



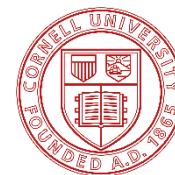
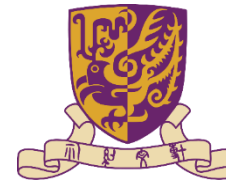
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ATHEMATICS  
THE CHINESE UNIVERSITY OF HONG KONG



# Rethink Deep Learning with Invariance in Data Representation

A Tutorial at The Web Conference 2025 in Sydney (WWW 2025)

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13:30 - 15:00, Tuesday, April 29, 2025

Room C3.4, ICC Sydney, Australia

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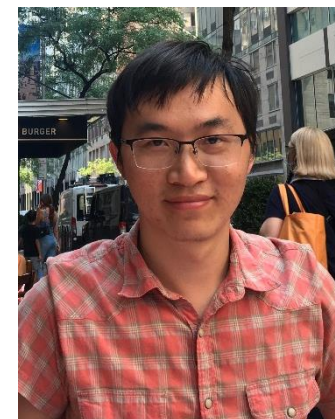


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# Tutorial Homepage

Tutorial proposal, slides, reading list, video, and more materials available at <https://shurenqi.github.io/wwwtutorial/>

# Rethink Deep Learning with Invariance in Data Representation

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## Abstract

Integrating **invariance** into data **representations** is a principled design in intelligent systems and web applications. Representations play a **fundamental** role, where systems and applications are both built on meaningful representations of digital inputs (rather than the raw data). In fact, the proper design/learning of such representations relies on prior **s.t.** the task of interest. Here, the concept of **symmetry** from the *early era* of deep learning, the most influential prior – informally, a symmetry of a system is a transformation that leaves a certain property of the system invariant. Symmetry priors are ubiquitous, e.g., translation as a symmetry of the object classification, where object category is invariant under translation.

The quest for invariance is as old as pattern recognition and machine learning itself. Invariant design has been the cornerstone of various representations in the *era before deep learning*, such as the SIFT. As we enter the *early era of deep learning*, the invariance principle is largely ignored and replaced by a data-driven paradigm, such as the CNN. However, this neglect did not return the *era* they resounded but belittled regarding robustness, interpretability, efficiency, and so on. The invariance principle has long been in *the era of rethinking deep learning*, forming a new field known as Geometric Deep Learning (GDL).

In this tutorial, we will give a **historical perspective** of the invariance in data representations. More importantly, we will identify those research dilemmas, promising works, future directions, and web applications.

## CCS Concepts

• Theory of computation → Theory and algorithms for artificial intelligence; • Computing methodologies → Artificial intelligence.

## Keywords

Pattern Recognition, Data Mining, Invariance, Symmetry, Representation, Tutorial



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## 1 Topic and Relevance

The topic of this tutorial is the historical review of the invariance in data representations. The scope of this tutorial covers (1) the invariance in the *era before deep learning*, or old-fashioned invariant designs from various hand-crafted representations; (2) the invariance in the *early era* of deep learning, on the slump of the invariance principle and the success of the data-driven paradigm; (3) the invariance in the *era of rethinking deep learning* on the revival of the invariance principle and the emergence of geometric deep learning as a way to bridge the research gap. For the depth within each era, the research dilemmas, promising works, future directions, and web applications will be sorted out. *More details are expanded in Section 2.*

The presenters are qualified for a high-quality introduction to the topic. We have extensive research experience and strong publication records in representation backgrounds and downstream applications of pattern recognition and data mining. *More details are expanded in Section 3.*

This tutorial is timely, due to the general limitations of today's intelligent systems and their web applications with respect to being only data-driven. Also, the invariance perspective (technology focus) and the historical perspective (broad horizon) are rarely seen in the tutorial tracks of related conferences.

This tutorial is relevant to the Web Conference. From a technological perspective, representations play a fundamental role in intelligent systems and their wide range of downstream web applications. From a practical perspective, the current popular data-driven paradigm has led to bottlenecks in intelligent systems and their web applications, regarding robustness, interpretability, efficiency, and so on. Understanding invariance in data representations is helpful in facilitating better web applications.

## 2 Content

Over the past decade (2014–2024), deep learning representations, e.g., convolutional neural networks (CNNs), have led to breakthrough results in numerous artificial intelligence (AI) tasks, e.g., processing human perceptual information, playing board games,

The figure displays a 3x3 grid of slides from a presentation titled "A Historical Perspective of Data Representation: Rethinking Deep Learning with Invariance".

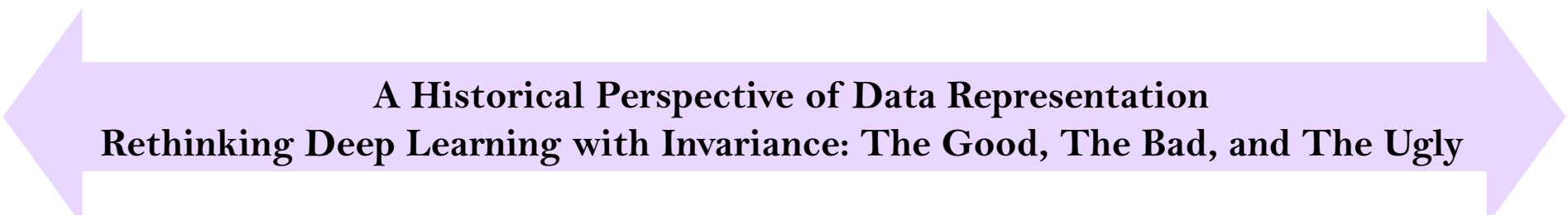
- Slide 1 (Top Left):** Titled "Towards Robust, Interpretable, and Efficient AI". It features a central image showing various data representations (a brain scan, a molecular structure, a face, a fingerprint, a DNA helix, and a network graph) surrounded by a hexagonal pattern of nodes. Below the image is the text: "Deep learning representations v.s. robustness, interpretability, and efficiency principles."
- Slide 2 (Top Middle):** Titled "Symmetry and Invariance Priors". It shows portraits of five influential figures in the history of symmetry: P. Dirac (1927), E. Noether (1918), H. Weyl (1929), C. N. Yang & R. L. Mills (1954), and S. Goldstone (1961). Below the portraits is a quote from LeCun, Bengio, & Hinton (2015): "Representations that are invariant to the aspects that are important for discrimination, but that are irrelevant to inessential aspects".
- Slide 3 (Top Right):** Titled "Representations Equipped with Symmetry and Invariance Geometric Deep Learning". It illustrates various geometric deep learning concepts: Perceptrons (function regularity), CNNs (translation), Group-CNNs (translation), LSTM (time varying), DeepSets/Foundations (permutation), GNNs (permutation), and Infix-CNN (learnable in-place choice).
- Slide 4 (Middle Left):** Titled "Symmetry and Invariance are Ubiquitous". It shows various applications of symmetry and invariance: Image Classification (rotation), Image Denoising (translation), Self-driving for object learning, Speech Denoising (time varying), Point Cloud Analysis (noise), and Prediction of Molecular Properties (permutation).
- Slide 5 (Middle Middle):** Titled "Outline of the Tutorial". It lists the following topics and durations: Introduction (20 min), Preliminaries of Invariance (20 min), Invariance in the era before deep learning (40 min), Invariance in the early era of deep learning (40 min), Invariance in the era of rethinking deep learning (40 min), and Conclusions and discussions (20 min).
- Slide 6 (Middle Right):** Titled "A Wide Range of Web-related Applications". It lists the following applications: Pattern recognition and data mining on graphs, Recommender systems and social networks, Cybersecurity and information forensics, Efficient web services, Non-learning end-side deployments, and Physical consistency enhancement for large generative models.
- Slide 7 (Bottom):** Titled "The good The ugly The bad". It features a large blue double-headed arrow pointing left and right. Inside the arrow is the text: "A Historical Perspective of Data Representation Rethinking Deep Learning with Invariance".

The image displays five book covers arranged in a collage. The top row features three books: 'Theory of Algebraic Invariants' by David Hilbert (Cambridge Mathematical Library), 'Geometric Invariant Theory' by D. Mumford, J. Fogarty, and B. Kirwan (Third Enlarged Edition, Springer), and 'Scale-Space Theory in Computer Vision' by Tony Lindeberg, Peter Taylor, Anders Forsberg, and David H. Stenstrom. The bottom row features two books: 'Moments and Moment Invariants in Pattern Recognition' by Jan Flusser, Tomáš Suk, and Barbara Zitová (Wiley), and 'Equivariant and Coordinate Independent Convolutional Networks: A Gauge Field Theory of Neural Networks' by Maurice Weiler, Patrick Forré, Erik Verlinde, and Max Welling (Springer).

# Tutorial Outline

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- **Part 1:** Background and challenges (20 min)
- **Part 2:** Preliminaries of invariance (20 min)
- *Q&A / Break (10 min)*
- **Part 3:** Invariance in the era before deep learning (30 min)
- **Part 4:** Invariance in the early era of deep learning (10 min)
- *Q&A / Coffee Break (30 min)*
- **Part 5:** Invariance in the era of rethinking deep learning (50 min)
- **Part 6:** Conclusions and discussions (20 min)
- *Q&A (10 min)*



**A Historical Perspective of Data Representation**  
**Rethinking Deep Learning with Invariance: The Good, The Bad, and The Ugly**