## Differential Equations Project: Phase 3

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A stock's price  $S_t$  (in USD) can be predicted with respect to time t (in days from an initial time) using a growth function; that is, by relating the rate at which the stock price is changing to the current stock price as a proportion:

$$\frac{\mathrm{d}S_t}{\mathrm{d}t} \propto S_t$$

The constant of proportionality is the drift  $\mu$  of the stock, which is the rate of change of the expected value of the stock price (which is not the expected value of its rate of change):

$$\frac{\mathrm{d}S_t}{\mathrm{d}t} = \mu S_t$$
 where  $\mu = \frac{\Delta \mathbb{E}[S_t]}{\Delta t}$ 

The stock market is constantly volatile, though, changing in unpredictable ways. This randomness element can be modeled by a randomness term, the rate of change of the standard Wiener process  $W_t$ :

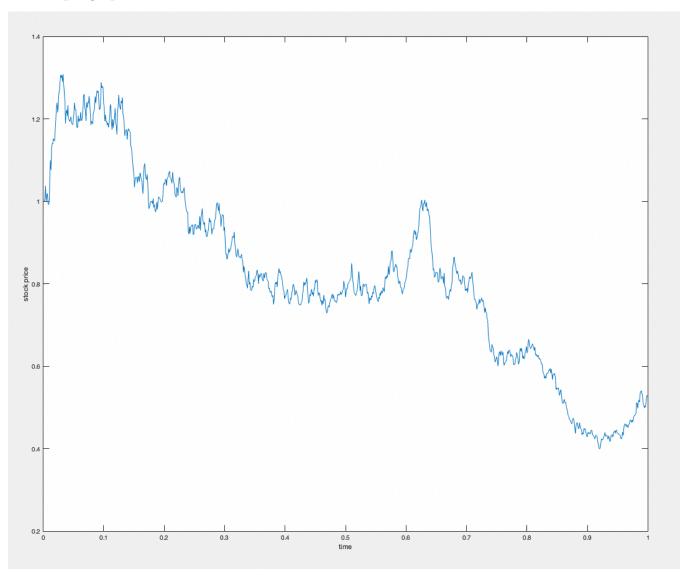
rate of randomness 
$$\propto \frac{\mathrm{d}W_t}{\mathrm{d}t}$$

The proportionality constant is the volatility  $\sigma$  of the stock, which is simply its standard deviation. Adding this term,

$$\frac{\mathrm{d}S_t}{\mathrm{d}t} = \mu S_t + \sigma \frac{\mathrm{d}W_t}{\mathrm{d}t}$$
 where  $\sigma = \frac{\sum (S_{t,i} - \bar{S}_t)}{n-1}$ 

The randomness term ensures that each trial of the model yields a different graph. The following

is a sample graph:



The DE can be rewritten as

$$dS_t = \mu_t dt + \sigma_t dW_t$$

where  $\mu_t = \mu S_t$  and  $\sigma_t = \sigma S_t$ . Integrating and reparameterizing  $\mu_t$ ,  $\sigma_t$  and  $W_t$  with s,

$$S_t = \int_0^t \mu_s \, \mathrm{d}s + \int_0^t \sigma_s \, \mathrm{d}W_s + S_0$$

where  $S_0$  is the constant of integration (the initial stock price). This makes  $S_t$  an Itô process, a stochastic process expressible as the sum of two integrals, one with respect to a stochastic process and another with respect to time, and a constant.

The Taylor expansion of a twice-differentiable scalar function f(t, s) is

$$df = \frac{\partial f}{\partial t} dt + \frac{\partial f}{\partial s} ds + \frac{1}{2} \frac{\partial^2 f}{\partial s^2} d^2 s + \cdots$$

Substituting  $S_t$  for s and appropriately substituting for ds yields

$$df + \frac{\partial f}{\partial t} dt + \frac{\partial f}{\partial s} (\mu_t dt + \sigma_t dW_t) + \frac{\partial^2 f}{\partial s^2} (\mu_t^2 dt^2 + 2\mu_t \sigma_t dt dW_t + \sigma_t^2 dW_t^2) + \cdots$$

As dt approaches 0, dt<sup>2</sup> and dt dW<sub>t</sub> tend to zero faster than dW<sub>t</sub><sup>2</sup>. Substituting 0 for dt<sup>2</sup> and dt dW<sub>t</sub> and dt for dW<sub>t</sub><sup>2</sup> yields

$$df = \left(\frac{\partial f}{\partial t} + \mu_t \frac{\partial f}{\partial s} + \frac{\sigma_t^2}{2} \frac{\partial^2 f}{\partial s^2}\right) dt + \sigma_t \frac{\partial f}{\partial s} dW_t$$

This is itself an Itô process. Itô's lemma states that for any Itô process  $S_t$  and any twice-differentiable function f(t,s),  $f(t,S_t)$  is an Itô process.

Let  $f(S_t) = \ln S_t$ . Applying Itô's lemma,

$$df = f'(S_t) dS_t + \frac{1}{2} f''(S_t) (dS_t)^2$$

$$= \frac{1}{S_t} dS_t - \frac{1}{2S_2^2} \left( S_t^2 \sigma^2 dt \right)$$

$$= \frac{1}{S_t} (\sigma S_1 dW_t + \mu S_t dt) - \frac{\sigma^2}{2} dt$$

$$= \sigma dW_t + \left( \mu - \frac{\sigma^2}{2} \right) dt$$

Integrating the separable DE,

$$f(t) = \ln S_t = \ln S_0 + \sigma W_t + \left(\mu - \frac{\sigma^2}{2}\right) dt$$

This can finally be exponentiated, yielding  $S_t$ :

$$S_t = S_0 e^{\left(\mu - \frac{\sigma^2}{2}\right)t + \sigma W_t}$$

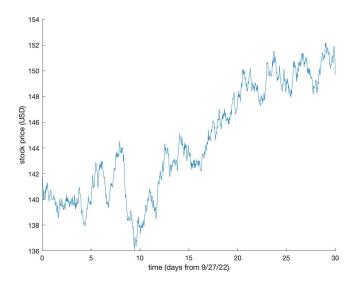
Substituting for  $S_0$ ,  $\mu$ , and  $\sigma$ ,

$$S_t = 141.501 e^{\left(0.00064 + \frac{4.356^2}{2}\right) + 4.356W_t}$$

The following are the Matlab code, solution (for the deterministic term), and graph:

```
Solution.m × +
            close all;
   2
            clear <u>all</u>;
   3
   4
            dom = [0, 30];
            n = 1000;
   5
   6
            dt = (dom(2)
                            dom(1))/50;
            S0 = 141.501;
   8
            ndist = makedist('Normal', 0 , sqrt(dt));
   9
  10
            mu = 0.00064;
  11
            sigma = 4.356;
  12
  13
            tvals = linspace(dom(1), dom(2), n);
Svals = zeros(1, n);
  14
  15
            Svals(1) = S0;
  16
       早
            for i = 2:n
  17
                t = dom(1) + (i - 1) * dt;

S = Svals(i - 1);
  18
  19
  20
                dW = random(ndist);
  21
                Svals(i) = S + mu .* dt + sigma .* dW
  22
            end
  23
            figure()
  24
            hold on;
  25
            plot(tvals, Svals);
  26
            xlabel('time (days from 9/27/22)')
  27
            ylabel('stock price (USD)')
  28
  29
            % Solving for the non-stochastic term
  30
            syms s(t
            ode = diff(s, t) == s;
  31
            sol(t) = dsolve(ode);
  32
                        sol ×
                        1x1 symfun
                       val(t) =
                       C1*exp(t)
```



The following is the Excel spreadsheet.