Workshop 7: Time Series (25pts)

~~Task 1: Loading the data – 5 pts~~

In this part, you will load the data from the file *volume_per_year.csv*. There are dates and market volume across the years. You can load this file into the variable *volume*.

```
print (volume.head())
     Month  volume
0  1949-01   22400
1  1949-02   23600
2  1949-03   26400
3  1949-04   25800
4  1949-05   24200
```

Be aware, when you load a file, the dates are loaded as strings. You will need to use *read_cvs* wisely.

Task 2: Stationarity – 5 pts

A common assumption in many time series techniques is that the data are stationary. 平稳的

A stationary process has the property that the mean, variance and autocorrelation structure do not change over time.

Questions:

~~A- Plot the volume across the years.~~ 画出数据图

~~B- What do you deduce from the plot?~~ 从数据图里可以推断出什么

C- Testing stationarity 检验平稳性

To test stationarity, we can use the Dickey-Fuller test or Rolling statistics (such as Moving Average and Moving variance)为了测试平稳性，可以使用Dickey-Fuller测试或滚动统计（例如移动平均和移动方差）

Step1: Calculate the moving average with a window of 1 year. Store into a variable *ma*
Step2: Calculate the moving standard deviation with a window of 1 year. Store into a variable *msd*
Step3: Plot on the same graph:
Volume (blue), ma (green) and msd (red)
Step4: What do you conclude?
Step5: Using the package `from statsmodels.tsa.stattools import adfuller`
You will confirm your conclusion of the Step4 by finding this ouput:

```
In [21]: print (adtestoutput)
Test Statistic                  0.815369
p-value                         0.991880
#Lags Used                     13.000000
Number of Observations Used   130.000000
Critical Value (1%)            -3.481682
Critical Value (10%)           -2.578770
Critical Value (5%)            -2.884042
```

第一步：用1年的窗口计算移动平均数。 存储到一个变量马
第二步：用1年的窗口计算移动标准偏差。 存入一个变量msd
第三步：绘制在同一个图上：
音量（蓝色），ma（绿色）和MSD（红色）
第四步：你有什么结论?
第五步：使用statsmodels.tsa.stattools中的包导入adfuller

~~What is the null hypothesis of the Dickey-Fuller test?~~
~~What do you conclude?~~

Task 3: Make a Time Series stationary – 5pts

If the time series is not stationary, we can often transform it to stationarity with one of the following techniques.

1- *We can difference the data.*
That is, given the series Z_t *we create the new series*

$$Y_i = Z_i - Z_{i-1}.$$

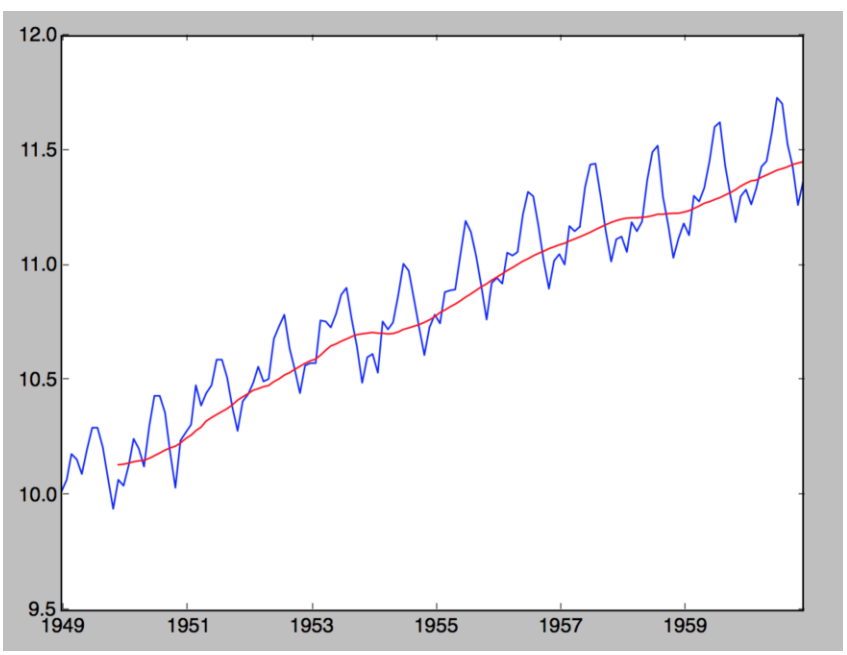
The differenced data will contain one less point than the original data. Although you can difference the data more than once, one difference is usually sufficient.

2- *For non-constant variance, taking the logarithm or square root of the series may stabilize the variance. For negative data, you can add a suitable constant to make all the data positive before applying the transformation. This constant can then be subtracted from the model to obtain predicted (i.e., the fitted) values and forecasts for future points.*

A-绘制音量的对数图。
B-你观察到什么?
C-平滑数据。
将对数数据存到变量logvolume中
将1年的滑动平均值存到变量mavolume中
绘制代表logvolume和mavolume的图形。

Questions:

~~A- We are going to try to eliminate the trend previously observed.~~
~~Plot the logarithm of the volume.~~
~~B- What do you observe?~~
~~C- We are now going to try to smooth the data.~~
~~Store the logarithm of the volume data into a variable *logvolume*~~
~~Store the moving average with a 1-year window into a variable *mavolume*~~
~~Plot the graph representing *logvolume* and *mavolume*.~~



红色线显示了趋势。只需要减去logvolume - mavolume并将其存储到volume_without_trend。
D-按照task2中重新测试平稳性。
E-重复研究half period of one year. pd.ewma(your_data,halflife=12)）的指数加权滑动平均
F-重新测试ewma的平稳性。
G-你用这种差分的方法得出什么结论?

The red shows the trend. You just need to subtract *logvolume* – *mavolume* and store it into volume_without_trend.

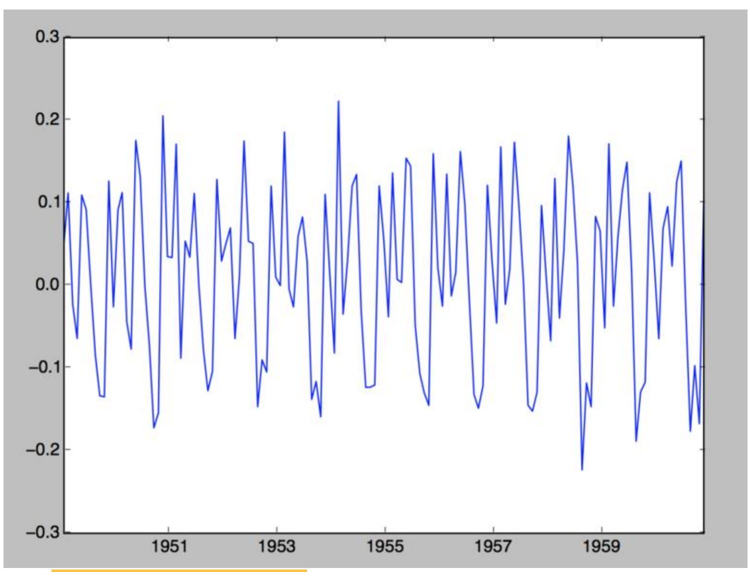
D- Retest stationarity the same way as you did in the task 2.
E- Redo the study with an exponentially weighted movin average with a half period of one year. pd.ewma(your_data,halflife=12)
F- Retest stationarity for ewma.
G- What do you conclude with this different method

Task 4: Removing trend and seasonality with differencing – 5pts

A-将平稳性差异应用于对数数据。 您将需要使用功能转移。
B-绘制图表
C-检验平稳性

Questions:

~~A- Remove the stationarity apply differencing to the log volume data.~~
~~You will need to use the function shift.~~
~~B- Plot the graph~~



C- Test stationarity

~~Task5: Forecast Time Series – 5pts~~

https://en.wikipedia.org/wiki/Autoregressive_integrated_moving_average
ARIMA (Auto-Regressive Integrated Moving Averages) forecasting for a stationary time series is a linear regression equation.
Predictors depend on the parameters (p Number of AR terms ,d Number of Differences,q Number of MA terms) of the ARIMA model.

~~A- You need to study the ACF~~

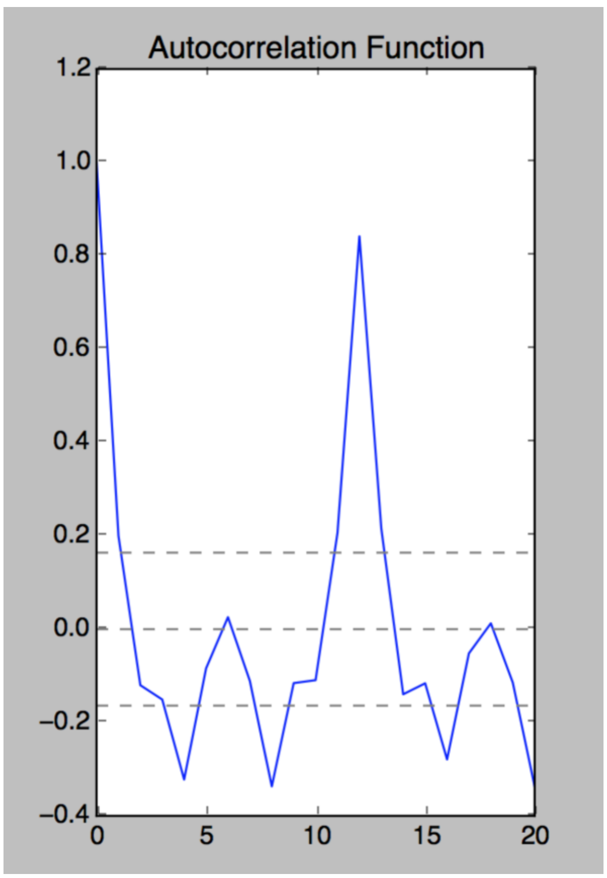
计算上一节中差分数据的acf。
请注意删除未定义的值。 如果你不这样做，ACF将返回NAs。 您可以使用函数dropna删除这些未定义的值。

Use the package:

from statsmodels.tsa.stattools import acf, pacf

Calculate the acf of the diff log volume obtained in the previous section.
Be aware of removing the non-defined values. If you don't do that, acf will return NAs. You can use the function dropna to remove these undefined values.

```
plt.subplot(121)
plt.plot(acf)
plt.axhline(y=0,linestyle='--',color='gray')
plt.axhline(y=-1.96/np.sqrt(len(volume_log_diff)),linestyle='--',color='gray')
plt.axhline(y=1.96/np.sqrt(len(volume _log_diff)),linestyle='--',color='gray')
plt.title('Autocorrelation Function')
```



B- Finally you will load the library

```
from statsmodels.tsa.arima_model import ARIMA
```

C-运行ARIMA模型，对log数据使用p=2，d=1，q=2（从d=1开始没有区分）。可以将此函数的结果存储到变量模型中
D-将model.fit（disp = -1）的结果存储到results_ARIMA中
E-使用results_ARIMA绘制log volume。
F-将预测值转换成原始的比例
G-应用指数回到最初的比例

C- ~~You will run the ARIMA model using p=2, d=1, q=2 on the log date (not differentiated since d=1). You can store the result of this function into the variable *model*~~

D- ~~You will store the result of model.fit(disp=-1) into *results_ARIMA*~~

E- ~~You will plot the log volume with *results_ARIMA*.~~

F- ~~We need to convert the predicted values into the original scale one~~

~~predictions_ARIMA_diff = pd.Series(results_ARIMA.fittedvalues, copy=True)~~

```
print (predictions_ARIMA_diff.head())
Month
1949-02-01    0.009580
1949-03-01    0.017491
1949-04-01    0.027670
1949-05-01   -0.004521
1949-06-01   -0.023890
```

~~Find the function converting diff values into real one. (you should be able to use cumsum)~~

~~predictions_ARIMA_diff_cumsum.head())~~

```
Month
1949-02-01    0.009580
1949-03-01    0.027071
1949-04-01    0.054742
1949-05-01    0.050221
1949-06-01    0.026331
```

~~G- Apply exponential to go back to the initial scale~~