A Living Review of Quantum Information Science in High Energy Physics Organized by QIS Topics - LIST Version

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 Computing for Data Analysis in High-Energy Physics [2]
- Quantum Simulation for 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 Annealing

- Quantum Machine Learning in High Energy Physics [1]
- Quantum Computing for Data Analysis in High-Energy Physics [2]
- Solving a Higgs optimization problem with quantum annealing for machine learning [8]
- Quantum adiabatic machine learning with zooming [9]
- Completely Quantum Neural Networks [10]
- Quantum algorithm for the classification of supersymmetric top quark events [11]

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

- Quantum Algorithms for Jet Clustering [12]
- Quantum Annealing for Jet Clustering with Thrust [13]
- Leveraging Quantum Annealer to identify an Event-topology at High Energy Colliders [14]
- Charged particle tracking with quantum annealing-inspired optimization [15]
- A pattern recognition algorithm for quantum annealers [16]
- Adiabatic Quantum Algorithm for Multijet Clustering in High Energy Physics [17]
- Degeneracy Engineering for Classical and Quantum Annealing: A Case Study of Sparse Linear Regression in Collider Physics [18]
- Track clustering with a quantum annealer for primary vertex reconstruction at hadron colliders [19]
- Particle track classification using quantum associative memory [20]
- Restricted Boltzmann Machines for galaxy morphology classification with a quantum annealer [21]
- A regression algorithm for accelerated lattice QCD that exploits sparse inference on the D-Wave quantum annealer [22]
- SU(2) lattice gauge theory on a quantum annealer [23]

4 Variational Quantum Circuits

- Quantum Machine Learning in High Energy Physics [1]
- Quantum Computing for Data Analysis in High-Energy Physics [2]
- 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 [24]
- Quantum Anomaly Detection for Collider Physics [25]
- Event Classification with Quantum Machine Learning in High-Energy Physics [26]
- Quantum Machine Learning for *b*-jet identification [27]

- Anomaly detection in high-energy physics using a quantum autoencoder [28]
- Quantum convolutional neural networks for high energy physics data analysis [29]
- Hybrid Quantum-Classical Graph Convolutional Network [30]
- Quantum Machine Learning for Particle Physics using a Variational Quantum Classifier [31]
- Quantum Support Vector Machines for Continuum Suppression in B Meson Decays [32]
- Higgs analysis with quantum classifiers [33]
- Unsupervised Quantum Circuit Learning in High Energy Physics [34]

5 Quantum Support Vector Machines

- Quantum Computing for Data Analysis in High-Energy Physics [2]
- Application of quantum machine learning using the quantum kernel algorithm on high energy physics analysis at the LHC [35]
- Quantum Support Vector Machines for Continuum Suppression in B Meson Decays [32]

6 Quantum Convolutional Neural Networks

- Quantum Computing for Data Analysis in High-Energy Physics [2]
- Quantum convolutional neural networks for high energy physics data analysis [29]
- Hybrid Quantum-Classical Graph Convolutional Network [30]

7 Algorithms Based on Amplitude Amplification

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- Application of a Quantum Search Algorithm to High- Energy Physics Data at the Large Hadron Collider [37]
- Quantum Algorithms for Jet Clustering [12]

8 Quantum Walks

- Collider Events on a Quantum Computer [38]
- A quantum walk approach to simulating parton showers [39]

9 Continuous Variable Quantum Computing

- Unsupervised event classification with graphs on classical and photonic quantum computers [40]
- Quantum Generative Adversarial Networks in a Continuous-Variable Architecture to Simulate High Energy Physics Detectors [41]

10 Quantum Autoencoders

- Anomaly detection in high-energy physics using a quantum autoencoder [28]

11 Quantum Generative Adversarial Networks

- Quantum Computing for Data Analysis in High-Energy Physics [2]
- Style-based quantum generative adversarial networks for Monte Carlo events [42]
- Dual-Parameterized Quantum Circuit GAN Model in High Energy Physics [43]
- Running the Dual-PQC GAN on noisy simulators and real quantum hardware [44]
- Quantum Generative Adversarial Networks in a Continuous-Variable Architecture to Simulate High Energy Physics Detectors [41]
- Quantum integration of elementary particle processes [45]

12 Quantum Circuit Born Machines

- Quantum Computing for Data Analysis in High-Energy Physics [2]
- Unsupervised Quantum Circuit Learning in High Energy Physics [34]

13 Quantum-Inspired Algorithms

- Quantum Computing for Data Analysis in High-Energy Physics [2]
- Quantum-inspired event reconstruction with Tensor Networks: Matrix Product States [46]
- Quantum-inspired machine learning on high-energy physics data [47]

14 Tensor Networks

- Quantum-inspired event reconstruction with Tensor Networks: Matrix Product States [46]
- Classical versus Quantum: comparing Tensor Network-based Quantum Circuits on LHC data [48]

15 Quantum Simulations

- Quantum Simulation for High Energy Physics [3]
- Simulating Collider Physics on Quantum Computers Using Effective Field Theories [49]
- SU(2) hadrons on a quantum computer via a variational approach [50]
- Quantum Algorithm for High Energy Physics Simulations [51]
- Scalar Quantum Field Theories as a Benchmark for Near-Term Quantum Computers [52]

16 Quantum Sensors

- New Horizons: Scalar and Vector Ultralight Dark Matter [6]
- Quantum Networks for High Energy Physics [7]
- Searching for Dark Matter with a Superconducting Qubit [53]

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- Quantum speedup for track reconstruction in particle accelerators [54]
- Hybrid Quantum Classical Graph Neural Networks for Particle Track Reconstruction [55]
- A Digital Quantum Algorithm for Jet Clustering in High-Energy Physics [56]
- A quantum algorithm for model independent searches for new physics [57]
- Lattice renormalization of quantum simulations [58]
- Quantum Algorithms for Fermionic Quantum Field Theories [59]
- Quantum Computation of Scattering in Scalar Quantum Field Theories [60]
- Efficient Representation for Simulating U(1) Gauge Theories on Digital Quantum Computers at All Values of the Coupling [61]
- Role of boundary conditions in quantum computations of scattering observables [62]
- Towards a quantum computing algorithm for helicity amplitudes and parton showers [63]
- Simulating lattice gauge theories on a quantum computer [64]
- Quantum algorithm for Feynman loop integrals [65]
- Partonic collinear structure by quantum computing [66]

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