

Geometric Brownian motion

$$\begin{aligned}
 X(t) &= X(0) + \mu t + \sigma B(t) \\
 Z(t) &= \exp^{X(t)} = z \exp^{\mu t + \sigma B(t)} \\
 \mathbb{E}(Z(t)) &= z e^{\mu t} \mathbb{E}\left(e^{\sigma B(t)}\right) \\
 \mathbb{E}\left(e^{\sigma B(t)}\right) &= \int_{-\infty}^{\infty} e^{\sigma x} \frac{1}{\sqrt{2\pi}} \frac{1}{\sqrt{t}} e^{-\frac{x^2}{2t}} dx = \int_{-\infty}^{\infty} e^{-\frac{x^2 - 2\sigma t x}{2t}} dx = e^{\frac{1}{2}\sigma^2 t} \int_{-\infty}^{\infty} e^{-\frac{(x-\sigma t)^2}{2t}} dx = e^{\frac{1}{2}\sigma^2 t} \\
 \mathbb{E}(Z(t)) &= z e^{(\mu + \frac{1}{2}\sigma^2)t} \quad (z e^{\alpha t})
 \end{aligned}$$

Introduce $\alpha = \mu + \frac{1}{2}\sigma^2$, (so $\mu = \alpha - \frac{1}{2}\sigma^2$)

$$\begin{aligned}
 X(t) &= X(0) + \left(\alpha - \frac{1}{2}\sigma^2\right)t + \sigma B(t) \\
 Z(t) &= z e^{(\alpha - \frac{1}{2}\sigma^2)t + \sigma B(t)} \\
 \text{Var}(Z(t)) &= z^2 e^{2\alpha t} \left(e^{\sigma^2 t} - 1\right)
 \end{aligned}$$

Like N and LN, B and GM, i.e. Theorem 8.3

$$\begin{aligned}
 u(x) &= \mathbb{P}\{X(\tau) = b | X(0) = x\} = \mathbb{E}(\mathbf{1}_{X(\tau)=b} | X(0) = x) \\
 u(x) &= \frac{e^{-\frac{2\mu}{\sigma^2}x} - e^{-\frac{2\mu}{\sigma^2}a}}{e^{-\frac{2\mu}{\sigma^2}b} - e^{-\frac{2\mu}{\sigma^2}a}} \\
 T &= \min_{t \geq 0} \{Z(t) \in \{Z(0)A, Z(0)B\}\} \\
 Z(t) &= Z(0)A \\
 \log(Z(t)) &= \log(Z(0)) + \log(A) \\
 \mathbb{P}\left\{\frac{Z(T)}{Z(0)} = B\right\} &= \frac{1 - A^{-\frac{2\alpha}{\sigma^2}}}{B^{-\frac{2\alpha}{\sigma^2}} - A^{-\frac{2\alpha}{\sigma^2}}}
 \end{aligned}$$

Black Scholes model

Stock price given by

$$S(t) = S(0)e^{(\alpha - \frac{1}{2}\sigma^2)t + \sigma B(t)}$$

An option gives the right to buy a stock at or before (fixed) time τ at some fixed price a . The Black Scholes model gives the fair price $F(z, \tau)$ of the option under some idealistic assumptions. Here z is the current value of the stock and τ is the remaining time to expiration.

An important parameter is r the interest rate of a risk free financial instrument (think US treasuries - bonds').

$$\begin{aligned}
Z(\tau) &= S(0)e^{(r-\frac{1}{2}\sigma^2)\tau+\sigma\sqrt{\tau}B(1)} \\
S(0) &= z \\
F(z, 0) &= (z - a)^+ = \max(z - a, 0) \\
F(Z, \tau) &= e^{-r\tau} \mathbb{E} [(Z(\tau) - a)^+ | Z(0) = z], \quad \text{Black Scholes formula} \\
Z(\tau) &\geq a \Leftrightarrow ze^{(r-\frac{1}{2}\sigma^2)\tau+\sigma\sqrt{\tau}B(1)} \geq a \\
\log(z) + (r - \frac{1}{2}\sigma^2)\tau + \sigma\sqrt{\tau}B(1) &\geq \log(a) \\
B(1) &\geq \frac{\log(\frac{a}{z}) - (r - \frac{1}{2}\sigma^2)\tau}{\sigma\sqrt{\tau}} = v_0 \\
\mathbb{E} [(Z(\tau) - a)^+ | Z(0) = z] &= \int_{v_0}^{\infty} \left(ze^{(r-\frac{1}{2}\sigma^2)\tau+\sigma\sqrt{\tau}x} - a \right) \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} dx \\
&= ze^{(r-\frac{1}{2}\sigma^2)\tau} \int_{v_0}^{\infty} e^{\sigma\sqrt{\tau}x} \frac{1}{\sqrt{\tau}} e^{-\frac{x^2}{2}} dx - a(1 - \Phi(v_0)) \\
&= ze^{(r-\frac{1}{2}\sigma^2)\tau} e^{\frac{\sigma^2\tau}{2}} \int_{v_0}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{(x-\sigma\sqrt{\tau})^2}{2}} dx - a(1 - \Phi(v_0)) \\
&= ze^{r\tau} (1 - \Phi(v_0 - \sigma\sqrt{\tau})) - a(1 - \Phi(v_0)) \\
&= ze^{r\tau} (\Phi(\sigma\sqrt{\tau} - v_0) - a\Phi(-v_0)) \\
&= ze^{r\tau} \Phi\left(\frac{\log(\frac{z}{a}) + (r + \frac{1}{2}\sigma^2)\tau}{\sigma\sqrt{\tau}}\right) - a\Phi\left(\frac{\log(\frac{z}{a}) + (r - \frac{1}{2}\sigma^2)\tau}{\sigma\sqrt{\tau}}\right) \\
F(z, \tau) &= z\Phi\left(\frac{\log(\frac{z}{a}) + (r + \frac{1}{2}\sigma^2)\tau}{\sigma\sqrt{\tau}}\right) - ae^{-r\tau}\Phi\left(\frac{\log(\frac{z}{a}) + (r - \frac{1}{2}\sigma^2)\tau}{\sigma\sqrt{\tau}}\right)
\end{aligned}$$

Ornstein Uhlenbeck process

Pathwise/distributional definition

$$\begin{aligned}
 V(t) &= ve^{-\beta t} + \frac{e^{-\beta t}\sigma}{\sqrt{2\beta}} B(e^{2\beta t} - 1) \\
 \mathbb{E}(V(t)) &= ve^{-\beta t} \\
 \text{Var}(V(t)) &= \frac{e^{-2\beta t}\sigma^2}{2\beta} (e^{2\beta t} - 1) = \sigma^2 \frac{1 - e^{-2\beta t}}{2\beta} \\
 \mathbb{P}(V(t) \leq x) &= \Phi\left(\frac{x - \mathbb{E}(V(t))}{\sqrt{\text{Var}(V(t))}}\right) \\
 \text{Cov}(V(u), V(s)) &= \mathbb{E}((V(u) - \mathbb{E}(V(u)))(V(s) - \mathbb{E}(V(s)))) = \mathbb{E}\left(\frac{e^{-\beta u}\sigma}{\sqrt{2\beta}} B(e^{2\beta u} - 1) \frac{e^{-\beta s}\sigma}{\sqrt{2\beta}} B(e^{2\beta s} - 1)\right) \\
 &= \frac{\sigma^2 \exp(-\beta(u+s))}{2\beta} \mathbb{E}(B(e^{2\beta u} - 1) B(e^{2\beta s} - 1)) \\
 &= \frac{\sigma^2 \exp(-\beta(u+s))}{2\beta} (e^{2\beta u} - 1) = \sigma^2 \left(\frac{\exp(-\beta(s-u)) - \exp(-\beta(s+u))}{2\beta}\right) \\
 \mathbb{E}(V(\Delta t)) &= ve^{-\beta\Delta t} = v(1 - \beta\Delta t + o(\Delta t)) \\
 \mathbb{E}(V(\Delta t) - V(0)) &= v(1 - \beta\Delta t + o(\Delta t)) - v = -\beta v\Delta t + o(\Delta t) \\
 \text{Var}(V(\Delta t)) &= \sigma^2 \frac{1 - e^{-2\beta\Delta t}}{2\beta} = \sigma^2 \frac{2\beta\Delta t + o(\Delta t)}{2\beta} = \sigma^2\Delta t + o(\Delta t)
 \end{aligned}$$

Position process

Model of velocity rather than position. Then position

$$S(t) = S(0) + \int_0^t V(t)dt$$

As $V(t)$ is continuous the integral is well-defined. For $S(0) = V(0) = 0$ the variance of $S(t)$ is calculated to be

$$\text{Var}(S(t)) = \frac{\sigma^2}{\beta^2} \left[t - \frac{2}{\beta} (1 - e^{-\beta t}) + \frac{1}{2\beta} (1 - e^{-2\beta t}) \right]$$

Limiting/stationary distribution

$$\begin{aligned}
\lim_{t \rightarrow \infty} \mathbb{E}(V(t)) &= \lim_{t \rightarrow \infty} ve^{-\beta t} = 0 \\
\lim_{t \rightarrow \infty} \text{Var}(V(t)) &= \lim_{t \rightarrow \infty} \sigma^2 \frac{1 - e^{-2\beta t}}{2\beta} = \frac{\sigma^2}{2\beta} \\
\lim_{t \rightarrow \infty} \mathbb{P}(V(t) \leq y) &= \Phi\left(\frac{y\sqrt{2\beta}}{\sigma}\right) \\
V^s(t) &= \sigma \frac{e^{-\beta t}}{\sqrt{2\beta}} B(e^{2\beta t}) \\
\text{Cov}(V^s(s), V^s(t)) &= \frac{e^{-\beta(t+s)}}{2\beta} \min(e^{2\beta t}, e^{2\beta s}) = \frac{e^{-\beta|t-s|}}{2\beta}
\end{aligned}$$

We define a bivariate normal vector $\mathbf{X} = \begin{pmatrix} X_1 \\ X_2 \end{pmatrix}$

$$\begin{pmatrix} X_1 \\ X_2 \end{pmatrix} \sim N\left(\begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix}, \begin{pmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{pmatrix}\right).$$

With

$$\mathbf{x} = \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}, \quad \boldsymbol{\mu} = \begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix}, \quad \boldsymbol{\Sigma} = \begin{pmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{pmatrix}$$

we can express the joint density as

$$\begin{aligned}
f(x_1, x_2) &= \frac{1}{2\pi\sqrt{\det(\boldsymbol{\Sigma})}} e^{-\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu})'\boldsymbol{\Sigma}^{-1}(\mathbf{x}-\boldsymbol{\mu})} \\
&= \frac{1}{2\pi\sigma_1\sigma_2\sqrt{1-\rho^2}} e^{-\frac{\left(\frac{x_1-\mu_1}{\sigma_1}\right)^2 - 2\rho\frac{x_1-\mu_1}{\sigma_1}\frac{x_2-\mu_2}{\sigma_2} + \left(\frac{x_2-\mu_2}{\sigma_2}\right)^2}{2\sigma_1^2\sigma_2^2(1-\rho^2)}}
\end{aligned}$$

we have the conditional density

$$f_{X_2|X_1=x_1}(x_2) = \frac{\frac{1}{2\pi\sigma_1\sigma_2\sqrt{1-\rho^2}} e^{-\frac{\left(\frac{x_1-\mu_1}{\sigma_1}\right)^2 - 2\rho\frac{x_1-\mu_1}{\sigma_1}\frac{x_2-\mu_2}{\sigma_2} + \left(\frac{x_2-\mu_2}{\sigma_2}\right)^2}{2\sigma_1^2\sigma_2^2(1-\rho^2)}}}{\frac{1}{\sqrt{2\pi}\sigma_1} e^{-\frac{(x_1-\mu_1)^2}{2\sigma_1^2}}} = \frac{1}{\sqrt{2\pi}\sigma_2\sqrt{1-\rho^2}} e^{-\frac{(x_2-\mu_2-\rho\frac{\sigma_2}{\sigma_1}(x_1-\mu_1))^2}{2\sigma_2^2(1-\rho^2)}}$$

to get

$$\mathbb{E}(X_2|X_1 = x_1) = \mu_2 + \rho\frac{\sigma_2}{\sigma_1}(x_1 - \mu_1), \quad \mathbb{E}(X_2|X_1) = \mu_2 + \rho\frac{\sigma_2}{\sigma_1}(X_1 - \mu_1)$$

or

$$\mathbb{E}(X_2 - \mu_2 | X_1 = x_1) = \rho \frac{\sigma_2}{\sigma_1} (x_1 - \mu_1), \quad \mathbb{E}(X_2 - \mu_2 | X_1) = \rho \frac{\sigma_2}{\sigma_1} (X_1 - \mu_1).$$

To ease notation and with no real loss of generality we assume $\mu_1 = \mu_2 = 0$

$$\mathbb{E}(X_2 | X_1 = x_1) = \rho \frac{\sigma_2}{\sigma_1} x_1, \quad \mathbb{E}(X_2 - \mu_2 | X_1) = \rho \frac{\sigma_2}{\sigma_1} X_1$$

and we rewrite to get

$$\sigma_1^2 \mathbb{E}(X_2 | X_1 = x_1) = \rho \sigma_1 \sigma_2 x_1, \quad \sigma_1^2 \mathbb{E}(X_2 | X_1) = \rho \sigma_1 \sigma_2 X_1$$

to finally obtain

$$\sigma_1^2 \mathbb{E}(X_2 | X_1) = \text{Cov}(X_1, X_2) X_1.$$

We now want to construct a one-dimensional Gaussian process where this relation holds for any pair $(X(t_1), X(t_2))$, so we assume that the covariance function $\Gamma(t_1, t_2) = \text{Cov}((X(t_1), X(t_2)))$ is time homogenous such that $\text{Cov}((X(t_1), X(t_2))) = \Gamma(t_2 - t_1)$. Our assumption amounts to $\sigma^2 \mathbb{E}(X(t) | X(0)) = \Gamma(t)X(0)$ or $\Gamma(0)\mathbb{E}(X(t) | X(0)) = \Gamma(t)X(0)$. We now evaluate $\Gamma(t_1 + t_2)$.

$$\begin{aligned} \Gamma(t_1 + t_2) &= \mathbb{E}[X(0)X(t_1 + t_2)] = \mathbb{E}[\mathbb{E}(X(0)X(t_1 + t_2) | X(0), X(t_1))] \\ &= \mathbb{E}[X(0)\mathbb{E}(X(t_1 + t_2) | X(0), X(t_1))] = \mathbb{E}[X(0)\mathbb{E}(X(t_1 + t_2) | X(t_1))] = \mathbb{E}\left[X(0)\frac{1}{\sigma^2}\Gamma(t_2)X(t_1)\right] \\ &= \frac{1}{\sigma^2}\Gamma(t_1)\Gamma(t_2), \end{aligned}$$

and get the functional equation

$$\sigma^2 \Gamma(t_1 + t_2) = \Gamma(t_1)\Gamma(t_2),$$

with solution

$$\Gamma(t) = \sigma^2 e^{-\alpha|t|}$$

for some α . We have defined a stationary Gaussian process with $X(t) \sim \mathcal{N}(0, \sigma^2)$, i.e. $\mu(t) = 0$ and covariance function $\Gamma(t) = \sigma^2 e^{-\alpha|t|}$. This process is called the stationary Ornstein-Uhlenbeck process.

The approach is taken from [1] Section 9.6 Page 407.

References

- [1] G. R. Grimmett and D. R. Stirzaker. *Probability and Random Processes*. Oxford University Press, third edition, 1995.