

## COURSEWORK 3

IMPERIAL COLLEGE LONDON

DEPARTMENT OF MATHEMATICS

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# Stochastic Simulation

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## 1 Question 1

Figure 1 shows the pretty plot of our Markov chain.

## 2 State Space Models

### 2.1 Gaussian Time Series With Noise

Figure 2 shows a simulation of our model. The following model is a AR(1) (Markov) process which can be used to model numerous situations. Some examples of what it can model could be wind velocity, asset price or disease processes.

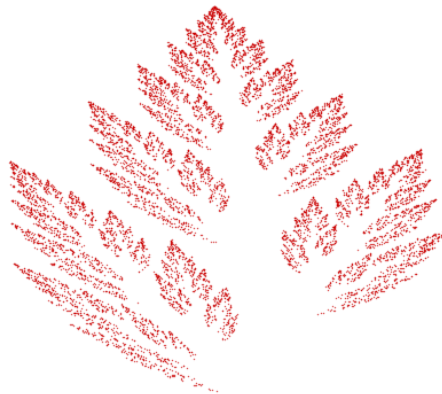
### 2.2 Stochastic Volatility Model

We develop a volatility model by defining our Markov transition kernel and likelihood by following a modified version of a model described by Kim, Shephard, and Chib (1998)<sup>[1]</sup>. Define our model as

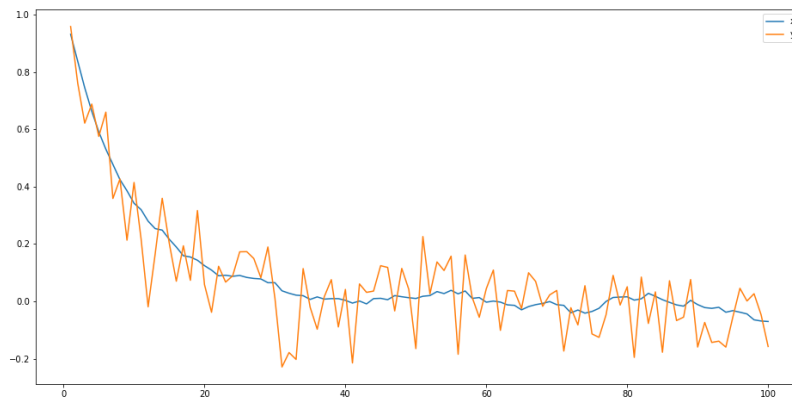
$$x_t|x_{t-1} \sim N(\mu + \phi(x_{t-1} - \mu), \sigma^2) \quad (1)$$

$$y_t|x_t \sim N(0, \exp(x_t/2)) \quad (2)$$

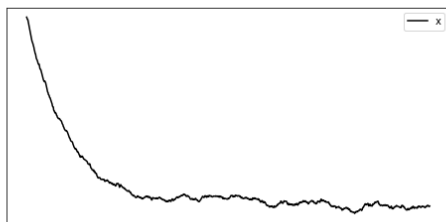
$$x_0 \sim N\left(\mu, \frac{\sigma^2}{1 - \phi^2}\right) \quad (3)$$



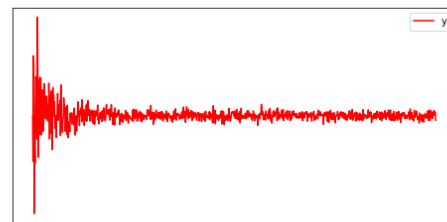
**Figure 1:** Scatter Plot of Markov Chain



**Figure 2:** Gaussian Time Series Corrupted By Noise



(a) Decaying System



(b) Variance of a Decaying System

**Figure 3:** Decaying System as our ‘Sanity’ Check

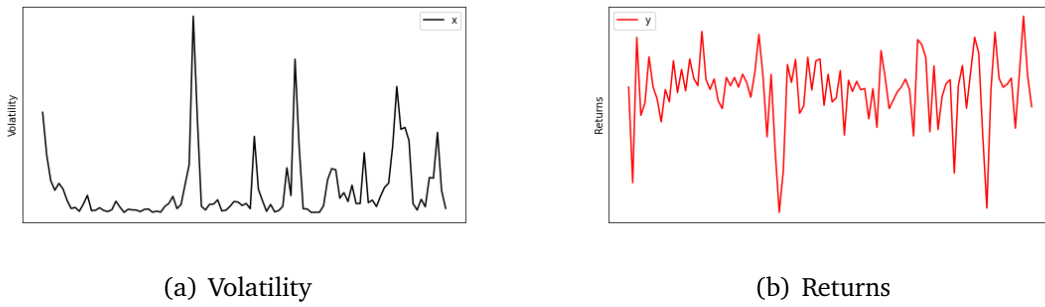
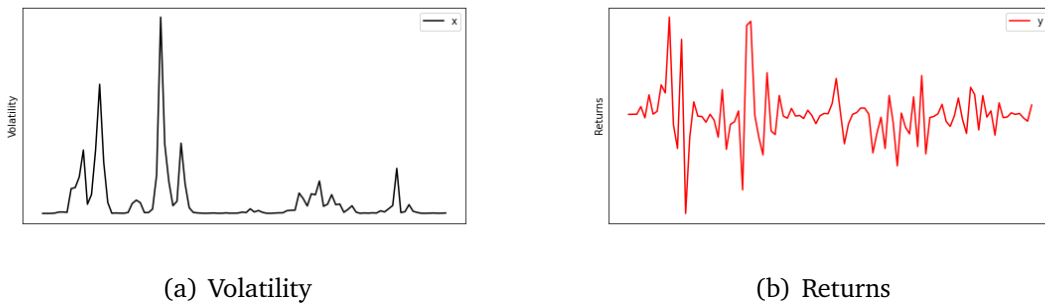
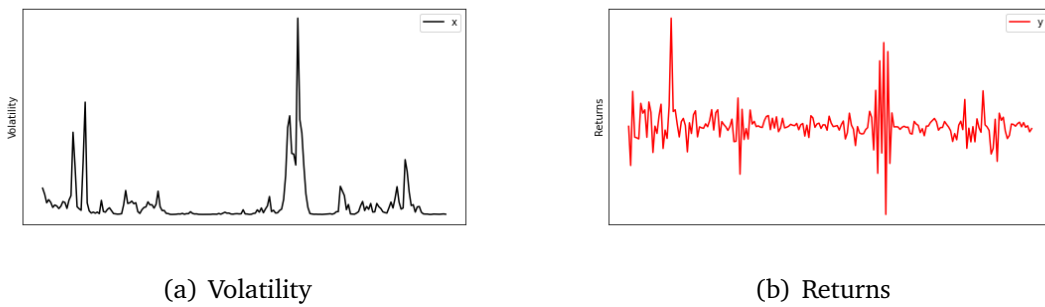
where (1) is our Markov transition kernel, (2) is our likelihood and (3) is our initial starting point. This Gaussian kernel would give negative values, however we note this kernel depicts log-volatility and so we can use it. Next we define our likelihood as (2) and will be used to model returns and can take negative values, additionally the use of the exponential is due to the ‘normally distributed’ nature of returns. As we can see in the figures below our model and simulations model the behaviour as expected.

## A Code for 1

```

1 def discrete(s, w):
2     cw = np.cumsum(w)
3     sample = []
4     u = np.random.uniform(0,1)
5     for k in range(len(cw)):
6         if cw[k] > u:
7             sample = s[k]
8             break

```

**Figure 4:** Simulation of our Model**Figure 5:** Simulation of our Model**Figure 6:** Simulation of our Model

```

9      return sample
10
11  A1 = np.array([[0.4, -0.3733], [0.06, 0.6]])
12  A2 = np.array([[-0.8, -0.1867], [0.1371, 0.8]])
13  b1 = np.array([[0.3533], [0.0]])
14  b2 = np.array([[1.1], [0.1]])
15
16  s = [1, 2]
17  w = [0.2993, 0.7007]
18  N = 10000
19  x0 = np.array([[0], [0]])
20

```

```
21 def Q1(x0, s, w, N):
22     x = x0
23     sample = np.zeros((2,N))
24     for j in range(N+1):
25         i = discrete(s, w)
26         if i == 1:
27             sample[0][j-1] = (A1@x + b1)[0]
28             sample[1][j-1] = (A1@x + b1)[1]
29             x = A1@x + b1
30         if i == 2:
31             sample[0][j-1] = (A2@x + b2)[0]
32             sample[1][j-1] = (A2@x + b2)[1]
33             x = A2@x + b2
34     return sample
35
36 x = Q1(x0, s, w, N)
37 fig1 = plt.figure(figsize=(12,8))
38 plt.scatter(x[0, 20:N], x[1, 20:N], s=0.1, color = [0.8, 0, 0])
39 plt.gca().spines['top'].set_visible(False)
40 plt.gca().spines['right'].set_visible(False)
41 plt.gca().spines['bottom'].set_visible(False)
42 plt.gca().spines['left'].set_visible(False)
43 plt.gca().set_xticks([])
44 plt.gca().set_yticks([])
45 plt.gca().set_xlim(0, 1.05)
46 plt.gca().set_ylim(0, 1)
47 plt.show()
48 fig1.savefig('1.png')
```

## B Code for 2.1

```
1 x0 = 1
2 a = 0.9
3 xsigma = 0.01
4 ysigma = 0.1
5 T = 100
6 x = np.zeros(T+1)
7 y = np.zeros(T+1)
8
9 for t in range(T+1):
10     if t == 0:
11         x[t] = x0
12     else:
13         x[t] = np.random.normal(a*x[t-1], xsigma)
14         y[t] = np.random.normal(x[t], ysigma)
15
16 fig2 = plt.figure(figsize=(16,8))
17 plt.plot(np.arange(1,101,1), x[1:], label= 'x')
18 plt.plot(np.arange(1,101,1), y[1:], label = 'y')
19 plt.legend()
20 fig2.savefig('2.png')
```

## C Code for 2.2

```
1 x = np.zeros(T)
2 y = np.zeros(T)
3
4 for i in range(T):
5     if i == 0:
6         x[i] = np.random.normal(mu, np.sqrt((sigma**2)/(1 - phi**2)))
7     else:
8         x[i] = np.random.normal(mu + phi * (x[i-1] - mu), sigma)
9         y[i] = np.random.normal(0, np.exp(x[i]/2))
10
11 plt.figure(figsize=(8,4))
12 plt.plot(np.exp(x), color = 'black', label = 'x')
13 plt.xticks([])
14 plt.yticks([])
15 plt.legend()
16 plt.ylabel('Volatility')
17
18 plt.figure(figsize=(8,4))
19 plt.plot(y, color = 'red', label = 'y')
20 plt.xticks([])
21 plt.yticks([])
22 plt.legend()
23 plt.ylabel('Returns')
```

## References

- [1] Sangjoon Kim, Neil Shephard, Siddhartha Chib (1998) Stochastic Volatility: Likelihood Inference and Comparison with ARCH Models.