

E- COMMERCE PROJECT



-BY

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1. Analysis of Data

First and foremost, the dataset needs to be analysed. Data analysis involves cleaning, changing, and processing raw data and extracting useful information that can help the businesses to take informed decisions.

It is most important to get familiar with the dataset. For this, open the E-Commerce.csv file in Excel and look at the various columns that make up the dataset and their features. In order to do the same in python, we will first read the E-Commerce dataset and load it in a dataset named ECom_Data.

Before issuing any commands, all the necessary libraries need to be imported. For our analysis, numpy, pandas, matplotlib and seaborn have to be imported.

a) First ten records and Last ten records of the dataset:

We print the first ten records and the last ten records of the E-Commerce dataset using the head and the tail commands respectively.

Output:

```
out[9]:
```

	Customer_uniq_id	Region	Order_Date	Expected_Delivery_Date	Delivered_Date	product_name	product_main_category	product_subcategory
0	e71017e22468848edfe856f2308806d	East	24-10-2021	25-10-2021	25-10-2021	Indcrown Net Embroidered Semi-stitched Lehenga...	Clothing	Women's Clothin
1	6286847ee2da18f587503db49511c539	East	24-10-2021	25-10-2021	25-10-2021	Shopmania Music Band A5 Notebook Spiral Bound	Pens & Stationery	Diaries & Notebook
2	0686fec9b70e5039583a38119ca0c835	West	24-10-2021	25-10-2021	25-10-2021	Shopmania Music Band A5 Notebook Spiral Bound	Pens & Stationery	Diaries & Notebook
3	ea2408dc597bee2abb6b867fa688501f	West	24-10-2021	25-10-2021	25-10-2021	Tiara Diaries 2016-2017 Designer LA Kaarta "TA...	Pens & Stationery	Diaries & Notebook
4	5935ed077915347dc695744df68c565c	East	03-09-2021	04-09-2021	04-09-2021	KAJCI Embroidered Women's Waistcoat	Clothing	Women's Clothin
5	89fcdddaad50084e395d0928a7426afe	East	03-09-2021	04-09-2021	04-09-2021	Packman 8 x 10 inches Security Bags Without PO...	Pens & Stationery	Office Supplie
						Pick Pocket		

b. No. of rows and columns in the dataset:

There are two ways to find the number of rows and columns in the dataset.

1) Use the shape command to get the number of rows and columns. The shape() method gives the dimensions of a Pandas dataset.

2) Use the length function with axis = 0 for number of rows and axis = 1 for number of columns in the dataset.

Output:

(8906, 17)

There are 8906 rows and 17 columns in the E-Commerce dataset.

c. To find the number of object datatypes in the given dataset:

The `dtypes()` function is used to find the datatype of a column in the dataset. We can use `dtypes.value_counts()` to get the number of different datatypes in the dataset. In the E-Commerce dataset, there are 14 object datatypes in the dataset.

Output:

```
object      14
int64        2
float64       1
dtype: int64
```

d. To check if Boolean datatype is in the dataset:

The `dtypes()` function can be used to find all the different datatypes in the dataset like int, float, object, Boolean etc.

Output: There is no Boolean datatype in the dataset.

2. Altering the dataset

a. Dropping columns:

In order to eliminate the non-informative columns from the dataset, the `drop` function is used. The `drop` function explicitly specifies the column to be deleted. The `axis=1` in the `drop` function suggests that a column has to be deleted. However, the column is temporarily deleted in this way is still present in the original dataset.

b. Dropping columns permanently:

In order to delete the columns permanently in the dataset, `inplace=True` has to be specified in the `drop()` function. When a column is deleted in this way, it is permanently deleted from the dataset. On describing the dataset now, you will not find this column anymore.

Output: The columns `product_specifications` and `description` have been permanently deleted by using the `drop()` function with `inplace=True`.

3. Summarizing data

a. Number of unique brands:

In order to get the number of unique brands in the dataset, use the `nunique()` function on the `Brand` column of the `Ecom_Data` dataset.

Output:

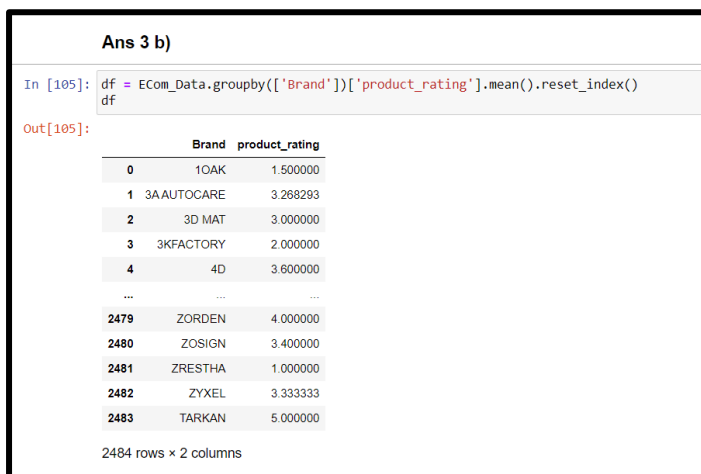
2484

There are 2484 unique brands in the dataset.

b. Average product rating within each brand:

The average product rating within each brand can be found by grouping the two columns, namely, `Brand` and `product_rating` and taking the mean of the product ratings of each brand. This will give you the required average rating of each brand.

Output:



The screenshot shows a Jupyter Notebook cell titled "Ans 3 b)". It contains the following code and output:

```
In [105]: df = Ecom_Data.groupby(['Brand'])['product_rating'].mean().reset_index()
df
```

Out[105]:

	Brand	product_rating
0	1OAK	1.500000
1	3A AUTOCARE	3.268293
2	3D MAT	3.000000
3	3KFACTORY	2.000000
4	4D	3.600000
...
2479	ZORDEN	4.000000
2480	ZOSIGN	3.400000
2481	ZRESTHA	1.000000
2482	ZYXEL	3.333333
2483	TARKAN	5.000000

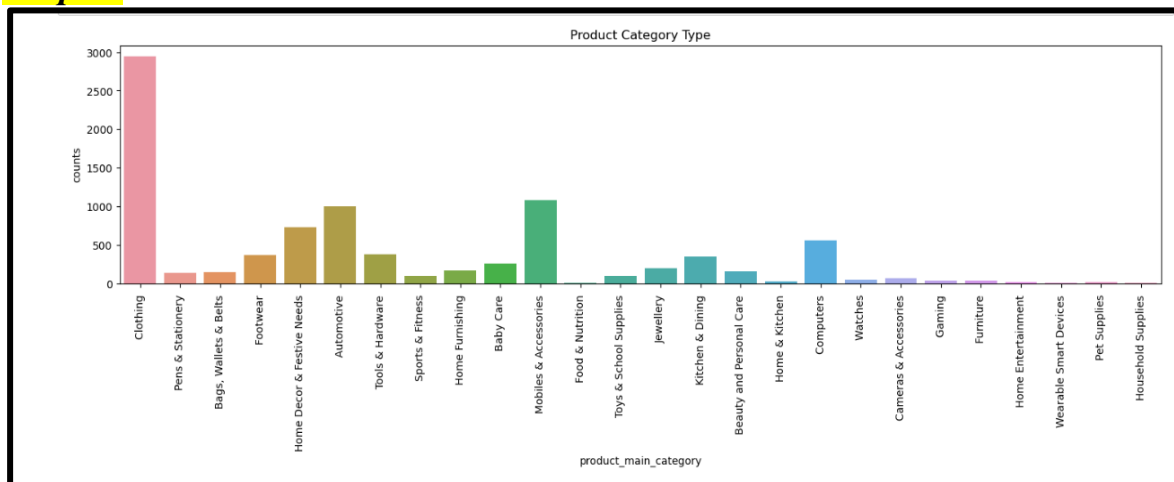
2484 rows x 2 columns

4. Main Categories of Products

a. Count of items ordered for each product_main_category:

The count of items ordered for each product can be found out by drawing the bar chart. For this, `countplot()` can be used. The plot can be made with `product_main_category` on the x-axis while the counts will be on the y-axis. For the labels to be very clear on the x-axis, use the `xticks()` function with `rotation = 900`. The bar graph should be customized by giving an appropriate title by using the `title()` command. Specify the scale by using the `figsize()` function.

Output:



b. Maximum orders and Minimum orders:

From the bar graph, it is very clearly visible that maximum orders were placed for Clothing category and Mobiles and Accessories category.

Minimum orders were placed for Wearable and Smart Devices category and Food & Nutrition category.

c. Top 5 product main category:

On using the `value_counts()` function on the `product_main_category` column of the `ECom_Data` dataset, we get the top 5 categories in the descending order.

Output:

Ans 4 c)

```
In [106]: ECom_Data['product_main_category'].value_counts().head(5).reset_index()
```

```
Out[106]:
```

	index	product_main_category	
0	Clothing	2943	
1	Mobiles & Accessories	1084	
2	Automotive	1001	
3	Home Decor & Festive Needs	727	
4	Computers	558	

5. Revenue Computation

Both the retailers and the company have to make profits to sustain in the business.

a. Total Revenue generated by the E-Commerce companies:

$$\text{Revenue} = 0.25 * (\text{discounted_price} > 600) + 0.15 * (\text{discounted_price} > 350 \ \& \ \text{discounted_price} \leq 600) + 0.10 * (\text{discounted_price} > 100 \ \& \ \text{discounted_price} \leq 350) + 0.05 * (\text{discounted_price} \leq 100)$$

Four columns can be added to the E-Commerce dataset with the four conditions of revenue generation, namely, 25%, 15%, 10% and 5%. Then merge the four columns using the fillna() function into one column called revenue. Then, take the sum() of the revenue column of the dataset.

Output:

2217486.85

The total Revenue is 2217486.85

6. Brand Revenue and top 10 brands

a. Total Brand Revenue:

The Brand Revenue of each brand is calculated by subtracting the revenue from the discounted price.

As the column called revenue has been added to the dataset, subtract the values of the two columns and create a new column called Brand Revenue.

Then, calculate the sum of all the rows of Brand Revenue column using the sum() function.

Output:

7522992.15

The total Brand Revenue is 7522992.15

b. Top 10 Brands having maximum revenue:

Use the groupby() function to group the two columns namely, Brand and Brand Revenue. Use the sum() function to calculate the sum of the Brand revenues of the same brands and then sort_values() function sorts these values. Use the ascending = False to sort the values in descending order.

Output:

The top 10 brands according to their Brand revenues are shown:

Ans 6

```
In [79]: ECom_Data['BrandRevenue'] = ECom_Data['discounted_price'] - ECom_Data['revenue']  
ECom_Data['BrandRevenue'].sum()
```

Out[79]: 7522992.15

```
In [111]: ECom_Data.groupby(['Brand'])['BrandRevenue'].sum().sort_values(ascending=False).head(10).reset_index()
```

Out[111]:

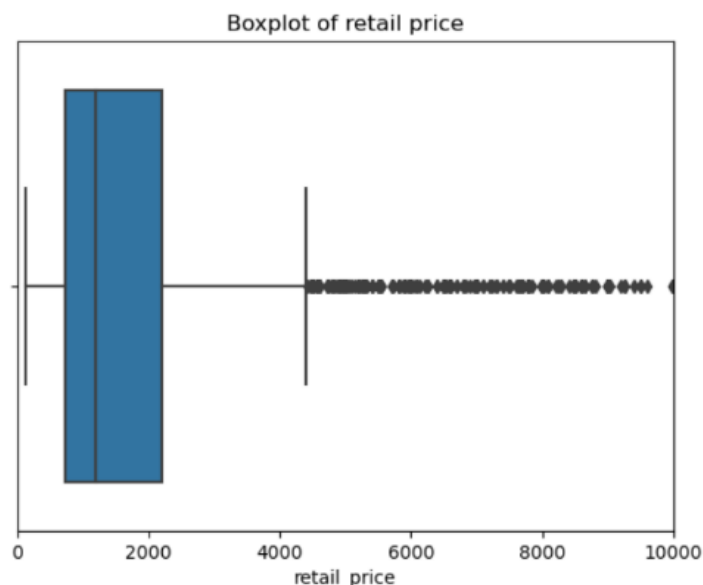
	Brand	BrandRevenue
0	ALLURE AUTO	498464.25
1	GAGA	237390.00
2	SLIM	212062.60
3	DAILYOBJECTS	181980.00
4	DIVINITI	143115.00
5	THELOSTPUPPY	127287.50
6	REGULAR	126536.50
7	ENTHOPIA	123146.25
8	ASUS	99241.50
9	SPRINGWEL	88978.50

7. Boxplot and Scatterplot

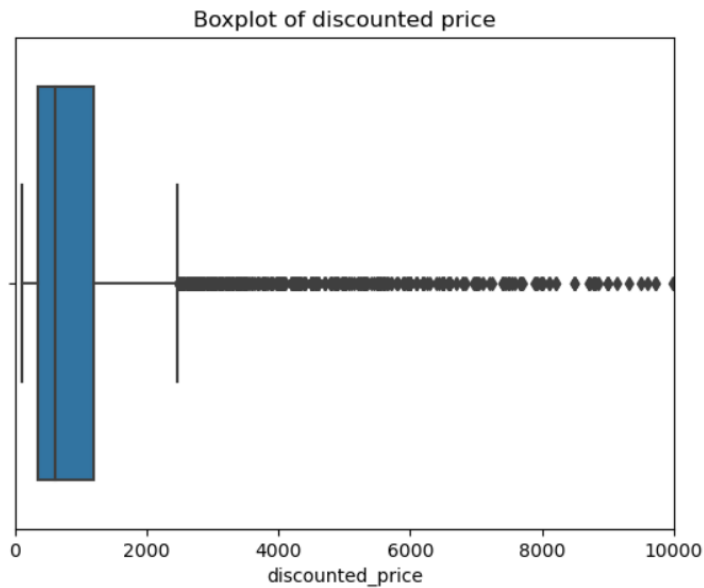
a. Boxplots of retail price and discounted price:

Use the boxplot() function to draw the boxplots of retail price and discounted price.

```
In [113]: plt.xlim(0,10000)  
plt.title("Boxplot of retail price")  
sns.boxplot(ECom_Data, x='retail_price');
```




```
In [115]: plt.xlim(0,10000)
plt.title("Boxplot of discounted price")
sns.boxplot(ECom_Data, x = 'discounted_price');
```

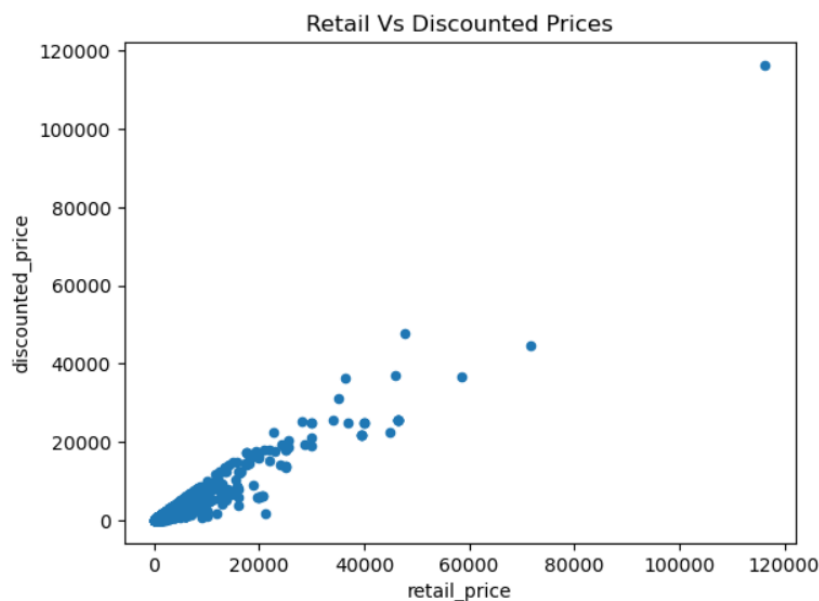


There are outliers in both the boxplots shown by the dots outside the maximum.

b. Scatter plot of retail price vs discounted price

Use the scatter() function to take the data as ECom_Data and specify the x-axis as retail price and y-axis as discounted price.

Output:



8. New Dataframe for Brand specific information

The first column of the new dataframe comprises of the total number of orders placed per Brand. Use the value_counts() function on the Brand column to get this information.

The second column comprises of the total retail price per brand. Use groupby() function to group Brand and retail price and use the sum() on the retail price column to get the second column values.

The third column comprises of the total discounted price per brand. Again, use the groupby() function to group Brand and discounted price and use the sum() function on the discounted price column.

The fourth column comprises of the total Brand Revenue generated per brand. This information can be procured by grouping the Brand and Brand revenue columns and applying sum() on the Brand revenue.

The new dataframe looks like this:

```
col2 = ECom_Data.groupby(['Brand'])['retail_price'].sum()
col3 = ECom_Data.groupby(['Brand'])['discounted_price'].sum()
col4 = ECom_Data.groupby(['Brand'])['BrandRevenue'].sum()

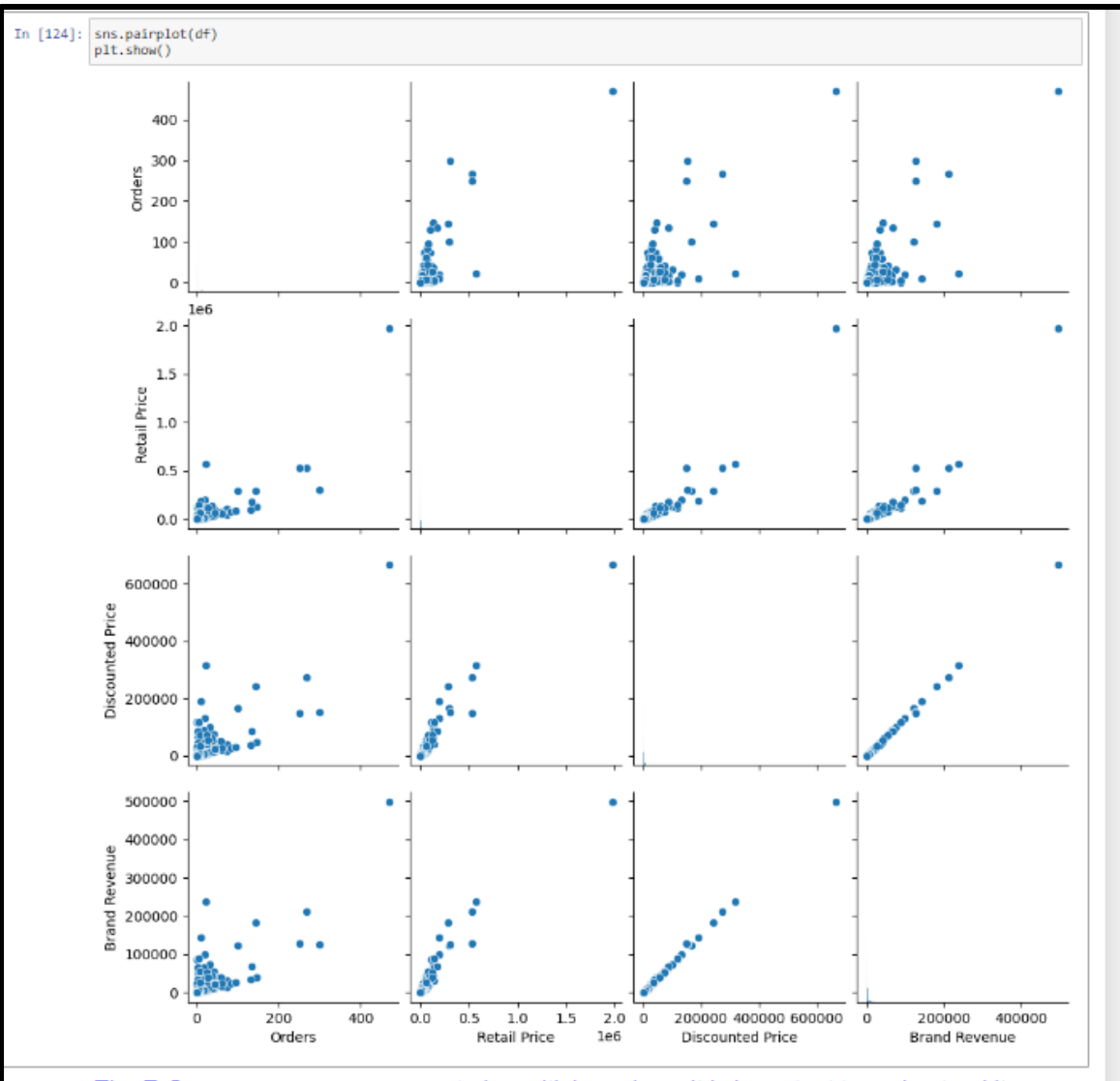
df = pd.DataFrame({'Orders':col1, 'Retail Price':col2, 'Discounted Price':col3, 'Brand Revenue': col4})
print(df)
```

	Orders	Retail Price	Discounted Price	Brand Revenue
10AK	2	1698	1274	1015.40
3A AUTOCARE	41	107059	74134	55647.90
3D MAT	1	7250	6999	5249.25
3KFACTORY	1	399	174	156.60
4D	5	17500	7948	5961.00
...
ZORDEN	1	3999	2799	2099.25
ZOSIGN	5	6995	6995	5246.25
ZRESTHA	1	1999	899	674.25
ZYXEL	9	64742	35392	26544.00
TARKAN	1	1999	349	314.10

[2484 rows x 4 columns]

a. Pairplot for the new dataframe:

Use the pairplot() function to get the pairplot of the new dataframe.



9. Comparison of Performance Regionwise:

a. Lineplot for each region:

Lineplot for each region is plotted using the `lineplot()` function in seaborn.

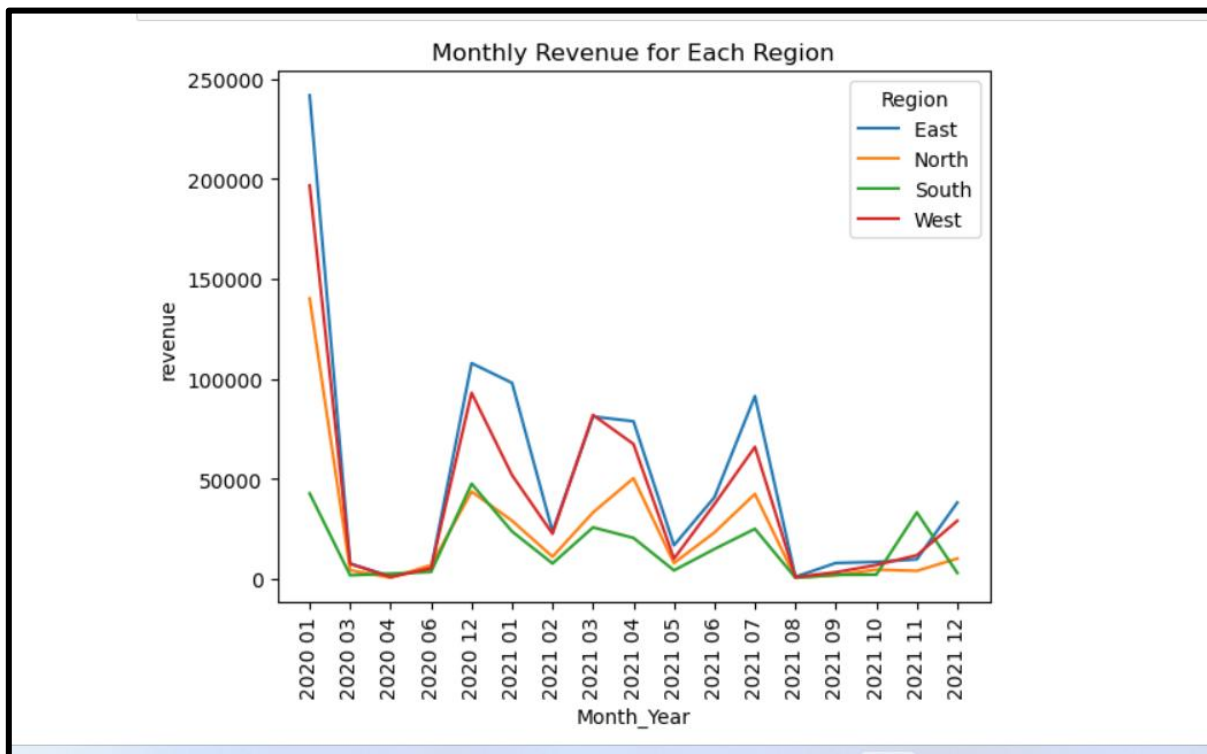
First, change the datatype of the `Order_Date` column from string to datetime using `to_datetime()` function.

Then, extract the year and the month using the `.dt.year` and `.dt.month` formats and make new columns. Also, extract the year and month together into a `Month_Year` column in the dataset.

Now, make a new dataframe with columns `Region`, `Month_Year` and total revenue in that particular month and year.

Using this dataframe, plot a lineplot with hue as `Region`, x-axis and `Month_Year` and y-axis as revenue respectively.

Output:



b. Best and Worst performing months for every region

East Region:

Best Performing Month - January, 2020

Worst Performing Month - August, 2021

North Region:

Best Performing Month - January, 2020

Worst Performing Month - August, 2021

South Region:

Best Performing Month - January, 2020

Worst Performing Month - August, 2021

West Region:

Best Performing Month - January, 2020

Worst Performing Month - August, 2021

In this way, we have analysed the dataset given to us and extracted the requisite information from the same to help us visualize the dataset in a better way.