A Living Review of Quantum Information Science in High Energy Physics

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.

Contents

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.

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

1 Introduction

1.1 High Energy Physics Categories

1.1.1 Jet Algorithms and Jet Tagging

To be written

1.1.2 Track Reconstruction

Given a set of signals, known as hits, from a detector's multiple layers of sensors, the goal is to cluster them into a collection of hits that come from the same particle. Each collision may produce a few thousand hits, making track reconstruction computationally demanding.

1.1.3 Event Generation

Event generators are programs that generate simulated events produced in collider experiments. In hadronic collisions, an event is composed of the following:

1. Incoming hadrons
2. Hard part of the process
3. Radiation
4. Underlying event
5. Hadronization

1.1.4 Detector Simulation

To be written

1.1.5 Signal-Background Discrimination

To be written

1.1.6 Anomaly Detection

To be written

1.1.7 Beyond the Standard Model

To be written

1.1.8 Quantum Field Theories

To be written

1.1.9 Lattice Field Theories

To be written

1.1.10 Neutrinos

To be written

1.1.11 Cosmology

To be written

1.1.12 Uncategorized by HEP - TEMPORARY

Temporary Category

1.2 Quantum Information Science Categories

1.2.1 Quantum Annealing

Quantum annealing is a quantum computing method used to solve optimization problems. It is currently the only quantum computing paradigm that enables architectures with large number of qubits, such as D-Wave Systems' Pegasus quantum processor chip with 5000 qubits. The classical counterpart, simulated annealing, mimics the process of heating up a material above its recrystallization temperature then cooled down slowly in order to change the material to a desirable structure. Simulated annealing is capable of finding global extrema as it is able to escape local extrema. The simulated annealing algorithm is as follows: (1) Start with an initial solution $s = s_0$ and an initial temperature $t = t_0$, Let $E(s)$ be the loss function of s; (2) Define a temperature reduction scheme. Some examples of temperature reduction schemes are: $t = t - \alpha$, $t = t\alpha$, and $t = \frac{t}{1+\alpha t}$; (3) Starting at $t = t_0$, consider some neighborhood of solution $N(s)$, and pick one of the solutions s'; (4) Calculate the difference of the loss function δE between the solutions s and s'. If $\delta E \geq 0$, accept the new solution. If $\delta < 0$, generate a uniform random number r between 0 and 1. Accept the solution if $r < e^{\frac{\delta E}{t}}$. Note that for large t, the probability of selecting s' is high; (5) Repeat steps (3) and (4) for n iterations, updating t given by the temperature reduction rule.

Quantum annealers solve very specific optimization problems called Quadratic Unconstrained Binary Optimization (QUBO) problems. The QUBO problem consists of finding a binary string that is minimal with respect to a quadratic polynomial over binary variables. The main challenge is to rephrase the loss function to a QUBO problem, which is equivalent to finding the ground state of a corresponding Ising model, whose Hamiltonian is given by

$$H(\sigma) = \sum_{i,j=1}^{n} J_{ij} s_i s_j + \sum_{i=1}^{n} h_i s_i$$

where $s_i \in \{-1, +1\}$ are the spin values, and h_i and J_{ij} are adjustable constants that represents biases and coupling strengths, respectively. The Hamiltonian of the quantum version of the Ising model, the transverse field Ising model, is given by

$$H_f = \sum_{i,j=1}^{n} J_{ij} \sigma_i^z \sigma_j^z + \sum_{i}^{n} h_i \sigma_i^z$$

where σ_i^z is the Pauli-Z acting on qubit i. In quantum annealing, one initializes the system in the ground state of the initial Hamiltonian H_i, given by

$$H_i = \sum_{i=1}^{n} \sigma_i^x$$

corresponding to the state $(|0\rangle + |1\rangle)^{\otimes n}$. The quantum adiabatic theorem states that if the transition between two Hamiltonians is gradual, the system will stay in the ground state. After initializing the system, it slowly evolves by changing the Hamiltonian given by

$$H(t) = \left(1 - \frac{t}{T}\right) H_i + \frac{t}{T} H_f$$

where T is the total time in the annealing process. Measuring the final state after the anneal will give the solution to the QUBO problem, since the final system is in an eigenstate of H_f. This section reviews papers that involve quantum annealing approaches in particle physics.

1.2.2 Variational Quantum Circuits

Variational quantum circuits, also known as parametrized quantum circuits,

1.2.3 Quantum Support Vector Machines

To be written

1.2.4 Quantum Convolutional Neural Networks

To be written

1.2.5 Algorithms Based on Amplitude Amplification

Amplitude amplification is a quantum algorithm which is a generalization of Grover's search algorithm. Grover's search algorithm is a quantum algorithm that solves the problem of finding a desired element in an unstructured list of N elements in roughly $\sqrt{N}$ steps.

1.2.6 Quantum Walks

A random walk is a random process that describes a path that consists of a sequence of steps that are determined randomly. An example of a one dimensional discrete random walk is a random walk on the integer number line starting at 0, and each step moves +1 or −1 with an equal probability, which analogous to flipping a coin then, depending on the outcome, move forward or backwards on the number line. This can be described as a Markov chain, a sequence of random variables with the property that the probability of moving to the next step only depends on the current step and not the previous step, i.e. $p(X_{n+1} = x|X_1 = x_1, X_2 = x_2, \ldots) = p(X_{n+1} = x|X_n = x_n)$. This can be extended to higher dimensions. An example of a continuous random walk is Brownian motion, the random motion of particles in a medium.

The quantum discrete random walk defines the movement of a walker in position basis, $\mathcal{H}_P = \{|i\rangle : i \in \mathbb{Z}\}$, controlled by the coin in the spin-$\frac{1}{2}$ basis, $\mathcal{H}_C = \{|\uparrow\rangle, |\downarrow\rangle\}$. The translation of the walker can be represented by the unitary operator $T = \sum |i+1\rangle\langle i| \otimes |\uparrow\rangle\langle\uparrow| + \sum |i-1\rangle\langle i| \otimes |\downarrow\rangle\langle\downarrow|$, where the index i runs over $\mathcal{Z}$. Therefore, $T|i\rangle|\uparrow\rangle = |i+1\rangle|\uparrow\rangle$ and $T|i\rangle|\downarrow\rangle = |i-1\rangle|\downarrow\rangle$. A single step of the random walk is constructed from a coin flip unitary operation C and the translation operator, T. Therefore, a single step can be represented as a unitary operator $U = T\cdot(C\otimes\mathbb{I})$. An N-step quantum walk is defined by U^N. In the quantum random walk, the coin register is not measured during each step. This introduces interference, which is drastically different from the classical random walk.

1.2.7 Continuous Variable Quantum Computing

Continuous variable quantum computing is a quantum computing paradigm that uses a large number of modes of the harmonic oscillator, which can be represented as $|\psi\rangle = \int dx\, \psi(x)|x\rangle$, whereas discrete variable quantum computing uses discrete number of quantum bits, for example, a qubit can be represented as $\psi\rangle = c_0|0\rangle + c_1|1\rangle$.

1.2.8 Quantum Autoencoders

To be written

1.2.9 Quantum Generative Adversarial Networks

The implementation of a classical model involves two main components: (1) generator model, which produces artificial data; (2) discriminator model, which tries to classify the data as either real or generated.

1.2.10 Quantum Circuit Born Machines

To be written

1.2.11 Quantum-Inspired Algorithms

To be written

1.2.12 Tensor Networks

To be written

1.2.13 Quantum Simulations

To be written

1.2.14 Quantum Sensors

To be written

1.2.15 Uncategorized by QIS - TEMPORARY

Temporary Category

2 High Energy Physics in Quantum Information Science

2.1 Reviews and Whitepapers

2.1.1 Reviews

2.1.1.1 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

2.1.2 Whitepapers

2.1.2.1 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

2.1.2.2 Quantum Simulation for High Energy Physics [3]

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

2.1.2.3 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

2.1.2.4 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

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

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

2.1.2.6 Quantum Networks for High Energy Physics [7]

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

2.1.2.7 Report of the Snowmass 2021 Theory Frontier Topical Group on Quantum Information Science [8]

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

2.2 Jet Algorithms and Jet Tagging

2.2.1 Quantum Annealing

2.2.1.1 Quantum Algorithms for Jet Clustering [9]

- **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 (encoded 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.

2.2.1.2 Quantum Annealing for Jet Clustering with Thrust [10]

- **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:** Quantum Annealing, where an optimization problem, in this case, thrust, is encoded as a QUBO.
- **Results and Conclusions:** To be written

2.2.1.3 Adiabatic Quantum Algorithm for Multijet Clustering in High Energy Physics [11]

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

2.2.2 Variational Quantum Circuits

2.2.2.1 Quantum Machine Learning for *b*-jet identification [12]

- **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

2.2.3 Algorithms Based on Amplitude Amplification

2.2.3.1 Quantum Algorithms for Jet Clustering [9]

- **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
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- **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.

2.2.4 Quantum-Inspired Algorithms

2.2.4.1 Quantum-inspired event reconstruction with Tensor Networks: Matrix Product States [13]

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

2.2.4.2 Quantum-inspired machine learning on high-energy physics data [14]

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

2.2.5 Tensor Networks

2.2.5.1 Quantum-inspired event reconstruction with Tensor Networks: Matrix Product States [13]

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

2.2.5.2 Classical versus Quantum: comparing Tensor Network-based Quantum Circuits on LHC data [15]

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

2.2.6 Uncategorized by QIS - TEMPORARY

2.2.6.1 A Digital Quantum Algorithm for Jet Clustering in High-Energy Physics [16]

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

2.3 Track Reconstruction

2.3.1 Quantum Annealing

2.3.1.1 Charged particle tracking with quantum annealing-inspired optimization [17]

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

2.3.1.2 A pattern recognition algorithm for quantum annealers [18]

- **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

2.3.1.3 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

2.3.1.4 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

2.3.2 Algorithms Based on Amplitude Amplification

2.3.2.1 Quantum speedup for track reconstruction in particle accelerators [21]

- **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.

2.3.3 Uncategorized by QIS - TEMPORARY

2.3.3.1 Hybrid Quantum Classical Graph Neural Networks for Particle Track Reconstruction [22]

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

2.4 Event Generation

2.4.1 Quantum Walks

2.4.1.1 Collider Events on a Quantum Computer [23]

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

2.4.1.2 A quantum walk approach to simulating parton showers [24]

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

2.4.2 Quantum Generative Adversarial Networks

2.4.2.1 Style-based quantum generative adversarial networks for Monte Carlo events [25]

- **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

2.4.2.2 Quantum integration of elementary particle processes [26]

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

2.4.3 Quantum Circuit Born Machines

2.4.3.1 Unsupervised Quantum Circuit Learning in High Energy Physics [27]

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

2.4.4 Uncategorized by QIS - TEMPORARY

2.4.4.1 Towards a quantum computing algorithm for helicity amplitudes and parton showers [28]

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

2.5 Detector Simulation

2.6 Signal-Background Discrimination

2.6.1 Quantum Annealing

2.6.1.1 Solving a Higgs optimization problem with quantum annealing for machine learning [29]

- **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).

2.6.1.2 Quantum adiabatic machine learning with zooming [30]

- **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.

2.6.2 Variational Quantum Circuits

2.6.2.1 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 [31]

- **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.

2.6.2.2 Event Classification with Quantum Machine Learning in High-Energy Physics [32]

- **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.

2.6.2.3 Quantum Machine Learning for Particle Physics using a Variational Quantum Classifier [33]

- **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

2.6.2.4 Quantum Support Vector Machines for Continuum Suppression in B Meson Decays [34]

- **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

2.6.2.5 Higgs analysis with quantum classifiers [35]

- **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

2.6.3 Quantum Support Vector Machines

2.6.3.1 Application of quantum machine learning using the quantum kernel algorithm on high energy physics analysis at the LHC [36]

- **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.

2.6.3.2 Quantum Support Vector Machines for Continuum Suppression in B Meson Decays [34]

- **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

2.7 Anomaly Detection

2.7.1 Variational Quantum Circuits

2.7.1.1 Quantum Anomaly Detection for Collider Physics [37]

- **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.

2.7.1.2 Anomaly detection in high-energy physics using a quantum autoencoder [38]

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

2.7.2 Continuous Variable Quantum Computing

2.7.2.1 Unsupervised event classification with graphs on classical and photonic quantum computers [39]

- **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

2.7.3 Quantum Autoencoders

2.7.3.1 Anomaly detection in high-energy physics using a quantum autoencoder [38]

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

2.7.4 Uncategorized by QIS - TEMPORARY

2.7.4.1 A quantum algorithm for model independent searches for new physics [40]

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

2.8 Beyond the Standard Model

2.8.1 Quantum Annealing

2.8.1.1 Completely Quantum Neural Networks [41]

- **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

2.8.1.2 Quantum algorithm for the classification of supersymmetric top quark events [42]

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

2.8.2 Algorithms Based on Amplitude Amplification

2.8.2.1 Implementation and analysis of quantum computing application to Higgs boson reconstruction at the large Hadron Collider [43]

- **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

2.8.2.2 Application of a Quantum Search Algorithm to High- Energy Physics Data at the Large Hadron Collider [44]

- **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

2.8.3 Quantum Sensors

2.8.3.1 Searching for Dark Matter with a Superconducting Qubit [45]

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

2.8.4 Uncategorized by QIS - TEMPORARY

2.8.4.1 A quantum algorithm for model independent searches for new physics [40]

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

2.9 Quantum Field Theories

2.9.1 Quantum Simulations

2.9.1.1 Scalar Quantum Field Theories as a Benchmark for Near-Term Quantum Computers [46]

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

2.9.2 Uncategorized by QIS - TEMPORARY

2.9.2.1 Quantum Algorithms for Fermionic Quantum Field Theories [47]

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

2.10 Lattice Field Theories

2.10.1 Quantum Annealing

2.10.1.1 A regression algorithm for accelerated lattice QCD that exploits sparse inference on the D-Wave quantum annealer [48]

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

2.10.1.2 SU(2) lattice gauge theory on a quantum annealer [49]

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

2.10.2 Quantum Simulations

2.10.2.1 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

2.10.3 Uncategorized by QIS - TEMPORARY

2.10.3.1 Lattice renormalization of quantum simulations [51]

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

2.10.3.2 Quantum Computation of Scattering in Scalar Quantum Field Theories [52]

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

2.10.3.3 Efficient Representation for Simulating U(1) Gauge Theories on Digital Quantum Computers at All Values of the Coupling [53]

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

2.10.3.4 Role of boundary conditions in quantum computations of scattering observables [54]

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

2.10.3.5 Simulating lattice gauge theories on a quantum computer [55]

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

2.11 Neutrinos

2.11.1 Variational Quantum Circuits

2.11.1.1 Quantum convolutional neural networks for high energy physics data analysis [56]

- **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

2.11.1.2 Hybrid Quantum-Classical Graph Convolutional Network [57]

- **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

2.12 Cosmology

2.12.1 Quantum Annealing

2.12.1.1 Restricted Boltzmann Machines for galaxy morphology classification with a quantum annealer [58]

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

2.13 Uncategorized by HEP - TEMPORARY

2.13.1 Quantum Annealing

2.13.1.1 Leveraging Quantum Annealer to identify an Event-topology at High Energy Colliders [59]

- **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

2.13.1.2 Degeneracy Engineering for Classical and Quantum Annealing: A Case Study of Sparse Linear Regression in Collider Physics [60]

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

2.13.2 Continuous Variable Quantum Computing

2.13.2.1 Quantum Generative Adversarial Networks in a Continuous-Variable Architecture to Simulate High Energy Physics Detectors [61]

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

2.13.3 Quantum Generative Adversarial Networks

2.13.3.1 Dual-Parameterized Quantum Circuit GAN Model in High Energy Physics [62]

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

2.13.3.2 Running the Dual-PQC GAN on noisy simulators and real quantum hardware [63]

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

2.13.3.3 Quantum Generative Adversarial Networks in a Continuous-Variable Architecture to Simulate High Energy Physics Detectors [61]

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

2.13.4 Quantum Simulations

2.13.4.1 Simulating Collider Physics on Quantum Computers Using Effective Field Theories [64]

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

2.13.5 Uncategorized by QIS - TEMPORARY

2.13.5.1 Quantum Algorithm for High Energy Physics Simulations [65]

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

2.13.5.2 Quantum algorithm for Feynman loop integrals [66]

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

2.13.5.3 Partonic collinear structure by quantum computing [67]

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

2.13.5.4 Quantum discord and steering in top quarks at the LHC [68]

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

2.13.5.5 Entanglement and quantum tomography with top quarks at the LHC [69]

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

2.13.5.6 Quantum information with top quarks in QCD [70]

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

2.13.5.7 Application of Quantum Machine Learning in a Higgs Physics Study at the CEPC [71]

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

2.13.5.8 Snowmass Computational Frontier: Topical Group Report on Quantum Computing [72]

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

2.13.5.9 Neutrino Oscillations in a Quantum Processor [73]

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

2.13.5.10 General Methods for Digital Quantum Simulation of Gauge Theories [74]

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

2.13.5.11 Quantum simulation of quantum field theory in the light-front formulation [75]

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

3 Quantum Information Science in High Energy Physics

3.1 Reviews and Whitepapers

3.1.1 Reviews

3.1.1.1 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

3.1.2 Whitepapers

3.1.2.1 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

3.1.2.2 Quantum Simulation for High Energy Physics [3]

- **HEP Context:** To be written

- **Methods:** To be written

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

3.1.2.3 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

3.1.2.4 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

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

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

3.1.2.6 Quantum Networks for High Energy Physics [7]

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

3.1.2.7 Report of the Snowmass 2021 Theory Frontier Topical Group on Quantum Information Science [8]

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

3.2 Quantum Annealing

3.2.1 Jet Algorithms and Jet Tagging

3.2.1.1 Quantum Algorithms for Jet Clustering [9]

- **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 (encoded 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.

3.2.1.2 Quantum Annealing for Jet Clustering with Thrust [10]

- **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:** Quantum Annealing, where an optimization problem, in this case, thrust, is encoded as a QUBO.
- **Results and Conclusions:** To be written

3.2.1.3 Adiabatic Quantum Algorithm for Multijet Clustering in High Energy Physics [11]

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

3.2.2 Track Reconstruction

3.2.2.1 Charged particle tracking with quantum annealing-inspired optimization [17]

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

3.2.2.2 A pattern recognition algorithm for quantum annealers [18]

- **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

3.2.2.3 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

3.2.2.4 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

3.2.3 Signal-Background Discrimination

3.2.3.1 Solving a Higgs optimization problem with quantum annealing for machine learning [29]

- **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).

3.2.3.2 Quantum adiabatic machine learning with zooming [30]

- **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.

3.2.4 Beyond the Standard Model

3.2.4.1 Completely Quantum Neural Networks [41]

- **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

3.2.4.2 Quantum algorithm for the classification of supersymmetric top quark events [42]

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

3.2.5 Lattice Field Theories

3.2.5.1 A regression algorithm for accelerated lattice QCD that exploits sparse inference on the D-Wave quantum annealer [48]

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

3.2.5.2 SU(2) lattice gauge theory on a quantum annealer [49]

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

3.2.6 Cosmology

3.2.6.1 Restricted Boltzmann Machines for galaxy morphology classification with a quantum annealer [58]

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

3.2.7 Uncategorized by HEP - TEMPORARY

3.2.7.1 Leveraging Quantum Annealer to identify an Event-topology at High Energy Colliders [59]

- **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

3.2.7.2 Degeneracy Engineering for Classical and Quantum Annealing: A Case Study of Sparse Linear Regression in Collider Physics [60]

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

3.3 Variational Quantum Circuits

3.3.1 Jet Algorithms and Jet Tagging

3.3.1.1 Quantum Machine Learning for b-jet identification [12]

- **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

3.3.2 Signal-Background Discrimination

3.3.2.1 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 [31]

- **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.

3.3.2.2 Event Classification with Quantum Machine Learning in High-Energy Physics [32]

- **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.

3.3.2.3 Quantum Machine Learning for Particle Physics using a Variational Quantum Classifier [33]

- **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

3.3.2.4 Quantum Support Vector Machines for Continuum Suppression in B Meson Decays [34]

- **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

3.3.2.5 Higgs analysis with quantum classifiers [35]

- **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

3.3.3 Anomaly Detection

3.3.3.1 Quantum Anomaly Detection for Collider Physics [37]

- **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.

3.3.3.2 Anomaly detection in high-energy physics using a quantum autoencoder [38]

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

3.3.4 Neutrinos

3.3.4.1 Quantum convolutional neural networks for high energy physics data analysis [56]

- **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

3.3.4.2 Hybrid Quantum-Classical Graph Convolutional Network [57]

- **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

3.4 Quantum Support Vector Machines

3.4.1 Signal-Background Discrimination

3.4.1.1 Application of quantum machine learning using the quantum kernel algorithm on high energy physics analysis at the LHC [36]

- **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.

3.4.1.2 Quantum Support Vector Machines for Continuum Suppression in B Meson Decays [34]

- **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

3.5 Quantum Convolutional Neural Networks

3.6 Algorithms Based on Amplitude Amplification

3.6.1 Jet Algorithms and Jet Tagging

3.6.1.1 Quantum Algorithms for Jet Clustering [9]

- **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 (encoded 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.

3.6.2 Track Reconstruction

3.6.2.1 Quantum speedup for track reconstruction in particle accelerators [21]

- **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.

3.6.3 Beyond the Standard Model

3.6.3.1 Implementation and analysis of quantum computing application to Higgs boson reconstruction at the large Hadron Collider [43]

- **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

3.6.3.2 Application of a Quantum Search Algorithm to High- Energy Physics Data at the Large Hadron Collider [44]

- **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

3.7 Quantum Walks

3.7.1 Event Generation

3.7.1.1 Collider Events on a Quantum Computer [23]

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

3.7.1.2 A quantum walk approach to simulating parton showers [24]

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

3.8 Continuous Variable Quantum Computing

3.8.1 Anomaly Detection

3.8.1.1 Unsupervised event classification with graphs on classical and photonic quantum computers [39]

- **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

3.8.2 Uncategorized by HEP - TEMPORARY

3.8.2.1 Quantum Generative Adversarial Networks in a Continuous-Variable Architecture to Simulate High Energy Physics Detectors [61]

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

3.9 Quantum Autoencoders

3.9.1 Anomaly Detection

3.9.1.1 Anomaly detection in high-energy physics using a quantum autoencoder [38]

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

3.10 Quantum Generative Adversarial Networks

3.10.1 Event Generation

3.10.1.1 Style-based quantum generative adversarial networks for Monte Carlo events [25]

- **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

3.10.1.2 Quantum integration of elementary particle processes [26]

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

3.10.2 Uncategorized by HEP - TEMPORARY

3.10.2.1 Dual-Parameterized Quantum Circuit GAN Model in High Energy Physics [62]

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

3.10.2.2 Running the Dual-PQC GAN on noisy simulators and real quantum hardware [63]

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

3.10.2.3 Quantum Generative Adversarial Networks in a Continuous-Variable Architecture to Simulate High Energy Physics Detectors [61]

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

3.11 Quantum Circuit Born Machines

3.11.1 Event Generation

3.11.1.1 Unsupervised Quantum Circuit Learning in High Energy Physics [27]

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

3.12 Quantum-Inspired Algorithms

3.12.1 Jet Algorithms and Jet Tagging

3.12.1.1 Quantum-inspired event reconstruction with Tensor Networks: Matrix Product States [13]

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

3.12.1.2 Quantum-inspired machine learning on high-energy physics data [14]

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

3.13 Tensor Networks

3.13.1 Jet Algorithms and Jet Tagging

3.13.1.1 Quantum-inspired event reconstruction with Tensor Networks: Matrix Product States [13]

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

3.13.1.2 Classical versus Quantum: comparing Tensor Network-based Quantum Circuits on LHC data [15]

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

3.14 Quantum Simulations

3.14.1 Quantum Field Theories

3.14.1.1 Scalar Quantum Field Theories as a Benchmark for Near-Term Quantum Computers [46]

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

3.14.2 Lattice Field Theories

3.14.2.1 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

3.14.3 Uncategorized by HEP - TEMPORARY

3.14.3.1 Simulating Collider Physics on Quantum Computers Using Effective Field Theories [64]

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

3.15 Quantum Sensors

3.15.1 Beyond the Standard Model

3.15.1.1 Searching for Dark Matter with a Superconducting Qubit [45]

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

3.16 Uncategorized by QIS - TEMPORARY

3.16.1 Jet Algorithms and Jet Tagging

3.16.1.1 A Digital Quantum Algorithm for Jet Clustering in High-Energy Physics [16]

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

3.16.2 Track Reconstruction

3.16.2.1 Hybrid Quantum Classical Graph Neural Networks for Particle Track Reconstruction [22]

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

3.16.3 Event Generation

3.16.3.1 Towards a quantum computing algorithm for helicity amplitudes and parton showers [28]

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

3.16.4 Anomaly Detection

3.16.4.1 A quantum algorithm for model independent searches for new physics [40]

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

3.16.5 Beyond the Standard Model

3.16.5.1 A quantum algorithm for model independent searches for new physics [40]

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

3.16.6 Quantum Field Theories

3.16.6.1 Quantum Algorithms for Fermionic Quantum Field Theories [47]

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

3.16.7 Lattice Field Theories

3.16.7.1 Lattice renormalization of quantum simulations [51]

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

3.16.7.2 Quantum Computation of Scattering in Scalar Quantum Field Theories [52]

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

3.16.7.3 Efficient Representation for Simulating U(1) Gauge Theories on Digital Quantum Computers at All Values of the Coupling [53]

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

3.16.7.4 Role of boundary conditions in quantum computations of scattering observables [54]

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

3.16.7.5 Simulating lattice gauge theories on a quantum computer [55]

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

3.16.8 Uncategorized by HEP - TEMPORARY

3.16.8.1 Quantum Algorithm for High Energy Physics Simulations [65]

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

3.16.8.2 Quantum algorithm for Feynman loop integrals [66]

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

3.16.8.3 Partonic collinear structure by quantum computing [67]

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

3.16.8.4 Quantum discord and steering in top quarks at the LHC [68]

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

3.16.8.5 Entanglement and quantum tomography with top quarks at the LHC [69]

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

3.16.8.6 Quantum information with top quarks in QCD [70]

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

3.16.8.7 Application of Quantum Machine Learning in a Higgs Physics Study at the CEPC [71]

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

3.16.8.8 Snowmass Computational Frontier: Topical Group Report on Quantum Computing [72]

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

3.16.8.9 Neutrino Oscillations in a Quantum Processor [73]

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

3.16.8.10 General Methods for Digital Quantum Simulation of Gauge Theories [74]

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

3.16.8.11 Quantum simulation of quantum field theory in the light-front formulation [75]

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

References

[1] W. Guan, G. Perdue, A. Pesah, M. Schuld, K. Terashi, S. Vallecorsa et al., *Quantum Machine Learning in High Energy Physics*, 2005.08582. 9, 29

[2] A. Delgado et al., *Quantum Computing for Data Analysis in High-Energy Physics*, in *2022 Snowmass Summer Study*, 3, 2022. 2203.08805. 10, 30

[3] C. W. Bauer et al., *Quantum Simulation for High Energy Physics*, 2204.03381. 10, 30

[4] T. S. Humble et al., *Snowmass White Paper: Quantum Computing Systems and Software for High-energy Physics Research*, in *2022 Snowmass Summer Study*, 3, 2022. 2203.07091. 10, 30

[5] T. Faulkner, T. Hartman, M. Headrick, M. Rangamani and B. Swingle, *Snowmass white paper: Quantum information in quantum field theory and quantum gravity*, in *2022 Snowmass Summer Study*, 3, 2022. 2203.07117. 10, 30

[6] D. Antypas et al., *New Horizons: Scalar and Vector Ultralight Dark Matter*, 2203.14915. 11, 31

[7] A. Derevianko et al., *Quantum Networks for High Energy Physics*, in *2022 Snowmass Summer Study*, 3, 2022. 2203.16979. 11, 31

[8] S. Catterall et al., *Report of the Snowmass 2021 Theory Frontier Topical Group on Quantum Information Science*, in *2022 Snowmass Summer Study*, 9, 2022. 2209.14839. 11, 31

[9] A. Y. Wei, P. Naik, A. W. Harrow and J. Thaler, *Quantum Algorithms for Jet Clustering*, *Phys. Rev. D* **101** (2020) 094015, [1908.08949]. 11, 12, 31, 39

[10] A. Delgado and J. Thaler, *Quantum Annealing for Jet Clustering with Thrust*, 2205.02814. 12, 32

[11] D. Pires, Y. Omar and J. a. Seixas, *Adiabatic Quantum Algorithm for Multijet Clustering in High Energy Physics*, 2012.14514. 12, 32

[12] A. Gianelle, P. Koppenburg, D. Lucchesi, D. Nicotra, E. Rodrigues, L. Sestini et al., *Quantum Machine Learning for b-jet identification*, 2202.13943. 12, 35

[13] J. Y. Araz and M. Spannowsky, *Quantum-inspired event reconstruction with Tensor Networks: Matrix Product States*, *JHEP* **08** (2021) 112, [2106.08334]. 13, 43

[14] T. Felser, M. Trenti, L. Sestini, A. Gianelle, D. Zuliani, D. Lucchesi et al., *Quantum-inspired machine learning on high-energy physics data*, *npj Quantum Inf.* **7** (2021) 111, [2004.13747]. 13, 43

[15] J. Y. Araz and M. Spannowsky, *Classical versus Quantum: comparing Tensor Network-based Quantum Circuits on LHC data*, 2202.10471. 13, 44

[16] D. Pires, P. Bargassa, J. a. Seixas and Y. Omar, *A Digital Quantum Algorithm for Jet Clustering in High-Energy Physics*, 2101.05618. 14, 45

[17] A. Zlokapa, A. Anand, J.-R. Vlimant, J. M. Duarte, J. Job, D. Lidar et al., *Charged particle tracking with quantum annealing-inspired optimization*, *Quantum Machine Intelligence* **3** (2021) 27, [1908.04475]. 14, 32

[18] F. Bapst, W. Bhimji, P. Calafiura, H. Gray, W. Lavrijsen, L. Linder et al., *A pattern recognition algorithm for quantum annealers*, *Comput. Softw. Big Sci.* **4** (2020) 1, [1902.08324]. 14, 32

[19] S. Das, A. J. Wildridge, S. B. Vaidya and A. Jung, *Track clustering with a quantum annealer for primary vertex reconstruction at hadron colliders*, 1903.08879. 14, 32

[20] G. Quiroz, L. Ice, A. Delgado and T. S. Humble, *Particle track classification using quantum associative memory*, *Nucl. Instrum. Meth. A* **1010** (2021) 165557, [2011.11848]. 14, 33

[21] D. Magano et al., *Quantum speedup for track reconstruction in particle accelerators*, *Phys. Rev. D* **105** (2022) 076012, [2104.11583]. 15, 39

[22] C. Tüysüz, C. Rieger, K. Novotny, B. Demirköz, D. Dobos, K. Potamianos et al., *Hybrid Quantum Classical Graph Neural Networks for Particle Track Reconstruction*, *Quantum Machine Intelligence* **3** (2021) 29, [2109.12636]. 15, 45

[23] G. Gustafson, S. Prestel, M. Spannowsky and S. Williams, *Collider Events on a Quantum Computer*, 2207.10694. 15, 40

[24] S. Williams, S. Malik, M. Spannowsky and K. Bepari, *A quantum walk approach to simulating parton showers*, 2109.13975. 15, 40

[25] C. Bravo-Prieto, J. Baglio, M. Cè, A. Francis, D. M. Grabowska and S. Carrazza, *Style-based quantum generative adversarial networks for Monte Carlo events*, 2110.06933. 16, 41

[26] G. Agliardi, M. Grossi, M. Pellen and E. Prati, *Quantum integration of elementary particle processes*, *Phys. Lett. B* **832** (2022) 137228, [2201.01547]. 16, 42

[27] A. Delgado and K. E. Hamilton, *Unsupervised Quantum Circuit Learning in High Energy Physics*, 2203.03578. 16, 43

[28] K. Bepari, S. Malik, M. Spannowsky and S. Williams, *Towards a quantum computing algorithm for helicity amplitudes and parton showers*, *Phys. Rev. D* **103** (2021) 076020, [2010.00046]. 16, 45

[29] A. Mott, J. Job, J. R. Vlimant, D. Lidar and M. Spiropulu, *Solving a Higgs optimization problem with quantum annealing for machine learning*, *Nature* **550** (2017) 375–379. 17, 33

[30] A. Zlokapa, A. Mott, J. Job, J.-R. Vlimant, D. Lidar and M. Spiropulu, *Quantum adiabatic machine learning with zooming*, 1908.04480. 17, 33

[31] S. L. Wu et al., *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*, *J. Phys. G* **48** (2021) 125003, [2012.11560]. 17, 35

[32] K. Terashi, M. Kaneda, T. Kishimoto, M. Saito, R. Sawada and J. Tanaka, *Event Classification with Quantum Machine Learning in High-Energy Physics*, *Comput. Softw. Big Sci.* **5** (2021) 2, [2002.09935]. 18, 36

[33] A. Blance and M. Spannowsky, *Quantum Machine Learning for Particle Physics using a Variational Quantum Classifier*, 2010.07335. 18, 36

[34] J. Heredge, C. Hill, L. Hollenberg and M. Sevior, *Quantum Support Vector Machines for Continuum Suppression in B Meson Decays*, *Comput. Softw. Big Sci.* **5** (2021) 27, [2103.12257]. 19, 20, 37, 39

[35] V. Belis, S. González-Castillo, C. Reissel, S. Vallecorsa, E. F. Combarro, G. Dissertori et al., *Higgs analysis with quantum classifiers*, *EPJ Web Conf.* **251** (2021) 03070, [2104.07692]. 19, 37

[36] S. L. Wu et al., *Application of quantum machine learning using the quantum kernel algorithm on high energy physics analysis at the LHC*, *Phys. Rev. Res.* **3** (2021) 033221, [2104.05059]. 19, 38

[37] S. Alvi, C. Bauer and B. Nachman, *Quantum Anomaly Detection for Collider Physics*, 2206.08391. 20, 37

[38] V. S. Ngairangbam, M. Spannowsky and M. Takeuchi, *Anomaly detection in high-energy physics using a quantum autoencoder*, *Phys. Rev. D* **105** (2022) 095004, [2112.04958]. 20, 21, 37, 41

[39] A. Blance and M. Spannowsky, *Unsupervised event classification with graphs on classical and photonic quantum computers*, *JHEP* **21** (2020) 170, [2103.03897]. 21, 41

[40] K. T. Matchev, P. Shyamsundar and J. Smolinsky, *A quantum algorithm for model independent searches for new physics*, 2003.02181. 21, 23, 46

[41] S. Abel, J. C. Criado and M. Spannowsky, *Completely Quantum Neural Networks*, 2202.11727. 21, 34

[42] P. Bargassa, T. Cabos, S. Cavinato, A. Cordeiro Oudot Choi and T. Hessel, *Quantum algorithm for the classification of supersymmetric top quark events*, *Phys. Rev. D* **104** (2021) 096004, [2106.00051]. 22, 34

[43] A. Alexiades Armenakas and O. K. Baker, *Implementation and analysis of quantum*

computing application to Higgs boson reconstruction at the large Hadron Collider, *Sci. Rep.* **11** (2021) 22850. 22, 40

[44] A. E. Armenakas and O. K. Baker, *Application of a Quantum Search Algorithm to High- Energy Physics Data at the Large Hadron Collider*, 2010.00649. 22, 40

[45] A. V. Dixit, S. Chakram, K. He, A. Agrawal, R. K. Naik, D. I. Schuster et al., *Searching for Dark Matter with a Superconducting Qubit*, *Phys. Rev. Lett.* **126** (2021) 141302, [2008.12231]. 22, 45

[46] K. Yeter-Aydeniz, E. F. Dumitrescu, A. J. McCaskey, R. S. Bennink, R. C. Pooser and G. Siopsis, *Scalar Quantum Field Theories as a Benchmark for Near-Term Quantum Computers*, *Phys. Rev. A* **99** (2019) 032306, [1811.12332]. 23, 44

[47] S. P. Jordan, K. S. M. Lee and J. Preskill, *Quantum Algorithms for Fermionic Quantum Field Theories*, 1404.7115. 23, 46

[48] N. T. T. Nguyen, G. T. Kenyon and B. Yoon, *A regression algorithm for accelerated lattice QCD that exploits sparse inference on the D-Wave quantum annealer*, *Sci. Rep.* **10** (2020) 10915, [1911.06267]. 23, 34

[49] S. A Rahman, R. Lewis, E. Mendicelli and S. Powell, *SU(2) lattice gauge theory on a quantum annealer*, *Phys. Rev. D* **104** (2021) 034501, [2103.08661]. 24, 34

[50] Y. Y. Atas, J. Zhang, R. Lewis, A. Jahanpour, J. F. Haase and C. A. Muschik, *SU(2) hadrons on a quantum computer via a variational approach*, *Nature Commun.* **12** (2021) 6499, [2102.08920]. 24, 44

[51] M. Carena, H. Lamm, Y.-Y. Li and W. Liu, *Lattice renormalization of quantum simulations*, *Phys. Rev. D* **104** (2021) 094519, [2107.01166]. 24, 46

[52] S. P. Jordan, K. S. M. Lee and J. Preskill, *Quantum Computation of Scattering in Scalar Quantum Field Theories*, *Quant. Inf. Comput.* **14** (2014) 1014–1080, [1112.4833]. 24, 46

[53] C. W. Bauer and D. M. Grabowska, *Efficient Representation for Simulating U(1) Gauge Theories on Digital Quantum Computers at All Values of the Coupling*, 2111.08015. 24, 47

[54] R. A. Briceño, J. V. Guerrero, M. T. Hansen and A. M. Sturzu, *Role of boundary conditions in quantum computations of scattering observables*, *Phys. Rev. D* **103** (2021) 014506, [2007.01155]. 25, 47

[55] T. Byrnes and Y. Yamamoto, *Simulating lattice gauge theories on a quantum computer*, *Phys. Rev. A* **73** (2006) 022328, [quant-ph/0510027]. 25, 47

[56] S. Y.-C. Chen, T.-C. Wei, C. Zhang, H. Yu and S. Yoo, *Quantum convolutional neural networks for high energy physics data analysis*, *Phys. Rev. Res.* **4** (2022) 013231, [2012.12177]. 25, 38

[57] S. Y.-C. Chen, T.-C. Wei, C. Zhang, H. Yu and S. Yoo, *Hybrid Quantum-Classical Graph Convolutional Network*, 2101.06189. 25, 38

[58] J. a. Caldeira, J. Job, S. H. Adachi, B. Nord and G. N. Perdue, *Restricted Boltzmann Machines for galaxy morphology classification with a quantum annealer*, 1911.06259. 26, 34

[59] M. Kim, P. Ko, J.-h. Park and M. Park, *Leveraging Quantum Annealer to identify an Event-topology at High Energy Colliders*, 2111.07806. 26, 35

[60] E. R. Anschuetz, L. Funcke, P. T. Komiske, S. Kryhin and J. Thaler, *Degeneracy Engineering for Classical and Quantum Annealing: A Case Study of Sparse Linear Regression in Collider Physics*, 2205.10375. 26, 35

[61] S. Y. Chang, S. Vallecorsa, E. F. Combarro and F. Carminati, *Quantum Generative Adversarial Networks in a Continuous-Variable Architecture to Simulate High Energy Physics Detectors*, 2101.11132. 26, 27, 41, 42

[62] S. Y. Chang, S. Herbert, S. Vallecorsa, E. F. Combarro and R. Duncan, *Dual-Parameterized Quantum Circuit GAN Model in High Energy Physics*, *EPJ Web Conf.* **251** (2021) 03050, [2103.15470]. 27, 42

[63] S. Y. Chang, E. Agnew, E. F. Combarro, M. Grossi, S. Herbert and S. Vallecorsa, *Running the Dual-PQC GAN on noisy simulators and real quantum hardware*, in *20th International Workshop on Advanced Computing and Analysis Techniques in Physics Research: AI Decoded - Towards Sustainable, Diverse, Performant and Effective Scientific Computing*, 5, 2022. 2205.15003. 27, 42

[64] C. W. Bauer, M. Freytsis and B. Nachman, *Simulating Collider Physics on Quantum Computers Using Effective Field Theories*, *Phys. Rev. Lett.* **127** (2021) 212001, [2102.05044]. 27, 44

[65] C. W. Bauer, W. A. de Jong, B. Nachman and D. Provasoli, *Quantum Algorithm for High Energy Physics Simulations*, *Phys. Rev. Lett.* **126** (2021) 062001, [1904.03196]. 27, 47

[66] S. Ramírez-Uribe, A. E. Rentería-Olivo, G. Rodrigo, G. F. R. Sborlini and L. Vale Silva, *Quantum algorithm for Feynman loop integrals*, *JHEP* **05** (2022) 100, [2105.08703]. 28, 47

[67] QuNu collaboration, T. Li, X. Guo, W. K. Lai, X. Liu, E. Wang, H. Xing et al., *Partonic collinear structure by quantum computing*, *Phys. Rev. D* **105** (2022) L111502, [2106.03865]. 28, 48

[68] Y. Afik and J. R. M. n. de Nova, *Quantum discord and steering in top quarks at the LHC*, 2209.03969. 28, 48

[69] Y. Afik and J. R. M. n. de Nova, *Entanglement and quantum tomography with top quarks at the LHC*, *Eur. Phys. J. Plus* **136** (2021) 907, [2003.02280]. 28, 48

[70] Y. Afik and J. R. M. n. de Nova, *Quantum information with top quarks in QCD*, *Quantum* **6** (2022) 820, [2203.05582]. 28, 48

[71] A. Fadol, Q. Sha, Y. Fang, Z. Li, S. Qian, Y. Xiao et al., *Application of Quantum Machine Learning in a Higgs Physics Study at the CEPC*, 2209.12788. 28, 48

[72] T. S. Humble, G. N. Perdue and M. J. Savage, *Snowmass Computational Frontier: Topical Group Report on Quantum Computing*, 2209.06786. 29, 48

[73] C. A. Argüelles and B. J. P. Jones, *Neutrino Oscillations in a Quantum Processor*, *Phys. Rev. Research.* **1** (2019) 033176, [1904.10559]. 29, 49

[74] NuQS collaboration, H. Lamm, S. Lawrence and Y. Yamauchi, *General Methods for Digital Quantum Simulation of Gauge Theories*, *Phys. Rev. D* **100** (2019) 034518, [1903.08807]. 29, 49

[75] M. Kreshchuk, W. M. Kirby, G. Goldstein, H. Beauchemin and P. J. Love, *Quantum simulation of quantum field theory in the light-front formulation*, *Phys. Rev. A* **105** (2022) 032418, [2002.04016]. 29, 49