Deep Learning on Exotic Derivatives Portfolio

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March 25, 2020

Abstract

In the last decades, the finance industry has consistently tried to exploit the computational power of modern hardware. Besides, we have witnessed the rapid growth of tools such as artificial intelligence (AI) and machine learning (ML) from supervisory agencies (suptech) as well. These advances in computational power have unlocked the application of algorithms that were not reachable in the past. In the present study, we aim to apply machine learning in order to price, simultaneously, the multiple payoffs of a portfolio that includes eight different exotic derivatives, in particular the performance of baskets of four stocks, and the respective vega hedges, composed of 16 plain vanilla options on the corresponding individual stocks. We present a novel combination of the Quasi-Monte Carlo (QMC) method and the Deep Neural Network (DNN) framework, where a massive dataset with 2^{26} training examples on 120 payoffs (including all possible combinations of four stocks) is generated with high accuracy, equivalent to $1M$ Monte Carlo (MC) scenarios. We generate our option payoff examples under Black-Scholes Merton (BSM) model using random sets of input parameters within appropriate ranges and distributions selected independently for each payoff. Next, we train multiple DNN models through an extensive experimental evaluation, varying the hyper-parameters of the proposed network architecture in order to explore the impact on model speed and accuracy.

The results confirm that the proposed methodology considerably outperforms the common method of option pricing, the MC technique, yielding comparably accurate results at a much greater speed, about a million times faster in the case of large sets of exotic options. This is made possible by the fact that, once a neural network is trained, it no longer requires the computationally-heavy scenario simulation of the MC technique. The methodology of this study can be seen as an extension of previous works in the same field, in particular [FG18], with an exploration of the problem for a vast dimension of inputs and outputs. As a possible area of future research, we highlight the possibility of providing risk sensitivities through the back propagation of neural networks.

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Chapter 1

Introduction

1.1 Background and Motivation

Since the introduction of Black-Scholes Merton (BSM) model in 1973, the foundations were laid for the development and the evaluation of increasingly sophisticated financial instruments, markets and valuation models. The insights gained over this period have substantially contributed to the growth in the efficiency in modern economies and the businesses operating in them. The gain in our understanding of finance allowed researchers and practitioners to progressively develop complex models to value instruments, allocate funds and manage principal-agent problems to varying degrees. A major advantage has been the opportunity to create financial securities which are customized to the particular needs of individual clients, whether they are funds, businesses or individuals.

The increases in complexity and distribution, however, required significant investments in automation. The huge number of transactions as well as the speed at which they are settled today would not have been possible without computer support. The same is also true for the valuation of securities, which typically requires significant development of models for forecasting and pricing, optimization of fund allocation as well as accurate and timely performance measurement and reporting. Particularly, in the case of exotic derivatives, the valuation can be generally a demanding task since in certain cases the structure of payoff can be very complex. In most cases, which there is no closed-form solution, the typical method is using Monte Carlo (MC) simulation which has been proved to be accurate only after a large number of scenarios.

In the meantime, there have been numerous attempts to approach the complexity and precision of data processing that the human brain possesses. Many researchers significantly suggested advancements in applying Artificial Neural Network (ANN) in various data processing fields such as image and voice recognition, genetics, economics, finance, and many others. However, it was only two decades ago in 1994 that Hutchinson [HMLP94] applied an artificial neural network model which was able to naturally explain the option price without assumptions made by parametric models, i.e. Black-Scholes formula. Since then, a great amount of literature using neural network in option pricing and related areas have been written. In the absence of a closed-form formula holding true in general market conditions, neural networks are an alternative way to traditional models, and their refinement is essential for the improvement of option pricing estimation.

1.2 Research Goals and Hypotheses

This research aims to not only compare the performance of Deep Neural Network (DNN) with traditional Monte Carlo (MC) methods, but also put in practice the concept of a hybrid model, in which we can improve the accuracy of the neural network by feeding a training data generated from Quasi-Monte Carlo (QMC) method and learning on a higher number of dimensions in the output. In addition, it is significant to study on the optimal choice of size and architecture of the neural network for the pricing of a portfolio of basket options. For this purpose, we have gained a valuable information and insights from two previous conducted studies, [FG18] and [SBK17]. We tried to enhance the former results through modification and application of more advanced techniques from both a theoretical and an implementation point of view. Hence, the present research aims at verifying the following hypotheses.

Hypothesis 1: With the help of QMC method, we can increase both accuracy and the speed of the sample set generation, which in turn leads to an improvement in the performance of the neural network.

Hypothesis 2: Deep neural network approach reveals itself much faster than traditional Monte Carlo models after training. However, this computational speed edge must be weighed against the additional time required to train the network.

Hypothesis 3: Scaling the dimensionality of the derivatives would not affect the generalization of the neural network in the sense that it would maintain the property of fitting the data properly without creating any false predictions. However, a lower number of outputs for the regression model could result in more accurate predictions.

Hypothesis 4: The out-of-sample prediction power of the neural network depends on both inputs and outputs distributions. Hence, having related parameters or similar payoffs would benefit us in the accuracy of obtained results.

Acronyms

AI artificial intelligence. 1

ANN Artificial Neural Network. 1

BSM Black-Scholes Merton. 1

DNN Deep Neural Network. 1

MC Monte Carlo. 1

ML machine learning. 1

QMC Quasi-Monte Carlo. 1

suptech supervisory agencies. 1

References

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