Aarhus Math&AI Workshop

27-30 January 2026

AIAS Aarhus

Alberto Alfarano *AxiomMath*

Generative methods in combinatorics

Abstract. Generative AI models learn to represent mathematical objects, encoded as sequences of tokens, as vectors in high-dimensional space. Once trained on elements of a particular class, these models can generate new elements of the same class. This has natural applications in combinatorial search: a model trained on candidate solutions to an optimization problem can generate new candidates, which are then refined through local search; retraining on the best results iteratively improves the solutions the model produces. I will present PatternBoost2, with applications to problems in extremal combinatorics including the construction of graphs avoiding short cycles and point configurations avoiding geometric constraints.

Seewoo Lee *Berkeley*

How machines learn Galois groups

Abstract. In earlier work by He, Lee, and Oliver, it was observed that classical machine learning algorithms can effectively predict various invariants of number fields, including their Galois groups. However, the reasoning behind the models' decision-making remained unclear. In this work, we interpret these models to explain how they achieve such high predictive accuracy for Galois groups. Our analysis leads to new theorems. This is joint work with Kyu-Hwan Lee.

Johannes Schmitt *ETH Zürich*

Benchmarking AI on Research Level Mathematics Problems

Abstract. Which available models are best at solving math problems? Are capabilities continuing to increase, or are we seeing a plateau? To answer such questions, I will discuss a range of benchmarking projects: what questions they include, how they evaluate the candidate AI models, and how model scores developed over time. I will also try to share some insights from developing IMProofBench, an example of such a benchmark developed within academia, which provides models with extensive tool access and combines both human and automated grading. The IMProofBench project is joint work with G. Bérczi, J. Dekoninck, J. Feusi, T. Gehrunger and over 30 other mathematicians who contributed or reviewed questions.

Terence Tao *UCLA*

AI contributions to Erdos problems

Abstract. Recently, AI tools have made a number of interesting contributions to several problems of Paul Erdos that were open (or thought to be open). We survey these developments, and speculate on further AI-assisted progress on these types of problems.

Kyu-Hwan Lee *Connecticut*

Extracting a Zeta Map Bijection on Dyck Paths from Machine Learning Models

Abstract. There is a large class of problems in algebraic combinatorics which can be distilled into the same challenge: construct an explicit combinatorial bijection. Traditionally, researchers have solved challenges like these by visually inspecting the data for patterns, formulating conjectures, and then proving them. But what is to be done if patterns fail to emerge until the data grows beyond human scale? In this talk, we propose a new workflow for discovering combinatorial bijections via machine learning. As a proof of concept, we train a transformer on paired Dyck paths and use its learned attention patterns to derive a new algorithmic description of the zeta map, which we call the Scaffolding Map.

Javier Gómez-Serrano *Brown*

Discovery of unstable singularities

Abstract. In this talk I will explain how to construct numerically several new unstable singularities to certain equations in fluids (CCF, IPM, Boussinesq) using machine learning methods. Our approach combines curated machine learning architectures and training schemes with a high-precision Gauss-Newton optimizer, achieving accuracies that significantly surpass previous work across all discovered solutions, reaching near double-float machine precision, attaining a level of accuracy constrained only by the round-off errors of the GPU hardware, potentially leading to rigorous mathematical validation via computer-assisted proofs.

Aurelien Dersy *Harvard*

Learning the language of scattering amplitudes

Abstract. Machine learning (ML) has grown dramatically in high-energy physics in recent years, yet its use for symbolic reasoning in theoretical physics is still emerging. In this talk, I will discuss how modern models can “learn the language” of scattering amplitudes and assist with analytic tasks. I will focus on simplifying amplitude expressions, reconstructing S-matrix phases, and aspects of the amplitude bootstrap. I will present a practical perspective on hybrid workflows, where ML-guided proposals combine with exact verification to produce reliable, checkable results.

María Inés de Frutos Fernández *Bonn*

The Carleson formalization project.

Abstract. A well-known result in Fourier analysis establishes that the partial Fourier sums of a smooth periodic function f converge uniformly to f, but the situation is a lot more subtle in more general settings (for instance, when f is a continuous function). However, in 1966 Carleson proved that they do converge at almost all points for L^2 periodic functions on the real line. Carleson’s proof is famously hard to read, and there are no known easy proofs of this theorem.

From June 2024 to July 2025, as a large collaborative project, we formalized in Lean a generalization of Carleson’s theorem proven by the Bonn harmonic analysis group in 2023, and Carleson’s original result as a corollary. In this talk I will give an overview of the project, focusing on the lessons we learned and the organization of the collaboration.

Daniel Zheng *Google DeepMind*

Expanding the envelope; Designing AI for informal mathematics

Abstract. Language models have made incredible progress in problem solving in the last few years, but the process of doing mathematics research is much broader than just solving problems. I will talk a little about how we got here, and ways to think about new capabilities that we could work towards in the future.