Question 1

Importing the data and required libraries.

In [ ]:

```
import pandas as pd
import matplotlib.pyplot as plt

data = pd.read_csv('complaint.csv')
data.head()
```

Out[ ]:

	Ticket #	Customer Complaint	Date	Date_month_year	Time	Received Via	City	State	Zip code	Status	Filing on Behalf of Someone
0	250635	Cable Internet Speeds	22-04-2015	22-Apr-15	3:53:50 PM	Customer Care Call	Abingdon	Maryland	21009	Closed	No
1	223441	Payment disappear - service got disconnected	04-08-2015	04-Aug-15	10:22:56 AM	Internet	Acworth	Georgia	30102	Closed	No
2	242732	Speed and Service	18-04-2015	18-Apr-15	9:55:47 AM	Internet	Acworth	Georgia	30101	Closed	Yes
3	277946	Imposed a New Usage Cap of 300GB that punishe...	05-07-2015	05-Jul-15	11:59:35 AM	Internet	Acworth	Georgia	30101	Open	Yes
4	307175	not working and no service to boot	26-05-2015	26-May-15	1:25:26 PM	Internet	Acworth	Georgia	30101	Solved	No

Analysis Tasks

Task 1 - Produce the trend chart about the monthly registered complaints

First, I extract the month using the `DatetimeIndex().month` value and store it in another column.

Then I group by the month, find each month's number of complaints using `size`, then plot a line chart.

In [ ]:

```
data['Month'] = pd.DatetimeIndex(data['Date_month_year']).month #Getting months from the
Date_month_year col as numbers
data.head() #New column, 'Month' added
```

Out[ ]:

	Ticket #	Customer Complaint	Date	Date_month_year	Time	Received Via	City	State	Zip code	Status	Filing on Behalf of Someone	Month
0	250635	Cable Internet Speeds	22-04-2015	22-Apr-15	3:53:50 PM	Customer Care Call	Abingdon	Maryland	21009	Closed	No	4
1	223441	Payment disappear - service got disconnected	04-08-2015	04-Aug-15	10:22:56 AM	Internet	Acworth	Georgia	30102	Closed	No	8
2	242732	Speed and Service	18-04-2015	18-Apr-15	9:55:47 AM	Internet	Acworth	Georgia	30101	Closed	Yes	4
3	277946	Imposed a New Usage Cap of 300GB that punishe...	05-07-2015	05-Jul-15	11:59:35 AM	Internet	Acworth	Georgia	30101	Open	Yes	7
4	307175	not working and no service to boot	26-05-	26-May-15	1:25:26 PM	Internet	Acworth	Georgia	30101	Solved	No	5

Ticket 2015 Received Zip Filing on

In [ ]:

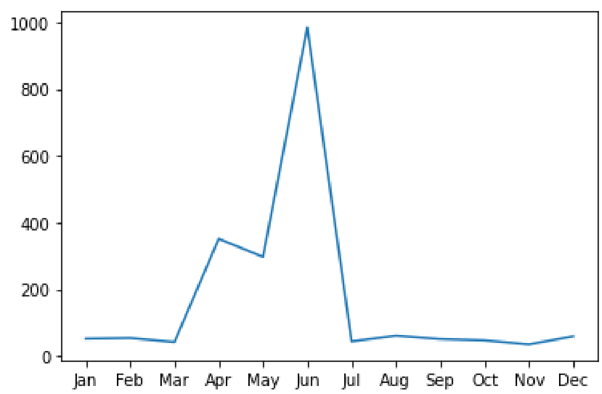
```
frequencies = data.groupby(['Month']).size() #groupby the month & get frequencies of each
monthly_complaints = pd.DataFrame()
monthly_complaints['Frequencies'] = frequencies #store the frequencies in this a dataframe
months_in_letters = ["Jan", "Feb", "Mar", "Apr", "May", "Jun", "Jul", "Aug", "Sep", "Oct", "Nov", "
Dec"] #months in letters
monthly_complaints['Month'] = months_in_letters #Added lettered month col
monthly_complaints
```

Out[ ]:

Month	Frequencies	Month
1	52	Jan
2	54	Feb
3	42	Mar
4	351	Apr
5	297	May
6	984	Jun
7	44	Jul
8	61	Aug
9	51	Sep
10	47	Oct
11	35	Nov
12	59	Dec

In [ ]:

```
# monthly_complaints.plot(kind='line', figsize=(10,5))  #For a bigger plot, but without letters
plt.plot(months_in_letters,frequencies)
plt.figure(figsize=(10,5))
plt.show()
```




```
<Figure size 720x360 with 0 Axes>
```

Task 2 - Generate a tabular output with frequencies of complaints

To do this task, I've used the `value_counts()` method on `Customer Complaint` column.
To print all, we can chain it with the `to_dict()` method or set `display.max_columns` and `display.max_rows` to `None`.

In [ ]:

```
table1 = pd.DataFrame()
table1['Frequencies'] = data['Customer Complaint'].value_counts() #If frequencies are per
complaint ty
table1
# with pd.option_context('display.max_rows', None, 'display.max_columns', None):  #Print All metho
d1
#     print(table1)
#data['Customer Complaint'].value_counts().to_dict() #Print all method2
```

Out[ ]:

	Frequencies
Internet	18
Data Cap	17
data cap	12
Billing	11
Data Caps	11
...	...
slow routing, dropped packets	1
Internet problems	1
Billing practices	1
has turned my business account to third-party collections when I legitimately canceled my contract per the terms	1
Cable	1

1783 rows × 1 columns

In [ ]:

```
# from difflib import SequenceMatcher

# def similar(a, b):
#     threshold = 0.8
#     return (SequenceMatcher(None, a, b).ratio() > threshold)

# pd.merge(table1['Frequencies'],table1)
```

If the frequencies are per month, then I've just used `value_counts` on `Month` column.

In [ ]:

```
pd.Series(data['Month'].value_counts())
```

Out[ ]:

```
6      984
4      351
5      297
8       61
12      59
2       54
1       52
9       51
10      47
7       44
3       42
11      35
Name: Month, dtype: int64
```

Task 3 - Find which complaint types are maximum i.e., internet, network issues, etc.

After getting the frequencies using `value_counts()`, I've chained it with the `head()` method to get the first few values, i.e. complaints with maximum frequencies.

In [ ]:

```
#The following are the max complaints, using head here
print("Maximum complaint types and their frequencies:")
pd.DataFrame(data['Customer Complaint'].value_counts().head())
```

```
Maximum complaint types and their frequencies:
```

Out[ ]:

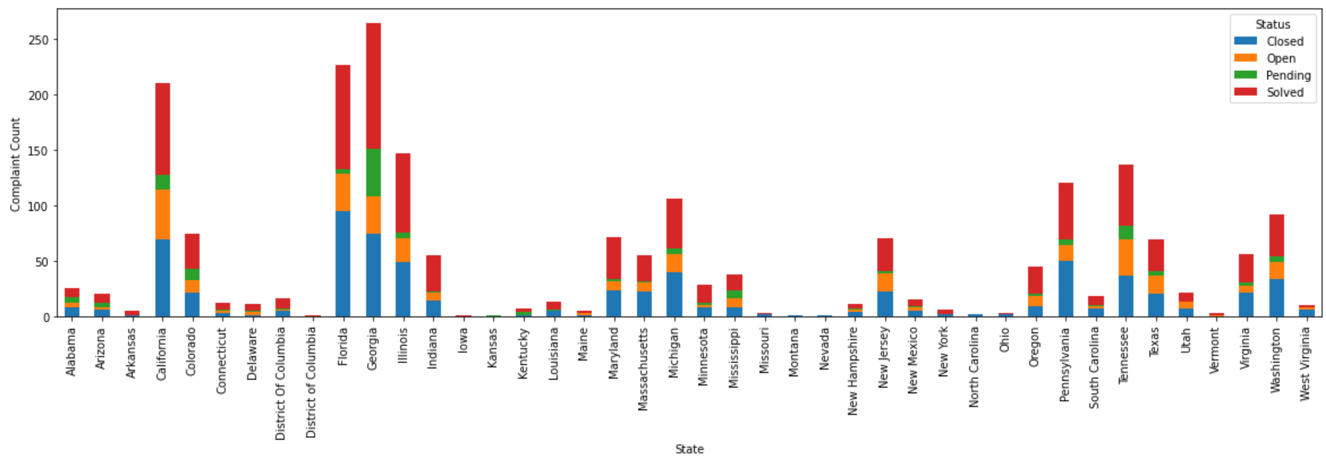
	Customer Complaint
Internet	18
Data Cap	17
data cap	12
Billing	11
Data Caps	11

Task 4 - Provide the state wise status of complaint in the form of stacked bar

To do this, I've refered to this stackoverflow answer.

In [ ]:

```
import matplotlib.pyplot as plt
state_wise = data.groupby(['State','Status']).size().unstack().fillna(0) #storing state wise complaints
state_wise.plot(kind='bar',stacked=True, figsize=(20,5)) #Plotting the graph of State wise complaints
plt.ylabel('Complaint Count')
plt.xlabel('State')
# plt.figure(figsize=(100,100))
plt.show()
```



Task 5 - Report which state has registered maximum and minimum complaint

I store the state wise frequencies in a dataframe, and then find `max()` and `min()` valued columns.
We can also use the idxmax and idxmin methods, as found in this stackoverflow answer, but it only gave me the one value.

In [ ]:

```
state_frequencies = pd.DataFrame(data['State'].value_counts()) #Store frequencies
state_frequencies.head()
```

Out[ ]:

	State
Georgia	264
Florida	226
California	210
Illinois	147
Tennessee	137

In [ ]:

```
print("States where maximum complaints are registered:\n")

state_frequencies[state_frequencies['State'] == state_frequencies['State'].max()] #Max complaints
```

```
States where maximum complaints are registered:
```

Out[ ]:

	State
Georgia	264

In [ ]:

```
print("States where minimum complaints are registered:\n")

state_frequencies[state_frequencies['State'] == state_frequencies['State'].min()] #Min complaints
```

```
States where minimum complaints are registered:
```

Out[ ]:

	State
Kansas	1
District of Columbia	1
Nevada	1
Montana	1
Iowa	1

In [ ]:

```
#Alternate
print("State with Maximum Complaints:", data['State'].value_counts().idxmax())
print("State with Minimum Complaints:", data['State'].value_counts().idxmin())
```

```
State with Maximum Complaints: Georgia
State with Minimum Complaints: Kansas
```

Task 6 - Which state has the highest and lowest percentage of unresolved complaints

Here, I reuse the `state_wise` dataframe. I sum the total complaints per state, then find the percentages of the unresolved complaints.

In [ ]:

```
state_wise.head() #Initial state wise dataframe
```

Out[ ]:

Status	Closed	Open	Pending	Solved
State				
Alabama	8.0	4.0	5.0	9.0
Arizona	6.0	2.0	4.0	8.0
Arkansas	1.0	0.0	0.0	4.0
California	69.0	45.0	14.0	82.0
Colorado	21.0	12.0	10.0	32.0

In [ ]:

```
state_wise['Total Complaints'] = state_wise.iloc[:,0:].sum(axis=1) #Getting total complaints as sum
of all types
state_wise['Resolved Percentage'] = ((state_wise['Closed'] +
state_wise['Solved'])/state_wise['Total Complaints']) * 100 #resolved complaints
state_wise['Unresolved Percentage'] = ((state_wise['Open'] +
state_wise['Pending'])/state_wise['Total Complaints']) * 100 #Unresolved complaints
state_wise.head() #Modified dataframe
```

Out[ ]:

Status	Closed	Open	Pending	Solved	Total Complaints	Resolved Percentage	Unresolved Percentage
State							
Alabama	8.0	4.0	5.0	9.0	152.0	11.184211	5.921053
Arizona	6.0	2.0	4.0	8.0	140.0	10.000000	4.285714
Arkansas	1.0	0.0	0.0	4.0	110.0	4.545455	0.000000
California	69.0	45.0	14.0	82.0	520.0	29.038462	11.346154
Colorado	21.0	12.0	10.0	32.0	250.0	21.200000	8.800000

Now that I've added the percentages, we can find the highest(`max`) and lowest(`min`) unresolved percentages.

In [ ]:

```
state_wise[state_wise['Unresolved Percentage'] == state_wise['Unresolved Percentage'].max()]
```

Out[ ]:

Status	Closed	Open	Pending	Solved	Total Complaints	Resolved Percentage	Unresolved Percentage
State							
Kansas	0.0	0.0	1.0	0.0	1.0	0.0	100.0

In [ ]:

```
state_wise[state_wise['Unresolved Percentage'] == state_wise['Unresolved Percentage'].min()]
```

Out[ ]:

Status	Closed	Open	Pending	Solved	Total Complaints	Resolved Percentage	Unresolved Percentage
State							
Arkansas	1.0	0.0	0.0	4.0	5.0	100.0	0.0
District of Columbia	0.0	0.0	0.0	1.0	1.0	100.0	0.0
Iowa	0.0	0.0	0.0	1.0	1.0	100.0	0.0
Missouri	2.0	0.0	0.0	1.0	3.0	100.0	0.0
Montana	1.0	0.0	0.0	0.0	1.0	100.0	0.0

Status	Closed	Open	Pending	Solved	Total Complaints	Resolved Percentage	Unresolved Percentage
State							
Nevada	1.0	0.0	0.0	0.0	1.0	100.0	0.0
New York	2.0	0.0	0.0	4.0	6.0	100.0	0.0
North Carolina	2.0	0.0	0.0	0.0	2.0	100.0	0.0
Ohio	2.0	0.0	0.0	1.0	3.0	100.0	0.0

Question 2

Importing the data and required libraries.

In [ ]:

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

%matplotlib inline
```

In [ ]:

```
data = pd.read_csv('Mart.csv')
data.head()
```

Out[ ]:

	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

Basic Statistical Tasks

Task 1 - Which store has maximum sales?

To do this, I get the store wise sales, then find the store corresponding to max value.

In [ ]:

```
store_sales = pd.DataFrame(data.groupby(['Store'])['Weekly_Sales'].sum())
print("Store with maximum sales:\n")
store_sales[store_sales['Weekly_Sales'] == store_sales['Weekly_Sales'].max()]
```

```
Store with maximum sales:
```

Out[ ]:

	Weekly_Sales
Store	
20	3.013978e+08

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

To do this, I use the `std()` and `mean()` methods on `DataFrame`.
For the coefficent, just divide the values.

In [ ]:

```
store_deviation = data.groupby('Store').std()    #groupby the Store, then standard deviation
store_deviation.head()
```

Out[ ]:

Store	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Unemployment
1	155980.767761	0.255926	14.250486	0.427313	4.350890	0.383749
2	237683.694682	0.255926	15.492766	0.427313	4.342286	0.615414
3	46319.631557	0.255926	12.645851	0.427313	4.434232	0.447245
4	266201.442297	0.255926	16.180023	0.416967	1.858300	1.421267
5	37737.965745	0.255926	14.225352	0.427313	4.364848	0.387415

In [ ]:

```
store_deviation[store_deviation['Weekly_Sales'] == store_deviation['Weekly_Sales'].max()]   #Max
Deviation in Sales
```

Out[ ]:

Store	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Unemployment
14	317569.949476	0.255926	16.271612	0.443029	3.59482	0.15146

In [ ]:

```
store_mean = data.groupby('Store').mean()      #Similar to standard deviation, here we get the mean
store_mean.head()
```

Out[ ]:

Store	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Unemployment
1	1.555264e+06	0.06993	68.306783	3.219699	215.996892	7.610420
2	1.925751e+06	0.06993	68.216364	3.219699	215.646311	7.623846
3	4.027044e+05	0.06993	71.434196	3.219699	219.391531	7.176986
4	2.094713e+06	0.06993	62.253357	3.216972	128.679669	5.964692
5	3.180118e+05	0.06993	69.410140	3.219699	216.565581	6.295406

In [ ]:

```
coefficients = pd.DataFrame()
coefficients['Store_wise_coefficient'] = store_deviation['Weekly_Sales']/store_mean['Weekly_Sales']
coefficients.head()
# coefficients[store_deviation['Weekly_Sales']==store_deviation['Weekly_Sales'].max()]    #To get
store 14's coefficient
```

Out[ ]:

Store	Store_wise_coefficient
1	0.100292
2	0.123424
3	0.115021

Store	Store_wise_coefficient
4	0.127083
5	0.118668

Task 3 - 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

1. **To do this, I find mean of weekly sales of non-holiday weeks, i.e., `Holiday_Flag` set to `0`.**
2. **Then I lookup the main DataFrame to find holiday weeks and sales are greater than this mean.**
3. **Finally, I print the unique date values from such weeks, to get the holidays which have higher sales than the mean of non-holiday weeks.**

In [ ]:

```
mean_sales_not_holiday = data[data.Holiday_Flag==0]['Weekly_Sales'].mean()     #Mean sales on non Holiday weeks
print("Mean of weekly sales on non holiday weeks: ", mean_sales_not_holiday)
```

```
Mean of weekly sales on non holiday weeks:  1041256.3802088564
```

In [ ]:

```
holidays_higher_sales = data[(data.Holiday_Flag==1) & (data.Weekly_Sales>mean_sales_not_holiday)]
#Weekly Sales of Holiday weeks that are greater than mean of non holiday weeks sales
holidays_higher_sales.head()
```

Out[ ]:

	Store	Date	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Unemployment
1	1	12-02-2010	1641957.44	1	38.51	2.548	211.242170	8.106
31	1	10-09-2010	1507460.69	1	78.69	2.565	211.495190	7.787
42	1	26-11-2010	1955624.11	1	64.52	2.735	211.748433	7.838
47	1	31-12-2010	1367320.01	1	48.43	2.943	211.404932	7.838
53	1	11-02-2011	1649614.93	1	36.39	3.022	212.936705	7.742

In [ ]:

```
holidays_higher_sales_dates = pd.DataFrame()
holidays_higher_sales_dates['Holiday Dates with high sales'] = holidays_higher_sales.Date.unique()
holidays_higher_sales_dates
```

Out[ ]:

	Holiday Dates with high sales
0	12-02-2010
1	10-09-2010
2	26-11-2010
3	31-12-2010
4	11-02-2011
5	09-09-2011
6	25-11-2011
7	30-12-2011
8	10-02-2012
9	07-09-2012

Task 4 - Stacked bar graph of year wise sales plotted on Month vs Sales

Task 4 - Stacked bar graph of year wise sales plotted on Month vs Sales

To do this, I've converted `Date` column to date time, extracted the `Month` and `Year`, then grouped the data by these two columns for the sum of sales.
Then, I've plotted the stacked bar graph.

In [ ]:

```
data['Date'] = pd.to_datetime(data['Date'])           #To datetime
data['Month'] = pd.DatetimeIndex(data['Date']).month  #Extract Month
data['Year'] = pd.DatetimeIndex(data['Date']).year    #Extract Year
monthly = data.groupby(['Month','Year'])['Weekly_Sales'].sum().unstack().fillna(0)
#Group by these two columns, fill with the sum of sales
print("Monthly sales for all the years:\n")
monthly
```

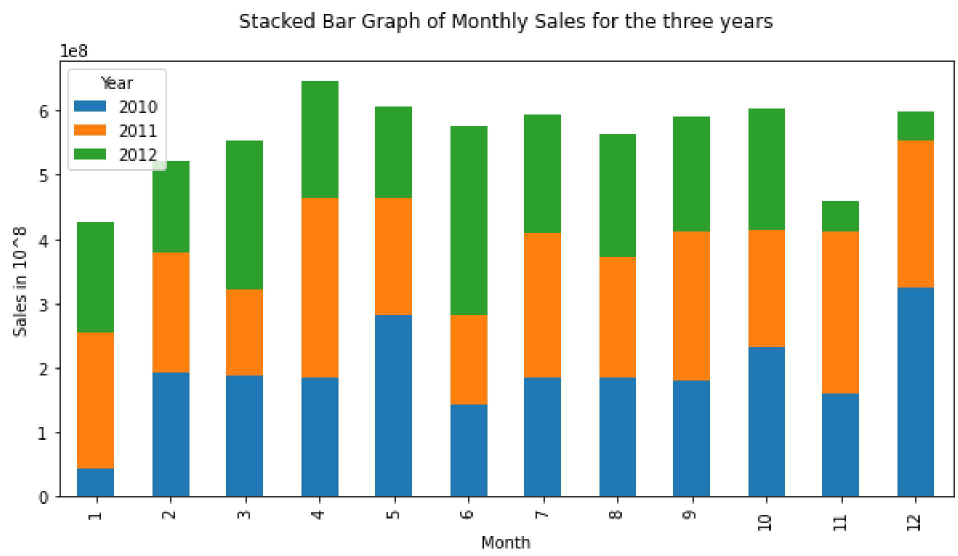
```
Monthly sales for all the years:
```

Out[ ]:

Year Month	2010	2011	2012
1	4.223988e+07	2.119657e+08	1.722207e+08
2	1.915869e+08	1.876092e+08	1.428296e+08
3	1.862262e+08	1.365205e+08	2.307397e+08
4	1.838118e+08	2.789693e+08	1.825428e+08
5	2.806119e+08	1.828017e+08	1.422830e+08
6	1.424361e+08	1.401936e+08	2.923883e+08
7	1.842664e+08	2.244611e+08	1.845865e+08
8	1.845381e+08	1.880810e+08	1.916126e+08
9	1.797041e+08	2.310323e+08	1.797959e+08
10	2.311201e+08	1.837193e+08	1.880794e+08
11	1.587731e+08	2.534703e+08	4.692588e+07
12	3.235716e+08	2.293760e+08	4.612851e+07

In [ ]:

```
monthly.plot(kind='bar',stacked=True,figsize=(10,5))     #Plotting the bar graph
plt.xlabel('Month')
plt.ylabel('Sales in 10^8')
plt.title('Stacked Bar Graph of Monthly Sales for the three years\n')
plt.show()
```



Statistical Model

- **To do this question, and sort the dates and index them from 0 onwards.**
- **Then I train a linear regression model, based on the Date.**
- **After plotting some graphs between the different features and the Sales, I notice that these features do impact the sales.**
- **So finally, I train a multi-variable linear regression model, with the other features like CPI along with the Date.**
- **I extract the individual coefficients of each, and plot a graph to show their impacts on the model.**

Extracting Store-2 Data

In [ ]:

```
store2_data = data[data['Store']==2]
store2_data.head()
```

Out[ ]:

	Store	Date	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Unemployment	Month	Year
143	2	2010-05-02	2136989.46	0	40.19	2.572	210.752605	8.324	5	2010
144	2	2010-12-02	2137809.50	1	38.49	2.548	210.897994	8.324	12	2010
145	2	2010-02-19	2124451.54	0	39.69	2.514	210.945160	8.324	2	2010
146	2	2010-02-26	1865097.27	0	46.10	2.561	210.975957	8.324	2	2010
147	2	2010-05-03	1991013.13	0	47.17	2.625	211.006754	8.324	5	2010

Simple Linear Regression Model

Convert the Dates to indices.

In [ ]:

```
# store2_data.shape
# store2_data.index
store2_data['Date Indices'] = store2_data.index - store2_data.shape[0]
store2_data.head(n=20)
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  This is separate from the ipykernel package so we can avoid doing imports until
```

Out[ ]:

	Store	Date	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Unemployment	Month	Year	Date Indices
143	2	2010-05-02	2136989.46	0	40.19	2.572	210.752605	8.324	5	2010	0
144	2	2010-12-02	2137809.50	1	38.49	2.548	210.897994	8.324	12	2010	1
145	2	2010-02-19	2124451.54	0	39.69	2.514	210.945160	8.324	2	2010	2
146	2	2010-02-26	1865097.27	0	46.10	2.561	210.975957	8.324	2	2010	3
147	2	2010-05-03	1991013.13	0	47.17	2.625	211.006754	8.324	5	2010	4
148	2	2010-12-03	1990483.78	0	57.56	2.667	211.037551	8.324	12	2010	5
149	2	2010-03-19	1946070.88	0	54.52	2.720	210.873332	8.324	3	2010	6
150	2	2010-03-26	1750197.81	0	51.26	2.732	210.676610	8.324	3	2010	7
151	2	2010-02-04	2066187.72	0	63.27	2.719	210.479887	8.200	2	2010	8

	Store	Date	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Unemployment	Month	Year	Date Indices
152	2	2010-09-04	1954689.21	0	65.41	2.770	210.283165	8.200	9	2010	9
153	2	2010-04-16	1874957.94	0	68.07	2.808	210.149546	8.200	4	2010	10
154	2	2010-04-23	1821990.93	0	65.11	2.795	210.100065	8.200	4	2010	11
155	2	2010-04-30	1802450.29	0	66.98	2.780	210.050583	8.200	4	2010	12
156	2	2010-07-05	2042581.71	0	71.28	2.835	210.001102	8.200	7	2010	13
157	2	2010-05-14	1880752.36	0	73.31	2.854	209.998458	8.200	5	2010	14
158	2	2010-05-21	1896937.10	0	74.83	2.826	210.276844	8.200	5	2010	15
159	2	2010-05-28	1957113.89	0	81.13	2.759	210.555230	8.200	5	2010	16
160	2	2010-04-06	2102539.93	0	81.81	2.705	210.833616	8.200	4	2010	17
161	2	2010-11-06	2025538.76	0	83.40	2.668	211.112002	8.200	11	2010	18
162	2	2010-06-18	2001636.96	0	85.81	2.637	211.109654	8.200	6	2010	19

Split the data into train and test, then train the model.

In [ ]:

```
from sklearn.model_selection import train_test_split
from sklearn import linear_model
X = store2_data[['Date Indices']]
y = store2_data[['Weekly_Sales']]
#Split the data into train = 90%, test = 10%
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size = 0.1,random_state = 42 )

simple_model = linear_model.LinearRegression()
simple_model.fit(X_train,y_train)
print("The model has been trained.")
print("The intercept is:", simple_model.intercept_, "and the coefficients are:", simple_model.coef
_)
```

```
The model has been trained.
The intercept is: [1960133.62504624] and the coefficients are: [[-547.70350259]]
```

In [ ]:

```
y_pred = simple_model.predict(X_test)    #Predictions on test values
y_pred
```

Out[ ]:

```
array([[1896052.31524298],
       [1949727.25849699],
       [1915221.9378337 ],
       [1907006.38529482],
       [1929462.22890109],
       [1953561.18301514],
       [1888384.46620669],
       [1924532.89737776],
       [1923985.19387517],
       [1950274.96199958],
       [1932200.74641405],
       [1917412.75184406],
       [1908649.49580259],
       [1887836.7627041 ],
       [1905363.27478704]])
```

In [ ]:

```
simple_model.score(X_test,y_test)    #Score of classifier
```

Out[ ]:

```
-0.06726219423951574
```

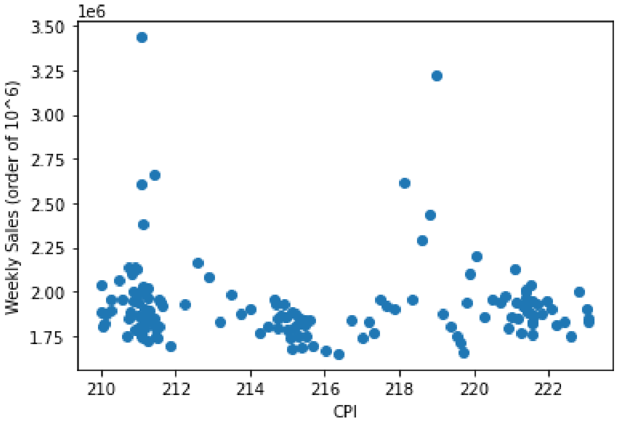
Hypothesize if CPI, unemployment, and fuel price have any impact on sales.

Let us plot the corresponding Variable vs Sales graphs to find out.

First, the graph of `CPI` vs `Weekly_Sales`.

In [ ]:

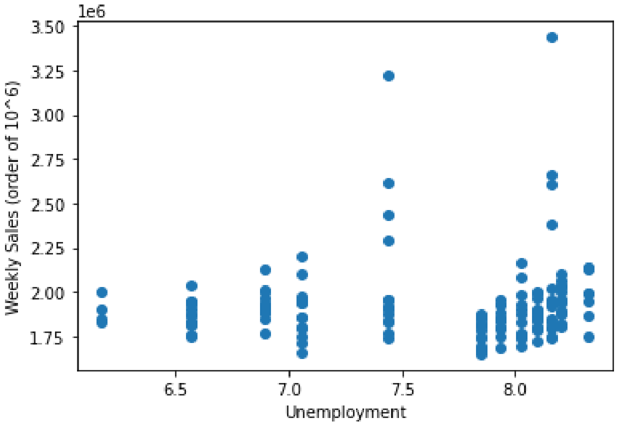
```
plt.scatter(store2_data['CPI'], store2_data['Weekly_Sales'])
plt.xlabel('CPI')
plt.ylabel('Weekly Sales (order of 10^6)')
plt.show()
```



Then, the graph of `Unemployment` vs `Weekly_Sales`

In [ ]:

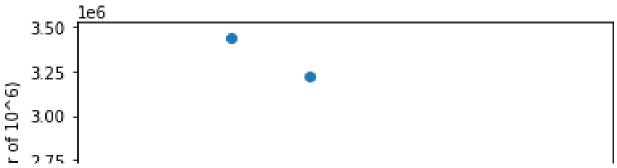
```
plt.scatter(store2_data['Unemployment'], store2_data['Weekly_Sales'])
plt.xlabel('Unemployment')
plt.ylabel('Weekly Sales (order of 10^6)')
plt.show()
```

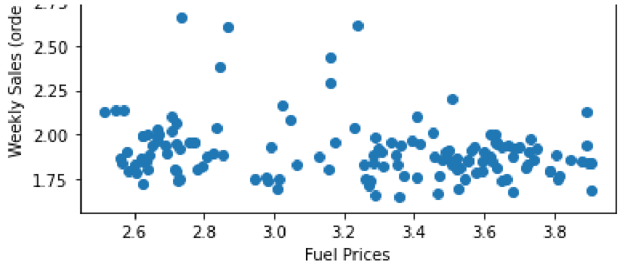


Finally, the graph of `Fuel_Price` vs `Weekly_Sales`.

In [ ]:

```
plt.scatter(store2_data['Fuel_Price'], store2_data['Weekly_Sales'])
plt.xlabel('Fuel Prices')
plt.ylabel('Weekly Sales (order of 10^6)')
plt.show()
```

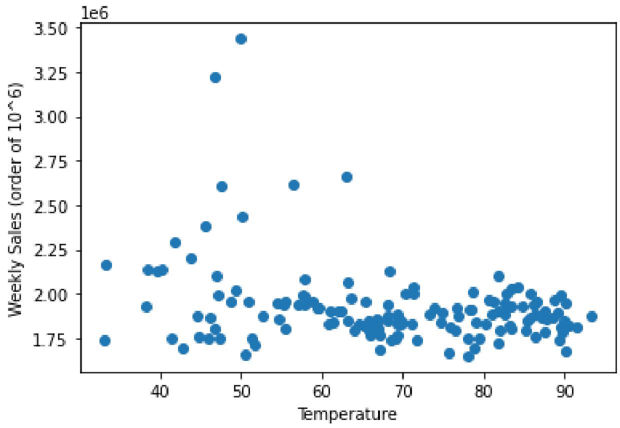




Let's also check for Temperature and Holidays.

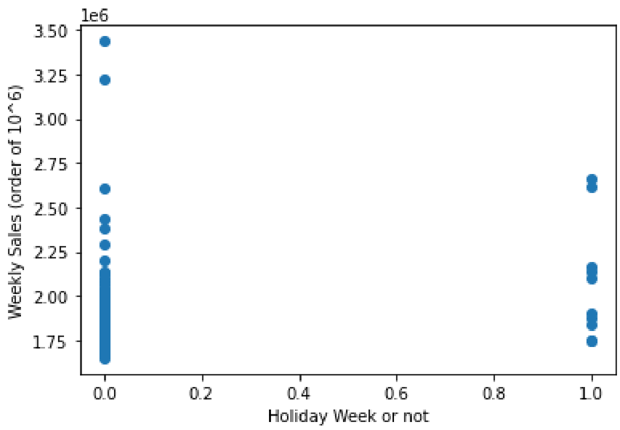
In [ ]:

```
plt.scatter(store2_data['Temperature'], store2_data['Weekly_Sales'])
plt.xlabel('Temperature')
plt.ylabel('Weekly Sales (order of 10^6)')
plt.show()
```



In [ ]:

```
plt.scatter(store2_data['Holiday_Flag'], store2_data['Weekly_Sales'])
plt.xlabel('Holiday Week or not')
plt.ylabel('Weekly Sales (order of 10^6)')
plt.show()
```



- **From the graphs, it is quite clear that `CPI`, `Fuel_Prices`, `Temperature` impact the Sales.**
- **`Unemplyment`, on the other hand, doesn't seem to impact Sales.**
- **`Holiday_Week` being a binary value, won't scatter much.**

Multi-Variable Linear Regression Model

Let us plot a multivariable regression model.

The above mentioned variables will be used as features for the model. Since the values are varying across a large scale, we normalise them first.

In [ ]:

```
from sklearn.preprocessing import MinMaxScaler

normalised_store2 = store2_data.drop(['Date','Month','Year'],axis=1)
normalised_store2 =
pd.DataFrame(MinMaxScaler().fit_transform(normalised_store2),columns=normalised_store2.columns)
# normalised_store2
variables = ['Holiday_Flag','Temperature','Fuel_Price','CPI','Unemployment','Date Indices']

X = normalised_store2[variables]
y = normalised_store2 ['Weekly_Sales']
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size = 0.1,random_state = 42 )

multivar_model = linear_model.LinearRegression()
multivar_model.fit(X_train,y_train)
print("The model has been trained.")
print("Score of Model is:",multivar_model.score(X_test,y_test))
```

```
The model has been trained.
Score of Model is: 0.15234951079516879
```

In [ ]:

```
y_pred = multivar_model.predict(X_test)    #Predictions on test values
y_pred
```

Out[ ]:

```
array([0.10147451, 0.12834684, 0.09343793, 0.23539127, 0.16480436,
       0.14042667, 0.10061966, 0.09693347, 0.06946697, 0.12888754,
       0.21809148, 0.06020325, 0.22065701, 0.101914  , 0.2214479 ])
```

In [ ]:

```
print("The intercept is:", multivar_model.intercept_)
coefficients = pd.DataFrame()
coefficients['Features'] = variables
coefficients['Coefficents'] = multivar_model.coef_
coefficients
```

```
The intercept is: 0.08282226716676368
```

Out[ ]:

	Features	Coefficents
0	Holiday_Flag	0.016333
1	Temperature	-0.139927
2	Fuel_Price	-0.165927
3	CPI	0.061614
4	Unemployment	0.160649
5	Date Indices	0.194308

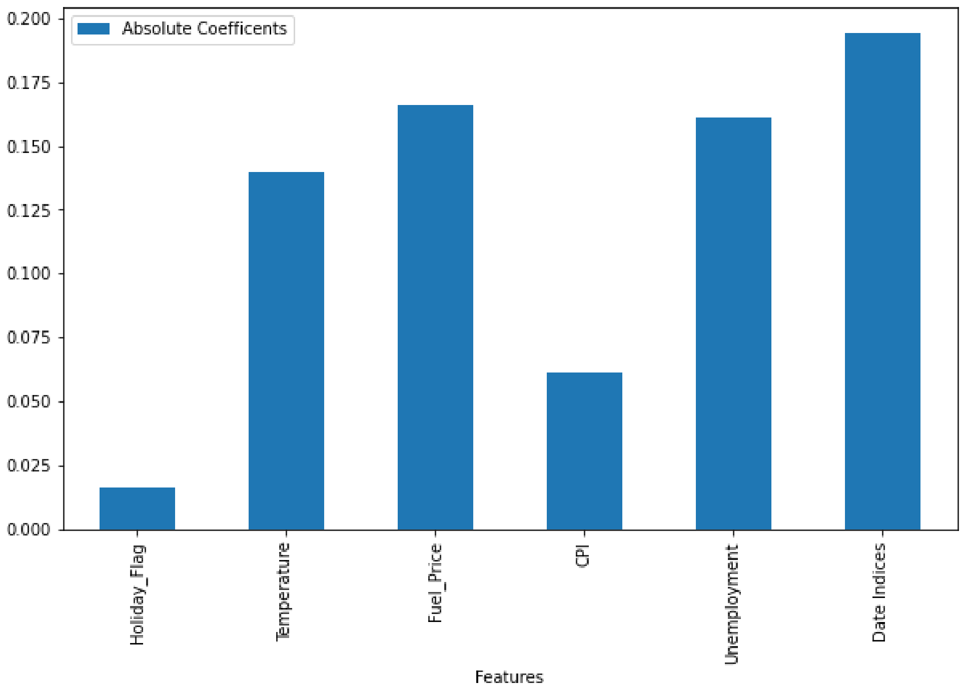
Let's plot the coefficients on a graph to visualise each features' impact.

In [ ]:

```
coefficients['Absolute Coefficents'] = coefficients['Coefficents'].abs()
coefficients.plot(kind='bar',x='Features',y='Absolute Coefficents',figsize=(10,6))
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f15a0e1a160>
```



From this graph, we see that all features do infact impact the sales. The higher the bar in the graph, the higher the weight in the model.