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Machine learning for quantitative finance: fast derivative pricing, hedging and fitting

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Abstract

In this paper, we show how we can deploy machine learning techniques in the context of traditional quant problems. We illustrate that for many classical problems, we can arrive at speed-ups of several orders of magnitude by deploying machine learning techniques based on Gaussian process regression. The price we have to pay for this extra speed is some loss of accuracy. However, we show that this reduced accuracy is often well within reasonable limits and hence very acceptable from a practical point of view. The concrete examples concern fitting and estimation. In the fitting context, we fit sophisticated Greek profiles and summarize implied volatility surfaces. In the estimation context, we reduce computation times for the calculation of vanilla option values under advanced models, the pricing of American options and the pricing of exotic options under models beyond the Black–Scholes setting.

Keywords:

Machine learning | Gaussian processes | Derivative pricing | Hedging | Volatility surface

Disclosure statement

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Notes

† Matrix inversion is often implemented via a Cholesky decomposition (Benoît 1924, Rasmussen and Williams 2006), which is more stable than actually inverting the matrix. For small matrices, i.e. small values of n, ordinary matrix inversion can be performed. For the results in this paper we used the Matlab functions fitrgp and predict. However if the dimension increases, special techniques need to be deployed. We mention LU-factorization and blockwise Cholesky decomposition, which aim at solving traditional memory problems that one encounters when inverting large matrices. For future work we will employ Cholesky and blockwise Cholesky routines to handle problems with many more data points.

† κ = rate of mean reversion, ρ = correlation stock – vol, θ = vol of vol, η = long run variance, = initial variance.

† For each parameter combination, the same random numbers are used to construct the 100 000 Heston-based price paths of the underlying.