Research on Stock Price Prediction Based on Hidden Markov Model and Elastic Feedback Algorithm

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Abstract: In the current financial market, predicting stock prices accurately is a major challenge. To address this, we propose a new hybrid algorithm. The stock market is known for its chaotic nature, and the hidden Markov model is a good fit for its current characteristics. However, due to the vast amount of market data and its randomness, a single Markov method isn't sufficient for accurate price forecasting. In our approach, we enhance the forecasting method with an elastic feedback algorithm. We first classify forecasts into three states: rising, falling, and staying relatively stable, using the hidden Markov model. Then, we backtest these predictions against the actual prices from the last 20 days. By incorporating the elastic feedback algorithm, we significantly improve forecasting accuracy from 60%, 65%, and 55% to 75%, 75%, 60%.

Keywords: Stocks Forecast; Hidden Markov Model; Elastic Feedback Algorithm

1 Introduction

1.1 Background

In recent years, stock markets have become an integral component of the global economy. Fluctuations in these markets exert significant influence on our personal and corporate financial well-being, as well as the overall economic health of a nation[1]. Due to the potential for substantial profits, the stock market consistently remains one of the most popular investment avenues. However, it's essential to recognize that higher returns are often accompanied by elevated risks[2]. Consequently, the development of more accurate stock market prediction models holds paramount significance and is a topic of profound interest to researchers[3].

1.2 Stock Price Forecasting Research Status

Scholars enhance HMM by integrating neural networks, considering Lyapunov exponent, and employing the K-means method to boost forecasting precision. Hassan and Nath[1] compared artificial neural networks and HMM in stock price prediction and found their average absolute percentage error (MAPE) values to be very similar[4]. However, traditional back propagation algorithm struggles with large neural networks, suffering from slow training and susceptibility to local minima[7]. In contrast, the elastic feedback algorithm, a derivative of the classic backpropagation approach, overcomes these issues by not relying on training error for weight adjustments[5]. In this paper, we introduce an innovative algorithm that combines the hidden Markov optimization model with the elastic feedback's inversion judgment algorithm. We tested

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this algorithm using three years of data from three different stocks, achieving impressive results in prediction accuracy and stock forecasting performance.

2 Model construction

Fig 1 is the flow chart of the entire model, the mixture of hidden markov model and elastic feedback algorithm. First we use Hidden Markov Model to get the hidden state sequence and then pour them into the neural network to do the particular price state classification.

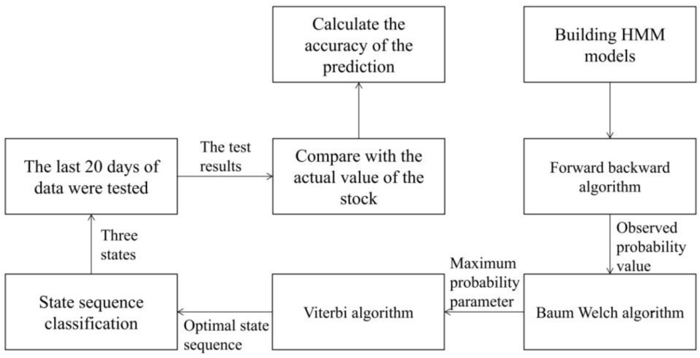


Fig 1 Stock rise and fall forecast flow chart

2.1 Establishment of Hidden Markov Model

Hidden Markov Model, is a probabilistic model for time series data. It can be represented as a concealed Markov chain. Typically, an HMM comprises three key components: the initial probability distribution, the state transition probability distribution, and the observation probability distribution[6] .

Three steps of HMM are needed: (a)given an observation sequence, calculate the probability of the observation sequence of the model, using forward backward algorithm(b)If the observation sequence is given in the model, find the potential state sequence with the maximum probability value with Baum-Welch algorithm (c)The space of observation sequence and probability model is given, maximize the whole probability value and optimize parameters, with Viterbi algorithm.

At time t, the probability of the state q is: $\alpha_t(t) = P(o_1, o_2, \ldots, o_t, t_t = q_i|\lambda)$. According to the recursive forward probability a, the probability value P of the observation sequence is obtained. The initialization, recursion and ternimation are as follows in Equation 1, Equation 2 and Equation 3:

$$a_1(t) = \alpha_1 b_1(o_1), 1 \leq i \leq N \tag{1}$$

$$\alpha_{t+1}(i) = \left[\sum_{j=1}^{N} \alpha_t\,(j) a_{ji}\right] b_i(o_{t+1}), 1 \leq i \leq N \tag{2}$$

$$P(O|\lambda) = \Sigma_{i=1}^{N} \alpha_T(t) \tag{3}$$

The definition probability value of backward algorithm is the observation sequence from time t+1 to T, and the probability of state q at this time is: $\beta_t(t) = P(o_{t+1}, o_{t+2}, \ldots, o_T, t_t = q_i|\lambda)$. According to the recursive backward probability a, the probability value P of the observation sequence is obtained. The initialization, recursion and ternimation are as follows in Equation 4, Equation 5 and Equation 6:

$$\beta_T(t) = 1, \quad 1 \le t \le N \tag{4}$$

$$\beta_t(t) = \Sigma_{j=1}^{N} a_{ij} b_j(o_{t+1})\beta_{t+1}(j), \quad 1 \le t \le N \tag{5}$$

$$P(O|\lambda) = \sum_{i=1}^{N} \pi_i\, b_i(o_1)\beta_1(i) \tag{6}$$

Combining forward and backward probability formulas, P can be unified as:

$$P(O|\lambda) = \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_t\,(i) a_{ij} b_j(o_{t+1})\beta_{t+1}(j), \quad t = 1,2, \ldots, T-1 \tag{7}$$

$\xi_t(i,j)$ in Equation 8 shows the potential state sequence with the maximum probability value

$$\xi_t(i,j) = \frac{\alpha_t(\theta) a_{ij} b_j(o_{t+1})\beta_{t+1}(j)}{\Sigma_{i=1}^{N} \Sigma_{j=1}^{N} a_t(i) a_{ij} b_j(o_{t+2})\beta_{t+2}(j)} \tag{8}$$

Define the maximum probability of all single paths at time t and the path with the maximum probability of all single paths, the t-1th node is expressed in Equation 9 and Equation 10. The ternimation is as follows in Equation 11.

$$\delta_t(t) = max_{1 \le \mathrm{j} \le \mathrm{N}}\left[\delta_{t-1}(j) a_{ji}\right] b_i(o_t), 1 \le \mathrm{i} \le \mathrm{N} \tag{9}$$

$$\psi_{\mathrm{t}}(t) = argmax_{1 \le \mathrm{j} \le \mathrm{N}}\left[\delta_{t-1}(j) a_{ji}\ \right], 1 \le \mathrm{i} \le \mathrm{N} \tag{10}$$

$$P^* = max_{1 \le i \le N}\delta_{\mathrm{T}}(i),\ i_T^* = argmax_{1 \le i \le N}[\delta_{\mathrm{T}}(i)] \tag{11}$$

The optimal path is obtained by way of path backtracking, and the state sequence at this time is as follows:

$$t_t^* = \psi_{t+1}(t_{t+1}^*),\ I^* = (t_1^*, t_2^*, \ldots, t_\tau^*) \tag{12}$$

2.2 Feature selection

Regarding feature selection, we evaluate features' impact on the model by assessing their contribution levels. Initially, we set a 20-day warehouse adjustment period and use a 20-day window in the Hidden Markov Model (HMM) to predict future price movements. After each trading day, we predict if the stock price will rise or fall in the next 20 trading days. We focus on three dataset stocks and select six observed values: opening price, highest price, lowest price, closing price, trading volume, and turnover rate. Our testing period spans from January 4, 2016, to October 30, 2020. We fine-tune model parameters with a grid search algorithm, resulting in these parameter combinations for testing and evaluation: number of hidden states: N=3; length of observation sequences: Q=10; number of distribution models in the Gaussian mixture model: M=2.

2.3 Data state classification processing with elastic feedback algorithm

The elastic algorithm is an improved gradient method based on classical backpropagation, designed to overcome issues like slow training and susceptibility to local minima [7][8]. The main process is illustrated in Fig 1. Fig 2 depicts the distribution of price fluctuations for the three stocks. The price rise and fall distribution closely resembles a Gaussian distribution, which is used to classify specific price increases and decreases based on statistical findings.

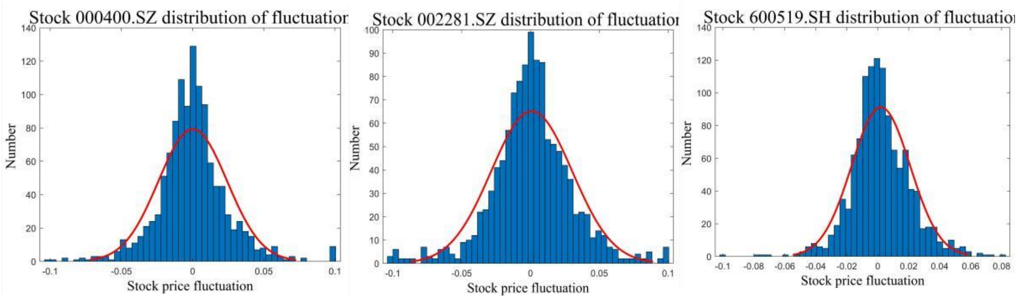


Fig 2 Test of normality of three stocks

Before the data set enters the model training, it is necessary to normalize the data to reduce the interference caused by the characteristic dimension difference.We divide the trend of stock's rise and fall into three categories based on the limit of 1%, and get the histogram shown in Fig 3. In the histogram of the three stock ups and downs, the proportion of each distribution interval is basically balanced, and the stock samples belonging to a small range of ups and downs (-1%~1%) are slightly more than the other two categories. In the multi-classification task, when the samples of each category are evenly distributed, the prediction effect is usually better. Therefore, in this paper, we choose the above-mentioned 3-category forecasting method to forecast stock ups and downs so that we can distinguish small-scale ups and downs, big rises, and significant falls in the forecasting results, which is more practical significance.

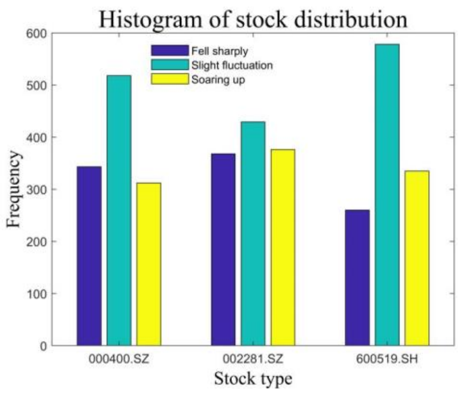


Fig 3 Histogram of 3 categories of three stocks

3 Results

3.1 Combined HMM with elastic feedback algorithm

Due to stock data fluctuations, the Hidden Markov Model primarily predicts the overall trend but lacks high accuracy for daily fluctuations. To improve this, we employ the Elastic Algorithm to enhance the model and consider data from the past 20 days to predict price movements. This modification significantly boosts prediction accuracy, as evidenced by stock 002281.SZ, which saw a 15% increase in accuracy, reaching 75% through combined forecasting. Table 1 and Table 3 reveals that, considering the tendency for stocks to rise after falling, both classification methods exhibit distinct characteristics. The Elastic Feedback Algorithm excels in short-term predictions based on stock periodicity.

Table 1 Three stock hybrid algorithm results[1]

Stock 000400.SZ				Stock 002281.SZ				Stock 600519.SH			
1.40%	1	1	1	-1.84%	1	-1	1	0.36%	1	0	0
-0.95%	1	0	1	-1.84%	1	-1	1	1.58%	1	1	0
1.98%	1	1	0	4.46%	1	1	1	-0.52%	1	0	1
-0.72%	1	0	1	-0.37%	1	0	1	0.98%	1	0	0
5.08%	0	1	0	0.51%	1	0	0	1.65%	1	1	0
4.56%	0	1	0	3.70%	1	1	0	3.22%	1	1	0
-1.39%	0	-1	1	-1.10%	1	-1	1	-0.66%	1	0	1
0.54%	0	0	1	-2.97%	1	-1	1	-0.58%	1	0	1
-1.13%	0	-1	1	-1.43%	1	-1	1	-0.23%	1	0	1
-0.81%	0	0	1	-3.28%	1	-1	1	-0.75%	1	0	1
0.07%	0	0	0	3.15%	1	1	0	-0.76%	1	0	1
0.48%	0	0	1	-3.52%	1	-1	1	2.06%	1	1	0
-3.24%	0	-1	1	-3.25%	1	-1	1	-0.04%	1	0	1
-1.26%	0	-1	0	0.97%	1	0	0	0.53%	1	0	0
-0.85%	0	0	1	-2.41%	1	-1	1	-1.56%	1	-1	1
2.57%	0	1	1	1.71%	1	1	1	-4.22%	1	-1	1
-0.70%	0	0	0	1.18%	1	1	0	-1.10%	1	-1	1
0.63%	0	0	1	-1.75%	2	-1	1	2.45%	1	1	1
1.18%	0	1	1	-0.78%	2	0	1	0.67%	1	0	0
-3.09%	0	-1	1	-1.07%	2	-1	1	-0.36%	1	0	1

According to Figure 4, the Elastic Feedback Algorithm enhances various stock data. Notably, stocks with strong periodicity, such as stock 000400.SZ, experience significant improvements in prediction accuracy due to their volatility. However, for stocks with less evident periodicity, like stock 600519.SH, the algorithm only marginally increases accuracy by 5%. Therefore, relying solely on individual algorithms for stock prediction isn't optimal. Combining the strengths of different algorithms yields better insights into stock trends, as demonstrated in

[1] Note: The first column of Table 1 is the up and down state of stock data, the second column is the state predicted by HMM, the third column is the state predicted by elastic feedback algorithm, and the fourth column is the specific number of days with accurate prediction.

Table 2. A comprehensive prediction approach is particularly effective for stocks with strong periodicity, emphasizing the importance of complementing different prediction models to achieve more accurate forecasts of stock movements.

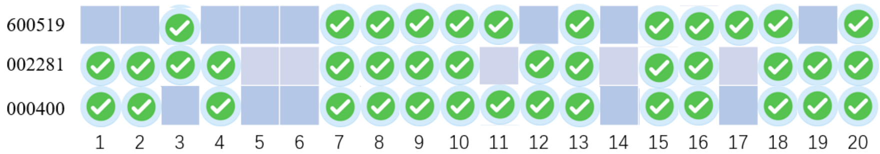


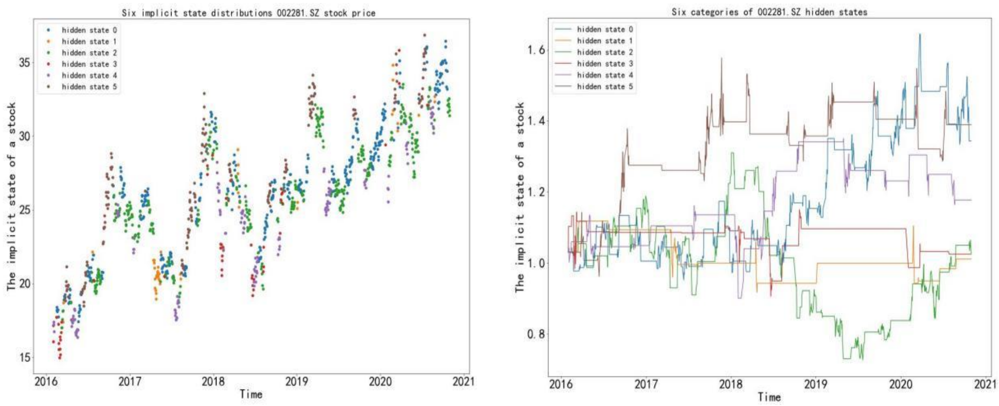
Fig 4 Precise diagram of mixed prediction model

Table 2 Three stocks predictive accuracy

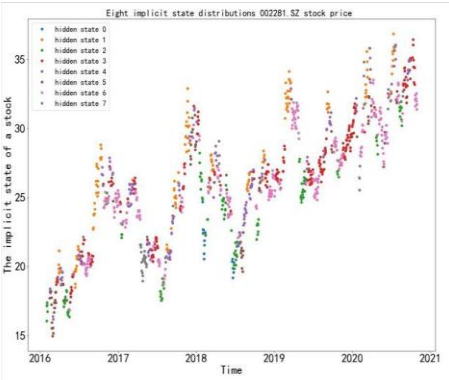
Stock name	Stock code	Accuracy
XJ electric	000400.SZ	75%
Accelink Technology	002281.SZ	75%
Kweichow Moutai	600519.SH	60%

3.2 Analysis of prediction results

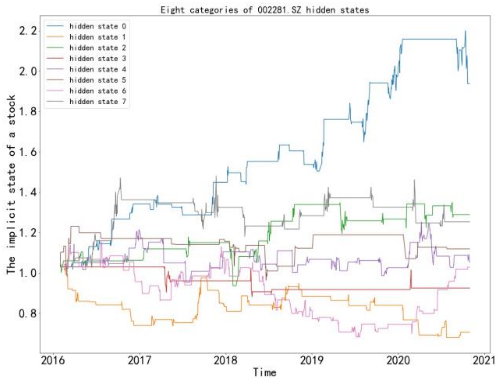
In the second part of the analysis process, we use the grid search algorithm to determine the whole parameters and finally choose the probability parameter combination as follows: ① Number of hidden states: N=3. ② Length of observation sequence: Q=10. ③ Distribution model number of Gaussian mixture model: M=2. Therefore, for stock 002281.SZ, we choose the number of hidden states N=8 to analyze the adaptability and sensitivity of the model under different states. The specific analysis results are shown in Fig 5 and Table 3.



(a) 6 Classification States of Stock 002281.SZ (b) 6 Hidden States of Stock 002281.SZ



(c) 8 Classification States of Stock 002281.SZ



(d) 8 Hidden States of Stock 002281.SZ

Fig 5 Different hidden states for stock 002281.SZ

When various numbers of hidden states are selected, it becomes evident that there is no significant difference in stock prediction accuracy when using HMM. Specifically, when considering 6-state and 8-state classifications, it is observed that increasing the number of hidden states does enhance the model's prediction accuracy to some extent. However, it also adds complexity to the analysis. As a result, we conclude that the choice of different numbers of hidden states has limited impact on the outcomes. The model displays low sensitivity to the number of hidden states, and the obtained results align well with real-world observations.

Table 3 Hidden state result classification

State	Color	Trend
0	Blue	Rose sharply
1	Green	Slight decline
2	Red	Vibrate decline
3	Purple	Slight rise
4	Yellow	Cliff fall
5	Light blue	Fall sharply

4 Conclusion

According to the daily, weekly, and monthly charts of the three stocks in recent five years, the three stocks showed a general upward trend of nonlinear fluctuations. In this paper,a hidden Markov model is established, and different hidden states of stocks are successfully classified by using forward-backward algorithm, Baum-Welch algorithm and Viterbi algorithm. The results show that there is no significant difference in prediction accuracy under different hidden state classifications. When the number of hidden states is 3, the prediction accuracy of the three stocks is 60%, 65%, and 55%, respectively.

In addition, based on the hidden Markov model, the elastic feedback algorithm is used to linearly combine the hidden state prediction of the HMM with the classification state prediction of the elastic feedback algorithm and predict the trend of stocks according to the final results. The results show that the prediction accuracy of the stock price reversal model established in this paper is 75%, 75%, and 60%, respectively, and the prediction accuracy is obviously improved.

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