Comparing the impact of subfields in scientific journals

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Abstract
The impact factor has been extensively used in the last years to assess journals visibility and prestige. While it is useful to compare journals, the specificities of subfields visibility in journals are overlooked whenever visibility is measured only at the journal level. In this paper, we analyze the subfields visibility in a subset of over 450,000 Physics papers. We show that the visibility of subfields is not regular in the considered dataset. In particular years, the variability in subfields impact factor in a journal reached 75% of the average subfields impact factor. We also found that differences of subfields visibility in the same journal can be even higher than differences of visibility between different journals. Our results show that subfields impact is an important factor accounting for journals visibility.

Keywords Citation success · Impact factor · Journal impact · Journal metrics

Introduction

In recent years, the visibility of scientific papers, authors, journals and conferences have been used as an important feature to quantify research impact (Waltman 2016). The number of citations has been an important quantity to gauge prestige, and for this reason, many research impact measurements have been devised based on citation counts (Redner 1998). At the author level, for example, the h-index has been widely used as a proxy to scientific visibility (Bornmann and Daniel 2007), despite the many criticisms (Wilhite et al. 2019; Haley 2017; Egghe 2006; Martin 2016).

Citations also plays an important role in evaluating journals research output. The prestige of scientific journals is oftentimes measured via citation counts, among other factors (Glänzel and Moed 2002). One important citation index for journals is the impact factor (IF), which essentially gives the average number of citations received by papers in a journal in the last 2 years. In many cases, researchers use journals impact

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factor (and other journal attributes) to identify the most relevant venue to disseminate their research. While the impact factor has been a disseminated index to measure journals visibility, it has been mostly used at the journal level (Alberts 2013). In this sense, differences in the visibility of subfields in the same journal have been mostly overlooked. Consider, for example, a general interest journal, publishing in many different subfields. In a high impact journal, some subfields might have a lower visibility. Conversely, in a low impact journal, particular subfields might be more visible than the journal as a whole.

Differences in major fields visibility is a well-known phenomenon (Li et al. 2013). This is one of the reasons why academic datasets (such as Web of Science) classifies journals into different subjects. For example, the difference in citations accrued by Biochemistry and Mathematics papers is typically very large (Waltman et al. 2011). Such differences have motivated several studies in the area of field normalization (Waltman et al. 2011). This research area, which aims at providing tools and methods to compare papers (or journals, researchers) from different fields, has devised some normalization procedures. A well-known normalization measure is the normalized citation score (Bornmann and Marx 2015), defined as the actual number of citations that a paper received normalized by the expected number of citations that a typical paper in the considered field receives. Variations of this measurement have also been proposed to normalize citation counts of papers and journals in different major fields. Some studies suggest the use of universal distributions across fields to normalize citation counts (Radicchi et al. 2008). Other studies suggest a more simple approach that normalizes citation counts by z-scores (Lundberg 2007).

Whilst most of the current studies on the difference of fields visibility have focused on major subfields, here we analyze the differences in the visibility of subfields within a major field. The comparison was performed at two different levels: within the same journal and across different journals.

A comparative analysis of subfields visibility in journals could be useful in several scenarios. For example, for a given journal, scholar assessment bodies might want to understand how the importance of different subfields evolve over time and which subfields are the most important for the journal. This type of information could be used e.g. to show that a journal is an important venue for a particular subfield. Conversely, one may find that particular subfields are not relatively visible, even in a prestigious journal. The impact of subfields could also be used by researchers when choosing a venue to disseminate their work. If the impact of subfields is provided along with journal information, authors could take a more informed decision on the visibility of the topic being approached for their paper. This detailed visibility information could be even more important in general purpose and multidisciplinary journals.

In this paper, we investigate the behavior of subfields visibility in scientific journals. More specifically, by visibility/impact we mean short term average citation impact. We analyze whether there is a significant difference of visibility for different subfields in the same venue. Our analysis was performed in 450,000 Physics papers published by the American Physical Society. Some interesting results have been found. First we found that there is a considerable variability in subfields impact in some cases. The variability in the subfields impact factor can reach up to 75% of the average impact factor of subfields in the Physical Review Letters (PRL) journal. In recent years, the variability reached 50% of PRL impact factor. We also found that differences in the visibility of subfields of the same journal might be higher than differences in the visibility of journals. This result suggests that not only the venue is an important factor to predict papers visibility, but also the subfield inside the journal.
This paper is organized as follow. In Sect. 2, we present related works on the factors affecting citations in journals. We also mention some works highlighting the fact that distinct fields have distinct citation behavior. The methodology used to compare subfields is presented in Sect. 3. Section 4 presents the results obtained when comparing subfields of journals published by the American Physical Society. Finally, Sect. 5 discusses perspectives for future works.

Related works

Many factors have been found to affect papers visibility. The total number of citations might not be influenced only by the inherent prestige and innovation (Bornmann and Leydesdorff 2015). The total number of citations received in the recent past might be an indicative of how many citations a paper will receive in the future (Amancio et al. 2012d). This process is referred to as preferential attachment in the network science field (Jeong et al. 2003; Newman 2001). This effect is also related to the Matthew effect of accumulated advantage (Petersen et al. 2011).

The journal in which the scientific paper is published is important to establish the correct audience for the paper, which may affect the future number of citations (Larivière and Gingras 2010; McKiernan et al. 2019; Bornmann and Leydesdorff 2015). Another important feature that could affect papers visibility is the prestige of the journal. Oftentimes, prestige is gauged by visibility measurements—such as the impact factor, CiteScore, eigenfactor and influence score (Abramo et al. 2010).

Prestige at the author level plays an important role in the success of papers. Renowned authors are naturally more visible and therefore tend to receive more citations (Amjad et al. 2017). The preferential attachment is also a relevant factor driving the dynamics of authors’ citations. Another model showed that a more reliable description of the citation curve of authors should take into consideration only the citations accrued by authors in recent years (Wang et al. 2008).

Some additional factors have also been found to influence the visibility of papers. This includes interdisciplinarity of the subject being approached, the number of tables, figures, references and some textual factors, such as the title length (Leydesdorff 2007; Rostami et al. 2014; Leydesdorff and Rafols 2011; Onodera and Yoshikane 2015; Amancio et al. 2012b). While many of these studies focus on the visibility of journals, papers and major fields, here we perform a visibility analysis at the subfield level. More specifically, we analyze the impact of different subfields inside journals.

Methodology

Dataset and PACS classification

The Physics and Astronomy Classification Scheme (PACS) is a hierarchical classification of Physics and Astronomy scientific papers. A PACS code comprises 3 elements: a pair of two digits separated by a dot. The digits are followed by two characters (letters or positive and negative symbols). In the first part of the code, the first digit represents the main category of the paper and the second digit is the subfield inside the field specified by the first digit. The last characters in the code provide an even more
specific characterization of subfields. For instance, the PACS code 05.45. – a refers to the following classification: “0” represents the “General” field, “05” denotes “Statistical physics, thermodynamics, and nonlinear dynamical systems”. Finally, the last part “-a” represents the “Nonlinear dynamics and chaos” subfield. The “45” part does not have a specific name in the PACS representation and includes more specialized subfields (such as “Fractals” and “Time series analysis”). In our work we focused our analysis at the third hierarchical level, which corresponds to the code “05.45” in the previous example. This is an intermediary hierarchical level that allows us to analyze subfields that are neither too general nor too specific. A list of all subfields mentioned in this paper is available in the Supplementary Information. While there is not a unique way to define a field or discipline, here we used the codes provided by authors as a representation of subfields. Different codes can co-occur in a given paper, however, they are not redundant. In other words, each code is related to a unique subfield.

The dataset we used for the current paper is the dataset provided by the American Physical Society (APS). This dataset provides citations for the APS journals: Physical Review Letters (PRL), Review of Modern Physics (RMP) and Physical Review A-E (PRA-E). We obtained the citation data for over 450,000 papers published in APS journals between 1983 and 2016. While our analysis used only the citation data, journal name, PACS code and publication date, the APS dataset also provides additional information, such as DOI, title, authors names and affiliations. For each journal and year, we considered a subfield relevant if at least 50 articles were published in that field in the last 2 years.

Comparing groups of papers

In this paper we compare the impact of subfields. The subfields might belong to the same journals or to different journals. The difference in the visibility of subfields was computed using the so-called citation success index (Milojević et al. 2017). We decided to use this measurement because it provides a clear interpretation of the differences in the impact factor (and citation distribution) between any two groups of papers. The success index \( S \) is designed to quantitatively compare the success of two journals, but the same concept can be extended to compare any set of papers. Given two set of papers, the reference \( (r) \) and target \( (t) \) sets, the success index \( S_{tr} \) is defined as the probability that a randomly drawn article from the target group will receive more citations than an article drawn from the reference group. \( S_{tr} \) can be computed directly from the citation distribution of \( t \) and \( r \) (Milojević et al. 2017):

\[
S_{tr} = \sum_{c=0}^{\infty} \left( P_t(c) + \frac{p_t(c)}{2} \right) p_r(c),
\]

where \( P_t(c) \) is the fraction of papers in \( t \) with more than \( c \) citations, and \( p_r(c) \) is the fraction of papers in \( r \) that received \( c \) citations.

The success index can be also derived by considering an approximation. This allows its use by taking as inputs the impact factor of journals (Milojević et al. 2017). While in this paper we used the full citation distribution to compute the success index, the approximation is still interesting to be used when only impact factors are available, i.e. when there is no access to the full citation distribution of the journals (or any other subset of papers) being compared.
A relationship between the citation success index and the impact factor can be derived from the definition of impact factor and the definition of the success index in Eq. 1. The following equation can also be used to compute the citation success index:

\[ S_{tr} = \frac{f_0}{2} + \frac{1 - f_0/2}{1 + q\rho^{-k}} \]  

(2)

where \( \rho = I_t/I_r \), is the ratio between impact factors of sets \( t \) and \( r \), respectively; \( k = 1.23 \), \( q \) is a normalization factor and \( f_0 \) is the rate of uncited papers in \( r \). It has been shown that \( f_0 \) can be described by a logistic function (Milojević et al. 2017). Thus \( q \) can be defined as \( q = 1/(1 - f_0) \). The computation of \( S_{tr} \) from Eq. 2 can be simplified whenever \( f_0 \) is low (which typically occurs when \( I_t > 10 \)) or \( I_t > I_r \). In this case,

\[ S_{tr} = \frac{1}{1 + \rho^{-k}}. \]  

(3)

Results and discussion

In Sect. 4.1, we analyze some subfields statistics in journals. In Sect. 4.2, we compare the visibility of subfields in the same journal. In Sect. 4.3, subfields of distinct journals are compared.

Subfields statistics

We start our study by analyzing the evolution in the number of relevant subfields of journals. Overall, in most of the considered journals, the number of subfields increases along the recent years (see blue curve in Fig. 1). We also measured the number of subfields by considering the heterogeneity in the number of articles published in each subfield. To do so, we computed the diversity of subfields, a measurement that has been used in network science and other fields (Tuomisto 2010; Corrêa Jr et al. 2017; Jost 2006; Amancio et al. 2012a). According to the diversity index, if all fields have the same size, the diversity of subfields corresponds to the total number of subfields. Conversely, if the only a few subfields have most of the published articles, the diversity of subfields will be much smaller than the total number of subfields. In the diversity index, such a heterogeneity is measured via entropy (Corrêa Jr et al. 2017).

The diversity of subfields measured in terms of the number of articles published for each subfield is shown in Fig. 1 (orange curve). Note that there is a heterogeneity in the number of papers in each subfield, since the of subfields diversity is much smaller than the total number of fields. In 2015, almost 60 subfields were found; however, the diversity points to effectively only 40 subfields. We also computed the diversity of subfields considering the number of citations received by subfields (rather than the number of published papers). For the PRD journal, Fig. 1 shows that both diversity measurements are similar. This suggests that citations received by subfields follow the respective number of published papers.

A different scenario can be observed for both PRE and PRL journals in recent years (result not shown). While the diversity curves for the number of papers and citations follow the same behavior, the diversity of subfields considering the number of papers is higher.
than the diversity measured via citations. For instance, in 2015, 115 subfields were identified in PRL. In this same year, the diversity of subfields in terms of the number of papers was about 90 subfields. Conversely, the diversity of subfields measured in terms of citations was only about 78 subfields. This result suggests that some subfields are more cited than others and this difference cannot be explained only by subfields size in PRL. To further investigate the differences in subfields visibility, in the next section we compare subfields in the same journal using the citation success index.

### Comparing subfields in the same journal

In order to analyze how subfields visibility varies along time, we computed the yearly impact factor (IF) of each PACS code. In Fig. 2a, we show the evolution of average impact factor of PRL subfields. We also show the evolution of PRL impact factor. Because we used the APS dataset, we are limited to the citations received by APS journals. As a consequence, impact factors might not be the same reported by Clarivate Analytics.\(^1\) Similarly to other results in literature, this sampling does not affect the comparison of journals and subfields citation data (Milojević et al. 2017).

The average subfield IF is consistent with the journal IF. This happens for all considered journals. We however observe a variability of subfields impact along time, meaning that different subfields are more (or less) visible than the journal as a whole. Such a variability

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\(^1\) [https://clarivate.com/](https://clarivate.com/).
is evident when analyzing the coefficient of variation of subfields IF. Figure 2b reveals that, in the most recent years, the typical deviation is roughly 50% of the average IF. An even higher heterogeneity of subfields impact occurred in 1990. In that year, a typical deviation of 75% of the average IF was observed. This result suggests that different subfields being published by PRL might have different visibility. Other APS journals display a similar behavior, however the coefficients of variation of subfields impact are typically below 0.50 (result not shown).

To further investigate how different is the impact of subfields inside a journal, we used the citation success index (see Sect. 3.2). This measurement provides a clearer interpretation regarding the difference of visibility (i.e. impact factor) between two subfields. In other words, given subfields $A$ and $B$, the success index $S_{AB}$ comparing them gives the probability that a randomly drawn article from $A$ will be more cited than an article drawn $B$ (see Sect. 3.2).

To understand the differences in visibility, for each journal, we measured the the success index between all pairs of subfields in the same journal. Because $S_{AB} + S_{BA} = 100\%$, in our analysis, for each pair $A$ and $B$, we only considered the maximum between $S_{AB}$ and $S_{BA}$. The results obtained for PRB is shown in Fig. 3. For this particular journal, we note that the median success index (comparing all pairs of subfields) varies between 55 and 57%. This means that typically the impact factor of subfields in PRB are similar. However, in particular cases, some subfields are much more visible than others. The highest values of success index are highlighted in the red curve. For comparison purposes, we also show the success index obtained when comparing PRL and PRB (gray curve). Typically, the difference of visibility between PRL and PRB is more significant than the difference in visibility of PRB subfields. However, for particular pairs of subfields, the difference of visibility
between subfields is more significant than the difference of impact between journals (PRL and PRB). In 2015, the success index comparing PACS 85.25 (superconducting devices) and 85.75 (magnetoelectronics and spintronics) reached almost 85%, while the difference between PRB and PRL was roughly 65%.

In Fig. 4, we show the distribution of success indexes when comparing all pairs of PRE subfields (boxplots). In all considered years, most of the success indexes are below 60%, revealing that there is no significant impact difference in PRE subfields for most of the considered pairs. However, as observed for PRB (see Fig. 3), some pairs of subfields display very distinct impact factors. In 2015, the comparison between PACS 89.20 and 85.75 yielded a success index higher than 85%. This is much higher than the success index obtained when comparing PRA and PRE. In recent years, we can see that the typical internal impact difference is lower than the impact difference between PRA and PRE (see gray curve). Differently from Fig. 3, in terms of visibility, it seems the choice of subfield inside PRE is more important than the choice between PRA and PRE in particular years. This is clear e.g. in 1995 and 1996, when more than 75% of all pairs of subfields were found to have a visibility difference higher than the one observed between PRA and PRE.

Figure 5 shows the distribution of success indexes comparing all pairs of PRA subfields. We also show the evolution of the success index comparing PRA and PRB. This comparison is shown in two different colors: gray; meaning that the impact of PRB is higher than the impact of PRA; and blue, to represent the opposite. Unlike the previous analysis, we observe an interesting behavior after 1997. The difference in impact between PRA and PRB becomes very small, as revealed by success indexes typically below 55%. At the same
Fig. 4 Evolution of success index comparing the impact of all pairs of PRE subfields. The red curve represents the highest success index obtained for a given year. The gray curve represents the success index resulting from the comparison of PRA and PRE. A list of PACS codes is shown in the Supplementary Information.

Fig. 5 Evolution of success index comparing the impact of all pairs of PRA subfields. The red curve represents the highest success index obtained for a given year. The gray and blue curves represent the success index resulting from the comparison of PRA and PRB impact. A list of PACS codes is shown in the Supplementary Information.
time, PRA subfields impact difference are typically larger than 55%, once again meaning that the internal (subfield) visibility differences might be more important than the visibility differences observed between journals. In extreme cases, the success index comparing two PRA subfields reaches almost 90%.

In order to analyze whether the observed differences in papers visibility can be described just by chance, the following robustness test was performed. For a given year, we associated randomly PACS codes to the papers, but keeping the original distribution of paper set size. We then analyzed for each random assignment the maximum success index. The distribution of success indexes is shown in Fig. 6. This figure shows the results obtained for PRA in 2013 and 2015. The red dashed line represents the corresponding value of success index observed in the real data. This result suggests that the differences in subfields visibility cannot be explained by a random division of papers in subfields. Similar results have been found for the other APS journals in the considered publication interval.

Comparing subfields of different journals

While in Figs. 3, 4 and 5 we focused our analysis on the comparison of subfields in the same journal, we now compare the impact factor of subfields in different journals. The comparison between all pairs of PRA and PRE subfields is shown in Fig. 7. One interesting pattern observed here is that the curve of success index comparing both journals follows the same behavior of the median comparing pairs of subfields. Therefore, in general, the visibility comparison of PRA and PRE is compatible with the comparison of the respective subfields visibility. However, particular subfields have very distinct visibility, as revealed by the dynamics of the red curve in Fig. 7. Particularly, in 2015, a large difference in visibility was found when comparing PACS 05.70 (from PRA) and
47.65 (from PRE). Note that such a difference in visibility is much higher than the typical visibility difference between PRA and PRE.

The relevance of comparing subfields (rather than journals) can be noted when comparing subfields from PRC and PRB journals, as shown in Fig. 8. From 1986 to 1994, the success index comparing PRB and PRC is compatible with the median of the success index comparing the respective subfields. However, from 2002 to 2015, it is clear that PRC and PRB have very similar values of impact factor, as revealed by values of success index very close to 50% (see gray and blue curves). In this same period, however, the typical difference between subfields visibility was close to 60%. Once again, for particular subfields, the citation success index reached values close to 85%. While in 2015 the journals have the same impact factor, the subfields represented by PACS 12.38 and 61.46 were found to have a difference in impact yielding a success index close to 80%.

A robustness test analogous to the one performed in Fig. 6 also revealed that the differences in visibility cannot be explained just by chance. The results corresponding to this test are shown in Fig. 9. While we show the results for the comparison of PRA and PRE subfields in 2013 and 2015, similar results have been found for the other comparisons of subfields visibility in different journals (result not shown).

All in all, the results presented in Sects. 4.2 and 4.3 revealed that subfields intra- and inter-journals might have very distinct visibility. This is an important result since it could be used as an additional information in research policies. From scholars’ perspective, the quantification of subfields visibility could assist researchers in their career path decisions. Along with other field attributes, it could be of interest to know beforehand the potential visibility of subfields before efforts are made to learn and produce knowledge in the field.
Another interesting conclusion arising from the obtained results concerns the comparison of journals. Our results show that in some cases the direct comparison of journals might not give all the information relevant. Two journals with similar impact factors might
have very distinct visibility values when subfields are compared. This information could be used e.g. to improve predictions and evaluations that use the impact factor (in combination with other established research impact indexes).

Conclusion

The analysis of subfields impact is relevant to provide a more detailed information of the factors affecting journals visibility. In this paper we studied the variability of subfields impact in a subset of Physics journals published by the American Physical Society. Despite its limitations and shortcomings, journals impact factors are one of the available well-known tools used to quantify short term average citation impact (Antonoyiannakis 2020; Bordons et al. 2002; Wallin 2005). Here, differences in impact were computed using the success index, a measure that compares the distribution of citations observed in two sets of papers. According to (Milojević et al. 2017), this measurement can also be computed, in a simplified way, using the impact factor of the considered sets of papers. The success index comparing two subsets of papers $A$ and $B$ gives the probability that a paper randomly drawn from $A$ will receive more citations than a paper randomly drawn from $B$.

The identification of subfields was performed using the classification scheme provided by APS. We compared the differences of subfields visibility in a twofold way. First, subfields in the same journal were compared. We found that some subfields are more visible than others in the same journal. For instance, for papers published in PRB in 2015, the success index comparing PACS 85.25 (superconducting devices) and 85.75 (magneto-electronics and spintronics) was found to be roughly 85%; while, in the same year, the success index comparing PRB and PRL was only 65%. We also found that, in particular years, the typical visibility difference for subfields of a journal (e.g. PRE subfields) can be higher than the visibility difference of journals (e.g. PRA vs. PRE in 1995 and 1996). A second type of analysis focused on comparing subfields in distinct journals. In this case, we also found that when subfields are considered, the differences of subfields visibility can be very different from the visibility differences of the respective journals.

Altogether, our results suggest that subfields visibility in specialized journals might be not uniform and this information could be used to better understand the components affecting journals impact. This information could be used e.g. for authors who researching the most adequate and visible venue for their work. While journals visibility metrics can help, a more detailed subfields visibility could allow authors to make more informed decisions. Editors could also rely on subfields visibility information to better understand how journals evolve over time. This could be used e.g. to highlight the main areas of the journals. The identification of relatively low impact subfields in a journal could be important to spot potential sources of low-quality scientific practices (e.g. low quality referee’s reports) adopted by the journal in a specific subfield. One should bear in mind that, despite the advantages of better understanding subfields visibility, this knowledge could also lead to biased behaviors. For example, if subfield $A$ is more visible than subfield $B$ in a journal, this information be use to raise the journal impact by accepting more papers in $A$. Similar conducts have been reported in recent studies Martin (2016) and should be avoided in case subfields visibility becomes widely available.

While we focused the subfields visibility analysis via PACS classification, this work could be extended by considering other notions of subfields, including information extracted from texts (Arruda et al. 2016). For example, subfields could be identified
without any type of classification scheme. In particular, the identification of subfields could be performed via community detection in citation (or co-citation) networks (Silva et al. 2016). Subfields could also be identified using co-occurrence word networks obtained from title and/or abstract (Castro and Stella 2019; Amancio et al. 2015; Stella et al. 2019). Collaboration networks could also be used to detect subfields, but in this case a disambiguation strategy is essential to construct author-based networks (Amancio et al. 2012c). Finally, we also intend to extend this study to analyze the variability of subfields visibility in other major fields.

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