Project - Walmart Weekly Sales Forecast

Group 11

In [1]:

```
# Importing pandas and numpy
import numpy as np
import pandas as pd
```

In [2]:

```
# Creating the dataframes using pd.read_csv()
train=pd.read_csv("https://raw.githubusercontent.com/Group11DSproject/Walmart-Sales-For
ecasting/main/train.csv")
stores=pd.read_csv("https://raw.githubusercontent.com/Group11DSproject/Walmart-Sales-Fo
recasting/main/stores.csv")
features=pd.read_csv("https://raw.githubusercontent.com/Group11DSproject/Walmart-Sales-
Forecasting/main/features.csv")
```

Displaying the datasets description

In [3]:

```
# Display the dataframe
train.head()
```

Out[3]:

	Store	Dept	Date	Weekly_Sales	IsHoliday
0	1	1	2/5/2010	24924.50	False
1	1	1	2/12/2010	46039.49	True
2	1	1	2/19/2010	41595.55	False
3	1	1	2/26/2010	19403.54	False
4	1	1	3/5/2010	21827.90	False

In [4]:

```
#Display rows and columns
train.shape
```

Out[4]:

```
(421570, 5)
```

In [5]:

```
# Column wise description
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 421570 entries, 0 to 421569
Data columns (total 5 columns):
 #   Column        Non-Null Count   Dtype  
---  ------        --------------   -----  
 0   Store         421570 non-null  int64  
 1   Dept          421570 non-null  int64  
 2   Date          421570 non-null  object 
 3   Weekly_Sales  421570 non-null  float64
 4   IsHoliday     421570 non-null  bool   
dtypes: bool(1), float64(1), int64(2), object(1)
memory usage: 13.3+ MB
```

In [6]:

```
stores.head()
```

Out[6]:

	Store	Type	Size
0	1	A	151315
1	2	A	202307
2	3	B	37392
3	4	A	205863
4	5	B	34875

In [7]:

```
stores.shape
```

Out[7]:

```
(45, 3)
```

In [8]:

```
stores.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45 entries, 0 to 44
Data columns (total 3 columns):
 #   Column  Non-Null Count  Dtype 
---  ------  --------------  ----- 
 0   Store   45 non-null     int64 
 1   Type    45 non-null     object
 2   Size    45 non-null     int64 
dtypes: int64(2), object(1)
memory usage: 1.2+ KB
```

In [9]:

```
features.head()
```

Out[9]:

	Store	Date	Temperature	Fuel_Price	MarkDown1	MarkDown2	MarkDown3	MarkDow
0	1	2/5/2010	42.31	2.572	NaN	NaN	NaN	Na
1	1	2/12/2010	38.51	2.548	NaN	NaN	NaN	Na
2	1	2/19/2010	39.93	2.514	NaN	NaN	NaN	Na
3	1	2/26/2010	46.63	2.561	NaN	NaN	NaN	Na
4	1	3/5/2010	46.50	2.625	NaN	NaN	NaN	Na

In [10]:

```
features.shape
```

Out[10]:

```
(8190, 12)
```

In [11]:

```
features.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8190 entries, 0 to 8189
Data columns (total 12 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   Store         8190 non-null   int64  
 1   Date          8190 non-null   object 
 2   Temperature   8190 non-null   float64
 3   Fuel_Price    8190 non-null   float64
 4   MarkDown1     4032 non-null   float64
 5   MarkDown2     2921 non-null   float64
 6   MarkDown3     3613 non-null   float64
 7   MarkDown4     3464 non-null   float64
 8   MarkDown5     4050 non-null   float64
 9   CPI           7605 non-null   float64
 10  Unemployment  7605 non-null   float64
 11  IsHoliday     8190 non-null   bool   
dtypes: bool(1), float64(9), int64(1), object(1)
memory usage: 712.0+ KB
```

In [12]:

```
# Checking for the null values in feature dataset
features.isnull().sum()
```

Out[12]:

```
Store              0
Date               0
Temperature        0
Fuel_Price         0
MarkDown1       4158
MarkDown2       5269
MarkDown3       4577
MarkDown4       4726
MarkDown5       4140
CPI              585
Unemployment     585
IsHoliday          0
dtype: int64
```

In [13]:

```
# Finding the median of the feature which has null values
features['CPI'].median()
```

Out[13]:

```
182.7640032
```

In [14]:

```
# Finding the mode of the feature which has null values
features['CPI'].mode()
```

Out[14]:

```
0    132.716097
dtype: float64
```

In [15]:

```
# Finding the median of the feature which has null values
features['Unemployment'].median()
```

Out[15]:

```
7.806
```

In [16]:

```
# Finding the mode of the feature which has null values
features['Unemployment'].mode()
```

Out[16]:

```
0    8.099
dtype: float64
```

In [17]:

```
# filling the missing values with mode(most repeating values)
features['CPI'].fillna(features['CPI'].mode()[0], inplace = True)
features['Unemployment'].fillna(features['Unemployment'].mode()[0],inplace=True)
```

In [18]:

```
# Displaying the Markdown1 unique number of values
features['MarkDown1'].value_counts().nunique()
```

Out[18]:

```
2
```

In [19]:

```
# Filling the missing values in Markdown 1-5 as 0
for i in range(1,6):
    features["MarkDown"+str(i)].fillna(value=0,inplace=True)
```

In [20]:

```
# Checking for null values again after filling the missing values
features.isna().sum()
```

Out[20]:

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

In [21]:

```
# Merging the [Train,Stores,Features] datasets on the Store and Date columns
df = pd.merge(train,stores,on='Store',how='left')
df = pd.merge(df,features,on=['Store','Date'],how='left')
```

In [22]:

```
# Displaying the merged dataset description
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 421570 entries, 0 to 421569
Data columns (total 17 columns):
 #   Column        Non-Null Count   Dtype  
---  ------        --------------   -----  
 0   Store         421570 non-null  int64  
 1   Dept          421570 non-null  int64  
 2   Date          421570 non-null  object 
 3   Weekly_Sales  421570 non-null  float64
 4   IsHoliday_x   421570 non-null  bool   
 5   Type          421570 non-null  object 
 6   Size          421570 non-null  int64  
 7   Temperature   421570 non-null  float64
 8   Fuel_Price    421570 non-null  float64
 9   MarkDown1     421570 non-null  float64
 10  MarkDown2     421570 non-null  float64
 11  MarkDown3     421570 non-null  float64
 12  MarkDown4     421570 non-null  float64
 13  MarkDown5     421570 non-null  float64
 14  CPI           421570 non-null  float64
 15  Unemployment  421570 non-null  float64
 16  IsHoliday_y   421570 non-null  bool   
dtypes: bool(2), float64(10), int64(3), object(2)
memory usage: 52.3+ MB
```

In [23]:

```
# Dropping duplicate column isHoliday
df.drop(['IsHoliday_y'], axis=1,inplace=True)

# Renaming the IsHoliday_x column as IsHoliday
df.rename(columns={'IsHoliday_x':'IsHoliday'},inplace=True)
df.head()
```

Out[23]:

	Store	Dept	Date	Weekly_Sales	IsHoliday	Type	Size	Temperature	Fuel_Price	M
0	1	1	2/5/2010	24924.50	False	A	151315	42.31	2.572	
1	1	1	2/12/2010	46039.49	True	A	151315	38.51	2.548	
2	1	1	2/19/2010	41595.55	False	A	151315	39.93	2.514	
3	1	1	2/26/2010	19403.54	False	A	151315	46.63	2.561	
4	1	1	3/5/2010	21827.90	False	A	151315	46.50	2.625	

In [24]:

```
# Computing the number of unique values in all the columns/features
unique_vals = {}
for col in df.columns:
    unique_vals[col] = df[col].value_counts().shape[0]

# Displaying the value counts using a dataframe
pd.DataFrame(unique_vals, index=['Value Counts']).transpose()
```

Out[24]:

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

In [25]:

```
# Displaying the mean weekly sales using store and dept wise pivot table
store_dept_pivot = pd.pivot_table(df, index='Store', columns='Dept',values='Weekly_Sale
s')

store_dept_pivot.head()
```

Out[25]:

Dept	1	2	3	4	5	6	
Store							
1	22513.322937	46102.090420	13150.478042	36964.154476	24257.941119	4801.780140	2
2	30777.980769	65912.922517	17476.563357	45607.666573	30555.315315	6808.382517	4
3	7328.621049	16841.775664	5509.300769	8434.186503	11695.366573	2012.411818	1
4	36979.940070	93639.315385	19012.491678	56603.400140	45668.406783	8241.777692	5
5	9774.553077	12317.953287	4101.085175	9860.806783	6699.202238	1191.057622	

5 rows × 81 columns

In [26]:

```
# Checking for the negative weekly sales if any (Sales cannot be negative so dropping)
neg_weekly_sales = df.loc[df['Weekly_Sales']<=0]
neg_weekly_sales.shape
```

Out[26]:

```
(1358, 16)
```

We can see there are 1358 rows out of 421570 rows where weekly sales are negative, So we can drop them

In [27]:

```
# Dropping the rows with negative weekly sales
df = df.loc[df['Weekly_Sales'] > 0]
df.shape
```

Out[27]:

```
(420212, 16)
```

In [28]:

```
# Changing the date column into datetime data type
df['Date'] = pd.to_datetime(df['Date'],errors='coerce')

# Because it is a weekly sales data, We sort the dataset using the datetime
df.sort_values(by=['Date'],inplace=True)
df.reset_index(inplace = True)
df.drop("index", inplace = True, axis = 1)
df.index = np.arange(1, len(df) + 1)
```

In [29]:

```
# Displaying the date column
df['Date']
```

Out[29]:

```
1         2010-02-05
2         2010-02-05
3         2010-02-05
4         2010-02-05
5         2010-02-05
             ...
420208    2012-10-26
420209    2012-10-26
420210    2012-10-26
420211    2012-10-26
420212    2012-10-26
Name: Date, Length: 420212, dtype: datetime64[ns]
```

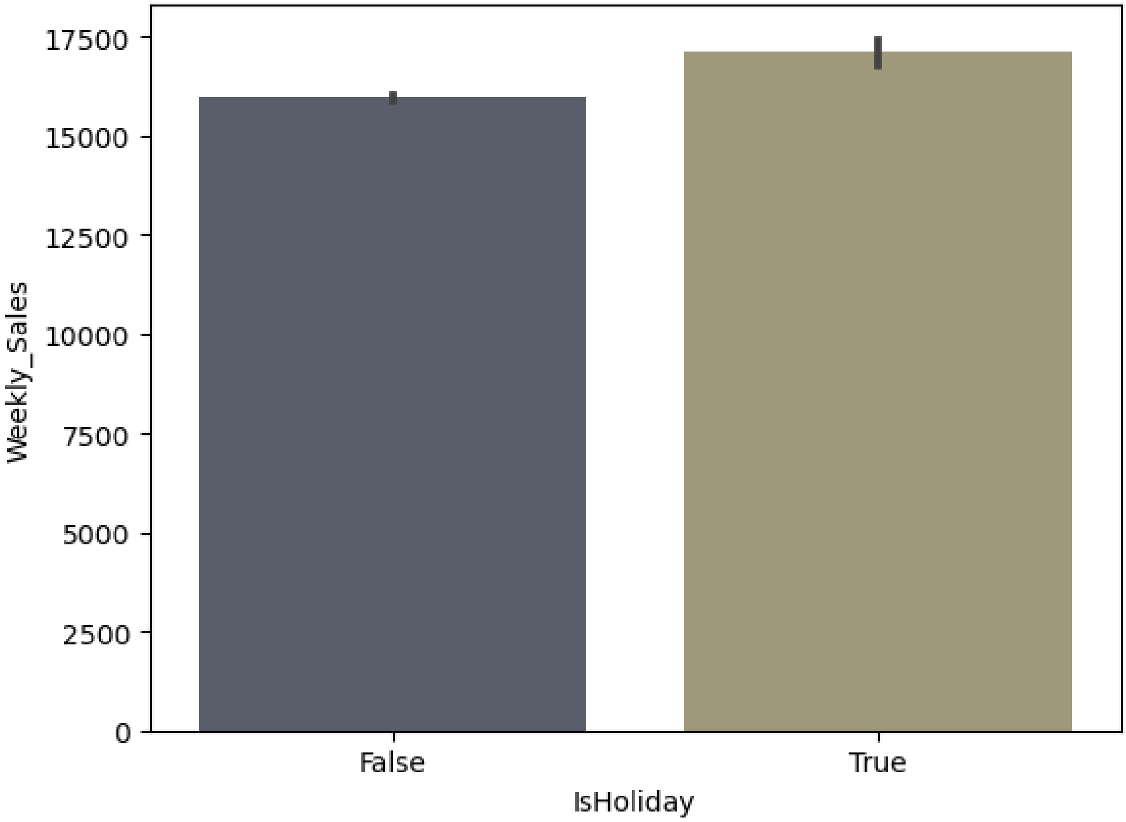
Visualization of the Data

In [30]:

```
# importing the visualization libraries
import seaborn as sns
import matplotlib.pyplot as plt

%matplotlib inline
```

In [31]:

```
# Barplot to see the weekly sales on Holiday and Non Holiday week
sns.barplot(x='IsHoliday', y='Weekly_Sales', data=df, palette="cividis" )
plt.savefig("Holiday_Sales.png")
```



In [32]:

```
# Checking for the number of holiday weeks in the dataset
holiday = df.loc[df['IsHoliday']==True]
print("Number of Holiday Weeks are: " + str(holiday['Date'].nunique()))
```

```
Number of Holiday Weeks are: 10
```

In [33]:

```
# Checking for the number of Non-holiday weeks in the dataset
non_holiday = df.loc[df['IsHoliday']==False]
print("Number of Non-Holiday Weeks are: " + str(non_holiday['Date'].nunique()))
```

```
Number of Non-Holiday Weeks are: 133
```

In [34]:

```
# Displaying the holiday weeks

holiday["Date"].dt.date.unique()
```

Out[34]:

```
array([datetime.date(2010, 2, 12), datetime.date(2010, 9, 10),
       datetime.date(2010, 11, 26), datetime.date(2010, 12, 31),
       datetime.date(2011, 2, 11), datetime.date(2011, 9, 9),
       datetime.date(2011, 11, 25), datetime.date(2011, 12, 30),
       datetime.date(2012, 2, 10), datetime.date(2012, 9, 7)],
      dtype=object)
```

Creating a new columns for the holiday weeks as they are one of the important factors

In [35]:

```
# Creating Christmas holiday column for the below dates
df.loc[(df['Date'] == '2010-12-31')|(df['Date'] == '2011-12-30'),'Christmas'] = True
df.loc[(df['Date'] != '2010-12-31')&(df['Date'] != '2011-12-30'),'Christmas'] = False
```

In [36]:

```
# Creating Labor Day holiday column for the below dates
df.loc[(df['Date'] == '2010-09-10')|(df['Date'] == '2011-09-09')|(df['Date'] == '2012-0
9-07'),'Labor_Day'] = True
df.loc[(df['Date'] != '2010-09-10')&(df['Date'] != '2011-09-09')&(df['Date'] != '2012-0
9-07'),'Labor_Day'] = False
```

In [37]:

```
# Creating Super Bowl holiday column for the below dates
df.loc[(df['Date'] == '2010-02-12')|(df['Date'] == '2011-02-11')|(df['Date'] == '2012-0
2-10'),'Super_Bowl'] = True
df.loc[(df['Date'] != '2010-02-12')&(df['Date'] != '2011-02-11')&(df['Date'] != '2012-0
2-10'),'Super_Bowl'] = False
```

In [38]:

```
# Creating Thanksgiving holiday column for the below dates
df.loc[(df['Date'] == '2010-11-26')|(df['Date'] == '2011-11-25'),'Thanksgiving'] = True
df.loc[(df['Date'] != '2010-11-26')&(df['Date'] != '2011-11-25'),'Thanksgiving'] = Fals
e
```

In [39]:

```
# Adding the week,month and year columns using the datetime function
df['week'] = df['Date'].dt.week
df['month'] = df['Date'].dt.month
df['year'] = df['Date'].dt.year
```

In [40]:

```
# Displaying the dataset after doing the above changes
df.head()
```

Out[40]:

	Store	Dept	Date	Weekly_Sales	IsHoliday	Type	Size	Temperature	Fuel_Price	Mark
1	1	1	2010-02-05	24924.50	False	A	151315	42.31	2.572	
2	15	21	2010-02-05	3253.19	False	B	123737	19.83	2.954	
3	15	20	2010-02-05	4606.90	False	B	123737	19.83	2.954	
4	15	19	2010-02-05	1381.40	False	B	123737	19.83	2.954	
5	15	18	2010-02-05	2239.25	False	B	123737	19.83	2.954	

5 rows × 23 columns

In [41]:

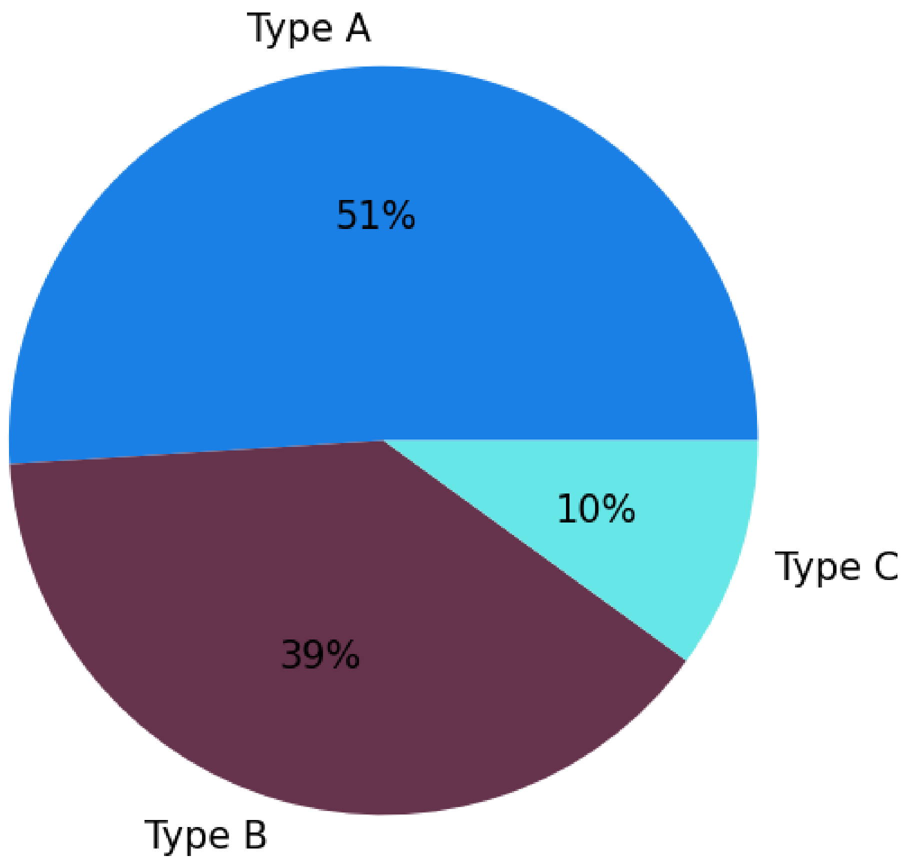
```
# Comparing Store Types and computing their percentage
type_per = df['Type'].value_counts()
type_per = round(type_per/type_per.sum() * 100)
percentage_type = list(type_per)

# Types of Stores
type_per.index
```

Out[41]:

```
Index(['A', 'B', 'C'], dtype='object')
```

In [42]:

```
# Displaying the Percentages for each store type
type_labels = 'Type A','Type B', 'Type C' # labels
plt.figure(figsize=(8,6))
plt.pie(percentage_type, labels=type_labels, autopct='%1.0f%%', textprops={'fontsize':
15}, colors= [[0.1,0.5,0.9],[0.4,0.2,0.3],[0.4,0.9,0.9]] ) #plot pie type and bigger th
e labels
plt.axis('equal')
plt.savefig("Store_Types.png")
plt.show()
```



In [43]:

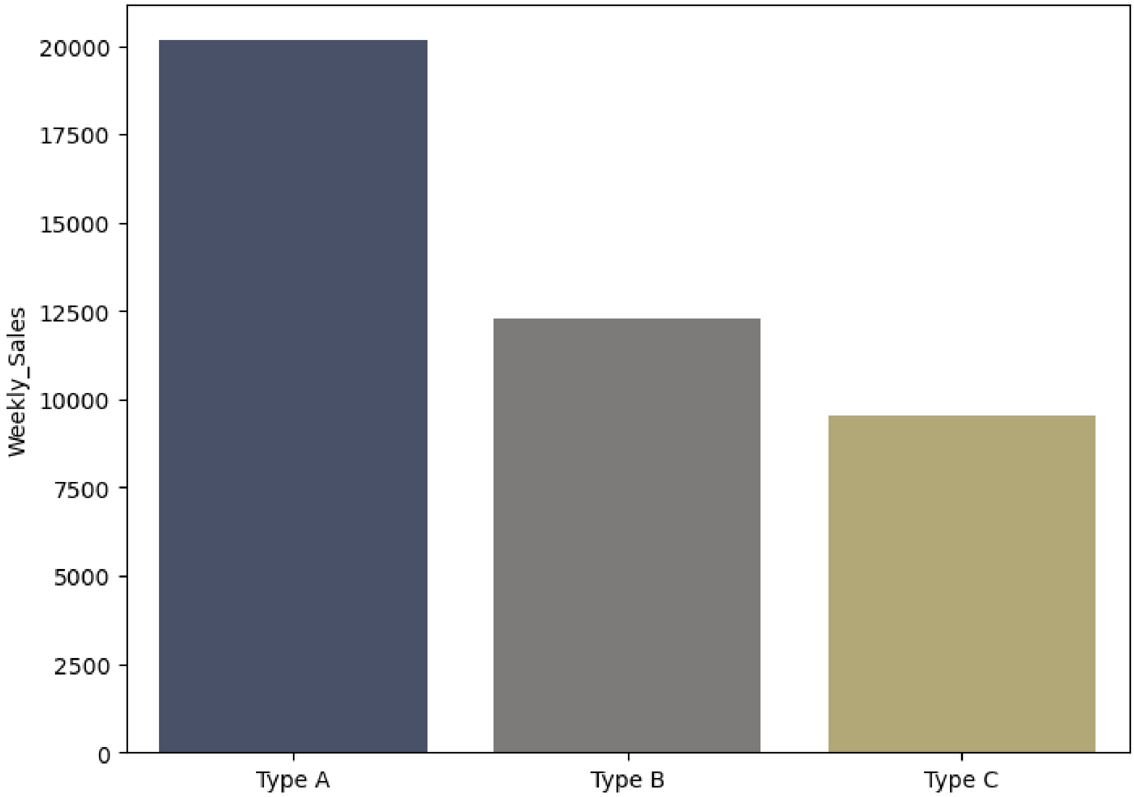
```
# Average weekly sales for each type of stores
df.groupby("Type")["Weekly_Sales"].mean()
weekly_sales = df.groupby("Type")["Weekly_Sales"].mean()
weekly_sales
```

Out[43]:

```
Type
A    20148.108162
B    12290.549297
C     9549.454168
Name: Weekly_Sales, dtype: float64
```

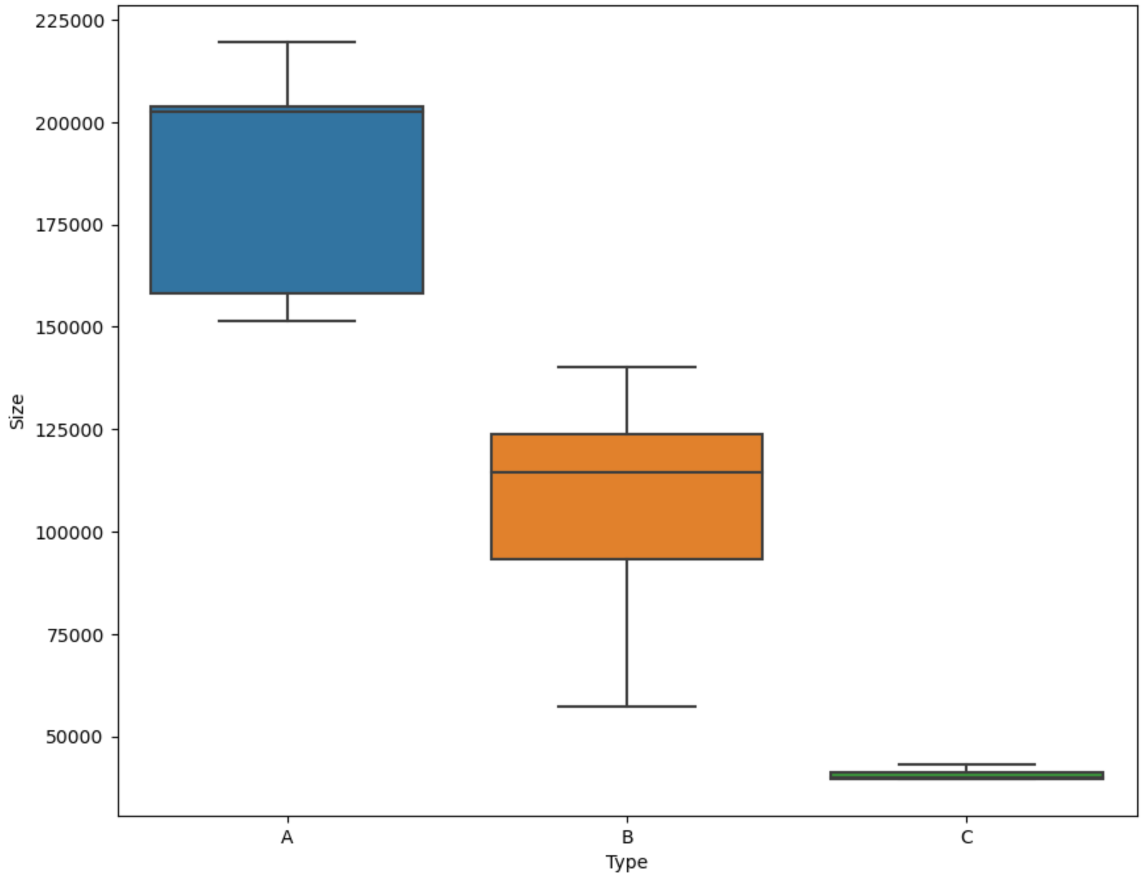
In [44]:

```
# Visulaizing the average weekly sales for Types of stores
plt.figure(figsize=(8,6))
fig = sns.barplot(x=["Type A", "Type B", "Type C"], y = weekly_sales, palette="cividis"
)
plt.savefig("Type_Sales.png")
```



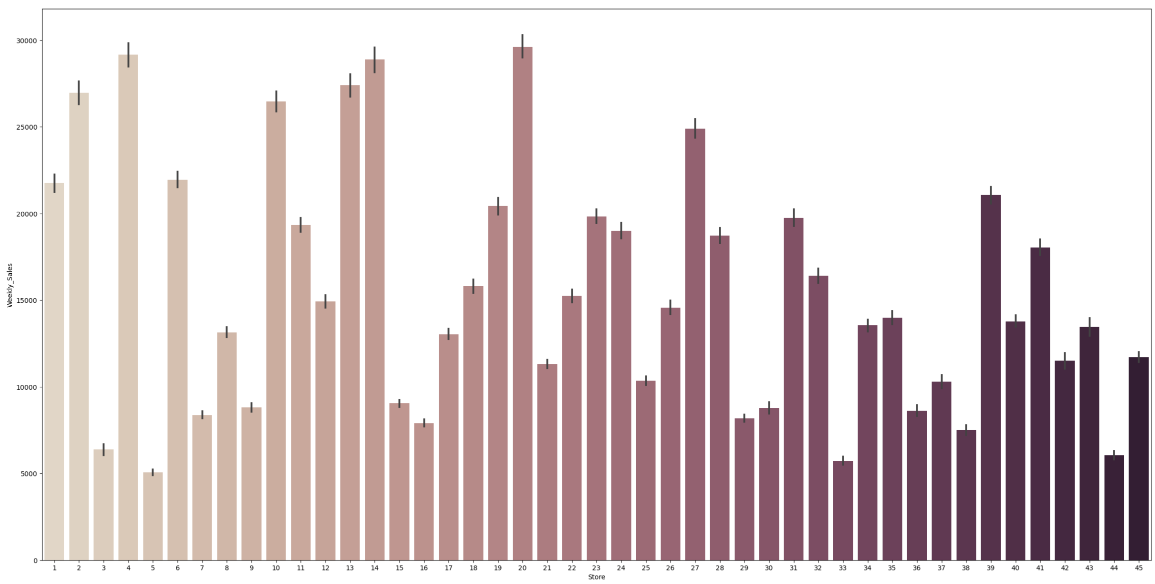
In [45]:

```
# Visulaizing the Type and Size columns relation
plt.figure(figsize=(10,8))
fig = sns.boxplot(x='Type', y='Size', data=df, showfliers=False)
plt.savefig("Type_Size.png")
```



In [46]:

```
# Visualizing the Store wise Weekly sales
plt.figure(figsize=(30,15))
fig = sns.barplot(x='Store', y='Weekly_Sales', data=df, palette="ch:.25")
plt.savefig("Store_Sales.png")
```

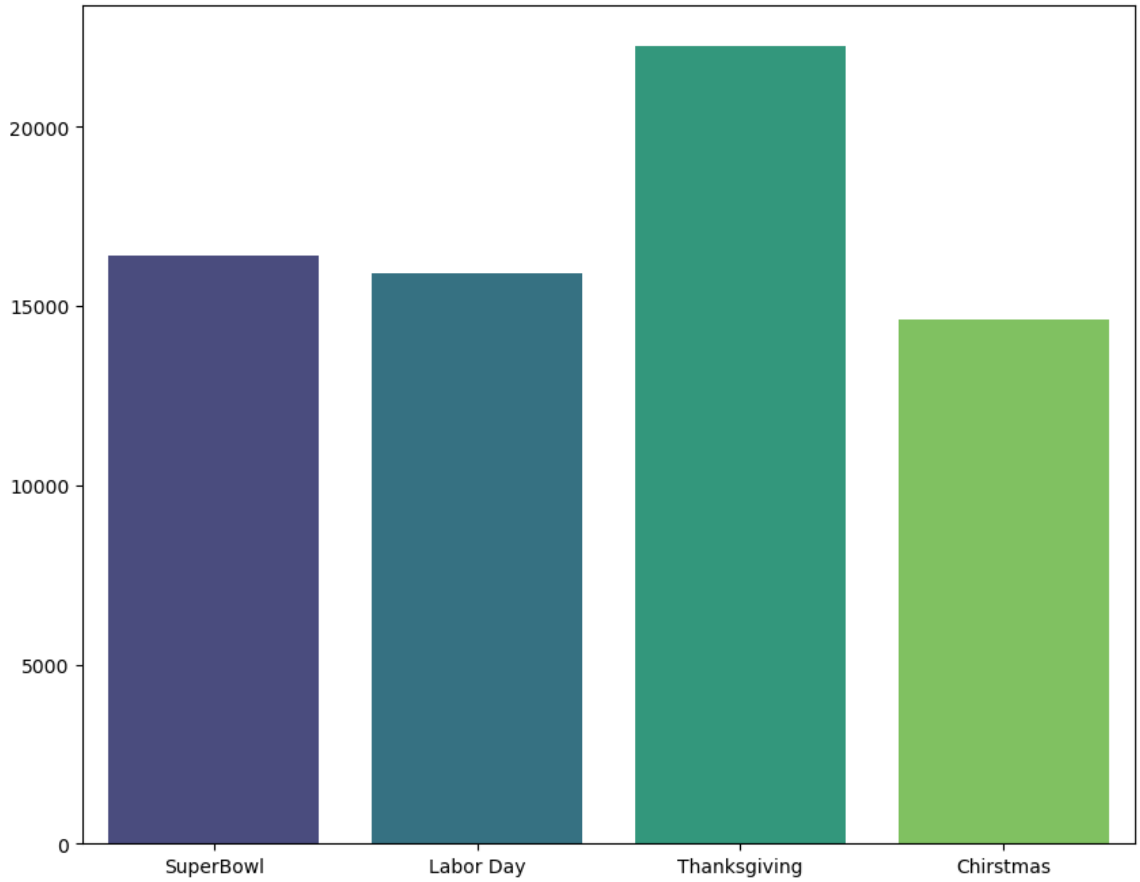


In [47]:

```
# Calculating the average weekly sales on each holiday week
hol_1 = round(df.groupby("Super_Bowl")["Weekly_Sales"].mean()[1])
hol_2 = round(df.groupby("Labor_Day")["Weekly_Sales"].mean()[1])
hol_3 = round(df.groupby("Thanksgiving")["Weekly_Sales"].mean()[1])
hol_4 = round(df.groupby("Christmas")["Weekly_Sales"].mean()[1])

holiday_sales = [hol_1,hol_2,hol_3,hol_4]
```

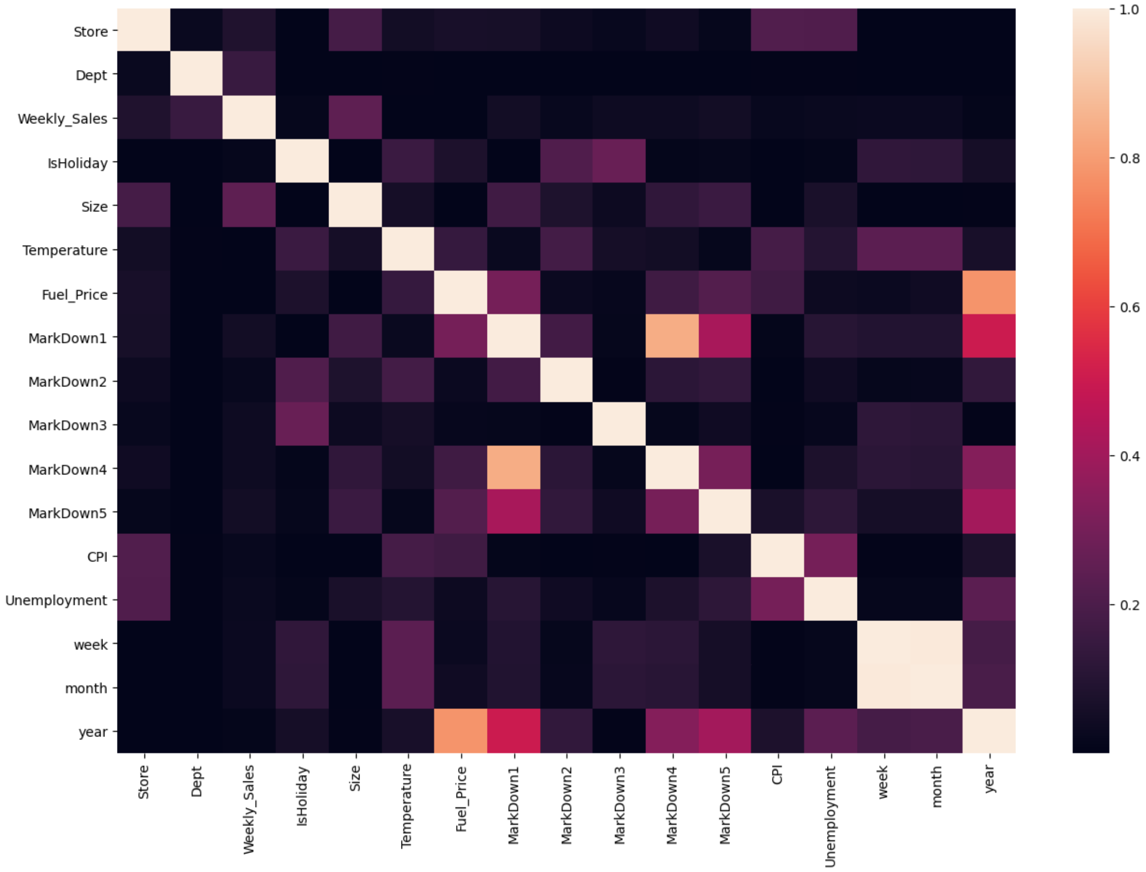
In [48]:

```
# Visualzing the average weekly sales on each holiday week
plt.figure(figsize=(10,8))
fig = sns.barplot(x=["SuperBowl", "Labor Day", "Thanksgiving", "Chirstmas"], y=holiday_
sales, palette="viridis")
plt.savefig("Holiday_Sales.png")
```



In [49]:

```
# Correlations between different features using the heatmap
plt.figure(figsize = (15,10))
sns.heatmap(df.corr().abs())
plt.savefig("Correlation.png")
plt.show()
```



In [50]:

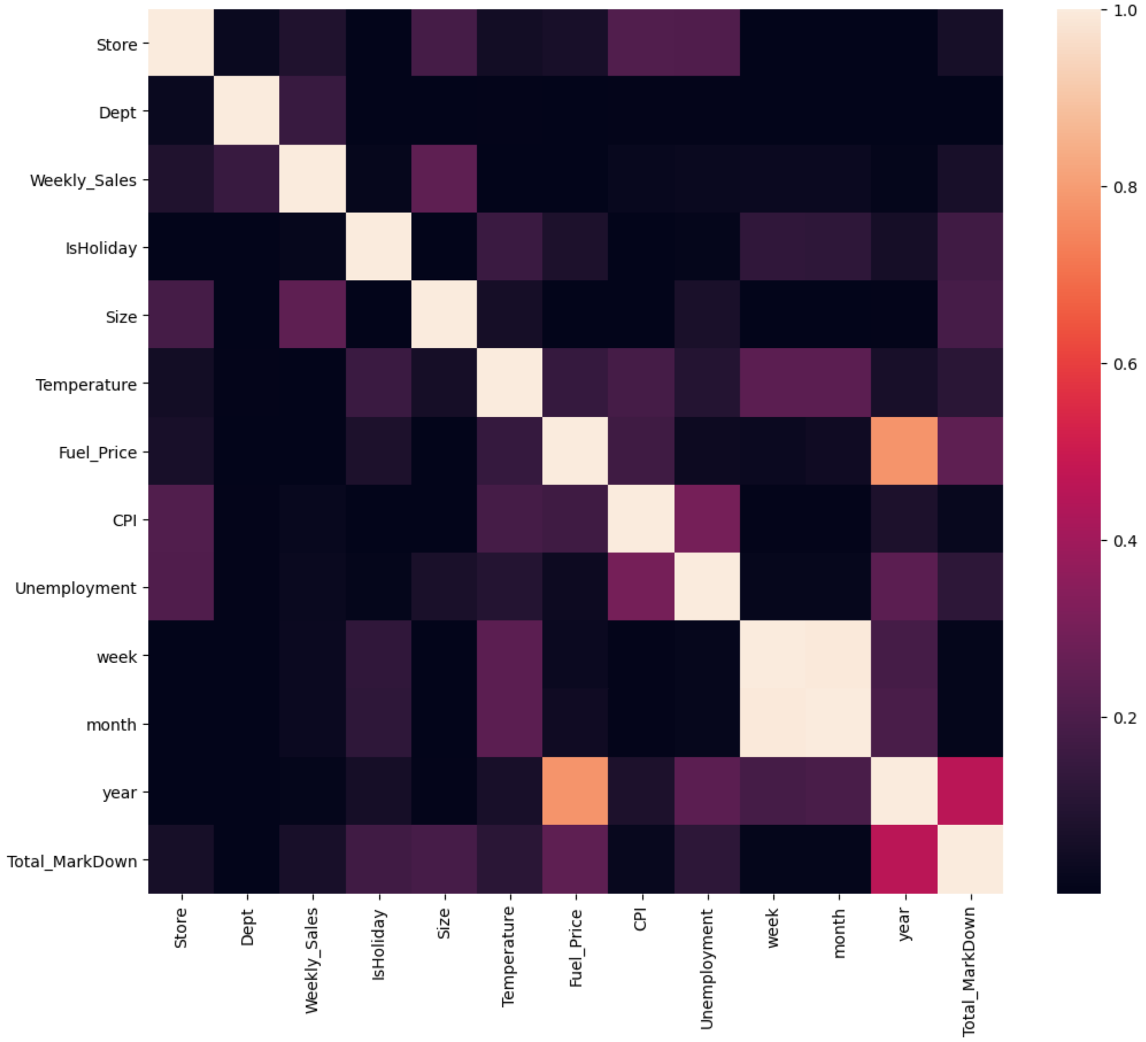
```
# Markdown Data are correlated to each other hence combining all the Markdown Data
df['Total_MarkDown'] = df['MarkDown1'] + df['MarkDown2'] + df['MarkDown3'] + df['MarkDo
wn4'] + df['MarkDown5']
df.drop(['MarkDown1','MarkDown2','MarkDown3','MarkDown4','MarkDown5'], axis = 1,inplace
=True)
df.head()
```

Out[50]:

	Store	Dept	Date	Weekly_Sales	IsHoliday	Type	Size	Temperature	Fuel_Price	
1	1	1	2010-02-05	24924.50	False	A	151315	42.31	2.572	211.0
2	15	21	2010-02-05	3253.19	False	B	123737	19.83	2.954	131.5
3	15	20	2010-02-05	4606.90	False	B	123737	19.83	2.954	131.5
4	15	19	2010-02-05	1381.40	False	B	123737	19.83	2.954	131.5
5	15	18	2010-02-05	2239.25	False	B	123737	19.83	2.954	131.5

In [51]:

```
# Checking the corrleation again after dropping the markdown columns
plt.figure(figsize = (12,10))
sns.heatmap(df.corr().abs())
plt.savefig("Correlation_2.png")
plt.show()
```



We can see that the year and Fuel Price are highly correlated

In [52]:

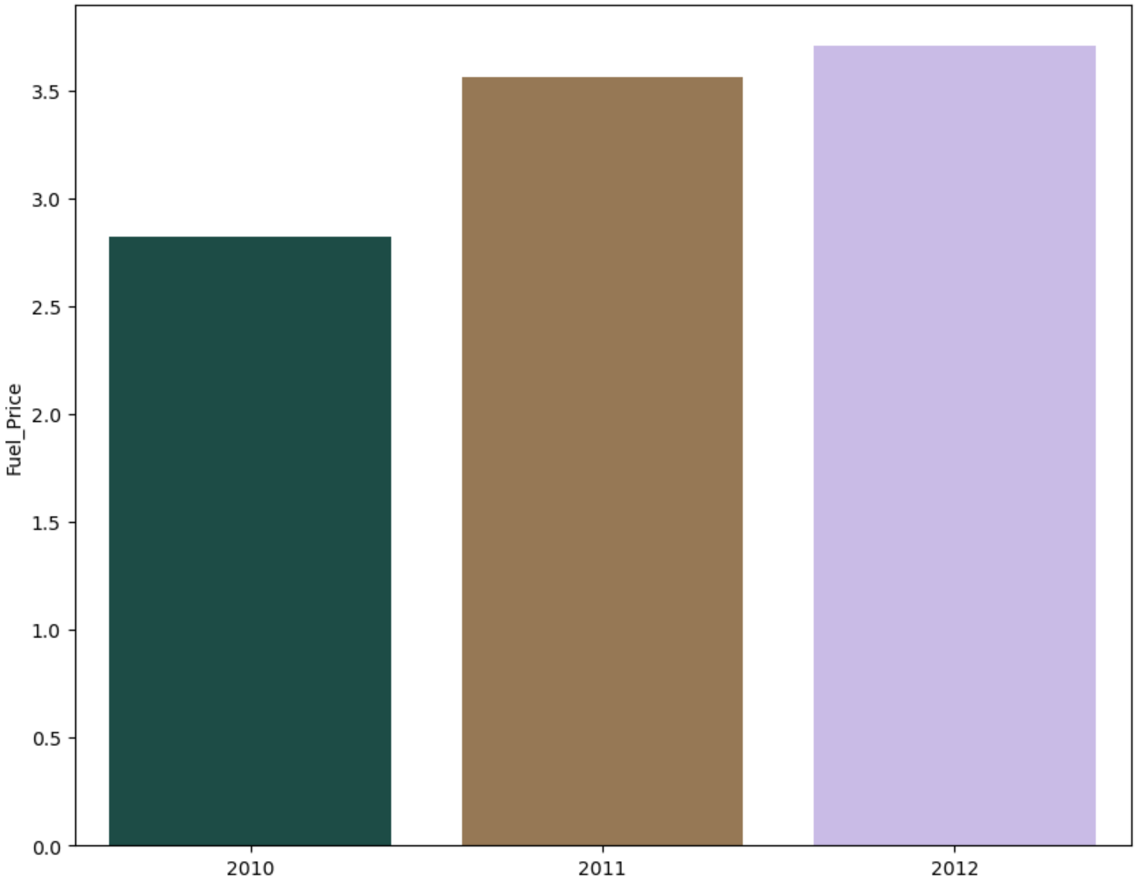
```
# Calculating the average fuel price for different years
year_fuel = df.groupby("year")['Fuel_Price'].mean()
year_fuel
```

Out[52]:

```
year
2010    2.823799
2011    3.563293
2012    3.710311
Name: Fuel_Price, dtype: float64
```

In [53]:

```
# Visualzing the average fuel price for different years
plt.figure(figsize=(10,8))
fig = sns.barplot(x=["2010","2011", "2012"], y=year_fuel, palette="cubehelix")
plt.savefig("Fuel_Price.png")
```



One-Hot Encoding on below catergorical features

In [54]:

```
# Storing the caterogical and numerical features for further processing
categorical_features = ["Type", "Christmas", "Labor_Day", "Super_Bowl","Thanksgivin
g","IsHoliday"]
numerical_features = df.select_dtypes(exclude = ["object", "bool"])
```

In [55]:

```
# Displaying the numercial Features
numerical_features
```

Out[55]:

	Store	Dept	Date	Weekly_Sales	Size	Temperature	Fuel_Price	CPI	Une
1	1	1	2010-02-05	24924.50	151315	42.31	2.572	211.096358	
2	15	21	2010-02-05	3253.19	123737	19.83	2.954	131.527903	
3	15	20	2010-02-05	4606.90	123737	19.83	2.954	131.527903	
4	15	19	2010-02-05	1381.40	123737	19.83	2.954	131.527903	
5	15	18	2010-02-05	2239.25	123737	19.83	2.954	131.527903	
...	...	...	...	...	...	...	...	...	
420208	18	52	2012-10-26	2226.10	120653	56.09	3.917	138.728161	
420209	36	16	2012-10-26	564.50	39910	74.39	3.494	222.113657	
420210	41	92	2012-10-26	131128.24	196321	41.80	3.686	199.219532	
420211	18	81	2012-10-26	14036.52	120653	56.09	3.917	138.728161	
420212	45	98	2012-10-26	1076.80	118221	58.85	3.882	192.308899	

420212 rows × 13 columns

In [56]:

```
# Performing the one hot encoding on categorical features
cat_feature_matrix = pd.get_dummies(df[categorical_features], columns = categorical_fea
tures,  drop_first = True)
cat_feature_matrix.head()
```

Out[56]:

	Type_B	Type_C	Christmas_True	Labor_Day_True	Super_Bowl_True	Thanksgiving_True	I
1	0	0	0	0	0	0	
2	1	0	0	0	0	0	
3	1	0	0	0	0	0	
4	1	0	0	0	0	0	
5	1	0	0	0	0	0	

In [57]:

```
# Concatinating the numerical and categorical Data
df_cleaned = pd.concat([numerical_features, cat_feature_matrix],axis=1)
df_cleaned.head()
```

Out[57]:

	Store	Dept	Date	Weekly_Sales	Size	Temperature	Fuel_Price	CPI	Unemploy
1	1	1	2010-02-05	24924.50	151315	42.31	2.572	211.096358	
2	15	21	2010-02-05	3253.19	123737	19.83	2.954	131.527903	
3	15	20	2010-02-05	4606.90	123737	19.83	2.954	131.527903	
4	15	19	2010-02-05	1381.40	123737	19.83	2.954	131.527903	
5	15	18	2010-02-05	2239.25	123737	19.83	2.954	131.527903	

Model Training and Predictions

In [58]:

```
# Because this is a weekly data which contains the datetime, We cannot randomly split t
he data
# We have to manually split the data into training and testing

# taking 0.75 percent data as training data
df_train = df_cleaned[:int(0.75*(len(df_cleaned)))]

# taking 0.25 percent data as testing data
df_test = df_cleaned[int(0.75*(len(df_cleaned))):]
```

In [59]:

```
# Splitting the data into X features and Y labels

# In the time_series data, We should drop the date column as we already have the week,
month and year as columns
# and drop labels(weekly sales) during training the model

X_train = df_train.drop(["Weekly_Sales", "Date"], axis = 1)
X_test =  df_test.drop(["Weekly_Sales", "Date"], axis = 1)
y_train = df_train['Weekly_Sales']
y_test = df_test['Weekly_Sales']
```

In [60]:

```
# Importing all the major regression models and metrics
import xgboost
from sklearn.ensemble import RandomForestRegressor
from sklearn.svm import SVR
from sklearn.tree import DecisionTreeRegressor
from sklearn.neighbors import KNeighborsRegressor
from sklearn.linear_model import Lasso, LinearRegression
from sklearn.metrics import mean_squared_error, mean_absolute_error, explained_variance
_score
from sklearn.pipeline import make_pipeline, Pipeline
from sklearn.preprocessing import RobustScaler
```

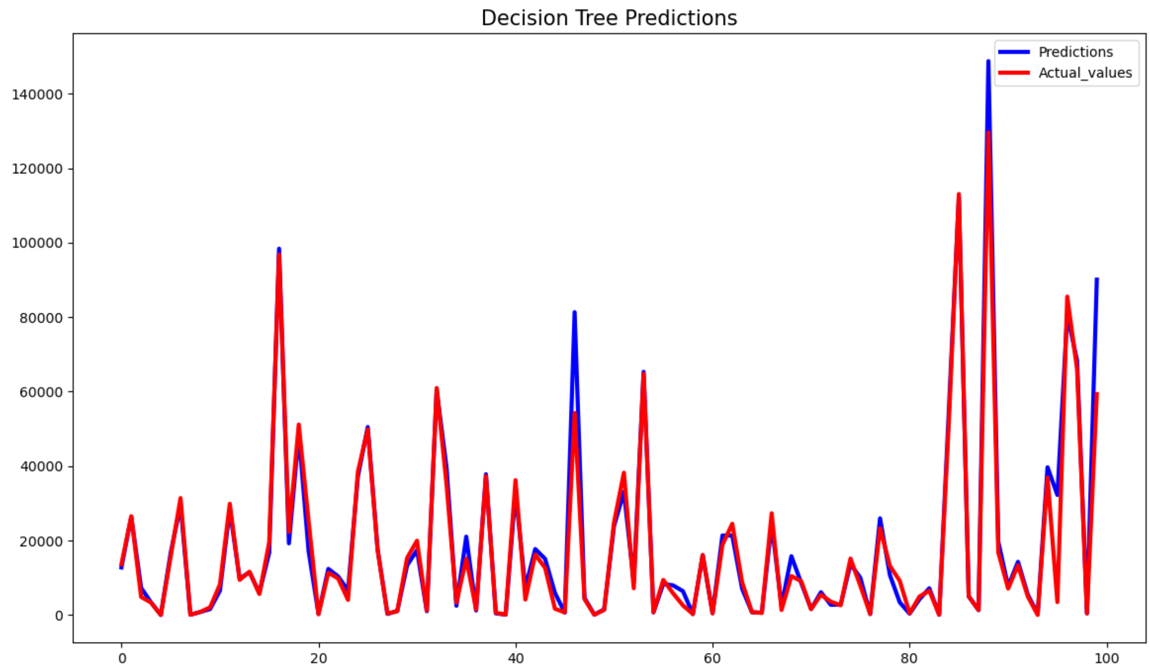
In [61]:

```
# Training and testing on the DecisionTree
dt = DecisionTreeRegressor()

model_1 = dt.fit(X_train, y_train)

y_pred_1 = model_1.predict(X_test)

mae_1 = mean_absolute_error(y_test, y_pred_1)
r2_score_1 = explained_variance_score(y_test, y_pred_1)

print("MAE" , mae_1)
print("R2" , r2_score_1)
```

```
MAE 2645.063044177701
R2 0.9283001650788607
```

In [62]:

```
# Visulaizing the decision tree predictions vs actual values
plt.figure(figsize=(14,8))
plt.title('Decision Tree Predictions', fontsize=15)
plt.plot(y_pred_1[:100], label="Predictions", linewidth=3.0,color='blue')
plt.plot(y_test[:100].values, label ="Actual_values", linewidth=3.0,color='red')
plt.legend(loc="best")
plt.savefig('Decision_tree.png')
plt.show()
```



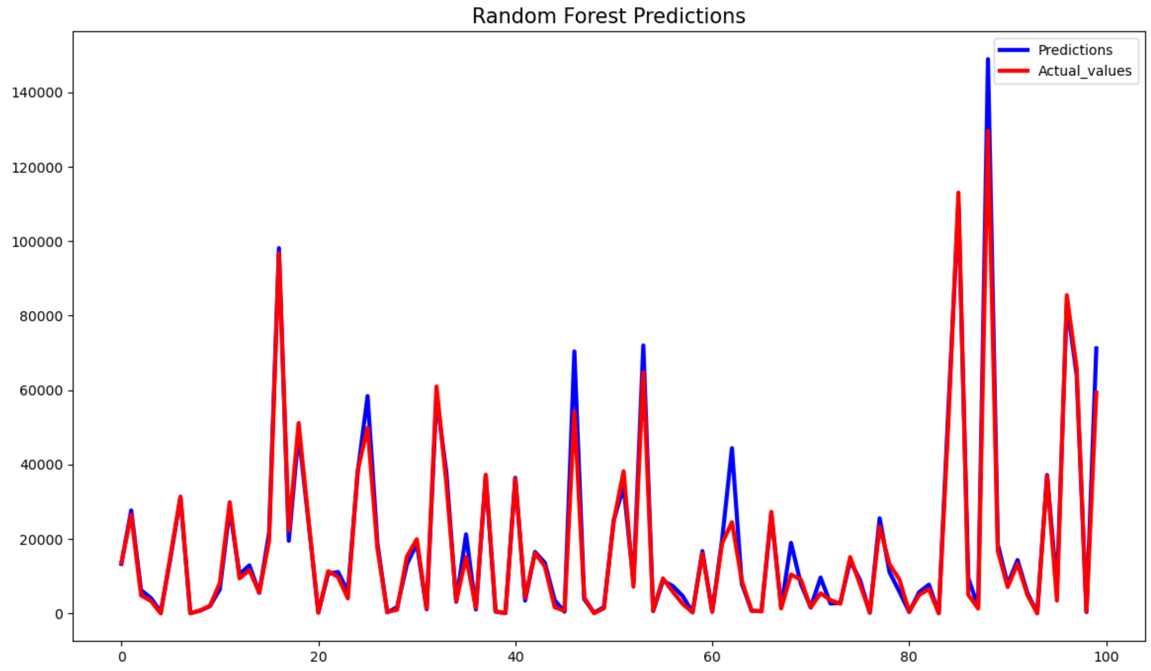
In [63]:

```
# Training and testing on Random Forest
rf_model2 = RandomForestRegressor()

model_2 = rf_model2.fit(X_train , y_train)
y_pred_2 = model_2.predict(X_test)


mae_2 = mean_absolute_error(y_test, y_pred_2)
r2_score_2 = explained_variance_score(y_test, y_pred_2)
print("MAE" , mae_2)
print("R2" , r2_score_2)
```

```
MAE 2045.4906577898778
R2 0.9598011097896455
```

In [64]:

```
# Visulaizing the Random Forest predictions vs actual values
plt.figure(figsize=(14,8))
plt.title('Random Forest Predictions', fontsize=15)
plt.plot(y_pred_2[:100], label="Predictions", linewidth=3.0,color='blue')
plt.plot(y_test[:100].values, label ="Actual_values", linewidth=3.0,color='red')
plt.legend(loc="best")
plt.savefig('Random_Forest.png')
plt.show()
```



In [65]:

```
# Making the feature selection using randomforest feature importance
imp_features = model_2.feature_importances_
```

In [66]:

```
# Displaying the feature importance by their rank
indices = np.argsort(imp_features)[::-1]
feature_rank = pd.DataFrame(columns = ['Rank', 'Feature', 'Importance'])

for f in range(X_train.shape[1]):
    feature_rank.loc[f] = [f+1,
                           X_train.columns[indices[f]],
                           imp_features[indices[f]]]

feature_rank
```

Out[66]:

	Rank	Feature	Importance
0	1	Dept	0.614246
1	2	Size	0.197226
2	3	Store	0.051854
3	4	week	0.032260
4	5	CPI	0.030696
5	6	Thanksgiving_True	0.021075
6	7	Unemployment	0.013549
7	8	Temperature	0.012150
8	9	Type_B	0.011104
9	10	Fuel_Price	0.005976
10	11	Total_MarkDown	0.002466
11	12	month	0.002287
12	13	Christmas_True	0.001781
13	14	Type_C	0.001498
14	15	IsHoliday_True	0.001145
15	16	year	0.000372
16	17	Super_Bowl_True	0.000182
17	18	Labor_Day_True	0.000133

In [67]:

```
# Dropping the columns which has less importance
drop_cols = ["Super_Bowl_True", "Labor_Day_True", "year", "IsHoliday_True"]
X_train_2 = X_train.drop(drop_cols, axis = 1)
X_test_2 = X_test.drop(drop_cols, axis = 1)
```

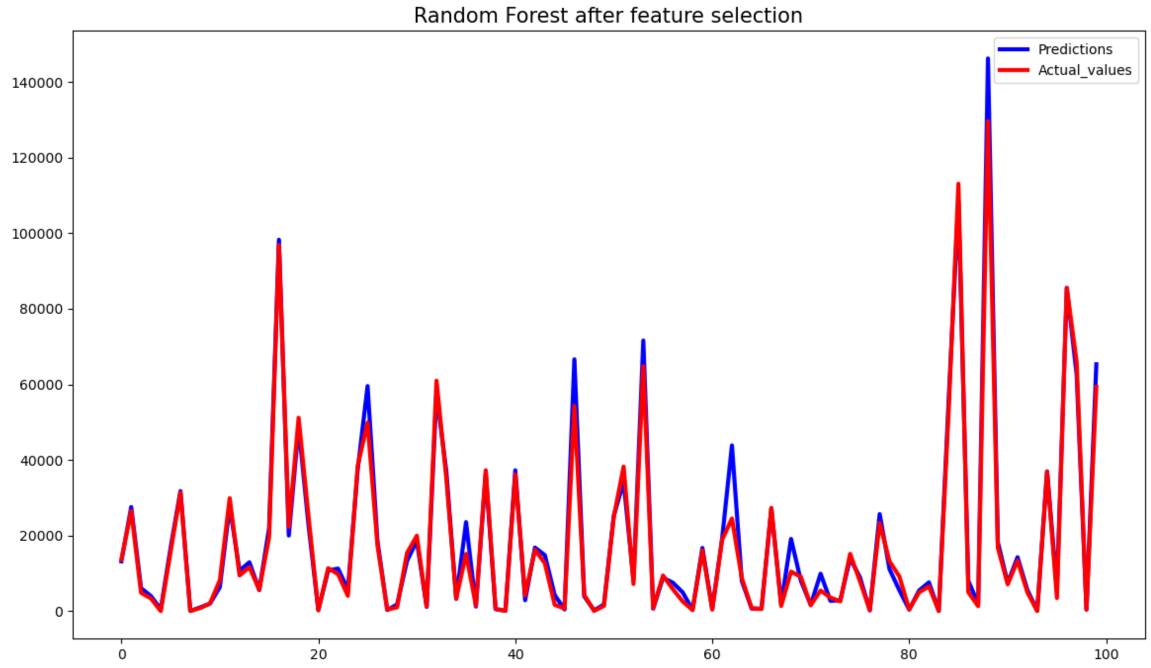
In [68]:

```
# Again training the randomforest model using the feature selection technique
rf_model3 = RandomForestRegressor()

model_3 = rf_model3.fit(X_train_2 , y_train)

y_pred_3 = model_3.predict(X_test_2)


mae_3 = mean_absolute_error(y_test, y_pred_3)
r2_score_3 = explained_variance_score(y_test, y_pred_3)
print("MAE" , mae_3)
print("R2" , r2_score_3)
```

```
MAE 2053.1048384710575
R2 0.95932711288045
```

In [69]:

```
# Visualizing the random forest predcitions after feature selection
plt.figure(figsize=(14,8))
plt.title('Random Forest after feature selection', fontsize=15)
plt.plot(y_pred_3[:100], label="Predictions", linewidth=3.0,color='blue')
plt.plot(y_test[:100].values, label ="Actual_values", linewidth=3.0,color='red')
plt.legend(loc="best")
plt.savefig('Random_feat_selections.png')
plt.show()
```



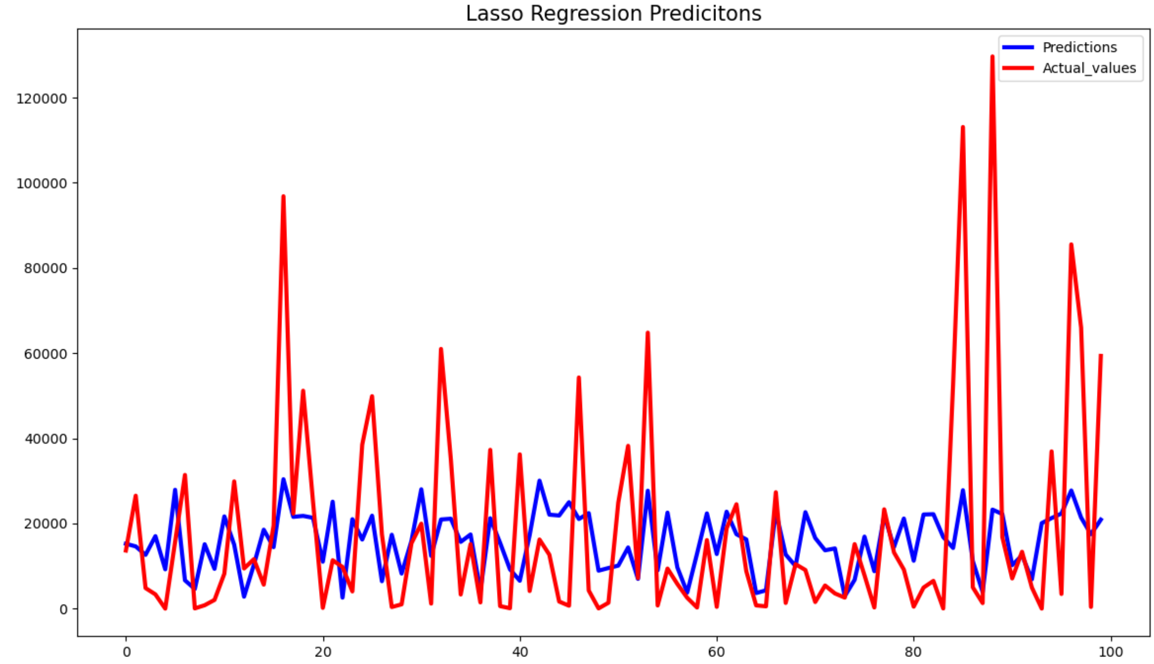
In [70]:

```
# Training the lasso regression model
lasso_model = Lasso()

model_4 = lasso_model.fit(X_train,y_train)

y_pred_4 = model_4.predict(X_test)

mae_4 = mean_absolute_error(y_test, y_pred_4)
r2_score_4 = explained_variance_score(y_test, y_pred_4)
print("MAE" , mae_4)
print("R2" , r2_score_4)
```

```
MAE 14356.493220411616
R2 0.09546175276116087

C:\Users\zuddi\anaconda3\lib\site-packages\sklearn\linear_model\_coordinat
e_descent.py:529: ConvergenceWarning: Objective did not converge. You migh
t want to increase the number of iterations. Duality gap: 39826551473445.2
5, tolerance: 16589045554.893476
  model = cd_fast.enet_coordinate_descent(
```

In [71]:

```
# Visulaizing the Lasso Reggresion predictions vs actual values
plt.figure(figsize=(14,8))
plt.title('Lasso Regression Predicitons', fontsize=15)
plt.plot(y_pred_4[:100], label="Predictions", linewidth=3.0,color='blue')
plt.plot(y_test[:100].values, label ="Actual_values", linewidth=3.0,color='red')
plt.legend(loc="best")
plt.savefig('model_4.png')
plt.show()
```



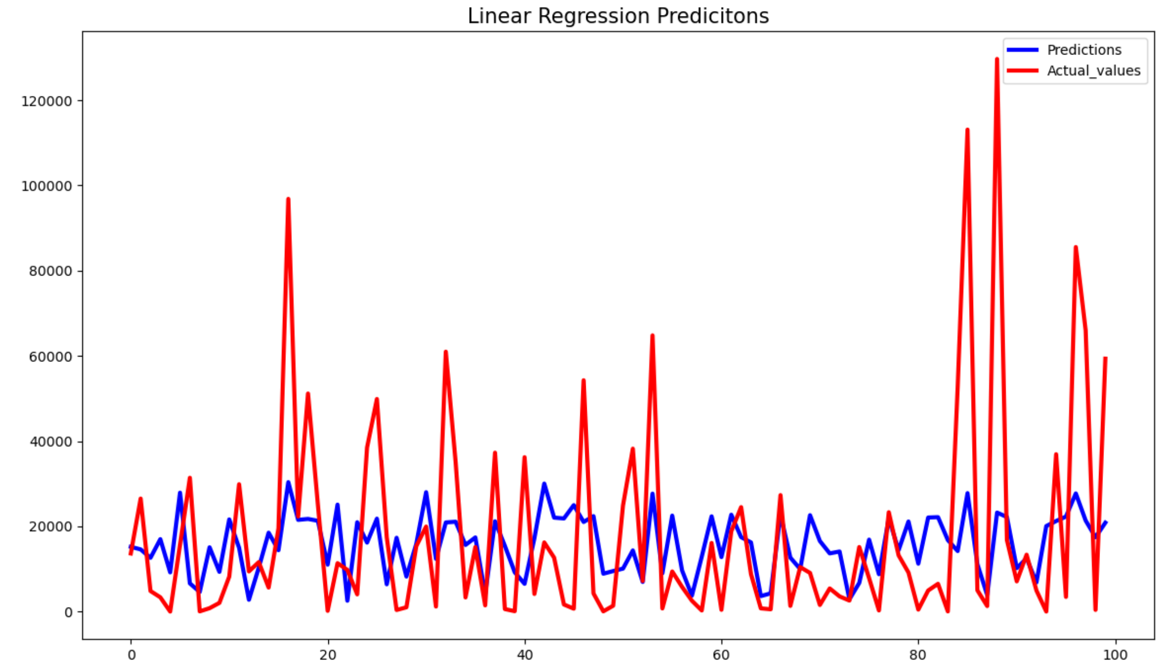
In [72]:

```
# Training the linear regression model
lr = LinearRegression()
model_5 = lr.fit(X_train, y_train)

y_pred_5 = model_5.predict(X_test)

mae_5 = mean_absolute_error(y_test, y_pred_5)
r2_score_5 = explained_variance_score(y_test, y_pred_5)
print("MAE" , mae_5)
print("R2" , r2_score_5)
```

```
MAE 14351.700683306091
R2 0.09546418942812318
```

In [73]:

```
# Visulaizing the Linear regression predictions vs actual values
plt.figure(figsize=(14,8))
plt.title('Linear Regression Predicitons', fontsize=15)
plt.plot(y_pred_5[:100], label="Predictions", linewidth=3.0,color='blue')
plt.plot(y_test[:100].values, label ="Actual_values", linewidth=3.0,color='red')
plt.legend(loc="best")
plt.savefig('Linear_Regression.png')
plt.show()
```



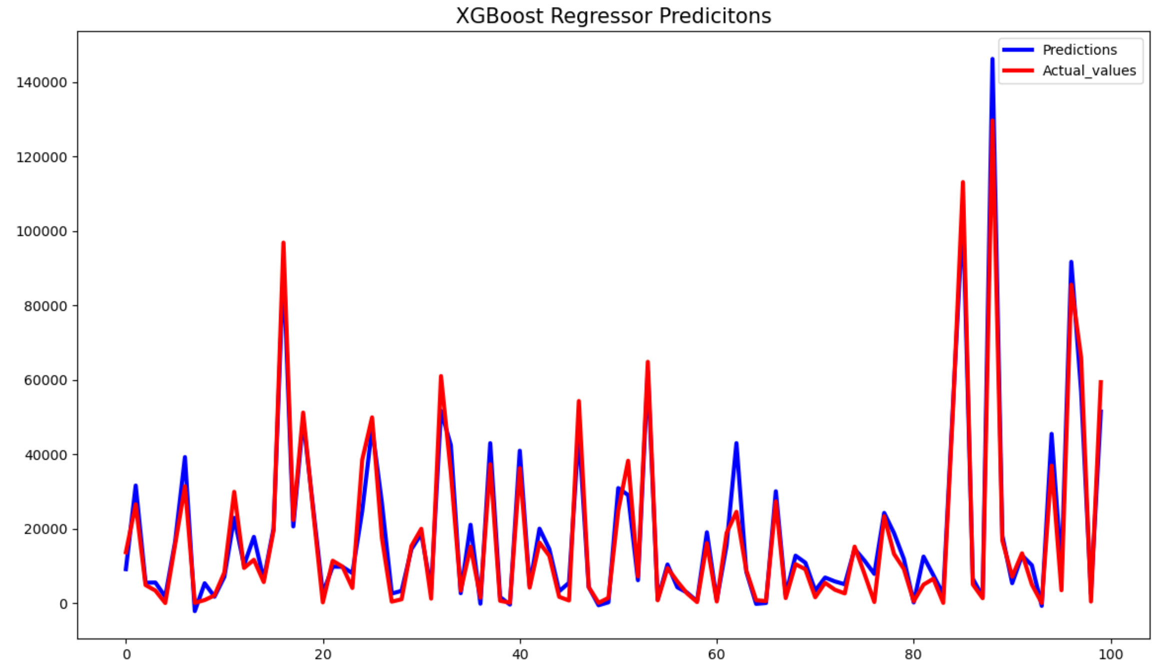
In [74]:

```
# Training the XGboost Regression model
xg = xgboost.XGBRegressor()

model_6 = xg.fit(X_train,y_train)

y_pred_6 = model_6.predict(X_test)

mae_6 = mean_absolute_error(y_test, y_pred_6)
r2_score_6 = explained_variance_score(y_test, y_pred_6)
print("MAE" , mae_6)
print("R2" , r2_score_6)
```

```
MAE 3210.730522560878
R2 0.9422400305051268
```

In [75]:

```
# Visulaizing the XGBoost predictions vs actual values
plt.figure(figsize=(14,8))
plt.title('XGBoost Regressor Predicitons', fontsize=15)
plt.plot(y_pred_6[:100], label="Predictions", linewidth=3.0,color='blue')
plt.plot(y_test[:100].values, label ="Actual_values", linewidth=3.0,color='red')
plt.legend(loc="best")
plt.savefig('XGBoost.png')
plt.show()
```



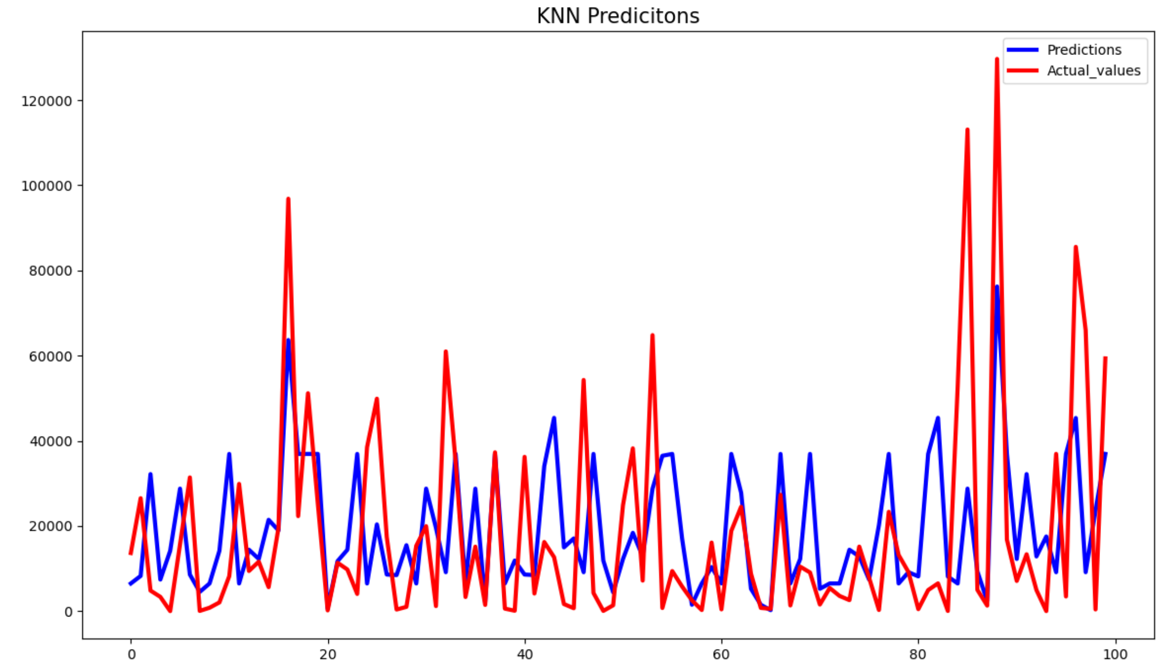
In [77]:

```
# Training the knn model on the data
knn = KNeighborsRegressor()

model_8 = knn.fit(X_train,y_train)

y_pred_8 = model_8.predict(X_test)

mae_8 = mean_absolute_error(y_test, y_pred_8)
r2_score_8 = explained_variance_score(y_test, y_pred_8)
print("MAE" , mae_8)
print("R2" , r2_score_8)
```

```
MAE 11293.418982723006
R2 0.3684994100692768
```

In [78]:

```
# Visulaizing the knn predictions vs actual values
plt.figure(figsize=(14,8))
plt.title('KNN Predicitons', fontsize=15)
plt.plot(y_pred_8[:100], label="Predictions", linewidth=3.0,color='blue')
plt.plot(y_test[:100].values, label ="Actual_values", linewidth=3.0,color='red')
plt.legend(loc="best")
plt.savefig('KNN.png')
plt.show()
```



In [79]:

```
df_cleaned.head()
```

Out[79]:

	Store	Dept	Date	Weekly_Sales	Size	Temperature	Fuel_Price	CPI	Unemploy
1	1	1	2010-02-05	24924.50	151315	42.31	2.572	211.096358	
2	15	21	2010-02-05	3253.19	123737	19.83	2.954	131.527903	
3	15	20	2010-02-05	4606.90	123737	19.83	2.954	131.527903	
4	15	19	2010-02-05	1381.40	123737	19.83	2.954	131.527903	
5	15	18	2010-02-05	2239.25	123737	19.83	2.954	131.527903	

As we can see from the data that Store and Dept are the categorical data though they are numerical. They are considered as nominal data which do not follow any order. So we do the hot encoding on these features

In [80]:

```
# Hot-encoding on the store and dept columns
categorical_features_new = ["Store", "Dept"]
encoded_data = pd.get_dummies(df_cleaned, columns=categorical_features_new)
encoded_data.head()
```

Out[80]:

	Date	Weekly_Sales	Size	Temperature	Fuel_Price	CPI	Unemployment	week
1	2010-02-05	24924.50	151315	42.31	2.572	211.096358	8.106	5
2	2010-02-05	3253.19	123737	19.83	2.954	131.527903	8.350	5
3	2010-02-05	4606.90	123737	19.83	2.954	131.527903	8.350	5
4	2010-02-05	1381.40	123737	19.83	2.954	131.527903	8.350	5
5	2010-02-05	2239.25	123737	19.83	2.954	131.527903	8.350	5

5 rows × 144 columns

Splitting the newly encoded data into training and testing

In [81]:

```
df_train_en = encoded_data[:int(0.75*(len(encoded_data)))]
df_test_en = encoded_data[int(0.75*(len(encoded_data))):]
```

In [82]:

```
X_train_en = df_train_en.drop(["Weekly_Sales", "Date"], axis = 1)
X_test_en =  df_test_en.drop(["Weekly_Sales", "Date"], axis = 1)
y_train_en = df_train_en['Weekly_Sales']
y_test_en = df_test_en['Weekly_Sales']
```

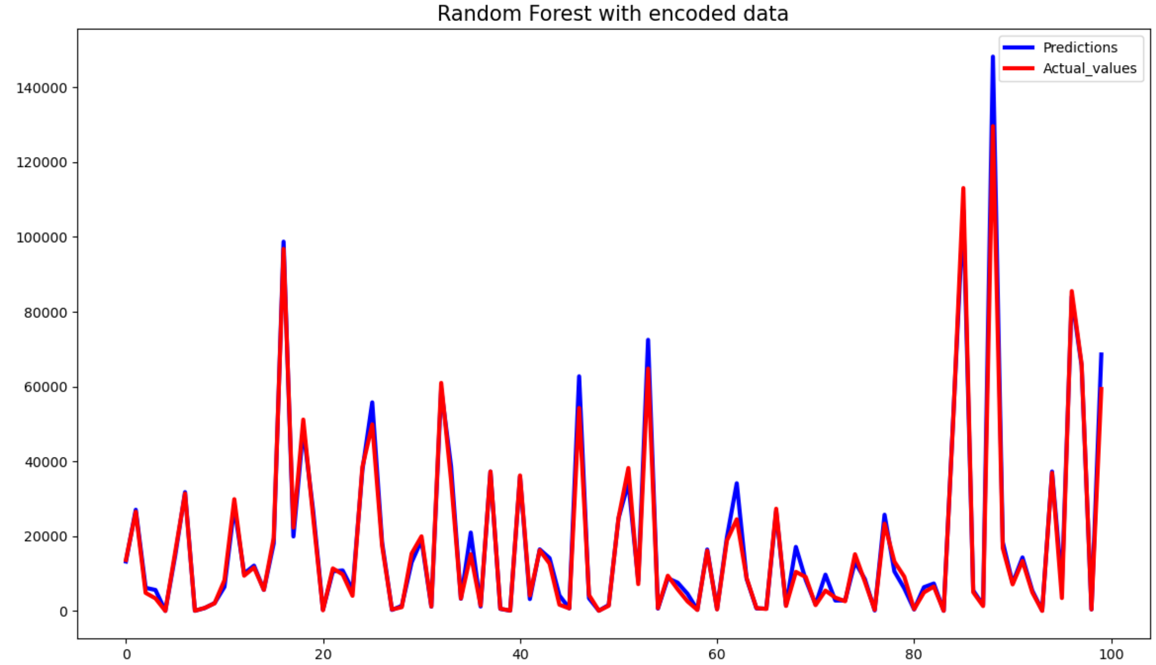
In [83]:

```
# Training the random forest model on the new encoded data
rf_model5 = RandomForestRegressor()

model_9 = rf_model5.fit(X_train_en , y_train_en)

y_pred_9 = model_9.predict(X_test_en)

mae_9 = mean_absolute_error(y_test, y_pred_9)
r2_score_9 = explained_variance_score(y_test, y_pred_9)
print("MAE" , mae_9)
print("R2" , r2_score_9)
```

```
MAE 1862.0963930140026
R2 0.9688082310592299
```

In [84]:

```
# Visualizing the random forest predictions vs actual values
plt.figure(figsize=(14,8))
plt.title('Random Forest with encoded data', fontsize=15)
plt.plot(y_pred_9[:100], label="Predictions", linewidth=3.0,color='blue')
plt.plot(y_test[:100].values, label ="Actual_values", linewidth=3.0,color='red')
plt.legend(loc="best")
plt.savefig('Rf_Encoded.png')
plt.show()
```



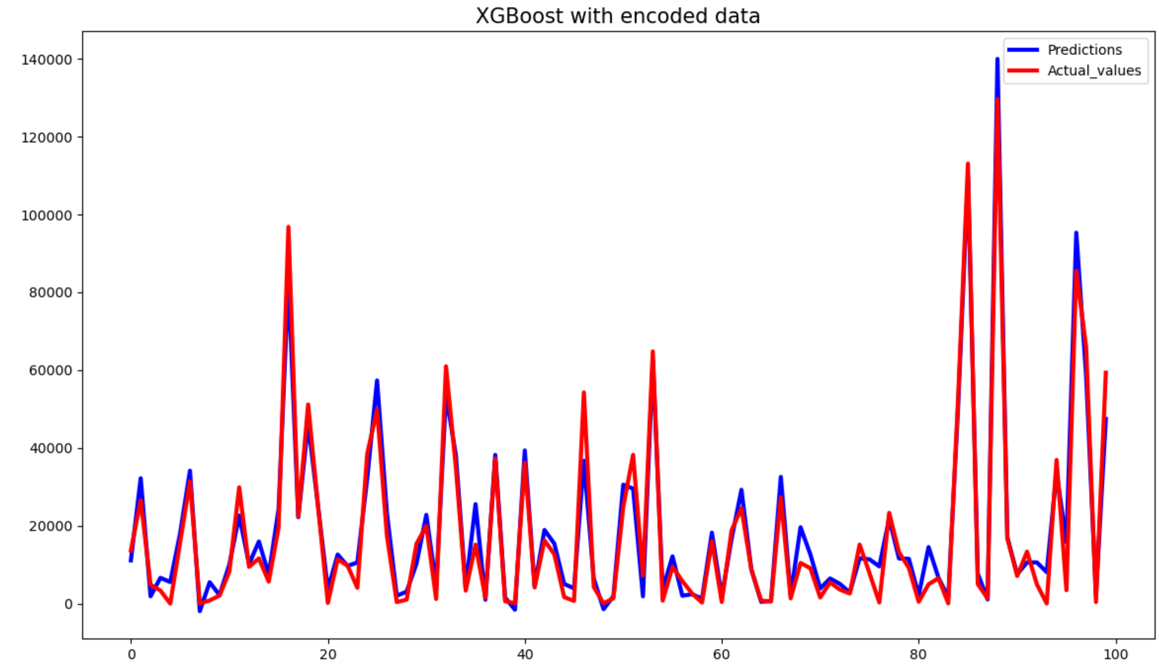
In [85]:

```
# Training the xgboost on encoded data
xg2 = xgboost.XGBRegressor()

model_10 = xg.fit(X_train_en,y_train)

y_pred_10 = model_10.predict(X_test_en)

mae_10 = mean_absolute_error(y_test_en, y_pred_10)
r2_score_10 = explained_variance_score(y_test_en, y_pred_10)
print("MAE" , mae_10)
print("R2" , r2_score_10)
```

```
MAE 3451.721261671048
R2 0.9352945980542312
```

In [86]:

```
# Visualizing the XGboost preditions vs actual values
plt.figure(figsize=(14,8))
plt.title('XGBoost with encoded data', fontsize=15)
plt.plot(y_pred_10[:100], label="Predictions", linewidth=3.0,color='blue')
plt.plot(y_test[:100].values, label ="Actual_values", linewidth=3.0,color='red')
plt.legend(loc="best")
plt.savefig('XGBoost_Encoded.png')
plt.show()
```



In [87]:

```
# Creating a dict results to store the mae and r2_score of all the trained models
results = {"Regression Algorithm":["Decision Tree", "Random Forest Default", "Random Fo
rest/Feature Selection",
                                    "Lasso Regression", "Linear Regression", "XGBoost R
egression",
                                   "KNN Regression", "Random Forest/Encoded Data", "XGB
oost/Encoded Data"],
           "Mean Absolute Error" : [mae_1,mae_2,mae_3, mae_4, mae_5, mae_6,mae_8,mae_9,
mae_10],
           "R2 Score": [r2_score_1,r2_score_2,r2_score_3,r2_score_4,r2_score_5,r2_score
_6,
                       r2_score_8,r2_score_9,r2_score_10]}
```

In [88]:

```
# Displaying the results as dataframe sorted by lowest Mean Absolute Error
results_df = pd.DataFrame(results)
results_df.sort_values("Mean Absolute Error")
```

Out[88]:

	Regression Algorithm	Mean Absolute Error	R2 Score
7	Random Forest/Encoded Data	1862.096393	0.968808
1	Random Forest Default	2045.490658	0.959801
2	Random Forest/Feature Selection	2053.104838	0.959327
0	Decision Tree	2645.063044	0.928300
5	XGBoost Regression	3210.730523	0.942240
8	XGBoost/Encoded Data	3451.721262	0.935295
6	KNN Regression	11293.418983	0.368499
4	Linear Regression	14351.700683	0.095464
3	Lasso Regression	14356.493220	0.095462

From the above results:

Best Model with lowest mean absolute error is: Random Forest with Encoded Data

In [89]:

```
# Saving the best trained model using the pickle library

# Importing the pickle library
import pickle

pickle.dump(model_9, open('Best_Model.pkl', 'wb'))
```

In [ ]: