

	MON	TUE	WED	THU	FRI	SAT
09.00-10.00	Breakfast	Breakfast	Breakfast	Breakfast	Breakfast	Breakfast
09.50-10.00	Opening	Free time	Free time	Free time	Free time	Departure for Moscow
10.00-10.30	Welcome Notes					
10.30-11.30	Ilya Chevyrev	Ilya Chevyrev	Ilya Chevyrev	Beatrice Acciaio	Beatrice Acciaio	
11.30-12.00			James Foster			
12.00-12.30	Coffee break	Coffee break	Coffee break	Coffee break	Coffee break	
12.30-13.30	Student Talks	Antoine Savine	Student Talks	Student Talks	Beatrice Acciaio	
13.30-14.00					Closing Notes	
14.00-15.30	lunch	lunch	lunch	lunch	lunch	
15.30-16.00	Ilya Chevyrev	Antoine Savine	Alfred Galichon	Beatrice Acciaio		
16.00-16.30						
16.30-17.00	Coffee break	Coffee break		Coffee break		
17.00-17.30			Coffee break		Student Trip	
17.30-18.00	Blanka Horvath	Mikko Pakkanen	Alfred Galichon	Alfred Galichon		
18.00-18.30						
18.30-19.00	Student Talks	Student Talks				
19.00-20.00	Dinner	Dinner	Dinner	Dinner	Closing dinner at the bonfire	
20.00-21.00						

# August 29th - September 4th

## Ilya Chevyrev

Topic: A Primer on the Signature Method in Machine Learning

## Antoine Savine

Topic: Differential Machine Learning

## Blanka Horvath

Topic: Harnessing quantitative finance by deep learning

## Mikko Pakkanen

Topic: Harnessing quantitative finance by deep learning

## James Foster

Topic: Neural Stochastic Differential Equations for Time Series Modelling

## Alfred Galichon

Topic: Optimal Transport Methods for Economic Models

## Beatrice Acciaio

Topic: Optimal Transport Methods in Machine Learning: from the Sinkhorn algorithm to Generative Adversarial Networks



# Abstracts

## Beatrice Acciaio

ETH Zurich, Switzerland

Optimal Transport Methods in Machine Learning: from the Sinkhorn algorithm to Generative Adversarial Networks

We start by recalling tools from the classical optimal transport (OT) theory, and then we introduce new developments in OT, specifically what is now called causal optimal transport (COT). We illustrate how the concept of causality in OT is the suitable one in order to tackle dynamic problems, where time plays a crucial role, especially in a financial context. We then consider regularized optimal transport problems, and the Sinkhorn algorithm used for computing entropic OT. Further, we review recent development of generative adversarial networks (GANs), which employ tools from OT theory. We then combine all the above concepts to train a network to generate or predict (financial) time series. Finally, we discuss the results and the numerical challenges.

## Ilya Chevyrev

University of Edinburgh, UK

A Primer on the Signature Method in Machine Learning

The signature of a path has been recognised in the last few years as a powerful method to store information about a path. At its basic level, the signature is the collection of iterated integrals of a path. This simple definition leads to surprisingly deep properties, which all indicate that the signature is a natural analogue of polynomials on paths. In this minicourse, I will present the definition of the signature and how it arises in several contexts, including control theory and stochastic differential equations. I will demonstrate some of its important properties: these include the shuffle identity, which is responsible for the polynomial-like behaviour on paths, and the Chen identity, which is important for computations. In the last part of the course, I will discuss some recent applications to machine learning, focusing on kernel learning and classification tasks.

## Antoine Savine

Danske Bank and Copenhagen University, Denmark

Differential Machine Learning

Differential machine learning (ML) extends supervised learning, with models trained on examples of not only inputs and labels, but also differentials of labels to inputs. Differential ML is applicable in all situations where high quality first order derivatives wrt training inputs are available. In the context of financial derivatives risk management, pathwise differentials are efficiently computed with automatic adjoint differentiation (AAD). Differential ML, combined with AAD, provides extremely effective pricing and risk approximations. We can produce fast pricing analytics in models too complex for closed form solutions, extract the risk factors of complex transactions and trading books, and effectively compute risk management metrics like reports across a large number of scenarios, backtesting and simulation of hedge strategies, or capital regulations.

## Alfred Galichon

New York University, USA

Optimal Transport Methods for Economic Models

This course is focused on the computation of competitive equilibrium, which is at the core of surge pricing engines and allocation mechanisms. It will investigate diverse applications such as network congestion, surge pricing, and matching platforms. It provides a bridge between theory, empirics and computation and will introduce tools from economics, mathematical and computer science. Mathematical concepts (such as lattice programming, supermodularity, discrete convexity, Galois connections, etc.) will be taught while studying various economic models. The same is true of computational methods (such as 'tatonnement' algorithms, asynchronous parallel computation, mathematical programming under equilibrium constraints, etc.).

## Blanka Horvath

King's College London, UK

## Mikko Pakkanen

Imperial College London, UK

Harnessing quantitative finance by deep learning

Deep learning is currently making headway in the realm of quantitative finance, whilst the financial industry is increasingly embracing data-driven workflows powered by machine learning and data science. In this minicourse, we shall present some of the recent advances of deep learning applied to quantitative finance. After a brief introduction to the basic principles of deep learning, we will explain how it can be applied to derivatives pricing, hedging and market data simulation in a novel way. We will demonstrate these methods by extensive numerical examples.

## James Foster

Oxford University, UK

Neural Stochastic Differential Equations for Time Series Modelling

Stochastic differential equations (SDEs) are a popular model for describing continuous-time phenomena and have seen particular success in the pricing and hedging of financial derivatives. However, given the current data science revolution and following the seminar paper "Neural Ordinary Differential Equations", it is natural to investigate how SDE methodologies could be improved using tools from machine learning. This has led to several recent works on so-called "Neural SDEs", which seek to combine the modelling capabilities of SDEs with the flexibility and efficient training of neural networks. In this talk, I will give an overview of these developments and show how SDEs can be viewed as time series models that fit nicely with well-known ideas from data science, such as generative adversarial networks (GANs).

The course focuses on differential deep learning (DL), arguably the strongest application. We will show how standard DL trains neural networks (NN) on punctual examples, whereas differential DL teaches them the shape of the target function, resulting in vastly improved performance, illustrating it with a number of numerical examples, both idealized and real world. We will also discuss how to apply differential learning to other ML models, like classic regression or principal component analysis (PCA).

