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

0.1.1 Quantum Machine Learning in High Energy Physics [1]

- **HEP Context:** Di-photon event classification, galaxy morphology classification, particle track reconstruction, and signal-background discrimination with the SUSY data set

- **Methods:** Quantum machine learning using quantum annealing, restrictive Boltzmann machines, quantum graph networks, and variational quantum circuits

- **Results and Conclusions:** To be written

0.2 Whitepapers

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

- **HEP Context:** Object reconstruction (tracking problem and thrust for jet clustering), signal-background discrimination, detector simulations, and Monte Carlo event generation

- **Methods:** Amplitude amplification (generalization of Grover's algorithm), quantum annealing, hybrid quantum-classical neural networks, variational quantum circuits, quantum support vector machines, quantum convolutional neural networks, quantum variational autoencoders, and quantum generative models (quantum generative adversarial network and quantum circuit born machine)

- **Results and Conclusions:** To be written

0.2.2 Quantum Simulation for High Energy Physics [3]

- **HEP Context:** To be written

- **Methods:** To be written

- **Results and Conclusions:** To be written

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

0.2.3 Snowmass White Paper: Quantum Computing Systems and Software for High-energy Physics Research [4]

- **HEP Context:** To be written
- **Methods:** To be written
- **Results and Conclusions:** To be written

0.2.4 Snowmass white paper: Quantum information in quantum field theory and quantum gravity [5]

- **HEP Context:** To be written
- **Methods:** To be written
- **Results and Conclusions:** To be written

0.2.5 New Horizons: Scalar and Vector Ultralight Dark Matter [6]

- **HEP Context:** To be written
- **Methods:** To be written
- **Results and Conclusions:** To be written

0.2.6 Quantum Networks for High Energy Physics [7]

- **HEP Context:** To be written
- **Methods:** To be written
- **Results and Conclusions:** To be written

1 Quantum Annealing

1.1 Jet Algorithms and Jet Tagging

1.1.1 Quantum Algorithms for Jet Clustering [8]

- **HEP Context:** Thrust, an event shape whose optimum corresponds to the most jet-like separating plane among a set of particles, focusing on the case of electron-positron collisions

- **Methods:** (1) Created a quantum algorithm based on quantum annealing (enconded optimization problem as a QUBO problem); (2) Created quantum algorithm based on Grover search and describes two computing models, sequential model and parallel model, for loading classical data into quantum memory.

- **Results and Conclusions:** This paper finds an algorithm that improves the previously best known $O(N^3)$ classical thrust algorithm to an $O(N^2)$ sequential algorithm, while also finding an improved $O(N^2 \log N)$ classical algorithm. The computational costs of data loading must be carefully considered when evaluating the potential for quantum speedups on classical datasets.

1.1.2 Quantum Annealing for Jet Clustering with Thrust [9]

- **HEP Context:** To be written

- **Methods:** To be written

- **Results and Conclusions:** To be written

1.1.3 Adiabatic Quantum Algorithm for Multijet Clustering in High Energy Physics [10]

- **HEP Context:** To be written

- **Methods:** To be written

- **Results and Conclusions:** To be written

1.2 Track Reconstruction

1.2.1 Charged particle tracking with quantum annealing-inspired optimization [11]

- **HEP Context:** To be written

- **Methods:** To be written

- **Results and Conclusions:** To be written

1.2.2 A pattern recognition algorithm for quantum annealers [12]

- **HEP Context:** Pattern recognition for track reconstruction using the TrackML dataset, relevant for analysis at the HL-LHC

- **Methods:** To be written

- **Results and Conclusions:** To be written

1.2.3 Track clustering with a quantum annealer for primary vertex reconstruction at hadron colliders [13]

- **HEP Context:** To be written
- **Methods:** To be written
- **Results and Conclusions:** To be written

1.2.4 Particle track classification using quantum associative memory [14]

- **HEP Context:** To be written
- **Methods:** Quantum Associated Memory Model (QAMM) and Quantum Content-Addressable Memory (QCAM) on quantum annealers
- **Results and Conclusions:** To be written

1.3 Signal-Background Discrimination

1.3.1 Solving a Higgs optimization problem with quantum annealing for machine learning [15]

- **HEP Context:** Higgs signal-background discrimination, in which kinematic variables describing diphoton processes corresponds to either to a Higgs boson decay (signal) or other Standard Model processes (background).
- **Methods:** The strong classifier is then constructed from a linear combination of weak classifiers, where the weights are obtained through an optimization problem, which have a mapping to a quadratic unconstrained binary optimization (QUBO) problem. D-Wave's quantum annealer is used to solve the QUBO problem.
- **Results and Conclusions:** Quantum and classical annealing-based classifiers perform comparably with no clear advantage to traditional machine learning methods, including deep neural network (DNN) and an ensemble of boosted decision trees (BDTs).

1.3.2 Quantum adiabatic machine learning with zooming [16]

- **HEP Context:** Higgs signal-background discrimination, in which kinematic variables describing diphoton processes corresponds to either to a Higgs boson decay (signal) or other Standard Model processes (background)
- **Methods:** By iteratively perform quantum annealing, the binary weights on the weak classifiers can be made continuous, which results in a stronger classifier.

- **Results and Conclusions:** QAML-Z does not show an obvious advantage over traditional machine learning methods, including deep neural networks (DNNs) and boosted decision trees (BDTs), however, its performance surpasses the QAML algorithm and simulated annealing with zooming.

1.4 Beyond the Standard Model

1.4.1 Completely Quantum Neural Networks [17]

- **HEP Context:** Signal-background discrimination, where signal is two tops are the decay products of a hypothetical new particle Z', and the background is known Standard Model processes

- **Methods:** To be written

- **Results and Conclusions:** To be written

1.4.2 Quantum algorithm for the classification of supersymmetric top quark events [18]

- **HEP Context:** To be written

- **Methods:** To be written

- **Results and Conclusions:** To be written

1.5 Lattice Field Theories

1.5.1 A regression algorithm for accelerated lattice QCD that exploits sparse inference on the D-Wave quantum annealer [19]

- **HEP Context:** To be written

- **Methods:** To be written

- **Results and Conclusions:** To be written

1.5.2 SU(2) lattice gauge theory on a quantum annealer [20]

- **HEP Context:** To be written

- **Methods:** To be written

- **Results and Conclusions:** To be written

1.6 Cosmology

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

- **HEP Context:** To be written
- **Methods:** To be written
- **Results and Conclusions:** To be written

1.7 Uncategorized by HEP - TEMPORARY

1.7.1 Leveraging Quantum Annealer to identify an Event-topology at High Energy Colliders [22]

- **HEP Context:** Identify an event-topology, a diagram to describe the history of the particles produced at the LHC
- **Methods:** To be written
- **Results and Conclusions:** To be written

1.7.2 Degeneracy Engineering for Classical and Quantum Annealing: A Case Study of Sparse Linear Regression in Collider Physics [23]

- **HEP Context:** To be written
- **Methods:** To be written
- **Results and Conclusions:** To be written

2 Variational Quantum Circuits

2.1 Jet Algorithms and Jet Tagging

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

- **HEP Context:** b-jet tagging at LHCb
- **Methods:** Variational quantum classifiers, using two different embeddings of the data: (1) Amplitude Embedding; (2) Angle Embedding
- **Results and Conclusions:** To be written

2.2 Signal-Background Discrimination

2.2.1 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]

- **HEP Context:** Signal-background discrimination, where signal events are $t\bar{t}H$ ($H \to \gamma\gamma$) and $H \to \mu\mu$, and background events are dominant Standard Model processes

- **Methods:** Variational quantum circuits

- **Results and Conclusions:** With 100 training events, 100 test events, and 10 encoded variables, the AUC of IBM's quantum computer simulator that includes a noise model with 10 qubits are similar to the AUC of a classical support vector machine (SVM) and a boosted decision tree (BDT) classifier. The results show that IBM's quantum computer and quantum simulator are in good agreement, however, the run time on the quantum computer is longer than the classical machine learning algorithms due to the limitations in quantum hardware.

2.2.2 Event Classification with Quantum Machine Learning in High-Energy Physics [26]

- **HEP Context:** Signal-background discrimination, where the signal is a SUSY process, in particular, a chargino-pair production via a Higgs boson, where the final state has two charged leptons and missing transverse momentum. The background event is a W boson pair production WW where each W decays into a charged lepton and a neutrino.

- **Methods:** Variational Quantum Circuits (VQC) and Quantum Circuit Learning (QCL)

- **Results and Conclusions:** The performance of the QCL algorithms on quantum simulators is characterized by a relatively flat AUC as a function of the number of training events. The AUC for QCL is higher than the AUC for BDT and DNN for a low number of training events, however, for high training events, the performance for BDT and DNN surpasses QCL. The VQC algorithm has been tested on IBM's quantum computer, and the performance is similar to that of the quantum simulator. However, there is an increase in uncertainty due to hardware noise. Other QCL and VQC models are tested, which do not show any improvement to the nominal QCL and VQC models. The behavior that variational quantum algorithms does better with a small number of training data could be considered as a possible advantage over classical machine learning.

2.2.3 Quantum Machine Learning for Particle Physics using a Variational Quantum Classifier [27]

- **HEP Context:** Signal-background discrimination, where the background is $pp \to t\bar{t}$ events, and the signal is $pp \to Z' \to t\bar{t}$ events
- **Methods:** Variational Quantum Classifier (VQC)
- **Results and Conclusions:** To be written

2.2.4 Quantum Support Vector Machines for Continuum Suppression in B Meson Decays [28]

- **HEP Context:** Signal-background classification, where signal is $B\bar{B}$ pair events, and background is $q\bar{q}$ pair events
- **Methods:** Quantum Support Vector Machine (QSVM)
- **Results and Conclusions:** To be written

2.2.5 Higgs analysis with quantum classifiers [29]

- **HEP Context:** Classification of $t\bar{t}H(b\bar{b}$ (signal) and $t\bar{t}b\bar{b}$ (background)
- **Methods:** Quantum Support Vector Machine (QSVM) and Variational Quantum Circuit (VQC)
- **Results and Conclusions:** To be written

2.3 Anomaly Detection

2.3.1 Quantum Anomaly Detection for Collider Physics [30]

- **HEP Context:** Anomaly detection in the four-lepton final state
- **Methods:** Variational Quantum Circuits (VQC) and Quantum Circuit Learning (QCL)
- **Results and Conclusions:** After comparing VQC and QCL to traditional classical machine learning algorithms, this paper states that there is no evidence that quantum machine learning provides any advantage to classical machine learning in collider physics.

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

- **HEP Context:** To be written
- **Methods:** Quantum Autoencoders using Variational Quantum Circuits (VQC)
- **Results and Conclusions:** To be written

2.4 Neutrinos

2.4.1 Quantum convolutional neural networks for high energy physics data analysis [32]

- **HEP Context:** Classification of μ^+, e^-, π^+, and p at the Liquid Argon Time Projection Chamber (LArTPC) at Deep Underground Neutrino Experiment (DUNE)
- **Methods:** Quantum Convolutional Neural Network (QCNN) using Variational Quantum Circuits (VQC)
- **Results and Conclusions:** To be written

2.4.2 Hybrid Quantum-Classical Graph Convolutional Network [33]

- **HEP Context:** Classification of μ^+, e^-, π^+, and p at the Liquid Argon Time Projection Chamber (LArTPC) at Deep Underground Neutrino Experiment (DUNE)
- **Methods:** Hybrid Quantum-Classical Graph Convolutional Neural Network (QGCNN) using Variational Quantum Circuits (VQC)
- **Results and Conclusions:** To be written

2.5 Uncategorized by HEP - TEMPORARY

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

- **HEP Context:** To be written
- **Methods:** Quantum Circuit Born Machines (QCBM)
- **Results and Conclusions:** To be written

3 Quantum Support Vector Machines

3.1 Signal-Background Discrimination

3.1.1 Application of quantum machine learning using the quantum kernel algorithm on high energy physics analysis at the LHC [35]

- **HEP Context:** Signal-background discrimination, where signal events are $t\bar{t}H$ ($H \to \gamma\gamma$), and background events are dominant Standard Model processes
- **Methods:** Support vector machine with a quantum kernel estimator (QSVM-Kernel)
- **Results and Conclusions:** The performance of these quantum simulators, using 15 qubits and 60 independent datasets of 20000 training events and 20000 testing events, are similar to the performance of a classical SVM and a classical BDT. The QSVM-Kernel algorithm is then implemented on IBM's quantum processor. The mean performance of QSVM-Kernel on IBM's quantum processor and IBM's quantum computer simulator is about 5% lower. This difference is expected due to hardware noise. The results on IBM's quantum processor does approach the performance of IBM's quantum computer simulator. The paper concludes that the running time is expected to be reduced with improved quantum hardware and predicts that quantum machine learning could potentially become a powerful tool for HEP data analyses.

3.1.2 Quantum Support Vector Machines for Continuum Suppression in B Meson Decays [28]

- **HEP Context:** Signal-background classification, where signal is $B\bar{B}$ pair events, and background is $q\bar{q}$ pair events
- **Methods:** Quantum Support Vector Machine (QSVM)
- **Results and Conclusions:** To be written

4 Quantum Convolutional Neural Networks

5 Algorithms Based on Amplitude Amplification

5.1 Jet Algorithms and Jet Tagging

5.1.1 Quantum Algorithms for Jet Clustering [8]

- **HEP Context:** Thrust, an event shape whose optimum corresponds to the most jet-like separating plane among a set of particles, focusing on the case of electron-positron collisions

- **Methods:** (1) Created a quantum algorithm based on quantum annealing (enconded optimization problem as a QUBO problem); (2) Created quantum algorithm based on Grover search and describes two computing models, sequential model and parallel model, for loading classical data into quantum memory.

- **Results and Conclusions:** This paper finds an algorithm that improves the previously best known $O(N^3)$ classical thrust algorithm to an $O(N^2)$ sequential algorithm, while also finding an improved $O(N^2 \log N)$ classical algorithm. The computational costs of data loading must be carefully considered when evaluating the potential for quantum speedups on classical datasets.

5.2 Beyond the Standard Model

5.2.1 Implementation and analysis of quantum computing application to Higgs boson reconstruction at the large Hadron Collider [36]

- **HEP Context:** Search for $H \to ZZ_d \to\to 4l$, where Z_d is a hypothetical Dark Sector vector boson

- **Methods:** To be written

- **Results and Conclusions:** To be written

5.2.2 Application of a Quantum Search Algorithm to High- Energy Physics Data at the Large Hadron Collider [37]

- **HEP Context:** Detection of the exotic decays of Higgs boson used in Dark Sector searches ($H \to ZZ_d \to 4l$

- **Methods:** Grover's Algorithm

- **Results and Conclusions:** To be written

6 Quantum Walks

6.1 Event Generation

6.1.1 Collider Events on a Quantum Computer [38]

- **HEP Context:** Parton shower algorithms

- **Methods:** To be written

- **Results and Conclusions:** To be written

6.1.2 A quantum walk approach to simulating parton showers [39]

- **HEP Context:** To be written
- **Methods:** To be written
- **Results and Conclusions:** To be written

7 Continuous Variable Quantum Computing

7.1 Anomaly Detection

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

- **HEP Context:** Anomaly detection, where background is $pp \to Z+$ jets events, and signal is $pp \to HZ$ events with subsequent decays $H \to A_1 A_2$, $A_2 \to gg$, and $A_1 \to gg$, and the Z boson decays leptonically to either e or μ
- **Methods:** To be written
- **Results and Conclusions:** To be written

7.2 Uncategorized by HEP - TEMPORARY

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

- **HEP Context:** To be written
- **Methods:** To be written
- **Results and Conclusions:** To be written

8 Quantum Autoencoders

8.1 Anomaly Detection

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

- **HEP Context:** To be written
- **Methods:** Quantum Autoencoders using Variational Quantum Circuits (VQC)
- **Results and Conclusions:** To be written

9 Quantum Generative Adversarial Networks

9.1 Event Generation

9.1.1 Style-based quantum generative adversarial networks for Monte Carlo events [42]

- **HEP Context:** To be written
- **Methods:** Hybrid quantum-classical system, where the generator model is a Quantum Neural Network (QNN) and the discriminator model is a Classical Neural Network (CNN).
- **Results and Conclusions:** To be written

9.1.2 Quantum integration of elementary particle processes [43]

- **HEP Context:** To be written
- **Methods:** To be written
- **Results and Conclusions:** To be written

9.2 Uncategorized by HEP - TEMPORARY

9.2.1 Dual-Parameterized Quantum Circuit GAN Model in High Energy Physics [44]

- **HEP Context:** To be written
- **Methods:** To be written
- **Results and Conclusions:** To be written

9.2.2 Running the Dual-PQC GAN on noisy simulators and real quantum hardware [45]

- **HEP Context:** To be written
- **Methods:** To be written
- **Results and Conclusions:** To be written

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

- **HEP Context:** To be written
- **Methods:** To be written
- **Results and Conclusions:** To be written

10 Quantum Circuit Born Machines

10.1 Uncategorized by HEP - TEMPORARY

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

- **HEP Context:** To be written
- **Methods:** Quantum Circuit Born Machines (QCBM)
- **Results and Conclusions:** To be written

11 Quantum-Inspired Algorithms

11.1 Jet Algorithms and Jet Tagging

11.1.1 Quantum-inspired event reconstruction with Tensor Networks: Matrix Product States [46]

- **HEP Context:** Classify between top quark jets and QCD jets
- **Methods:** To be written
- **Results and Conclusions:** Matrix Product States (MPS)

11.1.2 Quantum-inspired machine learning on high-energy physics data [47]

- **HEP Context:** To be written
- **Methods:** To be written
- **Results and Conclusions:** To be written

12 Tensor Networks

12.1 Jet Algorithms and Jet Tagging

12.1.1 Quantum-inspired event reconstruction with Tensor Networks: Matrix Product States [46]

- **HEP Context:** Classify between top quark jets and QCD jets
- **Methods:** To be written
- **Results and Conclusions:** Matrix Product States (MPS)

12.1.2 Classical versus Quantum: comparing Tensor Network-based Quantum Circuits on LHC data [48]

- **HEP Context:** To be written
- **Methods:** To be written
- **Results and Conclusions:** To be written

13 Quantum Simulations

13.1 Quantum Field Theories

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

- **HEP Context:** To be written
- **Methods:** To be written
- **Results and Conclusions:** To be written

13.2 Uncategorized by HEP - TEMPORARY

13.2.1 Simulating Collider Physics on Quantum Computers Using Effective Field Theories [50]

- **HEP Context:** To be written
- **Methods:** To be written
- **Results and Conclusions:** To be written

13.2.2 SU(2) hadrons on a quantum computer via a variational approach [51]

- **HEP Context:** To be written
- **Methods:** To be written
- **Results and Conclusions:** To be written

13.2.3 Quantum Algorithm for High Energy Physics Simulations [52]

- **HEP Context:** To be written
- **Methods:** To be written
- **Results and Conclusions:** To be written

14 Quantum Sensors

14.1 Beyond the Standard Model

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

- **HEP Context:** To be written
- **Methods:** To be written
- **Results and Conclusions:** To be written

15 Uncategorized by QIS - TEMPORARY

15.1 Jet Algorithms and Jet Tagging

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

- **HEP Context:** To be written
- **Methods:** Quantum k-means
- **Results and Conclusions:** To be written

15.2 Track Reconstruction

15.2.1 Quantum speedup for track reconstruction in particle accelerators [55]

- **HEP Context:** Track reconstruction
- **Methods:** To be written
- **Results and Conclusions:** This paper identifies the four fundamental routines in local track reconstruction methods: seeding, track building, cleaning, and selection.

15.2.2 Hybrid Quantum Classical Graph Neural Networks for Particle Track Reconstruction [56]

- **HEP Context:** To be written
- **Methods:** To be written
- **Results and Conclusions:** To be written

15.3 Event Generation

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

- **HEP Context:** To be written
- **Methods:** To be written
- **Results and Conclusions:** To be written

15.4 Anomaly Detection

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

- **HEP Context:** To be written
- **Methods:** To be written
- **Results and Conclusions:** To be written

15.5 Beyond the Standard Model

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

- **HEP Context:** To be written
- **Methods:** To be written
- **Results and Conclusions:** To be written

15.6 Quantum Field Theories

15.6.1 Quantum Algorithms for Fermionic Quantum Field Theories [59]

- **HEP Context:** To be written
- **Methods:** To be written
- **Results and Conclusions:** To be written

15.7 Lattice Field Theories

15.7.1 Lattice renormalization of quantum simulations [60]

- **HEP Context:** To be written
- **Methods:** To be written
- **Results and Conclusions:** To be written

15.7.2 Quantum Computation of Scattering in Scalar Quantum Field Theories [61]

- **HEP Context:** To be written
- **Methods:** To be written
- **Results and Conclusions:** To be written

15.7.3 Efficient Representation for Simulating U(1) Gauge Theories on Digital Quantum Computers at All Values of the Coupling [62]

- **HEP Context:** To be written
- **Methods:** To be written
- **Results and Conclusions:** To be written

15.7.4 Role of boundary conditions in quantum computations of scattering observables [63]

- **HEP Context:** To be written
- **Methods:** To be written
- **Results and Conclusions:** To be written

15.7.5 Simulating lattice gauge theories on a quantum computer [64]

- **HEP Context:** To be written
- **Methods:** To be written
- **Results and Conclusions:** To be written

15.8 Uncategorized by HEP - TEMPORARY

15.8.1 Quantum algorithm for Feynman loop integrals [65]

- **HEP Context:** To be written
- **Methods:** To be written
- **Results and Conclusions:** To be written

15.8.2 Partonic collinear structure by quantum computing [66]

- **HEP Context:** To be written
- **Methods:** To be written
- **Results and Conclusions:** To be written

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