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‘Technology Mining’ bibliometrics analysis: applying network analysis and cluster analysis

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Introduction

According to advances in text mining methods and tools, technology mining, or its brevity ‘tech mining’, is one of recent research areas progressively emerged in technology management area. Over past two decades, this area has been attractive for many scholars in business management, technology management, and computer science departments. The majority of tech mining applications is concentrated on analyzing patents which is also called patent mining by some scholars; moreover, there are some researchers reported tech mining applied to other types of technological documents like R&D reports (Porter and Newman 2011).

Porter as one of pioneers in technology mining has defined ‘tech mining’ in his book (Porter and Cunningham 2005): *the application of text mining tools to science and technology information, informed by understanding of technological innovation processes.* Therefore, tech mining has two significant characteristics: (1) using ‘text mining tools’, (2) applied for technology management purposes.

As shown in Fig. 1, the number of published papers and the number of citations in tech mining area illustrates a hyperbolically progress; there is a jump in the number of publications after 2005 and a huge rise in the number of citation after 2012.

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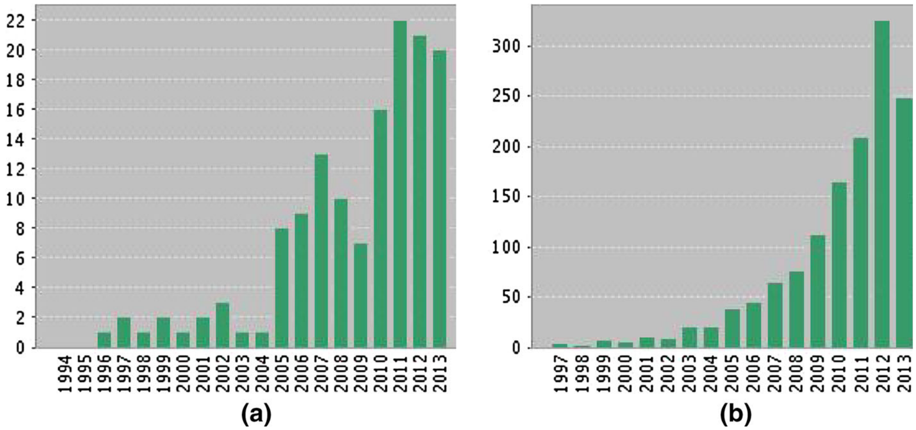


Fig. 1 **a** Published papers. **b** Citations. *Source*: Web of science

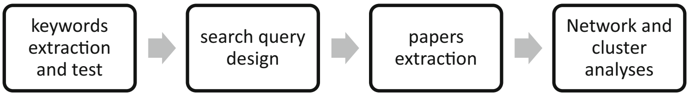


Fig. 2 Research process

In an editorial note (Chiavetta and Porter 2013), Porter and Chiavetta investigated six papers published in The First Global Tech Mining (GTM) Conference. They report four main analytics tools which are bibliometrics, data mining, network analyses and cluster analyses, and patent analyses. In addition, they reveal eight application areas including emerging technologies and technology dynamics (trend analyses), technology forecasting, roadmapping and foresight, R&D management, engineering industries, science and technology (S&T) indicators, evolutionary economics, technology assessment and impact analysis, and science, technology and innovation policy studies.

In this research, CiteSpace (Chen 2014), a free Java application for visualizing and analyzing citations and contents in scientific literature, is applied as the main analysis tool to figure out detecting and visualizing emerging trends. Professor Chaomei Chen who has developed CiteSpace does his research on 'information visualization' and has published several papers (Chen 2004, 2006; Chen et al. 2009). CiteSpace by co-citation network analysis enables to identify co-citation clusters of cited references and trace how the trend of researches is (Chen et al. 2009). The main techniques implemented in the software are spectral clustering and feature selection algorithms (Chen et al. 2009). Visualization of the results is the main characteristic of CiteSpace which assists more analysts to make sense about the trends and evolutions (Chen 2006). Information visualization in this software is much beyond just visualizing graphical displays. This method deploy cognitive, social, and collaborative activities (Chen 2004).

There are some papers in which the authors used CiteSpace as the main tool for bibliometrics analysis tool. Tonta and Darvish (2010) used CiteSpace in their research to do social network analysis (cluster methods and centrality measures), and co-occurrence analysis on authors and journals, bibliometrics methods (Lotka's Law). In another research, Dhami and Olsson (2008) used the software in bibliometrics analysis. They applied cluster analysis on co-citations, and focused on 17 clusters (out of 126). Furthermore, Citespace is deployed to study co-citation pattern over 1987 and 2006 to reveal overall evolution of S&T Policy (Xu-kun 2008).

Methodology

The stages of this research are shown in Fig. 2. Since CiteSpace is the core analysis tool used in this research, the procedure is designed to have a compatible procedure to CiteSpace capabilities. To have so, it is required to prepare paper information as the main input of CiteSpace.

To extract right papers, it is required to apply extended keywords covering different purposes and applications of tech mining because there are many alternative terminologies, and there are many research papers not used known terminologies but applied 'text mining' tools for technology management purposes. Furthermore, applying CiteSpace shows the more effective keywords, the more effective analyses, and the less time taken. In the first stage, all possible keywords are elicited based on a framework promising all of the papers be relevant to tech mining. There are many delicate points in applying CiteSpace in the last, so it is required to refer to CiteSpace tutorials (Chen 2014).

As mentioned above, 'tech mining' as the 'core keyword' is extended to three sub-categories including 'alternative terminologies', 'tech mining purposes', and 'tech mining' applications. It is mentionable that 'alternative terminologies' represent 'tech mining' directly, but the other sub-categories lonely do not address 'tech mining', so they need to be applied combinatorially. To figure out the keywords, reviewing publications of renowned authors is a quick trick. For example, the publications of Alan Porter as one of pioneers in 'tech mining' are beneficial to make a preliminary list of keywords. But as mentioned before, there are many authors used their own keywords, so to make sure to have all possible keywords identified, 'Keyword planner', an option of 'Google Adwords', is utilized to figure out what keywords people have been looking for in Google while they search for 'tech mining'. For example, of among suggested keywords for 'tech mining', 'text mining', 'text classification' are most relevant and applied keywords. The 'relevance' and 'applicability' of keywords found in 'Keyword planner' are tested.

To realize 'TM applications' keywords, two aspects are considered: (1) common 'source', and (2) common 'methods' used for 'tech mining'; types of both aspects are illustrated in Table 2. The meaningful combination of both aspects leads to 'TM applications' showed in Table 1.

To test the initial list of keywords, it is necessary to exam two aspects: 'relevance', and 'applicability'. In relevance aspect, this is questioned if the keyword is discussed in 'tech mining' papers and researches. For instance, 'patent mining' is one of the privilege tech mining usages. 'Applicability' observes whether the keyword introduces a method, tool, etc. potentially applicable in 'tech mining'. For example, 'citation analysis', 'patent citation', and 'patent analysis' are of those applicable methods in 'tech mining'. Three main techniques are used to test 'relevance' and 'applicability'. In the first technique, it is checked if there is any paper whose topic (title, abstract, and keywords) contain the keyword. In this case to check 'TM tools' keywords, it is required to use 'TM purpose' keywords at the same time as it is explained before. If there is no paper, or the papers contain the other keywords, the searched 'TM tool' keyword can be snubbed. Second, looking for the definition or general explanation of a keyword in common databases such

Table 1 The keyword

Framework	Tech mining (TM)		
	Alternative terminologies	TM purposes	TM applications
Keywords	Technology mining	Technology monitoring**	~~Bibliometrics~~
	~~Mining technology~~*	Competitive technical intelligence**	Document mining
		Technology forecasting**	Document mapping
		Technology roadmapping**	Web mining
		Technology assessment**	~~Link mining~~*
		Technology foresight**	Citation network
		Technology process management**	Citation analysis
		Science and technology indicators**	Patent analysis
		Technology analysis**	Patent citation
		Technology intelligence	Patent mapping
		Innovation forecasting	Patent mining
		Emerging technologies	~~Patent analysis~~
		R&D	~~Network analysis~~
		Technology management	~~Scientometrics~~
			Text mining
			Text classification

* Strikethrough words are eliminated in 'testing' stage

** Porter and Cunningham (2005 p. 18)

ts= (
("technology mining" or "tech mining" or "patent mining")

First search strategy

Or
(("Technology Monitoring" or "Competitive technical intelligence" or
"Technology Intelligence" or "technology foresight" or "Technology Forecasting"
or "Technology analysis" or "Innovation Forecasting" or "Emerging Technologies"
or "R&D" or "technology management") and
("text mining" or "text classification" or "Document mining" or "web mining" or
"document mapping" or "*Citation network" or "*Citation Analysis" or "Patent
citation" or "patent mapping"))
)

Second search

Fig. 3 Search query

as Wikipedia help exam how much it is relevant. Looking at some sample papers containing the keyword can help recognize its relevance and applicability. In this case, some keywords are eliminated which are strikethrough shown in Table 1 such 'bibliometrics', 'link mining', 'network analysis', 'scientometrics', and 'patent analysis'.

'Search query design' is an iterative activity. In this step by applying Boolean operators such as AND, OR, NOT, and field tags such as TS for 'topic', and SU for 'research area', which are Web of science standards, appropriate queries are designed to do searches in Web of Science database. Each search strategy must be tested several times to make sure that it addresses right papers. After finalizing the query shown in Fig. 3, the results, papers information, must be exported in a text format file to prepare CiteSpace input file.

The query used in this research, shown in Fig. 3, contains two main search strategies combined in it. The first strategy addresses directly to the concept of 'tech mining' through using 'alternative terminologies'. 'Patent mining' is considered in the first strategy keywords since patents are obviously technological documents, so 'patent mining' keyword certainly addresses 'tech mining' papers. The second search strategy addresses 'tech mining' papers by combining 'TM purpose' and 'TM applications' keywords.

Search results

By applying the query into Web of science database, the search came up with 143 papers demonstrated in Appendix 1 (see Online supplement). To have a more purified paper list, the search results are refined by the 'document type' to 'article', and ''proceeding papers'.

Of among top ten authors in 'tech mining', shown in Fig. 4, five are from Pohang University Science & Technology. This South Korean group authors have 11 papers published in 'tech mining' concentrated in patent analyses. Also, they have developed a patent intelligent tool based on Subject-Action-Object (SAO) method and applied it in various purposes such as R&D planning (Yoon and Kim 2011; Yoon et al. 2013), roadmapping (Choi et al. 2013), technology trend identification (Choi et al. 2011), identifying patent infringement (Park et al. 2012), technology planning (Choi et al. 2012), etc.

Table 2 Keywords used in generating 'TM applications'

Data source	Method
Text	Mining
Document	Mapping
Patent	Analysis
Web	Citation
Link	

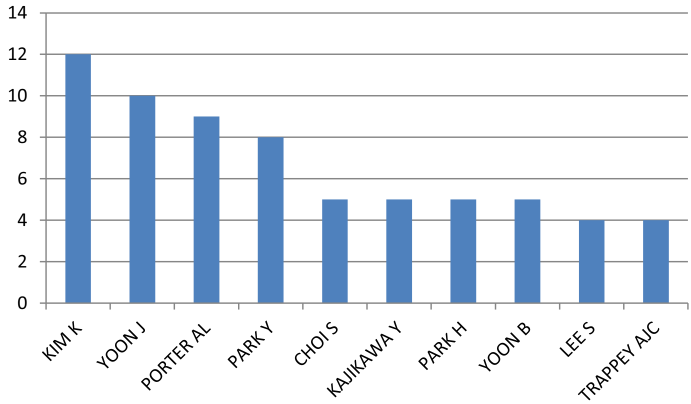


Fig. 4 Top 10 authors in 'tech mining'

The most renown author in ‘tech mining’ is Alan Porter teaching in Georgia Tech University. He has published ‘Tech mining’ book (Porter and Cunningham 2005), designed a five-step framework to incorporate external R&D information in management of technology decision makings (Porter and Newman 2011), and developed QTIP framework to search, compose and analyze ‘quickly’ information for technology analyses (Porter 2005). Also he has noticeable researches in applying ‘tech mining’ in nanotechnology (Porter et al. 2011; Guo et al. 2010; Alencar et al. 2007) and in ‘technology forecasting’ (Zhu and Porter 2002; Guo et al. 2012).

Analysis

To analyze the papers based on CiteSpace capabilities, several aspects including author, keyword, university, country, and journal are considered. Different views of ‘network analysis’ comprising ‘cluster view’, ‘timeline view’, and ‘timezone view’ as well as cluster analysis are practiced to analyze the patterns and trends in tech mining literature.

Authors network analysis

The network of cited authors, Fig. 5, contains both the authors of the papers and the authors cited in the references of the papers. The network aids to recognize most cited authors who have directly written tech mining papers, or who have been cited in the tech mining papers. The six-most cited authors are Kastoff, Porter, Narin, Jaffe, Yoon, and Trajtenberg with 37, 31, 30, 28, 26, and 25 citations, respectively.

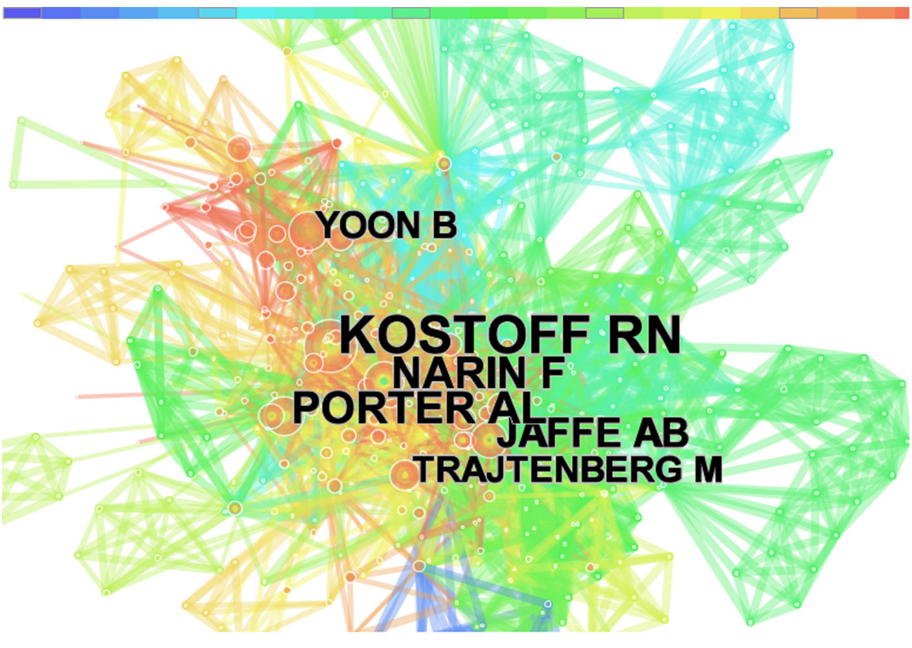


Fig. 5 The network of cited authors

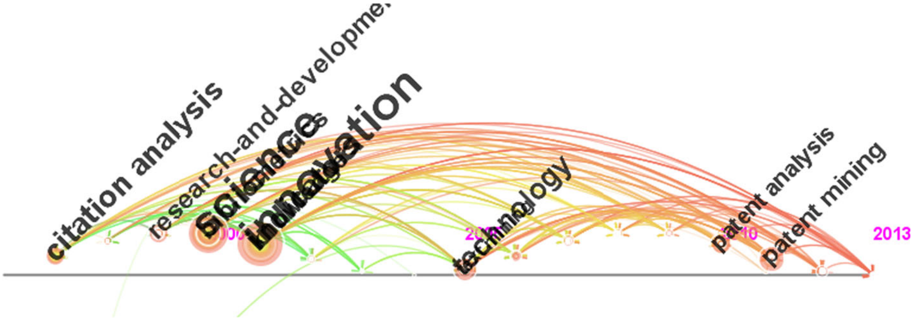


Fig. 6 Time line view of the keywords

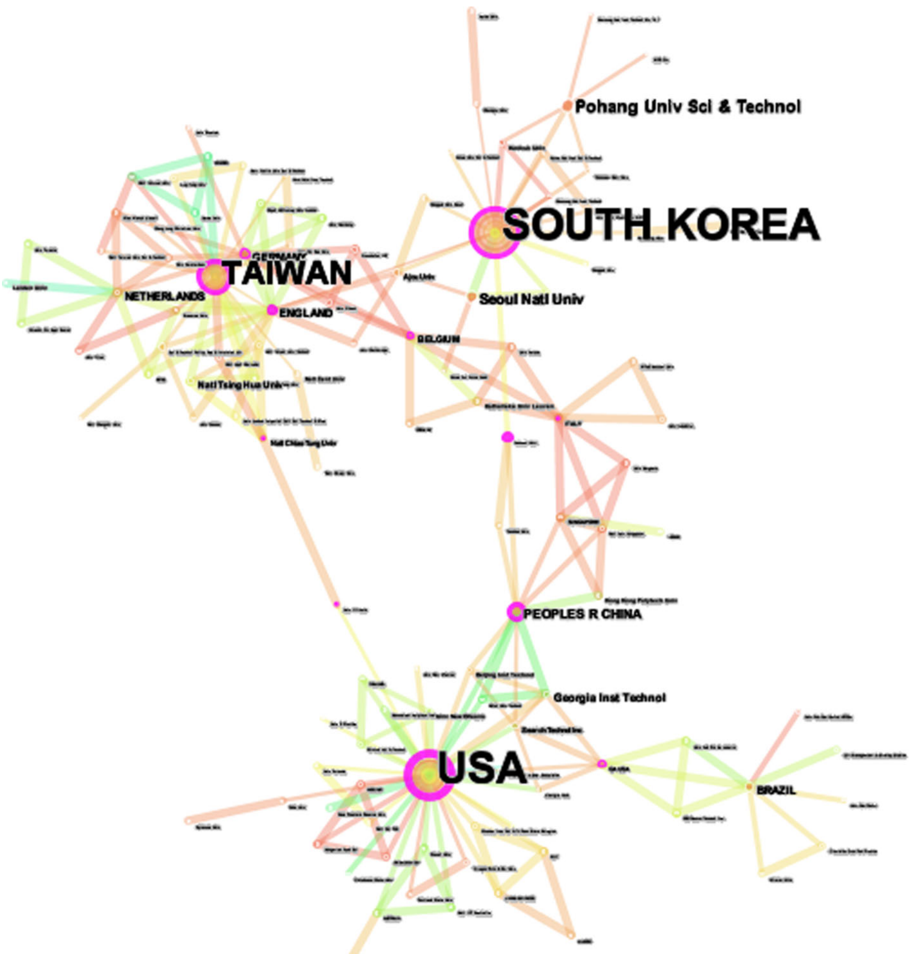


Fig. 7 Country–institute analysis

Keywords network analysis

The network of keywords, Fig. 6, is shown in time line view. This network helps recognize the most applied keywords which are innovation, science, indicators, citation analysis, technology, research-and-development, bibliometrics, knowledge, patent mining, patent analysis, text mining, patent citations, citations, industry, information, and nanotechnology. The time line view shows, however, ‘science’, and ‘innovation’ have been most used keywords in the papers; ‘patent analysis’ and ‘patent mining’ are more noticed by the authors in recent years.

Country and university network analysis

As shown in Fig. 7, among countries, the researches of South Korea, USA, Taiwan, and Japan have had most participation in ‘tech mining’ researches with 30, 29, 22, and 12 papers, respectively. Moreover, Pohang University, Seoul National University, University of Tokyo, and Georgia Tech are the most active universities in ‘tech mining’ with 11, 9, 6, and 6 papers, respectively.

Journals network analysis

To find more relevant ‘tech mining’ papers, ‘Sceintometrics’ and ‘Technological Forecasting and Social Change’ have published most papers in ‘tech mining’; see Fig. 8. Moreover, the first five journals contain more than 50 % of ‘tech mining’ papers. Moreover, Fig. 1 shows that more than 70 % of ‘tech mining’ papers have published after 2010. It means ‘tech mining’ publications have progressively accelerated over recent years.

Papers network analysis

To figure out the most effective papers in ‘tech mining’, the nodes in the network of the papers, Fig. 9, are drawn by applying ‘Eigenvector centrality’ measure, which acknowledges connections to a highly connected node. Eigenvector centrality assigns relative scores to all nodes in the network based on the concept that connections to high-scoring nodes contribute more to the score of the node in question than equal connections to low-scoring nodes (McCulloh et al. 2013). According to Eigenvector centrality, ten most effective papers are introduced in Table 3. Interestingly, South Korean authors have dominated in this ranking.

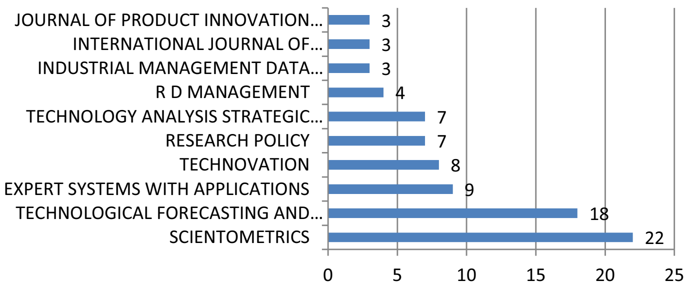
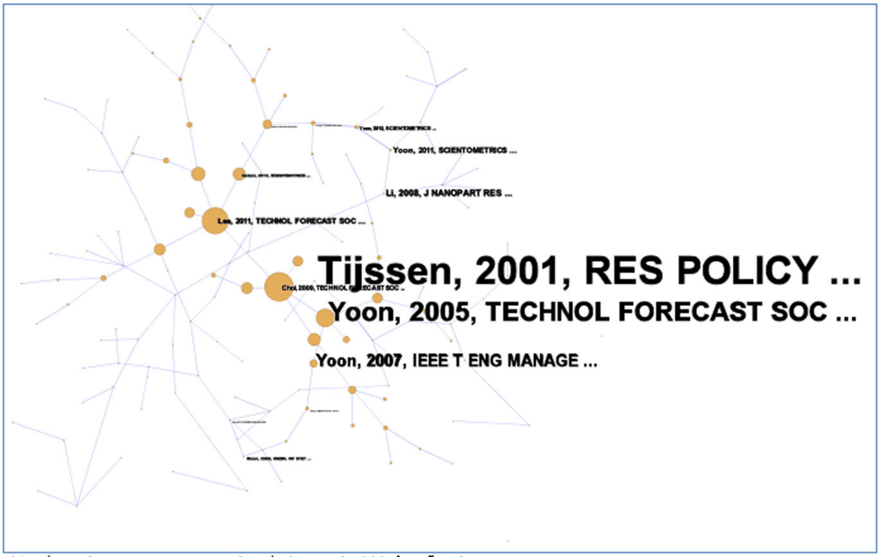


Fig. 8 Top 10 journals publishing ‘tech mining’ papers



- *Nodes size represents cited times in Web of science*

Fig. 9 The papers network

Papers cluster analysis

To recognize research different aspects of researches published in the papers, the papers network is made by applying ‘pathfinder’ as the pruning method and then is clustered by processing the title, the abstracts and the keywords. CiteSpace clustered the network to nine clusters whose information is reflected in Table 4.

To figure out the most appropriate clusters, ‘Silhouette’ measure is used. Silhouette is between positive one and negative one. When Silhouette is close to one, it means the datum is appropriately clustered, and when Silhouette is close to minus one, it means that would be better if the datum was clustered in their neighboring cluster, and Silhouette is near to zero, it means the datum is on the border of two natural clusters (Rousseeuw 1987). Therefore, silhouettes in Table 4 prove the resulted clusters have perfectly recognized.

Three methods including tf*idf, log-likelihood, and mutual information are applied to extract most participating terms in the titles, the abstracts, and the keywords of the papers. The terms represent main aspects of researches such as technology, geographical area, industrial sector, methodology, and tech mining application. For example, in cluster 0, triz and patent citation analysis are important methodologies applied among the papers of cluster 0, and energy sector and Taiwan are the other distinguishing aspects of the cluster. Given the terms reflected in Table 4, all main meaningful aspects are integrated in Table 5.

Conclusion

By advances in text mining tools and methods, tech mining has been rapidly growing among technology management scholars. In order to figure out how tech mining researches are being developed, after extracting reliable keywords, 143 papers are extracted from Web

Table 3 10 Most effective papers in 'tech mining' based on 'Eigenvector centrality'

Author(s)	Title	Publication year	Method	Application
Tijssen (Tijssen 2001)	Global and domestic utilization of industrial relevant science: patent citation analysis of science–technology interactions and knowledge flows	2001	Patent citation analysis	Policy making
Lee et al. (Lee et al. 2010)	Quantitative mapping of patented technology—The case of electrical conducting polymer nanocomposite	2010	Patent citation network analysis	Technology forecasting
Yoon (Yoon and Park 2005)	A systematic approach for identifying technology opportunities: keyword-based morphology analysis	2005	Patents morphology analysis	Technology forecasting
Gerken (Gerken 2012)	A new instrument for technology monitoring: novelty in patents measured by semantic patent analysis	2012	Semantic patent analysis	Technology monitoring
Lee et al. (Lee et al. 2012)	A stochastic patent citation analysis approach to assessing future technological impacts	2012	Stochastic patent citation analysis	Technology forecasting
Jeon et al. (Jeon et al. 2011)	How to use patent information to search potential technology partners in open innovation	2011	N/A	Technology partner selection
Kuan et al. (Kuan et al. 2013)	Capturing and tracking performance of patent portfolio using h-complement area centroid	2013	Patent citation analysis	Patent portfolio performance analysis and forecasting
Yoon (Yoon 2008)	On the development of a technology intelligence tool for identifying technology opportunity	2008	Morphology analysis Clustering analysis Network analysis	Identify technology opportunities
Lee et al. (Lee et al. 2011)	Monitoring trends of technological changes based on the dynamic patent lattice: a modified formal concept analysis approach	2011	Dynamic patent lattice (based on formal concept analysis)	Technology monitoring
Geum et al. (Geum et al. 2013)	Identifying and evaluating strategic partners for collaborative R&D: index-based approach using patents and publications	2013	Patent analysis Publication analysis	Technology partner selection

of science database. CiteSpace is the bibliometrics tool used to process the papers data including title, abstract, keywords, and citations.

Among tech mining authors, South Korean scholars particularly four researchers from Pohang University Science & Technology have had the most impact on tech mining area by publishing 11 papers. Also, applying Eigenvector centrality interestingly shows all top ten authors are from South Korea; however, Kastoff, Porter, Narin, Jaffe, Yoon, and

Table 4 The information of the clusters

Cluster #	Size	Silhouette	Year (mean)	Top terms (tf*idf)	Top terms (log-likelihood)	Terms (mutual information)
0	41	0.977	2009	(7.78) Triz; (7.03) energy; (6.28) patent citation analysis; (6.18) citation analysis; (5.01) management	Knowledge (5.69, 0.05); comparison (5.69, 0.05); patent citation analysis (5.69, 0.05);	Taiwan
1	22	0.981	2008	(6.44) Forecasting; (6.18) journal; (5.48) management; (5.18) text mining; (4.99) visualization	Field (7.4, 0.01); journal (7.4, 0.01); management (7.4, 0.01);	Evolution
2	16	0.991	2009	(4.99) Technology transfer; (4.27) case; (3.55) solar cell; (3.2) technology; (3.03) firm	Solar cell (5.25, 0.05); using non-exhaustive overlap (4.41, 0.05); d funding (4.41, 0.05);	Perspective
3	12	0.826	2006	(6.28) Europe; (6.28) convergence; (4.99) tech mining; (4.67) mining; (4.18) tool	Tech mining (6.17, 0.05); search (4.88, 0.05); role (4.88, 0.05);	Taiwan
4	11	0.88	2010	(6.28) Value; (6.28) semiconductor industry; (4.18) industry; (3.03) case; (2.12) search	Value (10.75, 0.005); semiconductor industry (10.75, 0.005); multiple technique (5.35, 0.05);	Evolution
5	9	0.99	2008	(3.55) Knowledge spillover; (3.03) firm; (2.63) search; (2.63) knowledge; (2.63) research	Knowledge spillover (5.87, 0.05); asymmetry (5.55, 0.05); empirical analysis (5.55, 0.05);	Patent citation network
6	8	0.899	2010	(6.28) Patent document summarization; (4.99) patent document; (4.18) concept; (3.75) mining; (3.55) management	Weak signal identification (6.36, 0.05); technological change (6.36, 0.05); collaborative knowledge system (6.36, 0.05);	…
7	7	0.994	2010	(3.55) Nanotechnology; (2.63) search; (2.56) map; (2.39) technology; (2.12) research	Sectoral system (6.2, 0.05); software research activities (6.2, 0.05); map (6.2, 0.05);	Patent data
8	5	0.985	2011	(4.18) Quality; (2.09) patent	Quality (6.74, 0.01); novelty (6.74, 0.01); technology monitoring (6.74, 0.01);	University patenting

Trajtenberg are the most cited authors with 37, 31, 30, 28, 26, and 25 citations, respectively. Furthermore, Scholars from South Korea, USA, Taiwan, and Japan have had most participation from country point of view. Beside, researchers working in Pohang University, Seoul National University, University of Tokyo, and Georgia Tech have been the most diligent scholars in publishing tech mining papers.

Table 5 Main aspects of the cluster

# Cluster	Technology	Methodology	Industrial sector	Geographical area	Application
0	–	Triz Citation analysis	Energy	Taiwan	–
1	–	Text mining Visualization	–	–	Forecasting
2	Solar cell	Non-exhaustive overlap	–	–	Technology transfer
3	–	Tech mining	–	Taiwan Europe	–
4	–	–	Semiconductor	–	–
5	–	Patent citation network Empirical analysis	–	–	Knowledge spill over
6	–	Summarization	–	–	Weak signal identification
7	Nanotechnology	–	–	–	–
8	–	–	–	–	University patenting Technology monitoring

The most applied keywords are Innovation, science, indicators, citation analysis, technology, research-and-development, bibliometrics, knowledge, patent mining, patent analysis, text mining, patent citations, citations, industry, information, and nanotechnology. However, 'science', and 'innovation' have been the most used keywords in the papers; 'patent analysis' and 'patent mining' are got more noticed by the authors in recent years.

Of among journals related to technology management, 'Sceintometrics' and 'Technological Forecasting and Social Change' have published more 'tech mining' papers. Moreover, the first five journals contain more than 50 % of 'tech mining' papers. Moreover, Fig. 1 shows that more than 70 % of 'tech mining' papers have published after 2010. It means 'tech mining' application has progressively accelerated over recent years.

Cluster analysis divided the papers into eight clusters. The most important aspects of the clusters are technology, methodology, industrial sector, geographical area, and application which are demonstrated in Table 5.

References

Alencar, M. S. M., Porter, A. L., & Antunes, A. M. S. (2007). Nanopatenting patterns in relation to product life cycle. *Technological Forecasting and Social Change, 40*, 1661–1680.

Chen, C. (2004). *Information visualization*. Berlin: Springer.

Chen, C. (2006). CiteSpace II : Detecting and visualizing emerging trends. *Journal of American Society for Information Science and Technology, 57*(3), 359–377.

Chen, C. (2014). "CiteSpac," [Online]. http://cluster.cis.drexel.edu/~cchen/citespace/.

Chen, C., Zhang, J., & Vogeley, M. S. (2009). Visual analysis of scientific discoveries and knowledge diffusion. In *The 12th international conference on scientometrics and informetrics*, pp. 14–17.

Chiavetta, D., & Porter, A. (2013). Tech mining for innovation management. *Technology Analysis & Strategic Management, 25*(6), 617–618.

Choi, S., Kim, H., Yoon, J., Kim, K., & Lee, J. (2013). An SAO-based text-mining approach for technology roadmapping using patent information. *R&D Management, 43*(1), 52–74.

Choi, S., Park, H., Kang, D., Lee, J. Y., & Kim, K. (2012). An SAO-based text mining approach to building a technology tree for technology planning. *Expert Systems with Applications, 39*(13), 11443–11455.

Choi, S., Yoon, J., Kim, K., & Kim, C.-H. (2011). SAO network analysis of patents for technology trends identification: A case study of polymer electrolyte membrane technology in proton exchange membrane fuel cells. *Scientometrics, 88*(3), 863–883.

Dhami M. K., & Olsson, H. (2008). Evolution of the interpersonal conflict paradigm. *Judgment and Decision Making, 3*(7), 547–569.

Gerken, J. M. (2012). A new instrument for technology monitoring: Novelty in patents measured by semantic patent analysis. *Scientometrics, 91*(3), 645.

Geum, Y., Lee, S., Yoon, B., & Park, Y. (2013). Identifying and evaluating strategic partners for collaborative R&D: Index-based approach using patents and publications. *Technovation, 33*(6–7), 211–224.

Guo, Y., Huang, L., & Porter, A. L. (2010). The research profiling method applied to nano-enhanced, thin-film solar cells. *R&D Management, 40*(2), 195–208.

Guo, Y., Ma, T., Porter, A. L., & Huang, L. (2012). Text mining of information resources to inform forecasting innovation pathways. *Technology Analysis & Strategic Management, 24*(8), 843–861.

Jeon, J., Lee, C., & Park, Y. (2011). How to use patent information to search potential technology partners in open innovation. *Journal of Intellectual Property Rights, 16*(5), 385–393.

Kuan, C., Huang, M., & Chen, D. (2013). Capturing and tracking performance of patent portfolio using h-complement area centroid. *IEEE Transactions of Engineering Management, 60*(3), 496–505.

Lee, C., Cho, Y., Seol, H., & Park, Y. (2012). A stochastic patent citation analysis approach to assessing future technological impacts. *Technological Forecasting and Social Change, 79*(1), 16–29.

Lee, C., Jeon, J., & Park, Y. (2011). Monitoring trends of technological changes based on the dynamic patent lattice: A modified formal concept analysis approach. *Technological Forecasting and Social Change, 78*(4), 690–702.

Lee, P.-C., Su, H.-N., & Wu, F.-S. (2010). Quantitative mapping of patented technology—The case of electrical conducting polymer nanocomposite. *Technological Forecasting and Social Change, 77*(3), 466–478.

McCulloh, I., Armstrong, H., & Johnson, A. (2013). *Social network analysis with applications* (p. 46). New Jersey: Wiley.

Park, H., Yoon, J., & Kim, K. (2012). Identifying patent infringement using SAO based semantic technological similarities. *Scientometrics, 90*(2), 515–529.

Porter, A. L. (2005). QTIP: Quick technology intelligence processes. *Technological Forecasting and Social Change, 72*(9), 1070–1081.

Porter, A. L., & Cunningham, S. W. (2005). *Tech mining: Exploiting new technologies for competitive advantage*. New Jersey: Wiley.

Porter, A. L., Guo, Y., & Chiavatta, D. (2011). Tech mining: Text mining and visualization tools, as applied to nanoenhanced solar cells. *WILEY Interdisciplilnary Reviews: Data Mining and Knowledge Discovery, 1*(2), 172–181.

Porter, A., & Newman, N. (2011, January). Mining external R&D. *Technovation*, no.

Rousseeuw, P. J. (1987). Silhouettes: A graphical aid to the interpretation and validation of cluster analysis. *Journal of Computational and Applied Mathematics, 20*, 53–65.

Tijssen, R. J. (2001). Global and domestic utilization of industrial relevant science: Patent citation analysis of science–technology interactions and knowledge flows. *Research Policy, 30*(1), 35–54.

Tonta, Y., & Darvish, H. R. (2010). Diffusion of latent semantic analysis as a research tool: A social network analysis approach. *Journal of Informetrics, 4*(2), 166–174.

Xu-kun, H. J. Z. C. W. (2008). *The information visualization analysis of the study in international S & T policy*, pp. 1–9.

Yoon, B. (2008). On the development of a technology intelligence tool for identifying technology opportunity. *Expert Systems with Applications, 35*(1–2), 124–135.

Yoon, J., & Kim, K. (2011). Identifying rapidly evolving technological trends for R&D planning using SAO-based semantic patent networks. *Scientometrics, 88*(1), 213–228.

Yoon, B., & Park, Y. (2005). A systematic approach for identifying technology opportunities: Keyword-based morphology analysis. *Technological Forecasting and Social Change, 72*(2), 145–160.

Yoon, J., Park, H., & Kim, K. (2013). Identifying technological competition trends for R&D planning using dynamic patent maps: SAO-based content analysis. *Scientometrics, 94*(1), 313–331.

Zhu, D., & Porter, A. L. (2002). Automated extraction and visualization of information for technological intelligence and forecasting. *Technological Forecasting and Social Change, 69*(5), 495–506.