A Living Review of Quantum Information Science in High Energy Physics

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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.

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1 Introduction

The purpose of this note is to collect references for quantum information science as applied to particle and nuclear physics. The papers are listed in reverse chronological 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.

1.1 High Energy Physics Categories

1.1.1 Anomaly Detection

One of the main goals of high energy physics is to search for Beyond the Standard Model (BSM) physics. The most common strategy in BSM searches is to pick a specific BSM signal model and estimate the background from Standard Model (SM) processes. The signal events are then combined with the background events to develop an analysis strategy to be appled on real data. This strategy is strongly model-dependent.

1.1.2 Beyond the Standard Model

The development of the Standard Model (SM) of particle physics was a collaborative effort among scientists around the world during the latter half of the 20th century. The SM explains the fundamental laws of nature that underlie the distinguishing properties of various elementary particles, as well as the three of the four known interactions between them, namely the electromagnetic and weak nuclear forces, which unite into the electroweak (EW), and the strong nuclear force. Its success lies not only in its capacity to provide an organizing principle for the subatomic world but also in its precise predictions regarding various physical processes that occur in this realm. Intriguingly, specific components of the SM were postulated before their eventual experimental validation, and the discovery of the Higgs Boson by the ATLAS and CMS collaborations at the Large Hardon Collider (LHC) at CERN in 2012 was the final missing piece of the SM, making it the most successful and precise scientific theory to date.

Despite its unprecedented explanatory and predictive power, the Standard Model (SM) of particle physics fails to explain several phenomena, necessitating the proposal of Beyond the Standard Model (BSM) physics. From the theoretical side, the SM cannot integrate Einstein's Theory of General Relativity, which explains gravity, the fourth fundamental interaction, in a mathematically consistent, united framework. On the phenomenological side, the SM cannot account for Dark Energy, which causes the accelerating expansion of the universe, or Dark Matter (DM), which constitutes about 85% of the matter in the universe but remains non-observable due to its weakly interacting nature. The SM also lacks a mechanism to explain the observed abundance of matter over antimatter in the universe or the generation of non-vanishing, yet tiny, neutrino masses, the existence of which can be inferred by the phenomenon of neutrino oscillations.

To deal with these major puzzles, the theoretical physics community refines the existing high-precision SM calculations and proposes various BSM extensions. At the same time, experimental collaborations are pursuing the quest of hunting down any potential evidence towards deviations from the SM predictions. The new experiments include both high-energy direct searches for new particles at colliders as well as the low-energy frontier of high-precision measurements. Even though experiments may exhibit certain discrepancies, they are univocally accepted as New Physics (NP) signals only if they surpass a certain threshold of confidence level (CL), which in statistical language is defined as 5σ standard deviations above background expectations. Therefore, the discrepancies under question are reexamined carefully upon the collection of more data in order to avoid statistical flukes or experimental errors.

At present, the SM seems to be a rather too good description of nature at the energy scales that we have access to. It is possible that the energy scales associated with BSM physics are higher than those probed by current experiments, new experimental techniques and facilities are required. However, it is also possible that these scales within the reach of LHC (and other experiments), but the relevant NP signal is buried within the uncertainties of measurements and theory predictions. As a matter of fact, the extraction of this information is challenging in many motivated BSM scenarios. In that case, all the available data as well as the ones that will be collected during the high-luminosity phase (HL-LHC) phase must be scrutinized to full extent.

1.1.3 Cosmology

1.1.4 Detector Simulation

1.1.5 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

1.1.6 Jet Algorithms and Jet Tagging

1.1.7 Lattice Field Theories

1.1.8 Neutrinos

1.1.9 Quantum Field Theories

1.1.10 Signal-Background Discrimination

1.1.11 Top Quarks

1.1.12 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.

1.2 Quantum Information Science Categories

1.2.1 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 $|\psi\rangle = c_0 |0\rangle + c_1 |1\rangle$.

1.2.2 Quantum Algorithms Based on Amplitude Amplification

The quantum search algorithm, also known as Grover's algorithm, performs a generic search for a solution to a search problem, using a technique known as amplitude amplification, which increases the amplitude of the desired states. Assuming that the solutions of the search problem can be expressed as binary strings of length n, such that $N = 2^n$, where N is the dimension of the search space, then any search problem can be represented as a function $f(x)$ where

$$f(x) = \begin{cases} 1 & \text{if } x \text{ is a solution} \\ 0 & \text{otherwise} \end{cases}$$

Grover's algorithm aims to find an input $x \in \{0,1\}^n$ such that $f(x) = 1$. Suppose the function f is implemented by an oracle, a black box that can recognize solutions to the search problem. Classically, it would take $\mathcal{O}(N)$ queries to the oracle to find the solution, however, using Grover's algorithm would allow this search to be sped up substatially, requiring only $\mathcal{O}(\sqrt{N})$ queries. The quantum oracle can be represented by a unitary operator U_f, defined by $U_f : |x\rangle |q\rangle \to |x\rangle |q \oplus f(x)\rangle$, where $|x\rangle$ is the index register, $|q\rangle$ is the oracle register consisting of a single qubit which is flipped if $f(x) = 1$ and unchanged otherwise, and $\oplus$ is addition modulo 2. Let $|q\rangle = |0\rangle$, then given a query value x, prepare the state $|x\rangle |0\rangle$, apply oracle U_f, and measure the oracle qubit. If the oracle qubit has flipped to $|1\rangle$, then x is a solution to the search problem. If the oracle qubit is $|q\rangle = \frac{1}{\sqrt{2}}(|0\rangle - |1\rangle)$, then the action of the oracle U_f is

$$U_f \;:\; |x\rangle \frac{1}{\sqrt{2}}(|0\rangle - |1\rangle) \longmapsto (-1)^{f(x)} |x\rangle \frac{1}{\sqrt{2}}(|0\rangle - |1\rangle)$$

Note that the state of the oracle qubit $|q\rangle$ has not changed, in other words $\frac{1}{\sqrt{2}}(|0\rangle - |1\rangle)$ is an eigenstate, therefore, the oracle can be ignored, and the action of U_f is given by

$$U_f \;:\; |x\rangle \longmapsto (-1)^{f(x)} |x\rangle$$

Therefore, the oracle marks the solution to the search problem by a phase shift. Define an n-qubit phase shift operator U_s with the following action, $U_s \;:\; |x\rangle \mapsto (-1)^{\delta_{x0}} |x\rangle$. U_s applies a phase shift to all n-qubit states orthogonal to $|00\ldots0\rangle$.

The Grover's algorithm is as follows:

1. Start with the n-qubit state initialized in the state $|00\ldots0\rangle$

2. Apply the n-qubit Hadamard gate H to prepare the state $\frac{1}{\sqrt{N}} |\psi\rangle = \sum_{x=0}^{N-1} |x\rangle$, where $N = 2^n$

3. Apply the following subroutine Grover iterate $G = HU_sHU_f$ a total of $\lfloor \frac{\pi}{4} \frac{1}{\sqrt{N}} \rfloor$ times

   (a) Apply the oracle U_f

   (b) Apply the n-qubit Hadamard gate H

   (c) Apply the phase shift operator U_s

   (d) Apply the n-qubit Hadamard gate

4. Measure the resulting state

Grover's search algorithm can be generalized to a process known as amplitude amplification.

1.2.3 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.

1.2.4 Quantum Autoencoders

1.2.5 Quantum Circuit Born Machines

1.2.6 Quantum Neural Networks

1.2.7 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.

1.2.8 Quantum Inspired Algorithms

1.2.9 Quantum Information Theory

Entanglement, Bell Inequality

1.2.10 Quantum Support Vector Machines

1.2.11 Quantum Sensors

1.2.12 Quantum Simulations

1.2.13 Quantum Unsupervised Clustering Algorithms

1.2.14 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 is 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 $T = \sum |i+1\rangle\langle i| \otimes |\uparrow\rangle\langle\uparrow| + \sum |i-1\rangle\langle k| \otimes |\downarrow\rangle\langle\downarrow|$, 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.

1.2.15 Tensor Networks

1.2.16 Variational Quantum Circuits

Variational quantum circuits, also known as parametrized quantum circuits,

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]

- **Authors:** Wen Guan, Gabriel Perdue, Arthur Pesah, Maria Schuld, Koji Terashi, Sofia Vallecorsa, Jean-Roch Vlimant

- **Posted on arXiv:** 18 May 2020

- **Published in Mach.Learn.Sci.Tech.:** 2021

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

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

- **Results and Conclusions:** This paper reviews two paradigms of quantum machine learning: quantum annealing and quantum circuit model. The paper discusses three papers using quantum annealing (1-3) and three papers using quantum circuits (4-6): (1) *Solving a Higgs Optimization Problem with Quantum Annealing for Machine Learning*; (2) *Quantum Adiabatic Machine Learning with Zooming*; (3) *Restricted Boltzmann Machines for Galaxy Morphology Classification with a Quantum Annealer*; (4) *Particle Track Reconstruction with Quantum Algorithms*; (5) *Application of Quantum Machine Learning to High Energy Physics Analysis at LHC Using IBM Quantum Computer Simulators and IBM Quantum Computer Hardware*; (6) *Event Classification with Quantum Machine Learning in High-Energy Physics.* The main themes throughout these papers is that there is no significant performance advantage between quantum and classical machine learning, however, QML has a slight advantage for smaller datasets. The paper discusses the challenges, such as the difficulty to map the problem onto a quantum annealer device with limited connectivity and the hardware limitations to perform quantum circuit-based machine learning, and outlooks, such as performing quantum machine learning directly on quantum objects and quantum simulations.

2.1.2 Whitepapers

2.1.2.1 Report of the Snowmass 2021 Theory Frontier Topical Group on Quantum Information Science [2]

- **Authors:** Simon Catterall, Roni Harnik, Veronika E. Hubeny, Christian W. Bauer, Asher Berlin, Zohreh Davoudi, Thomas Faulkner, Thomas Hartman, Matthew Headrick, Yonatan F. Kahn, Henry Lamm, Yannick Meurice, Surjeet Rajendran, Mukund Rangamani, Brian Swingle

- **Posted on arXiv:** 29 September 2022

2.1.2.2 Snowmass Computational Frontier: Topical Group Report on Quantum Computing [3]

- **Authors:** Travis S. Humble, Gabriel N. Perdue, Martin J. Savage

- **Posted on arXiv:** 14 September 2022

2.1.2.3 Quantum computing hardware for HEP algorithms and sensing [4]

- **Authors:** M. Sohaib Alam, Sergey Belomestnykh, Nicholas Bornman, Gustavo Cancelo, Yu-Chiu Chao, Mattia Checchin, Vinh San Dinh, Anna Grassellino, Erik J. Gustafson, Roni Harnik, Corey Rae Harrington McRae, Ziwen Huang, Keshav Kapoor, Taeyoon Kim, James B. Kowalkowski, Matthew J. Kramer, Yulia Krasnikova, Prem Kumar, Doga Murat Kurkcuoglu, Henry Lamm, Adam L. Lyon, Despina Milathianaki, Akshay Murthy, Josh Mutus, Ivan Nekrashevich, JinSu Oh, A. BarÖzgüler, Gabriel

Nathan Perdue, Matthew Reagor, Alexander Romanenko, James A. Sauls, Leandro Stefanazzi, Norm M. Tubman, Davide Venturelli, Changqing Wang, Xinyuan You, David M.T. van Zanten, Lin Zhou, Shaojiang Zhu, Silvia Zorzetti

- **Posted on arXiv:** 18 April 2022

2.1.2.4 Quantum Simulation for High-Energy Physics [5]

- **Authors:** Christian W. Bauer, Zohreh Davoudi, A. Baha Balantekin, Tanmoy Bhattacharya, Marcela Carena, Wibe A. de Jong, Patrick Draper, Aida El-Khadra, Nate Gemelke, Masanori Hanada, Dmitri Kharzeev, Henry Lamm, Ying-Ying Li, Junyu Liu, Mikhail Lukin, Yannick Meurice, Christopher Monroe, Benjamin Nachman, Guido Pagano, John Preskill, Enrico Rinaldi, Alessandro Roggero, David I. Santiago, Martin J. Savage, Irfan Siddiqi, George Siopsis, David Van Zanten, Nathan Wiebe, Yukari Yamauchi, Kübra Yeter-Aydeniz, Silvia Zorzetti

- **Posted on arXiv:** 07 April 2022

- **Published in PRX Quantum:** 01 May 2023

2.1.2.5 Quantum Networks for High Energy Physics [6]

- **Authors:** Andrei Derevianko, Eden Figueroa, Julián Martínez-Rincón, Inder Monga, Andrei Nomerotski, Cristián H. Peña, Nicholas A. Peters, Raphael Pooser, Nageswara Rao, Anze Slosar, Panagiotis Spentzouris, Maria Spiropulu, Paul Stankus, Wenji Wu, Si Xie

- **Posted on arXiv:** 31 March 2022

2.1.2.6 New Horizons: Scalar and Vector Ultralight Dark Matter [7]

- **Authors:** D. Antypas, A. Banerjee, C. Bartram, M. Baryakhtar, J. Betz, J.J. Bollinger, C. Boutan, D. Bowring, D. Budker, D. Carney, G. Carosi, S. Chaudhuri, S. Cheong, A. Chou, M.D. Chowdhury, R.T. Co, J.R. Crespo López-Urrutia, M. Demarteau, N. DePorzio, A.V. Derbin, T. Deshpande, M.D. Chowdhury, L. Di Luzio, A. Diaz-Morcillo, J.M. Doyle, A. Drlica-Wagner, A. Droster, N. Du, B. Döbrich, J. Eby, R. Essig, G.S. Farren, N.L. Figueroa, J.T. Fry, S. Gardner, A.A. Geraci, A. Ghalsasi, S. Ghosh, M. Giannotti, B. Gimeno, S.M. Griffin, D. Grin, D. Grin, H. Grote, J.H. Gundlach, M. Guzzetti, D. Hanneke, R. Harnik, R. Henning, V. Irsic, H. Jackson, D.F. Jackson Kimball, J. Jaeckel, M. Kagan, D. Kedar, R. Khatiwada, S. Knirck, S. Kolkowitz, T. Kovachy, S.E. Kuenstner, Z. Lasner, A.F. Leder, R. Lehnert, D.R. Leibrandt, E. Lentz, S.M. Lewis, Z. Liu, J. Manley, R.H. Maruyama, A.J. Millar, V.N. Muratova, N. Musoke, S. Nagaitsev, O. Noroozian, C.A.J. O'Hare, J.L. Ouellet, K.M.W. Pappas, E. Peik, G. Perez, A. Phipps, N.M. Rapidis, J.M. Robinson, V.H. Robles, K.K. Rogers, J. Rudolph, G. Rybka, M. Safdari, M. Safdari, M.S. Safronova, C.P. Salemi, P.O. Schmidt,

T. Schumm, A. Schwartzman, J. Shu, M. Simanovskaia, J. Singh, S. Singh, M.S. Smith, W.M. Snow, Y.V. Stadnik, C. Sun, A.O. Sushkov, T.M.P. Tait, V. Takhistov, D.B. Tanner, D.J. Temples, P.G. Thirolf, J.H. Thomas, M.E. Tobar, O. Tretiak, Y.-D. Tsai, J.A. Tyson, M. Vandegar, S. Vermeulen, L. Visinelli, E. Vitagliano, Z. Wang, D.J. Wilson, L. Winslow, S. Withington, M. Wooten, J. Yang, J. Ye, B.A. Young, F. Yu, M.H. Zaheer, T. Zelevinsky, Y. Zhao, K. Zhou

- **Posted on arXiv:** 28 March 2022

2.1.2.7 Quantum Computing for Data Analysis in High-Energy Physics [8]

- **Authors:** Andrea Delgado, Kathleen E. Hamilton, Prasanna Date, Jean-Roch Vlimant, Duarte Magano, Yasser Omar, Pedrame Bargassa, Anthony Francis, Alessio Gianelle, Lorenzo Sestini, Donatella Lucchesi, Davide Zuliani, Davide Nicotra, Jacco de Vries, Dominica Dibenedetto, Miriam Lucio Martinez, Eduardo Rodrigues, Carlos Vazquez Sierra, Sofia Vallecorsa, Jesse Thaler, Carlos Bravo-Prieto, su Yeon Chang, Jeffrey Lazar, Carlos A. Argüelles, Jorge J. Martinez de Lejarza, Leandro Cieri, Germán Rodrigo

- **Posted on arXiv:** 15 March 2022

2.1.2.8 Snowmass white paper: Quantum information in quantum field theory and quantum gravity [9]

- **Authors:** Thomas Faulkner, Thomas Hartman, Matthew Headrick, Mukund Rangamani, Brian Swingle

- **Posted on arXiv:** 14 March 2022

2.1.2.9 Snowmass White Paper: Quantum Computing Systems and Software for High-energy Physics Research [10]

- **Authors:** Travis S. Humble, Andrea Delgado, Raphael Pooser, Christopher Seck, Ryan Bennink, Vicente Leyton-Ortega, C.-C. Joseph Wang, Eugene Dumitrescu, Titus Morris, Kathleen Hamilton, Dmitry Lyakh, Prasanna Date, Yan Wang, Nicholas A. Peters, Katherine J. Evans, Marcel Demarteau, Alex McCaskey, Thien Nguyen, Susan Clark, Melissa Reville, Alberto Di Meglio, Michele Grossi, Sofia Vallecorsa, Kerstin Borras, Karl Jansen, Dirk Krücker

- **Posted on arXiv:** 14 March 2022

2.1.2.10 Tensor networks for High Energy Physics: contribution to Snowmass 2021 [11]

- **Authors:** Yannick Meurice, James C. Osborn, Ryo Sakai, Judah Unmuth-Yockey, Simon Catterall, Rolando D. Somma

- **Posted on arXiv:** 09 March 2022

2.2 Anomaly Detection

2.2.1 Continuous Variable Quantum Computing

2.2.1.1 Unsupervised event classification with graphs on classical and photonic quantum computers [12]

- **Authors:** Andrew Blance, Michael Spannowsky
- **Posted on arXiv:** 05 March 2021
- **Published in J. High Energ. Phys. 2021, 170:** 31 August 2021

2.2.2 Quantum Annealing

2.2.2.1 A Quantum Algorithm for Model-Independent Searches for New Physics [13]

- **Authors:** Konstantin T. Matchev, Prasanth Shyamsundar, Jordan Smolinsky
- **Posted on arXiv:** 04 March 2020
- **Published in LHEP:** 09 April 2023

2.2.3 Quantum Autoencoders

2.2.3.1 Anomaly detection in high-energy physics using a quantum autoencoder [14]

- **Authors:** Vishal S. Ngairangbam, Michael Spannowsky, Michihisa Takeuchi
- **Posted on arXiv:** 09 December 2021
- **Published in Phys. Rev. D 105, 095004, 2022:** 01 May 2022

2.2.4 Quantum Support Vector Machines

2.2.4.1 Quantum anomaly detection in the latent space of proton collision events at the LHC [15]

- **Authors:** Kinga Anna Woźniak, Vasilis Belis, Ema Puljak, Panagiotis Barkoutsos, Günther Dissertori, Michele Grossi, Maurizio Pierini, Florentin Reiter, Ivano Tavernelli, Sofia Vallecorsa
- **Posted on arXiv:** 25 January 2023
- **HEP Context:** Anomaly detection, where the following BSM processes are considered anomalies: (1) narrow Randall-Sundrum gravitons decaying to two W-bosons (Narrow $G \to WW$); (2) broad Randall-Sundrum graviton decaying to two W-bosons (Broad $G \to WW$); (3) scalar bosons A decaying to a Higgs and a Z boson ($A \to HZ$)

- **QIS Methods:** (1) Used a convolutional autoencoder model to map events into a latent representation of reduced dimensionality; (2) A Quantum Support Vector Machine (QSVM), the Quantum K-means (QK-means) algorithm, and the Quantum K-medians algorithm, are trained to find anomalous events in the latent representation, as well as their respective classical counterparts

- **Results and Conclusions:** With a training sample of size 600 and a fixed latent dimensionality $l = 8$, all classical and quantum ML methods performed worst on the broad Graviton and best with the narrow Graviton, which is expected since the broad Graviton is the most similar to SM processes, making it harder to identify, while the narrow Graviton is the least similar to SM processes, making it easier to identify. The unsupervised kernel machine outperforms both clustering algorithms and is the only model where the quantum classifier outperforms the classical counterpart. If entanglement is not present in the quantum feature map, the performance of the QSVM is worse or matches the performance of the CSVM. This paper demonstrates a consistent performance advantage of quantum models over classical models for an anomaly detection task, where a combination of an autoencoder with quantum anomaly detection models proved to be a viable strategy for data-driven searches for new physics.

2.2.4.2 Unravelling physics beyond the standard model with classical and quantum anomaly detection [16]

- **Authors:** Julian Schuhmacher, Laura Boggia, Vasilis Belis, Ema Puljak, Michele Grossi, Maurizio Pierini, Sofia Vallecorsa, Francesco Tacchino, Panagiotis Barkoutsos, Ivano Tavernelli

- **Posted on arXiv:** 25 January 2023

- **HEP Context:** Anomaly detection, where the background is Standard Model (SM) events, and the anomaly is either the Higgs boson or the Randall-Sundrum Graviton decaying to two Z bosons, where each of the Z bosons decay to a lepton pair

- **QIS Methods:** Applied Classical and Quantum Support Vector Classifiers (CSVCs and QSVCs respectively) trained to identify the artificial anomalies to distinguish between SM and BSM events. A dataset of artificial events that do not rely on a specific BSM theory is generated by using SM events and varying the different features by dataset scrambling, which is done by replacing a feature with a new value chosen according to a Gaussian distribution and a scrambling factor

- **Results and Conclusions:** An SVC trained to identify artificial anomalies was able to identify BSM events with high accuracy. In identifying artificial anomalies, the CSVC outperforms the QSVC, however, the difference in performance between the QSVC and the CSVC shrinks for increasing number of features and increasing scrambling strength. In identifying Higgs and Graviton events, the QSVC performs better than the CSVC with a low scrambling factor. When the scrambling factor increases, the performance gap shrinks when detecting Graviton events, and the CSVC outperforms the QSVC when detecting the Higgs. The paper concludes that while there is no advantage of using a quantum classifier, the limitations in performance could be due to using classical features that describe quantum HEP processes.

2.2.5 Quantum Unsupervised Clustering Algorithms

2.2.5.1 Quantum anomaly detection in the latent space of proton collision events at the LHC [15]

- **Authors:** Kinga Anna Woźniak, Vasilis Belis, Ema Puljak, Panagiotis Barkoutsos, Günther Dissertori, Michele Grossi, Maurizio Pierini, Florentin Reiter, Ivano Tavernelli, Sofia Vallecorsa
- **Posted on arXiv:** 25 January 2023
- **HEP Context:** Anomaly detection, where the following BSM processes are considered anomalies: (1) narrow Randall-Sundrum gravitons decaying to two W-bosons (Narrow $G \to WW$); (2) broad Randall-Sundrum graviton decaying to two W-bosons (Broad $G \to WW$); (3) scalar bosons A decaying to a Higgs and a Z boson ($A \to HZ$)
- **QIS Methods:** (1) Used a convolutional autoencoder model to map events into a latent representation of reduced dimensionality; (2) A Quantum Support Vector Machine (QSVM), the Quantum K-means (QK-means) algorithm, and the Quantum K-medians algorithm, are trained to find anomalous events in the latent representation, as well as their respective classical counterparts
- **Results and Conclusions:** With a training sample of size 600 and a fixed latent dimensionality $l = 8$, all classical and quantum ML methods performed worst on the broad Graviton and best with the narrow Graviton, which is expected since the broad Graviton is the most similar to SM processes, making it harder to identify, while the narrow Graviton is the least similar to SM processes, making it easier to identify. The unsupervised kernel machine outperforms both clustering algorithms and is the only model where the quantum classifier outperforms the classical counterpart. If entanglement is not present in the quantum feature map, the performance of the QSVM is worse or matches the performance of the CSVM. This paper demonstrates a consistent performance advantage of quantum models over classical models for an anomaly detection task, where a combination of an autoencoder with quantum anomaly detection models proved to be a viable strategy for data-driven searches for new physics.

2.2.5.2 Unsupervised event classification with graphs on classical and photonic quantum computers [12]

- **Authors:** Andrew Blance, Michael Spannowsky

- **Posted on arXiv:** 05 March 2021
- **Published in J. High Energ. Phys. 2021, 170:** 31 August 2021

2.2.6 Variational Quantum Circuits

2.2.6.1 Quantum anomaly detection for collider physics [17]

- **Authors:** Sulaiman Alvi, Christian W. Bauer, Benjamin Nachman
- **Posted on arXiv:** 16 June 2022
- **Published in JHEP:** 22 February 2023
- **HEP Context:** Anomaly detection in the four-lepton final state. A weakly/semi-supervised search where a classifier is trained to distinguish data from background-only simulation.
- **QIS Methods:** Two implementations of parameterized quantum circuits where the rotation angles are optimized using classical methods: Variational Quantum Circuits (VQC) and Quantum Circuit Learning (QCL)
- **Results and Conclusions:** A common theme from analyzing the performance of Quantum Machine Learning (QML) in High Energy Physics (HEP) is QML seems to outperform Classical Machine Learning (CML) with small training datasets. However, there are almost no problems in HEP with small number of events in training. This paper considers a realistic example, the four lepton final state, where the training set is limited by low statistics. After comparing VQC and QCL to CML algorithms, this paper states that there is no evidence that QML provides any advantage to CML in collider physics, and QML appears to be systematically worse.

2.2.6.2 Anomaly detection in high-energy physics using a quantum autoencoder [14]

- **Authors:** Vishal S. Ngairangbam, Michael Spannowsky, Michihisa Takeuchi
- **Posted on arXiv:** 09 December 2021
- **Published in Phys. Rev. D 105, 095004, 2022:** 01 May 2022

2.3 Beyond the Standard Model

2.3.1 Quantum Algorithms Based on Amplitude Amplification

2.3.1.1 Implementation and analysis of quantum computing application to Higgs boson reconstruction at the large Hadron Collider [18]

- **Authors:** Anthony Alexiades Armenakas, Oliver K. Baker
- **Published in Sci.Rep.:** 24 November 2021

2.3.1.2 Application of a Quantum Search Algorithm to High- Energy Physics Data at the Large Hadron Collider [19]

- **Authors:** Anthony E. Armenakas, Oliver K. Baker
- **Posted on arXiv:** 01 October 2020

2.3.2 Quantum Annealing

2.3.2.1 Completely quantum neural networks [20]

- **Authors:** Steve Abel, Juan C. Criado, Michael Spannowsky
- **Posted on arXiv:** 23 February 2022
- **Published in Phys.Rev.A:** 01 August 2022

2.3.2.2 Quantum algorithm for the classification of supersymmetric top quark events [21]

- **Authors:** Pedrame Bargassa, Timothèe Cabos, Samuele Cavinato, Artur Cordeiro Oudot Choi, Timothèe Hessel
- **Posted on arXiv:** 31 May 2021
- **Published in Phys. Rev. D 104 (2021) 096004:** 01 November 2021

2.3.2.3 A Quantum Algorithm for Model-Independent Searches for New Physics [13]

- **Authors:** Konstantin T. Matchev, Prasanth Shyamsundar, Jordan Smolinsky
- **Posted on arXiv:** 04 March 2020
- **Published in LHEP:** 09 April 2023

2.3.3 Quantum Support Vector Machines

2.3.3.1 Unravelling physics beyond the standard model with classical and quantum anomaly detection [16]

- **Authors:** Julian Schuhmacher, Laura Boggia, Vasilis Belis, Ema Puljak, Michele Grossi, Maurizio Pierini, Sofia Vallecorsa, Francesco Tacchino, Panagiotis Barkoutsos, Ivano Tavernelli
- **Posted on arXiv:** 25 January 2023
- **HEP Context:** Anomaly detection, where the background is Standard Model (SM) events, and the anomaly is either the Higgs boson or the Randall-Sundrum Graviton decaying to two Z bosons, where each of the Z bosons decay to a lepton pair

- **QIS Methods:** Applied Classical and Quantum Support Vector Classifiers (CSVCs and QSVCs respectively) trained to identify the artificial anomalies to distinguish between SM and BSM events. A dataset of artificial events that do not rely on a specific BSM theory is generated by using SM events and varying the different features by dataset scrambling, which is done by replacing a feature with a new value chosen according to a Gaussian distribution and a scrambling factor

- **Results and Conclusions:** An SVC trained to identify artificial anomalies was able to identify BSM events with high accuracy. In identifying artificial anomalies, the CSVC outperforms the QSVC, however, the difference in performance between the QSVC and the CSVC shrinks for increasing number of features and increasing scrambling strength. In identifying Higgs and Graviton events, the QSVC performs better than the CSVC with a low scrambling factor. When the scrambling factor increases, the performance gap shrinks when detecting Graviton events, and the CSVC outperforms the QSVC when detecting the Higgs. The paper concludes that while there is no advantage of using a quantum classifier, the limitations in performance could be due to using classical features that describe quantum HEP processes.

2.3.4 Quantum Sensors

2.3.4.1 Searching for Dark Matter with a Superconducting Qubit [22]

- **Authors:** Akash V. Dixit, Srivatsan Chakram, Kevin He, Ankur Agrawal, Ravi K. Naik, David I. Schuster, Aaron Chou

- **Posted on arXiv:** 28 August 2020

- **Published in Phys. Rev. Lett. 126, 141302 (2021):** 09 April 2021

2.4 Cosmology

2.4.1 Quantum Annealing

2.4.1.1 Restricted Boltzmann Machines for galaxy morphology classification with a quantum annealer [23]

- **Authors:** João Caldeira, Joshua Job, Steven H. Adachi, Brian Nord, Gabriel N. Perdue

- **Posted on arXiv:** 14 November 2019

2.5 Detector Simulation

2.5.1 Continuous Variable Quantum Computing

2.5.1.1 Quantum Generative Adversarial Networks in a Continuous-Variable Architecture to Simulate High Energy Physics Detectors [24]

- **Authors:** Su Yeon Chang, Sofia Vallecorsa, Elías F. Combarro, Federico Carminati

- **Posted on arXiv:** 26 January 2021

2.5.2 Quantum Generative Adversarial Networks

2.5.2.1 Running the Dual-PQC GAN on noisy simulators and real quantum hardware [25]

- **Authors:** Su Yeon Chang, Edwin Agnew, Elías F. Combarro, Michele Grossi, Steven Herbert, Sofia Vallecorsa
- **Posted on arXiv:** 30 May 2022
- **Published in J.Phys.Conf.Ser.:** 2023

2.5.2.2 Dual-Parameterized Quantum Circuit GAN Model in High Energy Physics [26]

- **Authors:** Su Yeon Chang, Steven Herbert, Sofia Vallecorsa, Elías F. Combarro, Ross Duncan
- **Posted on arXiv:** 29 March 2021
- **Published in EPJ Web Conf.:** 2021

2.5.2.3 Quantum Generative Adversarial Networks in a Continuous-Variable Architecture to Simulate High Energy Physics Detectors [24]

- **Authors:** Su Yeon Chang, Sofia Vallecorsa, Elías F. Combarro, Federico Carminati
- **Posted on arXiv:** 26 January 2021

2.6 Event Generation

2.6.1 Quantum Circuit Born Machines

2.6.1.1 Unsupervised quantum circuit learning in high energy physics [27]

- **Authors:** Andrea Delgado, Kathleen E. Hamilton
- **Posted on arXiv:** 07 March 2022
- **Published in Phys.Rev.D:** 01 November 2022

2.6.2 Quantum Generative Adversarial Networks

2.6.2.1 Generative Invertible Quantum Neural Networks [28]

- **Authors:** Armand Rousselot, Michael Spannowsky
- **Posted on arXiv:** 24 February 2023

2.6.2.2 Quantum integration of elementary particle processes [29]

- **Authors:** Gabriele Agliardi, Michele Grossi, Mathieu Pellen, Enrico Prati
- **Posted on arXiv:** 05 January 2022
- **Published in Phys.Lett.B:** 10 September 2022

2.6.2.3 Style-based quantum generative adversarial networks for Monte Carlo events [30]

- **Authors:** Carlos Bravo-Prieto, Julien Baglio, Marco Cè, Anthony Francis, Dorota M. Grabowska, Stefano Carrazza
- **Posted on arXiv:** 13 October 2021
- **Published in Quantum 6, 777 (2022):** 17 August 2022

2.6.3 Quantum Simulations

2.6.3.1 Towards a quantum computing algorithm for helicity amplitudes and parton showers [31]

- **Authors:** Khadeejah Bepari, Sarah Malik, Michael Spannowsky, Simon Williams
- **Posted on arXiv:** 13 October 2020
- **Published in Phys. Rev. D 103, 076020 (2021):** 27 April 2021

2.6.3.2 Quantum Algorithm for High Energy Physics Simulations [32]

- **Authors:** Christian W. Bauer, Wibe A. de Jong, Benjamin Nachman, Davide Provasoli
- **Posted on arXiv:** 05 April 2019
- **Published in Phys. Rev. Lett. 126, 062001 (2021):** 11 February 2021

2.6.4 Quantum Walks

2.6.4.1 Collider events on a quantum computer [33]

- **Authors:** Gösta Gustafson, Stefan Prestel, Michael Spannowsky, Simon Williams
- **Posted on arXiv:** 21 July 2022
- **Published in JHEP:** 07 November 2022

2.6.4.2 Quantum walk approach to simulating parton showers [34]

- **Authors:** Khadeejah Bepari, Sarah Malik, Michael Spannowsky, Simon Williams
- **Posted on arXiv:** 28 September 2021
- **Published in Phys. Rev. D 106 (2022) 056002:** 01 September 2022

2.6.5 Variational Quantum Circuits

2.6.5.1 Partonic collinear structure by quantum computing [35]

- **Authors:** Tianyin Li, Xingyu Guo, Wai Kin Lai, Xiaohui Liu, Enke Wang, Hongxi Xing, Dan-Bo Zhang, Shi-Liang Zhu
- **Posted on arXiv:** 07 June 2021
- **Published in Phys.Rev.D:** 01 June 2022

2.7 Jet Algorithms and Jet Tagging

2.7.1 Quantum Algorithms Based on Amplitude Amplification

2.7.1.1 Quantum Algorithms for Jet Clustering [36]

- **Authors:** Annie Y. Wei, Preksha Naik, Aram W. Harrow, Jesse Thaler
- **Posted on arXiv:** 23 August 2019
- **Published in Phys. Rev. D 101, 094015 (2020):** 15 May 2020
- **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
- **QIS 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.

2.7.2 Quantum Annealing

2.7.2.1 Degeneracy engineering for classical and quantum annealing: A case study of sparse linear regression in collider physics [37]

- **Authors:** Eric R. Anschuetz, Lena Funcke, Patrick T. Komiske, Serhii Kryhin, Jesse Thaler
- **Posted on arXiv:** 20 May 2022
- **Published in Phys. Rev. D 106, 056008 (2022):** 01 September 2022

2.7.2.2 Quantum annealing for jet clustering with thrust [38]

- **Authors:** Andrea Delgado, Jesse Thaler
- **Posted on arXiv:** 05 May 2022
- **Published in Phys.Rev.D:** 01 November 2022

2.7.2.3 Leveraging Quantum Annealer to identify an Event-topology at High Energy Colliders [39]

- **Authors:** Minho Kim, Pyungwon Ko, Jae-hyeon Park, Myeonghun Park
- **Posted on arXiv:** 15 November 2021

2.7.2.4 Adiabatic Quantum Algorithm for Multijet Clustering in High Energy Physics [40]

- **Authors:** Diogo Pires, Yasser Omar, João Seixas
- **Posted on arXiv:** 28 December 2020

2.7.2.5 Quantum Algorithms for Jet Clustering [36]

- **Authors:** Annie Y. Wei, Preksha Naik, Aram W. Harrow, Jesse Thaler
- **Posted on arXiv:** 23 August 2019
- **Published in Phys. Rev. D 101, 094015 (2020):** 15 May 2020
- **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
- **QIS 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.

2.7.3 Quantum Inspired Algorithms

2.7.3.1 Quantum-inspired event reconstruction with Tensor Networks: Matrix Product States [41]

- **Authors:** Jack Y. Araz, Michael Spannowsky
- **Posted on arXiv:** 15 June 2021
- **Published in JHEP 08 (2021) 112:** 23 August 2021

2.7.3.2 Quantum-inspired machine learning on high-energy physics data [42]

- **Authors:** Timo Felser, Marco Trenti, Lorenzo Sestini, Alessio Gianelle, Davide Zuliani, Donatella Lucchesi, Simone Montangero
- **Posted on arXiv:** 28 April 2020
- **Published in npj Quantum Inf.:** 15 July 2021

2.7.4 Quantum Unsupervised Clustering Algorithms

2.7.4.1 Quantum clustering and jet reconstruction at the LHC [43]

- **Authors:** Jorge J. Martínez de Lejarza, Leandro Cieri, Germán Rodrigo
- **Posted on arXiv:** 13 April 2022
- **Published in Physical Review D 106, 036021 (2022):** 01 August 2022

2.7.4.2 A Digital Quantum Algorithm for Jet Clustering in High-Energy Physics [44]

- **Authors:** Diogo Pires, Pedrame Bargassa, João Seixas, Yasser Omar
- **Posted on arXiv:** 11 January 2021

2.7.5 Tensor Networks

2.7.5.1 Classical versus quantum: Comparing tensor-network-based quantum circuits on Large Hadron Collider data [45]

- **Authors:** Jack Y. Araz, Michael Spannowsky
- **Posted on arXiv:** 21 February 2022
- **Published in Phys. Rev. A 106 (Dec, 2022) 062423:** 19 December 2022

2.7.5.2 Quantum-inspired event reconstruction with Tensor Networks: Matrix Product States [41]

- **Authors:** Jack Y. Araz, Michael Spannowsky
- **Posted on arXiv:** 15 June 2021
- **Published in JHEP 08 (2021) 112:** 23 August 2021

2.7.6 Variational Quantum Circuits

2.7.6.1 Quantum Machine Learning for b-jet charge identification [46]

- **Authors:** Alessio Gianelle, Patrick Koppenburg, Donatella Lucchesi, Davide Nicotra, Eduardo Rodrigues, Lorenzo Sestini, Jacco de Vries, Davide Zuliani
- **Posted on arXiv:** 28 February 2022
- **Published in JHEP:** 01 August 2022

2.8 Lattice Field Theories

2.8.1 Quantum Annealing

2.8.1.1 SU(2) lattice gauge theory on a quantum annealer [47]

- **Authors:** Sarmed A Rahman, Randy Lewis, Emanuele Mendicelli, Sarah Powell
- **Posted on arXiv:** 15 March 2021
- **Published in Phys. Rev. D 104, 034501 (2021):** 01 August 2021

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

- **Authors:** Nga T.T. Nguyen, Garrett T. Kenyon, Boram Yoon
- **Posted on arXiv:** 14 November 2019
- **Published in Sci Rep 10, 10915 (2020):** 02 July 2020

2.8.2 Quantum Simulations

2.8.2.1 Efficient representation for simulating U(1) gauge theories on digital quantum computers at all values of the coupling [49]

- **Authors:** Christian W. Bauer, Dorota M. Grabowska
- **Posted on arXiv:** 15 November 2021
- **Published in Phys.Rev.D:** 01 February 2023

2.8.2.2 Lattice renormalization of quantum simulations [50]

- **Authors:** Marcela Carena, Henry Lamm, Ying-Ying Li, Wanqiang Liu
- **Posted on arXiv:** 02 July 2021
- **Published in Phys.Rev.D:** 01 November 2021

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

- **Authors:** Yasar Y. Atas, Jinglei Zhang, Randy Lewis, Amin Jahanpour, Jan F. Haase, Christine A. Muschik
- **Posted on arXiv:** 17 February 2021
- **Published in Nature Communications 2021:** 11 November 2021

2.8.2.4 Role of boundary conditions in quantum computations of scattering observables [52]

- **Authors:** Raúl A. Briceño, Juan V. Guerrero, Maxwell T. Hansen, Alexandru M. Sturzu
- **Posted on arXiv:** 01 July 2020
- **Published in Phys. Rev. D 103, 014506 (2021):** 07 January 2021

2.8.2.5 Simulating lattice gauge theories on a quantum computer [53]

- **Authors:** Tim Byrnes, Yoshihisa Yamamoto
- **Posted on arXiv:** October 2005
- **Published in Phys.Rev.A:** 2006

2.9 Neutrinos

2.9.1 Quantum Simulations

2.9.1.1 Neutrino Oscillations in a Quantum Processor [54]

- **Authors:** C.A. Argüelles, B.J. P. Jones
- **Posted on arXiv:** 23 April 2019
- **Published in Phys. Rev. Research 1, 033176 (2019):** 13 December 2019

2.9.2 Variational Quantum Circuits

2.9.2.1 Hybrid Quantum-Classical Graph Convolutional Network [55]

- **Authors:** Samuel Yen-Chi Chen, Tzu-Chieh Wei, Chao Zhang, Haiwang Yu, Shinjae Yoo
- **Posted on arXiv:** 15 January 2021

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

- **Authors:** Samuel Yen-Chi Chen, Tzu-Chieh Wei, Chao Zhang, Haiwang Yu, Shinjae Yoo
- **Posted on arXiv:** 22 December 2020
- **Published in Phys.Rev.Res.:** 28 March 2022

2.10 Quantum Field Theories

2.10.1 Quantum Algorithms Based on Amplitude Amplification

2.10.1.1 Quantum algorithm for Feynman loop integrals [57]

- **Authors:** Selomit Ramírez-Uribe, Andrès E. Rentería-Olivo, Germán Rodrigo, German F.R. Sborlini, Luiz Vale Silva
- **Posted on arXiv:** 18 May 2021
- **Published in JHEP:** 16 May 2022

2.10.2 Quantum Information Theory

2.10.2.1 Minimal entanglement and emergent symmetries in low-energy QCD [58]

- **Authors:** Qiaofeng Liu, Ian Low, Thomas Mehen
- **Posted on arXiv:** 21 October 2022
- **Published in Phys.Rev.C:** 14 February 2023

2.10.2.2 Symmetry from entanglement suppression [59]

- **Authors:** Ian Low, Thomas Mehen
- **Posted on arXiv:** 21 April 2021
- **Published in Phys.Rev.D:** 01 October 2021

2.10.3 Quantum Simulations

2.10.3.1 Simulating Collider Physics on Quantum Computers Using Effective Field Theories [60]

- **Authors:** Christian W. Bauer, Marat Freytsis, Benjamin Nachman
- **Posted on arXiv:** 09 February 2021
- **Published in Phys.Rev.Lett.:** 18 November 2021

2.10.3.2 Quantum simulation of quantum field theory in the light-front formulation [61]

- **Authors:** Michael Kreshchuk, William M. Kirby, Gary Goldstein, Hugo Beauchemin, Peter J. Love
- **Posted on arXiv:** 10 February 2020
- **Published in Phys. Rev. A 105, 032418 (2022):** 08 March 2022

2.10.3.3 General Methods for Digital Quantum Simulation of Gauge Theories [62]

- **Authors:** Henry Lamm, Scott Lawrence, Yukari Yamauchi
- **Posted on arXiv:** 19 March 2019
- **Published in Phys. Rev. D 100, 034518 (2019):** 29 August 2019

2.10.3.4 Scalar Quantum Field Theories as a Benchmark for Near-Term Quantum Computers [63]

- **Authors:** Kubra Yeter-Aydeniz, Eugene F. Dumitrescu, Alex J. McCaskey, Ryan S. Bennink, Raphael C. Pooser, George Siopsis
- **Posted on arXiv:** 29 November 2018
- **Published in Phys. Rev. A 99, 032306 (2019):** 04 March 2019

2.10.3.5 Quantum Algorithms for Fermionic Quantum Field Theories [64]

- **Authors:** Stephen P. Jordan, Keith S. M. Lee, John Preskill
- **Posted on arXiv:** 28 April 2014

2.10.3.6 Quantum Computation of Scattering in Scalar Quantum Field Theories [65]

- **Authors:** Stephen P. Jordan, Keith S.M. Lee, John Preskill
- **Posted on arXiv:** December 2011

2.11 Signal-Background Discrimination

2.11.1 Quantum Annealing

2.11.1.1 Quantum adiabatic machine learning by zooming into a region of the energy surface [66]

- **Authors:** Alexander Zlokapa, Alex Mott, Joshua Job, Jean-Roch Vlimant, Daniel Lidar, Maria Spiropulu

- **Posted on arXiv:** 13 August 2019
- **Published in Phys. Rev. A 102, 062405 (2020):** 05 December 2020
- **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)
- **QIS 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.

2.11.1.2 Solving a Higgs optimization problem with quantum annealing for machine learning [67]

- **Authors:** Alex Mott, Joshua Job, Jean Roch Vlimant, Daniel Lidar, Maria Spiropulu
- **Published in Nature:** 18 October 2017
- **HEP Context:** 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).
- **QIS Methods:** The strong classifier is 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).

2.11.2 Quantum Support Vector Machines

2.11.2.1 Application of Quantum Machine Learning in a Higgs Physics Study at the CEPC [68]

- **Authors:** Abdualazem Fadol, Qiyu Sha, Yaquan Fang, Zhan Li, Sitian Qian, Yuyang Xiao, Yu Zhang, Chen Zhou
- **Posted on arXiv:** 26 September 2022

2.11.2.2 Application of quantum machine learning using the quantum kernel algorithm on high energy physics analysis at the LHC [69]

- **Authors:** Sau Lan Wu, Shaojun Sun, Wen Guan, Chen Zhou, Jay Chan, Chi Lung Cheng, Tuan Pham, Yan Qian, Alex Zeng Wang, Rui Zhang, Miron Livny, Jennifer Glick, Panagiotis Kl. Barkoutsos, Stefan Woerner, Ivano Tavernelli, Federico Carminati, Alberto Di Meglio, Andy C.Y. Li, Joseph Lykken, Panagiotis Spentzouris, Samuel Yen-Chi Chen, Shinjae Yoo, Tzu-Chieh Wei
- **Posted on arXiv:** 11 April 2021
- **Published in Phys. Rev. Research 3, 033221 (2021):** 08 September 2021
- **HEP Context:** Signal-background discrimination, where signal events are $t\bar{t}H$ ($H \rightarrow \gamma\gamma$), and background events are dominant Standard Model processes
- **QIS Methods:** Quantum 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.

2.11.2.3 Quantum Support Vector Machines for Continuum Suppression in B Meson Decays [70]

- **Authors:** Jamie Heredge, Charles Hill, Lloyd Hollenberg, Martin Sevior
- **Posted on arXiv:** 22 March 2021
- **Published in Comput.Softw.Big Sci.:** 30 November 2021

2.11.3 Variational Quantum Circuits

2.11.3.1 Higgs analysis with quantum classifiers [71]

- **Authors:** Vasileios Belis, Samuel González-Castillo, Christina Reissel, Sofia Vallecorsa, Elías F. Combarro, Günther Dissertori, Florentin Reiter
- **Posted on arXiv:** 15 April 2021
- **Published in EPJ Web Conf.:** 2021

2.11.3.2 Quantum Support Vector Machines for Continuum Suppression in B Meson Decays [70]

- **Authors:** Jamie Heredge, Charles Hill, Lloyd Hollenberg, Martin Sevior
- **Posted on arXiv:** 22 March 2021
- **Published in Comput.Softw.Big Sci.:** 30 November 2021

2.11.3.3 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 [72]

- **Authors:** Sau Lan Wu, Jay Chan, Wen Guan, Shaojun Sun, Alex Wang, Chen Zhou, Miron Livny, Federico Carminati, Alberto Di Meglio, Andy C.Y. Li, Joseph Lykken, Panagiotis Spentzouris, Samuel Yen-Chi Chen, Shinjae Yoo, Tzu-Chieh Wei
- **Posted on arXiv:** 21 December 2020
- **Published in J.Phys.G:** 26 October 2021
- **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
- **QIS 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.

2.11.3.4 Quantum Machine Learning for Particle Physics using a Variational Quantum Classifier [73]

- **Authors:** Andrew Blance, Michael Spannowsky
- **Posted on arXiv:** 14 October 2020
- **Published in JHEP:** 2021

2.11.3.5 Event Classification with Quantum Machine Learning in High-Energy Physics [74]

- **Authors:** Koji Terashi, Michiru Kaneda, Tomoe Kishimoto, Masahiko Saito, Ryu Sawada, Junichi Tanaka
- **Posted on arXiv:** 23 February 2020
- **Published in Comput. Softw. Big Sci. 5, 2 (2021):** 03 January 2021
- **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.
- **QIS 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.

2.12 Top Quarks

2.12.1 Quantum Information Theory

2.12.1.1 Quantum discord and steering in top quarks at the LHC [75]

- **Authors:** Yoav Afik, Juan Ramón Muñoz de Nova
- **Posted on arXiv:** 08 September 2022

2.12.1.2 Quantum information with top quarks in QCD [76]

- **Authors:** Yoav Afik, Juan Ramón Muñoz de Nova
- **Posted on arXiv:** 10 March 2022
- **Published in Quantum:** 29 September 2022

2.12.1.3 Entanglement and quantum tomography with top quarks at the LHC [77]

- **Authors:** Yoav Afik, Juan Ramón Muñoz de Nova
- **Posted on arXiv:** 04 March 2020
- **Published in Eur. Phys. J. Plus (2021) 136:907:** 03 September 2021

2.13 Track Reconstruction

2.13.1 Quantum Algorithms Based on Amplitude Amplification

2.13.1.1 Quantum speedup for track reconstruction in particle accelerators [78]

- **Authors:** Duarte Magano, Akshat Kumar, Mrti Klis, Andris Locns, Adam Glos, Sagar Pratapsi, Gonçalo Quinta, Maksims Dimitrijevs, Aleksander Rivos, Pedrame Bargassa, João Seixas, Andris Ambainis, Yasser Omar
- **Posted on arXiv:** 23 April 2021
- **Published in Physical Review D 105 (2022) 076012:** 01 April 2022

2.13.2 Quantum Annealing

2.13.2.1 Particle track classification using quantum associative memory [79]

- **Authors:** Gregory Quiroz, Lauren Ice, Andrea Delgado, Travis S. Humble
- **Posted on arXiv:** 23 November 2020
- **Published in Nucl.Instrum.Meth.A:** 11 September 2021

2.13.2.2 Charged particle tracking with quantum annealing-inspired optimization [80]

- **Authors:** Alexander Zlokapa, Abhishek Anand, Jean-Roch Vlimant, Javier M. Duarte, Joshua Job, Daniel Lidar, Maria Spiropulu
- **Posted on arXiv:** 12 August 2019
- **Published in Quantum Mach. Intell. 3, 27 (2021):** 02 November 2021

2.13.2.3 Track clustering with a quantum annealer for primary vertex reconstruction at hadron colliders [81]

- **Authors:** Souvik Das, Andrew J. Wildridge, Sachin B. Vaidya, Andreas Jung
- **Posted on arXiv:** 21 March 2019

2.13.2.4 A pattern recognition algorithm for quantum annealers [82]

- **Authors:** Frèdèric Bapst, Wahid Bhimji, Paolo Calafiura, Heather Gray, Wim Lavrijsen, Lucy Linder
- **Posted on arXiv:** 21 February 2019
- **Published in Comput.Softw.Big Sci.:** 09 December 2019

2.13.3 Quantum Neural Networks

2.13.3.1 Hybrid Quantum Classical Graph Neural Networks for Particle Track Reconstruction [83]

- **Authors:** Cenk Tüysüz, Carla Rieger, Kristiane Novotny, Bilge Demirköz, Daniel Dobos, Karolos Potamianos, Sofia Vallecorsa, Jean-Roch Vlimant, Richard Forster
- **Posted on arXiv:** 26 September 2021
- **Published in Quantum Machine Intelligence:** 26 October 2021

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]

- **Authors:** Wen Guan, Gabriel Perdue, Arthur Pesah, Maria Schuld, Koji Terashi, Sofia Vallecorsa, Jean-Roch Vlimant
- **Posted on arXiv:** 18 May 2020
- **Published in Mach.Learn.Sci.Tech.:** 2021
- **HEP Context:** Di-photon event classification, galaxy morphology classification, particle track reconstruction, and signal-background discrimination with the SUSY data set
- **QIS Methods:** Quantum machine learning using quantum annealing, restrictive Boltzmann machines, quantum graph networks, and variational quantum circuits
- **Results and Conclusions:** This paper reviews two paradigms of quantum machine learning: quantum annealing and quantum circuit model. The paper discusses three papers using quantum annealing (1-3) and three papers using quantum circuits (4-6): (1) *Solving a Higgs Optimization Problem with Quantum Annealing for Machine Learning*; (2) *Quantum Adiabatic Machine Learning with Zooming*; (3) *Restricted Boltzmann*

Machines for Galaxy Morphology Classification with a Quantum Annealer; (4) *Particle Track Reconstruction with Quantum Algorithms*; (5) *Application of Quantum Machine Learning to High Energy Physics Analysis at LHC Using IBM Quantum Computer Simulators and IBM Quantum Computer Hardware*; (6) *Event Classification with Quantum Machine Learning in High-Energy Physics*. The main themes throughout these papers is that there is no significant performance advantage between quantum and classical machine learning, however, QML has a slight advantage for smaller datasets. The paper discusses the challenges, such as the difficulty to map the problem onto a quantum annealer device with limited connectivity and the hardware limitations to perform quantum circuit-based machine learning, and outlooks, such as performing quantum machine learning directly on quantum objects and quantum simulations.

3.1.2 Whitepapers

3.1.2.1 Report of the Snowmass 2021 Theory Frontier Topical Group on Quantum Information Science [2]

- **Authors:** Simon Catterall, Roni Harnik, Veronika E. Hubeny, Christian W. Bauer, Asher Berlin, Zohreh Davoudi, Thomas Faulkner, Thomas Hartman, Matthew Headrick, Yonatan F. Kahn, Henry Lamm, Yannick Meurice, Surjeet Rajendran, Mukund Rangamani, Brian Swingle
- **Posted on arXiv:** 29 September 2022

3.1.2.2 Snowmass Computational Frontier: Topical Group Report on Quantum Computing [3]

- **Authors:** Travis S. Humble, Gabriel N. Perdue, Martin J. Savage
- **Posted on arXiv:** 14 September 2022

3.1.2.3 Quantum computing hardware for HEP algorithms and sensing [4]

- **Authors:** M. Sohaib Alam, Sergey Belomestnykh, Nicholas Bornman, Gustavo Cancelo, Yu-Chiu Chao, Mattia Checchin, Vinh San Dinh, Anna Grassellino, Erik J. Gustafson, Roni Harnik, Corey Rae Harrington McRae, Ziwen Huang, Keshav Kapoor, Taeyoon Kim, James B. Kowalkowski, Matthew J. Kramer, Yulia Krasnikova, Prem Kumar, Doga Murat Kurkcuoglu, Henry Lamm, Adam L. Lyon, Despina Milathianaki, Akshay Murthy, Josh Mutus, Ivan Nekrashevich, JinSu Oh, A. BarÖzgüler, Gabriel Nathan Perdue, Matthew Reagor, Alexander Romanenko, James A. Sauls, Leandro Stefanazzi, Norm M. Tubman, Davide Venturelli, Changqing Wang, Xinyuan You, David M.T. van Zanten, Lin Zhou, Shaojiang Zhu, Silvia Zorzetti
- **Posted on arXiv:** 18 April 2022

3.1.2.4 Quantum Simulation for High-Energy Physics [5]

- **Authors:** Christian W. Bauer, Zohreh Davoudi, A. Baha Balantekin, Tanmoy Bhattacharya, Marcela Carena, Wibe A. de Jong, Patrick Draper, Aida El-Khadra, Nate Gemelke, Masanori Hanada, Dmitri Kharzeev, Henry Lamm, Ying-Ying Li, Junyu Liu, Mikhail Lukin, Yannick Meurice, Christopher Monroe, Benjamin Nachman, Guido Pagano, John Preskill, Enrico Rinaldi, Alessandro Roggero, David I. Santiago, Martin J. Savage, Irfan Siddiqi, George Siopsis, David Van Zanten, Nathan Wiebe, Yukari Yamauchi, Kübra Yeter-Aydeniz, Silvia Zorzetti
- **Posted on arXiv:** 07 April 2022
- **Published in PRX Quantum:** 01 May 2023

3.1.2.5 Quantum Networks for High Energy Physics [6]

- **Authors:** Andrei Derevianko, Eden Figueroa, Julián Martínez-Rincón, Inder Monga, Andrei Nomerotski, Cristián H. Peña, Nicholas A. Peters, Raphael Pooser, Nageswara Rao, Anze Slosar, Panagiotis Spentzouris, Maria Spiropulu, Paul Stankus, Wenji Wu, Si Xie
- **Posted on arXiv:** 31 March 2022

3.1.2.6 New Horizons: Scalar and Vector Ultralight Dark Matter [7]

- **Authors:** D. Antypas, A. Banerjee, C. Bartram, M. Baryakhtar, J. Betz, J.J. Bollinger, C. Boutan, D. Bowring, D. Budker, D. Carney, G. Carosi, S. Chaudhuri, S. Cheong, A. Chou, M.D. Chowdhury, R.T. Co, J.R. Crespo López-Urrutia, M. Demarteau, N. DePorzio, A.V. Derbin, T. Deshpande, M.D. Chowdhury, L. Di Luzio, A. Diaz-Morcillo, J.M. Doyle, A. Drlica-Wagner, A. Droster, N. Du, B. Döbrich, J. Eby, R. Essig, G.S. Farren, N.L. Figueroa, J.T. Fry, S. Gardner, A.A. Geraci, A. Ghalsasi, S. Ghosh, M. Giannotti, B. Gimeno, S.M. Griffin, D. Grin, D. Grin, H. Grote, J.H. Gundlach, M. Guzzetti, D. Hanneke, R. Harnik, R. Henning, V. Irsic, H. Jackson, D.F. Jackson Kimball, J. Jaeckel, M. Kagan, D. Kedar, R. Khatiwada, S. Knirck, S. Kolkowitz, T. Kovachy, S.E. Kuenstner, Z. Lasner, A.F. Leder, R. Lehnert, D.R. Leibrandt, E. Lentz, S.M. Lewis, Z. Liu, J. Manley, R.H. Maruyama, A.J. Millar, V.N. Muratova, N. Musoke, S. Nagaitsev, O. Noroozian, C.A.J. O'Hare, J.L. Ouellet, K.M.W. Pappas, E. Peik, G. Perez, A. Phipps, N.M. Rapidis, J.M. Robinson, V.H. Robles, K.K. Rogers, J. Rudolph, G. Rybka, M. Safdari, M. Safdari, M.S. Safronova, C.P. Salemi, P.O. Schmidt, T. Schumm, A. Schwartzman, J. Shu, M. Simanovskaia, J. Singh, S. Singh, M.S. Smith, W.M. Snow, Y.V. Stadnik, C. Sun, A.O. Sushkov, T.M.P. Tait, V. Takhistov, D.B. Tanner, D.J. Temples, P.G. Thirolf, J.H. Thomas, M.E. Tobar, O. Tretiak, Y.-D. Tsai, J.A. Tyson, M. Vandegar, S. Vermeulen, L. Visinelli, E. Vitagliano, Z. Wang, D.J. Wilson, L. Winslow, S. Withington, M. Wooten, J. Yang, J. Ye, B.A. Young, F. Yu, M.H. Zaheer, T. Zelevinsky, Y. Zhao, K. Zhou

- **Posted on arXiv:** 28 March 2022

3.1.2.7 Quantum Computing for Data Analysis in High-Energy Physics [8]

- **Authors:** Andrea Delgado, Kathleen E. Hamilton, Prasanna Date, Jean-Roch Vlimant, Duarte Magano, Yasser Omar, Pedrame Bargassa, Anthony Francis, Alessio Gianelle, Lorenzo Sestini, Donatella Lucchesi, Davide Zuliani, Davide Nicotra, Jacco de Vries, Dominica Dibenedetto, Miriam Lucio Martinez, Eduardo Rodrigues, Carlos Vazquez Sierra, Sofia Vallecorsa, Jesse Thaler, Carlos Bravo-Prieto, su Yeon Chang, Jeffrey Lazar, Carlos A. Argüelles, Jorge J. Martinez de Lejarza, Leandro Cieri, Germán Rodrigo

- **Posted on arXiv:** 15 March 2022

3.1.2.8 Snowmass white paper: Quantum information in quantum field theory and quantum gravity [9]

- **Authors:** Thomas Faulkner, Thomas Hartman, Matthew Headrick, Mukund Rangamani, Brian Swingle

- **Posted on arXiv:** 14 March 2022

3.1.2.9 Snowmass White Paper: Quantum Computing Systems and Software for High-energy Physics Research [10]

- **Authors:** Travis S. Humble, Andrea Delgado, Raphael Pooser, Christopher Seck, Ryan Bennink, Vicente Leyton-Ortega, C.-C. Joseph Wang, Eugene Dumitrescu, Titus Morris, Kathleen Hamilton, Dmitry Lyakh, Prasanna Date, Yan Wang, Nicholas A. Peters, Katherine J. Evans, Marcel Demarteau, Alex McCaskey, Thien Nguyen, Susan Clark, Melissa Reville, Alberto Di Meglio, Michele Grossi, Sofia Vallecorsa, Kerstin Borras, Karl Jansen, Dirk Krücker

- **Posted on arXiv:** 14 March 2022

3.1.2.10 Tensor networks for High Energy Physics: contribution to Snowmass 2021 [11]

- **Authors:** Yannick Meurice, James C. Osborn, Ryo Sakai, Judah Unmuth-Yockey, Simon Catterall, Rolando D. Somma

- **Posted on arXiv:** 09 March 2022

3.2 Continuous Variable Quantum Computing

3.2.1 Anomaly Detection

3.2.1.1 Unsupervised event classification with graphs on classical and photonic quantum computers [12]

- **Authors:** Andrew Blance, Michael Spannowsky
- **Posted on arXiv:** 05 March 2021
- **Published in J. High Energ. Phys. 2021, 170:** 31 August 2021

3.2.2 Detector Simulation

3.2.2.1 Quantum Generative Adversarial Networks in a Continuous-Variable Architecture to Simulate High Energy Physics Detectors [24]

- **Authors:** Su Yeon Chang, Sofia Vallecorsa, Elías F. Combarro, Federico Carminati
- **Posted on arXiv:** 26 January 2021

3.3 Quantum Algorithms Based on Amplitude Amplification

3.3.1 Beyond the Standard Model

3.3.1.1 Implementation and analysis of quantum computing application to Higgs boson reconstruction at the large Hadron Collider [18]

- **Authors:** Anthony Alexiades Armenakas, Oliver K. Baker
- **Published in Sci.Rep.:** 24 November 2021

3.3.1.2 Application of a Quantum Search Algorithm to High- Energy Physics Data at the Large Hadron Collider [19]

- **Authors:** Anthony E. Armenakas, Oliver K. Baker
- **Posted on arXiv:** 01 October 2020

3.3.2 Jet Algorithms and Jet Tagging

3.3.2.1 Quantum Algorithms for Jet Clustering [36]

- **Authors:** Annie Y. Wei, Preksha Naik, Aram W. Harrow, Jesse Thaler
- **Posted on arXiv:** 23 August 2019
- **Published in Phys. Rev. D 101, 094015 (2020):** 15 May 2020
- **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
- **QIS 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.

3.3.3 Quantum Field Theories

3.3.3.1 Quantum algorithm for Feynman loop integrals [57]

- **Authors:** Selomit Ramírez-Uribe, Andrès E. Rentería-Olivo, Germán Rodrigo, German F.R. Sborlini, Luiz Vale Silva

- **Posted on arXiv:** 18 May 2021

- **Published in JHEP:** 16 May 2022

3.3.4 Track Reconstruction

3.3.4.1 Quantum speedup for track reconstruction in particle accelerators [78]

- **Authors:** Duarte Magano, Akshat Kumar, Mrti Klis, Andris Locns, Adam Glos, Sagar Pratapsi, Gonçalo Quinta, Maksims Dimitrijevs, Aleksander Rivos, Pedrame Bargassa, João Seixas, Andris Ambainis, Yasser Omar

- **Posted on arXiv:** 23 April 2021

- **Published in Physical Review D 105 (2022) 076012:** 01 April 2022

3.4 Quantum Annealing

3.4.1 Anomaly Detection

3.4.1.1 A Quantum Algorithm for Model-Independent Searches for New Physics [13]

- **Authors:** Konstantin T. Matchev, Prasanth Shyamsundar, Jordan Smolinsky

- **Posted on arXiv:** 04 March 2020

- **Published in LHEP:** 09 April 2023

3.4.2 Beyond the Standard Model

3.4.2.1 Completely quantum neural networks [20]

- **Authors:** Steve Abel, Juan C. Criado, Michael Spannowsky

- **Posted on arXiv:** 23 February 2022

- **Published in Phys.Rev.A:** 01 August 2022

3.4.2.2 Quantum algorithm for the classification of supersymmetric top quark events [21]

- **Authors:** Pedrame Bargassa, Timothèe Cabos, Samuele Cavinato, Artur Cordeiro Oudot Choi, Timothèe Hessel
- **Posted on arXiv:** 31 May 2021
- **Published in Phys. Rev. D 104 (2021) 096004:** 01 November 2021

3.4.2.3 A Quantum Algorithm for Model-Independent Searches for New Physics [13]

- **Authors:** Konstantin T. Matchev, Prasanth Shyamsundar, Jordan Smolinsky
- **Posted on arXiv:** 04 March 2020
- **Published in LHEP:** 09 April 2023

3.4.3 Cosmology

3.4.3.1 Restricted Boltzmann Machines for galaxy morphology classification with a quantum annealer [23]

- **Authors:** João Caldeira, Joshua Job, Steven H. Adachi, Brian Nord, Gabriel N. Perdue
- **Posted on arXiv:** 14 November 2019

3.4.4 Jet Algorithms and Jet Tagging

3.4.4.1 Degeneracy engineering for classical and quantum annealing: A case study of sparse linear regression in collider physics [37]

- **Authors:** Eric R. Anschuetz, Lena Funcke, Patrick T. Komiske, Serhii Kryhin, Jesse Thaler
- **Posted on arXiv:** 20 May 2022
- **Published in Phys. Rev. D 106, 056008 (2022):** 01 September 2022

3.4.4.2 Quantum annealing for jet clustering with thrust [38]

- **Authors:** Andrea Delgado, Jesse Thaler
- **Posted on arXiv:** 05 May 2022
- **Published in Phys.Rev.D:** 01 November 2022

3.4.4.3 Leveraging Quantum Annealer to identify an Event-topology at High Energy Colliders [39]

- **Authors:** Minho Kim, Pyungwon Ko, Jae-hyeon Park, Myeonghun Park
- **Posted on arXiv:** 15 November 2021

3.4.4.4 Adiabatic Quantum Algorithm for Multijet Clustering in High Energy Physics [40]

- **Authors:** Diogo Pires, Yasser Omar, João Seixas
- **Posted on arXiv:** 28 December 2020

3.4.4.5 Quantum Algorithms for Jet Clustering [36]

- **Authors:** Annie Y. Wei, Preksha Naik, Aram W. Harrow, Jesse Thaler
- **Posted on arXiv:** 23 August 2019
- **Published in Phys. Rev. D 101, 094015 (2020):** 15 May 2020
- **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
- **QIS 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.

3.4.5 Lattice Field Theories

3.4.5.1 SU(2) lattice gauge theory on a quantum annealer [47]

- **Authors:** Sarmed A Rahman, Randy Lewis, Emanuele Mendicelli, Sarah Powell
- **Posted on arXiv:** 15 March 2021
- **Published in Phys. Rev. D 104, 034501 (2021):** 01 August 2021

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

- **Authors:** Nga T.T. Nguyen, Garrett T. Kenyon, Boram Yoon
- **Posted on arXiv:** 14 November 2019
- **Published in Sci Rep 10, 10915 (2020):** 02 July 2020

3.4.6 Signal-Background Discrimination

3.4.6.1 Quantum adiabatic machine learning by zooming into a region of the energy surface [66]

- **Authors:** Alexander Zlokapa, Alex Mott, Joshua Job, Jean-Roch Vlimant, Daniel Lidar, Maria Spiropulu
- **Posted on arXiv:** 13 August 2019
- **Published in Phys. Rev. A 102, 062405 (2020):** 05 December 2020
- **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)
- **QIS 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.

3.4.6.2 Solving a Higgs optimization problem with quantum annealing for machine learning [67]

- **Authors:** Alex Mott, Joshua Job, Jean Roch Vlimant, Daniel Lidar, Maria Spiropulu
- **Published in Nature:** 18 October 2017
- **HEP Context:** 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).
- **QIS Methods:** The strong classifier is 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).

3.4.7 Track Reconstruction

3.4.7.1 Particle track classification using quantum associative memory [79]

- **Authors:** Gregory Quiroz, Lauren Ice, Andrea Delgado, Travis S. Humble
- **Posted on arXiv:** 23 November 2020
- **Published in Nucl.Instrum.Meth.A:** 11 September 2021

3.4.7.2 Charged particle tracking with quantum annealing-inspired optimization [80]

- **Authors:** Alexander Zlokapa, Abhishek Anand, Jean-Roch Vlimant, Javier M. Duarte, Joshua Job, Daniel Lidar, Maria Spiropulu
- **Posted on arXiv:** 12 August 2019
- **Published in Quantum Mach. Intell. 3, 27 (2021):** 02 November 2021

3.4.7.3 Track clustering with a quantum annealer for primary vertex reconstruction at hadron colliders [81]

- **Authors:** Souvik Das, Andrew J. Wildridge, Sachin B. Vaidya, Andreas Jung
- **Posted on arXiv:** 21 March 2019

3.4.7.4 A pattern recognition algorithm for quantum annealers [82]

- **Authors:** Frèdèric Bapst, Wahid Bhimji, Paolo Calafiura, Heather Gray, Wim Lavrijsen, Lucy Linder
- **Posted on arXiv:** 21 February 2019
- **Published in Comput.Softw.Big Sci.:** 09 December 2019

3.5 Quantum Autoencoders

3.5.1 Anomaly Detection

3.5.1.1 Anomaly detection in high-energy physics using a quantum autoencoder [14]

- **Authors:** Vishal S. Ngairangbam, Michael Spannowsky, Michihisa Takeuchi
- **Posted on arXiv:** 09 December 2021
- **Published in Phys. Rev. D 105, 095004, 2022:** 01 May 2022

3.6 Quantum Circuit Born Machines

3.6.1 Event Generation

3.6.1.1 Unsupervised quantum circuit learning in high energy physics [27]

- **Authors:** Andrea Delgado, Kathleen E. Hamilton
- **Posted on arXiv:** 07 March 2022
- **Published in Phys.Rev.D:** 01 November 2022

3.7 Quantum Neural Networks

3.7.1 Track Reconstruction

3.7.1.1 Hybrid Quantum Classical Graph Neural Networks for Particle Track Reconstruction [83]

- **Authors:** Cenk Tüysüz, Carla Rieger, Kristiane Novotny, Bilge Demirköz, Daniel Dobos, Karolos Potamianos, Sofia Vallecorsa, Jean-Roch Vlimant, Richard Forster
- **Posted on arXiv:** 26 September 2021
- **Published in Quantum Machine Intelligence:** 26 October 2021

3.8 Quantum Generative Adversarial Networks

3.8.1 Detector Simulation

3.8.1.1 Running the Dual-PQC GAN on noisy simulators and real quantum hardware [25]

- **Authors:** Su Yeon Chang, Edwin Agnew, Elías F. Combarro, Michele Grossi, Steven Herbert, Sofia Vallecorsa
- **Posted on arXiv:** 30 May 2022
- **Published in J.Phys.Conf.Ser.:** 2023

3.8.1.2 Dual-Parameterized Quantum Circuit GAN Model in High Energy Physics [26]

- **Authors:** Su Yeon Chang, Steven Herbert, Sofia Vallecorsa, Elías F. Combarro, Ross Duncan
- **Posted on arXiv:** 29 March 2021
- **Published in EPJ Web Conf.:** 2021

3.8.1.3 Quantum Generative Adversarial Networks in a Continuous-Variable Architecture to Simulate High Energy Physics Detectors [24]

- **Authors:** Su Yeon Chang, Sofia Vallecorsa, Elías F. Combarro, Federico Carminati
- **Posted on arXiv:** 26 January 2021

3.8.2 Event Generation

3.8.2.1 Generative Invertible Quantum Neural Networks [28]

- **Authors:** Armand Rousselot, Michael Spannowsky
- **Posted on arXiv:** 24 February 2023

3.8.2.2 Quantum integration of elementary particle processes [29]

- **Authors:** Gabriele Agliardi, Michele Grossi, Mathieu Pellen, Enrico Prati
- **Posted on arXiv:** 05 January 2022
- **Published in Phys.Lett.B:** 10 September 2022

3.8.2.3 Style-based quantum generative adversarial networks for Monte Carlo events [30]

- **Authors:** Carlos Bravo-Prieto, Julien Baglio, Marco Cè, Anthony Francis, Dorota M. Grabowska, Stefano Carrazza
- **Posted on arXiv:** 13 October 2021
- **Published in Quantum 6, 777 (2022):** 17 August 2022

3.9 Quantum Inspired Algorithms

3.9.1 Jet Algorithms and Jet Tagging

3.9.1.1 Quantum-inspired event reconstruction with Tensor Networks: Matrix Product States [41]

- **Authors:** Jack Y. Araz, Michael Spannowsky
- **Posted on arXiv:** 15 June 2021
- **Published in JHEP 08 (2021) 112:** 23 August 2021

3.9.1.2 Quantum-inspired machine learning on high-energy physics data [42]

- **Authors:** Timo Felser, Marco Trenti, Lorenzo Sestini, Alessio Gianelle, Davide Zuliani, Donatella Lucchesi, Simone Montangero
- **Posted on arXiv:** 28 April 2020
- **Published in npj Quantum Inf.:** 15 July 2021

3.10 Quantum Information Theory

3.10.1 Quantum Field Theories

3.10.1.1 Minimal entanglement and emergent symmetries in low-energy QCD [58]

- **Authors:** Qiaofeng Liu, Ian Low, Thomas Mehen
- **Posted on arXiv:** 21 October 2022
- **Published in Phys.Rev.C:** 14 February 2023

3.10.1.2 Symmetry from entanglement suppression [59]

- **Authors:** Ian Low, Thomas Mehen
- **Posted on arXiv:** 21 April 2021
- **Published in Phys.Rev.D:** 01 October 2021

3.10.2 Top Quarks

3.10.2.1 Quantum discord and steering in top quarks at the LHC [75]

- **Authors:** Yoav Afik, Juan Ramón Muñoz de Nova
- **Posted on arXiv:** 08 September 2022

3.10.2.2 Quantum information with top quarks in QCD [76]

- **Authors:** Yoav Afik, Juan Ramón Muñoz de Nova
- **Posted on arXiv:** 10 March 2022
- **Published in Quantum:** 29 September 2022

3.10.2.3 Entanglement and quantum tomography with top quarks at the LHC [77]

- **Authors:** Yoav Afik, Juan Ramón Muñoz de Nova
- **Posted on arXiv:** 04 March 2020
- **Published in Eur. Phys. J. Plus (2021) 136:907:** 03 September 2021

3.11 Quantum Support Vector Machines

3.11.1 Anomaly Detection

3.11.1.1 Quantum anomaly detection in the latent space of proton collision events at the LHC [15]

- **Authors:** Kinga Anna Woźniak, Vasilis Belis, Ema Puljak, Panagiotis Barkoutsos, Günther Dissertori, Michele Grossi, Maurizio Pierini, Florentin Reiter, Ivano Tavernelli, Sofia Vallecorsa

- **Posted on arXiv:** 25 January 2023

- **HEP Context:** Anomaly detection, where the following BSM processes are considered anomalies: (1) narrow Randall-Sundrum gravitons decaying to two W-bosons (Narrow $G \to WW$); (2) broad Randall-Sundrum graviton decaying to two W-bosons (Broad $G \to WW$); (3) scalar bosons A decaying to a Higgs and a Z boson ($A \to HZ$)

- **QIS Methods:** (1) Used a convolutional autoencoder model to map events into a latent representation of reduced dimensionality; (2) A Quantum Support Vector Machine (QSVM), the Quantum K-means (QK-means) algorithm, and the Quantum K-medians algorithm, are trained to find anomalous events in the latent representation, as well as their respective classical counterparts

- **Results and Conclusions:** With a training sample of size 600 and a fixed latent dimensionality $l = 8$, all classical and quantum ML methods performed worst on the broad Graviton and best with the narrow Graviton, which is expected since the broad Graviton is the most similar to SM processes, making it harder to identify, while the narrow Graviton is the least similar to SM processes, making it easier to identify. The unsupervised kernel machine outperforms both clustering algorithms and is the only model where the quantum classifier outperforms the classical counterpart. If entanglement is not present in the quantum feature map, the performance of the QSVM is worse or matches the performance of the CSVM. This paper demonstrates a consistent performance advantage of quantum models over classical models for an anomaly detection task, where a combination of an autoencoder with quantum anomaly detection models proved to be a viable strategy for data-driven searches for new physics.

3.11.1.2 Unravelling physics beyond the standard model with classical and quantum anomaly detection [16]

- **Authors:** Julian Schuhmacher, Laura Boggia, Vasilis Belis, Ema Puljak, Michele Grossi, Maurizio Pierini, Sofia Vallecorsa, Francesco Tacchino, Panagiotis Barkoutsos, Ivano Tavernelli

- **Posted on arXiv:** 25 January 2023

- **HEP Context:** Anomaly detection, where the background is Standard Model (SM) events, and the anomaly is either the Higgs boson or the Randall-Sundrum Graviton decaying to two Z bosons, where each of the Z bosons decay to a lepton pair

- **QIS Methods:** Applied Classical and Quantum Support Vector Classifiers (CSVCs and QSVCs respectively) trained to identify the artificial anomalies to distinguish between SM and BSM events. A dataset of artificial events that do not rely on a specific BSM theory is generated by using SM events and varying the different features by dataset scrambling, which is done by replacing a feature with a new value chosen according to a Gaussian distribution and a scrambling factor

- **Results and Conclusions:** An SVC trained to identify artificial anomalies was able to identify BSM events with high accuracy. In identifying artificial anomalies, the CSVC outperforms the QSVC, however, the difference in performance between the QSVC and the CSVC shrinks for increasing number of features and increasing scrambling strength. In identifying Higgs and Graviton events, the QSVC performs better than the CSVC with a low scrambling factor. When the scrambling factor increases, the performance gap shrinks when detecting Graviton events, and the CSVC outperforms the QSVC when detecting the Higgs. The paper concludes that while there is no advantage of using a quantum classifier, the limitations in performance could be due to using classical features that describe quantum HEP processes.

3.11.2 Beyond the Standard Model

3.11.2.1 Unravelling physics beyond the standard model with classical and quantum anomaly detection [16]

- **Authors:** Julian Schuhmacher, Laura Boggia, Vasilis Belis, Ema Puljak, Michele Grossi, Maurizio Pierini, Sofia Vallecorsa, Francesco Tacchino, Panagiotis Barkoutsos, Ivano Tavernelli

- **Posted on arXiv:** 25 January 2023

- **HEP Context:** Anomaly detection, where the background is Standard Model (SM) events, and the anomaly is either the Higgs boson or the Randall-Sundrum Graviton decaying to two Z bosons, where each of the Z bosons decay to a lepton pair

- **QIS Methods:** Applied Classical and Quantum Support Vector Classifiers (CSVCs and QSVCs respectively) trained to identify the artificial anomalies to distinguish between SM and BSM events. A dataset of artificial events that do not rely on a specific BSM theory is generated by using SM events and varying the different features by dataset scrambling, which is done by replacing a feature with a new value chosen according to a Gaussian distribution and a scrambling factor

- **Results and Conclusions:** An SVC trained to identify artificial anomalies was able to identify BSM events with high accuracy. In identifying artificial anomalies, the CSVC outperforms the QSVC, however, the difference in performance between the QSVC and the CSVC shrinks for increasing number of features and increasing scrambling strength. In identifying Higgs and Graviton events, the QSVC performs better than the CSVC with a low scrambling factor. When the scrambling factor increases, the performance gap shrinks when detecting Graviton events, and the CSVC outperforms the QSVC when detecting the Higgs. The paper concludes that while there is no advantage of using a quantum classifier, the limitations in performance could be due to using classical features that describe quantum HEP processes.

3.11.3 Signal-Background Discrimination

3.11.3.1 Application of Quantum Machine Learning in a Higgs Physics Study at the CEPC [68]

- **Authors:** Abdualazem Fadol, Qiyu Sha, Yaquan Fang, Zhan Li, Sitian Qian, Yuyang Xiao, Yu Zhang, Chen Zhou
- **Posted on arXiv:** 26 September 2022

3.11.3.2 Application of quantum machine learning using the quantum kernel algorithm on high energy physics analysis at the LHC [69]

- **Authors:** Sau Lan Wu, Shaojun Sun, Wen Guan, Chen Zhou, Jay Chan, Chi Lung Cheng, Tuan Pham, Yan Qian, Alex Zeng Wang, Rui Zhang, Miron Livny, Jennifer Glick, Panagiotis Kl. Barkoutsos, Stefan Woerner, Ivano Tavernelli, Federico Carminati, Alberto Di Meglio, Andy C.Y. Li, Joseph Lykken, Panagiotis Spentzouris, Samuel Yen-Chi Chen, Shinjae Yoo, Tzu-Chieh Wei
- **Posted on arXiv:** 11 April 2021
- **Published in Phys. Rev. Research 3, 033221 (2021):** 08 September 2021
- **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
- **QIS Methods:** Quantum 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.

3.11.3.3 Quantum Support Vector Machines for Continuum Suppression in B Meson Decays [70]

- **Authors:** Jamie Heredge, Charles Hill, Lloyd Hollenberg, Martin Sevior
- **Posted on arXiv:** 22 March 2021
- **Published in Comput.Softw.Big Sci.:** 30 November 2021

3.12 Quantum Sensors

3.12.1 Beyond the Standard Model

3.12.1.1 Searching for Dark Matter with a Superconducting Qubit [22]

- **Authors:** Akash V. Dixit, Srivatsan Chakram, Kevin He, Ankur Agrawal, Ravi K. Naik, David I. Schuster, Aaron Chou
- **Posted on arXiv:** 28 August 2020
- **Published in Phys. Rev. Lett. 126, 141302 (2021):** 09 April 2021

3.13 Quantum Simulations

3.13.1 Event Generation

3.13.1.1 Towards a quantum computing algorithm for helicity amplitudes and parton showers [31]

- **Authors:** Khadeejah Bepari, Sarah Malik, Michael Spannowsky, Simon Williams
- **Posted on arXiv:** 13 October 2020
- **Published in Phys. Rev. D 103, 076020 (2021):** 27 April 2021

3.13.1.2 Quantum Algorithm for High Energy Physics Simulations [32]

- **Authors:** Christian W. Bauer, Wibe A. de Jong, Benjamin Nachman, Davide Provasoli
- **Posted on arXiv:** 05 April 2019
- **Published in Phys. Rev. Lett. 126, 062001 (2021):** 11 February 2021

3.13.2 Lattice Field Theories

3.13.2.1 Efficient representation for simulating U(1) gauge theories on digital quantum computers at all values of the coupling [49]

- **Authors:** Christian W. Bauer, Dorota M. Grabowska
- **Posted on arXiv:** 15 November 2021
- **Published in Phys.Rev.D:** 01 February 2023

3.13.2.2 Lattice renormalization of quantum simulations [50]

- **Authors:** Marcela Carena, Henry Lamm, Ying-Ying Li, Wanqiang Liu
- **Posted on arXiv:** 02 July 2021
- **Published in Phys.Rev.D:** 01 November 2021

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

- **Authors:** Yasar Y. Atas, Jinglei Zhang, Randy Lewis, Amin Jahanpour, Jan F. Haase, Christine A. Muschik
- **Posted on arXiv:** 17 February 2021
- **Published in Nature Communications 2021:** 11 November 2021

3.13.2.4 Role of boundary conditions in quantum computations of scattering observables [52]

- **Authors:** Raúl A. Briceño, Juan V. Guerrero, Maxwell T. Hansen, Alexandru M. Sturzu
- **Posted on arXiv:** 01 July 2020
- **Published in Phys. Rev. D 103, 014506 (2021):** 07 January 2021

3.13.2.5 Simulating lattice gauge theories on a quantum computer [53]

- **Authors:** Tim Byrnes, Yoshihisa Yamamoto
- **Posted on arXiv:** October 2005
- **Published in Phys.Rev.A:** 2006

3.13.3 Neutrinos

3.13.3.1 Neutrino Oscillations in a Quantum Processor [54]

- **Authors:** C.A. Argüelles, B.J. P. Jones
- **Posted on arXiv:** 23 April 2019
- **Published in Phys. Rev. Research 1, 033176 (2019):** 13 December 2019

3.13.4 Quantum Field Theories

3.13.4.1 Simulating Collider Physics on Quantum Computers Using Effective Field Theories [60]

- **Authors:** Christian W. Bauer, Marat Freytsis, Benjamin Nachman
- **Posted on arXiv:** 09 February 2021
- **Published in Phys.Rev.Lett.:** 18 November 2021

3.13.4.2 Quantum simulation of quantum field theory in the light-front formulation [61]

- **Authors:** Michael Kreshchuk, William M. Kirby, Gary Goldstein, Hugo Beauchemin, Peter J. Love
- **Posted on arXiv:** 10 February 2020
- **Published in Phys. Rev. A 105, 032418 (2022):** 08 March 2022

3.13.4.3 General Methods for Digital Quantum Simulation of Gauge Theories [62]

- **Authors:** Henry Lamm, Scott Lawrence, Yukari Yamauchi
- **Posted on arXiv:** 19 March 2019
- **Published in Phys. Rev. D 100, 034518 (2019):** 29 August 2019

3.13.4.4 Scalar Quantum Field Theories as a Benchmark for Near-Term Quantum Computers [63]

- **Authors:** Kubra Yeter-Aydeniz, Eugene F. Dumitrescu, Alex J. McCaskey, Ryan S. Bennink, Raphael C. Pooser, George Siopsis
- **Posted on arXiv:** 29 November 2018
- **Published in Phys. Rev. A 99, 032306 (2019):** 04 March 2019

3.13.4.5 Quantum Algorithms for Fermionic Quantum Field Theories [64]

- **Authors:** Stephen P. Jordan, Keith S. M. Lee, John Preskill
- **Posted on arXiv:** 28 April 2014

3.13.4.6 Quantum Computation of Scattering in Scalar Quantum Field Theories [65]

- **Authors:** Stephen P. Jordan, Keith S.M. Lee, John Preskill
- **Posted on arXiv:** December 2011

3.14 Quantum Unsupervised Clustering Algorithms

3.14.1 Anomaly Detection

3.14.1.1 Quantum anomaly detection in the latent space of proton collision events at the LHC [15]

- **Authors:** Kinga Anna Woźniak, Vasilis Belis, Ema Puljak, Panagiotis Barkoutsos, Günther Dissertori, Michele Grossi, Maurizio Pierini, Florentin Reiter, Ivano Tavernelli, Sofia Vallecorsa
- **Posted on arXiv:** 25 January 2023
- **HEP Context:** Anomaly detection, where the following BSM processes are considered anomalies: (1) narrow Randall-Sundrum gravitons decaying to two W-bosons (Narrow $G \to WW$); (2) broad Randall-Sundrum graviton decaying to two W-bosons (Broad $G \to WW$); (3) scalar bosons A decaying to a Higgs and a Z boson ($A \to HZ$)
- **QIS Methods:** (1) Used a convolutional autoencoder model to map events into a latent representation of reduced dimensionality; (2) A Quantum Support Vector Machine (QSVM), the Quantum K-means (QK-means) algorithm, and the Quantum K-medians algorithm, are trained to find anomalous events in the latent representation, as well as their respective classical counterparts
- **Results and Conclusions:** With a training sample of size 600 and a fixed latent dimensionality $l = 8$, all classical and quantum ML methods performed worst on the broad Graviton and best with the narrow Graviton, which is expected since the broad Graviton is the most similar to SM processes, making it harder to identify, while the narrow Graviton is the least similar to SM processes, making it easier to identify. The unsupervised kernel machine outperforms both clustering algorithms and is the only model where the quantum classifier outperforms the classical counterpart. If entanglement is not present in the quantum feature map, the performance of the QSVM is worse or matches the performance of the CSVM. This paper demonstrates a consistent performance advantage of quantum models over classical models for an anomaly detection task, where a combination of an autoencoder with quantum anomaly detection models proved to be a viable strategy for data-driven searches for new physics.

3.14.1.2 Unsupervised event classification with graphs on classical and photonic quantum computers [12]

- **Authors:** Andrew Blance, Michael Spannowsky
- **Posted on arXiv:** 05 March 2021
- **Published in J. High Energ. Phys. 2021, 170:** 31 August 2021

3.14.2 Jet Algorithms and Jet Tagging

3.14.2.1 Quantum clustering and jet reconstruction at the LHC [43]

- **Authors:** Jorge J. Martínez de Lejarza, Leandro Cieri, Germán Rodrigo
- **Posted on arXiv:** 13 April 2022
- **Published in Physical Review D 106, 036021 (2022):** 01 August 2022

3.14.2.2 A Digital Quantum Algorithm for Jet Clustering in High-Energy Physics [44]

- **Authors:** Diogo Pires, Pedrame Bargassa, João Seixas, Yasser Omar
- **Posted on arXiv:** 11 January 2021

3.15 Quantum Walks

3.15.1 Event Generation

3.15.1.1 Collider events on a quantum computer [33]

- **Authors:** Gösta Gustafson, Stefan Prestel, Michael Spannowsky, Simon Williams
- **Posted on arXiv:** 21 July 2022
- **Published in JHEP:** 07 November 2022

3.15.1.2 Quantum walk approach to simulating parton showers [34]

- **Authors:** Khadeejah Bepari, Sarah Malik, Michael Spannowsky, Simon Williams
- **Posted on arXiv:** 28 September 2021
- **Published in Phys. Rev. D 106 (2022) 056002:** 01 September 2022

3.16 Tensor Networks

3.16.1 Jet Algorithms and Jet Tagging

3.16.1.1 Classical versus quantum: Comparing tensor-network-based quantum circuits on Large Hadron Collider data [45]

- **Authors:** Jack Y. Araz, Michael Spannowsky
- **Posted on arXiv:** 21 February 2022
- **Published in Phys. Rev. A 106 (Dec, 2022) 062423:** 19 December 2022

3.16.1.2 Quantum-inspired event reconstruction with Tensor Networks: Matrix Product States [41]

- **Authors:** Jack Y. Araz, Michael Spannowsky
- **Posted on arXiv:** 15 June 2021
- **Published in JHEP 08 (2021) 112:** 23 August 2021

3.17 Variational Quantum Circuits

3.17.1 Anomaly Detection

3.17.1.1 Quantum anomaly detection for collider physics [17]

- **Authors:** Sulaiman Alvi, Christian W. Bauer, Benjamin Nachman
- **Posted on arXiv:** 16 June 2022
- **Published in JHEP:** 22 February 2023
- **HEP Context:** Anomaly detection in the four-lepton final state. A weakly/semi-supervised search where a classifier is trained to distinguish data from background-only simulation.
- **QIS Methods:** Two implementations of parameterized quantum circuits where the rotation angles are optimized using classical methods: Variational Quantum Circuits (VQC) and Quantum Circuit Learning (QCL)
- **Results and Conclusions:** A common theme from analyzing the performance of Quantum Machine Learning (QML) in High Energy Physics (HEP) is QML seems to outperform Classical Machine Learning (CML) with small training datasets. However, there are almost no problems in HEP with small number of events in training. This paper considers a realistic example, the four lepton final state, where the training set is limited by low statistics. After comparing VQC and QCL to CML algorithms, this paper states that there is no evidence that QML provides any advantage to CML in collider physics, and QML appears to be systematically worse.

3.17.1.2 Anomaly detection in high-energy physics using a quantum autoencoder [14]

- **Authors:** Vishal S. Ngairangbam, Michael Spannowsky, Michihisa Takeuchi
- **Posted on arXiv:** 09 December 2021
- **Published in Phys. Rev. D 105, 095004, 2022:** 01 May 2022

3.17.2 Event Generation

3.17.2.1 Partonic collinear structure by quantum computing [35]

- **Authors:** Tianyin Li, Xingyu Guo, Wai Kin Lai, Xiaohui Liu, Enke Wang, Hongxi Xing, Dan-Bo Zhang, Shi-Liang Zhu
- **Posted on arXiv:** 07 June 2021
- **Published in Phys.Rev.D:** 01 June 2022

3.17.3 Jet Algorithms and Jet Tagging

3.17.3.1 Quantum Machine Learning for b-jet charge identification [46]

- **Authors:** Alessio Gianelle, Patrick Koppenburg, Donatella Lucchesi, Davide Nicotra, Eduardo Rodrigues, Lorenzo Sestini, Jacco de Vries, Davide Zuliani
- **Posted on arXiv:** 28 February 2022
- **Published in JHEP:** 01 August 2022

3.17.4 Neutrinos

3.17.4.1 Hybrid Quantum-Classical Graph Convolutional Network [55]

- **Authors:** Samuel Yen-Chi Chen, Tzu-Chieh Wei, Chao Zhang, Haiwang Yu, Shinjae Yoo
- **Posted on arXiv:** 15 January 2021

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

- **Authors:** Samuel Yen-Chi Chen, Tzu-Chieh Wei, Chao Zhang, Haiwang Yu, Shinjae Yoo
- **Posted on arXiv:** 22 December 2020
- **Published in Phys.Rev.Res.:** 28 March 2022

3.17.5 Signal-Background Discrimination

3.17.5.1 Higgs analysis with quantum classifiers [71]

- **Authors:** Vasileios Belis, Samuel González-Castillo, Christina Reissel, Sofia Vallecorsa, Elías F. Combarro, Günther Dissertori, Florentin Reiter
- **Posted on arXiv:** 15 April 2021
- **Published in EPJ Web Conf.:** 2021

3.17.5.2 Quantum Support Vector Machines for Continuum Suppression in B Meson Decays [70]

- **Authors:** Jamie Heredge, Charles Hill, Lloyd Hollenberg, Martin Sevior
- **Posted on arXiv:** 22 March 2021
- **Published in Comput.Softw.Big Sci.:** 30 November 2021

3.17.5.3 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 [72]

- **Authors:** Sau Lan Wu, Jay Chan, Wen Guan, Shaojun Sun, Alex Wang, Chen Zhou, Miron Livny, Federico Carminati, Alberto Di Meglio, Andy C.Y. Li, Joseph Lykken, Panagiotis Spentzouris, Samuel Yen-Chi Chen, Shinjae Yoo, Tzu-Chieh Wei
- **Posted on arXiv:** 21 December 2020
- **Published in J.Phys.G:** 26 October 2021
- **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
- **QIS 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.

3.17.5.4 Quantum Machine Learning for Particle Physics using a Variational Quantum Classifier [73]

- **Authors:** Andrew Blance, Michael Spannowsky
- **Posted on arXiv:** 14 October 2020
- **Published in JHEP:** 2021

3.17.5.5 Event Classification with Quantum Machine Learning in High-Energy Physics [74]

- **Authors:** Koji Terashi, Michiru Kaneda, Tomoe Kishimoto, Masahiko Saito, Ryu Sawada, Junichi Tanaka
- **Posted on arXiv:** 23 February 2020
- **Published in Comput. Softw. Big Sci. 5, 2 (2021):** 03 January 2021
- **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.
- **QIS 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.

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