ICIAM 2023: MS 02515

Novel DL methodologies in IAM

An overview

SX, EU Moya, U Cortés

IMTech & BSC

25/August/2023

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- Novel methodologies in IAM
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MARTA BARROSO (Chair): Research Engineer at the Barcelona Supercomputer Center (BSC), Leader of the European project KnowlEdge (Horizon 2020)

SILVIA FRANCHINI: Researcher at the National Research Council of Italy, Institute for High-Performance Computing and Networking.

YOLANDA VIDAL (Coorganizer): Associate Professor, Institute of Mathematics of UPC-BarcelonaTech (IMTech), Research group on Control, Data and Artificial Intelligence (CoDAlab), Department of Mathematics of UPC-BarcelonaTech.

Eduardo U. Moya (Coorganizer): Director of AI of the Jalisco Government (Mexico). Universidad Autónoma de Guadalajara (Mexico).

Sebastian Xambó-Descamps (Organizer): UPC Emeritus Professor, IMTech and BSC (Senior Visitor).

MARTA BARROSO: *AI Lifecycle Zero-touch Orchestration within the Edge-to-Cloud Continuum for Industry 5.0*.

SILVIA FRANCHINI: *Innovative Models for Explainable Artificial Intelligence*.

YOLANDA VIDAL: *Artificial Intelligence for Wind Turbine Predictive Maintenance*.

EDUARDO U. MOYA: *Applications of Quaternion Monogenic Signal ConvNet Layer*.

Scope Novel AI techniques in IAM and promising opportunities.

Instances

- wind turbine preventive maintenance;
- or predicting molecular weights of industrial polymers using diffusion NMR spectroscopy (Francisco M. Arrabal Campos);
- to advance in making AI more reliable by enabling it to cope with causality and thereby enhancing its explainability;
- to promote neural networks capable of directly processing geometric entities and use them for robust deep learning in various domains, including artificial vision;
- and to tackle with the engineering problems of multiphasic electric power generation (Francisco G. Montoya).
- harnessing AI for manufacturing pipelines in Industry 5.0.

[1] (xambo-moya-2021) *Geometric Calculi for DL: An outline*

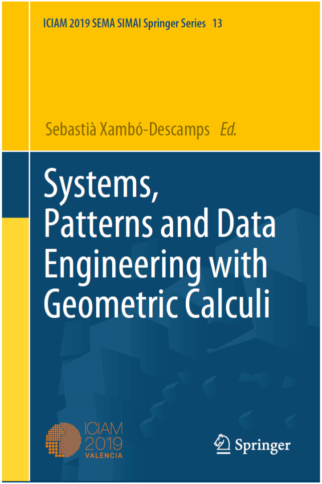
§1 Overview of conventional automatic learning

§2 Conventional NNs

§3 Geometric NNs*

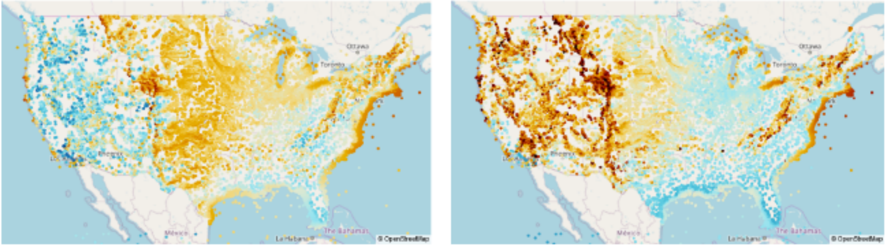
§4 Outlook

§5 References (179 items)



* A sketch of GA.
$\mathcal{A}$-neurons and $\mathcal{A}$-networks ($\mathcal{A}$-NNs).
Complex NNs (CxNNs).
Quaternion NNs (QNNs).
Geometric NNs (GNNs).
Other $\mathcal{A}$-NNs

- Work to be presented by Marta Barroso
- Work to be presented by Eduardo U. Moya
- [2] (salazar-moya-et4-2020)
  Fast single image defogging with robust sky detection
- [3] (manero-bejar-cortes-2022)
  Wind prediction using DL and high performance computing



(a) Wind-speed mean   (b) Wind-speed Variance

Fig. 1: Variance and Mean of the 126,692 NREL sites. The geography defines different site topologies with several combinations of mean and variance

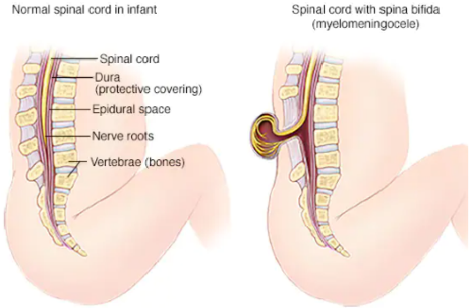
- [4] (alvarez-moya-sanchez-cortes-2022) *Automatic vehicle counting area creation based on vehicle DL detection and DBSCAN*
- [5] (arias-gimenez-cortes-garcia-2023) *Assessing Biases through Visual Contexts*

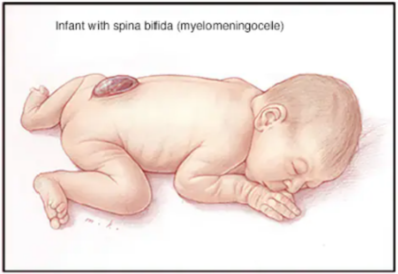
Figure 1. Sample instances by class and dataset. Each dataset is shown in a different column (from left to right): context (*C*); no context (*NC*); and white background (*WB*) dataset. Class examples are separated by row (from top to bottom): bench; plane; fire hydrant; and mug.

[6] (sayols-et6)
Robust tracking of deformable anatomical structures with severe occlusions applied to prenatal repair of Open Spina Bifida.

This paper develops a robust methodology to detect and track anatomical structures in real time to be used in automatic control of robotic systems and augmented reality. The work focuses on the experimental validation in highly challenging surgery: fetoscopic repair of Open Spina Bifida.

The proposed method is based on two sequential steps: first, selection of relevant points (contour) using a CNN and, second, reconstruction of the anatomical shape by means of deformable geometric primitives.





Spina bifida (myelomeningocele)

Myelomeningocele is a severe type of spina bifida in which the membranes and the spinal nerves protrude at birth, forming a sac on the baby's back. The exposed nervous system may become infected, so prompt surgery is needed after birth.

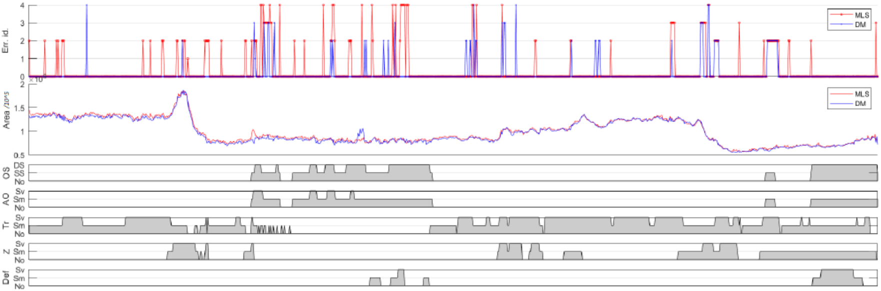


Fig. 7. Evolution of the obtained results per method (MLS and DM). Err. id. shows the observed error, classified by type (Err id: 0,..,4). The area shows the evolution of the ellipses areas (pixel^2) generated by MLS and DM. Finally, observed events (OS, AO, Tr, Z and Def) classified by severity (0,..,2) during the video sequence presented for the real scenario study.

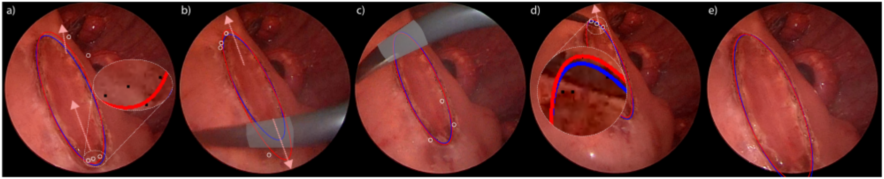


Fig. 8. Different illustrative examples of events and errors that occur in real scenarios. MLS reconstruction is represented in red and DM reconstruction in blue.

A. What can mathematics, physics, engineering do to improve/develop learning algorithms?

B. How can learning algorithms be used to fuel research in mathematics, physics, engineering?

C. In terms of **A** or **B**, what challenges and opportunities can be envisioned from the fast ongoing advances in AI?

[7] (berner-grohs-kutyniok-petersen-2021): *The modern mathematics of DL*

[8] (abbas-sutter-figalli-woerner-2021): *Effective dimension of machine learning models*

[9] (ye-2022) *Geometry of Deep Learning. A signal processing perspective*

[10] (bach-2023): *Learning Theory from First Principles*

[11] (lample-charton-2019): *Deep learning for symbolic mathematics*.

"In this paper we show that [supervised learning algorithms] can be surprisingly good at more elaborated tasks in mathematics, such as symbolic integration and solving differential equations. We propose a syntax for representing mathematical problems, and methods for generating large datasets that can be used to train sequence-to-sequence models. We achieve results that outperform commercial Computer Algebra Systems such as Matlab or Mathematica" (from the Abstract).

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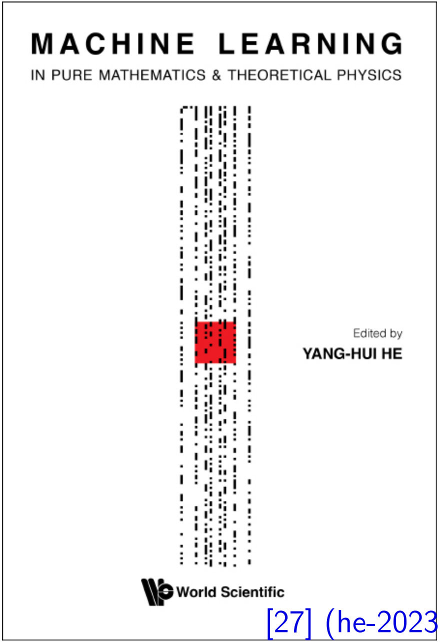
[14] (alessandretti-baronchelli-he-2019)
[15] (he-yau-2020)
[16] (cranmer-et6-2020)
[17] (peifer-stillman-halpern-2020)
Learning selection strategies in Buchberger's algorithm
[18] (heal-kulkarni-sertoz-2020)
[19] (hughes-2020)
[20] (li-et6-2020)
[21] (wagner-2021) *Constructions in combinatorics via NNs*
[22] (davies-et3-2021)
[23] (he-2021)
[24] (palermo-ye-singh-2021) (reasoning)
[25] (mitchell-2021) (reasoning)
[26] (drori-et13-2022)
[27] (he-2023) *ML in pure mathematics and theoretical physics*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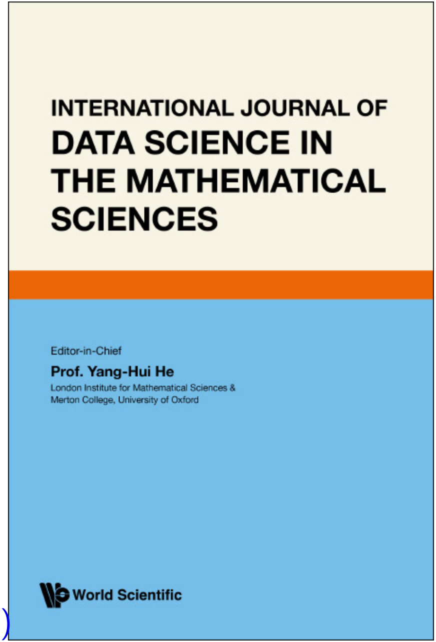
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Editor-in-Chief
Prof. Yang-Hui He
London Institute for Mathematical Sciences &
Merton College, University of Oxford
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[27] (he-2023)

[28] (he-2021-CY) (to math/phys),
[29] (raayoni-et8-2021) (to math/physics),
[30] (brunton-kutz-2019) (dynamical systems and control),
[31] (brandstetter-vandenberg-welling-gupta-2022) (PDE modeling),
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[35] (zaplana-2021) (robotics),
[36] (lavor-alves-2021) (molecular distance geometry),
[37] (davies-et13-2021) (guiding intuition with AI),
[38] (alet-et5-2021) (meta-learning conserved quantities),
[39] (jumper-et33-2021) (protein folding),
[40] (wani-et2-2021) (DL apps, vol 2),
[41] (wani-et3-2021) (DL apps, vol 3),

Electrical Power Systems

[42] (montoya-et3-2021),
[43] (montoya-eid-2021),
[44] (montoya-et4-2021-GA),
[45] (montoya-et4-2021vectorGA),
[46] (castro-londono-castro-2022)

PGA

[47] (dorst-dekeninck-2022-1),
[48] (dorst-dekeninck-2022-2) *A Guided Tour to the PGA*

Other

[49] (dechant-he-heyes-hirst-2022) (cluster algebras)
[50] (zaplana-hadfield-jlasenby-2022) (robotics w GA)

GNN, general

[51] (wang-shi-cao-2019),
[52] (townshend2-eismann-dror-2020) (geometric prediction),
[53] (dang-mai-qian-2022) (monogenic reproducing kernels),

CxNN

[54] (dramsch-soren-lutje-etal-2021),
[55] (wang-gui-gacanin-etal-2021),
[56] (bassey-li-qian-2021) (survey)

QNN

[57] (parcollet-et6-2019)
[58] (zhao-birdal-lenssen-menegatti-guibas-tombari-2020)
[59] (moya-xambo-perez-salazar-mzortega-cortes-2020-PRL)
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[62] (moya-xambo-sanchez-salazar-cortes-2021)
[63] (cao-li-zhong-2022) (human motion prediction)
[64] (roelfs-2021-quaternionic) (quaternionic step derivative)

Graph Neural networks

[65] (zhou-zheng-huang-2020),
[66] (pan-chen-ortega-2020),
[67] (jin-li-xu-wang-ji-aggarwal-tang-2020),
[68] (pan-chen-ortega-2021) (graph scattering transform),
[69] (batzner-et6-2021) (SE(3) equivariance),
[70] (chami-abuelhaija-perozzi-re-murphy-2022) (taxonomy),
[71] (zafeiriou-et8-2022) (non-eucl ML, guest editorial)

Open problems

[72] (murdoch-et3-2019),
[73] (hasan-calvet-rabbani-bartoli-2021) (3D pose of surgical tools).

Philosophies, speculations

[74] (ramge-2019)
[75] (samoili-et5-2020) (AI taxonomy)
[76] (henning-2020) (AI, gamechanger),
[77] (marcus-2020) (AI, next decade),
[78] (molnar-2020) (Interpretable ML),
[79] (macaskill-2022) (what we owe to the future)

AI, quo vadis?

[80] (taylor-et8-2022-galactica)

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[84] (parcollet-morchid-linares-2020) *A survey of **quaternion neural networks***

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[86] (jiang-luo-2021) *Graph neural network for **traffic forecasting**: A survey*

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[90] (bayro-2021) *A aurvey on quaternion algebra and geometric algebra applications in engineering and computer science 1995-2020*

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[95] (ding-xu-tong-liu-2022) *Data augmentation for **deep graph learning**: a survey*

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Showing 1–50 of 20,074 results for title: survey

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[101] (pan-et5-2023) *Automatically Correcting **Large Language Models**: Surveying the landscape of diverse **self-correction** strategies*

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[103] (li-wu-pan-2023) ***Network Security** in the Industrial Control System: A Survey*

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Thank you!

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