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.

0.1 Reviews

- Quantum Machine Learning in High Energy Physics [1]

0.2 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]

1 Quantum Annealing

1.1 Jet Algorithms and Jet Tagging

- Quantum Algorithms for Jet Clustering [8]
- Quantum Annealing for Jet Clustering with Thrust [9]
- Adiabatic Quantum Algorithm for Multijet Clustering in High Energy Physics [10]

1.2 Track Reconstruction

- Charged particle tracking with quantum annealing-inspired optimization [11]
- A pattern recognition algorithm for quantum annealers [12]
- Track clustering with a quantum annealer for primary vertex reconstruction at hadron colliders [13]
- Particle track classification using quantum associative memory [14]

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

1.3 Signal-Background Discrimination

- Solving a Higgs optimization problem with quantum annealing for machine learning [15]
- Quantum adiabatic machine learning with zooming [16]

1.4 Beyond the Standard Model

- Completely Quantum Neural Networks [17]
- Quantum algorithm for the classification of supersymmetric top quark events [18]

1.5 Lattice Field Theories

- A regression algorithm for accelerated lattice QCD that exploits sparse inference on the D-Wave quantum annealer [19]
- SU(2) lattice gauge theory on a quantum annealer [20]

1.6 Cosmology

- Restricted Boltzmann Machines for galaxy morphology classification with a quantum annealer [21]

1.7 Uncategorized by HEP - TEMPORARY

- Leveraging Quantum Annealer to identify an Event-topology at High Energy Colliders [22]
- Degeneracy Engineering for Classical and Quantum Annealing: A Case Study of Sparse Linear Regression in Collider Physics [23]

2 Variational Quantum Circuits

2.1 Jet Algorithms and Jet Tagging

- Quantum Machine Learning for b-jet identification [24]

2.2 Signal-Background Discrimination

- 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 [25]
- Event Classification with Quantum Machine Learning in High-Energy Physics [26]
- Quantum Machine Learning for Particle Physics using a Variational Quantum Classifier [27]
- Quantum Support Vector Machines for Continuum Suppression in B Meson Decays [28]
- Higgs analysis with quantum classifiers [29]

2.3 Anomaly Detection

- Quantum Anomaly Detection for Collider Physics [30]
- Anomaly detection in high-energy physics using a quantum autoencoder [31]

2.4 Neutrinos

- Quantum convolutional neural networks for high energy physics data analysis [32]
- Hybrid Quantum-Classical Graph Convolutional Network [33]

2.5 Uncategorized by HEP - TEMPORARY

- Unsupervised Quantum Circuit Learning in High Energy Physics [34]

3 Quantum Support Vector Machines

3.1 Signal-Background Discrimination

- 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 [28]

4 Quantum Convolutional Neural Networks

5 Algorithms Based on Amplitude Amplification

5.1 Jet Algorithms and Jet Tagging

- Quantum Algorithms for Jet Clustering [8]

5.2 Beyond the Standard Model

- Implementation and analysis of quantum computing application to Higgs boson reconstruction at the large Hadron Collider [36]
- Application of a Quantum Search Algorithm to High- Energy Physics Data at the Large Hadron Collider [37]

6 Quantum Walks

6.1 Event Generation

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

7 Continuous Variable Quantum Computing

7.1 Anomaly Detection

- Unsupervised event classification with graphs on classical and photonic quantum computers [40]

7.2 Uncategorized by HEP - TEMPORARY

- Quantum Generative Adversarial Networks in a Continuous-Variable Architecture to Simulate High Energy Physics Detectors [41]

8 Quantum Autoencoders

8.1 Anomaly Detection

- Anomaly detection in high-energy physics using a quantum autoencoder [31]

9 Quantum Generative Adversarial Networks

9.1 Event Generation

- Style-based quantum generative adversarial networks for Monte Carlo events [42]
- Quantum integration of elementary particle processes [43]

9.2 Uncategorized by HEP - TEMPORARY

- Dual-Parameterized Quantum Circuit GAN Model in High Energy Physics [44]
- Running the Dual-PQC GAN on noisy simulators and real quantum hardware [45]
- Quantum Generative Adversarial Networks in a Continuous-Variable Architecture to Simulate High Energy Physics Detectors [41]

10 Quantum Circuit Born Machines

10.1 Uncategorized by HEP - TEMPORARY

- Unsupervised Quantum Circuit Learning in High Energy Physics [34]

11 Quantum-Inspired Algorithms

11.1 Jet Algorithms and Jet Tagging

- Quantum-inspired event reconstruction with Tensor Networks: Matrix Product States [46]
- Quantum-inspired machine learning on high-energy physics data [47]

12 Tensor Networks

12.1 Jet Algorithms and Jet Tagging

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

13 Quantum Simulations

13.1 Quantum Field Theories

- Scalar Quantum Field Theories as a Benchmark for Near-Term Quantum Computers [49]

13.2 Uncategorized by HEP - TEMPORARY

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

14 Quantum Sensors

14.1 Beyond the Standard Model

- Searching for Dark Matter with a Superconducting Qubit [53]

15 Uncategorized by QIS - TEMPORARY

15.1 Jet Algorithms and Jet Tagging

- A Digital Quantum Algorithm for Jet Clustering in High-Energy Physics [54]

15.2 Track Reconstruction

- Quantum speedup for track reconstruction in particle accelerators [55]
- Hybrid Quantum Classical Graph Neural Networks for Particle Track Reconstruction [56]

15.3 Event Generation

- Towards a quantum computing algorithm for helicity amplitudes and parton showers [57]

15.4 Anomaly Detection

- A quantum algorithm for model independent searches for new physics [58]

15.5 Beyond the Standard Model

- A quantum algorithm for model independent searches for new physics [58]

15.6 Quantum Field Theories

- Quantum Algorithms for Fermionic Quantum Field Theories [59]

15.7 Lattice Field Theories

- Lattice renormalization of quantum simulations [60]
- Quantum Computation of Scattering in Scalar Quantum Field Theories [61]
- Efficient Representation for Simulating U(1) Gauge Theories on Digital Quantum Computers at All Values of the Coupling [62]
- Role of boundary conditions in quantum computations of scattering observables [63]
- Simulating lattice gauge theories on a quantum computer [64]

15.8 Uncategorized by HEP - TEMPORARY

- Quantum algorithm for Feynman loop integrals [65]
- Partonic collinear structure by quantum computing [66]

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