Symbiosis Skills and Professional University
Kiwale, Pune

PROJECT REPORT

On

"Supply Chain Forecasting"

<u>Submitted by</u>

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DA-Batch-3

Under The Guidance of

Trainer's Name: ______________________

STUDENT DECLARATION AND ATTESTATION BY TRAINER

This is to declare that this report has been written by me. No part of the report is plagiarized from other sources. All information included from other sources have been duly acknowledged. I aver that if any part of the report is found to be plagiarized, I shall take full responsibility for it.

Signature of student

Name of student:

Registration Number:

Signature of trainer

Name of trainer:

CERTIFICATE

This is to certify that the report entitled, “**------------------< project title> -------------------------------------**” submitted by**”-----------------<student name>**------------------” to Symbiosis Skills and Professional University, Pune, Maharashtra, India, is a record of bonafide Project work carried out by him under my supervision and guidance and is worthy of consideration for the completion of certificate course in ‘Machine Learning Engineer”.

Signature of Trainer
Name of Trainer
Date: / / 2021

Supervisor
Date:

Supervisor

ACKNOWLEDGEMENTS

INDEX (Sample)

Purpose of Project:

Supply chain analytics serves as a critical tool for organizations aiming to enhance the efficiency and effectiveness of their supply chain operations. By leveraging data-driven insights, supply chain analytics helps optimize operational processes, streamline workflows, and allocate resources efficiently. It plays a pivotal role in demand forecasting and inventory management, enabling organizations to predict market trends, reduce stockouts, and maintain optimal inventory levels. Additionally, supply chain analytics contributes to cost reduction by identifying areas for improvement in procurement, transportation, and overall supply chain costs.

Risk management is another key focus, as analytics aids in identifying and mitigating potential disruptions and uncertainties. The visibility provided by analytics promotes transparency throughout the supply chain, facilitating better collaboration among stakeholders. Strategic decision-making is empowered by data-driven insights, supporting continuous improvement initiatives and fostering resilience. Ultimately, supply chain analytics aims to enhance overall customer satisfaction by ensuring accurate order fulfilment, timely deliveries, and a proactive approach to addressing quality issues, positioning organizations to adapt to evolving market dynamics and gain a competitive advantage.

The purpose of supply chain management is to deliver the product to the customer safely and completely and to satisfy the customer. The ultimate goal of the supply chain is for the customer to have a good experience, to meet their expectations, and for the company to have more sales.

Analysing a company's supply chain data can help it run more smoothly and efficiently. The supply chain can discover patterns and trends in past shipment data to help predict future needs, prevent disruptions and stockouts, and better manage the company's inventory. Furthermore, data analytics can assist supply chains in optimising their routes, schedules and tracking their performance over time. (DFreight, 2022)

Problem Statement/ Objective of Project :

Problem Statement: Supply Chain Forecasting of an Organization

Inefficient supply chain forecasting poses a significant challenge to our organization, leading to suboptimal inventory management, increased carrying costs, and potential disruptions in meeting customer demands.

The current forecasting processes lack accuracy and fail to adapt effectively to dynamic market conditions, resulting in overstock situations, stockouts, and an overall inefficiency in resource allocation. The absence of robust predictive analytics contributes to an inability to foresee demand patterns, making it challenging to optimize production, distribution, and inventory levels. Additionally, inadequate visibility across the supply chain hinders timely decision-making and leaves the organization vulnerable to uncertainties and risks.

The need for a comprehensive and data-driven supply chain forecasting solution is evident to address these challenges, improve operational efficiency, reduce costs, and enhance customer satisfaction.

Therefore, the objective is to implement an advanced forecasting system that leverages predictive analytics, machine learning, and real-time data to provide accurate demand predictions, optimize inventory levels, and enhance overall supply chain resilience.

Demand forecasting is essential for businesses to anticipate and plan for future customer demand accurately. By predicting consumer preferences and market trends, organizations can optimize inventory levels, streamline production processes, and enhance overall operational efficiency. This proactive approach minimizes the risk of stockouts or excess inventory, allowing businesses to meet customer needs efficiently. Additionally, demand forecasting supports strategic decision-making, resource allocation, and risk management, contributing to improved financial performance and sustained competitiveness in dynamic markets. In essence, the importance of demand forecasting lies in its ability to provide valuable insights that empower businesses to align their operations with market demands and achieve long-term success.

Data Description:

A Data Set of Supply Chains used by the company DataCo Global was used for the analysis. Dataset of Supply Chain, which allows the use of Machine Learning Algorithms and R Software. Areas of important registered activities: Provisioning, Production, Sales, Commercial Distribution. It also allows the correlation of Structured Data with Unstructured Data for knowledge generation.

Type Data:

Structured Data: DataCoSupplyChainDataset.csv
Types of Products: Clothing, Sports, and Electronic Supplies

Dataset Overview:

- **Rows:** 180519
- **Columns:** 53
('Type', 'Days for shipping (real)', 'Days for shipment (scheduled)','Benefit per order', 'Sales per customer', 'Delivery Status','Late_delivery_risk', 'Category Id', 'Category Name', 'Customer City','Customer Country', 'Customer Email', 'Customer Fname', 'Customer Id', 'Customer Lname', 'Customer Password', 'Customer Segment', 'Customer State', 'Customer Street', 'Customer Zipcode','Department Id', 'Department Name', 'Latitude', 'Longitude', 'Market', 'Order City', 'Order Country', 'Order Customer Id','order date (DateOrders)', 'Order Id', 'Order Item Cardprod Id', 'Order Item Discount', 'Order Item Discount Rate', 'Order Item Id', 'Order Item Product Price', 'Order Item Profit Ratio', 'Order Item Quantity', 'Sales', 'Order Item Total','Order Profit Per Order', 'Order Region', 'Order State', 'Order Status', 'Order Zipcode', 'Product Card Id', 'Product Category Id', 'Product Description', 'Product Image', 'Product Name', 'Product Price','Product Status', 'shipping date (DateOrders)', 'Shipping Mode'

In [5]:
```
#Checking the top 10 rows in the dataset
SC.head(10)
```

Out[5]:

	ï»¿Type	Days for shipping (real)	Days for shipment (scheduled)	Benefit per order	Sales per customer	Delivery Status	Late_delivery_risk	Category Id	Category Name	Customer City	...	Order Zipcode	Product Card Id	Product Category Id	D
0	DEBIT	3	4	91.250000	314.640015	Advance shipping	0	73	Sporting Goods	Caguas	...	NaN	1360	73	
1	TRANSFER	5	4	-249.089996	311.359985	Late delivery	1	73	Sporting Goods	Caguas	...	NaN	1360	73	
2	CASH	4	4	-247.779999	309.720001	Shipping on time	0	73	Sporting Goods	San Jose	...	NaN	1360	73	
3	DEBIT	3	4	22.860001	304.809998	Advance shipping	0	73	Sporting Goods	Los Angeles	...	NaN	1360	73	
4	PAYMENT	2	4	134.210007	298.250000	Advance shipping	0	73	Sporting Goods	Caguas	...	NaN	1360	73	
5	TRANSFER	6	4	18.580000	294.980011	Shipping canceled	0	73	Sporting Goods	Tonawanda	...	NaN	1360	73	
6	DEBIT	2	1	95.180000	288.420013	Late delivery	1	73	Sporting Goods	Caguas	...	NaN	1360	73	
7	TRANSFER	2	1	68.430000	285.140015	Late delivery	1	73	Sporting Goods	Miami	...	NaN	1360	73	
8	CASH	3	2	133.720001	278.589996	Late delivery	1	73	Sporting Goods	Caguas	...	NaN	1360	73	
9	CASH	2	1	132.149994	275.309998	Late delivery	1	73	Sporting Goods	San Ramon	...	NaN	1360	73	

10 rows × 53 columns

Dataset Characteristics:

- Scope: Sales data across various cities and countries.
- Granularity: Transaction-level data capturing individual sales.
- Temporal Dimension: Monthly sales data across multiple years.
- Hierarchy: Hierarchical structure with information on products, sales, customers and orders
- Timeline: The data values lie within the date 1-1-2015 to 31-1-2018.

Introduction:

In this report, "Total amount per order", "Order Item Quantity" and "Late Delivery" are considered the three main effective parameters of supply chain management efficiency.

1)Forecasting the "Total amount per order"(or Sale per Customer) is done in order to help the business identify in advance any problems and opportunities related to sales of products.

2)The "Order Item Quantity" (or Demand) forecasting helps in identifying customer purchasing trends and predicting future market demand for products. The company is able to determine which customer segments produce the highest profits, which products receive the most customer orders, and which markets have the highest demand.

3)"Late deliveries" reduce customer retention. It also undermines the customer's trust in the company. As a result, the company loses credibility and profit over time through losing customers. By preventing late delivery, the company may help retain customers, increase customer lifetime value, and increase its ROI.

Data Description:

In [7]:

```
# Returning statistical description of the data in the Dataset
SC.describe()
```

Out[7]:

	Days for shipping (real)	Days for shipment (scheduled)	Benefit per order	Sales per customer	Late_delivery_risk	Category Id	Customer Id	Customer Zipcode	Department Id
count	180519.000000	180519.000000	180519.000000	180519.000000	180519.000000	180519.000000	180519.000000	180516.000000	180519.000000
mean	3.497654	2.931847	21.974989	183.107609	0.548291	31.851451	6691.379495	35921.126914	5.443460
std	1.623722	1.374449	104.433526	120.043670	0.497664	15.640064	4162.918106	37542.461122	1.629246
min	0.000000	0.000000	-4274.979980	7.490000	0.000000	2.000000	1.000000	603.000000	2.000000
25%	2.000000	2.000000	7.000000	104.379997	0.000000	18.000000	3258.500000	725.000000	4.000000
50%	3.000000	4.000000	31.520000	163.990005	1.000000	29.000000	6457.000000	19380.000000	5.000000
75%	5.000000	4.000000	64.800003	247.399994	1.000000	45.000000	9779.000000	78207.000000	7.000000
max	6.000000	4.000000	911.799988	1939.989990	1.000000	76.000000	20757.000000	99205.000000	12.000000

8 rows × 29 columns

A brief explanation about the values in the table above:

1)According to the information obtained in the previous tables, the values in each row are 180519, by seeing the count row of the above table, it can be concluded "Customer Lname, Customer Zipcode, Order Zipcode, and Product Description" have missing values. Their number will be specified below.

2)The Late Delivery Risk column in this dataset has the values 0 and 1, that is if there is a delay, the number 1 is assigned to the order, and if there is no delay, the number 0 is assigned to the order. According to the table above, the average of this feature is 0.548. So, it can be concluded that the number of delays is higher and this can lead to the loss of customers and, consequently, the loss of profit.

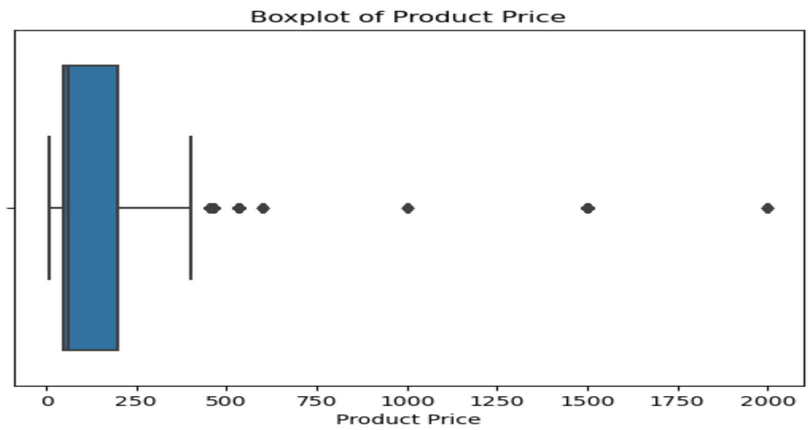
Key Data Characteristics:

•**Type of Data:** In our data we have both categorical and numerical data. The column ‘shipping date (DateOrders)’ and ‘order date (DateOrders)’ are of data type object we have to change it to the datatype ‘datetime’. Also, we have to encode the categorical data to numerical data using encoding methods.

•**Missing Values**: The dataset includes some missing values: Customer Lname, Customer Zipcode, Order Zipcode, and Product Description. These missing values should be replaced or removed. I decided to replace the missing values of Customer Name, Customer Zipcode and Order Zipcode with the "NotDetermined" and "0" respectively, and drop the Product Description columns.

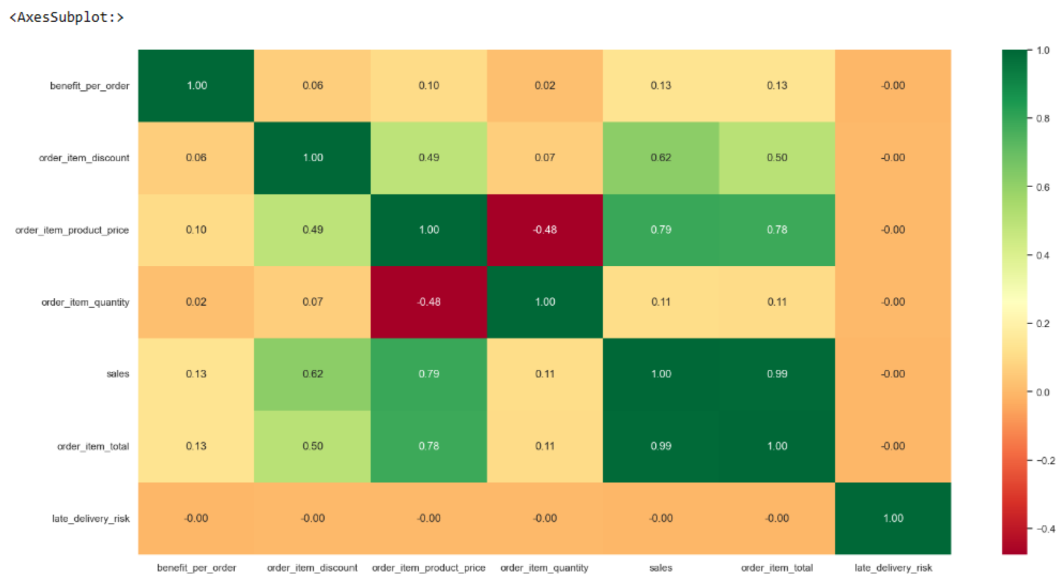
•**Seasonality:** The data values exhibit some level of seasonality. In most cases there is a pronounced shift in trend over the weekends as compared to the weekdays. In some cases, the there is a 7 day seasonality that is exhibited.

•**Outliers**: There are number of outliers (i.e. when values are more than 3 standard deviations away). We can detect the outliers using boxplot. We have outlier in column ‘product price’ and when the column ‘order date (DateOrders)’ is drill down from year. We used IQR method to remove outliers.



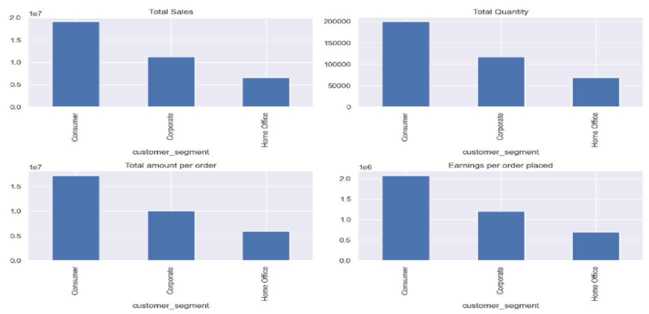
The box represents the interquartile range (IQR) between the first (Q1) and third (Q3) quartiles, while the whiskers extend to the minimum and maximum values within a specified range. Outliers beyond this range are individually plotted points.

•**Feature Selection:** With the help of heatmap we can visualize the correlation matrix of data features and detect the feature having strong relation with the target variable and we can drop the remaining the features to reduce the dimensionality of data



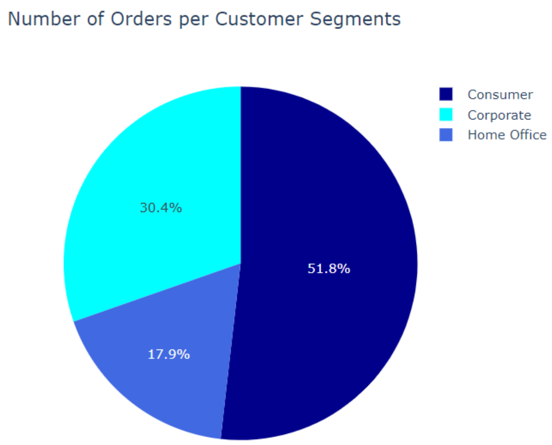
Each cell is marked with a color ranging from -1 to +1. (I have used green color for positive numbers and red color for negative numbers.) The closer this number is to -1, it means that two characteristics are inversely related to each other, and the closer this number is to +1, it means that two characteristics are directly related to each other.

Customer Segment Analysis:

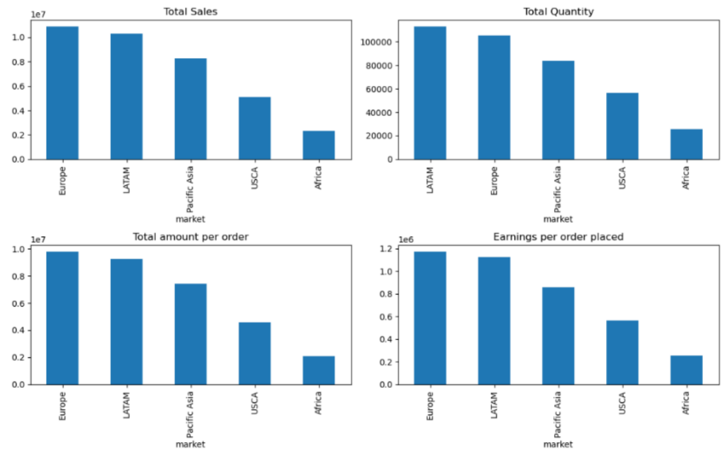


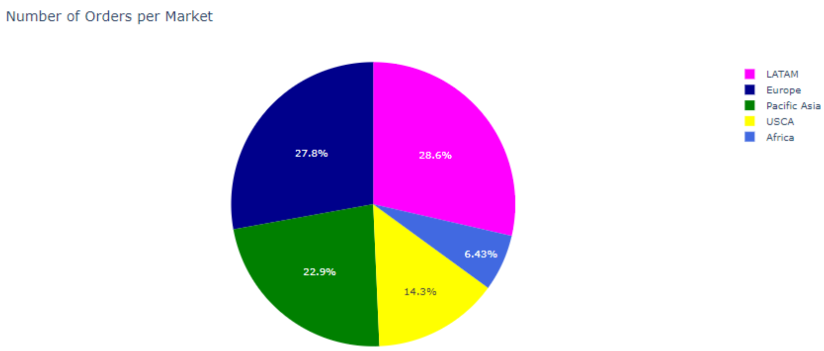
The consumer category has the biggest share approximately of 51.8%, as seen in all the above charts.

So, accurate demand forecasting and on-time delivery are very important for this group of customers, as the risk of late delivery leads to lost profits.



Market Analysis:

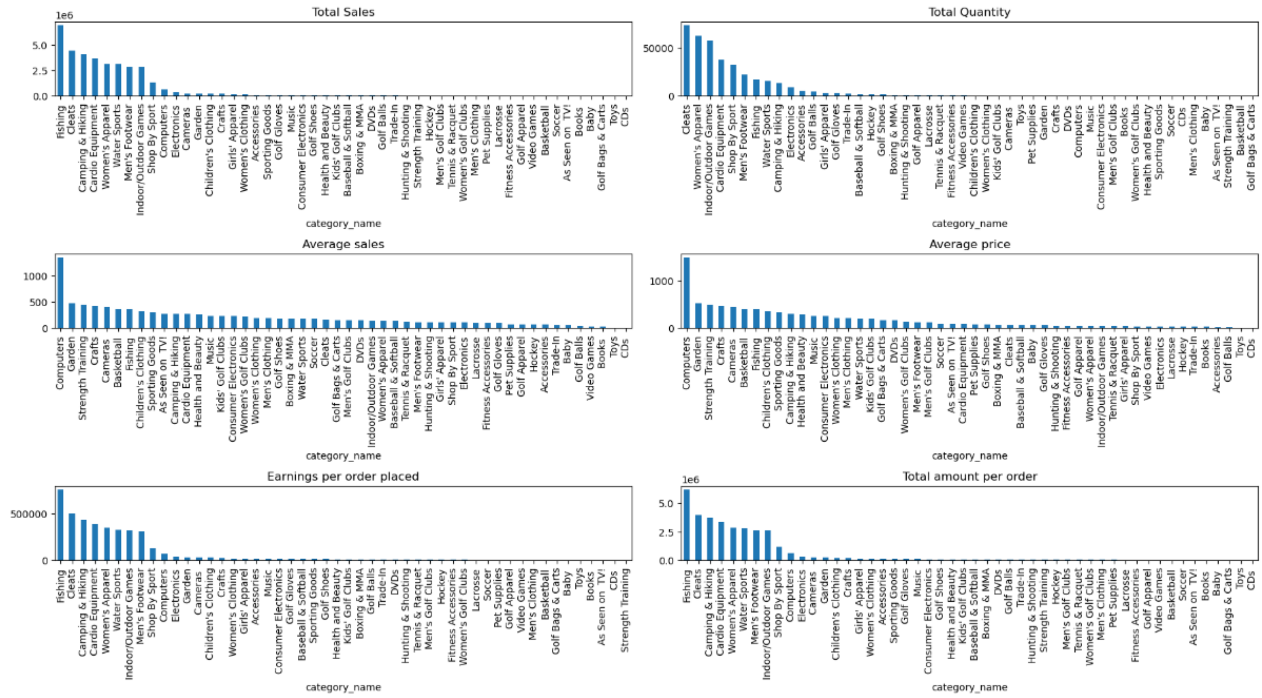




From the graph, it can be seen that the European market has the highest sales and thus the highest earnings per order, while LATAM has the highest total quantity of orders. This indicates that the average order item product price in Europe is higher than in LATAM. Due to the high volume of orders in these markets, the company can make it possible to build more warehouses in these regions, which reduces transportation costs and delivers products faster.

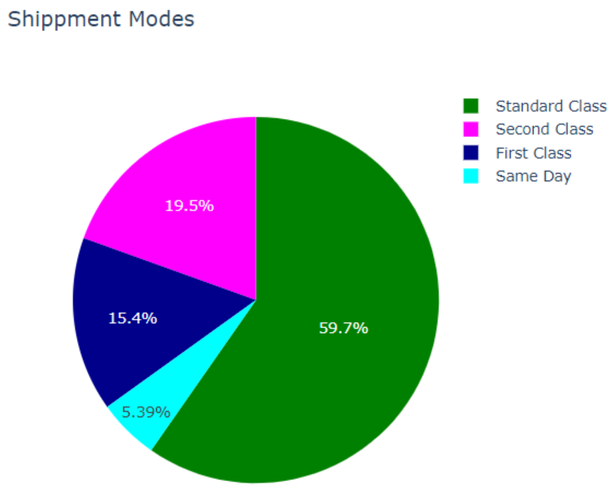
Product Category Analysis:

As we can see from Figure 1, the "Fishing" category has the most sales, followed by "Cleatts". However, in the top seven categories with the highest average price, the best-selling category is "Computers" with an average of 1,347 sales. Since the correlation between price and sales was high (0.79), the effect of price on sales of all products should be investigated to determine the trend.

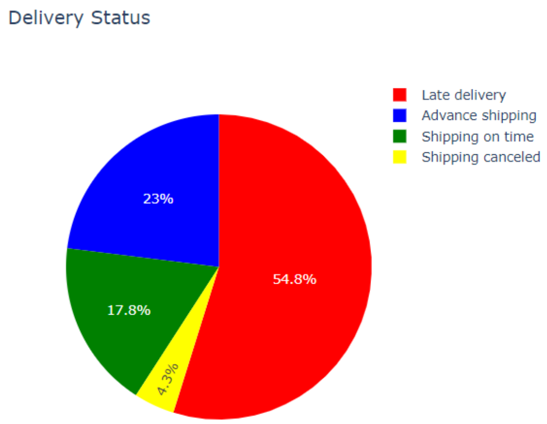


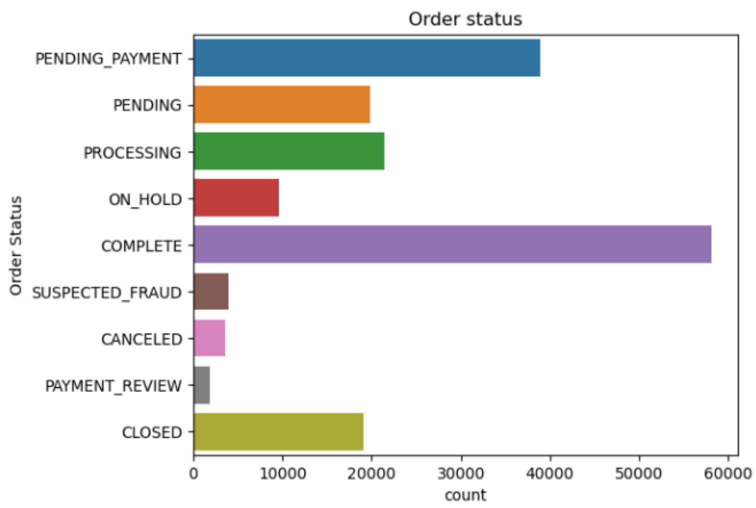
Order Status:

In this Pie Chart, it is clear that Standard Class is the majority of shipping mode among the others, while Same Day shipping mode only shares a small portion. so can be concluded that customers tend to use the shipping method at a lower price.



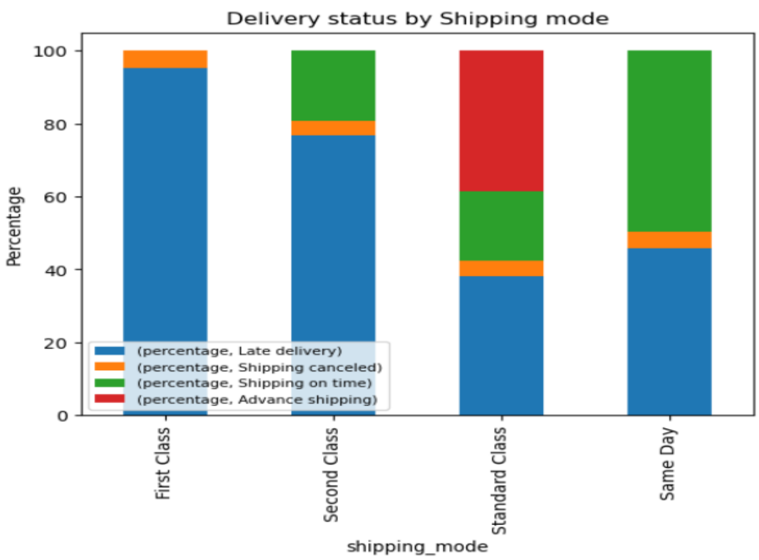
In this graph, it is clear that late delivery has the highest share while shipping on time accounts for only about 18%. Late delivery not only has cost implications but can also damage a company's reputation. Loss of credit leads to the loss of existing customers and the failure to attract new ones.





As shown in the figure it’s clear that most order have completed status. This suggests streamlined operations, accurate inventory management, and a positive brand image, with potential financial benefits from timely order processing. Continuous monitoring allows organizations to uphold transparency and identify areas for improvement.

The stacked bar chart shows the poor performance of all shipping modes. Almost 55% of orders are delivered late. For First Class items, the late delivery rate is about 95%; for Second Class orders, it is 77%. Late delivery can noticeably negatively impact customer satisfaction, company image, and cash flow. Additionally, it has a significant impact on a company's ability to retain customers because unsatisfied customers are much more likely to switch to rival companies.



Techniques for Demand Forecasting:

Methods of demand forecasting can be classified into two broad categories: qualitative and quantitative. **Qualitative** methods involve using judgment and experience to make forecasts, while methods use historical data and statistical techniques.

In this report we are using **statistical method** for the demand forecasting. This approach uses historical data to identify patterns and trends that can be used to make predictions about future demand. This method is best suited for businesses with a long sales data history.

The statistical method can be divided into two sub-categories:

- **Time Series Analysis**: In this approach, demand is forecasted by extrapolating past demand data into the future. This method can be used when demand grows at a constant rate or when there is a clear trend in the data.

- **Regression Analysis**: This approach uses historical data to identify relationships between different factors and demand. The sourced information can be utilised to make predictions about demand in the future. This method is best suited for businesses with a large amount of data that can be analysed.

Time Series Models for Order Item Quantity:

Time series models for order item quantity involve analysing and forecasting data points collected over time, considering temporal patterns and trends. These models aim to capture and predict variations in order item quantities based on historical information. Techniques such as **ARIMA** (Auto Regressive Integrated Moving Average), Exponential Smoothing methods, and advanced models like **SARIMA** (Seasonal ARIMA), alongside newer approaches such as the **Facebook Prophet** model are commonly used for time series forecasting in the context of order item quantities. Each model has its strengths, and the choice depends on the characteristics of the data and the specific forecasting requirements. The goal is to leverage historical patterns to make accurate predictions for future order quantities, aiding in effective inventory management and decision-making.

1) Prophet Model

Prophet is a time series forecasting model developed by Facebook that excels in predicting future values with daily observations, handling seasonality, holidays, and special events. Its key features include automatic detection of seasonal patterns, flexibility for incorporating custom seasonality, and robustness to missing data. Prophet decomposes time series data into trend, seasonality, and holiday components, providing a powerful tool for accurate and interpretable forecasting. It is particularly useful for business applications, offering simplicity and efficiency in generating reliable predictions for various time series datasets.

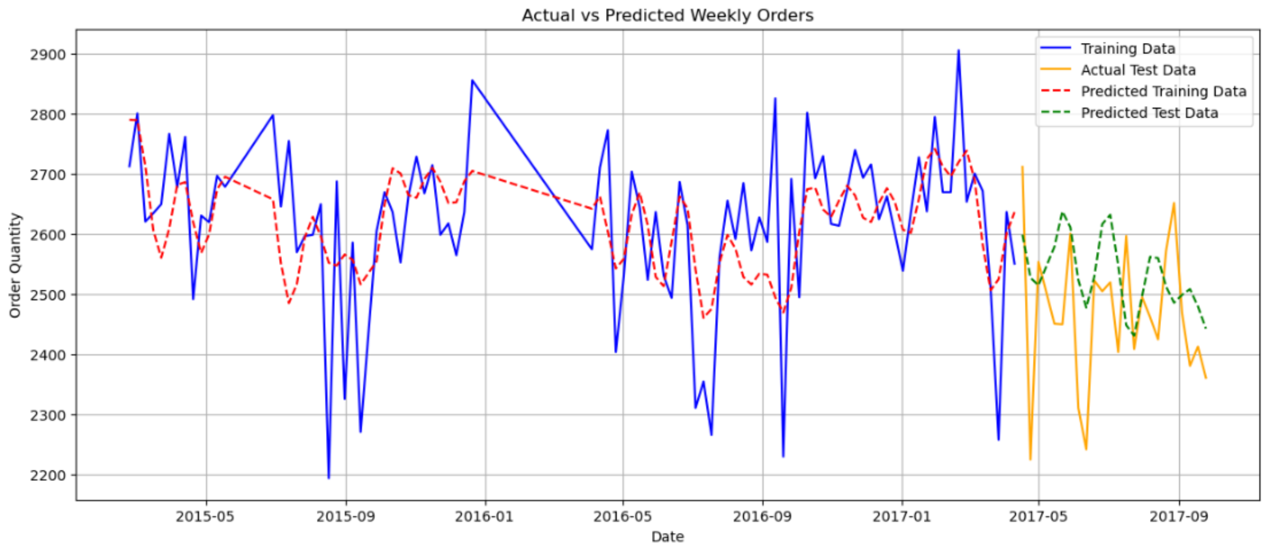


Figure: Actual vs Predicted Weekly Orders Graph Forecasted using Prophet Model

	horizon	mse	rmse	mae	mape	mdape	smape	coverage
0	7 days	10863.387875	104.227577	96.208619	0.034892	0.034892	0.035392	1.0
1	14 days	2314.123895	48.105342	44.122763	0.016525	0.016525	0.016646	1.0
2	21 days	23775.499819	154.193060	138.006930	0.048543	0.048543	0.050026	0.5
3	28 days	32483.345453	180.231366	152.745252	0.053495	0.053495	0.055289	0.5
4	35 days	1873.835149	43.287818	38.403245	0.014410	0.014410	0.014302	1.0
5	42 days	1335.152581	36.539740	28.426489	0.010628	0.010628	0.010722	1.0
6	49 days	4329.018557	65.795278	64.196070	0.024975	0.024975	0.024821	1.0
7	56 days	69881.074560	264.350288	218.192952	0.095098	0.095098	0.088790	0.5
8	63 days	65778.594735	256.473380	204.125169	0.088846	0.088846	0.082895	0.5
9	70 days	10485.978037	102.401065	92.769438	0.036050	0.036050	0.035270	1.0

The Symmetric Mean Absolute Percentage Error (SMAPE) is a metric used to evaluate the accuracy of predictions in a predictive model, particularly in forecasting tasks. Lower SMAPE values, closer to 0% (0.041415126478039375), suggest high accuracy and good predictive performance. A low S MAPE indicates that the model's predictions are relatively close to the actual values on average.

2) ARIMA Model

ARIMA, which stands for AutoRegressive Integrated Moving Average, is a popular time series forecasting model known for its effectiveness in capturing complex temporal patterns. ARIMA combines autoregressive (AR) and moving average (MA) components, and the "integrated" term represents differencing, used to make the time series stationary. The model is defined by three parameters: p (order of autoregression), d (degree of differencing), and q (order of moving average). ARIMA is widely used for its ability to handle various time series data, making it a versatile tool for forecasting trends, seasonality, and future values based on historical patterns.

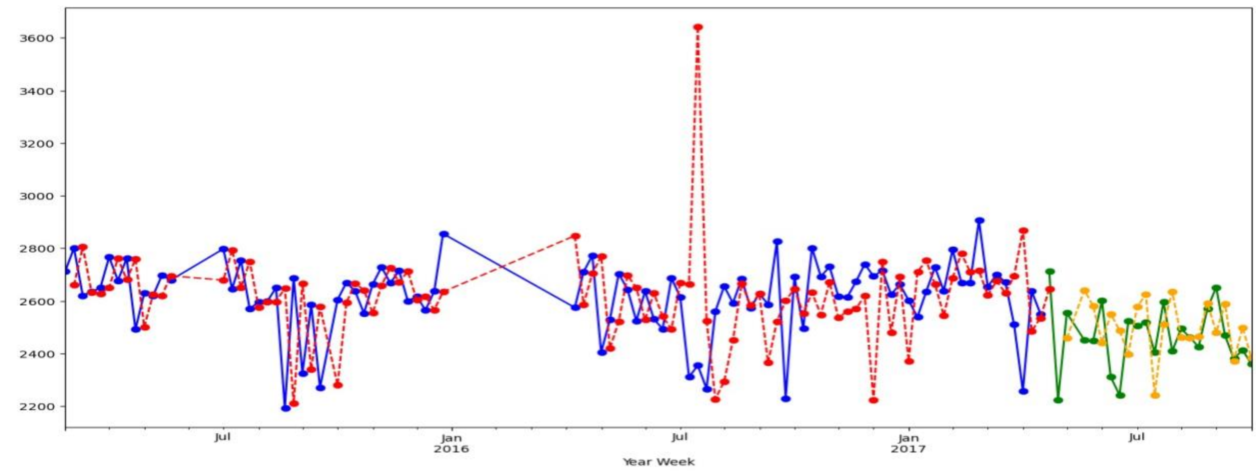


Figure: Actual vs Predicted Weekly Orders Graph Forecasted using ARIMA Model

```
smape_arima = smape(weekly_orders[split_point:], weekly_predictions[split_point:])
smape_arima
```

```
4.240584934393888
```

The Symmetric Mean Absolute Percentage Error (SMAPE) is a metric used to evaluate the accuracy of predictions in a predictive model, particularly in forecasting tasks. Lower SMAPE values, closer to 0% (4.240585), suggest high accuracy and good predictive performance. A low SMAPE indicates that the model's predictions are relatively close to the actual values on average.

3)SARIMA Model

SARIMA, or Seasonal AutoRegressive Integrated Moving Average, is an extension of the ARIMA model designed to handle time series data with seasonal patterns. Similar to ARIMA, SARIMA incorporates autoregressive (AR), differencing (I), and moving average (MA) components, but it also includes seasonal terms. The key parameters for SARIMA are denoted as (p, d, q) for the non-seasonal components and (P, D, Q, s) for the seasonal components, where "s" represents the length of the seasonal cycle. SARIMA is effective for modeling and forecasting time series data that exhibit both non-seasonal and seasonal patterns, providing a powerful tool for capturing complex temporal relationships.

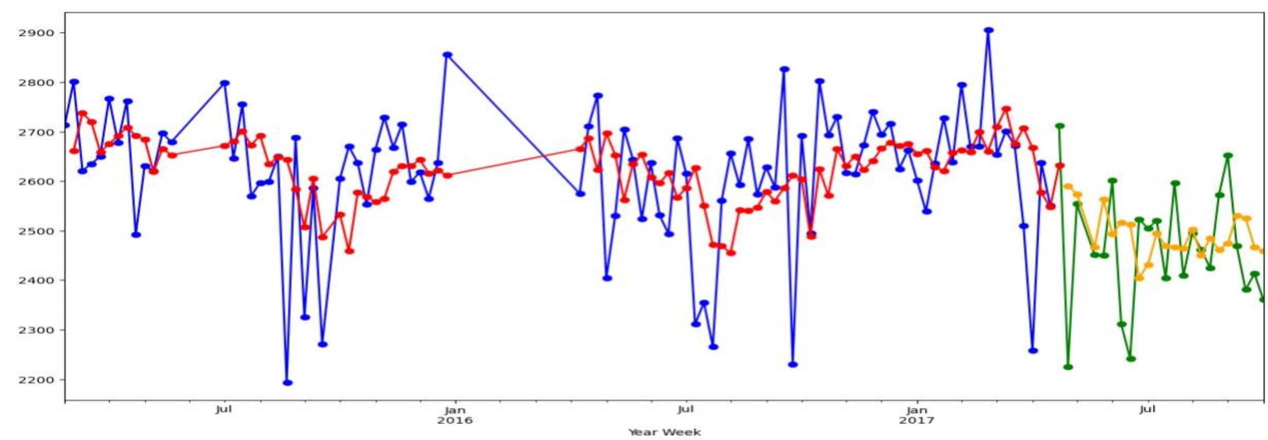


Figure: Actual vs Predicted Weekly Orders Graph Forecasted using SARIMA Model

```
smape_arima = smape(weekly_orders[split_point:], sarima_pred[split_point:])
smape_arima
```

```
4.588393338255046
```

The Symmetric Mean Absolute Percentage Error (SMAPE) is a metric used to evaluate the accuracy of predictions in a predictive model, particularly in forecasting tasks. Lower SMAPE values, closer to 0% (4.5884), suggest high accuracy and good predictive performance. A low SMAPE indicates that the model's predictions are relatively close to the actual values on average.

Regression Models for Order Item Quantity:

Demand (Order Item Quantity) forecasting enables company to make more informed supply decisions that estimate total sales and revenue for the future. Regression models can find patterns, recognise demand indications, and identify correlations between variables in large datasets. According to a McKinsey ML-based supply chain solutions can cut prediction mistakes by up to 50%.

The regression models used are Random Forest regression, Decision Tree Regression, and Linear Regression to predict "Order Item Quantity" which are compared with **mean absolute error (MAE)** and **root mean square error (RMSE).**

Data Modeling:

The data in some columns is of the object type, which cannot be used in the regression model. One option is to remove the column corresponding to this data, but since customer category, market, product name, order region, category name, etc. might affect the Order Item Quantity, removing these columns creates a poor model. So, all object types are converted to the 'int' type using the **label encoding**.

Train-Test split for Machine Learning:

```
train_SCData=train_SC.drop(['shipping_date_dateorders','order_date_dateorders'],axis=1)
```

```
xorderitemquantity=train_SCData .loc[:, train_SCData .columns !='order_item_quantity']
yorderitemquantity=train_SCData['order_item_quantity']
xorderitemquantity_train, xorderitemquantity_test,
yorderitemquantity_train,yorderitemquantity_test = train_test_split(xorderitemquantity,
                                                                    yorderitemquantity,
                                                                    test_size = 0.3,
                                                                    random_state = 42)
```

```
xorderitemquantity_train.shape,xorderitemquantity_test.shape,yorderitemquantity_train.shape,yorderitemquantity_test.shape
```

```
((126363, 42), (54156, 42), (126363,), (54156,))
```

1)Linear Regression

Linear Regression

```
model_orderitemquantity=LinearRegression()
regressionmodel(model_orderitemquantity,xorderitemquantity_train, xorderitemquantity_test,
                yorderitemquantity_train,yorderitemquantity_test)
```

```
Model parameter used are: LinearRegression()
MAE of Total amount per order is          : 0.33750719157356357
RMSE of Total amount per order is         : 0.5253302133399745
```

RMSE means a measure of how far data points from the regression line whose value is 0.525351, and MAE measures the average magnitude of the error without considering the directions between the actual and prediction observation which value is 0.338233.

Model Evaluation:

Performance metrics in regression models assess the accuracy and effectiveness of predictions, crucial for evaluating model performance. Common metrics include **Mean Absolute Error** (MAE), measuring the average absolute difference between actual and predicted values; **Mean Squared Error** (MSE), emphasizing larger errors through squared differences; **Root Mean Squared Error** (RMSE), providing a more interpretable metric in the same units as the target variable; **Mean Absolute Percentage Error** (MAPE), **Symmetric Mean Absolute Percentage Error** (SMAPE) expressing errors as a percentage of actual values; R-squared (R2) Score, indicating the proportion of variance explained by the model; Adjusted R-squared, considering the number of predictors; Explained Variance Score, measuring the proportion of variance explained; and Max Error, capturing the maximum absolute difference. The choice of metric depends on the specific characteristics of the dataset and the goals of the regression model, balancing the need for accuracy, interpretability, and relevance to the problem at hand.

Model Evaluation for Time Series Model:

The model selection criterion is based on minimum value of **SMAPE**. In this scenario, **Prophet** model outperforms the **ARIMA** and **SARIMA** model.

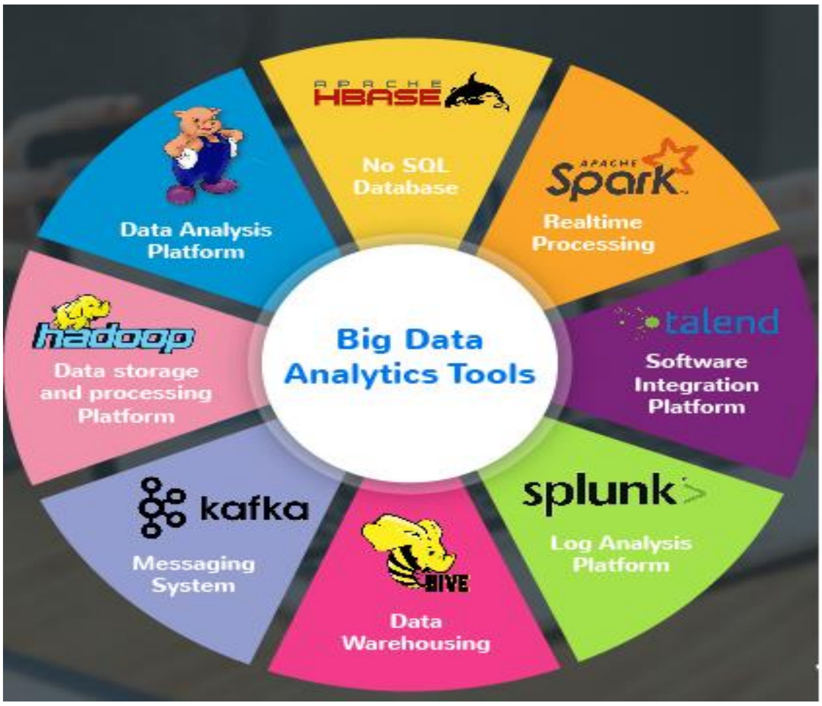
Model Evaluation for Regression Model:

The model selection criterion is based on the minimum values of MAE and RMSE. Linear Regression model

Business Perspective:

Demand (Order Item Quantity) forecasting is an important part of supply chain management. The company must forecast actual future demand for production planning, purchasing decisions, and capital cost minimization. Accurate demand forecasting can lead to increased customer satisfaction and significant financial savings. Therefore, it is very important to choose the right regression model that can provide the most accurate demand forecast.

Big Data Tools Used in the Project:



The utilization of Big Data tools has become integral, offering scalable solutions to handle vast amounts of data efficiently. These tools, such as **Hadoop Distributed File System (HDFS)**, **Apache Spark**, and **Apache Kafka**, address various aspects of the machine learning workflow. They enable distributed storage and retrieval of large datasets, facilitating seamless data preprocessing and feature engineering. These tools also play a crucial role in resource management, ensuring optimal utilization of computing resources, and in enhancing data governance and security in machine learning projects.

Big Data tools play a pivotal role in supporting the **scalability, efficiency**, and **effectiveness of machine learning projects**, particularly when dealing with large volumes of data. The integration of these tools enhances the capabilities of machine learning models, making them more robust and applicable to real-world, data-intensive scenarios.

Learning of Project:

A demand forecasting project can provide several valuable learning insights for businesses. Here are key takeaways that organizations can glean from engaging in demand forecasting initiatives: **Understanding of Seasonal Patterns**, **Customer Behaviour Insights, Product Lifecycle Understanding**, **Effective Resource Allocation, Collaboration Across Departments, Strategic Decision-Making, Optimized Inventory Management, Continuous Improvement, Supply Chain Optimization, Integration of Technology** these are some of the learning we get from demand forecasting which we can use for our business development in future. The knowledge gained contributes to strategic decision-making, adaptability, and continuous improvement, positioning the business for sustained success in a competitive landscape.

IMPORTANCE OF DEMAND FORECASTING

Optimizing Inventory Management:

Helps maintain optimal stock levels by predicting future demand, reducing the risk of overstocking or stockouts.

Cost Efficiency:

Enables efficient allocation of resources, minimizing carrying costs associated with excess inventory and reducing the need for expedited shipments.

Enhancing Customer Service:

Improves customer satisfaction by ensuring product availability and timely deliveries, leading to increased loyalty and positive customer experiences.

Strategic Decision-Making:

Provides valuable insights for strategic planning, allowing businesses to make informed decisions regarding production, marketing, and resource allocation.

Resource Planning:

Facilitates effective allocation of resources, including labor, production capacity, and raw materials, based on anticipated demand.

Risk Management:

Helps identify potential risks and uncertainties, allowing businesses to develop contingency plans and mitigate the impact of unexpected events on operations.

Financial Planning:

Supports accurate financial forecasting by providing insights into future sales, allowing for better budgeting and financial planning.

Supply Chain Optimization:

Contributes to a more efficient supply chain by aligning production and distribution with anticipated demand, reducing inefficiencies and enhancing overall supply chain performance.

New Product Introductions:

Facilitates the successful launch of new products by estimating potential demand and guiding production and marketing strategies.

Operational Efficiency:

Contributes to overall operational efficiency by aligning production and distribution processes with actual demand, reducing waste and optimizing efficiency throughout the supply chain.

Innovation in Demand Forecasting:

Innovations in demand forecasting have become increasingly important as businesses seek more accurate and dynamic approaches to understanding and predicting customer needs. Several innovations have emerged in this field to enhance forecasting precision, adaptability, and efficiency:

Machine Learning and AI Algorithms:

Implementation of advanced machine learning and artificial intelligence algorithms allows for more nuanced analysis of historical data and the incorporation of multiple variables. These algorithms can identify complex patterns and relationships that traditional methods might miss.

Predictive Analytics Platforms:

The integration of sophisticated predictive analytics platforms facilitates a more comprehensive and automated approach to demand forecasting. These platforms often include machine learning models, automation tools, and real-time data processing capabilities.

Big Data Analytics:

Leveraging big data analytics allows organizations to analyze vast datasets, including structured and unstructured data. This includes social media sentiment analysis, customer reviews, and other external factors that can impact demand.

IoT Integration:

The Internet of Things (IoT) has enabled the collection of real-time data from interconnected devices. This data, when incorporated into demand forecasting models, provides a more accurate representation of current market conditions.

Blockchain for Supply Chain Visibility:

The use of blockchain technology enhances supply chain visibility. Transparent and secure data sharing across the supply chain ensures that all stakeholders have access to the same information, reducing discrepancies and improving forecasting accuracy.

Demand Sensing:

Demand sensing involves using real-time data and analytics to sense changes in demand patterns immediately. This agile approach allows organizations to respond rapidly to shifts in customer behavior.

Hybrid Forecasting Models:

Combining various forecasting models, such as integrating both quantitative and qualitative approaches, results in hybrid models that offer a more comprehensive view. This approach is particularly effective in handling uncertain and rapidly changing market conditions.

Continuous Model Improvement:

Emphasizing continuous improvement involves regularly updating and refining forecasting models based on feedback, new data, and changes in market dynamics. This iterative process ensures models stay relevant and accurate over time.

Innovation in demand forecasting is an ongoing process, driven by technological advancements and the evolving nature of markets. The integration of these innovations allows organizations to stay ahead of the curve, adapt to changing conditions, and make more informed decisions for better business outcomes.