Toutelia 2021 – Geometry Topology and AI

Friday September the 10th 2021

Amphiteatre Schwartz

Institut de Mathématiques de Toulouse

118 Route de Narbonne

Toulouse

Programme :

9h00-9h30	Welcome		
9h30-10h30	Yang Hui He The London Institute, Royal Institution of Great Britain	*Machine-Learning Mathematical Structures*	We report and summarize some of the recent experiments in supervised machine-learning of various structures from different fields of mathematics, ranging from geometry, to representation theory, to combinatorics, to number theory. We speculate on a hierarchy of inherent difficulty and where geometric and compbinatorial problems tend to reside.
10h30-11h00	Coffee break		
11h00-12h00	Steve Oudot Inria Saclay	*Toward Explainable Topological Features for AI*	This talk will be a review of the efforts of the Topological Data Analysis (TDA) community to design effective features for data, to be used in applications, and to make these features explainable. After a general introduction on TDA, the main focus will be on recent attempts to invert the TDA operator. While this line of work is still in its infancy, the hope on the long run is to use inverses for feature interpretation. The mathematical tools involved in the analysis come mainly from metric geometry, spectral theory, and the theory of constructible functions---specific pointers will be given in the course of the exposition.
12h00-14h00	Lunch break		
14h00-15h00	Piotr Sulkowski Faculty of Physics, University of Warsaw	*Knots and AI - Learning to unknot*	I will discuss various features of knot theory that make it a particularly interesting playground from the viewpoint of machine learning. In particular, I will focus on the unknot recognition problem, and show how successfully it can be solved combining techniques from machine learning and natural language processing
15h00-15h30	Coffee break		
15h30-16h30	Fabian Ruehle (via zoom) College of Science Northeastern University	*Moduli-dependent Calabi-Yau and SU(3)-structure metrics from Machine Learning*	Calabi-Yau manifolds play a crucial role in string compactifications. Yau's theorem guarantees the existence of a metric that satisfies the string's equation of motion. However, Yau's proof is non-constructive, and no analytic expressions for metrics on Calabi-Yau threefolds are known. We use machine learning, more precisely neural networks, to learn Calabi-Yau metrics and their Kahler and complex structure moduli dependence. I will start with an introduction to Calabi-Yau manifolds and their moduli. I will then illustrate in an example how we train neural networks to find Calabi-Yau metrics by solving a Monge-Ampere type partial differential equation. The approach generalizes to manifolds with reduced structure, such as SU(3) structure or G2 manifolds, which feature in string compactifications with flux and in the M-theory formulation of string theory, respectively. I will illustrate this generalization for a particular SU(3) structure metric and compare the machine learning result to the known, analytic expression.