Plenary Lectures
Conférences plénières

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REDIET ABEBE, University of California Berkley
What Can Algorithms Tell Us About Inequality?

The dynamic nature of poverty presents a challenge in designing effective assistance policies. A significant gap in our understanding of poverty is related to the role of income shocks in triggering or perpetuating cycles of poverty. Such shocks can constitute unexpected expenses – such as a medical bill or a parking ticket – or an interruption to one's income flow. Shocks have recently garnered increased public attention, in part due to prevalent evictions and food insecurity during the COVID-19 pandemic. However, shocks do not play a corresponding central role in the design and evaluation of poverty-alleviation programs.

To bridge this gap, we present a model of economic welfare that incorporates dynamic experiences with shocks and pose a set of algorithmic questions related to subsidy allocations. We then computationally analyze the impact of shocks on poverty using a longitudinal, survey-based dataset. We reveal insights about the multi-faceted and dynamic nature of shocks and poverty. We discuss how these insights can inform the design of poverty-alleviation programs and highlight directions at this emerging interface of algorithms, economics, and social work.

RICHARD HOSHINO, Northeastern University
Creating Authentic Mathematical Experiences

Several years ago, I published an op-ed in the Toronto Star newspaper, arguing that far too many of our students spend their formative years doing what no mathematician would call mathematics. Instead of providing high school students and undergraduate students with authentic mathematical experiences that develop their creativity and problem-solving skills, the majority of students receive a watered-down product, the equivalent of learning art using Paint By Numbers.

In this interactive presentation, I will share six stories of authentic mathematical experiences, three stories from my life as a student and three stories from my life as an educator. I will share the key characteristics of each story that led to transformational change in the learner, and explore how these stories might relate to each of our lives, as mathematicians and as mathematics educators.

DIMITRIS KOUKOULOPOULOS, University of Montreal
Rational approximations of irrational numbers

Given quantities $\Delta_1, \Delta_2, \cdots \geqslant 0$, a fundamental problem in Diophantine approximation is to understand which irrational numbers x have infinitely many reduced rational approximations a/q such that $|x - a/q| < \Delta_q$. Depending on the choice of Δ_q and of x, this question may be very hard. However, Duffin and Schaeffer conjectured in 1941 that if we assume a "metric" point of view, the question is governed by a simple zero–one law: writing φ for Euler's totient function, we either have $\sum_{q=1}^{\infty} \varphi(q)\Delta_q = \infty$ and then almost all irrational numbers (in the Lebesgue sense) are approximable, or $\sum_{q=1}^{\infty} \varphi(q)\Delta_q < \infty$ and almost no irrationals are approximable. In this talk, I will present the history of the Duffin–Schaeffer conjecture and the main ideas behind the recent work in collaboration with James Maynard that settled it.

DOINA PRECUP, McGill University / Mila / DeepMind
On Hierarchical Reinforcement Learning

Reinforcement Learning allows intelligent agents to learn by interacting with their environment over time and receiving rewards. Hierarchical Reinforcement Learning (HRL) approaches promise to provide more efficient solutions to sequential decision making problems, both in terms of statistical as well as computational efficiency. While this has been demonstrated empirically over time in a variety of tasks, theoretical results quantifying the benefits of such methods are still few and far between. In this talk, I will discuss the theoretical underpinnings of HRL in the framework of Markov and semi-Markov Decision Processes. I will describe the kind of structure in a Markov decision process which gives rise to efficient HRL methods. Specifically, we formalize the intuition that HRL can exploit repeating sub-structures. We show that, under reasonable assumptions, such algorithms can achieve statistical efficiency, as established through a finite-time regret bound, as well as near-optimal and computationally efficient planning, using hierarchical models.