

Amazon Project

By Faiz Khan

First we have to import basic Libraries

```
In [9]: import pandas as pd
import numpy as np
import seaborn as sns
import plotly.express as px
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings("ignore")
```

Now we have to load DataSet

| n [11]: | df | | | | | | | | | | | | | | |
|----------|----|--|--------------------------|--------------------|------------------|-------------------|---------------|-----------|-----------|---------------|---------------|--------------|------------------|------------|---------------|
| Out[11]: | | Region | Country | Item Type | Sales Channel | Order Priority | Order Date | Order ID | Ship Date | Units Sold | Unit Price | Unit Cost | Total Revenue | Total Cost | Tota Profi |
| | 0 | Australia and Oceania | Tuvalu | Baby Food | Offline | Н | 5/28/2010 | 669165933 | 6/27/2010 | 9925 | 255.28 | 159.42 | 2533654.00 | 1582243.50 | 951410.5 |
| | 1 | Central America and the Caribbean | Grenada | Cereal | Online | С | 8/22/2012 | 963881480 | 9/15/2012 | 2804 | 205.70 | 117.11 | 576782.80 | 328376.44 | 248406.3 |
| | 2 | Europe | Russia | Office Supplies | Offline | L | 5/2/2014 | 341417157 | 5/8/2014 | 1779 | 651.21 | 524.96 | 1158502.59 | 933903.84 | 224598.7 |
| | 3 | Sub- Saharan Africa | Sao Tome and Principe | Fruits | Online | С | 6/20/2014 | 514321792 | 7/5/2014 | 8102 | 9.33 | 6.92 | 75591.66 | 56065.84 | 19525.8 |
| | 4 | Sub- Saharan Africa | Rwanda | Office Supplies | Offline | L | 2/1/2013 | 115456712 | 2/6/2013 | 5062 | 651.21 | 524.96 | 3296425.02 | 2657347.52 | 639077.5 |
| | | | | | | | | | | | | | | | |

Applying Python's Basic Funtions

| TH [SA]. | u1.1311a().34111() | | | |
|----------|--------------------|---------|---|--|
| Out[20]: | Region | 0 | | |
| | Country | 0 | | |
| | Item Type | 0 | | |
| | Sales Channel | 0 | | |
| | Order Priority | 0 | | |
| | Order Date | 0 | | |
| | Order ID | 0 | | |
| | Ship Date | 0 | | |
| | Units Sold | 0 | | |
| | Unit Price | 0 | | |
| | Unit Cost | 0 | | |
| | Total Revenue | 0 | | |
| | | 0 | | |
| | | 0 | | |
| | dtype: int64 | | | |
| | | | | |
| In [18]: | df.Country.value_ | counts(|) | |
| Out[18]: | The Gambia | | 4 | |

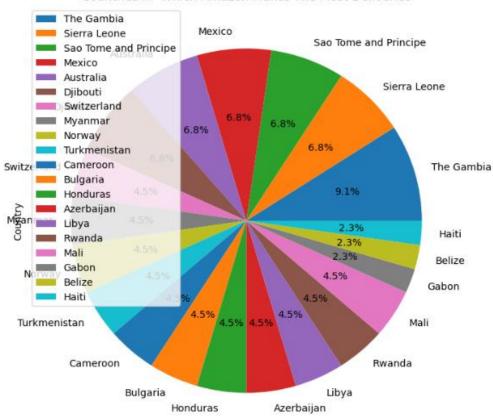
| In [15]: | df.des | cribe() | | | | | | |
|----------|---|--------------|---|-----------------------|------------|---------------|--------------|-----------|
| Out[15]: | | Order ID | Units Sold | Unit Price | Unit Cost | Total Revenue | Total Cost | Total P |
| | count | 1.000000e+02 | 100.000000 | 100.000000 | 100.000000 | 1.000000e+02 | 1.000000e+02 | 1.000000€ |
| | mean | 5.550204e+08 | 5128.710000 | 276.761300 | 191.048000 | 1.373488e+06 | 9.318057e+05 | 4.416820€ |
| | std | 2.606153e+08 | 2794.484562 | 235.592241 | 188.208181 | 1.460029e+06 | 1.083938e+06 | 4.385379€ |
| | min | 1.146066e+08 | 124.000000 | 9.330000 | 6.920000 | 4.870260e+03 | 3.612240e+03 | 1.258020€ |
| | 25% | 3.389225e+08 | 2836.250000 | 81.730000 | 35.840000 | 2.687212e+05 | 1.688680e+05 | 1.214436€ |
| | 50% | 5.577086e+08 | 5382.500000 | 179.880000 | 107.275000 | 7.523144e+05 | 3.635664e+05 | 2.907680€ |
| | 75% | 7.907551e+08 | 7369.000000 | 437.200000 | 263.330000 | 2.212045e+06 | 1.613870e+06 | 6.358288€ |
| | max | 9.940222e+08 | 9925.000000 | 668.270000 | 524.960000 | 5.997055e+06 | 4.509794e+06 | 1.719922€ |
| In [17]: | df.mea | n().round(2 |) | | | | | |
| Out[17]: | Order ID Units Sold Unit Price Unit Cost Total Revenue Total Cost Total Profit dtype: float64 | | 5.550204e+0 5.128710e+0 2.767600e+0 1.910500e+0 1.373488e+0 9.318057e+0 4.416820e+0 | 3 2 2 6 5 | | | | |

Visualisation With Python

```
In [31]: plt.figure(figsize=(12,8))
    df.Country.value_counts().head(20).plot(kind="pie",autopct="%1.1f%%")
    plt.legend()
    plt.title("Countries in Which Amazon Makes The Most Deliveries")
```

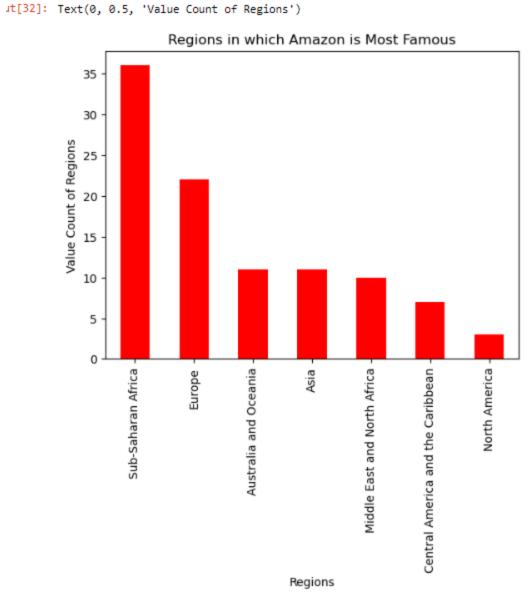
Out[31]: Text(0.5, 1.0, 'Countries in Which Amazon Makes The Most Deliveries')

Countries in Which Amazon Makes The Most Deliveries



We can clearly see that in The Gambia amazon deliver most products so they shoould target more to the people of The Gambia and then Diibouti. Australia. Mexico. Sao Tome and Principe. Sierra Leone

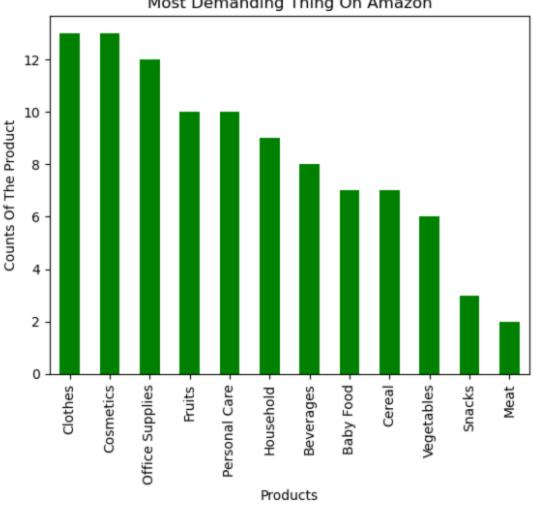
```
1 [32]: df.Region.value_counts().head(25).plot(kind="bar",color="Red")
        plt.title("Regions in which Amazon is Most Famous")
        plt.xlabel("Regions")
        plt.ylabel("Value Count of Regions")
```



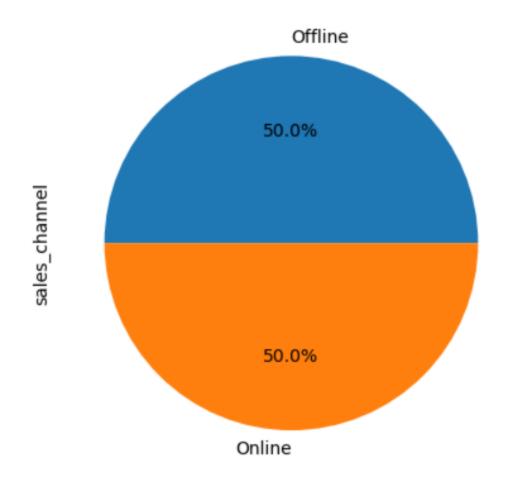
```
In [47]: df.item_type.value_counts().head(15).plot(kind="bar",color="green")
         plt.title("Most Demanding Thing On Amazon")
         plt.ylabel("Counts Of The Product")
         plt.xlabel("Products")
```

Out[47]: Text(0.5, 0, 'Products')





```
In [51]: df.sales_channel.value_counts().plot(kind="pie",autopct="%1.1f%%")
Out[51]: <Axes: ylabel='sales_channel'>
```



Amazon uses both Online Offline mode equally as their Sales Channel

In [60]: df["total_sales"]=df.total_revenue-df.total_cost

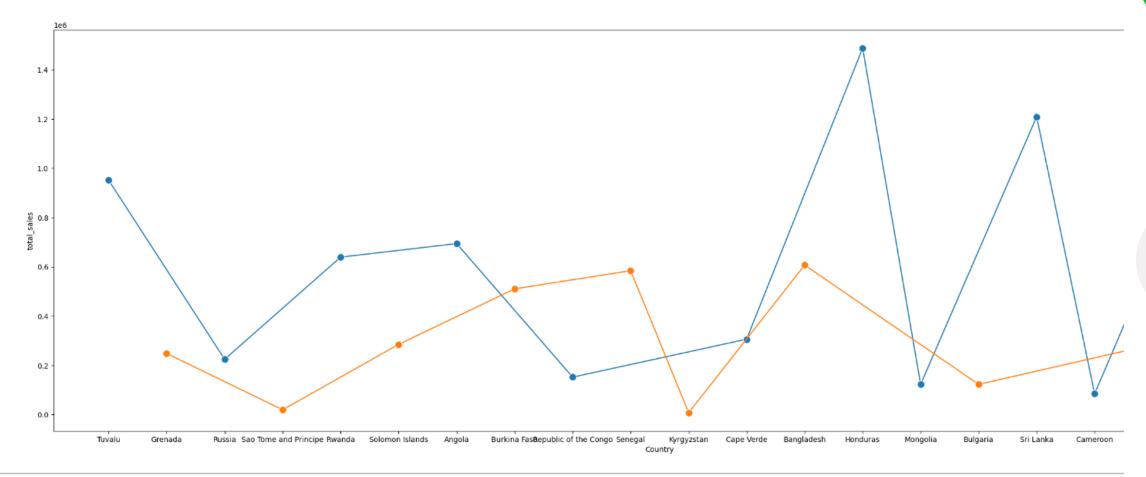
In [61]: df

Out[61]:

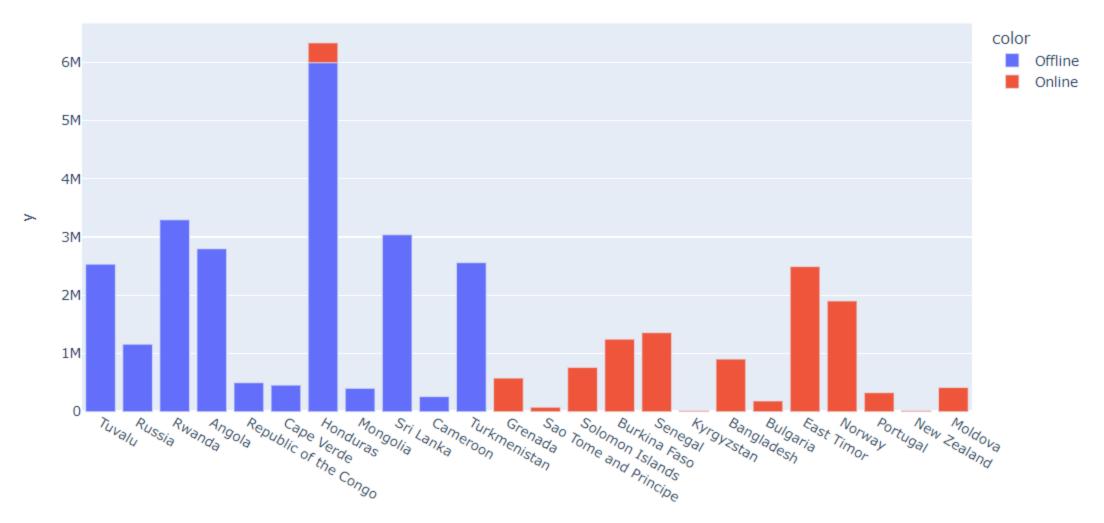
|]: _ | | Region | Country | item_type | sales_channel | order_priority | order_date | order_id | ship_date | units_sold | unit_price | unit_cost | total_revenue | total_ |
|------|----|--|--------------------------|--------------------|---------------|----------------|------------|-----------|------------|------------|------------|-----------|---------------|--------|
| | 0 | Australia and Oceania | Tuvalu | Baby Food | Offline | Н | 5/28/2010 | 669165933 | 6/27/2010 | 9925 | 255.28 | 159.42 | 2533654.00 | 158224 |
| | 1 | Central America and the Caribbean | Grenada | Cereal | Online | С | 8/22/2012 | 963881480 | 9/15/2012 | 2804 | 205.70 | 117.11 | 576782.80 | 32837 |
| | 2 | Europe | Russia | Office Supplies | Offline | L | 5/2/2014 | 341417157 | 5/8/2014 | 1779 | 651.21 | 524.96 | 1158502.59 | 93390 |
| | 3 | Sub- Saharan Africa | Sao Tome and Principe | Fruits | Online | С | 6/20/2014 | 514321792 | 7/5/2014 | 8102 | 9.33 | 6.92 | 75591.66 | 5606 |
| | 4 | Sub- Saharan Africa | Rwanda | Office Supplies | Offline | L | 2/1/2013 | 115456712 | 2/6/2013 | 5062 | 651.21 | 524.96 | 3296425.02 | 265734 |
| | | | | | | | | | | | | | | |
| ! | 95 | Sub- Saharan Africa | Mali | Clothes | Online | М | 7/26/2011 | 512878119 | 9/3/2011 | 888 | 109.28 | 35.84 | 97040.64 | 3182 |
| | 96 | Asia | Malaysia | Fruits | Offline | L | 11/11/2011 | 810711038 | 12/28/2011 | 6267 | 9.33 | 6.92 | 58471.11 | 4336 |
| | 97 | Sub- Saharan | Sierra Leone | Vegetables | Offline | С | 6/1/2016 | 728815257 | 6/29/2016 | 1485 | 154.06 | 90.93 | 228779.10 | 13503 |

1]: plt.figure(figsize=(30,10)) sns.lineplot(x=df.Country.head(20),y=df.total_sales.head(20),hue=df.sales_channel.head(20),marker="o",markersize=

1]: <Axes: xlabel='Country', ylabel='total_sales'>



In [23]: px.bar(x=df.Country.head(25),y=df.total_revenue.head(25),color=df.sales_channel.head(25))



```
1 [92]: c=df.groupby("Country")["total_revenue"].unique().reset_index()
ı [95]: c
ıt[95]:
                     Country
                                                          total revenue
                     Albania
                                                             [247956.32]
                      Angola
                                                            [2798046.49]
           2
                                         [1904138.04, 140287.4, 445508.05]
                    Australia
           3
                      Austria
                                                             [1244708.4]
                   Azerbaijan
                                                  [3162704.8, 1316095.41]
           4
           ...
```

The Gambia [1583799.9, 2011149.63, 435466.9, 1419101.52]

[2559474.1, 3262562.1]

[2533654.0]

71

72

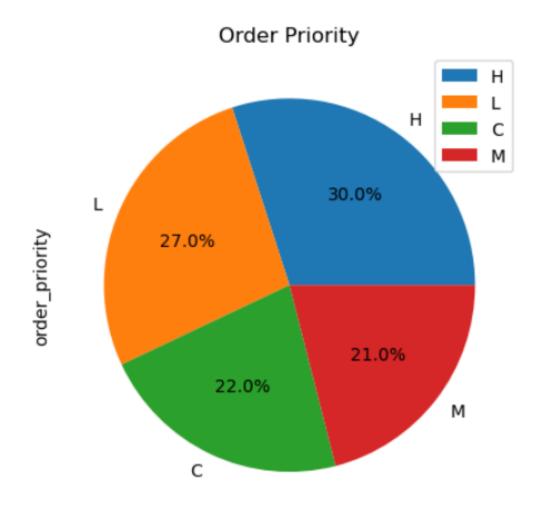
73

Turkmenistan

Tuvalu

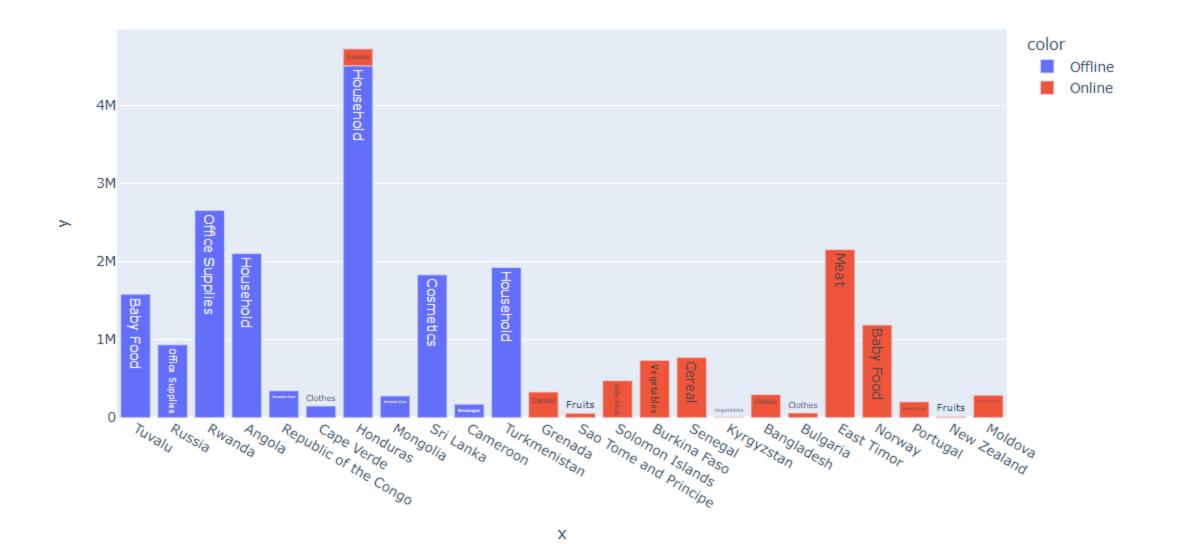
```
In [113]: df.order_priority.value_counts().plot(kind="pie",autopct="%1.1f%%")
   plt.legend()
   plt.title("Order Priority")
```

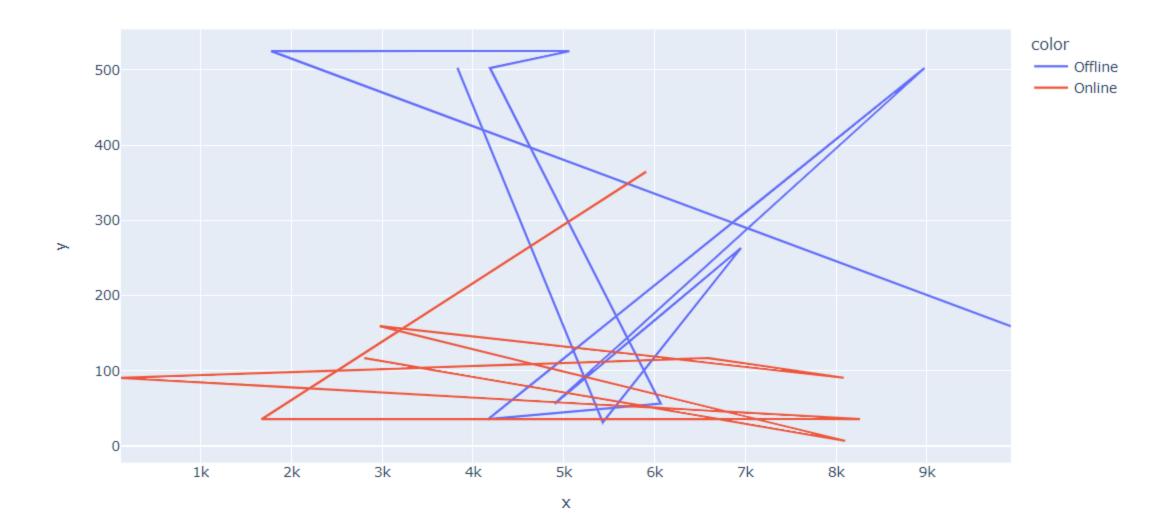
Out[113]: Text(0.5, 1.0, 'Order Priority')



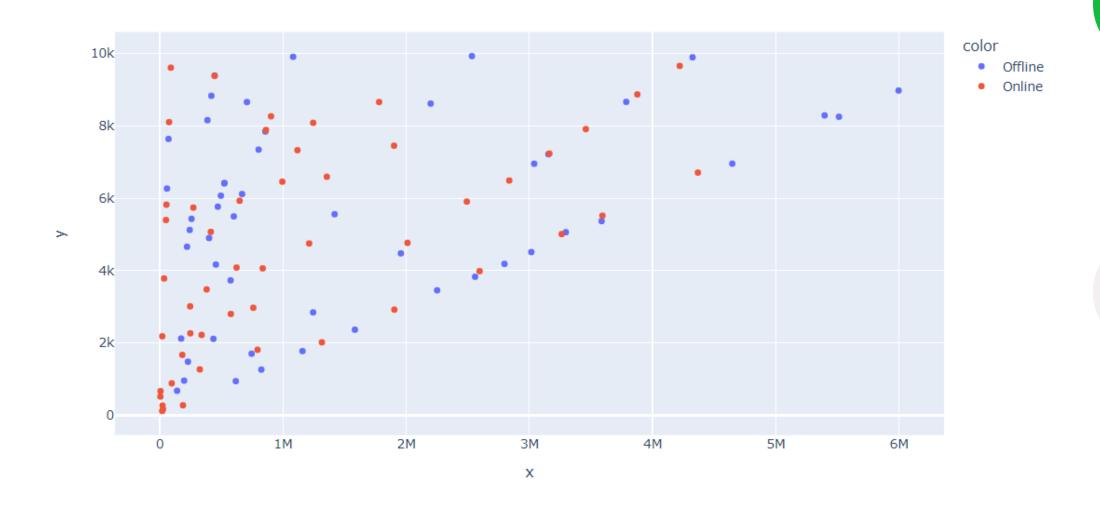
H is the highest order Prioprity of People in diffrent Countries

In [24]: px.bar(x=df.Country.head(25),y=df.total_cost.head(25),color=df.sales_channel.head(25),text=df.item_type.head(25))



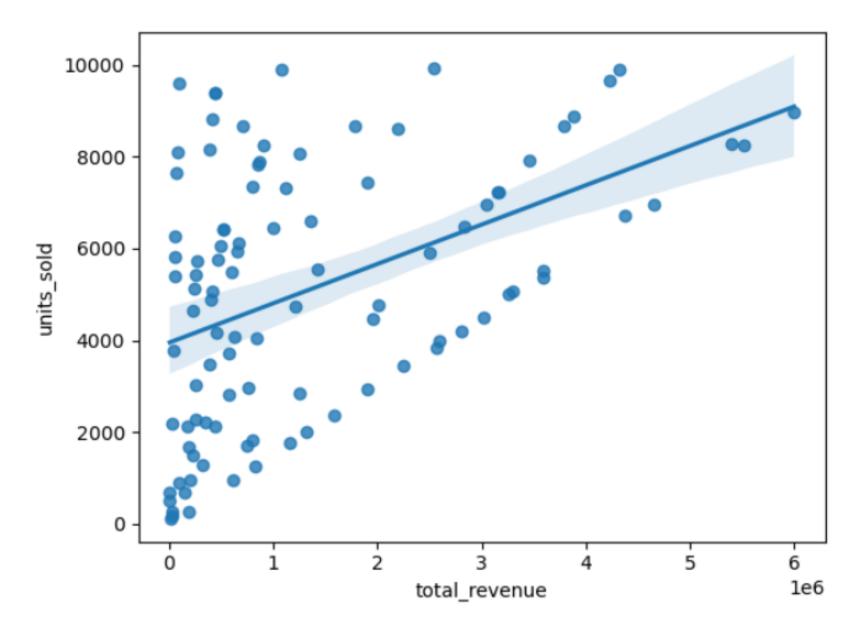


In [26]: px.scatter(x=df.total_revenue,y=df.units_sold,color=df.sales_channel)



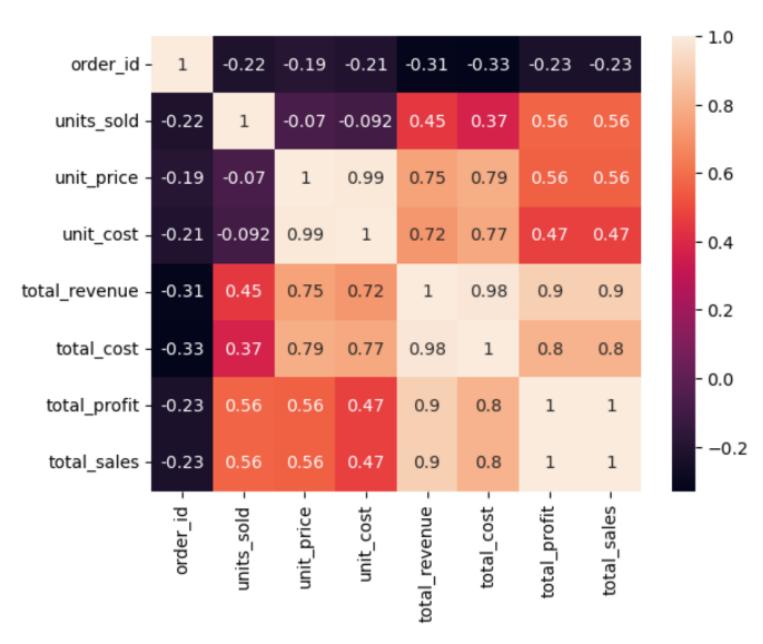
```
In [140]: sns.regplot(x=df.total_revenue,y=df.units_sold)
```

Out[140]: <Axes: xlabel='total_revenue', ylabel='units_sold'>



In [143]: sns.heatmap(df.corr(numeric_only=True),annot=True)

Out[143]: <Axes: >



Applying ML Algorithm

```
In [241]: from sklearn.model selection import train test split
In [259]: x=df.drop(["Region", "Country", "item_type", "sales_channel", "order_priority", "order_id", "order_date", "ship_date", "units_sold", "unit
In [260]: y=df.total_sales
In [262]: x.astype("int")
Out[262]:
                total revenue total cost total profit total sales
                     2533654
                               1582243
                                          951410
                                                     951410
                     576782
                               328376
                                          248406
                                                     248406
                     1158502
                               933903
                                          224598
                                                     224598
                      75591
                                56065
                                           19525
                                                     19525
                     3296425
                              2657347
                                          639077
                                                     639077
                      97040
                                31825
                                           65214
                                                      65214
                      58471
                                43367
                                           15103
                                                      15103
                               135031
                                           93748
                                                      93748
                      228779
                      471336
                               326815
                                          144521
                                                     144521
                     3586605
                              2697132
                                          889472
                                                     889472
            100 rows × 4 columns
In [263]: y.astype("int")
```

In [262]: x.astype("int")

Out[262]:

| | total_revenue | total_cost | total_profit | total_sales |
|----|---------------|------------|--------------|-------------|
| 0 | 2533654 | 1582243 | 951410 | 951410 |
| 1 | 576782 | 328376 | 248406 | 248406 |
| 2 | 1158502 | 933903 | 224598 | 224598 |
| 3 | 75591 | 56065 | 19525 | 19525 |
| 4 | 3296425 | 2657347 | 639077 | 639077 |
| | | | | |
| 95 | 97040 | 31825 | 65214 | 65214 |
| 96 | 58471 | 43367 | 15103 | 15103 |
| 97 | 228779 | 135031 | 93748 | 93748 |
| 98 | 471336 | 326815 | 144521 | 144521 |
| 99 | 3586605 | 2697132 | 889472 | 889472 |
| | | | | |

100 rows × 4 columns

```
In [263]: y.astype("int")
```

Out[263]: 0

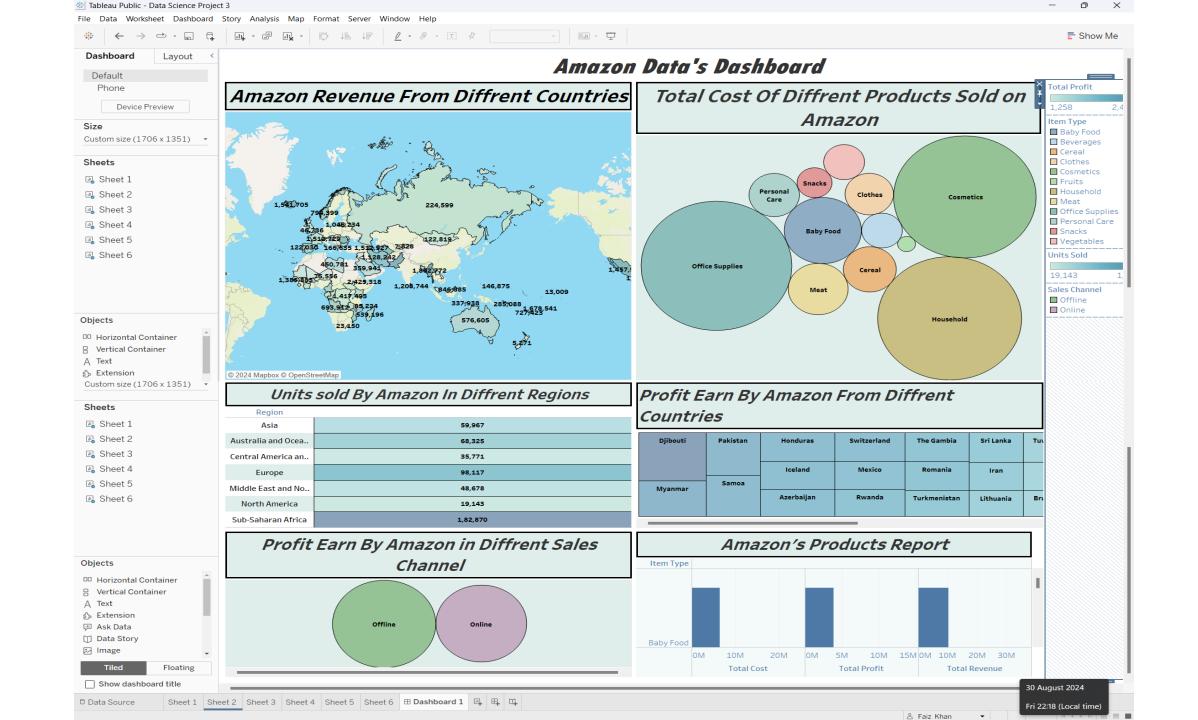
. . .

Name: total_sales, Length: 100, dtype: int32

```
In [264]: x train,x test,y train,y test=train test split(x,y,test size=0.25,random state=44)
In [265]: x_train.shape,x_test.shape
Out[265]: ((75, 4), (25, 4))
In [266]: from sklearn.preprocessing import MinMaxScaler
In [267]: norm=MinMaxScaler()
In [268]: norm
Out[268]: MinMaxScaler()
                              In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
                              On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.
In [269]: x train=pd.DataFrame(norm.fit transform(x train))
In [270]: x test=pd.DataFrame(norm.fit transform(x test))
In [249]: x_train[["Region", "Country", "item_type", "sales_channel", "order_priority"]]=oe.fit_transform(x_train[["Region", "Country", "item_type", "item_typ
In [250]: x_test[["Region", "Country", "item_type", "sales_channel", "order_priority"]]=oe.fit_transform(x_test[["Region", "Country", "item_type")
In [271]: from sklearn.linear_model import LinearRegression
In [272]: lr=LinearRegression()
In [273]: lr
Out[273]: LinearRegression()
```

```
In [273]: lr
Out[273]: LinearRegression()
           In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
           On CitUub, the UTML representation is unable to render, please try loading this page with nbviewer.org.
click to expand output; double click to hide output
In [274]: lr.fit(x train,y train)
Out[274]: LinearRegression()
           In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
           On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.
In [275]: y pred=lr.predict(x test)
In [276]: from sklearn.metrics import r2_score
In [277]: r2_score(y_pred,y_test)
Out[277]: 0.9984731605620133
```

Tableau'Dashboard of Amazon DataSet



Important Points

- We can clearly see that in The Gambia amazon deliver most products so they shoould target more to the people of The Gambia and then Djibouti, Australia, Mexico, Sao Tome and Principe, Sierra Leone.
- Sub-Saharan Africa is the region where Amazon delivers the most Products(182870 units sold).
- Clothes are most demanding product on Amazon that people prefer to buy.
- Amazon uses both Online Offline mode equally as their Sales Channel.
- H is the highest order Prioprity of People in diffrent Countries.
- Product with the Highest Total Cost Sold on Amazon is Office Supplies.
- · Amazon earns highest revenue from the country DJIBOUTI.
- Profit earn by Amazon in offine mode i.e of Rs 2,49,20,727 as compare to offline mode i.e of Rs 1,92,47,472.
- Highest Revenue that the Amazon gets is form Baby Food of Rs 1,03,50,328.