Citation Evidence Report

EB-2 NIW Petition — National Interest Waiver

Matter of Dhanasar · Prong 2 (well-positioned)

Guillaume Rabusseau

Assistant Professor - Canada CIFAR AI Chair, Université de Montréal / Mila

Google Scholar profile

Generated 2026-06-10 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

814	1,576	30	20
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.

86.4% independent of 1,429 classified citing papers

Citation type	Count
Independent	1,235
Self-citation	72
Co-author	122
Same-institution	0

75 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 established a foundational framework for low-rank regression with tensor responses, subsequently extending this methodology to graph neural networks and theoretical bounds for tensor network models.

CLAIM: The researcher's core contribution is the development of low-rank regression techniques for tensor responses, as demonstrated in the seminal 2016 paper. This work serves as the foundation for subsequent research, including applications to high-order pooling in graph neural networks and the derivation of theoretical bounds for tensor network models.

ORIGINALITY: This line of work appears to address the challenge of handling complex, multi-dimensional data structures efficiently. By introducing low-rank assumptions for tensor responses, the researcher provided a novel approach to dimensionality reduction and regression. The follow-up papers suggest an expansion of these principles into deep learning architectures, specifically graph neural networks, and a rigorous theoretical analysis of the capacity of such tensor-based models.

SIGNIFICANCE: The foundational 2016 paper has garnered 111 citations, indicating strong recognition within the field. The subsequent works on graph neural networks and pseudo-dimension bounds have also attracted significant attention, with 61 and 22 citations respectively. Notably, 86.4% of the citations across the researcher's classified works originate from independent researchers, suggesting that this methodological framework has been widely adopted and built upon by the broader scientific community beyond the researcher's immediate circle.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 167

CORE PAPER

Low-Rank Regression with Tensor Responses

2016 · 111 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	Tensors in Modern Statistical Learning	Google DeepMind, Purdue University, University of California, Irvine Medical Center	United Kingdom, United States	—
2	Theories, algorithms and applications in tensor learning	—	—	—
3	Image response regression via deep neural networks.	University of California, Irvine Medical Center, University of Michigan, University of North Carolina at Chapel Hill	United States	—
4	CPD-Structured Multivariate Polynomial Optimization	KU Leuven	Belgium	—
5	Tensor Linear Regression: Degeneracy and Solution	Renmin University of China, Texas A&M University	China, United States	—
6	A randomized algorithm to solve reduced rank operator regression	Italian Institute of Technology	Italy	—
7	Poisson-response Tensor-on-Tensor Regression and Applications	Sandia National Laboratories	United States	—
8	STORE: Sparse Tensor Response Regression and Neuroimaging Analysis	University of California, Berkeley, University of Miami	United States	—
9	Beyond Unfolding: Exact Recovery of Latent Convex Tensor Decomposition Under Reshuffling	Guangdong University of Technology, Hong Kong Baptist Uni-	China, Japan	—

No.	Citing paper	Citing institution(s)	Country	S2
		versity, Hong Kong Baptist University; RIKEN AIP		
10	Statistical inference on the significance of rows and columns for matrix-valued data in an additive model	Beijing Jiaotong University, Beijing Normal University, Beijing Technology and Business University	China	—
11	Tensor Regression Meets Gaussian Processes	Caltech, University of Southern California	United States	—
12	LOCUS: A REGULARIZED BLIND SOURCE SEPARATION METHOD WITH LOW-RANK STRUCTURE FOR INVESTIGATING BRAIN CONNECTIVITY.	Emory University	United States	—
13	Sparse higher order partial least squares for simultaneous variable selection, dimension reduction, and tensor denoising	University of Wisconsin, University of Wisconsin–Madison	United States	—
14	Scalable Spatiotemporally Varying Coefficient Modeling with Bayesian Kernelized Tensor Regression	HEC Montréal, McGill University	Canada	—
15	Tensor Contraction & Regression Networks	—	—	—
16	Robust Knowledge Discovery via Low-rank Modeling	—	—	—
17	Randomized algorithms for tensor response regression	Nantong University	China	—
18	High-dimensional Tensor Response Regression using the t-Distribution	Beijing Normal University, Florida State University	China, United States	—
19	Learning Robust Data Representation: A Knowledge Flow Perspective	Adobe Research, Indiana University – Purdue University Indianapolis, University of Georgia	United States	—
20	Robust Linear Predictions: Analyses of Uniform Concentration, Fast Rates and Model Misspecification	Department of Statistics, University of California, Berkeley, Indian Statistical Institute, University of California, Irvine Medical Center	India, United States	—
21	Multivariate Convolutional Sparse Coding with Low Rank Tensor	École Normale Supérieure Paris-Saclay, Université Paris 13	France	—
22	Low-rank tensor ring learning for multi-linear regression	University of Electronic Science and Technology of China	China	—
23	Regularized high dimension low tubal-rank tensor regression	University of Florida	United States	—
24	Tensor-on-Tensor Regression: Riemannian Optimization, Over-parameterization, Statistical-computational Gap, and Their Interplay	Duke University, University of Chicago	United States	—
25	Vector-Valued Least-Squares Regression under Output Regularity Assumptions	Aalto University, École normale supérieure - PSL, Mathématiques et Informatique Appliquées Toulouse	Finland, France	—

No.	Citing paper	Citing institution(s)	Country	S2
26	Bayesian Supervised Clustering of Undirected Networks with Cluster Specific Inference on significant Nodes and Edges Related to Predictors	—	—	—
27	High-dimensional Quantile Tensor Regression	Fudan University, Toronto Metropolitan University	Canada, China	—
28	Learning Multiple Networks via Supervised Tensor Decomposition	—	—	—
29	Tensor Convolutional Dictionary Learning With CP Low-Rank Activations	Centre National de la Recherche Scientifique, University of Fribourg	France, Switzerland	—
30	Dynamic fMRI networks predict success in a behavioral weight loss program among older adults	University of North Carolina at Chapel Hill, Virginia Tech - Wake Forest University School of Biomedical Engineering & Sciences, Wake Forest University	United States	—

Showing the 30 most-cited of 66 independent citing papers.

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).

FOLLOW-UP WORK

High-order pooling for graph neural networks with tensor decomposition

2022 · 61 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	Structure-Preserving Margin Distribution Learning for High-Order Tensor Data with Low-Rank Decomposition	Yanshan University	China	—
2	Dynamic Graph Forecasting for Interacting Moving Objects via Multiplicative Interaction Networks	—	—	—
3	Tensor Networks Meet Neural Networks: A Survey	—	—	—
4	Tensor Networks Meet Neural Networks: A Survey and Future Perspectives	City University of Hong Kong, Fudan University, Harbin Institute of Technology Shenzhen	China, Poland	—
5	Neighbourhood Transformer: Switchable Attention for Monophily-Aware Graph Learning	School of Information and Software Engineering, University of Electronic Science and Technology of China	—	—
6	TTF-GNN: Memory-Efficient GNNs via Tensor Train Decomposition and Network Folding	—	—	—
7	Rayleigh Quotient Graph Neural Networks for Graph-level Anomaly Detection	The Chinese University of Hong Kong	China	—

No.	Citing paper	Citing institution(s)	Country	S2
8	Tensor Network-Constrained Kernel Machines as Gaussian Processes	Delft University of Technology	Netherlands	—
9	Polynormer: Polynomial-Expressive Graph Transformer in Linear Time	Cornell University	United States	—
10	GraphTARIF: Linear Graph Transformer with Augmented Rank and Improved Focus	United Arab Emirates University, Zhejiang University	China, United Arab Emirates	—
11	Fedvuln: Scalable and privacy-preserving federated graph learning for smart contract vulnerability detection on parallel systems	Vietnam National University Ho Chi Minh City	Vietnam	—
12	Comprehensive Information Extraction With Separable Representation Learning for Multi-View Clustering	Northwestern Polytechnical University, Northwest University, South China University of Technology	China	—
13	From Distortion to Expression: Parallel Multi-Hop Graph Signal Processing Under Heterophily	Pennsylvania State University, Rochester Institute of Technology	United States	—
14	Sheaf Hypergraph Networks	Sapienza University of Rome, University of Cambridge	Italy, United Kingdom	—
15	Tensorized High-Order Hypergraph Convolutional Network for Hyperspectral Image Classification	Mississippi State University, Northwestern Polytechnical University, Southwest Jiaotong University	China, Spain, United States	—
16	Lying Graph Convolution: Learning to Lie for Node Classification Tasks	University of Florence	Italy	—
17	Multi-view Graph Condensation via Tensor Decomposition	University of California, Irvine Medical Center, University of São Paulo	Brazil, United States	—
18	Entropy Computing: A Paradigm for Optimization in an Open Quantum System	—	—	—
19	Multi-view graph neural networks by augmented aggregation	Eindhoven University of Technology, Karlsruhe Institute of Technology, Trinity College Dublin	France, Germany, Ireland	—
20	Graph Mamba: Towards Learning on Graphs with State Space Models	Cornell University	—	—
21	Tensor Network: from the Perspective of AI4Science and Science4AI	Fudan University, Shanghai Jiao Tong University	China	—
22	Entropy computing, a paradigm for optimization in open photonic systems	Computing Center	Russia	—
23	Hypergraph Neural Sheaf Diffusion: A Symmetric Simplicial Set Framework for Higher-Order Learning	Institute for Basic Science, Korea Advanced Institute of Science and Technology	South Korea	—
24	Derivation of Runge--Kutta Order Conditions via Functional Tree Tensor Networks	—	—	—
25	Tensorized Hypergraph Neural Networks	ByteDance Research, City University of Hong Kong, Harbin	China, Hong Kong	—

No.	Citing paper	Citing institution(s)	Country	S2
		Institute of Technology Shenzhen		
26	Reinvent the Operation not the Architecture: Quantum-inspired High-order Product for Compatible and Improved LLMs Training	Shanghai Jiao Tong University	China	—
27	Adaptive multi-scale Graph Neural Architecture Search framework	Ningbo University, University of Cambridge	China, United Kingdom	—
28	Heterogeneous Sheaf Neural Networks	University of Cambridge	United Kingdom	—
29	T-HyperGNNs: Hypergraph Neural Networks via Tensor Representations	University of Delaware	United States	—
30	On the Ability of Graph Neural Networks to Model Interactions Between Vertices	Princeton Language and Intelligence; Princeton University, Princeton University, Tel Aviv University	Israel, United States	—

Showing the 30 most-cited of 89 independent citing papers.

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).

FOLLOW-UP WORK

Lower and upper bounds on the pseudo-dimension of tensor network models

2021 · 22 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	Randomized tensor network reservoir computing: validity and learnability phase transitions	National Grid (United States), University of Electro-Communications	Japan, United States	—
2	Alternating Local Enumeration (TnALE): Solving Tensor Network Structure Search with Fewer Evaluations	Guangdong University of Technology, Harbin Engineering University, Instituto Argentino de Radioastronomía	Argentina, China, Japan	—
3	Permutation Search of Tensor Network Structures via Local Sampling	Guangdong University of Technology, RIKEN Center for Advanced Intelligence Project, Tokyo University of Agriculture and Technology	China, Japan	—
4	Tensor Wheel Decomposition and Its Tensor Completion Application	—	—	—
5	Guideline-Grounded Evidence Accumulation for High-Stakes Agent Verification	Tsinghua University, University of Cambridge	China, United Kingdom	—
6	Novel extended NI-MWMOTE-based fault diagnosis method for data-limited and noise-imbalanced scenarios	Guizhou University, Tianjin University, Zhejiang Normal University	China	—
7	Covariate-dependent Graphical Model Estimation via Neural Networks with Statistical Guarantees	Morgan Stanley, UCLA	United States	—

No.	Citing paper	Citing institution(s)	Country	S2
8	Tensor-based Kernel Machines with Structured Inducing Points for Large and High-Dimensional Data	—	—	—
9	iFCTN: an intra-block Fully-Connected Tensor Network Decomposition for Tensor Completion	Beihang University	China	—
10	Quantized Fourier and Polynomial Features for more Expressive Tensor Network Models	The University of Hong Kong	—	—
11	A survey on the complexity of learning quantum states	Harvard University, IBM Research - Almaden	United States	—
12	On Ranking-based Tests of Independence	Institut Polytechnique de Paris, University of Copenhagen	Denmark, France	—

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 established a foundational benchmark for temporal graph machine learning, subsequently expanding the framework to knowledge graphs and unifying model perspectives.

The researcher's core contribution is the development of a seminal benchmark for machine learning on temporal graphs, published in 2023. This work serves as the foundation for a sustained research line that addresses critical infrastructure gaps in the field. The titles suggest that prior to this work, the community lacked standardized evaluation protocols for dynamic graph structures, necessitating a unified platform to assess algorithmic performance reliably.

Originality is evident in the progression from the initial benchmark to specialized extensions. The 2024 follow-up, TGB 2.0, appears to broaden the scope to include temporal knowledge graphs and heterogeneous graphs, indicating an effort to handle more complex data modalities. Another 2024 paper proposes a unified view of snapshot and event-based models, suggesting the researcher is actively working to reconcile disparate methodological approaches within the temporal graph domain.

The significance of this line of work is demonstrated by its rapid adoption. The core paper has accumulated 254 citations, while the follow-ups have garnered 43 and 20 citations respectively. Notably, 86.4% of the citations across the researcher's classified works originate from independent researchers, indicating that this benchmark has become a widely accepted standard utilized by the broader scientific community rather than just the researcher's immediate circle.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 248

CORE PAPER

Temporal graph benchmark for machine learning on temporal graphs

2023 · 254 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	Graph deep learning for time series forecasting	Università della Svizzera italiana	Switzerland	—
2	Current and future directions in network biology	Brigham and Women's Hospital, Brookhaven National Laboratory, Carnegie Mellon University	Brazil, France, Israel	—

No.	Citing paper	Citing institution(s)	Country	S2
3	Exploring Time Granularity on Temporal Graphs for Dynamic Link Prediction in Real-world Networks	University of Sheffield	United Kingdom	—
4	Systems biology Current and future directions in network biology	—	—	—
5	Exploring the Performance of Continuous-Time Dynamic Link Prediction Algorithms	Ghent University	Belgium	—
6	Gaussian Embedding of Temporal Networks	Ghent University, Université Côte d'Azur, University College Dublin	Belgium, France, Ireland	—
7	Machine learning on dynamic graphs: a survey on applications	Michigan State University	United States	—
8	Graph Representation Learning in Complex Networks: Recent Advances and Open Challenges	Friedrich Schiller University Jena, Martin Luther University Halle-Wittenberg	Germany	—
9	Expressivity of Representation Learning on Continuous-Time Dynamic Graphs: An Information-Flow Centric Review	KTH Royal Institute of Technology, Microsoft	Sweden, United States	—
10	Are a Thousand Words Better Than a Single Picture? Beyond Images -- A Framework for Multi-Modal Knowledge Graph Dataset Enrichment	Aarhus University, University of Amsterdam	Denmark, Netherlands	—
11	Temporal graph models fail to capture global temporal dynamics	Synerise S.A., Warsaw University of Technology	Poland	—
12	GNNBleed: Inference Attacks to Unveil Private Edges in Graphs with Realistic Access to GNN Models	Penn State University	United States	—
13	Scalable and Efficient Temporal Graph Representation Learning via Forward Recent Sampling	Georgia Institute of Technology	United States	—
14	FUDD: Threat Hunting Framework Utilizing Graph-Based Anomaly Detection on Log Data	Hanover University of Music Drama and Media, Universität der Bundeswehr München	Germany	—
15	Perseus: Tracing the Masterminds Behind Cryptocurrency Pump-and-Dump Schemes	—	—	—
16	Valid Conformal Prediction for Dynamic GNNs	Maxwell Institute for Mathematical Sciences, The University of Melbourne, University of Bristol	Australia, United Kingdom	—
17	Temporal Graph Networks for Bank Customer Churn Prediction with Dynamic	University of Washington	United States	—
18	Graph Machine Learning Meets Multi-Table Relational Data	Amazon	United States	—
19	Security analysis and prediction of multi-relay networks over Fisher-Snedecor F fading channels	Henan Polytechnic University	China	—
20	Machine Learning on Dynamic Graphs: A Survey on Applications	Michigan State University	United States	—

No.	Citing paper	Citing institution(s)	Country	S2
21	What Do Temporal Graph Learning Models Learn?	GESIS - Leibniz-Institute for the Social Sciences, RWTH Aachen University, University of Mannheim	Germany	—
22	Learning Dynamic Graph Embeddings With Neural Controlled Differential Equations	City University of Hong Kong, University of Oxford, University of Oxford; Alan Turing Institute	United Kingdom	—
23	Dynamic Graph Unlearning: A General and Efficient Post-Processing Method via Gradient Transformation	RMIT University, The University of Melbourne, The University of Sydney	Australia	—
24	Between Linear and Sinusoidal: Rethinking the Time Encoder in Dynamic Graph Learning	Johns Hopkins University, New York University, University of Texas at Austin	United States	—
25	Recent Link Classification on Temporal Graphs Using Graph Profiler	—	—	—
26	On the Review of the Methodologies Evolution and Metrics Towards Graph Neural Networks	Eindhoven University of Technology, Karlsruhe Institute of Technology, Trinity College Dublin	France, Germany, Ireland	—
27	Using Causality-Aware Graph Neural Networks to Predict Temporal Centralities in Dynamic Graphs	Emory University, Lehigh University, University of California, Irvine Medical Center	United States	—
28	Deep Learning for Dynamic Graphs: Models and Benchmarks	University of Pisa	Italy	—
29	Gradient Transformation: Towards Efficient and Model-Agnostic Unlearning for Dynamic Graph Neural Networks	—	—	—
30	Temporal-Aware Evaluation and Learning for Temporal Graph Neural Networks	Hefei University of Technology, University of Hong Kong	China	—

Showing the 30 most-cited of 172 independent citing papers.

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).

FOLLOW-UP WORK

Tgb 2.0: A benchmark for learning on temporal knowledge graphs and heterogeneous graphs

2024 · 43 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	FOS: A Large-Scale Temporal Graph Benchmark for Scientific Interdisciplinary Link Prediction	Michigan State University, Shahid Beheshti University of Medical Sciences, University of Guilan	Iran, United States	—
2	Graph Representation Learning in Complex Networks: Recent Advances and Open Challenges	Friedrich Schiller University Jena, Martin Luther University Halle-Wittenberg	Germany	—

No.	Citing paper	Citing institution(s)	Country	S2
3	What Do Temporal Graph Learning Models Learn?	GESIS - Leibniz-Institute for the Social Sciences, RWTH Aachen University, University of Mannheim	Germany	—
4	Between Linear and Sinusoidal: Rethinking the Time Encoder in Dynamic Graph Learning	Johns Hopkins University, New York University, University of Texas at Austin	United States	—
5	TriAdapt-DGNN: Triple adaptive dynamic graph neural network for temporal link prediction	Jilin University	China	—
6	When Speed meets Accuracy: an Efficient and Effective Graph Model for Temporal Link Prediction	Guangzhou HKUST Fok Ying Tung Research Institute, Hong Kong Polytechnic University, Hong Kong University of Science and Technology	China, Hong Kong	—
7	Synthetic Datasets for Machine Learning on Spatio-Temporal Graphs using PDEs	Berlin Institute for the Foundations of Learning and Data, Fraunhofer Institute for Telecommunications, Heinrich Hertz Institute	Germany	—
8	Permutation Equivariant Neural Controlled Differential Equations for Dynamic Graph Representation Learning	City University of Hong Kong, Heidelberg Institute for Theoretical Studies, University of Oxford	Germany, United Kingdom	—
9	Never Skip a Batch: Continuous Training of Temporal GNNs via Adaptive Pseudo-Supervision	Sber	Russia	—
10	A Survey of Link Prediction in Temporal Networks	University of Manchester, University of Sheffield	United Kingdom	—
11	How Do Large Language Models Perform in Dynamical System Modeling	Ludwig-Maximilians-Universität München, Technical University of Munich	Germany	—
12	A Temporal Graph Dataset of Bitcoin Entity-Entity Transactions	Université Claude Bernard Lyon 1	France	—
13	Unfolded Laplacian Spectral Embedding: A Theoretically Grounded Approach to Dynamic Network Representation	The University of Tokyo	Japan	—
14	TGB-Seq Benchmark: Challenging Temporal GNNs with Complex Sequential Dynamics	Fudan University, Huawei Technology Ltd., Renmin University of China	Canada, China	—
15	Integrating Sequential and Relational Modeling for User Events: Datasets and Prediction Tasks	Capital One	United States	—
16	Learnable Spatial-Temporal Positional Encoding for Link Prediction	Arizona State University, Meta AI, University of Illinois Urbana-Champaign	United States	—
17	ChronoGraph: A Real-World Graph-Based Multivariate Time Series Dataset	Bitdefender, Bitdefender; University of Bucharest, Bitdefender; University of Bucharest, Romania	Germany, Romania	—

No.	Citing paper	Citing institution(s)	Country	S2
18	Multi-Scale Heterogeneous Text-Attributed Graph Datasets From Diverse Domains	State Key Laboratory of New Technology of Computer Software	China	—
19	Toward Better Temporal Structures for Geopolitical Events Forecasting	Information Sciences Institute, University of Southern California	United States	—
20	When Facts Expire: Benchmarking Temporal Validity in Knowledge Graphs	Centre National de la Recherche Scientifique	France	—
21	A Survey of Link Prediction in Temporal Networks	University of Manchester, University of Sheffield	United Kingdom	—
22	A Temporal Graph Dataset of Bitcoin Entity-Entity Transactions	Université Claude Bernard Lyon 1	France	—
23	Between Linear and Sinusoidal: Rethinking the Time Encoder in Dynamic Graph Learning	Johns Hopkins University, New York University, University of Texas at Austin	United States	—
24	ChronoGraph: A Real-World Graph-Based Multivariate Time Series Dataset	Bitdefender, Bitdefender; University of Bucharest, Max Planck Institutes for Intelligent Systems & Solid State Research Library	Germany, Romania	—
25	FOS: A Large-Scale Temporal Graph Benchmark for Scientific Interdisciplinary Link Prediction	Michigan State University, Shahid Beheshti University of Medical Sciences, University of Guilan	Iran, United States	—
26	Graph Representation Learning in Complex Networks: Recent Advances and Open Challenges	Friedrich Schiller University Jena, Martin Luther University Halle-Wittenberg	Germany	—
27	How Do Large Language Models Perform in Dynamical System Modeling	Ludwig-Maximilians-Universität München, Technical University of Munich	Germany	—
28	Integrating Sequential and Relational Modeling for User Events: Datasets and Prediction Tasks	Capital One	United States	—
29	Learnable Spatial-Temporal Positional Encoding for Link Prediction	Arizona State University, Meta AI, University of Illinois Urbana-Champaign	United States	—
30	Multi-Scale Heterogeneous Text-Attributed Graph Datasets From Diverse Domains	State Key Laboratory of New Technology of Computer Software	China	—

Showing the 30 most-cited of 60 independent citing papers.

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).

FOLLOW-UP WORK

UTG: Towards a unified view of snapshot and event based models for temporal graphs

2024 · 20 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	What Do Temporal Graph Learning Models Learn?	GESIS - Leibniz-Institute for the Social Sciences, RWTH Aachen University, University of Mannheim	Germany	—
2	Base3: a simple interpolation-based ensemble method for robust dynamic link prediction	Mila - Quebec Artificial Intelligence Institute	Canada	—
3	EMA-Affinity: A Statistical Approach for Node Affinity Prediction in Dynamic Graphs	Amirkabir University of Technology	Iran	—
4	Evaluating explainability techniques on discrete-time graph neural networks	—	—	—
5	Understanding and Improving Laplacian Positional Encodings For Temporal GNNs	Ben-Gurion University of the Negev, Technion – Israel Institute of Technology, University of Cambridge	Israel, United Kingdom	—
6	From Link Prediction to Forecasting: Addressing Challenges in Batch-based Temporal Graph Learning	University of Würzburg	Germany	—
7	Base3: a simple interpolation-based ensemble method for robust dynamic link prediction	Mila - Quebec Artificial Intelligence Institute	Canada	—
8	EMA-Affinity: A Statistical Approach for Node Affinity Prediction in Dynamic Graphs	Amirkabir University of Technology	Iran	—
9	From Link Prediction to Forecasting: Addressing Challenges in Batch-based Temporal Graph Learning	University of Würzburg	Germany	—
10	Understanding and Improving Laplacian Positional Encodings For Temporal GNNs	Ben-Gurion University of the Negev, Technion – Israel Institute of Technology, University of Cambridge	Israel, United Kingdom	—
11	What Do Temporal Graph Learning Models Learn?	GESIS - Leibniz-Institute for the Social Sciences, RWTH Aachen University, University of Mannheim	Germany	—
12	Base3: a simple interpolation-based ensemble method for robust dynamic link prediction	Mila - Quebec Artificial Intelligence Institute	Canada	—
13	EMA-Affinity: A Statistical Approach for Node Affinity Prediction in Dynamic Graphs	Amirkabir University of Technology	Iran	—
14	From Link Prediction to Forecasting: Addressing Challenges in Batch-based Temporal Graph Learning	University of Würzburg	Germany	—
15	Understanding and Improving Laplacian Positional Encodings For Temporal GNNs	Ben-Gurion University of the Negev, Technion – Israel Institute of Technology, University of Cambridge	Israel, United Kingdom	—
16	What Do Temporal Graph Learning Models Learn?	GESIS - Leibniz-Institute for the Social Sciences, RWTH Aachen University, University of Mannheim	Germany	—

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 3

Claim — Contribution 3

The researcher advanced spectral learning for weighted automata, establishing theoretical links to tensor networks and RNNs while optimizing approximation methods.

The researcher's core contribution rests on the 2017 paper 'Multitask spectral learning of weighted automata,' which appears to have introduced a foundational approach to learning these models. This work serves as the anchor for a sustained line of inquiry into the structural and computational properties of weighted automata.

Originality in this line of work is suggested by the chronological progression from the core paper to subsequent studies. The 2021 follow-up on optimal spectral-norm approximate minimization indicates a refinement of the initial methods, while the 2024 paper suggests the researcher successfully bridged weighted automata with tensor networks and recurrent neural networks, expanding the theoretical scope of the original framework.

The significance of this research is evidenced by its uptake in the field. The core paper has accumulated 11 citations, while the later works have garnered 10 and 22 citations respectively. Given that 86.4% of the researcher's total citations come from independent sources, this specific line of work appears to have resonated beyond the immediate research group, indicating broad independent recognition.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 32

CORE PAPER

Multitask spectral learning of weighted automata

2017 · 11 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	Distillation of weighted automata from recurrent neural networks using a spectral approach	Université de Provence Aix-Marseille I, Univ Lyon, UJM-Saint-Etienne	France	—
2	Explaining Black Boxes on Sequential Data using Weighted Automata	Université Aix-Marseille-III	France	—
3	Fusing Vector Space Models for Domain-Specific Applications	École Normale Supérieure Paris-Saclay, HES-SO Fribourg	France, Switzerland	—

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).

FOLLOW-UP WORK

Connecting weighted automata, tensor networks and recurrent neural networks through spectral learning

2024 · 22 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	Generalizable Neural Network Design Methodology of Digital Integrated Circuits for Reusable Implementations on Neuromorphic System	Universiti Teknologi PETRONAS	Malaysia	—
2	Toward AI-Augmented Formal Verification: A Preliminary Investigation of ENGRU and Its Challenges	Chulalongkorn University, Khon Kaen University	Thailand	—
3	Comparative Study on the Transition from Neural Networks to Erudition Automata	Lovely Professional University, Saveetha University, Sri Ramakrishna Institute of Paramedical Sciences	India	—
4	Beyond Pass/Fail: The Story of Learning-Based Testing	University of Tennessee at Knoxville	United States	—
5	Inference of Deterministic Finite Automata via Q-Learning	University of Lübeck	Germany	—
6	Logic Network Circuits for Neural network Realization in Machine Learning Application using Graphene Nano Ribbon Field Effect Transistors	Sri Venkateswara University	India	—
7	An Investigation of Machine Learning Solutions to Demonstrate Black Box Software Conformity in Regulated Measuring Instruments	—	—	—
8	Modal Abstractions for Smart Contract Validation	IMDEA Software Institute, Institut Input, University of Buenos Aires	Argentina, Germany, Spain	—
9	Beyond Pass/Fail: The Story of Learning-Based Testing	University of Tennessee at Knoxville	United States	—
10	Comparative Study on the Transition from Neural Networks to Erudition Automata	Lovely Professional University, Saveetha University, Sri Ramakrishna Institute of Paramedical Sciences	India	—
11	Generalizable Neural Network Design Methodology of Digital Integrated Circuits for Reusable Implementations on Neuromorphic System	Universiti Teknologi PETRONAS	Malaysia	—
12	Inference of Deterministic Finite Automata via Q-Learning	University of Lübeck	Germany	—
13	Logic Network Circuits for Neural network Realization in Machine Learning Application using Graphene Nano Ribbon Field Effect Transistors	Sri Venkateswara University	India	—
14	Modal Abstractions for Smart Contract Validation	IMDEA Software Institute, Institut Input, University of Buenos Aires	Argentina, Germany, Spain	—
15	Toward AI-Augmented Formal Verification: A Preliminary Investigation of ENGRU and Its Challenges	Chulalongkorn University, Khon Kaen University	Thailand	—
16	Beyond Pass/Fail: The Story of Learning-Based Testing	University of Tennessee at Knoxville	United States	—
17	Comparative Study on the Transition from Neural Networks to Erudition Automata	Lovely Professional University, Saveetha University, Sri Ra-	India	—

No.	Citing paper	Citing institution(s)	Country	S2
		makrishna Institute of Paramedical Sciences		
18	Generalizable Neural Network Design Methodology of Digital Integrated Circuits for Reusable Implementations on Neuromorphic System	Universiti Teknologi PETRONAS	Malaysia	—
19	Inference of Deterministic Finite Automata via Q-Learning	University of Lübeck	Germany	—
20	Logic Network Circuits for Neural network Realization in Machine Learning Application using Graphene Nano Ribbon Field Effect Transistors	Sri Venkateswara University	India	—
21	Modal Abstractions for Smart Contract Validation	IMDEA Software Institute, Institut Input, University of Buenos Aires	Argentina, Germany, Spain	—
22	Toward AI-Augmented Formal Verification: A Preliminary Investigation of ENGRU and Its Challenges	Chulalongkorn University, Khon Kaen University	Thailand	—

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).

FOLLOW-UP WORK

Optimal spectral-norm approximate minimization of weighted finite automata

2021 · 10 citations (GS)

No.	Citing paper	Citing institution(s)	Country	S2
1	MM Algorithms to Estimate Parameters in Continuous-time Markov Chains	Aalborg University, Reykjavík University	Denmark, Iceland	—
2	Hankel low-rank approximation and completion in time series analysis and forecasting: a brief review	Cardiff University, Université de Lorraine	France, United Kingdom	—
3	48th International Colloquium on Automata, Languages, and Programming, ICALP 2021, Glasgow, Scotland (Virtual Conference), July 12-16, 2021	—	—	—
4	Hankel low-rank approximation and completion in time series analysis and forecasting: a brief review	Cardiff University, Université de Lorraine	France, United Kingdom	—
5	MM Algorithms to Estimate Parameters in Continuous-time Markov Chains	Aalborg University, Reykjavík University	Denmark, Iceland	—
6	Hankel low-rank approximation and completion in time series analysis and forecasting: a brief review	Cardiff University, Université de Lorraine	France, United Kingdom	—
7	MM Algorithms to Estimate Parameters in Continuous-time Markov Chains	Aalborg University, Reykjavík University	Denmark, Iceland	—

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).

D. Citing-Institution Prestige & Geography

Top citing institutions

Institution	Country	World ranking	Citing papers
McGill University	Canada	SCImago #168 · THE =41 · QS 27	47
Université de Montréal	Canada	SCImago #692 · THE 150 · QS 168	36
Mila - Quebec Artificial Intelligence Institute	Canada	SCImago #366	24
University of California, Irvine Medical Center	United States	—	22
University of Oxford	United Kingdom	SCImago #26 · THE 1 · QS 4	20
Stanford University	United States	SCImago #18 · THE =5 · QS 3	15
Tianjin University	China	SCImago #90 · THE 201–250 · QS =257	14
University of Cambridge	United Kingdom	SCImago #63 · THE =3 · QS 6	13
Massachusetts Institute of Technology	United States	SCImago #41 · THE 2 · QS 1	13
University of Illinois Urbana-Champaign	United States	QS =70	11
University of Southern California	United States	SCImago #192 · THE =73 · QS 146	11
Imperial College London	United Kingdom	SCImago #69 · THE 8 · QS 2	11
Shanghai Jiao Tong University	China	SCImago #10 · THE 40 · QS =47	10
University of Electronic Science and Technology of China	China	SCImago #129 · THE 301–350 · QS =519	10
University of Toronto	Canada	SCImago #39 · THE 21 · QS 29	10

Geographic distribution of citing authors

Country	Citing papers
United States	275
China	159
Canada	124
United Kingdom	77
Germany	51
France	35
Singapore	25
Japan	22
Switzerland	22
Italy	21
India	20
Australia	18

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	Low-Rank Regression with Tensor Responses	167	Dhanasar — Prong 2 (well-positioned)
Contribution 2	Temporal graph benchmark for machine learning on temporal graphs	248	Dhanasar — Prong 2 (well-positioned)
Contribution 3	Multitask spectral learning of weighted automata	32	Dhanasar — Prong 2 (well-positioned)