MODERN MATHEMATICAL METHODS, MODELS AND INFORMATION TECHNOLOGIES IN THE ECONOMY

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FORECASTING FINANCIAL VOLATILITY USING DEEP LEARNING APPROACH

ПРОГНОЗУВАННЯ ФІНАНСОВОЇ ВОЛАТИЛЬНОСТІ ЗА ДОПОМОГОЮ МЕТОДУ ГЛИБОКОГО НАВЧАННЯ

Financial volatility measures the intensity of changes in the currency and market as a whole. The importance of volatility is difficult to overestimate – it helps manage uncertainty. This is crucial for investors, so it is no surprise that volatility is an input to various financial models. It is used as a proxy of risk among the most important variables in many fields, including risk management, asset pricing, and portfolio optimization [1]. Conventional volatility models, like Autoregressive Conditional Heteroscedasticity (ARCH) and Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models can cause failures like volatility clustering or information asymmetry [2]. For example, an attempt to use GARCH modeling or its variant for considering the market as a whole can cause volatility spillovers. Even though different models address these issues, recent fluctuations in financial markets forced us to reconsider approaches to measure volatility. It is also important to note the rapid advancement in Machine Learning (ML). One of the main advantages of ML compared to classical volatility models is the ability to explore underlying patterns from a large amount of financial time-series data automatically [3]. Machine Learning is a subset of artificial intelligence concerned with creating algorithms that can modify themselves without human intervention to produce the desired result. Machine Learning Algorithm requires structured data for proper operation [4]. Each ML project has a set of specific factors that affect the size of the AI training datasets needed for successful modeling.

Modeling volatility amounts to modeling uncertainty, so it is necessary to differentiate between types of volatility, and calculating each requires a different approach. Implied volatility is calculated based on the current value of the financial instrument, assuming that the market value of the financial instrument reflects the expected risks – implied volatility is about the assumption about future volatility. Unlike the Implied volatility, Realized volatility measures what happened in the past.

Deep learning algorithms can be viewed as a complex and mathematically sophisticated evolution of machine learning algorithms [5]. The learning process is called deep because the structure of artificial neural networks comprises several input, output, and hidden layers. Each layer contains units that transform input data into information that the next layer can use for a particular prediction task. Because of this structure, the computer can learn with its own data processing, similar to how a human would conclude.

The forecasting process has several steps. For the prediction, we will take data from one of the most followed equity indices tracking the stock performance of 500 large companies listed on stock exchanges in the United States. Firstly, we will configure the network structure by deciding the number of hidden layers and the number of neurons. We will take two hidden layers with 256 and 128 neurons. The next step includes compiling the model with loss and optimizer. Optimization is an important process that optimizes the input weights by comparing the prediction and the loss function. The loss function is used to find errors or deviations in the learning process. After that, we will set how many times the learning algorithm will work through the entire training dataset and the number of samples to work through before updating the internal model parameters. The next step consists of model fitting. This measure is very important. It generalizes data to that on which it was trained. The cause of poor performance in machine learning models is overfitting or underfitting the data. A well-balanced model produces more accurate outcomes. After completing all the steps, we can predict the financial volatility based on the weights obtained from the training phase and finally calculate the RMSE score.

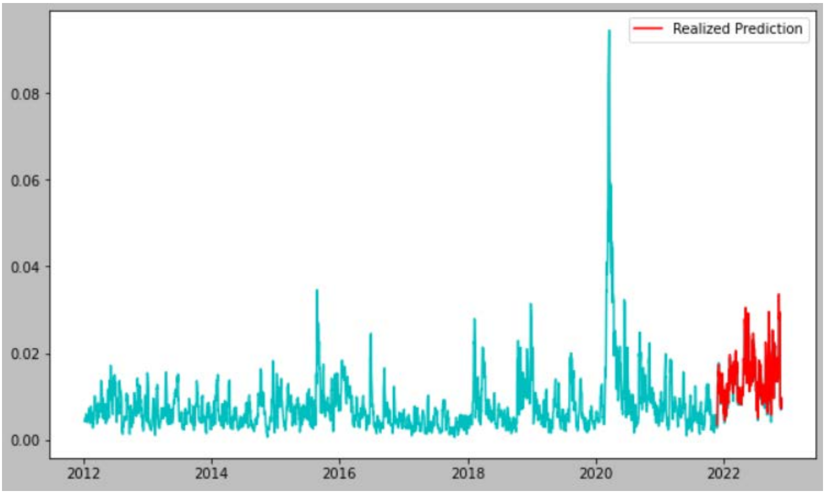

Fig. 1. The result of volatility prediction based on Deep Learning

As we can see from the picture (Fig. 1), the volatility of returns is well-fitted by Deep learning approach. This shows that increasing the complexity of the model does not necessarily imply high predictive performance. The key is to find a sweet spot between the complexity and predictive performance. For example, let us investigate the widely used ARCH model (Fig. 2). The ARCH model is unable to capture the influence of historical innovations and much less accurate in her predictions.

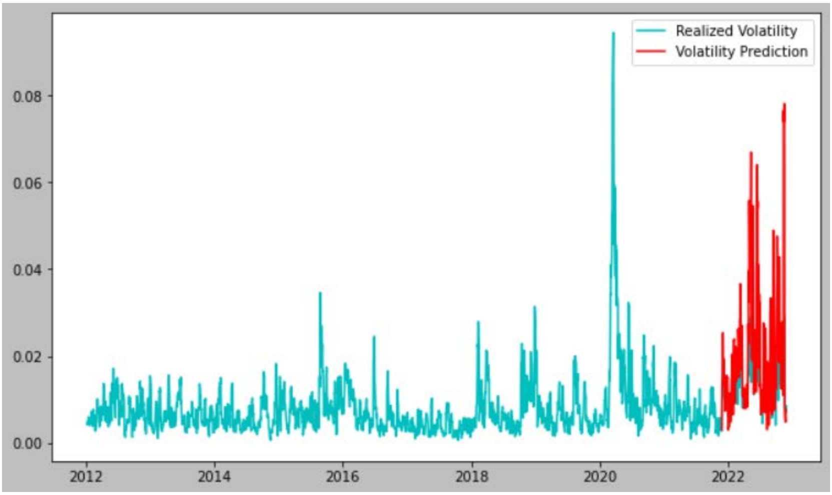

Fig. 2. Forecasting Financial Volatility Using ARCH model

The results showed that Machine Learning models outperformed the traditional ARCH models with lower forecasting errors in most cases. Of course, perfection is extremely difficult to achieve. Because there are always factors that are difficult to take into account. However, the development of technology, in particular Neural Networks will allow us to improve the models.

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