

# **PCCP Workshop Series : Bayesian Deep Learning for Cosmology and Gravitational waves**

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PCCP, APC laboratory, Université de Paris

## **Recueil des résumés**



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## **Tutorial: overview of the differences between MCMC and Variational Inference**

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## **TensorFlow Probability - Brian Patton, Junpeng Lao (TensorFlow Probability - Google)**

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## **Deep learning dark matter map reconstructions and parameter inference with Dark Energy Survey data**

Auteur: Niall Jeffrey<sup>1</sup>

<sup>1</sup> École normale supérieure

Auteur correspondant niall.jeffrey@phys.ens.fr

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## **Neural networks estimation of the dense-matter equation of state from neutron-star observables**

Auteur: Filip Morawski<sup>1</sup>

<sup>1</sup> Nicolaus Copernicus Astronomical Center of the Polish Academy of Sciences

**Auteur correspondant** fmorawski@camk.edu.pl

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## Star-galaxy separation via Gaussian Processes with Neural Network Dual Kernels

**Auteur:** Imene Goumiri<sup>1</sup>

<sup>1</sup> llnl

**Auteur correspondant** goumiri1@llnl.gov

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## Detection of gravitational-wave signals from binary neutron star signals using machine learning

**Auteur:** Marlin Benedikt Schäfer<sup>1</sup>

<sup>1</sup> Albert Einstein Institut Hannover (AEI Hannover)

**Auteur correspondant** marlin.schaefer@aei.mpg.de

**Contribution talks / 34**

## Deep learning for a faster Hamiltonian Monte Carlo sampler

**Auteur:** Marc Arène<sup>1</sup>

<sup>1</sup> APC

**Auteur correspondant** marc.arene@apc.in2p3.fr

**Contribution talks / 35**

## Galaxy Zoo: Probabilistic Morphology through Bayesian CNNs and Active Learning

**Auteur:** Mike Walmsley<sup>1</sup>

<sup>1</sup> University of Oxford

**Auteur correspondant** mike.walmsley@physics.ox.ac.uk

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## **Bayesian parameter estimation using conditional variational autoencoders for gravitational wave astronomy**

**Auteur:** Hunter Gabbard<sup>1</sup>

<sup>1</sup> *University of Glasgow*

**Auteur correspondant** h.gabbard.1@research.gla.ac.uk

**Contribution talks / 37**

## **Denoising gravitational wave signals with a variational autoencoder**

**Auteur:** Philippe BACON<sup>1</sup>

<sup>1</sup> *Laboratoire Astroparticule et Cosmologie*

**Auteur correspondant** philippe.bacon@apc.in2p3.fr

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## **Solving source separation problem for LISA data analysis with Autoencoders**

**Auteur:** Natalia Korsakova<sup>1</sup>

<sup>1</sup> *Observatoire de la Côte d'Azur*

**Auteur correspondant** natalia.korsakova@oca.eu

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## **The devil is in the details: interpreting probabilities from machine learning**

**Auteur:** Alex Malz<sup>1</sup>

<sup>1</sup> *German Centre of Cosmological Lensing*

**Auteur correspondant** aimalz@astro.rub.de

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## **Graphcore: Innovation in Machine Intelligence Hardware & Software**

**Auteur correspondant** alexandert@graphcore.ai

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## **Microsoft Azure**

**Auteur correspondant** alexandre.jean@microsoft.com

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## **Large-scale Machine Learning on LightOn's Optical Processing Units**

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## **Contrib 5**

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## **An Introduction to Bayesian Deep Learning**

**Auteur:** Frédéric Pennerath<sup>1</sup>

<sup>1</sup> CentraleSupélec

Bayesian Deep Learning (BDL) fills an important gap in the current deep neural networks, no matter powerful they are: in figurative terms, one could say BDL gives to AI the introspective ability to assess its own level of ignorance due to a lack of observations.

In more technical terms, BDL adopts the view of Bayesian statistics by replacing the weights of neural networks by distributions.

While this idea is nothing new, BDL has recently undergone new developments, thanks in particular to the seminal work of Y. Gal.

This presentation is designed to be a gentle introduction of the main concepts of BDL.

It introduces the required notions of Deep Learning and Bayesian statistics before developing the BDL framework.

It will not assume any particular piece of knowledge, but some general notions in machine Learning and Neural Networks.

**Invited talk / 47**

## **Bayesian analysis and Supernova Photometric Cosmology**

**Auteur:** Emille Ishida<sup>1</sup>

<sup>1</sup> LPC-UCA

**Auteur correspondant** emille.ishida@clermont.in2p3.fr

In the end of the 20th century type Ia supernovae provided the first evidence for accelerated cosmic expansion – completely changing the cosmological model paradigm. Since then, the astronomical

community has devoted much of its resources to the construction of large scale sky surveys which are expected to achieve first light in the next few years. The upcoming Large Survey of Space and Time at the Vera Rubin Observatory (LSST) is one of the most ambitious of such experiments. In the new data paradigm raised by the next generation of surveys, which will deliver larger and more complex astronomical data than ever before, the methods of data analysis will need to be adapted to the new reality. In this talk, I will briefly describe the traditional pipeline for supernova cosmology, highlighting the new challenges to be faced and list a number of potential improvements already achieved by the application of Bayesian analysis. In particular, I will focus on how the combination of Bayesian techniques with adaptive machine learning algorithms can enable purely photometric supernova cosmology in the next decade.

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## **TensorFlow Probability**

**Auteur correspondant** bjp@google.com

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## **Organizers wrap-up**