report

August 16, 2024

[ ]:
```
import pandas as pd
from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.arima.model import ARIMA
import statsmodels.api as sm
import matplotlib.pyplot as plt
```

[ ]:
```
df = pd.read_csv("./../data/perrin-freres-monthly-champagne.csv")
```

[ ]:
```
df.head()
```

[ ]:

	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

[ ]:
```
df.tail()
```

[ ]:

	Month	\
102	1972-07	
103	1972-08	
104	1972-09	
105	NaN	
106	Perrin Freres monthly champagne sales millions…	

	Perrin Freres monthly champagne sales millions ?64-?72
102	4298.0
103	1413.0
104	5877.0
105	NaN
106	NaN

[ ]:
```
df.info()
```

```
<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
```

[ ]:
```
df = df.dropna()
```

[ ]:
```
df.columns = ["month", "sales"]
```

[ ]:
```
df.info()
```

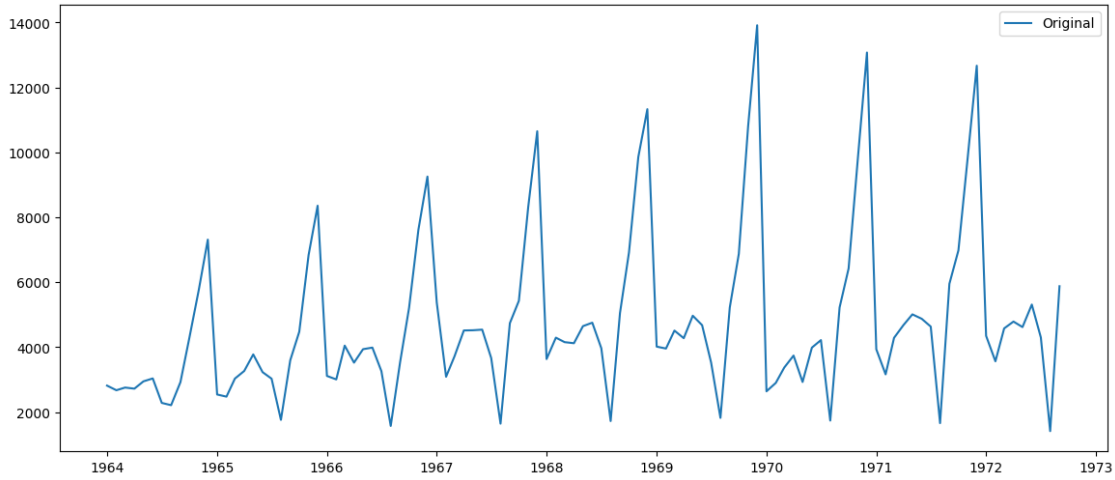
```
<class 'pandas.core.frame.DataFrame'>
Index: 105 entries, 0 to 104
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   month   105 non-null    object
 1   sales   105 non-null    float64
dtypes: float64(1), object(1)
memory usage: 2.5+ KB
```

[ ]:
```
df["month"] = pd.to_datetime(df["month"])
df.set_index("month", inplace=True)
```

[ ]:
```
decom = seasonal_decompose(df["sales"])
```

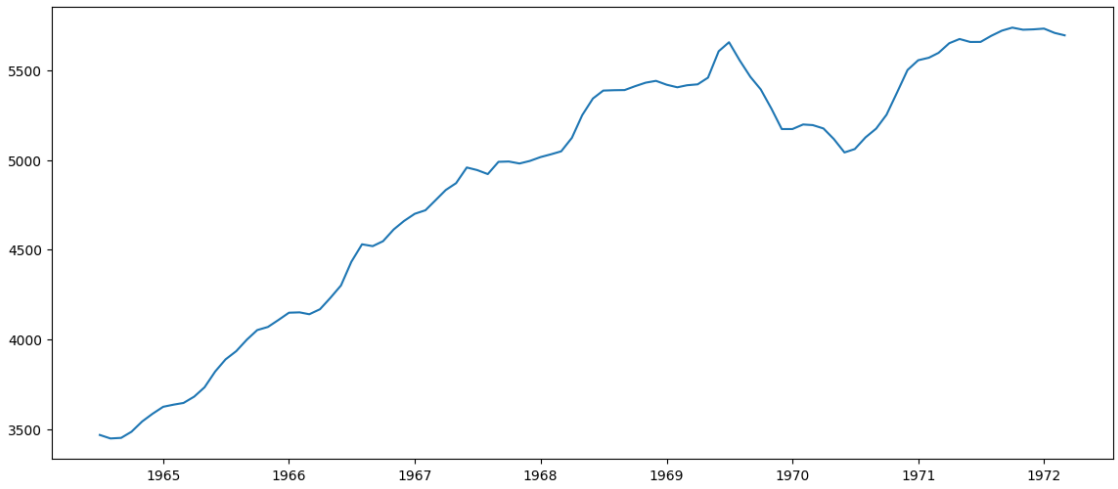
[ ]:
```
plt.figure(figsize=(14,6))
plt.plot(df["sales"], label = "Original")
plt.legend(loc = "best")
```

[ ]:
```
<matplotlib.legend.Legend at 0x2ae5b99df10>
```



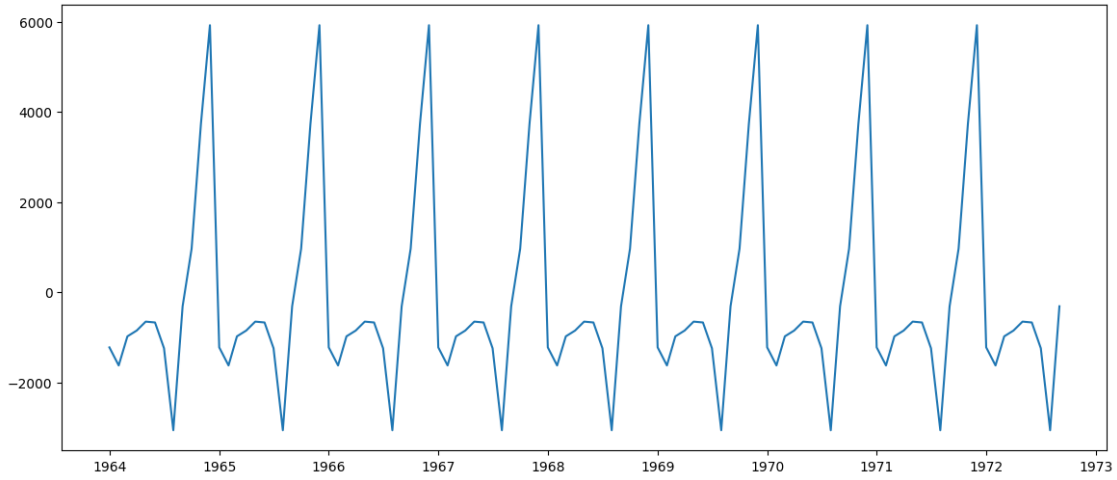
[ ]:
```
plt.figure(figsize=(14,6))
plt.plot(decom.trend, label="Trend")
```

[ ]:
```
[<matplotlib.lines.Line2D at 0x2ae50bfa270>]
```



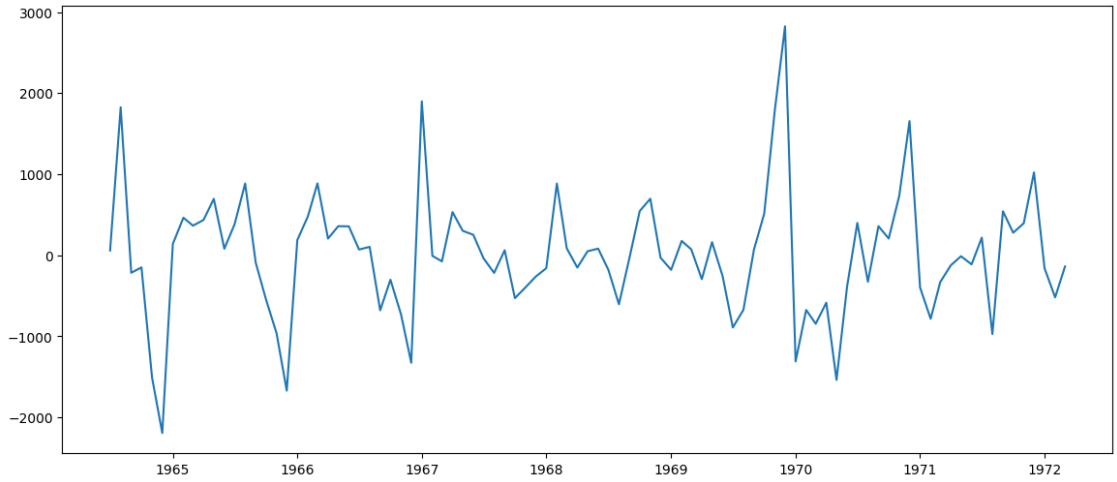
[ ]:
```
plt.figure(figsize=(14,6))
plt.plot(decom.seasonal, label="Sesonality")
```

[ ]:
```
[<matplotlib.lines.Line2D at 0x2ae50e00710>]
```



[ ]:
```
plt.figure(figsize=(14,6))
plt.plot(decom.resid, label="Residual")
```

[ ]:
```
[<matplotlib.lines.Line2D at 0x2ae521ebf80>]
```



[ ]:
```
def adfuller_test(data):
    result = adfuller(data)
    print("Test Statistics: " ,result[0])
    print("p value: " ,result[1])
    print("#lags: " ,result[2])
    if(result[1] < 0.05):
        print("There is no unit root presence (Stationary)")
    else:
```

```
        print("There is a unit root presence (Non Stationary)")
```

[ ]:
```
adfuller_test(df["sales"])
```

```
Test Statistics:  -1.8335930563276195
p value:  0.3639157716602467
#lags:  11
There is a unit root presence (Non Stationary)
```

[ ]:
```
rolling_mean = df.rolling(window=11).mean()
rolling_std = df.rolling(window=11).std()
```

[ ]:
```
df["ma_sales"] = rolling_mean["sales"]
df["rolling_std_sales"] = rolling_std["sales"]
```

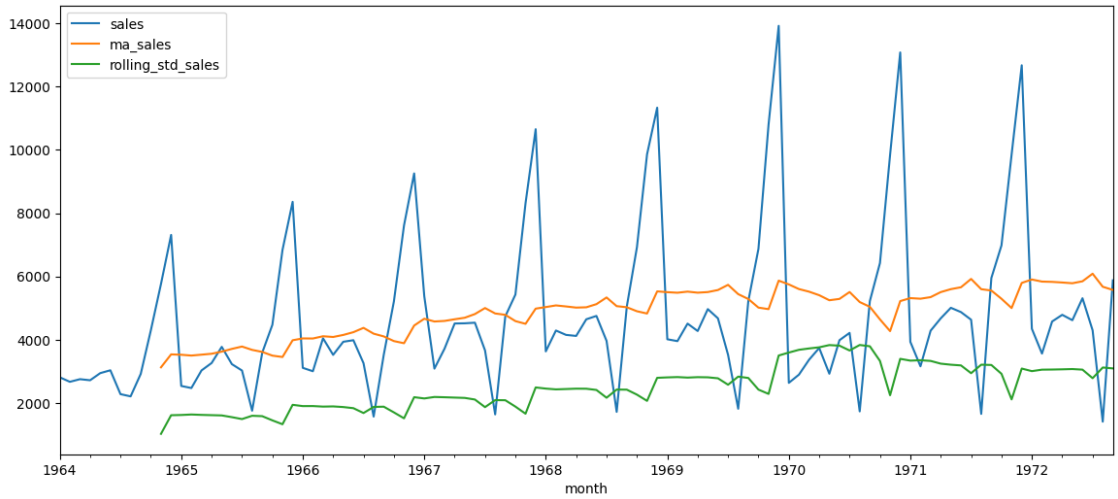
[ ]:
```
df.head(20)
```

[ ]:

month	sales	ma_sales	rolling_std_sales
1964-01-01	2815.0	NaN	NaN
1964-02-01	2672.0	NaN	NaN
1964-03-01	2755.0	NaN	NaN
1964-04-01	2721.0	NaN	NaN
1964-05-01	2946.0	NaN	NaN
1964-06-01	3036.0	NaN	NaN
1964-07-01	2282.0	NaN	NaN
1964-08-01	2212.0	NaN	NaN
1964-09-01	2922.0	NaN	NaN
1964-10-01	4301.0	NaN	NaN
1964-11-01	5764.0	3129.636364	1028.293467
1964-12-01	7312.0	3538.454545	1616.433999
1965-01-01	2541.0	3526.545455	1623.921203
1965-02-01	2475.0	3501.090909	1639.345568
1965-03-01	3031.0	3529.272727	1627.213759
1965-04-01	3266.0	3558.363636	1618.580939
1965-05-01	3776.0	3625.636364	1610.054737
1965-06-01	3230.0	3711.818182	1555.385214
1965-07-01	3028.0	3786.000000	1494.986689
1965-08-01	1759.0	3680.272727	1599.660095

[ ]:
```
df.plot(figsize=(14,6))
```

[ ]:
```
<Axes: xlabel='month'>
```



[ ]:
```
df_diff_ma_sales = df["sales"] - df["ma_sales"]
```

[ ]:
```
adfuller_test(df_diff_ma_sales.dropna())
```

```
Test Statistics:  -2.012208203713638
p value:  0.28124601445642117
#lags:  12
There is a unit root presence (Non Stationary)
```

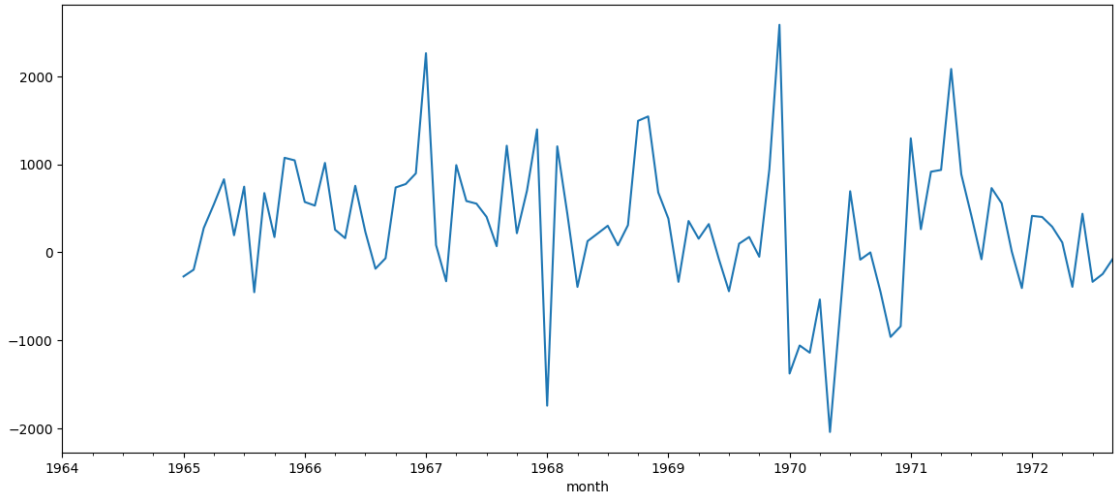
[ ]:
```
df_diff_12 = df["sales"] - df["sales"].shift(12)
```

[ ]:
```
adfuller_test(df_diff_12.dropna())
```

```
Test Statistics:  -7.626619157213166
p value:  2.0605796968136632e-11
#lags:  0
There is no unit root presence (Stationary)
```

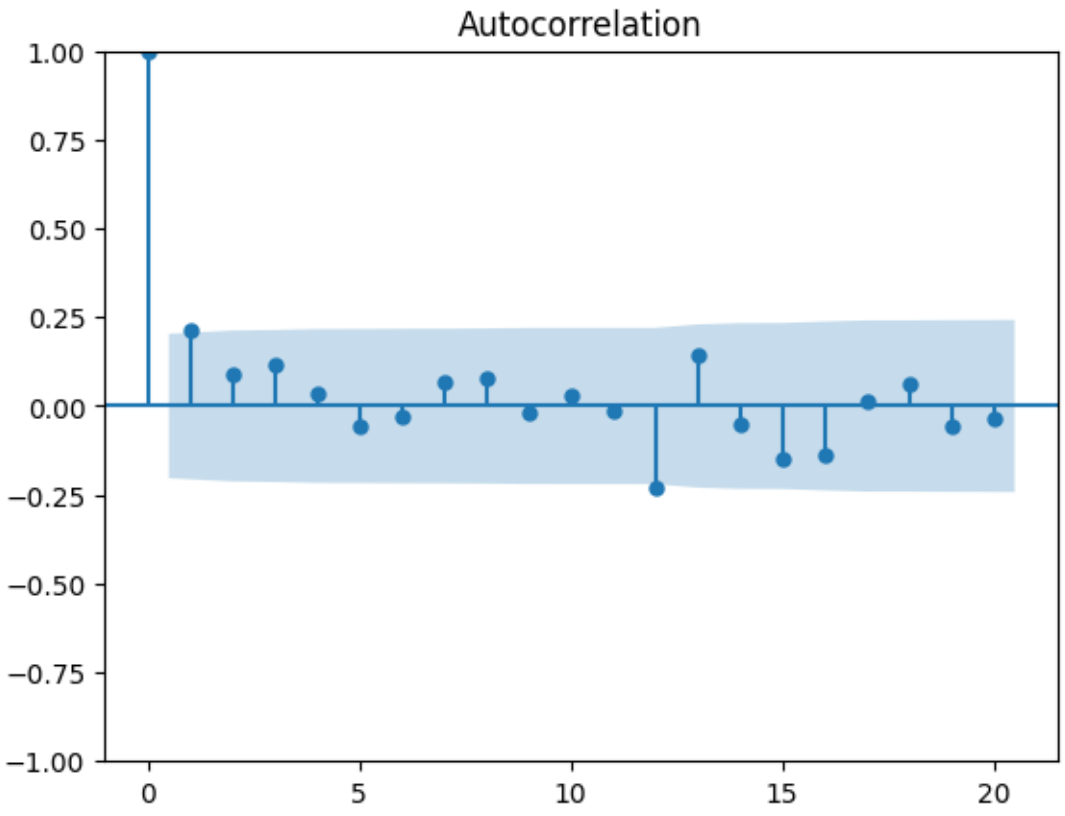
[ ]:
```
df_diff_12.plot(figsize=(14,6))
```

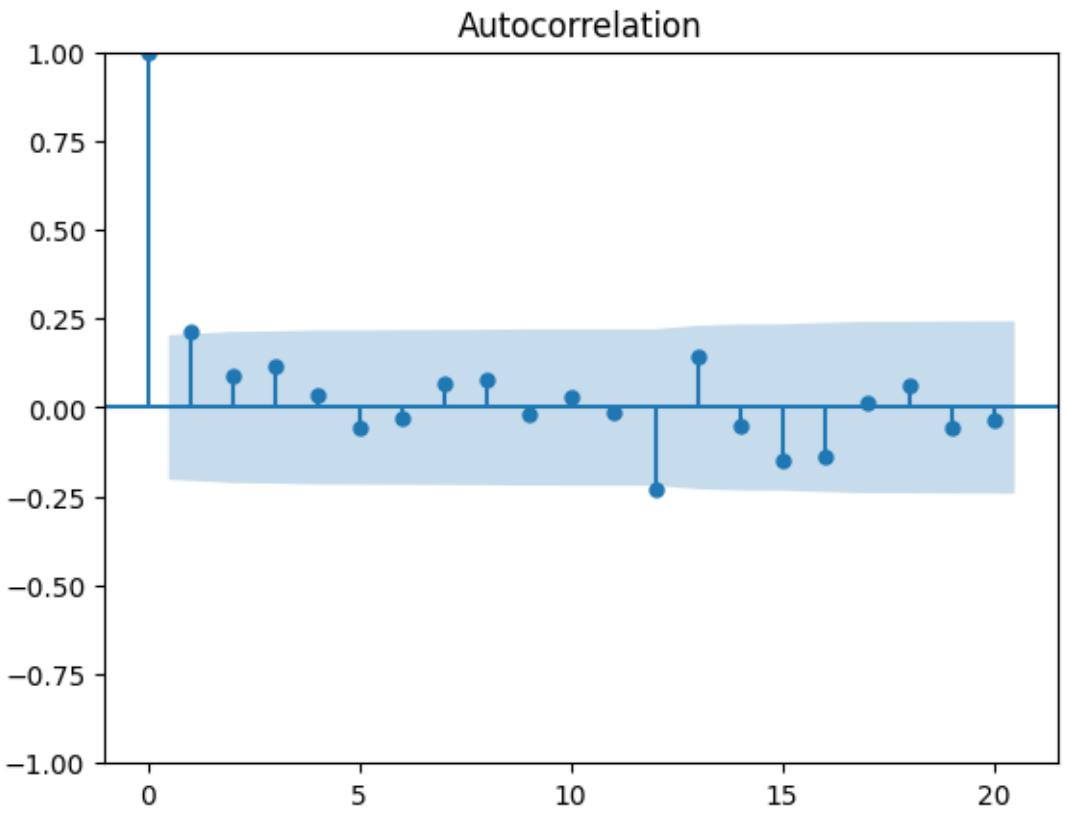
[ ]: <Axes: xlabel='month'>



[ ]:
```
plot_acf(df_diff_12.dropna())
```

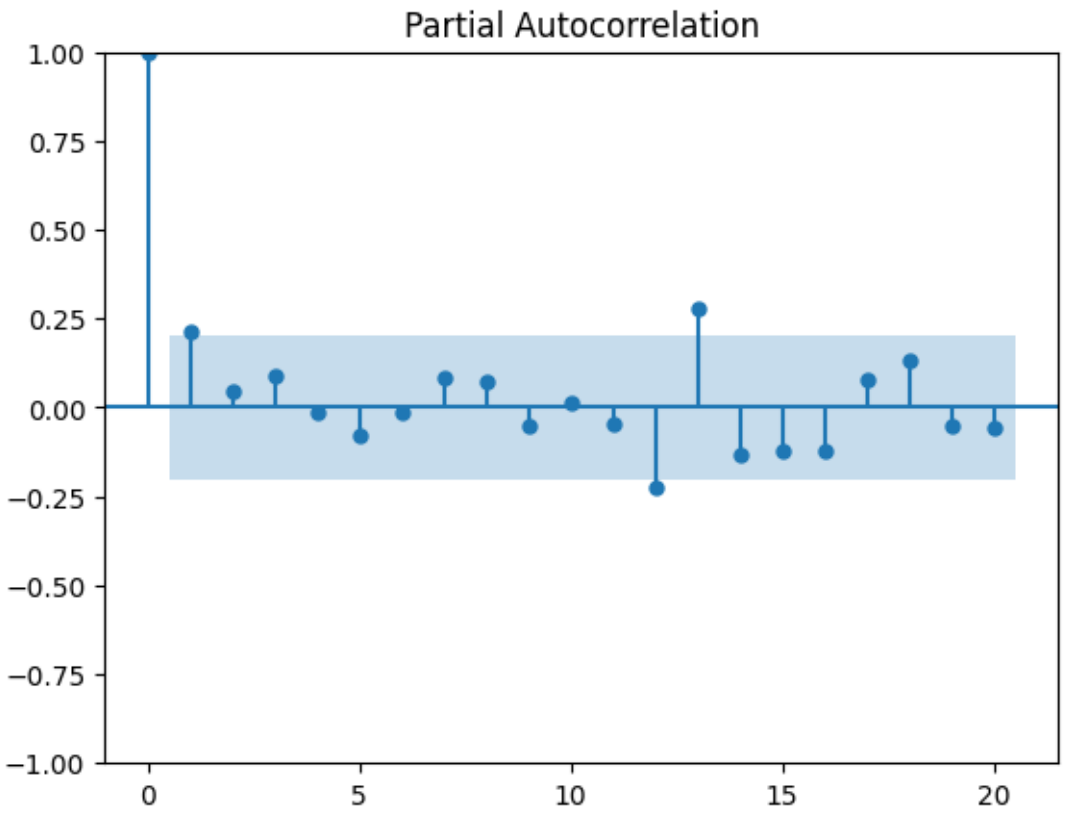
[ ]:

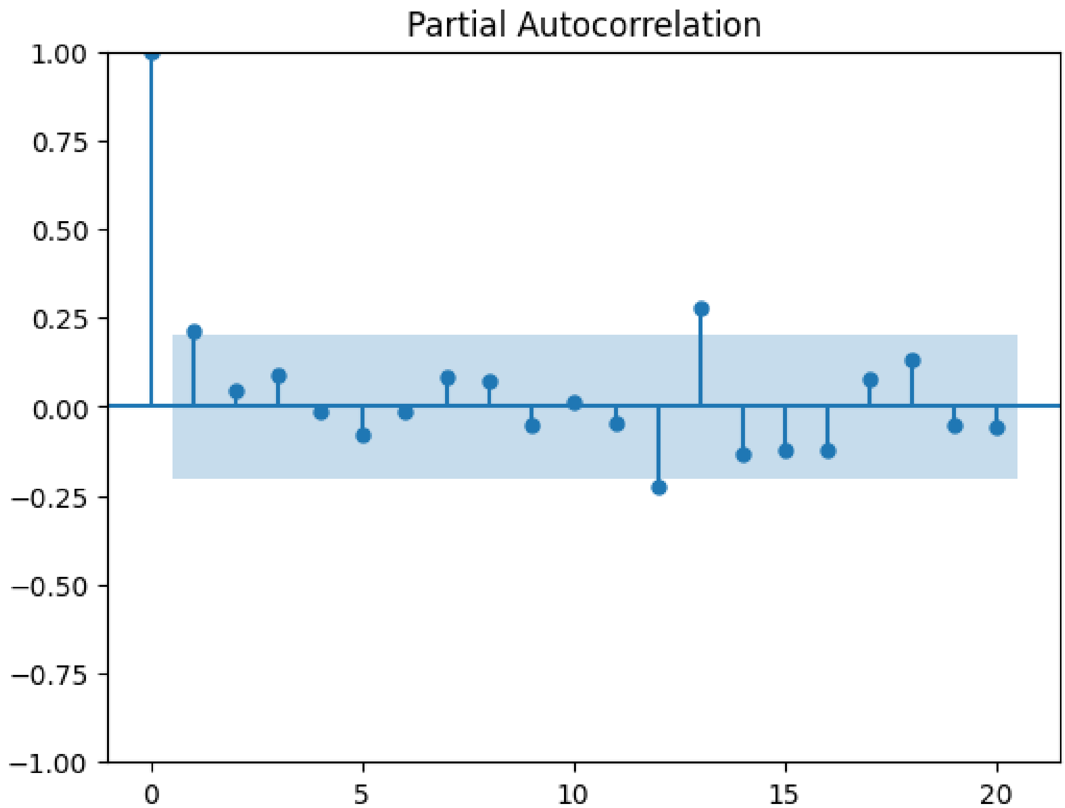




[ ]:
```
plot_pacf(df_diff_12.dropna())
```

[ ]:


Partial Autocorrelation
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
5
10
15
20



[ ]:
```
arima_model = ARIMA(df["sales"], order=(1,1,1))
arima_model_fit = arima_model.fit()
```

```
d:\Projects\champagne-time-series-analysis\venv\Lib\site-
packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: No frequency
information was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)
d:\Projects\champagne-time-series-analysis\venv\Lib\site-
packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: No frequency
information was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)
d:\Projects\champagne-time-series-analysis\venv\Lib\site-
packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: No frequency
information was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)
```

[ ]:
```
arima_model_fit.summary()
```

[ ]:

Dep. Variable:	sales	**No. Observations:**	105
Model:	ARIMA(1, 1, 1)	**Log Likelihood**	-952.814
Date:	Fri, 16 Aug 2024	**AIC**	1911.627
Time:	18:55:00	**BIC**	1919.560
Sample:	01-01-1964 - 09-01-1972	**HQIC**	1914.841
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

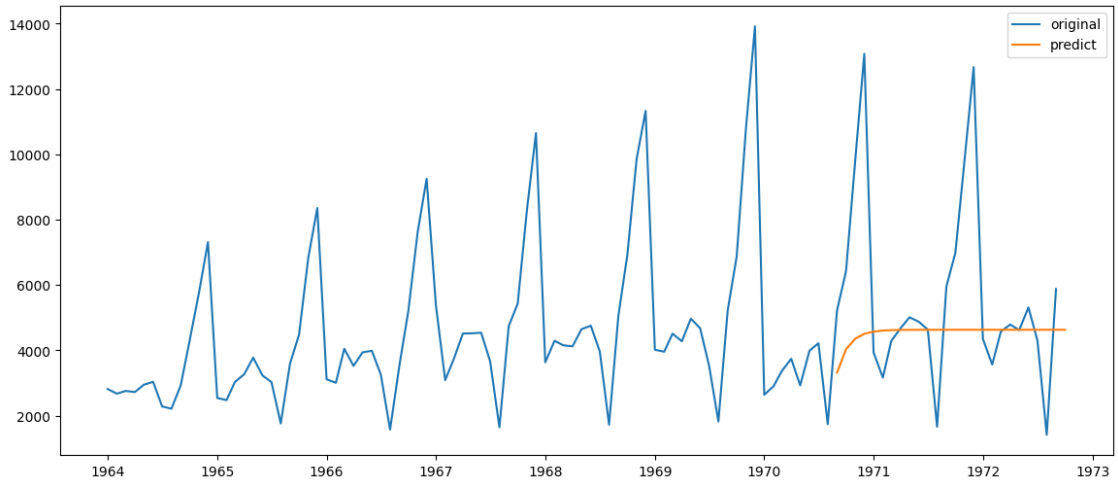
Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

[ ]:
```
arima_predict = arima_model_fit.predict(start = 80, end = 105, dynamic= True)

plt.figure(figsize=(14,6))
plt.plot(df["sales"], label = "original")
plt.plot(arima_predict, label = "predict")

plt.legend(loc = "best")
```

[ ]:
```
<matplotlib.legend.Legend at 0x2ae5fb85f10>
```



[ ]:
```
sarimax_model = sm.tsa.statespace.SARIMAX(df["sales"], order=(1,1,1),␣
↪seasonal_order=(1,1,1,12))
sarimax_model_fit = sarimax_model.fit()
```

```
d:\Projects\champagne-time-series-analysis\venv\Lib\site-
packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: No frequency
information was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)
d:\Projects\champagne-time-series-analysis\venv\Lib\site-
packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: No frequency
information was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)
```

[ ]:
```
sarimax_model_fit.summary()
```

[ ]:

Dep. Variable:	sales	**No. Observations:**	105
Model:	SARIMAX(1, 1, 1)x(1, 1, 1, 12)	**Log Likelihood**	-738.402
Date:	Fri, 16 Aug 2024	**AIC**	1486.804
Time:	20:32:11	**BIC**	1499.413
Sample:	01-01-1964 - 09-01-1972	**HQIC**	1491.893
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

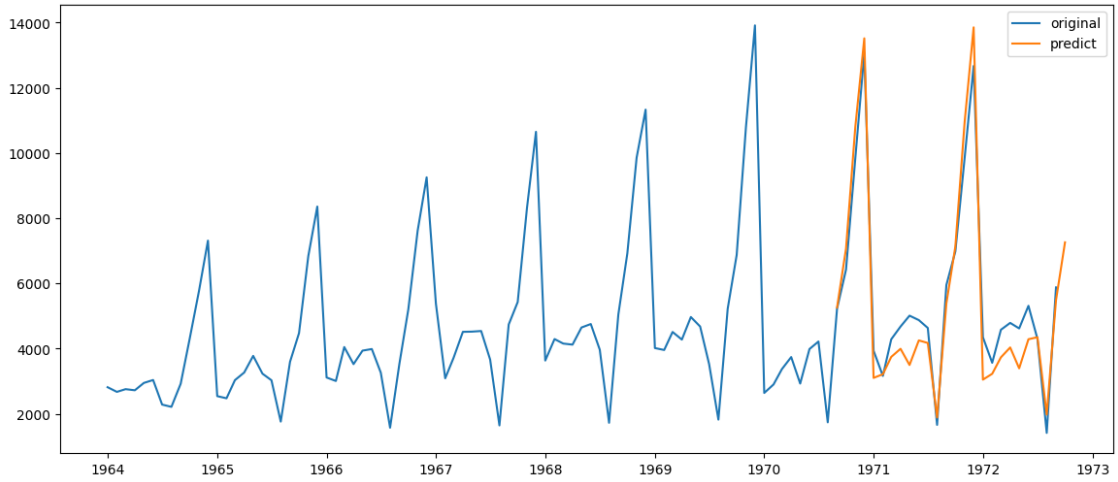
Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

[ ]:
```
sarimax_predict = sarimax_model_fit.predict(start = 80, end = 105, dynamic=␣
↪True)

plt.figure(figsize=(14,6))
plt.plot(df["sales"], label = "original")
plt.plot(sarimax_predict, label = "predict")

plt.legend(loc = "best")
```

[ ]:
```
<matplotlib.legend.Legend at 0x2ae5f66c410>
```



[ ]:
```
sarimax_forecast = sarimax_model_fit.forecast(steps=24)


plt.figure(figsize=(14,6))
plt.plot(df["sales"], label = "original")
plt.plot(sarimax_forecast, label = "forecast")

plt.legend(loc = "best")
```

[ ]:
```
<matplotlib.legend.Legend at 0x2ae5fb28650>
```