INVENTORY STOCK DEMAND FORECASTING

A PROJECT REPORT

Submitted by

Godfrey Ashwanth
[Reg No: RA2112704010020]

Under the Guidance of

Dr. A.V. Kalpana
(Assistant Professor, Department of Data Science and Business Systems)

In partial fulfillment of the Requirements for the Degree of

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SRM INSTITUTE OF SCIENCE AND TECHNOLOGY

SRM INSTITUTE OF SCIENCE AND TECHNOLOGY

KATTANKULATHUR-603203

BONAFIDE CERTIFICATE

Certified that this project report titled "**INVENTORY STOCK DEMAND FORECASTING"** is the bonafide work of **"Godfrey Ashwanth Reg No: RA211270401002** who carried out the project work under my supervision. Certified further, that to the best of my knowledge the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion for this or any other candidate.

Dr. A.V.Kalpana	Dr. G.Vadivu	Dr. M.Lakshmi
GUIDE	**PROGRAM**	**HEAD OF THE**
Assistant Professor	**COORDINATOR**	**DEPARTMENT**
Dept. of DSBS	Dept. of DSBS	Dept. of DSBS

Signature of Internal Examiner

Signature of External Examiner

ABSTRACT

Forecasting is predicting or estimating a future event or trend. Supply chains have been constantly growing in most countries ever since the industrial revolution of the 18th century. As the competitiveness between supply chains intensifies day by day, companies are shifting their focus to predictive analytics techniques to minimize costs and boost productivity and profits. Excessive inventory (overstock) and stock outs are very significant issues for suppliers. Excessive inventory levels can lead to loss of revenue because the company's capital is tied up in excess inventory. Excess inventory can also lead to increased storage, insurance costs and labour as well as lower and degraded quality based on the nature of the product. Shortages or out of stock can lead to lost sales and a decline in customer contentment and loyalty to the store.

If clients are unable to find the right products on the shelves, they may switch to another vendor or purchase alternative items. Demand forecasting is valuable for planning, scheduling and improving the coordination of all supply chain activities. This paper discusses the use of neural networks for seasonal time series forecasting. Our objective is to evaluate the contribution of the correct choice of the transfer function by proposing a new form of the transfer function to improve the quality of the forecast. customers will turn to similar products to fulfil their expectations. A lack of coherence between the demand and the means implemented to satisfy it can lead to important stocks, or sales losses due to stock shortage, which, beyond the notion of costs inherent to the logistic means, represents a deterioration of the company's image and a damaging loss of its turnover.

The goal of companies is to be able to satisfy an increasingly diversified demand, in a short period of time and with minimum stocks. To achieve this, they must have a global vision of the chain that allows them to reach an optimization as a whole. Demand forecasting is a key tool by which the company can face the uncertainties

related to the future. sufficient to absorb the peak demand. It is therefore necessary to launch production in advance based on sales forecasts.

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We register our immeasurable thanks to our Faculty Advisor**, Dr.K.Shantha Kumari,** Assistant Professor, Department of Data Science and Business Systems, SRM Institute of Science and Technology, for leading and helping us to complete our course.

Our inexpressible respect and thanks to my guide, **Dr. A.V Kalpana,** Assistant Professor, Department of Data Science and Business Systems, for providing me with an opportunity to pursue my project under her mentorship. She provided us with the freedom and support to explore the research topics of our interest. Her passion for solving problems and making a difference in the world has always been inspiring. She has motivated us with good intentions towards life as well subject wise. Her love and affection towards the student is proving her interests.

We sincerely thank the Data Science and Business Systems staff and students, SRM Institute of Science and Technology, for their help during our project. Finally, we would like to thank parents, family members, and friends for their unconditional love, constant support, and encouragement.

Godfrey Ashwanth

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ABBREVIATIONS

PD Pandas

GUI Graphical User Interface

SNS Seaborn

PLT MatPlotLib

CHAPTER 1

INTRODUCTION

1.1 General

Forecasting the inventory supplies and probable future demands is a necessary part of efficiently managing stocks and capital. In this competitive ecosystem, the philosophy of just-in-time manufacturing and deliveries is crucial. This not only helps customers get products on time, saves in wasteful stocking, and saves capital to invest in areas that could be more beneficial. Thus, an inventory management system can be deemed useful if it could generate insights to properly estimate the demands from current
trends. If we could model the generation of results within a particular tolerance band. It will lead to effectively managing supplies and thus keep the system running at optimal operational efficiency also raising confidence in clients. Day by day the use of ML algorithms in the different applications are being applied scrupulously.

Each managerial decision in the company is more or less based on the estimate of the future, while most of these decisions are based on the future demand forecast. Therefore, demand forecasting represents an important corporate management tool, which makes it possible for the managers not only to make rational decisions, but also to manage the other corporate processes effectively. In such cases, timely and reliable estimate of future sales is crucial for planning sales, manufacturing, purchase, as well as other subsequent corporate processes. Such a forecast can only be obtained through a systematically managed process of demand forecasting, involving representatives of all the corporate departments.

1.2 MOTIVATION

It's no secret that businesses across many sectors, including healthcare, retail, manufacturing, energy, and logistics, are adopting IoT technologies to streamline and automate their operations. All eyes are on the energy industry and its use of IoT technology from citizens, corporations, and governments throughout the world. In addition to paving the way for the creation of new, more intelligent grids, Internet of Things (IoT) energy management systems also drastically cut costs, improved security, and increased overall efficiency in the distribution of electrical energy. Very little of modern life can continue in any significant way without the ubiquitous presence of electricity. The Internet of Things heralds a new era of technical innovation in the manufacturing of electrical products (IoT). The main objective of this initiative is to educate homeowners about their personal energy use and the ways in which they may optimize appliance efficiency. The monthly collection of readings would be easier for staff with this method in place, and billing cycle hiccups would be reduced. Users of this technology may be able to contribute to a reduction in energy consumption by keeping tabs on the amount of power used by individual appliances on a daily basis and adjusting their habits accordingly, in addition to saving money. The amount owed and any other payment details required to settle the account will be included in the electrical board section of the bill. If the client does not pay the bill by the due date, they will get a message reminding them to do so. In the event that a user's bill is paid in full, they will get a single text message indicating this fact.

CHAPTER 2

LITERATURE REVIEW

Title1: A Bayesian approach to demand forecasting for new equipment programs

(2017)

Demand forecasting is a fundamental component in a range of industrial problems (e.g., inventory management, equipment maintenance). Forecasts are crucial to accurately estimating spare or replacement part demand to determine inventory stock levels. Estimating demand becomes challenging when parts experience intermittent demand/failures versus demand at more regular intervals or high quantities. In this paper, we develop a demand forecasting approach that utilizes Bayes' rule to improve the forecast accuracy of parts from new equipment programs where established demand patterns have not had sufficient time to develop. In these instances, the best information available tends to be "engineering estimates" based on like /similar parts or engineering projections. A case study is performed to validate the forecasting methodology. The validation compared the performance of the proposed Bayesian method and traditional forecasting methods for both forecast accuracy and overall inventory fill rate performance. The analysis showed that for specific situations the Bayesian-based forecasting approach more accurately predicts part demand, impacting part availability (fill rate) and inventory cost. This improved forecasting ability will enable managers to make better inventory investment decisions for new equipment programs.

Title 2: Safety stock planning under causal demand forecasting
(2018)

Mainstream inventory management approaches typically assume a given theoretical demand distribution and estimate the required parameters from historical data. A time series based framework uses a forecast (and a measure of forecast error) to parameterize the demand model. However, demand might depend on many other factors rather than just time and demand history. Inspired by a retail inventory management application where customer demand, among other factors, highly depends on sales prices, price changes, weather conditions, this paper presents two data-driven frameworks to set safety stock levels when demand depends on several exogenous variables. The first approach uses regression models to forecast demand and illustrates how estimation errors in this framework can be utilized to set required safety stocks. The second approach uses Linear Programming under different objectives and service level constraints to optimize a (linear) target inventory function of the exogenous variables. We illustrate the approaches using a case example and compare two methods with respect to their ability to achieve target service levels and the impact on inventory levels in a numerical study. We show that considerable improvements of the overly simplifying method of moments are possible and that the ordinary least squares approach yields a better performance than the LP-method, especially when the data sample for estimation is small and the objective is to satisfy a non-stockout probability constraint. However, if some of the standard assumptions of ordinary least squares regression are violated, the LP approach provides more robust inventory levels.

Title 3: Joint optimisation of demand forecasting and stock control parameters

(2017)

Exponential smoothing methods are very commonly used for forecasting demand in a supply chain context. When estimating the parameters used in these methods, a common practice is to optimise only the smoothing constants and not the initial parameter values. In this paper we show that if we treat initial values as well as smoothing constants as decision variables, a considerable reduction in forecast error can be achieved. Additionally, the optimisation of the forecasting method should not be treated separately from the production or inventory model in which forecasts are used. The case of a centralised supply chain with an order-up-to inventory policy shows that calculated forecasts of demand, determined by minimising mean absolute error (MAE) or mean squared error (MSE), are not optimal. Finally, a method for simultaneous optimisation of demand forecasting and a stock control policy is described. Initial and smoothing parameters in the forecasting methods can be determined to minimise the total costs

Title 4: Inventory stock and demand forecasting for stock control

(2015)

This paper investigates the gap between research and practice in spare parts management, with specific reference to durable goods addressed to private or professional customers. The paper provides a critical literature review of theoretical contributions about spare parts classification and demand forecasting for stock control. The discussion of ten case studies, then, allows to analyze the reasons for this gap, by addressing the limitations of models developed in literature, the role of contextual factors and the maturity in companies' spare parts management practices. Four main directions for research are proposed in order to bridge the gap, namely: to develop integrated approaches to spare parts management; to define contingencybased managerial guidelines, to favor the knowledge accumulation process in companies, and to supplement theoretical models with practical relevance.

Title 5: Demand Forecasting in the Fashion Industry

Demand forecasting plays an important role in basic Operations Management as an input for planning activities. Poor forecasting effects are stock outs or high inventory, obsolescence, low service level, rush orders, inefficient resource utilization and bullwhip propagating through the upstream supply chain. As such, demand forecasting is a popular research topic and many models for forecasting fashion products have been proposed in the literature over the past few decades.

Typically, high performance companies focus on robust demand forecasting approaches; however, the challenge of demand forecasting varies greatly according to company and industry. In the fashion industry, products are usually characterized by long replenishment lead times, short selling seasons and nearly unpredictable demand and therefore, inaccurate forecasts . All these features make the issue of forecasting demand particularly challenging. Companies in the fashion industry have been trying to manage the demand for many years, which has brought about the development of a number of specific forecasting methods and techniques.

Title 6: IIoT quality global enterprise inventory management

(2018)

Inventory management is an important function of every global enterprise. Enterprises often make financial loss when the goods get misplaced and when they are lost. There is a need for a quality inventory management model that enterprises can implement easily. Enterprises can make more revenue when the inventory is managed efficiently with computational intelligence and predictive analytics. Industrial Internet of Things (IIoT) collects useful data from machines and sensors which can be used for demand forecasting of the enterprise and automation. The proposed IIoT Quality Inventory Management Model can be used for automation and demand forecasting of the inventories

CHAPTER 3

OBJECTIVES

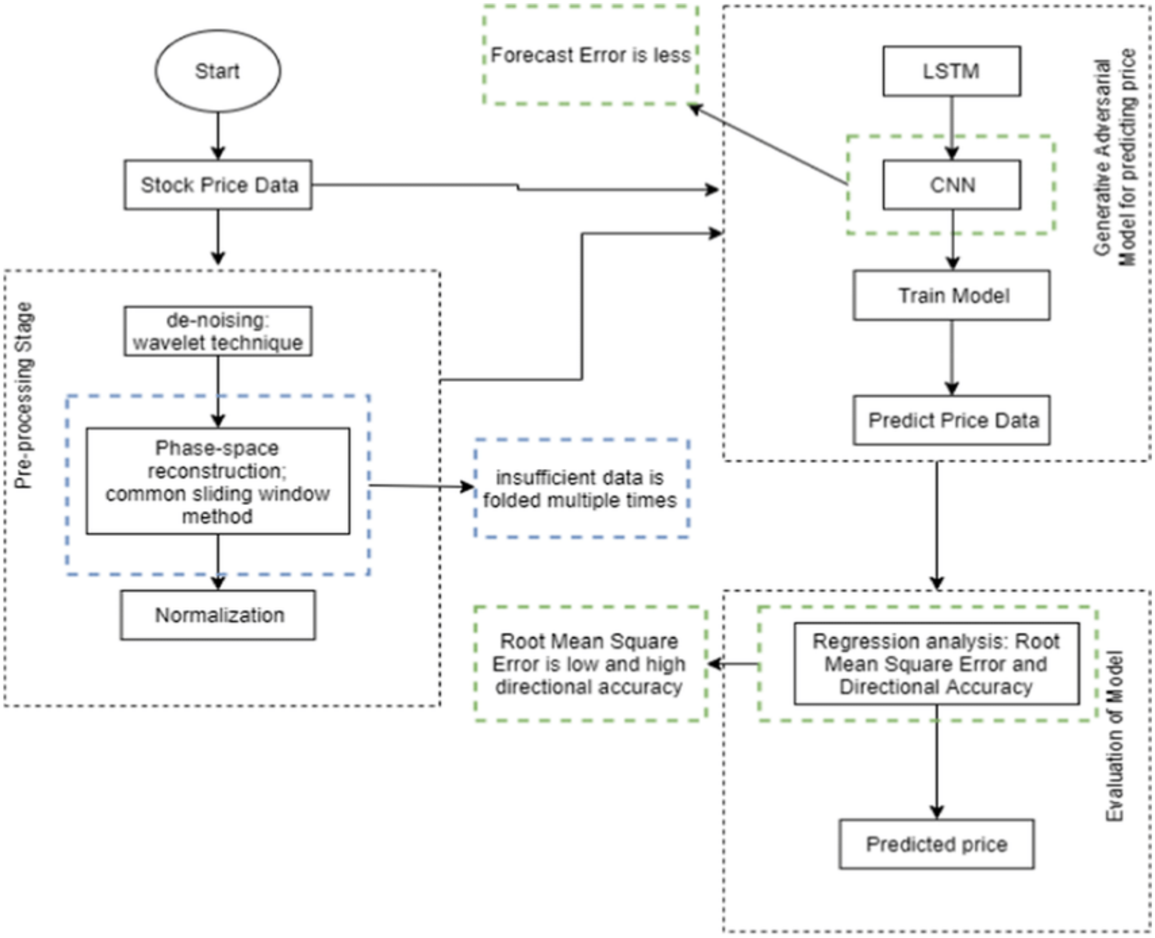
The efforts of the sales, marketing, finance and operations departments to match demand and supply contributes to the appropriate use of resources in the fulfillment of customer demand forecasts. Demand forecasts enable the manufacturing department to plan production to meet customer requirements.

The forecasts also support the purchasing department's efforts to correlate deliveries of materials and supplies with production schedules. In turn, a forecast also alerts finance to the level of investment in plant, equipment and inventory required to meet demand as well as the budgets to be created to manage the business.

The demand forecasts also affect the personnel department's hiring and training decisions and the marketing department's assignment of resources to particular product groups or marketing campaigns.

CHAPTER 4

BLOCK DIAGRAM



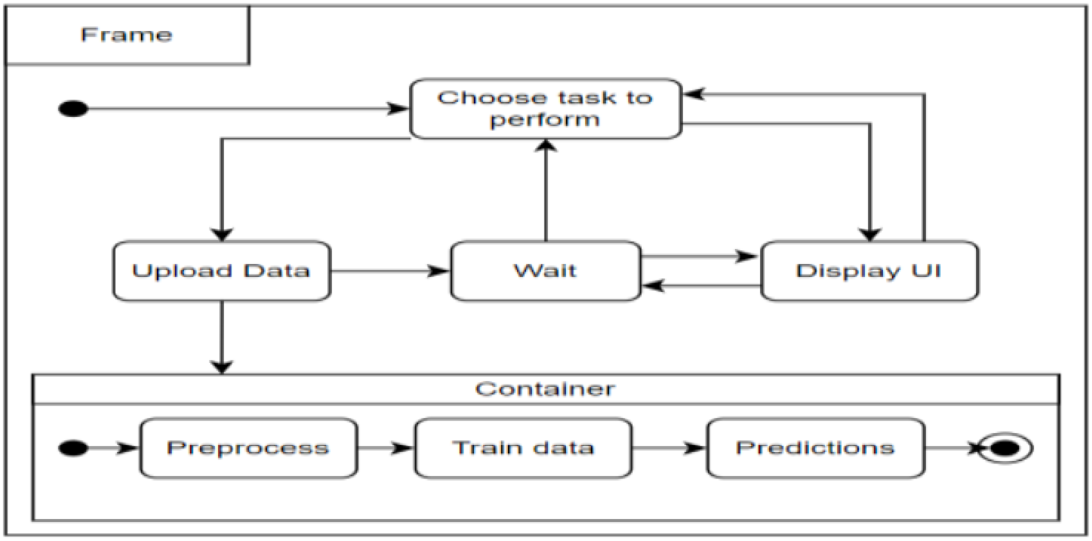
CHAPTER 5

PROJECT CODE

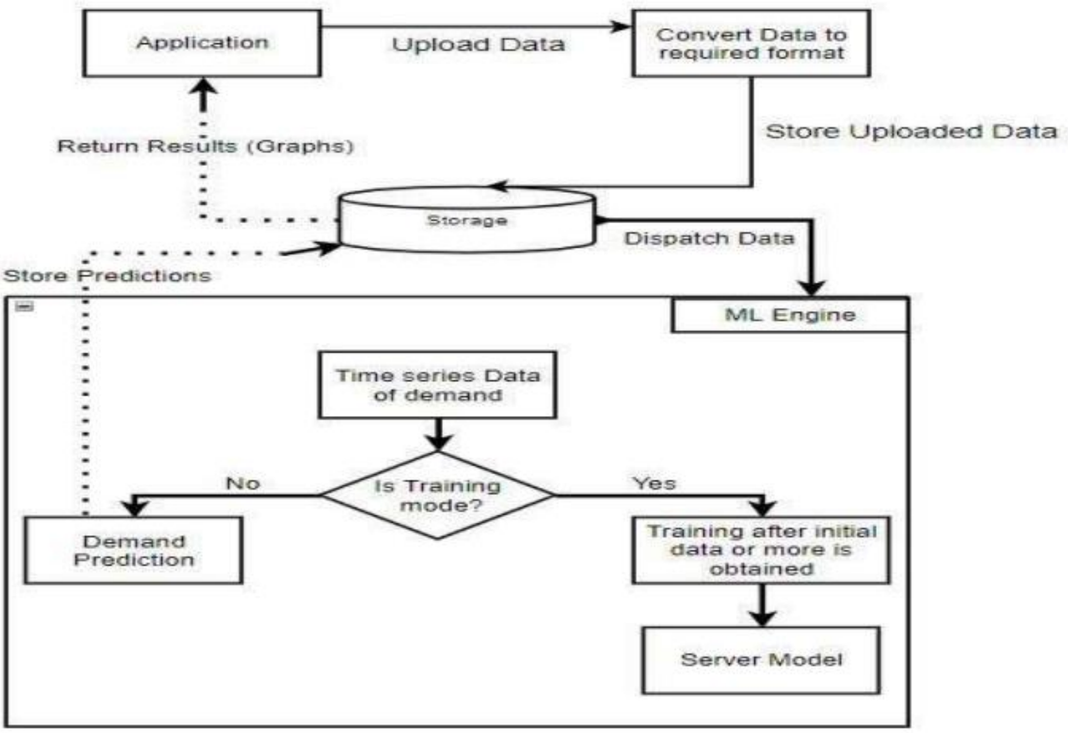
5.1 Algorithm

- Step 1: Download the data set from Kaggel based on “Stock demand forecasting”.
- Step 2: Initialize the data set into colab or Jupiter note, for better experience use python idle.
- Step 3: Load the data set in Co-laboratory.
- Step 4: Check the data type of the downloaded file.
- Step 5: Check for different availability of data’s.
- Step 6: Import the required modules.
- Step 7: Use the quired modules for categorizing the datas.
- Step 8: Use different models for better understanding of the particular data set.
- Step 9: Linear regression to calculate the predicted output
- Step 10: Hierarchical Cluster for knowing the priority.
- Step 11: K-means for mean calculation.

Activity Diagram:



System Architecture:



5.2 Code

```
import numpy as np

import pandas as pd

import matplotlib.pyplot as plt

import seaborn as sb

from sklearn.model_selection import train_test_split

from sklearn.preprocessing import LabelEncoder, StandardScaler

from sklearn import metrics

from sklearn.linear_model import LinearRegression, Lasso, Ridge

from sklearn.metrics import mean_absolute_error as mae



df = pd.read_csv('dataset.csv')

print(df.head(2))

print(df.tail(2))



df.shape
```

```
df.info()

features = ['CountryName','State']
plt.subplots(figsize=(20, 10))
for i, col in enumerate(features):
    plt.subplot(2, 3, i + 1)
    df.groupby(col).mean()['Profit'].plot.bar()
plt.show()

plt.figure(figsize=(10,5))
df.groupby('CountryName').mean()['Profit'].plot()
plt.show()

plt.figure(figsize=(20, 15))
# Calculating Simple Moving Average
# for a window period of 30 days
```

```
window_size = 10

data = df[df['RegionName']=='Asia']

windows = data['TotalItemQuantity'].rolling(window_size)

sma = windows.mean()

sma = sma[window_size - 2:]

data['Profit'].plot()

sma.plot()

plt.legend()

plt.show()



plt.subplots(figsize=(12, 5))

plt.subplot(1, 2, 1)

sb.distplot(df['TotalItemQuantity'])


plt.subplot(1, 2, 2)

sb.boxplot(df['TotalItemQuantity'])

plt.show()
```

```
import seaborn as sb

plt.figure(figsize=(8, 8))

sb.heatmap(df.corr() > 0.8,

           annot=True,

           cbar=False)

plt.show()




#MODEL-1

#Linear Regression

data = pd.read_csv("dataset.csv")

# converting column of data frame to list

x = data["Profit"].values.tolist()

y = data["OrderItemQuantity"].values.tolist()

# splitting them to test and train data

X_train = x[:20]

Y_train = y[:20]

X_test = x[20:]
```

```
Y_test = y[20:]


#MODEL-1

#Linear Regression

# to find mean of the list input

def mean(x):

    return sum(x)/len(x)


# To find the coefficients a,b for the given train data

def Coefficients(X_train,Y_train):

    '''

    input: X_train, Y_trains lists

    output : a,b integers

    '''

    N = len(X_train)

    nr = 0

    dr = 0

    for i in range(N):

        nr += (X_train[i]-mean(X_train))*(Y_train[i]-mean(Y_train))
```

```
        dr += (X_train[i]-mean(X_train))**2
    a = nr/dr
    b = mean(Y_train)-a*mean(X_train)
    return a,b


# Predicts the output for the test input
def predict(X_train,Y_train,X_test):
    '''
    input: X_train, Y_trains, X_test lists
    output : Y_pred list
    '''
    a,b = Coefficients(X_train,Y_train)
    Y_pred = []
    for val in X_test:
        y_pred = (a*val)+b
        Y_pred.append(y_pred)
    return Y_pred


# Prediciting output for test input
```

```
Y_pred = predict(X_train,Y_train,X_test)

out = {'Y_test':Y_test,'Y_pred':Y_pred}

predict_out = pd.DataFrame(out)



# Displaying output as DataFrame for better comparision between Y_test and Y_pred

predict_out



#MODEL-1

#Linear Regression

# plotting Y_test vs X_test

plt.scatter(X_test,Y_test,color='r', label='Actual')

# plotting regression line

plt.plot(X_test,Y_pred,color='b', label='Predicted')

plt.grid()

plt.ylabel("Profit")

plt.xlabel("CustomerCreditLimit")

plt.title("Linear Regression")

plt.legend()

plt.show()
```

```
from sklearn.model_selection import train_test_split

X_train,X_test,y_train,y_test=
train_test_split(X,y,test_size=0.30,random_state=21)

from sklearn.linear_model import LinearRegression

regression_model = LinearRegression()

print("Linear Aggregation Accuracy")

regression_model.fit(X_train, y_train)

regression_model.score(X_test, y_test)



y_pred= regression_model.predict(X_test)

y_pred




#K-means

 #a centroid-based clustering algorithm,

 #where we calculate the distance between each data point and a centroid to
assign it to a cluster.

from sklearn.cluster import KMeans

import matplotlib.pyplot as plt
```

```
import seaborn as sns

X = df[['OrderItemQuantity', 'TotalItemQuantity']].copy()

inertias = []



for i in range(1, 11):

    kmeans = KMeans(n_clusters=i, random_state=0)

    kmeans.fit(X)

    inertias.append(kmeans.inertia_)

sns.set()

plt.plot(range(1,11), inertias)

plt.title('K-means')

plt.xlabel('Clusters')

plt.ylabel('WCSS')

plt.show()

print("K-Means predcition")

print(kmeans.predict(X))

from sklearn.neighbors import KNeighborsClassifier

knn= KNeighborsClassifier(n_neighbors=10)

print("K-Means Accuracy")
```

```
knn.fit(X_train,y_train)

knn.score(X_test,y_test)



import pandas as pd

import matplotlib.pyplot as plt

from scipy.stats import linregress


df = pd.read_csv("dataset.csv")

df.index = df.index.map(int)#change the index value to type integer

df.plot(kind = 'area',stacked=False, figsize = (10,5),#pass a tuple (x,y) size

        )

plt.title('Profit Trend of Top5 Countries')

plt.ylabel('Number of Profit')

plt.xlabel('Years')

plt.show()



import pandas as pd
```

```
import matplotlib.pyplot as plt

import seaborn as sns

df = pd.read_csv("dataset.csv")


plt.figure(figsize=(18, 5))

sns.countplot(x=df['RegionName'], data=df)

plt.xticks(rotation=90)




import pandas as pd

import matplotlib.pyplot as plt

import seaborn as sns

train = pd.read_csv("dataset.csv")

train.corr()

#pairwise correlation of all columns in the Pandas Dataframe


import pandas as pd

import matplotlib.pyplot as plt

import seaborn as sns
```

```
train = pd.read_csv("dataset.csv")

sns.pairplot(train)
```

CHAPTER 6

REQUIREMENTS

6.1 Tools and Technologies required

1. Windows 7 and above

2. Programming Language: Python (3+)

3. Machine Learning/ Deep Learning libraries: sklearn, NumPy, pandas,etc.

4. IDE: Jupyter Notebook/ Sublime Text

5. SQLite Server (For system administrator only)

6. Application Server: Flask

7. Front End Web Browser: Google Chrome, Mozilla Firefox, etc.

8. Analytic toolkit: bokeh, matplotlib

CHAPTER 7

PROJECT FINDINGS

```
     RegionName              CountryName  State       City PostalCode  \
0  South America  United States of America  Texas  Southlake      26192
1  South America  United States of America  Texas  Southlake      26192

     WarehouseAddress    WarehouseName   EmployeeName  \
0  2014 Jabberwocky Rd  Southlake Texas   Summer Payne
1  2014 Jabberwocky Rd  Southlake Texas  Rose Stephens

              EmployeeEmail  EmployeePhone  ...    CustomerName  \
0   summer.payne@example.com   5.151238e+09  ...      Flor Stone
1  rose.stephens@example.com   5.151238e+09  ...  Lavera Emerson

                  CustomerAddress CustomerCreditLimit  \
0                2904 S Salina St                5000
1  5344 Haverford Ave, Philadelphia                5000

                        CustomerEmail CustomerPhone   Status  OrderDate  \
0              flor.stone@raytheon.com  1.317123e+10  Shipped  17-Nov-16
1  lavera.emerson@plainsallamerican.com  1.317123e+10  Shipped  20-Feb-17

   OrderItemQuantity PerUnitPrice TotalItemQuantity
0                132       469.99               122
1                124       519.99               123

[2 rows x 28 columns]
    RegionName CountryName        State    City PostalCode  \
398       Asia       India  Maharashtra  Bombay     490231
399       Asia       India  Maharashtra  Bombay     490231

      WarehouseAddress WarehouseName  EmployeeName          EmployeeEmail  \
398  1298 Vileparle (E)        Bombay  Zima Colleen  ZimaColleen@gmail.com
399  1298 Vileparle (E)        Bombay  Volk Colleen   VolkCollen@gmail.com

     EmployeePhone  ...    CustomerName  CustomerAddress CustomerCreditLimit  \
398   8.690991e+09  ...  Lucy Cechtelar      44 W 4th St                3000
399   9.426827e+09  ...       John Snow  11279 Loytan St                2000

              CustomerEmail CustomerPhone    Status  OrderDate  \
398  LucyCechtelar@gmail.com   964940981.0   Shipped  27-May-17
399       JohnSnow@gmail.com   567897474.0  Canceled  27-May-17

     OrderItemQuantity PerUnitPrice TotalItemQuantity
398                157       821.99                95
399                 32       579.59                92

[2 rows x 28 columns]
```

Fig 1

```
(400, 28)
```

Fig 2

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 400 entries, 0 to 399
Data columns (total 28 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   RegionName            400 non-null    object
 1   CountryName           400 non-null    object
 2   State                 400 non-null    object
 3   City                  400 non-null    object
 4   PostalCode            400 non-null    object
 5   WarehouseAddress      400 non-null    object
 6   WarehouseName         400 non-null    object
 7   EmployeeName          400 non-null    object
 8   EmployeeEmail         400 non-null    object
 9   EmployeePhone         400 non-null    float64
 10  EmployeeHireDate      400 non-null    object
 11  EmployeeJobTitle      400 non-null    object
 12  CategoryName          400 non-null    object
 13  ProductName           400 non-null    object
 14  ProductDescription    400 non-null    object
 15  ProductStandardCost   400 non-null    float64
 16  Profit                400 non-null    float64
 17  ProductListPrice      400 non-null    float64
 18  CustomerName          400 non-null    object
 19  CustomerAddress       400 non-null    object
 20  CustomerCreditLimit   400 non-null    int64
 21  CustomerEmail         400 non-null    object
 22  CustomerPhone         400 non-null    float64
 23  Status                400 non-null    object
 24  OrderDate             400 non-null    object
 25  OrderItemQuantity     400 non-null    int64
 26  PerUnitPrice          400 non-null    float64
 27  TotalItemQuantity     400 non-null    int64
dtypes: float64(6), int64(3), object(19)
memory usage: 87.6+ KB
```

Fig 3

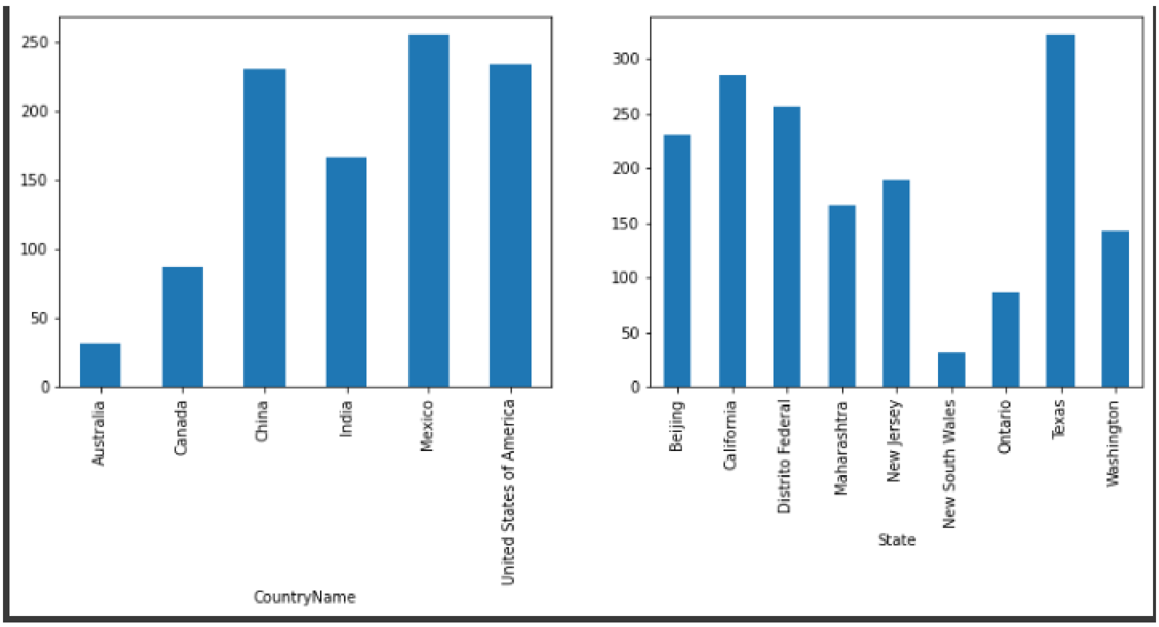


Fig 4

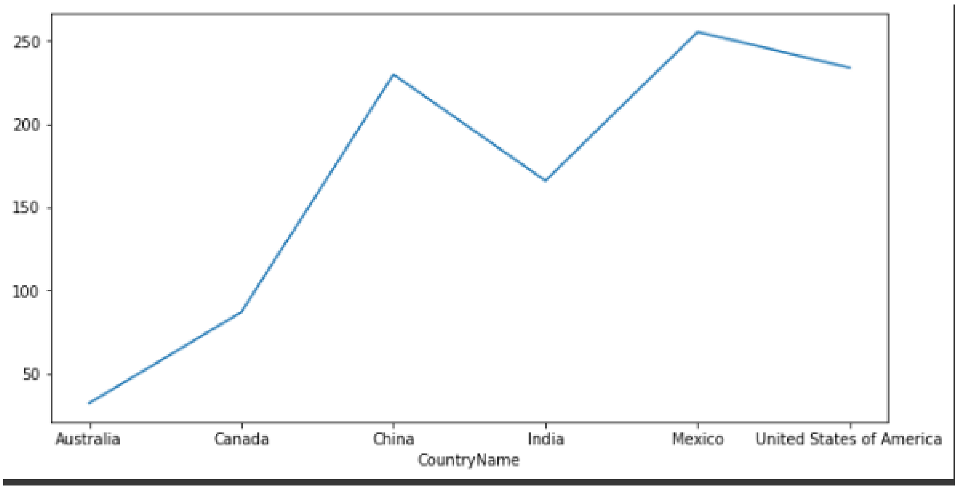

250
200
150
100
50
Australia
Canada
China
India
Mexico
United States of America
CountryName

Fig 5

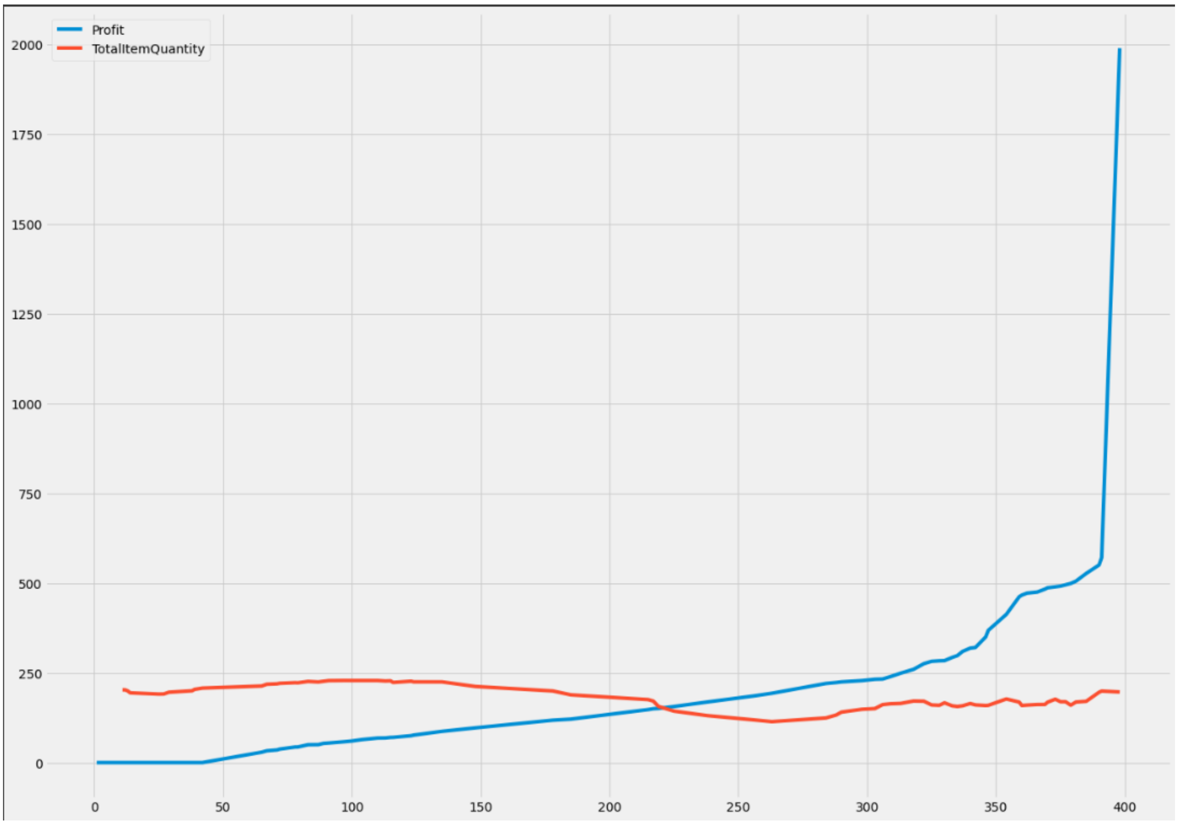
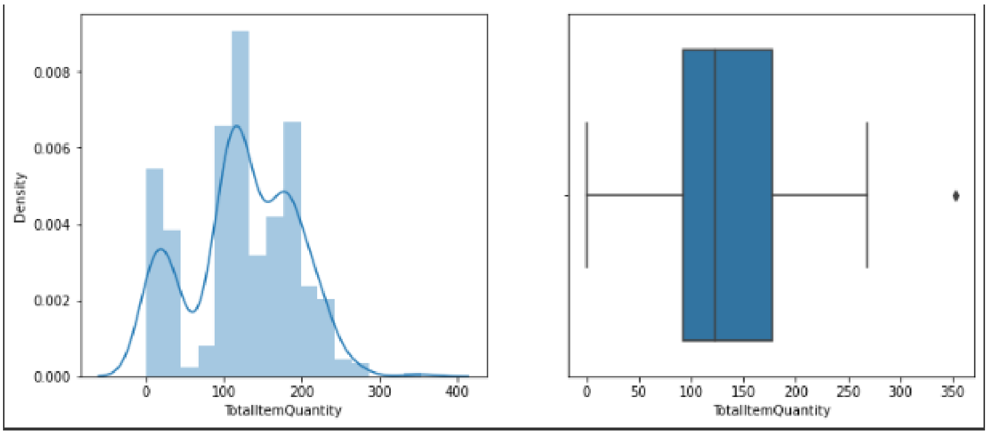
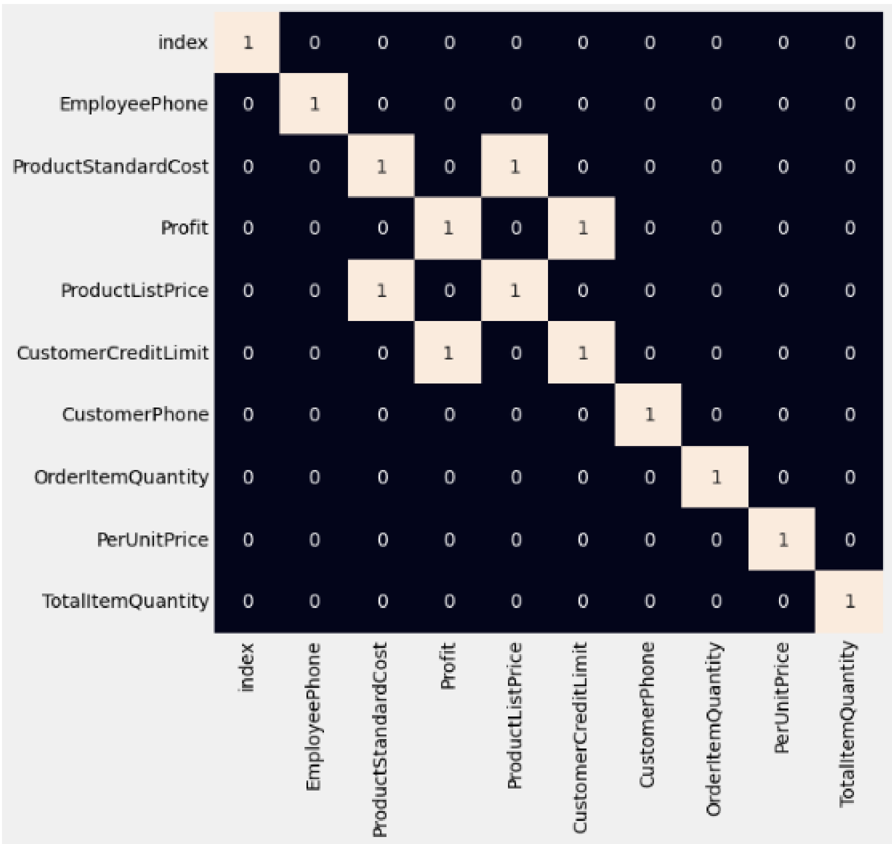

Profit
TotalItemQuantity
2000
1750
1500
1250
1000
750
500
250
0
0
50
100
150
200
250
300
350
400

Fig 6



Density
0.000
0.002
0.004
0.006
0.008
0
100
200
300
400
TotalItemQuantity
0
50
100
150
200
250
300
350
TotalItemQuantity

Fig 7



index
EmployeePhone
ProductStandardCost
Profit
ProductListPrice
CustomerCreditLimit
CustomerPhone
OrderItemQuantity
PerUnitPrice
TotalItemQuantity
1 0 0 0 0 0 0 0 0 0
0 1 0 0 0 0 0 0 0 0
0 0 1 0 1 0 0 0 0 0
0 0 0 1 0 1 0 0 0 0
0 0 1 0 1 0 0 0 0 0
0 0 0 1 0 1 0 0 0 0
0 0 0 0 0 0 1 0 0 0
0 0 0 0 0 0 0 1 0 0
0 0 0 0 0 0 0 0 1 0
0 0 0 0 0 0 0 0 0 1

Fig 8

	Y_test	Y_pred
0	116	101.852076
1	119	99.159489
2	148	99.514635
3	111	107.098635
4	111	99.293272
...	...	...
375	32	98.110056
376	66	97.603006
377	82	96.159470
378	157	96.962777
379	32	95.427737

380 rows × 2 columns

Fig 9


```
Linear Aggregation Accuracy
1.0
```

Fig 10

```
array([137.,  34., 116., 112.,  60.,  62., 114.,  70.,  98.,  45., 129.,
        65.,  33., 143.,  39.,  62.,  58., 149., 138.,  47.,  98., 129.,
        39.,  38., 147.,  61.,  86., 123., 109.,  74., 119., 105.,  74.,
       116., 106., 127.,  70.,  97., 110., 107.,  70.,  49.,  46.,  93.,
       134.,  49., 118., 148.,  83.,  60.,  80.,  86.,  45.,  54., 128.,
        99., 111.,  84.,  67.,  42.,  56., 113., 101., 150.,  41.,  57.,
        61.,  52.,  84.,  99.,  77., 146., 134., 116., 131., 104., 134.,
        88.,  60., 140.,  82.,  76., 115.,  77., 121.,  42.,  52., 127.,
        65., 127.,  40.,  50., 141., 111.,  58., 106.,  83., 146., 118.,
        69.,  97.,  73., 105., 136.,  57.,  37., 112.,  37., 121.,  87.,
        82., 120.,  75., 117., 131., 111.,  98., 126., 137., 137.])
```

Fig 11


```
K-Means predcition
[2 2 5 2 2 2 2 7 7 8 8 3 5 2 3 2 2 2 5 5 2 2 2 2 2 3 5 5 5 5 2 7 7 8 8 7 7
 8 1 8 7 8 1 9 8 7 0 0 0 4 4 4 4 4 4 0 0 0 4 0 4 0 0 4 4 4 0 4 4 4 4 0 4 4
 0 0 4 0 4 4 4 0 4 0 0 4 4 0 0 4 0 4 0 0 0 0 0 4 0 4 0 0 4 0 4 4 0 0 4 0 0
 4 4 4 0 4 4 0 4 4 0 4 4 4 4 0 4 0 4 5 3 5 2 3 5 2 3 5 2 3 3 2 5 2 3 5 3 2
 5 2 3 2 2 5 5 2 2 5 5 5 3 3 2 8 8 1 8 7 8 8 8 8 7 5 5 5 2 3 5 3 2 3 3 5 2
 5 3 2 2 2 3 5 2 1 8 8 1 1 1 6 8 6 1 1 6 9 6 6 5 3 2 5 5 5 5 2 5 5 2 3 3 3
 5 3 2 5 2 2 2 2 2 5 3 2 5 5 3 2 3 3 5 3 3 5 5 2 8 8 8 8 8 7 7 7 3 2 5 5 3
 5 3 1 7 7 2 5 2 7 1 2 7 7 7 8 1 1 7 7 1 7 7 1 1 1 7 7 8 1 8 7 2 5 1 8 2 3
 1 8 3 2 1 2 3 2 5 2 2 5 5 5 2 2 2 7 7 7 8 8 8 7 8 7 8 7 7 1 8 8 1 7 8 1 1
 1 1 8 1 1 6 1 8 7 1 7 1 6 1 6 1 6 9 1 6 1 1 1 1 9 6 6 6 9 6 9 6 9 9 9 9 6
 1 1 9 9 6 1 1 6 9 9 9 9 9 9 9 2 2 2 5 5 2 3 2 0 5 3 5 5 2 3]
K-Means Accuracy
0.025
```

Fig 12

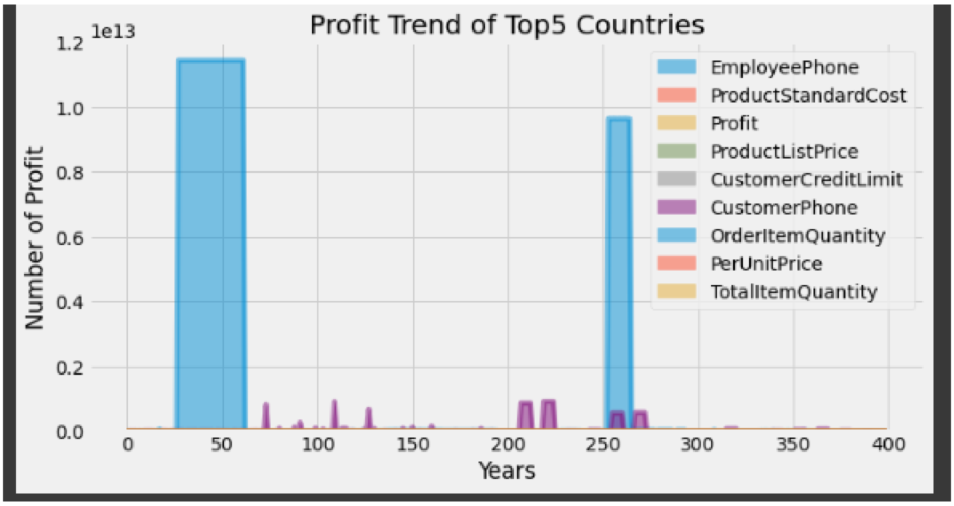


Fig 13

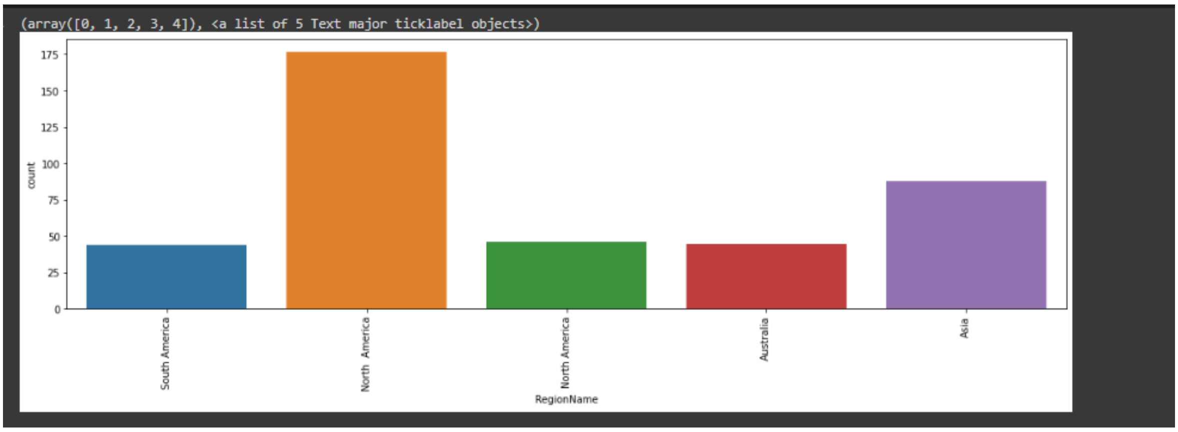


Fig 14

	EmployeePhone	ProductStandardCost	Profit	ProductListPrice	CustomerCreditLimit	CustomerPhone	OrderItemQuantity	PerUnitPrice	TotalItemQuantity
EmployeePhone	1.000000	0.034866	-0.056564	0.030562	-0.028780	0.021839	-0.011821	-0.075295	-0.063024
ProductStandardCost	0.034866	1.000000	0.507970	0.998778	0.070278	0.038726	0.124290	0.101954	0.076066
Profit	-0.056564	0.507970	1.000000	0.549919	0.052779	-0.122882	0.075729	-0.029464	-0.133516
ProductListPrice	0.030562	0.998778	0.549919	1.000000	0.071172	0.030500	0.124860	0.097168	0.066096
CustomerCreditLimit	-0.028780	0.070278	0.052779	0.071172	1.000000	0.020241	0.000280	-0.090863	-0.053989
CustomerPhone	0.021839	0.038726	-0.122882	0.030500	0.020241	1.000000	-0.050917	0.039928	-0.066911
OrderItemQuantity	-0.011821	0.124290	0.075729	0.124860	0.000280	-0.050917	1.000000	0.058542	-0.042426
PerUnitPrice	-0.075295	0.101954	-0.029464	0.097168	-0.090863	0.039928	0.058542	1.000000	-0.003527
TotalItemQuantity	-0.063024	0.076066	-0.133516	0.066096	-0.053989	-0.066911	-0.042426	-0.003527	1.000000

Fig 15

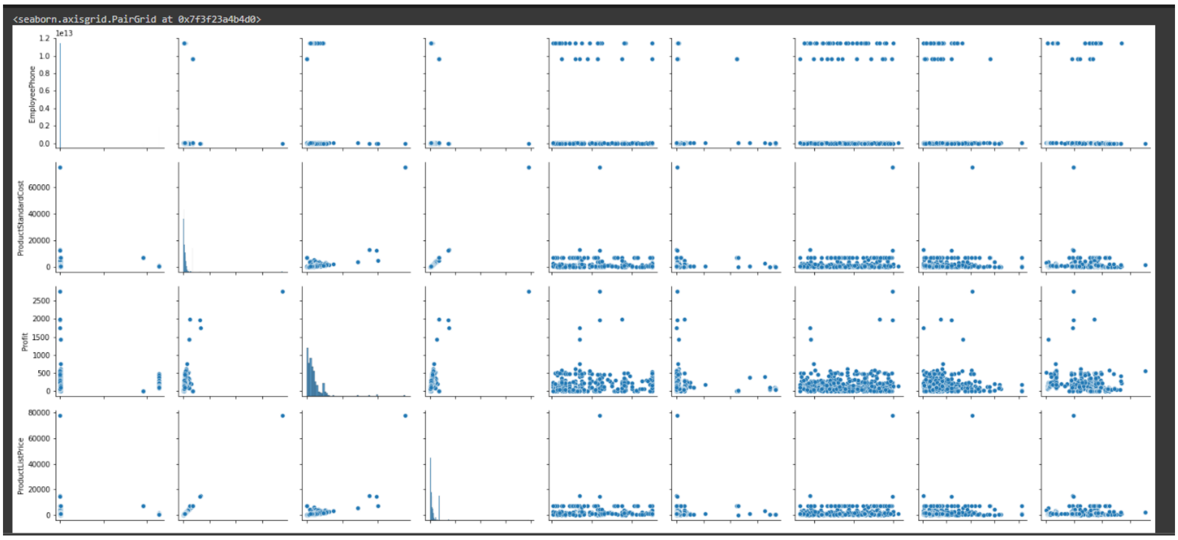


Fig 16

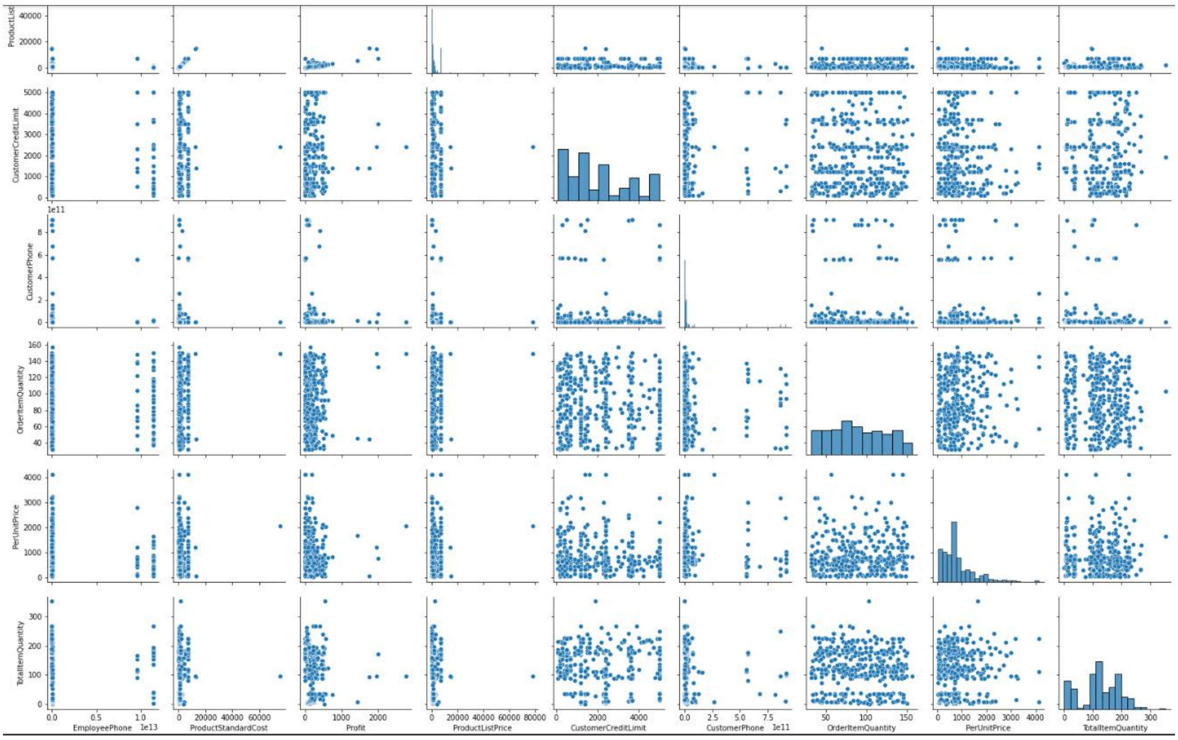


Fig 17

All requirements of the business sector need the technique of accurate and practical reading into the future. Forecasts are, therefore, very essential requirement for the survival of business. Management requires forecasting information when making a wide range of decisions.

The sales forecast is particularly important as it is the foundation upon which all company plans are built in terms of markets and revenue. Management would be a simple matter if business was not in a continual state of change, the pace of which has quickened in recent years.

It is becoming increasingly important and necessary for business to predict their future prospects in terms of sales, cost and profits. The value of future sales is crucial as it affects costs profits, so the prediction of future sales is the logical starting point of all business planning.

CHAPTER 8

CONCLUSION

Correspondingly with the technological development, the importance of the demand forecast has been increasing day by day for the enterprises. Nowadays, the forecasting period which was being managed with irrational techniques in the past has been extremely critical work tracing to structures like forecasting manager (director). Along with markets' becoming more dynamic, managers' understanding the importance of forecasting has caused to changes in organizational structure, business philosophy, and corporation culture and has increased the support of the executives to this function. As a result of these developments, the significance of the transparency and cooperation has increased and many concepts and structures such as updating have been come up. In this paper, the activities oriented to demand forecast of the firms in the paint sector, the increase of the operational productivity, working in cooperation with close relationship and constant circle of the sales and supply departments are designated. Demand forecasting is a "period". And in this paper, the demand forecasting is discussed as a period and it is understood that a process-based model as "An Econometric Model in Demand Forecasting Period" should be improved and applied in XYZ Company. High forecast accuracy and in parallel with this, improving more accurate market strategy, increase in the stock turnover, decrease in the supply chain costs and increase in the customer satisfaction are described as the output of the period. The reformed economic models can but used as simulation tools in decision support systems. In the policy and strategy that will be developed in short, mid and late phase, one can use these relations. Demand forecasting is not only a function of the marketing. The factors affecting the forecasting accuracy can be grouped as technical difficulties, behavioral problems and organizational impediments. In order to carry out the period smoothly, the union of all the participants inside and outside the firm should be ensured and the support of the executives should be taken. In this process, the S&OP and similar methods should be used. Besides, taking a co-decision and understanding the new decisions, strategies and targets to be developed in high level, standard statistical approaches; increasing the accuracy of the forecasts can be available with S&OP style application. Cooperation with the customer, smoothening of the demand, proactive cooperation approaches that put together a bilateral relation network between the supplier and customers take place among S&OP works. It is necessary to watch out three criteria in order to reach the needed demand forecast results: "accurate and sufficient data, appropriate model and correct assumption". The most important role while providing these criteria lights to the people carrying out the demand period. Demand forecasting is a "period". Seeing it as only a sub-period of the marketing function will make it difficult for forecasting to be adopted by the entire corporation. Out of the possible negative results only the people making the forecast will be responsible, the others will not feel themselves responsible. In order to carry out works about the period successfully, the activities about the period should be carried out as a period; owner of the period, customer of the period, activities in the period and performance indicators of the period should be described. The performance indicators of the period should be followed up constantly and the whole period should be viewed regularly. In technical literature, using econometric methods in demand forecasting works is mentioned as time-consuming and costly. This paper shows that approaching to databases has become easier depending on the developing computer technology and increasing use of internet and those econometric models can be used in demand forecasting of the paint sector. Model is not only used in paint sector, it is but also used in different sectors. While making prediction about future, basic forecast acquired by econometric models, can reflect possible event's effect. As an example, legal changes (reforms), implementation oriented by authorization process, changes on social insurance systems, oversea trends, budget limits (saving limits for specific period) and delay with putting productions on the market (authorization) can be given. Each event can be rendered quantitative method by using incidence date, possibility and effect percentage on basic sales forecast and its effects on period parameters

CHAPTER 9

FUTURE ENHANCEMENTS

Demand forecasting is one of the most difficult parts of supply chain management, especially when you consider the number of factors that can affect it. Natural disasters, product shortages or delays (like when a cargo ship gets stuck in the Suez Canal), and, of course, a global pandemic can impact an organization's supply chain.

We can develop it more by

- Use AI to improve predictions
- Analyze order history to identify trends
- Keep an eye on competitors
- Consider inventory elasticity
- Best supply chain management software for demand forecasting
- Better demand forecasting lowers operating costs

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