Eng Int Syst (2019) 3: 133–139

Engineering
Intelligent Systems

National Governance Based on Deep Learning and Neural Networks

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By examining the governance of big data in local and foreign governments, we can improve government data governance capabilities, reduce the level of risk faced by open data, and improve the quality of data openness, so that data assets can bring real benefits to society and promote social development. In view of the current big data environment, in this paper we carry out a comprehensive investigation and analysis of the ways that foreign governments adopt and implement big data governance, and compare these with China's own government governance capabilities, in order to identify problems that need to be resolved in the context of big data. Then, according to the specific problem, we find a feasible and scientific path to improve government governance, and propose a big data mining model based on deep learning and a neural network to facilitate national governance, which has practical significance.

Keywords: deep learning, neural network, national governance, model, data analysis

1. INTRODUCTION

Due to the strong promotion of big data openness policies of governments around the world, government information systems have undergone considerable changes. These have had a significant impact on our lives and work, from our family life and business operations to local and national government operations. Societies nowadays are fast-paced and technologically advanced, giving rise to big data as a product of the high-tech era [1]. However, this author believes that the value, rather than the volume, of big data is its most important feature. However, due to the diversity of the data, its great volume, and the rapidity with which it is disseminated, how to effectively manage and apply governance is a key issue [2] for governments as well industries who want to have a competitive edge. Governments face several problems in respect to big data: how to use big data technology, change the governance concept, innovate the governance model, optimize the governance process, and the role of the government in the governance process [3].

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Today, China has a good market environment and development prospects, which provides it with certain basic conditions in the field of big data governance and application. However, China also has some shortcomings in terms of big data: there is no broad access to government data, the sharing of big data is limited, the industrial base is weak, the design of the top level and the norms of the system are lacking, and the follow-up measures are difficult to implement. These issues need to be taken seriously and need to be resolved successfully.

Due to the strong promotion of the big data openness policies of governments around the world, government information systems have undergone great change. This requires not only an appropriate government data governance philosophy, but also the appropriate technology that can be applied to the new environment to guide its development and maintain it.

The emergence of big data has created new requirements and challenges for the government's digital governance capabilities. In theory, government agencies can achieve the theoretical governance goals of big data, but it is difficult to prove whether the implementation measures can have a practical impact on specific businesses. By examining the governance of big data in local and foreign governments, we can improve government data governance capabilities, reduce the level of risk faced by open data, and improve data transparency for the benefit of society and promote social development. Government should recognize the importance of providing mobile information services and further advocates that big data should provide information literacy programs to help more people and organizations adapt to the new way of providing information services with big data.

2. RELATED WORK

The field of big data governance is mainly based on traditional information governance disciplines. Costello [4] explained that although big data has diverse characteristics, this diversity can also be applied to big data governance, offering a variety of choices in terms of governance approaches [5]. Zhixu [6] argues that the role of big data governance is to facilitate the rapid discovery of a large amount of structured and unstructured data that is secure, private, and cost-effective, and that can be collected, run, analyzed, stored, and protected. Moreover, it also includes advanced management methods, techniques, processes and practices. According to research, foreign big data governance has the following characteristics: diversified governance principles [7] and legal norms [8], multi-dimensional governance frameworks, methods and activities [9], multi-industry governance functions [10]. Some governance models need to be understood, including the Data Governance Framework proposed by the Data Governance Association [11] and the International Data Management Association [12].

Helliwell [13] pointed out that smart governments implement vertical single-level government management at city, state or national levels, or horizontal management involving interstate and local governments. Moreover, the government uses modern communication and information technology to implement integrated management, and then continuously innovate it to generate social value.

Some scholars believe that in an increasingly democratic society and with more transparent government management, a new environment can be created for government big data governance. It is unreasonable to expect the government to share data openly and actively and not pay attention to the participation of other social groups [14]. Jänicke recognized [15] that the governments of the United States, the United Kingdom, and Australia have paid more attention to the following aspects when formulating government big data governance policies: whether the dissemination of relevant government big data is timely and adequate, whether the construction of government big data technology facilities is sound, whether the protection of citizens' privacy is in place during the development and utilization of big data, whether information security can be guaranteed, and whether there is sufficient financial support for the development and utilization of government big data.

3. SPARSE ENCODER MODEL

Self-encoding neural networks belong to a commonly used deep learning model and involve unsupervised learning algorithms. The core of the network is the deployment of a back-propagation algorithm to approximate the output value of the model to the input value. Figure 1 shows a self-encoding neural network model.

Self-encoding neural networks attempt to learn a hypothesis function $h_{w,b}(x)$ by training to make $h_{w,b}(x) \approx x$. That is, the network attempts to approximate an identity hypothesis function $\hat{x} = x$ whose input is equal to the output. $\hat{x}$ is the output of the model. Sparsity Auto-encoders (SAE) is a neural network structure that adds sparse constraints to hidden neurons based on self-encoding neural networks to mine useful features related to input data. When the activation function of the neural network is sigmoid, the neuron is considered to be activated when the output value of the neuron is close to 1, and the neuron is suppressed when the output is close to 0. Therefore, the sparsity limit can be interpreted as limiting the neurons in the neural network so that they are suppressed for most of the time. This process in a sparse encoder can be expressed as follows:

$a_j^{(2)}$ represents the activation degree of the hidden neuron j, and $a_j^{(2)}\left(x^{(i)}\right)$ represents the activation degree of the hidden neuron j in the self-encoding neural network when the input $x^{(i)}$ is given, and $**\rho_j$ represents the average activation of the hidden neuron j. Then, the sparsity $**\rho_j = \rho$ is added to the network model. Among them ρ is the sparsity parameter, which is usually a small value close to 0, and $**\rho_j$ is calculated as shown in equation (1).

$$**\rho_j = \frac{1}{m}\sum_{i=1}^{m}\left[a_j^{(2)}\left(x^{(i)}\right)\right] \tag{1}$$

In order to achieve sparse constraints, an additional penalty factor β is added to the model's optimization objective function. It is mainly used to 'punish' those hidden layer neurons whose $**\rho_j$ and ρ are significantly different, so that their average activation is kept within a narrow range. There are many different options for the specific form of sparse restrictions. In this paper we choose a form based on relative entropy, $\sum_{j=1}^{s_2} KL\left(\rho|| **\rho_j\right)$, as shown in equation (2), where s_2 is the number of hidden neurons.

$$\sum_{j=1}^{s_2} KL\left(\rho|| **\rho_j\right) = \sum_{j=1}^{s_2}\log\frac{\rho}{**\rho_j} + (1-\rho)\log\frac{1-\rho}{1-**\rho_j} \tag{2}$$

At this time, the overall cost function $J(w,b)$ of the sparse encoder is based on the self-encoding neural network cost function $J_{sparse}(w,b)$ and then merged with the sparse restriction portion, as shown in equations (3) and (4):

$$J_{\text{spare}}(w,b) = J(w,b) + \beta\sum_{j=1}^{s_2} KL\left(\rho\| **\rho_j\right) \tag{3}$$

$$J(w,b) = \frac{1}{m}\sum_{i=1}^{m}\frac{1}{2}\left\|^{(i)} - x^{(i)}\right\|^2 + \frac{\lambda}{2}\sum_{l=1}^{n_{i-1}}\sum_{i=1}^{s_i}\frac{s_{i+1}}{j_{j-1}}\left(w_{ji}^{(l)}\right)^2 \tag{4}$$

In the formula, m represents the number of training samples, $w_{ji}^{(l)}$ is the parameter of the l-th layer self-encoder, λ is the weight penalty term, $\hat{x}^{(i)}$ is the output of the model for the

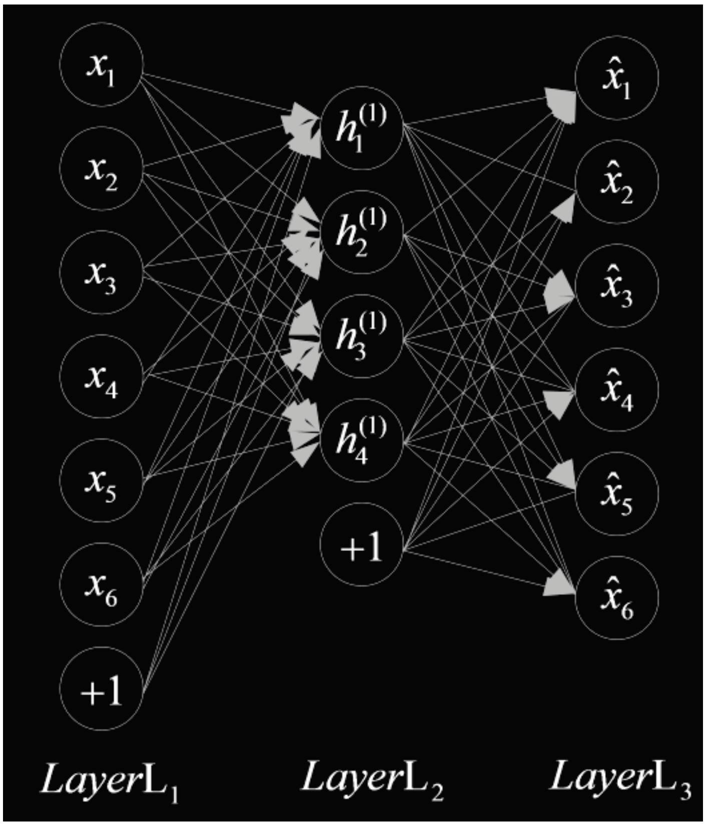

Figure 1 Self-encoding neural network.

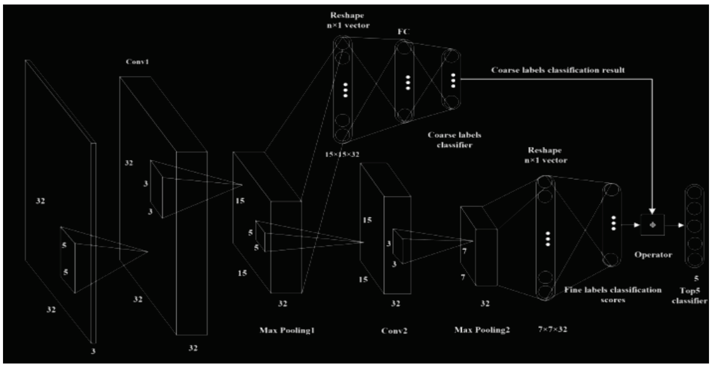

Figure 2 Multi-label convolutional neural network model.

i-th input data $x^{(i)}$, and n_1 is the number of network layers. For the sparse encoder model, there is $n_1 = 2$. Moreover, β is a sparse penalty term.

4. MULTI-LABEL CONVOLUTIONAL NEURAL NETWORK MODEL

In the modeling of the first-level label classification process and the secondary label task classification process, combined with the multi-task learning method, some parameters are shared between two different tasks and have the same low-dimensional characteristics. Figure 2 shows the parts shared by the two processes of the Conv1 layer and the Max Pooling1 layer. The introduction of tag semantics is performed in the ϕ unit of the diagram.

In constructing different classification tasks for tags with different semantic levels, except for the two classification processes sharing the low-dimensional features of the data, the classifiers used all select the Softmax classifier. In the deep learning theory research, the Softmax classifier is discussed and studied in detail. We will introduce the first-level label classification result in the secondary label classification process in combination with the characteristics of the Softmax classifier. The following will analyze the use of label semantics at different semantic levels.

Similar to the Logistic regression model, Softmax regression is often used in multi-category classification models, especially in deep learning related models. For a given data set:

$\left\{x^{(i)}, y^{(i)}\right\}_{i=1}^{m}$, where $y^{(i)} \in \{1, 2, \cdots, n\}$ is the label space;

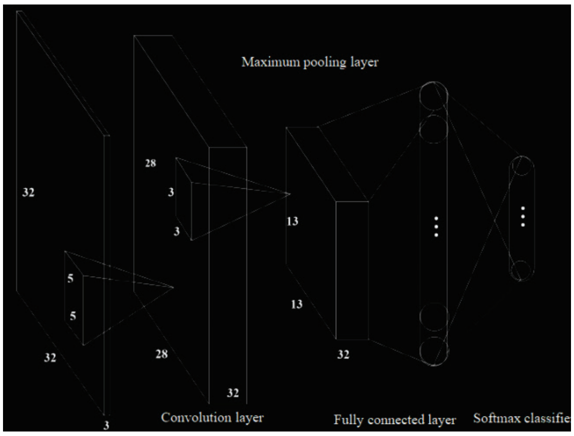

Figure 3 Shallow Convolutional Neural Network.

$$h_\theta\left(x^{(i)}\right)=\begin{bmatrix} p\left(y^{(i)}=1|x^{(i)};\theta\right)\\ p\left(y^{(i)}=1|x^{(i)};\theta\right)\\ \vdots \\ p\left(y^{(i)}=1|x^{(i)};\theta\right)\end{bmatrix} = \frac{1}{\sum_{j=1}^{k}\exp\left(-\theta_j^T x^{(i)}\right)}\begin{bmatrix}\exp\left(-\theta_1^T x^{(i)}\right)\\ \exp\left(-\theta_2^T x^{(i)}\right)\\ \vdots \\ \exp\left(-\theta_k^T x^{(i)}\right)\end{bmatrix} \tag{5}$$

Softmax regression learns the hidden mapping between data and labels in the form of equation (5) through data training. Moreover, the use of $\frac{1}{\sum_{j=1}^{k}\exp\left(-\theta_j^T x^{(i)}\right)}$ normalizes the output of the model to [0, 1], making the output of the model probabilistic $\theta_1, \theta_2, \cdots, \theta_k$ is the parameter that the model needs to learn.

In this study, the maximum confidence threshold ε is set, and the maximum probability value of the first-level label classification result is sequentially added to the threshold $\sum_{j=1}^{k} h_{\theta_2}\left(Y_j\right) \leq \varepsilon$. Moreover, this paper selects the sample categories corresponding to the probability values involved in the calculation, that is, the first-level tag categories, and calculates the number num_{loc_k} of secondary tag categories to be extracted for each class by probability. In addition, this study combines num_{loc_k} to output the corresponding secondary label category under the selected primary label, which is the top-5 result. Among them, the calculation method of num_{loc_k} is as shown in equation (6).

$$num_{loo_k} = floor\left(\frac{h_{\theta_2}\left(Y_k\right)}{\sum_{j=1}^{k} h_{\theta_2}\left(Y_j\right)}\right) \tag{6}$$

5. EXPERIMENTAL RESULTS FOR THE CIFAR-10 DATASET

In this paper, the network national governance data set is used for data enhancement experiments, and a shallow convolution depth learning model is designed, as shown in Figure 2. The details of the model and the experimental results are shown in Figure 3 below.

In order to keep the network parameters unchanged, in this paper we increase the training set using data enhancement techniques. Based on the shallow neural network shown in Figure 2, four experiments are repeated using the same test set of different training data sets, sets, which are the raw data set, the data set enhanced by the flip transform data, the data set enhanced by the scale transform data, and the data set enhanced by the noise transform data. Of these, the inversion transform data enhancement uses the left and right mirror transform, the scaling of the scale transform is reduced by 2 times, and the noise added in the noise transform is Gaussian noise, and the experimental result is shown in Figure 4.

The use of data enhancement techniques for national governance data sets to increase the training set has a certain impact on the performance of the network; that is, different data enhancement techniques have slightly different improvements in the average recognition rate of the model. The image transformation improves the recognition rate of the model by 2$\sim$3% on average; the noise transformation has no obvious effect on the average recognition rate of the model; and the scale transformation reduces the average recognition rate of the model to a certain extent. The main reason is that the size of the image in the CIFAR-10 data set is 32 $\times$ 32 which belongs to the small size image sample, so scaling the original image and increasing the noise operation will increase the difficulty of extracting the invariant features of the image, or will interfere with the features extracted from the original data set. Therefore, data enhancement technology can improve the performance of the network to a certain extent, but it is necessary to select the appropriate data enhancement technology according to the data set.

6. EXPERIMENTAL RESULTS AND ANALYSIS

The multi-label convolutional neural network model is divided into a first-level label classification process and a secondary label classification process, and the two processes share the Conv1 layer and the Max pooling1 layer of the model. Therefore, when training the entire network, the first-level label classification process is first removed, and the network

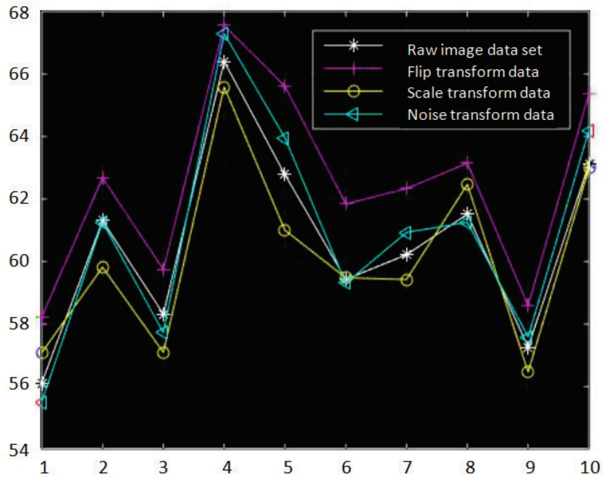

Figure 4 The result of the data enhancement experiment.

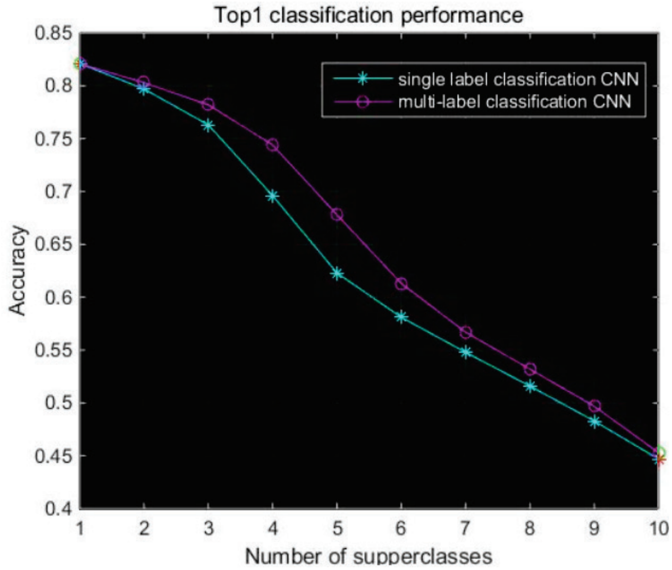

Figure 5 Comparison chart of Top-1 classification recognition rates.

corresponding to the secondary label classification process is separately trained. When the training error of the model converges or the number of iterations reaches the set upper limit, the training of the first-level label classification process begins. Moreover, the parameters in the Conv1 layer and the Max pooling1 layer are kept unchanged.

A multi-label convolutional neural network model introduces tag semantics in the classification process of convolutional neural networks to improve the classification performance of the model. Therefore, in the experimental stage, the image classification recognition rate of the multi-label convolutional neural network model and the single-label convolutional neural network model will be compared. The 10 categories of CIFAR-100, that is, the training data of 50 subcategories, are selected. In the course of the experiment, the superclass category that is, the dataset first-level label category is gradually added, and the top-1 and top-5 classification identification of the model is observed. Figures 5 and 6 show the comparison of the Top-1 classification recognition rate and the Top-5 classification recognition rate.

The experiment was performed on CIFAR-100 data and the experimental results showed that:

(1) The multi-label convolutional neural network model proposed in this study can obtain better image classification effects on the national governance dataset than the traditional convolutional neural network model using only a single label. For example, the recognition rate of top-1 is increased by 2.3% on average, and the recognition rate of top-5 is increased by 2.7% on average.

(2) Regardless of the multi-label convolutional neural network model proposed in this study or the traditional convolutional neural network model, the classification accuracy of the model including top-1 and top-5 recognition rates decreases with the increase of classification categories.

(3) In the top-1 classification recognition rate comparison experiment, with the increase of the number of classification categories, the trend of the classification

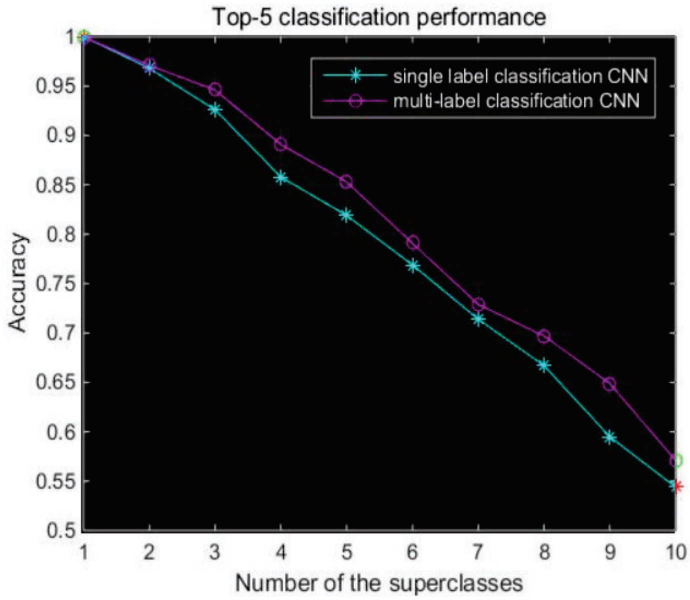

Figure 6 Comparison chartof Top-5 classification recognition rates.

difference between the research model and the single-label convolutional neural network model is relatively small, then gradually narrows the gap. Experiments show that when the number of classification categories is small, the output of the research model has the same distribution as that of the single-label convolutional neural network model, but as the number of classification categories increases, the difference of top-1 recognition rate becomes larger. This is because multi-label convolutional neural networks introduce tag semantics when classifying. Specifically, in the process of classifying the secondary tags, the probability distribution of the primary tag classification is introduced. When the number of classification categories is moderate, the greater accuracy of the primary label classification has a good guiding and limiting effect on the secondary label classification results.

(4) In the top-five classification recognition rate comparison experiment, similar trends as mentioned in (3) can be found, but the biggest difference is that when the number of classification categories is greater than 7, there is a small increase in the difference in top-5 classification recognition rate. The reason is that the top-5 classification of the multi-label convolutional neural network considers the first-level label probability distribution output by the first-level label classification in the output and introduces the output result of the first-level label classification in the probabilistic form in the secondary label classification process.

7. CONCLUSION

The measures taken by the government's big data governance can provide citizens with access to the government's business and a better understanding of the government's business operations, and enable the public to participate in government decision-making, so that this is no longer the sole privilege of the government. At the same time, through this method, the government can listen to the voices of people from all walks of life, so that public officials can understand the real needs of citizens in a down-to-earth manner, which not only allows citizens to get in touch with government work and provide more opportunities to realize individual life value, but also improves the quality of government decision-making. Collaboration between governments at all levels and between governments and non-profit organizations, businesses and the private sector can achieve a win-win situation, generate new opportunities for cooperation, and innovate tools and methods for government decision-making.

The concept of big data first emerged in American companies and used in the commercial sector. The United States has now applied the big data strategy of the commercial sector to the national government level. The United States, the United Kingdom, Canada and other countries have made remarkable progress in big data governance in terms of, promoting the government's open data, meeting the immediate needs of citizens, improving the transparency mechanism and open technologies, and providing protection for data governance. Compared with other countries, China has made a relatively late start in data governance compared to other countries, but we should not be hasty. We need to learn from the rich experiences of foreign countries to lay the foundation for the Chinese government's governance of big data.

The government needs to define its responsibilities, develop data transparency strategies, develop framework standards for data governance and data quality, and provide multiple mechanisms include those for the sharing of data resources. At the same time, the government needs to strengthen the construction of government data governance capabilities, and enable the big data industry to promote economic development and social progress in order to serve the people.

ACKNOWLEDGEMENTS

This paper is part of the Youth Project of the National Social Science Foundation of China "Research on the internal mechanism and realization path of socialist consultative democracy to promote the modernization of national governance" (17cks013), and the construction project of "first class discipline" of Marxism theory of Xiamen University (2017s008).

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