REGRESSION TIME SERIES MODEL COURSE GROUP PROJECT

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github repo for project > https://github.com/Gaurav05082002/Time-Series-Analysis-Project

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Definition of Linear Regression Analysis

A model called linear regression analysis, in which one variable predicts the response variable, aims to explain the functional relationship between two variables. Regression analysis often has three goals: to assess the strength of the association, to evaluate the impact, and to forecast or predict

Basic Model of Simple Linear Regression

$$Y = \alpha + \beta x + \varepsilon$$

Where:

Y is the dependent / response / dependent variable

X is independent variables / predictors / independent α is the intercept parameter (constant)
β slope parameter (coefficient)

ε is a residual which is a random

A simple linear regression model is an equation that states the relationship between one predictor variable (X) and one response variable (Y), which is usually depicted in a straight line. Regression analysis is a model that attempts to explain the functional relationship between two variables, where one variable acts as a predictor of the response variable
$Y = a + bX$
a = constant
b = regression coefficient
Y = dependent variable / dependent variable / dependent variable (incident)
X = independent variable / independent variable / variable predictor (cause)

1. **Simple Linear Regression Testing Steps**

This test is conducted to determine whether the independent variable (x) affects the dependent variable (Y). Hypothesis testing of the regression coefficient is carried out through the following steps(statistics, 2020):

a) <u>Significance Test of Constants a</u>

- Hypothesis:

- Ho= α = 0 →constanta has no significant effect
- $H1$= $\alpha \neq 0$ →constantsta has a significant effect

- Determine the significance level of α {find t table with df = n-2}
- Test Statistics: t = = depending on the initial hypothesis Test = $(a-\alpha)sx\sqrt{n}(n-1)$
$Se\sqrt{\sum xi}$ 2

- Test criteria:
if $|thitung| \geq ttabel$ then Ho is rejected
If $|thitung| < ttabel$ then Ho is accepted

b) <u>Test of Significance of Coefficient b</u>

- Hypothesis:

- Ho= β = 0 →Coefficient has no significant effect
- $H1$= β ≠ 0 → Coefficient has a significant effect

- Determine the significance level of α {find t table with df = n-2}

- Test Statistics: t = : t = $(b-\beta0\ )sx\sqrt{(n-1)}\ Se$, $\beta 0$= depending on the initial hypothesis

- Test criteria:
if $|thitung| \geq ttabel$ then Ho is rejected
If $|thitung| < ttabel$ then Ho is accept

2. Correlation Coefficient and Coefficient of Determination

Correlation coefficient is used to measure the degree of closeness of the relationship between the independent variable and the dependent variable. The coefficient of determination is used to measure how much influence the independent variable has on the dependent variable. The measurement can be used the Pearson correlation formula or the formula below:

The Pearson Correlation Coefficient formula is as follows:

$$\mathbf{r} = \frac{\mathbf{n}(\sum \mathbf{xy}) - (\sum \mathbf{x})(\sum \mathbf{y})}{\sqrt{[\mathbf{n}\sum \mathbf{x}^2 - (\sum \mathbf{x})^2][\mathbf{n}\sum \mathbf{y}^2 - (\sum \mathbf{y})^2]}}$$

LEAST SQUARES AND THE FITTED MODEL

After determining the model, the next step is to determine the method for estimating the parameters or regression coefficients from the $.(\Sigma\ ^2)-(\Sigma\ )^2$ formed model. The regression coefficient is a parameter and its value is unknown, but these parameters can be estimated from the sample data. We will use least squares method for estimation .

Ordinary Least Squares (OLS) Method The least squares method is a method for determining the estimation linear equation by selecting one linear curve from several possible linear curves that can be made from existing data that has the smallest error from the actual data with the estimation data. If simple linear regression equation: Y=a+bX

The regression coefficients can be calculated by the formula:

$$\boxed{a = \frac{\sum y_i - b\sum x_i}{n}}$$

$$\boxed{b = \frac{n.\sum xi.yi - (\sum xi).(\sum yi)}{n.(\sum x_i{}^2)\ - (\sum xi)^2}}$$

Sample case

There was a sample of 12 students of Class IX at SMPN 1 Medan which were taken for the test scores and final scores for each student. We want to see how the test scores affect the final grade . As for the following is the data:

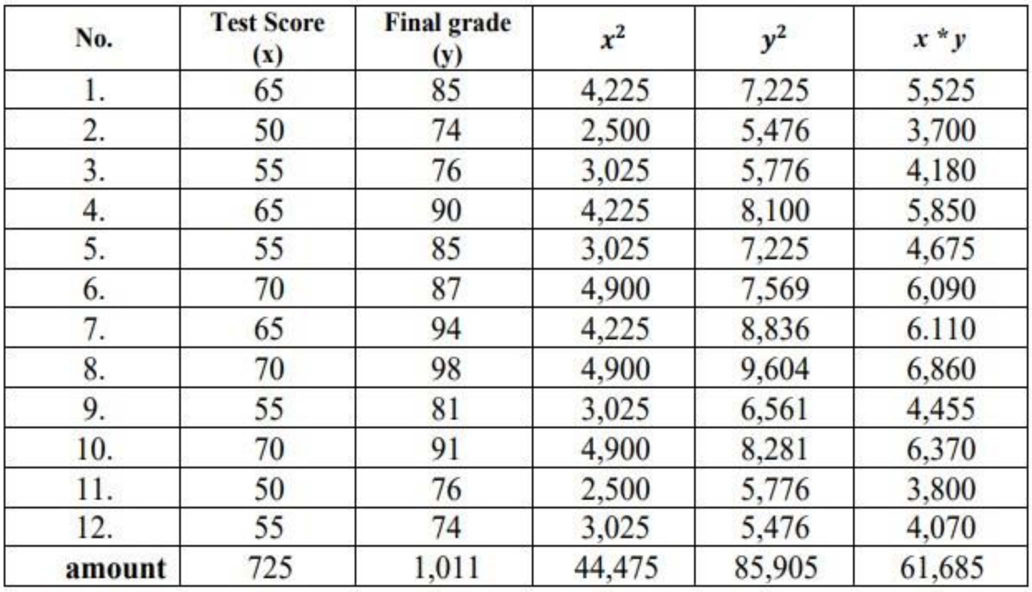
No.	Test score (x)	Final Grade (y)
1.	65	85
2.	50	74
3.	55	76
4.	65	90
5.	55	85
6.	70	87
7.	65	94
8.	70	98
9.	55	81
10.	70	91
11.	50	76
12.	55	74

STEPS:

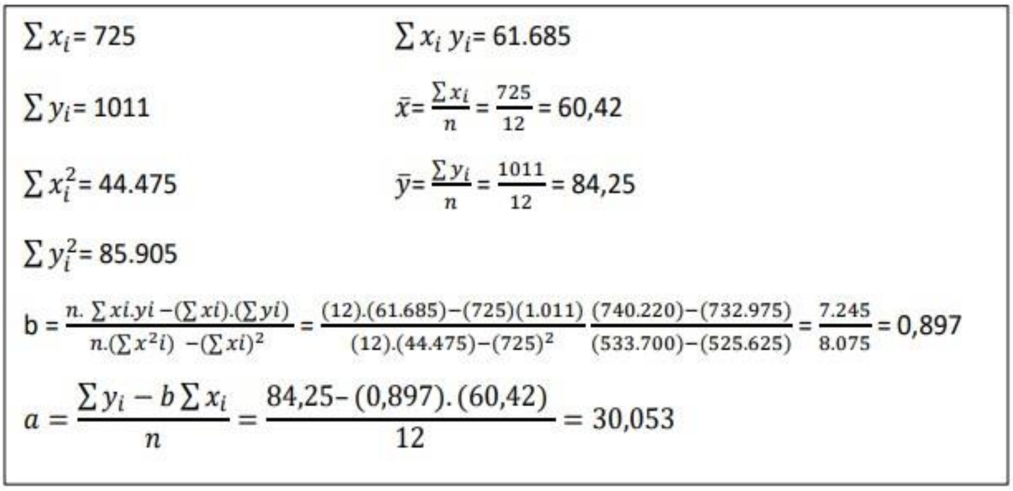
1. Write down the regression equation, then explain what the equation means!
2. Describe the linearity of the data, then conclude!
3. The partial significance test for the constant value and the regression coefficient? Use a significance level of 0.05 (5%).
4. Simultaneous significance test of the parameter assessment results? Use the real level 0.05 (5%)
5. How strong is the relationship between test scores and final grades?
6. What is the coefficient of determination? Explain what that value means!

ANSWER!

1. Its Regression Equation and Its Interpretation



No.	Test Score (x)	Final grade (y)	x^2	y^2	$x * y$
1.	65	85	4,225	7,225	5,525
2.	50	74	2,500	5,476	3,700
3.	55	76	3,025	5,776	4,180
4.	65	90	4,225	8,100	5,850
5.	55	85	3,025	7,225	4,675
6.	70	87	4,900	7,569	6,090
7.	65	94	4,225	8,836	6.110
8.	70	98	4,900	9,604	6,860
9.	55	81	3,025	6,561	4,455
10.	70	91	4,900	8,281	6,370
11.	50	76	2,500	5,776	3,800
12.	55	74	3,025	5,476	4,070
amount	725	1,011	44,475	85,905	61,685



$\sum x_i$= 725

$\sum x_i\, y_i$= 61.685

$\sum y_i$= 1011

$\bar{x}= \frac{\sum x_i}{n} = \frac{725}{12}$ = 60,42

$\sum x_i^2$= 44.475

$\bar{y}= \frac{\sum y_i}{n} = \frac{1011}{12}$ = 84,25

$\sum y_i^2$= 85.905

$$b = \frac{n.\sum xi.yi - (\sum xi).(\sum yi)}{n.(\sum x^2 i)\ - (\sum xi)^2} = \frac{(12).(61.685) - (725)(1.011)}{(12).(44.475) - (725)^2}\ \frac{(740.220) - (732.975)}{(533.700) - (525.625)} = \frac{7.245}{8.075} = 0,897$$

$$a = \frac{\sum y_i - b \sum x_i}{n} = \frac{84,25 - (0,897).(60,42)}{12} = 30,053$$

Then the regression equation is obtained:

Y = a + bx

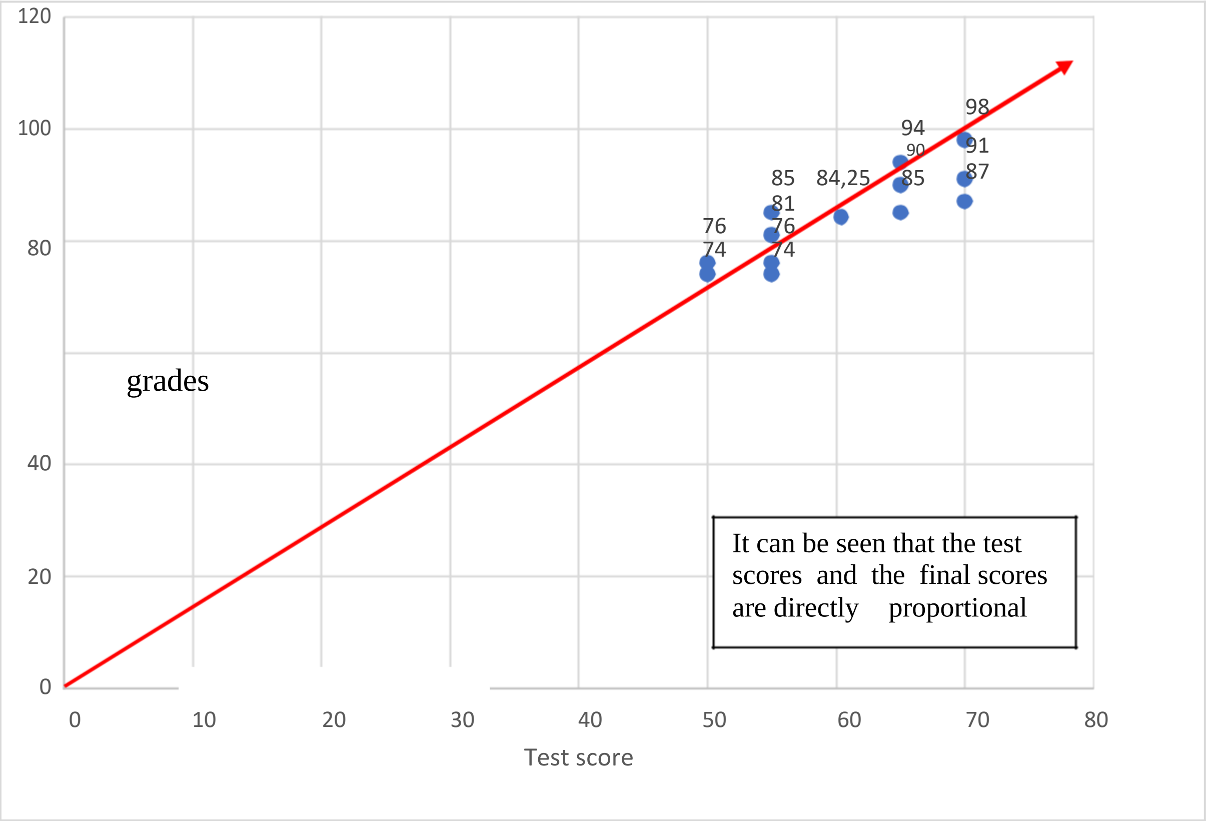
Y = 30.053 + 0.897x

From the above equation, it can be interpreted:

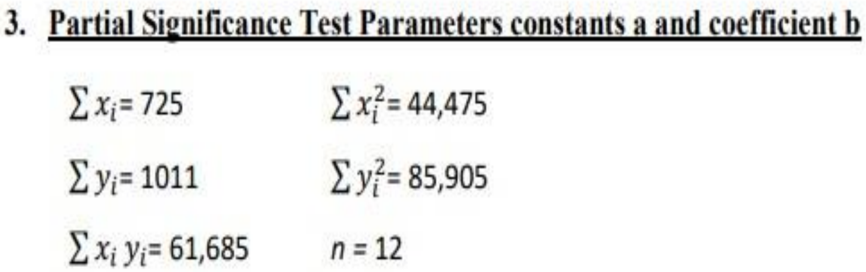
constant a = 30.053→ Expresses the average final score of students on the exam (X) zero amounted to **30,053**

coefficient b = 0.897→ Every increase of 1 in the test score (X), then the grade end (Y) students are likely to increase amounting to 0.897

2. Scatter Plot Data linearity



It can be seen that the test scores and the final scores are directly proportional



3. Partial Significance Test Parameters constants a and coefficient b

$\sum x_i$= 725 $\sum x_i^2$= 44,475

$\sum y_i$= 1011 $\sum y_i^2$= 85,905

$\sum x_i\ y_i$= 61,685 n = 12

$s_x{}^2 = \frac{n.\sum xi^2-(\sum xi)^2}{n.\,(n-1)} = \frac{(12).(44.475)-(725)^2}{12.(12-1)} = \frac{533.700-525.625}{12.(11)} = \frac{8.075}{132} = 61,174$

$s_x = \sqrt{61,174} = 7,821$

$s_y{}^2 = \frac{n.\sum yi^2-(\sum yi)^2}{n.\,(n-1)} = \frac{(12).(85.905)-(1011)^2}{12.(12-1)} = \frac{1.030.860-1.022.121}{12.(11)} = \frac{8.739}{132} = 66,205$

$s_y = \sqrt{66,205} = 8,137$

$S_e{}^2 = \frac{n-1}{n-2}(s_y{}^2 - b^2.s_x{}^2) = \frac{12-1}{(12-2)}.[66.205-(0,897^2).(61.174)] = \frac{11}{10}.[66.205-(0,805)(61.174)]$

$=(1,1).(66.205-49.245)=(11).(16,96)= 18,66$

$S_e = \sqrt{18,66} = 4,319$

a) Significance test of constants a

1) Hypothesis:

$H_o = \alpha = 0$ → constantsta has no significant effect on the final value

$H_1 = \alpha \neq 0$ → constant has a significant effect on the final value

2) Significance Level

α= 5% = 0,05/2 = 0,025→ see Tabel t

df=n-2 =12-2=10 → $t\ tabel$ = 2,228

Test Statistics

$$t = \frac{(a-\alpha)s_x\sqrt{n(n-1)}}{S_e\sqrt{\sum x_i{}^2}} = \frac{(30,053-0).(7,821)\sqrt{12(12-1)}}{(4,319)\sqrt{44.475}} = \frac{(30,053).(7,821)\sqrt{132}}{(4,319).(210,891)}$$

$$= \frac{(30,053).(7,821).(11,489)}{(910,838)} = \frac{2700,426}{(910,838)} = 2,965 \rightarrow t_{hitung}$$

3) Test Criteria

If, $|t_{hitung}| \geq t_{tabel}$ then H_o it is rejected

If, $|t_{hitung}| < t_{tabel}$ then H_o accepted

4) **Conclusion:**

Because 2,965 > 2,228 → then Ho is rejected

$\boldsymbol{"H_1"}$ → Constants have a significant effect on the final value

b) Significance coefficient test b

1) Hypothesis:

H_o= β= 0 → the coefficient of test scores has no significant effect on the final score

H_1=β $\neq$ 0 → the coefficient of the test score has a significant effect on the final score

2) Significance Level

α = 5% = 0,05/2 = 0,025→ see Tabel t

Df = n-2 = 12 – 2 = 10 → $t\ tabel$ = 2,228

3) Test Statistics

$$t = \frac{(b-\beta_0)s_x\sqrt{(n-1)}}{S_e} = \frac{(0,897-0).(7,821)\sqrt{(12-1)}}{(4,319)} = \frac{(0,897).(7,821).(3,317)}{(4,319)} = \frac{(23,270)}{(4,319)} = 5,388 \rightarrow t_{hitung}$$

4) Test Criteria

If $|t_{hitung}| \geq t_{tabel}$ then H_o is rejected

If $|t_{hitung}| < t_{tabel}$ then H_o accepted

5) **Conclusion:**

Because 5,388 > 2,228 → then Ho is rejected

"$\boldsymbol{H_1}$" → The test score coefficient has a significant effect on the final score

4. Silmultan Significance Test Results Of Parameter Assessment

- Hypothesis:

  H_o = independent has no effect on the dependent variable

  H_1 = independent variabel have effects to the dependent variable

- Significance level

  α= 5% = 0,05 → see tabel F

  df_1 =1; df_2 =12-2=10 → $F\ tabel$ = 4,96

- Test Statistics ($\sum y_i$= 1011 dan $\sum y_i^2$= 85.905)

▪ JKT = $\sum {y_i}^2 - \frac{(\sum y_i)^2}{n}$ = (85.905) $-$ $\frac{(1011)^2}{12}$ = (85.905) $-$ $\frac{(1.022.121)}{12}$

= 85.905-85.176,75 = 728,25

▪ JKR = b [$\sum x_i . \sum y_i$ - $\frac{\sum x_i . \sum y_i}{n}$] = (0,897) [(61685)- $\frac{(725).(1011)}{12}$] = [(0,897) [(61.685)- $\frac{(732.975)}{12}$]

- JKR = (0.897) [(61,685) - (61,081.25)] = 7). (603.75) = 541,564
- JKG = JKT-JKR = 728.25 - 541,564 = 186,686
- RJKR =$\frac{JKR}{1} = \frac{541,564}{1} = 541,564$
- RJKG = = = 18,669$\frac{JKG}{n-2}\frac{186,686}{12-2}$

- Test Criteria

  If $\left|F_{hitung}\right| \geq F_{tabel}$ then H_o is rejected

  If $\left|F_{hitung}\right| < F_{tabel}$ then H_o accepted

- Conclusion

  Because 29.009 > 4.96 → H_0 is rejected

  "H_1" → The independent variable has an effect on the dependent variable

Number of Variations	Sum of Squares	Degrees of Freedom	Average Sum of Squares	F Count
Regression	541,564	1	641,564	29,009
Error	186,686	10	18,669	
Total	728.25	11		

5. Correlation Coefficient between Test Score (X) and Final Score (Y)

To measure the degree of closeness of the relationship, you can use the Pearson correlation formula or the formula below:

$$r_{xy} = \text{b}.\frac{S_x}{S_y} = (0,897).\frac{(7,821)}{(8,137)} = 0,862$$

Based on Guilford's criteria, the relationship between test scores and final scores is **"strong"**

6. Coefficient of Determination (R^2)

The coefficient of determination is the square of the correlationr_{xy}

$r_{xy} \rightarrow r_{xy}^2$
r_{xy}^2 = 0,862^2= 0,743 = 74,3%

The test score affects the final score by 74.3%. The rest (100% -74.3% = 25.7%) the final score is influenced by other factors that are not explained in the model

7. Prediction

What is the approximate final grade of a student if the test score is 75?

X = 75

Y = a + bx

Y = 30.053 + 0.897x

Y = 30.053 + 0.897 (75)

Y = 30,053 + 67,275

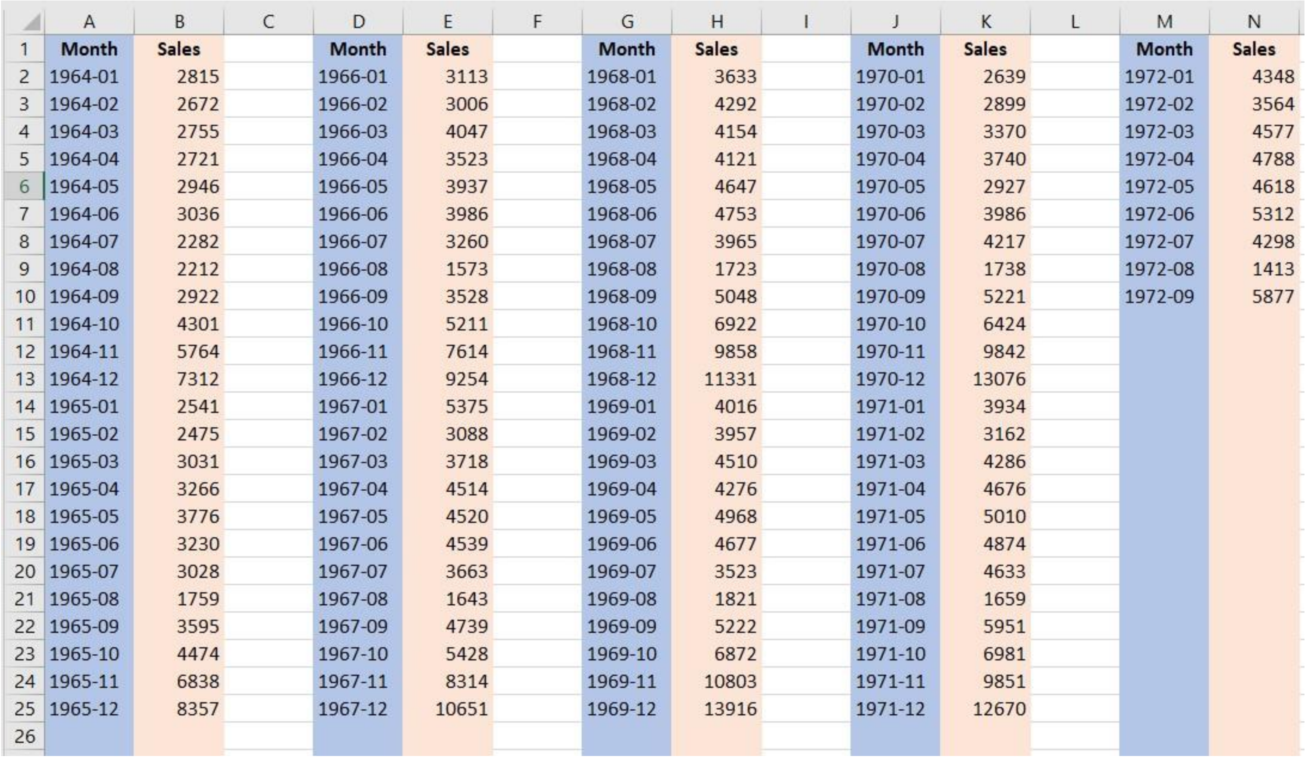
Y = 97.328

If the student has a test score of 75, the estimated final score is **97.328**

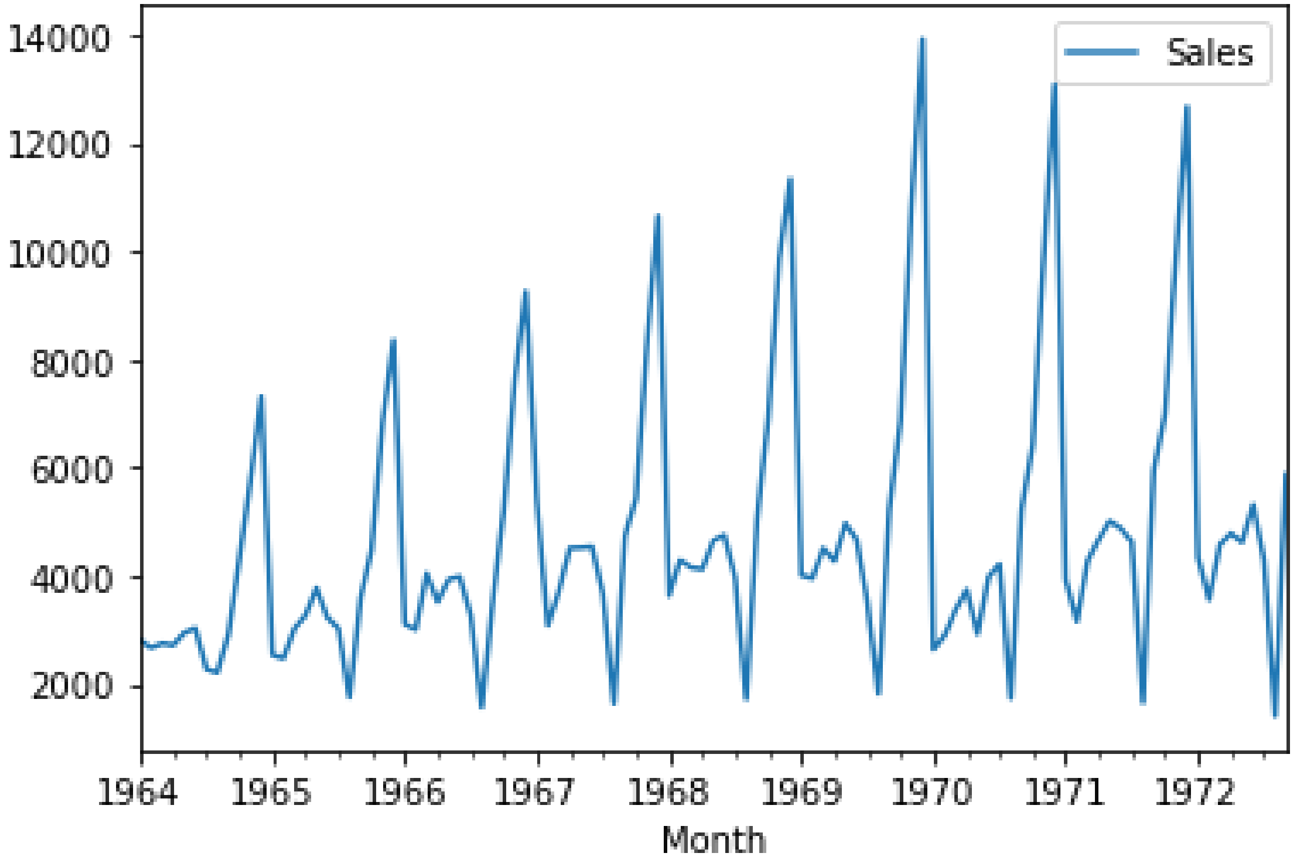
Time Series Model

ARIMA MODEL TO FORECAST FUTURE MONTHLY SALES

The monthly sales data of perrin freres champagne from January 1964 to September 1972 was analyzed for this project. We checked the stationarity of the data , found the autocorrelation factor (***ACF***) and partial autocorrelation factor (***PACF***). We also performed an Augmented ***Dicky-Fuller*** test. We also applied ARIMA Model to make the sales forecast for the upcoming 2 years



	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	**Month**	**Sales**		**Month**	**Sales**		**Month**	**Sales**		**Month**	**Sales**		**Month**	**Sales**
2	1964-01	2815		1966-01	3113		1968-01	3633		1970-01	2639		1972-01	4348
3	1964-02	2672		1966-02	3006		1968-02	4292		1970-02	2899		1972-02	3564
4	1964-03	2755		1966-03	4047		1968-03	4154		1970-03	3370		1972-03	4577
5	1964-04	2721		1966-04	3523		1968-04	4121		1970-04	3740		1972-04	4788
6	1964-05	2946		1966-05	3937		1968-05	4647		1970-05	2927		1972-05	4618
7	1964-06	3036		1966-06	3986		1968-06	4753		1970-06	3986		1972-06	5312
8	1964-07	2282		1966-07	3260		1968-07	3965		1970-07	4217		1972-07	4298
9	1964-08	2212		1966-08	1573		1968-08	1723		1970-08	1738		1972-08	1413
10	1964-09	2922		1966-09	3528		1968-09	5048		1970-09	5221		1972-09	5877
11	1964-10	4301		1966-10	5211		1968-10	6922		1970-10	6424			
12	1964-11	5764		1966-11	7614		1968-11	9858		1970-11	9842			
13	1964-12	7312		1966-12	9254		1968-12	11331		1970-12	13076			
14	1965-01	2541		1967-01	5375		1969-01	4016		1971-01	3934			
15	1965-02	2475		1967-02	3088		1969-02	3957		1971-02	3162			
16	1965-03	3031		1967-03	3718		1969-03	4510		1971-03	4286			
17	1965-04	3266		1967-04	4514		1969-04	4276		1971-04	4676			
18	1965-05	3776		1967-05	4520		1969-05	4968		1971-05	5010			
19	1965-06	3230		1967-06	4539		1969-06	4677		1971-06	4874			
20	1965-07	3028		1967-07	3663		1969-07	3523		1971-07	4633			
21	1965-08	1759		1967-08	1643		1969-08	1821		1971-08	1659			
22	1965-09	3595		1967-09	4739		1969-09	5222		1971-09	5951			
23	1965-10	4474		1967-10	5428		1969-10	6872		1971-10	6981			
24	1965-11	6838		1967-11	8314		1969-11	10803		1971-11	9851			
25	1965-12	8357		1967-12	10651		1969-12	13916		1971-12	12670			
26														



The monthly data seems to be non stationary and has ***seasonality***

Augmented Dicky-Fuller Test and Differencing

Original Data

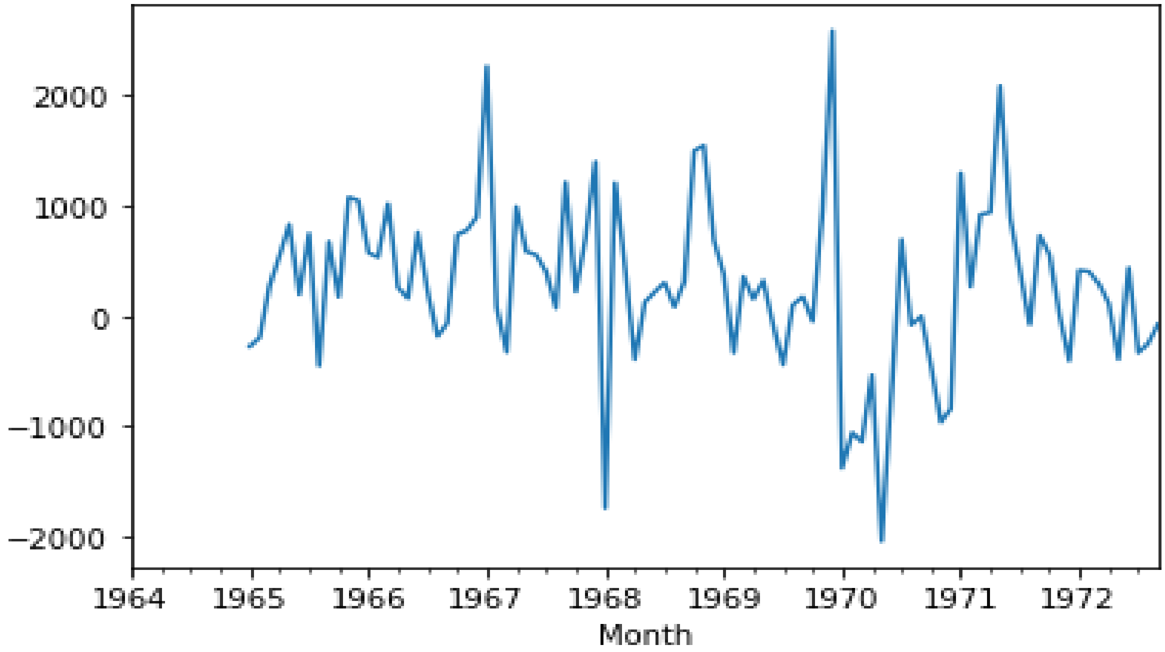
ADF Test Statistic	-1.8335930563276297
p-value	0.3639157716602417
Lags Used	11
Number of Observations Used	93

Since the p value is greater than 0.05 , it indicates that the time series is non stationary and has a unit root. To make the time series data stationary, we used differencing. The plot of sales suggests the presence of seasonality, so we used the seasonal differencing (12 months).

First Seasonal Difference Data

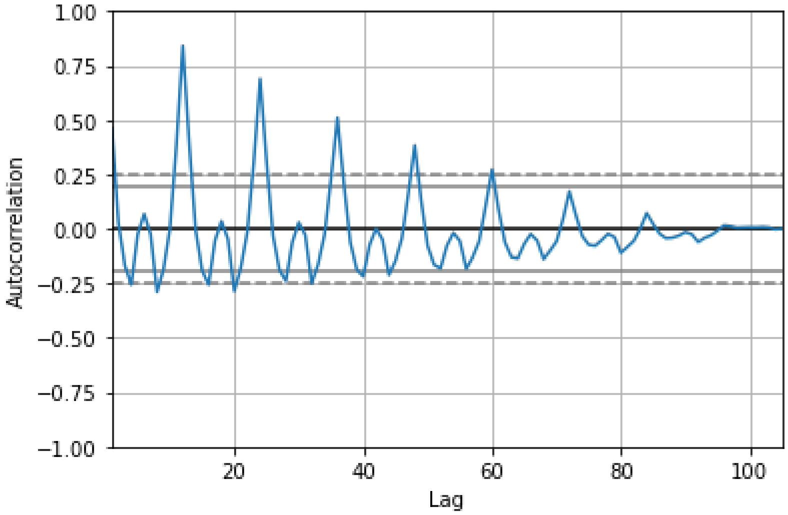
ADF Test Statistic	-7.626619157213163
p-value	2.060579696813685e-11
Lags Used	0
Number of Observations Used	92

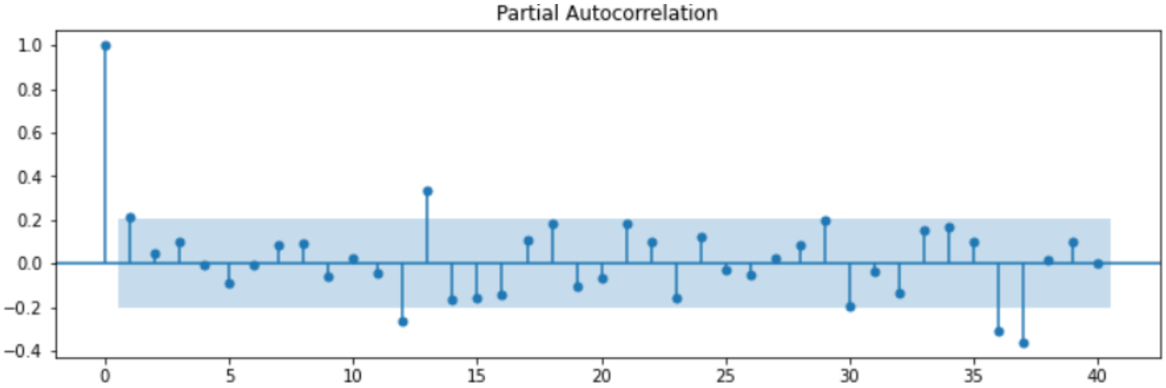
ADF test suggests that the first seasonal difference data is stationary which is also event from the below plot.

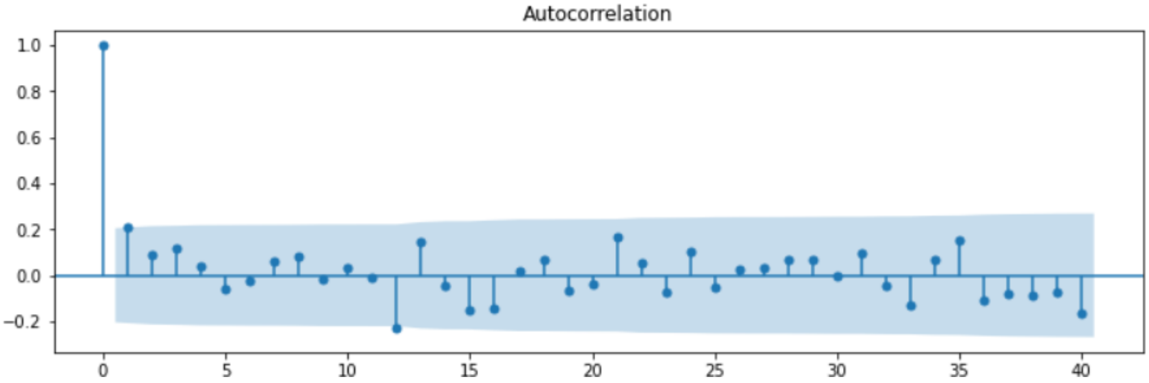


Selecting ARIMA Model Parameters

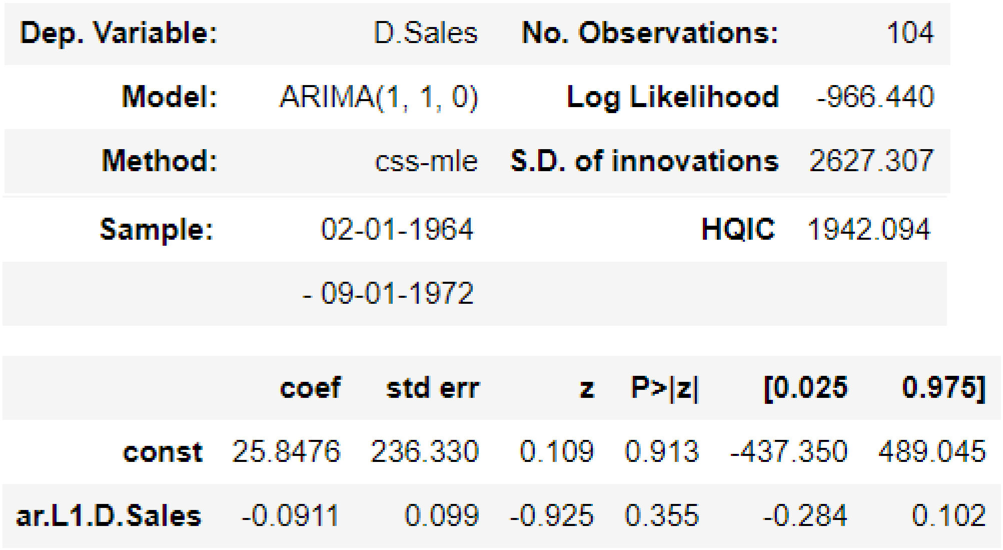
- d=1 as we did only one seasonal differencing to make the data stationary
- q=1 from the Autocorrelation plot
- p=1 from the Partial Autocorrelation plot





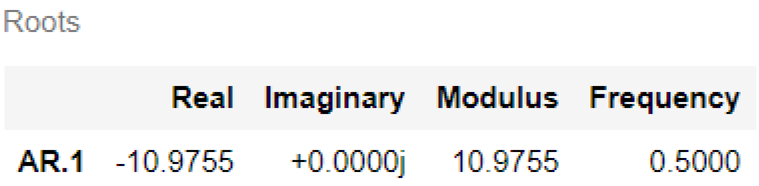


ARIMA Model Results



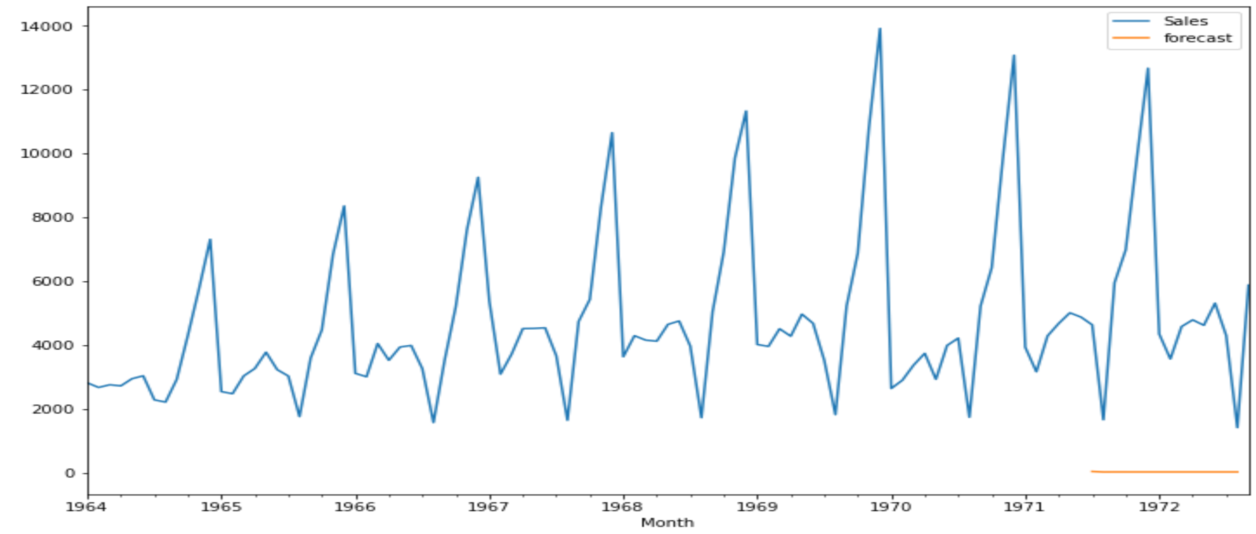
Dep. Variable:	D.Sales	**No. Observations:**	104
Model:	ARIMA(1, 1, 0)	**Log Likelihood**	-966.440
Method:	css-mle	**S.D. of innovations**	2627.307
Sample:	02-01-1964	**HQIC**	1942.094
	- 09-01-1972		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
const	25.8476	236.330	0.109	0.913	-437.350	489.045
ar.L1.D.Sales	-0.0911	0.099	-0.925	0.355	-0.284	0.102



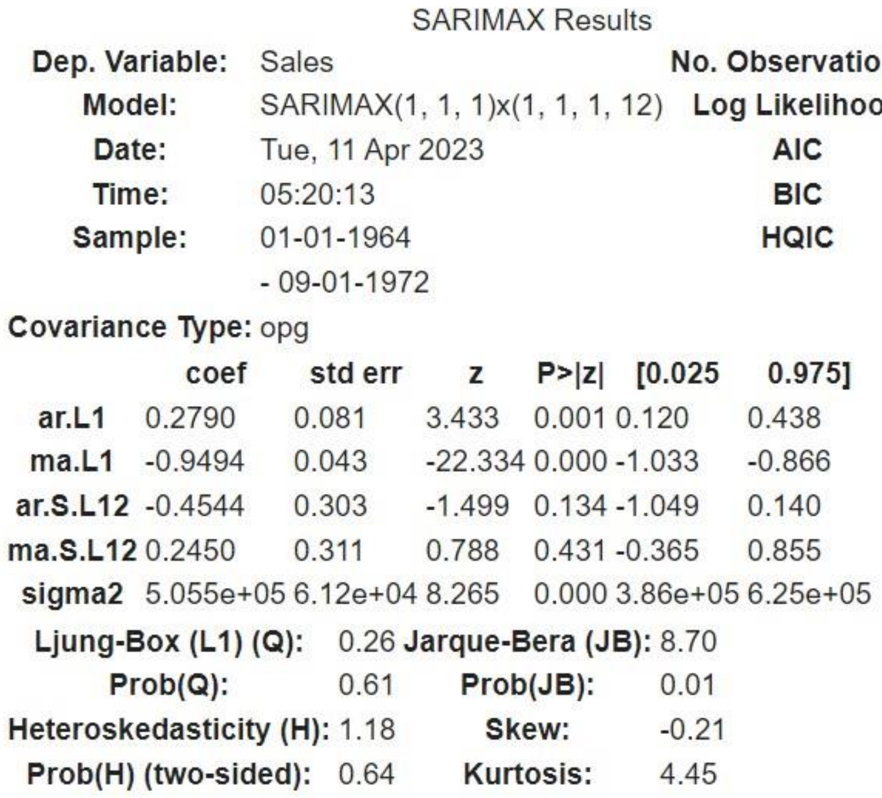
Roots

	Real	**Imaginary**	**Modulus**	**Frequency**
AR.1	-10.9755	+0.0000j	10.9755	0.5000

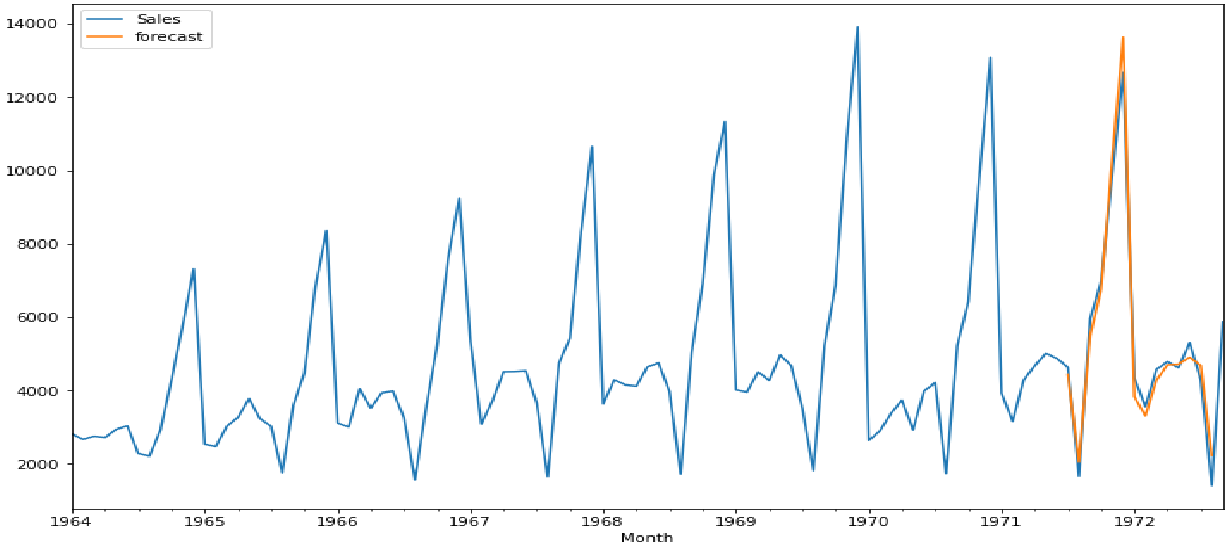


ARIMA Model didn't give good results and also the p values are very high which suggests that the model is not good.

SARIMAX Model Results



```
                              SARIMAX Results
 Dep. Variable:      Sales                                No. Observations: 105
          Model:     SARIMAX(1, 1, 1)x(1, 1, 1, 12)  Log Likelihood     -738.402
           Date:     Tue, 11 Apr 2023                            AIC     1486.804
           Time:     05:20:13                                    BIC     1499.413
         Sample:     01-01-1964                                 HQIC     1491.893
                     - 09-01-1972
Covariance Type: opg
                coef      std err    z      P>|z|  [0.025    0.975]
   ar.L1    0.2790      0.081      3.433   0.001 0.120      0.438
   ma.L1    -0.9494     0.043      -22.334 0.000 -1.033     -0.866
 ar.S.L12  -0.4544      0.303      -1.499  0.134 -1.049     0.140
ma.S.L12   0.2450      0.311      0.788   0.431 -0.365     0.855
 sigma2    5.055e+05 6.12e+04 8.265   0.000 3.86e+05 6.25e+05
   Ljung-Box (L1) (Q):      0.26 Jarque-Bera (JB): 8.70
          Prob(Q):              0.61      Prob(JB):          0.01
Heteroskedasticity (H): 1.18        Skew:              -0.21
  Prob(H) (two-sided):    0.64      Kurtosis:           4.45
```

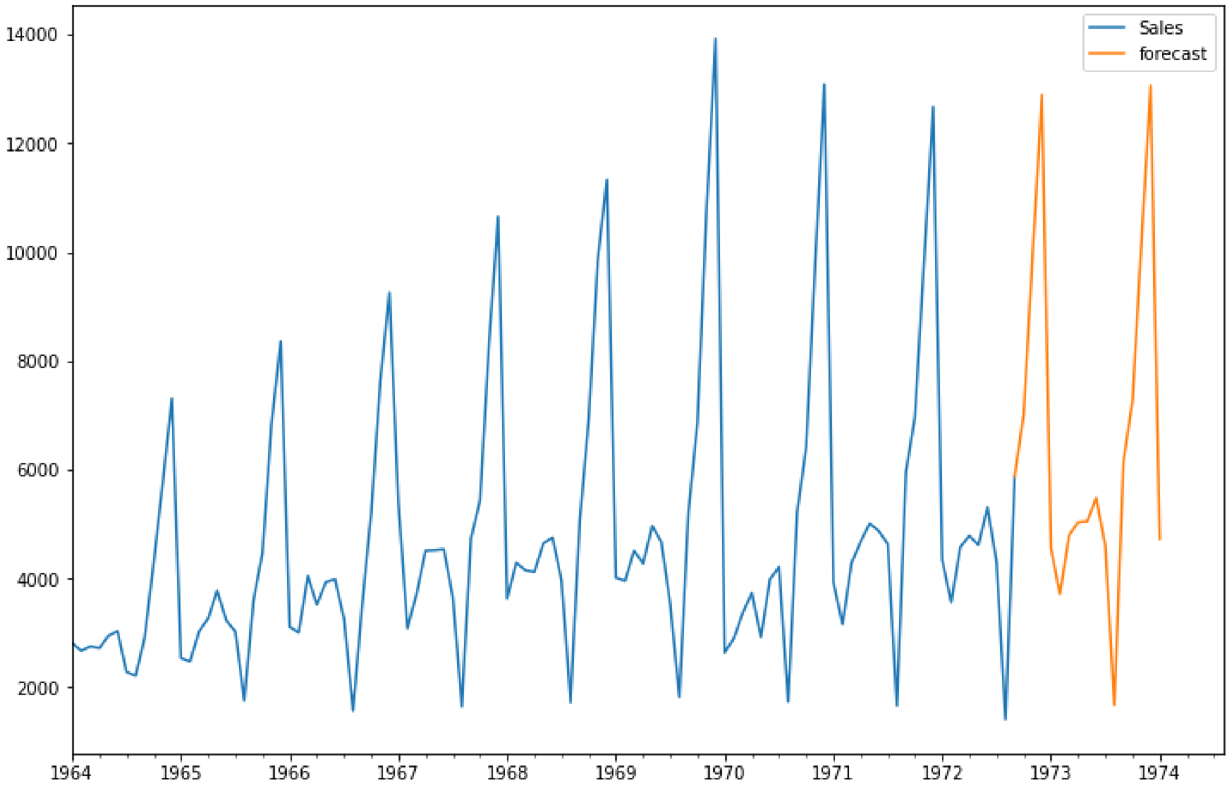


The SARIMAX Model is better than the ARIMA Model which is evident from the comparison of actual sales and the forecasted values . In addition to this, low p values also indicate that the SARIMAX model can be used to forecast the monthly sales .

Forecasting future monthly sales for 2 years

We used the SARIMAX Model to forecast monthly sales for 2 years. Sales forecasting is very important for any company. Some of the benefits of forecasting sales are listed below.

- To predict and plan for demand throughout the year
- To make wise business investments
- To quickly identify And mitigate potential problems
- To improve sales process
- To improve company morale



CODE

In [21]:

```
import pandas as pd
import numpy as np
import statsmodels as sm
from matplotlib import pyplot as plt
%matplotlib inline
```

In [2]:

```
df = pd.read_csv(r"rtsm project.csv")
```

In [3]:

```
df.head()
```

Out[3]:

	Month	Sales
0	1964-01	2815
1	1964-02	2672
2	1964-03	2755
3	1964-04	2721
4	1964-05	2946

In [4]:

```
df.tail()
```

Out[4]:

	Month	Sales
100	1972-05	4618
101	1972-06	5312
102	1972-07	4298
103	1972-08	1413
104	1972-09	5877

In [5]:

```
# Convert Month into Datetime
df['Month']=pd.to_datetime(df['Month'])
```

In [6]:

```
df.set_index('Month',inplace=True)
```

In [7]:

```
df.describe()
```

Out[7]:

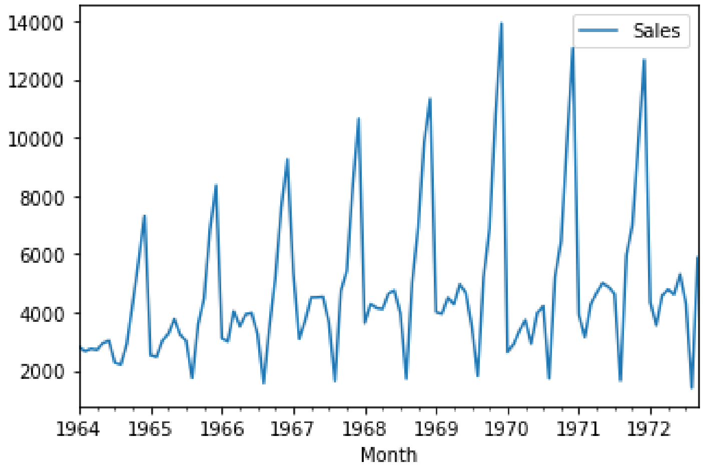
	Sales
	Sales
count	105.000000
mean	4761.152381
std	2553.502601
min	1413.000000
25%	3113.000000
50%	4217.000000
75%	5221.000000
max	13916.000000

In [8]:

```
df.plot()
```

Out[8]:

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



Testing Stationarity

In [9]:

```
from statsmodels.tsa.stattools import adfuller
test_result=adfuller(df['Sales'])
```

```
C:\Users\abhin\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:7: FutureWar
ning: pandas.Int64Index is deprecated and will be removed from pandas in a future version
. Use pandas.Index with the appropriate dtype instead.
  from pandas import (to_datetime, Int64Index, DatetimeIndex, Period,
C:\Users\abhin\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:7: FutureWar
ning: pandas.Float64Index is deprecated and will be removed from pandas in a future versi
on. Use pandas.Index with the appropriate dtype instead.
  from pandas import (to_datetime, Int64Index, DatetimeIndex, Period,
```

In [10]:

```
#Ho: It is non stationary
#H1: It is stationary

def adfuller_test(sales):
    result=adfuller(sales)
    labels = ['ADF Test Statistic','p-value','#Lags Used','Number of Observations Used']
    for value,label in zip(result,labels):
        print(label+' : '+str(value) )
    if result[1] <= 0.05:
        print("strong evidence against the null hypothesis(Ho), reject the null hypothesi
s. Data has no unit root and is stationary")
    else:
        print("weak evidence against null hypothesis, time series has a unit root, indic
ating it is non-stationary ")
```

In [11]:

```
adfuller_test(df['Sales'])
```

```
ADF Test Statistic : -1.8335930563276297
p-value : 0.3639157716602417
#Lags Used : 11
Number of Observations Used : 93
weak evidence against null hypothesis, time series has a unit root, indicating it is non-
stationary
```

Differencing

In [12]:

```
df['Sales First Difference'] = df['Sales'] - df['Sales'].shift(1)
```

In [13]:

```
df['Seasonal First Difference']=df['Sales']-df['Sales'].shift(12)
```

In [14]:

```
df.head(20)
```

Out[14]:

	Sales	Sales First Difference	Seasonal First Difference
Month			
1964-01-01	2815	NaN	NaN
1964-02-01	2672	-143.0	NaN
1964-03-01	2755	83.0	NaN
1964-04-01	2721	-34.0	NaN
1964-05-01	2946	225.0	NaN
1964-06-01	3036	90.0	NaN
1964-07-01	2282	-754.0	NaN
1964-08-01	2212	-70.0	NaN
1964-09-01	2922	710.0	NaN
1964-10-01	4301	1379.0	NaN
1964-11-01	5764	1463.0	NaN
1964-12-01	7312	1548.0	NaN
1965-01-01	2541	-4771.0	-274.0
1965-02-01	2475	-66.0	-197.0
1965-03-01	3031	556.0	276.0
1965-04-01	3266	235.0	545.0
1965-05-01	3776	510.0	830.0
1965-06-01	3230	-546.0	194.0
1965-07-01	3028	-202.0	746.0
1965-08-01	1759	-1269.0	-453.0

In [15]:

```
## Again test dickey fuller test
adfuller_test(df['Seasonal First Difference'].dropna())
```

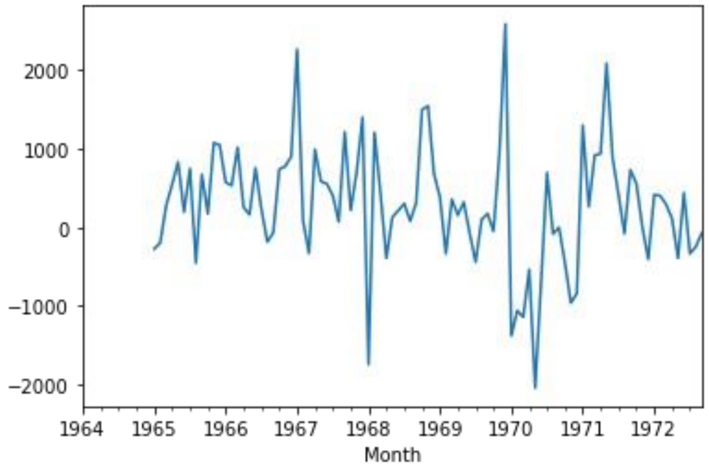
```
ADF Test Statistic : -7.626619157213163
p-value : 2.060579696813685e-11
#Lags Used : 0
Number of Observations Used : 92
strong evidence against the null hypothesis(Ho), reject the null hypothesis. Data has no
unit root and is stationary
```

In [16]:

```
df['Seasonal First Difference'].plot()
```

Out[16]:

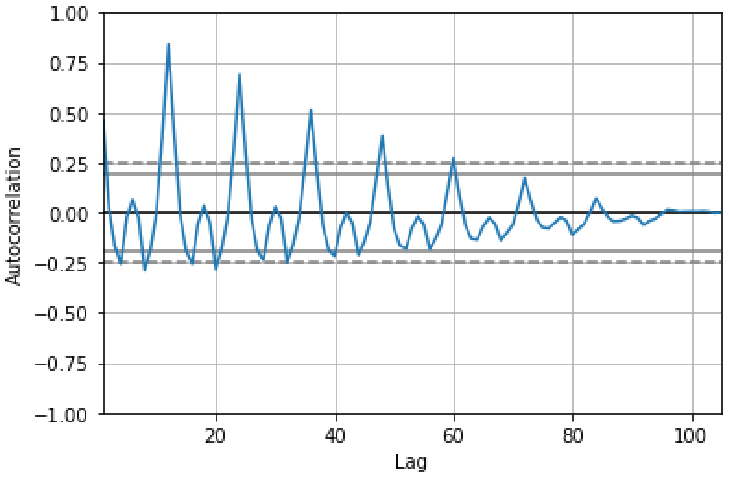
```
<AxesSubplot:xlabel='Month'>
```



AUTO REGRESSIVE MODEL

In [17]:

```
from pandas.plotting import autocorrelation_plot
autocorrelation_plot(df['Sales'])
plt.show()
```

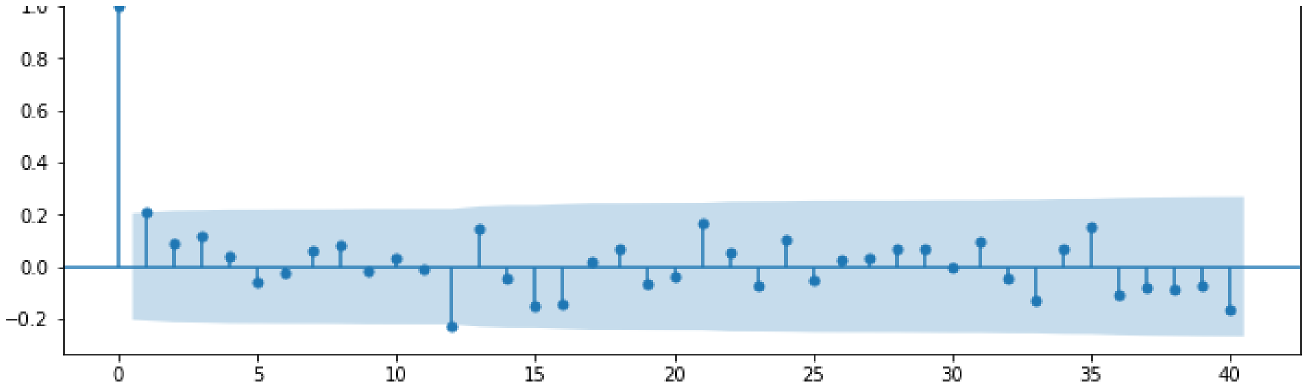


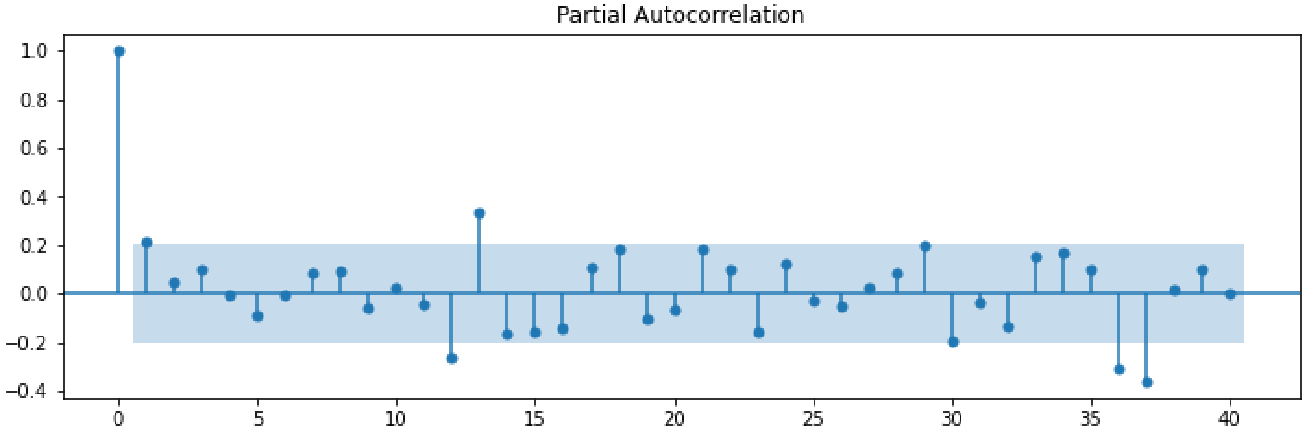
In [18]:

```
from statsmodels.graphics.tsaplots import plot_acf,plot_pacf
```

In [23]:

```
fig = plt.figure(figsize=(12,8))
ax1 = fig.add_subplot(211)
fig = plot_acf(df['Seasonal First Difference'].iloc[13:],lags=40,ax=ax1)
ax2 = fig.add_subplot(212)
fig = plot_pacf(df['Seasonal First Difference'].iloc[13:],lags=40,ax=ax2)
```





In [40]:

```
# For non-seasonal data
#p=1, d=1, q=1
from statsmodels.tsa.arima_model import ARIMA
```

In [29]:

```
model=ARIMA(df['Sales'],order=(1,1,1))
```

```
C:\Users\abhin\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:524: ValueWa
rning: No frequency information was provided, so inferred frequency MS will be used.
  warnings.warn('No frequency information was'
C:\Users\abhin\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:524: ValueWa
rning: No frequency information was provided, so inferred frequency MS will be used.
  warnings.warn('No frequency information was'
```

In [30]:

```
model_fit=model.fit()
```

In [31]:

```
model_fit.summary()
```

Out[31]:

ARIMA Model Results

Dep. Variable:	D.Sales	**No. Observations:**	104
Model:	ARIMA(1, 1, 0)	**Log Likelihood**	-966.440
Method:	css-mle	**S.D. of innovations**	2627.307
Date:	Tue, 11 Apr 2023	**AIC**	1938.880
Time:	05:19:06	**BIC**	1946.813
Sample:	02-01-1964	**HQIC**	1942.094
	- 09-01-1972		

	coef	std err	z	P>|z|	[0.025	0.975]
const	25.8476	236.330	0.109	0.913	-437.350	489.045

ar.L1.D.Sales	-0.0911	0.099	-0.925	0.355	-0.284	0.102

Roots

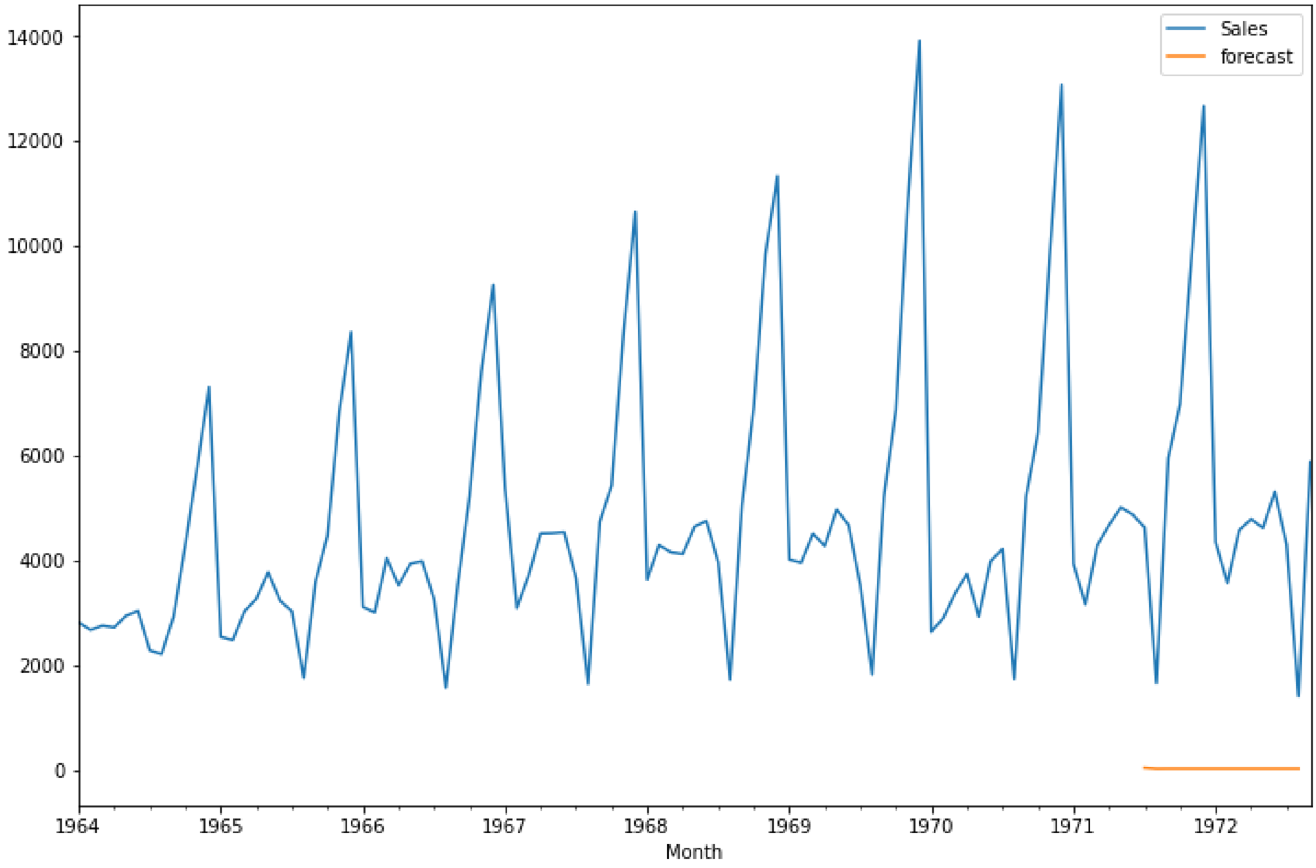
	Real	Imaginary	Modulus	Frequency
AR.1	-10.9755	+0.0000j	10.9755	0.5000

In [32]:

```
df['forecast']=model_fit.predict(start=90,end=103,dynamic=True)
df[['Sales','forecast']].plot(figsize=(12,8))
```

Out[32]:

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



In [41]:

```
import statsmodels.api as sm
model=sm.tsa.statespace.SARIMAX(df['Sales'],order=(1, 1, 1),seasonal_order=(1,1,1,12))
results=model.fit()
```

```
C:\Users\abhin\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:524: ValueWa
rning: No frequency information was provided, so inferred frequency MS will be used.
  warnings.warn('No frequency information was'
C:\Users\abhin\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:524: ValueWa
rning: No frequency information was provided, so inferred frequency MS will be used.
  warnings.warn('No frequency information was'
```

In [43]:

```
results.summary()
```

Out[43]:

SARIMAX Results

Dep. Variable:	Sales	**No. Observations:**	105
Model:	SARIMAX(1, 1, 1)x(1, 1, 1, 12)	**Log Likelihood**	-738.402

Date:	Tue, 11 Apr 2023	**AIC**	1486.804
Time:	05:19:06	**BIC**	1499.413
Sample:	01-01-1964	**HQIC**	1491.893
	- 09-01-1972		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	0.2790	0.081	3.433	0.001	0.120	0.438
ma.L1	-0.9494	0.043	-22.334	0.000	-1.033	-0.866
ar.S.L12	-0.4544	0.303	-1.499	0.134	-1.049	0.140
ma.S.L12	0.2450	0.311	0.788	0.431	-0.365	0.855
sigma2	5.055e+05	6.12e+04	8.265	0.000	3.86e+05	6.25e+05

Ljung-Box (L1) (Q):	0.26	**Jarque-Bera (JB):**	8.70
Prob(Q):	0.61	**Prob(JB):**	0.01
Heteroskedasticity (H):	1.18	**Skew:**	-0.21
Prob(H) (two-sided):	0.64	**Kurtosis:**	4.45

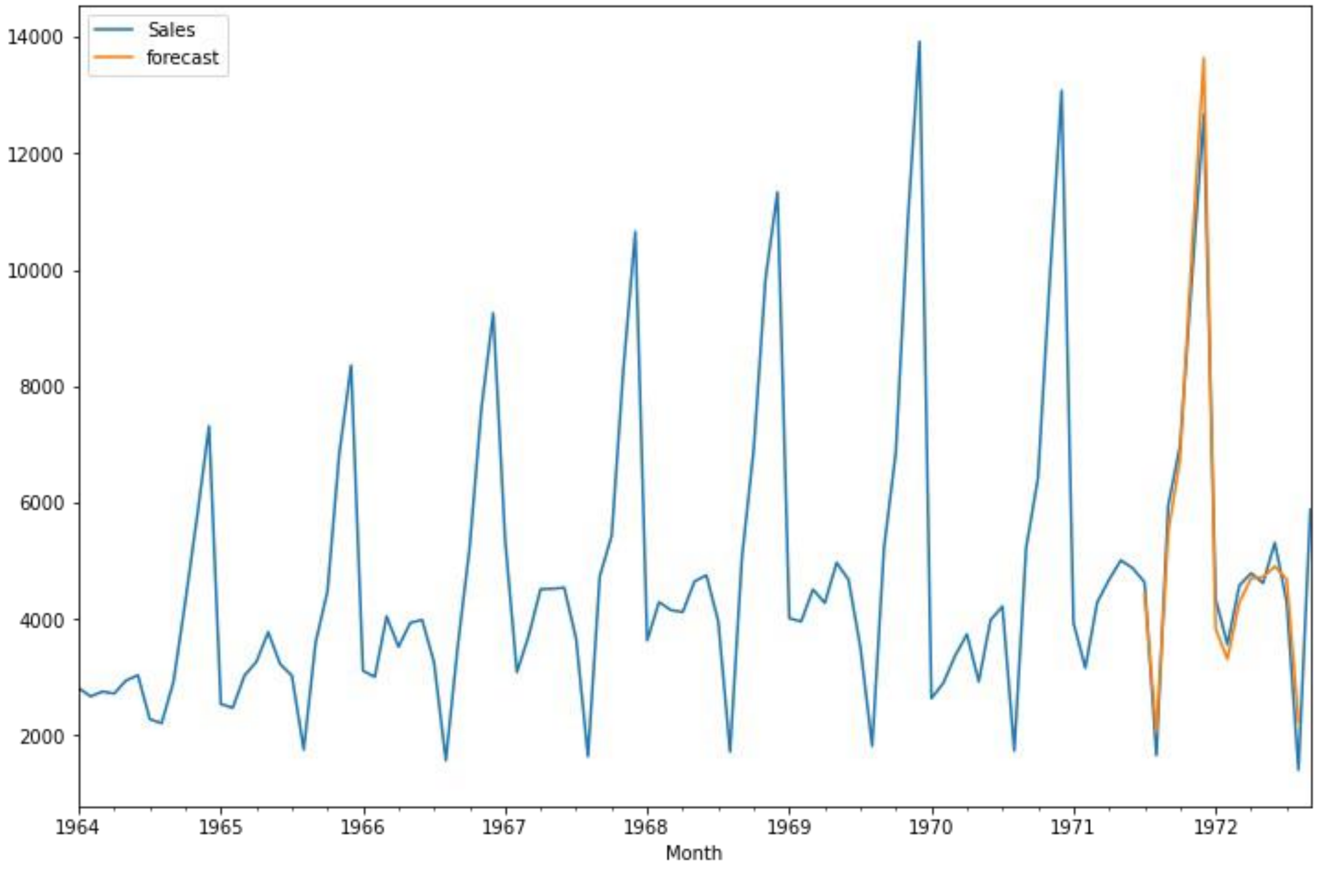
Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

In [44]:

```
df['forecast']=results.predict(start=90,end=103,dynamic=True)
df[['Sales','forecast']].plot(figsize=(12,8))
```

Out[44]:

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



In [45]:

```
from pandas.tseries.offsets import DateOffset
```

```
future_dates=[df.index[-1]+ DateOffset(months=x)for x in range(0,24)]
```

In [46]:

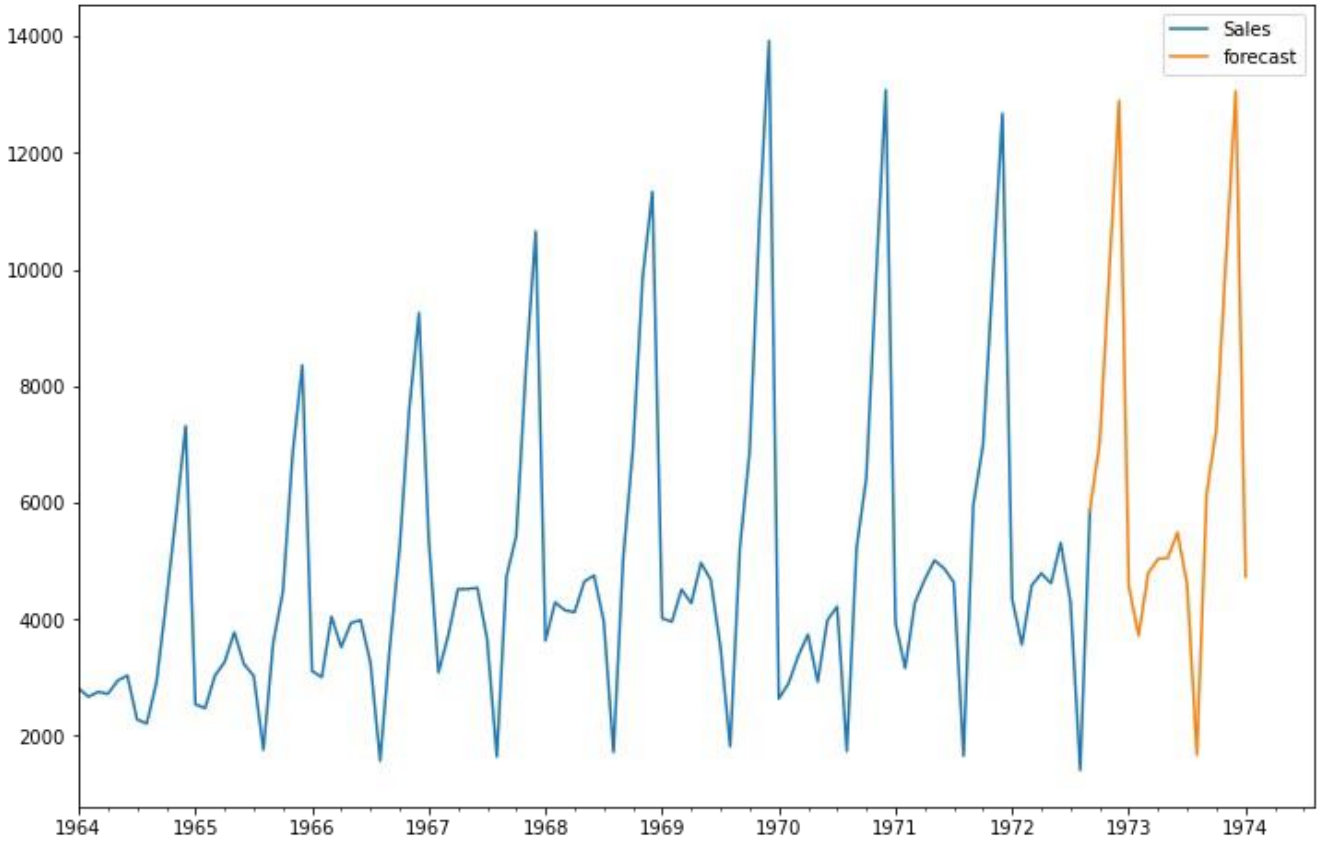
```
future_datest_df=pd.DataFrame(index=future_dates[1:],columns=df.columns)
```

In [47]:

```
future_df=pd.concat([df,future_datest_df])
future_df['forecast'] = results.predict(start = 104, end = 120, dynamic= True)
future_df[['Sales', 'forecast']].plot(figsize=(12, 8))
```

Out[47]:

```
<AxesSubplot:>
```



In [ ]: