Analyzing selling price of used cars using Python

Last Updated : 12 Dec, 2019

Now-a-days, with the technological advancement, Techniques like Machine Learning, etc are being used on a large scale in many organisations. These models usually work with a set of predefined data-points available in the form of datasets. These datasets contain the past/previous information on a specific domain. Organising these datapoints before it is fed to the model is very important. This is where we use Data Analysis. If the data fed to the machine learning model is not well organised, it gives out false or undesired output. This can cause major losses to the organisation. Hence making use of proper data analysis is very important.

About Dataset:

The data that we are going to use in this example is about cars. Specifically containing various information datapoints about the used cars, like their price, color, etc. Here we need to understand that simply collecting data isn't enough. Raw data isn't useful. Here data analysis plays a vital role in unlocking the information that we require and to gain new insights into this raw data.

Consider this scenario, our friend, Otis, wants to sell his car. But he doesn't know how much should he sell his car for! He wants to maximize the profit but he also wants it to be sold for a reasonable price for someone who would want to own it. So here, us, being a data scientist, we can help our friend Otis.

Let's think like data scientists and clearly define some of his problems: For example, is there data on the prices of other cars and their characteristics? What features of cars affect their prices? Colour? Brand? Does horsepower also affect the selling price, or perhaps, something else?

As a data analyst or data scientist, these are some of the questions we can start thinking about. To answer these questions, we're going to need some data. But this data is in raw form. Hence we need to analyze it first. The data is available in the form of `.csv/.data` format with us

To download the file used in this example click here. The file provided is in the .data format. Follow the below process for converting a .data file to .csv file.

Process to convert .data file to .csv:

open MS Excel
Go to DATA
Select From text
Check box tick on comas(only)

Save as .csv to your desired location on your pc!

Modules needed:

pandas: Pandas is an opensource library that allows you to perform data manipulation in Python. Pandas provide an easy way to create, manipulate and wrangle the data.
numpy: Numpy is the fundamental package for scientific computing with Python. `numpy` can be used as an efficient multi-dimensional container of generic data.
matplotlib: Matplotlib is a Python 2D plotting library which produces publication quality figures in a variety of formats.
seaborn: Seaborn is a Python data-visualization library that is based on matplotlib. Seaborn provides a high-level interface for drawing attractive and informative statistical graphics.
scipy: Scipy is a Python-based ecosystem of open-source software for mathematics, science, and engineering.

Steps for installing these packages:

If you are using anaconda- jupyter/ syder or any other third party softwares to write your python code, make sure to set the path to the "scripts folder" of that software in command prompt of your pc.
Then type – pip install package-name
Example:

```
pip install numpy
```

Then after the installation is done. (Make sure you are connected to the internet!!) Open your IDE, then import those packages. To import, type – import package name
Example:

```
import numpy
```

Steps that are used in the following code

(Short description):

Import the packages
Set the path to the data file(.csv file)
Find if there are any null data or NaN data in our file. If any, remove them
Perform various data cleaning and data visualisation operations on your data. These steps are illustrated beside each line of code in the form of comments for better understanding, as it would be better to see the code side by side than explaining it entirely here, would be meaningless.
Obtain the result!

Lets start analyzing the data.

Step 1: Import the modules needed.

```
# importing section
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import scipy as sp
```

Step 2: Let's check the first five entries of dataset.

```
# using the Csv file
df = pd.read_csv('output.csv')

# Checking the first 5 entries of datase
df.head()
```

Output:

```
In [54]: df = pd.read_csv('output.csv') #using the Csv file
         df.head() #Checking the first 5 entries of dataset
```

Out[54]:

	3	?	alfa-romero	gas	std	two	convertible	rwd	front	88.60	...	130	mpfi	3.47	2.68	9.00	111	5000	21	27	13495
0	3	?	alfa-romero	gas	std	two	convertible	rwd	front	88.6	...	130	mpfi	3.47	2.68	9.0	111	5000	21	27	16500
1	1	?	alfa-romero	gas	std	two	hatchback	rwd	front	94.5	...	152	mpfi	2.68	3.47	9.0	154	5000	19	26	16500
2	2	164	audi	gas	std	four	sedan	fwd	front	99.8	...	109	mpfi	3.19	3.40	10.0	102	5500	24	30	13950
3	2	164	audi	gas	std	four	sedan	4wd	front	99.4	...	136	mpfi	3.19	3.40	8.0	115	5500	18	22	17450
4	2	?	audi	gas	std	two	sedan	fwd	front	99.8	...	136	mpfi	3.19	3.40	8.5	110	5500	19	25	15250

5 rows × 26 columns

Step 3: Defining headers for our dataset.

```
headers = ["symboling", "normalized-loss
           "fuel-type", "aspiration","nu
           "body-style","drive-wheels",
           "wheel-base","length", "width
           "engine-type","num-of-cylinde
           "fuel-system","bore","stroke"
           "horsepower", "peak-rpm","cit

df.columns=headers
df.head()
```

Output:

```
In [28]: headers = ["symboling", "normalized-losses", "make", "fuel-type",
                    "aspiration","num-of-doors", "body-style","drive-wheels",
                    "engine-location","wheel-base","length", "width","height",
                    "curb-weight","engine-type","num-of-cylinders", "engine-size",
                    "fuel-system","bore","stroke", "compression-ratio","horsepower",
                    "peak-rpm","city-mpg","highway-mpg","price"]

         df.columns=headers
         df.head()
```

Out[28]:

	symboling	normalized-losses	make	fuel-type	aspiration	num-of-doors	body-style	drive-wheels	engine-location	wheel-base	...	engine-size	fuel-system	bore	stroke	compression-ratio	horsepowe
0	3	?	alfa-romero	gas	std	two	convertible	rwd	front	88.6	...	130	mpfi	3.47	2.68	9.0	11
1	1	?	alfa-romero	gas	std	two	hatchback	rwd	front	94.5	...	152	mpfi	2.68	3.47	9.0	15
2	2	164	audi	gas	std	four	sedan	fwd	front	99.8	...	109	mpfi	3.19	3.40	10.0	10
3	2	164	audi	gas	std	four	sedan	4wd	front	99.4	...	136	mpfi	3.19	3.40	8.0	11
4	2	?	audi	gas	std	two	sedan	fwd	front	99.8	...	136	mpfi	3.19	3.40	8.5	11

5 rows × 26 columns

Step 4: Finding the missing value if any.

```
data = df

# Finding the missing values
data.isna().any()

# Finding if missing values
data.isnull().any()
```

Output:

```
In [56]: data=df
         data.isna().any() #Finding the missing values
         data.isnull().any() #Finding if missing values

Out[56]: 3              False
         ?              False
         alfa-romero    False
         gas            False
         std            False
         two            False
         convertible    False
         rwd            False
         front          False
         88.60          False
         168.80         False
         64.10          False
         48.80          False
         2548           False
         dohc           False
         four           False
         130            False
         mpfi           False
         3.47           False
         2.68           False
         9.00           False
         111            False
         5000           False
         21             False
         27             False
         13495          False
         dtype: bool
```

Step 4: Converting mpg to L/100km and checking the data type of each column.

```
# converting mpg to L / 100km
data['city-mpg'] = 235 / df['city-mpg']
data.rename(columns = {'city_mpg': "city

print(data.columns)
```

```
# checking the data type of each column
data.dtypes
```

Output:

```
In [30]: # converting mpg to L/100km
         data['city-mpg'] = 235/df['city-mpg']
         data.rename(columns = {'city_mpg': "city-L/100km"}, inplace = True)

         print(data.columns)
         data.dtypes #checking the data type of each column

         Index(['symboling', 'normalized-losses', 'make', 'fuel-type', 'aspiration',
                'num-of-doors', 'body-style', 'drive-wheels', 'engine-location',
                'wheel-base', 'length', 'width', 'height', 'curb-weight', 'engine-type',
                'num-of-cylinders', 'engine-size', 'fuel-system', 'bore', 'stroke',
                'compression-ratio', 'horsepower', 'peak-rpm', 'city-mpg',
                'highway-mpg', 'price'],
               dtype='object')

Out[30]: symboling           int64
         normalized-losses  object
         make               object
         fuel-type          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               object
         stroke             object
         compression-ratio  float64
         horsepower         object
         peak-rpm           object
         city-mpg           float64
         highway-mpg          int64
         price              object
         dtype: object
```

Step 5: Here, price is of object type(string), it should be int or float, so we need to change it

```
data.price.unique()

# Here it contains '?', so we Drop it
data = data[data.price != '?']
```

```
# checking it again
data.dtypes
```

Output:

```
In [70]: #Here, price is of object type(string), it should be int or float, so we need to change it
         data.price.unique()

Out[70]: array([16500, 13950, 17450, 15250, 17710, 18920, 23875, 16430, 16925,
                20970, 21105, 24565, 30760, 41315, 36880,  5151,  6295,  6575,
                 5572,  6377,  7957,  6229,  6692,  7609,  8558,  8921, 12964,
                 6479,  6855,  5399,  6529,  7129,  7295,  7895,  9095,  8845,
                10295, 12945, 10345,  6785, 11048, 32250, 35550, 36000,  5195,
                 6095,  6795,  6695,  7395, 10945, 11845, 13645, 15645,  8495,
                10595, 10245, 10795, 11245, 18280, 18344, 25552, 28248, 28176,
                31600, 34184, 35056, 40960, 45400, 16503,  5389,  6189,  6669,
                 7689,  9959,  8499, 12629, 14869, 14489,  6989,  8189,  9279,
                 5499,  7099,  6649,  6849,  7349,  7299,  7799,  7499,  7999,
                 8249,  8949,  9549, 13499, 14399, 17199, 19699, 18399, 11900,
                13200, 12440, 13860, 15580, 16900, 16695, 17075, 16630, 17950,
                18150, 12764, 22018, 32528, 34028, 37028,  9295,  9895, 11850,
                12170, 15040, 15510, 18620,  5118,  7053,  7603,  7126,  7775,
                 9960,  9233, 11259,  7463, 10198,  8013, 11694,  5348,  6338,
                 6488,  6918,  7898,  8778,  6938,  7198,  7788,  7738,  8358,
                 9258,  8058,  8238,  9298,  9538,  8449,  9639,  9980, 11199,
                11549, 17669,  8948, 10698,  9988, 10898, 11248, 16558, 15998,
                15690, 15750,  7975,  7995,  8195,  9495,  9995, 11595,  9980,
                13295, 13845, 12290, 12940, 13415, 15985, 16515, 18420, 18950,
                16845, 19045, 21485, 22470, 22625], dtype=int64)
```

```
In [71]: # Here it contains '?', so we Drop it
         data = data[data.price!= '?']

         data['price'] = data['price'].astype(int)
         #checking it again
         data.dtypes

Out[71]: symboling              int64
         normalized-losses     object
         make                  object
         fuel-type             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                  object
         stroke                object
         compression-ratio    float64
         horsepower            object
         peak-rpm              object
         city-mpg             float64
         highway-mpg            int64
         price                  int32
         price-binned        category
         dtype: object
```

Step 6: Normalizing values by using simple feature scaling method examples(do for the rest) and binning- grouping values

```
data['length'] = data['length']/data['le
data['width'] = data['width']/data['widt
data['height'] = data['height']/data['he

# binning- grouping values
bins = np.linspace(min(data['price']), m
group_names = ['Low', 'Medium', 'High']
data['price-binned'] = pd.cut(data['pric
                              labels = g
                              include_lo
```

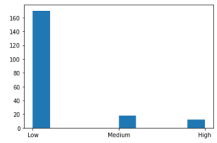
```
print(data['price-binned'])
plt.hist(data['price-binned'])
plt.show()
```

Output:

```
In [69]: #Normalizing values by using simple feature scaling method examples(do for the rest)
         data['length'] = data['length']/data['length'].max()
         data['width'] = data['width']/data['width'].max()
         data['height'] = data['height']/data['height'].max()

         #binning- grouping values
         bins = np.linspace(min(data['price']), max(data['price']), 4)
         group_names = ['Low','Medium', 'High']
         data['price-binned'] = pd.cut(data['price'], bins, labels=group_names, include_lowest=True)
         print(data['price-binned'])
         plt.hist(data['price-binned'])
         plt.show()

0         Low
1         Low
2         Low
3         Low
4         Low
        ...
199       Low
200    Medium
201    Medium
202    Medium
203    Medium
Name: price-binned, Length: 200, dtype: category
Categories (3, object): [Low < Medium < High]
```



Step 7: Doing descriptive analysis of data categorical to numerical values.

```
# categorical to numerical variables
pd.get_dummies(data['fuel-type']).head()

# descriptive analysis
# NaN are skipped
data.describe()
```

Output:

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```
In [46]: #categorical to numerical variables
         pd.get_dummies(data['fuel-type']).head()

         #descriptive analysis
         #NaN are skipped
         data.describe()
```

Out[46]:

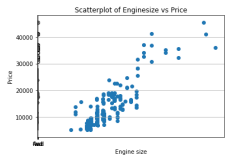
	symboling	wheel-base	length	width	height	curb-weight	engine-size	compression-ratio	city-mpg	highway-mpg	price
count	200.000000	200.000000	200.000000	200.000000	200.000000	200.000000	200.000000	200.000000	200.000000	200.000000	200.000000
mean	0.830000	98.848000	0.837232	0.915250	0.899523	2555.705000	126.860000	10.170100	9.937914	30.705000	13205.690000
std	1.248557	6.038261	0.059333	0.029207	0.040610	518.594552	41.650501	4.014163	2.539415	6.827227	7966.982558
min	-2.000000	86.600000	0.678039	0.837500	0.799331	1488.000000	61.000000	7.000000	4.795918	16.000000	5118.000000
25%	0.000000	94.500000	0.800937	0.891319	0.869565	2163.000000	97.750000	8.575000	7.833333	25.000000	7775.000000
50%	1.000000	97.000000	0.832292	0.909722	0.904682	2414.000000	119.500000	9.000000	9.791667	30.000000	10270.000000
75%	2.000000	102.400000	0.881788	0.926042	0.928512	2928.250000	142.000000	9.400000	12.368421	34.000000	16500.750000
max	3.000000	120.900000	1.000000	1.000000	1.000000	4066.000000	326.000000	23.000000	18.076923	54.000000	45400.000000

Step 8: Plotting the data according to the price based on engine size.

```
# examples of box plot
plt.boxplot(data['price'])

# by using seaborn
sns.boxplot(x ='drive-wheels', y ='price

# Predicting price based on engine size
# Known on x and predictable on y
plt.scatter(data['engine-size'], data['p
plt.title('Scatterplot of Enginesize vs
plt.xlabel('Engine size')
plt.ylabel('Price')
plt.grid()
plt.show()
```

Output:

```
In [48]: #examples of box plot
         plt.boxplot(data['price'])

         #by using seaborn
         sns.boxplot(x='drive-wheels', y='price', data=data)

         # Predicting price based on engine size
         # Known on x and predictable on y
         plt.scatter(data['engine-size'], data['price'])
         plt.title('Scatterplot of Enginesize vs Price')
         plt.xlabel('Engine size')
         plt.ylabel('Price')
         plt.grid()
         plt.show()
```



Step 9: Grouping the data according to wheel, body-style and price.

```
# Grouping Data
test = data[['drive-wheels', 'body-style
data_grp = test.groupby(['drive-wheels',
                         as_index = Fals

data_grp
```

Output:

```
In [49]: #Grouping Data
         test=data[['drive-wheels','body-style','price']]
         data_grp=test.groupby(['drive-wheels','body-style'], as_index=False).mean()
         data_grp
```

Out[49]:

	drive-wheels	body-style	price
0	4wd	hatchback	7603.000000
1	4wd	sedan	12647.333333
2	4wd	wagon	9095.750000
3	fwd	convertible	11595.000000
4	fwd	hardtop	8249.000000
5	fwd	hatchback	8396.387755
6	fwd	sedan	9811.800000
7	fwd	wagon	9997.333333
8	rwd	convertible	26563.250000
9	rwd	hardtop	24202.714286
10	rwd	hatchback	14337.777778
11	rwd	sedan	21711.833333
12	rwd	wagon	16994.222222

Step 10: Using the pivot method and plotting the heatmap according to the data obtained by pivot method

```
# pivot method
data_pivot = data_grp.pivot(index = 'dri
                            columns = 'b
data_pivot

# heatmap for visualizing data
plt.pcolor(data_pivot, cmap ='RdBu')
plt.colorbar()
plt.show()
```

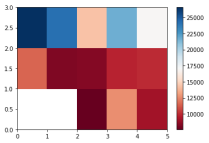
Output:

```
In [50]: #pivot method
         data_pivot = data_grp.pivot(index = 'drive-wheels', columns= 'body-style')
         data_pivot
```

Out[50]:

	price					
body-style	convertible	hardtop	hatchback	sedan	wagon	
drive-wheels						
4wd	NaN	NaN	7603.000000	12647.333333	9095.750000	
fwd	11595.00	8249.000000	8396.387755	9811.800000	9997.333333	
rwd	26563.25	24202.714286	14337.777778	21711.833333	16994.222222	

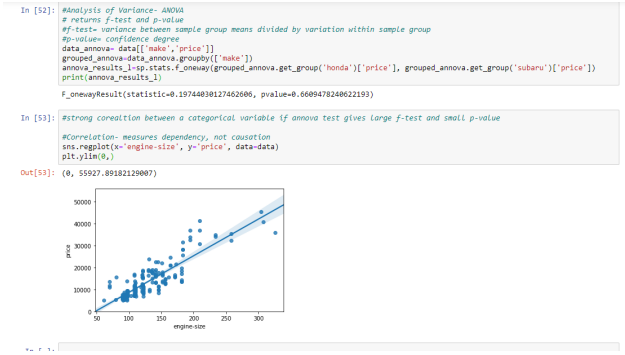
```
In [51]: #heatmap for visualizing data
         plt.pcolor(data_pivot, cmap='RdBu')
         plt.colorbar()
         plt.show()
```



Step 11: Obtaining the final result and showing it in the form of a graph. As the slope is increasing in a positive direction, it is a positive linear relationship.

```
# Analysis of Variance- ANOVA
# returns f-test and p-value
# f-test = variance between sample group
# variation within sample group
# p-value = confidence degree
data_annova = data[['make', 'price']]
grouped_annova = data_annova.groupby(['m
annova_results_l = sp.stats.f_oneway(
                            grouped_ann
                            grouped_ann
                                   )
print(annova_results_l)

# strong corealtion between a categorica
# if annova test gives large f-test and

# Correlation- measures dependency, not
sns.regplot(x ='engine-size', y ='price'
plt.ylim(0, )
```

Output:



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