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Multilayer Perceptron model efficacy for S&P 500 Stock Option Pricing

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Abstract: **Option pricing is of key importance for stock markets and traders to reduce risk, avoid loss and on the other hand speculate on stock price movements. This work explores the efficacy of using artificial neural network approach in call option pricing. We built a multilayer perceptron model trained it with real market option contracts data and tested it in option data originated from fifty S&P 500 stocks. In our approach both training and testing data are market oriented and this is a unique contribution to existing research, where training is usually based on artificially generated data. Our findings demonstrate that multilayer perceptron performs very well in actual market data and is competitive to Black-Scholes pricing formula. Further exploration and experimentation is required, however, so machine learning approaches reach required robustness and become less ad hoc and data sensitive. Despite its limitations, it is a very promising approach and can play a substantial role in option pricing, provided that it is supported by relevant software solutions.**

Keywords: **stock option pricing, artificial neural network, multilayer perceptron.**

I. INTRODUCTION

Option pricing domain is evolving in financial research and numerous models for have been introduced during the past years. The models can be roughly divided in traditional, that rely on theory and they were introduced in the early decades, and novel ones that rely on data and follow recent machine learning developments. Conventional models, like the Black-Scholes, offer closed form formulas for option pricing, but with limitations to option types and under strict assumptions. However, they are very popular due to their computational speed, flexibility, and accuracy. Alternative models, that also follow theory, but rely on numerical procedures, simulate the underlying asset behavior to estimate option prices for wider option types compared to Black-Scholes model. Monte Carlo simulation and the Binomial method are the key representative methods [1], [2], [3], [4]. In general, the so called traditional approaches rely on theoretical formulation and their performance is affected by the ability to model the mechanism of the underlying process using algebraic methods. So they are subject to limitations and they do not perform accurately or in a timely manner in every case.

In parallel to traditional algebraic approaches, many researchers in an effort to surpass their limitations introduced pricing models that rely on data instead of theory using machine learning methods with either empirical or synthetic data. Artificial neural networks are the most representative machine learning approach, and it performs comparable or competitive to conventional models in many research works. Machine learning models do not rely on theory, so they can model any type of nonlinear behavior and interaction. However, an inherent limitation of artificial neural networks is that they are not interpretable and cannot generate explainable models for practitioners or theorists. Also, machine learning models require, in general, relatively large dataset for efficient training, something that is not always feasible in underdeveloped option markets. They also rely on the specific training approach and the domain dataset, so they are not easy to generalise, contrasted to the traditional methods. So, even if machine learning based models are becoming a competitive alternative to traditional pricing methods, further research is needed to offer more robust and widely used approaches [5], [6], [7], [8], [9].

Following the above overview, in this work we explore the feasibility of using an artificial neural network model for option pricing using market data for training and testing. Relevant approaches propose the utilization of artificial neural networks trained to learn Black-Scholes function, but very few works use market data to train the models. The majority use simulated or generated datasets for both training and prediction. In this work, we train and test the network using market data collected from fifty S&P 500 stock option contracts. So, testing data are oriented from the same distribution as training, and not the theoretical Black-Scholes model, so we can examine model performance in real market data adding thus a unique contribution to existing research.

The paper is structured as follows. Initially, some background information on options and their pricing is provided, along with the Black-Scholes model. Next, we refer to artificial neural networks, along with some review of key publications for their applicability in pricing. Following the background, we introduce the method and the datasets we used, followed by key results and discussion. Findings, demonstrate that multilayer perceptron models can be very effective for option pricing, although further exploration and experimentation is required to increase robustness and become less ad hoc and data domain specific.

II. BACKGROUND

A. Options

An option is a contract between a seller and a buyer, that offers the holder the right to buy or sell some specified quantity of an underlying asset at a specified price (strike price), either on the expiration of the option (maturity date), or earlier. Considering some fundamental asset types, options can be either stock options, stock index options, future options, or product options. Options may not be exercised by the holder and let expire, as they holder has the right and not the obligation to execute. European options do not allow for exercise prior to maturity and the exercise date is defined at the option contract, while American options allow for exercise at any point of time prior to maturity. Options are distinguished in call and put options with respect to the right to buy or sell the underlying asset.

Call options offer the right to buy a specified quantity of the underlying asset at the strike price, either on maturity, or any time before. If the option is not exercised until the expiration date, it expires without any benefit for the holder. The holder pays a price to purchase the option expecting a benefit if the price of the underlying asset is higher than the strike price. In this case, the holder exercises the option at strike price and buys the underlying asset at this price, instead of the higher market price. The difference is the gross investment profit. If the asset price is lower than the strike price at maturity or earlier, the option is not exercised. So, the net profit is the difference between the gross profit and the call purchase price, if the option is exercised.

Put options offer the right to sell a specified quantity of the underlying asset, at strike price, again either at maturity or earlier. A put option has a price paid by the investor who expects a profit in case the price of the underlying asset is less than the strike price of the option. If the underlying asset has a price lower than the strike price of the put option on maturity or before, the option is exercised and the option holder sells the underlying asset at a higher price compared to the market value, which comprises the gross profit of the investment. In case the underlying asset has a price higher than the strike price, the option is left to expire. The net profit again comprises the difference between the gross profit and the put option purchase price [2].

B. Pricing methods

Option buyer pays at the initiation of an option contract the option price (or premium) to option seller (writer). The premium is the benefit for the seller and it is the maximum profit the seller might gain from the transaction. Thus, accurate option pricing is very important for option markets. Determinants of option price derived from financial theory are the:

- Current value of the underlying asset.
- Value variance of the underlying asset or volatility.
- Dividends of the underlying asset.
- Strike price of the option.
- Expiration date of the option or time to maturity.
- Risk free interest rate during the option life.

A variety of pricing methods and variations have been introduced to price options accurately. Black-Scholes model [3] set the ground for the domain and since its introduction in 1973 remains influential. It offers an analytical method to estimate the theoretical arbitrage-free price of an option provided that some market parameters are known. Another widely used model is the Binomial [4] that was introduced in 1978 and follows a discrete time approach. Except those two, variations and novel approaches have been introduced, however, despite the introduction of more sophisticated methods, the traditional ones seem to outperform in some comparative studies for American options, where analytical solutions cannot be generated [5].

C. Black-Scholes

Black-Scholes model was introduced by Fisher Black and Myron Scholes in 1973 [3] and is one of the most influential models in finance. It assumes that stock prices move following a random walk and that stock prices should not follow a pattern that could be predicted, for a market to be efficient. If this does not hold, stock future prices can be predicted and there could be financial gain. Since its introduction there have been many variations, but in its initial version there is no dividend until the option maturity date, no transaction fees are charged and the risk-free rate and volatility are known constants. The model is parametric and its famous formula for the arbitrage free price of an option can be used to price options as a function of current stock or underlying asset price, option strike price, option time to maturity or expiration, risk free rate and volatility of the underlying stock return. The model is referenced in almost every work related to pricing options, and the interested reader can find enough details on the model at the work of Hull [6] among others.

D. Artificial Neural Networks

Artificial neural networks were initiated in 1943 by McCulloch and Pitts, as mathematical formulation of a biological neuron in order to be able to execute computations mimicking brain neurons functionality. Big data and computing power evolution in the past decade has led to substantial developments in the field and we can find numerous domains which utilize the power of artificial neural networks and deep learning models. The universal approximation theorem was the work that actually set the ground for recent developments, which proves that an even plain artificial neural network can approximate any continuous function in a closed interval based on input variables [9]. This is a key benefit of artificial neural networks models, as the majority of real-world problems cannot be modelled and solved analytically.

Option pricing is an example of a key problem in financial industry, that can partially be modelled by parametric methods and solved analytically, like Black-Scholes variations and Monte Carlo simulation. Thus, researchers proposed alternative non parametric approaches based on machine learning, focusing mainly on artificial neural networks for option pricing [10]. Initial approaches opened a new research direction for derivative pricing and early works reported very low errors [11], [12], something that recent works seem to confirm [7], [8]. Not all works however agree to positive results and artificial neural networks outperformance compared to traditional methods is still under research. Usually, plain neural network architectures and limited data are used, so weak results for neural networks compared to Black-Scholes are expected as neural networks require large training datasets. Other researchers claimed that results differ if we examine options in the money or out of the money or other factors, but in overall, neural networks accuracy for option pricing compared to traditional models is a common outcome. In all works Black-Scholes model is still used as a benchmark to test for the errors in pricing, so, despite the promising performance of artificial neural networks, theoretical models are still dominant.

III. DATA AND METHODS

The aim of this work is to explore the efficacy of neural network architecture for call option pricing using empirical data for training and testing. This work builds on related works [13], [14], however it focuses on real market data, instead of artificially generated. The approach we followed comprises the phases below:

- Collect market data for fifty S&P 500 stock call options.
- Define a multilayer perceptron model with initial parameters.
- Train, validate and test the model with the market dataset.
- Evaluate the model using the real market data as the benchmark, and not Black-Scholes benchmark.

The entire work and collection of market data, was executed by specific modules developed in Python 3.11 [15]. The multilayer perceptron was implemented in Python, using Keras library and Tensorflow as the computational engine. For the computations, a typical desktop computer was used with Intel Core i5-at 2.90 GHz and 8GB RAM.

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A. Training and testing dataset

For training and testing phase we used publicly available market data for fifty randomly selected S&P 500 stocks. As market data do not strictly follow the theoretical calculations, and on the other hand include some extreme values that are not met in practical trading, we performed a number of pre-processing tasks. In total a number of 3500 records were collected, following the approach below:

- The stocks represent a random subset of S&P 500 stocks, in order to include diverse data.
- Stock prices are the previous day closing price.
- Dividend was also collected from market data as provided (forward dividend and yield).
- For implied volatility we used the values as provided from market, as they reflect market's opinion on the asset.
- We focused on call options.
- We collected only in-the-money call options.
- We filtered the data, excluding not realistic and non-representative observations from the data and to obtain more meaningful results [13], [14].

The distributions of the call and strike prices for the dataset are depicted below (Fig. 1, Fig. 2).

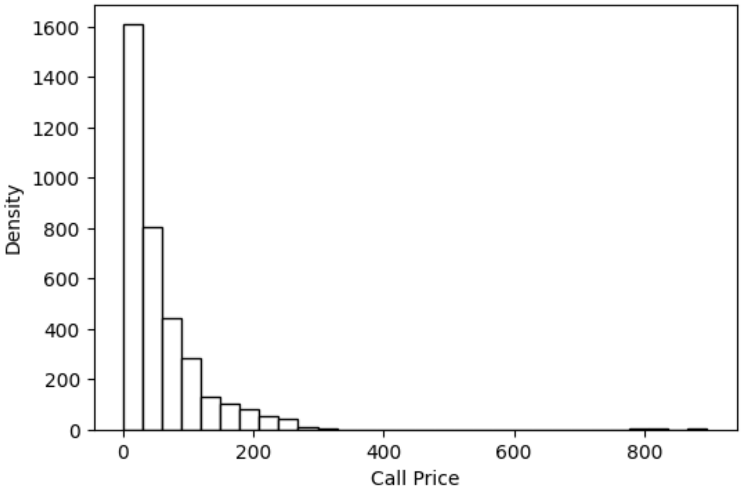

Figure 1: Call prices

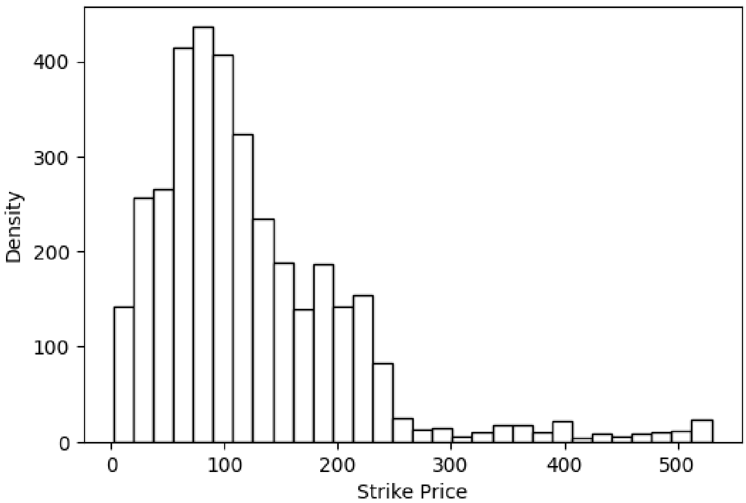

Figure 2: Strike prices

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B. Multilayer perceptron model

For the neural network, we used multilayer perceptron (MLP) architecture, a widely used approach that well in finance settings. The model was trained using the entire set of parameters as input features, namely:

- strike price,
- stock price,
- risk free interest rate,
- time to maturity and
- implied volatility
- and the call price as the output.

Input variables were normalized and after some experimentation, we used a network of one input layer, three hidden layers of 80 neurons each, and one output layer for the call option price output. The first and the third hidden layers utilize Elu activation function and the second the Relu activation function. The model was trained using the market dataset, split into 70% for training, 10% for validation and remaining 20% for testing. The model hyperparameters were tuned to 25% dropout rate, a rule of thumb dropout rate to prevent overfitting [14]. The epochs for training were 80 and the batch size (the number of samples processed before updating the model) was set to 64. Finally, the loss function was optimized using mean square error (MSE).

IV. RESULTS

In this work we explored the efficacy of an artificial neural network for option pricing on real market data. The approach we followed was to train and test the model on a random set of fifty S&P 500 stocks and their market option data. For both training and testing we utilized Python tailor made libraries [15] along with Tensorflow module. The set of tuned parameters was exported into a file that was used in all testing scenarios using the market dataset. We focused at in-the-money call options, but the same approach can fit at out-of-the-money options.

The results from the testing phase of the model are presented in Table 1, and the normalized predicted call prices against the actual ones are depicted in Fig. 3. As we can see, the Root mean square error is relatively low (8.8315). Compared to relevant benchmark study [14], where neural network was trained with Black-Scholes artificial data, we see that in the Black-Scholes benchmark, the Root mean square value is 0.0284, so it looks that the multilayer perceptron is not performing adequately well. However, although the value looks high, given the fact that we followed an approach based solely on market data, it can be considered within reasonable limits.

TABLE I. TESTING ERROR RESULTS WITH MARKET DATA

Mean Squared Error:	77.99668136113569
Root Mean Squared Error:	8.831572983400845
Mean Absolute Error:	4.301720359374898

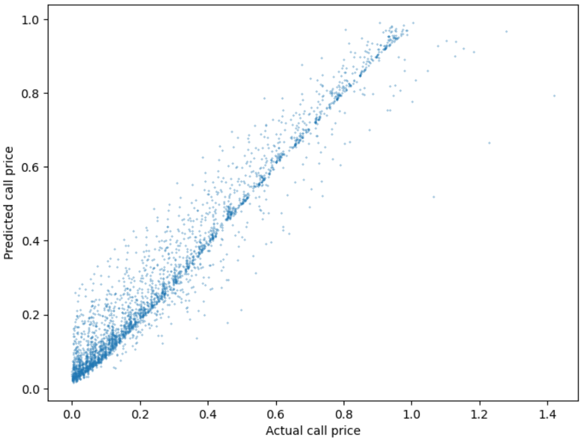

Figure 3: Predicted call prices against actual ones

So, in overall we can claim that the model, even at a preliminary setting, is comparable to the Black-Scholes formula for calculating option prices at market data, and can valuate options in acceptable accuracy. Provided that market prices are not strictly derived from Black-Scholes formula, it is reasonable to assert that the aforementioned level of error is within reasonable limits. Some additional experiments can be performed including put options and combining variations of volatility estimations for both in and out-of-the money options. Also, the trained model can be benchmarked to various alternative machine learning models in terms of accuracy and computational performance.

V. CONCLUSION

In this work we explored the efficacy of an artificial neural network on call option pricing using real market data for training and testing. We used a multilayer perceptron model, and a real market dataset, comprising fifty randomly selected S&P 500 stocks. From the results, we can see that a multilayer perceptron is capable to price options with high level of accuracy, competitive to Black-Scholes formula.

Other relevant works using artificial neural networks conclude in similar results, however this work adds the experimentation of using actual market data. Provided that the model is not static, but it can be retrained using additional data, including mixed artificial and actual data, its accuracy can be increased and it can become more valuable for practitioners, who might select machine learning paradigms for option pricing in various assets and markets. Some limitations in this work include the training sample, the specific network architecture and the limited focus on S&P 500 stock options. As artificial neural networks are data driven, developing appropriate training datasets is critical for their performance, so there is need for diverse training datasets. Also, in this work we did not proceed to feature engineering or advanced sampling, for the training, something that can be examined further in subsequent works. In addition, alternative network architectures can be tested or further experimentation with hyperparameters can be performed and focus can be expanded to additional assets. In future we plan to develop training processes using market data from a variety of sources.

Despite the limitations, it is evident that machine learning models can be used from practitioners as main or alternative methods for option pricing, however it is necessary to build appropriate user friendly software solutions to deploy similar machine learning models on web environment or mobile phone settings. This work, and any future contributions, aim on the development of this fats evolving area.

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