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A Comparative Study of Academic Networks in Computer Science and Physics

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By

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ABSTRACT

Academic networks derived from research papers, in particular citation and co-author networks, have been studied widely. Although networks in an individual discipline particularly physics have been studied substantially, the difference across different disciplines remains unclear. This thesis shows that networks generated in computer science differ greatly the networks in Physics. The data used in our experiment contain more than two million papers in DBLP and half a million papers in Physical Review journals. We observe that both citation networks can be classified as scale-free networks. Papers in DBLP has a shorter life than PR. And physicists collaborate more closely than computer scientists in both citation and co-author networks. Collaborations evolve over time in both disciplines. For the ranking of papers, we find that the traditional PageRank algorithm is not appropriate for citation networks. We investigate the small-world characteristics in both kinds of networks in terms of small average shortest path.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER I

Introduction

Large number of academic papers are available through various sources. Bibliometrics is developed to study the papers and their connections. One topic in this area is the study of citation networks and co-author network. Although networks in an individual discipline especially physics have been studied widely[29][10][26], the difference between different areas is still unclear. The goal of this thesis is to analyze academic networks of citation and co-author in two disciplines, computer science and physics. We construct these networks based on the data from DBLP and Physical Review journals. Then, we analyze and compare them by computing network properties such as the degree distribution, connected component, clustering coefficient and pagerank. Our goal is to find the commonalities and differences between these two fields. Considering of the long time period of these two datasets, we also investigate the trends of citation and collaboration in both disciplines.

Citation network and co-author network are two kinds of social networks that can be extracted from academic research papers. In a citation network, a node represents a paper, and a directed edge is a citation link if paper A cites paper B. The citation network that is established from a collection of 6 papers(Table 1) is given in Fig. 1. It is a directed graph, and mostly acyclic because a paper normally cites those papers that have been published earlier. In a co-author network, nodes are authors and an undirected edge represents the collaborations between two authors if they co-author a paper. The co-author network of authors of the collection of 6 papers is shown is Fig. 2. Compared with citation network, it is undirected. Both kinds of network have been studied substantially and can reveal the patterns of academic research. For instance, citation network can help us understand the connections among papers and co-author network can shed light on the the patterns of collaboration among authors.

Paper	Year	Authors	References
A	1997	x, y	-
B	2012	y	A, C, D
C	1997	y, z	-
D	2003	e, f, g	C
E	2003	g, h	-
F	2012	g	D, E

TABLE 1: A collection of 6 papers

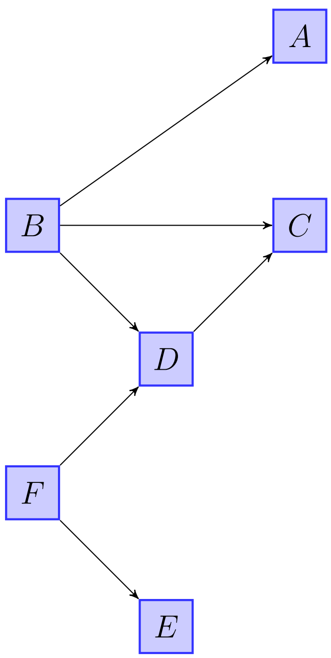


FIGURE 1: An example of citation network

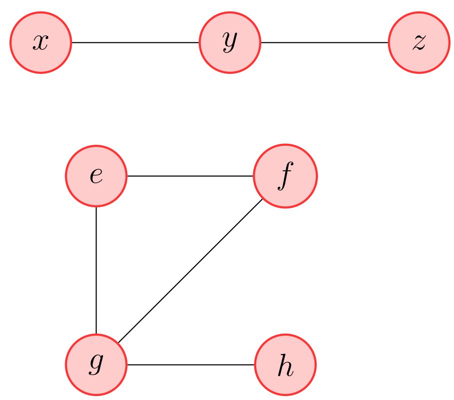


FIGURE 2: An example of co-author network

1 Main results in citation networks

In citation network of PR and DBLP, we studied their degree distributions, life cycle of the papers, clustering coefficient, path length, and PageRank. We find that in both

PR and DBLP, their in-degree distributions have a long tail that resembles power laws with similar exponent that is close to 2.5. The inequality of citations is larger in DBLP: 28% of the citations in DBLP go to top 1% of the papers, compared with 19$\% in PR$. Out-degrees resemble log-normal distributions in both PR and DBLP.

Papers attract more citations in their young age. The citation count decreases in an exponential speed. The average life expectancy of a paper is 6.5 years in DBLP and 8 years in PR, papers in DBLP has a shorter life than PR.

Clustering coefficient is an important metric for social network, and often a criteria to judge whether a network is a social network. Contrary to the believe that citation networks have high CC, we find that in both PR and DBLP, their CCs are rather low (0.023 for PR and 0.012 for DBLP). The higher CC in PR indicates that papers in PR knit closer than papers in DBLP.

Both DBLP and PR papers form a small world. In both data sets, their degree of separations are close to six, which is also the degree of separation between people in real life [21]. Their degree of separations are significantly larger than online social network such as Twitter(4.12), Facebook(4.7), and Weibo(3.44) from [16]. The diameter in PR almost doubles that of DBLP.

PageRank algorithms on these two datasets are also explored. We find that the direct application of the PageRank algorithm with damping factor 0.85 lead the large bias in favor of old papers. Changing damping factor to 0.5 can ameliorate the problem.

2 Main results in co-author network

In co-author network, we studied their degree distributions, component distributions, clustering coefficient, and path length. Unlike citation network, the degree distribution of co-author network in PR and DBLP are very different. Although networks have long tail distributions that resemble a power law, their slopes differ greatly. The average degree in PR is 119.978, which is 15 times higher than that of DBLP (7.807). In both PR and DBLP, the most frequent pattern is authors working with two authors

(17.5% in DBLP and 11% in PR).

For the distribution of network components, both networks have a single large component, whose size is 88% for DBLP and 95% for PR. There are some small isolated components. Notably there are 24,744 isolated pairs in DBLP and 3,258 in PR, and 11,125 isolated triples in DBLP and 1,523 in PR. CS community has more isolated small components than PR.

Their CC is also very different in two networks. The average CC of the entire PR co-author network is 0.738, and 0.718 in DBLP. The higher CC in PR indicates that authors in PR cluster much tightly than authors in DBLP. Both high CC value indicates that the co-author networks are social networks.

More collaborations happen in physicists than computer scientists in terms of the degree distribution and clustering coefficients. However, for both PR and DBLP, collaborations evolve over time. The number of co-authors per author and the number of authors per paper has risen significantly over the past century. The productivity of scientists in physics is higher than computer science, but we should notice that the author name in PR data contains the last name and the initial of the first name. Thereby many names with the same initials are aggregated as the same person, while authors of DBLP have first name. Both co-author networks show the small-world effect in terms of the average shortest path length.

CHAPTER II

Review of The Literature

This chapter reviews the existing works of the analysis of citation and co-author networks. Section 1 reviews two papers that build and analyze the citation network. Section 2 reviews one paper that address the construction and analysis of co-author network. Section 3 reviews two papers which combine both kinds of networks together.

1 Citation Network

1.1 How popular is your paper? An empirical study of the citation distribution

According to Redner [28] states that, the problem is how to analyze the citation distribution of scientific publications so that people can have the basic insight about the popularity of publications.

Dataset

Redner used two relatively large data sets, one is the collection of 783,339 papers published in 1981 that have been cataloged by the Institute for Scientific Information. This dataset is ranging from 1981 to 1997. The second is the corpus of 24,296 papers, which have 20 years of publications in volumes 11 to 50 of Physical Review D, from 1975 to 1994.

Experiment

The author plotted the number of papers as a function of x citations, namely, the citation distribution. The author found that the number of papers is decreasing with the citations but can not be described by a single function over the whole range of citations. And Redner found that the asymptotic tail of citation distribution for two datasets appears to follow the power law, $N(x) \sim x^{-\alpha}$, with α almost equal to 3.

Result and conclusion

The author analyze the citation distribution based on two large datasets, which can provide a measure of popularity of scientific publications. And the number of papers with x citations, has a large-x power law decay, with exponent almost 3.

1.2 Citation Statistics From More Than a Century of Physical Review

Redner [29] studied the statistics of the complete sets of citations of all publications that published in Physical Review from 1893 to 2003.

Dataset

According to the author, the data was provided by the Physical Review Editorial Office. There are a total of 353,268 publications and 3,110,839 citations. The number of publications have at least one citation is 329,847. This dataset is special for its long time history so that people can examine the time evolution of citations.

Experiment

The author analyzed the citation distribution, the attachment rate, age characteristics of citations and citation histories of individual publications.

- The citation distribution: the author examined the growth of citations in time, that is the total number of citations (received and made) over each year; showed the citation distribution for entire dataset and the citations from 50 to 300 follows a power law with exponent 2.55.

- The attachment rate: the author found that the attachment rate is a linear function of the number of citations.

- Age characteristics of citations: the author analyzed the average citation age versus total citations, the distribution of citation ages from citing and to cited publications.

- Citation histories of individual publications: the author states that the citation histories of individual publications show great diversity.

Result and conclusion

The author observed how citations evolve and how individual publication influence the research in this paper. The author found that the citation distribution can be described by linear preferential attachment, and the age distribution of citations to a paper follows a slow power-law decay.

2 Co-author Network

2.1 Scientific collaboration networks. I. Network construction and fundamental results

Newman [22] studied the co-author network in three disciplines, physics, biomedical research and computer science.

Dataset

The author used bibliographic data collected from four public databases of papers.

- The physics data from Los Alamos e-Print Archive starting from 1992 to the present. This database contains subdomains within physics, such as condensed matter and high-energy physics.

- A database of articles on biomedical research from Medline, ranging from 1961 to the present.
- A corpus of papers in high-energy physics(theoretical and experimental) from Stanford Public Information Retrieval System (SPIRES), from 1974 to the present.
- A database of papers in computer science from Networked Computer Science Technical Reference Library (NCSTRL).

Since the coverage provided by both the Los Alamos Archive and the NCSTRL database is relatively poor before 1995, and the author want to make comparison of collaboration patterns among these different disciplines, the time period should be the same. Thus the author construction co-author networks using data from 1995 to 1999 inclusive.

Experiment

The author provided some basic measures to compare these co-author networks.

- The number of authors
- The number of papers per author
- The number of authors per paper
- The number of collaborators per author
- Size of the giant component
- Clustering coefficient

Result and conclusion

The author compare and study the co-author networks among three disciplines from different aspects. And he found that the distribution of the number of papers per author, the number of authors per paper and the number of co-authors per author roughly follow a power law. Also for all networks, there exists a giant component in which any two authors can be connected by a path.

As to the differences, researchers in experimental disciplines have more collaborators on average than those in theoretical disciplines, and high-energy physicists have the largest number of co-authors. The author also found that the degree of network clustering in biomedical research is lower than other fields.

3 Citation and Co-authorship Network

Rather than focus solely on either citation or co-authorship networks, as most previous studies have done, this section reviews two papers that studied both kinds of networks.

3.1 Co-authorship and citation patterns in the Physical Review

Martin et al. [19] constructed citation and co-author networks based on a large dataset Physical review to explore the temporal changes in citation and collaboration over the whole time period of the data. The author also studied the correlation and interaction between the two.

Dataset

The authors states that the Physical Review dataset derived from American Physical Society(APS), which consists of bibliographic and citation data for the physical journals from 1893 to 2009. Besides, the authors preprocessed this dataset, first they disambiguate the authors' name, then remove those papers with 50 or more authors.

Experiment

The author made a variety of analyses to this dataset, such as authorship and co-authorship patterns, citation patterns, interactions between citation and co-authorship, self-citation and co-author citation and transitivity.

- Authorship patterns: a cumulative distribution function for the number of papers an author published, the changes in the number of papers, the number of authors, the number of authors per paper and co-authors per author over time.
- Citation patterns: the average number of citations received and made by a paper over time, testing the aging of papers.
- Interactions between citation and co-authorship: the author divided citations into three kinds, self-citation, co-author citation and distant citation and then plot the fraction of citations (three kinds) as a function of year.
- Self-citation and co-author citation: gave the percentage of papers that make or receive self-citation and co-author citation.
- Transitivity: calculate the clustering coefficient that the percentage of the pair of authors have a common co-author but didn't collaborate previously and write a paper later together.

Result and conclusion

In this paper, the authors studied both networks together and the changes in citation and collaboration patterns. And they found that the Physical Review grows exponentially, as well as the number of citations per paper. The percentage of self-citations and co-author citations are more constant than distant citations over time. Authors is more likely to cite their own papers than their co-authors', and who in turn cite more often than non-coauthors. They also observed a phenomenon that one author cite another's paper often receive a citation in return later, especially happens between co-authors. And two authors who have a common co-author but never collaborated before have only a small chance,3.5% of collaborating later.

3.2 The structure and analysis of nanotechnology co-author and citation networks

Onel et al. [23] built the co-author network to study the patterns of collaboration and analyzed the citation network to study the structure of information flow in nano science.

Dataset

The authors constructed these networks by extracting information from the scientific literature database, "Web of Science". The time spans from year 1993 to 2008. They collected those papers that contain the word "nano" in their abstract, keywords or title to build the citation and co-author network in nano science, the total is 30,550 records of papers.

Experiment

The authors measured some statistics of citation and co-author networks to interpret their significance in nano science.

- Network demographics:

	Co-author network	Citation network
#nodes	62,664	580,073
#edges	238,580	871,130
#isolated nodes	689	0
#weakly connected component	3,415	901
#nodes of the giant component	46,429	565,958
#edges of the giant component	207,464	857,711

TABLE 2: Basic statistics of both networks

- Degree distributions: the co-author network has an average degree of 7.7 and 3.004 for citation network.
- Giant component: the giant component of co-author network contains 74% of all scientists, and 98% for citation network.
- Average shortest path length: 5.92 for co-author network, 7.79 for citation network.
- Diameter: 21 for co-author network, 23 for citation network.
- clustering coefficient: 0.84 for co-author network, 0.012 for citation network.

Result and conclusion

The authors analyzed the undirected collaboration network and directed citation network in nano science. And they found that the distribution of degree for both kinds of networks follow a power law form. Both networks have small-world characteristics, and co-author network is highly clustered. The citation network has a low clustering coefficent compared to other real-world networks.

4 Summary

In this chapter, we reviewed five previous works that related to citation and co-author networks. Previous works [28] and [29] analyzed the citation network by the same author S. Redner based on the same dataset. Newman [22] built the co-author network in three different disciplines. Previous works byMartin et al. [19] and Onel et al. [23] analyze both kinds of networks in single area.

Meanwhile, there are some existing works in Physical Review dataset [26],[25],[10] and works in DBLP dataset [15],[18],[27],[8],[35]. In this thesis, we use the tool gephi and igraph to help us analyze the basic properties of networks. And the previous works about gephi:[20],[7],[12],[14],[4] and about igraph: [13],[9],[30],[17].

Some previous works combined citation and co-author network together, however the dataset just come from a single field. Other previous works did not provide a complete analysis of network, situations can be summarized as follows, one or more can met in those previous works.

- just analyze one of citation and co-author networks.
- did not provide a view of citation or co-author patterns over time.
- only focus on a short time window.
- did not make basic analysis of networks (the properties of network).

CHAPTER III

Dataset

This thesis analyzes academic networks of citation and co-authorship generated in computer science and physics. The first dataset refers to computer science called DBLP, the other data about physics is Physical Review. In this thesis, graph properties including PageRank, clustering coefficient and connected components are calculated by using Gephi; shortest path and diameter are calculated by using igraph, a collection of network analysis tools programmed in Python. The experiments are conducted on iMac machine with Core i5 2.7GHz CPU and 16 GB memory. And all the figures are plotted using Matlab.

1 DBLP

DBLP is a computer science bibliography provided by University of Trier in Germany [1]. It contains meta-data for different types of publications, including journal articles, thesis, and conference papers and so on. The meta-data includes authors, date of publications, titles, and venues. Unfortunately, DBLP itself does not include citation data. Since our goal is to study the citation network of computer science, we used a citation network provided by ArnetMiner[37][34][33][35][36], which covers a subset of DBLP. They extract the citation relation for DBLP papers from ACM and other sources. There are progressive developments for the data. The data used in this thesis is the one released in May, 2014 that consists of 2,146,341 papers and 4,191,677 references. The papers were published in the years ranging from 1936 to 2013. In the rest of our discussion, we will use DBLP to denote this enhanced DBLP data with citation network[2].

2 Physical Review(PR)

Physical Review dataset is a repository for physical publications which consists of 12 kinds of journals and is available from APS (American Physical Society)[3]. Table 3 lists the number of papers in each journal and the total number of papers in PR is 541,447. This dataset contains citation and bibliographic data that covers a long time period, spanning more than 100 years from 1893 to 2013. Each paper has a unique numerical label as identification. And data for each paper include title, year, authors, affiliations of authors and so on.

Journals	**Papers**
Physical Review(PR)	47,939
Physical Review A(PRA)	65,170
Physical Review B(PRB)	161,257
Physical Review C(PRC)	34,443
Physical Review D(PRD)	69,481
Physical Review E (PRE)	46,009
Physical Review X(PRX)	214
Physical Review Series I(PRI)	1,469
Reviews of Modern Physics(RMP)	3,139
Physical Review Letters(PRL)	110,080
Physical Review Special Topics - Physics Education Research(PRSTPER)	251
Physical Review Special Topics - Accelerators and Beams(PRSTAB)	1995
Total	541,447

TABLE 3: Number of papers in each journal of PR

3 Comparison of two datasets

A comparison between PR dataset and DBLP dataset is listed in Table 4. The DBLP dataset contains more than 2 million papers, and PR has half a million papers. Both datasets provide two data, i.e., citation and metadata, and cover a long time period. The metadata of PR and DBLP includes authors, year, title, venue and citation. Both PR and DBLP do not contain abstract. DBLP has no data on authors affiliation.

These two datasets are useful for two reasons: the length of time it spans and it contains citation and co-authorship in the same body of papers which allow us to study and compare the changes in both citation and collaboration patterns over time.

	Physical Review	DBLP(ArnetMiner)
#Papers	541,447	2,146,341
#Citations	6,039,994	4,191,677
Time span	1893 - 2013	1936 - 2013
Areas	Physics	Computer Science
Metadata: authors	$\surd$	$\surd$
year	$\surd$	$\surd$
title	$\surd$	$\surd$
venue	$\surd$	$\surd$
citation	$\surd$	$\surd$
affliation	$\surd$	X
abstract	X	$\surd$

TABLE 4: Comparison of the two datasets

CHAPTER IV

Citation Network

1 Degree Distribution

In citation network, we remove those isolated nodes that have no citation links. The number of remaining nodes in PR is 531,480, and 781,108 in DBLP. These two networks are of similar size in terms of nodes (see in Table 5). However, the number of edges are very different: the average degree of PR is almost twice of DBLP. Since the citation graph is directed, vertices have both an inbound degree, or in-degree and an outbound degree, or out-degree. That is, the in-degree/out-degree of a node is the number of incoming/outgoing edges connected to it. For better understanding the difference between two networks, we will look deep into the basic properties of them in the following sections.

	Physical Review	DBLP
Time span	1893 - 2013	1954 - 2013
Number of Edges	6,039,994	4,191,677
Number of Nodes	531,480	781,108
Number of papers that have been cited	459,796 (87%)	528,263(68%)
Number of papers that have citations	516,163(97%)	564,705(72%)
Average Degree	11.364	5.366

TABLE 5: Statistics of citation network

Networks with power-law degree distribution are called scale-free networks. The power-law degree distribution was first observed by Barabási and Albert[6]. Firstly, they argued that most real networks grow by the addition of new nodes and edges. Secondly, real-world networks exhibit preferential attachment, that is the probability of connecting to a node depends on the node's degree. For instance, a new paper prefers to cite well-known papers thus have more citations than less cited papers. Based on this two theories, the Barabási-Albert model has been proposed which led to the power-law distribution.

The algorithm of Barabási-Albert model can be described as two steps[5]:

1) Growth: Starting from a small number of nodes N, add a node at each time step with $N_0(\leq \text{N})$ edges link to N_0 nodes already in the network.

2) Preferential attachment: We assume that the probability P of a new node connected to node i depends on the degree k_i of node i, the formula is as follows:

$$P_i = \frac{k_i}{\sum_j k_j} \tag{1}$$

Here, j presents all pre-existing nodes. The degree distribution resulting from this model is scale free, the probability of a node has k edges follows a power law with the exponent 3.

1.1 In-degree distribution

In our citation network, the in-degree of a node can also be seen as the number of citations this paper received. Figure 3 shows the in-degree distribution, the proportion of papers as a function of the number of cited values. The middle section of the data appears to be described by a power law, $N(x) \sim x^{-\alpha}$, with $\alpha \approx 2.5$(see the green line). And as S. Redner examined in[28], the citations distribution of 24,296 papers in Physical Review D has a large-x power law decay, with exponent -3. We can see from the figure, PR and DBLP have a similar slope. Due to it's a log-log plot, the percentage of papers with 0 cited value hasn't be shown. However, our results show that 32% papers in DBLP never been cited and 13% in PR. Also around 70% papers in DBLP have been cited less than 4 times, 40% in PR. These all means that papers in DBLP have been cited less than PR in average.

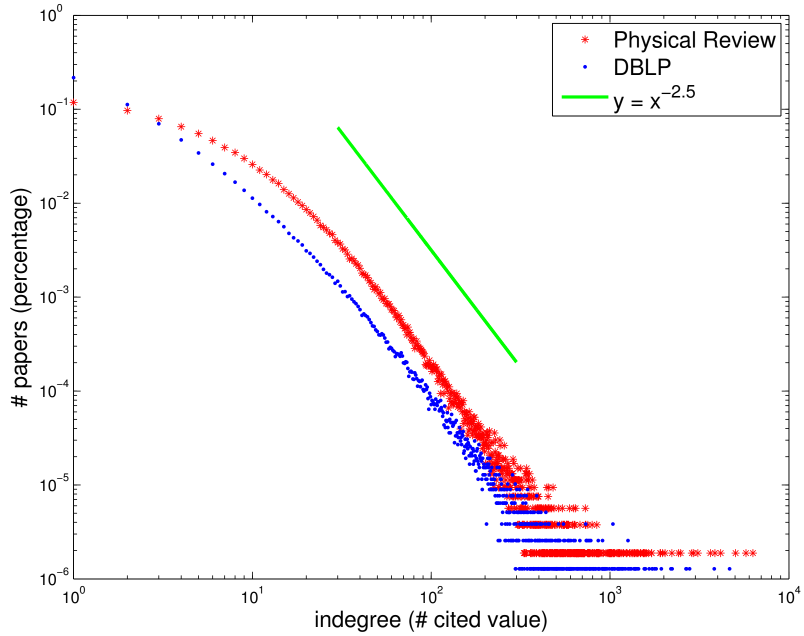


FIGURE 3: Indegree distribution of PR and DBLP. About 10 percent of papers are cited only once in both DBLP and PR.

The degree distribution plot in Fig. 3 is good for inspecting low degrees, but the popular papers with high citations are not discernible. So we plot the degree against ranking in Fig. 4, where the citation is plotted a function of its rank. The figure shows that the top cited paper in PR has been cited 6291 times, 2758 in DBLP. We also list the top10 cited papers of PR and DBLP respectively (Table 6 and Table 7) for reference. The top 1% papers' citations in DBLP accounts for 28% of the whole citations, 19% of PR. In both DBLP and PR, citations concentrated in the top papers. However, in the community of computer science, mega stars attract more citations than physics (28% vs 19%).

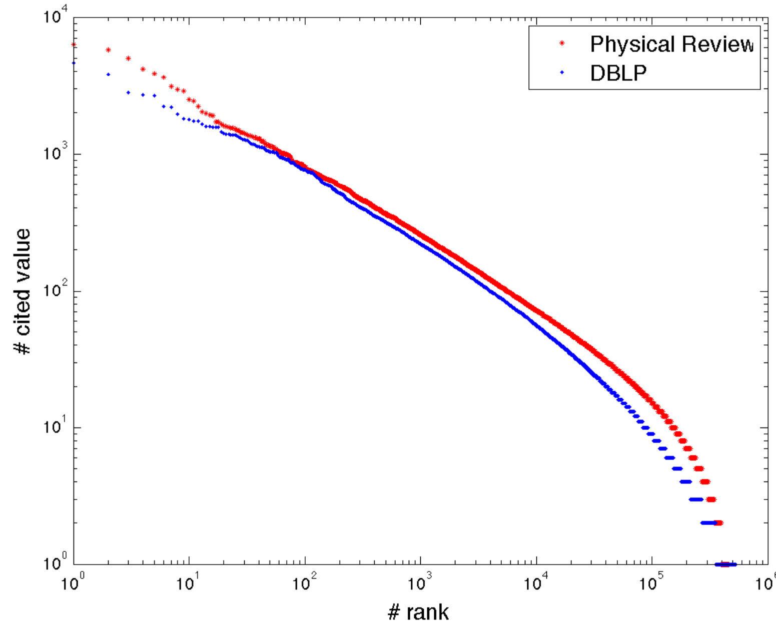


FIGURE 4: Citation count as a function of ranking. The top paper is cited 6291 times in PR and 2785 in DBLP.

Physical Review					
Rank	# cites	Title	Author	Journal	Year
1	6291	Self-Consistent Equations Inclucing Exchange and Correlation Effects	W. Kohn, L. J. Sham	PR	1965
2	5763	Generalized Gradient Approximation Made Simple	John P. Perdew, Kieron Burke, Matthias Ernzerhof	PRL	1996
3	5035	Inhomogeneous Electron Gas	P. Hohenberg, W. Kohn	PR	1964
4	4159	Efficient Iterative Schemes for ab initio Total-energy Calculations Using a Plane-Wave Basis Set	G. Kresse, J. Furthmuller	PRB	1996
5	3860	Self-interaction Correction to Density-functional Approximations for Many-Electron Systems	J. P. Perdew, Alex Zunger	PRB	1981
6	3640	Special Points for Brillouin-zone Integrations	Hendrik J. Monkhorst, James D. Pack	PRB	1976
7	3097	Ground State of the Electron Gas by a Stochastic Method	D. M. Ceperley, B. J. Alder	PRL	1980
8	2940	Projector Augmented-Wave Method	P. E. Blochl	PRB	1994
9	2868	From Ultrasoft Pseudopotentials to the Projector Augmented-Wave Method	G. Kresse, D. Joubert	PRB	1999
10	2481	Efficient Pseudopotentials for Plane-Wave Calculations	N. Troullier, Jose Luriaas Martins	PRB	1991

TABLE 6: Top10 cited papers in PR

DBLP					
Rank	# cites	Title	Author	Journal	Year
1	2785	Distinctive Image Features from Scale-Invariant Keypoints	David G. Lowe	International Journal of Computer Vision	2004
2	2678	Fast Algorithms for Mining Association Rules in Large Databases	Rakesh Agrawal, Ramakrishnan Srikant	VLDB	1994
3	2224	Mining Association Rules between Sets of Items in Large Databases	Rakesh Agrawal, Tomasz Imielinski, Arun N. Swami	SIGMOD Conference	1993
4	1935	The Anatomy fo a Large-Scale Hypertextual Web Search Engine	Sergey Brin, Lawrence Page	Computer Networks	1998
5	1811	Chord: A Scalable Peer-to-Peer Lookup Service for Internet Applications	Ion Stoica, Robert Morris, David R. Karger, M. Frans Kaashoek, Hari Balakrishnan	SIGCOMM	2001
6	1724	A Method for Obtaining Digital Signatures and Public-Key Cryptosystems	Ronald L. Rivest, Adi Shamir, Leonard M. Adleman	Commun. ACM	1978
7	1722	Graph-Based Algorithms for Boolean Function Manipulation	Randal E. Bryant	IEEE Trans. Computers	1986
8	1656	Bagging Predictors	Leo Breiman	Machine Learning	1996
9	1577	Genetic Programming - on the Programming of Computers by Means of Natural Selection	John R. Koza	Complex adaptive systems	1993
10	1563	Induction of Decision Trees	J. Ross Quinlan	Machine Learning	1986

TABLE 7: Top10 cited papers in DBLP

1.2 Out-degree distribution

The out-degree of a node is the number of papers citing the given paper and the out-degree distribution is shown in Fig. 5. It plots the proportion of papers as a function of the number of citing values. Like the in-degree distribution, the out-degree distribution also shows preferential attachment characteristics in the middle section of data (green line with slope -3.8), although the initial segment deviates significantly from power law distribution. Since it's a log-log plot, it didn't show the percentage of papers with 0 citing value. Actually, 28% papers in DBLP never cite any paper, 3% in PR. And around 17% papers cite more than 10 papers in DBLP, 43% in PR. Papers in DBLP citing less papers than PR in average. Also papers in DBLP have been cited less than PR, that's why the average degree of PR is greater than DBLP.

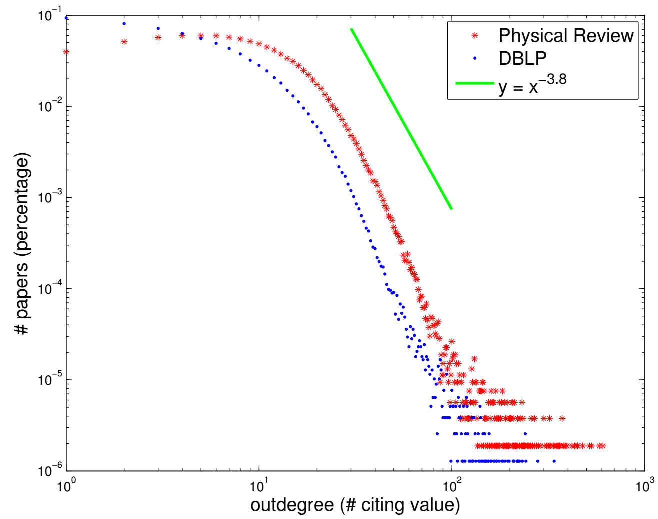


FIGURE 5: Outdegree distribution of PR and DBLP

Figure 6 plots the citing value as a function of its rank to focus on the papers which citing large number of papers. The top paper cites 607 papers in PR, 339 in DBLP. And we list the papers that have top10 citing values of PR in Table 8 and of DBLP in Table 9 respectively for reference.

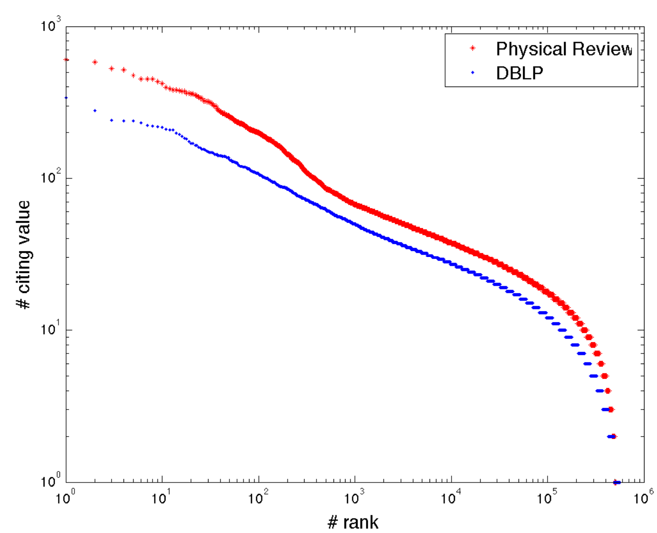


FIGURE 6: Ranking of #citing papers

Physical Review					
Rank	# cites	Title	Author	Journal	Year
1	607	Electrodynamics of Correlated electron materials	D.N. basov, Richard D. Averitt, Dirk van der Marel, Martin Dressel, Kristjan Haule	RMP	2011
2	582	Metal-insulator Transitions	Masatoshi Imada, Atsushi Fujimori, Yoshinori Tokura	RMP	1998
3	530	Table of Isotopes	G. T. Seaborg, I. Perlman	RMP	1948
4	517	Energy Levels of Light Nuclei. III	W. F. Hornyak, T. Lauritsen, P. Morrison, W. A. Fowler	RMP	1950
5	477	Spintronics: Fundamentals and Applications	Igor Zutic, Jaroslav Fabian, S. Das Sarma	RMP	2004
6	449	Electronic Properties of Two-dimentional Systems	Tsuneya Ando, Alan B. Fowler, Frank Stern	RMP	1982
7	448	Quantum Entanglement	Ryszard Horodecki, Pawel Horodecki, Michal Horodecki, Karol Horodecki	RMP	2009
8	447	Energy Levels of Light Nuclei. V	F. Ajzenberg, T. Lauritsen	RMP	1955
9	432	Many-body Physics with Ultracold Gases	Immanuel Bloch, Jean Dalibard, Wilhelm Zwerger	RMP	2008
10	419	Energy Levels of Light Nuclei(Z=11 to Z=20)	P. M. Endt, J. C. Kluyver	RMP	1954

TABLE 8: Papers have top10 citing value of PR

DBLP					
Rank	# cites	Title	Author	Journal	Year
1	339	Algorithm Engineering: Bridging the Gap between Algorithm Theory and Practice	Matthias Muller-Hannemann, Stefan Schirra	Algorithm Engineering	2010
2	279	A Brief Survey of Program Slicing	Baowen Xu, Ju Qian, Xiaofang Zhang, Zhongqiang Wu, Lin Chen	ACM SIGSOFT Software Engineering Notes	2005
3	242	Location-dependent Query Processing: Where we are and where we are heading	Sergio Ilarri, Eduardo Mena, Arantza Illarramendi	ACM Comput. Surv.	2010
4	240	Agent-Oriented Programming, From Prolog to Guarded Definite Clauses	Matthew M. Huntbach, Graem A. Ringwood	Lecture Notes in Computer Science	1999
5	240	Modern Development Methods and Tools for Embedded Reconfigurable Systems: A Survey	Lech Jozwiak, Nadia Nedjah, Miguel Figueroa	Integration	2010
6	232	Query Evaluation Techniques for Large Databases	Goetz Graefe	ACM Comput. Surv.	1993
7	224	Learning Bayesian Networks: Approaches and Issues	Ronan Daly, Qiang Shen, J. Stuart Aitken	Knowledge Eng. Review	2011
8	221	Research Frontiers in Object Technology	Salvatore T. March, Charles A. Wood, Gove N. Allen	Information Systems Frontiers	1999
9	219	Synopses for Massive Data: Samples, Histograms, Wavelets, Sketches	Graham Cormode, Minos N. Garofalakis, Peter J. Haas, Chris Jermaine	Foundations and Trends in Databases	2012
10	218	A Survey on Content-centric Technologies for the Current Internet: CDN and P2P solutions	Andrea Passarella	Computer Communications	2012

TABLE 9: Papers have top10 citing value of DBLP

2 Life Cycle of Papers

Now we look deep into the time dimension to see the citation received distribution over the whole time.

Fig. 7 shows the average number of citations received per paper. We can make several observations that are common for both DBLP and PR. First, recent papers receive less citations in average. The older the paper is, the more citation it receives. This trend grows almost linearly for about 13 years from year 2013 to 2000. The trend does not continue beyond 13 years. When papers are 13 years or older, their average citation number do not grow. This corroborates the theory that the life cycle of a paper is roughly 10 years as reported in [38]. For papers older than 13 years, they receive few new citations.

Secondly, the plateau spans almost 40 years from the sixties to the year 2000. During this time period, papers receives 13 citations on average for PR, and 8 for DBLP.

Thirdly, for papers that are more than 50 years old, their citation numbers taper off gradually to zero. It is interesting that the plateau does not extend beyond 50 years. That can be explained by the fact that there are very few papers in that age.

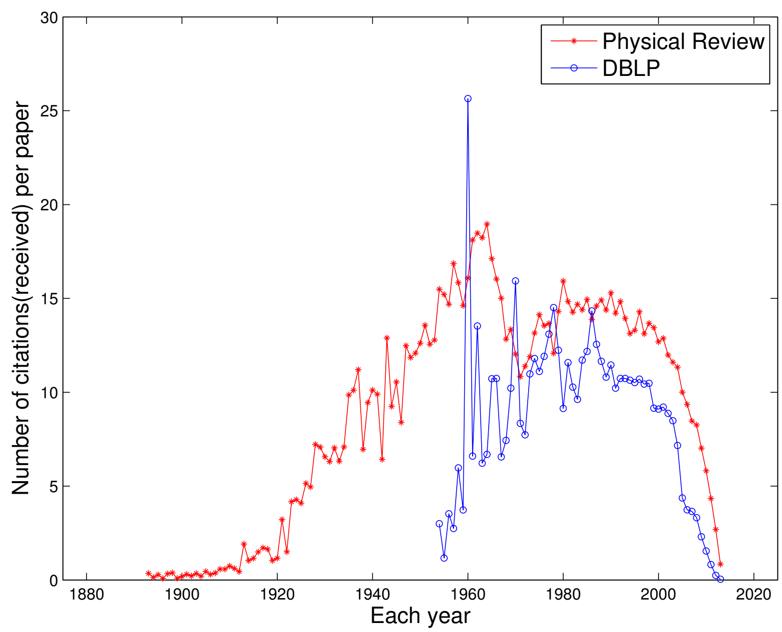


FIGURE 7: Average number of citations received per paper

Figure 8-9 show for each year the total number of citations and the number of papers. Fig. 8 illustrates the trends of total citations are consistent for PR and DBLP, increasing first and dropping then. This maybe related to the productivity of the entire field of physics and computer science over time. Figure 9 shows the total number of papers published over the whole time period of PR and DBLP respectively. For Physical Review, the number of papers are increasing steadily over time and slightly dropping since year 2012. This accounts for the increasing of citations received, and the dropping of citations in recent years maybe caused by these papers are too recent to be cited. As for DBLP, we can see that the number of papers increase drastically since year 1980, however the growth in number of papers do not continue to the end of time, since DBLP dataset we obtained does not include so many recent papers. Hence we expect a drop in the citations as seen in the figure 8. The other reason should also be that recent papers have less opportunity to be cited. We can also see that computer science area develop faster than Physics from Fig. 9.

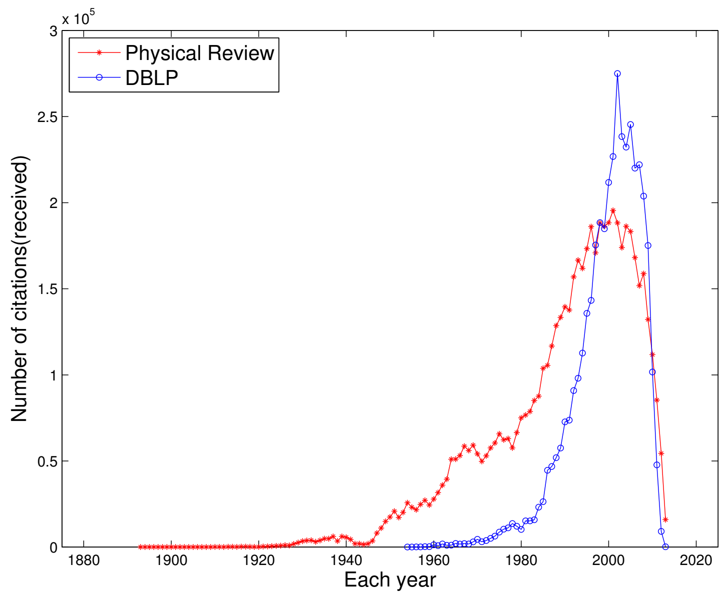


FIGURE 8: Total number of citations received

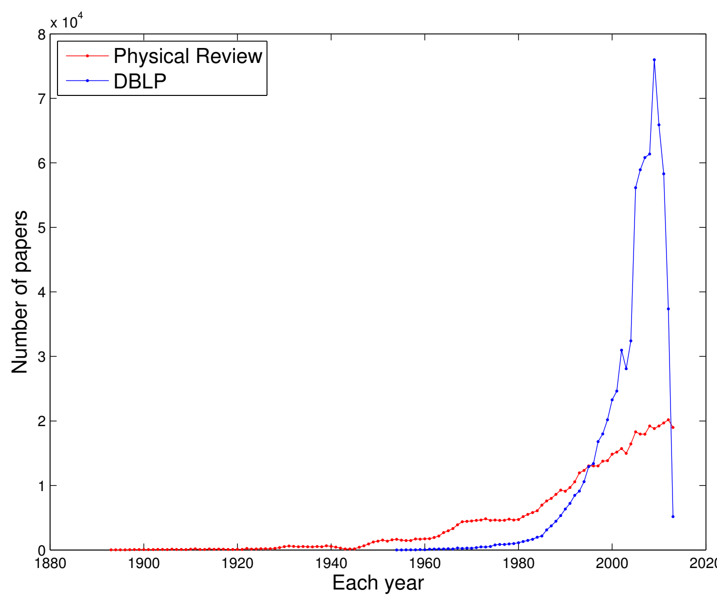


FIGURE 9: Number of papers in every year

Figure 10 shows the total number of citations made each year. We can see that the total number of citations of PR is increasing steadily, but there is a dip in around year 2010 in the blue curve. Combining with the figure 9, it maybe because the total number of papers decreasing from this year due to the incompletion of DBLP dataset. We can not tell the citation(made) trends just from this figure, so we plot Fig. 11. It shows the average number of citations made per paper over the whole time period. These two curves show steady increase over time, which means that authors used to cite fewer papers and tend to cite more papers in recent times. Maybe the reason is the increase in the volume of publications available to be cited.

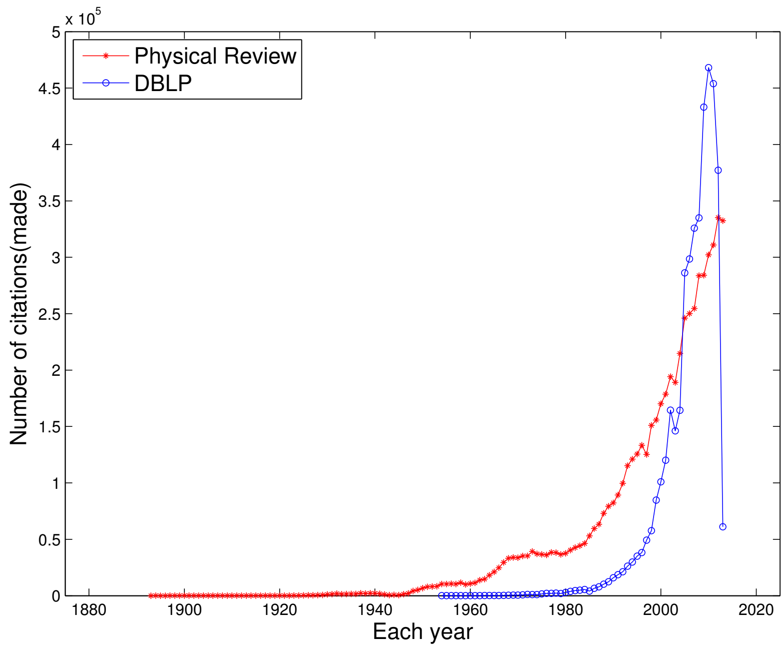


FIGURE 10: Total number of citations made

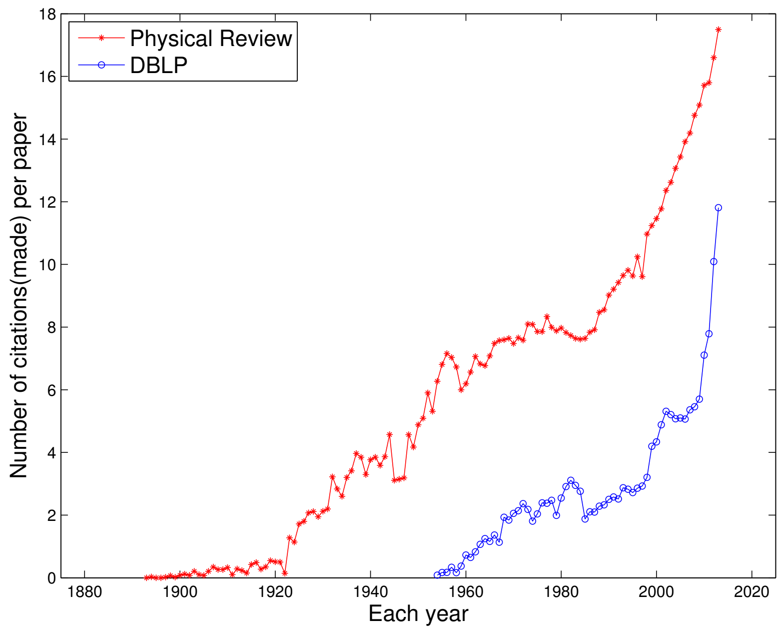


FIGURE 11: Average number of citations made per paper

3 The Large Component

In the theory of complex network, most of the nodes in a network tend to be connected in a large component, regardless of the density of the graph. In citation networks, papers also form a large component. In PR, 99.8% of the nodes are connected in one large component. In DBLP, 98.1% are connected despite diverse areas covered by DBLP and its low average degree. In addition to the large component, we need to know what are the remaining component. This can be typically described using the size distribution of all the components. In directed graphs, a distinction is often made between weakly and strongly connected components. In a weakly connected component(WCC), determination of connectivity ignores edge direction, whereas in a strongly connected component(SCC), the direction is considered. An SCC is a component where every node can reach every other node in the component. A WCC is a component where each node can reach every other node when the direction is ignored.

3.1 Weakly connected component

In this experiment, we treat the citation networks as undirected graphs and find the size of each weakly connected component. Figure 12 shows the size distribution of weakly connected components in the citation graph. One can see that for both PR and DBLP, there is a single large component that dwarfs the other components in size. The citation network of PR is comprised of 330 WCC; the largest component consists of 530,681 nodes, which occupy 99.8% of all papers (Table 10). And the citation network of DBLP contains 6027 WCC, 98.1% of all the papers are in the largest component of 766,128 nodes. The size of the second largest component in two networks are 11 and 22 respectively, which are far less than the largest. There are about four thousands WCC in DBLP that contain two nodes only, two hundreds WCC in PR.

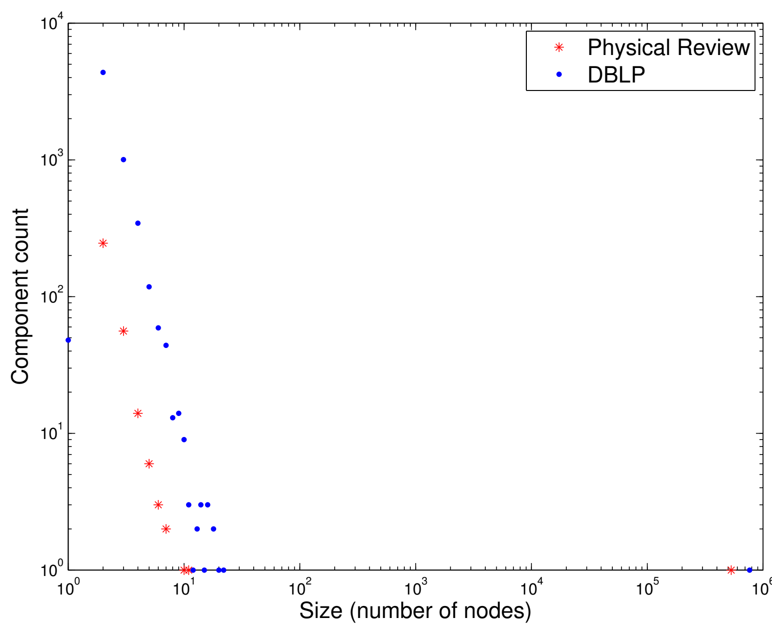


FIGURE 12: Distribution of WCC

	#nodes(PR)	#nodes(DBLP)
Citation network	531,480	781,108
The largest component	530,681(99.8%)	766,128(98.1%)
2nd largest component	11	22

TABLE 10: The first two largest WCC

3.2 Strongly connected component

Now we turn to the strongly connected component of citation networks as directed graphs. Figure 13 and Table 11 show that the largest SCC of PR citation network contains 42% of all the papers, which is 225,618 nodes. The second largest connected component has size 6, four orders of magnitude smaller. Of the remaining vertices not in this largest component, the majority are completely disconnected because they contain no edges at all, they default to component sizes of one. In contrast, the largest SCC in DBLP just occupy 0.003% of all nodes, which can be ignored. And the disconnected nodes accounts for 99% of all nodes, which is 774,737.

It is a very interesting difference between these two networks. Actually, the citation network should be acyclic graph, that means the SCC should not exist. One may now ask: why almost half of nodes in the largest SCC of PR? The answer to this question reveals some fascinating details in PR dataset; to expose this, we investigate deeply into the largest SCC in PR.

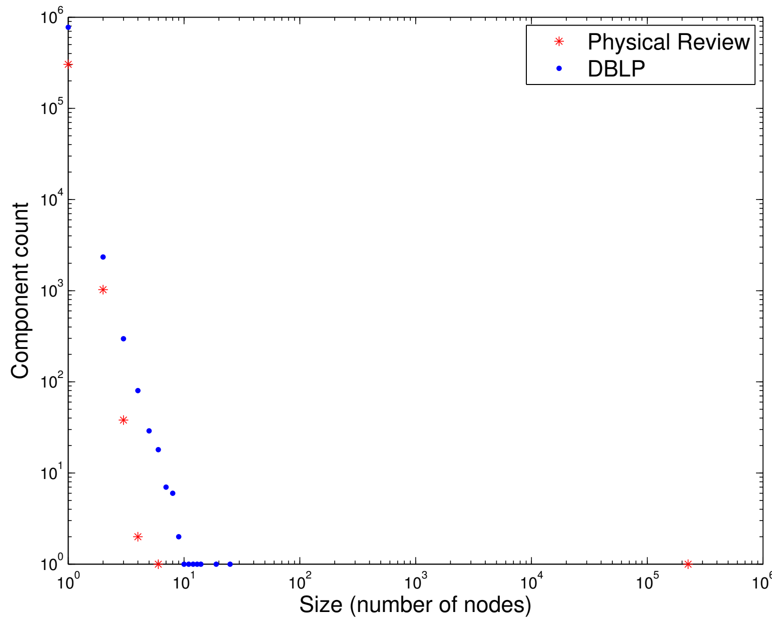


FIGURE 13: Distribution of SCC

	#nodes(PR)	#nodes(DBLP)
Citation network	531,480	781,108
The largest component	225,618(42%)	25(0.003%)
2nd largest component	6	19

TABLE 11: The fisrt two largest SCC

3.3 The largest SCC in PR

The largest strongly connected component in PR contains 225,618 papers, ranging from 1923 to 2010. There must exist a path between every pair of nodes in the largest SCC, so we find one path that from the earliest paper to the latest paper to see what happens. Take one path from 1923 to 2010 for example:

1923: 10.1103/PhysRev.22.333 →

1922: 10.1103/Physics.2.15 →

1994: 10.1103/PhysRevLett.72.4129 →

1992: 10.1103/PhysRevB.46.15233 →

1986: 10.1103/RevModPhys.58.323 →

1972: 10.1103/PhysRevB.6.3189 →

1969: 10.1103/PhysRev.179.690 →

1968: 10.1103/PhysRev.171.515 →

1967: 10.1103/Physics.3.27 →

2010: 10.1103/PhysRevLett.104.137001

We can see there is an unnormal citation relation between the second paper(10.1103/Physics.2.15) and the third paper(10.1103/PhysRevLett.72.4129); the second last paper(10.1103/Physics.3.27) and the last paper(10.1103/PhysRevLett.104.137001). Other papers all cite paper backwards in time except these two edges. Then we extract these papers and the papers citing 10.1103/Physics.2.15 and 10.1103/Physics.3.27 and list in Table 12.

Journal	Title	Author	Year
PhysRev.22.333	On the Motions of Electrons in Gases	K. T. Compton	1923
Physics.2.15	-	Hertz	1922
Physics.2.15	A View from the Edge	H. Fertig	2009
PhysRevLett.72.4129	Randomness at the edge: Theory of quantum Hall transport at filling v=2/3	C. L. Kane, Matthew P. A. Fisher, and J. Polchinski	1994
PhysRev.171.515	Theory of $s-d$ Scattering in Dilute Magnetic Alloys with Spin- Impurities	H. J. Spencer	1968
Physics.3.27	-	H. Suhl and D. Wong	1967
Physics.3.27	Viewpoint: Dirac cone in iron-based superconductors	M. Zahid Hasan and B. Andrei Bernevig	2010
PhysRevLett.104.137001	Observation of Dirac Cone Electronic Dispersion in $BaFe_2As_2$	P. Richard, K. Nakayama, T. Sato, M. Neupane, Y.-M. Xu, J. H. Bowen, G. F. Chen, J. L. Luo, N. L. Wang, X. Dai, Z. Fang, H. Ding, and T. Takahashi	2010

TABLE 12: The unnormal citing papers in PR

Checking with the references of PhysRev.22.333 from website, Physics.2.15 of 1922 is one of the references. Notice that Physics journal is not included in the PR metadata, but appear in citation graph, that's why we can not find the title of this paper. The year and authors of Physics.2.15 are obtained from the references list of PhysRev.22.333. Similarly, we check the citing papers of PhysRevLett.72.4129 that citing this paper from website, Physics.2.15 of 2009 cite it. And we can see that Physics.2.15 of 1922 and Physics.2.15 of 2009 have the same id but different authors. Maybe these two papers are different papers but the citation graph just record Physics.2.15 in 1922. And the other possible explanation is PhysRev.22.333 cited Physics.2.15 of 1922, and after many years Physics.2.15 has been republished by H.Fertig in 2009 and cite PhysRevLett.72.4129 of 1994. As for the other unnormal citing papers, PhysRev.171.515, Physics.3.27 and PhysRevLett.104.137001, we found the reason is the same, Physics.3.27 is not the unique id. To understand the citation graph structure better, let's take a look at the life cycle of papers in PR in the next section.

4 Life cycle of papers

People tend to cite recent papers, because recent papers reflect new developments in the area. Papers have their high probability being cited when they are young. With time passes by, they are barely cited, become irrelevant, and practically dead. Fig. 14 plots such life cycle of papers for PR and DBLP. Newly born papers are most energetic, attracting more citations. Their energy drops exponentially over years, as evidenced by the straight line in fig of the log-scale plot.

Despite the commonalities shared by two disciplines, there is a striking difference between them as depicted in Panel (d): papers in physics tend to cite more recent papers. About 13% citations refer to papers published in one year before in Physics, while in computer science first year citation only accounts for slightly above 10%. The majority of the citings are made in the second year-about 12%. This is rather surprising, given that DBLP contains many conference papers, and CS is normally regarded as a discipline that evolves in a faster pace.

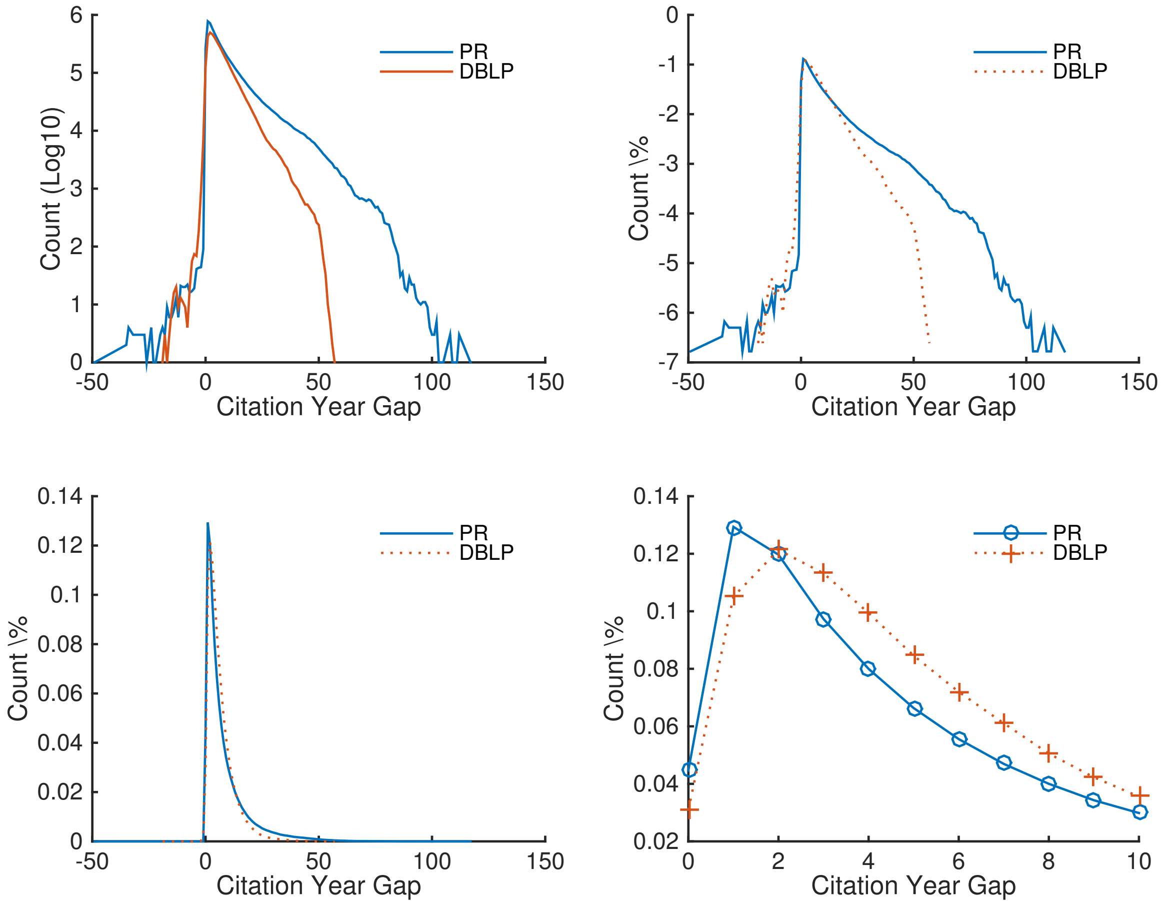


FIGURE 14: Citation year gap

Panel (a) also shows the negative citation year gap in X-axis, which represents the unnormal citation relationship. There are some papers cite the papers have yet to be written, we extract one citation which citation year gap is -49 for example. This citation is from PhysRev.91.699(1953) to RevModPhys.74.1(2002). And we list their metadata in Table 13, searching from the website, we find that the paper RevModPhys.74.1 of 1951 is in the references list of PhysRev.91.699, but in the citation graph, the id PevModPhys.74.1 represents the paper that published in 2002. So the unnormal citation relation maybe due to the duplicate id.

Journal	Title	Author	Year
PhysRev.91.699	Photoneutron Production Excitation Functions to 320 Mev	Lawrence W. Jones and Kent M. Terwilliger	1953
RevModPhys.74.1	-	Barschall, Rosen, Taschek, and Williams	1951
RevModPhys.74.1	Optical simulations of electron diffraction by carbon nanotubes	A. A. Lucas, F. Moreau, and Ph. Lambin	2002

TABLE 13: The papers whose citation year gap is -49 in PR

We also extract one citation which citation year gap is -19 in figure 14. This citation is from paper "1123623"(1980) to paper "891982"(1999). And we list their metadata in Table 14, searching from the website, we find that the paper "Applicability of Software Validation Techniques to Scientific Programs" of 1980 cite the paper "Design and Code Inspections to Reduce Errors in Program Development" of 1976. After 23 years, the author republished the paper "Design and Code Inspections to Reduce Errors in Program Development" in 1999. Thus it has been recorded in the citation graph as "1123623"(1980) citing "891982"(1999).

ID	Title	Author	Year
1123623	Applicability of Software Validation Techniques to Scientific Programs	W. E. Howden	1980
891982	Design and Code Inspections to Reduce Errors in Program Development	Michael E. Fagan	1999

TABLE 14: The papers whose citation year gap is -19 in DBLP

Conclusions: citation number of a paper decreases exponentially over years. The average life expectancy of a PR paper is 8 years, and 6.5 years for DBLP paper, that is, papers in DBLP has a shorter life than PR.

5 Clustering Coefficient

The clustering coefficient, along with the average shortest path length, can indicate a "small-world" effect. Clustering coefficient(CC) is an important measure for the network connectivity[39]. Three versions of this measure exist: local CC, average CC of entire network and global CC. The local CC is a measurement of the connectivity of a specific node, it indicates how nodes are embedded in their neighborhood. And the formula of local CC of a node is as follows:

$$C_i = \frac{\#\text{triangles connected to } i}{\#\text{triples centered on } i} \tag{2}$$

The average CC of entire network is the average local CC of all nodes in the network, it gives an overall indication of the clustering in the network and the formula is as follows:

$$\bar{C} = \frac{1}{n}\sum_{i=1}^{n} C_i \tag{3}$$

The global CC gives an indication of clustering in the network. The global CC formula is defined as:

$$C = \frac{3 \times \#\text{triangles in the network}}{\#\text{connected triples of vertices}} \tag{4}$$

Any two edges connected to node i can be seen as a triple centered on i. And the global CC measures the fraction of triples that have their third edge filled in to complete the triangle. Each triangle forms three triples, that's why the factor of three multiplied in the numerator(see Fig. 15).

Here, we treat the citation networks as undirected graphs, and Fig. 16 plots the local CC as a function of degree. As we can see, C_i falls off with degree k_i approximately as k_i^{-1}, which has been observed in[32]. They found that the clustering coefficient as a function of the degree of the nodes often follows a power law: $C(k) \propto k^{-\alpha}$ for scale-free networks. The value of α is close to 1. The average CC of PR is 0.239 and global CC is 0.023, as for DBLP, the average CC is 0.142 and global is 0.012. The clustering coefficient value of these two citation networks are rather a high value compared to those of many real-world networks.

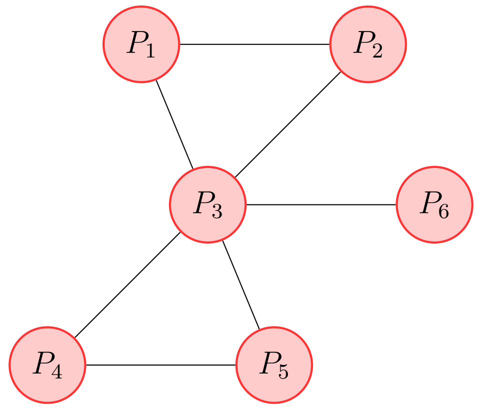


FIGURE 15: Illustration of the definition of CC, Eq.(2)(3)(4). There are 2 triangles connected to node P3 and C_5^2 triples centered on it, so P3 has local CC: $C_{P3} = \frac{2}{C_5^2} = 0.2$. The average CC of the network: $\bar{C} = \frac{1}{6} \times (\frac{1}{1} + \frac{1}{1} + \frac{1}{5} + \frac{1}{1} + \frac{1}{1} + 0) = 0.7$. The global CC is: $C = \frac{3 \times 2}{C_2^2 + C_2^2 + C_5^2 + C_2^2 + C_2^2 + 0} = 0.43$

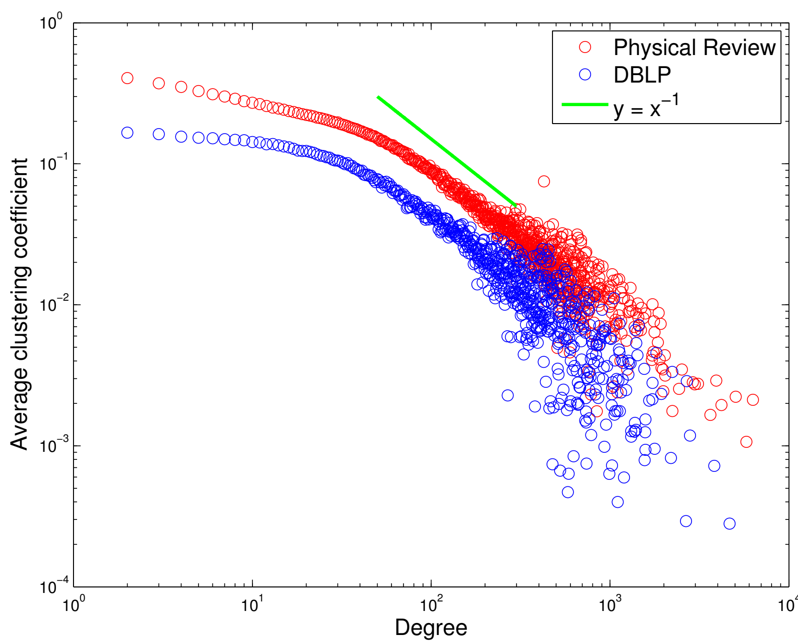


FIGURE 16: Clustering coeffcient of papers as a function of their degree

Conclusions: We find that these two citation networks are not social networks considering extremely small global CC even when their directions are ignored. The global CC is 0.023 for PR and 0.012 for DBLP. This data also shows that CS papers cluster more loosely than papers in physics, almost half in terms of CC.

6 Small World and Average Shortest Path Length

The small-world network was originally proposed by Duncan Watts and Steven Strogatz in 1998[39]. It's a class of random graphs in which most of the node-pairs are connected by a short path, this characteristic is called the small-world effect. The small-world networks can be highly clustered, yet have small average-shortest path length. Many real-world networks, such as World Wide Web and neural network, are shown to be small-world networks. In order to explore our citation network belongs to small-world network or not, we investigate the average shortest path length of citation networks.

The average shortest path length of a connected network is defined as the average of the shortest paths for all possible pairs of nodes in the network. It measures the efficiency of information transfer in a network. It is given by

$$l = \frac{1}{N(N-1)} \sum_{i \neq j} d(v_i, v_j) \tag{5}$$

N is the number of nodes in the network, $d(v_i, v_j)$ denotes the shortest distance between nodes v_i and v_j, $d(v_i, v_j) = 0$ if v_j can not be reached from v_i.

We convert the citation networks into undirected networks and calculate the average shortest path length between all pairs of papers in the citation networks. Here we ignore the direction-otherwise many nodes can not be reached and the average path length would be infinitely long.

We found that the average shortest path between all pairs of PR papers is about 5.09, and 5.88 for DBLP. For instance, that means it takes five steps on average when information transfer from one physical review paper to another physical review paper, while it needs almost 6 steps between DBLP papers. Thus it proves that the PR citation network is more tight than DBLP citation network. In the study of Shi et al.[31], the average shortest path is 7.60 for ACM and 6.29 for CiteSeer citation networks.

The diameter of a network is defined as the longest shortest paths between any pair of nodes in a network. It is another measurement of network graphs, it represents the linear size of network. Treating the citation networks as undirected networks, we calculate the shortest path length from every paper to all other papers, and we find the diameter of PR citation network is 31 and 18 in DBLP citation network, which indicates that there is an order of at most 31 links connecting any two PR publications and 18 links for DBLP respectively.

Conclusion: According to the small average shortest path length of PR and DBLP citation networks, both networks can be classified as small-world network.

7 PageRank

PageRank was originally used to measure the importance of website pages and proposed by Larry Page[24]. It is a link analysis algorithm that assigns a numerical weighting to each element/vertex. In our citation network, the vertex is academic paper and link(directed) is citation relations between papers. So the PageRank measures the importance of papers based on the citation relations. The basic idea of how to calculate page rank is to use power iteration to calculate page rank score for each paper several times. The page rank for the $k+1^{th}$ node is defined by the recursion formula (5):

$$r_{k+1} = (\beta M + (1-\beta)\frac{1}{n} e \cdot e^T) r_k \tag{6}$$

Here, n is the number of papers in the citation graph, r_k is n-dimensional vector represents each paper's page rank value in k^{th} iteration. Based on the equation, we iteratively calculate the r until the stop criteria has been met. M is $n \times n$ column stochastic matrix and used to represent the connection probability of each node to any node. The i^{th} column represent the probability of jumping to all the other papers from paper i(Random Walk). If there is a directed edge from i to j, then

$$M[j][i] = \frac{1}{\#\text{papers that } i \text{ pointing to}} \tag{7}$$

In Fig.17, let's take paper 3 for example. There are two papers, P1 and P4, that

P3 cite or point to. So the $M[1][3]$ and $M[4][3]$ should be equal 1/2. And there is no link from P3 to P2 and itself, so $M[2][3]$ and $M[3][3]$ are 0, like the 3^{th} column shows and the M is the following matrix:

$$M = \begin{pmatrix} 0 & 0 & 1/2 & 0 \\ 0 & 0 & 0 & 1/2 \\ 1 & 1 & 0 & 1/2 \\ 0 & 0 & 1/2 & 0 \end{pmatrix} \tag{8}$$

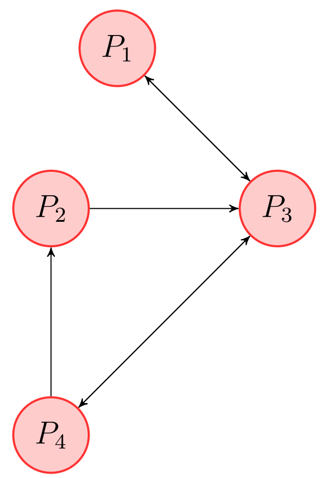


FIGURE 17: Example

However, a trap usually occurs in a citation network (just like the P1 and P3 in Fig. 17), paper can not jump out of the loop. To prevent this situation, we use $1 - \beta$ in Eq. (5) to control the probability of randomly restarting the paper-selecting(random walk). Now the calculation is not based on the citation links, there is equal probability, 1/n, that jumping to all the other nodes in the graph. So for Fig. 17, the probability of jumping to any of the papers is 1/4 and the $\frac{1}{n}e \cdot e^T$ matrix is:

$$\frac{1}{n}e \cdot e^T = \begin{pmatrix} 1/4 & 1/4 & 1/4 & 1/4 \\ 1/4 & 1/4 & 1/4 & 1/4 \\ 1/4 & 1/4 & 1/4 & 1/4 \\ 1/4 & 1/4 & 1/4 & 1/4 \end{pmatrix} \tag{9}$$

So the PageRank calculation process can be described as 3 steps:

- Initialize n-dimensional vector $r_0 = (1/n, 1/n, ..., 1/n)^T$
- Start power iteration: $r_{k+1} = (\beta M + (1-\beta)\frac{1}{n} e \cdot e^T) r_k$
- Stop criterion: When $|r_{k+1} - r_k| < \epsilon$

The first step of PageRank is to initialize the page rank value for each node. Then start the power iteration, we will gradually get the latest r value, and the r value tends to become stable if the times of iteration is enough. Finally, the parameter ϵ is used to set the stop criterion, if the differences between r vector in two iterations smaller than ϵ, then output the latest r vector as a page rank for each node.

7.1 PageRank when damping factor is 0.85

Here, we set the parameters damping factor β to be 0.85, $1-\beta$ to be 0.15 and ϵ to be 0.001. Fig. 18 shows the average page rank value for papers with k citations(in-degree) as a function of k. For both dataset, there are many papers have the same number of citations received when k is small. The average page rank value increases with k, which means the more citations received, the higher pagerank of this paper.

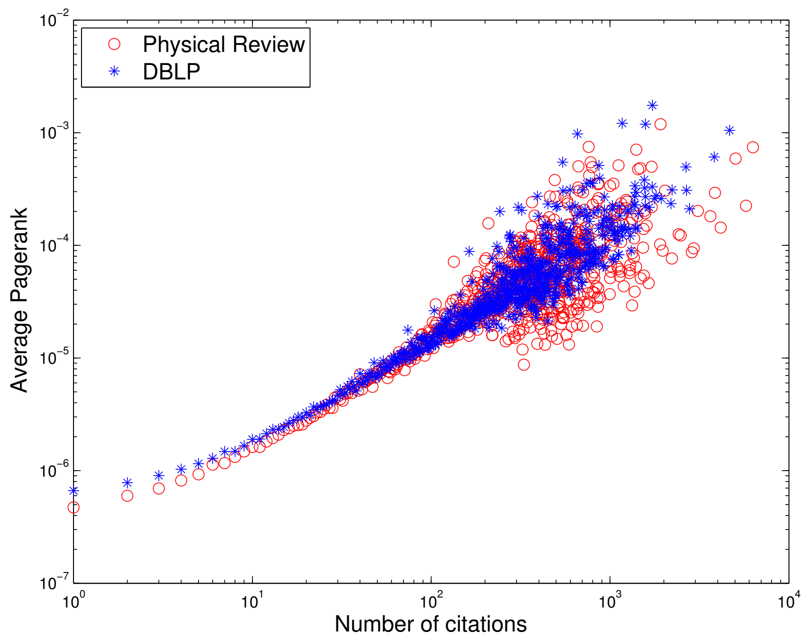
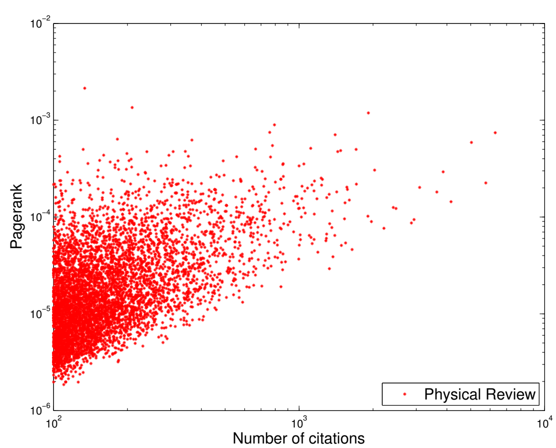
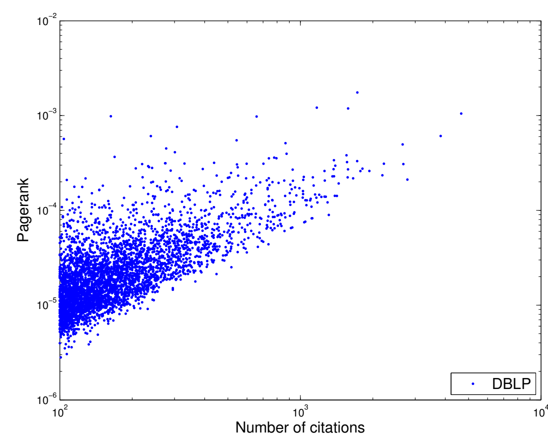


FIGURE 18: Average Pagerank versus #citations k

However, for large k, there is only one paper with k citations. Thus we plot the individual pagerank as a function of k citations when k greater than 100(Fig. 19). There are many outliers compared with Fig. 18, and we list the top10 ranked papers in PR and DBLP based on their page rank value in Table 15 and Table 16 respectively. Also given in these two table are the number of citations, paper title, author, journal and year. While those papers have high number of citations appear on this list, several papers have low number of citations have been ranked highly according to PageRank algorithm, for instance, the articles "Cohesion in Monovalent Metals" in PR and "A Computer System for Inference Execution and Data Retrieval" in DBLP. The third ranked paper in DBLP just has been cited 13, and we found an interesting phenomenon that this paper was cited by the second ranked paper "A Relational Model of Data for Large Shared Data Banks" with 1170 citations. That means citations from more important papers make more contribution to the rank of this cited paper, which way the PageRank algorithm implement in. The PageRank algorithm is a good measure to rank those papers high although not cited often but important when $1 - \beta = 0.15$.



(A) PR



(B) DBLP

FIGURE 19: Individual PageRank as a function of citation count when damping factor is 0.85.

Physical Review					
PageRank	# cites	Title	Author	Journal	Year
1	134	The Theory of Complex Spectra	J. C. Slater	PR	1929
2	40	Cohesion in Monovalent Metals	J. C. Slater	PR	1930
3	209	On the Consititution of Metallic Sodium	E. Wigner, F. Seitz	PR	1933
4	1915	Theory of Superconductivity	J. Bardeen, L. N. Cooper, J. R. Schrieffer	PR	1957
5	794	Crystal Statistics. I. A Two-Dimensional Model with an Order-Disorder Transition	Lars Onsager	PR	1944
6	759	On the Interaction of Electrons in Metals	E. Wigner	PR	1934
7	6291	Self-Consistent Equations Inclucing Exchange and Correlation Effects	W. Kohn, L. J. Sham	PR	1965
8	66	Electronic Energy Bands in Metals	J. C. Slater	PR	1934
9	1402	Can Quantum-Mechanical Description Physical Reality Be Considered Complete?	A. Einstein, B. Podolsky, N.Rosen	PR	1935
10	182	Statistics of the Two-Dimentional Ferromagnet	H. A. Kramers, G. H. Wannier	PR	1941

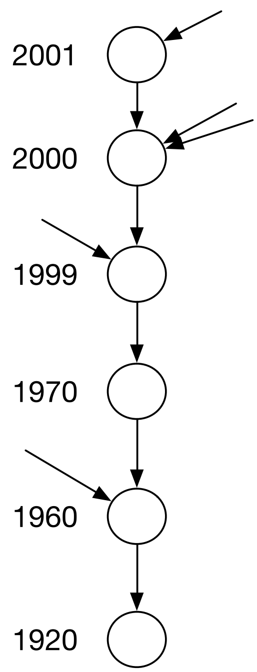
TABLE 15: The top 10 pagerank publications when $1 - \beta = 0.15$ in PR

DBLP					
PageRank	# cites	Title	Author	Journal	Year
1	1724	A Method for Obtaining Digital Signatures and Public-Key Cryptosystems	Ronald L. Rivest, Adi Shamir, Leonard M. Adleman	Commun. ACM	1978
2	1170	A Relational Model of Data for Large Shared Data Banks	E. F. Codd	Commun. ACM	1970
3	13	A Computer System for Inference Execution and Data Retrieval	Roger E. Levien, M. E. Maron	Commun. ACM	1967
4	163	Programming Semantics for Multiprogrammed Computations	Jack B. Dennis, Earl C. Van Horn	Commun. ACM	1966
5	658	The Complexity of Theorem-Proving Procedures	Stephen A. Cook	STOC	1971
6	74	Secure Communications over Insecure Channels	Ralph C. Merkle	Commun. ACM	1978
7	307	Database Abstractions: Aggregation	John Miles Smith, Diane C. P. Smith	Commun. ACM	1977
8	18	Riemann's Hypothesis and Tests for Primality	Gary L. Miller	STOC	1975
9	239	Illumination for Computer Generated Pictures	Bui Tuong Phong	Commun. ACM	1975
10	104	A Characterization of Ten Hidden-Surface Algorithm	Ivan E. Sutherland, Robert F. Sproull, Robert A. Schumacker	ACM Comput. Surv	1974

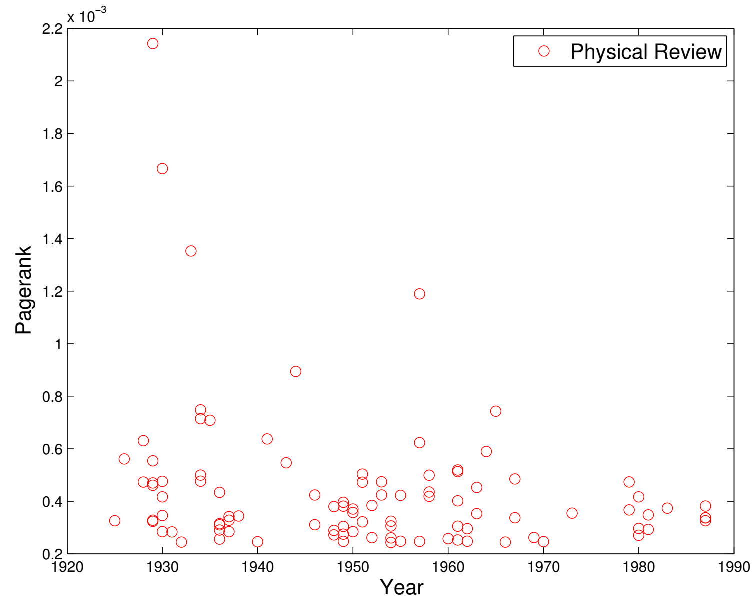
TABLE 16: The top 10 pagerank publications when $1 - \beta = 0.15$ in DBLP

When inspecting the top papers in CS, we can find that some of the highly ranked papers have very few citations. The one ranked number 3 and 8 have 13 and 18 citations, respectively. This is caused by the almost acyclic structure of the network: papers normally cite backwards to older papers, therefore there are almost no links pointing forward. The flow of random walks are directed to older papers, as evidenced by the table that all the top 10 papers are published in the sixties and seventies. This bias towards old papers need to be corrected.

In Web data, it is empirically decided that it is optimal to have damping factor set as 0.85[24]. This value also has an intuitive interpretation that models the way people surfing the Web: one surfs the Web by following randomly 6 hyperlinks on average. Correspondingly, there is a probability $1 - \beta = 1/6 \approx 0.15$ that jumps to a random page. When researchers read academic papers, they may not follow this pattern. P. Chen et. al. [11] proposed that, for surfing the citation network, people is more likely to follow 2 citation links, making $1-\beta = 0.5$ more appropriate for citation network. On the other hand, the more links to be followed, the high probability that the much older paper will get a high page rank value(see Fig. 20(A)). And we can see the top100 pagerank papers in PR are relatively early papers(Fig. 20(B)), in order to find those relatively recent important papers, we do experiments in the next section by choosing the parameter $1 - \beta$ to be 0.5.



(A) Citation network



(B) Top 100 pagerank papers in PR when $1 - \beta = 0.15$

FIGURE 20: PageRank vesus year

7.2 PageRank when damping factor is 0.5

Figure 21 shows the average pagerank as a function of number of citations. Comparing with Fig. 18, the plot of average pagerank versus k is smooth and still increases with k. And the dispersion in pagerank is smaller when $1-\beta = 0.5$ than $1-\beta = 0.15$. Here we introduce one definition, Pearson correlation coefficient(PCC), that is a measure of the linear correlation between two variables. It's ranging from +1 to -1, 1 is total positive correlation, -1 is total negative correlation and 0 is no correlation. Table 17 lists PCC value between pagerank value and the number of citations for PR and DBLP when $1 - \beta$ is 0.15 and 0.5 respectively. When changing the parameter value, both PCC value for PR and DBLP is increasing, which means the larger $1 - \beta$, the more correlate between pagerank and citations, thus indicating that citations and PageRank are similar measures of importance.

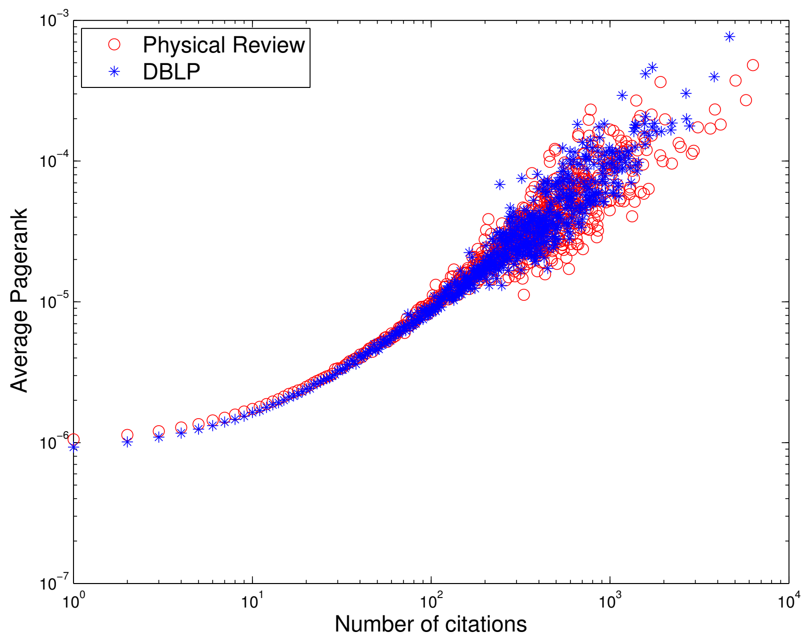


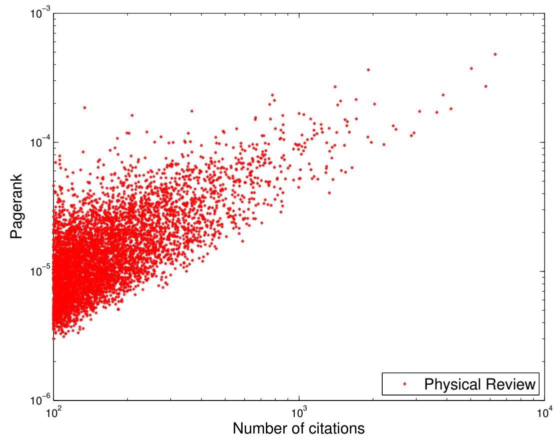
FIGURE 21: Average Pagerank versus #citations k

	PCC($1-\beta=0.15$)	PCC($1-\beta=0.5$)
PR	0.4704	0.8210
DBLP	0.6163	0.8723

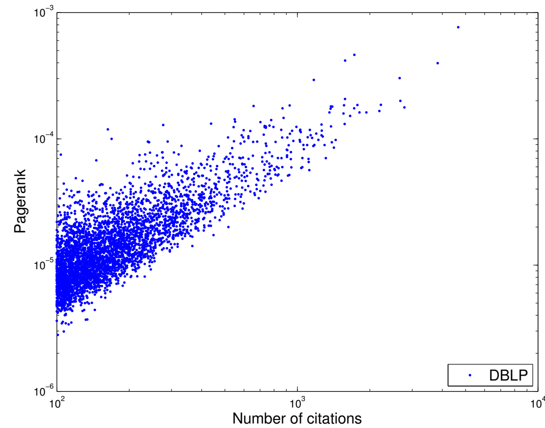
TABLE 17: Pearson correlation coefficient

We also plot the individual pagerank as a function of number of citations k when $k \geq 100$(see Fig. 22), and the dispersion is smaller compared to Fig. 19. We extract the top10 pagerank papers of PR and DBLP in Table 18 and Table 19, and more high-cited and recent papers appear on the lists, which proves that PageRank algorithm can choose more recent important papers by increasing $1-\beta$ value.

Conclusions: We demonstrate that in citation network, PageRank algorithm with damping factor 0.85 leads to significant bias in favor of old papers. When damping factor is adjusted to 0.5, more recent papers are ranked higher.



(A) PR



(B) DBLP

FIGURE 22: Individual Pagerank vesus #citations k

Physical Review					
PageRank	# cites	Title	Author	Journal	Year
1	6291	Self-Consistent Equations Inclucing Exchange and Correlation Effects	W. Kohn, L. J. Sham	PR	1965
2	5035	Inhomogeneous Electron Gas	P. Hohenberg, W. Kohn	PR	1964
3	1915	Theory of Superconductivity	J. Bardeen, L. N. Cooper, J. R. Schrieffer	PR	1957
4	5763	Generalized Gradient Approximation Made Simple	John P. Perdew, Kieron Burke, Matthias Ernzerhof	PRL	1996
5	1402	Can Quantum-Mechanical Description Physical Reality Be Considered Complete?	A. Einstein, B. Podolsky, N.Rosen	PR	1935
6	3860	Self-interaction Correction to Density-functional Approximations for Many-Electron Systems	J. P. Perdew, Alex Zunger	PRB	1981
7	779	Stochastic Problems in Physics and Astronomy	S. Chandrasekhar	RMP	1943
8	1707	Absence of Diffusion in Certain Random Lattices	P. W. Anderson	PR	1958
9	794	Crystal Statistics. I. A Two-Dimensional Model with an Order-Disorder Transition	Lars Onsager	PR	1944
10	1476	A Model of Leptons	Steven Weinberg	PRL	1967

TABLE 18: The top 10 pagerank publications when $1 - \beta = 0.5$ in PR

DBLP					
PageRank	# cites	Title	Author	Journal	Year
1	1724	A Method for Obtaining Digital Signatures and Public-Key Cryptosystems	Ronald L. Rivest, Adi Shamir, Leonard M. Adleman	Commun. ACM	1978
2	1170	A Relational Model of Data for Large Shared Data Banks	E. F. Codd	Commun. ACM	1970
3	1577	Genetic Programming - on the Programming of Computers by Means of Natural Selection	John R. Koza	Complex adaptive systems	1993
4	2678	Fast Algorithms for Mining Association Rules in Large Databases	Rakesh Agrawal, Ramakrishnan Srikant	VLDB	1994
5	2224	Mining Association Rules between Sets of Items in Large Databases	Rakesh Agrawal, Tomasz Imielinski, Arun N. Swami	SIGMOD Conference	1993
6	1563	Induction of Decision Trees	J. Ross Quinlan	Machine Learning	1986
7	929	A Theory for Multiresolution Signal Decomposition: The Wavelet Representation	Stephane Mallat	IEEE Trans. Pattern Anal. Mach. Intell	1989
8	658	The Complexity of Theorem-Proving Procedures	Stephen A. Cook	STOC	1971
9	1396	Support-Vector Networks	Corinna Cortes, Vladimir Vapnik	Machine Learning	1995
10	2785	Distinctive Image Features from Scale-Invariant Keypoints	David G. Lowe	International Journal of Computer Vision	2004

TABLE 19: The top 10 pagerank publications when $1 - \beta = 0.5$ in DBLP

CHAPTER V

Co-author Network

We construct co-author network of authors in which an edge between two authors is established if they collaborate one paper together. We extract co-authors from 541,447 papers in PR and 2,146,341 in DBLP(see Table. 20). That's why the number of authors of DBLP is far greater than PR, however the number of edges of DBLP co-author network is far less than PR. The degree of a node is the number of edges connected to it, also the number of co-authors. Since the co-author network is undirected, the average degree should be the twice of $\frac{\#edges}{\#nodes}$. The average number of co-authors of PR is almost 120, but 8 of DBLP, which means the collaborations in PR are much higher than DBLP at first sight. Thus we check this from more aspects in next several sections.

	Physical Review	DBLP
Time span	1893 - 2013	1936 - 2013
Number of Papers	541,447	2,146,341
Number of Edges	22,787,959	4,542,331
Number of Nodes	379,869	1,163,723
Average Degree	119.978	7.807

TABLE 20: Statistics of co-author network

1 Degree Distribution

The figure 23 shows the degree distribution, the proportion of authors as a function of the number of co-authors value. From our result data, we get that 72% authors have less than 6 co-authors in DBLP, 51% in PR. More authors in PR have large number of co-authors than DBLP. Hence in average, authors in PR have more co-authors than in DBLP. However, the authors who have large number of co-authors are not recognizable in this figure.

We plot the number of co-authors as a function of its rank to focus on the top authors in Fig. 24. The top 10000 authors in PR have surprisingly large number of co-authors, which are above a thousand. After these top 10000 authors, the co-author number drops quickly. This is probably caused by the name abbreviation in PR data: an author name in PR data contains the last name and the initial of the first name. Thereby many names with the same initials are aggregated as the same person. We list the top10 ranked authors in Table 21 to explore that. Notice that authors of DBLP have first name.

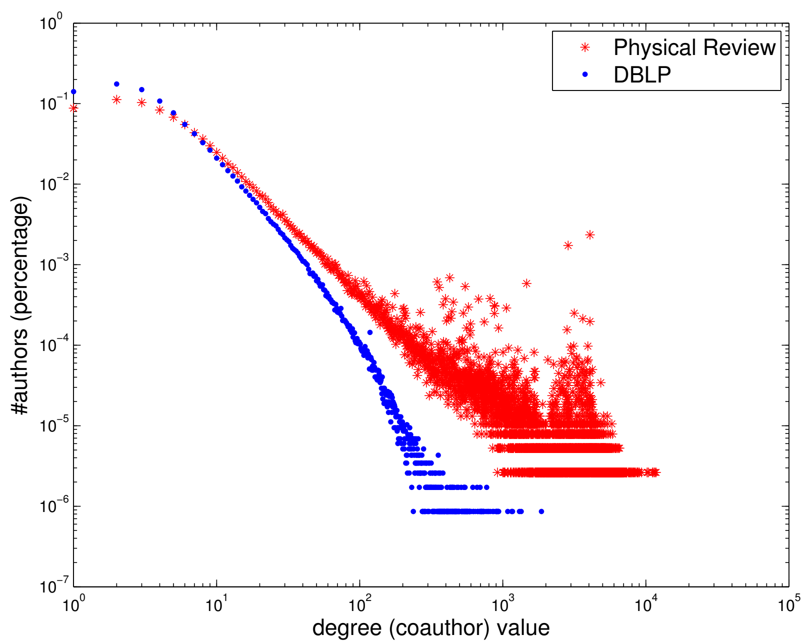


FIGURE 23: Degree distribution of PR and DBLP

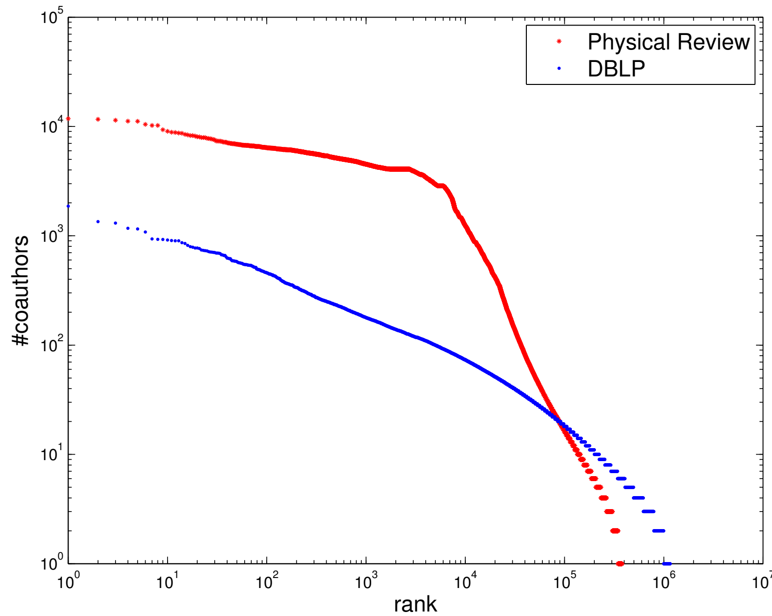


FIGURE 24: Ranking of #coauthors

PR			DBLP	
Rank	# co-authors	Author	# co-authors	Author
1	11804	J. Zhang	1864	Wei Wang
2	11617	Y. Liu	1346	Wei Li
3	11408	H. Liu	1308	Wei Zhang
4	11178	J. Wang	1171	Lei Zhang
5	11143	L. Zhang	1155	Lei Wang
6	10446	Y. Chen	1083	Li Zhang
7	10223	H. Kim	936	Yang Liu
8	10217	M. Weber	929	Wei Chen
9	9347	M. Jones	924	Jun Wang
10	9040	Z. Zhang	914	Jun Zhang

TABLE 21: Top10 ranked authors in PR and DBLP

2 Author and co-author trends over time

Figure 25 shows the total number of authors over the whole time period. In both PR and DBLP, the number of authors increases exponentially. In DBLP, the author number drops in the most recent two year probably because of the incompleteness of the data. DBLP manually collects publications in the past, and there is a delay in including publications from some venues. For PR, year 2012 has the most authors, which is 360,144 (the highest point in Fig. 25).

This trend is consistent with the increase of paper numbers as depicted in Fig. 26. An interesting observation is the dip in the 1940s, which may coincide with the second world war[19], also appears in DBLP. Moreover, we can see that the number of authors of DBLP increase drastically since the year of 1940s. The general trend of number of papers over time and of number of authors over time are pretty much the same by comparing Fig. 25 and Fig. 26.

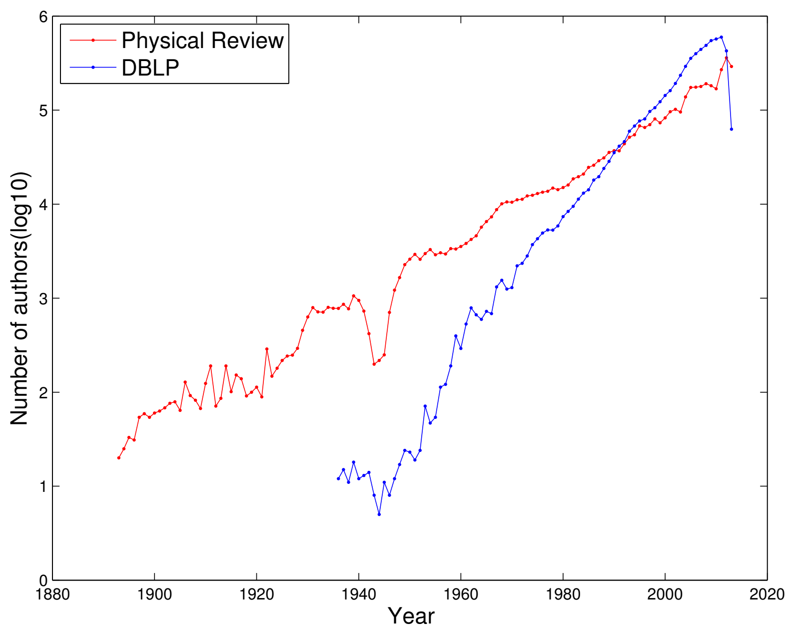


FIGURE 25: Number of authors in each year

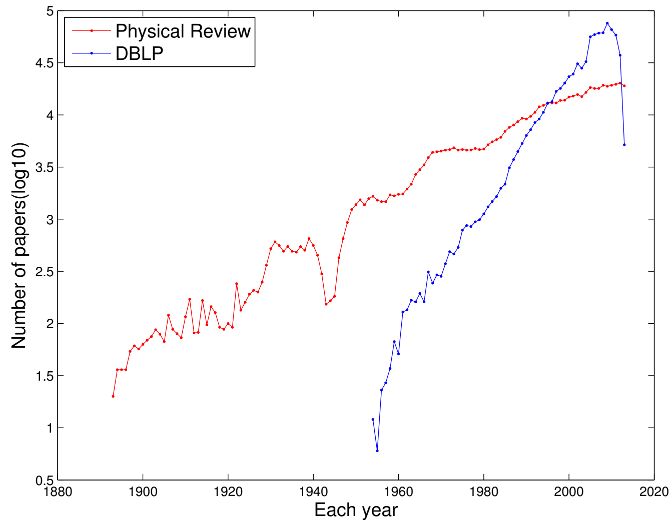
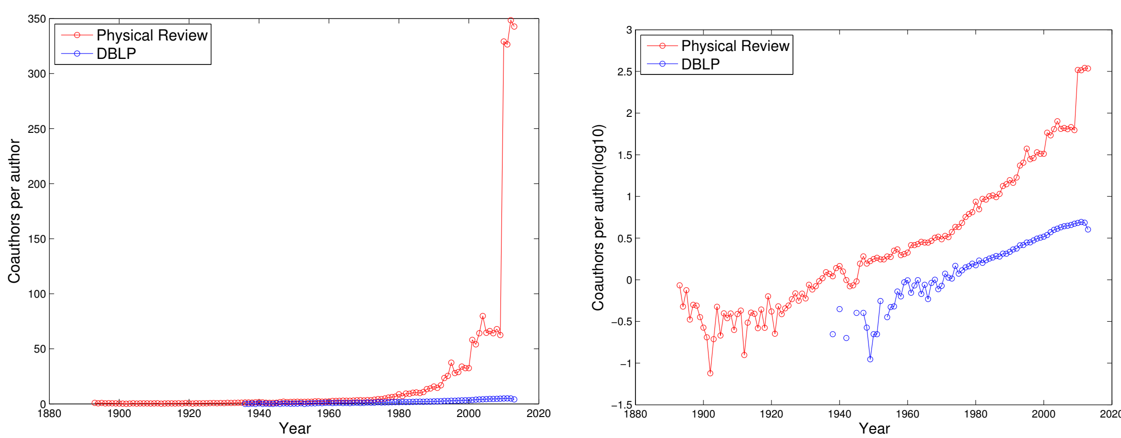


FIGURE 26: Number of papers for each year

An alternative view of degree distribution is given in Fig. 27, which shows the number of co-authors an author has, on average, in every year. As the figure 27(A) shows, this number has risen significantly over the past century, from a little over one to more than 300 today in PR. And the number of co-authors per author of PR is far greater than DBLP, but the value is not discernible, thus we plot the log figure 27(B) instead of Fig. 27(A). We can see that the trends of co-authors per author is similar and increasing in general. Obviously, the collaborations among PR authors are more than DBLP, but are all increasing over time in both fields.



(A) coauthor per author

(B) coauthor per author (Log10)

FIGURE 27: Number of coauthors per author

3 Weakly Connected Component

Since the co-author network is undirected, we just talk about the weakly connected component(WCC) here. Figure 28 shows the size distribution of weakly connected components in co-author graph. The co-author network of PR is composed of 6,336 WCC, the large component encompasses 95% of all the physics area authors(Table 22). And 88% of all authors of DBLP are in the largest component of 1,025,555 nodes. We can infer that 95% of authors in PR and 88% in DBLP are engaged in collaborations. The size of second largest component in two datasets is far smaller than the largest, which shows the co-author network is highly connected.

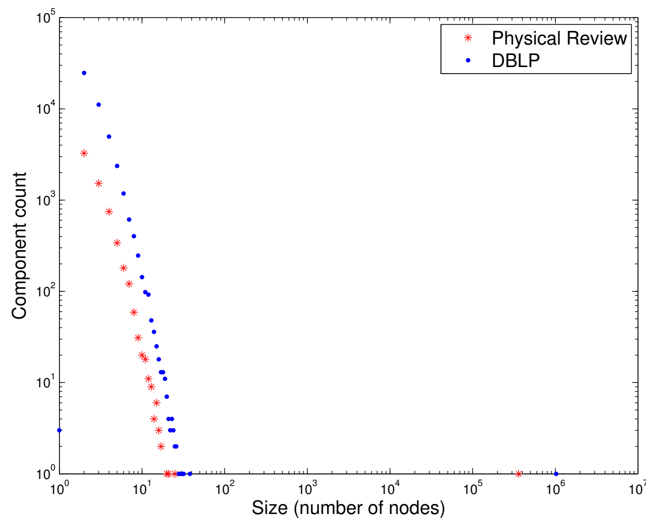


FIGURE 28: Distribution of WCC

	#nodes(PR)	#nodes(DBLP)
Co-author network	379,869	1,163,723
The largest component	360,477(95%)	1,025,555(88%)
2nd largest component	25	38

TABLE 22: The first two largest WCC

4 Clustering Coefficient

The clustering coefficient in co-author network refers to the probability that two authors collaborate if they have a common co-author. Figure 29 plots the average local clustering coefficient as a function of degree. For DBLP, the local CC value is dropping off with degree, that means if one author has more neighbors, the probability of interaction and collaboration between them is less. But for PR, the local CC value is increasing from degree 20 and very high, we can infer from this fact that when the degree is larger than 20, the collaborations between its neighbors are tight. The average CC of the entire PR co-author network is 0.738, and 0.718 in DBLP. This indicates that a pair of authors in both fields has an over 70% chance of collaborating if they collaborated with a common third author. This high clustering coefficient implies that it is highly likely that any two friends of a person are also friends themselves. And the high clustering coefficient can be expected in two aspects: the three authors write one common paper or every two authors write one paper.

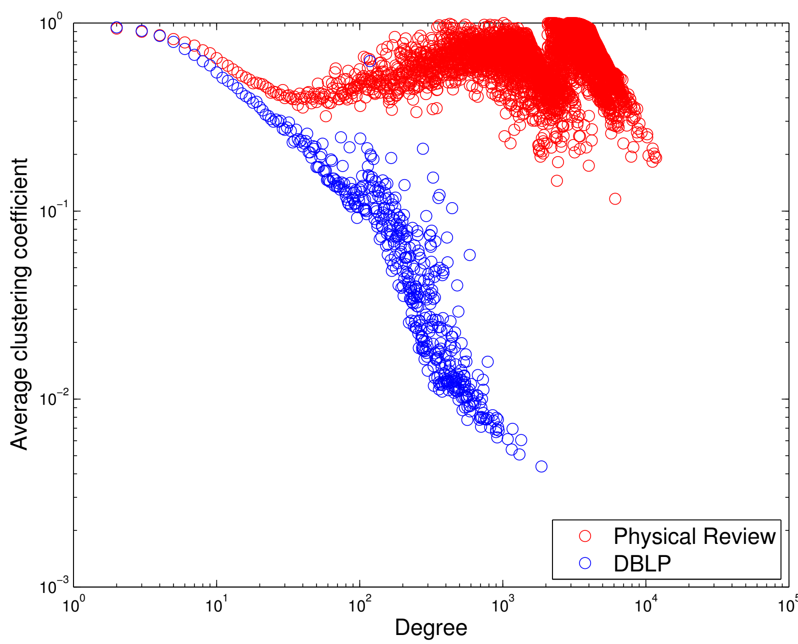


FIGURE 29: The clustering coeffcient of authors as a function of their degree

5 Small World and Average Shortest Path Length

The average shortest path length between a pair of PR authors in terms of collaboration links is about 5.06, and 5.99 for DBLP. This implies that any author in both areas can reach any other authors in the according field through a relatively small number of intermediary collaborators. Stanley Milgram proposed the concept of six degrees of separation[21], he found that the average shortest path length of the social network of people in US is 6, that means any two people can be connected through the chain of "friend's friend" in a maximum of six steps.

Conclusion: The lower average shortest path and higher clustering coefficient of PR co-author network indicate that the collaboration network of PR is more tight than DBLP. However, both co-author networks show the small-world characteristics with a high clustering coefficient and a small average shortest path length.

We have also calculated the greatest distance among pairs of authors for both networks. For PR co-author network, the diameter is about 18; 24 for DBLP. It means that the length of the chain of co-authors links connecting any two PR authors is less than or equal to 18. And in DBLP co-author network, the length is less than or equal to 24.

6 Authors and Papers

Figure 30 shows a complementary cumulative distribution function for the number of papers an author writes, aggregated over the entire data set. That is, this figure shows the proportion of authors that wrote more than a given number of papers, the x-axis and y-axis in the figure are logarithmic. As can be seen in the figure, the red curve includes all the literatures in Physical Review, when Y-axis equal to 0.01, the value of X-axis equal to 100, which means 1% of the authors of PR published more than 100 papers, just 0.4% in DBLP from the blue curve. Also we can see that the percentage that an author write more than one paper is 1 for both curves, because one author write at least one paper, and the plot of percentage versus the number of papers n decreases with n. And also we notice an interesting thing, there are two irregular drops in red curves, first is between the range of 70 and 80 in x-axis, second is around 500 and 600. This significant dip is perhaps because there are more authors between these ranges than other ranges. In order to check this, rather than just counting up all the papers an author was listed on, we can instead find out the relationship between the number of paper and number of authors. As we can see in Fig. 31, there are some outliers in the same range of the two drops for PR in Fig. 30. These outliers have significantly more number of authors than the neighbor nodes, that means these outliers contribute to the high percentage of the two ranges, which is according with our predict. From these two figures, we can infer that the scientific productivity in physics is higher than DBLP.

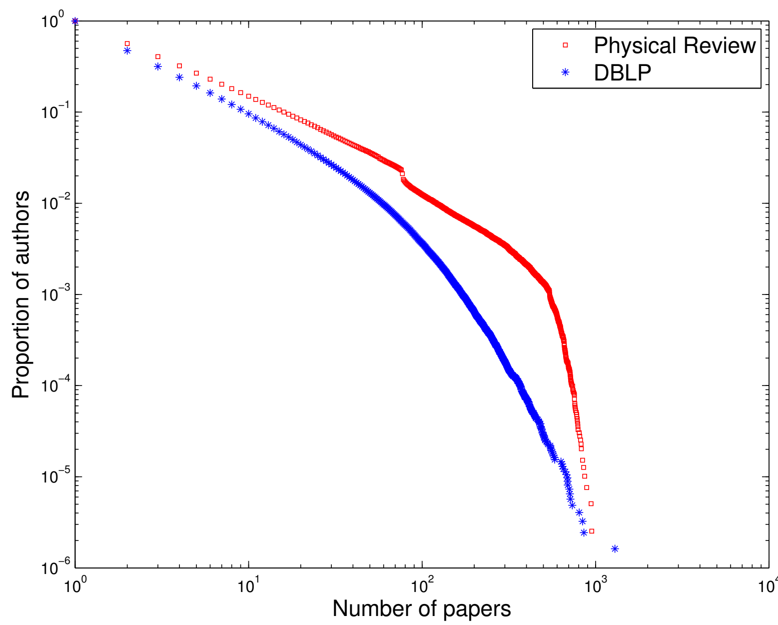


FIGURE 30: Proportion that an author wrote more than a given number of papers.

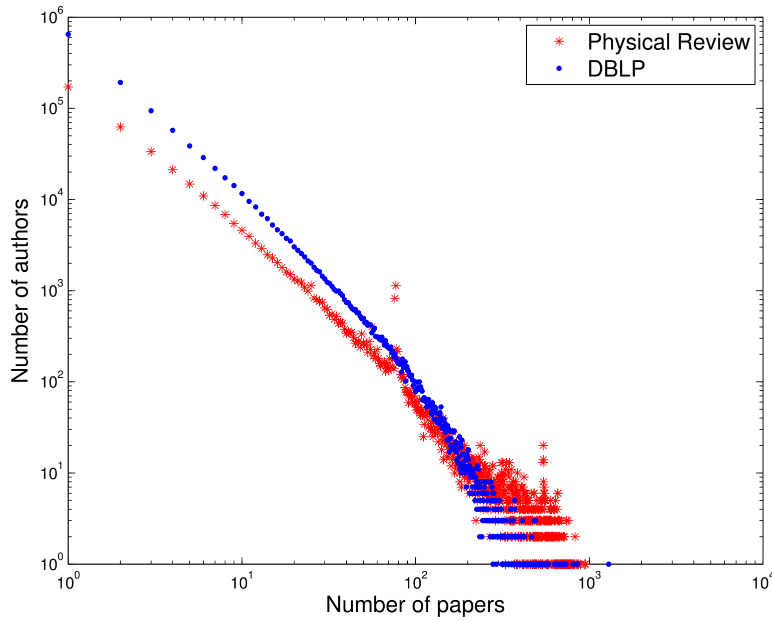


FIGURE 31: Number of authors who wrote a given number of papers

The above figures are good for the crude scientific productivity, however, the individual is not recognizable. In order to focus on the most productive authors, we plot the number of papers that an author writes versus his rank in figure 32. As the figure shows, the most productive author in both fields write almost 1000 papers, which is amazing, thus we list the top10 authors in Table 23 with their name and the number of papers. The reason that authors write so many papers can be summarized: the author is truly famous and elite in his field, like Philip S. Yu in computer science; the authors' name are duplicate, such as the universal name Wei Wang in DBLP; or due to the initial of their first name, like D. N. Brown in PR.

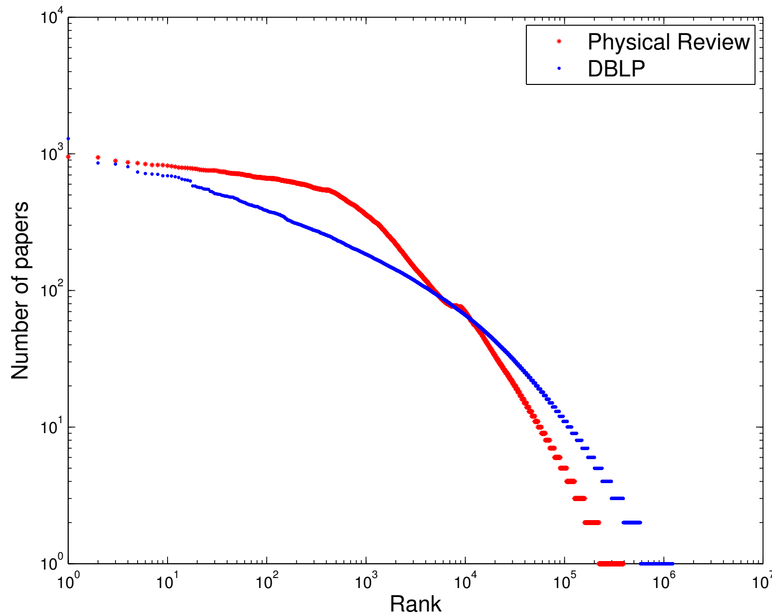
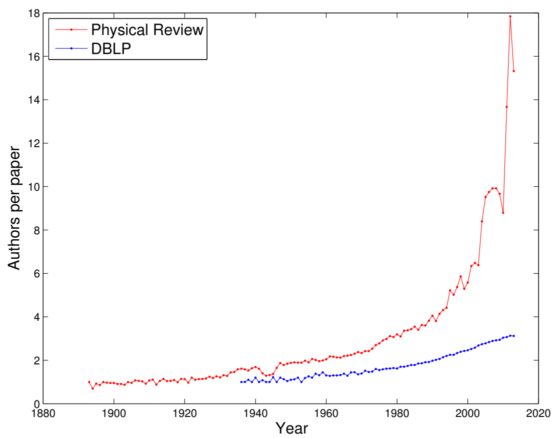


FIGURE 32: The ranking of #papers an author publish

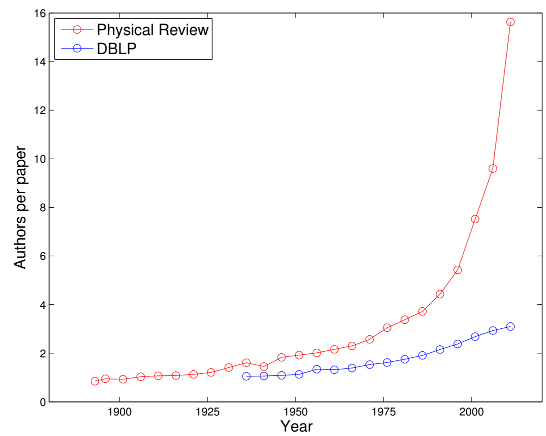
Physical Review			DBLP	
Rank	Author	#Papers	Author	#Papers
1	D. N. Brown	951	Wei Wang	1293
2	M. S. Alam	942	Wei Zhang	856
3	J. Zhang	889	Lei Zhang	842
4	W. T. Ford	866	Wei Li	805
5	J. G. Smith	854	H. Vincent Poor	735
6	R. Kass	841	Jun Wang	717
7	G. Eigen	829	Philip S. Yu	711
8	J. Li	829	Wen Gao	707
9	K. Hara	826	Thomas S. Huang	691
10	D. Strom	819	Lei Wang	690

TABLE 23: Most productive authors in two datasets

Now let's turn to the trend of the number of authors per paper, the size of collaborative groups. Figure 33 shows the mean number of authors per paper as a function of time. From figure 33(A) and figure 33(B), we can see that there is a clear increasing trend for authors per paper throughout the whole physical Review time period, with the average size of a collaborative group rising from one a century ago to about 16 today. Although the number of authors per paper in DBLP has not increased drastically, increased steadily in general. That means huge collaborations become more and more prevalent recently. Also, more collaborations happen in physics than computer science.



(A) #authors per paper in each year



(B) #authors per paper in five year blocks

FIGURE 33: Number of authors per paper

CHAPTER VI

Conclusion

In this thesis, we make a comparative study of academic networks in computer science and physics. We construct citation and co-author networks based on the data from DBLP and Physical Review journals. Then we analyze and compare them from several aspects such as, the degree distribution, connected component, clustering coefficient and pagerank. In terms of the long time period of these two datasets, we also investigate the trends of citation and collaboration in both disciplines to find the commonalities and differences between these two fields. The results show that both kinds of networks generated in computer science differ greatly the networks in Physics.

In citation network of PR and DBLP, we find that in both PR and DBLP, their in-degree distributions follow a power-law form and out-degrees resemble log-normal distributions, which show the characteristics of scale-free network. Also we observe that the productivity in both areas is growing over time, and a higher rate of growth in computer science than physics. The papers in the middle section of time period in both areas have more citations received than early and recent years that's because papers in early age and recent have less opportunity to be cited. Papers attract more citations in their young age. The citation count decreases in an exponential speed. The average life expectancy of a paper is 6.5 years in DBLP and 8 years in PR, papers in DBLP has a shorter life than PR. Another interesting difference between these two citation networks is a large SCC in PR, which related to the dataset-self. The higher CC in PR indicates that papers in PR knit closer than papers in DBLP. Both citation networks show the characteristics of "small-world" according to the small average shortest path length. We also find that the direct application of the PageRank algorithm with damping factor 0.85 lead the large bias in favor of old papers. Changing damping factor to 0.5 can ameliorate the problem.

In co-author network, we find that unlike citation network, the degree distribution of co-author network in PR and DBLP are very different. Although networks have long tail distributions that resemble a power law, their slopes differ greatly. Their CC is also very different in two networks. The higher CC in PR indicates that PR co-author network cluster more tightly than DBLP. Thus we can infer that physicists collaborate more closely than computer scientists in terms of the degree distribution and clustering coefficients. For instance, physicists collaborate on average with 120 others, while computer scientists collaborate with only 8. For both PR and DBLP, collaborations evolve over time. The productivity of scientists in physics is higher than computer science, this maybe caused by the difference of records of name in two datasets. Both co-author networks show the small-world effect in terms of the average shortest path length.

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