

Variance reduction techniques: Around B&S (Lecture 3 part 1)

Christophe Chorro (christophe.chorro@gmail.com)

University Paris 1

June 28 2008

- Variance reduction techniques
 - Introduction
 - Reminder on B&S Model
 - Control Variate

Biblio: • Stochastic Calculus and Black Scholes:

<http://christophe.chorro.fr/docs/CSangl.pdf>

- A.G.Z Kemna and A.C.F. Vorst, *A pricing method for options based on average asset values*, J. Banking Finan., 1990, March, 113–129.

- 1 Variance reduction techniques
 - Variance reduction techniques: Introduction
 - Reminder on B&S model
 - Control Variate

Variance reduction techniques: Introduction

Let $(X_n)_{n \in \mathbb{N}}$ be i.i.d random variables with values in \mathbb{R} such that $\mathbb{E}[|X_1|^2] < \infty$.

For large n , with a confidence of 95%,

$$\mathbb{E}[X_1] \in \left[\frac{S_n}{n} - \frac{1.96\sigma}{\sqrt{n}}, \frac{S_n}{n} + \frac{1.96\sigma}{\sqrt{n}} \right]$$

with $\sigma^2 = \text{Var}(X_1)$.

The magnitude of the error is given by $\frac{1.96\sigma}{\sqrt{n}}$: the size of σ is fundamental for the speed of convergence.

Idea: Reduce σ

Find Y such that $\mathbb{E}[X_1] = \mathbb{E}[Y]$ and $\text{Var}(X_1) > \text{Var}(Y)$.

- 1 Variance reduction techniques
 - Variance reduction techniques: Introduction
 - **Reminder on B&S model**
 - Control Variate

Brownian motion

We consider a probability space (Ω, \mathcal{A}, P) .

Definition

Standard Brownian motion (B.M) is a stochastic process $(B_t)_{t \in [0, T]}$ fulfilling :

a) $B_0 = 0$ *P*-a.s.

b) *B* is **continuous** i.e $t \rightarrow B_t(w)$ is continuous for *P* almost all *w*.

c) *B* has **independent increments**: For $t > s$, $B_t - B_s$ is independent of $\mathcal{F}_s^B = \sigma(B_u, u \leq s)$.

d) the increments of *B* are **stationary and gaussian**: For $t \geq s$, $B_t - B_s$ follows a $\mathcal{N}(0, t - s)$.

Brownian motion

We consider a subdivision $0 = t_0 < \dots < t_n = T$ of $[0, T]$. We want to **simulate**

$$(\mathbf{B}_{t_0}, \dots, \mathbf{B}_{t_n}).$$

Idea:

$$\mathbf{B}_{t_k} = \mathbf{B}_{t_{k-1}} + \underbrace{\mathbf{B}_{t_k} - \mathbf{B}_{t_{k-1}}}_{\mathcal{N}(\mathbf{0}, t_k - t_{k-1}) \perp \mathbf{B}_{t_{k-1}}, \dots, \mathbf{B}_0}.$$

Proposition

If (G_1, \dots, G_n) are i.i.d $\mathcal{N}(0, 1)$, we define

$$X_0 = 0, \quad X_i = \sum_{j=1}^i \sqrt{t_j - t_{j-1}} G_j \quad i > 0.$$

Then

$$(X_0, \dots, X_n) \stackrel{\mathcal{D}}{=} (\mathbf{B}_{t_0}, \dots, \mathbf{B}_{t_n}).$$

Brownian motion

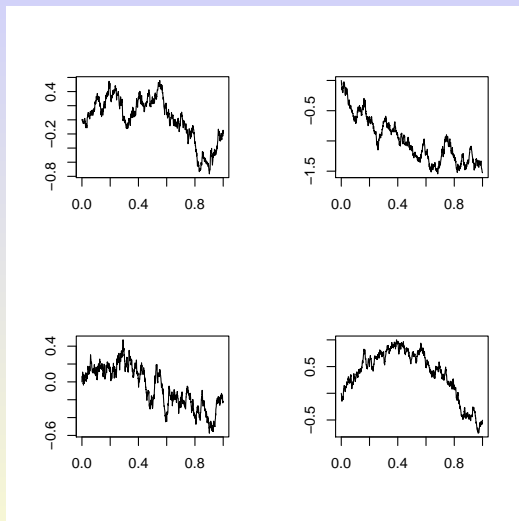


Figure: 4 paths of the Brownian motion on $[0, 1]$ generated using the preceding method with the regular subdivision of step 0.001.

Black Scholes model

We consider the time interval $[0, T]$ and r the risk free rate (supposed to be constant) during this period.

Non-risky asset: Its dynamic is given by

$$S_0^0 = 0, S_t^0 = e^{rt}.$$

Risky asset: Under the historical probability P its dynamic is given by the following SDE:

$$\underline{dS_t = \mu S_t dt + \sigma S_t dB_t} \quad (1)$$

with initial condition $S_0 = x_0 > 0$ and where B is a standard BM under P .

$$\text{It\^o formula} \Rightarrow S_t = x_0 e^{(\mu - \frac{1}{2}\sigma^2)t + \sigma B_t}.$$

Black Scholes model

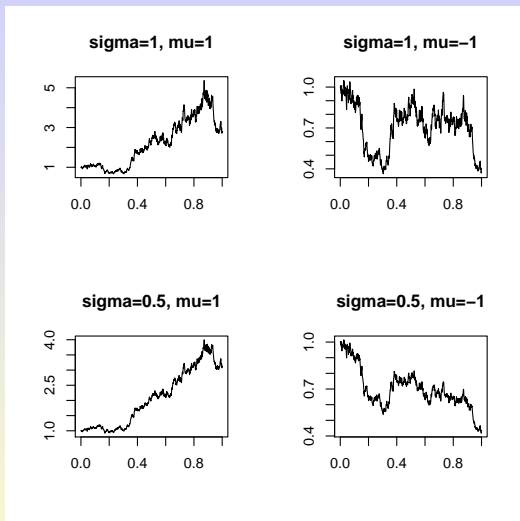


Figure: Simulation of a path of the risky asset in the B&S model for different parameters

Black Scholes model

What is, in this model, the price of a contingent claim with payoff Φ_T at T ?

Proposition

In the B&S model there exists a unique probability $Q \sim P$ such that the price at $t = 0$ of a contingent claim with payoff Φ_T at T is given by

$$\text{price} = e^{-rT} \mathbb{E}_Q[\Phi_T].$$

Moreover the dynamic of the risky asset under Q is given by

$$\underline{dS_t = rS_t dt + \sigma S_t dW_t} \quad (\mu \Leftrightarrow r) \quad (2)$$

where W is a standard BM under Q .

Black Scholes model

Examples: The Black Scholes Formulas

- For **Call options** ($\Phi_T = (S_T - K)_+$) one has

$$\mathbb{E}_{\mathbf{Q}}[(S_T - K)_+] = S_0 N(d_1) - Ke^{-rT} N(d_2) \quad (3)$$

where

$$d_1 = \frac{\log(\frac{S_0}{K}) + (r + \frac{\sigma^2}{2})T}{\sigma\sqrt{T}} \text{ and } d_2 = \frac{\log(\frac{S_0}{K}) + (r - \frac{\sigma^2}{2})T}{\sigma\sqrt{T}} \quad (4)$$

and where N is the distribution function of a $\mathcal{N}(0, 1)$.

- For **Put options** ($\Phi_T = (K - S_T)_+$) one has

$$\mathbb{E}_{\mathbf{Q}}[(K - S_T)_+] = -S_0 N(-d_1) + Ke^{-rT} N(-d_2). \quad (5)$$

Black Scholes model

This formulas are fundamental because

- They are **easy** to compute in practice
- They are a **Benchmark** to test numerical methods (for example variance reduction techniques)

In the sequel, all the variance reduction methods will be test computing by Monte carlo simulations

$$\mathbb{E}[(K - e^{\sigma G})_+] \text{ or } \mathbb{E}[(e^{\sigma G} - K)_+]$$

where $G \hookrightarrow \mathcal{N}(0, 1)$ i.e computing (up to some coefficients) the price of a call or a put option in a B&S model where $S_0 = 1$ and $r = 0$.

Black Scholes model: Numerical example

- Price of a call $\mathbb{E}[(e^{\sigma G} - K)_+]$ with $\sigma = 0.5$ and $K = 1$
 - Exact value=0.28353
 - Estimated value (N=100) = 0.249, confidence interval at 95% : [0.164; 0.334]
 - Estimated value (N=1000) = 0.279, confidence interval [0.248; 0.308]
 - Estimated value (N=10000) = 0.276, confidence interval [0.267; 0.285]

- Price of a put $\mathbb{E}[(e^{-\sigma G} + K)_+]$ with $\sigma = 0.5$ and $K = 1$.
 - Exact value=0.15038
 - Estimated value (N=100) = 0.154, confidence interval at 95% : [0.112; 0.195]
 - Estimated value (N=1000) = 0.155, confidence interval [0.143; 0.167]
 - Estimated value (N=10000) = 0.149, confidence interval [0.145; 0.152]

Black Scholes model

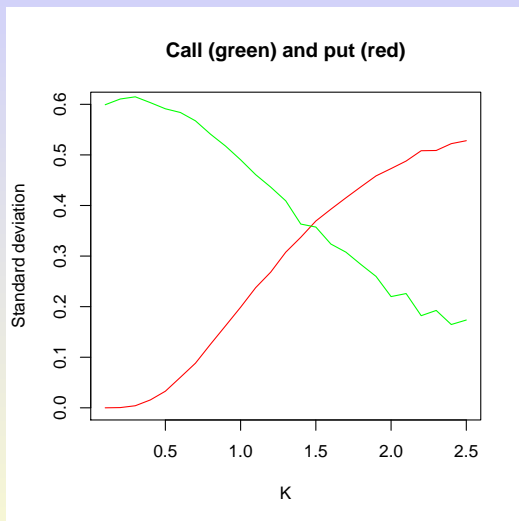


Figure: Standard deviation of the preceding payoffs ($\sigma = 0.5$) for different strikes

Black Scholes model

In practical cases, the moneyness $\frac{S_0}{K}$ of most liquid options (in our example $S_0 = 1$) belongs in general to $[0.7, 1.3]$.

Thus, It's better to price put than call by Monte Carlo methods.

To recover the price of the call we may use the **Call-Put parity**:

$$\mathbb{E}[(e^{\sigma G} - K)_+] = \mathbb{E}[(-e^{\sigma G} + K)_+] + e^{\frac{\sigma^2}{2}} - K.$$

- Price of a call $\mathbb{E}[(e^{\sigma G} - K)_+]$ with $\sigma = 0.5$ and $K = 1$ computed by Call-Put parity and MC
 - **Exact value=0.28353**
 - **Estimated value (N=100) = 0.281**, confidence interval at 95% : **[0.240; 0.320]**
 - **Estimated value (N=1000) = 0.285**, confidence interval **[0.272; 0.297]**
 - **Estimated value (N=10000) = 0.287**, confidence interval **[0.283; 0.291]**

- 1 Variance reduction techniques
 - Variance reduction techniques: Introduction
 - Reminder on B&S model
 - **Control Variate**

We want to compute by Monte Carlo method $\mathbb{E}[f(X)]$.

Idea:

$$\mathbb{E}[f(X)] = \mathbb{E}[f(X) - h(X)] + \mathbb{E}[h(X)]$$

where h is chosen to ensure that

- $\mathbb{E}[h(X)]$ may be **computed explicitly**
- $\text{Var}(f(X) - h(X)) \ll \text{Var}(f(X))$ (intuitively we look for $f(X) - h(X)$ small).

Example: Call-Put parity

Control Variate: Asian Options with Kemna and Vorst Method

Aim: Price by MC method an asian call in the B&S model

Thus we have to approximate (no closed form formula)

$$e^{-rT} \mathbb{E} \left[\left(\frac{1}{T} \int_0^T S_s ds - K \right)_+ \right]$$

where $\forall t \in [0, T]$

$$S_t = x_0 e^{(r - \frac{1}{2}\sigma^2)t + \sigma W_t}$$

First Idea:

$$\frac{1}{T} \int_0^T S_s ds \approx \frac{1}{p} \sum_{k=0}^p S_{\frac{kT}{p}} + MC$$

With $\sigma = 0.2$, $x_0 = K = 100$, $r = 0.1$, $T = 1$ and $p = 50$ one obtains

- **Estimated value (N=10000) = 6.93**, confidence interval at 95% :
[6.769; 7.101]

Control Variate: Asian Options with Kemna and Vorst Method

Second Idea: When σ and r are small Kemna and Vorst tell us that

$$\frac{1}{T} \int_0^T S_s ds \approx \exp \left(\frac{1}{T} \int_0^T \log(S_s) ds \right) = A_T.$$

We are going to use the identity

$$\begin{aligned} e^{-rT} \mathbb{E} \left[\left(\frac{1}{T} \int_0^T S_s ds - K \right)_+ \right] &= \underbrace{e^{-rT} \mathbb{E} \left[\left(\frac{1}{T} \int_0^T S_s ds - K \right)_+ - (A_T - K)_+ \right]}_{(1)} \\ &+ \underbrace{e^{-rT} \mathbb{E} [(A_T - K)_+]}_{(2)} \end{aligned}$$

Controle Variate: Asian Options with Kemna and Vorst Method

For (1) We use the first idea (Approximation by Riemann sums)

For (2) We just have to remark that

$$A_T = \exp\left(\frac{1}{T} \int_0^T \log(S_s) ds\right) \hookrightarrow \exp\left(\mathcal{N}\left((\tilde{r} - \frac{\tilde{\sigma}^2}{2})T, \tilde{\sigma}^2 T\right)\right)$$

where $\tilde{r} = \frac{r}{2} - \frac{\sigma^2}{12}$ and $\tilde{\sigma} = \frac{\sigma}{\sqrt{3}}$.

Thus we may use **Black Scholes formula** to compute explicitly (2).

With $\sigma = 0.2$, $x_0 = K = 100$, $r = 0.1$, $T = 1$ and $p = 50$ one obtains

- **Estimated value (N=10000) = 6.981**, confidence interval at 95% : **[6.969; 6.993]**.