A splitting deep Ritz method for option pricing in Lévy models

Stochastic Methods in Finance and Physics (SMFP 2023)

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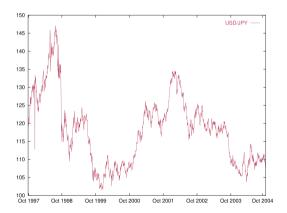
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Objectives

- ▶ Pricing options in scenarios where the underlying stock values exhibit discontinuities.
- ▶ Our focus is on options involving a large number of underlying assets.







We assume d correlated stocks with values modelled by the stochastic processes

$$S_t^{(i)} = S_0^{(i)} \exp\left(\mu_i t + \sigma_i W_t^{(i)} + \sum_{k=1}^{N_t} Z_k^{(i)}\right), \ t \in \mathbb{T} = [0, T], \ i = 1, \dots, d$$

 $W_{\star}^{(i)}$: Brownian motions

 $Z_{\nu}^{(i)}$: Normal random variables

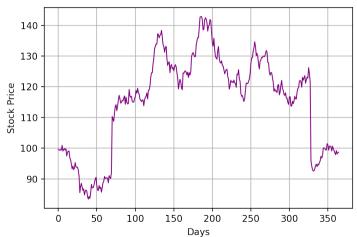
 N_t : Poisson process

$$Corr[W_t^{(i)}, W_t^{(j)}] = \rho_{ij} \in [-1, 1], \quad Corr[Z_t^{(i)}, Z_t^{(j)}] = \rho_{Jij} \in [-1, 1]$$





► Synthetic path







European basket call option

- $\{\alpha_i\}_{i=1,\dots,d}$: weights on underlyings $(\sum_i \alpha_i = 1)$
- ightharpoonup K: the strike price

Payoff function

$$\mathsf{Payoff}(s) = \left(\sum_{i=1}^d \alpha_i s_i - K\right)^+$$

Moneynesses : $x_i = s_i/K$

$$\mathsf{Payoff}(x) = \left(\sum_{i=1}^{d} \alpha_i x_i - 1\right)^+$$





 $ightharpoonup \mathbb{E}^{\mathbb{Q}}[e^{-rt} \mathsf{Payoff}(S_t) | S_0]$, where t expresses the time of maturity.

Using FTAP and Feynman-Kac the option price is provided by:

$$\partial_t u(t,x) + \mathcal{A}u(t,x) = 0, \ t > 0, \ x \in [0,\infty)^d$$

$$u(0,x) = \mathsf{Payoff}(x), \ x \in [0,\infty)^d$$

 \blacktriangleright \mathcal{A} : PIDE operator

$$Au = -\sum_{i,j=1}^{d} a_{ij}(x) \frac{\partial^{2} u}{\partial x_{i} \partial x_{j}} + \sum_{i=1}^{d} b_{i}(x) \frac{\partial u}{\partial x_{i}} + ru + g[u]$$

where $a_{ij}(x) = a_{ji}(x), \ i, j = 1, \dots, d$ and g[u] is an integral operator.



Operator Splitting

$$\mathcal{A}u = -\sum_{i,j=1}^{d} a_{ij}(x) \frac{\partial^{2} u}{\partial x_{i} \partial x_{j}} + \sum_{i=1}^{d} b_{i}(x) \frac{\partial u}{\partial x_{i}} + ru + g[u]$$

We rewrite the operator as follows

$$\mathcal{A}u = -\sum_{j=1}^{d} \frac{\partial}{\partial x_{j}} \left(\sum_{i=1}^{d} a_{ij}(x) \frac{\partial u}{\partial x_{i}} \right) + \sum_{i=1}^{d} \left(b_{i}(x) + \sum_{j=1}^{d} \frac{\partial}{\partial x_{j}} a_{ij}(x) \right) \frac{\partial u}{\partial x_{i}} + ru + g[u]$$

$$\mathcal{A}u = \mathcal{L}u + f[u]$$

$$\mathcal{L}u = -\sum_{j=1}^{d} \frac{\partial}{\partial x_{j}} \left(\sum_{i=1}^{d} a_{ij}(x) \frac{\partial u}{\partial x_{i}} \right) + ru \quad \text{(symmetric)}$$

$$f[u] = \sum_{i=1}^{d} \left(b_{i}(x) + \sum_{j=1}^{d} \frac{\partial}{\partial x_{j}} a_{ij}(x) \right) \frac{\partial u}{\partial x_{i}} + g[u] \quad \text{(remainder)}$$



Variational Formulation

$$\mathcal{A}u = \mathcal{L}u + f[u], \quad \mathcal{E}[u] = \int_{\Omega} L(x, u, \nabla u) dx$$

$$\frac{\delta \mathcal{E}[u]}{\delta u} = \frac{d}{d\epsilon} \mathcal{E}[u + \epsilon v] \Big|_{\epsilon = 0} = \int_{\Omega} \sum_{k=1}^{d} \frac{\partial L}{\partial (\nabla u)_{k}} \frac{\partial v}{\partial x_{k}} + \frac{\partial L}{\partial u} v \, dx$$
$$= \int_{\Omega} \left(-\sum_{k=1}^{d} \frac{\partial}{\partial x_{k}} \left(\frac{\partial L}{\partial (\nabla u)_{k}} \right) + \frac{\partial L}{\partial u} \right) v \, dx.$$

$$\frac{\delta \mathcal{E}[u]}{\delta u} = 0 \Leftrightarrow -\sum_{k=1}^{d} \frac{\partial}{\partial x_{k}} \left(\frac{\partial L}{\partial (\nabla u)_{k}} \right) + \frac{\partial L}{\partial u} = 0 \quad \text{(Euler-Lagrange)}$$

$$L_{\mathcal{L}} = \frac{1}{2} \sum_{i,j=1}^d a_{ij}(x) \frac{\partial u}{\partial x_i} \frac{\partial u}{\partial x_j} + \frac{1}{2} r u^2 \quad \text{(Lagrangian)} \\ \Rightarrow - \sum_{k=1}^d \frac{\partial}{\partial x_k} \left(\frac{\partial L_{\mathcal{L}}}{\partial (\nabla u)_k} \right) + \frac{\partial L_{\mathcal{L}}}{\partial u} = \mathcal{L} u = 0$$

Time deep Ritz method (TDRM)

Suppose we would like to estimate the solution of the following equation:

$$\begin{array}{rcl} \partial_t u(t,x) + \mathcal{L} u(t,x) + f[u(t,x)] & = & 0, \quad x \in [0,x_{\max}]^d = \Omega, \quad t \in [0,T] \\ u(0,x) & = & \mathsf{Payoff}(x) \end{array}$$

We consider a time subdivision of the time interval [0, T]

$$\tau = T/n, \quad t_k = k\tau, \quad k = 0, \dots, n$$

$$u^k(x) \doteq u(t_k, x)$$

BDF-2 method (implicit - explicit)

$$\frac{u^k - 4/3u^{k-1} + 1/3u^{k-2}}{\tau} + \frac{2}{3}\mathcal{L}u^k + \frac{2}{3}(2f[u^{k-1}] - f[u^{k-2}]) = 0$$



Time deep Ritz method (TDRM)

BDF-2 method (implicit - explicit)

ightharpoonup Approximate u^1, u^2 using the implicit-explicit Euler method

$$u - \frac{4}{3}u^{k-1} + \frac{1}{3}u^{k-2} + \frac{2}{3}\tau\mathcal{L}u + \frac{2}{3}\tau(2f[u^{k-1}] - f[u^{k-2}])) = 0, \quad u^{k-2}, \ u^{k-1} \ \text{given}, \ k \geq 3$$

Lagrangian (BDF-2)

$$L = \frac{1}{2} \left(u - \frac{4}{3} u^{k-1} + \frac{1}{3} \right)^2 + \frac{2}{3} \tau L_{\mathcal{L}}(u) + \frac{2}{3} \tau (2f[u^{k-1}] - f[u^{k-2}])u$$

Minimization Problem

$$\mathcal{C}(\theta; \theta^{k-2}, \theta^{k-1}) \doteq \frac{1}{2} \left\| u - \frac{4}{3} u^{k-1} + \frac{1}{3} u^{k-2} \right\|_{L^2(\Omega)}^2 + \frac{2}{3} \tau \mathcal{E}_{\mathcal{L}}[u] + \frac{2}{3} \tau \int_{\Omega} (2f[u^{k-1}] - f[u^{k-2}]) u \, dx,$$

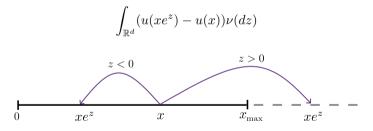
$$\theta^k \to \min_{\theta} \mathcal{C}(\theta; \theta^{k-2}, \theta^{k-1}), \ k \in \{3, \dots, n\}$$





$$\partial_t u(t,x) + \mathcal{L}u(t,x) + f(u(t,x)) = 0, \quad x \in [0, x_{\text{max}}]^d = \Omega, \quad t > 0$$

 $u(0,x) = u^0(x)$

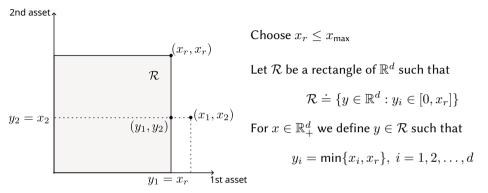


where the measure is given as

$$\nu(dz) = \lambda p(z)dz, \ p(z) = (2\pi)^{-d/2} |\Sigma_J|^{-1/2} \exp\left[-\frac{1}{2}(z-\mu_J)^T \Sigma_J^{-1}(z-\mu_J)\right]$$







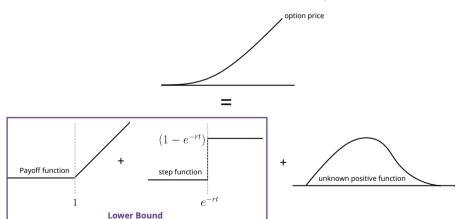
The approach: Taking into account the asymptotic behaviour of the solution

$$u(t,x) \doteq u(t,y) + \sum_{i=1}^{d} \alpha_i(x_i - y_i), \ x \in \mathbb{R}^d_+$$



Model : Decomposition of the solution in ${\mathcal R}$

(Solution at time t_k) = (Lower Bound at time t_k) + (positive function)









$$\mathcal{C}(\theta; \theta^{k-1}, \theta^{k-2}) \stackrel{\dot{=}}{=} \frac{1}{2} \| u(x; \theta^k) - \frac{4}{3} u^{k-1} + \frac{1}{3} u^{k-2} \|_{L^2(\Omega)}^2 \\
+ \frac{2}{3} \tau \mathcal{E}_{\mathcal{L}}[u(x; \theta^k)] + \frac{2}{3} \tau \int_{\Omega} (2f[u^{k-1}] - f[u^{k-2}]) u(x; \theta^k) \, dx,$$

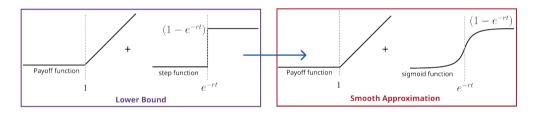
Is the cost functional smooth?

$$\theta^k \approx \theta^{k-1} \approx \theta^{k-2} \Rightarrow u(x;\theta^k) - \frac{4}{3}u^{k-1} + \frac{1}{3}u^{k-2} \approx \text{step function}$$

Model : Decomposition of the solution in ${\cal R}$

(Solution at time
$$t_k$$
) = (Lower Bound at time t_k) + (positive function)
$$u(t_k,y) = \tilde{u}_{\rm LB}(t_k,y) + w^k(y,\theta^k)$$

Lower bound at each time-step



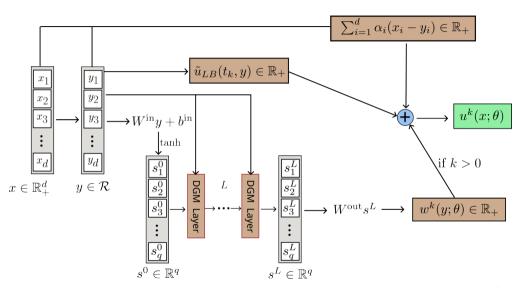
$$\tilde{u}_{\mathsf{LB}}(t,x;\gamma) = \mathsf{Payoff}(x) + (1 - e^{-rt})\mathsf{Sigmoid}(\sum_{i=1}^{d} \alpha_i x_i - e^{-rt/2};\gamma), \ \gamma > 0$$

Sigmoid
$$(x; \gamma) = \frac{1}{1 + e^{-\gamma x}}$$
.





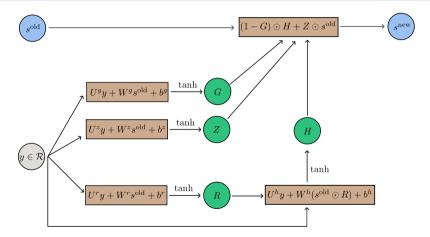
Model: Neural Network





Model: Neural Network

DGM Layer







Output:
$$u^k(x;\theta) = (1 - \delta_{k0})w^k(y;\theta) + \tilde{u}_{\mathsf{LB}}(t_k,y) + \sum_{i=1}^d \alpha_i(x_i - y_i),$$

We sample N points in the interval $[0, x_{\text{max}}]^d$. By applying Monte-Carlo to approximate the integrals of the cost functional, we get:

$$\mathcal{C}(\theta; \theta^{k-2}, \theta^{k-1}) \approx \frac{(x_{\text{max}})^d}{N} \sum_{i=1}^N \left[(u(x_i; \theta) - \frac{4}{3} u^{k-1}(x_i) + \frac{1}{3} u^{k-2}(x_i))^2 + \frac{2}{3} \tau \left(L(x_i) + (2f[u^{k-1}(x_i)] - f[u^{k-2}(x_i)])u(x_i; \theta) \right) \right]$$



Merton model

$$\mathcal{A}u = -\sum_{i,j=1}^{a} a_{ij}(x) \frac{\partial^{2}u}{\partial x_{i}\partial x_{j}} + \sum_{i=1}^{a} b_{i}(x) \frac{\partial u}{\partial x_{i}} + ru + g[u]$$

$$a_{ij}(x) = \frac{1}{2} \sigma_{i} \rho_{ij} \sigma_{j} x_{i} x_{j}, \qquad b_{i}(x) = [-r + \lambda \exp(\mu_{Ji} + \frac{1}{2} \sigma_{Ji}^{2}) - \lambda] x_{i}$$

$$g[u] = -\int_{\mathbb{T}^{d}} (u(xe^{z}) - u(x)) \nu(dz)$$

$$\sigma_i = 0.5, \ \rho_{ij} = \delta_{ij} + 0.5(1 - \delta_{ij}), \ i, j = 1, \dots, d, \ r = 0.05, \ \mathsf{time-step} = 0.02$$

Morever, the parameters of the jumps are

$$\lambda = 1, \ \mu_{Ii} = 0, \ \sigma_{Ii} = 0.5, \ \rho_{Iii} = \delta_{ii} + 0.2(1 - \delta_{ii}), \ i, j = 1, \dots, d$$



The integral: Gauss-Hermite quadrature

In Merton model, the integral is simply the expected value of the function $h(z) = u(xe^z) - u(x)$ multiplied by the Poisson parameter λ .

▶ Singular Value Decomposition (SVD) of Σ_J

$$\Sigma_J = U\Lambda U^T = U\Lambda^{1/2}\Lambda^{1/2}U^T = VV^T,$$

where $V = U\Lambda^{1/2}$.

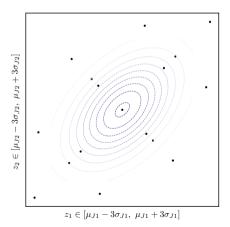
• change of variable $Z - \mu = \sqrt{2}VY$

$$\begin{split} \int_{\mathbb{R}^d} h(z) \nu(dz) &= \lambda \pi^{-d/2} \int_{\mathbb{R}^d} \exp(y^T y) h(\mu + \sqrt{2} V y) dy \\ &\approx \lambda \pi^{-d/2} \sum_{\mathbf{i} \in \Theta_n} h(\mu + \sqrt{2} V y^{\mathbf{i}}) W^{\mathbf{i}}, \end{split}$$





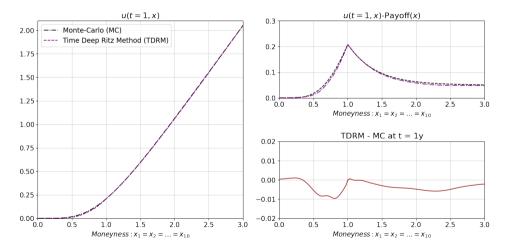
The integral: Gauss-Hermite quadrature







10 Assets - Maturity: 1 year









Conclutions and Future work

- ▶ We proposed a modified splitting deep Ritz method for option pricing.
- ► Our method is capable of accurately approximating the solutions of the partial integro-differential equations (PIDEs) that arise in European basket call options.
- ► To evaluate the effectiveness of our method, we compared its results with those obtained using Monte-Carlo simulations.

▶ We are working on the multivariate variance Gamma model (infinite jump activity)





Thank you for your attention



