Be part of a better internet.
Get 20% off membership for a limited time

This member-only story is on us. Upgrade to access all of Medium.

✨ Member-only story

Exploratory data analysis in Python.

Let us understand how to explore the data in python.

Tanu N Prabhu · Follow
Published in Towards Data Science
9 min read · Aug 10, 2019

Listen Share More

Image Credits: Morioh

Introduction

What is Exploratory Data Analysis?

Exploratory Data Analysis or (EDA) is understanding the data sets by summarizing their main characteristics often plotting them visually. This step is very important especially when we arrive at modeling the data in order to apply Machine learning. Plotting in EDA consists of Histograms, Box plot, Scatter plot and many more. It often takes much time to explore the data. Through the process of EDA, we can ask to define the problem statement or definition on our data set which is very important.

How to perform Exploratory Data Analysis?

This is one such question that everyone is keen on knowing the answer. Well, the answer is it depends on the data set that you are working. There is no one method or common methods in order to perform EDA, whereas in this tutorial you can understand some common methods and plots that would be used in the EDA process.

What data are we exploring today?

Since I am a huge fan of cars, I got a very beautiful data-set of cars from Kaggle. The data-set can be downloaded from here. To give a piece of brief information about the data set this data contains more of 10, 000 rows and more than 10 columns which contains features of the car such as Engine Fuel Type, Engine Size, HP, Transmission Type, highway MPG, city MPG and many more. So in this tutorial, we will explore the data and make it ready for modeling.

Let's get started !!!

1. Importing the required libraries for EDA

Below are the libraries that are used in order to perform EDA (Exploratory data analysis) in this tutorial. **The complete code can be found on my GitHub.**

```
# Importing required libraries.
import pandas as pd
import numpy as np
import seaborn as sns #visualisation
import matplotlib.pyplot as plt
#visualisation
%matplotlib inline
sns.set(color_codes=True)
```

2. Loading the data into the data frame.

Loading the data into the pandas data frame is certainly one of the most important steps in EDA, as we can see that the value from the data set is comma-separated. So all we have to do is to just read the CSV into a data frame and pandas data frame does the job for us.

To get or load the dataset into the notebook, all I did was one trivial step. In **Google Colab** at the left-hand side of the notebook, you will find a “>” (greater than symbol). When you click that you will find a tab with three options, you just have to select Files. Then you can easily upload your file with the help of the Upload option. No need to mount to the google drive or use any specific libraries just upload the data set and your job is done. One thing to remember in this step is that uploaded files will get deleted when this runtime is recycled. This is how I got the data set into the notebook.

```
df = pd.read_csv(“data.csv”)
# To display the top 5 rows
df.head(5)
```

	Make	Model	Year	Engine Fuel Type	Engine HP	Engine Cylinders	Transmission Type	Driven_Wheels	Number of Doors	Market Category	Vehicle Size	Vehicle Style	highway MPG	city mpg	Popularity	MSRP
0	BMW	1 Series M	2011	premium unleaded (required)	335.0	6.0	MANUAL	rear wheel drive	2.0	Factory Tuner,Luxury,High-Performance	Compact	Coupe	26	19	3916	46135
1	BMW	1 Series	2011	premium unleaded (required)	300.0	6.0	MANUAL	rear wheel drive	2.0	Luxury,Performance	Compact	Convertible	28	19	3916	40650
2	BMW	1 Series	2011	premium unleaded (required)	300.0	6.0	MANUAL	rear wheel drive	2.0	Luxury,High-Performance	Compact	Coupe	28	20	3916	36350
3	BMW	1 Series	2011	premium unleaded (required)	230.0	6.0	MANUAL	rear wheel drive	2.0	Luxury,Performance	Compact	Coupe	28	18	3916	29450
4	BMW	1 Series	2011	premium unleaded (required)	230.0	6.0	MANUAL	rear wheel drive	2.0	Luxury	Compact	Convertible	28	18	3916	34500

Displaying the top 5 rows.

```
# To display the bottom 5 rows
df.tail(5)
```

Make	Model	Year	Engine Fuel Type	Engine HP	Engine Cylinders	Transmission Type	Driven_Wheels	Number of Doors	Market Category	Vehicle Size	Vehicle Style	highway MPG	city mpg	Popularity	MSRP
Acura	ZDX	2012	premium unleaded (required)	300.0	6.0	AUTOMATIC	all wheel drive	4.0	Crossover,Hatchback,Luxury	Midsize	4dr Hatchback	23	16	204	46120
Acura	ZDX	2012	premium unleaded (required)	300.0	6.0	AUTOMATIC	all wheel drive	4.0	Crossover,Hatchback,Luxury	Midsize	4dr Hatchback	23	16	204	56670
Acura	ZDX	2012	premium unleaded (required)	300.0	6.0	AUTOMATIC	all wheel drive	4.0	Crossover,Hatchback,Luxury	Midsize	4dr Hatchback	23	16	204	50620
Acura	ZDX	2013	premium unleaded (recommended)	300.0	6.0	AUTOMATIC	all wheel drive	4.0	Crossover,Hatchback,Luxury	Midsize	4dr Hatchback	23	16	204	50920
Lincoln	Zephyr	2006	regular unleaded	221.0	6.0	AUTOMATIC	front wheel drive	4.0	Luxury	Midsize	Sedan	26	17	61	28995

Displaying the last 10 rows.

3. Checking the types of data

Here we check for the datatypes because sometimes the MSRP or the price of the car would be stored as a string or object, if in that case, we have to convert that string to the integer data only then we can plot the data via a graph. Here, in this case, the data is already in integer format so nothing to worry.

```
# Checking the data type
df.dtypes
```

```
Make                object
Model               object
Year                 int64
Engine Fuel Type    object
Engine HP          float64
Engine Cylinders   float64
Transmission Type   object
Driven_Wheels       object
Number of Doors    float64
Market Category     object
Vehicle Size        object
Vehicle Style       object
highway MPG          int64
city mpg             int64
Popularity           int64
MSRP                 int64
dtype: object
```

Checking the type of data.

4. Dropping irrelevant columns

This step is certainly needed in every EDA because sometimes there would be many columns that we never use in such cases dropping is the only solution. In this case, the columns such as Engine Fuel Type, Market Category, Vehicle style, Popularity, Number of doors, Vehicle Size doesn't make any sense to me so I just dropped for this instance.

```
# Dropping irrelevant columns
df = df.drop(['Engine Fuel Type', 'Market
Category', 'Vehicle Style', 'Popularity',
```

```
'Number of Doors', 'Vehicle Size'], axis=1)
df.head(5)
```

	Make	Model	Year	Engine HP	Engine Cylinders	Transmission Type	Driven_Wheels	highway MPG	city mpg	MSRP
0	BMW	1 Series M	2011	335.0	6.0	MANUAL	rear wheel drive	26	19	46135
1	BMW	1 Series	2011	300.0	6.0	MANUAL	rear wheel drive	28	19	40650
2	BMW	1 Series	2011	300.0	6.0	MANUAL	rear wheel drive	28	20	36350
3	BMW	1 Series	2011	230.0	6.0	MANUAL	rear wheel drive	28	18	29450
4	BMW	1 Series	2011	230.0	6.0	MANUAL	rear wheel drive	28	18	34500

Dropping irrelevant columns.

5. Renaming the columns

In this instance, most of the column names are very confusing to read, so I just tweaked their column names. This is a good approach it improves the readability of the data set.

```
# Renaming the column names
df = df.rename(columns={"Engine HP": "HP",
"Engine Cylinders": "Cylinders",
"Transmission Type": "Transmission",
"Driven_Wheels": "Drive Mode","highway
MPG": "MPG-H", "city mpg": "MPG-C", "MSRP":
"Price" })
df.head(5)
```

	Make	Model	Year	HP	Cylinders	Transmission	Drive Mode	MPG-H	MPG-C	Price
0	BMW	1 Series M	2011	335.0	6.0	MANUAL	rear wheel drive	26	19	46135
1	BMW	1 Series	2011	300.0	6.0	MANUAL	rear wheel drive	28	19	40650
2	BMW	1 Series	2011	300.0	6.0	MANUAL	rear wheel drive	28	20	36350
3	BMW	1 Series	2011	230.0	6.0	MANUAL	rear wheel drive	28	18	29450
4	BMW	1 Series	2011	230.0	6.0	MANUAL	rear wheel drive	28	18	34500

Renaming the column name.

6. Dropping the duplicate rows

This is often a handy thing to do because a huge data set as in this case contains more than 10, 000 rows often have some duplicate data which might be disturbing, so here I remove all the duplicate value from the data-set. For example prior to removing I had 11914 rows of data but after removing the duplicates 10925 data meaning that I had 989 of duplicate data.

```
# Total number of rows and columns
df.shape
```

```
(11914, 10)
```

```
# Rows containing duplicate data
duplicate_rows_df = df[df.duplicated()]
print("number of duplicate rows: ",
duplicate_rows_df.shape)
```

```
number of duplicate rows:  (989, 10)
```

Now let us remove the duplicate data because it's ok to remove them.

```
# Used to count the number of rows before removing the data
df.count()
```

```
Make              11914
Model             11914
Year              11914
HP                11845
Cylinders         11884
Transmission      11914
Drive Mode        11914
MPG-H             11914
MPG-C             11914
Price             11914
dtype: int64
```

So seen above there are 11914 rows and we are removing 989 rows of duplicate data.

```
# Dropping the duplicates
df = df.drop_duplicates()
df.head(5)
```

	Make	Model	Year	HP	Cylinders	Transmission	Drive Mode	MPG-H	MPG-C	Price
0	BMW	1 Series M	2011	335.0	6.0	MANUAL	rear wheel drive	26	19	46135
1	BMW	1 Series	2011	300.0	6.0	MANUAL	rear wheel drive	28	19	40650
2	BMW	1 Series	2011	300.0	6.0	MANUAL	rear wheel drive	28	20	36350
3	BMW	1 Series	2011	230.0	6.0	MANUAL	rear wheel drive	28	18	29450
4	BMW	1 Series	2011	230.0	6.0	MANUAL	rear wheel drive	28	18	34500

```
# Counting the number of rows after removing duplicates.
df.count()
```

```
Make              10925
Model             10925
Year              10925
HP                10856
Cylinders         10895
Transmission      10925
Drive Mode        10925
MPG-H             10925
MPG-C             10925
Price             10925
dtype: int64
```

7. Dropping the missing or null values.

This is mostly similar to the previous step but in here all the missing values are detected and are dropped later. Now, this is not a good approach to do so,

because many people just replace the missing values with the mean or the average of that column, but in this case, I just dropped that missing values. This is because there is nearly 100 missing value compared to 10, 000 values this is a small number and this is negligible so I just dropped those values.

```
# Finding the null values.
print(df.isnull().sum())
```

```
Make              0
Model             0
Year              0
HP               69
Cylinders        30
Transmission      0
Drive Mode        0
MPG-H             0
MPG-C             0
Price             0
dtype: int64
```

This is the reason in the above step while counting both Cylinders and Horsepower (HP) had 10856 and 10895 over 10925 rows.

```
# Dropping the missing values.
df = df.dropna()
```

```
df.count()
```

```
Make              10827
Model             10827
Year              10827
HP                10827
Cylinders         10827
Transmission      10827
Drive Mode        10827
MPG-H             10827
MPG-C             10827
Price             10827
dtype: int64
```

Now we have removed all the rows which contain the Null or N/A values (Cylinders and Horsepower (HP)).

```
# After dropping the values
print(df.isnull().sum())
```

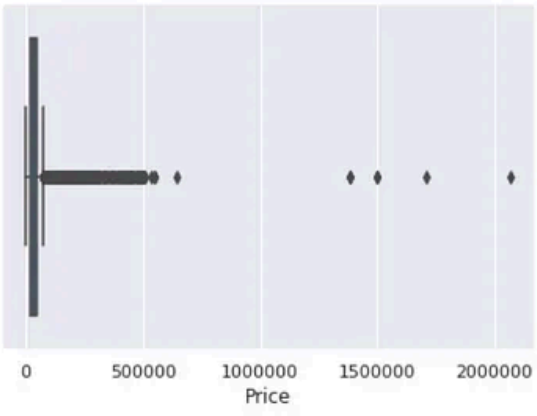
```
Make              0
Model             0
Year              0
HP                0
Cylinders         0
Transmission      0
Drive Mode        0
MPG-H             0
MPG-C             0
Price             0
dtype: int64
```

8. Detecting Outliers

An outlier is a point or set of points that are different from other points. Sometimes they can be very high or very low. It's often a good idea to detect and remove the outliers. Because outliers are one of the primary reasons for resulting in a less accurate model. Hence it's a good idea to remove them. The outlier detection and removing that I am going to perform is called IQR score technique. Often outliers can be seen with visualizations using a box plot. Shown below are the box plot of MSRP, Cylinders, Horsepower and EngineSize. Herein all the plots, you can find some points are outside the box they are none other than outliers. The technique of finding and removing outlier that I am performing in this assignment is taken help of a tutorial from towards data science.

```
sns.boxplot(x=df['Price'])
```

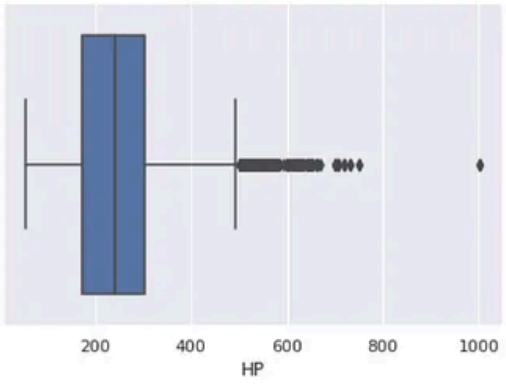
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f69f68edc18>
```



Box plot of Price

```
sns.boxplot(x=df['HP'])
```

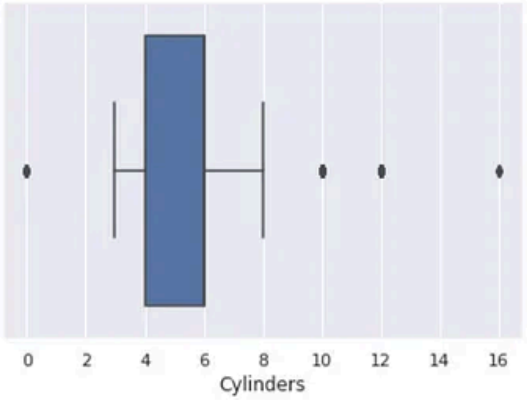
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f69f3d68240>
```



Box Plot of HP

```
sns.boxplot(x=df['Cylinders'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f69f3d2d400>
```



Box Plot of Cylinders

```
Q1 = df.quantile(0.25)
Q3 = df.quantile(0.75)
IQR = Q3 - Q1
print(IQR)
```

```
Year              9.0
HP              130.0
Cylinders         2.0
MPG-H             8.0
MPG-C             6.0
Price         21327.5
dtype: float64
```

Don’t worry about the above values because it’s not important to know each and every one of them because it's just important to know how to use this technique in order to remove the outliers.

```
df = df[~((df < (Q1-1.5 * IQR)) |(df > (Q3
+ 1.5 * IQR))).any(axis=1)]
df.shape
```

```
(9191, 10)
```

As seen above there were around 1600 rows were outliers. But you cannot completely remove the outliers because even after you use the above technique there maybe 1–2 outlier unremoved but that ok because there were more than 100 outliers. Something is better than nothing.

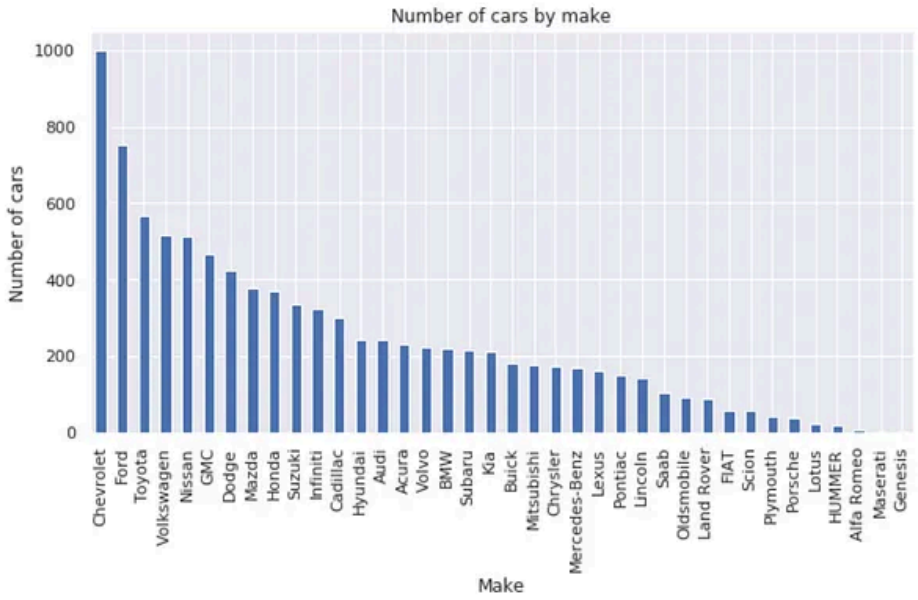
9. Plot different features against one another (scatter), against frequency (histogram)

Histogram

Histogram refers to the frequency of occurrence of variables in an interval. In this case, there are mainly 10 different types of car manufacturing companies, but it is often important to know who has the most number of cars. To do this histogram is one of the trivial

solutions which lets us know the total number of car manufactured by a different company.

```
# Plotting a Histogram
df.Make.value_counts().nlargest(40).plot(ki
nd='bar', figsize=(10,5))
plt.title("Number of cars by make")
plt.ylabel('Number of cars')
plt.xlabel('Make');
```



Histogram

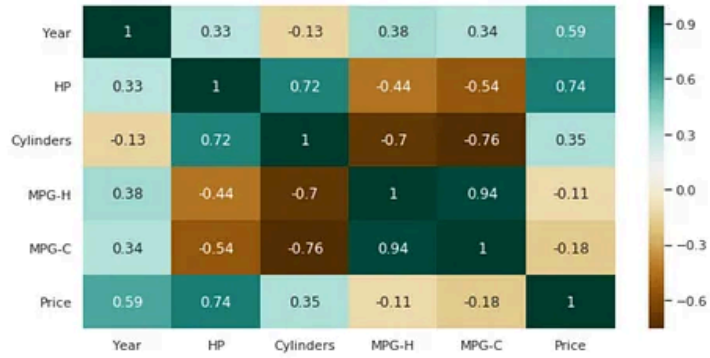
Heat Maps

Heat Maps is a type of plot which is necessary when we need to find the dependent variables. One of the best way to find the relationship between the features c be done using heat maps. In the below heat map we

know that the price feature depends mainly on the Engine Size, Horsepower, and Cylinders.

```
# Finding the relations between the variables.
plt.figure(figsize=(20,10))
c= df.corr()
sns.heatmap(c,cmap="BrBG",annot=True)
c
```

	Year	HP	Cylinders	MPG-H	MPG-C	Price
Year	1.000000	0.326726	-0.133920	0.378479	0.338145	0.592983
HP	0.326726	1.000000	0.715237	-0.443807	-0.544551	0.739042
Cylinders	-0.133920	0.715237	1.000000	-0.703856	-0.755540	0.354013
MPG-H	0.378479	-0.443807	-0.703856	1.000000	0.939141	-0.106320
MPG-C	0.338145	-0.544551	-0.755540	0.939141	1.000000	-0.180515
Price	0.592983	0.739042	0.354013	-0.106320	-0.180515	1.000000



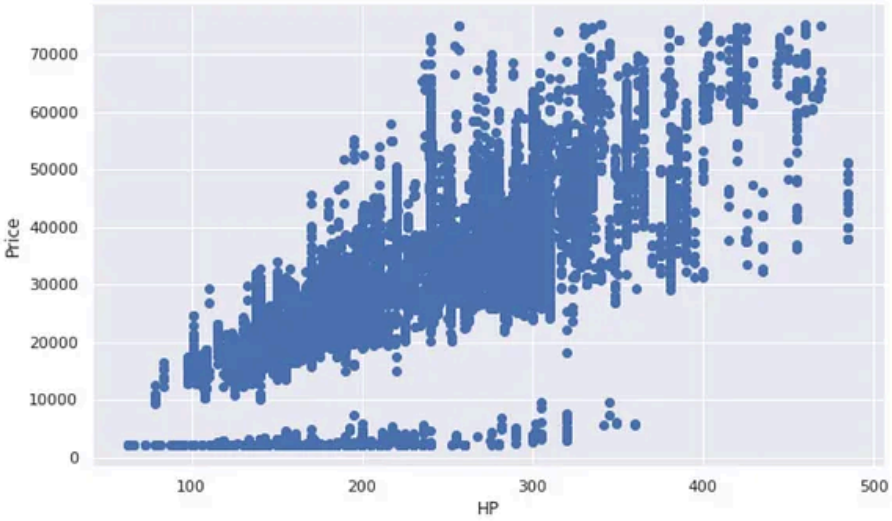
Heat Maps.

Scatterplot

We generally use scatter plots to find the correlation between two variables. Here the scatter plots are plotted between Horsepower and Price and we can

the plot below. With the plot given below, we can easily draw a trend line. These features provide a good scattering of points.

```
# Plotting a scatter plot
fig, ax = plt.subplots(figsize=(10,6))
ax.scatter(df['HP'], df['Price'])
ax.set_xlabel('HP')
ax.set_ylabel('Price')
plt.show()
```



Scatter Plot

Hence the above are some of the steps involved in Exploratory data analysis, these are some general s

that you must follow in order to perform EDA. There are many more yet to come but for now, this is more than enough idea as to how to perform a good EDA given any data sets. Stay tuned for more updates. If you have some doubts then the comment section is all yours. I'll try my level best to answer your questions.

Thank you.

Data Science | Programming | Python | Python Programming | Data Analysis

Follow

Written by Tanu N Prabhu

1.6K Followers · Writer for Towards Data Science