Future Generation Computer Systems 125 (2021) 672–676

Contents lists available at ScienceDirect

Future Generation Computer Systems

journal homepage: www.elsevier.com/locate/fgcs

E-commerce products recognition based on a deep learning architecture: Theory and implementation

Peng Zhang

School of Logistics, Chengdu University of Information Technology, Chengdu, Sichuan, 610225, China

ARTICLE INFO

Article history:
Received 7 June 2021
Received in revised form 28 June 2021
Accepted 29 June 2021
Available online 3 July 2021

Keywords:
E-commerce
Products recognition
Deep learning
LSTM
Big data

ABSTRACT

Nowadays, the number of goods in the market is increasing rapidly. In order to realize the efficient circulation of e-business products, it is necessary to apply the state-of-the-art image recognition technologies to improve the service quality. In this paper, on the basis of the deep learning towards the characteristics of product image, we formulate a novel deep architecture for searching products in e-business context. Specifically, we have designed a product image recognition platform, which consists of various actual cases. We have analyzed the application of this platform. Meanwhile, this work also discusses the theoretical basis of deep learning technology in time series forecasting, and sums up the commodity sales forecasting as multivariable time series. Using the historical sales data of an e-commerce online store, we also formulate the mechanism of constructing the LSTM network model under the well-known Tensorflow framework. We evaluate our method by comparing it with diverse AR models, it can be concluded that LSTM network model is simple and with convenient data input. Besides, it can be shown that good marketing decisions and reasonable inventory management is significant in products purchasing.

© 2021 Elsevier B.V. All rights reserved.

1. Introduction

Today, with the rapid development of e-commerce, smart phones and electronic payment are ubiquitous nowadays. The change of people's consumption and shopping habits has greatly influenced the traditional supply chain operation mode. Its dimensions are mainly reflected in the capital flow, information flow and product flow. In practice, demand forecasting is the most difficult problem for most enterprises to solve. A large number of online marketing data of enterprises can be viewed in the current mainstream e-commerce platform through query software. However, most e-commerce enterprises often cannot effectively use background data to assist business decision-making. Demand forecasting is still a key challenge for many enterprises Due to the characteristics of seasonality, dynamism and periodicity of data, the data series are often nonlinear, it is difficult to solve the cross performance multi time series problem with the traditional method of statistical time series model. However, the machine learning method is very flexible, which can assist business decision by predicting the sales volume of goods. Deep learning architectures [1], compared with shallow architectures, can automatically extract effective features from a large number of original data. Therefore, the model established by deep learning is not easy to implement, LSTM time recurrent neural network is suitable for forecasting and processing important events with relatively longer interval and delay in time series. In recent years, the deep feature has been widely applied in many related fields [2]. Based on LSTM network, we discuss the e-commerce sales forecasting model, wherein an effective and simple LSTM network model is established. In the experiment, the LSTM network model is built under the TensorFlow framework. The historical data of online stores are used for analysis and prediction, and the real value is compared with the predicted value. During designing, in order to stimulate consumers' desire to buy and ensure the identification of goods, the image features of goods are very rich, typical visual features can be divided into two categories, one is the underlying visual features, that is, the global and local features of goods, while the other is the intermediate semantic features of goods. During commodity recognition, the underlying visual features are usually applied. In other words, the image features of commodities can be divided into the following types, including color features, shape features, texture features, point features, semantic features and so on. Among these features, the color feature is the most direct way. The distribution of commodity image can be obtained by using the color histogram, and the shape region and contour boundary can be distinguished. Using an effective computer vision model, the feature points of commodity can be extracted.

Deep learning can be deemed as a perception technology based on neural network. Common neural networks include neuron model, perceptron, BP algorithm [3], convolution neural network, etc. Taking convolution neural network as an example,

E-mail address: zhangpeng@cuit.edu.cn.

https://doi.org/10.1016/j.future.2021.06.058
0167-739X/© 2021 Elsevier B.V. All rights reserved.

it is the most widely used neural network at present. It has been pervasively used in face recognition, speech recognition, license plate recognition, object detection and so on. Convolutional neural network and BP neural network are similar, they are composed of input layer, middle layer and output layer. But the middle layer of the former is more complex. In practice, such neural network has clear advantages. In the depth of the network, huge image data processing, the most important thing is that the use of this neural network can optimize the learning and training processes [4]. After determining the specific neural network, we can carry out deep learning using massive-scale data, learning with the assistance of network model. Feature learning in data is a very important, which can ensure that the accuracy of model prediction is improvable. After comparative analysis of multiple well-known deep architecture, the MXNET is selected as the experimental framework.

In the literature, deep learning has a great advantage in image classification and recognition. Nowadays, it has been widely used in many fields. It can further reduce labor cost and intelligently avoid the time and space limitations. The use of the commodity image recognition platform based on deep learning can improve the effectiveness and efficiency of commodity transportation. During application process, it can be divided into five stages: Alex net network structure, database preparation, data iterator generation, training process and commodity identification process. Neural network, according to the aforementioned platform, Alexnet network structure is highly important for the subsequent model training. This model has 60 million parameters and 65000 neurons [5]. The neural network adopts convolution operation, which is not only efficient but is also high accuracy. It is noticeable that the Alex net network structure involves several parameters, including: network layer, number of cores, kernel size, step size, filling, output size, etc. Second, database preparation. According to the environment system where the software is located, the database is developed by the Python. All the commodity images are named by letters and numbers. Third, the generation of data iterators. In the process of practical application, the method of commodity image recognition based on deep learning must leverages massive-scale data. In this process, it may be applied to dozens of GB of data [6], so the training and learning time is relatively large. Through the design of data iterator, we can improve the efficiency of training and learning and save cost. The MXNET used in this paper has the function of data iterator. Fourth, practical training. On the basis of creating network model, we can train formally until the accuracy rate is stable, the training model can be saved. Finally, the trained network model is applied to the commodity identification system. The method based on deep learning has a high accuracy, which can train the commodity recognition system continuously and update the parameters of the network model. Most importantly, it can meet the identification requirements of multiple different retail sites. For example, the schematic diagram of commodity portrait identification is the identification completed by this recognition method, which can accurately identify all commodities simultaneously. In order to develop the product image recognition technology according to development of retail stores, we should design a reasonable platform and database [7]. In practice, we should use the platform to collect and preprocess the image, and establish the image database that will lay a good foundation for the subsequent image recognition and analysis. The so-called experimental platform is to build an automatic recognition platform. The main hardware and equipment include camera lens, light source, storage platform, mechanical support, computer, to complete the acquisition of commodity image, and the work of commodity image database and model training will also be completed on the platform. In the software aspect, vs013 and python is utilized as the main development environment. The openCV is selected as the image processing tools, which has perfect computer vision and image processing algorithms. By combining the two, we can realize the functions of image acquisition, processing and data set construction.

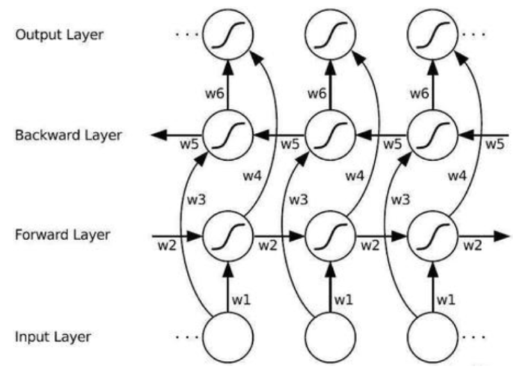

Fig. 1. An illustration of our adopted LSTM framework.

To our knowledge, the outer packaging of commodities is varied, as the structure and shape of the goods are different. To ensure the accurate identification of the diverse products, we in this work collect the commodity images comprehensively. The total number of shots of each commodity must be more than 50, and each side shall take pictures. Taking the box commodity as an example, six surface commodity images should be considered, so at least 9–10 pictures should be taken on each side. If it is a plastic packaging commodity, you can usually choose two sides to shoot, at least 25 pictures on each side. After the image collection is completed, the image preprocessing can be conducted. The key areas can be extracted by threshold segmentation, and then the preprocessing image can be generated. subsequently, the pre-processing image is added with pepper salt noise, Gaussian noise, Poisson noise respectively to make the model training more accurate. Then, we transform the geometry of the graphics, and further expand the preprocessing data by using the angle of Mirror Turning and multi angle rotation, so as to meet the requirements of the training of deep learning model for a large number of samples, In this way, the product image based on deep learning is improved.

2. Ours proposed method

2.1. The mechanism and architecture of lstm

Long term and short-term memory neural network is also called cyclic neural network [3]. RNN is widely used in time series prediction, and it is a special neural network for predicting and processing series data [4]. The structure and expansion of RNN neural network is shown in Fig. 1, which represents a cyclic neuron. In the figure, the expansion diagram on the right side expands the calculation diagram of cyclic neural network according to the time sequence, Where XT represents the input of time t, St represents the memory of time t, and ot represents the output of time T. it can be concluded that the output ot of the current time depends on the memory time of ST-1 and the input XT of the current time. The sequence data can be imported into the input layer of RNN in turn, RNN is good at solving time related problems. However, the last input signal (i.e. the deepest memory of the last input signal) is the main assistant to RNN decision-making, and the strength of the previous signal will become weaker and weaker with the delay of time, LSTM is produced to solve the problem that the memory distance is too short. Compared with the traditional recurrent neural network, LSTM designs the internal structure more carefully, adding three gates, i.e. input gate, forgetting gate and output gate, and an internal memory unit. The specific structure is shown in Fig. 2, In the structure diagram, XT represents the input of nerve cells at time t, HT represents the state value of nerve cells at time T. the three large boxes in the diagram represent the states of cells at different time sequences. The large diagram drawn by enlarging nerve cells at time t is shown in Fig. 3. In the diagram, there are symbols in the cells "δ" The small box represents the neural network layer with sigmoid activation function, which is composed of forgetting gate, then input gate and output gate. The small box with sign "tanh" represents the feedforward network layer with tanh activation function

It can be seen from Fig. 1 that LSTM obtains four state functions and outputs when XT and HT-1 transferred from the previous state are spliced and multiplied by the weight matrix

$$\text{it} = \delta(\text{wi}^*(\text{xt, ht-1} + \text{bi})) \tag{1}$$

$$\text{ft} = \delta(\text{wf}^*(\text{xt, ht-1} + \text{bf})) \tag{2}$$

$$\text{ot} = \delta(\text{wi}^*(\text{xt, ht-1} + \text{bo})) \tag{3}$$

$$\text{gt} = \tanh(\text{wg}^*(\text{xt, ht-1} + \text{bg})) \tag{4}$$

$$\text{ct} = \text{ct-1}^*\text{ft} + \text{it} * \text{gt} \tag{5}$$

$$\text{ht} = \text{ot} * \tanh(\text{ct}) \tag{6}$$

Among these equations, it, FT and OT are converted into values between 0 and 1 through the previous sigmoid activation function to form the gating unit, while gt is converted into values between −1 and 1 through the tanh activation function to be the candidate state values of the input cells at time t [8].

As shown in Fig. 1, the main task is to selectively forget the state value of CT-1 input by the previous node. Specifically, the result ft calculated by formula (2) is used as the forget gating to control which state CT-1 needs to forget. Selective memory is made for the input XT, and the specific content of the current input is expressed by the result GT calculated by formula (4). The gate control signal to be selected is the it control calculated by Eq. (1). Adding the results of the above two parts is formula (5) to get the CT transmitted to the next state.

LSTM outputs the current state HT. It mainly controls CT scaling through OT and tanh activation functions, so that it has long-term memory function. Our launched the TensorFlow on GitHub, which is an open source software library for adopted LSTM network model construction. In November 2015 [9], Google numerical calculation of data flow graph. It has successfully implemented deep learning algorithm, Keras is an API encapsulated on the basis of TensorFlow. These APIs encapsulate many small components of TensorFlow in the form of modules, which can greatly reduce the difficulty of programming. Users can easily arrange the modules built by the API according to the requirements, and then they can design various neural networks, which is easy to understand and use, Keras takes model as its core technology, and has two models, including functional model and sequential model. Among them, functional model is widely used in various experiments, while sequential model is a special case relative to functional model [10]. In this way, the root mean square error (RMSE) is utilized to compare and revise the experimental results of our model.

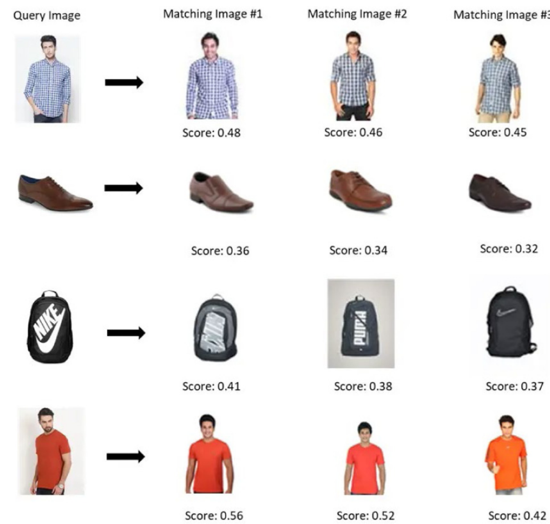

Fig. 2. An example of searching various e-business products.

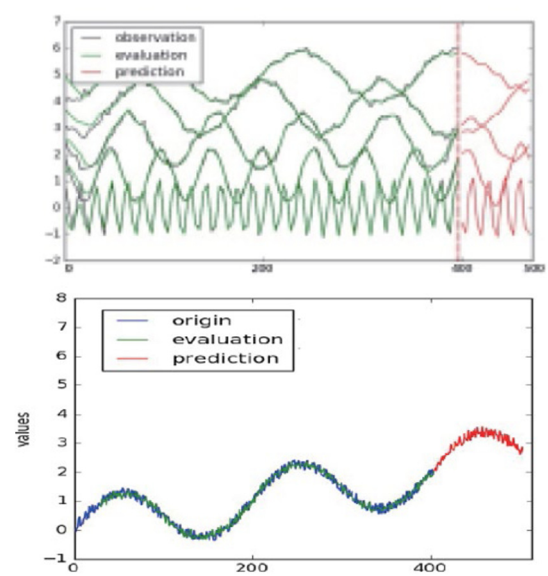

Fig. 3. Visualization results of the LSTM training accuracy.

2.2. Implementation details of our product search engine

The product sales data is converted into CSV file. The time point is listed in the first column of the file. At the same time point, there are 5 data including SALE, PAY, number of views (PV), number of views (UV) and display volume of the product. The code read into the CSV file using TFTS is shown in Figure 5.3.2 Data Preprocessing is to reduce the impact of noise data on the selected 400 training data, and the garble codes and empty values in the selected training data are cleaned and processed, and the processed input data shall meet the requirements of supervised learning data [11].

There are many characteristic factors that affect the sales volume of goods. When making a decision, it is often necessary to understand the influence degree of each characteristic factor on the result, so it is necessary to evaluate the characteristics. There are many feature evaluation methods [10]. In this test, the dependent variable is a numerical interval variable with a linear relationship between its expected value and multiple independent variables, so the mathematical model of feature extraction uses linear regression algorithm. The formula of multiple linear regression algorithm is shown in Eq. (7):

$$f(x) = a1 \times 1 + a2 \times 2 + a3 \times 3 + a4 \times 4 + a5 \times 5 + \cdots + c \quad (7)$$

where X1 and X5 are the characteristic data that affect the sales volume of goods, namely the extracted five data of SALE, price PAY, number of visits, number of visitors, UV and display volume of goods, while A1 is obtained through model training of the algorithm. A5, c is the model coefficient, where c is the random error term. The objective of data normalization is to reduce the impact of dimensionality on calculation, process the data and limit its value between [0,1], which can accelerate the convergence speed of the algorithm. The specific calculation method of normalization is shown in Formula 8. In the formula, Maxvalue and Minvalue are the maximum and minimum values of each field data respectively. X is the specific value of the field data, and Y is the final result of data normalization. Because ReLU is the activation function in the experiment, it is necessary to convert the data set to [−1,1] in order to do the experiment. Num_FEeartures = 6 means that the observed value is a 5-dimensional vector at each point in time, and Num_Units = 128 means that the LSTM model with the hidden layer size of 128 is used. Finally, this is done using the Pyplot module of Matplotlib [12].

3. Experimental results and analysis

3.1. Experimental setups and platform

In our experiment, the order data of the experimental object is from the e-commerce sales data of a luggage company. The reason for choosing the sales data of luggage is that the bags are not affected by seasonal factors, and the SKU types are relatively stable without frequent changes. The collected data is convenient for training and verification. Founded in 2009 [13], the company is a professional fashion and leisure brand manufacturer and distributor integrating design, development, production and sales. It has more than 200 product categories, and the number of SKUs has reached more than 500. In recent years, the company's operating status is on the rise in the ranking of luggage industry. Faced with more and more sales volume and more SKUs, whether the company can accurately predict the online sales volume has become an important link in the online sales, especially for the preparation of "Double 11" and other e-commerce activities plays a key role. The SKU with large sales volume in the company has relatively perfect historical sales data. If we can make a more accurate prediction of SKU's future sales volume through these perfect data, it will be of great help to the future operation and development of the company. Therefore, the experimental object of this paper selected the SKU of a popular logo backpack which ranks the top in Tmall mall, and the data set was the original log data extracted by the business staff in the past two years (a total of 500 pieces). Each data includes the sales volume of the product (the daily sales number of the backpack), price PAY (the daily sales price of the backpack), and browse times PV (the daily page views or clicks of the backpack sales page. The user has opened or refreshed the page many times. The index value accumulation), the number of visitors UV (into the backpack sales page of the independent visitors, the same visitor into the index value will be calculated to repeat), the amount of display (when the user search related keywords, the number of backpack display) and other indicators data and the actual sales of correlation analysis. There are 500 pieces of original log data in two years, among which 400 pieces are taken as training samples of LSTM time recursive neural network model, and the remaining 100 pieces are used to test the training results and verify the accuracy of the neural network model. The experimental training process is completed in the following steps: data downloading, data preprocessing, data feature extraction, data normalization, model training, fine-tuning parameters, sales volume prediction, etc. [8].

Table 1
Compared recognition accuracy of the searching methods.

	SPM	SSC-SPM	AlexNet	Ours
Set 1	76.541%	74.456%	80.665%	85.454%
Set 2	65.565%	67.557%	70.565%	84.345%
Set 3	56.665%	49.879%	62.342%	72.331%

3.2. Visualization results on products search

The visualization task of the result, and the final running result is shown in Fig. 3. The first 400 steps in the figure are the training data, and the predicted value is after 400 steps. It can be seen from the figure that there is still a big gap between the fitting value of the LSTM [14] model and the actual original data in the training process of the first 50 steps. After 100 steps of training, the two values are very similar. This experimental result shows that the LSTM neural network model is relatively accurate in extracting the main features of the problem and can carry out the overall training efficiently. Have effective training methods. It can also be seen from the experimental results that, in the training calculation, the local data did not affect its predicted value and the phenomenon of gradient disappearance did not occur. After 200 steps of training, the fitting value of the model was basically the same as the original data, which indicated that the model had a good fitting degree [15,16]. In this way, the prediction data after 400 steps will be relatively more accurate, which proves that this multi-layer LSTM network model has less technical complexity and efficient and accurate prediction performance. Compared with autoregressive model (AR), autoregressive model, also referred to as AR model, is a basic method of processing as a time series model in statistics. AR model uses a certain mathematical model to describe the similarity of a random sequence. This random sequence is the predicted object through the passage of time. And the gradual formation of a data sequence. After this model is recognized by the system, it can predict the future value through the past value and the present value contained in the time series. AR model is one of the most common stable Time Series models nowadays [12]. TensorFlow1.3 version introduced a Time Series module (TensorFlow Time Series (TFTS).TFTS provides a set of basic Time Series model API. Provide a variety of prediction models including AR, LSTM and so on. The AR model provided by TFTS of TensorFlow was used to train the data, and then the future data was predicted after verification. In the experiment, 500 data sequences were selected for the whole length of the training, and the first 30 data sequences were used in the experiment when the "initial observation sequence" was input. Calculate the value of the next 10 steps from this action. And then the experiment is going to take another 30 values.

3.3. Visualization results on products search

From the above, it can be seen that deep learning has great advantages in image classification and recognition. Nowadays, it has been widely applied in many fields. Its application in the field of commodity image recognition can further reduce labor costs and get rid of the limitations of time and space. It can be seen from the above that the commodity image recognition platform based on deep learning can improve the level and efficiency of commodity transportation. In the practical application process, it can be divided into five stages, which are: Alex Net network structure, database preparation, data iterator generation, training process, and actual application of commodity identification process. First, neural networks. According to the platform designed above, the AlexNet network structure can lay a good foundation for subsequent computational training. This model has 60 million parameters and 65,000 neurons. Its neural network adopts convolution operation, which is not only efficient but also relatively high in accuracy. It should be noted that there are several parameter items involved in the Alex Net network structure, including: number of network layers, number of kernels, kernel size, step size, padding, output size, etc. Second, database preparation. According to the environment system where the software is located, Python language is finally chosen to develop the database, and the names of all commodity images are replaced by letters and numbers [3]. Third, the generation of data iterators. The commodity image recognition method based on deep learning must carry out big data learning in the practical application process. In this process, tens of GB of data may be applied, so the training and learning time is relatively large. By designing the data iterator, the efficiency of training and learning can be improved and the cost can be saved. The MXNet framework used in this article has data iterators. Fourth, practical training. On the basis of creating the network model, the training can be formally carried out. When the accuracy rate tends to be stable, the training model can be saved, and finally the trained network model can be applied in the commodity identification system. According to the actual application, the product image recognition method based on deep learning has a high accuracy rate, which can continuously train the product recognition system and update the parameter files of the network model. Most importantly, it can meet the identification requirements of multiple different retail outlets. As shown in Table 1, the identification diagram of commodity portrait is accomplished by using this identification method, which can accurately identify all commodities at one time.

4. Conclusions

For e-commerce enterprises, demand prediction is the most common and important application in the daily operation of most enterprises. This paper formulates the theoretical basis of deep learning technology in temporal series prediction and the prediction of commodity sales volume into multivariable temporal series. Using the historical data of an e-commerce store, The method of building LSTM network model under TensorFlow framework is introduced in detail. The sales forecast results obtained from model calculation are accurate and intuitive. Compared with AR model, which is a common time series prediction model, the results have demonstrated that LSTM network model has more advantages in terms of network structure, efficiency and effectiveness of training method and accuracy of prediction. The forecast model of e-commerce commodity sales based on our LSTM neural network has the advantages of simple data input, simple model technology and higher accuracy than other forecasting models. Our constructed deep neural network can be leveraged to analyze and mine the correlation coefficient between the characteristics and attributes of commodities. It can also visually display the influence degree of the sales volume of commodities as well as its key information. The research is significant for enterprises to improve marketing decisions and reasonable inventory management.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] G.T. Gudhmundsson, L. Amsaleg, B.T. Jónsson, M.J. Franklin, Towards engineering a web-scale multimedia service: A case study using spark, in: Proceedings of the 8th ACM on Multimedia Systems Conference, MMSys'17, ACM, New York, NY, USA, 2017, pp. 1–12, http://dx.doi.org/10.1145/3083187.3083200, 705 URL http://doi.acm.org/10.1145/3083187.3083200.

[2] E. Valle, M. Cord, S. Philipp-Foliguet, High-dimensional descriptor indexing for large multimedia databases, in: Proceeding of the 17th ACM Conference on Information and Knowledge Management, CIKM, 2008, pp. 739–748, http://doi.acm.org/10.1145/1458082.1458181.

[3] P. Ram, D. Lee, H. Ouyang, A.G. Gray, Rank-approximate nearest neighbor search: Retain710 ing meaning and speed in high dimensions, in: Advances in Neural Information Processing Systems (NIPS) 22 (Dec 2009), MIT Press, 2010.

[4] M. Muja, D.G. Lowe, Scalable nearest neighbor algorithms for high dimensional data, IEEE Trans. Pattern Anal. Mach. Intell. 36 (11) (2014) 2227–2240, http://dx.doi.org/10.1109/TPAMI.2014.2321376.715.

[5] C. Silpa-Anan, R. Hartley, Optimised KD-trees for fast image descriptor matching, in: IEEE Conference on Computer Vision and Pattern Recognition, 2008, pp. 1–8, http://dx.doi.org/10.1109/CVPR.2008.4587638.

[6] D. Nister, H. Stewenius, Scalable recognition with a vocabulary tree, in: IEEE Computer Society Conference on Computer Vision and Pattern Recognition, CVPR, 2006, pp. 2161–2168, http://dx.doi.org/10.1109/CVPR.2006.264, 720;
A Stupar, S. Michel, R. Schenkel, RankReduce - processing K-nearest neighbor queries on top of MapReduce, in: In LSDS-IR, 2010.

[7] B. Bahmani, A. Goel, R. Shinde, Efficient distributed locality sensitive hashing, in: Proceedings of the 21st ACM International Conference on Information and Knowledge Management, CIKM 725 '12, ACM, 2012, pp. 2174–2178, http://dx.doi.org/10.1145/2396761.2398596.

[8] J. Pan, D. Manocha, Fast GPU-based locality sensitive hashing for K-nearest neighbor computation, in: Proceedings of the 19th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems, GIS '11, ACM, New York, NY, USA, 2011, pp. 211–220, http://dx.doi.org/10.1145/2093973.2094002, 730 URL http://doi.acm.org/10.1145/2093973.2094002.

[9] M. Krulis, T. Skopal, J. Lokos, C. Beecks, Combining CPU and GPU architectures for fast similarity search, Distrib. Parallel Databases 30 (2012) 179–207, http://dx.doi.org/10.1007/s10619-012-7092-4.

[10] X. Yang, Y. Hu, A landmark-based index architecture for general similarity search in peer-topeer networks, in: IEEE International Parallel and Distributed Processing Symposium, 2007. 740 IPDPS 2007, 2007, pp. 1–10, http://dx.doi.org/10.1109/IPDPS.2007.370230.

[11] G. Teodoro, E. Valle, N. Mariano, R. Torres, W. Meira Jr., Adaptive parallel approximate 735 similarity search for responsive multimedia retrieval, in: Proc. of the 20th ACM Int. Conf. on Information and Knowledge Management, CIKM '11, 2011, URL http://doi.acm.org/10.1145/2063576.2063651.

[12] L. Cayton, Accelerating nearest neighbor search on manycore systems, in: International Parallel and Distributed Processing Symposium (IPDPS 2012), 2012, pp. 402–413, http://dx.doi.org/10.1109/IPDPS.2012.45.

[13] The Message Passing Interface (MPI). 745 URL http://www-unix.mcs.anl.gov/mpi/.

[14] J. Johnson, M. Douze, H. Jégou, Billion-scale similarity search with GPUs, 2017, arXiv preprint arXiv:1702.08734.

[15] A. Wakatani, A. Murakami, GPGPU implementation of nearest neighbor search with product quantization, in: 2014 IEEE International Symposium on Parallel and Distributed Processing 750 with Applications (ISPA), IEEE, 2014, pp. 248–253, http://dx.doi.org/10.1109/ISPA.2014.42.

[16] D. Moise, D. Shestakov, G. Gudmundsson, L. Amsaleg, Indexing and searching 100M images with map-reduce, in: Proceedings of the 3rd ACM Conference on International Conference on Multimedia Retrieval, ICMR '13, ACM, New York, NY, USA, 2013, pp. 17–24, http://dx.doi.org/10.1145/2461466.2461470.

Peng Zhang was born in Mengcheng, Anhui.P.R. China, in 1981. He received the bachelor and master's degree from Wuhan University, P.R. China. Now, he works in School of Logistics, Chengdu University of Information Technology. His research interest include Application of e-commerce technology, big data analysis. E-mail: zhangpeng@cuit.edu.cn