Sales Forecasting

The dataset for this project originates from the Superstore Sales Dataset

Notebook File - Sales_Forecasting.ipynb

Github Repo - Sales Forecasting

Background:

In this modern times where every business is highly dependent on its data to make better decisions for developing business, time series analysis plays an important role in helping different business entities to get an idea about how good their sales are by implementing sales forecating on the historic data.

I have ultisied the dataset to perform expolratory data analysis to gain valuable insights and further apply time series analysis to get a forecast of sales after time period of 7 days.

Problem Statement:

Analyze the sales of the store and predict the sales of the next 7 days from the last date in the dataset.

Dataset Information

1) **Row ID:** Index of the entry

2) **Order ID:** ID created when a product order is placed.

3) **Order Date:** Date on which a customer places his/her order.

4) **Ship Date:** Date on which the order is shipped.

5) **Ship Mode:** Mode of shipment of each order.

6) **Customer ID:** ID assigned to each customer who places an order.

7) **Customer Name:** Name of Customer

8) **Segment:** Section from where the order is placed

9) **Country:** Country details of this data set. We are looking only for US store data.

10) **City:** Cities of US are listed here.

11) **State:** States of US are listed here.

12) **Postal Code:** pin code

13) **Region:** Region - east, west, north, south

14) **Product ID:** Product ID of each product

15) **Category:** Category to which each product belongs to.

16) **Sub-Category:** Sub-Category of each Category

17) **Product Name:** Name of products.

18) **Sales:** Selling Price of each product.

19) **Quantity:** number of quantity available for a particular product.

20) **Discount:** Discount available on each product.

21) **Profit:** Profit gained on each product.

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1. Environment Setup

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1.1. Install Packages

Install required packages

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In [1]:

```
# Install pandas
! pip install pandas

# Install matplotlib
! pip install matplotlib

# Install seaborn
! pip install seaborn

# Install sklearn
! pip install sklearn

# Install tqdm to visualize iterations
! pip install tqdm
```

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Requirement already satisfied: pandas in c:\users\arun\anaconda3\envs\data_science\l
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Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\arun\anaconda3\envs
\data_science\lib\site-packages (from scikit-learn->sklearn) (2.1.0)
Requirement already satisfied: tqdm in c:\users\arun\anaconda3\envs\data_science\lib
\site-packages (4.59.0)
```

1.2. Load Dependencies

Import required packages

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In [588…

```
# Import libraries necessary for this project
import numpy as np
import pandas as pd
import scipy.stats as stats
import math
from tqdm import tqdm
import matplotlib.pyplot as plt
import itertools

# Pretty display for notebooks
%matplotlib inline

import seaborn as sns

# Set default setting of seaborn
sns.set()
```

In [577…

```
# Packages for timeseries modeling
import statsmodels.api as sm
from statsmodels.tsa.stattools import adfuller
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from pylab import rcParams

# Import performance metric
from sklearn.metrics import mean_squared_error

# Import warning to ignore them
import warnings
warnings.filterwarnings('ignore')
```

In [6]:

```
# To save the model
import joblib
```

In [7]:

```
# Create output folder to save model and plots
import os

# Get current working directory
current_dir = os.getcwd()

# Folder to save model
```

```python
model_dir = current_dir + "/model"
os.makedirs(model_dir, exist_ok=True)

# Folder to save plots
plots_dir = current_dir + "/plots"
os.makedirs(plots_dir, exist_ok=True)
```

2. Load dataset

Read data from personal_loan.csv file using pandas method read_csv().

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In [8]:

```python
# read the data
raw_data = pd.read_excel(current_dir + '/data/US Superstore data.xls')

# print the first five rows of the data
raw_data.head()
```

Out[8]:

	Row ID	Order ID	Order Date	Ship Date	Ship Mode	Customer ID	Customer Name	Segment	Country	City	...
0	1	CA-2016-152156	2016-11-08	2016-11-11	Second Class	CG-12520	Claire Gute	Consumer	United States	Henderson	...
1	2	CA-2016-152156	2016-11-08	2016-11-11	Second Class	CG-12520	Claire Gute	Consumer	United States	Henderson	...
2	3	CA-2016-138688	2016-06-12	2016-06-16	Second Class	DV-13045	Darrin Van Huff	Corporate	United States	Los Angeles	...
3	4	US-2015-108966	2015-10-11	2015-10-18	Standard Class	SO-20335	Sean O'Donnell	Consumer	United States	Fort Lauderdale	...
4	5	US-2015-108966	2015-10-11	2015-10-18	Standard Class	SO-20335	Sean O'Donnell	Consumer	United States	Fort Lauderdale	...

5 rows × 21 columns

3. Data Types and Dimensions

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In [9]:

```
print("Superstore Sales Data Set has \033[4m\033[1m{}\033[0m\033[0m data points with
```

```
Superstore Sales Data Set has 9994 data points with 21 variables each.
```

In [10]:

```
# check the data types of the features
raw_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9994 entries, 0 to 9993
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Row ID         9994 non-null   int64
 1   Order ID       9994 non-null   object
 2   Order Date     9994 non-null   datetime64[ns]
 3   Ship Date      9994 non-null   datetime64[ns]
 4   Ship Mode      9994 non-null   object
 5   Customer ID    9994 non-null   object
 6   Customer Name  9994 non-null   object
 7   Segment        9994 non-null   object
 8   Country        9994 non-null   object
 9   City           9994 non-null   object
 10  State          9994 non-null   object
 11  Postal Code    9994 non-null   int64
 12  Region         9994 non-null   object
 13  Product ID     9994 non-null   object
 14  Category       9994 non-null   object
 15  Sub-Category   9994 non-null   object
 16  Product Name   9994 non-null   object
 17  Sales          9994 non-null   float64
 18  Quantity       9994 non-null   int64
 19  Discount       9994 non-null   float64
 20  Profit         9994 non-null   float64
dtypes: datetime64[ns](2), float64(3), int64(3), object(13)
memory usage: 1.6+ MB
```

4. Data Preprocessing

Data preprocessing is a data mining technique which is used to transform the raw data in a useful and efficient format.

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4.1. Data Cleaning

Data cleaning refers to preparing data for analysis by removing or modifying data that is incomplete, irrelevant, duplicated, or improperly formatted.

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4.1.1. Remove irrelevant features

The first and foremost thing you should do is remove useless pieces of data from your system. Any useless or irrelevant data is the one you don’t need. It might not fit the context of your issue.

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In [11]:

```
# Create copy of the dataframe
data_1 = raw_data.copy(deep = True)
```

In [12]:

```
data_1.columns.values
```

Out[12]:

```
array(['Row ID', 'Order ID', 'Order Date', 'Ship Date', 'Ship Mode',
       'Customer ID', 'Customer Name', 'Segment', 'Country', 'City',
       'State', 'Postal Code', 'Region', 'Product ID', 'Category',
       'Sub-Category', 'Product Name', 'Sales', 'Quantity', 'Discount',
       'Profit'], dtype=object)
```

In [13]:

```
# Dropping Unneccesary columns
data_1.drop(['Row ID', 'Order ID', 'Customer ID', 'Product ID'], axis=1, inplace=Tru

# print first five rows
data_1.head()
```

Out[13]:

	Order Date	Ship Date	Ship Mode	Customer Name	Segment	Country	City	State	Postal Code	Region	Ca
0	2016-11-08	2016-11-11	Second Class	Claire Gute	Consumer	United States	Henderson	Kentucky	42420	South	Fu
1	2016-11-08	2016-11-11	Second Class	Claire Gute	Consumer	United States	Henderson	Kentucky	42420	South	Fu
2	2016-06-12	2016-06-16	Second Class	Darrin Van Huff	Corporate	United States	Los Angeles	California	90036	West	S
3	2015-10-11	2015-10-18	Standard Class	Sean O'Donnell	Consumer	United States	Fort Lauderdale	Florida	33311	South	Fu
4	2015-10-11	2015-10-18	Standard Class	Sean O'Donnell	Consumer	United States	Fort Lauderdale	Florida	33311	South	S

In [14]:

```
data_1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9994 entries, 0 to 9993
Data columns (total 17 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Order Date      9994 non-null   datetime64[ns]
 1   Ship Date       9994 non-null   datetime64[ns]
 2   Ship Mode       9994 non-null   object
 3   Customer Name   9994 non-null   object
 4   Segment         9994 non-null   object
```

```
 5   Country        9994 non-null   object
 6   City           9994 non-null   object
 7   State          9994 non-null   object
 8   Postal Code    9994 non-null   int64
 9   Region         9994 non-null   object
 10  Category       9994 non-null   object
 11  Sub-Category   9994 non-null   object
 12  Product Name   9994 non-null   object
 13  Sales          9994 non-null   float64
 14  Quantity       9994 non-null   int64
 15  Discount       9994 non-null   float64
 16  Profit         9994 non-null   float64
dtypes: datetime64[ns](2), float64(3), int64(2), object(10)
memory usage: 1.3+ MB
```

In [15]:

```
# Reorder the dataset with respect to Order Date
data_1.sort_values(by = 'Order Date').reset_index(drop = True, inplace = True)
```

In [16]:

```
data_1.head(2)
```

Out[16]:

	Order Date	Ship Date	Ship Mode	Customer Name	Segment	Country	City	State	Postal Code	Region	Cate
0	2016-11-08	2016-11-11	Second Class	Claire Gute	Consumer	United States	Henderson	Kentucky	42420	South	Furı
1	2016-11-08	2016-11-11	Second Class	Claire Gute	Consumer	United States	Henderson	Kentucky	42420	South	Furı

4.1.3. Missing Data Treatment

If the missing values are not handled properly we may end up drawing an inaccurate inference about the data. Due to improper handling, the result obtained will differ from the ones where the missing values are present.

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In [17]:

```
# Function to get missing values
def get_missing(data):

    # Create the dataframe
    missing_values = pd.DataFrame()

    # Get list of all columns
    missing_values['Features'] = data.columns.values

    # get the count of missing values
    missing_values['Count'] = data.isnull().sum().values

    # Calculate percentage of missing values
    percentage = data.isna().mean()*100
    missing_values['Percentange'] = percentage.values
```

```python
    # return the dataframe
    return missing_values
```

In [109…

```python
# Function to plot missing values
def plot_missing(missing_values):
    # Plot missing values

    # Get list of features
    columns = missing_values.Features.values.tolist()

    # Get index's
    ind = missing_values.index.to_list()

    if missing_values.Count.values.sum() == 0:
        print("\033[1mNo Missing values found in the dataset\033[0m")
        return
    # Create subplots
    fig, ax = plt.subplots(2,1,figsize=(18, 18))

    # Plot missing values based on count
    rects = ax[0].barh(ind, missing_values.Count.values.tolist(), color='lightblue')
    ax[0].set_yticks(ind)
    ax[0].set_yticklabels(columns, rotation='horizontal')
    ax[0].set_xlabel("Count of missing values")
    ax[0].set_title("Variables with missing values")

    # Plot missing values based on percentage
    rects = ax[1].barh(ind, missing_values.Percentange.values.tolist(), color='pink'
    ax[1].set_yticks(ind)
    ax[1].set_yticklabels(columns, rotation='horizontal')
    ax[1].set_xlabel("Percentage of missing values")
    ax[1].set_title("Variables with missing values")
```

In [110…

```python
plot_missing(get_missing(data_1))
```

No Missing values found in the dataset

In [21]:

```python
# Get categorical features
categorical_features = data_1.select_dtypes('object').columns.values.tolist()

# Get nuemric features
numerical_features = [col for col in data_1.columns.values if col not in categorical
```

In [22]:

```python
print("Superstore Sales Data Set has \033[4m\033[1m{}\033[0m\033[0m data points with
print(f"Numeric features: \033[4m\033[1m{len(numerical_features)}\033[0m\033[0m \nCa
```

```
Superstore Sales Data Set has 9994 data points with 17 variables each.
Numeric features: 7
Categorical features: 10
```

Summary

Number of Instances	Number of Attributes	Numeric Features	Categorical Features	Missing Values
9994	17	7	10	Null

4.2. Exploratory Analysis

The preliminary analysis of data to discover relationships between measures in the data and to gain an insight on the trends, patterns, and relationships among various entities present in the data set with the help of statistics and visualization tools is called Exploratory Data Analysis (EDA).

Exploratory data analysis is cross-classified in two different ways where each method is either graphical or non-graphical. And then, each method is either univariate, bivariate or multivariate.

...goto toc

In [23]:
```
# Create copy of the dataframe
data = data_1.copy()
```

4.2.1. Product Level Analysis

...goto toc

Let's look at the revenue generated by each category!

In [24]:
```
# Get list of categories of products and their count
data['Category'].value_counts()
```

Out[24]:
```
Office Supplies    6026
Furniture          2121
Technology         1847
Name: Category, dtype: int64
```

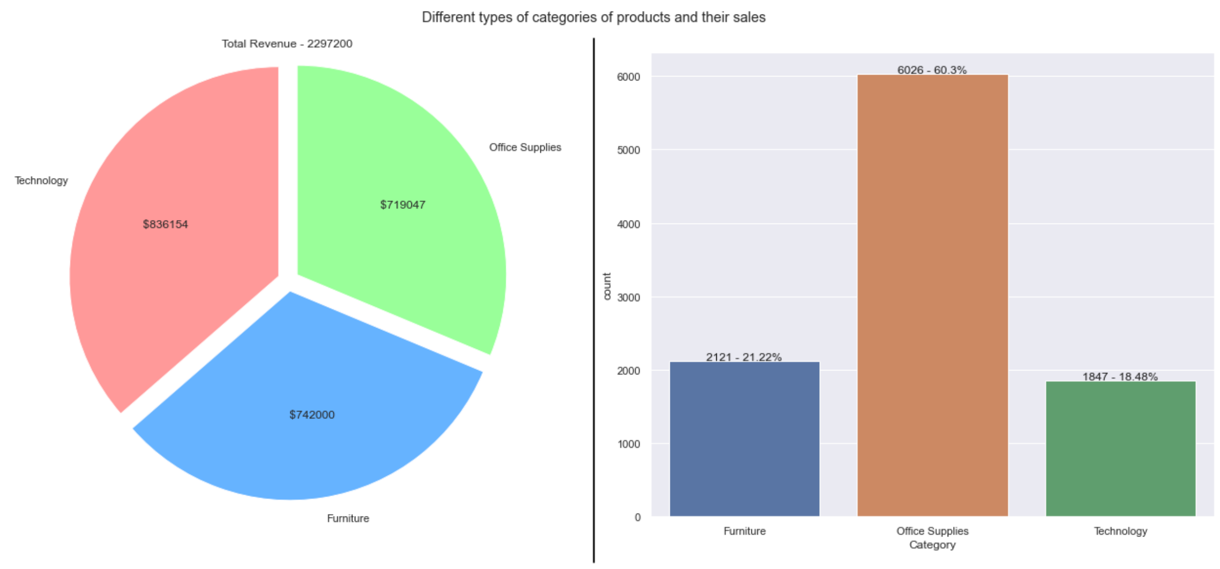
In [25]:
```
# Sort the Categories as per the sales
data_category = data.groupby(["Category"]).sum().sort_values("Sales", ascending=Fals

# Get revenue generated as per category
total_revenue_category = int(data_category.sum())
print(f"Total revenue earned by selling products of all category - $\033[4m\033[1m{t
```

```
Total revenue earned by selling products of all category - $2297200
```

In [26]:
```
# Function to get exact value generated on each category
def autopct_format(values):
    def my_format(pct):
        total = sum(values)
        val = int(round(pct*total/100.0))
        return ' ${v:d}'.format(v=val)
    return my_format
```

In [342…
```
explode = (0.05, 0.05, 0.05)

# Set width and height of the figure
fig, axes = plt.subplots(1, 2, figsize = (18, 8))

# Add title to the figure
fig.suptitle("Different types of categories of products and their sales")

# Set font size and weight
plt.rcParams.update({'font.size': 12,
```

```
                     "font.weight": 6})

# Set colors of the piechart
colors = ['#ff9999','#66b3ff','#99ff99']

# Plot piechart
axes[0].pie(data_category.values, colors = colors, labels = data_category.index, aut
       startangle = 90, explode = explode)

# Equal aspect ratio ensures that pie is drawn as a circle
axes[0].axis('equal')

# place total revenue generated by individual categories at the center
#label = ax[0].annotate('Total Revenue \n' + str(total_revenue_category), color = 'r
axes[0].title.set_text('Total Revenue - ' + str(total_revenue_category))

# Plot catplot
sns.countplot(x = "Category", data = data, ax = axes[1])

# To show the exact revenue generated on the figure
count_categories = [2121, 6026, 1847]
for i in range(len(count_categories)):
    text = f"{str(count_categories[i])} - {round((count_categories[i] * 100) / sum(c
    plt.text(i, count_categories[i] + 15, text, fontsize=12, color='k', horizontalal

# Reduce padding
plt.tight_layout(w_pad = 0, h_pad = 5)

# Add a horizontal line
line = plt.Line2D((.5,.5),(0,.93), color="k", linewidth = 2)
fig.add_artist(line)


# Save the figure
plt.savefig(current_dir + "/plots/analysis_of_categories.png")

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



Important Inferences

- The store have highest number of **Office Supplies** products with total **60.3%** while minimum number of **Technology** products (1847) i.e **18.48%**.
- But the store have earned highest revenue of **$836154** from **Technology** products.

- Even though the store have higher number of office supplies but have a less revenue as compared to other categories.
- The Total Revenue generated by all the categories - **$2,261,536**

Let's look at the revenue generated by each sub-category!

In [345…

```
# Create the dataframe to store sales and profits earned on each sub-category
data_subcat = pd.DataFrame(columns = ['Category', "Sub-Category", "Sales", "Profit"]

# Variable to store count of indexs
index = 0

# Iterate over each sub-category
for i in data["Sub-Category"].unique().tolist():
    # Add category of the current sub-category
    data_subcat.loc[index, "Category"] = data[data["Sub-Category"] == i]["Category"]

    # Add subcategory to the dataframe
    data_subcat.loc[index, "Sub-Category"] = i

    # Add total sales generated by the sub-category
    data_subcat.loc[index, "Sales"] = data[data["Sub-Category"] == i]["Sales"].sum()

    # Add total profit generated on each sub-category
    data_subcat.loc[index, "Profit"] = data[data["Sub-Category"] == i]["Profit"].sum

    # Update the index
    index += 1

# print the dataframe
data_subcat
```

Out[345…

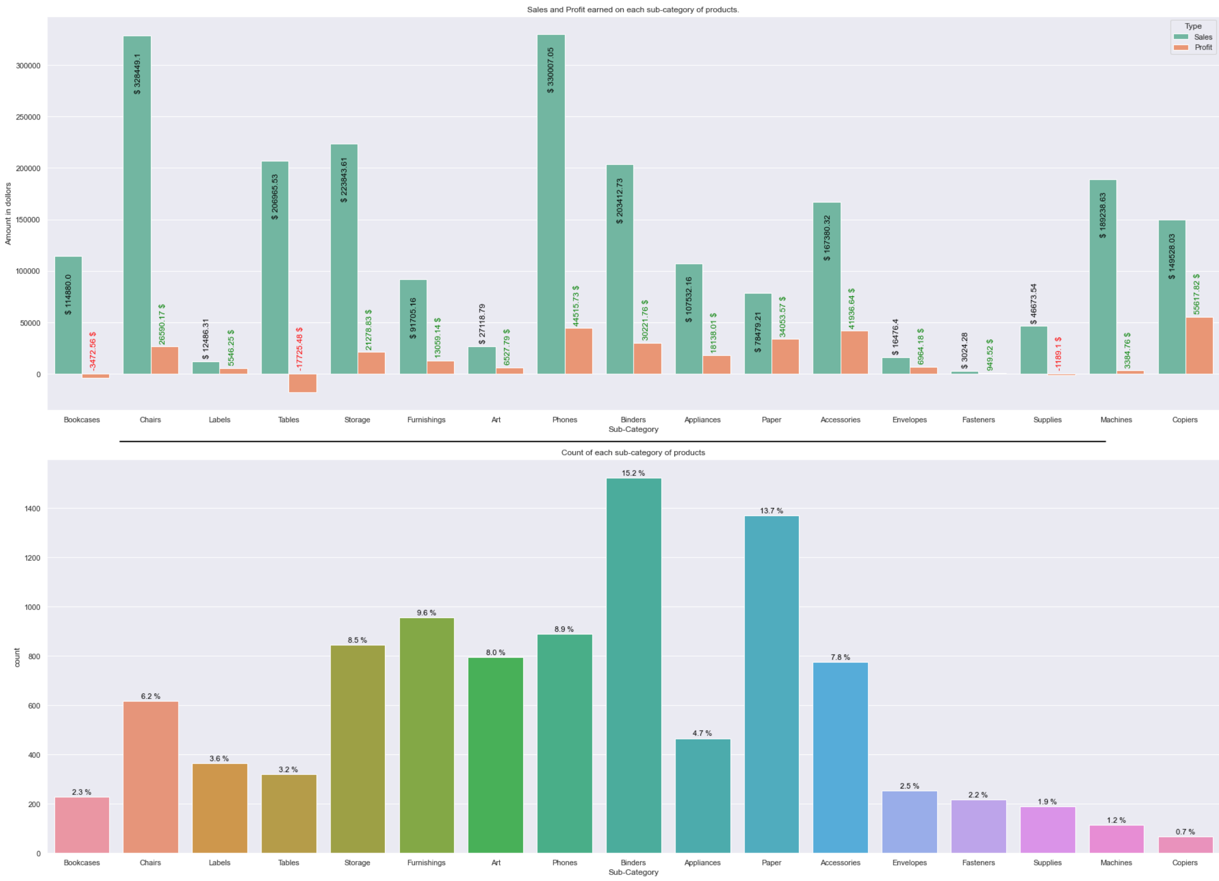
	Category	Sub-Category	Sales	Profit
0	Furniture	Bookcases	114879.9963	-3472.556
1	Furniture	Chairs	328449.103	26590.1663
2	Office Supplies	Labels	12486.312	5546.254
3	Furniture	Tables	206965.532	-17725.4811
4	Office Supplies	Storage	223843.608	21278.8264
5	Furniture	Furnishings	91705.164	13059.1436
6	Office Supplies	Art	27118.792	6527.787
7	Technology	Phones	330007.054	44515.7306
8	Office Supplies	Binders	203412.733	30221.7633
9	Office Supplies	Appliances	107532.161	18138.0054
10	Office Supplies	Paper	78479.206	34053.5693
11	Technology	Accessories	167380.318	41936.6357
12	Office Supplies	Envelopes	16476.402	6964.1767
13	Office Supplies	Fasteners	3024.28	949.5182
14	Office Supplies	Supplies	46673.538	-1189.0995
15	Technology	Machines	189238.631	3384.7569

	Category	Sub-Category	Sales	Profit
16	Technology	Copiers	149528.03	55617.8249

In [343…

```
# Create the dataframe to merge sales and profits
temp = pd.DataFrame()

# Merge sales and profits
temp["Count"] = data_subcat["Sales"].values.tolist() + data_subcat["Profit"].values.

# Add sub-categories
temp["Sub-Category"] = data_subcat["Sub-Category"].values.tolist() + data_subcat["Su
temp["Type"] = ["Sales" if i < 17 else "Profit" for i in range(34) ]

# Plot the figure representing sales, profits and count of each sub-category
fig, ax = plt.subplots(2, 1, figsize = (25,18))

# Plot a barplot to show the sales and profits on each sub-category
sns.barplot(x = "Sub-Category", y = "Count", hue = "Type", data = temp, ax = ax[0],

# Set ylabel of the plot
ax[0].set_ylabel("Amount in dollors")

# Set title of the plot
ax[0].set_title("Sales and Profit earned on each sub-category of products.")

# Iterate over sales, to add it's value on the bars
for k,v in enumerate([round(i, 2) for i in temp[temp.Type == "Sales"].Count.values.t
    if v > 50000:
        ax[0].text(k - 0.18,  v - 55000 ,'$ '+ str(v), fontsize = 12, rotation = 90,
    else:
        ax[0].text(k - 0.18,  v + 4000 ,'$ '+ str(v), fontsize = 12, rotation = 90,

# Iterate over profits, to add it's value on the bars
for k,v in enumerate([round(i, 2) for i in temp[temp.Type == "Profit"].Count.values.
    if v < 0:
        ax[0].text(k + 0.18,  5000, str(v) + ' $', fontsize = 12, rotation = 90, col
        continue
    ax[0].text(k + 0.18,  v + 4000, str(v) + ' $', fontsize = 12, rotation = 90, col


# Plot as countplot
sns.countplot(x = "Sub-Category", data = data, ax = ax[1])

# Add title to the countplot
ax[1].set_title("Count of each sub-category of products")

# List to store all the sub-categories of the products
sub_categories = ["Bookcases", "Chairs", "Labels", "Tables", "Storage", "Furnishings
                  "Paper", "Accessories", "Envelopes", "Fasteners", "Supplies", "Mac

# Get values count of each sub-category
sub_cat_count = data["Sub-Category"].value_counts()

# Get total number of products sold by the store
total = sub_cat_count.sum()

# iterate of each sub-category to write their percentage
for k,v in enumerate(sub_categories):
    # Calculate percentage
    percent = round((sub_cat_count.loc[v] * 100) / total, 1)
    # Add percentage to the graph
    ax[1].text(k,  sub_cat_count.loc[v] + 10, str(percent) + " %", fontsize = 11, ro
```

```
                horizontalalignment = 'center')

# Remove width padding and set height padding
plt.tight_layout(w_pad = 0, h_pad = 2)

# Create a horizontal line
line = plt.Line2D((.1,.9), (.5,.5), color="k", linewidth = 2, transform = plt.gcf().

# Add the horizontal line to the plot
fig.add_artist(line)

# Save the plot
plt.savefig(current_dir + "/plots/analysis_of_sub_categories.png")

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



Important Inferences

- The store has wide variety of Office Supplies especially in Binders and Paper department.
- **Phones** generated the highest revenue of about **$327782**
- Lowest revenue from **Fasteners** of **$3001.96**
- Highest profit is earned in Copiers while Selling price for Chairs and Phones is extremely high compared to other products.
- Another interesting fact- people dont prefer to buy Tables and Bookcases from Superstore. Hence these departments are in loss.

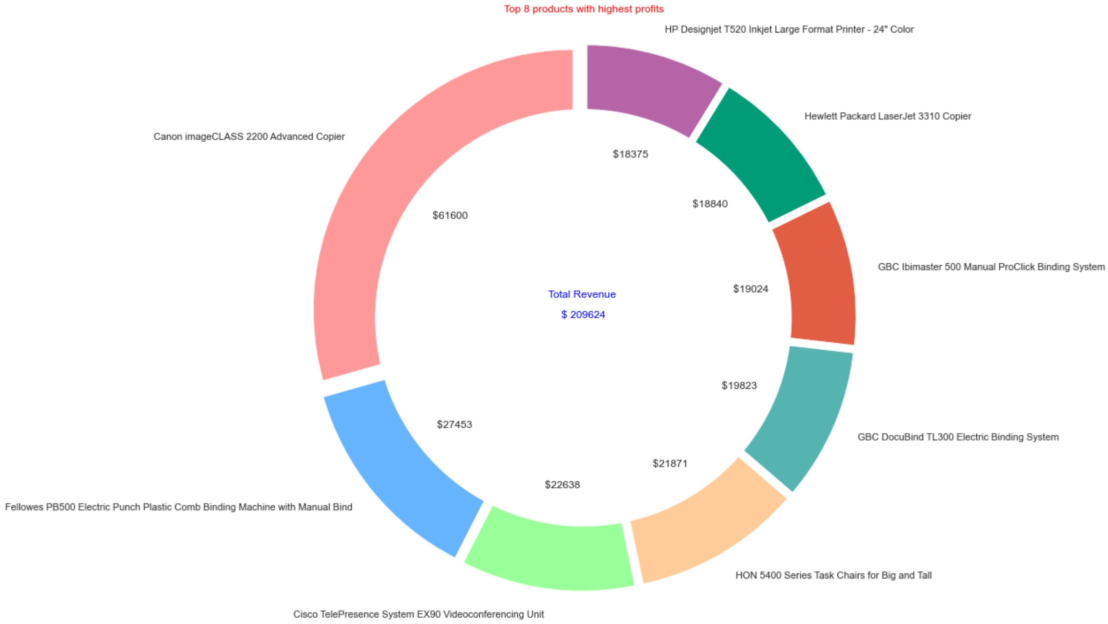
Let's see which products contributed most to the revenue

In [431…

```
# Which products contributed most to the revenue?

# Sort the product names as per the sales
top_products = data.groupby(["Product Name"]).sum().sort_values("Sales",ascending=Fa

# Round off the Sales Value up to 2 decimal places
top_products = top_products[["Sales"]].round(2)

# Since we have used groupby, we will have to reset the index to add the product nam
top_products.reset_index(inplace=True)

# To find the total revenue generated by all the top products
total_revenue_products = top_products["Sales"].sum()

# Convert the total_revenue_products from float to int and then to string
total_revenue_products = str(int(total_revenue_products))

# Adding '$' sign before the Value
total_revenue_products = '$ ' + total_revenue_products
```

In [439…

```
# Set width and height of figure is defined in inches
plt.rcParams["figure.figsize"] = (20, 10)

# Set font size
plt.rcParams['font.size'] = 12.0

# List to store colors for the pie chart
colors = ['#ff9999','#66b3ff','#99ff99','#ffcc99','#55B4B0','#E15D44','#009B77','#B5
explode = (0.05,0.05,0.05,0.05,0.05,0.05,0.05,0.05)

# Create a figure
fig1, ax1 = plt.subplots()

# Draw the pie-chart
ax1.pie(Top_products['Sales'], colors = colors, labels=Top_products['Product Name'],
        autopct= autopct_format(Top_products['Sales']), startangle=90,explode=explod

# Draw a circle on the pie chart
centre_circle = plt.Circle((0,0), 0.8,fc='white')

# Add circle to pie-chart
fig = plt.gcf()
fig.gca().add_artist(centre_circle)

# Equal aspect ratio ensures that pie is drawn as a circle
ax1.axis('equal')

# Add title to the plot
#plt.title("Top 8 products with highest profits")
ax1.set_title('Top 8 products with highest profits', color = "red")


# Create a label to show total revenue
label = ax1.annotate('Total Revenue \n\n'+str(total_revenue_products),color = 'Blue'

# Remove redudant spaces
plt.tight_layout(w_pad=0, h_pad=0)

# Save the plot
plt.savefig(current_dir + "/plots/highest_profit_products.png")

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



Observation

- We can see that Product - Canon imageCLASS 2200 Advanced Copier generated the highest revenue of about $61600
- The Total Revenue generated by all these products - $209624!

4.2.2. Customer Level Analysis

...goto toc

Analysis of the type of customers - Segement

In [350…
```
data['Segment'].value_counts()
```

Out[350…
```
Consumer       5191
Corporate      3020
Home Office    1783
Name: Segment, dtype: int64
```

In [351…
```
# Create the dataframe to store sales and profits earned on each segment of customer
data_segment = pd.DataFrame(columns = ['Segment', "Count", "Sales", "Profit"])

# Variable to store count of indexs
index = 0

# Iterate over each Segment of customers
for i in data["Segment"].unique().tolist():
    # Add segment to the dataframe
    data_segment.loc[index, "Segment"] = i

    # Get count of each category
    data_segment.loc[index, "Count"] = data[data["Segment"] == i].shape[0]

    # Add total sales generated by the Segment of customer
    data_segment.loc[index, "Sales"] = data[data["Segment"] == i]["Sales"].sum()

    # Add total profit generated on each segment of customers
    data_segment.loc[index, "Profit"] = data[data["Segment"] == i]["Profit"].sum()
```

```
    # Update the index
    index += 1

# print the dataframe
data_segment
```

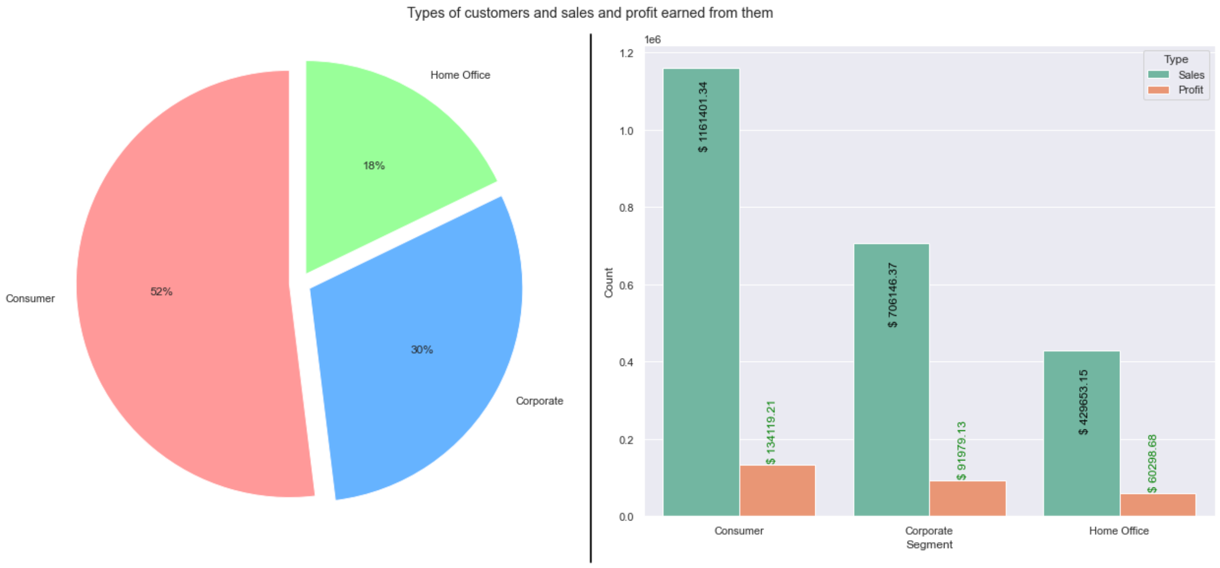
Out[351…

	Segment	Count	Sales	Profit
0	Consumer	5191	1161401.345	134119.2092
1	Corporate	3020	706146.3668	91979.134
2	Home Office	1783	429653.1485	60298.6785

In [405…

```
# Set width and height of the figure
fig, axes = plt.subplots(1, 2, figsize = (18, 8))

# Add title to the figure
fig.suptitle("Types of customers and sales and profit earned from them")

# Set font size and weight
plt.rcParams.update({'font.size': 12,
                    "font.weight": 6})

# Set colors of the piechart
colors = ['#ff9999','#66b3ff','#99ff99']

# Plot piechart
axes[0].pie(data_segment.Count.values, colors = colors, labels = data_segment.Segmen
       startangle = 90, explode = explode)


# Equal aspect ratio ensures that pie is drawn as a circle
axes[0].axis('equal')



# Create the dataframe to merge sales and profits
temp = pd.DataFrame()

# Merge sales and profits
temp["Count"] = data_segment["Sales"].values.tolist() + data_segment["Profit"].value

# Add sub-categories
temp["Segment"] = data_segment["Segment"].values.tolist() + data_segment["Segment"].
temp["Type"] = ["Sales" if i < 3 else "Profit" for i in range(6) ]

# Plot the profit and sales of the store on individual customer segments
sns.barplot(x = "Segment", y = "Count", data = temp, hue = "Type", ax = axes[1], pal

# Iterate over sales, to add it's value on the bars
for k,v in enumerate([round(i, 2) for i in temp[temp.Type == "Sales"].Count.values.t
    axes[1].text(k - 0.18,  v - 210000 ,'$ '+ str(v), fontsize = 12, rotation = 90,

# Iterate over profits, to add it's value on the bars
for k,v in enumerate([round(i, 2) for i in temp[temp.Type == "Profit"].Count.values.
    axes[1].text(k + 0.18,  v + 10000, "$ " + str(v), fontsize = 12, rotation = 90,

# Add a horizontal line
line = plt.Line2D((.5,.5),(0,.93), color="k", linewidth = 2)
fig.add_artist(line)

# Remove blank spaces
```

```
plt.tight_layout(w_pad=0, h_pad=0)

# Save the plot
plt.savefig(current_dir + "/plots/segments.png")
# Show the plot
plt.show()
```



Important Inferences

- The store have three types of customers - **Consumers**, **Corporates**, and **Home office**
- Out the total number of customers the store have **50 percent** of them are consumer and they provide a highest profit of 134,119 dollor with sales of 1,161,401 dollors.
- Store need to work on improving profits earned on consumers

In [402…

```
# Get top 10 frequently ordered customers
cust_top10 = data['Customer Name'].value_counts().head(10)
cust_top10
```

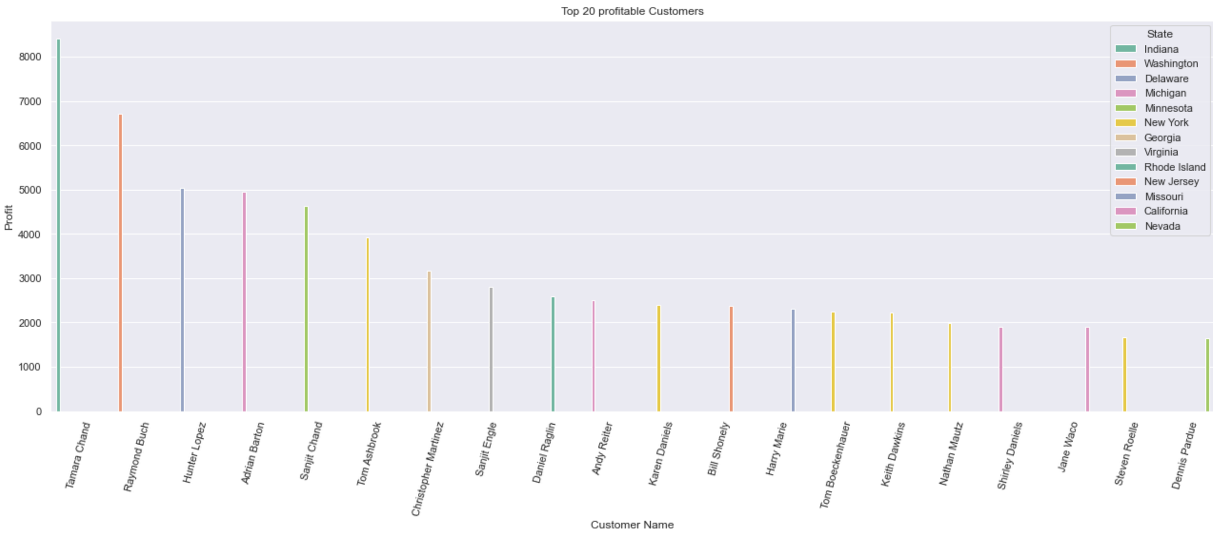
Out[402…

```
William Brown          37
John Lee               34
Matt Abelman           34
Paul Prost             34
Edward Hooks           32
Chloris Kastensmidt    32
Seth Vernon            32
Jonathan Doherty       32
Arthur Prichep         31
Zuschuss Carroll       31
Name: Customer Name, dtype: int64
```

In [418…

```
# Get top 20 Customers who benefitted the store
sortedTop20 = data.sort_values(['Profit'], ascending=False).head(20)

# Plot a figure
fig, ax = plt.subplots(1, figsize=(18,8))
# Plot barplot
p = sns.barplot(x = 'Customer Name', y = 'Profit', hue = 'State', palette = 'Set2',

# Set title pf the plot
ax.set_title("Top 20 profitable Customers")

# Rotate xaxis labels
```

```
ax.set_xticklabels(p.get_xticklabels(), rotation=75)

# Remove unwanted space
plt.tight_layout()

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



Note: We see that majority of the Profitable Customers are from New York and Michigan State.

Region with hightest number of sales

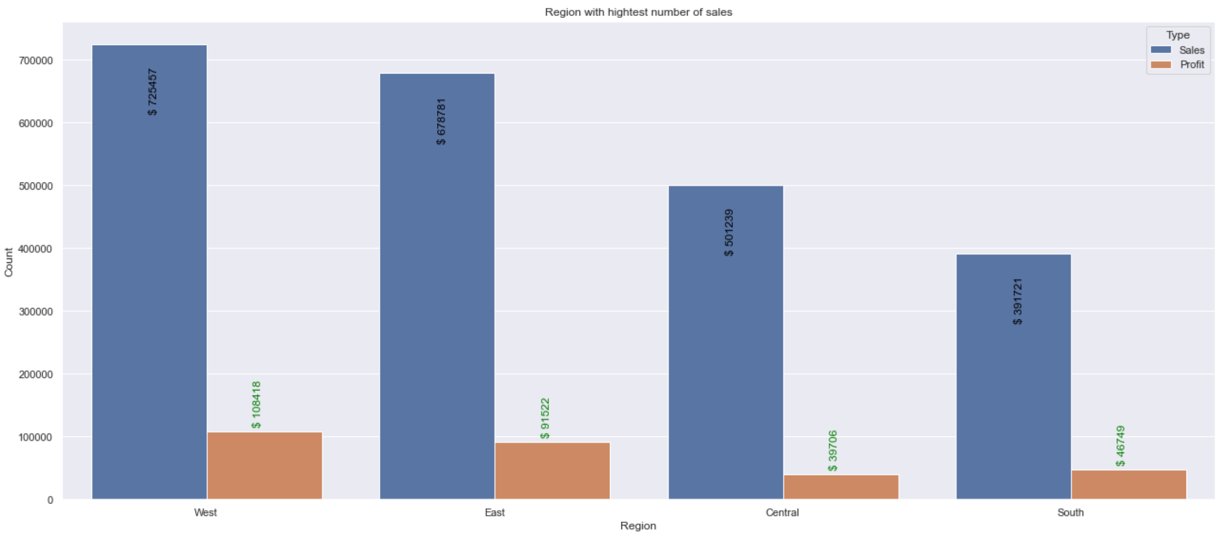
In [444…

```
# Sort the Region as per the sales
top_region = data.groupby(["Region"]).sum().sort_values("Sales", ascending=False)

# Cast Sales column to integer data type
top_region = top_region[["Sales", "Profit"]].astype(int)

# Since we have used groupby, we will have to reset the index to add the Region colu
top_region.reset_index(inplace=True)
```

In [464…

```
# Create the dataframe to merge sales and profits
temp = pd.DataFrame()

# Merge sales and profits
temp["Count"] = top_region["Sales"].values.tolist() + top_region["Profit"].values.to

# Add sub-categories
temp["Region"] = top_region["Region"].values.tolist() + top_region["Region"].values.
temp["Type"] = ["Sales" if i < 4 else "Profit" for i in range(8)]

# Plot the figure
fig, ax = plt.subplots(1, figsize = (18,8))

# Plot the profit and sales of the store on individual customer segments
sns.barplot(x = "Region", y = "Count", data = temp, hue = "Type", ax = ax)

# Iterate over sales, to add it's value on the bars
for k,v in enumerate([round(i, 2) for i in temp[temp.Type == "Sales"].Count.values.t
    ax.text(k - 0.18,  v - 108500,'$ '+ str(v), fontsize = 12, rotation = 90, color

# Iterate over profits, to add it's value on the bars
for k,v in enumerate([round(i, 2) for i in temp[temp.Type == "Profit"].Count.values.
    ax.text(k + 0.18,  v + 10000, "$ " + str(v), fontsize = 12, rotation = 90, color
```

```
# Set title of the plot
plt.title("Region with hightest number of sales")

# Remove blank spaces
plt.tight_layout(w_pad=0, h_pad=0)

# Save the plot
plt.savefig(current_dir + "/plots/region_profit.png")

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



Observations

- The store have higher number of sales (**725,457**) from West region with a net profit of **$ 108,418**
- Even though the store have majority of sales from central as compared to south, it's profit earned from central region is less than south region.

Shipping mode with the highest sales

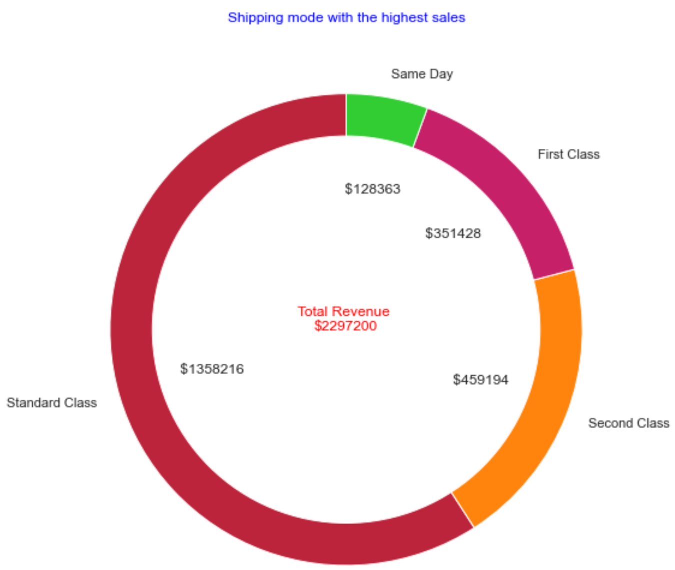
In [468…

```
# Sort the Shipping modes as per the sales
top_shipping = data.groupby(["Ship Mode"]).sum().sort_values("Sales", ascending=Fals

# keep only the sales column in the dataframe
top_shipping = top_shipping[["Sales"]]

# Since we have used groupby, we will have to reset the index to add the Ship Mode c
top_shipping.reset_index(inplace=True)

# To find the total revenue generated as per shipping mode
total_revenue_ship = top_shipping["Sales"].sum()

# Convert the total_revenue_ship from float to int and then to string
total_revenue_ship = str(int(total_revenue_ship))

# Adding '$' sign before the Value
total_revenue_ship = '$' + total_revenue_ship
```

In [482…

```
# Set width and height of figure is defined in inches
plt.rcParams["figure.figsize"] = (18, 8)

# Set Font size
plt.rcParams['font.size'] = 12.0
```

```
# Set Font weight is defined
plt.rcParams['font.weight'] = 6

# define colors for the pie chart
colors = ['#BC243C','#FE840E','#C62168',"limegreen"]

# Plot the figure
fig1, ax1 = plt.subplots()

# Plot the pie chart
ax1.pie(top_shipping['Sales'], colors = colors, labels = top_shipping['Ship Mode'],
        autopct= autopct_format(top_shipping['Sales']), startangle=90)


# Add title to the plot
ax1.set_title("Shipping mode with the highest sales", pad=40, color = "blue")
# Draw a circle on the pie chart
centre_circle = plt.Circle((0,0),0.82,fc='white')

# Add circle to pie-chart
fig = plt.gcf()
fig.gca().add_artist(centre_circle)

# Equal aspect ratio ensures that pie is drawn as a circle
ax1.axis('equal')

# Add total revenue to pie-chart
label = ax1.annotate('Total Revenue \n'+str(total_revenue_ship),color = 'red', xy=(0


# Remove redundant spaces from the plot
#plt.tight_layout(w_pad= 0, h_pad=0)

# Save the plot
plt.savefig(current_dir + "/plots/shipping_mode.png")

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



Observation

We can see that Shipping mode - Standard Class generated the highest revenue of about **$ 1,340,831**.

The Total Revenue generated by all the shipping modes - **$ 2,261,536**

4.2.3. Order Level Analysis

...goto toc

In [492...

```
# Add year feature to data
data['Year'] = data["Order Date"].dt.year
```

In [494...

```
# Get sales and profit as per year
data_year = data.groupby("Year")[["Sales", "Profit"]].sum()
```

In [499...

```

```

Out[499...

```
array([2014, 2015, 2016, 2017], dtype=int64)
```

In [502...

```
# Create the dataframe to merge sales and profits
temp = pd.DataFrame()

# Merge sales and profits
temp["Count"] = data_year["Sales"].values.tolist() + data_year["Profit"].values.toli

# Add sub-categories
temp["Year"] = data_year.index.values.tolist() + data_year.index.values.tolist()
temp["Type"] = ["Sales" if i < 4 else "Profit" for i in range(8) ]


# Set width and height of the figure
fig, axes = plt.subplots(1, figsize = (18, 8))

# Add title to the figure
fig.suptitle("Types of customers and sales and profit earned from them")

# Set font size and weight
plt.rcParams.update({'font.size': 12,
                    "font.weight": 6})


# Plot the profit and sales of the store on individual customer segments
sns.barplot(x = "Year", y = "Count", data = temp, hue = "Type", ax = axes, palette="

# Iterate over sales, to add it's value on the bars
for k,v in enumerate([round(i, 2) for i in temp[temp.Type == "Sales"].Count.values.t
    axes.text(k - 0.18,  v - 210000 ,'$ '+ str(v), fontsize = 12, rotation = 90, col

# Iterate over profits, to add it's value on the bars
for k,v in enumerate([round(i, 2) for i in temp[temp.Type == "Profit"].Count.values.
    axes.text(k + 0.18,  v + 10000, "$ " + str(v), fontsize = 12, rotation = 90, col
```

Note: It is clear that store sales and profits keeps on increasing over time peroid now we can develop a time-series model capacble enough to predict sales and profit of the store.

7. Time Series Modeling

...goto toc

There are several things that are time dependent, I mean, today's values can have an effective relationship to values that have occurred in the past.

Some examples related to the subject are demand of products during a certain period, harvest of commodities, stock prices and of course what we will try to predict, the sales of next 7 days of the store.

Currently there are several types of time series forecast models, in this notebook we will trying to use **Seasonal ARIMA** models.

Get the data ready

In [520…

```
# Convert Order Date to Datetime datatype
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9994 entries, 0 to 9993
Data columns (total 18 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Order Date     9994 non-null   datetime64[ns]
 1   Ship Date      9994 non-null   datetime64[ns]
 2   Ship Mode      9994 non-null   object
 3   Customer Name  9994 non-null   object
 4   Segment        9994 non-null   object
 5   Country        9994 non-null   object
 6   City           9994 non-null   object
 7   State          9994 non-null   object
 8   Postal Code    9994 non-null   int64
 9   Region         9994 non-null   object
 10  Category       9994 non-null   object
 11  Sub-Category   9994 non-null   object
 12  Product Name   9994 non-null   object
```

```
 13   Sales          9994 non-null   float64
 14   Quantity       9994 non-null   int64
 15   Discount       9994 non-null   float64
 16   Profit         9994 non-null   float64
 17   Year           9994 non-null   int64
dtypes: datetime64[ns](2), float64(3), int64(3), object(10)
memory usage: 1.4+ MB
```

In [673…

```python
# Get order date and sales from the data as we only need them for forecasting
time_series = data[["Order Date", "Sales"]]

# Rename the columns
time_series.columns = ["Date", "Sales"]

# Sort the dataset with respect to date
time_series = time_series.sort_values( by = ['Date'], ascending = True).reset_index(

# Group the series with date
time_series = time_series.groupby("Date")[["Sales"]].sum()

time_series.index = pd.to_datetime(time_series.index)
time_series = pd.DataFrame(time_series['Sales'].resample('D').mean())
time_series =  time_series.interpolate(method='linear')

# Print first five rows
time_series.head()
```

Out[673…

	Sales
Date	
2014-01-03	16.448
2014-01-04	288.060
2014-01-05	19.536
2014-01-06	4407.100
2014-01-07	87.158

In [674…

```python
time_series['month'] = [i.month for i in time_series.index]
time_series['year'] = [i.year for i in time_series.index]
time_series.head()
```

Out[674…

	Sales	month	year
Date			
2014-01-03	16.448	1	2014
2014-01-04	288.060	1	2014
2014-01-05	19.536	1	2014
2014-01-06	4407.100	1	2014
2014-01-07	87.158	1	2014

In [675…

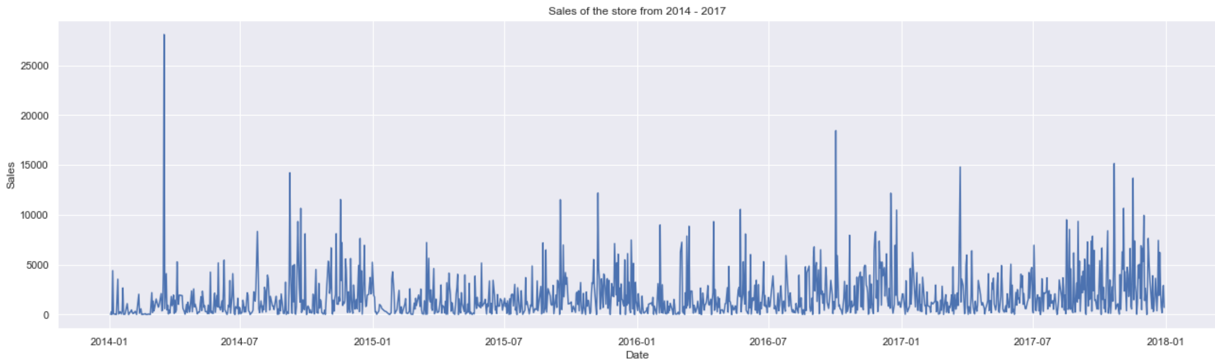
```python
#time_series = time_series.dropna()
```

7.1. Visualize the Time Series

...goto toc

In [676...

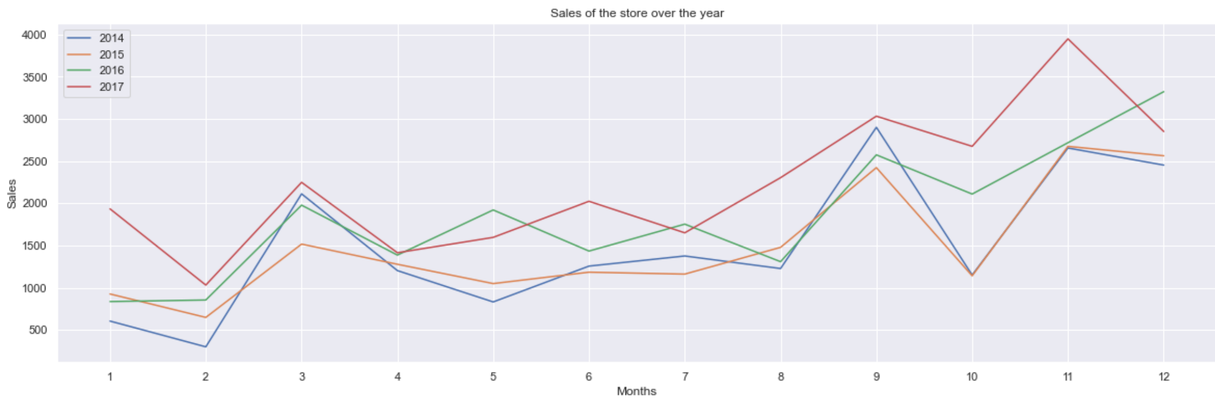
```
plt.figure(figsize=(22,6))
sns.lineplot(x = time_series.index, y = time_series['Sales'])
plt.title('Sales of the store from 2014 - 2017')
plt.show()
```



Check for seasonality

In [677...

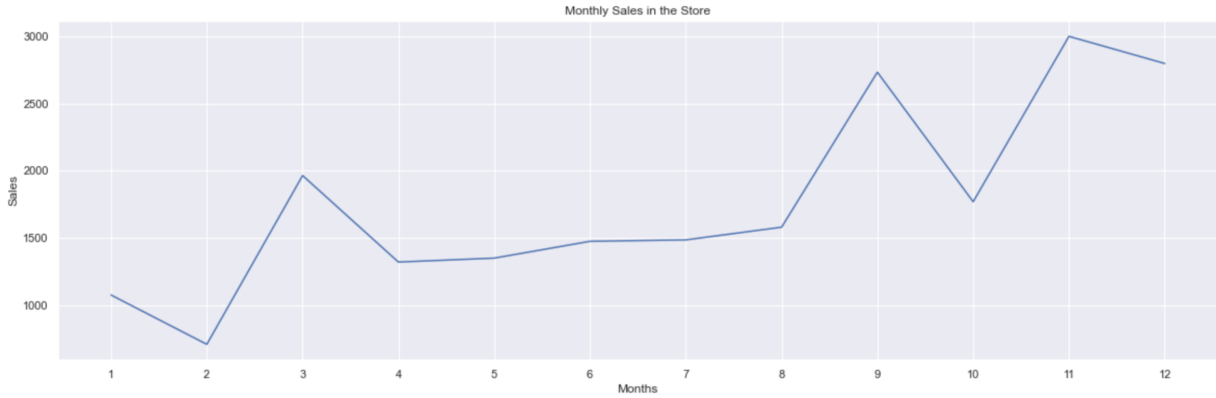
```
# Create a pivot table
pivot = pd.pivot_table(time_series, values='Sales', index='month', columns='year', a

# Plot pivot
pivot.plot(figsize=(20,6))
plt.title('Sales of the store over the year')
plt.xlabel('Months')
plt.ylabel('Sales')
plt.xticks([x for x in range(1,13)])
plt.legend()
plt.show()
```



Series seems to have some seasonality. Just to make the things clear, let's merge these lines into just one line by averaging the monthly levels.

In [678...

```
monthly_seasonality = pivot.mean(axis=1)
monthly_seasonality.plot(figsize=(20,6))
plt.title('Monthly Sales in the Store')
plt.xlabel('Months')
plt.ylabel('Sales')
plt.xticks([x for x in range(1,13)])
plt.show()
```



Important Inferences

The series clearly has some seasonality,

- The sales of the store are lowest in the month of jan i.e start of the year
- The sales keeps on increasing as the year passes

7.2. Stationarize the Series

...goto toc

To create a time series forecast, the series must be stationary.

Conditions for Stationarity:

1. Time series should have a constant mean.
2. Time series should have a constant standard deviation.
3. Time series's auto-covariance should not depend on time.

Check for Stationarity

One way to check if the series is stationary is perform the **Adfuller test**.In adfuller test we use **ACF** and **PACF**.

- *Auto Correlation Function (ACF)*: It shows the correlation between the current temperatures versus the lagged versions of itself.

- *Partial autocorrelation (PACF)*: It shows the correlation between the current temperatures versus the lagged version excluding the effects of earlier lags.

After performing Adfuller test if p-value is

- Lower than 5% (usual number used for this kind of study) the series is stationary and we can start modelling.
- Greater than 5% then the series isn't stationary and we need do some data transformation like using natural logarithm, deflation, differencing, etc.

Let's create a function which check the stationarity and plots:

- The series itself;
- The autocorrelation function (ACF): It shows the correlation between the current temperatures versus the lagged versions of itself.

- The partial autocorrelation (PACF): It shows the correlation between the current temperatures versus the lagged version excluding the effects of earlier lags, for example, it show the effective influence of the lag 3 in the current temperatures excluding the effects of the lags 1 and 2.

In [679…

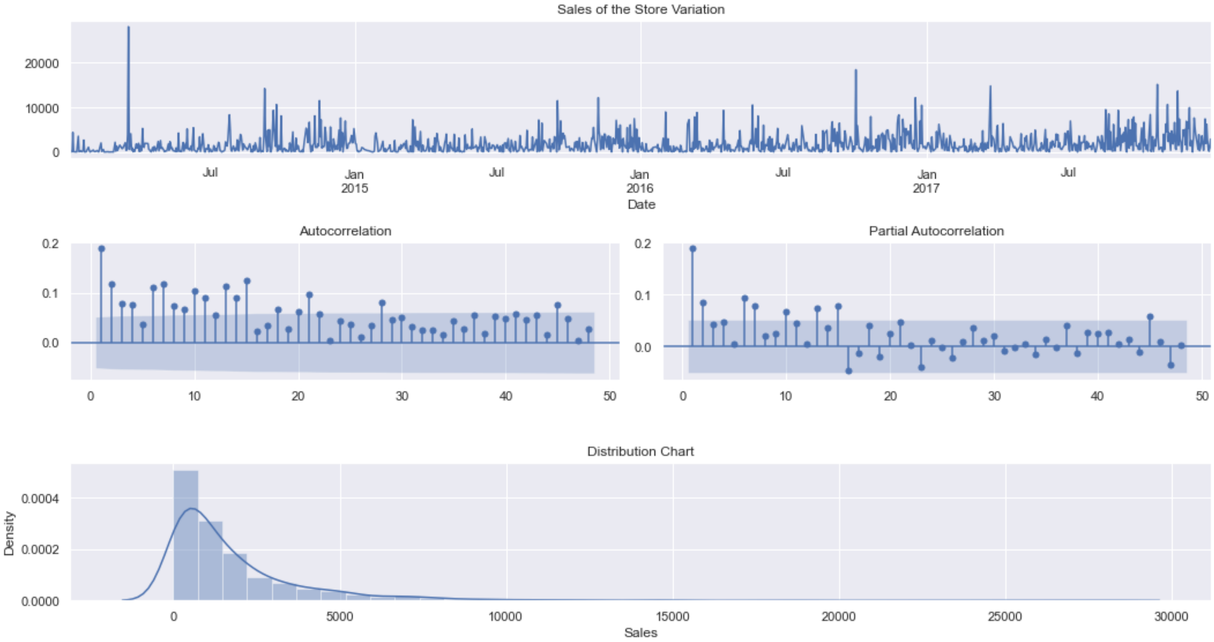
```
def check_stationarity(y, lags_plots=48, figsize=(22,8)):

    # Convert to pandas series
    y = pd.Series(y)

    # Creating plots of the DF
    fig = plt.figure()
    ax1 = plt.subplot2grid((3, 3), (0, 0), colspan=2)
    ax2 = plt.subplot2grid((3, 3), (1, 0))
    ax3 = plt.subplot2grid((3, 3), (1, 1))
    ax4 = plt.subplot2grid((3, 3), (2, 0), colspan=2)

    # Plot the temperature
    y.plot(ax=ax1, figsize=figsize)
    # Set title
    ax1.set_title("Sales of the Store Variation")

    # Plot Auto Correlation using plot_acf of statsmodels
    plot_acf(y, lags=lags_plots, zero=False, ax=ax2);

    # Plot Partial Auto Correlation using plot_pacf of statsmodels
    plot_pacf(y, lags=lags_plots, zero=False, ax=ax3);

    # Plot temperature as distibution
    sns.distplot(y, bins=int(math.sqrt(len(y))), ax=ax4)
    ax4.set_title('Distribution Chart')

    plt.tight_layout()


    print('Results of Dickey-Fuller Test:')

    # Perform the Adfuller test
    adfinput = adfuller(y)

    # Create a series object
    adftest = pd.Series(adfinput[0:4], index=['Test Statistic','p-value','Lags Used'

    # Round them to four decimals
    adftest = round(adftest,4)

    for key, value in adfinput[4].items():
        adftest[f"Critical Value ({key})"] = value.round(4)

    print(adftest)
    if adftest[0].round(2) < adftest[5].round(2):
        print('\nThe Test Statistics is lower than the Critical Value of 5%. The ser
    else:
        print("\nThe Test Statistics is higher than the Critical Value of 5%. The se
```

In [680…

```
# Check stationarity
check_stationarity(time_series.Sales)
```

```
Results of Dickey-Fuller Test:
Test Statistic                 -6.4212
p-value                         0.0000
```

```
Lags Used                        15.0000
Number of Observations Used    1442.0000
Critical Value (1%)              -3.4349
Critical Value (5%)              -2.8635
Critical Value (10%)             -2.5678
dtype: float64

The Test Statistics is lower than the Critical Value of 5%. The series seems to be s
tationary
```

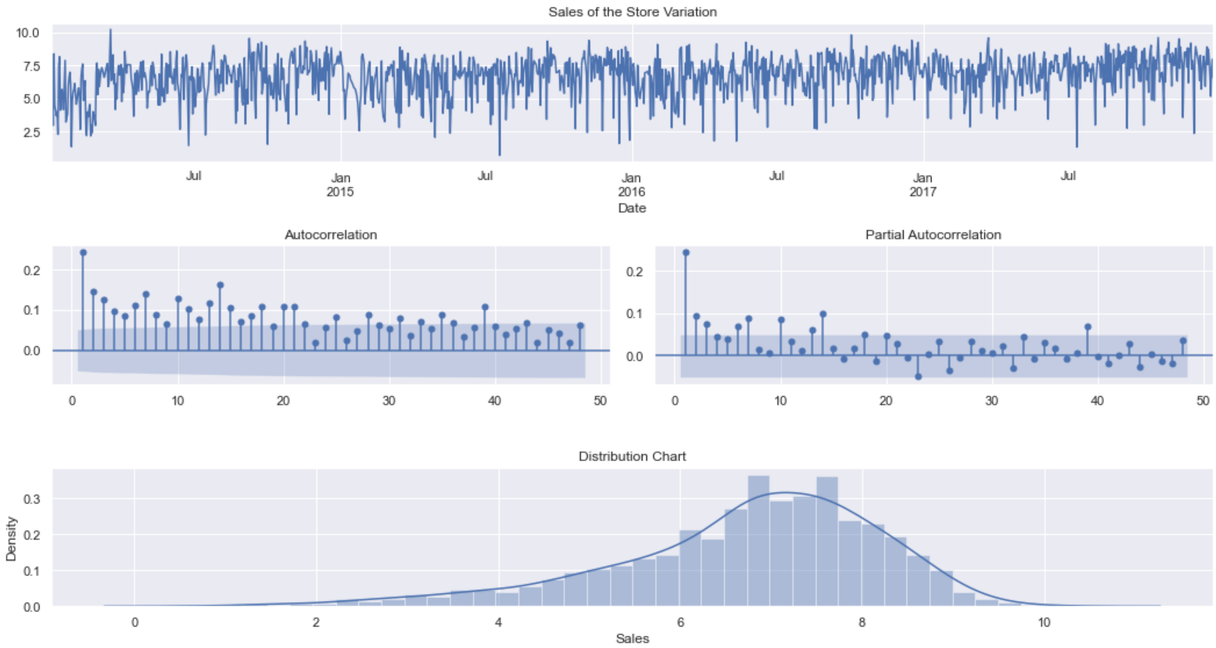


Note: The data is not complete stationary to do so we will perform log transformation

In [681…

```python
# Check stationarity
check_stationarity(np.log(time_series.Sales))
```

```
Results of Dickey-Fuller Test:
Test Statistic                   -6.4661
p-value                           0.0000
Lags Used                        13.0000
Number of Observations Used    1444.0000
Critical Value (1%)              -3.4349
Critical Value (5%)              -2.8635
Critical Value (10%)             -2.5678
dtype: float64

The Test Statistics is lower than the Critical Value of 5%. The series seems to be s
tationary
```



Note:

Now that we know our time series is data is stationary. Let us begin with model training for forecasting the sales. We have chosen SARIMA model to forecast the sales.

Seasonal Autoregressive Integrated Moving Average, SARIMA or Seasonal ARIMA, is an extension of ARIMA that supports univariate time series data with a seasonal component. It requires selecting hyperparameters for both the trend and seasonal elements of the series.

- Trend Elements - There are three trend elements that require configuration
    - p: Trend autoregression order
    - d: Trend difference order
    - q: Trend moving average order.
- Seasonal Elements - There are four seasonal elements
    - P: Seasonal autoregressive order
    - D: Seasonal difference order
    - Q: Seasonal moving average order
    - m: The number of time steps for a single seasonal period.

The notation for a SARIMA model is specified as: SARIMA(p,d,q)(P,D,Q)m

7.3. Find Optimal Parameters

...goto toc

We will use **grid search** to find the optimal set of parameters that yields the best performance for our model

In [682...
```
# Tuple of parameters
paras = ((2,0,0),(0,1,1,12),'c')
```

In [683...
```
# Create combinations of parameter for grid search
p = d = q = range(0, 2)
```

```python
pdq = list(itertools.product(p, d, q))

# Create list of possible combinations
seasonal_pdq = [(x[0], x[1], x[2], 12) for x in list(itertools.product(p, d, q))]

print('Examples of parameter combinations for Seasonal ARIMA...')
print('SARIMAX: {} x {}'.format(pdq[1], seasonal_pdq[1]))
print('SARIMAX: {} x {}'.format(pdq[1], seasonal_pdq[2]))
print('SARIMAX: {} x {}'.format(pdq[2], seasonal_pdq[3]))
print('SARIMAX: {} x {}'.format(pdq[2], seasonal_pdq[4]))
```

```
Examples of parameter combinations for Seasonal ARIMA...
SARIMAX: (0, 0, 1) x (0, 0, 1, 12)
SARIMAX: (0, 0, 1) x (0, 1, 0, 12)
SARIMAX: (0, 1, 0) x (0, 1, 1, 12)
SARIMAX: (0, 1, 0) x (1, 0, 0, 12)
```

In [684…

```python
# Get Sales
y = time_series.Sales.copy(deep = True)
```

In [685…

```python
min_aic, best_param, best_seasonal_param = 10**10, [], []

# Iterate over the list and fit on Seasonal-ARIMA Model
for param in pdq:
    for param_seasonal in seasonal_pdq:
        try:
            # Initialize the SARIMA model
            mod = sm.tsa.statespace.SARIMAX(y, order = param, seasonal_order=param_s
                                            enforce_invertibility = False)
            # Fit the model
            results = mod.fit()

            print('ARIMA{}x{}12 - AIC:{}'.format(param, param_seasonal, results.aic)

            # We are selecting those parameter which has minimum AIC score
            if results.aic < min_aic:
                min_aic, best_param, best_seasonal_param = results.aic, param, param



        except:
            continue

print("-"*50)
print(f"Best AIC Score achieved \033[4m\033[1m{min_aic}\033[0m\033[0m")
print(f"Parameter - ARIMA\033[4m\033[1m{best_param}\033[0m\033[0mx\033[4m\033[1m{bes
```

```
ARIMA(0, 0, 0)x(0, 0, 0, 12)12 - AIC:27286.893842684796
ARIMA(0, 0, 0)x(0, 0, 1, 12)12 - AIC:26901.118814805974
ARIMA(0, 0, 0)x(0, 1, 0, 12)12 - AIC:27252.851149525137
ARIMA(0, 0, 0)x(0, 1, 1, 12)12 - AIC:26180.3901446449
ARIMA(0, 0, 0)x(1, 0, 0, 12)12 - AIC:26793.46783553277
ARIMA(0, 0, 0)x(1, 0, 1, 12)12 - AIC:26345.75416476258
ARIMA(0, 0, 0)x(1, 1, 0, 12)12 - AIC:26650.85099413861
ARIMA(0, 0, 0)x(1, 1, 1, 12)12 - AIC:26181.5741136617
ARIMA(0, 0, 1)x(0, 0, 0, 12)12 - AIC:27009.22000204731
ARIMA(0, 0, 1)x(0, 0, 1, 12)12 - AIC:26727.749980684468
ARIMA(0, 0, 1)x(0, 1, 0, 12)12 - AIC:27224.56213607592
ARIMA(0, 0, 1)x(0, 1, 1, 12)12 - AIC:26099.366318682863
ARIMA(0, 0, 1)x(1, 0, 0, 12)12 - AIC:26724.751520275782
ARIMA(0, 0, 1)x(1, 0, 1, 12)12 - AIC:26429.869820270975
ARIMA(0, 0, 1)x(1, 1, 0, 12)12 - AIC:26678.234957535315
ARIMA(0, 0, 1)x(1, 1, 1, 12)12 - AIC:26101.36518011739
ARIMA(0, 1, 0)x(0, 0, 0, 12)12 - AIC:27233.430247980526
```

```
ARIMA(0, 1, 0)x(0, 0, 1, 12)12 - AIC:27011.320982112797
ARIMA(0, 1, 0)x(0, 1, 0, 12)12 - AIC:28092.662753476965
ARIMA(0, 1, 0)x(0, 1, 1, 12)12 - AIC:26827.767735913563
ARIMA(0, 1, 0)x(1, 0, 0, 12)12 - AIC:27028.54512295907
ARIMA(0, 1, 0)x(1, 0, 1, 12)12 - AIC:27011.89989524464
ARIMA(0, 1, 0)x(1, 1, 0, 12)12 - AIC:27392.022564424395
ARIMA(0, 1, 0)x(1, 1, 1, 12)12 - AIC:26824.07406538116
ARIMA(0, 1, 1)x(0, 0, 0, 12)12 - AIC:26461.3294796302
ARIMA(0, 1, 1)x(0, 0, 1, 12)12 - AIC:26249.145034548244
ARIMA(0, 1, 1)x(0, 1, 0, 12)12 - AIC:27251.879305733622
ARIMA(0, 1, 1)x(0, 1, 1, 12)12 - AIC:26467.350023779025
ARIMA(0, 1, 1)x(1, 0, 0, 12)12 - AIC:26283.92494679504
ARIMA(0, 1, 1)x(1, 0, 1, 12)12 - AIC:26251.176823993417
ARIMA(0, 1, 1)x(1, 1, 0, 12)12 - AIC:26780.603675856793
ARIMA(0, 1, 1)x(1, 1, 1, 12)12 - AIC:26054.04355151766
ARIMA(1, 0, 0)x(0, 0, 0, 12)12 - AIC:26845.735045293724
ARIMA(1, 0, 0)x(0, 0, 1, 12)12 - AIC:26618.01997373436
ARIMA(1, 0, 0)x(0, 1, 0, 12)12 - AIC:27241.929746099653
ARIMA(1, 0, 0)x(0, 1, 1, 12)12 - AIC:26107.664755354617
ARIMA(1, 0, 0)x(1, 0, 0, 12)12 - AIC:26610.633184775354
ARIMA(1, 0, 0)x(1, 0, 1, 12)12 - AIC:26341.546007202902
ARIMA(1, 0, 0)x(1, 1, 0, 12)12 - AIC:26603.02471709458
ARIMA(1, 0, 0)x(1, 1, 1, 12)12 - AIC:26351.832748262088
ARIMA(1, 0, 1)x(0, 0, 0, 12)12 - AIC:26474.83828463442
ARIMA(1, 0, 1)x(0, 0, 1, 12)12 - AIC:26262.87078175918
ARIMA(1, 0, 1)x(0, 1, 0, 12)12 - AIC:27225.90907631068
ARIMA(1, 0, 1)x(0, 1, 1, 12)12 - AIC:26089.438275499342
ARIMA(1, 0, 1)x(1, 0, 0, 12)12 - AIC:26280.223830949264
ARIMA(1, 0, 1)x(1, 0, 1, 12)12 - AIC:26278.33947173415
ARIMA(1, 0, 1)x(1, 1, 0, 12)12 - AIC:26658.15797478427
ARIMA(1, 0, 1)x(1, 1, 1, 12)12 - AIC:26061.131785699105
ARIMA(1, 1, 0)x(0, 0, 0, 12)12 - AIC:26896.927891287178
ARIMA(1, 1, 0)x(0, 0, 1, 12)12 - AIC:26677.835490343
ARIMA(1, 1, 0)x(0, 1, 0, 12)12 - AIC:27751.46845454941
ARIMA(1, 1, 0)x(0, 1, 1, 12)12 - AIC:26496.906941395962
ARIMA(1, 1, 0)x(1, 0, 0, 12)12 - AIC:26677.695171743486
ARIMA(1, 1, 0)x(1, 0, 1, 12)12 - AIC:26679.443967151667
ARIMA(1, 1, 0)x(1, 1, 0, 12)12 - AIC:27052.606344165208
ARIMA(1, 1, 0)x(1, 1, 1, 12)12 - AIC:26494.038972584065
ARIMA(1, 1, 1)x(0, 0, 0, 12)12 - AIC:26446.073210719085
ARIMA(1, 1, 1)x(0, 0, 1, 12)12 - AIC:26234.190331711852
ARIMA(1, 1, 1)x(0, 1, 0, 12)12 - AIC:27242.459010290942
ARIMA(1, 1, 1)x(0, 1, 1, 12)12 - AIC:26036.07088716987
ARIMA(1, 1, 1)x(1, 0, 0, 12)12 - AIC:26231.258502924178
ARIMA(1, 1, 1)x(1, 0, 1, 12)12 - AIC:26236.122470721166
ARIMA(1, 1, 1)x(1, 1, 0, 12)12 - AIC:26742.78252702645
ARIMA(1, 1, 1)x(1, 1, 1, 12)12 - AIC:26036.75457040976
--------------------------------------------------
Best AIC Score achieved 26036.07088716987
Parameter - ARIMA(1, 1, 1)x(0, 1, 1, 12)12
```

Important Inference

We have got a best AIC score of 2132.43 with parameters (1,0,1) and seasonal parameters (0,1,1,12)

7.4. Build SARIMA Model

...goto toc

In [686…

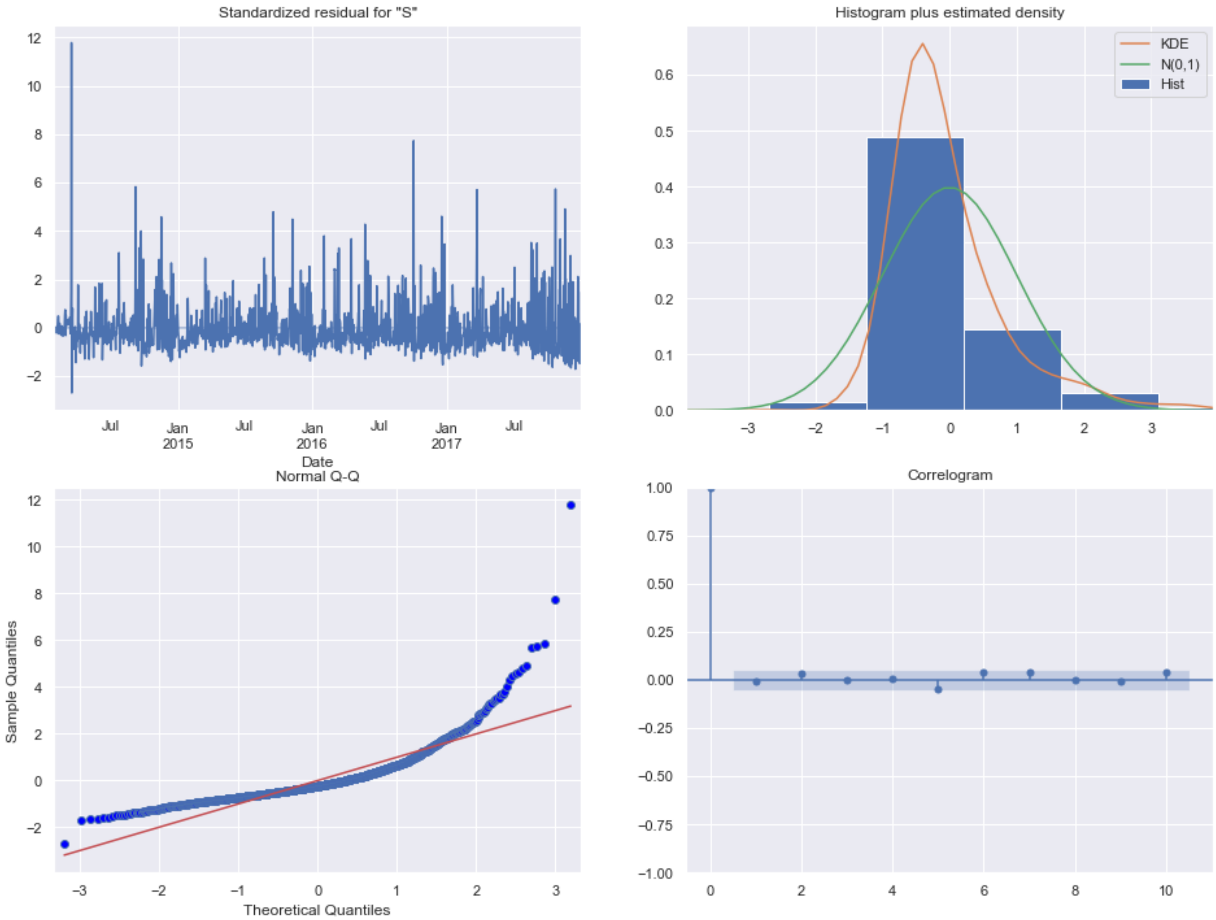
```
time_series_model = sm.tsa.statespace.SARIMAX(y, order = best_param, seasonal_order
                                enforce_invertibility=False)

# Fit the SARIMA Model
results = time_series_model.fit()
```

```
# Print summary table
print(results.summary().tables[1])
```

```
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.1249      0.019      6.750      0.000       0.089       0.161
ma.L1         -0.9717      0.007   -134.257      0.000      -0.986      -0.957
ma.S.L12      -1.0018      0.012    -81.309      0.000      -1.026      -0.978
sigma2      4.528e+06   2.73e-09   1.66e+15      0.000    4.53e+06    4.53e+06
==============================================================================
```

In [687…

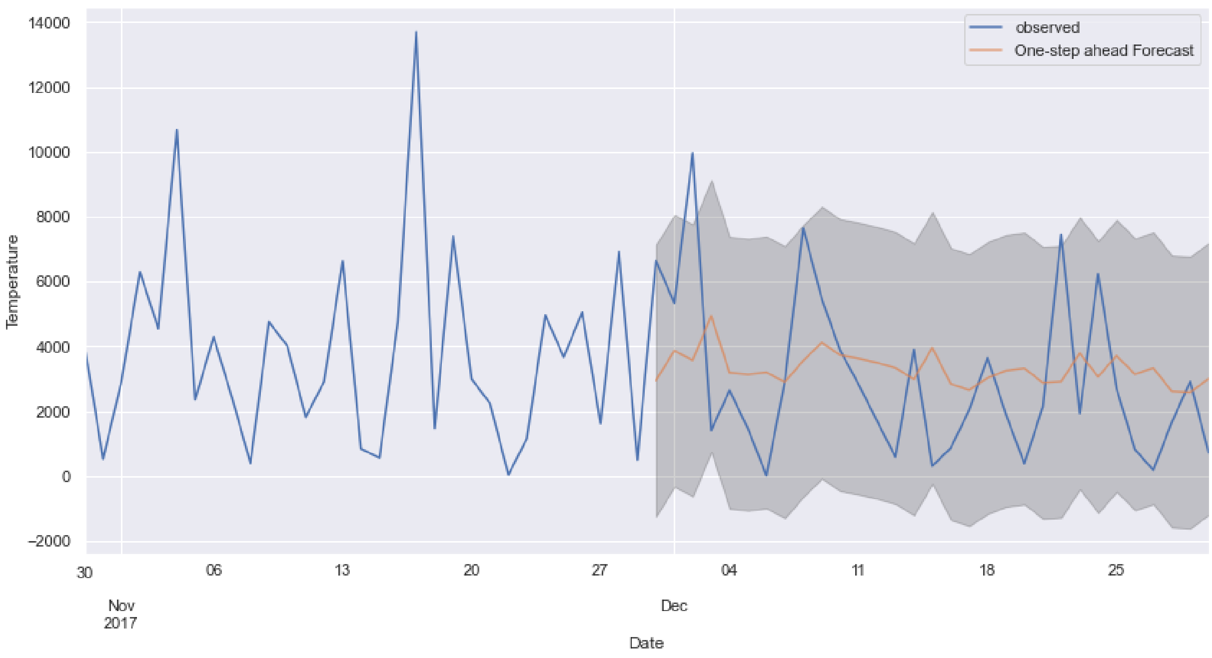
```
# Running model diagnostiscs to check any unusual behaviour
results.plot_diagnostics(figsize=(16, 12))
plt.savefig(current_dir + "/model/inference.png")
plt.show()
```



The model diagnostics indicates that the model residuals are near normally distributed

In [688…

```
# set forecasts to start at 2017-11-30 to the end of the data to forecast
pred = results.get_prediction(start = pd.to_datetime('2017-11-30'), dynamic=False)
pred_ci = pred.conf_int()

# Plot the forecast
ax = y['2017-10-30':].plot(label='observed')
pred.predicted_mean.plot(ax=ax, label='One-step ahead Forecast', alpha=.7, figsize=(
ax.fill_between(pred_ci.index,
                pred_ci.iloc[:, 0],
                pred_ci.iloc[:, 1], color='k', alpha=.2)
ax.set_xlabel('Date')
ax.set_ylabel('Temperature')
plt.legend()
plt.show()
```



Calculating MSE and RMSE

In [689...

```
# Get predicted values
y_forecasted = pred.predicted_mean.values

# Get actual values
y_truth = y['2017-11-30':].values

# Calculate MSE and RMSE
mse = mean_squared_error(y_forecasted, y_truth)
print('The Mean Squared Error of our model is \033[4m\033[1m{}\033[0m\033[0m'.format
print('The Root Mean Squared Error of our model is \033[4m\033[1m{}\033[0m\033[0m'.f
```

```
The Mean Squared Error of our model is 6412760.75
The Root Mean Squared Error of our model is 2532.34
```

In [690...

```
time_series.tail()
```

Out[690...

Date	Sales	month	year
2017-12-26	814.5940	12	2017
2017-12-27	177.6360	12	2017
2017-12-28	1657.3508	12	2017
2017-12-29	2915.5340	12	2017
2017-12-30	713.7900	12	2017

7.5. Make Predictions

...goto toc

We will predict the sales of store for next 7 days - **2018-01-06**

In [692...

```python
# Make forecasting
pred_uc = results.get_forecast(steps = 7)
print(pred_uc.predicted_mean)
```

```
2017-12-31    2643.753696
2018-01-01    3202.046211
2018-01-02    3117.684597
2018-01-03    2988.869680
2018-01-04    3005.314723
2018-01-05    3060.751662
2018-01-06    3058.604692
Freq: D, Name: predicted_mean, dtype: float64
```

In [693...

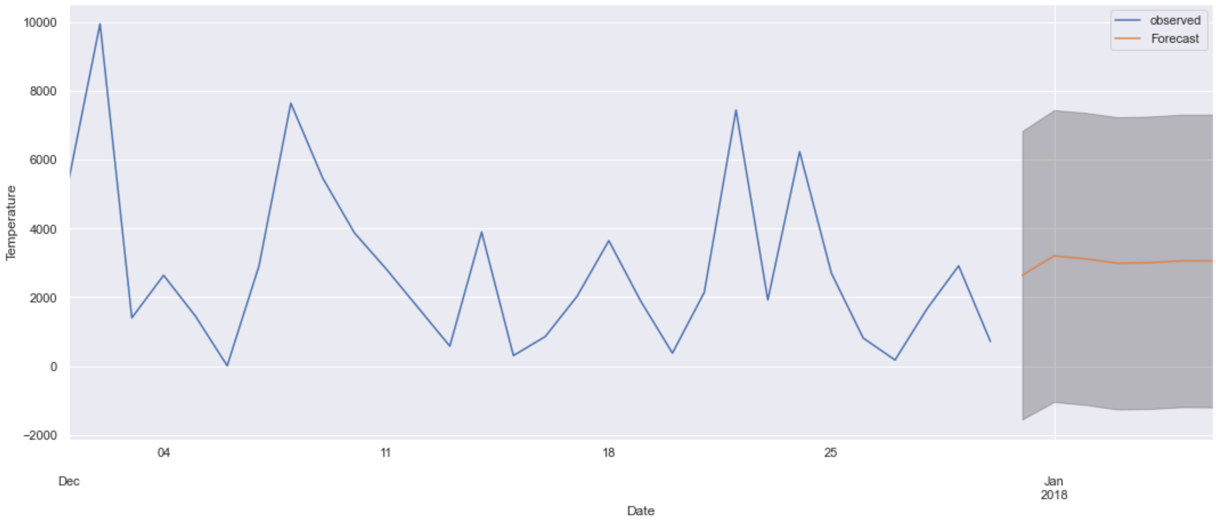
```python
pred_ci = pred_uc.conf_int()
pred_ci
```

Out[693...

	lower Sales	upper Sales
2017-12-31	-1547.695766	6835.203157
2018-01-01	-1038.439308	7442.531731
2018-01-02	-1127.476452	7362.845645
2018-01-03	-1258.722087	7236.461448
2018-01-04	-1244.477946	7255.107392
2018-01-05	-1191.175399	7312.678723
2018-01-06	-1195.470658	7312.680042

In [696...

```python
# Visualizing the Forecast

ax = y[y.index > '2017-11-30'].plot(label='observed', figsize=(18, 7))
pred_uc.predicted_mean.plot(ax = ax, label='Forecast')
ax.fill_between(pred_ci.index,
                pred_ci.iloc[:, 0],
                pred_ci.iloc[:, 1], color='k', alpha=.25)
ax.set_xlabel('Date')
ax.set_ylabel('Temperature')
plt.legend()
plt.savefig("Forecast.png")
plt.show()
```



Save Forecasting

In [697…

```
# Create a dataframe to save forecast
forecast = pd.DataFrame()
forecast["Date"] = pred_uc.predicted_mean.index
forecast["Temp"] = pred_uc.predicted_mean.values
forecast
```

Out[697…

	Date	Temp
0	2017-12-31	2643.753696
1	2018-01-01	3202.046211
2	2018-01-02	3117.684597
3	2018-01-03	2988.869680
4	2018-01-04	3005.314723
5	2018-01-05	3060.751662
6	2018-01-06	3058.604692

In [698…

```
# Save forecast
forecast.to_csv(current_dir + "/model/forecast.csv", index=False)
```

Save the SARIMA Model

In [699…

```
# save model
results.save(current_dir + '/model/model.pkl')
```

Conclusion

During my research it was found that the store have highest number of Office Supplies products with total 60.3% while minimum number of Technology products (1847) i.e 18.48%. But the store have earned highest revenue of $836154 from Technology products.

The Store earn highest profit in Copiers while Selling price for Chairs and Phones is extremely high compared to other products. The Store earn highest profit in Copiers while Selling price for Chairs and Phones is extremely high compared to other products.

The Total Revenue generated by all these products - $209624!

Out the total number of customers the store have 50 percent of them are consumer and they provide a highest profit of 134,119 dollor with sales of 1,161,401 dollors. Store need to work on improving profits earned on consumers

Additionally, majority of the Profitable Customers are from New York and Michigan State. The store have higher number of sales (725,457) from West region with a net profit of $ 108,418

The sales of the store keeps on increasing over time peroid now we can develop a time-series model capacble enough to predict sales and profit of the store.

Additionaly, I have build a **Seasonal-ARIMA** model to forecast the sales. And stored the predictions in model directory.

The built model is than used to predict the sales of store for next 7 days.

According to the forecasting sales of the store will be **$ 3058.604692** on **2018-01-06**

```
In [ ]:
```