

Computational Finance PDE

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Outline

- Recap
- The finite difference operators
- Let's get practical.

Material

- Andreassen, J (2011): “Finite Difference Methods for Financial Problems.”
PhD Course Copenhagen University.
- Andreassen, J (2022): “Catch-Up.” Forthcoming Wilmott.
- Andreassen, J, B Huge and F Kryger-Baggesen (2022):
<https://github.com/brnohu>.

Recap

- Let

$$ds = \mu(t, s)dt + \sigma(t, s)dW \tag{1}$$

$$db/b = r(t, s)dt$$

- then the expectation

$$f(t, s(t)) = E_t[e^{-\int_t^T r(u)du} f(T, s(T))] \tag{2}$$

- ... is the solution to the *backward* PDE

$$0 = f_t + Af, \quad A = -r + \mu \partial_s + \frac{1}{2} \sigma^2 \partial_{ss} \quad (3)$$

- ... and

$$f(0, s(0)) = \int f(T, s) p(T, s) ds \quad (4)$$

- Backward theta scheme:

$$f(t_{h+1/2}) = [1 + (1 - \theta) \Delta t \bar{A}] f(t_{h+1})$$

$$[1 - \theta \Delta t \bar{A}] f(t_h) = f(t_{h+1/2}) \quad (6)$$

- where

$$f(t_h) = (f(t_h, s_0), \dots, f(t_h, s_{n-1}))' \quad (7)$$

- ... is a vector of solution values.
- ... and \bar{A} is a *finite difference* approximation to A

$$\bar{A} = -r + \mu \delta_s + \frac{1}{2} \sigma^2 \delta_{ss} \quad (8)$$

- ... can be represented as a *tridiagonal* matrix.

$$\underbrace{f(t_h) \xleftarrow{\quad} f(t_{h+1/2})}_{\substack{\text{tridiagonal matrix} \\ \text{inversion}}} \underbrace{\xleftarrow{\quad} f(t_{h+1})}_{\substack{\text{tridiagonal matrix} \\ \text{multiplication}}} \quad (9)$$

The finite difference operators

- First and second order $n \times n$ matrix operator δ_s and δ_{ss}
- ... meaning
$$\begin{aligned}\delta_s f(t_h) &\approx (f_s(t_h, s_0), \dots, f_s(t_h, s_{n-1}))' \\ \delta_{ss} f(t_h) &\approx (f_{ss}(t_h, s_0), \dots, f_{ss}(t_h, s_{n-1}))'\end{aligned}\tag{10}$$
- Use finite differences to estimate
- First order we use weighted average of upward and downward differencing.

- Upward first order finite difference

$$\left(\delta_s^+ f(t_h)\right)_i = \frac{f(s_{i+1}) - f(s_i)}{s_{i+1} - s_i} \quad (11)$$

- ... so upward $n \times 3$ finite difference operator

$$(\delta_s^+)_i = \left[0, \frac{-1}{s_{i+1} - s_i}, \frac{1}{s_{i+1} - s_i}\right] \quad , \quad 0 \leq i < n - 1 \quad (12)$$

- Downward first order finite difference

$$\left(\delta_s^- f(t_h)\right)_i = \frac{f(s_i) - f(s_{i-1})}{s_i - s_{i-1}} \quad (13)$$

- ... so downward $n \times 3$ finite difference operator

$$(\delta_s^-)_i = \left[\frac{-1}{s_i - s_{i-1}}, \frac{1}{s_i - s_{i-1}}, 0 \right] \quad , \quad 0 < i \leq n - 1 \quad (14)$$

- Central first order finite difference

$$\left(\delta_s f(t_h)\right)_i = \frac{s_{i+1}-s_i}{s_{i+1}-s_{i-1}} \delta_s^- f(s_i) + \frac{s_i-s_{i-1}}{s_{i+1}-s_{i-1}} \delta_s^+ f(s_i) \quad (15)$$

- ... so central $n \times 3$ finite difference operator

$$(\delta_s)_i = \frac{1}{s_{i+1}-s_{i-1}} \left[-\frac{s_{i+1}-s_i}{s_i-s_{i-1}}, \frac{s_{i+1}-s_i}{s_i-s_{i-1}} - \frac{s_i-s_{i-1}}{s_{i+1}-s_i}, \frac{s_i-s_{i-1}}{s_{i+1}-s_i} \right], \quad 0 < i < n-1 \quad (16)$$

- Second order difference operator

$$(\delta_{ss}f(t_h))_i = 2 \frac{(\delta_s^+ f(t_h))_i - (\delta_s^- f(t_h))_i}{s_{i+1} - s_{i-1}} \quad (17)$$

- ... so second order $n \times 3$ difference operator

$$(\delta_{ss})_i = \frac{2}{s_{i+1} - s_{i-1}} \left[\frac{1}{s_i - s_{i-1}}, \left(\frac{-1}{s_i - s_{i-1}} + \frac{-1}{s_{i+1} - s_i} \right), \frac{1}{s_{i+1} - s_i} \right], \quad 0 < i < n - 1 \quad (18)$$

- Difference operators δ_s and δ_{ss} are tridiagonal matrices
- So $\bar{A} = -r + \mu\delta_s + \frac{1}{2}\sigma^2\delta_{ss}$ is tridiagonal and so is $I + \Delta t\bar{A}$

Let's get practical

- Implement `kFiniteDifference::dx()` and `kFiniteDifference::dxx()` such that they construct the finite difference operators
- Implement `kFd1d::calcAx()` to construct the $I + \Delta t \bar{A}$ matrix
- Test your implementations via `xFd1d()`