

Preface

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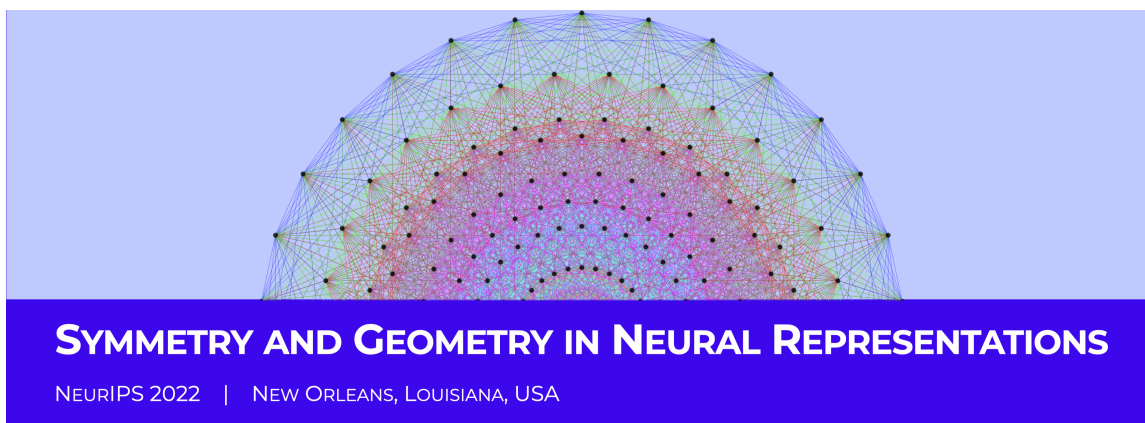
Editors: Sophia Sanborn, Christian Shewmake, Simone Azeglio, Arianna Di Bernardo, Nina Miolane

1. Symmetry and Geometry in Neural Representations

An emerging set of findings in sensory and motor neuroscience is beginning to illuminate a new paradigm for understanding the neural code. Across sensory and motor regions of the brain, neural circuits are found to mirror the geometric and topological structure of the systems they represent—either in their synaptic structure, or in the implicit manifold generated by their activity. This phenomenon can be observed in the circuit of neurons representing head direction in the fly [Kim et al. \(2017\)](#); [Wolff et al. \(2015\)](#), in the activities of grid cells [Chaudhuri et al. \(2019\)](#); [Gardner et al. \(2022\)](#), and in the low-dimensional manifold structure observed in motor cortex [Gallego et al. \(2017\)](#). This suggests a general computational strategy that is employed throughout the brain to preserve the geometric structure of data throughout stages of information processing.

Independently but convergently, this very same computational strategy has emerged in the field of deep learning. The nascent sub-field of Geometric Deep Learning [Bronstein et al. \(2021\)](#) incorporates geometric priors into artificial neural networks to preserve the geometry of signals as they are passed through layers of the network. This approach provably demonstrates gains in the computational efficiency, robustness, and generalization performance of these models.

The convergence of these findings suggests deep, substrate-agnostic principles for information processing. Symmetry and geometry were instrumental in unifying models of fundamental forces and elementary particles in 20th-century physics. Likewise, they have the potential to illuminate unifying principles for how neural systems form useful representations of the world.



2. The Workshop

The first annual **NeurIPS Workshop on Symmetry and Geometry in Neural Representations (NeurReps)** was conceived to bring together researchers at the nexus of applied geometry, deep learning, and neuroscience, with the goal of advancing this understanding and illuminating geometric principles for neural information processing. Ultimately, we hope that this venue and associated community will support the development of the geometric approach to understanding neural representations, while strengthening ties to the mathematics community. The **Neural Information Processing Systems (NeurIPS)** conference historically emerged from the field of theoretical neuroscience or “connectionism.” This venue thus further serves the workshop’s goal of reinforcing the bond between deep learning and neuroscience.

2.1. Call for Papers

Our call for papers invited submissions for publication in this volume and presentation at the conference. The call requested submissions contributing novel research at the intersection of geometric deep learning, computational neuroscience, geometric statistics, and topological data analysis, which incorporate symmetry, geometry, or topology into the *design of artificial neural networks*, the *analysis of neural data*, or *theories of neural computation*. Both theoretical contributions and applied results were encouraged, as well as the use of diverse mathematical objects such as quotient spaces, fiber bundles, Lie groups, Riemannian manifolds, graphs, and group representations. Two tracks were established:

1. **Proceedings Track:** NeurReps Proceedings papers are up to 10 pages long, excluding references and appendices. This track is intended for self-contained research papers with a high degree of development. Accepted papers are published in this volume.
2. **Extended Abstract Track:** Extended abstracts are up to 5 pages long, excluding references and appendices. This track is a space for contributions such as early-stage results, insightful negative findings, opinion pieces, or novel datasets. Extended abstracts are not included in this volume.

The call for papers yielded 91 submissions, which were reviewed double-blind. Submitted work spanned from questions in statistical learning theory for geometric models, to novel

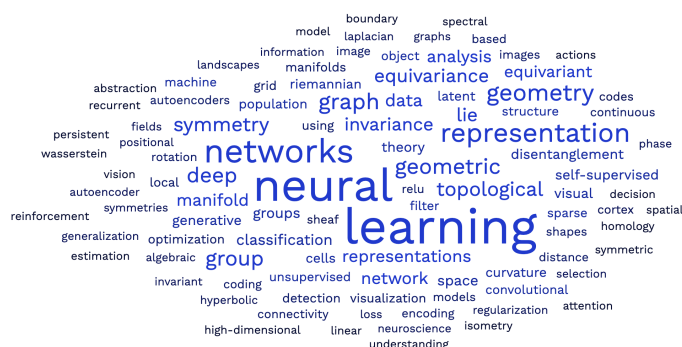


Figure 1: A word cloud constructed from the abstracts of all submissions.

geometric deep learning architectures, to methods for neural data analysis. Each submission received a minimum of three reviews, which were aggregated and assessed by the editors for final inclusion. This resulted in 65 accepted works: 25 full-length papers, and 41 extended abstracts. Of the 25 full-length papers, 21 are published in this volume, by choice of the authors. Reviews of the accepted works can be found on the [NeurReps OpenReview Portal](#).

2.2. The Schedule

The workshop was held on December 3rd, 2022 in New Orleans, Louisiana, USA, and attracted between 300 and 400 in-person attendees. The workshop featured six invited keynote speakers with talks spanning topics in neuroscience, machine learning, and their intersection. In addition, two discussion panels were held. All accepted works were presented as posters during the workshop, with the top ten submissions selected for oral presentation. Three submissions were selected for ten-minute spotlights and the remainder selected for five-minute lightning talks. Awards were given to the best proceedings paper and best extended abstract. All talks and panels were live-streamed and recorded and can be found online on [SlidesLive](#).

KEYNOTES

In search of invariance in brains and machines

Bruno Olshausen

Symmetry-based representations for artificial and biological intelligence

Irina Higgins

From equivariance to naturality

Taco Cohen

Generative models of non-Euclidean neural population dynamics

Kristopher Jensen

Robustness of representations in artificial and biological neural networks

Gabriel Kreiman

Neural ideograms and equivariant representation learning

Erik Bekkers

DISCUSSION PANELS

Geometric and topological principles for representation learning in ML

Panelists: Irina Higgins, Taco Cohen, Erik Bekkers, Rose Yu

Moderator: Nina Miolane

Geometric and topological principles for representations in the brain

Panelists: Bruno Olshausen, Kristopher Jensen, Gabriel Krieman, Manu Madhav

Moderator: Christian Shewmake

SPOTLIGHT TALKS

Is the information geometry of probabilistic population codes learnable?

Vastola[†], Cohen, Drugowitsch

Computing representations for Lie Algebraic Networks

Shutty[†], Wierzynski

Awarded Best Proceedings Paper

Kendall Shape-VAE : Learning shapes in a generative framework

Vadgama[†], Tomczak, Bekkers

LIGHTNING TALKS

Equivariance with learned canonical mappings

Kaba^{†*}, Mondal^{*}, Zhang, Bengio, Ravanbakhsh

Capacity of group-invariant linear readouts from equivariant representations: How many objects can be linearly classified under all possible views?

Farrell[†], Bordelon, Trivedi, Pehlevan

Do neural networks trained with topological features learn different internal representations?

McGuire, Jackson, Emerson, Kvinge[†]

Expander Graph Propagation

Deac[†], Lackenby, Veličković

Homomorphism AutoEncoder: Learning group structured representations from observed transitions

Keurti[†], Pan, Besserve, Grewe, Schölkopf

Awarded Best Extended Abstract

Sheaf Attention Networks

Barbero[†], Bodnar, Sáez de Ocáriz Borde, Liò

On the expressive power of geometric graph neural networks

Joshi^{*}, Bodnar^{*}, Mathis[†], Cohen, Liò

[†] Denotes presenting author. ^{*} Denotes shared first-authorship

3. The Community

To support the growth of this nascent research area outside of the annual workshop, we have established a digital community for NeurReps, which at the time of writing has over 800 members. Instructions for joining and contributing to the community can be found on the [community page](#) of our website.

4. Program Committee

We are immensely grateful to our 95-member program committee, who collectively submitted 267 high-quality reviews for the workshop’s 91 submissions. Thank you to:

Adele Myers	Erik Bekkers	Noah Shutty
Adrian Valente	Federico Claudi	Oded Stein
Alessandro Sarti	Francesco Di Giovanni	Ondrej Biza
Alex Williams	Francisco Acosta	Patrick Rubin-Delanchy
Alexandra Libby	Frank Nielsen	Pim de Haan
Alice Le Brigant	Frédéric Barbaresco	Rana Shahroz
Alison Poupin	Geoffrey Woollard	Rongjie Lai
Andrew Ligeralde	Grégoire Sergeant-Perthuis	Rucha Joshi
Anna Calissano	Hannah Lawrence	Santiago Cadena
Balasubramaniam Srinivasan	Henry Adams	Sarah Marzen
Bastian Rieck	Hrittik Roy	Sharvaree Vadgama
Bilal Alsallakh	Ilyes Batatia	Shayan Shekarforoush
Blake Bordelon	Jacob Zavatone-Veth	Shubhendu Trivedi
Boyan Beronov	James Whittington	Simon Mathis
Bruno Olshausen	Joey Bose	Sina Tootoonian
Chris Kymn	Johan Mathe	Søren Hauberg
Christoph Ortner	Jonathan Huml	Stéphane Deny
Christopher Hillar	Justin Solomon	Sylvain Chevallier
Christopher Kim	Kaitlin Maile	Tamar Flash
Claire Donnat	Kartik Sharma	Tatyana Sharpee
Clementine Domine	Kathryn Hess	Uri Cohen
David Klee	Khanh Dao Duc	Valentino Maiorca
David Klindt	Kristopher Jensen	Vincent Benenati
David Robin	Maksim Zhdanov	Wei Ye
Davide Boscaini	Manos Theodosios	Will Dorrell
Donlapark Ponnoprat	Manu Madhav	Wolfgang Polonik
Dorina Thanou	Marco Fumero	Xiangru Huang
Dylan Paiton	Marco Pegoraro	Xiaoling Hu
Edouard Oyallon	Mathilde Papillon	Xinling Yu
Elodie Maignant	Maurice Weiler	Yann Thanwerdas
Emanuele Marconato	Mikhail Khona	Yubei Chen
Emanuele Rodolà	Mitchell Ostrow	
Emanuele Rossi	Nicolas Guigui	



Figure 2: The NeurReps poster session.

5. Moving Forward

We believe it is both timely and important to create a research venue and supportive community for the exchange of knowledge at the intersection of differential geometry, topology, machine learning and neuroscience. Moving forward, we will continue to create opportunities for dialogue and discussion on these themes at NeurIPS and other meetings. Furthering our broader aim of community-building, we have also established an active community of students and researchers which we believe will act as a gathering place to organize related events, such as seminars and hackathons.

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