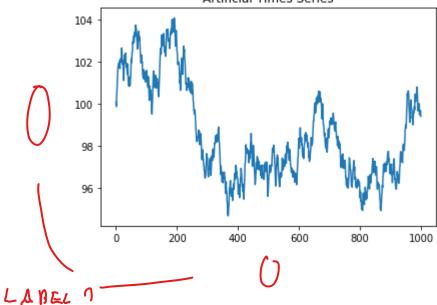
Computational Finance

Series 4

Tientso Ning

```
In [69]: import numpy as np
import pandas as pd
import time
import matplotlib.pyplot as plt
%matplotlib inline
In [6]: np.random.seed(1) #set random seed to 1
```

Time Average



```
In [61]: #draw the moving average for N = 100
N = 100
a = [2/(N+1),0.1,0.01]

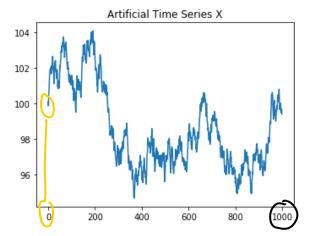
def MA(ts, N):
    L = len(ts)
    assert L%N == 0

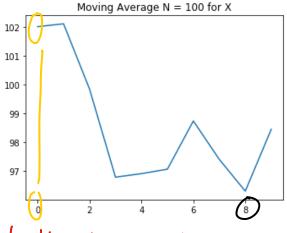
    ma = []
    for i in range(0,L,N):
        ma.append(np.sum(ts[i:i+N])/N)
    return ma

def EMA(ts, t, a):
    if t == 0:
        return ts[t]*a
    else:
        return (a*ts[t]) + (1-a)*EMA(ts, t-1, a)
```

```
In [19]: f, ax = plt.subplots(1,2, figsize=(12,4))
    ax[0].plot(x)
    ax[0].set_title("Artificial Time Series X")
    ax[1].plot(MA(x, N))
    ax[1].set_title("Moving Average N = 100 for X")
```

Out[19]: Text(0.5, 1.0, 'Moving Average N = 100 for X')





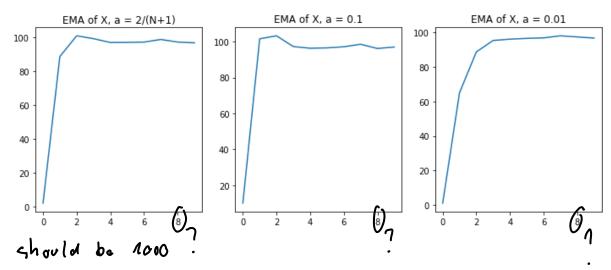
LABEL?

Why the MA is not done on all the generated interval?

At 0, the valve are very different, it's strange because the NA should start at 101 as we need 100 values to compute it.

```
In [65]:
         ema = []
         for i in range(0, len(x), N):
             ema.append(EMA(x, i, a[0]))
         ema1 = []
         for i in range(0, len(x), N):
             ema1.append(EMA(x, i, a[1]))
         ema2 = []
         for i in range(0, len(x), N):
             ema2.append(EMA(x, i, a[2]))
         f, ax = plt.subplots(1,3, figsize=(12,4))
         ax[0].plot(ema)
         ax[1].plot(ema1)
         ax[2].plot(ema2)
         ax[0].set_title("EMA of X, a = 2/(N+1)")
         ax[1].set_title("EMA of X, a = 0.1")
         ax[2].set_title("EMA of X, a = 0.01")
```

Out[65]: Text(0.5, 1.0, 'EMA of X, a = 0.01')



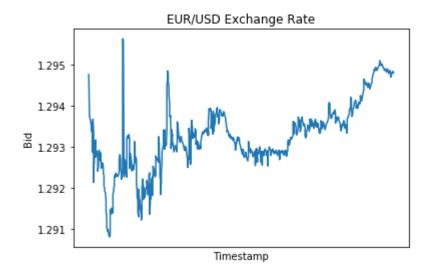
Here we can see that with alpha = 0.1 and 0.01, we notice that the increase in smoothing factor removes this sort of "bump" or decrease as time progresses. Additionally, we notice that 2/(N+1) as a scaling factor is prone to this as well.

How the MA and the EMA fit the data?

Scaling Law

```
In [70]: #read data from file
    data = pd.read_table("./timeseries.dat", header=None, names=["timestamp", "bi
    d", "ask"])
    data["timestamp"] = data["timestamp"].apply(lambda x : time.strftime("%Y-%m-%d
%H:%M:%S", time.gmtime(x)))
    print(data.head())
    print(len(data))
    #plot test
    plt.plot("timestamp","bid",data=data.head(1000))
    plt.xticks([])
    plt.title("EUR/USD Exchange Rate")
    plt.xlabel("Timestamp")
    plt.ylabel("Bid")
    plt.show()
```

```
timestamp bid ask
0 2012-01-01 16:57:32 1.29475 1.29575
1 2012-01-01 16:57:44 1.29375 1.29475
2 2012-01-01 16:58:23 1.29366 1.29466
3 2012-01-01 17:00:43 1.29359 1.29459
4 2012-01-01 17:01:41 1.29343 1.29443
1519768
```

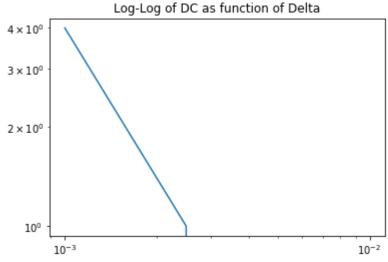


```
It's not the algo seen in course!
```

In [113]:

You need to count the number of overshot in both direction.

```
In [114]:
          #compute the number of directional changes with delta = 0.01 and 0.001
          delta = [0.01, 0.0075, 0.005, 0.0025, 0.001]
          dcs = []
          for i in range(0, len(delta)):
              dc = DC(data['bid'].head(200000), delta[i])
              print("Delta = {0}: ".format(delta[i]), dc)
              dcs.append(dc)
          Delta = 0.01: 0
          Delta = 0.0075: 0
          Delta = 0.005: 0
          Delta = 0.0025: 1
          Delta = 0.001: 4
In [115]: plt.loglog(delta, dcs)
          plt.title("Log-Log of DC as function of Delta")
Out[115]: Text(0.5, 1.0, 'Log-Log of DC as function of Delta')
```



We can see that the more we decrease the delta value, we get more events that can be considered a directional change.