NPCN: A Study on the Normalization Method for Patent Citation Counts Based on Centripetal Citation Networks (Postprint)

Authors: Li Xian, Yang Ruixian

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Abstract

[Purpose/Significance] The citation frequency of patents serves as a crucial indicator for measuring patent impact. Owing to substantial variations in citation potential across disciplines and publication years, patent citation frequencies must undergo standardization to enable cross-disciplinary and cross-year comparisons. [Method/Process] We construct a novel standardized indicator for patent citation frequency—NPCN (Network-based Patent Citation Normalization)—based on the patent centripetal citation network. To validate its effectiveness, we retrieved patents granted between 2005 and 2010 in the 3D printing domain from the Dimension database, classified them into disciplines using FoR categories, analyzed the distribution of citation frequencies and NPCN values across different disciplines and years, and compared the correlation relationships between citation frequency and four standardization methods: mean-ratio method, reference-ratio method, Z-score, and NPCN. [Results/Conclusions] Patents in the 3D printing field are distributed across 22 FoR discipline categories, yet exhibit considerable disparities in citation frequencies across different disciplines and years. Following NPCN standardization, the gaps between patents diminish, demonstrating a pronounced trend toward identical distribution. Regarding correlation, NPCN shows a relatively lower correlation with citation frequency compared to other standardized indicators.

Full Text

NPCN: A New Method of Patent Citations Normalization Based on Ego Patent Citation Networks

Li Xian[1] Yang Ruixian[2,3]

Abstract

[**Purpose/Significance**] The number of citations received by patents is an important indicator for measuring patent influence. Since the citation potential of patents varies significantly across disciplines and publication years, patent citation frequencies must be normalized before cross-disciplinary and cross-year comparisons can be made. [**Method/Process**] Based on the ego patent citation network, we construct a new standardized indicator for patent citation frequency—NPCN. To verify the effectiveness of this indicator, we retrieved patents granted between 2005-2010 in the 3D printing field from the Dimensions database, classified them by discipline using the FoR classification, analyzed the distribution of citation frequencies and NPCN values for patents across different disciplines and years, and compared the correlation between these indicators and raw citation frequencies using the mean ratio method, reference ratio method, Z-score, and NPCN. [**Results/Conclusions**] Patents in the 3D printing field are distributed across all 22 FoR disciplines, but show large disparities in citation frequencies across different disciplines and years. After normalization by NPCN, the gaps between different patents decrease, showing a clear trend toward identical distribution. In terms of correlation, NPCN exhibits a lower correlation with citation frequency compared to other standardized indicators.

Keywords: ego citation networks; patent citations; normalized indicators; cross-disciplinary comparison; cross-year comparison

Introduction

Patent citation frequency is a crucial metric for measuring patent impact, with highly cited patents generally exhibiting higher quality, technological value, degree of innovation, and broader knowledge diffusion patterns. However, due to varying publication and citation practices across disciplines, citation frequencies cannot be directly compared between different fields. For instance, biomedical patents typically have large publication volumes and rapid update cycles, resulting in higher citation frequencies, whereas mathematics and physics have longer research cycles and slower citation accumulation, leading to generally lower citation frequencies. Even within the same discipline, older patents tend to accumulate more citations than recently published ones. To eliminate these differences and enable fair measurement and evaluation of patent impact across disciplines and years, researchers require standardized methods that mathematically transform raw citation counts to achieve approximately identical distributions, thereby facilitating cross-disciplinary and cross-year comparisons. Patents serve as carriers of technological innovation, and proper comparison of their citation frequencies is essential for identifying important patents, exploring technological development trajectories, and assessing patent value.

Citation normalization fundamentally aims to eliminate interference from variables affecting citation potential, such as disciplinary field, publication year, and document type. Since the 1980s, researchers have devoted increasing attention to citation normalization studies, proposing various methods grounded in different theories and models. Broadly speaking, normalization approaches fall into two categories: cited-side normalization and citing-side normalization. Cited-side normalization uses fixed disciplinary classification systems to correct citation potential differences across fields and years, with common methods including those based on average citations per paper, average references per paper, and percentile-based normalization. Citing-side normalization methods correct for differences in citing behavior across disciplines, with common approaches including active references, normalized citation scores, and the pi-index.

Building upon this literature, we propose a novel network-based indicator for normalizing patent citation frequency. To validate its effectiveness, we examine patents granted between 2005-2010 in the 3D printing field, classify them into different disciplines, analyze the distribution of citation frequencies and NPCN values, and compare correlations with other normalization methods including the mean ratio method, reference ratio method, and Z-score. Following previous research, an effective normalization indicator should produce approximately identical distributions across different objects, enabling fair impact comparisons. We adopt this criterion to evaluate the effectiveness of our proposed NPCN (Normalized Patent Citations based on Network) indicator.

Literature Review

Reference Standard Selection

Currently, citation normalization methods primarily employ field normalization, with disciplinary reference standards used to characterize citation potential. Fixed disciplinary classification systems such as Web of Science' s JCR categories serve as common reference standards, though these suffer from issues like overlapping themes and inability to classify multidisciplinary journal articles. Additionally, JCR-based normalization indicators are sensitive to clustering levels, potentially yielding contradictory conclusions at different aggregation levels. Consequently, researchers have explored numerous improvements and alternatives. Glänzel et al. proposed assigning papers from multidisciplinary journals (e.g., *Nature* or *Science*) to specific disciplines based on their reference lists, addressing classification challenges for many papers. To resolve thematic overlap in JCR categories, Rons employed the Partition-Based Field Normalization (PBFN) method to obtain more detailed classifications, creating independent topic classes from overlapping themes to achieve citation normalization. Bornmann et al. recommended using alternative disciplinary classifications such as Chemical Abstracts or Medical Subject Headings for specific fields. Waltman et al. proposed a citation-clustering-based disciplinary classification system that covers all papers while assigning each to a unique discipline. Kostoff et al. utilized expert opinion to identify paper sets with similar topics to the target paper, arguing that normalization is meaningful only when comparing a paper' s citations to those of similar papers. Colliander simplified this process by using shared references and keywords instead of expert opinion to obtain similar paper sets. Beyond fixed disciplinary classifications, references, citation contexts, or journals can also serve as reference standards. Schubert and Braun used a paper’ s publishing journal as the reference standard to calculate relative impact indicators, while Hutchins et al. constructed paper co-citation networks as reference standards to propose new academic impact evaluation metrics.

Citation Frequency Normalization Methods

Normalizing citation frequencies for cross-disciplinary comparison has become widely accepted. Current approaches primarily include cited-side and citing-side normalization. Cited-side normalization has a long history, with the relative citation indicator being the most common method. This involves dividing a paper’ s citation count by the average citation count in its discipline, which represents the expected citation frequency. Depending on calculation sequence, relative impact indicators can be categorized as Averages of Ratios (AoR) or Ratios of Averages (RoA). Abramo et al. proposed the FSS indicator to assess individual scientists’ academic impact, incorporating author contribution rates into the relative citation indicator framework. However, they later argued that all ratio-based indicators are fundamentally flawed and that improvements to such methods are futile.

Percentile-based normalization indicators have also been proposed as an alternative. These categorize papers into ranks rather than using arithmetic means, employing distribution patterns to describe citation frequencies. Bornmann et al. advocated using distributions over arithmetic means, proposing percentile-based evaluation methods. In subsequent work, they divided papers into six citation-based tiers, assigning different weights to each percentile distribution and calculating weighted averages. Another cited-side normalization approach uses average reference counts. Garfield and Merton suggested that the most accurate measure of a field’ s citation potential is the average number of references per paper. In 2011, Kosmulski proposed the Number of Successful Papers (NSP) indicator, normalizing citation counts by reference counts. Subsequent research replaced single-paper reference counts with average reference counts of paper sets, yielding indicators such as CSNCR (Citation Score Normalized by Cited References), MCSNCR (Mean Citation Score Normalized by Cited References), and SNCS (Source Normalized Citation Score).

Citing-side normalization methods adjust for citing behavior differences across disciplines. Small and Sweeney first applied co-citation analysis in 1985 to balance disciplinary differences in co-citation values. Waltman et al. later proposed the Normalized Citation Score, which uses the number of references in individual citing documents as the normalization standard, enabling cross-disciplinary comparison of academic impact. However, since active reference counts differ significantly across disciplines, Waltman et al. introduced the pi-index to reduce biases arising from varying citation densities, a method subsequently validated in empirical studies. They also compared these indicators with SNCS and MNCS (Mean Normalized Citation Score), finding that different indicators perform differently across contexts.

Reviewing this literature reveals several limitations: (1) existing normalization methods use average disciplinary characteristics rather than target paper-specific features to represent citation potential; (2) most methods do not simultaneously consider both cited and citing perspectives; and (3) current citation normalization methods have not been extended to patent analysis.

Methodology

Ego Patent Citation Network

In network theory, when a citation network focuses on a specific target node, it is termed "ego-centric." In an ego patent citation network, the focal point is a specific patent. We construct the ego citation network for patent p (see [Figure 1: see original paper]), where nodes represent patents and edges represent citation relationships. From p' s perspective, the ego citation network comprises four sub-networks: the CC sub-network, RC sub-network, CR sub-network, and RR sub-network.

The CC sub-network includes all citing patents that cite patent p. Through the CC sub-network, we can determine patent p' s relative position in its forward citation network based on citation counts of p and its forward citations, using second-order citations to construct this sub-network.

The RC sub-network includes all reference patents of patents that cite p. Patents in the RC sub-network share a "co-citation" relationship with patent p. From p' s perspective, the RC sub-network measures its influence as a knowledge source on subsequent citing patents through co-citation relationships.

The CR sub-network includes all citing patents of patents cited by p. Patents in the CR sub-network share a "bibliographic coupling" relationship with patent p. From p' s perspective, the CR sub-network measures p' s knowledge base and technological complexity through coupling relationships.

The RR sub-network includes all reference patents of patents cited by p. From p' s perspective, the RR sub-network uses p' s citing relationships to determine its position in the second-order backward citation network.

References and citation frequencies reflect patent characteristics from different dimensions: references indicate a patent' s knowledge base and technological complexity, while citation frequencies reflect the extent to which a patent is used by others. After publication, nodes and edges in the RR sub-network remain static, while those in the CR, RC, and CC sub-networks continue to grow over time.

NPCN Indicator Construction

We construct a novel network-based indicator to normalize patent citation frequency. Using patent p as an example, we detail the NPCN calculation:

$$NPCN = \frac{CIT_p}{TSI}$$

where CIT_p represents the citation count of patent p, and TSI (Technological Span Index) measures the expected impact of patent p. TSI is expressed as the product of patent p' s exogenous index (OI_p) and technological interest index (TII):

$$TSI = OI_p \times TII$$

The exogenous index (OI_p) reflects patent p' s relative position in the network comprising p and its reference patents:

$$OI = \frac{1}{T(p)+1} \times R(p)$$

where $T(p)$ is the number of patents cited by p. Additionally, patent p and its reference patents form a patent set sorted in descending order by citation count, with R_p representing p' s rank in this set.

The technological interest index (TII) measures the innovation density of technological knowledge flowing from reference patents to patent p:

$$TII = \frac{CIT_T(R_p)}{T(R_p)}$$

where $CIT_T(R_p)$ is the sum of citation counts of all reference patents of patent p (see the CR sub-network in [Figure 1: see original paper]).

In practice, reference patents of p fall into three categories: (1) no reference patents; (2) non-zero reference patents but none have been cited; and (3) non-zero reference patents with at least one cited reference. In the first two cases, patent p' s TSI equals zero, and such patents are excluded from this study.

Data Collection and Disciplinary Classification

3D printing technology, which emerged in the mid-1980s, represents a disruptive innovation that generates parts directly from computer graphics data without molds or mechanical processing, dramatically shortening product development cycles and improving productivity. Recent years have witnessed sustained growth in 3D printing patents, with applications now spanning industrial design, biotechnology, and other fields. Normalizing patents in this domain appropriately facilitates measurement and evaluation of technological impact.

We selected the Dimensions database as our data source, which provides comprehensive patent, publication, reference, and citation information accessible through programmatic batch download, making it ideal for patent citation normalization analysis. Our search strategy was: `title_{{{abstract}}_{{claims}}}:((three dimensional print*) OR (3 dimensional print*) OR (3D print*) OR (3-D print*) OR (additive manufactur*) OR (material increas* manufactur*) OR (rapid manufactur*) OR (rapid prototyp*) OR (layer* manufactur*))`. To ensure stable and reliable citation data, we required at least a 10-year citation window, also avoiding shortcomings of short-term windows. Therefore, we limited publication years to 2005-2010, retrieving data in June 2022 and obtaining 415,827 granted patents. Using the Dimensions API, we downloaded reference and citation data for each patent and constructed individual ego citation networks.

We employed the Fields of Research (FoR) classification to define patent disciplines. Developed jointly by Australia and New Zealand in 2008, FoR comprises 22 categories. Dimensions uses machine learning combined with expert opinion to assign patents to the most appropriate FoR categories. In this study, patents classified into multiple categories were normalized separately within each discipline.

Descriptive Statistical Analysis

presents annual descriptive statistics for patents published during 2005-2010. Using full counting for classification, the total number of patents across disciplines slightly exceeds the downloaded count. The results show substantial and relatively stable patent output in 3D printing during this period, with distribution across all 22 FoR categories. The six most represented categories are 09 Engineering, 03 Chemical Sciences, 08 Information and Computing Sciences, 02 Physical Sciences, 11 Medical and Health Sciences, and 06 Biological Sciences, indicating close relationships between 3D printing development and engineering, chemistry, information technology, physics, and medicine.

Cross-Disciplinary Normalization Effects

To validate NPCN' s normalization effectiveness, we compared the mean and overall distributions of citation frequencies and NPCN values across disciplines (see). In terms of mean values, citation frequencies vary substantially: 13 Education shows the highest mean and median (46.50), while 07 Agricultural and Veterinary Sciences shows the lowest (6.71), a 6.93-fold difference. This demonstrates that raw citation frequencies are not directly comparable across disciplines. After normalization, NPCN mean values range from [3, 5.75] and medians from [2.54, 5.75], reducing the maximum difference to 1.92-fold for means and 2.26-fold for medians. Both mean and median NPCN distributions are more concentrated and compact than raw citation frequencies, indicating effective normalization.

To further analyze NPCN' s effects, we examined overall distributions. As shown in [Figure 2: see original paper] and , citation frequencies differ markedly across disciplines and remain highly dispersed even within the same field. After normalization, NPCN distributions become more concentrated with significantly reduced variance. Both mean and overall distributions demonstrate that NPCN values across disciplines exhibit clear identical distribution patterns, confirming NPCN' s effectiveness in normalizing cross-disciplinary patent citations.

Cross-Year Normalization Effects

We similarly examined NPCN' s effectiveness in normalizing across publication years from both mean and overall perspectives. shows mean distributions: 2005 patents have the highest mean citation frequency (24.04), while 2010 patents have the lowest (16.25), a 1.48-fold difference. After normalization, this gap narrows to 1.11:1, with similar results using medians.

Analyzing overall distributions ([Figure 3: see original paper] and) reveals substantial differences in citation frequencies across publication years, while NPCN values achieve near-identical distributions after normalization. These results demonstrate that NPCN effectively enables cross-year comparison of patents.

Correlation Analysis Between Indicators and Citation Frequency

This section analyzes correlations between four normalization methods (mean ratio method: citations/field average; reference ratio method: citations/number of references; Z-score; NPCN) and raw citation frequencies. Given non-normal data distributions, we employed Spearman correlation coefficients, interpreting $|r| \geq 0.8$ as high correlation, $0.5 \leq |r| < 0.8$ as moderate, $0.3 \leq |r| < 0.5$ as low, and $|r| < 0.3$ as negligible.

As shown in [Figure 4: see original paper], for 3D printing patents, raw citation frequency shows high positive correlation with mean ratio method ($r = 0.99$) and Z-score ($r = 0.97$), moderate correlation with reference ratio method ($r = 0.74$), and low correlation with NPCN ($r = 0.43$). Correlation analysis among normalization indicators reveals that NPCN shows positive but low correlations with the other three methods. This indicates that mean ratio, Z-score, and reference ratio methods produce distributions similar to raw citation frequencies, whereas NPCN' s low correlation with both raw citations and other indicators suggests it preserves inter-patent differences while maintaining independence from raw citation distributions.

Discussion

As China' s scientific and technological evaluation reform reaches a critical juncture, patents—as carriers of technological innovation—require fair and reasonable impact comparison for accurate innovation trend analysis and resource allocation. NPCN provides a novel analytical perspective using ego citation networks for patent citation normalization. Two key aspects warrant discussion:

First, NPCN uses a patent' s own expected impact to represent its citation potential rather than average field characteristics. Normalization effectiveness is heavily influenced by the choice of citation potential measure. Most existing indicators place patents within their fields, which has limitations: field average impact represents only the disciplinary mean and does not fully capture a specific patent' s citation potential, and different disciplinary classification schemes at varying granularity levels can produce substantially different normalization results. NPCN addresses these issues by leveraging the patent' s own network characteristics.

Second, NPCN simultaneously considers both reference and citation perspectives when normalizing. References measure a patent's knowledge base and technological complexity, while citations reflect its influence on subsequent patents. Thus, compared to purely cited-side or citing-side methods, NPCN not only normalizes citation frequencies but also captures technological complexity.

Conclusion

As an external indicator of patent impact, citation frequency serves as an important reference for both impact measurement and peer review. However, disciplinary and temporal differences necessitate normalization for fair cross-disciplinary and cross-year comparisons. Radicchi et al. propose that ideal normalization should yield approximately identical distributions across disciplines and years. Our NPCN indicator, based on ego citation networks, was validated using 3D printing patents from 2005-2010 in Dimensions. Results show: (1) 3D printing patents span all 22 FoR disciplines, concentrated in Engineering, Chemical Sciences, Information and Computing Sciences, Physical Sciences, Medical and Health Sciences, and Biological Sciences; (2) Raw citation frequencies vary substantially across disciplines and years, while NPCN values show significantly reduced variance and clear identical distribution patterns; (3) NPCN exhibits lower correlation with citation frequency than mean ratio, Z-score, and reference ratio methods.

We conclude that NPCN is a citation-frequency-independent normalization indicator that effectively eliminates large differences in citation frequencies across disciplines and years, producing clearly identical distributions. Therefore, NPCN demonstrates significant effectiveness in normalizing patent citations.

Limitations include validation in only the 3D printing field; future research will examine additional domains. Additionally, normalization indicators are unreliable for short citation windows, as citations have not yet accumulated, while long windows delay timely evaluation. Patent citation synchronization sequences offer a solution, and future work will incorporate them to improve NPCN for timely and fair normalization.

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Author Contributions: Li Xian: data collection, processing, analysis, and manuscript writing; Yang Ruixian: conceptualization, manuscript writing, and revision.

Note: Figure translations are in progress. See original paper for figures.