IAIFI

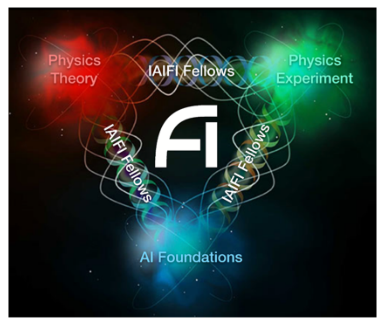
Summer School & Workshop

August 1–9, 2022

Welcome to the first Summer School hosted by the NSF Institute for Artificial Intelligence and Fundamental Interactions (IAIFI)!

The mission of the IAIFI PhD Summer School is to leverage the expertise of IAIFI researchers, affiliates, and partners toward promoting education and workforce development by illustrating interdisciplinary research at the intersection AI and Physics.

About IAIFI



The NSF AI Institute for Artificial Intelligence and Fundamental Interactions (IAIFI, pronounced /aɪ-faɪ/) is one of the inaugural NSF AI research institutes. The IAIFI is enabling physics discoveries and advancing foundational AI through the development of novel AI approaches that incorporate first principles, best practices, and domain knowledge from fundamental physics (*ab initio* AI).

The IAIFI's primary goals are to: conduct cutting-edge research; promote training, education, and outreach at the physics/AI intersection; cultivate early-career talent; foster connections to physics facilities and industry; build strong multidisciplinary collaborations; and advocate for shared solutions across subfields. In pursuing these goals, the IAIFI is working toward advancing physics knowledge---from the smallest building blocks of nature to the largest structures in the Universe---and galvanizing AI research innovation.

Financial Support for the Summer School

The Summer School is funded primarily by support from the **National Science Foundation** under Cooperative Agreement PHY-2019786.

Thank you to **DeepMind** and **Unlearn** for additional financial support for the Summer School.

Who we are

The IAIFI is a collaboration of both physics and AI researchers at MIT, Harvard, Northeastern, and Tufts.

Get Involved

- Apply to be an **IAIFI Fellow**: https://iaifi.org/fellows.html
- Attend **IAIFI Colloquia**: https://iaifi/.org/events.html
- Watch **past Colloquia on YouTube:** https://www.youtube.com/IAIFIInstituteforAIFundamentalInteractions

Management

IAIFI Director: Jesse Thaler, Professor, MIT

IAIFI Deputy Director: Mike Williams, Associate Professor, MIT

IAIFI Project Manager: Marisa LaFleur

Summer School Committee

Chair: Jim Halverson, Associate Professor, Northeastern

Project Manager: Marisa LaFleur

Tess Smidt, Assistant Professor, MIT

Taritree Wongjirad, Assistant Professor, Tufts

Anna Golubeva, IAIFI Fellow

Jeffrey Lazar, Grad Student, Harvard

Peter Lu, Grad Student, MIT

Dylan Rankin, Postdoc, MIT

Have a question? Look for us in the purple shirts!

https://iaifi.org iaifi@mit.edu @iaifi-news IAIFI

IAIFI Code of Conduct

Regardless of their position or seniority, members of the IAIFI and participants in IAIFI activities are expected to:

- Act in an ethical and collaborative manner at all times and abide by the MIT Physics Community Values (https://physics.mit.edu/about-physics/community-values/)
- Work with the utmost scientific integrity and respect the confidentiality of information and work presented at internal IAIFI meetings
- Treat each other with dignity and respect, support and encourage each other's growth, and step in as needed to maintain an environment free of discrimination, harassment, and bullying

Furthermore, members of the IAIFI and participants in IAIFI activities may not engage in retaliation against anyone for objecting to a behavior that may violate this code, reporting a violation of this code, or participating in the resolution of such a complaint.

MIT Physics Community Values

Our Physics Community Values stem from the basic principle that members of our community should treat each other with respect and decency at all times. In turn, we should not alienate, diminish or insult each other, either in word or deed.

- Well-being: We support each other at all times and remember that we are not alone.
- Respect: We value the multitude of ways to be a physicist and the many paths through our field and Department.
- Inclusion: We strive to speak and act in ways that support and include all members of our community.
- Collaboration: Physics is a social endeavor and we proudly collaborate with others to advance the field.
- Mentorship: All physicists are here because of the mentorship we have received and continue to receive, and the mentorship we offer to others.

Join the IAIFI Summer School Slack workspace!

Monday, August 1, 2022

8:30–9:00am

Breakfast is served

9:00–9:30am

Welcome and introduction from Jesse Thaler, IAIFI Director

9:30–10:30am

Taco Cohen, Research Scientist, Qualcomm Research Netherlands

Foundations of Geometric Deep Learning I

The success of deep learning applied to images, speech, and text has spurred research into the application of similar techniques to other kinds of data, such as graphs, points clouds, data on homogeneous spaces, and other manifolds. This field has come to be known as geometric deep learning. In this talk I will discuss the foundations of GDL, focusing on the basic concepts of symmetry groups, representations, and equivariant maps, as well as group & gauge equivariant convolutions for fields over homogeneous spaces and general manifolds.

10:30–11:00am

Coffee break

11:00am–12:00pm

Javier Duarte, Assistant Professor, University of California, San Diego

Representations, networks, and symmetries for learning from particle physics data

In experimental high energy physics (HEP), we collide high energy particle beams millions of times per second and observe the remnants of the collisions with hundreds of millions of detector channels. There is a growing interest in exploiting machine learning methods to extract physics from this raw detector data. In order to benefit from modern deep learning algorithms initially designed for computer vision or natural language processing tasks, it is common practice to transform HEP data into tabular data, images, or sequences. In this lecture, I will review these machine learning methods, as well as emerging methods like graph neural networks and symmetry-equivariant networks, which provide alternative ways of incorporating specialized domain knowledge.

12:00pm–1:00pm

Lunch

1:00–2:00pm

Denis Boyda, Incoming IAIFI Fellow

Tutorial I for Foundations of Geometric Deep Learning

2:00–3:00pm

Dylan Rankin, Postdoc, MIT/IAIFI

Tutorial I for Model compression and fast machine learning in particle physics: Training Invariant Networks

In this tutorial, we will explore neural network architectures that are capable of respecting the different inherent symmetries in datasets. We will use simulated data from particle physics and consider both symmetries of permutation invariance and Lorentz equivariance. We will construct successively more complex models that are capable of respecting these symmetries, and analyze how the architecture choices we make affect the model performance and learning. Finally, we will offer an opportunity to explore more complex symmetries and give participants an opportunity to test what they have learned on these more difficult problems.

3:00–4:00pm

Virtual Networking using Remotely Green

4:00–6:00pm

Welcome Dinner

Tuesday, August 2, 2022

8:30–9:00am

Breakfast is served

9:00–9:30am

Lightning Talks
See page 20 for abstracts

- Leonardo Petrini, leonardo.petrini@epfl.ch, "Relative stability toward diffeomorphisms indicates performance in deep nets"
- LOIC ELNATHAN TIOKOU FANGANG, elnathan.tiokou@aims-cameroon.org, "Adversarial Robustness of Different Federated Learning (FL) Frameworks"
- Krish Desai, krish.desai@berkeley.edu, "Moment Unfolding"
- Matthew Mould, mmould@star.sr.bham.ac.uk, "Gravitational-wave population modeling with deep learning"
- Megan Schuyler Moss, msmoss@uwaterloo.ca, "Combining data-driven and Hamiltonian-driven training for learning quantum ground states"
- Rodrigo Barbosa, rbarbosa@scgp.stonybrook.edu, "Towards Numerical G2 Metrics"
- Aryeh Brill, aryeh.brill@gmail.com, "Towards a Self-Supervised Model of Short-Timescale Gamma-ray Variability in Blazars"

9:30–10:30am

Taco Cohen, Research Scientist, Qualcomm Research Netherlands

Foundations of Geometric Deep Learning II

10:30–11:00am

Coffee break

11:00am–12:00pm

Javier Duarte, Assistant Professor, University of California, San Diego

Model compression and fast machine learning in particle physics

Efficient machine learning implementations optimized for inference in hardware have wide-ranging benefits, from lower inference latency to higher data throughput and reduced energy consumption. In this lecture, I will give an overview of effective techniques for reducing computation in neural networks, including pruning, or removing insignificant synapses, quantization, or reducing the precision of the calculations, and knowledge distillation, or transferring the knowledge from a large model to a smaller model. I will also review the connections to the lottery ticket hypothesis, interpretability, neural efficiency, robustness, and generalizability.

12:00pm–1:00pm

Lunch

1:00–2:00pm

Denis Boyda, Incoming IAIFI Fellow

Tutorial II for Foundations of Geometric Deep Learning

2:00–3:00pm

Dylan Rankin, Postdoc, MIT/IAIFI

Tutorial for Model compression and fast machine learning in particle physics: Compressing Neural Networks for Ultrafast Inference

In this tutorial, we will explore how to apply different techniques to reduce the size and necessary computation for neural network inference while maintaining model performance. We will begin with models trained using standard techniques using floating point numbers. We will show how to apply pruning techniques to reduce the size of the networks by removing unnecessary connections. We will also show how to quantize the networks to reduce the number of bits necessary for encoding values during inference. In both cases, we will show how these techniques can be applied while maintaining desired model performance to allow for inference on low-power devices such as FPGAs. Finally, participants will analyze the ramifications of these techniques on the latency and resources of synthesized designs for FPGA-based inference.

3:00–3:30pm

Coffee break

3:30–4:30pm

Yasaman Bahri, Research Scientist, Google Research (Brain Team)

Deep learning in the large-width regime I

We will review some of the foundational connections that arise between deep neural networks and other classic machine learning methods, albeit modified with new ingredients, in the limit where the neural network hidden layers have many nodes. These connections have been used across different research areas, including in the development of deep learning theory; in building new connections between machine learning and statistical physics; as well as in machine learning practice, including applications to physics. In the tutorials, we will gain experience with neural network libraries built to enable the recursive computations that form the core of these connections.

5:00–6:00pm

Virtual Networking using Remotely Green

Wednesday, August 3, 2022

8:00–9:00am

Virtual Networking using Remotely Green

8:30–9:00am

Breakfast is served

9:00–9:30am

Lightning Talks
See page 20 for abstracts

- Nicole Hartman, nicole22@stanford.edu, “High dimensional background interpolation with generative models on ATLAS”

- Polina Abratenko, polina.abratenko@tufts.edu, “A Data-Driven Light Model using Neural Networks for the MicroBooNE Experiment”
- Ahmed Youssef, youssead@ucmail.uc.edu, “ML for Hadronization”
- Anindita Maiti, maiti.a@northeastern.edu, “Where Neural Network Meets Fundamental Physics”
- Zev Imani, zeviel.imani@tufts.edu, “Score-Based Generative Modeling”
- Varun Shankar, varunshankar@cmu.edu, “Machine Learning Turbulence Closures”
- William Lewis, willewi@sandia.gov, “Data-driven design and discovery for Magnetized Liner Inertial Fusion at Sandia’s Z Facility*

9:30–10:30am

Yasaman Bahri, Research Scientist, Google Research (Brain Team)

Deep learning in the large-width regime II

10:30–11:00am

Coffee break

11:00am–12:00pm

Sven Krippendorf, Senior Researcher, Mathematical Physics and String Theory, Ludwig Maximilian University of Munich

Machine Learning for Beyond-the-Standard-Model Physics I

These lectures aim to give an overview on how we can tackle questions in Beyond-The-Standard-Model (BSM) physics using Machine Learning (ML). I will discuss a few types of questions to showcase how ML approaches can be adapted to fit into standard physics pipelines:

1. How can we understand the pattern of experimentally viable BSM theories? Such models feature on the one hand consistency conditions from their respective UV-completion selecting a subset of theories at low-energies. On the other hand, the requirement of matching observations at low-energies poses apriori unknown constraints on the UV parameters, a classic inverse problem. I discuss how ML can help in addressing this inverse problem. A short preview can be obtained at 2111.11466.
2. How can we phrase the search for mathematical structures as optimisation problems? This is to discuss how we can identify the symmetries associated

to a dynamical system using ML and how we can accelerate the search for solutions of PDEs using ML. References of interest for this part are: 1906.01563, 2104.14444, 2003.13679, 2012.04656

3. How can we use ML to accelerate the physics inference pipeline? Depending on time, this part will feature heavily in the tutorials.

12:00pm–1:00pm

Lunch

1:00–3:00pm

Anna Golubeva, IAIFI Fellow

Tutorial for Deep learning in the large-width regime

3:00–3:30pm

Coffee break

3:30–4:30pm

Career Panel

- Yasaman Bahri, Research Scientist, Google Research (Brain Team)
- Juan Carrasquilla, Faculty Member, Vector Institute; Adjunct Assistant Professor, University of Waterloo
- Taco Cohen, Research Scientist, Qualcomm Research Netherlands
- Javier Duarte, Assistant Professor, University of California, San Diego
- Anna Golubeva, IAIFI Fellow
- Sven Krippendorf, Senior Researcher, Mathematical Physics and String Theory, Ludwig Maximilian University of Munich

Thursday, August 4, 2022

8:00–9:00am

Virtual Networking using Remotely Green

8:30–9:00am

Breakfast is served

9:00–9:30am

Lightning Talks
See page 20 for abstracts

- Tianji Cai, tianji_cai@ucsb.edu, "How to Make Statistical Inference on Theory Parameters when Simulations are Expensive?"
- Jerry Ling, jling@g.harvard.edu, "HEP meets Julia: Doing physics analysis with speed, elegance, and flexibility"
- Omar Alterkait, omar.alterkait@tufts.edu, "Particle Trajectory Reconstruction and Euclidian Equivariance"
- Ankur singha, anksing@iitk.ac.in, "Conditional Normalizing Flow for Markov Chain Monte Carlo Sampling in the Critical Region of Lattice Field Theory"
- Sebastian Larsen, sebastian.larsen16@imperial.ac.uk, "Graph Neural Networks for 3D defect mapping in Laser Powder Bed Fusion"
- Dimitrios Athanasakos, dimitrios.athanasakos@stonybrook.edu, "Jet Tagging with Deep Sets of Subjets"
- Dr. Lingxiao Wang, lwang@fias.uni-frankfurt.de, "Solving inverse problems with physics-driven deep learning"
- Astrid Anker, aanker@uci.edu, "Deep learning techniques for a real-time neutrino classifier"

9:30–10:30am

Sven Krippendorf, Senior Researcher, Mathematical Physics and String Theory, Ludwig Maximilian University of Munich

Machine Learning for Beyond-the-Standard-Model Physics II

10:30–11:00am

Coffee break

11:00am–12:00pm

Juan Carrasquilla, Research Scientist, Vector Institute; Adjunct Assistant Professor, University of Waterloo

Machine learning for many-body physics I

Over the past few years, machine learning (ML) has emerged as a powerful computational tool to tackle complex problems in various scientific disciplines. In particular, ML has been successfully used to mitigate the exponential complexity often encountered in many-body physics, the study of properties of quantum and classical systems built from a large number of interacting particles. In these lectures, we review some applications of ML in statistical mechanics, condensed matter physics, and quantum information. We will discuss select examples drawing from ML areas including supervised machine learning of phase transitions, unsupervised learning of quantum states, and the variational Monte Carlo method for approximating the ground state of a many-body Hamiltonian. For each algorithm, we briefly review the key ingredients and their corresponding implementation and show numerical experiments for a system of interacting Rydberg atoms in two dimensions among other systems.

12:00pm–1:00pm

Lunch

1:00–3:00pm

Siddharth Mishra-Sharma, IAIFI Fellow

Tutorial for Machine Learning for Beyond-the-Standard-Model Physics: Modeling and inference: connecting theory and data

Principled comparison of theory with observations is a bedrock of the scientific method, underlying in particular how information about fundamental physics can be extracted from data. Using contemporary physics examples, these hands-on tutorials will introduce strategies for defining statistical models, implementing them as (differentiable) probabilistic programs, and performing inference on them. Various inference methods will be discussed, including sampling-based (e.g., Markov Chain Monte Carlo), variational inference and, time permitting, simulation-based (“likelihood-free”) inference.

3:00–3:30pm

Coffee break

3:30–4:30pm

Di Luo, IAIFI Fellow

Tutorial I for Machine learning for many-body physics

6:00–8:00pm

Pizza social with IAIFI at Harvard University

Friday, August 5, 2022

8:30–9:00am

Breakfast is served

9:00–9:30am

Lightning Talks
See page 20 for abstracts

- Alexandre Falcao, alexandre.falcao@uib.no, "Constraining jet quenching models in heavy-ion collisions using Bayesian Inference"
- Mehmet Demirtas, m.demirtas@northeastern.edu, "Machine Learning for String Theory and Algebraic Topology"
- Matthew Duschenes, mduschen@uwaterloo.ca, "Learning and Overparameterization of Constrained Variational Quantum Circuits"
- Xiaolong Li, lixl@udel.edu, "Preparing to Discover the Unknown with Rubin LSST: Time Domain"
- Ivy Li, il11@rice.edu, "Autoencoders for the Inference of the Optical Properties of a Dual-Phase Time Projection Chamber"
- Nayantara Mudur, nmudur@g.harvard.edu, "Towards better spatial regularization for astrophysical fields"

9:30–10:30am

Juan Carrasquilla, Research Scientist, Vector Institute; Adjunct Assistant Professor, University of Waterloo

Machine learning for many-body physics II

10:30–11:00am

Coffee break

11:00am–12:00pm

Di Luo, IAIFI Fellow

Tutorial II for Machine learning for many-body physics

12:00pm–1:00pm

Lunch

1:00–5:00pm

Mini-hackathon: Choose a problem to work on in a team

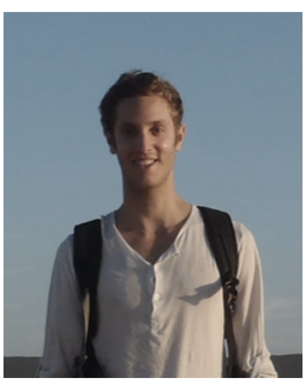
Lecturers

Yasaman Bahri, Research Scientist, Google Research (Brain Team)

Yasaman Bahri is a Research Scientist at Google Brain working at the interface of machine learning and physical science, with a recent focus on the foundations of deep learning. She obtained her PhD (2017) at UC Berkeley in theoretical condensed matter physics. Her work is multidisciplinary in nature, and she has received recognition & given invited lectures in both physics and computer science. Most recently, she was a recipient of the Rising Stars Award in EECS (2020).

Juan Carrasquilla, Faculty Member, Vector Institute; Adjunct Assistant Professor, University of Waterloo

Juan Felipe Carrasquilla Álvarez is a research scientist at the Vector Institute and a Canada CIFAR artificial intelligence chair. Juan's research interests are at the intersection of condensed matter physics, quantum computing, and machine learning. He completed his Ph.D. in Physics at SISSA and held postdoctoral positions at Georgetown University and the Perimeter Institute, as well as a research scientist position at D-Wave Systems Inc.



Taco Cohen, Research Scientist, Qualcomm Research Netherlands

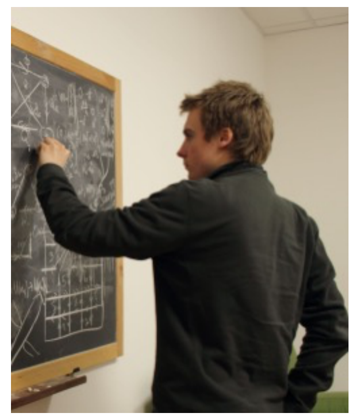
Taco Cohen is a machine learning researcher at Qualcomm AI Research in Amsterdam and co-director at the ELLIS Geometric Deep Learning program. He was a co-founder of Scyfer, a company focused on deep active learning, acquired by Qualcomm in 2017. He received a BSc in theoretical computer science from Utrecht University, and a MSc in artificial intelligence and PhD in machine learning (with prof. Max Welling) from the University of Amsterdam. His research is focused on equivariant networks and geometric deep learning, causality and interactive learning. He has interned at Google Deepmind (working with Geoff Hinton) and OpenAI.

Javier Duarte, Assistant Professor, University of California, San Diego

As part of the CMS experiment at the CERN Large Hadron Collider, Javier Duarte's group performs measurements of high-momentum Higgs bosons and searches for exotic new physics. They are also interested in hardware-accelerated machine learning for trigger and computing as well as geometric deep learning for particle physics.

Sven Krippendorf, Senior Researcher, Ludwig Maximilian University of Munich

Dr Sven Krippendorf is a senior researcher at LMU Munich. His research interests are at the interface of physics and machine learning, using machine learning to gain insights into fundamental physics and to use the theoretical physicist's toolbox to understand the dynamics of neural networks. In teaching, he is currently working towards the realisation of a new Master's degree in physics with a specialisation in artificial intelligence at LMU Munich.



Tutorial Leads

Denis Boyda, Incoming IAIFI Fellow

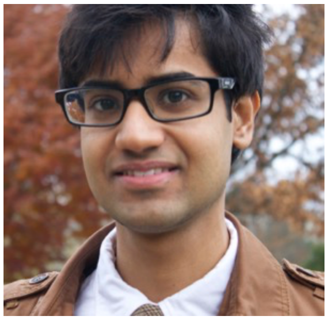
Denis Boyda has been working on the application of the Machine Learning method to simulations of physical systems and bringing physical ideas to Machine Learning. His research is devoted to developing algorithms enabling simulations of nuclear and particle physics, which are currently computationally intractable. Denis Boyda is interested in the Monte Carlo techniques and generation modeling. He develops equivariant models that respect the symmetry of a target problem and runs simulations at leading supercomputer machines.

Anna Golubeva, IAIFI Fellow

Anna is currently a postdoctoral fellow at IAIFI, working on developing a theoretical foundation of deep learning with methods from statistical physics. She obtained her PhD in 2021 at the Perimeter Institute for Theoretical Physics and the University of Waterloo, where she was advised by Roger Melko. During her PhD, she was also a graduate affiliate at the Vector Institute for AI in Toronto. Previously, she completed the Perimeter Scholars International master's program (2017), a MSc in Theoretical Physics with focus on computational approaches to quantum many-body systems (2016), and a BSc in Biophysics (2014) at the Goethe University in Frankfurt, Germany.

Di Luo, IAIFI Fellow

Di Luo received his undergraduate degree with majors in physics and mathematics from the University of Hong Kong in 2016. He graduated with master degree in mathematics and Ph.D. degree in physics at the University of Illinois, Urbana-Champaign in 2021. Di Luo is working on research in the intersection of quantum many-body physics, quantum information science, and artificial intelligence. He has been developing quantum algorithms and machine learning approaches for condensed matter physics, high energy physics, and quantum information science. Di Luo is interested in understanding nature from the perspectives of information and computation as well as developing intelligence inspired by ideas from nature.



Siddharth Mishra-Sharma, IAIFI Fellow

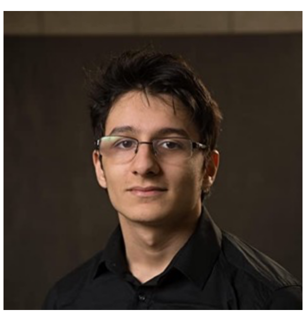
Siddharth is an IAIFI Fellow at MIT interested in developing novel statistical methods for accelerating the discovery of new physics in astrophysical and cosmological observations at all accessible scales. He is especially focused on developing analysis techniques based on machine learning that enable new ways of searching for signatures of physics beyond the Standard Model, in particular the nature of dark matter, using data from ongoing and upcoming cosmological surveys.

Dylan Rankin, Postdoc, MIT/IAIFI

Dylan Rankin received his Ph.D. in 2018 from BU under Tulika Bose, and is currently a postdoc at MIT with Phil Harris. He will start as a faculty member at UPenn this coming spring. He is interested in machine learning, heterogeneous computing, trigger and data acquisition systems, Higgs physics, and exotic searches. His work is focused on using novel analysis methods both at the CERN Large Hadron Collider and beyond.

Virtual TAs

Virtual TAs will be available on Slack during the tutorials and the hackathon to answer questions and provide support to virtual attendees.



Ouail Kitouni
MIT, Grad Student

Peter Y. Lu
MIT, Grad Student

Tri Nguyen
MIT, Grad Student

Niklas Nolte
MIT, Postdoc

Lightning Talk Abstracts

In alphabetical order by speaker last name

Abratenko, Polina, polina.abratenko@tufts.edu, A Data-Driven Light Model using Neural Networks for the MicroBooNE Experiment
MicroBooNE is a short baseline neutrino oscillation experiment that employs Liquid Argon Time Projection Chamber (LArTPC) technology in conjunction with an array of Photomultiplier Tubes (PMTs), which detect scintillation light. Scintillation light detection is critical to the operation of the detector, as it provides the means for triggering on beam-related interactions and the rejection of cosmic ray backgrounds. As a result, modeling of the expected optical detector signal is important. Currently, the model for the optical signal is based on simulation. This generated photon library has some known limitations, however, including time intensive generation as well as inaccurate response in certain regions of the detector. We propose a data-driven approach to mapping the light yield in the MicroBooNE detector through the use of a neural network, which allows for specific conditioning based on MicroBooNE data.

Alterkait, Omar, omar.alterkait@tufts.edu, Particle Trajectory Reconstruction and Euclidian Equivariance
Training neural networks to operate on three-dimensional trajectories from particle detectors is challenging due to the large combinatorial complexity of the data in three dimensions. Using networks that incorporate Euclidian Equivariance could prove to be very beneficial in reducing the need for data augmentation. Our focus is on data from neutrino experiments using liquid argon time projection chambers.

Anker, Astrid, aanker@uci.edu, Deep learning techniques for a real-time neutrino classifier
The ARIANNA experiment is a neutrino detector located in Antarctica. To increase the ability to measure neutrinos, one method is to lower the trigger threshold and collect more data, but in the most remote locations in Antarctica, data transmission speed is limited. This work demonstrates that deep learning techniques can be used to reject thermal noise in real time, which will increase the detector's sensitivity to neutrino signals.

Athanasakos, Dimitrios, dimitrios.athanasakos@stonybrook.edu, Jet Tagging with Deep Sets of Subjets
We introduce a complete basis of subjets for machine learning-based jet tagging. The subjets are obtained with (i) a fixed radius or (ii) the clustering is performed until a fixed number of subjets is obtained. The subjet momenta, relative angles and (optionally) the subjet masses are taken as input to a permutation invariant neural network. For nonzero values of the subjet radius, the resulting classifier is Infrared-Collinear (IRC) safe. By lowering the subjet radius, we can increase the sensitivity to nonperturbative physics. In the limit of a vanishing subjet radius, the exclusive subjet basis approximates deep sets/particle flow networks (IRC unsafe). The basis introduced here is thus ideally suited to quantify the information content of jets at the boundary of perturbative vs. nonperturbative physics.

Barbosa, Rodrigo, rbarbosa@scgp.stonybrook.edu, Towards Numerical G2 Metrics
G2 manifolds are a cornerstone of M-theory - they provide minimally supersymmetric compactifications in four spacetime dimensions, and thus are needed to recover standard model physics. However, they are notoriously difficult to construct. In this talk I will explain a numerical

approach to approximate G2 metrics based on the success of machine learning techniques for Calabi-Yau metrics. This is work in progress with Michael Douglas, Daniel Platt and Yidi Qi.

Brill, Aryeh, aryeh.brill@gmail.com, Towards a Self-Supervised Model of Short-Timescale Gamma-ray Variability in Blazars
Blazars, active galactic nuclei with relativistic jets pointed almost directly at Earth, exhibit strong, apparently stochastic flux variability at virtually all observed wavelengths and timescales, from minutes to years. The physical origin of this variability is poorly understood. For 14 years, the Large Area Telescope aboard the Fermi space telescope (Fermi-LAT) has conducted regular monitoring of thousands of blazars in the high-energy gamma-ray band. Measurements with Fermi-LAT on short timescales (days or less) have revealed complex variability patterns involving multiple gamma-ray-emitting bursts, but these measurements are generally possible only during rare, bright flares due to Fermi-LAT's finite sensitivity. However, short-timescale phenomena may still leave statistical imprints on the light curves derived from integrating over intermediate timescales, such as weeks. Using self-supervised deep learning, we propose to construct a non-parametric representation of blazar gamma-ray variability, incorporating measurement errors, upper limits, and missing data using trainable encodings. The self-supervised architecture can be used to produce an embedded representation of stochastic variability patterns, possibly exhibiting complex long-range dependencies, that can be studied to extract scientifically relevant information.

Cai, Tianji, tianji_cai@ucsb.edu, How to Make Statistical Inference on Theory Parameters when Simulations are Expensive?
From fundamental particle physics to astrophysics and cosmology, our knowledge of Nature is often summarized in a chain of complex simulators which allows high-fidelity data to be generated, serving as the pillar of our modern scientific inquiries. Yet what we ultimately wish to probe are the theory parameters whose values are to be inferred and constrained by comparing the simulated data with experimental observations. Due to the complexity of real-world simulators, it is usually impossible to explicitly calculate the likelihood function, making it difficult to perform inference using traditional statistical methods. Several approaches—collectively termed as simulation-based or likelihood-free inference—have been proposed in such setting, utilizing recent advances in machine learning. Here we focus on one type of such techniques called Bayesian Optimization for Likelihood-free Inference (BOLFI), which includes the implementation of active learning for expensive simulations. We introduce Optimal Transport distances as the metric for gauging the discrepancy between simulations and observations and demonstrate the power of this new framework by applying it to the analysis of dark matter subhalos.

Demirtas, Mehmet, m.demirtas@northeastern.edu, Machine Learning for String Theory and Algebraic Topology
It is notoriously difficult to obtain solutions of string theory that are similar to our universe, in part because the space of solutions is huge and the algebraic topology calculations required are computationally expensive. I will describe a supervised learning algorithm that bypasses these calculations in a class of solutions that are relatively well understood, and comment on possible applications.

Desai, Krish, krish.desai@berkeley.edu, Moment Unfolding
Deconvolving ('unfolding') detector distortions is a critical step in the comparison of cross section measurements with theoretical predictions. However, most of these approaches require

binning while many predictions are at the level of moments. We develop a new approach to directly unfold distribution moments as a function of any other observables without having to first discretize. Our Moment Unfolding technique uses machine learning and is inspired by Generative Adversarial Networks (GANs). We demonstrate the performance of this approach using jet substructure measurements in collider physics. We also discuss challenges with unfolding all moments simultaneously, drawing connections to the renormalization of the partition function.

Duschenes, Matthew, mduschen@uwaterloo.ca, Learning and Overparameterization of Constrained Variational Quantum Circuits
Many problems in quantum information, including simulation, state preparation, control, and compilation, can be mapped to learning an optimal quantum circuit, given a variational ansatz. These parameterized quantum systems have recently been shown to display curious phenomena of different regimes of training during optimization, depending on the specific ansatz. An important regime is the overparameterized, or lazy regime, where parameters may negligibly vary over the course of optimization, and global optima may potentially be reached exponentially quickly (Larocca et al., arXiv:2109.11676, 2021). Here, we study the case where there are constraints on the ansatz, both with respect to the available circuit components, such as from restrictions of which gates are native to hardware, as well as with respect to constraints on the variable parameters of the circuit, such as bounds on parameters, or the locality or sharing of parameters across components of the circuit. Given these constraints, we investigate their effect on the regimes of training, the convergence of optimization, and the resulting parameters of the circuit using metrics such as variants of the quantum geometric tensor.

Falcao, Alexandre, alexandre.falcao@uib.no, Constraining jet quenching models in heavy-ion collisions using Bayesian Inference
In relativistic heavy-ion collisions, like at the RHIC and LHC, a phase of Quantum Chromodynamics (QCD) of hot and dense nuclear matter, so called Quark Gluon Plasma (QGP), is briefly formed. Within this resulting QGP, we observe the same hard QCD processes that occur in proton-proton collisions, producing collimated sprays of energetic particles referred to as jets. The structure of these jets are relatively well known from proton-proton collisions. While traversing the QGP, the jets will lose energy by medium-induced radiation, a process known as jet quenching. QCD factorization allows us to model jet quenching as a convolution between the jet cross section in proton-proton collisions and an energy loss probability distribution, $D(\varepsilon)$, in order to obtain the nucleus-nucleus jet cross section. Our main goal is then to learn the parameterization of $D(\varepsilon)$, from experimental data using machine learning methods. We employ Bayesian Inference to learn and constrain the model according to the current available data. We can then validate against similar observables and use them for prediction in other processes where jet quenching plays an important role.

"FANGANG, LOIC ELNATHAN TIOKOU, elnathan.tiokou@aims-cameroon.org, Adversarial Robustness of Different Federated Learning (FL) Frameworks
Intelligent machines have significantly enhanced human living conditions since the introduction of Machine Learning. Ranging, from powerful systems detecting and identifying an object in the image, to automatic car driving, or intelligent and complex software such as Google which daily is indispensable for our living; Machine Learning has become
omnipresent in our century. However, to achieve milestones as done so far, we need to nurture our systems with data, but unfortunately, there are certain domains where the protection of data is the utmost concern, hence are not easily available; this includes the health sector, banking,

etc. Federated Learning (FL) develops as an effective way to not only do tasks that may be done with traditional machine learning but also to preserve and secure data in accordance with new laws and regulations.Federated Learning systems, like any other system, are vulnerable to quality issues such as assaults and byzantine flaws. As a result, various efforts have been undertaken to resolve quality issues and strengthen FL systems. However, the effective robustness of different FL frameworks is not guaranteed and is still yet to be improved. In this study, we are going to first all present the fundamentals around Federated Learning and different notions involved in the robustness of an FL system. Second, we present a detailed architecture of some FL frameworks, with a summary comparison. Third, we conduct an empirical investigation to assess the quality of the SOTA FL systems in facing some simulated attacks. Finally, we review the limitations and make recommendations for further research works."

Hartman, Nicole, nicole22@stanford.edu, High dimensional background interpolation with generative models on ATLAS
The 4b channel is attractive for di-Higgs searches because of its high branching ratio and leading sensitivity at high mass. The fully hadronic final state necessitates the use of a data-driven background estimate, and obtaining a precise estimate with an accurate uncertainty assessment is the central challenge for this analysis. In this work, we explore conditional neural density estimation techniques to learn the distribution over the smoothly varying kinematics of background HH candidate events. In particular, we utilize a normalizing flow, which uses a sequence of invertible transformations to set up an exact likelihood parametrization. This normalizing flow is conditioned on the Higgs candidate masses, allowing us to sample from the learned multi-dimensional probability distribution for each given Higgs candidate mass pair. A Gaussian Process (GP) models the joint distribution over Higgs candidate masses. The samples from the GP are used to condition the flow to form a combined model which allows interpolation over blinded values of Higgs candidate masses. We conclude with some preliminary results comparing this interpolation work with our current analysis strategy of using likelihood-ratio based reweighting for data-driven background estimation in the various validation regions for background validation used in the analysis.

Imani, Zev, zeviel.imani@tufts.edu, Score-Based Generative Modeling
A brief overview of score-based generative modeling through stochastic differential equations and an application of this method for the MicroBooNE experiment.

Larsen, Sebastian, sebastian.larsen16@imperial.ac.uk, Graph Neural Networks for 3D defect mapping in Laser Powder Bed Fusion
Since defects form due to the stochastic nature of the LPBF process, stringent post-build inspection regulations are a required burden. However, locating defects in-situ would enable a component to be qualified in real time, automating this requirement.
A graph neural network model was developed to provide a geometric invariant method for localising defects in the material. The model was trained on high-speed melt pool monitoring data, collected from a component manufactured with seeded defects. A k-fold cross validation was performed where each seeded defect was detected and localised. The defect sizes were correlated with the 3D probability map which showed positive correlation with number of detections. Graph neural networks provide an efficient way to locate defects in a component, while remaining invariant to geometry. We believe the effectiveness comes from incorporating this physical structure into a machine learning model.

Lewis, William, willewi@sandia.gov, Data-driven design and discovery for Magnetized Liner Inertial Fusion at Sandia's Z Facility*

Magnetized Liner Inertial Fusion (MagLIF) is a magneto-inertial fusion concept studied at Sandia's Z pulsed power facility. By combining an external magnetic field, laser preheating of the deuterium fuel contained within a cylindrical Beryllium tube or liner, and finally compression of the liner with an ~100ns rise time ~20MA peak current pulse, we achieve fusion relevant conditions. However, experiments are costly and complex multiphysics simulations used for analysis can be prohibitively expensive for regular application. Furthermore, the extreme high-energy density (HED) environments generated challenge diagnostic development and application. As a result, extraction of detailed physical quantities of interest is often complicated by the highly spatio-temporally integrated diagnostics commonly fielded. The recent application of methods ranging from Bayesian data assimilation to data-driven model emulation and experimental data processing are accelerating the rate of design and discovery. In this lightning talk, I provide an overview of several published and ongoing efforts to apply modern data science methods to understand the structure and conditions of the HED plasma generated in MagLIF experiments.

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Li, Xiaolong, lixl@udel.edu, Preparing to Discover the Unknown with Rubin LSST Time Domain

Based in Chile and expected to start in 2024, with a sensitivity and resolution similar to those of the Hubble Space Telescope, the Rubin LSST will take pictures of the whole southern hemisphere sky in six different colors repeating observations of each sky position every few days an unprecedented survey to revolutionize our understanding of the Universe from Solar System asteroids to the shape and evolution delivering 20Tb of information-rich data every night for 10 years. LSST is certain of the Universe itself. But most importantly LSST will have the potential to make unexpected discoveries. But how can we assure that the choices we are making in designing the LSST observing strategy will not prevent us from discovering of the unknown? The operations of LSST are evaluated by metrics under the Metric Analysis Framework (MAF) API. Although many metrics have been designed to assess how well a proposed strategy would discover planets, or exploding stars, and allow us to extract their physical properties, given a set of observational choices (points, alternation of filters, cadence of observations), designing a metric to evaluate LSST's ability to discover unknown phenomena is a conceptually and practically challenging task. We present such a metric by mapping LSST planned observations to a phase space defined by the brightness, color and the change of those features. Based on the distribution in phase space we will be able to tell which regions support detection and which do not. Our results allow us to design a survey that maximizes our chances to discover unknown unknowns.

Li, Ivy, il11@rice.edu, Autoencoders for the Inference of the Optical Properties of a Dual-Phase Time Projection Chamber

A dual-phase time projection chamber (TPC) uses photosensors to measure the light produced by particle interactions occurring inside the detector. The optical properties of the TPC are driven by the detector's geometry and materials. Simulations of these optical properties will depend on physical parameters inside the detector and can be computationally expensive to generate. However, an unsupervised method such as autoencoders provide a way to infer these optical properties more efficiently. Autoencoders are unsupervised neural networks built around learning a representation of its input data. An autoencoder's architecture consists of an encoder, which maps an input to some latent space representation, and a decoder, which uses the latent space representation to reconstruct the input. During this talk, I will expand on this methodology and discuss the current status of measuring a TPC's optical parameters with autoencoders.

Ling, Jerry, jling@g.harvard.edu, HEP meets Julia: Doing physics analysis with speed, elegance, and flexibility
The High-Energy Physics (HEP) community, especially the group doing analysis, has facing the two-language problem for a long time. Often, physicists would start prototyping with a Python front-end which glues to a C/C++/Fortran back-end. Soon they will hit a task which is extremely hard to express in columnar (i.e. ""vectorized"") style, a type of problems which are normally tackled with libraries like numpy or pandas. This usually leads to either writing C++ kernels and interface them with Python, or porting the prototype to C++ and start to maintain two code bases including the wrapper code. Julia, a high-performance language with simple and expressive syntax [@Julia]. Julia is designed to solve the two-language problem in general. The talk would present technical merit of Julia and the stat of Julia ecosystem for HEP at large.

Maiti, Anindita, maiti.a@northeastern.edu, Where Neural Network Meets Fundamental Physics
Ensembles of initialized Neural Networks behave as 'field theories', the mathematical framework describing fundamental particles, that constitute our universe, and their interactions. The asymptotic Gaussian Process limit of Neural Networks, at infinite width and i.i.d. parameters, describe the theory of fundamental particles when they do not interact with each other. Close to the GP limit, ensembles of Neural Networks behave as fundamental particles that interact weakly with each other – such phenomena are well understood in theoretical physics. As non-Gaussianities become large, away from the GP limit, NN ensembles resemble fundamental particles interacting strongly – such systems lack proper understanding via theoretical physics. In this talk, I will discuss how correlation functions, partition functions and symmetries of non-Gaussian Neural Nets, at finite width and / or parameter correlations, can lead to a better understanding of correlation functions, partition functions and symmetries of strongly interacting fundamental particles. Thus, we can use initialized Neural Networks to potentially contribute to the fundamental physics of our universe.

Moss, Megan Schuyler, msmoss@uwaterloo.ca, Combining data-driven and Hamiltonian-driven training for learning quantum ground states.
Rydberg atom arrays are programmable quantum simulators capable of preparing interacting qubit systems in a variety of quantum states. Due to long experimental preparation times, obtaining projective measurement data can be relatively slow for large arrays, which poses a challenge for state reconstruction methods such as tomography. Today, novel groundstate wavefunction ansätze like recurrent neural networks (RNNs) can be efficiently trained not only from projective measurement data, but also through Hamiltonian-guided variational Monte Carlo (VMC). In the linked paper (below), we demonstrate how pretraining modern RNNs on even small amounts of data significantly reduces the convergence time for a subsequent variational optimization of the wavefunction. This suggests that essentially any amount of measurements obtained from a state prepared in an experimental quantum simulator could provide significant value for neural-network-based VMC strategies. This talk will specifically focus on the simplicity of combining the two types of training for the same RNN in order to leverage all available information about the system of interest.

Mould, Matthew, mmould@star.sr.bham.ac.uk, Gravitational-wave population modeling with deep learning
The catalog of gravitational-wave events is growing, and so are our hopes of constraining the underlying astrophysics of stellar-mass black-hole mergers by inferring the distributions of, e.g., masses and spins. While conventional analyses parametrize this population with simple phenomenological models, we develop a flexible approach in which the population model is learnt by a deep neural network and can be used to perform hierarchical Bayesian inference with data from the most recent LIGO/Virgo catalog. Applying this pipeline to simple numerical simulations of hierarchical stellar-mass black hole formation –in which first-generation black holes born in stellar collapse form binaries whose merger remnants can undergo further mergers– we find that features in the current gravitational-wave catalog can be accommodated by this scenario. Our deep learning model predicts at least 15% of the intrinsic population is made up of higher-generation black holes. This approach readily extends to more realistic astrophysical simulations, and we demonstrate how it can be extended to model subpopulations within a given formation channel, as well as to perform astrophysics-agnostic population inference.

Mudur, Nayantara, nmudur@g.harvard.edu, Towards better spatial regularization for astrophysical fields
Galactic extinction maps play a crucial role in astronomy as they are needed to derive the true magnitudes of samples of extragalactic objects that enable cosmological analyses. While emission-based maps have high resolution, they have been shown to contain localized systematic issues, creating a need for alternative extinction maps based on measurements of starlight. Current stellar posterior inference frameworks only yield noisy stochastic measurements of the underlying extinction field, making existing star-based maps either lower resolution or much noisier. We generate a spatial prior over dust images by learning the wavelet-scattering-transform (WST) coefficients of patches of emission-based maps. We then do gradient descent on this analytically-differentiable WST prior and the likelihood derived from star-based measurements. I will describe some preliminary results on using analytically-differentiable wavelet-scattering-transform (WST) coefficient-based priors to generate more realistic, lower noise star-based extinction maps.

Petrini, Leonardo, leonardo.petrini@epfl.ch, Relative stability toward diffeomorphisms indicates performance in deep nets
Understanding why deep nets can classify data in large dimensions remains a challenge. It has been proposed that they do so by becoming stable to diffeomorphisms, yet existing empirical measurements support that it is often not the case. We revisit this question by defining a maximum-entropy distribution on diffeomorphisms, that allows to study typical diffeomorphisms of a given norm. We confirm that stability toward diffeomorphisms does not strongly correlate to performance on benchmark data sets of images. By contrast, we find that the stability toward diffeomorphisms relative to that of generic transformations Rf correlates remarkably with the test error ϵt. It is of order unity at initialization but decreases by several decades during training for state-of-the-art architectures, while it increases for fully connected nets. For CIFAR10 and 15 known architectures, we find ϵt≈0.2*Rf**0.5, suggesting that obtaining a small Rf is important to achieve good performance. We provide simple models of invariant learning that rationalize our findings.

Shankar, Varun, varunshankar@cmu.edu, Machine Learning Turbulence Closures
There are two emerging approaches to differentiable physics, (i) incorporating symmetry in machine learning architectures ensuring physicality of the predictions with respect to the underlying system and (ii) pairing differentiable programming with classical numerical methods for physical simulation. In this talk, we will address both of these approaches towards turbulence modeling. In the first category, we propose a novel implementation of SO(3)-equivariant tensor graph networks to model moderate Reynolds number fluid systems in an arbitrary point-cloud domain. We use our model to predict, a-priori, turbulent quantities such as the eddy viscosity field. The resulting field is used in conjunction with standard CFD codes to solve for the steady-state pressure and velocity fields. The encoded symmetries allow for natural representation of the tensor fields involved in fluid dynamics calculations while respecting their geometric properties. Our framework reduces the computational cost of simulations by removing the need to solve additional turbulence closure equations during the simulation. We validate our outputs with a-posteriori analysis of the solution fields. In the second category, we will discuss an approach using the universal differential equations paradigm that can combine physics along with machine learning to develop turbulence closure models. We consider the 1D Burgers system as the ideal test problem for modeling the energy spectra observed in advection-dominated turbulence problems. Rather than naively training a coarse-grid correction term (called turbulence closure) to the Burgers equation, we train components of the transport equation to the closure in an end-to-end fashion. Addition of structure in the form of physics information brings a level of interpretability to the model, potentially offering a stepping stone to the future of closure modeling.

Singha, Ankur, anksing@iitk.ac.in, Conditional Normalizing Flow for Markov Chain Monte Carlo Sampling in the Critical Region of Lattice Field Theory
In Lattice Field Theory, one of the key drawbacks of the Markov Chain Monte Carlo(MCMC) simulation is the high correlation between the generated samples in the critical region. Generative machine learning methods, such as normalizing flows, offer a promising solution to speed up MCMC simulations, especially in the critical region. However, training these models for different parameter values of the lattice theory is inefficient. We address this issue by interpolating or extrapolating the flow model in the critical region. We demonstrate the effectiveness of the proposed method for MCMC sampling in critical regions for multiple parameter values of phi4 scalar theory in 1+1 dimensions and compare its performance against HMC and flow-based methods.

Wang, Dr.Lingxiao, lwang@fias.uni-frankfurt.de, Solving inverse problems with physics-driven deep learning
Inverse problems occur in almost all physical research, especially in inferring properties of many-body systems from finite noisy observations. The prior knowledge for specific physical systems routinely offers essential regularization schemes for solving the ill-posed problem approximately. Aiming at this point, we propose an automatic differentiation framework as a generic tool for the reconstruction from observable data. In lattice calculations and compact star cases, we represent spectral functions and equation of states by neural networks respectively, and set chi-square as loss function to optimize the parameters with backward propagation unsupervisedly. Our reconstructions approach compatible results compared with existing methods, moreover, it should be noted that the freedom of introducing regularization are inherent advantages and may lead to improvements of solving inverse problem in the future.

Youssef, Ahmed, youssead@ucmail.uc.edu, ML for Hadronization
In this talk, I will give an overview on the first steps in the development of a new class of Hadronization Models utilizing machine learning techniques. We successfully implement, validate, and train a conditional sliced-Wasserstein autoencoder to replicate the Pythia generated kinematic distributions of first-hadron emissions when the Lund string model of hadronization implemented in Pythia is restricted to the emissions of pions only. The trained models are then used to generate the full hadronization chains, with an IR cutoff energy imposed externally. The hadron multiplicities and cumulative kinematic distributions are shown to match the Pythia generated ones. I will also discuss possible future generalizations of our results.

	Monday, August 1, 2022	Tuesday, August 2, 2022	Wednesday, August 3, 2022	Thursday, August 4, 2022	Friday, August 5, 2022
8:30–9:00am	Breakfast	Breakfast	Breakfast	Breakfast	Breakfast
9:00–9:30am	Welcome/Introduction from IAIFI Director, Jesse Thaler	Lightning Talks	Lightning Talks	Lightning Talks	Lightning Talks
9:30–10:00am	Foundations of Geometric Deep Learning I: Taco Cohen, Research Scientist, Qualcomm Research Netherlands	Foundations of Geometric Deep Learning II: Taco Cohen, Research Scientist, Qualcomm Research Netherlands	Deep learning in the large-width regime II: Yasaman Bahri, Research Scientist, Google Research (Brain Team)	Machine Learning for Beyond-the-Standard-Model Physics II: Sven Krippendorf, Senior Researcher, Mathematical Physics and String Theory, Ludwig-Maximilians Universität	Machine learning for many-body physics II: Juan Carrasquilla, Research Scientist, Vector Institute; Adjunct Assistant Professor, University of Waterloo
10:00–10:30am					
10:30–11:00am	Coffee break	Coffee break	Coffee break	Coffee break	Coffee break
11:00am–11:30am	Representations, networks, and symmetries for learning from particle physics data: Javier Duarte, Assistant Professor, University of California, San Diego	Model compression and fast machine learning in particle physics: Javier Duarte, Assistant Professor, University of California, San Diego	Machine Learning for Beyond-the-Standard-Model Physics I: Sven Krippendorf, Senior Researcher, Mathematical Physics and String Theory, Ludwig-Maximilians Universität	Machine learning for many-body physics I: Juan Carrasquilla, Research Scientist, Vector Institute; Adjunct Assistant Professor, University of Waterloo	Tutorial II for Machine learning for many-body physics: Di Luo, IAIFI Fellow
11:30am–12:00pm					
12:00–12:30pm	Lunch	Lunch	Lunch	Lunch	Lunch
12:30–1:00pm					
1:00–1:30pm	Tutorial I for Foundations of Geometric Deep Learning: Denis Boyda, Incoming IAIFI Fellow	Tutorial II for Foundations of Geometric Deep Learning: Denis Boyda, Incoming IAIFI Fellow	Tutorial for Deep learning in the large-width regime: Anna Golubeva, IAIFI Fellow	Tutorial for Machine Learning for Beyond-the-Standard-Model Physics: Modeling and inference: connecting theory and data: Siddharth Mishra-Sharma, IAIFI Fellow	Mini-Hackathon
1:30–2:00pm					
2:00–2:30pm	Tutorial I for Model compression and fast machine learning in particle physics: Training Invariant Networks: Dylan Rankin, Postdoc, MIT/IAIFI	Tutorial II for Model compression and fast machine learning in particle physics: Compressing Neural Networks for Ultrafast Inference: Dylan Rankin, Postdoc, MIT/IAIFI			
2:30–3:00pm					
3:00–3:30pm	Break	Coffee Break	Coffee Break	Coffee Break	
3:30–4:00pm		Deep learning in the large-width regime I: Yasaman Bahri, Research Scientist, Google Research (Brain Team)	Career Panel	Tutorial I for Machine learning for many-body physics: Di Luo, IAIFI Fellow	
4:00–4:30pm	Welcome Dinner				
4:30–5:00pm				Break	
5:00–5:30pm					
5:30–6:00pm					
6:00–8:00pm				IAIFI Social and Dinner	