches:
    ax.annotate(f'{p.get_width():.2f}', (p.get_width(), p.get_y() + p.get_height()/2), ha='left', va='center')
plt.title("Top 5 Name based on weight")
plt.show()
```



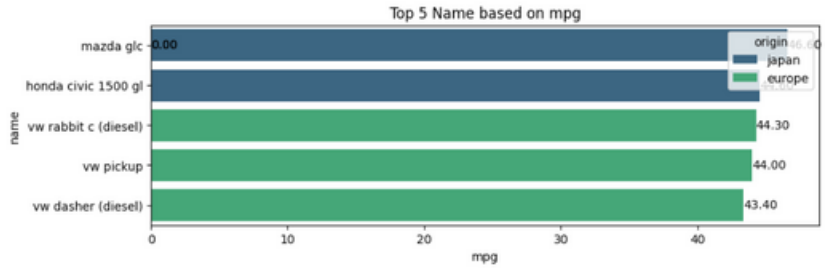

```
# Displays the top 5 car names based on horsepower
top5_acceleration = mpg.nlargest(5, 'horsepower')
# Create a horizontal bar chart with Seaborn and add numbers
plt.figure(figsize=(10, 3))
ax = sns.barplot(x=top5_acceleration['horsepower'], y=top5_acceleration['name'], hue=top5_acceleration['origin'], palette='viridis', orient='h')
# Add numbers to the diagram
for p in ax.patches:
    ax.annotate(f'{p.get_width():.2f}', (p.get_width(), p.get_y() + p.get_height()/2), ha='left', va='center')
plt.title("Top 5 Name based on horsepower")
plt.show()
```




```
# Displays the top 5 car names based on displacement
top5_acceleration = mpg.nlargest(5, 'displacement')
# Create a horizontal bar chart with Seaborn and add numbers
plt.figure(figsize=(10, 3))
ax = sns.barplot(x=top5_acceleration['displacement'], y=top5_acceleration['name'], hue=top5_acceleration['origin'], palette='viridis', orient='h')
# Add numbers to the diagram
for p in ax.patches:
    ax.annotate(f'{p.get_width():.2f}', (p.get_width(), p.get_y() + p.get_height()/2), ha='left', va='center')
plt.title("Top 5 Name based on displacement")
plt.show()
```



```
# Displays the top 5 car names based on mpg
top5_acceleration = mpg.nlargest(5, 'mpg')
# Create a horizontal bar chart with Seaborn and add numbers
plt.figure(figsize=(10, 3))
ax = sns.barplot(x=top5_acceleration['mpg'], y=top5_acceleration['name'], hue=top5_acceleration['origin'], palette='viridis', orient='h')
# Add numbers to the diagram
for p in ax.patches:
    ax.annotate(f'{p.get_width():.2f}', (p.get_width(), p.get_y() + p.get_height()/2), ha='left', va='center')
plt.title("Top 5 Name based on mpg")
plt.show()
```



1. Conclusion :
2. The name of the Pontiac Catalina car has the highest displacement, Pontiac Grand Prix is the name of the car with the highest horsepower and Pontiac Safari (SW) is the name of the car that has the highest weight. Of the three categories of variables with the highest value comes from USA origin
3. Meanwhile, the one with the highest MPG is the Mazda GLC from Japan and the car from the USA is not included in the top 5 cars with the highest MPG.

THANK YOU

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