y1bxiijmt

November 6, 2025

[ ]:
```python
import numpy as np
import pandas as pd
import seaborn as sns; sns.set(style="ticks", color_codes=True)
import matplotlib.pyplot as plt
import plotly.graph_objs as go
from plotly.subplots import make_subplots
import seaborn as sns
import plotly.express as px
%matplotlib inline

from plotly.offline import download_plotlyjs, init_notebook_mode, plot, iplot
init_notebook_mode(connected = True)
```

[12]:
```python
df = pd.read_csv(r'C://Users//anand//Downloads//DataCoSupplyChainDataset.csv',␣
 ↪encoding='ISO-8859-1')

pd.set_option('display.max_rows', 500)
pd.set_option('display.max_columns', 500)
pd.set_option('display.width', 1000)

df.head()
```

[12]:
```
       Type  Days for shipping (real)  Days for shipment (scheduled)  Benefit
per order  Sales per customer   Delivery Status  Late_delivery_risk  Category Id
Category Name Customer City Customer Country Customer Email Customer Fname
Customer Id Customer Lname Customer Password Customer Segment Customer State
Customer Street  Customer Zipcode  Department Id Department Name   Latitude
Longitude        Market  Order City Order Country  Order Customer Id order date
(DateOrders)  Order Id  Order Item Cardprod Id  Order Item Discount  Order Item
Discount Rate  Order Item Id  Order Item Product Price  Order Item Profit Ratio
Order Item Quantity   Sales  Order Item Total  Order Profit Per Order    Order
Region      Order State     Order Status  Order Zipcode  Product Card Id
Product Category Id  Product Description                                Product
Image  Product Name  Product Price  Product Status shipping date (DateOrders)
Shipping Mode
0     DEBIT                        3                              4
91.250000          314.640015  Advance shipping                  0           73
```

```
Sporting Goods        Caguas      Puerto Rico      XXXXXXXXX         Cally
20755       Holloway         XXXXXXXXX        Consumer             PR  5365
Noble Nectar Island            725.0             2        Fitness  18.251453
-66.037056  Pacific Asia      Bekasi     Indonesia            20755
1/31/2018 22:56     77202                   1360           13.110000
0.04         180517                   327.75                    0.29
1  327.75        314.640015              91.250000  Southeast Asia  Java
Occidental         COMPLETE             NaN            1360                  73
NaN  http://images.acmesports.sports/Smart+watch   Smart watch          327.75
0             2/3/2018 22:56  Standard Class
1  TRANSFER                        5                              4
-249.089996          311.359985     Late delivery                1
73  Sporting Goods        Caguas      Puerto Rico      XXXXXXXXX          Irene
19492           Luna         XXXXXXXXX        Consumer             PR
2679 Rustic Loop            725.0             2        Fitness  18.279451
-66.037064  Pacific Asia     Bikaner         India             19492
1/13/2018 12:27     75939                   1360           16.389999
0.05         179254                   327.75                   -0.80
1  327.75        311.359985             -249.089996      South Asia
Rajastán          PENDING            NaN            1360                  73
NaN  http://images.acmesports.sports/Smart+watch   Smart watch          327.75
0            1/18/2018 12:27  Standard Class
2     CASH                         4                              4
-247.779999          309.720001  Shipping on time                0
73  Sporting Goods      San Jose         EE. UU.      XXXXXXXXX        Gillian
19491      Maldonado         XXXXXXXXX        Consumer             CA      8510
Round Bear Gate           95125.0             2        Fitness  37.292233
-121.881279  Pacific Asia     Bikaner         India             19491
1/13/2018 12:06     75938                   1360           18.030001
0.06         179253                   327.75                   -0.80
1  327.75        309.720001             -247.779999      South Asia
Rajastán           CLOSED            NaN            1360                  73
NaN  http://images.acmesports.sports/Smart+watch   Smart watch          327.75
0            1/17/2018 12:06  Standard Class
3    DEBIT                         3                              4
22.860001          304.809998  Advance shipping                0          73
Sporting Goods   Los Angeles         EE. UU.      XXXXXXXXX           Tana
19490           Tate         XXXXXXXXX      Home Office            CA
3200 Amber Bend           90027.0             2        Fitness  34.125946
-118.291016  Pacific Asia  Townsville     Australia             19490
1/13/2018 11:45     75937                   1360           22.940001
0.07         179252                   327.75                    0.08
1  327.75        304.809998              22.860001         Oceania
Queensland         COMPLETE             NaN            1360                  73
NaN  http://images.acmesports.sports/Smart+watch   Smart watch          327.75
0            1/16/2018 11:45  Standard Class
4   PAYMENT                        2                              4
```

```
134.210007          298.250000  Advance shipping                  0
73  Sporting Goods        Caguas      Puerto Rico      XXXXXXXXX           Orli
19489      Hendricks         XXXXXXXXX        Corporate             PR  8671
Iron Anchor Corners              725.0             2         Fitness  18.253769
-66.037048  Pacific Asia  Townsville     Australia              19489
1/13/2018 11:24     75936                   1360           29.500000
0.09         179251                    327.75                    0.45
1  327.75        298.250000             134.210007         Oceania
Queensland  PENDING_PAYMENT            NaN             1360                   73
NaN  http://images.acmesports.sports/Smart+watch   Smart watch          327.75
0            1/15/2018 11:24  Standard Class
```

[15]:
```
df.tail()
```

[15]:
```
            Type  Days for shipping (real)  Days for shipment (scheduled)
Benefit per order  Sales per customer   Delivery Status  Late_delivery_risk
Category Id Category Name Customer City Customer Country Customer Email Customer
Fname  Customer Id Customer Lname Customer Password Customer Segment Customer
State            Customer Street  Customer Zipcode  Department Id Department
Name   Latitude   Longitude        Market Order City Order Country  Order
Customer Id order date (DateOrders)  Order Id  Order Item Cardprod Id  Order
Item Discount  Order Item Discount Rate  Order Item Id  Order Item Product Price
Order Item Profit Ratio  Order Item Quantity       Sales  Order Item Total
Order Profit Per Order  Order Region        Order State     Order Status  Order
Zipcode  Product Card Id  Product Category Id  Product Description
Product Image                            Product Name  Product Price  Product
Status shipping date (DateOrders)  \
180514      CASH                        4                              4
40.000000          399.980011  Shipping on time                  0          45
Fishing      Brooklyn          EE. UU.      XXXXXXXXX          Maria
1005       Peterson          XXXXXXXXX      Home Office             NY
1322 Broad Glade           11207.0             7         Fan Shop  40.640930
-73.942711  Pacific Asia   Shanghái         China              1005
1/16/2016 3:40     26043                 1004                    0.0
0.00          65177                399.980011                    0.10
1  399.980011        399.980011             40.000000  Eastern Asia
Shanghái            CLOSED           NaN            1004                  45
NaN  http://images.acmesports.sports/Field+%26+Stre…  Field & Stream Sportsman
16 Gun Fire Safe      399.980011              0            1/20/2016 3:40
180515     DEBIT                        3                              2
-613.770019          395.980011     Late delivery                  1
45       Fishing   Bakersfield         EE. UU.      XXXXXXXXX         Ronald
9141          Clark          XXXXXXXXX        Corporate             CA     7330
Broad Apple Moor           93304.0             7         Fan Shop  35.362545
-119.018700  Pacific Asia   Hirakata          Japón              9141
1/16/2016 1:34     26037                 1004                    4.0
0.01          65161                399.980011                   -1.55
```

```
1  399.980011        395.980011             -613.770019  Eastern Asia
Osaka         COMPLETE            NaN             1004                  45
NaN  http://images.acmesports.sports/Field+%26+Stre…  Field & Stream Sportsman
16 Gun Fire Safe     399.980011              0           1/19/2016 1:34
180516  TRANSFER                        5                              4
141.110001          391.980011     Late delivery                  1
45       Fishing       Bristol          EE. UU.      XXXXXXXXX          John
291          Smith         XXXXXXXXX       Corporate             CT          97
Burning Landing             6010.0             7        Fan Shop  41.629959
-72.967155  Pacific Asia   Adelaide     Australia               291
1/15/2016 21:00     26024                  1004                 8.0
0.02          65129               399.980011                  0.36
1  399.980011        391.980011              141.110001       Oceania  Australia
del Sur          PENDING           NaN             1004                  45
NaN  http://images.acmesports.sports/Field+%26+Stre…  Field & Stream Sportsman
16 Gun Fire Safe     399.980011              0         1/20/2016 21:00
180517   PAYMENT                       3                              4
186.229996          387.980011  Advance shipping                  0
45       Fishing        Caguas      Puerto Rico      XXXXXXXXX          Mary
2813          Smith         XXXXXXXXX         Consumer             PR  2585
Silent Autumn Landing            725.0             7        Fan Shop
18.213350  -66.370575  Pacific Asia   Adelaide     Australia            2813
1/15/2016 20:18     26022                  1004                12.0
0.03          65126               399.980011                  0.48
1  399.980011        387.980011              186.229996       Oceania  Australia
del Sur  PENDING_PAYMENT           NaN             1004                  45
NaN  http://images.acmesports.sports/Field+%26+Stre…  Field & Stream Sportsman
16 Gun Fire Safe     399.980011              0         1/18/2016 20:18
180518   PAYMENT                       4                              4
168.949997          383.980011  Shipping on time                  0
45       Fishing        Caguas      Puerto Rico      XXXXXXXXX        Andrea
7547         Ortega         XXXXXXXXX         Consumer             PR
697 Little Meadow            725.0             7        Fan Shop  18.290380
-66.370613  Pacific Asia  Nagercoil         India            7547
1/15/2016 18:54     26018                  1004                16.0
0.04          65113               399.980011                  0.44
1  399.980011        383.980011              168.949997    South Asia
Tamil Nadu  PENDING_PAYMENT           NaN             1004                  45
NaN  http://images.acmesports.sports/Field+%26+Stre…  Field & Stream Sportsman
16 Gun Fire Safe     399.980011              0         1/19/2016 18:54

         Shipping Mode
180514  Standard Class
180515    Second Class
180516  Standard Class
180517  Standard Class
180518  Standard Class
```

[13]:
```
df.shape
```

[13]:
```
(180519, 53)
```

[14]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 180519 entries, 0 to 180518
Data columns (total 53 columns):
 #   Column                         Non-Null Count   Dtype
---  ------                         --------------   -----
 0   Type                           180519 non-null  object
 1   Days for shipping (real)       180519 non-null  int64
 2   Days for shipment (scheduled)  180519 non-null  int64
 3   Benefit per order              180519 non-null  float64
 4   Sales per customer             180519 non-null  float64
 5   Delivery Status                180519 non-null  object
 6   Late_delivery_risk             180519 non-null  int64
 7   Category Id                    180519 non-null  int64
 8   Category Name                  180519 non-null  object
 9   Customer City                  180519 non-null  object
 10  Customer Country               180519 non-null  object
 11  Customer Email                 180519 non-null  object
 12  Customer Fname                 180519 non-null  object
 13  Customer Id                    180519 non-null  int64
 14  Customer Lname                 180511 non-null  object
 15  Customer Password              180519 non-null  object
 16  Customer Segment               180519 non-null  object
 17  Customer State                 180519 non-null  object
 18  Customer Street                180519 non-null  object
 19  Customer Zipcode               180516 non-null  float64
 20  Department Id                  180519 non-null  int64
 21  Department Name                180519 non-null  object
 22  Latitude                       180519 non-null  float64
 23  Longitude                      180519 non-null  float64
 24  Market                         180519 non-null  object
 25  Order City                     180519 non-null  object
 26  Order Country                  180519 non-null  object
 27  Order Customer Id              180519 non-null  int64
 28  order date (DateOrders)        180519 non-null  object
 29  Order Id                       180519 non-null  int64
 30  Order Item Cardprod Id         180519 non-null  int64
 31  Order Item Discount            180519 non-null  float64
 32  Order Item Discount Rate       180519 non-null  float64
 33  Order Item Id                  180519 non-null  int64
 34  Order Item Product Price       180519 non-null  float64
 35  Order Item Profit Ratio        180519 non-null  float64
```

```
 36  Order Item Quantity            180519 non-null  int64
 37  Sales                          180519 non-null  float64
 38  Order Item Total               180519 non-null  float64
 39  Order Profit Per Order         180519 non-null  float64
 40  Order Region                   180519 non-null  object
 41  Order State                    180519 non-null  object
 42  Order Status                   180519 non-null  object
 43  Order Zipcode                  24840 non-null   float64
 44  Product Card Id                180519 non-null  int64
 45  Product Category Id            180519 non-null  int64
 46  Product Description            0 non-null       float64
 47  Product Image                  180519 non-null  object
 48  Product Name                   180519 non-null  object
 49  Product Price                  180519 non-null  float64
 50  Product Status                 180519 non-null  int64
 51  shipping date (DateOrders)     180519 non-null  object
 52  Shipping Mode                  180519 non-null  object
dtypes: float64(15), int64(14), object(24)
memory usage: 73.0+ MB
```

[4]:
```
df.columns
```

[4]:
```
Index(['Type', 'Days for shipping (real)', 'Days for shipment (scheduled)',
'Benefit per order', 'Sales per customer', 'Delivery Status',
'Late_delivery_risk', 'Category Id', 'Category Name', 'Customer City', 'Customer
Country', 'Customer Email', 'Customer Fname', 'Customer Id', 'Customer Lname',
'Customer Password', 'Customer Segment', 'Customer State', 'Customer Street',
'Customer Zipcode', 'Department Id', 'Department Name', 'Latitude', 'Longitude',
'Market', 'Order City', 'Order Country', 'Order Customer Id', 'order date
(DateOrders)', 'Order Id', 'Order Item Cardprod Id', 'Order Item Discount',
'Order Item Discount Rate', 'Order Item Id', 'Order Item Product Price', 'Order
Item Profit Ratio', 'Order Item Quantity', 'Sales', 'Order Item Total', 'Order
Profit Per Order', 'Order Region', 'Order State', 'Order Status', 'Order
Zipcode', 'Product Card Id', 'Product Category Id', 'Product Description',
'Product Image', 'Product Name', 'Product Price', 'Product Status',
       'shipping date (DateOrders)', 'Shipping Mode'],
      dtype='object')
```

deleting duplicate and not reated features

[5]:
```
data=df.copy()
FeatureList=['Type', 'Benefit per order', 'Sales per customer',
          'Delivery Status', 'Late_delivery_risk', 'Category Name', 'Customer␣
↪City', 'Customer Country',
           'Customer Id', 'Customer Segment',
          'Customer State', 'Customer Zipcode', 'Department Name', 'Latitude',␣
↪'Longitude',
```

```
        'Market', 'Order City', 'Order Country', 'Order Customer Id', 'order␣
↪date (DateOrders)', 'Order Id',
        'Order Item Cardprod Id', 'Order Item Discount', 'Order Item Discount␣
↪Rate', 'Order Item Id',
        'Order Item Product Price', 'Order Item Profit Ratio', 'Order Item␣
↪Quantity', 'Sales', 'Order Item Total',
        'Order Profit Per Order', 'Order Region', 'Order State', 'Order␣
↪Status', 'Order Zipcode', 'Product Card Id',
        'Product Category Id', 'Product Description', 'Product Image',␣
↪'Product Name', 'Product Price', 'Product Status',
      'shipping date (DateOrders)', 'Shipping Mode']

df1=df[FeatureList]
df1.head()
```

[5]:

```
       Type  Benefit per order  Sales per customer   Delivery Status
Late_delivery_risk   Category Name Customer City Customer Country  Customer Id
Customer Segment Customer State  Customer Zipcode Department Name   Latitude
Longitude        Market  Order City Order Country  Order Customer Id order date
(DateOrders)  Order Id  Order Item Cardprod Id  Order Item Discount  Order Item
Discount Rate  Order Item Id  Order Item Product Price  Order Item Profit Ratio
Order Item Quantity   Sales  Order Item Total  Order Profit Per Order    Order
Region      Order State     Order Status  Order Zipcode  Product Card Id
Product Category Id  Product Description                                 Product
Image  Product Name  Product Price  Product Status shipping date (DateOrders)
Shipping Mode
0     DEBIT          91.250000          314.640015  Advance shipping
0  Sporting Goods        Caguas      Puerto Rico        20755         Consumer
PR             725.0         Fitness  18.251453  -66.037056  Pacific Asia
Bekasi     Indonesia             20755         1/31/2018 22:56     77202
1360            13.110000                      0.04         180517
327.75                    0.29                          1  327.75        314.640015
91.250000  Southeast Asia  Java Occidental         COMPLETE             NaN
1360                  73                   NaN
http://images.acmesports.sports/Smart+watch   Smart watch          327.75
0             2/3/2018 22:56  Standard Class
1  TRANSFER        -249.089996          311.359985     Late delivery
1  Sporting Goods        Caguas      Puerto Rico        19492         Consumer
PR             725.0         Fitness  18.279451  -66.037064  Pacific Asia
Bikaner          India             19492         1/13/2018 12:27     75939
1360            16.389999                      0.05         179254
327.75                   -0.80                          1  327.75        311.359985
-249.089996      South Asia         Rajast n          PENDING            NaN
1360                  73                   NaN
http://images.acmesports.sports/Smart+watch   Smart watch          327.75
0            1/18/2018 12:27  Standard Class
2      CASH        -247.779999          309.720001  Shipping on time
```

```
0  Sporting Goods      San Jose          EE. UU.        19491         Consumer
CA           95125.0         Fitness  37.292233 -121.881279  Pacific Asia
Bikaner          India              19491         1/13/2018 12:06     75938
1360            18.030001                      0.06         179253
327.75                  -0.80                      1  327.75        309.720001
-247.779999      South Asia         Rajast n          CLOSED           NaN
1360                73                   NaN
http://images.acmesports.sports/Smart+watch   Smart watch          327.75
0            1/17/2018 12:06  Standard Class
3     DEBIT          22.860001          304.809998  Advance shipping
0  Sporting Goods   Los Angeles          EE. UU.        19490       Home Office
CA           90027.0         Fitness  34.125946 -118.291016  Pacific Asia
Townsville     Australia              19490         1/13/2018 11:45     75937
1360            22.940001                      0.07         179252
327.75                   0.08                      1  327.75        304.809998
22.860001          Oceania       Queensland         COMPLETE            NaN
1360                73                   NaN
http://images.acmesports.sports/Smart+watch   Smart watch          327.75
0            1/16/2018 11:45  Standard Class
4   PAYMENT          134.210007          298.250000  Advance shipping
0  Sporting Goods          Caguas      Puerto Rico        19489         Corporate
PR             725.0         Fitness  18.253769  -66.037048  Pacific Asia
Townsville     Australia              19489         1/13/2018 11:24     75936
1360            29.500000                      0.09         179251
327.75                   0.45                      1  327.75        298.250000
134.210007          Oceania       Queensland  PENDING_PAYMENT            NaN
1360                73                   NaN
http://images.acmesports.sports/Smart+watch   Smart watch          327.75
0            1/15/2018 11:24  Standard Class
```

1 Data Visualization

2 delvery status

[6]:
```
data_delivery_status=df1.groupby(['Delivery Status'])['Order Id'].count().
↪reset_index(name='Number of Orders').sort_values(by= 'Number of Orders',␣
↪ascending= False)
px.bar(x=data_delivery_status['Delivery Status'] ,␣
↪y=data_delivery_status['Number of Orders']  ,␣
↪color=data_delivery_status['Number of Orders'],
      labels = { 'Delivery Status': 'Delivery Status', 'Number of Orders':␣
↪'Number of Orders'})
```

[7]:
```
data_delivery_status_region=df1.groupby(['Delivery Status', 'Order␣
↪Region'])['Order Id'].count().reset_index(name='Number of Orders').
↪sort_values(by= 'Number of Orders', ascending= False)
```

```
px.bar(data_delivery_status_region, x='Delivery Status', y='Number of Orders' ␣
↪, color='Order Region',
      )
```

Central America and Western Europa have the most lated delivered Orders

3 Top 20 Customers regarding the quanitity of orders

[8]:
```
df1['Customer_ID_STR']=df1['Customer Id'].astype(str)

data_customers=df1.groupby(['Customer_ID_STR'])['Order Id'].count().
↪reset_index(name='Number of Orders').sort_values(by= 'Number of Orders',␣
↪ascending= False)
px.bar(data_customers.head(20),x='Number of Orders', y='Customer_ID_STR' ,␣
↪color='Number of Orders'      )
```

```
/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:1:
SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```

4 Top 20 Customers regarding profit of all orders

[9]:
```
df1['Customer_ID_STR']=df1['Customer Id'].astype(str)

data_customers_profit=df1.groupby(['Customer_ID_STR'])['Order Profit Per␣
↪Order'].sum().reset_index(name='Profit of Orders').sort_values(by= 'Profit␣
↪of Orders', ascending= False)
px.bar(data_customers_profit.head(20),x='Profit of Orders', y='Customer_ID_STR'␣
↪, color='Profit of Orders'      )
```

```
/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:1:
SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
```

docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

5 Customer Segment

[10]:
```
#Customer Segments
data_Customer_Segment=df1.groupby(['Customer Segment'])['Order Id'].count().
 ↪reset_index(name='Number of Orders').sort_values(by= 'Number of Orders',␣
 ↪ascending= False)
px.pie(data_Customer_Segment, values='Number of Orders', names= 'Customer␣
 ↪Segment' , title= 'Number of Orders of different Customer Segments',
       width=600 , height=600 , color_discrete_sequence = px.colors.sequential.
 ↪RdBu)
```

6 Category

[11]:
```
#Category Name
data_Category_Name=df1.groupby(['Category Name'])['Order Id'].count().
 ↪reset_index(name='Number of Orders').sort_values(by= 'Number of Orders',␣
 ↪ascending= True)
px.bar(data_Category_Name, x='Number of Orders',y = 'Category Name',color␣
 ↪='Number of Orders')
```

7 Geo Features

[12]:
```
data_Region=df1.groupby(['Order Region'])['Order Id'].count().
 ↪reset_index(name='Number of Orders').sort_values(by= 'Number of Orders',␣
 ↪ascending= True)
px.bar(data_Region, x='Number of Orders',y = 'Order Region',color ='Number of␣
 ↪Orders')
```

[13]:
```
data_countries=df1.groupby(['Order Country'])['Order Id'].count().
 ↪reset_index(name='Number of Orders').sort_values(by= 'Number of Orders',␣
 ↪ascending= True)
px.bar(data_countries.head(20), x='Number of Orders',y = 'Order Country',color␣
 ↪='Number of Orders')
```

[14]:
```
df_geo=df1.groupby([ 'Order Country', 'Order City'])['Order Profit Per Order'].
 ↪sum().reset_index(name='Profit of Orders').sort_values(by= 'Profit of␣
 ↪Orders', ascending= False)

df_geo
```

[14]:
```
                Order Country      Order City  Profit of Orders
3260  Rep blica Dominicana  Santo Domingo      51111.670019
1492        Estados Unidos  New York City      47889.759868
2152              Honduras    Tegucigalpa      40973.640056
1430        Estados Unidos    Los Angeles      38014.360024
2837             Nicaragua        Managua      34319.950107
…                      …              …               …
738                  China         Dalian      -1588.609972
3                Afganist n       Kandahar      -1681.830001
3110           Reino Unido         Dudley      -1742.079996
2463                Italia     Cerignola      -2212.530012
125               Alemania        Pulheim      -3152.150012

[3665 rows x 3 columns]
```

[15]:
```
fig = px.choropleth(df_geo ,  locationmode='country names', locations='Order␣
↪Country',
                    color='Profit of Orders', # lifeExp is a column of data
                    hover_name='Order Country',
                    #hover_data ='Order City',
                    color_continuous_scale=px.colors.sequential.Plasma)

fig.show()
```

8 Sales Analysis

[16]:
```
#Order Country
df_sales_country=df1.groupby([ 'Order Country'])['Sales'].sum().
↪reset_index(name='Sales of Orders').sort_values(by= 'Sales of Orders',␣
↪ascending= False)
px.bar(df_sales_country.head(10), x='Sales of Orders',y = 'Order Country',color␣
↪='Sales of Orders')
```

[ ]:
```
```

[17]:
```
#Order Country
df_sales_country=df1.groupby([ 'Order Country'])['Sales'].sum().
↪reset_index(name='Sales of Orders').sort_values(by= 'Sales of Orders',␣
↪ascending= False)
px.bar(df_sales_country.head(10), x='Sales of Orders',y = 'Order Country',color␣
↪='Sales of Orders')
```

[18]:
```
#Product
df_sales_country=df1.groupby([ 'Product Name'])['Sales'].sum().
↪reset_index(name='Sales of Orders').sort_values(by= 'Sales of Orders',␣
↪ascending= False)
```

```
px.bar(df_sales_country.head(10), x='Sales of Orders',y = 'Product Name',color␣
↪='Sales of Orders')
```

[19]:
```
#Product and deliveray status
df_sales_pd=df1.groupby([ 'Product Name', 'Delivery Status'])['Sales'].sum().
↪reset_index(name='Sales of Orders').sort_values(by= 'Sales of Orders',␣
↪ascending= False)
px.bar(df_sales_pd.head(10), x='Sales of Orders',y = 'Product Name',color␣
↪='Delivery Status')
```

[20]:
```
#Product and order region
df_sales_pr=df1.groupby([ 'Product Name', 'Order Region'])['Sales'].sum().
↪reset_index(name='Sales of Orders').sort_values(by= 'Sales of Orders',␣
↪ascending= False)
px.bar(df_sales_pr.head(10), x='Sales of Orders',y = 'Product Name',color␣
↪='Order Region')
```

[21]:
```
#'Category Name'
df_sales_pr=df1.groupby([  'Category Name'])['Sales'].sum().
↪reset_index(name='Sales of Orders').sort_values(by= 'Sales of Orders',␣
↪ascending= False)
px.bar(df_sales_pr.head(10), x='Sales of Orders',y = 'Category Name',color␣
↪='Sales of Orders')
```

[22]:
```
#'Type of payment
df_sales_pr=df1.groupby([ 'Type'])['Sales'].sum().reset_index(name='Sales of␣
↪Orders').sort_values(by= 'Sales of Orders', ascending= False)
px.bar(df_sales_pr.head(10), x='Sales of Orders',y = 'Type',color ='Sales of␣
↪Orders')
```

[23]:
```
df_sales_tp=df1.groupby([ 'Type', 'Product Name'])['Sales'].sum().
↪reset_index(name='Sales of Orders').sort_values(by= 'Sales of Orders',␣
↪ascending= False)
px.bar(df_sales_tp.head(10), x='Sales of Orders',y = 'Type',color ='Product␣
↪Name')
```

9 Date and sales analysis

[24]:
```
import datetime as dt

data_orderdate=df[['order date (DateOrders)', 'Sales']]
data_orderdate['order_date'] = pd.to_datetime(data_orderdate['order date␣
↪(DateOrders)'])
```

```
/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:4:
SettingWithCopyWarning:
```

```
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```

[25]:
```
data_orderdate["Quarter"] = data_orderdate['order_date'].dt.quarter
data_orderdate["Month"] = data_orderdate['order_date'].dt.month
data_orderdate["year"] = data_orderdate['order_date'].dt.year
```

```
/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:1:
SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:2:
SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:3:
SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```

[26]:
```
data_orderdate['YearStr']=data_orderdate['year'].astype(str)
```

```
df_sales_year=data_orderdate.groupby([ 'YearStr'])['Sales'].sum().
 ↪reset_index(name='Sales of Orders').sort_values(by= 'Sales of Orders',␣
 ↪ascending= False)
px.bar(df_sales_year, x='Sales of Orders',y = 'YearStr',color ='Sales of␣
 ↪Orders')
```

```
/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:1:
SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```

[27]:
```
data_orderdate['QuarterStr']=data_orderdate['Quarter'].astype(str)
df_sales_quarter=data_orderdate.groupby([ 'YearStr','QuarterStr'])['Sales'].
 ↪sum().reset_index(name='Sales of Orders').sort_values(by= 'Sales of Orders',␣
 ↪ascending= False)
px.bar(df_sales_quarter, x='Sales of Orders',y = 'QuarterStr',color ='YearStr')
```

```
/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:1:
SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```

[28]:
```
data_orderdate['MonthStr']=data_orderdate['Month'].astype(str)
df_sales_m=data_orderdate.groupby([ 'QuarterStr', 'MonthStr'])['Sales'].sum().
 ↪reset_index(name='Sales of Orders').sort_values(by= 'Sales of Orders',␣
 ↪ascending= False)
px.bar(df_sales_m, x='Sales of Orders',y = 'QuarterStr',color ='MonthStr')
```

```
/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:1:
SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

[ ]:
```

```

10 Forecasting

Predicting if an order is fraud or not

[29]:
```
data=df1.copy()
data['SUSPECTED_FRAUD'] = np.where(data['Order Status'] == 'SUSPECTED_FRAUD',␣
↪1, 0)
```

[30]:
```
from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
def Labelencoder_feature(x):
    le=LabelEncoder()
    x=le.fit_transform(x)
    return x
```

[31]:
```
features=data.drop(columns=['SUSPECTED_FRAUD','Order Status' ])
target=data['SUSPECTED_FRAUD']
```

[32]:
```
features.isnull().sum()
```

[32]:
```
Type                                   0
Benefit per order                      0
Sales per customer                     0
Delivery Status                        0
Late_delivery_risk                     0
Category Name                          0
Customer City                          0
Customer Country                       0
Customer Id                            0
Customer Segment                       0
Customer State                         0
Customer Zipcode                       3
Department Name                        0
Latitude                               0
Longitude                              0
Market                                 0
Order City                             0
Order Country                          0
Order Customer Id                      0
order date (DateOrders)                0
Order Id                               0
```

```
Order Item Cardprod Id            0
Order Item Discount               0
Order Item Discount Rate          0
Order Item Id                     0
Order Item Product Price          0
Order Item Profit Ratio           0
Order Item Quantity               0
Sales                             0
Order Item Total                  0
Order Profit Per Order            0
Order Region                      0
Order State                       0
Order Zipcode                155679
Product Card Id                   0
Product Category Id               0
Product Description          180519
Product Image                     0
Product Name                      0
Product Price                     0
Product Status                    0
shipping date (DateOrders)        0
Shipping Mode                     0
Customer_ID_STR                   0
dtype: int64
```

we can consider NaN values as a separte class using LabelEncoder

[33]:
```
features=features.apply(Labelencoder_feature)
features.head()
```

[33]:
```
   Type  Benefit per order  Sales per customer  Delivery Status
Late_delivery_risk  Category Name  Customer City  Customer Country  Customer Id
Customer Segment  Customer State  Customer Zipcode  Department Name  Latitude
Longitude  Market  Order City  Order Country  Order Customer Id  order date
(DateOrders)  Order Id  Order Item Cardprod Id  Order Item Discount  Order Item
Discount Rate  Order Item Id  Order Item Product Price  Order Item Profit Ratio
Order Item Quantity  Sales  Order Item Total  Order Profit Per Order  Order
Region  Order State  Order Zipcode  Product Card Id  Product Category Id
Product Description  Product Image  Product Name  Product Price  Product Status
shipping date (DateOrders)  Shipping Mode  Customer_ID_STR
0     1              18934                 2568                0
0            40             66                  1        20649                 0
36                 7                4       3624       4420       3          331
70              20649                     5961      65749                    114
426                         4        180516                              62
140                       0     166              2568                  18934
15           475          12733              114                    47
```

```
0               78              78               62                 0
27149                3             11912
1      3                2272                2559                 1
1               40               66                 1        19386                0
36                   7               4       5522      4419        3         391
69                19386                      1147     64486                    114
498                          5          179253                     62
44                    0     166                2559                   2272
13            841         100315               114                  47
120339               78              78                62                0
2209               3             10509
2      0                2293                2555                 3
0               40              452                 0        19385                0
5                 941              4       9146      232        3         391
69                19385                      1146     64485                    114
529                          6          179252                     62
44                    0     166                2555                   2293
13            841         100316               114                  47
120340               78              78                62                0
1980               3             10508
3      1               13638                2546                 0
0               40              285                 0        19384                2
5                 720              4       8467      663        3        3226
8                19384                     1145     64484                    114
600                          7          179251                     62
119                    0     166                2546                   13638
11            835         100317               114                  47
120341               78              78                62                0
1752               3             10507
4      2               20599                2526                 0
0               40               66                 1        19383                1
36                   7               4       3783      4421        3         3226
8                19383                     1144     64483                    114
682                          8          179250                     62
156                    0     166                2526                   20599
11            835         100318               114                  47
120342               78              78                62                0
1528               3             10505
```

[34]:
```
#deleting features which high-correlated with other features to avoid␣
 ↪multicollinarity
data1=pd.concat([features,target],axis=1)
```

[35]:
```
#deleting features which high-correlated with other features to avoid␣
 ↪multicollinarity

corr = data1.corr()
```

```python
columns = np.full((corr.shape[0],), True, dtype=bool)
for i in range(corr.shape[0]):
    for j in range(i+1, corr.shape[0]):
        if corr.iloc[i,j] >= 0.8:
            if columns[j]:
                columns[j] = False
selected_columns = data1.columns[columns]
selected_columns
```

[35]:
```
Index(['Type', 'Benefit per order', 'Sales per customer', 'Delivery Status',
'Late_delivery_risk', 'Category Name', 'Customer City', 'Customer Country',
'Customer Id', 'Customer Segment', 'Customer State', 'Customer Zipcode',
'Department Name', 'Latitude', 'Longitude', 'Market', 'Order City', 'Order
Country', 'order date (DateOrders)', 'Order Id', 'Order Item Cardprod Id',
'Order Item Discount', 'Order Item Discount Rate', 'Order Item Product Price',
'Order Item Quantity', 'Order Region', 'Order State', 'Order Zipcode', 'Product
Description', 'Product Image', 'Product Status', 'Shipping Mode',
'Customer_ID_STR', 'SUSPECTED_FRAUD'], dtype='object')
```

[36]:
```python
features1=features[['Type', 'Benefit per order', 'Sales per customer',␣
 ↪'Delivery Status', 'Late_delivery_risk',
                    'Category Name', 'Customer City', 'Customer Country',␣
 ↪'Customer Id', 'Customer Segment',
                    'Customer State', 'Customer Zipcode', 'Department Name',␣
 ↪'Latitude', 'Longitude', 'Market',
                    'Order City', 'Order Country', 'order date (DateOrders)',␣
 ↪'Order Id', 'Order Item Cardprod Id',
                    'Order Item Discount', 'Order Item Discount Rate', 'Order␣
 ↪Item Product Price', 'Order Item Quantity',
                    'Order Region', 'Order State', 'Order Zipcode', 'Product␣
 ↪Description', 'Product Image',
                    'Product Status', 'Shipping Mode', 'Customer_ID_STR']]
```

[37]:
```python
from scipy.stats import pearsonr

corre=pd.DataFrame()

for i in features1.columns:
    corre[i]= pearsonr(target, features1[i])


corre
```

```
/opt/conda/lib/python3.7/site-packages/scipy/stats/stats.py:3913:
PearsonRConstantInputWarning:

An input array is constant; the correlation coefficent is not defined.
```

[37]:
```
       Type  Benefit per order  Sales per customer  Delivery Status
Late_delivery_risk  Category Name  Customer City  Customer Country  Customer Id
Customer Segment  Customer State  Customer Zipcode  Department Name  Latitude
Longitude    Market  Order City  Order Country  order date (DateOrders)  Order
Id  Order Item Cardprod Id  Order Item Discount  Order Item Discount Rate  Order
Item Product Price  Order Item Quantity  Order Region  Order State  Order
Zipcode  Product Description  Product Image  Product Status  Shipping Mode
Customer_ID_STR
0  0.202094          -0.002586           -0.000807          0.128768
-0.167158      -0.002104      -0.003561          0.006756      0.009375
-0.005935         0.005670         -0.005600         -0.000837 -0.004709
0.005100 -0.000293    -0.005889      -0.004928                0.003002  0.002222
-0.001109             0.002893                  0.002271
0.000315             -0.000757      0.009077    -0.006105  -4.274182e-02
-5.615812e-02      -0.000741             NaN       -0.004641          0.000490
1  0.000000           0.271923            0.731807          0.000000
0.000000       0.371352       0.130283          0.004098      0.000068
0.011686        0.016001          0.017337          0.722187   0.045427   0.030231
0.900798    0.012345       0.036290                0.202217  0.345187
0.637360             0.219059                   0.334515
0.893383             0.747677      0.000115      0.009491   9.230621e-74
5.077551e-126       0.752963             NaN       0.048639          0.835012
```

[38]:
```
corre1=corre.T
```

[39]:
```
coore2= corre1.iloc[:,0].sort_values(ascending=False)

coore2
```

[39]:
```
Type                         0.202094
Delivery Status              0.128768
Customer Id                  0.009375
Order Region                 0.009077
Customer Country             0.006756
Customer State               0.005670
Longitude                    0.005100
order date (DateOrders)      0.003002
Order Item Discount          0.002893
Order Item Discount Rate     0.002271
Order Id                     0.002222
Customer_ID_STR              0.000490
Order Item Product Price     0.000315
Market                      -0.000293
Product Image               -0.000741
Order Item Quantity         -0.000757
```

```
Sales per customer          -0.000807
Department Name             -0.000837
Order Item Cardprod Id      -0.001109
Category Name               -0.002104
Benefit per order           -0.002586
Customer City               -0.003561
Shipping Mode               -0.004641
Latitude                    -0.004709
Order Country               -0.004928
Customer Zipcode            -0.005600
Order City                  -0.005889
Customer Segment            -0.005935
Order State                 -0.006105
Order Zipcode               -0.042742
Product Description         -0.056158
Late_delivery_risk          -0.167158
Product Status                    NaN
Name: 0, dtype: float64
```

[40]:
```
coore2.index
```

[40]:
```
Index(['Type', 'Delivery Status', 'Customer Id', 'Order Region', 'Customer
Country', 'Customer State', 'Longitude', 'order date (DateOrders)', 'Order Item
Discount', 'Order Item Discount Rate', 'Order Id', 'Customer_ID_STR', 'Order
Item Product Price', 'Market', 'Product Image', 'Order Item Quantity', 'Sales
per customer', 'Department Name', 'Order Item Cardprod Id', 'Category Name',
'Benefit per order', 'Customer City', 'Shipping Mode', 'Latitude', 'Order
Country', 'Customer Zipcode', 'Order City', 'Customer Segment', 'Order State',
'Order Zipcode', 'Product Description', 'Late_delivery_risk', 'Product Status'],
dtype='object')
```

omit all features which have less than +-0.004 correlation with target

[41]:
```
new_features= ['Type', 'Delivery Status', 'Order Region', 'Customer Country',␣
↪'Customer State', 'Order Zipcode',
               'Shipping Mode', 'Order Country', 'Customer Zipcode', 'Order␣
↪City', 'Customer Segment', 'Order State',
               'Late_delivery_risk', 'Product Description', 'Product Status']
```

[42]:
```
#Feature Selection

# Feature Selection based on importance
from sklearn.feature_selection import f_regression
F_values, p_values  = f_regression(features, target)
```

```
/opt/conda/lib/python3.7/site-
packages/sklearn/feature_selection/_univariate_selection.py:302: RuntimeWarning:
```

```
invalid value encountered in true_divide
```

[43]:
```
import itertools
f_reg_results = [(i, v, z) for i, v, z in itertools.zip_longest(features.
 ↪columns, F_values,  ['%.3f' % p for p in p_values])]
f_reg_results=pd.DataFrame(f_reg_results, columns=['Variable','F_Value',␣
 ↪'P_Value'])
```

[44]:
```
f_reg_results=pd.DataFrame(f_reg_results, columns=['Variable','F_Value',␣
 ↪'P_Value'])
f_reg_results = f_reg_results.sort_values(by=['P_Value'])
f_reg_results.P_Value= f_reg_results.P_Value.astype(float)
f_reg_results=f_reg_results[f_reg_results.P_Value<0.06]
f_reg_results
```

[44]:

	Variable	F_Value	P_Value
0	Type	7686.615869	0.000
18	Order Customer Id	15.868141	0.000
3	Delivery Status	3043.655705	0.000
4	Late_delivery_risk	5188.953532	0.000
33	Order Zipcode	330.383488	0.000
8	Customer Id	15.868141	0.000
31	Order Region	14.875551	0.000
36	Product Description	571.103804	0.000
7	Customer Country	8.239934	0.004
32	Order State	6.728235	0.009
16	Order City	6.260807	0.012
9	Customer Segment	6.358072	0.012
10	Customer State	5.802926	0.016
11	Customer Zipcode	5.662017	0.017
14	Longitude	4.696175	0.030
17	Order Country	4.383497	0.036
13	Latitude	4.002769	0.045
42	Shipping Mode	3.887812	0.049
41	shipping date (DateOrders)	3.875811	0.049

[45]:
```
f_reg_list=f_reg_results.Variable.values
f_reg_list
```

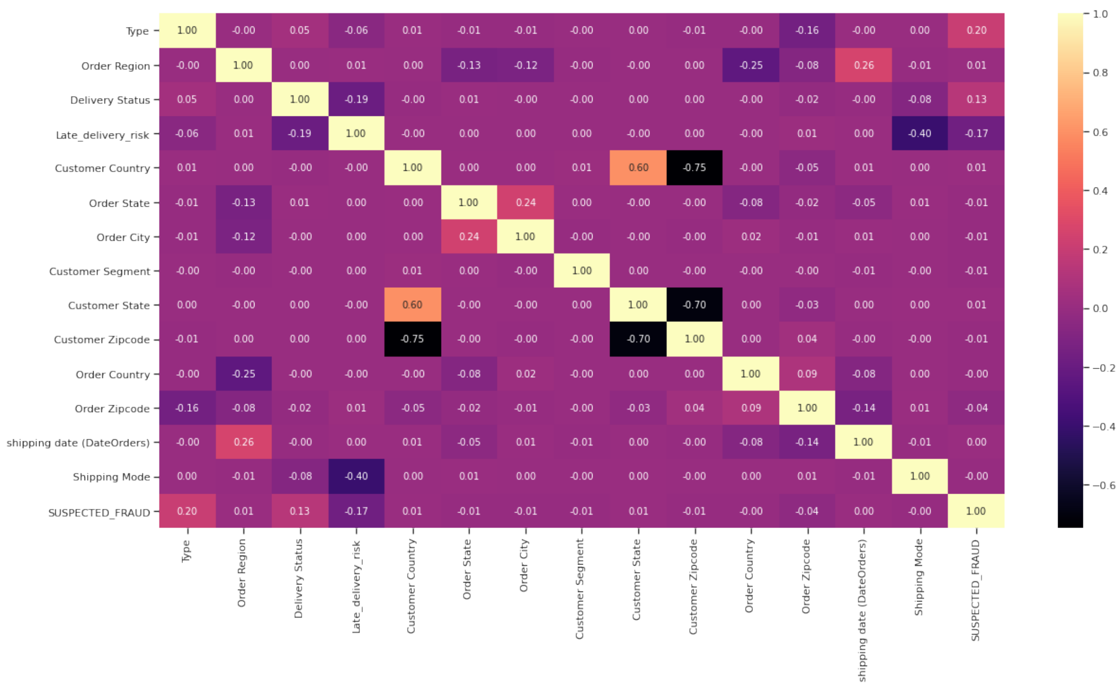
[45]:
```
array(['Type', 'Order Customer Id', 'Delivery Status',
       'Late_delivery_risk', 'Order Zipcode', 'Customer Id',
       'Order Region', 'Product Description', 'Customer Country',
       'Order State', 'Order City', 'Customer Segment', 'Customer State',
       'Customer Zipcode', 'Longitude', 'Order Country', 'Latitude',
       'Shipping Mode', 'shipping date (DateOrders)'], dtype=object)
```

```
[46]: #final features list is both f_ref_list and new_feature
final_features=features[['Type', 'Order Region', 'Delivery Status',␣
 ↪'Late_delivery_risk',
       'Customer Country', 'Order State', 'Order City',
       'Customer Segment', 'Customer State', 'Customer Zipcode',
       'Order Country', 'Order Zipcode', 'shipping date (DateOrders)',
       'Shipping Mode']]
```

```
[47]: final_data=pd.concat([final_features, target], axis=1)
```

```
[48]: fig = plt.figure(figsize=(20,10))
sns.heatmap(final_data.corr(), annot = True, fmt = '.2f', cmap = 'magma')
```

```
[48]: <AxesSubplot:>
```



customer ZipCode and Customer state have high correlation with Customer Country. we can omit them and keep only customer country

```
[49]: final_features2=final_features.drop(columns=['Customer State', 'Customer␣
 ↪Zipcode'])
```

```
[50]: from sklearn.pipeline import make_pipeline
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import cross_val_score, cross_validate
```

```
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import SGDClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.preprocessing import StandardScaler
from xgboost import XGBClassifier
from sklearn.metrics import *
from sklearn import metrics
from sklearn.metrics import classification_report
```

[51]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(final_features2, target,␣
 ↪test_size = 0.2, random_state = 42)
```

I use several classifiaction models using also CV to find the best model with best hyper parameter. pre-proccessing method is standard scaler

[52]:
```
lgr_pipline  = Pipeline([("scaler", StandardScaler()), ("LogisticRegression",␣
 ↪LogisticRegression())])
rfc_pipline = Pipeline([("scaler", StandardScaler()),␣
 ↪("RandomForestClassifier", RandomForestClassifier())])
knn_pipline = Pipeline([("scaler", StandardScaler()), ("KNeighborsClassifier",␣
 ↪KNeighborsClassifier())])
gnb_pipline = Pipeline([("scaler", StandardScaler()), ("GaussianNB",␣
 ↪GaussianNB())])
sgd_pipline = Pipeline([("scaler", StandardScaler()), ("SGDClassifier",␣
 ↪SGDClassifier())])
dt_pipline = Pipeline([("scaler", StandardScaler()), ("DecisionTreeClassifier",␣
 ↪DecisionTreeClassifier())])
```

[53]:
```
pip_dict1 ={0:'Logistic Regression' , 1:'RandomForestClassifier' , 2:␣
 ↪'KNeighborsClassifier' ,
            3: 'GaussianNB', 4: 'SGDClassifier', 5: 'DecisionTreeClassifier' }
```

[54]:
```
piplines1=[lgr_pipline, rfc_pipline , knn_pipline, gnb_pipline  , sgd_pipline ,␣
 ↪dt_pipline ]
```

[55]:
```
scores_df = pd.DataFrame(columns = ["Model", "CVScores"])
for i, pipe in enumerate(piplines1):
    score = cross_val_score(pipe, final_features2, target, cv = 10)
    print(pip_dict1[i], ": ", score.mean())
```

```
Logistic Regression :  0.9751217455582278
RandomForestClassifier :  0.9743850467720389
```

```
KNeighborsClassifier :  0.9748503332686301
GaussianNB :  0.9795478562150082
SGDClassifier :  0.9774982135396149
DecisionTreeClassifier :  0.972224585735939
```

[56]:
```
grid_params = [
    {"classifier": [RandomForestClassifier()],
    "classifier__n_estimators": [50,100,150,200,250,300],
    "classifier__criterion": ["gini", "entropy"],
    "classifier__max_features": ["auto", "sqrt", "log2"],
    },





]
```

[57]:
```
pipeline_new = Pipeline([("scaler", StandardScaler()), ("classifier",␣
 ↪RandomForestClassifier())])

random_search = RandomizedSearchCV(estimator = pipeline_new,␣
 ↪param_distributions = grid_params, scoring = 'neg_mean_absolute_error',␣
 ↪n_jobs= -1, cv = 8, verbose = 10, random_state = 42)
```

[58]:
```
best_model = random_search.fit(X_train, y_train)
```

```
Fitting 8 folds for each of 10 candidates, totalling 80 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done   5 tasks      | elapsed:  1.1min
[Parallel(n_jobs=-1)]: Done  10 tasks      | elapsed:  1.3min
[Parallel(n_jobs=-1)]: Done  17 tasks      | elapsed:  1.7min
[Parallel(n_jobs=-1)]: Done  24 tasks      | elapsed:  2.0min
[Parallel(n_jobs=-1)]: Done  33 tasks      | elapsed:  2.5min
[Parallel(n_jobs=-1)]: Done  42 tasks      | elapsed:  3.1min
[Parallel(n_jobs=-1)]: Done  53 tasks      | elapsed:  4.1min
[Parallel(n_jobs=-1)]: Done  64 tasks      | elapsed:  4.3min
[Parallel(n_jobs=-1)]: Done  80 out of  80 | elapsed:  5.7min finished
```

[59]:
```
best_model.best_params_
```

[59]:
```
{'classifier__n_estimators': 300,
 'classifier__max_features': 'log2',
 'classifier__criterion': 'gini',
 'classifier': RandomForestClassifier(max_features='log2', n_estimators=300)}
```

[60]:
```
pipeline_rf = Pipeline([('scaler', StandardScaler()),
```

```
                        ('Random Forest Calssifer',␣
↪RandomForestClassifier(criterion='entropy', max_features='sqrt',
                         n_estimators=150))])
```

[61]:
```
model = pipeline_rf.fit(X_train, y_train)
```

[62]:
```
rf_train_predict = pd.DataFrame({'actual' : y_train,
                                 'predicted' : model.predict(X_train)})
rf_train_predict.head()
```

[62]:

	actual	predicted
116587	0	0
36340	0	0
175763	0	0
96918	0	0
71197	0	0

[63]:
```
rf_test_predict = pd.DataFrame({'actual' : y_test,
                                'predicted' : model.predict(X_test)})
rf_test_predict.head()
```

[63]:

	actual	predicted
80120	0	0
19670	0	0
114887	0	0
120110	0	0
56658	0	0

[64]:
```
print('Accuracy Score for train dataset : ' , metrics.
 ↪accuracy_score(rf_train_predict.actual, rf_train_predict.predicted))
print('Accuracy Score for test dataset : ' , metrics.
 ↪accuracy_score(rf_test_predict.actual, rf_test_predict.predicted))
```

```
Accuracy Score for train dataset :  1.0
Accuracy Score for test dataset :  0.9962054066031465
```

[65]:
```
print('ROC-AUC Score for train dataset : ' , metrics.
 ↪roc_auc_score(rf_train_predict.actual, rf_train_predict.predicted))
print('ROC-AUC Score for validation dataset : ' , metrics.
 ↪roc_auc_score(rf_test_predict.actual, rf_test_predict.predicted))
```

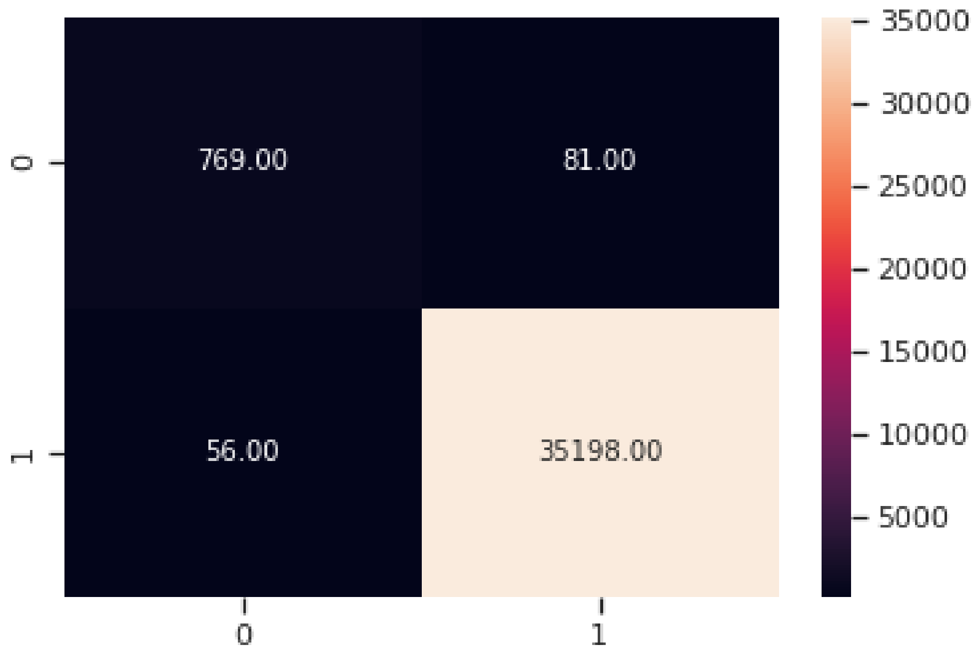
```
ROC-AUC Score for train dataset :  1.0
ROC-AUC Score for validation dataset :  0.9515587050614198
```

[66]:
```
conn_cm_test = metrics.confusion_matrix(rf_test_predict.actual, rf_test_predict.
 ↪predicted, [1,0])
sns.heatmap(conn_cm_test, fmt= '.2f', annot=True)
```

```
/opt/conda/lib/python3.7/site-packages/sklearn/utils/validation.py:70:
FutureWarning:

Pass labels=[1, 0] as keyword args. From version 0.25 passing these as
positional arguments will result in an error
```

[66]: <AxesSubplot:>



[67]:
```python
print(metrics.classification_report(rf_test_predict.actual, rf_test_predict.
 ↪predicted))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     35254
           1       0.93      0.90      0.92       850

    accuracy                           1.00     36104
   macro avg       0.96      0.95      0.96     36104
weighted avg       1.00      1.00      1.00     36104
```

[ ]:

Forecasting of an order has tardiness

[68]:
```
data=df[['Type', 'Benefit per order', 'Sales per customer', 'Delivery Status',␣
↪'Late_delivery_risk', 'Category Name',
             'Customer City', 'Customer Country', 'Customer Segment', 'Customer␣
↪State', 'Customer Zipcode',
             'Department Name', 'Market', 'Order City', 'Order Country',␣
↪'Customer Id',
             'order date (DateOrders)', 'Order Item Cardprod Id', 'Order Item␣
↪Discount', 'Order Item Discount Rate',
             'Order Item Id', 'Order Item Profit Ratio', 'Sales', 'Order␣
↪Status',
             'Order Item Total', 'Order Profit Per Order', 'Order Region',␣
↪'Order State', 'Order Zipcode',
             'Product Card Id', 'Product Category Id', 'Product Description',␣
↪'Product Image', 'Product Name', 'Product Price',
             'Product Status', 'shipping date (DateOrders)', 'Shipping Mode']]
```

[69]:
```
features=data.drop(columns=['Late_delivery_risk'])
target=data['Late_delivery_risk']
```

[70]:
```
features=features.apply(Labelencoder_feature)
features.head()
```

[70]:
```
   Type  Benefit per order  Sales per customer  Delivery Status  Category Name
Customer City  Customer Country  Customer Segment  Customer State  Customer
Zipcode  Department Name  Market  Order City  Order Country  Customer Id  order
date (DateOrders)  Order Item Cardprod Id  Order Item Discount  Order Item
Discount Rate  Order Item Id  Order Item Profit Ratio  Sales  Order Status
Order Item Total  Order Profit Per Order  Order Region  Order State  Order
Zipcode  Product Card Id  Product Category Id  Product Description  Product
Image  Product Name  Product Price  Product Status  shipping date (DateOrders)
Shipping Mode
0     1              18934                  2568                 0             40
66                   1                 0                36                 7
4       3          331               70         20649                      5961
114                 426                          4         180516
140    166               2              2568                     18934            15
475          12733              114                      47                    0
78            78              62                0                       27149
3
1     3               2272                  2559                 1             40
66                   1                 0                36                 7
4       3          391               69         19386                      1147
114                 498                          5         179253
44    166               5             2559                     2272            13
841         100315              114                      47                   120339
78            78              62                0                        2209
```

```
3
2      0                2293                2555                3          40
452               0                  0               5              941
4       3        391           69         19385                       1146
114                529                         6         179252
44     166             1             2555                  2293           13
841          100316         114                  47              120340
78             78             62                0                     1980
3
3      1               13638                2546                0          40
285               0                  2               5              720
4       3       3226             8         19384                       1145
114                600                         7         179251
119     166             2             2546                 13638           11
835          100317         114                  47              120341
78             78             62                0                     1752
3
4      2               20599                2526                0          40
66               1                  1               36              7
4       3       3226             8         19383                       1144
114                682                         8         179250
156     166             6             2526                 20599           11
835          100318         114                  47              120342
78             78             62                0                     1528
3
```

[71]:
```python
#Feature Selection

# Feature Selection based on importance
from sklearn.feature_selection import f_regression
F_values, p_values  = f_regression(features, target)
```

```
/opt/conda/lib/python3.7/site-
packages/sklearn/feature_selection/_univariate_selection.py:302: RuntimeWarning:

invalid value encountered in true_divide
```

[72]:
```python
import itertools
f_reg_results = [(i, v, z) for i, v, z in itertools.zip_longest(features.
 ↪columns, F_values,  ['%.3f' % p for p in p_values])]
f_reg_results=pd.DataFrame(f_reg_results, columns=['Variable','F_Value',␣
 ↪'P_Value'])
```

[73]:
```python
f_reg_results=pd.DataFrame(f_reg_results, columns=['Variable','F_Value',␣
 ↪'P_Value'])
f_reg_results = f_reg_results.sort_values(by=['P_Value'])
```

```
f_reg_results.P_Value= f_reg_results.P_Value.astype(float)
f_reg_results=f_reg_results[f_reg_results.P_Value<0.06]
f_reg_results
```

[73]:

```
                     Variable       F_Value  P_Value
0                        Type    685.999651    0.000
30        Product Description     72.142896    0.000
27              Order Zipcode     25.191994    0.000
36              Shipping Mode  34666.398337    0.000
3             Delivery Status   6798.252477    0.000
25               Order Region      6.848744    0.009
5               Customer City      4.662629    0.031
35  shipping date (DateOrders)      3.556568    0.059
```

[74]:

```
f_reg_list=f_reg_results.Variable.values
f_reg_list
```

[74]:

```
array(['Type', 'Product Description', 'Order Zipcode', 'Shipping Mode',
       'Delivery Status', 'Order Region', 'Customer City',
       'shipping date (DateOrders)'], dtype=object)
```

[75]:

```
df['Delivery Status'].value_counts()
```

[75]:

```
Late delivery        98977
Advance shipping     41592
Shipping on time     32196
Shipping canceled     7754
Name: Delivery Status, dtype: int64
```

'Delivery Status' should also be omited. it has directly related to the target

[76]:

```
final_features=features[['Type', 'Shipping Mode', 'Order Region',
       'Customer City', 'shipping date (DateOrders)']]
```

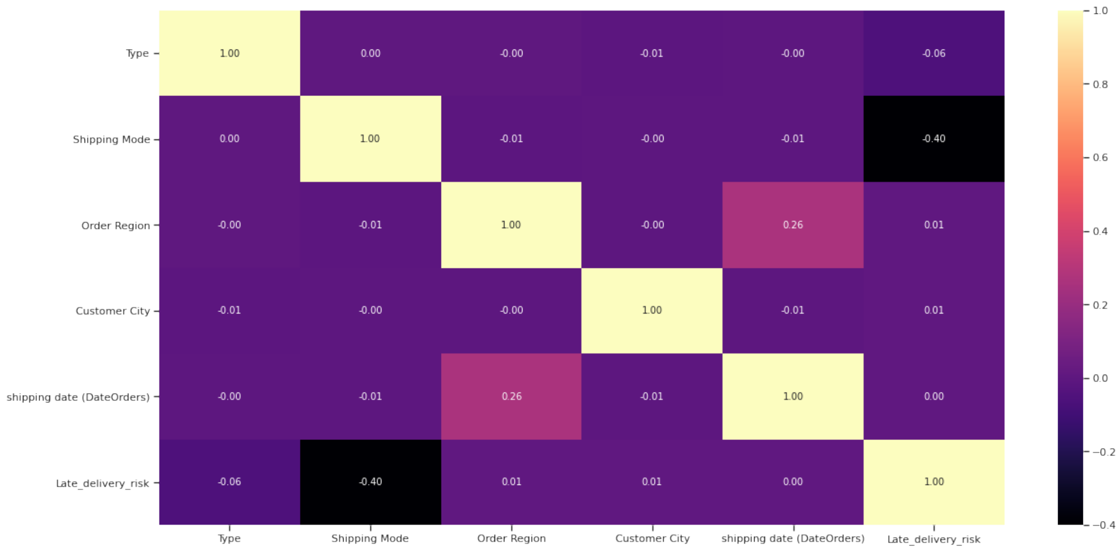
[77]:

```
final_data=pd.concat([final_features, target], axis=1)
```

[78]:

```
fig = plt.figure(figsize=(20,10))
sns.heatmap(final_data.corr(), annot = True, fmt = '.2f', cmap = 'magma')
```

[78]: <AxesSubplot:>



[79]:
```python
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(final_features, target, test_size = 0.2, random_state = 42)
```

[80]:
```python
scores_df = pd.DataFrame(columns = ["Model", "CVScores"])
for i, pipe in enumerate(piplines1):
    score = cross_val_score(pipe, final_features, target, cv = 10)
    print(pip_dict1[i], ": ", score.mean())
```

```
Logistic Regression :  0.6906918386309326
RandomForestClassifier :  0.8926758576651675
KNeighborsClassifier :  0.7423094244520747
GaussianNB :  0.6718960851534189
SGDClassifier :  0.6906918386309326
DecisionTreeClassifier :  0.8855353163083501
```

[81]:
```python
grid_params = [
    {"classifier": [RandomForestClassifier()],
    "classifier__n_estimators": [50,100,150,200,250,300],
    "classifier__criterion": ["gini", "entropy"],
    "classifier__max_features": ["auto", "sqrt", "log2"],
    },

    {"classifier": [KNeighborsClassifier()],
     "classifier__n_neighbors": [2,3,4,5,6],
     "classifier__algorithm": ['auto', 'ball_tree', 'kd_tree', 'brute'],
     "classifier__leaf_size": [10,20,30,40,50],

    },
```

```
    {"classifier": [DecisionTreeClassifier()],
    "classifier__splitter" :["best", "random"],
    "classifier__criterion": ["gini", "entropy"],
    "classifier__max_features": ["auto", "sqrt", "log2"],
    },

]
```

[82]:
```
pipeline_new = Pipeline([("scaler", StandardScaler()), ("classifier",␣
↪RandomForestClassifier())])

random_search = RandomizedSearchCV(estimator = pipeline_new,␣
↪param_distributions = grid_params, scoring = 'neg_mean_absolute_error',␣
↪n_jobs= -1, cv = 8, verbose = 10, random_state = 42)
```

[83]:
```
best_model = random_search.fit(X_train, y_train)
```

```
Fitting 8 folds for each of 10 candidates, totalling 80 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done   5 tasks      | elapsed:  2.6min
[Parallel(n_jobs=-1)]: Done  10 tasks      | elapsed:  2.6min
[Parallel(n_jobs=-1)]: Done  17 tasks      | elapsed:  2.7min
[Parallel(n_jobs=-1)]: Done  24 tasks      | elapsed:  2.7min
[Parallel(n_jobs=-1)]: Done  33 tasks      | elapsed:  4.3min
[Parallel(n_jobs=-1)]: Done  42 tasks      | elapsed:  4.6min
[Parallel(n_jobs=-1)]: Done  53 tasks      | elapsed:  5.0min
[Parallel(n_jobs=-1)]: Done  64 tasks      | elapsed:  6.7min
[Parallel(n_jobs=-1)]: Done  80 out of  80 | elapsed:  9.2min finished
```

[84]:
```
best_model.best_params_
```

[84]:
```
{'classifier__n_estimators': 100,
 'classifier__max_features': 'log2',
 'classifier__criterion': 'entropy',
 'classifier': RandomForestClassifier(criterion='entropy', max_features='log2')}
```

[85]:
```
pipeline_rfl = Pipeline([('scaler', StandardScaler()),
                         ('andomForestClassifier',␣
↪RandomForestClassifier(criterion='entropy'))])
```

[86]:
```
model_rfl = pipeline_rfl.fit(X_train, y_train)
```

[87]:
```
rfl_train_predict = pd.DataFrame({'actual' : y_train,
                                  'predicted' : model_rfl.predict(X_train)})
rfl_train_predict.head()
```

[87]:

	actual	predicted
116587	1	1
36340	0	0
175763	1	1
96918	1	1
71197	1	1

[88]:
```
rfl_test_predict = pd.DataFrame({'actual' : y_test,
                                 'predicted' : model_rfl.predict(X_test)})
rfl_test_predict.head()
```

[88]:

	actual	predicted
80120	1	1
19670	1	1
114887	0	1
120110	1	1
56658	0	0

[89]:
```
print('Accuracy Score for train dataset : ' , metrics.
 ↪accuracy_score(rfl_train_predict.actual, rfl_train_predict.predicted))
print('Accuracy Score for test dataset : ' , metrics.
 ↪accuracy_score(rfl_test_predict.actual, rfl_test_predict.predicted))
```

```
Accuracy Score for train dataset :  0.9999861510230932
Accuracy Score for test dataset :  0.9475958342565921
```

[90]:
```
print('ROC-AUC Score for train dataset : ' , metrics.
 ↪roc_auc_score(rfl_train_predict.actual, rfl_train_predict.predicted))
print('ROC-AUC Score for validation dataset : ' , metrics.
 ↪roc_auc_score(rfl_test_predict.actual, rfl_test_predict.predicted))
```

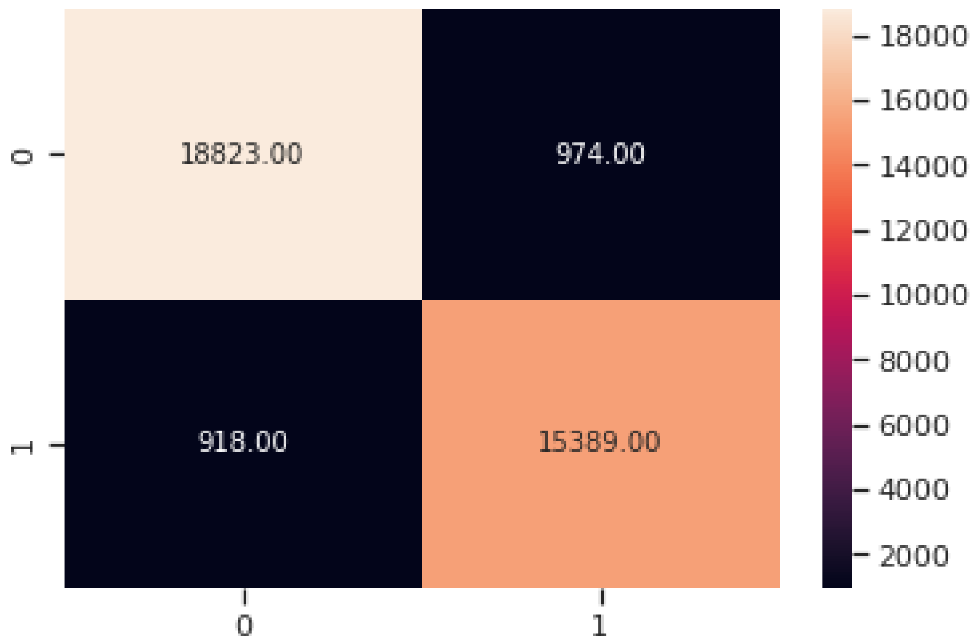
```
ROC-AUC Score for train dataset :  0.9999873705481181
ROC-AUC Score for validation dataset :  0.9472528918259713
```

[91]:
```
conn_cm_test = metrics.confusion_matrix(rfl_test_predict.actual,␣
 ↪rfl_test_predict.predicted, [1,0])
sns.heatmap(conn_cm_test, fmt= '.2f', annot=True)
```

```
/opt/conda/lib/python3.7/site-packages/sklearn/utils/validation.py:70:
FutureWarning:

Pass labels=[1, 0] as keyword args. From version 0.25 passing these as
positional arguments will result in an error
```

[91]: <AxesSubplot:>



[92]:
```
print(metrics.classification_report(rfl_test_predict.actual, rfl_test_predict.
 ↪predicted))
```

```
              precision    recall  f1-score   support

           0       0.94      0.94      0.94     16307
           1       0.95      0.95      0.95     19797

    accuracy                           0.95     36104
   macro avg       0.95      0.95      0.95     36104
weighted avg       0.95      0.95      0.95     36104
```

[ ]:
```

```

11 Forecasting Sales of different products

[93]:
```
data_sales=df[['Type', 'Benefit per order', 'Sales per customer',
          'Delivery Status', 'Late_delivery_risk', 'Category Name', 'Customer␣
 ↪City', 'Customer Country',
           'Customer Id', 'Customer Segment',
          'Customer State', 'Customer Zipcode', 'Department Name', 'Latitude',␣
 ↪'Longitude',
```

```
        'Market', 'Order City', 'Order Country', 'Order Customer Id', 'order␣
↪date (DateOrders)', 'Order Id',
        'Order Item Cardprod Id', 'Order Item Discount', 'Order Item Discount␣
↪Rate', 'Order Item Id',
        'Order Item Product Price', 'Order Item Profit Ratio', 'Order Item␣
↪Quantity', 'Sales', 'Order Item Total',
        'Order Profit Per Order', 'Order Region', 'Order State', 'Order␣
↪Status', 'Order Zipcode', 'Product Card Id',
        'Product Category Id', 'Product Description', 'Product Image',␣
↪'Product Name', 'Product Price', 'Product Status',
     'shipping date (DateOrders)', 'Shipping Mode']]
```

[94]:
```
features=data_sales.drop(columns=['Sales', 'Order Item Quantity', 'Order Item␣
↪Product Price'])
target=data_sales['Sales']
```

[95]:
```
features=features.apply(Labelencoder_feature)
features.head()
```

[95]:
```
   Type  Benefit per order  Sales per customer  Delivery Status
Late_delivery_risk  Category Name  Customer City  Customer Country  Customer Id
Customer Segment  Customer State  Customer Zipcode  Department Name  Latitude
Longitude  Market  Order City  Order Country  Order Customer Id  order date
(DateOrders)  Order Id  Order Item Cardprod Id  Order Item Discount  Order Item
Discount Rate  Order Item Id  Order Item Profit Ratio  Order Item Total  Order
Profit Per Order  Order Region  Order State  Order Status  Order Zipcode
Product Card Id  Product Category Id  Product Description  Product Image
Product Name  Product Price  Product Status  shipping date (DateOrders)
Shipping Mode
0     1              18934                 2568                 0
0             40             66                1        20649                0
36                 7                4       3624       4420       3          331
70              20649                    5961      65749                     114
426                         4          180516                        140
2568                     18934            15          475                2
12733               114                   47                    0          78
78             62              0                         27149               3
1     3             2272                 2559                 1
1             40             66                1        19386                0
36                 7                4       5522       4419       3          391
69              19386                    1147      64486                     114
498                         5          179253                         44
2559                      2272            13          841                5
100315               114                   47                120339          78
78             62              0                          2209               3
2     0             2293                 2555                 3
```

```
0             40            452                 0        19385                0
5              941                4       9146        232        3          391
69             19385                      1146     64485                    114
529                          6        179252                      44
2555                   2293            13          841             1
100316             114                  47             120340              78
78             62                0                     1980             3
3     1            13638                2546              0
0             40            285                 0        19384                2
5              720                4       8467        663        3         3226
8             19384                      1145     64484                    114
600                          7        179251                     119
2546                   13638           11          835             2
100317             114                  47             120341              78
78             62                0                     1752             3
4     2            20599                2526              0
0             40             66                 1        19383                1
36                 7               4       3783        4421       3          3226
8             19383                      1144     64483                    114
682                          8        179250                     156
2526                   20599           11          835             6
100318             114                  47             120342              78
78             62                0                     1528             3
```

[96]:
```python
#Feature Selection based on importance
from sklearn.feature_selection import f_regression
F_values, p_values  = f_regression(features, target)
```

```
/opt/conda/lib/python3.7/site-
packages/sklearn/feature_selection/_univariate_selection.py:302: RuntimeWarning:

invalid value encountered in true_divide
```

[97]:
```python
import itertools
f_reg_results = [(i, v, z) for i, v, z in itertools.zip_longest(features.
 ↪columns, F_values,  ['%.3f' % p for p in p_values])]
f_reg_results=pd.DataFrame(f_reg_results, columns=['Variable','F_Value',␣
 ↪'P_Value'])
```

[98]:
```python
f_reg_results=pd.DataFrame(f_reg_results, columns=['Variable','F_Value',␣
 ↪'P_Value'])
f_reg_results = f_reg_results.sort_values(by=['P_Value'])
f_reg_results.P_Value= f_reg_results.P_Value.astype(float)
f_reg_results=f_reg_results[f_reg_results.P_Value<0.06]
f_reg_results
```

[98]:
```
                     Variable         F_Value  P_Value
20                   Order Id     1165.171704    0.000
22        Order Item Discount    57166.125441    0.000
21      Order Item Cardprod Id   12782.968321    0.000
39  shipping date (DateOrders)     142.652140    0.000
19     order date (DateOrders)     128.461963    0.000
18           Order Customer Id     673.464036    0.000
27      Order Profit Per Order   13782.670150    0.000
15                     Market      240.910781    0.000
28               Order Region      140.517795    0.000
29                Order State       27.935380    0.000
26           Order Item Total   481682.347274    0.000
12            Department Name      524.094617    0.000
32            Product Card Id    12782.968321    0.000
8                 Customer Id      673.464036    0.000
33        Product Category Id    10095.780861    0.000
35              Product Image    37751.723070    0.000
5               Category Name    26066.331991    0.000
36               Product Name    37751.723070    0.000
37              Product Price   116680.120560    0.000
2          Sales per customer   481682.347274    0.000
1            Benefit per order   13782.670150    0.000
24              Order Item Id     1133.743612    0.000
16                 Order City        8.764240    0.003
9            Customer Segment        4.266892    0.039
31              Order Zipcode        4.200315    0.040
```

[99]:
```
f_reg_list=f_reg_results.Variable.values
f_reg_list
```

[99]:
```
array(['Order Id', 'Order Item Discount', 'Order Item Cardprod Id',
       'shipping date (DateOrders)', 'order date (DateOrders)',
       'Order Customer Id', 'Order Profit Per Order', 'Market',
       'Order Region', 'Order State', 'Order Item Total',
       'Department Name', 'Product Card Id', 'Customer Id',
       'Product Category Id', 'Product Image', 'Category Name',
       'Product Name', 'Product Price', 'Sales per customer',
       'Benefit per order', 'Order Item Id', 'Order City',
       'Customer Segment', 'Order Zipcode'], dtype=object)
```

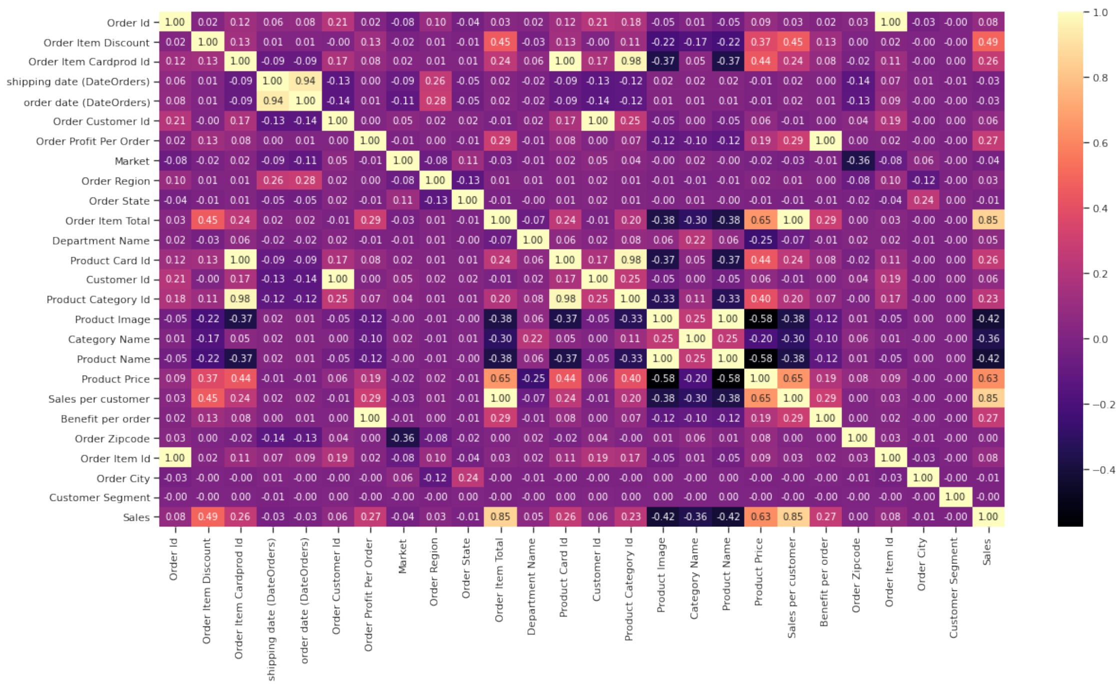
[100]:
```
final_features=features[['Order Id', 'Order Item Discount', 'Order Item␣
 ↪Cardprod Id',
       'shipping date (DateOrders)', 'order date (DateOrders)',
       'Order Customer Id', 'Order Profit Per Order', 'Market',
       'Order Region', 'Order State', 'Order Item Total',
       'Department Name', 'Product Card Id', 'Customer Id',
       'Product Category Id', 'Product Image', 'Category Name',
```

```
       'Product Name', 'Product Price', 'Sales per customer',
       'Benefit per order', 'Order Zipcode', 'Order Item Id',
       'Order City', 'Customer Segment']]
```

[101]:
```
final_data=pd.concat([final_features, target], axis=1)
```

[102]:
```
fig = plt.figure(figsize=(20,10))
sns.heatmap(final_data.corr(), annot = True, fmt = '.2f', cmap = 'magma')
```

[102]: <AxesSubplot:>



[103]:
```
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import cross_val_score
from sklearn.ensemble import RandomForestRegressor
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV

from sklearn.metrics import *
from sklearn.linear_model import LinearRegression, RANSACRegressor, Lasso,␣
 ↪Ridge, SGDRegressor
from sklearn.ensemble import RandomForestRegressor
from xgboost import XGBRegressor
from sklearn.neighbors import KNeighborsRegressor
from sklearn.tree import DecisionTreeRegressor
```

[104]:
```python
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(final_features, target,␣
↪test_size = 0.3, random_state = 42)
```

[105]:
```python
lr_pipeline = Pipeline([("scaler", StandardScaler()), ("linear_regression",␣
↪LinearRegression())])
ridge_pipeline = Pipeline([("scaler", StandardScaler()), ("ridge_regressor",␣
↪Ridge(random_state = 42))])
lasso_pipeline = Pipeline([("scaler", StandardScaler()), ("lasso_regressor",␣
↪Lasso(random_state = 42))])
random_forest_pipeline = Pipeline([("scaler", StandardScaler()),␣
↪("randomforest_regression", RandomForestRegressor(random_state = 42))])
xgboost_pipeline = Pipeline([("scaler", StandardScaler()),␣
↪("xgboost_regression", XGBRegressor())])
knn_pipeline = Pipeline([("scaler", StandardScaler()), ("knn_regression",␣
↪KNeighborsRegressor())])
```

[106]:
```python
pipelines = [lr_pipeline, ridge_pipeline, lasso_pipeline,
             random_forest_pipeline, xgboost_pipeline, knn_pipeline]
```

[107]:
```python
pipe_dict = {0: "Linear Regression", 1: "Ridge",
             2: "Lasso", 3: "RandomForest", 4: "XGBoost",
             5: "Decision Tree", 6: "KNN"}
```

[108]:
```python
scores_df = pd.DataFrame(columns = ["Model", "CVScores"])
for i, pipe in enumerate(pipelines):
    score = cross_val_score(pipe, final_features,target, cv = 5)
    print(pipe_dict[i], ": ", score.mean())
```

```
Linear Regression :  0.7852647150644007
Ridge :  0.785264849136577
Lasso :  0.7805693158852282
RandomForest :  0.9995414205129233
XGBoost :  0.999651640861491
Decision Tree :  0.9333894519285579
```

[109]:
```python
grid_params = [

{"classifier": [XGBRegressor()],
     "classifier__n_estimators": [100,150,200,250,300],

}

]
```

[110]:
```
pipeline_new = Pipeline([("scaler", StandardScaler()), ("classifier",␣
↪XGBRegressor())])
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
```

[111]:
```
random_search = RandomizedSearchCV(estimator = pipeline_new,␣
↪param_distributions = grid_params, scoring = 'neg_mean_absolute_error',␣
↪n_jobs= -1, cv = 8, verbose = 10, random_state = 42)
```

[112]:
```
best_model = random_search.fit(X_train, y_train)
```

```
Fitting 8 folds for each of 5 candidates, totalling 40 fits
```

```
/opt/conda/lib/python3.7/site-packages/sklearn/model_selection/_search.py:282:
UserWarning:

The total space of parameters 5 is smaller than n_iter=10. Running 5 iterations.
For exhaustive searches, use GridSearchCV.

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done   5 tasks      | elapsed:  4.7min
[Parallel(n_jobs=-1)]: Done  10 tasks      | elapsed:  8.3min
[Parallel(n_jobs=-1)]: Done  17 tasks      | elapsed: 16.5min
[Parallel(n_jobs=-1)]: Done  24 tasks      | elapsed: 21.5min
[Parallel(n_jobs=-1)]: Done  33 tasks      | elapsed: 40.3min
[Parallel(n_jobs=-1)]: Done  38 out of  40 | elapsed: 47.5min remaining:  2.5min
[Parallel(n_jobs=-1)]: Done  40 out of  40 | elapsed: 47.6min finished
```

[113]:
```
best_model.best_params_
```

[113]:
```
{'classifier__n_estimators': 300,
 'classifier': XGBRegressor(base_score=None, booster=None,
colsample_bylevel=None,
              colsample_bynode=None, colsample_bytree=None, gamma=None,
              gpu_id=None, importance_type='gain', interaction_constraints=None,
              learning_rate=None, max_delta_step=None, max_depth=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              n_estimators=300, n_jobs=None, num_parallel_tree=None,
              random_state=None, reg_alpha=None, reg_lambda=None,
              scale_pos_weight=None, subsample=None, tree_method=None,
              validate_parameters=None, verbosity=None)}
```

[114]:
```
pipeline_XGBRegressor = Pipeline([('scaler', StandardScaler()),␣
↪('XGBRegressor',  XGBRegressor(importance_type='gain', n_estimators=300, ))])
```

[115]:
```
model = pipeline_XGBRegressor.fit(X_train, y_train)
```

[116]:
```python
XGB_train_predict = pd.DataFrame({'actual' : y_train,
                                  'predicted' : model.predict(X_train)})
XGB_train_predict.head()
```

[116]:

	actual	predicted
99963	149.940002	149.975128
63538	210.850006	210.474564
6661	179.970001	179.993896
93913	129.990005	129.989929
90626	129.990005	129.990906

[117]:
```python
XGB_test_predict = pd.DataFrame({'actual' : y_test,
                                  'predicted' : model.predict(X_test)})
XGB_test_predict.head()
```

[117]:

	actual	predicted
80120	199.990005	199.987198
19670	250.000000	249.987595
114887	249.899994	249.878433
120110	299.980011	299.969971
56658	119.970001	119.918625

[118]:
```python
predict = model.predict(X_test)
```

[119]:
```python
r2_score(y_test, predict, multioutput='uniform_average')
```

[119]: 0.9974757060247059

[120]:
```python
fig = go.Figure()
fig.add_trace(go.Scatter(x=y_test, y=predict, mode='markers' ,  name='predicted␣
 ↪vs actual'))
fig.add_trace(go.Scatter(x=y_test , y=y_test, mode='lines' , name='actual'))


fig.update_layout(title='actual Sales vs predicted Sales', xaxis_title= 'Actual␣
 ↪Score', yaxis_title = 'Predicted Score' , template= 'plotly_dark')
```

[ ]:
```python

```