In [1]:
```python
#imported libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```python
df = pd.read_csv(r'perrin-freres-monthly-champagne-.csv') #Imported Data
df
```

Out[2]:

	Month	Perrin Freres monthly champagne sales millions ?64-?72
0	1964-01	2815.0
1	1964-02	2672.0
2	1964-03	2755.0
3	1964-04	2721.0
4	1964-05	2946.0
...	...	...
102	1972-07	4298.0
103	1972-08	1413.0
104	1972-09	5877.0
105	NaN	NaN
106	Perrin Freres monthly champagne sales millions...	NaN

107 rows × 2 columns

In [3]:
```python
df.info() #Checking the Data type and null values
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 107 entries, 0 to 106
Data columns (total 2 columns):
 #   Column                                                  Non-Null Count  Dtype  
---  ------                                                  --------------  -----  
 0   Month                                                   106 non-null    object 
 1   Perrin Freres monthly champagne sales millions ?64-?72  105 non-null    float64
dtypes: float64(1), object(1)
memory usage: 1.8+ KB
```

In [4]:
```python
round(df.describe(),2) #Checking statistical properties
```

Out[4]:

	Perrin Freres monthly champagne sales millions ?64-?72
count	105.00
mean	4761.15
std	2553.50
min	1413.00
25%	3113.00
50%	4217.00
75%	5221.00
max	13916.00

In [5]:
```
df.dropna(inplace=True) #Dropping null values
df.isnull().sum() #Checking null values
```

Out[5]:
```
Month                                                     0
Perrin Freres monthly champagne sales millions ?64-?72    0
dtype: int64
```

In [6]:
```
df['Month'] = pd.to_datetime(df['Month'],format='mixed') #Converting month Dtype in
df.info() #Checking info of the data
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 105 entries, 0 to 104
Data columns (total 2 columns):
 #   Column                                                  Non-Null Count  Dtype
---  ------                                                  --------------  -----
 0   Month                                                   105 non-null    datetim
e64[ns]
 1   Perrin Freres monthly champagne sales millions ?64-?72  105 non-null    float64
dtypes: datetime64[ns](1), float64(1)
memory usage: 2.5 KB
```

In [7]:
```
df.tail() #shows top 5 bottom rows
```

Out[7]:

	Month	Perrin Freres monthly champagne sales millions ?64-?72
100	1972-05-01	4618.0
101	1972-06-01	5312.0
102	1972-07-01	4298.0
103	1972-08-01	1413.0
104	1972-09-01	5877.0

In [8]:
```
df.shape #shows shape of the data
```

Out[8]: (105, 2)

In [9]:
```
df.columns = ['Month','Sale'] #Changes the aname of the columns
df
```

Out[9]:

	Month	Sale
0	1964-01-01	2815.0
1	1964-02-01	2672.0
2	1964-03-01	2755.0
3	1964-04-01	2721.0
4	1964-05-01	2946.0
...	...	...
100	1972-05-01	4618.0
101	1972-06-01	5312.0
102	1972-07-01	4298.0
103	1972-08-01	1413.0
104	1972-09-01	5877.0

105 rows × 2 columns

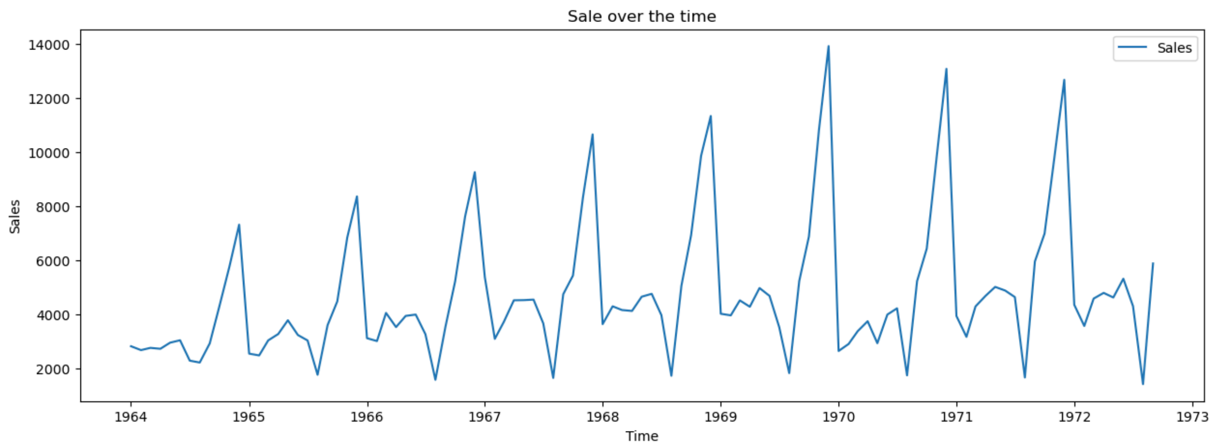
In [10]:
```
df.set_index('Month', inplace=True) #Set month columns into index
```

In [11]:
```
df.head() #Shows top 5 columns
```

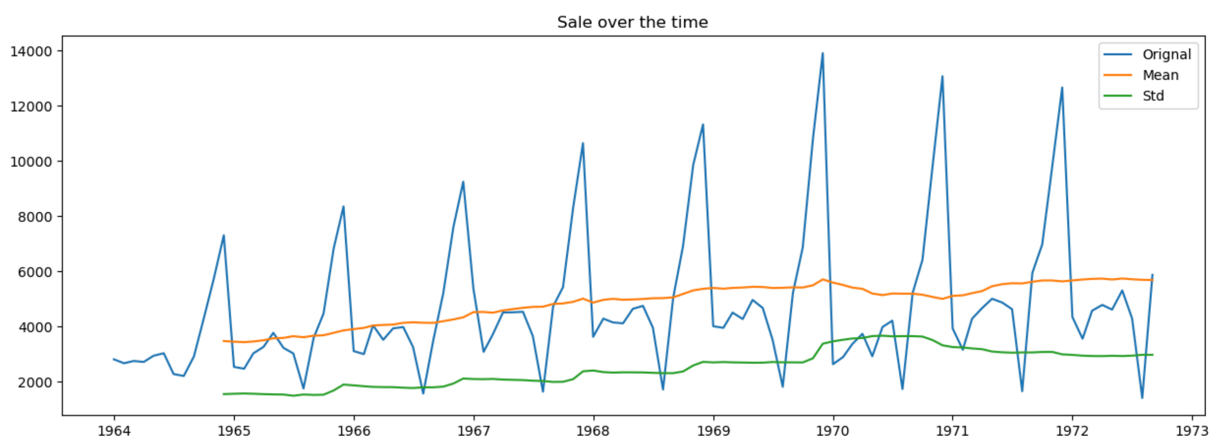
Out[11]:

	Sale
Month	
1964-01-01	2815.0
1964-02-01	2672.0
1964-03-01	2755.0
1964-04-01	2721.0
1964-05-01	2946.0

In [12]:
```
plt.figure(figsize=(15,5))
plt.title('Sale over the time')
plt.plot(df, label = 'Sales')
plt.xlabel('Time')
plt.ylabel('Sales')
plt.legend()
plt.show()
```



In [13]:
```
rollmean = df.rolling(window=12).mean()
rollstd = df.rolling(window=12).std()

plt.figure(figsize=(15,5))
plt.title('Sale over the time')
plt.plot(df, label = 'Orignal')
plt.plot(rollmean, label = 'Mean')
plt.plot(rollstd, label = 'Std')
plt.legend()
plt.show()
```



In [14]:
```
#checking stationarity
from statsmodels.tsa.stattools import adfuller
```

In [15]:
```
# H0: Data is not stationary
# H1: Data is stationary

def test_stationarity(x):
    adf_test = adfuller(x)
    print('ADF Test Results')
    print(f'Statistic Value: {adf_test[0]}')
    p_value = adf_test[1]
    print(f'P-Value: {p_value}')
    print('Critical Values:')
    for key, value in adf_test[4].items():
        print(f'    {key}: {value}')
```

```
    if p_value < 0.05:
        print('✅ Series is stationary. Reject the null hypothesis (H0).')
    else:
        print('❌ Series is NOT stationary. accept the null hypothesis (H0).')
```

In [16]:

```
test_stationarity(df)
```

```
ADF Test Results
Statistic Value: -1.833593056327623
P-Value: 0.363915771660245
Critical Values:
   1%: -3.502704609582561
   5%: -2.8931578098779522
   10%: -2.583636712914788
❌ Series is NOT stationary. accept the null hypothesis (H0).
```

In [17]:

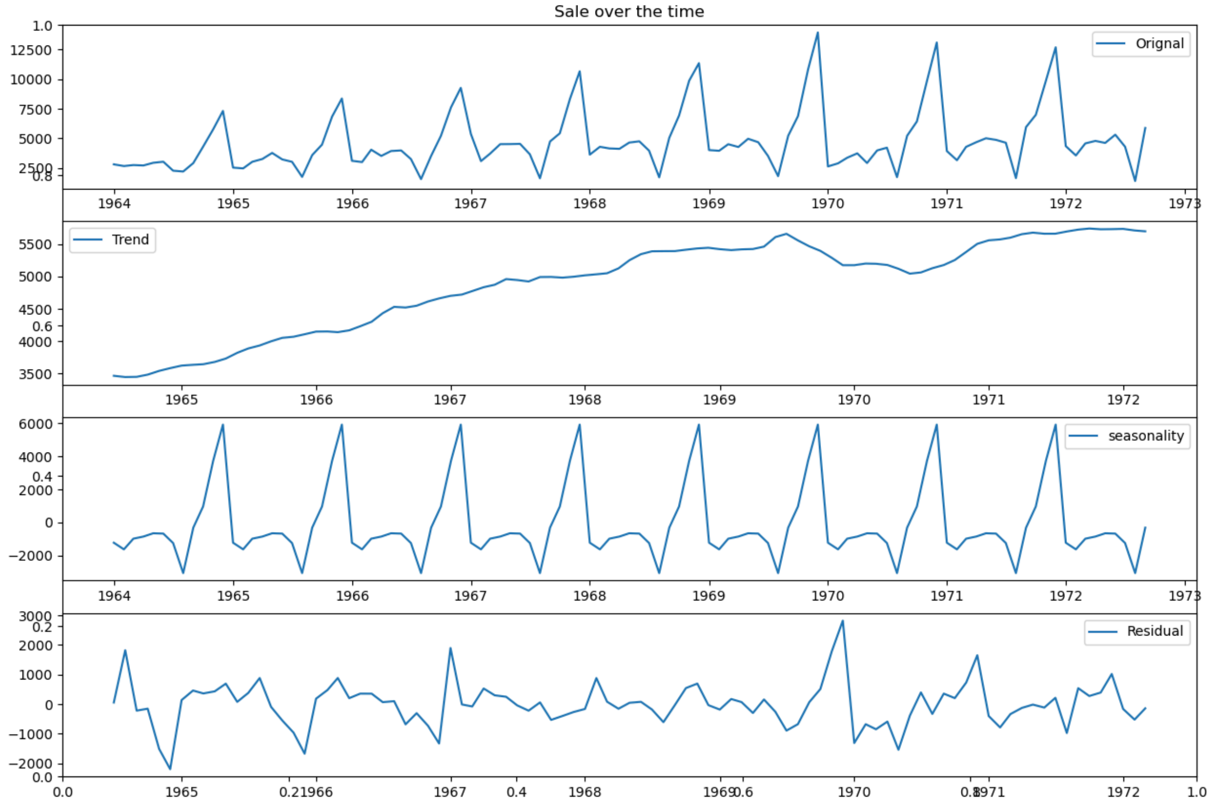
```
from statsmodels.tsa.seasonal import seasonal_decompose
seasonl_additive = seasonal_decompose(df, period=12, model = 'addative')
```

In [18]:

```
trend = seasonl_additive.trend
seasonal = seasonl_additive.seasonal
residual = seasonl_additive.resid
```

In [19]:

```
plt.figure(figsize=(15,10))
plt.title('Sale over the time')

plt.subplot(411)
plt.plot(df,label = 'Orignal')
plt.legend()

plt.subplot(412)
plt.plot(trend, label = 'Trend')
plt.legend()

plt.subplot(413)
plt.plot(seasonal, label = 'seasonality')
plt.legend()

plt.subplot(414)
plt.plot(residual, label = 'Residual')
plt.legend()
plt.show()
```



Making data stationarity

In [20]:
```
#Shifting by 1 and Differencing
df['firstDiff'] = df['Sale'] - df['Sale'].shift(1)
df
```

Out[20]:

Month	Sale	firstDiff
1964-01-01	2815.0	NaN
1964-02-01	2672.0	-143.0
1964-03-01	2755.0	83.0
1964-04-01	2721.0	-34.0
1964-05-01	2946.0	225.0
...	...	...
1972-05-01	4618.0	-170.0
1972-06-01	5312.0	694.0
1972-07-01	4298.0	-1014.0
1972-08-01	1413.0	-2885.0
1972-09-01	5877.0	4464.0

105 rows × 2 columns

In [21]:

```
#Shifting by 12 and Differencing
df['SeasonalSale'] = df['firstDiff'] - df['firstDiff'].shift(12)
df
```

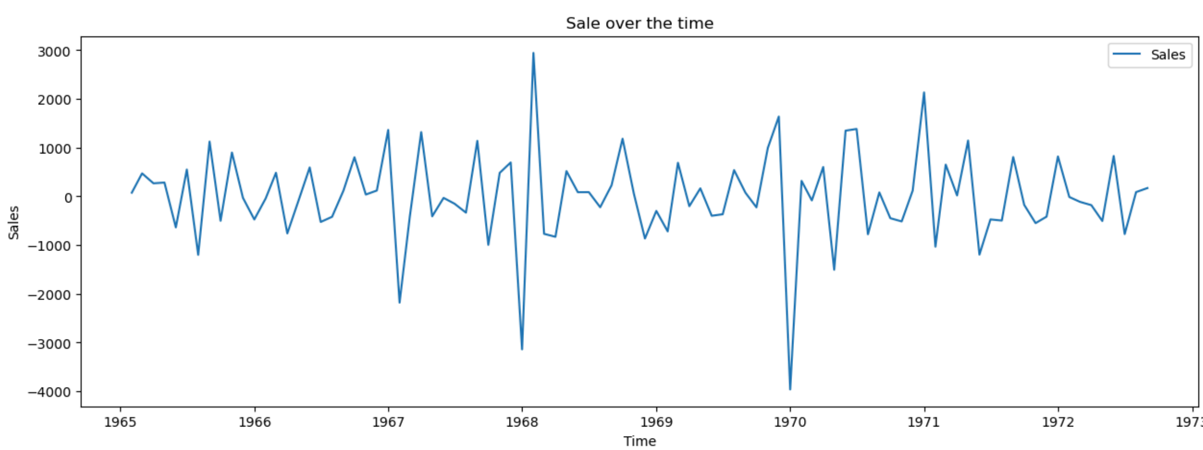
Out[21]:

Month	Sale	firstDiff	SeasonalSale
1964-01-01	2815.0	NaN	NaN
1964-02-01	2672.0	-143.0	NaN
1964-03-01	2755.0	83.0	NaN
1964-04-01	2721.0	-34.0	NaN
1964-05-01	2946.0	225.0	NaN
...	...	...	...
1972-05-01	4618.0	-170.0	-504.0
1972-06-01	5312.0	694.0	830.0
1972-07-01	4298.0	-1014.0	-773.0
1972-08-01	1413.0	-2885.0	89.0
1972-09-01	5877.0	4464.0	172.0

105 rows × 3 columns

In [22]:

```
plt.figure(figsize=(15,5))
plt.title('Sale over the time')
plt.plot(df['SeasonalSale'], label = 'Sales')
plt.xlabel('Time')
plt.ylabel('Sales')
plt.legend()
plt.show()
```



In [23]:

```
test_stationarity(df['SeasonalSale'].dropna())
```

```
ADF Test Results
Statistic Value: -4.427713497307538
P-Value: 0.00026504628492931003
Critical Values:
   1%: -3.5148692050781247
   5%: -2.8984085156250003
   10%: -2.58643890625
✅ Series is stationary. Reject the null hypothesis (H0).
```

In [24]:

```
#impoting library for ACF and PACF plot

from statsmodels.tsa.stattools import acf, pacf
lag_acf = acf(df['SeasonalSale'].dropna(), nlags=20)
lag_pacf = pacf(df['SeasonalSale'].dropna(), nlags=20)
```

In [25]:

```
lag_acf
```

Out[25]:

```
array([ 1.        , -0.42195114, -0.09430821,  0.07434433,  0.0043774 ,
       -0.08104485, -0.03665555,  0.04535312,  0.07818965, -0.09834564,
        0.0646181 ,  0.11215009, -0.37966041,  0.3588898 , -0.0527602 ,
       -0.07515121, -0.08502832,  0.06181156,  0.10858334, -0.09818183,
       -0.10793321])
```

In [26]:

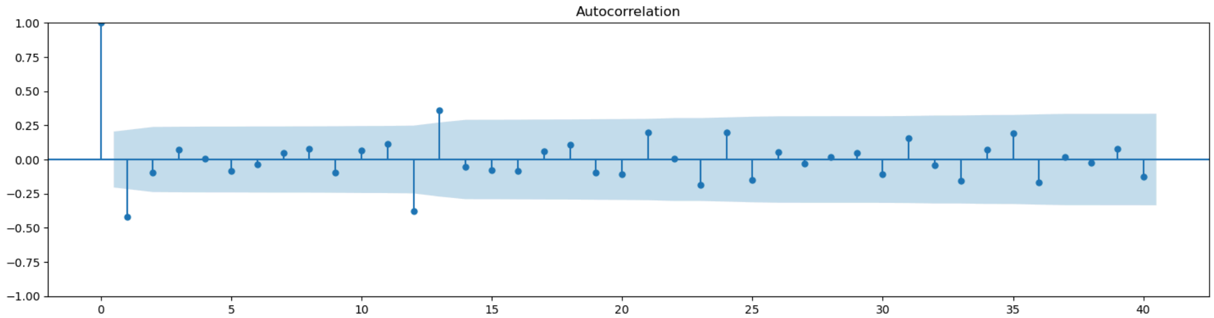
```
lag_pacf
```

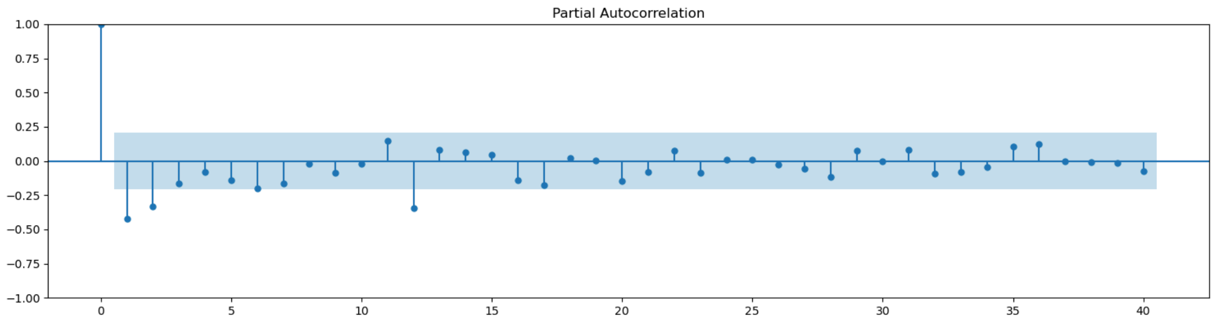
Out[26]:

```
array([ 1.        , -0.42658796, -0.34030991, -0.17066773, -0.08834766,
       -0.15160867, -0.22471162, -0.19396218, -0.03684659, -0.11393605,
       -0.03676525,  0.16475062, -0.41289325,  0.09005412,  0.07105284,
        0.04751972, -0.19093674, -0.24796865,  0.01782106, -0.00986552,
       -0.24534446])
```

In [27]:

```
import matplotlib.pyplot as plt
import statsmodels.api as sm

plt.figure(figsize=(15, 8))

# ACF plot
plt.subplot(211)
sm.graphics.tsa.plot_acf(df['SeasonalSale'].dropna(), lags=40, ax=plt.gca())

# PACF plot
plt.subplot(212)
sm.graphics.tsa.plot_pacf(df['SeasonalSale'].dropna(), lags=40, ax=plt.gca())

plt.tight_layout()
plt.show()
```





ARIMA Model

In [28]:
```
from statsmodels.tsa.arima.model import ARIMA
```

In [29]:
```
arima_model = ARIMA(df['Sale'], order = (1,1,1)) #p = 1, d = 1, q = 1
model_fi = arima_model.fit()
```

```
C:\Users\Admin\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: Va
lueWarning: No frequency information was provided, so inferred frequency MS will be
used.
  self._init_dates(dates, freq)
C:\Users\Admin\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: Va
lueWarning: No frequency information was provided, so inferred frequency MS will be
used.
  self._init_dates(dates, freq)
C:\Users\Admin\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: Va
lueWarning: No frequency information was provided, so inferred frequency MS will be
used.
  self._init_dates(dates, freq)
```

In [30]:
```
model_fi.summary()
```

Out[30]:

SARIMAX Results

Dep. Variable:	Sale	**No. Observations:**	105
Model:	ARIMA(1, 1, 1)	**Log Likelihood**	-952.814
Date:	Fri, 18 Jul 2025	**AIC**	1911.627
Time:	11:48:43	**BIC**	1919.560
Sample:	01-01-1964	**HQIC**	1914.841
	- 09-01-1972		
Covariance Type:	opg		

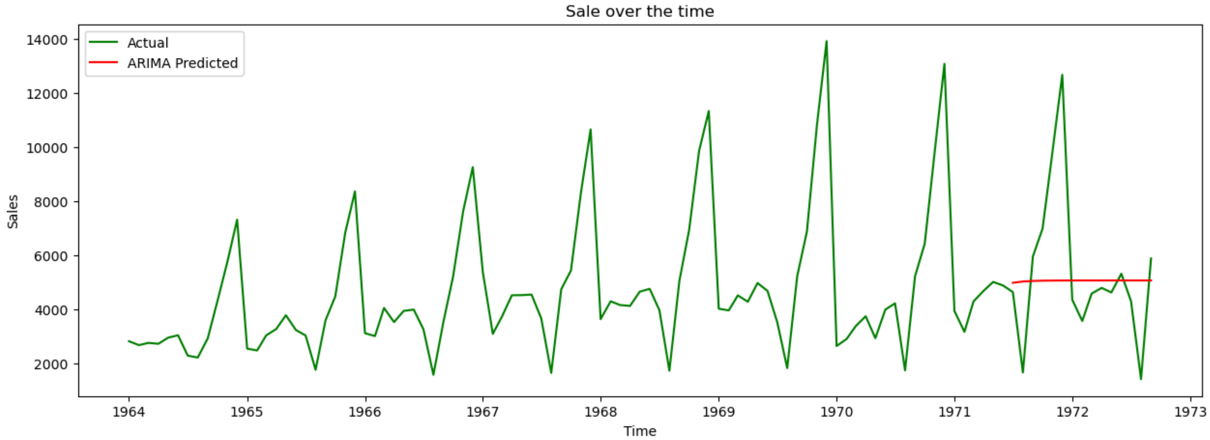
	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
ar.L1	0.4545	0.114	3.999	0.000	0.232	0.677
ma.L1	-0.9666	0.056	-17.316	0.000	-1.076	-0.857
sigma2	5.226e+06	6.17e+05	8.473	0.000	4.02e+06	6.43e+06

Ljung-Box (L1) (Q):	0.91	**Jarque-Bera (JB):**	2.59
Prob(Q):	0.34	**Prob(JB):**	0.27
Heteroskedasticity (H):	3.40	**Skew:**	0.05
Prob(H) (two-sided):	0.00	**Kurtosis:**	3.77

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

In [31]:
```
df['ArimaPred'] = model_fi.predict(start = 90, end = 105, dynamic = True)
```

In [32]:
```
plt.figure(figsize=(15,5))
plt.title('Sale over the time')
plt.plot(df['Sale'], label = 'Actual', color = 'green')
plt.plot(df['ArimaPred'], label = 'ARIMA Predicted', color = 'red')
plt.xlabel('Time')
plt.ylabel('Sales')
plt.legend()
plt.show()
```



As the data is seasonal, So ARIMA model is not giving best prediction

SARIMAX Model

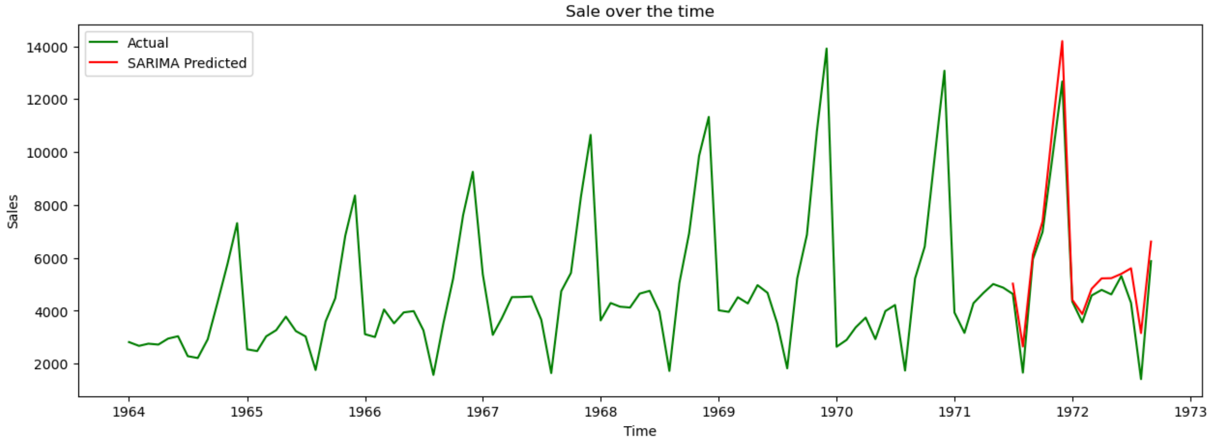
In [33]:
```
import statsmodels.api as sm
```

In [34]:
```
model = sm.tsa.statespace.SARIMAX(df['Sale'], order=(1,2,1), seasonal_order=(1,1,1,
result =  model.fit()
```

```
C:\Users\Admin\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: Va
lueWarning: No frequency information was provided, so inferred frequency MS will be
used.
  self._init_dates(dates, freq)
C:\Users\Admin\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: Va
lueWarning: No frequency information was provided, so inferred frequency MS will be
used.
  self._init_dates(dates, freq)
```

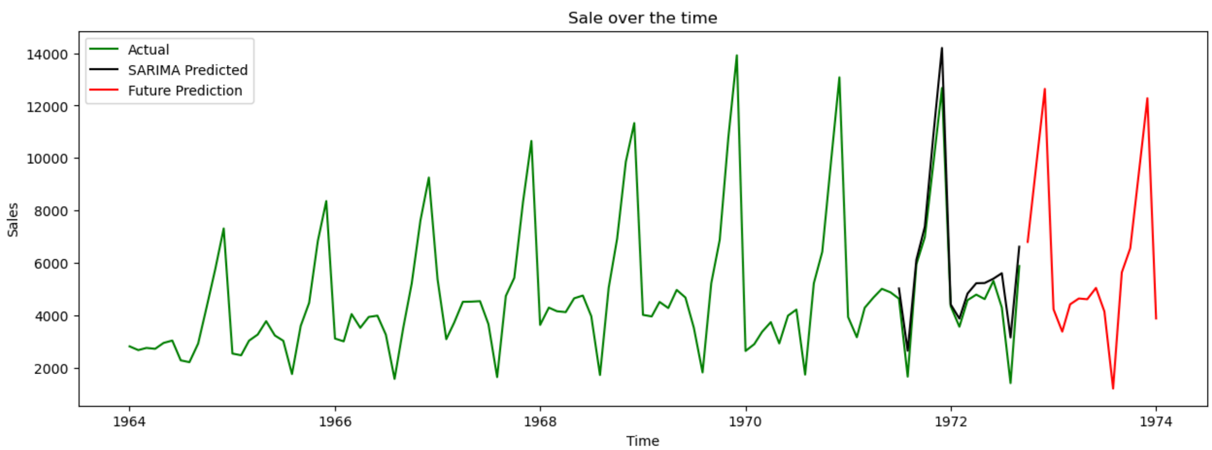
In [35]:
```
df['forcast'] = result.predict(start = 90, end = 105, dynamic = True)
```

In [36]:
```
plt.figure(figsize=(15,5))
plt.title('Sale over the time')
plt.plot(df['Sale'], label = 'Actual', color = 'green')
plt.plot(df['forcast'], label = 'SARIMA Predicted', color = 'red')
plt.xlabel('Time')
plt.ylabel('Sales')
plt.legend()
plt.show()
```



In [37]:
```
FuturPred = result.predict(start = 105, end = 120, dynamic = True)
```

In [38]:
```
plt.figure(figsize=(15,5))
plt.title('Sale over the time')
plt.plot(df['Sale'], label = 'Actual', color = 'green')
plt.plot(df['forcast'], label = 'SARIMA Predicted', color = 'black')
plt.plot(FuturPred, label = 'Future Prediction', color = 'red')
plt.xlabel('Time')
plt.ylabel('Sales')
plt.legend()
plt.show()
```



In [ ]: