Mathematical Artificial Intelligence for Networking and Communications

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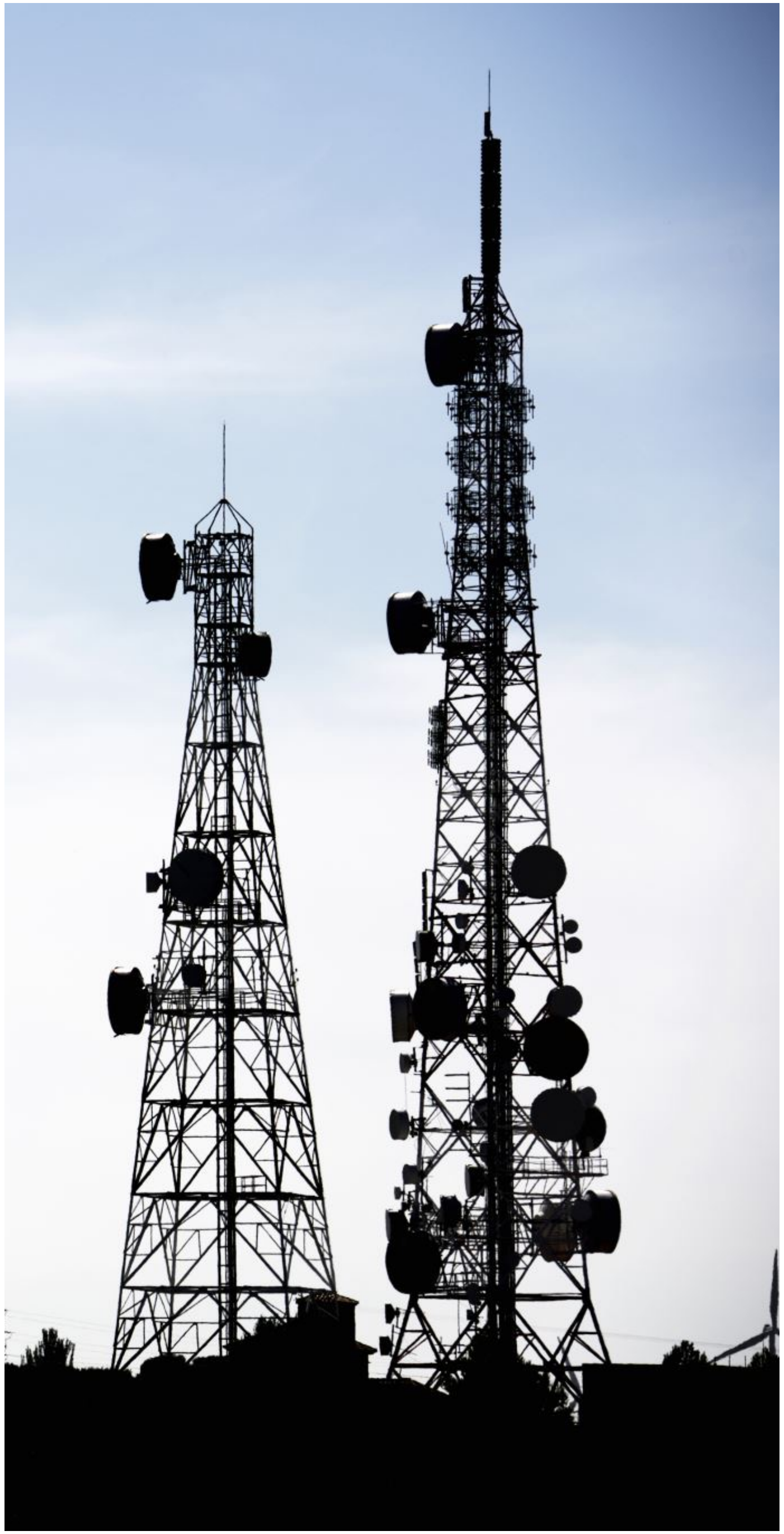
Outline

- Introduction
- Mathematical AI Current Status
- Mathematical AI Challenges
- Mathematical AI Applications in Networking and Communications
- Q&A

Introduction

AI becomes the core and engine in science and technology

- Large language models
- Fancy applications
- AI 4 Science
- You name it
- …



1. Introduction

Industrial roadmap (around 2020)

- 5G, AI for Networking
- 6G, Networking for AI

  - from GPU centered AI

  to network centered AI

1. Introduction

Big data（AI）and networking

Song Guo, Shui Yu, Jie Li, and Nirwan Ansari, “Big data for networking,” IEEE Network, vol 30, no 1, 2016.

Shui Yu, Xiaodong Lin, and Jelena Misic, “Networking for Big Data,” IEEE Network, vol 28, no 4, 2014.

AI application is brilliant, AI itself is mainly stalled

Has AI become alchemy ?（2018）

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IN DEPTH | COMPUTER SCIENCE

Has artificial intelligence become alchemy?

Matthew Hutson
+ See all authors and affiliations

Science 04 May 2018:
Vol. 360, Issue 6388, pp. 478
DOI: 10.1126/science.360.6388.478

Article | Figures & Data | Info & Metrics | eLetters | PDF

Summary

Ali Rahimi, a researcher in artificial intelligence (AI) at Google in San Francisco, California, has charged that machine learning algorithms, in which computers learn through trial and error, have become a form of "alchemy." Researchers, he says, do not know why some algorithms work and others don't, nor do they have rigorous criteria for choosing one AI architecture over another. Now, in a paper presented on 30 April at the International Conference on Learning Representations in Vancouver, Canada, Rahimi and his collaborators document examples of what they see as the alchemy problem and offer prescriptions for bolstering AI's rigor. The issue is distinct from AI's reproducibility problem, in which researchers can't replicate each other's results because of inconsistent experimental and publication practices. It also differs from the "black box" or "interpretability" problem in machine learning: the difficulty of explaining how a particular AI has come to its conclusions.

Limited progress in recent decades（2020）

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Core progress in AI has stalled in some fields

Matthew Hutson
+ See all authors and affiliations

Science 29 May 2020:
Vol. 368, Issue 6494, pp. 927
DOI: 10.1126/science.368.6494.927

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Summary

Artificial intelligence (AI) just seems to get smarter and smarter. The surge reflects faster chips, more data, and better algorithms. But some of the improvement comes from tweaks rather than the core innovations their inventors claim—and some of the gains may not exist at all. Researchers have evaluated 81 pruning algorithms, programs that make neural networks, a type of AI, more efficient by trimming unneeded connections. All claimed superiority in slightly different ways. But when the researchers tried to evaluate them side by side, there was no clear evidence of performance improvements over a 10-year period. There are other signs of shaky progress across AI. A 2019 meta-analysis of information retrieval algorithms used in search engines concluded the "high-water mark … was actually set in 2009." Another study in 2019 reproduced seven recommendation systems, of the kind used by media streaming services. It found that six failed to outperform much simpler algorithms developed years before, at least when the earlier techniques were fine-tuned, revealing "phantom progress."

The Current Landscape of AI Research

Current AI research is mainly application oriented

(Reasoning is less important, or not the top priority)

Statistics of AI for communication papers on the leading journals (early access)

Journal name	AI related papers	Total number of papers	Percentage
IEEE/ACM Trans. on Networking	2	30	6.7%
IEEE Trans. On Communications	8	162	4.9%
IEEE Trans. On Wireless Communications	6	125	4.8%

Assessed on

October 7, 2019

Journal name	AI related papers	Total number of papers	Percentage
IEEE/ACM Trans. on Networking	9	99	9.1%
IEEE Trans. On Communications	9	287	3.1%
IEEE Trans. On Wireless Communications	40	531	7.5%

Assessed on

July 1, 2024

The Current Landscape of AI Research

Data based

- Do you have the data?

Computing power demanding

- Do you have the money ?

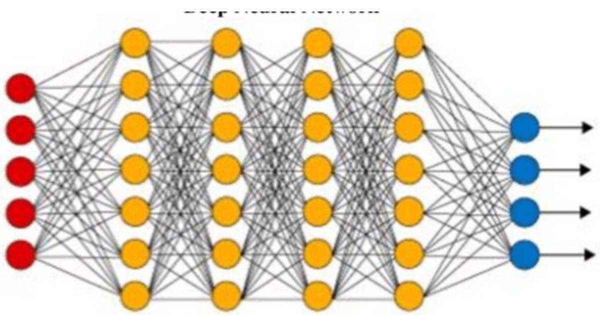
It is time for theoretical solutions – mathematical AI (MAI)

2. Current Research Landscape of Mathematical AI

Explainable AI (XAI)

Sample level:

Heatmap for learning contributions

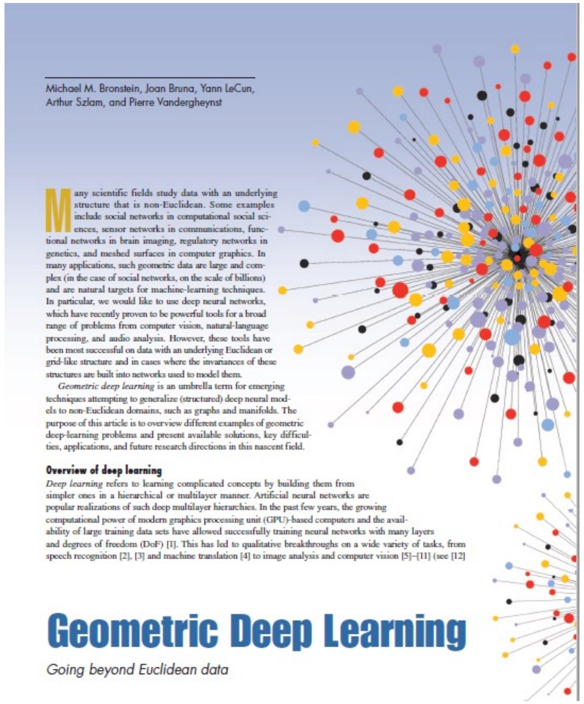


Model level:

Contribution of neural nodes

Explainable AI (XAI)

Geometric deep learning



Michael M. Bronstein, Joan Bruna, Yann LeCun, Arthur Szlam, and Pierre Vandergheynst

Many scientific fields study data with an underlying structure that is non-Euclidean. Some examples include social networks in computational social sciences, sensor networks in communications, functional networks in brain imaging, regulatory networks in genetics, and meshed surfaces in computer graphics. In many applications, such geometric data are large and complex (in the case of social networks, on the scale of billions) and are natural targets for machine-learning techniques. In particular, we would like to use deep neural networks, which have recently proven to be powerful tools for a broad range of problems from computer vision, natural-language processing, and audio analysis. However, these tools have been most successful on data with an underlying Euclidean or grid-like structure and in cases where the invariances of these structures are built into networks used to model them.

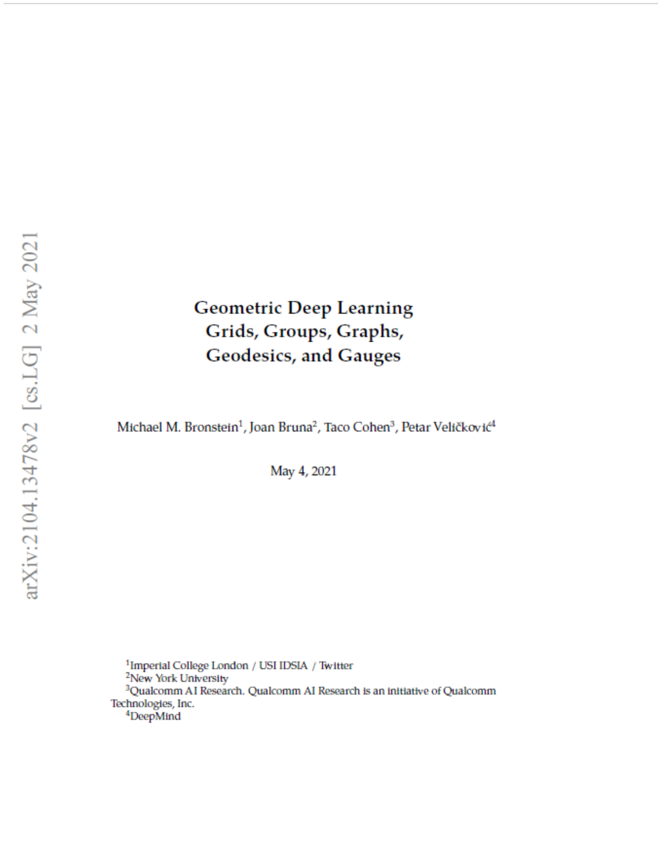
Geometric deep learning is an umbrella term for emerging techniques attempting to generalize (structured) deep neural models to non-Euclidean domains, such as graphs and manifolds. The purpose of this article is to overview different examples of geometric deep-learning problems and present available solutions, key difficulties, applications, and future research directions in this nascent field.

Overview of deep learning

Deep learning refers to learning complicated concepts by building them from simpler ones in a hierarchical or multilayer manner. Artificial neural networks are popular realizations of such deep multilayer hierarchies. In the past few years, the growing computational power of modern graphics processing unit (GPU)-based computers and the availability of large training data sets have allowed successfully training neural networks with many layers and degrees of freedom (DoF) [1]. This has led to qualitative breakthroughs on a wide variety of tasks, from speech recognition [2], [3] and machine translation [4] to image analysis and computer vision [5]–[11] (see [12]

Geometric Deep Learning

Going beyond Euclidean data



arXiv:2104.13478v2 [cs.LG] 2 May 2021

Geometric Deep Learning
Grids, Groups, Graphs,
Geodesics, and Gauges

Michael M. Bronstein[1], Joan Bruna[2], Taco Cohen[3], Petar Veličković[4]

May 4, 2021

[1]Imperial College London / USI IDSIA / Twitter
[2]New York University
[3]Qualcomm AI Research. Qualcomm AI Research is an initiative of Qualcomm Technologies, Inc.
[4]DeepMind

Capability of XAI

XAI is NOT the core of the business.

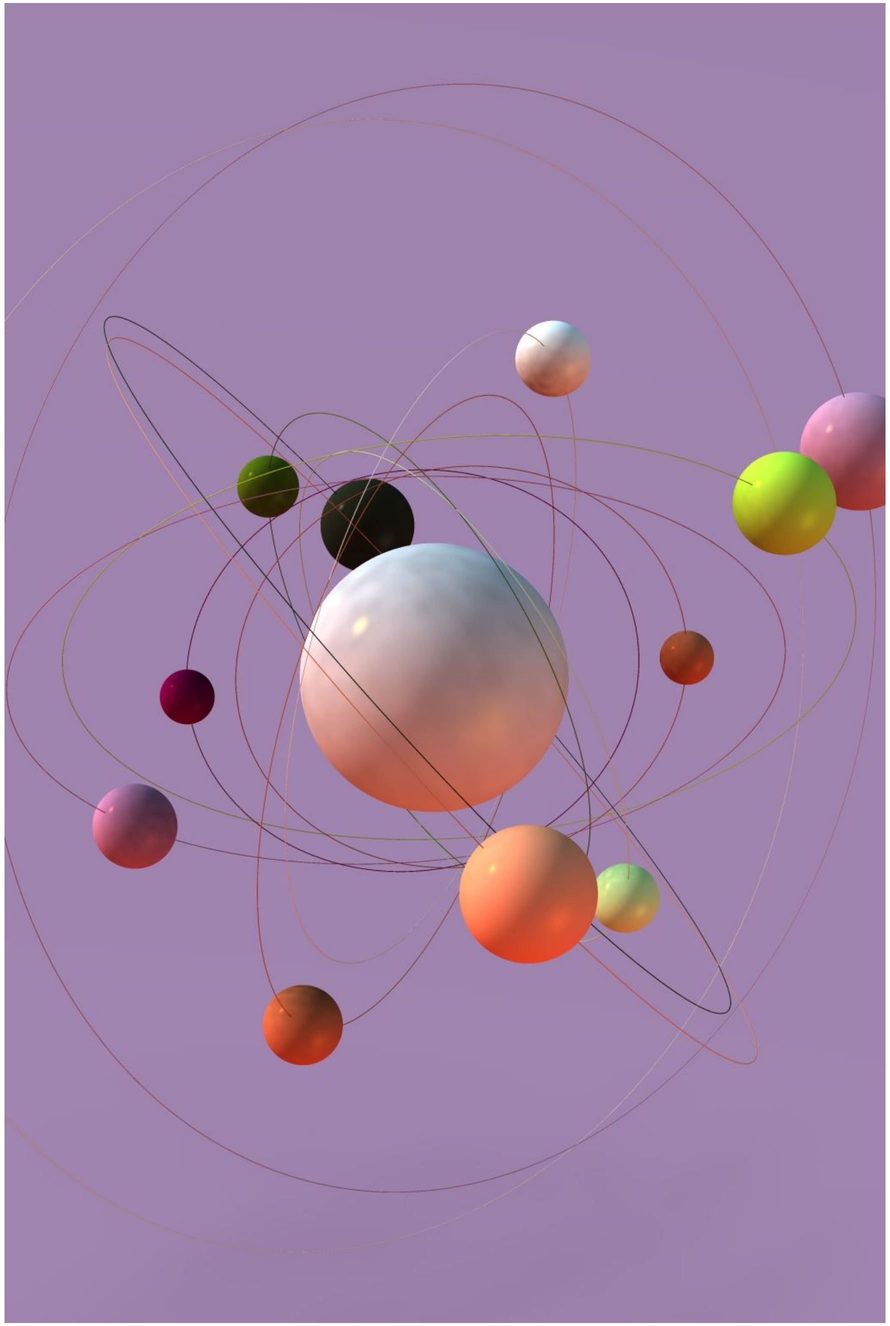
XAI can NOT predict **directly** in general.

Two Fundamental Problems of MAI

- High dimensional space

  - The curse of dimensionality in AI

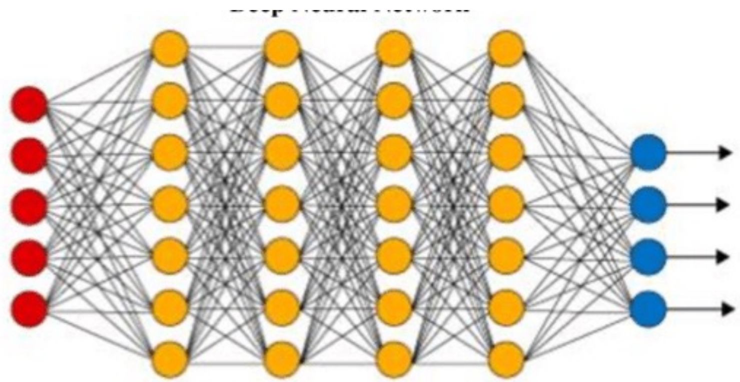
- Non-linearity (Riemannian Space)



3. Mathematical AI Challenges and Promising Directions

Mathematical AI (MAI)

[vectors matrices vectors]

X →  **Y**

high dimensional space

high dimensional space

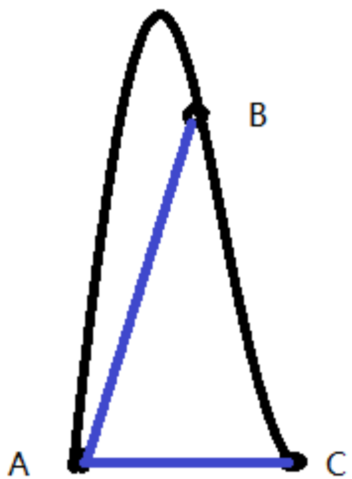
Challenge 1: Deal with high dimensional space

A popular solution: reduce the dimension
e.g. Primary Component Analysis (PCA),
an Euclidean space solution

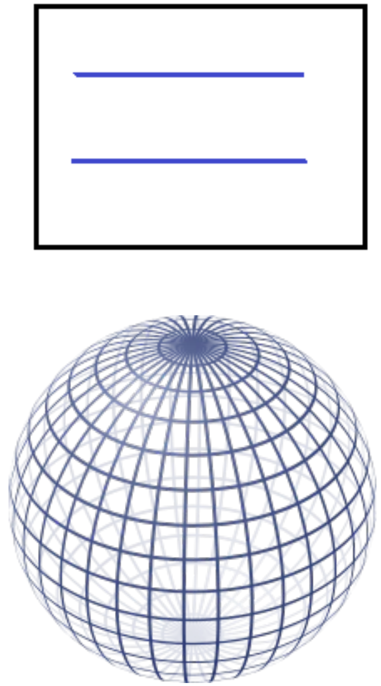
Problems in Dimension Reduction

High dimensional space is DIFFERENT from lower dimension space

Euclid space vs Riemannian space

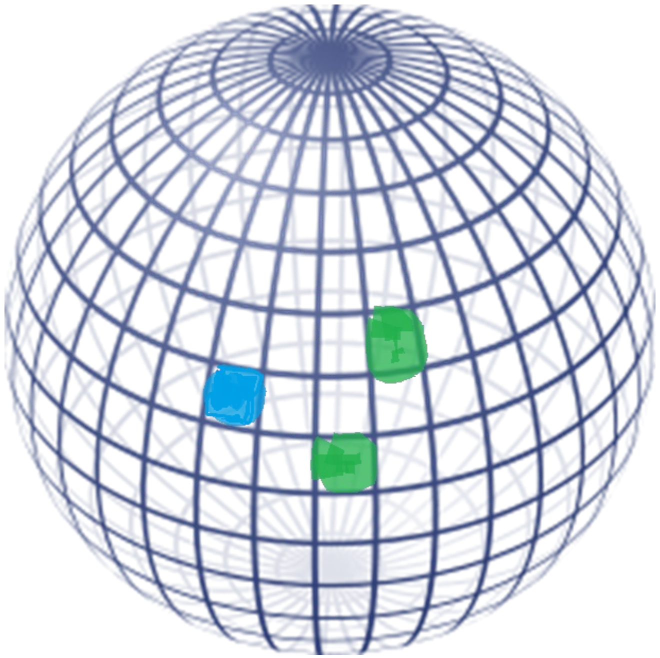


Distance

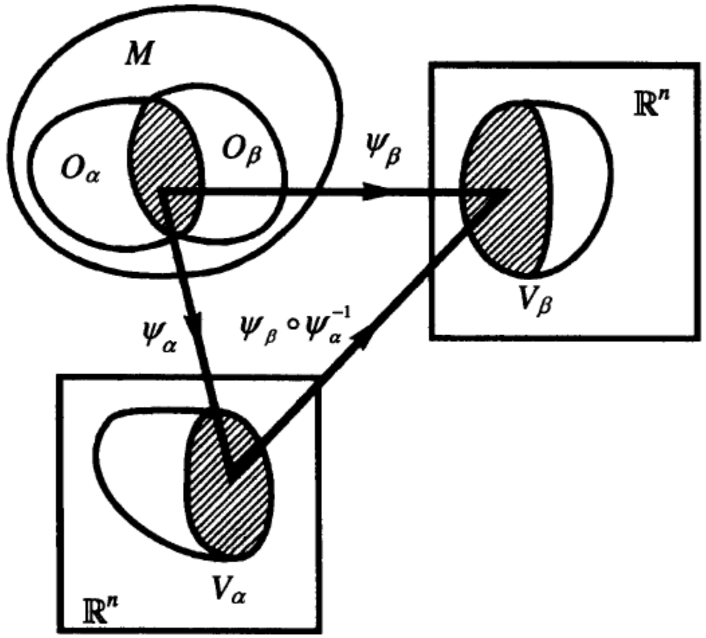


Parallel lines

Differential Geometry
– a tool for high dimensional space



Manifold



Basic Concepts of Differential Geometry

- Vector (space), v (V)
- Dual vector (space), $\omega : V \to \mathbb{R}$ (V*)
- Tensor, $T : \underbrace{V^* \times \cdots \times V^*}_{k\text{个}} \times \underbrace{V \times \cdots \times V}_{l\text{个}} \to \mathbb{R}\,.$
- Metric, curvature, parameterised curves, geodesic, …

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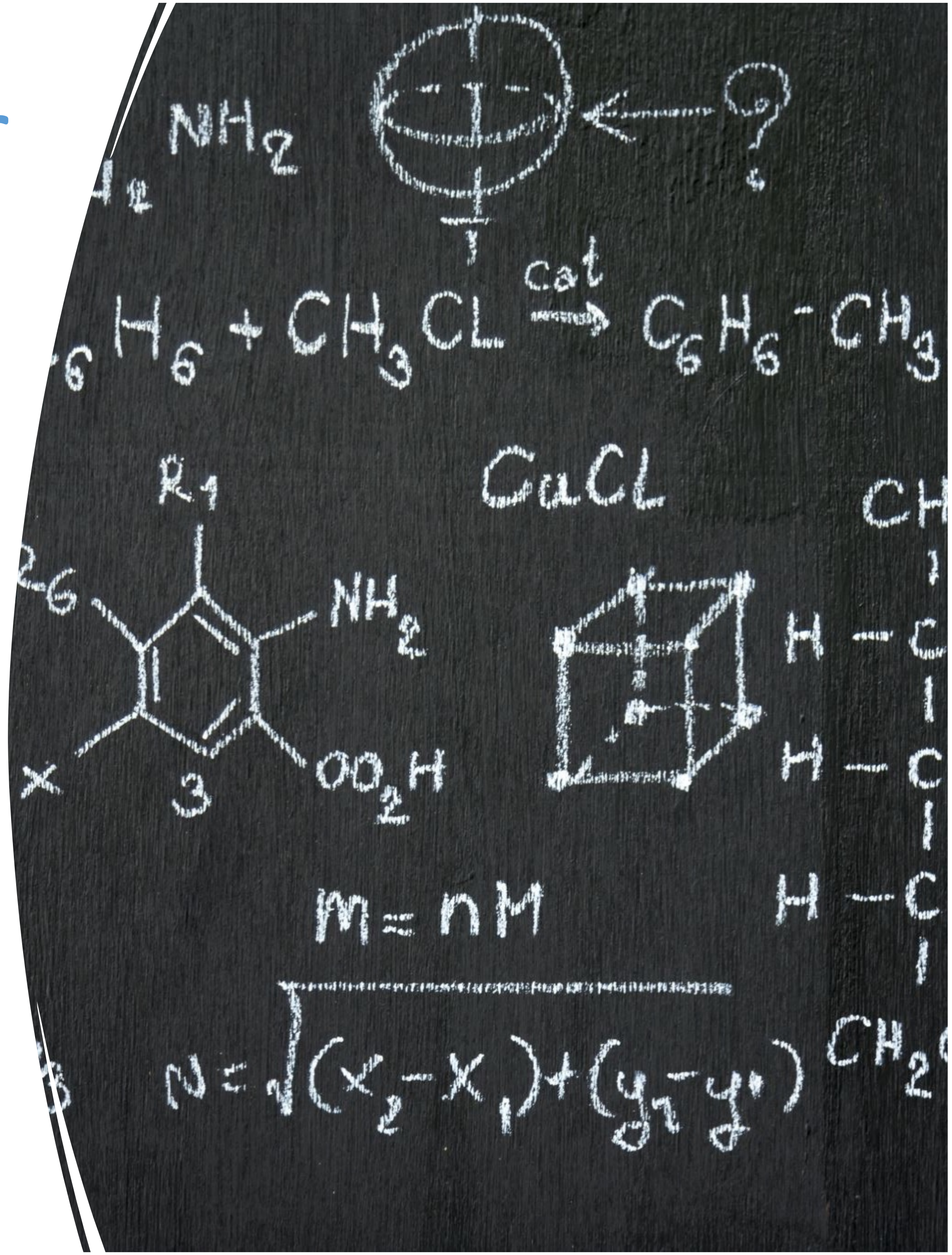
How to model our AI problems

Mathematical tools

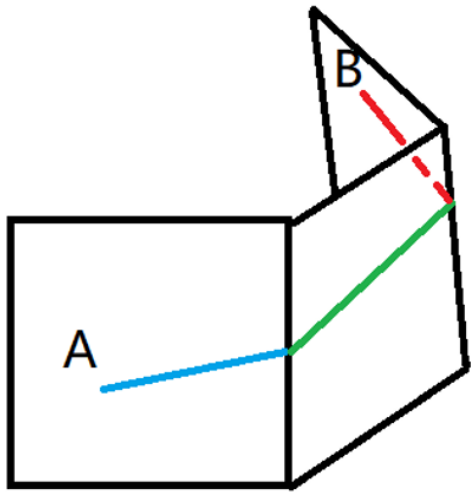
- **Digital Differential Geometry**
- **Optimal Transport**
- **Wasserstein Distance**
- **Persistent Homology**
- **Lie Group, Lie Algebra**
- **…**

Many Engineering Problems



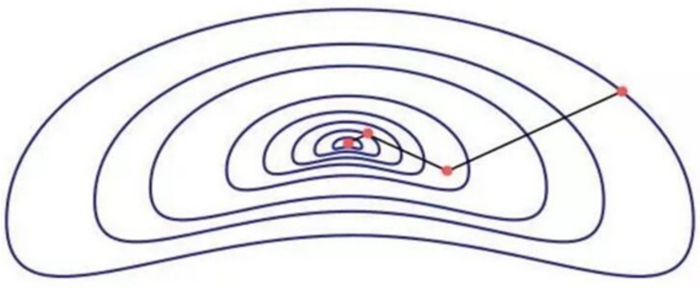
Example 1 Geodesic

- Shortest distance in curved surface (then high dimensional space)



AI Model Training

Geodesic for convergence optimization in AI training



First-Order Algorithms for Min-Max Optimization in Geodesic Metric Spaces

Michael I. Jordan Tianyi Lin Emmanouil V. Vlatakis-Gkaragkounis
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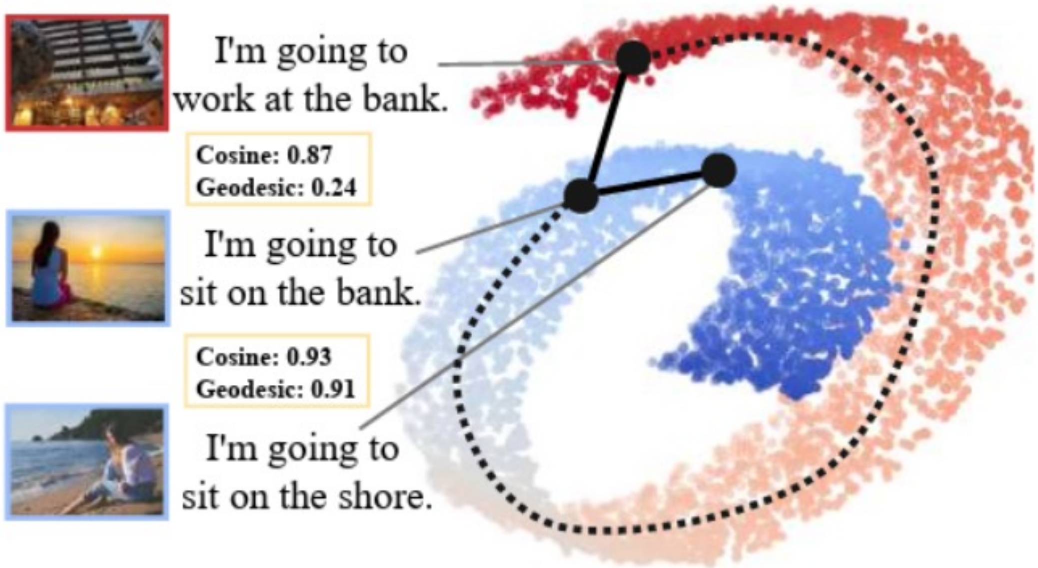
Abstract

From optimal transport to robust dimensionality reduction, a plethora of machine learning applications can be cast into the min-max optimization problems over Riemannian manifolds. Though many min-max algorithms have been analyzed in the Euclidean setting, it has proved elusive to translate these results to the Riemannian case. Zhang et al. have recently shown that geodesic convex concave Riemannian problems always admit saddle-point solutions. Inspired by this result, we study whether a performance gap between Riemannian and optimal Euclidean space convex-concave algorithms is necessary. We answer this question in the negative—we prove that the Riemannian corrected extragradient (RCEG) method achieves last-iterate convergence at a linear rate in the geodesically strongly-convex-concave case, matching the Euclidean result. Our results also extend to the stochastic or non-smooth case where RCEG and Riemanian gradient ascent descent (RGDA) achieve near-optimal convergence rates up to factors depending on curvature of the manifold.

NeurIPS 2022

Accurate Distance Measure

Geodesic for similarity measurement

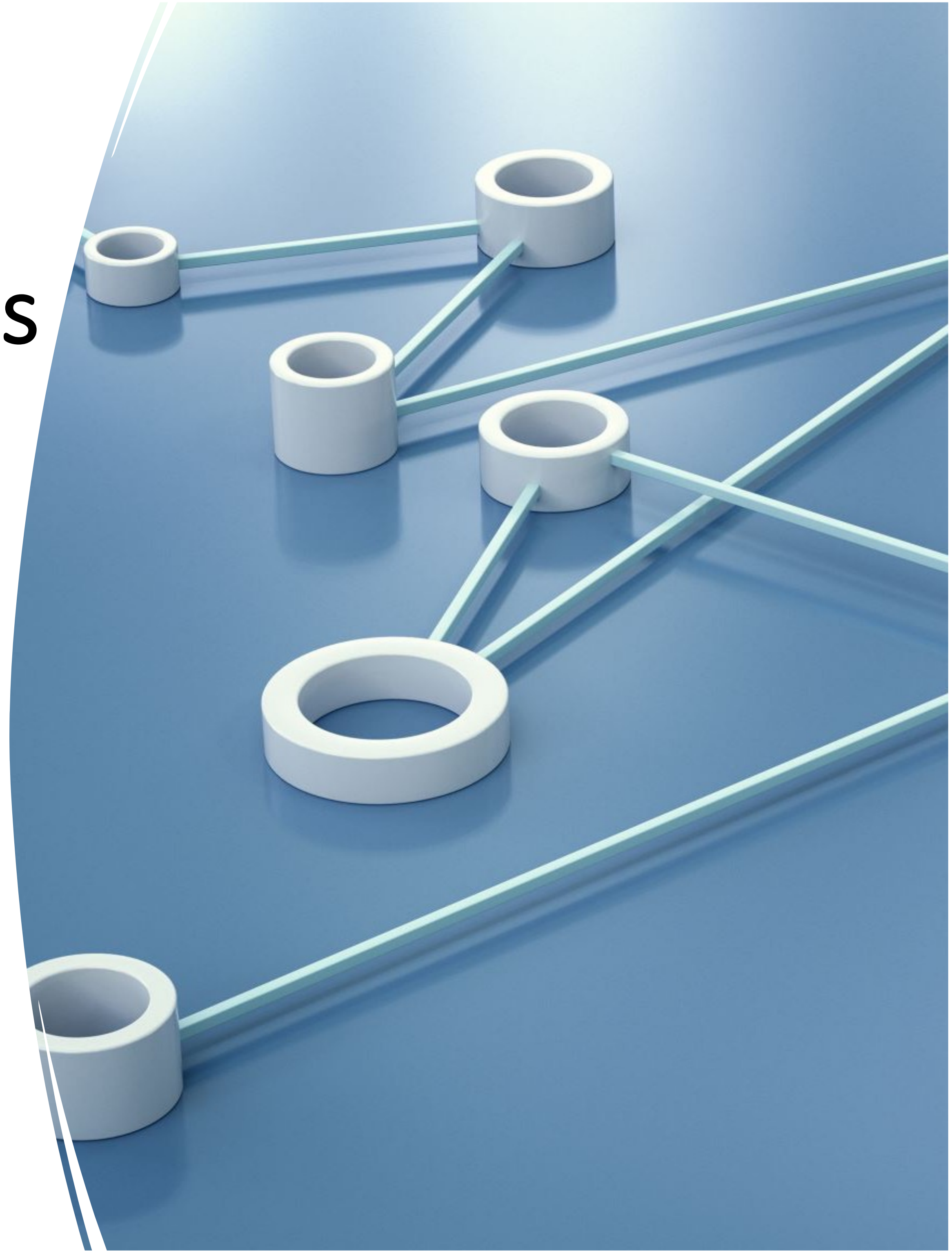


S. Mei, H. Wang, and B. Ni, GeoMM: On Geodesic Perspective for Multi-modal Learning, CVPR 2025

4. MAI for Networking and Communications

Semantic Communications

AI + Communications
AI + networking



Three levels of communication

Existing Communications →

As Weaver and Shannon summarized communications problems in a broad sense comprise three serially escalating levels as following:

- LEVEL A. The technical problem: How accurately can the symbols of communication be transmitted?

Semantic Communications →

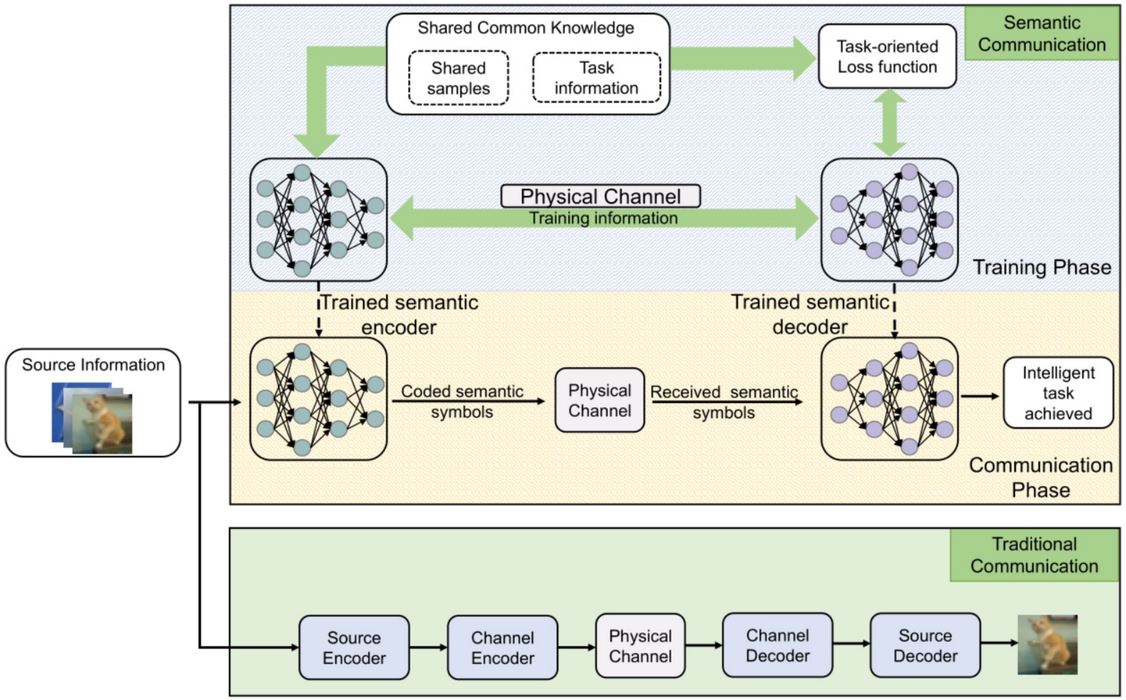
- LEVEL B. The semantic problem: How precisely do the transmitted symbols convey the desired meaning?

- LEVEL C. The effectiveness problem: How effectively does the received meaning affect con- duct in the desired way?

Critical Problems in Semantic Communications

- Semantic extraction
- Knowledge alignment
- Encoding & decoding

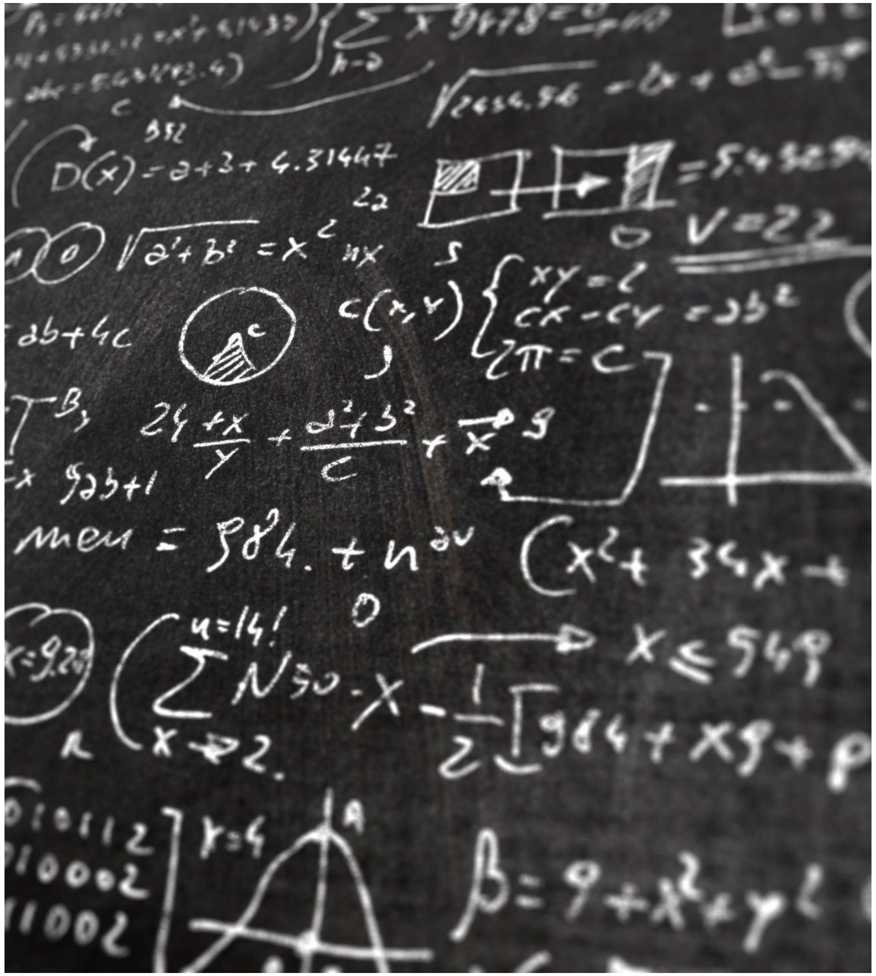
…



An Asynchronous Multi-Task Semantic Communication Method, Zhiyi Tian, Hiep Vo, et al., IEEE Network, Vol: 38, Issue: 4, July 2024.

Simple Examples

- Knowledge base alignment, integration
- GAI for many tasks, e.g., image compress, recovery
- …



Take away points

- It is time for theoretical research for AI.
- Morden math tools should and can be hired to tackle the challenges.

LET US WORK TOGETHER TO EXPLORE

We must know, we will know - David Hilbert

Thank you
&
Questions

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