String Data 2024

Abstracts for the invited talks

James Halverson (Northeastern University)

"Conformality and Unitarity in NN-FT"
https://www.arxiv.org/abs/2409.12222
A neural network architecture and its parameter density together define a partition function that constitutes a new approach to field theory. In this talk I'll present recent progress achieving conformal symmetry with the embedding formalism, and unitarity via reflection positivity.

François Charton (META AI)

"Transforming the Bootstrap: Using Transformers to Compute Scattering Amplitudes in Planar N = 4 Super Yang-Mills Theory"
https://www.arxiv.org/abs/2405.06107
Amplitude bootstrap is a powerful technique that allows the calculation of high precision scattering amplitudes, represented as symbols: homogeneous polynomials with integer coefficients. We show that language models can be trained to predict these integer coefficients to very high accuracy, allowing for higher loop calculations, and suggesting the presence of yet unknown regularities in the symbol.

Hyun-Sik Jeong (Institute for Theoretical Physics UAM-CSIC in Madrid)

"Machine Learning in Applied Holography: Introduction to a New Era"
Applied holography (holographic duality) has become a valuable tool for studying strongly interacting systems and quantum gravity. This introductory review provides minimal background for those unfamiliar with the field and discusses recent advances involving machine learning, including my own research. It also sets the stage for an

upcoming talk on deep learning applications in holographic spacetime.

Keun-Young Kim (GIST)

"Deep learning holographic bulk spacetime from boundary quantum data"
https://www.arxiv.org/abs/2406.07395
https://www.arxiv.org/abs/2401.00939
https://www.arxiv.org/abs/2011.13726
According to the holographic principle, there exists a relationship between quantum systems and higher-dimensional gravitational theories. We apply a deep learning approach to infer the holographic bulk spacetime from boundary quantum data, such as conductivity and entanglement entropy. This method is intriguing, as it models AdS space through a deep neural network framework. Moreover, it is universal in that it applies to a wide range of physics problems involving differential equations and integrals.

Yago Bea (University of Barcelona)

"Gravitational duals from equations of state"
https://www.arxiv.org/abs/2403.14763
Holography relates gravitational theories in five dimensions to four-dimensional quantum field theories in flat space. Under this map, the equation of state of the field theory is encoded in the black hole solutions of the gravitational theory. Solving the five-dimensional Einstein's equations to determine the equation of state is an algorithmic, direct problem. Determining the gravitational theory that gives rise to a prescribed equation of state is a much more challenging, inverse problem. We present a novel approach to solve this problem based on physics-informed neural networks. The resulting algorithm is not only data-driven but also informed by the physics of the Einstein's equations. We successfully apply it to theories with crossovers, first- and second-order phase transitions.

Song He (Ningbo University and Max-Planck Institute for Gravitational

physics (AEI))
"Neural ODE Approach to the Magnetic QCD Phase Diagram via Holography"
https://www.arxiv.org/abs/2406.12772
https://www.arxiv.org/abs/2201.02004

Edward Hirst (Queen Mary, University of London)

"Gaussian Weight Matrix Models: Breaking Permutation Invariance"
On initialisation Neural Network Weight Matrices satisfy a permutation invariance which is broken through the training process. Modelling the initialisation distribution as a Gaussian weight matrix model, in terms of irreducible representations of the permutation group, we study how this permutation symmetry is broken by tracking model invariants throughout training. We study this for the industry-standard Gaussian and Uniform initialisation distributions for the classification of MNIST, considering the effects of regularisation, and large layer size limits.

Gabriel Lopes Cardoso (Lisbon, IST)

"Classical integrability in the presence of a cosmological constant: analytic and machine learning results"
https://www.arxiv.org/abs/2404.18247
We study the integrability of two-dimensional theories that are obtained by a dimensional reduction of certain four-dimensional gravitational theories describing the coupling of Maxwell fields and neutral scalar fields to gravity in the presence of a potential for the neutral scalar fields. For a certain solution subspace, we demonstrate partial integrability by showing that a subset of the equations of motion in two dimensions are the compatibility conditions for a linear system. Subsequently, we study the integrability of these two-dimensional models from a complementary one-dimensional point of view, framed in terms of Liouville integrability. In this endeavour, we employ various ML techniques to search for numerical Lax pair matrices for these models, as well as conserved currents expressed as functions of phase space variables.

Matthew Schwartz (Harvard University)

“Machine learning the S matrix”

Yuji Hirono (Osaka U)

“Understanding diffusion models by path integral”
https://www.arxiv.org/abs/2403.11262
Score-based diffusion models have emerged as a powerful tool for image generation. We present a new perspective on these models through Feynman's path integral formulation of quantum physics. This approach enables us to derive key equations of diffusion models through the lens of physics. We introduce a parameter that bridges stochastic and deterministic sampling, which reveals an intriguing parallel with quantum mechanics - it plays a role analogous to Planck's constant. Leveraging this connection, we apply the WKB expansion to evaluate model likelihood, shedding light on the performance differences between stochastic and deterministic sampling schemes.

Sven Krippendorf (University of Cambridge)

“Deep Observations of the Flux Landscape”

Vishnu Jejjala (University of the Witwatersrand in Johannesburg)

“Colored Jones Polynomials and the Volume Conjecture”

Rak-Kyeong Seong (UNIST)

“Generative AI for Brane Configurations, Tropical Coamoeba and 4d N=1 Quiver Gauge Theories”
https://www.arxiv.org/abs/2411.16033
https://www.arxiv.org/abs/2310.19276

https://www.arxiv.org/abs/2309.05702
https://www.arxiv.org/abs/1704.03462
We introduce a generative AI model to obtain Type IIB brane configurations that realize toric phases of a family of 4d N=1 supersymmetric gauge theories. These theories are worldvolume theories of a D3-brane probing a toric Calabi-Yau 3-fold. The generative AI allows us not only to construct a high-resolution phase space representation of this family of 4d N=1 theories, but allows us to track the movements of the corresponding mirror curve and individual branes in the corresponding Type IIB brane configuration.

Hajime Otsuka (Kyushu U)

"Machine learning-based analysis of the Atiyah-Singer index in string compactifications"
https://www.arxiv.org/abs/2003.11880
https://www.arxiv.org/abs/2312.07181
We study distributions of the Atiyah-Singer index in string compactifications such as type IIA intersecting D-brane models and heterotic line bundle models. By utilizing deep autoencoder networks, we find that the generation number of massless fermions is specified by tadpole charges.

Anindita Maiti (Perimeter Institute)

"A Wilsonian RG framework for Regression Tasks in Supervised Learning"
https://arxiv.org/abs/2405.06008
The performance of machine learning (ML) models fundamentally hinges on their ability to discriminate between relevant and irrelevant features in data. We introduce a first-of-its-kind Wilsonian RG framework to analyze the predictions of overparameterized neural networks (NN), which are models characterized by an excess of parameters relative to the complexity of the task. These networks, trained via supervised learning, are known to produce noisy outputs in regression tasks. In our formulation, irrelevant features within the data are systematically coarse-grained

through momentum shell RG, inducing an RG flow that governs the evolution of noise in the predictions. When the irrelevant features follow a Gaussian distribution, this RG flow exhibits universality across different NN architectures. In contrast, non-Gaussian features give rise to more intricate, data-dependent RG flows. This approach reveals novel behaviors in NNs that have eluded conventional ML methods. By advancing beyond philosophical analogies between RG and ML, our framework offers a field theory-based methodology for understanding feature learning.

Elia Cellini (University of Turin, INFN)

"Flow-based sampling for Effective String Theory"
https://www.arxiv.org/abs/2307.01107
https://www.arxiv.org/abs/2409.15937
Effective String Theory (EST) is a powerful tool used to study confinement in pure gauge theories by modeling the confining flux tube connecting a static quark-anti-quark pair as a thin vibrating string. Recently, flow-based samplers have been applied as an efficient numerical method to study EST regularized on the lattice, opening the route to study observables previously inaccessible to standard analytical methods. Flow-based samplers are a class of algorithms based on Normalizing Flows (NFs), deep generative models recently proposed as a promising alternative to traditional Markov Chain Monte Carlo methods in lattice field theory calculations. In this talk, I will outline EST and flow-based samplers, then, I will show some new numerical results for the width and shape of the effective string.

Fabian Ruehle (Northeastern University)

"Learning knot Invariance"
Knots are embedded circles in a R^3 and are considered equivalent if related by ambient isotopy. We propose to use techniques from generative AI and contrastive learning to automate the process of learning knot invariance. We set up a neural network with a contrastive loss that clusters different representations from the same knot equivalence class in the embedding dimension. We also use transformers to map

different representations from the same knot equivalence class to a single (arbitrary) representative of their class. We explain how to use the generative model to study the Jones unknotting conjecture and how we examine which invariants are learned by the trained model.

Sergei Gukov (Caltech)

"Searching for unicorns"
https://arxiv.org/abs/2408.15332