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RESEARCH ARTICLE

Co-citations in context: disciplinary heterogeneity is relevant

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ABSTRACT

Citation analysis of the scientific literature has been used to study and define disciplinary boundaries, to trace the dissemination of knowledge, and to estimate impact. Co-citation, the frequency with which pairs of publications are cited, provides insight into how documents relate to each other and across fields. Co-citation analysis has been used to characterize combinations of prior work as conventional or innovative and to derive features of highly cited publications. Given the organization of science into disciplines, a key question is the sensitivity of such analyses to frame of reference. Our study examines this question using semantically-themed citation networks. We observe that trends reported to be true across the scientific literature do not hold for focused citation networks, and we conclude that co-citation analysis requires a contextual perspective.

INTRODUCTION

Citation and network analysis of scientific literature reveals information on semantic relationships between publications, collaboration between scientists, and the practice of citation itself (de Solla Price, 1965; Garfield, 1955; Newman, 2001; Patience, Patience, Blais, & Bertrand, 2017; Shi, Leskovec, & McFarland, 2010). Co-citation, the frequency with which two documents are cited together in other documents provides additional insights, including the identification of semantically related documents, fields, ideas, and specializations in science (Boyack & Klavans, 2010; Marshakova-Shaikevich, 1973; Small, 1973).

(Uzzi, Mukherjee, Stringer, & Jones, 2013) used a novel approach for co-citation analysis of 17.9 million articles and their cited references from the Web of Science (WoS) to characterize a subset of highly cited articles with respect to both novel and conventional combinations of prior research. Observed co-citation frequencies, mapped to journals, were computed across the dataset and normalized (shifted and scaled) to expected values generated by Monte Carlo simulations under a random graph model. These normalized journal pair frequencies were termed *z-scores* (Materials and Methods). Thus, every article was associated with multiple z-scores corresponding with the journal pairs represented by its citations. For each article, positional statistics of these z-scores were calculated to describe conventionality: high conventionality (HC) if the median z-score for an article was greater than the median of median z-scores of all articles and low conventionality for the converse

(LC). Similarly, an article was deemed to have high novelty (HN) if the tenth percentile of its z-scores was negative and low novelty (LN) for the converse. Accordingly, each article was labeled with respect to conventionality and novelty, e.g, HCHN (denoting that the article exhibits high conventionality and high novelty), with all four combinations being possible. (Uzzi et al., 2013) observed that HCHN articles were twice as likely to be highly cited, suggesting that novel combinations of ideas flavoring a body of conventional thought were a recipe for impact across the scientific literature.

Key to Uzzi *et al.*, however, is their random graph model and its underlying assumptions. A careful examination of the model (as defined by the Monte Carlo simulation) reveals that all substitutions of references are equiprobable, which means that a reference in an article can be substituted by any other reference randomly chosen from those published in the same year, irrespective of subject matter, disciplinary focus, and citation count. For example, the model permits substitution of a reference in quantum physics with equal probability by a reference in classical literature, evolutionary biology, or anthropology. Such substitutions poorly model documented citation behavior (Garfield, 1979; Klavans & Boyack, 2017; Moed, 2010; Wallace, Lariviere, & Gingras, 2012). In addition, under this random model, a reference cited over 100 times in a given year is selected with the same probability as a reference cited only once, which is inconsistent with the actual frequency of citation and also the power law or lognormal distributions observed in citations (Perline, 2005; Stringer, Sales-Pardo, & Amaral, 2010). Accordingly, the expected value calculations generated by the (Uzzi et al., 2013) simulations and used in characterizing journal pairs in terms of conventionality and novelty can be reasonably questioned on grounds of model mis-specification.

A follow-up study by (Boyack & Klavans, 2014) explored the impact of discipline and journal effects on the definition of conventionality and novelty. While their study had some methodological differences from (Uzzi et al., 2013) in the use of Scopus data and a χ^2 calculation for the expected number of journal pair citations, Boyack and Klavans find the same basic trend that HCHN is more probably in highly cited papers. However, they note that “only 64.4% of 243 WoS subject categories” in the Uzzi *et al.* study met the criterion of having the highest probability of hit papers in the HCHN category. Further, they observed that journals vary widely in terms of size and influence and that 20 journals accounted for nearly 15% of co-citations in their measurements. Lastly, they noted that three multidisciplinary journals accounted for 9.4% of all atypical combinations, suggesting strong effects from both disciplines and journals that were not reported by Uzzi et al.

Despite different methods used to generate expected values, both (Uzzi et al., 2013) and (Boyack & Klavans, 2014) measured observed frequencies across the scientific literature without disciplinary constraints and subsequently used normalized frequencies to examine disciplinary subsets. In contrast, we chose instead to first construct semantically related sets of documents (disciplinary networks) and to measure observed and expected frequencies within these networks. (or cite Sitaram’s statistics here so as to add specificity to this sentence, which could have this appended to it: “consistent with researchers’ patterns of citing predominantly work from their own field. This doesn’t preclude citations from outside of the discipline of focus, but constrains the random substitutions to more plausibly related literature.”)

Accordingly, we used keyword searches of the scientific literature to create three citation networks themed around broad search terms. Within these disciplinary frameworks, we calculated expected values using a random graph model that accounted for existing citation frequencies and an efficient Monte Carlo simulation algorithm that permitted a substantially greater number of simulations while preserving the number of publications, references, and disciplinary proportions in the network. We hypothesized that our approach would reduce model misspecification and better simulate citation practice, in turn leading to different and more relevant conclusions. Our study on these semantically-themed citation networks reveals significantly different patterns of conventionality and novelty between citation networks and disciplines that challenges the conclusion that HCHN articles have a greater probability of being represented in highly cited publications. Instead, we conclude that conventional thought as commonly defined in our study, in (Uzzi et al., 2013), and (Boyack & Klavans, 2014), is more likely to drive higher citations. *these are just filler conclusions that must be carefully rewritten and added to- need Jim's conclusions to be stated here.*.

MATERIALS AND METHODS

Bibliographic data We have previously developed ERNIE, an open source knowledge platform into which we parse the Web of Science (WoS) Core Collection (Keserci, Davey, Pico, Korobskiy, & Chacko, 2018). WoS data stored in ERNIE spans the period 1900-2019 and consists of over 72 million publications. For this study, we generated an analytical dataset from years 1985 to 2005 from ERNIE. The total number of publications in this dataset was just over 25 million publications (25,134,073). For each of these years, we further restricted analysis to those of type Article. Since WoS data also contains incomplete references or references that point at other indexes, we also considered only those references for which there were complete records (Table 1). For example, WoS data for year 2005 contained 1,753,174 publications, which after restricting to type Article and considering only those references described above resulted in 916,573 publications, 6,095,594 unique references (set of references), and 17,167,347 total references (multiset of references). Given consistent trends in the data, we analyzed the two boundary years (1985 and 2005) and the mid-point (1995) performing 1,000 simulations for each dataset.

Disciplinary datasets We constructed three disciplinary datasets based on keyword searches. (i) immunology (ii) metabolism (iii) applied physics. For the first two, rooted in biomedical research, we searched Pubmed for the term 'immunology' or 'metabolism' in the years 1985, 1995, and 2005. Pubmed IDs (pmids) returned were matched to WoS IDs (wos_ids) and used to retrieve relevant articles. For the applied physics dataset, we directly searched subject labels in WoS for 'applied physics'.

Normalization of observed and expected values Building upon prior work Uzzi et al. (2013), all $\binom{n}{2}$ reference pairs were generated for each publication, where n is the number of cited references in the publication. These reference pairs were then mapped to the journals they were published in using ISSN numbers, creating journal pairs. Where multiple ISSN numbers exist for a journal, the most frequently used one in the WoS was assigned to the journal. In addition, publications containing fewer than two references were discarded. Journal pair frequencies were summed up across the dataset to create observed frequencies (F_{obs}). In contrast to the preceding study (Uzzi et al., 2013), we generated 1,000 rather than 10 null models for each dataset by randomly shuffling references while preserving the number of publications, the number of references in each publication, and the frequency with which these references were cited within the year of interest. Expected values (F_{exp}) were generated by averaging the result of 1,000 simulations. z-scores were calculated for each journal-pair using the formula $(F_{obs} - F_{exp})/\sigma$ where σ is the standard deviation of the frequencies generated by simulation. (Do we need a comment here that while we are using the term z-score, we do not imply that these are related to a normal distribution. Rather, we are using the terminology from Uzzi et al.) As a result of these calculations, each publication becomes associated with a set of z-scores corresponding to the journal pairs derived from pairwise combinations of its cited references and positional statistics (quantiles) of z-scores were calculated for each publication. Publications were also labeled according to conventionality and novelty. (i) HC if the median z-score exceeded the median of median z-scores for all publications. LC if the median z-score was equal to or less than the median of median z-scores for all publications (ii) HN if the tenth percentile of z-scores for a publication was less than zero. LN if the tenth percentile of z-scores for a publication was greater than zero.

We investigated multiple definitions of hit articles, as did Uzzi et al., with hits defined as the 1%, 2%, 5%, and 10% top-cited articles. Do we want to report on the percentile being used for novelty at both the 1 and 10th percentile, or just focus on the 10th percentile?

Table 1. Summary of WoS Analytical Dataset. UP: unique publications, UR: unique references, TR: total references. The number of publications, unique references, total references and the ratio of total references to unique references increases monotonically with each year indicating that both the number of documents and citation activity increase over time. Data for reference years is flanked by horizontal lines and shown in boldface. Only publications of type Article and references with complete WoS records are included in these counts.

Year	UP	UR	TR	TR/UR
1985	**418495**	**2281297**	**5615496**	**2.46**
1986	402309	2316451	5708796	2.46
1987	412936	2427347	5998513	2.47
1988	426001	2545647	6354917	2.50
1989	443144	2673092	6749319	2.52
1990	458768	2827517	7209413	2.55
1991	477712	2977784	7729776	2.60
1992	492181	3134109	8188940	2.61
1993	504488	3278102	8676583	2.65
1994	523660	3458072	9255748	2.68
1995	**559685**	**3692575**	**9897946**	**2.68**
1996	663110	4144581	11641286	2.81
1997	677077	4340733	12135104	2.80
1998	693531	4573584	12728629	2.78
1999	709827	4784024	13280828	2.78
2000	721926	5008842	13810746	2.76
2001	727816	5203078	14261189	2.74
2002	747287	5464045	15001390	2.75
2003	786284	5773756	16024652	2.78
2004	826834	6095594	17167347	2.82
2005	**916573**	**6629595**	**19066249**	**2.88**

RESULTS

Table 2. Disciplinary Datasets. PubMed and WoS were searched for articles using search terms, 'immunology', 'metabolism', and 'applied physics'. Counts of retrieved publications are shown for each of the three years analyzed.

Year	Immunology	Metabolism	Applied Physics
1985	21,606	78,998	10,298
1995	29,320	121,247	21,012
2005	37,296	200,052	35,600

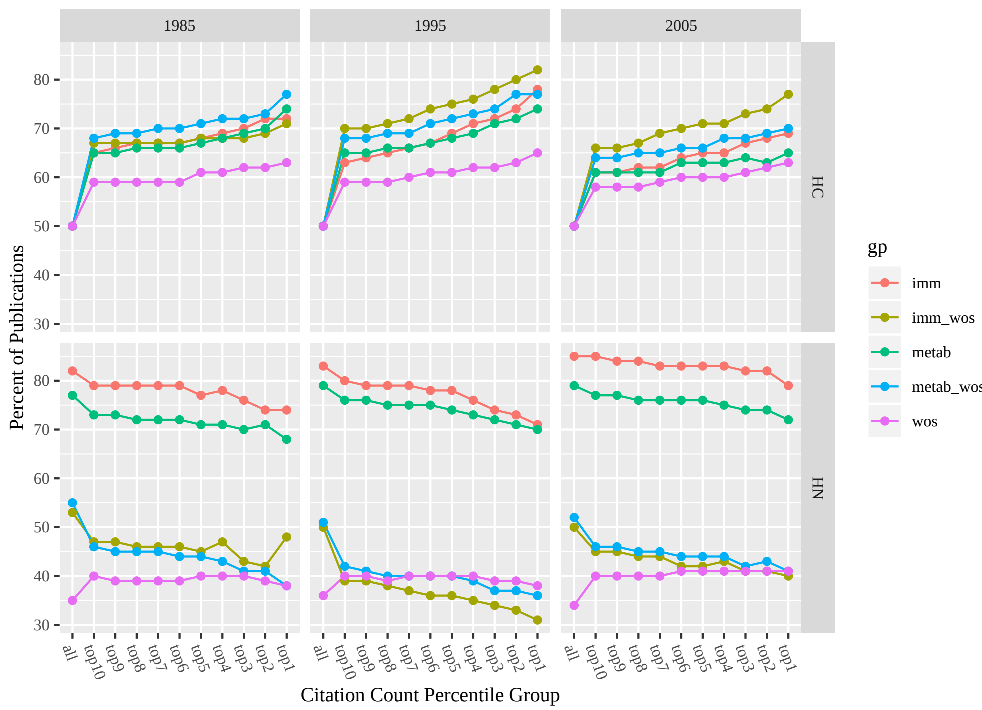

Figure 1. Fraction of publications with high conventionality (HC) and high novelty (HN) signatures relative to citation count.

Chacko

In our study, we also use a Monte Carlo approach to simulate under a random graph model. A principal consideration, however, was to restrict model misspecification arising from disciplinarily irrelevant references. We addressed this consideration by restricting random substitutions to only those references in the disciplinary network being studied. We estimated model misspecification by measuring the Kullback-Leibler (K-L) Divergence (?) between observed and simulated frequencies for the set of journals common to both a disciplinary network and the WoS superset (Table 3). The results indicate that simulations under our model consistently have a lower K-L divergence compared to simulations that draw from the WoS superset and its attendant substitutions that are ectopic with respect to field and discipline (Introduction).

Bradley

Table 3. Measuring Model Misspecification. For the set of journal pairs in common between a disciplinary network and the full WoS dataset, Kullback-Leibler (K-L) divergences between empirical and simulated journal pair frequencies were computed for the years 1985, 1995, and 2005 for the three disciplinary datasets (applied_physics, immunology, and metabolism) using either the disciplinary network as background or the WoS superset (all_wos) to generate the null model (Background). K-L divergence was calculated using the R seewave package with a base (logarithm) of 2. The ratio between the K-L divergence for disciplinary networks versus the full WoS ranges from 1.96 to 2.77 and is greater than 2.0 for eight out of nine cases, strongly suggesting that simulations that constrain substitutions to the given disciplinary network better model the observed data.

	Disciplinary Network	Year	Background	K-L Divergence	Ratio
1	appl_physics	1985	appl_physics	1.21	
2		1985	all_wos	2.37	1.96
3		1995	appl_physics	0.86	
4		1995	all_wos	2.37	2.77
5		2005	appl_physics	0.95	
6		2005	all_wos	2.35	2.47
7	immunology	1985	immunology	0.75	
8		1985	all_wos	1.68	2.24
9		1995	immunology	0.78	
10		1995	all_wos	1.70	2.19
11		2005	immunology	0.73	
12		2005	all_wos	1.92	2.63
13	metabolism	1985	metabolism	1.11	
14		1985	all_wos	2.24	2.02
15		1995	metabolism	1.07	
16		1995	all_wos	2.33	2.17
17		2005	metabolism	1.19	
18		2005	all_wos	2.60	2.18

Figure 2 shows that the z-scores for the same journal pair can be positive (negative) when computed with respect to one data set but be negative (positive) for another data set. The journal-pair z-scores in Figure 2 have consistent signs for both Immunology and WoS data sets in 71.4% of the instances and different signs for 28.6% of the journal pairs. A negative journal pair z-score in one context increases the likelihood that articles citing it will be deemed to be novel while articles citing it in another context, where the journal pair z-score is positive, are less likely to be classified as novel and possibly more likely to be classified as conventional. Figure 2 reflects that the WoS data set has approximately 44,000 fewer negative z-scores than does the immunology data set, which contributes to its significantly lower percentage of high-novelty articles as shown in Figure 2.

Figure 3, Panels (a) and (b), compares hit rates for the four categories among the Immunology, Applied Physics, and WoS datasets for 1995: the hit rate is defined as the number of hit articles in each category divided by the number of articles in the category. We evaluated the statistical significance of the categorical hit rates using multiple methods, some of which we describe here. Our first test was based on the null hypotheses that hits were distributed randomly among the four categories with uniform probability in proportion to the number of articles in each category. Using a Chi-Square Goodness of Fit test, rejecting the null hypothesis in favor of the alternate hypothesis supports a non-uniform dispersion of hits: that is, some of the four categories are individually associated with higher than

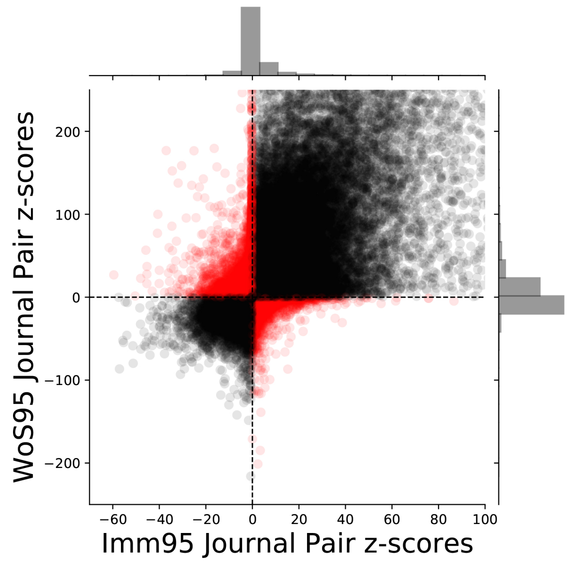

Figure 2. Journal pair z-scores vary with reference dataset. Scatter plot points (319,005) indicate journal pair z-scores for the 1995 Immunology dataset along the x-axis and the 1995 Web of Science dataset on the y-axis. Black indicates journal pairs whose z-scores have the same sign when computed for both reference datasets while red points indicate the 28.6% of journal pairs whose z-scores change sign across datasets. Regions with deeper hues indicate higher point densities and the histograms show the marginal distributions for each dataset separately.

Table 4. Hit Rates by Category. The last four columns indicate the proportion of publications that are hits for each respective category.

Data Set	Hits as % of Articles	Novelty Percentile	LNLC	LNHC	HNLC	HNHC
Imm95	1%	10%	0.000	0.019	0.005	0.014
Imm95	10%	10%	0.017	0.128	0.076	0.129
Metab95	1%	10%	0.001	0.017	0.006	0.014
Metab95	10%	10%	0.019	0.130	0.074	0.133
AP95	1%	10%	0.002	0.007	0.012	0.010
AP95	10%	10%	0.047	0.079	0.123	0.109
WoS95	1%	10%	0.004	0.013	0.009	0.017
WoS95	10%	10%	0.056	0.115	0.104	0.156

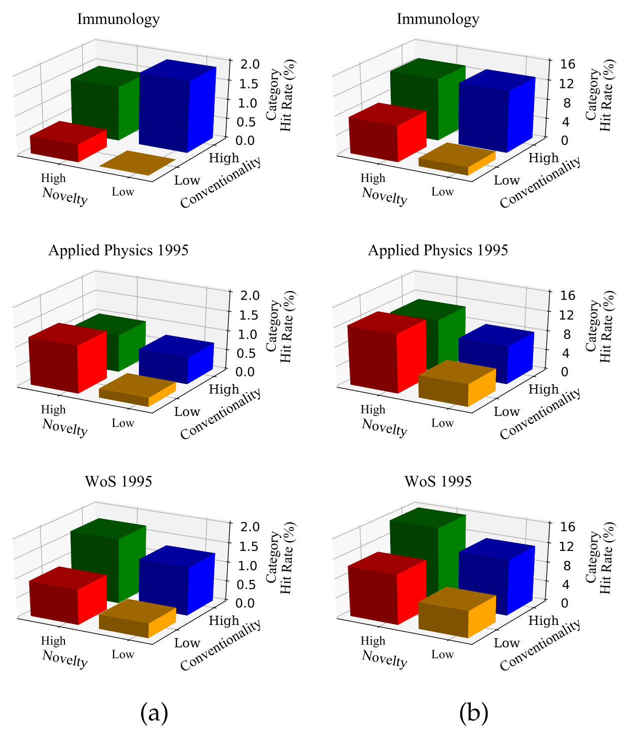

Figure 3. Effect of Context on Journal-Pair z-scores and Categorical Hit Rates: Immunology, Applied Physics, and WoS for 1995. Panels (a) and (b) show hit rates for the LNLC, LNHC, HNLC, and HNHC categories for the immunology, applied physics, and WoS datasets when hit articles are defined as the top 1% and top 10% of articles, respectively. Novelty in both panels is defined at the 10th percentile of articles' z-score distributions. The number of data points in the immunology, applied physics, and WoS data sets are 21,917, 18,305, and 476,288, respectively. The results for the WoS data set mirrored previous results from Uzzi et al. Uzzi et al. (2013) where the highest hit rate was for the HNHC category. The highest hit rates for the immunology dataset, in contrast, are in the LNHC category. The LNHC category often had the highest hit rate for the immunology dataset for various parameter settings with the HCHN category having the highest hit rate in other cases: metabolism results are similar. The applied physics dataset shows further contrast as the hit rate for it was highest in the HNLC category. The HNLC category demonstrated the highest hit rate often for applied physics: otherwise the highest hit rate was for HNHC articles.

expected, or lower than expected hit rates. The null hypothesis was rejected at a $p < 0.001$ in all cases in Figure 3, with the exception of the immunology and applied datasets where hit articles are designated as the top 1% of articles: valid tests were not possible in those instances due to too few expected hits. The null hypothesis was rejected with $p < 0.001$ for all valid tests for all parameter settings, all datasets, and all years: hypotheses tests were valid in 73 of 96 instances. We conclude that it is likely that the distribution of hits among categories is not uniform but, rather, hit rates vary among the categories in all datasets. (Should we insert a table with all statistical results?)

We computed hit rates for the WoS dataset, which mirrored Uzzi et al.'s results whereby the largest hit rates were for the HNHC category, despite our methodological improvement of sampling citations in proportion to their frequency. We found contrary results in the 1995 immunology dataset where articles in the LNHC category often had the greatest hit rates, as reflected in Table 4 and Figure 3. Across all year's data, all datasets, and all parameter settings, the highest hit rates in the immunology datasets were sometimes in the LNHC category and sometimes in the HNHC category. The metabolism hit rates reflected this same pattern. The greatest hit rates for the applied physics data were often in the HNLC category as reflected in Table 4 and Figure 3, and otherwise in the HNHC category. We conclude that Uzzi et al.'s finding of high hit rates in the HNHC category does not hold generally for disciplinary-based datasets and that novel citation patterns are not always indicative of impactful research, as was the case with immunology. Furthermore, the categories displaying the greatest hit rate vary with parameter settings and with the year. The lack of stable results across parameter settings suggests that parameters must be selected judiciously.

We also tested the explanatory power of each framework dimension by classifying articles as Low Novelty (LN) or High Novelty (HN) and, separately, as having Low Conventionality (LC) or High Conventionality (HC). We tested the null hypothesis that hits are distributed between LN and HN (LC and HC) in proportion to the total number of articles assigned to those categories. That null hypothesis was rejected for the WoS data along both dimensions. Consistent with previous analysis, hit articles were overrepresented in the HC category in every instance of WoS data at a $p < 0.001$ and hit articles were overrepresented in the HN category at a $p < 0.001$ in all but two cases. The p-values, in those cases, were 0.002 and 0.007. Hits in the immunology and metabolism data were overrepresented in the HC category with the same statistical significance as for WoS. The relationship of novelty with hits in the immunology and metabolism data differed dramatically from the WoS, however, with statistically significant findings of hit articles being sometimes overrepresented in the LN category, and sometimes being underrepresented. Of the 12 tests for applied physics, the statistical significance supporting a positive relationship between hit articles and HN were all $p < 0.10$, and 10 of 12 were $p < 0.05$. These tests also indicated strong support for the relationship between LN and hit articles in applied physics in a limited number of tests, with $p < 0.10$ in 5 of 12 instances and $p < 0.05$ in 3 of 12 instances. These results suggest that (1) both conventionality and novelty are strongly related to hits in the WoS, (2) the conventionality dimension is strongly related with hits in immunology and metabolism and novelty is not, (3) novelty is more strongly related with hits in applied physics than is conventionality. More generally, we find that the dimensions most strongly related with hit articles vary across disciplines and between disciplinary and broad data sets.

DISCUSSION

We conclude that Uzzi et al.'s finding of high hit rates in the HNHC category does not hold generally for all datasets and that novel citation patterns are not always indicative of impactful research.

The z-scores that change sign across datasets is either contradictory or an acceptable variation due to the difference in reference sets. We contend that it is the former because the inappropriate substitution of citations with those from disciplines that are implausible and because the observed citation frequencies are ignored. That fewer z-scores are negative in the WoS dataset relative to the immunology dataset may be directly due to the uniform sampling of references whereby many resulting journal pairs are never observed in the literature and so that the expected frequencies of those observed pairs have lower expected values, thus biasing their z-scores upward. In addition, treating citation as a set versus a multiset means that a random model will sample popular citations downward, thus further increasing their z-scores.

Contrary to Uzzi et al. we found the category displaying the highest hit rate to be sensitive to the experimental parameter settings, which included the percentage of articles deemed to be hits and the percentile of articles' z-score distributions that delineated between articles of low novelty and high novelty. Thus, with this lack of robustness, studies are faced with the necessity of defining which parameters are the best parameters to classify articles.

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AUTHOR CONTRIBUTIONS

This study was designed by GC, JB, SD, and TW. Simulations and analysis were performed by AD, GC, JB, and SD. Infrastructure and workflows used to generate data used in this study were developed by AD, DK, SL, SD, and GC. All authors reviewed and commented on the manuscript, which was written by GC, JB, and TW.

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