In [1]:
```
import statsmodels.api as sm
import numpy as np
```

1. AR Models

(a) Search for 4 parameters $\phi_1 \cdots \phi_4$ such that the corresponding AR(4) model is stationary. Choose your own σ_ϵ value for the variance of the gaussian white noise. Generate 4 years worth of data points (1008 observations). Calculate ACF and PACF for the data that you generated.

- AR(4) model parameters setting

In [2]:
```
arparams = np.array([-0.4,0.6,0.15,-0.1])
ar = np.r_[1,-arparams]
arma_process = sm.tsa.ArmaProcess(ar,[1])
```

- Stationarity and invertibility

In [3]:
```
arma_process.isstationary
```

Out[3]:
```
True
```

In [4]:
```
arma_process.isinvertible
```

Out[4]:
```
True
```

- Generate samples with chosen standard deviation noise equals to 0.1

In [5]:
```
y = arma_process.generate_sample(nsample=1008,scale=0.1)
```

- Fit data

In [6]:
```
model = sm.tsa.ARMA(y,(4,0)).fit(trend='nc')
```

In [7]:
```
model.params
```

Out[7]:
```
array([-0.39926036,  0.57584369,  0.14407966, -0.08935232])
```

In [8]:
```
model.summary()
```

Out[8]:

ARMA Model Results

Dep. Variable:	y	**No. Observations:**	1008
Model:	ARMA(4, 0)	**Log Likelihood**	874.526
Method:	css-mle	**S.D. of innovations**	0.102
Date:	Thu, 15 Mar 2018	**AIC**	-1739.052
Time:	18:28:05	**BIC**	-1714.474
Sample:	0	**HQIC**	-1729.714

	coef	std err	z	P>|z|	[95.0% Conf. Int.]
ar.L1.y	-0.3993	0.031	-12.723	0.000	-0.461 -0.338
ar.L2.y	0.5758	0.034	17.181	0.000	0.510 0.642
ar.L3.y	0.1441	0.034	4.296	0.000	0.078 0.210
ar.L4.y	-0.0894	0.031	-2.845	0.005	-0.151 -0.028

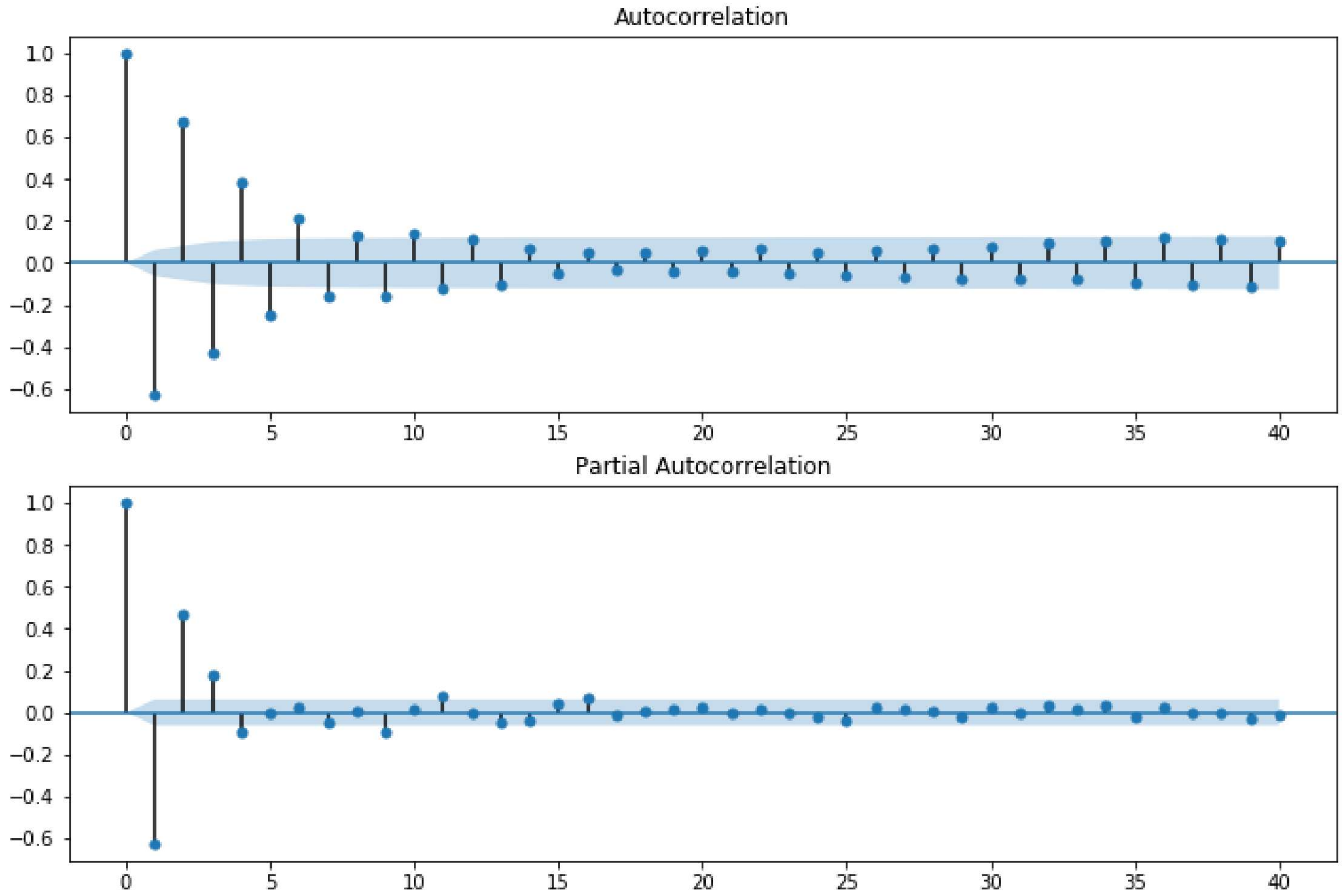
-1.4888 -0.1867j 1.5004 -0.4801 -1.4888 +0.1867j 1.5004 0.4801 1.7510 -0.0000j 1.7510 -0.0000 2.8390 -0.0000j 2.8390 -0.0000

Roots

	Real	Imaginary	Modulus	Frequency
AR.1				
AR.2				
AR.3				
AR.4				

```
In [9]: # autocorrelation
        import matplotlib.pyplot as plt
        def autocorrelation_check(timeseries,alpha):
            fig = plt.figure(figsize=(12,8))
            ax1 = fig.add_subplot(211)
            fig = sm.graphics.tsa.plot_acf(timeseries, alpha=alpha, lags=40, ax=ax1)
            ax2 = fig.add_subplot(212)
            fig = sm.graphics.tsa.plot_pacf(timeseries, alpha=alpha, lags=40, ax=ax2)
            plt.show()
```

```
In [10]: autocorrelation_check(y,0.05)
```



(b) Write a paragraph detailing the differences between the two graphs. What is the recommended order of the corresponding model based on the data and the graphs you plotted?

> ACF: Autocorrelation Function ACF(h) is the correlation between data with different lags. And it's assumed to be invariant as process to be stationary.
>
> PACF: Partial Autocorrelation function PACF(h) is the conditional correlation between x_t and x_{t-h}, conditional on $x_{t-h+1}, \cdots, x_{t-1}$. It can be viewed as an added attribution of x_{t-h} to x_t over an AR(h-1) model.
>
> Based on the **PACF** graph, using 5% significant level, we identify an AR(4) model for the data (i.e. p=4)

(c) Using a method of your choice and the recommended order from the previous point estimate the parameters present in the model. Benchmark the estimates with respect to the known parameter values. Remember to pay attention to the form of the model used (standard or alternate form).

```
In [11]: model = sm.tsa.ARMA(y,(4,0)).fit(trend='nc')
```

```
In [12]: model.params
```

```
Out[12]: array([-0.39926036,  0.57584369,  0.14407966, -0.08935232])
```

In [13]:
```
model.summary()
```

Out[13]:

ARMA Model Results

Dep. Variable:	y	No. Observations:	1008
Model:	ARMA(4, 0)	Log Likelihood	874.526
Method:	css-mle	S.D. of innovations	0.102
Date:	Thu, 15 Mar 2018	AIC	-1739.052
Time:	18:28:07	BIC	-1714.474
Sample:	0	HQIC	-1729.714

	coef	std err	z	P>|z|	[95.0% Conf. Int.]
ar.L1.y	-0.3993	0.031	-12.723	0.000	-0.461 -0.338
ar.L2.y	0.5758	0.034	17.181	0.000	0.510 0.642
ar.L3.y	0.1441	0.034	4.296	0.000	0.078 0.210
ar.L4.y	-0.0894	0.031	-2.845	0.005	-0.151 -0.028

-1.4888 -0.1867j 1.5004 -0.4801 -1.4888 +0.1867j 1.5004 0.4801 1.7510 -0.0000j 1.7510 -0.0000 2.8390 -0.0000j 2.8390 -0.0000

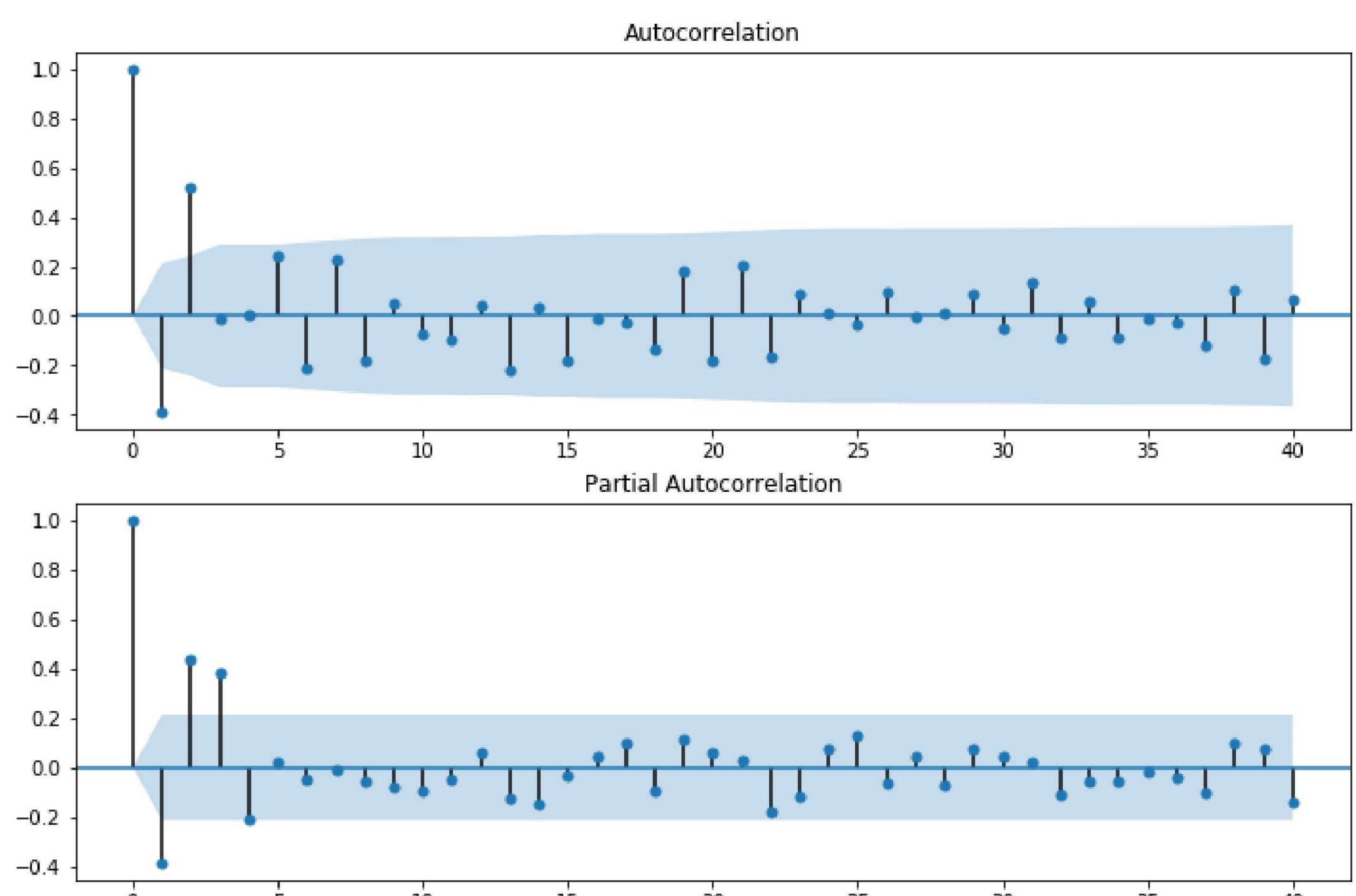
Roots

	Real	Imaginary	Modulus	Frequency
AR.1				
AR.2				
AR.3				
AR.4				

> Conclusion: The AR order is correct and the coefficients are all within its confidence interval.

(c) Repeat the entire procedure above (previous parts) however now generate data for 4 months (84 observations). Compare these estimates with the original values and the estimates in part (c). Please comment.

In [14]:
```
y_4_months = arma_process.generate_sample(nsample=84, scale=0.1)
autocorrelation_check(y_4_months,0.05)
```



> Based on the PACF graph, using 5% significant level, we identify an AR(2) model for the data (i.e. p=2)

In [15]:
```
model_4_months = sm.tsa.ARMA(y_4_months,(2,0)).fit(trend='nc')
```

In [16]:
```
model_4_months.params
```

Out[16]: `array([-0.21668523,  0.43225407])`

In [17]:
```
model_4_months.summary()
```

Out[17]:

ARMA Model Results

Dep. Variable:	y	**No. Observations:**	84
Model:	ARMA(2, 0)	**Log Likelihood**	75.362
Method:	css-mle	**S.D. of innovations**	0.098
Date:	Thu, 15 Mar 2018	**AIC**	-144.725
Time:	18:28:07	**BIC**	-137.432
Sample:	0	**HQIC**	-141.793

	coef	**std err**	**z**	**P>|z|**	**[95.0% Conf. Int.]**
ar.L1.y	-0.2167	0.097	-2.234	0.028	-0.407 -0.027
ar.L2.y	0.4323	0.097	4.450	0.000	0.242 0.623

-1.2909 +0.0000j 1.2909 0.5000 1.7922 +0.0000j 1.7922 0.0000

Roots

	Real	**Imaginary**	**Modulus**	**Frequency**
AR.1				
AR.2				

> Conclusion: The AR order is different from the original data and the recommanded calibrated model. It is because we use only 84 observations which is too small and it increase the variance of the estimation of parameters.

2 MA Models

a) Search for 4 parameters $\theta_1 \cdots \theta_4$ such that the corresponding MA(4) model is invertible. Choose your own σ_ϵ value for the variance of the gaussian white noise. Generate 4 years worth of data points (1008 observations). Calculate ACF and PACF for the data that you generated.

In [18]:
```
maparams = np.array([0.3,0.4,0.2,0.1])
ma = np.r_[1,maparams]
ma_process = sm.tsa.ArmaProcess(ar=[1],ma=ma)
```

In [19]:
```
ma_process.isstationary
```

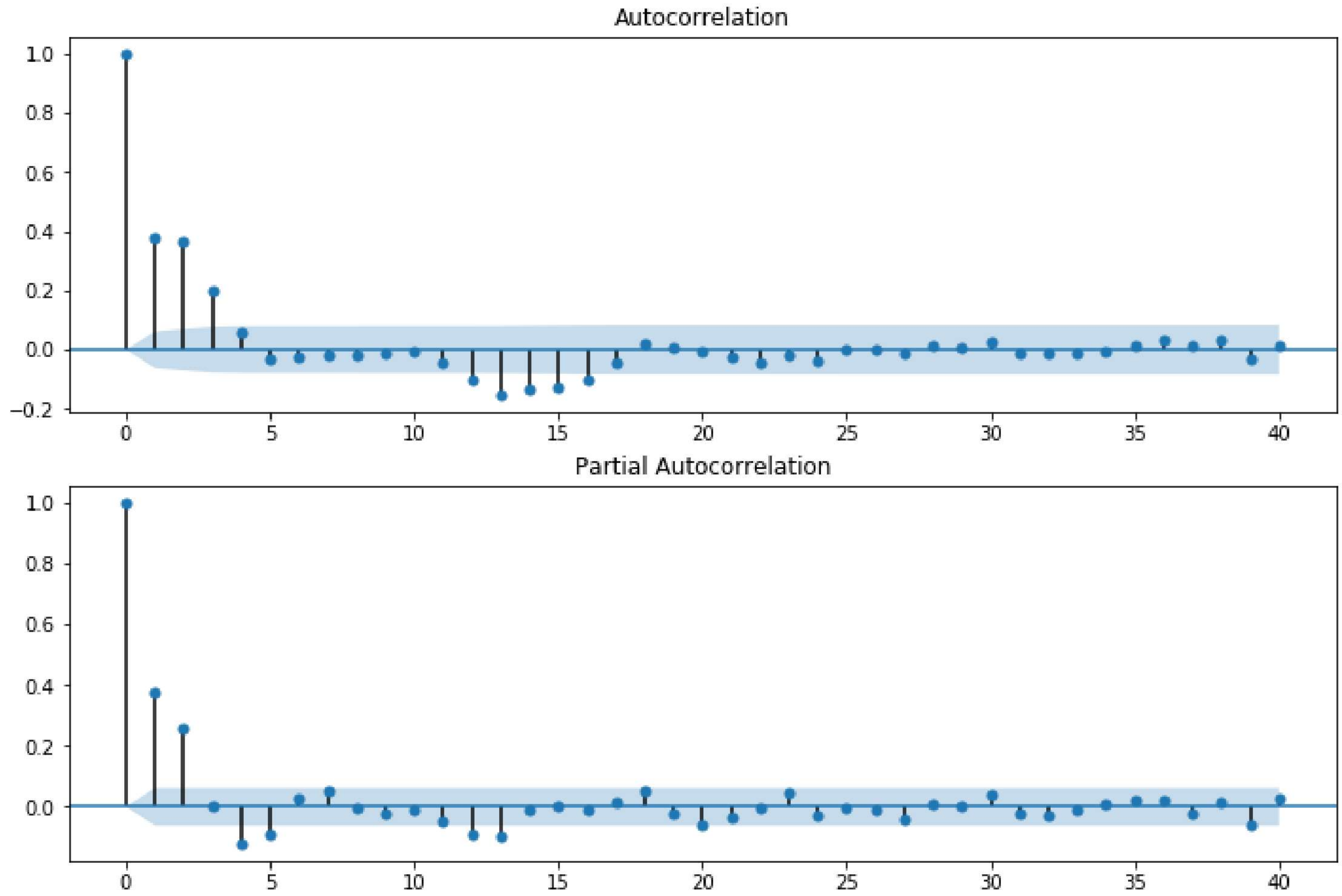
Out[19]: `True`

In [20]:
```
ma_process.isinvertible
```

Out[20]: `True`

In [21]:
```
y_ma = ma_process.generate_sample(1008,scale=0.1)
```

In [22]:
```
autocorrelation_check(y_ma,0.05)
```



b) Write a paragraph detailing the differences between the two graphs. What is the recommended order of the corresponding model based on the data and the graphs you plotted?

ACF: Autocorrelation Function ACF(h) is the correlation between data with different lags. And it's assumed to be invariant as process to be stationary.

PACF: Partial Autocorrelation function PACF(h) is the conditional correlation between x_t and x_{t-h}, conditional on $x_{t-h+1}, \cdots, x_{t-1}$. It can be viewed as an added attribution of x_{t-h} to x_t over an AR(h-1) model.

Based on the **ACF** graph, using 5% significant level, we identify an MA(4) model for the data (i.e. q=4)

(c) Using a method of your choice and the recommended order from the previous point estimate the parameters present in the model. Benchmark the estimates with respect to the known parameter values. Remember to pay attention to the form of the model used (standard or alternate form).

In [23]:
```
model_ma = sm.tsa.ARIMA(y_ma,(0,0,4)).fit(trend="nc")
```

In [24]:
```
model_ma.params
```

Out[24]:
```
array([ 0.27120312,  0.37720839,  0.24831774,  0.09539629])
```

In [25]:
```
model_ma.summary()
```

Out[25]:

ARMA Model Results

Dep. Variable:	y	**No. Observations:**	1008
Model:	ARMA(0, 4)	**Log Likelihood**	930.006
Method:	css-mle	**S.D. of innovations**	0.096
Date:	Thu, 15 Mar 2018	**AIC**	-1850.012
Time:	18:28:08	**BIC**	-1825.433
Sample:	0	**HQIC**	-1840.674

	coef	std err	z	P>|z|	[95.0% Conf. Int.]
ma.L1.y	0.2712	0.031	8.645	0.000	0.210 0.333
ma.L2.y	0.3772	0.031	12.032	0.000	0.316 0.439
ma.L3.y	0.2483	0.031	8.123	0.000	0.188 0.308
ma.L4.y	0.0954	0.033	2.926	0.004	0.032 0.159

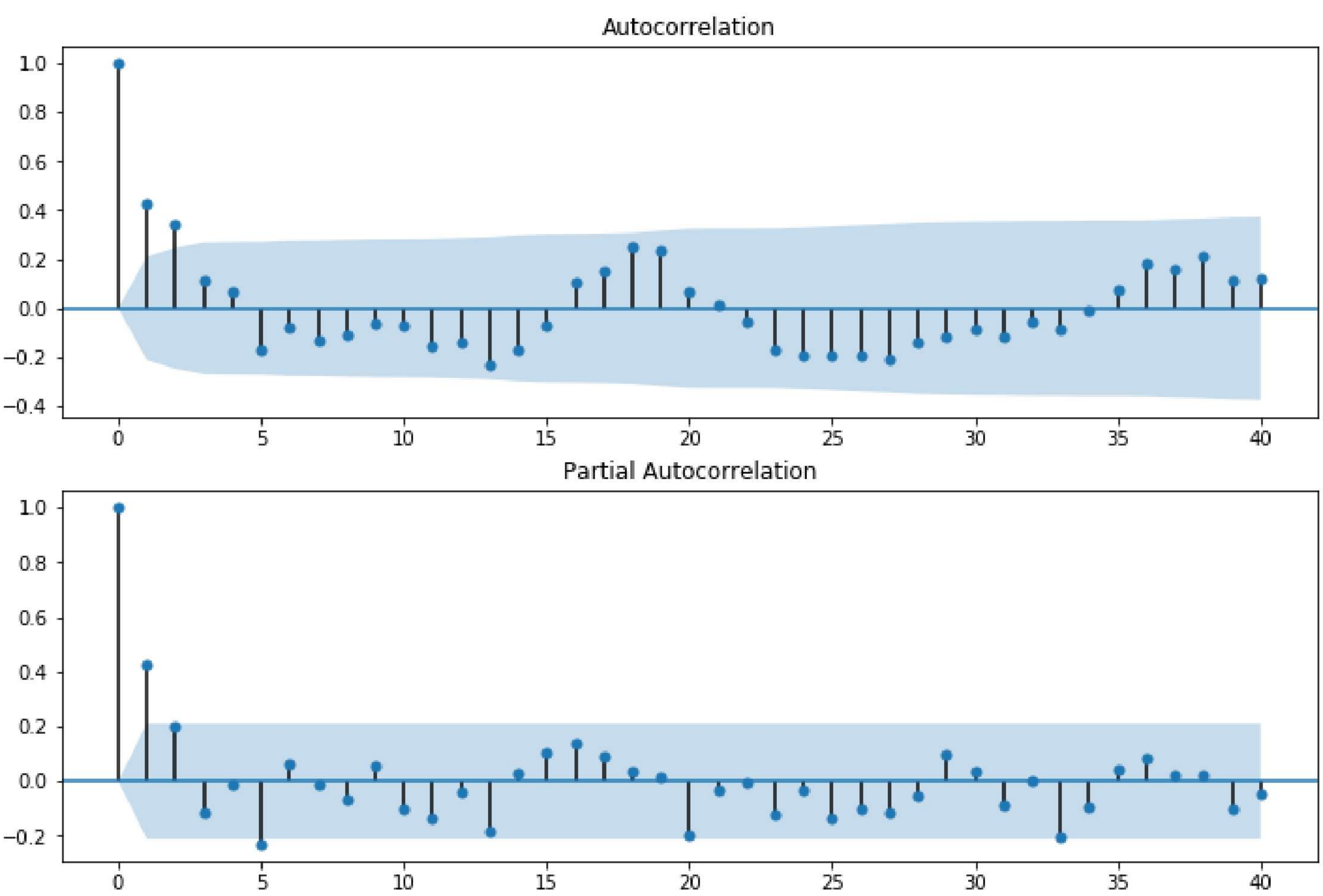
0.4490 -1.3761j 1.4475 -0.1998 0.4490 +1.3761j 1.4475 0.1998 -1.7505 -1.3923j 2.2367 -0.3931 -1.7505 +1.3923j 2.2367 0.3931

Roots

	Real	Imaginary	Modulus	Frequency
MA.1				
MA.2				
MA.3				
MA.4				

> Conclusion: The estimation is approximately accurate. All lay in the confidence intervals.

In [26]:
```
autocorrelation_check(y_ma[:86],alpha=0.05)
```



In [27]:
```
model_ma_4_months = sm.tsa.ARIMA(y_ma[:86],(0,0,2)).fit(trend="nc")
```

In [28]:
```
model_ma_4_months.params
```

Out[28]: `array([ 0.34955912,  0.26604034])`

In [29]:
```
model_ma_4_months.summary()
```

Out[29]:

ARMA Model Results

Dep. Variable:	y	**No. Observations:**	86
Model:	ARMA(0, 2)	**Log Likelihood**	69.275
Method:	css-mle	**S.D. of innovations**	0.108
Date:	Thu, 15 Mar 2018	**AIC**	-132.549
Time:	18:28:08	**BIC**	-125.186
Sample:	0	**HQIC**	-129.586

	coef	**std err**	**z**	**P>|z|**	**[95.0% Conf. Int.]**
ma.L1.y	0.3496	0.111	3.137	0.002	0.131 0.568
ma.L2.y	0.2660	0.085	3.128	0.002	0.099 0.433

-0.6570 -1.8241j 1.9388 -0.3050 -0.6570 +1.8241j 1.9388 0.3050

Roots

	Real	**Imaginary**	**Modulus**	**Frequency**
MA.1				
MA.2				

> Conclusion: When we decrease the observations, the MA order turns out to be smaller because of the increasing in variance of paramteter estimations (i.e. compare the attributes *std err* of coefficients). Still, true value lays in its confidence interval. But not that persuasive since the large variance.

3. ARMA Models

Generate three year worth of daily data for an ARMA(4,4) model using the combination of parameters in parts (a) from the two problems above. Turn in the two graphs (ACF, PACF). What is the recommended order of the corresponding model based on the data and the graphs you plotted? Repeat parts (b), (c), and (d) of the above problems with this model.

In [30]:
```
ar
```

Out[30]:
```
array([ 1.  ,  0.4 , -0.6 , -0.15,  0.1 ])
```

In [31]:
```
ma
```

Out[31]:
```
array([ 1. ,  0.3,  0.4,  0.2,  0.1])
```

In [32]:
```
model = sm.tsa.ArmaProcess(ar=ar,ma=ma)
```

In [33]:
```
model.isstationary
```

Out[33]:
```
True
```

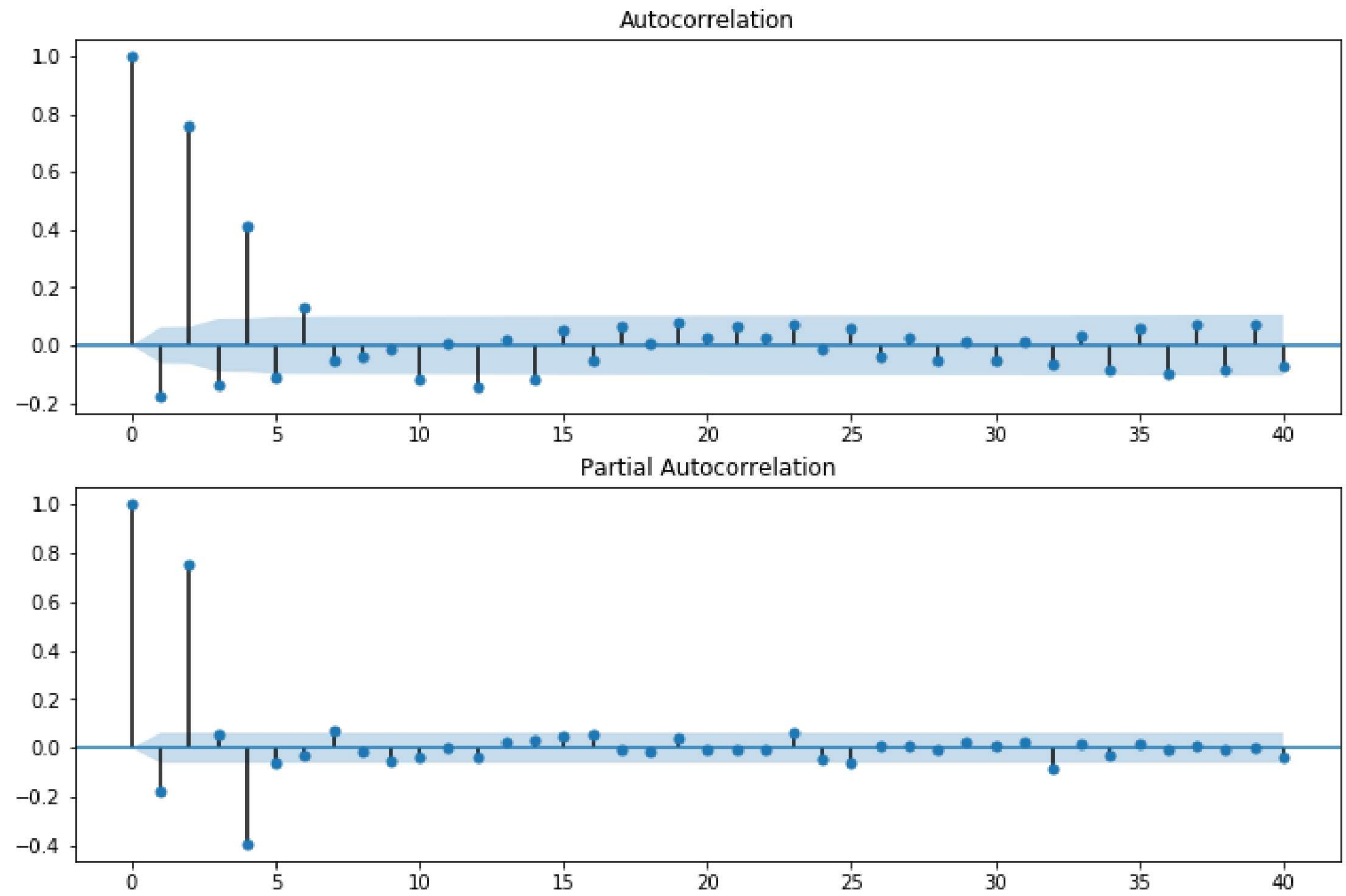
In [34]:
```
model.isinvertible
```

Out[34]:
```
True
```

In [35]:
```
y_arma = model.generate_sample(1008,scale=0.1)
```

b)

In [36]:
```
autocorrelation_check(y_arma,alpha=0.05)
```



Conclusion: Using 5% significant level, based on ACF PACF graphs, we cannot concluded that p=4, q=6. The ACF and PACF are not informative in determining the order of an ARMA model. Should use EACF or information criterion to determine the model order.

c) 4 years observations

In [51]:
```
def IdentifyOrderArma(y, pmax, qmax, method="bic"):
    a = np.zeros((pmax,qmax))
    if(method=="bic"):
        for i in range(6):
            for j in range(6):
                try:
                    a[i,j] = sm.tsa.ARMA(y_arma,(i+1,j+1)).fit(trend='nc',method='css-mle').bic
                except ValueError:
                    a[i,j] = np.nan
    elif(method=="aic"):
        for i in range(6):
            for j in range(6):
                try:
                    a[i,j] = sm.tsa.ARMA(y_arma,(i+1,j+1)).fit(trend='nc',method='css-mle').aic
                except ValueError:
                    a[i,j] = np.nan
    else:
        print("error method can only be bic or aic")
        return
    i,j = np.unravel_index(np.nanargmin(a), a.shape)
    p = i+1
    q = j+1
    return ((p,q),a)
```

In [53]:
```
(p,q),a = IdentifyOrderArma(y_arma,6,6,'bic')
```

```
D:\Softwares\Anaconda3\envs\py36\lib\site-packages\statsmodels\base\model.py:466: ConvergenceWarning: Maximum L
ikelihood optimization failed to converge. Check mle_retvals
  "Check mle_retvals", ConvergenceWarning)
D:\Softwares\Anaconda3\envs\py36\lib\site-packages\statsmodels\base\model.py:466: ConvergenceWarning: Maximum L
ikelihood optimization failed to converge. Check mle_retvals
  "Check mle_retvals", ConvergenceWarning)
D:\Softwares\Anaconda3\envs\py36\lib\site-packages\statsmodels\base\model.py:466: ConvergenceWarning: Maximum L
ikelihood optimization failed to converge. Check mle_retvals
  "Check mle_retvals", ConvergenceWarning)
D:\Softwares\Anaconda3\envs\py36\lib\site-packages\statsmodels\base\model.py:466: ConvergenceWarning: Maximum L
ikelihood optimization failed to converge. Check mle_retvals
  "Check mle_retvals", ConvergenceWarning)
D:\Softwares\Anaconda3\envs\py36\lib\site-packages\statsmodels\base\model.py:466: ConvergenceWarning: Maximum L
ikelihood optimization failed to converge. Check mle_retvals
  "Check mle_retvals", ConvergenceWarning)
```

In [54]:
```
(p,q)
```

Out[54]: (4, 1)

In [55]:
```
a
```

Out[55]:
```
array([[ -906.64836344,           nan,           nan, -1652.38051864,
        -1663.24933625, -1699.06588836],
       [-1552.3749238 , -1689.96551374, -1686.22070277, -1700.05508891,
        -1693.50912559, -1696.6786516 ],
       [-1603.67616928, -1692.14049136, -1687.3753953 , -1698.15617666,
        -1696.15441697, -1689.91585993],
       [-1713.28756199, -1706.48672659, -1705.67468947, -1698.75919968,
        -1693.17735066, -1686.37834276],
       [-1706.39578396, -1700.28694541, -1698.75907146, -1691.88173754,
        -1686.31702426, -1683.32174278],
       [-1704.90872236, -1704.90294854, -1698.38071441, -1691.56424779,
        -1679.12004002, -1680.37071466]])
```

Based on BIC, we choose p=4, and q=1

In [56]:
```
fitted_model = sm.tsa.ARMA(y_arma,(4,1)).fit(trend='nc',method='css-mle')
```

In [57]:
```
fitted_model.params
```

Out[57]:
```
array([ 0.05935429,  1.06661093, -0.06595409, -0.40145169, -0.14376154])
```

In [71]:
```
np.r_[arparams[:p],maparams[:q]]
```

Out[71]:
```
array([-0.4 ,  0.6 ,  0.15, -0.1 ,  0.3 ])
```

Conclusion: **It's not satisfactory here!! And I don't know how to detect and diagnosis it!** Maybe MA algorithm rather than MLE is more suitable for parameters estimation in Time-Series analysis

d) 3 months observations

In [ ]:
```
autocorrelation_check(y_arma[:86],alpha=0.05)
```

In [63]:
```
(p,q),a = IdentifyOrderArma(y_arma[:86],6,6,'bic')
```

```
D:\Softwares\Anaconda3\envs\py36\lib\site-packages\statsmodels\base\model.py:466: ConvergenceWarning: Maximum L
ikelihood optimization failed to converge. Check mle_retvals
  "Check mle_retvals", ConvergenceWarning)
D:\Softwares\Anaconda3\envs\py36\lib\site-packages\statsmodels\base\model.py:466: ConvergenceWarning: Maximum L
ikelihood optimization failed to converge. Check mle_retvals
  "Check mle_retvals", ConvergenceWarning)
D:\Softwares\Anaconda3\envs\py36\lib\site-packages\statsmodels\base\model.py:466: ConvergenceWarning: Maximum L
ikelihood optimization failed to converge. Check mle_retvals
  "Check mle_retvals", ConvergenceWarning)
D:\Softwares\Anaconda3\envs\py36\lib\site-packages\statsmodels\base\model.py:466: ConvergenceWarning: Maximum L
ikelihood optimization failed to converge. Check mle_retvals
  "Check mle_retvals", ConvergenceWarning)
D:\Softwares\Anaconda3\envs\py36\lib\site-packages\statsmodels\base\model.py:466: ConvergenceWarning: Maximum L
ikelihood optimization failed to converge. Check mle_retvals
  "Check mle_retvals", ConvergenceWarning)
```

In [64]:
```
(p,q)
```

Out[64]:
```
(4, 1)
```

Based on BIC, we identify the order of the ARMA model as p=4, q=1

In [68]:
```
fitted_model= sm.tsa.ARMA(y_arma[:86],(4,1)).fit(trend='nc',method='css-mle')
```

In [70]:
```
fitted_model.params
```

Out[70]:
```
array([-0.16526793,  1.01796842,  0.15274868, -0.35785296,  0.06873086])
```

In [72]:
```
np.r_[arparams[:p],maparams[:q]]
```

Out[72]:
```
array([-0.4 ,  0.6 ,  0.15, -0.1 ,  0.3 ])
```

Conclusion: **It's not satisfactory here!! And I don't know how to detect and diagnosis it!** Maybe MA algorithm rather than MLE is more suitable for parameters estimation in Time-Series analysis

Why even the data from ARMA model itself fits bad?

4. Stock Returns (10 Points) Download the past 4 years of daily prices of a stock of your choice. Compute the time series of continuously compounded returns (log returns) rt, and find the best ARMA model for rt. To help you determine the order you may use ACF, PACF, EACF, as well as any information criteria measures (e.g., AIC, BIC, etc.). You need to be able to explain what you are doing (and why).

In [73]:
```
import numpy as np
import pandas as pd
import scipy as sp
import matplotlib.pyplot as plt
```

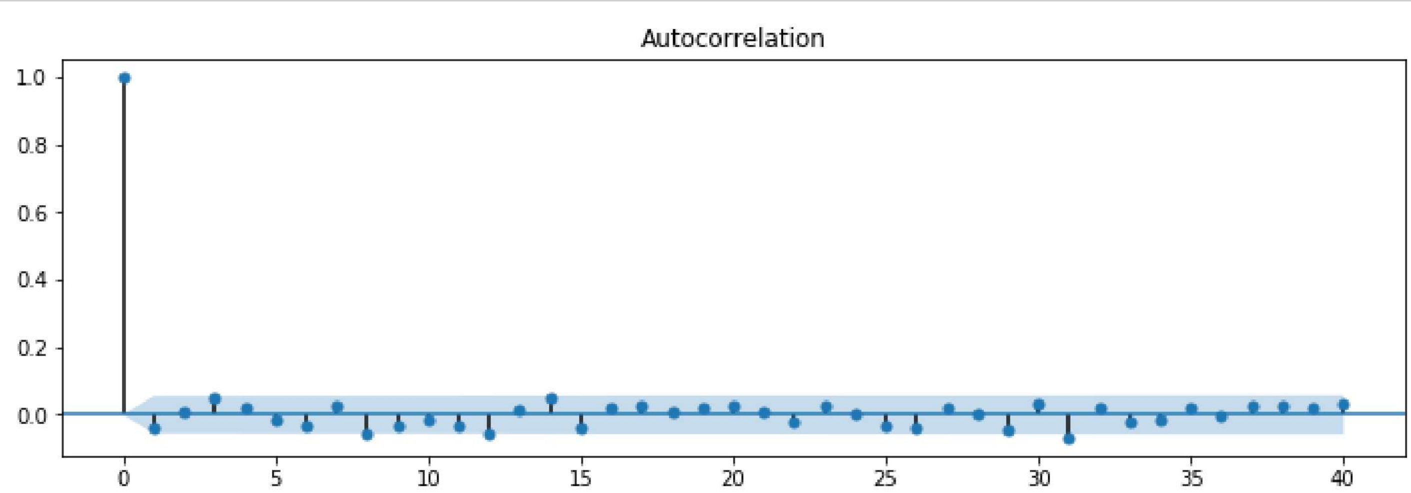
In [74]:
```
import datetime
def preprocess_wrds_data(df):
    df['date'] = df['date'].apply(lambda x: datetime.datetime.strptime(str(x),"%Y%m%d"))
#     print(df.head())
    df.index = df.date
    df.drop(['date'],axis=1,inplace=True)
    df['simple_return'] = (df.PRC-df.PRC.shift(1))/df.PRC.shift(1)
    df['log_return'] = np.log(df.PRC/df.PRC.shift(1))
#     spdf = df.totval
#     print(spdf.head())
```

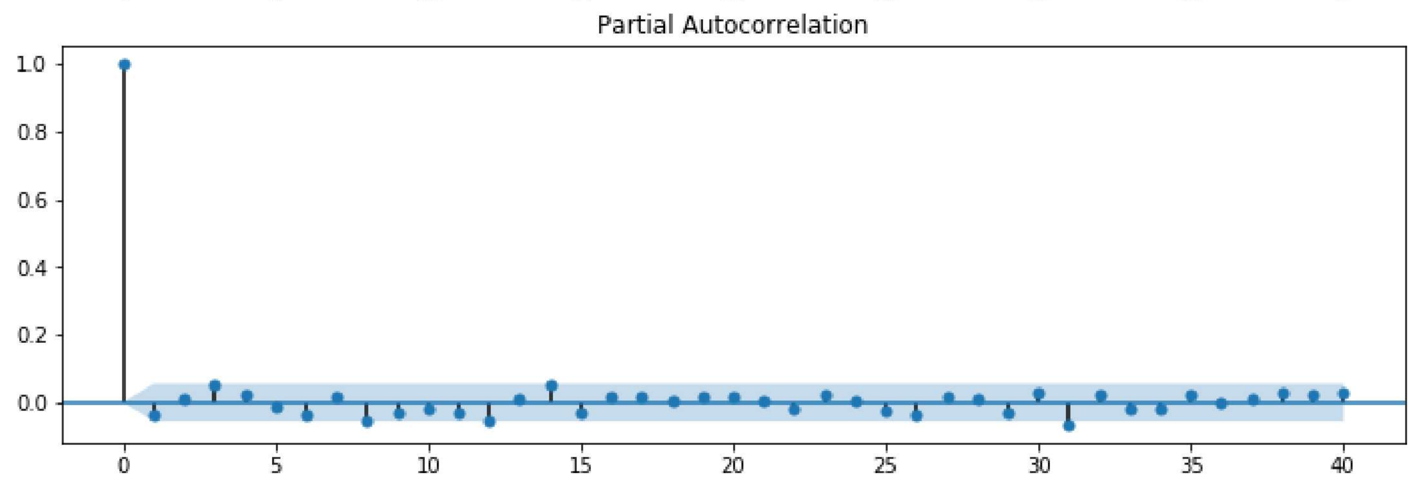
In [75]:
```
df_5y_d = pd.read_csv("NVDA_5yr_d.csv")
preprocess_wrds_data(df_5y_d)
print(df_5y_d.head())
```

```
            PERMNO      PRC      RETX    sprtrn  simple_return  log_return
date
2013-01-02   86580  12.7200  0.037520  0.025403            NaN         NaN
2013-01-03   86580  12.7300  0.000786 -0.002086       0.000786    0.000786
2013-01-04   86580  13.1500  0.032993  0.004865       0.032993    0.032460
2013-01-07   86580  12.7700 -0.028897 -0.003123      -0.028897   -0.029323
2013-01-08   86580  12.4915 -0.021809 -0.003242      -0.021809   -0.022050
```

In [76]:
```
df_5y_d.log_return.dropna(axis=0,inplace=True)
```

In [77]:
```
autocorrelation_check(df_5y_d.log_return,0.05)
```





In [78]:
```
(p,q),a = IdentifyOrderArma(df_5y_d.log_return,6,6,'bic')
```

```
D:\Softwares\Anaconda3\envs\py36\lib\site-packages\statsmodels\base\model.py:466: ConvergenceWarning: Maximum L
ikelihood optimization failed to converge. Check mle_retvals
  "Check mle_retvals", ConvergenceWarning)
D:\Softwares\Anaconda3\envs\py36\lib\site-packages\statsmodels\base\model.py:466: ConvergenceWarning: Maximum L
ikelihood optimization failed to converge. Check mle_retvals
  "Check mle_retvals", ConvergenceWarning)
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  "Check mle_retvals", ConvergenceWarning)
D:\Softwares\Anaconda3\envs\py36\lib\site-packages\statsmodels\base\model.py:466: ConvergenceWarning: Maximum L
ikelihood optimization failed to converge. Check mle_retvals
  "Check mle_retvals", ConvergenceWarning)
```

In [79]:
```
(p,q)
```

Out[79]:
```
(4, 1)
```

In [80]:
```
a
```

Out[80]:
```
array([[ -906.64836344,            nan,            nan, -1652.38051864,
        -1663.24933625, -1699.06588836],
       [-1552.3749238 , -1689.96551374, -1686.22070277, -1700.05508891,
        -1693.50912559, -1696.6786516 ],
       [-1603.67616928, -1692.14049136, -1687.3753953 , -1698.15617666,
        -1696.15441697, -1689.91585993],
       [-1713.28756199, -1706.48672659, -1705.67468947, -1698.75919968,
        -1693.17735066, -1686.37834276],
       [-1706.39578396, -1700.28694541, -1698.75907146, -1691.88173754,
        -1686.31702426, -1683.32174278],
       [-1704.90872236, -1704.90294854, -1698.38071441, -1691.56424779,
        -1679.12004002, -1680.37071466]])
```

> Conclusion: Based on minimum BIC, p=4,q=1

In [81]:
```
model = sm.tsa.ARMA(df_5y_d.log_return,(4,1)).fit(trend='nc')
```

In [82]:
```
model.params
```

Out[82]:
```
ar.L1.log_return   -0.070733
ar.L2.log_return    0.018167
ar.L3.log_return    0.063562
ar.L4.log_return    0.037017
ma.L1.log_return    0.041197
dtype: float64
```

In [83]:
```
model.summary()
```

Out[83]:

ARMA Model Results

Dep. Variable:	log_return	No. Observations:	1258
Model:	ARMA(4, 1)	Log Likelihood	3044.625
Method:	css-mle	S.D. of innovations	0.022
Date:	Thu, 15 Mar 2018	AIC	-6077.249
Time:	18:54:41	BIC	-6046.426
Sample:	01-03-2013	HQIC	-6065.665
	- 12-29-2017		

	coef	std err	z	P>|z|	[95.0% Conf. Int.]
ar.L1.log_return	-0.0707	0.484	-0.146	0.884	-1.019 0.877
ar.L2.log_return	0.0182	0.031	0.583	0.560	-0.043 0.079
ar.L3.log_return	0.0636	0.030	2.132	0.033	0.005 0.122
ar.L4.log_return	0.0370	0.041	0.913	0.362	-0.042 0.117
ma.L1.log_return	0.0412	0.484	0.085	0.932	-0.906 0.989

1.9834 -0.0000j 1.9834 -0.0000 -0.5121 -2.1970j 2.2559 -0.2864 -0.5121 +2.1970j 2.2559 0.2864 -2.6763 -0.0000j 2.6763 -0.5000 -24.2734 +0.0000j 24.2734 0.5000

Roots

	Real	Imaginary	Modulus	Frequency
AR.1				
AR.2				
AR.3				
AR.4				
MA.1				

Nevertheless, the std err are too large for our model parameters.

Question: How to handle it in financial data? Change model? What does the suitable std err look like?

In [ ]: