CIVE_Homework6_Q45

March 29, 2022

1 Question 4-

You are provided with daily annual rainfall in Boston for 65 years (1950-2014). Calculate monthly mean of the dataset. Use 50 years of data for training (using ARIMA process) and predict the Precipitation of Boston for the last 15 years. Report performance measure (MSE).
Try box-cox transformation where =2 and predict again. Retransform the dataset to initial form of the time series and find out the performance measure (MSE).

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

ts = pd.read_csv('/content/data_Precipitation.csv', index_col = 'Date',␣
↪usecols=['Date','Precipitation'], parse_dates = True)
ts.head()
```

[1]:
```
            Precipitation
Date
1950-01-01       0.005900
1950-01-02       0.057000
1950-01-03       4.413605
1950-01-04      27.583983
1950-01-05       1.988475
```

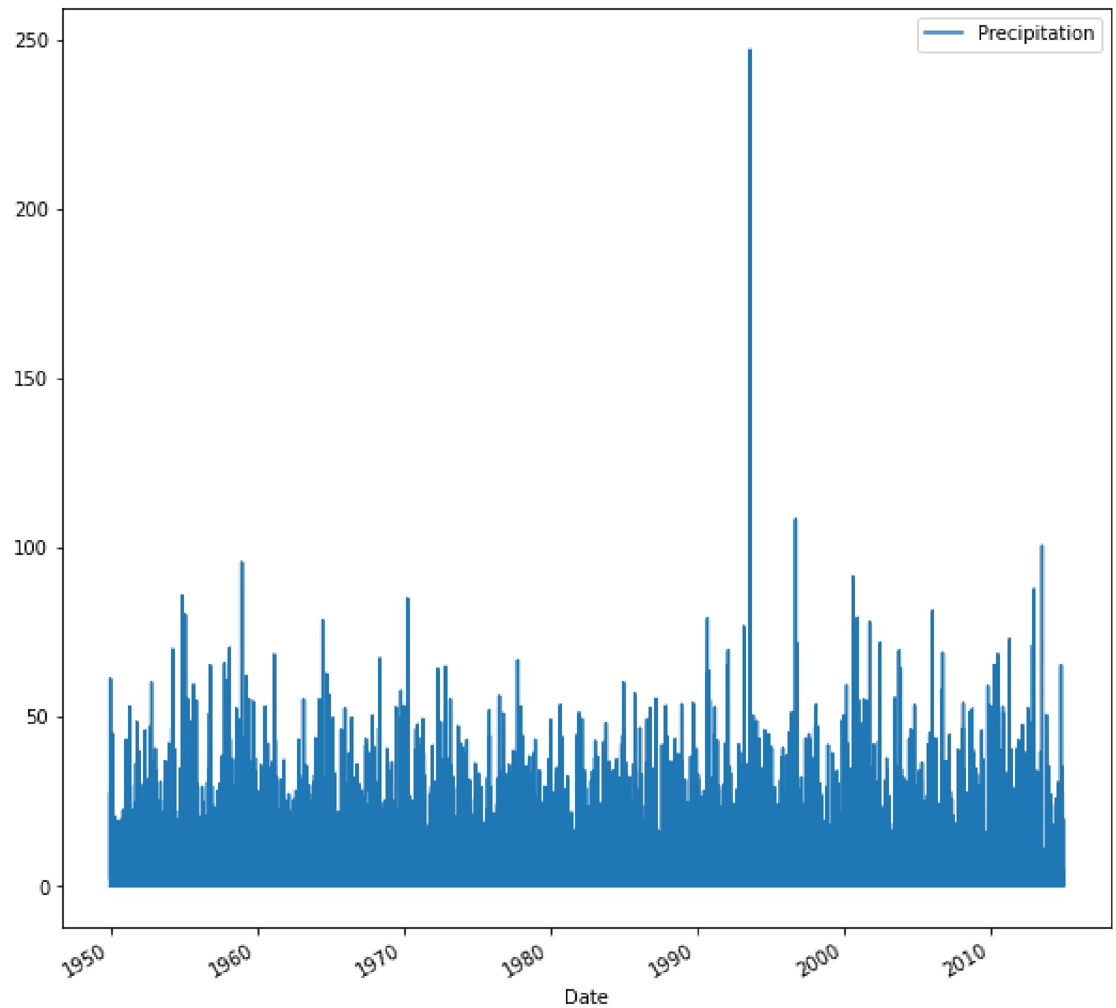
monthly mean

[2]:
```
mm = pd.read_csv('/content/data_Precipitation.csv')
mm['Date'] = pd.to_datetime(mm['Date'])
mm.resample('M', on='Date').mean()
```

[2]:
```
            Precipitation
Date
1950-01-31       7.474498
1950-02-28       4.236547
1950-03-31       2.909981
1950-04-30       3.584058
1950-05-31       2.503505
…                     …
```

```
2014-08-31       2.246686
2014-09-30       2.606470
2014-10-31       6.045129
2014-11-30       5.069574
2014-12-31       3.551625

[780 rows x 1 columns]
```

[3]:
```
#plotting my data
ts.plot(figsize=(10,10))
plt.show()
```



[4]:
```
#checking if data is stationary
from statsmodels.tsa.stattools import adfuller
results = adfuller(ts['Precipitation'])
```

```python
print(results[0])
print('P value is:', results[1])
```

```
-108.39772634860783
P value is: 0.0
```

2 the above data is stationary

[5]:
```python
!pip install pmdarima
```

```
Requirement already satisfied: pmdarima in /usr/local/lib/python3.7/dist-
packages (1.8.5)
Requirement already satisfied: pandas>=0.19 in /usr/local/lib/python3.7/dist-
packages (from pmdarima) (1.3.5)
Requirement already satisfied: statsmodels!=0.12.0,>=0.11 in
/usr/local/lib/python3.7/dist-packages (from pmdarima) (0.13.2)
Requirement already satisfied: scikit-learn>=0.22 in
/usr/local/lib/python3.7/dist-packages (from pmdarima) (1.0.2)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.7/dist-
packages (from pmdarima) (1.1.0)
Requirement already satisfied: scipy>=1.3.2 in /usr/local/lib/python3.7/dist-
packages (from pmdarima) (1.4.1)
Requirement already satisfied: urllib3 in /usr/local/lib/python3.7/dist-packages
(from pmdarima) (1.24.3)
Requirement already satisfied: setuptools!=50.0.0,>=38.6.0 in
/usr/local/lib/python3.7/dist-packages (from pmdarima) (57.4.0)
Requirement already satisfied: numpy>=1.19.3 in /usr/local/lib/python3.7/dist-
packages (from pmdarima) (1.21.5)
Requirement already satisfied: Cython!=0.29.18,>=0.29 in
/usr/local/lib/python3.7/dist-packages (from pmdarima) (0.29.28)
Requirement already satisfied: pytz>=2017.3 in /usr/local/lib/python3.7/dist-
packages (from pandas>=0.19->pmdarima) (2018.9)
Requirement already satisfied: python-dateutil>=2.7.3 in
/usr/local/lib/python3.7/dist-packages (from pandas>=0.19->pmdarima) (2.8.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/dist-
packages (from python-dateutil>=2.7.3->pandas>=0.19->pmdarima) (1.15.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.7/dist-packages (from scikit-learn>=0.22->pmdarima)
(3.1.0)
Requirement already satisfied: packaging>=21.3 in /usr/local/lib/python3.7/dist-
packages (from statsmodels!=0.12.0,>=0.11->pmdarima) (21.3)
Requirement already satisfied: patsy>=0.5.2 in /usr/local/lib/python3.7/dist-
packages (from statsmodels!=0.12.0,>=0.11->pmdarima) (0.5.2)
Requirement already satisfied: pyparsing!=3.0.5,>=2.0.2 in
/usr/local/lib/python3.7/dist-packages (from
packaging>=21.3->statsmodels!=0.12.0,>=0.11->pmdarima) (3.0.7)
```

[6]:
```
from pmdarima import auto_arima
import warnings
warnings.filterwarnings('ignore')

Wise_fit = auto_arima(ts['Precipitation'], trace = True, suppress_warnings=True)
```

```
Performing stepwise search to minimize aic
 ARIMA(2,0,2)(0,0,0)[0] intercept   : AIC=167418.179, Time=20.06 sec
 ARIMA(0,0,0)(0,0,0)[0] intercept   : AIC=167799.476, Time=1.29 sec
 ARIMA(1,0,0)(0,0,0)[0] intercept   : AIC=167488.572, Time=1.50 sec
 ARIMA(0,0,1)(0,0,0)[0] intercept   : AIC=167455.838, Time=6.76 sec
 ARIMA(0,0,0)(0,0,0)[0]             : AIC=172002.343, Time=0.54 sec
 ARIMA(1,0,2)(0,0,0)[0] intercept   : AIC=167418.717, Time=24.50 sec
 ARIMA(2,0,1)(0,0,0)[0] intercept   : AIC=167416.599, Time=14.49 sec
 ARIMA(1,0,1)(0,0,0)[0] intercept   : AIC=167431.898, Time=13.21 sec
 ARIMA(2,0,0)(0,0,0)[0] intercept   : AIC=167415.898, Time=1.33 sec
 ARIMA(3,0,0)(0,0,0)[0] intercept   : AIC=167416.453, Time=3.06 sec
 ARIMA(3,0,1)(0,0,0)[0] intercept   : AIC=167418.447, Time=9.84 sec
 ARIMA(2,0,0)(0,0,0)[0]             : AIC=170268.896, Time=0.59 sec

Best model:  ARIMA(2,0,0)(0,0,0)[0] intercept
Total fit time: 97.209 seconds
```

[7]:
```
df2 = pd.read_csv('/content/data_Precipitation.csv')
df2['Date'] = pd.to_datetime(df2['Date'])
```

[8]:
```
#Splitting into train and test
train = df2.loc[df2['Date'] <= '1999-12-31']
test = df2.loc[df2['Date']>= '2000-01-01']
```

[9]:
```
from statsmodels.tsa.arima.model import ARIMA
model_train = ARIMA(train['Precipitation'], order = (2,0,0))
model_train = model_train.fit()
```

[10]:
```
model_train.summary()
```

[10]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                               SARIMAX Results
==============================================================================
Dep. Variable:          Precipitation   No. Observations:                18250
Model:                 ARIMA(2, 0, 0)   Log Likelihood              -64178.035
Date:                Tue, 29 Mar 2022   AIC                         128364.070
Time:                        00:16:21   BIC                         128395.318
Sample:                             0   HQIC                        128374.339
                              - 18250
Covariance Type:                  opg
```

```
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const          3.6417      0.088     41.593      0.000       3.470       3.813
ar.L1          0.1283      0.005     24.032      0.000       0.118       0.139
ar.L2         -0.0541      0.007     -8.026      0.000      -0.067      -0.041
sigma2        66.3814      0.185    359.510      0.000      66.020      66.743
================================================================================
===
Ljung-Box (L1) (Q):                   0.01   Jarque-Bera (JB):
2719339.23
Prob(Q):                              0.92   Prob(JB):
0.00
Heteroskedasticity (H):               1.12   Skew:
4.86
Prob(H) (two-sided):                  0.00   Kurtosis:
62.01
================================================================================
===

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

[11]:
```
test.head()
```

[11]:
```
             Date  Precipitation
18250  2000-01-01       0.000046
18251  2000-01-02       5.651877
18252  2000-01-03       7.189747
18253  2000-01-04       0.971326
18254  2000-01-05      50.309398
```

[12]:
```
#testing part
import datetime
start = len(train)

end = len(train)+len(test)-1
test['forecast']= model_train.predict( start=start, end=end, dynamic=False)
#test[['Precipitation','forecast']].plot(figsize=(12,8))
```

[13]:
```
test.head()
```

[13]:
```
             Date  Precipitation  forecast
18250  2000-01-01       0.000046  2.625337
18251  2000-01-02       5.651877  3.708418
```

```
18252 2000-01-03       7.189747  3.705288
18253 2000-01-04       0.971326  3.646247
18254 2000-01-05      50.309398  3.638839
```

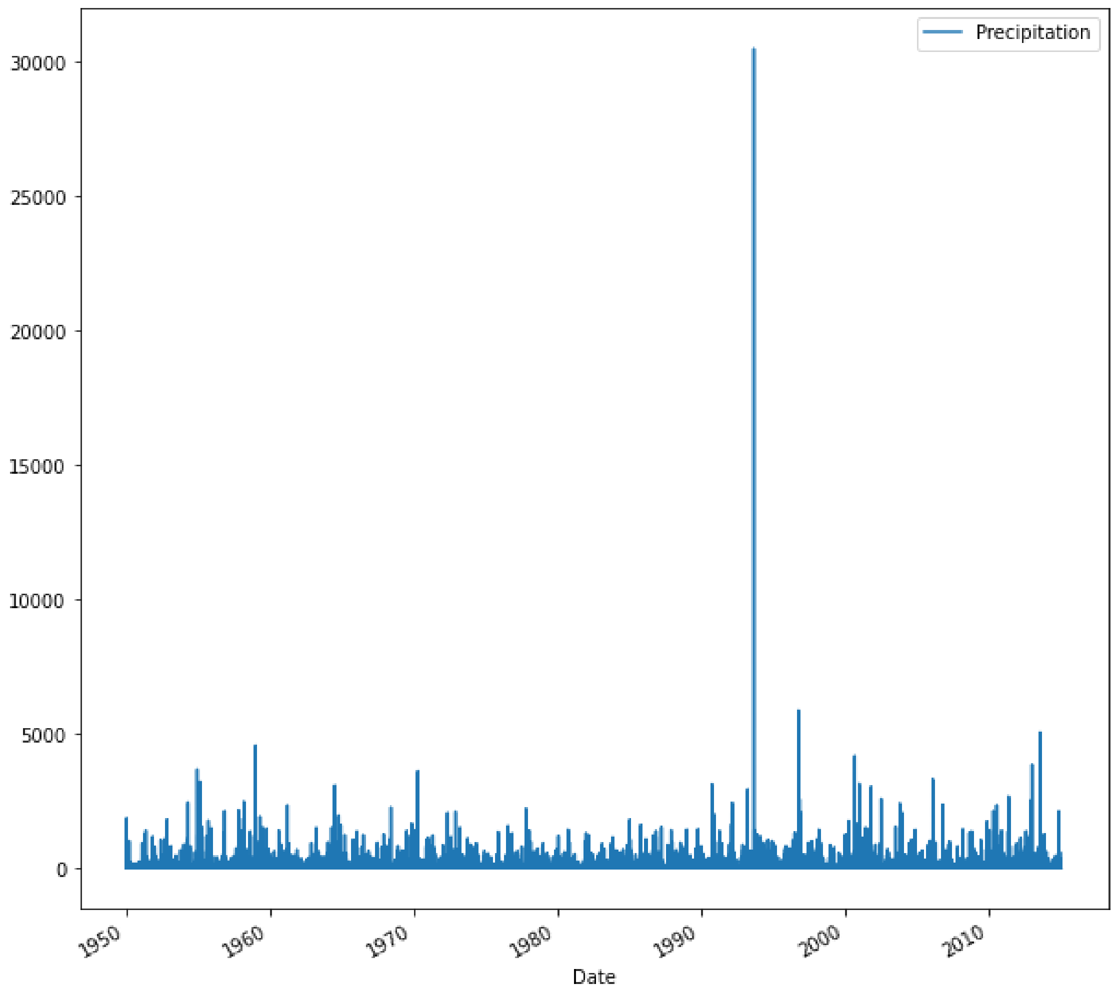
[37]:
```python
from sklearn.metrics import mean_squared_error

print('MSE without using the boxcox transform:',mean_squared_error(test1.
 ↪Precipitation, test1.forecast))
```

```
MSE without using the boxcox transform: 73.91905514465313
```

3 uisng boxcox transformation

[16]:
```python
from scipy.stats import boxcox
df_pos = ts.loc[ts['Precipitation'] > 0]
df_pos['Precipitation'] = boxcox(df_pos['Precipitation'], lmbda=2)
```

[17]:
```python
#plotting my data
df_pos.plot(figsize=(10,10))
plt.show()
```



[18]:
```
#checking if data is stationary
from statsmodels.tsa.stattools import adfuller
results = adfuller(df_pos['Precipitation'])
print(results[0])
print('P value is:', results[1])
```

```
-54.96325537226066
P value is: 0.0
```

[19]:
```
from pmdarima import auto_arima
import warnings
warnings.filterwarnings('ignore')

good_fit = auto_arima(df_pos['Precipitation'], trace = True,␣
↪suppress_warnings=True)
```

```
Performing stepwise search to minimize aic
```

```
ARIMA(2,0,2)(0,0,0)[0] intercept   : AIC=313999.568, Time=8.44 sec
ARIMA(0,0,0)(0,0,0)[0] intercept   : AIC=314019.859, Time=1.15 sec
ARIMA(1,0,0)(0,0,0)[0] intercept   : AIC=313993.856, Time=1.34 sec
ARIMA(0,0,1)(0,0,0)[0] intercept   : AIC=313994.401, Time=2.88 sec
ARIMA(0,0,0)(0,0,0)[0]             : AIC=314560.038, Time=0.92 sec
ARIMA(2,0,0)(0,0,0)[0] intercept   : AIC=313995.844, Time=2.04 sec
ARIMA(1,0,1)(0,0,0)[0] intercept   : AIC=313995.853, Time=7.58 sec
ARIMA(2,0,1)(0,0,0)[0] intercept   : AIC=313997.845, Time=12.64 sec
ARIMA(1,0,0)(0,0,0)[0]             : AIC=314485.343, Time=0.32 sec

Best model:  ARIMA(1,0,0)(0,0,0)[0] intercept
Total fit time: 37.351 seconds
```

[20]:
```python
df3 = pd.read_csv('/content/data_Precipitation.csv')
df3['Date'] = pd.to_datetime(df3['Date'])

#Splitting into train and test
train1 = df3.loc[df3['Date'] <= '1999-12-31']
test1 = df3.loc[df3['Date']>= '2000-01-01']
```

[21]:
```python
from statsmodels.tsa.arima.model import ARIMA
model_boxcox = ARIMA(train1['Precipitation'], order = (1,0,0))
model_boxcox = model_boxcox.fit()
model_boxcox.summary()
```

[21]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                               SARIMAX Results
==============================================================================
Dep. Variable:          Precipitation   No. Observations:                18250
Model:                 ARIMA(1, 0, 0)   Log Likelihood              -64204.834
Date:                Tue, 29 Mar 2022   AIC                         128415.668
Time:                        00:17:08   BIC                         128439.104
Sample:                             0   HQIC                        128423.370
                              - 18250
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const          3.6417      0.088     41.221      0.000       3.469       3.815
ar.L1          0.1217      0.005     23.079      0.000       0.111       0.132
sigma2        66.5739      0.170    392.136      0.000      66.241      66.907
================================================================================
===
Ljung-Box (L1) (Q):                   0.79   Jarque-Bera (JB):
2625661.25
Prob(Q):                              0.37   Prob(JB):
```

```
0.00
Heteroskedasticity (H):                1.12   Skew:
4.84
Prob(H) (two-sided):                   0.00   Kurtosis:
60.96
================================================================================
===

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

[22]:
```
#testing part
import datetime
start = len(train1)

end = len(train1)+len(test1)-1
test1['forecast']= model_boxcox.predict( start=start, end=end, dynamic=False)
```

[23]:
```
test1.head()
```

[23]:

	Date	Precipitation	forecast
18250	2000-01-01	0.000046	3.198375
18251	2000-01-02	5.651877	3.587729
18252	2000-01-03	7.189747	3.635129
18253	2000-01-04	0.971326	3.640900
18254	2000-01-05	50.309398	3.641602

[36]:
```
from sklearn.metrics import mean_squared_error

print('MSE using the boxcox transform:',mean_squared_error(test1.Precipitation,␣
 ↪test1.forecast))
```

```
MSE using the boxcox transform: 73.91905514465313
```

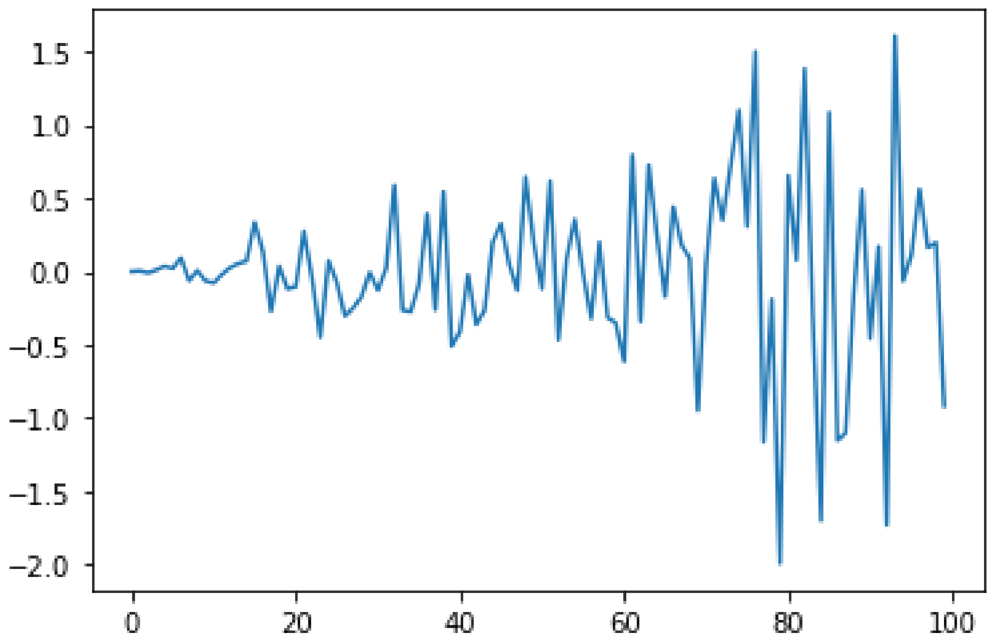
4 The boxcox transform hasn't made the MSE any better. Boxcox transforms do not always yield a better MSE. Probably a log transform could have worked better in our case.

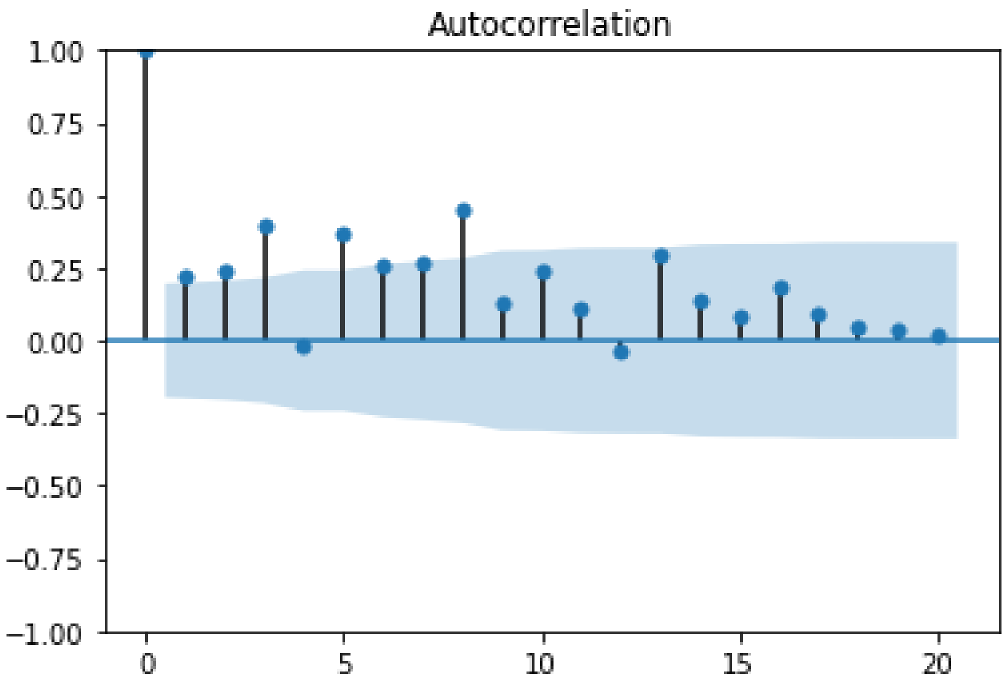
5 Question 5-

Simulate Model variance with ARCH and GARCH for Time Series Forecasting. Consider a time series of random noise where the mean is zero and the variance starts at 0.0 and steadily increases.

[26]:

```
from random import gauss
from random import seed
import numpy as np
import matplotlib.pyplot as plt
from statsmodels.graphics.tsaplots import plot_acf

#set seed
seed(4)
df = [gauss(0,i*0.01) for i in range (0, 100)]
df_sq = [ x**2 for x in df]

#plot the data
plt.plot(df)
plt.show()

#plot acf
plot_acf(np.asarray(df_sq))
plt.show()
```





significant positive correlatin till lag 15.

[27]:
```
#train, test split
n_test = 10
train, test = df[:-n_test], df[-n_test:]
```

[28]:
```
!pip install arch
```

```
Collecting arch
  Downloading
arch-5.1.0-cp37-cp37m-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (902 kB)
     |                  | 902 kB 5.3 MB/s
Requirement already satisfied: scipy>=1.3 in
/usr/local/lib/python3.7/dist-packages (from arch) (1.4.1)
Requirement already satisfied: statsmodels>=0.11 in
/usr/local/lib/python3.7/dist-packages (from arch) (0.13.2)
Requirement already satisfied: numpy>=1.17 in /usr/local/lib/python3.7/dist-
packages (from arch) (1.21.5)
Collecting property-cached>=1.6.4
  Downloading property_cached-1.6.4-py2.py3-none-any.whl (7.8 kB)
Requirement already satisfied: pandas>=1.0 in /usr/local/lib/python3.7/dist-
packages (from arch) (1.3.5)
Requirement already satisfied: pytz>=2017.3 in /usr/local/lib/python3.7/dist-
packages (from pandas>=1.0->arch) (2018.9)
Requirement already satisfied: python-dateutil>=2.7.3 in
```

```
/usr/local/lib/python3.7/dist-packages (from pandas>=1.0->arch) (2.8.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/dist-
packages (from python-dateutil>=2.7.3->pandas>=1.0->arch) (1.15.0)
Requirement already satisfied: patsy>=0.5.2 in /usr/local/lib/python3.7/dist-
packages (from statsmodels>=0.11->arch) (0.5.2)
Requirement already satisfied: packaging>=21.3 in /usr/local/lib/python3.7/dist-
packages (from statsmodels>=0.11->arch) (21.3)
Requirement already satisfied: pyparsing!=3.0.5,>=2.0.2 in
/usr/local/lib/python3.7/dist-packages (from
packaging>=21.3->statsmodels>=0.11->arch) (3.0.7)
Installing collected packages: property-cached, arch
Successfully installed arch-5.1.0 property-cached-1.6.4
```

[29]:
```python
import arch
from arch import arch_model
model = arch_model(train, mean='Zero', vol ='ARCH', p = 15)
```

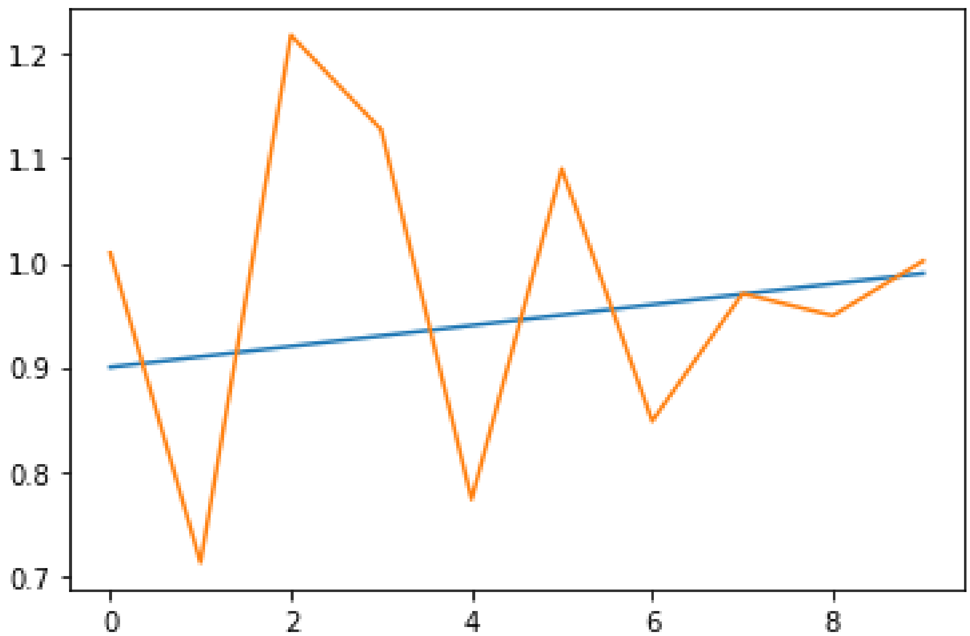
[30]:
```python
modelfit = model.fit()
```

```
Iteration:      1,   Func. Count:     18,   Neg. LLF: 41.504522451939415
Iteration:      2,   Func. Count:     37,   Neg. LLF: 39.84160048057239
Iteration:      3,   Func. Count:     56,   Neg. LLF: 38.86152368289243
Iteration:      4,   Func. Count:     75,   Neg. LLF: 38.168837835452294
Iteration:      5,   Func. Count:     94,   Neg. LLF: 37.359456060716816
Iteration:      6,   Func. Count:    113,   Neg. LLF: 36.916153438658235
Iteration:      7,   Func. Count:    132,   Neg. LLF: 36.62927642773087
Iteration:      8,   Func. Count:    150,   Neg. LLF: 35.61568157968252
Iteration:      9,   Func. Count:    169,   Neg. LLF: 35.38236084253256
Iteration:     10,   Func. Count:    188,   Neg. LLF: 34.976965684955985
Iteration:     11,   Func. Count:    207,   Neg. LLF: 34.77947643918447
Iteration:     12,   Func. Count:    226,   Neg. LLF: 34.636329032030794
Iteration:     13,   Func. Count:    245,   Neg. LLF: 34.471421979520954
Iteration:     14,   Func. Count:    264,   Neg. LLF: 34.42026461625432
Iteration:     15,   Func. Count:    283,   Neg. LLF: 34.392186193914
Iteration:     16,   Func. Count:    302,   Neg. LLF: 34.36862004978023
Iteration:     17,   Func. Count:    320,   Neg. LLF: 34.364987911329905
Iteration:     18,   Func. Count:    338,   Neg. LLF: 34.36367196211154
Iteration:     19,   Func. Count:    356,   Neg. LLF: 34.36340962881595
Iteration:     20,   Func. Count:    374,   Neg. LLF: 34.363378087592224
Iteration:     21,   Func. Count:    392,   Neg. LLF: 34.363374904072806
Optimization terminated successfully.    (Exit mode 0)
            Current function value: 34.36337484867552
            Iterations: 21
            Function evaluations: 392
            Gradient evaluations: 21
```

[31]:
```
#making predictions
pred = modelfit.forecast(horizon= n_test)
```

6 Plot using ARCH model

[32]:
```
#plotting variance and predicted variance

var = [i*0.01 for i in range(0,100)]
plt.plot(var[-n_test:])
#plt.show()
plt.plot(pred.variance.values[-1, :])
plt.show()
```



[33]:
```
#For the GARCH model
garch_model = arch_model(train, mean = 'Zero', vol = 'GARCH', p = 15)
garchfit = garch_model.fit()
```

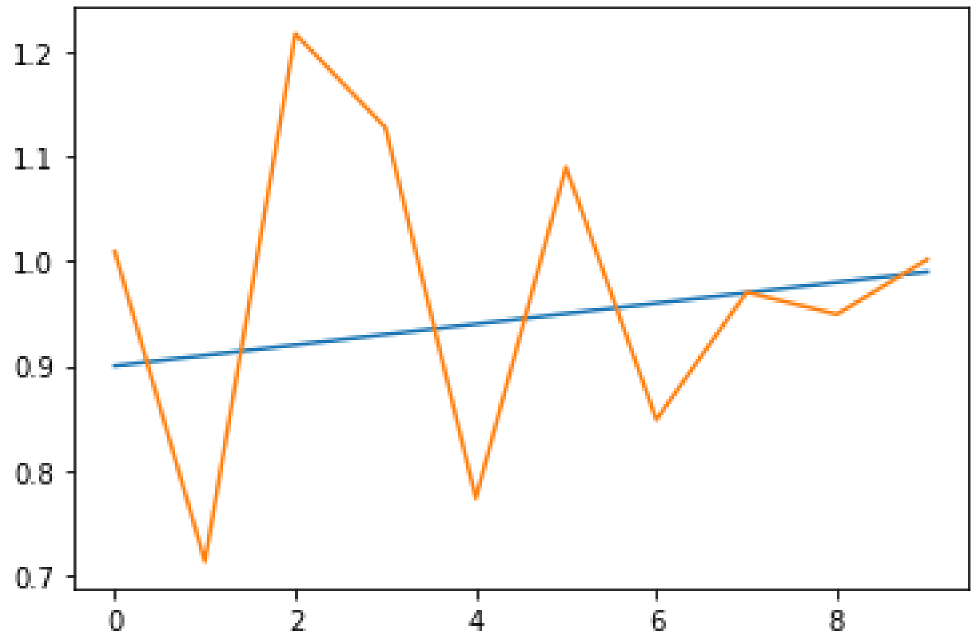
```
Iteration:      1,   Func. Count:     19,   Neg. LLF: 43.295844959877854
Iteration:      2,   Func. Count:     44,   Neg. LLF: 43.243747831930406
Iteration:      3,   Func. Count:     64,   Neg. LLF: 38.99409977757669
Iteration:      4,   Func. Count:     84,   Neg. LLF: 38.219348236710395
Iteration:      5,   Func. Count:    104,   Neg. LLF: 37.77063814140541
Iteration:      6,   Func. Count:    124,   Neg. LLF: 36.85448822464735
Iteration:      7,   Func. Count:    144,   Neg. LLF: 36.28818440487556
```

```
Iteration:      8,   Func. Count:    164,   Neg. LLF: 36.018309596460604
Iteration:      9,   Func. Count:    184,   Neg. LLF: 35.83299193687124
Iteration:     10,   Func. Count:    204,   Neg. LLF: 35.72128260333963
Iteration:     11,   Func. Count:    224,   Neg. LLF: 35.24655924885105
Iteration:     12,   Func. Count:    244,   Neg. LLF: 35.0392646130409
Iteration:     13,   Func. Count:    264,   Neg. LLF: 34.84989174046595
Iteration:     14,   Func. Count:    284,   Neg. LLF: 34.713980500093484
Iteration:     15,   Func. Count:    303,   Neg. LLF: 34.442002549444915
Iteration:     16,   Func. Count:    322,   Neg. LLF: 34.37225246057246
Iteration:     17,   Func. Count:    342,   Neg. LLF: 34.36782095082328
Iteration:     18,   Func. Count:    361,   Neg. LLF: 34.36464767933175
Iteration:     19,   Func. Count:    380,   Neg. LLF: 34.36346035724202
Iteration:     20,   Func. Count:    399,   Neg. LLF: 34.36338081608357
Iteration:     21,   Func. Count:    418,   Neg. LLF: 34.36337487879584
Optimization terminated successfully.    (Exit mode 0)
            Current function value: 34.36337490653557
            Iterations: 21
            Function evaluations: 418
            Gradient evaluations: 21
```

[34]:
```
pred1 = garchfit.forecast(horizon = n_test)
```

7 Plot using GARCH model

[35]:
```
#plotting variance and predicted variance

var1 = [i*0.01 for i in range(0,100)]
plt.plot(var1[-n_test:])
#plt.show()
plt.plot(pred1.variance.values[-1, :])
plt.show()
```



[38]:
```
!jupyter nbconvert --to pdf /content/CIVE_Homework6_Q4&5.ipynb
```

```
/bin/bash: 5.ipynb: command not found
[NbConvertApp] WARNING | pattern '/content/CIVE_Homework6_Q4' matched no files
This application is used to convert notebook files (*.ipynb)
        to various other formats.

        WARNING: THE COMMANDLINE INTERFACE MAY CHANGE IN FUTURE RELEASES.

Options
=======
The options below are convenience aliases to configurable class-options,
as listed in the "Equivalent to" description-line of the aliases.
To see all configurable class-options for some <cmd>, use:
    <cmd> --help-all

--debug
    set log level to logging.DEBUG (maximize logging output)
    Equivalent to: [--Application.log_level=10]
--show-config
    Show the application's configuration (human-readable format)
    Equivalent to: [--Application.show_config=True]
--show-config-json
    Show the application's configuration (json format)
    Equivalent to: [--Application.show_config_json=True]
--generate-config
```

```
    generate default config file
    Equivalent to: [--JupyterApp.generate_config=True]
-y
    Answer yes to any questions instead of prompting.
    Equivalent to: [--JupyterApp.answer_yes=True]
--execute
    Execute the notebook prior to export.
    Equivalent to: [--ExecutePreprocessor.enabled=True]
--allow-errors
    Continue notebook execution even if one of the cells throws an error and
include the error message in the cell output (the default behaviour is to abort
conversion). This flag is only relevant if '--execute' was specified, too.
    Equivalent to: [--ExecutePreprocessor.allow_errors=True]
--stdin
    read a single notebook file from stdin. Write the resulting notebook with
default basename 'notebook.*'
    Equivalent to: [--NbConvertApp.from_stdin=True]
--stdout
    Write notebook output to stdout instead of files.
    Equivalent to: [--NbConvertApp.writer_class=StdoutWriter]
--inplace
    Run nbconvert in place, overwriting the existing notebook (only
            relevant when converting to notebook format)
    Equivalent to: [--NbConvertApp.use_output_suffix=False
--NbConvertApp.export_format=notebook --FilesWriter.build_directory=]
--clear-output
    Clear output of current file and save in place,
            overwriting the existing notebook.
    Equivalent to: [--NbConvertApp.use_output_suffix=False
--NbConvertApp.export_format=notebook --FilesWriter.build_directory=
--ClearOutputPreprocessor.enabled=True]
--no-prompt
    Exclude input and output prompts from converted document.
    Equivalent to: [--TemplateExporter.exclude_input_prompt=True
--TemplateExporter.exclude_output_prompt=True]
--no-input
    Exclude input cells and output prompts from converted document.
            This mode is ideal for generating code-free reports.
    Equivalent to: [--TemplateExporter.exclude_output_prompt=True
--TemplateExporter.exclude_input=True]
--log-level=<Enum>
    Set the log level by value or name.
    Choices: any of [0, 10, 20, 30, 40, 50, 'DEBUG', 'INFO', 'WARN', 'ERROR',
'CRITICAL']
    Default: 30
    Equivalent to: [--Application.log_level]
--config=<Unicode>
    Full path of a config file.
```

```
    Default: ''
    Equivalent to: [--JupyterApp.config_file]
--to=<Unicode>
    The export format to be used, either one of the built-in formats
            ['asciidoc', 'custom', 'html', 'latex', 'markdown', 'notebook',
'pdf', 'python', 'rst', 'script', 'slides']
            or a dotted object name that represents the import path for an
            `Exporter` class
    Default: 'html'
    Equivalent to: [--NbConvertApp.export_format]
--template=<Unicode>
    Name of the template file to use
    Default: ''
    Equivalent to: [--TemplateExporter.template_file]
--writer=<DottedObjectName>
    Writer class used to write the
                                    results of the conversion
    Default: 'FilesWriter'
    Equivalent to: [--NbConvertApp.writer_class]
--post=<DottedOrNone>
    PostProcessor class used to write the
                                    results of the conversion
    Default: ''
    Equivalent to: [--NbConvertApp.postprocessor_class]
--output=<Unicode>
    overwrite base name use for output files.
                can only be used when converting one notebook at a time.
    Default: ''
    Equivalent to: [--NbConvertApp.output_base]
--output-dir=<Unicode>
    Directory to write output(s) to. Defaults
                                  to output to the directory of each notebook.
To recover
                                  previous default behaviour (outputting to the
current
                                  working directory) use . as the flag value.
    Default: ''
    Equivalent to: [--FilesWriter.build_directory]
--reveal-prefix=<Unicode>
    The URL prefix for reveal.js (version 3.x).
            This defaults to the reveal CDN, but can be any url pointing to a
copy
            of reveal.js.
            For speaker notes to work, this must be a relative path to a local
            copy of reveal.js: e.g., "reveal.js".
            If a relative path is given, it must be a subdirectory of the
            current directory (from which the server is run).
            See the usage documentation
```

```
            (https://nbconvert.readthedocs.io/en/latest/usage.html#reveal-js-
html-slideshow)
            for more details.
    Default: ''
    Equivalent to: [--SlidesExporter.reveal_url_prefix]
--nbformat=<Enum>
    The nbformat version to write.
            Use this to downgrade notebooks.
    Choices: any of [1, 2, 3, 4]
    Default: 4
    Equivalent to: [--NotebookExporter.nbformat_version]

Examples
--------

    The simplest way to use nbconvert is

            > jupyter nbconvert mynotebook.ipynb

            which will convert mynotebook.ipynb to the default format (probably
HTML).

            You can specify the export format with `--to`.
            Options include ['asciidoc', 'custom', 'html', 'latex', 'markdown',
'notebook', 'pdf', 'python', 'rst', 'script', 'slides'].

            > jupyter nbconvert --to latex mynotebook.ipynb

            Both HTML and LaTeX support multiple output templates. LaTeX
includes
            'base', 'article' and 'report'.  HTML includes 'basic' and 'full'.
You
            can specify the flavor of the format used.

            > jupyter nbconvert --to html --template basic mynotebook.ipynb

            You can also pipe the output to stdout, rather than a file

            > jupyter nbconvert mynotebook.ipynb --stdout

            PDF is generated via latex

            > jupyter nbconvert mynotebook.ipynb --to pdf

            You can get (and serve) a Reveal.js-powered slideshow

            > jupyter nbconvert myslides.ipynb --to slides --post serve
```

```
            Multiple notebooks can be given at the command line in a couple of
            different ways:

            > jupyter nbconvert notebook*.ipynb
            > jupyter nbconvert notebook1.ipynb notebook2.ipynb

            or you can specify the notebooks list in a config file, containing::

                c.NbConvertApp.notebooks = ["my_notebook.ipynb"]

            > jupyter nbconvert --config mycfg.py

To see all available configurables, use `--help-all`.
```