

On the Kernel of the Black-Scholes Equation in the Form of White Noise

A. Kananthai

Department of Mathematics
Chiangmai University
Chiangmai, 50200, Thailand
malamnka@science.cmu.ac.th

Abstract

In this paper, we study the well known equation which is the Black-Scholes equation in the form of white noise. We found the kernel of such equation and obtained some interesting properties of such kernel.

Mathematics Subject Classification: 35K05, 60H40, 60J65

Keywords: Black-Scholes equation, white noise, kernel

1 Introduction

In financial mathematics, the famous equation named the Black-Scholes equation plays an important role in solving the option price of stocks. The Black-Scholes equation is given by

$$\frac{\partial u(s, t)}{\partial t} + rs \frac{\partial u(s, t)}{\partial s} + \frac{\sigma^2}{2} s^2 \frac{\partial^2 u(s, t)}{\partial s^2} - ru(s, t) = 0 \quad (1)$$

with the terminal condition

$$u(s, t) = (s - p)^+ \quad (2)$$

for $0 \leq t \leq T$ where $u(s, t)$ is the option price at time t , r is the interest rate, s is the price of stock at time t , σ is the volatility of stock and p is the strike price.

In this work, we transformed the option price $u(s, t)$ to $V(\xi, t)$ where ξ is the white noise and ξ can be obtained from the Geometric Brownian motion of the stock model

$$ds = \mu s dt + \sigma s dB$$

where μ is the drift, σ is the volatility and B is the Brownian motion. Thus (1) can be transformed to the equation

$$\frac{\partial V(\xi, t)}{\partial t} + \frac{1}{2t^2} \frac{\partial^2 V(\xi, t)}{\partial \xi^2} + \left(\frac{r}{t\sigma} - \frac{\sigma}{2t} \right) \frac{\partial V(\xi, t)}{\partial \xi} - rV(\xi, t) = 0. \quad (3)$$

We study (3) for the case $0 \leq t \leq 1$ with the condition

$$V(\xi, 1) = f(\xi) \quad (4)$$

where $f(\xi)$ is the given generalized function. We can show that $\xi = \frac{dB}{dt}$ is a tempered distribution and $V(\xi, t)$ is also a tempered distribution see [1]. Thus we can apply the Fourier transform to (3) and (4), we obtain

$$V(\xi, t) = K(\xi, t) * f(\xi) \quad (5)$$

in the convolution form as a solution of (3) with satisfies the condition (4) and $K(\xi, t)$ is the kernel of the form

$$K(\xi, t) = \sqrt{\frac{t}{2\pi(1-t)}} e^{-(1-t)r} \exp \left[\frac{-t \left(\xi - \left(\frac{r}{\sigma} - \frac{\sigma}{2} \right) \ln t \right)^2}{2(1-t)} \right]. \quad (6)$$

It can be shown that $\lim_{t \rightarrow 1} K(\xi, t) = \delta(\xi)$. Thus from (5)

$$V(\xi, 1) = \lim_{t \rightarrow 1} V(\xi, t) = \delta(\xi) * f(\xi) = f(\xi)$$

thus (4) holds.

2 Preliminary Notes

Recall the stock model

$$ds = \mu s dt + \sigma s dB \quad (7)$$

or

$$ds = \mu s dt + \sigma s \dot{B}(t) dt$$

where B is the Wiener process or the Brownian motion, $\dot{B}(t) = \frac{dB}{dt}$ is the white noise. From (7), by using the Itô's formula, we obtain

$$\int_0^t d(\ln s(\tau)) = \left(\mu - \frac{\sigma^2}{2} \right) \int_0^t d\tau + \sigma \int_0^t \dot{B}(\tau) d\tau \quad \text{where } 0 \leq \tau \leq t.$$

Thus

$$\ln s(t) - \ln s_0 = \left(\mu - \frac{\sigma^2}{2} \right) t + \sigma \int_0^t \dot{B}(\tau) d\tau \quad (8)$$

where $s(0) = s_0$.

Now consider $\int_0^t \dot{B}(\tau)d\tau$, we regard $\dot{B}(\tau)$ as a stochastic process with smooth sample path. By the mean value theorem, there exists some point τ^* for $0 < \tau^* < t$ such that

$$\int_0^t \dot{B}(\tau^*)d\tau = \dot{B}(\tau^*) \int_0^t d\tau = \dot{B}(\tau^*)t$$

where $\dot{B}(\tau^*)$ is the mean value of such integral and let $\xi(\tau^*)$ denote the mean value $\dot{B}(\tau^*)$. Actually $\xi(\tau^*)$ also the white noise. Thus from (7), $\ln\left(\frac{s}{s_0}\right) = \left(\mu - \frac{\sigma^2}{2}\right)t + \sigma\xi t$ or

$$\xi = \frac{1}{t\sigma} \ln\left(\frac{s}{s_0}\right) - \frac{\mu}{\sigma} + \frac{\sigma}{2} \tag{9}$$

Let us discuss briefly some properties of ξ . It has been shown that ξ is a tempered distribution, that is $\forall \xi \in \mathcal{S}'(\mathbb{R})$ —the space of tempered distribution and for any testing function $\varphi \in \mathcal{S}(\mathbb{R})$ —the Schwartz space, define $\langle \xi, \varphi \rangle$ on $\mathcal{S}'(\mathbb{R})$, we can apply the Minlos Theorem to obtain a probability measure μ on its dual space $\mathcal{S}'(\mathbb{R})$ such that

$$\int_{\mathcal{S}'(\mathbb{R})} e^{ix\varphi} d\mu(x) = e^{-\frac{1}{2}|\varphi|_0^2}, \quad \forall \varphi \in \mathcal{S}(\mathbb{R})$$

where $|\varphi|_0^2 = \int_{\mathbb{R}} |\varphi|^2 dx$ see [1]. Moreover $\langle \xi, \varphi \rangle$ has the Gaussain distribution with mean 0 and variance $|\varphi|_0^2$.

Now we show how to construct equation (3). From (9)

$$\frac{\partial \xi}{\partial s} = \frac{1}{t\sigma} \cdot \frac{s_0}{s} \cdot \frac{1}{s_0} = \frac{1}{t\sigma s},$$

thus

$$\frac{\partial u(s, t)}{\partial s} = \frac{\partial V(\xi, t)}{\partial s} = \frac{\partial V(\xi, t)}{\partial \xi} \cdot \frac{\partial \xi}{\partial s} = \frac{1}{t\sigma s} \frac{\partial V(\xi, t)}{\partial \xi},$$

and

$$\begin{aligned} \frac{\partial^2 u(s, t)}{\partial s^2} &= \frac{\partial^2 V(\xi, t)}{\partial s^2} = \frac{\partial}{\partial \xi} \left(\frac{1}{t\sigma s} \frac{\partial V(\xi, t)}{\partial \xi} \right) \cdot \frac{\partial \xi}{\partial s} \\ &= \left(\frac{1}{t\sigma s} \frac{\partial^2 V(\xi, t)}{\partial \xi^2} + \frac{1}{t\sigma} \frac{\partial V(\xi, t)}{\partial \xi} \left(-\frac{1}{s^2} \right) \frac{\partial s}{\partial \xi} \right) \frac{\partial \xi}{\partial s} \\ &= \frac{1}{t^2 \sigma^2 s^2} \frac{\partial^2 V(\xi, t)}{\partial \xi^2} - \frac{1}{t\sigma s^2} \frac{\partial V(\xi, t)}{\partial \xi} \end{aligned}$$

substitute into (1) we obtain (3).

Definition 2.1. Let $f(x)$ is a locally integrable function. The Fourier transform $\widehat{f}(\omega)$ of $f(x)$ is defined by

$$\widehat{f}(\omega) = \int_{-\infty}^{\infty} e^{-i\omega x} f(x) dx \quad (10)$$

and the inverse Fourier transform of $\widehat{f}(\omega)$ also defined by

$$f(x) = \mathcal{F}^{-1}\widehat{f}(\omega) = \frac{1}{2\pi} \int_{-\infty}^{\infty} e^{i\omega x} \widehat{f}(\omega) d\omega \quad (11)$$

3 Main Results

Theorem 3.1. *Given the white noise form of the Black-Scholes equation*

$$\frac{\partial V(\xi, t)}{\partial t} + \frac{1}{2t^2} \frac{\partial^2 V(\xi, t)}{\partial \xi^2} + \left(\frac{r}{t\sigma} - \frac{\sigma}{2t} \right) \frac{\partial V(\xi, t)}{\partial \xi} - rV(\xi, t) = 0 \quad (12)$$

for $0 \leq t \leq 1$ and ξ is the white noise given by (9) with the condition

$$V(\xi, 1) = f(\xi) \quad (13)$$

where $f(\xi)$ is the given generalized function. Then we obtain

$$V(\xi, t) = K(\xi, t) * f(\xi) \quad (14)$$

as the solution of (12) where

$$K(\xi, t) = \sqrt{\frac{t}{2\pi(1-t)}} e^{-(1-t)r} \exp \left[\frac{-t \left(\xi - \left(\frac{r}{\sigma} - \frac{\sigma}{2} \right) \ln t \right)^2}{2(1-t)} \right]. \quad (15)$$

is the kernel of (12).

Proof. Take the Fourier transform defined by (10) to both sides of (12) and obtain

$$\frac{\partial \widehat{V}(\omega, t)}{\partial t} - \frac{\omega^2}{2t^2} \widehat{V}(\omega, t) + \frac{1}{t} \left(\frac{r}{\sigma} - \frac{\sigma}{2} \right) i\omega \widehat{V}(\omega, t) - r\widehat{V}(\omega, t) = 0.$$

Thus

$$\widehat{V}(\omega, t) = C(\omega) e^{rt} e^{-\frac{\omega^2}{2t} - i\omega \left(\frac{r}{\sigma} - \frac{\sigma}{2} \right) \ln t}.$$

Now, from (13),

$$\widehat{V}(\omega, 1) = \widehat{f}(\omega).$$

Thus

$$C(\omega) = e^{-r + \frac{\omega^2}{2}} \widehat{f}(\omega),$$

and we obtain

$$\widehat{V}(\omega, t) = e^{-(1-t)r} \exp\left(\frac{-(1-t)}{2t}\omega^2 - i\omega\left(\frac{r}{\sigma} - \frac{\sigma}{2}\right)\ln t\right) \widehat{f}(\omega),$$

for $0 < t \leq 1$. Now

$$|\widehat{V}(\omega, t)| \leq e^{-(1-t)r} \left\| e^{\frac{-(1-t)}{2t}\omega^2} \right\| |\widehat{f}(\omega)|.$$

Let $M = \max |\widehat{f}(\omega)|$, thus

$$|\widehat{V}(\omega, t)| \leq e^{-(1-t)r} \left\| e^{\frac{-(1-t)}{2t}\omega^2} \right\| M \leq K.$$

where K is a constant. It follows that $\widehat{V}(\omega, t)$ is bounded for any fixed t with $0 < t \leq 1$. Moreover $\widehat{V}(\omega, t)$ is a tempered distribution. Now, from (11),

$$\begin{aligned} V(\xi, t) &= \frac{1}{2\pi} \int_{-\infty}^{\infty} e^{i\omega\xi} \widehat{V}(\omega, t) d\omega \\ &= \frac{1}{2\pi} e^{-(1-t)r} \int_{-\infty}^{\infty} \exp\left[\frac{-(1-t)}{2t}\omega^2 - i\omega\left(\frac{r}{\sigma} - \frac{\sigma}{2}\right)\ln t + i\omega\xi\right] \widehat{f}(\omega) d\omega \\ &= \frac{1}{2\pi} e^{-(1-t)r} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \exp\left[\frac{-(1-t)}{2t}\left(\omega^2 - \frac{2\omega t i(\xi - y - (\frac{r}{\sigma} - \frac{\sigma}{2})\ln t)}{1-t}\right)\right] f(y) dy d\omega \\ &= \frac{1}{2\pi} e^{-(1-t)r} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \exp\left[\frac{-t(\xi - y - (\frac{r}{\sigma} - \frac{\sigma}{2})\ln t)^2}{2(1-t)}\right] \times \\ &\quad \exp\left[\frac{-(1-t)}{2t}\left(\omega - \frac{it(\xi - y - (\frac{r}{\sigma} - \frac{\sigma}{2})\ln t)}{1-t}\right)^2\right] f(y) dy d\omega \\ &= \frac{1}{2\pi} e^{-(1-t)r} \int_{-\infty}^{\infty} \exp\left[\frac{-t(\xi - y - (\frac{r}{\sigma} - \frac{\sigma}{2})\ln t)^2}{2(1-t)}\right] \times \\ &\quad \int_{-\infty}^{\infty} \exp\left[\frac{-(1-t)}{2t}\left(\omega - \frac{it(\xi - y - (\frac{r}{\sigma} - \frac{\sigma}{2})\ln t)}{1-t}\right)^2\right] d\omega f(y) dy. \end{aligned}$$

Let $u = \sqrt{\frac{(1-t)}{2t}}\left(\omega - \frac{it(\xi - y - (\frac{r}{\sigma} - \frac{\sigma}{2})\ln t)}{1-t}\right)$, then $du = \sqrt{\frac{1-t}{2t}}d\omega$ and we have

$d\omega = \sqrt{\frac{2t}{1-t}} du$. Thus

$$\begin{aligned} V(\xi, t) &= \frac{1}{2\pi} e^{-(1-t)r} \sqrt{\frac{2t}{1-t}} \int_{-\infty}^{\infty} \exp \left[\frac{-t \left(\xi - y - \left(\frac{r}{\sigma} - \frac{\sigma}{2} \right) \ln t \right)^2}{2(1-t)} \right] \\ &\quad \left(\int_{-\infty}^{\infty} e^{-u^2} du \right) f(y) dy \\ &= \frac{\sqrt{\pi}}{2\pi} \sqrt{\frac{2t}{1-t}} e^{-(1-t)r} \int_{-\infty}^{\infty} \exp \left[\frac{-t \left(\xi - y - \left(\frac{r}{\sigma} - \frac{\sigma}{2} \right) \ln t \right)^2}{2(1-t)} \right] f(y) dy \\ &= \sqrt{\frac{t}{2\pi(1-t)}} e^{-(1-t)r} \int_{-\infty}^{\infty} \exp \left[\frac{-t \left(\xi - y - \left(\frac{r}{\sigma} - \frac{\sigma}{2} \right) \ln t \right)^2}{2(1-t)} \right] f(y) dy. \end{aligned}$$

Let

$$K(\xi, t) = \sqrt{\frac{t}{2\pi(1-t)}} e^{-(1-t)r} \exp \left[\frac{-t \left(\xi - \left(\frac{r}{\sigma} - \frac{\sigma}{2} \right) \ln t \right)^2}{2(1-t)} \right] \quad \text{for } 0 < t \leq 1.$$

Then $V(\xi, t) = K(\xi, t) * f(\xi)$ for $0 < t \leq 1$.

Thus we obtain (15). $K(\xi, t)$ is called the kernel of (12). \square

Theorem 3.2. (The properties of $K(\xi, t)$).

The kernel $K(\xi, t)$ define by (15) has the following properties

- (i) $K(\xi, t)$ satisfies equation (12).
- (ii) $K(\xi, t)$ is a tempered distribution, that is $K(\xi, t) \in \mathcal{S}'(\mathbb{R})$.
- (iii) $K(\xi, t) > 0$ for $0 < t \leq 1$.
- (iv) $e^{(1-t)r} \int_{-\infty}^{\infty} K(\xi, t) d\xi = 1$.
- (v) $\lim_{t \rightarrow 1} K(\xi, t) = \delta(\xi)$ where $\delta(\xi)$ is the Dirac-delta distribution.
- (vi) $K(\xi, t)$ is a Gaussian (or normal) distribution with mean $e^{-(1-t)r} \left(\frac{r}{\sigma} - \frac{\sigma}{2} \right) \ln t$, variance $e^{-2(1-t)r} \frac{(1-t)}{t}$.

Proof. (i) By computing directly, $K(\xi, t)$ satisfies (12).

(ii) Since $K(\xi, t)$ is a Gaussian function and $K(\xi, t) \in \mathcal{L}(\mathbb{R})$ where $\mathcal{L}(\mathbb{R})$ is the space of integrable function on the real \mathbb{R} . It follows that $K(\xi, t)$ is a tempered distribution.

(iii) $K(\xi, t) > 0$ for $0 < t \leq 1$ is obvious.

(iv)

$$\begin{aligned} e^{(1-t)r} \int_{-\infty}^{\infty} K(\xi, t) d\xi &= e^{(1-t)r} \int_{-\infty}^{\infty} \sqrt{\frac{t}{2\pi(1-t)}} e^{-\frac{t}{2(1-t)} \left(\xi - \left(\frac{r}{\sigma} - \frac{\sigma}{2}\right) \ln t\right)^2} d\xi \\ &= \sqrt{\frac{t}{2\pi(1-t)}} \int_{-\infty}^{\infty} \exp\left[-\frac{t}{2(1-t)} \left(\xi - \left(\frac{r}{\sigma} - \frac{\sigma}{2}\right) \ln t\right)^2\right] d\xi. \end{aligned}$$

Let $u = \frac{\sqrt{t}\left(\xi - \left(\frac{r}{\sigma} - \frac{\sigma}{2}\right) \ln t\right)}{\sqrt{2(1-t)}}$, then $d\xi = \sqrt{\frac{2(1-t)}{t}} du$. Thus

$$\begin{aligned} e^{(1-t)r} \int_{-\infty}^{\infty} K(\xi, t) d\xi &= \sqrt{\frac{t}{2\pi(1-t)}} \int_{-\infty}^{\infty} e^{-u^2} \sqrt{\frac{2(1-t)}{t}} du \\ &= \sqrt{\frac{t}{2\pi(1-t)}} \sqrt{\frac{2(1-t)}{t}} \sqrt{\pi} \\ &= 1. \end{aligned}$$

Thus $e^{(1-t)r} \int_{-\infty}^{\infty} K(\xi, t) d\xi = 1$.

(v)

$$\begin{aligned} \lim_{t \rightarrow 1} K(\xi, t) &= \lim_{t \rightarrow 1} e^{-(1-t)r} \lim_{t \rightarrow 1} \sqrt{\frac{t}{2\pi(1-t)}} \exp\left[\frac{-t \left(\xi - \left(\frac{r}{\sigma} - \frac{\sigma}{2}\right) \ln t\right)^2}{2(1-t)}\right] \\ &= \lim_{t \rightarrow 1} \sqrt{\frac{t}{2\pi(1-t)}} \exp\left[\frac{-t \left(\xi - \left(\frac{r}{\sigma} - \frac{\sigma}{2}\right) \ln t\right)^2}{2(1-t)}\right] \\ &= \delta(\xi) \qquad \text{see [2, pp 36-37].} \end{aligned}$$

(vi) Now, the mean

$$\begin{aligned} E(K(\xi, t)) &= E\left(e^{-(1-t)r} \sqrt{\frac{t}{2\pi(1-t)}} \exp\left[\frac{-t \left(\xi - \left(\frac{r}{\sigma} - \frac{\sigma}{2}\right) \ln t\right)^2}{2(1-t)}\right]\right) \\ &= e^{-(1-t)r} E\left(\sqrt{\frac{t}{2\pi(1-t)}} \exp\left[\frac{-\left(\xi - \left(\frac{r}{\sigma} - \frac{\sigma}{2}\right) \ln t\right)^2}{\frac{2(1-t)}{t}}\right]\right) \\ &= e^{-(1-t)r} \left(\frac{r}{\sigma} - \frac{\sigma}{2}\right) \ln t. \end{aligned}$$

Since the function in the is a Gaussian or normal distribution. Thus $E(K(\xi, t))$ is the mean $e^{-(1-t)r} \left(\frac{r}{\sigma} - \frac{\sigma}{2}\right) \ln t$.

The variance

$$\begin{aligned} V(K(\xi, t)) &= V\left(e^{-(1-t)r} \sqrt{\frac{t}{2\pi(1-t)}} \exp\left[\frac{-t\left(\xi - \left(\frac{r}{\sigma} - \frac{\sigma}{2}\right) \ln t\right)^2}{2(1-t)}\right]\right) \\ &= e^{-2(1-t)r} \left(\frac{1-t}{t}\right) \quad \text{for } 0 < t \leq 1. \end{aligned}$$

□

Note: The solution $V(\xi, t)$ of (12) of the Theorem (3.1) is called the option price in the white noise form where the white noise ξ can be computed from (8) when the price s of the stock is known. The solution $V(\xi, t)$ can be written by

$$V(\xi, t) = K(\xi, t) * f(\xi)$$

or for $0 < t \leq 1$,

$$\begin{aligned} V(\xi, t) &= e^{-(1-t)r} \sqrt{\frac{t}{2\pi(1-t)}} \int_{-\infty}^{\infty} \exp\left[\frac{-t\left(\xi - y - \left(\frac{r}{\sigma} - \frac{\sigma}{2}\right) \ln t\right)^2}{2(1-t)}\right] f(y) dy, \\ e^{(1-t)r} V(\xi, t) &= \sqrt{\frac{t}{2\pi(1-t)}} \int_{-\infty}^{\infty} \exp\left[\frac{-t\left(\xi - y - \left(\frac{r}{\sigma} - \frac{\sigma}{2}\right) \ln t\right)^2}{2(1-t)}\right] f(y) dy. \end{aligned}$$

The left hand side of the above equation is the value of the option price of the riskless interest rate r (constant) at the time $1 - t$ ($0 \leq t \leq 1$) which equals the convolution form on the right hand side.

Acknowledgement

The author would like to thank the Centre of Excellence in Mathematics, a national centre under the Postgraduate Education and Research Development Office (PERDO), Commission on Higher Education of the Ministry of Education for financial support.

References

- [1] H. H Kuo, *White Noise Distribution Theory*, CRC Press, Boca Raton, 1996.
- [2] I. M. Gel'fand, G. E Shilov, *Generalized Function*, Vol 1, Academic Press, 1972.

Received: November, 2009