Journal of Computing and Electronic Information Management
ISSN: 2413-1660 | Vol. 10, No. 2, 2023

Classification of Government Consulting Departments Based on Deep Learning

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Abstract: To further facilitate the resolution of problems encountered by the public in handling affairs, the government has opened many government service platforms. As a result of the large number of government departments, messages on platforms cannot be accurately and timely divided into various departments. Based on messages on the national government service platform, this paper establishes a deep learning model to classify messages. Sixteen government departments were involved in the analysis and the study found that the operational boundaries between some departments were not clear. In this paper, we analyzed the departments with more misclassifications and proposed targeted improvement solutions. Since there is a business transfer between the Bureau of Administrative Approval Service and the Bureau of Housing and Urban-Rural Development, we will not consider it in the subsequent analysis. In this paper, LSTM, bidirectional LSTM, GRU and bidirectional GRU were used to classify messages on the platform in 14 departments, with an accuracy of more than 80%. Among them, the accuracy of bidirectional GRU was the highest, and the speed of GRU and bidirectional GRU was fast, which realized the rapid and accurate classification of mass problems to the relevant government departments.

Keywords: Text classification; Deep Learning; LSTM; GRU; Bidirectional LSTM; Bidirectional GRU; Message from the masses.

1. Introduction

With the existing government consultation platform, the masses need to choose the department when they leave a message, which may lead to the consulting public not being able to find the correct department for their needs. This situation will affect the efficiency of government departments and the orderly life of the public. Therefore, how to solve the current confusion of the masses seeking help has become a hot issue at present.

In recent years, the establishment of intelligent government service systems based on natural language processing has become a new trend in the development of government work and social governance, which has greatly contributed to improving the efficiency of government administration and saving human and material resources. Therefore, it is of far-reaching practical significance to design a consultation system that can effectively and accurately classify the problems of the masses, no matter for the relevant government departments or the masses [1].

Most of the existing studies have clustered the problems of classifying mass messages into seven categories, such as transportation, social security, health, education, etc., which cannot fundamentally solve the demands of mass online messages implemented to the direct departments. Based on the messages left by the masses on Shandong government service platform and 16 departments with the largest number of messages left by the masses (including the Administrative Approval Service Bureau, the Housing and Urban-Rural Development Bureau, the Public Security Bureau and the Education Bureau, etc.), this paper establishes an efficient and accurate classifier by classifying the messages left on the national government service platform through deep learning method, and analyzes the messages left by the departments with poor classification effect.

2. Method

2.1. Long Short-Term Memory (LSTM)

LSTM proposes the structure of cellular states, resulting in its stored historical information that is not easily changed. It has better memory and can better portray long sequences [2,3].

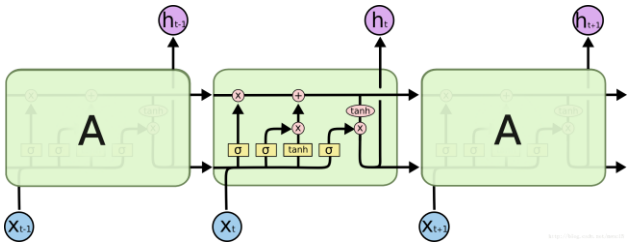


Fig. 1 LSTM network structure

There are three "gates" in the classic LSTM structure. The forgetting gate is used to help RNN selectively forget certain historical information. The input gate is used to

enhance the memory of certain historical information; The output gate is responsible for synthesizing the long-term and short-term memory information to generate the output signal.

2.2. Gate Recurrent Unit (GRU)

GRU is a variant of LSTM [4].

The whole process is as follows:

$$r_t = \sigma\left(W_r \bullet \left[h_{t-1}, x_t\right] + b_r\right) \quad (1)$$

$$z_t = \sigma\left(W_z \cdot \left[h_{t-1}, x_t\right] + b_z\right) \quad (2)$$

$$\tilde{h}_t = tanh\left(W_h \bullet \left[r_t \times h_{t-1}, x_t\right] + b_h\right) \quad (3)$$

$$h_t = \left(1 - z_t\right) \bullet h_{t-1} + z_t \times \tilde{h}_t \quad (4)$$

Because of the model simplification, the training efficiency

of the model is significantly improved, which can save a lot of time. At the same time, some problems of LSTM model are solved.

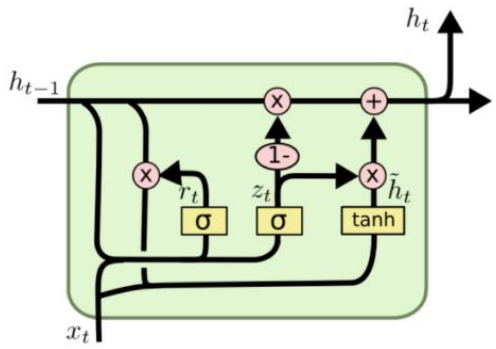


Fig. 2 GRU network structure

2.3. Bidirectional Long Short Term (Bi-LSTM)

Bi-LSTM is one of the common variants of LSTM neural networks. The difference is that the hidden layer of the model contains both positive and negative directions [5].

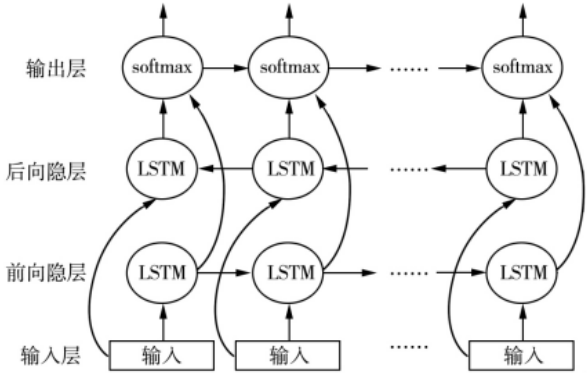


Fig. 3 Bi-LSTM network structure

The hidden units in both directions are independent and connected to the output layer without interfering with each other. This two-way setup takes into account the contextual environment of the sequence data and is suitable for processing natural language data.

2.4. Bidirectional Gate Recurrent Unit (Bi-GRU)

A bidirectional GRU can be regarded as the combination of two unidirectional gate re-urrent units [6].

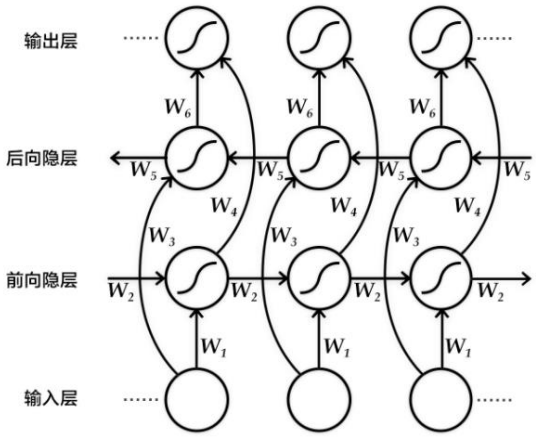


Fig. 4 Bi-GRU network structure

Bidirectional networks process input sequences sequentially and in reverse order in the time dimension so that each output node contains complete context information for the current moment in the input sequence.

3. Research and Analysis

3.1. Data Sources

The data in this paper are all from the real messages on the national government service platform. We crawled 13021 messages from the masses in Jinan, Qingdao, Zibo, Zaozhuang and Dongying in Shandong Province. After the duplicate and invalid messages are removed, there are 7930 valid messages left. We analyzed the data of 5650 messages from 16 government service departments with a total number of messages greater than 90, including the Bureau of Administrative Approval Service, the Bureau of Housing and Urban-Rural Development, the Bureau of Public Security, the Bureau of Education, etc.

3.2. Model Study

3.2.1. Model Building and Analysis

After 8 iterations of the model, the line graphs of loss and accuracy of test set and verification set are output respectively.

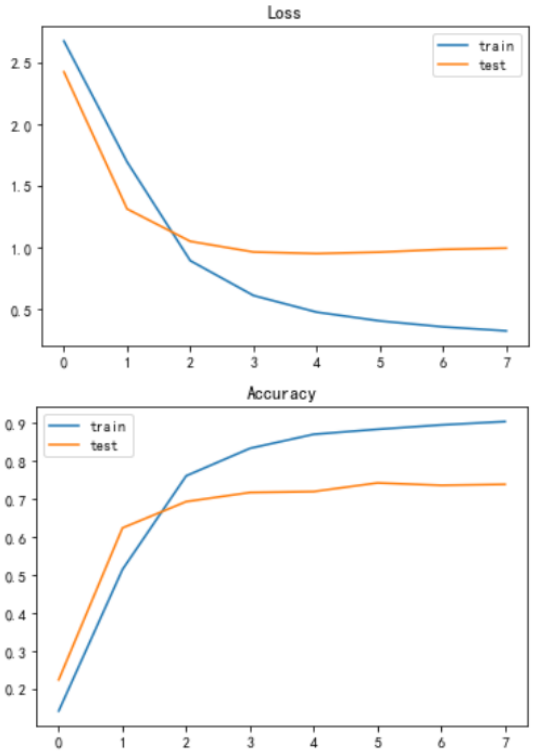


Fig. 5 Loss and accuracy graph

As can be seen from the figure above, the model gradually stabilizes after 5 iterations,

with an accuracy of 90% on the training set. The model also performs well in the test set, achieving 75% accuracy and reducing the loss to a relatively low level of 0.9. To gain further insight into the predictive power of the model, we also output the following metrics.

Based on the data in the above table, we find that the wide variety of departmental operations and unclear business scope can affect the message classification results. We analyze the misclassified data in relation to the actual situation, and we suggest countermeasures in the conclusion section of this paper.

3.2.2. Improvements

As it is found in the previous study that there is a business transfer phenomenon between the Bureau of Administrative Examination and Approval Service and the Bureau of Housing and Urban-Rural Development, that is to say, the data of these two departments in the data set we selected is somewhat correlated. Besides these two departments, we analyzed the data of other 14 departments by using LSTM, GRU, two-way LSTM and two-way GRU methods respectively.

As in the previous section, we still use the LSTM method to model and analyze the remaining 14 sectors, and the results are as follows.

Table 1. Table of forecast frequency of 16 departments

Department	Accuracy	Recall rate	F1 score	Number of correct predictions
Safety Production Supervision Administration	0.80	0.80	0.80	55
Development and Reform Commission	0.82	0.79	0.81	58
Public Security Bureau	0.85	0.72	0.78	71
Transportation Bureau	0.73	0.65	0.69	37
Education Bureau	0.89	0.75	0.82	53
Civil Affairs Bureau	0.58	0.85	0.69	41
Human Resources and Social Security Bureau	0.66	0.65	0.66	72
Bureau of Ecology and Environment	1.00	1.00	1.00	37
Market Supervision Administration	0.78	0.66	0.71	58
Justice Bureau	0.90	0.98	0.94	47
Health and Family Planning Commission	0.82	0.85	0.84	55
Culture and Tourism Bureau	0.91	0.89	0.90	55
Administrative Approval Service Bureau	0.53	0.56	0.54	90
Medical Security Bureau	0.68	0.80	0.74	35
Housing and Urban-Rural Development Bureau	0.54	0.48	0.51	65
Bureau of Natural Resources and Planning	0.82	0.94	0.88	53
macro average	0.77	0.77	0.77	882
weighted average	0.76	0.75	0.75	882
Accuracy: 0.7517006802721088				

Table 2. Table of forecast frequency of 14 departments

Department	Accuracy	Recall rate	F1 score	Number of correct predictions
Safety Production Supervision Administration	0.96	0.90	0.93	59
Development and Reform Commission	0.72	0.90	0.80	51
Public Security Bureau	0.72	0.79	0.76	66
Transportation Bureau	0.73	0.53	0.61	36
Education Bureau	0.90	0.76	0.82	58
Civil Affairs Bureau	0.88	0.60	0.72	48
Human Resources and Social Security Bureau	0.58	0.82	0.68	73
Bureau of Ecology and Environment	0.95	0.95	0.95	39
Market Supervision Administration	0.89	0.83	0.86	60
Justice Bureau	0.89	0.82	0.86	40
Health and Family Planning Commission	0.68	0.81	0.76	42
Culture and Tourism Bureau	0.93	0.95	0.94	57
Medical Security Bureau	0.79	0.70	0.75	44
Bureau of Natural Resources and Planning	0.95	0.85	0.90	67
macro average	0.83	0.80	0.81	740
weighted average	0.83	0.81	0.81	740
Accuracy: 0.8094594594594594				

After training the message data of 14 departments except the above two departments, the accuracy rate of the test increased from 75.2% to 81.0%, and the accuracy rate of many departments reached more than 90%. The accuracy and F1 scores of the Civil Affairs Bureau have improved slightly from the previous section, but they are still at a low level, possibly due to the lack of clear business lines between the Civil Affairs Bureau and other departments.

For the 14 departments mentioned above, we also used GRU, bidirectional LSTM and bidirectional GRU methods for training and testing, respectively, and obtained the following results.

After our analysis and improvement, the prediction accuracy of all four methods is relatively high, reaching more than 80%, and can predict the department to which the masses' messages belong more accurately.

Table 3. Comparison of the accuracy of the four methods

Method	LSTM	GRU	Bi-LSTM	Bi-GRU
Accuracy	80.95%	81.22%	81.62%	81.76%

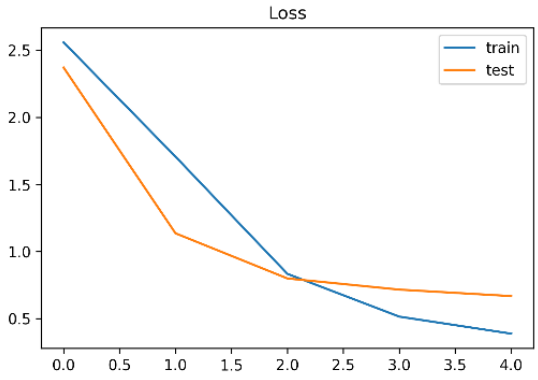


Fig. 6 Loss diagram of LSTM method

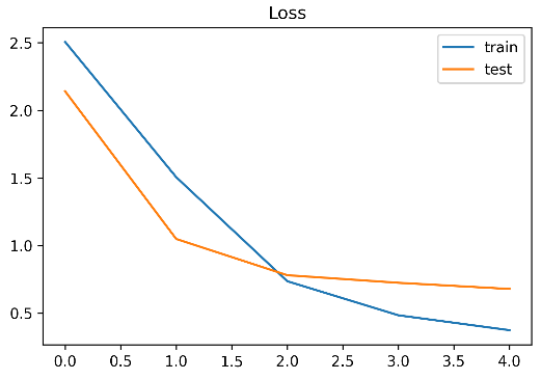


Fig. 7 Loss diagram of GRU method

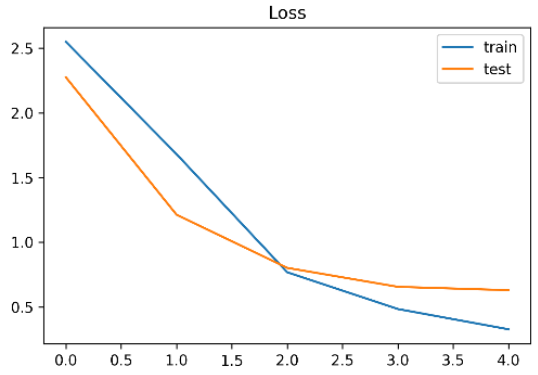


Fig. 8 Loss diagram of Bi-LSTM method

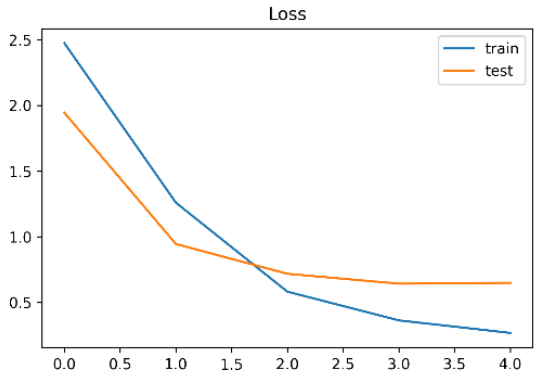


Fig. 9 Loss diagram of Bi-GRU method

It is easy to see that the four methods converge at a comparable rate with relatively

high accuracy in all cases. The following shows the time consumption of the four methods.

The four models converge in five iterations. Because GRU model has fewer parameters, the GRU and bidirectional GRU take less time and can realize efficient classification.

Table 4. The time consumption of the four methods

Method	LSTM	GRU	Bi-LSTM	Bi-GRU
Convergence cycle	5	5	5	5
Total time consuming	2164ms	1179ms	2035ms	1242ms

4. Conclusions and Recommendations

In this paper, LSTM and other methods were used for modeling to help the government efficiently solve the classification problem of public messages, with an accuracy of 75.17%. We found that business similarities and business linkages between government departments can reduce efficiency. The existence of business adjustment between the Administrative Approval Service Bureau and the Housing and Urban-Rural Development Bureau has led to a high rate of misclassification in these two categories. After we removed the relevant data of these two departments, the accuracy rate was improved to more than 80%. Since the bidirectional GRU method has fewer parameters, the method is easier to converge and has a shorter running time, which is more capable of improving government efficiency. We also analyzed accuracy rate, recall rate and F1 score for each department. The results show that the accuracy of the test for most departments reaches more than 80%, which shows that we can predict the corresponding service departments more accurately for the messages from the public.

Based on some problems found in the research process, we make the following recommendations:

When the masses leave messages and ask questions on the government affairs platform, they should describe the problem as concisely and clearly as possible, and try to avoid irrelevant words.

For the business and related changes, the relevant departments may increase publicity to ensure that the public clearly identifies the business department.

When several departments collaborate on business, the department needs to set up association reminders between government departments. When the masses leave a message in any of these departments, the department should remind the information and procedures of other departments involved in the business, and should set up a jumping interface or direct channel.

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