Citation network centrality: a scientific awards predictor?

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Abstract

The $K$-index is an easily computable centrality index in complex networks, such as a scientific citations network. A researcher has a $K$-index equal to $K$ if he or she is cited by $K$ articles that have at least $K$ citations. The $K$-index has several advantages over Hirsh’s $h$-index and, in previous studies, has shown better correlation with Nobel prizes than any other index given by the Web of Science, including the $h$-index. It is plausible that researchers who are the most connected to other scientifically well-connected researchers are the most likely to be doing important work and more likely to be awarded major prizes in a given area. However, the correlation found does not imply causation. Here we perform an experiment using the $K$-index, producing a shortlist of twelve candidates for major scientific prizes, including the Physics Nobel award, in the near future. For example, our top-12 $K$-index list naturally selects the 2019 Nobel laureate James Peebles. The list can be updated annually and should be compared to laureates of the following years.

Keywords: Complex networks, Node centrality, Hirsch index, $K$-index, Nobel prizes.

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Highlights

• We propose that the $K$-index could be a good network centrality index for the physics community and relevant to predict the likelihood of scientific prizes;

• We propose an experiment where a list of highly cited candidates is refined to predict Physics Nobel Prizes in the near future;

• We present a list with twelve candidates with highest $K$-index mostly based on an initial list of 133 physicists from Clarivate Highly Cited Researchers 2019 (HCR).

• We find that the 2019 Nobel laureate James Peebles is ranked 11th on a list where graphene researchers, of an area already awarded in 2010, are filtered out.

• We present the $K$ versus $h$ plane for the HCR list.

1. Introduction

Statistical physicists have made important contributions to the interdisciplinary area of complex networks [10, 1]. In particular, physicists have intensively studied scientometric networks thanks to the availability of large and reliable data banks [11, 2, 15, 12, 4, 16]. Indeed, an important advancement for the area came with the introduction of the $h$-index by physicist Jorge E. Hirsch [6]. A researcher has $h$-index $h$ if he/she has published $h$ papers each one with at least $h$ citations. Centrality indexes proposals for citation networks experienced a boom after the introduction of the $h$-index [3, 5, 7, 13, 14].

A decisive advantage of the $h$-index over its competitors is its ease of calculation. However, it also is known that the $h$-index has several drawbacks. For example, if a researcher has published a small or moderate number $N$ of papers, then necessarily $h \leq N$, even if every paper is of very high quality and has received thousands of citations.

Recently, we have proposed the $K$-index, a centrality index that is complementary to $h$-index and also very easy to calculate in the Web of Science (WoS) [9, 8]. In these publications, we verified that Physics and Physiology Nobel Prizes laureates have very high $K$-index (often above $K = 300$) but sometimes moderate $h$-index. It is very plausible that researchers who are the most scientifically connected to other scientifically well-connected researchers are the most likely to be doing very relevant research and are more likely to be awarded major prizes in a given area. However, this is only a correlation, and the growth of the $K$-index could have occurred after the acceptance of the prize.

Here we propose to test $K$-index’s predictive power by using it to refine the Clarivate Highly Cited Researchers 2019 (HCR) list of candidates to the 2019 Physics Nobel Prizes. Our task is a hard one since it depends only on a brute correlation between a scientometric index and the awards, and does not take into account nuanced and sociological guesses about the actual candidates for scientific prizes, including the Nobel prize.

2. Materials and Methods

2.1. The Highly Cited Researchers list of Clarivate Analytics

As a primary source, we used Clarivate Highly Cited Researchers 2019 (HCR) list to furnish an initial sample of 133 candidates that have Research ID or Orcid. The methodology used by HCR to achieve this sample list is not of our concern now, and can be found in:

https://hcr.clarivate.com/methodology/purpose-and-methodology/

To the HCR list we added the three 2019 Physics Nobel Prize laureates. Our data and automated ranking script is available for public use at:

https://github.com/ajholanda/k-index/blob/master/disclosure.md

Our task is to refine the HCR list by using the $K$-index. We will produce a shortlist of twelve candidates which is the maximum number of Nobel laureates for a period of four years and about 8.8% of the original HCR 2019 list.

For comparison, the $K$ and $h$-indexes for the 136 physicists from the HCR list are presented in Fig. 1. The $h$-index is furnished directly by the WoS.
2.2. Calculation of the K-index

The $K$-index has been devised to measure the impact of the papers that cite a researcher, not just to measure the quantity or distribution of citations. If a maximum number of $K$ papers cite a given author, each one with at least $K$ citations, then the researcher has $K$-index equal to $K$ [9, 8].

Centrality indexes that tried to improve the $h$-index, in general, involve impractical calculations [14]. The decisive advantage of the $K$-index is that it is easily determined by simple inspection of the WoS platform. We presume that other platforms like Google Scholar Citations could also be easily adapted to provide $K$ automatically.

On the WoS, currently, one can obtain the $K$-index of a researcher from the following simple steps:

- Search the production of a given author;
- Click on the link Create Citation Report;
- Click on the link Citing Articles (CA) (or Citing Articles without self-citations, if desired);
- Have the list of citing articles ranked from the most cited (defined as rank $r = 1$) to the least cited (that is the default ranking presented by WoS);
- Compare the article rank $r$ (on the left) with its citation count $c(r)$ on the right. When $r \leq c(r)$ but $r+1 > c(r+1)$, stop: the $K$-index is $K = r$.

3. Results and Discussion

In Table I, we present twelve candidates from the Clarivate HCR list ranked by the $K$-index. In Fig. 1, we present the $K$ versus $h$ plane for the 133 researchers from the HCR list (blue circles) and the 2019 Nobelists (red squares). We see that the laureates have $K$ and $h$-indexes comparable to the HCR group.

Our objective with Fig. 1 is to show that scientists with high $K$ do not necessarily have high $h$ and vice-versa. $K$ and $h$ have complementary information. Fig. 1 should be compared to the $K$ vs. $h$ plots in [9, 8], where 28 Nobel laureates show $K$ values well above other scientists’ of similar $h$. However, it is not clear how much their $K$ indexes have grown after receiving their prizes. A considerable inertial growth is a plausible hypothesis and correlation effects are difficult to separate.

| Rank | Name                 | $K$ | $h$ |
|------|----------------------|-----|-----|
| 1    | Paul Alivisatos      | 617 | 149 |
| 2    | Michael Graetzel     | 611 | 204 |
| 3    | Sergey V Morozov     | 559 | 38  |
| 4    | Younan Xia           | 542 | 190 |
| 5    | Philip Kim           | 519 | 84  |
| 6    | Zhong Lin (Z.L.) Wang| 515 | 195 |
| 7    | Yi Cui               | 495 | 124 |
| 8    | Mikhail I. Katsnelson| 489 | 89  |
| 9    | Yang Yang            | 471 | 118 |
| 10   | Phaedon Avouris      | 465 | 122 |
| 11   | Alex K. Zettl        | 460 | 104 |
| 12   | James Hone           | 440 | 72  |

Table 1: List of twelve Nobel Prize candidates as ranked by the $K$-index

Fig. 1 intends not to be correlational but predictive. All candidates have high citation rates and comparable $h$-index. However, we have chosen the top twelve $K$ as our (crude) test of the predictive power of the $K$-index.

A limitation of our study is that our original sample is from Clarivate HCR: if possible nominee candidates are not initially on the list, then our present $K$ ranking cannot detect and select them. This indeed occurred in the 2019 Nobel Prize: the laureates P. James E. Peeble, Michel Mayor and Didier Queloz were not included in the 2019 HCR list.
Here, we added them to the list and compared their $K$ and $h$-indexes to the other researchers. Of course, it is possible that other high $K$ researchers exist but have not been included in the HCR list, and their inclusion would change the ranking by $K$ (from here, the $K$-rank).

Another limitation of our study is that the chosen names are, in principle, uncorrelated, that is, do not refer to a common discovery or a similar research topic. By contrast, the Nobel Prize for a given year is typically awarded to researchers who have made progress on similar topics or discoveries. Also, it is possible that researchers with very high $K$ or $h$ will not be laureate because they work on a topic that has already been awarded in the recent past.

Our methodology can be adjusted to incorporate this kind of information. For example, we have noticed a very high proportion of authors with large $K$ in the area of materials science, especially graphene research – which has already been an awarded topic in 2010. To correct for this bias, we have produced a second list where graphene researchers are removed. The new list with twelve candidates and with graphene scientists filtered out is given in Table 2 and has seven new names as a replacement.

We conclude that, if the 2019 Nobel laureates were included in the HCR list, James Peeble (rank 11° of Table 2) would pertain to our top twelve filtered list. So, in a sense, we can say that our very crude method (ranking by the $K$-index plus a filter to already awarded topics) predicted one of the 2019 Nobel laureates.

In the unfiltered list, we have that James Peebles ($K = 380$ and $h = 73$) has $K$-rank of 23° and $h$-rank of 53°, Michel Mayor ($K = 253$ and $h = 44$) has $K$-rank of 76° and $h$-rank of 86° and Didier Queloz ($K = 219$ and $h = 90$) has $K$-rank of 96° and $h$-rank of 42°. The low $K$-rank of Mayor and Queloz is understandable: the area of exoplanets research is small and citations cannot be accumulated. We conclude that ranking by the $K$-index has outperformed ranking by the $h$-index in the case of James Peebles and Michel Mayor, but has not outperformed $h$-ranking for Didier Queloz.

The average and standard deviation values for $K$ and $h$ in the list are $K = 287 \pm 104$ and $h = 71 \pm 33$. So, although the 2019 laureates have not been included in the original HCR list due to the (defective?) Clarivate’s methodology, their $K$-index and $h$-index have the same level of the other researchers and stay at less than one standard deviation of the HCR mean. We notice also that the coefficient of variation for the $K$ index is $CV_K = \sigma_K / \bar{K} = 0.36$ and for the $h$-index is $CV_h = \sigma_h / \bar{h} = 0.46$. This means that the $K$-index characterizes and defines better the HCR sample than the $h$-index.
| Rank | Name                        | K    | h    |
|------|-----------------------------|------|------|
| 1    | Paul Alivisatos             | 617  | 149  |
| 2    | Michael Graetzel            | 611  | 204  |
| 3    | Younan Xia                  | 542  | 190  |
| 4    | Zhong Lin (Z.L.) Wang       | 515  | 195  |
| 5    | Yang Yang                   | 471  | 118  |
| 6    | Mohammad K Nazeeruddin      | 436  | 126  |
| 7    | Naomi Halas                 | 427  | 122  |
| 8    | Zhenan Bao                  | 412  | 104  |
| 9    | John Rogers                 | 405  | 127  |
| 10   | Arthur J. Nozik             | 386  | 77   |
| 11   | P. James E. Peebles         | 380  | 73   |
| 12   | Peter Zoller                | 379  | 117  |

Table 2: List of twelve Nobel Prize candidates as ranked by the $K$-index with graphene scientists filtered out. 2019 laureate James Peebles has rank 11th when compared to researchers that pertain to the HCR list.

4. Conclusion

It is an open question whether bibliometric information can have predictive power for scientific prizes. Prizes denote qualitative scientific recognition at the sociological level, where human factors are very important. Nobody would think that a prize should be decided by ranking the production of scientists by some automatic metric. At the same time, prizes intend to recognize original contributions whose impact is reflected in the bibliometric indexes, so it is plausible that predictive information is hidden in these indexes.

From a list of highly cited researchers, we proposed twelve candidates for the 2019 or following years Physics Nobel Prizes. We have presented a naive ranking and also an improved ranking where a citation bias for materials scientists studying graphene was filtered out. In this new list, the 2019 Physics Nobel laureate James Peeble appears having the 11th rank. Our list of candidates can be updated and also used in future years.

The fact that the 2019 laureates were not included to the original HCR list means that Clarivate’s ranking methodology has problems: for example, the HCR is based only in highly cited papers in the 2006-2016 period but the seminal papers of the 2019 laureates are from the 90’s or earlier. For an ideal test, we would need a complete database of $K$-indexes for all researchers with ResearchID or Orcid. In any case, we have showed that the Nobel laureates have $K$ and $h$ comparable (within one standard deviation from the average) to the rest of the HCR list.

The shortlisting study of this paper could be extended to other scientific prizes and other scientific disciplines. The only difference is that the sample of initial candidates should be selected in accord with the specific scientific area. These predictive tests, perhaps in the form of annual contests, could be useful benchmarks for evaluation of centrality indexes that can then be used in other, less monitored and less well-studied, complex networks.

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Declarations of interest

None.
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