

# Preface

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## 1. Symmetry and Geometry in Neural Representations

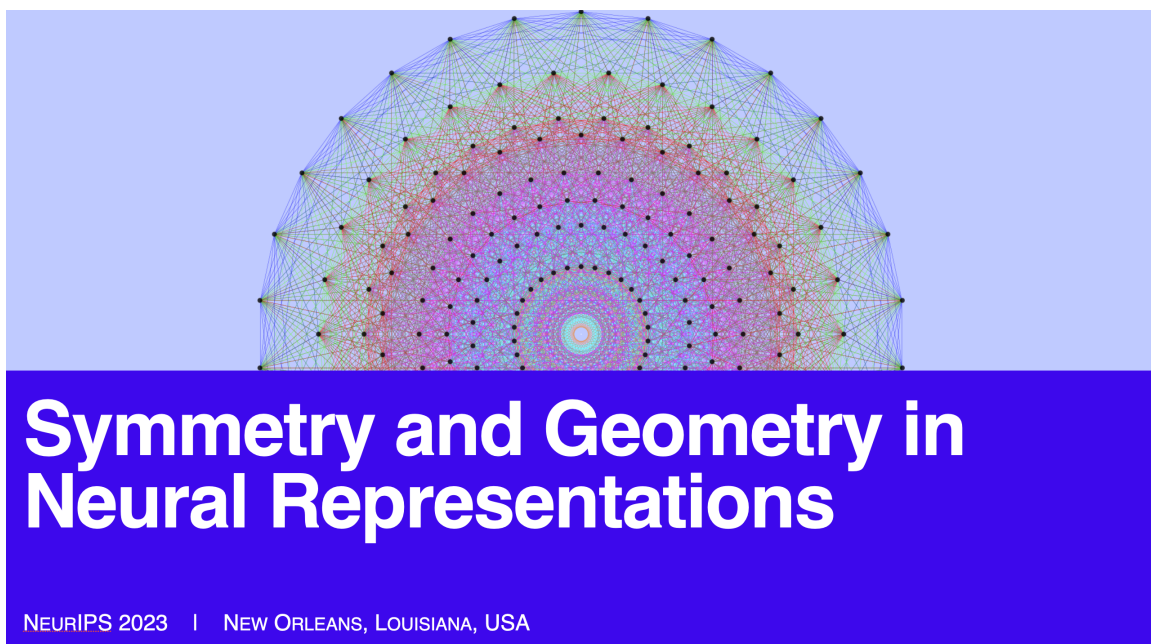
An emerging set of findings in sensory and motor neuroscience is beginning to illuminate a new paradigm for understanding the neural code. Across sensory and motor regions of the brain, neural circuits are found to mirror the geometric and topological structure of the systems they represent—either in 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 second 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

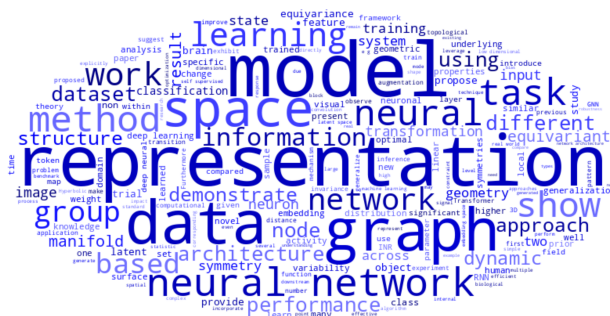


geometric approach to understanding neural representations, while strengthening ties to the mathematics community. The **Neural Information Processing Systems (NeurIPS)** conference historically emerged from the field of theoretical neuroscience or “connectionism.” This venue thus further serves the 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.



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

The call for papers yielded 75 submissions, which were reviewed double-blind. Submitted work spanned from questions in statistical learning theory for geometric models, to novel 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: 23 full-length papers, and 42 extended abstracts. All of the 23 full-length papers 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 16th, 2023 in New Orleans, Louisiana, USA, and attracted between 300 and 400 in-person attendees. The workshop featured five invited keynote speakers with talks spanning topics in neuroscience, machine learning, topology and their intersection. In addition, one discussion panel was held. All accepted works were presented as posters during the workshop, with the top eleven submissions selected for ten-minute oral presentation. Awards were given to the best contribution for each area: *Neuroscience & Interpretability*, *Topology & Graphs* and *Algebra & Geometry*. All talks and the panel were live-streamed and recorded and can be found online on [SlidesLive](#).

## KEYNOTES

# Pre-structured low-dimensional manifolds for rapid and efficient learning, memory, and inference in the brain

Ila Fiete

## Topological deep learning: going beyond graph data

Mustafa Hajji

## From local diffeomorphism detection to symbolic representation

Doris Tsao

## Physics priors in machine learning

Max Welling

**Rotation-equivariant predictive modeling reveals the functional organization of primary visual cortex**

Alexander Ecker

DISCUSSION PANEL

**The Role of world models in intelligence**

*Panelists:* Ila Fiete, Mustafa Hajij, Doris Tsao, Max Welling, Alexander Ecker

*Moderator:* Sophia Sanborn

CONTRIBUTED TALKS

**Neuroscience & Intepretability**

**Expressive dynamics models with nonlinear injective readouts enable reliable recovery of latent features from neural activity  $\star$**

Versteeg<sup>†</sup>, Sedler, McCart, Pandarinath

**On Complex Network Dynamics of an In-Vitro Neuronal System during Rest and Gameplay**

Khajehnejad<sup>†\*</sup>, Habibollahi\*, Loeffler, Kagan, Razi

**Topology & Graphs**

**Spectral Maps for Learning on Subgraphs  $\star$**

Marco Pegoraro<sup>†</sup>, Riccardo Marin, Arianna Rampini, Simone Melzi, Luca Cosmo, Emanuele Rodolà

**Algebra & Geometry**

**Towards Information Theory-Based Discovery of Equivariances  $\star$**

Hippolyte Charvin<sup>†</sup>, Nicola Catenacci Volpi, Daniel Polani

**Internal Representations of Vision Models Through the Lens of Frames on Data Manifolds**

Henry Kvinge, Grayson Jorgenson, Davis Brown<sup>†</sup>, Charles Godfrey, Tegan Emerson

**Data Augmentations in Deep Weight Spaces**

Aviv Shamsian<sup>†</sup>, David Zhang, Aviv Navon, Yan Zhang, Miltiadis Kofinas, Idan Achituve, Riccardo Valperga, Gertjan Burghouts, Efstratios Gavves, Cees Snoek, Ethan Fetaya, Gal Chechik, Haggai Maron

**Joint Group Invariant Functions on Data-Parameter Domain Induce Universal Neural Networks**

Sho Sonoda<sup>†</sup>, Hideyuki Ishi, Isao Ishikawa, Masahiro Ikeda

**Euclidean, Projective, Conformal: Choosing a Geometric Algebra for Equivariant Transformers**

Pim De Haan<sup>†</sup>, Taco Cohen, Johann Brehmer

**Symmetry Breaking and Equivariant Neural Networks**

Sékou-Oumar Kaba<sup>†</sup>, Siamak Ravanbakhsh

**From Bricks to Bridges: Product of Invariances to Enhance Latent Space Communication**

Irene Cannistraci<sup>†</sup>, Luca Moschella, Marco Fumero, Valentino Maiorca, Emanuele Rodolà

**Geometry of abstract learned knowledge in deep RL agents**

James Mochizuki-Freeman<sup>†</sup>, Md Rysul Kabir, Mitesh Gulecha, Zoran Tiganj

★ Denotes best area contribution. † 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 1200 members. Instructions for joining and contributing to the community can be found on the [community page](#) of our website.

### 4. 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 165 reviewers, whose collective efforts resulted in 230 high-quality reviews for the workshop’s 75 submissions. Their dedication and expertise have been integral to the success of this workshop. Thank you :

#### Area Chairs

**Neuroscience  
& Interpretability**

James Whittington

**Topology  
& Graphs**

Michael Schaub

**Algebra  
& Geometry**

Henry Kvinge

#### Reviewers

Abiy Tasissa

Adrian Bertagnoli

Adrish Dey

Ahmed Imtiaz Humayun

Alex Gabel

Alex H Williams

Alpha Renner

Andreea Danielescu

Ankita Shukla

Anton Tsitsulin

Antonio Briola

Arjun Karuvally

Artem Moskalev

Augustine N. Mavor-Parker

Behrooz Tahmasebi

Bilal Alsallakh

Binxu Wang

Bo Zhao

Bongjin Koo

Brian Wesley Bell

Charles Godfrey

Clinton Wang

Daniel McNeela

Daniel Ordonez-Apraez

Daniel Platt

Danil Akhtiamov

David A. Klindt

David A. R. Robin	Jonathan Raymond Huml	Sarthak Chandra
David Klee	Joshua Robinson	Sékou-Oumar Kaba
David Robert Reich	Joshua Southern	Semih Cantürk
David Sheard	Julian Suk	Sepideh Maleki
David W. Romero	Kartik Sharma	Seunghyuk Cho
Davis Brown	Katharina Limbeck	Shahira Abousamra
Dehong Xu	Kijung Yoon	Sharvaree Vadgama
Dennis George Wilson	Konstantinos Barmpas	Siba Smarak Panigrahi
Derek Lim	Kristopher T Jensen	Sigurd Gaukstad
Dimitris Kalatzis	Lazar Supic	Sjoerd van Steenkiste
Domas Buracas	Leander Girrback	Sohir Maskey
Dongmian Zou	Liu Ziyin	Sourabh Palande
Edward Paxon Frady	Lorenzo Giusti	Sree Harsha Tanneru
Ekdeep Singh Lubana	Luca Baroni	Stefan Mihalas
Eloy Geenjaar	Luca Moschella	Stephan Chalup
Emanuele Rodolà	Maghesree Chakraborty	Sungjun Cho
Eric Qu	Maksim Zhdanov	Takashi Matsubara
Erik J Bekkers	Manos Theodosis	Tananun Songdechakraiwut
Federico Barbero	Marco Pegoraro	Tara Akhound-Sadegh
Filip Cornell	Mathilde Papillon	Tegan Emerson
Filippo Maggioli	Matt Thomson	Thomas Gebhart
Francisco Acosta	Matthew Farrell	Tom Needham
Frank Yuchen Qiu	Matthew James Sargent	Tycho F. A. van der Ouderaa
Gergely Berczi	Michael G. Rawson	Uri Cohen
Giovanni Luca Marchetti	Mikail Khona	Valentino Maiorca
Grégoire Sergeant-Perthuis	Nello Blaser	Vasco Portilheiro
Guillaume Hugué	Nima Dehmamy	Vinayak Abrol
Hooman Shayani	Noah Lewis	Vincent Peter Grande
Ilyes Batatia	Ondrej Biza	Wenhao Zhang
Irene Cannistraci (	Peiran Jiang	Wu Lin
Jacob A Zavatore-Veth	Pim De Haan	Xinyue Cui
Javier Gonzalvo	Qingsong Wang	Xue-Xin Wei
Jeffrey Seely	Ramakrishnan Iyer	Yan HU
Jens Agerberg	Randall Balestrieri	Ying Nian Wu
Jianke Yang	Rishabh Anand National	Yivan Zhang
Joey Bose	Rishi Sonthalia	Yonatan Gideoni
Johan Mathe	Robin Walters	
John Vastola	Santiago Velasco-Forero	



**Figure 2:** The NeurReps 2023 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.

## References

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