Identifying Economic Factors of Local Government Transparency: Based on Apriori and LSTM-Attention

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Abstract. This study examines the impact of economic factors on local government transparency and proposes a prediction framework called AP-LSTM, which uses feature extraction and Apriori to select highly correlated economic factors as input for the LSTM-Attention network. The proposed method is validated using historical data from Shandong Province. Results show an interval correspondence between economic factors and transparency, and the prediction accuracy of the network is improved with the feature extraction method. The LSTM-Attention network's prediction results have an important influence on rank derivation and benchmark improvement for local government transparency.

Keywords: LSTM-Attention model · Features extraction · Deep learning · Apriori · Economy

1 Introduction

Government transparency is vital for democracy and efficient governance [1]. Countries and international organizations disclose tax and financial information to enhance credibility, while authorities are encouraged to adopt better policies to consolidate finances and reduce corruption [2]. Research shows a two-way effect between government transparency and the economy, with economic efficiency and government transparency [3] complementing each other to increase government efficiency and citizen well-being. The success of government transparency depends on compatibility with economic factors. Therefore, it is essential to study the correlation between economic factors [4] and government transparency and predict its development.

With the increasing interest in this issue, many scholars have put forward different methods, such as SFA and Tobit Regression [5], Vector Auto-Regression (VAR) [6], MIT Economic Projection and Policy Analysis (EPPA) [7], and Vector Error-Correction Models [8]. In addition, the Delphi method is also widely used. Although these methods all produce good results, they are more subjective than objective to some extent, such as the weighting method based on expert opinion or questionnaire method, which may bring forth biased or unrealistic results. Furthermore, most of these studies evaluate the

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importance of transparency for monetary policy or the impact caused by economic policy on government transparency but ignore the research on local government transparency [9] and correlative factors [10]. Therefore, how to use more objective and accurate machine algorithms to discover the intrinsic connection between local government transparency and economic factors and how to achieve high-precision prediction of the development of local government transparency has become an urgent issue. This paper proposes a deep learning-based AP-LSTM framework solution to solve the above problems.

2 Materials and Methods

2.1 Mining Association Rules

Mining association rules are divided into two steps: firstly, all frequent item sets should be found out. In this process, join and prune steps are fused to obtain the maximum frequent itemset. Further, strong association rules are generated from frequent item sets. Strick association rules satisfy minimum support and minimum confidence.

Support indicates the frequency of occurrence of an item set. If there are two items, including A and B, that we want to analyze its correlation, the corresponding support is calculated as shown in Eq. 1:

$$Support(A, B) = p(B \cup A) = \frac{Support - Count(A \cup B)}{Total - Count} \tag{1}$$

Minimum support measures the threshold of support and represents the minimum importance of item sets in a statistical sense. The confidence degree is the probability of item set B when item set A occurs, while the confidence degree of A to B is calculated by Eq. 2.

$$\text{Confidence } (A => B) = p(B \mid A) = \frac{\text{Support} - \text{Count}(A \cup B)}{\text{Support} - \text{Count}(A)}. \tag{2}$$

2.2 Prediction Models

LSTM-Attention Mechanism

LSTM is a kind of cyclic neural network, which has three gating mechanisms: input gate, forget gate and output gate. It can deal with long-term dependence problem better. The attention mechanism constructs weights to assign attention to data during training, allocating more resources to critical information for better efficiency and prediction. LSTM-Attention retains intermediate outputs and calculates weight for each time step. The vectors are combined to rein information, improving accuracy. The model learns inputs and associates them with the output sequence. The final prediction result is the probability of true and false targets. The architectural model is in Fig. 1.

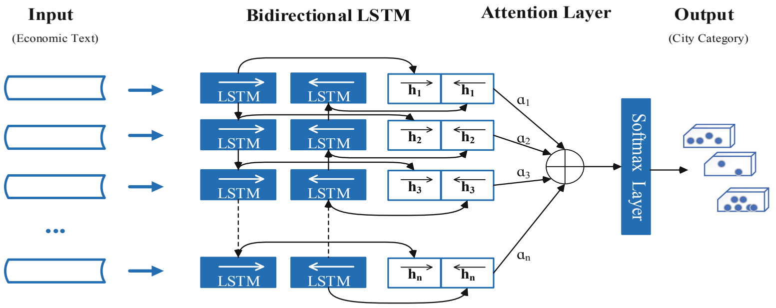


Fig. 1. The architectural of the LSTM-Attention model

3 Experiments

In this section, the association rule algorithm performs feature identification to mine the economic factors correlated to government transparency. The optimal prediction accuracy is obtained by the effect of input data on the accuracy of the algorithm and by adjusting the network parameters. The specific work flow is shown in Fig. 2.

3.1 Economic Factors Identification Correlated with Local Government Transparency

Data Processing

To test the prediction model's performance, 16 cities in Shandong Province, China, are selected for empirical study. Additionally, the economic factors are from the Statistical Yearbook of Shandong Province. After calculating the principal components of each component, the variance rotation method is used to rotate the factors. According to the frequency distribution of the histogram, the level of local government transparency can be divided into three classes such as high quality, medium quality, and low quality.

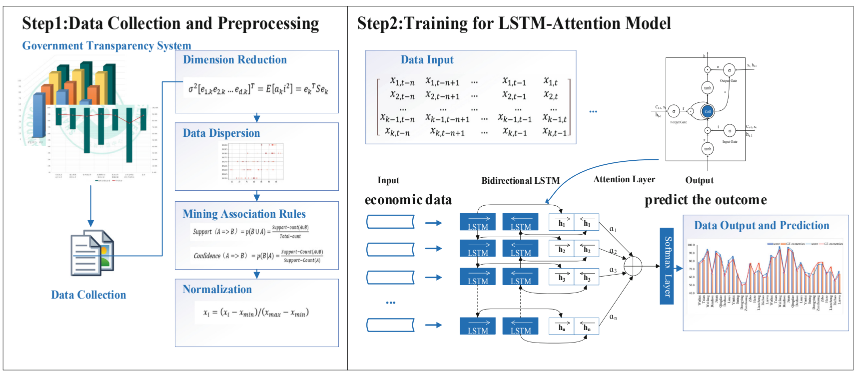


Fig. 2. Flow of AP-LSTM

The index of economic development level is split into many intervals, including high, medium, and low development.

Mining Strong Association Rules

When mining association rules with the Apriori algorithm, it is usually necessary to customize evaluation criteria to select frequent data sets in datasets. The most common evaluation criteria are customer support or a combination of customer sup-port and confidence. In this experiment, we set the minimum support to 20% and the minimum confidence to 70%. The strong association rules are shown in Table 1.

Where A: Total score of local governments transparency; B: Open operation of administrative power; C: Information Disclosure in key areas; D: Open application; E: Policy interpretation and response; F: Guarantee mechanism for transparency in government performances; G: GDP; H: Consumption index; I: Population; G: Employment and unemployment; K: Investment; L: Finance; M: Industry; N: Agriculture; O: Transportation industry; P: Construction industry; Q: Cultural industry; R: Education; S: Health care. After the letter, the corresponding 1, 2, and 3 represent the low, medium, and high levels of development, respectively.

Feature Selection and Normalization

The default activation function for LSTM is the hyperbolic tangent line, whose output value is between -1 and 1, which is the preferred range of input data for the time series model. Among the selected economic features, the order of magnitude and units of feature data are different, so data normalization is needed before inputting into the model to improve the fitting effect of the model. The normalization method adopted in this paper is Max/Min method, as shown in Eq. 3:

$$x_i = (x_i - x_{min})/(x_{max} - x_{min}) \tag{3}$$

Table 1. Strong association rules.

ID	Rule	Confidence	Support	ID	Rule	Confidence	Support
1	B1 → G1 → H1	20.28	93.33	**12**	F1 → H1	26.09	75.00
2	F1 → A1	26.08	90.00	**13**	I3 → D3	20.29	73.68
3	G3 → A3	24.63	80.95	**14**	G1 → H1 → B1	20.29	73.68
4	C1 → H1	27.53	79.16	**15**	B1 → H1	26.09	72.00
5	F2 → J2 → D2	20.28	77.77	**16**	A1 → P1	26.09	72.00
6	D2 → J2 → F2	20.28	77.77	**17**	A2 → S2	21.74	71.43
7	B1 → H1 → G1	20.28	77.77	**18**	N2 → E2	27.54	70.37
8	A3 → G3	24.63	77.27	**19**	H1 → C1	27.54	70.37
9	F2 → Q2	33.33	76.67	**20**	D2 → F2	30.43	70.00
10	Q1 → A1	23.19	76.19	**21**	E3 → S3	27.53	70.00
11	S3 → E3	25.26	76.00				

3.2 Prediction Model Setting

Parameter Setting

Accuracy comparison corresponding to different sizes of the hidden layer is shown in Fig. 3. Based on this figure, the parameters are set to the LSTM hidden layer dimension 256 and the LSTM layer number 2 to obtain the best classification accuracy. During model training, the learning rate was set to 0.005, dropout to 0.3, random inactivation parameter to 30%, and batch size to 64 with 50 epochs. The experimental results show that this setup offers the best experimental results.

The LSTM-CNN model combines LSTM's loop structure and CNN's max-pooling layer to learn time-series information and obtain critical information about the urban economy. This model is designed with a hidden layer dimension of 200 and two LSTM layers, followed by one convolutional layer and one pooling layer. The last step of the LSTM hidden layer is added to the pooled vector in the CNN for feature extraction. The fully connected layer prediction uses these two splices for local government transparency. Experimental results show that this setup produces the best results.

Experimental Result

LSTM network, CNN network, LSTM-CNN network, and the proposed algorithm are both selected to make comparison for the prediction performance, and the Adam optimization method is performed for optimization training. The lost functions of the above experiments adopt the mean square loss function MSELoss. Figure 4 shows the training process of the four networks, where part (a) shows the variation of the training accuracy and part (b) shows the variation of the training loss. From the figure, the four selected networks can gradually become a stable state after training.

The performance comparison is shown in Table 2. The table shows that CNN has the lowest accuracy of 0.69, the mean square error (MSE), root mean square error (RMSE) and mean absolute error (MAE) are 0.0075, 0.0871 and 0.0501 respectively with the worst performance. With higher accuracy of LSTM-CNN and LSTM-Attention, LSTM-Attention is slightly higher than LSTM-CNN, reaching 0.93. In the experiment, even though there are more hidden layers and parameters, the LSTM network cannot reach the accuracy of LSTM-Attention. The LSTM-Attention model covers all the advantages of the LSTM network, which can fully mine various information about the urban economy through memory and generalization. The attention mechanism is introduced to assign different weights for each piece of information. For this experiment, the importance of

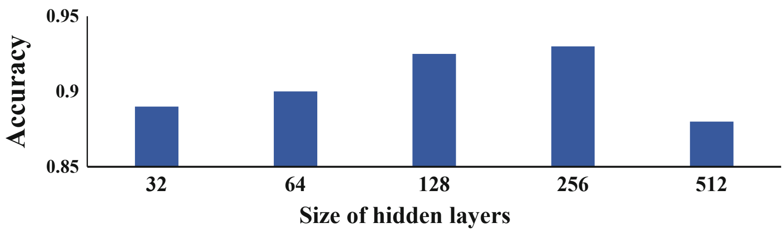
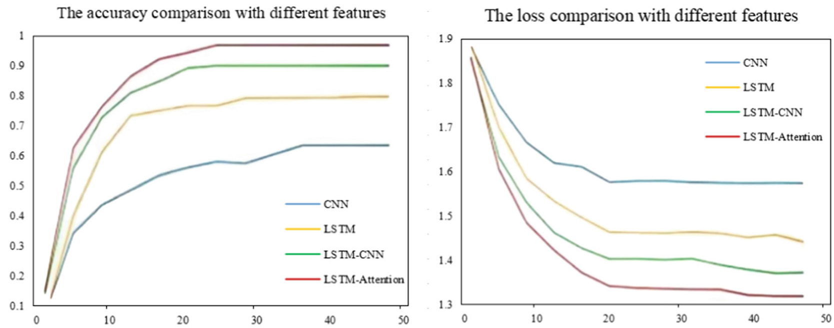


Fig. 3. The accuracy corresponding to different sizes of hidden layer



(a) (b)

Fig. 4. Training process of the four networks.

information increases with the time-step approach, so more accurate prediction results can be obtained.

In addition to accuracy, precision, and recall, the F1-scores of the four networks are also compared. The comparison of F1- score of the four networks is shown in Fig. 5. The CNN network shows the worst performance in all cases. This is because the convolution kernel of CNN emphasizes the Windows in space, which is like the sequence problem when the front and the back are also considered. However, RNN does not take the up and down problems in space into consideration. Among the four kinds of networks, the LSTM-Attention network proposed in this paper can produce the best performance, with F1- score of the three categories reaching 0.94, 0.96, and 0.95, respectively. In addition, we compared multiple sets of data under the same parameters, and obtained the error level of accuracy. The fluctuation of CNN was about 0.03, and the LSTM-Attention was about 0.01. More stable and better than other baseline models.

The frequent local government transparency indicator item-sets and the main characteristics of the correlated economic database indicated that the leading indicators in each time unit in the study area needed to be focused on comprehensive development indicators such as consumption index, population, employment and unemployment, investment, and finance. In contrast, the industrial development indicators have less impact. The training, validation, and testing results show that the model's performance reaches stability after several training sessions, and the training loss decreases substantially. The prediction accuracy is as high as 0.93, and the fitting curve performs well. The MSE,

Table 2. Performance comparison with GT-Economics as input

Network	**Accuracy**	**MSE**	**RMSE**	**MAE**
CNN	0.62 ± 0.03	0.0076	0.0871	0.0501
LSTM	0.74 ± 0.02	0.0020	0.0450	0.0361
LSTM-CNN	0.85 ± 0.01	0.0007	0.0273	0.0212
LSTM-Attention	0.93 ± 0.01	0.0003	0.0178	0.0123

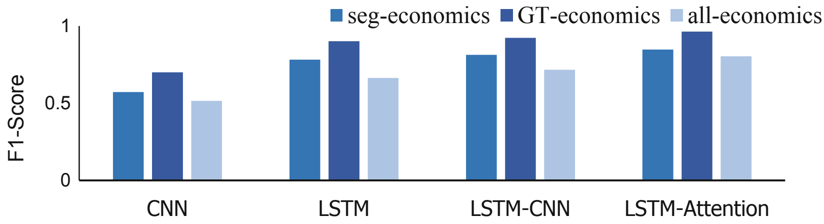


Fig. 5. Comparison of F1-Score of networks in different economies.

RMSE, and MAE are 0.0003, 0.0178, and 0.0123, respectively. The F1-Score reaches 0.963.

4 Conclusions

A new framework is raised in this paper for exploring the correlation relationship between economic factors and local government transparency. First, this paper excavates the economic factors related to local government transparency and establishes a database which is helpful to deduce the level of local government transparency. Subsequently, predictions are made with the LSTM-Attention network based on correlation analysis. Compared with CNN, LSTM network is more suitable for dealing with time series problems of remarkably high correlation. It can extract and fuse different features from different parts of the input data. In addition, an attention mechanism is introduced to help the model capture the underlying information. Experiments show that the AP-LSTM ensemble framework outperforms other prediction methods and achieves the desired effect. As the results show, the above research positively impacts the ranking derivation of local governments' transparency, thus making recommendations for benchmark improvement.

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