Exploratory Data Analysis

SW

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Objectives

After completing this lab you will be able to:

- Explore features or characteristics to predict price of car
- Analyze patterns and run descriptive statistical analysis
- Group data based on identified parameters and create pivot tables
- Identify the effect of independent attributes on price of cars

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Descriptive Statistical Analysis

Basics of Grouping

Correlation and Causation

Import Data from Module 2

Setup Import libraries:

```
import pandas as pd
import numpy as np
```

Download the dataset and store it in dataframe `df`:

```
filepath='https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/\
IBMDeveloperSkillsNetwork-DA0101EN-SkillsNetwork/labs/Data%20files/automobileEDA.csv'
df = pd.read_csv(filepath, header=0)
```

View the first 5 values of the dataframe using `datafame.head()`:

```
df.head()
```

```
##    symboling  normalized-losses         make  ... horsepower-binned diesel gas
## 0          3                122  alfa-romero  ...             Medium      0   1
## 1          3                122  alfa-romero  ...             Medium      0   1
## 2          1                122  alfa-romero  ...             Medium      0   1
## 3          2                164         audi  ...             Medium      0   1
## 4          2                164         audi  ...             Medium      0   1
##
## [5 rows x 29 columns]
```

Analyzing Individual Feature Patterns Using Visualization

Import visualization packages "Matplotlib" and "Seaborn". Don't forget about "%matplotlib inline" to plot in a Jupyter notebook.

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

```
# list the data types for each column
print(df.dtypes)
```

```
## symboling              int64
## normalized-losses      int64
## make                  object
## aspiration            object
## num-of-doors          object
## body-style            object
## drive-wheels          object
## engine-location       object
## wheel-base           float64
## length               float64
## width                float64
## height               float64
## curb-weight            int64
## engine-type           object
## num-of-cylinders      object
## engine-size            int64
## fuel-system           object
## bore                 float64
## stroke               float64
## compression-ratio    float64
## horsepower           float64
## peak-rpm             float64
## city-mpg               int64
## highway-mpg            int64
## price                float64
## city-L/100km         float64
## horsepower-binned     object
## diesel                 int64
## gas                    int64
## dtype: object
```

```
numeric_df = df.select_dtypes(include=['float64', 'int64'])
numeric_df.corr()
```

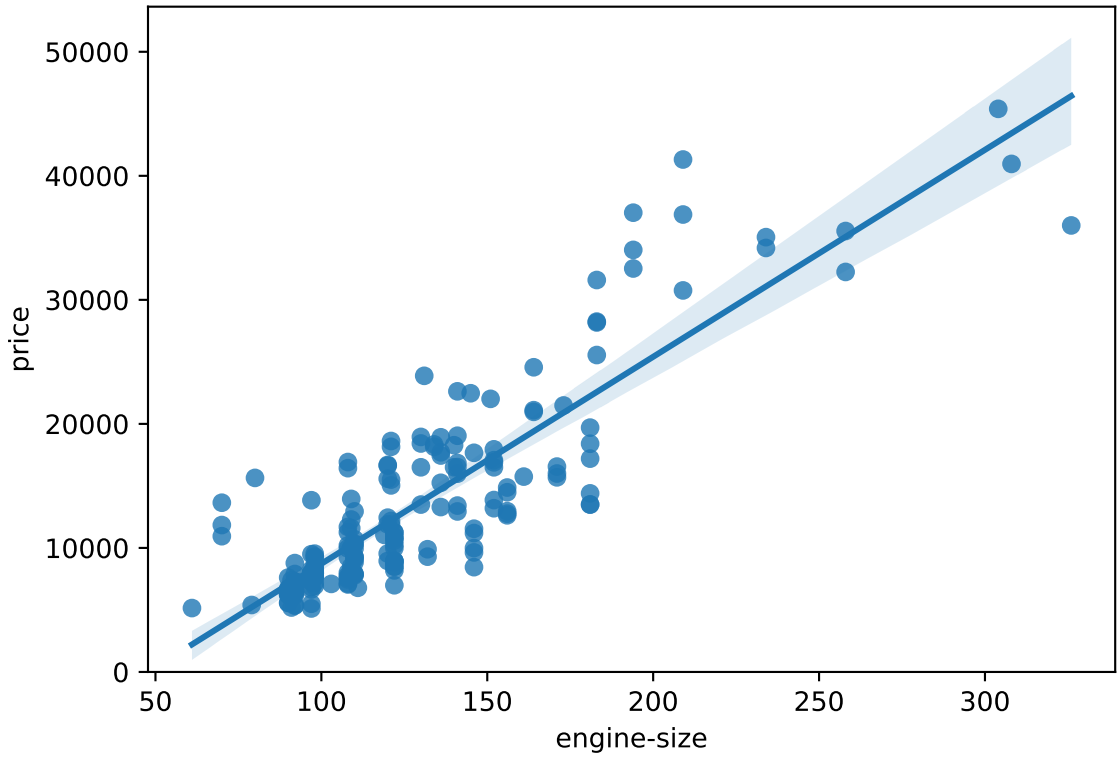
```
##                    symboling  normalized-losses  ...    diesel       gas
## symboling           1.000000           0.466264  ... -0.196735  0.196735
## normalized-losses   0.466264           1.000000  ... -0.101546  0.101546
## wheel-base         -0.535987          -0.056661  ...  0.307237 -0.307237
## length             -0.365404           0.019424  ...  0.211187 -0.211187
## width              -0.242423           0.086802  ...  0.244356 -0.244356
## height             -0.550160          -0.373737  ...  0.281578 -0.281578
## curb-weight        -0.233118           0.099404  ...  0.221046 -0.221046
## engine-size        -0.110581           0.112360  ...  0.070779 -0.070779
## bore               -0.140019          -0.029862  ...  0.054458 -0.054458
## stroke             -0.008245           0.055563  ...  0.241303 -0.241303
## compression-ratio  -0.182196          -0.114713  ...  0.985231 -0.985231
## horsepower          0.075819           0.217299  ... -0.169053  0.169053
## peak-rpm            0.279740           0.239543  ... -0.475812  0.475812
## city-mpg           -0.035527          -0.225016  ...  0.265676 -0.265676
## highway-mpg         0.036233          -0.181877  ...  0.198690 -0.198690
## price              -0.082391           0.133999  ...  0.110326 -0.110326
## city-L/100km        0.066171           0.238567  ... -0.241282  0.241282
## diesel             -0.196735          -0.101546  ...  1.000000 -1.000000
## gas                 0.196735           0.101546  ... -1.000000  1.000000
##
## [19 rows x 19 columns]
```

```
df[['bore', 'stroke', 'compression-ratio', 'horsepower']].corr()
```

```
##                      bore    stroke  compression-ratio  horsepower
## bore             1.000000 -0.055390           0.001263    0.566936
## stroke          -0.055390  1.000000           0.187923    0.098462
## compression-ratio  0.001263  0.187923           1.000000   -0.214514
## horsepower       0.566936  0.098462          -0.214514    1.000000
```

```
# Engine size as potential predictor variable of price
sns.regplot(x="engine-size", y="price", data=df)
plt.ylim(0,)
```

```
## (0.0, 53637.15290863124)
```



Reference

How to Disable Warnings in Jupyter Notebook