

STAT 753: Stochastic Models and Simulations

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University of Nevada, Reno - Spring 2024

Homework 12

Theory

1. Consider the switch SDE: $dX(t) = -c \cdot \text{sgn}(X(t) - m)dt + \sigma dW(t)$. Here, $c, \sigma > 0$, and sgn is the *signum function*:

$$\text{sgn}(y) := \begin{cases} +1, y > 0; \\ 0, y = 0; \\ -1, y < 0. \end{cases} \quad (1)$$

Show that the Laplace distribution with mean m and variance v is a stationary distribution, and find the variance v .

Solution For a SDE with density $\varphi(y)$, if it has a stationary distribution it will solve the equation

$$\int_{-\infty}^{\infty} Af(x)\varphi(x)dx = 0. \quad (2)$$

where

$$Af(x) = g(x)f'(x) + \frac{1}{2}\sigma^2(x)f''(x).$$

Integrating this equation gives the expression

$$-(g(x)\varphi(x))' + \frac{1}{2}(\sigma^2(x)\varphi(x))'' = 0. \quad (3)$$

Since $\varphi(y)$ represents a density function, Equation 3 has the boundary conditions $\varphi(\infty) = 0$ and $\varphi(-\infty) = 0$. For a Laplace distribution with mean $m = \mu$ and variance $v = 2b^2$, $\varphi(x)$ is equal to

$$\varphi(x) = \frac{1}{2b} \exp\left(\frac{-|x - \mu|}{b}\right). \quad (4)$$

This problem can then be broken up into the cases where (1): $X(t) - m > 0$ and (2): $X(t) - m < 0$. For (1), $g(x) = -c$ and $\sigma(x) = \sigma$. We can solve Equation 3 such that:

$$\begin{aligned} -(-c\varphi(x))' + \frac{\sigma^2}{2}(\varphi(x))'' &= 0 \\ \int_{-\infty}^{\infty} c\varphi'(x) + \frac{\sigma^2}{2}(\varphi(x))'' &= 0 \\ c\varphi(x) + \frac{\sigma^2}{2}(\varphi(x))' &= k_1. \end{aligned} \quad (5)$$

For the Laplace distribution where $|x - \mu| > 0$,

$$\begin{aligned}\varphi(x) &= \frac{1}{2b} \exp\left(\frac{-(x - \mu)}{b}\right) \\ \varphi'(x) &= -\frac{1}{2b^2} \exp\left(\frac{-(x - \mu)}{b}\right).\end{aligned}\tag{6}$$

If we let $k_1 = 0$, we can then plug in $\varphi(x)$ and $\varphi'(x)$ and solve for $v = 2b^2$:

$$\begin{aligned}c\varphi(x) + \frac{\sigma^2}{2}(\varphi(x))' &= k_1 \\ c\frac{1}{2b} \exp\left(\frac{-(x - \mu)}{b}\right) + \frac{\sigma^2}{2}\left(-\frac{1}{2b^2} \exp\left(\frac{-(x - \mu)}{b}\right)\right) &= 0 \\ \frac{c}{2b} &= \frac{\sigma^2}{4b^2} \\ b &= \frac{\sigma^2}{2c} \\ 2b^2 &= \frac{\sigma^4}{2c^2}.\end{aligned}\tag{7}$$

Thus, for case (1), the mean is μ and variance is $\frac{\sigma^4}{2c^2}$. Now, for case (2), $g(x) = c$ and $\sigma(x) = \sigma$, which gives the expression $-c\varphi(x) + \frac{\sigma^2}{2}(\varphi(x))' = k_1$ when integrating Equation 3. Since $|x - \mu| < 0$, the density function can be rewritten as

$$\begin{aligned}\varphi(x) &= \frac{1}{2b} \exp\left(\frac{-(\mu - x)}{b}\right) \\ \varphi'(x) &= \frac{1}{2b^2} \exp\left(\frac{-(\mu - x)}{b}\right).\end{aligned}\tag{8}$$

Solving, once again, gives

$$\begin{aligned}-c\varphi(x) + \frac{\sigma^2}{2}(\varphi(x))' &= k_1 \\ -c\frac{1}{2b} \exp\left(\frac{-(\mu - x)}{b}\right) + \frac{\sigma^2}{2}\left(\frac{1}{2b^2} \exp\left(\frac{-(\mu - x)}{b}\right)\right) &= 0 \\ \frac{c}{2b} &= \frac{\sigma^2}{4b^2} \\ b &= \frac{\sigma^2}{2c} \\ 2b^2 &= \frac{\sigma^4}{2c^2}.\end{aligned}\tag{9}$$

Thus, the variance and mean are the same as in case (1). The Laplace distribution is thus stationary with mean $\mu = m$ and variance $2b^2 = \frac{\sigma^4}{2c^2}$.

For the first coding problem, we are asked to simulate this process for chosen parameters. By choosing $\sigma = .2$, $m = .5$, and $c = .5$, we can see that this process will have Laplace distribution with mean $m = 0.5$ and variance $\frac{\sigma^4}{2c^2} = 0.0032$.

2. Consider the Ornstein-Uhlenbeck process in the log scale modeling the Volatility Index VIX:

$$d\ln V(t) = (-0.1188\ln V(t) + 0.3482)dt + 0.1589dW(t), V(0) = 16. \quad (10)$$

Find the mean and variance of V in its stationary distribution.

Solution

For an OU process $dX(t) = c(m - X(t))dt + \sigma dW(t)$, the stationary distribution is normal with mean m and variance $\sigma^2/2c$. So, $\ln(X(t)) \sim N(\mu = m, \sigma^2 = \sigma^2/2c)$ as $t \rightarrow \infty$. We can find the mean and variance of $\ln(X(t))$ so that

$$\begin{aligned} \mu &= E[e^{t\ln(X(t))}] \Big|_{t=1} \\ \sigma^2 &= E[e^{t\ln(X(t))}] \Big|_{t=2} - E[e^{t\ln(X(t))}]^2 \Big|_{t=1} \end{aligned} \quad (11)$$

The MGF for the normal distribution is

$$E[e^{tx}] = e^{\mu t + \sigma^2 t^2/2} \quad (12)$$

For this problem, $m = 0.3482/0.1188 \approx 2.931$ and variance $\sigma^2 = 0.1589^2/2(0.1188) \approx 0.1063$. We can plug in these values and solve:

$$\begin{aligned} \mu &= e^{\mu + \sigma^2/2} \\ &= e^{2.931 + 0.1063/2} \\ &\approx 19.769 \\ v &= e^{\mu(2) + \sigma^2(4)/2} - (e^{\mu + \sigma^2/2})^2 \\ &= e^{2(2.931) + 0.1063(2)} - (e^{2.931 + 0.1063/2})^2 \\ &= 434.627 - 19.769^2 \\ &\approx 43.818. \end{aligned} \quad (13)$$

The stationary distribution for this process is $\sim N(19.769, 43.818)$ after the burn-in period.

Code

1. Q1

Solution

```

1
2 import numpy as np
3 import seaborn as sns
4
5 def SDE1(mu, sigma,c, dt, T):
6     simX=[0]
7     N=int(T/dt)
8     #X = np.random.laplace(mu, var/np.sqrt(2),N)
9     noise = np.random.normal(0,np.sqrt(dt),N)
10
11     for i in range(N):
12         old = simX[-1]
13         if (old-mu)>0:
14             new= -c*dt + sigma*noise[i] + old
15         elif (old-mu)<0:
16             new= c*dt + sigma*noise[i] + old
17         elif (old-mu)==0:
18             sigma*noise[i] + old
19
20     simX.append(new)
21     return simX
22
23 sigma=.2
24 m=.5
25 c=.5
26 b= sigma**2/(2*c)
27 dt=0.01
28 T=20
29
30 sims=[]
31 for i in range(2000):
32     sims.append(SDE1(m,sigma,c, dt, T))
33
34 print('Empirical mean:', np.mean(np.array(sims)[: ,500]))
35 print('Empirical variance:', np.var(np.array(sims)[: ,500]))
36
37 print('Theoretical mean:', m)
38 print('Theoretical variance:', 2*b**2)
39
40 >> Empirical mean: 0.5035253512152671
41 >> Empirical variance: 0.0034892051137381036
42 >> Theoretical mean: 0.5
43 >> Theoretical variance: 0.0032000000000000015
44

```

After a break-in period of 5 seconds, we can see that the empirical and theoretical means and variances of the stationary distribution are quite close.

2. Q2

Solution

```

1  def SDE2(m,c, sigma, dt, T, X0):
2      simX=[X0]
3      N= int(T/dt)
4      noise = np.random.normal(0,np.sqrt(dt),N)
5
6      for i in range(N):
7          old = simX[-1]
8          new= (np.exp(c*m*dt)) * (old**(-c*dt)) * np.exp(sigma*noise[i]) *
              ↪ old
9          simX.append(new)
10     return simX
11
12     c = .1188
13     m = 0.3482/c
14     sigma=0.1589
15     dt= .01
16     T=30
17     X0=16
18
19     p2 = sigma**2 / 2*c
20
21     np.random.seed(1)
22     sims=[]
23     for i in range(4000):
24         sims.append(SDE2(m,c,sigma, dt, T, X0))
25
26     p2 = sigma**2 / (2*c)
27     print('Empirical mean:', np.mean(np.array(sims)[: ,1000:]))
28     print('Empirical variance:', np.var(np.array(sims)[: ,1000:]))
29
30     print('Theoretical mean:', np.exp(m + (p2/2)))
31     print('Theoretical variance:', (np.exp(2*m + 4*p2/2) - np.exp(m +
              ↪ p2/2)**2))
32
33     >> Empirical mean: 19.42318764448729
34     >> Empirical variance: 42.29081056308366
35     >> Theoretical mean: 19.76890582446917
36     >> Theoretical variance: 43.81740930293188

```

After a break-in period of 10 seconds, the theoretical and empirical solutions are similar.

Stat753_HW12_JaleesaHoule

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```
[1]: import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

1 Question 1

Consider the switch SDE: $dX(t) = -c \cdot \text{sgn}(X(t) - m)dt + \sigma dW(t)$. Here, $c, \sigma > 0$, and sgn is the signum function:

$$\text{sgn}(y) := \begin{cases} +1, & y > 0; \\ 0, & y = 0; \\ -1, & y < 0. \end{cases} \quad (1)$$

Show that the Laplace distribution with mean m and variance v is a stationary distribution, and find the variance v .

```
[2]: def SDE1(mu, sigma, c, dt, T):
    simX=[0]
    N=int(T/dt)
    noise = np.random.normal(0,np.sqrt(dt),N)

    for i in range(N):
        old = simX[-1]
        if (old-mu)>0:
            new= -c*dt + sigma*noise[i] + old
        elif (old-mu)<0:
            new= c*dt + sigma*noise[i] + old
        elif (old-mu)==0:
            new= sigma*noise[i] + old

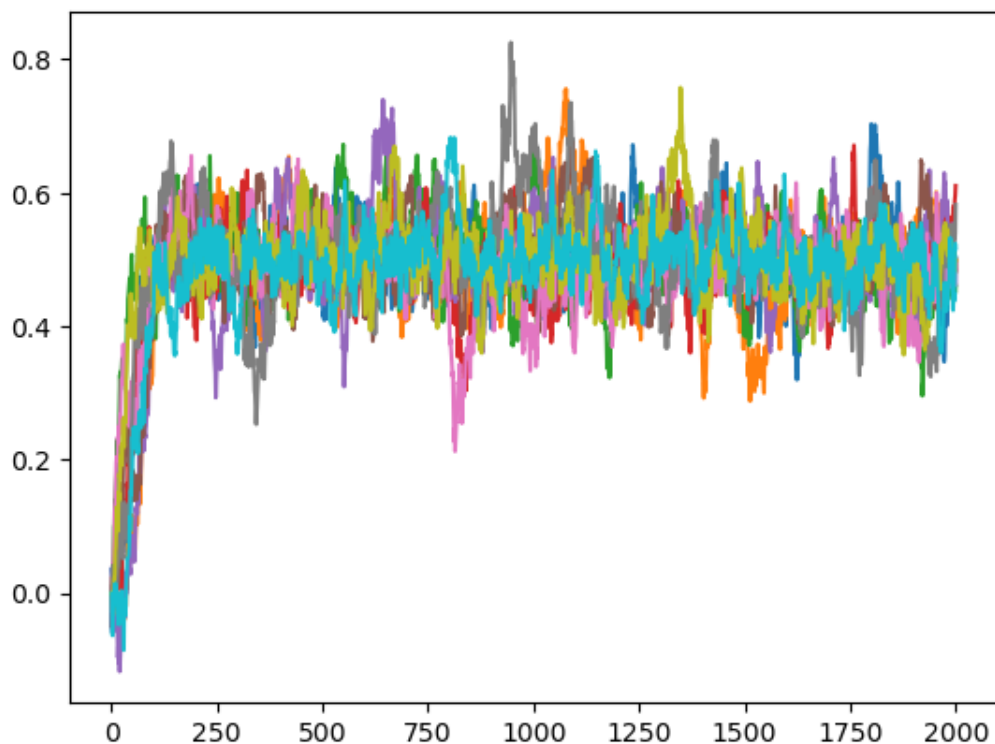
        simX.append(new)
    return simX
```

```
[3]: sigma=.2
m=.5
c=.5
b= sigma**2/(2*c)
dt=0.01
```

```
T=20
```

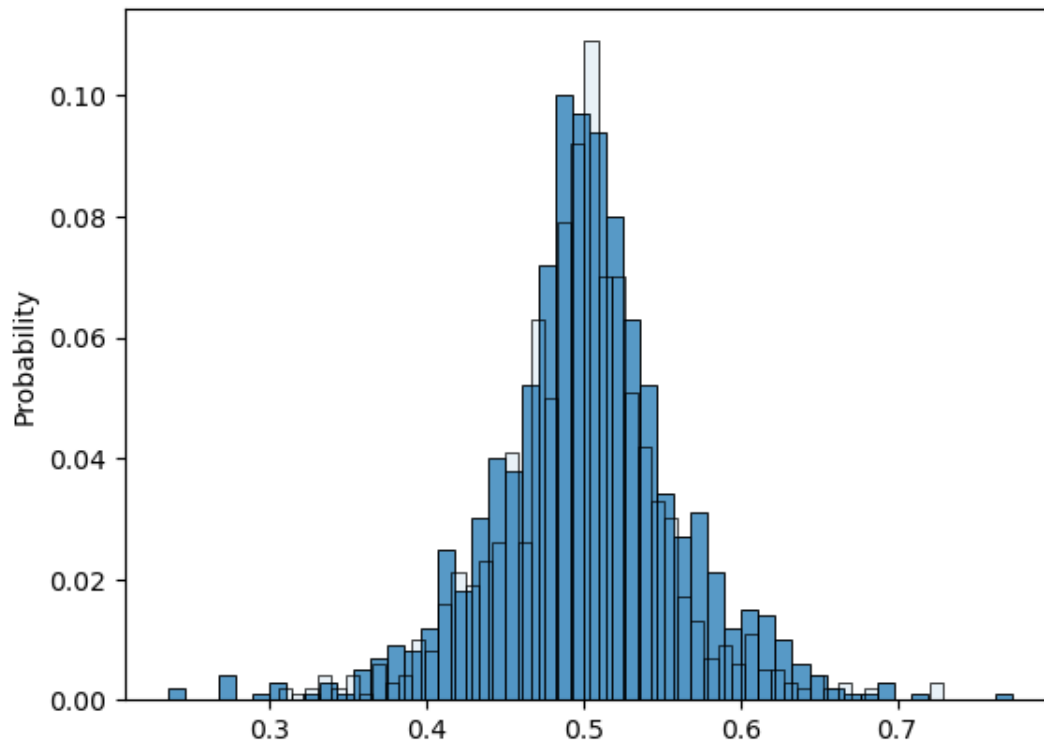
```
[4]: sims=[]  
     np.random.seed(1)  
     for i in range(1000):  
         sims.append(SDE1(m,sigma,c, dt, T))
```

```
[5]: for i in range(10):  
     plt.plot(sims[i])
```



```
[6]: X = np.random.laplace(loc=m, scale=b , size=1000)  
     sns.histplot(np.array(sims)[:1000],stat='probability', bins=50)  
     sns.histplot(X, bins=50,stat='probability', alpha=.1)
```

```
[6]: <AxesSubplot:ylabel='Probability'>
```



```
[7]: print('Empirical mean:', np.mean(np.array(sims)[: ,500]))
      print('Empirical variance:', np.var(np.array(sims)[: ,500]))

      print('Theoretical mean:', m)
      print('Theoretical variance:', 2*b**2)
```

```
Empirical mean: 0.5038519384972718
Empirical variance: 0.0035413485192730544
Theoretical mean: 0.5
Theoretical variance: 0.00320000000000000015
```

2 Question 2

Consider the Ornstein-Uhlenbeck process in the log scale modeling the Volatility Index VIX:

$$d\ln V(t) = (-0.1188\ln V(t) + 0.3482)dt + 0.1589dW(t), V(0) = 16. \quad (2)$$

Find the mean and variance of V in its stationary distribution.

```
[8]: def SDE2(m,c, sigma, dt, T, X0):
      simX=[X0]
      N= int(T/dt)
```



```

noise = np.random.normal(0,np.sqrt(dt),N)

for i in range(N):
    old = simX[-1]
    new= (np.exp(c*m*dt)) * (old**(-c*dt)) * np.exp(sigma*noise[i]) * old
    simX.append(new)
return simX

```

```

[9]: c = .1188
m = 0.3482/c
sigma=0.1589
dt= .01
T=30
X0=16

p2 = sigma*2 / 2*c

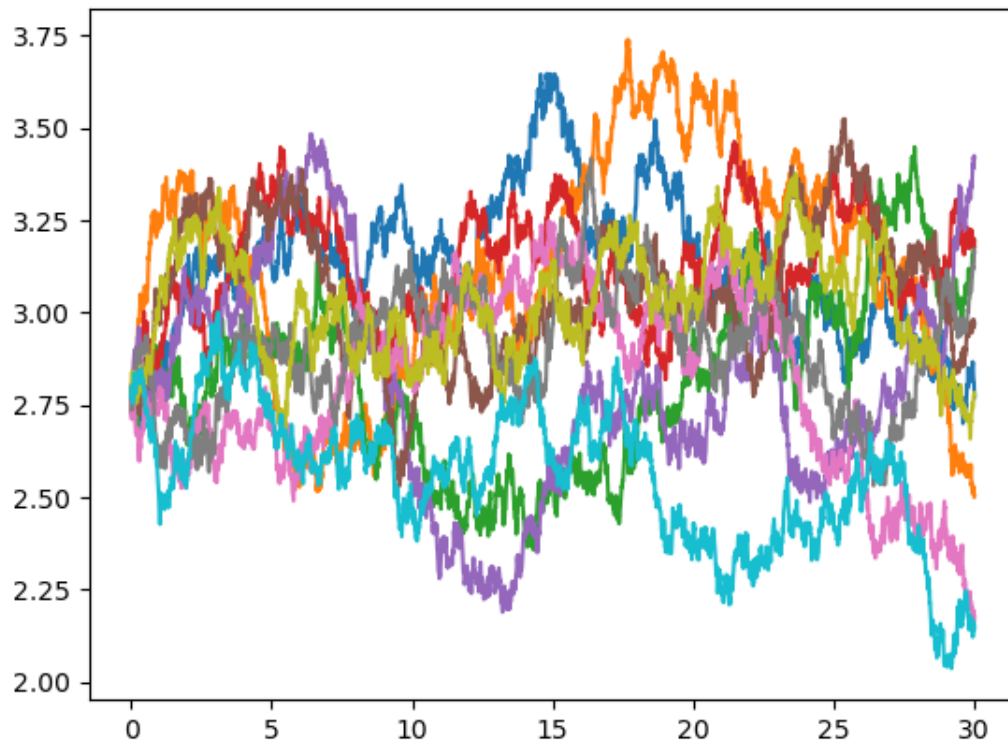
np.random.seed(1)
sims=[]
for i in range(1000):
    sims.append(SDE2(m,c,sigma, dt, T, X0))

```

```

[10]: time = np.linspace(0,T,int(T/dt)+1)
for i in range(10):
    plt.plot(time, np.log(sims[i]))

```



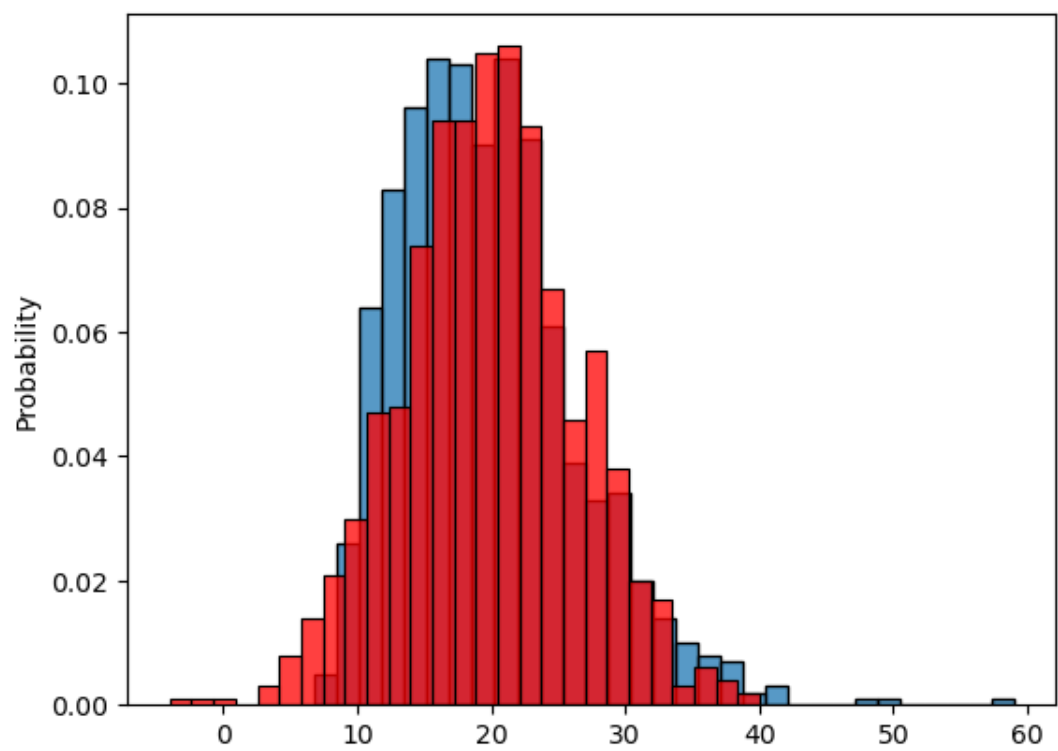
```
[11]: p2 = sigma**2 / (2*c)
print('Empirical mean:', np.mean(np.array(sims)[: ,1000:]))
print('Empirical variance:', np.var(np.array(sims)[: ,1000:]))

print('Theoretical mean:', np.exp(m + (p2/2)))
print('Theoretical variance:', (np.exp(2*m + 4*p2/2) - np.exp(m + p2/2)**2))
```

```
Empirical mean: 19.335080974581142
Empirical variance: 43.44341712167216
Theoretical mean: 19.76890582446917
Theoretical variance: 43.81740930293188
```

```
[17]: X = np.random.normal(19.76890582446917, np.sqrt(43.81740930293188), size=1000)
sns.histplot(np.array(sims)[: ,2500], stat='probability')
sns.histplot(X, stat='probability', color='red')
```

```
[17]: <AxesSubplot:ylabel='Probability'>
```



[]: