Prediction of employment figures in the three main industries based on extreme learning machine

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Abstract

Extreme learning machine, with a fast speed of training, achieves globally optimal solutions and excellent generalization ability. This work is based on the production value and employment figure of the three main industries in China during 1996-2012 as research objects. An ELM employment figure prediction model was constructed with production value and the employment figure of the three main industries respectively as the input and output of extreme learning machine. Simulation test results proved a good effect and high accuracy of ELM employment figure prediction model. Besides, the comparison of ELM, BP and RBF algorithms further proved the effectiveness and precision of ELM, which has certain practical application value.

Keywords: three main industries, extreme learning machine, production value, neural network, training samples, test samples

1 Introduction

With the rapid development of economy and continuous upgrading of industrial structure in China, the total employment and structure of labor force have experienced dramatic changes. Under the combined effects of incoming labor force and transfer of laid-off labor and rural labor, employment in China becomes an increasingly severe problem.

Since there are some interconnection influences between industrial structure and employment, additional investment to some industries can directly create large amount of employment opportunities. Additional investments to some industries may not create more employment opportunities, but it can directly or indirectly influence consumption of products in other industries, thus providing employment opportunities. Therefore, the employment opportunities of the whole economic system will be increased accordingly [1].

Adjusting industrial structure is an important way to realize optimization of internal structure of economic system, solving employment problems and increasing employment opportunities in each industry. Therefore, researches on the potential of employment in the three major industries are of great significances to employment.

In recent decades, China has achieved high-speed growth in economy, but employment growth is relatively slow. At present, rural surplus labor and college graduates become main employment forces. They are faced with various employment pressures; some of them are even faced with unemployment. As a result, Chinese people are facing big pressure from employment at present. Besides, the total labor force exceeds the demands of employment, but some places are in a shortage of labors. Therefore, employment structural contradictions become increasingly fierce [2-3].

With huge employment pressure, it is of important theory value and practical significance to broaden visions and fully consider national situations while absorbing employment theory from western economics researches. Only on such basis can prediction of employment figure be achieved effectively.

2 Extreme learning machine neural network

It is clear that the learning speed of feed forward neural networks is in general far slower than required and it has been a major bottleneck in their applications for past decades. Two key reasons behind may be: (1) the slow gradient based learning algorithms are extensively used to train neural networks, and (2) all the parameters of the networks are tuned iteratively by using such learning algorithms. Unlike the traditional implementations, we applied a new learning algorithm called extreme learning machine (ELM) for SLFNs which randomly chooses the input weights and analytically determines the output weights of SLFNs. This algorithm tends to provide the best generalization performance at extremely fast learning speed.

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As pointed out by [4-9], for feedforward networks with many small weights but small squared error on the training examples, the Vapnik-Chervonenkis (VC) dimension (and hence number of parameters) is irrelevant to the generalization performance. Instead, the magnitude of the weights in the network is more important. The smaller the weights are, the better generalization performance the network tends to have. As analyzed above, our method not only reaches the smallest squared error on the training examples but also obtains the smallest weights. Thus, it is reasonable to think that our method tends to have better generalization performance. It should be pointed out that it may be difficult for gradient-based learning algorithms like back-propagation to reach the best generalization performance since they only try to obtain the smallest training errors without considering the magnitude of the weights.

3 Data sources and variable selection

In order to predict employment figure in the three main industries in China, this work selected the production value and employment data during 1996~2012 from each industry as samples (Table 1). Employment figure of each industry was considered as explanatory variable \(L_i\), GDP of each industry as the explained variable \(Y_i\). All data comes from 1996~2012 China Statistical Yearbook [10,11].

<table>
<thead>
<tr>
<th>Year</th>
<th>(Y_1/100) Million RMB</th>
<th>(L_1/10) Thousand People</th>
<th>(Y_2/100) Million RMB</th>
<th>(L_2/10) Thousand People</th>
<th>(Y_3/100) Million RMB</th>
<th>(L_3/10) Thousand People</th>
</tr>
</thead>
<tbody>
<tr>
<td>1996</td>
<td>5,866.6</td>
<td>38.49</td>
<td>11,699.5</td>
<td>14,226</td>
<td>9,557.3765</td>
<td>12,979</td>
</tr>
<tr>
<td>1997</td>
<td>6,963.629</td>
<td>37.43</td>
<td>16,544.431</td>
<td>14,868</td>
<td>11,915.731</td>
<td>14,071</td>
</tr>
<tr>
<td>1998</td>
<td>9,572.6948</td>
<td>36.49</td>
<td>22,445.399</td>
<td>15,254</td>
<td>16,179.763</td>
<td>15,456</td>
</tr>
<tr>
<td>1999</td>
<td>12,135.811</td>
<td>35.468</td>
<td>28,679.458</td>
<td>15,628</td>
<td>19,978.46</td>
<td>16,851</td>
</tr>
<tr>
<td>2000</td>
<td>14,015.39</td>
<td>34.769</td>
<td>33,834.959</td>
<td>16,180</td>
<td>23,326.243</td>
<td>17,901</td>
</tr>
<tr>
<td>2001</td>
<td>14,441.886</td>
<td>34.73</td>
<td>37,543.002</td>
<td>16,495</td>
<td>26,988.147</td>
<td>18,375</td>
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<tr>
<td>2002</td>
<td>14,817.626</td>
<td>34.838</td>
<td>39,004.189</td>
<td>16,440</td>
<td>30,580.466</td>
<td>18,679</td>
</tr>
<tr>
<td>2003</td>
<td>14,770.28</td>
<td>35.364</td>
<td>41,033.582</td>
<td>16,235</td>
<td>33,873.845</td>
<td>18,987</td>
</tr>
<tr>
<td>2004</td>
<td>14,944.723</td>
<td>36.043</td>
<td>45,555.878</td>
<td>16,217</td>
<td>38,713.954</td>
<td>19,823</td>
</tr>
<tr>
<td>2005</td>
<td>15,781.269</td>
<td>36.513</td>
<td>49,512.291</td>
<td>16,284</td>
<td>44,361.611</td>
<td>20,228</td>
</tr>
<tr>
<td>2006</td>
<td>16,537.02</td>
<td>36.87</td>
<td>53,896.768</td>
<td>15,780</td>
<td>49,898.902</td>
<td>21,090</td>
</tr>
<tr>
<td>2007</td>
<td>17,381.718</td>
<td>36.546</td>
<td>62,436.312</td>
<td>16,077</td>
<td>56,004.726</td>
<td>21,809</td>
</tr>
<tr>
<td>2008</td>
<td>21,412.734</td>
<td>35.269</td>
<td>73,904.312</td>
<td>16,920</td>
<td>64,561.292</td>
<td>23,011</td>
</tr>
<tr>
<td>2009</td>
<td>22,420</td>
<td>33.97</td>
<td>87,364.579</td>
<td>18,084</td>
<td>73,432.866</td>
<td>23,771</td>
</tr>
<tr>
<td>2010</td>
<td>24,040</td>
<td>32.561</td>
<td>103,162</td>
<td>19,226</td>
<td>84,721.4</td>
<td>24,614</td>
</tr>
<tr>
<td>2011</td>
<td>28,627</td>
<td>31.444</td>
<td>124,799</td>
<td>20,629</td>
<td>103,879.59</td>
<td>24,917</td>
</tr>
<tr>
<td>2012</td>
<td>34,000</td>
<td>30.654</td>
<td>146,183.4</td>
<td>21,109</td>
<td>120,486.61</td>
<td>25,717</td>
</tr>
</tbody>
</table>

\(Y_1\) refers to the production value of the first industry; \(Y_2\) the production value of the second industry; \(Y_3\) the production value of the third industry. \(L_1\) is the employment figure of the first industry; \(L_2\) the employment figure of the second industry; \(L_3\) the employment figure of the third industry.
Figures 2 and 3 show that production values of the 2nd and 3rd industries increased year by year since 1996. And, the growth rate of the 2nd industry was greater than that of the 3rd industry. On the contrary, employment figure of the 1st industry declined year by year, implying that the 1st industry’s allocation of labor ability was getting weaker. However, employment figures of the 2nd and 3rd industries also increased year by year. It means employment absorption capacity of the 2nd and 3rd industries is far greater than that of the 1st industry.

4 Employment figure prediction based on extreme learning machine

With production value and employment figure of the three main industries, respectively, as the input and output of extreme learning machine, a training model was established to predict employment figure. There were two sets of samples: 17 training samples and 5 test samples, all verifying the prediction ability of extreme learning machine network.
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**FIGURE 5** Prediction results and errors of employment figure of the 2\textsuperscript{nd} Industry

- **a)** Prediction results of training samples
- **b)** Prediction results of test samples
- **c)** Absolute error
- **d)** Relative error

**FIGURE 6** Prediction results and errors of employment figure of the 3\textsuperscript{rd} Industry

- **a)** Prediction results of training samples
- **b)** Prediction results of test samples
- **c)** Absolute error
- **d)** Relative error
Figure 3-5 respectively showed the prediction results of extreme learning machine. Figure 3a-5a, explained prediction results of training samples, presenting a good prediction and strong generalization ability. Figure 3 (b), Figure 4 (b) and Figure 5 (b) presented prediction results of test samples, mainly verifying the effectiveness and accuracy of extreme learning machine. It can be seen from Figure 3 (c) (d), Figure 4 (c) (d) and Figure 5 (c) (d) that this algorithm achieves good effects.

In order to compare and verify the superiority of this algorithm, the prediction results of ELM, BP neural network and RBF neural network were compared. It can be seen that ELM has the best prediction results; RBF neural network has a worse prediction results compared with ELM; BP neural network has the worst. Comparison of those different algorithms verified the effectiveness and accuracy of ELM. Therefore, extreme learning machine, with certain practical application significance, can be used to classify and predict problems.

5 Conclusions

Based on production value and employment figure of the three main industries during 1996-2012 in China as research objects, this work established ELM employment figure prediction model. It was used to predict employment figures when production value and employment figure of the three main industries were respectively used as output and input of extreme learning machine. Comparison of ELM, BP and RBF further proved the effectiveness and high accuracy of ELM. Thus, this algorithm, with certain practical application value, can be used to classify and forecast problems.

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