

Minimax Option Pricing: How Robust is Black-Scholes?

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Joint work with Jake Abernethy and Andre Wibisono



Jake Abernethy
now at UPenn



Andre Wibisono
in 1225 this summer!

Financial Derivatives

A new financial instrument which is a function of old ones.

Class of derivatives we consider:

- Expiration date T (typically 1)
- Base stock/asset S
- Derivative pays out $g(S(T))$ at time T
 $S(t)$ is the value of S at time t

E.g. $\cos(\text{gas price on Aug 1})$

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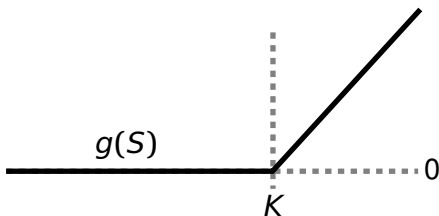
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Options

Running example: European call option

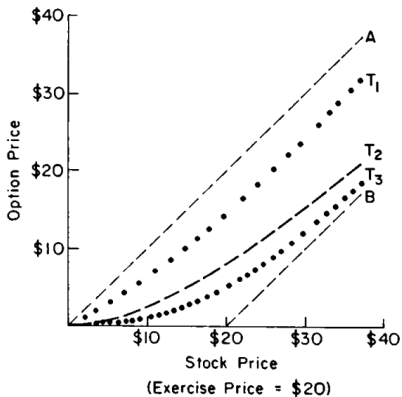


$g(S) = \max(0, S - K)$, where K is the *strike price*

Note: will use “option” and “derivative” interchangeably

How to Price?

What is a derivative g worth?



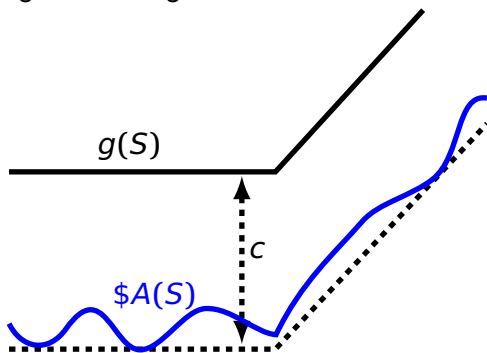
Black-Scholes Pricing

Fischer Black and Myron Scholes, 1973

- Intuition: price of derivative is cost of implementing it with existing instruments
- The algorithm which implements a derivative is a *replication strategy*
- The replication strategy has a fixed initial investment, which should be precisely the price of the derivative

Replication Strategies

Idea: As stock S fluctuates, use an algorithm A to “hedge” the option by buying and selling S



Result: guarantee the payoff of the option, minus a fixed cost c

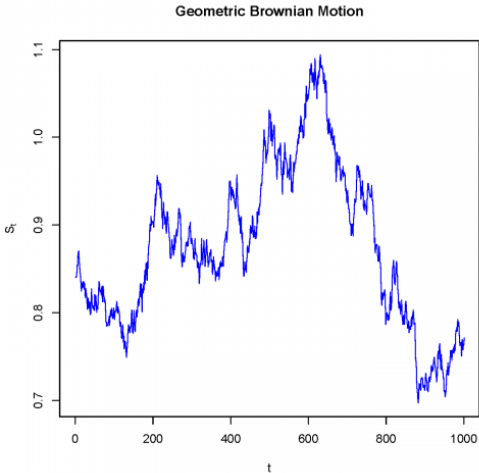
Black-Scholes Assumptions

- No arbitrage opportunities
- 0% interest borrowing
- Can trade continuously
- No transaction fees, no dividend payments, etc
- Stock prices follow Geometric Brownian Motion (GBM)

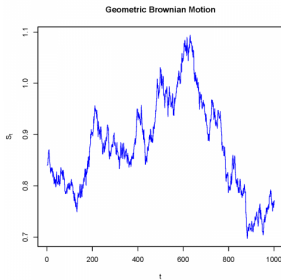
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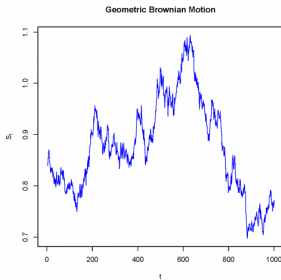


Let $W(t)$ be Brownian Motion with drift μ and volatility σ^2

- $W(0) = 0$
- $W(t) - W(s)$ and $W(u) - W(t)$ are indep. for $s < t < u$
- $W(t) - W(s) \sim N(\mu(t - s), \sigma^2(t - s))$

$G(t)$ is GBM $\iff \log(G(t))$ is Brownian Motion

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Delta-hedge Portfolio

Given option/derivative g :

- Let $V(S, t)$ be the value of the option at t
- Let $\frac{\partial V}{\partial S}$ be the replication portfolio
Hold \$ $\frac{\partial V}{\partial S}(t)$ of stock @ time t

Now solve for V using the no-arbitrage condition:

Stochastic PDE from Ito's Lemma:

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

Solution is:

$$V(S, t) = E_{Q^*}[\text{conv}[g(SG(T-t))]]$$

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The Black-Scholes Price

Price of option is therefore:

$$V(S, 0) = \mathbb{E}[g(S_{\text{GBM}}(T))]$$

Some surprises:

- Replication succeeds with probability 1!
- GBM above has drift 0 not μ !

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Beyond Black-Scholes

Problems with Black-Scholes

- Continuous-time trading
- Assumes GBM!

Why stochastic prices?

Prices respond to decisions of other traders!

Why not *adversarial* prices? [DeMarzo, Kremer, Mansour '08]

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An Option-Pricing Game

$$\inf_{A \in \mathcal{A}} \sup_{X \in \mathcal{X}} \mathbb{E} \left[g(X(1)) - \sum_{m=1}^n T_m \Delta_m \right]$$

- An n -round game between Investor and Nature
- Discrete-time trades at $t = m/n$, $m \in [n]$

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- Difference = "Regret"

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Value of the game \geq option price!

Upper bound because of the worst-case assumptions

Interested continuous trading limit as $n \rightarrow \infty$

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What price paths \mathcal{X} can Nature choose from?

We require: $\mathbb{E}[T_m^2 | T_{m-1}] \leq \frac{C}{n}$

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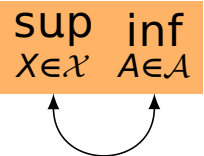
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Step I: Duality

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By Sion's Minimax Theorem, we can swap inf and sup!

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Step II: Martingale

$$\sup_{X \in \mathcal{X}} \inf_{A \in \mathcal{A}} \mathbb{E} \left[g(X(1)) - \sum_{m=1}^n T_m \Delta_m \right]$$

Now $\{T_m\}$ must be a martingale sequence

Assume not $\mathbb{E}[T_m | T_{m-1}] \neq 0$

Investor can choose $\Delta_m \rightarrow \pm\infty$

Nature would have unbounded loss!

But now the algorithm is completely irrelevant!

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$$\sup_{\substack{X \in \mathcal{X} \\ \{T_m\} \text{ mtg.}}} \mathbb{E} \left[g(X(1)) \right]$$

When g is convex, Nature wants to maximize variance

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Let X_n^* be Nature's OPT price path at n

Martingale sequence with conditional variance c/n

Applying a martingale CLT: *Lindeberg–Feller Theorem*

Theorem

As $n \rightarrow \infty$, $X_n^* \xrightarrow{d} GBM$

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What Just Happened?

Black-Scholes Option Pricing

- Assume stock \sim GBM
- Construct optimal replication strategy

$$\text{Price}(g) = \mathbb{E}[g(\text{GBM}(1))]$$

Minimax Option Pricing

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- Analyze *dual* of the game
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Back to DMK

Our constraint on Nature:

$$\mathbb{E}[T_m^2 | T_{m-1}] \leq \frac{c}{n}$$

[DeMarzo, Kremer, Mansour '08] use a *cumulative* constraint:

$$\sum_{m=1}^n \mathbb{E}[T_m^2 | T_{m-1}] \leq c$$

- Weaker constraint
- Allows for price jumps

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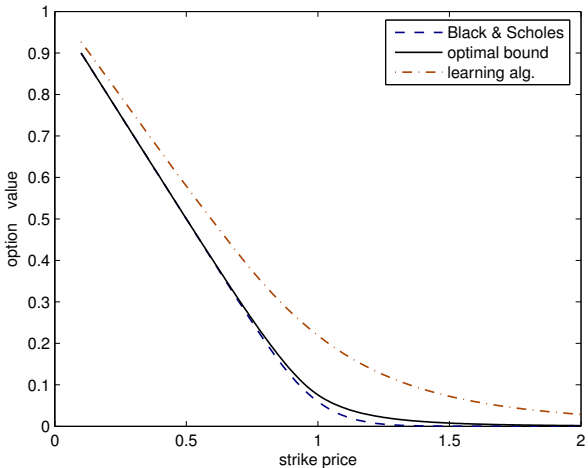
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Still Obtain Black-Scholes Price?

From [DeMarzo, Kremer, Mansour '08]:



Some Speculation

We believe:

- $X_n^* \not\rightarrow$ GBM
- $X_n^*(1) \rightarrow$ GBM(1)

Hence, we would still obtain the Black-Scholes price!

Proof ideas:

- $\text{support}(T_m) = 2$ in dual game
- Optimal Δ_m balances these two points
- Then Δ_m is a discrete derivative of V
- This V approaches Black-Scholes V , and Δ_m approaches the delta-hedge portfolio!

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New Analysis

Consider the value function for this game:

$$V_n(S, n) := g(S)$$

$$V_n(S, m) := \inf_{\Delta \in \mathbb{R}} \sup_{t \in [-z, z]} \Delta t + V_n(S(1+t), m-1)$$

And let $\Delta = \Delta(S, m)$ be the optimal investment for Investor

Lemma

If $\Delta = \Delta(S, m)$, then Nature's \sup_t is achieved by at least two points $t_1, -t_2$ with $t_1, t_2 > 0$

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By the Lemma, Δ must *balance* $V_n(S, m - 1)$ at t_1 and $-t_2$:

$$\begin{aligned}V_n(S, m) &= \Delta(S, m) t_1 + V_n(S(1 + t_1), m - 1) \\ &= -\Delta(S, m) t_2 + V_n(S(1 - t_2), m - 1)\end{aligned}$$

Solving for Δ :

$$\Delta(S, m) = \frac{V_n(S(1 - t_2), m - 1) - V_n(S(1 + t_1), m - 1)}{t_1 + t_2}$$

Foreshadowing

A discrete derivative... reminiscent of the delta-hedge portfolio!

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Martingale??

Plugging Δ back in:

$$V_n(S, m) = \frac{t_1}{t_1 + t_2} V_n(S(1 - t_2), m - 1) + \frac{t_2}{t_1 + t_2} V_n(S(1 + t_1), m - 1)$$

Introduce a random variable $T = \begin{cases} t_1 & \text{w.p. } \frac{t_2}{t_1 + t_2} \\ -t_2 & \text{w.p. } \frac{t_1}{t_1 + t_2} \end{cases}$ Note $\mathbb{E}[T] = 0$

$$V_n(S, m) = \mathbb{E}_T [V_n(S(1 + T), m - 1)] \quad (!)$$

Martingale??

Plugging Δ back in:

$$V_n(S, m) = \frac{t_1}{t_1 + t_2} V_n(S(1 - t_2), m - 1) + \frac{t_2}{t_1 + t_2} V_n(S(1 + t_1), m - 1)$$

Introduce a random variable $T = \begin{cases} t_1 & \text{w.p. } \frac{t_2}{t_1 + t_2} \\ -t_2 & \text{w.p. } \frac{t_1}{t_1 + t_2} \end{cases}$ *Note* $\mathbb{E}[T] = 0$

$$V_n(S, m) = \mathbb{E}_T [V_n(S(1 + T), m - 1)] \quad (!)$$

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Applying this at every round:

$$\begin{aligned}V_n(S, 0) &= \mathbb{E} \left[V_n \left(S \cdot \prod_{m=1}^n (1 + T_m), n \right) \right] \\ &= \mathbb{E} \left[g \left(S \cdot \prod_{m=1}^n (1 + T_m) \right) \right]\end{aligned}$$

Conjectures

- $V_n(S, n) \longrightarrow V_{B-S}(S, 1)$
- $\Delta(S, m) \longrightarrow \frac{\partial}{\partial S} V_{B-S}(S, \frac{m}{n})$

thank you