In [1]:
```python
# Importing the libraries

import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import mean_squared_error, mean_absolute_error
import numpy as np
```

In [2]:
```python
# importing the dataset

data = pd.read_csv("D:\Intellipaat\Assignments\Capstone Project\Capstone-Dataset\Walmart
```

In [3]:
```python
data.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 [4]:
```python
# converting the data to datetime object type

data['Date'] = pd.to_datetime(data['Date'], dayfirst=True)
```

In [5]:
```python
data.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   datetime64[ns]
 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: datetime64[ns](1), float64(5), int64(2)
memory usage: 402.3 KB
```

In [6]:
```python
# Changing the column to index

data.index = data['Date']
del data['Date']
```

In [7]:
```python
data.head()
```

Out[7]:

	Store	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Unemployment
Date							

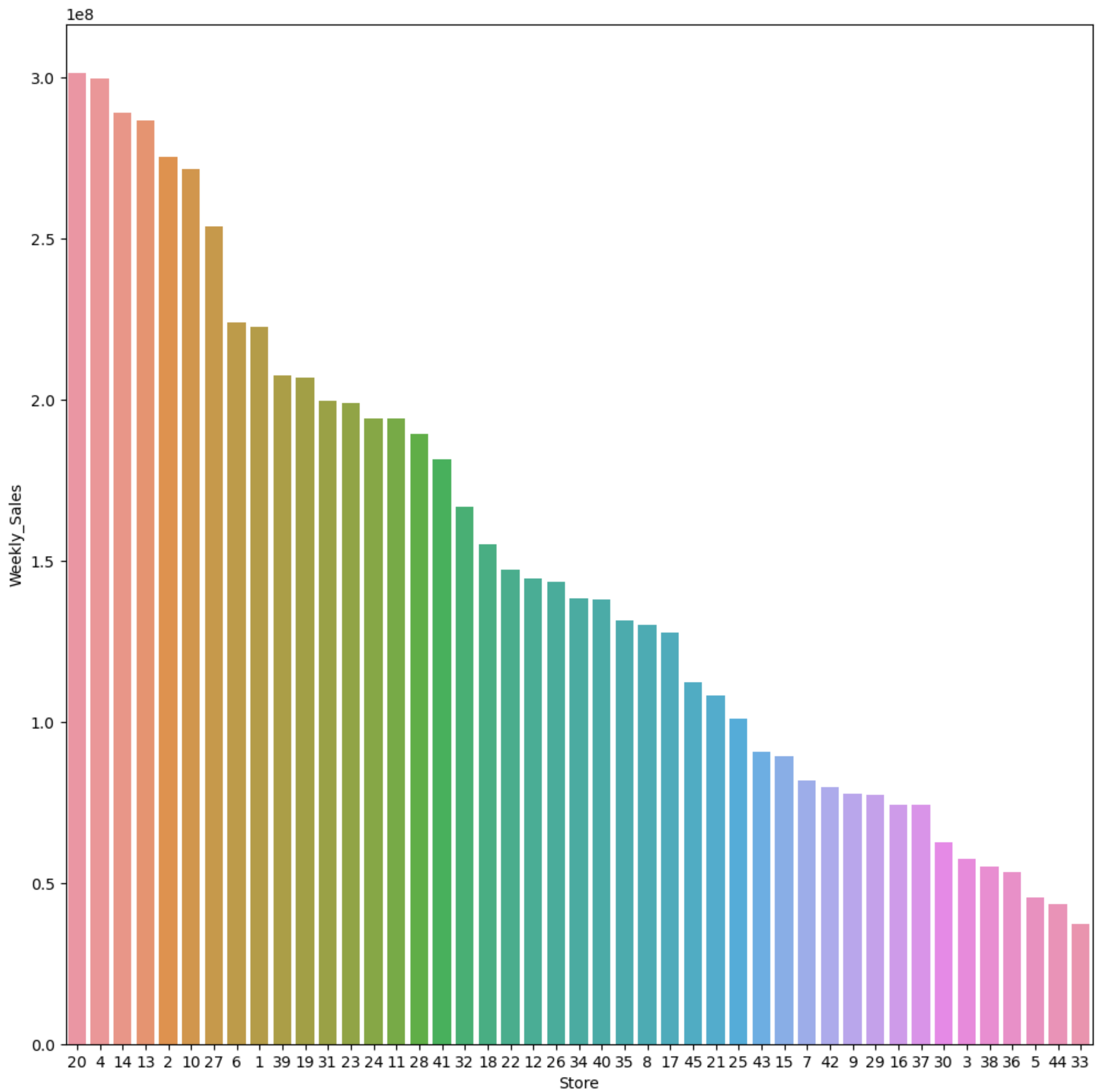
2010-02-05	1	1643690.90	0	42.31	2.572	211.096358	8.106
2010-02-12	1	1641957.44	1	38.51	2.548	211.242170	8.106
2010-02-19	1	1611968.17	0	39.93	2.514	211.289143	8.106
2010-02-26	1	1409727.59	0	46.63	2.561	211.319643	8.106
2010-03-05	1	1554806.68	0	46.50	2.625	211.350143	8.106

In [8]:

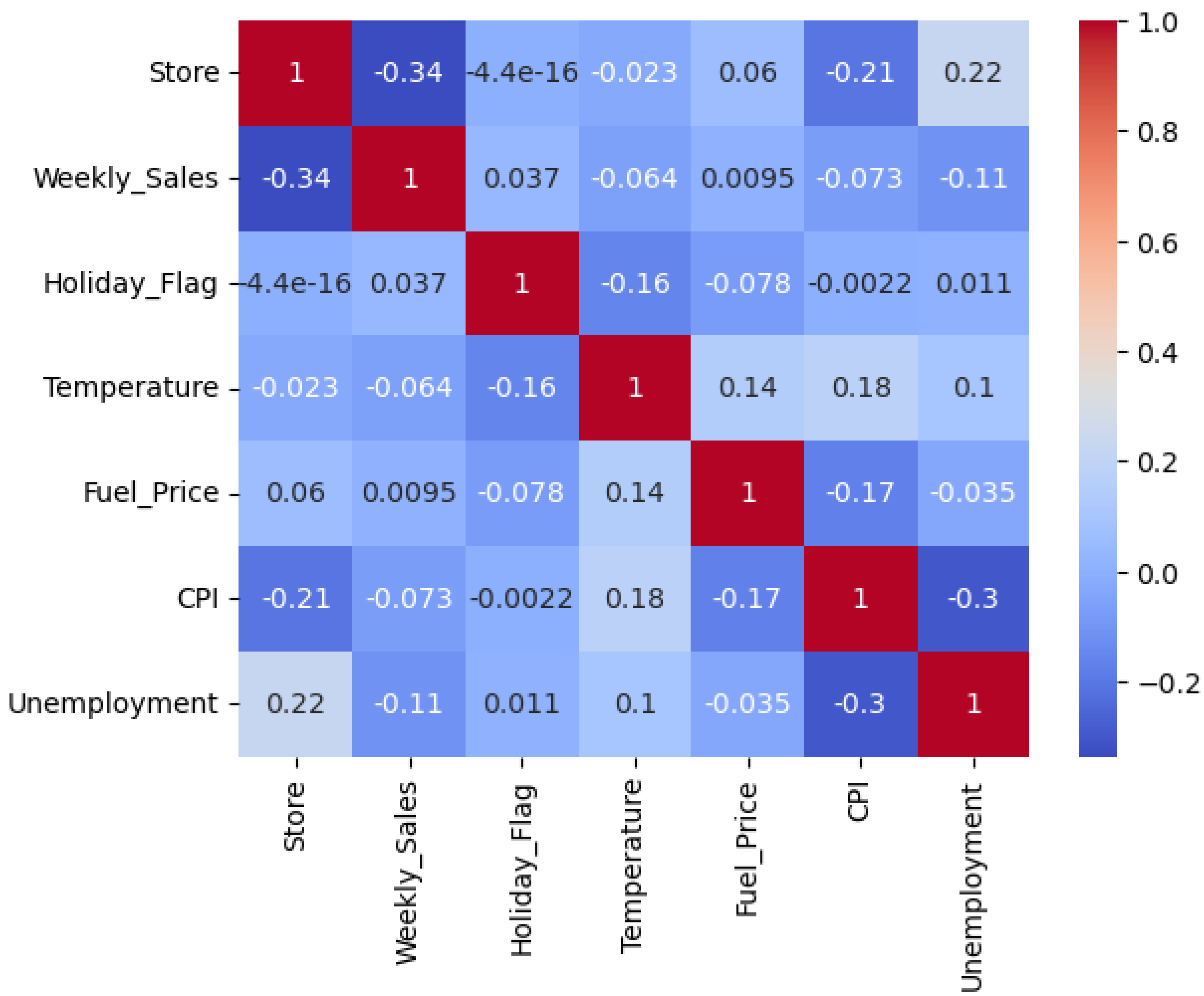
```
# Store Analysis : Store performance based on Total Sales

store_total_sales = data.groupby('Store')['Weekly_Sales'].sum().reset_index()
sorted_store_total_sales = store_total_sales.sort_values('Weekly_Sales', ascending=False

plt.figure(figsize = (12,12))
sns.barplot(data=sorted_store_total_sales, x='Store', y='Weekly_Sales',
            order=store_total_sales.sort_values('Weekly_Sales', ascending=False).Store)
```

Out[8]:

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



In [9]:
```python
sns.heatmap(data.corr(), annot=True, cmap='coolwarm')
plt.show()
```



In [10]:
```python
# Inference from the above correlation graph

    # Unemployment data has a negative correlation with Weekly sales, which shows the wh
    # the weekly sales.

    # CPI (Consumer Price Index) data also has negative effect with Weekly Sales, indica
    # weekly sales tend to decrease

    # Holiday_Flag data has a (+) positive effect in Weekly Sales

    # Temperature data has a (-) negative effect in Weekly Sales, people tend to shop du
    # The sales peaks during the Winter season (December) as it is a month of celebratio
```

In [11]:
```python
a= int(input("Enter the store id:"))
store = data[data.Store == a]
```

```
Enter the store id:7
```

In [12]:
```python
# Time Series Vizualization
store
```

Out[12]:

	Store	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Unemployment
Date							
2010-02-05	7	496725.44	0	10.53	2.580	189.381697	9.014
2010-02-12	7	524104.92	1	25.90	2.572	189.464272	9.014

2010-02-19	7	506760.54	0	27.28	2.550	189.534100	9.014
2010-02-26	7	496083.24	0	24.91	2.586	189.601802	9.014
2010-03-05	7	491419.55	0	35.86	2.620	189.669505	9.014
...	...	...	...	...	...	...	...
2012-09-28	7	525545.76	0	50.64	3.789	198.590328	7.872
2012-10-05	7	505830.56	0	48.43	3.779	198.822132	7.557
2012-10-12	7	503463.93	0	41.43	3.760	199.053937	7.557
2012-10-19	7	516424.83	0	43.01	3.750	199.148196	7.557
2012-10-26	7	495543.28	0	42.53	3.686	199.219532	7.557

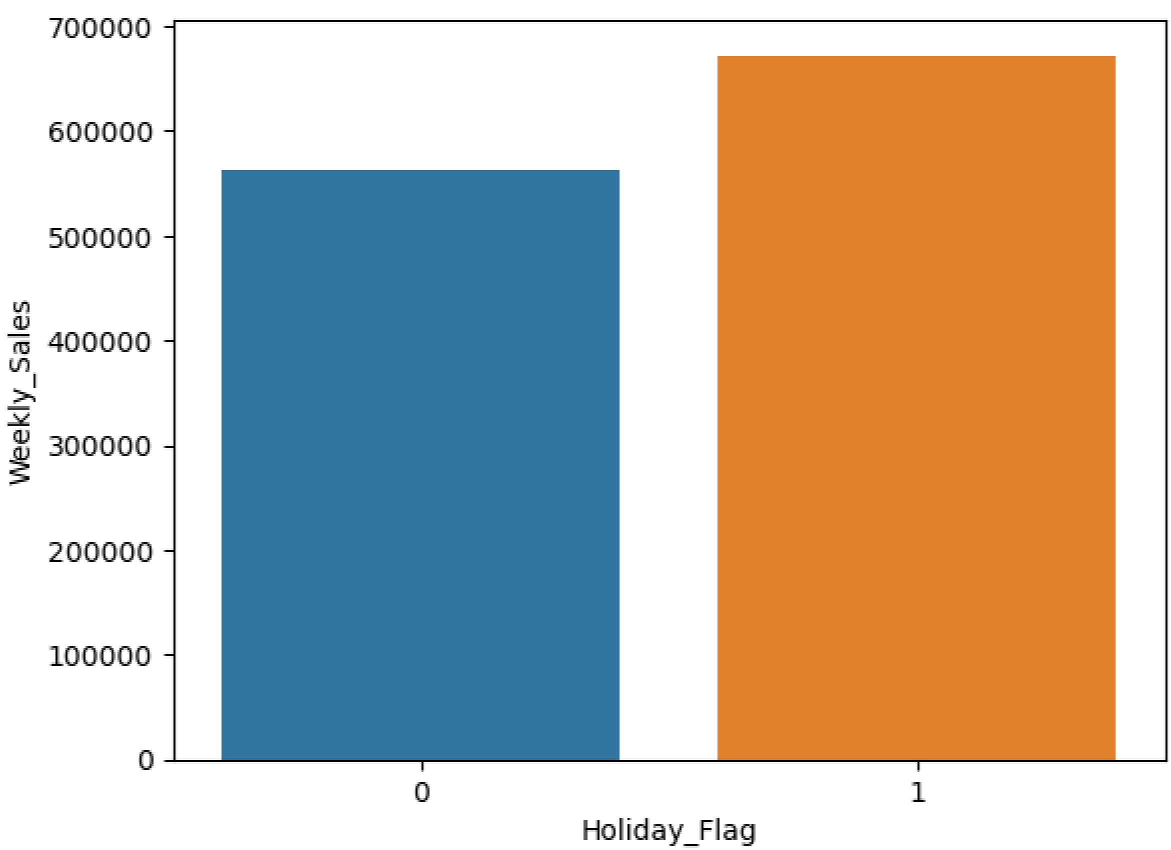
143 rows × 7 columns

In [13]:

```
# Holiday Analysis: To identify any increase or decrease in sales during holiday periods

holiday_total_sales = store.groupby('Holiday_Flag')['Weekly_Sales'].mean().reset_index()
sns.barplot(data=holiday_total_sales, x='Holiday_Flag', y='Weekly_Sales')
```

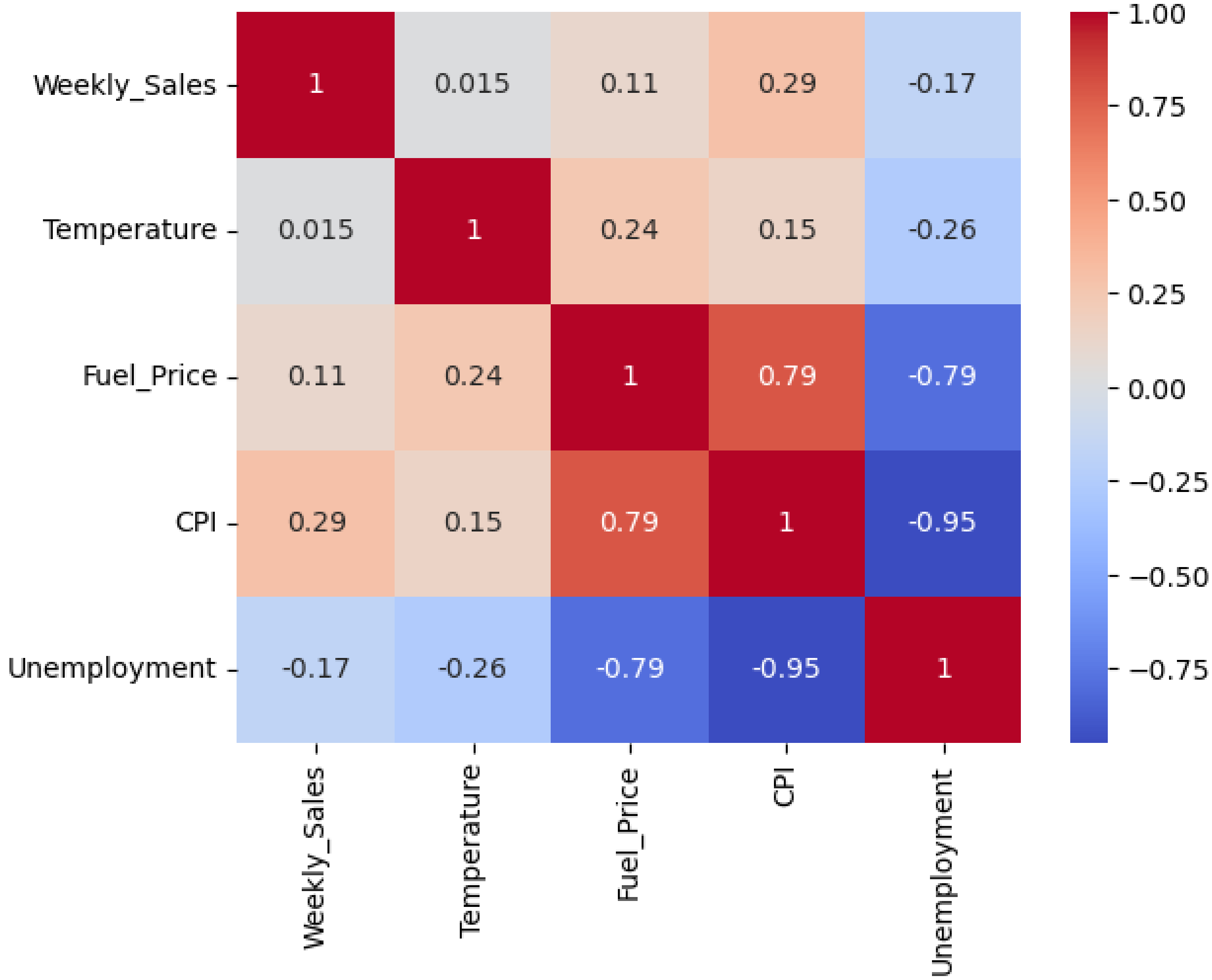
Out[13]:

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



In [14]:

```
store_correlation = store[['Weekly_Sales','Temperature','Fuel_Price','CPI','Unemployment
sns.heatmap(store_correlation.corr(), annot=True, cmap='coolwarm')
plt.show()
```

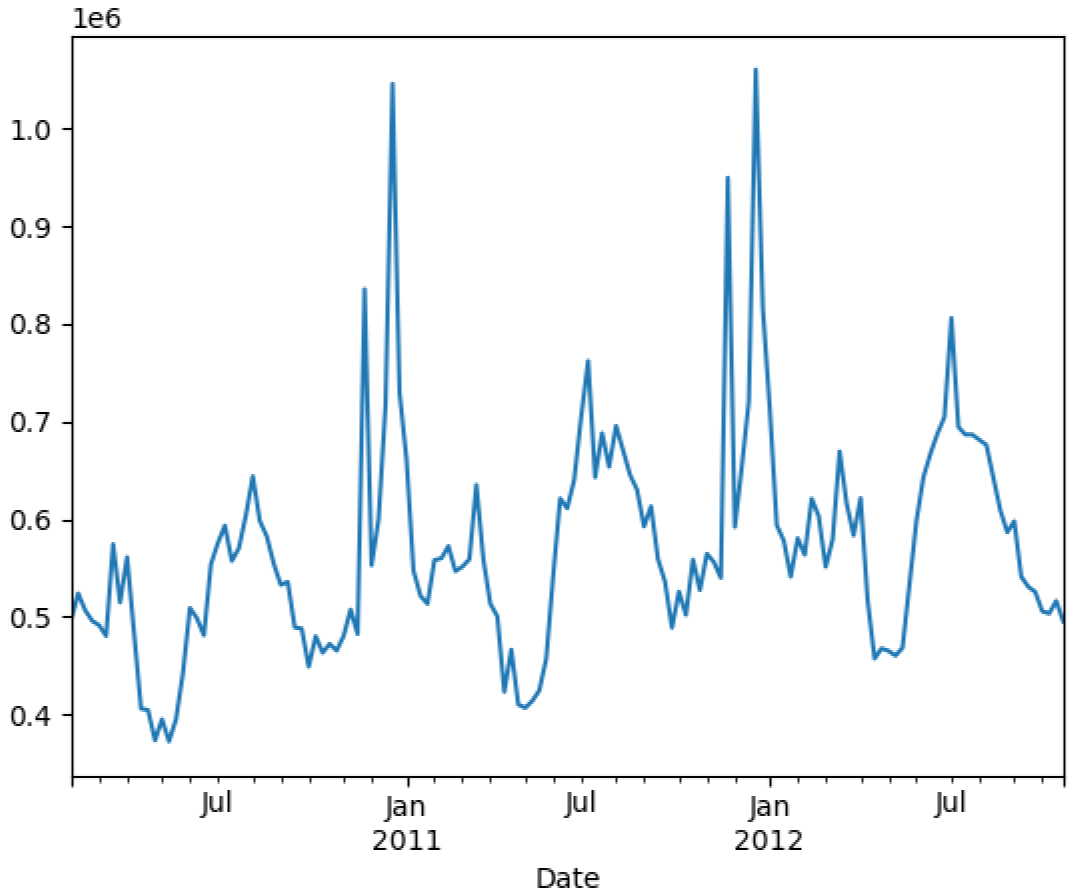


In [15]:

```
store['Weekly_Sales'].plot()
```

Out[15]:

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



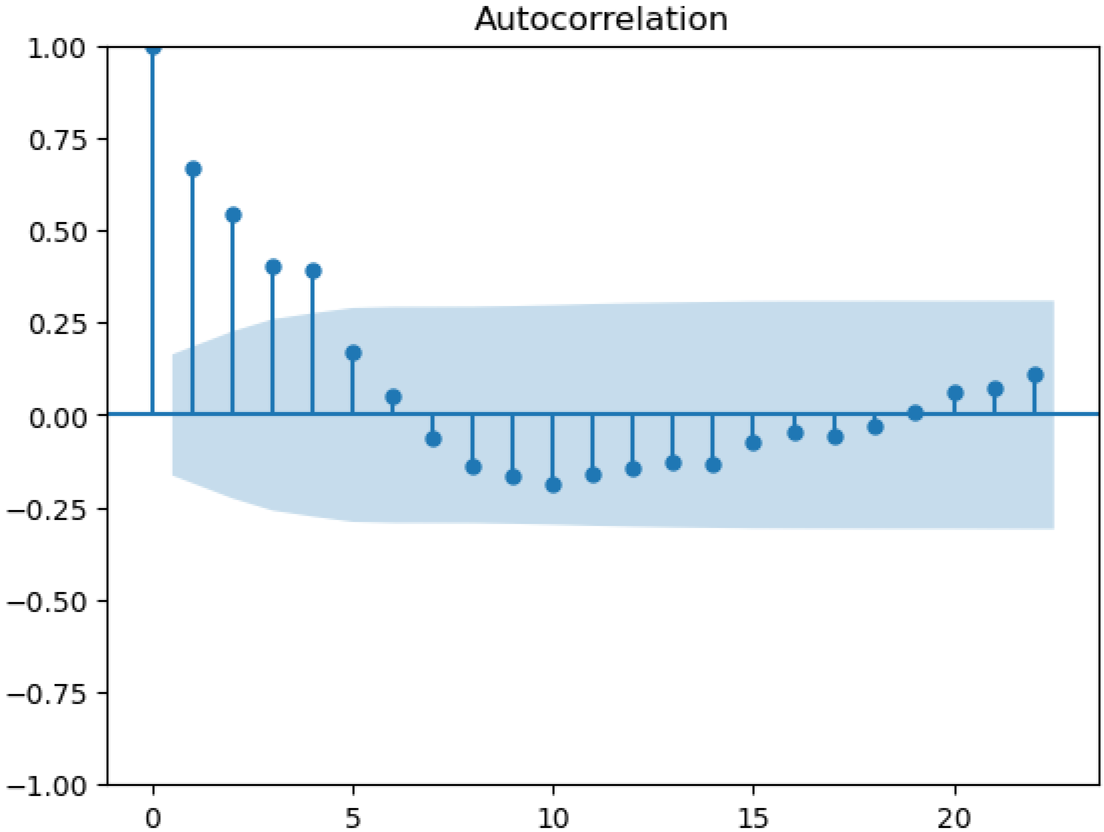
In [16]:

```
# Checking the stationarity of the data

from statsmodels.tsa.stattools import adfuller

result = adfuller(store['Weekly_Sales'])
p_value = result[1]
print(p_value)
if p_value < 0.05:
    print("The time series is stationary")
else:
    print("The time series is non-stationary")
```

```
0.00021700718907117402
The time series is stationary
```

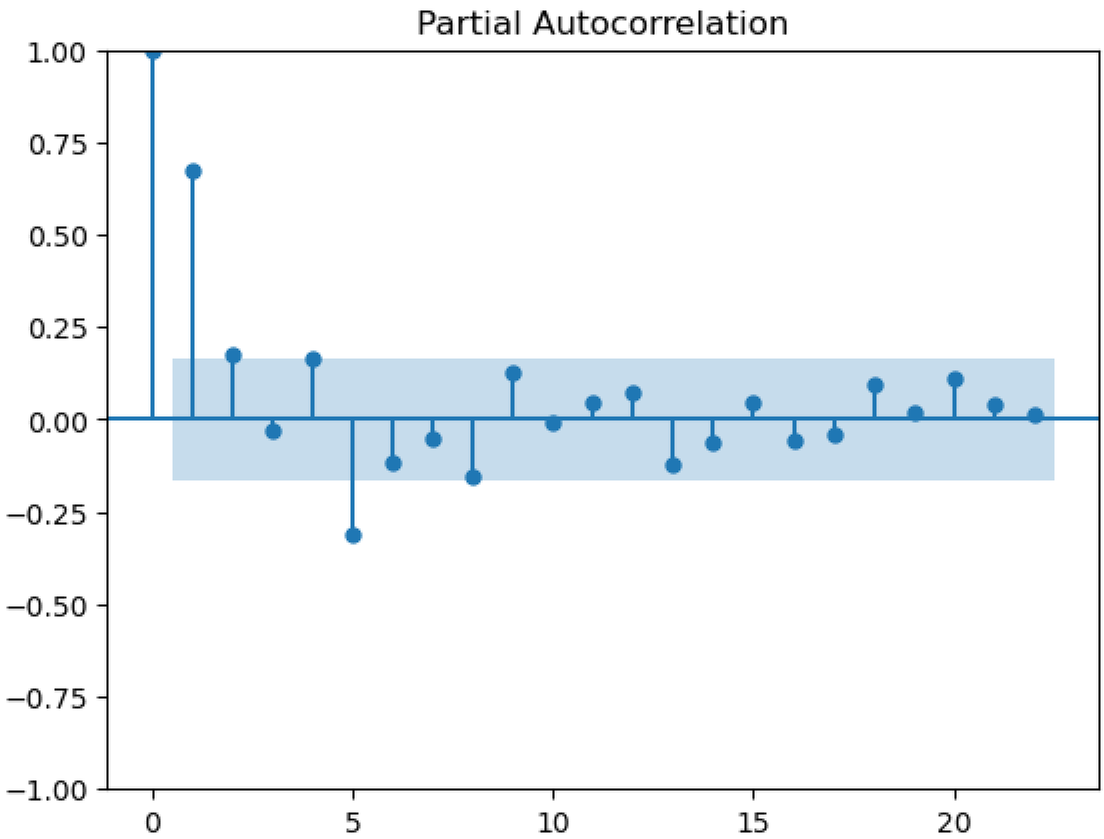
In [17]:

```
# Autocorrelation

from pandas.plotting import autocorrelation_plot
from statsmodels.graphics.tsaplots import plot_acf

plot_acf(store['Weekly_Sales']);
```



In [18]:
```
# Partial Autocorrelation

from statsmodels.graphics.tsaplots import plot_pacf

plot_pacf(store['Weekly_Sales']);
```

```
C:\Users\Vignesh Murali\anaconda3\lib\site-packages\statsmodels\graphics\tsaplots.py:34
8: FutureWarning: The default method 'yw' can produce PACF values outside of the [-1,1]
interval. After 0.13, the default will change tounadjusted Yule-Walker ('ywm'). You can
use this method now by setting method='ywm'.
  warnings.warn(
```



In [19]:
```python
from pmdarima import auto_arima

order = auto_arima(store['Weekly_Sales'], trace=True)
order.summary()
```

```
Performing stepwise search to minimize aic
 ARIMA(2,1,2)(0,0,0)[0] intercept   : AIC=3636.920, Time=0.25 sec
 ARIMA(0,1,0)(0,0,0)[0] intercept   : AIC=3649.620, Time=0.03 sec
 ARIMA(1,1,0)(0,0,0)[0] intercept   : AIC=3640.902, Time=0.05 sec
 ARIMA(0,1,1)(0,0,0)[0] intercept   : AIC=3639.145, Time=0.07 sec
 ARIMA(0,1,0)(0,0,0)[0]             : AIC=3647.623, Time=0.03 sec
 ARIMA(1,1,2)(0,0,0)[0] intercept   : AIC=3641.331, Time=0.13 sec
 ARIMA(2,1,1)(0,0,0)[0] intercept   : AIC=3636.408, Time=0.16 sec
 ARIMA(1,1,1)(0,0,0)[0] intercept   : AIC=3640.685, Time=0.06 sec
 ARIMA(2,1,0)(0,0,0)[0] intercept   : AIC=3642.191, Time=0.05 sec
 ARIMA(3,1,1)(0,0,0)[0] intercept   : AIC=3635.110, Time=0.11 sec
 ARIMA(3,1,0)(0,0,0)[0] intercept   : AIC=3636.887, Time=0.05 sec
 ARIMA(4,1,1)(0,0,0)[0] intercept   : AIC=3635.576, Time=0.12 sec
 ARIMA(3,1,2)(0,0,0)[0] intercept   : AIC=3634.959, Time=0.16 sec
 ARIMA(4,1,2)(0,0,0)[0] intercept   : AIC=3636.384, Time=0.30 sec
 ARIMA(3,1,3)(0,0,0)[0] intercept   : AIC=3636.583, Time=0.26 sec
 ARIMA(2,1,3)(0,0,0)[0] intercept   : AIC=3635.761, Time=0.16 sec
 ARIMA(4,1,3)(0,0,0)[0] intercept   : AIC=3633.319, Time=0.37 sec
 ARIMA(5,1,3)(0,0,0)[0] intercept   : AIC=3634.799, Time=0.52 sec
 ARIMA(4,1,4)(0,0,0)[0] intercept   : AIC=3638.697, Time=0.35 sec
 ARIMA(3,1,4)(0,0,0)[0] intercept   : AIC=3634.757, Time=0.34 sec
 ARIMA(5,1,2)(0,0,0)[0] intercept   : AIC=3639.555, Time=0.21 sec
 ARIMA(5,1,4)(0,0,0)[0] intercept   : AIC=inf, Time=0.71 sec
 ARIMA(4,1,3)(0,0,0)[0]             : AIC=3631.146, Time=0.36 sec
 ARIMA(3,1,3)(0,0,0)[0]             : AIC=3634.577, Time=0.25 sec
 ARIMA(4,1,2)(0,0,0)[0]             : AIC=3634.374, Time=0.29 sec
 ARIMA(5,1,3)(0,0,0)[0]             : AIC=3633.152, Time=0.42 sec
 ARIMA(4,1,4)(0,0,0)[0]             : AIC=3636.706, Time=0.29 sec
 ARIMA(3,1,2)(0,0,0)[0]             : AIC=3632.947, Time=0.17 sec
 ARIMA(3,1,4)(0,0,0)[0]             : AIC=3632.473, Time=0.27 sec
 ARIMA(5,1,2)(0,0,0)[0]             : AIC=3637.527, Time=0.14 sec
 ARIMA(5,1,4)(0,0,0)[0]             : AIC=inf, Time=0.56 sec
```

```
Best model:  ARIMA(4,1,3)(0,0,0)[0]
Total fit time: 7.253 seconds
```

Out[19]:

SARIMAX Results

Dep. Variable:	y	**No. Observations:**	143
Model:	SARIMAX(4, 1, 3)	**Log Likelihood**	-1807.573
Date:	Fri, 21 Apr 2023	**AIC**	3631.146
Time:	21:21:22	**BIC**	3654.793
Sample:	02-05-2010	**HQIC**	3640.755
	- 10-26-2012		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	-0.3604	0.314	-1.149	0.251	-0.975	0.255
ar.L2	0.1928	0.171	1.130	0.259	-0.142	0.527
ar.L3	0.3643	0.216	1.690	0.091	-0.058	0.787
ar.L4	0.2191	0.094	2.333	0.020	0.035	0.403
ma.L1	0.0817	0.310	0.263	0.792	-0.527	0.690
ma.L2	-0.4255	0.138	-3.091	0.002	-0.695	-0.156
ma.L3	-0.5682	0.255	-2.231	0.026	-1.067	-0.069
sigma2	6.65e+09	1.13e-10	5.89e+19	0.000	6.65e+09	6.65e+09

Ljung-Box (L1) (Q):	0.71	**Jarque-Bera (JB):**	348.56
Prob(Q):	0.40	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.50	**Skew:**	1.58
Prob(H) (two-sided):	0.02	**Kurtosis:**	10.00

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 1.2e+35. Standard errors may be unstable.

In [20]:

```python
# ARIMA Model for Time Series Forecasting

from statsmodels.tsa.arima_model import ARIMA
import statsmodels.api as sm

train = store.iloc[:100]['Weekly_Sales']
test = store.iloc[101:]['Weekly_Sales']
```

In [21]:

```python
model = sm.tsa.arima.ARIMA(train, order=(4,1,3))
model_fit = model.fit()
model_fit.summary()
```

```
C:\Users\Vignesh Murali\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:47
1: ValueWarning: No frequency information was provided, so inferred frequency W-FRI will
```

```
be used.
  self._init_dates(dates, freq)
C:\Users\Vignesh Murali\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:47
1: ValueWarning: No frequency information was provided, so inferred frequency W-FRI will
be used.
  self._init_dates(dates, freq)
C:\Users\Vignesh Murali\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:47
1: ValueWarning: No frequency information was provided, so inferred frequency W-FRI will
be used.
  self._init_dates(dates, freq)
C:\Users\Vignesh Murali\anaconda3\lib\site-packages\statsmodels\tsa\statespace\sarimax.p
y:966: UserWarning: Non-stationary starting autoregressive parameters found. Using zeros
as starting parameters.
  warn('Non-stationary starting autoregressive parameters'
C:\Users\Vignesh Murali\anaconda3\lib\site-packages\statsmodels\tsa\statespace\sarimax.p
y:978: UserWarning: Non-invertible starting MA parameters found. Using zeros as starting
parameters.
  warn('Non-invertible starting MA parameters found.'
```

Out[21]:

SARIMAX Results

Dep. Variable:	Weekly_Sales	**No. Observations:**	100
Model:	ARIMA(4, 1, 3)	**Log Likelihood**	-1271.879
Date:	Fri, 21 Apr 2023	**AIC**	2559.758
Time:	21:21:23	**BIC**	2580.519
Sample:	02-05-2010	**HQIC**	2568.158
	- 12-30-2011		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	0.1232	0.346	0.356	0.722	-0.555	0.802
ar.L2	0.0114	0.351	0.033	0.974	-0.676	0.699
ar.L3	-0.3832	0.332	-1.156	0.248	-1.033	0.267
ar.L4	0.1783	0.141	1.264	0.206	-0.098	0.455
ma.L1	-0.4863	0.358	-1.359	0.174	-1.188	0.215
ma.L2	0.0160	0.426	0.038	0.970	-0.819	0.851
ma.L3	0.3587	0.382	0.938	0.348	-0.390	1.108
sigma2	8.362e+09	2.81e-10	2.98e+19	0.000	8.36e+09	8.36e+09

Ljung-Box (L1) (Q):	0.30	**Jarque-Bera (JB):**	128.57
Prob(Q):	0.58	**Prob(JB):**	0.00
Heteroskedasticity (H):	3.18	**Skew:**	1.30
Prob(H) (two-sided):	0.00	**Kurtosis:**	7.94

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 4.54e+34. Standard errors may be unstable.

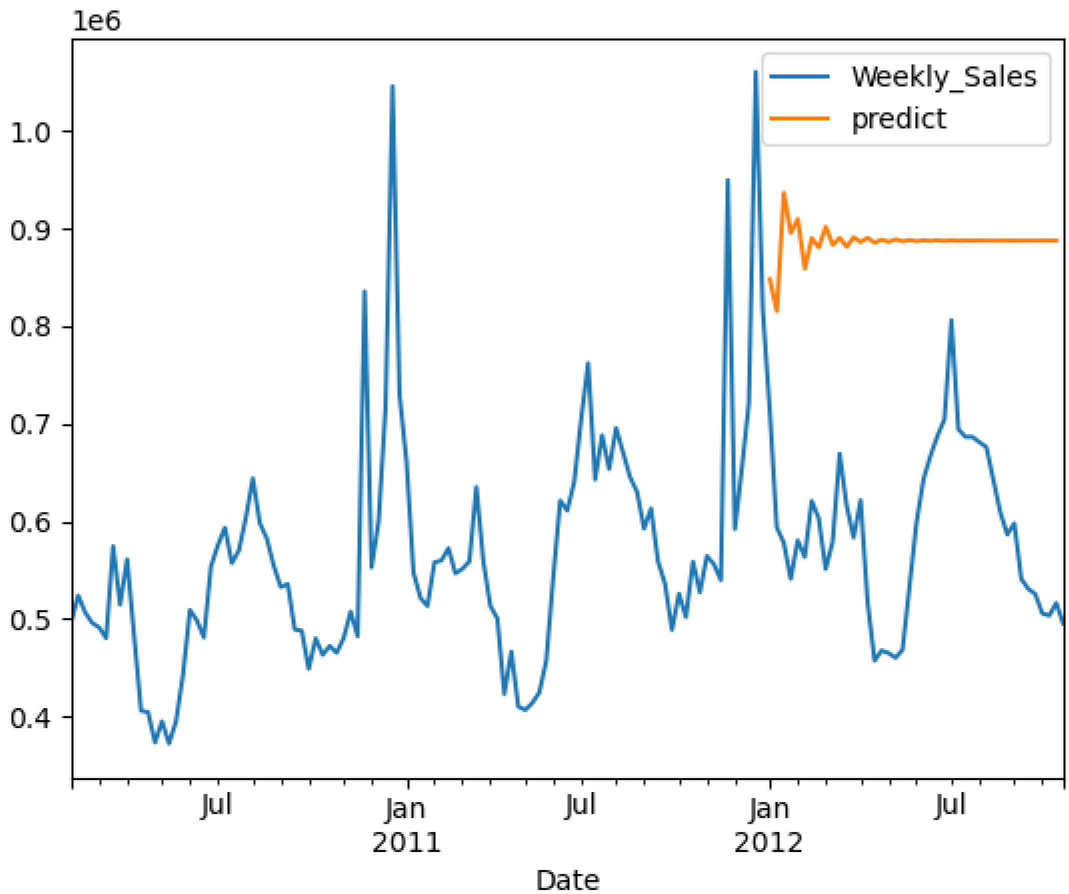
In [22]:

```python
store['predict'] = model_fit.predict(start= len(train),
                                      end=len(train)+len(test)-1,
                                      dynamic=True)

store[['Weekly_Sales','predict']].plot()
```

```
C:\Users\Vignesh Murali\AppData\Local\Temp\ipykernel_14400\1936169350.py:1: 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
  store['predict'] = model_fit.predict(start= len(train),
```

Out[22]:

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



In [23]:

```python
# We can see the predictions are way away from the actual test values.
# Thus we are moving to Seasonal ARIMA model for our forecasting (SARIMAX)

from statsmodels.tsa.statespace.sarimax import SARIMAX

model = SARIMAX(train, order=(4,1,3), seasonal_order=(4,1,3,52))
model = model.fit()
```

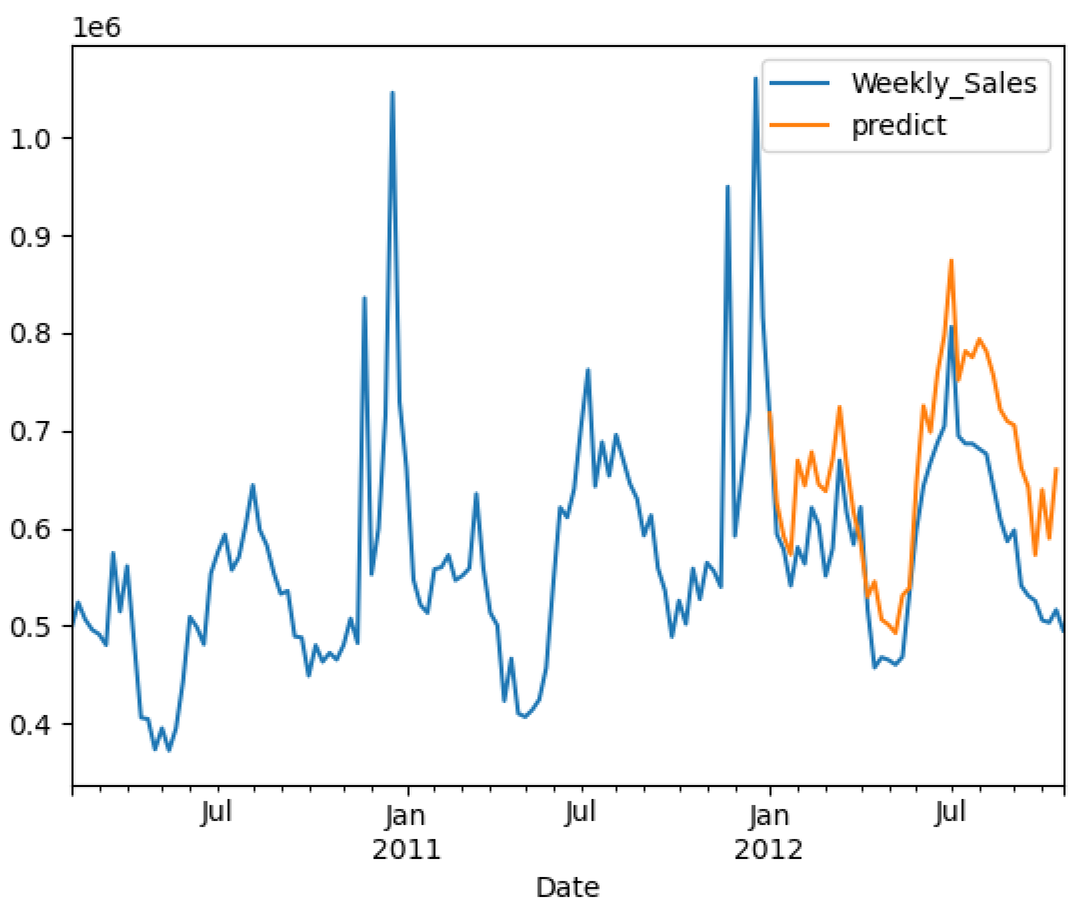
```
C:\Users\Vignesh Murali\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: No frequency information was provided, so inferred frequency W-FRI will be used.
  self._init_dates(dates, freq)
C:\Users\Vignesh Murali\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: No frequency information was provided, so inferred frequency W-FRI will be used.
  self._init_dates(dates, freq)
C:\Users\Vignesh Murali\anaconda3\lib\site-packages\statsmodels\tsa\statespace\sarimax.py:866: UserWarning: Too few observations to estimate starting parameters for seasonal ARMA. All parameters except for variances will be set to zeros.
```

```
  warn('Too few observations to estimate starting parameters%s.'
C:\Users\Vignesh Murali\anaconda3\lib\site-packages\statsmodels\base\model.py:604: Conve
rgenceWarning: Maximum Likelihood optimization failed to converge. Check mle_retvals
  warnings.warn("Maximum Likelihood optimization failed to "
```

In [24]:
```
store['predict'] = model.predict(start= len(train),
                                  end=len(train)+len(test)-1,
                                  dynamic=True)

store[['Weekly_Sales','predict']].plot()
```

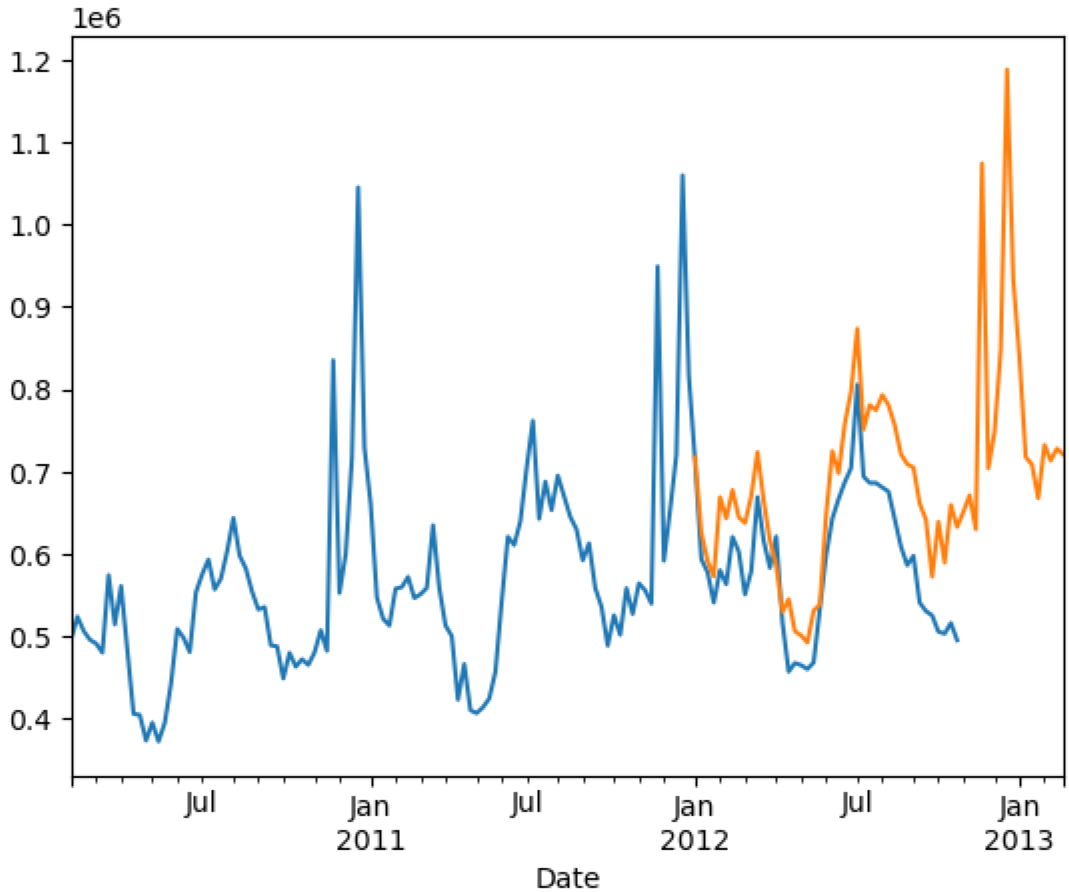
```
C:\Users\Vignesh Murali\AppData\Local\Temp\ipykernel_14400\595716230.py:1: SettingWithCo
pyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_
guide/indexing.html#returning-a-view-versus-a-copy
  store['predict'] = model.predict(start= len(train),
```

Out[24]: <AxesSubplot:xlabel='Date'>



In [25]:
```
# We can observe the the test data and predicted data are almost following a same patter
# predicting the projection for the next 12 weeks

forecast = model.forecast(steps=60)
store['Weekly_Sales'].plot()
forecast.plot()
```

Out[25]: <AxesSubplot:xlabel='Date'>

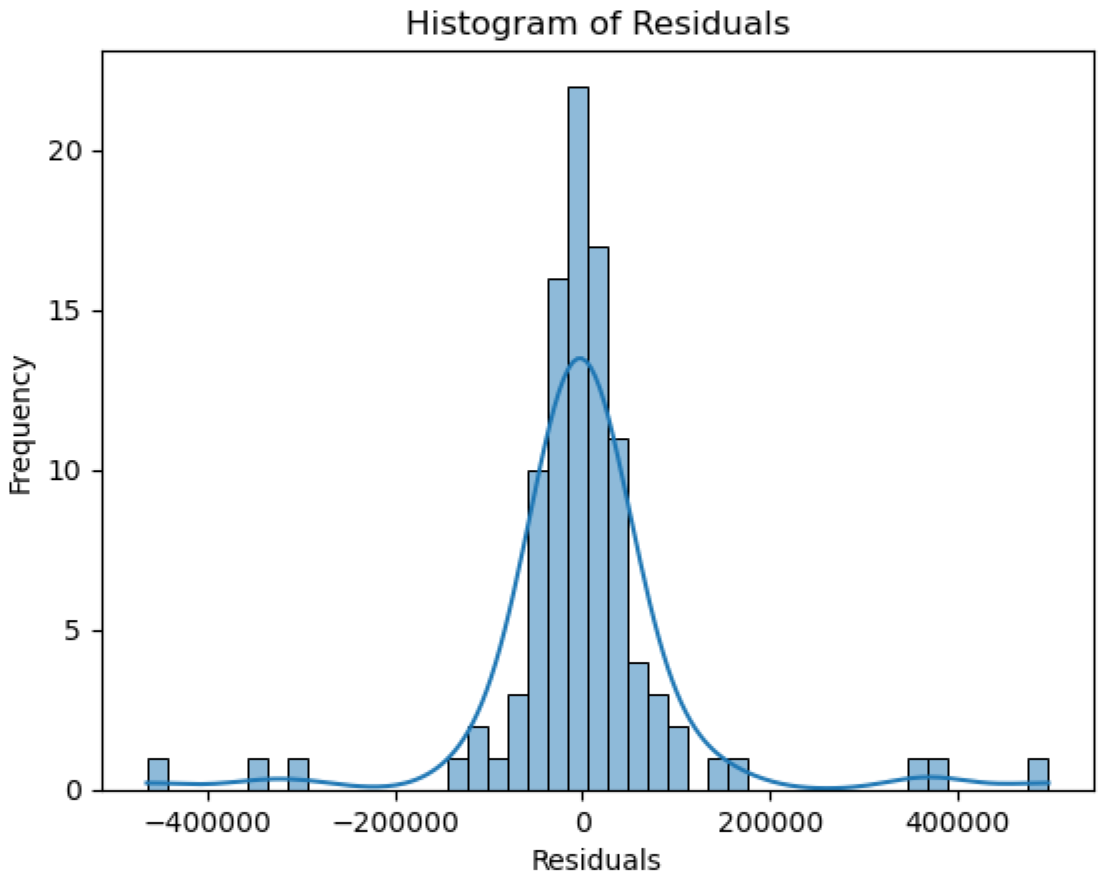


In [26]:
```
forecast.tail(17)
```

Out[26]:
```
2012-11-02    6.511736e+05
2012-11-09    6.713182e+05
2012-11-16    6.302026e+05
2012-11-23    1.074182e+06
2012-11-30    7.040335e+05
2012-12-07    7.482543e+05
2012-12-14    8.489533e+05
2012-12-21    1.188140e+06
2012-12-28    9.333088e+05
2013-01-04    8.379857e+05
2013-01-11    7.177353e+05
2013-01-18    7.086692e+05
2013-01-25    6.678757e+05
2013-02-01    7.325739e+05
2013-02-08    7.134663e+05
2013-02-15    7.281028e+05
2013-02-22    7.209120e+05
Freq: W-FRI, Name: predicted_mean, dtype: float64
```

In [27]:
```
# Model Evaluation using Residuals

residuals = model.resid
```

In [28]:
```
sns.histplot(residuals, kde=True)
plt.xlabel('Residuals')
plt.ylabel('Frequency')
plt.title('Histogram of Residuals')
plt.show()
```



In [29]:
```
pred = model.predict(start= len(train), end=len(train)+len(test)-1, dynamic=True)

mse = mean_squared_error(test, pred)
mae = mean_absolute_error(test, pred)
rmse = np.sqrt(mse)
mape = np.mean(np.abs((test - pred) / test)) * 100

print('MSE:', mse)
print('MAE:', mae)
print('RMSE:', rmse)
print('MAPE:', mape,'%')
```

```
MSE: 8328880543.283994
MAE: 77000.867412333
RMSE: 91262.7007231541
MAPE: 12.19831297082327 %
```

In [ ]:

In [ ]: