A Living Review of Quantum Information in High Energy Physics

Abstract: Inspired by "A Living Review of Machine Learning for Particle Physics"[1], the goal of this document is to provide a nearly comprehensive list of citations for those developing and applying quantum information approaches to experimental, phenomenological, or theoretical analyses. Applications of quantum information science to high energy physics is a relatively new field of research. As a living document, it will be updated as often as possible with the relevant literature with the latest developments. Suggestions are most welcome.

[1]See https://github.com/iml-wg/HEPML-LivingReview.

The purpose of this note is to collect references for quantum information science as applied to particle and nuclear physics. The papers listed are in no particular order. In order to be as useful as possible, this document will continually change. Please check back[2] regularly. You can simply download the .bib file to get all of the latest references. Suggestions are most welcome.

1 Reviews

- Quantum Machine Learning in High Energy Physics [1]

2 Whitepapers

- Quantum Simulation for High Energy Physics [2]
- Quantum Computing for Data Analysis in High-Energy Physics [3]
- Snowmass White Paper: Quantum Computing Systems and Software for High-energy Physics Research [4]
- Snowmass white paper: Quantum information in quantum field theory and quantum gravity [5]
- New Horizons: Scalar and Vector Ultralight Dark Matter [6]
- Quantum Networks for High Energy Physics [7]

3 Quantum Optimization Algorithms Based on Gate-Based Quantum Computers

- Quantum Algorithms for Jet Clustering [8]
- Quantum speedup for track reconstruction in particle accelerators [9]

4 Quantum Optimization Algorithms Based on Quantum Annealing

- Quantum Algorithms for Jet Clustering [8]

[2] See https://github.com/PamelaPajarillo/HEPQIS-LivingReview.

- Quantum Annealing for Jet Clustering with Thrust [10]
- Degeneracy Engineering for Classical and Quantum Annealing: A Case Study of Sparse Linear Regression in Collider Physics [11]
- Leveraging Quantum Annealer to identify an Event-topology at High Energy Colliders [12]
- Charged particle tracking with quantum annealing-inspired optimization [13]
- A pattern recognition algorithm for quantum annealers [14]
- Adiabatic Quantum Algorithm for Multijet Clustering in High Energy Physics [15]

5 Quantum Machine Learning Algorithms Based on Gate-Based Quantum Computers

- Application of quantum machine learning using the quantum variational classifier method to high energy physics analysis at the LHC on IBM quantum computer simulator and hardware with 10 qubits [16]
- Application of quantum machine learning using the quantum kernel algorithm on high energy physics analysis at the LHC [17]
- Application of Quantum Machine Learning to High Energy Physics Analysis at LHC Using Quantum Computer Simulators and Quantum Computer Hardware [18]
- Quantum Anomaly Detection for Collider Physics [19]
- Event Classification with Quantum Machine Learning in High-Energy Physics [20]
- Quantum Machine Learning for b-jet identification [21]
- Classical versus Quantum: comparing Tensor Network-based Quantum Circuits on LHC data [22]
- Anomaly detection in high-energy physics using a quantum autoencoder [23]
- Implementation and analysis of quantum computing application to Higgs boson reconstruction at the large Hadron Collider [24]
- Style-based quantum generative adversarial networks for Monte Carlo events [25]

- Quantum convolutional neural networks for high energy physics data analysis [26]
- Hybrid Quantum-Classical Graph Convolutional Network [27]
- Quantum Machine Learning for Particle Physics using a Variational Quantum Classifier [28]
- Application of a Quantum Search Algorithm to High- Energy Physics Data at the Large Hadron Collider [29]
- Quantum Support Vector Machines for Continuum Suppression in B Meson Decays [30]
- Higgs analysis with quantum classifiers [31]
- Unsupervised Quantum Circuit Learning in High Energy Physics [32]

6 Quantum Machine Learning Algorithms Based on Quantum Annealing

- Solving a Higgs optimization problem with quantum annealing for machine learning [33]
- Quantum adiabatic machine learning with zooming [34]
- Quantum algorithm for the classification of supersymmetric top quark events [35]

7 Quantum Simulations

- SU(2) hadrons on a quantum computer via a variational approach [36]
- Quantum Algorithm for High Energy Physics Simulations [37]
- Scalar Quantum Field Theories as a Benchmark for Near-Term Quantum Computers [38]

8 Quantum-Inspired Algorithms

- Quantum-inspired event reconstruction with Tensor Networks: Matrix Product States [39]

9 TBD

- Unsupervised event classification with graphs on classical and photonic quantum computers [40]
- Collider Events on a Quantum Computer [41]
- Track clustering with a quantum annealer for primary vertex reconstruction at hadron colliders [42]
- Particle track classification using quantum associative memory [43]
- Hybrid Quantum Classical Graph Neural Networks for Particle Track Reconstruction [44]
- A Digital Quantum Algorithm for Jet Clustering in High-Energy Physics [45]
- A quantum algorithm for model independent searches for new physics [46]
- Dual-Parameterized Quantum Circuit GAN Model in High Energy Physics [47]
- Running the Dual-PQC GAN on noisy simulators and real quantum hardware [48]
- Quantum Generative Adversarial Networks in a Continuous-Variable Architecture to Simulate High Energy Physics Detectors [49]
- Quantum integration of elementary particle processes [50]
- Quantum-inspired machine learning on high-energy physics data [51]
- Lattice renormalization of quantum simulations [52]

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