

Evaluation of Homogenous Graph Indices to Rank Authors



By

Sahar Maqsood UL HassanMS141002

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DEDICATION

I dedicate all my efforts to my beloved father “**Maqsood UL Hassan**” and my fiancé “**Basit Suhaib**” who supported me to accomplish my degree. Because of them, I never remain isolated through any thick or thin while pursuing my MSCS. Endless prayers of my **mother** and encouragement of my **brothers** helped me a lot to achieve my goals. True friends are like bright shadows in the dark, who thinks you a good egg even if you are half-cracked. I want to dedicate the part of my success with my best friends “**Asma Mehmood**”, “**Narmeen Kanwal**” and “**Shanza Ibrar**”. My dedications also lead towards my always supporting friends “**Kinza Shabbir**” and “**Salman Munawwar**” who encouraged me to persue MSCS in every way.

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DECLARATION

It is declared that it is an original piece of my own work, except references mentioned in the text. This work has not been submitted in any form for another degree or diploma at any university or other institution and shall not be submitted to pursue another degree from any other university or institution by me in future.

Sahar Maqsood UL Hassan

Ms141002

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Abstract

With the growing literature in the scientific community, authors have been ranked for various purposes such as they could be hired as editor in journal, granted for tenure ship, call for speaker in conference or offer them scholarships. To achieve these purposes, several bibliometric indices have been proposed by scientists that have been evaluated by scientific community to consider the authors based on those indices. Such bibliometric indices are an author's publications, h-index, g-index and the variants of h-index that have been serving best to bring the authors on top. All of these indices except publication count are based on author's certain number of citations which are received in the specific time period of 2-3 years which is enough time to present the credit to the author to achieve the narrated purposes. Authors who are at the start of their career suffer due to insufficient number of citations, their publications gain. They are being neglected by the scientific community to be considered for one of the narrated positions to be offered. In other words, to reduce the limitation of this criterion of evaluating authors, researchers should consider the co-author network of new researchers in the scientific society. There are many reasons behind considering the co-author network of any author. As it is being known that co-authorship composes social network and to find the most promising and influential author from the co-author network, researchers belong to the field of graph theory and social network analysts have proposed various graph centralities such as Degree, Closeness, Betweenness and PageRank. In our study, we are constructing co-author network of Mathematics domain that consist of 57533 authors and 62033 total numbers of publications. In several researchers, purpose of co-authorship is to identify the trend of publications in particular area of study and finding the influential author in the who co-author network. In our study, we are focusing on identifying influential author in the co-author network and evaluating those authors with the resultant authors obtained from bibliometric indices with the help of benchmark "Awards". Award is said to be an honor in the form of medal, certificate or shield that is presented people to admire their research contribution in the scientific community. To evaluate our study, we have used four bibliometric indices; Publication count, citation count, h-index and g-index and four graph based indices that are degree closeness, betweenness and PageRank

Table of Contents

Table of Contents	vii
Chapter 1 Introduction	1
1.1 Background of research	2
1.2 Problem Statement	5
1.3 Research questions	5
1.4 Purpose	5
1.5 Scope	6
1.6 Definitions, Acronyms, and Abbreviations.....	6
1.7 Application of Proposed Approach	6
Chapter 2 Literature Review	8
2.1 Scientometrics	8
2.1.1 Article level Metrics	9
2.1.2 Journal level Metrics	9
2.1.3 Author Level Metrics.....	10
2.1.4 Bibliometric Indices.....	11
2.2 Social Networks.....	13
2.2.1 Co-author Network	13
2.2.2 Graph Centralities	15
2.3 Literature Review Summary.....	19
2.4 Observation.....	21
Chapter 3 Methodology	Error! Bookmark not defined.
3.1 Dataset Description.....	24
3.1.1 Pre-processing.....	24
3.1.2 Index Extraction	25
3.1.3 Edge List	25
3.1.4 R and igraph	26
3.2 Graph centralities.....	26
3.2.1 Degree Centrality	27
3.2.2 Closeness Centrality.....	27

3.2.3	Betweenness Centrality	27
3.2.4	PageRank Centrality	28
3.3	Bibliometric Indices.....	28
3.3.1	No of Publications	28
3.3.2	No of Citations	29
3.3.3	h-index	29
3.3.4	g-index.....	29
3.4	Awarding Societies and their significance	30
3.4.1	American Mathematics Society (AMS)	30
3.4.2	International Mathematics Union (IMU)	31
3.4.3	London Mathematics Union (LMS)	32
3.4.5	Norwegian Academy of Science and Letters (NASL).....	32
3.4.6	Awardees Extraction	33
3.4.7	Awards as a Benchmark.....	33
3.5	Evaluation	33
3.5.1	Evaluation of Correlation between ranking lists.....	33
3.5.2	Evaluation of Awardees in the Ranking Lists of authors.....	34
3.5.3	Evaluation of Dependency of Prestigious Awardees on Graph Based Indices	34
3.5.4	Evaluation of Graph Based Indices to Bring the Awardees on Top	34
Chapter 4	Results and Discussion	Error! Bookmark not defined.
4.1	Correlation Evaluation	35
4.1.1	Correlation between Ranking Lists from Graph Based and non-Graph Based Indices.....	35
1)	Graph Based.....	36
2)	Bibliometric ranking indices.....	40
3)	Graph VS Traditional.....	42
4.2	Summary of correlation experiments	48
4.3	Dependence of awarding societies on graph indices	49
4.3.1	American Mathematics Society	50
4.3.2	International Mathematics Union.....	50
4.3.3	London Mathematics Society.....	50
4.3.4	NASL.....	50
4.4	Summary of Awardees Experiments.....	54

Chapter 5 Conclusion and Future Work.....	55
5.1 Conclusion.....	55
5.2 Future Work.....	57

List of Figures

Figure 2.1 Co-author Network	14
Figure 2.2: Degree.....	17
Figure 2.3: Closeness.....	17
Figure 2.4: Betweenness.....	17
Figure 2.5: PageRank.....	17
Figure 3.1 Proposed Methodology	23
Figure 3.2 Cases of Ambiguous Names.....	25
Figure 4.1 Correlation of Degree with Graph Indices (TOP 20%)	36
Figure 4.2: Correlation of Closeness with Graph Indices (TOP 20%)	37
Figure 4.3: Correlation of Betweenness with Graph Indices (TOP 20%)	38
Figure 4.4: Correlation of Betweenness with Graph Indices (TOP 40%)	38
Figure 4.5: Correlation of Betweenness with Graph Indices (TOP 100%)	39
Figure 4.6: Correlation of PageRank with Graph Indices (TOP 20%)	39
Figure 4.7: Correlation of Citation Count with Non-Graph Indices (TOP 20%).....	40
Figure 4.8: Correlation of Publication Count with Non-Graph Indices (TOP 20%)	41
Figure 4.9: Correlation of h-index with Non-Graph Indices (TOP 20%).....	41
Figure 4.10: Correlation of g-index with Non-Graph Indices (TOP 20%)	42
Figure 4.11: Correlation of Citation Count with All Indices (TOP 20%).....	43
Figure 4.12: Correlation of Publication Count with All Indices (TOP 20%)	44
Figure 4.13: Correlation of h-index with All Indices (TOP 20%).....	44
Figure 4.14: Correlation of g-index with All Indices (TOP 20%)	45
Figure 4.16: Correlation of Degree with All Indices (TOP 20%)	45
Figure 4.17: Correlation of Closeness with All Indices (TOP 20%)	46
Figure 4.18: Correlation of Closeness with All Indices (TOP 80%)	46
Figure 4.19: Correlation of Betweenness with All Indices (TOP 20%)	47
Figure 4.20: Correlation of PageRank with All Indices (TOP 20%)	47
Figure 4.21: Dependence of Awarding Societies on Indices	51
Figure 4.22: Percentage of Awardees by All Indices.....	52
Figure 4.23: Contribution of Each Index Independently.....	53

List of Tables

Table 3-1 Awards and Awardees of AMS Society	31
Table 3-2 Awards and Awardees of IMU Society	32
Table 3-3 Awards and Awardees of LMS Society	32
Table 3-4 Awards and Awardees of NASL Society	33
Table 4-1 Total Awardees Found	49

Chapter 1

Introduction

To acknowledge the contributions of authors in the scientific community, different metrics or indices have been proposed such as an authors number of publications, number of citations etc. On the basis of such indices, they are ranked by the journals or scientific societies to identify the important authors. There are various purposes to rank authors such as best authors could be chosen as editor or reviewer in the journal (James D., et al, 2005). It is important to rank the authors so that best author could be selected and award is to be presented to him (James, 2014). Another purpose of ranking is to identify scientific impact of author and consider him for post-doctoral positions, tenure and junior faculty (A.M. Peterson, 2010). Universities or journals can call the best authors as a guest, editor or speakers in their conferences. To rank the authors, there exist many techniques which have been proposed to rank the authors, journals, institutions or papers. In such techniques, publication count, citation count, author's impact, h-index and its variants are commonly known and used. An individual's publication count is considered sufficient to be chosen on top (Balog et al, 2006). Then researchers proposed the citation count index for the same purpose (Bogers et al 2008). With the growth of scientific literature in the society, many other indices have been proposed such as h-index (Hirsch, 2005) which is considered to be author level metric. Another author level metric g-index (Leo Egghe, 2006) has been proposed too. While studying the literature, it has been observed that the contributions of authors have been measured by using their number of publications and citations (A.M. Peterson, 2010). Identification of experts for peer review process has become crucial because of unproductive work. Various techniques including no of publications are helping to extract the experts from different field of studies (Cameron, 2007). Among expert finding approaches, social citation network has been used and proved to be very effective with respect to citation in Degree (Bogers et al, 2008). All of these traditional ranking indices depends upon the author's citation index and this index considerably takes 2-3 years to get healthy citations for any scientific publication (Dorta-Gonzalez, P., & Dorta-González, M. I, 2013).

By analyzing the recent problem in our study, there are some Bibliometric and graph based approaches used by the researchers to find the experts from different fields of studies. In this scenario, everyone tries to justify their approaches to be the best but there exist no benchmark which can be used to evaluate the performance of new technique. With the correspondence to our research problem, the former researcher (Imama Syed, 2015) has used the benchmark which is called “Awards” for the evaluation of ranking indices. This benchmark has been used against highly ranked authors and awardees from the domain of Mathematics. In this research, same benchmark “Awards” has been utilized to evaluate graph based and traditional ranking indices. Then the comparison have made between both type of indices to find whether there is any association in their results or not and the dependency of awarding societies on the graph indices is measured.

1.1 Background of research

Scientometrics is a research field which uses quantitative and qualitative approaches to rank the journals and institutions. Scientometrics is based upon three types of metrics which involves Journal Level metric, Paper level metrics and Author level metrics¹. Researchers have been proposing their technique to rank the institutions, journals, papers and authors. The Chinese researchers have used database of Scientometrics to rank the worldwide universities (Liu, Nian Cai, Ying Cheng, and Li Liu, 2005). The study was conducted to identify the reason of gap between Chinese universities and world class universities and tried to rank the research universities based on their research activities. One of the researchers has used h-index to measure the performance of authors by including their publication and citation count (Saad, Gad, 2006). Same metric (h-index) can be used to find the impact factor of journals (Saad, Gad, 2006).

Authors have been ranked by many researchers by using their Bibliometric indices, a decade ago. The influence of author in the scientific community is measured by using his h-index, g-index and publication count. Researchers have proposed various indices who have contributed in scientific community. But this has become the problem for those researchers who have recently published their articles and gained no citations. The authors who are at the stage of starting their career in the academia need to be recognized by scientific societies or ranking experts so that

¹ <https://en.wikipedia.org/wiki/Scientometrics>

they could get better hiring positions at university, call for supervision or editor in any journal. To resolve this problem, we have introduced graph based centralities to apply on co-author network on the basis of co-authors of any particular author. Every centrality will measure the influence of each author in the network and will rank the authors according to its influential position in the network. For this purpose, graph based and non-graph based centralities have been compared to evaluate the performance of graph based indices.

Among these topics, constructing the co-author network and ranking authors on the basis of their research contributions are significant research area for the scientists. In scientific literature, impactful journals are trying to find the best authors based on the research contribution they have made (Abbott, Alison, et al, 2010). Several researchers have proposed their own qualitative, quantitative or hybrid techniques to evaluate the highly ranked authors which have been previously discussed. Apart from h-index, publication count and citation count researchers are using different variants of h-index such as g-index, m-co-efficient etc to measure the scientific contributions of authors (Bornmann, Lutz, Rüdiger Mutz, and Hans-Dieter Daniel, 2008). The author may be solo writer or co-author who has written the papers with other authors. The authors who have written papers with other authors can be presented in the form of co-author network.

Network/Graph is a combination of ordered pair (V, E) where V represents vertices/nodes and E means an edge/link between pair of vertices². Networks can be directed or undirected. Network can also be classified as heterogeneous and homogeneous. Some researchers are using heterogeneous networks and some are using homogenous depending on the nature of their task. Homogeneous networks are made up of similar objects and links where all objects are of same category. Facebook, twitter, Gmail etc are all considered as homogeneous network (Sun, Yizhou, et al, 2011). For example; in homogenous network co-author network is considered to be homogenous because of there is only one type of objects author and one type of link co-authorship. Heterogeneous network is made up of dissimilar objects and links. Movie network and bibliographic network are examples of heterogeneous network (Sun, Yizhou, et al, 2011). In bibliographic network; there are multiple types of links and objects. Objects may involve venues,

² https://en.wikipedia.org/wiki/Graph_theory

topics and papers. Social networks have become a wide research domain for the computer scientist to explore the information from the network.

Other researchers have worked on graph centralities by using Erdos co-author network (Gang, Jiatai, et al, 2015). In this paper, new algorithm based on PageRank algorithm was proposed which is said to be LeaderRank algorithm. This algorithm is effective to use with the h-index to influence the author's impact in the society. Another researcher has narrated the importance of co-authors other than number of publications and citations (Ausloos, Marcel, 2013). It is empirically found that there is a relationship between number of joint publications of co-authors and their rank of importance. To distribute the credit among multiple authors of single paper is now considered to be an issue. And to resolve this issue, researchers have proposed co-authorship credit allocation model which has its own characteristics such as directed, self looped and weighted network (Kim, Jinseok, and Jana Diesner, 2015).

As we have discussed, there are two types of graphs; Directed and Undirected. Our focus will remain on undirected network of co-authors known as co-author network. To see the most influential authors, some graph centralities such as Betweenness, Degree, PageRank and Closeness will be used to rank the authors.

Both types of indices have their own importance. Some researchers might find non-graph indices better to evaluate authors ranking and some might consider co-author network by using traditional ranking indices to evaluate the authors ranking. Graph indices are applied in networks which comprehend information with great understanding in the form of nodes and edges.

For this purpose we have constructed co-author network and we applied graph indices to obtain the quantitative values of co-authors in order to rank them. In addition, awardees of that domain are compared with the highly ranked authors who had achieved the awards too. The list of awardees and highly ranked authors are acquired and by using the benchmark "Awards", results are evaluated.

1.2 Problem Statement

In the scientific community, awarding societies and institutions are using expert ranking parameters to find the best authors for various reasons. But the criteria of best chosen authors are not yet clear by the researcher that's why researchers are proposing their qualitative and quantitative parameters to make the evaluation of authors ranking better. Moreover, in literature, there is no comprehensive study on evaluation of both type of indices; Graph based and Traditional ranking indices. By considering these problems from the literature, research gap is identified.

From the above discussion, we have derived the following problem statement. "Whether there is any correlation between and graph indices and can we find any association among awardees and highly ranked authors?"

1.3 Research questions

To answer research question, we have chosen the dataset from the field of Mathematics and performed our analysis. For this purpose, we have constructed following research questions.

1. Whether the international prestigious awardees lie on the top ranking obtained from graph indices or non-graph indices?
2. Which graph index contributes the most to bring the international awardees in the list of top ranked authors?
3. Which Mathematical awarding society is more dependent on the graph indices used in this thesis?
4. Is there any correlation between the non-graph indices and graph indices?

1.4 Purpose

The purpose of the thesis is to evaluate the expert ranking via graph indices such as Closeness, Betweenness, PageRank and Degree. Further we will compare the rankings obtained from Graph Indices with the ranking obtained from non-graph indices such as author's publications, citations, g-index and h-index which have been used by former researchers.

Graph based indices have an edge over traditional indices with respect to rank the authors on the basis of their co-author network. Most of the authors whose publications are new in the scientific community are overlooked because of no citations they receive. The limitation of citation is that it takes time which consists of around 2-5 years or may be more. In this case, such authors are not considered to be hired on some position or to get any award in exchange of the contributions. This study may raise level of consideration for such authors to be ranked in scientific community by analyzing their position in their co-author network.

1.5 Scope

The experiments in the present study will conduct in the domain of mathematics. Highly ranked co-authors will be analyzed with the help of graph ranking indices such as Betweenness, Closeness, Degree and page rank etc for the domain of mathematics.

1.6 Definitions, Acronyms, and Abbreviations

LMS	London Mathematical Society ³
AMS	American Mathematical Society ⁴
IMU	International Mathematical Union ⁵
NASL	Norwegian Academy of Science and Letters ⁶
MSC	Mathematics Subject Classification

1.7 Application of Proposed Approach

The results of our research will help the following people in a certain way:

(i) Decision makers of scientific societies

As the results of our research are comprehensive enough to make the decision makers to hire the researchers who have no or low citations as editors or to give promotions t or present the awards or membership of international bodies or tenured appointments etc.

³ <https://www.lms.ac.uk/>

⁴ <http://www.ams.org/home/page>

⁵ <http://www.mathunion.org/>

⁶ <http://english.dnva.no/>

(ii) Authors who want to be known as expert ones

A researcher can easily find his place in the scientific society with the help of his co-author network which may bring good options to build his career in the scientific community.

(iii) Expert finding systems

Expert finding systems from different domains of study can use these parameters for the ranking purpose. The results of our research can be beneficial for the expert finding systems in order to introduce more effective author ranking parameters.

Chapter 2

Literature Review

Finding the ranking of authors based on their research contribution in the scientific community is getting considerable attention now-a-days. The techniques used to obtain such rankings come under the umbrella of Scientometrics. As the data is growing in scientific community, scientific societies are engaged in finding the expertise of researchers while using different Bibliometric indices. On the other side, several researchers have proposed their own qualitative and quantitative parameters to find the highly ranked authors in the different fields of study such as Mathematics, Medical, Social Sciences, Management Science, and Computer Science and so on. For this literature review, relevant research papers and techniques have been critically reviewed. Moreover, this chapter has been divided into two sections. First section is related to the tools and techniques which have been commonly used by scientific researchers in domain of ranking experts with the help of Graph based and non-Graph based indices. Second section will provide the information about mathematics scientific societies and their awardees.

2.1 Scientometrics

Scientometrics is a research field, which uses quantitative and qualitative techniques to rank the journals, authors and institutions. It helps in obtaining top authors and institutions with respect to their research contribution. There are other such scientific studies which are in progress and working as a variant of Scientometrics such as Bibliometric Information System, Information Sciences and science of science policy. In the scientific study of American Institute of Aeronautics and Astronautics, scientific community have collected the records of papers, books, journals and information of its members (Aswathy, S.,2015)(Srimanta Pal,2015). In this study, data is collected from web of science and results reveal that chemistry is the subject which has produced more number of papers.

Moreover, multi-authorship has played a vital role in this subject. The area of Scientometrics is also used in identification of co-authorship via network mapping. In other words, the prediction of co-authors has been explored (Boutin Eric, 2008)(Pei Liu, 2008). In this article, Chinese

philosophy, the ideas of Gaunxi and Shi are used spontaneously. Scientometrics method has been used to identify the latent associations. By latent association, it means that the collaboration between two authors or researchers yet to be occur in future. Scientometrics is also used to classify the hierarchy of social sciences to put the papers in their correct corresponding branch of social sciences (Glanzel Wolfgang, 2003)(Andras Schubert, 2003).

With the growth of articles published in different journals every year, it has opened the gates for the researchers to be on top based on their research contributions. Web of science, Scopus and articles published in impactful journals are considered as valuable Articles. The comparison among Scientometrics, Bibliometric and Informatics has been made in the paper (Hood et al, 2001) with respect to find growth, interrelationships and productivity. All three terms are closely related to each other to measure the scientific publications respectively⁷. We have identified three categories of metrics referred in Scientometrics.

2.1.1 Article level Metrics

Article level Metrics are used to quantify the impact of published research now a day. Based on the citations of any paper, a paper is considered to be impactful. Previously, an article was regarded as important if it has been published in highly-cited journal⁸. The importance was only measured by its number of citations. With the passage of time, multiple metrics to evaluate articles have been introduced. For example, Almetrics, Public Library of Science and SPARC primer are now in the trend to measure the diverse impact of research material. Widely used ranking parameter to find the top articles are publication count, citation count, h-index and g-index (Egghe, Leo, 2006).

2.1.2 Journal level Metrics

In the past, citation metrics was the only tool available to evaluate the journals and authors systematically. The methodology used by Thomson Reuters in 1970 only uses citations for the journal year which means it does not distinguishes between citations, reviews or editorials. That's why score of journal may raise up to remarkable unit. The fact is these articles are receiving frequent citations. As these type of articles are not considered to be the part of journals but there citations are counted. For this purpose, classification of articles to be made and

⁷<http://microsites.oii.ox.ac.uk/tidsr/kb/48/what-Bibliometrics-and-scientometrics>

⁸<http://sparcopen.org/our-work/article-level-metrics/>

Thomson Reuters have classified the articles which are to be considered are extended abstract and author commentaries. The methodology related to evaluate Bibliometric is proposed by Thompson Reuters has been explained in the article by two researchers (PenDlebury, David A, 2009).It includes counting, measuring, analyzing measurements considered to be main tools of science to gather knowledge about something through publications.

With the passage of time, citation metric became a common tool when impact factor was published as a part of journal citation report. We can find the impact factor of any journal with the help of the following formula. Impact factor for a journal can be calculate as follows.

Impact factor = no of citations received in corresponding year / no of publications received in corresponding year

Other scientific metrics of journals have been created to calculate the impact factors based upon Scopus and web of science database such as SNIP, Eigenvector, Article Influence Score, and **SJR Invalid source specified..**

Scientometrics is a concept covering the concept of science citation index. While working on science citation index, researcher created the journal impact factor to help select journals for the new science citation index (Garfield, 2006). Usually journals are ranked based on number of articles published in that journal.

2.1.3 Author Level Metrics

Finding the experts from the organization or from scientific community has become the attention for the researchers (Fawaz et al, 2012). Many different methods and techniques have been used for this purpose. Several academia and researchers are evaluating parameters to measure the performance of individual author

Before author level, scientific societies used to rank the journals by using number of publications in the corresponding journal but there were some problems associated with it. To overcome the issues of journal level metrics, it is valuable to evaluate author's work based on his independent contribution in the journal.

Therefore it is prefer to use author level metrics to evaluate author's contribution in research instead of journal level metrics⁹. In author level metric, individual authors, scholars, researchers can be considered to rank them by measuring their Bibliometric impact. H-index is considered as common and valuable metric to measure the performance of author as it takes the publications and citation counts of any author equally. Author level Eigen vector and author impact factor are also contributing to rank them. Among the reasons of finding best authors, some more reasons are stated in the research (Alarfaj, Fawaz et al, 2012).

In author level metrics, there are many problems associated regarding co-authors such as what if there would be 1000 or more authors of a single paper or whom should be considered as first author. To resolve such questions, some measures are used to evaluate the author's performance, regardless of the number of authors or position of the authors in the paper. Such as authors are listed and assigned a count to each author accordingly.

2.1.4 Bibliometric Indices

Bibliometric Indices are frequently used by the researchers to rank the experts. Author's publications, citations, h-index are said to be the Bibliometric indices. On the other hand there is a metric that is commonly used called 'total number of citations' of any published work. Mean citation and median citations are used as variants of 'total number of citations'. Both variants produced some limitations. Mean citation distribution becomes highly skewed which is not satisfactory and median citation produces very long tail which is also not worthy to consider as good results. Therefore h-index was introduced as a new metric to measure an author's impact.

Some commonly used qualitative and quantitative metrics (ranking indices) have been used by the scientific community to rank the authors which have been explained below:

- **Number of publications**

In scientific literature, the author who secures highest no of publications is considered as high research contributor (Crowder et al, 2002). The authors are supposed to be ranked on the basis of their no of publications by many journals. The limitation of considering only number of citations reflects the inaccurate research contribution of author. Moreover, only number of publications does not guarantee the quality work of researchers.

⁹ <http://libguides.nus.edu.sg/researchimpact/author>

- **Number of Citations**

Citations have their own importance to rank the authors along with their Bibliometric information (Moreira and Wichert, 2013). It shows the impact of authors in the field where he has shown his contributions. Only citations are not sufficient to rank the author because there are several reasons by which people cite the papers which are cited to criticize the author's work (West & Krestin, 2008).

- **H-index**

Jorge Hirsch proposed h-index in 2005 to measure the research contribution of an individual author (Bormann Lutz, 2008). It is a scientific measure which is calculated by taking the number of publications of author as equal number of citations. Scientists are busy in exploiting the use of h-index with different perspectives. In the field of physics, Michael has tried to find out topics and compounds. H-index of average candidates who got fellowship for post doctoral was consistently higher than the candidates who were not selected in the study (Bornmann, L., & Daniel, H. D, 2005). A revolutionary move of H-index is becoming state of the art approach in terms of indexing now a day. This approach can be used to differentiate between new topics with the older one. It helps new researchers to explore the work which is already been done in their respected fields. H-index measures the quality of paper and impact factor of the community where paper is published.

The strong point of h-index involves h-index is used to measure the impact of research as well as quality of the paper. And with the help of h-index, we can rank the authors easily. On the other side, it has fewer limitations such as H-index varies with the change in number citations. Obviously with the time, number of citation may constant or varies with respect to the citations. Many researchers have already worked upon using h-index to find the largest research contributions of any author. Another limitation of h-index is, it gives no credit to lowly cited paper.

- **G-index**

To measure the citation performance of research articles, G-index have been proposed as the extension of H-index (Egghe, Leo, 2006). Like H-index, g-index is an author level metric. It is used to measure the importance of top articles of authors. to compute the g-index, citations of authors in descending order gets double by taking its square root. The advantage to use the g-

index is that it returns the unique largest number. It helps to give the credit to the lowly or not cited papers while giving credit to the highly cited papers. It is computed by ranking the articles in decreasing order of number of citations they receive. g-index is the largest number that top g articles receives together at least g^2 citations¹⁰.

2.2 Social Networks

The concept of social network with scientific collaboration was proposed by another researcher (Barabasi, 2002). In other study (Yong li et al, 2014), author has worked on finding the influential authors from the network by using two parameters α and β (Yong li et al, 2014). The Yong Li has applied Katz Bonanccih centrality to define the network prestige which uses the idea of page-rank algorithm. To find the influential authors, each author's influential score is calculated with the help of mathematical formula $(g) = \alpha$. This study (Yong li et al, 2014) provides the tool to find the influential authors in the coauthor network can be regarded as a useful tool for application in knowledge management. This study is also helpful in finding the information of influential authors, papers, journals and books (Li, Yongli, et al, 2014).

Researchers have worked on predicting the link between co-authors to know whether same authors will write the papers in future (Sun, Yizhou, et al, 2011). Link prediction has already been tried to find in homogenous network such as Facebook, Twitter etc. Homogenous network is made up of same objects and same links. It was predicted that whether the link will be obtained in the future or not according to the topological feature of the network. Heterogeneous network is made up of dissimilar objects and links such as movie network or bibliographic network. There are multiple types of objects in bibliographic network such as venues, papers and topic along with different types of links. In this study (Sun, Yizhou, et al, 2011) co-authorship relation will be predicted in heterogeneous network.

2.2.1 Co-author Network

Co-author network is considered to be the most important type of social network (Zhang, Li Xian, Yu Jia Liu, and Xin Zhong Lu, 2014). An Example graph of co-author network is presented as follows:

¹⁰ <http://guides.library.cornell.edu/c.php?g=32272&p=203392>

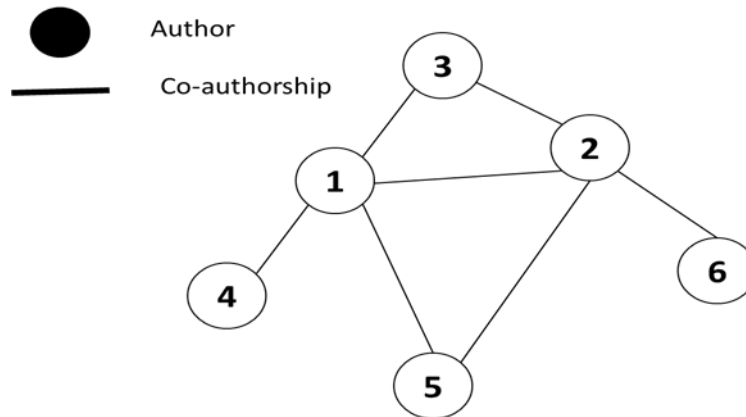


Figure 2.1 Co-author Network

In the above given graph, there are 6 nodes and 7 edges between them. Each node is connected to its corresponding node in the form of undirected network. In research (McCarty, Christopher, et al, 2013), to analyze the h-index of author by using the characteristics of co-author network, authors randomly selected a sample of 238 authors from the Web of Science, calculated their h-index as well as the h-index of all co-authors from their h-index articles, and calculated an adjacency matrix where the relation between co-authors is the number of articles they published together (McCarty, Christopher, et al, 2013). Their model was highly predictive of the variability in the h-index ($R^2 = 0.69$). Other significant variables are those associated with highly productive co-authors. In research (McCarty, Christopher, et al, 2013), the behavior of collaboration of authors has been investigated. For this purpose, three metrics have been used as variables and classified them as Number of co-authors, structure of collaboration, characteristics of co-authors. Contrary to the hypothesis, network structure as measured by components was not predictive. This analysis suggests that the highest h-index will be achieved by working with many co-authors, at least some with high h-indexes themselves. Little improvement in h-index can be gained by formalizing a co-author network to maintain separate research communities. Social network studies have broadened our understanding of the relationship between co-authorship and productivity.

These Studies evaluate the relationship between productivity and the position of authors in the co-author network have found that authors who publish with many different co-authors act as communication bridge and tend to show higher rates of publications (McCarty, Christopher, et al, 2013). Those co-authors belong to different discipline of studies. During the course of experiments, while extracting the authors along with their affiliations, it causes some types of

disambiguation. Such ambiguities like affiliations, topic and publication record was been corrected by the undergraduate and graduate teams of students. Then h-indexes were calculated for 594 authors randomly selected from that lists. The strength of this approach is co-author network is constructed and the h-index of particular author has been gained by using the characteristics such as affiliated institution. But the limitation of this study is Changes in h-index will need to be made with the number of publications increasingly with respect to the years or impact factor of journals.

Upon the working of co-author network, researchers have made significant work such as extension of PageRank algorithm. PageRank algorithm has been modified as LeaderRank algorithm.

Leader Rank algorithm takes Paul Erdos number to construct the co-author network and helps to choose collaborator to find the influence in the scientific community (Gang, Jiatai, et al, 2015).Leader Rank algorithm is used to measure the influence of only author's co-author. Apart from measuring the author's impact factor by using his number of citations, it is best to find his impact factor by his co-authors role in the literature (Ausloos, Marcel, 2013). A new technique has been proposed in their research to rank the number of co-authors according to the number of joint publications they have done. It is found in the results that there is a strong association exists between joint publications of the co-authors and their rank .

The number of occurrence of co-authors in a paper does not consider being prior that's why equal credit of the paper is distributed among co-authors (Kim, Jinseok, and Jana Diesner, 2015). But there is a critical issue in credit allocation among co-authors of a paper which arises due to some of the problems. Solution to this problem is co-authorship credit allocation model which is proposed in this paper (Kim, Jinseok, and Jana Diesner, 2015). Co-author Network is considered to be weighted, self looped and directed network in this approach whereas in other approach (De Stefano, Domenico, Giuseppe Giordano, and Maria Prosperina Vitale.,2011), co-author network is considered to be as undirected or sometimes weighted network.

2.2.2 Graph Centralities

The purpose of Centrality is to measure the importance of one node with other node (Freeman, Linton C et al, 1991). The edge between nodes indicates the association between two nodes (J, Kim, 2015).The common node centrality methods are degree centrality, closeness betweenness, Katz Bonanccih and page rank etc.

In paper (J, Kim, 2015), authors have introduced new type of centrality called C_F which is based upon network flows. It's similar to the Freeman's C_B but different in two ways. Firstly, C_F defined for both valued and non-valued graphs. Secondly, C_F is not based on length of paths but on all the independent paths between all the pairs of nodes in a network (Freeman, Linton C, 1991).

Centrality has two different perceptions. Let's take an example of social networking where a person might have central position which shows its closeness with every other person connected to him. And centrality shows that a person closer to every other person will likely to access more information. Secondly, the person's closeness maybe revealed that they may stand on the others path of communication. Such those people can exhibit the communication of others or act as mediator between two people to access their information, power, influence or prestige. In this paper, to overcome the limitations of previous centrality C_B with C_F , different type of centrality has been calculated. C_B had three measures of centralities used in the graph theory which have been used in number of applications. There were two limitations aroused. This centrality was applicable only for simple graphs. Secondly graph structured analysts showed the objections upon binary approach, because it surrounds by only qualitative relationships. Binary approach is not sufficient to encapsulate the strength of interpersonal relationship according to the some of the researchers. To overcome such limitations, C_F was introduced by the authors. It is appropriate for both valued and non-valued graphs. Secondly, C_F considers all pairs of nodes in the network unlike C_B . Detailed explanation of centralities is discussed in next chapter. In this chapter, Centralities have been shown in pictorial form to clear the image of graph based centralities below:

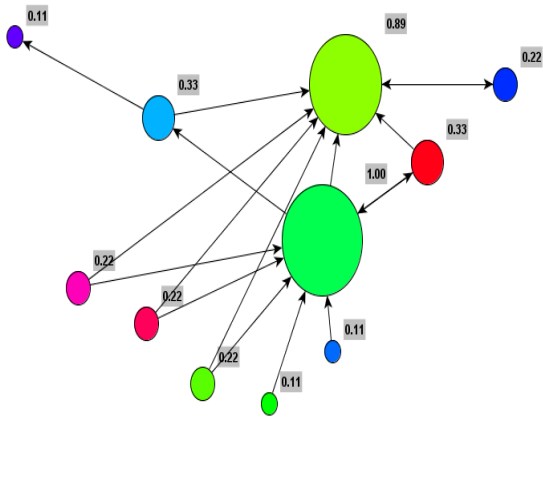


Figure 2.2: Degree

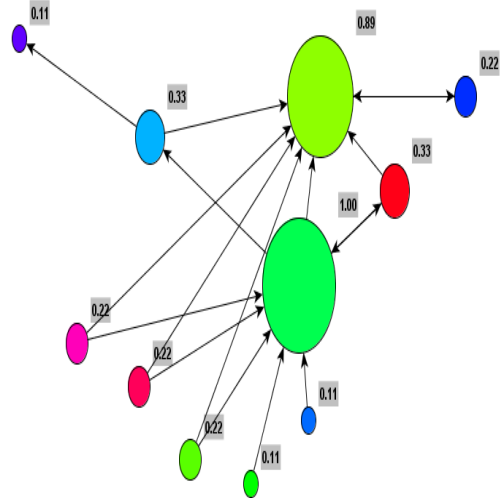


Figure 2.3: Closeness

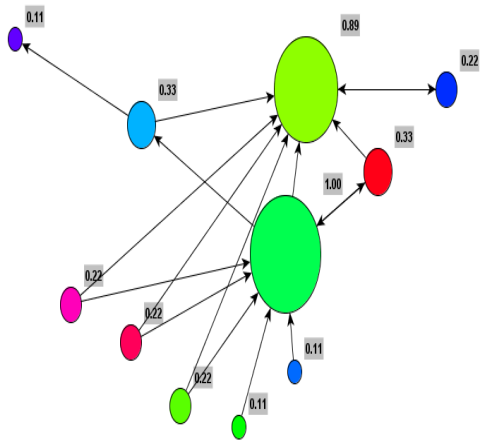


Figure 2.4: Betweenness

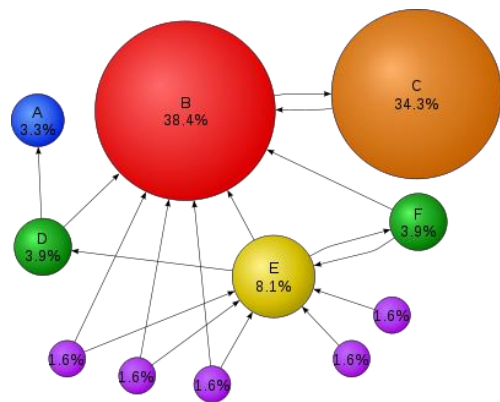


Figure 2.5: PageRank

In 2, graph shows degree centrality in which different colors differentiate the authors and size of each node represents the strength of author with respect to maximum number of edges connected to it. In figure 3, graph shows the representation of closeness centrality. Strength of node is shown with the help of maximum closer node on its shortest distance with other node with the help of closeness. In figure 4, as similar as degree and closeness centrality, betweenness centrality has been computed on its maximum number of times it occurs between two nodes at shortest distance. In figure 5, PageRank centrality has been computed for each node which is represented in the form of graph. A node is influential and bigger with respect to its maximum number of incoming edges and is connected to existing influential node.

2.3 Literature Review Summary

Indices	Reference	Types of Indices	Strength	Weaknesses
No of Publications	Babineau, M., Fischer, C., (2014). Survey of publications and the H-index of academic emergency medicine professors.	Non-Graph Based indices	No of publications play a vital role in academic promotion.	No of publications may not provide accurate measure of impact and quality of researcher's work.
No of Citations	Moreira, C., & Wichert, A. (2013). Finding academic experts on a multisensor approach using Shannon's entropy. West, R. O. B. E. R. T., & Stenius, K. (2008). The use and abuse of citations. Publishing addiction science.		It is Bibliometric metrics to rank the authors on the basis of no of citations they receive.	This metric is not reliable to use as people often cite the papers to criticize the work of authors.
h-index	Bornmann, Lutz, and Hans-Dieter Daniel, (2007) "What do we know about the h index?."		This measure is useful to quantify the impact of researcher by using research contribution as well as measure the quality of work.	Lowly cited articles may not get chance to be considered. Moreover, the change in number of citations changes the h-index.
g-index	Egghe, Leo (2006) Egghe, Leo. "Theory and practice of the g-index."		It is an author level index to rank the authors which gives credit to lowly cited papers too.	The precision of g-index is inaccurate as it doubles the citations of the author.

Degree	Zhong Lu. (2014) "Using Networks to Measure Influence and Impact." Applied Mechanics and Materials.	Graph Based indices	This index measures the performance of author by considering his number of co-authors connected to it. This is simple index to measure the performance of author to rank them.	It is computed by measuring no of edges connected to the particular node which may not show the strength if it is not connected to the influential nodes.
Closeness	Zhong Lu. (2014) "Using Networks to Measure Influence and Impact." Applied Mechanics and Materials. Opsahl, T., Agneessens, F., & Skvoretz, J. (2010). Node centrality in weighted networks: Generalizing degree and shortest paths. <i>Social networks</i> , 32(3), 245-251.		It measures the author's impact on the basis of shortest distance with other authors.	Closeness relies on the length of the shortest paths from author to all other authors in the network. The value of closeness may produce doubtful results with respect to weighted and un weighted network (Opsahl, T, 2010)This measure also does not considers the importance of adjacent authors.
Betweenness	Zhong Lu. (2014) "Using Networks to Measure Influence and Impact." Applied Mechanics and Materials. Opsahl, T., Agneessens, F., & Skvoretz, J. (2010). Node centrality in weighted networks: Generalizing degree and shortest paths. <i>Social networks</i> , 32(3), 245-251.		It chooses the influential author who is most central and connects other authors with shortest distance.	Betweenness relies on identification on shortest paths which measures the no of count passes through it for a node. The tie in the network affects the strength of edge between nodes
PageRank	Zhong Lu. (2014) "Using Networks to Measure Influence and Impact." Applied Mechanics and Materials.		Author is said to be influential if it has higher page rank and connected with the authors who have higher page rank.	The formula of PageRank depends upon the damping factor. To retrieve desired results from PageRank, appropriate value of damping factor must be chosen

2.4 Observation

During the scientific literature survey, relevant papers are critically reviewed and former approaches have been studied. Some observations which were found are numbered as follows:

1. From the literature, widely used Bibliometric parameters are publications, citations, h-index.
2. Widely used Graph Based indices which have been used in the literature are Closeness, Betweenness, Degree, PageRank centralities.
3. Some of the researchers have used the combinations of the Bibliometric approaches.
4. In the domain of graph, many researchers have used these centralities in the Erdos co-author network to rank the researchers.
5. The criteria of presenting awards to the best author are not clearly defined in the literature.
6. However, awards are used as a reward to the authors for the best contribution in the field of Mathematics was found.

Chapter 3

Methodology

From the observations from previous chapter “Literature review”, expert ranking systems use Degree, Closeness and Betweenness centralities in terms of graph based centralities to find the influential authors from co-author network. Expert ranking systems from the scientific community have proposed the Bibliometric author ranking indices that include an individual’s no of publications, citations and h-index and g-index to evaluate the researcher’s performance. There is no comprehensive study found in the literature to evaluate the performance of both types of ranking indices to rank the fresh graduates or the authors with most recent publications in the scientific community. To perform the evaluation, international prestigious awards are taken as benchmark. We have evaluated whether the awardees from traditional ranking indices also rank on the top by using graph based indices or not. With the help of proposed methodology, we will be able to answer our four research questions which were discussed in chapter no 1.

- 1) Whether the international prestigious awardees lie on the top ranking obtained from graph indices or non-graph indices?
- 2) Which graph index contributed a lot to bring the awardees on the top?
- 3) Which mathematical awarding society is more dependent on the graph indices used in this thesis?
- 4) Is there any correlation between non-graph and graph based indices?

Following figure shows the overall structure of the adopted methodology.

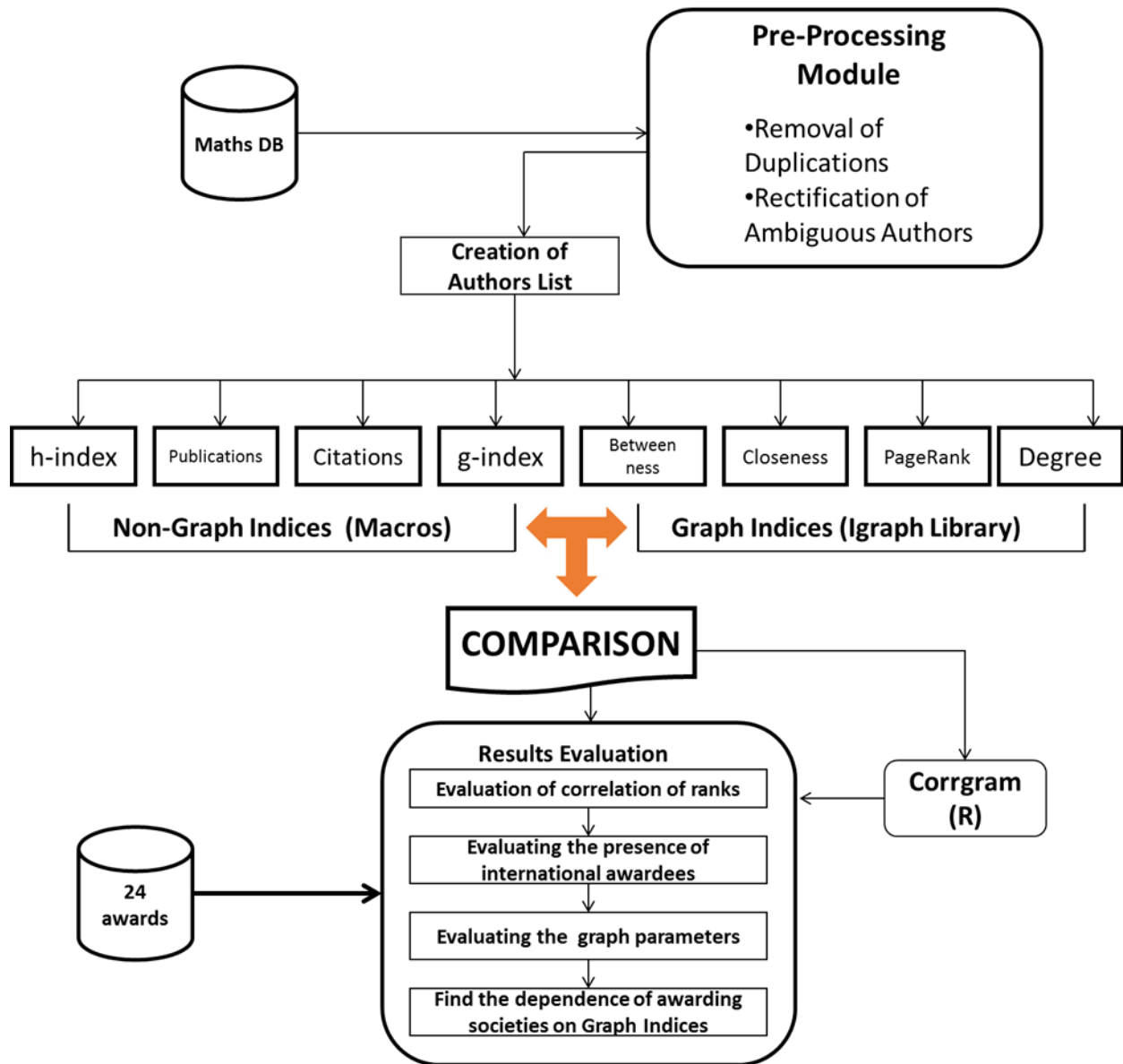


Figure 3.1 Proposed Methodology

As discussed earlier domain of Mathematics has been selected to acquire the lists of experts. Data set has been received by the former research (Imama Syed, 2015). We have selected this domain for certain number of reasons. We selected this dataset because it has already been used

in one of the comprehensive study (Imama Syed, 2015). Additionally Mathematics domain is associated with all other field of studies such as Physics, Chemistry and Computer Sciences etc. This shows that the selected domain is the versatile field and ranking the authors from this domain is quite significant contribution. On this dataset, pre-processing has been done to filter the dataset which includes removal of duplications and correction of ambiguous last and initial names of authors. In this section, the methodology is summarized in a way that the ranking list from homogenous graph indices and traditional ranking indices and evaluated to identify the presence in the awardees on the top who are given prestigious awards in exchange of their remarkable contribution in scientific community.

3.1 Dataset Description

The dataset had collected by the former researcher (Imama Syed, 2015), who collected this data from Google scholar with the help of crawler as well as manually. To ensure the correctness of data, all 64 categories were compiled and verified from the domain experts. The dataset consists of 57533 and found 57515 authors after removal of ambiguities by former researchers but there remains the problem of duplication and ambiguous author names which have been corrected manually.

In above given ERD, there are seven relations and each relation is associated with other with the help of primary key. Primary key in master table has been changed into foreign key when associated with child table. Master/Parent table in the ERD is table_authors_paper. This table is connected with table_authors and table_papers which is further connected to their child tables. Whole process of pre-processing has been shown in the ERD.

3.1.1 Pre-processing

The dataset was received in the form of relational database in this research; I have got the version of dataset of containing 57533 authors and found occurrence of duplications and presence of ambiguous names. After correction of ambiguous names and duplications, we obtained 57515 authors. These cases were verified and then rectified by visiting each URL of ambiguous named author to ensure that respective publication belongs to him. Whole process has been shown in figure 8.

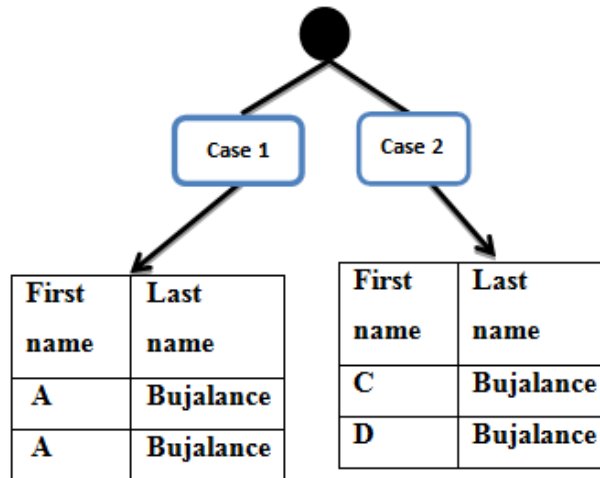


Figure 3.2 Cases of Ambiguous Names

Afterwards the data remained consist of 48130 authors after constructing co-author network. Then the indices were applied on this dataset. The method of acquiring both types of indices has been explained in the following subpart.

3.1.2 Index Extraction

As we have selected four well known state of the art indices from graph based centralities such as Degree, Closeness, Betweenness and PageRank and four commonly used state of the art traditional bibliometric author ranking indices such as Publication Count, Citation Count, h-index and g-index. Both types of indices are extracted using scripts. The data is stored in relational database in which we have written macros to find the total number of citations, h-index, g-index and total publications respectively (Onofri, A, 2001). To find the values of graph based indices, we have used the tool “R” which supports igraph library (Csardi, G., & Nepusz, T, 2006). With the help of igraph we have constructed co-author network by importing edgelist of co-authors and obtained the results of all graph based centralities.

3.1.3 Edge List

The graph centralities (Degree, Closeness, Betweenness and PageRank) which we have considered to use in our research have been computed by first creating edgelist with the help of

Macros in Excel VBA. In the Edgelist every author is place along with its corresponding author and then the author is place with another co-author similarly. This is how edgelist is formed and to create the edgelist we have following code.

```
Sub EdgeList()  
For i = 2 To 62033  
k = 3  
For n = 3 To 4  
Do While Worksheets("coAuthors").Cells(i, k).Value <> 0  
If Worksheets("coAuthors").Cells(i,1).Value <  
Worksheets("coAuthors").Cells(i, k).Value Then  
Worksheets("EdgeList").Cells(j,1).Value =  
Worksheets("coAuthors").Cells(i, 1).Value  
Worksheets("EdgeList").Cells(j,2).Value =  
Worksheets("coAuthors").Cells(i, k).Value  
End Sub
```

After creation of edgelist, data is transformed in the form of graph into R by using igraph library. Then with the help of graph.data.frame, the co-author network has been constructed in a form by which we can extract the values of graph centralities simultaneously. For every graph centrality, function needs to be called within igraph library (Csardi, G., & Nepusz, T, 2006)

3.1.4 R and igraph

R is a software environment that provides programming platform to perform statistical analysis on the data. By using R, a programmer or data analyst can use it for data mining and acquire the outputs after experiments. R supports igraph library which provides handy tools to the researchers who belong to the network sciences. R facilitates the programmer with an open source library which is capable of handling graphs made of millions of nodes and edges. It also provides the mechanism of importing and exporting files in .xls, .csv, .txt, .sas and .xml (Csardi, G, 2006).

3.2 Graph centralities

The purpose of Centrality is to measure the relationship of one author with other authors (Freeman, Linton C et al, 1991). The edge between nodes indicates the association between two people (Kim, Jinseok, and Jana Diesner, 2015).The common node centrality methods are Degree Centrality, Closeness Betweenness, Katz Bonanccih and Page Rank etc.

3.2.1 Degree Centrality

A Degree refers to the number of nodes connected to the host node. It indicates the influential author based on the connected author with him. Collaborators are such authors with whom you write the paper or publish an article. The formula has been taken from the paper of Kim and Jinseok (Kim, Jinseok, and Jana Diesner, 2015).

$$C_D(n_i) = d(n_i) \quad (3.3)$$

In this formula n_i represents the current authors whose degree centrality is to be computed. And $d(n_i)$ means total n of edges connected to a particular node.

3.2.2 Closeness Centrality

By the context of Closeness, authors will not be having direct co-authorship with other authors but will exist between the authors which are not far from the other authors too. In the graph network, Closeness centrality plays an important role (Kim, Jinseok, and Jana Diesner, 2015). The Closeness of the node is measured by the average length of shortest path between node and all other nodes.

$$C_C(n_i) = \sum_{j=1}^N 1/d(n_i, n_j) \quad (3.2)$$

In this formula, total sum is computed for all the average length of shortest between authors with all other authors and then its reciprocal claims the value of Closeness. n_i represents the current authors whose closeness centrality is to be computed. Shortest distance of between each pair of authors is shown by $d(n_i, n_j)$.

3.2.3 Betweenness Centrality

Betweenness is the centrality measure which is calculated based on finding the shortest path between nodes. It is measured by a number of times a author act as a bridge between two nodes. Minimum number of hops will be identified in order to find the influential author. The formula to calculate Betweenness is as follows (J. Kim, 2015):

$$C_B(n_i) = \sum_{j,k \neq i} g_{ijk} / g_{jk} \quad (3.1)$$

$C_B(n_i)$ is Betweenness of particular node. And g_{ijk} / g_{jk} is the sum of nodes present in total shortest paths of each pair and it is divided by total no of existing shortest paths of particular author.

3.2.4 PageRank Centrality

PageRank is basically an algorithm which is mostly used by Web pages. Normally PageRank is calculated by the number of pages connected to the main website. In the graph network, it works like Katz centrality and Eigenvector with the difference of scaling. The PageRank centrality in graph has its own properties. An author is said to be influential if it will be associated with other influential author who has large amount of associated links¹¹.

$$PR(P_i) = \frac{1-d}{N} + d \cdot \sum_{p \in M(P_i)} \frac{PR(P_j)}{L(P_j)} \quad (3.4)$$

This formula has been explained according to our study following.

N is the number of authors.

D is the dumping factor that is fixed in the formula

PR(p_i) is the PageRank of author

L(p_i) is the number of outgoing edges from the author

M(p_i) is the set of PageRank of rest of the authors.

3.3 Bibliometric Indices

Traditional ranking indices centralities are said to be Bibliometric indices which are commonly used by scientific communities to measure the research contribution of an author. Along time ago, researchers have been using these bibliometric indices. Among these indices, no of publications, no of citations, h-index and g-index are widely used. Such Bibliometric indices are explained below;

3.3.1 No of Publications

This parameter shows the highest number of publications of author on which basis, an author is said to be expert in the community (Singh et al, 2013). The formula to calculate the number of Publications has been stated below:

$$Pub_{Count} = \sum_{i=1}^n P_i \quad (3.5)$$

In the given formula, p_i refers to the paper number.

¹¹ <http://checkpagerank.net/>

3.3.2 No of Citations

No of citations of any publication of author also shows the impact of author in the community which has been cited by other researchers (Bogers, T., Kox, K., & van den Bosch, 2008). The formula to compute the no of citations is stated below:

$$\text{Cit}_{\text{count}} = \sum_{i=1}^n \text{cit}(p_i) \quad (3.6)$$

In the given formula, $\text{cit}(p_i)$ means the citation of corresponding papers.

3.3.3 h-index

H-index was proposed by Jorge Hirsh in 2005 which is now considered to be useful index to measure the scientific impact of authors to rank them (Bornmann Lutz, 2008). Author's h-index can be computed by sorting no of publications and citations in ascending order. The formula to compute the h-index is stated below:

$$h_{\text{pub}} \leq h_{\text{cit}} \quad (3.7)$$

On the left hand side of the formula, there are author's number of publications which should be less than or equal to the author's number of citations in the same row.

3.3.4 g-index

G-index is another index a like h-index with the difference is it is useful to give credit to lowly cited papers (Egghe Leo, 2006). It is calculated by taking square of both publications and citations. The formula to compute g-index is stated below:

$$g^2 = \sum_{i \leq g} c^i \quad (3.8)$$

With the help of above given formula, citations of authors get double by taking the square. c_i means total number of corresponding citations.

Above given formulas have been used in Excel VB with the help of macros. One of the following macros explains the functionality of computing the values of all these centralities.

```
For rowNo = 2 To endRow
    authorStartRow = rowNo
    citation = 0
    counter = 1
    authorID = Worksheets("authorCitations").Cells(rowNo, 1).Value
```



```

        citation = Worksheets("authorCitations").Cells(rowNo, 3).Value
        rowNo = rowNo + 1
        Do While Worksheets("authorCitations").Cells(rowNo, 1).Value =
Worksheets("authorCitations").Cells(rowNo - 1, 1).Value
            If counter <= citation Then
                citation = Worksheets("authorCitations").Cells(rowNo,
3).Value
                counter = counter + 1
            End If
            rowNo = rowNo + 1
        Loop
        rowNo = rowNo - 1
        If counter > citation Then
            counter = counter - 1
        End If
        Worksheets("authorCitations").Cells(authorStartRow, 6).Value =
counter 'set values in author_hindex column in authorCitations sheet
        If Worksheets("authorIndices").Cells(j, 1).Value = authorID Then
'against the matching author_id
            Worksheets("authorIndices").Cells(j, 3).Value = counter 'set
values in author_hindex column in authorIndices sheet as well
        End If
        j = j + 1
    Next rowNo
End Sub

```

The given macro has been written to compute the values of h-index with respect to author's citations which are stored against the author's id and respective no of publications. By similar way, values of g-index, citation count and no of publications have been acquired.

3.4 Awarding Societies and their significance

Awarding societies are established to play vital role in any field of study. One of the purposes of its establishment is to acknowledge the work and contribution of people. With the same perspective, in the field of Mathematics, awarding societies have been made. These awarding societies with brief explanation have been mentioned below:

3.4.1 American Mathematics Society (AMS)

American Mathematics Society (AMS) is an association of professional Mathematicians is established according to the interest of Mathematical research and scholarship and serves the national and international community through its publications, meetings and other programs¹². It

¹²<http://www.ams.org/home/page>

has many awarding programs associated. This society was formed in 1988 by inspiring from London Mathematics Society on the visit to England. The AMS largest annual research meetings related to Mathematics in all over the world along with the mutual collaboration of other organizations. The AMS publishes Mathematical Reviews, a database of reviews, books and journals. The list of associated awards of American Mathematics Society and its achievers has been stated below;

Table 3-1 Awards and Awardees of AMS Society

Awards	No of Awardees
Cole prize in Algebra	26
Bocher Memorial Prize	33
Cole Prize in number theory	29
Delbert Ray Fulkerson Prize	67
Joseph L.Doob	6
Leoroy P. Steel Prize for Lifetime Achievement	25
Leoroy P. Steel Prize Mathematical Exposition	29
Leoroy P. Steel Prize	34
Levi L.Contant Prize	18
Oswald Veblan Prize in Germany	29

3.4.2 International Mathematics Union (IMU)

International Mathematics Union (IMU) is an international scientific organization which purpose is to promote international cooperation in Mathematics¹³. The objectives of this society are to promote international cooperation in mathematics, to support the scientific meeting or conferences and contribution in all sub branches of mathematics. The list of awards and number of awardees of IMU has been given below:

¹³<http://www.mathunion.org/general/about>

Table 3-2 Awards and Awardees of IMU Society

Awards	No of awardees
Chern Medal Prize	2
Fields Medal	56
Gauss Prize	3
Leelavati Prize	2
Rolf Novanlinna Prize	9

3.4.3 London Mathematics Union (LMS)

London Mathematics Society (LMS) is UK learned mathematics society. The purpose of this society is to publish journals and books, providing grants to support mathematics and provide grants to support mathematics and organizing scientific meeting and lectures¹⁴. The list of associated awards of this society and number of awardees is given below:

Table 3-3 Awards and Awardees of LMS Society

Awards	No of awardees
Berwick Prize	32
De Morgan	44
Frohlich Prize	6
Naylor Prize and lectureship in applied Mathematics	19
Polya prize	19
Senior Berwick prize	38
Senior whitehead prize	20
Whitehead prize	111

3.4.5 Norwegian Academy of Science and Letters (NASL)

Norwegian Academy of Science and Letters (NASL) is not a specific domain of study. It collaborates with all fields of study¹⁵. The most prestigious awards of this society are small in

¹⁴<https://www.lms.ac.uk/>

¹⁵<http://english.dnva.no/c41973/seksjon/vis.html?tid=41986>

number as compared to other prestigious awarding societies. Those awards have been given below:

Table 3-4 Awards and Awardees of NASL Society

Award	No of Awardees
Able Prize	14
Kavli Prize	9

3.4.6 Awardees Extraction

Awardees from four international prestigious communities have been gathered from their corresponding websites. And the awardees along with their specific awards were stored in relational database and then the list of such awardees that were present in our dataset consisting of 48130 authors got separated. Then the presence of awardees have been measured with respect to the awarding society, they belong to.

3.4.7 Awards as a Benchmark

In this research, prestigious awards of mathematical Societies have been taken as a benchmark to validate our experiments. These prestigious awards are given by prestigious awarding societies form the field of Mathematics to admire the work of researchers and present them with a reward in the form of prestigious awards. The details of those awardees and awards from the societies have been given in Appendix B.

3.5 Evaluation

In the module of evaluation, after acquiring the ranking lists from both types of indices, every one of the research question will be answered by using the results from the experiments.

3.5.1 Evaluation of Correlation between ranking lists

In this step of evaluation, acquired ranking lists will be measured in a way to find the association among them. Spearman correlation will be used to measure their performance. Spearman correlation measures the strength of two variables. It works fine for rank correlation¹⁶. Spearman Correlation will be applied to find the following types of association among ranking lists such as;

- i) Correlation between ranking lists from graph based indices.

¹⁶ <https://statistics.laerd.com/statistical-guides/spearmans-rank-order-correlation-statistical-guide.php>

- ii) Correlation between ranking lists from traditional ranking indices
- iii) Correlation among ranking lists from Graph and Traditional ranking indices Indices.

Correlation for all of these indices has been computed with the help Corrgram library in R. formula if spearman correlation is given in equation.

$$\rho = 1 - \frac{6 \sum_{i=1}^n d^2}{n(n^2 - 1)} \quad (3.9)$$

It helps to visualize the data in the form of correlation matrices after importing data in igraph library¹⁷.

3.5.2 Evaluation of Awardees in the Ranking Lists of authors

After acquiring the ranking lists, the presence of awardees will be tried to find out. Whether the awardees are present in the ranking lists or not, it will be answer of our research question. For this purpose, the dataset will be divided in the form of percentage and the authors will be searched in the distribution of 10%, 20%, 30% and so on.

3.5.3 Evaluation of Dependency of Prestigious Awardees on Graph Based Indices

To find the dependency of prestigious awardees of mathematics on graph indices, this part of evaluation will be performed. It is also the answer of one of our research questions. To perform this evaluation, same percentage of authors will be taken as mention in section 3.5.2. The results of this evaluation will be discussed in the chapter of results in detail.

3.5.4 Evaluation of Graph Based Indices to Bring the Awardees on Top

It is another interesting question to explore the behavior of graph indices to bring the awardees on top. Contribution of awarding societies will be tried to find in the acquired ranking lists from the Graph based indices. The results of this evaluation will be explained in chapter no 4. For this purpose same percentage of authors has been carried as discussed in previous sections.

¹⁷ <http://www.statmethods.net/advgraphs/correlograms.html>

Chapter 4

Results and Experiments

This chapter consist of results computed from several experiments which are based on methodology discussed in chapter no 3. The methodology is built up on ranking the experts from the domain of mathematics by evaluating homogenous graph indices and traditional ranking indices.

4.1 Correlation Evaluation

In this section, our constructed research questions to make our research validate has been tried to answer. The following section comprises to find the correlation between homogenous graph indices and traditional ranking indices in order to rank the experts from the domain of mathematics. Then the dependency of awarding societies on these indices and the contribution of indices to bring the awardees on top has been found. In the last, section encloses by drawing interesting observations gained by the results for the new publications of such authors who gained no citations or yet to receive the citations as citation of any scientific publication requires the time of around 2-5 years (Dorta-Gonzalez, P., & Dorta-González, M. I, 2013). In the meantime, authors who deserve to be considered on ranking by scientific societies may come up with the help of their co-author network.

4.1.1 Correlation between Ranking Lists from Graph Based and non-Graph Based Indices

To perform the results and acquire the ranking lists, dataset has been divided into sorted lists such as top 20%, top 40%, top 60%, top 80%, and 100% to import in R with respect to all of the indices. Ranking lists of Graph-Based indices have been acquired from R after importing edgelist into it. The ranking lists from non-graph indices have been acquired with the help of macros script. The details of R and macros has been discussed in chapter no 3. To answer our fourth research question “*Is there any correlation between graph based and bibliometric indices*”. We have divided this question into three subparts. First we have computed the correlation of graph-based indices with graph-based indices itself. Secondly, non-graph based indices are correlated with non-graph indices and thirdly graph-based indices are correlated with non-graph indices.

The results have been shown in the form of figures and detailed section of tables in which the values of correlation exist is given in Appendix A.

We have used Corrgram for correlation experiments. The output of the experiment is in the form of grid pie charts. In the charts, there are three different colors and their shades; Dark Blue represents strong positive correlation, light blue represents weak positive, pink color represents weak negative correlation and dark red strong negative correlation.

1) Graph Based

- **Sorted with respect to Degree**

In the figure 4.1, degree has strong relationship with Betweenness and PageRank as compared to the closeness. The light color in lower panel of the figure shows the weak correlation between degree and closeness. It has been clearly seen on the upper panel of the figure which shows in the form of pie and the ratio in the pie shows the correlation between degree and closeness. Similarly, the correlation between degree and other graph indices can be seen by observing the colors in the figure 4.1 which shows the results for the top 20% authors from the data set of 48130 authors.

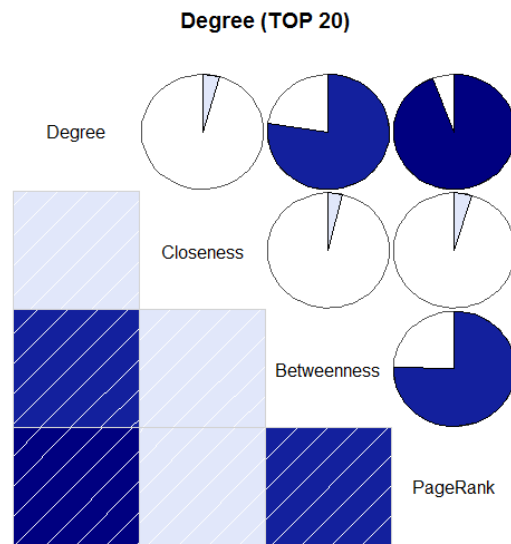


Figure 0.1 Correlation of Degree with Graph Indices (TOP 20%)

- **Sorted with respect to Closeness**

In figure 4.2, the ranking lists are sorted based on closeness and astonishing results have been found. The relationship of closeness is found to be weaker with Degree, Betweenness and PageRank in top 20% of the ranking list.

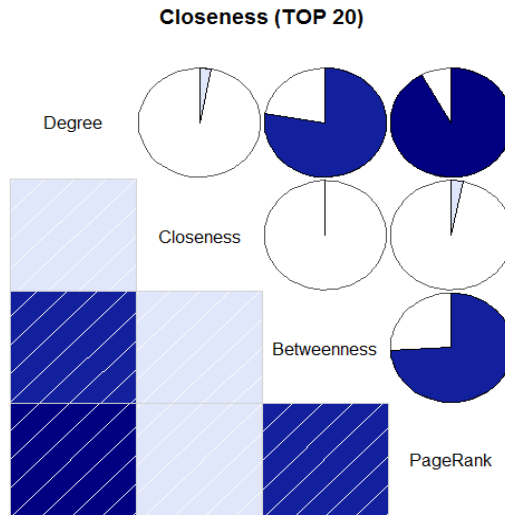


Figure 0.2: Correlation of Closeness with Graph Indices (TOP 20%)

The shades of colors in the figures for top 40%, top 60%, top 80% and top 100% are similar but the difference can be distinguished with the help of tables given in Appendix A

- **Sorted with respect to Betweenness**

Ranking lists have been acquired with respect to Betweenness and results have been divided in different ranking lists from top 20% to top 100%. In top 20%, Betweenness has strong correlation with degree and PageRank but weak correlation with closeness.

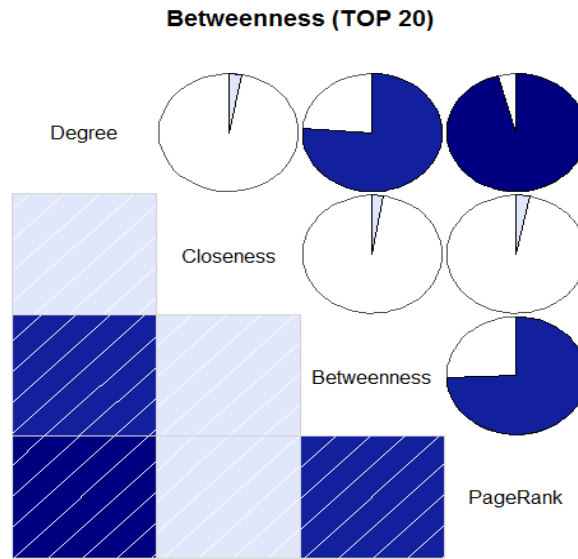


Figure 0.3: Correlation of Betweenness with Graph Indices (TOP 20%)

Ranking lists of top 40% based on Betweenness, variation in results shows that Betweenness has negative correlation with Closeness which is shown by pink color but positive correlation with Degree and PageRank in figure 4.4.

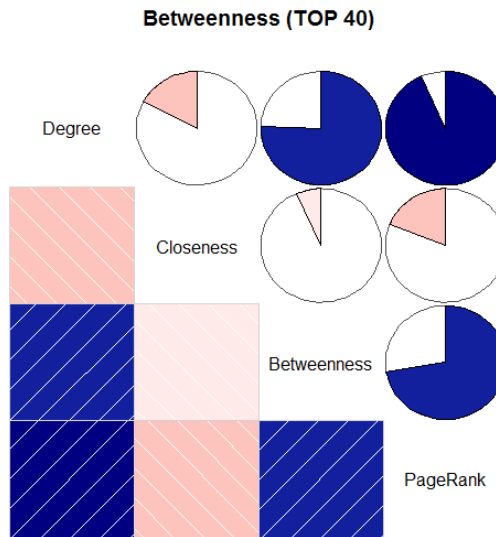


Figure 0.4: Correlation of Betweenness with Graph Indices (TOP 40%)

The results of correlation of Betweenness with other graph indices have been slightly change in top 100%. The correlation is found to be still weak but positive with closeness and strong positive with degree and PageRank.

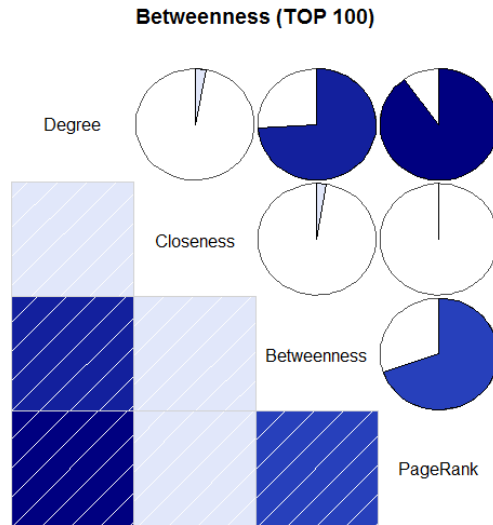


Figure 0.5: Correlation of Betweenness with Graph Indices (TOP 100%)

- **Sorted with respect to Page Rank**

The ranking list is based on top 20% has been acquired based on PageRank has very strong correlation with degree than Betweenness but weak positive correlation with closeness which is distinguished in colors in figure 4.6.

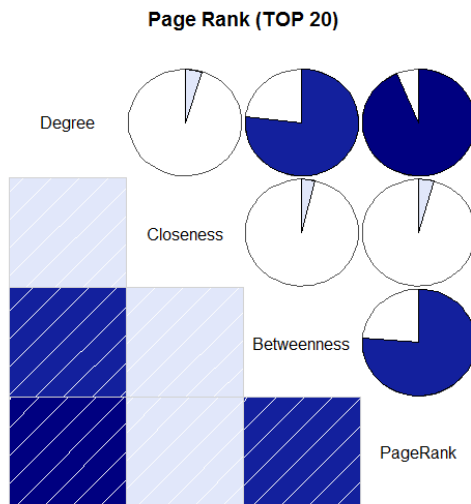


Figure 0.6: Correlation of PageRank with Graph Indices (TOP 20%)

The correlation of PageRank has been measured with other graph indices and the results for top 40%, top 60%, top 80% and top 100% are consistently same as were obtained for top 20%. The behavior of colors in figures is same so the variations of values in correlation can be seen in the tables given in Appendix A.

2) Bibliometric ranking indices

- **Sorted with respect to Citation Count**

After finding the correlations between graph indices, the correlation between non-graph indices have been computed and shown in the form of graphs. First index which has been taken to find correlation is citation count. Same percentages of ranking lists have been taken for these indices as well. In top 20% of ranking list, the correlation of Citation count with h-index, g-index and publication is weak positive. In other ranking lists such as top 40%, top 60%, top 80% and 100%, the correlation is consistently same. Further the variations in values can be seen from the table in Appendix A.

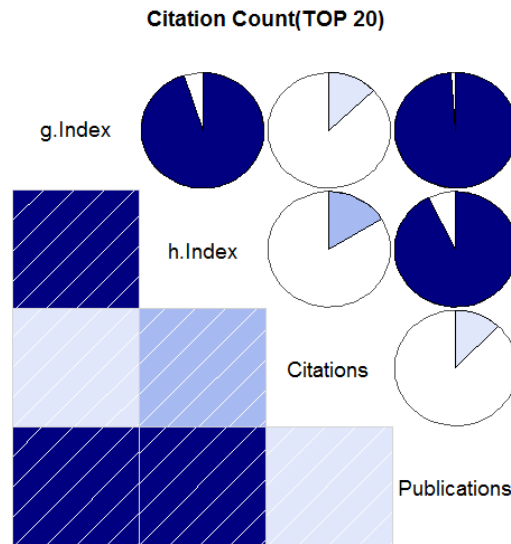


Figure 0.7: Correlation of Citation Count with Non-Graph Indices (TOP 20%)

- **Sorted with respect to Publication Count**

On sorting based on Publication Count, it has been observed that for all ranking lists correlation of Publication with h-index and g-index consistently remained high but weak positive with

citation count which can be seen in figure 4.8. The results of correlation on the basis of Publication count are consistently same in all ranking lists with the minor change in values.

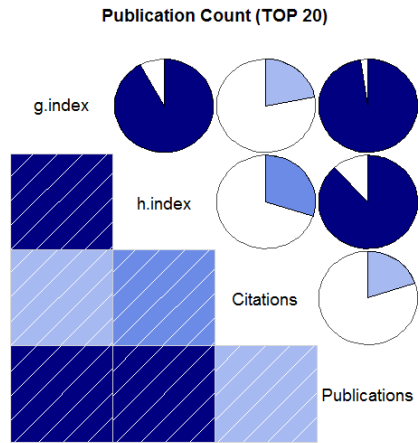


Figure 0.8: Correlation of Publication Count with Non-Graph Indices (TOP 20%)

- **Sorted with respect to h-index**

On sorting based on h-index, the behavior of correlation between ranking lists is same which can be observed from figure 4.9. The correlation of h-index with g-index and Publication is strongly positive but weak positive with citation count. The shades of colors are same in all ranking lists but there is a little change in values which have been mentioned in Appendix A.

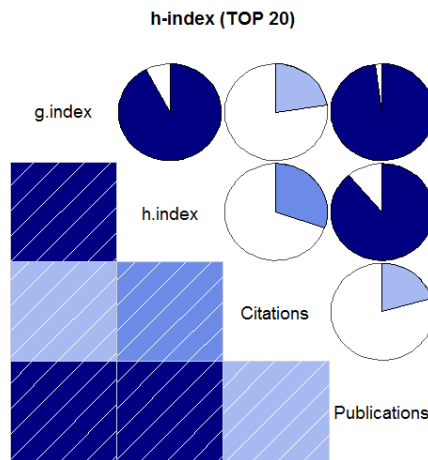


Figure 0.9: Correlation of h-index with Non-Graph Indices (TOP 20%)

- **Sorted with respect to g-index**

On sorting based on g-index, it is observed that g-index has strong positive correlation with h-index and publication but weak positive with citation count in all ranking lists. The results can be seen from figure 4.10.

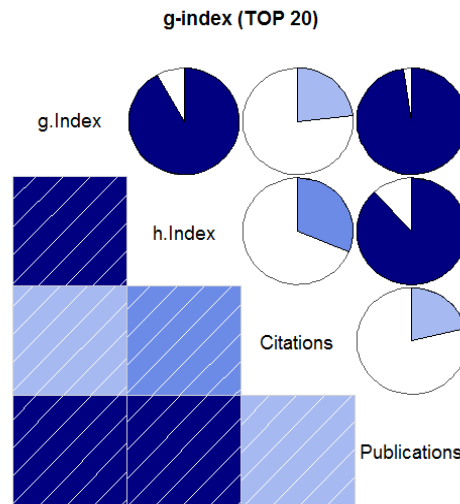


Figure 0.10: Correlation of g-index with Non-Graph Indices (TOP 20%)

3) Graph VS Traditional Bibliometric Indices

After computing results from both graph and non-graph indices separately, now the ranking lists from all types of indices have been acquired by sorting each index simultaneously.

- **Sorted with respect to Citation Count**

With respect to citation count, the correlation between citation and closeness has been indicated by pink color which can be seen in figure 4.11. Pink color indicates negative correlation between closeness and citation. Citation has weak positive correlation with Betweenness, degree and PageRank. The correlation of citation is relatively better with publications, g-index and h-index.

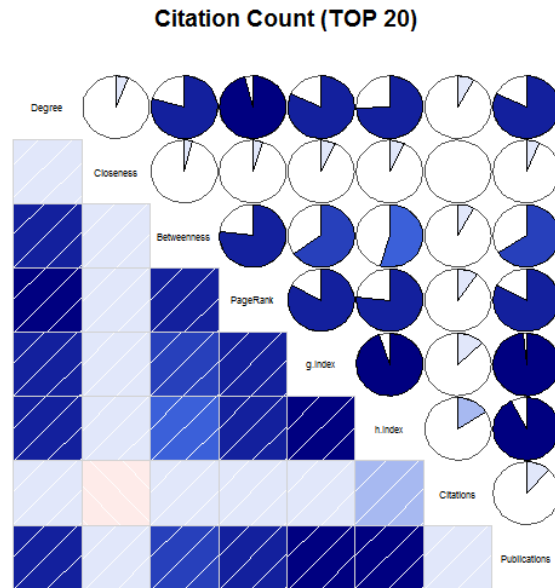


Figure 0.11: Correlation of Citation Count with All Indices (TOP 20%)

The results of correlation have been slightly changed in top 40% of ranking list which have been sorted with respect to citation count. The negative correlation between citation count and closeness has been changed into weak but positive correlation which means that in large ranking list, negative correlation may improve somehow. Interestingly, same type of correlation has been found in further top 60%, top 80% and top 100% too.

- **Sorted with respect to Publication Count**

On sorting with respect to publication count, the correlation between publication count with closeness and citation count is found to be weak positive whereas publication count has strong positive correlation with other indices and results are consistently same for all ranking lists.

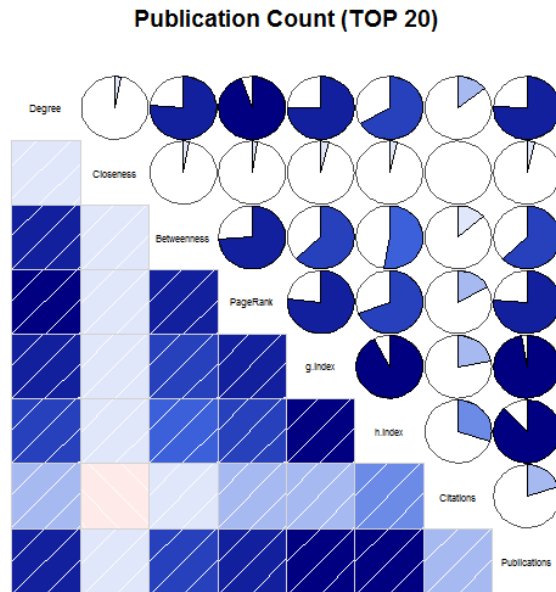


Figure 0.12: Correlation of Publication Count with All Indices (TOP 20%)

- **Sorted with respect to h-index**

On sorting based on h-index, it has been found that h-index also behaves like publication. It has weak positive correlation with closeness and citation count. Apart from it, h-index has strong positive correlation with g-index, Publication, degree, Betweenness, PageRank.

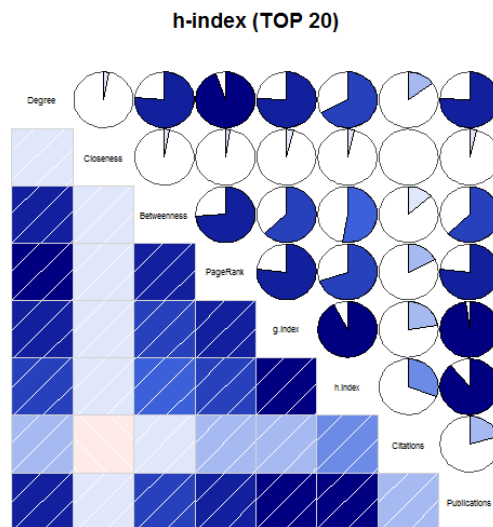


Figure 0.13: Correlation of h-index with All Indices (TOP 20%)

- **Sorted with respect to g-index**

The correlation of g-index with other indices is found to be positive but weak positive with citation and closeness and strong positive with degree, Betweenness, PageRank, h-index and publications.

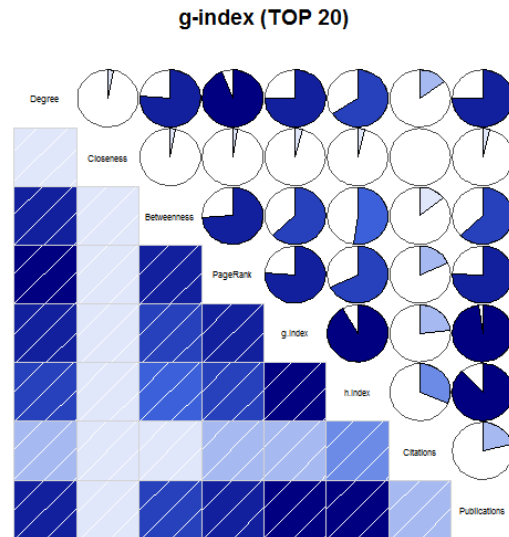


Figure 0.14: Correlation of g-index with All Indices (TOP 20%)

- **Sorted with respect to Degree**

The correlation of degree with other indices is found to be strong positive with all of the indices in all ranking lists except closeness and citations.

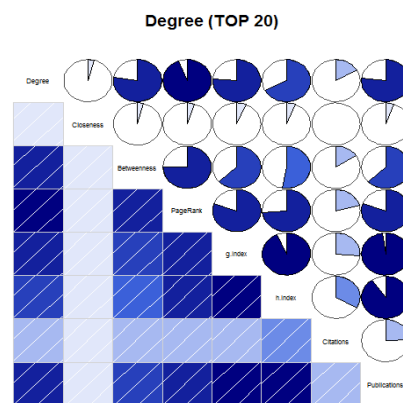


Figure 0.15: Correlation of Degree with All Indices (TOP 20%)

- **Sorted with respect to Closeness**

When ranking lists were sorted with respect to closeness, it was found that closeness has weak positive relation with all of the indices in ranking lists of top 20%, top 40% , top 60% and top 100%. In top 80% correlation between closeness and citation become negative and the results are clearly distinguished in figure 4.17 and figure 4.18.

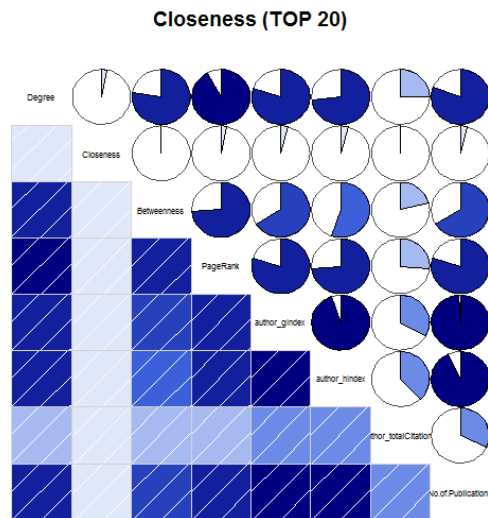


Figure 0.16: Correlation of Closeness with All Indices (TOP 20%)

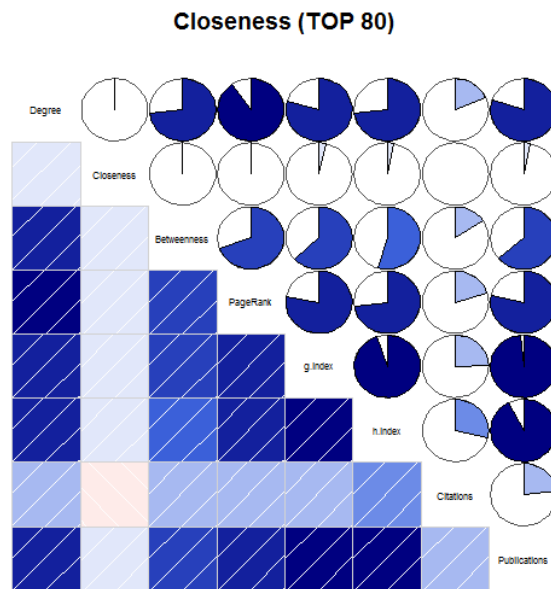


Figure 0.17: Correlation of Closeness with All Indices (TOP 80%)

- **Sorted with respect to Betweenness**

When the ranking lists were sorted based on Betweenness, it was found that Betweenness has low positive correlation with closeness in top 20% and top 100% of the ranking lists. In top 40%, top 60% and top 80% the correlation between closeness and Betweenness became negative.

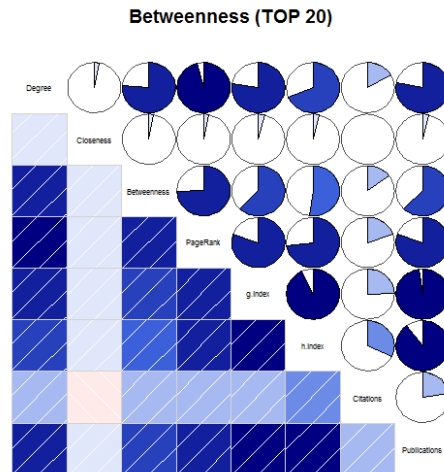


Figure 0.18: Correlation of Betweenness with All Indices (TOP 20%)

- **Sorted with respect to PageRank**

Ranking lists with respect to PageRank shows that PageRank has strong positive correlation with all of ranking indices except closeness and citation. It has weak positive correlation with closeness and citation. The results are consistently same from top 20% to 100%.

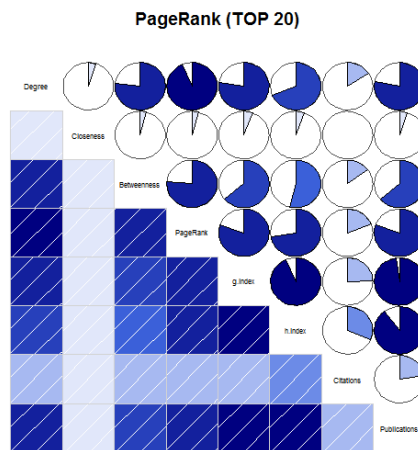


Figure 0.19: Correlation of PageRank with All Indices (TOP 20%)

According to the results, it has been explored that closeness and citation are found to be such indices which had low positive correlation with all of the indices whereas other indices are strongly correlated with each other approximately from 0.5% to 0.9% based on the obtained results, it can be revealed that graph indices can be use to rank the authors by ranking experts as well.

4.2 Summary of correlation experiments

- **On the basis of Graph VS Graph Indices: interesting findings have been stated as follows:**

With respect to degree, it has been observed that degree has strong correlation with Betweenness and PageRank but weak positive correlation with closeness in all ranking lists.

With respect to Closeness, it has been observed that Closeness found to be weakly correlated with all graph indices in all ranking lists.

With respect to Betweenness, in top 20% and 100% weak positive correlation has been obtained between Betweenness and Closeness. In top 40%, top 60% and top 80%, the correlation has been found negative whereas the correlation of Betweenness with Degree and PageRank has found to be strong positive.

With respect to PageRank, the correlation of PageRank was found to be strongly positive with Degree and Betweenness but weak positive with Closeness in all ranking lists.

- **On the basis of Graph VS Traditional ranking indices: interesting findings have been stated as follows:**

With respect to publication, the correlation of Publication with h-index and g-index has found to be strong positive but weak positive with Citation count.

With respect to citations, the correlation of Citation with all non-graph indices has found to be weakly positive in all ranking lists.

With respect to h-index and g-index, it has been observed that both indices are strongly correlated with publications and with each other but weakly correlated with Citations.

- **On the basis of Graph VS Traditional ranking indices: interesting findings have been stated as follows:**

With respect to degree, it is found to be weakly correlated with Closeness and Citations but strongly positive correlated with all other indices in all ranking lists. With respect to Closeness,

the correlation of Closeness with all other indices has been found to be weakly correlated in all ranking lists.

With respect to Betweenness, the correlation between Betweenness and closeness is found to be negative correlated in top 40%, top 60%, and top 80% but strongly positive with all other indices.

With respect to PageRank, it has been found that PageRank is strongly correlated with all Graph and Traditional ranking indices except Closeness and Citations.

With respect to Publications, the correlation of Publications with Citation and Closeness has found to be weak but strong positive with rest of the indices.

With respect to Citations, the correlation of citation with closeness has found negative in top 20% which changes into weak positive in further ranking lists. The correlation remained weak positive with all other indices.

With respect to h-index and g-index, it has been observed that both are strongly correlated with all indices except Closeness and Citations.

In the result, it can be conclude that both type of indices performed almost similar to rank the authors in the ranking lists. The performance of Citation Count from Traditional ranking indices and Closeness from Graph Indices has found to be independent.

4.3 Dependence of awarding societies on graph indices

Our question no 3, “*which awarding society depends upon the graph based indices*” is being answered in this section. The dependence of each society on indices is shown in figure 65. This dependency has been explored by computing the percentage of occurrence of awardees with respect to each awarding society. For this purpose, the results of top 10% of the ranking list has been taken to measure the dependency of awarding society upon graph and non-graph based indices. Following observations will exhibit the contribution of each index.

Table 4-1 Total Awardees Found

Awarding Societies	Total awardees	Awardees in dataset (57150 Authors)	Awardees in dataset (47130 Authors)
AMS	235	196	146
IMU	62	52	36

LMS	226	173	115
NASL	14	5	4

4.3.1 American Mathematics Society

In AMS, from graph based indices, Betweenness performed better than all other graph indices to bring the awardees in top 10% as 48% awardees are present in it. From non-graph indices, h-index performed well in bringing the awardees on top 10% as 57% awardees are present in it. Degree and PageRank performed almost similar in bringing the awardees on top with the around 36% of Awardees are present in top 10% of ranking list. In non-graph indices, citations, publications and g-index performed almost equal with aspect percentage of 53%. The performance of closeness was low as compared to all other indices.

4.3.2 International Mathematics Union

Degree, Betweenness and PageRank performed nearly equal to bring the awardees on top with the percentage of 47% in top 10% ranking lists. The performance of closeness remained low for this society as well. The contribution of all non-graph indices was equal to bring almost 55% of the authors in top 10% ranking lists.

4.3.3 London Mathematics Society

In LMS, Betweenness performed better than other graph indices which brought almost 37% awardees in top 10%. Closeness performed consistently low. In non-graph indices, the performance of citations was low as compared to h-index, g-index and publications. The performance of h-index is still better as it brought 48% awardees in top 10%. G-index also performed.

4.3.4 NASL

All Graph indices performed equally to bring the awardees in the top 10% of ranking lists. In non-graph indices, citations performed better to bring the awardees in top ranking of 10%. Above narrated observations have been presented graphically in figure 4.21. Each trend line shows percentage of awardees in top rankings. Our question no 2 *“which graph index contributed a lot to bring the authors on top”* is also answered in this section. The answer to this question, the performance of Betweenness remained better in bringing the awardees on top.

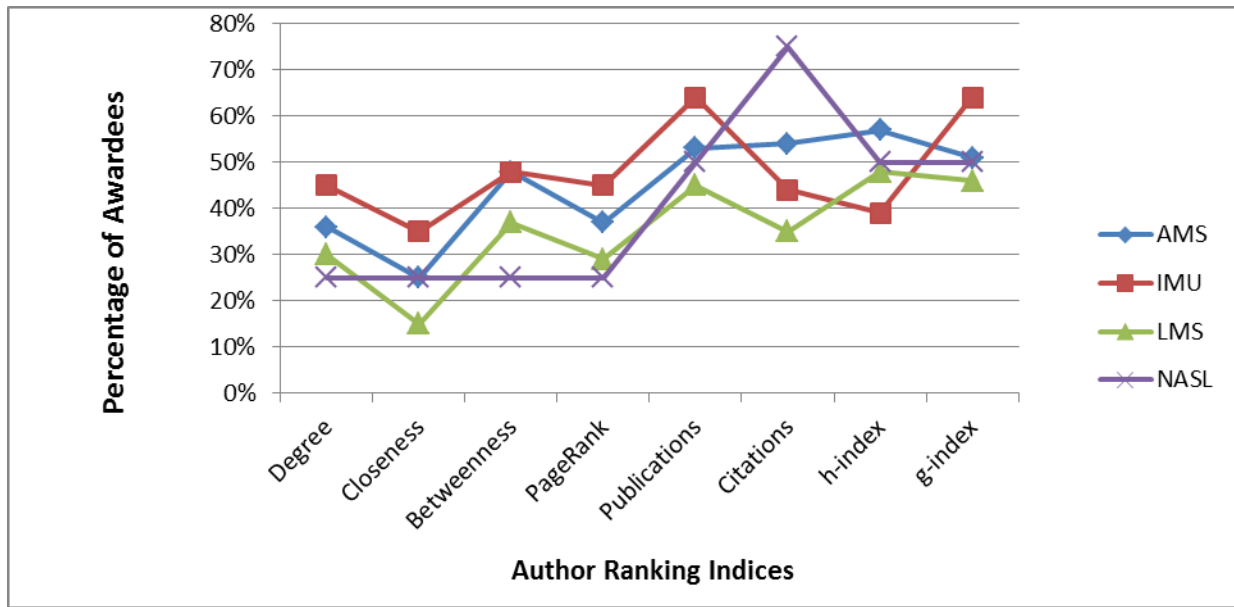


Figure 0.20: Dependence of Awarding Societies on Indices

4.3.5 Awardees from graph based and non-graph based

Awardees are those people whose contributions are acknowledged in any particular domain by prestigious awarding societies. To recognize their efforts, they are honored with prestigious awards. In our research, we have taken the domain of Mathematics and prestigious awardees are found in top 10% to top 100% of the ranking lists. Interesting results have been shown in the figure 4.22. In this part of evaluation, question no 1 *“whether the international prestigious awardees lie in top rankings”*. It can be answered by figure 4.22, it can be clearly seen that awardees are present in top 10%, 20% and so on. The results are very astonishing and the observations have been drawn from figure 66 are following.

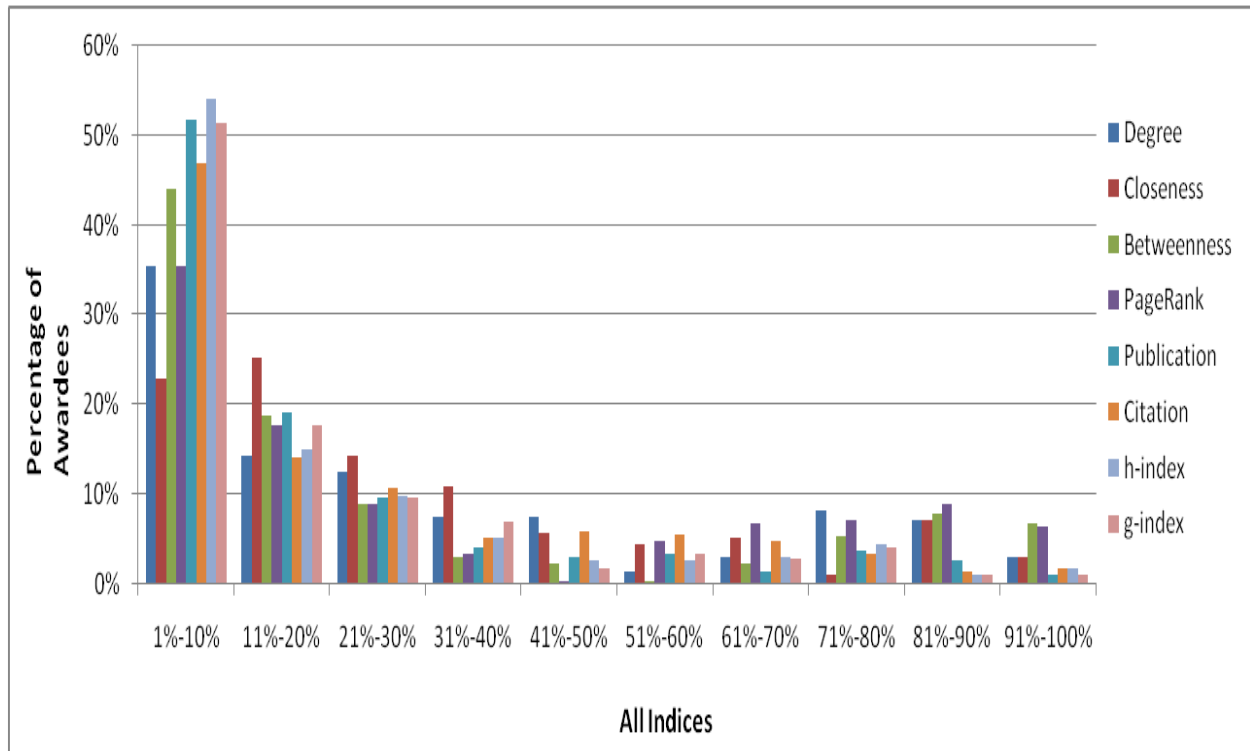


Figure 0.21: Percentage of Awardees by All Indices

In the ranking of top 10% the performance of non-graph indices were better than graph-based indices, however, in top 20%, 30% and so on, graph based indices performed nearly equal to bibliometric indices on bringing the awardees on top. From the dataset of co-author network, we have found 334 authors in which 17 authors were those authors who got multiple awards. So we got 313 unique authors from the dataset of co-authors. Moreover, to answer our question no 2, ***“Which graph index contributed a lot to bring the awardees on top”***, we can consider figure 4.23. Contribution of graph indices can be seen in multiple dimensions to recognize the awardees on top.

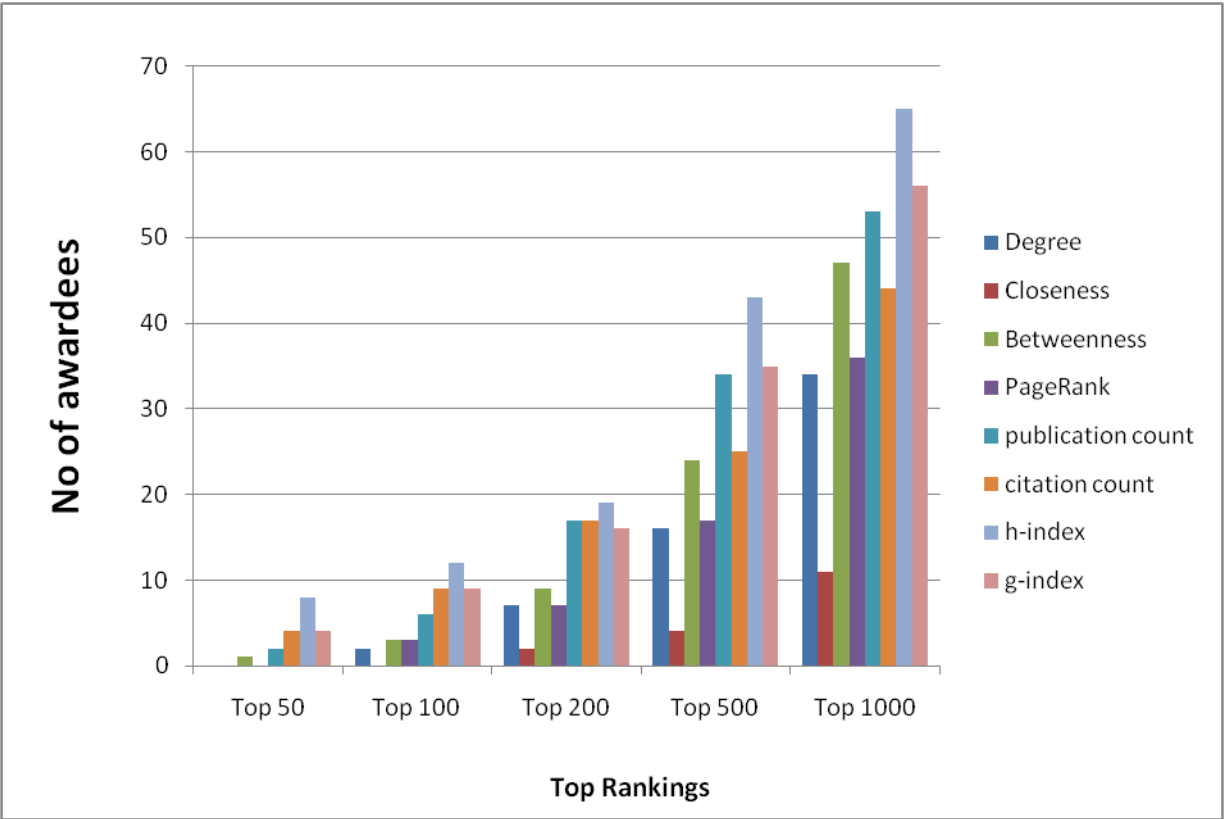


Figure 0.22: Contribution of Each Index Independently

The following observations about figure 4.23 have been drawn:

The performance of all indices is found to be nearly equal to bring the awardees on top. This evaluation may prove beneficial for the fresh graduates or the authors who do not get citations in the early years of their publications may be considered to get faculty positions, short term tenureships, call for supervisions or as an editor in any journal. We have evaluated graph based and traditional ranking indices to compared in a way and found interesting contributions. Citation count has performed less than all other indices which show that rest of the indices performed almost similar with each other. As non-graph indices are also known as bibliometric indices and have been proposed as ranking indices to rank the experts from all fields of studies. In our study, we have taken the domain of Mathematics and evaluated homogenous graph indices with traditional ranking indices to nominate experts from different field of studies whose publications are yet to receive citations.

4.4 Summary of Awardees Experiments

Graph based indices contributed to bring the awardees on top which is the indication that it can perform as equal as traditional bibliometric Indices. From the graph based indices, the performance of Betweenness and Degree has proven to be considerable whereas from traditional indices, Publication Count and H-index performed well to bring the awardees on top. The performance of Closeness has found to be independent. It has brought the awardees on top in bottom level of rankings which can be seen from figure. Another observation which has been drawn from the results is that the overall performance of graph indices remained low with a minor difference. A reason of this ratio, correlation co-efficient of overall co-author network is found to 2.3444, which is low because of less collaboration in dataset. Our indices may perform better in dataset of other domains of study where trend of collaboration is larger and correlation co-efficient of co-author network is found to be higher.

Chapter 5

Conclusion and Future Work

5.1 Conclusion

With the growth of the literature in scientific community, finding the experts and evaluate their expertise has gained considerable attention of the researchers. A decade ago, researchers are busy in finding experts from different fields of study in order to rank them by considering their contributions in their field of study. Evaluators from expert ranking domains emphasizes on individual's publication count to measure his performance but publication count has limitation on its side that it gives equal importance to all work of the author as his publication may involve some articles, blogs or scientific paper. Another index has been introduced to measure the author's performance was citation count. But there are two limitations of citation count. Other authors may cite to criticize the paper and citations requires time to collect for any paper.

To overcome the limitations of publication count and citation count, different researchers introduces various indices to evaluate an author's performance in the community. Among those indices, h-index, g-index, m-co-efficient, and variants of h-index are involved. Every index evaluates the performance of author in its own fashion. But there is still debate on all of these indices in the scientific community that which index is best among all. Another index co-author count has also been considered for the same purpose. But it has also limitation for the new researchers who has no or less collaborators. He needs time to make his impact in the scientific community by publishing articles. Therefore some authors use one type of approaches and some use hybrid approaches to acquire the better results.

These approaches are known as traditional bibliometric indices which have been using by the researchers and declared for author ranking indices in the scientific community. As mentioned earlier, co-author count is the index which is computed by using the no of collaborators of any author to find his contribution in his field of expertise. The motivation behind this thesis is to use

the co-author network to measure the contribution of authors by ranking them with the help of graph centralities. Graph centralities are known as graph indices which have been using by many researchers belonging to the graph network. They have been using these indices to measure the influence of authors or people in their co-author network. In our study, we have been mainly focusing on graph based indices; Degree, Closeness, Betweenness and PageRank to evaluate the performance of authors in the co-author network.

The idea behind this thesis urged us to use four well known graph based indices with four traditional widely used non-graph indices to evaluate the author's rank in their community. For this purpose, we have received the dataset which have been collected and normalized by former student (Imama Syed, 2015). This comprehensive dataset belongs to the field of Mathematics which consists of 57,533 authors along with their 62033 publications. For our experiments, firstly we filtered the dataset and found duplications and ambiguous authors. To correct the dataset, we removed the duplications of authors and remained left with 57513 authors with 62033 publications. Secondly we corrected the ambiguous names of authors whose last names and initials were same but on visiting their profile were found to be different. The whole process was completed manually and found to be accurate after completion then co-authors were extracted and kept separated in other relational database.

From the relational database of co-authors, an edgelist was created which was further imported into a tool "R" by using its igraph library. Then ranking lists were acquired from both types of indices. On creating the edgelist, we were left with 47513 authors who were connected with each other in the co-author network. Out of 57513, almost 10k authors were eliminated who had no collaborations and found to be solo authors of a paper. So after elimination of such authors, their publications were also eliminated and at the final stage we were left with almost 52033 publications. To extract the ranking lists from the traditional bibliometric indices, we used macros scripts in Excel VBA.

After acquiring the ranking lists from both type of indices, our research questions have been tried to answer. The presence of awardees on top rankings has been identified. The **Spearman correlation** between Graph based and Traditional ranking indices Indices have been computed by using Corrgram. The correlation graphs have been shown in chapter 4. The dependency if awarding societies upon Graph based indices and the contribution of graph indices to bring the

awardees on top has been found. According to the results, AMS and LMS are found as those prestigious awarding societies who were more dependent upon Graph based Indices. The Betweenness index has contributed a lot to bring the awardees in top ranking list.

The closeness was found to be negative correlated with all other indices but its contribution to bring the awardees on top has been independent. However, from the NASL society, mostly awardees found to be those awardees who received more than one prestigious award from more than one prestigious awarding society. Based on this fact, it has been concluded that NASL is the society which is found to be more dependent over all indices.

Based on these findings, our evaluation of comparison from both type of indices is found to be accomplished. By considering table 4-1, limitation of co-author network arises is a way that the no of awardees become reduced when they were co-occurred in the form of collaboration. There is a scientific study behind this limitation in which it has been stated that Mathematics domain is such a domain in which the trend of collaboration is comparatively low from other domains of study (Grossman, J. W, 2002). That's why when the dataset was formalized in the form of co-author network, maximum no of awardees were not included, because they had no co-author and won the prizes on individual basis.

By using these finding, we can conclude that our research might be helpful for ranking domains to consider the authors based on their co-author network. Another important findings in our study is based on the assumption that there may be two types of authors. The first author is an author who has published his paper with the author who is not well known in the community. The second author is an author who has published his paper with most renowned authors in the community but its paper has yet to receive citations. This author may deserve to be considering in rankings based on his co-author network. In this perspective, graph centralities helps to find the influential author from the co-author network.

5.2 Future Work

This research is the new direction to rank the authors by using their co-author network for the ranking experts. They can recognize the prestige of author's contribution in the community by measuring the quality of their work with whom they have published the paper. This research can be explored in more directions as follows:

- It is applicable in other fields of studies other than Mathematics.
- We have used unweighted graph, whereas weighted graph can be used to evaluate the credit allocation of authors in a paper as well.
- PageRank and Degree can be used to rank the journals other than ranking the authors. The authors having publication in high ranking journals should be rank higher.
- More Graph centralities can be used for the author ranking purpose e-g; Katz centrality, Eigen Vector, Percolation centrality etc.
- Temporal analysis can be made to rank the authors from their co-author network.

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Appendix A

Results of All Correlations

i) Graph VS Graph Correlation

a) Degree Based Sorted

Degree (Top 20%)	Degree	Closeness	Betweenness	PageRank
Degree	1	0.044266261	0.773966425	0.941299254
Closeness	0.044266261	1	0.037914244	0.046471851
Betweenness	0.773966425	0.037914244	1	0.752888066
PageRank	0.941299254	0.046471851	0.752888066	1

Degree (Top 40%)	Degree	Closeness	Betweenness	PageRank
Degree	1	0.040207792	0.766660118	0.935545688
Closeness	0.040207792	1	0.034652754	0.038538138
Betweenness	0.766660118	0.034652754	1	0.737379118
PageRank	0.935545688	0.038538138	0.737379118	1

Degree (Top 60%)	Degree	Closeness	Betweenness	PageRank
Degree	1	0.025662	0.760748	0.930017
Closeness	0.025662	1	0.025723	0.02206
Betweenness	0.760748	0.025723	1	0.727663
PageRank	0.930017	0.02206	0.727663	1

Degree (Top 80%)	Degree	Closeness	Betweenness	PageRank
Degree	1	0.020271854	0.747511752	0.91728
Closeness	0.020271854	1	0.024260662	0.016445
Betweenness	0.747511752	0.024260662	1	0.710445
PageRank	0.917280078	0.016445332	0.710445247	1

Degree (Top 100%)	Degree	Closeness	Betweenness	PageRank
Degree	1	0.031275497	0.738437201	0.899689171
Closeness	0.031275497	1	0.025590884	0.0222937
Betweenness	0.738437201	0.025590884	1	0.697769129
PageRank	0.899689171	0.0222937	0.697769129	1

b) Closeness Based Sorted

Closeness (Top 20%)	Degree	Closeness	Betweenness	PageRank
Degree	1	0.029242052	0.775954916	0.920009433
Closeness	0.029242	1	0.018782696	0.030246095
Betweenness	0.775955	0.018782696	1	0.740581163
PageRank	0.920009	0.030246095	0.740581163	1

Closeness (Top 40%)	Degree	Closeness	Betweenness	PageRank
Degree	1	0.015093011	0.762454439	0.913412634
Closeness	0.015093	1	0.018815905	0.012426112
Betweenness	0.762454	0.018815905	1	0.732199844
PageRank	0.913413	0.012426112	0.732199844	1

Closeness (Top 60%)	Degree	Closeness	Betweenness	PageRank
Degree	1	0.01277223	0.749154343	0.907825911
Closeness	0.01277223	1	0.014509967	0.010467922
Betweenness	0.749154343	0.014509967	1	0.712576578
PageRank	0.907825911	0.010467922	0.712576578	1

Closeness (Top 80%)	Degree	Closeness	Betweenness	PageRank
Degree	1	0.018254072	0.733171895	0.903518455
Closeness	0.018254072	1	0.020070227	0.011072027
Betweenness	0.733171895	0.020070227	1	0.695071809
PageRank	0.903518455	0.011072027	0.695071809	1

Closeness (Top 100%)	Degree	Closeness	Betweenness	PageRank
Degree	1	0.031275462	0.738437201	0.899689215
Closeness	0.031275462	1	0.025590859	0.022293691
Betweenness	0.738437201	0.025590859	1	0.697769129
PageRank	0.899689215	0.022293691	0.697769129	1

c) **Betweenness Based Sorted**

Betweenness (Top 20%)	Degree	Closeness	Betweenness	PageRank
Degree	1	0.031374699	0.760337874	0.958235149
Closeness	0.031374699	1	0.025447534	0.030487905
Betweenness	0.760337874	0.025447534	1	0.744977454
PageRank	0.958235149	0.030487905	0.744977454	1

Betweenness (Top 40%)	Degree	Closeness	Betweenness	PageRank
Degree	1	-0.17136	0.754043	0.934377
Closeness	-0.17136	1	-0.06851	-0.18866
Betweenness	0.754043	-0.06851	1	0.723096
PageRank	0.934377	-0.18866	0.723096	1

Betweenness (Top 60%)	Degree	Closeness	Betweenness	PageRank
Degree	1	-0.25276	0.748998	0.923658
Closeness	-0.25276	1	-0.11349	-0.2695
Betweenness	0.748998	-0.11349	1	0.714017
PageRank	0.923658	-0.2695	0.714017	1

Betweenness (Top 80%)	Degree	Closeness	Betweenness	PageRank
Degree	1	-0.06199	0.744106	0.912403
Closeness	-0.06199	1	-0.01491	-0.06336
Betweenness	0.744106	-0.01491	1	0.7068
PageRank	0.912403	-0.06336	0.7068	1

Betweenness (Top100%)	Degree	Closeness	Betweenness	PageRank
Degree	1	0.031275497	0.738437201	0.899689171
Closeness	0.031275497	1	0.025590884	0.0222937
Betweenness	0.738437201	0.025590884	1	0.697769129
PageRank	0.899689171	0.0222937	0.697769129	1

d) PageRank Based Sorted

PageRank (Top 20%)	Degree	Closeness	Betweenness	PageRank
Degree	1	0.048814176	0.769106587	0.93586828
Closeness	0.048814176	1	0.037885677	0.044199246
Betweenness	0.769106587	0.037885677	1	0.76361062
PageRank	0.93586828	0.044199246	0.76361062	1

PageRank(Top 40%)	Degree	Closeness	Betweenness	PageRank
Degree	1	0.001643	0.748876	0.940179
Closeness	0.001643	1	0.019462	0.013978
Betweenness	0.748876	0.019462	1	0.761427
PageRank	0.940179	0.013978	0.761427	1

PageRank (Top 60%)	Degree	Closeness	Betweenness	PageRank
Degree	1	0.049185	0.74726	0.934689
Closeness	0.049185	1	0.034533	0.048906
Betweenness	0.74726	0.034533	1	0.759692
PageRank	0.934689	0.048906	0.759692	1

PageRank (Top 80%)	Degree	Closeness	Betweenness	PageRank
Degree	1	0.039848	0.744199	0.913767
Closeness	0.039848	1	0.029845	0.036112
Betweenness	0.744199	0.029845	1	0.73962
PageRank	0.913767	0.036112	0.73962	1

PageRank (Top 100%)	Degree	Closeness	Betweenness	PageRank
Degree	1	0.031275497	0.738437201	0.899689171
Closeness	0.031275497	1	0.025590884	0.0222937
Betweenness	0.738437201	0.025590884	1	0.697769129
PageRank	0.899689171	0.0222937	0.697769129	1

ii) Graph VS Traditional Indices Correlation
a) Publication Count Based

Pub (Top 20%)	g.index	h.index	Citations	Publications
g.index	1	0.920716685	0.220686062	0.975272378
h.index	0.920716685	1	0.300028954	0.880155379
Citations	0.220686062	0.300028954	1	0.199116471
Publications	0.975272378	0.880155379	0.199116471	1

Pub (Top 40%)	g.index	h.index	Citations	Publications
g.index	1	0.938255	0.159035	0.980283
h.index	0.938255	1	0.203198	0.905159
Citations	0.159035	0.203198	1	0.146026
Publications	0.980283	0.905159	0.146026	1

Pub (Top 60%)	g.index	h.index	Citations	Publications
g.index	1	0.948124	0.189051	0.983226
h.index	0.948124	1	0.229929	0.919743
Citations	0.189051	0.229929	1	0.176598
Publications	0.983226	0.919743	0.176598	1

Pub (Top 80%)	g.index	h.index	Citations	Publications
g.index	1	0.951936	0.217175	0.984337
h.index	0.951936	1	0.257984	0.92548
Citations	0.217175	0.257984	1	0.204577
Publications	0.984337	0.92548	0.204577	1

Pub (Top 100%)	g.index	h.index	Citations	Publications
g.index	1	0.950893618	0.234825802	0.984427676
h.index	0.950893618	1	0.276067231	0.925063167
Citations	0.234825802	0.276067231	1	0.221875278
Publications	0.984427676	0.925063167	0.221875278	1

b) Citation Count Based

Citation (Top 20%)	g.Index	h.Index	Citations	Publications
g.Index	1	0.951232	0.127599	0.98714
h.Index	0.951232	1	0.162509	0.927163
Citations	0.127599	0.162509	1	0.119817
Publications	0.98714	0.927163	0.119817	1

Citation (Top 40%)	g.Index	h.Index	Citations	Publications
g.Index	1	0.95209	0.171715	0.986522
h.Index	0.95209	1	0.20872	0.927898
Citations	0.171715	0.20872	1	0.161887
Publications	0.986522	0.927898	0.161887	1

Citation (Top 60%)	g.Index	h.Index	Citations	Publications
g.Index	1	0.953033	0.19927	0.986646
h.Index	0.953033	1	0.237684	0.929352
Citations	0.19927	0.237684	1	0.188508
Publications	0.986646	0.929352	0.188508	1

Citation (Top 80%)	g.Index	h.Index	Citations	Publications
g.Index	1	0.953389	0.219007	0.986212
h.Index	0.953389	1	0.258828	0.929413
Citations	0.219007	0.258828	1	0.207336
Publications	0.986212	0.929413	0.207336	1

Citation (Top 100%)	g.Index	h.Index	Citations	Publications
g.Index	1	0.950894	0.234826	0.984428
h.Index	0.950894	1	0.276067	0.925063
Citations	0.234826	0.276067	1	0.221875
Publications	0.984428	0.925063	0.221875	1

c) H-index Based

h-index(Top 20%)	g.index	h.index	Citations	Publications
g.index	1	0.923696	0.224909	0.977372
h.index	0.923696	1	0.30459	0.886811
Citations	0.224909	0.30459	1	0.204474
Publications	0.977372	0.886811	0.204474	1

h-index(Top 40%)	g.index	h.index	Citations	Publications
g.index	1	0.938127	0.229433	0.98188
h.index	0.938127	1	0.286794	0.907715
Citations	0.229433	0.286794	1	0.213451
Publications	0.98188	0.907715	0.213451	1

h-index(Top 60%)	g.index	h.index	Citations	Publications
g.index	1	0.948072	0.236725	0.98449
h.index	0.948072	1	0.284658	0.921527
Citations	0.236725	0.284658	1	0.222779
Publications	0.98449	0.921527	0.222779	1

h-index(Top 80%)	g.index	h.index	Citations	Publications
g.index	1	0.951942	0.232707	0.985442
h.index	0.951942	1	0.275782	0.926907
Citations	0.232707	0.275782	1	0.219917
Publications	0.985442	0.926907	0.219917	1

h-index(Top 100%)	g.index	h.index	Citations	Publications
g.index	1	0.950894	0.234826	0.984428
h.index	0.950894	1	0.276067	0.925063
Citations	0.234826	0.276067	1	0.221875
Publications	0.984428	0.925063	0.221875	1

d) G-index Based

g-index(Top 20%)	g.Index	h.Index	Citations	Publications
g.Index	1	0.919254021	0.233200013	0.976781419
h.Index	0.919254021	1	0.314392264	0.881351341
Citations	0.233200013	0.314392264	1	0.211868264
Publications	0.976781419	0.881351341	0.211868264	1

g-index(Top 40%)	g.Index	h.Index	Citations	Publications
g.Index	1	0.937883	0.229541	0.98188
h.Index	0.937883	1	0.286909	0.907467
Citations	0.229541	0.286909	1	0.213554
Publications	0.98188	0.907467	0.213554	1

g-index(Top 60%)	g.Index	h.Index	Citations	Publications
g.Index	1	0.946542	0.238658	0.98449
h.Index	0.946542	1	0.287039	0.919994
Citations	0.238658	0.287039	1	0.224627
Publications	0.98449	0.919994	0.224627	1

g-index(Top 80%)	g.Index	h.Index	Citations	Publications
g.Index	1	0.949657	0.235402	0.985473
h.Index	0.949657	1	0.27929	0.924668
Citations	0.235402	0.27929	1	0.222511
Publications	0.985473	0.924668	0.222511	1

g-index(Top 100%)	g.Index	h.Index	Citations	Publications
g.Index	1	0.950894	0.234826	0.984428
h.Index	0.950894	1	0.276067	0.925063
Citations	0.234826	0.276067	1	0.221875
Publications	0.984428	0.925063	0.221875	1

iii) Graph VS Traditional Correlation

a) Degree Based Sorted

Degree(Top 20%)	Degree	Closeness	Betweenness	PageRank	g.Index	h.Index	Citations	Publications
Degree	1	0.044266	0.773966	0.941299	0.763524	0.672075	0.168308	0.770534998
Closeness	0.044266	1	0.037914	0.046472	0.063168	0.062152	0.007215	0.05736566
Betweenness	0.773966	0.037914	1	0.752888	0.63101	0.528468	0.15511	0.630140218
PageRank	0.941299	0.046472	0.752888	1	0.805543	0.73332	0.207987	0.804204817
g.Index	0.763524	0.063168	0.63101	0.805543	1	0.936448	0.262537	0.978964387
h.Index	0.672075	0.062152	0.528468	0.73332	0.936448	1	0.333806	0.901428109
Citations	0.168308	0.007215	0.15511	0.207987	0.262537	0.333806	1	0.241445358
Publications	0.770535	0.057366	0.63014	0.804205	0.978964	0.901428	0.241445	1

Degree(Top 40%)	Degree	Closeness	Betweenness	PageRank	g.Index	h.Index	Citations	Publications
Degree	1	0.044266	0.773966	0.941299	0.763524	0.672075	0.168308	0.770535
Closeness	0.044266	1	0.037914	0.046472	0.063168	0.062152	0.007215	0.057366
Betweenness	0.773966	0.037914	1	0.752888	0.63101	0.528468	0.15511	0.63014
PageRank	0.941299	0.046472	0.752888	1	0.805543	0.73332	0.207987	0.804205
g.Index	0.763524	0.063168	0.63101	0.805543	1	0.936448	0.262537	0.978964
h.Index	0.672075	0.062152	0.528468	0.73332	0.936448	1	0.333806	0.901428
Citations	0.168308	0.007215	0.15511	0.207987	0.262537	0.333806	1	0.241445
Publications	0.770535	0.057366	0.63014	0.804205	0.978964	0.901428	0.241445	1

Degree(Top 60%)	Degree	Closeness	Betweenness	PageRank	g.Index	h.Index	Citations	Publications
Degree	1	0.025662	0.760748	0.930017	0.796123	0.727198	0.179901	0.80137
Closeness	0.025662	1	0.025723	0.02206	0.042609	0.041198	0.000291	0.03968
Betweenness	0.760748	0.025723	1	0.727663	0.636349	0.542278	0.148073	0.639419
PageRank	0.930017	0.02206	0.727663	1	0.812883	0.757632	0.205395	0.812699
g.Index	0.796123	0.042609	0.636349	0.812883	1	0.94989	0.247946	0.983988
h.Index	0.727198	0.041198	0.542278	0.757632	0.94989	1	0.295552	0.92285
Citations	0.179901	0.000291	0.148073	0.205395	0.247946	0.295552	1	0.233425
Publications	0.80137	0.03968	0.639419	0.812699	0.983988	0.92285	0.233425	1

Degree(Top 80%)	Degree	Closeness	Betweenness	PageRank	g.Index	h.Index	Citations	Publications
Degree	1	0.020272	0.747512	0.91728	0.780184	0.714108	0.184931	0.784577
Closeness	0.020272	1	0.024261	0.016445	0.043438	0.042679	0.000131	0.040503
Betweenness	0.747512	0.024261	1	0.710445	0.6307	0.53582	0.148467	0.634393
PageRank	0.91728	0.016445	0.710445	1	0.783811	0.728346	0.204068	0.783786
g.Index	0.780184	0.043438	0.6307	0.783811	1	0.949492	0.248894	0.98398
h.Index	0.714108	0.042679	0.53582	0.728346	0.949492	1	0.294486	0.922699
Citations	0.184931	0.000131	0.148467	0.204068	0.248894	0.294486	1	0.23473
Publications	0.784577	0.040503	0.634393	0.783786	0.98398	0.922699	0.23473	1

Degree(Top 100%)	Degree	Closeness	Betweenness	PageRank	g.Index	h.Index	Citations	Publications
Degree	1	0.031275	0.738437	0.899689	0.790708	0.73028	0.176751	0.794255
Closeness	0.031275	1	0.025591	0.022294	0.048635	0.048774	0.001234	0.04574
Betweenness	0.738437	0.025591	1	0.697769	0.631082	0.537383	0.14059	0.635169
PageRank	0.899689	0.022294	0.697769	1	0.776281	0.72347	0.190251	0.77638
g.Index	0.790708	0.048635	0.631082	0.776281	1	0.950894	0.234826	0.984428
h.Index	0.73028	0.048774	0.537383	0.72347	0.950894	1	0.276067	0.925063
Citations	0.176751	0.001234	0.14059	0.190251	0.234826	0.276067	1	0.221875
Publications	0.794255	0.04574	0.635169	0.77638	0.984428	0.925063	0.221875	1

b) Closeness Based Sorted

Closeness (Top 20%)	Degree	Closeness	Betweenness	PageRank	g-index	h-index	citations	Publications
Degree	1	0.029242	0.775955	0.920009	0.804191	0.729678	0.247212	0.806410337
Closeness	0.029242	1	0.018783	0.030246	0.039064	0.043475	0.024884	0.036751398
Betweenness	0.775955	0.018783	1	0.740581	0.661011	0.553003	0.206818	0.663321902
PageRank	0.920009	0.030246	0.740581	1	0.798966	0.732325	0.263618	0.799661132
g-index	0.804191	0.039064	0.661011	0.798966	1	0.948382	0.331251	0.99167773
h-index	0.729678	0.043475	0.553003	0.732325	0.948382	1	0.381546	0.933646411
citations	0.247212	0.024884	0.206818	0.263618	0.331251	0.381546	1	0.320988173
Publications	0.80641	0.036751	0.663322	0.799661	0.991678	0.933646	0.320988	1

Closeness (Top 40%)	Degree	Closeness	Betweenness	PageRank	g.index	h.index	Citations	Publications
Degree	1	0.015306	0.762454	0.913413	0.798792	0.725523	0.224309	0.804999
Closeness	0.015306	1	0.019199	0.012668	0.033893	0.037436	0.016118	0.031484
Betweenness	0.762454	0.019199	1	0.7322	0.66416	0.558002	0.197816	0.664035
PageRank	0.913413	0.012668	0.7322	1	0.790141	0.725489	0.241334	0.79194
g.index	0.798792	0.033893	0.66416	0.790141	1	0.949037	0.305256	0.985387
h.index	0.725523	0.037436	0.558002	0.725489	0.949037	1	0.35312	0.925572
Citations	0.224309	0.016118	0.197816	0.241334	0.305256	0.35312	1	0.291056
Publications	0.804999	0.031484	0.664035	0.79194	0.985387	0.925572	0.291056	1

Closeness (Top 60%)	Degree	Closeness	Betweenness	PageRank	g.index	h.index	Citations	Publications
Degree	1	0.012772	0.749154	0.907826	0.799168	0.737241	0.197704	0.80201
Closeness	0.012772	1	0.01451	0.010468	0.020311	0.017932	0.003138	0.020273
Betweenness	0.749154	0.01451	1	0.712577	0.654191	0.5594	0.16879	0.651872
PageRank	0.907826	0.010468	0.712577	1	0.788031	0.733627	0.211843	0.787601
g.index	0.799168	0.020311	0.654191	0.788031	1	0.950854	0.257951	0.986567
h.index	0.737241	0.017932	0.5594	0.733627	0.950854	1	0.300901	0.928755
Citations	0.197704	0.003138	0.16879	0.211843	0.257951	0.300901	1	0.246028
Publications	0.80201	0.020273	0.651872	0.787601	0.986567	0.928755	0.246028	1

Closeness (Top 80%)	Degree	Closeness	Betweenness	PageRank	g.index	h.index	Citations	Publications
Degree	1	0.018254	0.733172	0.903518	0.794007	0.734861	0.188262	0.799364
Closeness	0.018254	1	0.02007	0.011072	0.031088	0.029973	-0.00047	0.029049
Betweenness	0.733172	0.02007	1	0.695072	0.632826	0.542611	0.153467	0.637661
PageRank	0.903518	0.011072	0.695072	1	0.781344	0.730185	0.201919	0.782573
g.index	0.794007	0.031088	0.632826	0.781344	1	0.950778	0.246264	0.984597
h.index	0.734861	0.029973	0.542611	0.730185	0.950778	1	0.288893	0.925247
Citations	0.188262	-0.00047	0.153467	0.201919	0.246264	0.288893	1	0.232865
Publications	0.799364	0.029049	0.637661	0.782573	0.984597	0.925247	0.232865	1

Closeness (Top 100%)	Degree	Closeness	Betweenness	PageRank	g.index	h.index	Citations	Publications
Degree	1	0.031275	0.738437	0.899689	0.790708	0.73028	0.176751	0.794255
Closeness	0.031275	1	0.025591	0.022294	0.048635	0.048774	0.001234	0.04574
Betweenness	0.738437	0.025591	1	0.697769	0.631082	0.537383	0.14059	0.635169
PageRank	0.899689	0.022294	0.697769	1	0.776281	0.72347	0.190251	0.776379
g.index	0.790708	0.048635	0.631082	0.776281	1	0.950894	0.234826	0.984428
h.index	0.73028	0.048774	0.537383	0.72347	0.950894	1	0.276067	0.925063
Citations	0.176751	0.001234	0.14059	0.190251	0.234826	0.276067	1	0.221875
Publications	0.794255	0.04574	0.635169	0.776379	0.984428	0.925063	0.221875	1

c) Betweenness Based Sorted

Betweenness(Top 20%)	Degree	Closeness	Betweenness	PageRank	g.index	h.index	Citations	Publications
Degree	1	0.01855	0.625217	0.913995	0.60133	0.575084	0.368373	0.604286
Closeness	0.01855	1	0.027632	0.011895	0.036437	0.033107	0.00388	0.035735
Betweenness	0.625217	0.027632	1	0.624292	0.538753	0.521528	0.356514	0.537875
PageRank	0.913995	0.011895	0.624292	1	0.63397	0.611776	0.408031	0.635693
g.index	0.60133	0.036437	0.538753	0.63397	1	0.942912	0.49673	0.991459
h.index	0.575084	0.033107	0.521528	0.611776	0.942912	1	0.591791	0.930014
Citations	0.368373	0.00388	0.356514	0.408031	0.49673	0.591791	1	0.474771
Publications	0.604286	0.035735	0.537875	0.635693	0.991459	0.930014	0.474771	1

Betweenness(Top 40%)	Degree	Closeness	Betweenness	PageRank	g.index	h.index	Citations	Publications
Degree	1	-0.17136	0.754043	0.934377	0.798996	0.732583	0.1878	0.802231
Closeness	-0.17136	1	-0.06851	-0.18866	-0.17291	-0.20177	-0.06508	-0.16782
Betweenness	0.754043	-0.06851	1	0.723096	0.633702	0.536679	0.153043	0.63573
PageRank	0.934377	-0.18866	0.723096	1	0.804411	0.74761	0.210095	0.80327
g.index	0.798996	-0.17291	0.633702	0.804411	1	0.945278	0.259542	0.98254
h.index	0.732583	-0.20177	0.536679	0.74761	0.945278	1	0.315848	0.915819
Citations	0.1878	-0.06508	0.153043	0.210095	0.259542	0.315848	1	0.242789
Publications	0.802231	-0.16782	0.63573	0.80327	0.98254	0.915819	0.242789	1

Betweenness(Top 60%)	Degree	Closeness	Betweenness	PageRank	g.index	h.index	Citations	Publications
Degree	1	-0.25276	0.748998	0.923658	0.803481	0.742036	0.196664	0.806598
Closeness	-0.25276	1	-0.11349	-0.2695	-0.2611	-0.29457	-0.09101	-0.2535
Betweenness	0.748998	-0.11349	1	0.714017	0.635144	0.540803	0.156922	0.638334
PageRank	0.923658	-0.2695	0.714017	1	0.800942	0.748114	0.215135	0.800178
g.index	0.803481	-0.2611	0.635144	0.800942	1	0.949267	0.262628	0.983914
h.index	0.742036	-0.29457	0.540803	0.748114	0.949267	1	0.312669	0.922181
Citations	0.196664	-0.09101	0.156922	0.215135	0.262628	0.312669	1	0.247345
Publications	0.806598	-0.2535	0.638334	0.800178	0.983914	0.922181	0.247345	1

Betweenness(Top 80%)	Degree	Closeness	Betweenness	PageRank	g.index	h.index	Citations	Publications
Degree	1	-0.06199	0.744106	0.912403	0.797431	0.736714	0.182593	0.800818
Closeness	-0.06199	1	-0.01491	-0.06336	-0.03921	-0.04772	-0.02249	-0.03876
Betweenness	0.744106	-0.01491	1	0.7068	0.633839	0.540244	0.145575	0.637401
PageRank	0.912403	-0.06336	0.7068	1	0.790769	0.738341	0.198571	0.790367
g.index	0.797431	-0.03921	0.633839	0.790769	1	0.950502	0.242666	0.9844
h.index	0.736714	-0.04772	0.540244	0.738341	0.950502	1	0.286476	0.924349
Citations	0.182593	-0.02249	0.145575	0.198571	0.242666	0.286476	1	0.229082
Publications	0.800818	-0.03876	0.637401	0.790367	0.9844	0.924349	0.229082	1

Betweenness(Top 100%)	Degree	Closeness	Betweenness	PageRank	g.index	h.index	Citations	Publications
Degree	1	0.031275	0.738437	0.899689	0.790708	0.73028	0.176751	0.794255
Closeness	0.031275	1	0.025591	0.022294	0.048635	0.048774	0.001234	0.04574
Betweenness	0.738437	0.025591	1	0.697769	0.631082	0.537383	0.14059	0.635169
PageRank	0.899689	0.022294	0.697769	1	0.776281	0.72347	0.190251	0.77638
g.index	0.790708	0.048635	0.631082	0.776281	1	0.950894	0.234826	0.984428
h.index	0.73028	0.048774	0.537383	0.72347	0.950894	1	0.276067	0.925063
Citations	0.176751	0.001234	0.14059	0.190251	0.234826	0.276067	1	0.221875
Publications	0.794255	0.04574	0.635169	0.77638	0.984428	0.925063	0.221875	1

d) PageRank Based Sorted

PR(Top 20%)	Degree	Closeness	Betweenness	PageRank	g.index	h.index	Citations	Publications
Degree	1	0.048814	0.769107	0.935868	0.777326	0.690032	0.158902	0.78213
Closeness	0.048814	1	0.037886	0.044199	0.057792	0.054971	0.006447	0.051889
Betweenness	0.769107	0.037886	1	0.763611	0.639206	0.536316	0.146608	0.637331
PageRank	0.935868	0.044199	0.763611	1	0.805379	0.725224	0.189112	0.805119
g.index	0.777326	0.057792	0.639206	0.805379	1	0.934551	0.242331	0.978364
h.index	0.690032	0.054971	0.536316	0.725224	0.934551	1	0.312871	0.898709
Citations	0.158902	0.006447	0.146608	0.189112	0.242331	0.312871	1	0.221983
Publications	0.78213	0.051889	0.637331	0.805119	0.978364	0.898709	0.221983	1

PR(Top 40%)	Degree	Closeness	Betweenness	PageRank	g.index	h.index	Citations	Publications
Degree	1	0.001643	0.748876	0.940179	0.816306	0.758124	0.19261	0.817638
Closeness	0.001643	1	0.019462	0.013978	0.022149	0.016794	-0.0075	0.01945
Betweenness	0.748876	0.019462	1	0.761427	0.6449	0.550472	0.155481	0.646272
PageRank	0.940179	0.013978	0.761427	1	0.838218	0.777217	0.211742	0.837465
g.index	0.816306	0.022149	0.6449	0.838218	1	0.948467	0.255378	0.982937
h.index	0.758124	0.016794	0.550472	0.777217	0.948467	1	0.308092	0.91966
Citations	0.19261	-0.0075	0.155481	0.211742	0.255378	0.308092	1	0.239125
Publications	0.817638	0.01945	0.646272	0.837465	0.982937	0.91966	0.239125	1

PR (Top 60%)	Degree	Closeness	Betweenness	PageRank	g.index	h.index	Citations	Publications
Degree	1	0.049185	0.74726	0.934689	0.816931	0.760372	0.187459	0.818795
Closeness	0.049185	1	0.034533	0.048906	0.06268	0.062878	0.002095	0.058922
Betweenness	0.74726	0.034533	1	0.759692	0.644631	0.552428	0.149791	0.647016
PageRank	0.934689	0.048906	0.759692	1	0.840468	0.781746	0.205362	0.840342
g.index	0.816931	0.06268	0.644631	0.840468	1	0.951197	0.244647	0.984018
h.index	0.760372	0.062878	0.552428	0.781746	0.951197	1	0.290688	0.924269
Citations	0.187459	0.002095	0.149791	0.205362	0.244647	0.290688	1	0.230282
Publications	0.818795	0.058922	0.647016	0.840342	0.984018	0.924269	0.230282	1

PR (Top 80%)	Degree	Closeness	Betweenness	PageRank	g.index	h.index	Citations	Publications
Degree	1	0.039848	0.744199	0.913767	0.800775	0.740841	0.179678	0.804168
Closeness	0.039848	1	0.029845	0.036112	0.054763	0.054926	0.002368	0.051725
Betweenness	0.744199	0.029845	1	0.73962	0.6366	0.543722	0.144282	0.640139
PageRank	0.913767	0.036112	0.73962	1	0.81642	0.758427	0.196573	0.817189
g.index	0.800775	0.054763	0.6366	0.81642	1	0.95115	0.241323	0.984405
h.index	0.740841	0.054926	0.543722	0.758427	0.95115	1	0.285311	0.924999
Citations	0.179678	0.002368	0.144282	0.196573	0.241323	0.285311	1	0.227702
Publications	0.804168	0.051725	0.640139	0.817189	0.984405	0.924999	0.227702	1

PR (Top 100%)	Degree	Closeness	Betweenness	PageRank	g.index	h.index	Citations	Publications
Degree	1	0.031275	0.738437	0.899689	0.790708	0.73028	0.176751	0.794255
Closeness	0.031275	1	0.025591	0.022294	0.048635	0.048774	0.001234	0.04574
Betweenness	0.738437	0.025591	1	0.697769	0.631082	0.537383	0.14059	0.635169
PageRank	0.899689	0.022294	0.697769	1	0.776281	0.72347	0.190251	0.77638
g.index	0.790708	0.048635	0.631082	0.776281	1	0.950894	0.234826	0.984428
h.index	0.73028	0.048774	0.537383	0.72347	0.950894	1	0.276067	0.925063
Citations	0.176751	0.001234	0.14059	0.190251	0.234826	0.276067	1	0.221875
Publications	0.794255	0.04574	0.635169	0.77638	0.984428	0.925063	0.221875	1

e) Publication Count Based

Pub(Top 20%)	Degree	Closeness	Betweenness	PageRank	g.index	h.index	Citations	Publications
Degree	1	0.028986	0.760031	0.946596	0.752753	0.664536	0.144116	0.755006
Closeness	0.028986	1	0.027441	0.026582	0.041822	0.037287	-0.00251	0.035428
Betweenness	0.760031	0.027441	1	0.73753	0.632732	0.524659	0.133922	0.629328
PageRank	0.946596	0.026582	0.73753	1	0.764649	0.688204	0.172306	0.761029
g.index	0.752753	0.041822	0.632732	0.764649	1	0.920717	0.220686	0.975272
h.index	0.664536	0.037287	0.524659	0.688204	0.920717	1	0.300029	0.880155
Citations	0.144116	-0.00251	0.133922	0.172306	0.220686	0.300029	1	0.199116
Publications	0.755006	0.035428	0.629328	0.761029	0.975272	0.880155	0.199116	1

Pub(Top 40%)	Degree	Closeness	Betweenness	PageRank	g.index	h.index	Citations	Publications
Degree	1	0.028378	0.750829	0.933204	0.770822	0.698321	0.113901	0.774258
Closeness	0.028378	1	0.025245	0.020671	0.040513	0.036867	-0.01226	0.036369
Betweenness	0.750829	0.025245	1	0.719868	0.632714	0.532973	0.107307	0.633762
PageRank	0.933204	0.020671	0.719868	1	0.774649	0.712195	0.134415	0.773363
g.index	0.770822	0.040513	0.632714	0.774649	1	0.938255	0.159035	0.980283
h.index	0.698321	0.036867	0.532973	0.712195	0.938255	1	0.203198	0.905159
Citations	0.113901	-0.01226	0.107307	0.134415	0.159035	0.203198	1	0.146026
Publications	0.774258	0.036369	0.633762	0.773363	0.980283	0.905159	0.146026	1

Pub(Top 60%)	Degree	Closeness	Betweenness	PageRank	g.index	h.index	Citations	Publications
Degree	1	0.041696	0.747342	0.92348	0.783173	0.71833	0.138416	0.786731
Closeness	0.041696	1	0.030868	0.033304	0.0597	0.059686	-0.00154	0.055876
Betweenness	0.747342	0.030868	1	0.71548	0.630889	0.535849	0.121186	0.633496
PageRank	0.92348	0.033304	0.71548	1	0.781542	0.724889	0.156787	0.781047
g.index	0.783173	0.0597	0.630889	0.781542	1	0.948124	0.189051	0.983226
h.index	0.71833	0.059686	0.535849	0.724889	0.948124	1	0.229929	0.919743
Citations	0.138416	-0.00154	0.121186	0.156787	0.189051	0.229929	1	0.176598
Publications	0.786731	0.055876	0.633496	0.781047	0.983226	0.919743	0.176598	1

Pub(Top 80%)	Degree	Closeness	Betweenness	PageRank	g.index	h.index	Citations	Publications
Degree	1	0.039146	0.743123	0.912038	0.788922	0.72841	0.161653	0.7923
Closeness	0.039146	1	0.029723	0.030079	0.058253	0.058654	0.002889	0.054902
Betweenness	0.743123	0.029723	1	0.707142	0.63121	0.538671	0.133059	0.634393
PageRank	0.912038	0.030079	0.707142	1	0.781238	0.728635	0.177704	0.780852
g.index	0.788922	0.058253	0.63121	0.781238	1	0.951936	0.217175	0.984337
h.index	0.72841	0.058654	0.538671	0.728635	0.951936	1	0.257984	0.92548
Citations	0.161653	0.002889	0.133059	0.177704	0.217175	0.257984	1	0.204577
Publications	0.7923	0.054902	0.634393	0.780852	0.984337	0.92548	0.204577	1

Pub(Top 100%)	Degree	Closeness	Betweenness	PageRank	g.index	h.index	Citations	Publications
Degree	1	0.031275	0.738437	0.899689	0.790708	0.73028	0.176751	0.794254904
Closeness	0.031275	1	0.025591	0.022294	0.048635	0.048774	0.001234	0.045739938
Betweenness	0.738437	0.025591	1	0.697769	0.631082	0.537383	0.14059	0.635168783
PageRank	0.899689	0.022294	0.697769	1	0.776281	0.72347	0.190251	0.77637953
g.index	0.790708	0.048635	0.631082	0.776281	1	0.950894	0.234826	0.984427676
h.index	0.73028	0.048774	0.537383	0.72347	0.950894	1	0.276067	0.925063167
Citations	0.176751	0.001234	0.14059	0.190251	0.234826	0.276067	1	0.221875278
Publications	0.794255	0.04574	0.635169	0.77638	0.984428	0.925063	0.221875	1

f) Citation Count Based

Cit (Top 20%)	Degree	Closeness	Betweenness	PageRank	g.Index	h.Index	Citations	Publications
Degree	1	0.058399	0.793334	0.957648	0.820616	0.747376	0.079927	0.821178
Closeness	0.058399	1	0.040265	0.051601	0.069075	0.071058	-0.00297	0.063541
Betweenness	0.793334	0.040265	1	0.771279	0.654226	0.547721	0.077952	0.659351
PageRank	0.957648	0.051601	0.771279	1	0.830085	0.764368	0.094956	0.827823
g.Index	0.820616	0.069075	0.654226	0.830085	1	0.951232	0.127599	0.98714
h.Index	0.747376	0.071058	0.547721	0.764368	0.951232	1	0.162509	0.927163
Citations	0.079927	-0.00297	0.077952	0.094956	0.127599	0.162509	1	0.119817
Publications	0.821178	0.063541	0.659351	0.827823	0.98714	0.927163	0.119817	1

Cit (Top 40%)	Degree	Closeness	Betweenness	PageRank	g.Index	h.Index	Citations	Publications
Degree	1	0.049684	0.765701	0.72258	0.63256	0.627618	0.189344	0.632695
Closeness	0.049684	1	0.085513	0.030831	0.102128	0.098715	0.024678	0.102345
Betweenness	0.765701	0.085513	1	0.709096	0.818162	0.811205	0.219517	0.818344
PageRank	0.72258	0.030831	0.709096	1	0.589944	0.585452	0.218007	0.589801
g.Index	0.63256	0.102128	0.818162	0.589944	1	0.988498	0.231081	0.999639
h.Index	0.627618	0.098715	0.811205	0.585452	0.988498	1	0.245517	0.988662
Citations	0.189344	0.024678	0.219517	0.218007	0.231081	0.245517	1	0.230274
Publications	0.632695	0.102345	0.818344	0.589801	0.999639	0.988662	0.230274	1

Cit (Top 60%)	Degree	Closeness	Betweenness	PageRank	g.Index	h.Index	Citations	Publications
Degree	1	0.039189	0.72656	0.655471	0.580472	0.575207	0.250712	0.580819
Closeness	0.039189	1	0.079772	0.021714	0.100162	0.096769	0.018652	0.100176
Betweenness	0.72656	0.079772	1	0.662028	0.800806	0.792957	0.276565	0.80126
PageRank	0.655471	0.021714	0.662028	1	0.528928	0.524501	0.261606	0.528825
g.Index	0.580472	0.100162	0.800806	0.528928	1	0.984997	0.283418	0.999186
h.Index	0.575207	0.096769	0.792957	0.524501	0.984997	1	0.300106	0.985365
Citations	0.250712	0.018652	0.276565	0.261606	0.283418	0.300106	1	0.281908
Publications	0.580819	0.100176	0.80126	0.528825	0.999186	0.985365	0.281908	1

Cit (Top 80%)	Degree	Closeness	Betweenness	PageRank	g.Index	h.Index	Citations	Publications
Degree	1	0.038244	0.744914	0.912974	0.793532	0.733953	0.163884	0.796017
Closeness	0.038244	1	0.029626	0.029375	0.057726	0.05884	0.003494	0.054195
Betweenness	0.744914	0.029626	1	0.708314	0.631972	0.539896	0.13355	0.635112
PageRank	0.912974	0.029375	0.708314	1	0.785217	0.733429	0.179708	0.784071
g.Index	0.793532	0.057726	0.631972	0.785217	1	0.953389	0.219007	0.986212
h.Index	0.733953	0.05884	0.539896	0.733429	0.953389	1	0.258828	0.929413
Citations	0.163884	0.003494	0.13355	0.179708	0.219007	0.258828	1	0.207336
Publications	0.796017	0.054195	0.635112	0.784071	0.986212	0.929413	0.207336	1

Cit (Top 100%)	Degree	Closeness	Betweenness	PageRank	g.Index	h.Index	Citations	Publications
Degree	1	0.031275	0.738437	0.899689	0.790708	0.73028	0.176751	0.794255
Closeness	0.031275	1	0.025591	0.022294	0.048635	0.048774	0.001234	0.04574
Betweenness	0.738437	0.025591	1	0.697769	0.631082	0.537383	0.14059	0.635169
PageRank	0.899689	0.022294	0.697769	1	0.776281	0.72347	0.190251	0.77638
g.Index	0.790708	0.048635	0.631082	0.776281	1	0.950894	0.234826	0.984428
h.Index	0.73028	0.048774	0.537383	0.72347	0.950894	1	0.276067	0.925063
Citations	0.176751	0.001234	0.14059	0.190251	0.234826	0.276067	1	0.221875
Publications	0.794255	0.04574	0.635169	0.77638	0.984428	0.925063	0.221875	1

g) H-index Based

h-index (Top 20%)	Degree	Closeness	Betweenness	PageRank	g.index	h.index	Citations	Publications
Degree	1	0.022827	0.752016	0.93369	0.768034	0.694588	0.163334	0.77079
Closeness	0.022827	1	0.024337	0.018939	0.037923	0.033924	-0.00458	0.034274
Betweenness	0.752016	0.024337	1	0.721556	0.633444	0.533976	0.138811	0.633634
PageRank	0.93369	0.018939	0.721556	1	0.773361	0.710184	0.185553	0.77132
g.index	0.768034	0.037923	0.633444	0.773361	1	0.938127	0.229433	0.98188
h.index	0.694588	0.033924	0.533976	0.710184	0.938127	1	0.286794	0.907715
Citations	0.163334	-0.00458	0.138811	0.185553	0.229433	0.286794	1	0.213451
Publications	0.77079	0.034274	0.633634	0.77132	0.98188	0.907715	0.213451	1

h-index (Top 40%)	Degree	Closeness	Betweenness	PageRank	g.index	h.index	Citations	Publications
Degree	1	0.022827	0.752016	0.93369	0.768034	0.694588	0.163334	0.77079
Closeness	0.022827	1	0.024337	0.018939	0.037923	0.033924	-0.00458	0.034274
Betweenness	0.752016	0.024337	1	0.721556	0.633444	0.533976	0.138811	0.633634
PageRank	0.93369	0.018939	0.721556	1	0.773361	0.710184	0.185553	0.77132
g.index	0.768034	0.037923	0.633444	0.773361	1	0.938127	0.229433	0.98188
h.index	0.694588	0.033924	0.533976	0.710184	0.938127	1	0.286794	0.907715
Citations	0.163334	-0.00458	0.138811	0.185553	0.229433	0.286794	1	0.213451
Publications	0.77079	0.034274	0.633634	0.77132	0.98188	0.907715	0.213451	1

h-index(Top 60%)	Degree	Closeness	Betweenness	PageRank	g.index	h.index	Citations	Publications
Degree	1	0.037623	0.744538	0.920466	0.791379	0.729413	0.176628	0.793373
Closeness	0.037623	1	0.029168	0.027386	0.055186	0.054651	-0.00156	0.051551
Betweenness	0.744538	0.029168	1	0.728208	0.631395	0.536457	0.14271	0.633555
PageRank	0.920466	0.027386	0.728208	1	0.76961	0.706143	0.188817	0.770013
g.index	0.791379	0.055186	0.631395	0.76961	1	0.948072	0.236725	0.98449
h.index	0.729413	0.054651	0.536457	0.706143	0.948072	1	0.284658	0.921527
Citations	0.176628	-0.00156	0.14271	0.188817	0.236725	0.284658	1	0.222779
Publications	0.793373	0.051551	0.633555	0.770013	0.98449	0.921527	0.222779	1

h-index(Top 80%)	Degree	Closeness	Betweenness	PageRank	g.index	h.index	Citations	Publications
Degree	1	0.035841	0.743871	0.912454	0.787655	0.726666	0.174298	0.790348
Closeness	0.035841	1	0.02842	0.027575	0.054951	0.055031	-9.88E-05	0.051614
Betweenness	0.743871	0.02842	1	0.726382	0.631686	0.539132	0.140525	0.63448
PageRank	0.912454	0.027575	0.726382	1	0.778527	0.719297	0.187417	0.778768
g.index	0.787655	0.054951	0.631686	0.778527	1	0.951942	0.232707	0.985442
h.index	0.726666	0.055031	0.539132	0.719297	0.951942	1	0.275782	0.926907
Citations	0.174298	-9.88E-05	0.140525	0.187417	0.232707	0.275782	1	0.219917
Publications	0.790348	0.051614	0.63448	0.778768	0.985442	0.926907	0.219917	1

h-index(Top 100%)	Degree	Closeness	Betweenness	PageRank	g.index	h.index	Citations	Publications
Degree	1	0.031275	0.738437	0.899689	0.790708	0.73028	0.176751	0.794254904
Closeness	0.031275	1	0.025591	0.022294	0.048635	0.048774	0.001234	0.045739938
Betweenness	0.738437	0.025591	1	0.697769	0.631082	0.537383	0.14059	0.635168783
PageRank	0.899689	0.022294	0.697769	1	0.776281	0.72347	0.190251	0.77637953
g.index	0.790708	0.048635	0.631082	0.776281	1	0.950894	0.234826	0.984427676
h.index	0.73028	0.048774	0.537383	0.72347	0.950894	1	0.276067	0.925063167
Citations	0.176751	0.001234	0.14059	0.190251	0.234826	0.276067	1	0.221875278
Publications	0.794255	0.04574	0.635169	0.77638	0.984428	0.925063	0.221875	1

h) G-index Based

g-index(Top 20%)	Degree	Closeness	Betweenness	PageRank	g.Index	h.Index	Citations	Publications
Degree	1	0.030469	0.760905	0.94433	0.748155	0.657821	0.152079	0.750344
Closeness	0.030469	1	0.02772	0.02636	0.041269	0.035859	0.000767	0.035361
Betweenness	0.760905	0.02772	1	0.742543	0.631554	0.521727	0.139092	0.627624
PageRank	0.94433	0.02636	0.742543	1	0.758972	0.678145	0.180082	0.755827
g.Index	0.748155	0.041269	0.631554	0.758972	1	0.919254	0.2332	0.976781
h.Index	0.657821	0.035859	0.521727	0.678145	0.919254	1	0.314392	0.881351
Citations	0.152079	0.000767	0.139092	0.180082	0.2332	0.314392	1	0.211868
Publications	0.750344	0.035361	0.627624	0.755827	0.976781	0.881351	0.211868	1

g-index(Top 40%)	Degree	Closeness	Betweenness	PageRank	g.Index	h.Index	Citations	Publications
Degree	1	0.025036	0.751675	0.933563	0.766569	0.692083	0.162837	0.769403
Closeness	0.025036	1	0.02524	0.020073	0.040684	0.03724	-0.00366	0.036908
Betweenness	0.751675	0.02524	1	0.7215	0.633444	0.53363	0.138844	0.633634
PageRank	0.933563	0.020073	0.7215	1	0.773161	0.709379	0.185516	0.771129
g.Index	0.766569	0.040684	0.633444	0.773161	1	0.937883	0.229541	0.98188
h.Index	0.692083	0.03724	0.53363	0.709379	0.937883	1	0.286909	0.907467
Citations	0.162837	-0.00366	0.138844	0.185516	0.229541	0.286909	1	0.213554
Publications	0.769403	0.036908	0.633634	0.771129	0.98188	0.907467	0.213554	1

g-index(Top 60%)	Degree	Closeness	Betweenness	PageRank	g.Index	h.Index	Citations	Publications
Degree	1	0.038295	0.743916	0.920079	0.793021	0.730302	0.178382	0.794866
Closeness	0.038295	1	0.029098	0.027279	0.05499	0.054337	-0.00094	0.051362
Betweenness	0.743916	0.029098	1	0.728156	0.631395	0.534707	0.143506	0.633555
PageRank	0.920079	0.027279	0.728156	1	0.769473	0.70355	0.189785	0.769881
g.Index	0.793021	0.05499	0.631395	0.769473	1	0.946542	0.238658	0.98449
h.Index	0.730302	0.054337	0.534707	0.70355	0.946542	1	0.287039	0.919994
Citations	0.178382	-0.00094	0.143506	0.189785	0.238658	0.287039	1	0.224627
Publications	0.794866	0.051362	0.633555	0.769881	0.98449	0.919994	0.224627	1

g-index(Top 80%)	Degree	Closeness	Betweenness	PageRank	g.Index	h.Index	Citations	Publications
Degree	1	0.036205	0.742961	0.912475	0.786829	0.723655	0.175767	0.789532
Closeness	0.036205	1	0.028672	0.028058	0.055641	0.055947	-0.00071	0.05233
Betweenness	0.742961	0.028672	1	0.727713	0.631686	0.536846	0.141739	0.634493
PageRank	0.912475	0.028058	0.727713	1	0.776919	0.713883	0.188786	0.777379
g.Index	0.786829	0.055641	0.631686	0.776919	1	0.949657	0.235402	0.985473
h.Index	0.723655	0.055947	0.536846	0.713883	0.949657	1	0.27929	0.924668
Citations	0.175767	-0.00071	0.141739	0.188786	0.235402	0.27929	1	0.222511
Publications	0.789532	0.05233	0.634493	0.777379	0.985473	0.924668	0.222511	1

g-index(Top 100%)	Degree	Closeness	Betweenness	PageRank	g.Index	h.Index	Citations	Publications
Degree	1	0.031275	0.738437	0.899689	0.790708	0.73028	0.176751	0.794255
Closeness	0.031275	1	0.025591	0.022294	0.048635	0.048774	0.001234	0.04574
Betweenness	0.738437	0.025591	1	0.697769	0.631082	0.537383	0.14059	0.635169
PageRank	0.899689	0.022294	0.697769	1	0.776281	0.72347	0.190251	0.77638
g.Index	0.790708	0.048635	0.631082	0.776281	1	0.950894	0.234826	0.984428
h.Index	0.73028	0.048774	0.537383	0.72347	0.950894	1	0.276067	0.925063
Citations	0.176751	0.001234	0.14059	0.190251	0.234826	0.276067	1	0.221875
Publications	0.794255	0.04574	0.635169	0.77638	0.984428	0.925063	0.221875	1

Appendix B

1) American Mathematics Society

a) Cole Prize in Algebra	
Year	Awardees
1928	Leonard E. Dickson
1939	Abraham Adrian Albert
1944	Oscar Zariski
1949	Richard Brauer
1954	Harish-Chandra
1960	Maxwell A. Rosenlicht
1960	Serge Lang
1965	John G. Thompson
1965	Walter Feit
1970	John R. Stallings
1970	Richard G. Swan
1975	Daniel G. Quillen, Hyman Bass
1980	Michael Aschbacher
1980	Melvin Hochster
1985	George Lusztig
1990	Shigefumi Mori
1995	David Harbater, Michel Raynaud
2000	Andrei Suslin
2000	Aise Johan de Jong
2003	Hiraku Nakajima
2006	János Kollár
2009	James McKernan

2009	Christopher Hacon
2012	Alexander Merkurjev
2015	Peter Scholze

b) Bocher Memorial Prize	
Year	Awardees
1923	George David Birkhoff
1924	Eric Temple Bell, Solomon Lefchetz
1928	James W. Alexander II
1933	Marston Morse, Norbert Weiner
1938	John von Neumann
1943	Jesse Douglas
1948	Albert Schaeffer
1953	Norman Levinson
1959	Louis Nirenberg
1964	Paul Cohen
1969	Isadore Singer
1974	Donald Samuel Ornstein
1979	Alberto Calderón
1984	Luis Caffarelli
1989	Richard Schoen
1994	Leon Simon
1999	Demetrios Christodoulou, Sergiu Kiainerman, Thomas Wolff
2002	Daniel Tătaru, Terence Tao
2005	Frank Merle

2008	Alberto Bressan, Carlos Kenig (de)
2011	Assaf Naor, Gunther Uhlmann
2014	Simon Brendle
2017	András Vasy

c) Cole Prize in Number Theory	
Year	Awardees
1931	H S Vandiver
1941	Claude Chevalley
1946	H B Mann
1951	Paul Erdős
1956	John T Tate
1962	Kenkichi Iwasawa
1962	Bernard M Dwork
1967	James B Ax and Simon B Kochen
1972	Wolfgang M. Schmidt
1977	Goro Shimura
1982	Robert P Langlands
1982	Barry Mazur
1987	Dorian M Goldfeld
1987	Benedict H Gross, Don B Zagier
1992	Karl Rubin
1992	Paul Vojta
1997	Andrew J Wiles

2002	Henryk Iwaniec
2002	Richard Taylor
2005	Peter Sarnak
2008	Manjul Bhargava

d) Delbert Ray Fulkerson Prize	
Year	Awardees
1979	Richard M. Karp , Kenneth Appel, Wolfgang Haken, Paul Seymour
1982	D.B. Judin, Arkadi Nemirovski, Leonid Khachiyan, Martin Grottschel, Lazlo Lovasz, Alexander Shrijver, G.P. Egorychev, D.I. Falikman
1985	Jozsef Beck , H.W. Lenstra, Jr, Eugene M. Luks
1988	Éva Tardos, Narendra Karmarkar
1991	Martin E. Dyer, Alan M. Frieze, Ravindran Kannan, Alfred Lehman, Nikolai E. Mnev
1994	Louis Billera, Gil Kalai, Neil Robertson, Paul Seymour, Robin Thomas
1997	Jeong Han Kim
2000	Michel X. Goemans, David P. Williamson, Michele Conforti, M.R. Rao
2003	J. F. Geelen, A.M.H. Gerards, A. Kapoor, Bertrand Guenin, Satoru Iwata
2006	Manindra Agrawal, Neeraj Kayal, Nitin Saxena, Alistair Sinclair, Eric Vigoda, Neil Robertson, Paul Seymour
2009	Maria Chudnovsky, Neil Robertson, Paul Seymour, Robin Thomas, Daniel A. Spielman, Shang-hua Teng, Thomas C. Hales, Sameul P. Ferguson
2012	Sanjeev Arora, Satish Rao. Umesh Vazirani, Anders Johansson, Jeff Kahn, Van H. Vu, Lazlo Lovasz, Balazs Szegedy
2015	Francisco Santos Leal

e) Joseph L Doob	
Year	Awardees

2005	William P. Thurston
2008	Walter Gubler, Enrico Bombieri
2011	Tomasz Mrowka , Peter Kronheimer
2014	Cleric Villani

f) Leroy P. Steel Prize for Lifetime Achievement	
Year	Awardees
1993	Eugene B. Dynkin
1994	Louis Nirenberg
1995	John T. Tate
1996	Goro Shimura
1997	Ralph S. Phillips
1998	Nathan Jacobson
1999	Richard V. Kadison
2000	Isadore M. Singer
2001	Harry Kesten
2002	Michael Artin, Elias Stein
2003	Ronald Graham, Victor Guillemin
2004	Cathleen Synge Morawetz
2005	Israel M. Gelfand
2006	Frederick W. Gehring, Dennis P. Sullivan
2007	Henry P. McKean
2008	George Lusztig
2009	Luis Caffarelli
2010	William Fulton
2011	John W. Milnor
2012	Ivo M. Babuška

2013	Yakov G. Sinai
2014	Phillip A. Griffiths
2015	Victor Kac
2016	Barry Simon
2017	James G. Arthur

g) Leroy P. Steel Prize Mathematical Exposition

Year	Awardees
1993	Walter Rudin
1994	Ingrid Daubechies
1995	Jean-Pierre Serre
1996	William Fulton
1996	Bruce Berndt
1997	Anthony W. Knapp
1998	Joseph Silverman
1999	Serge Lang
2000	John H. Conway
2001	Richard Stanley
2002	Yitzhak Katznelson
2003	John Garnet
2004	John Milnor
2005	BrankoGrünbaum
2006	Lars Hörmander
2007	David Mumford
2008	Neil Trudinger
2009	I.G. Macdonald
2010	David Eisenbud

2011	Henryk Iwaniec
2012	Michael Aschbacher, Richard Lyons, Steve Smith, Ronald Solomon
2013	John Guckenheimer, Phillip Holmes
2014	Yuri Burago, Dmitri Burago, Sergei Ivanov
2015	Robert Lazarsfeld
2016	David A. Cox, John Little, Donal O'Shea
2017	Dusa McDuff, Dietmar Salamon

h) Leroy P. Steel Prize

Year	Awardees
1993	George Daniel Mostow
1994	Louis de Branges
1995	Edward Nelson
1996	Daniel Stroock, S.R. Srinivasa Varadhan
1997	Mikhail Gromov
1998	Herbert Wilf, Doron Zeilberger
1999	John F. Nash, Michael G. Crandall
2000	Barry Mazur
2001	Leslie F. Greengard, Vladimir Rokhlin
2002	Mark Goresky, Robert MacPherson
2003	Ronald Jensen, Michael Morley
2004	Lawrence C. Evans, Nicolai V. Krylov
2005	Robert P. Langlands
2006	Clifford S. Gardner, John M. Greene, Martin D. Kruska, Robert M. Miura
2007	Karen Uhlenbeck
2008	Endre Szemerédi
2009	Richard S. Hamilton

2010	Robert Griess
2011	Ingrid Daubechies
2012	William Thurston
2013	Saharon Shelah
2014	Luis Caffarelli, Robert Kohn, Louis Nirenberg
2015	Rostislav Grigorchuk
2016	Andrew Majda
2017	Leon Simon

i) Levi L. Conant Prize	
Year	Awardees
2001	Carl Pomerance
2002	Elliott Lieb, Jakob Yngvason
2003	Nicholas Katz, Peter Sarnak
2004	Noam Elkies
2005	Allen Knutson, Terence Tao
2006	Ronald Solomon
2007	Jeffrey Weeks
2008	J. Brian Conrey
2009	John Morgan
2010	Bryna Kra
2011	David Vogan
2012	Persi Diaconis
2013	John C. Baez, John Huerta
2014	Alex Kontorovich
2015	Jeffrey Lagarias, Zong Chaunming
2016	Daniel Rothman

j) Oswald Veblen Prize in Germany

Year	Awardees
1964	Christos Papakyriakopoulos, Raoul Bott
1966	Stephen Smale, Morton Brown, Barry Mazur
1971	Robion Kirby, Dennis Sullivan
1976	William Thurston, James Harris Simons
1981	Mikhail Gromov, Shing-Tung Yau
1986	Michael Freedman
1991	Andrew Casson, Clifford Taubes
1996	Richard S. Hamilton, Gang Tian
2001	Jeff Cheeger, Yakov Eliashberg
2004	David Gabai
2007	Peter Kronheimer, Tomasz Mrowka, Peter Ozsvath, Zoltan Szabo
2010	Tobias Colding, William Minicozzi II, Paul Seidel
2013	Ian Agol, Daniel Wise
2016	Fernando Codá Marques, Andre Neves

2) London Mathematics Society

a) Berwick Prize

Year	Awardees
1947	Arthur Geoffrey Walker
1949	Lionel Cooper
1951	David Bernard Scott

1953	Douglas Northcott
1955	Walter Hayman
1957	Claude Ambrose Rogers
1959	I M James
1961	Michael Atiyah
1963	Frank Adams
1965	C T C Wall
1967	John Kingman
1969	Graham Robert Allan
1971	John Horton Conway
1973	D G Larman
1975	R G Haydon
1977	George Lusztig
1979	Bob Vaughan
1981	Roger Heath-Brown
1983	D H Hamilton
1985	C J Read
1987	P A Linnell
1989	G R Robinson
1991	W W Crawley-Boevey
1993	Trevor Wooley
1995	J P C Greenlees
1997	Dugald Macpherson
1999	D Burns
2001	Marcus du Sautoy
2003	Tom Bridgeland
2005	I G Gordon
2007	No award

2009	Joseph Chuang, RadhaKessar
2011	No award
2013	No award
2015	Pierre Emmanuel Caprace, Nicolas Monod

b) De Morgan

Year	Awardees
1884	Arthur Cayley
1887	James Joseph Sylvester
1890	Lord Rayleigh
1893	Felix Klein
1896	S. Roberts
1899	William Burnside
1902	A. G. Greenhill
1905	H. F. Baker
1908	J. W. L. Glaisher
1911	Horace Lamb
1914	J. Larmor
1917	W. H. Young
1920	E. W. Hobson
1923	P. A. MacMahon
1926	A. E. H. Love
1929	Godfrey Harold Hardy
1932	Bertrand Russell
1935	E. T. Whittaker
1938	J. E. Littlewood
1941	Louis Mordell
1944	Sydney Chapman
1947	George Neville Watson
1950	A. S. Besicovitch

1953	E. C. Titchmarsh
1956	G. I. Taylor
1959	W. V. D. Hodge
1962	Max Newman
1965	Philip Hall
1968	Mary Cartwright
1971	Kurt Mahler
1974	Graham Higman
1977	C. Ambrose Rogers
1980	Michael Atiyah
1983	K. F. Roth
1986	J. W. S. Cassels
1989	D. G. Kendall
1992	Albrecht Fröhlich
1995	W. K. Hayman
1998	R. A. Rankin
2001	J. A. Green
2004	Roger Penrose
2007	Bryan John Birch
2010	Keith William Morton
2013	John Griggs Thompson
2016	Timothy Gowers

c) Frohlich Prize	
Year	Awardees
2004	Ian Grojnowski
2006	Michael Weiss

2008	Nicholas Higham
2010	Jonathan Keating
2012	Trevor Wooley
2014	Martin Hairer
2016	Dominic Joyce

d) Naylor Prize and lectureship in applied Mathematics	
Year	Awardees
1977	James Lighthill
1979	Basil John Mason
1981	H. Christopher Longuet-Higgins
1983	Michael J. D. Powell
1985	I C Percival
1987	D S Jones
1989	J D Murray
1991	Roger Penrose
1993	Michael Berry
1995	John Ball
1997	Frank Kelly
1999	Stephen Hawking
2000	Athanasios S. Fokas
2002	Mark H. A. Davis
2004	Richard Jozsa
2007	Michael Green

2009	Philip Maini
2011	John Bryce McLeod
2013	Nick Trefethen
2015	S. Jonathan Chapman

e) Polya prize

Year	Awardees
1987	John Horton Conway
1988	C. T. C. Wall
1990	Graeme B. Segal
1991	Ian G. Macdonald
1993	David Rees
1994	David Williams
1996	David Edmunds
1997	John Hammersley
1999	Simon Donaldson
2000	Terence Lyons
2002	Nigel Hitchin
2003	Angus Macintyre
2005	Michael Berry
2006	Peter Swinnerton-Dyer
2008	David Preiss
2009	Roger Heath-Brown
2011	E. Brian Davies
2012	Dan Segal

2014	Miles Reid
2015	Boris Zilber

f) Senior Berwick prize

Year	Awardees
1946	Louis Mordell
1948	J H C Whitehead
1950	Kurt Mahler
1952	William V D Hodge
1954	Harold Davenport
1956	Edward Charles Titchmarsh
1958	Philip Hall
1960	John Edensor Littlewood
1962	Graham Higman
1964	Walter Hayman
1966	F FBonsall
1968	George Leo Watson
1970	Alfred Goldie
1972	Richard Rado
1974	Paul Cohn
1976	Albrecht Fröhlich
1978	E. M. Wright
1980	Christopher Hooley
1982	John G Thompson
1984	James Alexander Green
1986	G Peter Scott

1988	David B A Epstein
1990	Nigel Hitchin
1992	James Eells
1994	Andrew A Ranicki
1996	Roger Heath-Brown
1998	E B Davies
2000	John Toland
2002	Jeremy C Rickard
2004	Boris Zilber
2006	Miles Reid
2008	Kevin Buzzard
2010	DusaMcDuff
2012	Ian Agol
2014	Daniel Freed, Michael Hopkins, ConstantinTeleman

g) Whitehead prize	
Year	Awardees
1979	Peter Cameron, Peter Tennant Johnstone
1980	H. G. Dales, J.Toby Stafford
1981	Nigel Hitchin, Derek F. Holt
1982	John M. Ball, Martin j.Taylor
1983	Jeff Paris, Andrew Ranicki
1984	Simon Donaldson, Sameuljames Patterson
1985	Dan Segal, Philip J.Rippon
1986	Terence Lyons, David A.Rand
1987	C. M. Series, Aidan H. Schofield
1988	S. M. Rees, P.J.Webb, Andrew Wiles
1989	D. E. Evans, Frances Kirwan, R.S.Ward

1990	Martin T. Barlow, Richard Taylor, A.J.Wassermann
1991	N. S. Manton, A.J.Scoll
1992	K. M. Ball, Richard Borchers
1993	D. J. Benson, Peter B.Kronheimer, D.G. Vassiliev
1994	P. H. Kropholler, R.S.Mackay
1995	Timothy Gowers, J.Rickard
1996	John Roe, Y.Safarov
1997	Brian Bowditch, A. Grigor'yan, Dominic Joyce
1998	S. J. Chapman, Igor Rivin, Jan Nekovar
1999	Martin Bridson, G.Friesecke, N.J. Higham, Imre Leader
2000	M. A. J. Chaplain, G.M.Stallard, Andrew M. Stuart, Burt Totaro
2001	M. McQuillan, A.N. Skorobogatov, V.Smyshlyaev, J.R.King
2002	Kevin Buzzard, Alessio Corti, Marianna Csornyei, C.Teleman
2003	N. Dorey, T.Hall, M.Lackenby, M.Nazarov
2004	M. Ainsworth, Viadimir Markovic, Richard Thomas, Ulrike Tillmann
2005	Ben Green, Bernard Kirchem, Neil Strickland, Peter Topping
2006	Raphaël Rouquier, Jonathan Sherratt, Paul Sutchliffe, Agata Smoktunowicz
2007	Nikolay Nikolov, Oliver Riordan, Ivn Smith, Catharina Stroppel
2008	Timothy Browning, Tamas Hausel, Martin Hairer, Nina Snaith
2009	Mihalis Dafermos, Cornelia Drutu, Robert James Marsh, Markus Owen
2010	Harald Helfgott, Jens Marklof, Lasse Rempe, Françoise Tisseur
2011	Jonathan Bennet, Alexander Gorodnik, Barbara Neithammer, Alexander Pushnitski
2012	Toby Gee, Eugen Varvaruca, Sarah Waters, Andreas Winter
2013	Luis Alday, Andre Neves, Tom Sanders, Corinna Ulcigrai
2014	Clément Mouhot, Ruth Baker, Tom Coates, Daniela Kuhn, Deryk Osthus
2015	Peter Keevash, James Maynard, Christoph Ortner, Mason Ported, Dominic Vella, David Loeffler, Zerbès
2016	A. Bayer, G.Holzegel, J.Miller, C.B.Schonlieb

g) Senior Whitehead prize

Year	Awardees
1974	Frank Adams
1976	C. T. C. Wall
1978	Ioan Mackenzie James
1980	David George Kendall
1982	Christopher Zeeman
1984	John Trevor Stuart
1987	Robert Alexander Rankin
1989	Edward Fraenkel
1991	W. B. R. Lickorish
1993	Bryan John Birch
1995	Colin J. Bushnell
1997	John H. Coates
1999	Michael J. D. Powell
2001	Derek W. Moore
2003	Peter M. Neumann
2005	Keith Moffatt
2007	Béla Bollobás
2009	Vladimir Gilelevich Maz'ya
2011	Jonathan Pila
2013	Frances Clare Kirwan

3) International Mathematics Union

a) Chern Medal Award	
Year	Awardees
2010	Louis Nirenberg
2014	Phillip Griffiths

b) Fields Medal	
Year	Awardees
1936	Lars Ahlfors, Jesse Douglas
1950	Laurent Schwartz, Atle Selberg
1954	Kunihiko Kodaira, Jean-Pierre Serre
1958	Klaus Roth, Rene Thom
1962	Lars Hörmander, John Milnor
1966	Michael Atiyah, Paul Joseph Cohen, Alexander Grothendieck, Stephen Smale
1970	Alan Baker, Heisuke Hironaka, John G. Thompson, Sergei Novikov
1974	Enrico Bombieri, David Mumford
1978	Pierre Deligne, Charles Fefferman, Daniel Quillen, Grigori Margulis
1982	Alain Connes, William Thurston, Shing-Tung Yau, Simon Donaldson
1986	Simon Donaldson, Gerd Faltings, Michael Freedman
1990	Vladimir Drinfeld, Vaughan F.R. Jones, Shigefumi Mori, Edward Witten
1994	Jean Bourgain, Pierre-Louis Lions, Jean-Christophe Yoccoz, Efim Zelmanov
1998	Richard Borcherds, Timothy Gowers, Maxim Kontsevich, Curtis T. McMullen
2002	Laurent Lafforgue, Viadimir Voevodsky
2006	Andrei Okounkov, Grigori Perelman, Terence Tao, Wendelin Werner

2010	ElonLindenstrauss, Ngo BaoChau, StanislavSmirnov, Cedric Villani
2014	Artur Avila, ManjulBhargava, Martin Hairer, Maryam MirzaKhani

c) Gauss Prize	
Year	Awardees
2006	Kiyosi Ito
2010	Yves Meyer
2014	Stanley Osher

d) Leelavati Prize	
Year	Awardees
2010	Simon Singh
2014	Adrian Paenza

e) Rolf Novanlinna Prize	
Year	Awardees
1982	Robert Tarjan
1986	Leslie Valiant
1990	Alexander Razborov
1994	AviWigderson
1998	Peter Shor
2002	Madhu Sudan
2006	Jon Kleinberg
2010	Daniel Spielma
2014	SubhashKho

5) Norwegian Academy of Science and Letter

a) Able Prize

Year	Awardees
2003	Jean-Pierre Serre
2004	Michael Atiyah, Isadore Singe
2005	Peter Lax
2006	Lennart Carleson
2007	S. R. Srinivasa Varadhan
2008	John G. Thompson, Jacques Tits
2009	Mikhail, Gromov
2010	John Tate
2011	John Milnor
2012	Endre , Szemerédi
2013	Pierre Deligne
2014	Yakov Sinai
2015	John F. Nash, Louis Nirenberg
2016	Andrew Wiles, Louis

d) Kavli Prize

Year	Awardees
2008	Maarten Schmidt, Donald Lynden-Bell
2010	Jerry E. Nelson, Raymond N. Wilson, James Roger Angel, David C. Jewitt
2012	Jane X. Luu, Michael E. Brown, Alan H. Guth
2014	Andrei D. Linde, Alexei A. Starobinsky, Ronald W.P. Drever
2016	Kip S. Thorne, Rainer Weiss