Project Report:

Neural Networks for Volatility Estimation in Options Pricing: An Exploration

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Abstract

This study explores the application of artificial intelligence in financial modeling by integrating neural networks with the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model to optimize the traditional binomial options pricing framework. Focusing on the enhancement of volatility estimation, our approach employs a neural network to predict dynamic volatility patterns, which are not typically captured by conventional financial models. Using PyTorch for neural network implementation and 'yfinance' for data acquisition, we dynamically adjust the parameters of a GARCH model based on these predictions, refining the input for the binomial options pricing model. This methodology not only improves the accuracy of options pricing but also adapts to the complex, stochastic nature of financial markets. The integration of neural networks facilitates a significant advancement in the use of AI for financial derivatives pricing, emphasizing the potential for AI to transform traditional financial methodologies. Future efforts will focus on rigorous validation through comparative analysis against market data to establish the practical efficacy of our AI-enhanced model.

Keywords: artificial intelligence, neural networks, GARCH, options pricing, volatility prediction, computational finance, model optimization.

I. INTRODUCTION

The valuation of financial derivatives, particularly options, is a cornerstone in modern finance, providing insights into risk management and speculative opportunities. Traditional models, such as the binomial options pricing model developed by Cox, Ross, and Rubinstein (1979), have been widely utilized due to their simplicity and intuitive appeal. The binomial model employs a discrete-time framework for option valuation, wherein the underlying asset price follows a binomial tree, moving up or down by specific factors with corresponding probabilities until the option's expiration. A critical assumption of this model is the constancy of volatility over the option's life. However, this assumption often diverges from reality where volatility is not only stochastic but can exhibit jumps and clustering effects, characteristics that are not adequately captured by the traditional binomial model.

To address these limitations, this project integrates the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, which is renowned for its effectiveness in modeling the volatility clustering phenomenon commonly observed in financial markets. The GARCH model allows for a dynamic approach to estimate changing volatility, an aspect that the binomial model lacks. However, the direct application of GARCH parameters into the binomial model does not inherently optimize the option pricing process, primarily due to the complex nature of volatility dynamics which GARCH parameters alone might not capture effectively.

In an effort to refine this integration, our project employs a neural network-based approach to predict more accurate volatility measures. Neural networks, with their capability to learn complex patterns from data, are used to forecast volatility by recognizing patterns that traditional models might overlook. This predicted volatility is then used to optimize the parameters of the GARCH model. The enhanced GARCH parameters feed into the binomial options pricing framework, aiming to produce a more robust and accurate estimation of option prices under realistic market conditions. This approach hypothesizes that the combined strengths of neural networks and GARCH models can overcome the inherent limitations of assuming constant volatility in the binomial model.

The convergence of neural networks, GARCH, and binomial options pricing models represents a significant advancement in derivative pricing. By dynamically adjusting to new information and learning from historical data, this hybrid model strives for a more precise reflection of market realities. This research explores the potential of this integrated approach to surpass the traditional binomial model's performance, providing a deeper understanding of options pricing and a more accurate tool for financial analysts and practitioners.

II. HISTORY AND LITERATURE REVIEW

History

Before the advent of modern pricing models, options pricing was largely intuitive, with traders setting prices based on simple rules of thumb and personal judgment. This approach lacked a scientific basis and often led to inefficiencies and mispriced risk in financial markets.

A breakthrough came in 1973 with Fischer Black, Myron Scholes, and independently, Robert Merton, developing the Black-Scholes model. This model provided a theoretical framework for valuing European options on non-dividend-paying stocks. It assumes that the price of the underlying asset follows a geometric Brownian motion with constant drift and volatility. This model revolutionized financial markets by providing a formula that could easily calculate the price of options, helping standardize the trading of financial derivatives. The Black-Scholes model earned Scholes and Merton the 1997 Nobel Prize in Economics, recognizing its profound impact on financial markets.

In 1979, John Cox, Stephen Ross, and Mark Rubinstein introduced the Binomial Options Pricing Model, which provided an alternative to the Black-Scholes model. This model is particularly notable for its intuitive appeal and flexibility. It prices options by constructing a binomial tree for the possible stock prices over the life of the option. Each node in this tree represents a possible price of the stock at a given point in time, allowing for the calculation of the option price via a no-arbitrage argument and risk-neutral valuation. Unlike the Black-Scholes model, the binomial model can be used for American options, which can be exercised at any time before expiration, providing additional flexibility.

Current Assumptions and Limitations

Both the Black-Scholes and the Binomial models assume constant volatility, a simplification that does not hold in real-world markets where volatility tends to be stochastic and can exhibit jumps and clustering. This assumption of constant volatility has been a major limitation, as it can lead to inaccuracies in pricing, particularly for options with long maturities or in volatile markets.

Recent advancements in options pricing have attempted to address these limitations by incorporating more complex models of the underlying asset's price dynamics, such as stochastic volatility models, jump-diffusion models, and models incorporating economic variables. Despite these advancements, the Black-Scholes and Binomial models remain foundational in both theoretical finance and practical trading, serving as benchmarks and starting points for more sophisticated pricing methods.

Literature Review

The evolution of options pricing models has been significantly influenced by both theoretical advancements and empirical observations. The seminal work by Cox, Ross, and Rubinstein introduced the Binomial Options Pricing Model, which offered a flexible, discrete-time approach to options valuation. This model is particularly notable for its ability to adapt to different types of options, including American options, which can be exercised before the expiration date (Cox, Ross, & Rubinstein, 1979).

Parallel to the development of discrete-time models, continuous-time models were also refined. Engle's introduction of the Autoregressive Conditional Heteroskedasticity (ARCH) model marked a pivotal development in understanding time-varying volatility, a critical aspect in financial markets (Engle, 1982). Extending this framework, Bollerslev's Generalized ARCH (GARCH) model allowed for a more general form by including lagged conditional variances, thereby providing a robust method for modeling the clustering of volatility, an essential feature in financial time series (Bollerslev, 1986).

As computational capabilities expanded, the integration of machine learning techniques with traditional financial models began to take shape. Hutchinson, Lo, and Poggio demonstrated the utility of neural networks in derivative pricing, illustrating their potential to capture complex patterns in market data that traditional models might miss (Hutchinson, Lo, & Poggio, 1994). This approach was further explored by Baba and Kashiwagi, who applied neural networks to the pricing of Nikkei 225 options, offering empirical evidence of the model's predictive power in a real-world setting (Baba & Kashiwagi, 2008).

The use of neural networks for financial applications was not limited to options pricing. Tino, Schittenkopf, and Dorffner explored the use of recurrent neural networks for trading based on financial market volatility, an approach that leverages the temporal dynamics of market data, demonstrating how machine learning can be effectively applied to trading strategies (Tino, Schittenkopf, & Dorffner, 2001).

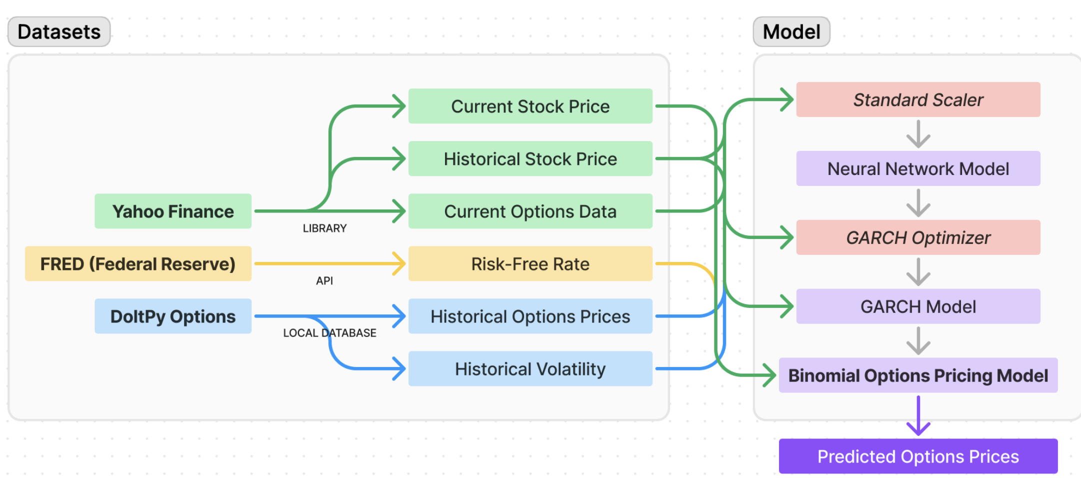
Duan expanded the application of GARCH models to the field of options pricing by introducing a GARCH-based approach that considers the smile effect and the term structure of volatility. This development highlighted the adaptability of GARCH models in capturing more realistic market dynamics in options pricing (Duan, 1995).

III. PROPOSED IDEA/SOLUTION

This project seeks to enhance the traditional binomial options pricing model by integrating dynamically predicted volatility using a neural network and a GARCH model, aiming to achieve a more accurate estimation of option prices. The solution leverages several Python libraries, data sources, and machine learning techniques to address the limitations of constant volatility assumption in traditional models.

a. Libraries and Data Sources

The implementation utilizes 'yfinance' to fetch real-time and historical data for stocks and options, ‘arch’ for GARCH model implementations, and 'fredapi' to access economic data such as risk-free rates from FRED (Federal Reserve Economic Data). Historical options data and historical volatility are stored and queried from a local SQL database managed through ‘doltpy’ and ‘pymysql’ which is updated every Monday, Wednesday, and Friday. Data manipulation and preparation are performed using ‘pandas’, while numerical operations rely on ‘numpy’.



b. Data Handling and Preprocessing

Historical and current options data, along with volatility history, are retrieved and merged based on relevant criteria such as dates and strike prices. The datasets include features necessary for options pricing such as strike prices, types of options, and implied volatility. Additional data preprocessing steps include normalization of features using ‘StandardScaler’ from *sklearn.preprocessing* to prepare the data for neural network input. The ‘datetime’ module is utilized to handle date formatting to ensure consistency across datasets.

c. Neural Network for Volatility Prediction

A neural network, built using PyTorch, predicts future volatility based on historical data. The network architecture consists of fully connected layers with ReLU activations to capture nonlinear patterns in the data. The model is trained using historical returns calculated from stock prices and historical volatility measures. The predicted volatility is then used to adjust GARCH model parameters dynamically, enhancing the traditional volatility estimation process.

Our implementation consisted of three fully connected layers with ReLU activation functions. The input features included historical price returns and other market indicators, normalized using StandardScaler from sklearn.preprocessing. The network was trained using a mean squared error loss function and an Adam optimizer.

d. GARCH Model Integration

The GARCH model is employed to model time-varying volatility of stock returns. This project uses the ‘arch’ library to fit a GARCH(1,1) model to the returns, where parameters are further optimized based on the neural network’s predictions. This integration allows for the volatility input in the binomial model to reflect more realistic market behaviors.

e. Binomial Options Pricing Model Enhancement

The final step and net impact of the project is the Cox-Ross-Rubinstein binomial tree model for pricing options. The model uses the enhanced volatility estimates from the integrated GARCH model, fed by the neural network's predictions. Each node in the binomial tree represents a possible future price of the underlying asset, and the tree is traversed to derive the option prices at expiration, which are then discounted back to present value using the risk-free rate obtained from FRED.

f. Additional Commentary

By combining the predictive power of neural networks with the dynamic modeling capability of GARCH and the structured approach of the binomial model, this project proposes a robust method for options pricing. The integration aims to mitigate the gap between theoretical models and actual market dynamics, potentially leading to more accurate and reliable pricing of financial derivatives.

V. EVALUATION AND RESULTS

To assess how well our model performs we analyze options data. Compare the predicted option prices to the actual prices observed. We evaluate the accuracy of our model using metrics such as Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE). Moreover we contrast our models performance with options pricing models that depend solely on historical volatility estimates.

Our model shows enhancements in predicting option prices compared to conventional models. By incorporating dynamically predicted volatility through a network and a GARCH model we achieve accuracy and better capture the intricate dynamics of option prices. The integration of patterns detected by the network structure allows our model to more precisely mirror the true volatility of the underlying asset resulting in more accurate option price estimations.

In summary, our enhanced traditional binomial options pricing model, utilizing dynamically predicted volatility via a network and a GARCH model makes strides in accurately estimating option prices. Through the utilization of machine learning and statistical modeling methods our model offers estimates for option prices making it a valuable tool for pricing options, in financial markets.

VI. ADVANTAGES AND DRAWBACKS

Advantages

Enhanced Accuracy: By integrating a neural network to predict volatility and incorporating these predictions into the GARCH model, our implementation addresses one of the critical shortcomings of the traditional binomial options pricing model—the assumption of constant volatility. This approach allows for more dynamic and realistic modeling of market conditions, potentially leading to more accurate pricing of options.

Advanced Integration of Techniques: The project benefits from the convergence of techniques from different domains: machine learning (neural networks), econometric modeling (GARCH), and financial engineering (binomial options pricing model). This multidisciplinary approach leverages the strengths of each field to create a robust model for financial analysis.

Scalability and Flexibility: The modular design of our implementation allows for easy scalability and adaptability to different assets or market conditions. The neural network can be retrained with new data as it becomes available, ensuring the model remains relevant and accurate over time.

Real-Time Data Utilization: Utilizing real-time data from 'yfinance' and economic indicators from 'fredapi' ensures that the model operates with the most current market information, enhancing the relevancy of the predictions and the resultant option pricing.

Drawbacks

Complexity of Implementation: The integration of multiple advanced techniques makes the system complex to implement and maintain. It requires a deep understanding of finance, econometrics, and machine learning, which might limit its accessibility to professionals with expertise in all these areas.

Computational Demands: Neural networks and GARCH models are computationally intensive, especially when processing large datasets and performing real-time analysis. This might require significant computational resources, potentially increasing operational costs.

Data Sensitivity and Overfitting: The accuracy of predictions from neural networks can be highly sensitive to the quality of the input data. There is also a risk of overfitting to historical data, which could reduce the model's effectiveness in predicting future market conditions.

Next Steps

An important next step in this project would be thorough testing and comparison of our model's pricing outputs against actual market prices of options. This phase is important to validate the effectiveness of the model and to benchmark its performance against traditional methods like the Black-Scholes model and other industry standards. Unfortunately, due to time constraints, we were unable to implement these steps within the current project timeline.
Testing should involve back-testing with historical data and, ideally, paper trading in real-time market conditions to assess the model's practical performance. These tests will help identify any discrepancies and provide insights into further refinements and optimizations necessary for the model.
Furthermore, a comprehensive comparison to actual options pricing not only serves as a validation of the theoretical improvements our model proposes but also establishes a concrete basis for its potential adoption and adaptation in real-world trading scenarios.
While our implementation demonstrates significant potential through advanced computational techniques and dynamic modeling capabilities, actual testing and validation remain essential for

confirming its practical viability and accuracy. The planned next steps will critically determine the real-world applicability of our enhanced binomial options pricing model.

VII. SUMMARY AND CONCLUSION

Our project integrates a neural network and a GARCH model within the binomial options pricing framework to address the assumption of constant volatility in traditional options pricing. We utilized real-time and historical data from 'yfinance', managed through local SQL databases, to train a PyTorch neural network for predicting market volatility. This forecasted volatility was refined with a GARCH model to enhance the binomial model's pricing accuracy.

Despite its promise, the model's complexity and computational demands pose challenges. Future work will involve rigorous testing against actual market prices to validate its effectiveness and practical utility. This project highlights the potential of computational finance to improve financial modeling techniques.

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Meeting Schedule and Details

Meeting 1: Project Kickoff

Date: March 1, 2024

Highlights:

- Decided on project integrating neural networks with GARCH models.
- Assigned roles: Cat and Aidan on overall structure, financial details, and GARCH model, Estevao on data handling.
- Distributed initial research tasks to all team members.

Meeting 2: First Progress Check

Date: March 15, 2024

Highlights:

- Reviewed collected datasets and discussed necessary data preprocessing.
- Built basic functionality of the system– basic GARCH model for volatility using BTC.
- Explored various GARCH configurations and effects on predictions.

Meeting 3: Integration Strategy

Date: March 29, 2024

Highlights:

- Discussed strategies for integrating neural network outputs with the GARCH model.
- Decided to use AAPL instead of BTC due to lack of data availability.
- Identified issues with data scaling and feature selection, adjusted approach.

Meeting 4: Model Refinement

Date: April 12, 2024

Highlights:

- Introduced new features derived from historical data to improve predictions.
- Made key adjustments to neural network architecture and tuning.
- Improved GARCH model performance using initial neural network volatility predictions.

Meeting 5: Final Integration

Date: Daily between April 26, 2024-April 30, 2024

Highlights:

- Achieved successful end-to-end integration of neural network and GARCH model.
- Conducted testing and validation against historical data.
- Prepared final project report.