# A Living Review of Quantum Information Science in High Energy Physics Organized by HEP 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 Jet Clustering

- Quantum Computing for Data Analysis in High-Energy Physics [2]
- 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]
- A Digital Quantum Algorithm for Jet Clustering in High-Energy Physics [11]

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

# 4 Track Reconstruction

- Quantum Computing for Data Analysis in High-Energy Physics [2]
- Charged particle tracking with quantum annealing-inspired optimization [12]
- A pattern recognition algorithm for quantum annealers [13]
- Quantum speedup for track reconstruction in particle accelerators [14]
- Track clustering with a quantum annealer for primary vertex reconstruction at hadron colliders [15]
- Particle track classification using quantum associative memory [16]
- Hybrid Quantum Classical Graph Neural Networks for Particle Track Reconstruction [17]

# 5 Event Generation

- Quantum Computing for Data Analysis in High-Energy Physics [2]
- Style-based quantum generative adversarial networks for Monte Carlo events [18]
- Collider Events on a Quantum Computer [19]
- A quantum walk approach to simulating parton showers [20]
- Quantum integration of elementary particle processes [21]

# 6 Detector Simulation

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

# 7 Signal-Background Discrimination

- 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 [22]

- Application of quantum machine learning using the quantum kernel algorithm on high energy physics analysis at the LHC [23]
- Event Classification with Quantum Machine Learning in High-Energy Physics [24]
- Solving a Higgs optimization problem with quantum annealing for machine learning [25]
- Quantum adiabatic machine learning with zooming [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]
- Completely Quantum Neural Networks [30]

## 8 Jet Classification

- Quantum Machine Learning for $b$-jet identification [31]

## 9 Anomaly Detection

- Quantum Anomaly Detection for Collider Physics [32]
- Anomaly detection in high-energy physics using a quantum autoencoder [33]
- A quantum algorithm for model independent searches for new physics [34]

## 10 Supersymmetry

- Event Classification with Quantum Machine Learning in High-Energy Physics [24]
- Quantum algorithm for the classification of supersymmetric top quark events [35]

## 11 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]
- Completely Quantum Neural Networks [30]
- A quantum algorithm for model independent searches for new physics [34]

## 12 Quantum Field Theories

## 13 Lattice Field Theories

- Lattice renormalization of quantum simulations [38]
- A regression algorithm for accelerated lattice QCD that exploits sparse inference on the D-Wave quantum annealer [39]
- Quantum Computation of Scattering in Scalar Quantum Field Theories [40]
- Efficient Representation for Simulating U(1) Gauge Theories on Digital Quantum Computers at All Values of the Coupling [41]
- SU(2) lattice gauge theory on a quantum annealer [42]
- Role of boundary conditions in quantum computations of scattering observables [43]

## 14 Neutrinos

- Quantum convolutional neural networks for high energy physics data analysis [44]
- Hybrid Quantum-Classical Graph Convolutional Network [45]

## 15 Cosmology

- Quantum Machine Learning in High Energy Physics [1]
- Quantum Computing for Data Analysis in High-Energy Physics [2]
- Restricted Boltzmann Machines for galaxy morphology classification with a quantum annealer [46]

## 16 Uncategorized by HEP - TEMPORARY

- 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]
- Leveraging Quantum Annealer to identify an Event-topology at High Energy Colliders [47]
- Quantum-inspired event reconstruction with Tensor Networks: Matrix Product States [48]
- Simulating Collider Physics on Quantum Computers Using Effective Field Theories [49]
- Unsupervised event classification with graphs on classical and photonic quantum computers [50]
- Unsupervised Quantum Circuit Learning in High Energy Physics [51]
- SU(2) hadrons on a quantum computer via a variational approach [52]
- Quantum Algorithm for High Energy Physics Simulations [53]
- Degeneracy Engineering for Classical and Quantum Annealing: A Case Study of Sparse Linear Regression in Collider Physics [54]
- Dual-Parameterized Quantum Circuit GAN Model in High Energy Physics [55]
- Running the Dual-PQC GAN on noisy simulators and real quantum hardware [56]
- Quantum Generative Adversarial Networks in a Continuous-Variable Architecture to Simulate High Energy Physics Detectors [57]
- Quantum-inspired machine learning on high-energy physics data [58]

- Scalar Quantum Field Theories as a Benchmark for Near-Term Quantum Computers [59]
- Searching for Dark Matter with a Superconducting Qubit [60]
- Classical versus Quantum: comparing Tensor Network-based Quantum Circuits on LHC data [61]
- Quantum Algorithms for Fermionic Quantum Field Theories [62]
- Towards a quantum computing algorithm for helicity amplitudes and parton showers [63]
- Simulating lattice gauge theories on a quantum computer [64]

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