Retail Analysis with Walmart Data

DESCRIPTION

One of the leading retail stores in the US, Walmart, would like to predict the sales and demand accurately. There are certain events and holidays which impact sales on each day. There are sales data available for 45 stores of Walmart. The business is facing a challenge due to unforeseen demands and runs out of stock some times, due to the inappropriate machine learning algorithm. An ideal ML algorithm will predict demand accurately and ingest factors like economic conditions including CPI, Unemployment Index, etc.

Walmart runs several promotional markdown events throughout the year. These markdowns precede prominent holidays, the four largest of all, which are the Super Bowl, Labour Day, Thanksgiving, and Christmas. The weeks including these holidays are weighted five times higher in the evaluation than non-holiday weeks. Part of the challenge presented by this competition is modeling the effects of markdowns on these holiday weeks in the absence of complete/ideal historical data. Historical sales data for 45 Walmart stores located in different regions are available.

Dataset Description

This is the historical data that covers sales from 2010-02-05 to 2012-11-01, in the file Walmart_Store_sales. Within this file you will find the following fields:

- Store - the store number
- Date - the week of sales
- Weekly_Sales - sales for the given store
- Holiday_Flag - whether the week is a special holiday week 1 – Holiday week 0 – Non-holiday week
- Temperature - Temperature on the day of sale
- Fuel_Price - Cost of fuel in the region
- CPI – Prevailing consumer price index
- Unemployment - Prevailing unemployment rate

Holiday Events

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

Analysis Tasks

Basic Statistics tasks

1) Which store has maximum sales

2) Which store has maximum standard deviation i.e., the sales vary a lot. Also, find out the coefficient of mean to standard deviation

3) Which store/s has good quarterly growth rate in Q3'2012

4) Some holidays have a negative impact on sales. Find out holidays which have higher sales than the mean sales in non-holiday season for all stores together

5) Provide a monthly and semester view of sales in units and give insights

Statistical Model

For Store 1 – Build prediction models to forecast demand

1) Linear Regression – Utilize variables like date and restructure dates as 1 for 5 Feb 2010 (starting from the earliest date in order). Hypothesize if CPI, unemployment, and fuel price have any impact on sales.

2) Change dates into days by creating new variable.

In [1]:
```
#importing necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from matplotlib import style
%matplotlib inline
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn import metrics
from statsmodels.formula.api import ols
import datetime as dt
import warnings
```

In [2]:
```
#read the dataset using pandas dataframe
walmart_df = pd.read_csv('Walmart_Store_sales.csv')
warnings.filterwarnings('ignore')
```

In [3]:
```
#to display first 5 rows
walmart_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]:
```
#to display last 5 rows
walmart_df.tail()
```

Out[4]:

	Store	Date	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Unemployment
6430	45	28-09-2012	713173.95	0	64.88	3.997	192.013558	8.684
6431	45	05-10-2012	733455.07	0	64.89	3.985	192.170412	8.667
6432	45	12-10-2012	734464.36	0	54.47	4.000	192.327265	8.667
6433	45	19-10-2012	718125.53	0	56.47	3.969	192.330854	8.667
6434	45	26-10-2012	760281.43	0	58.85	3.882	192.308899	8.667

In [5]:
```
#info() is used to complete description of data
walmart_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6435 entries, 0 to 6434
Data columns (total 8 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   Store         6435 non-null   int64
 1   Date          6435 non-null   object
 2   Weekly_Sales  6435 non-null   float64
 3   Holiday_Flag  6435 non-null   int64
 4   Temperature   6435 non-null   float64
 5   Fuel_Price    6435 non-null   float64
 6   CPI           6435 non-null   float64
 7   Unemployment  6435 non-null   float64
dtypes: float64(5), int64(2), object(1)
memory usage: 402.3+ KB
```

In [6]:
```
#to get column names
walmart_df.columns
```

Out[6]:
```
Index(['Store', 'Date', 'Weekly_Sales', 'Holiday_Flag', 'Temperature',
       'Fuel_Price', 'CPI', 'Unemployment'],
      dtype='object')
```

In [7]:
```
#generalizing column names by loweringcase
walmart_df.columns = walmart_df.columns.str.lower()
walmart_df.columns
```

Out[7]:
```
Index(['store', 'date', 'weekly_sales', 'holiday_flag', 'temperature',
       'fuel_price', 'cpi', 'unemployment'],
      dtype='object')
```

In [8]:
```
#looking for null values in dataset
walmart_df.isnull().sum()
```

Out[8]:
```
store           0
date            0
weekly_sales    0
holiday_flag    0
temperature     0
fuel_price      0
cpi             0
unemployment    0
dtype: int64
```

In [ ]:

Maximum sales

In [9]:
```
# groupby stores and get total sales
store_totalweeklysales = walmart_df.groupby('store')['weekly_sales'].sum()
store_totalweeklysales.to_frame()
```

Out[9]:

store	weekly_sales
1	2.224028e+08
2	2.753824e+08
3	5.758674e+07
4	2.995440e+08
5	4.547569e+07
6	2.237561e+08
7	8.159828e+07
8	1.299512e+08
9	7.778922e+07
10	2.716177e+08
11	1.939628e+08
12	1.442872e+08
13	2.865177e+08
14	2.889999e+08
15	8.913368e+07
16	7.425243e+07
17	1.277821e+08
18	1.551147e+08
19	2.066349e+08
20	3.013978e+08
21	1.081179e+08
22	1.470756e+08
23	1.987506e+08
24	1.940160e+08
25	1.010612e+08
26	1.434164e+08
27	2.538559e+08
28	1.892637e+08
29	7.714155e+07
30	6.271689e+07
31	1.996139e+08
32	1.668192e+08
33	3.716022e+07
34	1.382498e+08
35	1.315207e+08
36	5.341221e+07
37	7.420274e+07
38	5.515963e+07
39	2.074455e+08
40	1.378703e+08
41	1.813419e+08
42	7.956575e+07
43	9.056544e+07
44	4.329309e+07
45	1.123953e+08

In [10]:
```
print("{:.2f}".format(store_totalweeklysales.max()))
# using argmax to get the max sales store index
print(store_totalweeklysales.index[store_totalweeklysales.argmax()])
```

```
301397792.46
20
```

Store number : 20 has the maximum sales of 301397792.46

In [ ]:

Maximum Sales Standard Deviation

In [11]:
```
# groupby stores and get std.dev
store_sales_std = walmart_df.groupby('store')['weekly_sales'].std()
store_sales_std.to_frame()
```

Out[11]:

store	weekly_sales
1	155980.767761
2	237683.694682
3	46319.631557
4	266201.442297
5	37737.965745
6	212525.855862
7	112585.469220
8	106280.829881
9	69028.666585
10	302262.062504
11	165833.887863
12	139166.871880
13	265506.995776
14	317569.949476
15	120538.652043
16	85769.680133
17	112162.936087
18	176641.510839
19	191722.638730
20	275900.562742
21	128752.812853
22	161251.350631
23	249788.038068
24	167745.677567
25	112976.788600
26	110431.288141
27	239930.135688
28	181758.967539
29	99120.136596
30	22809.665590
31	125855.942933
32	138017.252087
33	24132.927322
34	104630.164676
35	211243.457791
36	60725.173579
37	21837.461190
38	42768.169450
39	217466.454833
40	119002.112858
41	187907.162766
42	50262.925530
43	40598.413260
44	24762.832015
45	130168.526635

In [12]:
```
print("{:.2f}".format(store_sales_std.max()))
# using argmax to get the max std.dev store index
print(store_sales_std.index[store_sales_std.argmax()])
```

```
317569.95
14
```

Store number : 14 has the maximum sales standard seviation 317569.95

In [ ]:

Coeffcient of Mean to Standard Deviation

In [13]:
```
# groupby stores and get mean values
store_sales_mean = walmart_df.groupby('store')['weekly_sales'].mean()
store_sales_mean.to_frame()
```

Out[13]:

store	weekly_sales
1	1.555264e+06
2	1.925751e+06
3	4.027044e+05
4	2.094713e+06
5	3.180118e+05
6	1.564728e+06
7	5.706173e+05
8	9.087495e+05
9	5.439806e+05
10	1.899425e+06
11	1.356383e+06
12	1.009002e+06
13	2.003620e+06
14	2.020978e+06
15	6.233125e+05
16	5.192477e+05
17	8.935814e+05
18	1.084718e+06
19	1.444999e+06
20	2.107677e+06
21	7.560691e+05
22	1.028501e+06
23	1.389864e+06
24	1.356755e+06
25	7.067215e+05
26	1.002912e+06
27	1.775216e+06
28	1.323522e+06
29	5.394514e+05
30	4.385796e+05
31	1.395901e+06
32	1.166568e+06
33	2.598617e+05
34	9.667816e+05
35	9.197250e+05
36	3.735120e+05
37	5.189003e+05
38	3.857317e+05
39	1.450668e+06
40	9.641280e+05
41	1.268125e+06
42	5.564039e+05
43	6.333247e+05
44	3.027489e+05
45	7.859814e+05

In [14]:
```
#cv=(mean/std.dev)*100
covariance_std_mean = (store_sales_std / store_sales_mean) * 100
```

Covariance Values (Cv)

```
- Cv less than 10 = Very Good
- Cv between 10 - 20 = Good
- Cv between 21 - 30 = Acceptable
- Cv greater than 30 = Not Acceptable
```

In [15]:
```
covariance_std_mean.to_frame()
```

Out[15]:

store	weekly_sales
1	10.029212
2	12.342388
3	11.502141
4	12.708254
5	11.866844
6	13.582286
7	19.730469
8	11.695283
9	12.689547
10	15.913349
11	12.226183
12	13.792532
13	13.251363
14	15.713674
15	19.338399
16	16.518065
17	12.552067
18	16.284550
19	13.268012
20	13.090269
21	17.029239
22	15.678288
23	17.972115
24	12.363738
25	15.986040
26	11.011066
27	13.515544
28	13.732974
29	18.374247
30	5.200804
31	9.016105
32	11.831049
33	9.286835
34	10.822524
35	22.968111
36	16.257891
37	4.208412
38	11.087545
39	14.990779
40	12.342978
41	14.817711
42	9.033533
43	6.410363
44	8.179331
45	16.561273

Store numbers : 30,31,33,37,42,43,44 has very good co-efficients of mean to standard deviation

In [ ]:

Good Quarterly3 growth rate in year 2010

In [16]:
```
# Converting date column from object dtype to datetime dtype
walmart_df['date'] = walmart_df['date'].apply(lambda x:dt.datetime.strptime(x,"%d-%m-%Y"))
```

In [17]:
```
# Using datetimeindex to get year/month/day from dataset
walmart_df['year'] = pd.DatetimeIndex(walmart_df['date']).year
walmart_df['month'] = pd.DatetimeIndex(walmart_df['date']).month
walmart_df['day'] = pd.DatetimeIndex(walmart_df['date']).day
```

In [18]:
```
walmart_df.head()
```

Out[18]:

	store	date	weekly_sales	holiday_flag	temperature	fuel_price	cpi	unemployment	year	month	day
0	1	2010-02-05	1643690.90	0	42.31	2.572	211.096358	8.106	2010	2	5
1	1	2010-02-12	1641957.44	1	38.51	2.548	211.242170	8.106	2010	2	12
2	1	2010-02-19	1611968.17	0	39.93	2.514	211.289143	8.106	2010	2	19
3	1	2010-02-26	1409727.59	0	46.63	2.561	211.319643	8.106	2010	2	26
4	1	2010-03-05	1554806.68	0	46.50	2.625	211.350143	8.106	2010	3	5

In [19]:
```
# Converting date back to string with our desired format
walmart_df['date'] = walmart_df['date'].apply(lambda x:dt.datetime.strftime(x,"%d-%b-%y"))
```

In [20]:
```
month_dict = {1:"Jan",2:"Feb",3:"Mar",4:"Apr",5:"May",6:"Jun",7:"Jul",8:"Aug",9:"Sep",10:"Oct",11:"Nov"
,12:"Dec"}
# Converting month int values to corresponding month names using apply function and dictionary
walmart_df['month'] = walmart_df['month'].apply(lambda x: month_dict[x])
```

In [21]:
```
walmart_df.head()
```

Out[21]:

	store	date	weekly_sales	holiday_flag	temperature	fuel_price	cpi	unemployment	year	month	day
0	1	05-Feb-10	1643690.90	0	42.31	2.572	211.096358	8.106	2010	Feb	5
1	1	12-Feb-10	1641957.44	1	38.51	2.548	211.242170	8.106	2010	Feb	12
2	1	19-Feb-10	1611968.17	0	39.93	2.514	211.289143	8.106	2010	Feb	19
3	1	26-Feb-10	1409727.59	0	46.63	2.561	211.319643	8.106	2010	Feb	26
4	1	05-Mar-10	1554806.68	0	46.50	2.625	211.350143	8.106	2010	Mar	5

In [22]:
```
# grouping data by years
yearly_walmartdata = walmart_df.groupby('year')
yearly_walmartdata.ngroups
```

Out[22]: 3

In [23]:
```
# getting groups of different years(2010,2011,2012)
stores_2012_sales = yearly_walmartdata.get_group(2012)
stores_2011_sales = yearly_walmartdata.get_group(2011)
stores_2010_sales = yearly_walmartdata.get_group(2010)
```

In [24]:
```
stores_2012_sales.head()
```

Out[24]:

	store	date	weekly_sales	holiday_flag	temperature	fuel_price	cpi	unemployment	year	month	day
100	1	06-Jan-12	1550369.92	0	49.01	3.157	219.714258	7.348	2012	Jan	6
101	1	13-Jan-12	1459601.17	0	48.53	3.261	219.892526	7.348	2012	Jan	13
102	1	20-Jan-12	1394393.84	0	54.11	3.268	219.985689	7.348	2012	Jan	20
103	1	27-Jan-12	1319325.59	0	54.26	3.290	220.078852	7.348	2012	Jan	27
104	1	03-Feb-12	1636339.65	0	56.55	3.360	220.172015	7.348	2012	Feb	3

In [25]:
```
# adding new column to find and store quartile values
stores_2012_sales['quartile'] = 0
```

In [26]:
```
stores_2012_sales.head()
```

Out[26]:

	store	date	weekly_sales	holiday_flag	temperature	fuel_price	cpi	unemployment	year	month	day	quartile
100	1	06-Jan-12	1550369.92	0	49.01	3.157	219.714258	7.348	2012	Jan	6	0
101	1	13-Jan-12	1459601.17	0	48.53	3.261	219.892526	7.348	2012	Jan	13	0
102	1	20-Jan-12	1394393.84	0	54.11	3.268	219.985689	7.348	2012	Jan	20	0
103	1	27-Jan-12	1319325.59	0	54.26	3.290	220.078852	7.348	2012	Jan	27	0
104	1	03-Feb-12	1636339.65	0	56.55	3.360	220.172015	7.348	2012	Feb	3	0

In [27]:
```
stores_2012_sales['month'].unique()
```

Out[27]:
```
array(['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Sep',
       'Oct'], dtype=object)
```

In [28]:
```
# using python code to split months into quartiles
for i in stores_2012_sales['month']:
    if i in ['Jan','Feb','Mar']:
        stores_2012_sales['quartile'][stores_2012_sales[stores_2012_sales['month'] == i].index] = "Q1"
    elif i in ['Apr','May','Jun']:
        stores_2012_sales['quartile'][stores_2012_sales[stores_2012_sales['month'] == i].index] = "Q2"
    elif i in ['Jul','Aug','Sep']:
        stores_2012_sales['quartile'][stores_2012_sales[stores_2012_sales['month'] == i].index] = "Q3"
    elif i in ['Oct','Nov','Dec']:
        stores_2012_sales['quartile'][stores_2012_sales[stores_2012_sales['month'] == i].index] = "Q4"
```

In [29]:
```
stores_2012_sales
```

Out[29]:

	store	date	weekly_sales	holiday_flag	temperature	fuel_price	cpi	unemployment	year	month	day	quartile
100	1	06-Jan-12	1550369.92	0	49.01	3.157	219.714258	7.348	2012	Jan	6	Q1
101	1	13-Jan-12	1459601.17	0	48.53	3.261	219.892526	7.348	2012	Jan	13	Q1
102	1	20-Jan-12	1394393.84	0	54.11	3.268	219.985689	7.348	2012	Jan	20	Q1
103	1	27-Jan-12	1319325.59	0	54.26	3.290	220.078852	7.348	2012	Jan	27	Q1
104	1	03-Feb-12	1636339.65	0	56.55	3.360	220.172015	7.348	2012	Feb	3	Q1
...	...	...	...	...	...	...	...	...	...	...	...	...
6430	45	28-Sep-12	713173.95	0	64.88	3.997	192.013558	8.684	2012	Sep	28	Q3
6431	45	05-Oct-12	733455.07	0	64.89	3.985	192.170412	8.667	2012	Oct	5	Q4
6432	45	12-Oct-12	734464.36	0	54.47	4.000	192.327265	8.667	2012	Oct	12	Q4
6433	45	19-Oct-12	718125.53	0	56.47	3.969	192.330854	8.667	2012	Oct	19	Q4
6434	45	26-Oct-12	760281.43	0	58.85	3.882	192.308899	8.667	2012	Oct	26	Q4

1935 rows × 12 columns

In [30]:
```
# grouping data by quartiles
quartiles_2012sales = stores_2012_sales.groupby('quartile')
quartiles_2012sales.ngroups
```

Out[30]: 4

In [31]:
```
# get individual quartile groups(Q1,Q2,Q3,Q4)
q1_data = quartiles_2012sales.get_group('Q1')
q2_data = quartiles_2012sales.get_group('Q2')
q3_data = quartiles_2012sales.get_group('Q3')
q4_data = quartiles_2012sales.get_group('Q4')
```

In [32]:
```
# getting total sales of all stores in each quarters
q1_sales = q1_data.groupby('store')['weekly_sales'].sum()
q2_sales = q2_data.groupby('store')['weekly_sales'].sum()
q3_sales = q3_data.groupby('store')['weekly_sales'].sum()
q4_sales = q4_data.groupby('store')['weekly_sales'].sum()
```

In [33]:
```
q2_sales.head(3)
```

Out[33]:
```
store
1    20978760.12
2    25083604.88
3     5620316.49
Name: weekly_sales, dtype: float64
```

In [34]:
```
q3_sales.head(3)
```

Out[34]:
```
store
1    20253947.78
2    24303354.86
3     5298005.47
Name: weekly_sales, dtype: float64
```

In [35]:
```
# finding the Q3 growth rate for each store
q3_salesgrowth = q3_sales - q2_sales
q3_salesgrowth.to_frame()
```

Out[35]:

store	weekly_sales
1	-724812.34
2	-780250.02
3	-322311.02
4	-657571.21
5	-302572.70
6	-666597.68
7	971928.12
8	-170678.25
9	-462785.55
10	-713110.41
11	-271290.51
12	-826064.21
13	-587947.84
14	-3967974.76
15	-343162.04
16	557205.66
17	-132947.88
18	-406429.38
19	-163745.39
20	-632670.34
21	-266997.03
22	-642754.35
23	152606.33
24	292158.81
25	-213930.25
26	520356.34
27	-436301.34
28	-426188.16
29	-454073.36
30	-147612.43
31	-460524.05
32	-92742.10
33	-115380.03
34	-367622.08
35	484108.12
36	-320299.94
37	-96481.13
38	-32436.44
39	500987.77
40	145457.84
41	433901.28
42	-271479.93
43	-168264.19
44	104845.38
45	-809499.45

In [36]:
```
# using argmax to find the store that has maximum sales growth in quarter 3
print(q3_salesgrowth.index[q3_salesgrowth.argmax()])
print("{:.2f}".format(q3_salesgrowth.max()))
```

```
7
971928.12
```

Store number : 7 has good quarterly 3 sales growth than other stores

In [ ]:

Holiday and Non-Holiday Sales

```
1) Super Bowl: 12-Feb-10, 11-Feb-11, 10-Feb-12, 8-Feb-13
2) Labour Day: 10-Sep-10, 9-Sep-11, 7-Sep-12, 6-Sep-13
3) Thanksgiving: 26-Nov-10, 25-Nov-11, 23-Nov-12, 29-Nov-13
4) Christmas: 31-Dec-10, 30-Dec-11, 28-Dec-12, 27-Dec-13
```

In [37]:
```
# finding mean sales on superbowl for all stores each year
superbowl_sales = walmart_df[(walmart_df['date'] == '12-Feb-10')|(walmart_df['date'] == '11-Feb-11')|(w
almart_df['date'] == '10-Feb-12')]
print("{:.2f}".format(superbowl_sales['weekly_sales'].mean()))
```

```
1079127.99
```

In [38]:
```
# finding mean sales on labourday for all stores each year
labourday_sales = walmart_df[(walmart_df['date'] == '10-Sep-10')|(walmart_df['date'] == '09-Sep-11')|(w
almart_df['date'] == '07-Sep-12')]
print("{:.2f}".format(labourday_sales['weekly_sales'].mean()))
```

```
1042427.29
```

In [39]:
```
# finding mean sales on thanksgiving for all stores each year
thanksgiving_sales = walmart_df[(walmart_df['date'] == '26-Nov-10')|(walmart_df['date'] == '25-Nov-11')
|(walmart_df['date'] == '23-Nov-12')]
print("{:.2f}".format(thanksgiving_sales['weekly_sales'].mean()))
```

```
1471273.43
```

In [40]:
```
# finding mean sales on christmas for all stores each year
christmas_sales = walmart_df[(walmart_df['date'] == '31-Dec-10')|(walmart_df['date'] == '30-Dec-11')|(w
almart_df['date'] == '28-Dec-12')]
print("{:.2f}".format(christmas_sales['weekly_sales'].mean()))
```

```
960833.11
```

Thanksgiving Holiday have Higher mean sales than any other Holiday sales

In [ ]:

Holiday and Non-Holiday data

In [41]:
```
# grouping dataset by holidayflag
holidaysdf = walmart_df.groupby('holiday_flag')
```

In [42]:
```
# getting only holiday data
holiday_sales = holidaysdf.get_group(1)
print("{:.2f}".format(holiday_sales['weekly_sales'].mean()))
```
```
1122887.89
```

In [43]:
```
# getting only non-holiday data
nonholiday_sales = holidaysdf.get_group(0)
print("{:.2f}".format(nonholiday_sales['weekly_sales'].mean()))
```
```
1041256.38
```

Holidays have higher sales mean than non-holiday sales mean

In [44]:
```
# Each holiday vs Non-holiday mean sales
```

In [45]:
```
print("{:.2f}".format(superbowl_sales['weekly_sales'].mean()))
print("{:.2f}".format(labourday_sales['weekly_sales'].mean()))
print("{:.2f}".format(thanksgiving_sales['weekly_sales'].mean()))
print("{:.2f}".format(christmas_sales['weekly_sales'].mean()))
```
```
1079127.99
1042427.29
1471273.43
960833.11
```

In [46]:
```
print("{:.2f}".format(nonholiday_sales['weekly_sales'].mean()))
```
```
1041256.38
```

Christmas holiday sales has a negative impact on sales than other holidays when compared to Non-holiday sales mean

In [ ]:

Monthly and Semester view of Sales (Year-wise)

In [47]:
```
# grouping by month for all years
totalmonthly_sales = walmart_df.groupby('month')
totalmonthly_sales.ngroups
```
Out[47]: 12

In [48]:
```
totalmonthly_sales['weekly_sales'].describe()
```
Out[48]:

month	count	mean	std	min	25%	50%	75%	max
Apr	630.0	1.026762e+06	543864.624192	232769.09	534583.5075	948789.575	1402726.700	2565259.92
Aug	585.0	1.048017e+06	542653.059046	224031.19	575997.7800	969387.480	1442819.280	2283540.30
Dec	450.0	1.281864e+06	774037.720767	209986.25	616295.8450	1154880.920	1714442.515	3818686.45
Feb	540.0	1.053200e+06	564207.057354	234218.03	554628.6350	980765.180	1431376.635	2623469.95
Jan	360.0	9.238846e+05	472616.460339	231155.90	521051.0125	830944.935	1256202.130	2047766.07
Jul	630.0	1.031748e+06	531141.778886	224806.96	577830.8550	953770.830	1396269.865	2358055.30
Jun	585.0	1.064325e+06	548683.953608	238172.66	581745.7200	984336.040	1442092.080	2363601.47
Mar	585.0	1.013309e+06	529805.743801	238084.08	544408.1400	943951.670	1365824.970	2237544.75
May	540.0	1.031714e+06	536589.412470	239206.26	543588.2225	969562.080	1388603.735	2370116.52
Nov	360.0	1.147266e+06	648832.347036	224639.76	585869.0500	1044710.505	1542527.595	3004702.33
Oct	585.0	9.996321e+05	517186.653614	213538.32	534738.4300	937956.890	1363365.050	2246411.89
Sep	585.0	9.893353e+05	510532.949375	229731.98	533161.6400	922440.640	1345167.610	2202742.90

In [ ]:

In [49]:
```
# grouping by month for year 2010
monthlysales_2010 = stores_2010_sales.groupby('month')
monthlysales_2010['weekly_sales'].describe()
```
Out[49]:

month	count	mean	std	min	25%	50%	75%	max
Apr	225.0	1.028499e+06	545424.247706	257361.30	527019.7800	969594.470	1.391256e+06	2495630.51
Aug	180.0	1.042445e+06	539322.149800	224031.19	573235.4675	981237.730	1.418366e+06	2219813.50
Dec	225.0	1.283380e+06	793498.247838	209986.25	599730.0700	1149612.040	1.707298e+06	3818686.45
Feb	180.0	1.057405e+06	571029.268079	267956.30	534468.2225	997074.975	1.470286e+06	2623469.95
Jul	225.0	1.033689e+06	534340.296029	242047.03	570231.2100	959229.090	1.371987e+06	2334788.42
Jun	180.0	1.068034e+06	556849.016817	259419.91	551924.8925	1002244.665	1.423940e+06	2363601.47
Mar	180.0	1.010666e+06	531192.529079	262893.76	519202.3825	964763.590	1.340757e+06	2237544.75
May	180.0	1.037283e+06	542985.021379	267065.35	530713.0675	973124.460	1.368593e+06	2370116.52
Nov	180.0	1.126963e+06	642755.592239	224639.76	558963.6550	995672.600	1.508792e+06	2939946.38
Oct	225.0	9.651637e+05	496358.362753	213538.32	514485.9000	891152.330	1.286599e+06	2091663.20
Sep	180.0	9.848216e+05	508207.747513	231976.84	530738.3025	910702.500	1.304980e+06	2191767.76

In [50]:
```
semester1_2010 = stores_2010_sales[stores_2010_sales['month'].isin(['Jan','Feb','Mar','Apr','May','Jun'
])]
semester1_2010.head()
```
Out[50]:

	store	date	weekly_sales	holiday_flag	temperature	fuel_price	cpi	unemployment	year	month	day
0	1	05-Feb-10	1643690.90	0	42.31	2.572	211.096358	8.106	2010	Feb	5
1	1	12-Feb-10	1641957.44	1	38.51	2.548	211.242170	8.106	2010	Feb	12
2	1	19-Feb-10	1611968.17	0	39.93	2.514	211.289143	8.106	2010	Feb	19
3	1	26-Feb-10	1409727.59	0	46.63	2.561	211.319643	8.106	2010	Feb	26
4	1	05-Mar-10	1554806.68	0	46.50	2.625	211.350143	8.106	2010	Mar	5

In [51]:
```
semester2_2010 = stores_2010_sales[stores_2010_sales['month'].isin(['Jul','Aug','Sep','Oct','Nov','Dec'
])]
semester2_2010.head()
```
Out[51]:

	store	date	weekly_sales	holiday_flag	temperature	fuel_price	cpi	unemployment	year	month	day
21	1	02-Jul-10	1492418.14	0	80.91	2.669	211.223533	7.787	2010	Jul	2
22	1	09-Jul-10	1546074.18	0	80.48	2.642	211.108414	7.787	2010	Jul	9
23	1	16-Jul-10	1448938.92	0	83.15	2.623	211.100385	7.787	2010	Jul	16
24	1	23-Jul-10	1385065.20	0	83.36	2.608	211.235144	7.787	2010	Jul	23
25	1	30-Jul-10	1371986.60	0	81.84	2.640	211.369903	7.787	2010	Jul	30

In [ ]:

In [52]:
```
# grouping by month for year 2011
monthlysales_2011 = stores_2011_sales.groupby('month')
monthlysales_2011['weekly_sales'].describe()
```
Out[52]:

month	count	mean	std	min	25%	50%	75%	max
Apr	225.0	1.006784e+06	532258.833292	232769.09	534578.7800	937473.130	1.372485e+06	2313861.81
Aug	180.0	1.047774e+06	549887.085283	237095.82	570423.6150	955710.315	1.445838e+06	2273470.62
Dec	225.0	1.280347e+06	755843.504954	215359.21	630327.2800	1158708.980	1.781529e+06	3676388.98
Feb	180.0	1.035174e+06	552442.387986	234218.03	556183.5800	961012.950	1.420064e+06	2351143.07
Jan	180.0	9.094665e+05	466122.257495	231155.90	513597.3125	812167.545	1.215770e+06	1886393.94
Jul	225.0	1.021828e+06	526841.700020	224806.96	582381.9500	936001.980	1.396927e+06	2123787.79
Jun	180.0	1.054297e+06	543819.984741	238172.66	585639.7750	974263.155	1.441112e+06	2182246.69
Mar	180.0	9.964247e+05	522341.244321	238084.08	536784.3775	929977.755	1.352847e+06	2143424.61
May	180.0	1.009156e+06	523438.331445	239206.26	543719.8250	943238.085	1.371667e+06	2095599.93
Nov	180.0	1.167569e+06	656014.430247	236157.12	597808.1050	1061735.140	1.559386e+06	3004702.33
Oct	180.0	1.018118e+06	533282.121588	231319.96	537294.8075	943328.485	1.406234e+06	2207742.13
Sep	225.0	9.815455e+05	511836.769295	229731.98	537124.7600	899834.750	1.347608e+06	2202742.90

In [53]:
```
semester1_2011 = stores_2011_sales[stores_2011_sales['month'].isin(['Jan','Feb','Mar','Apr','May','Jun'
])]
semester1_2011.head()
```
Out[53]:

	store	date	weekly_sales	holiday_flag	temperature	fuel_price	cpi	unemployment	year	month	day
48	1	07-Jan-11	1444732.28	0	48.27	2.976	211.404742	7.742	2011	Jan	7
49	1	14-Jan-11	1391013.96	0	35.40	2.983	211.457411	7.742	2011	Jan	14
50	1	21-Jan-11	1327405.42	0	44.04	3.016	211.827234	7.742	2011	Jan	21
51	1	28-Jan-11	1316899.31	0	43.83	3.010	212.197058	7.742	2011	Jan	28
52	1	04-Feb-11	1606629.58	0	42.27	2.989	212.566881	7.742	2011	Feb	4

In [54]:
```
semester2_2011 = stores_2011_sales[stores_2011_sales['month'].isin(['Jul','Aug','Sep','Oct','Nov','Dec'
])]
semester2_2011.head()
```
Out[54]:

	store	date	weekly_sales	holiday_flag	temperature	fuel_price	cpi	unemployment	year	month	day
73	1	01-Jul-11	1488538.09	0	85.55	3.524	215.184137	7.962	2011	Jul	1
74	1	08-Jul-11	1534849.64	0	85.83	3.480	215.277175	7.962	2011	Jul	8
75	1	15-Jul-11	1455119.97	0	88.54	3.575	215.361109	7.962	2011	Jul	15
76	1	22-Jul-11	1396926.82	0	85.77	3.651	215.422278	7.962	2011	Jul	22
77	1	29-Jul-11	1352219.79	0	86.83	3.682	215.483448	7.962	2011	Jul	29

In [ ]:

In [55]:
```
# grouping by month for year 2012
monthlysales_2012 = stores_2012_sales.groupby('month')
monthlysales_2012['weekly_sales'].describe()
```
Out[55]:

month	count	mean	std	min	25%	50%	75%	max
Apr	180.0	1.049561e+06	558183.253234	249798.75	548516.0000	950743.050	1.456415e+06	2565259.92
Aug	225.0	1.052670e+06	541866.268723	237129.81	576620.3100	976137.730	1.497055e+06	2283540.30
Feb	180.0	1.067020e+06	571613.468771	242526.70	564122.8100	970644.815	1.448538e+06	2462978.28
Jan	180.0	9.383026e+05	479887.956347	236920.49	540523.1525	855680.105	1.269834e+06	2047766.07
Jul	180.0	1.041719e+06	535223.017499	249134.32	577204.6500	960529.395	1.456741e+06	2358055.30
Jun	225.0	1.069379e+06	548322.510590	244338.31	583648.5900	988764.840	1.451782e+06	2245257.18
Mar	225.0	1.028932e+06	536489.204740	246970.97	557547.2500	952264.910	1.427881e+06	2214967.44
May	180.0	1.048703e+06	545296.384619	261851.74	549055.7525	988833.255	1.428744e+06	2207214.81
Oct	180.0	1.024232e+06	526815.738642	253731.13	548829.2100	962230.855	1.413769e+06	2246411.89
Sep	180.0	1.003586e+06	513766.298200	242813.51	532581.7925	949096.910	1.371256e+06	2165796.31

In [56]:
```
semester1_2012 = stores_2012_sales[stores_2012_sales['month'].isin(['Jan','Feb','Mar','Apr','May','Jun'
])]
semester1_2012.head()
```
Out[56]:

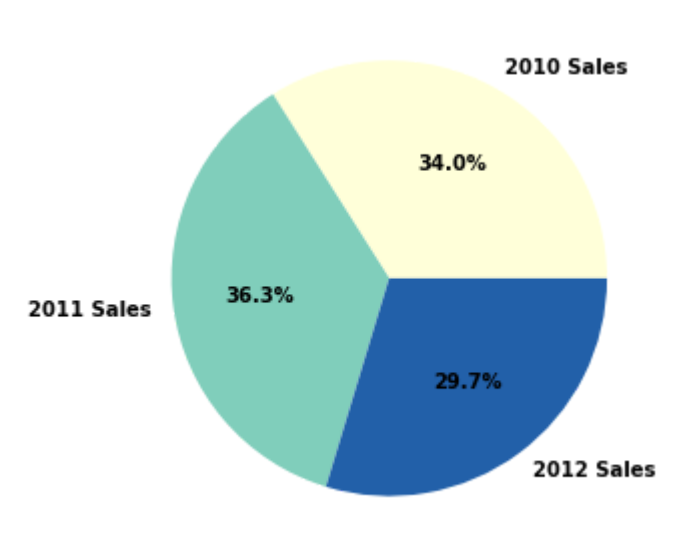
	store	date	weekly_sales	holiday_flag	temperature	fuel_price	cpi	unemployment	year	month	day	quartile
100	1	06-Jan-12	1550369.92	0	49.01	3.157	219.714258	7.348	2012	Jan	6	Q1
101	1	13-Jan-12	1459601.17	0	48.53	3.261	219.892526	7.348	2012	Jan	13	Q1
102	1	20-Jan-12	1394393.84	0	54.11	3.268	219.985689	7.348	2012	Jan	20	Q1
103	1	27-Jan-12	1319325.59	0	54.26	3.290	220.078852	7.348	2012	Jan	27	Q1
104	1	03-Feb-12	1636339.65	0	56.55	3.360	220.172015	7.348	2012	Feb	3	Q1

In [57]:
```
semester2_2012 = stores_2012_sales[stores_2012_sales['month'].isin(['Jul','Aug','Sep','Oct','Nov','Dec'
])]
semester2_2012.head()
```
Out[57]:

	store	date	weekly_sales	holiday_flag	temperature	fuel_price	cpi	unemployment	year	month	day	quartile
126	1	06-Jul-12	1769854.16	0	81.57	3.227	221.883779	6.908	2012	Jul	6	Q3
127	1	13-Jul-12	1527014.04	0	77.12	3.256	221.924158	6.908	2012	Jul	13	Q3
128	1	20-Jul-12	1497954.76	0	80.42	3.311	221.932727	6.908	2012	Jul	20	Q3
129	1	27-Jul-12	1439123.71	0	82.66	3.407	221.941295	6.908	2012	Jul	27	Q3
130	1	03-Aug-12	1631135.79	0	86.11	3.417	221.949864	6.908	2012	Aug	3	Q3

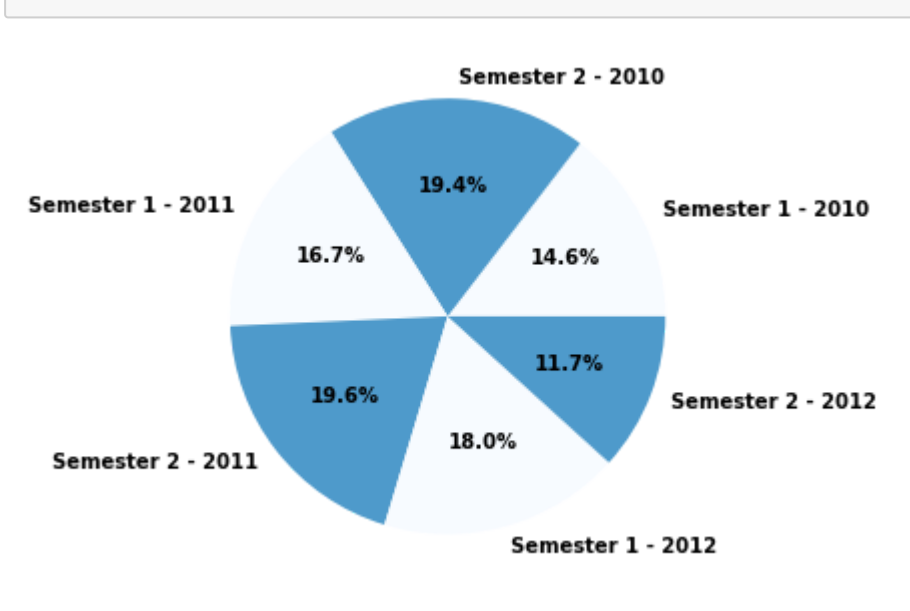
Visualization

In [58]:
```
# Visualizing total sales percentage for each year
list1 = [stores_2010_sales['weekly_sales'].sum(),stores_2011_sales['weekly_sales'].sum(),stores_2012_sa
les['weekly_sales'].sum()]
labels = '2010 Sales','2011 Sales','2012 Sales'
cmap = plt.get_cmap('YlGnBu')
colors = cmap(np.arange(3)*95)
txt={'weight':'bold'}
plt.figure(figsize=(15,5))
plt.pie(list1,labels=labels,autopct='%.1f%%',colors=colors,textprops=txt)
plt.show()
```



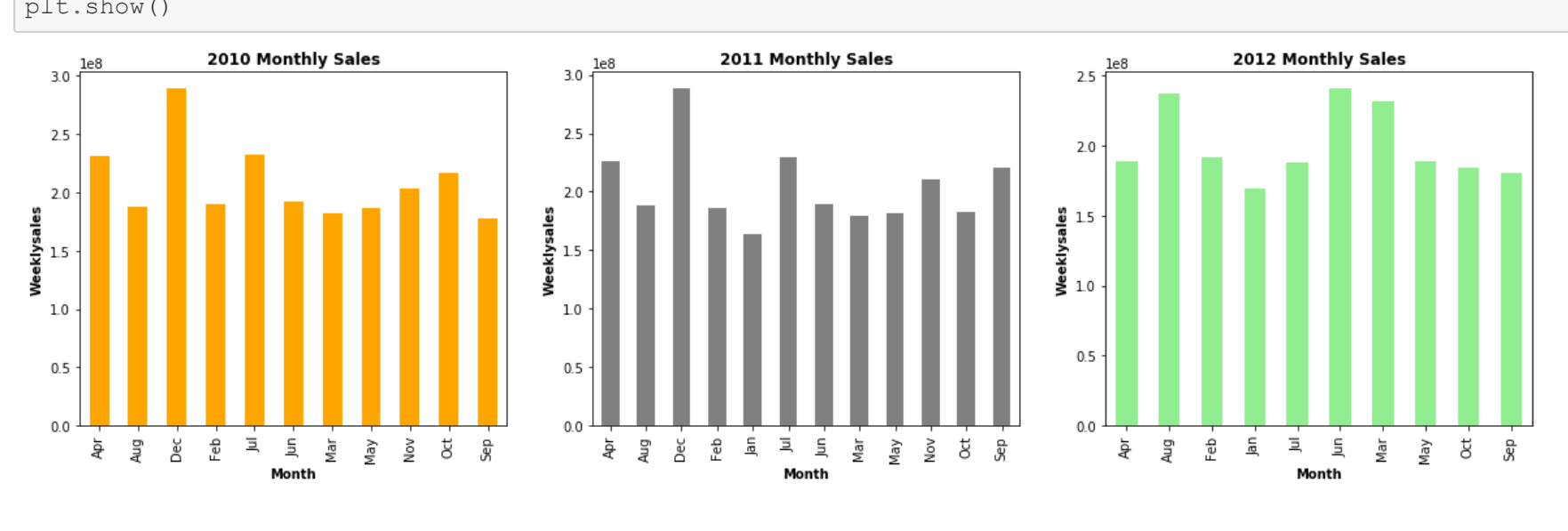
The sales was maximum in the year 2011

In [59]:
```
# Visualizing total sales percentage semester wise for different years
list1 = [semester1_2010['weekly_sales'].sum(),semester2_2010['weekly_sales'].sum(),
         semester1_2011['weekly_sales'].sum(),semester2_2011['weekly_sales'].sum(),
         semester1_2012['weekly_sales'].sum(),semester2_2012['weekly_sales'].sum()]
labels = 'Semester 1 - 2010','Semester 2 - 2010','Semester 1 - 2011','Semester 2 - 2011','Semester 1 -
 2012','Semester 2 - 2012'
cmap = plt.get_cmap('Blues')
colors = cmap(np.arange(2)*150)
txt={'weight':'bold'}
plt.figure(figsize=(15,5))
plt.pie(list1,labels=labels,autopct='%.1f%%',colors=colors,textprops=txt)
plt.show()
```



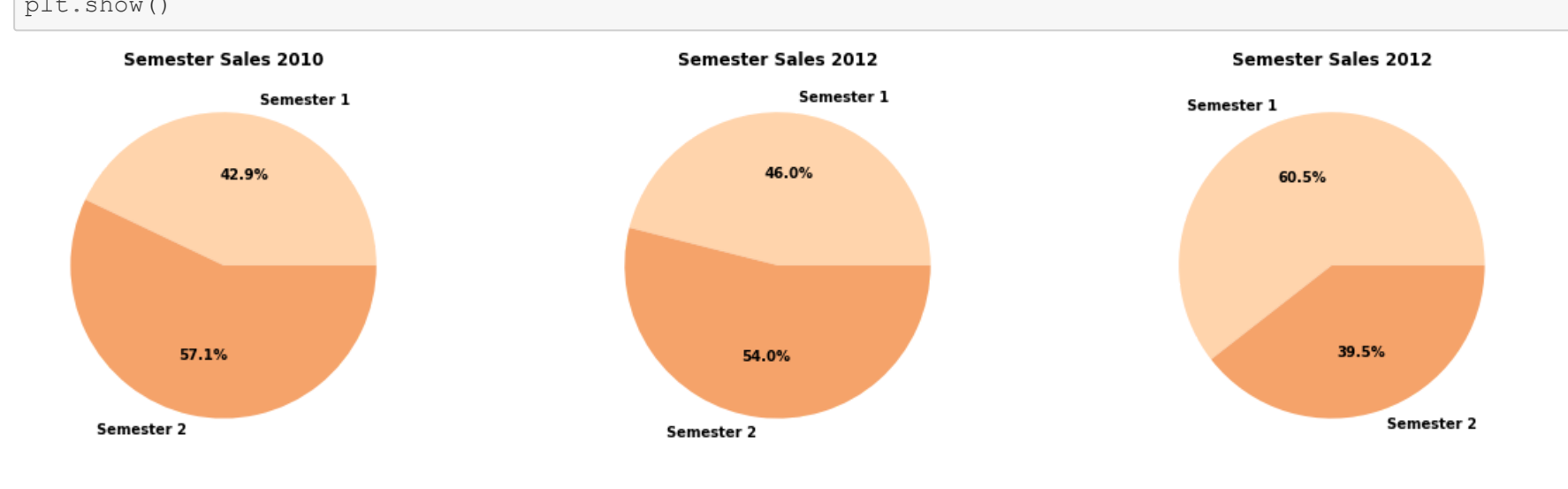
The sale was maximum in the 2nd semester of the year 2011

In [60]:
```
# Visualizing Monthly sales for each year
plt.figure(figsize=(20,5))
plt.subplots_adjust(hspace=.25)
txt={'weight':'bold'}
plt.subplot(1,3,1)
plt.title('2010 Monthly Sales',fontdict=txt)
monthlysales_2010['weekly_sales'].sum().plot.bar(color = 'orange')
plt.xlabel('Month',fontdict=txt)
plt.ylabel('Weeklysales',fontdict=txt)
plt.subplot(1,3,2)
plt.title('2011 Monthly Sales',fontdict=txt)
monthlysales_2011['weekly_sales'].sum().plot.bar(color='gray')
plt.xlabel('Month',fontdict=txt)
plt.ylabel('Weeklysales',fontdict=txt)
plt.subplot(1,3,3)
plt.title('2012 Monthly Sales',fontdict=txt)
monthlysales_2012['weekly_sales'].sum().plot.bar(color='lightgreen')
plt.xlabel('Month',fontdict=txt)
plt.ylabel('Weeklysales',fontdict=txt)
plt.show()
```



These Bar-graphs show monthly sales for each year.

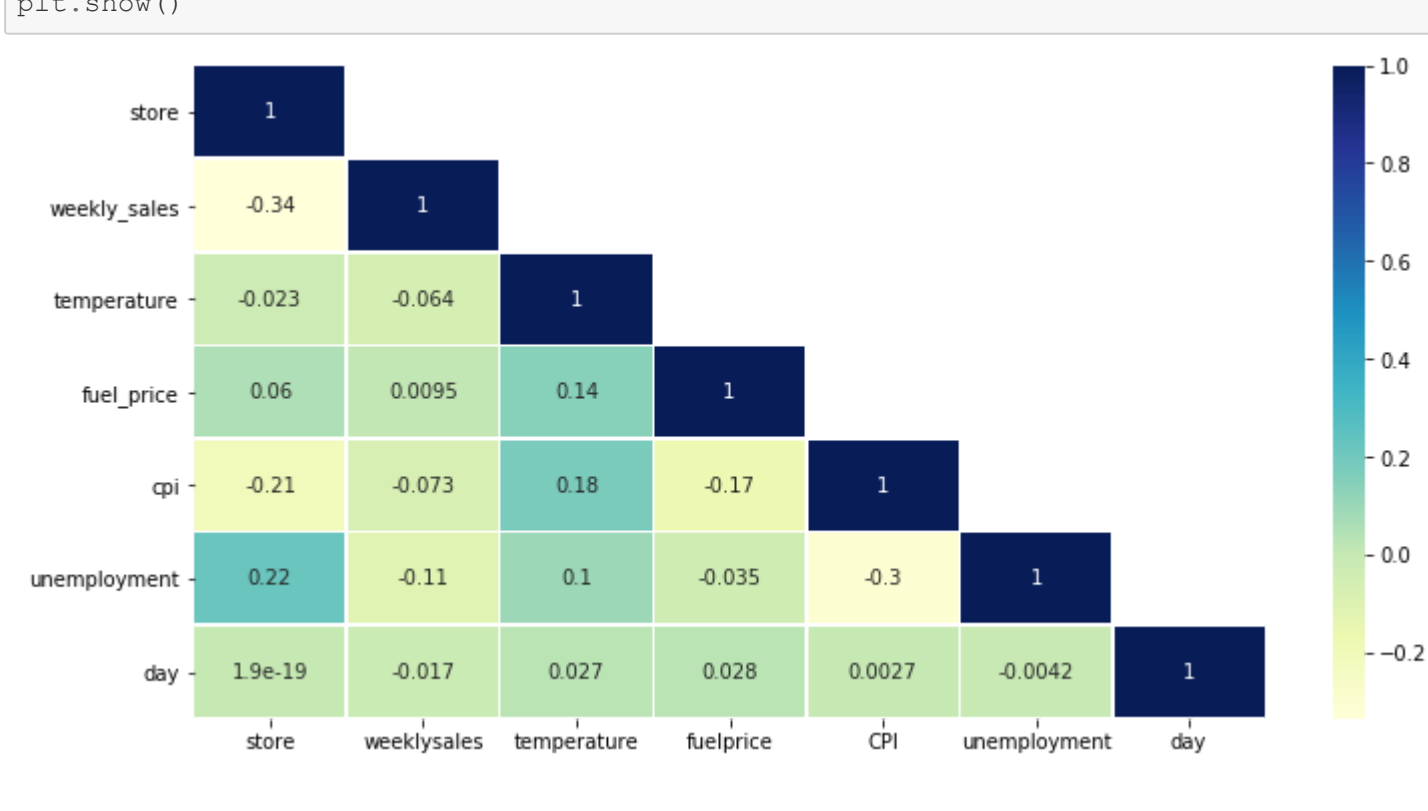
In [61]:
```
# Visualizing semester-wise sales percentage for each year
list1 = [semester1_2010['weekly_sales'].sum(),semester2_2010['weekly_sales'].sum()]
list2 = [semester1_2011['weekly_sales'].sum(),semester2_2011['weekly_sales'].sum()]
list3 = [semester1_2012['weekly_sales'].sum(),semester2_2012['weekly_sales'].sum()]
label = 'Semester 1','Semester 2'
cmap = plt.get_cmap('icefire_r')
colors = cmap(np.arange(2)*18)
txt={'weight':'bold'}
plt.figure(figsize=(20,5))
plt.subplots_adjust(hspace=.25)
plt.subplot(1,3,1)
plt.title("Semester Sales 2010",fontdict=txt)
plt.pie(list1,labels=label,autopct='%.1f%%',colors=colors,textprops=txt)
plt.subplot(1,3,2)
plt.title("Semester Sales 2012",fontdict=txt)
plt.pie(list2,labels=label,autopct='%.1f%%',colors=colors,textprops=txt)
plt.subplot(1,3,3)
plt.title("Semester Sales 2012",fontdict=txt)
plt.pie(list3,labels=label,autopct='%.1f%%',colors=colors,textprops=txt)
plt.show()
```



These Pie-charts show semester wise sales percentage for each year

In [ ]:

In [62]:
```
#HeatMap
m = np.ones_like(walmart_df.drop(columns=['holiday_flag','year']).corr())
m[np.tril_indices_from(m)]=0
labels = ['store','weeklysales','temperature','fuelprice','CPI','unemployment','day']
plt.figure(figsize=(12,6))
sns.heatmap(walmart_df.drop(columns=['holiday_flag','year']).corr(),annot=True,mask=m,cmap='YlGnBu',lin
ewidths=.5,xticklabels=labels)
plt.show()
```



CPI , Unemployment and Fuel price does not have any significant impact on Weekly_sales

In [ ]:

Statistical Model

For Store 1 – Build prediction models to forecast demand

In [63]:
```
# getting data for store 1
store_data = walmart_df.groupby('store')
store1_dataset = store_data.get_group(1)
store1_dataset['strdate'] = pd.to_datetime(store1_dataset['date'])
store1_dataset['month'] = store1_dataset['strdate'].dt.month
store1_dataset.head()
```
Out[63]:

	store	date	weekly_sales	holiday_flag	temperature	fuel_price	cpi	unemployment	year	month	day	strdate
0	1	05-Feb-10	1643690.90	0	42.31	2.572	211.096358	8.106	2010	2	5	2010-02-05
1	1	12-Feb-10	1641957.44	1	38.51	2.548	211.242170	8.106	2010	2	12	2010-02-12
2	1	19-Feb-10	1611968.17	0	39.93	2.514	211.289143	8.106	2010	2	19	2010-02-19
3	1	26-Feb-10	1409727.59	0	46.63	2.561	211.319643	8.106	2010	2	26	2010-02-26
4	1	05-Mar-10	1554806.68	0	46.50	2.625	211.350143	8.106	2010	3	5	2010-03-05

Restructuring dates as 1 for 5th Feb 2010 and so on

In [64]:
```
# Restructuring dates to numbers to use them in model as categorical data cannot be used in linear mode
l.
dummy = []
for i in range(1,144):
    dummy.append(i)
store1_dataset['dummy_date'] = dummy
```

In [65]:
```
store1_dataset.head()
```
Out[65]:

	store	date	weekly_sales	holiday_flag	temperature	fuel_price	cpi	unemployment	year	month	day	strdate	dummy_date
0	1	05-Feb-10	1643690.90	0	42.31	2.572	211.096358	8.106	2010	2	5	2010-02-05	1
1	1	12-Feb-10	1641957.44	1	38.51	2.548	211.242170	8.106	2010	2	12	2010-02-12	2
2	1	19-Feb-10	1611968.17	0	39.93	2.514	211.289143	8.106	2010	2	19	2010-02-19	3
3	1	26-Feb-10	1409727.59	0	46.63	2.561	211.319643	8.106	2010	2	26	2010-02-26	4
4	1	05-Mar-10	1554806.68	0	46.50	2.625	211.350143	8.106	2010	3	5	2010-03-05	5

LinearRegression Model

In [66]:
```
model_dataset = store1_dataset[['store','holiday_flag','temperature','fuel_price','cpi','unemployment',
'year','month','day','dummy_date','weekly_sales']]
model_dataset.head()
```
Out[66]:

	store	holiday_flag	temperature	fuel_price	cpi	unemployment	year	month	day	dummy_date	weekly_sales
0	1	0	42.31	2.572	211.096358	8.106	2010	2	5	1	1643690.90
1	1	1	38.51	2.548	211.242170	8.106	2010	2	12	2	1641957.44
2	1	0	39.93	2.514	211.289143	8.106	2010	2	19	3	1611968.17
3	1	0	46.63	2.561	211.319643	8.106	2010	2	26	4	1409727.59
4	1	0	46.50	2.625	211.350143	8.106	2010	3	5	5	1554806.68

In [67]:
```
# Splitting data into train and test for the linear model
train,test=train_test_split(model_dataset,test_size=0.20,random_state=0)
lr = LinearRegression()
x_train = train.drop(columns=['weekly_sales'])
x_test = test.drop(columns=['weekly_sales'])
y_train = train['weekly_sales']
y_test = test['weekly_sales']
```

In [68]:
```
# Fitting the model
lr.fit(x_train,y_train)
```
Out[68]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)

In [69]:
```
# Finding beta0 value
lr.intercept_
```
Out[69]: -2364627031.7073054

In [70]:
```
# Predicting the weekly_sales using the test data
y_pred = lr.predict(x_test)
y_pred.shape , y_test.shape
```
Out[70]: ((29,), (29,))

In [71]:
```
# Finding R2 score
print("Test Score = {:.2f}".format(metrics.r2_score(y_test,y_pred)))
```
```
Test Score = 0.36
```

Our Linear model has a R2 score 36%

In [72]:
```
print("Train Score = {:.2f}".format(lr.score(x_train,y_train)))
```
```
Train Score = 0.24
```

Using Ordinary Least Square Method

In [73]:
```
# Performing Ordinary Least Square method
fts = '+'.join(train.drop(columns=['weekly_sales']).columns)
linearmodel = ols('weekly_sales~'+fts,data=train).fit()
linearmodel.summary()
```
Out[73]:

OLS Regression Results

Dep. Variable:	weekly_sales	R-squared:	0.237
Model:	OLS	Adj. R-squared:	0.171
Method:	Least Squares	F-statistic:	3.585
Date:	Tue, 01 Sep 2020	Prob (F-statistic):	0.000644
Time:	08:50:12	Log-Likelihood:	-1506.8
No. Observations:	114	AIC:	3034.
Df Residuals:	104	BIC:	3061.
Df Model:	9		
Covariance Type:	nonrobust		

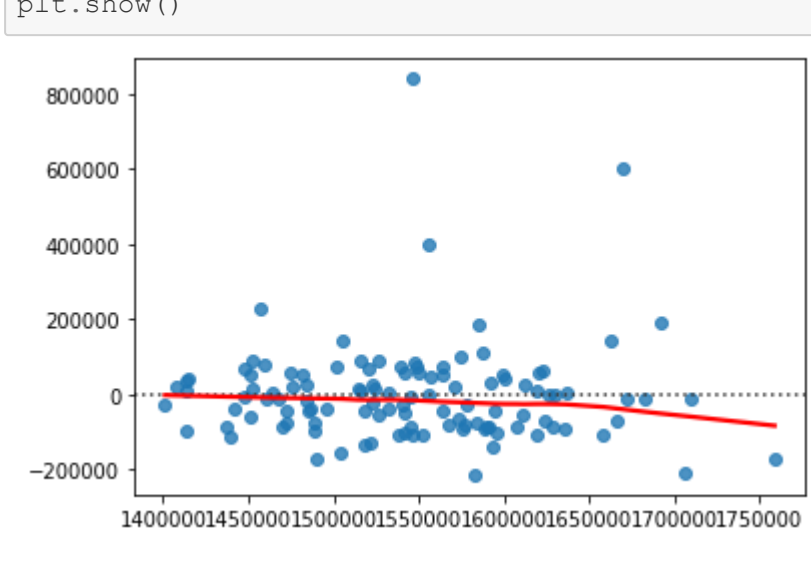
	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-1.182e+09	1.02e+10	-0.116	0.908	-2.14e+10	1.9e+10
store	-1.182e+09	1.02e+10	-0.116	0.908	-2.14e+10	1.9e+10
holiday_flag	5.748e+04	5.19e+04	1.107	0.271	-4.55e+04	1.6e+05
temperature	-2791.4208	1171.719	-2.382	0.019	-5114.984	-467.857
fuel_price	4.154e+04	7.15e+04	0.581	0.562	-1e+05	1.83e+05
cpi	2.514e+04	1.46e+04	1.717	0.089	-3892.399	5.42e+04
unemployment	1.591e+04	6.82e+04	0.233	0.816	-1.19e+05	1.51e+05
year	1.174e+06	1.01e+07	0.116	0.908	-1.89e+07	2.13e+07
month	1.114e+05	8.44e+05	0.132	0.895	-1.56e+06	1.78e+06
day	-1522.8776	2.77e+04	-0.055	0.956	-5.65e+04	5.34e+04
dummy_date	-2.452e+04	1.94e+05	-0.127	0.900	-4.09e+05	3.6e+05

Omnibus:	107.827	Durbin-Watson:	2.041
Prob(Omnibus):	0.000	Jarque-Bera (JB):	1379.530
Skew:	3.169	Prob(JB):	2.75e-300
Kurtosis:	18.819	Cond. No.	9.63e+19

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 5.04e-32. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

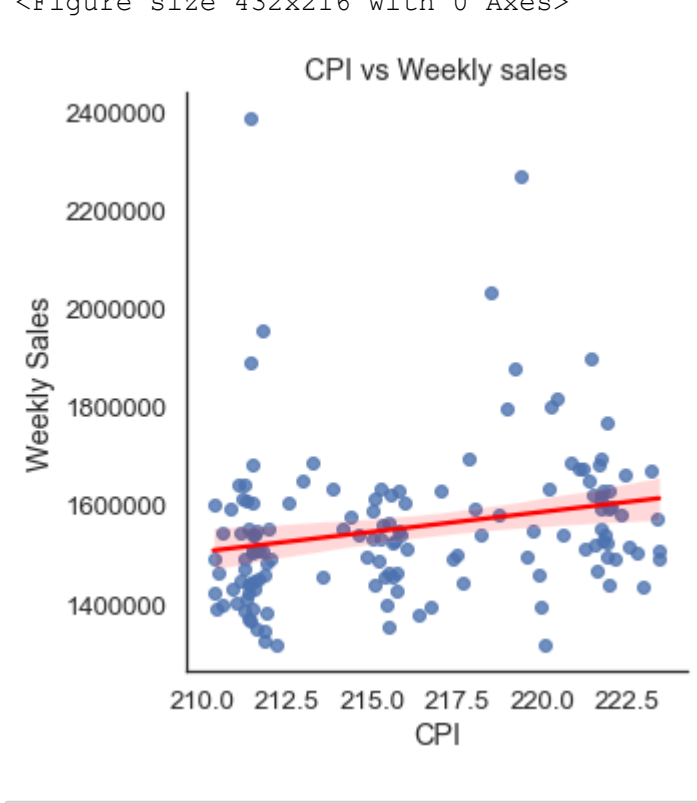
```
                  p-value                    alpha
  1)CPI            0.089                      0.05
  2)Fuel Price     0.562                      0.05
  3)Unemployment   0.816                      0.05
```

In [74]:
```
# Residual plot
fitted = linearmodel.fittedvalues
residuals = linearmodel.resid
sns.residplot(fitted,residuals,lowess=True,line_kws={'color':'red'})
plt.show()
```

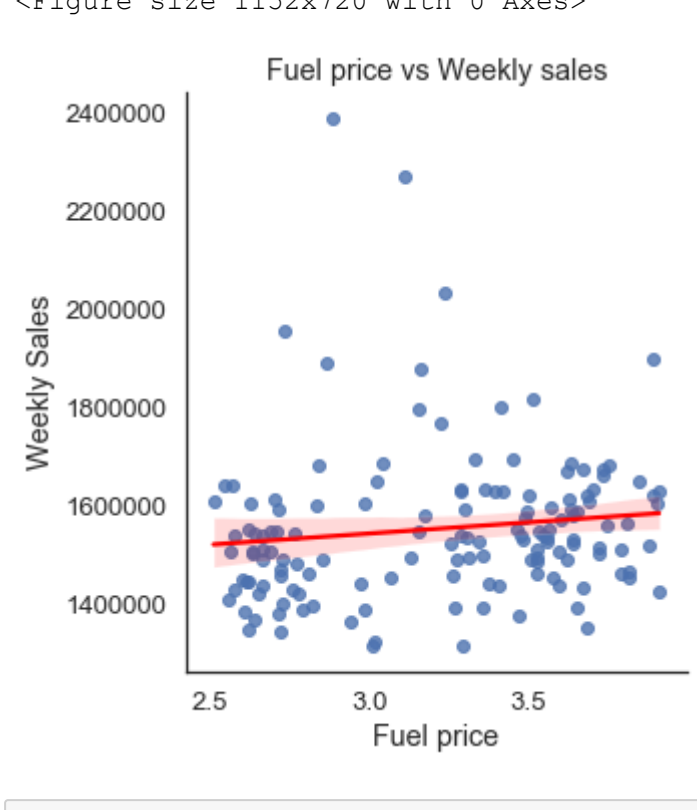


CPI , Unemployment Index and Fuel price vs Weekly Sales

In [75]:
```
# Visualizing weekly sales and CPI using a line plot
plt.figure(figsize=(6,3))
sns.set(font_scale=1.2,style="white")
sns.lmplot(x='cpi',y='weekly_sales',data = store1_dataset,line_kws={'color':'red'})
plt.title("CPI vs Weekly sales")
plt.xlabel("CPI")
plt.ylabel("Weekly Sales")
plt.show()
```
```
<Figure size 432x216 with 0 Axes>
```



In [76]:
```
# Visualizing weekly sales and fuel price using a line plot
plt.figure(figsize=(16,10))
sns.set(font_scale=1.2,style="white")
sns.lmplot(x='fuel_price',y='weekly_sales',data = store1_dataset,line_kws={'color':'red'})
plt.title("Fuel price vs Weekly sales")
plt.xlabel("Fuel price")
plt.ylabel("Weekly Sales")
plt.show()
```
```
<Figure size 1152x720 with 0 Axes>
```



In [77]:
```
# Visualizing weekly sales and unemployment index using a line plot
plt.figure(figsize=(6,3))
sns.set(font_scale=1.2,style="white")
sns.lmplot(x='unemployment',y='weekly_sales',data = store1_dataset,line_kws={'color':'red'})
plt.title("Unemployment vs Weekly sales")
plt.xlabel("Unemployment")
plt.ylabel("Weekly Sales")
plt.show()
```
```
<Figure size 432x216 with 0 Axes>
```

Changing date to day of the week

In [78]:
```
# Converting string object to datetime object
walmart_df['date'] = pd.to_datetime(walmart_df['date'])
```

In [79]:
```
# Changing dates to the day of the week
walmart_df['dayofweek'] = walmart_df['date'].dt.day_name()
```

In [80]:
```
walmart_df.head(10)
```
Out[80]:

	store	date	weekly_sales	holiday_flag	temperature	fuel_price	cpi	unemployment	year	month	day	dayofweek
0	1	2010-02-05	1643690.90	0	42.31	2.572	211.096358	8.106	2010	Feb	5	Friday
1	1	2010-02-12	1641957.44	1	38.51	2.548	211.242170	8.106	2010	Feb	12	Friday
2	1	2010-02-19	1611968.17	0	39.93	2.514	211.289143	8.106	2010	Feb	19	Friday
3	1	2010-02-26	1409727.59	0	46.63	2.561	211.319643	8.106	2010	Feb	26	Friday
4	1	2010-03-05	1554806.68	0	46.50	2.625	211.350143	8.106	2010	Mar	5	Friday
5	1	2010-03-12	1439541.59	0	57.79	2.667	211.380643	8.106	2010	Mar	12	Friday
6	1	2010-03-19	1472515.79	0	54.58	2.720	211.215635	8.106	2010	Mar	19	Friday
7	1	2010-03-26	1404429.92	0	51.45	2.732	211.018042	8.106	2010	Mar	26	Friday
8	1	2010-04-02	1594968.28	0	62.27	2.719	210.820450	7.808	2010	Apr	2	Friday
9	1	2010-04-09	1545418.53	0	65.86	2.770	210.622857	7.808	2010	Apr	9	Friday

In [ ]: