

The multidimensional COS method for option pricing

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- Aim: solve numerically

$$\int_{\mathbb{R}^d} w(\mathbf{x})g(\mathbf{x})d\mathbf{x}.$$

- g density, e.g., of log-returns
- w function of interest
- solutions: Fourier-methods (COS, Fang&Oosterlee (2009), Lewis, Wavelets,...), MC, numerical integration.
- Example for w indicator function or "digital put option"

$$w(\mathbf{x}) = \prod_{h=1}^d 1_{[0, K_h]}(e^{x_h})$$

or basket option

$$w(\mathbf{x}) = \max(K - \sum_{h=1}^d e^{x_h}, 0).$$

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Constraints

- Aim: solve numerically

$$\int_{\mathbb{R}^d} w(\mathbf{x})g(\mathbf{x})d\mathbf{x}.$$

- g unknown but Fourier-transform known

$$\hat{g}(\mathbf{u}) := \int_{\mathbb{R}^d} g(\mathbf{x})e^{i\mathbf{u}\cdot\mathbf{x}}d\mathbf{x}.$$

- Sum of independent random variables, Lévy processes, Heston model,...
- $w \notin \mathcal{L}_1$ but \hat{w} is given, e.g., for basket option:

$$\hat{w}(\mathbf{z}) = K^{(1+i\sum_{h=1}^d z_h)} \frac{\prod_{h=1}^d \Gamma(iz_h)}{\Gamma\left(i\sum_{h=1}^d z_h + 2\right)}, \quad \Im\{z_h\} < 0.$$

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Damping

- For scaling factor $\lambda > 0$, shift parameter $\boldsymbol{\mu} \in \mathbb{R}^d$ and a damping factor $\boldsymbol{\alpha} \in \mathbb{R}^d$, define the *damped density* by

$$f(\mathbf{x}) = \lambda e^{\boldsymbol{\alpha} \cdot (\mathbf{x} + \boldsymbol{\mu})} g(\mathbf{x} + \boldsymbol{\mu}), \quad \mathbf{x} \in \mathbb{R}^d$$

and the *damped payoff function* by

$$v(\mathbf{x}) = \frac{1}{\lambda} e^{-\boldsymbol{\alpha} \cdot (\mathbf{x} + \boldsymbol{\mu})} w(\mathbf{x} + \boldsymbol{\mu}), \quad \mathbf{x} \in \mathbb{R}^d.$$

By definition, it follows that

$$\int_{\mathbb{R}^d} w(\mathbf{x}) g(\mathbf{x}) d\mathbf{x} = \int_{\mathbb{R}^d} v(\mathbf{x}) f(\mathbf{x}) d\mathbf{x}.$$

- Further,

$$v \in \mathcal{L}_1,$$

\hat{f} is known if \hat{g} is known,

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Problem: f unknown

$$f \approx f 1_{[-L,L]} \approx \sum'_{\mathbf{0} \leq \mathbf{k} \leq \mathbf{N}} a_{\mathbf{k}} e_{\mathbf{k}} 1_{[-L,L]} \approx \sum'_{\mathbf{0} \leq \mathbf{k} \leq \mathbf{N}} c_{\mathbf{k}} e_{\mathbf{k}} 1_{[-L,L]},$$

where

$$e_{\mathbf{k}}(\mathbf{x}) = \prod_{h=1}^d \cos\left(k_h \pi \frac{x_h + L_h}{2L_h}\right), \quad \mathbf{k} \in \mathbb{N}_0^d$$

and

$$\begin{aligned} a_{\mathbf{k}} &= \frac{1}{\prod_{h=1}^d L_h} \int_{[-L,L]} f(\mathbf{x}) e_{\mathbf{k}}(\mathbf{x}) d\mathbf{x} \\ &\approx \frac{1}{\prod_{h=1}^d L_h} \int_{\mathbb{R}^d} f(\mathbf{x}) e_{\mathbf{k}}(\mathbf{x}) d\mathbf{x} \\ &= \frac{1}{2^{d-1} \prod_{h=1}^d L_h} \sum_{\mathbf{s}=(1,\pm 1,\dots,\pm 1) \in \mathbb{R}^d} \Re \left\{ \hat{f}\left(\frac{\pi}{2} \frac{\mathbf{s}\mathbf{k}}{\mathbf{L}}\right) \exp\left(i \frac{\pi}{2} \mathbf{s} \cdot \mathbf{k}\right) \right\} \\ &=: c_{\mathbf{k}}. \end{aligned}$$

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Definition

A function $f \in \mathcal{L}^1$ is called *COS-admissible*, if $\min_{h=1,\dots,d} L_h \rightarrow \infty$ implies

$$B(\mathbf{L}) := \sum'_{\mathbf{k} \in \mathbb{N}_0^d} \frac{1}{\prod_{h=1}^d L_h} \left| \int_{\mathbb{R}^d \setminus [-L, L]} f(\mathbf{x}) e_{\mathbf{k}}(\mathbf{x}) d\mathbf{x} \right|^2 \rightarrow 0.$$

Proposition

Assume $f \in \mathcal{L}^1 \cap \mathcal{L}^2$ with $\int_{\mathbb{R}^d} |\mathbf{x}|^{2d} |f(\mathbf{x})|^2 d\mathbf{x} < \infty$. Then

$$B(\mathbf{L}) \leq \frac{\frac{\pi^2}{3} \sum_{h=1}^d \left(\frac{\pi^2}{3} + 1\right)^{h-1}}{d \min_{h=1,\dots,d} L_h^{2d}} \int_{\mathbb{R}^d \setminus [-L, L]} |\mathbf{x}|^{2d} |f(\mathbf{x})|^2 d\mathbf{x} +$$
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Example

Stable and Pareto densities, bounded densities with existing moments.

Theorem

Assume that $f \in \mathcal{L}^1 \cap \mathcal{L}^2$ and that f is COS-admissible. For any $\varepsilon > 0$ there is $\mathbf{L} \in \mathbb{R}_+^d$ and $\mathbf{N} \in \mathbb{N}^d$ such that

$$\left\| f - \sum_{0 \leq k \leq \mathbf{N}} c_k e_k 1_{[-\mathbf{L}, \mathbf{L}]} \right\|_2 < \varepsilon.$$

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Solve the integral

- Let $\mathbf{M} = (M_1, \dots, M_d) \in \mathbb{R}_+^d$ such that $\mathbf{M} \leq \mathbf{L}$. Then, intuitively,

$$\begin{aligned} \int_{\mathbb{R}^d} v(\mathbf{x}) f(\mathbf{x}) d\mathbf{x} &\approx \int_{[-M, M]} v(\mathbf{x}) \sum'_{\mathbf{0} \leq \mathbf{k} \leq \mathbf{N}} c_{\mathbf{k}} e_{\mathbf{k}}(\mathbf{x}) d\mathbf{x} \\ &= \sum'_{\mathbf{0} \leq \mathbf{k} \leq \mathbf{N}} c_{\mathbf{k}} \underbrace{\int_{[-M, M]} v(\mathbf{x}) e_{\mathbf{k}}(\mathbf{x}) d\mathbf{x}}_{=: v_{\mathbf{k}}} \\ &\approx \sum'_{\mathbf{0} \leq \mathbf{k} \leq \mathbf{N}} c_{\mathbf{k}} \underbrace{\int_{\mathbb{R}^d} v(\mathbf{x}) e_{\mathbf{k}}(\mathbf{x}) d\mathbf{x}}_{=: \tilde{v}_{\mathbf{k}}}, \end{aligned}$$

the last approximation works if $v \in \mathcal{L}_1$ and \mathbf{M} large enough.

- Classical COS method:* $\alpha = \mathbf{0}$ and $v_{\mathbf{k}}$ can be obtained explicitly or is approximated by numerical integration.
- Damped COS method:* $\alpha \neq \mathbf{0}$ and obtain $\tilde{v}_{\mathbf{k}}$ through \hat{v} .

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Theorem

Let $f \in \mathcal{L}^1 \cap \mathcal{L}^2$ with $f \geq 0$ and $\int_{\mathbb{R}^d} |\mathbf{x}|^{2d} |f(\mathbf{x})|^2 d\mathbf{x} < \infty$. Let $v : \mathbb{R}^d \rightarrow \mathbb{R}$ with $\|v\|_\infty \in (0, \infty)$. Let $n \geq 2$ be even. Let

$$m_h(n) := \int_{\mathbb{R}^d} x_h^n f(\mathbf{x}) d\mathbf{x} = i^{-n} \left. \frac{\partial^n}{\partial u_h^n} \hat{f}(\mathbf{u}) \right|_{\mathbf{u}=\mathbf{0}} \in (0, \infty), \quad h = 1, \dots, d.$$

Assume that f decays exponentially. Let $\varepsilon > 0$ be small enough. Define

$$M_h := \left(\frac{3d \|v\|_\infty}{\varepsilon} m_h(n) \right)^{\frac{1}{n}}, \quad h = 1, \dots, d,$$

and $\mathbf{L} = \mathbf{M} = (M_1, \dots, M_d) \in \mathbb{R}_+^d$. There is a $\mathbf{N} \in \mathbb{N}_0^d$ so that

$$\left| \int_{\mathbb{R}^d} v(\mathbf{x}) f(\mathbf{x}) d\mathbf{x} - \sum'_{0 \leq k \leq \mathbf{N}} c_k v_k \right| \leq \varepsilon.$$

Corollary

If, additionally, $v \in \mathcal{L}^1 \cap \mathcal{L}^2$ with $\int_{\mathbb{R}^d} |\mathbf{x}|^{2d} |v(\mathbf{x})|^2 d\mathbf{x} < \infty$ and v decays exponentially, then

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Corollary

The number of terms can be chosen by any $N \in \mathbb{N}_0^d$ such that

$$\left| (2\pi)^{-d} \int_{\mathbb{R}^d} |\hat{f}(\mathbf{u})|^2 d\mathbf{u} - \prod_{h=1}^d L_h \sum'_{0 \leq k \leq N} |c_k|^2 \right| \leq \frac{\varepsilon^2}{162 \|v\|_2^2}.$$

Junike & Stier (2024).

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Theorem

Assume $d = 1$. Assume all technical assumptions from the previous theorem are met. Assume $f \in C_b^{J+1}(\mathbb{R})$. For $k \in \{1, \dots, J\}$ let

$$N \geq \left(12 \frac{2^{k+\frac{5}{2}} \|f^{(k+1)}\|_\infty L^{k+4} \|v\|_\infty}{k\pi^{k+1}\varepsilon} \right)^{\frac{1}{k}}.$$

Then,

$$\left| \int_{\mathbb{R}} v(\mathbf{x}) f(\mathbf{x}) d\mathbf{x} - \sum'_{0 \leq k \leq N} c_k \tilde{v}_k \right| \leq \varepsilon.$$

Junike (2024).

	d	Model	N	CPU time COS (num. int.)
Minimal N	1	BS	25	0.02
Cor.	1	BS	28	0.03
Junike (2024)	1	BS	34	0.03
Minimal N	2	BS	65	5.35
Cor.	2	BS	116	17.02
Minimal N	2	VG	55	8.55
Cor.	2	VG	154	68.20 (1092.2)

Table: Basket option $K = 200$, $\varepsilon = 10^{-3}$, $T = 1$ and $r = 0$. CPU time in milliseconds.

Theorem: Order of Convergence

- Let

$$\text{err}(L(N), N) = \left| \int_{\mathbb{R}} v(x) f(x) dx - \sum_{k=0}^N c_k v_k \right|.$$

- If f has semi-heavy tails, i.e., $|f(x)| \leq O(e^{-C_2|x|})$ and f is smooth then $\text{err}(L(N), N)$ converges exponentially.
- If f has heavy tails with Pareto index $\theta > 0$, i.e., $|f(x)| \leq O(|x|^{-1-\theta})$ and f is smooth then

$$\text{err}(L(N), N) \leq O(N^{-\theta}), \quad \text{as } N \rightarrow \infty.$$

- There is a multidimensional version without the assumption that f is differentiable to treat, e.g., the VG model.

Junike(2024) and Junike & Stier (2024).

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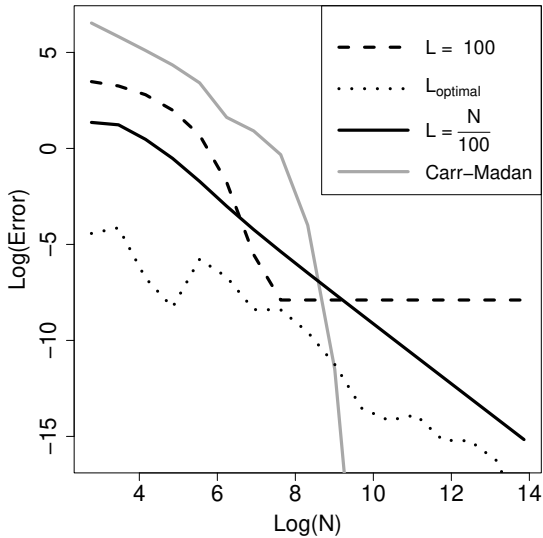
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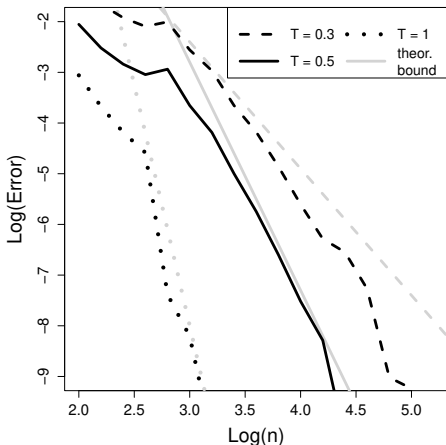
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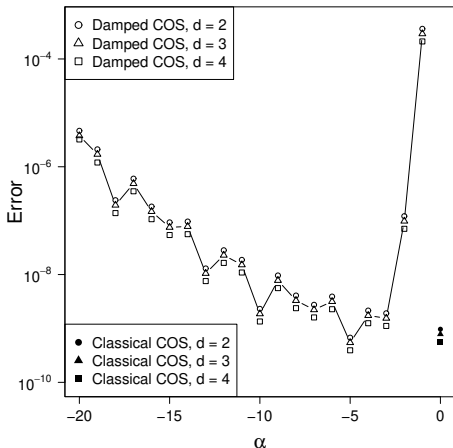
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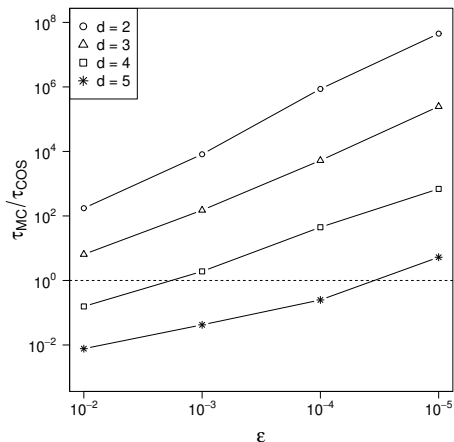


Error of the price for the VG model over the number of terms for an arithmetic basket put option and $d = 2$. We choose $\mathbf{N} = (n, n)$ and $\mathbf{M} = \mathbf{L} = (\frac{1}{2}n^\beta, \frac{1}{2}n^\beta)$ with $\beta = \frac{1}{2}$. Theor. slope $-(1 - \beta) \left(\frac{2T}{\nu} - \frac{d}{2} \right)$.

Damping factor



Error of the price of a cash-or-nothing put option in the BS model for $\mathbf{M} = \mathbf{L} = (20\sigma, \dots, 20\sigma)$ and $\mathbf{N} = (70, \dots, 70)$.



CPU time of the COS method (τ_{COS}) and the CPU time of a MC simulation (τ_{MC}) for the BS model pricing a cash-or-nothing put option.

- Fang, F., & Oosterlee, C. W. (2009). A novel pricing method for European options based on Fourier-cosine series expansions. *SIAM Journal on Scientific Computing*, 31(2), 826-848.
- Ruijter, M. J., & Oosterlee, C. W. (2012). Two-dimensional Fourier cosine series expansion method for pricing financial options. *SIAM Journal on Scientific Computing*, 34(5), B642-B671.
- Junike, G., & Pankrashkin, K. (2022). Precise option pricing by the cos method—how to choose the truncation range. *Applied Mathematics and Computation*, 421, 126935.
- Junike, G. (2024). On the number of terms in the COS method for European option pricing. *Numerische Mathematik*.
- Junike, G., & Stier, H. (2024). From characteristic functions to multivariate distribution functions and European option prices by the damped COS method. *arXiv preprint arXiv:2307.12843*.