Sales Forecasting - Time Series Analysis

Data: https://www.kaggle.com/code/imkushwaha/project-forecasting-the-furniture-sales/data

In [67]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

In [68]:
```
df = pd.read_csv('data.csv', encoding='unicode_escape')
```

In [69]:
```
df.head(2)
```

Out[69]:

	Row ID	Order ID	Order Date	Ship Date	Ship Mode	Customer ID	Customer Name	Segment	Country	City	...	Pos Co
0	1	CA-2016-152156	11/8/2016	11/11/2016	Second Class	CG-12520	Claire Gute	Consumer	United States	Henderson	...	424
1	2	CA-2016-152156	11/8/2016	11/11/2016	Second Class	CG-12520	Claire Gute	Consumer	United States	Henderson	...	424

2 rows × 21 columns

In [70]:
```
df.describe()
```

Out[70]:

	Row ID	Postal Code	Sales	Quantity	Discount	Profit
count	2121.000000	2121.000000	2121.000000	2121.000000	2121.000000	2121.000000
mean	5041.643564	55726.556341	349.834887	3.785007	0.173923	8.699327
std	2885.740258	32261.888225	503.179145	2.251620	0.181547	136.049246
min	1.000000	1040.000000	1.892000	1.000000	0.000000	-1862.312400
25%	2568.000000	22801.000000	47.040000	2.000000	0.000000	-12.849000
50%	5145.000000	60505.000000	182.220000	3.000000	0.200000	7.774800
75%	7534.000000	90032.000000	435.168000	5.000000	0.300000	33.726600
max	9991.000000	99301.000000	4416.174000	14.000000	0.700000	1013.127000

In [71]:
```
df.columns
```

Out[71]:
```
Index(['Row ID', 'Order ID', 'Order Date', 'Ship Date', 'Ship Mode',
       'Customer ID', 'Customer Name', 'Segment', 'Country', 'City', 'State',
       'Postal Code', 'Region', 'Product ID', 'Category', 'Sub-Category',
       'Product Name', 'Sales', 'Quantity', 'Discount', 'Profit'],
      dtype='object')
```

In [72]:
```
col = ['Row ID', 'Order ID', 'Ship Date', 'Ship Mode',
       'Customer ID', 'Customer Name', 'Segment', 'Country', 'City', 'State',
```

```
       'Postal Code', 'Region', 'Product ID', 'Category', 'Sub-Category',
       'Product Name', 'Quantity', 'Discount', 'Profit']
```

In [73]:
```
df.drop(columns=col, axis=1, inplace=True)
```

In [74]:
```
df = df.sort_values('Order Date')
df.head(2)
```

Out[74]:

	Order Date	Sales
845	1/1/2017	474.43
1707	1/1/2017	141.42

In [75]:
```
df = df.groupby('Order Date')['Sales'].sum().reset_index()
```

In [76]:
```
df.head(2)
```

Out[76]:

	Order Date	Sales
0	1/1/2017	975.49
1	1/10/2014	51.94

In [77]:
```
df['Order Date'] = pd.to_datetime(df['Order Date'])
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 889 entries, 0 to 888
Data columns (total 2 columns):
 #   Column      Non-Null Count  Dtype         
---  ------      --------------  -----         
 0   Order Date  889 non-null    datetime64[ns]
 1   Sales       889 non-null    float64       
dtypes: datetime64[ns](1), float64(1)
memory usage: 14.0 KB
```

In [78]:
```
df = df.set_index('Order Date')
df.head(2)
```

Out[78]:

	Sales
Order Date	
2017-01-01	975.49
2014-01-10	51.94

In [79]:
```
mean_all = df['Sales'].resample('MS').mean()
```

In [80]:
```
print(mean_all)
```

```
Order Date
2014-01-01     480.194231
2014-02-01     367.931600
2014-03-01     857.291529
2014-04-01     567.488357
2014-05-01     432.049188
2014-06-01     695.059242
2014-07-01     601.169500
2014-08-01     457.521656
2014-09-01     992.353367
2014-10-01     769.015437
2014-11-01     980.221486
2014-12-01    1532.298325
2015-01-01     978.328467
2015-02-01     522.395667
2015-03-01     781.236437
2015-04-01     805.822962
2015-05-01     624.996700
2015-06-01     428.565500
2015-07-01     719.706316
2015-08-01     602.412012
2015-09-01    1382.790684
2015-10-01     632.980184
2015-11-01    1286.701354
2015-12-01    1049.355418
2016-01-01     508.182867
2016-02-01     356.868273
2016-03-01     609.575810
2016-04-01     695.373158
2016-05-01     687.265227
2016-06-01     816.910750
2016-07-01     768.736412
2016-08-01     734.307782
2016-09-01    1135.953371
2016-10-01     624.872474
2016-11-01    1271.345152
2016-12-01    1410.719808
2017-01-01     397.602133
2017-02-01     528.179800
2017-03-01     544.672240
2017-04-01     453.297905
2017-05-01     678.302328
2017-06-01     826.460291
2017-07-01     562.524857
2017-08-01     857.881889
2017-09-01    1209.508583
2017-10-01     875.362728
2017-11-01    1277.817759
2017-12-01    1256.298672
Freq: MS, Name: Sales, dtype: float64
```

In [81]:
```
df = pd.DataFrame({'Date': mean_all.index, 'Sales': mean_all.values})
```

In [82]:
```
df.info()
df.tail(2)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 48 entries, 0 to 47
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype         
---  ------  --------------  -----         
 0   Date    48 non-null     datetime64[ns]
 1   Sales   48 non-null     float64       
dtypes: datetime64[ns](1), float64(1)
memory usage: 896.0 bytes
```

Out[82]:

	Date	Sales
46	2017-11-01	1277.817759
47	2017-12-01	1256.298672

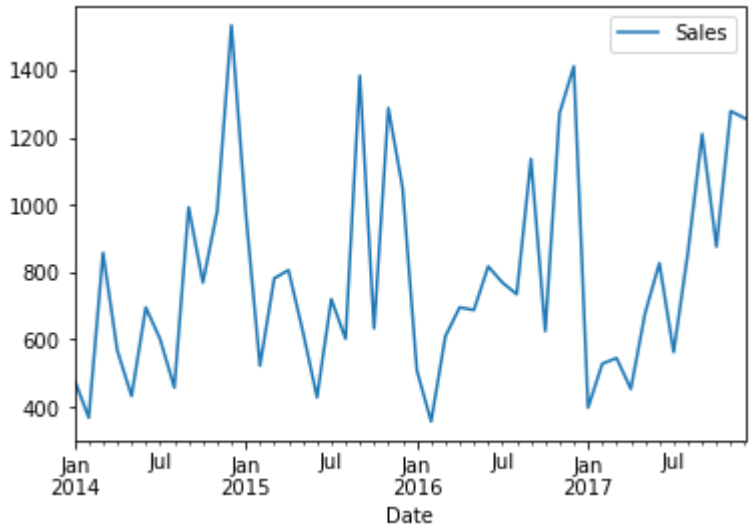
In [83]:
```
df.set_index('Date', inplace = True)
df.index.freq = 'MS'
df.head()
```

Out[83]:

	Sales
Date	
2014-01-01	480.194231
2014-02-01	367.931600
2014-03-01	857.291529
2014-04-01	567.488357
2014-05-01	432.049188

In [84]:
```
df.plot()
```

Out[84]:
```
<AxesSubplot:xlabel='Date'>
```



In order to check the seasonality of the data we will perform Augmented Dickey-Fuller Test

H0 (Null Hypothesis) : Series is non statitonary in nature

HA (Alternate Hypothesis) : Series is stationary in nature

In [85]:
```
from statsmodels.tsa.stattools import adfuller
```

In [86]:
```
test_result = adfuller(df['Sales'])
```

In [87]:
```
print(test_result)
```

```
(-5.191070187339274, 9.1687566556655e-06, 10, 37, {'1%': -3.6209175221605827, '5%': -2.943539
4610388332, '10%': -2.6104002410518627}, 521.9616303121272)
```

If p(value) < 0.05 we reject H0 (Date is stationary)

if p(value) > 0.05 we accept H0 (Data is not stationary)

In [88]:
```
def adfuller_test(Sales):
    result = adfuller(Sales)
    label = ['ADF Test Statistic', 'P Value', '#Lags Used', 'Number of Observations Used']
    for value, label in zip(result, label):
        print(label+ ':' + str(value))
    if result[1]< 0.05:
        print("Reject the null hypothesis, data is stationary")
    else:

         print("Accept the null hypothesis, data is non-stationary")
```

In [89]:
```
adfuller_test(df['Sales'])
```

```
ADF Test Statistic:-5.191070187339274
P Value:9.1687566556655e-06
#Lags Used:10
Number of Observations Used:37
Reject the null hypothesis, data is stationary
```

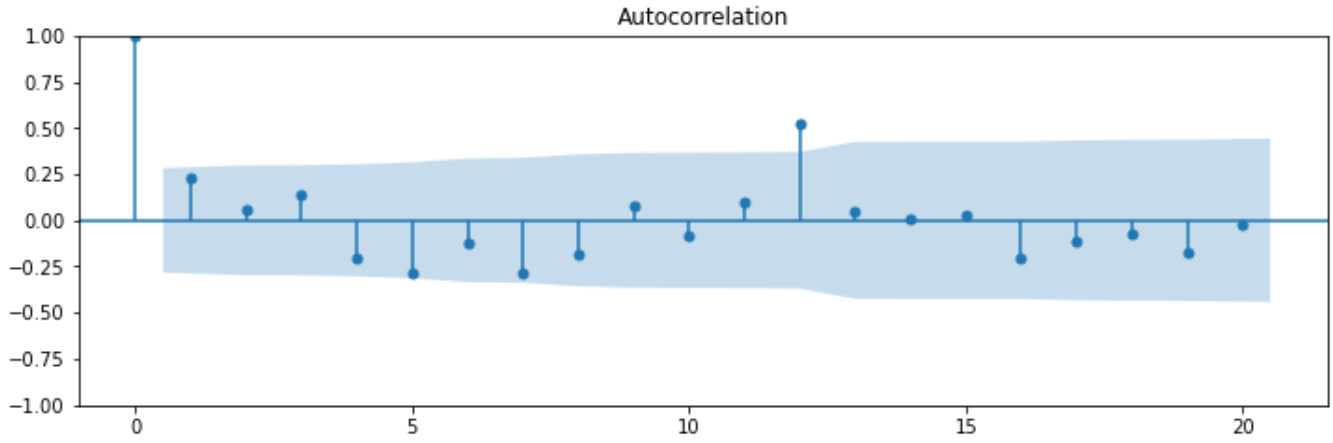
Identifying the p,q,r values in the Auto Regressive Model

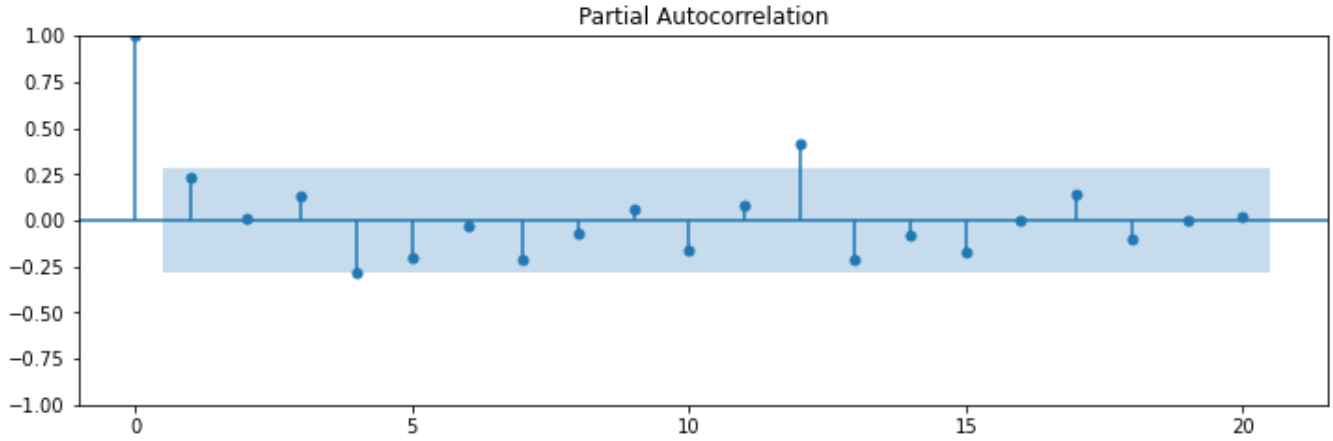
pacf -> value of p

acf -> value of q

In [90]:
```
import warnings
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
```

In [91]:
```
warnings.filterwarnings('ignore', message="The default method 'yw' can produce PACF values ou
fig = plt.figure(figsize=(12,8))
ax1 = fig.add_subplot(211)
fig = plot_acf(df['Sales'].dropna(), lags = 20, ax= ax1)
ax2 = fig.add_subplot(212)
fig = plot_pacf(df['Sales'].dropna(), lags = 20, ax= ax2, method='ywm')
```





Taking p =1, d = 1(seasonal difference) , q = 0

In [92]:
```
import statsmodels.api as sm
```

In [93]:
```
model = sm.tsa.ARIMA(df['Sales'], order=(1, 1, 0))
model_fit = model.fit()
```

In [94]:
```
model_fit.summary()
```

Out[94]:

SARIMAX Results

Dep. Variable:	Sales	**No. Observations:**	48
Model:	ARIMA(1, 1, 0)	**Log Likelihood**	-340.488
Date:	Mon, 24 Jul 2023	**AIC**	684.977
Time:	14:04:50	**BIC**	688.677
Sample:	01-01-2014	**HQIC**	686.369
	- 12-01-2017		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	-0.4072	0.135	-3.024	0.002	-0.671	-0.143
sigma2	1.167e+05	2.29e+04	5.092	0.000	7.18e+04	1.62e+05

Ljung-Box (L1) (Q):	1.16	**Jarque-Bera (JB):**	2.09
Prob(Q):	0.28	**Prob(JB):**	0.35
Heteroskedasticity (H):	1.32	**Skew:**	-0.47
Prob(H) (two-sided):	0.58	**Kurtosis:**	3.44

Warnings:

[1] Covariance matrix calculated using the outer product of gradients (complex-step).

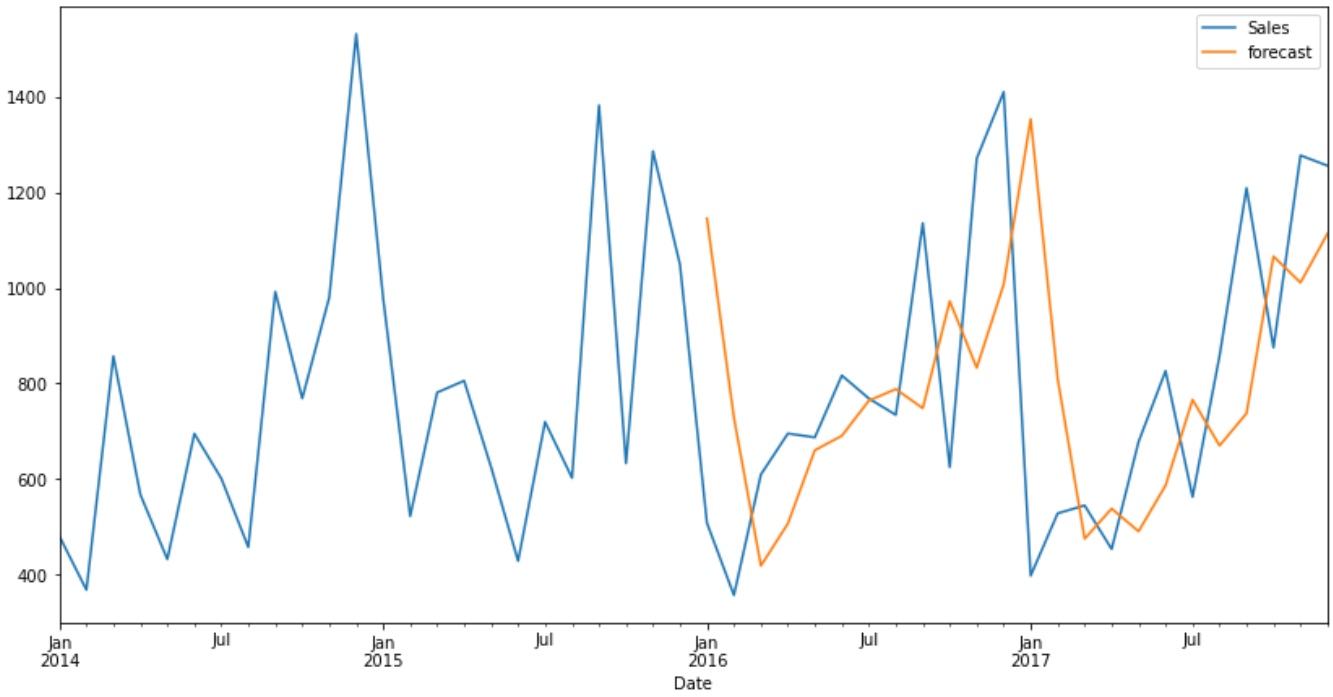
Predicting ARIMA Model

Data Exhibiting strong seasonal patterns, hence ARIMA is not a good fit for predicting the results. In order to have better results we will train SARIMAX model and predict the values.

In [95]:
```
df['forecast'] = model_fit.predict(start=pd.to_datetime('2016-01-01'), dynamic = False)
df[['Sales', 'forecast']].plot(figsize = (14,7))
```

Out[95]:

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



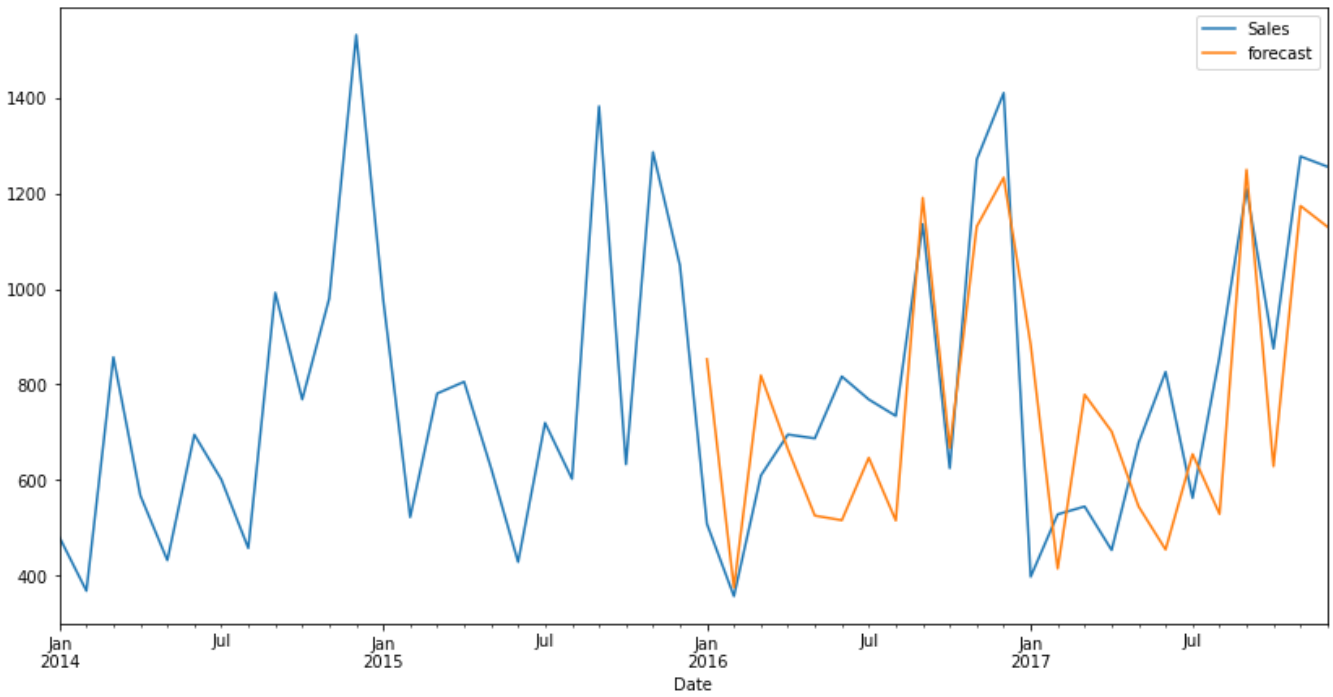
In [96]:
```
model = sm.tsa.statespace.SARIMAX(df['Sales'], order = (1,1,0), seasonal_order = (1,1,0,12))
results = model.fit()
```

Predicting the results of SARIMAX

Improved Data Fitting

In [97]:
```
df['forecast'] = results.predict(start=pd.to_datetime('2016-01-01'), dynamic = True)
df[['Sales','forecast']].plot(figsize = (14,7))
```

Out[97]:
```
<AxesSubplot:xlabel='Date'>
```



Forecasting Future Sales from Historical Data (2018-2020)

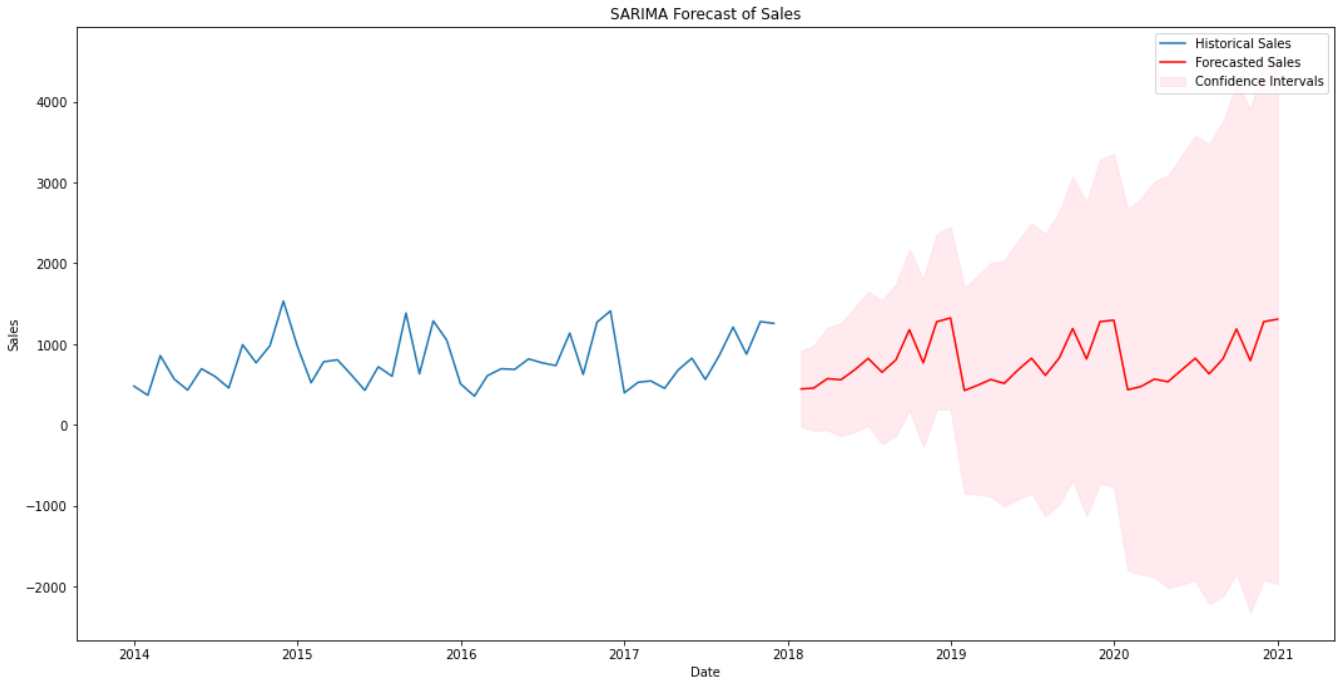
In [98]:
```
# Number of periods to forecast into the future (months)
forecast_periods = 36

# Make predictions for the future sales
forecast = results.get_forecast(steps=forecast_periods)

forecast_values = forecast.predicted_mean
confidence_intervals = forecast.conf_int()

# Generating date range for the future predictions
future_dates = pd.date_range(start=df.index[-1], periods=forecast_periods + 1, freq='M')[1:]

# Plotting the historical sales and the forecasted sales
plt.figure(figsize=(18, 9))
plt.plot(df.index, df['Sales'], label='Historical Sales')
plt.plot(future_dates, forecast_values, label='Forecasted Sales', color='r')
plt.fill_between(future_dates, confidence_intervals.iloc[:, 0], confidence_intervals.iloc[:,
                 alpha=0.3, label='Confidence Intervals')
plt.xlabel('Date')
plt.ylabel('Sales')
plt.title('SARIMA Forecast of Sales')
plt.legend()
plt.show()
```



In [99]:
```
forecast_df = pd.DataFrame({'Date': future_dates, 'Forecasted Sales': forecast_values})
```

In [100…
```
forecast_df.drop(columns=['Date'], inplace=True)
```

In [101…
```
print(forecast_df)
```

	Forecasted Sales
2018-01-01	445.791734
2018-02-01	455.285005
2018-03-01	573.360587
2018-04-01	558.404676
2018-05-01	682.936039
2018-06-01	823.141935
2018-07-01	652.146661
2018-08-01	805.434860
2018-09-01	1178.607167
2018-10-01	768.237544
2018-11-01	1275.816910
2018-12-01	1323.612749
2019-01-01	425.819003
2019-02-01	487.476670
2019-03-01	561.789228
2019-04-01	513.911565
2019-05-01	681.727656
2019-06-01	825.359384
2019-07-01	614.324611
2019-08-01	828.817402
2019-09-01	1192.707656
2019-10-01	815.175950
2019-11-01	1277.466762
2019-12-01	1295.401079
2020-01-01	435.211312
2020-02-01	474.396065
2020-03-01	567.562146
2020-04-01	533.867484
2020-05-01	683.036107
2020-06-01	825.191954
2020-07-01	631.406574
2020-08-01	819.531851
2020-09-01	1187.420900
2020-10-01	795.742311
2020-11-01	1277.543858
2020-12-01	1308.342800

In [ ]: