

# Lecture 6: Computation of Greeks

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# Outline of The Talk

- 1 Sensitivities
- 2 Bump method
- 3 Pathwise method

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- 2 Bump method
- 3 Pathwise method

- Let  $Z$  be a random variable on  $(\Omega, \mathcal{F}, \mathbb{R}) \rightarrow (\mathbb{R}, \mathcal{B}(\mathbb{R}))$  and  $F$  a function  $F : (x, Z) \mapsto F(x, Z)$  where  $x \in I \subset \mathbb{R}$ . We set

$$f(x) = \mathbb{E}[F(x, Z)], \quad \text{with } F(x, Z) \in \mathcal{L}^2(\Omega), \forall x \in I.$$

- Our aim is to compute  $f'(x)$ .

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- Evaluating sensitivities is essential for portfolio hedging and gives informations on the sensitivity of option prices with respect to a given parameter.

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# Forward scheme

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# Forward scheme

- Assume that we know how to simulate  $F(x, Z)$  and **no explicit formula is available to evaluate**  $f(x)$  ?
- In such a case a **Monte Carlo method** is recommended

$$f(x) \approx \frac{1}{M} \sum_{i=1}^M F(x, Z_i) \text{ where } (Z_i)_{1 \leq i \leq M} \text{ are i.i.d. copies of } Z$$

- Hence,

$$f'(x) \approx \frac{f(x + \varepsilon) - f(x)}{\varepsilon} \stackrel{\varepsilon \rightarrow 0}{\sim} f'(x).$$

Then,

$$f'(x) \approx \frac{1}{M} \sum_{i=1}^M \frac{F(x + \varepsilon, Z_i) - F(x, Z_i)}{\varepsilon}$$



# Centred Scheme

$$\begin{aligned} f'(x) &\stackrel{\varepsilon \rightarrow 0}{\approx} \frac{f(x + \varepsilon) - f(x - \varepsilon)}{2\varepsilon} \\ &\approx \frac{1}{M} \sum_{i=1}^M \frac{F(x + \varepsilon, Z_i) - F(x - \varepsilon, Z_i)}{2\varepsilon} \end{aligned}$$

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### Theorem 1

Let  $x \in \mathbb{R}$ , and  $f \in \mathcal{C}^2$  s.t.  $f''$  is Lipschitz.

$$\exists \varepsilon_0 > 0, \forall x \in ]x - \varepsilon_0, x + \varepsilon_0[, \|F(x, Z) - F(x', Z)\|_2 \leq C_{F,Z} |x - x'|$$

$$\begin{aligned} RMSE &:= \left\| f'(x) - \frac{1}{M} \sum_{i=1}^M \frac{F(x + \varepsilon, Z_i) - F(x - \varepsilon, Z_i)}{2\varepsilon} \right\|_2 \\ &\leq [f'']_{lip} \frac{\varepsilon^2}{2} + \frac{C_{F,Z}}{\sqrt{M}} \end{aligned}$$

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- Recall that RMSE=root mean square error satisfies

$$\text{MSE} = (\text{RMSE})^2 = (\text{bias})^2 + \text{Var}$$

$$\text{bias} = f'(x) - \mathbb{E} \left[ \frac{\frac{1}{M} \sum_{i=1}^M F(x + \varepsilon, Z_i) - F(x - \varepsilon, Z_i)}{2\varepsilon} \right]$$

$$\text{Var} = \text{Var} \left( \frac{\frac{1}{M} \sum_{i=1}^M F(x + \varepsilon, Z_i) - F(x - \varepsilon, Z_i)}{2\varepsilon} \right)$$

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- The error for the other schemes (Forward and Backward) is of order  $\varepsilon$ .

# Optimal choice :

How to choose the sample size  $M$  ?

$$\frac{1}{\sqrt{M}} \approx \frac{\varepsilon^2}{2} \iff \frac{1}{M} = \frac{\varepsilon^4}{4} \iff M = \frac{4}{\varepsilon^4}$$

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**Implementation advise:** Attention : must not  $\frac{1}{M\varepsilon^2} \longrightarrow \infty$



- **Particular case:** Assume that the samples

$$(F(x + \varepsilon, Z_i))_{1 \leq i \leq M} \perp (F(x - \varepsilon, Z_i))_{1 \leq i \leq M}$$

Then,

$$\begin{aligned} \text{Var} \left( \frac{\frac{1}{M} \sum_{i=1}^M F(x + \varepsilon, Z_i) - F(x - \varepsilon, Z_i)}{2\varepsilon} \right) \\ = \frac{1}{4M\varepsilon^2} [\text{Var}(F(x + \varepsilon, Z)) + \text{Var}(F(x - \varepsilon, Z))] \\ \stackrel{\varepsilon \rightarrow 0}{\sim} \frac{1}{4M\varepsilon^2} * 2\text{Var}(F(x, Z)) = \frac{\text{Var}(F(x, Z))}{M\varepsilon^2} \end{aligned}$$

In the above Theorem 1,

$$\begin{aligned} \left\| f'(x) - \frac{\frac{1}{M} \sum_{i=1}^M F(x + \varepsilon, Z_i) - F(x - \varepsilon, Z_i)}{2\varepsilon} \right\|_2^2 \\ \leq \left( [f'']_{lip} \frac{\varepsilon^2}{2} \right)^2 + \frac{\text{Var}(F(x, Z))}{2M\varepsilon^2} \end{aligned}$$

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## Example : The Black Scholes model

Let  $Z \sim \mathcal{N}(0, 1)$  and  $h$  a call or put function, then

$$F(x, Z) = \exp(-rT) h \left( x \exp \left( \left( r - \frac{\sigma^2}{2} \right) T + \sigma \sqrt{T} Z \right) \right)$$

Theorem 1 applies and we have

$$\begin{aligned} & \|F(x, Z) - F(x', Z)\|_2 \\ \leq & e^{-rT} \left( \mathbb{E} \left[ \left| h \left( x \exp \left( \left( r - \frac{\sigma^2}{2} \right) T + \sigma \sqrt{T} Z \right) \right) \right. \right. \right. \\ & \left. \left. \left. - h \left( x' \exp \left( \left( r - \frac{\sigma^2}{2} \right) T + \sigma \sqrt{T} Z \right) \right) \right|^2 \right] \right)^{\frac{1}{2}} \\ \leq & e^{-rT} [h]_{lip} \left( \mathbb{E} \left[ |x - x'|^2 \exp \left( 2 \left( r - \frac{\sigma^2}{2} \right) T + 2\sigma \sqrt{T} Z \right) \right] \right)^{\frac{1}{2}} \\ \leq & [h]_{lip} |x - x'| e^{\frac{\sigma}{2} T} \end{aligned}$$

```
function [deltaFT] = deltaBS(S_0, K, T, r, sigma, N_MC,h)
z = rand(N_MC,1,'norm');
S=S_0*exp((r-0.5*sigma^ 2)*T*ones(N_MC,1)+sigma*sqrt(T)*z);
payoff = max(S-K*ones(N_MC,1), 0);
BS_Price = exp(-r*T)*mean(payoff);
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
S_h_up=(S_0+h)*exp((r-0.5*sigma^ 2)*T*
ones(N_MC,1)+sigma*sqrt(T)*z);
payoff_h_up = max(S_h_up-K*ones(N_MC,1), 0);
BS_Price_h_up = exp(-r*T)*mean(payoff_h_up);
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
S_h_down=(S_0-h)*exp((r-0.5*sigma^ 2)*T*
ones(N_MC,1)+sigma*sqrt(T)*z);
payoff_h_down = max(S_h_down-K*ones(N_MC,1), 0);
BS_Price_h_down = exp(-r*T)*mean(payoff_h_down);
deltaFT=(BS_Price_h_up-BN_Price)/h;
endfunction
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# Pathwise method

Let  $x \in \mathbb{R}$ ,  $Z$  be a r.v. on  $(\Omega, \mathcal{F}, \mathbb{R})$

$$f(x) = \mathbb{E}[F(x, Z)], \quad F(x, Z) \in \mathcal{L}^2(\Omega)$$

$$\frac{\partial}{\partial x} f(x) = \frac{\partial}{\partial x} \mathbb{E}[F(x, Z)]$$

**Question** : Under which assumption could we switch  $\mathbb{E}$  et  $\frac{\partial}{\partial x}$  ?

## Theorem 2

Let  $I \subset \mathbb{R}$  an open subset ,  $\psi : I \times \Omega \longrightarrow \mathbb{R}$

A. Local version : Let  $x_0 \in I$ , if  $\psi$  satisfies:

- i.  $\forall x \in I, \psi(x, \cdot) \in \mathcal{L}^2(\Omega)$

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 $\forall x \in I \mathbb{P}(d\omega)$  p.s.,  $|\psi(x, \omega) - \psi(x_0, \omega)| \leq Y(\omega)|x - x_0|$

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Then :  $\varphi(x) = \mathbb{E}[\psi(x, \cdot)]$  is defined for all  $x \in I$

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# Example 1 : Black-Scholes Delta

(Call under risk neutral probability  $\mathbb{P}^*$ )

$$\begin{aligned} F(x, Z) &= e^{-rT} (S_T - K)_+ \\ &= e^{-rT} \left( x \exp \left( \left( r - \frac{\sigma^2}{2} \right) T + \sigma \sqrt{T} Z \right) - K \right)_+ \end{aligned}$$

$f(x) = \mathbb{E}[F(x, Z)]$ , (Global version case).

$$f'(x) \stackrel{theo}{=} \mathbb{E} \left[ \frac{\partial F}{\partial x}(x, Z) \right] = e^{-rT} \mathbb{E} \left[ \frac{\partial}{\partial x} (S_T - K)_+ \right]$$

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$f(x) = \mathbb{E}[F(x, Z)]$ , (Global version case).

$$\begin{aligned} f'(x) &\stackrel{theo}{=} \mathbb{E} \left[ \frac{\partial F}{\partial x}(x, Z) \right] = e^{-rT} \mathbb{E} \left[ \frac{\partial}{\partial x} (S_T - K)_+ \right] \\ &= e^{-rT} \mathbb{E} \left[ \frac{\partial}{\partial S_T} (S_T - K)_+ \times \frac{\partial S_T}{\partial x} \right] \\ &= e^{-rT} \mathbb{E} \left[ \mathbf{1}_{S_T \geq K} \times \frac{S_T}{x} \right] = \phi(d_1) \end{aligned}$$

```
function [delta_PT] = deltaBS(S_0, K, T, r, sigma, N_MC,h)
z = rand(N_MC,1,'norm');
S_PT=(S_0)*exp((r-0.5*sigma^ 2)*T*ones(N_MC,1)+sigma*sqrt(T)*z);
payoff_PT = S_PT.*(S_PT> K)/S_0;
delta_PT = exp(-r*T)*mean(payoff_PT);
endfunction
```

## Example 2 : Black-Scholes Vega

(Call under  $\mathbb{P}^*$ )

$$f(\sigma, Z) = \mathbb{E}[F(\sigma, Z)]$$

$$f'(\sigma) = e^{-rT} \mathbb{E} \left[ \frac{\partial}{\partial S_T} (S_T - K)_+ \times \frac{\partial S_T}{\partial \sigma} \right]$$

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(Call under  $\mathbb{P}^*$ )

$$f(\sigma, Z) = \mathbb{E} [F(\sigma, Z)]$$

$$\begin{aligned} f'(\sigma) &= e^{-rT} \mathbb{E} \left[ \frac{\partial}{\partial S_T} (S_T - K)_+ \times \frac{\partial S_T}{\partial \sigma} \right] \\ &= e^{-rT} \mathbb{E} \left[ \mathbf{1}_{S_T \geq K} \left( \sqrt{T} Z - \sigma T \right) S_T \right] \end{aligned}$$

## Exemple 3: Asian Delta

No explicit formula in the path dependent case for Asian options in the Black-Scholes model under  $\mathbb{P}^*$ . For  $0 < t_1 < \dots < t_m \leq T$

$$\begin{aligned}\bar{S} &= \frac{1}{m} \sum_{i=1}^m S_{t_i} \\ F(x, \bar{S}) &= e^{-rT} (\bar{S} - K)_+ \\ S_t &= x \exp \left( \left( r - \frac{\sigma^2}{2} \right) t + \sigma W_t \right)\end{aligned}$$

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Goal:  $f'(x) = \mathbb{E} \left[ \frac{\partial}{\partial x} F(x, \bar{S}) \right]$  ?

$$\begin{aligned}f'(x) &= \mathbb{E} \left[ \frac{\partial}{\partial x} F(x, \bar{S}) \right] = \mathbb{E} \left[ \frac{\partial}{\partial S} F(x, \bar{S}) \times \frac{\partial \bar{S}}{\partial x} \right] \\ &= e^{-rT} \mathbb{E} \left[ \mathbf{1}_{\{\bar{S} \geq K\}} \frac{\partial \bar{S}}{\partial x} \right]\end{aligned}$$



But,

$$\frac{\partial \bar{S}}{\partial x} = \frac{\partial}{\partial x} \left( \frac{1}{m} \sum_{i=1}^n S_{t_i} \right) = \frac{1}{m} \sum_{i=1}^m \frac{\partial}{\partial x} S_{t_i} = \frac{1}{m} \sum_{i=1}^m \frac{S_{t_i}}{x} = \frac{\bar{S}}{x}.$$

Therefore :

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Therefore :

$$f'(x) = e^{-rT} \mathbb{E} \left[ \mathbf{1}_{\{\bar{S} \geq K\}} \times \frac{\bar{S}}{x} \right]$$

```
function [deltaPT] = deltaAsiat(S_0, K, T, N_time, r,
sigma, N_MC)
z = rand(N_MC,N_time,'norm');
dt = T/N_time;
LogPaths= cumsum([log(S_0)*ones(N_MC,1),(r-0.5*sigma^ 2)*dt
+ sigma*sqrt(dt)*z],'c');
S = exp(LogPaths);
payoff = max(mean(S, 'c')-K, 0);
indic = mean(S, 'c') > K;
g = indic.*mean(S, 'c')/S_0;
deltaPT = exp(-r*T)*mean(g);
endfunction
```