Citation Evidence Report

EB-1A Petition — Original Contributions of Major Significance

8 CFR § 204.5(h)(3)(v) · Criterion 5

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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 Criterion 5 (original contributions of major significance). 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

261	261	7	3
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.

88.8% independent of 160 classified citing papers

Citation type	Count
Independent	142
Self-citation	0
Co-author	17
Same-institution	1

101 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 Gcomb, a framework for learning budget-constrained combinatorial algorithms on billion-sized graphs, establishing a scalable approach to large-scale graph optimization.

The researcher's primary contribution is the development of Gcomb, introduced in a 2020 paper titled 'Gcomb: Learning budget-constrained combinatorial algorithms over billion-sized graphs.' This work stands as a seminal piece in the field, addressing the challenge of applying learning-based methods to combinatorial algorithms within the constraints of massive graph structures. The title suggests a novel integration of machine learning techniques with traditional algorithmic design to handle scale and resource limitations simultaneously.

This line of work appears to address a critical gap in processing billion-sized graphs, where traditional combinatorial algorithms often struggle with computational complexity and budget constraints. By proposing a learning-based approach, the researcher likely offered a more adaptive and efficient solution for large-scale graph problems. The absence of follow-up papers by the same researcher indicates that this single publication serves as the foundational contribution, with its impact measured primarily through external adoption rather than an extended internal research program.

The significance of this contribution is evidenced by its substantial citation count of 251, indicating strong recognition within the academic community. Furthermore, citation analysis reveals that 88.8% of citing papers originate from independent researchers, suggesting that the work has been widely adopted and built upon by the broader scientific community rather than just the researcher's immediate circle. This high degree of independent uptake underscores the general utility and influence of the Gcomb framework in advancing the state of the art for large-scale graph algorithms.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 137 · 8 flagged influential by Semantic Scholar

CORE PAPER

Gcomb: Learning budget-constrained combinatorial algorithms over billion-sized graphs

2020 · Advances in Neural Information Processing Systems 33, 20000-20011, 2020 · 251 citations (GS)

Field-normalised: 93 Semantic Scholar citations place it in the top 5% of Computer Science papers from 2020 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	Reinforcement learning for combinatorial optimization: A survey	Criteo, Optimate AI, Skolkovo Institute of Science and Technology	Canada, France, Russia	—
2	Challenges and opportunities in deep reinforcement learning with graph neural networks: A comprehensive review of algorithms and applications	Pacific Northwest National Laboratory (PNNL)	United States	—
3	Deep graph representation learning and optimization for influence maximization	Dakota State University, Emory University, Fudan University	China, United States	—
4	An efficient graph convolutional network technique for the travelling salesman problem	Loyola Marymount University, Nanyang Technological University	Singapore, United States	—
5	Flexible job shop scheduling via dual attention network-based reinforcement learning	Beijing Institute of Technology, Tongji University	China	—
6	Learning to schedule job-shop problems: representation and policy learning using graph neural network and reinforcement learning	KAIST, Samsung Electronics	South Korea	—

No.	Citing paper	Citing institution(s)	Country	S2
7	A reinforcement learning-based routing algorithm for large street networks	Texas A&M University	United States	—
8	Learning combinatorial optimization on graphs: A survey with applications to networking	Research Institutes of Sweden, RISE AB, Royal Institute of Technology	Sweden	—
9	Deep reinforcement learning for the electric vehicle routing problem with time windows	Ivey Business School, Western University, University of Toronto, University of Waterloo	Canada	—
10	Exploratory combinatorial optimization with reinforcement learning	Facebook AI Research, indust.ai, University of Oxford	France, United Kingdom, United States	—
11	Deep reinforcement learning enabled multi-UAV scheduling for disaster data collection with time-varying value	—	—	—
12	A survey on influence maximization: From an ml-based combinatorial optimization	BNU-HKBU United International College, The University of Texas at Dallas	China, United States	—
13	Balanced influence maximization in social networks based on deep reinforcement learning	Hefei University of Technology, Jiangxi University of Science and Technology, Nanjing Forestry University	China	—
14	Deep reinforcement learning for transportation network combinatorial optimization: A survey	Brigham and Women's Hospital, Harvard University, Fudan University	China, United States	—
15	Matrix encoding networks for neural combinatorial optimization	Samsung SDS	South Korea	—
16	ToupleGDD: A fine-designed solution of influence maximization by deep reinforcement learning	The University of Texas at Dallas, University of Texas at Dallas	United States	**Influential**
17	Network planning with deep reinforcement learning	Facebook Inc., Johns Hopkins University, Peking University	China, United States	—
18	PIANO: Influence maximization meets deep reinforcement learning	Nanyang Technological University, National University of Singapore, Xidian University	China, Singapore	—
19	Deep reinforcement learning for combinatorial optimization: Covering salesman problems	National University of Defense Technology	China	—
20	Attention enhanced reinforcement learning for flexible job shop scheduling with transportation constraints	Beijing Institute of Technology, Beijing Institute of Technology, Harbin Institute of Technology	China	—
21	Revisiting sampling for combinatorial optimization	Georgia Tech, Google DeepMind	United Kingdom, United States	—
22	SEAL: Learning heuristics for community detection with generative adversarial networks	Ant Financial Services Group, Fudan University, University of Illinois at Chicago	China, United States	—

No.	Citing paper	Citing institution(s)	Country	S2
23	A deep reinforcement learning algorithm using dynamic attention model for vehicle routing problems	Sun Yat-sen University	China	—
24	ASP: Learn a universal neural solver!	Carnegie Mellon University, Peking University, the Chinese University of Hongkong	China, United States	—
25	Efficient meta neural heuristic for multi-objective combinatorial optimization	Singapore Management University, Sun Yat-sen University	China, Singapore	—
26	Intelligent path planning algorithm system for printed display manufacturing using graph convolutional neural network and reinforcement learning	Huazhong University of Science and Technology	China	—
27	Influence maximization in complex networks by using evolutionary deep reinforcement learning	Shenzhen University, Brunel University of London	China	—
28	Graph reinforcement learning for combinatorial optimization: A survey and unifying perspective	University College London, University College London; University of Bologna	United Kingdom, United Kingdom; Italy	—
29	Solving combinatorial optimization problems with deep neural network: A survey	—	—	—
30	Algorithms and applications of intelligent swarm cooperative control: A comprehensive survey	National University of Defense Technology	China	—

Showing the 30 most-cited of 137 independent citing papers.

Independent citing papers only; self- and co-author citations excluded. The **S2** column flags citations Semantic Scholar identifies as *influential* — ones that substantively build on the work (S2's isInfluential signal, Valenzuela et al. 2015) — the "built on / relied upon" pattern the AAO credits. Counsel should quote the citing text for the strongest of these.

D. Citing-Institution Prestige & Geography

Top citing institutions

Institution	Country	World ranking	Citing papers
Fudan University	China	SCImago #46 · THE 36 · QS 30	9
University of Illinois	United States	—	8
Indian Institute of Technology	India	—	7
National University of Defense Technology	China	SCImago #488	7
The University of Texas at Dallas	United States	THE 401–500 · QS =597	4
Indian Institute of Technology, Delhi	India	SCImago #1897 · QS =123	4
IBM	United States	—	4
Peking University	China	SCImago #11 · THE 13 · QS 14	3
University College London	United Kingdom	SCImago #30	3

Institution	Country	World ranking	Citing papers
University of Oxford	United Kingdom	SCImago #26 · THE 1 · QS 4	3
University of Florida	United States	SCImago #166 · THE =134 · QS =212	3
Rice University	United States	SCImago #818 · THE =103 · QS =119	3
University at Buffalo	United States	THE 301–350	3
IIT Delhi	India	—	3
Tsinghua University	China	SCImago #8 · THE 12 · QS =17	3

Geographic distribution of citing authors

Country	Citing papers
China	60
United States	48
India	13
France	7
United Kingdom	7
Singapore	5
Canada	5
Germany	4
Sweden	4
Russia	3
Italy	3
Netherlands	3

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.

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	Gcomb: Learning budget-constrained combinatorial algorithms over billion-sized graphs	137	8 CFR 204.5(h)(3)(v) — Criterion 5