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Exploratory Data Analysis(EDA): Python

Learning the basics of Exploratory Data Analysis using Python with Numpy, Matplotlib, and Pandas.

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What is Exploratory Data Analysis(EDA)?

We can find

> *In statistics, **exploratory data analysis** is an approach to analyzing data sets to summarize their main characteristics, often with visual methods. A statistical model can be used or not, but primarily EDA is for seeing what the data can tell us beyond the formal modeling or hypothesis testing task.*

EDA in Python uses data visualization to draw meaningful patterns and insights. It also involves the preparation of data sets for analysis by removing irregularities in the data.

Based on the results of EDA, companies also make business decisions, which can have repercussions later.

- If EDA is not done properly then it can hamper the further steps in the machine learning model building process.
- If done well, it may improve the efficacy of everything we do next.

In this article we'll see about the following topics:

1. Data Sourcing
2. Data Cleaning
3. Univariate analysis
4. Bivariate analysis
5. Multivariate analysis

1. Data Sourcing

Data Sourcing is the process of finding and loading the data into our system. Broadly there are two ways in which we can find data.

1. Private Data
2. Public Data

Private Data

Public Data

This type of Data is available to everyone. We can find this in government websites and public organizations etc. Anyone can access this data, we do not need any special permissions or approval.

We can get public data on the following sites.

- https://data.gov
- https://data.gov.uk
- https://data.gov.in
- https://www.kaggle.com/
- https://archive.ics.uci.edu/ml/index.php
- https://github.com/awesomedata/awesome-public-datasets

The very first step of EDA is Data Sourcing, we have seen how we can access data and load into our system. Now, the next step is how to clean the data.

2. Data Cleaning

After completing the Data Sourcing, the next step in the process of EDA is **Data Cleaning**. It is very important to get rid of the irregularities and clean the data after sourcing it into our system.

Irregularities are of different types of data.

- Missing Values
- Incorrect Format
- Incorrect Headers
- Anomalies/Outliers

To perform the data cleaning we are using a sample data set, which can be found **here**.

```python
#impor
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

# Read the data set of "Marketing Analysis" in data.
data= pd.read_csv("marketing_analysis.csv")

# Printing the data
data
```

libraries_data_store.py hosted with ❤ by GitHub view raw

Now, the data set looks like this,

	banking marketing	Unnamed: 1	Unnamed: 2	Unnamed: 3	Unnamed: 4	Unnamed: 5	Unnamed: 6	Unnamed: 7	Unnamed: 8	Unnamed: 9	Unnamed: 10	Unnamed: 11
0	customer id and age.	NaN	Customer salary and balance.	NaN	Customer marital status and job with education...	NaN	particular customer before targeted or not	NaN	Loan types: loans or housing loans	NaN	Contact type	NaN
1	customerid	age	salary	balance	marital	jobedu	targeted	default	housing	loan	contact	day
2	1	58	100000	2143	married	management,tertiary	yes	no	yes	no	unknown	5
3	2	44	60000	29	single	technician,secondary	yes	no	yes	no	unknown	5
4	3	33	120000	2	married	entrepreneur,secondary	yes	no	yes	yes	unknown	5
...	...	...	...	...	...	...	...	...	...	...	...	...
45208	45207	51	60000	825	married	technician,tertiary	yes	no	no	no	cellular	17
45209	45208	71	55000	1729	divorced	retired,primary	yes	no	no	no	cellular	17
45210	45209	72	55000	5715	married	retired,secondary	yes	no	no	no	cellular	17
45211	45210	57	20000	668	married	blue-collar,secondary	yes	no	no	no	telephone	17
45212	45211	37	120000	2971	married	entrepreneur,secondary	yes	no	no	no	cellular	17

Marketing Analysis Dataset

If we observe the above dataset, there are some discrepancies in the Column header for the first 2 rows. The correct data is from the index number 1. So, we have to fix the first two rows.

This is called **Fixing the Rows and Columns.** Let's ignore the first two rows and load the data again.

```
import
import
import matplotlib.pyplot as plt
%matplotlib inline

# Read the file in data without first two rows as it is of no use.
data = pd.read_csv("marketing_analysis.csv",skiprows = 2)

#print the head of the data frame.
data.head()
```

fixing_rows_columns.py hosted with ❤ by GitHub view raw

Now, the dataset looks like this, and it makes more sense.

	customerid	age	salary	balance	marital	jobedu	targeted	default	housing	loan	contact	day	month	duration	campaign	pdays	previous
0	1	58.0	100000	2143	married	management,tertiary	yes	no	yes	no	unknown	5	may, 2017	261 sec	1	-1	0
1	2	44.0	60000	29	single	technician,secondary	yes	no	yes	no	unknown	5	may, 2017	151 sec	1	-1	0
2	3	33.0	120000	2	married	entrepreneur,secondary	yes	no	yes	yes	unknown	5	may, 2017	76 sec	1	-1	0
3	4	47.0	20000	1506	married	blue-collar,unknown	no	no	yes	no	unknown	5	may, 2017	92 sec	1	-1	0
4	5	33.0	0	1	single	unknown,unknown	no	no	no	no	unknown	5	may, 2017	198 sec	1	-1	0

Dataset after fixing the rows and columns

Following are the steps to be taken while **Fixing Rows and Columns:**

1. Delete Summary Rows and Columns in the Dataset.
2. Delete Header and Footer Rows on every page.
3. Delete Extra Rows like blank rows, page numbers, etc.
4. We can merge different columns if it makes for better understanding of the data
5. Similarly, we can also split one column into multiple columns based on our requirements or understanding.
6. Add Column names, it is very important to have column names to the dataset.

Now if we observe the above dataset, the `customerid` column has of no importance to our analysis, and also the `jobedu` column has both the information of `job` and as well.

```python
# Drop the customer id as it is of no use.
data.drop('customerid', axis = 1, inplace = True)

#Extract job  & Education in newly from "jobedu" column.
data['job']= data["jobedu"].apply(lambda x: x.split(",")[0])
data['education']= data["jobedu"].apply(lambda x: x.split(",")[1])

# Drop the "jobedu" column from the dataframe.
data.drop('jobedu', axis = 1, inplace = True)

# Printing the Dataset
data
```

drop_split_columns.py hosted with ❤ by GitHub view raw

Now, the dataset looks like this,

ince	marital	targeted	default	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	response	job	education
2143	married	yes	no	yes	no	unknown	5	may, 2017	261 sec	1	-1	0	unknown	no	management	tertiary
29	single	yes	no	yes	no	unknown	5	may, 2017	151 sec	1	-1	0	unknown	no	technician	secondary
2	married	yes	no	yes	yes	unknown	5	may, 2017	76 sec	1	-1	0	unknown	no	entrepreneur	secondary
1506	married	no	no	yes	no	unknown	5	may, 2017	92 sec	1	-1	0	unknown	no	blue-collar	unknown
1	single	no	no	no	no	unknown	5	may, 2017	198 sec	1	-1	0	unknown	no	unknown	unknown
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
825	married	yes	no	no	no	cellular	17	nov, 2017	16.2833333333333 min	3	-1	0	unknown	yes	technician	tertiary
1729	divorced	yes	no	no	no	cellular	17	nov, 2017	7.6 min	2	-1	0	unknown	yes	retired	primary
5715	married	yes	no	no	no	cellular	17	nov, 2017	18.7833333333333 min	5	184	3	success	yes	retired	secondary
668	married	yes	no	no	no	telephone	17	nov, 2017	8.46666666666667 min	4	-1	0	unknown	no	blue-collar	secondary
2971	married	yes	no	no	no	cellular	17	nov, 2017	6.01666666666667 min	2	188	11	other	no	entrepreneur	secondary

Dropping `Customerid` and jobedu columns and adding job and education columns

Missing Values

If there are missing values in the Dataset before doing any statistical analysis, we need to handle those missing values.

2. MAR(Missing at random): These values may be dependent on some other features.

3. MNAR(Missing not at random): These missing values have some reason for why they are missing.

Let’s see which columns have missing values in the dataset.

```
# Checking the missing values
data.isnull().sum()
```

The output will be,

```
age          20
salary        0
balance       0
marital       0
targeted      0
default       0
housing       0
loan          0
contact       0
day           0
month        50
duration      0
campaign      0
pdays         0
previous      0
poutcome      0
response     30
job           0
education     0
dtype: int64
```

Null Values in Data Set

As we can see three columns contain missing values. Let’s see how to handle the missing values. We can handle missing values by dropping the missing records or by imputing the values.

```
# Dropp
data = data[~data.age.isnull()].copy()

# Checking the missing values in the dataset.
data.isnull().sum()
```

drop_missing_values.py hosted with ❤ by **GitHub** **view raw**

Let’s check the missing values in the dataset now.

```
age           0
salary        0
balance       0
marital       0
targeted      0
default       0
housing       0
loan          0
contact       0
day           0
month        50
duration      0
campaign      0
pdays         0
previous      0
poutcome      0
response     30
job           0
education     0
dtype: int64
```

Missing Values after handling age column

Let’s impute values to the missing values for the month column.

Since the month column is of an object type, let’s calculate the mode of that column and impute those values to the missing values.

```
# Fill
data.month.fillna(month_mode, inplace = True)

# Let's see the null values in the month column.
data.month.isnull().sum()
```

impute_missing.py hosted with ❤ by GitHub view raw

Now output is,

```
# Mode of month is
'may, 2017'

# Null values in month column after imputing with mode
0
```

Handling the missing values in the **Response** column. Since, our target column is Response Column, if we impute the values to this column it'll affect our analysis. So, it is better to drop the missing values from Response Column.

```
#drop the records with response missing in data.
data = data[~data.response.isnull()].copy()

# Calculate the missing values in each column of data frame
data.isnull().sum()
```

Let's check whether the missing values in the dataset have been handled or not,

```
targeted     0
default      0
housing      0
loan         0
contact      0
day          0
month        0
duration     0
campaign     0
pdays        0
previous     0
poutcome     0
response     0
job          0
education    0
dtype: int64
```

All the missing values have been handled

We can also, fill the missing values as **'NaN'** so that while doing any statistical analysis, it won't affect the outcome.

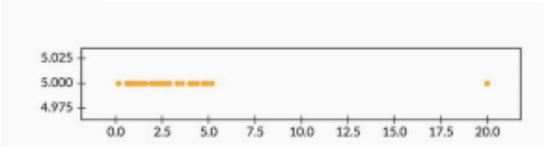
Handling Outliers

We have seen how to fix missing values, now let's see how to handle outliers in the dataset.

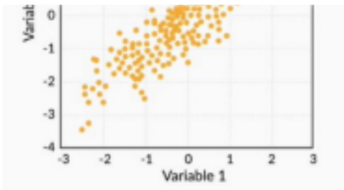
> ***Outliers are the values that are far beyond the next nearest data points.***

There are two types of outliers:

1. **Univariate outliers:** Univariate outliers are the data points whose values lie beyond the range of expected values based on one variable.
2. **Multivariate outliers:** While plotting data, some values of one variable may not lie beyond the expected range, but when you plot the data with some other variable, these values may lie far from the expected value.



Univariate Outlier



Multivariate Outlier

So, after understanding the causes of these outliers, we can handle them by dropping those records or imputing with the values or leaving them as is, if it makes more sense.

Standardizing Values

To perform data analysis on a set of values, we have to make sure the values in the same column should be on the same scale. For example, if the data contains the values of the top speed of different companies' cars, then the whole column should be either in meters/sec scale or miles/sec scale.

Now, that we are clear on how to source and clean the data, let's see how we can analyze the data.

3. Univariate Analysis

If we analyze data over a single variable/column from a dataset, it is known as Univariate Analysis.

Categorical Unordered Univariate Analysis:

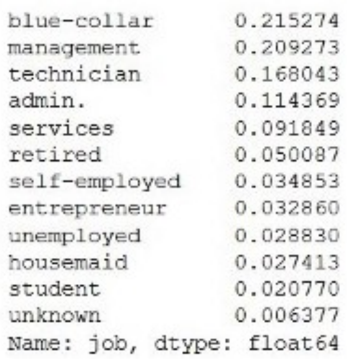
An unordered variable is a categorical variable that has no defined order. If we take our data as an example, the **job** column in the dataset is divided into many sub-categories like technician, blue-collar, services, management, etc. There is no weight or measure given to any value in the '**job**' column.

Now, let's analyze the job category by using plots. Since Job is a category, we will plot the bar plot.

```
#plot t
data.job.value_counts(normalize=True).plot.barh()
plt.show()
```

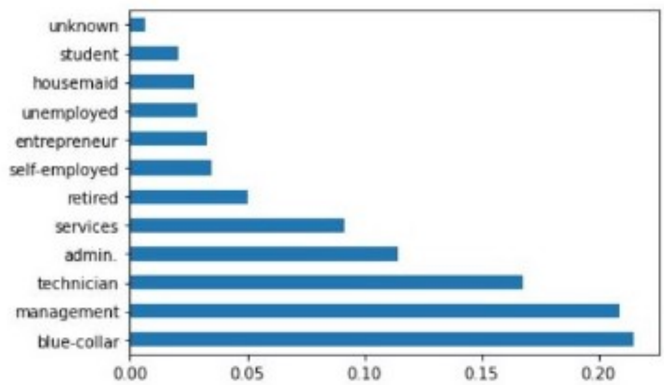
job_analysis.py hosted with ❤ by **GitHub** **view raw**

The output looks like this,



```
blue-collar      0.215274
management       0.209273
technician       0.168043
admin.           0.114369
services         0.091849
retired          0.050087
self-employed    0.034853
entrepreneur     0.032860
unemployed       0.028830
housemaid        0.027413
student          0.020770
unknown          0.006377
Name: job, dtype: float64
```

Percentage of Job Categories



Bar Plot of Job Column

By the above bar plot, we can infer that the data set contains more number of blue-collar workers compared to other categories.

Categorical Ordered Univariate Analysis:

Ordered variables are those variables that have a natural rank of order. Some examples of categorical ordered variables from our dataset are:

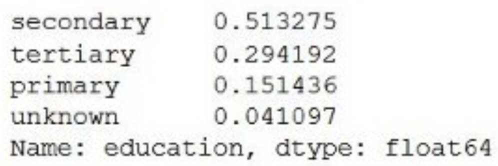
- Month: Jan, Feb, March……
- Education: Primary, Secondary,……

Now, let's analyze the Education Variable from the dataset. Since we've already seen a bar plot, let's see how a Pie Chart looks like.

```
#plot t
data.education.value_counts(normalize=True).plot.pie()
plt.show()
```

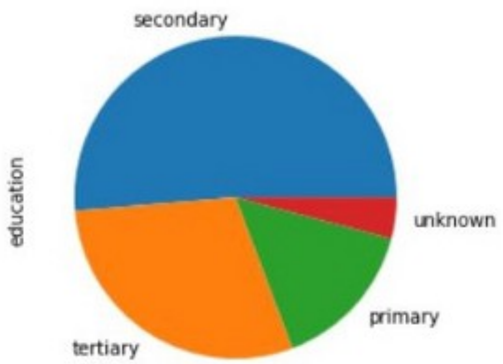
education_analysis.py hosted with ❤ by **GitHub** **view raw**

The output will be,



```
secondary    0.513275
tertiary     0.294192
primary      0.151436
unknown      0.041097
Name: education, dtype: float64
```

Percentage of Education Category



Education Category in Pie Chart

By the above analysis, we can infer that the data set has a large number of them belongs to secondary education after that tertiary and next primary. Also, a very small percentage of them have been unknown.

This is how we analyze univariate categorical analysis. If the column or variable is of numerical then we'll analyze by calculating its mean, median, std, etc. We can get those values by using the describe function.

```
data.salary.describe()
```

The output will be,

```
25%        20000.000000
50%        60000.000000
75%        70000.000000
max       120000.000000
Name: salary, dtype: float64
```

4. Bivariate Analysis

If we analyze data by taking two variables/columns into consideration from a dataset, it is known as Bivariate Analysis.

a) Numeric-Numeric Analysis:

Analyzing the two numeric variables from a dataset is known as numeric-numeric analysis. We can analyze it in three different ways.

- Scatter Plot
- Pair Plot
- Correlation Matrix

Scatter Plot

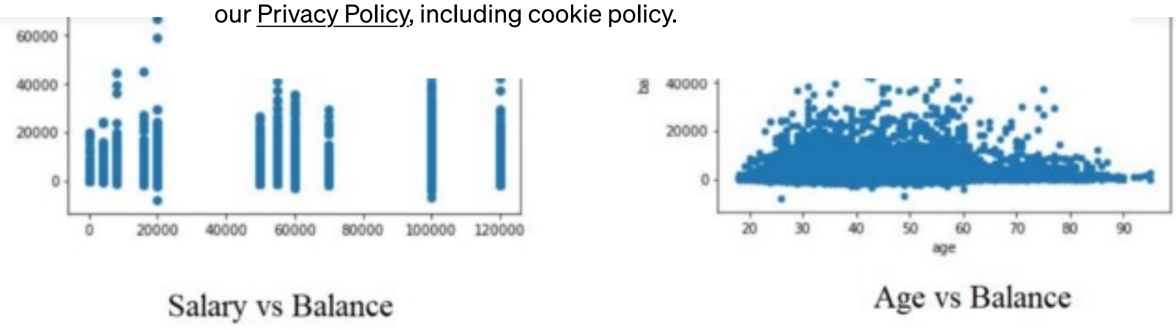
Let's take three columns 'Balance', 'Age' and 'Salary' from our dataset and see what we can infer by plotting to scatter plot between `salary` `balance` and `age` `balance`

```
#plot the scatter plot of balance and salary variable in data
plt.scatter(data.salary,data.balance)
plt.show()

#plot the scatter plot of balance and age variable in data
data.plot.scatter(x="age",y="balance")
plt.show()
```

bivariate_scatter.py hosted with ❤ by **GitHub** **view raw**

Now, the scatter plots looks like,



Scatter Plots

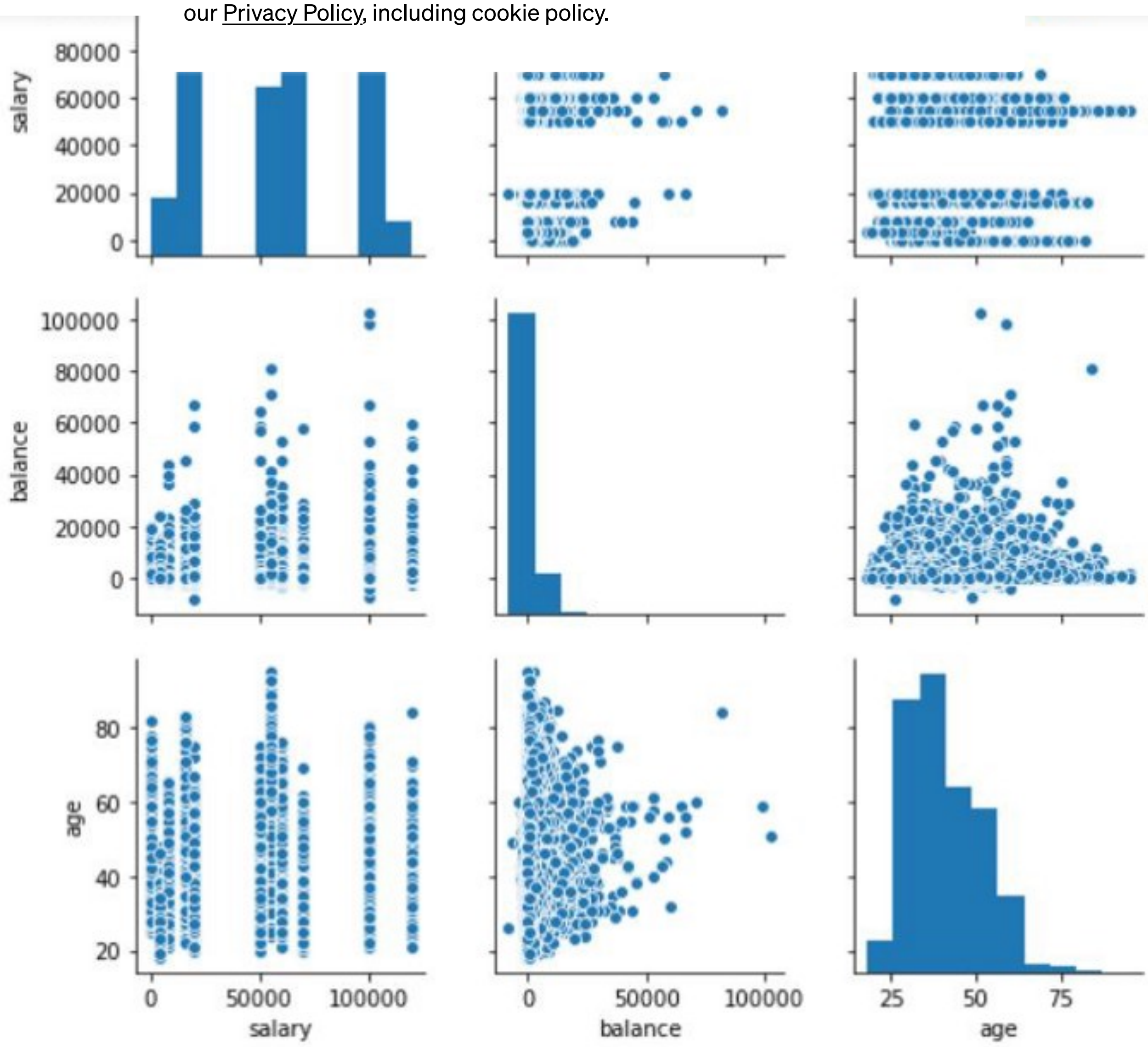
Pair Plot

Now, let’s plot Pair Plots for the three columns we used in plotting Scatter plots. We’ll use the seaborn library for plotting Pair Plots.

```python
#plot the pair plot of salary, balance and age in data dataframe.
sns.pairplot(data = data, vars=['salary','balance','age'])
plt.show()
```

pair_plot.py hosted with ❤ by **GitHub** **view raw**

The Pair Plot looks like this,



Pair Plots for Age, balance, Salary

Correlation Matrix

Since we cannot use more than two variables as x-axis and y-axis in Scatter and Pair Plots, it is difficult to see the relation between three numerical variables in a single graph. In those cases, we'll use the correlation matrix.

```
# Creating a matrix using age, salry, balance as rows and columns
data[['age','salary','balance']].corr()

#plot the correlation matrix of salary, balance and age in data dataframe.
sns.heatmap(data[['age','salary','balance']].corr(), annot=True, cmap = 'Reds')
plt.show()
```

	age	salary	balance
age	1.000000	0.024513	0.097710
salary	0.024513	1.000000	0.055489
balance	0.097710	0.055489	1.000000

Correlation Matrix

Heatmap

b) Numeric - Categorical Analysis

Analyzing the one numeric variable and one categorical variable from a dataset is known as numeric-categorical analysis. We analyze them mainly using mean, median, and box plots.

Let's take `salary` and `response` columns from our dataset.

First check for mean value using `groupby`

```
#groupby the response to find the mean of the salary with response no
& yes separately.

data.groupby('response')['salary'].mean()
```

The output will be,

```
response
no      56769.510482
yes     58780.510880
Name: salary, dtype: float64
```

Response and Salary using mean

```
#groupby the response to find the median of the salary with response
no & yes separately.

data.groupby('response')['salary'].median()
```

The output will be,

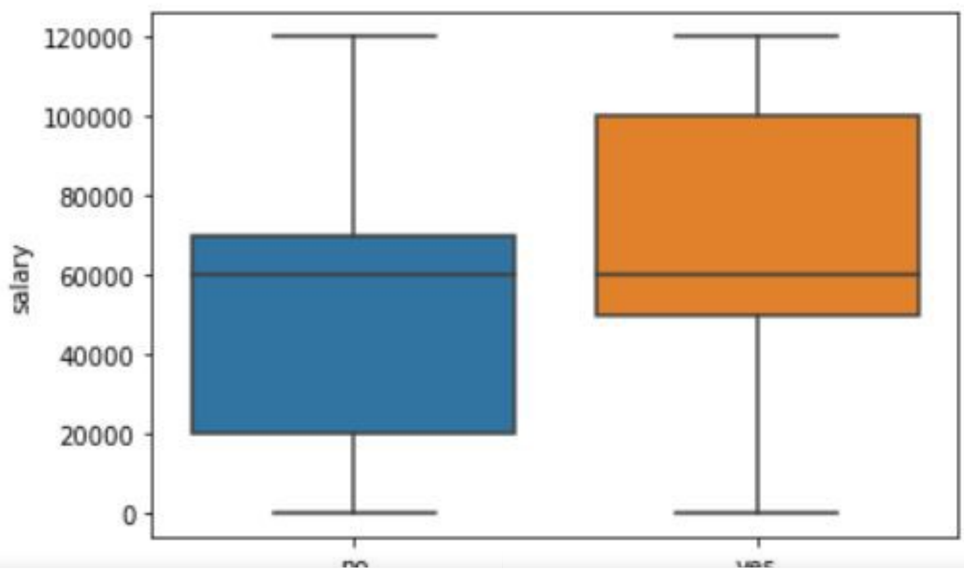
```
response
no      60000
yes     60000
Name: salary, dtype: int64
```

By both mean and median we can say that the response of yes and no remains the same irrespective of the person's salary. But, is it truly behaving like that, let's plot the box plot for them and check the behavior.

```
#plot the box plot of salary for yes & no responses.

sns.boxplot(data.response, data.salary)
plt.show()
```

The box plot looks like this,



salary side.

This is how we analyze Numeric-Categorical variables, we use mean, median, and Box Plots to draw some sort of conclusions.

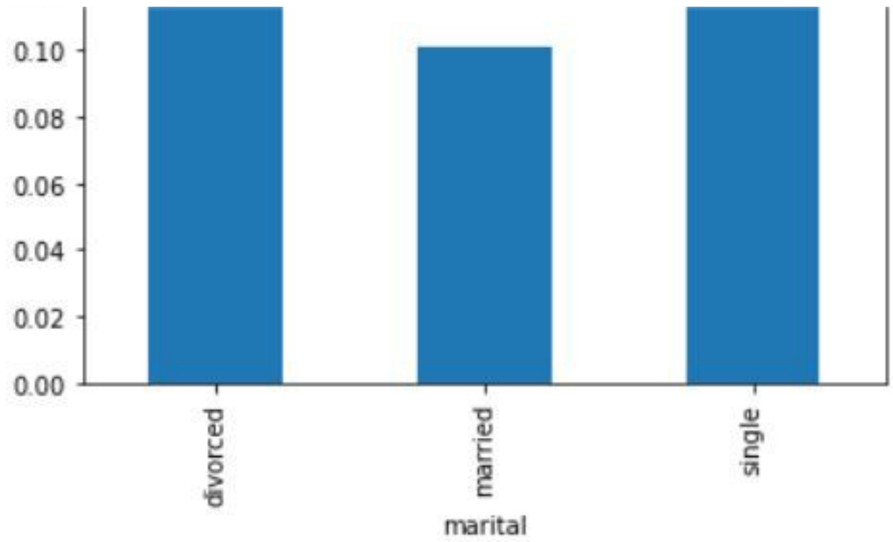
c) Categorical — Categorical Analysis

Since our target variable/column is the Response rate, we'll see how the different categories like Education, Marital Status, etc., are associated with the Response column. So instead of 'Yes' and 'No' we will convert them into '1' and '0', by doing that we'll get the "Response Rate".

```
1      5285
Name: response_flag, dtype: int64
```

Let's see how the response rate varies for different categories in marital status.

The graph looks like this,



By the above graph, we can infer that the positive response is more for Single status members in the data set. Similarly, we can plot the graphs for Loan vs Response rate, Housing Loans vs Response rate, etc.

5. Multivariate Analysis

If we analyze data by taking more than two variables/columns into consideration from a dataset, it is known as Multivariate Analysis.

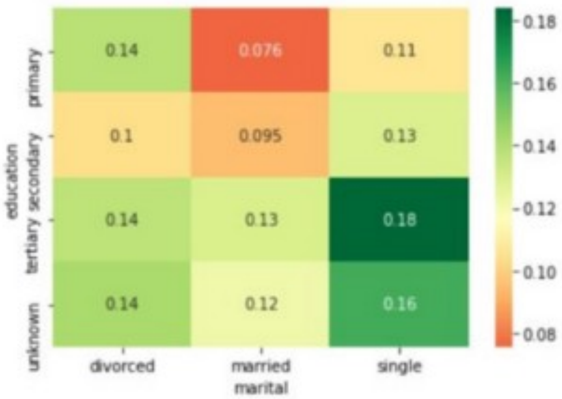
Let's see how 'Education', 'Marital', and 'Response_rate' vary with each other.

First, we'll create a pivot table with the three columns and after that, we'll create a heatmap.

The Pivot table and heatmap looks like this,

marital	divorced	married	single
education			
primary	0.138852	0.075601	0.106808
secondary	0.103559	0.094650	0.129271
tertiary	0.137415	0.129835	0.183737
unknown	0.142012	0.122519	0.162879

Pivot Table



likely to res

Similarly, we can plot the graphs for Job vs marital vs response, Education vs poutcome vs response, etc.

Conclusion

This is how we'll do Exploratory Data Analysis. Exploratory Data Analysis (EDA) helps us to look beyond the data. The more we explore the data, the more the insights we draw from it. a data analyst, almost 80% of our time will be spent understanding data and solving various business problems through EDA.

Thank you for reading and **Happy Coding!!!**

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- **Exploratory Data Analysis using Python:** https://www.activestate.com/blog/exploratory-data-analysis-using-python/