SEASONAL ARIMA APPLIED TO FASHION RETAIL

In this wotk, we have analysed data from fashion sales from 4 years in one category. The objective is sales forecasting for the following years. To achieve this goal, we have used Sarima Model as fashion sales is known to have an stationary performance. The steps followed were:

1. Import data already filtered and grouped by month
2. Visualize data
3. Analize stationarity with Addfuller test
4. Analize Autocorrelation and Partial Autocorrelation to see stationarity and seasonality
5. Diferentiation
6. Apply SARIMA model
7. Comparing results between the chosen parameters
8. Forecasting with new model

1. Import Data

In [12]:
```
import numpy as np
import pandas as pd
import warnings
warnings.filterwarnings("ignore")
import matplotlib.pyplot as plt
%matplotlib inline
from statsmodels.tsa.stattools import adfuller
import statsmodels.api as sm
from statsmodels.graphics.tsaplots import plot_acf,plot_pacf
```

In [15]:
```
df=pd.read_csv('sales-textiles3.csv')
```

In [16]:
```
df.head()
```

Out[16]:

	Date	Sales
0	1997-01-01	16475
1	1997-02-01	26996
2	1997-03-01	41323
3	1997-04-01	31550
4	1997-05-01	8226

In [17]:
```
## Cleaning up the data
df.columns=["Month","Sales"]
df.head()
```

Out[17]:

	Month	Sales
0	1997-01-01	16475
1	1997-02-01	26996
2	1997-03-01	41323
3	1997-04-01	31550
4	1997-05-01	8226

In [18]:
```
# Convert Month into Datetime
df['Month']=pd.to_datetime(df['Month'])
```

In [19]:
```
df.head()
```

Out[19]:

	Month	Sales
0	1997-01-01	16475
1	1997-02-01	26996
2	1997-03-01	41323
3	1997-04-01	31550
4	1997-05-01	8226

In [20]:
```
df.set_index('Month',inplace=True)
```

In [21]:
```
df.head()
```

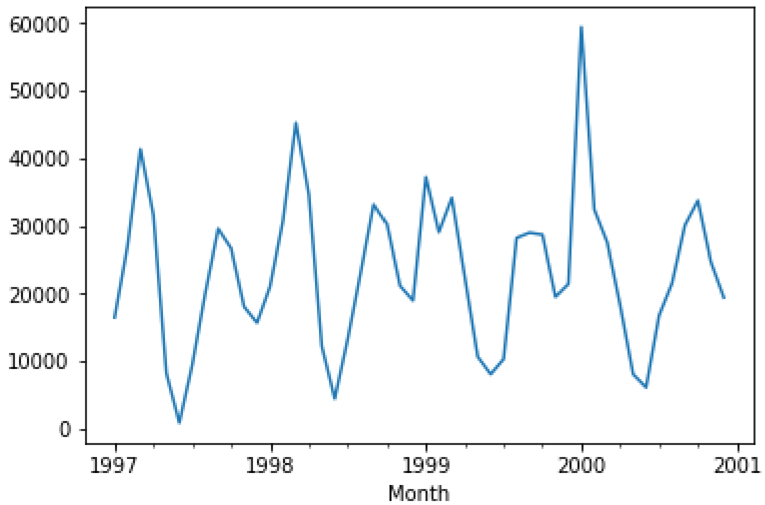
Out[21]:

	Sales
Month	
1997-01-01	16475
1997-02-01	26996
1997-03-01	41323
1997-04-01	31550
1997-05-01	8226

2. Visualize the Data

In [24]:
```
df['Sales'].plot()
```

Out[24]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x224ae3ab320>
```



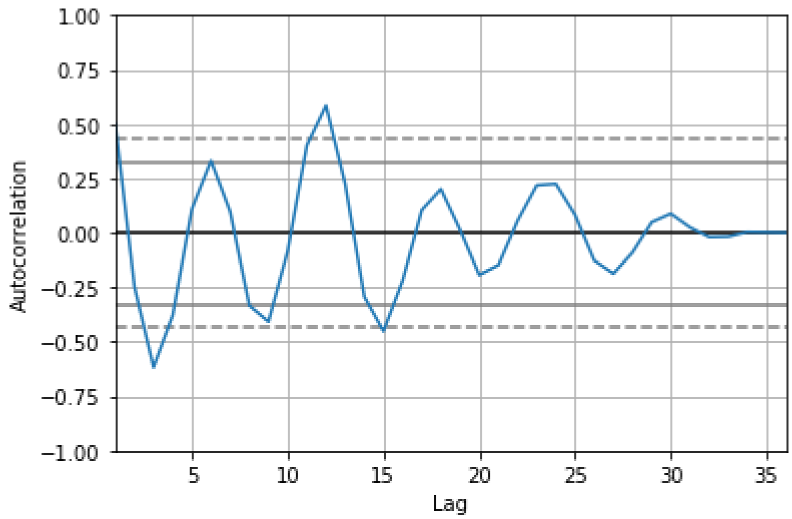
In [26]:
```
# Here we divide data into train and test parts
# The test part will be the last year
y_train=df[:36]
y_test=df[36:]
```

In [ ]:
```
# We can observe that date is Seasonal, as it responds to a fashion sector per
formance.
```

Auto Regressive Model

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \varepsilon_t,$$

In [28]:
```
from pandas.tools.plotting import autocorrelation_plot
autocorrelation_plot(y_train['Sales'])
plt.show()
```



In [ ]:
```
#The example above shows positive first-order autocorrelation, where first ord
er indicates that observations that are one apart are correlated, and positive
means that the correlation between the observations is positive.
#As the points appear in a smooth snake-like curve, it means the correlation i
s positive
```

3. Analize stationarity

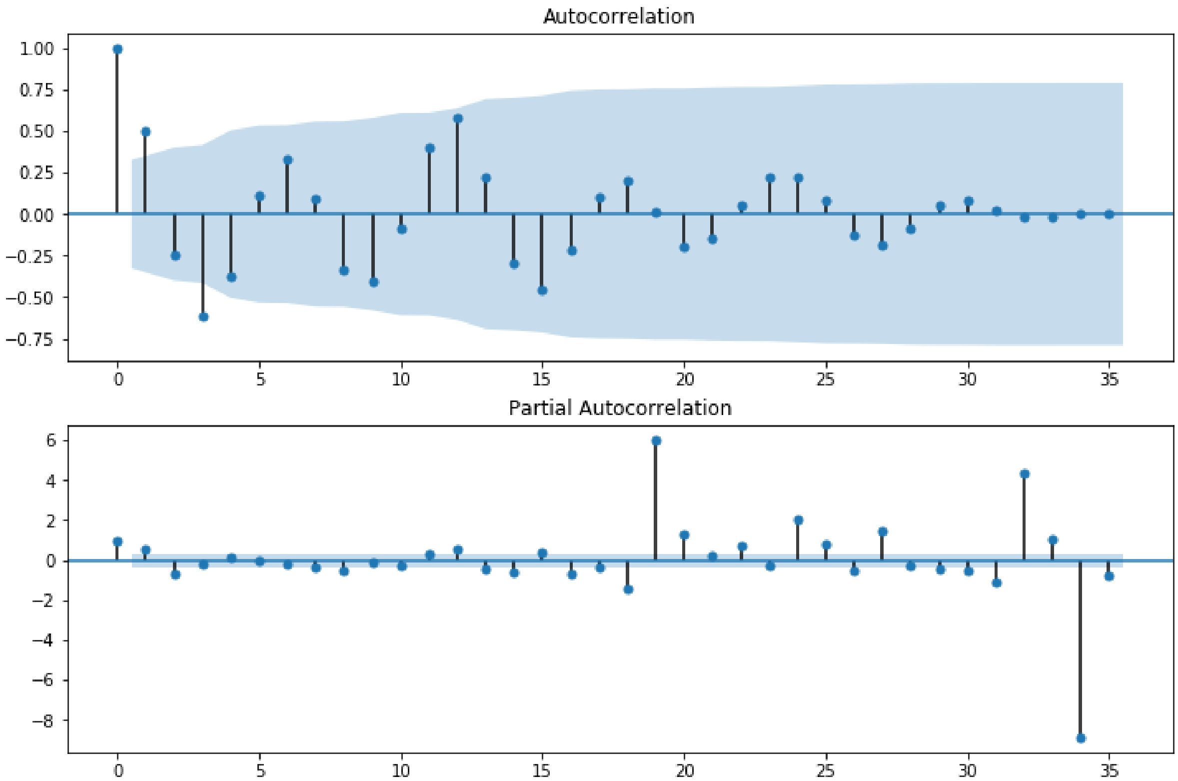
In [27]:
```
test_result=adfuller(y_train['Sales'])
#Ho: It is non stationary
#H1: It is stationary

def adfuller_test(sales):
    result=adfuller(sales)
    labels = ['ADF Test Statistic','p-value','#Lags Used','Number of Observati
ons 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 nul
l hypothesis. Data has no unit root and is stationary")
    else:
        print("weak evidence against null hypothesis, time series has a unit r
oot, indicating it is non-stationary ")

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

```
ADF Test Statistic : -4.19604101801485
p-value : 0.000669141717223674
#Lags Used : 7
Number of Observations Used : 28
strong evidence against the null hypothesis(Ho), reject the null hypothesis.
Data has no unit root and is stationary
```

In [ ]:
```
#The Adfuller test tell us that it is stationary to, so we don't need to diffe
renciate
```

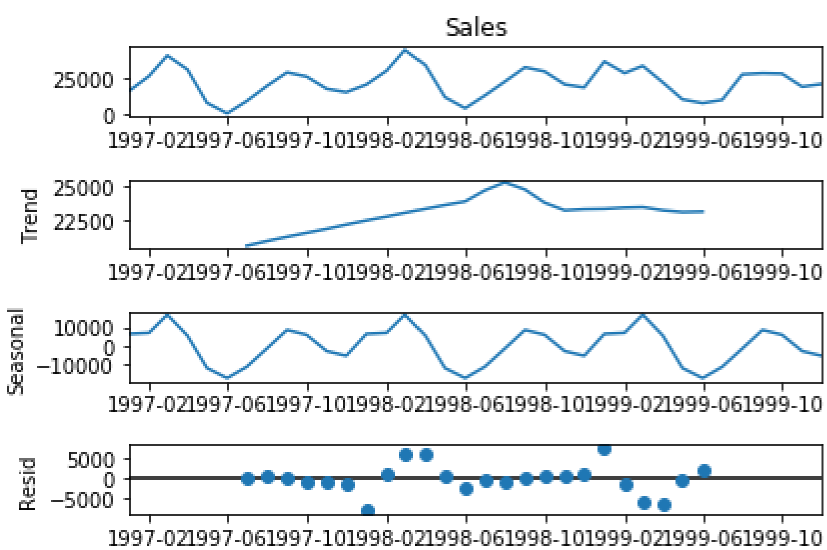
4. Analize Autocorrelation and Partial Autocorrelation

In [29]:
```
fig = plt.figure(figsize=(12,8))
ax1 = fig.add_subplot(211)
fig = sm.graphics.tsa.plot_acf(y_train['Sales'],lags=35,ax=ax1)
ax2 = fig.add_subplot(212)
fig = sm.graphics.tsa.plot_pacf(y_train['Sales'],lags=35,ax=ax2)
```



In [ ]:
```
#With AFC we can visualize seasonality  at first year. We can see the asesonl
 patron better in the following image
```

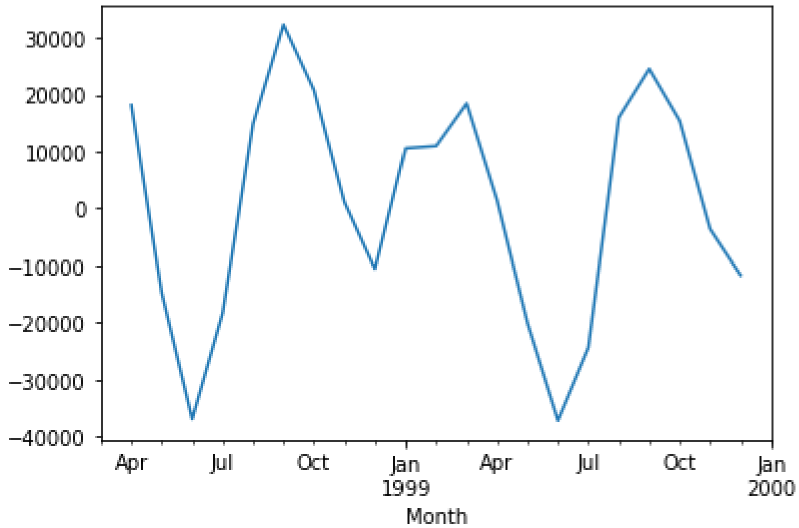
In [30]:
```
ts_decomp=sm.tsa.seasonal_decompose(y_train['Sales'],model='additive')
ts_decomp.plot()
plt.show()
```



5. Differentiation

In [31]:
```
y_train['Seasonal First Difference']=y_train['Sales']-y_train['Sales'].shift(1
5)
y_train['Seasonal First Difference'].plot()
#As we know that there is seasonality, we have firts shift 12. But As we have
 seen there is no stationarity with this differentiation, we have then shift 3
more (15)
```

Out[31]: <matplotlib.axes._subplots.AxesSubplot at 0x224af775198>

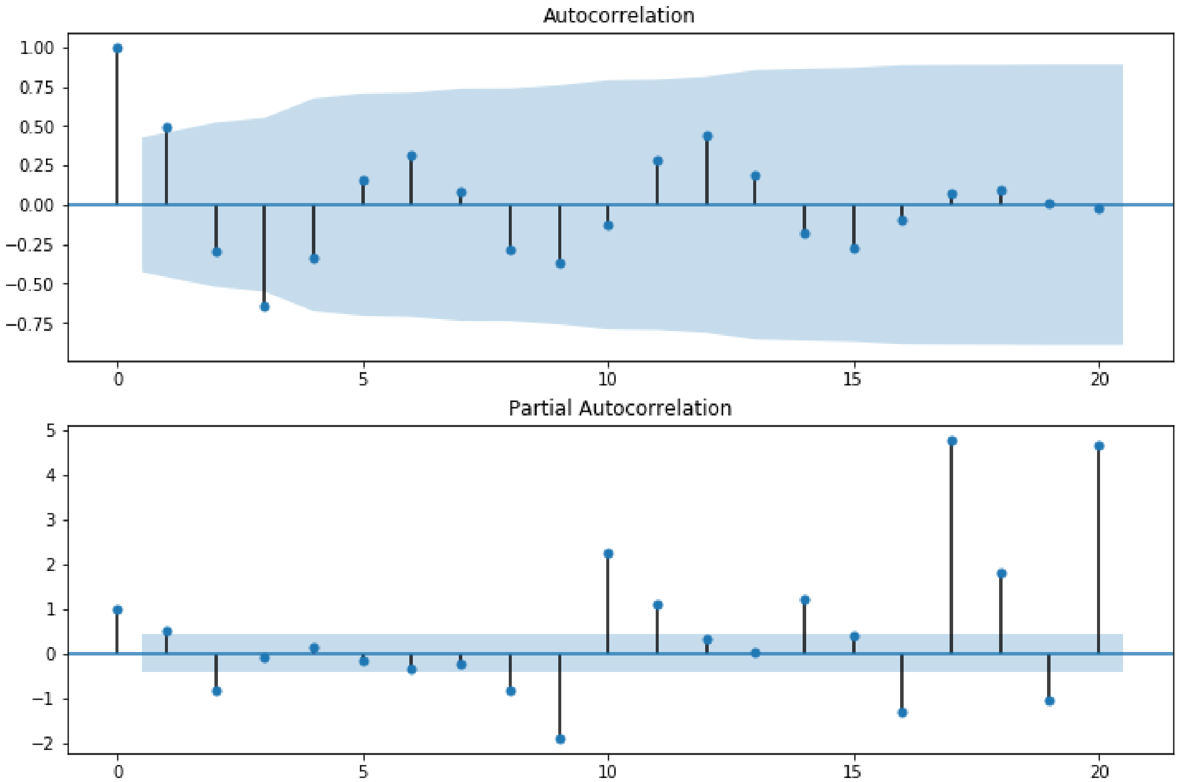


In [ ]:
```
#We have performed adfuller test until having stationarity
```

In [32]:
```
test_result=adfuller(y_train['Seasonal First Difference'].iloc[15:])
def adfuller_test(sales):
    result=adfuller(sales)
    labels = ['ADF Test Statistic','p-value','#Lags Used','Number of Observati
ons 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 nul
l hypothesis. Data has no unit root and is stationary")
    else:
        print("weak evidence against null hypothesis, time series has a unit r
oot, indicating it is non-stationary ")

adfuller_test(y_train['Seasonal First Difference'].iloc[15:])
```

```
ADF Test Statistic : -6.351479265416526
p-value : 2.604405490424686e-08
#Lags Used : 1
Number of Observations Used : 19
strong evidence against the null hypothesis(Ho), reject the null hypothesis.
Data has no unit root and is stationary
```

In [33]:
```
fig = plt.figure(figsize=(12,8))
ax1 = fig.add_subplot(211)
fig = sm.graphics.tsa.plot_acf(y_train['Seasonal First Difference'].iloc[15:],
lags=20, ax=ax1)
ax2 = fig.add_subplot(212)
fig = sm.graphics.tsa.plot_pacf(y_train['Seasonal First Difference'].iloc[15
:],lags=20,ax=ax2)
```



In [ ]:
```
#We can not conclude something with the graphics,
#We will perform iterations so we will wee best parameters for SARIMA
```

6. Applying SARIMA model

In [34]:
```
 y_train.index = pd.DatetimeIndex(y_train.index.values,
                               freq=y_train.index.inferred_freq)
```

In [ ]:
```
#We have performed iterations with 1, 2 and 3 number of pdq. Here I leave the
 iteration with number 1
```

In [36]:
```
import itertools

p=d=q=range(0,2)
pdq=list(itertools.product(p,d,q))
seasonal_pdq=[(x[0],x[1],x[2],12) for x in list(itertools.product(p,d,q)) ]
print(seasonal_pdq)
print ('Examples of parameter combinations for Seasonal ARIMA...')
print('SARIMAX:{}X{}'.format(pdq[0],seasonal_pdq[0]))
```

```
[(0, 0, 0, 12), (0, 0, 1, 12), (0, 1, 0, 12), (0, 1, 1, 12), (1, 0, 0, 12),
(1, 0, 1, 12), (1, 1, 0, 12), (1, 1, 1, 12)]
Examples of parameter combinations for Seasonal ARIMA...
SARIMAX:(0, 0, 0)X(0, 0, 0, 12)
```

In [37]:
```
metric_aic_dict=dict()
for pm in pdq:
    for pm_seasonal in seasonal_pdq:
        try:
            model=sm.tsa.statespace.SARIMAX(y_train['Sales'],
                                              order=pm,
                                              seasonal_order=pm_seasonal,
                                              enforce_stationarity=False,
                                              enforce_invertibility=False
                                               )
            model_fit=model.fit()
            print('SARIMA{}X{}12 - AIC:{}'.format(pm,pm_seasonal,model_fit.aic
))
            metric_aic_dict.update({(pm,pm_seasonal):model_fit.bic})
        except:
            continue
```

```
SARIMA(0, 0, 0)X(0, 0, 0, 12)12 - AIC:810.3107683340173
SARIMA(0, 0, 0)X(0, 0, 1, 12)12 - AIC:512.5318568681995
SARIMA(0, 0, 0)X(0, 1, 0, 12)12 - AIC:465.20083573684155
SARIMA(0, 0, 0)X(0, 1, 1, 12)12 - AIC:220.92269922440235
SARIMA(0, 0, 0)X(1, 0, 0, 12)12 - AIC:486.90354702832656
SARIMA(0, 0, 0)X(1, 0, 1, 12)12 - AIC:478.0942465724045
SARIMA(0, 0, 0)X(1, 1, 0, 12)12 - AIC:250.99144098582636
SARIMA(0, 0, 0)X(1, 1, 1, 12)12 - AIC:222.47824164007164
SARIMA(0, 0, 1)X(0, 0, 0, 12)12 - AIC:760.2162374052343
SARIMA(0, 0, 1)X(0, 0, 1, 12)12 - AIC:471.742008614918
SARIMA(0, 0, 1)X(0, 1, 0, 12)12 - AIC:444.3094989817134
SARIMA(0, 0, 1)X(0, 1, 1, 12)12 - AIC:203.57371601301926
SARIMA(0, 0, 1)X(1, 0, 0, 12)12 - AIC:550.986052580633
SARIMA(0, 0, 1)X(1, 0, 1, 12)12 - AIC:487.7711520891767
SARIMA(0, 0, 1)X(1, 1, 0, 12)12 - AIC:251.80191286749474
SARIMA(0, 0, 1)X(1, 1, 1, 12)12 - AIC:205.3034218803646
SARIMA(0, 1, 0)X(0, 0, 0, 12)12 - AIC:728.2092083597857
SARIMA(0, 1, 0)X(0, 0, 1, 12)12 - AIC:459.20277790229835
SARIMA(0, 1, 0)X(0, 1, 0, 12)12 - AIC:450.79369617745346
SARIMA(0, 1, 0)X(0, 1, 1, 12)12 - AIC:202.77719782465013
SARIMA(0, 1, 0)X(1, 0, 0, 12)12 - AIC:468.58035819736926
SARIMA(0, 1, 0)X(1, 0, 1, 12)12 - AIC:447.1273483957379
SARIMA(0, 1, 0)X(1, 1, 0, 12)12 - AIC:233.31991014924887
SARIMA(0, 1, 0)X(1, 1, 1, 12)12 - AIC:205.43611944734752
SARIMA(0, 1, 1)X(0, 0, 0, 12)12 - AIC:704.1480775842399
SARIMA(0, 1, 1)X(0, 0, 1, 12)12 - AIC:438.9991433259569
SARIMA(0, 1, 1)X(0, 1, 0, 12)12 - AIC:430.16598457879934
SARIMA(0, 1, 1)X(0, 1, 1, 12)12 - AIC:183.35240821973133
SARIMA(0, 1, 1)X(1, 0, 0, 12)12 - AIC:465.1789965200763
SARIMA(0, 1, 1)X(1, 0, 1, 12)12 - AIC:437.5033281512461
SARIMA(0, 1, 1)X(1, 1, 0, 12)12 - AIC:227.09919145406244
SARIMA(0, 1, 1)X(1, 1, 1, 12)12 - AIC:186.72632791183227
SARIMA(1, 0, 0)X(0, 0, 0, 12)12 - AIC:750.1182176042614
SARIMA(1, 0, 0)X(0, 0, 1, 12)12 - AIC:480.6501650967293
SARIMA(1, 0, 0)X(0, 1, 0, 12)12 - AIC:463.48112766037684
SARIMA(1, 0, 0)X(0, 1, 1, 12)12 - AIC:222.34642879389077
SARIMA(1, 0, 0)X(1, 0, 0, 12)12 - AIC:479.2475854304206
SARIMA(1, 0, 0)X(1, 0, 1, 12)12 - AIC:479.98268978067205
SARIMA(1, 0, 0)X(1, 1, 0, 12)12 - AIC:224.8283373225528
SARIMA(1, 0, 0)X(1, 1, 1, 12)12 - AIC:223.9439680897846
SARIMA(1, 0, 1)X(0, 0, 0, 12)12 - AIC:724.6869847459585
SARIMA(1, 0, 1)X(0, 0, 1, 12)12 - AIC:458.51987038484543
SARIMA(1, 0, 1)X(0, 1, 0, 12)12 - AIC:446.1357737985943
SARIMA(1, 0, 1)X(0, 1, 1, 12)12 - AIC:205.56596640901193
SARIMA(1, 0, 1)X(1, 0, 0, 12)12 - AIC:475.5533631945233
SARIMA(1, 0, 1)X(1, 0, 1, 12)12 - AIC:457.03110618710144
SARIMA(1, 0, 1)X(1, 1, 0, 12)12 - AIC:226.58981409787648
SARIMA(1, 0, 1)X(1, 1, 1, 12)12 - AIC:207.28234128817883
SARIMA(1, 1, 0)X(0, 0, 0, 12)12 - AIC:727.5705796560088
SARIMA(1, 1, 0)X(0, 0, 1, 12)12 - AIC:460.32096160056415
SARIMA(1, 1, 0)X(0, 1, 0, 12)12 - AIC:451.7896977934569
SARIMA(1, 1, 0)X(0, 1, 1, 12)12 - AIC:205.55468759202444
SARIMA(1, 1, 0)X(1, 0, 0, 12)12 - AIC:459.212871336873
SARIMA(1, 1, 0)X(1, 0, 1, 12)12 - AIC:459.51172759285146
SARIMA(1, 1, 0)X(1, 1, 0, 12)12 - AIC:210.24225011225886
SARIMA(1, 1, 0)X(1, 1, 1, 12)12 - AIC:207.4126038014479
SARIMA(1, 1, 1)X(0, 0, 0, 12)12 - AIC:699.1410793411434
```

```
SARIMA(1, 1, 1)X(0, 0, 1, 12)12 - AIC:437.0892335544464
SARIMA(1, 1, 1)X(0, 1, 0, 12)12 - AIC:430.60551465582694
SARIMA(1, 1, 1)X(0, 1, 1, 12)12 - AIC:186.33341905894557
SARIMA(1, 1, 1)X(1, 0, 0, 12)12 - AIC:456.0424032256515
SARIMA(1, 1, 1)X(1, 0, 1, 12)12 - AIC:436.4921606265953
SARIMA(1, 1, 1)X(1, 1, 0, 12)12 - AIC:209.23315518105352
SARIMA(1, 1, 1)X(1, 1, 1, 12)12 - AIC:185.71420846266625
```

In [ ]:

```
# The warnings means basically, the covariates are so big that the model has a
pretty hard time trying to fit coefficients for the linear regression and ever
ything else gets messed up.
# https://stats.stackexchange.com/questions/340054/scaling-control-time-series
-with-causalimpact
```

In [38]:
```
{k: v for k,v in sorted(metric_aic_dict.items(),key=lambda x: x[1])}
```

Out[38]:
```
{((0, 1, 1), (0, 1, 1, 12)): 183.94408195173997,
 ((1, 1, 1), (1, 1, 1, 12)): 186.70033134934735,
 ((1, 1, 1), (0, 1, 1, 12)): 187.1223173682904 5,
 ((0, 1, 1), (1, 1, 1, 12)): 187.51522622117716,
 ((0, 1, 0), (0, 1, 1, 12)): 203.38236801063823,
 ((0, 0, 1), (0, 1, 1, 12)): 204.4814712920014,
 ((0, 1, 0), (1, 1, 1, 12)): 206.34387472632966,
 ((1, 1, 0), (0, 1, 1, 12)): 206.46244287100657,
 ((0, 0, 1), (1, 1, 1, 12)): 206.51376225234077,
 ((1, 0, 1), (0, 1, 1, 12)): 206.7763067809881,
 ((1, 1, 0), (1, 1, 1, 12)): 208.62294417342406,
 ((1, 0, 1), (1, 1, 1, 12)): 208.79526675314906,
 ((1, 1, 1), (1, 1, 0, 12)): 210.4434955530297,
 ((1, 1, 0), (1, 1, 0, 12)): 211.150005391241,
 ((0, 0, 0), (0, 1, 1, 12)): 221.71848976999908,
 ((1, 0, 0), (0, 1, 1, 12)): 223.5401146122859,
 ((0, 0, 0), (1, 1, 1, 12)): 223.67192745846677,
 ((1, 0, 0), (1, 1, 1, 12)): 225.53554918097808,
 ((1, 0, 0), (1, 1, 0, 12)): 226.02202314094794,
 ((1, 0, 1), (1, 1, 0, 12)): 228.18139518906997,
 ((0, 1, 1), (1, 1, 0, 12)): 228.29287727245756,
 ((0, 1, 0), (1, 1, 0, 12)): 234.1157006948456,
 ((0, 0, 0), (1, 1, 0, 12)): 251.96125428540236,
 ((0, 0, 1), (1, 1, 0, 12)): 253.25663281685874,
 ((0, 1, 1), (0, 1, 0, 12)): 432.2550294542462,
 ((1, 1, 1), (0, 1, 0, 12)): 433.7390819689972,
 ((1, 1, 1), (0, 0, 1, 12)): 441.26732330534014,
 ((0, 1, 1), (1, 0, 1, 12)): 441.6814179021398,
 ((1, 1, 1), (1, 0, 1, 12)): 441.7147728152124,
 ((0, 1, 1), (0, 0, 1, 12)): 442.13271063912714,
 ((0, 0, 1), (0, 1, 0, 12)): 446.49158388843,
 ((1, 0, 1), (0, 1, 0, 12)): 449.40890115866927,
 ((0, 1, 0), (1, 0, 1, 12)): 450.40047575581286,
 ((0, 1, 0), (0, 1, 0, 12)): 451.8847386308118,
 ((1, 1, 0), (0, 1, 0, 12)): 453.97178270017355,
 ((1, 1, 1), (1, 0, 0, 12)): 460.4065730390848,
 ((0, 1, 0), (0, 0, 1, 12)): 461.384862809015,
 ((1, 1, 0), (1, 0, 0, 12)): 462.48599869694795,
 ((1, 0, 1), (1, 0, 1, 12)): 462.48631845389303,
 ((1, 0, 1), (0, 0, 1, 12)): 462.8840401982787,
 ((1, 1, 0), (0, 0, 1, 12)): 463.5940889606391,
 ((1, 1, 0), (1, 0, 1, 12)): 463.8758974062847,
 ((1, 0, 0), (0, 1, 0, 12)): 465.75211609223516,
 ((0, 0, 0), (0, 1, 0, 12)): 466.3363299527707,
 ((0, 1, 1), (1, 0, 0, 12)): 468.58547916786375,
 ((0, 1, 0), (1, 0, 0, 12)): 470.8513466292276,
 ((0, 0, 1), (0, 0, 1, 12)): 475.015135974993,
 ((1, 0, 1), (1, 0, 0, 12)): 480.0953400582399,
 ((0, 0, 0), (1, 0, 1, 12)): 481.50072922019194,
 ((1, 0, 0), (1, 0, 0, 12)): 482.65406807820807,
 ((1, 0, 0), (0, 0, 1, 12)): 484.0566477445168,
 ((1, 0, 0), (1, 0, 1, 12)): 484.5246666443886,
 ((0, 0, 0), (1, 0, 0, 12)): 489.25965468902245,
 ((0, 0, 1), (1, 0, 1, 12)): 492.13532190261,
 ((0, 0, 0), (0, 0, 1, 12)): 514.8028453000578,
 ((0, 0, 1), (1, 0, 0, 12)): 554.5202140716768,
 ((1, 1, 1), (0, 0, 0, 12)): 703.6306020255428,
```

```
 ((0, 1, 1), (0, 0, 0, 12)): 707.1410927071729,
 ((1, 0, 1), (0, 0, 0, 12)): 729.266066319807,
 ((0, 1, 0), (0, 0, 0, 12)): 729.7355688844019,
 ((1, 1, 0), (0, 0, 0, 12)): 730.6233007052411,
 ((1, 0, 0), (0, 0, 0, 12)): 753.2289137272403,
 ((0, 0, 1), (0, 0, 0, 12)): 763.2689584544667,
 ((0, 0, 0), (0, 0, 0, 12)): 811.8661163955068}
```

In [ ]:

```
# We will compare models that better fit with pdq until 1, 2 and 3
```

In [43]:

```
model=sm.tsa.statespace.SARIMAX(y_train['Sales'],order=(0,1,1),seasonal_order=(0,1,1,12))
model_fit1=model.fit()
model_fit1.summary()
```

Out[43]:

SARIMAX Results

Dep. Variable:	Sales	**No. Observations:**	36
Model:	SARIMAX(0, 1, 1)x(0, 1, 1, 12)	**Log Likelihood**	-232.841
Date:	Sun, 20 Dec 2020	**AIC**	471.681
Time:	18:19:06	**BIC**	475.088
Sample:	01-01-1997	**HQIC**	472.538
	- 12-01-1999		
Covariance Type:	opg		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
ma.L1	-0.4063	0.178	-2.286	0.022	-0.754	-0.058
ma.S.L12	-0.2952	0.200	-1.476	0.140	-0.687	0.097
sigma2	4.368e+07	1.33e-09	3.28e+16	0.000	4.37e+07	4.37e+07

Ljung-Box (Q):	9.74	**Jarque-Bera (JB):**	0.54
Prob(Q):	0.99	**Prob(JB):**	0.76
Heteroskedasticity (H):	1.92	**Skew:**	-0.37
Prob(H) (two-sided):	0.38	**Kurtosis:**	2.85

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 1.32e+32. Standard errors may be unstable.

In [39]:
```
model=sm.tsa.statespace.SARIMAX(y_train['Sales'],order=(0,0,2),seasonal_order=(0,2,0,12))
model_fit2=model.fit()
model_fit2.summary()
```

Out[39]:

SARIMAX Results

Dep. Variable:	Sales	**No. Observations:**	36
Model:	SARIMAX(0, 0, 2)x(0, 2, [], 12)	**Log Likelihood**	-124.712
Date:	Sun, 20 Dec 2020	**AIC**	255.425
Time:	18:18:40	**BIC**	256.879
Sample:	01-01-1997	**HQIC**	254.886
	- 12-01-1999		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ma.L1	0.2829	0.233	1.216	0.224	-0.173	0.739
ma.L2	0.0461	0.225	0.205	0.838	-0.394	0.487
sigma2	6.203e+07	5.55e-10	1.12e+17	0.000	6.2e+07	6.2e+07

Ljung-Box (Q):	8.29	**Jarque-Bera (JB):**	1.58
Prob(Q):	0.69	**Prob(JB):**	0.45
Heteroskedasticity (H):	0.16	**Skew:**	0.86
Prob(H) (two-sided):	0.10	**Kurtosis:**	3.44

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 1.39e+34. Standard errors may be unstable.

In [41]:
```
model=sm.tsa.statespace.SARIMAX(y_train['Sales'],order=(0,3,3),seasonal_order=
(0,2,0,12))
model_fit3=model.fit()
model_fit3.summary()
```

Out[41]:

SARIMAX Results

Dep. Variable:	Sales	**No. Observations:**	36
Model:	SARIMAX(0, 3, 3)x(0, 2, [], 12)	**Log Likelihood**	-93.005
Date:	Sun, 20 Dec 2020	**AIC**	194.010
Time:	18:18:50	**BIC**	194.799
Sample:	01-01-1997	**HQIC**	192.308
	- 12-01-1999		
Covariance Type:	opg		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
ma.L1	-2.1833	0.869	-2.511	0.012	-3.887	-0.479
ma.L2	1.4463	1.323	1.093	0.274	-1.147	4.040
ma.L3	-0.2382	0.646	-0.369	0.712	-1.503	1.027
sigma2	5.165e+07	4.87e-08	1.06e+15	0.000	5.16e+07	5.16e+07

Ljung-Box (Q):	3.70	**Jarque-Bera (JB):**	0.49
Prob(Q):	0.88	**Prob(JB):**	0.78
Heteroskedasticity (H):	0.21	**Skew:**	-0.31
Prob(H) (two-sided):	0.23	**Kurtosis:**	2.04

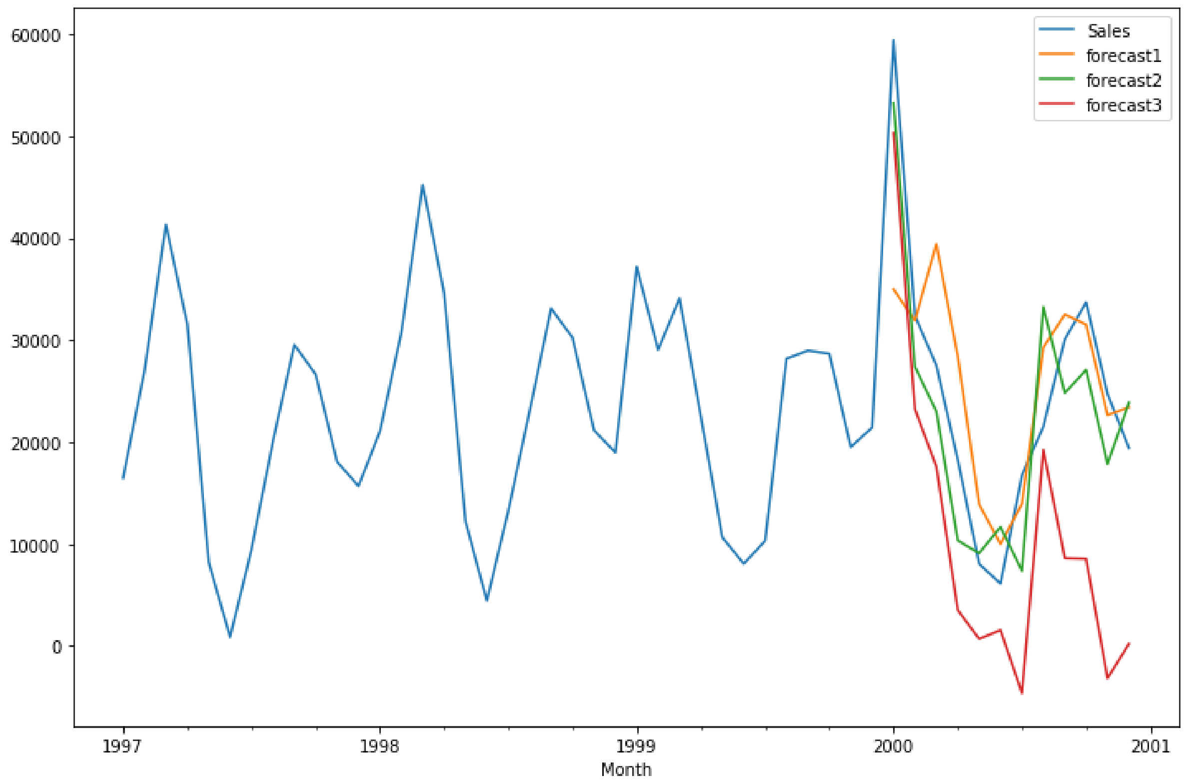
Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 1.15e+31. Standard errors may be unstable.

In [ ]:
```
#From the three Sarima models, we sse that the one that has the best performan
ce is the thirds one.
#This is logical because we have differentiated 3 lags
```

7. Comparing results

In [44]:
```
from datetime import datetime
df['forecast1']=model_fit1.predict(start=datetime(2000,1,1), end=datetime(2000
,12,1),dynamic=True)
df['forecast2']=model_fit2.predict(start=datetime(2000,1,1), end=datetime(2000
,12,1),dynamic=True)
df['forecast3']=model_fit3.predict(start=datetime(2000,1,1), end=datetime(2000
,12,1),dynamic=True)
df[['Sales','forecast1','forecast2','forecast3']].plot(figsize=(12,8))
```

Out[44]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x224afa2ada0>
```



In [45]:
```
actual=y_test['Sales']['2000-01-01':]
forecast1=model_fit1.get_prediction(start=pd.to_datetime('2000-01-01'),end=pd.
to_datetime('2000-12-01'),dynamic=False)
predictions1=forecast1.predicted_mean
rmse1=np.sqrt((predictions1 - actual)**2).mean()

forecast2=model_fit2.get_prediction(start=pd.to_datetime('2000-01-01'),end=pd.
to_datetime('2000-12-01'),dynamic=False)
predictions2=forecast2.predicted_mean
rmse2=np.sqrt((predictions2 - actual)**2).mean()

forecast3=model_fit3.get_prediction(start=pd.to_datetime('2000-01-01'),end=pd.
to_datetime('2000-12-01'),dynamic=False)
predictions3=forecast3.predicted_mean
rmse3=np.sqrt((predictions3 - actual)**2).mean()
print('Rmse1: {}'.format(rmse1))
print('Rmse2: {}'.format(rmse2))
print('Rmse3: {}'.format(rmse3))
```

```
Rmse1: 6495.958370396597
Rmse2: 6208.075242555135
Rmse3: 14346.355962425181
```

In [ ]:
```
#We can see that even aic is better for sarima model3, the one that fits best
 with the test part is the second model
# It is maybe because the testing year  doesn't have the same trend as the pre
vious year
```

8. Forecasting with new model

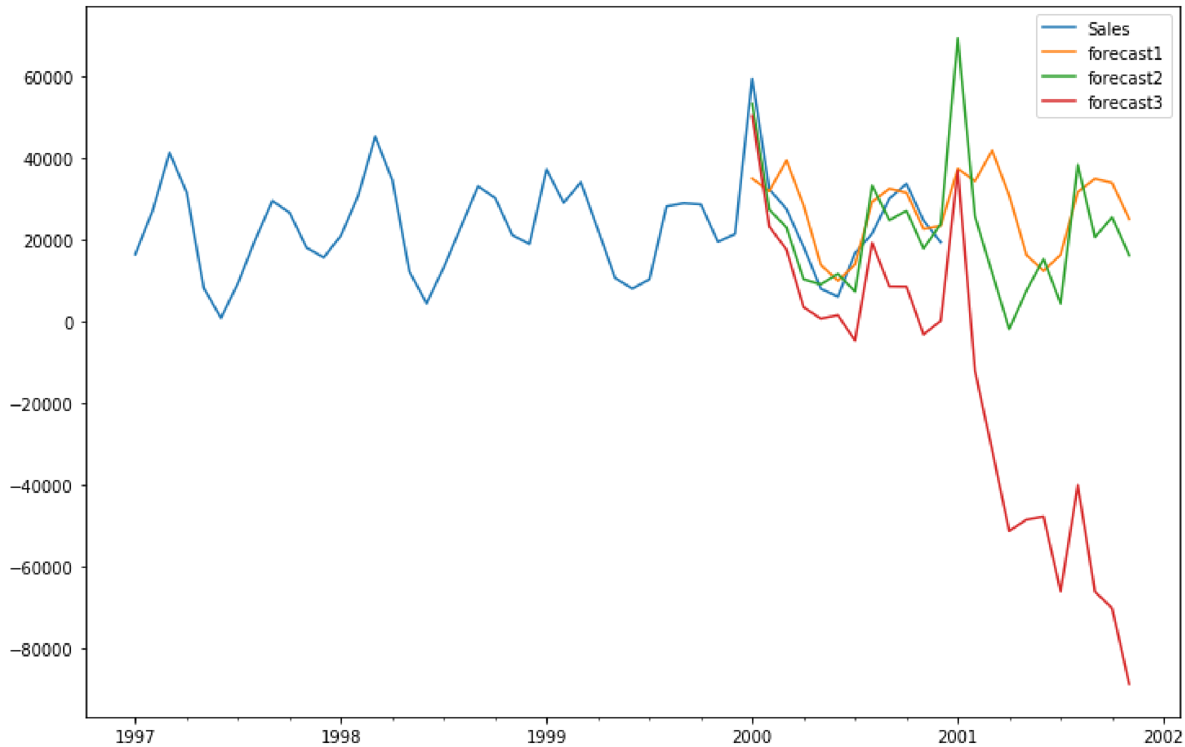
In [46]:
```
from pandas.tseries.offsets import DateOffset
future_dates=[df.index[-1]+ DateOffset(months=x)for x in range(0,12)]
```

In [47]:
```
future_datest_df=pd.DataFrame(index=future_dates[1:],columns=df.columns)
```

In [48]:
```
future_df=pd.concat([df,future_datest_df])
```

In [49]:
```
future_df['forecast1'] = model_fit1.predict(start = datetime(2000,1,1), end =
datetime(2003,1,1), dynamic= True)
future_df['forecast2'] = model_fit2.predict(start = datetime(2000,1,1), end =
datetime(2003,1,1), dynamic= True)
future_df['forecast3'] = model_fit3.predict(start = datetime(2000,1,1), end =
datetime(2003,1,1), dynamic= True)
future_df[['Sales', 'forecast1','forecast2','forecast3']].plot(figsize=(12, 8
))
```

Out[49]: <matplotlib.axes._subplots.AxesSubplot at 0x224afb140b8>



In [ ]:
```
#this graphic finally gives us a view in which we can see that model3 is not g
ood at all. The ideal model would be a combination between the first and the s
econd model
#the third model is bad, maybe because it is detecting a descending trend
```