# Supply Chain Analysis using Python

Let's get started with the task of Supply Chain Analysis by importing the necessary Python libraries and the dataset:

```
In [4]: import pandas as pd
import plotly.express as px
import plotly.io as pio
import plotly.graph_objects as go
pio.templates.default = "plotly_white"
```

```
In [5]: data =pd.read_csv("supply_chain_data.csv")
```

```
In [6]: data.head()
```

Out[6]:

| | Product type | SKU | Price | Availability | Number of products sold | Revenue generated | Customer demographics | Stock levels | Lead times | Order quantities | ... | Location | Lead time |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | haircare | SKU0 | 69.808006 | 55 | 802 | 8661.996792 | Non-binary | 58 | 7 | 96 | ... | Mumbai | 29 |
| 1 | skincare | SKU1 | 14.843523 | 95 | 736 | 7460.900065 | Female | 53 | 30 | 37 | ... | Mumbai | 23 |
| 2 | haircare | SKU2 | 11.319683 | 34 | 8 | 9577.749626 | Unknown | 1 | 10 | 88 | ... | Mumbai | 12 |
| 3 | skincare | SKU3 | 61.163343 | 68 | 83 | 7766.836426 | Non-binary | 23 | 13 | 59 | ... | Kolkata | 24 |
| 4 | skincare | SKU4 | 4.805496 | 26 | 871 | 2686.505152 | Non-binary | 5 | 3 | 56 | ... | Delhi | 5 |

5 rows × 24 columns

```
In [7]: data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100 entries, 0 to 99
Data columns (total 24 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   Product type             100 non-null    object
 1   SKU                      100 non-null    object
 2   Price                    100 non-null    float64
 3   Availability             100 non-null    int64
 4   Number of products sold  100 non-null    int64
 5   Revenue generated        100 non-null    float64
 6   Customer demographics    100 non-null    object
 7   Stock levels             100 non-null    int64
 8   Lead times               100 non-null    int64
 9   Order quantities         100 non-null    int64
 10  Shipping times           100 non-null    int64
 11  Shipping carriers        100 non-null    object
 12  Shipping costs           100 non-null    float64
 13  Supplier name            100 non-null    object
 14  Location                 100 non-null    object
 15  Lead time                100 non-null    int64
 16  Production volumes       100 non-null    int64
 17  Manufacturing lead time  100 non-null    int64
 18  Manufacturing costs      100 non-null    float64
 19  Inspection results       100 non-null    object
 20  Defect rates             100 non-null    float64
 21  Transportation modes     100 non-null    object
 22  Routes                   100 non-null    object
 23  Costs                    100 non-null    float64
dtypes: float64(6), int64(9), object(9)
memory usage: 18.9+ KB
```

```
In [8]: print(data.head())
```

```
  Product type   SKU      Price  Availability  Number of products sold  \
0     haircare  SKU0  69.808006            55                      802
1     skincare  SKU1  14.843523            95                      736
2     haircare  SKU2  11.319683            34                        8
3     skincare  SKU3  61.163343            68                       83
4     skincare  SKU4   4.805496            26                      871

   Revenue generated Customer demographics  Stock levels  Lead times  \
0        8661.996792            Non-binary            58           7
1        7460.900065                Female            53          30
2        9577.749626               Unknown             1          10
3        7766.836426            Non-binary            23          13
4        2686.505152            Non-binary             5           3

   Order quantities  ...  Location Lead time  Production volumes  \
0                96  ...    Mumbai        29                 215
1                37  ...    Mumbai        23                 517
2                88  ...    Mumbai        12                 971
3                59  ...   Kolkata        24                 937
4                56  ...     Delhi         5                 414

  Manufacturing lead time Manufacturing costs  Inspection results  \
0                      29           46.279879             Pending
1                      30           33.616769             Pending
2                      27           30.688019             Pending
3                      18           35.624741                Fail
4                       3           92.065161                Fail

   Defect rates  Transportation modes   Routes       Costs
0      0.226410                  Road  Route B  187.752075
1      4.854068                  Road  Route B  503.065579
2      4.580593                   Air  Route C  141.920282
3      4.746649                  Rail  Route A  254.776159
4      3.145580                   Air  Route A  923.440632

[5 rows x 24 columns]
```

Let's have a look at the descriptive statistics of the dataset:

```
In [10]: print(data.describe())
```

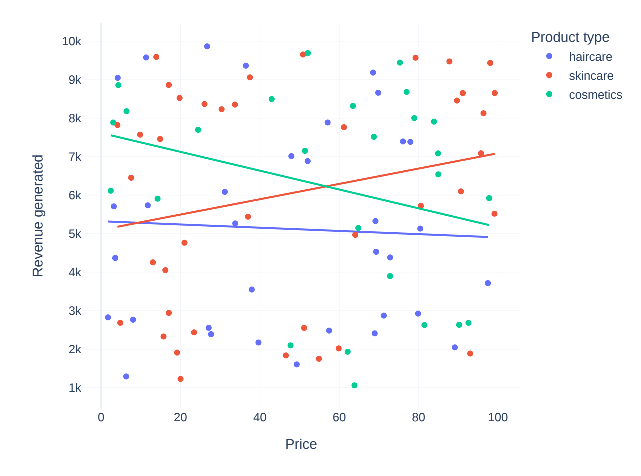
```
            Price  Availability  Number of products sold  Revenue generated  \
count  100.000000    100.000000               100.000000         100.000000
mean    49.462461     48.400000               460.990000        5776.048187
std     31.168193     30.743317               303.780074        2732.841744
min      1.699976      1.000000                 8.000000        1061.618523
25%     19.597823     22.750000               184.250000        2812.847151
50%     51.239831     43.500000               392.500000        6006.352023
75%     77.198228     75.000000               704.250000        8253.976921
max     99.171329    100.000000               996.000000        9866.465458

       Stock levels  Lead times  Order quantities  Shipping times  \
count    100.000000  100.000000        100.000000      100.000000
mean      47.770000   15.960000         49.220000        5.750000
std       31.369372    8.785801         26.784429        2.724283
min        0.000000    1.000000          1.000000        1.000000
25%       16.750000    8.000000         26.000000        3.750000
50%       47.500000   17.000000         52.000000        6.000000
75%       73.000000   24.000000         71.250000        8.000000
max      100.000000   30.000000         96.000000       10.000000

       Shipping costs   Lead time  Production volumes  \
count      100.000000  100.000000          100.000000
mean         5.548149   17.080000          567.840000
std          2.651376    8.846251          263.046861
min          1.013487    1.000000          104.000000
25%          3.540248   10.000000          352.000000
50%          5.320534   18.000000          568.500000
75%          7.601695   25.000000          797.000000
max          9.929816   30.000000          985.000000

       Manufacturing lead time  Manufacturing costs  Defect rates       Costs
count                100.00000           100.000000    100.000000  100.000000
mean                  14.77000            47.266693      2.277158  529.245782
std                    8.91243            28.982841      1.461366  258.301696
min                    1.00000             1.085069      0.018608  103.916248
25%                    7.00000            22.983299      1.009650  318.778455
50%                   14.00000            45.905622      2.141863  520.430444
75%                   23.00000            68.621026      3.563995  763.078231
max                   30.00000            99.466109      4.939255  997.413450
```

```
In [11]: data.columns
```

```
Out[11]: Index(['Product type', 'SKU', 'Price', 'Availability',
       'Number of products sold', 'Revenue generated', 'Customer demographics',
       'Stock levels', 'Lead times', 'Order quantities', 'Shipping times',
       'Shipping carriers', 'Shipping costs', 'Supplier name', 'Location',
       'Lead time', 'Production volumes', 'Manufacturing lead time',
       'Manufacturing costs', 'Inspection results', 'Defect rates',
       'Transportation modes', 'Routes', 'Costs'],
      dtype='object')
```

Now let's get started with analyzing the Supply Chain by looking at the relationship between the price of the products and the revenue generated by them:

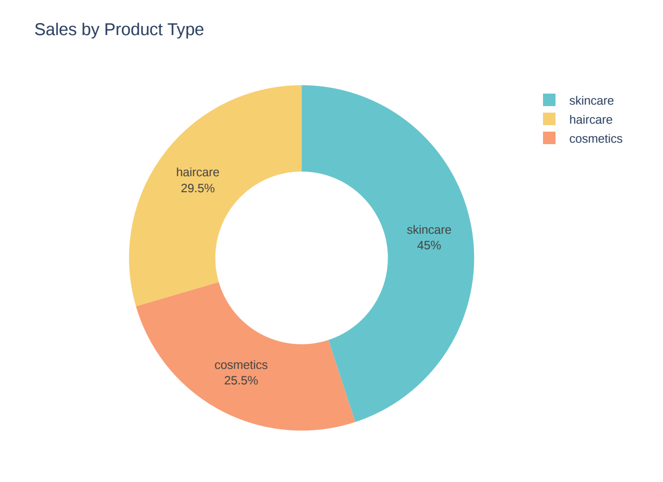
```
In [13]: fig = px.scatter(data, x='Price',
                 y='Revenue generated',
                 color='Product type',
                 hover_data=['Number of products sold'],
                 trendline="ols")
fig.show()
```




Thus, the company derives more revenue from skincare products, and the higher the price of skincare products, the more revenue they generate.

Now let's have a look at the sales by product type:

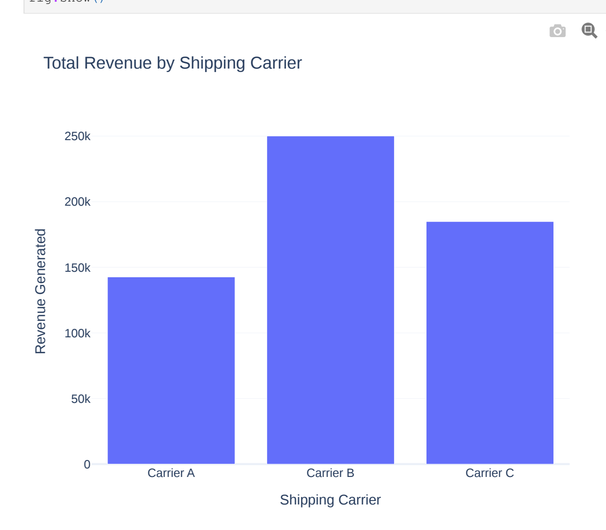
```
In [15]: sales_data = data.groupby('Product type')['Number of products sold'].sum().reset_index()

pie_chart = px.pie(sales_data, values='Number of products sold', names='Product type',
                   title='Sales by Product Type',
                   hover_data=['Number of products sold'],
                   hole=0.5,
                   color_discrete_sequence=px.colors.qualitative.Pastel)

pie_chart.update_traces(textposition='inside', textinfo='percent+label')
pie_chart.show()
```




So 45% of the business comes from skincare products, 29.5% from haircare, and 25.5% from cosmetics.

Now let's have a look at the total revenue generated from shipping carriers:

```
In [17]: total_revenue = data.groupby('Shipping carriers')['Revenue generated'].sum().reset_index()
fig = go.Figure()
fig.add_trace(go.Bar(x=total_revenue['Shipping carriers'],
                     y=total_revenue['Revenue generated']))
fig.update_layout(title='Total Revenue by Shipping Carrier',
                  xaxis_title='Shipping Carrier',
                  yaxis_title='Revenue Generated')
fig.show()
```




So the company is using three carriers for transportation, and Carrier B helps the company in generating more revenue.

Now let's have a look at the Average lead time and Average Manufacturing Costs for all products of the company:

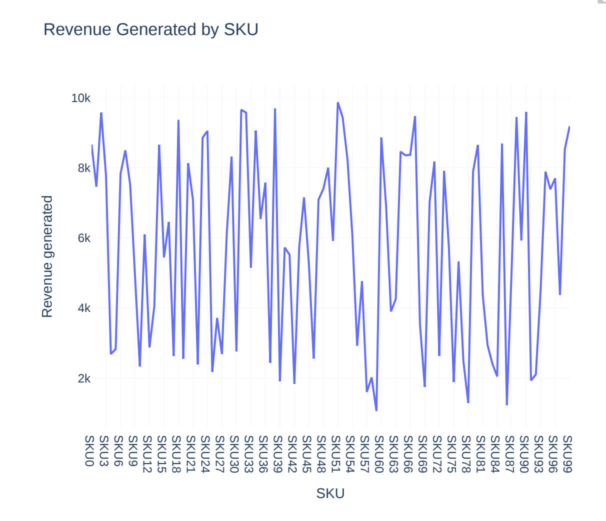
```
In [19]: avg_lead_time = data.groupby('Product type')['Lead time'].mean().reset_index()
avg_manufacturing_costs = data.groupby('Product type')['Manufacturing costs'].mean().reset_index()
result = pd.merge(avg_lead_time, avg_manufacturing_costs, on='Product type')
result.rename(columns={'Lead time': 'Average Lead Time', 'Manufacturing costs': 'Average Manufacturing
print(result)
```

```
  Product type  Average Lead Time  Average Manufacturing Costs
0    cosmetics          13.538462                    43.052740
1     haircare          18.705882                    48.457993
2     skincare          18.000000                    48.993157
```

Now let's analyze the revenue generated by each SKU-stands for Stock Keeping Units.

SKU stands for Stock Keeping Units. They're like special codes that help companies keep track of all the different things they have for sale.

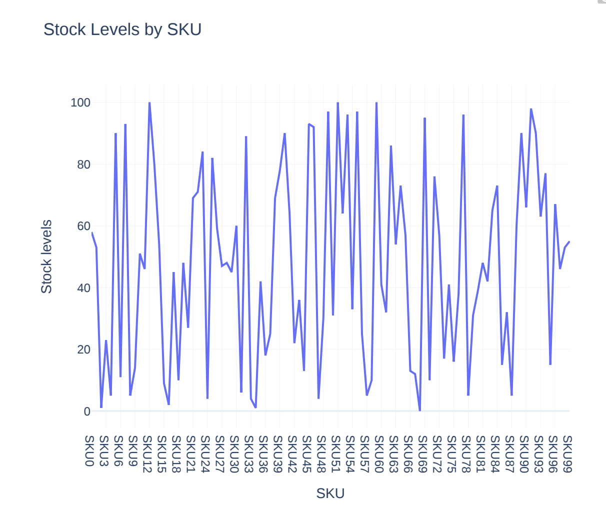
```
In [21]: revenue_chart = px.line(data, x='SKU',
                        y='Revenue generated',
                        title='Revenue Generated by SKU')
revenue_chart.show()
```




Now let's have a look at the stock levels of each SKU:

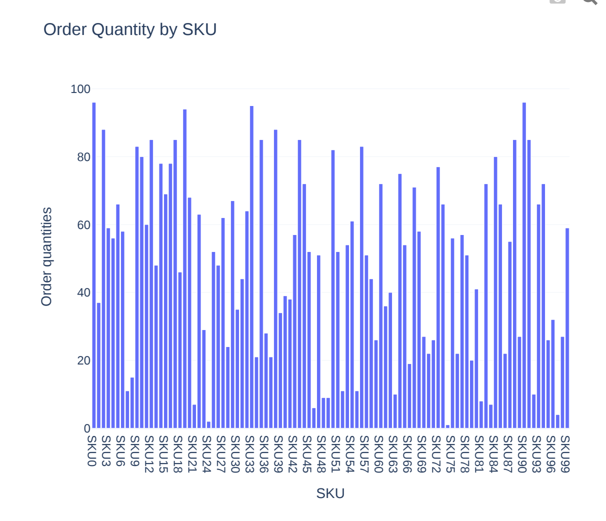
There's another column in the dataset as Stock levels. Stock levels refer to the number of products a store or business has in its inventory.

```
In [23]: stock_chart = px.line(data, x='SKU',
                      y='Stock levels',
                      title='Stock Levels by SKU')
stock_chart.show()
```




Now let's have a look at the order quantity of each SKU:

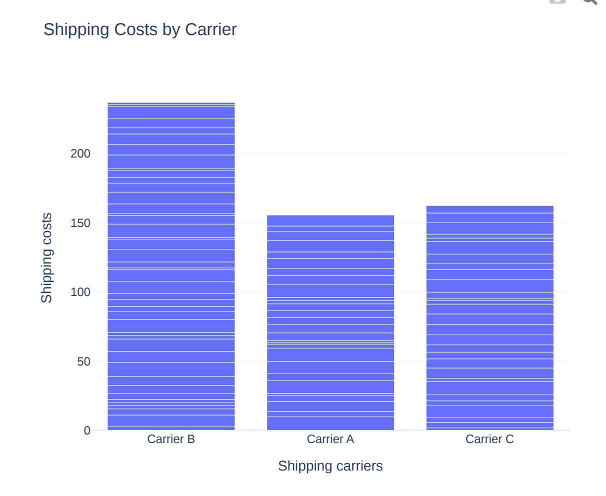
```
In [25]: order_quantity_chart = px.bar(data, x='SKU',
                              y='Order quantities',
                              title='Order Quantity by SKU')
order_quantity_chart.show()
```




## Cost Analysis

Now let's analyze the shipping cost of Carriers:

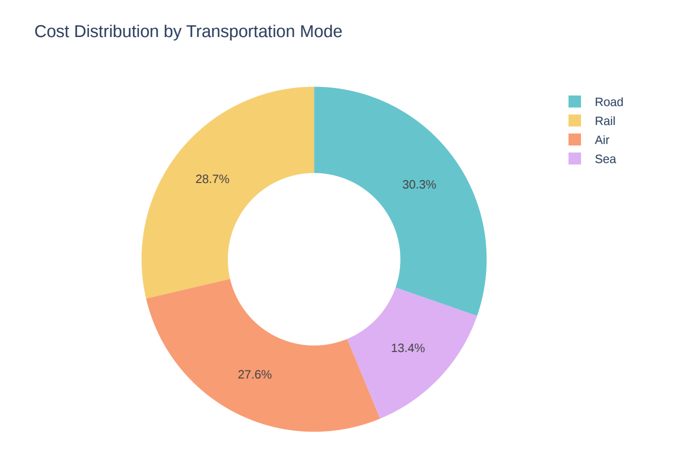
```
In [27]: shipping_cost_chart = px.bar(data, x='Shipping carriers',
                             y='Shipping costs',
                             title='Shipping Costs by Carrier')
shipping_cost_chart.show()
```




In one of the above visualizations, we discovered that Carrier B helps the company in more revenue. It is also the most costly Carrier among the three.

Now let's have a look at the cost distribution by transportation mode:

```
In [30]: transportation_chart = px.pie(data,
                              values='Costs',
                              names='Transportation modes',
                              title='Cost Distribution by Transportation Mode',
                              hole=0.5,
                              color_discrete_sequence=px.colors.qualitative.Pastel)
transportation_chart.show()
```

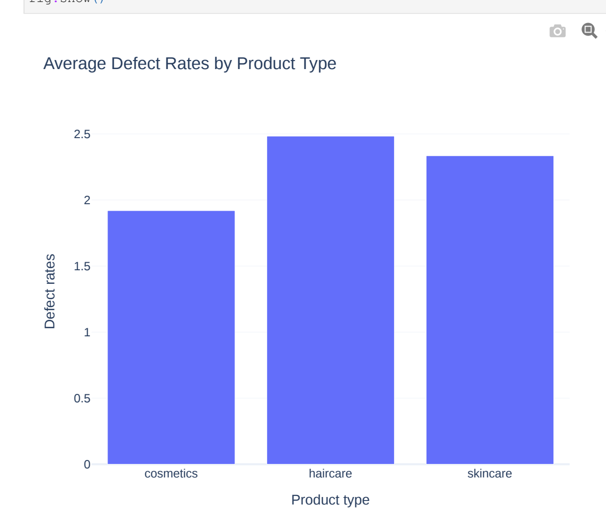



So the company spends more on Road and Rail modes of transportation for the transportation of Goods.

## Analyzing Defect Rate

The defect rate in the supply chain refers to the percentage of products that have something wrong or are found broken after shipping. Let's have a look at the average defect rate of all product types:

```
In [32]: defect_rates_by_product = data.groupby('Product type')['Defect rates'].mean().reset_index()

fig = px.bar(defect_rates_by_product, x='Product type', y='Defect rates',
             title='Average Defect Rates by Product Type')
fig.show()
```




So the defect rate of haircare products is higher. Now let's have a look at the defect rates by mode of transportation:

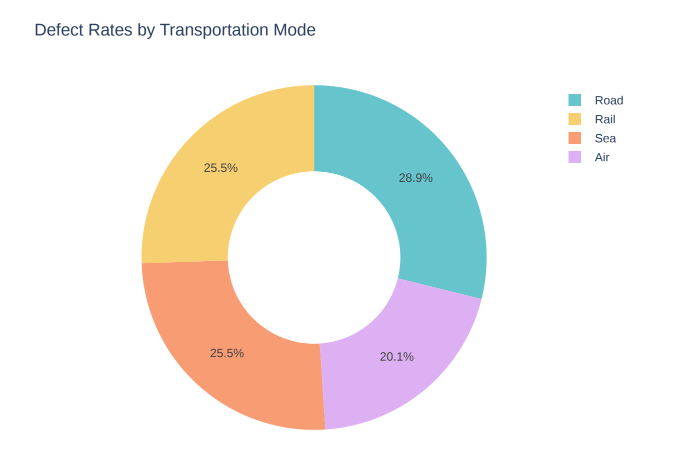
```
In [33]: pivot_table = pd.pivot_table(data, values='Defect rates',
                             index=['Transportation modes'],
                             aggfunc='mean')
```

```
In [34]: pivot_table
```

Out[34]:

| Transportation modes | Defect rates |
|---|---|
| Air | 1.823924 |
| Rail | 2.318814 |
| Road | 2.620938 |
| Sea | 2.315281 |

```
In [35]: transportation_chart = px.pie(values=pivot_table["Defect rates"],
                              names=pivot_table.index,
                              title='Defect Rates by Transportation Mode',
                              hole=0.5,
                              color_discrete_sequence=px.colors.qualitative.Pastel)
transportation_chart.show()
```




Road transportation results in a higher defect rate, and Air transportation has the lowest defect rate.

Supply Chain Analysis means analyzing various components of a Supply Chain to understand how to improve the effectiveness of the Supply Chain to create more value for customers.

## Summary

1. Thus, the company derives more revenue from skincare products, and the higher the price of skincare products, the more revenue they generate.

2. 45% of the business comes from skincare products, 29.5% from haircare, and 25.5% from cosmetics.

3. The company is using three carriers for transportation, and Carrier B helps the company in generating more revenue

4. Carrier B helps the company in more revenue. It is also the most costly Carrier among the three.

5. The company spends more on Road and Rail modes of transportation for the transportation of Goods

6. The defect rate of haircare products is higher that is 2.5%

7. Road transportation results in a higher defect rate (28.9%), and Air transportation has the lowest defect rate (20.1%)