Hypothesis_Testing_Cars_dataset

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1 Hypothesis Testing on Cars Dataset

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2 *Import Libraries*

[8]:
```
import pandas as pd
import numpy as np
from scipy import stats
import seaborn as sns
import matplotlib.pyplot as plt
```

3 *Load Dataset*

[7]:
```
cars = pd.read_excel('CARS.xlsx')
cars.head(10)
```

[7]:
```
    Make                    Model    Type  Origin DriveTrain   MSRP  Invoice  \
0  Acura                      MDX     SUV    Asia        All  36945    33337
1  Acura           RSX Type S 2dr   Sedan    Asia      Front  23820    21761
2  Acura                  TSX 4dr   Sedan    Asia      Front  26990    24647
3  Acura                   TL 4dr   Sedan    Asia      Front  33195    30299
4  Acura               3.5 RL 4dr   Sedan    Asia      Front  43755    39014
5  Acura  3.5 RL w/Navigation 4dr   Sedan    Asia      Front  46100    41100
6  Acura   NSX coupe 2dr manual S  Sports    Asia       Rear  89765    79978
7   Audi               A4 1.8T 4dr   Sedan  Europe      Front  25940    23508
8   Audi   A41.8T convertible 2dr   Sedan  Europe      Front  35940    32506
9   Audi               A4 3.0 4dr   Sedan  Europe      Front  31840    28846

   EngineSize  Cylinders  Horsepower  MPG_City  MPG_Highway  Weight  \
0         3.5        6.0         265        17           23    4451
1         2.0        4.0         200        24           31    2778
2         2.4        4.0         200        22           29    3230
3         3.2        6.0         270        20           28    3575
4         3.5        6.0         225        18           24    3880
5         3.5        6.0         225        18           24    3893
6         3.2        6.0         290        17           24    3153
```

```
7          1.8        4.0          170        22            31     3252
8          1.8        4.0          170        23            30     3638
9          3.0        6.0          220        20            28     3462

   Wheelbase  Length
0        106     189
1        101     172
2        105     183
3        108     186
4        115     197
5        115     197
6        100     174
7        104     179
8        105     180
9        104     179
```

[10]:
```
cars.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 428 entries, 0 to 427
Data columns (total 15 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   Make         428 non-null    object
 1   Model        428 non-null    object
 2   Type         428 non-null    object
 3   Origin       428 non-null    object
 4   DriveTrain   428 non-null    object
 5   MSRP         428 non-null    int64
 6   Invoice      428 non-null    int64
 7   EngineSize   428 non-null    float64
 8   Cylinders    426 non-null    float64
 9   Horsepower   428 non-null    int64
 10  MPG_City     428 non-null    int64
 11  MPG_Highway  428 non-null    int64
 12  Weight       428 non-null    int64
 13  Wheelbase    428 non-null    int64
 14  Length       428 non-null    int64
dtypes: float64(2), int64(8), object(5)
memory usage: 50.3+ KB
```

- **load the dataset and check columns, data types, and missing values.**

4 *Data Cleaning*

[11]:
```
cars.isnull().sum()
```

[11]:
```
Make           0
Model          0
Type           0
Origin         0
DriveTrain     0
MSRP           0
Invoice        0
EngineSize     0
Cylinders      2
Horsepower     0
MPG_City       0
MPG_Highway    0
Weight         0
Wheelbase      0
Length         0
dtype: int64
```

[13]:
```
# Handle missing values in Cylinders
cars['Cylinders'].fillna(cars['Cylinders'].median(), inplace=True)
```

```
C:\Users\hp\AppData\Local\Temp\ipykernel_17696\3393017961.py:2: FutureWarning: A
value is trying to be set on a copy of a DataFrame or Series through chained
assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behaves as
a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  cars['Cylinders'].fillna(cars['Cylinders'].median(), inplace=True)
```

[14]:
```
print(cars.isnull().sum())
```

```
Make           0
Model          0
Type           0
Origin         0
DriveTrain     0
MSRP           0
Invoice        0
EngineSize     0
```

```
Cylinders      0
Horsepower     0
MPG_City       0
MPG_Highway    0
Weight         0
Wheelbase      0
Length         0
dtype: int64
```

- **We replace missing values (only 2 in Cylinders) with the median — suitable for numerical data.**

5 *Descriptive Statistics*

[15]:
```
cars.describe()
```

[15]:
```
                MSRP        Invoice  EngineSize   Cylinders  Horsepower  \
count     428.000000     428.000000  428.000000  428.000000  428.000000
mean    32774.855140   30014.700935    3.196729    5.808411  215.885514
std     19431.716674   17642.117750    1.108595    1.554844   71.836032
min     10280.000000    9875.000000    1.300000    3.000000   73.000000
25%     20334.250000   18866.000000    2.375000    4.000000  165.000000
50%     27635.000000   25294.500000    3.000000    6.000000  210.000000
75%     39205.000000   35710.250000    3.900000    6.000000  255.000000
max    192465.000000  173560.000000    8.300000   12.000000  500.000000

         MPG_City  MPG_Highway       Weight   Wheelbase      Length
count  428.000000   428.000000   428.000000  428.000000  428.000000
mean    20.060748    26.843458  3577.953271  108.154206  186.362150
std      5.238218     5.741201   758.983215    8.311813   14.357991
min     10.000000    12.000000  1850.000000   89.000000  143.000000
25%     17.000000    24.000000  3104.000000  103.000000  178.000000
50%     19.000000    26.000000  3474.500000  107.000000  187.000000
75%     21.250000    29.000000  3977.750000  112.000000  194.000000
max     60.000000    66.000000  7190.000000  144.000000  238.000000
```

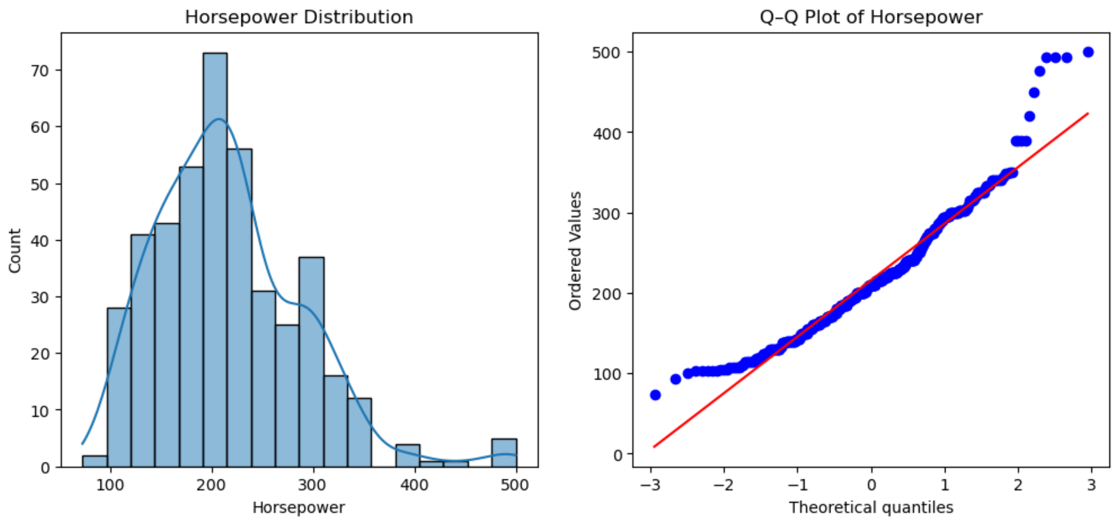
- This gives the mean, median, min, max, std for numeric columns like MSRP, Horsepower, EngineSize, etc.
- It helps understand data distribution before testing hypotheses.

6 *Normality*

- before Parametric Tests

6.1 Histogram & Q–Q Plot

[17]:
```python
import scipy.stats as stats

plt.figure(figsize=(12,5))
plt.subplot(1,2,1)
sns.histplot(cars['Horsepower'], kde=True)
plt.title("Horsepower Distribution")

plt.subplot(1,2,2)
stats.probplot(cars['Horsepower'], dist="norm", plot=plt)
plt.title("Q-Q Plot of Horsepower")
plt.show()
```



7 *Parametric Tests*

- **when data is normal**

8 Hypothesis Tests Overview

Test	**Use Case**	**Hypothesis Example**	**Decision Rule**
One-Sample t-test	Compare sample mean to value	H : Horsepower = 200	Reject / Fail based on $p < 0.05$
Independent t-test	Compare two independent groups	H : Mean MSRP (USA) = Mean MSRP (Europe)	Based on p-value significance

Test	Use Case	Hypothesis Example	Decision Rule
ANOVA	Compare 3+ groups	H : Mean Horsepower (Sedan = SUV = Sports)	$p < 0.05 \rightarrow$ at least one mean differs
Mann–Whitney U	Non-parametric 2-group comparison	H : Distributions equal (USA vs Europe)	Based on p-value significance
Kruskal–Wallis	Non-parametric ANOVA (3+ groups)	H : All medians equal (car types)	$p < 0.05 \rightarrow$ at least one differs
Chi-Square	Relationship between categories	H : Origin and DriveTrain independent	$p < 0.05 \rightarrow$ variables related

9 *One-Sample t-test*

- **checking if there is a significant difference between a sample and hypothesized population means.**

[26]:
```
from scipy.stats import ttest_1samp
```

[18]:
```
t_stat, p_val = stats.ttest_1samp(cars['Horsepower'], 200)
print("t-value:", t_stat)
print("p-value:", p_val)

if p_val < 0.05:
    print("Reject H  → Mean horsepower is significantly different from 200.")
else:
    print("Fail to reject H  → Mean horsepower   200.")
```

```
t-value: 4.574891766789726
p-value: 6.253344784284048e-06
Reject H  → Mean horsepower is significantly different from 200.
```

10 *Independent Two-Sample t-test*

- **A two-sample t-test is used for comparing the significant difference between two independent groups. This test is also known as an independent samples t-test.**

[25]:
```
from scipy.stats import ttest_ind
```

[20]:
```
usa = cars[cars['Origin'] == 'USA']['MSRP']
europe = cars[cars['Origin'] == 'Europe']['MSRP']

t_stat, p_val = stats.ttest_ind(usa, europe)
print("t-value:", t_stat)
print("p-value:", p_val)
```

```
if p_val < 0.05:
    print("Reject H  → Mean MSRP differs between USA and Europe cars.")
else:
    print("Fail to reject H  → No significant difference in MSRP.")
```

```
t-value: -8.5368542432442
p-value: 1.0436671157614213e-15
Reject H  → Mean MSRP differs between USA and Europe cars.
```

11 *ANOVA (One-Way)*

- **With the one-way ANOVA method, we compare multiple groups based on only one independent variable**

[22]:
```
from scipy.stats import f_oneway
```

[24]:
```
stat, p=f_oneway(cars["Invoice"],cars["MSRP"],cars["Horsepower"])
print("p_value:",p)
print("ANOVA:",stat)
if p < 0.05:
    print("Reject H  → At least one group mean is different.")
else:
    print("Fail to reject H  → All group means are equal.")
```

```
p_value: 2.7292133264922565e-186
ANOVA: 607.5629296531739
Reject H  → At least one group mean is different.
```

12 *Non-Parametric Tests*

- if data not normal

13 *Mann–Whitney U Test*

- Alternative to independent t-test (used when data is not normal).

[27]:
```
stat, p_val = stats.mannwhitneyu(usa, europe)
print("U-statistic:", stat)
print("p-value:", p_val)
if p_val < 0.05:
    print("Reject H  → Median MSRP differs between USA and Europe cars.")
else:
    print("Fail to reject H  → No significant difference in median MSRP.")
```

```
U-statistic: 3489.5
p-value: 3.749254035965752e-18
Reject H  → Median MSRP differs between USA and Europe cars.
```

14 *Kruskal–Wallis Test*

- Non-parametric version of ANOVA.

[29]:
```
groups = [grp['MSRP'].values for name, grp in cars.groupby('Type')]
stat, p_val = stats.kruskal(*groups)
print("Statistic:", stat)
print("p-value:", p_val)
if p_val < 0.05:
    print("Reject H  → At least one car type has a different median MSRP.")
else:
    print("Fail to reject H  → Median MSRP is similar across car types.")
```

```
Statistic: 49.18863253683512
p-value: 2.030713990529349e-09
Reject H  → At least one car type has a different median MSRP.
```

15 *Chi-Square Test of Independence*

[32]:
```
from scipy.stats import chi2_contingency
```

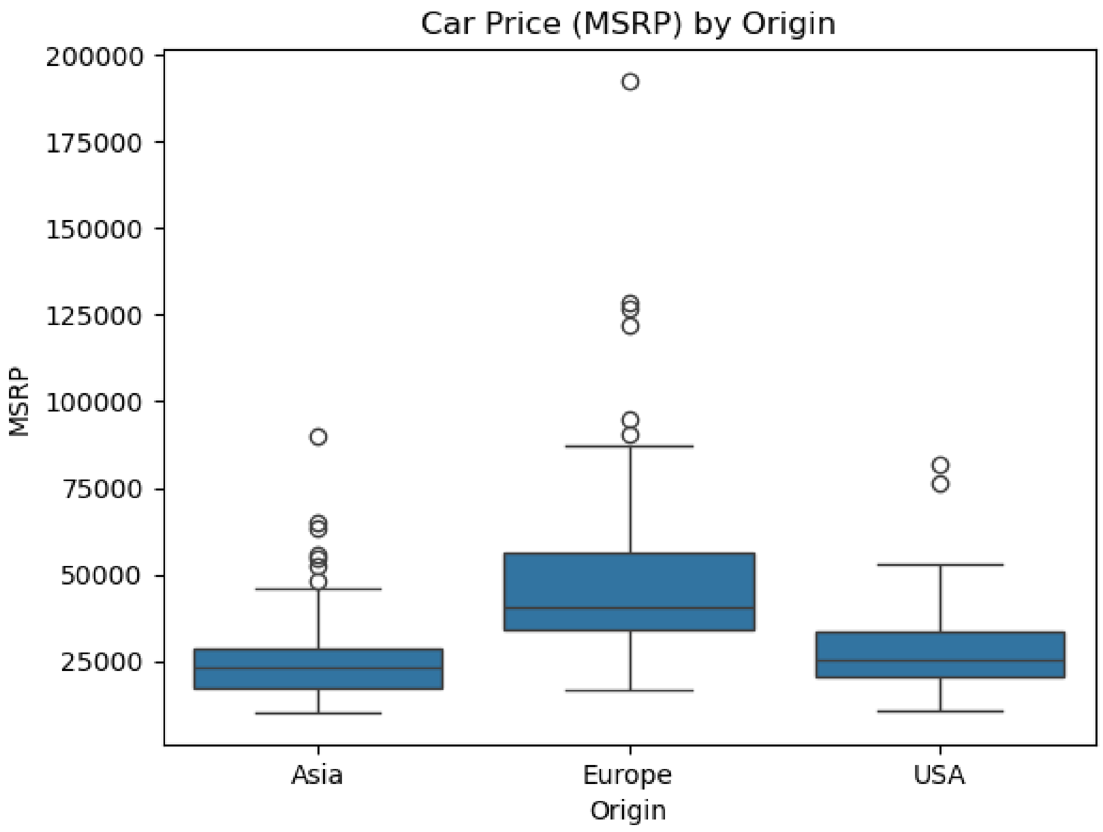
[33]:
```
contingency_table = pd.crosstab(cars['Origin'], cars['DriveTrain'])
chi2, p, dof, expected = chi2_contingency(contingency_table)
print("Chi2:", chi2)
print("p-value:", p)

if p < 0.05:
    print("Reject H  → Origin and DriveTrain are related.")
else:
    print("Fail to reject H  → No relation between Origin and DriveTrain.")
```

```
Chi2: 40.17843276388697
p-value: 3.9758008515569337e-08
Reject H  → Origin and DriveTrain are related.
```

16 *Visualizing*

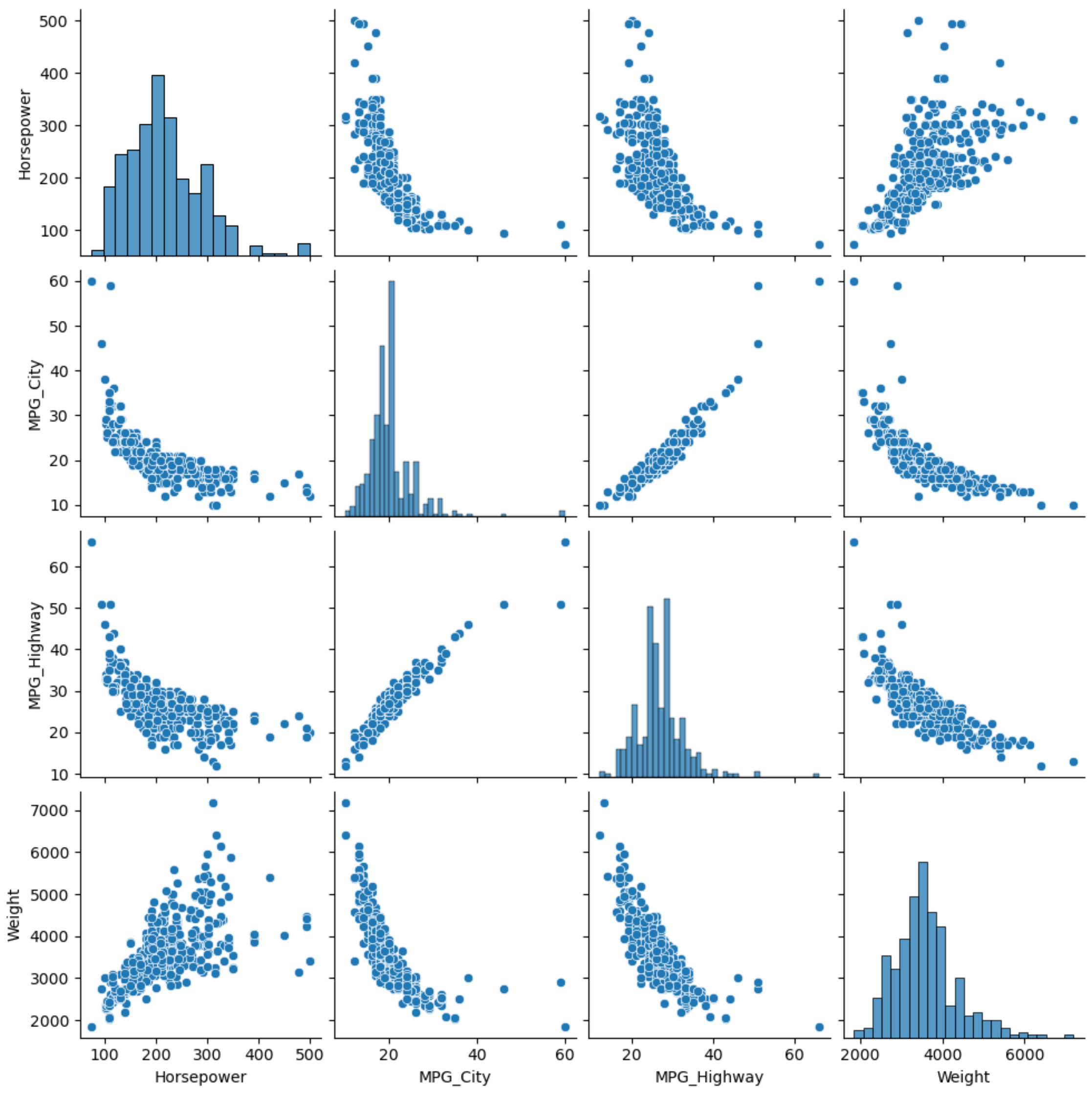
17 *Boxplot of MSRP by Origin*

[35]:
```
sns.boxplot(x='Origin', y='MSRP', data=cars)
plt.title("Car Price (MSRP) by Origin")
plt.show()
```



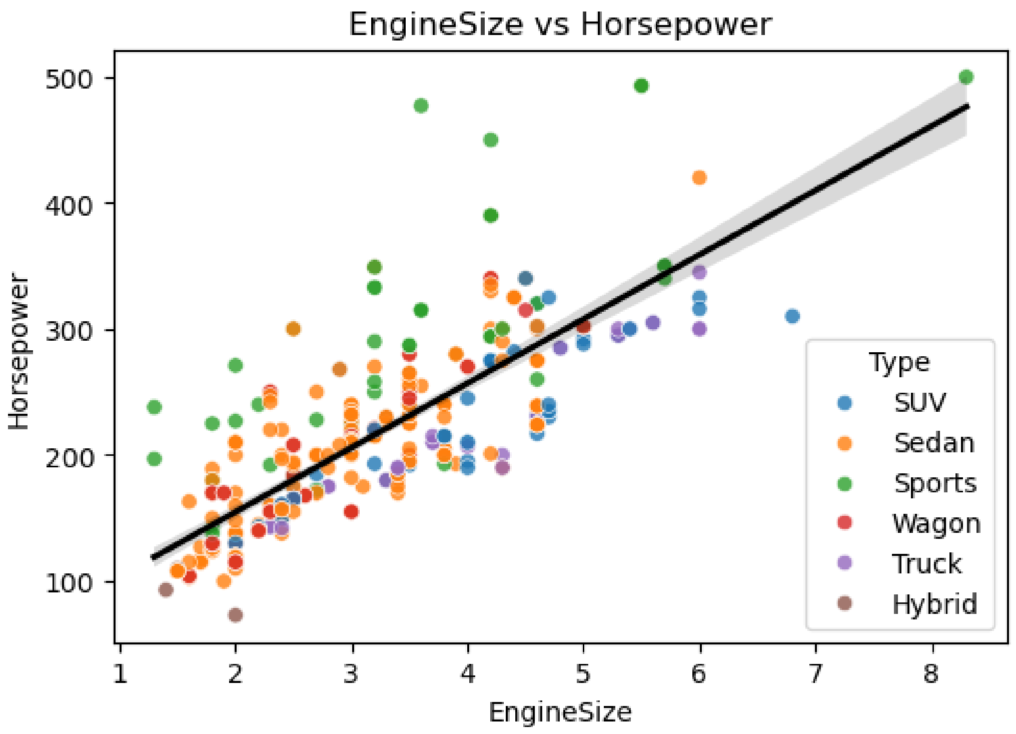
18 *Pairplot*

[36]:
```
sns.pairplot(cars[['Horsepower', 'MPG_City', 'MPG_Highway', 'Weight']])
plt.show()
```



19 *scatterplot*

```
[39]: plt.figure(figsize=(6,4))
sns.scatterplot(x='EngineSize', y='Horsepower', hue='Type', data=cars, alpha=0.
 ↪8)
sns.regplot(x='EngineSize', y='Horsepower', data=cars, scatter=False,␣
 ↪color='black')
plt.title("EngineSize vs Horsepower")
plt.show()
```


EngineSize vs Horsepower
Horsepower
EngineSize
500
400
300
200
100
1
2
3
4
5
6
7
8
Type
SUV
Sedan
Sports
Wagon
Truck
Hybrid

```
[ ]:
```