In [1]:
```
#importing required packages
import pandas as pd
import datetime
import calendar
from pylab import rcParams

import matplotlib.pylab as plt
%matplotlib inline
import matplotlib
matplotlib.rc('xtick', labelsize=40)
matplotlib.rc('ytick', labelsize=40)


import numpy as np

import seaborn as sns
sns.set(style="whitegrid", color_codes=True)

import statsmodels.formula.api as smf
import statsmodels.api as sm

from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score
from sklearn import model_selection
from sklearn import metrics
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error
from sklearn.ensemble import RandomForestRegressor
from sklearn.tree import DecisionTreeRegressor

#import warnings
#warnings.filterwarnings('ignore')
```

In [2]:
```
df= pd.read_csv("E:\Simplilearn\Data Science with Python\Projects\Walmart\Walmar
t_Store_sales.csv")
```

In [3]:
```
df.head()
```

Out[3]:

	Store	Date	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Unemployment
0	1	05-02-2010	1643690.90	0	42.31	2.572	211.096358	8.106
1	1	12-02-2010	1641957.44	1	38.51	2.548	211.242170	8.106
2	1	19-02-2010	1611968.17	0	39.93	2.514	211.289143	8.106
3	1	26-02-2010	1409727.59	0	46.63	2.561	211.319643	8.106
4	1	05-03-2010	1554806.68	0	46.50	2.625	211.350143	8.106

In [4]:
```
df.isnull().sum()
```

Out[4]:
```
Store           0
Date            0
Weekly_Sales    0
Holiday_Flag    0
Temperature     0
Fuel_Price      0
CPI             0
Unemployment    0
dtype: int64
```

In [5]:
```
df.dtypes
```

Out[5]:
```
Store              int64
Date              object
Weekly_Sales     float64
Holiday_Flag       int64
Temperature      float64
Fuel_Price       float64
CPI              float64
Unemployment     float64
dtype: object
```

In [6]:
```
df.shape
```

Out[6]:
```
(6435, 8)
```

In [7]:
```
#Adding Week, Quarter, Month, Year

df['Date'] = pd.to_datetime(df['Date'], format='%d-%m-%Y')
df['Week_Number'] = df['Date'].dt.week
df['Quarter'] = df['Date'].dt.quarter
df['Month'] = df['Date'].dt.month.apply(lambda x: calendar.month_abbr[x])
df['Year'] = df['Date'].dt.year
df['yr_qr'] = df['Year'].astype(str) + '_' + 'Q' + df['Quarter'].astype(str)
```

In [8]:
```
df_aux=df
df_aux
```

Out[8]:

	Store	Date	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Unemployment
0	1	2010-02-05	1643690.90	0	42.31	2.572	211.096358	8.106
1	1	2010-02-12	1641957.44	1	38.51	2.548	211.242170	8.106
2	1	2010-02-19	1611968.17	0	39.93	2.514	211.289143	8.106
3	1	2010-02-26	1409727.59	0	46.63	2.561	211.319643	8.106
4	1	2010-03-05	1554806.68	0	46.50	2.625	211.350143	8.106
...	...	...	...	...	...	...	...	...
6430	45	2012-09-28	713173.95	0	64.88	3.997	192.013558	8.684
6431	45	2012-10-05	733455.07	0	64.89	3.985	192.170412	8.667
6432	45	2012-10-12	734464.36	0	54.47	4.000	192.327265	8.667
6433	45	2012-10-19	718125.53	0	56.47	3.969	192.330854	8.667
6434	45	2012-10-26	760281.43	0	58.85	3.882	192.308899	8.667

6435 rows × 13 columns

In [9]:
```
#Maximum Sales - groupby Store and sum the sales

df1 = df.groupby(['Store']).agg({'Weekly_Sales': 'sum'})
df1["%"] = df1.apply(lambda x:  100*x / x.sum()).applymap('{:.2f}%'.format)
df1.head()
```

Out[9]:

Store	Weekly_Sales	%
1	2.224028e+08	3.30%
2	2.753824e+08	4.09%
3	5.758674e+07	0.85%
4	2.995440e+08	4.45%
5	4.547569e+07	0.67%

In [10]:
```
max_storeSales = df1.max()['Weekly_Sales']
max_storeSales
```

Out[10]:
```
301397792.46000004
```

In [11]:
```
print(df1[df1.Weekly_Sales == df1.Weekly_Sales.max()])
```

```
       Weekly_Sales      %
Store
20     3.013978e+08  4.47%
```

In [12]:
```
#Maximum Standard Deviation

df2 = df.groupby(['Store']).agg({'Weekly_Sales': 'std'})
max_storeSales = df2.max()['Weekly_Sales']
max_storeSales
print(df2[df2.Weekly_Sales == df2.Weekly_Sales.max()])
```

```
        Weekly_Sales
Store
14     317569.949476
```

In [13]:
```
#Coefficient of Variation - the coefficient of mean to standard deviation
#Coefficient of Variation = Standard deviation / mean

SD = df1.std()['Weekly_Sales']
Mean = df1.mean()['Weekly_Sales']
CoV = "{:.2%}".format(SD/Mean)
print(CoV)
```

```
52.21%
```

In [14]:
```
#good quarterly growth rate in Q3'2012

#Maximum Sales - groupby Store and sum the sales

df3 = df.groupby(['Store','yr_qr']).agg({'Weekly_Sales': 'sum'})
df3.sort_values("yr_qr", axis = 0, ascending = True,
                 inplace = True, na_position ='last')

max_QtrSales = df3.max()['Weekly_Sales']
print(df3[df3.Weekly_Sales == df3.Weekly_Sales.max()])
```

```
               Weekly_Sales
Store yr_qr
20    2010_Q4   32573122.65
```

In [15]:
```
qtrs=['2012_Q2','2012_Q3']
sol_df=df[df.yr_qr.isin(qtrs)]
sol_df.head()

df4=pd.DataFrame(sol_df.groupby(['Store','yr_qr'])['Weekly_Sales'].sum())
df4.reset_index(inplace=True)

# Reshaping the data frame from long to wide format
df5=df4.pivot(index='Store', columns='yr_qr', values='Weekly_Sales')

df5['Growth'] = (df5['2012_Q3']/df5['2012_Q2'])-1
df5.head()
```

Out[15]:

yr_qr	2012_Q2	2012_Q3	Growth
Store			
1	20978760.12	20253947.78	-0.034550
2	25083604.88	24303354.86	-0.031106
3	5620316.49	5298005.47	-0.057347
4	28454363.67	27796792.46	-0.023110
5	4466363.69	4163790.99	-0.067745

In [16]:
```
Store_max_growth = df5.max()['Growth']
print(df5[df5.Growth == df5.Growth.max()])
```

```
yr_qr      2012_Q2     2012_Q3    Growth
Store
7       7290859.27  8262787.39  0.133308
```

In [17]:
```
#holidays which have higher sales than the mean sales - Creating subsets and fin
ding means

holiday_df=df.loc[df['Holiday_Flag']==1]
Nonholiday_df=df.loc[df['Holiday_Flag']==0]

Nonholiday_df=pd.DataFrame(Nonholiday_df.groupby(['Year','Month'])['Weekly_Sales
'].mean())
holiday_df=pd.DataFrame(holiday_df.groupby(['Year','Month'])['Weekly_Sales'].mea
n())
```

In [18]:
```
# holidays which have higher sales than the mean sales - merge and difference
Holiday_sales_impact= pd.merge(Nonholiday_df,
                 holiday_df,
                 on=['Year', 'Month'],
                 how='inner')

Holiday_sales_impact.rename(columns={'Weekly_Sales_x':'Average_Sales_Non-Holiday
', 'Weekly_Sales_y':'Average_Sales_Holiday'} , inplace = True)

Holiday_sales_impact['Difference'] = Holiday_sales_impact["Average_Sales_Holida
y"] > Holiday_sales_impact["Average_Sales_Non-Holiday"]

Holiday_sales_impact
```

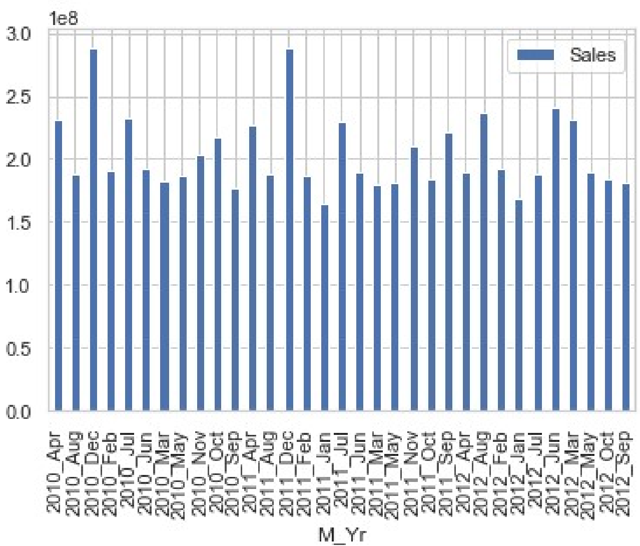
Out[18]:

Year	Month	Average_Sales_Non-Holiday	Average_Sales_Holiday	Difference
2010	**Dec**	1.379600e+06	8.985004e+05	False
	Feb	1.051824e+06	1.074148e+06	True
	Nov	1.015055e+06	1.462689e+06	True
	Sep	9.750630e+05	1.014098e+06	True
2011	**Dec**	1.344642e+06	1.023166e+06	False
	Feb	1.029594e+06	1.051915e+06	True
	Nov	1.063472e+06	1.479858e+06	True
	Sep	9.671362e+05	1.039183e+06	True
2012	**Feb**	1.052253e+06	1.111320e+06	True
	Sep	9.801147e+05	1.074001e+06	True

In [19]:
```
#monthly and semester view of sales in units and give insights

#Montly_Sales_Trend
Monthly_Sales = df.groupby(['Year','Month']).agg(['sum'])['Weekly_Sales'].reset_
index().rename(columns={'sum':'Sales'})
Monthly_Sales['M_Yr'] = Monthly_Sales['Year'].astype(str) + '_' + Monthly_Sales
['Month'].astype(str)
Monthly_Sales.head()
Monthly_Sales.plot.bar(x='M_Yr', y='Sales')
```

Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0x45448dbf48>



In [20]:
```
max_MonthlySales = Monthly_Sales.max()['Sales']
print(Monthly_Sales[Monthly_Sales.Sales == Monthly_Sales.Sales.max()])
```

```
   Year Month         Sales      M_Yr
2  2010   Dec  2.887605e+08  2010_Dec
```

In [21]:
```
#Montly_Sales_Trend - Store wise

Monthly_Sales = df.groupby(['Store','Year','Month']).agg(['sum'])['Weekly_Sales
'].reset_index().rename(columns={'sum':'Sales'})
Monthly_Sales['M_Yr'] = Monthly_Sales['Year'].astype(str) + '_' + Monthly_Sales
['Month'].astype(str)
max_MonthlySalesStore = Monthly_Sales.max()['Sales']
print(Monthly_Sales[Monthly_Sales.Sales == Monthly_Sales.Sales.max()])
```

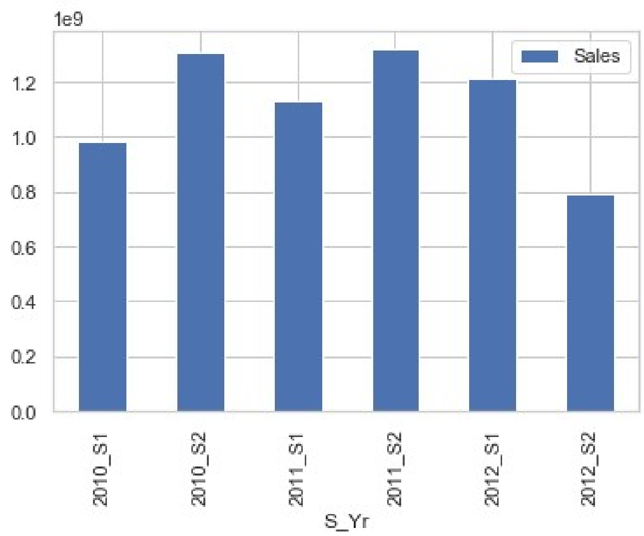
```
     Store  Year Month        Sales      M_Yr
629     20  2010   Dec  13553791.64  2010_Dec
```

In [22]:
```
#semester field
conditions = [
    (df['Quarter'] == 1) | (df['Quarter'] == 2) ,
    (df['Quarter'] == 3) | (df['Quarter'] == 4)
]
choices = [1, 2]
df['Semester'] = np.select(conditions, choices)

#Semester_Sales_Trend
Semester_Sales = df.groupby(['Year','Semester']).agg(['sum'])['Weekly_Sales'].re
set_index().rename(columns={'sum':'Sales'})
Semester_Sales['S_Yr'] = Semester_Sales['Year'].astype(str) + '_' + 'S' + Semest
er_Sales['Semester'].astype(str)

Semester_Sales.plot.bar(x='S_Yr', y='Sales')
```

Out[22]: <matplotlib.axes._subplots.AxesSubplot at 0x4545a16a48>



In [23]:
```
max_SemesterSales = Semester_Sales.max()['Sales']
print(Semester_Sales[Semester_Sales.Sales == Semester_Sales.Sales.max()])
```

```
   Year  Semester         Sales     S_Yr
3  2011         2  1.320860e+09  2011_S2
```

In [24]:
```
#Semester_Sales_Trend - Storewise

Semester_Sales = df.groupby(['Store','Year','Semester']).agg(['sum'])['Weekly_Sa
les'].reset_index().rename(columns={'sum':'Sales'})
Semester_Sales['S_Yr'] = Semester_Sales['Year'].astype(str) + '_' + 'S' + Semest
er_Sales['Semester'].astype(str)
max_SemesterSalesStore = Semester_Sales.max()['Sales']
print(Semester_Sales[Semester_Sales.Sales == Semester_Sales.Sales.max()])
```

```
    Store  Year  Semester        Sales     S_Yr
21      4  2011         2  60366595.85  2011_S2
```

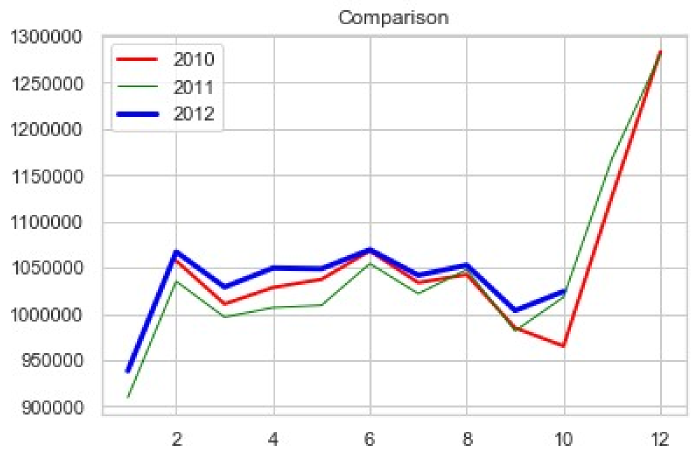
In [25]:
```
df["Month1"] = df["Date"].apply(lambda x: x.month)
```

In [26]:
```
x = df.groupby(["Year", "Month1"]).mean().Weekly_Sales.unstack()
x
```

Out[26]:

Month1	1	2	3	4	5	6
Year						
2010	NaN	1.057405e+06	1.010666e+06	1.028499e+06	1.037283e+06	1.068034e+06	1.033689e+
2011	909466.482389	1.035174e+06	9.964247e+05	1.006784e+06	1.009156e+06	1.054297e+06	1.021828e+
2012	938302.620333	1.067020e+06	1.028932e+06	1.049561e+06	1.048703e+06	1.069379e+06	1.041719e+

In [27]:
```
plt.plot(x.loc[2010, :], label = "2010", color = "red", linewidth = 2)
plt.plot(x.loc[2011, :], label = "2011", color = "green", linewidth = 1)
plt.plot(x.loc[2012, :], label = "2012", color = "blue", linewidth=3)
plt.legend(loc = "best")
plt.title("Comparison")
plt.show()
```



In [28]:
```
# B. Statistical Model - For Store 1 - Build prediction models to forecast deman
d
#Change dates into days by creating new variable.

df['Day'] = df.Date.apply(lambda x: x.day)
df['WeekNum'] = pd.cut(df.Day, bins = [1,7,14,21,28, 31], labels = [1,2,3,4,5],
include_lowest=True)
df.drop(['Date','yr_qr','Month'], axis = 1, inplace = True)
df = df.astype(np.float64)
df.head()
```

Out[28]:

	Store	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Unemployment	Week_Number
0	1.0	1643690.90	0.0	42.31	2.572	211.096358	8.106	5.0
1	1.0	1641957.44	1.0	38.51	2.548	211.242170	8.106	6.0
2	1.0	1611968.17	0.0	39.93	2.514	211.289143	8.106	7.0
3	1.0	1409727.59	0.0	46.63	2.561	211.319643	8.106	8.0
4	1.0	1554806.68	0.0	46.50	2.625	211.350143	8.106	9.0

In [29]:
```
df.head()
```

Out[29]:

	Store	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Unemployment	Week_Number
0	1.0	1643690.90	0.0	42.31	2.572	211.096358	8.106	5.0
1	1.0	1641957.44	1.0	38.51	2.548	211.242170	8.106	6.0
2	1.0	1611968.17	0.0	39.93	2.514	211.289143	8.106	7.0
3	1.0	1409727.59	0.0	46.63	2.561	211.319643	8.106	8.0
4	1.0	1554806.68	0.0	46.50	2.625	211.350143	8.106	9.0

In [30]:
```
#Creating a subset for Store 1
Store1_df=df.loc[df['Store']==1]
Store1_df=Store1_df[['Weekly_Sales','Day','Month1','WeekNum','Year', 'Fuel_Price
', 'CPI', 'Unemployment','Holiday_Flag', 'Temperature']]
```

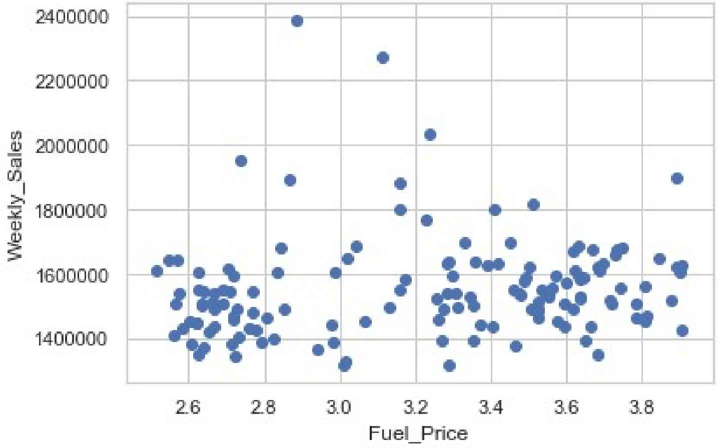
In [31]:
```
Store1_df.corr()
```

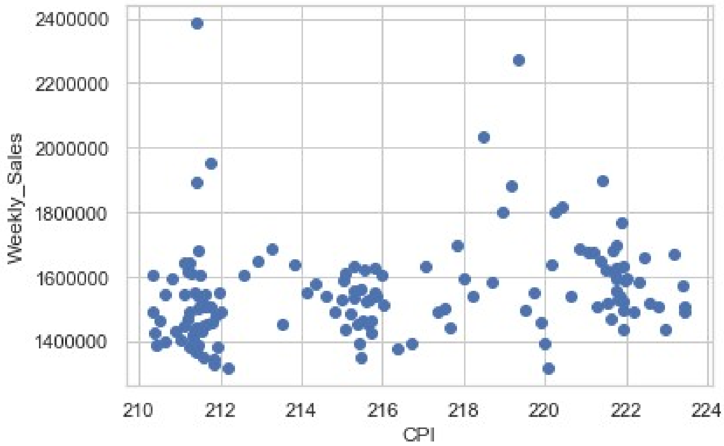
Out[31]:

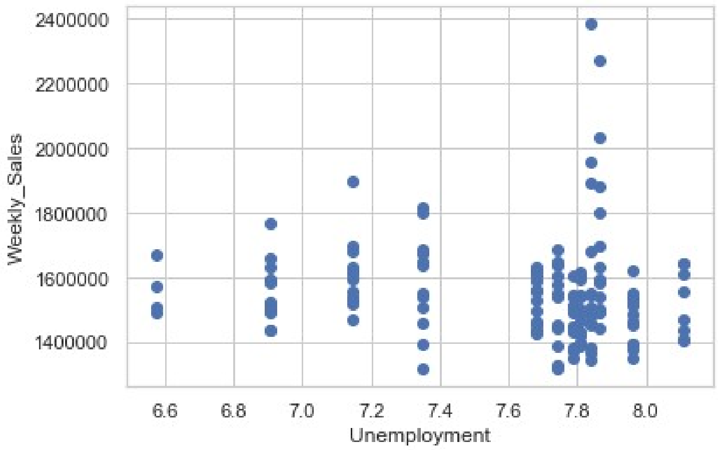
	Weekly_Sales	Day	Month1	WeekNum	Year	Fuel_Price	CPI	Unemployr
Weekly_Sales	1.000000	-0.271685	0.202188	-0.249095	0.152396	0.124592	0.225408	-0.09
Day	-0.271685	1.000000	0.015192	0.975592	0.006406	0.030806	0.033588	-0.01
Month1	0.202188	0.015192	1.000000	0.047315	-0.194465	-0.101256	0.050952	0.04
WeekNum	-0.249095	0.975592	0.047315	1.000000	-0.010680	0.033077	0.024007	0.01
Year	0.152396	0.006406	-0.194465	-0.010680	1.000000	0.809769	0.948141	-0.79
Fuel_Price	0.124592	0.030806	-0.101256	0.033077	0.809769	1.000000	0.755259	-0.51
CPI	0.225408	0.033588	0.050952	0.024007	0.948141	0.755259	1.000000	-0.81
Unemployment	-0.097955	-0.018342	0.040821	0.015458	-0.798149	-0.513944	-0.813471	1.00
Holiday_Flag	0.194905	0.044526	0.122996	0.045056	-0.056783	-0.085903	-0.028919	0.08
Temperature	-0.222701	0.051077	0.246417	0.081582	0.068843	0.228493	0.118503	-0.18

In [32]:
```
def scatter(Store1_df, column):
    plt.figure()
    plt.scatter(Store1_df[column] , Store1_df['Weekly_Sales'])
    plt.ylabel('Weekly_Sales')
    plt.xlabel(column)

scatter(Store1_df, 'Fuel_Price')
scatter(Store1_df, 'CPI')
scatter(Store1_df, 'Unemployment')
```





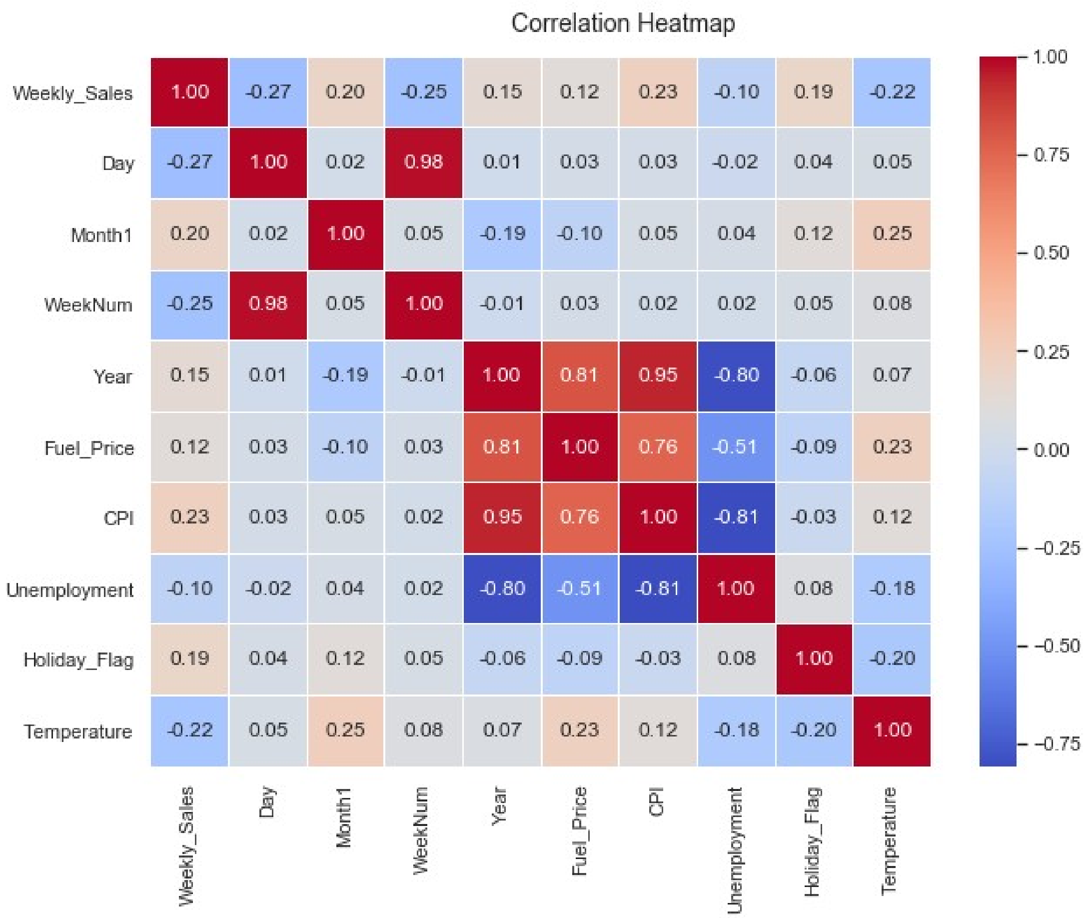


In [33]:

```
# Correlation Matrix Heatmap

f, ax = plt.subplots(figsize=(10, 7))
corr = Store1_df.corr()

hm = sns.heatmap(round(corr,2), annot=True, ax=ax, cmap="coolwarm",fmt='.2f',
                 linewidths=.05)
f.subplots_adjust(top=0.93)
t= f.suptitle('Correlation Heatmap', fontsize=14)
```



In [34]:

```
features=Store1_df[['Weekly_Sales','Day','Month1','Year', 'CPI', 'Unemployment
','Holiday_Flag', 'Temperature']]
features.head()
```

Out[34]:

	Weekly_Sales	Day	Month1	Year	CPI	Unemployment	Holiday_Flag	Temperature
0	1643690.90	5.0	2.0	2010.0	211.096358	8.106	0.0	42.31
1	1641957.44	12.0	2.0	2010.0	211.242170	8.106	1.0	38.51
2	1611968.17	19.0	2.0	2010.0	211.289143	8.106	0.0	39.93
3	1409727.59	26.0	2.0	2010.0	211.319643	8.106	0.0	46.63
4	1554806.68	5.0	3.0	2010.0	211.350143	8.106	0.0	46.50

In [35]:

```
#Splitting data into train and test

train,test = train_test_split(features,test_size=0.2,random_state=39)
```

In [36]:
```
#Linear Regression - Hypothesize if CPI, unemployment, and fuel price have any i
mpact on sales.

lm = smf.ols(formula='Weekly_Sales ~ Temperature + Holiday_Flag  + CPI ' , data=
train).fit()
lm.summary()
```

Out[36]:

OLS Regression Results

Dep. Variable:	Weekly_Sales	**R-squared:**	0.196
Model:	OLS	**Adj. R-squared:**	0.174
Method:	Least Squares	**F-statistic:**	8.935
Date:	Fri, 05 Jun 2020	**Prob (F-statistic):**	2.39e-05
Time:	14:32:00	**Log-Likelihood:**	-1503.6
No. Observations:	114	**AIC:**	3015.
Df Residuals:	110	**BIC:**	3026.
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-4.474e+05	6.32e+05	-0.707	0.481	-1.7e+06	8.06e+05
Temperature	-2779.9958	915.429	-3.037	0.003	-4594.161	-965.831
Holiday_Flag	1.064e+05	4.96e+04	2.148	0.034	8220.541	2.05e+05
CPI	1.009e+04	2930.164	3.442	0.001	4279.643	1.59e+04

Omnibus:	43.875	**Durbin-Watson:**	1.907
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	139.782
Skew:	1.350	**Prob(JB):**	4.43e-31
Kurtosis:	7.705	**Cond. No.**	1.16e+04

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.16e+04. This might indicate that there are
strong multicollinearity or other numerical problems.

In [37]:
```
features1=features[['Weekly_Sales','Day','Month1','Year']]
```

In [38]:
```
#Loading test and train data set

X = features1
Y = Store1_df['Weekly_Sales']

X_train,X_test,Y_train,Y_test = train_test_split( X, Y, test_size=0.20, random_s
tate=42)
```

In [39]:
```
#Linear Regression

linear_reg = LinearRegression()
linear_reg.fit(X_train,Y_train)

print("Intercept: ", linear_reg.intercept_)
print("Coefficient: " , linear_reg.coef_)
```

```
Intercept:  -1.862645149230957e-09
Coefficient:  [ 1.00000000e+00  1.03982846e-13 -8.81859399e-14  9.10074316e-1
3]
```

In [40]:
```
y_pred = linear_reg.predict(X_test)
print(y_pred)
```

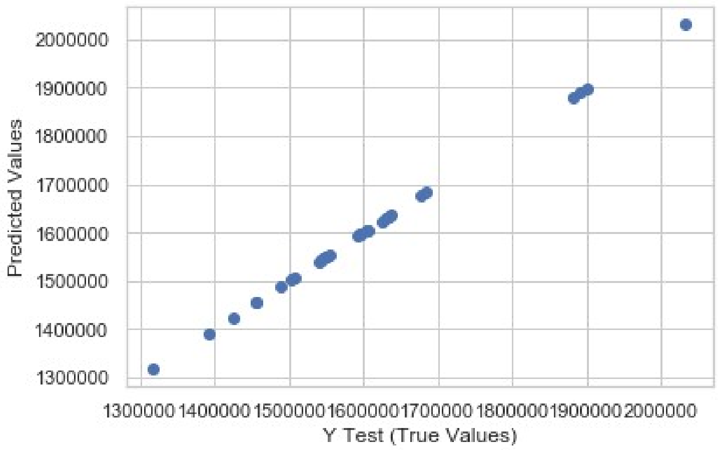
```
[1684519.99 1503284.06 1550229.22 1881176.67 1636263.41 1425100.71
 1592409.97 1629391.28 1604775.58 1542561.09 1316899.31 1624383.75
 2033320.66 1597868.05 1550369.92 1455090.69 1508237.76 1635078.41
 1540421.49 1488538.09 1391256.12 1595901.87 1677472.78 1899676.88
 1456800.28 1891034.93 1545418.53 1554806.68 1605491.78]
```

In [41]:
```
mse = metrics.mean_squared_error(Y_test,y_pred)
rmse = np.sqrt(mse)
print('%.2f'%rmse)
```

```
0.00
```

In [42]:
```
plt.scatter(Y_test,y_pred)
plt.xlabel('Y Test (True Values)')
plt.ylabel('Predicted Values')
```

Out[42]:
```
Text(0, 0.5, 'Predicted Values')
```



In [43]:
```
print('MAE:', '%.2f'%metrics.mean_absolute_error(Y_test,y_pred))
print('MSE:', '%.2f'%metrics.mean_squared_error(Y_test,y_pred))
print('RMSE:', '%.2f'%np.sqrt(metrics.mean_squared_error(Y_test,y_pred)))
```

```
MAE: 0.00
MSE: 0.00
RMSE: 0.00
```

In [44]:
```
##1.Linear Regression

clf = LinearRegression()

clf.fit(X_train, Y_train)

y_pred_lr=clf.predict(X_test)

acc_lr=round( clf.score(X_train, Y_train) * 100, 2)

print ("Accuracy:%i %% \n"%acc_lr)
```

```
Accuracy:100 %
```

In [45]:
```
##2. Random Forest

clf = RandomForestRegressor(n_estimators=100)

clf.fit(X_train, Y_train)

y_pred_rf=clf.predict(X_test)

acc_rf= round(clf.score(X_train, Y_train) * 100, 2)

print ("Accuracy: %i %% \n"%acc_rf)
```

```
Accuracy: 99 %
```

In [46]:
```
##3. Decision Tree

clf=DecisionTreeRegressor()

clf.fit(X_train, Y_train)

y_pred_dt= clf.predict(X_test)

acc_dt = round( clf.score(X_train, Y_train) * 100, 2)

print ("Accuracy: %i %% \n"%acc_dt)
```

```
Accuracy: 100 %
```

In [48]:
```
##Comparing Models - Let's compare the accuracy score of all the regression mode
ls used above.

models = pd.DataFrame({
    'Model': ['Linear Regression','Random Forest','Decision Tree'],

    'Score': [acc_lr, acc_rf,acc_dt]
    })

models.sort_values(by='Score', ascending=False)
```

Out[48]:

	Model	Score
0	Linear Regression	100.00
2	Decision Tree	100.00
1	Random Forest	99.37

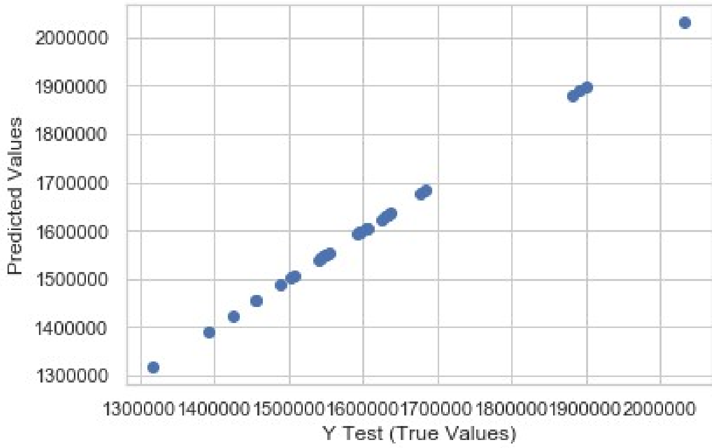
In [49]:
```
submission = pd.DataFrame({
        "Store_Weekly_Sales": test.Weekly_Sales,
        "Predicted_Weekly_Sales_linear": y_pred_lr
    })
submission.head()
```

Out[49]:

	Store_Weekly_Sales	Predicted_Weekly_Sales_linear
6	1472515.79	1684519.99
122	1697230.96	1503284.06
112	1649604.63	1550229.22
119	1595901.87	1881176.67
97	1881176.67	1636263.41

In [50]:
```
plt.scatter(Y_test,y_pred_lr)
plt.xlabel('Y Test (True Values)')
plt.ylabel('Predicted Values')
```

Out[50]: Text(0, 0.5, 'Predicted Values')



In [51]:
```
print('MAE ', metrics.mean_absolute_error(Y_test,y_pred_lr))
print('MSE ', metrics.mean_squared_error(Y_test,y_pred_lr))
print('RMSE ', np.sqrt(metrics.mean_squared_error(Y_test,y_pred_lr)))
```

```
MAE  0.0
MSE  0.0
RMSE  0.0
```