Knowledge Extraction from Academic Journals Using Data Mining Techniques

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목 차

Key Words : Data Mining, Knowledge Extraction, Link Analysis, Knowledge Spillover

Abstract

최근 우리는 인접학문 간 그리고 학계와 산업계 간의 연구협조가 점차 증가하고 있음을 보아오고 있다. 이러한 현상은 특히 학술저널 간 지식의존성을 촉진하는 계기를 제공하고 있다고 할 수 있다. 본 논문의 목적은 관련저널 간 지식상호 의존성을 규명하고 저널지식의 구조화를 위하여 연관성 (association), 군집화, 링크분석 등 데이터마이닝 기법을 적용하는 방법론을 제시하는 것이다. 제시된 방법을 통하여 기대되는 점들은 1) 논문의 기본 속성인 키워드, 저자, 그리고 인용데이터를 통합하는 규칙 집합을 통하여 논문지식검색기능의 향상, 2) 키워드를 기반으로 관련 저널 간 그리고 저널내부의 군집분석으로 지식동향 파악, 3) Kleinberg (1999)의 권위와 허브 개념을 인용데이터 분석에 활용하여 기존의 양적 평가 기준인 영향력지수 (impact factor)의 문제점을 보완하며, 4) 특정 논문이나 저널의 지식파급과 관련한 영향력을 산출하는 잠재적 지식파급 지수를 제안하는 것이다.

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I. Introduction

The process of knowledge creation, diffusion, specialization, generalization, and application depends on the dynamics of the research community network involved: the typology and strength of links among nodes in the network.

Scholastic research papers have been considered as one of the most important sources of powerhouse for R&D activities which in turn differentiate corporate competitiveness from many perspectives such as core technology, product or service conceptualization, and production.

We also notice that the identity of a specific academic area becomes ambiguous since interdisciplinary nature is a popular theme in research community.

Advance in searching technology and database makes it easier for users to retrieve relevant information from diverse scholastic journals. However, the search is usually based on a combination of keywords, which doesn't provide much insight for understanding inter-relationship among academic journals or papers. (In this paper there are two meanings of "keyword": 1) User-provided keywords which are usually given after abstract. Journals require authors to specify small number of keywords. Our analysis refers to this type of keywords. And 2) Noun-form of words in the main body of a paper, which are usually employed for text mining. He (1999) followed this definition.

Data mining techniques are useful to find out hidden patterns and trends which are embedded in data, so that the techniques are used extensively in business settings for such purposes as enhanced customer relationships, marketing, customer segmentations, fraud detection etc., (See Berry & Linoff (2004) for more details of applications).

Compared with the emphasis of previous research on studying the evolution and dynamics of science knowledge from ex-ante perspectives, a meaningful guideline for scholars to search appropriate knowledge will be useful for the knowledge creation process.

In this paper we propose a new methodology employing data mining technologies such as clustering, association, and link analysis to identify interrelationship among journals and papers. In specific we use the main attributes of academic paper such as keywords, authors and citations. The structure of this paper is as follows:

We provide related previous research in section II. Data structures in consideration are provided in section III. In section IV, based on keyword, author, and citation data, we apply the association technique to

making knowledge searching mechanism more effective by generating rules. We show that how clustering techniques are applied to dealing with keyword in section V, followed by link analysis for identifying influential papers using citation data in section VI. In section VII knowledge spillover effect of a paper and journal is proposed to measure the potential of knowledge diffusion and the conclusion in VIII is reached.

II. Previous research on structuring knowledge of academic journals

Key components of academic paper consist of title, authors, keywords, main body and citations. Of course the main body of papers is the essence. However considering the evolutionary and cooperative nature of research, there should be some methods to identify the relationship among journals and papers. To identify the underlying relationship, a set of attributes such as authors, keywords, and citations are frequently used since they contain condensed information representing the knowledge.

Lately, stimulated by bio-informatics, text mining techniques are gradually employed for a detailed and extensive analysis of the main body (Sullivan, 2001). This method might be effective for both detecting important links between related research and to discovering knowledge itself from a huge set of papers.

The "impact factor" (Garfield, 1999) has been widely used to differentiate journals. The impact factor for a journal is obtained in the following way: Let $C_{j,t}$ be the total number of citations which refer to journal j during t and $C_{j,t,b}$ be the number of citations to journal j during the previous b years, or between the years of t-b and t-1. Notice that $C_{j,t,b} \subset C_{j,t}$. Also define $P_{j,t,b}$ to be the total number of papers published in journal j during t-b and t-1. Then, the impact factor of time window of b years for journal j and year t, $IF_{j,t,b}$, is calculated as

$$IF_{j,t,b} = C_{j,t,b} / P_{j,t,b}. \qquad (1)$$

Two-year time window (b=2) is generally accepted as a good indicator to measure the influence of a journal. However if a journal deals with subjects which don't decay fast, a bigger b may be used. Notice the number of citations during the time window tends to increase as the frequency of publications of the journal is high and the number of papers in a volume of that journal is bigger. But this effect is offset by the denominator. To measure an appropriate b, the cited half life can be used. The half life is obtained by finding b such that 50% of $C_{j,t}$ are included

in the previous b years.

Impact factor is to measure how influential a journal is. However, the influence is based mostly on the magnitude of counting not on the quality of citation. The concept of impact factor can be applied to authors and individual papers, but the citation records for these are much less than for journals.

Since impact factor is largely based on the simple counting of citations, the relevance of the measure is often questioned (Amin and Mabe. 2000).

Kleinberg (1999) observed that the quantitative concept of impact factor might mislead the importance of a journal or a paper, by differentiating the importance into three category: authority, hub, and popularity. A simplified version of his algorithm was originally adopted by Internet search community such as Google, but the complete version can be easily extended to scholastic community too.

Author attribute was used to measure research collaboration (Hicks et al., 1996). They compared the degree of research collaboration of firms in Japan and Europe in time series, examining co-authors of research papers. They found firms in Europe were more active in the collaboration than in those in Japan. Moreover, the gap between the two regions were getting bigger, indicating different technological opportunities available to firms in the two regions.

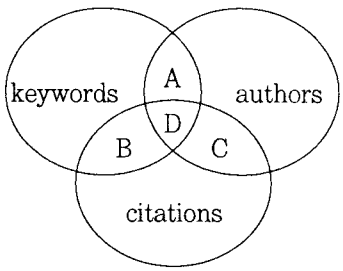
Jaffe et al. (1986) shows how to use R&D spillover using patents which require a rigorous citation by law (Jaffe and Trajtenberg, 1996). He explained the amount of knowledge creation in terms of R&D efforts and potential spillover pool at firm level. Knowledge creation was measured by the number of patents; R&D efforts by R&D expenditures; and spillover pool by the proximity of a firm's knowledge creation weighted by R&D efforts by other firms. We import the idea of Jaffe(1986) to measure the potential knowledge spillover of a paper, an author or a journal using citation and impact factor information.

Advances in computer processing capability make co-word analysis feasible and widely used to extract knowledge from the text and to find linkage among arbitrary papers (He, 1999). The analysis does not depend on any priori definition like user-provided keywords or citations. Assuming that the words in the main text are the "actors", the analysis can be used to provide a diverse set of quantitative associations among words. The central theme of co-word analysis is to find the inclusion and proximity indexes which are used to determine the major and minor research areas. From the indexes, inclusion and proximity maps are created to view the linkage among research areas.

However, as we see in the previous

research, the three important dimensions of author, keyword, and citation are not utilized in integrative ways. Therefore in this paper we present ways of extracting knowledge from integral point of view as in Figure 1.

〈Figure 1: Interaction of three attributes of a paper〉



In section IV we extend the co-word analysis by accommodating intersecting area such as A in 〈Figure 1〉 and generating rules so that a richer information can be extracted using association techniques.

III. Data structures

To explain our methodology we use a vector which consists of 3 elements; author supplied keywords, citations, and authors.

Consider an imaginary set of j journals whose subject are categorized as similar. Then we may assume that there exists some similarity in keywords, authors, and citations among journals in the group. We consider a certain period of time window. In that time frame we prepare three sets such as A for author, K for keyword, and C for citation, with cardinality of a, k, and c, respectively. From this, we create a vector of size w which is the sum of a, k, and c. Let $T_{p,j}$ be a paper p in journal j. Then each element of $T_{p,j}$ is either 0 or 1, depending on whether the paper has the corresponding attribute element. All the subsequent analyses depend on $T_{p,j}$.

To show the data structures visually, consider the following fictitious data for papers on journals, keywords, authors, and citations as in 〈Table 1〉. Since a paper can only cite papers published before, the citation is time dependent. Also note that a paper can cite many papers and references other than those in the collection. To reduce the size of the vector space, we can consider the citations to those papers in the collection; in the following example, pa and pb are outside the collection. The vector space in the collection consists of j1 – j2, p1 – p5, a1 – a4, k1 – k3, and the citation space of p1 – p5.

〈Table 1: Example of Source Data〉

journal	paper	author	keyword	citation
j1	p1	a2	k3	pa
j1	p2	a1 a3	k1 k2	p1
j1	p3	a4	k1	p1 p2
j2	p4	a3	k2 k3	pb p1 p2
j2	p5	a1	k2	p1

Then the first, third, and fourth rows of 〈Table 1〉 can be compiled as vectors, $T_{p,j}$, in 〈Table 2〉 based on whether a paper has the corresponding attribute. If the attribute exists, assign 1, and 0, if it doesn't.

〈Table 2: Compiled Data Structure〉

ID	set A				set K			set C				
	a1	a2	a3	a4	k1	k2	k3	p1	p2	p3	p4	p5
j1p1	0	1	0	0	0	0	1	0	0	0	0	0
j1p3	0	0	0	1	1	0	0	1	1	0	0	0
j2p4	1	0	0	0	0	1	1	1	1	0	0	0

IV. Application of Association

In business world, association techniques are widely used in customer relationship management. Association means that some events occur simultaneously, as in the purchase of beer and salted peanuts together. However, it does not convey any cause and effect relation. If there is a high tendency that beer triggers the purchase of salted peanuts, then the relation can be thought of as a rule. A set of rules can be effectively used for promotion, shelf arrangement and layout, and recommendation to customers, especially in Internet shopping environment.

Several methods for analyzing the degree of association of keywords are proposed in He (1999). Two related major indexes are inclusion index (I_{ij}) and proximity index (PR_{ij}) defined in the following way:

$$I_{ij} = n(k_i, k_j) / \min(n(k_i), n(k_j)), \quad (2)$$

where

$n(k_i)$ = the number of papers containing the keyword k_i;

$n(k_j)$ = the number of papers containing the keyword k_j;

$n(k_i, k_j)$ = the number of papers containing keywords of both k_i and k_j.

min (a, b) = the minimum of two quantities, a and b.

Also the proximity index is defined as,

$$PR_{ij} = n(k_i, k_j) \cdot N / (n(k_i)\, n(k_j)), \quad (3)$$

where

N = the total number of papers in the set.

Now let's introduce the notions of support, confidence, and lift (See Berry and Linoff, 2004 for more detailed description). Note that (2) and (3) just measure the strength of types of combination without any directional consideration.

Suppose now that a rule, if k_i, then k_j, stating that if a paper has a keyword k_i, then that paper also contains keyword k_j with certain probability. Call the probability of co-occurring k_i and k_j the support of the rule or $s(k_i, k_j)$ which can be expressed as

$$s(k_i, k_j) = n / (k_i, k_j) / N, \quad (4)$$

Note that $s(k_i, k_j)$ applies to a rule, if k_j, then k_i, in the symmetric way. But to measure the effectiveness of an rule by taking into account of the direction, we need another probability. We call it "confidence". For the rule, if k_i, then k_j, define the confidence,

$$C(k_i \rightarrow k_j) = S(k_i, k_j) / P(k_i), \quad (5)$$

where $P(k_i) = n(k_i) / N$. It is easy to see that (5) is a probability conditioned on the set of papers containing keyword .

Now compare equations (2) and (5). Equation (5) undershoots due to the denominator. However the main difference is that equation (2) does not convey any directional information, while equation (5) does. Moreover, He (1999) does only consider the inclusion index between two keywords, but we can extend (5) to a general case of a rule such that if k_i & k_j & $\cdots$ & k_t, then k_z.

To determine how much better a rule performs we need another measure, "lift", which is defined as (see Berry and Linoff, 2004, pp 310):

$$L(k_i \rightarrow k_j) = C(k_i \rightarrow k_j) / P(k_j). \quad (6)$$

Equation (6) measures the ratio of the rule's confidence, $C(k_i \rightarrow k_j)$, to the random probability of getting keyword k_j, $P(k_j)$. $L(k_i \rightarrow k_j) > 1$ implies that the rule is significant. But if $L(k_i \rightarrow k_j) \leq 1$, then the rule is not meaningful.

The equations (3) and (6) are the exactly the same. But equation (3) not only does not contain directional information but also cannot be extended to many keywords situations.

Based on the equations (5) and (6), we can provide scholars with more flexible ways of searching mechanism by way of rule generation. The rules can include elements from the sets of *A*, *K*, and *C*. For example, if there is a rule base stating that

Rule 1: If k_i, then k_j.
Rule 2: If k_i & k_j, then a_t,

and the user searches related information k_i, then the search engine can search the rule base to provide both keyword k_j and the author a_t. Compared with the co-word linkage map mechanism, our proposed rule base can be extended to accommodate other attributes other than keywords and knowledge search can be flexible through both forward and backward directions.

To accommodate all the possible combinations of rules, we need to overcome the exponential growth of problem space derived from the vector size *w*. The complexity of this problem is non-polynomial. There are several ways of handling this problem: 1) For a rule to be useful, a threshold for the support can be predefined. That is, if $S(k_i)$ is less than the threshold, any further combination including k_i can be eliminated from consideration, which significantly reduces the size of problem space. 2) To handle the rule generation process efficiently in terms of memory space and time, we may use the apriori algorithm (see Han & Kamber, 2001). 3) If there are many keywords, the keywords can be aggregated into more general keywords so that the vector size is reduced.

V. Application of Clustering

In section III we assumed that the journals in consideration are similar in terms of research area. However, there might be intrinsic differences among journals due to the differences in editorial policy and research community among journals. If that is the case, the extraction of major research area of each journal can be useful for researchers. In this section we propose techniques both to test whether the journals in the set deal with the same research area or not and to provide clusters of research subjects for each journal.

User supplied keywords convey condensed meanings of the paper. Analysis of the keywords can give us such information as research area, research methodology, and so on. Given a set of j journals, it is interesting question to ask whether those journals are different with respect to keywords. If there is no significant difference, editorial board of each journal must try to figure out its identity. Moreover, if a governmental level organization oversees the journals, funding to those journal might not be effectively utilized.

Hypothesis: There is no significant differences of research subject among the journals in consideration.

To test the hypothesis we need to rearrange the vectors $T_{p,j}$ so that only the keyword portion remains. Note that th element of the vector of $T_{p,j}$ is 1, if paper p in journal j contains keyword k_i and 0, otherwise.

Since we don't have any priori knowledge on keywords, an agglomeration clustering technique (see Han and Kamber, 2001 for details) is better to identify the appropriate number of clusters for keywords. General idea of finding a good cutting point for agglomeration clustering is to build up clusters from scratch so that the homogeneity of a cluster is high and the between clusters difference is high. One way of choosing the number of clusters is the clustering coefficient in SPSS. Choi & Lee (2002) recommends the number which makes the slope of the clustering coefficient maximum.

From this procedure assume that we have come up with g clusters. To test the null hypothesis we build a contingent table with rows and columns representing g clusters and j journals, respectively. For each cell we assign two numbers; one is the real number of papers for each cluster and journal; the other is the expected number of occurrence. From the table filled up with cells of two numbers, a x^2 test with the degree of freedom, $(g-1)(j-1)$, can be performed.

If the null hypothesis is rejected, we can look into detail of each journal to specify the research area. For this analysis we may us a top down clustering algorithm such as K-means. We can choose an arbitrary number of clusters for each journal.

VI. Link structure analysis

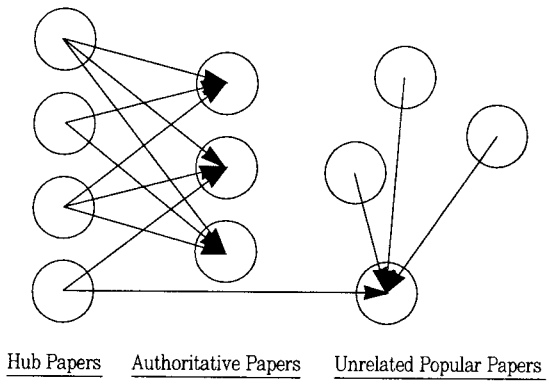
1. Problems of assessing importance of journals and papers

As we saw the impact factor for a journal

or a paper is based on the counting of citations to that journal or paper. The number of hits at Internet sites had been considered an important factor to evaluate the sites, making it a baseline for assessing advertisement fees. However, the number itself does not reflect the real value of the sites (Hoffman and Novak, 2000). Also all hits are not equally important: some hits are more important than others in terms of purchasing propensity. This phenomena can be applied to scholastic papers. In this sense, the impact factor is not a good indicator to measure the paper's influence. Kleinberg (1999) proposed a new way of determining the importance of a webpage. The main observation by Kleinberg is that the importance of paper j depends on both the amount of citation received and the importance of those citations. Note the recursive relationship of importance between paper j and the citing papers. He suggested that a set of relevant sample webpages are selected, from which a bigger set of webpages is derived through the links from and to the smaller set. Compared with the web environment where the number of related webpages is huge, the number of papers in academic journals is much less. So in the following analysis we use the full set of papers to assess the importance of papers.

The key idea of the Kleinberg's algorithm is to differentiate papers into three classes: the first group is represented as authoritative; the second as hub; and the third as popular (Berry and Linoff, 2004) as in 〈Figure 2〉.

〈Figure 2: Three classes of papers, Revised from Berry & Linoff, 2004, p 335〉



2. Application of link structure analysis on scholastic journals

We provide a brief procedure of the derivation of these sets of papers (see Chakrabarti et al., 1999 for detailed description of the HITS algorithm which is implemented in statistical packages such as SPSS).

Consider the portion of citation data from the vector T_{pJ}. That portion of data refers to the existence of citation to other papers. These other papers may be included in the set J or not. For efficient processing we can limit the size of citation vector by considering those papers in J only (See

section III). Thus when a paper in J cites another paper not in J, that cited paper is not included in constructing the adjacency matrix. Suppose the total number of papers in J during the time window of consideration is n. Define the adjacency matrix as C, a $n \times n$ square matrix. Also define $C_{ij} = 1$, if paper i cites paper j, and 0, otherwise. Then the relations between the vectors of authoritative (x) and hub (y) can be written as:

$$x = C^T y. \quad (7)$$

$$y = C x. \quad (8)$$

Note that C^T is the transpose of C. Since C_{ij} represents the existence of citation from paper i to paper j, equation (8) captures the outgoing (hub) force. In similar way Equation (8) can be interpreted as incoming (authority) strength. Also note that Equations (7) and (8) are recursively related. So substituting each other we can rewrite these two variable equations into a single variable ones as follows: $x = (C^T C)x$, and $y = (CC^T)y$. Solutions for both x and y can be obtained numerically by these equations.

We can apply Kleinberg' s algorithm either on the citation data obtained from across the set J or on the citation data created from the clusters of the set J.

VII. Knowledge spillover effect

1. Background

Academic papers are considered as the important sources of codified knowledge. Since the knowledge is made public, it has many aspects of a public goods. Moreover, the existence of related knowledge published by other scholars makes a given researcher put much less efforts than he creates the knowledge from the scratch. In general, if research subjects and ideas of paper are promising, the papers induce many other subsequent papers, which we call the phenomena of a knowledge spillover. Impact factor and authoritativeness can be proxies to measure the degree of knowledge spillover contributed by a paper. The main characteristic of the set of papers of both inducing and induced spillover is that their proximity is very close. In this section we propose a measure of proximity so that we can measure the importance of a paper from the knowledge spillover perspective. Jaffe (1986) derived a model to estimate R&D productivity at firm level. His conjectured that if any two firms have a close proximity of patent composition across the 49 patent categories, the

potential of R&D spillover will be high, which in turn stimulate the given firm's R&D productivity. He called the potential as "potential R&D spillover pool", whose concept will be used for our measure of knowledge spillover effect.

2. Measuring knowledge spillover with citation

We measure knowledge spillover of a paper or a journal using citation information. To do it, we deal with the citation matrix, C, introduced in section VI. Select any two rows, C_i and C_j from C. Then the similarity of the two rows (s_{ij}) can be obtained by the cosine angle of the two vectors as follows:

$$s_{ij} = \cos\theta_{ij} = \frac{C_i \cdot C_j}{\| C_i \| \, \| C_i \|}, \qquad (9)$$

where the numerator denotes the inner product of two vectors and it is normalized by the product of the norms. Note that $0 \leq \cos\theta_{ij} \leq 1$; when the two citation vectors have the exactly same components, the cosine value is 1, and 0, otherwise. We believe the angular separation measure (see Sullivan, 2001, for measuring the separation of vectors with text data) of similarity as in Equation (9) is better than the Euclidean distance since it is more computationally efficient due to the sparsity of the matrix and the composition of elements of the vector is more important than the length of the vector.

Another index affecting the magnitude of spillover is the degree of importance of papers. We can use the authoritativeness defined in section VI or impact factor in section II. Denote the importance of paper i as w_i. Based on the similarity index between any two papers and the importance index, the potential knowledge spillover pool into the paper i ($KSP_{\rightarrow i}$) is given as:

$$KSP_{\rightarrow i} = \sum_{j \neq i} s_{ij} w_j . \qquad (10)$$

The index, $KSP_{\rightarrow i}$, is the product of the similarity between the two papers with respect to citation and it is weighted by the importance of the neighboring paper. So the index measures the gravity into the given paper from the neighboring environment. If it is high, it is conjectured that the externality of that paper is high.

This concept can be extended to the potential knowledge spillover induced by authors and journals by aggregating the citations of papers according to authors or journals.

VIII. Conclusion

We extended the previous related research on knowledge discovery from academic journals by employing data mining techniques such as association, clustering, and link analysis. In specific, we extended the domain of simple keyword searching to that of rule based searching which integrates diverse dimensions such as keywords, authors, and citation information. We also augmented the counting based impact factor with authoritativeness of citation.

Utilization of scholastic papers are important for the governmental research policy setting toward R&D and promoting cooperation between academic institutes and industries. In this sense the knowledge spillover effect should be considered as important factor for assessing papers, journals, and authors. To do that we introduced the concept of potential knowledge spillover pool using citation information.

Considering the recent governmental initiative for Digital Library which requires to provide higher utility to users through efficient knowledge creating efforts as well as enhanced and customized searching capability, we hope this research brings attention to further research. Since the objective of this research is to explore more comprehensive ways of extracting knowledge from academic papers by employing existing theories, we didn't test the proposed methodology in real world data, which should be considered as the future research.

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