Journal of Robotics, Networking and Artificial Life, Vol. 3, No. 4 (March 2017), 265-269

Detection of changes in the employment environment in Japan based on the numbers of people leaving and entering employment using NMF

Masao Kubo, Hiroshi Sato
Computer Science, National Defense Academy, Hashirimizu 1-10-20
Yokosuka, Kanagawa 239-8686, Japan

Akihiro Yamaguchi
Fukuoka Institute of Technology, 3-30-1 Wajiro-higashi,
Higashi-ku, Fukuoka, Japan

Yuji Aruka
Faculty of Commerce, Chuo University, Higashinakano
Hachioji-shi, Tokyo, Japan
E-mail: masaok@nda.ac.jp, hsato@nda.ac.jp, aki@fit.ac.jp, aruka@tamacc.chuo-u.ac.jp
www.nda.ac.jp/cs/stuff/masaok.html

Abstract

If there were no changes in the environment surrounding businesses, the numbers of people leaving and entering employment would stay almost the same. Therefore, understanding the numbers allow us to make assumptions about the changes inside and outside companies. However, when categorizing businesses into industry sectors and clusters of business, you will see that the numbers of people leaving and entering employment have been nearly opposed for the last 15 years, and it is difficult to detect changes in the employment environment of Japan's businesses. This study tried to improve the sensitivity of detecting changes by applying NMF (non-negative matrix factorization) into the Survey of Employment Trends. While businesses maintain the number of people they employ at a certain level because of severe restrictions, we assumed they respond to the surroundings by changing the composition of employment. Accordingly, we identified the correlation between the numbers of people leaving and entering employment in each sector characterized by employment patterns that we found by applying NMF. As a result we successfully improved the sensitivity level of detecting changes, which we would like to report in this study.

Key words: resilience, data mining, machine learning

1. Introduction

In principle, it is assumed that more employees leave companies when employers believe that the current number of employees is too many; conversely, the number of people entering companies increases when employers believe that the number of employees is too few. Therefore, if these numbers are the same, you can assume that the employer thinks their business environment is stable. While, if the numbers are largely different, you can assume that companies were forced to make corporate changes due to changes in their surrounding environment. Applying this assumption to industry sectors, which are clusters of businesses in the same fields, by studying the numbers of people leaving and entering employment, you must be able to make assumptions about the country-wide changes in the employment environment from the difference between the numbers.

The survey of employment trends is statistical data based on a questionnaire survey of businesses and people leaving and entering employment conducted by the Ministry of Health, Labour and Welfare (MHLW). It has been conducted for several decades, and the results have been published on the Internet twice a year since 2000. This survey reported employment information of about 45 types of industries (hereinafter called "sectors") categorized on the basis of the Japan Standard Industrial Classification, excluding agriculture and fisheries.

According to this open data, although a catastrophic incident called the Lehman crisis has occurred, the numbers of people leaving and entering employment in industry sectors in Japan have stayed nearly the same for the last 15 years and it is hard to say that it indicates the changes in employment environment during the period at a glance. One reason is based on the fact that companies have significant restrictions and social responsibilities. Even if companies have deteriorated business performance and more people leave employment, companies are obligated to acquire skills and knowledge provided by new employees to maintain a certain level of business performance and have the social responsibilities to survive the competition and support permanent employees. Therefore, it is assumed that even though the change in the number of employees is small, there should be large changes in the type and characters of human resources they hire.

In this study, we visualize the changes in the environment surrounding employment in Japanese industries, incorporating the changes in human resources they employee from their abilities point of view into the numbers of people leaving and entering employment. Therefore, here we extracted the employment patterns using NMF and defined the characteristics of the numbers of people leaving and entering employment in each sector. It is assumed that the required human resources should be distributed across various sectors in industries, and in certain sectors, employers' employing those human resources must give impact on the number of people leaving and entering employment in the related sectors. Also, these types of human resources probably are likely to be in demand in other sectors. If we can find a set of potential patterns related to the numbers employed, we believe that we can more clearly visualize the changes in the surrounding environment by looking at the changes in the composition of each pattern of the number of people leaving and entering employment.

Non-negative Matrix Factorization (NMF) (Ref.7) is a method to decompose the matrix with elements of either zero or a positive value into the product of two non-negative matrices. Using its feature that subtracting is not allowed, in principle, the method has been widely used in the field of signal separation (Ref.2,4,8). Although there are some application examples of this method to economic activities (Ref.1), there were no examples of this method applied to visualize the employment environment.

2. Survey on Employment Trends

This study examined the MHLW Survey on Employment Trends (Ref.5,6,3). The MHLW conducts the questionnaire survey twice a year and publishes the number of employees, those changing careers, and hired employees by industry. This study used 15 years of annual data between 2000 and 2014. The industry classification is based on the Japan Standard Industrial Classification. The following studies use the industrial sector classification called middle classification. It is, roughly speaking, a classification dividing industrial areas, except for agriculture and fisheries into smaller areas. Although the classification has been changing slightly since 2000, this study classification employed a total of 55 types of industries reflecting the changes and including duplication.

3. Recent employment trends in Japan

Using this data, this study provides the data of recent employment trends in Japan. It founds that there is no large difference between the numbers of people leaving and entering employment in each industrial sector in the last 15 years. The number of hired employees refers to the number of persons who started working in the sector as of this year, while the number of separated employees refers to the number of persons who left the sector. Figure 1 illustrates the numbers of hired employees and separated employees in each sector included in the survey on employment trends in 2014. Those leaving and entering employment are shown on a bar graph in order of sector. The vertical axis shows the number of people (unit: 1000 people).

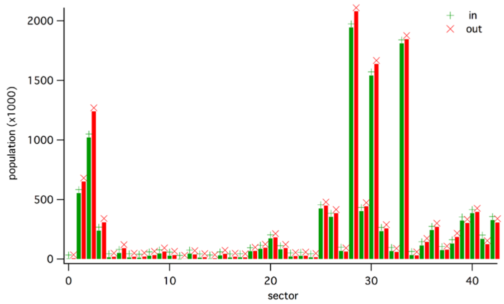

Fig. 1 Results of the Survey on Employment Trends in 2014

Bars with “+” on the top of it represent the number entering employment and bars with “×” represents those leaving employment. You can see that those entering and leaving employment are significantly different across sectors but they are nearly the same if they are in the same sector and same year.

Table 2 Similarities among the numbers of entering and leaving employment between 2000 and 2014

2000	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**
0.998	0.993	0.992	0.997	0.996	0.997	0.997	0.999
2008	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	
0.996	0.936	0.996	0.997	0.996	0.997	0.994	

Table 2 shows the results of these changes in a quantitative manner. When the number of people entering employment in the year y in the sector i is set as $a_{y,i}$, and the number of people leaving employment is $s_{y,i}$, the cosine of the vector of the people entering employment a_y = ($a_{y,0}$, ..., $a_{y,i}$, ..., $a_{y,54}$) and that of the people leaving employment s_y = ($s_{y,0}$, ..., $s_{y,i}$, ..., $s_{y,54}$) is

$$\cos(\angle a_y, s_y) = a_y \cdot s_y / |a_y||s_y| \qquad (1).$$

The value given from this formula in each year is shown in Table 2. The values except 0.936 in 2009, immediately after the Lehman crisis, were over 0.99, which shows that the numbers of people entering and leaving employment are nearly the same across all the sectors at all times except in 2009.

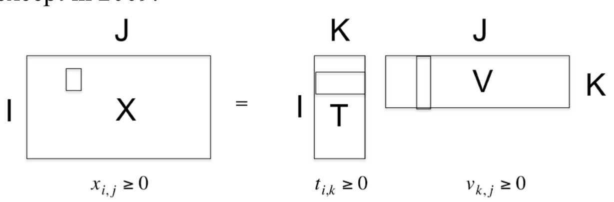

Fig. 2 NMF

4. Non-negative Matrix Factorization (NMF)

The multivariate analysis method to analyze non-negative data into additive components is called non-negative matrix factorization (NMF) and used in various fields (Ref.2,4). Figure 2 shows the schematic diagram of NMF. It decomposes matrix X, where all the factors are non-negative, into matrix T and V, where all the factors are non-negative. The size K of matrix after the decomposition is given in advance. See Ref.2 for the detailed algorithm.

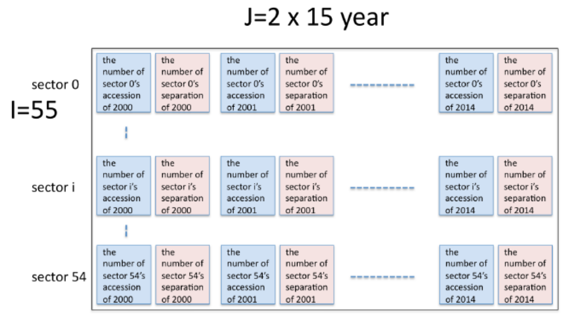

Fig. 3 matrix X in this analysis

4.1. *Structure of matrix X*

This section explains the structure of the decomposed matrix X. Figure 3 shows the structure of matrix X. This matrix is structured by listing the numbers of people entering and leaving employment in sector i in row i by year. The data in blue boxes shows factors related to the number of people entering and red shows those related to the number of people leaving employment.

4.2. *Analysis results*

Figure 4 shows the relationship between the number of parameters K and the accuracy of NMF decomposition. The vertical axis shows the sum of squares of the difference between the products of T, original matrices listing the numbers of people entering and leaving employment in sectors for 15 years, and V, matrices gained by NMF decomposition. The horizontal axis shows K, the number of patterns, which is equivalent to the horizontal axis of matrix T. It was found that when K is about 20, the error becomes nearly zero.

Figures 5 and 6 show the results of decomposition when K=20. Figure 5 shows the patterns where matrix T is transposed. The vertical axis shows pattern numbers and horizontal axis shows sectors. The size of each symbol indicates the importance of the sector included in the pattern. In Figure 5, the combinations of sectors where employment increases around the same time are estimated. For example, in manufacturing and retailing industries you can see that growth in employment is expected in any patterns. Also, in the 17th pattern, when the numbers in wholesales and services industries significantly increase, that in manufacturing industry also increases though the number is small.

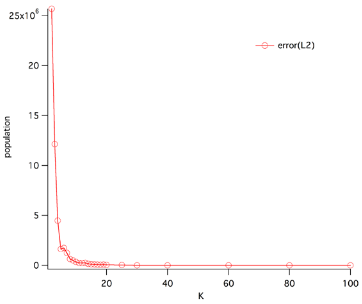

Fig. 4 Decomposition errors

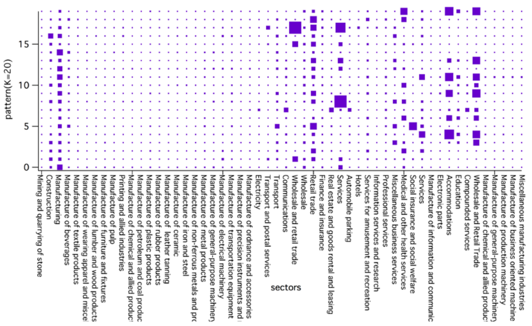

Fig. 5 The obtained matrix T transposed

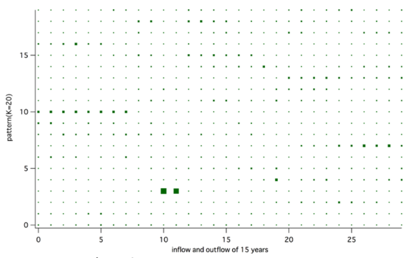

Fig. 6 The obtained matrix V

Figure 6 shows matrix V; the vertical axis shows patterns and horizontal axis shows the size of entering and leaving employment. In even rows the breakdown of each pattern of the number of people leaving employment in each year is shown in the size of each symbol. For example the row 10 shows the number of people entering employment in 2005 and row 11 shows that of the people leaving in 2005. You can see that in both rows pattern 3 accounts for a large portion. Looking at the structure of pattern 3 in Figure 5, employments in wholesales and retail trade have large population. Also, in some industries the breakdowns of patterns of people entering and leaving employment vary. For example, the row 2 and row 3 in Figure 5 represents the numbers of people entering and leaving employment in 2001 respectively. The importance of people entering employment is high in pattern 8, while that of those leaving is high in pattern 16. In pattern 8 more employment is seen in service industry, while in pattern 16 more employment is seen in construction industry. As a result of these, when using matrix V, you can see that the breakdowns of the numbers of people entering and leaving employment change.

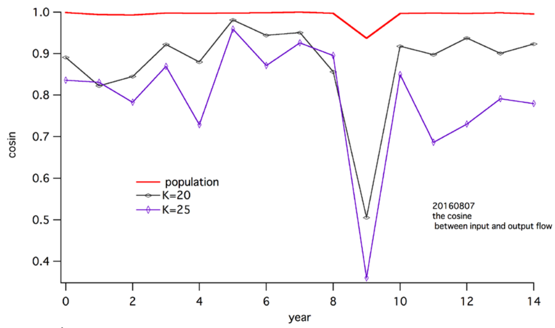

Fig. 7 Differences between patterns supported in each year.

Now, in order to quantify the difference of breakdowns, the cosines were obtained in accordance with eq.1 and by setting the breakdowns of the numbers of people entering and leaving employment in Figure 6 as the vector, which were then illustrated in Figure 7. The horizontal axis shows years and vertical axis shows the cosines. The cosines related to the number of people entering and leaving employment each year described in the Table 2 where K = {20, 25} with different NMFs are shown in thick lines. We found that although simple calculation hardly provides any changes even in the time of Lehman crisis, the suggested method using NMF visualizes detailed changes.

5. Conclusions

This study suggests a method of detecting the changes in the employment environment based on the Survey of Employment Trends. We suggest vectorizing the numbers of people entering and leaving employment based on the industrial sector middle classification of the Survey of Employment Trends by employment patterns found in NMF and using the cosines as the detection index. As a result, we were able to clearly visualize the impact of Lehman crisis, which we assume to have increased the level of detection of the changes in employment environment.

References

1. K. Kajitori, An Attempt to Detect Industry Clusters by Using Non-negative Matrix Factorizations, *Journal of National Fisheries University* 64 (4), pp. 227-239(2016)
2. H. Kameoka, Non-negative Matrix Factorization. *Journal of the Society of Instrument and Control Engineers* 51,9, pp. 835–844(2012)
3. http://hdl.handle.net/10086/15136.
4. Y. Kubo, M. Kubo, H. Sato, and A. Namatame: Estimation of Locations of Densely Distributed Subjects Using NMF with Nonpixel Information. *Journal of Advanced Computational Intelligence and Intelligent Informatics* Vol. 18 No. 4, 2014
5. Ministry of Health, Labour and Welfare (2016) *Survey on Employment Trends*
6. http://www.mhlw.go.jp/toukei/list/9-23-1.html.
7. H. Sawai: Nonnegative Matrix Factorization and Its Applications to Data/Signal Analysis. *Journal of the Institute of Electronics, Information, and Communication Engineers* 95(9), pp. 829–833 (2012)
8. P. Smaragdis, J.C. Brown: Non-Negative Matrix Factorization for Polyphonic Music Transcription, *2003 IEEE Workshop on Applications of Signal Processing to Audio and Acoustics*, pp.177-180 (2003)