학계와 산업계의 정보 대중성 변동과 인용 정보에 기반한 최신 기술 동향 식별 시스템

An Emerging Technology Trend Identifier based on the Citation and the Change of Academic and Industrial Popularity

김선호* · 이준규** · Waqas Rasheed*** · 여운동****

I. INTRODUCTION

Most OECD countries, including Korea, are striving for economic growth and innovation. One of the major efforts of Korea government is to support medium and small-sized enterprises to develop their own competitive technologies by advising promising future technologies suitable for each companies. Detecting emerging technology trend is a key technology for this purpose.

Research on emerging technology trend detection has been conducted by many researchers and organizations, because identifying emerging trends and predict-ing the near future can improve efficient resource distribution and effective policy establishment. Traditional research on detecting emerging trends is based on massive data analysis, literature review, and brainstorming of intellectuals (Shibata, Kajikawa, & Matsushima, November 2008). However, as the amount of informa-tion to analyze increases and computing technology develops, recent trends of this research are focused on automating the processing by utilizing text mining and data analysis techniques (Kontostathis, Galitsky, Pottenger, Roy, & Phelps, 2003; Smalheiser, October 2001). In this study, we propose a semi-automatic ma-chine learning technology for recognizing emerging technology trends from academic and industrial text data. The experiments, training features, training data, and evaluation data used in this study are new or ex-tended version of those used in our previous research (Kim et al., 2011).

II. METHODS

1. Previous Research

Traditional research on emerging trend detection in text data is conducted by two major methods, fully automatic detection and semi-automatic detection. The fully automatic methods,

* 한국과학기술정보연구원 선임연구원, haebang@kisti.re.kr, 02-3299-6281
** 고려대학교 석사과정, onleejk@korea.ac.kr, 02-3290-3566
*** 고려대학교 박사과정, waqas@korea.ac.kr, 02-3290-3566
**** 한국과학기술정보연구원 선임연구원, wdyeo@kisti.re.kr, 02-3299-6017

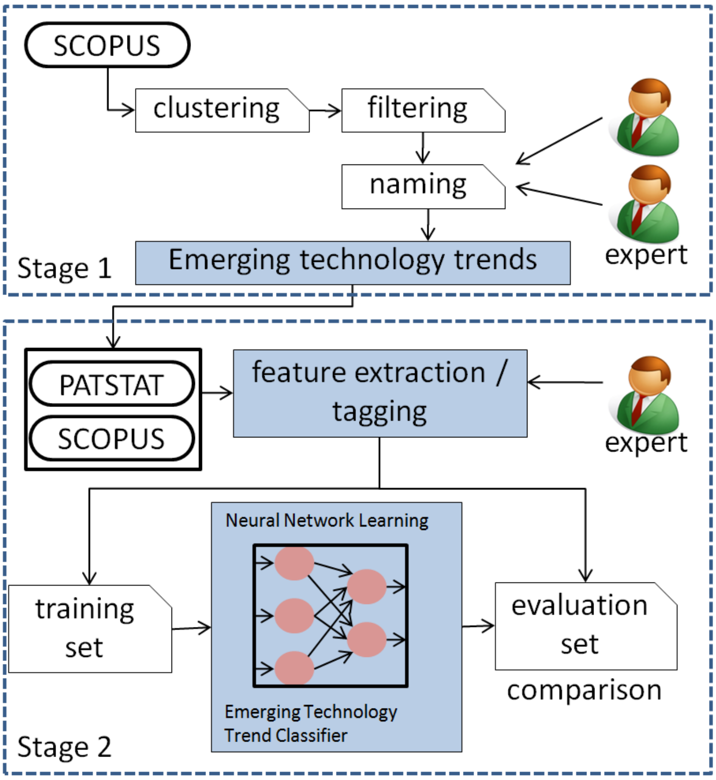
such as TimeMines (Swan & Jensen, 2000), VUDM (Kim, Spring 2008), and on-line event detection by Allan (Allan, Papka, & Lavrenko, 1998), have employed unsupervised learning methods, in which learning is achieved in a fully automatic manner by detecting topics describing technologies to analyze their trends. These approaches tend to show good performance in recall, which represents the portion of emerging trends found over the total number of emerging trends in the system, but only medium performance in precision, which expresses the rate of correctly determined emerging trends over the total number of trends found. The reason for the good recall of the method is that it uses bottom-up methods to test every possible combination of noun phrases as topics describing emerging trends. After finding topics, the trends of each topic are analyzed, and emerging trends are selected from among the topics based on certain criteria. However, the results of this approach can be noisy for some decision makers because, in most cases, the identification of several correct targets is more meaningful than identifying as many correct targets as possible without missing.

For this reason, in order to increase precision rather than the recall, semi-automatic methods which use supervised learning are attracting attention. These approaches, such as CIMEL (Roy, Gevry, & Pottenger, April 2002), PatentMiner (Lent, Agrawal, & Srikant, 1997), and HDDI (Pottenger, Kim, & Meling, 2001), use experts to provide guidance to the machine along with the training data. For example, the training data of the machine learning is tagged by the experts to identify whether or not the data is about an emerging trend, or the experts interact with the software during learning. Therefore, the machine can learn more correct patterns of emerging trends and classify new trends more pre-cisely.

2. Semi-automatic Supervised Machine Learning

Our proposed method is a semi-automatic system in which experts provide guidance to an artificial neural network machine learning system. The guidance from the experts in our system is the classification tags attached to the training data, so that the machine is directed as to whether or not the information currently being learned is about emerging technology. In a machine learning system, selecting the correct features for learning is most critical. HDDI (Pottenger et al., 2001) used the frequencies of concepts within a fixed length of periods and the count of concepts in semantically defined regions, which can be obtained automatically. Oh (Oh, Choi, Shin, Jeong, & Myaeng, March 2009) also provided the results of a comparison experiment for testing the strength of impact of the most famous features of trends generally used for emerging trend detection, such as change, persistency, stability, and volume. According to Oh's result, the strongest impact feature of a trend is expressed by the change, stability, volume, and persistency in descending order. However, because every emerging trend detection systems have different purposes, available source data, and training methods, the features to be learned need to be selected and tested themselves. Our system uses both academic data, SCOPUS (Elsevier, 2011), and industrial data, PATSTAT (PATSTAT, 2011). Thus, in addition to the usual term-frequency based trend changes in academic data, the latency between the weak academic signal and the industrial legal activity (patent application) could be trained. Also, our system uses a stability of change feature and a citation half-life feature, which are described in the next section, to train the stability and aging factor of technology. We assume that the age of the emerging technology is relatively young and young technology tends to have an unstable popularity and a later, short, citation half-life than matured technology.

This study consists of three stages, 1) emerging trend detection, 2) training data generation, and 3) learning and experimentation. Figure 1 shows the brief structure of the proposed system.



<Figure 1> Emerging technology trend classifier

At stage 1, a set of emerging technology trends are identified from SCOPUS. The process contains cluster-ing, filtering, and naming. The field experts intervene during the process. After that, in the second stage, the training data is generated by extracting learning features from SCOPUS and PATSTAT. Experts also join in this process to add their guidance to the learning data.

3. Emerging Technology Trends

Detecting emerging trend from SCOPUS is conducted to generate tagged feature vectors of training data for neural network learning. Only 1% of the highly cited papers are used. The papers are clustered using the scientometrics techniques, which use the citation information, classification code, core paper identification, and shared term frequency. As a result of clustering, 512 clusters are identified. Then, about 50 field experts are selected for the naming of the clusters and voting on the prospects of the technologies as expressed by their names. Clusters that do not have any consistent topic, based on the knowledge of the field experts, are filtered out, and final 87 clusters are selected as emerging technology trends. From this result, 60 technologies are selected for positive training data. In addition, 26 matured, non-emerging, technologies, such as compact discs, fountain pens, optical character recognition, and bluetooth technology, are prepared as negative training data.

4. Feature Extraction and Tagging

An artificial neural network is trained with positive training data, which consist of features from emerging technology trends, and negative training data, which consist of features from matured, non-emerging, technology trends.

The training features are extracted from SCOPUS and PATSTAT data from 1996 to 2010. Two types of feature, linguistic and statistical, are used. For the linguistic features, the trend change for 2 different periods from SCOPUS and PATSTAT are used. In addition, the stability of change is used. For statistical features, the citation half-life in SCOPUS is used.

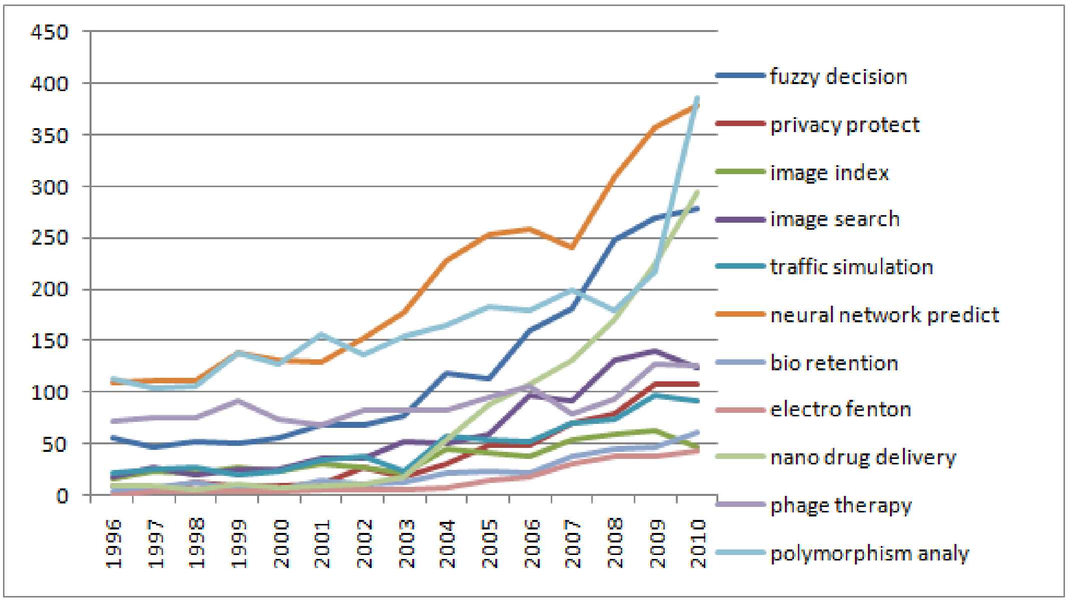
The change value represents the slope of the change between the start and end point of the trend curve. A positive change value means that the trend is emerging, while a negative change value means that the trend is submerging (Oh et al., March 2009).

$$diff(f) = LR_f(T_{end}) - LR_f(T_{start}) \quad (1)$$

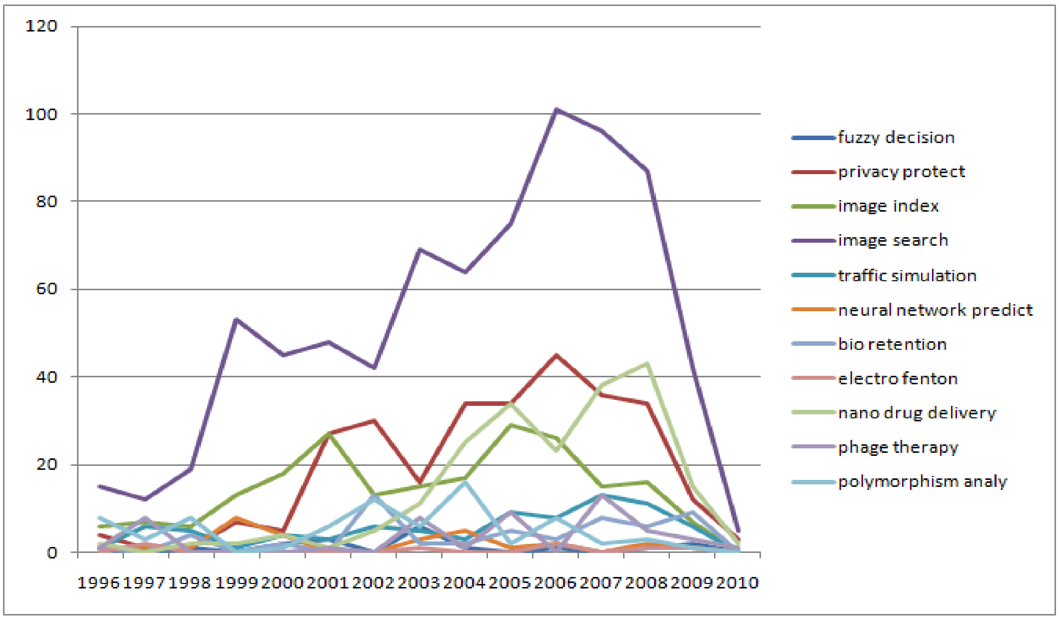
$$Change(f) = \frac{diff(f)}{\sqrt{diff(f)^2 + (T_{end} - T_{start})^2}} \quad (2)$$

The change feature is obtained by calculating the linear regression, which is represented by equations (1) and (2). In these equations, f is a trend function expressed by an independent value, time, and a dependent value, the popularity in SCOPUS and PATSTAT. LR_f is the linear regression function about f. T_{end} expresses the popularity at the end point of the period of interest, and T_{start} is the popularity at the start point of the period. For the machine learning part of this study, four change features, 1) the change in the first 11 years in SCOPUS, 2) the change in the last 4 years in SCOPUS, 3) the change in the first 11 years in PATSTAT, and 4) the change in the last 4 years in PATSTAT, are extracted from one technology trend curve.

The reason for dividing the period into two sections, 11 years and 4 years, is based on our basic interpretation about the data. Figure 2 and figure 3 show some examples of trend curves of emerging technologies in SCOPUS and PATSTAT, respectively, and both charts show that the trend curves changed noticeably in the last 4~5 years.



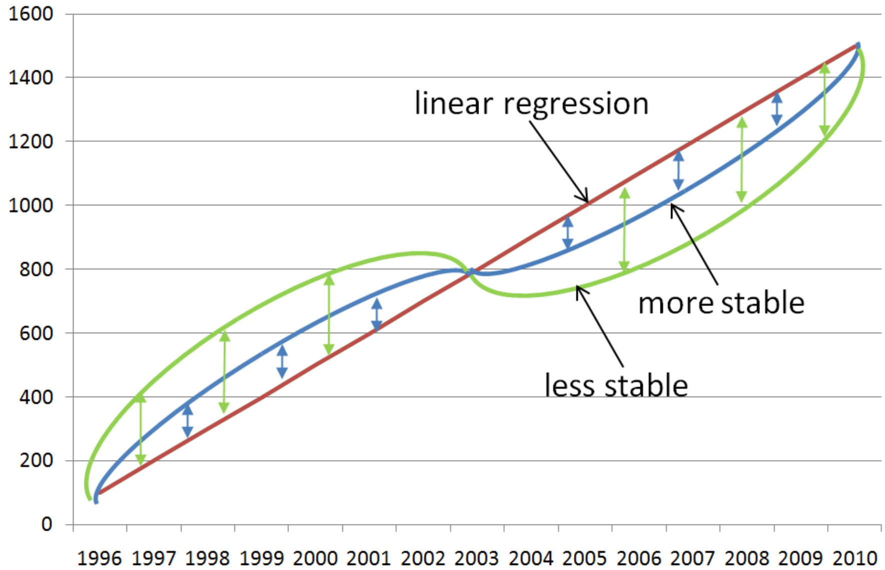
<Figure 2> Emerging technologies' popularity in SCOPUS



<Figure 3> Emerging technologies' popularity in PATSTAT

According to the figure 2, the popularity of emerging technology trends had increased steadily in the first 11 years and its changes escalated during the last 4 years in SCOPUS. In figure 3 the speed of change dropped rapidly during the last 4 years in PATSTAT.

Another linguistic feature used for this study is the stability of change. The concept of stability is illustrated in Figure 4. In this chart, all the three trends showed the same degree of increase during the observed period. However, the degrees of the change of three trends, the difference from the common linear regression line, at each time interval between the start and end of the period are different. That is, the change of the blue trend is more stable than the change of the green trend because the difference of the blue trend from the linear regression line is smaller than that of the green trend.



<Figure 4> the concept of stability

The stability feature is normally used for measuring the strength of the trends, as in Oh (Oh et al., March 2009)'s experiment, however, in this study, it is employed by an assumption that the trends of academic and industrial documents of the matured, non-emerging, technologies will change stably, whether increase or decrease, because they are popular technology and well studied by many researchers already, while that of the emerging technologies change unstably. This assumption is based on the basic analysis of SCOPUS data.

The stability of the change in this paper is calculated by the equations expressed by (3) and (4).

$$AvgOfDifference(f) = \frac{\sum_{i=1}^{n} (f(t_i) - LR(t_i))^2}{|E|} \tag{3}$$

$$Stability(f) = (k)^{AvgOfDifference(f)} \tag{4}$$

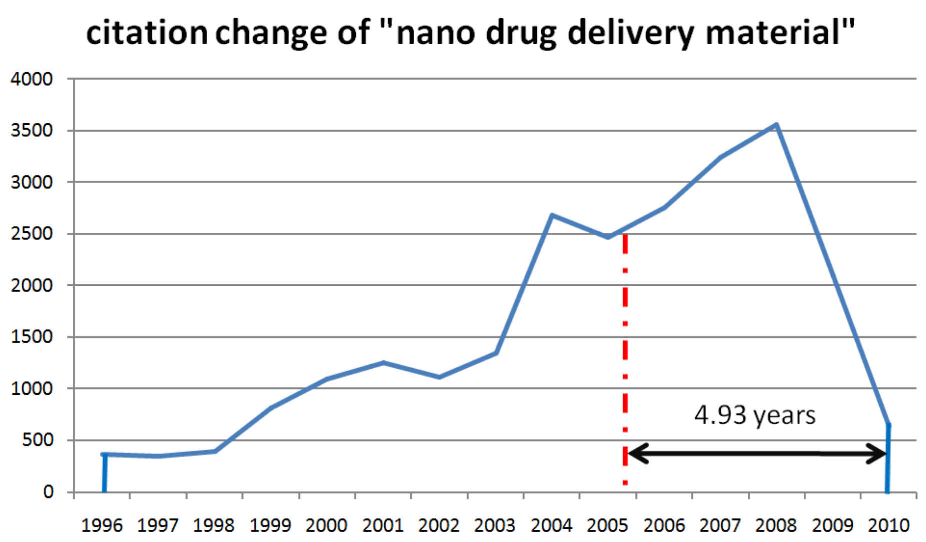
where, the n is the number of time intervals $<t_1, t_2, t_3, \ldots t_n>$ between T_{start} and T_{end}. E represent the set containing all the papers or patents related with the technology of concern. k is a constant number between 0 and 1. Thus, the stability will be between 0 and 1. In this study, 0.9 is used for k.

Table 1 shows the examples of the stability of some emerging technologies and matured, non-emerging, technologies. Emerging technologies tend to show near-zero stability, while non-emerging technologies tend to show near 1 stability.

<Table 4> the examples of the stability

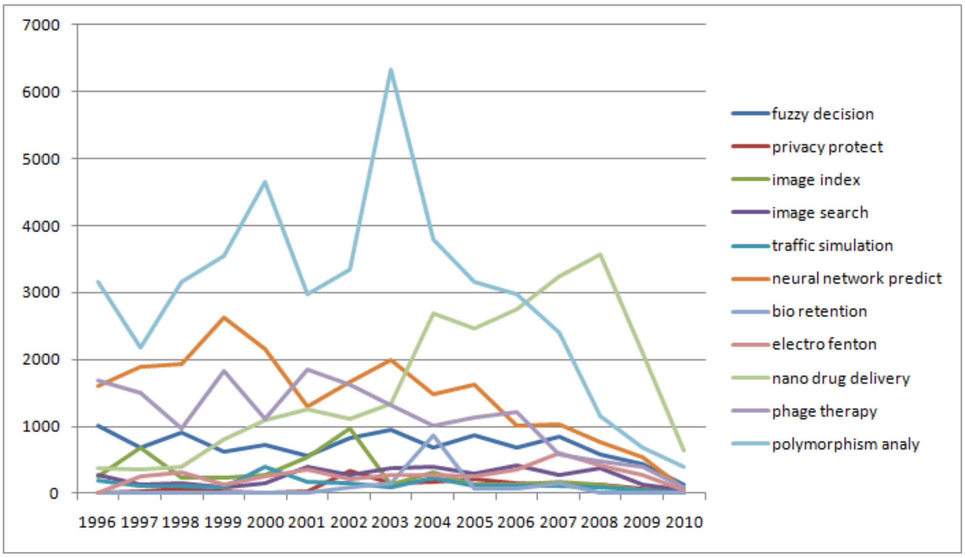
Emerging-technology	Stability	Non-emerging technology	Stability
Fuzzy decision	0.037	Compact disc	0.901
Privacy protection	0.191	Film camera	0.956
Image index	0.865	Gold mine	0.931
Image search	0.375	Fountain pen	0.904
Traffic simulation	0.578	Food preservation	0.906
Neural network prediction	0.309	CRT display	0.943
Bio-retention	0.619	Polarized film	0.899
Electro-fenton	0.525	Infrared communication	0.906
Nano drug delivery material	0.0001	Personal digital assistance	0.422
Phage therapy	0.828	Diamond mine	0.849
Polymorphism analysis	0.216	Optical character recognition	0.705

The other type of feature selected for this study is the citation half-life, which is a statistical feature. The citation half-life is the number of years that have passed after half of the total number of citations concerning a particular technology. The citation half-life represents the center of the total group of citations. Figure 5 illustrates the concept of citation half-lifetime.



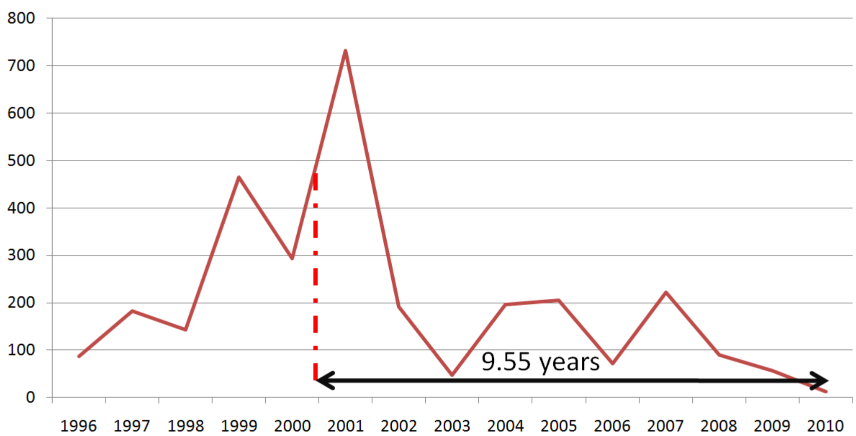
<Figure 5> the concept of citation half-life

The number of citation on “nano drug delivery materials” increased steadily until its peak in 2008, and then it decreased rapidly until the present year, 2010. The total number of citations on the technology during the observation period in SCOPUS is 24,225 and the half of the total number of citations, 12,112.5, is met around 2005. Therefore, the citation half-life of the “nano drug delivery material” technology is 4.93 years.



<Figure 6> Emerging technologies's citation number in SCOPUS

Every technology has a distinct trend in citation. Figure 6 shows the citation trends of some example emerging technologies. The trend curves tend to bias to the left or right based on the age of the technology. Ac-cording to the basic analysis of the source data, relatively new, or emerging, technologies, such as the “nano drug delivery material”, tend to have short citation half-life as shown in the Figure 5. In contrast, the matured, non-emerging, technologies, such as “compact disc” and “CRT display”, showed long citation half-life. The Figure 7 is an example of citation half-life of a non-emerging technology, “food preservation”.



<Figure 7> the citation half-life of the technology “food preservation”

We include the citation half-life for learning feature because we assume that a emerging technology is relatively new, and the citation half-life is a good feature to represent the age of technology.

5. Learning

In this study, the feature vector, a series of feature entering to the machine for training at one time, prepared for training the neural network for emerging technologies identification is consists of 6 real numbers and 1 integer, 1) the change in the first 11 years in SCOPUS, 2) the change in the last 4 years in SCOPUS, 3) the change in the first 11 years in PATSTAT, 4) the change in the last years in PATSTAT, 5) the citation half-life in SCOPUS, 6) the stability of change in the 15 years in SCOPUS, and 7) the decision tag to show whether or not emerging technology.

The goal of machine learning in this study is to edu-cate the neural network with the features of emerging technologies and non-emerging technologies, and evaluate the performance of the trained neural network as an emerging technology trend classifier.

During learning, a total 83 feature vectors, 57 from positive data and 26 from negative data, and tagged as to whether or not it is emerging technology, are entered into the neural network for training.

In the evaluation session, the precision of the classification performance is measured. In order to evaluate the precision of the learned neural network model, 61 new feature vectors, which have not been used for training, are entered. The evaluation data is not tagged but are already classified by field experts and compared with the decisions made by the neural network.

6. Evaluation and Results

The final status of a neural network, the learned status, is different in every trial, even if it is trained with identical training data, because the neural network assigns random initial weights to the links among the neurons in the hidden layers. Therefore, we repeated the training and evaluations 10 thousand times, with the same evaluation data, and determined the average precision and a standard deviation.

The average precision of classification of the neural network is 70.47% and the standard deviation is 0.39. Regarding precision only, this result is better than the normal precision rate, which is about 45, for normal un-supervised learning for emerging trend technology.

Another round of experiment is performed to test the impact of including the stability feature for emerging technology identification. In this experiment, the stability is excluded from the training and the performance is measured by the same way with the previous round. The performance of the neural network without the stability feature is 74.48% and the standard deviation is 0.38.

As a result, excluding the stability feature from training performed better. We interpret this that the stability is not a strong positive feature for distinguishing an emerging technology from non-emerging technology.

The performance of our neural network model can be improved by iterative tuning of the training data by filtering out noisy data and adding correct data. Also, the standard deviation can be decreased by enlarging the size of training data.

III. CONCLUSIONS AND FUTURE WORK

An emerging technology trend identification system is proposed, which is based on semi-automatic supervised machine learning technology, and its performance is evaluated. Our method learns from both academic data, SCOPUS, and industrial data, PATSTAT. The change in trend, the stability of change, and citation half-life is selected as the learning feature. By using a supervised learning method, our system places the focus on enhancing the precision of classification rather than recall. This system can be applied for fast classification of emerging technology, such as a real time online technology evaluator or competitive intelligence system.

For future work, we will tune the training data to make the learning process more efficient. Also, a larger volume of training data and evaluation data may im-prove the precision of the classifier. Furthermore, we plan to apply the standard test set for emerging trend detection, such as the Topic Detection and Tracking (TDT) corpora (NIST, 2011), to make our system applicable as a general purpose topic detection system. Finally, we will test more various trend features, such as changes and statistics about search queries.

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