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期刊影響力之研究

Issues in the Measures for Journal Influence

指導教授：沈培輝 博士 Pui-Fai Sum, PhD

研究生：宋長翰 Chang-Han Song

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中文摘要

目前在學術界有許多期刊排序因子，我們可以依照因子的定義將之分為三大類。分別是 **Author-Based**：觀察作者偏好與出版習慣、**Citation-Based**：觀察引用次數，以及 **Perception-Based**：詢問專家意見。而在 **Author-Based** 中，一項特別的排序方法 **Publication Power Approach** 採用了兩個因子，一為 **Publishing Intensity**(出版密度)，二為 **Publishing Breadth**(出版寬度)，給定一組活躍的學者(**Active Scholars**)以及一段特定的時間範圍，一本期刊的出版密度可被定義為該組學者在該本期刊出版篇數的總數量，而出版寬度則是該組學者中曾經在該本期刊中出版過一篇文章以上的總數量；雖然出版密度與出版寬度已經被套用在期刊排序方法上面，但兩者之間的關係並沒有深入討論。

有鑑於此，本論文提供實際的數據分析去探討出版密度與寬度的關係，焦點將放在六個不同的領域之上，該六領域包含人工智慧、資訊科學與圖書科學、管理學、護士學、人類學以及地理學。對每個領域，我們從 **Journal Citation Report (JCR)**資料庫 **2012** 版本中取得該領域的期刊列表。接著，一組活躍的學者應該滿足以下三項條件：**(1)** 活躍的學者應要擔任該領域任一期刊現任編輯，**(2)** 活躍的學者應要在美國 **Top 25** 公立大學內任教 **(3)** 該活躍的學者應該在 **1999-2003** 年間出版過一篇以上的文章。最後一項規則確保學者在該領域中活躍時間超過 **10** 年以上，接著，我們將選出來合格的期刊以及學者藉由 **Thomson-Reuter Web of Knowledge** 資料庫去計算出每本期刊之出版密度與寬度，最後，我們分析 **log-log** 在兩者之間的關係，結果顯示出版密度跟出版寬度有 **log** 的線性關係。在經過六個不同領域的檢驗之後，**log-log** 關係也顯現出相同的結果，我們相信這個 **log** 線性關係在其他領域也能適用。得到上述的結果，我們很好奇此結果是否適用在相同分類中的排序因子之間，因此，我們一併探討了 **Eigenfactor** 與 **Raw citations** 之間的關係。

最後，回到期刊排序因子探討，現今有許多種期刊排序因子，但每一個都有相關的缺點，單獨使用其中一種因子無法完美呈現出最客觀的結果，許多缺點需藉由不同因子的結合才能克服，一本好的期刊應該能吸引高質量的研究文章，也應吸引更多的讀者來閱讀並做後續研究；我們提出新的排序方式：”**Knowledge Transfer Impact**(知識轉移因子)”，該方法結合了前文所提的出版密度以及目前普遍使用的 **Impact Factor**，將出版者的偏好以及讀者的引用次數納入考量中，希望反應出最真實的排序結果。在文中，我們將知識轉移因子套用在 **AI** 的領域並列出其他排序方式之結果，提供讀者更多元的排序方案。

關鍵字：期刊排序、對數線性、出版密度，出版寬度

ABSTRACT

While conducting journal ranking, selecting measure is crucial. Different measures will lead to different ranking results. Generally speaking, these measures could be classified in three categories. The first category is the Author-Based measures which ranks journals by the publishing preference of the authors. The second category is the Citation-Based measures which ranks journals based on the number of citations. The last category is the Perception-Based measures which ranks journals by active scholars' opinions. Many journal ranking methods are thus defined in terms of the measure(s) in either one of these categories. While many measures have been proposed in the literature, little has been done on the relations amongst measures. Nevertheless, not much work has been done on ranking journals by combining measures from different categories. Therefore, this thesis presents the results on (1) the relations between publishing intensity and publishing breath, (2) the relations between Eigenfactor and raw citations, and (3) a new ranking method called Knowledge Transfer Impact.

Given a set of active scholars and a period of time, publishing intensity (PI) of a journal is defined as the total number of publications appeared in the journal that are co-written by the active scholars. Publishing breadth (PB) is defined as the total number of active scholars who have publications in that journal. On the other hand, the definition of Eignefactor is intricate. Suppose an article is randomly picked from any journal. The reader reads the article and then randomly picks another article in the references and reads. The process repeats until no article can be picked. The Eigenfactor of Journal-J is the proportion of times that the articles being picked in the process are from Journal-J. Raw citation is the total number of times a journal has been cited by the published papers. While PI and PB have been applied in journal

ranking, their dependency has not been investigated. So do the Eigenfactor and the raw citations, little has been done to investigate if there is any relation between them. In this regard, this thesis presents empirical analyses on the relation between different measures, with focus on six fields namely Artificial Intelligence, Information Science and Library Science, Management, Anthropology, Geography, and Nursing.

To investigate the relation between publishing intensity and publishing breadth, we first extract the list of journals from the JCR 2012 edition. The list of active scholars of a field is compiled based on three rules: (1) an active scholar must currently be an editorial member of a journal which is in our journal list (published more than 15 years), (2) an active scholar must be affiliated with one of the Top 25 US universities compiled by US News, and (3) an active scholar must have publications in the field during 1999 to 2003. The last rule ensures that an active scholar has been active in the field for more than ten years. Based on the lists of journals and active scholars, we count from the Thomas Reuter WoK Database the PI and PB for each journal. Finally, we analyze the log-log relation between the PI and the PB of the journals in the list. Results show that log PI and the log PB have log-linear relation. The same result appears in all six fields. As the six fields have quite diverse natures, we argue that this log-linear relation is a common behavior across other research fields.

To investigate the relation between Eigenfactor and raw citations, we also extract the list of journals from the JCR 2012 Version and screen out those journals which have life time less than 15 years. The Eigenfactors are thus simply retrieved from the JCR 2012 database. For the raw citations, we count for each journal the total number of citations in between the years 2006 to 2010. Finally, we analyze the log-log relation between the Eigenfactors and the raw citations of the journals in the list. Results show that Eigenfactors and the raw citations have log-linear relation. The same result appears in all six fields. As the six fields have quite diverse natures, we argue that this log-linear relation is a common behavior across other research fields.

A good journal should satisfy two conditions. First, it has to attract very high quality research from active scholars. Second, it should attract lots of readers to read the paper and then follow the research, which means having high dissemination power. Therefore, a better journal ranking method should consist of measures from both author-based and citation-based categories. It leads to the development of a new method called Knowledge Transfer Impact (KTI), which is defined as the multiplication of publishing intensity and Impact Factor. In essence, it measures the number of new knowledge which is inspired by the articles published in a journal. From the ranking results, it is found that KTI supplements the current journal ranking methods by trading off the biases from either citation-based or author-based journal ranking methods.

Keywords: Journal Ranking, Log-Linear, Publishing Intensity, Publishing Breadth

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CHAPTER 1 INTRODUCTION

Scholars who are planning to publish may face a question – which journal should I submit? However, it is not a simple question. To measure the quality of a journal can be done in various ways, either by citations or the opinions of the experts. No matter what, all of these measures have the common goal. To compile a list of journals to let the readers select the most suitable journal for publishing their research findings. In general, quality, influence, popularity, reputation and amongst others are considered as indicators in ranking. However, these indicators are not easily defined. Many well accepted indicators, like Impact Factor and Eigenfactor, are defined in terms of the number of citations. Some others, like author affiliation index and publication power, are defined based on the publication behavior of the authors. None of them considers combining measures from both author-based and citation-based. In this regard, creating a new journal ranking method that can reflect the real quality of a journal by combining both author-based and citation-based measure is vital and yet indispensable.

In the past decades, a considerable amount of literatures related to journal ranking have been published. Clearly, every ranking method has its drawbacks. For instance, journal rankings using author-based measures could be very subjective as the ranker needs to define the set of 'good' affiliations and the set of 'leading' scholars. While rankings using citation counts are objective, citation counts could be manipulated simply by enforcing authors to co-cite amongst journals. Without a universal acceptable ranking method, both author-based and citation-based measures seem to be the only choice that we can rely on.

1.1 Problems

While many measures have been proposed, journal ranking should aim to answer three fundamental questions:

(1) While a lot of measures have been developed, which one is the best measure for journal ranking?

(2) Amongst all these measures, are some of them basically correlated?

(3) In the literature, there are many journal ranking methods are defined in terms of citation-based measures and many are defined in terms of author-based measures. It indicates that both citation-based and author-based measures are essential in journal ranking. So, would it be possible to develop a more meaningful measure that makes use of the measures in these two categories?

The answer for the first question is open-ended. It is impossible to have a correct answer. Many researchers have agreed that all the measures have their own pros and cons. No particular one of them can be claimed to be the best measure. In reality, it all depends on the managerial decision. For the second question, only Davis (2008) has provided a few answers to it. In his analysis, the research for discovering the relations among Eigenfactor, Impact Factor and raw citations are conducted in the field of medical science. He found that Eigenfactor are correlated with both the Impact Factor and raw citations.

For the third question, the answer is clearly yes. One possible solution is to define a new measure as a weighted sum of multiple measures. Although it is straightforward, the physical meanings of these new measures are usually missing. The other possible solution is the Publication Power Approach (PPA) which is defined as the multiplication of publishing intensity (PI) and publishing breadth (PB)**.** While using "combined measures" is a possible solution for ranking journals, many researchers have not investigated if the "measures" in the "combined measures" are independent. If some of these measures are basically correlated, reduction of the "combine measures" to a simpler form would be desirable.

In this regard, this primary objective of this project is to provide answers and solution to the second and the third questions. The contributions of the project are three folds: *(a) to provide an empirical analyses on the relation between PI and PB, with focuses on six fields: Artificial Intelligence, Information Science and Library Science, Management, Anthropology, Geography, and Nursing; (b) to report on the relation between journal Eigenfactor and journal raw citations, with focuses on six fields: Artificial Intelligence, Information Science and Library Science, Management, Anthropology, Geography, and Nursing;; and (c) to propose a new journal ranking method Knowledge Transfer Impact (KTI), with the focus on the field of Artificial Intelligence.*

Fifteen datasets have been collected for the completion of this research. Three of them were used for preliminary studies, and the other twelve datasets were used for comprehensive studies. Amongst the fifteen dataset, one of them is based on the data listed in Davis (2008). Fourteen datasets were extracted from Thomson-Reuter Web of Knowledge. The steps to collect the dataset will be elucidated in the subsequent chapters.

1.2 Thesis Organization

This thesis is organized into six chapters. After this Introduction, Chapter 2 introduces the definitions of various measures for journal influences and discusses their usages. Then, the preliminary results on the log-linear relations amongst measures (publishing intensity versus publishing breath, and Eigenfactor versus raw citations) are presented in Chapter 3. Chapter 4 presents two comprehensive results in regard to publishing intensity versus publishing breath and Eigenfactor versus raw citations, with focuses on six fields: Artificial Intelligence, Information Science and Library Science, Management, Anthropology, Geography, and Nursing. To alleviate the problem that some fields might not have fellowship offering, a new method is proposed to define the "active scholars" and "qualified journals". A new "combined measure" called Knowledge Transfer Impact (KTI) for journal ranking is then presented in Chapter 5. Its definition will be introduced and an illustrative example is presented to highlight the differences between the new ranking method and other methods. Finally, the conclusion of the thesis is presented in Chapter 6.

CHAPTER 2 MEASURES FOR JOURNAL INFLUENCE

In this chapter the common measures for journal ranking will be presented. Based on the definition of the measures, we can classify them into three categories. The first category is the Author-Based measures which ranks journals by the publishing preference of the authors. The second category is the Citation-Based measures which ranks journals based on the number of citations. The last category is the Perception-Based measures which ranks journals by active scholars' opinions.

2.1 Author-Based Measures

The measures are based on the observation of the behavior of a set of scholars. For it observes the scholars' preferences and the publishing behaviors, some people may call it behavior-based.

2.1.1 Publication Power Approach

Publication Power Approach (PPA) was proposed by Holsapple (Holsapple, 2008). He provides an interesting perspective while doing journal ranking. He observed the publishing preference of a group of scholars to rank journals. The measures he used are publishing intensity, publishing breadth. (Holsapple, 2008). PPA collects the publishing behaviors of a set of active scholars, which includes how many papers a scholar published and what journals they have published in a given time period. Some people may say that it is a behavior-based method. In here, we put it in the category of author-based measure. The method is defined as follows:

Let I_j and B_j be the publishing intensity and the publishing breadth of the j-th journal respectively. The publishing intensity and breath are defined as follows:

$\boldsymbol{I_j}$ (Publishing intensity of journal j) is defined as the total numbers of articles authored by the active scholars. $\boldsymbol{B_j}$(Publishing breadth of journal j) is defined as the total numbers of active scholars who have authored articles in the journal.

With the definition of publishing intensity and publishing breath, CW Holsapple proposed a measure called publication power which is defined as follows

Publication power = publishing intensity * publishing breadth

Let publication power be U,

$$U = I_j * B_j$$

Here's an example, there're two journals: DSS and I&M.

Table 2.1 Example of PPA

	Breadth		Intensity		Power	
Journal	Total	Rank	Total	Rank	Product	Rank
DSS	34	1	136	1	4624	1
I&M	27	2	50	2	1350	2

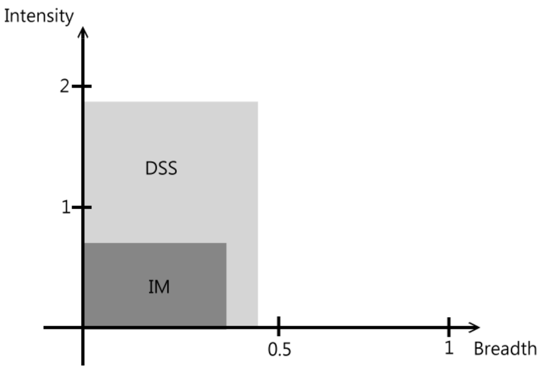

Figure 2.1 The production of Publishing Intensity and Publishing Breadth

In this example, we can see that the publication power of DSS is higher than IM (4624>1350), so the ranking for DSS is No.1 and for IM is No.2

2.1.2 Author Affiliation Index

Instead of looking at the journal citations, Moore (1972), Gorman & Kanet, (2005) and Fry & Donohue, (2013) started to consider author affiliations. If a journal can attract large number of authors who are from top universities, the journal should be considered as a prestigious journal.

There are many definitions on author affiliation index (AAI). Readers can refer to Fry & Donohue, (2013) for a survey of all these definitions. As an introduction of the idea, we follow a simple definition from Gorman & Kanet, (2005).

Suppose that a journal i has M_i papers. For paper $l \in M_i$, there are n_l authors. A_l authors are from top universities and B_l are not. Then, the AAI of the journal i, denoted as AAI_i, is given by

$$AAI_i = \frac{\sum_{l \in M_i} A_l / n_l}{\sum_{l \in M_i} (A_l + B_l) / n_l}$$

While AAI can be applied as a measure of the journal influence, a controversial issue is how to define top universities. In the earlier studies Moore (1972), Gorman & Kanet (2005), the set of top universities is limited to American universities. Some of the journals which are popularized in Europe are under-ranked.

2.2 Citation-Based Measures

Citation index is a database that contains the information of the citation relationship between publications. By checking the citation index database, we can know the number a paper has been cited by other papers. Taking Thomas Reuter Impact Factor for example, it uses the number of citations to be its measures. Since it is based on the citation number, we can call it citation-based measure.

The main advantage of citation index method is that it is more current than most subject measures (Garfield, 1972). The first method was developed in 1873 by Frank Shepard, which was called Shepard's citations. It was initially designed to provide a tool for searching legal decisions. In 1960, the first edition of Science Citation Index (SCI) was first developed by Eugene Garfield [http://wokinfo.com/essays/history-of-citation-indexing/]. At an interview with Eugene Garfield, he said that the concept of this database was influenced heavily by Shepard's citation. Since Science Citation Index (SCI) was published, it has now become the most dominant and comprehensive citation index to the scientific journal papers.

However, there exist other citation databases, such as Google Scholars, that are used widely. Google Scholar is a freely accessible web search engine that indexes the full text of scholarly literature across an array of publishing formats and disciplines. But there're still some criticisms saying that some highly cited papers in a journal may result in high citation number of that journal but it doesn't mean that all the papers in the journal has the same quality.

2.2.1 Impact Factor

Impact Factor is defined by Thomson-Reuter Web of Knowledge to measure the impact of a journal. Roughly speaking, it aims to measure how likely a research will read and cite a paper of a journal. Thus, it is practically defined as the ratio of "the total number of citations the journal has received in the last two years" to "the total number of papers published in the journal in the last two years".

Let F_j be the Impact Factor of j-th journal, C_j be the number of citations of j-th journal, A_j be the number of articles published in the j-th journal. The Impact Factor can be written as follows:

$$F_j = \frac{C_j}{A_j}, \mathrm{j} = 1 \ldots \mathrm{N}$$

For example, a journal has received 300 citations from 2010 to 2011, and those citations were cited by articles during 2012. In the 2 year period, the journal has published 100 articles. Then the 2 year Impact Factor of the journal is $\frac{300}{100} = 3$. This information will be reported in the 2012 Journal Citation Report.

It is important to know that the Impact Factor of 2012 is published 2013 (the Impact Factor of 2012 can only be calculated until all of the 2012 publications have been collected). Basically, Impact Factor provides an indicator of citation impact normalized by the size of the journal.(Davis, 2008)

2.2.2 Raw Citations

Clearly, a straight forward citation-based measure is based on the raw citations, the total number of citing a journal. For example, raw citations of 2012 is the total number of the citations it received in 2012 and those citations are cited to the articles published in the journal from 2007 to 2011.

2.2.3 Eigenfactor

It was developed by Jevin West and Carl Bergstrom (C. T. Bergstrom, West, & Wiseman, 2008). The definition of Eignefactor is intricate. Suppose an article is randomly picked from any journal. The reader reads the article and then randomly picks another article in the references and reads. The process repeats until no article can be picked. Assuming that each randomly picked article does not have self-citation, the Eigenfactor of Journal-J is the proportion of times that the articles being picked in the process are from Journal-J. In reality, it is for sure that almost all articles must have self-citations. But this proportion is normally small, as compared with non-self-citations.

The main difference between Eigenfactor and Impact Factor is that Impact Factor of a journal is defined as the citations per article and the citations include self-citations. For Eigenfactor, self-citations are excluded. In other words, citations from the same journals will not be contributed to the Eigenfactor. (C. Bergstrom, 2007). It is believed that Eigenfactor is more robust than Impact Factor. The explanation is that Impact Factor counts every incoming citation regardless the quality of those journals. In the JCR database, the citation counts of a journal for calculating the Eigenfactor is based on the time period of 5 years. For example, the Eigenfactor in 2012 is calculated by the citations of journals to other journals during the years 2007 to 2011.

2.2.4 H-index

H-index is based on the citations received by a journal's articles. A journal having index h means that h of its N articles have at least h citations for each articles, and the other (N − h) articles have no more than h citations for each articles.(Hirsch, 2005) In other words, a journal with an index of h has published h articles each of which has been cited in other articles at least h times. Thus, the h-index reflects both the number of publications and the number of citations per publication. Google Scholar Metrics uses the concept of h-index to rank journal as well.

2.2.5 C-index

C-index is based on h-index but counting only those citations that are considered significant, where the significance of a citation is proportional to the collaboration distance between the cited and the citing authors. (Bras-Amoros, Domingo-Ferrer, & Torra, 2011)

2.2.6 G-index

For the citations received and given a number of papers ranked in a decreasing order according to the citations received till now, the G-index is the biggest number such that the top g papers received at least g^2 times. As such, g-index is capable of highlighting papers that are highly cited, namely, papers with higher impact. A higher g-index means more and better papers (Tol, 2007).This index assists the h-index and gives more weight to the highly-cited papers. (Egghe, 2006)

2.2.7 SCImago Journal Rank (SJR)

The SJR indicator is a size-independent metric aimed at measuring the current “average prestige per paper” of journals for use in research evaluation processes. Prestige is estimated by the usage of PageRank algorithm in the journal citation network. It ranks scholarly journals based on citation weighting schemes and Eigenfactor centrality. (González-Pereira, Guerrero-Bote, & Moya-Anegón, 2010). Different from Impact Factor, the SJR indicator is based on Scopus database instead of Thomson-Reuter Web of Knowledge database. Also, the SJR indicator prevents the influence of journal self-citations.

2.3 Perception-Based Measures

Scholar opinion is a relatively informal technique which can be used to serve a variety of purposes, and may be used to assist in problem identification, in clarifying the issues relevant to a particular topic, in the evaluation of products, and of course, in the ranking of journal quality. Though individual experts can be consulted, it is usually better to bring groups of experts together so that a wide range of experience can be drawn on and the result may be more objective.(Hirsch, 2005)

2.3.1 Expert Survey

Expert survey is a general terms for the method that may collect the opinion of a certain set of scholars. The way to conduct the questionnaire may various from different conductors.

To evaluate the quality of journals, the simplest ways is conducting a questionnaire survey to the experts and ask for their opinions. By asking the experts, we may have a brief understanding of the picture of what they expected to be the best journal. There is no strict regulation of how you are going to make the questionnaires. The basic principle is to make a questionnaire to the set of the scholars who are the experts in your chosen journal field. The ranking was determined by the opinions of the experts, therefore it may involve some personal preferences and the result may become subjective(Donohue & Fox, 2000). There're some limitations and drawbacks when using expert survey. First of all, the responses may vary with the different set of experts; the factors include region, gender, and experts' interest and so on. Secondly, this method is time-consuming; some experts may respond you after a long period of time or even not respond you, which mean that it will take a lot of time waiting and tracking their responses. Lowry mentioned that when large, predefined lists are used, it is less effective (Lowry, Romans, & Curtis, 2004).

2.3.2 Delphi method

Delphi method is a method that is similar to expert survey. "Project DELPHI" is the name for a study of the use of expert opinion that has been conducted at the Rand

Corporation in 1950s. And here is how the Delphi method work: A facilitator conducts a questionnaire (or interview) to the expert. All the experts will answer the questionnaires for more than one round. The facilitator will avoid direct confrontation of the experts with each other. When a round is done, facilitator will retrieve the questionnaires to make some correction and adjustment to questionnaires according the answer respond by the expert. The correction and adjustment .The new questionnaires will be sent again to the experts to start a new round. After many rounds, it will achieve its object, which is obtaining the most reliable consensus of opinion of the experts(Dalkey & Helmer, 1963). Delphi method can also apply to journal ranking. In 1972, Hawkins, Ritter, and Walter used Delphi method to rank economic journals.(Hawkins, Ritter, & Walter, 1973)

CHAPTER 3 MEASURES RELATIONS: PRELIMINARY RESULTS

Publication power approach is a new ranking method that has our interests. Publication power approach uses the product of two measures to be its final ranking method. However, no one explore the relation between publishing intensity and publishing breadth. Therefore, we follow the guide from the original paper to obtain our own statistic.

3.1 Fellow-Based Publishing Intensity/Breadth

While the author Rokach was collecting data for PPA, he used AAAI to be its active scholars(Rokach, 2012). We are curious that what the result will be if we change the active scholars, for what is the standard to determine an association to be active scholars is still debatable and there isn't always a prestigious association for every journal field. As a result, we choose IEEE CIS fellow to be our active scholars and see whether the result may be different from the original one. The results are in the Table 3.2. Interestingly, when we applied log model to both of the measures and then plot them, it came out to graphs as Figure 3.1 and Figure 3.2. As a result, we make a hypothesis: Publishing intensity and publishing breadth are log-linear-related.

3.1.1 Methodology

To study the relation between publishing intensity and publishing breadth, the survey conducted by (Rokach, 2012) is repeated. But the setting is slightly difference. A list of 206 AAAI Fellows (up to 2013) is compiled as the active scholars. The list of AAAI Fellows is depicted in Appendix A. A list of 108 journals indexed by TR WoK

2010 Edition subcategory CS-AI is solicited. One should note that the actual year of release of the 2010 Edition is in 2011. Those papers authored by these 206 AAAI Fellows and published in the period from 1995 to 2010 are extracted. The number of papers published by each active scholar in each journal is counted. The publishing intensity and the publishing breadth of each of the journals are calculated. It is found that 80 out of 108 journals have at least one paper authored by an AAAI Fellow. We call them the qualified journals. In other words, 28 journals have no paper authored by any one of the AAAI Fellows.

We repeat the survey by using the same list of journals. The list of active scholars is compiled from the Fellows of IEEE who are affiliated in the Computational Intelligence Society. A list of 204 Fellows (up to 2013) is depicted in Appendix B. will be shown. Again, those papers authored by these 204 IEEE Fellows and published in the period from 1995 to 2010 are extracted. The number of papers published by each active scholar in each journal is counted. The publishing intensity and the publishing breadth of each of the journals are calculated. It is found that 93 out of 108 journals are qualified journals.

3.1.2 Log-Linear Relation

The statistics the number of qualified journals and active scholars obtained from AAAI Fellows and IEEE Fellows are depicted in Table 3.1. While the numbers of both AAAI Fellows and IEEE Fellows are more than 200, the numbers of fellows who have published in the period from 1995 to 2010 are fewer, 181 and 158 respectively. Figure 3.1 and Figure 3.2 show the plots of log (Intensity) against log (Breadth). Suppose the relation between $\log(I_j)$ and $\log(B_j)$ for j=1…, N, is given by:

$$\log\left(I_j\right) = \alpha \log\left(B_j\right) + \beta + \varepsilon_j,$$

which ε_j,is the model error. Table 3.2 summarizes the results on the coefficients of the regression lines obtained by least regression method in SPSS. For more information, please refer to (Albert & Anderson, 1984).

Table 3.1 Statistics regarding the number of qualified journals and active scholars for Figure 3.1 and Figure 3.2

Association (Fellow Group)	Fellows Number	Qualified Journals	Active Scholars
IEEE CIS	204	93	158
AAAI	206	80	181

Table 3.2 Coefficients obtained by least squares regression for Figure 3.1 and Figure 3.2

Association (Fellow Group)	α (t-value)	B (t-value)	R^2 (t-value)
IEEE CIS	1.140 (29.956)	0.101 (3.049)	0.908
AAAI	1.219 (46.168)	0.007 (0.285)	0.965

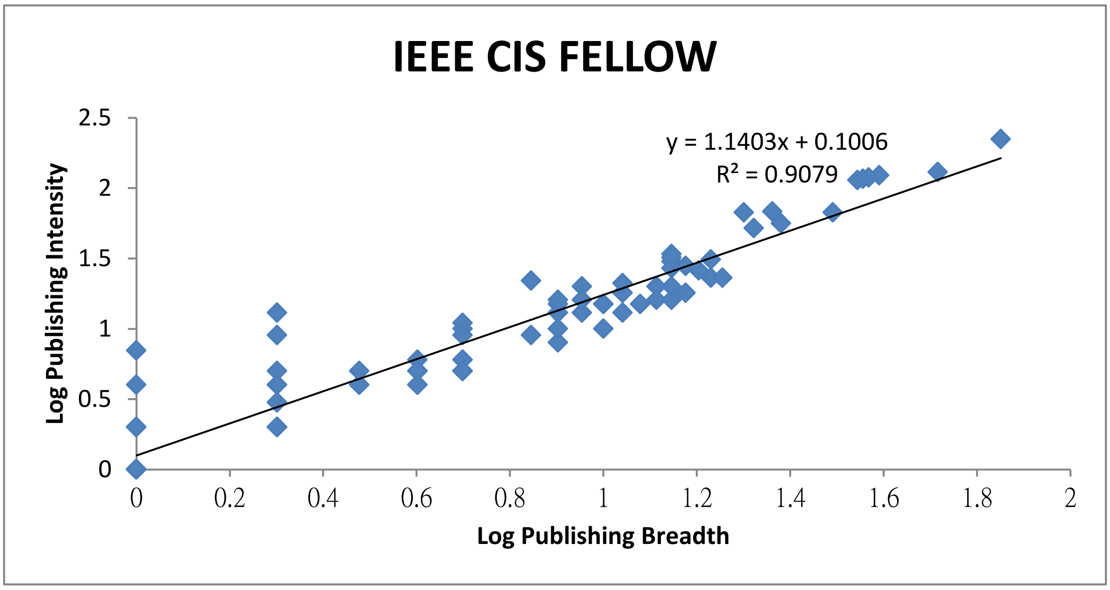

Figure 3.1The relation between log PI and log PB of IEEE CIS Fellow

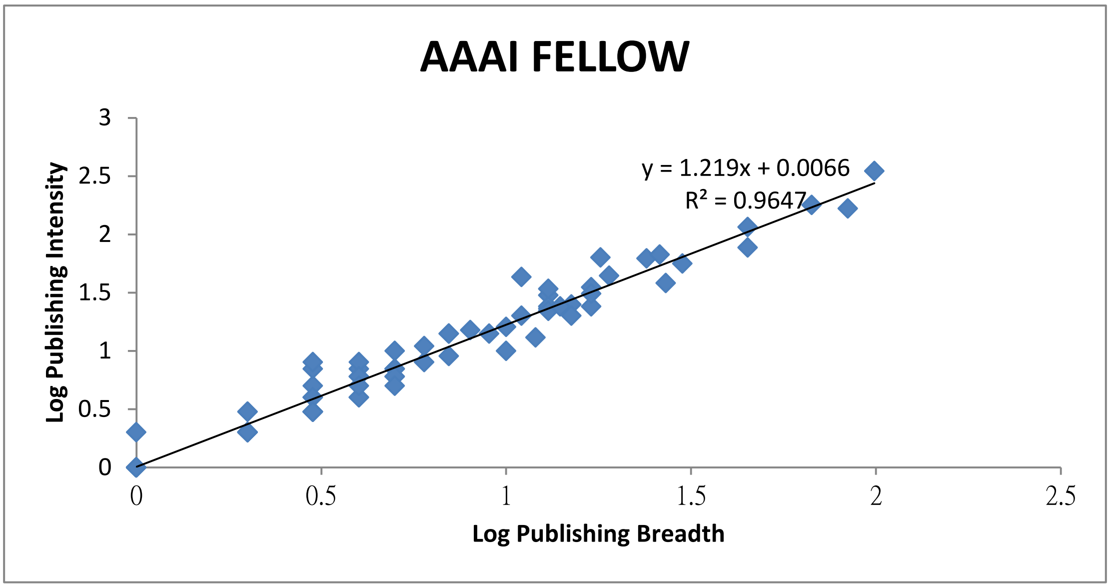

Figure 3.2 The relation between log PI and log PB of AAAI Fellow

Table 3.3 Top 10 CS-AI journals ranked by publication power.

AAAI (L Rokach)	IEEE	AAAI
ARTIF INTELL	IEEE T NEURAL NETWOR	ARTIF INTELL
AI MAG	IEEE T SYST MAN CY B	AI MAG
J ARTIF INTELL RES	IEEE T FUZZY SYST	J ARTIF INTELL RES
MACH LEARN	PATTERN RECOGN	MACH LEARN
IEEE INTELL SYST	NEUROCOMPUTING	IEEE INTELL SYST
IEEE T PATTERN ANAL	NEURAL NETWORKS	J MACH LEARN RES
AUTON AGENT MULTI-AG	IEEE T IMAGE PROCESS	ANN MATH ARTIF INTEL
ANN MATH ARTIF INTEL	NEURAL COMPUT	AUTON AGENT MULTI-AG
IEEE T KNOWL DATA EN	PATTERN RECOGN LETT	IEEE T PATTERN ANAL
COMPUT INTELL-US	INT J INTELL SYST	COMPUT INTELL-US

The column of AAAI(L Rokach) lists the ranking results from the paper written by Rokach (2012). The IEEE and AAAI columns show the ranking result repeated by us.

3.1.3 Journal Ranking

One important result should be noted from Table 3.3. It clearly shows that different selection of active scholars (AAAI Fellows versus IEEE Fellows) will give different rankings. It indicates that different group of scholars normally have difference focuses in their fields of research. In the end, their publishing preferences will be different. For this reason, we will present in the next chapter a new methodology for the selection of the active scholars. It is based on the editorial board members.

3.2 Eigenfactor & Raw Citations

When we have discovered the relation between publishing intensity and publishing breadth, we are curious if this log-linear relation exists amongst citation-based measures. In 2008, Philip M. Davis has conducted a research on the relation between Eigenfactor and total raw citations. The concept of Eigenfactor is similar to the Google Pagerank. The definition of raw citations of a journal in Davis's paper is the total citation it has received from the year it has been published.

3.2.1 Methodology

Philip M. Davis use the set of 171 journals from the category Medicine (General and Internal; relation) .The data were retrieved from the JCR 2006 edition. The Eigenfactor of each journal is retrieved from Eigenfactor.org. Journals which did not have an Eigenfactor were removed, leaving a set of 165 journals. The Eigenfactor of these 165 journals were then plotted against total raw citations (Davis, 2008). The relation between log Eigenfactor and log total raw citations for top 20 journals in the field of Medicine is plotted in Figure 3.3.

3.2.2 Log-Linear Relation

In his research paper, the Eigenfactor and total raw citations number seemed to have a strong correlation between them (Spearman rho=0.95). We're quite interesting in this result. However, he only conducted the research in the field of medicine. Therefore, in the Chapter 4, we will present a comprehensive result by conduct a new survey in six different research fields namely Artificial Intelligence, Information Science and Library Science, Management, Anthropology, Geography, and Nursing.

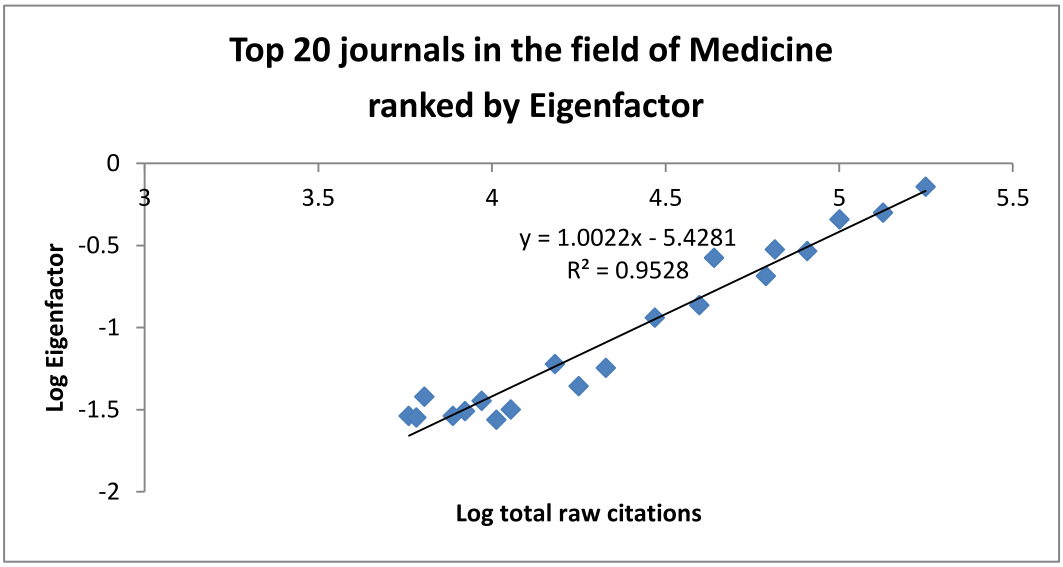

Figure 3.3 Top 20 journals in the field of Medicine ranked by Eigenfactor

CHAPTER 4 MEASURES RELATIONS: COMPREHENSIVE RESULTS

In the previous chapter, we have confirmed the log-linear relation between PI&PB and between Eigenfactor & raw citations. It brings out an issue: Will this log-linear relation also apply to other fields? In this chapter we are going to present the comprehensive studies which shows whether the relation still exist in six different fields. The six fields include Artificial Intelligence, information science & library science, management, anthropology, geography and nursing.

4.1 Publishing Intensity and Publishing Breadth

In order to discover the correlation between publishing intensity and publishing breadth, we must know the definition of publishing intensity and publishing breadth. In the next paragraph we will introduce the definition of publishing intensity and publishing breadth and then give an illustration to show the way to calculate them. Publishing intensity is defined as the total numbers of articles authored by the active scholars. Publishing breadth is defined as the total numbers of active scholars who have authored articles in the journal.

The example in Table 4.1 illustrates an example showing how publishing intensity and publishing breadth can be calculated. For instance, there are two active scholars: Prof. Ho and Prof. Sum respectively. There are journals in the field of Technology Management, namely Journal of Information Systems (IS), Journal of Technology Management (TM) and Journal of Electronic Commerce (EC).

Table 4.1 Example of publishing intensity and publishing breadth

	IS	TM	EC
Prof. Ho	3 (articles)	1(articles)	0(articles)
Prof. Sum	2(articles)	3(articles)	2(articles)
Breadth	**2**	**2**	**1**
Intensity	**5**	**4**	**2**

Publishing breadth is the total numbers of active scholars who have authored articles in the journal. For IS and TM, both scholars have published articles in these journals. So, their publishing breadth is two. For the journal EC, only Prof. Sum has published articles in it. So, its publishing breadth is one. As the publishing intensity is defined as the total numbers of articles authored by the active scholars, their values are clearly five, four and two respectively.

Talking about the data collecting process, we need to clarify our standard for filtering qualified journals and active scholars first. For the qualified journal, the quality of journal is not easy to measure, thus, we make a simple rule: only to include the journals that have been published for no less than 15 years. We believe that the longer time a journal has been published, the more scholars and readers it may attracted. On the other hand, it needs lots of effort and research output to become a journal editor. However, to make sure that each editor has the higher reputation and more research, we add two more rules about the working place and publishing time. In sum, the active scholars must fulfill these three rules: A journal editor who also works in top 25 universities (see Appendix C) and has publishing record between 1999 and 2013. The purpose of having publishing record from 1999 to 2013 is to exclude the scholars that only publish papers in recent years.

4.1.1 Methodology

In this section we illustrate the modified method in different fields. The principles to perform the analysis are as follows:

Step 1: Find Journal List

For the benchmark journals, the first step is retrieving the list of journals from JCR database in 2012 social science (or science) edition in Thomson-Reuters Web of Knowledge (WoK). All the list of journals we used was extracted from WoK.

Step2: Find Qualified Journals

To make sure the quality of the journal, we exclude the journals that have published for less than 15 years. The reason why we do this is journals with older published years may attract more professors to publish their papers in it and thus attract more reader. After the filtering, the remaining journals become our qualified journals.

Step 3: Find Editors

In order to find the set of active scholars, we must find a way to choose scholars who make great effort to the research field. Thus, we decided to use editorial board to be the potential active scholars list. Those scholars may come from all over the world and would have made significant and huge contribution to the research field. As a result, choosing this set will make the result more reliable and more convincing. We retrieve the editorial name from the office website of each journal; it includes editors, associate editors, editor member/board and advisory editors.

Step 4: Find Qualified Editors (Active Scholars)

We search the editorial teams/board of those journals and check if those editors are in the top 25 public schools proposed by USNews. It is now known as the leader for ranking colleges, graduate schools and hospitals. The schools are UCLA, UC Berkeley, UC Davis, UCSD, UCSB, UC Irvine, Georgia, Michigan, Maryland, Wisconsin, Texas, Texas A&M, Florida, William and Mary, Penn State, Rutgers, Illinois, Washington, Virginia, North Carolina, Georgia Institute of Technology, Ohio State, Pittsburgh, Connecticut, Purdue, Clemson and Minnesota. The professors teaching in these schools have higher chance to produce high quality papers. By comparing the editorial list with the top 25 public schools list, if they are matched, they become our active scholars. Moreover, we check whether they've been published in this field for more than 10 years to make sure that those active scholars are not publishing their articles only in recent years.

Step 5: Data Collection Process

We use Thomson-Reuter Web of Knowledge database in the data collection step. We match the list of active scholars and qualified journal to get the Publishing Intensity and Publishing Breadth. Only the papers classified as "Article" are consolidated. "Editorial Material" and "Proceeding Paper" are excluded.

Take Management field for example, 172 journals were found in the TR WoK database. 146 out of 172 journals published more than 15 years. By searching all the editors in these 146 journals and matching them with top 25 public schools list, there still remained 643 editors. We traced the 643 editors' publishing history, came out that only 194 senior professors have published papers in Management field for more than 10 years (during 1999-2003). In other word, we compared about twenty eight thousands (194x146) items for management field. In the whole progress, this is the most time-consumed step. Detail steps for collecting the data is elucidated in Appendix D.

Step 6: Analysis

By analyzing the data with Microsoft Excel and IBM SPSS software, we can calculate the linear regression equation and find the Slope, T-ratio and R-Squared value. In order to get the T-ratio, we set the confidence interval to be 95%. With these statistics and figures, we can understand the relation between LPI and LPB.

Linear regression is a statistic approach used to model the dependence of a scalar variable and one(or more) explanatory variables In our case, there is only one explanatory variable, so it is called simple linear regression. We can represent it mathematically

$$\text{Intensity} = \text{b} \cdot Breadth^{a}$$

$$\log Intensity = \text{a} \cdot \log Breadth + c$$

In the next page, we have simplified the steps of collecting data into a single flow chart Figure 4.1.It is easier to understand the whole process. And after that, we will introduce the definition of R-Squared value and T-ratio value. R-Squared is mostly being used for measuring the strength of correlation in linear regression model. Its value indicates how well the resulting line matches the original data point. From the statistic point of view, if R-Squared value of a data set equals to 1 means that the regression line perfectly fits the data. In other words, R-Squared value of the regression is relatively high indicates the points will be very close to the regression line. In the case of Management field, the R-squared values for the line is 0.946, suggesting that LPI and LPB are highly correlated.

T-ratio value is the indicator to determine the significance of regression coefficient. The significance of a regression coefficient is determined by dividing the estimated coefficient over the standard deviation of this estimate in a regression model. We can look for the appropriate α/2 significance level to find the exact critical value from the t-distribution table. To find the significance of their relationships, we expect the t-ratio value to be greater than 2.

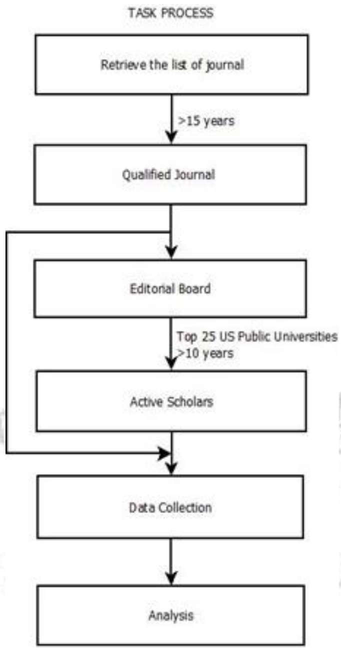

Figure 4.1 Process of data collection

Some people may question the sequence of data collecting process. We first filtered the journal published less than 15 years and then find the editorial members of these journals. This sequence will exclude some active scholars who are the editorial members in those unqualified journal. To make sure that the sequence may not influence the result, we use journals in the field of Artificial Intelligence to re-examine the question. We swap step 2 and step 3. We first find editorial members in all journals and then filter the qualified journal. The difference is that there’re 10 more active scholars being collected. The R-Squared value changed from 0.902 to 0.894. Therefore, we believe that it is fine to collect the data in both ways.

4.1.2 Result

Figure 4.2 to 4.7 show the scatter plots of the data obtained for the six fields of research. The corresponding slopes and interceptions obtained by using linear regression method are depicted in Table 4.4. From their t-values, it is clear that the values of the slopes are all significant. By these results, we conclude that log PI and log PB have linear relation and this relation exists for all six fields of research, While their slopes are slightly different, their values are larger than 1. We conjecture that log-linear relation between publishing intensity and publishing breadth should be a universal property that exists in other fields of research. In other words, the relation between publishing intensity and publishing breath could be expressed as follows:

$$\Delta \mathrm{log I} = \alpha \Delta \mathrm{log B} ==> \frac{\Delta I}{I} = \alpha \frac{\Delta B}{B}.$$

The percentage change of publishing intensity is proportional to the percentage change of publishing breadth.

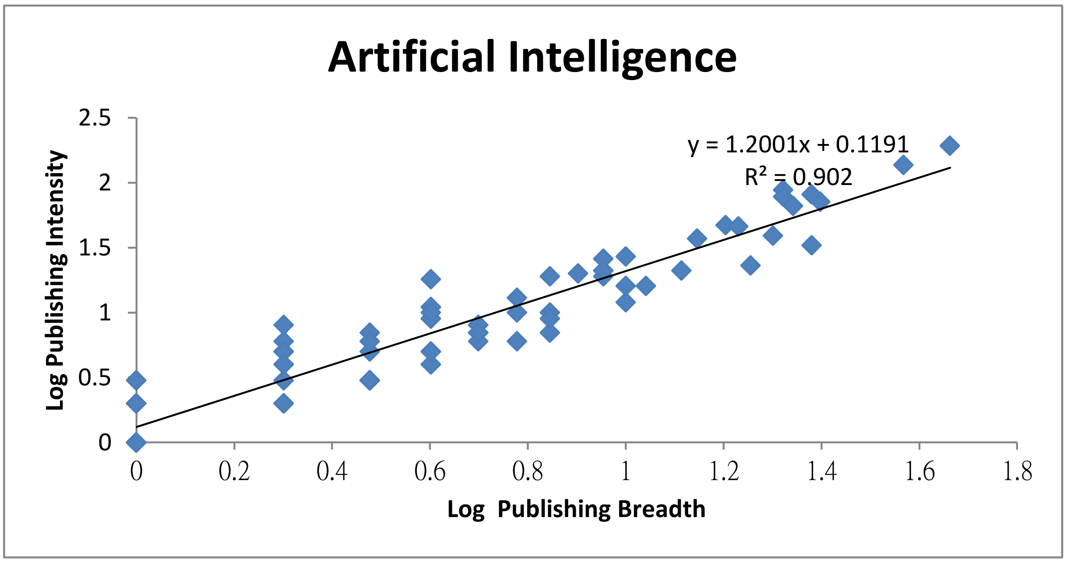

Figure 4.2 The relation between log PI and log PB in the field of Artificial Intelligence

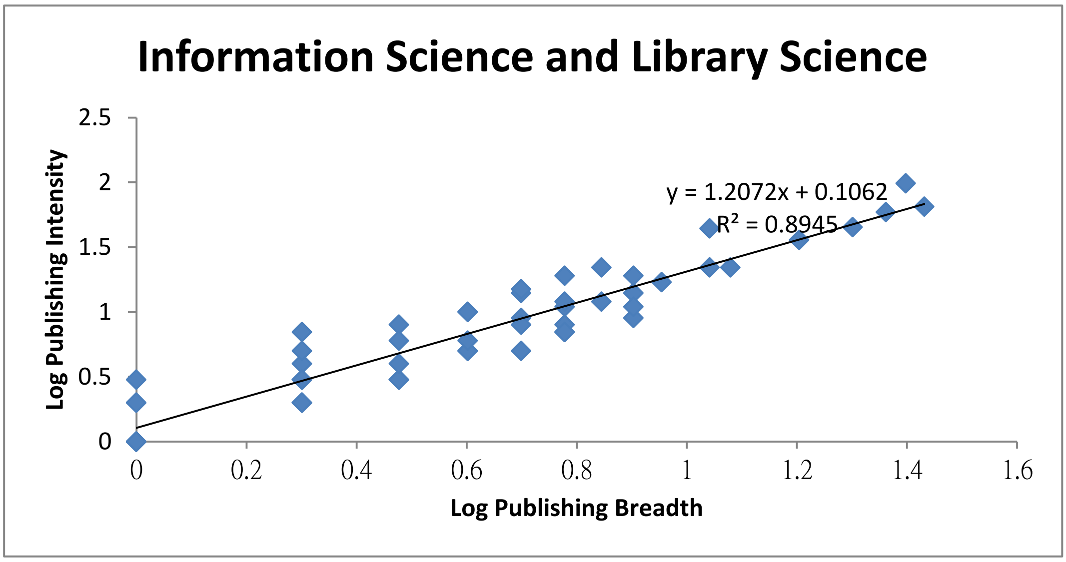

Figure 4.3 The relation between log PI and log PB in the field of Information Science and Library Science

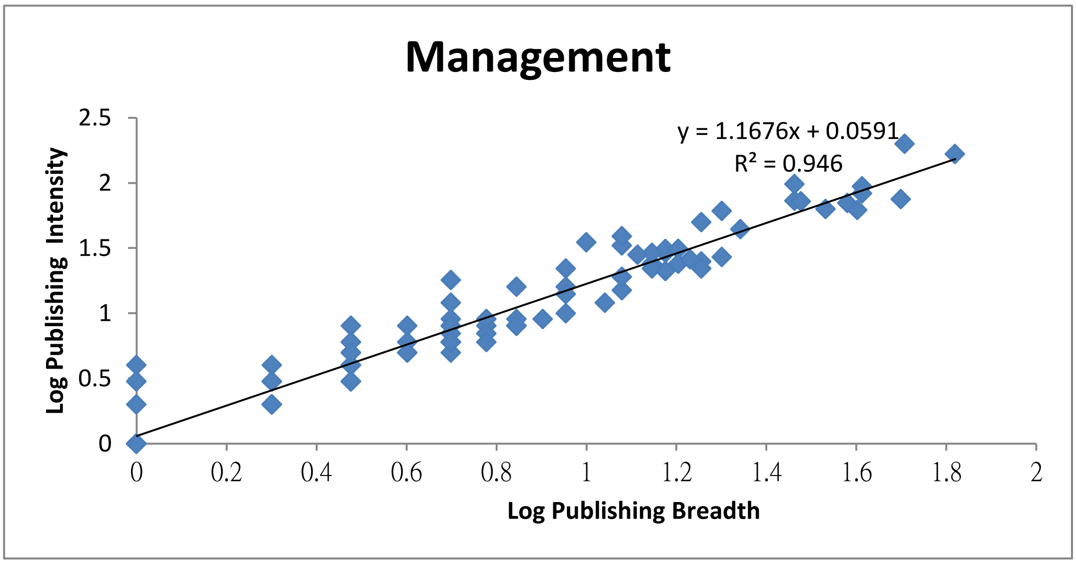

Figure 4.4 The relation between log PI and log PB in the field of Management

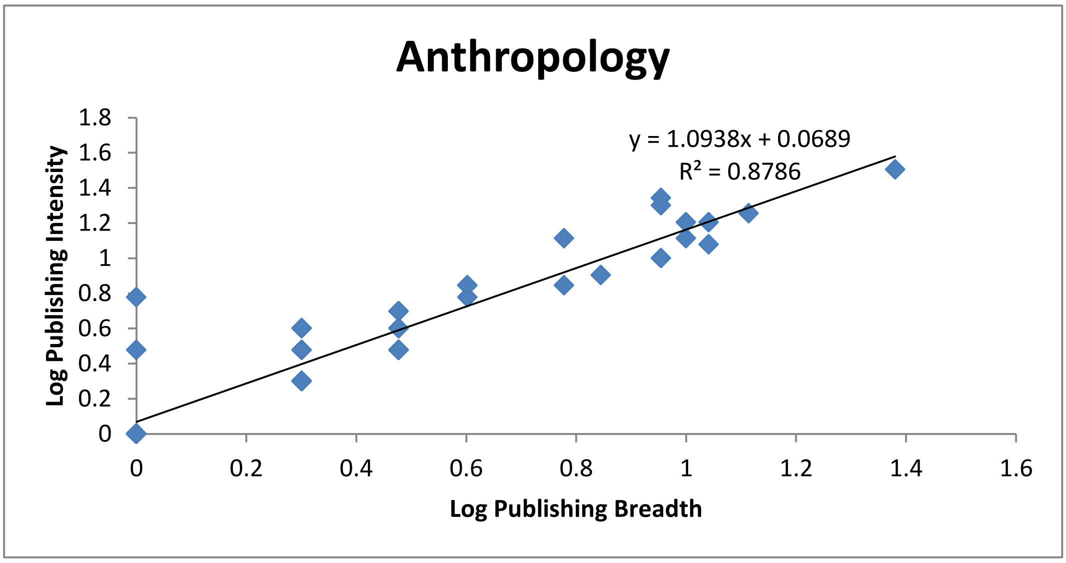

Figure 4.5 The relation between log PI and log PB in the field of Anthropology

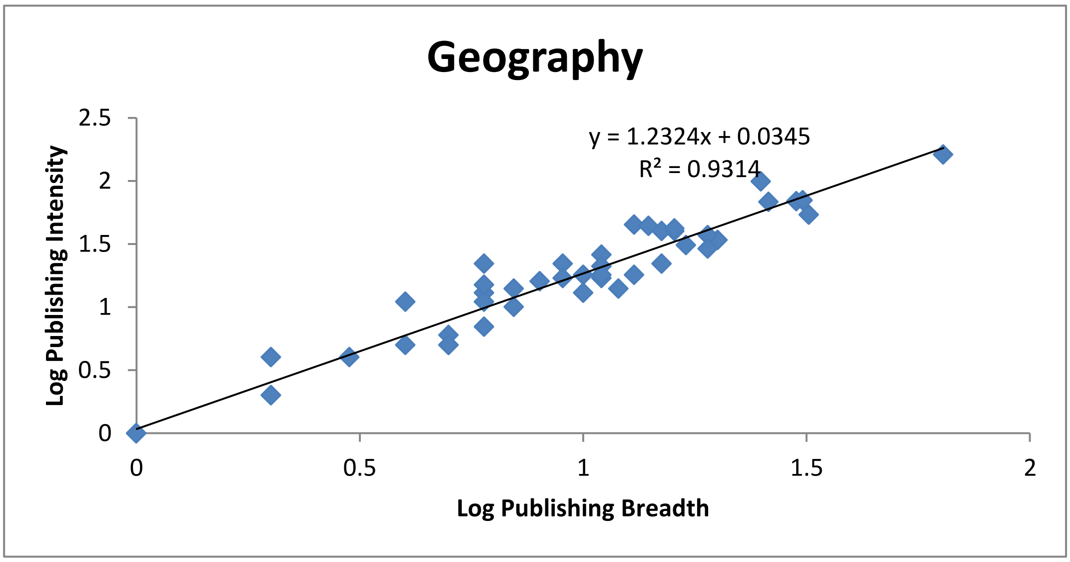

Figure 4.6 The relation between log PI and log PB in the field of Geography

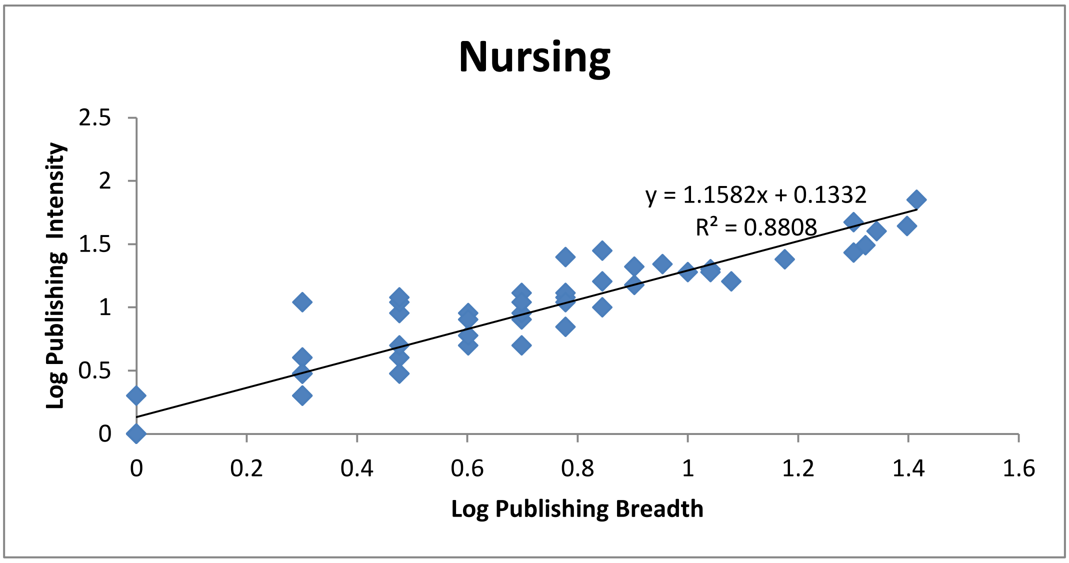

Figure 4.7 The relation between log PI and log PB in the field of Nursing

Table 4.2 The total journals number, qualified journals number, total active scholars number

Journal field	Journals	Qualified Journals	Active Scholars
Artificial Intelligence	115	90	219
Information Science and Library Science	85	73	97
Management	174	115	194
Anthropology	83	73	164
Geography	72	47	120
Nursing.	104	81	168

Table 4.2 summarizes the number of total journals, qualified journals and total active scholars. In the total process, we need to check all the publications published by active scholars from 1999 to 2013. That's the reason why this is a time-consuming method.

Table 4.3 Coefficients obtained by least squares regression for the journals in six different fields

Journal field	Slope (t value)	b value (t value)	R-Squared Value
Artificial Intelligence	1.225 (25.943)	0.110 (3.076)	0.899
Information Science and Library Science	1.207 (21.193)	0.106 (2.612)	0.894
Management	1.168 (44.478)	0.059 (2.666)	0.946
Anthropology	1.094 (19.024)	0.069 (2.158)	0.879
Geography	1.232 (24.433)	0.035 (0.677)	0.931
Nursing.	1.158 (20.345)	0.133 (3.205)	0.881

4.2 Eigenfactor and Raw Citations

In the previous chapter, we have presented the log-linear relation between Eigenfactor and raw citation based on the data depicted in the paper of Davis (2008). Now, we are going to check if this log-linear relation also appears in other fields of research. However, the method for collecting the raw citations is slightly different from the method presented in Davis (2008). In his paper, Davis counts the raw citation as the total number of citations all the way back to the journal's very first issue. It is clear that this counting method would cause two problems. First, raw citation of a journal with longer life-time will definitely get more counts. It will be unfair to some new journals. Second, in Eigenfactor, the time window for counting co-citations is the recent five years. That is, Eigenfactor focus on the recent influence of a journal more than the historical influence of a journal. In this regard, we believe that the data collection period for the raw citations should be the same as the collection period for generating the Eigenfactor. So we slightly modified the methodology of in Davis (2008). The time period for collecting raw citations is changed to the recent 5 years.

4.2.1 Methodology

The lists of the journals in the six fields of research are the same as the lists of qualified journals which have been compiled and presented in Section 3.1. In other words, only journals being published for more than 15 years are included. All the Eigenfactors are looked up from the JCR 2012 edition. Also, the journals without the statistic of Eigenfactor are excluded. The raw citation of a journal is the total number of times the papers published in the journal in the period from 2007 to 2011 that have been cited in 2012. We retrieved the raw citations number from the JCR database. The statistics are in the journal information page individually. Detail steps for collecting the data is elucidated in Appendix E.

4.2.2 Results

The scatter plots of the log Eigenfactor versus raw citations are shown in Figure 4.8 to Figure 4.13. Clearly, log-linear relation between Eigenfactor and raw citations exists in all six fields of research. The result is similar to the one we presented in Section 3.2 and shown in Figure 3.3. The slopes, interceptions, the corresponding t-values and R-squared values are depicted in Table 4.4. In accordance with the t-values, the values for the slopes are significant. Thus, we conjecture that log-linear relation between Eigenfactor and raw citations should exist in other fields of research. Moreover, for each field of research, the points fit very well to a straight line.

Especially, in the fields of geography and nursing, the points almost perfectly fit. The R-squared values are 0.9698 and 0.9482 respectively.

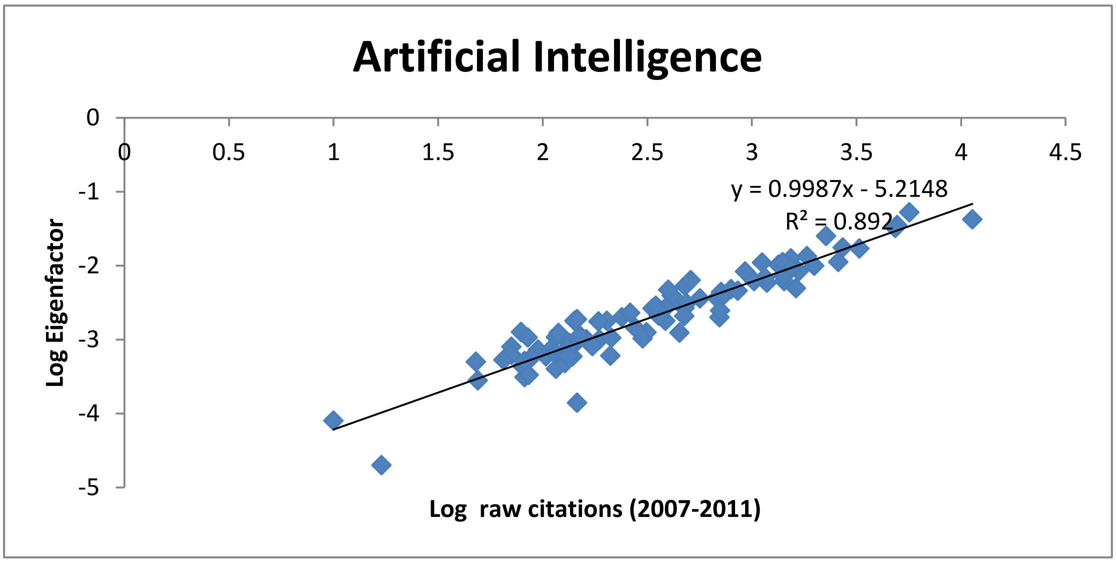

Figure 4.8 The relation between log Eigenfactor and log raw citations in the field of Artificial Intelligence

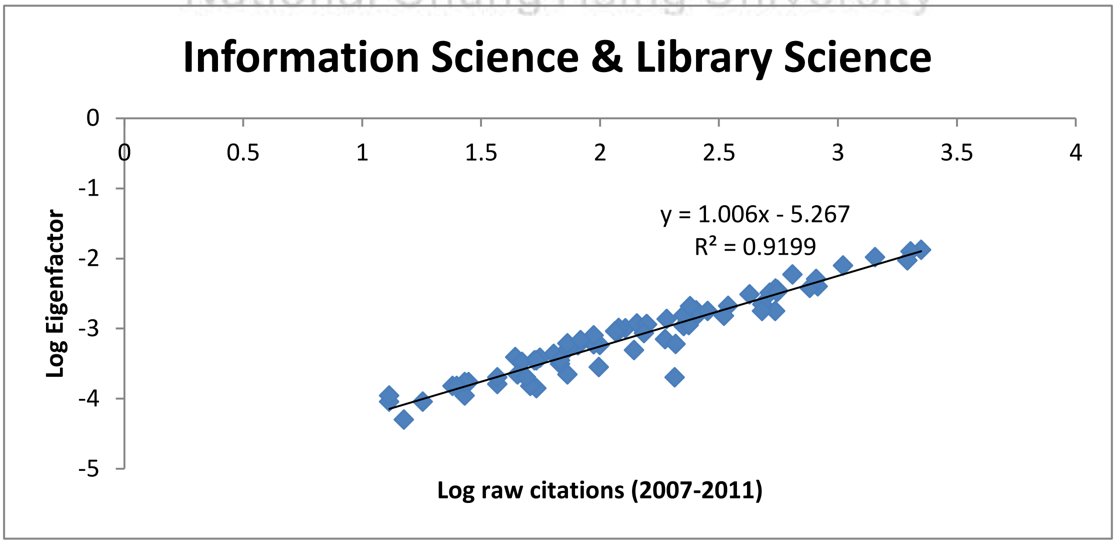

Figure 4.9 The relation between log Eigenfactor and log raw citations in the field of Information Science& Library Science

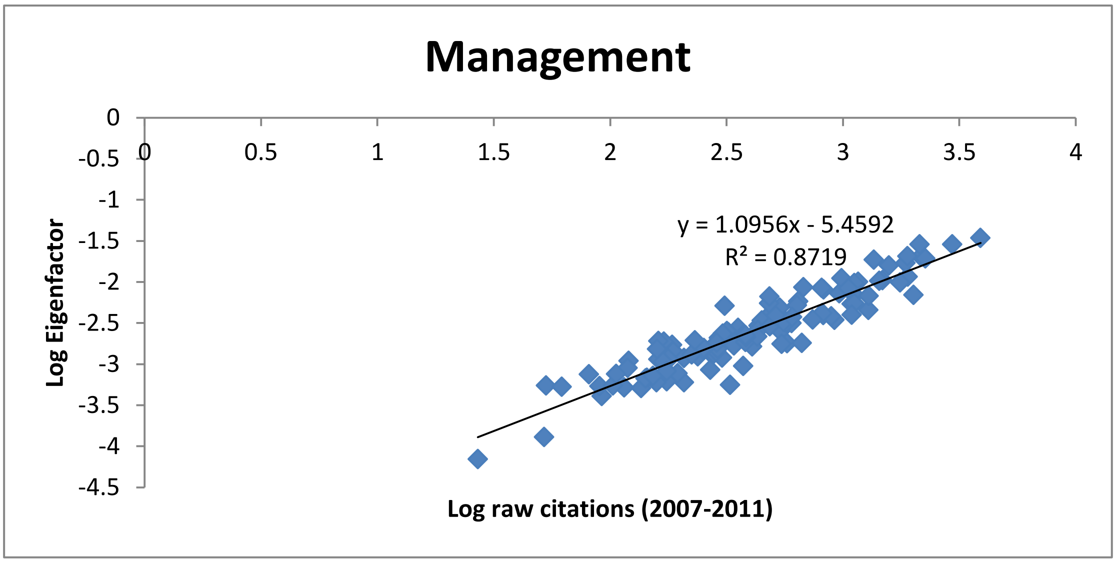

Figure 4.10 The relation between log Eigenfactor and log raw citations in the field of Management

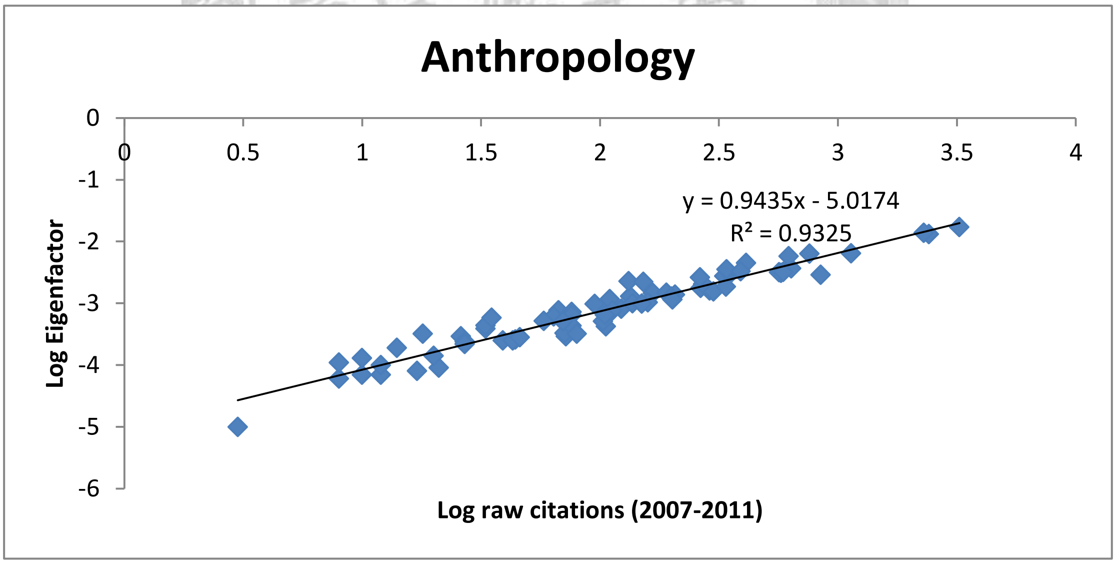

Figure 4.11 The relation between log Eigenfactor and log raw citations in the field of Anthropology

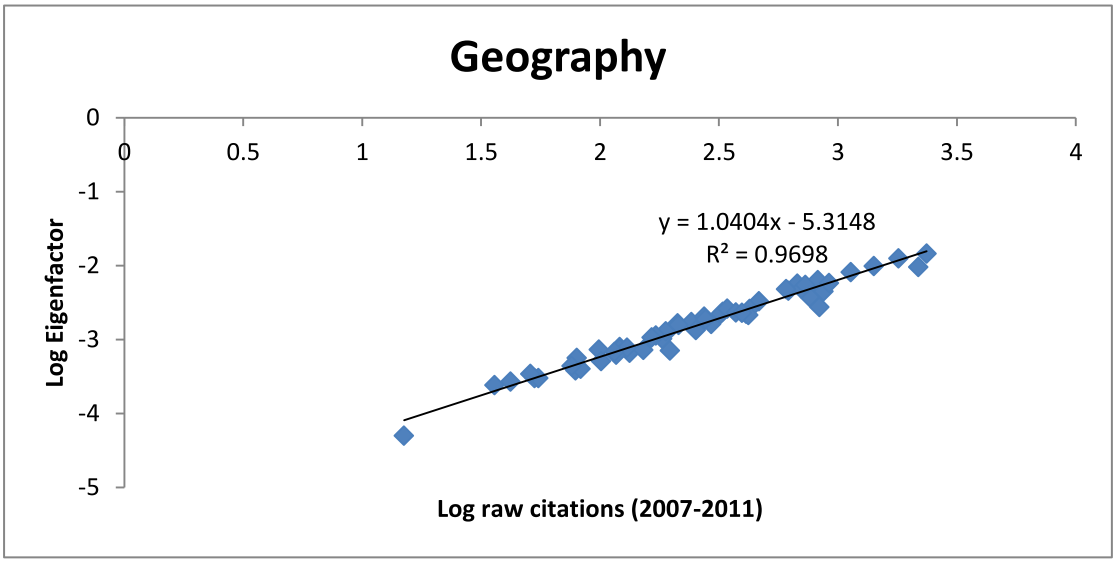

Figure 4.12 The relation between log Eigenfactor and log raw citations in the field of Geography

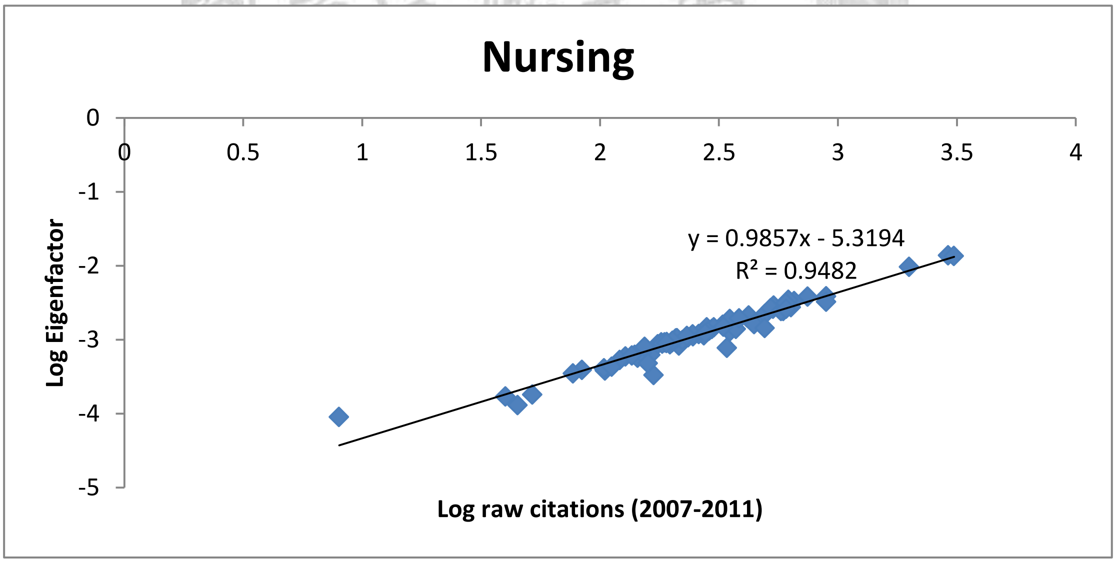

Figure 4.13 The relation between log Eigenfactor and log raw citations in the field of Nursing

Table 4.4 Coefficients obtained by least squares regression for the journals in six different fields

Journal field	Slope (t value)	b value (t value)	R-Squared Value
Artificial Intelligence	0.999 (26.806)	-5.215 (-53.702)	0.892
Information Science and Library Science	1.006 (28.352)	-5.267(-66.903)	0.920
Management	1.096 (27.736)	-5.459 (-52.286)	0.872
Anthropology	0.943 (31.105)	-5.017 (-77.995)	0.933
Geography	1.040 (42.046)	-5.315 (-87.542)	0.970
Nursing.	0.986 (37.786)	-5.319 (-82.806)	0.948

Table 4.4 summarizes the coefficients statistics obtained by least squares regression for the journals in six different fields. The R-Squared value are higher than 0.9 except for the fields of Artificial Intelligence and management. This can be seen in the plots for each field.

CHAPTER 5 KNOWLEDGE TRANSFER IMPACT

In this chapter, we are going to present a new result which is independent from the previous study. Although there're variety of methods can be used to rank journals, neither any of them can present a complete and object result. Those methods only present single perspective based on the publishing preference of either active scholars or readers. Publication Power Approach has improved some drawbacks of citation-based measures and perception-based measures. But still, it is not enough. As a result, in order to get an object ranking result, we should not rank journals only with a single measure.

A good journal should satisfy two conditions. First, it must attract very high quality researches from the active scholars. Second, it has to attract lots of reader to read the paper and then be inspired by these researches, which means having high dissemination power. Meanwhile, a good journal ranking method should not only concern the single aspect of reader or author. Instead, they should be complement with each other. Finding a way to put both readers' and authors' preferences into consideration is a necessary. However, the PPA still have some problem to be solved. For example, the author didn't investigate the relation between PI and PB but just simply multiply them instead. That's the reason why we're going to propose a new journal ranking method: Knowledge Transfer Impact (KTI).

5.1 Methodology

We propose a new method for ranking journals. It combines two measures from author-based category and citation-based category, which are publishing intensity and Impact Factor respectively. From Figure 5.1 we can know that Knowledge Transfer Impact is composed of two journal ranking measures. The first measure is Impact

Factor. It reflects the average number of citations received by recent articles published in a journal. The higher Impact Factor may indicate that there're more people read the paper and the knowledge of the article has been transfer to the reader successfully.

The second measure is publishing intensity. It is the number of articles that the active scholars have published in a journal in a given time period. The higher publishing intensity indicates that the journal collect more articles from active scholars.

The concept of knowledge transfer impact is shown in Figure 5.1. From the left hand side to the right hand side, it is the whole process of the knowledge transfer from the knowledge generator to the reader. For an author who writes articles, he/she will become a knowledge generator. In order to let more people know about the new idea or new knowledge, knowledge generator may publish their research articles to the journal he/she prefer most. People may read the articles and if they have some comment or regard the article as useful, they may cite the article.

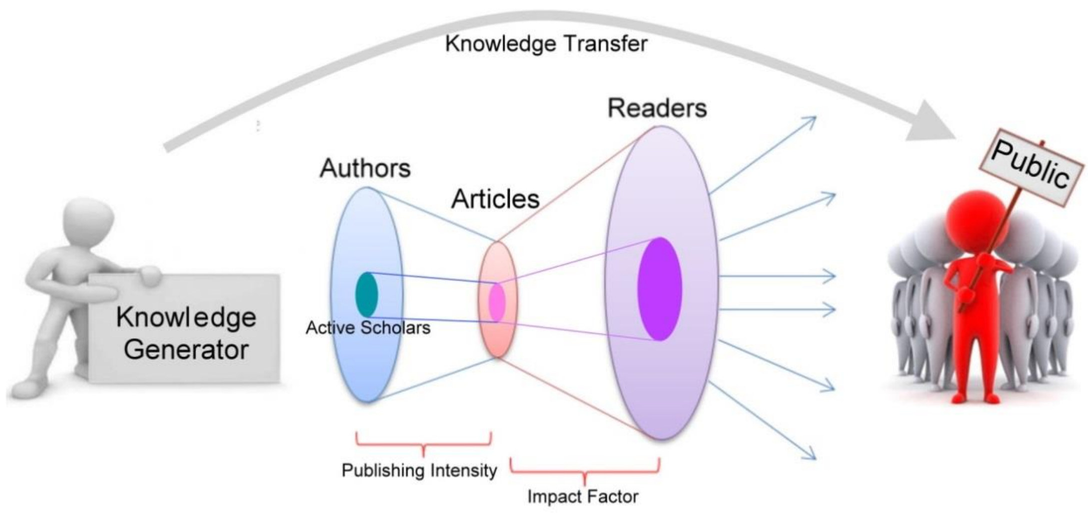

Figure 5.1 The concept of Knowledge Transfer Impact

Knowledge Transfer Impact method considers both perspective of publishing preference of the active scholars and the perspective of readers. The definition of KTI is the product of publishing intensity and the Impact Factor. It will be the best way to put both side into consideration so that the result will be different from the existing methods. If the journal has high KTI, it is considered widely read by scholars and other readers. As a result, we believe that scholars are more likely to publish their papers in the journals with higher KTI. With this new journal ranking method, the new ranking result is expected to be more objective and appropriate with the real circumstances.

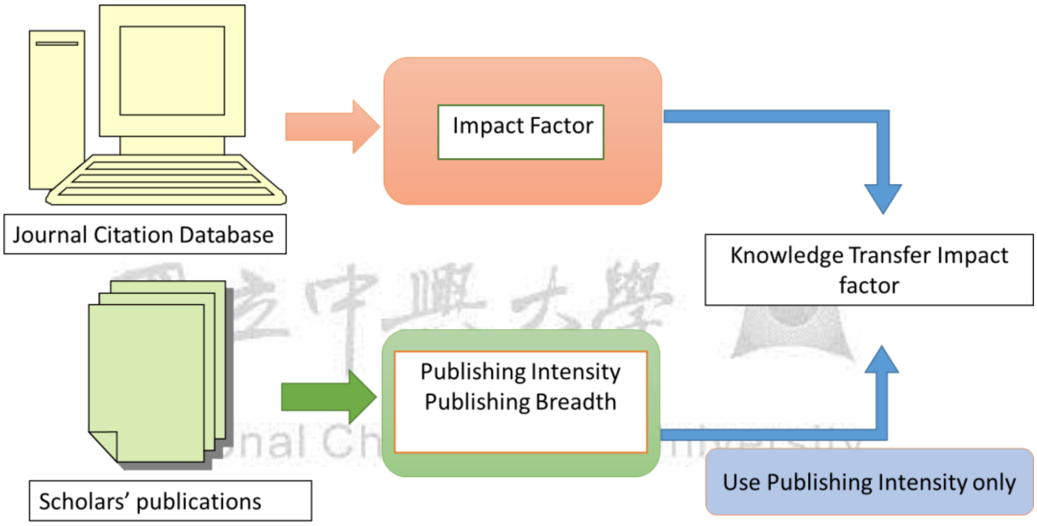

Figure 5.2 The concept of the generation of KTI

From the above paragraph we have the concept and the definition of Knowledge Transfer Impact. We want to know how much new knowledge can be created by the knowledge generated from active scholars. So we combined the publishing intensity we've collected in Chapter 3 and the Impact Factor retrieved by JCR database 2012 edition. In our research, we use these statistics to calculate the Knowledge Transfer Impact and rank journals. The new ranking results are shown in Table 5.1.

5.2 Results

To illustrate the differences between the results taken by KTI and by other methods, Table 5.1 summary the different ranking results including Eigenfactor, Impact Factor, PPA and KTI. One should note that we are not going to claim the preference of any method. In other words, we are not going to conclude which one is 100% better than others because it is very subjective. The ranking results show that KTI is a tradeoff of citation-based measure and author-based measure. And it can reflect the preference of both the reader and author side. As a result, we believe it should be a better method.

Table 5.1 Top 10 Journal ranking comparison table in the field of AI

Rank	**Eigenfactor**	**5-Year Impact Factor**	**PPA**	**KTI**
1	IEEE T PATTERN ANAL	IEEE T EVOLUT COMPUT	IEEE T PATTERN ANAL	IEEE T PATTERN ANAL
2	EXPERT SYST APPL	IEEE T PATTERN ANAL	INT J COMPUT VISION	INT J COMPUT VISION
3	IEEE T IMAGE PROCESS	SIAM J IMAGING SCI	NEURAL COMPUT	IEEE T IMAGE PROCESS
4	PATTERN RECOGN	IEEE T FUZZY SYST	IEEE T IMAGE PROCESS	PATTERN RECOGN
5	INT J COMPUT VISION	INT J COMPUT VISION	COMPUT VIS IMAGE UND	NEURAL COMPUT
6	J MACH LEARN RES	MED IMAGE ANAL	NEUROCOMPUTING	COMPUT VIS IMAGE UND
7	IEEE T SYST MAN CY B	J MACH LEARN RES	PATTERN RECOGN	NEUROCOMPUTING
8	NEUROCOMPUTING	IEEE T IMAGE PROCESS	MACH LEARN	NEURAL NETWORKS
9	IEEE T NEUR NET LEAR	IEEE T SYST MAN CY B	NEURAL NETWORKS	IEEE T KNOWL DATA EN
10	PATTERN RECOGN LETT	IEEE COMPUT INTELL M	IMAGE VISION COMPUT	MED IMAGE ANAL

CHAPTER 6 CONCLUSION

In the thesis, we have introduced three types of measures for journal influence and presented studies on 1) log-linear relation between publishing intensity and publishing, and 2) log-linear relation between Eigenfactor and raw citations, and 3) new journal ranking method: Knowledge Transfer Impact.

The thesis is separated into two parts; the first part examined the relations of the ranking measures. By conducting an analysis on six fields of research, we have found that publishing intensity and publishing breadth have a log-linear relation. The log-linear relation is dependent on the group of active scholars. The log-linear relations of respective fields are different. Take Artificial Intelligence for instance, the log-linear relation based on AAAI fellow for active scholars is different from that of IEEE CIS fellow. The above results add to the Publication Power Approach (Holsapple, 2008) in two ways. First, the list of premier obtained by Publication Power is dependent on the list of active scholars. Second, journal rankings obtained by Publication Power, Publishing Intensity and Publishing Breadth are correlated, as evidenced in (Holsapple, 2008, Table 4.2 and Table 4.3).We have established that the log-linear relation between Eigenfactor and raw citations exists. These two factors indicated that collinearity exists between different measures in the same field/category thus providing us with more options to combine journal ranking measures.

From our analysis, we conclude that PI & PB are identical in six different fields of journal publication. Furthermore, we created a new journal ranking method "Knowledge Transfer Impact" to provide new insight to identify journal quality. It presents a drastically different perspective to approaching journal ranking. Although we applied KTI to six different fields and the result are consistent, our research still has some limitations. First, most of our results rely on the definition of active scholars.

In this research, we defined active scholars as 1) the editorial member of qualified journals and 2) working in top 25 public universities in the US. The result may be influenced by the selection of top universities based on who is serving as editorial members in the journal among other issues. Moreover, KTI focuses on the top 25 US public universities in the US, which means that if the journal is from outside of the United States or if the editorial board members work outside of the top 25 universities in the US, the results can be biased due to exclusion of journals from ranking.

In sum, the Knowledge Transfer Impact is a new method to systems ranking to rank journal. It successfully combines the concept of prestige (measured by publishing intensity) and popularity (measured by Impact Factor) and presents a new perspective of ranking journals. In the future, we will work on mathematical modeling to explain why publishing intensity and publishing breadth demonstrated log-linear relation to optimize the efficiency of KTI.

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Appendix A: 2013 Top 25 Public Universities is US

University of California–Berkeley
University of California–Los Angeles
University of Virginia
University of Michigan–Ann Arbor
University of North Carolina–Chapel Hill
College of William and Mary
Georgia Institute of Technology
University of California–Davis
University of California–San Diego
University of California–Santa Barbara
University of Wisconsin–Madison
University of California–Irvine
Pennsylvania State University–University Park
University of Illinois–Urbana-Champaign
University of Texas–Austin
University of Washington
University of Florida
Ohio State University–Columbus
University of Maryland–College Park
University of Pittsburgh
University of Connecticut
University of Georgia
Purdue University–West Lafayette
Texas A&M University–College Station
Clemson University
Rutgers, the State University of New Jersey–New Brunswick
University of Minnesota–Twin Cities

Appendix B: IEEE CIS fellows list

A Stankovic
Abdul-Rahman Arkadan
Abraham Kandel (Life Fellow)
Akaviir Rao 2010
Alan Murray
Alan Willsky
Alan Yuille 2009
Alexander Fradkov
Anders Lindquist
Andrew Barto
Andrew Laine 2010
Annamaria Varkonyi-Koczy
Anthony Kuh
Aurel Lazar
Bart De Moor
Bart Kosko 2010
Bernard Widrow (Life Fellow)
Bin-Da Liu
Bir Bhanu
Bogdan Wilamowski
C L Philip Chen
Cesare Alippi
Changxin Fan
Charles Robinson
Chen Sen
Chi-Hau Chen (Life Fellow)
Chih-Min Lin 2010
Chin Teng Lin
Ching Li (Life Fellow)
Ching Suen (Life Fellow)
Christian Jutten
Christian Roux
Chung-Yu Wu
Clifford Lau (Life Fellow)
David Cooper (Life Fellow)
David Fogel
David Orin
David Root
David Zhang 2009
Deliang Wang
Derong Liu
Dimitre Filev
Dimitris Anastassiou
Dominic Ho 2009
Donald Kraft
Donald Wunsch
E Bakken (Life Fellow)
Emil Petriu
Enrique Ruspini
Erkki Oja
Fathi Salem
Feiyue Wang
Frank Lewis
Fred Lee
Frederic Ham 2009
Frederick Petry
Fumio Harashima (Life Fellow)
G Friedman (Life Fellow)
G Lendaris (Life Fellow)
Gang (Gary) Feng 2009
Gary May
Gary Yen 2009
George Klir (Life Fellow)
Gerald Sheble
Grace Clark 2007
Hamid Berenji
Hans-A Loeliger
Hans-Paul Schwefel
Herve Bourlard
Hironori Hirata
Hong Yan
Igor Vajda
Imre Rudas
Innocent Kamwa

Ioannis Pitas
Ira Gerson
Jacek Zurada
James Bezdek
James Kaiser (Life Fellow)
James Keller
James Smith
Janusz Kacprzyk
Jay Farrell
Jerry Mendel (Life Fellow)
Jhing Wang
Jie Si
Johan Reiber
John Burg (Life Fellow)
John Clark (Life Fellow)
John Kieffer
John Yen
Jon Benediktsson
Jong-Hwan Kim 2009
Joos Vandewalle
Jose Principe
Josef Nossek
Joseph Mitola,III 2010
Joydeep Ghosh
Jujang Lee
Jun Wang
Juyang Weng 2009
K Narendra (Life Fellow)
Kazuhiko Kawamura (Life Fellow)
Kevin Passino
Kim Man 2009
Kit Wong
Kiyohiro Shikano
Koichi Inada (Life Fellow)
Kouhei Ohnishi
Kwang Lee (Life Fellow)
Lars Eriksson 2009
Lawrence Hall
Lei Xu
Leszek Rutkowski
Ling Guan
Loi Lei Lai
M Rahman (Life Fellow)
Magdy Bayoumi
Marco Dorigo
Marco Gori
Marios Polycarpou
Martin Hasler
Masayoshi Tomizuka
Mathukumal Vidyasagar
Minoru Asada
Mitsumasa Koyanagi
Mohamed El-Hawary 1990
Mohamed El-Sharkawi
Mohamed Kamel
Mohamed Najim
Moshe Kam
Mo-Yuen Chow
N De Claris (Life Fellow)
N Sundararajan
Nan-Ning Zheng
Nasser-M Nasrabadi
Nelson Morgan
Nicholas Georganas
Nikhil Pal
Nikola Kasabov 2010
Nikolaos Bourbakis
Nozomu Hoshimiya (Life Fellow)
Okyay Kaynak
Osama Mohammed
Pau Choo Chung
Paul Werbos
Peter Hart (Life Fellow)
Peter Luh
Piero Bonissone
Qiang Yang 2009

Qi-Jun Zhang
R Newcomb (Life Fellow)
Radhakisan Baheti
Raman Mehra
Raymond Jarvis
Rejean Plamondon
Robert Hecht-Nielsen
Robert Marks
Roberto Battiti 2009
Rodney Goodman
Ronald Harley
Ronald Patton 2010
Ronald Yager
Rudolf Kruse
Russell Eberhart
Ryuichi Yokoyama 2009
S Pookaiyaudom
Said El-Khamy
Sankar Basu
Sergios Theodoridis
Sheng Chen 2009
Shigeru Katagiri
Shiro Usui
Shun-Feng Su 2010
Shun-Ichi Amari (Life Fellow)
Shunpei Yamazaki 2010
Soo-Chang Pei
Stephen Furber
Stephen Grossberg
Sukhan Lee
Sven Treitel (Life Fellow)
Tamas Roska
Terrence Sejnowski
Tharam Dillon
Toshio Fukuda
Tsu-Tian Lee
Tzyh-Jong Tarn (Life Fellow)
U Galil (Life Fellow)
Ulrich Reimers
Vincenzo Piuri
Vladimir Cherkassky
Vladimiro Miranda
Wai-Chi Fang
Wei Bo Gong
Will Leland
Witold Pedrycz
Xin Yao
Xinghuo Yu
Yasuo Matsuyama
Yong-Zai Lu
Yutaka Hata 2010
Zeungnam Bien
Zhengyou Zhang
Zong Sha (Life Fellow)

Appendix C: AAAI fellows list

Aaron Sloman
Adnan Youssef Darwiche
Alan Bundy
Alan K. Mackworth
Alan W. Biermann
Andrew McCallum
Anthony G. Cohn
Aravind K. Joshi
Austin Tate
B. Chandrasekaran
Barbara J. Grosz
Bart Selman
Benjamin Kuipers
Bernhard Nebel
Bill J. Clancey
Boi V. Faltings
Bonnie L. Webber
Brian C. Williams
Bruce G. Buchanan
Candy Sidner
Carla Pedro Gomes
Casimir A. Kulikowski
Charles Rich
Christopher D. Manning
Christopher K. Riesbeck
Cordell C. Green
Craig A. Knoblock
Craig Boutilier
Dan Roth
Dana S. Nau
Daniel G. Bobrow
Daniel Weld
Daniela Rus
Daphne Koller
David E. Smith
David Haussler
David Heckerman
David McAllester
David Poole
Dieter Fox
Donald W. Loveland
Doug Smith
Douglas B. Lenat
Drew McDermott
Edmund H. Durfee
Edward Feigenbaum
Edwina L. Rissland
Elaine A. Rich
Elaine Kant
Ellen C. Hildreth
Eric Horvitz
Erik J. Sandewall
Eugene C. Freuder
Eugene Charniak
Fahiem Bacchus
Fernando C.N. Pereira
Francesca Rossi
Geoffrey E. Hinton
George A. Bekey
Gerald DeJong
Gerald Jay Sussman
Gerard G. Medioni
Glenn R. Shafer
Gregory Cooper
Guy L. Steele Jr.
Harry G. Barrow
Hector Geffner
Hector Levesque
Henry A. Kautz
Howard Shrobe
Jack Minker
Jacques Pitrat
Jaime Carbonell
James A. Hendler

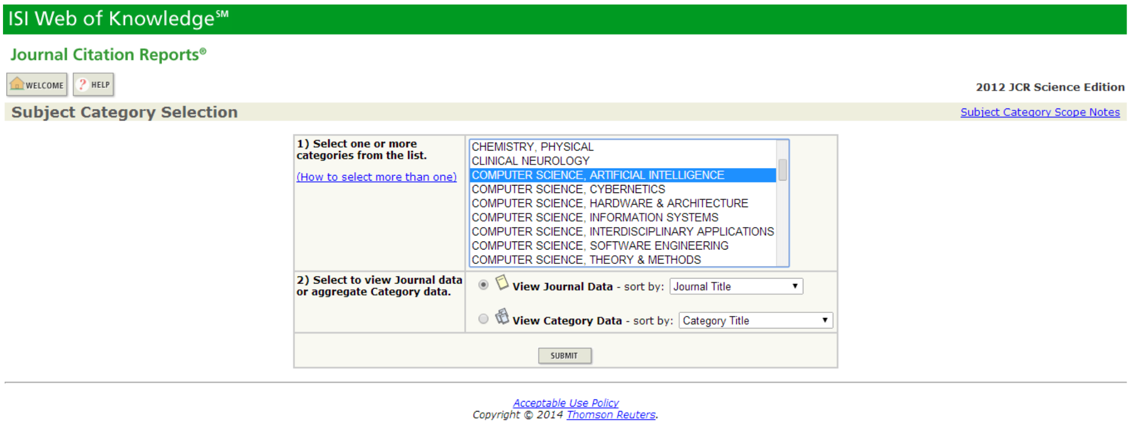
James F. Allen
Janet Kolodner
Jay M. Tenenbaum
Jeffrey S. Rosenschein
Jerry Hobbs
Jim Howe
Johan de Kleer
John E. Laird
John F. Sowa
John Gero
Jon Doyle
Jonathan Schaeffer
Joseph Halpern
Jude W. Shavlik
Judea Pearl
Julia Hirschberg
Kathy McKeown
Katia Sycara
Ken Forbus
Ken Ford
Kevin D. Ashley
Lenhart K. Schubert
Leslie G. Valiant
Leslie Kaelbling
Lotfi A. Zadeh
Luigia Carlucci Aiello
Lydia E. Kavraki
Maggie A. Boden
Makoto Yokoo
Manuela M. Veloso
Maria Gini
Mark E. Stickel
Mark J. Stefik
Mark S. Fox
Mark Steedman
Martha Pollack
Marvin Minsky
Matt T. Mason
Matthew L. Ginsberg
Michael Gelfond
Michael Genesereth
Michael I. Jordan
Michael John Wooldridge
Michael L. Littman
Michael P. Georgeff
Michael P. Wellman
Michael Pazzani
Milind Tambe
Moshe Tennenholtz
Moshe Y. Vardi
Murray S. Campbell
Narendra Ahuja
Nicholas R. Jennings
Nils Nilsson
Oliviero Stock
Oren Etzioni
Padhraic Smyth
Pascal Van Hentenryck
Pat Langley
Patrick Winston
Paul S. Rosenbloom
Pedro Domingos
Peter F. Patel-Schneider
Peter Friedland
Peter H. Stone
Peter Norvig
Peter Szolovits
Peter van Beek
Phil Klahr
Philip R. Cohen
Piero P. Bonissone
Pierre Baldi
Pradeep K. Khosla
Raj Reddy
Ramakant Nevatia
Ramesh Jain

Ramesh Patil
Ranan B. Banerji
Randall Davis
Raymond Mooney
Raymond Perrault
Reid G. Smith
Reid Simmons
Rich E. Korf
Richard E. Fikes
Richard S. Sutton
Richmond H. Thomason
Rick Hayes-Roth
Rina Dechter
Robert C. Holte
Robert C. Moore
Robert Schapire
Rodney A. Brooks
Ronald J. Brachman
Sarit Kraus
Satinder Singh Baveja
Scott Fahlman
Sebastian Thrun
Sheila A. McIlraith
Shlomo Zilberstein
Sholom M. Weiss
Stephen F. Smith
Stephen H. Muggleton
Steven Minton
Stuart C. Shapiro
Stuart J. Russell
Stuart Shieber
Subbarao Kambhampati
Takeo Kanade
Ted H. Shortliffe
Thomas G. Dietterich
Thomas L. Dean
Toby Walsh
Tom Mitchell
Tomas Lozano-Perez
Tomaso A. Poggio
Tuomas Sandholm
Usama Fayyad
Venkatramanan Subrahmanian
Victor R. Lesser
Vladimir Lifschitz
W. Eric L. Grimson
William A. Woods
William Cohen
William Swartout
Wolfgang Bibel
Wolfgang Wahlster
Wolfram Burgard
Yoav Shoham
Yolanda Gil
Yoram Singer
Yorick A. Wilks

Appendix D: Demonstration of the data collection processes (PI&PB)

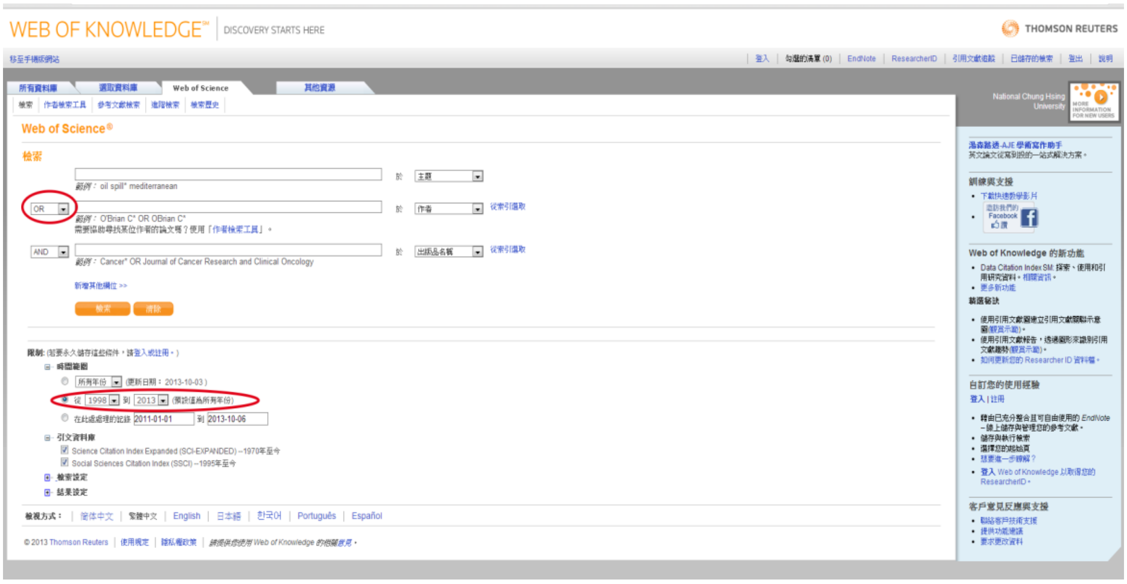
1. To enter the JCR database, we need to go to the website of our school library (http://www.lib.nchu.edu.tw). The screen will look like this.

In the middle of the page, we can see that there's a link which can enter JCR database. In this demonstration, we choose Artificial Intelligence to be the target field. Please login with your own account, and then go to the next page. We choose "JCR Sciences Edition 2012" and the category of "Computer Science: Artificial Intelligence".



2. The next thing we do is checking whether the journal in the list have been published more than 15 years. If not, we delete it.
3. Third, we collect the editorial board from the qualified journal (journal that published more than 15 years). We stored the name list and compare them with the US Top 25 public university to check (the list is in the appendix). If the name matches, we save it.
4. Now, we create an Excel table, there should be journal name in the first column and qualified editors name in the first row.

Open a new page (http://www.lib.nchu.edu.tw/), click SSCI, after you log in, you will see this page:



Change the setting of the button in red circle. The time period is from 1998 to 2013.

5. Start to collect the data, find the articles that are published by the active scholars.

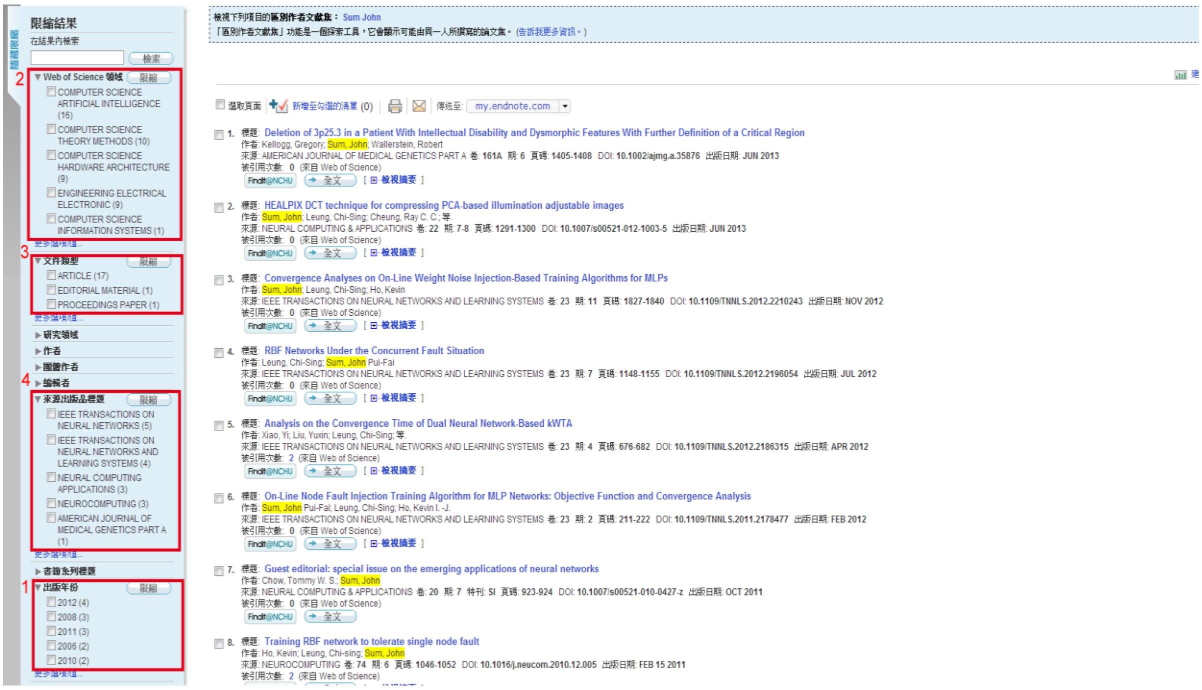
6. In the graph above, there are four red circle that emphasize for functions:

   A. Publication Years : Check the publication years，make sure that those scholars have published articles before 2003.

   B. Web of Science Categories: Choose the field of the journal.

   C. Document Types: Make sure that the categories of “Editorial Material” and “Proceeding Paper” have been removed.

   D. Source Titles: A tool to calculate the total number of articles a journal has published.



7. Compare the scholar’s articles with the journal names, and find out the how many articles he/she have published in each journal. Record it in the excel file. The result excel file would be like this:

A8 =CV8*DX8

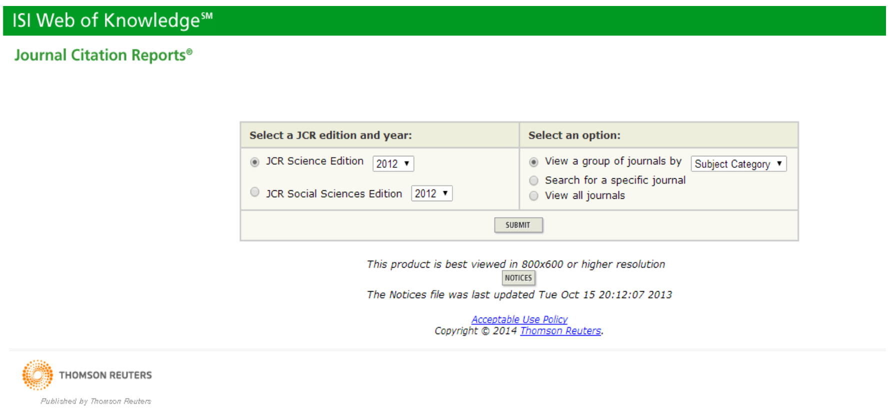
	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V
1		John	Daqin	Diane	Lynn	Dennis	Jason	Lorien	Debon	Philip	P.T. Ja	J. Car	R. Gel	S. Str	Joann	G. Bo	B.S. B	D Oar	Christi	Bonni	Chris
2																					
3	MIS QUART						2										2				2
4	INFORM SYST RES					2											4				2
5	J MANAGE INFORM SYST					2											2				1
6	J AM SOC INF SCI TEC	1		4	4						1	1						3	3		
7	J HEALTH COMMUN																				
8	INFORM TECHNOL MANAG																				1
9	J INF TECHNOL																1				
10	LIBR QUART	10			1						9	10									
11	LIBR INFORM SCI RES	4			2						5	4									
12	INFORM SOC								1	1				3							
13	INFORM MANAGE-AMSTER																				
14	ANNU REV INFORM SCI																	1	1		
15	INFORM PROCESS MANAG		4	3	1											2		4	1		
16	J ASSOC INF SYST															1					
17	EUR J INFORM SYST					1	2														
18	J ACAD LIBR	3			1						1	3	1								
19	J DOC				4														2		
20	TELECOMMUN POLICY										2			3							
21	INT J GEOGR INF SCI							1								1					
22	LIBR TRENDS	3	1		1						1	3			9	3					
23	COLL RES LIBR			1	2																
24	LEARN PUBL																		1		
25	J AM MED INFORM ASSN																				
26	INFORM TECHNOL LIBR	4									4	4									
27	J COMPUT-MEDIAT COMM						1														
28	MIS Q EXEC						1														
29	RES EVALUAT																				
30	J INF SCI		2		1																
31	LIBR RESOUR TECH SER																				
32	ELECTRON LIBR		2					5													
33	SERIALS REV																				
34	J STRATEGIC INF SYST																				
35	INFORM ORGAN-UK															1					
36	J MED LIBR ASSOC														3						
37	LIBR J	2									1	2									
38	ONLINE INFORM REV		3																		
39	PORTAL-LIBR ACAD				1																
40	INFORM SYST J																				
41	INFORM TECHNOL PEOPL																1			1	
42	SCIENTOMETRICS																				
43	KNOWL ORGAN																				
44	DATA BASE ADV INF SY						1														

	B	W	X	Y	Z	AA	AB	AC	AD	AE	AF	AG	AH	AI	AJ	AK	AL	AM	AN	AO	AP	AQ	AR	AS	AT
1		Ram	Sanjee	Alok	Il-Hon	Andre	Anura	RituA	Sirkka	Gary J	Arvind	James	Walee	Sridha	Gauta	Micha	Geoffr	Peter	Bonni	F. Har	W. va	Ken K	Jason	Beth K	Vinc
2																									
3	MIS QUART			8	1	5		4	1		4		1		1			1				2	4		
4	INFORM SYST RES	5	4	8		12		18	3	2	3			1	3			1				7			
5	J MANAGE INFORM SYST	2		2	2	12		2	2	2	2	5		2	1	3		1				3	1		
6	J AM SOC INF SCI TEC					1																			
7	J HEALTH COMMUN																								
8	INFORM TECHNOL MANAG			2		2	4			1						2									
9	J INF TECHNOL								3							2						1			
10	LIBR QUART																								
11	LIBR INFORM SCI RES																								
12	INFORM SOC																			1		8		1	
13	INFORM MANAGE-AMSTER	1										1	3										1		
14	ANNU REV INFORM SCI																								
15	INFORM PROCESS MANAG																2								
16	J ASSOC INF SYST			1		2											1								
17	EUR J INFORM SYST					1																2	1		
18	J ACAD LIBR																				8				
19	J DOC																								
20	TELECOMMUN POLICY																					1			
21	INT J GEOGR INF SCI												1				1			4					
22	LIBR TRENDS																3								
23	COLL RES LIBR																				1				
24	LEARN PUBL																								
25	J AM MED INFORM ASSN							2																	
26	INFORM TECHNOL LIBR																								
27	J COMPUT-MEDIAT COMM																						1		
28	MIS Q EXEC							1															1		
29	RES EVALUAT																								
30	J INF SCI																								
31	LIBR RESOUR TECH SER																								
32	ELECTRON LIBR																		1						
33	SERIALS REV																								
34	J STRATEGIC INF SYST																					2			
35	INFORM ORGAN-UK																1								
36	J MED LIBR ASSOC																								
37	LIBR J																								
38	ONLINE INFORM REV																								
39	PORTAL-LIBR ACAD																								
40	INFORM SYST J																								
41	INFORM TECHNOL PEOPL																		1						
42	SCIENTOMETRICS																								
43	KNOWL ORGAN																								
44	DATA BASE ADV INF SY																								1		

Appendix E: Demonstration of the data collection processes (Eigenfactor&Raw citations)

1. Go to the JCR database website. In here, we use NCHU Library to enter the JCR database.

2. Choose the journal category to collect the Eigenfactor and raw citations. We‘re going to collect the Eigenfactor and raw citations of the qualified journals. The qualified journal means that it has been published for more than 15 years. In here, we use the field of Artificial Intelligence as an example.



3. Click the journal that matches the qualified journal list. The Eigenfactor is shown in the right hand side of the website.

Rank	Abbreviated Journal Title (linked to journal information)	ISSN	JCR Data						Eigenfactor® Metrics	
			Total Cites	Impact Factor	5-Year Impact Factor	Immediacy Index	Articles	Cited Half-life	Eigenfactor® Score	Article Influence® Score
1	ACM T AUTON ADAP SYS	1556-4665	161	1.000	1.302	0.108	37	3.8	0.00093	0.557
2	ADAPT BEHAV	1059-7123	490	1.113	1.545	0.414	29	7.5	0.00100	0.475
3	ADV ELECTR COMPUT EN	1582-7445	142	0.552	0.479	0.067	60	2.4	0.00035	0.072
4	ADV ENG INFORM	1474-0346	730	1.593	1.708	0.362	69	5.3	0.00178	0.451
5	AI COMMUN	0921-7126	249	0.449	0.617	0.333	30	9.1	0.00080	0.399
6	AI EDAM	0890-0604	348	0.407	0.935	0.000	23	8.5	0.00107	0.494
7	AI MAG	0738-4602	691	0.726	0.959	0.057	35	>10.0	0.00178	0.687
8	ANN MATH ARTIF INTEL	1012-2443	409	0.200	0.391	0.059	34	>10.0	0.00126	0.357
9	APPL ARTIF INTELL	0883-9514	422	0.475	0.505	0.174	46	9.5	0.00059	0.164
10	APPL INTELL	0924-669X	927	1.853	1.936	0.186	102	5.9	0.00124	0.304
11	APPL ONTOL	1570-5838	93	1.080		0.062	16		0.00032	
12	APPL SOFT COMPUT	1568-4946	3117	2.140	2.526	0.323	341	3.1	0.01165	0.622
13	ARTIF INTELL	0004-3702	5407	2.194	2.566	0.435	46	>10.0	0.00827	1.308
14	ARTIF INTELL MED	0933-3657	1281	1.355	1.767	0.255	51	7.3	0.00267	0.566
15	ARTIF INTELL REV	0269-2821	605	1.565	1.191	0.100	40	9.0	0.00100	0.419
16	ARTIF LIFE	1064-5462	715	1.585	1.545	0.300	20	9.8	0.00081	0.417
17	AUTON AGENT MULTI-AG	1387-2532	500	0.790	1.410	0.242	33	6.7	0.00178	0.706
18	AUTON ROBOT	0929-5593	1240	1.908	1.890	0.231	52	8.3	0.00323	0.783

4. In this page, you can see the total citations to recent items within 5 years. In this example, the raw citation of the *ACM Transactions on Autonomous and Adaptive Systems* is 125.

Journal Impact Factor

Cites in 2012 to items published in: 2011 =18, 2010 =24, Sum: 42
Number of items published in: 2011 =28, 2010 =14, Sum: 42

Calculation: Cites to recent items / Number of recent items = 42 / 42 = **1.000**

5-Year Journal Impact Factor

Cites in {2012} to items published in: 2011 =18, 2010 =24, 2009 =41, 2008 =29, 2007 =13, Sum: 125
Number of items published in: 2011 =28, 2010 =14, 2009 =21, 2008 =19, 2007 =14, Sum: 96

Calculation: Cites to recent items / Number of recent items = 125 / 96 = **1.302**

Journal Self Cites

The tables show the contribution of the journal's self cites to its impact factor. This information is also represented in the cited journal graph.

Total Cites	161
Cites to Years Used in Impact Factor Calculation	42
Impact Factor	1.000

Self Cites	12 (7% of 161)
Self Cites to Years Used in Impact Factor Calculation	3 (7% of 42)
Impact Factor without Self Cites	0.929

Journal Immediacy Index

Cites in 2012 to items published in 2012 =4
Number of items published in 2012 =37

Calculation: Cites to current items / Number of current items = 4 / 37 = **0.108**