Importing Required Libraries

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import plotly.express as px
import seaborn as sns; sns.set_theme()
import plotly.figure_factory as ff
from itertools import combinations
from collections import Counter
import datetime as dt
import warnings
warnings.filterwarnings('ignore')

!pip install openpyxl plotly -q
```

```
[notice] A new release of pip is available: 23.3.2 -> 24.0
[notice] To update, run: C:\Users\tamra\anaconda3\python.exe -m pip
install --upgrade pip
```

Gathering Data

```python
Customers_data = pd.read_excel('G:/DATA ANALYTIC ROADMAP/POWER BI/my
projects/Budget_Sales_Data_Analysis/Data/AdventureWorks_Database.xlsx'
,
                              'Customers',
                              dtype={'CustomerKey':str},

parse_dates=['BirthDate','DateFirstPurchase']
                              )

Product_data = pd.read_excel('G:/DATA ANALYTIC ROADMAP/POWER BI/my
projects/Budget_Sales_Data_Analysis/Data/AdventureWorks_Database.xlsx'
,
                              'Product',
                              dtype={'ProductKey':str},
                              parse_dates=['StartDate']
                              )

Sales_data = pd.read_excel('G:/DATA ANALYTIC ROADMAP/POWER BI/my
projects/Budget_Sales_Data_Analysis/Data/AdventureWorks_Database.xlsx'
,
                              'Sales',
                              dtype={'ProductKey':str,
                                     'CustomerKey':str,
                                     'PromotionKey':str,
                                     'SalesTerritoryKey':str},
                              parse_dates=['OrderDate', 'ShipDate']
```

```
                              )
Sales_data['DateKey'] = Sales_data['OrderDate'].astype(str)

Territory_data = pd.read_excel('G:/DATA ANALYTIC ROADMAP/POWER BI/my
projects/Budget_Sales_Data_Analysis/Data/AdventureWorks_Database.xlsx'
,
                              'Territory',
                              dtype={'SalesTerritoryKey':str}
                              )
```

Merging Data into one Dataframe

```
temp_data = pd.merge(Sales_data, Product_data, on='ProductKey',
how='inner')
df = pd.merge(temp_data, Customers_data, on='CustomerKey',
how='inner')
df = pd.merge(df, Territory_data, on='SalesTerritoryKey', how='inner')
```

Assessing data

```
df.head()

  ProductKey  OrderDate   ShipDate CustomerKey PromotionKey
SalesTerritoryKey  \
0        310 2014-01-01 2014-01-08       21768            1
6
1        600 2016-04-16 2016-04-23       21768            1
6
2        310 2014-01-30 2014-02-06       21727            1
6
3        479 2016-11-29 2016-12-05       21727            1
6
4        477 2016-11-29 2016-12-05       21727            1
6

  SalesOrderNumber  SalesOrderLineNumber  OrderQuantity
UnitPrice  ...  \
0          SO43697                     1              2
1789.1350  ...
1          SO56212                     1              1
539.9900  ...
2          SO43833                     1              4
894.5675  ...
3          SO71614                     2              1
8.9900  ...
4          SO71614                     3              1
4.9900  ...

       Occupation  HouseOwnerFlag  NumberCarsOwned
AddressLine1  \
```

```
0      Management               1                3  601 Asilomar Dr.

1      Management               1                3  601 Asilomar Dr.

2  Skilled Manual               1                0     4082 Shell Ct

3  Skilled Manual               1                0     4082 Shell Ct

4  Skilled Manual               1                0     4082 Shell Ct


  DateFirstPurchase  CommuteDistance  Region  Country          Group
\
0        2014-01-01       10+ Miles  Canada   Canada  North America

1        2014-01-01       10+ Miles  Canada   Canada  North America

2        2014-01-30       1-2 Miles  Canada   Canada  North America

3        2014-01-30       1-2 Miles  Canada   Canada  North America

4        2014-01-30       1-2 Miles  Canada   Canada  North America


                                        RegionImage
0  http://www.avising.com/me/LearnPBI/DataSources...
1  http://www.avising.com/me/LearnPBI/DataSources...
2  http://www.avising.com/me/LearnPBI/DataSources...
3  http://www.avising.com/me/LearnPBI/DataSources...
4  http://www.avising.com/me/LearnPBI/DataSources...

[5 rows x 58 columns]
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 58189 entries, 0 to 58188
Data columns (total 58 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   ProductKey            58189 non-null  object
 1   OrderDate             58189 non-null  datetime64[ns]
 2   ShipDate              58189 non-null  datetime64[ns]
 3   CustomerKey           58189 non-null  object
 4   PromotionKey          58189 non-null  object
 5   SalesTerritoryKey     58189 non-null  object
 6   SalesOrderNumber      58189 non-null  object
 7   SalesOrderLineNumber  58189 non-null  int64
 8   OrderQuantity         58189 non-null  int64
 9   UnitPrice             58189 non-null  float64
 10  TotalProductCost      58189 non-null  float64
```

```
 11  SalesAmount           58189 non-null  float64
 12  TaxAmt                58189 non-null  float64
 13  Unnamed: 13           0 non-null      float64
 14  Unnamed: 14           0 non-null      float64
 15  Unnamed: 15           58189 non-null  float64
 16  Unnamed: 16           58189 non-null  float64
 17  Unnamed: 17           0 non-null      float64
 18  Unnamed: 18           58189 non-null  float64
 19  Unnamed: 19           0 non-null      float64
 20  StandardCost_x        58189 non-null  float64
 21  List Price            58189 non-null  float64
 22  Unnamed: 22           0 non-null      float64
 23  diif std cost         58189 non-null  int64
 24  diff list price       58189 non-null  int64
 25  DateKey               58189 non-null  object
 26  ProductName           58189 non-null  object
 27  SubCategory           58189 non-null  object
 28  Category              58189 non-null  object
 29  StandardCost_y        58189 non-null  float64
 30  Color                 30747 non-null  object
 31  ListPrice             58189 non-null  float64
 32  DaysToManufacture     58189 non-null  int64
 33  ProductLine           58189 non-null  object
 34  ModelName             58189 non-null  object
 35  Photo                 58189 non-null  object
 36  ProductDescription    58189 non-null  object
 37  StartDate             58189 non-null  datetime64[ns]
 38  FirstName             58189 non-null  object
 39  LastName              58189 non-null  object
 40  FullName              58189 non-null  object
 41  BirthDate             58189 non-null  datetime64[ns]
 42  MaritalStatus         58189 non-null  object
 43  Gender                58189 non-null  object
 44  YearlyIncome          58189 non-null  int64
 45  TotalChildren         58189 non-null  int64
 46  NumberChildrenAtHome  58189 non-null  int64
 47  Education             58189 non-null  object
 48  Occupation            58189 non-null  object
 49  HouseOwnerFlag        58189 non-null  int64
 50  NumberCarsOwned       58189 non-null  int64
 51  AddressLine1          58189 non-null  object
 52  DateFirstPurchase     58189 non-null  datetime64[ns]
 53  CommuteDistance       58189 non-null  object
 54  Region                58189 non-null  object
 55  Country               58189 non-null  object
 56  Group                 58189 non-null  object
 57  RegionImage           58189 non-null  object
dtypes: datetime64[ns](5), float64(16), int64(10), object(27)
memory usage: 25.7+ MB
```

```python
# Checking shape of the data after merging
print(f"Number of Rows: {df.shape[0]}")
print(f"Number of Columns: {df.shape[1]} \n")
```

```
Number of Rows: 58189
Number of Columns: 58
```

```python
df.describe().T
```

```
                       count                           mean  \
OrderDate              58189  2016-06-03 03:56:09.605939200
ShipDate               58189  2016-06-10 04:03:24.657237760
SalesOrderLineNumber 58189.0                       1.887453
OrderQuantity        58189.0                       1.569386
UnitPrice            58189.0                     413.888218
TotalProductCost     58189.0                     296.539185
SalesAmount          58189.0                      503.66627
TaxAmt               58189.0                      40.293303
Unnamed: 13              0.0                            NaN
Unnamed: 14              0.0                            NaN
Unnamed: 15          58189.0                     503.666269
Unnamed: 16          58189.0                       0.000001
Unnamed: 17              0.0                            NaN
Unnamed: 18          58189.0                      38.398254
Unnamed: 19              0.0                            NaN
StandardCost_x       58189.0                     296.539185
List Price           58189.0                      503.66627
Unnamed: 22              0.0                            NaN
diif std cost        58189.0                            0.0
diff list price      58189.0                            0.0
StandardCost_y       58189.0                     296.539185
ListPrice            58189.0                      503.66627
DaysToManufacture    58189.0                       1.045215
StartDate              58189  2007-05-14 02:44:51.848974848
BirthDate              58189  1962-03-02 12:33:19.305710720
YearlyIncome         58189.0                   59769.887779
TotalChildren        58189.0                       1.838921
NumberChildrenAtHome 58189.0                       1.073502
HouseOwnerFlag       58189.0                        0.69056
NumberCarsOwned      58189.0                       1.502466
DateFirstPurchase      58189  2015-12-23 02:50:33.356820224

                                      min                  25%  \
OrderDate             2014-01-01 00:00:00  2016-04-01 00:00:00
ShipDate              2014-01-08 00:00:00  2016-04-08 00:00:00
SalesOrderLineNumber                  1.0                  1.0
OrderQuantity                         1.0                  1.0
UnitPrice                          0.5725                 4.99
TotalProductCost                   0.8565               3.3623
```

```
SalesAmount                            2.29                 8.99
TaxAmt                               0.1832               0.7192
Unnamed: 13                             NaN                  NaN
Unnamed: 14                             NaN                  NaN
Unnamed: 15                            2.29                 8.99
Unnamed: 16                             0.0                  0.0
Unnamed: 17                             NaN                  NaN
Unnamed: 18                      -5106.9068               1.4335
Unnamed: 19                             NaN                  NaN
StandardCost_x                       0.8565               3.3623
List Price                             2.29                 8.99
Unnamed: 22                             NaN                  NaN
diif std cost                           0.0                  0.0
diff list price                         0.0                  0.0
StandardCost_y                       0.8565               3.3623
ListPrice                              2.29                 8.99
DaysToManufacture                       0.0                  0.0
StartDate               2005-07-01 00:00:00  2007-07-01 00:00:00
BirthDate               1910-08-13 00:00:00  1954-12-20 00:00:00
YearlyIncome                        10000.0              30000.0
TotalChildren                           0.0                  0.0
NumberChildrenAtHome                    0.0                  0.0
HouseOwnerFlag                          0.0                  0.0
NumberCarsOwned                         0.0                  1.0
DateFirstPurchase       2014-01-01 00:00:00  2015-06-21 00:00:00

                                        50%                  75%  \
OrderDate               2016-07-07 00:00:00  2016-10-10 00:00:00
ShipDate                2016-07-14 00:00:00  2016-10-17 00:00:00
SalesOrderLineNumber                    2.0                  2.0
OrderQuantity                           1.0                  2.0
UnitPrice                             24.49              269.995
TotalProductCost                    12.1924             343.6496
SalesAmount                            32.6               539.99
TaxAmt                                2.608              43.1992
Unnamed: 13                             NaN                  NaN
Unnamed: 14                             NaN                  NaN
Unnamed: 15                            32.6               539.99
Unnamed: 16                             0.0                  0.0
Unnamed: 17                             NaN                  NaN
Unnamed: 18                          6.2537              21.9037
Unnamed: 19                             NaN                  NaN
StandardCost_x                      12.1924             343.6496
List Price                             32.6               539.99
Unnamed: 22                             NaN                  NaN
diif std cost                           0.0                  0.0
diff list price                         0.0                  0.0
StandardCost_y                      12.1924             343.6496
ListPrice                              32.6               539.99
```

```
DaysToManufacture                       0.0                  4.0
StartDate             2007-07-01 00:00:00  2007-07-01 00:00:00
BirthDate             1963-09-19 00:00:00  1970-07-08 00:00:00
YearlyIncome                      60000.0              80000.0
TotalChildren                         2.0                  3.0
NumberChildrenAtHome                  0.0                  2.0
HouseOwnerFlag                        1.0                  1.0
NumberCarsOwned                       2.0                  2.0
DateFirstPurchase     2016-03-12 00:00:00  2016-07-26 00:00:00

                                      max           std
OrderDate             2016-12-30 00:00:00           NaN
ShipDate              2017-01-07 00:00:00           NaN
SalesOrderLineNumber                  8.0      1.018829
OrderQuantity                         4.0      1.047532
UnitPrice                         3578.27    833.052938
TotalProductCost                2171.2942    560.171436
SalesAmount                       3578.27    941.462817
TaxAmt                           286.2616     75.317027
Unnamed: 13                           NaN           NaN
Unnamed: 14                           NaN           NaN
Unnamed: 15                       3578.27    941.462815
Unnamed: 16                        0.0003      0.000014
Unnamed: 17                           NaN           NaN
Unnamed: 18                     1487.8356    667.349417
Unnamed: 19                           NaN           NaN
StandardCost_x                  2171.2942    560.171436
List Price                        3578.27    941.462817
Unnamed: 22                           NaN           NaN
diif std cost                         0.0           0.0
diff list price                       0.0           0.0
StandardCost_y                  2171.2942    560.171436
ListPrice                         3578.27    941.462817
DaysToManufacture                     4.0      1.757395
StartDate             2007-07-01 00:00:00           NaN
BirthDate             1980-12-26 00:00:00           NaN
YearlyIncome                     170000.0  33128.041818
TotalChildren                         5.0      1.614467
NumberChildrenAtHome                  5.0      1.580055
HouseOwnerFlag                        1.0      0.462267
NumberCarsOwned                       4.0      1.155496
DateFirstPurchase     2016-12-30 00:00:00           NaN
```

```
# Checking for duplicate data
df.duplicated().sum()
```

```
0
```

```
# Checking for null data
df.isnull().sum()
```

```
ProductKey                  0
OrderDate                   0
ShipDate                    0
CustomerKey                 0
PromotionKey                0
SalesTerritoryKey           0
SalesOrderNumber            0
SalesOrderLineNumber        0
OrderQuantity               0
UnitPrice                   0
TotalProductCost            0
SalesAmount                 0
TaxAmt                      0
Unnamed: 13             58189
Unnamed: 14             58189
Unnamed: 15                 0
Unnamed: 16                 0
Unnamed: 17             58189
Unnamed: 18                 0
Unnamed: 19             58189
StandardCost_x              0
List Price                  0
Unnamed: 22             58189
diif std cost               0
diff list price             0
DateKey                     0
ProductName                 0
SubCategory                 0
Category                    0
StandardCost_y              0
Color                   27442
ListPrice                   0
DaysToManufacture           0
ProductLine                 0
ModelName                   0
Photo                       0
ProductDescription          0
StartDate                   0
FirstName                   0
LastName                    0
FullName                    0
BirthDate                   0
MaritalStatus               0
Gender                      0
YearlyIncome                0
TotalChildren               0
NumberChildrenAtHome        0
Education                   0
Occupation                  0
HouseOwnerFlag              0
```

```
NumberCarsOwned                0
AddressLine1                   0
DateFirstPurchase              0
CommuteDistance                0
Region                         0
Country                        0
Group                          0
RegionImage                    0
dtype: int64
```

```python
# Check for na data
df.isna().sum()
```

```
ProductKey                     0
OrderDate                      0
ShipDate                       0
CustomerKey                    0
PromotionKey                   0
SalesTerritoryKey              0
SalesOrderNumber               0
SalesOrderLineNumber           0
OrderQuantity                  0
UnitPrice                      0
TotalProductCost               0
SalesAmount                    0
TaxAmt                         0
Unnamed: 13                58189
Unnamed: 14                58189
Unnamed: 15                    0
Unnamed: 16                    0
Unnamed: 17                58189
Unnamed: 18                    0
Unnamed: 19                58189
StandardCost_x                 0
List Price                     0
Unnamed: 22                58189
diif std cost                  0
diff list price                0
DateKey                        0
ProductName                    0
SubCategory                    0
Category                       0
StandardCost_y                 0
Color                      27442
ListPrice                      0
DaysToManufacture              0
ProductLine                    0
ModelName                      0
Photo                          0
ProductDescription             0
```

```
StartDate                      0
FirstName                      0
LastName                       0
FullName                       0
BirthDate                      0
MaritalStatus                  0
Gender                         0
YearlyIncome                   0
TotalChildren                  0
NumberChildrenAtHome           0
Education                      0
Occupation                     0
HouseOwnerFlag                 0
NumberCarsOwned                0
AddressLine1                   0
DateFirstPurchase              0
CommuteDistance                0
Region                         0
Country                        0
Group                          0
RegionImage                    0
dtype: int64
```

Handling missing data

```
def missing_pct(df):
    # Calculate missing value and their percentage for each column
    missing_count_percent = df.isnull().sum() * 100 / df.shape[0]
    df_missing_count_percent = 
pd.DataFrame(missing_count_percent).round(2)
    df_missing_count_percent = 
df_missing_count_percent.reset_index().rename(
                    columns={
                            'index':'Column',
                            0:'Missing_Percentage (%)'
                    }
                )
    df_missing_value = df.isnull().sum()
    df_missing_value = df_missing_value.reset_index().rename(
                    columns={
                            'index':'Column',
                            0:'Missing_value_count'
                    }
                )
    # Sort the data frame
    #df_missing = df_missing.sort_values('Missing_Percentage (%)', 
ascending=False)
    Final = df_missing_value.merge(df_missing_count_percent, how = 
'inner', left_on = 'Column', right_on = 'Column')
```

```
    Final = Final.sort_values(by = 'Missing_Percentage (%)',ascending
= False)
    return Final

# Applying the custom function
missing_pct(df)
```

	Column	Missing_value_count	Missing_Percentage (%)
22	Unnamed: 22	58189	100.00
19	Unnamed: 19	58189	100.00
14	Unnamed: 14	58189	100.00
13	Unnamed: 13	58189	100.00
17	Unnamed: 17	58189	100.00
30	Color	27442	47.16
0	ProductKey	0	0.00
42	MaritalStatus	0	0.00
41	BirthDate	0	0.00
39	LastName	0	0.00
40	FullName	0	0.00
38	FirstName	0	0.00
37	StartDate	0	0.00
36	ProductDescription	0	0.00
35	Photo	0	0.00
34	ModelName	0	0.00
43	Gender	0	0.00
44	YearlyIncome	0	0.00
32	DaysToManufacture	0	0.00
45	TotalChildren	0	0.00
46	NumberChildrenAtHome	0	0.00
47	Education	0	0.00
48	Occupation	0	0.00
49	HouseOwnerFlag	0	0.00
50	NumberCarsOwned	0	0.00
51	AddressLine1	0	0.00
52	DateFirstPurchase	0	0.00
53	CommuteDistance	0	0.00
54	Region	0	0.00
55	Country	0	0.00
56	Group	0	0.00
33	ProductLine	0	0.00
29	StandardCost_y	0	0.00
31	ListPrice	0	0.00
12	TaxAmt	0	0.00
2	ShipDate	0	0.00
3	CustomerKey	0	0.00
4	PromotionKey	0	0.00
5	SalesTerritoryKey	0	0.00
6	SalesOrderNumber	0	0.00
7	SalesOrderLineNumber	0	0.00
8	OrderQuantity	0	0.00

```
9              UnitPrice                        0                   0.00
10      TotalProductCost                        0                   0.00
11           SalesAmount                        0                   0.00
15           Unnamed: 15                        0                   0.00
1              OrderDate                        0                   0.00
16           Unnamed: 16                        0                   0.00
18           Unnamed: 18                        0                   0.00
20        StandardCost_x                        0                   0.00
21            List Price                        0                   0.00
23         diif std cost                        0                   0.00
24       diff list price                        0                   0.00
25               DateKey                        0                   0.00
26           ProductName                        0                   0.00
27           SubCategory                        0                   0.00
28              Category                        0                   0.00
57           RegionImage                        0                   0.00

#  Drop columns with nan values
df= df.dropna(axis=1)
```

Adding columns

```
# Extracting Year from OrderDate
df['sale_year'] = df['OrderDate'].dt.year

# Extracting Month from OrderDate
df['sale_month'] = df['OrderDate'].dt.month

# Extracting day from OrderDate
df['sale_day'] = df['OrderDate'].dt.day

# Extracting dayofweek from OrderDate
df['sale_week'] = df['OrderDate'].dt.dayofweek

# Extracting day_name from OrderDate
df['sale_day_name'] = df['OrderDate'].dt.day_name()

# Extracting Month Year from OrderDate
df['year_month'] = df['OrderDate'].apply(lambda x:x.strftime('%Y-%m'))

# Calculate Total Invoice Amount
df['total_Invoice_amount'] = df['SalesAmount'] + df['TaxAmt']

# Considering only salesamount and total_sales_amount to calculate
profit
df['profit'] = (df['UnitPrice']*df['OrderQuantity']) -
df['TotalProductCost']

# Removing extra character from the string
df['ProductName'] = df['ProductName'].str.replace(',','-')
```

```python
# Calculate Age
df['Age'] = df['OrderDate'].dt.year - df['BirthDate'].dt.year
```

Performing EDA

```python
# List of product's category
df['Category'].unique().tolist()
```

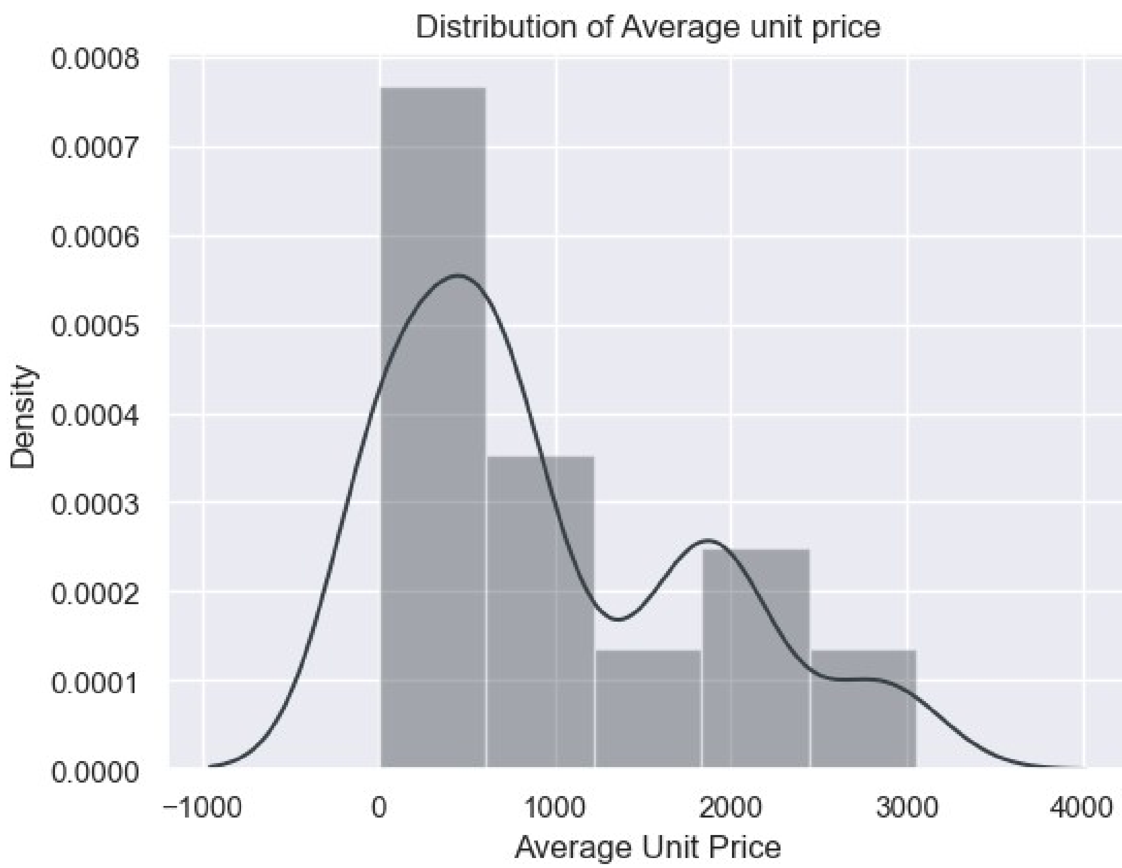
```
['Bikes', 'Accessories', 'Clothing']
```

```python
# List of product's subcategory
df['SubCategory'].unique().tolist()
```

```
['Road Bikes',
 'Mountain Bikes',
 'Bottles and Cages',
 'Gloves',
 'Tires and Tubes',
 'Helmets',
 'Touring Bikes',
 'Jerseys',
 'Cleaners',
 'Caps',
 'Hydration Packs',
 'Socks',
 'Fenders',
 'Vests',
 'Bike Racks',
 'Bike Stands',
 'Shorts']
```

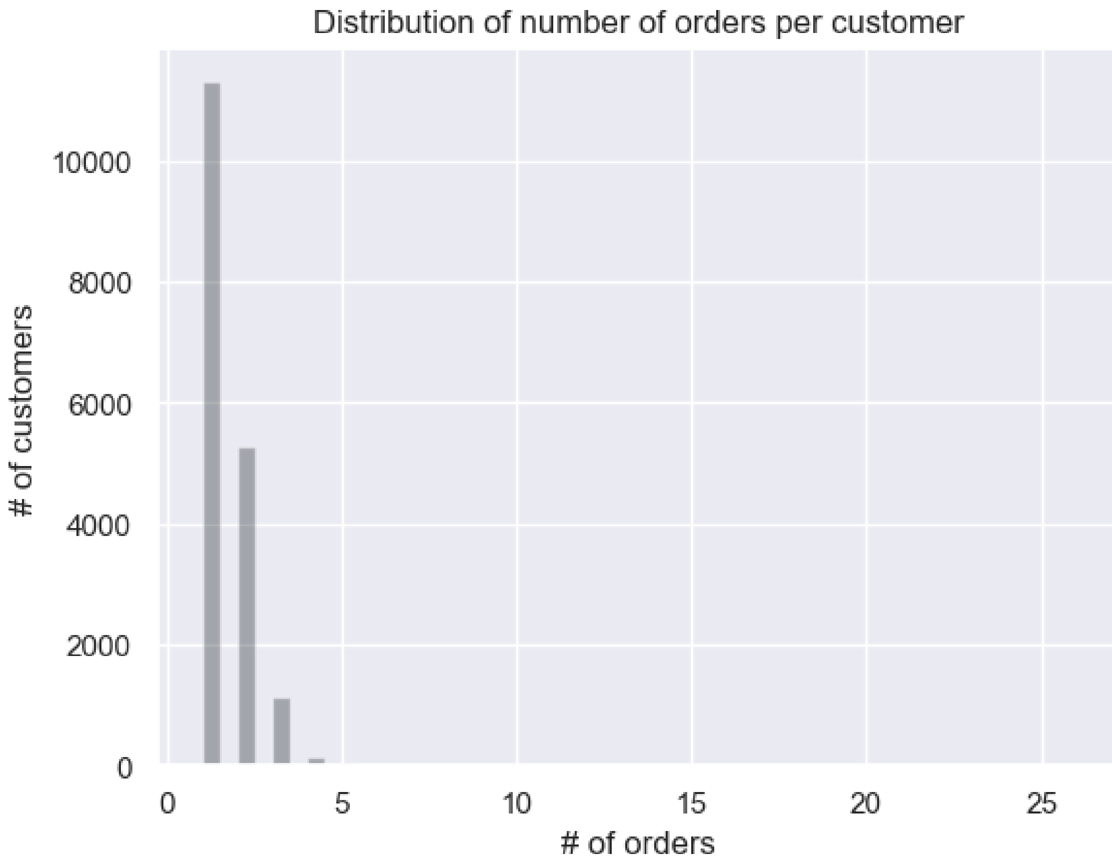
```python
# Analysing UnitPrice
Avg_unit_price = df.groupby(['ProductKey'])['UnitPrice'].mean()
ax = sns.distplot(Avg_unit_price, kde=True, hist=True,
color='#374045')
ax.set(title='Distribution of Average unit price',
       xlabel='Average Unit Price')
```

```
[Text(0.5, 1.0, 'Distribution of Average unit price'),
 Text(0.5, 0, 'Average Unit Price')]
```



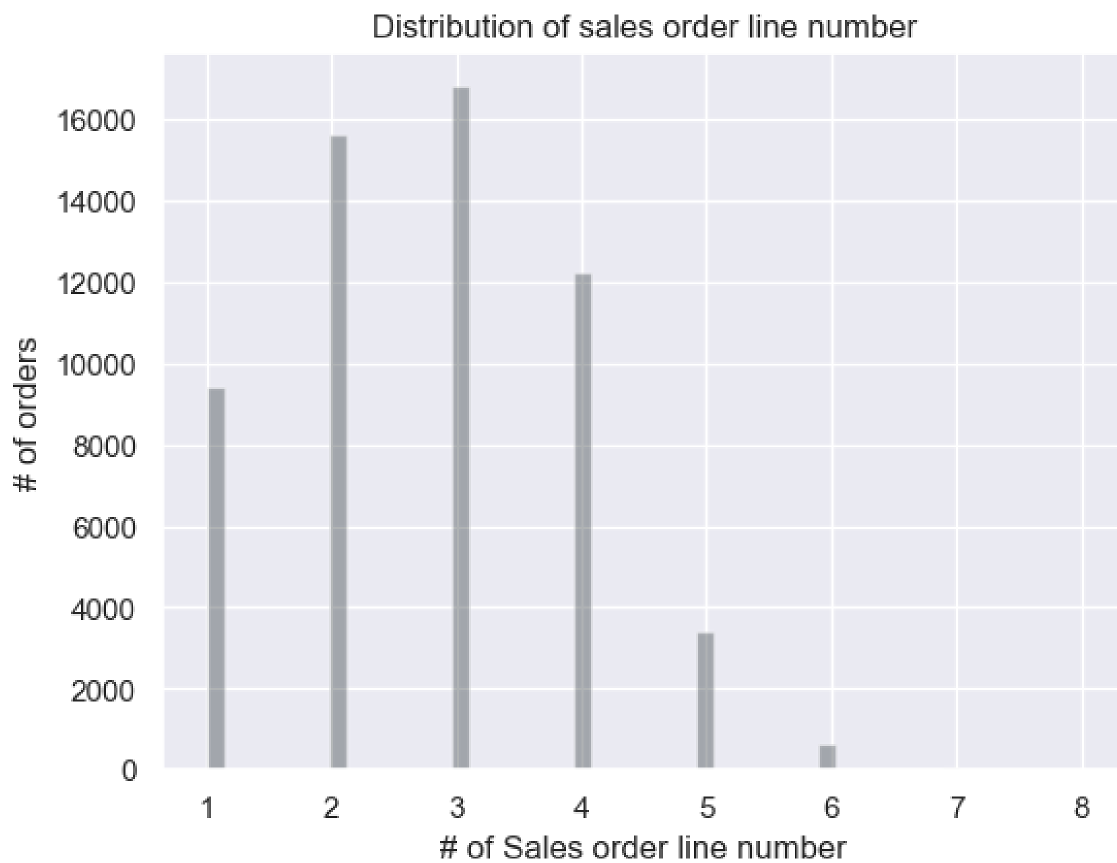
- Maximum of the product unit price is below $1000

```
# Sales order number distribution
n_orders = df.groupby(['CustomerKey'])['SalesOrderNumber'].nunique()
multi_orders_perc = np.sum(n_orders > 1)/df['CustomerKey'].nunique()
print(f"{100*multi_orders_perc:.2f}% of customers ordered more than
once.")

36.97% of customers ordered more than once.

ax = sns.distplot(n_orders, kde=False, color='#374045')
ax.set(title='Distribution of number of orders per customer',
       xlabel='# of orders',
       ylabel='# of customers')

[Text(0.5, 1.0, 'Distribution of number of orders per customer'),
 Text(0.5, 0, '# of orders'),
 Text(0, 0.5, '# of customers')]
```




```
# Sales order line number distribution
n_salesordernumber = df.groupby(['SalesOrderNumber'])
['SalesOrderLineNumber'].transform('max')
ax = sns.distplot(n_salesordernumber, kde=False, color='#374045')
ax.set(title='Distribution of sales order line number',
       xlabel='# of Sales order line number',
       ylabel='# of orders')
```

```
[Text(0.5, 1.0, 'Distribution of sales order line number'),
 Text(0.5, 0, '# of Sales order line number'),
 Text(0, 0.5, '# of orders')]
```

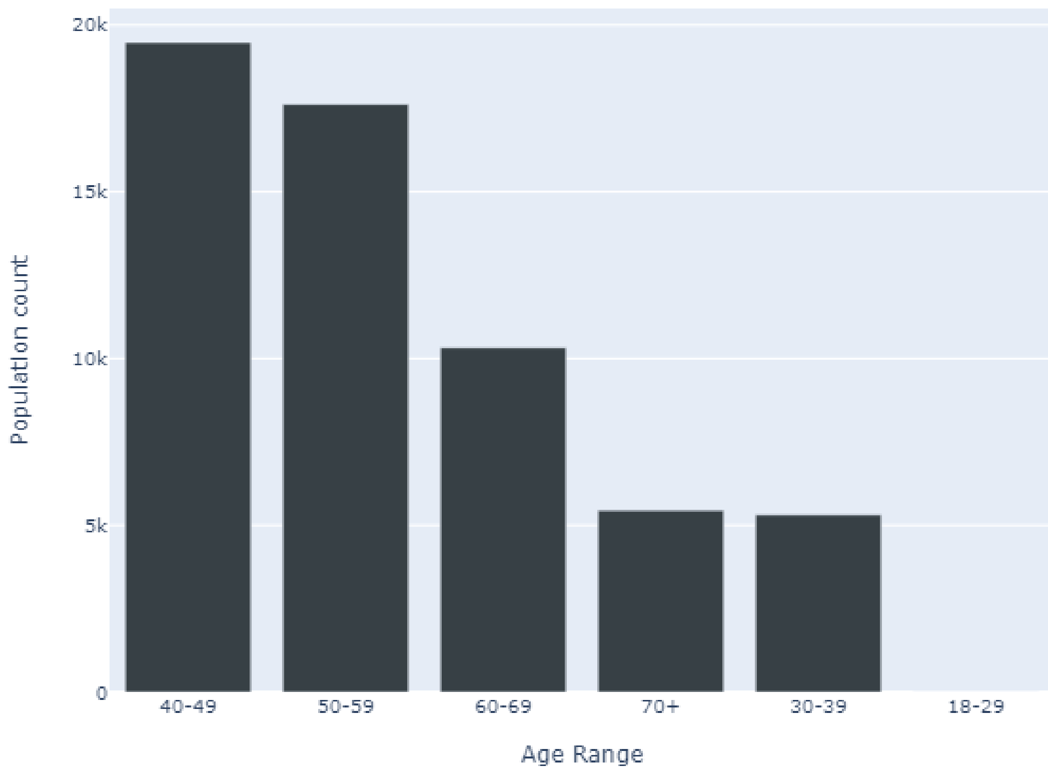


- Most of the time **three to two** products are ordered in a single order

```
# Sales Order Quantity distribution
n_order_quantity = df.groupby(['SalesOrderNumber'])
['OrderQuantity'].sum()
ax = sns.distplot(n_order_quantity, kde=True,
hist=True,color='#374045')
ax.set(title='Distribution of order_quantity',
       xlabel='# of order_quantity',
       )

[Text(0.5, 1.0, 'Distribution of order_quantity'),
 Text(0.5, 0, '# of order_quantity')]
```

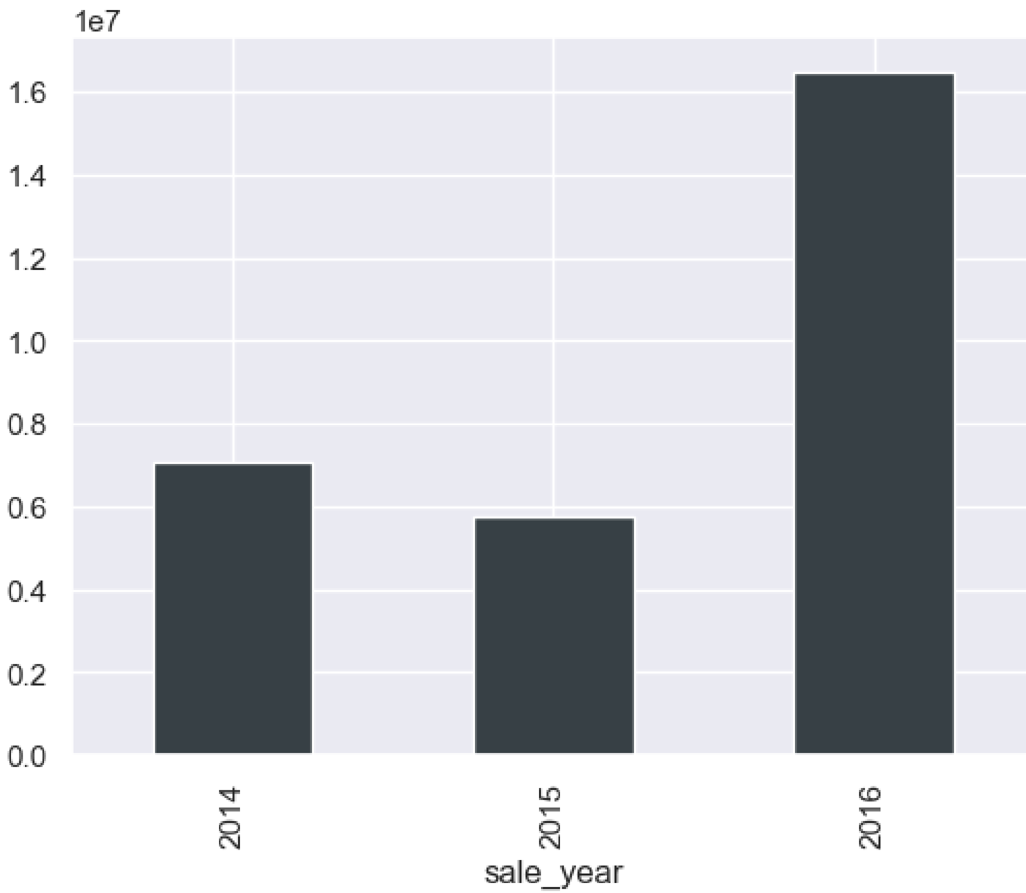
- maximum quantity ordered for a product is below 5

```
# Age Distribution
bins = [18, 30, 40, 50, 60, 70, 120]
labels = ['18-29', '30-39', '40-49', '50-59', '60-69', '70+']
df['agerange'] = pd.cut(df.Age, bins, labels = labels,include_lowest =
True)

age_distribution =
df['agerange'].value_counts().to_frame().reset_index()

age_distribution.columns = ['Age Range','Population count']

fig = px.bar(age_distribution, x='Age Range', y='Population count',
color_discrete_sequence=['#374045'])
fig.update_layout(
    autosize=True,
    width=500,
    height=500,
    font=dict(size=10))
fig.show()
```



- A sizable portion of the clientele is made up of people between the ages of **40 and 59**.

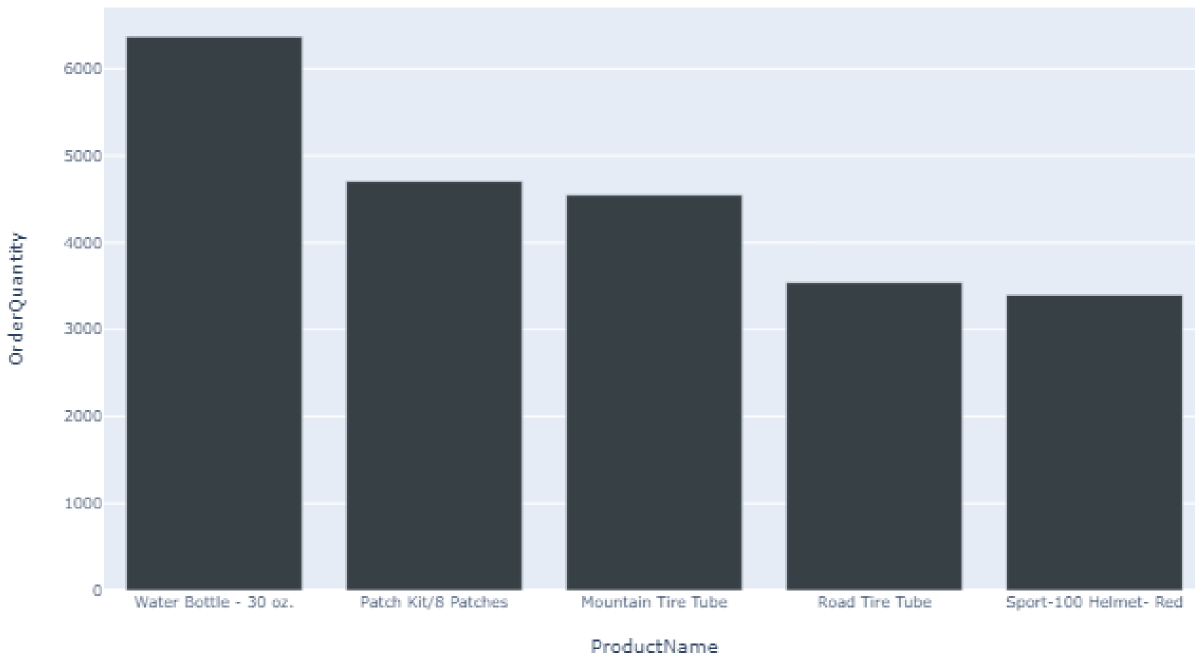
```
# Year wise sales
df.groupby('sale_year')['SalesAmount'].sum().plot(kind='bar',
color='#374045');
```



- The year 2016 saw an exponential surge in sales

```
# Top 5 Selling Product
top_selling_product = df.groupby(['Category', 'SubCategory',
'ProductName'])['OrderQuantity'].sum().nlargest(5).to_frame()
top_selling_product

                                                            OrderQuantity
Category    SubCategory       ProductName
Accessories Bottles and Cages Water Bottle - 30 oz.                  6370
            Tires and Tubes   Patch Kit/8 Patches                    4705
                              Mountain Tire Tube                     4551
                              Road Tire Tube                         3544
            Helmets           Sport-100 Helmet- Red                  3398

top_selling_product.reset_index(inplace=True)
fig = px.bar(top_selling_product, x='ProductName',
y='OrderQuantity',color_discrete_sequence=['#374045'])
fig.update_layout(
    autosize=True,
    width=500,
    height=300,
    margin=dict(
```

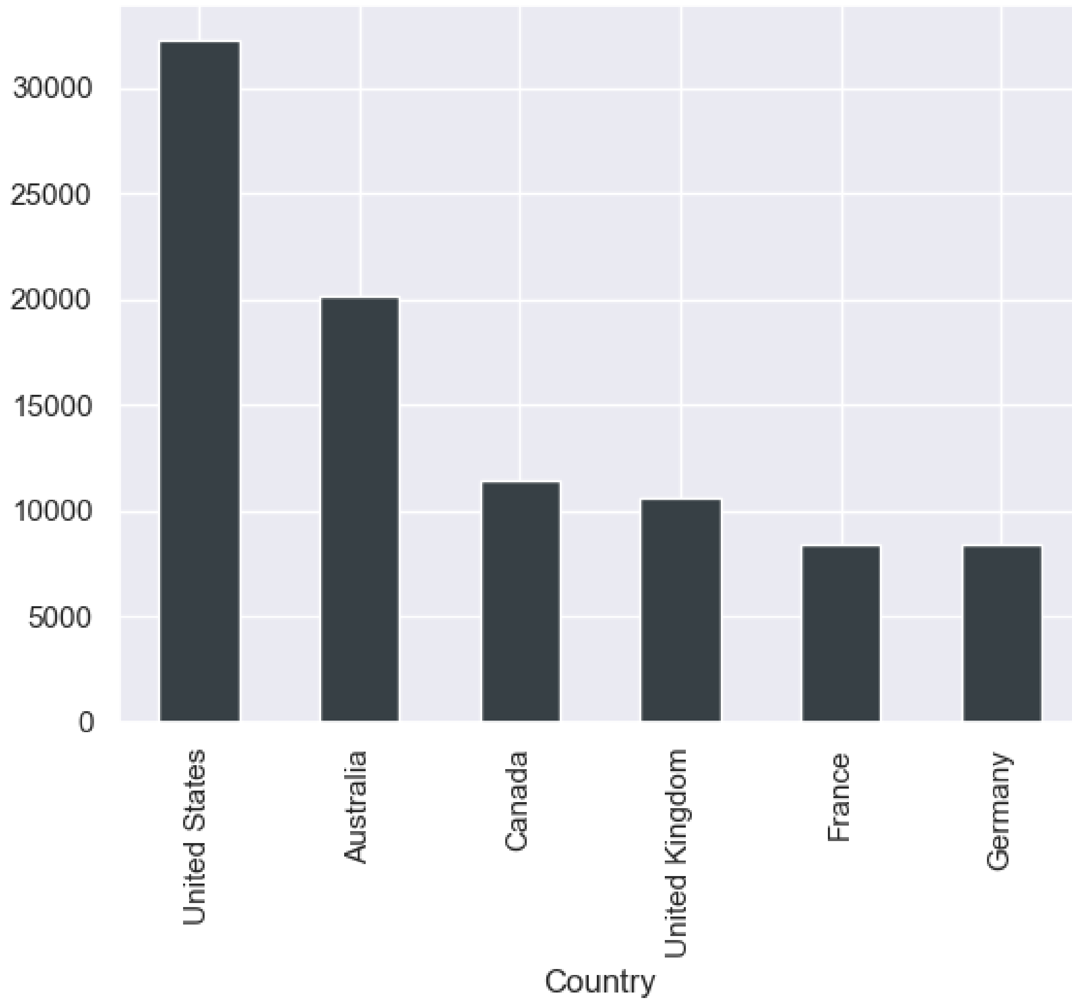
```
        l=25,
        r=25,
        b=10,
        t=10,
    ),
    font=dict(size=8))
fig.show()
```




```
# Quantity ordered based on category and subcategory from 2014 to 2016
cat_subcat_qty = df.groupby(['sale_year','Category', 'SubCategory'])
['OrderQuantity'].sum().to_frame()
cat_subcat_qty = cat_subcat_qty.sort_values(['sale_year', 'Category'],
ascending=True)
cat_subcat_qty.style.bar(subset=['OrderQuantity'], color='#D9B300')
```

```
<pandas.io.formats.style.Styler at 0x1f148369dd0>
```

```
# Country wise quantity ordered
country_qty_sales = df.groupby('Country')
['OrderQuantity'].sum().sort_values(ascending=False)
country_qty_sales.plot(kind='bar', color='#374045');
```



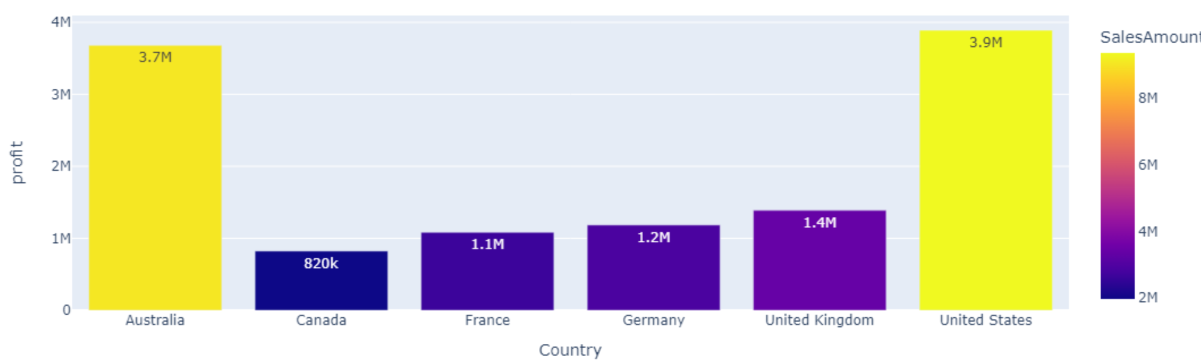
- High quantity of products is ordered from **Australia and United States**

```
# Overall profit based on order year, category and subcategory
cat_subcat_profit = df.groupby(['sale_year','Category',
'SubCategory'])['profit'].sum().to_frame()

#Sorting the results
cat_subcat_profit = cat_subcat_profit.sort_values(['sale_year',
'Category'], ascending=True)
cat_subcat_profit.style.bar(subset=['profit'], color='#D9B300')

<pandas.io.formats.style.Styler at 0x1f14a32a4d0>
```

- Major Profit is contributed by the Bike Category

```
# Low profit contributing product
df.groupby(['Category', 'SubCategory','ProductName'])
['profit'].sum().nsmallest(10).to_frame()
```

```
                                                                profit
Category    SubCategory     ProductName
Clothing    Socks           Racing Socks- L                  1474.4574
                            Racing Socks- M                  1581.3837
Accessories Cleaners        Bike Wash - Dissolver            4299.8688
            Tires and Tubes Patch Kit/8 Patches              4314.8350
Clothing    Caps            AWC Logo Cap                     4331.8315
Accessories Tires and Tubes Touring Tire Tube                4363.8089
Clothing    Jerseys         Long-Sleeve Logo Jersey- XL      4495.6007
                            Short-Sleeve Classic Jersey- L   4544.8782
                            Long-Sleeve Logo Jersey- S       4610.5777
                            Short-Sleeve Classic Jersey- M   4793.2322

# Profitability by country
country_sales =
pd.DataFrame(df.groupby('Country').sum(numeric_only=True)
[['SalesAmount', 'profit']])
country_sales.reset_index(inplace=True)

fig = px.bar(country_sales, x='Country', y='profit',text_auto='.2s',
             color='SalesAmount',
             height=400)
fig.show()
```



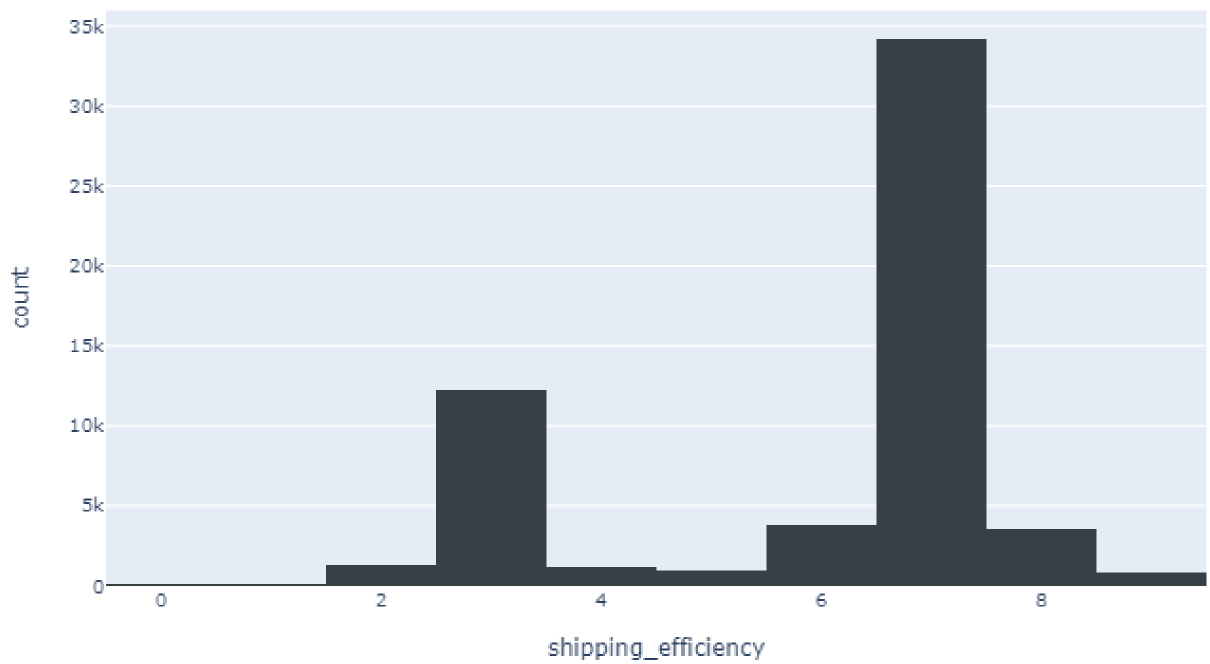
- High volume of profit is earned from **Australia and United States**

Question and Answers

Q1. How efficient are the logistics?

```
# Adding manufacturing days to the order received date
df['OrderreadyDate'] = df['OrderDate'] +
pd.to_timedelta(df['DaysToManufacture'], unit='D')

# Check the delay between order shipment date and order ready to
supply
```

```
df['shipping_efficiency'] = (df['ShipDate'] -
df['OrderreadyDate']).dt.days

fig = px.histogram(df, x="shipping_efficiency",
color_discrete_sequence=['#374045'])
fig.update_layout(
    autosize=True,
    width=300,
    height=300,
    margin=dict(
        l=25,
        r=25,
        b=10,
        t=10,
    ),
    font=dict(size=10))
fig.show()
```



- The average order has a gap of 7 days between the day the order is ready for export from the factory and the date it was shipped
- Management must work to reduce this gap toward 3 days.

Q2. What was the best month for sales? How much was earned that month ?

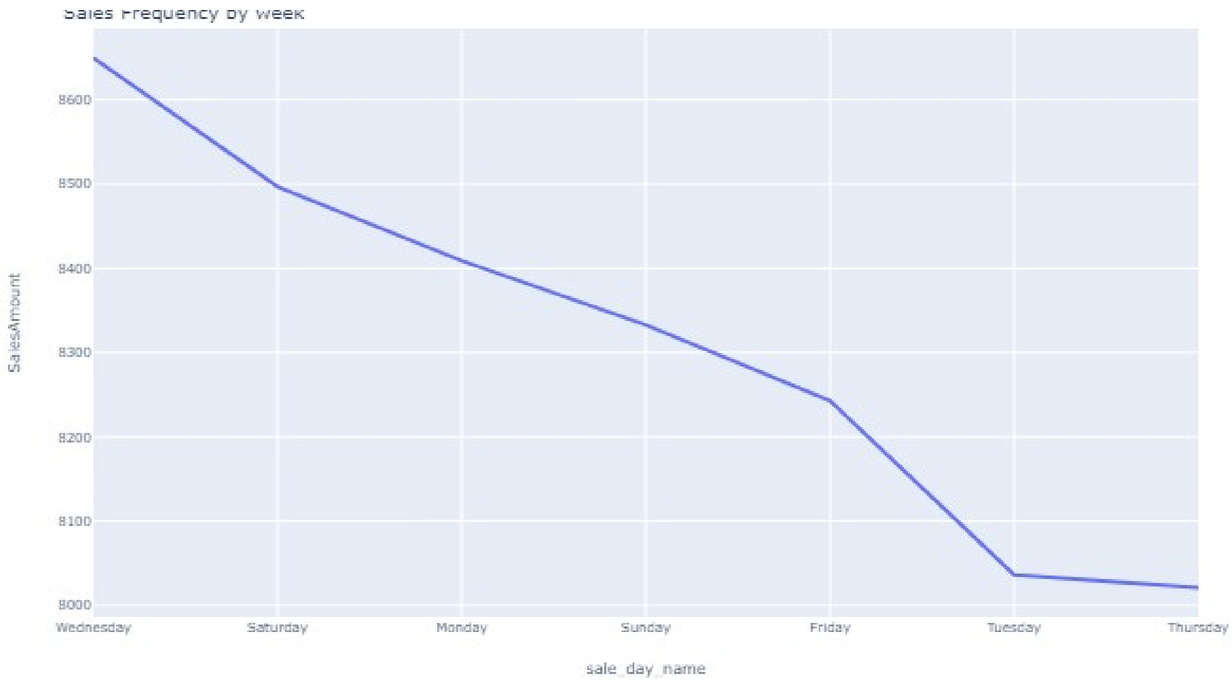
```
month_sales = df.groupby('sale_month').sum(numeric_only=True)
[['SalesAmount', 'profit']]
month_sales.reset_index(inplace=True)
fig = px.bar(month_sales, x='sale_month',
y='SalesAmount',text_auto='.2s',
```

```
             hover_data=['sale_month', 'SalesAmount'], color='profit',
             height=400)
fig.show()
```

- There are large profit transactions in the months of **June, November, and December**

Q3. What time should we display advertisement to maximize likelihood of customerls buying product?

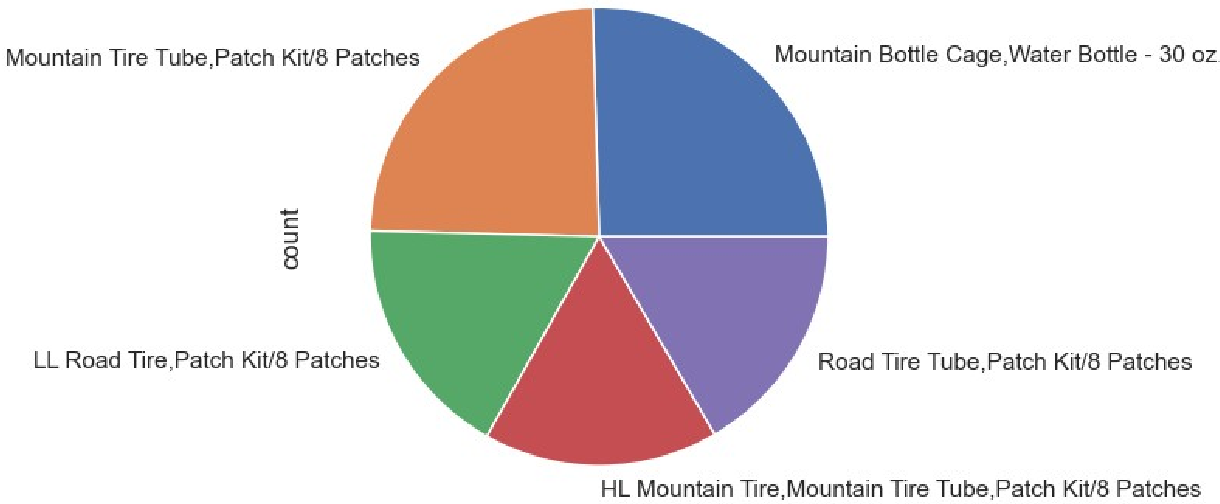
```
sales_by_week = df.groupby(['sale_day_name']).count()
['SalesAmount'].reset_index().sort_values('SalesAmount',
ascending=False)

fig = px.line(sales_by_week, x='sale_day_name', y='SalesAmount',
title='Sales Frequency by week')
fig.update_layout(
    autosize=True,
    width=300,
    height=300,
    margin=dict(
        l=25,
        r=25,
        b=10,
        t=10,
    ),
    font=dict(size=7))
fig.show()
```



- High sales orders are seen on **Wednesday and Saturday**, therefore we can promote our product during these workweek

Q4. Which products are most often sold together?

```
# By setting keep on False, all duplicates are True since we only want
repeated order number
dup_order = df[df['SalesOrderNumber'].duplicated(keep=False)]

# Group the data based on sales order number and product name because
the products
# that bought together will have share same order number
dup_order['grouped'] = df.groupby('SalesOrderNumber')
['ProductName'].transform(lambda x: ','.join(x))
dup_order = dup_order[['SalesOrderNumber',
'grouped']].drop_duplicates()

count = dup_order['grouped'].value_counts()[0:5].plot.pie()
```



- From the above pie diagram we can draw a conclusion that these products are mostly Purchased together

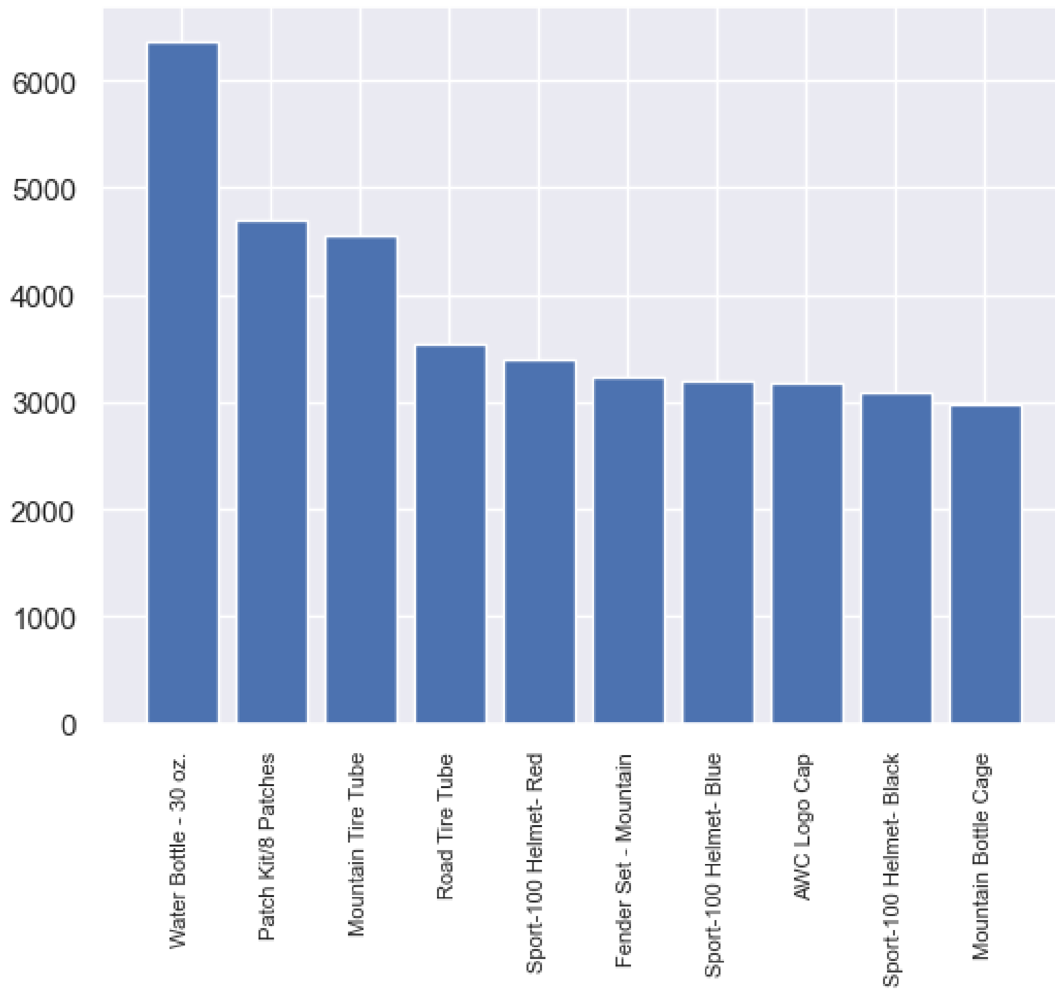
```
count = Counter()

for row in dup_order['grouped']:
    row_list  = row.split(',')
    count.update(Counter(combinations(row_list, 2)))

for key, value in count.most_common(10):
    print(key, value)

('Mountain Bottle Cage', 'Water Bottle - 30 oz.') 1623
('Road Bottle Cage', 'Water Bottle - 30 oz.') 1513
('HL Mountain Tire', 'Mountain Tire Tube') 915
('Touring Tire', 'Touring Tire Tube') 758
('Mountain Tire Tube', 'Patch Kit/8 Patches') 737
('Mountain Tire Tube', 'ML Mountain Tire') 727
('Water Bottle - 30 oz.', 'AWC Logo Cap') 599
('Road Tire Tube', 'ML Road Tire') 580
('Road Tire Tube', 'Patch Kit/8 Patches') 556
('HL Road Tire', 'Road Tire Tube') 552
```

- The above product can be sold in a bundle or a combined package for discount

Q5. Which product sold the most? why do you think it sold the most?

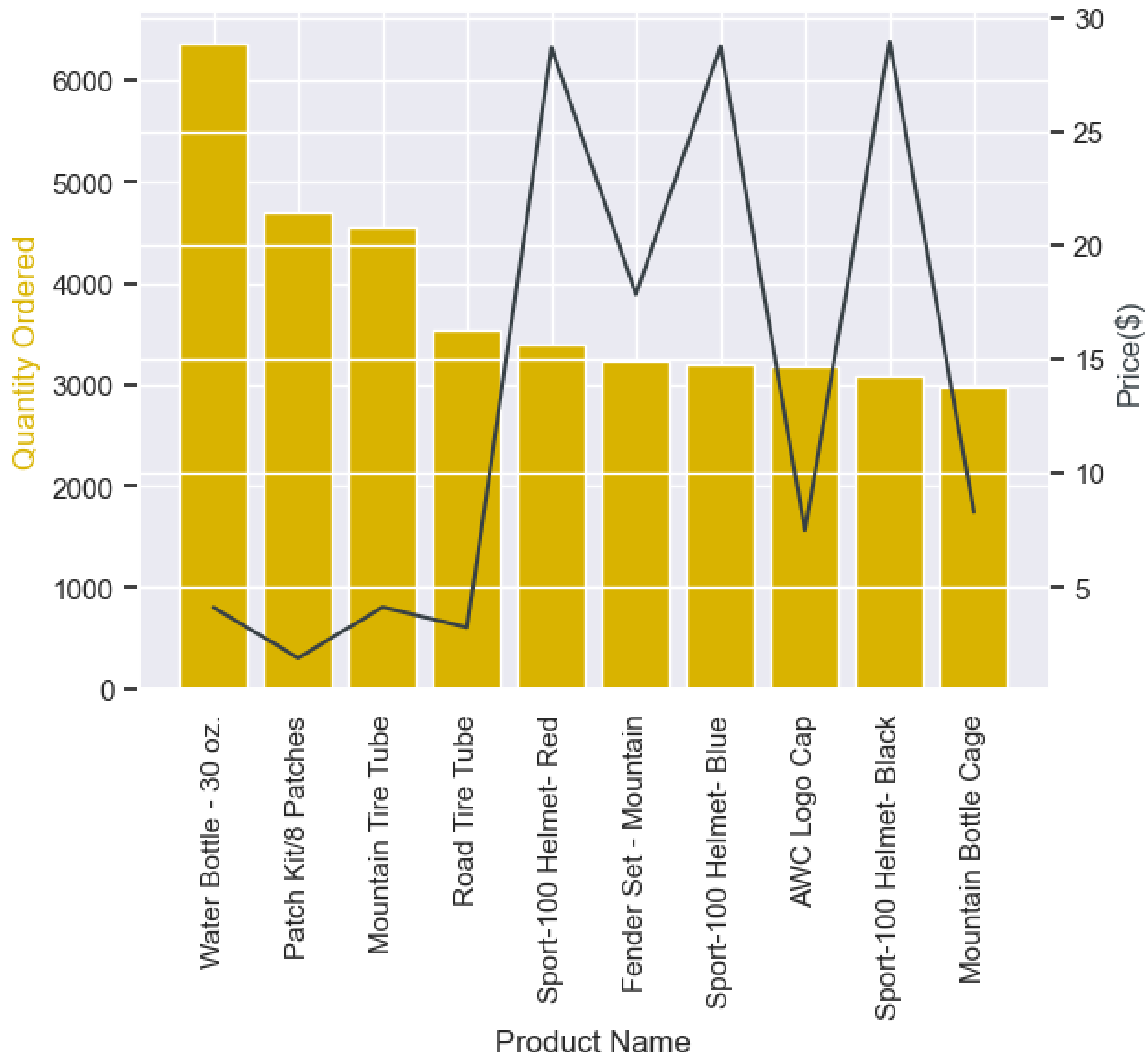
```
product_group = df.groupby('ProductName')
quantity_ordered =
product_group['OrderQuantity'].sum().sort_values(ascending=False)[:10]
products = quantity_ordered.index.tolist()

plt.bar(products, quantity_ordered, )
```

```
plt.xticks(products, rotation='vertical', size=8)
plt.show()
```




```
# Convert 'UnitPrice' to numeric, coercing errors to NaN (which will
be ignored in the mean calculation)
df['UnitPrice'] = pd.to_numeric(df['UnitPrice'], errors='coerce')

# Group by 'ProductName' and calculate the mean of 'UnitPrice'
prices = df.groupby('ProductName')['UnitPrice'].mean()

# Select only the prices for the specified products
prices = prices[products]

fig, ax1 = plt.subplots()

ax2 = ax1.twinx()
ax1.bar(products, quantity_ordered, color='#D9B300')
ax2.plot(products, prices, '#374045')
```

```
ax1.set_xlabel('Product Name')
ax1.set_ylabel('Quantity Ordered', color='#D9B300')
ax2.set_ylabel('Price($)', color='#374045')
ax1.set_xticklabels(products, rotation='vertical')

plt.show();
```

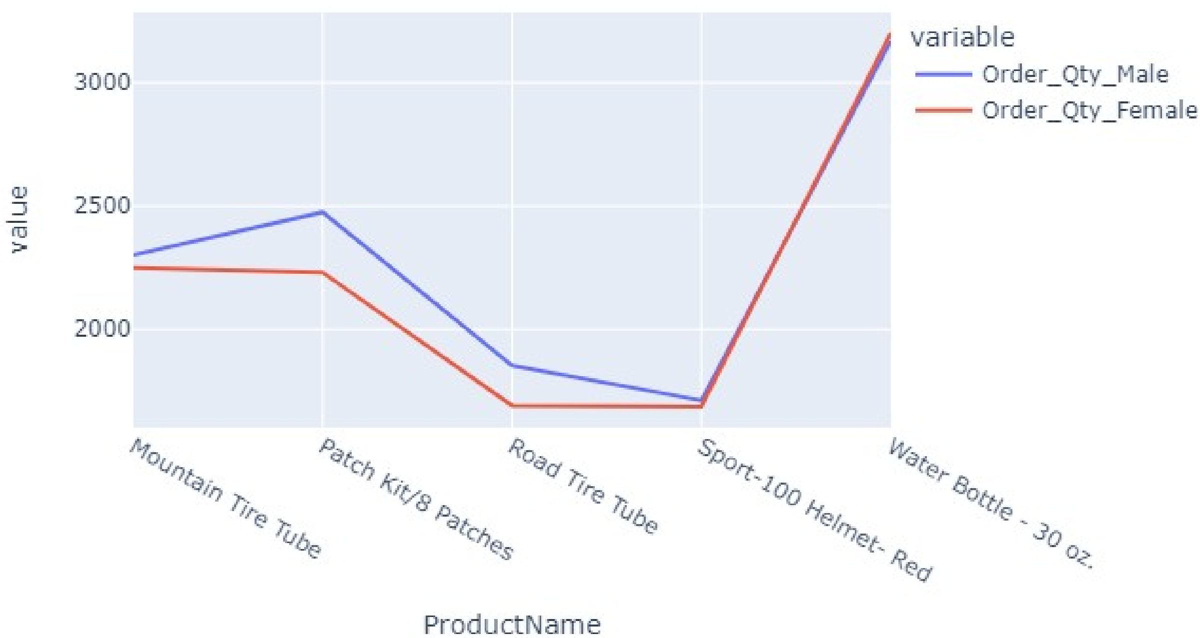



```
prices.corr(quantity_ordered)
```

```
-0.5333019792658484
```

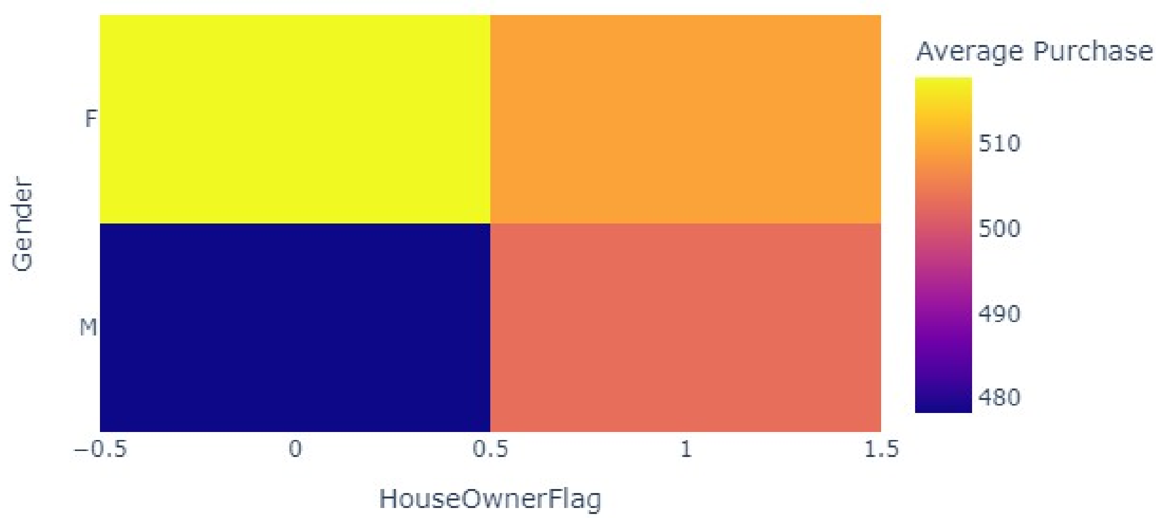
- There is a **high negative correlation** between **Price and number of Quantity ordered**
- we can conclude that **low price product has high demand**

```
# Compare most ordered product by gender
male = df[df["Gender"]=="M"]
female = df[df["Gender"]=="F"]

male_ord_qty = male.groupby(['ProductName'],as_index=False)
['OrderQuantity'].sum().nlargest(5,'OrderQuantity').sort_values('Produ
ctName')
male_ord_qty.columns=['ProductName','Order_Qty_Male']

female_ord_qty = female.groupby(['ProductName'],as_index=False)
['OrderQuantity'].sum().nlargest(5,'OrderQuantity').sort_values('Produ
ctName')
female_ord_qty.columns=['ProductName','Order_Qty_Female']

df_merge = pd.merge(male_ord_qty, female_ord_qty, on='ProductName')

fig = px.line(df_merge, x="ProductName",
y=["Order_Qty_Male","Order_Qty_Female"])
fig.update_layout(
    autosize=True,
    width=800,
    height=400)
fig.show()
```



Q6. Does Gender and home ownership matter in order purchasing ?

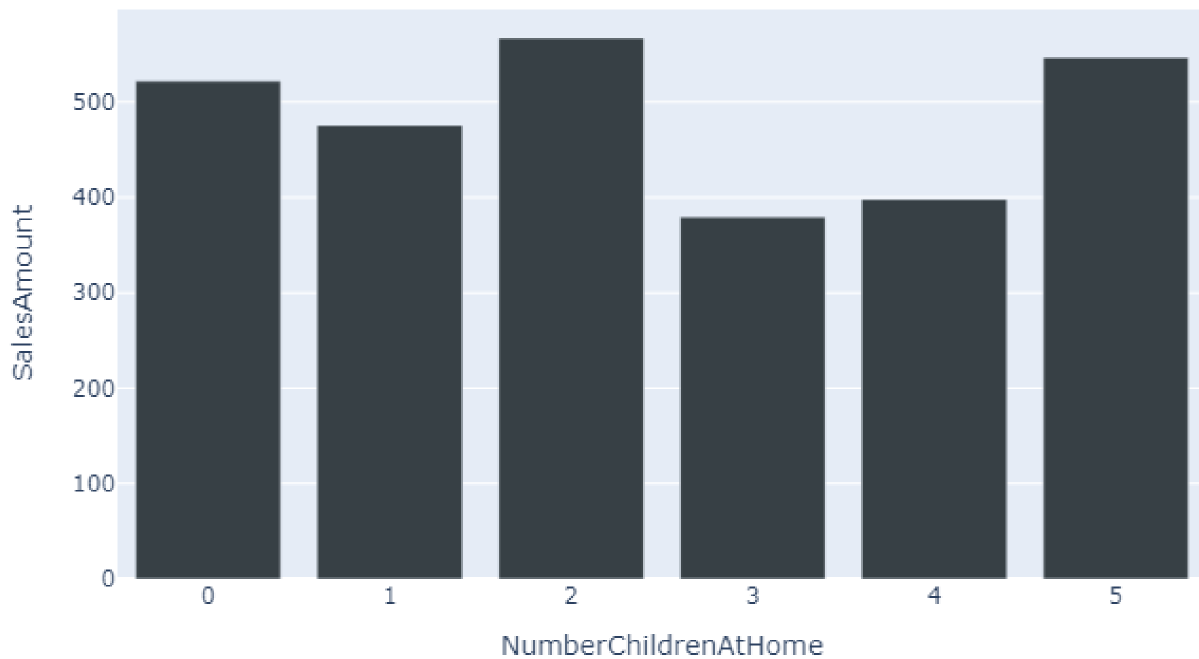
```
fig = px.imshow(df.groupby(["Gender", "HouseOwnerFlag"])
["SalesAmount"].mean().unstack(),
                labels=dict(color="Average Purchase"))
fig.show()
```



- It's interesting to note that the average amount spent by men without permanent addresses is low, whilst the average amount spent by women without permanent addresses is higher.

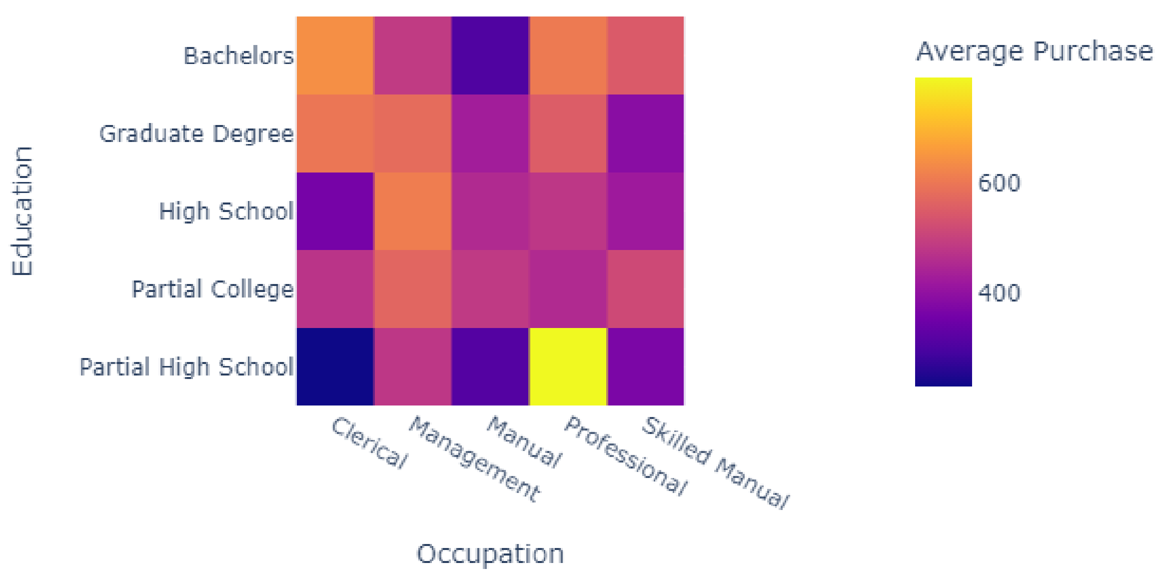
Q7. Number of childer and Purchase correlation

```
df_1 = df.groupby(["NumberChildrenAtHome"])
["SalesAmount"].mean().to_frame()
df_1.reset_index(inplace=True)
fig = px.bar(df_1, x='NumberChildrenAtHome',
y='SalesAmount',color_discrete_sequence=['#374045'])
fig.update_layout(
    autosize=False,
    width=300,
    height=300,
    margin=dict(
        l=25,
        r=25,
        b=10,
        t=10,
    ))
fig.show()
```



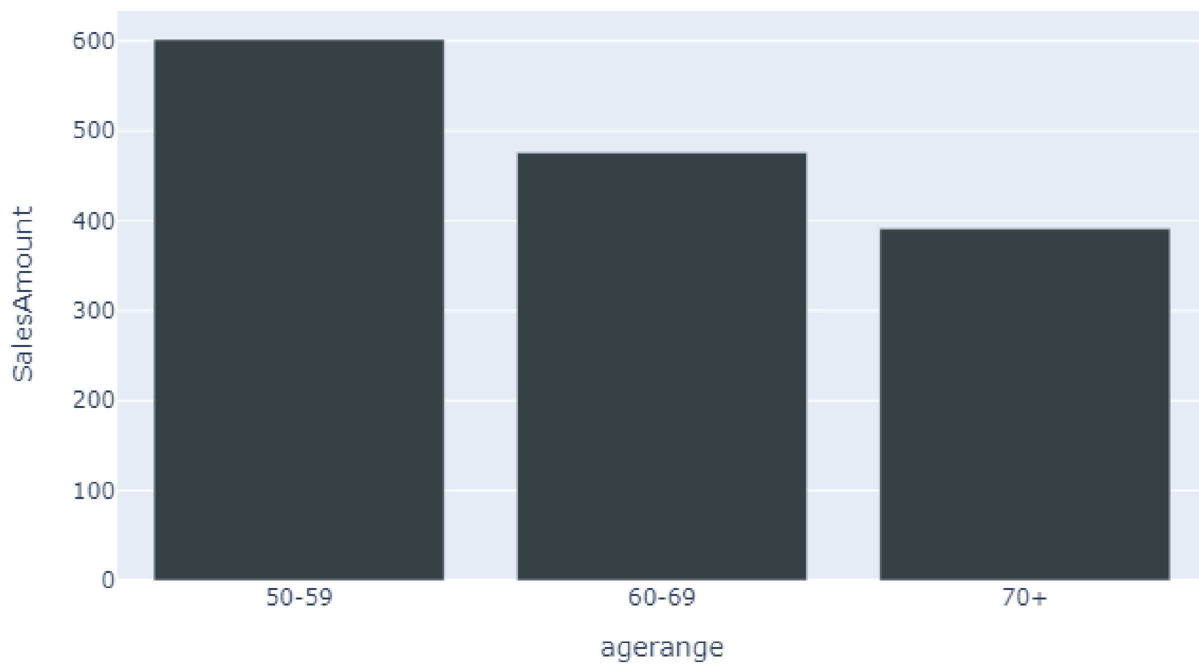
Education, Occupation and Purchase correlation

```
fig = px.imshow(df.groupby(["Education", "Occupation"])
["SalesAmount"].mean().unstack(),
                labels=dict(color="Average Purchase"))
fig.show()
```



Maritial Status single and above 50 age purchase

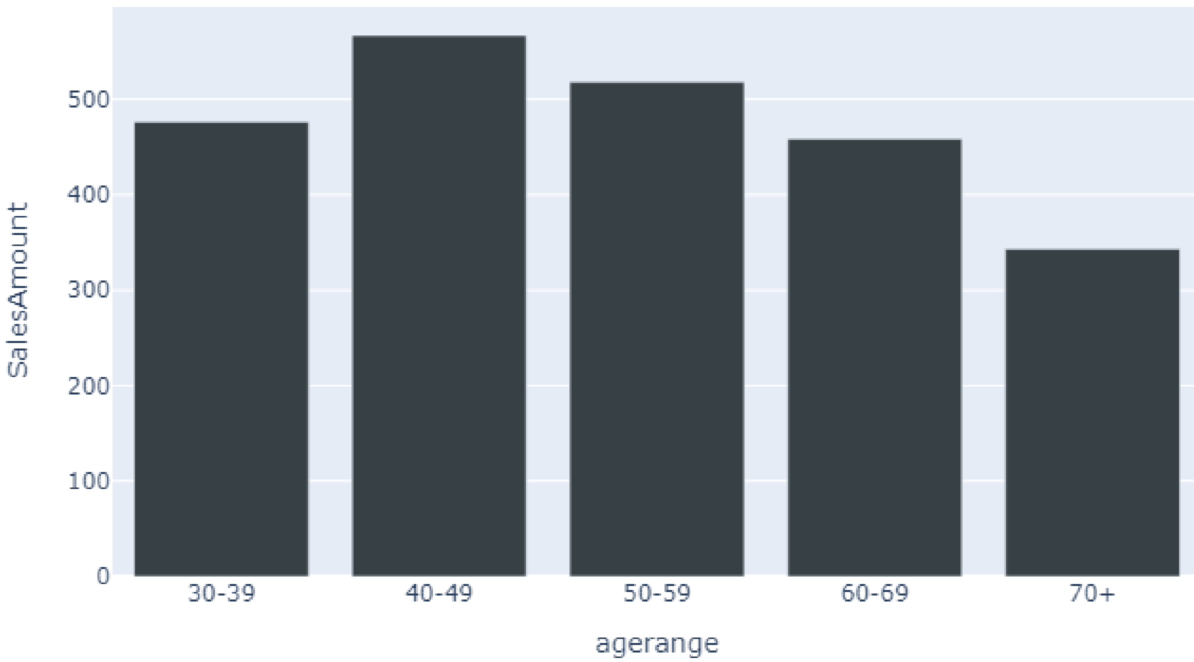
```
df_2 = df[(df['MaritalStatus']=='S')&(df['Age']>50)]

df_2 = df_2.groupby('agerange')
['SalesAmount'].mean().to_frame().dropna()
df_2.reset_index(inplace=True)
fig = px.bar(df_2, x='agerange', y='SalesAmount',
color_discrete_sequence=['#374045'])
fig.update_layout(
    autosize=False,
    width=300,
    height=300,
    margin=dict(
        l=25,
        r=25,
        b=10,
        t=10,
    ))
fig.show()
```



Which age group has produced the most revenue?

```
df_3 = df.groupby('agerange')
['SalesAmount'].mean().to_frame().dropna()
df_3.reset_index(inplace=True)
fig = px.bar(df_3, x='agerange', y='SalesAmount',
color_discrete_sequence=['#374045'])
fig.update_layout(
    autosize=False,
```

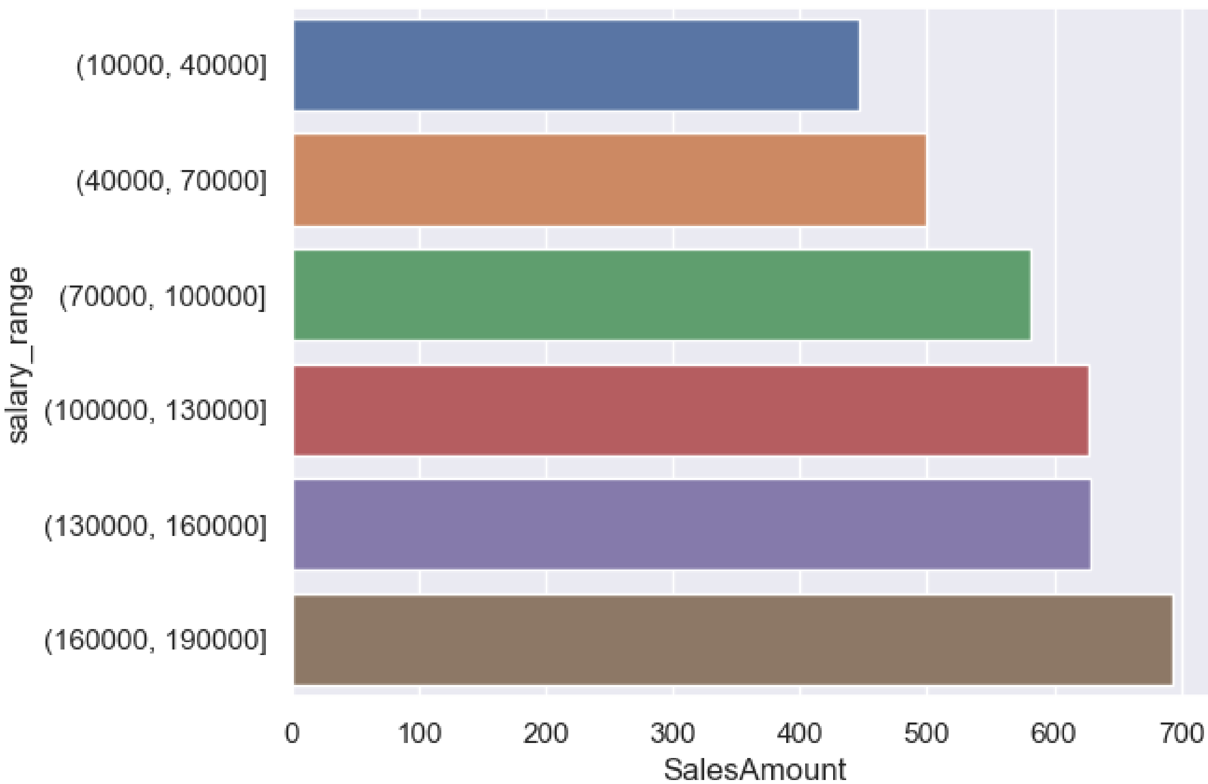
```
    width=300,
    height=300,
    margin=dict(
        l=25,
        r=25,
        b=10,
        t=10,
    ))
fig.show()
```



Yearly income range and purchase correlation

```
def create_bins(lower_bound, width, quantity):
    """ create_bins returns an equal-width (distance) partitioning.
        It returns an ascending list of tuples, representing the
intervals.
        A tuple bins[i], i.e. (bins[i][0], bins[i][1])  with i > 0
        and i < quantity, satisfies the following conditions:
            (1) bins[i][0] + width == bins[i][1]
            (2) bins[i-1][0] + width == bins[i][0] and
                bins[i-1][1] + width == bins[i][1]
    """


    bins = []
    for low in range(lower_bound,
                     lower_bound + quantity*width + 1, width):
        bins.append((low, low+width))
    return bins
```

```
bins = create_bins(lower_bound=10000,
                   width=30000,
                   quantity=5)
bins2 = pd.IntervalIndex.from_tuples(bins)
df['salary_range'] = pd.cut(df['YearlyIncome'], bins2)

df_4 = df.groupby('salary_range')['SalesAmount'].mean().to_frame()
df_4.reset_index(inplace=True)
sns.barplot(x="SalesAmount", y="salary_range", data=df_4)

<Axes: xlabel='SalesAmount', ylabel='salary_range'>
```

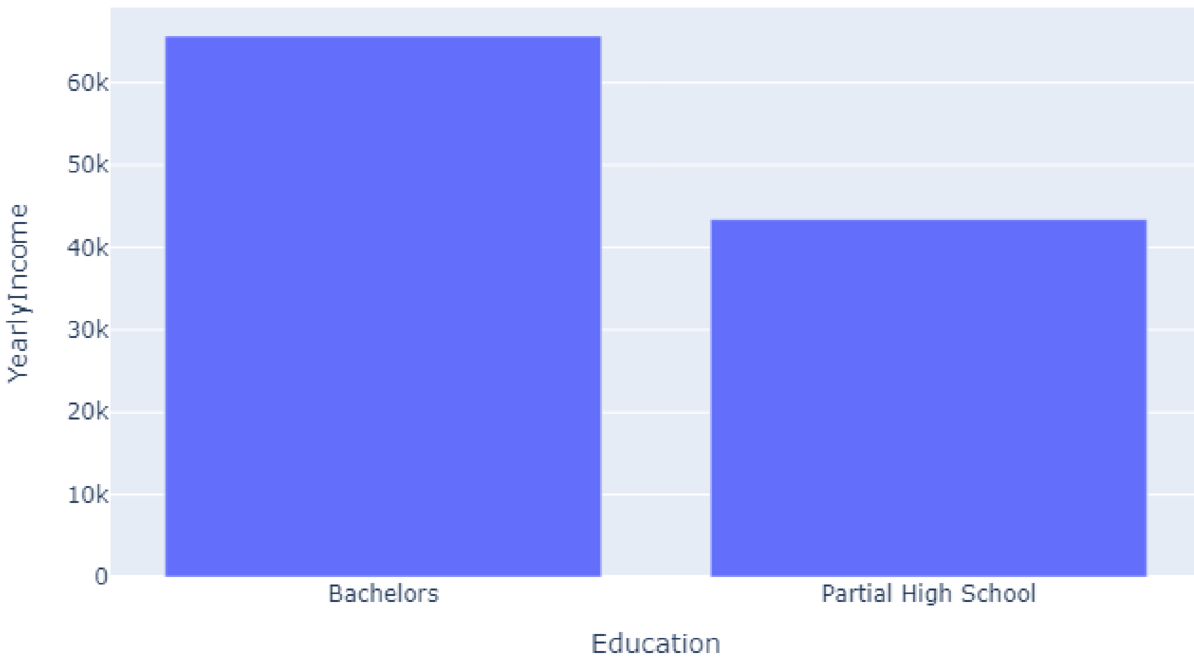


- High salary range leads to increase in purchase

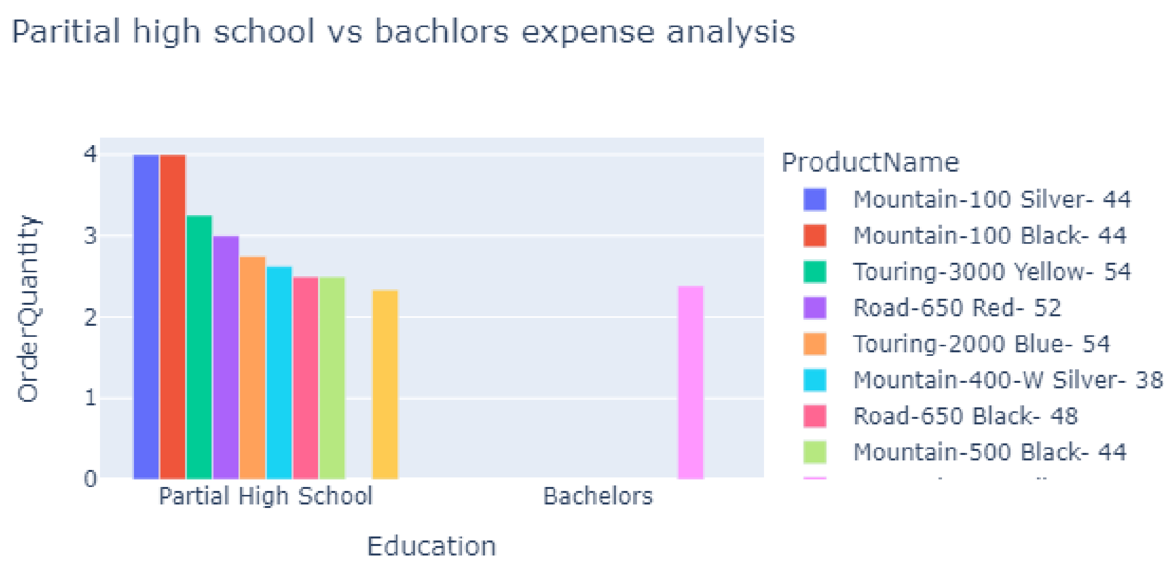
Paritial high school vs bachlors income mean and most ordered product

```
df_6 = df[(df['Education']=='Partial High School')|
(df['Education']=='Bachelors')].groupby('Education')
['YearlyIncome'].mean().to_frame()

df_6.reset_index(inplace=True)
fig = px.bar(df_6, x='Education', y='YearlyIncome')
fig.update_layout(
    autosize=False,
    width=300,
    height=300,
```

```
    margin=dict(
        l=25,
        r=25,
        b=10,
        t=10,
    ))
fig.show()
```




```
df_7 = df[(df['Education']=='Partial High School')|
(df['Education']=='Bachelors')]
df_7 = df_7.groupby(['Education','ProductName'])
['OrderQuantity'].mean().to_frame().sort_values('OrderQuantity',
ascending=False)[:10]
df_7.reset_index(inplace=True)
fig = px.bar(df_7, x="Education",
             y="OrderQuantity", color="ProductName",
             title="Paritial high school vs bachlors expense
analysis",
             barmode="group")
fig.show()
```



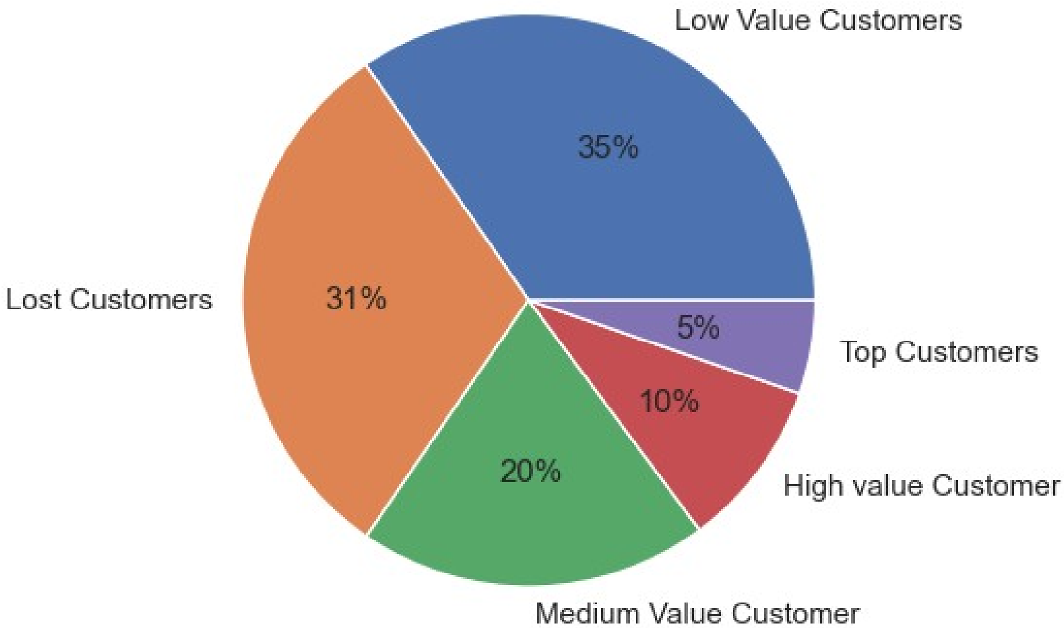
- Customers with a **high school diploma and modest annual income buy more products** than people with bachelor's degrees

Customer Segmentation

- RFM stands for recency, frequency, monetary value.
- In business analytics, we often use this concept to divide
- customers into different segments, like high-value customers,
- medium value customers or low-value customers, and similarly many others.
- Recency: How recently has the customer made a transaction with us
- Frequency: How frequent is the customer in ordering/buying some product from us
- Monetary: How much does the customer spend on purchasing products from us

```
#  calculating recency for customers who had made a purchase with a
company

df_recency = df.groupby(by='FullName',
                        as_index=False)['OrderDate'].max()
df_recency.columns = ['CustomerName', 'LastPurchaseDate']
recent_date = df_recency['LastPurchaseDate'].max()
df_recency['Recency'] = df_recency['LastPurchaseDate'].apply(
    lambda x: (recent_date - x).days)

#  calculating the frequency of frequent transactions of the
#  customer in ordering/buying some product from the company.


frequency_df = df.drop_duplicates().groupby(
    by=['FullName'], as_index=False)['OrderDate'].count()
```

```python
frequency_df.columns = ['CustomerName', 'Frequency']
# frequency_df.head()

monetary_df = df.groupby(by='FullName', as_index=False)
['SalesAmount'].sum()
monetary_df.columns = ['CustomerName', 'Monetary']
# monetary_df.head()

# merging dataset
rf_df = df_recency.merge(frequency_df, on='CustomerName')
rfm_df = rf_df.merge(monetary_df, on='CustomerName').drop(
    columns='LastPurchaseDate')
# rfm_df.head()

rfm_df['R_rank'] = rfm_df['Recency'].rank(ascending=False)
rfm_df['F_rank'] = rfm_df['Frequency'].rank(ascending=True)
rfm_df['M_rank'] = rfm_df['Monetary'].rank(ascending=True)

# normalizing the rank of the customers
rfm_df['R_rank_norm'] = (rfm_df['R_rank']/rfm_df['R_rank'].max())*100
rfm_df['F_rank_norm'] = (rfm_df['F_rank']/rfm_df['F_rank'].max())*100
rfm_df['M_rank_norm'] = (rfm_df['F_rank']/rfm_df['M_rank'].max())*100

rfm_df.drop(columns=['R_rank', 'F_rank', 'M_rank'], inplace=True)

# rfm_df.head()

rfm_df['RFM_Score'] = 0.15*rfm_df['R_rank_norm']+0.28 * \
    rfm_df['F_rank_norm']+0.57*rfm_df['M_rank_norm']
rfm_df['RFM_Score'] *= 0.05
rfm_df = rfm_df.round(2)
# rfm_df[['CustomerName', 'RFM_Score']].head(7)

rfm_df["Customer_segment"] = np.where(rfm_df['RFM_Score'] >
                                      4.5, "Top Customers",
                                      (np.where(
                                        rfm_df['RFM_Score'] > 4,
                                        "High value Customer",
                                        (np.where(
    rfm_df['RFM_Score'] > 3,
                             "Medium Value Customer",
                             np.where(rfm_df['RFM_Score'] > 1.6,
                            'Low Value Customers', 'Lost
Customers'))))))
# rfm_df[['CustomerName', 'RFM_Score', 'Customer_segment']].head(20)

plt.pie(rfm_df.Customer_segment.value_counts(),
        labels=rfm_df.Customer_segment.value_counts().index,
        autopct='%.0f%%')
plt.show()
```



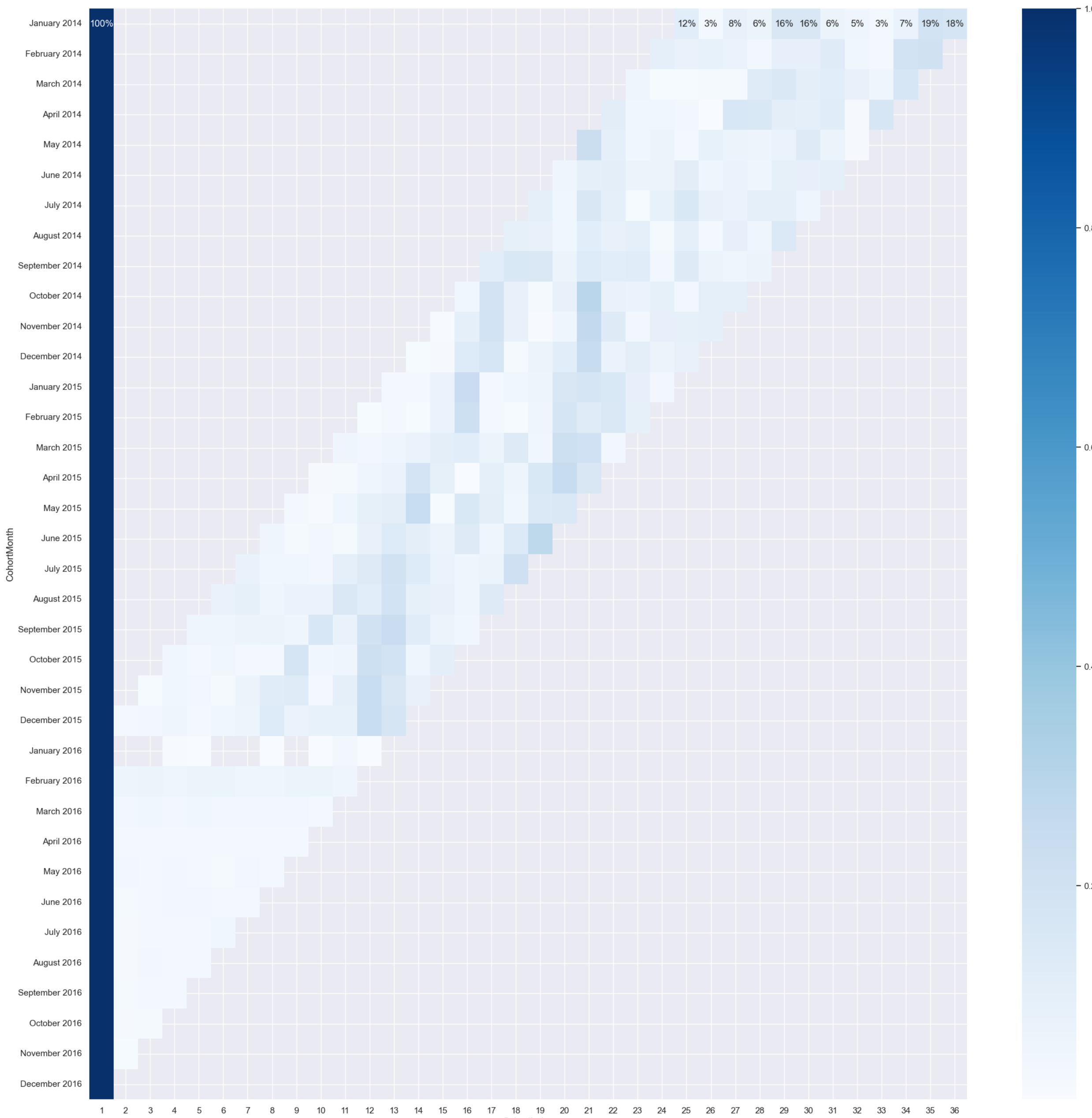
- According to the customer segmentation described above, approximately **15% of our clients are high value clients**, whereas the **majority of our clientele are low value and lost clients**

Cohort Analysis

```
# create an invoice month

# Function for month
def get_month(x):
  return dt.datetime(x.year, x.month,1)

# apply the function
df['InvoiceMonth'] = df['OrderDate'].apply(get_month)
# create a column index with the minimum invoice date aka first time customer was aquired
df['CohortMonth'] = df.groupby('CustomerKey')
['InvoiceMonth'].transform('min')

# create a date element function to get a series for subtranction
def get_date_elements(data,column):
  day = data[column].dt.day
  month = data[column].dt.month
  year = data[column].dt.year
  return day, month, year

# get date elements for our cohort and invoice columns(one dimentional Series)
```

```python
_, Invoice_month, Invoice_year = get_date_elements(df, 'InvoiceMonth')
_, Cohort_month, Cohort_year = get_date_elements(df, 'CohortMonth')

# create a cohort index
year_diff = Invoice_year - Cohort_year
month_diff = Invoice_month - Cohort_month
df['CohortIndex'] = year_diff*12+month_diff+1

# count the customer ID by grouping by Cohort Month and Cohort index
cohort_data = df.groupby(['CohortMonth','CohortIndex'])
['CustomerKey'].apply(pd.Series.nunique).reset_index()

# create pivot table
cohort_table = cohort_data.pivot(index='CohortMonth',
columns=['CohortIndex'],values='CustomerKey')

# change index
cohort_table.index = cohort_table.index.strftime('%B %Y')

# cohort table for percentage
new_cohort_table = cohort_table.divide(cohort_table.iloc[:,0],axis=0)

# create percentages
plt.figure(figsize=(25,25))
sns.heatmap(new_cohort_table, annot=True, cmap='Blues',fmt='.0%')
```

```
<Axes: xlabel='CohortIndex', ylabel='CohortMonth'>
```



- We can infer from the heatmap above that client retention in 2014 was subpar
- Since August of 2015, we have noticed some customers returning, though not in large numbers
- 2016 brought about a slight improvement in retention