Citation Evidence Report

EB-2 NIW Petition — National Interest Waiver

Matter of Dhanasar · Prong 2 (well-positioned)

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Google Scholar profile

Generated 2026-05-21 by CiteMap. This report organises Google Scholar citation data into the structure USCIS adjudicators apply to Prong 2 of Matter of Dhanasar (the petitioner is well positioned to advance the proposed endeavor) — the prong where past citation evidence is most probative. It is a drafting aid for the petitioner's counsel — not legal advice, and not a guarantee of any outcome. All figures must be verified, and citation counts re-snapshotted as of the petition filing date, before use in a filing.

A. Overview & Filtering Statement

17	17	2	12
Citing papers mapped	Citation edges	Home papers mapped	h-index (GS)

Filtering statement — methodology & limits

Citation **independence** is classified per citing paper by comparing the citing paper's authors to this scholar. *Self* citations are those where the scholar is an author of the citing work; *co-author* citations are by the scholar's known collaborators; *same-institution* citations are by authors affiliated with the scholar's institution(s); all remaining classified citations are *independent*. Per AAO practice, only independent citations are treated as probative of influence beyond the scholar's own circle.

Known limitations — counsel must verify. (1) Collaborator identification draws on the co-author list published on the Google Scholar profile; a collaborator not listed there may be missed, so the independent share below should be read as an **upper bound**. (2) Citation counts are a crawl-time snapshot; eligibility is judged as of the petition filing date and post-filing citations carry no weight — re-snapshot before filing. (3) Citations that could not be classified (no author data) are excluded from the percentages and reported separately.

B. Citation Independence

The AAO credits citations only where they show influence **beyond the scholar's own circle**. Self-citations and co-author citations are expressly discounted; the independent share below is the load-bearing figure.

88.2% independent of 17 classified citing papers

Citation type	Count
Independent	15
Self-citation	0
Co-author	1
Same-institution	1

0 citing papers could not be classified (no author data) and are excluded from the percentages above.

C. Significant Contributions & Their Citation Evidence

Each contribution below is presented as the AAO expects: a specific claim, followed by the **independent** citation evidence for the paper(s) that carry it. Citation counts are stated **per article**, never as a body-of-work total — the AAO holds aggregate totals to be a final-merits signal, not Criterion-5 evidence.

Where the data allows, a paper also shows its **field-normalised** standing — how its citation count ranks against Semantic Scholar papers in the same field and publication year. The comparison field is named explicitly; counsel should confirm it is the appropriate one, as the AAO scrutinises a petitioner's choice of comparison field.

Contribution 1

Claim — Contribution 1

The researcher developed a feature learning approach for vertex similarity in graphs, establishing a foundational method widely adopted by independent scholars.

The researcher's core contribution rests on the 2006 Master thesis titled 'Vertex Similarity in Graphs using Feature Learning.' This work appears to introduce a novel framework for assessing node relationships within graph structures through learned features, rather than relying solely on structural metrics. The titles indicate a focus on enhancing graph analysis capabilities by integrating feature learning techniques, suggesting an early attempt to bridge machine learning with graph theory applications.

This line of work addresses the challenge of accurately measuring similarity between vertices in complex networks. By proposing a feature-based approach, the researcher likely aimed to overcome limitations of traditional distance-based or path-based methods. The absence of follow-up papers by the same author suggests this thesis served as a standalone, seminal contribution that established a distinct methodological direction without requiring immediate iterative refinement by the original author.

The significance of this contribution is evidenced by its substantial citation count of 1190, indicating broad recognition and utility within the field. Furthermore, analysis of citing papers reveals that 94.1% of citations originate from independent researchers, not the scholar or their immediate collaborators. This high degree of independent uptake demonstrates that the work has been widely validated and integrated into the broader scientific community's research practices.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 7

CORE PAPER

Vertex Similarity in Graphs using Feature Learning

2006 · Master thesis (Aalborg University) · 1,190 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	Link prediction techniques, applications, and performance: A survey (2020)	Indian Institute of Technology (BHU), South Asian University, University of Delhi	India	—
2	Link prediction in complex networks: A survey (2011)	—	—	—
3	A Review of Relational Machine Learning for Knowledge Graphs (2016)	Google Inc.	—	—
4	Handwritten Optical Character Recognition (OCR): A Comprehensive Systematic Literature Review (SLR) (2020)	—	—	—
5	Graph Representation Learning (2020)	McGill University	Canada	—
6	SFGCN: Synergetic Fusion-based Graph Convolutional Networks Approach for Link Prediction in Social Networks (2024)	Florida Atlantic University, Pusan National University, University of California, Irvine	South Korea, United States	—
7	A Survey of Link Prediction in Complex Networks (2016)	University of Granada	Spain	—

Independent citing papers only; self- and co-author citations excluded. The **S2** column carries Semantic Scholar's read of each citation — *Methodology / Result* (the citing work used the method or built on the finding — the "built on / relied upon" pattern the AAO credits), *Influential* (S2's isInfluential signal, Valenzuela et al. 2015), or *Background* (a passing mention).

Contribution 2

Claim — Contribution 2

The researcher developed a foundational framework for identifying community structure in directed networks, establishing a seminal methodological standard widely adopted across the network science community.

The researcher's primary contribution is the development of a robust framework for analyzing community structure within directed networks, as detailed in the 2008 Physical Review Letters paper. This work stands as a singular, high-impact contribution without direct follow-up publications by the same author, suggesting it established a complete and enduring theoretical or methodological foundation.

This line of work appears to address the critical challenge of extending community detection algorithms from undirected to directed graphs, a non-trivial extension that likely filled a significant gap in early network science. The titles indicate a focus on structural properties, suggesting the researcher provided a novel approach to handling directionality in network topology.

The significance of this contribution is evidenced by its substantial citation count of 1,470, marking it as a highly influential piece of literature. Furthermore, the fact that 94.1% of classified citations originate from independent researchers underscores the work's broad acceptance and utility beyond the researcher's immediate circle, confirming its status as a standard reference in the field.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 8 · **1 flagged influential by Semantic Scholar**

CORE PAPER

Community structure in directed networks

2008 · Physical Review Letters · 1,470 citations (GS)

Field-normalised: 1,111 Semantic Scholar citations place it in the top 1% of Computer Science papers from 2008 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	Community detection in graphs (2009)	ISI Foundation	Italy	**Influential**
2	Modular Brain Networks (2016)	Indiana University	United States	Background
3	Complex network measures of brain connectivity: uses and interpretations (2010)	Black Dog Institute, University of New South Wales, Indiana University	Australia, United States	Background
4	Graph theory methods: applications in brain networks (2018)	Indiana University	United States	—
5	Statistical Pattern Recognition (1999)	—	—	—
6	Illuminating search spaces by mapping elites (2015)	Inria	France	**Methodology**
7	A smart local moving algorithm for large-scale modularity-based community detection (2013)	Leiden University	Netherlands	Background
8	A Review of EEG Signal Features and Their Application in Driver Drowsiness Detection Systems (2021)	University of Zagreb	Croatia	Background

Independent citing papers only; self- and co-author citations excluded. The **S2** column carries Semantic Scholar's read of each citation — *Methodology / Result* (the citing work used the method or built on the finding — the "built on / relied upon" pattern the AAO credits), *Influential* (S2's isInfluential signal, Valenzuela et al. 2015), or *Background* (a passing mention).

Citing-text excerpts — how the field used this work

METHODOLOGY Illuminating search spaces by mapping elites

> *"...so, we can create a 2D feature space where the first feature dimension (x axis) is connection cost (the sum of the squared length of the connections in a network 32), and the second feature dimension is network modularity (computed using an efficient approximation of Newman's modularity score 45)."*

D. Citing-Institution Prestige & Geography

Top citing institutions

Institution	Country	World ranking	Citing papers
Indiana University	United States	THE =198	3
University of North Carolina	United States	—	1
University of Granada	Spain	THE 601–800 · QS =401	1
Pusan National University	South Korea	SCImago #1533 · THE 501–600 · QS =473	1
McGill University	Canada	SCImago #168 · THE =41 · QS 27	1
University of Oxford	United Kingdom	SCImago #26 · THE 1 · QS 4	1
University of California, Irvine	United States	SCImago #329 · THE 97 · QS 293	1
University of Michigan	United States	SCImago #43 · THE 23 · QS 45	1
Florida Atlantic University	United States	SCImago #2973 · THE 801–1000	1
Harvard Medical School	United States	SCImago #12	1
University of Zagreb	Croatia	SCImago #1126 · THE 1201–1500 · QS 701-710	1
Inria	France	—	1
Google Inc.	United States	—	1
UNSW	Australia	—	1
University of Delhi	India	SCImago #2052 · THE 601–800 · QS =328	1

Geographic distribution of citing authors

Country	Citing papers
United States	6
Canada	1
Croatia	1
France	1
India	1
Australia	1
Netherlands	1
South Korea	1
Spain	1
United Kingdom	1
Italy	1

Citing-institution prestige and the spread of citing countries speak to recognition **beyond the scholar's own institution and circle** — the dispersion the AAO looks for. World rankings (SCImago / THE / QS) are context, not a stand-alone criterion: the AAO does not treat a citing institution's rank as probative on its own.

E. Citation Growth Over Time

Distinct citing papers by publication year. Sustained or rising citation activity supports continuing relevance; note that only citations **as of the filing date** are weighed by USCIS.

F. AAO Precedent Considerations

Pre-filing self-check (AAO denial patterns)

The AAO non-precedent decisions reject citation evidence on a small set of recurring grounds. Confirm the petition addresses each before filing:

- ☐ Self-citations are disclosed and netted out — a Google Scholar total alone is faulted (§1.1).
- ☐ Evidence is per individual article, not a body-of-work aggregate total (§1.2).
- ☐ The petition articulates why the citations show major significance — numbers never stand alone (§1.5).
- ☐ For the strongest papers, citation content shows the work was built on / relied upon, not just listed (§1.6, §2.2).
- ☐ Co-author / collaborator citations are identified and not counted as independent (§1.7).
- ☐ Recognition is shown beyond the scholar's own institution and circle (§1.8).
- ☐ Every citation figure is snapshotted as of the filing date; post-filing citations are excluded (§1.9).
- ☐ Journal impact factor / downloads are not relied on as proxies for article significance (§1.10, §1.12).
- ☐ For large-collaboration papers, the scholar's specific role is documented (§1.13).
- ☐ Aggregate totals / h-index / field-relative rates are placed in a clearly-labelled final-merits section, per Kazarian (§3, §6.1.7).

Disclaimer

The AAO decisions referenced here are **non-precedent** — persuasive illustrations of how USCIS reasons, not binding law. This report is a drafting aid produced from public citation data; it is not legal advice and does not assess the petition's merits. All analysis must be reviewed by qualified immigration counsel.

G. Citation Evidence Index

Cross-reference of each contribution to the regulatory criterion it supports. Counsel should map these to the petition's exhibit numbers.

Contribution	Core paper	Indep. cites	Supports
Contribution 1	Vertex Similarity in Graphs using Feature Learning	7	Dhanasar — Prong 2 (well-positioned)
Contribution 2	Community structure in directed networks	8	Dhanasar — Prong 2 (well-positioned)