

Preface to Geometry-grounded Representation Learning and Generative Modeling (GRaM) Workshop

Editors: *Sharvaree Vadgama, Erik Bekkers, Alison Pouplin, Sekou-Oumar Kaba, Robin Walters, Hannah Lawrence, Tegan Emerson, Henry Kvinge, Jakub Tomczak, Stephanie Jegelka*

Motivation

By recognizing that nearly all data is rooted in our physical world, and thus inherently grounded in geometry and physics, it becomes evident that representation learning should preserve this grounding in order to remain meaningful.

For example, preserving group transformation laws and symmetries through equivariant layers is crucial in domains such as computational physics, chemistry, robotics, and medical imaging, and leads to effective and generalizable architectures and improved data efficiency. Similarly, in generative models applied to non-Euclidean data spaces, maintaining the manifold structure is essential in order to obtain meaningful samples. This workshop focused on the principle of *grounding in geometry*. We define this as follows:

A representation, method, or theory is grounded in geometry if it can be amenable to geometric reasoning, that is, it abides by the mathematics of geometry.

We accepted submissions that present theoretical research, methodologies, applications, insightful analysis, and even open problems, within the following topics:

1. **Structure-preserving learning** : Preservation of symmetries, e.g., through equivariant operators, dynamical systems on manifolds, representation learning and generative modeling using ordinary, stochastic and differential equations (ODEs, SDEs, PDEs) on manifolds, computing with geometric representations, such as the processing of multi-vectors using geometric algebra, steerable vectors using Clebsch-Gordan products, and hyperbolic features using Fréchet means.
2. **Structure-inducing learning**: Self-supervised learning, e.g., learning to embed data in geometric latent spaces through (geodesic) distance-based similarity metrics, geometric priors, e.g., soft constraints on model weights, physics-informed neural networks, e.g., inducing the structure of established physical and geometric laws into neural networks through dedicated losses.
3. **Generative modeling and density estimation**: Geometric latent variable models, i.e., the use of Latent variables that live in a manifold, new methods and adaptations of methods capable of generating geometric objects, e.g., generating atomic point clouds or shapes, generating fields over manifolds, e.g., generating vector fields or spherical signals.
4. **Grounding in theory**: Theoretical frameworks, unifying analyses and formulations that provide a generalizing perspective on deep learning paradigms, open problems identifying and addressing unresolved questions and challenges that lie at the intersection of geometry and learning.

GRaM Workshop at ICML

The first edition of GRaM Workshop at ICML took place on the 27th of July 2024 in Vienna Austria.



Figure 1: A jam-packed audience at GRaM workshop in Vienna, Austria

Call for Papers

The workshop accepted submissions in the following tracks

1. **Proceedings track:** 8-page paper submissions (excluding appendices and references). All submissions were peer-reviewed (double-blind via openreview). Accepted papers are published in these proceedings, Volume 251 of PMLR.
2. **Extended abstract track:** 4-page paper submissions (excluding appendices and references). All submissions were peer-reviewed (double-blind via openreview). Accepted papers can be viewed on openreview as well as the workshop website.
3. **Blogpost and Tutorial track:** Blog posts and Tutorials that explain previously published papers or important topics in the field or include easy-to-use code for the same. GRaM workshop accepted submissions in markdown format for blog posts and colab files for tutorials. Selected submissions were posted on the GRaM website. All the submissions were reviewed single-blind.
4. **Topological deep learning challenge:** We teamed up with TAG and hosted an ICML Topological Deep Learning Challenge 2024: Beyond the Graph Domain challenge.

The call for papers yielded **97** submissions combined in the paper tracks, **15** in the Blogpost and Tutorial Track, and **56** submissions in the Competition Track. Each submission in the proceedings track received a minimum of three reviews, which were aggregated and assessed by the Area Chairs for final inclusion. Each submission in the rest of the tracks received a minimum of two reviews which were assessed by the program chairs of the respective tracks. This resulted in **147** accepted works: **29** proceedings papers, **52** extended abstract tracks, **14** blog posts/tutorials, and **52** in the competition track. All of the 29 papers in the proceedings track are published in this volume, by choice of the authors. Reviews of the accepted works can be found on the GRaM openreview page.

Schedule

The workshop was held on July 27th, 2024, in Vienna Austria, and attracted between 300 and 400 in-person attendees. The workshop featured five invited speakers, listed below, with talks spanning topics in geometric representations, the geometry of generative models, improving sampling using geometric-generative models, discovering symmetries, and learning representation beyond the Euclidean manifold. In addition, one discussion panel was held. All accepted works were presented as posters during the workshop, with the top five submissions selected for contributed talks. Awards were given to the best contribution in the proceedings track and extended paper track. All talks and the panel were live-streamed and recorded and can be found online on [SlidesLive](#). GRaM attendees joining online, had their posters displayed on the main screen during afternoon breaks.

Talks

Keynote presentations

1. The Platonic Representation Hypothesis - **Phillip Isola**, MIT.
2. Automatic Symmetry Discovery from Data - **Rose Yu**, UCSD.

Invited talks

1. Simulation Free Generative Models for Protein Structures, Single-Cell RNA, DNA sequences and Beyond!, **Joey Bose**, Oxford University.
2. Generalization in diffusion models arises from geometry-adaptive harmonic representations, **Zahra Kadkhodaie**, Flatiron Institute.
3. Beyond Euclid: An Illustrated Guide to Modern Machine Learning with Geometric, Topological, and Algebraic Structures, **Nina Mialone**, UCSB.

Contributed talks

1. Adaptive Sampling for Continuous Group Equivariant Neural Networks, **Berfin Inal**, University of Amsterdam.
2. Variational Inference Failures Under Model Symmetries: Permutation Invariant Posteriors for Bayesian Neural Networks, **Yoav Gelberg**, University of Oxford.
3. Probabilistic World Modeling with Asymmetric Distance Measure, **Meng Song**, UCSD.
4. Lift Your Molecules: Molecular Graph Generation in Latent Euclidean Space, **Mohamed Amine Ketata**, Technical University of Munich.
5. Bundle Neural Networks for message diffusion on graphs, **Jacob Bamberger**, University of Oxford.

Panel Discussion

The panel topic was “Geometric deep learning and Generative modeling: Past and Future.” The panelists were **Max Welling**, **Phillip Isola**, **Zahra Kadkhodaie**, **Joey Bose**, and **Rianne van der Berg**. The panel was moderated by **Erik Bekkers**.



Figure 2: Panel discussion at GRaM workshop

Program Committee

We extend our immense gratitude to our area chairs, who have diligently supervised the reviewing process and led the selection of contributed talks. Our heartfelt thanks also go out to the 87 reviewers, whose collective efforts resulted in high-quality reviews for the submissions. Their dedication and expertise have been integral to the success of this workshop.

Area Chairs

Alison Pouplin, Erik Bekkers, Hannah Lawrence, Henry Kvinge, Robin Walters, Sekou Oumar Kaba, Sharvaree Vadgama, Shubhendu Trivedi, Tegan Emerson served as Area Chairs.



Figure 3: A few members of GRaM team at GRaM workshop

Reviewers

Guillaume Huguet	Hae Jin Song	Luca Thiede
Martin Uray	Babak Esmaili	Axel Flinth
Serguei Barannikov	David Wessels	Mit Kotak
Georg Bökman	Sharut Gupta	Nina Miolane
Kumar Krishna Agrawal	Yingying Wu	Teodora Reu
Nikhil Akalwadi	Sugandha Sharma	YuQing Xie
Maksim Zhdanov	Elyssa Hofgard	Gautam Pai
Bálint Máté	Putri A Van der Linden	Farzaneh Heidari
Siba Smarak Panigrahi	Noga Mudrik	Xinhe Zhang
Dhananjay Bhaskar	Luca Ambrogioni	Mingyu Kim
Giovanni Luca Marchetti	Gabriele Cesa	Santiago Velasco-Forero
Georgios Arvanitidis	Xiushi Li	Sampada Malagi
Benjamin Kurt Miller	Marimuthu Kalimuthu	Cong Liu
Victor Livernoche	Jinwoo Kim	Rohith Peddi
Jan E Gerken	Anna Kuzina	Bo Zhao
Artur Petrov Toshev	Deepak Kumar Pokkalla	Julia Balla
Tycho F. A. van der Ouderaa	Dimitra Maoutsa	Zhenjie Zhao
Emanuele Sansone	Ameya Daigavane	Puck Van Gerwen
Yun Young Choi	Ayon Borthakur	Julian Suk
Mathilde Papillon	Federico Barbero	Daniel Levy
Peter Potaptchik	Thien Le	Liheng Ma
Mary Letey	Vineet Jain	David M Knigge
Patryk Rygiel	Thijs P. Kuipers	Tobias Cheung
Kunvar Thaman	Leo Zhang	Vasco Portilheiro
Floor Eijkelboom	Max van Spengler	David Ruhe
Tara Akhound-Sadegh	Sven Dummer	Yan Zhang
Stefanie Jegelka	Jakub Tomczak	

served as reviewers.

ELLIS Mobility Grant for GRaM workshop

ELLIS Amsterdam Unit, ELLIS Linz Unit, and Elise Network generously supported GRaM workshop. With their support, we were able to fund 18 GRaM attendees from 10 countries across 4 continents with a travel grant to attend the GRaM workshop in person in Vienna, Austria.

GRaM Social

With ICML, we were able to create a strong community in the emerging field of geometric representations.



Figure 4: A snapshot from post-workshop GRaM social

Continuing GRaM

We will review blog posts and tutorials regularly and post them on the GRaM website. We believe that continuing to accept submissions for blog posts and tutorials would be a great way to build easily accessible resources for learning geometric deep learning and generative modeling.