



بيانات
الاتصالات
وتقنيات معرفة



GROUP:

RS-2367 ALX1_DAT1_G1e

PROJECT:

Supply Chain Dataset Analysis

DATA ANALYSIS FINAL PROJECT

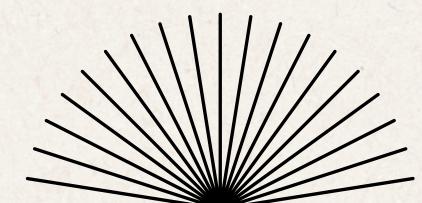
BRIEF DECK

PRESENTED BY:

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Hussien Khaled
Mohamed Nabil

PRESENTED TO:

Eng : Hafssa , Eng : Mayar



Our team



Bahaa Mohamed



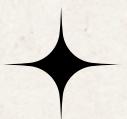
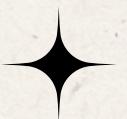
Mohamed Idress



Hussien Khaled



Mohamad Nabil





Objective

The project is designed to deliver actionable insights for decision-makers by addressing critical analysis and forecasting questions. It will culminate in the development of a visualization dashboard that highlights key findings. Leveraging tools like SQL, Python (with pandas, matplotlib, seaborn, and numpy), and Tableau, the project will enable data-driven decisions through thorough analysis, trend forecasting, and compelling visualizations.

Key Questions:

- Which product types generate the highest revenue?
- How does stock availability impact sales?
- What are the future sales trends for top-selling products?
- Which suppliers have the most consistent lead times?
- How do shipping costs affect profitability across regions?

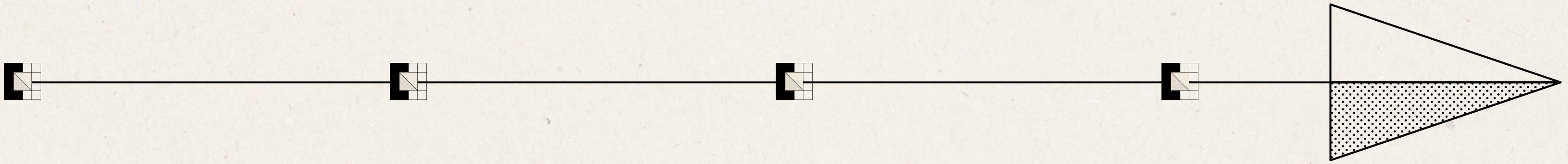
By answering these questions, the project will support decision-makers in making informed, strategic choices based on trends and data forecasts.

Agenda

WEEK 1	Build Data Model, Data Cleaning and Preprocessing
WEEK 2	Visualization Dashboard and Final Presentation
WEEK 3	Forecasting Questions Phase
WEEK 4	Visualization Dashboard and Final Presentation

Timeline

Briefly discuss the key dates for the project.



WEEK 1

- Understanding Data
- Exploration using **Python**
- Split data to tables and building data modeling and make ERD and mapping using **ERDplus** website
- Build a data model and clean and preprocess the data using **SQL**

WEEK 2

- Determine all possible analysis questions that can be deducted from the given dataset
- Set of analysis questions that can be answered via the dataset

WEEK 3

- Determine a set of forecasting questions and answer them using the trends found in the given dataset using **Python , Excel**

WEEK 4

- Convert all insights and answers to Visualization Dashboard using **Tableau**

Build Data Model, Data Cleaning and Preprocessing

WEEK 1

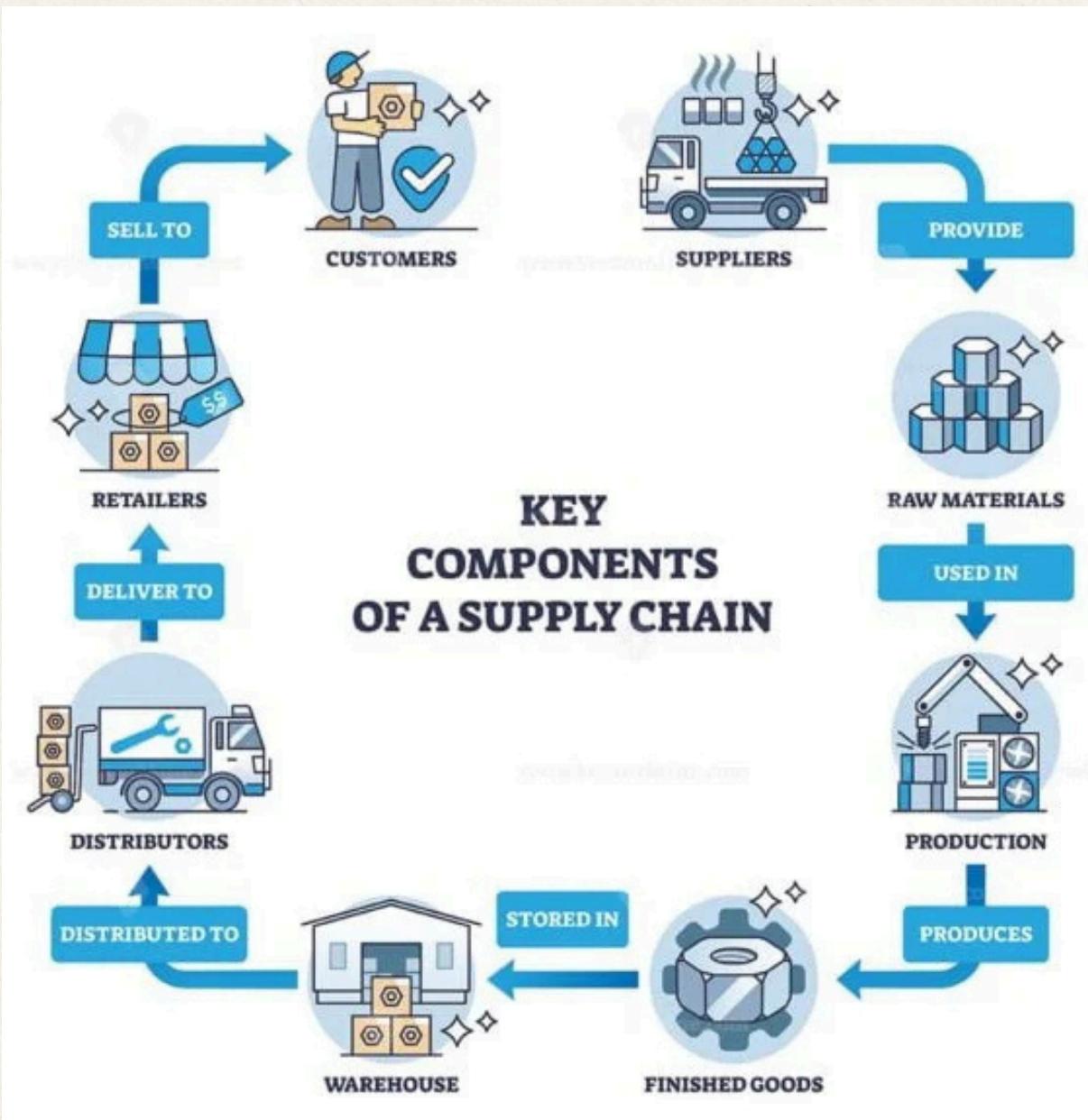


UNDERSTANDING THE INDUSTRY

WEEK 1

WHAT IS SUPPLY CHAIN ?

The supply Chain is the network of production and logistics involved in producing and delivering goods to customers. And 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



UNDERSTANDING THE INDUSTRY

WEEK 1

Dataset exploration and understanding what columns refer to .

The dataset consists of 24 columns and 100 entries, covering various aspects of supply chain data. Here's a brief overview of key columns:

- **Product type, SKU, Price:** Basic product information.
- **Availability, Stock levels, Order quantities:** Inventory-related data.
- **Number of products sold, Revenue generated:** Sales data.
- **Shipping times, Shipping costs, Shipping carriers:** Logistics data.
- **Supplier name, Location, Lead time:** Supplier-related details.
- **Manufacturing costs, Defect rates:** Production and quality control metrics.
- **Transportation modes, Routes:** Transportation data.
- **Customer demographics:** Customer-related insights.

Exploration & Manipulation using Python

WEEK 1

Import library and understand the ship of data then make some statistics to deep understanding data trend and behiver and check for **nulls** and **duplicates** values

- Importing necessary libraries for data manipulation, analysis

Code :

```
import pandas as pd  
import numpy as np  
import matplotlib.pyplot as plt  
import seaborn as sns
```

- Reading data

Code :

```
df=pd.read_csv  
("supply_chain_data.csv",index_col=0)  
df
```

The screenshot shows a Jupyter Notebook interface. The code cell contains the imports and the command to read the CSV file. The resulting DataFrame is displayed as a table below.

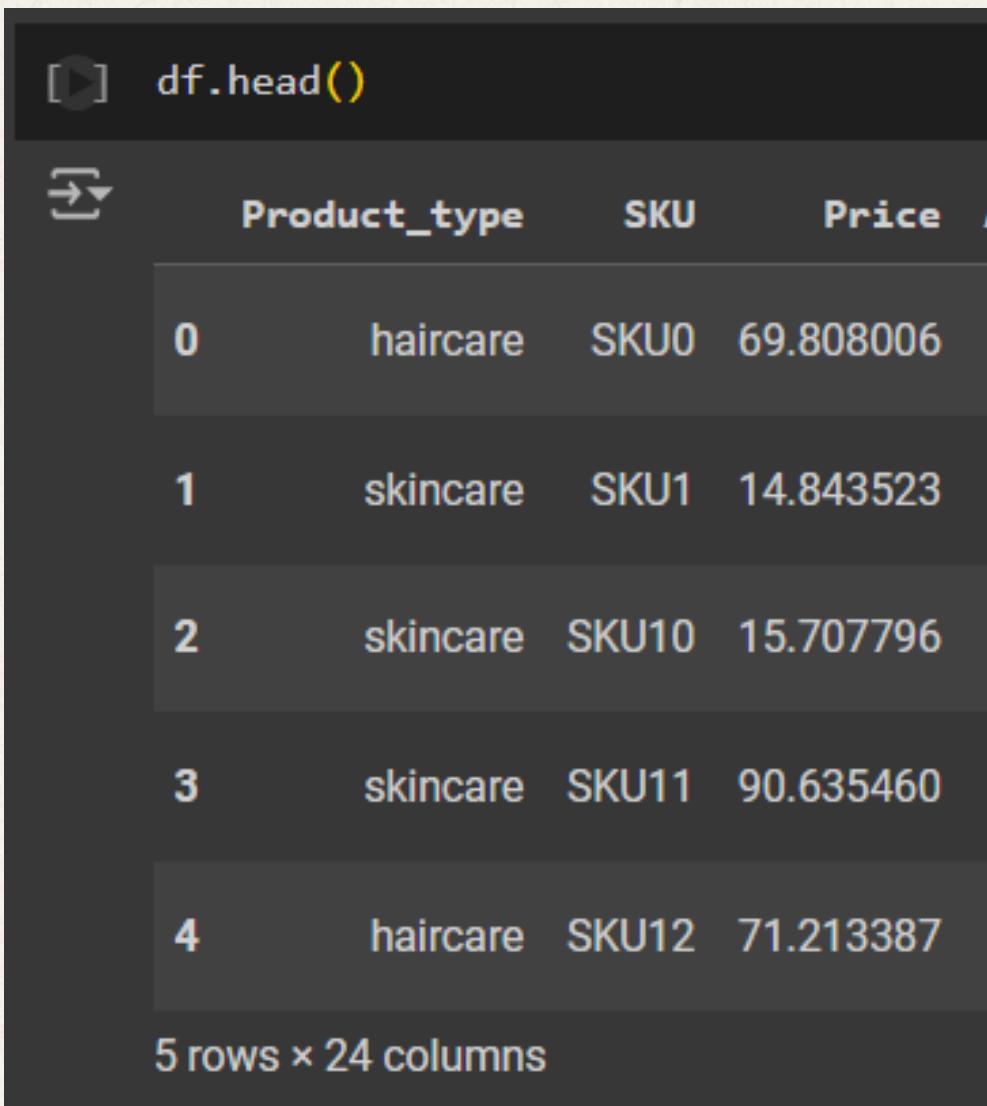
	Product_type	SKU	Price	Availability	Number_of_products_sold	Revenue_generated	Customer_demographics	Stock_levels	Lead_times	Order_quantities	...	Location	Lead_time	Production_vo
0	haircare	SKU0	69.808006	55	802	8661.997070	Non-binary	58	7	96	...	Mumbai	29	
1	skincare	SKU1	14.843523	95	736	7460.899902	Female	53	30	37	...	Mumbai	23	
2	skincare	SKU10	15.707796	11	996	2330.965820	Non-binary	51	13	80	...	Kolkata	18	
3	skincare	SKU11	90.635460	95	960	6099.944336	Female	46	23	60	...	Kolkata	28	

Exploration & Manipulation using Python

WEEK 1

Reading Data

Code : df.head()

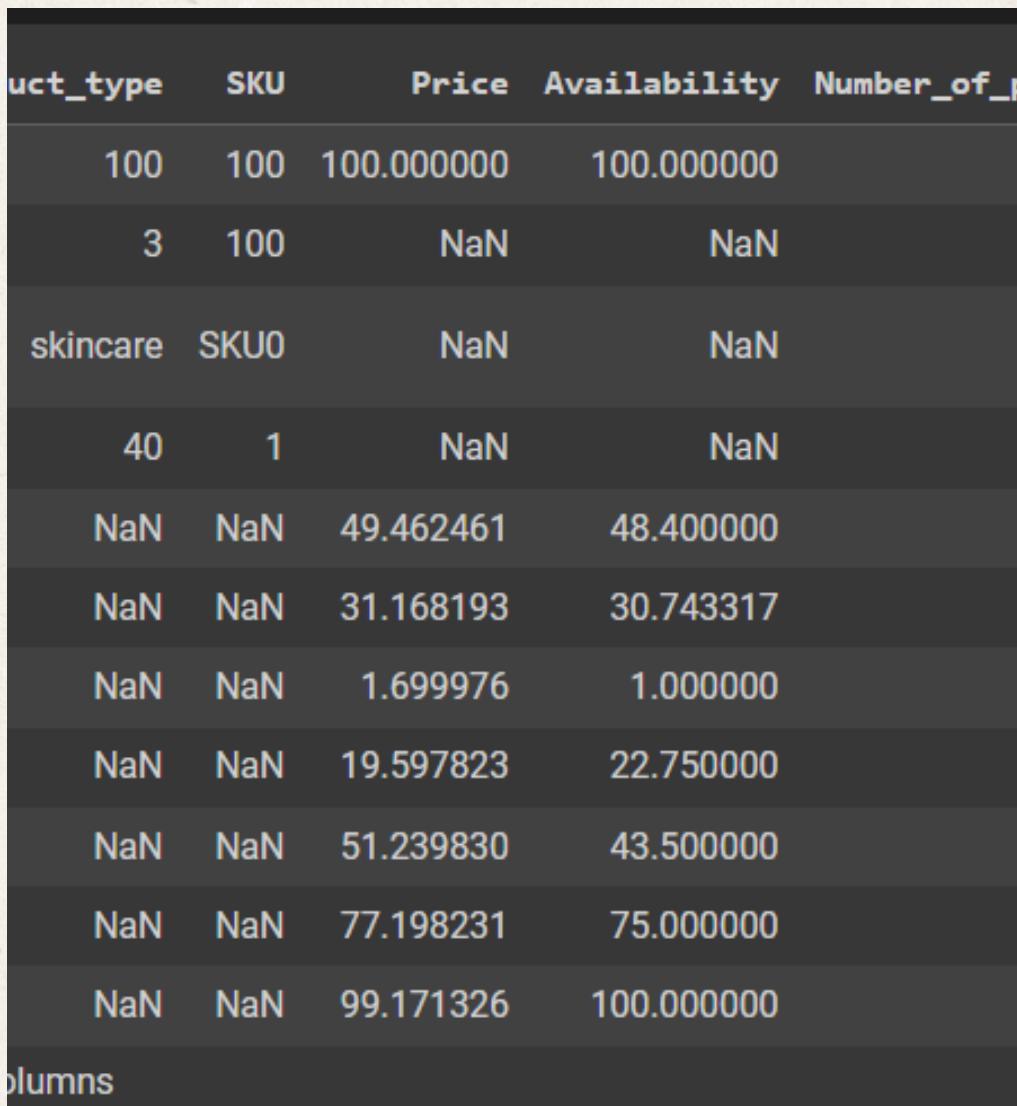


A screenshot of a Jupyter Notebook cell showing the output of `df.head()`. The output displays the first 5 rows of a DataFrame. The columns are labeled `Product_type`, `SKU`, `Price`, and `Availability`. The data shows two rows for haircare (index 0) and three rows for skincare (index 1, 2, 3). The `Availability` column contains values like 100.000000, 100.000000, and NaN. The code cell is labeled `[1] df.head()`.

	Product_type	SKU	Price	Availability
0	haircare	SKU0	69.808006	100.000000
1	skincare	SKU1	14.843523	3 100 NaN NaN
2	skincare	SKU10	15.707796	40 1 NaN NaN
3	skincare	SKU11	90.635460	NaN NaN 49.462461 48.400000
4	haircare	SKU12	71.213387	NaN NaN 31.168193 30.743317

5 rows × 24 columns

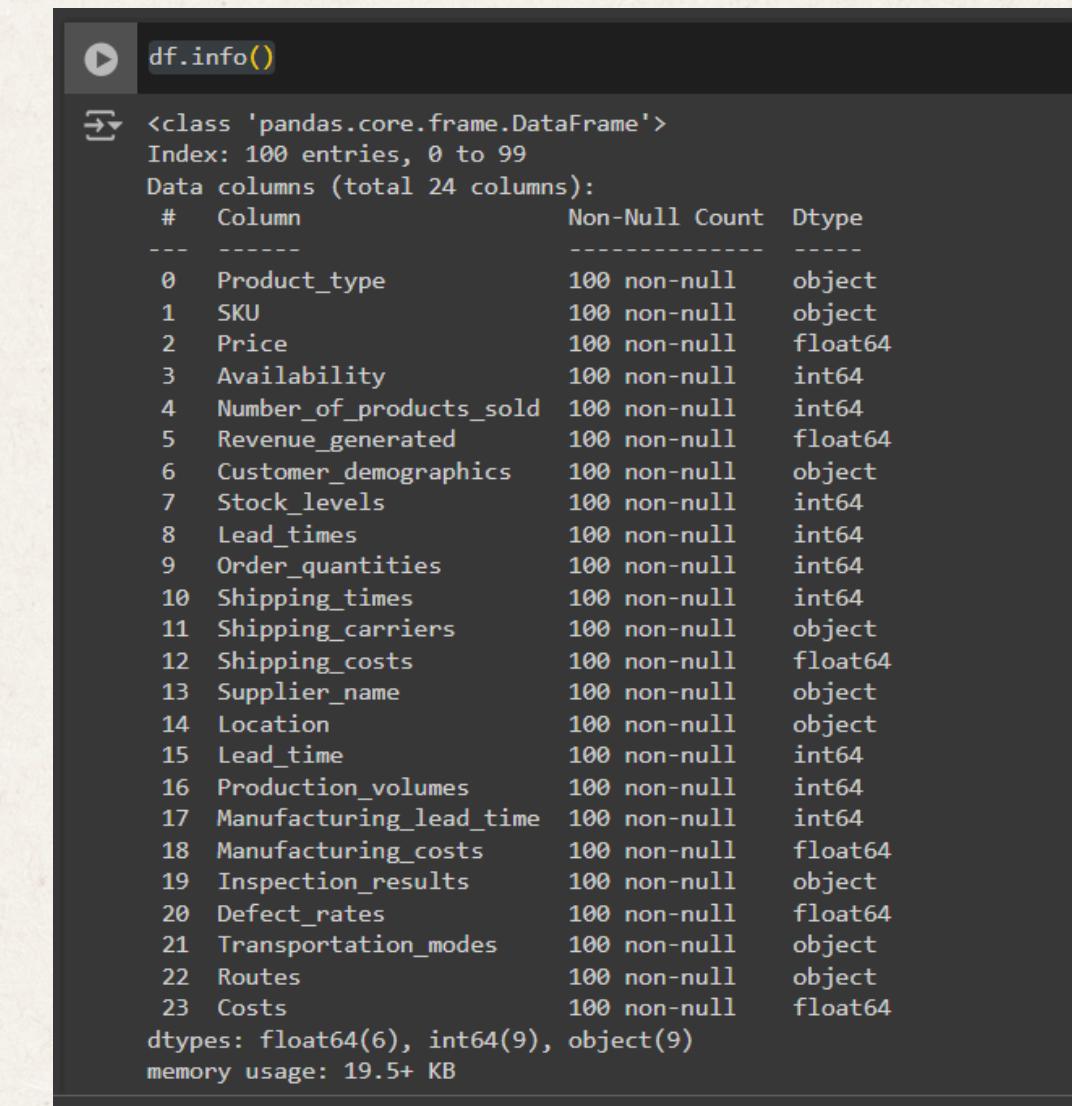
Code : df.describe(include="all")



A screenshot of a Jupyter Notebook cell showing the output of `df.describe(include="all")`. The output displays statistical summary information for all columns. The columns are labeled `Product_type`, `SKU`, `Price`, and `Availability`. The data shows various summary statistics like count, mean, std, min, and max for each column. The code cell is labeled `[2] df.describe(include='all')`.

	Product_type	SKU	Price	Availability
count	100	100	100.000000	100.000000
mean	3	100	NaN	NaN
std				
min	0	SKU0	NaN	NaN
25%	40	1	NaN	NaN
50%	NaN	NaN	49.462461	48.400000
75%	NaN	NaN	1.699976	1.000000
max	NaN	NaN	19.597823	22.750000

Code : df.info()



A screenshot of a Jupyter Notebook cell showing the output of `df.info()`. The output displays detailed information about the DataFrame, including the class, index, data columns, non-null counts, and data types. The code cell is labeled `[3] df.info()`.

#	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: 19.5+ KB

Exploration & Manipulation using Python

WEEK 1

Checking for nulls

The `isnull()` function checks for missing (null) values in the DataFrame `df` and returns a DataFrame of the same shape with `True` where values are null and `False` where they're not. The `sum()` function then counts the total number of null values in each column.

```
df.isnull().sum()>0
```

Product_type	False
SKU	False
Price	False
Availability	False
Number_of_products_sold	False
Revenue_generated	False
Customer_demographics	False
Stock_levels	False
Lead_times	False
Order_quantities	False
Shipping_times	False
Shipping_carriers	False
Shipping_costs	False
Supplier_name	False
Location	False
Lead_time	False
Production_volumes	False
Manufacturing_lead_time	False
Manufacturing_costs	False
Inspection_results	False
Defect_rates	False
Transportation_modes	False
Routes	False
Costs	False
	dtype: bool

Exploration & Manipulation using Python

WEEK 1

Check and Remove Duplicates

The `duplicated()` function checks for duplicate rows in the DataFrame `df`. It returns a Boolean Series where True indicates that a row is a duplicate. The `sum()` function counts how many True values there are, i.e., the number of duplicate rows.

Check for Duplicates

The `duplicated()` function checks for duplicate rows in the DataFrame `df`.

It returns a Boolean Series where True indicates that a row is a duplicate.

The `sum()` function counts how many True values there are, i.e., the number of duplicate rows.

```
[ ] if df.duplicated().sum() > 0:  
    # If the count of duplicates is greater than 0, print a message indicating duplicates are present.  
    print("Duplicates are present")  
else:  
    # If there are no duplicates, print a message indicating no duplicates exist.  
    print("No Duplicates exist")
```

→ No Duplicates exist

Remove Duplicates

```
[ ] df = df.drop_duplicates(keep='first')  
# The `keep='first'` argument ensures that only the first occurrence of each duplicate row is kept,  
# and all subsequent duplicates are dropped. The resulting DataFrame without duplicates is assigned back to `df`.
```

Exploration & Manipulation using Python

WEEK 1

Check that dataset has no null or duplicate

```
▶ df.info()
→ <class 'pandas.core.frame.DataFrame'>
Index: 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)
```

```
▶ df.isnull().sum()
```

Exploration & Manipulation using Python

WEEK 1

Create boxplot graph to detect outliers of the data

▼ Create boxplot graph to detect outliers of the data

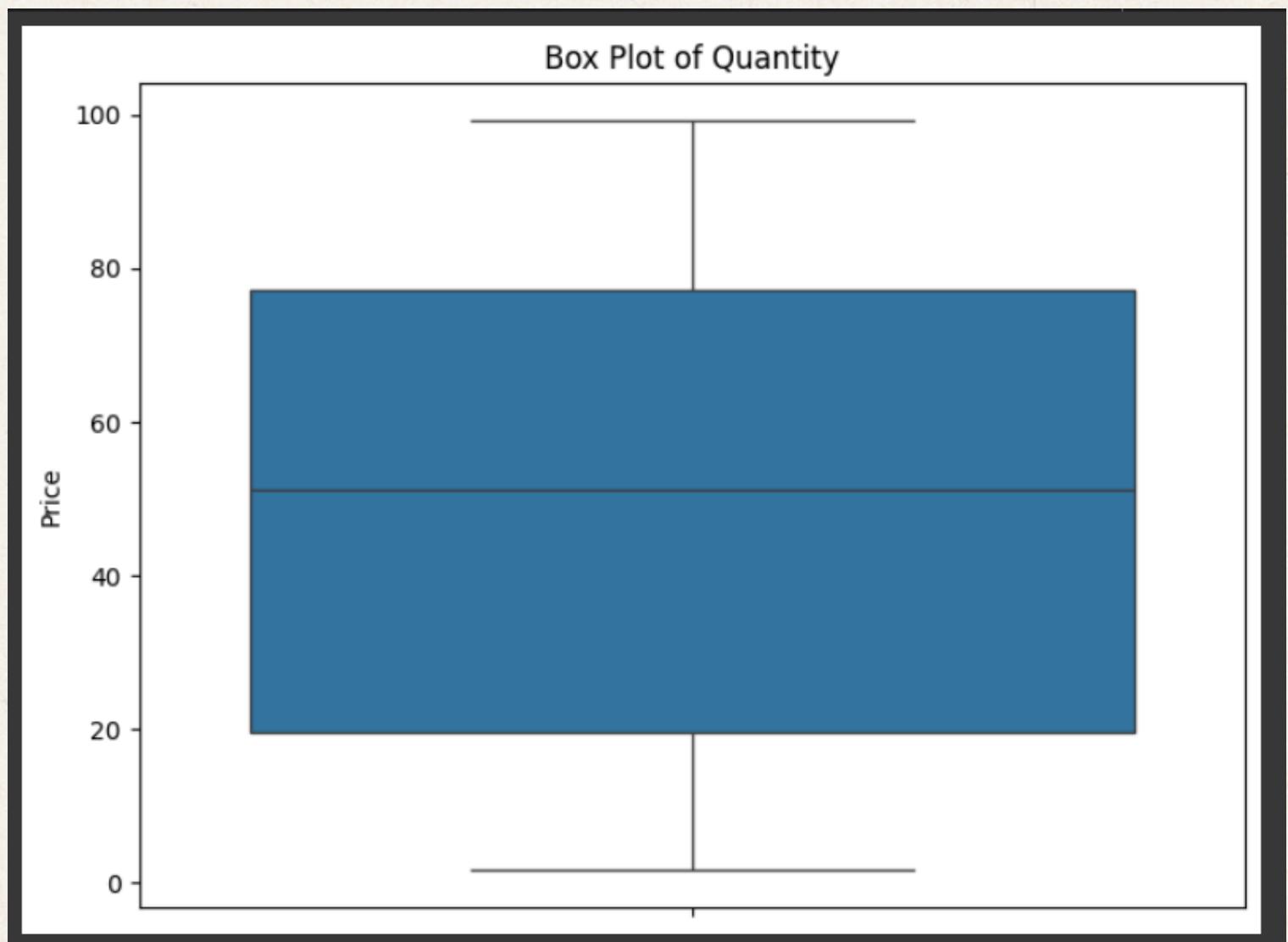
```
▶ # Box plot for Quantity
plt.figure(figsize=(8, 6))

# Use Seaborn's `boxplot()` function to create a box plot.
# The `data` parameter specifies the DataFrame `df`, and `y='Quantity'` indicates that
# we want to plot the 'Quantity' column on the y-axis.
sns.boxplot(data=df, y='Price')

# Set the title of the plot to 'Box Plot of Quantity'.
plt.title('Box Plot of Quantity')

# Set the label for the y-axis to 'Quantity'.
plt.ylabel('Price')

# Display the plot.
plt.show()
```



Exploration & Manipulation using Python

WEEK 1

Calculate outliers and their index

▼ Calculate outliers and their index

+ Code + Text

```
[ ] # Calculate the first quartile (Q1), which is the 25th percentile of the 'Price' column.  
Q1 = df['Price'].quantile(0.25)  
  
# Calculate the third quartile (Q3), which is the 75th percentile of the 'Price' column.  
Q3 = df['Price'].quantile(0.75)  
  
# Calculate the Interquartile Range (IQR), which is the difference between Q3 and Q1.  
IQR = Q3 - Q1  
  
# Calculate the lower bound for detecting outliers, which is Q1 minus 1.5 times the IQR.  
lower_bound = Q1 - 1.5 * IQR  
  
# Calculate the upper bound for detecting outliers, which is Q3 plus 1.5 times the IQR.  
upper_bound = Q3 + 1.5 * IQR  
  
# Detect outliers in the 'Price' column.  
# Rows where 'Price' is less than the lower bound or greater than the upper bound are considered outliers.  
outliers = df[(df['Price'] < lower_bound) | (df['Price'] > upper_bound)]  
  
# Print the outliers detected in the 'Price' column.  
print("Outliers in Price:")  
print(outliers)
```

→ Outliers in Price:

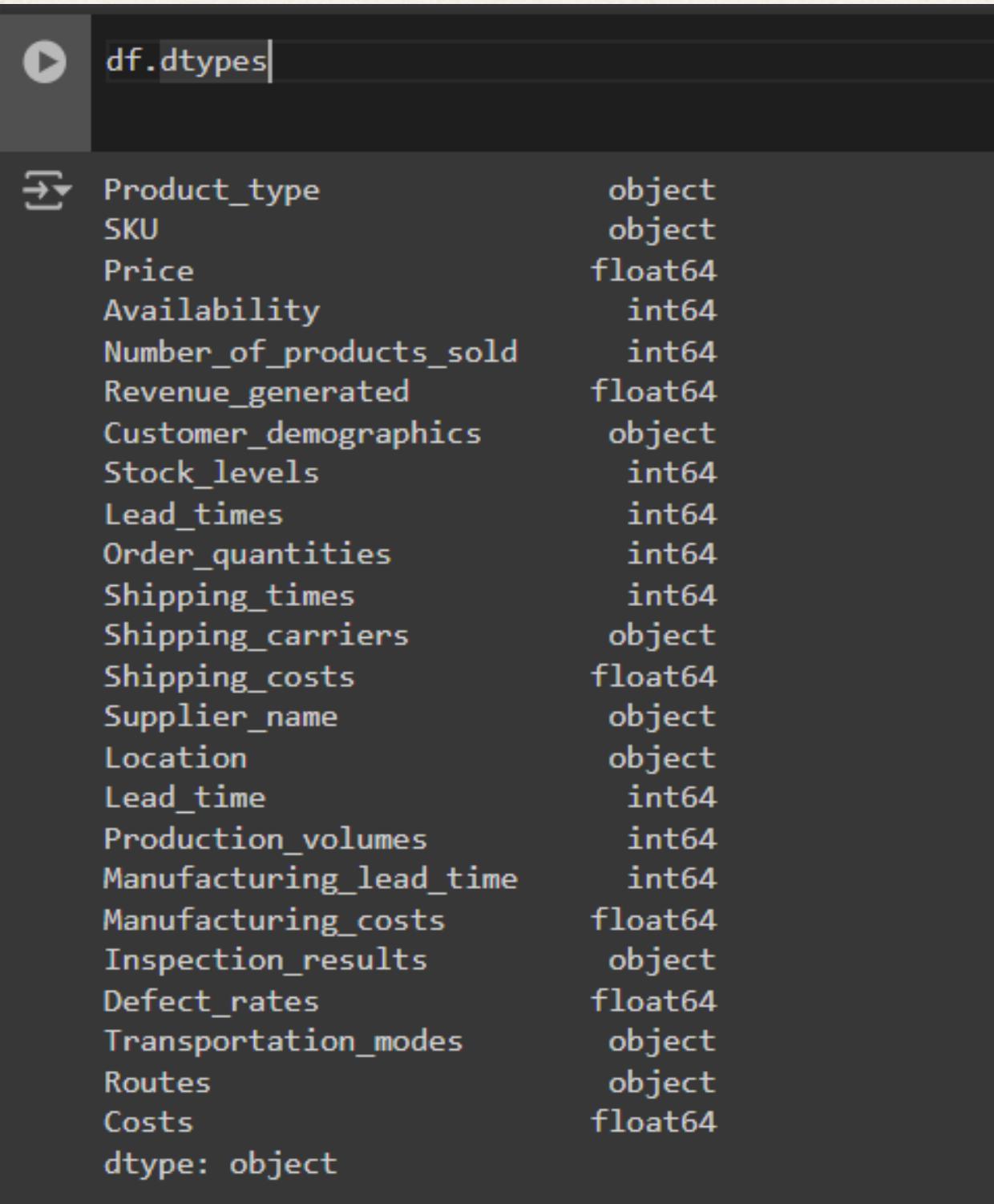
Empty DataFrame
Columns: [Product_type, SKU, Price, Availability, Number_of_products_sold, Revenue_generated, Customer_demographics,
Index: []]

[0 rows x 24 columns]

Exploration & Manipulation using Python

WEEK 1

Data types and converting to the right types



A screenshot of a Jupyter Notebook cell showing the output of `df.dtypes`. The output displays the data types for various columns in a DataFrame. The columns and their corresponding data types are:

Column	Type
Product_type	object
SKU	object
Price	float64
Availability	int64
Number_of_products_sold	int64
Revenue_generated	float64
Customer_demographics	object
Stock_levels	int64
Lead_times	int64
Order_quantities	int64
Shipping_times	int64
Shipping_carriers	object
Shipping_costs	float64
Supplier_name	object
Location	object
Lead_time	int64
Production_volumes	int64
Manufacturing_lead_time	int64
Manufacturing_costs	float64
Inspection_results	object
Defect_rates	float64
Transportation_modes	object
Routes	object
Costs	float64
<code>dtype: object</code>	

Exploration & Manipulation using Python

WEEK 1

Create the Revenue column

```
# Create the Revenue column
df['Profit'] = df['Revenue_generated'] - df['Costs']
df.head()

[ ] df.tail()
```

	Product_type	SKU	Price	Availability	Number_of_products_sold	Revenue_generated	Customer_demographics	Profit
0	haircare	SKU0	69.808006	55		802	Non-binary	8661.997070
1	skincare	SKU1	14.843523	95		736	Female	7460.899902
2	skincare	SKU10	15.707796	11		996	Non-binary	2330.965820
3	skincare	SKU11	90.635460	95		960	Female	6099.944336
4	haircare	SKU12	71.213387	41		336	Unknown	2873.741455

5 rows × 25 columns

	Product_type	SKU	Price	Availability	Number_of_products_sold	Revenue_generated	Customer_demographics	Profit
95	haircare	SKU95	77.903931	65		672	Unknown	7386.363770
96	cosmetics	SKU96	24.423132	29		324	Non-binary	7698.424805

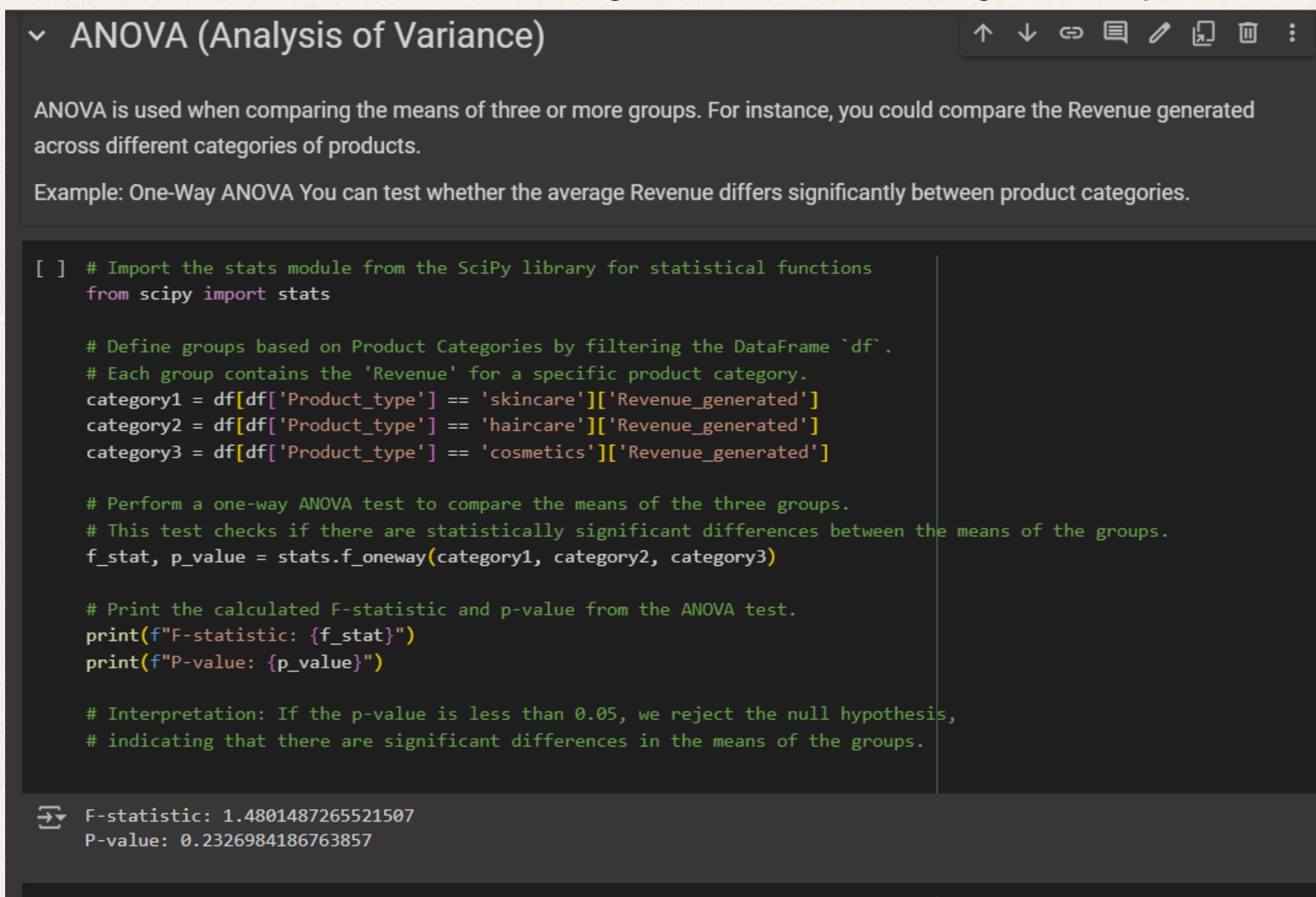
Exploration & Manipulation using Python

WEEK 1

ANOVA (Analysis of Variance)

ANOVA is used when comparing the means of three or more groups. For instance, you could compare the Revenue generated across different categories of products.

Example: One-Way ANOVA You can test whether the average Revenue differs significantly between product categories.



The screenshot shows a Jupyter Notebook cell with the title "ANOVA (Analysis of Variance)". The cell contains the following text and code:

ANOVA is used when comparing the means of three or more groups. For instance, you could compare the Revenue generated across different categories of products.

Example: One-Way ANOVA You can test whether the average Revenue differs significantly between product categories.

```
[ ] # Import the stats module from the SciPy library for statistical functions
from scipy import stats

# Define groups based on Product Categories by filtering the DataFrame `df`.
# Each group contains the 'Revenue' for a specific product category.
category1 = df[df['Product_type'] == 'skincare']['Revenue_generated']
category2 = df[df['Product_type'] == 'haircare']['Revenue_generated']
category3 = df[df['Product_type'] == 'cosmetics']['Revenue_generated']

# Perform a one-way ANOVA test to compare the means of the three groups.
# This test checks if there are statistically significant differences between the means of the groups.
f_stat, p_value = stats.f_oneway(category1, category2, category3)

# Print the calculated F-statistic and p-value from the ANOVA test.
print(f"F-statistic: {f_stat}")
print(f"P-value: {p_value}")

# Interpretation: If the p-value is less than 0.05, we reject the null hypothesis,
# indicating that there are significant differences in the means of the groups.
```

The output of the cell shows the results of the ANOVA test:

F-statistic: 1.4801487265521507
P-value: 0.2326984186763857

Exploration & Manipulation using Python

WEEK 1

Box plot for Quantity



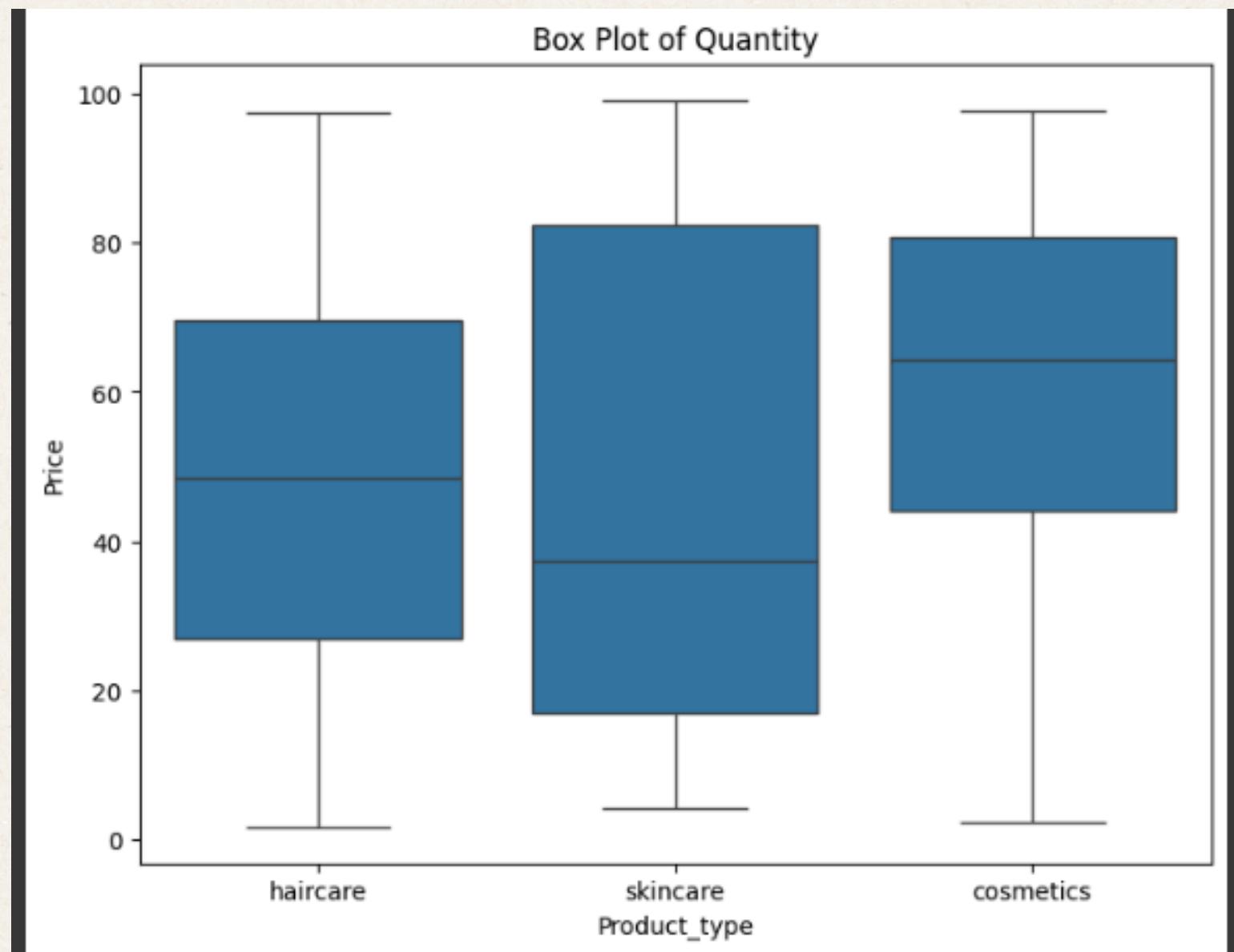
```
# Box plot for Quantity
plt.figure(figsize=(8, 6))

# Use Seaborn's `boxplot()` function to create a box plot.
# The `data` parameter specifies the DataFrame `df`, and `y='Quantity'` indicates that
# we want to plot the 'Quantity' column on the y-axis.
sns.boxplot(data=df, x='Product_type' , y='Price')

# Set the title of the plot to 'Box Plot of Quantity'.
plt.title('Box Plot of Quantity')

# Set the label for the y-axis to 'Quantity'.
plt.ylabel('Price')

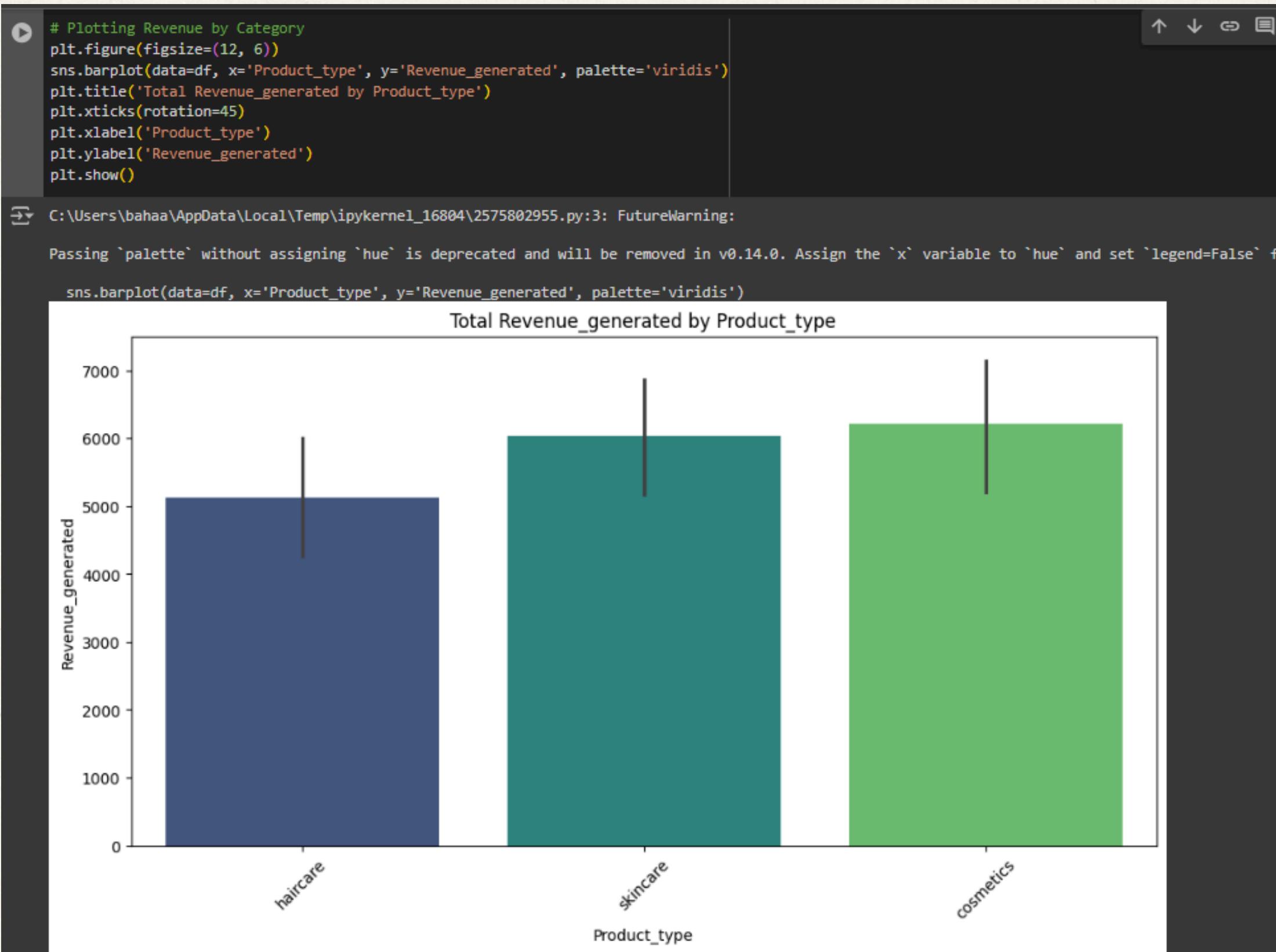
# Display the plot.
plt.show()
```



Exploration & Manipulation using Python

WEEK 1

Plotting Revenue by Category



Exploration & Manipulation using Python

WEEK 1

Extract file to csv file

```
[ ] # to save file to csv  
df.to_csv("Output . csv" , index=False)
```



Exploration & Manipulation using SQL

WEEK 1

Import data into Microsoft SQL Server Management studio and creating relational database with splitted tables then insert data into this new tables

```
-Create database supply_chain
use supply_chain

select * from supply_chain_data
-----split the data into multiple tables---

CREATE TABLE Products (
    SKU VARCHAR(50) PRIMARY KEY,
    ProductType VARCHAR(50),
    Price FLOAT,
    StockLevels INT,
    Availability INT,
    LeadTimes INT,
    OrderQuantities INT)

CREATE TABLE Sales (
    SKU VARCHAR(50) PRIMARY KEY,
    NumberOfProductsSold INT,
    RevenueGenerated FLOAT,
    CustomerDemographics VARCHAR(50),
    ShippingTimes INT,
    ShippingCosts FLOAT,
    FOREIGN KEY (SKU) REFERENCES Products(SKU))
```

```
CREATE TABLE Suppliers (
    SKU VARCHAR(50) PRIMARY KEY,
    SupplierName VARCHAR(50),
    Location VARCHAR(50),
    LeadTime INT,
    ProductionVolumes INT,
    ManufacturingLeadTime INT,
    ManufacturingCosts FLOAT)

CREATE TABLE Inspections (
    SKU VARCHAR(50) PRIMARY KEY,
    InspectionResults VARCHAR(50),
    DefectRates FLOAT,
    FOREIGN KEY (SKU) REFERENCES Products(SKU))

CREATE TABLE Shipping (
    SKU VARCHAR(50) PRIMARY KEY,
    ShippingCarriers VARCHAR(50),
    TransportationModes VARCHAR(50),
    Routes VARCHAR(50),
    Costs FLOAT,
    FOREIGN KEY (SKU) REFERENCES Products(SKU))
```

Exploration & Manipulation using SQL

WEEK 1

Insert data into this new tables and Check for it

-- Inserting data into tables

```
-- Inserting data into Products table from supply_chain_data
-- INSERT INTO Products (SKU, ProductType, Price, StockLevels, Availability, LeadTimes, OrderQuantities)
-- SELECT SKU, Product_type, Price, Stock_levels, Availability, lead_time, Order_quantities
-- FROM supply_chain_data

select * from Products

-- Inserting data into Sales table from supply_chain_data
-- INSERT INTO Sales (SKU, NumberOfProductsSold, RevenueGenerated, CustomerDemographics, ShippingTimes, ShippingCosts)
-- SELECT SKU, Number_of_products_sold, Revenue_generated, Customer_demographics, Shipping_times, Shipping_costs
-- FROM supply_chain_data

select * from Sales
```

-- Inserting data into Suppliers table from supply_chain_data

```
INSERT INTO Suppliers (SKU,SupplierName, Location, LeadTime, ProductionVolumes, ManufacturingLeadTime, ManufacturingCosts)
SELECT SKU,Supplier_name, Location, Lead_time, Production_volumes, Manufacturing_lead_time, Manufacturing_costs
FROM supply_chain_data

select * from Suppliers

-- Inserting data into Inspections table from supply_chain_data
-- INSERT INTO Inspections (SKU, InspectionResults, DefectRates)
-- SELECT SKU, Inspection_results, Defect_rates
-- FROM supply_chain_data

select * from Inspections

-- Inserting data into Shipping table from supply_chain_data
-- INSERT INTO Shipping (SKU, ShippingCarriers, TransportationModes, Routes, Costs)
-- SELECT SKU, Shipping_carriers, Transportation_modes, Routes, Costs
-- FROM supply_chain_data

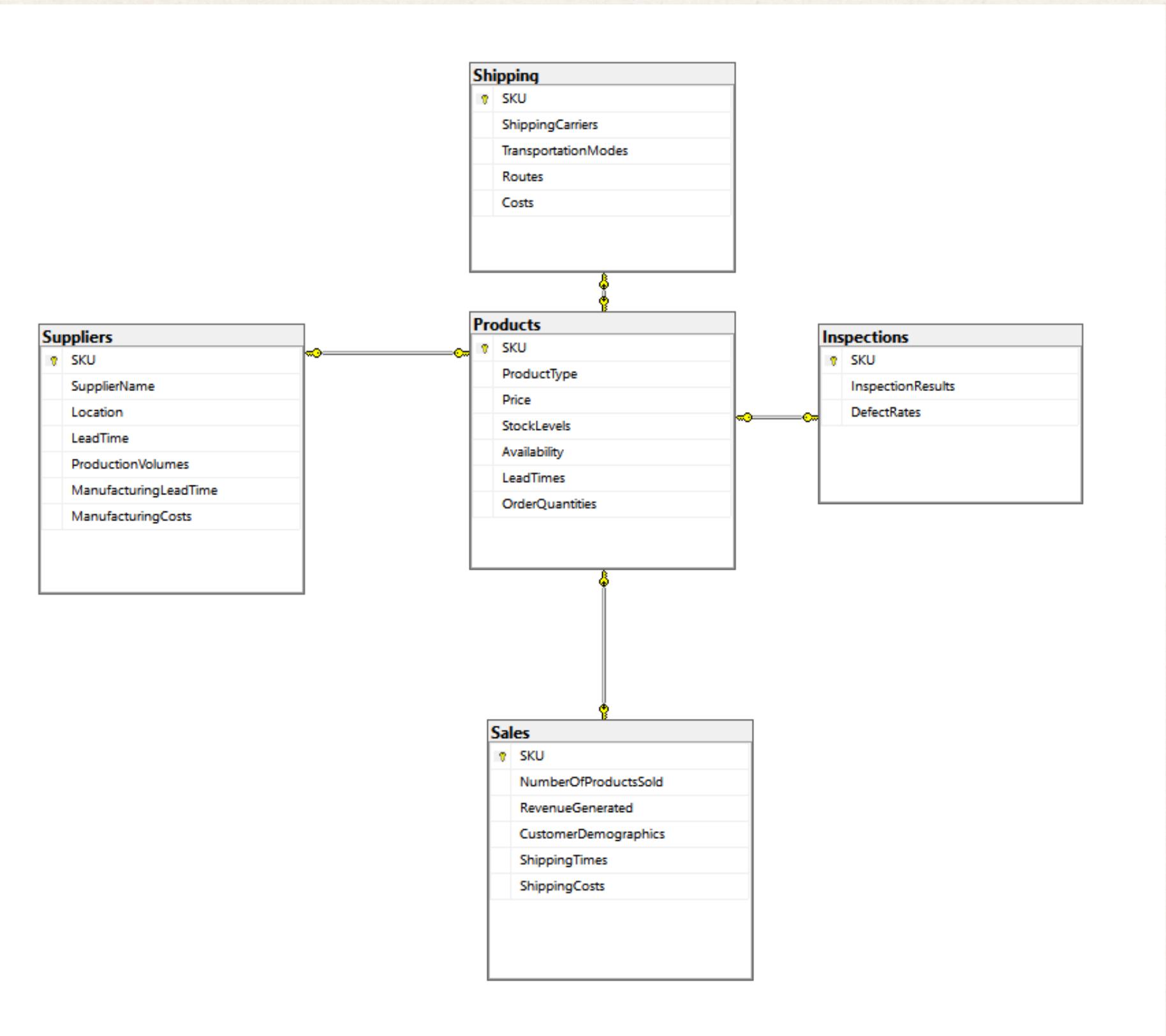
select * from Shipping
```

```
select * from Inspections
select * from Products
select * from Sales
select * from Shipping
select * from Suppliers
```

Exploration & Manipulation using SQL

WEEK 1

Create new degrame and relation between new tables



Questions Phase

WEEK 2



Questions Phase

WEEK 2

Determine all possible analysis questions that can be deducted from the given dataset and would be of interest to the organization's decision makers

Sales and Revenue

- What is the impact of product type on sales and revenue?
- How does price correlate with the number of products sold?
- Which products/SKUs generate the most revenue and why?

Shipping and Logistics

- How do shipping times and costs vary by transportation mode and carrier?
- What are the most efficient shipping routes for minimizing costs and delivery times?
- How do shipping delays impact customer satisfaction and future orders?

Inventory and Stock Management

- How does stock availability influence revenue generation?
- What are the optimal stock levels for maximizing sales while avoiding overstock?
- How do lead times affect stock levels and overall inventory management?

Customer Demographics and Behavior

- How do customer demographics influence purchasing behavior?
- What is the relationship between customer demographics and product preference?
- How does customer location affect shipping times and costs?

Supplier and Manufacturing Performance

- Which suppliers have the most reliable lead times and lowest manufacturing costs?
- How do defect rates vary by supplier or product type?
- What impact does manufacturing lead time have on order fulfillment?

Cost and Profitability

- What is the relationship between manufacturing costs and profitability?
- Which products or suppliers have the highest cost-to-revenue ratio, and how can this be optimized?

Forecasting Questions Phase

WEEK 3



Forecasting Questions Phase

WEEK 3

The objective is to use historical data to predict future trends in sales, stock, and other relevant metrics. Here are forecasting questions you can focus on, with a summary of each.

Forecasting Summary for Product Sales:

- Skincare: Currently the top-selling category with a total of **20,731** units sold. It is expected to continue performing well.
- Haircare: Currently has sold **13,611** units, with future sales predicted to rise slightly.
- Cosmetics: Currently at **11,757** units sold, future sales are projected to remain steady.

Recommendation :

- Skincare remains the dominant product category, with strong projected sales.
- Haircare shows moderate growth potential.
- Cosmetics may see steady but slightly lower sales compared to the other categories.

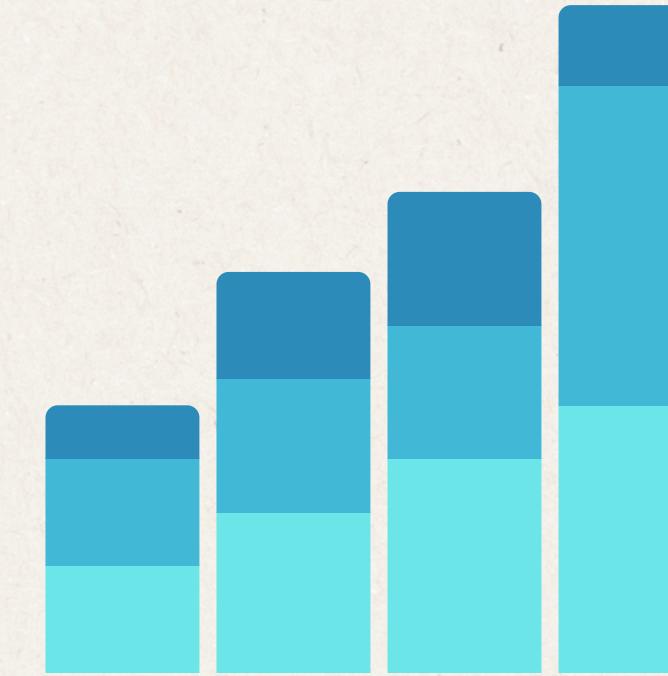
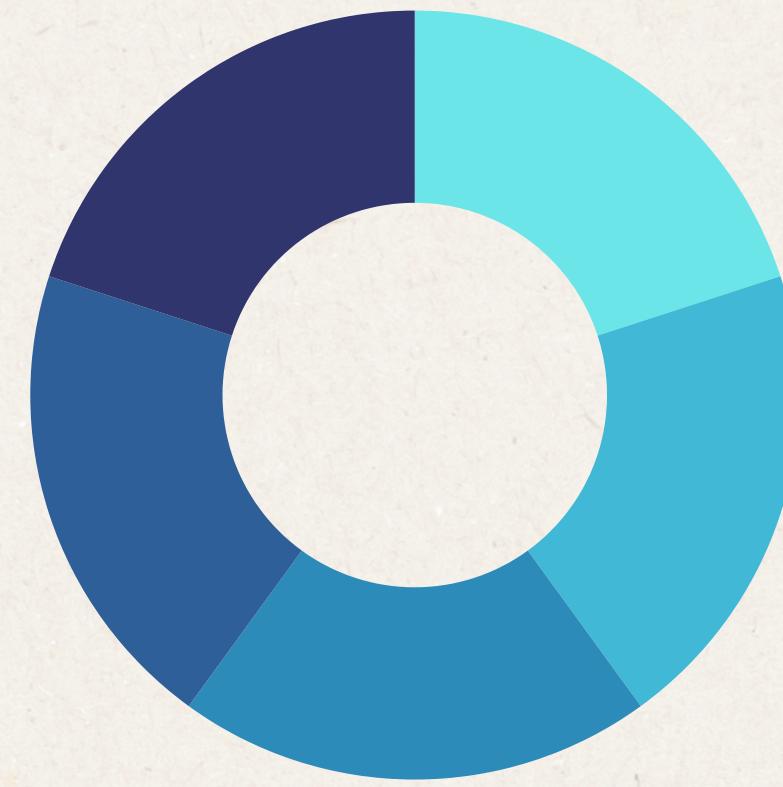
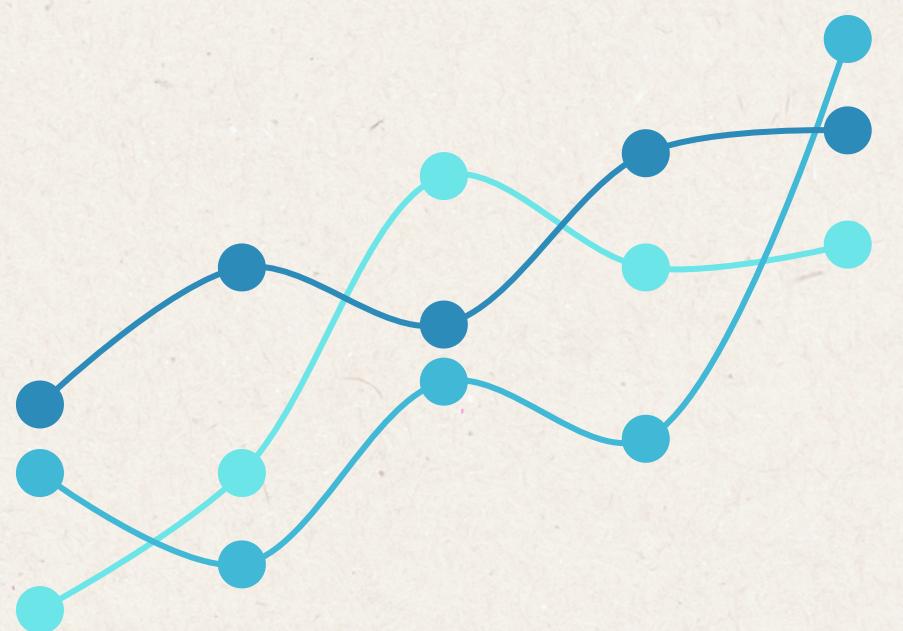
Row Labels	Sum of Number of products sold
skincare	20,731
haircare	13,611
cosmetics	11,757
Grand Total	46,099

Top 5 Product Sold	
Row Labels	Sum of Number of products sold
SKU10	996
SKU94	987
SKU9	980
SKU36	963
SKU37	963
Grand Total	4,889

Lowest 5 Product Sold	
Row Labels	Sum of Number of products sold
SKU2	8
SKU45	24
SKU85	25
SKU48	29
SKU70	32
Grand Total	118

Visualization Dashboard and Final Presentation

WEEK 4

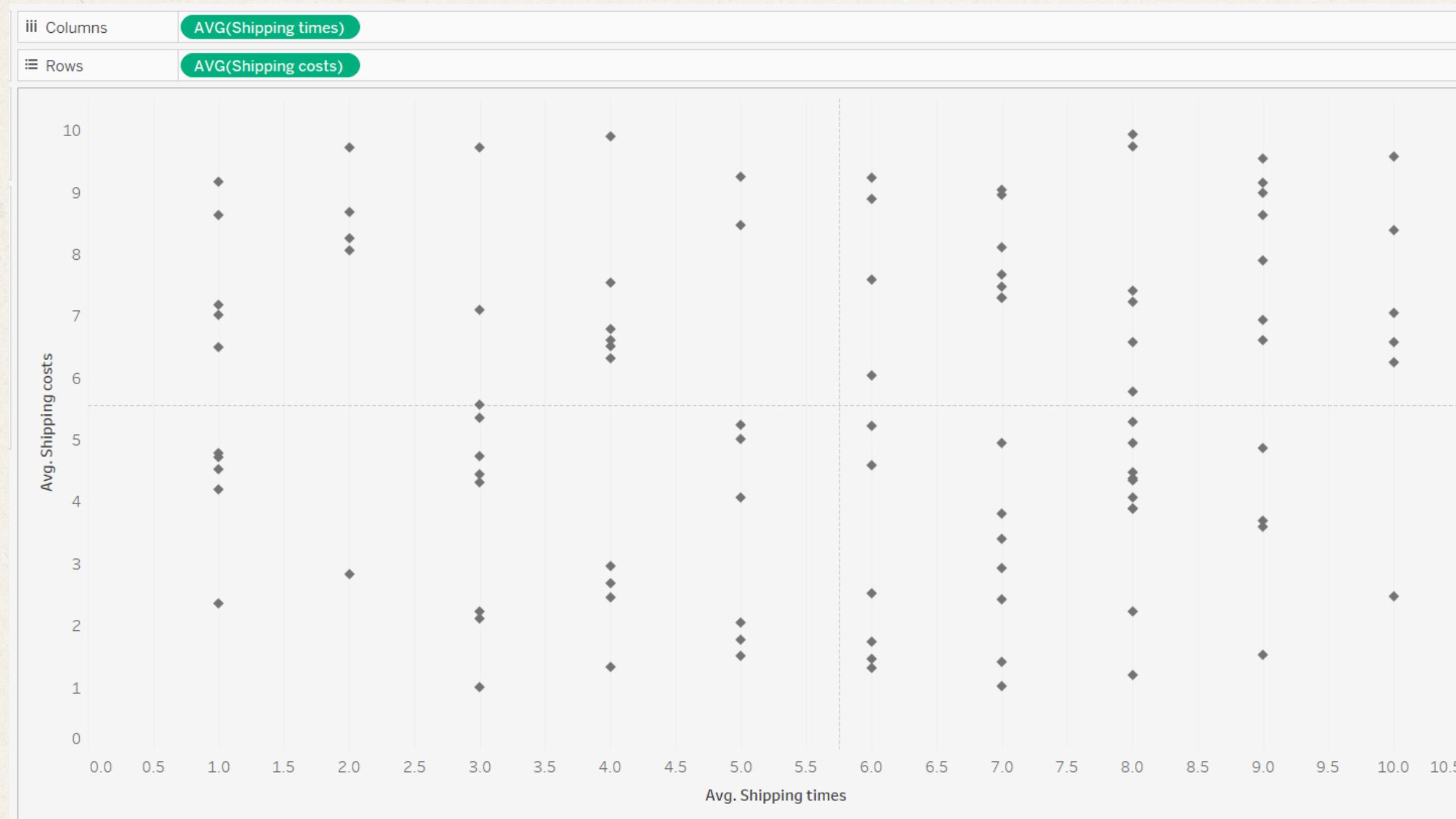


Visualization Dashboard using Tableau

WEEK 4

Build a Visualization Dashboard: Build a Tableau visualization dashboard that visualize the answers to all answered questions.

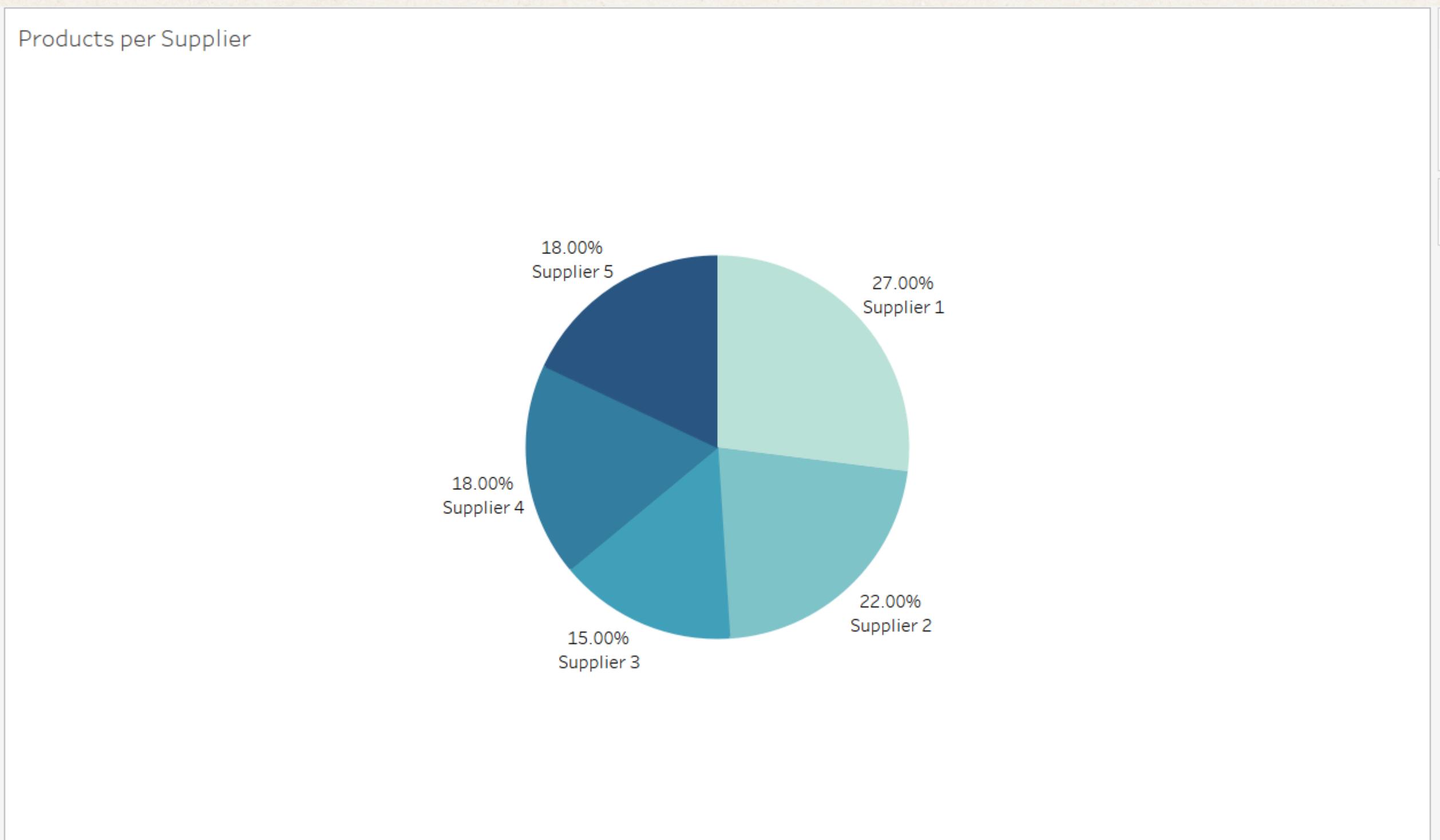
Shipping Costs Vs Shipping Times



Visualization Dashboard using Tableau

WEEK 4

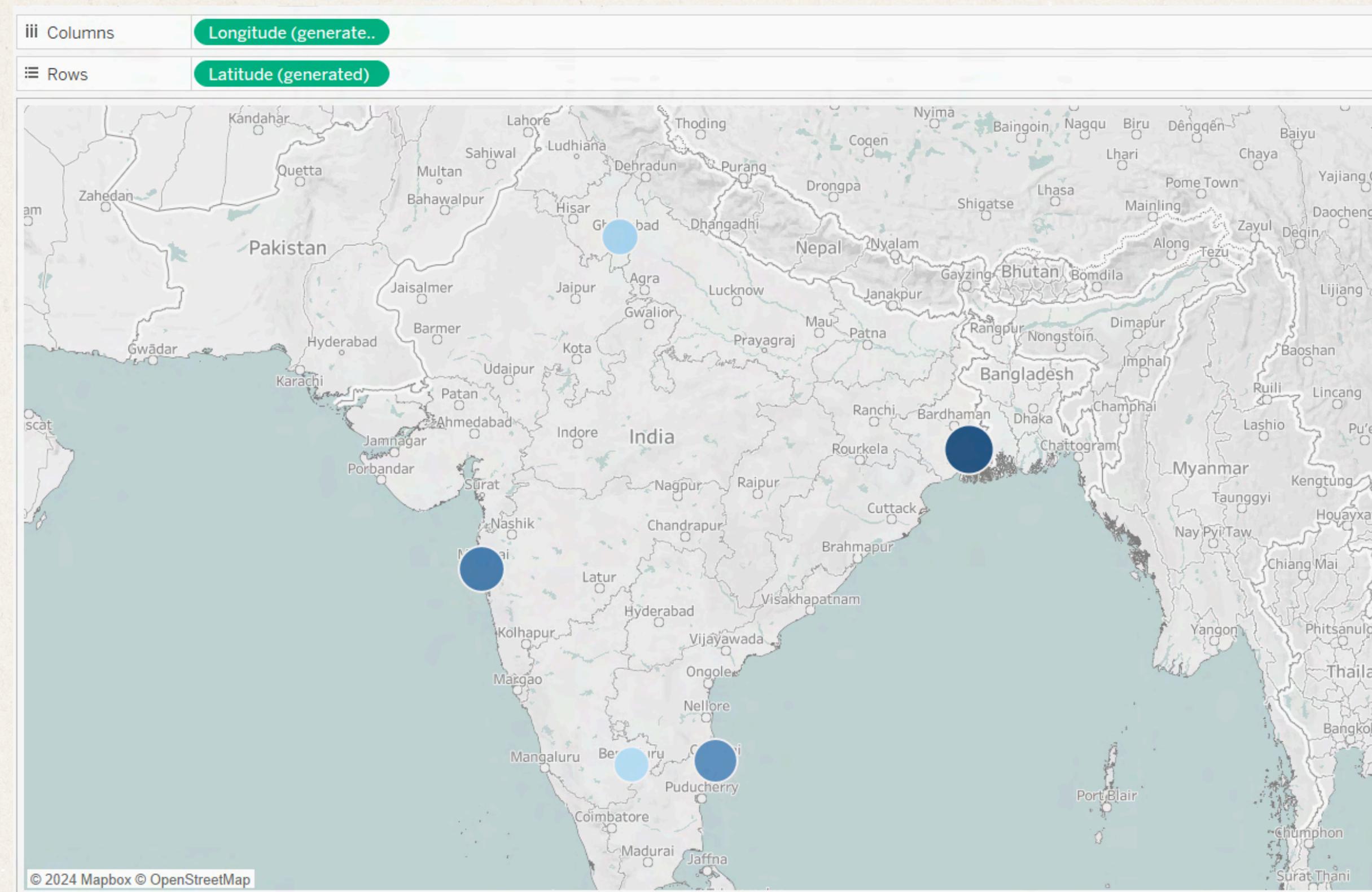
Products per Supplier



Visualization Dashboard using Tableau

WEEK 4

Location



Visualization Dashboard using Tableau

WEEK 4

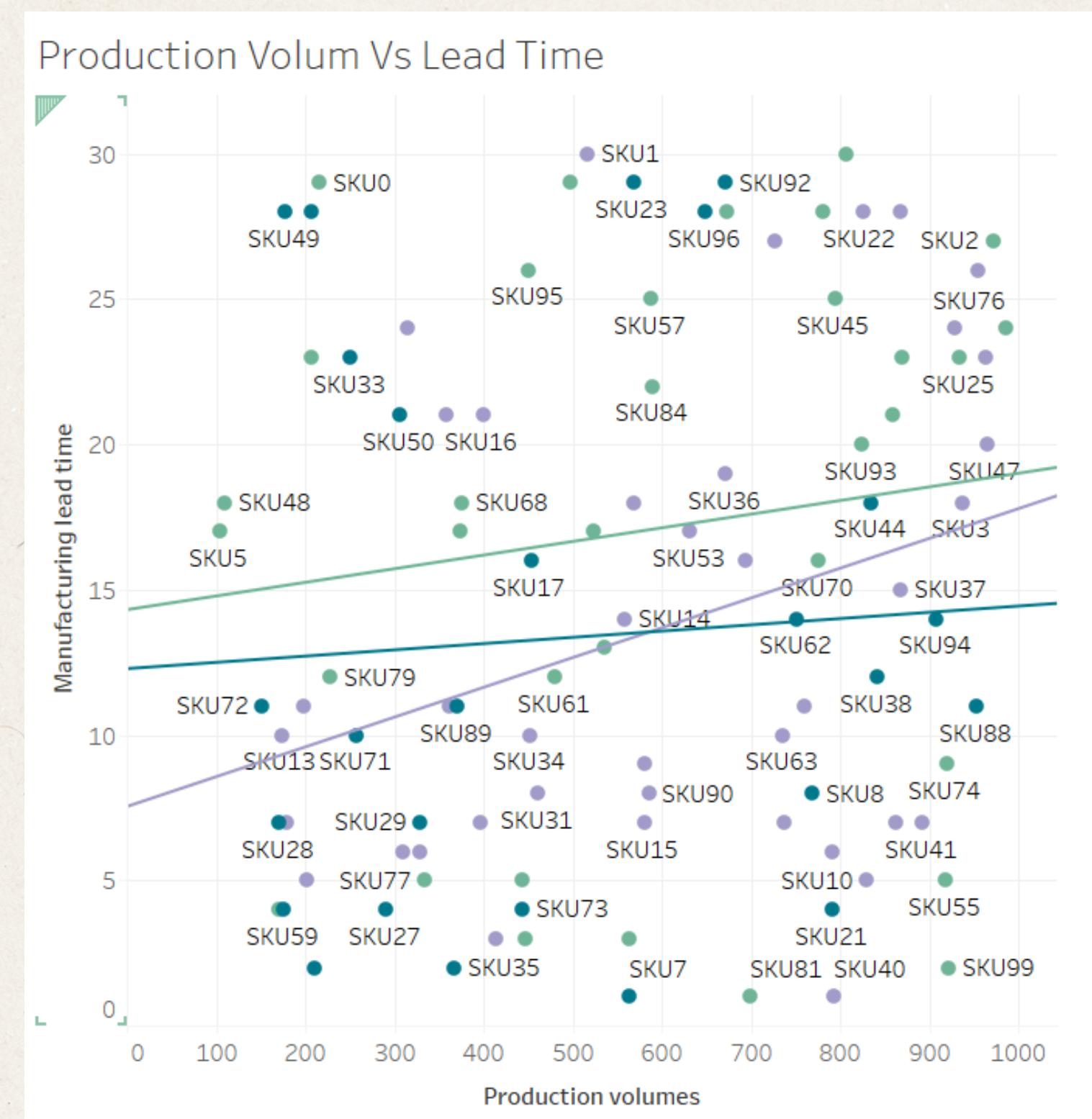
Fastest 10 products to Manufacture



Visualization Dashboard using Tableau

WEEK 4

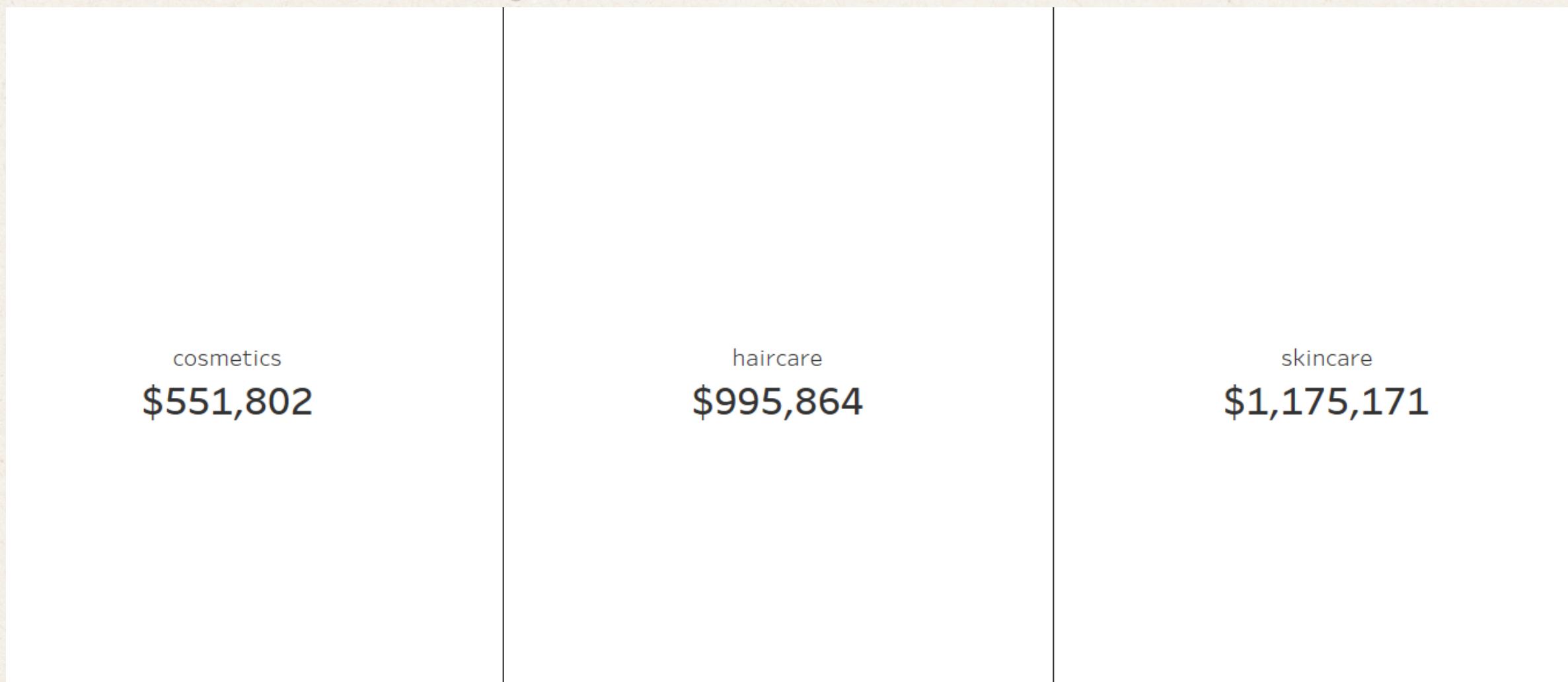
Production Volum Vs Lead Time



Visualization Dashboard using Tableau

WEEK 4

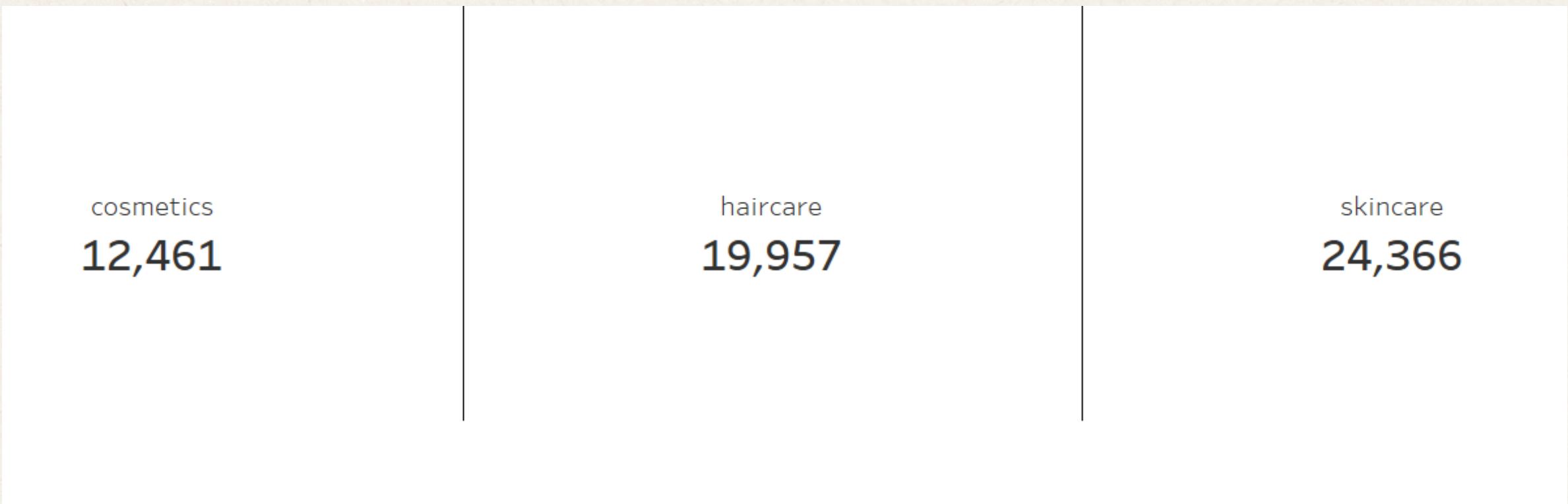
Total Manufacturing Cost



Visualization Dashboard using Tableau

WEEK 4

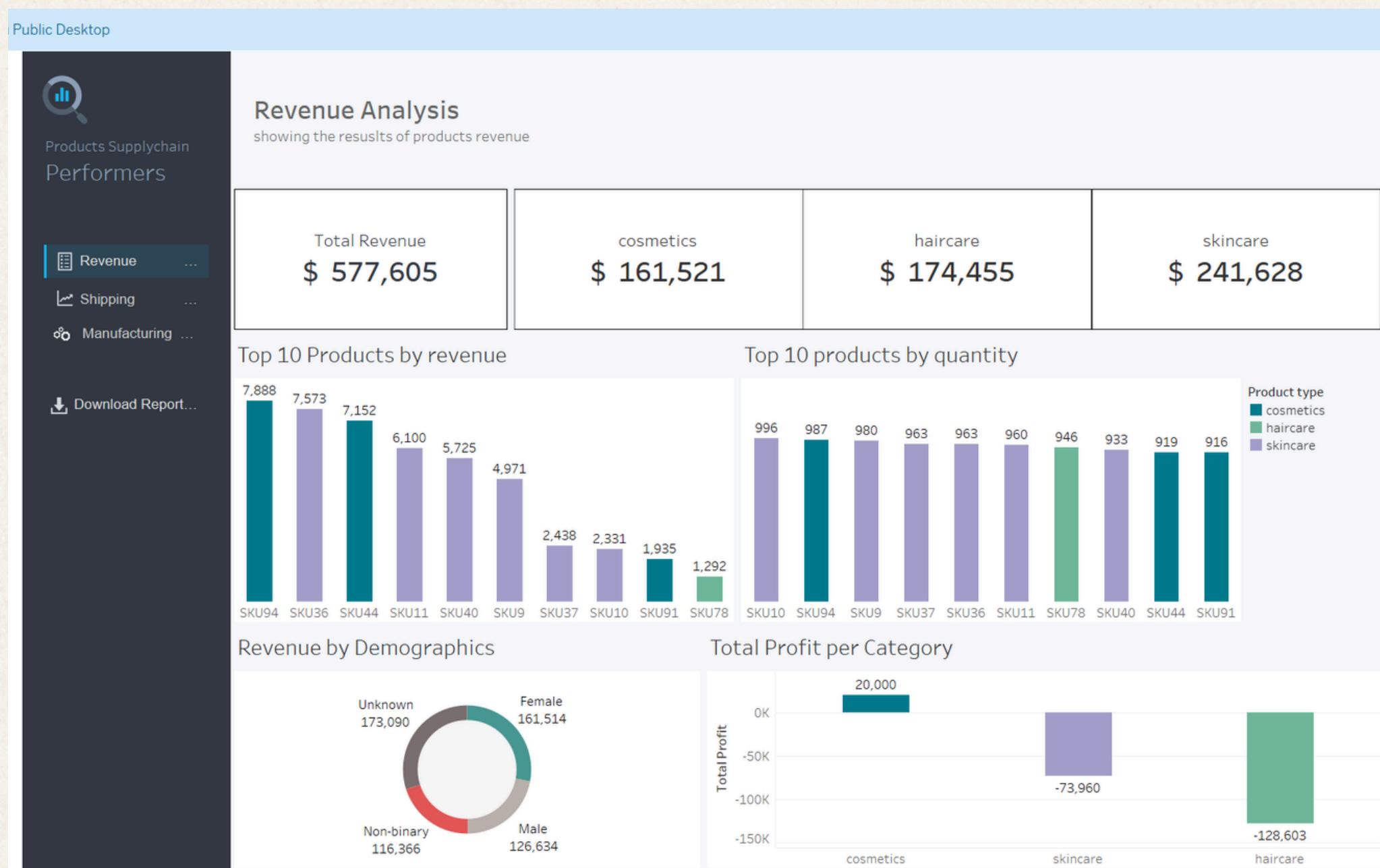
Total Production Volum



Visualization Dashboard using Tableau

WEEK 4

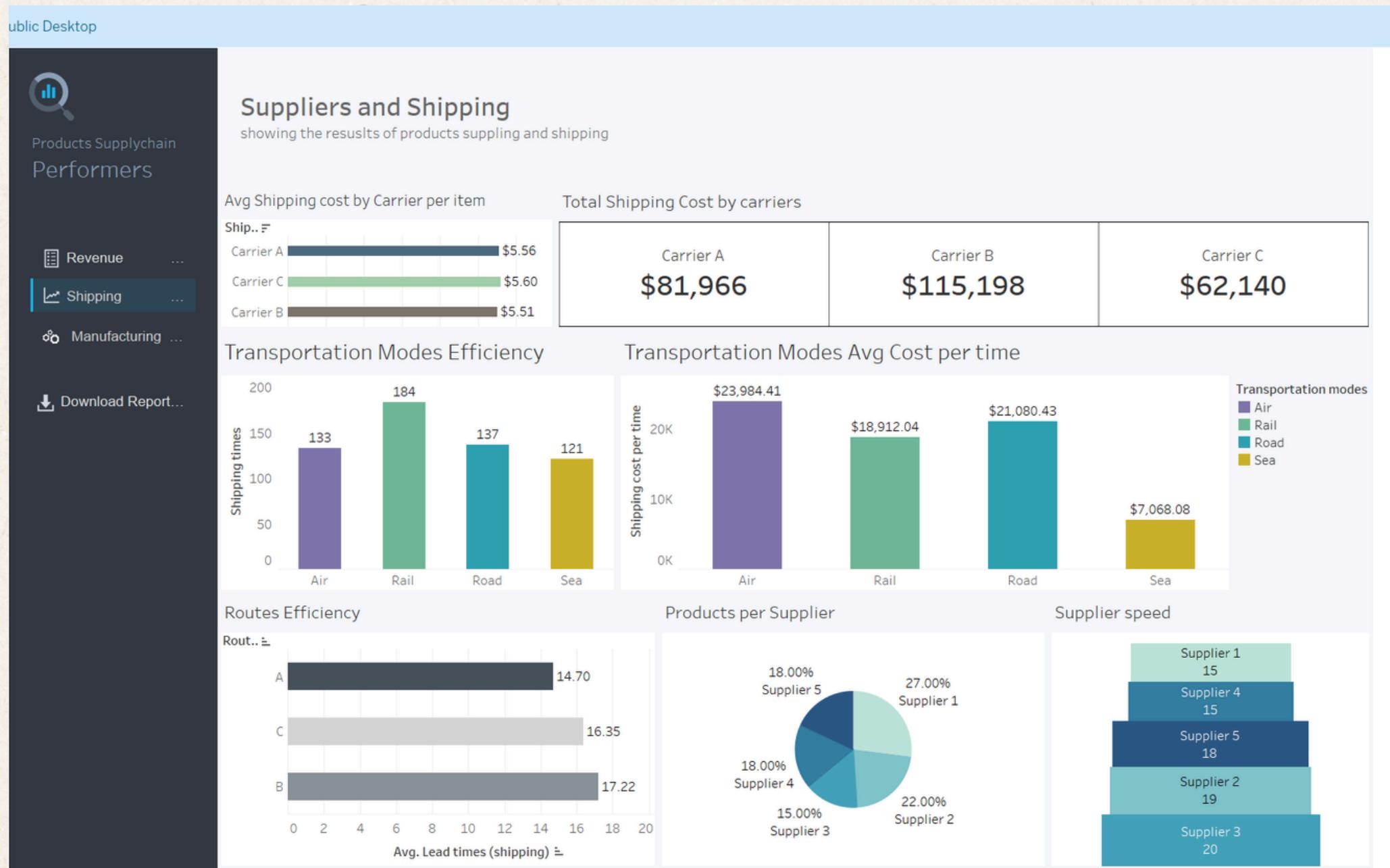
Revenue Dashboard



Visualization Dashboard using Tableau

WEEK 4

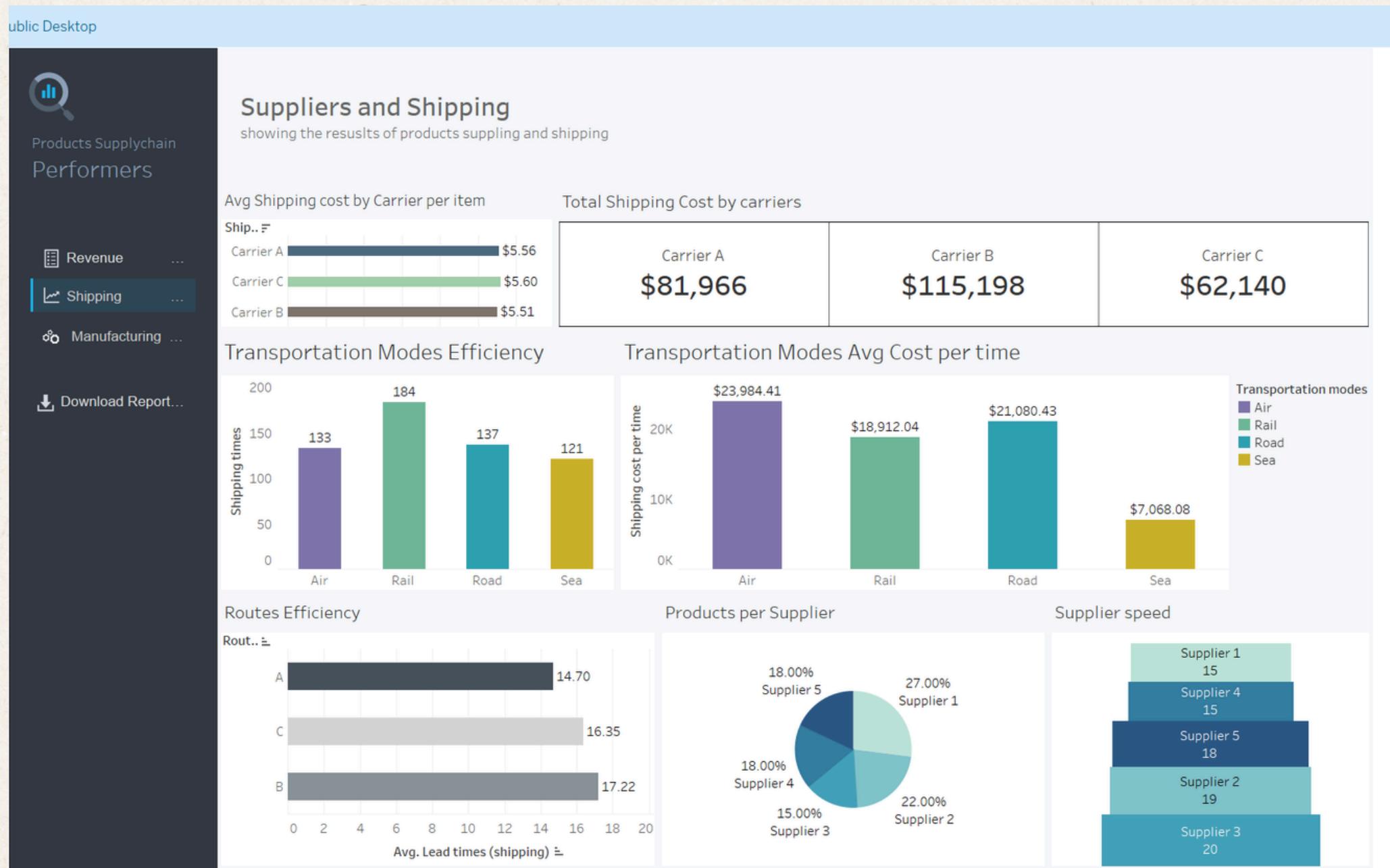
Revenue Dashboard



Visualization Dashboard using Tableau

WEEK 4

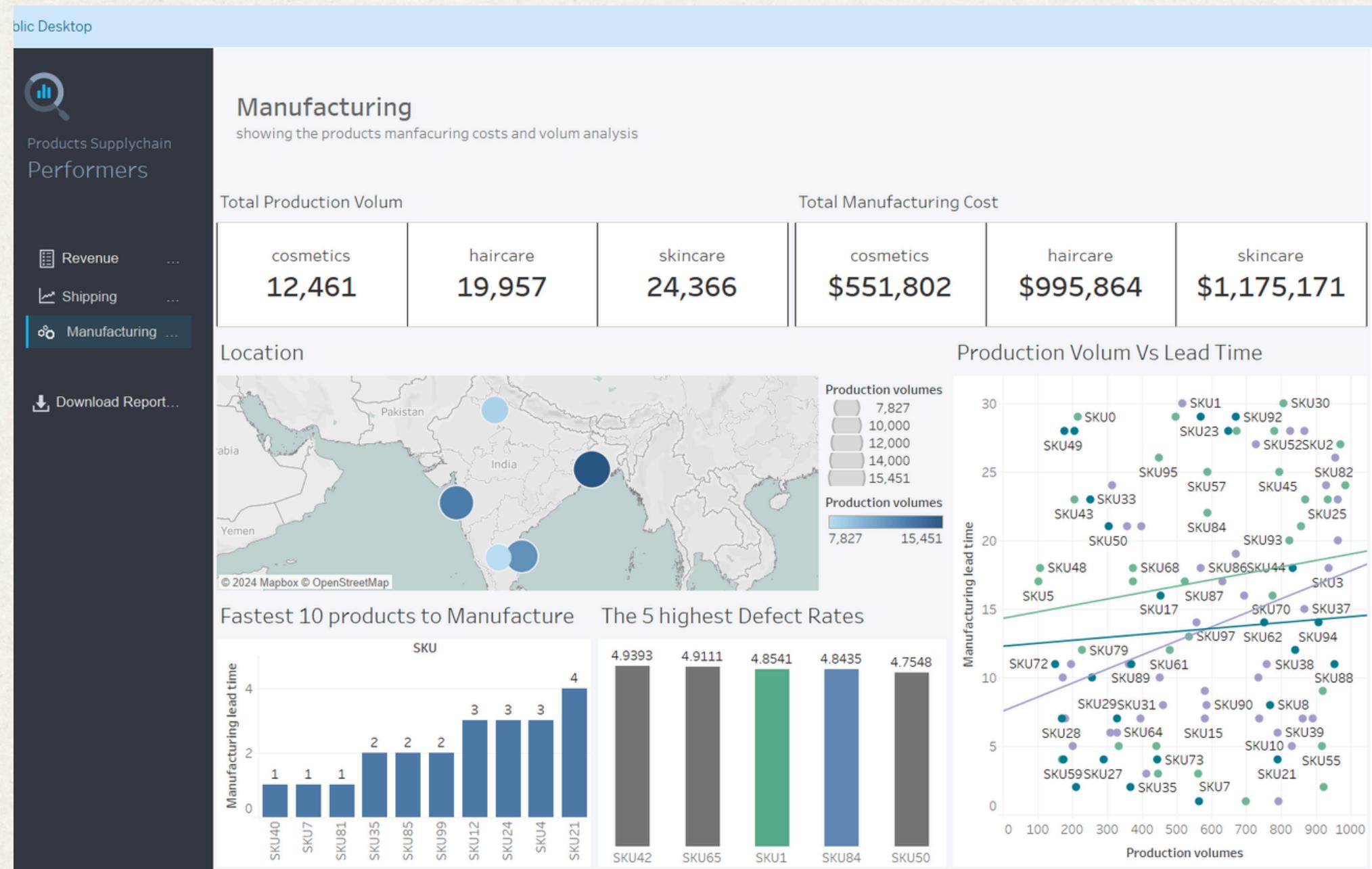
Shipping Dashboard



Visualization Dashboard using Tableau

WEEK 4

Manufacturing Dashboard



recommendation and conclusion

WEEK 4

Top Revenue-Generating Product And Categories:

- Skincare is the leading revenue generator with \$241,628 in total, from 20,731 units sold.
- Haircare follows, contributing \$174,455 in revenue, with 13,611 units sold.
- Cosmetics brings in \$161,521 from 11,757 units sold.

For example, the product type "haircare" (SKU0) generates \$8,661 from 802 units sold, while "skincare" (SKU1) generates \$7,460 from 736 units sold

Conclusion:

Skincare products dominate both in terms of revenue and units sold. The other two categories, haircare and cosmetics, also perform well but generate slightly less revenue and have fewer units sold.

Recommendation:

- Prioritize skincare products for restocking and production due to their strong sales performance and high revenue generation.
- For haircare and cosmetics, focus on improving inventory efficiency, marketing, or product variety to drive higher sales and revenue to match skincare's performance.
- Prioritize high-revenue products like these for production, while reducing stock for lower-selling products to optimize resources.

recommendation and conclusion

WEEK 4

Cost Optimization for Transportation:

- Transportation by Sea has the lowest cost at **\$7,103**, followed by Air at **\$14,605**.
- Rail incurs a cost of **\$15,169**, while Road is the most expensive at **\$16,048**.

for example Products transported via Route C by Air (e.g., SKU2) have a lower transportation cost of **\$141.92**, compared to Route A by Rail (e.g., SKU3), which costs **\$254.78**.

Recommendation:

- Shift more shipments to Sea transport when possible to take advantage of its lower costs. Consider reducing reliance on Road transport, which is the most expensive mode, and explore more efficient planning for Air and Rail to balance cost and speed.

Sales Driven by City:

- Mumbai generates the highest revenue at **\$137,755.03**, closely followed by Kolkata with **\$137,077.55**.
- Chennai also performs well, contributing **\$119,142.82** to the total revenue.
- Bangalore and Delhi bring in **\$102,601.72** and **\$81,027.70**, respectively.

Recommendation:

- Tailor marketing efforts toward Mumbai and Kolkata, as these cities generate the most significant revenue. Consider running targeted promotions or expanding product availability in these cities to further capitalize on their sales potential. Additionally, explore opportunities to increase revenue in Delhi and Bangalore by enhancing customer engagement or product offerings specific to these regions.

Thank you



وزارة الاتصالات
وتقنيات مهنية المعلومات

