Rethink Deep Learning with Invariance in Data Representation

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

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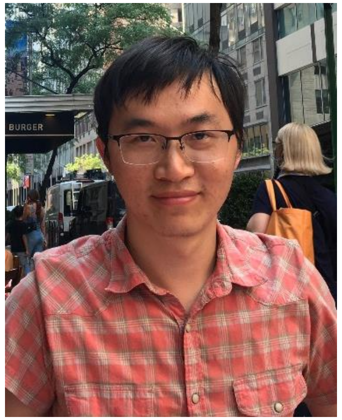

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Tutorial Homepage

Tutorial proposal, slides, reading list, video, and more materials available at

https://shurenqi.github.io/wwwtutorial/

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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 priors w.r.t. the task of interest. Here, the concept of *symmetry* from the *Erlangen Program* may be the most fruitful 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 data mining 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 last long before they encountered bottlenecks regarding robustness, interpretability, efficiency, and so on. The invariance principle has returned 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 application domains; • 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 a historical review of the invariance in data representations. The scope of this tutorial covers 1) the invariance in the era before deep learning, on 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***.

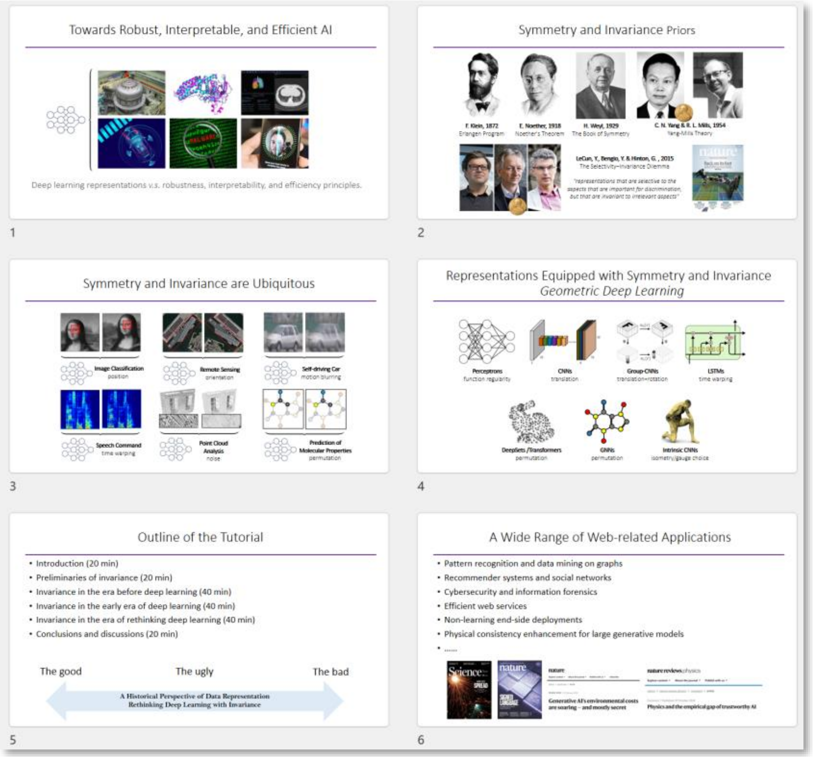
The presenters are qualified for a high-quality introduction to the topic. We have extensive research experience and strong publication records in representation backbones and downstream applications of pattern recognition and data mining. *More details are expanded in* ***Section 3***.

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 horizons) 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 currently 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, deep learning representations, e.g., convolutional neural networks (CNN) and transformer, have led to breakthrough results in numerous artificial intelligence (AI) tasks, e.g., processing human perceptual information, playing board games,



Tutorial Outline

- **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