The system of predictive analysis of Bank investments using technologies of supercomputer simulation

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Abstract. The article discusses an approach to building a system for generating a bank investment prediction with the technology of parallel computing. We develop a predictive model of the price of securities for the banking business on the stock market. For predictive analysis of investments, the choice of a mathematical model was justified using the Monte Carlo method. Computer simulation was carried out to form a forecast of securities prices based on historical data on securities of Goldman Sachs. Estimates of the execution time of the forecasting algorithm by the parallel programming method are obtained. The conclusion is made about the applicability of the proposed model when using the method of algorithmic trading in the stock market. The technical requirements for the development of a predictive analytics system for the Bank's investment portfolio are formulated.

1. Introduction

The implementation of technological products to optimize the activities of the financial sector, in particular the banking sector, is currently happening very quickly. We can give various examples of banks with a developed retail information infrastructure: for example, Sberbank Online, Tinkoff Bank, VTB, etc. All technological changes in banks occur due to high competition in the financial technology sector (Fintech). Banks are interested in increasing risk-free profit (operating and commission income), as well as in reducing risk income (interest income). This circumstance explains the large volume of investments in remote banking services. And these changes in banks were made to reduce banking costs (staff reduction, increase in operational efficiency, decrease in the number of errors due to the human factor).

Improving the efficiency of banks with the help of information technology concerns not only the retail business of banks, but also the corporate and investment business. Currently, a large number of methods and tools are used to automate investment banking services [1, 2]. However, there are a number of problems in the implementation of the deals in the stock market that require new approaches. These tasks are associated with the implementation of the mathematical models and methods and new information technologies that make it possible to make decisions on the banking deals quickly and more reasonably.

This paper discusses the development and implementation of information technologies in the field of trade / management of bank assets. Several examples of the financial technologies in this area: trading
robots, the predictive analysis methods for managing credit activities, for solving problems of managing bank assets, etc. [3, 4, 5, 6]. The high-performance computing systems, as well as supercomputer simulation technologies, are used to analyze exchange information and in general to manage the bank's trading activities. Reducing decision-making time as well as improving the accuracy and correctness of decisions in securities management is an extremely urgent task in the financial sector. The result of this research is an algorithm and software for a predictive analysis system for bank investments.

The following terminals were considered as sources of financial information on stock markets: Bloomberg Terminal, Thomas Reuters Eikon, MetaStock, SMARTX and QUIK. Bloomberg Terminal was chosen as the data source for the computational experiment. The data was received for the period 04/05/1999 - 16/05/2020.

2. Mathematical Model and Simulation

We compare two approaches to forecasting bank investments: neural networks to forecast time series and the Monte Carlo method [7]. The adequacy of these forecasting methods as well as the approach used to assess the effectiveness of bank investments will be verified by the computer simulation [8]. After computer experiments we measure the speed and computational complexity of the proposed methods. We show the advantages of implementing parallel programming methods for a predictive analysis system.

2.1. Prediction algorithm based on Neural network

We will use recurrent neural networks (RNN) to forecast the value of a security.

Prediction algorithm:
Step 1. Downloading historical data on Goldman Sachs (GS) securities for the period: 04/05/1999 - 05/16/2020. The dataset contains the following stock price information: High, Low, Volume, Open, Close and Adj Close.
Due to the fact that the data is provided daily, we will build a forecast of the behavior of the securities for the next 90 days. That is, until the next payment of dividends by the Bank since the amount of the payment of dividends affects the future value of the security. There are many factors that can affect the payment of dividends. There are 5294 values in our dataset in total, the first 2647 will be the training dataset and the rest will be the validation dataset.

Step 2. We will train the model using only one feature (Adj Close) for forecasting. Time series for Adj Close is shown at Fig. 1. The y-axis is Adj Close data, the x-axis is the time interval.

![Adj Close historical data of GS Security](image)

Fig. 1 Adj Close historical data of GS Security

Step 3. Before training a recurrent neural network you need to normalize the data. Let's construct a prediction data as the average of the last 90 normalized values. Let's call the Baseline Prediction for
prediction the next value as the average of the last observations we specified. Baseline Prediction is shown at Fig. 2

![Baseline Prediction Example](image)

**Fig. 2 Baseline Prediction**

Step 4. We are using a recurrent neural network with Long Short-Term Memory (LSTM) architecture. Such a neural network gradually processes time series, supporting and summarizing the information contained. One of the advantages of this model is that it remembers information for a long time and because of this there is practically no need to train them.

LSTM has the following architecture [9]:

\[ f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \]  

\[ i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \]  

\[ \tilde{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \]  

\[ C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \]  

\[ o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \]  

\[ h_t = o_t \cdot \tanh(C_t) \]

Where \( x_t \) - input, \( h_t \) - output, \( \tilde{C}_t, C_t \) - state vectors, \( W_f, W_i, W_c, W_o, b_f, b_i, b_c, b_o \) - are matrices of parameters, \( \tanh \) and \( \sigma \) - neural network layers, \( i_t, f_t, o_t \) - gates.

The formation of the target vector (Y) for operation for two time series (one-dimensional and multidimensional) is the same. The target vector is based on the attribute - Adj Close. The difference is only in the formed set of features that are given to the input of the model: in the case of a one-dimensional time series for predicting the future value, the input vector (X) consists only of the feature: Adj Close; and for the second row, we will take volatility indicators such as High, Low and Volume.

Now we compare the forecast result of the simple LSTM model with the prediction based on the baseline (Fig. 3). As we can see the prediction based on neural networks is more accurate (blue is history, red cross is the correct future value, green circle is the predicted value of the model). The y-axis is normalized data, the x-axis is the time interval.
Further, using this model, we will predict the sequence of values in the future. The time period for generating the forecast is the next 90 days. This task is more difficult, and the model consists of two LSTM layers, the output layer contains 90 neurons. Figure 4 shows the result of applying the constructed neural network. The forecast is red, and the blue is real historical data (as it actually was). On the y-axis - the normalized data (also three features - High, Low, Volume), on the x-axis - the time step (in our case - 5 stock exchange working days).

2.2. Prediction algorithm based on Monte Carlo method
The Monte Carlo (MC) mathematical model is also used to assess the effectiveness of bank investments [10]. Monte Carlo modeling allows you to take into account different levels of risk in different scenarios, and therefore can be applied to many types of investments [11]. The Monte Carlo method for solving the problem of forming a prediction of the value of securities has a number of limitations: as for example - the prediction model built using MC does not take into account the impact of the current financial crisis, which may significantly affect the results obtained. But Monte Carlo also has a number of advantages in solving the problem of forming a forecast of the value of securities in the financial market:
1) provides a large number of possible scenarios for use in quantitative financial analysis and for final decision making;
2) The method shows not only what kind of income / profitability we can get, but also it can be used to determine the probability of each scenario being executed.
3) Monte Carlo simulation of the Goldman Sachs share price will allow us to display the data as a dashboard for bank employees.
4) Also, the method allows you to analyze the sensitivity (assessment of the impact of input parameters on the final price) and the value of the security quote in various scenarios. You can analyze events that may not happen in real life.

We apply the computer simulation with the following formula (7) Monte-Carlo to form the predicted value of the security [12]. Applying 10 iterations, we get 10 possible forecasts of the expected price of GS securities, the time interval is 90 days:

\[ S(T) = S(0) \exp \left[ \left( \mu - \frac{\sigma^2}{2} \right) T + \sigma \epsilon \sqrt{T} \right] \]  (7)

Neural networks also allow forecasting, but MC has a wider range of applications and the ability to look at various scenarios with uncertainties. Since stock quotes change on the stock exchange within a microsecond, in order to have advantages in the stock market, we need to increase the speed of information processing. MC simulation was carried out with and without parallel computations. The simulation result showed the effectiveness of using the parallel programming to speed up the forecast of the expected price of GS securities.

2.3. Computer simulation

To carry out a computer experiment with the prediction algorithm under the MC method, a program in Python was developed. Received execution time of the implementation of computer modeling of the Monte Carlo without parallelization of the algorithm (10 iterations, 90 predicted values without using parallelization):

```python
end_time = datetime.now()
print('Duration: {}' .format(end_time - start_time))
```

```
Duration: 0:00:04.230451
```

As tools of parallel programming we used python-multiprocessing package. The resulting time was:

```python
start_time = time.time()
p = parallel_monte_carlo(10)
print('MP--- %s seconds ---' % (time.time() - start_time))
```

```
MP--- 0.09462165832519531 seconds ---
```
3. Conclusion and Future work
Several models for predictive analysis were considered and implemented: the neural networks for forecasting a time series and the Monte Carlo method. It is preferred to use parallelization for supercomputer in order to increase the forecast speed for making a decision on investing in securities. Since the data on the exchange changes within a microseconds, such an increase will bring the Bank additional profitability from trading operations.

In the future, we will work on the implementation of the proposed mathematical methods for the banking information system. We will use different methods and choose the appropriate one for future parallelization. As a result of computer simulation we plan to choose the most efficient machine learning algorithm. First of all we will parallelize one derivative, after that; we will try several derivatives (portfolio).

4. REFERENCES
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