greatlearning

PGP DSE FT Capstone Project – Final Report

Project Group Info:

BATCH DETAILS	DSE Offline Bangalore Oct 2022
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DOMAIN OF PROJECT	Retail
PROJECT TITLE	Weekly Sales Forecasting using Non-linear Regression and Time Series models
GROUP NUMBER	GROUP – 3
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INDEX

1. Abstract 3
2. Overview 3
3. Step-by-Step Walk through of the Solution with Visualizations 4
4. Model Evaluation 56
5. Comparison to Benchmark 57
6. Implications 58
7. Limitations 59
8. Closing Reflections 60

1. Abstract:

Predicting future sales for a company is one of the most important aspects of strategic planning. We wanted to analyze how internal and external factors of one of the biggest companies in the US can affect their Weekly Sales in the future.

This project contains complete analysis of data, includes time series analysis, identifies the best performing stores, performs sales prediction with the help of non-linear regression models.

Outset of this project was Linear Regression Model with Time Series Analysis. But the solution led us to Non-Linear Regression model followed where we got Random Forest Regressor as a better fit model followed by Time series analysis from which we acquired Auto-ARIMA model to be the best fit model.

2. Overview

The data collected ranges from 2010 to 2013, where 45 Walmart stores across the country (US) were included in this analysis. It is important to note that we also have external data available like CPI, Unemployment Rate and Fuel Prices in the region of each store which, hopefully, help us to make a more detailed analysis.

In this report, we focus on examining the machine learning methods that are the most suitable method for weekly sales prediction with training data. Therefore, this study will have more variety in combining models for an accurate claim prediction, looking for the alternative and more complex machine learning model to predict the weekly sales occurring in the next span by using a real database.

This report comprises of data understanding, data visualization, Feature engineering, EDA, OLS model, Non-linear Regression models. The regression models used are Decision Tree, Random Forest, AdaBoost, GradientBoost, XGBoost and Bagging (with best estimators being Random Forest, AdaBoost, GradientBoost, XGBoost). And Time Series Analysis with Auto-ARIMA model and exponential smoothing model.

3. Step-by-Step Walk through of the Solution with Visualizations

Problem Statement:

- Forecast the department-wise weekly_sales
- Model the effects of markdowns on holiday weeks
- Provide recommended actions based on the insights drawn, with prioritization placed on largest business impact

Data Understanding:

The data is from Retail domain and is related to Walmart and are provided with historical sales data for 45 stores located in different regions - each store contains a number of departments. The company also runs several promotional markdown events throughout the year. These markdowns precede prominent holidays, the four largest of which are the Super Bowl, Labor Day, Thanksgiving, and Christmas. The weeks including these holidays are weighted five times higher in the evaluation than non-holiday

Input variables (Features):

- Store - The store number
- Dept - The department number
- Date - The week
- Temperature - Average temperature in the region
- Fuel_Price - Cost of fuel in the region
- MarkDown1-5 - Anonymized data related to promotional markdowns. MarkDown data is only available after Nov 2011, and is not available for all stores all the time. Any missing value is marked with an NA
- CPI - The consumer price index
- Unemployment - The unemployment rate
- Type - Type of Store
- Size - Size of Store
- IsHoliday - Whether the week is a special holiday week

Output variable (desired target):

Weekly_Sales - Sales for the given department in the given store

- Initiated by importing the necessary libraries

Importing Libraries

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

import warnings
warnings.filterwarnings('ignore')

import statsmodels.api as sm
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import mean_squared_error,mean_absolute_percentage_error,r2_score
from sklearn.ensemble import RandomForestRegressor
from sklearn.preprocessing import RobustScaler, StandardScaler
from sklearn.pipeline import make_pipeline

import xgboost as xgb
from sklearn.ensemble import AdaBoostRegressor
from sklearn.neighbors import KNeighborsRegressor
from sklearn.svm import SVR

import itertools
import statsmodels.tsa.api as smt
import statsmodels.formula.api as smf

from sklearn.model_selection import train_test_split
from statsmodels.tsa.seasonal import seasonal_decompose as season
from sklearn.metrics import accuracy_score, balanced_accuracy_score
from sklearn.model_selection import cross_val_score
from sklearn.pipeline import make_pipeline, Pipeline
from sklearn import metrics

from statsmodels.tsa.holtwinters import ExponentialSmoothing
from statsmodels.tsa.stattools import adfuller, acf, pacf
from statsmodels.tsa.arima_model import ARIMA
import pmdarima as pm
from pmdarima.utils import decomposed_plot
from pmdarima.arima import decompose
from pmdarima import auto_arima
```

- Reading data and merging all 3 data files into a single unique dataframe;

```
features=pd.read_csv('Features data set.csv')
sales=pd.read_csv('sales data-set.csv')
stores=pd.read_csv('stores data-set.csv')
```

```
# changing date to date type
features['Date'] = pd.to_datetime(features['Date'])
sales['Date'] = pd.to_datetime(sales['Date'])
```

```
print(features.shape)
print(sales.shape)
print(stores.shape)

print(sales[0:1].Date, sales[-1:].Date)

print(features[0:1].Date, features[-1:].Date)
```

```
(8190, 12)
(421570, 5)
(45, 3)
0   2010-05-02
Name: Date, dtype: datetime64[ns] 421569   2012-10-26
Name: Date, dtype: datetime64[ns]
0   2010-05-02
Name: Date, dtype: datetime64[ns] 8189   2013-07-26
Name: Date, dtype: datetime64[ns]
```

Merging data into Unique DataFrame

```
df=pd.merge(sales,features, on=['Store','Date', 'IsHoliday'], how='left')
df=pd.merge(df,stores, on=['Store'], how='left')

# converting temperature in degree celcius from farenhite
df['Temperature'] = (df['Temperature']- 32) * 5./9.


df.head()
```

	Store	Dept	Date	Weekly_Sales	IsHoliday	Temperature	Fuel_Price	MarkDown1	MarkDown2	MarkDown3	MarkDown4	MarkDown5	CPI	Unemploy
0	1	1	2010-05-02	24924.50	False	5.727778	2.572	NaN	NaN	NaN	NaN	NaN	211.096358	
1	1	1	2010-12-02	46039.49	True	3.616667	2.548	NaN	NaN	NaN	NaN	NaN	211.242170	
2	1	1	2010-02-19	41595.55	False	4.405556	2.514	NaN	NaN	NaN	NaN	NaN	211.289143	
3	1	1	2010-02-26	19403.54	False	8.127778	2.561	NaN	NaN	NaN	NaN	NaN	211.319643	
4	1	1	2010-05-03	21827.90	False	8.055556	2.625	NaN	NaN	NaN	NaN	NaN	211.350143	

```
df.to_csv('mergedDf.csv')
```

- Further checking data and features in which we look into the shape (number of rows and columns), check for info() to find the numerical and categorical data with null or non-null values, and then check for duplicated.

Checking data and features

```
df.head()
```

	Store	Dept	Date	Weekly_Sales	IsHoliday	Temperature	Fuel_Price	MarkDown1	MarkDown2	MarkDown3	MarkDown4	MarkDown5	CPI	Unemploy
0	1	1	2010-05-02	24924.50	False	5.727778	2.572	NaN	NaN	NaN	NaN	NaN	211.096358	
1	1	1	2010-12-02	46039.49	True	3.616667	2.548	NaN	NaN	NaN	NaN	NaN	211.242170	
2	1	1	2010-02-19	41595.55	False	4.405556	2.514	NaN	NaN	NaN	NaN	NaN	211.289143	
3	1	1	2010-02-26	19403.54	False	8.127778	2.561	NaN	NaN	NaN	NaN	NaN	211.319643	
4	1	1	2010-05-03	21827.90	False	8.055556	2.625	NaN	NaN	NaN	NaN	NaN	211.350143	

```
df.shape
```

```
(421570, 16)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 421570 entries, 0 to 421569
Data columns (total 16 columns):
 #   Column        Non-Null Count   Dtype
---  ------        --------------   -----
 0   Store         421570 non-null  int64
 1   Dept          421570 non-null  int64
 2   Date          421570 non-null  datetime64[ns]
 3   Weekly_Sales  421570 non-null  float64
 4   IsHoliday     421570 non-null  bool
 5   Temperature   421570 non-null  float64
 6   Fuel_Price    421570 non-null  float64
 7   MarkDown1     150681 non-null  float64
 8   MarkDown2     111248 non-null  float64
 9   MarkDown3     137091 non-null  float64
 10  MarkDown4     134967 non-null  float64
 11  MarkDown5     151432 non-null  float64
 12  CPI           421570 non-null  float64
 13  Unemployment  421570 non-null  float64
 14  Type          421570 non-null  object
 15  Size          421570 non-null  int64
dtypes: bool(1), datetime64[ns](1), float64(10), int64(3), object(1)
memory usage: 51.9+ MB
```

INFERENCE

- There are 13 numeric (10 float, 3 int), 2 categorical (1 object, 1 bool) and 1 Date type of data variables in our merged dataset
- We can see that there are null values in Markdown 1, 2, 3, 4, 5
- All other columns except Markdowns are non-null

```
df.duplicated().sum()     # No duplicates
```

```
0
```

- Followed by converting the necessary datatypes of the variables.

Converting Datatypes

```
df['Store'] = df['Store'].astype('object')
```

```
df['Dept'] = df['Dept'].astype('object')
```

```
df['IsHoliday'] = df['IsHoliday'].astype('object')
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 421570 entries, 0 to 421569
Data columns (total 16 columns):
 #   Column        Non-Null Count   Dtype
---  ------        --------------   -----
 0   Store         421570 non-null  object
 1   Dept          421570 non-null  object
 2   Date          421570 non-null  datetime64[ns]
 3   Weekly_Sales  421570 non-null  float64
 4   IsHoliday     421570 non-null  object
 5   Temperature   421570 non-null  float64
 6   Fuel_Price    421570 non-null  float64
 7   MarkDown1     150681 non-null  float64
 8   MarkDown2     111248 non-null  float64
 9   MarkDown3     137091 non-null  float64
 10  MarkDown4     134967 non-null  float64
 11  MarkDown5     151432 non-null  float64
 12  CPI           421570 non-null  float64
 13  Unemployment  421570 non-null  float64
 14  Type          421570 non-null  object
 15  Size          421570 non-null  int64
dtypes: datetime64[ns](1), float64(10), int64(1), object(4)
memory usage: 54.7+ MB
```

- Store, Dept and IsHoliday have been converted into object datatype

- Now, checking for null values and treating accordingly

```
df.isnull().mean()
```

```
Store           0.000000
Dept            0.000000
Date            0.000000
Weekly_Sales    0.000000
IsHoliday       0.000000
Temperature     0.000000
Fuel_Price      0.000000
MarkDown1       0.642572
MarkDown2       0.736110
MarkDown3       0.674808
MarkDown4       0.679847
MarkDown5       0.640790
CPI             0.000000
Unemployment    0.000000
Type            0.000000
Size            0.000000
dtype: float64
```

```
df.fillna(0,inplace=True)
```

- Walmart gave Markdown columns to see the effect of Markdowns on Sales. When I check columns, there are many NaN values for Markdowns. So, decided to change them with 0, because if there is a Markdown in the row, it is shown with numbers. So, if its shown as 0, it infers that there is no markdown at that date.

```
df.isnull().sum()
```

```
Store           0
Dept            0
Date            0
Weekly_Sales    0
IsHoliday       0
Temperature     0
Fuel_Price      0
MarkDown1       0
MarkDown2       0
MarkDown3       0
MarkDown4       0
MarkDown5       0
CPI             0
Unemployment    0
Type            0
Size            0
dtype: int64
```

- Now, we can see that there are no null values

- Now, looking into the description of our numerical data

```
df.describe().T
```

	count	mean	std	min	25%	50%	75%	max
Store	421570.0	22.200546	12.785297	1.000000	11.000000	22.000000	33.000000	45.000000
Dept	421570.0	44.260317	30.492054	1.000000	18.000000	37.000000	74.000000	99.000000
Weekly_Sales	421570.0	15981.258123	22711.183519	-4988.940000	2079.650000	7612.030000	20205.852500	693099.360000
Temperature	421570.0	15.605588	10.248851	-18.922222	8.155556	16.716667	23.488889	37.855556
Fuel_Price	421570.0	3.361027	0.458515	2.472000	2.933000	3.452000	3.738000	4.468000
MarkDown1	421570.0	2590.074819	6052.385934	0.000000	0.000000	0.000000	2809.050000	88646.760000
MarkDown2	421570.0	879.974298	5084.538801	-265.760000	0.000000	0.000000	2.200000	104519.540000
MarkDown3	421570.0	468.087665	5528.873453	-29.100000	0.000000	0.000000	4.540000	141630.610000
MarkDown4	421570.0	1083.132268	3894.529945	0.000000	0.000000	0.000000	425.290000	67474.850000
MarkDown5	421570.0	1662.772385	4207.629321	0.000000	0.000000	0.000000	2168.040000	108519.280000
CPI	421570.0	171.201947	39.159276	126.064000	132.022667	182.318780	212.416993	227.232807
Unemployment	421570.0	7.960289	1.863296	3.879000	6.891000	7.866000	8.572000	14.313000
Size	421570.0	136727.915739	60980.583328	34875.000000	93638.000000	140167.000000	202505.000000	219622.000000

Weekly_Sales : Target Variable

- average weekly sales of all the 45 stores is 15981.2
- one of the store has 693099 as its highest weekly sale
- some of the stores are running under loss as they have negative weekly sales
- 75% of the stores has upto 20205 weekly sale

Temperature

- average temperature around 45 regions is 15.6 degree celcius
- minimum temperature for some region falls down to -18.9 degree celcius
- maximum temperature for some region reaches upto 37.8 degree celcius
- for half of the regions i.e. 50% temperature remains between 8.1 - 23.4 degree celcius

Fuel_Price

- average fuel price around 45 regions is 3.36 dollars
- minimum fuel price for some region falls down to 2.47 dollars
- maximum fuel price for some region reaches upto 4.47 dollars
- for half of the regions i.e. 50% fuel price remains between 2.9 - 3.7 dollars

MarkDown 1

- average value for Mark Down 1 is 7246
- minimum value for Markdown1 is 0.27
- maximum value for MarkDown1 is 88646
- 50% of the MarkDown value lies between 2240-9210

MarkDown 2

- average value for Mark Down 1 is 3334
- minimum value for Markdown1 is -265
- maximum value for MarkDown1 is 104519
- 50% of the MarkDown value lies between 41.6-1926.6

MarkDown 3

- average value for Mark Down 1 is 1439
- minimum value for Markdown1 is -29
- maximum value for MarkDown1 is 141630
- 50% of the MarkDown value lies between 5-103

MarkDown 4

- average value for Mark Down 1 is 3383
- minimum value for Markdown1 is 0.22
- maximum value for MarkDown1 is 67474
- 50% of the MarkDown value lies between 504-3595

MarkDown 5

- average value for Mark Down 1 is 4628
- minimum value for Markdown1 is 135
- maximum value for MarkDown1 is 108519
- 50% of the MarkDown value lies between 1878-5563

CPI :

- the minimum CPI for the given duration is 126.06
- highest CPI for the given duration is 227.23
- the average CPI throughout the duration was 17.20
- There was around 44% increase in Inflation during this period

Unemployment

- minimum unemployement rate for the duration was 3.8
- maximum unemployement rate for the duration was 14.3
- average unemployement rate for the duration was 7.9

Size

- smallest Store had area around 34875 sq feet
- largest Store had area around 219622 sq feet
- Most of the Stores had enough space around 136727.9 sq feet

- Now, describing the categorical variable present in our dataframe, there is only but which is in object data type but in further steps, we'll be converting the data type of Store and Dept accordingly

```python
df.describe(include='object')
```

	Type
count	421570
unique	3
top	A
freq	215478

Categorical Variables:

- Store : There are total 45 Stores in the Data
- Dept : The data consist of unique 81 deparments withing different stores
- Type : The Data consist of three types of Stores A,B,C

- Looking into the unique variables with respect to all the columns

```python
# Looking into the unique variables with respect to all the columns
for i in df.columns:
    print(i)
    print(df[i].unique())
    print()
```

```
Store
[ 1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45]

Dept
[ 1  2  3  4  5  6  7  8  9 10 11 12 13 14 16 17 18 19 20 21 22 23 24 25
 26 27 28 29 30 31 32 33 34 35 36 37 38 40 41 42 44 45 46 47 48 49 51 52
 54 55 56 58 59 60 67 71 72 74 77 78 79 80 81 82 83 85 87 90 91 92 93 94
 95 96 97 98 99 39 50 43 65]

Date
['2010-05-02T00:00:00.000000000' '2010-12-02T00:00:00.000000000'
 '2010-02-19T00:00:00.000000000' '2010-02-26T00:00:00.000000000'
 '2010-05-03T00:00:00.000000000' '2010-12-03T00:00:00.000000000'
 '2010-03-19T00:00:00.000000000' '2010-03-26T00:00:00.000000000'
 '2010-02-04T00:00:00.000000000' '2010-09-04T00:00:00.000000000'
 '2010-04-16T00:00:00.000000000' '2010-04-23T00:00:00.000000000'
 '2010-04-30T00:00:00.000000000' '2010-07-05T00:00:00.000000000'
 '2010-05-14T00:00:00.000000000' '2010-05-21T00:00:00.000000000'
```

- Looking into number of unique variables of all columns in the data

```
# number of unique variables of all columns in the data
for i in df.columns:
    print(i,':',df[i].nunique())
```

```
Store : 45
Dept : 81
Date : 143
Weekly_Sales : 359464
IsHoliday : 2
Temperature : 3528
Fuel_Price : 892
MarkDown1 : 2278
MarkDown2 : 1499
MarkDown3 : 1662
MarkDown4 : 1945
MarkDown5 : 2294
CPI : 2145
Unemployment : 349
Type : 3
Size : 40
```

- Value counts of all variables in the columns

```
# Value counts of all variables in the columns
for i in df.drop('Date',axis=1).columns:
    print(i)
    print(df[i].value_counts())
    print()
```

```
Store
13    10474
10    10315
4     10272
1     10244
2     10238
24    10228
27    10225
34    10224
20    10214
6     10211
32    10202
19    10148
31    10142
28    10113
41    10088
11    10062
23    10050
14    10040
```

- Categorizing the data into numeric and categorical data

```
# Categorizing the data into numeric and categorical
df_numeric = df.select_dtypes(np.number)
df_numeric.columns
```

```
Index(['Store', 'Dept', 'Weekly_Sales', 'Temperature', 'Fuel_Price',
       'MarkDown1', 'MarkDown2', 'MarkDown3', 'MarkDown4', 'MarkDown5', 'CPI',
       'Unemployment', 'Size'],
      dtype='object')
```

```
df_categoric = df.select_dtypes(include='object')
df_categoric.columns
```

```
Index(['Type'], dtype='object')
```

- Distribution of our target variable: **Weekly_Sales**

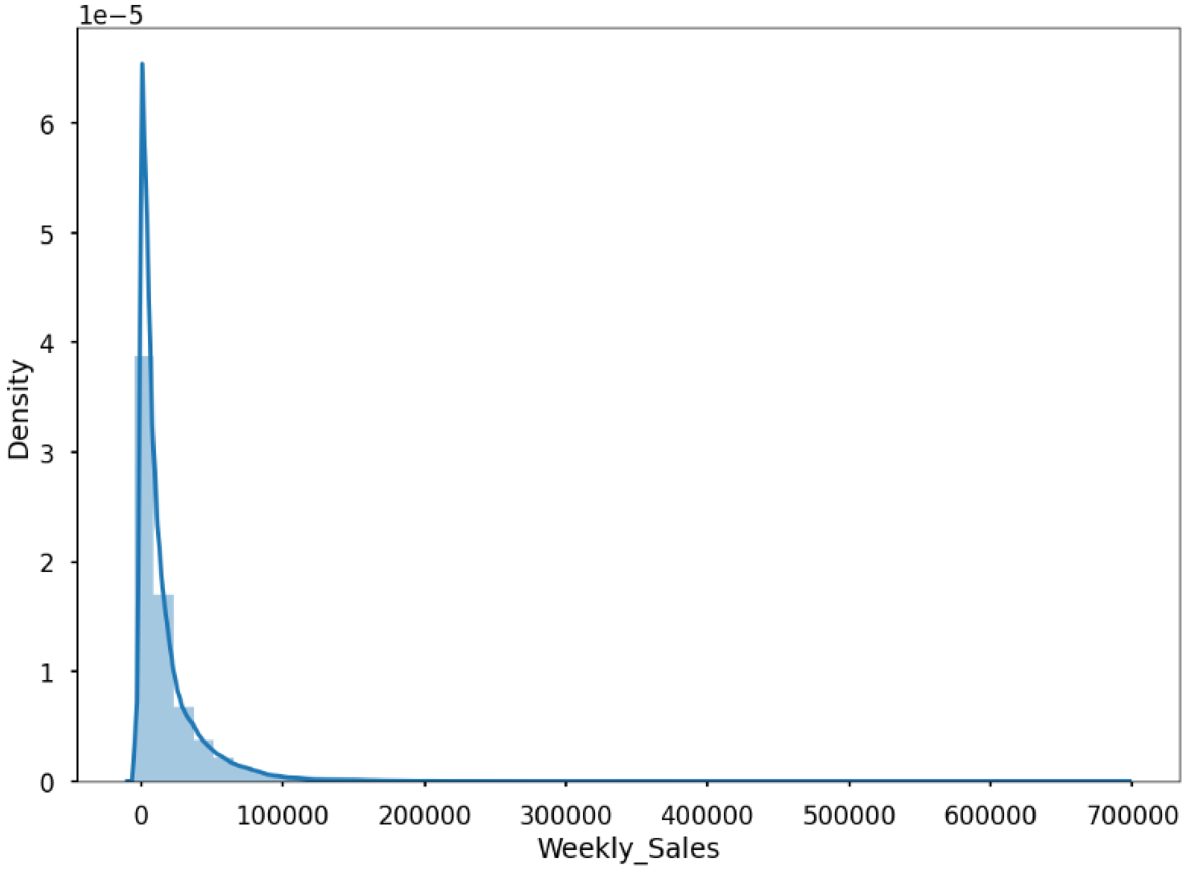
```
df['Weekly_Sales'].describe()
```

```
count    421570.000000
mean      15981.258123
std       22711.183519
min       -4988.940000
25%        2079.650000
50%        7612.030000
75%       20205.852500
max      693099.360000
Name: Weekly_Sales, dtype: float64
```

```
interval = [0.10, 0.20,0.30,0.40,0.50,0.60,0.70,0.80,0.90]
for i in interval:
    print(i*100,'% of weekly sales data lies below',df['Weekly_Sales'].quantile(i))
print('In 100% data  maximum weekly_sales is',df['Weekly_Sales'].max())
```

```
10.0 % of weekly sales data lies below 291.09700000000004
20.0 % of weekly sales data lies below 1340.9800000000002
30.0 % of weekly sales data lies below 2913.381
40.0 % of weekly sales data lies below 4887.96
50.0 % of weekly sales data lies below 7612.03
60.0 % of weekly sales data lies below 11274.632
70.0 % of weekly sales data lies below 16619.324999999997
80.0 % of weekly sales data lies below 25217.612
90.0 % of weekly sales data lies below 42845.673000000046
In 100% data  maximum weekly_sales is 693099.36
```

```
sns.distplot(df['Weekly_Sales'],kde=True)
plt.show()
```



Skewness of the data:

```
print('Skewness of the variable are:')
print(df_numeric.skew())
```

```
Skewness of the variable are:
Store            0.077763
Dept             0.358223
Weekly_Sales     3.262008
Temperature     -0.321404
Fuel_Price      -0.104901
MarkDown1        4.731304
MarkDown2       10.645956
MarkDown3       14.922341
MarkDown4        8.077666
MarkDown5        9.964519
CPI              0.085219
Unemployment     1.183743
Size            -0.325850
dtype: float64
```

INFERENCE

- As we know, if skew values are <0 left skewed; =0 normally distributed/symetric distribution; >0 right skewed
- We can infer that All 5 Markdowns, Weekly_Sales, CPI and Unemployment are right skewed
- Fuel_Price, Size and Temperature are left skewed
- Comparitively CPI is near normal

Kurtosis of the data:

```
print('Kurtosis of the variable are:')
print(df_numeric.kurt())
```

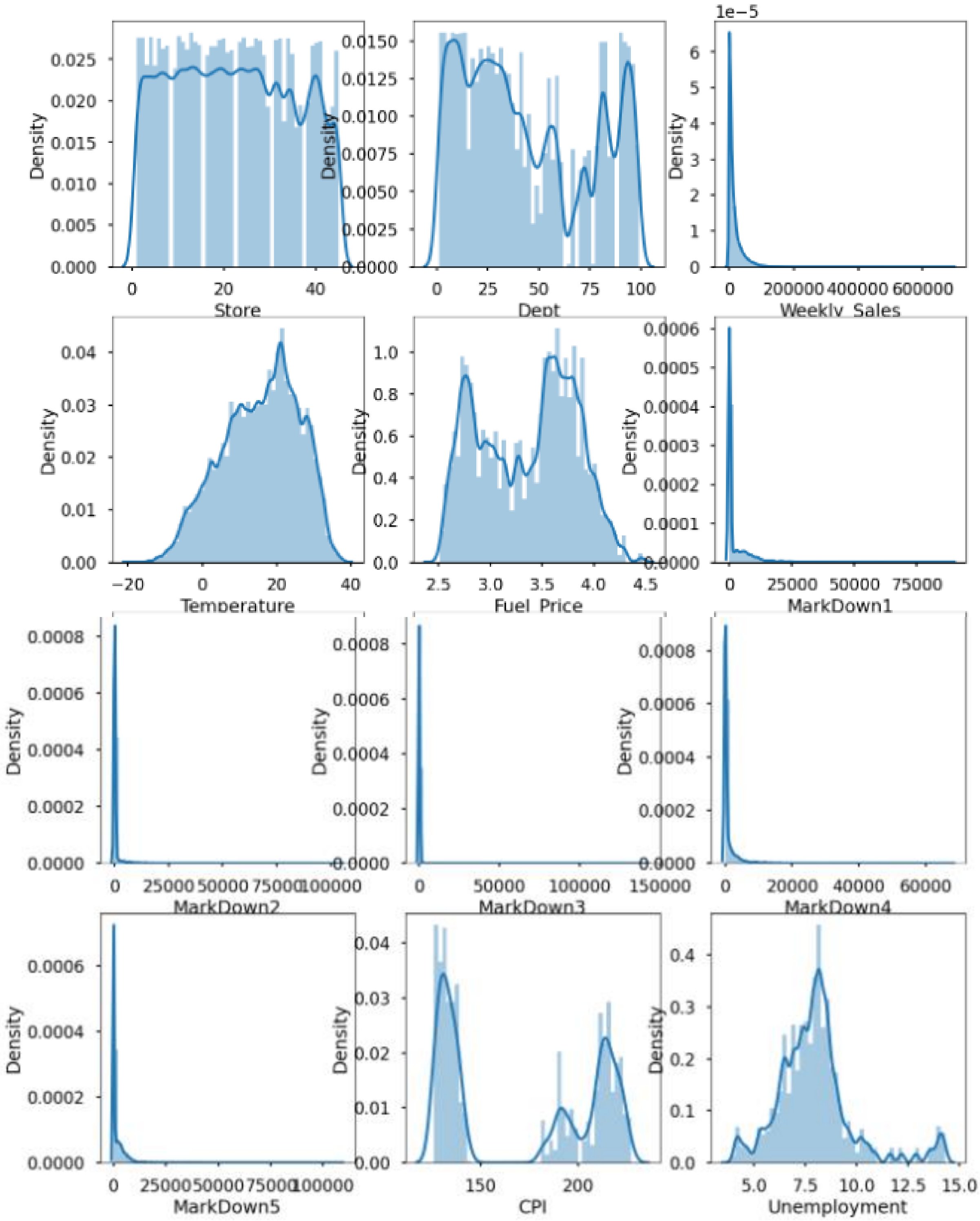
```
Kurtosis of the variable are:
Store            -1.146503
Dept             -1.215571
Weekly_Sales     21.491290
Temperature      -0.635922
Fuel_Price       -1.185405
MarkDown1        34.917236
MarkDown2       145.421293
MarkDown3       248.095371
MarkDown4        86.242339
MarkDown5       183.408065
CPI              -1.829714
Unemployment      2.731217
Size             -1.206346
dtype: float64
```

INFERENCE

- As we know if kurt values are <0 platykurtic; =0 mesokurtic; >0 leptokurtic
- We can infer that All 5 Markdowns, Weekly_Sales and Unemployment are leptokurtic
- Fuel_Price, Size, CPI and Temperature are platykurtic

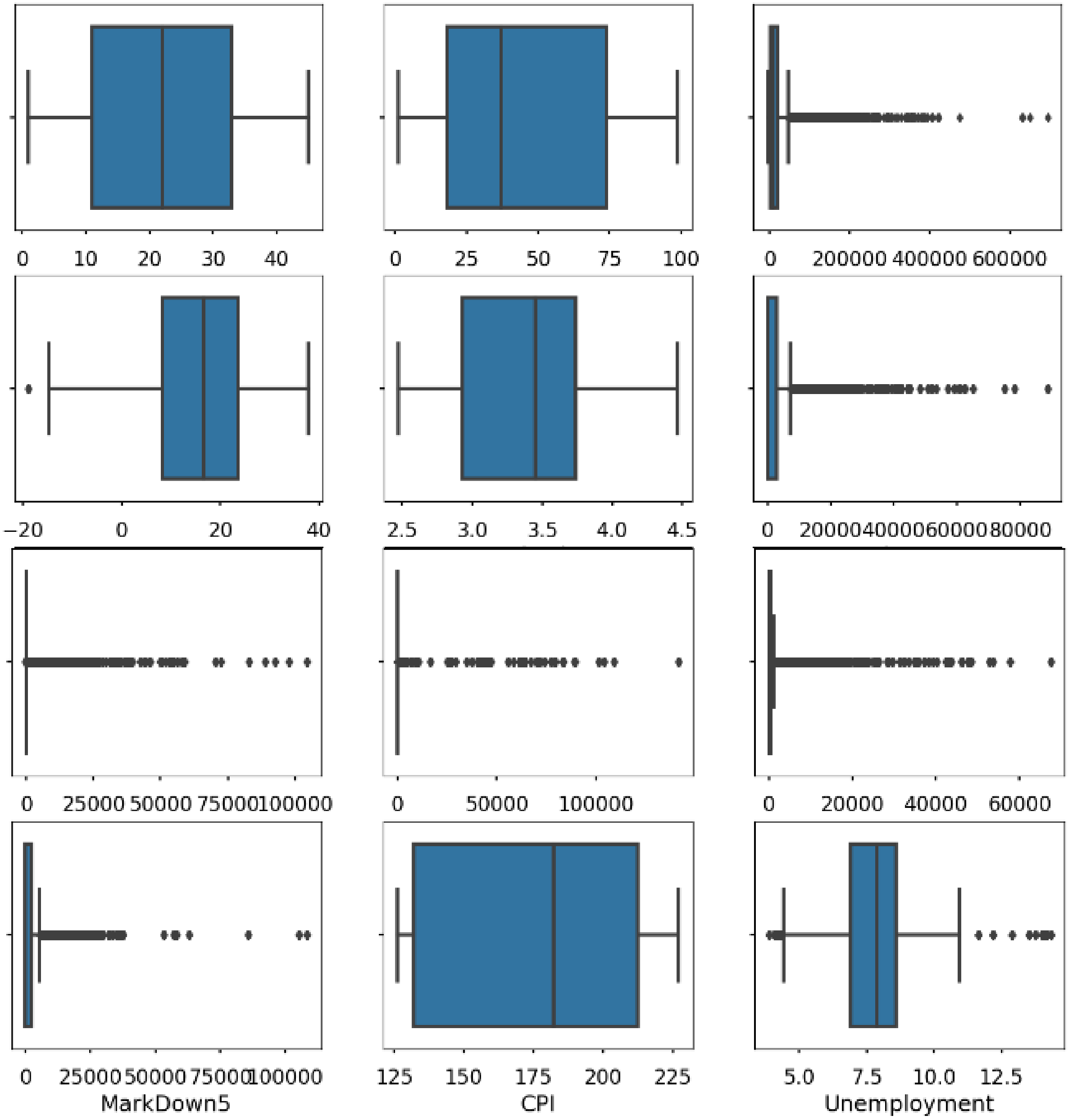
UNIVARIATE ANALYSIS: Starting with the analysis of Numeric variables

```
fig, ax = plt.subplots(nrows=4, ncols =3, figsize=(15,20))
for variable, subplot in zip(df_numeric.columns, ax.flatten()):
    sns.distplot(df[variable], kde=True, ax = subplot)
plt.show()
```



- Plotting boxplot for the numerical features

```python
fig, ax = plt.subplots(nrows=4, ncols =3, figsize=(15,15))
for variable, subplot in zip(df_numeric.columns, ax.flatten()):
    sns.boxplot(df[variable], ax = subplot)
plt.show()
```

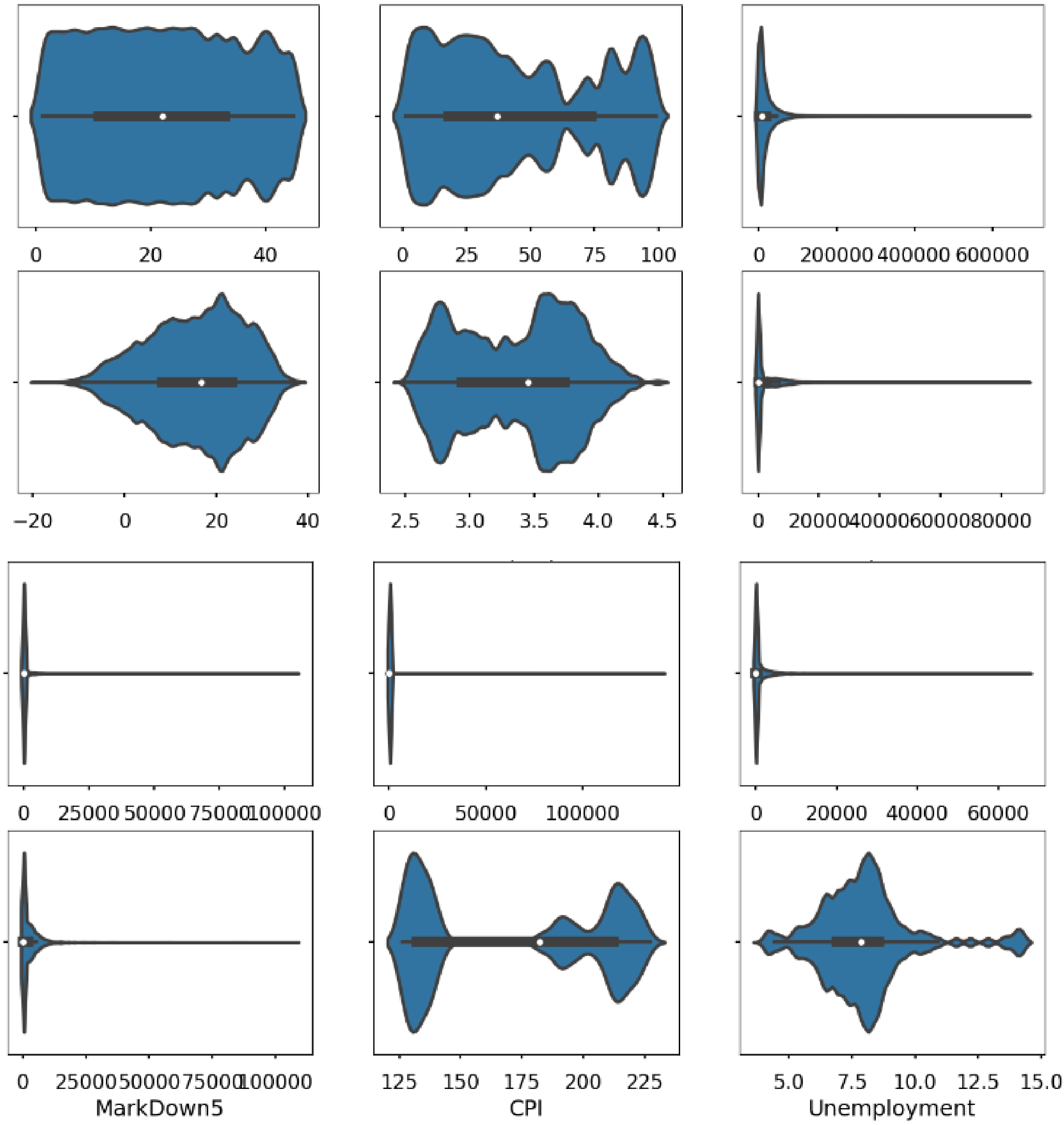


- Converting IsHoliday into object data type:

```python
df['IsHoliday'] = df['IsHoliday'].astype('object')
```

- Now, for the numerical columns left, plotting violin plots using subplots

```
fig, ax = plt.subplots(nrows=4, ncols =3, figsize=(15,15))
for variable, subplot in zip(df_num.columns, ax.flatten()):
    sns.violinplot(df_num[variable], ax = subplot)
plt.show()
```

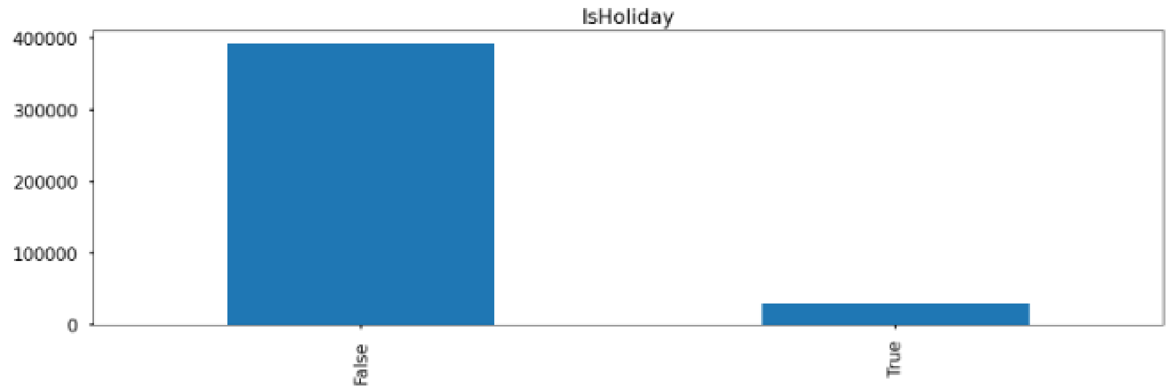


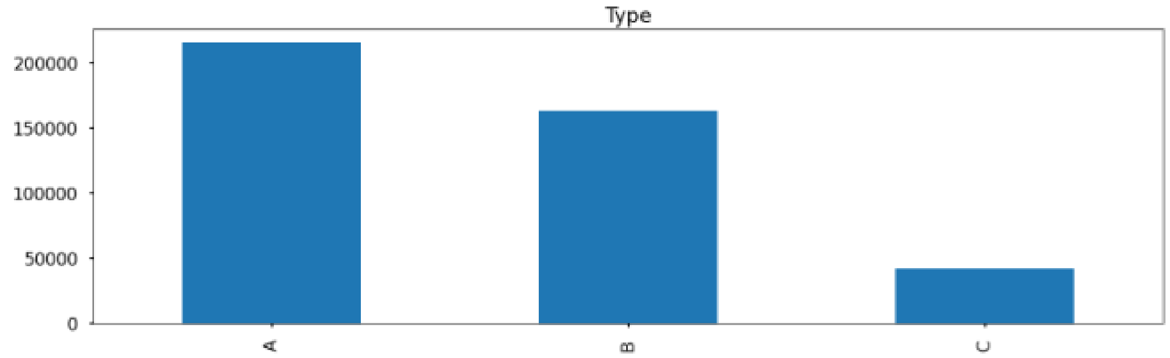
Univariate Analysis for Categorical data:

```
df_cat = df.select_dtypes(include='object')
df_cat.columns
```

```
Index(['IsHoliday', 'Type'], dtype='object')
```

```
for i in df_cat.columns:
    plt.figure(figsize=(18,5))
    df_cat[i].value_counts().plot(kind='bar')
    plt.title('{}'.format(i))
    plt.show()
```



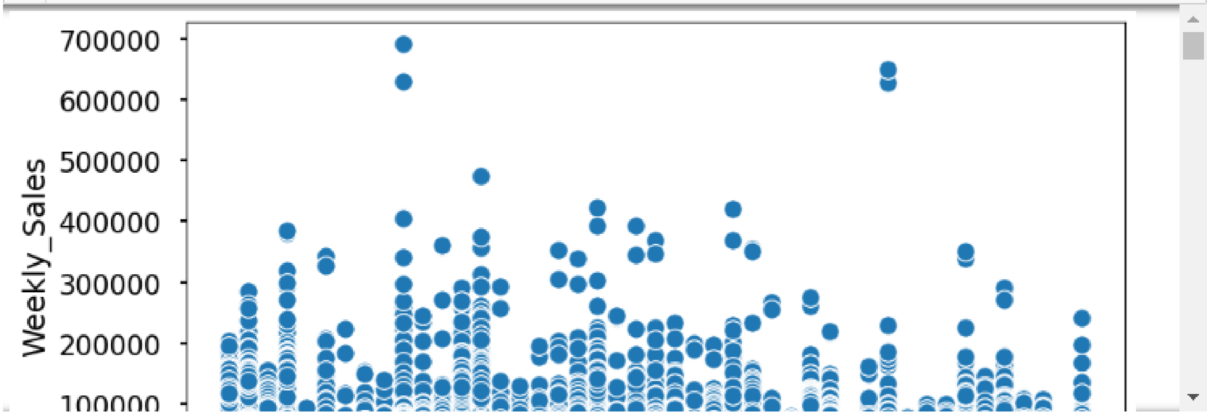


Bivariate Analysis - For Numerical v/s Numerical data:

Bivariate Analysis

```
# Numerical vs Numerical
```

```
num=df_num.drop('Weekly_Sales', axis=1)
for i in num:
    plt.figure(figsize=(10,5))
    sns.scatterplot(x =i, y ='Weekly_Sales', data = df_numeric)
    plt.show()
```



Bivariate Analysis - For Numerical (Weekly_Sales) v/s Categorical data

```
# Numerical vs Catogorical :
```

```
df.columns
```

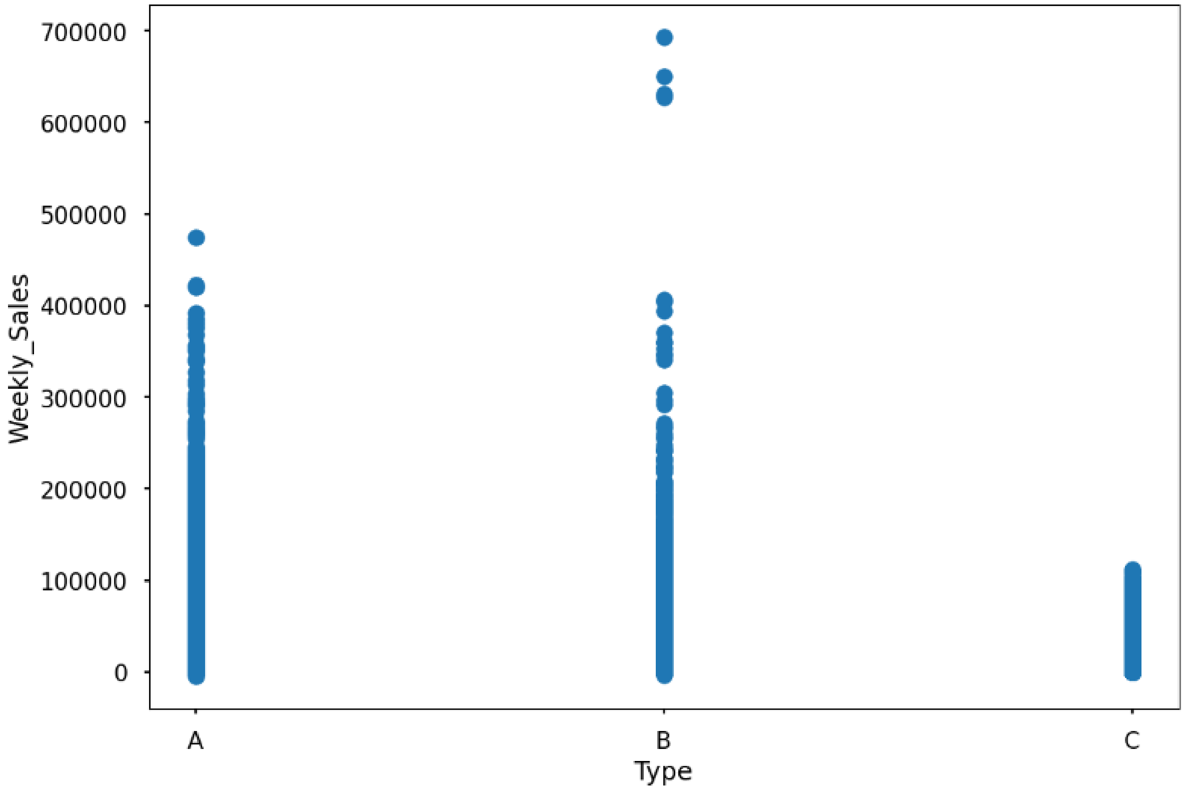
```
Index(['Store', 'Dept', 'Date', 'Weekly_Sales', 'IsHoliday', 'Temperature',
       'Fuel_Price', 'MarkDown1', 'MarkDown2', 'MarkDown3', 'MarkDown4',
       'MarkDown5', 'CPI', 'Unemployment', 'Type', 'Size'],
      dtype='object')
```

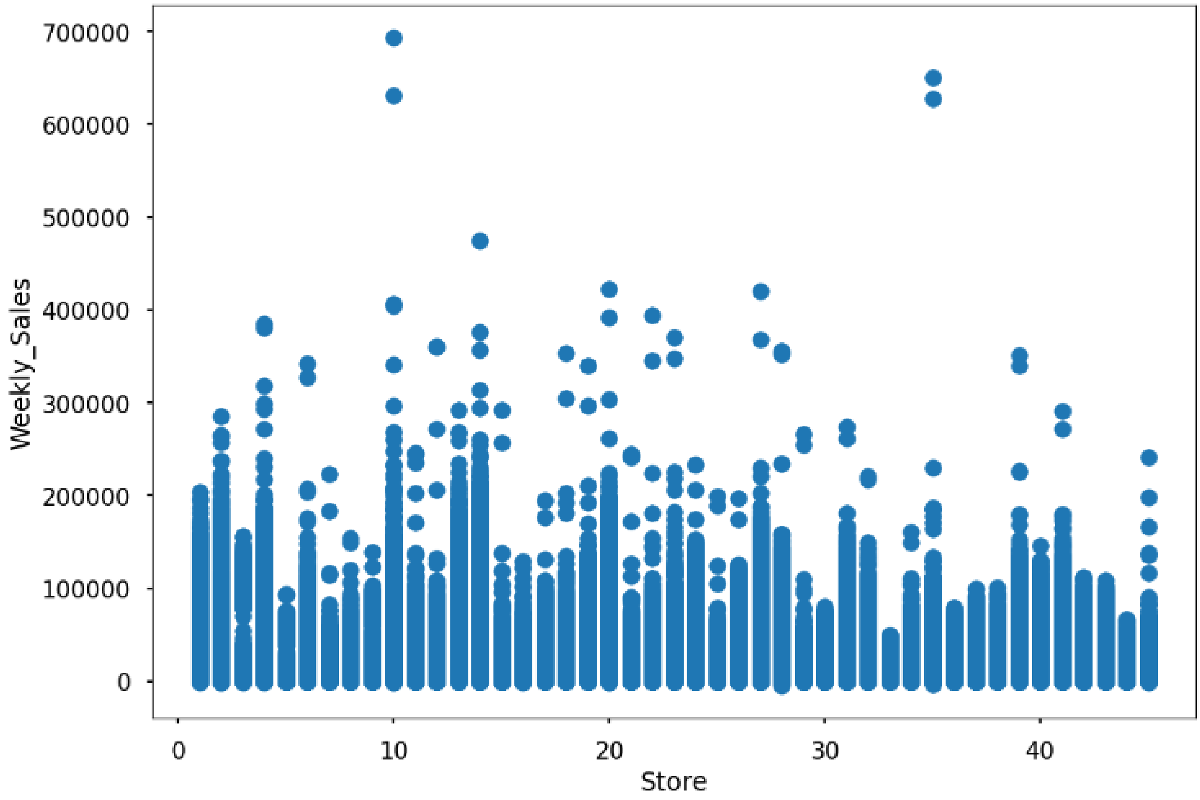
```
def scatter(dataset, column):
    plt.figure()
    plt.scatter(dataset[column] , dataset['Weekly_Sales'])
    plt.ylabel('Weekly_Sales')
    plt.xlabel(column)
```

```
df_cat.columns
```

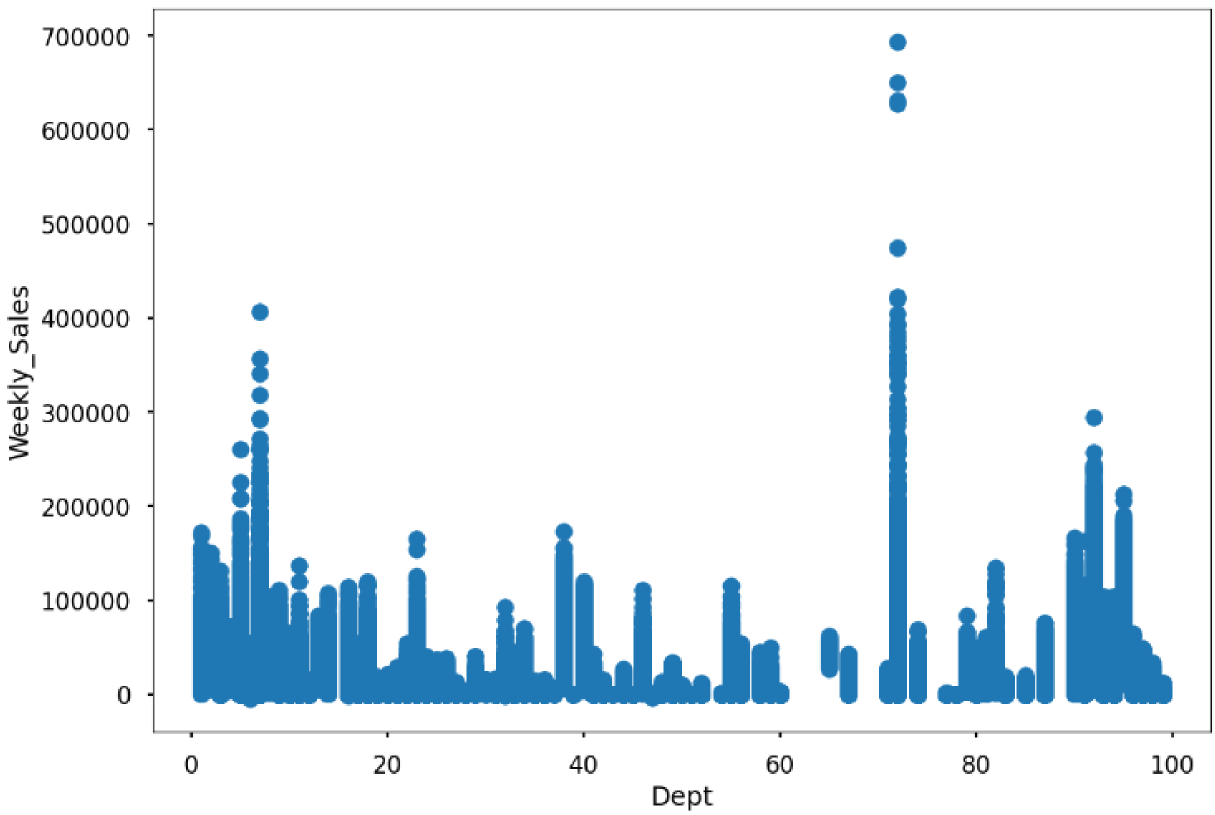
```
Index(['IsHoliday', 'Type'], dtype='object')
```

```
scatter(df, 'Type')
scatter(df, 'Store')
scatter(df, 'Dept')
scatter(df, 'IsHoliday')
```

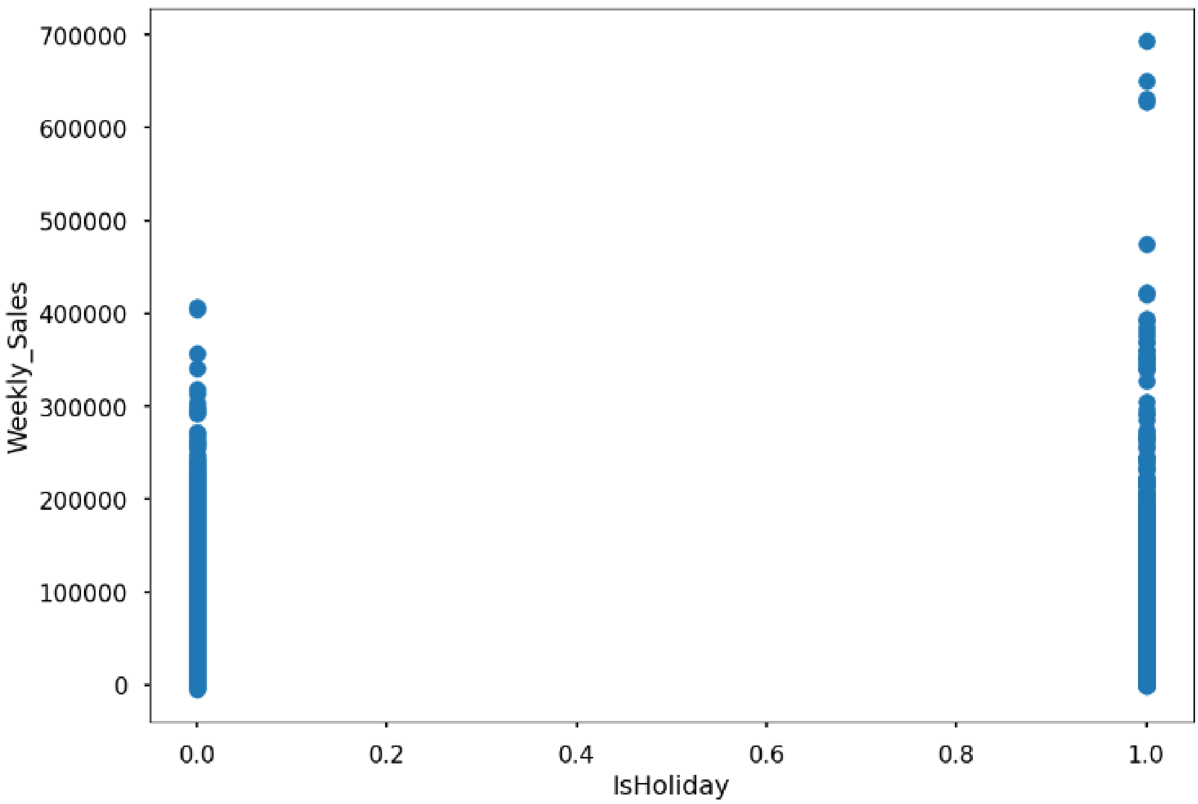




700000
600000
500000
400000
300000
200000
100000
0
Weekly_Sales
0
10
20
30
40
Store



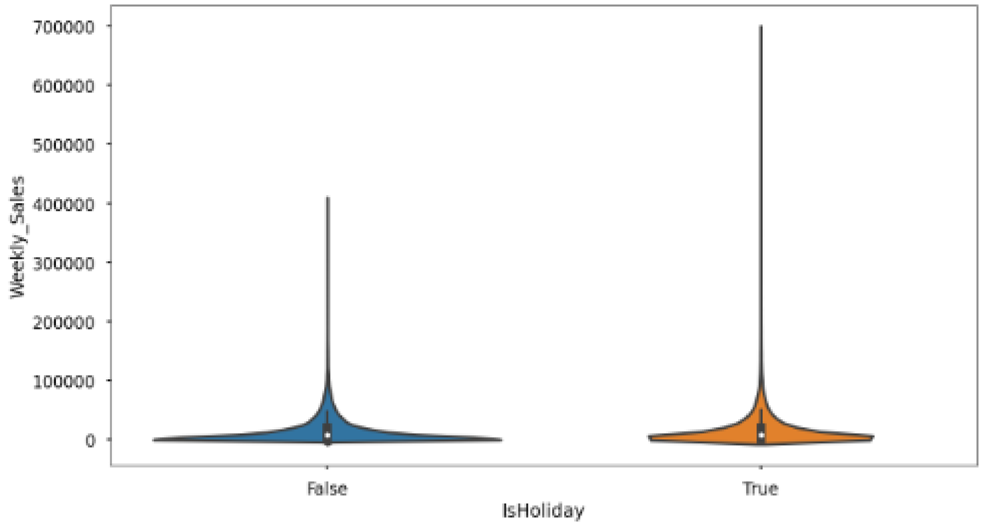
700000
600000
500000
400000
300000
200000
100000
0
Weekly_Sales
0
20
40
60
80
100
Dept

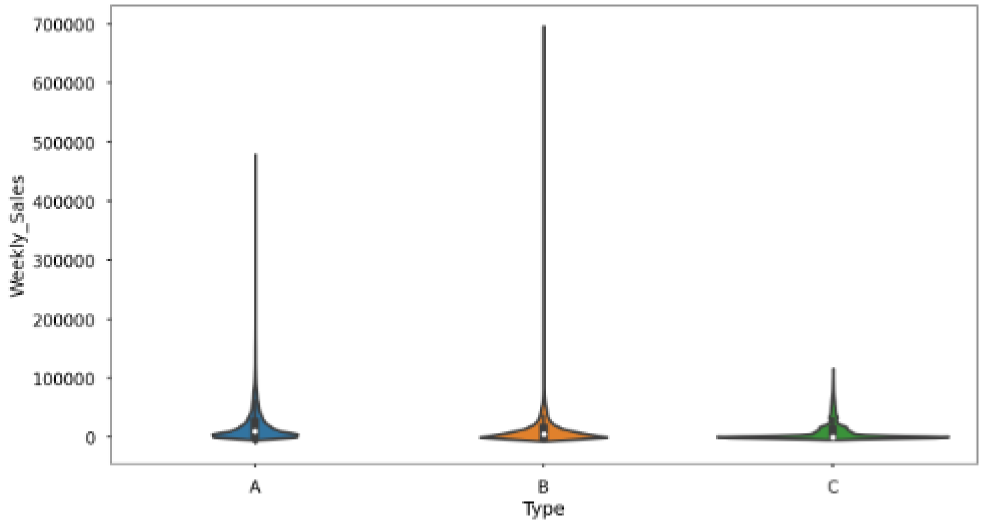


700000
600000
500000
400000
300000
200000
100000
0
Weekly_Sales
0.0
0.2
0.4
0.6
0.8
1.0
IsHoliday

- Plotting violin plots for Type of stores and IsHoliday with Weekly_Sales on the y-axis

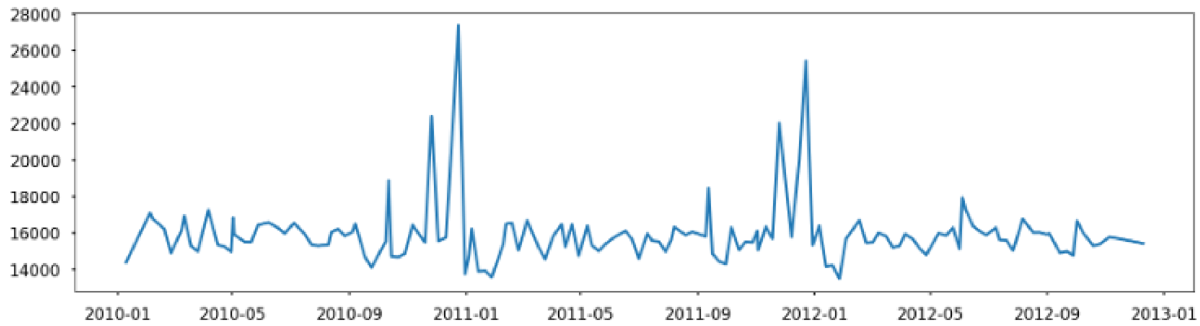
```
for i in df_cat.columns:
    plt.figure(figsize=(15,8))
    sns.violinplot(x =i, y ='Weekly_Sales', data = df)
    plt.show()
```





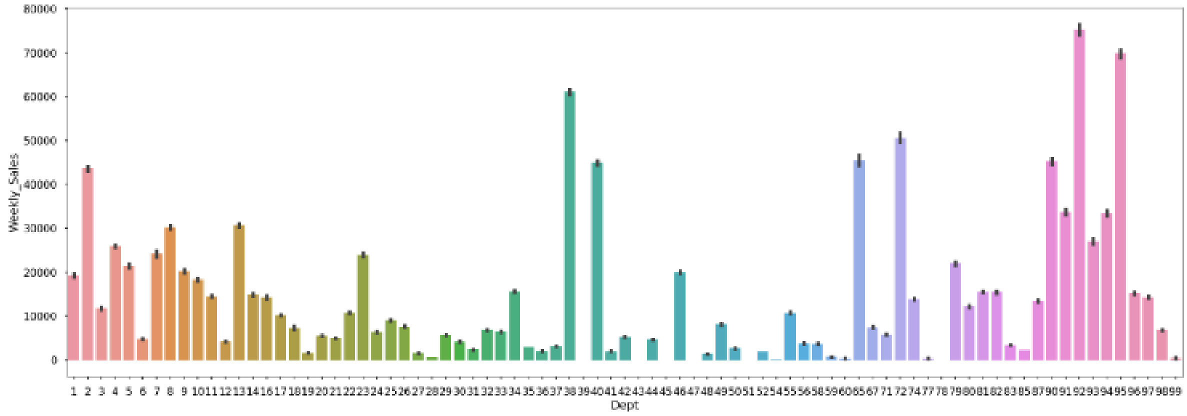
- Plotting Date grouping with weekly_sales with Weekly_Sales

```
df_average_sales_week = df.groupby(by=['Date'], as_index=False)['Weekly_Sales'].mean()
df_average_sales = df_average_sales_week.sort_values('Weekly_Sales', ascending=False)

plt.figure(figsize=(20,5))
plt.plot(df_average_sales_week.Date, df_average_sales_week.Weekly_Sales)
plt.show()
```

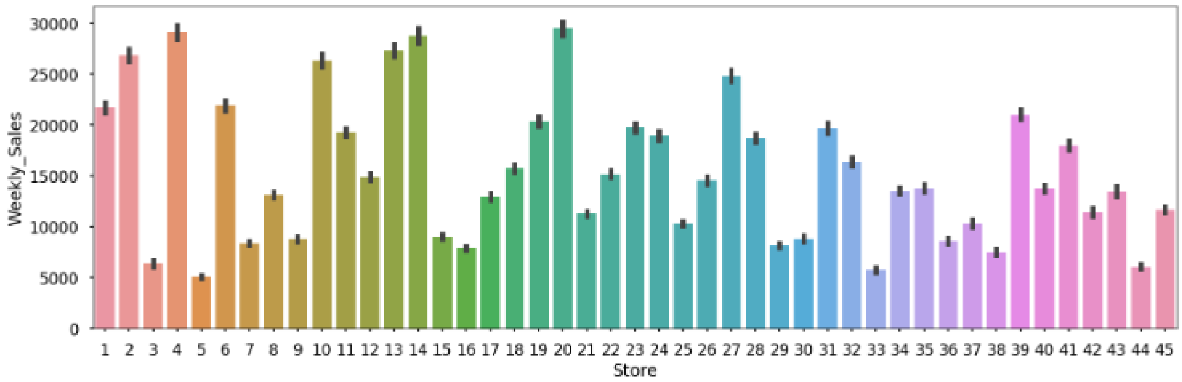


- Plotting barplots for Dept and Store with Weekly Sales for better understanding comparatively to the scatterplots

```python
plt.figure(figsize=(30,10))
fig = sns.barplot(x='Dept', y='Weekly_Sales', data=df)
```




```python
plt.figure(figsize=(20,6))
fig = sns.barplot(x='Store', y='Weekly_Sales', data=df)
```



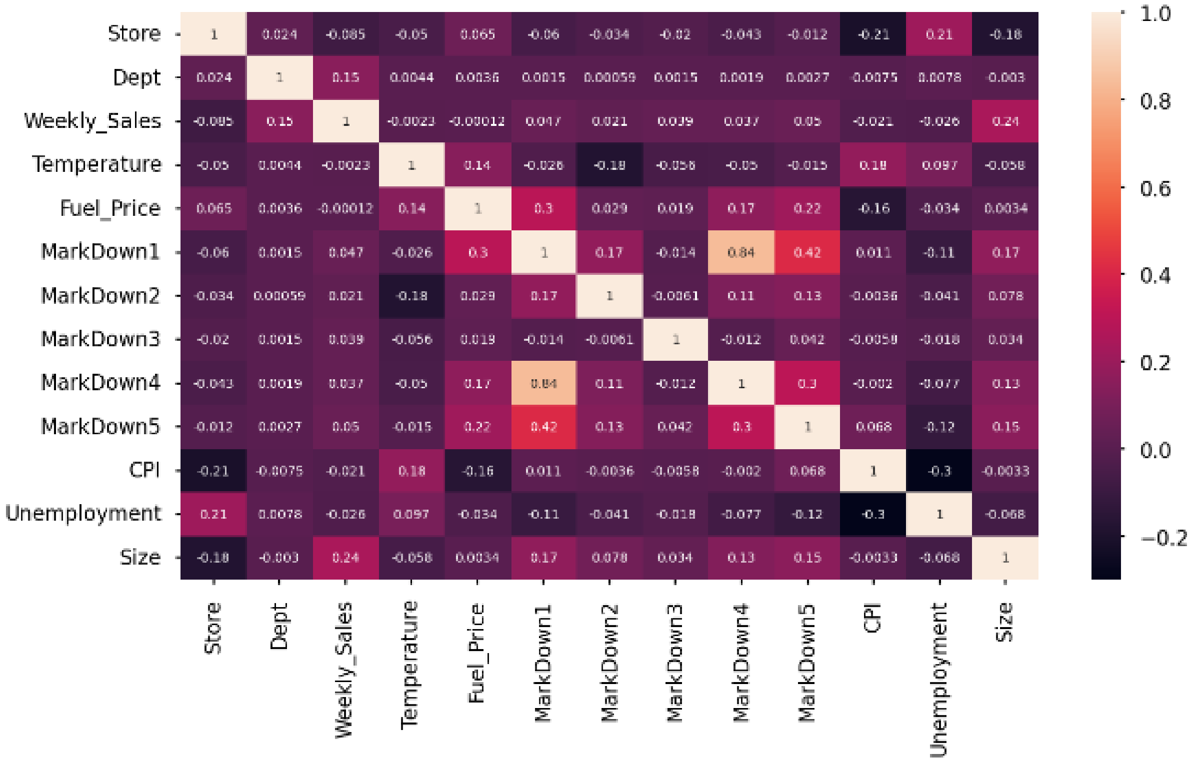
MULTIVARIATE ANALYSIS:

Plotting heatmap to view the correlation between the features and target variable

MULTIVARIATE ANALYSIS

```
plt.figure(figsize=(15,8))
sns.heatmap(df_num.corr(),annot=True)
```

<AxesSubplot:>



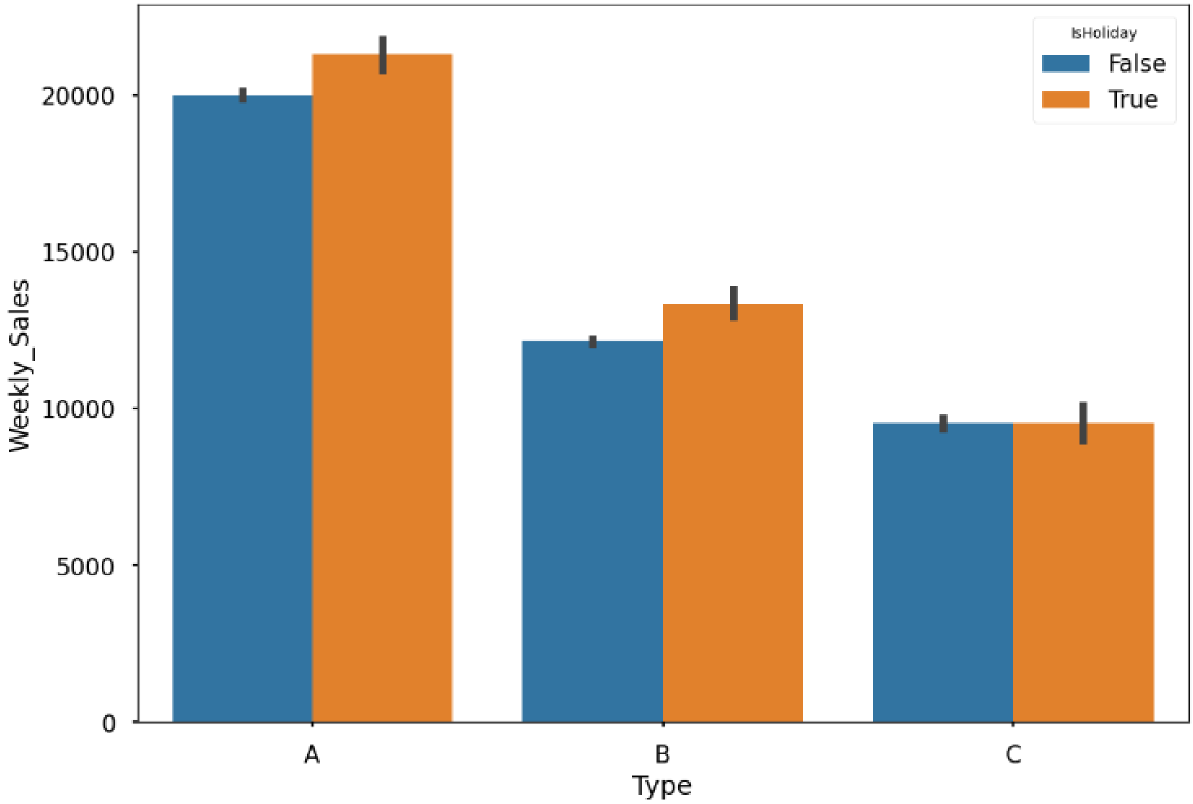
INFERENCE

- This shows that there is high correlation between the Markdowns columns
- There is no significant relationship of any columns except size with our target variable viz., Weekly_Sales which implies there is high multicollinearity, autocorrelation; So, we are proceeding with OLS model to check the multicollinearity with Condition Number and look for a more solid inference

Multivariate Analysis:

- Barplot between 2 categorical (Type & Store) and 1 numerical (Weekly_Sales) variable

```
# plot between 2 categorical (IsHoliday & Type) and one numerical column(Weekly_Sales)
sns.barplot(x='Type', y='Weekly_Sales', hue='IsHoliday', data=df)
plt.show()
```

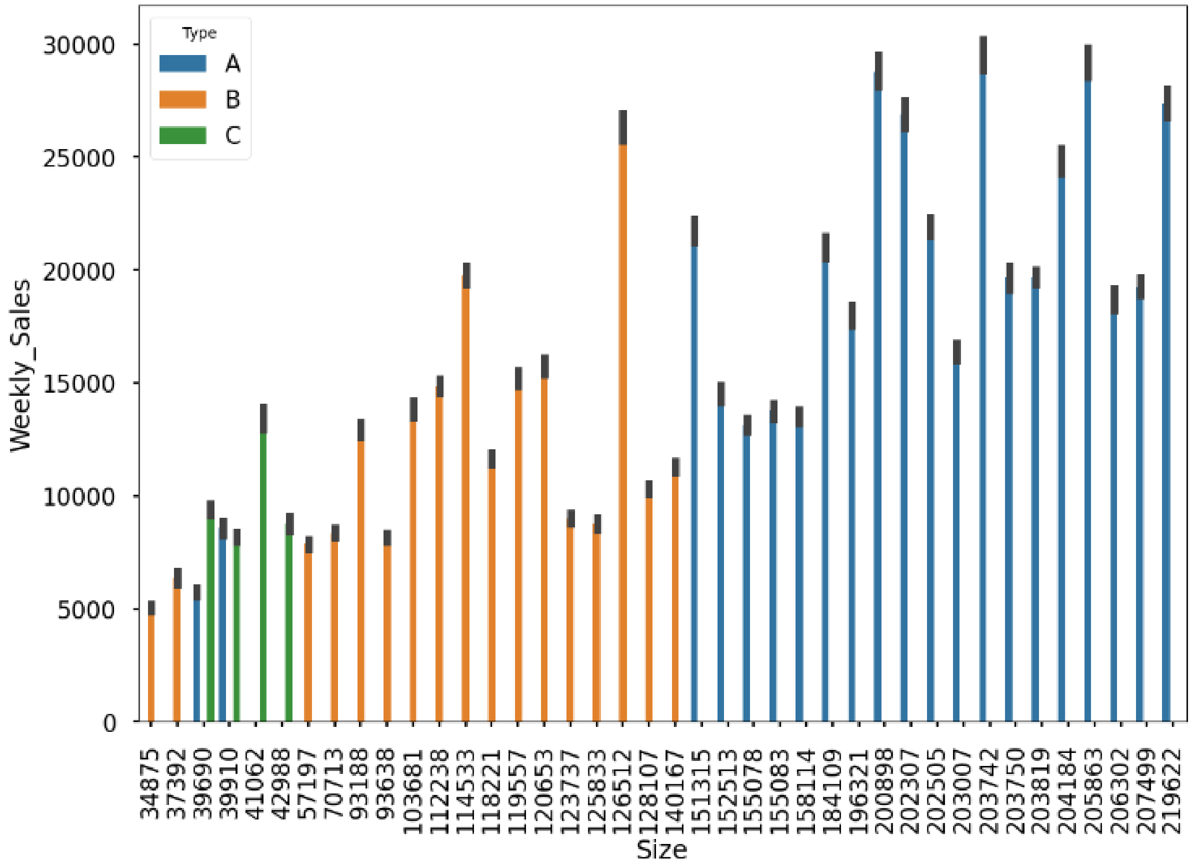


- There very Less Increase in Weekly Sales with the occurance of Holdiday in the week.
- This pattern can be observed among all three types of Stores.

Multivariate Analysis:

- Barplot between 2 categorical (Size & Type) and 1 numerical (Weekly_Sales) variable

```
sns.barplot(x=df['Size'].sort_values(), y='Weekly_Sales', hue='Type', data=df)
plt.xticks(rotation=90)
plt.show()
```



Feature Engineering:

```
df_holiday = df.loc[df['IsHoliday']==True]
df_holiday['Date'].unique()
```

```
array(['2010-12-02T00:00:00.000000000', '2010-10-09T00:00:00.000000000',
       '2010-11-26T00:00:00.000000000', '2010-12-31T00:00:00.000000000',
       '2011-11-02T00:00:00.000000000', '2011-09-09T00:00:00.000000000',
       '2011-11-25T00:00:00.000000000', '2011-12-30T00:00:00.000000000',
       '2012-10-02T00:00:00.000000000', '2012-07-09T00:00:00.000000000'],
      dtype='datetime64[ns]')
```

```
df_not_holiday = df.loc[df['IsHoliday']==False]
df_not_holiday['Date'].nunique()
```

```
133
```

All holidays are not in the data. There are 4 holiday values such as;

Super Bowl: 12-Feb-10, 11-Feb-11, 10-Feb-12, 8-Feb-13

Labor Day: 10-Sep-10, 9-Sep-11, 7-Sep-12, 6-Sep-13

Thanksgiving: 26-Nov-10, 25-Nov-11, 23-Nov-12, 29-Nov-13

Christmas: 31-Dec-10, 30-Dec-11, 28-Dec-12, 27-Dec-13

After the 07-Sep-2012 holidays are in test set for prediction. When we look at the data, average weekly sales for holidays are significantly higher than not-holiday days. In train data, there are 133 weeks for non-holiday and 10 weeks for holiday.

We want to see differences between holiday types. So, I create new columns for 4 types of holidays and fill them with boolean values. If date belongs to this type of holiday it is True, if not False.

```
# Super bowl dates in data set
df.loc[(df['Date'] == '2010-02-12')|(df['Date'] == '2011-02-11')|(df['Date'] == '2012-02-10')|(df['Date'] == '2013-02-08'),'
df.loc[(df['Date'] != '2010-02-12')&(df['Date'] != '2011-02-11')&(df['Date'] != '2012-02-10')&(df['Date'] != '2013-02-08'),'
```

```
n data set
== '2010-09-10')|(df['Date'] == '2011-09-09')|(df['Date'] == '2012-09-07')|(df['Date'] == '2013-09-06'),'Labor_Day'] = True
!= '2010-09-10')&(df['Date'] != '2011-09-09')&(df['Date'] != '2012-09-07')&(df['Date'] != '2013-09-06'),'Labor_Day'] = False
```

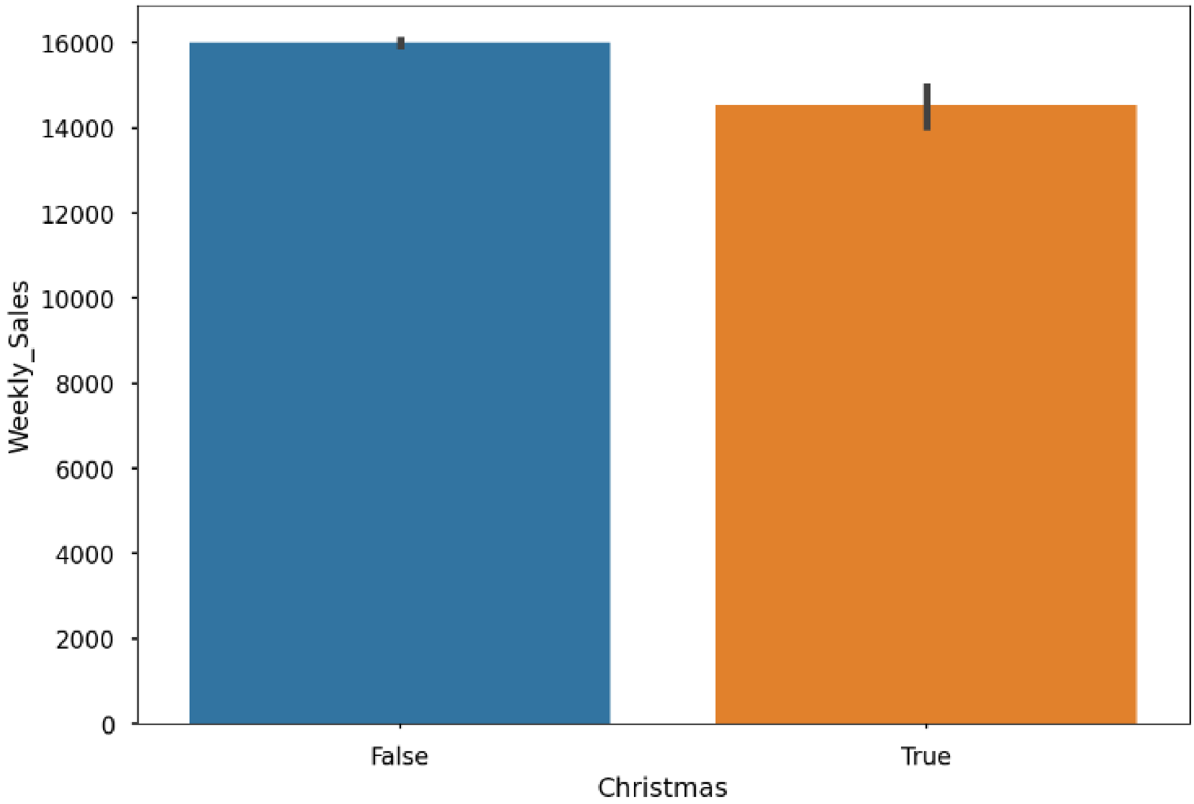
```
n data set
'2010-11-26')|(df['Date'] == '2011-11-25')|(df['Date'] == '2012-11-23')|(df['Date'] == '2013-11-29'),'Thanksgiving'] = True
'2010-11-26')&(df['Date'] != '2011-11-25')&(df['Date'] != '2012-11-23')&(df['Date'] != '2013-11-29'),'Thanksgiving'] = False
```

```
 data set
== '2010-12-31')|(df['Date'] == '2011-12-30')|(df['Date'] == '2012-12-28')|(df['Date'] == '2013-12-27'),'Christmas'] = True
!= '2010-12-31')&(df['Date'] != '2011-12-30')&(df['Date'] != '2012-12-28')&(df['Date'] != '2013-12-27'),'Christmas'] = False
```

- Now plotting barplots to see the difference between True and False (referring Holiday and No-Holiday respectively) with respect to all 4 holidays

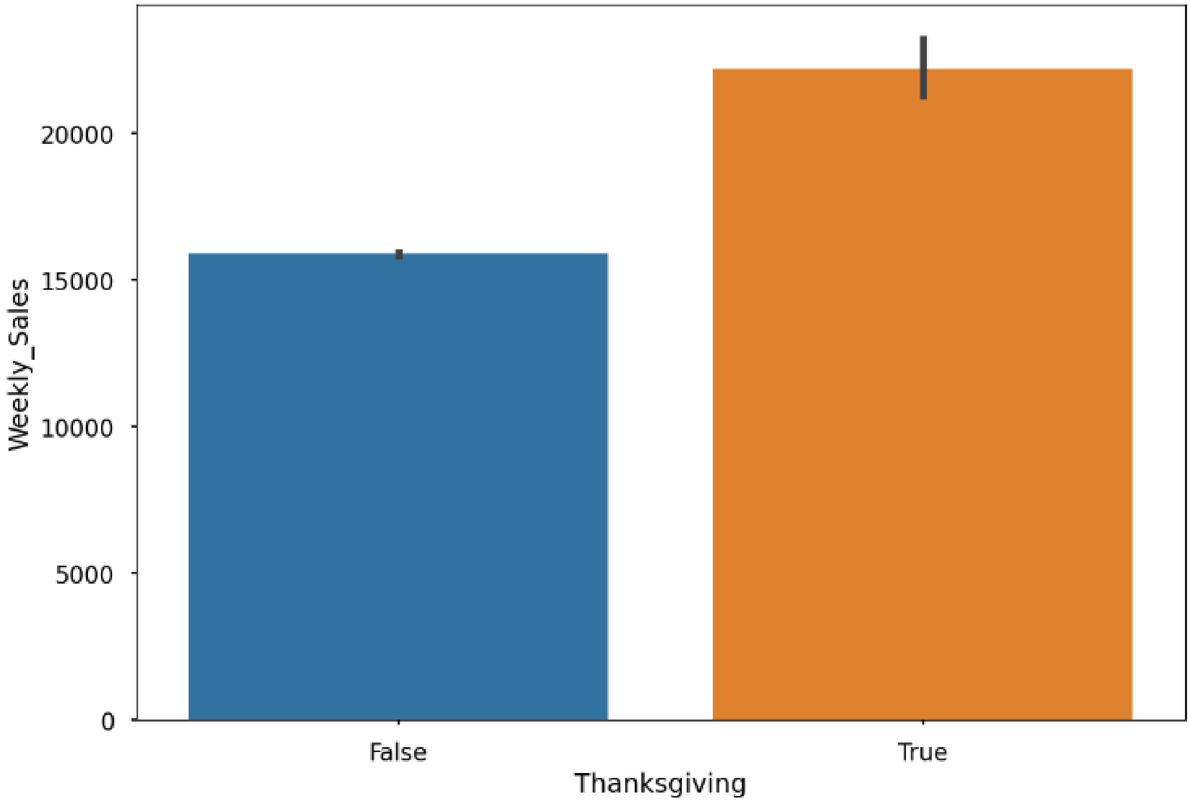
```
sns.barplot(x='Christmas', y='Weekly_Sales', data=df) # Christmas holiday vs not-Christmas
```

```
<AxesSubplot:xlabel='Christmas', ylabel='Weekly_Sales'>
```



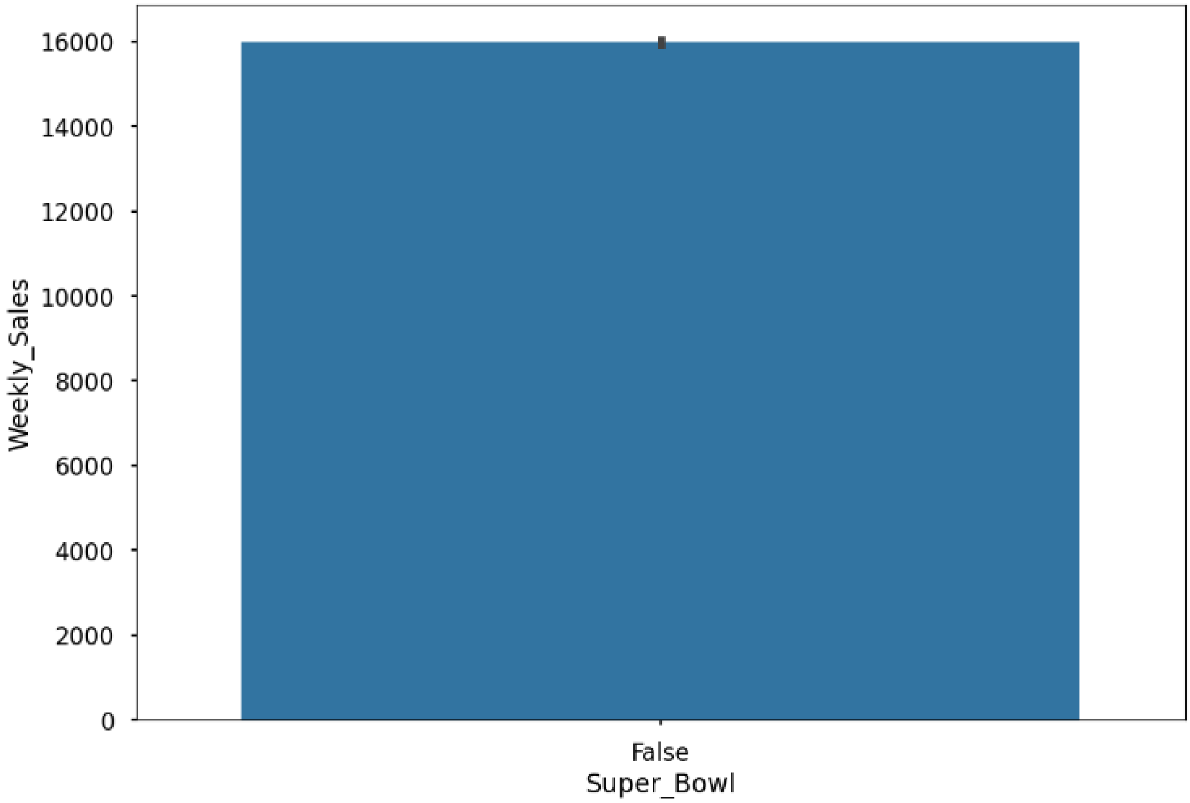
```
sns.barplot(x='Thanksgiving', y='Weekly_Sales', data=df) # Thanksgiving holiday vs not-thanksgiving
```

<AxesSubplot:xlabel='Thanksgiving', ylabel='Weekly_Sales'>



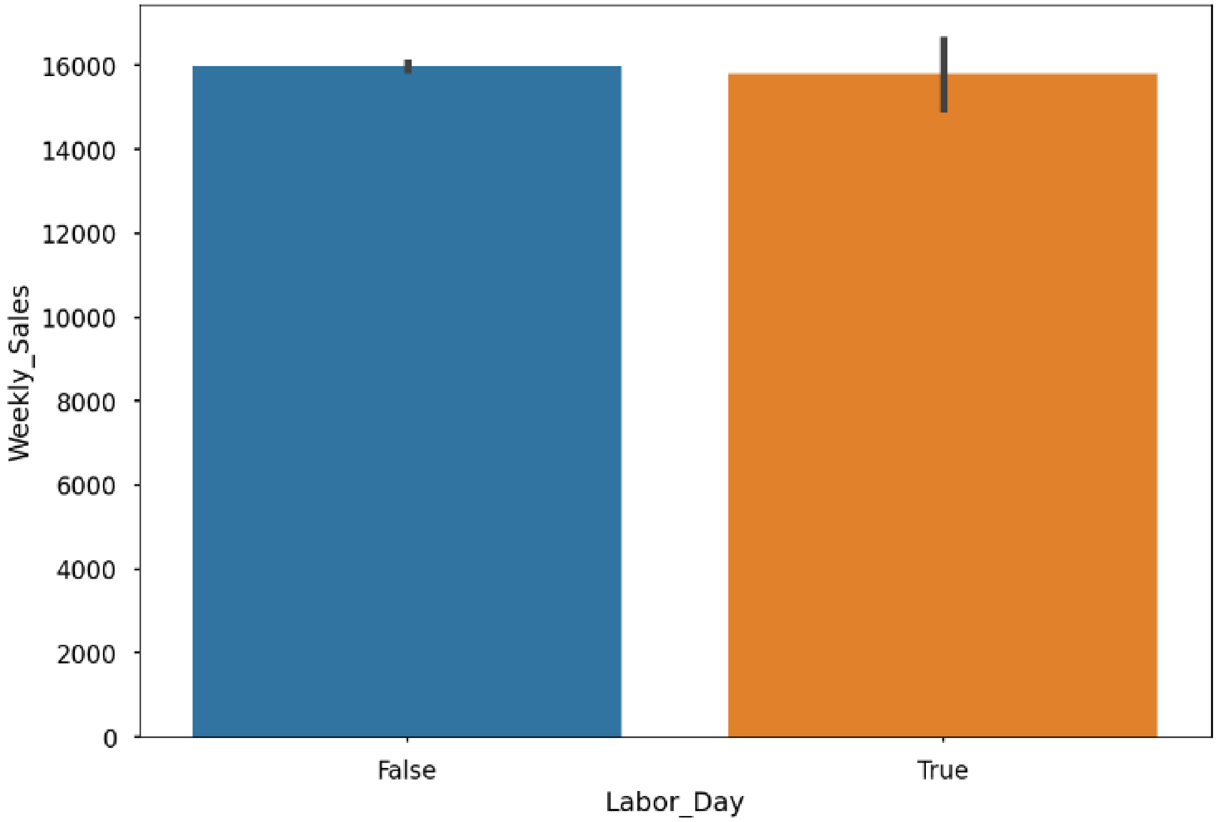

```
sns.barplot(x='Super_Bowl', y='Weekly_Sales', data=df) # Super bowl holiday vs not-super bowl
```

<AxesSubplot:xlabel='Super_Bowl', ylabel='Weekly_Sales'>



```
1 sns.barplot(x='Labor_Day', y='Weekly_Sales', data=df) # Labor day holiday vs not-labor day
```

<AxesSubplot:xlabel='Labor_Day', ylabel='Weekly_Sales'>



It is shown that for the graphs, Labor Day and Christmas do not increase weekly average sales. There is positive effect on sales in Super bowl, but the highest difference is in the Thanksgiving. I think, people generally prefer to buy Christmas gifts 1-2 weeks before Christmas, so it does not change sales in the Christmas week. And, there is Black Friday sales in the Thanksgiving week.

Effects of Type on Holidays:

```
df.groupby(['Christmas','Type'])['Weekly_Sales'].mean()  # Avg weekly sales for types on Christmas
```

```
Christmas  Type
False      A       20126.297990
           B       12249.152357
           C        9541.691864
True       A       18231.031306
           B       11394.051524
           C        7963.228980
Name: Weekly_Sales, dtype: float64
```

```
df.groupby(['Labor_Day','Type'])['Weekly_Sales'].mean()  # Avg weekly sales for types on Labor Day
```

```
Labor_Day  Type
False      A       20101.134269
           B       12238.798217
           C        9519.284506
True       A       19879.540598
           B       11991.583442
           C        9554.978581
Name: Weekly_Sales, dtype: float64
```

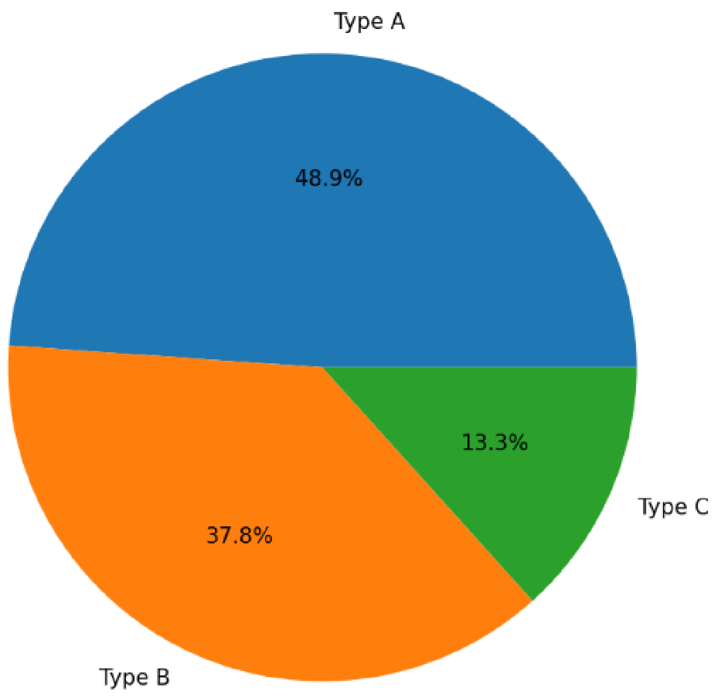
```
df.groupby(['Thanksgiving','Type'])['Weekly_Sales'].mean()  # Avg weekly sales for types on Thanksgiving
```

```
Thanksgiving  Type
False         A       19995.309014
              B       12144.563438
              C        9517.272388
True          A       27370.728296
              B       18661.296519
              C        9679.900152
Name: Weekly_Sales, dtype: float64
```

```
df.groupby(['Super_Bowl','Type'])['Weekly_Sales'].mean()  # Avg weekly sales for types on Super Bowl
```

```
Super_Bowl  Type
False       A       20099.568043
            B       12237.075977
            C        9519.532538
Name: Weekly_Sales, dtype: float64
```

```
#percentages of store types.
my_data = [48.88, 37.77 , 13.33 ]  #percentages
my_labels = 'Type A','Type B', 'Type C' # labels
plt.pie(my_data,labels=my_labels,autopct='%1.1f%%', textprops={'fontsize': 15}) #plot pie type and bigger the labels
plt.axis('equal')

plt.show()
```

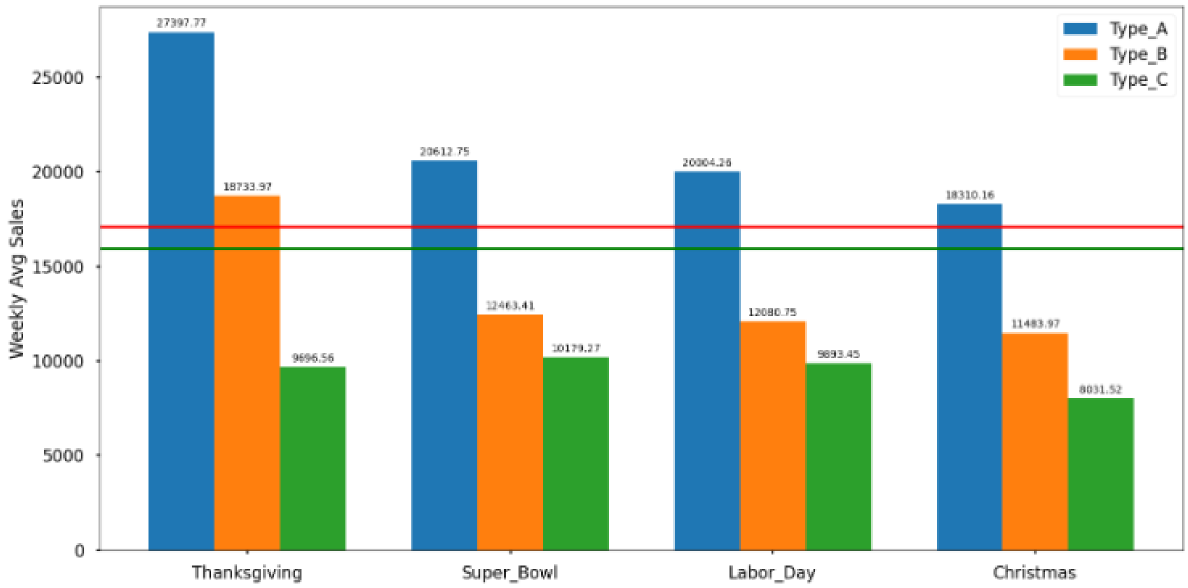


```
df.groupby('IsHoliday')['Weekly_Sales'].mean()
```

```
IsHoliday
False    15901.445069
True     17035.823187
Name: Weekly_Sales, dtype: float64
```

Nearly, half of the stores are belongs to Type A.

```
# Plotting avg weekly sales according to holidays by types
plt.style.use('seaborn-poster')
labels = ['Thanksgiving', 'Super_Bowl', 'Labor_Day', 'Christmas']
A_means = [27397.77, 20612.75, 20004.26, 18310.16]
B_means = [18733.97, 12463.41, 12080.75, 11483.97]
C_means = [9696.56,10179.27,9893.45,8031.52]

x = np.arange(len(labels))  # the label locations
width = 0.25  # the width of the bars

fig, ax = plt.subplots(figsize=(16, 8))
rects1 = ax.bar(x - width, A_means, width, label='Type_A')
rects2 = ax.bar(x , B_means, width, label='Type_B')
rects3 = ax.bar(x + width, C_means, width, label='Type_C')

# Add some text for labels, title and custom x-axis tick labels, etc.
ax.set_ylabel('Weekly Avg Sales')
ax.set_xticks(x)
ax.set_xticklabels(labels)
ax.legend()

def autolabel(rects):
    """Attach a text label above each bar in *rects*, displaying its height."""
    for rect in rects:
        height = rect.get_height()
        ax.annotate('{}'.format(height),
                    xy=(rect.get_x() + rect.get_width() / 2, height),
                    xytext=(0, 3),  # 3 points vertical offset
                    textcoords="offset points",
                    ha='center', va='bottom')

autolabel(rects1)
autolabel(rects2)
autolabel(rects3)
plt.axhline(y=17094.30,color='r') # holidays avg
plt.axhline(y=15952.82,color='green') # not-holiday avg

fig.tight_layout()
plt.show()
```



It is seen from the graph that, highest sale average is in the Thanksgiving week between holidays. And, for all holidays Type A stores has highest sales

```
df.sort_values(by='Weekly_Sales',ascending=False).head(5)
```

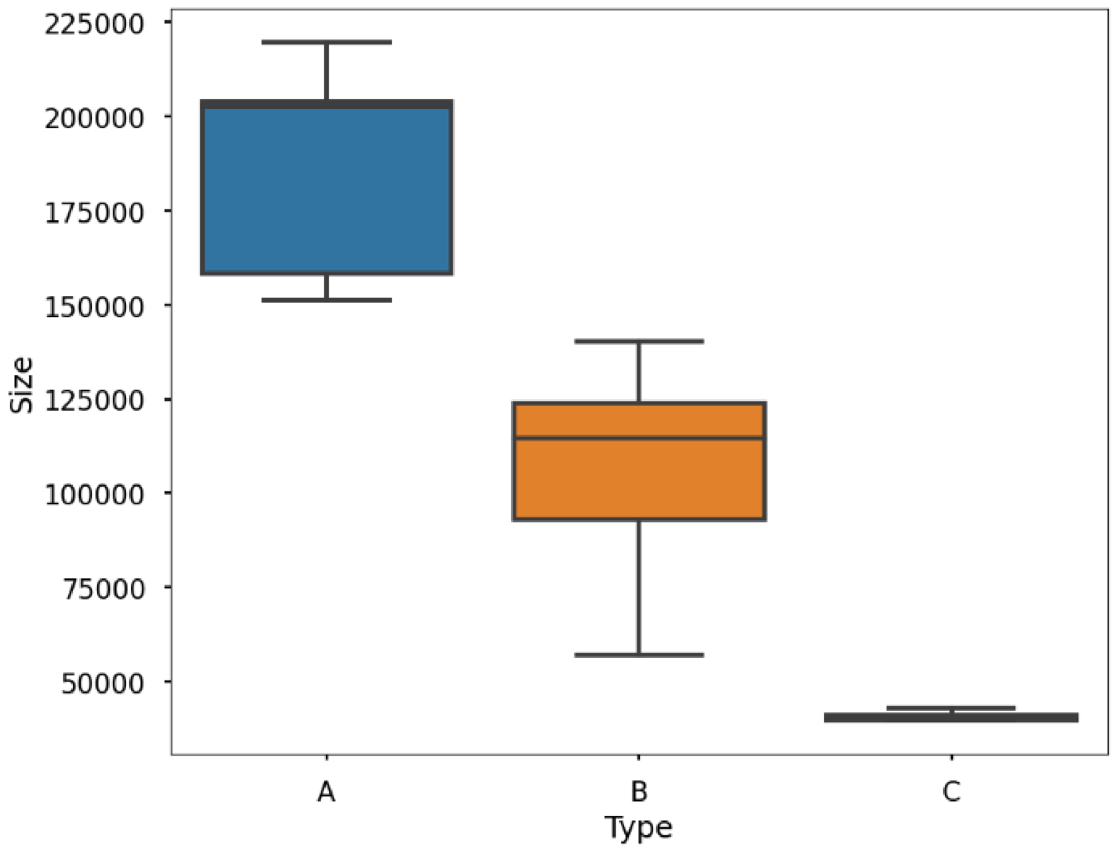
	Store	Dept	Date	Weekly_Sales	IsHoliday	Temperature	Fuel_Price	MarkDown1	MarkDown2	MarkDown3	MarkDown4	MarkDown5	CPI	Une
95373	10	72	2010-11-26	693099.36	True	12.961111	3.162	0.00	0.0	0.00	0.00	0.00	126.669267	
338013	35	72	2011-11-25	649770.18	True	8.822222	3.492	1333.24	0.0	58563.24	20.97	6386.86	140.421786	
95425	10	72	2011-11-25	630999.19	True	15.933333	3.760	174.72	329.0	141630.61	79.00	1009.98	129.836400	
337961	35	72	2010-11-26	627962.93	True	8.150000	3.039	0.00	0.0	0.00	0.00	0.00	136.689571	
135665	14	72	2010-11-26	474330.10	True	7.861111	3.039	0.00	0.0	0.00	0.00	0.00	182.783277	

To See the Size - Type Relation

```
df.groupby('Type').describe()['Size'].round(2) # See the Size-Type relation
```

Type	count	mean	std	min	25%	50%	75%	max
A	215478.0	182231.29	41534.53	39690.0	158114.0	202505.0	203819.0	219622.0
B	163495.0	101818.74	30921.78	34875.0	93188.0	114533.0	123737.0	140167.0
C	42597.0	40535.73	1194.43	39690.0	39690.0	39910.0	41062.0	42988.0

```
plt.figure(figsize=(10,8)) # To see the type-size relation
fig = sns.boxplot(x='Type', y='Size', data=df, showfliers=False)
```



Sizes of the type of stores are consistent with sales, as expected. Higher size stores has higher sales. And, Walmart classify stores according to their sizes according to graph. After the smallest size value of Type A, Type B begins. After the smallest size value of Type B, Type C begins.

- **Feature Engineering** Date variable into week, month and year and looking into the best sales for each category.

```
df['week'] =df['Date'].dt.week
df['month'] =df['Date'].dt.month
df['year'] =df['Date'].dt.year
```

```
df.groupby('month')['Weekly_Sales'].mean() # to see the best months for sales
```

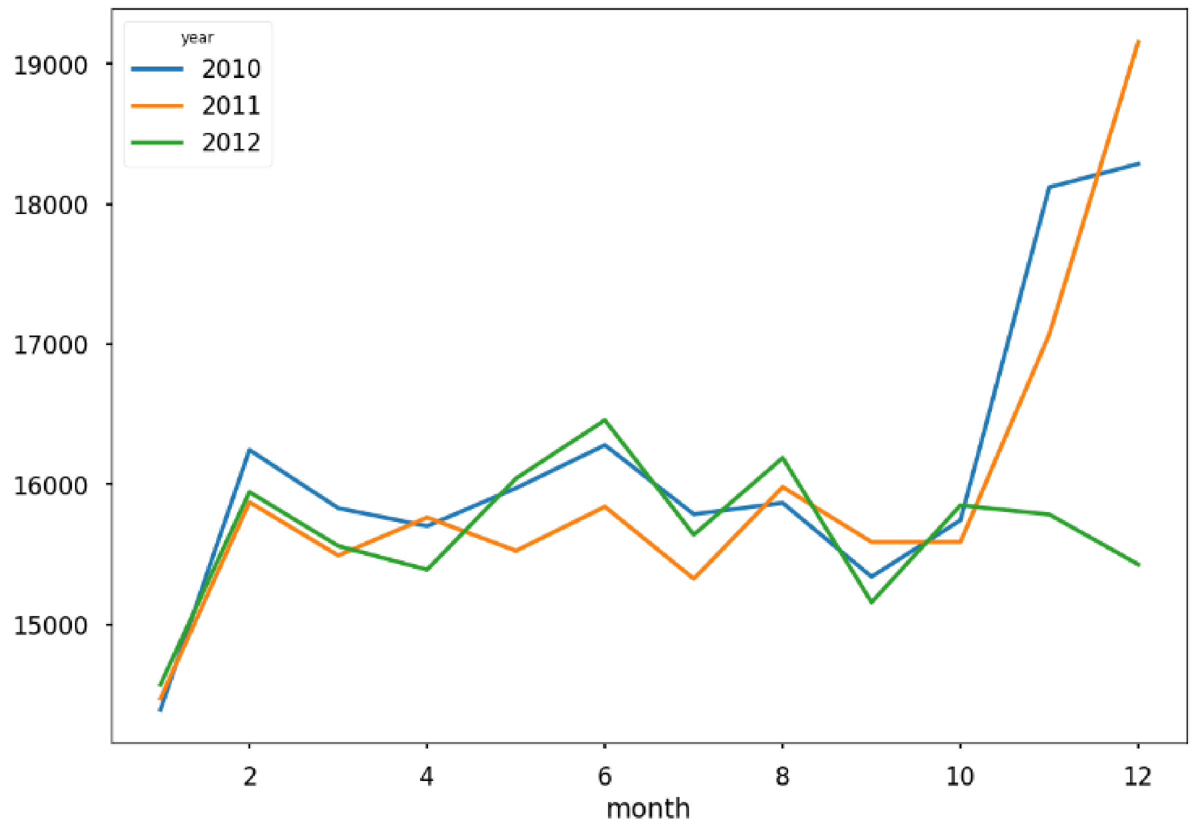
```
month
1     14503.308110
2     16026.823127
3     15631.676728
4     15638.149799
5     15850.122787
6     16258.141930
7     15563.149206
8     16012.023938
9     15378.844836
10    15728.044488
11    17271.744814
12    18342.245834
Name: Weekly_Sales, dtype: float64
```

```
df.groupby('year')['Weekly_Sales'].mean() # to see the best years for sales
```

```
year
2010    16270.275737
2011    15954.070675
2012    15694.948597
Name: Weekly_Sales, dtype: float64
```

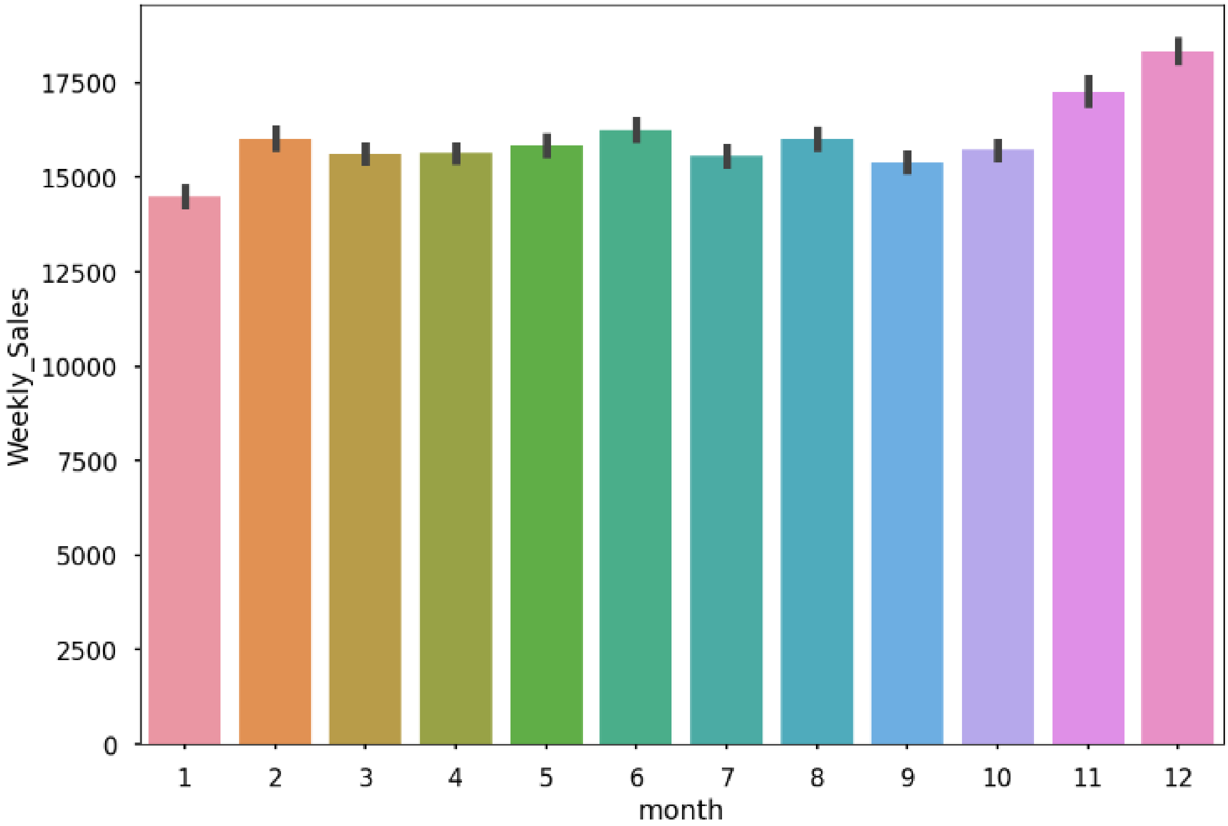
```
monthly_sales = pd.pivot_table(df, values = "Weekly_Sales", columns = "year", index = "month")
monthly_sales.plot()
```

```
<AxesSubplot:xlabel='month'>
```



From the graph, it is seen that 2011 has lower sales than 2010 generally. When we look at the mean sales it is seen that 2010 has higher values. In 2012 it's mean is near to 2010. Sales in 2011 has suddenly rised for last two months.

```
1 fig = sns.barplot(x='month', y='Weekly_Sales', data=df)
```



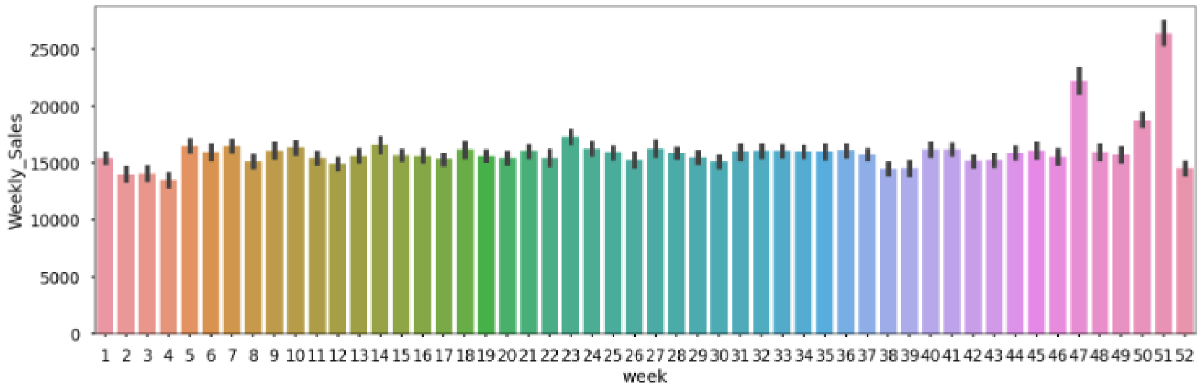
When we look at the graph above, the best sales are in December and November, as expected. The highest values are belongs to Thankgiving holiday but when we take average it is obvious that December has the best value.

```
1 df.groupby('week')['Weekly_Sales'].mean().sort_values(ascending=False).head()
```

```
week
51    26396.399283
47    22220.944538
50    18749.722165
23    17279.748856
14    16592.112711
Name: Weekly_Sales, dtype: float64
```

Top 5 sales averages by weekly belongs to 1-2 weeks before Christmas, Thanksgiving, Black Friday and end of May, when the schools are closed.

```
1 plt.figure(figsize=(20,6))
2 fig = sns.barplot(x='week', y='Weekly_Sales', data=df)
```

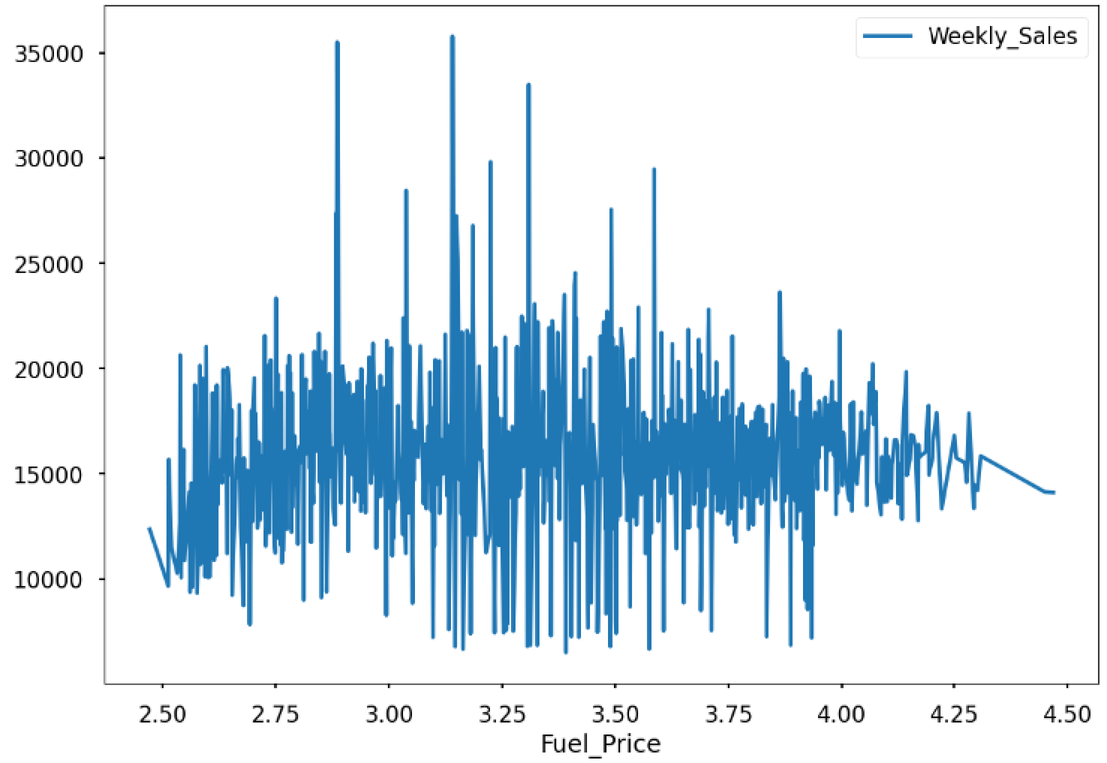


From graphs, it is seen that 51th week and 47th weeks have significantly higher averages as Christmas, Thankgiving and Black Friday effects.

- Line plot between certain numeric variables with target for better understanding over the aspects of whether being stationary, found with any trends etc.,

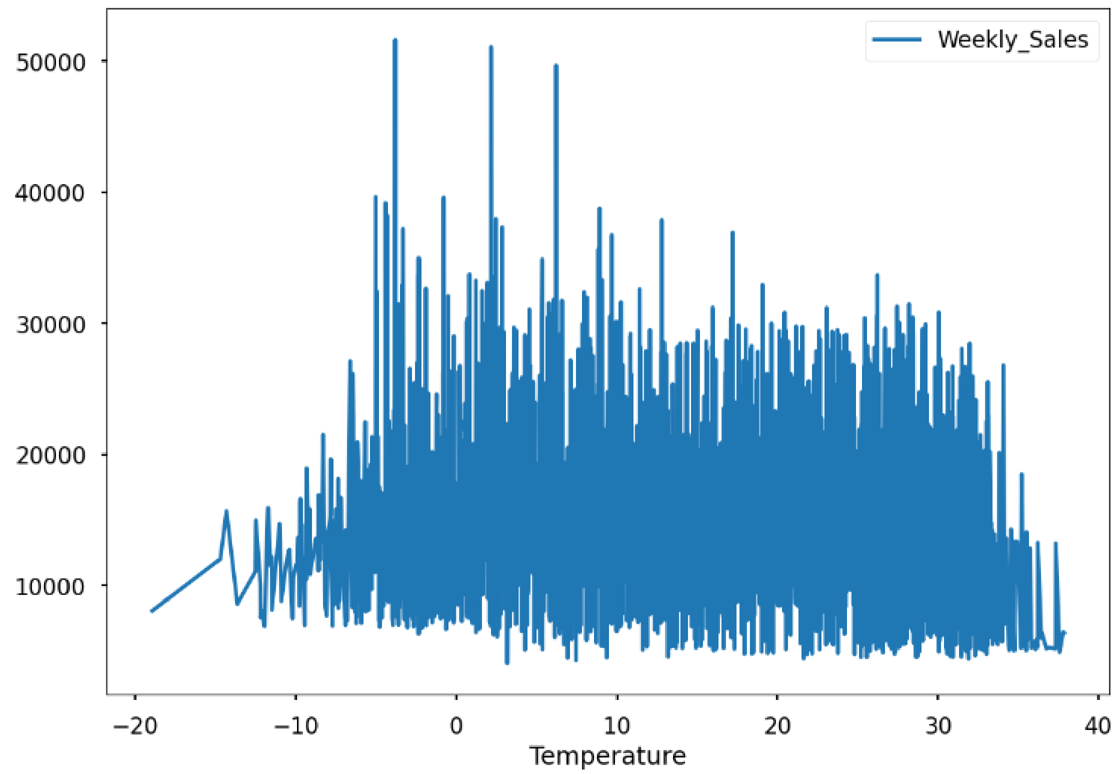
```
fuel_price = pd.pivot_table(df, values = "Weekly_Sales", index= "Fuel_Price")
fuel_price.plot()
```

```
<AxesSubplot:xlabel='Fuel_Price'>
```



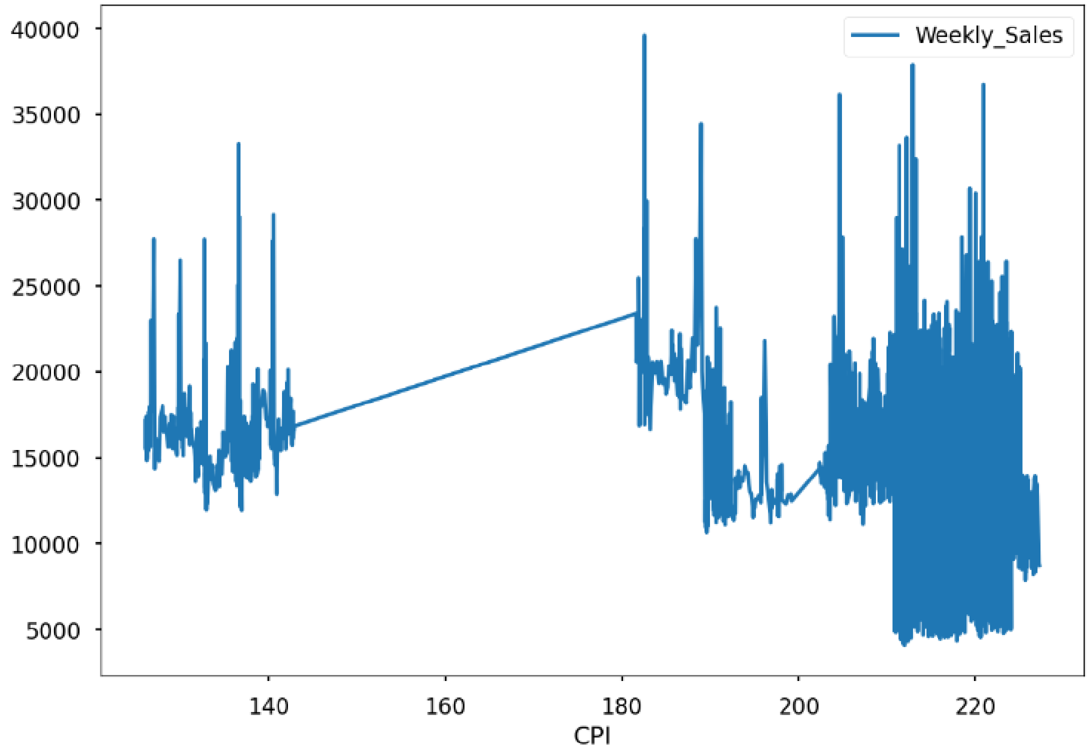

```
temp = pd.pivot_table(df, values = "Weekly_Sales", index= "Temperature")
temp.plot()
```

```
<AxesSubplot:xlabel='Temperature'>
```



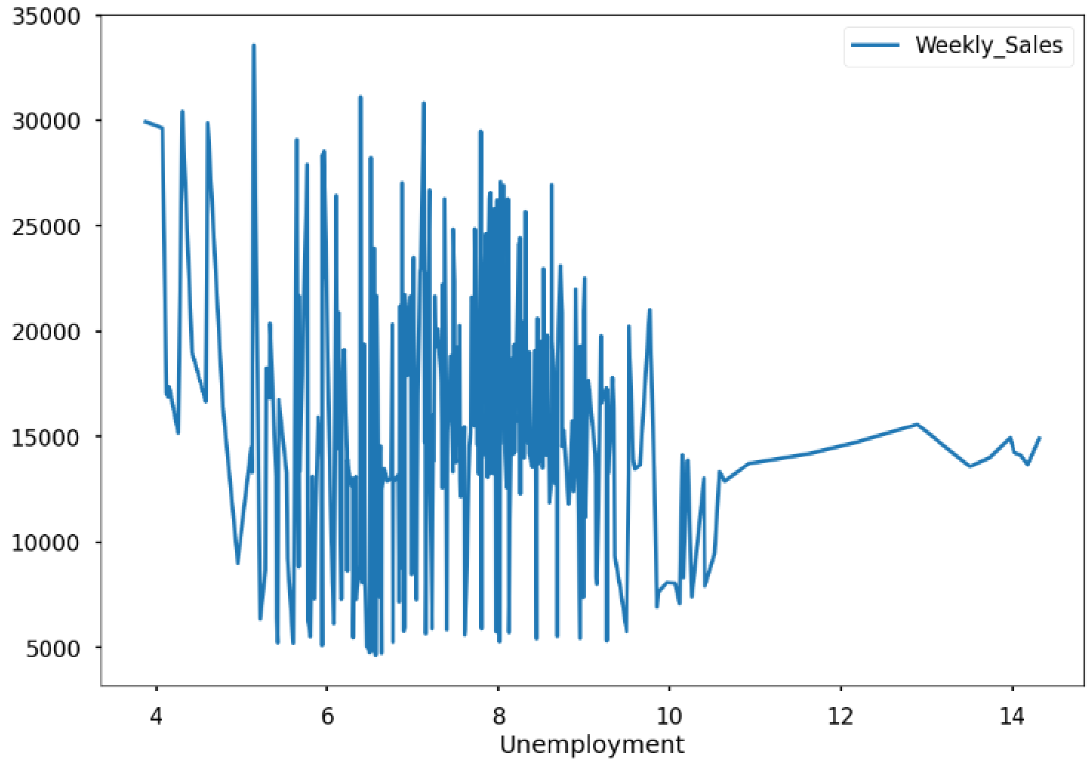
```
CPI = pd.pivot_table(df, values = "Weekly_Sales", index= "CPI")
CPI.plot()
```

<AxesSubplot:xlabel='CPI'>




```
unemployment = pd.pivot_table(df, values = "Weekly_Sales", index= "Unemployment")
unemployment.plot()
```

<AxesSubplot:xlabel='Unemployment'>



From graphs, it is seen that there are no significant patterns between CPI, temperature, unemployment rate, fuel price vs weekly sales. There is no data for CPI between 140-180 also.

Transforming the data:

```
df_num = df.select_dtypes(np.number)
df_num.columns
```

```
Index(['Store', 'Dept', 'Weekly_Sales', 'Temperature', 'Fuel_Price',
       'MarkDown1', 'MarkDown2', 'MarkDown3', 'MarkDown4', 'MarkDown5', 'CPI',
       'Unemployment', 'Size', 'week', 'month', 'year'],
      dtype='object')
```

```
from sklearn.preprocessing import PowerTransformer
```

```
pt=PowerTransformer(method='yeo-johnson')
trans_col=pt.fit_transform(df[['Temperature', 'Fuel_Price', 'MarkDown1', 'MarkDown2',
        'MarkDown3', 'MarkDown4', 'MarkDown5', 'CPI', 'Unemployment', 'Size']])
```

```
df_trans=pd.DataFrame(trans_col, columns=['Temperature', 'Fuel_Price', 'MarkDown1', 'MarkDown2',
        'MarkDown3', 'MarkDown4', 'MarkDown5', 'CPI', 'Unemployment', 'Size'])
df_trans.head()
```

	Temperature	Fuel_Price	MarkDown1	MarkDown2	MarkDown3	MarkDown4	MarkDown5	CPI	Unemployment	Size
0	-0.975433	-1.685399	-0.740128	-0.210481	-0.317239	-0.679836	-0.74778	1.020121	0.204134	0.22807
1	-1.178323	-1.734136	-0.740128	-0.210481	-0.317239	-0.679836	-0.74778	1.022987	0.204134	0.22807
2	-1.102718	-1.802972	-0.740128	-0.210481	-0.317239	-0.679836	-0.74778	1.023911	0.204134	0.22807
3	-0.742949	-1.707752	-0.740128	-0.210481	-0.317239	-0.679836	-0.74778	1.024510	0.204134	0.22807
4	-0.749968	-1.577351	-0.740128	-0.210481	-0.317239	-0.679836	-0.74778	1.025109	0.204134	0.22807

```
df.columns
```

```
Index(['Store', 'Dept', 'Date', 'Weekly_Sales', 'IsHoliday', 'Temperature',
       'Fuel_Price', 'MarkDown1', 'MarkDown2', 'MarkDown3', 'MarkDown4',
       'MarkDown5', 'CPI', 'Unemployment', 'Type', 'Size', 'Super_Bowl',
       'Labor_Day', 'Thanksgiving', 'Christmas', 'week', 'month', 'year'],
      dtype='object')
```

```
df_trans.shape
```

```
(421570, 10)
```

- Default settings of yeo-jhonson will apply standard scaler to the data hence we will not scale our data prior to model building. And it will also reduce the impact of outliers in the dataset. Now, continuing with Encoding

```
# Taking a copy of df
df_encoded=df[['Store', 'Dept', 'Date', 'Weekly_Sales','Type','IsHoliday','Super_Bowl','Thanksgiving','Labor_Day','Christmas
```

Label encoding Type and IsHoliday columns

```
type_group = {'A':1, 'B': 2, 'C': 3}  # changing A,B,C to 1-2-3
df_encoded['Type'] = df_encoded['Type'].replace(type_group)
```

```
df_encoded['IsHoliday'] = df_encoded['IsHoliday'].astype(bool).astype(int) # changing T,F to 0-1
```

```
df_encoded['Super_Bowl'] = df_encoded['Super_Bowl'].astype(bool).astype(int) # changing T,F to 0-1
```

```
df_encoded['Thanksgiving'] = df_encoded['Thanksgiving'].astype(bool).astype(int) # changing T,F to 0-1
```

```
df_encoded['Labor_Day'] = df_encoded['Labor_Day'].astype(bool).astype(int) # changing T,F to 0-1
```

```
df_encoded['Christmas'] = df_encoded['Christmas'].astype(bool).astype(int) # changing T,F to 0-1
```

```
df_encoded.shape
```

```
(421570, 13)
```

```python
df_encoded.head()
```

	Store	Dept	Date	Weekly_Sales	Type	IsHoliday	Super_Bowl	Thanksgiving	Labor_Day	Christmas	week	month	year
0	1	1	2010-05-02	24924.50	1	0	0	0	0	0	17	5	2010
1	1	1	2010-12-02	46039.49	1	1	0	0	0	0	48	12	2010
2	1	1	2010-02-19	41595.55	1	0	0	0	0	0	7	2	2010
3	1	1	2010-02-26	19403.54	1	0	0	0	0	0	8	2	2010
4	1	1	2010-05-03	21827.90	1	0	0	0	0	0	18	5	2010

```python
final_data = pd.concat([df_encoded, df_trans], axis=1)
final_data.head()
```

	Store	Dept	Date	Weekly_Sales	Type	IsHoliday	Super_Bowl	Thanksgiving	Labor_Day	Christmas	...	Temperature	Fuel_Price	MarkDown1	MarkDown2
0	1	1	2010-05-02	24924.50	1	0	0	0	0	0	...	-0.975433	-1.685399	-0.740128	-0.210481
1	1	1	2010-12-02	46039.49	1	1	0	0	0	0	...	-1.178323	-1.734135	-0.740128	-0.210481
2	1	1	2010-02-19	41595.55	1	0	0	0	0	0	...	-1.102718	-1.802972	-0.740128	-0.210481
3	1	1	2010-02-26	19403.54	1	0	0	0	0	0	...	-0.742949	-1.707752	-0.740128	-0.210481
4	1	1	2010-05-03	21827.90	1	0	0	0	0	0	...	-0.749968	-1.577351	-0.740128	-0.210481

5 rows × 23 columns

```python
# we will drop Date before model as we already have week month and year columns to show that
dft=final_data.drop('Date', axis=1)
dft.head()
```

	Store	Dept	Weekly_Sales	Type	IsHoliday	Super_Bowl	Thanksgiving	Labor_Day	Christmas	week	...	Temperature	Fuel_Price	MarkDown1	MarkDown2
0	1	1	24924.50	1	0	0	0	0	0	17	...	-0.975433	-1.685399	-0.740128	-0.210481
1	1	1	46039.49	1	1	0	0	0	0	48	...	-1.178323	-1.734135	-0.740128	-0.210481
2	1	1	41595.55	1	0	0	0	0	0	7	...	-1.102718	-1.802972	-0.740128	-0.210481
3	1	1	19403.54	1	0	0	0	0	0	8	...	-0.742949	-1.707752	-0.740128	-0.210481
4	1	1	21827.90	1	0	0	0	0	0	18	...	-0.749968	-1.577351	-0.740128	-0.210481

5 rows × 22 columns

OLS Model Building:

```
y = dft.Weekly_Sales
x = dft.drop('Weekly_Sales',axis=1)
```

```
Xc = sm.add_constant(x)
model = sm.OLS(y,Xc).fit()
model.summary()
```

OLS Regression Results

Dep. Variable:	Weekly_Sales	R-squared:	0.089
Model:	OLS	Adj. R-squared:	0.089
Method:	Least Squares	F-statistic:	2058.
Date:	Thu, 20 Apr 2023	Prob (F-statistic):	0.00
Time:	12:30:12	Log-Likelihood:	-4.8071e+06
No. Observations:	421570	AIC:	9.614e+06
Df Residuals:	421549	BIC:	9.615e+06
Df Model:	20		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	3.569e+06	2.69e+05	13.282	0.000	3.04e+06	4.1e+06
Store	-101.9961	2.833	-36.002	0.000	-107.549	-96.443
Dept	111.2790	1.095	101.590	0.000	109.132	113.426
Type	1896.5994	87.803	21.601	0.000	1724.508	2068.691
IsHoliday	2.7262	194.404	0.014	0.989	-378.301	383.753
Super_Bowl	-1.15e-05	8.66e-07	-13.282	0.000	-1.32e-05	-9.8e-06
Thanksgiving	4359.8779	358.724	12.154	0.000	3656.789	5062.967
Labor_Day	-320.9529	443.421	-0.724	0.469	-1190.045	548.139
Christmas	-2074.6882	364.741	-5.688	0.000	-2789.569	-1359.807
week	-204.2004	29.721	-6.871	0.000	-262.453	-145.948
month	977.4679	129.516	7.547	0.000	723.620	1231.315
year	-1770.2942	133.617	-13.249	0.000	-2032.179	-1508.410
Temperature	380.6472	36.728	10.364	0.000	308.661	452.634
Fuel_Price	502.2102	68.769	7.303	0.000	367.425	636.996
MarkDown1	-307.0558	336.605	-0.912	0.362	-966.792	352.681
MarkDown2	113.7756	36.886	3.085	0.002	41.480	186.071
MarkDown3	369.6765	39.443	9.372	0.000	292.369	446.984
MarkDown4	-1325.9669	117.432	-11.291	0.000	-1556.130	-1095.804
MarkDown5	2385.8811	283.854	8.405	0.000	1829.536	2942.226
CPI	-675.2339	38.436	-17.568	0.000	-750.568	-599.900
Unemployment	-402.1309	37.353	-10.766	0.000	-475.342	-328.920
Size	6467.2099	58.764	110.053	0.000	6352.034	6582.386

Omnibus:	295130.879	Durbin-Watson:	0.117
Prob(Omnibus):	0.000	Jarque-Bera (JB):	8636185.803
Skew:	3.007	Prob(JB):	0.00
Kurtosis:	24.342	Cond. No.	1.66e+20

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 6.2e-29. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

INFERENCE

- Getting r square of 9% aprox
- Now, removing less signicant columns and rebuilding model and checking the summary

- Removing the columns whose p_value is greater than 0.05 and then looking into summary to check if any changes would have occurred in the r-square value

```
cols = list(Xc.columns)
while len(cols)>1:
    Xc = Xc[cols]
    model = sm.OLS(y, Xc).fit()
    p = model.pvalues
    pmax = max(p)
    pid = p.idxmax()
    if pmax>0.05:
        cols.remove(pid)
        print('Var removed:', pid, 'pvalue :', pmax)
    else:
        break

cols
```

```
Var removed: IsHoliday pvalue : 0.9888112227344332
Var removed: Labor_Day pvalue : 0.4324921105433247
Var removed: MarkDown1 pvalue : 0.3652301700675279

['const',
 'Store',
 'Dept',
 'Type',
 'Super_Bowl',
 'Thanksgiving',
 'Christmas',
 'week',
 'month',
 'year',
 'Temperature',
 'Fuel_Price',
 'MarkDown2',
 'MarkDown3',
 'MarkDown4',
 'MarkDown5',
 'CPI',
 'Unemployment',
 'Size']
```

```
model.summary()
```

OLS Regression Results

Dep. Variable:	Weekly_Sales	**R-squared:**	0.089
Model:	OLS	**Adj. R-squared:**	0.089
Method:	Least Squares	**F-statistic:**	2421.
Date:	Thu, 20 Apr 2023	**Prob (F-statistic):**	0.00
Time:	12:30:16	**Log-Likelihood:**	-4.8071e+06
No. Observations:	421570	**AIC:**	9.614e+06
Df Residuals:	421552	**BIC:**	9.615e+06
Df Model:	17		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	3.6e+06	2.64e+05	13.641	0.000	3.08e+06	4.12e+06
Store	-101.9351	2.832	-35.992	0.000	-107.486	-96.384
Dept	111.2807	1.095	101.592	0.000	109.134	113.428
Type	1896.7334	87.802	21.602	0.000	1724.644	2068.823
Super_Bowl	1.271e-06	9.32e-08	13.641	0.000	1.09e-06	1.45e-06
Thanksgiving	4379.7043	306.269	14.300	0.000	3779.427	4979.981
Christmas	-2085.9518	314.808	-6.626	0.000	-2702.966	-1468.937
week	-202.4224	29.148	-6.945	0.000	-259.551	-145.293
month	969.3734	126.386	7.670	0.000	721.661	1217.086
year	-1785.5382	131.219	-13.607	0.000	-2042.723	-1528.354
Temperature	378.4238	36.548	10.354	0.000	306.792	450.056
Fuel_Price	503.4904	67.752	7.431	0.000	370.699	636.282
MarkDown2	113.4371	36.882	3.076	0.002	41.150	185.724
MarkDown3	369.4770	39.436	9.369	0.000	292.183	446.771
MarkDown4	-1392.2713	92.177	-15.104	0.000	-1572.935	-1211.608

MarkDown5	2153.0413	111.223	19.358	0.000	1935.047	2371.035
CPI	-674.1029	38.374	-17.567	0.000	-749.314	-598.891
Unemployment	-402.4640	37.297	-10.791	0.000	-475.565	-329.362
Size	6467.3040	58.764	110.056	0.000	6352.129	6582.479

Omnibus:	295127.523	**Durbin-Watson:**	0.117
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	8635495.702
Skew:	3.007	**Prob(JB):**	0.00
Kurtosis:	24.341	**Cond. No.**	4.96e+18

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 6.92e-26. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

INFERENCE

- Still the r square is aproxx 9%
- We can observe that the OLS model is having very high multicollinearity as its condition number is very high(1.14e+09)
- Since value of Durbin-Watson number is much below 2, it shows our data has positive Autocorrelation
- Low value of F(Statistic) indicates that our linear model does not provide best fit line to our data
- All these leads to the inference that our model is leaning towards Non-linear, non-parametric models

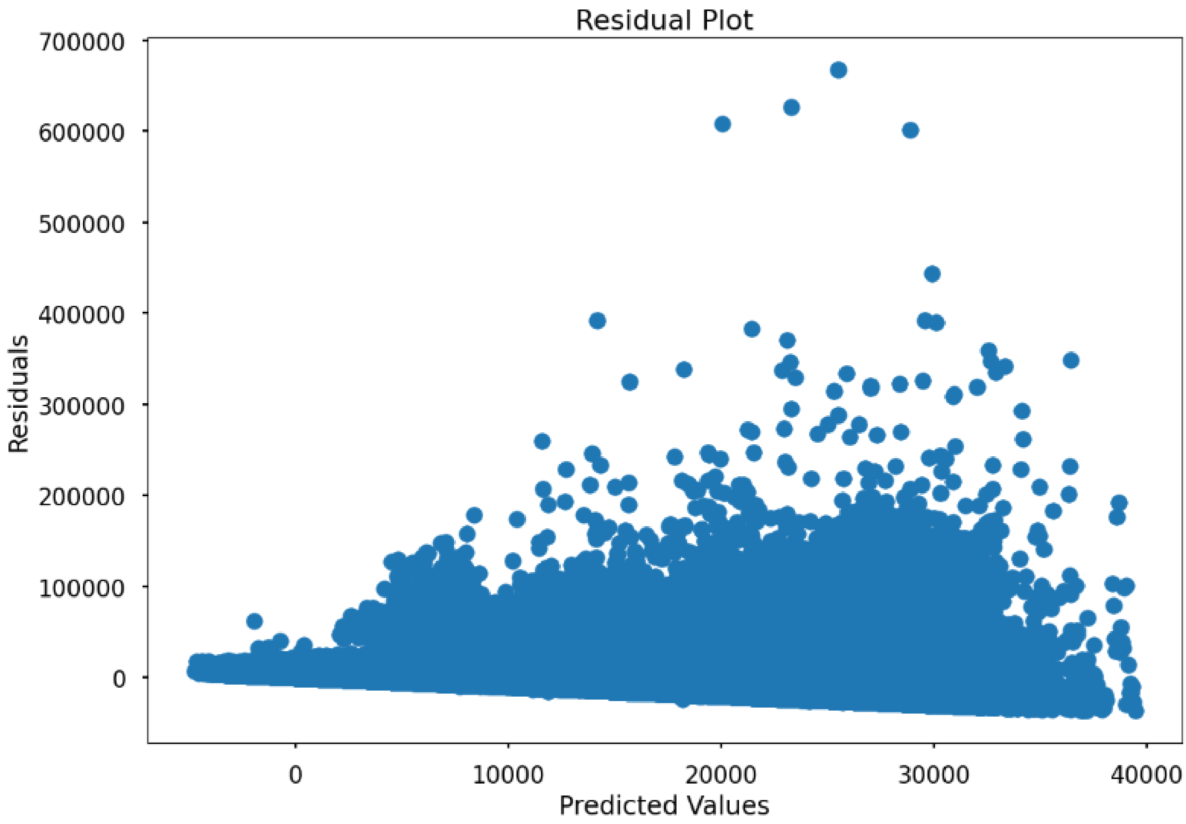
Conclusion

- So, we plan to build Non Linear Machine Learning Models to predict Weekly_Sales

```
y_predict = model.predict(Xc)
```

```
residuals = y - y_predict
```

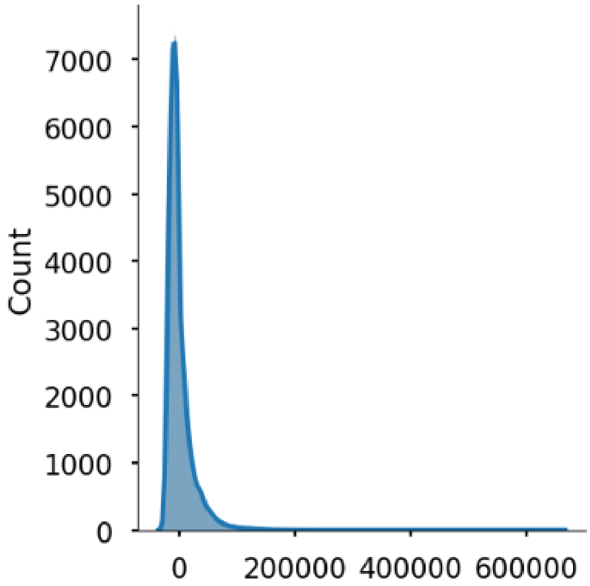
```
# Create scatter plot of residuals against predicted values
plt.scatter(y_predict, residuals)
plt.xlabel('Predicted Values')
plt.ylabel('Residuals')
plt.title('Residual Plot')
plt.show()
```



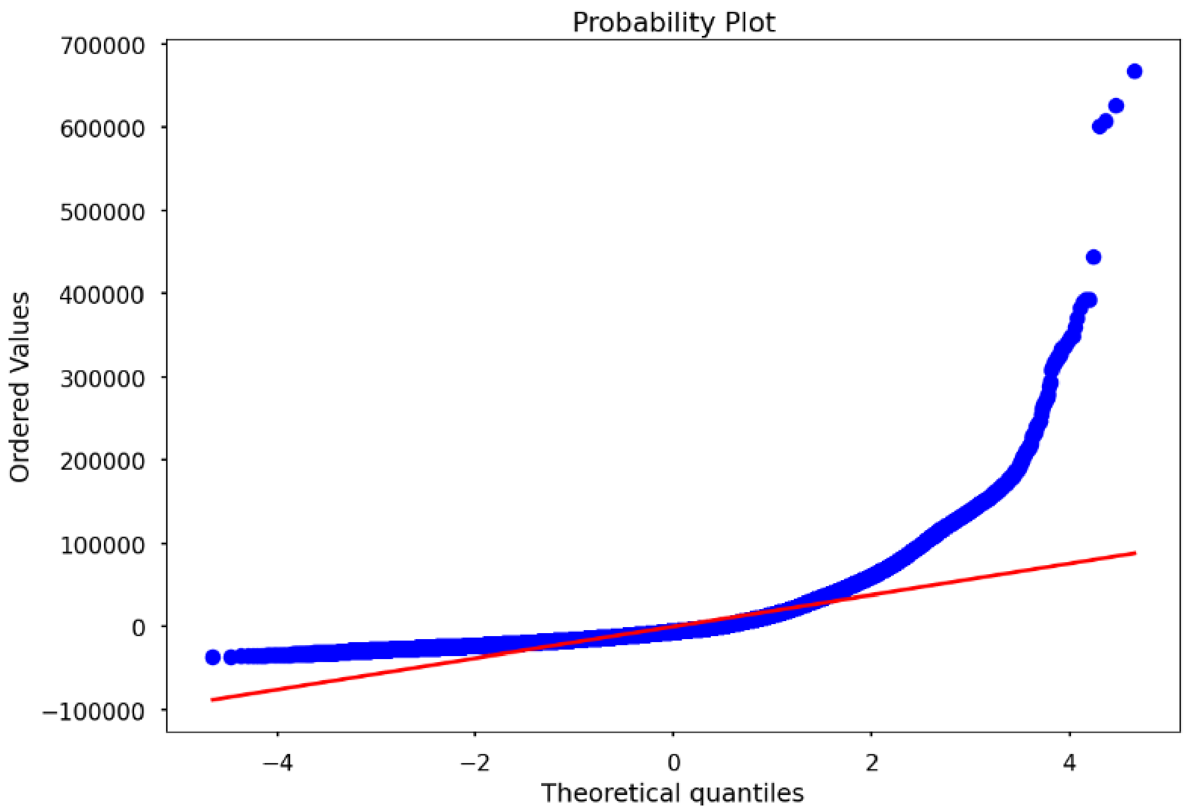
```
residuals = model.resid
sum(residuals)
```

-0.6374908866964688

```
sns.displot(residuals, kde=True)
plt.show()
```




```
import scipy.stats as stats
stats.probplot(residuals, plot=plt)
plt.show()
```



- Since the points show a curved pattern, such as a U-shaped pattern, we can conclude that a linear model is not appropriate and that a non-linear model might fit better.

Performing statistical test (jarque-bera) on the residuals:

```
print(stats.jarque_bera(residuals))
```

```
Jarque_beraResult(statistic=8635495.701538017, pvalue=0.0)
```

data_train = data_table[data_table.Weekly_Sales.notnull()] data_test = data_table[data_table.Weekly_Sales.isnull()]

```
from sklearn.metrics import mean_squared_error, mean_absolute_error, mean_absolute_percentage_error

from sklearn.svm import SVR, LinearSVR, NuSVR
from sklearn.linear_model import ElasticNet, Lasso, RidgeCV,LinearRegression
from sklearn.kernel_ridge import KernelRidge
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import GradientBoostingRegressor,AdaBoostRegressor,RandomForestRegressor
import xgboost as xgb
from sklearn.ensemble import BaggingRegressor
```

```
X = dft.drop('Weekly_Sales', axis=1)
y = dft['Weekly_Sales']
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3)
```

```
clfs = {'linreg': LinearRegression(),
        'DecisionTree': DecisionTreeRegressor(),
        'RandomForest':RandomForestRegressor(),
        'AdaBoost': AdaBoostRegressor(),
        'GradientBoost': GradientBoostingRegressor(),
        'XGBoost': xgb.XGBRegressor(),
        'BaggingRF': BaggingRegressor(base_estimator=RandomForestRegressor()),
        'BaggingAda': BaggingRegressor(base_estimator=AdaBoostRegressor()),
        'BaggingGB': BaggingRegressor(base_estimator=GradientBoostingRegressor()),
        'BaggingXGB': BaggingRegressor(base_estimator=xgb.XGBRegressor())
       }

model_report = pd.DataFrame(columns = ['RMSE', 'MAE','MAPE'])

for clf, clf_name in list(zip(clfs.values(), clfs.keys())):
    clf.fit(X_train,y_train)
    y_pred = clf.predict(X_test)
    print('Fitting the model .......', clf_name)
    t= pd.Series({
        'Model': clf_name,
        'RMSE': np.sqrt(mean_squared_error(y_test, y_pred)),
        'MAE': mean_absolute_error(y_test, y_pred),
        'MAPE': mean_absolute_percentage_error(y_test, y_pred)
    })
    model_report = model_report.append(t,ignore_index=True)
model_report = model_report.sort_values(by='RMSE', ascending=False)
model_report
```

```
Fitting the model ....... linreg
Fitting the model ....... DecisionTree
Fitting the model ....... RandomForest
Fitting the model ....... AdaBoost
Fitting the model ....... GradientBoost
Fitting the model ....... XGBoost
Fitting the model ....... BaggingRF
Fitting the model ....... BaggingAda
Fitting the model ....... BaggingGB
Fitting the model ....... BaggingXGB
```

Out[118]:

	RMSE	MAE	MAPE	Model
3	25149.505187	20899.200534	2.231152e+16	AdaBoost
7	24019.518984	20337.238983	2.360682e+16	BaggingAda
0	21632.518678	14520.065125	1.527174e+16	linreg
4	11436.858622	6898.035092	7.250579e+15	GradientBoost
8	11379.094906	6870.075744	7.486204e+15	BaggingGB
1	5700.940944	2237.058091	4.547542e+13	DecisionTree
5	5567.051001	3181.882342	2.459306e+15	XGBoost
9	5513.587386	3067.856414	2.538852e+15	BaggingXGB
6	4313.342273	1760.144736	6.027600e+14	BaggingRF
2	4126.491742	1701.296088	4.760115e+14	RandomForest

- We can infer that **Random Forest Regressor** model gives the least RMSE value comparatively
- To tune the regressor, we are using gridsearch but it takes too much time for this type of data which has many rows and columns. So, we choose regressor parameters manually. We changed the parameters each time and try to find the best result

```
rf = RandomForestRegressor(n_estimators=50, random_state=42, n_jobs=-1, max_depth=35,
                           max_features = 'sqrt',min_samples_split = 10)

from sklearn.preprocessing import RobustScaler
scaler = RobustScaler()



#making pipe tp use scaler and regressor together
pipe = make_pipeline(scaler,rf)

pipe.fit(X_train, y_train)

# predictions on train set
y_pred = pipe.predict(X_train)

# predictions on test set
y_pred_test = pipe.predict(X_test)
```

- Usually, we perform Grid search in the below way.

Hyper Parameter Tuning using GridSearchCV finding best parameters

```
from sklearn.model_selection import GridSearchCV
X = dft.drop('Weekly_Sales', axis=1)
y = dft['Weekly_Sales']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3)

# Define the parameter grid to search over
param_grid = {
    'n_estimators': [100, 150, 200 ],
    'max_depth': [10, 50, 100],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
}

rf = RandomForestRegressor(random_state=42)

# Perform the grid search using GridSearchCV
grid_search = GridSearchCV(estimator=rf, param_grid=param_grid, cv=5, n_jobs=-1)
grid_search.fit(X_train, y_train)

# Make predictions on the test set
y_pred = grid_search.predict(X_test)

# Calculate the RMSE value
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
print("RMSE:", rmse)

# Print the best parameters found by the grid search
print("Best Parameters:", grid_search.best_params_)
```

- Looking into RMSE and accuracy scores for training and testing data of Random Forest Model.

```
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.3, random_state=42)
```

```
# Create a Random Forest Regressor model
rf_regressor = RandomForestRegressor(n_estimators=100, random_state=42)

# Fit the model to the training data
rf_regressor.fit(X_train, y_train)

# Make predictions on the testing data
y_pred_rf = rf_regressor.predict(X_test)

# Evaluate the model's performance
mse = mean_squared_error(y_test, y_pred_rf)
r2 = r2_score(y_test, y_pred_rf)

print('Root Mean squared error:', np.sqrt(mse))
print('R-squared:', r2)
```

```
Mean squared error: 17891427.989189506
R-squared: 0.965094194019948
```

```
train_score = rf_regressor.score(X_train, y_train)
print('Training_Score', train_score)
```

```
Training_Score 0.9953228632739162
```

```
test_score = rf_regressor.score(X_test, y_test)
print('Training_Score', test_score)
```

```
Training_Score 0.965094194019948
```

As per Random Forest Regressor our Model is predicting Weekly Sales with 96.5% accuracy.

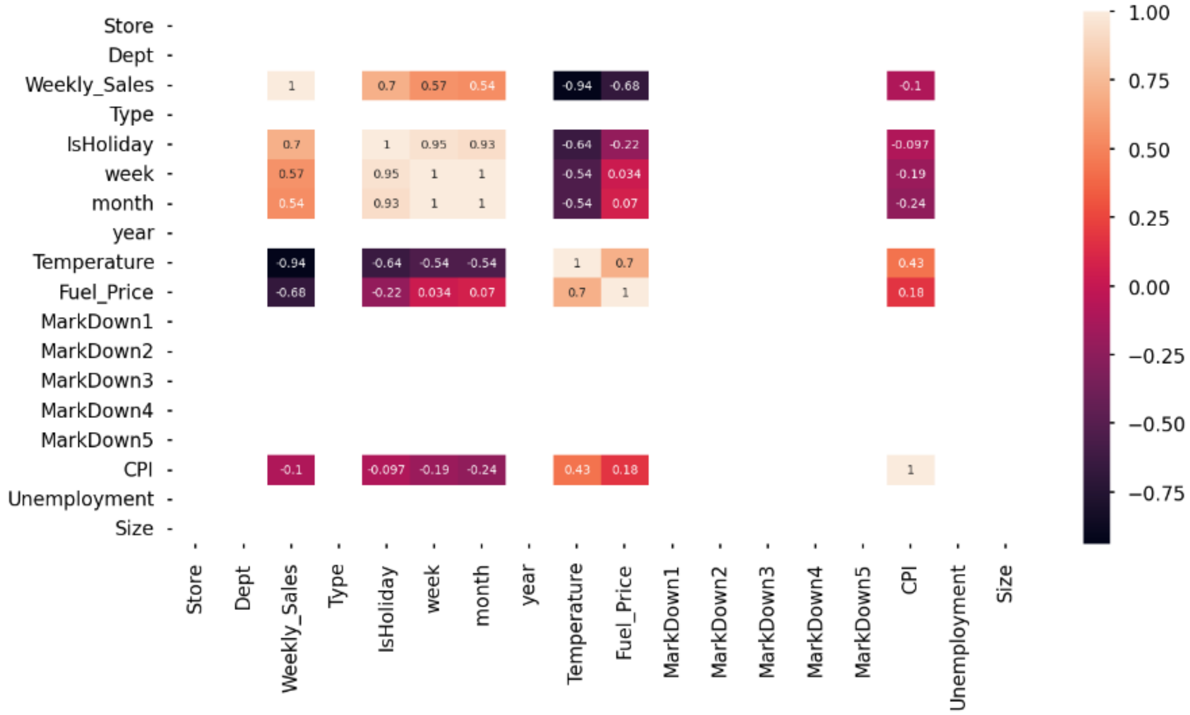
- Observation of interactions between features after dropping newly created columns of Holidays.

```
df_new=final_data.head()
```

Firstly, i will drop divided holiday columns from my data and try without them. To keep my encoded data safe, I assigned my dataframe to new one and I will use for this.

```
drop_col = ['Super_Bowl','Labor_Day','Thanksgiving','Christmas']
df_new.drop(drop_col, axis=1, inplace=True) # dropping columns
```

```
plt.figure(figsize = (16,8))
sns.heatmap(df_new.corr(),annot=True)     # To see the correlations
plt.show()
```




```
df_new = df_new.sort_values(by='Date', ascending=True) # sorting according to date
```

```
# dropping columns will very less correlation to weekly sales to improvethe model
df_new.drop(['Store','Dept','Type','year',
             'MarkDown1','MarkDown2','MarkDown3','MarkDown4','MarkDown5','Unemployment','Size'], axis=1, inplace=True)
```

Creating Train-Test Splits

- Our date column has continuos values, to keep the date features continue, I will not take random splitting. so, I split data manually according to 70%.

```
train_data = df_new[:int(0.7*(len(df_new)))] # taking train part
test_data = df_new[int(0.7*(len(df_new))):] # taking test part

target = "Weekly_Sales"
used_cols = [c for c in df_new.columns.to_list() if c not in [target]] # all columns except weekly sales

X_train = train_data[used_cols]
X_test = test_data[used_cols]
y_train = train_data[target]
y_test = test_data[target]
```

```
X = df_new[used_cols] # to keep train and test X values together
```

- We have enough information in our date such as week of the year. So, we drop date columns.

```
X_train = X_train.drop(['Date'], axis=1) # dropping date from train
X_test = X_test.drop(['Date'], axis=1) # dropping date from test
```

```
# Create a Random Forest Regressor model
rf_regressor = RandomForestRegressor(n_estimators=100, random_state=42)

# Fit the model to the training data
rf_regressor.fit(X_train, y_train)

# Make predictions on the testing data
y_pred_rf = rf_regressor.predict(X_test)

# Evaluate the model's performance
mse = mean_squared_error(y_test, y_pred_rf)
r2 = r2_score(y_test, y_pred_rf)

print('Root Mean squared error:', np.sqrt(mse))
print('R-squared:', r2)
```

```
Root Mean squared error: 11872.729260813316
R-squared: 0.03813416640575884
```

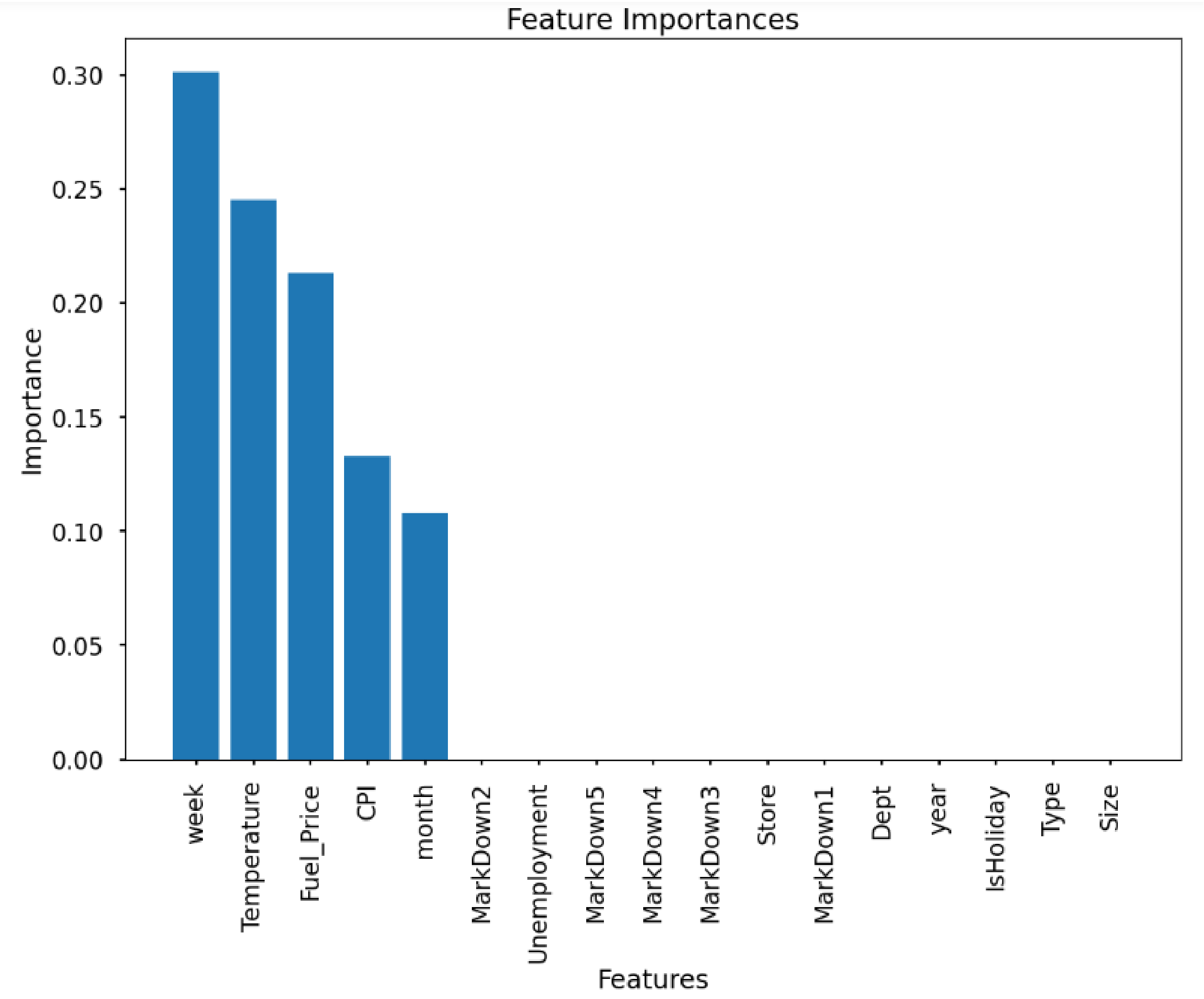
we can note that even after dropping less correlated attributes there is no improvement in RMSE hence we will chose our first random forest model as best fit model with 4126 RMSE value, it means our model can learn from columns which I dropped before.

FINDING IMPORTANT FEATURES:

```
# create a Random Forest Regressor
rf = RandomForestRegressor()

# fit the model on the training data
rf.fit(X_train, y_train)
# extract feature importances
importances = rf.feature_importances_

# create a DataFrame to store feature importances
feature_importances = pd.DataFrame({'feature': X_train.columns, 'importance': importances})

# sort the DataFrame by feature importance
feature_importances = feature_importances.sort_values('importance', ascending=False).reset_index(drop=True)

# print the top 10 features by importance
print(feature_importances.head(10))

```

```
        feature  importance
0          week    0.301181
1   Temperature    0.245044
2    Fuel_Price    0.213108
3           CPI    0.132770
4         month    0.107897
5     MarkDown2    0.000000
6  Unemployment    0.000000
7     MarkDown5    0.000000
8     MarkDown4    0.000000
9     MarkDown3    0.000000
```

```
plt.bar(feature_importances['feature'], feature_importances['importance'])

# add labels and title to the chart
plt.xlabel('Features')
plt.ylabel('Importance')
plt.title('Feature Importances')

# rotate the x-axis labels for better visibility
plt.xticks(rotation=90)

# display the chart
plt.show()
```



TIME SERIES ANALYSIS:

Time Series Analysis

```
df.head()
```

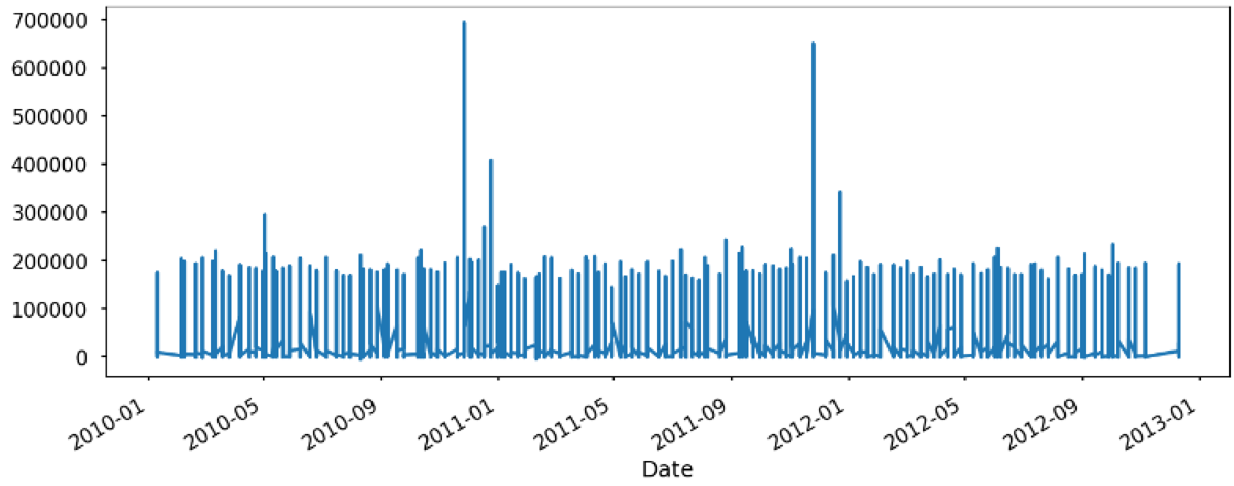
	Store	Dept	Date	Weekly_Sales	IsHoliday	Temperature	Fuel_Price	MarkDown1	MarkDown2	MarkDown3	...	Unemployment	Type	Size	Super_Bowl
0	1	1	2010-05-02	24924.50	False	5.727778	2.572	0.0	0.0	0.0	...	8.106	A	151315	False
1	1	1	2010-12-02	46039.49	True	3.616667	2.548	0.0	0.0	0.0	...	8.106	A	151315	False
2	1	1	2010-02-19	41595.55	False	4.405556	2.514	0.0	0.0	0.0	...	8.106	A	151315	False
3	1	1	2010-02-26	19403.54	False	8.127778	2.561	0.0	0.0	0.0	...	8.106	A	151315	False
4	1	1	2010-05-03	21827.90	False	8.055556	2.625	0.0	0.0	0.0	...	8.106	A	151315	False

5 rows × 23 columns

```
df.set_index('Date', inplace=True) #seting date as index
```

Plotting Sales

```
plt.figure(figsize=(16,6))
df['Weekly_Sales'].plot()
plt.show()
```



In this data, there are lots of same data values. So, we will collect them together as weekly.

- Checking for null values to make sure there are no missing values

```
df.isnull().sum()
```

```
Store           0
Dept            0
Weekly_Sales    0
IsHoliday       0
Temperature     0
Fuel_Price      0
MarkDown1       0
MarkDown2       0
MarkDown3       0
MarkDown4       0
MarkDown5       0
CPI             0
Unemployment    0
Type            0
Size            0
Super_Bowl      0
Labor_Day       0
Thanksgiving    0
Christmas       0
week            0
month           0
year            0
dtype: int64
```

Resampling the data as weekly:

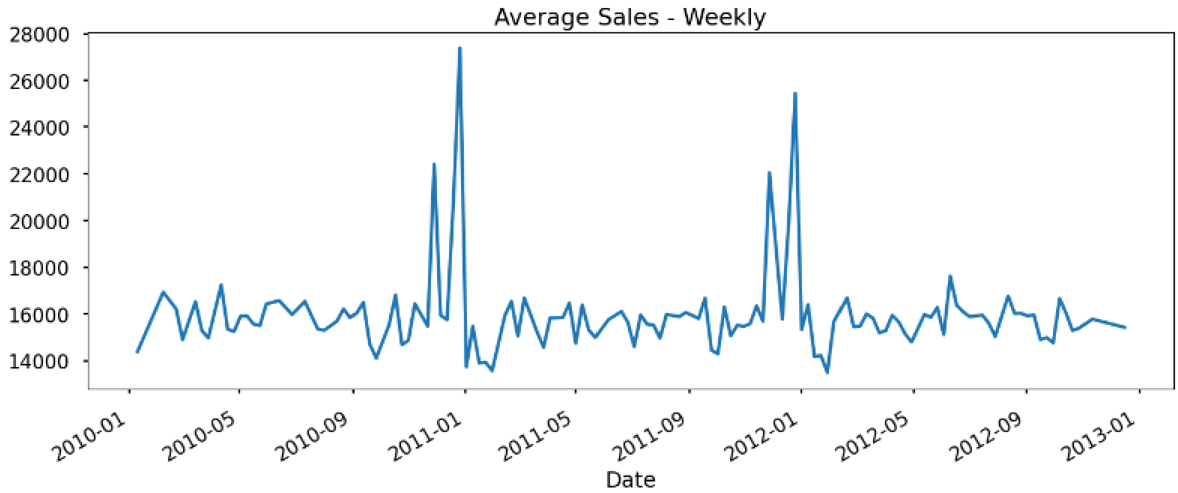
```
df_week = df.resample('W').mean() #resample data as weekly
```

```
df_week=df_week.dropna(axis=0)
```

```
df_week[df_week.isnull()].sum()
```

```
Store           0.0
Dept            0.0
Weekly_Sales    0.0
Temperature     0.0
Fuel_Price      0.0
MarkDown1       0.0
MarkDown2       0.0
MarkDown3       0.0
MarkDown4       0.0
MarkDown5       0.0
CPI             0.0
Unemployment    0.0
Size            0.0
week            0.0
month           0.0
year            0.0
dtype: float64
```

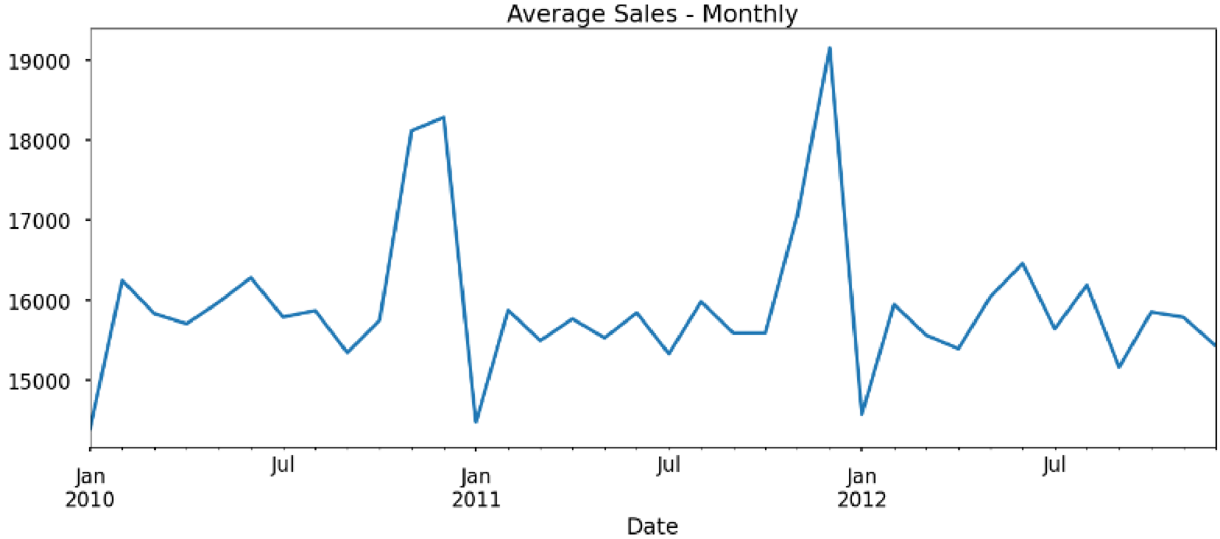
```
plt.figure(figsize=(16,6))
df_week['Weekly_Sales'].plot()
plt.title('Average Sales - Weekly')
plt.show()
```



- With the collecting data as weekly, we can see average sales clearly. To see monthly pattern , we resampled our data to monthly also

```
df_month = df.resample('MS').mean() # resampling as monthly
```

```
plt.figure(figsize=(16,6))
df_month['Weekly_Sales'].plot()
plt.title('Average Sales - Monthly')
plt.show()
```



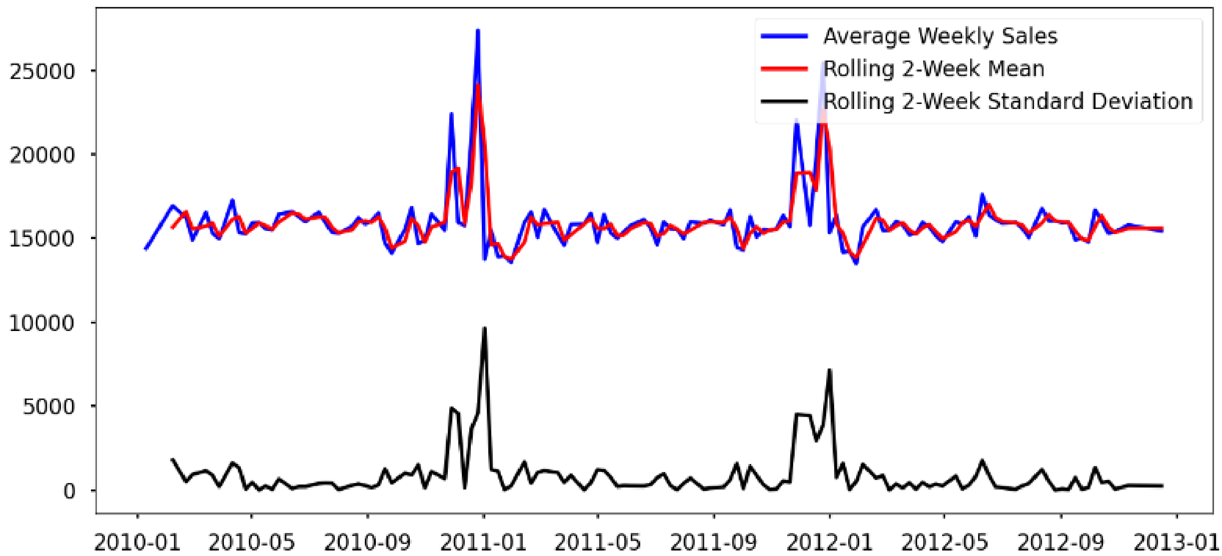
- When we turned data to monthly, realized that we lost some patterns in weekly data. So, we will continue with weekly resampled data

To Observe 2-weeks Rolling Mean and Std:

- Our data is non-stationary. So, we will try to find more stationary version on it.

```
# finding 2-weeks rolling mean and std
roll_mean = df_week['Weekly_Sales'].rolling(window=2, center=False).mean()
roll_std = df_week['Weekly_Sales'].rolling(window=2, center=False).std()
```

```
fig, ax = plt.subplots(figsize=(13, 6))
ax.plot(df_week['Weekly_Sales'], color='blue',label='Average Weekly Sales')
ax.plot(roll_mean, color='red', label='Rolling 2-Week Mean')
ax.plot(roll_std, color='black', label='Rolling 2-Week Standard Deviation')
ax.legend()
fig.tight_layout()
```



Adfuller Test to Make Sure

```
adfuller(df_week['Weekly_Sales'])
```

```
(-9.33036800879878,
 9.364103857376136e-16,
 0,
 126,
 {'1%': -3.4833462346078936,
  '5%': -2.8847655969877666,
  '10%': -2.5791564575459813},
 2028.9397895101497)
```

- From test and our observations, the data is not stationary. So, we will try to find more stationary version of it.

Train - Test Split of Weekly Data:

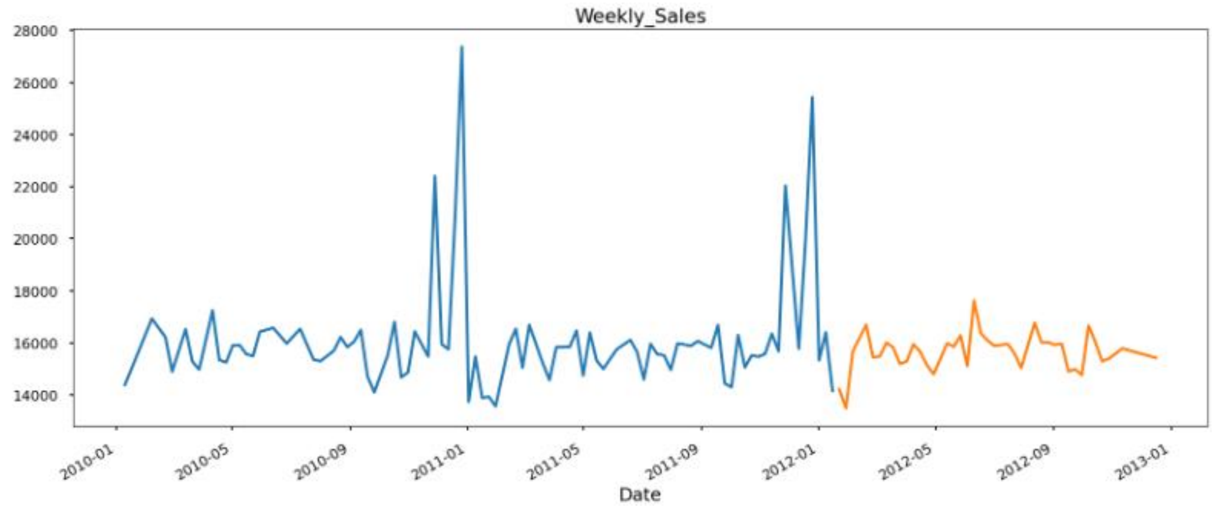
To take train-test splits continuously, we split them manually, and not random.

```
train_data = df_week[:int(0.7*(len(df_week)))]
test_data = df_week[int(0.7*(len(df_week))):]

print('Train:', train_data.shape)
print('Test:', test_data.shape)
```

```
Train: (88, 16)
Test: (39, 16)
```

```
target = "Weekly_Sales"
used_cols = [c for c in df_week.columns.to_list() if c not in [target]] # all columns except price

# assigning train-test X-y values

X_train = train_data[used_cols]
X_test = test_data[used_cols]
y_train = train_data[target]
y_test = test_data[target]
```

```
train_data['Weekly_Sales'].plot(figsize=(20,8), title= 'Weekly_Sales', fontsize=14)
test_data['Weekly_Sales'].plot(figsize=(20,8), title= 'Weekly_Sales', fontsize=14)
plt.show()
```

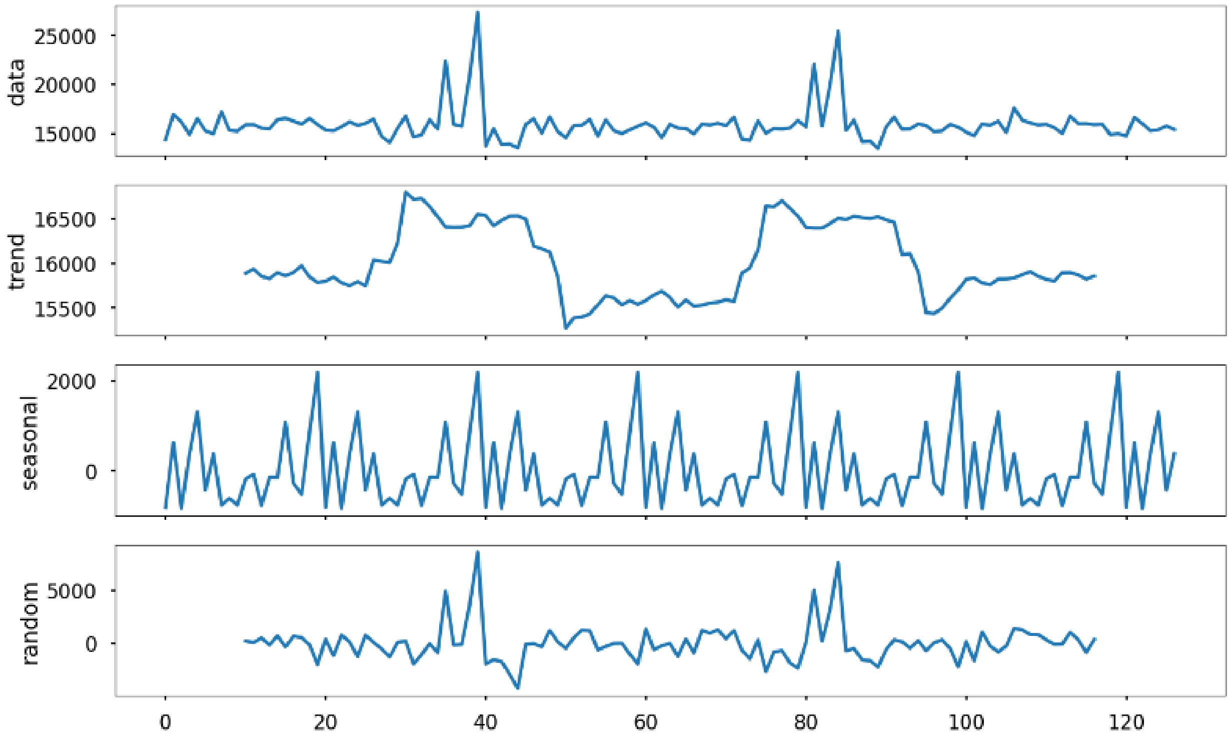


- Here, blue line represents the train data and yellow line represents the test data

Decomposing Weekly Data to observe Seasonality:

```
decomposed = decompose(df_week['Weekly_Sales'].values, 'additive', m=20) #decomposing of weekly data
```

```
decomposed_plot(decomposed, figure_kwargs={'figsize': (16, 10)})
plt.show()
```



- From the graphs above, every 20-step seasonality converges to beginning point. This helps us to tune my model.

To Make Data More Stationary:

- Now, we will try to make my data more stationary. To do this, we will try model with differenced, logged and shifted data.

1. Difference

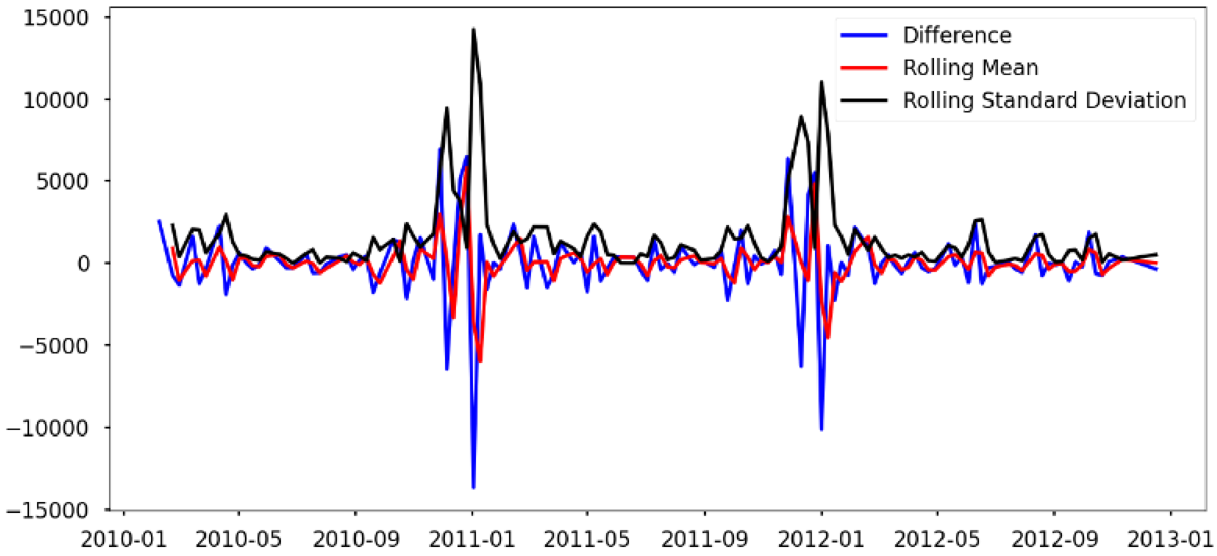
```
df_week_diff = pd.DataFrame(df_week['Weekly_Sales'].diff().dropna()) #creating difference values
```

```
df_week_diff.columns
```

```
Index(['Weekly_Sales'], dtype='object')
```

```
# taking mean and std of differenced data
diff_roll_mean = df_week_diff.rolling(window=2, center=False).mean()
diff_roll_std = df_week_diff.rolling(window=2, center=False).std()
```

```
fig, ax = plt.subplots(figsize=(13, 6))
ax.plot(df_week_diff, color='blue',label='Difference')
ax.plot(diff_roll_mean, color='red', label='Rolling Mean')
ax.plot(diff_roll_std, color='black', label='Rolling Standard Deviation')
ax.legend()
fig.tight_layout()
```

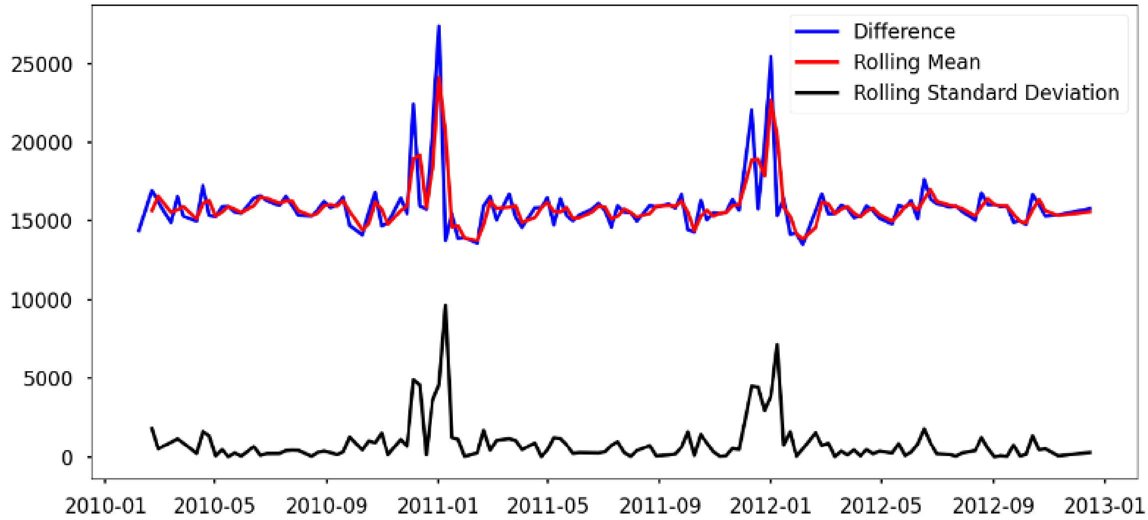


2. Shift

```
df_week_lag = df_week['Weekly_Sales'].shift().dropna() #shifting the data
```

```
lag_roll_mean = df_week_lag.rolling(window=2, center=False).mean()
lag_roll_std = df_week_lag.rolling(window=2, center=False).std()
```

```
fig, ax = plt.subplots(figsize=(13, 6))
ax.plot(df_week_lag, color='blue',label='Difference')
ax.plot(lag_roll_mean, color='red', label='Rolling Mean')
ax.plot(lag_roll_std, color='black', label='Rolling Standard Deviation')
ax.legend()
fig.tight_layout()
```

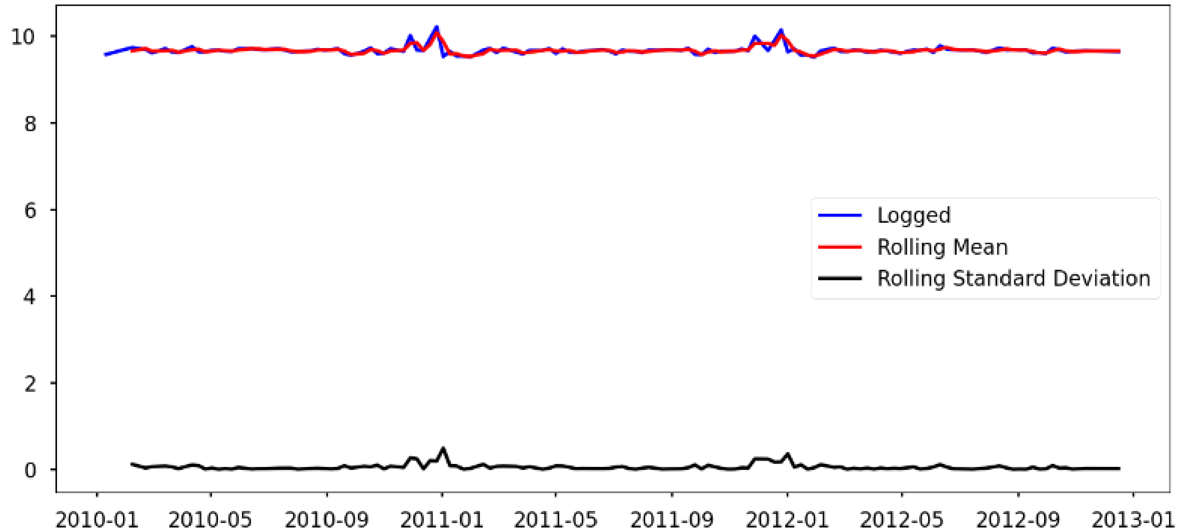


3.Log

```
logged_week = np.log1p(df_week['Weekly_Sales']).dropna() #taking log of data
```

```
log_roll_mean = logged_week.rolling(window=2, center=False).mean()
log_roll_std = logged_week.rolling(window=2, center=False).std()
```

```
fig, ax = plt.subplots(figsize=(13, 6))
ax.plot(logged_week, color='blue',label='Logged')
ax.plot(log_roll_mean, color='red', label='Rolling Mean')
ax.plot(log_roll_std, color='black', label='Rolling Standard Deviation')
ax.legend()
fig.tight_layout()
```



Auto-ARIMA MODEL:

- Tried our data without any changes, then tried with shifting, taking log and difference version of data. Differenced data gave best results. So, we decided to take difference and use this data.

```
train_data_diff = pd.DataFrame(df_week_diff[:int(0.7*(len(df_week_diff )))])
test_data_diff = pd.DataFrame(df_week_diff[int(0.7*(len(df_week_diff ))):])
```

```
df_week_diff.head()
```

Date	Weekly_Sales
2010-02-07	2543.322731
2010-02-21	-718.444287
2010-02-28	-1317.109291
2010-03-14	1628.669119
2010-03-21	-1241.445229

```
train_data = train_data_diff['Weekly_Sales']
test_data = test_data_diff['Weekly_Sales']
model = pm.auto_arima(train_data, seasonal=False, suppress_warnings=True)

# Make predictions on a test set of data
train_data = train_data[:-38] # use all but the last 30% data points for training
test_data = test_data[-38:] # use the last 30% data points for testing
y_pred1 = model.predict(n_periods=len(test_data))

# Calculate the RMSE value
mse = mean_squared_error(test_data, y_pred1)
rmse = np.sqrt(mse)
print("RMSE:", rmse)

```

```
RMSE: 963.3702668718358
```

Exponential Smoothing Model:

- Our difference data has some minus and zero values, so we used additive seasonal and trend instead of multiplicative. Seasonal periods are chosen from the decomposed graphs above. For tuning the model with iterations take too much time so, we changed and tried model for different parameters and found the best parameters and fit them to model.

```
model_holt_winters = ExponentialSmoothing(train_data, seasonal_periods=20, seasonal='additive',
                                          trend='additive',damped=True).fit() #Taking additive trend and seasonality.

# Make predictions on the test set
y_pred = model_holt_winters.forecast(len(test_data))# Predict the test data

# Calculate the RMSE value
mse = mean_squared_error(test_data, y_pred)
rmse = np.sqrt(mse)
print("RMSE:", rmse)
```

```
RMSE: 1759.180094518985
```

- At the end, we found best results for our data with **Auto ARIMA Model**.

- The best result for our data is 963 RMSE value. According to sales amounts, this value is roughly around 4-5% error. If we can take our average sales and take percentage of 963 errors, it gives 4-5% roughly.

4. Model Evaluation

RMSE is easy to understand. It serves as a heuristic for training models. It is computationally simple and easily differentiable which many optimization algorithms desire.

RMSE is the model evaluation metric which we are using in our case. As we know, RMSE is a popular evaluation metric for regression problems. Because it not only calculates how close the prediction is to the actual value on average, but it also indicates the effect of large errors. Large errors will have a major impact on the RMSE result indicating whether our prediction is close or far.

RMSE does not penalize the errors as much as MSE does due to the square root. We use RMSE more often because it is measured in the same units as the response variable. Conversely, the MSE is measured in squared units of the response variable.

RMSE is more sensitive to outliers than MAPE. MAPE returns the error as a percentage whilst RMSE is an absolute measure in the same scale as the target. RMSE can be used on any regression dataset, whilst MAPE can’t be used when the actual values are close to 0 due to the division by 0 gives error.

5. Comparison to Benchmark

Initially, we started out our project under the impression of it to be a Regression model. So, our initial benchmark was that our Linear Regression model (OLS model) is where it ends, checking the linear model assumptions like linearity, multicollinearity, no autocorrelation and others., followed by retaining just the significant features and building up regression model.

But first diversion from our initial benchmark occurred when our OLS model led towards the inference that our data is non-linear and we would further have to perform Non-Linear Regression models for the solution. At this point our speculation was that Decision Tree Regressor model would be the better fit model for our case but as a contrary we reached the solution of Random Forest Regressor being a better fit model with least RMSE value comparatively.

To improve the performance of our model, we went ahead with forecasting of weekly sales using Time-Series analysis with resampling, rolling, ADFuller test to check whether the data is stationary or not, then decomposing to observe seasonality, further going on with shifted, logged and differenced data, and followed by Auto-ARIMA model and exponential smoothing model.

We would say that we definitely improved on the benchmark

6. Implications

We have modeled the effects of holiday weeks on Weekly sales, effects of markdowns on holiday weeks from which the Retailer can gain profit through their hold on weekly sales.

Starting with managing the inventory to meet those particular forecasted sales and Retailer can manage his employment situation by looking into the needs as we also have unemployment rate as one of our features. The owner could also be able to take decisions on markdowns during specific time periods looking into its effects on sales considering the factors like promotions, campaigns, coupons etc., through which there is a positive chance for boosting of sales.

One of our main objectives is to provide recommended actions based on the insights drawn, with prioritization placed on largest business impact by analyzing both the internal and external factors. And we believe our recommendations have quite met the needs with the level of confidence of 96%.

7. Limitations

The data is very big. So, during the usage of GridSearchCV from which we find the best parameters, we had to compromise at some point because of the issue of our data being bid data.

Through the result we have obtained we can infer that, our model is still overfitting which is leading to high bias in the data

Also for analyzing the trend and pattern of the data, the availability of data became a hinge as we are provided with data of only 45 stores and with specific time bound. So, this leads to incomplete evaluation in the broader prospect

Lack of high computational resources became a key hindrance as there was only availability of basic systems with minimal RAM usage capacity. So, evaluating the data and applying other models were not possible.

Since, it is a big data, executing complex models was computationally expensive and due to this, feasibility of machine learning algorithms were hampered a bit to obtain significant results

In the case of Time Series, we expect the observations to be close to each other in the ideal situation but in real-time data such as ours, the data is pretty wide-spread. Being that the case, it led to less accurate predictability.

For the purpose of time series analysis, we had to take a small sample of the continuous data to understand and work-on because it was a difficult task to process that much of a big data which might affect our forecasting.

8. Closing Reflections

We learnt application of Time Series Analysis, critical thinking and problem-solving, technical expertise, risk management, team-work, time management in this process of learning.

As we had chosen big data, we were facing many issues with aspect to computational expense, so spending efficient time with data plays a huge role for model-building. And choosing data wisely plays a major role with things we had planned on performing analysis with.

The availability of data with efficient information with things which we are focusing on is highly needful in this case. This might lead us to a better evaluation of our model in various different aspects.

Due to lack of high computational resources, we had to face few hindrances along the way as there was only availability of basic systems with minimal RAM usage capacity. So, evaluating the data and applying other complex models were not possible from which feasibility of the machine learning algorithms were hampered a bit to obtain significant results.

These are few things which we would do differently next time.