

UROPS Project 16124 Full report
Financial Mathematics with Python

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March 29, 2017

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1 Derivation of Black Scholes PDE

1.1 Basics

We assume that the following two SDE hold:

$$dM_t = rM_t dt$$

$$dS_t = \mu S_t dt + \sigma S_t dW_t$$

We assume that the following Itô's Lemma hold:

$$\text{As } dS_t = \mu S_t dt + \sigma S_t dW_t,$$

$$dV_t = \left(\frac{\partial V}{\partial t} + \frac{1}{2} \sigma^2 S_t^2 \frac{\partial^2 V}{\partial S^2} \right) dt + \frac{\partial V}{\partial S} dS_t$$

1.2 Delta-hedging Argument

Our first aim is to find ϕ_t

for $\Pi_t = V_t - \phi_t S_t$

such that

$$d\Pi_t = dV_t - \phi_t dS_t \text{ (Self-financing)}$$

$$d\Pi_t = r\Pi_t dt \text{ (risk free)}$$

From the equations, we can obtain that

$$r\Pi_t dt = dV_t - \phi_t dS_t$$

$$r(V_t - \phi_t S_t) dt = dV_t - \phi_t dS_t$$

$$dV_t = r(V_t - \phi_t S_t) dt + \phi_t dS_t$$

By Itô's Lemma,

$$dV_t = \left(\frac{\partial V}{\partial t} + \frac{1}{2} \sigma^2 S_t^2 \frac{\partial^2 V}{\partial S^2} \right) dt + \frac{\partial V}{\partial S} dS_t$$

Hence we obtain two equations:

$$\phi_t = \frac{\partial V}{\partial S}$$

$$r(V_t - \phi_t S_t) = \frac{\partial V}{\partial t} + \frac{1}{2} \sigma^2 S_t^2 \frac{\partial^2 V}{\partial S^2}$$

$$r(V_t - \frac{\partial V}{\partial S} S_t) = \frac{\partial V}{\partial t} + \frac{1}{2} \sigma^2 S_t^2 \frac{\partial^2 V}{\partial S^2}$$

$$\frac{\partial V}{\partial t} + \frac{1}{2} \sigma^2 S_t^2 \frac{\partial^2 V}{\partial S^2} + r \frac{\partial V}{\partial S} S_t - rV_t = 0$$

At time t , we have

$$\frac{\partial V}{\partial t} + \frac{1}{2} \sigma^2 S^2 \frac{\partial^2 V}{\partial S^2} + r \frac{\partial V}{\partial S} S - rV = 0$$

1.3 Replicating portfolio

Our aim is to find a_t and b_t such that

$\Pi_t = a_t S_t + b_t M_t$ can entirely replicate V_t

And also, the self-financing condition holds:

$$d\Pi_t = a_t dS_t + b_t dM_t$$

As $dS_t = \mu S_t dt + \sigma S_t dW_t$ and $dM_t = r M_t dt$,

$$\begin{aligned} d\Pi_t &= a_t(\mu S_t dt + \sigma S_t dW_t) + b_t(r M_t dt) \\ &= (a_t \mu S_t + r b_t M_t) dt + (\sigma a_t S_t) dW_t \end{aligned}$$

By Itô's Lemma,

$$\begin{aligned} dV_t &= \left(\frac{\partial V}{\partial t} + \frac{1}{2} \sigma^2 S_t^2 \frac{\partial^2 V}{\partial S^2} \right) dt + \frac{\partial V}{\partial S} dS_t \\ &= \left(\frac{\partial V}{\partial t} + \frac{1}{2} \sigma^2 S_t^2 \frac{\partial^2 V}{\partial S^2} \right) dt + \frac{\partial V}{\partial S} (\mu S_t dt + \sigma S_t dW_t) \\ &= \left(\frac{\partial V}{\partial t} + \frac{1}{2} \sigma^2 S_t^2 \frac{\partial^2 V}{\partial S^2} + \frac{\partial V}{\partial S} \mu S_t \right) dt + (\sigma S_t \frac{\partial V}{\partial S}) dW_t \end{aligned}$$

As Π_t fully replicates V_t ,

$$d\Pi_t = (a_t \mu S_t + r b_t M_t) dt + (\sigma a_t S_t) dW_t = dV_t$$

Also by Itô's Lemma,

$$dV_t = \left(\frac{\partial V}{\partial t} + \frac{1}{2} \sigma^2 S_t^2 \frac{\partial^2 V}{\partial S^2} + \frac{\partial V}{\partial S} \mu S_t \right) dt + (\sigma S_t \frac{\partial V}{\partial S}) dW_t$$

Hence we obtain that,

$$a_t = \frac{\partial V}{\partial S}$$

$$a_t \mu S_t + r b_t M_t = \frac{\partial V}{\partial t} + \frac{1}{2} \sigma^2 S_t^2 \frac{\partial^2 V}{\partial S^2} + \frac{\partial V}{\partial S} \mu S_t$$

$$\frac{\partial V}{\partial S} \mu S_t + r b_t M_t = \frac{\partial V}{\partial t} + \frac{1}{2} \sigma^2 S_t^2 \frac{\partial^2 V}{\partial S^2} + \frac{\partial V}{\partial S} \mu S_t$$

$$r b_t M_t = \frac{\partial V}{\partial t} + \frac{1}{2} \sigma^2 S_t^2 \frac{\partial^2 V}{\partial S^2}$$

$$r a_t S_t + r b_t M_t = \frac{\partial V}{\partial t} + \frac{1}{2} \sigma^2 S_t^2 \frac{\partial^2 V}{\partial S^2} + r a_t S_t$$

$$r V_t = \frac{\partial V}{\partial t} + \frac{1}{2} \sigma^2 S_t^2 \frac{\partial^2 V}{\partial S^2} + r \frac{\partial V}{\partial S} S_t$$

$$\frac{\partial V}{\partial t} + \frac{1}{2} \sigma^2 S_t^2 \frac{\partial^2 V}{\partial S^2} + r \frac{\partial V}{\partial S} S_t - r V_t = 0$$

Hence,

$$\frac{\partial V}{\partial t} + \frac{1}{2} \sigma^2 S^2 \frac{\partial^2 V}{\partial S^2} + r \frac{\partial V}{\partial S} S - r V = 0$$

2 Finite Difference Model for Numerical PDE

2.1 One factor model

2.2 Feynman–Kac formula

2.3 Crank–Nicolson method

3 Variance Reduction Techniques for Monte Carlo Simulation

3.1 Control Variate

3.2 Stratified Sampling

3.3 Importance Sampling

4 European call

4.1 Closed-form formula

4.2 Numerical PDE

4.3 Monte Carlo Simulation

5 European put

5.1 Closed-form formula

5.2 Numerical PDE

5.3 Monte Carlo Simulation

6 Amercian call

6.1 Closed-form formula

6.2 Numerical PDE

6.3 Monte Carlo Simulation

7 American put

7.1 Closed-form formula

7.2 Numerical PDE

7.3 Monte Carlo Simulation

8 Barrier option

8.1 Closed-form formula

8.2 Numerical PDE

8.3 Monte Carlo Simulation