Research on Stock Price Prediction Based on Autoregressive Model of Maximum Corentropy Criterion

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Abstract: As a barometer of the financial market, the stock market is closely related to national economic development, corporate financing and investors' interests. However, there are many and complex factors affecting stock price volatility, which makes accurate prediction of stock price volatility still a challenging problem. In order to predict the stock price more accurately, the maximum correlation entropy autoregression model is proposed in this paper. Specifically, the maximum entropy criterion is used to replace the minimum mean square error criterion in the autoregressive model to eliminate the influence of singular values. Then a new clustering method is used to cluster the segmented stock price curves, and a regression model is built for each class, which reduces the influence of the order of the regression model on the prediction accuracy. In addition, the open set identification method is adopted in this paper to add boundary constraints to each curve after clustering, which is used to enhance the pertinence of the regression model and effectively improve the prediction accuracy. The experimental results show that the proposed method has high prediction accuracy.

1 INTRODUCTION

As an important part of the national economy, the stock market plays an irreplaceable role in the economic development, and its changing trend is considered as the barometer of the economic market. The development of the stock market is of great significance to the national macro economy, enterprises and individual investors (Zeqiraj 2020). At the national level, the changing trend of the stock market can accurately reflect the development trend of the national economy, which is conducive to the country's macro-market regulation (Zhou 2021). From the perspective of enterprises, the stock market can help enterprises to make strategic adjustment and enhance the liquidity and flexibility of investment (Wu 2021). From the perspective of individuals, accurate prediction of stock prices can improve investment returns and reduce investment risks for individual investors (Chen 2022). Therefore, stock price prediction has very important research significance, and has become a research hotspot of many scholars at home and abroad.

At present, domestic and foreign scholars have studied stock price prediction methods from different angles, and have achieved relatively good results. Generally speaking, the commonly used stock price prediction methods at present mainly include investment analysis method (Li 2022, Nti 2020, Jordan 2018), statistical model (Khoojine 2020, Ji 2021, Wang 2020) and machine learning (Zhang 2021, Zhang 2018, Xiao 2020). Among them, autoregressive (AR) model is regarded as a crucial forecasting method in time series analysis, which is a process of using itself as a regression variable as well as adopting the minimum mean square error criterion

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to estimate the model. Further, AR model and its variant versions have been extensively used in field of economics and finance (Ye 2017, Santosa 2022, Tash 2011). For example, Ye proposed an ARIMA-SVR stock prediction model based on wavelet analysis, which improved the forecasting accuracy but did not overcome the influence of singularities in the time series (Ye 2017). ARIMA model was employed to predict the prices of 45 stocks with different characteristics, and the stock sequence suitable for the model was procured by classification (Santosa 2022). Tash and Modarres applied the AR/GARCH model to Tehran stocks, and the prediction results show ed that their method could improve the prediction accuracy (Tash 2011).

However, the method based on autoregressive model still has two deficiencies, which may lead to prediction bias in the model.

(1) The mean square error criterion used in the autoregressive model will lead to errors in prediction. Specifically, if some data points of random variables are far away from each other in the coordinate system of the same name, the error will expand in the form of square, which makes a huge gap between the two random variables.

(2) The autoregressive model uses the same order to predict different fluctuations, which will lead to prediction errors. Specifically, because of the complexity of the stock price curve, a regression model is used to predict the change of the price curve of all stocks, resulting in low prediction accuracy.

In order to accurately predict the stock price trend, this paper proposes a stock price trend prediction method based on the maximum correlation entropy autoregressive model. Specifically, firstly, the stock price curve is segmented and correlational entropy is used as the similarity measure to cluster the price curve segments. Then, for each class of clustered data, a regression model is constructed using the maximum corentropy criterion as the constraint function, which is used to predict the change trend of the stock price curve. In summary, this paper mainly does the following four aspects :(1) based on the maximum correlationentropy criterion, a new regression prediction model is constructed. Traditional autoregressive models are sensitive to singularities because of the minimum mean square error criterion. In this paper, the maximum corentropy criterion is used as the constraint function, and the Gaussian corentropy is used to limit the infinite expansion of the error, which effectively weakens the influence of the singularity on the curve similarity measurement. (2) Based on the clustering strategy, a well-targeted regression prediction model is constructed for each type of price curve. The prediction accuracy of regression model is greatly affected by model order. Because of the complexity of using the stock price curve, using one regression model to predict the change of the price curve of all stocks leads to low prediction accuracy. Using the clustering strategy, the price curves with similar change trends are grouped into a group, and a regression model is constructed for price prediction, which can effectively improve the accuracy of prediction. (3) Based on correlational entropy, a new similarity measure of price curve is proposed. The existing clustering methods are generally based on Euclidean distance and the clustering results are particularly sensitive to the singularity of the stock price curve. Correlational entropy is used to measure the similarity of any two curves. Essentially, two curves are taken as random variables to measure the similarity based on the difference of their probability distribution, which can better overcome the influence of singularities. (4) Based on the open set identification, the singularity problem in the clustering process is optimized. In this paper, the open set recognition strategy is adopted to add boundary constraints to the clustering results, which makes the clustering results more accurate and can better deal with the problem of singular point classification in the clustering process. In order to visually illustrate the advantages of open set recognition, this paper clustering the data containing singularities. As shown in Figure 1, Figure 1 (b) represents the original data, where sample points ①~④ represent the data to be classified. Figure 1 (a) shows the result obtained by using closed sets, and symbols "⊕" and "○,—" represent different categories. It is obvious that singularities ② and ④ do not fit into any category. If open set identification is adopted, the result is shown in FIG. 1 (c). It can be seen that singularities ② and ④ are outside the boundary constraints and can eliminate this problem.

2 RELATED METHODS

This section mainly introduces the methods related to this paper, including similarity measures and autoregressive models. This paper uses uppercase letters (e.g. X, Y) to represent time series data, lowercase letters with subscripts (e.g. x_i, y_i) to represent individual data, uppercase bold letters (e.g.$\boldsymbol{X}, \boldsymbol{Y}$)to represent matrices, and superscript letter d to represent distances (e.g.d^E, Euclidean distances).

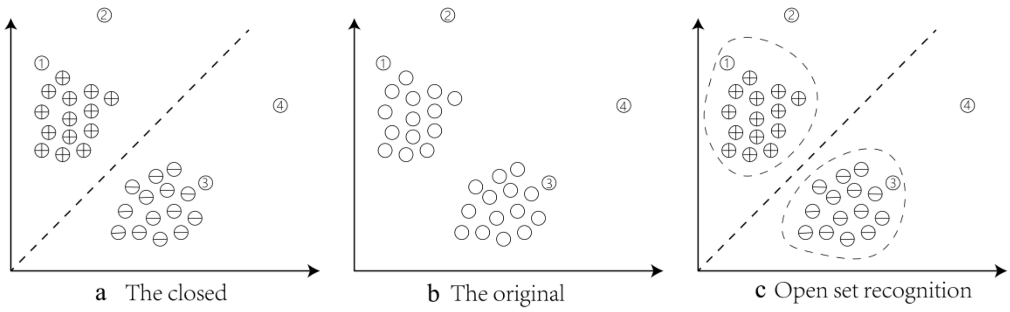


Figure 1: Comparison of classification results.

2.1 Autoregressive Model

For the multidimensional regression model, the N-order regression process of data series $\{X_t\}$ is :

$$X_t = \beta_1 X_{t-1} + \beta_2 X_{t\text{-}2} + \cdots \beta_N X_{t-N} + E_t \quad (1)$$

According to the linear theory, the *p*-dimensional regression model is expressed as:

$$X_t(i) = \beta_1(i) X_{t-1} + \cdots + \beta_N(i) X_{t-N} + E_t(i) \quad (2)$$

Among them $i = 1, 2, \cdots, P$

The least square algorithm is used to minimize the sum of squares of errors, so that $\beta = [\beta_1, \beta_2, \ldots \beta_N]$ and $Y_t = [X_{t-1}, X_{t-2}, \cdots, X_{t-\mathrm{N}}]$,get the target function:

$$\min_{\beta} (X_t - \beta Y_t)^2 \quad (3)$$

The final regression coefficient is : $\beta = ({Y_t}^T Y_t)^{-1} {Y_t}^{-1} \mathrm{X}_t$.

However, the use of the minimum mean square error criterion in the autoregressive model and the use of the same order to predict different stock volatility will lead to the model being more sensitive to singular points. Specifically, if some data points of a random variable are far away from each other in the coordinate system with the same name, the error will be expanded by the square situation, thus making a huge gap between the two random variables. As stock prices are affected by abnormal and unexpected events, there are many singular points in stock price data, so autoregressive model can not accurately predict stock prices. Aiming at this problem, this paper adopts an improved prediction method to establish a robust regression prediction model based on the maximum correlationentropy criterion.

3 CONSTRUCTION OF AUTOREGRESSIVE MODEL BASED ON CORRELATIONENTROPY

In order to eliminate the singularity sensitivity problem of stock price data, the correlational entropy autoregressive model is adopted in this paper, and its flow chart is shown in FIG. 2, where (a) represents the training stage process of the model, and (b) represents the prediction stage process of the model. In the model training stage, the segmented stock price curves are firstly clustered, corentropy is used as the similarity measure in the clustering process, and the open-set recognition method is integrated to improve the accuracy of clustering results, as shown in step 1 in FIG. 2 (a). Secondly, after the completion of clustering, a regression model is constructed for each class, and the prediction value is obtained by using the constructed model, as shown in step 2 in FIG. 2 (a). Finally, Step 1 and step 2 are repeated with different orders and the error with the real value is calculated to select the optimal order. In the model prediction stage, firstly, the distance between the data to be predicted and each class center is calculated, and the class with the smallest distance is selected as its category, as shown in step 1 in FIG. 2 (b). Secondly, the correlational entropy autoregressive model is used for prediction, and the final predicted value is obtained, as shown in step 2 in FIG. 2 (b).

3.1 Construction of Curve Similarity Measure Based on Correlationentropy

Aiming at the sensitivity of Euclidean distance to singularity, correlational entropy is chosen as the similarity measure of curves in this paper. When the statistical distributions of the two random variables

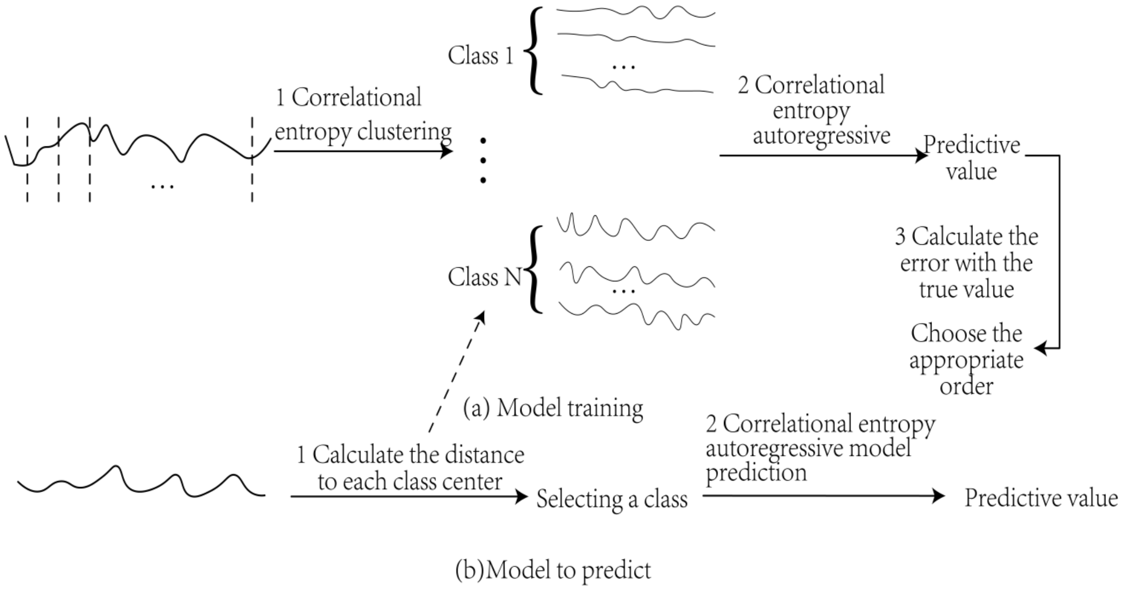


Figure 2: Flowchart of correlational entropy autoregressive model.

are closest, the objective function of Equation (8) is the smallest. Correlational entropy is a measure of similarity between two random variables, which can be expressed as:

$$d^C(X,Y) = E[k_\sigma(X,Y)] \quad (4)$$

Among them, $E[\cdot]$ Said expectations, $k_\sigma(\mathrm{X},\mathrm{Y})$ denote Gaussian kernel:

$$k_\sigma(X,Y) = exp(-\frac{(Y-X)^2}{2\sigma^2}) \quad (5)$$

σ represents the kernel width, selected using density estimation.

In actual calculation, because only some finite samples can be obtained, the joint probability density cannot be calculated, so the correlational entropy of finite samples is estimated by the Parzen window method：

$$d^C(X,Y) = \frac{1}{N}\sum_{i=1}^{N} k_\sigma(y_i - \mathrm{x}_i) \quad (6)$$

The main advantages of the method adopted in this paper are as follows: 1. Considering the influence of abnormal data, correlational entropy adopts kernel width to control the adjustable window, which can effectively reduce the adverse influence of outliers. 2. Considering the algorithm complexity, the sample estimation method is simpler than the traditional moment expansion method. 3. From the geometric perspective, in the sample space, the mean square error (MSE) in the least squares is expressed as the 2-norm of the distance. In correlational entropy theory, when the distance between two points is close, it is equivalent to the distance measured as 2 norm. With the increase of the distance between two points, it is similar to 1 norm, and even tends to 0 norm eventually. Therefore, correlational entropy has the characteristic of suppressing abnormal data, and introducing correlational entropy can enhance the robustness of the training model.

3.2 Correlational Entropy Autoregressive Model Construction

In the autoregressive model, the least mean square error criterion is used to make the model more sensitive to the singularity. Specifically, if there are singular values in the data, the error will also be expanded in a quadratic way, making the influence of these samples far greater than that of other samples, resulting in a huge gap between the two random variables. Aiming at this problem, this paper establishes a new regression model by transforming the constraint function. For the convenience of calculation, the equality constraint is introduced $\Phi^T\Phi = 1$, then the constraint problem is：

$$\max_{\Phi} \sum_{j=1}^{N} k_\sigma(\mathrm{x}_i - \Phi \mathrm{Y}_j)^2$$

$$s.t.\, \Phi^T\Phi = 1 \quad (7)$$

Equation (11) is a nonlinear non-convex constrained optimization problem, which cannot be solved directly. In this paper, we use the properties of conjugate convex functions to solve the semi-quadratic technique, define the matrix $R = diag(\omega_j)$,among them, $\omega_j = [-\omega_1, -\omega_2, \cdots, \omega_N]$,Based on this equation (11), it can be written as:

$$\min_{\Phi} \mathrm{R}\|\mathrm{X} - \Phi\mathrm{Y}\|^2$$
$$\mathrm{s.t.}\, \Phi^{\mathrm{T}}\Phi = 1 \quad (8)$$

The variable t is introduced to solve the non-convex quadratic programming problem shown in Equation (12), when the initial conditions $R(0) = diag(1)$ and $\mathrm{t}^2 = 1$,The above equation can be transformed into a homogeneous constrained programming problem:

$$\min_{\Phi} \|tX - \Phi\mathrm{Y}\|^2$$
$$s.t.\, \mathrm{t}^2 = 1,\ \Phi^T\Phi = 1 \quad (9)$$

And then:

$$\min_{\Phi} [\Phi^T\ t] \begin{bmatrix} \mathrm{Y}^T\mathrm{Y} & -\mathrm{Y}^T\mathrm{X} \\ -\mathrm{X}^T\mathrm{Y} & \|\mathrm{Y}\|^2 \end{bmatrix} \begin{bmatrix} \Phi \\ t \end{bmatrix}$$
$$s.t.\, \mathrm{t}^2 = 1,\ \Phi^T\Phi = 1 \quad (10)$$

Make $\xi = [\Phi^T\ t]^T, B = \begin{bmatrix} I_{N\times N} & 0 \\ 0 & 0 \end{bmatrix}$, $C = \begin{bmatrix} \mathrm{Y}^T\mathrm{Y} & -\mathrm{Y}^T\mathrm{X} \\ -\mathrm{X}^T\mathrm{Y} & \|\mathrm{Y}\|^2 \end{bmatrix}$,Equation (14) can be written as:

$$\min_{\Phi} \xi^T C \xi$$
$$s.t.\, \xi^T B \xi = 1 \quad (11)$$

Using the semidefinite relaxation (SDR) method, the objective function and constraints in Equation (15) are respectively equivalent to:

$$\xi^T C \xi = Tr\{\xi^T C \xi\} = Tr\{C\xi\xi^T\}$$
$$\xi^T B \xi = Tr\{\xi^T B \xi\} = Tr\{B\xi\xi^T\} \quad (12)$$

Where Tr denotes the trace of the matrix and defines the matrix:

$$\Omega = \xi\xi^T. \quad (13)$$

Ω is a symmetric positive semidefinite (PSD) matrix with rank 1, and the final semidefinite relaxation optimization constraint is obtained:

$$\min_{\Phi} Tr\{C\Omega\}$$
$$s.t. Tr\{B\Omega\} = 1, \Omega \geq 0\ . \quad (14)$$

The eigendecomposition of matrix Ω can be expressed as:

$$\Omega = V\mathrm{R}V^T. \quad (15)$$

Among them, $V = [v_1, v_2, \cdots, v_N]$ the Ω eigenvector of lambda, $R = diag(r_1, r_2, \cdots, r_N)$ represents the corresponding eigenvalue, Because when rank is one, $\Omega(1) = r_1 v_1 {v_1}^T$ the closest Ω, Therefore, the following equation is used to estimate ξ.

$$\xi = \sqrt{r_1 v_1}\ . \quad (16)$$

The solution of the final regression prediction parameter Φ is the first N values of ξ. Finally, the coefficient value optimized by MCC model is obtained, and the predicted value at the future moment is obtained by the weighted sum of historical data.

3.3 Open Set Identification Method

Traditional clustering uses Euclidean distance, which treats the differences between different attributes of samples equally, which will lead to the deviation of its results. In this paper, the open set identification method is integrated with the traditional clustering method, which can effectively deal with the singularity problem in clustering results.

Algorithm 1. Open set recognition algorithm that makes stock price prediction more accurate.

Step 1: Randomly select K cluster centers, and then calculate the correlational entropy distance between each stock price index series and the selected cluster centers.

Step 2: According to the principle of minimum distance, each sample point is assigned to the corresponding cluster center, and then a new cluster center is obtained.

Step 3: For the new clustering results, this paper calculates the correlational entropy distance from the sample point to the cluster center, as well as the mean and standard errors. Then we judge whether the distance between each sample point and the cluster center is within three standard deviations of the cluster distance. After the judgment is completed, a new cluster center is calculated for the sample points in its range.

Step 4: Continue to perform steps 2)~3) until the loop terminates. For sample points that are not within the scope, this paper considers that they do not belong to any category and are left for subsequent processing.

The open set identification method used in this paper can effectively identify outliers. The reason is that the traditional clustering method does not add boundary constraints to the clustering results, which leads to more outliers. However, the proposed method can solve this problem well.

4 EXPERIMENTAL RESULTS AND ANALYSIS

4.1 Selection of Experimental Data and Evaluation Index

The experimental data in this paper are the daily closing price data of CSI 300 Index, Dow Jones Index and Nikkei Index, and the data collection parameters are shown in Table 1. In this paper, stock price data are divided into groups of every 10 by sliding window, and the data source is British Finance and Economics.

Table 1: Experimental data.

	Csi 300 Index	Dow Jones Index	Nikkei Index
Data interval	2010.1.1 ~2020.12.30	2010.1.1~2020.12.31	2010.1.1~2020.12.32
The training set	2010.1.1~2019.12.31	2010.1.1~2019.12.32	2010.1.1~2019.12.33
The test set	2020.1.1~2020.12.31	2020.1.1~2020.12.32	2020.1.1~2020.12.33
The amount of data	2675	2769	2719

In this paper, mean absolute error (MAE) and mean absolute percentage error (MAPE) are selected as the evaluation indexes to measure the performance of the model. The formula is shown in Table 2,Where $X = (x_1, x_2, \dots, x_n)$ is the true value and $\hat{X} = (\hat{x}_1, \hat{x}_2, \dots, \hat{x}_n)$ is the predicted value.

Table 2: Definition of evaluation indicators.

Measure	Expression
MAE	$\frac{1}{n}\sum_{i=1}^{n}\lvert\hat{x}_i - x_i\rvert$
MAPE	$\frac{100\%}{n}\sum_{i=1}^{n}\left\lvert\frac{\hat{x}_i - x_i}{x_i}\right\rvert$

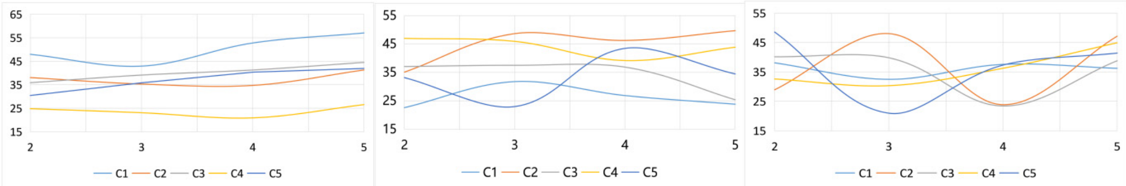
4.2 The Effect of Order on the Prediction Result

To explore order for predicting results, the influence of this article by selecting different order number, for different categories using maximal entropy regression model to forecast, forecast range of the csi 300 index, the dow Jones index, the nikkei 2010 January 1 to December 31, 2019, the closing price data, including Shanghai and shenzhen 300 index data for 2433, Data volume for the Dow was 2,516 and for the Nikkei 2,476. The prediction results are shown in FIG. 3. In FIG. 3 (A1), (B1) and (C1), the abscissa represents the order, and the ordinate represents the MAE value. In FIG. 3 (A2), (B2) and (C2), the abscissa represents the data points, and the ordinate represents the index data.

According to the above results, the following conclusions can be drawn :(1) in FIG. 3, the prediction errors of different orders (a1), (b1) and (c1) are different, indicating that the order has a great influence on the prediction results. (2) The minimum points of curves in FIG. 3 (A1), (B1) and (C1) are different, indicating that the optimal order of different categories is different. (3) Gently fluctuating curve order has little influence on the prediction effect, such as C5 curve in FIG. 3 (A1) and (A2), while sharply fluctuating curve order has great influence on the prediction effect, such as C5 curve in FIG. 3 (B1) and (B2).

4.3 Measure of Similarity

In order to verify the correlational entropy distance performance used in this paper, the following experiments were conducted to construct three groups of fluctuation curves, calculate the distance with different similarity measures, and compare the performance of each similarity measure through the results. Among them, the first set of volatility curves contains singularities, the second set of volatility curves contains time offset, and the third set of volatility curves contains singularities and time offset. The experimental results are shown in FIG. 4, where the abscissa represents the data point and the ordinate represents the value.In the figure $d^E(X,Y)$ Euclidean distance calculation is used,$d^L(X,Y)$ is



(a1) The prediction effect of different classes and orders of CSI 300 index
(b1) Dow Jones Index different class and order forecast effect
(c1) Nikkei index different class and order forecast effect
(a2) Csi 300 index class mean line
(b2) Dow Jones Average class mean line
(c2) Nikkei class mean line

Figure 3: Order selection and class mean line.

calculated using Rangelis distance, $d^{DTW}(X,Y)$ indicates the use of dynamic bending distance calculation, $d^{C}(X,Y)$ is calculated using correlational entropy.

From Fig.4, it is obvious that:(1) as can be seen from FIG. 4 (a), for sequences containing singularities. The correlational entropy measure distance is 0.32, which is the smallest, indicating that correlational entropy can obviously eliminate the influence of singular points. (2) As can be seen from FIG. 4 (b), for the time offset series. The correlational entropy measure distance is 0.44, which is the smallest, indicating that this method can better deal with the problem of time offset. (3) As can be seen from FIG. 4 (c), for the sequence containing time offset and singular points, the correlational entropy measure distance is 0.51, with the minimum distance, indicating that the proposed method can effectively deal with the problem of singular points and time offset.

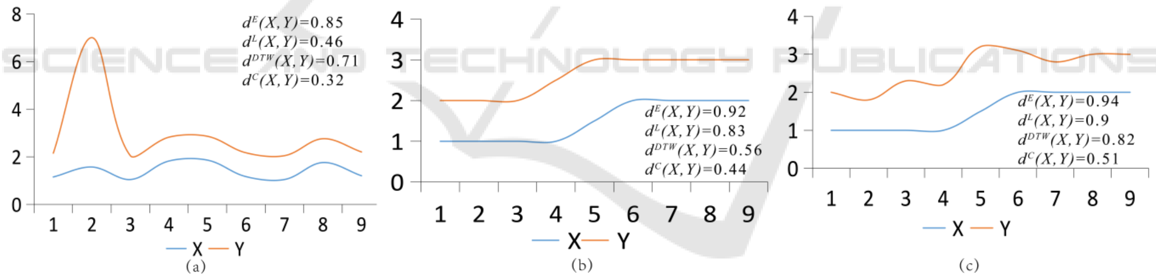


Figure 4: Results of different similarity measures.

4.4 Correlational Entropy Autoregressive Model

In order to verify the model adopted by the performance, this article USES the following scheme to forecast experiments, using clustering to construct a regression model, do not use the open set after build regression model, clustering using open set after three kinds of schemes to build regression model, and compare forecast results, to validate the clustering method and open set method for predicting effect for ascension. The data used are the daily closing price data of CSI 300 index from January 1 to December 31, 2020, with a volume of 243. Meanwhile, to verify the performance of the proposed model, the results are compared with the prediction results of statistical models and machine learning models. The results are shown in Table 3 and Table 4. The rows in the table represent the prediction scheme used, the columns represent the error indexes, and the optimal results are represented in bold,In the table, A represents The regression model was constructed without clustering scheme, B represents Open set is not used to build regression model after clustering scheme, and C represents Open set was used to construct regression model after clustering scheme.

Table 3: Comparison of errors.

Prediction method	MAE	MAPE
A	92.175	9.64
B	76.512	7.76
C	**40.964**	**0.0474**

From Table 3, it is obvious that:(1) the effect of constructing regression model after clustering is significantly better than that of constructing regression model without clustering, indicating that the addition of clustering method can effectively improve the accuracy of prediction. The reason is that the stock price fluctuation curve is different between categories, so a single regression model is not applied. (2) The effect of using open set method to construct regression model after clustering is significantly better than that of not using open set method. The reason is that the traditional clustering method can not deal with the outlier problem well. In this paper, the accuracy of clustering results can be effectively improved after the clustering results are constrained.

Table 4: Results compared with statistical models and machine learning models.

Prediction method		MAE	MAPE
Machine learning	Adaptive RNN	57.621	6.6
	GRU	59.225	6.86
Statistical models	AR	63.695	7.44
	ARIMA	60.727	7.08
	GARCH	61.03	7.13
Our proposed	MCC-AR	**40.964**	**4.74**

From Table 4, it is obvious that :(1) the proposed method is superior to the machine learning method. The reason is that the maximum corentropy criterion is used as the constraint function, and gaussian corentropy is used to limit the infinite expansion of errors, which effectively reduces the influence of singularities. Moreover, the machine learning model uses a large amount of data in training and testing, and the method in this paper can get better prediction results even when the sample size is small. (2) The method in this paper is superior to the statistical model method. The reason is that the statistical model uses the same order to predict different fluctuations, and does not consider the difference between curves.

5 CONCLUSION

In order to eliminate the influence of singularities on stock price prediction, a maximum correlational entropy criterion autoregressive model is proposed. The experimental results show that: 1. Using the clustering strategy, the price curves with similar change trends are clustered into a group, and a regression model is constructed for price prediction, which effectively improves the prediction accuracy. 2. Correlational entropy is used to measure the similarity of any two curves. Essentially, two curves are taken as random variables to measure the similarity based on the difference of their probability distribution, which can better overcome the influence of singularities. 3. In this paper, the open-set recognition strategy is adopted to add boundary constraints to the clustering results, which makes the clustering results more accurate and can better deal with the problem of singularity classification in the clustering process. 4. In this paper, the maximum corentropy criterion is used as the constraint function, and the Gaussian corentropy is used to limit the infinite expansion of the error, which effectively weakens the influence of singularity points on the curve similarity measurement.

To sum up, the correlational entropy measure used in this paper can better deal with the singularity problem in stock series. Correlational entropy autoregressive model can deal with the singularity problem in stock prediction. The open-set strategy and the strategy of constructing a regression model for each class can effectively improve the prediction accuracy. The experimental results show that the method proposed in this paper has a good prediction effect.

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