

Numerical methods MATHMODS course:  
Exercise sheet 3

1. Let  $(B_t)_{t \geq 0}$  be a standard one-dimensional Brownian motion starting from 0. Let  $a > 0$  and define

$$\tau_a := \inf\{t > 0 : B_t \geq a\}$$

- (i) Prove that  $\mathbb{P}(\tau_a < \infty) = 1$ .

*Hint:* Consider the stochastic process  $(Z_t)_{t \geq 0}$  defined by

$$Z_t = \exp\left(\beta B_t - \frac{\beta^2}{2} t\right), \quad t \geq 0, \quad \beta > 0.$$

Use Novikov's theorem to show that  $Z_t$  is a martingale, and thus that

$$\mathbb{E}(Z_{t \wedge \tau_a}) = 1, \quad \forall t \geq 0.$$

Write

$$\mathbb{E}(Z_{t \wedge \tau_a}) = \mathbb{E}(Z_{t \wedge \tau_a} 1_{\{\tau_a = \infty\}}) + \mathbb{E}(Z_{t \wedge \tau_a} 1_{\{\tau_a < \infty\}})$$

and use this to show that

$$1 = \mathbb{E}\left(\exp\left(\beta a - \frac{\beta^2}{2} \tau_a\right) 1_{\{\tau_a < \infty\}}\right). \quad (1)$$

Finally, take the limit in the above as  $\beta \rightarrow 0$ .

- (ii) Use part (i) and (1) to prove that the Laplace transform of  $\tau_a$  is given by

$$\mathbb{E}(e^{-\lambda \tau_a}) = e^{-a\sqrt{2\lambda}}, \quad \forall \lambda > 0.$$

2. **Practical:** Let  $(W_t)_{t \geq 0}$  be a standard Brownian motion starting from 0 and define the first hitting time of 1 by

$$\tau_1 = \inf\{t > 0 : W_t \geq 1\}.$$

Write code that approximates  $\tau_1$  using the first naive method described in lectures. Use this code to produce a figure of the approximate density of  $\tau_1$  on  $[0, 1]$  (using for

example 100000 particles and time steps of 0.001). Overlay on this figure the exact density calculated from lectures, which we recall to be

$$\mathbb{P}(\tau_1 \in dt) = \frac{1}{\sqrt{2\pi}} t^{-\frac{3}{2}} e^{-\frac{1}{2t}}, \quad t \geq 0.$$

Modify your code to use one of the other two methods from lectures, and compare the results.

### 3. Brownian bridge.

A zero-mean continuous Gaussian process  $B = (B(t))_{t \in [0,1]}$  is called a Brownian bridge if the covariance function of  $B$  is given by

$$C(s, t) = \min\{s, t\} - st, \quad \forall s, t \in [0, 1].$$

Show that  $B(t) = W(t) - tW(1) = (1-t)W\left(\frac{t}{1-t}\right)$ ,  $t \in [0, 1]$ , where  $(W(t))_{t \in [0,1]}$  is a standard Brownian motion.

Let  $(W(t))_{t \geq 0}$  be a 1-dimensional Brownian motion, and fix three deterministic times  $T_0 < T_1 < T_2$ . Define

$$Y_{\alpha, \beta} = W(T_1) - \alpha W(T_0) - \beta W(T_2), \quad \alpha, \beta \geq 0.$$

- (a) What is the law of  $Y_{\alpha, \beta}$ ?
- (b) Find conditions on  $\alpha$  and  $\beta$  such that: (i)  $Y_{\alpha, \beta}$  and  $W(T_0)$  are independent; (ii)  $Y_{\alpha, \beta}$  and  $W(T_2)$  are independent; and (iii)  $Y_{\alpha, \beta}$  is independent of both  $W(T_0)$  and  $W(T_2)$ .
- (c) Write  $W(T_1)$  as a function of  $W(T_0)$ ,  $W(T_2)$  and  $Y_{\alpha, \beta}$ . Assume that you have already simulated  $W(T_0), W(T_2), \dots, W(T_{2N})$  for some  $N \in \mathbb{N}$ , and you want to know the path on a finer grid  $T_0 < T_1 < T_2 < \dots < T_{2N}$ . Describe an algorithm to generate  $W(T_1), W(T_3), \dots, W(T_{2N-1})$ .

# Homework 3

## Exercise 1

$$P(T_\alpha < \infty) = 1.$$

Novikov Thm: Let  $X_t$  real valued, adapted in  $(\Omega, \mathcal{F}_t, P)$  and  $\beta_t$  a BM

for  $X_t$   
 $0 \leq t \leq T$

if  $\mathbb{E} \left[ e^{\frac{1}{2} \int_0^T |X_s|^2 dt} \right] < \infty \Rightarrow Z_t = e^{\int_0^t X_s dB_s - \frac{1}{2} \int_0^t X_s^2 ds}$

(BIG T)

is a Martingale in  $P$ .  
 (small  $t$ )  $0 \leq t \leq T$

We have  $X_t = \beta$  so  $\mathbb{E} \left[ e^{\frac{1}{2} \beta^2 t} \right] < \infty$

and  $Z_t = \exp \left[ \beta \beta_t - \frac{\beta^2 t}{2} \right]$  is a Martingale

Proof

$$\mathbb{E} \left[ e^{\int_0^t \theta_s dB_s - \frac{1}{2} \int_0^t \theta_s^2 ds} \mid \mathcal{F}_s \right] = \mathbb{E}[Z_t \mid \mathcal{F}_s]$$

$$= e^{-\frac{1}{2} \int_s^t \theta_s^2 ds} \underbrace{\mathbb{E} \left[ e^{\int_s^t \theta_s dB_s} \mid \mathcal{F}_s \right]}_{\int_s^t + \int_s^t}$$

$$= e^{-\frac{1}{2} \int_0^t \theta_s^2 ds} e^{\int_0^s \theta_s dB_s} \underbrace{\mathbb{E} \left[ e^{\int_s^t \theta_s dB_s} \right]}_{\text{momentum generator}}$$

$$= e^{-\frac{1}{2} \int_0^t \theta_s^2 ds} + \int_0^s \theta_s dB_s + \frac{1}{2} \int_s^t \theta_s^2 ds \cdot e^{m\lambda + \frac{1}{2} \lambda^2 \text{var}}$$

$$= e^{-\frac{1}{2} \int_0^s \theta_s^2 ds} + \int_0^s \theta_s dB_s = Z_s \quad \checkmark$$

$\int_0^s \mathcal{F}_s \Rightarrow \text{cthe}$   
 $\int_0^s \mathcal{F}_s \cap \mathcal{F}_s$   
 $s$  and inc, cf BM

$\int_0^t \theta_s dB_s \sim N(0, \int_0^t \theta_s^2 ds)$

## Doob's Optional Stopping Theorem

Let  $Z_t$  a Martingale,  $T_a$  an stopping time.

$$\mathbb{E}[Z_{T_a}] = \mathbb{E}[Z_0]$$

$$\mathbb{E} Z_0 = 1$$

$t \wedge T_a$  is stopping time.

$$\mathbb{E}[Z_{t \wedge T_a}] = \mathbb{E}[Z_{t \wedge T_a} \mathbb{1}_{T_a=\infty}]$$

$$+ \mathbb{E}[Z_{t \wedge T_a} \mathbb{1}_{T_a < \infty}]$$

$$1 = \underbrace{\mathbb{E}[Z_{t \wedge T_a} \mathbb{1}_{T_a=\infty}]}_{=0 \text{ as } t \rightarrow \infty} + \mathbb{E}[Z_{t \wedge T_a} \mathbb{1}_{T_a < \infty}]$$

$$1 = \mathbb{E}\left[e^{\beta B_{T_a} - \frac{\beta^2}{2} T_a} \mathbb{1}_{T_a < \infty}\right]$$

when  $\beta \rightarrow 0$

$$1 = \mathbb{E}\left[\mathbb{1}_{T_a < \infty}\right]$$

$$1 = \mathbb{P}(T_a < \infty)$$

$$1 = \mathbb{E}\left(e^{\beta a - \frac{\beta^2}{2} T_a} \mathbb{1}_{T_a < \infty}\right) \Rightarrow e^{-\beta a} = \mathbb{E}\left[e^{-\frac{\beta^2}{2} T_a}\right]$$

$$\gamma = \frac{\beta^2}{2} \quad \beta = \sqrt{2\gamma}$$

$$\Rightarrow e^{-\sqrt{2\gamma} a} = \mathbb{E}\left[e^{-\gamma T_a}\right]$$

Laplace transform of  $T_a$

### Exercise 3

$$Y_{\alpha, \beta} = -\beta \beta T_2 + \beta \beta_{T_1} - \alpha \beta_{T_0}$$

$$= -\beta \beta_{T_2} + \underline{\beta \beta_{T_1} - \beta \beta_{T_0}} + \beta_{T_1} - \alpha \beta_{T_0}$$

$$= -\beta (\beta_{T_2} - \beta_{T_1}) - (\beta - 1) \beta_{T_1} - \alpha \beta_{T_0}$$

$$- (\beta - 1) \beta_{T_1} + \underline{(\beta - 1) \beta_{T_0} - (\beta - 1) \beta_{T_0} - \alpha \beta_{T_0}}$$

$$= -\beta (\beta_{T_2} - \beta_{T_1}) - (\beta - 1) (\beta_{T_1} - \beta_{T_0}) - (\beta - 1 + \alpha) \beta_{T_0}$$

$\text{var } Y_{\alpha, \beta} = \beta^2 (\beta_{T_2} - \beta_{T_1})^2$  or use  $\text{var } x+y = \text{var } x + \text{var } y + 2 \text{cov } x, y$ .

$$\beta^2 (\beta_{T_2} - \beta_{T_1})^2 + (\beta - 1)^2 (\beta_{T_1} - \beta_{T_0}) + (\beta + \alpha - 1)^2 \beta_{T_0}$$

$$\begin{aligned} \text{cov} (\beta_{T_1}, \beta_{T_0}) &= \mathbb{E} [\beta_{T_1} \beta_{T_0}] = \mathbb{E} [(\beta_{T_1} - \beta_{T_0} + \beta_{T_0}) \beta_{T_0}] \\ &= \mathbb{E} [(\beta_{T_1} - \beta_{T_0}) \beta_{T_0}] + \mathbb{E} (\beta_{T_0})^2 \\ &= \beta_{T_0}. \end{aligned}$$

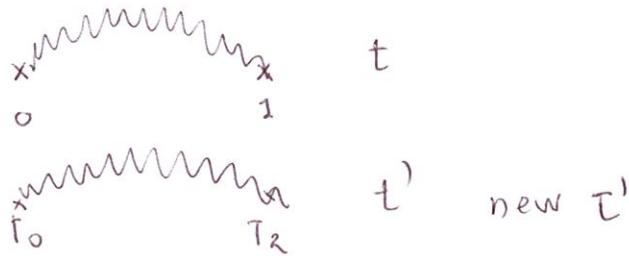
$$\text{cov} (\beta_{T_2}, \beta_{T_0}) = \beta_{T_0}.$$

$$\text{cov} (Y_{\alpha, \beta}, \beta_{T_2}) = \beta_{T_1} - \alpha \beta_{T_0} - \beta \beta_{T_2}$$

$$\text{cov} (Y_{\alpha, \beta}, \beta_{T_0}) = \beta_{T_0} (1 - \alpha - \beta)$$

simulate a Brownian Bridge

between  $T_0$  and  $T_2$



$$T_0 + (T_2 - T_0) t = t'$$

$$\text{so } t = \frac{t' - T_0}{T_2 - T_0}$$

substitute in BBridge.



simulate gaussian with cov = Bridge

Substitute  $t$  by  $\mathbb{E}$

check

$$\mathbb{E}[B_t - t B_1] \stackrel{?}{=} (1-t) \mathbb{E}\left[B\left(\frac{t}{1-t}\right)\right] = (1-t) \frac{\sqrt{t}}{\sqrt{1-t}} B_2 = \sqrt{t} (\sqrt{1-t}) B_1$$

$$\sqrt{t} B_1 - t B_1$$

$$(\sqrt{t} - t) B_1$$

$$\sqrt{t} (1 - \sqrt{t}) B_1$$

Numerical methods MATHMODS course:  
Exercise sheet 4

- Suppose that there exists a risky asset with stochastic price process  $(S_t)_{t \geq 0}$  and a risk-free asset  $(B_t)_{t \geq 0}$  that evolves at the risk-free rate  $r$  i.e.  $dB_t = rB_t dt$ . Let  $\Pi(t, S_t)$  be a portfolio built on this market (i.e. it consists of long and short positions in both the risky and risk-free asset), and suppose that the evolution of  $\Pi$  is deterministic.

*Definition:* There exists **arbitrage** in the market if there is the possibility of making a risk free profit.

Under the assumption that there is no arbitrage in the market, prove that  $\Pi$  must evolve at the risk-free rate  $r$ .

- Suppose that we in the Black-Scholes set up: we have a risky asset modeled as a geometric Brownian motion (with constant drift  $\mu$  and volatility  $\sigma$ ), and a risk-free asset that evolves deterministically according to the interest rate  $r$ .

Let  $V(t, S)$ ,  $t \geq 0$ ,  $S \in \mathbb{R}$  be the price of an option on the asset at time  $t$  and when the price of the underlying is  $S$ . Suppose the option has expiry  $T$  and payoff function given by  $\Psi : \mathbb{R} \rightarrow \mathbb{R}$ . Recall the general pricing formula for  $V$  is

$$V(t, S) = e^{-r(T-t)} \mathbb{E}_{\mathbb{Q}} (\Psi(S_T) | S_t = S),$$

where (under the risk-neutral measure  $\mathbb{Q}$ ),

$$dS_t = rS_t dt + \sigma S_t dW_t,$$

and  $(W_t)_{t \geq 0}$  is a standard 1-dimensional Brownian motion. Show that this implies

$$V(t, S) = e^{-r(T-t)} \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} \Psi \left( Se^{(r-\frac{1}{2}\sigma^2)(T-t)+\sigma\sqrt{T-t}z} \right) e^{-\frac{z^2}{2}} dz.$$

In the case of a European call option with strike price  $K$ , so that  $\Psi(S) = \max\{S - K, 0\}$ , show that in fact we can explicitly write

$$V(t, S) = S\Phi(d_1) - Ke^{-r(T-t)}\Phi(d_2), \quad (1)$$

where

$$d_i = \frac{\log\left(\frac{S}{K}\right) + \left(r + (-1)^{i+1}\frac{1}{2}\sigma^2\right)(T-t)}{\sigma\sqrt{T-t}}, \quad i \in \{1, 2\},$$

and  $\Phi(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^x e^{-z^2/2} dz$  is the cumulative distribution function for a standard  $\mathcal{N}(0, 1)$  random variable. This is the world-famous **Black-Scholes formula** for the price of a European call option!

**3. Generalised Feynman-Kac:** Suppose that there exists a solution  $F \in C^{1,2}([0, T] \times \mathbb{R}^d, \mathbb{R})$  to the equation

$$\begin{cases} \partial_t F(t, x) + \mathcal{L}F(t, x) - k(t, x)F(t, x) + g(t, x) = 0, & t \in [0, T], x \in \mathbb{R}^d \\ F(T, x) = \Psi(x) \end{cases},$$

where

$$\mathcal{L} = \sum_{i=1}^d b_i(\cdot)\partial_i + \frac{1}{2} \sum_{i,j=1}^d a_{ij}(\cdot)\partial_{ij},$$

- and the  $d \times d$  matrix  $a(x) = (a_{ij}(x))$  can be written as  $\sigma\sigma^T(x)$  for every  $x \in \mathbb{R}^d$ ;
- $b : \mathbb{R}^d \rightarrow \mathbb{R}^d$  and  $\sigma : \mathbb{R}^d \rightarrow \mathbb{R}^{d \times d}$  given by  $b(x) = (b_i(x))_{i \in \{1, \dots, d\}}$  and  $\sigma(x) = (\sigma_{ij}(x))_{i,j \in \{1, \dots, d\}}$  for  $x \in \mathbb{R}^d$  are globally Lipschitz;
- $\Psi : \mathbb{R}^d \rightarrow \mathbb{R}$ ,  $k : [0, T] \times \mathbb{R}^d \rightarrow \mathbb{R}$  and  $g : \mathbb{R}^d \rightarrow \mathbb{R}$  are “sufficiently” regular.

Show that  $F$  has the following representation

$$F(t, x) = \mathbb{E} \left( \Psi(X_T) e^{-\int_t^T k(s, X_s) ds} + \int_t^T g(s, X_s) e^{-\int_t^s k(r, X_r) dr} ds \middle| X_t = x \right),$$

for all  $t \in [0, T]$   $x \in \mathbb{R}^d$ , where

$$dX_t = b(X_t)dt + \sigma(X_t)dW_t$$

and  $(W_t)_{t \geq 0}$  is a standard  $d$ -dimensional Brownian motion.

*Hint:* For  $s \in [t, T]$ , apply Itô to  $F(s, X_s)$ , and then to

$$G(s, X_s) := e^{-\int_t^s k(r, X_r) dr} F(s, X_s) + \int_t^s e^{-\int_t^r k(u, X_u) du} g(r, X_r) dr.$$

4. (Practical). Once again, suppose that we are in the Black-Scholes setup, and that we would like to find the price  $C$  of a European call option with strike  $K = 80$  and  $T = 1$  year, given that the current price of the underlying is  $S_0 = 100$  (we are currently at  $t = 0$ ). Suppose that  $r = 0.03$  and  $\sigma = 0.2$ .

Of course, thanks to the Black-Scholes formula (equation (1) in Question 2 above), we can calculate the exact value of  $C$  using the given parameters. What is it? •

However, suppose we don't know the exact formula. We therefore instead decide to price the option using a Monte-Carlo method, starting from the general pricing formula from lectures

$$C = \mathbb{E}_{\mathbb{Q}} [e^{-rT} (S_T - K)_+ | S_0 = 100]$$

where as usual (under the risk-neutral measure  $\mathbb{Q}$ ),  $dS_t = rS_t dt + \sigma S_t dW_t$ , so that  $S_T = S_0 e^{(r - \frac{1}{2}\sigma^2)T + \sigma W_T}$ .

- (a) Calculate an approximate value of  $C$  by a Monte-Carlo method, with  $N$  large enough so that we are 95% sure of being within 1% of the true value. Justify the calculation of the confidence interval and the choice of  $N$ .
- (b) We now look to improve the convergence (i.e. reduce the variance) of the previous estimator by the method of antithetic control. Define  $S_1^-$  by

$$S_1^- := S_0 \exp \left( \left( r - \frac{1}{2}\sigma^2 \right) T - \sigma W_T \right).$$

Show that

$$C = \mathbb{E} \left[ e^{-rT} \frac{(S_T - K)_+ + (S_1^- - K)_+}{2} \right].$$

Calculate another approximate value for  $C$  with the help of this formula. Compare the precision of this value with the previous method for  $N = 1000, 10000$  and  $100000$  by calculating both the approximate value  $\hat{C}$  and the size of the 95% confidence interval for each value of  $N$  and each method.

- (c) We now look to improve the convergence by importance sampling.
  - (i) Check that size of the 95% confidence interval as a percentage of the approximate value  $\hat{C}$ , calculated with either of the above two methods, increases as  $K$  increases. Why is this?
  - (ii) Use the Girsanov Theorem to show that

$$\mathbb{E}[f(W_t)] = \mathbb{E} \left[ \exp \left( -\lambda W_t - \frac{\lambda^2}{2} t \right) f(W_t + \lambda t) \right],$$

for all positive measurable functions  $f$ ,  $t \geq 0$ .

- (iii) Propose a value of  $\lambda$  that allows us to reduce the variance of the estimator for a strike  $K = 200$ .



## Homework

$$1) d\beta_t = r\beta_t dt \quad \text{risk free}$$

$$dX_t = \mu X_t dt + \sigma X_t dB_t \quad \text{risky asset}$$

$$\nabla_t = a(t) X_t + b(t) \beta_t \quad \text{portfolio}$$

$\nabla_0 = \nabla(t=0)$  initial investment

We can put  $\nabla_0$  in Bank  $\rightarrow e^{rT} \nabla_0$  after  $T$   
 or in the portfolio  $\rightarrow \nabla(T)$

Suppose  $\nabla$  is deterministic (its evolution in  $t$ )  $\rightarrow$  we know  $\nabla(T)$

$$\text{if } e^{rT} \nabla_0 < \nabla(T)$$

$\Rightarrow$  Borrow  $\nabla_0$  from Bank at interest rate  $r$ . Invest it on the portfolio  
 Get  $\nabla(T)$ . Repay the Bank.

$$\text{riskless profit } \nabla(T) - e^{rT} \nabla_0 > 0$$

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$$\text{if } e^{rT} \nabla_0 > \nabla(T) \Rightarrow e^{rT} a_0 X_0 + e^{rT} b_0 \beta_0 > a_0 X_T + b_0 \beta_T$$

go short on  $X(T)$ : get  $X_0$

put  $X_0$  on the Bank: get  $e^{rT} X_0$

otherwise pay back

Pay the promise stock. for  $X_T$

$$\text{profit } e^{rT} X_0 - X_T > 0$$

Selling short  
 is selling something  
 you don't have  
 but you promise  
 to give

## Exercise 2

$$V_t = E_Q [e^{-rt} h(X_T) | F_t] \quad Q \text{ is risk free measure}$$

contingent claim

$$V_T = h(X_T) = (x - K)^+$$

1) Discounted price of an stock.

$$\tilde{X}_t = e^{-rt} X_t \quad \text{if value of stock } X_t \\ \text{on money value future} \quad //$$

Itô on  $\tilde{X}_t$

$$f = e^{-rt} x \quad f_1 = -r e^{-rt} x, \quad f_2 = e^{-rt}, \quad f_{22} = 0$$

$$df = -r e^{-rt} X dt + e^{-rt} dX$$

$$d(e^{-rt} X_t) = d\tilde{X}_t = -r e^{-rt} X_t dt + e^{-rt} dX_t \\ = \dots - \dots - \dots - \dots [X_t dt + \sigma X_t dB_t]$$

$$= e^{-rt} X_t [(c-r) dt + \sigma dB_t]$$

$$= \tilde{X}_t d \underbrace{[(c-r) dt + \sigma B_t]}_{\tilde{B}_t}$$

$$= \tilde{X}_t d\tilde{B}_t = d\tilde{X}_t$$

Girsanov  $\Rightarrow \exists$  and  $Q$  s.t.  $\tilde{B}_t$  is a BM

$$\tilde{X}_t = X_0 e^{-0.5\sigma^2 t + \sigma \tilde{B}_t}$$

is a Martingale in  $Q$ .  $\tilde{S}_t \subset \sigma(\tilde{B}_t)$

2) Discounted value of  $V_t = a_t X_t + b_t \beta_t$

$$\tilde{V}_t = e^{-rt} V_t$$

$$d\tilde{V}_t = -re^{-rt} V_t + e^{-rt} dV_t \quad \text{self financing}$$

$$= -r e^{-rt} [a_t X_t + b_t \beta_t] + e^{-rt} [a_t dX_t + b_t d\beta_t]$$

$$= a_t [-r e^{-rt} X_t + e^{-rt} dX_t]$$

$$= a_t d\tilde{X}_t$$

$$d\tilde{V}_t = a_t d\tilde{X}_t$$

$$\tilde{V}_t = \tilde{V}_0 + \sigma \int_0^t a_s \tilde{X}_s d\tilde{B}_s \quad \begin{matrix} \tilde{V}_t \\ \text{is Martingale} \\ \text{in } Q \end{matrix}$$

3) Martingale property

$$\tilde{V}_t = E_Q [\tilde{V}_T | F_t]$$

$$\tilde{V}_T = e^{-rT} V_T = e^{-rT} h(X_T)$$

$$V_t = e^{rt} e^{-rT} E_Q [h(X_T) | F_t]$$

$$V_t = e^{-r\theta} E_Q [h(X_T) | F_t]$$

$$V_t = E_Q [ e^{-r\theta} h(X_T) | F_t ] \\ = E_Q [ e^{-r\theta} h(X_t e^{(r-0.5\sigma^2)\theta + \sigma(\tilde{B}_T - \tilde{B}_t)}) | F_t ]$$

$\tilde{B}_T - \tilde{B}_t$  is ind. mcr. of  $F_t$ ,  $\sim N(0, \theta)$ ,  $X_t$  is const

$$= e^{-r\theta} \int_{-\infty}^{\infty} h(x e^{(r-0.5\sigma^2)\theta + \sigma\theta^{1/2}y}) \rho(y) dy$$

$$h = \max(x - K, 0) \quad e^{-r\theta} \left( x e^{(r-0.5\sigma^2)\theta + \sigma\theta^{1/2}y} - K \right) > 0 \\ e^{(r-0.5\sigma^2)\theta + \sigma\theta^{1/2}y} > \frac{K}{x}.$$

$$(r - 0.5\sigma^2)\theta + \sigma\theta^{1/2}y > \ln \frac{K}{x}.$$

$$y > \frac{\ln \frac{K}{x} - (r - 0.5\sigma^2)\theta}{\sigma\theta^{1/2}}$$

$$y < \frac{\ln \frac{x}{K} + (r - 0.5\sigma^2)\theta}{\sigma\theta^{1/2}}$$

$$J_t = \underbrace{\int_{-\infty}^{y_2} x e^{-0.5\sigma^2\theta + \sigma\theta^{1/2}y} \rho(y) dy}_{I} - \underbrace{\int_{-\infty}^{y_2} K e^{-r\theta} \rho(y) dy}_{-K e^{-r\theta} \Phi(y_2)}$$

$$I) \int_{-\infty}^{y_2} x e^{-0.5\sigma^2\theta + \sigma\theta^{1/2}y} \frac{1}{\sqrt{2\pi}} e^{-\frac{y^2}{2}} dy$$

$$\text{ans} \frac{1}{2} [y^2 + 2\sigma\theta^{1/2}y] = \frac{1}{2} [y^2 + 2\sigma\theta^{1/2}y + \sigma^2\theta] - \frac{\sigma^2\theta}{2}$$

$$= \frac{1}{2} [y - \sigma\theta^{1/2}]^2 - \frac{\sigma^2\theta}{2}$$

$$I) \int_{-\infty}^{y_2} x e^{-0.5 \sigma_\theta^2} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2} [y - \sigma_\theta^{1/2}]^2 + \frac{\sigma_\theta^2}{2}} dy$$

$$= \int_{-\infty}^{y_2} x e^{+0.5 \cancel{\sigma^2} \theta - 0.5 \cancel{\sigma^2} \theta} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2} [y - \sigma_\theta^{1/2}]^2} dy$$

$$u = y - \sigma_\theta^{1/2} \quad du = dy$$

$$= \int_{-\infty}^{u_1} x \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2} u^2} du \quad * u_1 = y_2 - \sigma_\theta^{1/2}$$

$$= x \Phi(u_1)$$

What a good student!  
It's your moment!! Surprise him

conf  
int.

$$\hat{C} \pm \frac{1.96 \hat{\sigma}}{\sqrt{N}}$$

$$\frac{1.96}{\sqrt{N}} \hat{\sigma}_{(n)} \leq 0.01 \cdot C$$

choose  $N = N_0$

run MC

for  $i: 1 \dots N$

simulate  $W_i$

compute  $C_i$

sum = sum +  $C_i$

squares = squares +  $C_i^2$

end

$$\hat{C} = \frac{1}{N} \cancel{\text{average}} \text{sum}$$

$$\hat{C}^2 = \frac{1}{N-1} (\text{squares}) - \cancel{\text{average}}_{N-1} \hat{C}^2$$

$$= \frac{2 \hat{C}}{N-1} \text{sum} + \frac{N}{N-1} \hat{C}^2$$

check  $\frac{1.96}{\sqrt{N}} \hat{\sigma} \leq 0.01 \cdot C$

true → done

$$\text{not true} \rightarrow N \geq \frac{1.96^2 \hat{\sigma}^2}{0.01 (0.01)^2 C^2}$$

## Generalized Feynman Kac.

$$\begin{cases} \frac{\partial F}{\partial t} + \int F - K F + g = 0 & F(t, x) \\ F(T, x) = \Psi(x) \end{cases}$$

Consider  $G(s, X_s) := e^{-\int_t^s K(r, X_r) dr} F(s, X_s)$

$$+ \int_t^s e^{-\int_r^s K(u, X_u) du} g(r, X_r) dr$$

If  $dX = X dY + Y dX + dX dY$ ,  $s \in [t, T]$   $t, T$  fixed.

$$dG = e^{-\int_t^s K dr} dF - \left( K \int_t^s e^{-\int_r^s K dr} \right) F - \underbrace{\left( K \int_t^s e^{-\int_r^s K dr} \right)}_{\text{order } dF dt \text{ drop it}} dF$$

$$+ e^{-\int_t^s K du} g dr$$

If to  $F(t, X_t)$

$$dF = \frac{\partial F}{\partial t} dt + \frac{\partial F}{\partial x} dx_t + \frac{1}{2} \frac{\partial^2 F}{\partial x^2} (\dot{x}_t)^2$$

$$dx_t = b(x_t) dt + \sigma(x_t) dB_t$$

$$= \frac{\partial F}{\partial t} + \frac{1}{2} \frac{\partial^2 F}{\partial x^2} dt \sigma^2(x_t) dB_t + \frac{\partial F}{\partial x} \left[ b dt + \sigma dB_t \right]$$

$$= \underbrace{\left[ \frac{\partial F}{\partial t} + \frac{1}{2} \frac{\partial^2 F}{\partial x^2} \sigma^2 + \frac{\partial F}{\partial x} b \right]}_{\text{drift term}} dt + \frac{\partial F}{\partial x} \sigma dB_t$$

$$dG = e^{-\int_t^s K dr} \left\{ \left[ \frac{\partial F}{\partial t} + \frac{1}{2} \frac{\partial^2 F}{\partial x^2} \sigma^2 + \frac{\partial F}{\partial x} b \right] ds + \frac{\partial F}{\partial x} \sigma d\beta_s \right\}$$

$$-KF e^{-\int_t^s K dr} dr + g e^{-\int_t^s K dr} dr$$

PDE

$$= e^{-\int_t^s K dr} \left[ \underbrace{\text{PDE}}_{=0} \right] + e^{-\int_t^s K dr} \frac{\partial F}{\partial x} \sigma d\beta_s.$$

$$= e^{-\int_t^s K dr} \frac{\partial F}{\partial x} \sigma d\beta_s.$$

$$G(T, X_T) = G(t, X_t) + \int_t^T e^{-\int_t^s K dr} \frac{\partial F}{\partial x} \sigma d\beta_s$$

$$\mathbb{E}[G(T, X_T) | X_t = x] \stackrel{\text{def of } G.}{=} \underbrace{\mathbb{E}[G(t, X_t) | X_t = x]}_{\mathbb{E}[F(t, X_t) | X_t = x]} + 0$$

$$\mathbb{E} \left[ e^{-\int_t^T K dr} F(T, X_T) + \int_t^T e^{-\int_t^r K du} g dr \mid X_t = x \right] = \mathbb{E}[F(t, X_t) | X_t = x]$$

$\Psi(X_T)$

$$F(t, x) = \mathbb{E} \left[ \Psi(X_T) e^{-\int_t^T K ds} + \int_t^T e^{-\int_t^r K du} g dr \mid X_t = x \right]$$

$$\frac{d}{dt} \int_a^{\underline{t}} K(s) ds$$

$F'(s) = k(s)$       <sup>thm</sup> Fund calculus

$$\frac{d}{dt} [ F(t) - F(a) ] = F'(t) = K(\underline{t})$$


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$$\frac{d}{dt} \int_t^a K(s) ds = \frac{d}{dt} [ F(a) - F(t) ] \\ = -F'(t) = -K(\underline{t})$$

$$\frac{d}{dt} \int_a^{h(t)} K(s) ds = K(h(t)) \frac{d}{dt} h(t)$$

26(12)X      32  
36  
mult  
wholes but  $12N + 12$

$(H)Y = (g)^T$        $\{ (w)^T - (H)^T \} Y$   
                        32  
                        36

$\{ (w)^T - (w)^T \}$        $26(20)X$   
                        35      b  
                        35      35

$(H)Y = (w)^T =$   
 $(w)^T b - (H)Y = 26(27)X$   
                        35      b  
                        35      35