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# Nonlocal Continuum Models for Oscillatory Media: Dynamics of Phase Equations

*By Bard Ermentrout, Cameron Watt, and Gavin Zhang*

Recent experimental developments in biology and neuroscience allow researchers to record dynamical behavior from large spatial regions at high temporal resolution. Because this activity is often oscillatory, we can represent it with spatiotemporal phase maps that use phase equations to naturally model the dynamics. But despite a great deal of progress in the analysis of networks that comprise coupled phase oscillators (and recent generalizations such as higher-order phase models), the dynamics of spatially coupled phase models have seen limited results — particularly when the coupling is nonlocal.

Given this shortage, our group has been studying the dynamics of continuum systems of phase models in the form

$$\frac{\partial\theta(x,t)}{\partial t}=\omega(x)+\int_D W(|x-y|)H(\theta(y,t)-\theta(x,t))\ dy. \tag{1}$$

Here, $x \in D$ and $D$ is a one-dimensional (1D) or two-dimensional domain, $W(|x|)$ determines the way in which interactions decay with distance, $\omega(x)$ represents frequency heterogeneities, and $H(\phi)$ is the phase interaction function (e.g., $\sin(\phi)$ in the Kuramoto model). By varying the choice of domain shape and other parameters in (1), we can explain a variety of spatiotemporal patterns in biological data while simultaneously developing new mathematical tools for their analysis.

We are especially curious about the existence of phase-locked solutions to (1)—i.e., $\theta(x,t)=\Omega t+\phi(x)$—as well as their stability. We are also investigating the loss of phase locking as the frequency heterogeneities $\omega(x)$ get too large, for example. Our interest in this class of models stems from our collaborations with several experimental groups that have successfully recorded large-scale oscillatory behavior (see Figure 1). Figure 1a illustrates the extracted *phases* from the local field potentials (LFPs) on a grid of implanted electrodes on a human cortex. First, the LFP is filtered, then a Hilbert transform is applied to extract the analytic phase. The top panel depicts a source, or *bullseye*, that propagates outward in a nearly radial wave; the bottom panel shows a counterclockwise rotating wave that is centered at the circled "core," where the nearest neighbor phase differences are maximal. In Figure 1b, calcium activity from a piece of mouse colon shows that ripple contractions form traveling waves that move in the aboral to oral direction at regular intervals of about 10 cycles per minute. Patterns such as those in the top panel of Figure 1a and Figure 1b arise due to *heterogeneities*—i.e., in the local frequencies $\omega(x)$—while the rotating wave in the lower panel of Figure 1a results from a *topological singularity*.

Modeling patterns like the ones in Figure 1a, where the apparent presence of a wave source leads to radially outward waves, is a relatively straightforward process. The top panel of Figure 2a (on page 3) depicts the steady state phase for (1),

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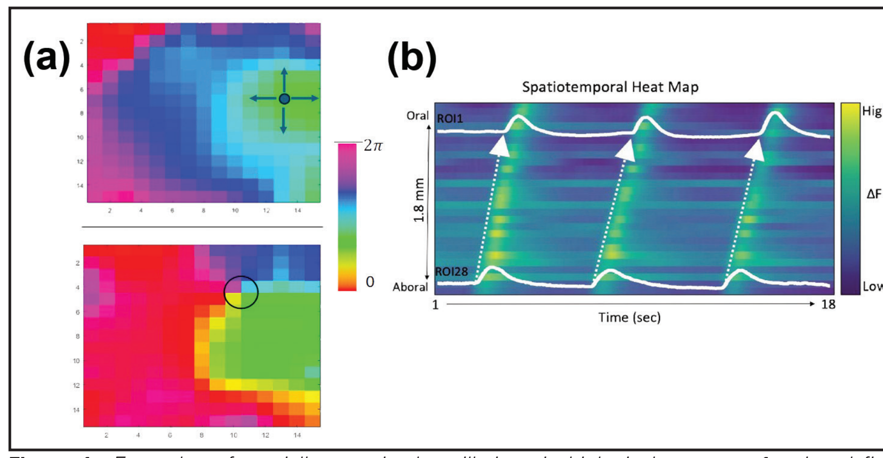


**Figure 1.** *Examples of spatially organized oscillations in biological systems.* **1a.** *Local field potential recordings from a grid of implanted electrodes on a human cortex at two different epochs.* **1b.** *Cellular calcium activity across the proximal colon of a mouse indicates organized, small-amplitude ripple contractions. Figure 1a adapted from [1] and 1b courtesy of the author.*

# Commutative Algebra Meets Data Science: A New Paradigm in Mathematical Artificial Intelligence

*By Guo-Wei Wei*

Commutative algebra is a longstanding pillar of pure mathematics that underpins subjects such as algebraic geometry and number theory and addresses fundamental structures like rings, ideals, and modules [2]. In the past, the field appeared to be quite removed from the practical concerns of data science. More recently, however, an unexpected transformation occurred — ideas from commutative algebra began to influence real-world data analysis; machine learning (ML); and even modeling efforts in biology, chemistry, and materials science.

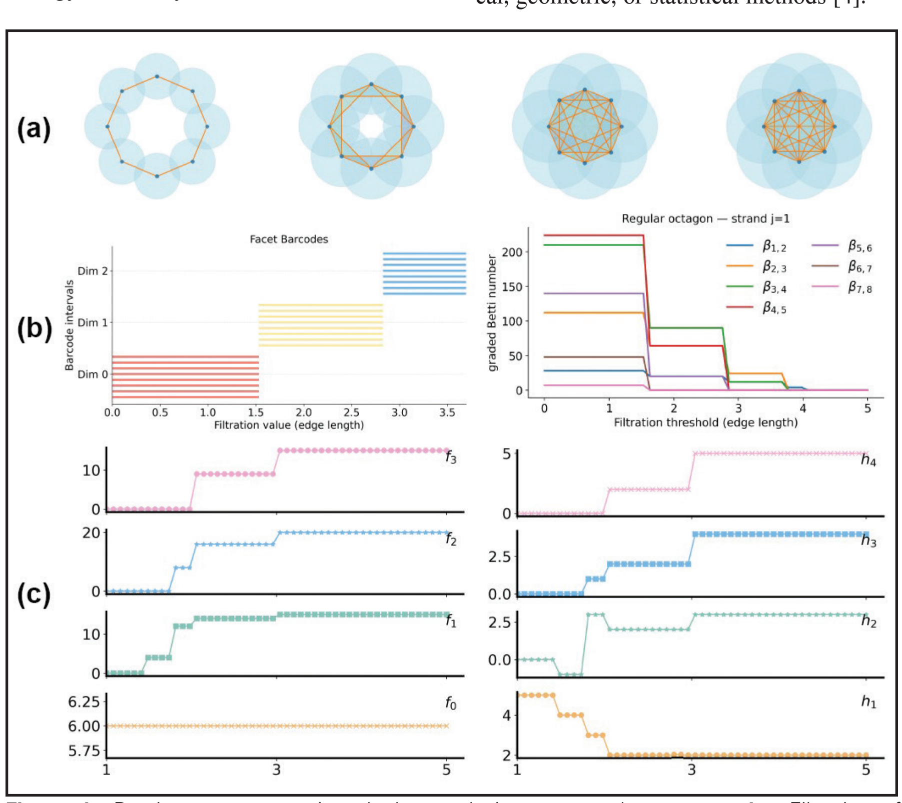


**Figure 1.** *Persistent commutative algebra analysis on a regular octagon.* **1a.** *Filtration of the octagon.* **1b.** *Persistent facet ideals and persistent graded Betti curves.* **1c.** *Persistent $f$-vectors and persistent $h$-vectors. Figure courtesy of Yiming Ren and adapted from [6].*

## The Emergence of Persistent Commutative Algebra

A burgeoning discipline called *persistent commutative algebra* (PCA) applies algebraic concepts in a multiscale, data-driven setting [8]. Much like topological data analysis (TDA) and persistent homology [1], PCA extracts structural "signatures" that remain stable across multiple scales or levels of resolution. But unlike TDA—which focuses primarily on topological invariants such as loops and voids—PCA captures algebraic relationships, constraints, and interactive patterns that are often invisible to topological, geometric, or statistical methods [4].

PCA is both mathematically elegant and practically powerful, with applications in genomics, molecular binding prediction, protein-nucleic acid interactions, and other complex biological systems. These developments suggest that the field may soon become a vital component of *rational learning*, which is guided by interpretable mathematics rather than opaque computation.

## Why Commutative Algebra, and Why Now?

While classical ML—particularly deep learning—has made extraordinary progress, it often lacks interpretability and structural awareness. Many existing models operate as *black boxes,* offering minimal insight into their behavior under perturbations or the rationale of their predictions. A key obstacle in the development of the next generation of artificial intelligence (AI)—specifically *world models*—is the lack of physical and structural insights in current large language models. As scientific datasets grow progressively more complex, these limitations become increasingly problematic.

Commutative algebra offers a different perspective by providing tools that capture algebraic relations, combinatorial dependencies, topological invariants, and geometric constraints. These mathematical structures arise naturally in point clouds, graphs, directed graphs, hypergraphs, networks, sequences, and other forms of data. PCA adapts the structures to data science by examining the emergence, evolution, and persistence of patterns across scales [8], yielding a multiscale viewpoint that parallels the success of TDA but extends far beyond the capabilities of topology. Recent work affirms that PCA can use concepts such as persistent facet ideals, persistent graded Betti numbers, persistent

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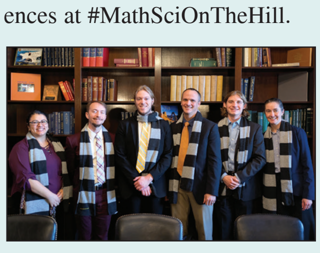

# Strengthening SIAM's Northern and Central California Research and Development Community at NCC25

*By Sherry Li, Andy Nonaka, and Stefan M. Wild*

*Attendees of the 2nd SIAM Northern and Central California Sectional Conference, which took place at Lawrence Berkeley National Laboratory in October 2025, pose for a group photo. Participants enjoyed two days of collaboration, innovation, and community in applied mathematics and scientific computing. Photo courtesy of Bonnie Powell.*

The Northern and Central California (NCC) Section of SIAM[1] serves as a regional catalyst for researchers whose work blends applied mathematics, computation, and the physical sciences. Founded in 2024, the section strives to provide students, early-career scientists, and other West-Coast-based SIAM members—some of whom may not be able to attend major SIAM conferences—with an opportunity to connect and experience the many offerings of local academic, national laboratory, and private sector communities. Following the highly successful inaugural NCC conference at the University of California (UC) Merced in 2024[2] [1], the 2nd SIAM Northern and Central California Sectional Conference (NCC25)[3] took place at Lawrence Berkeley National Laboratory (LBNL) in October 2025.

This two-day gathering attracted more than 200 participants who ranged from high school, undergraduate, and graduate students to postdoctoral fellows, faculty members, laboratory scientists, and industry engineers. While the event primarily catered to the NCC community, the robust program drew presenters and attendees from across the U.S., as well as a few international scholars.

NCC25 opened with a plenary address by Robert Falgout of Lawrence Livermore National Laboratory (LLNL), who offered a state-of-the-art overview of multigrid methods for extreme-scale scientific computing. Falgout highlighted recent algorithmic breakthroughs that enable scalable solvers on exascale architectures and set the tone for the meeting's technical prowess. The next day's plenary by Suzanne Sindi of UC Merced explored the use of mathematical models as discovery tools in complex biological systems. Her talk combined multiscale modeling and uncertainty quantification to illuminate biological processes that span many orders of magnitude in space and time.

Beyond the plenary lectures, the program included 40 additional talks—organized across eight thematic sessions—that were selected by the Technical Program Committee through an open solicitation. The committee consisted of Shima Alizadeh of Amazon Web Services, Anthony Austin of the Naval Postgraduate School (NPS), Harun Bayraktar of NVIDIA, Bert Debusschere of Sandia National Laboratories, Alyson Fox of LLNL, Serkan Hosten of San Francisco State University, Tamara Kolda of MathSci.ai, Dongwook Lee of UC Santa Cruz, Vivek Pallipuram of the University of the Pacific, and Andy Wan of UC Merced. The thematic sessions comprised the following topics:

- *High performance computing (HPC) and simulation of complex dynamical systems*, which showcased advances in vortex-method simulations, high-order time integrators for cloud microphysics, and hierarchical reconstruction methods for real-time synchrotron tomography.
- *Uncertainty quantification and data-driven modeling*, with talks that addressed interpolation-model error bounds, multi-fidelity Bayesian optimization, determinant-free Gaussian process regression, and sub-Gaussian mean estimation.
- *Machine learning for scientific computing* (in two parts), where speakers introduced statistics-informed neural surrogates, convolution-only deep networks for phase-field extrapolation, reinforcement-learning-guided tuning of atmospheric models, and geometry-aware rational neural networks.
- *Linear algebra and numerical methods*, which covered tensor-eigenvalue subspace projections, weight-matrix analysis of implicit neural networks, column subset selection via nuclear scores, and multigrid methods.
- *Scientific computing for life sciences*, which emphasized the growing demand for quantitative tools in biology and medicine.
- *Computational methods for partial differential equations (PDEs)*, with lectures that spanned turbulent flux algorithms, advection and diffusion, and dispersive hydrodynamic models.
- *Control theory and system optimization*, where presenters spoke about optimal control and collaborative autonomy, decentralized and PDE-constrained optimization, and fault-tolerant Kalman filtering.

In addition to the many talks, conference attendees enjoyed 44 posters—highlighted through a plenary poster blitz—during two interactive poster sessions. Judges scouted both sessions and awarded best poster awards to Alexander Aghili of UC Santa Cruz, Jonathan Forstater and Kelli Gutierrez of UC Davis, Irabiel Romero of UC Merced, and Larry Wigington of NPS.

Moreover, two panel discussions connected the technical program to broader career prospects. During the first panel, Kolda, Alizadeh, Michael Mahoney of LBNL, and Habib Najm of Sandia pondered the role of artificial intelligence and large language models in reshaping research workflows, reproducibility, and the dissemination of scientific knowledge. The second panel—titled "Challenges in Mentoring Early-career Professionals"—featured Sindi, Bayraktar, Falgout, and Ann Almgren of LBNL, who shared advice on mentorship, networking, and career transitions. Their session, which targeted more established researchers, was held concurrently with an interviewing and resume workshopping event for students and junior scientists. Bill Cannan, Senior Human Resources Division Partner at LBNL, reviewed interview strategies with attendees, who then broke into small groups for roundtable feedback on their CVs and resumes. Lively participation in both the panels and workshop reflected attendees' strong appetites for practical professional development guidance alongside technical content.

To maximize the use of its location, NCC25 offered tours of two national user facilities at LBNL. Participants visited the National Energy Research Scientific Computing Center[4]—a flagship HPC facility that hosts the Perlmutter supercomputer—and the Advanced Light Source,[5] a cutting-edge synchrotron-radiation facility on LBNL's campus.

Support from the U.S. National Science Foundation (NSF) provided funding for more than 60 travel awards for students and early-career professionals in the NCC region. These awards, which allowed for significant attendance from local scientists, were a highlight for the Local Organizing Committee and NSF support principal investigators Roel Van Beeumen, Aydın Buluç, Hannah Klion, Lin Lin, Paul Lin, Dmitriy Morozov, Per-Olof Persson, James Sethian, and Erika Ye (all of LBNL).

Looking ahead, the NCC Section of SIAM hopes to continue the momentum from its first two meetings with NCC26, which will take place at UC Davis in October of this year.

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*Sherry Li is a senior scientist and leader of the Scalable Solvers Group in the Applied Mathematics and Computational Research Division at Lawrence Berkeley National Laboratory (LBNL). Andy Nonaka is a staff scientist and group lead of the Center for Computational Sciences and Engineering in the Applied Mathematics and Computational Research Division at LBNL. Stefan M. Wild is a senior scientist and director of the Applied Mathematics and Computational Research Division at LBNL.*


[1] https://www.siam.org/get-involved/connect-with-a-community/sections/northern-and-central-california-section-of-siam
[2] https://www.siam.org/conferences-events/past-event-archive/northern-and-central-california-section-of-siam-annual-meeting-2024
[3] https://www.siam.org/conferences-events/section-meetings/2nd-siam-northern-and-central-california-sectional-conference-ncc25
[4] https://www.nersc.gov
[5] https://als.lbl.gov


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## Oscillatory Media

*Continued from page 1*

where $D$ is a square, $W(x)$ is a Gaussian, $H(\phi)=\sin(\phi+d)-\sin(d)$, and $\omega(x)$ is a radially symmetric frequency gradient.

If we choose an annulus for domain $D$, we can then examine rotating waves of the form $\theta(x,t)=\Omega t+\psi+f(r)$, where $\psi$ is the polar angle and $f(r)$ is an unknown function that satisfies a 1D integral equation [2]. The middle panel of Figure 2a is an example solution for the Gaussian $W(x)$ and $H(\theta)=\sin(\theta+d)-\sin(d)$ on an annulus with an outer diameter $r=5$ and inner diameter $r=1$. When the hole shrinks, the solution fails to exist; in the absence of a hole, the "core" of the rotating wave produces asynchronous dynamics called a *spiral chimera* [4] (see the bottom panel of Figure 2a). As such, no true rotating waves appear in pure phase models without a central hole. Instead, the waves are broken up by disorganized activity at the core.

A specialized class of spontaneously oscillating pacemaker cells called the *interstitial cells of Cajal* (ICCs) cause the oscillations in Figure 1b (on page 1). The top panel of Figure 2b shows the results of a simulated 1D network of coupled phase oscillators when the coupling is Gaussian, a linear frequency gradient is present, and $H(\phi)$ is taken from a mechanistic model for ICCs after the application of weakly coupled oscillator theory [3]. As expected, the resulting pattern consists of periodic waves that travel from $x=1$ to $x=0$. In the late 1970s, John Neu explored a phase model approximation for a system of reaction-diffusion equations with weak diffusive coupling and found that the phase evolved as

$$\theta_t=\omega(x)+a\theta_x^2+b\theta_{xx}, \quad 0<x<1,$$

with appropriate boundary conditions [5]. As long as $b>0$, there will always be phase-locked solutions: $\theta(x,t)=\Omega t+\int_0^x \phi(y)dy$.

Our recent work considered phase-locked solutions to (1), where $D=[0,1]$ and $W(x)$ is a symmetric Gaussian or exponential kernel with width $\sigma$ [6]. By letting $\sigma$ get small, we were able to explicitly establish phase-locked solutions away from the boundaries of the domain. In the reaction-diffusion case, locking *always* occurs regardless of the value of $\omega(x)$; however, such an outcome is not true for (1). The lower panel of Figure 2b utilizes the same model as the upper panel but increases the frequency gradient, which leads to a loss of locking and the emergence of so-called *frequency plateaus*: regions that are locked at the same frequency and separated by gaps. Three distinct plateaus are present in Figure 2b.

This brief article highlights multiple recent accounts of phase models that facilitate our understanding of the spatiotemporal organization of oscillatory media. Nonlocal coupling yields several new mathematical phenomena, such as spiral chimeras and frequency plateaus, that do not exist in continuum diffusion models. We look forward to continued advances in this area of study.

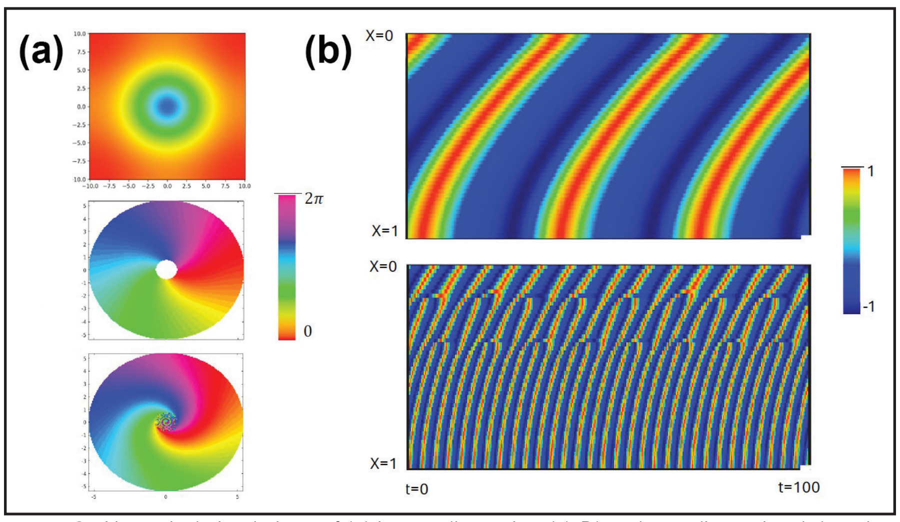


**Figure 2.** *Numerical simulations of (1) in one-dimensional (1D) and two-dimensional domains.* **2a.** *The top panel depicts a square domain with a radially symmetric frequency gradient, where $\omega(r)$ leads to outwardly propagating waves. The middle panel illustrates rotating waves in an annulus. Removal of the "hole" in the bottom panel triggers the emergence of a desynchronized core called a chimera.* **2b.** *The top panel portrays a 1D network with Gaussian connectivity and a linear frequency gradient. If the gradient is too large, as in the bottom panel, frequency plateaus arise. Top panel of Figure 2a and Figure 2b courtesy of Bard Ermentrout, middle and bottom panels of Figure 2a courtesy of [2].*

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*Bard Ermentrout is a professor of mathematics at the University of Pittsburgh. He works in many areas of mathematical biology, with a focus on neuroscience. Cameron Watt and Gavin Zhang are Ph.D. students in the Department of Mathematics at the University of Pittsburgh under the direction of Bard Ermentrout. Their research focuses on dynamical systems.*

## Commutative Algebra

*Continued from page 1*

$f$-vectors, and persistent $h$-vectors—mathematical invariants that record changing relationships in the data during filtration—to deliver combined interpretations of the data at hand [6] (see Figure 1, on page 1).

### Algebraic Signatures for Real Data

Instead of merely describing data by shape or distribution, PCA focuses on algebraic relations that remain meaningful across various levels of resolution. As such, it extracts multiscale algebraic "fingerprints" that summarize the interactions between data variables and are effective across the following domains.

**Genomics:** One of the earliest applications of PCA in computational biology is a framework called *commutative algebra k-mer learning* (CAKL) [7]. This method uses algebraic structures derived from $k$-mer sets to capture deep combinatorial patterns in genomic sequences. When tested on 11 benchmark datasets, CAKL outperformed several state-of-the-art methods during tasks like viral variant detection, phylogenetic tree analysis, and viral classification. This result demonstrates that PCA-based sequence analysis can be robust, scalable, and interpretable, even in the presence of noisy or highly variable genomic data.

**Biomolecular interactions:** PCA can also predict biomolecular interactions via *commutative algebra ML* (CAML) and *commutative algebra neural networks* (CANNs). These approaches utilize persistent Stanley-Reisner theory to generate algebraic signatures for molecular structures. In recent studies, CAML and CANNs have achieved competitive or superior performance when predicting protein-ligand binding affinities [3] and mutation-induced human diseases [9].

A new direction further builds on this idea via *graded Betti number learning* (GBNL) [10], which uses primary sequence data to directly predict protein-nucleic acid binding affinities. By combining PCA with modern sequence embeddings, GBNL offers interpretability and strong predictive performance without requiring three-dimensional structural information.

**Materials science:** *Category-specific commutative algebra* (CSCA) is the first PCA implementation in materials science [5]. It utilizes chemically aware, multiscale algebraic invariants to model metal-organic frameworks. CSCA has achieved state-of-the-art predictive accuracy for gas adsorption properties, thus providing superior interpretability, stability, and data efficiency when compared to traditional geometric or graph-based methods. It introduces a rigorous new paradigm for the discovery and understanding of porous materials.

### What Makes PCA Distinct?

PCA is unique in its ability to capture the evolution of algebraic relationships across scales, which reveals persistent combinatorial features. And unlike geometry-based methods, it exhibits natural compatibility with discrete, symbolic, and relational data and works seamlessly with sequences, graphs, and other non-Euclidean data types. Moreover, the unique algebraic invariants of PCA correspond to meaningful structural patterns and provide insights that are otherwise unavailable from black box neural networks.

PCA also enriches feature spaces with algebraic information, improving the performance and stability of downstream ML models and algebra-grounded neural networks. Finally, PCA-based models have already exceeded traditional methods in accuracy and robustness for a variety of application areas, from genomics and macromolecules to materials science. Collectively, these advantages establish the discipline as a promising mathematical foundation for data science.

### The Road Ahead

Although the field of PCA is young, several factors are accelerating its growth. Persistent Stanley-Reisner theory serves as the theoretical foundation for data analysis; computational tools like Macaulay2[1] make algebraic computations tractable for medium- and large-scale datasets; and recent publications show strong empirical results and increasing interest across mathematics, computer science, and the physical sciences. Nonetheless, challenges remain. Broader adoption of the PCA framework will require user-friendly software packages, standardized benchmarks, and scalable algorithms for massive datasets; in particular, the computation of graded Betti numbers for large data remains an obstacle. Additionally, the interpretation of algebraic invariants in domain-specific contexts will be essential for scientists and engineers.

Despite these challenges, PCA brings a new language to data science — a language that is not centered on points or shapes, but on relationships, constraints, algebraic stability, and invariants. As datasets become more complex and interconnected over time, the demand for interpretable, mathematical AI methods will continue to grow. PCA is poised to complement existing tools—e.g., linear algebra, statistics, topology, and geometry—as a standard component of the modern data scientist's toolkit. Its rising success suggests that it will play a key role in the next stage of rational learning: scientifically meaningful machine intelligence that is guided by profound mathematical structures.

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*Guo-Wei Wei is an MSU Research Foundation Distinguished Professor at Michigan State University. His research explores the mathematical foundations of bioscience and data science.*

# Modeling Social Systems: Transparency, Reproducibility, and Responsibility

*By the Casa Matemática Oaxaca Workgroup on Collective Social Phenomena*

Researchers frequently use mathematical modeling to enrich theory, guide interventions, and inform policy on a variety of issues, from voting behavior to economic inequality and urban development. Modeling's expanding role in the social sciences introduces novel opportunities and places new responsibilities on the creation, communication, and interpretation of the models in question. Because these models influence decisions that impact millions of lives, developers must consider transparency, reproducibility, and humility — especially under the constraints of privacy and limited data.

Mathematical modeling in the social sciences is uniquely challenging; researchers lack controlled experiments, and observational data are often sparse, noisy, or systematically missing. Social variables are also subject to substantial measurement error, and populations are heterogeneous and often nonstationary, with behaviors and definitions that change over time. In many contexts, essential social data are simply unavailable at the local scales where questions matter most — especially for sensitive issues like crime or corruption. Modelers may be forced to rely on coarse aggregates or assumptions in place of missing empirical grounding. Given these limitations, how can we build models that support science and decision-making processes in transparent and responsible ways?

This question motivated a recent workshop titled "Collective Social Phenomena: Dynamics and Data,"[1] which took place last June at Casa Matemática Oaxaca[2] in Mexico (see Figure 1). During the weeklong event, mathematicians, statisticians, engineers, and computational social scientists discussed modeling frameworks, ethical challenges, and disciplinary norms. Based on these conversations, participants distilled six guiding principles for transparent and responsible modeling of social systems:

1. *Be explicit about modeling aims*
2. *Clearly communicate model assumptions and researcher perspectives*
3. *Match models to real-world stakes*
4. *Quantify and communicate uncertainty*
5. *Share code and data*
6. *Collaborate across disciplines and perspectives.*

Here, we expand on these principles with examples from the workshop and the broader literature [1]. We hope that they will serve as useful starting points for quantitative modelers of social systems.

### Why Model?

In the famed words of computational social scientist Paul Smaldino, "Models are stupid, and we need more of them" [5]. Part of Smaldino's argument is that models may serve purposes other than the detailed reconstruction of their target systems — purposes that might warrant considerable simplifications. The appropriateness of a given simplification depends on the intended objective of the model. In the social domain, scientists use models to *explore* possible connections between social mechanisms, *explain* observed individual or collective behaviors, and *predict* the outcomes of social processes or interventions. These purposes are distinct from a model's target system or application area and can address questions of social conformity, voting behavior, economic inequality, or urban development in *exploratory*, *explanatory*, or *predictive* forms.

[1] https://www.birs.ca/events/2025/5-day-workshops/25w5326

[2] https://www.iimas.unam.mx/cmo

**Figure 1.** *Arturo García Bustos' mural, "Oaxaca en la historia y en el mito," was completed in 1980 in the Palacio de Gobierno in Oaxaca City, Mexico — a short walk from Casa Matemática Oaxaca. The mural portrays the region's complex social history, from pre-Columbian civilizations through the present. Similarly, mathematical models distill some aspects of social systems while omitting others. Unlike art, however, models should make their exploratory, explanatory, or predictive aims clear and transparent. Photo courtesy of Nick Saum at www.nicksaum.com.*

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*Exploratory models* show that simple individual preferences can generate stark, large-scale patterns. Because they explore consequences that *could* arise from minimal assumptions, they illustrate both the value and risks of counterfactual modeling in the social sciences. In contrast, *explanatory models* seek to capture the proposed mechanisms behind observed phenomena; for example, compartmental epidemic models demonstrate the way in which simple infection and recovery processes can reproduce familiar outbreak patterns and support scenario analysis for public health interventions. Both types of models challenge intuition by making assumptions explicit and identifying the places where common narratives break down — especially in domains where outcomes emerge from network structures, feedback, or randomness that defy straightforward storytelling [6].

Unlike exploratory and explanatory work, *predictive models* aim to forecast future outcomes based on past data, often without representing underlying mechanisms. Prediction in the social sciences is especially difficult because data are frequently partial or biased, behaviors shift over time, and highly flexible models can be hard to interpret or trust in policy-based contexts. Consider the 2017 "Fragile Families Challenge," which asked 160 teams from across the world to utilize machine learning algorithms to predict six different life outcomes for children based on a common dataset [3]. The resulting models—which relied on widely different approaches—yielded surprisingly similar predictions with low levels of accuracy. Sophisticated models barely outperformed simple baselines, thus highlighting the limits of prediction even with significant modeling efforts.

Because social systems are reflexive, trouble arises when these categories are conflated. Once a model is public, people and institutions may respond to it — potentially altering the very behavior that the model seeks to describe. This reflexivity amplifies the ethical and political stakes of model use in policy settings. Exploratory models that double as explanations can be misleading. For instance, economist Thomas Schelling's model of segregation [4] cannot serve as an account of U.S. housing patterns because it obscures the role of discriminatory policy and institutions. Strong predictive performance is sometimes taken to supersede explanatory insight, echoing claims that abundant data can replace theory [6]. Conversely, reliance on simple explanatory models for prediction can reduce accuracy in settings where predictive performance is paramount. However, all three types of models are valuable in the social sciences when matched transparently to their purpose; usefulness depends less on realism and more on clarity of aim.

### Communicating Assumptions and Context

Every model that attempts to represent the world contains either implicit or explicit simplifying assumptions. Transparent modeling requires the clear communication of these assumptions. As such, modelers should be forthcoming about their choices and reflect on the potential influence of disciplinary and institutional contexts. For example, the possible features for inclusion in a predictive model often reflect subjective judgments by the creators in terms of factors that are relevant, measurable, and available.

In some cases, researchers may find it helpful to document modeling plans or assumptions in advance. While doing so is not always feasible—particularly in exploratory work—early transparency about motivations, simplified assumptions, and conceivable alternatives can clarify a model's purpose and scope. This practice also reduces risks of overfitting or confirmation bias and improves interpretability and accountability.

Techniques such as documenting modeling decisions, sharing code and intermediate results, and inviting external critiques can also expose implicit choices. Furthermore, adversarial collaborations—where researchers with contrasting viewpoints collectively co-design and analyze a model—can clarify the way in which differing modeler assumptions may shape overall conclusions.

### Matching Models to Stakes

Models of social systems can have real consequences when they inform policy or guide interventions. Responsible modeling hence requires careful attention to a model's intended use and the harms that could arise if its purpose is misunderstood. Institutional data constraints—including administrative data that is collected for compliance rather than research, uneven population coverage, and systematic biases in who and what is measured—compound these risks.

*See* **Social Systems** *on page 5*

# Don't Matricize, Tensorize!

## *Tensor-tensor Algebras for Optimal Representations of Multiway Data*

*By Elizabeth Newman*

From medical imaging and scientific simulations to neural dynamics and more, multiway data is having its moment. This multiway moment is met with exciting questions about how to manipulate, analyze, and learn from data that are intrinsically multidimensional. This is where data analysis, the singular value decomposition (SVD), and tensors come into play.

### The Holy Grail of Classical Data Analysis

Data analysis encapsulates methods to understand and utilize data effectively, often by extracting interpretable features and building compressed representations. The SVD is a powerful tool that tackles these common data analysis imperatives, including principal component analysis, linear inverse problems, and dimensionality reduction. Mathematically, the (economic) SVD decomposes any matrix $\mathbf{A}\in\mathbb{C}^{n_1\times n_2}$ into

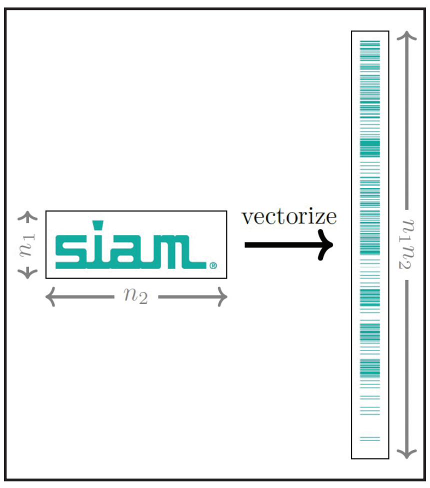


**Figure 1.** *Vectorization that converts the two-dimensional SIAM logo to a one-dimensional vector removes inherent spatial correlations. Figure courtesy of the author.*

$$\mathbf{A}=\mathbf{U}\mathbf{\Sigma}\mathbf{V}^H=\sum_{i=1}^{r}\sigma_i\mathbf{U}(:,i)\mathbf{V}(:,i)^H, \quad (1)$$

where $r=\operatorname{rank}(\mathbf{A})$. Here, $\mathbf{U}\in\mathbb{C}^{n_1\times r}$ and $\mathbf{V}\in\mathbb{C}^{n_2\times r}$ have unitary columns (e.g., $\mathbf{U}^H\mathbf{U}=\mathbf{V}^H\mathbf{V}=\mathbf{I}_r$, the $r\times r$ identity matrix) and $\mathbf{\Sigma}\in\mathbb{R}^{r\times r}$ is a diagonal matrix with real, non-negative diagonal entries (singular values) ordered from largest to smallest; i.e., $\sigma_1\geqslant\sigma_2\geqslant\cdots\geqslant\sigma_r>0$, where $\sigma_i:=\mathbf{\Sigma}(i,i)$.

We can readily understand the SVD from geometric, statistical, and algebraic perspectives. Geometrically, it diagonalizes $\mathbf{A}$ through two unitary coordinate transformations. Statistically, the singular vectors (columns of $\mathbf{U}$ and $\mathbf{V}$) align in unitary directions of maximal variance of the data stored in $\mathbf{A}$; the singular values quantify the standard deviation per direction. Algebraically, the SVD is a rank-revealing decomposition where the rank is determined by the number of nonzero singular values. The ordering of the singular values gives rise to a natural truncation strategy to produce a low-rank (i.e., compressed) approximation of $\mathbf{A}$; namely, the truncated SVD retains terms that correspond to the largest singular values. This strategy leads to the beautiful Eckart-Young theorem [2], which states that for $k\leqslant r$, the truncated SVD $\mathbf{A}_k$ is the *optimal* rank-$k$ (or less) approximation to the rank-$r$ matrix $\mathbf{A}$ in the Frobenius norm, i.e.,

$$\mathbf{A}_k=\sum_{i=1}^{k}\sigma_i\mathbf{U}(:,i)\mathbf{V}(:,i)^H=\operatorname*{argmin}_{\operatorname{rank}(\mathbf{B})\leqslant k}\|\mathbf{A}-\mathbf{B}\|_F.$$

Because of its combination of explicability, compressibility, and optimality properties, we playfully call the SVD the "holy grail" of data analysis.

The SVD's "divine" properties come with one major assumption: that the underlying data are represented by a matrix. As a result, many data analysis pipelines begin with a preprocessing step that reshapes the data into a matrix form before applying SVD-based methods. Such matricization can hide valuable high-dimensional correlations (see Figure 1). This realization has propelled the modern search for a multiway analog of the SVD — a decomposition that gives rise to interpretable features, compressible representations, and optimality guarantees while simultaneously respecting native multilinear structure.

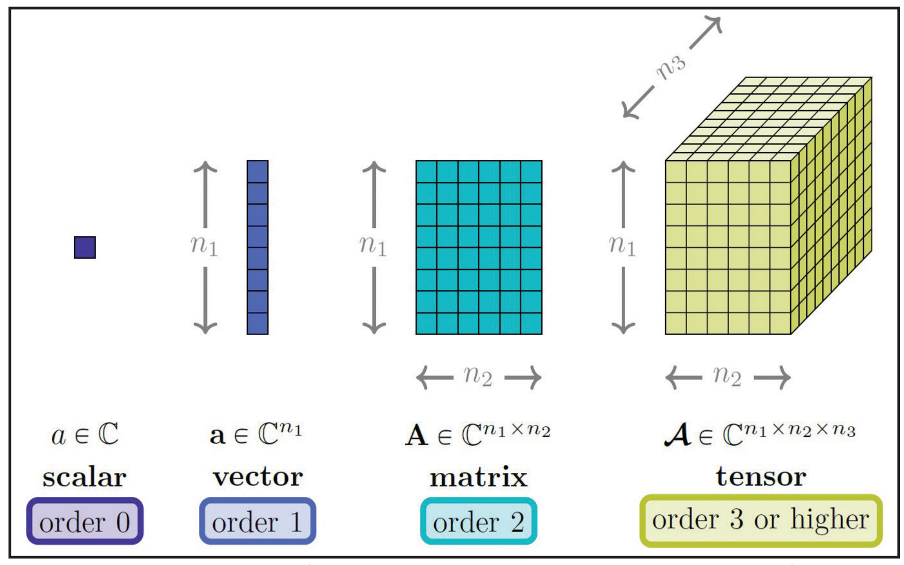


**Figure 2.** *The building blocks of multidimensional linear algebra. Figure courtesy of the author.*

### The Quest for the Tensor Holy Grail

Before delving into multiway SVDs, let's first introduce tensors to encode multidimensionality mathematically. Tensors serve as high-dimensional extensions of the building blocks of linear algebra: scalars (order-0 tensors), vectors (order-1 tensors), and matrices (order-2 tensors). We use the term "tensor" to refer to any multiway array or multilinear operator of order-3 or higher (see Figure 2).

The quest for the tensor holy grail—a multiway analog of the SVD and a multilinear Eckart-Young theorem—has inspired the development of a host of tensor decompositions [1]. Among the earliest strategies is the canonical polyadic or CANDECOMP/PARAFAC (CP) decomposition, which, in the spirit of the SVD summation formulation in (1), expresses multiway arrays as a sum of rank-1 tensors. This summation form yields interpretable CP factors that are fairly unique without additional constraints. Other classical tensor factorization strategies—namely the Tucker decomposition and its popular variant, the higher-order SVD (HOSVD)—generalize the coordinate transformation formulation of the SVD in (1) to multiway arrays. As a result, the HOSVD serves as a high-dimensional form of principle component analysis and is well suited for multilinear dimensionality reduction and data compression. Beyond multiway data

*See* **Don't Matricize, Tensorize** *on page 6*

## Social Systems

*Continued from page 4*

As we noted earlier, scientists may misread exploratory models as explanations. Explanatory models like the susceptible-infected-recovered compartmental framework can inform public health decisions, but their conclusions depend on simplified assumptions that might overlook economic, social, or demographic realities. Predictive models, including those in the aforementioned Fragile Families Challenge, can shape interventions in people's lives despite limited accuracy and known biases in race, gender, and other demographic attributes.

Modelers should therefore ask themselves the following questions: *What are this model's intended uses and likely misuses? Who might benefit, and who might be harmed or excluded? Could communication of the model itself cause harm?* Reflection on these queries helps to align modeling practices with the social contexts and real-world stakes they seek to illuminate.

It is also important to remember that mathematical models can shape public discourse. When divorced from context, models can mislead, be co-opted for political ends, or create a false sense of certainty. During the COVID-19 pandemic, for example, models became lightning rods in public debate and were sometimes misunderstood or misrepresented by decision-makers and the general public. Stylized models of opinion dynamics or economic behavior have likewise appeared in editorials as if they were policy recommendations; some machine learning models have even claimed to predict criminality or sexuality from facial images alone, which lends visibility to unfounded and harmful ideas.

Although modelers cannot control their work's reception, they can reduce misinterpretation by clearly stating their aims and assumptions, appropriately labeling exploratory models, and explicitly articulating limitations and sensitivity. Collaboration with domain experts supports proper interpretation, and engagement with affected communities reveals perspectives that may otherwise go unnoticed. Involving the individuals and communities that are most impacted by a model's use can identify potential harms, clarify priorities, and foster accountability — ultimately aligning modeling efforts more closely with the lived realities they aim to represent.

### Open Practices for Social Science Modeling

Mathematical modelers in the social sciences must grapple with forms of uncertainty that differ sharply from those in the physical sciences. Uncertainty in social systems is often dominated not only by sampling variation, but by measurement error, evolving population definitions, and institutional inconsistencies in data collection. Social phenomena typically stem from partial, biased, or institutionally defined data (e.g., census categories that shift over time, administrative records that are shaped by policy rather than measurement, or surveys with nonrepresentative samples). Because these uncertainties reflect both data limitations and social realities, modelers should make their assumptions visible, identify places where evidence is thin, and work with domain experts who understand the data.

Transparent practices also look different when humans and communities are the units of analysis. The sharing of code and documentation of modeling decisions remain essential, but unrestricted data release is often impossible when privacy, consent, and community ownership are at stake. In such cases, reproducibility comes from clear workflows, synthetic or heavily deidentified datasets, and multi-team modeling efforts that reveal conclusions' dependencies on assumptions. Engaging with social scientists and affected stakeholders helps to ensure that transparency is an active part of responsible scientific practice.

### Expanding Mathematical Modeling in the Social Sciences

As new forms of data, computation, and policy analysis become increasingly quantitative, mathematical modeling's role in the social sciences will continue to grow. Because social systems are adapting to measurements and models, reflexivity is becoming a central challenge that is largely absent from the physical sciences; namely, models can shape the very behavior that they aim to describe. Populations that are affected by policy interventions are rarely stationary and often require mechanistic models that explicitly account for evolving contexts, incentives, and feedback. As these models take on more public weight, people will rightly demand to know what assumptions they make, what causes they claim to identify, and what consequences they carry. Without clear evidence of this type of understanding, mathematical models can quickly lose public trust.

### Concluding Thoughts

The Modelers' Hippocratic Oath, proposed after the 2008 financial crisis, begins with, "I will remember that I didn't make the world, and it doesn't satisfy my equations" [2]. The reasoning processes that surround models are not the same as the rationale about the systems they represent, but with appropriate caution—as Smaldino notes—even simple models can illuminate complex behaviors [5]. As modeling tools advance, so too must our commitment to responsible use.

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*The Casa Matemática Oaxaca Workgroup on Collective Social Phenomena includes Maximino Aldana (National Autonomous University of Mexico), Heather Zinn Brooks (Harvey Mudd College), Phil Chodrow (Middlebury College), Fillipe Georgiou (University of Bath), Joseph Johnson (Carleton College), Krešimir Josić (University of Houston), Zachary Kilpatrick (University of Colorado Boulder), Kath Landgren (Stanford University), Andrew Nugent (University College London), Maurizio Porfiri (New York University), Nancy Rodriguez (University of Colorado Boulder), Pablo Suárez-Serrato (National Autonomous University of Mexico), Roni Barak Ventura (New Jersey Institute of Technology), David White (Denison University), Alexander Wiedemann (Hamline University), and Sam Zhang (University of Vermont).*

## Don't Matricize, Tensorize

*Continued from page 5*

analysis, modern tensor network representations like tensor train (TT) impose practical tensorial structure in order to solve extremely high-dimensional problems (e.g., order-$d$ for large $d$) and break the infamous *curse of dimensionality*. The wide range of tensor decompositions have impacted multiple scientific disciplines, including psychometrics, chemometrics, computer vision, and quantum chemistry.

While these tensor factorizations inherit characteristics of the matrix SVD, all lack one crucial algebraic property: *provable optimality* (i.e., the Eckart-Young theorem does not hold). In fact, many cornerstones of linear algebra fail when multilinearity is introduced (e.g., determining the CP rank is NP-hard). Borrowing from a familiar catchphrase, we call this phenomenon the *curse of multidimensionality*.

### Tensor-tensor Algebras: Breaking the Curse of Multidimensionality

The story of tensor-tensor algebras begins with a decades-long open question: Can tensor-based approaches mirror their matrix-based counterparts? In other words, can a tensor framework break the curse of multidimensionality? The seminal work of Misha Kilmer and Carla Martin [5] offered a key breakthrough called the *t-product*, a tensor-tensor product that mimicked matrix multiplication. Subsequent research extended to a family of *matrix-mimetic* tensor operators that preserved familiar linear algebraic properties [3]. Our work leverages these matrix-mimetic operators to achieve our ultimate goal: an Eckart-Young-like theorem for tensors [4].

### Matrix-mimetic Tensor Operations

To construct a tensor operation that "looks and feels" like matrix multiplication, we view an order-3 tensor $\boldsymbol{\mathcal{X}} \in \mathbb{C}^{n_1 \times n_2 \times n_3}$ as an $n_1 \times n_2$ matrix where each entry is a $1 \times 1 \times n_3$ array or *tube* (see Figure 3a). From this perspective, scalars are to matrices what tubes are to tensors. In the same way that matrix-vector products stem from scalar multiplication, tensor-tensor products are built on tubal operations. These principles extend to tensors of arbitrary order, beyond order-3 [6].

Let us denote the tubal product as $\star_{\mathbf{M}}$, pronounced "star-M," where $\mathbf{M} \in \mathbb{C}^{n_3 \times n_3}$ is a user-defined invertible matrix. Given tubes $\mathbf{a}, \mathbf{b} \in \mathbb{C}^{1 \times 1 \times n_3}$, we define tubal multiplication $\mathbf{a} \star_{\mathbf{M}} \mathbf{b} \in \mathbb{C}^{1 \times 1 \times n_3}$ (see Figure 3b) by

$$\mathbf{a} \star_{\mathbf{M}} \mathbf{b} = \operatorname{tube}(\mathbf{R}_{\mathbf{M}}[\mathbf{a}] \operatorname{vec}(\mathbf{b})),$$

$$\text{where} \qquad (2)$$

$$\mathbf{R}_{\mathbf{M}}[\mathbf{a}] = \mathbf{M}^{-1} \operatorname{diag}(\mathbf{M} \operatorname{vec}(\mathbf{a}))\mathbf{M}.$$

We say that the action of $\mathbf{a}$ on $\mathbf{b}$ is equivalent to the multiplication by a structured matrix $\mathbf{R}_{\mathbf{M}}[\mathbf{a}]$ parameterized by $\mathbf{a}$. Consequently, tubal multiplication operates under an algebraic ring operation. The set of all structured matrices $\mathbf{R}_{\mathbf{M}}[\cdot]$ forms a matrix subalgebra; this is to what we refer when we say "tensor-tensor algebra."

The underlying structure of $\mathbf{R}_{\mathbf{M}}[\cdot]$ and the resulting algebra depends on the choice of invertible matrix $\mathbf{M}$. For example, the matrices $\mathbf{M} = \mathbf{I}$ (the identity matrix) and $\mathbf{M} = \mathbf{F}$ (the discrete Fourier transform matrix) respectively lead to the structured operators

$$\mathbf{R}_{\mathbf{I}}[\mathbf{a}] = \operatorname{diag}(\mathbf{a}) = \begin{pmatrix} a_1 & & & \\ & a_2 & & \\ & & \ddots & \\ & & & a_{n_3} \end{pmatrix}$$

$$\text{and} \qquad (3)$$

$$\mathbf{R}_{\mathbf{F}}[\mathbf{a}] = \operatorname{circ}(\mathbf{a}) = \begin{pmatrix} a_1 & a_{n_3} & \cdots & a_2 \\ a_2 & a_1 & \cdots & a_3 \\ \vdots & \vdots & \ddots & \vdots \\ a_{n_3} & a_{n_3-1} & \cdots & a_1 \end{pmatrix}.$$

The former gives rise to the algebra defined by the Hadamard pointwise product, and the latter induces the algebra of circulants, which is the foundation of the original *t*-product.

With tubal multiplication in place, we extend the $\star_{\mathbf{M}}$-product through a tubal entry-wise definition (see Figure 3a). Given tensors $\boldsymbol{\mathcal{A}} \in \mathbb{C}^{n_1 \times m \times n_3}$ and $\boldsymbol{\mathcal{B}} \in \mathbb{C}^{m \times n_2 \times n_3}$, the $\star_{\mathbf{M}}$-product $\boldsymbol{\mathcal{A}} \star_{\mathbf{M}} \boldsymbol{\mathcal{B}} \in \mathbb{C}^{n_1 \times n_2 \times n_3}$ is

$$(\boldsymbol{\mathcal{A}} \star_{\mathbf{M}} \boldsymbol{\mathcal{B}})(i,j,:) = \sum_{\ell=1}^{m} \boldsymbol{\mathcal{A}}(i,\ell,:) \star_{\mathbf{M}} \boldsymbol{\mathcal{B}}(\ell,j,:)$$

$$\text{for } i = 1, \ldots, n_1 \text{ and } j = 1, \ldots, n_2. \qquad (4)$$

A matrix-mimetic, mathematical framework for tensor operators enables natural generalizations of properties such as a $\star_{\mathbf{M}}$-identity (e.g., $\boldsymbol{\mathcal{I}} \star_{\mathbf{M}} \boldsymbol{\mathcal{A}} = \boldsymbol{\mathcal{A}} \star_{\mathbf{M}} \boldsymbol{\mathcal{I}} = \boldsymbol{\mathcal{A}}$), $\star_{\mathbf{M}}$-transposition (e.g., $(\boldsymbol{\mathcal{A}} \star_{\mathbf{M}} \boldsymbol{\mathcal{B}})^H = \boldsymbol{\mathcal{B}}^H \star_{\mathbf{M}} \boldsymbol{\mathcal{A}}^H$), and $\star_{\mathbf{M}}$-unitary (e.g., $\boldsymbol{\mathcal{Q}}^H \star_{\mathbf{M}} \boldsymbol{\mathcal{Q}} = \boldsymbol{\mathcal{I}}$). Notably, we obtain a $\star_{\mathbf{M}}$-analog of the SVD.

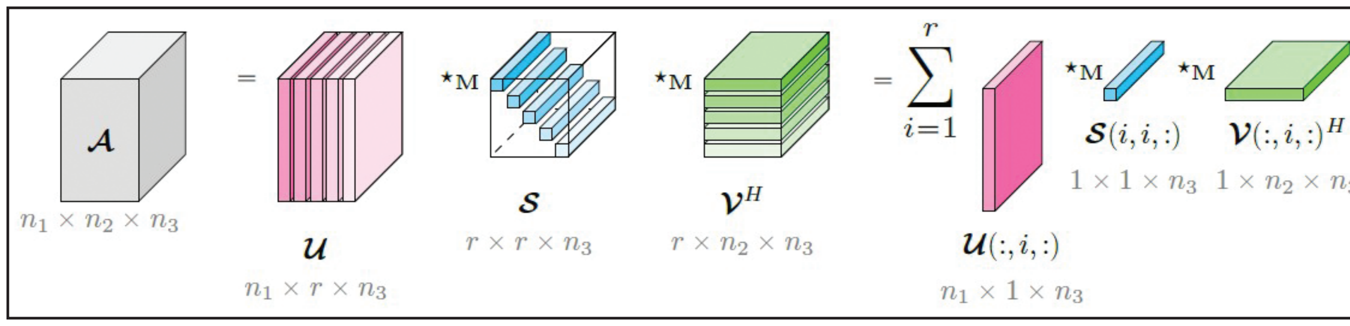


**Figure 4.** *Illustration of the (economic) $\star_{\mathbf{M}}$-SVD. Figure courtesy of the author.*

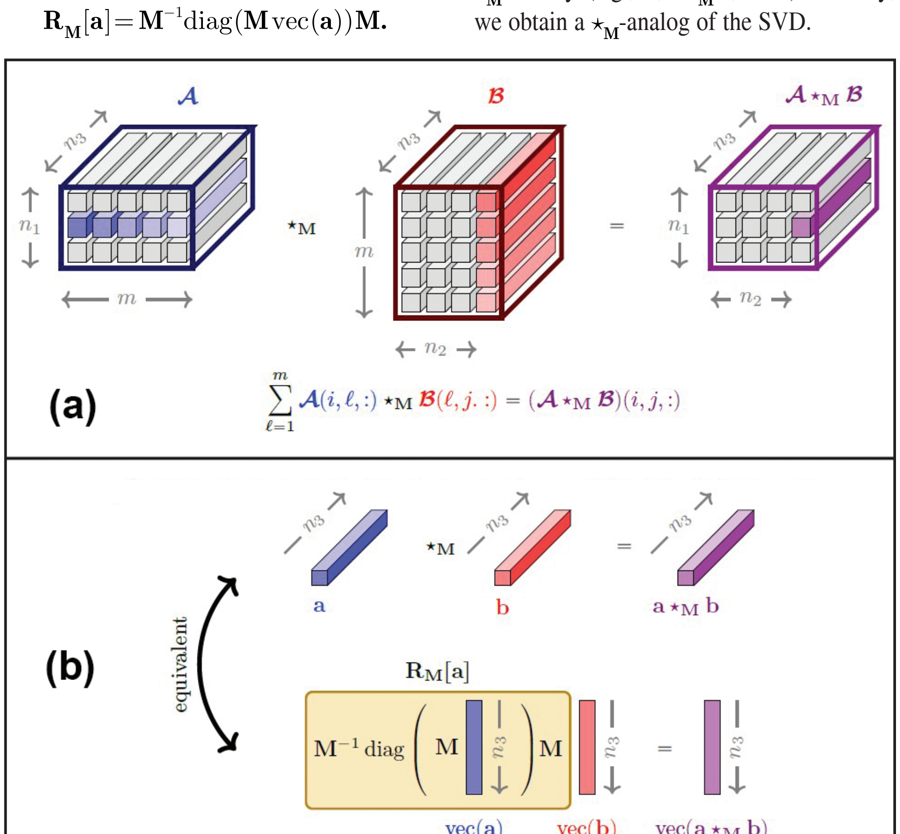


**Figure 3.** *The mechanics of matrix-mimetic tensor-tensor products.* **3a.** *Tensor-tensor multiplication where tubes ($1 \times 1 \times n_3$ arrays) imitate scalars.* **3b.** *Tubal multiplication under the $\star_{\mathbf{M}}$-product. Figure courtesy of the author.*

### Provable Optimality

Like its matrix counterpart in (1), the (economic) $\star_{\mathbf{M}}$-SVD in Figure 4 factorizes any tensor $\boldsymbol{\mathcal{A}} \in \mathbb{C}^{n_1 \times n_2 \times n_3}$ as

$$\boldsymbol{\mathcal{A}} = \boldsymbol{\mathcal{U}} \star_{\mathbf{M}} \boldsymbol{\mathcal{S}} \star_{\mathbf{M}} \boldsymbol{\mathcal{V}}^H = \qquad (5)$$

$$\sum_{i=1}^{r} \boldsymbol{\mathcal{U}}(:,i,:) \star_{\mathbf{M}} \boldsymbol{\mathcal{S}}(i,i,:) \star_{\mathbf{M}} \boldsymbol{\mathcal{V}}(:,i,:)^H.$$

Matrix mimeticity guarantees that the factors of $\star_{\mathbf{M}}$-SVD retain familiar properties: (i) $\star_{\mathbf{M}}$-unitary of the left and right singular tensors, $\boldsymbol{\mathcal{U}}$ and $\boldsymbol{\mathcal{V}}$; (ii) tubal-diagonal structure of $\boldsymbol{\mathcal{S}}$ with ordered singular tubes $\|\boldsymbol{\mathcal{S}}(1,1,:)\|_F \geqslant \|\boldsymbol{\mathcal{S}}(2,2,:)\|_F \geqslant \cdots \geqslant \|\boldsymbol{\mathcal{S}}(r,r,:)\|_F \geqslant 0$; and (iii) $\star_{\mathbf{M}}$-rank of $\boldsymbol{\mathcal{A}}$ given by the number of nonzero singular tubes.

The piéce de résistance is that the $\star_{\mathbf{M}}$-SVD satisfies an Eckart-Young-like theorem for tensors, a unique advantage of the $\star_{\mathbf{M}}$-framework. In short, we have found the tensor holy grail! Formally, under appropriate assumptions—namely, that $\mathbf{M}$ is a nonzero multiple of a unitary matrix—the truncated $\star_{\mathbf{M}}$-SVD produces the best low-$\star_{\mathbf{M}}$-rank approximation of a $\star_{\mathbf{M}}$-rank-$r$ tensor $\boldsymbol{\mathcal{A}}$; i.e., for $k \leqslant r$,

$$\boldsymbol{\mathcal{A}}_k = \sum_{i=1}^{k} \boldsymbol{\mathcal{U}}(:,i,:) \star_{\mathbf{M}} \boldsymbol{\mathcal{S}}(i,i,:) \star_{\mathbf{M}} \boldsymbol{\mathcal{V}}(:,i,:)^H = \operatorname*{argmin}_{\star_{\mathbf{M}}\text{-rank}(\boldsymbol{\mathcal{B}}) \leqslant k} \|\boldsymbol{\mathcal{A}} - \boldsymbol{\mathcal{B}}\|_F. \qquad (6)$$

The implications of (6) go beyond the optimality of low-$\star_{\mathbf{M}}$-rank representations. Notably, for any $\mathbf{M}$ that satisfies the same assumptions as (6) and a shared truncation parameter $k$, the truncated $\star_{\mathbf{M}}$-SVD of tensor data $\boldsymbol{\mathcal{A}} \in \mathbb{C}^{n_1 \times n_2 \times n_3}$ is guaranteed to be more accurate than the truncated matrix SVD of a matricized version of the data $\mathbf{A} \in \mathbb{C}^{n_1 \times n_3 \times n_2}$; i.e.,

$$\|\boldsymbol{\mathcal{A}} - \boldsymbol{\mathcal{A}}_k\|_F \leqslant \|\mathbf{A} - \mathbf{A}_k\|_F, \qquad (7)$$

where $\mathbf{A}(:,j) = \operatorname{vec}(\boldsymbol{\mathcal{A}}(:,j,:))$ for $j = 1, \ldots, n_2$. Similar statements can be proven when comparing the $\star_{\mathbf{M}}$-SVD to other tensor decompositions that rely on intermediate matricization, such as the HOSVD and TT factorization (see Figure 5).

### Unifying Algebraic Framework

Beyond performance comparisons, many points of connection exist between the $\star_{\mathbf{M}}$-framework and other factorization strategies. As indicated in (7), we can relate the $\star_{\mathbf{M}}$-SVD and the matrix SVD through a specific matricization of the data. Moreover, we can employ a clever choice of tensor-tensor algebra to express the HOSVD as the $\star_{\mathbf{M}}$-product of special factor tensors. We can even use other multiway frameworks to improve $\star_{\mathbf{M}}$-representations, such as storing the $\star_{\mathbf{M}}$-SVD in CP format to further reduce computational overhead. The rigorous algebraic foundations of the $\star_{\mathbf{M}}$-framework reveal these surprising and useful links between multiway methods.

### A Call to Multidimensional Action

We end this overview of matrix-mimetic tensor-tensor algebras with a call to action. Join us in pursuing novel applications like precision medicine [8]; developing new computational tools, such as optimal tensor-tensor-tensor products [9]; and pushing the algebraic framework to infinity and beyond [7]. Most importantly, we encourage readers to think multidimensionally; many data and operators are inherently high-dimensional, and modern tensor tools can help get the most out of this rich multiway information.

In short, don't matricize, tensorize!

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*Elizabeth Newman is an assistant professor in the Department of Mathematics at Tufts University and a 2025-2026 Merrin Faculty Fellow. She earned her Ph.D. from Tufts in 2019. Newman received an Air Force Fiscal Year 2025 Young Investigator Program Award and is a joint recipient of the 2025 SIAM Activity Group on Computational Science and Engineering Best Paper Prize.*

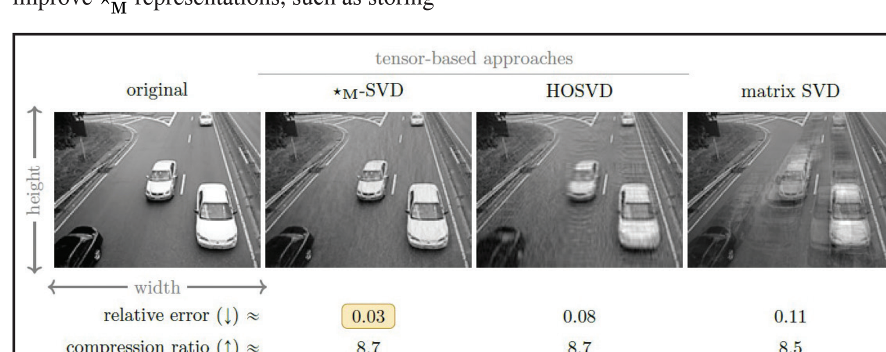



**Figure 5.** *Compression of MATLAB's traffic video stored as a width × time × height tensor $\boldsymbol{\mathcal{A}} \in \mathbb{R}^{120 \times 120 \times 160}$. For comparable storage costs (higher compression ratios are better), the $\star_{\mathbf{M}}$-SVD with $\mathbf{M} = \mathbf{F}$—the discrete Fourier transform matrix—produces a more accurate approximation (lower relative error) than the higher-order singular value decomposition (HOSVD). Both tensor-based approaches outperform the matrix SVD, which loses spatial correlations from vectorizing the video frames. By using inherently multilinear operations and avoiding intermediate matricization, the $\star_{\mathbf{M}}$-SVD produces the sharpest approximation overall. See the online version of this article for a corresponding animation. Figure courtesy of the author.*

# Pythagorean Theorem on a Sphere

Figure 1 shows a right triangle on a unit sphere, each side being an arc of a great circle. The Pythagorean theorem on the sphere has a beautiful form:

$$\cos\alpha\cos\beta=\cos\gamma, \qquad (1)$$

where $\alpha$ and $\beta$ are the lengths of the legs and $\gamma$ is the length of the hypotenuse.[1] Our Euclidean version is a limiting case of (1).[2]

Several very nice and simple proofs of (1) exist, but none that I saw gave that "aha!" feeling — until I realized that the Pythagorean theorem expresses the fact that *the area of a triangle is invariant under rotations around an endpoint of its hypotenuse.*

To see this, let us rotate the triangle in Figure 2 around the end $B$ of the hypotenuse with some angular velocity $\omega$. We can also think of rotating the whole sphere with the triangle, as one rigid object, around the radius $OB$ (where $O$ is the center of the sphere).

[1] If the sphere's radius $R\neq 1$, we should replace the lengths $\alpha$, $\beta$, and $\gamma$ in (1) with $\alpha/R$, $\beta/R$, and $\gamma/R$. Thus, $\alpha$, $\beta$, and $\gamma$ are simply the angles between the appropriate radii of the sphere.

[2] Indeed, $\cos\alpha=1-\alpha^2/2+\ldots$, etc., and (1) reduces to $\alpha^2+\beta^2=\gamma^2$ to the leading order of approximation if $\alpha$ and $\beta$ become small.

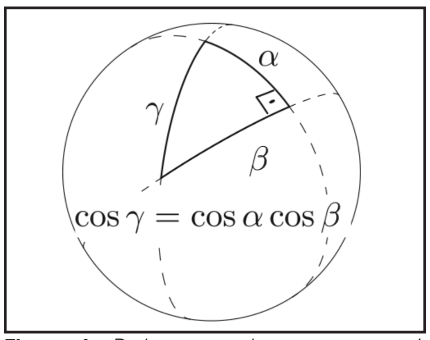



**Figure 1.** *Pythagorean theorem on a unit sphere.*

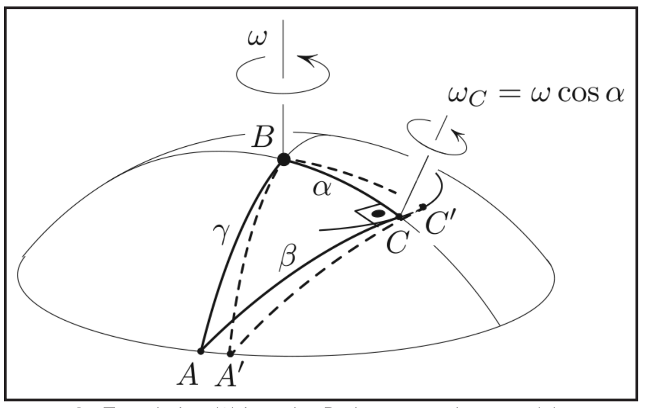



**Figure 2.** *Translating (2) into the Pythagorean theorem (1).*

MATHEMATICAL CURIOSITIES
*By Mark Levi*

During this rotation, the area that is gained through each of the legs cancels the area that is lost through the hypotenuse, and so the rates of area gain and loss cancel each other out:

$$\boxed{\mathrm{rate}_\alpha+\mathrm{rate}_\beta=\mathrm{rate}_\gamma.} \qquad (2)$$

I claim that this amounts to (1). Indeed, according to Figure 3,

$$\begin{aligned}\mathrm{rate}_\alpha&=\omega(1-\cos\alpha),\\ \mathrm{rate}_\gamma&=\omega(1-\cos\gamma).\end{aligned} \qquad (3)$$

Similarly, as we will see shortly,

$$\mathrm{rate}_\beta=\omega\cos\alpha(1-\cos\beta). \qquad (4)$$

Substituting this and (3) into (2) and simplifying yields (1).

### Justification of (4)

I claim that

$$\mathrm{rate}_\beta=\omega_C(1-\cos\beta), \qquad (5)$$

where $\omega_C=\omega\cos\alpha$ is the angular velocity projected onto the radius $OC$.[3] This looks just like (3), but unlike in (3), neither end of $CA$ is fixed. And so to apply (3) to $AC$, we need to say more. Thankfully, $C$'s velocity is tangent to $CA$ because our triangle is right. We can therefore decompose the motion of $CA$ into two simultaneous ones: (i) sliding along $CA$ and (ii) pivoting on $C$. But since (i) does not contribute to the sweeping of area, $\mathrm{rate}_\beta$ is the same as if $C$ were fixed and (5) holds by the earlier argument. And with $\omega_C=\omega\cos\alpha$ in (5), we get (4).

[3] Putting it differently, as the sphere's inhabitant at $B$ twirls a rigid "stick" $BC$ with angular velocity $\omega$ (see Figure 3), the direction of the other end $C$ rotates with $\omega_C=\omega\cos\alpha$. For $C$ on the equator, $\omega_C=0$; on the south pole, $\omega_C=-\omega$ (which is not surprising, since the observer is upside down). So in a curved space, the angular velocity of a rigid object varies from point to point, unlike in the Euclidean world.

As an aside, we can view (2) as a consequence of Green's theorem; instead of rotating the triangle, we can consider a vector field on the sphere that is given by rigid rotation around the $OB$ axis. Then, (2) expresses the vanishing of the flux through the boundary of the triangle.

We can derive the theorem of cosines on the sphere in a similar way from the area invariance.

*The figures in this article were provided by the author.*

*Mark Levi (levi@math.psu.edu) is a professor of mathematics at the Pennsylvania State University.*

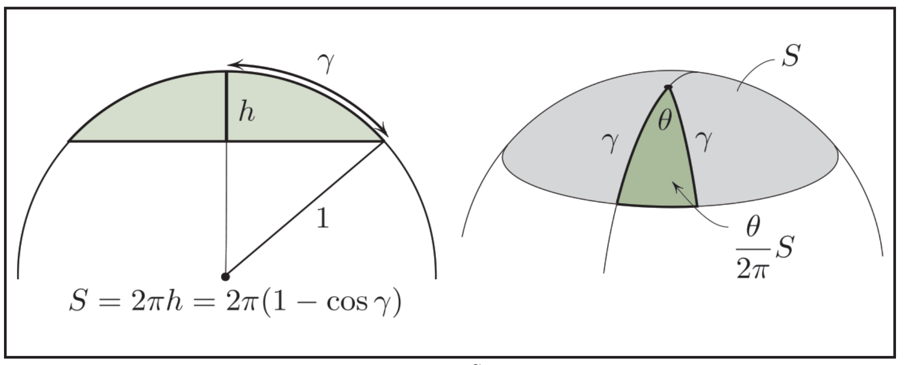



**Figure 3.** *According to Archimedes, the area $S$ of a spherical cap is a linear function of $h=1-\cos\gamma$. Thus, $S=2\pi h=2\pi(1-\cos\gamma)$ for the shaded cap. And so the segment $\gamma$ that pivots through angle $\theta$ sweeps area $\frac{\theta}{2\pi}S=1-\cos\gamma$, proving (3).*

# #MathSciOnTheHill Advocacy Event Unites Hundreds of Mathematicians in Washington, D.C.

*By Jonas A. Actor and Emily Evans*

On January 8—after the conclusion of the Joint Mathematics Meetings,[1] which took place in Washington, D.C.—nearly 300 mathematical scientists descended on Capitol Hill to advocate for and communicate the importance of mathematics, statistics, and related fields to U.S. senators, representatives, and their staff members. These mathematicians represented 12 different professional societies, including SIAM, and hailed from 47 states as part of a coordinated advocacy initiative called #MathSciOnTheHill, which sought to gain federal support for mathematics research and education. Attendees at all stages of their careers—from undergraduates to senior faculty members—came out on behalf of the event and sported distinctive scarves, which made it easy for participants to find each other while walking the grounds of Capitol Hill.

Here, we reflect on our individual experiences at #MathSciOnTheHill, which took place on the same day that the U.S. House of Representatives overwhelmingly passed a spending package that included near-stable funding for the U.S. National Science Foundation (NSF).

### The Utah Delegation

*Emily Evans*

Our Utah delegation consisted of three faculty members from Brigham Young University (BYU) and Westminster University, and three undergraduate students from BYU. As a member of the SIAM Committee on Science Policy[2] and a former SIAM Science Policy Fellow[3] from the inaugural 2018-2019 class [1], I am used to advocating for federal math and science funding on Capitol Hill. However, bringing undergraduates to Capitol Hill for the first time was a new and exciting experience. Their voices were particularly relevant as we talked in different offices — not only because they were closer in age to the congressional staffers, but because they were able to provide staff with direct insight as to why their age group is so interested in funding for mathematics and related fields.

One of the highlights of our day was the opportunity to meet with Rep. Mike Kennedy (R-Utah), who graciously carved out time in his busy schedule to visit with us in his office. He actively listened to what we had to say, asked hard-hitting questions about the benefits of math and science funding in the state of Utah, and spoke to the undergraduate students about the direct impact of such funding within their demographic.

In addition to our visit with Congressman Kennedy, we also met with a staffer from Rep. Burgess Owens' (R-Utah) office. This valuable conversation allowed us to share our thoughts with a wider audience and affirmed to the undergraduates that their opinions and viewpoints are indeed valued.

Since most senators and representatives from Utah serve on committees that address scientific funding, our primary message focused on the importance of funding for the NSF. We also talked about the growing influence of artificial intelligence (AI) and Utah's role to help guide AI policy decisions. The message about AI was well received by all of the offices during #MathSciOntheHill, and especially by the staffers of our two Utah senators.

When reflecting on the day's experiences, undergraduate Ethan Petersen spoke highly about the benefits of witnessing governmental action in person. "My favorite part was to simply be in the office buildings and feel the energy," he said. "It was a remarkable thing to be in a place where decisions are made that impact many people. I was so happy to represent the math community and be involved to a new degree in government."

### The New Mexico Delegation

*Jonas Actor*

Our New Mexico delegation comprised a total of six mathematicians from a variety of professional backgrounds: a faculty member from the University of New Mexico, a staff member from Sandia National Laboratories, a postdoctoral researcher from the U.S. Air Force Research Laboratory, the executive director of a mathematics nonprofit residential summer camp in New Mexico called the CAMP for Algorithmic and Mathematical Play,[4] and two undergraduate New Mexico constituents. After morning visits with staffers from the offices of New Mexico senators, we proceeded to the office of Rep. Melanie Stansbury (D-NM) to meet with members of her team. As with our previous appointments, we thanked them for their prior support of funding for basic research and the mathematical sciences, detailed the positive impacts of sustained investment in mathematical research on emerging technologies, and explained how math-based opportunities at all stages of the educational pipeline translate into benefits for both local economies and the state at large. Specific facts that staffers could relay to the Representative were particularly welcome (for example, "New Mexico has the most mathematics Ph.D.s per capita in the country!").

As we were departing, the door opened and Rep. Stansbury entered her office. She immediately joined the conversation and listened as we described the purpose of #MathSciOnTheHill. After talking for nearly 15 minutes, she casually mentioned that she was headed to the House chamber floor to vote on the afternoon agenda and invited us to accompany her and observe from the House gallery. She escorted us through the members-only warren of passageways that connect the House office buildings to the basement of the Capitol, pointing out details as we went: artwork from high school students that line the walls; the terrifying bundle of cables and wires—three feet in diameter—that support the information technology systems for the Capitol offices and dangle from the basement ceiling; and the variations in types of tile within the Capitol, each reflecting the age of different additions to the building.

From the Capitol Rotunda, Rep. Stansbury proceeded to the chamber floor while a staffer escorted us to the House gallery. After divesting our possessions at the security desk, we continued upstairs to the gallery and watched the proceedings on the floor below. The staffer made sure to discretely point out notable figures on the floor—including Rep. Nancy Pelosi (D-Calif.), Rep. Alexandria Ocasio-Cortez (D-NY), and Speaker Mike Johnson (R-La.)—as the representatives mingled between votes.

As it turns out, the House was actively in session and voting on various pieces of legislation. When we entered, voting had just commenced for a round of appropriations to fund minibus packages — including the budgets for federal science and energy funding for agencies such as the NSF and U.S. Department of Energy (DOE). These agencies have broadly supported my past and current research and fund many of the main federal mathematical and computational science research programs.

Watching Congress approve these budgets was a high point of my two years as a SIAM Science Policy Fellow. Throughout the course of the Fellowship, I have engaged with the SIAM Committee on Science Policy to debate merits, priorities, and strategies for how the applied mathematics community can best inform federal policy and stakeholders—such as the NSF's Division of Mathematical Sciences[5] and the DOE Office of Science's Advanced Scientific Computing Research program[6]—about the necessity, importance, and impact of applied mathematics and computational science research. It was therefore fitting that at the end of my two-year term as a Science Policy Fellow, I had the incredible privilege of observing the federal funding process in its entirety. #MathSciOnTheHill provided a concrete demonstration of the power of SIAM's science policy work and its ability to influence the direction of mathematics research across the country.

At the #MathSciOnTheHill advocacy event, which took place on January 8 in Washington, D.C., members of the New Mexico delegation gather in front of the U.S. Capitol after watching the U.S. House of Representatives pass legislation that funded mathematics and science research. From left to right: Isa Chou (Williams College), Tommy Denny-Martins (Purdue University), Anita Chou (CAMP for Algorithmic and Mathematical Play), Nick Allgood (U.S. Air Force Research Laboratory), Anna Nelson (University of New Mexico), and Jonas Actor (Sandia National Laboratories). Photo courtesy of Anna Nelson.

### What You Can Do

Although we have been actively involved with the SIAM Committee on Science Policy over the years, you do not have to be a committee member to serve as a champion of mathematics and science. It was certainly exciting—and frankly a lot of fun—to bring such a large contingent of mathematicians to Capitol Hill. However, plenty of advocacy work for scientific funding is possible from the comfort of your own home or office. The most powerful thing that SIAM members can do is educate their peers about the way in which math and science funding directly benefits them. Whether you are explaining how AI is driven by mathematics or talking about how math and science research improve medicine, every individual with whom you speak has the potential to become an advocate. For more information about SIAM's ongoing efforts in the realm of U.S. science policy, please visit the Society's "Science Policy" webpage.[7]

Additionally, if you are feeling bolder, you may wish to email and/or call your senators and representatives, especially in this challenging political environment. Doing so sends a message that their constituents care about funding in math and science. If you are not sure what to say, we encourage you to take a look at SIAM's guidelines for engaging with congressional offices,[8] as well as a series of one-pagers that are available online.[9] And as always, please feel free to share your outreach stories with SIAM to help inform future initiatives, activities, and advocacy efforts.

### References


[1] Evans, E. (2020, September 1). It's all about the story: Reflections of a former Science Policy Fellowship recipient. *SIAM News, 53*(7), p. 8.



*Jonas A. Actor is a Senior Member of Technical Staff in the Center for Computing Research at Sandia National Laboratories. He served as a 2024-2025 SIAM Science Policy Fellow. Emily Evans is a professor and associate chair in the Department of Mathematics at Brigham Young University. She is a member of the SIAM Committee on Science Policy and previously served as a 2018-2019 SIAM Science Policy Fellow.*


Members of the Utah delegation pose for a photo in their matching scarves during the #MathSciOnTheHill advocacy event, which took place on Capitol Hill in Washington, D.C., after the conclusion of the Joint Mathematics Meetings in January. From left to right: Bianca Thompson (Westminster University) and Xavier Zaitzeff, Ethan Petersen, Curtis Kent, Maxwell Marre, and Emily Evans (all of Brigham Young University). Photo courtesy of Emily Evans.

[1] https://jointmathematicsmeetings.org/jmm
[2] https://www.siam.org/get-involved/connect-with-a-community/committees/committee-on-science-policy-csp
[3] https://www.siam.org/programs-initiatives/programs/siam-science-policy-fellowship-program
[4] https://campersand.org
[5] https://www.nsf.gov/mps/dms
[6] https://www.energy.gov/science/ascr/advanced-scientific-computing-research
[7] https://www.siam.org/programs-initiatives/science-policy
[8] https://www.siam.org/programs-initiatives/science-policy/siam-best-practices-for-engaging-with-congressional-offices
[9] https://jointmathematicsmeetings.org/meetings/national/jmm2026/hill-visits

InsideSIAM

Conferences, books, journals, and activities of Society for Industrial and Applied Mathematics

siam | conferences

A Place to Network and Exchange Ideas

# Upcoming Deadlines

siam 2026

## SIAM Conference on Nonlinear Waves and Coherent Structures (NWCS26)

**May 26–29, 2026 | Montréal, Québec, Canada**
***siam.org/nwcs26*** | #SIAMNWCS26

**ORGANIZING COMMITTEE CO-CHAIRS**
Jason Bramburger, *Concordia University, Canada*
Manuela Girotti, *Emory University, U.S.*

**EARLY REGISTRATION RATE DEADLINE**
April 28, 2026

**HOTEL AND TRANSPORTATION INFORMATION**
April 10, 2026

***The following conferences will be held jointly:***

## SIAM Conference on Mathematics of Data Science (MDS26)

**November 16–20, 2026 | Salt Lake City, Utah, U.S.**
***siam.org/mds26*** | #SIAMMDS26

**ORGANIZING COMMITTEE CO-CHAIRS**
Andreas Mang, *University of Houston, U.S.*
Rebecca Morrison, *University of Colorado, Boulder, U.S.*
Rebecca Willett, *University of Chicago, U.S.*

**SUBMISSION AND TRAVEL SUPPORT DEADLINES**
April 20, 2026: Minisymposium Proposal Submission Deadline
May 18, 2026: Contributed Lecture, Poster, and Minisymposium Presentation Abstract Submissions
August 17, 2026: Travel Support Application Deadline

## SIAM Conference on Imaging Science (IS26)

**November 16–19, 2026 | Salt Lake City, Utah, U.S.**
***siam.org/is26*** | #SIAMIS26

**ORGANIZING COMMITTEE CO-CHAIRS**
Weihong Guo, *Case Western Reserve University, U.S.*
Yifei Lou, *University of North Carolina at Chapel Hill, U.S.*

**SUBMISSION AND TRAVEL SUPPORT DEADLINES**
April 20, 2026: Minisymposium Proposal Submission Deadline
May 18, 2026: Contributed Lecture, Poster, and Minisymposium Presentation Abstract Submissions
August 17, 2026: Travel Support Application Deadline

## SIAM International Conference Data Mining (SDM26)

**November 19–20, 2026 | Salt Lake City, Utah, U.S.**
***siam.org/sdm26*** | #SIAMSDM26

**ORGANIZING COMMITTEE CO-CHAIRS**
Arindam Banerjee, *University of Illinois Urbana-Champaign, U.S.*
Matteo Riondato, *Amherst College, U.S.*

**SUBMISSION AND TRAVEL SUPPORT DEADLINES**
April 10, 2026: Abstract Submissions (abstract required to submit a full paper)
April 17, 2026: Full Paper Submissions
August 17, 2026: Travel Support Application Deadline

Information is current as of February 20, 2026. Visit *siam.org/conferences* for the most up-to-date information.

## Upcoming SIAM Events

**SIAM Conference on Uncertainty Quantification**
March 22–25, 2026
Minneapolis, Minnesota, U.S.
Sponsored by the SIAM Activity Group on Uncertainty Quantification

**SIAM Conference on Nonlinear Waves and Coherent Structures**
May 26–29, 2026
Montréal, Québec, Canada
Sponsored by the SIAM Activity Group on Nonlinear Waves and Coherent Structures

**SIAM Conference on Optimization**
June 2–5, 2026
Edinburgh, United Kingdom
Sponsored by the SIAM Activity Group on Optimization

**SIAM Conference on Discrete Mathematics**
June 22–25, 2026
San Diego, California, U.S.
Sponsored by the SIAM Activity Group on Discrete Mathematics

**SIAM Conference on Mathematics of Planet Earth**
July 6–8, 2026
Cleveland, Ohio, U.S.
Sponsored by the SIAM Activity Group on Mathematics of Planet Earth

**SIAM Conference on the Life Sciences**
July 6–9, 2026
Cleveland, Ohio, U.S.
Sponsored by the SIAM Activity Group on Life Sciences

**2026 SIAM Annual Meeting**
July 6–10, 2026
Cleveland, Ohio, U.S.

**SIAM Conference on Applied Mathematics Education**
July 9–10, 2026
Cleveland, Ohio, U.S.
Sponsored by the SIAM Activity Group on Applied Mathematics Education

**SIAM Conference on Mathematics of Data Science**
November 16–20, 2026
Salt Lake City, Utah, U.S.
Sponsored by the SIAM Activity Group on Data Science

**SIAM Conference on Imaging Science**
November 16–19, 2026
Salt Lake City, Utah, U.S.
Sponsored by the SIAM Activity Group on Imaging Science

**SIAM International Conference on Data Mining**
November 19–20, 2026
Salt Lake City, Utah, U.S.
Sponsored by the SIAM Activity Group on Data Science

**ACM-SIAM Symposium on Discrete Algorithms**
January 24–27, 2027
Philadelphia, Pennsylvania, U.S.
Sponsored by the SIAM Activity Group on Discrete Mathematics

**SIAM Symposium on Algorithm Engineering and Experiments**
January 24–25, 2027
Philadelphia, Pennsylvania, U.S.

FOR MORE INFORMATION ON SIAM CONFERENCES: *siam.org/conferences* siam | membership

Network | Access | Outreach | Lead

# Congratulations Newly Elected SIAM Activity Group Officers

New officers have been elected for the following SIAM activity groups (SIAGs). Thanks to all candidates for participating in this election, members who voted, and all outgoing officers for volunteering their time and knowledge serving these past few years. SIAM activity groups enhance and strengthen the objectives of SIAM as a whole and provide an intellectual space for peers to exchange ideas centered around a subject in applied mathematics, computational science, or cross-disciplinary application.

**Join an activity group when renewing or creating your SIAM membership. If your membership is current, join activity groups at *my.siam.org*.**

*Algebraic Geometry*
*(SIAG/AG)*
Chair: Anton Leykin
Vice Chair: Anna Seigal
Program Director: Kathlén Kohn
Secretary: Carlos D'Andrea

*Control and Systems Theory*
*(SIAG/CST)*
Chair: Eduardo Cerpa
Vice Chair: Jun Liu
Program Director: Dante Kalise
Secretary: Boris Kramer

*Data Science*
*(SIAG/DATA)*
Chair: Gitta Kutyniok
Vice Chair: Eric Chi
Program Director: Elizabeth Munch
Secretary: Michael Perlmutter

*Dynamical Systems*
*(SIAG/DS)*
Chair: Martin Wechselberger
Vice Chair: Jonathan E. Rubin
Program Director: Yangyang Wang
Secretary: Alexandria Volkening

*Equity, Diversity, and Inclusion*
*(SIAG/EDI)*
Chair: Suzanne Sindi
Vice Chair: Aasifa Rounak
Program Director: Tammy Kolda
Secretary: Arielle Carr

*Financial Mathematics and Engineering*
*(SIAG/FME)*
Chair: Christa Cuchiero
Vice Chair: Mathieu Rosenbaum
Program Director: Ibrahim Ekren
Secretary: Silvana Pesenti

*Imaging Science*
*(SIAG/IS)*
Chair: Kui Ren
Vice Chair: Yifei Lou
Program Director: Matthias Chung
Secretary: Weihong Guo

*Optimization*
*(SIAG/OPT)*
Chair: Michael Ulbrich
Vice Chair: Frank Curtis
Program Director: Giacomo Nannicini
Secretary: Ana Custodio

Elections of officers for the following activity groups will be held in 2026 for terms beginning January 1, 2027. Please nominate a colleague or yourself for election at ***siam.org/forms/siam-activity-group-leadership-suggestions***.

- Analysis of Partial Differential Equations
- Applied and Computational Discrete Algorithms
- Applied Mathematics Education
- Computational Science and Engineering
- Discrete Mathematics
- Geometric Design
- Geosciences
- Life Sciences
- Mathematics of Planet Earth
- Nonlinear Waves and Coherent Structures
- Orthogonal Polynomials and Special Functions
- Uncertainty Quantification

*Supercomputing*
*(SIAG/SC)*
Chair: Matthias Bolten
Vice Chair: Erin Claire Carson
Program Director: Martin Berzins
Secretary: Albert-Jan N. Yzelman

# 2025-2026 Student Chapter Spotlight

SIAM awarded approximately $50,000 to more than 120 chapters for the 2025–2026 academic year. This funding supports SIAM student chapters as they organize meetings, host seminars, engage in professional development activities, and cultivate their passion for applied mathematics. Each year, our chapters plan and deliver a diverse range of engaging and impactful events. Below are some highlights from chapter activities during the 2024–2025 academic year.

For details on obtaining funding for your chapter or forming a new one, visit ***siam.org/start-a-chapter***.

**Berlin Area Student Chapter** organized and hosted a four day meeting for SIAM and GAMM student chapters across Europe. The event featured a distinguished lineup, including opening remarks from SIAM President Carol S. Woodward. Highlights of the program included plenary talks, a dedicated poster session, and a specialized workshop for early career researchers. Additionally, the chapter hosted an industry speaker event designed to facilitate professional networking and career development.

**Indiana University at Indianapolis Student Chapter** organized an on-campus outreach event for 40 visiting middle school and high school students titled "STEM Yes!". Chapter members welcomed students for a full day of STEM activities. During the event, professors shared their current research, chapter members facilitated math and logic games, and visiting students were given a guided campus tour. The group also participated in a mathematical modeling activity on the transmission of the common cold using the SIR model.

**Oklahoma State University Student Chapter** hosted the first joint SIAM–CSS Student Conference in collaboration with SIAM's Central States Section. The conference featured four plenary talks and six student presentations, fostering a vibrant academic environment and providing an excellent opportunity for interdisciplinary connections and the exchange of research ideas.

Attendees of Oklahoma State University Student Chapter's joint SIAM-CSS Student Conference pose for a photograph.

**SIAM would like to extend a warm welcome to our new student chapters for the 2025–2026 academic year:**

Cali Area, Colombia Student Chapter
Government College Women University, Faisalabad Student Chapter
Karlsruhe Institute of Technology Student Chapter
University of California San Diego Student Chapter
University of Hartford Student Chapter
University of Milano-Bicocca Student Chapter
University of Texas San Antonio Student Chapter

## Nominate your students for free membership in 2026!

SIAM members (excluding student members) can nominate up to two students per year for free membership. Go to ***siam.org/nominate-student*** to make your nominations.

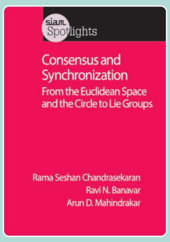
FOR MORE INFORMATION ON SIAM MEMBERSHIP: ***siam.org/membership***

# siam | books

Quality and Value in Mathematical Science Literature

## New from SIAM

### Consensus and Synchronization: From the Euclidean Space and the Circle to Lie Groups

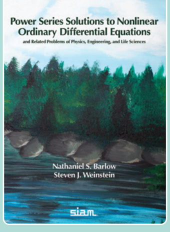



Ravi N. Banavar, and Arun D. Mahindrakar

Coordination, consensus, and synchronization are found in diverse natural phenomena and engineering applications. Examples are flocking birds, illuminating fireflies, schooling fish, and distributed control and sensing. The simplest of such problems are set in the Euclidean spaces and the circle. This book moves beyond this domain to the more sophisticated setting of Lie groups with bi-invariant metrics and extends the mathematical theories of consensus and synchronization for generic scenarios. This is relevant to applications such as robotics, autonomous vehicles, and spacecraft.

*2025 / xii + 86 pages / Softcover / 978-1-61197-879-7*
*List $54.00 / SIAM Member $37.80 / SL09*

### Power Series Solutions to Nonlinear Ordinary Differential Equations and Related Problems of Physics, Engineering, and Life Sciences

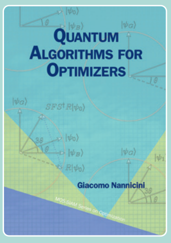


Nathaniel S. Barlow and Steven J. Weinstein

This book introduces a systematic approach to solving nonlinear ODEs using power series, with a focus on problems in mathematical physics. It equips readers with tools to streamline recursive computations and tackle convergence challenges, making power series methods both practical and accessible. Grounded in a hands-on teaching philosophy, the text features idea-driven examples and research-based problems, with minimal proofs. Ideal for applied mathematicians, scientists, and engineers, the book demonstrates how power series techniques can complement numerical methods as a versatile problem-solving tool.

*2025 / xii + 261 pages / Softcover / 978-1-61197-853-7*
*List $84.00 / SIAM Member $58.80 / OT208*

### Quantum Algorithms for Optimizers



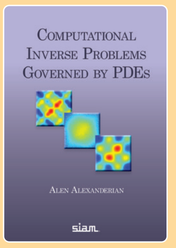

Giacomo Nannicini

This book presents a self-contained introduction to quantum algorithms, with a focus on quantum optimization—quantum approaches to solving optimization problems. It equips readers with the essential tools to assess the strengths and limitations of these algorithms, emphasizing provable guarantees and computational complexity. The first comprehensive treatment of quantum optimization, it provides a rigorous introduction to the computational model of quantum computers and to the theory of quantum algorithms, contains detailed discussions of some of the most important developments in quantum optimization algorithms, and summarizes the most significant advances in the open literature.

*2025 / xiv + 273 pages / Softcover / 978-1-61197-875-9*
*List $79.00 / SIAM Member $55.30 / MO37*

## Coming Soon

### Computational Inverse Problems Governed by PDEs

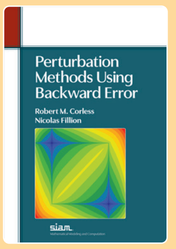



Alen Alexanderian

This textbook focuses on computational methods for inverse problems that are governed by partial differential equations (PDEs). The author considers deterministic and Bayesian formulations and highlights how traditional tools from deterministic inversion can be integrated into solution methods for Bayesian inverse problems. Advanced topics such as post-optimality sensitivity analysis, optimal design of experiments, and Bayesian inversion under model uncertainty are also included. The book offers readers a balance of theoretical and computational insight, an example-driven approach that provides an accessible presentation, and over 150 theoretical and computational exercises.

*February 2026 / xvi + 320 pages / Softcover / 978-1-61197-881-0 / List $89.00 / SIAM Member $62.30 / OT211*

### Perturbation Methods Using Backward Error

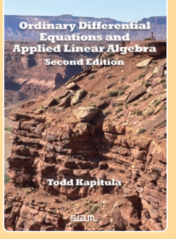



Robert M. Corless and Nicolas Fillion

Perturbation methods are old but powerful, and they remain in widespread use. Rather than producing numbers or pictures, they yield formulas whose value depends on the skill of the person (or machine!) interpreting them. This unique book presents several classical methods for solving perturbation problems. To ensure a uniform presentation and more reliable, interpretable results, it consistently uses backward error analysis. This provides a systematic way to assess the validity of approximate solutions while encouraging the modeler to examine how small changes in the data or model affect the result. To support this, the book uses the concept of a condition number, familiar from numerical analysis.

*April 2026 / xx + 414 pages / Softcover / 978-1-61197-885-8 / List $81.00 / SIAM Member $56.70 / MM25*

### Ordinary Differential Equations and Applied Linear Algebra, Second Edition




Todd Kapitula

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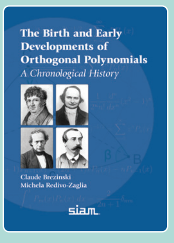


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