Affiliations based bibliometric analysis of publications on Parkinson's Disease

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Abstract

Parkinson's Disease is the second most common neurodegenerative disorder in the world. Thousands of scientific works are published every year. We have analyzed more than 3 thousand organizations, who have published works on various aspects of Parkinson's Disease in the period from 2015 to 2021.

We have evaluated 4 classical centrality indices (In-degree, Eigenvector, Pagerank and Betweenness) and 2 new centrality indices. The new indices allow to take into account group influence and to identify pivotal nodes. Using the method, we have extracted the most influential organizations in the scientific area of Parkinson's Disease. Stability analysis allows us to measure the value of dynamic changes in the network during the period under consideration.

1. Introduction

Parkinson’s Disease (PD) is a neurodegenerative disorder of the central nervous system. People over the age of 60 are at risk of it, and men are twice as likely to have it as women. The cost of treating Parkinson's disease only in the United States is more than $50 billion per year. PD is the second most common neurodegenerative disease. Currently, the disease is considered incurable, but early diagnosis can significantly slow its progression and increase a lifespan of the patient.

There is a huge community of PD researchers and more than 5000 papers on the different issues of the disease are published every year. Considering such a large number of publications, it is important to identify main trends and the most influential authors and organizations. It can be useful, for example, in order to detect areas for investment.

We have already analyzed papers and journals in the same way. In that work we have collected information about more than 70 thousand publications on Parkinson’s Disease from 2015 to 2021. We have computed and analyzed several classical centrality indices and two new centrality indices, introduced in (Aleskerov Yakuba, 2020) for citation networks of papers and journals. New centrality indices take into account different parameters of vertices and group influence. They can be used to identify groups of journals that intensively cite each other.

In this work our purpose is to apply network analysis to evaluate the impact of certain authors and their organizations. We have built citation networks that include more than 27 thousand authors and 3 thousand organizations. Citation network is presented as a list of weighted edges from one author or organization to another in the certain year.

The indices have been computed over the whole period and over the years. The certain parameters of the new indices can be used in order to identify groups of authors, actively citing each other, and the most influential scientific organizations in the field of Parkinson’s Disease.

2. Literature review

One way to study the importance and the impact of scientific publications and their authors is to analyze a number of citations. (Sorensen, Weedon 2011) evaluated an impact of 100 most cited researchers in PD since 1985 using H-Indices as a means to assess productivity, as well as the total-citations ranking and "broad impact" citations. (Xue et al., 2018) provides the analysis of citations, impact factor, information about the country and authors of top-100 cited articles on PD. In (Ruiz, Benito-León, 2019) 50 most cited publications on orthostatic tremor have been analyzed with the Web of Science Analyze Tool. Supplementary analyses have been undertaken to clarify authorship, study design, level of evidence, and category. The key idea of this work is to determine what properties make these articles relevant for further studies and clinical practices. Statistical methods and exponential regression models are used in (Li et al., 2008) to analyze research trends in PD from 1991 to 2006. Scientific output characters, world collaboration and the frequency of author keywords have been considered for analysis.

The other way to analyze scientific fields is to use network analysis. For instance, cluster and bibliometric analysis of citation networks are used in (Kusumastuti et al., 2016) and (Martinez-Perez et al., 2020) to explore articles about successful ageing and Coronavirus Disease. In (Higaki, 2020) various characteristics of co-authorship network in cardiovascular medicine were calculated and most central authors were identified. In (Aleskerov et al., 2020) a combination of semantic and centrality analysis has been applied. Long-Range Interaction and Short-Range Interaction centrality indices have been computed for publications on studies of PD in order to rank the importance of the scientific fields and track changes of attention to previously unknown patents and developments.

3. Data description

The data have been collected as a part of the study on papers and journals of Parkinson's Disease (Aleskeov, Khutorskaya, Yakuba, Stepochkina, Zinoveva 2023). The data have been collected from Microsoft Academic (Sinha, et al. 2015), (Wang 2019). It is an open search system for academic publications developed by Microsoft Research. A publication has been selected if it contains words "parkinson" and "disease" both in the normalized title or abstract. Normalization of the text is the process that involves converting text into a single canonical form.

Moreover, only publications from 2015 to 2021 have been taken into account. This time period has been chosen in order to analyze trends in the research society of Parkinson's disease in recent years.

Microsoft Academic provides a number of attributes for each publication. In this work we use

- Paper ID
- List of authors with information (names, affiliations, etc.)
- Abstract in inverted form (list of words and their corresponding position in the original abstract)
- List of references

A total of 70119 papers have been downloaded. Date of access to database: 20.11.2021.

4. Affiliations citation network

We have constructed a citation network for affiliations of the authors. We have decided to use the affiliation of the first author in the list in order to compare the results for authors and their institutions. Furthermore, usually the first author in the list is the main author and his organization funds the research.

Not all of the publications contained the affiliation id of the authors. Some of them do not contain the name of the affiliation, the rest have been written with mistakes or an incorrect form was indicated (for example, only the city or country), according to which it is impossible to determine the affiliation. We have deleted such vertices from the network. After this preprocessing 5631 papers without correct information about affiliation have been deleted.

The citation network has the following structure: an edge between AfId1 and AfId2 affiliation means that an article with AfId1 affiliation refers to an article with AfId2 affiliation. The weight of the edge is the number of such citations in a given year Y. The sample of the net is given on Figure 1.

AfId1	AfId2	Y	weight
4605	138006243	2017	1
9507	9507	2021	1
9507	35928602	2021	2
9507	40120149	2021	1
9507	177639307	2021	1

Figure 1. Sample of the citation network

There are 170340 edges and 3029 vertices in the network. There are 5 connected components in the network. 3025 organizations are contained in the largest component,while the remaining 4 organizations are isolated. They have only one self-citation, there are no other edges. These are the institutions:

- Universidad del Tolima, Tolima, Colombia
- Northern Kentucky University, Kentucky, U.S.
- Chiba Institute of Science, Chiba, Japan
- Savitribai Phule Pune University, Pune, Maharashtra, India

5. Centrality analysis

Methods of the network analysis can be applied to the citation network in order to evaluate the influence of organizations. For this purpose a number of different indices can be used. We have decided to compute classical indices such as In-degree, PageRank, Betweenness and Eigenvector indices (Newman, 2010) and new Bundle and Pivotal indices introduced in (Aleskerov and Yakuba, 2020).

These indices represent the measure of vertex importance. It is important to note that all of the indices have been normalized to 1.

Given that A is an adjacent matrix of the graph, we can denote $A_{ij} = 1$ if there is an directed edge from vertex v_i to v_j, and $A_{ij} = 0$ else.

Eigenvector index (Bonacich, 1972) of the vertex is a solution of the equation $Ax = k_1 x$, where k_1 is the greatest eigenvalue of the matrix A

$$x_i = \frac{1}{k_1} \sum_j A_{ij} x_j .$$

The eigenvector centrality represents the importance of the vertex, which is proportional to the importances of its adjacent vertices.

PageRank centrality (Brin and Page, 1998) is a version of the eigenvector centrality, it takes into account the out-degree of the vertex neighbors in order to consider vertices with a large amount of outcoming edges,

$$x_i = \alpha \sum_j A_{ij} \frac{x_j}{k^{out}_j} + \beta$$

Coefficients α and β are used to avoid zero centralities.

Betweenness centrality (Freeman 1997) shows vertices that lie on the path between two other vertices, so they are important connectors and transporters of information in the network. It is defined as

$$x_i = \sum_{kj} \frac{n^i{}_{kj}}{g_{kj}},$$

where $n^i{}_{kj}$ is the number of shortest paths from k to j through the vertex i, g_{kj} is the number of shortest paths from k to j.

In-degree index is defined as the sum of weights of the incoming edges for each vertex,

$$In\text{-}degree(i) = \sum_j w_{ji}$$

In order to introduce new centrality measures, we have to define critical set and quota.

Quota q_i is defined for each vertex individually, it takes into account parameters of the vertex. We have taken quota as a percentage of sum of the incoming edges for every node.

Critical set S is defined as a set of nodes, which have an influence on the given vertex, with the sum of the edges' weights larger than quota. The size of the critical set is not greater than k, i.e.

$$S \subseteq V \backslash \{i\}, |S| \leq k, \sum_{j \in S} w_{ji} \geq q_i$$

The larger is the quota value, the smaller is the number of critical sets for vertices with a large value of incoming edges in comparison with vertices with smaller one. Taking a larger quotas can help us to detect authors and institutions which are not the most popular but have significant influence on particular societies and fields of research, respectively.

Bundle index (BI) takes into account the influence on a vertex by a group of vertices. BI uses quotas q_i and the maximum number of vertices in the group k. Then BI is defined for each critical set as

$$BI_i(S) = \begin{cases} 1, if \sum_{j \in S} w_{ji} \geq q_i \\ 0, else \end{cases}$$

Then for each vertex i the sum of $BI_i(S)$ is evaluated for all considered subsets

$$BI(i) = \sum_S BI_i(S) .$$

Pivotal index (PI) represents an influence of the pivotal vertices to each vertex.

One of the main differences between BI and PI is that the second one calculates the number of pivotal vertices instead of the number of groups. This number is defined in the following way. The vertex j_p is pivotal if

$$\sum_{j \in S} w_{ji} \geq q_i \text{ and } \sum_{j \in S \backslash \{i_p\}} w_{ji} < q_i ,$$

where S is a critical set for node i with quota q_i. It means that excluding a pivotal node from the set makes the sum of the weights less than the quota.

Pivotal index for each subset is equal to the number of pivotal nodes in S.

The final value of PI is defined as a sum of $PI_i(S)$ for each critical set of the vertex multiplied by the cardinality of the subsets,

$$PI(i) = \sum_S |S| \times PI_i(S)$$

Those indices describe direct, indirect and group vertex influences on each other. It can be noticed that the total influence can be calculated as a linear combination of the described indices, i. e.

$$TI(i) = \alpha_1 BI(i) + \alpha_2 PI(i) + \alpha_3 In\text{-}degree(i)$$

Coefficients are often chosen equal to each other, that is

$$\alpha_1 = \alpha_2 = \alpha_3 = \frac{1}{3},$$

but they can also be different, for example, if one of the indices is of great importance for a specific task.

6. Centrality analysis: results

6.1. Classical indices

The In-degree index value is proportional to the number of citations or incoming edges. Table 1 shows 10 organizations with the largest In-degree values. National Institutes of Health (#1) is an association of 27 separate institutions and research medical centers in the USA. UCL Institute of Neurology (#2) is an institute of the Faculty of Brain Sciences of University College London. These institutions are specialized in a wide range of medicine, including neurodegenerative disorders such as Parkinson disease. Other universities from Table 1 are located in the UK, USA, Belgium and Sweden. These are some of the largest and the oldest universities in the world with the research carried out in various scientific fields.

№	**Name**	**In-degree**	**Betweenness rank**	**Eigenvector rank**	**Pagerank rank**
1	National Institutes of Health	0,0156	5	1	1
2	UCL Institute of Neurology	0,0134	3	4	2
3	University of Cambridge	0,0131	1	3	4
4	University of Oxford	0,0122	2	2	3
5	University College London	0,0120	6	5	5
6	Northwestern University	0,0114	14	6	6
7	Harvard University	0,0100	8	8	7
8	University of Pennsylvania	0,0085	24	7	8
9	Katholieke Universiteit Leuven	0,0080	26	10	12
10	Karolinska Institutet	0,0079	10	9	9

Table 1. Top 10 affiliations by In-degree index

The Betweenness index shows vertices that are important connectors. The same results for the Betweenness index (Table 2) are slightly different from the results for In-degree index, there are some other universities that are not the most cited of all: Shanghai Jiao Tong University (#4), the Radboud University Nijmegen (#7) in the Netherlands and the Capital Medical University in Beijing (#9). Other institutions are similar to the ones in Table 1.

№	Name	Betweenness	In-degree rank	Eigenvector rank	Pagerank rank
1	University of Cambridge	0,0221	3	3	4
2	University of Oxford	0,0191	4	2	3
3	UCL Institute of Neurology	0,0179	2	4	2
4	Shanghai Jiao Tong University	0,0176	18	32	24
5	National Institutes of Health	0,0175	1	1	1
6	University College London	0,0173	5	5	5
7	Radboud University Nijmegen	0,0170	14	19	11
8	Harvard University	0,0151	7	8	7
9	Capital Medical University	0,0150	12	17	17
10	Karolinska Institutet	0,0144	10	9	9

Table 2. Top 10 affiliations by Betweenness index

Table 3 shows the top 10 affiliations by Eigenvector index. They are completely similar with the most cited organizations from Table , but the order is slightly different.

№	Name	Eigenvector	In-degree rank	Betweenness rank	Pagerank rank
1	National Institutes of Health	0,4312	1	5	1
2	University of Oxford	0,2865	4	2	3
3	University of Cambridge	0,2842	3	1	4

4	UCL Institute of Neurology	0,2780	2	3	2
5	University College London	0,2505	5	6	5
6	Northwestern University	0,2209	6	14	6
7	University of Pennsylvania	0,1582	8	24	8
8	Harvard University	0,1564	7	8	7
9	Karolinska Institutet	0,1290	10	10	9
10	Katholieke Universiteit Leuven	0,1276	9	26	12

Table 3. Top 10 affiliations by Eigenvector index

Top 10 affiliations by PageRank are also similar, only King's College London (#10) appears in the list.

№	Name	PageRank	In-degree rank	Betweenness rank	Eigenvector rank
1	National Institutes of Health	0,0125	1	5	1
2	UCL Institute of Neurology	0,0117	2	3	4
3	University of Oxford	0,0114	4	2	2
4	University of Cambridge	0,0107	3	1	3
5	University College London	0,0100	5	6	5
6	Northwestern University	0,0095	6	14	6
7	Harvard University	0,0091	7	8	8
8	University of Pennsylvania	0,0076	8	24	7
9	Karolinska Institutet	0,0072	10	10	9
10	King's College London	0,0067	11	17	11

Table 4. Top 10 affiliations by PageRank index

6.2. New indices

For new centrality indices we have chosen the following parameters: the maximal size *S* of a critical set of vertices, that can influence on the given one, as 3 and several quota values

q = 0.1%, q = 0.5%, q = 1%, q = 3%, q = 5%, q = 10%

One organization can quote itself, so there are loops in the network. Since in one organization the authors could quote not only their articles, it was decided to take the vertex into a critical set to itself.

Table 5 shows top 10 organizations by TI q = 0.1% - the lowest value of the quota . The results are similar to the In-degree index, because the value of the quota is very small and the number of critical sets is high. However, it can be noticed that the relative order is different and Capital Medical University appears, which was also in the top 10 by the Betweenness index.

№	Name	In-degree	BI, q = 0.1%	PI, q = 0.1%	TI, q = 0.1%
1	UCL Institute of Neurology	0,0134	0,0436	0,2107	0,0892
2	National Institutes of Health	0,0156	0,0365	0,1600	0,0707
3	University of Cambridge	0,0131	0,0321	0,1390	0,0614
4	University College London	0,0120	0,0367	0,1054	0,0514
5	Harvard University	0,01	0,0331	0,1088	0,0506
6	University of Oxford	0,0122	0,0312	0,1029	0,0487
7	Northwestern University	0,0114	0,0306	0,0972	0,0464
8	University of Pennsylvania	0,0085	0,0193	0,0685	0,0321
9	Capital Medical University	0,0078	0,0225	0,0004	0,0102
10	Karolinska Institutet	0,0079	0,0198	0,0003	0,0093

Table 5. Top 10 affiliations by TI q = 0.1%

When analyzing the new indexes with a larger quota, it turned out that there is a difference from the network of articles. In the network of articles, when the quota was increased, the number of critical sets decreased, and the articles with the largest number of citations had small values of the new indexes. Thus, articles that are not cited a lot by the whole community became significant, they are actively cited in highly specialized groups. In the affiliation network, due to the loops and the assumption that the vertex can be in a critical set to itself even for large quotas the most cited affiliations are mainly in the top 10 (Table 6). This is due to the fact that they have a large percentage of self-citation, which allows sets with a given vertex to become critical and exceed the threshold.

№	Name	In-degree rank	Citation number	Proportion of self-citations
1	National Institutes of Health	1	3757	0,112
2	University of Cambridge	3	3165	0,125
3	University of Oxford	4	2933	0,122
4	Capital Medical University	12	1878	0,111
5	University of Pennsylvania	8	2046	0,010
6	Radboud University Nijmegen	14	1799	0,125
7	Shanghai Jiao Tong University	18	1677	0,103
8	University of Florida	21	1573	0,122
9	Katholieke Universiteit Leuven	9	1927	0,107
10	Newcastle University	16	1702	0,147

Table 6. Top 10 affiliations by TI q = 10%

7. Stability analysis

In the networks with temporary structure, various changes can occur during their existence. For instance, new vertices can appear in the network, centrality of the vertices or the relationships between vertices can change. Therefore it is important to understand how much the network has changed over time in order to identify different patterns and trends, and to assess the stability of the scientific community.

The simplest methods involve calculating the correlation between two consecutive adjacency matrices or vertex ranks in such networks, which do not take into account topological changes in the network. In (Aleskerov, Shvydun, 2019), a new approach to measuring graph stability is presented. This metric of stability takes into account both topological similarity and the similarity of importance of elements. Two networks are considered similar if they share a similar structure (with vertices having the same effect on each other) and similar central elements.

7.1. Similarity of central nodes

Networks have similar central elements if their vertices have the same ranks by the centrality indices. The centrality index can be chosen by any one that is suitable for the task. Let c_i be the rank of the vertex i, n is the number of vertices, then a matrix of interval order $R^t = [r^t{}_{ij}]$ is introduced at time t

$$r_{ij}^t = \begin{cases} 1, if\ |c_i^t - c_j^t| > \varepsilon \\ 0, else \end{cases}$$

That means that the values are equal to 1 if the ranks of the vertices differ by more than ε. Therefore it is possible to calculate the distance between the matrices at two consecutive time slots t and $t + 1$

$$d(R^t, R^{t+1}) = \frac{\sum_{i\neq j}^{n} |r_{ij}^t - r_{ij}^{t+1}|}{n(n-1)}$$

If $d(R^t, R^{t+1}) = 0$, then the nodes ranking in this time slot are equal. In another case, if $d(R^t, R^{t+1}) = 1$ then the ranking of nodes is completely different.

7.2. Similarity of structure

Let $\widetilde{c_{ij}^t}$ be the influence of vertex i on vertex j at time t. The influence can be described in different ways, in this paper it is proposed to use the proportion of weights from vertex i to vertex j of the total sum of weights incoming vertex j, that is $c_{ij}^t = \frac{w_{ij}}{\sum_k w_{kj}}$.

Then the distance between the matrices of influence can be calculated as follows

$$\delta(G^t, G^{t+1}) = \frac{\sum_{j!=i}^{n} \left|\widetilde{c_{ij}^t} - \widetilde{c_{ij}^{t+1}}\right|}{n^2 \gamma}$$

Where

$$\gamma = \max_{i,j}\left(\widetilde{c_{ij}^t}, \widetilde{c_{ij}^{t+1}}\right)$$

In the same way, for identical graphs the distance will be 0, and for different graphs 1.

7.3. Stability mesure

The final similarity metric takes into account changes in centrality nodes and in the network structure. Let G^t be the graph G at the time slot t, and G^{t+1}- at time $t+1$, R^t and $\widetilde{C_t}$ are matrices of interval order and influence at time slot t. Then the distance is calculated by the formula

$$d(G^t, G^{t+1}) = \sqrt{\frac{d(R^t, R^{t+1})^2 + \delta(\widetilde{C_t}, \widetilde{C_{t+1}})^2}{2}}.$$

The closer this value is to 0, the more stable the network is over time.

8. Stability analysis: results

In order to determine the level of similarity of networks for all the years under consideration, interval order and influence matrices for consecutive years as well as the distance between them have been calculated (Table 7). ε was taken as 10 and it means that if the affiliation rank changes by less than 10, the change is not considered significant and the ranks are considered equal.

	2015 - 2016	**2016 - 2017**	**2017 - 2018**	**2018 - 2019**	**2019 - 2020**	**2020 - 2021**
Distance between matrices of interval order	0.0555	0.0554	0.0422	0.0581	0.0541	0.0523
Distance between matrices of influence	0.00016	0.00023	0.00029	0.00034	0.00039	0.00044
Stability measure	0.03921	0.03916	0.02983	0.04108	0.03826	0.03697

Table 7. Stability of affiliation citation network

The distance between the matrices of interval orders is close to 0, it changes slightly over time, which indicates small changes in the ranking of affiliations over time. That means that the most important affiliations have barely changed their positions. The values for the influence matrices are closer to 0. That means that organizations cite each other every time in similar proportions. Accordingly, the final values of the stability metric are also close to 0 and do not change much over time. Thus, affiliation citations are stable and there are no significant trends that can change the structure of citations in subsequent years. Therefore, when choosing potential organizations for investment, we can rely on their popularity and importance in previous years.

9. Conclusion

Centrality analysis is a useful way of analyzing bibliometric data. We have applied it to the organizations in the research area of Parkinson's Disease. We have evaluated and compared the results for different centrality indices. Classical centrality indices and the new ones, such as Pivotal Index and Bundle Index, have been evaluated for more than 3 thousand affiliations. New centrality models allow us to take into account different parameters of the vertices such as group interaction and influence of the key nodes. Stability analysis helps us to evaluate the changes in network structure and key participants of Parkinson's Disease community.

Finally, these methods of analysis can be used in various scientific fields in order to extract organizations and authors that are good for investment and partnership.

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