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

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:** This paper presents several papers on performing classification using quantum machine learning. The studies presented some of the challenges faced, such as the restrictive problem formulation for quantum annealers and the limited performance due to hardware restrictions for quantum-circuit-based machine learning.

2 Whitepapers

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

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

2.2 Quantum Simulation for High Energy Physics [3]

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

2.3 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

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

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

2.6 Quantum Networks for High Energy Physics [7]

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

3 Quantum Annealing

3.1 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:** This paper presents several papers on performing classification using quantum machine learning. The studies presented some of the challenges faced, such as the restrictive problem formulation for quantum annealers and the limited performance due to hardware restrictions for quantum-circuit-based machine learning.

3.2 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

3.3 Solving a Higgs optimization problem with quantum annealing for machine learning [8]

- **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).

3.4 Quantum adiabatic machine learning with zooming [9]

- **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.

3.5 Completely Quantum Neural Networks [10]

- **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

3.6 Quantum algorithm for the classification of supersymmetric top quark events [11]

- **HEP Context:** To be written

- **Methods:** To be written

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

3.7 Quantum Algorithms for Jet Clustering [12]

- **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:** The computational costs of data loading must be carefully considered when evaluating the potential for quantum speedups on classical datasets.

3.8 Quantum Annealing for Jet Clustering with Thrust [13]

- **HEP Context:** To be written

- **Methods:** To be written

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

3.9 Leveraging Quantum Annealer to identify an Event-topology at High Energy Colliders [14]

- **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

3.10 Charged particle tracking with quantum annealing-inspired optimization [15]

- **HEP Context:** To be written

- **Methods:** To be written

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

3.11 A pattern recognition algorithm for quantum annealers [16]

- **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

3.12 Adiabatic Quantum Algorithm for Multijet Clustering in High Energy Physics [17]

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

3.13 Degeneracy Engineering for Classical and Quantum Annealing: A Case Study of Sparse Linear Regression in Collider Physics [18]

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

3.14 Track clustering with a quantum annealer for primary vertex reconstruction at hadron colliders [19]

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

3.15 Particle track classification using quantum associative memory [20]

- **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

3.16 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

3.17 A regression algorithm for accelerated lattice QCD that exploits sparse inference on the D-Wave quantum annealer [22]

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

3.18 SU(2) lattice gauge theory on a quantum annealer [23]

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

4 Variational Quantum Circuits

4.1 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:** This paper presents several papers on performing classification using quantum machine learning. The studies presented some of the challenges faced, such as the restrictive problem formulation for quantum annealers and the limited performance due to hardware restrictions for quantum-circuit-based machine learning.

4.2 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

4.3 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]

- **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.

4.4 Quantum Anomaly Detection for Collider Physics [25]

- **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.

4.5 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:** To be written

4.6 Quantum Machine Learning for b-jet identification [27]

- **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

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

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

4.8 Quantum convolutional neural networks for high energy physics data analysis [29]

- **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

4.9 Hybrid Quantum-Classical Graph Convolutional Network [30]

- **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

4.10 Quantum Machine Learning for Particle Physics using a Variational Quantum Classifier [31]

- **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

4.11 Quantum Support Vector Machines for Continuum Suppression in B Meson Decays [32]

- **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

4.12 Higgs analysis with quantum classifiers [33]

- **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

4.13 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

5 Quantum Support Vector Machines

5.1 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

5.2 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:** To be written

5.3 Quantum Support Vector Machines for Continuum Suppression in B Meson Decays [32]

- **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

6 Quantum Convolutional Neural Networks

6.1 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

6.2 Quantum convolutional neural networks for high energy physics data analysis [29]

- **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

6.3 Hybrid Quantum-Classical Graph Convolutional Network [30]

- **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

7 Algorithms Based on Amplitude Amplification

7.1 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

7.2 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

7.3 Quantum Algorithms for Jet Clustering [12]

- **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:** The computational costs of data loading must be carefully considered when evaluating the potential for quantum speedups on classical datasets.

8 Quantum Walks

8.1 Collider Events on a Quantum Computer [38]

- **HEP Context:** Parton shower algorithms

- **Methods:** To be written

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

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

- **HEP Context:** To be written

- **Methods:** To be written

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

9 Continuous Variable Quantum Computing

9.1 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

9.2 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 Autoencoders

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

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

11 Quantum Generative Adversarial Networks

11.1 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

11.2 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

11.3 Dual-Parameterized Quantum Circuit GAN Model in High Energy Physics [43]

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

11.4 Running the Dual-PQC GAN on noisy simulators and real quantum hardware [44]

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

11.5 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

11.6 Quantum integration of elementary particle processes [45]

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

12 Quantum Circuit Born Machines

12.1 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

12.2 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

13 Quantum-Inspired Algorithms

13.1 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

13.2 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)

13.3 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

14 Tensor Networks

14.1 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)

14.2 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

15 Quantum Simulations

15.1 Quantum Simulation for High Energy Physics [3]

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

15.2 Simulating Collider Physics on Quantum Computers Using Effective Field Theories [49]

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

15.3 SU(2) hadrons on a quantum computer via a variational approach [50]

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

15.4 Quantum Algorithm for High Energy Physics Simulations [51]

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

15.5 Scalar Quantum Field Theories as a Benchmark for Near-Term Quantum Computers [52]

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

16 Quantum Sensors

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

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

16.2 Quantum Networks for High Energy Physics [7]

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

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

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

17 Uncategorized by QIS - TEMPORARY

17.1 Quantum speedup for track reconstruction in particle accelerators [54]

- **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.

17.2 Hybrid Quantum Classical Graph Neural Networks for Particle Track Reconstruction [55]

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

17.3 A Digital Quantum Algorithm for Jet Clustering in High-Energy Physics [56]

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

17.4 A quantum algorithm for model independent searches for new physics [57]

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

17.5 Lattice renormalization of quantum simulations [58]

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

17.6 Quantum Algorithms for Fermionic Quantum Field Theories [59]

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

17.7 Quantum Computation of Scattering in Scalar Quantum Field Theories [60]

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

17.8 Efficient Representation for Simulating U(1) Gauge Theories on Digital Quantum Computers at All Values of the Coupling [61]

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

17.9 Role of boundary conditions in quantum computations of scattering observables [62]

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

17.10 Towards a quantum computing algorithm for helicity amplitudes and parton showers [63]

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

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

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

17.12 Quantum algorithm for Feynman loop integrals [65]

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

17.13 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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