# A Living Review of Quantum Information Science in High Energy Physics Organized by HEP Topics - LIST Version

ABSTRACT: Inspired by "A Living Review of Machine Learning for Particle Physics"[1], the goal of this document is to provide a nearly comprehensive list of citations for those developing and applying quantum information approaches to experimental, phenomenological, or theoretical analyses. Applications of quantum information science to high energy physics is a relatively new field of research. As a living document, it will be updated as often as possible with the relevant literature with the latest developments. Suggestions are most welcome.

[1]See https://github.com/iml-wg/HEPML-LivingReview.

The purpose of this note is to collect references for quantum information science as applied to particle and nuclear physics. The papers listed are in no particular order. In order to be as useful as possible, this document will continually change. Please check back[2] regularly. You can simply download the .bib file to get all of the latest references. Suggestions are most welcome.

### 0.1 Reviews

- Quantum Machine Learning in High Energy Physics [1]

### 0.2 Whitepapers

- Quantum Computing for Data Analysis in High-Energy Physics [2]
- Quantum Simulation for High Energy Physics [3]
- Snowmass White Paper: Quantum Computing Systems and Software for High-energy Physics Research [4]
- Snowmass white paper: Quantum information in quantum field theory and quantum gravity [5]
- New Horizons: Scalar and Vector Ultralight Dark Matter [6]
- Quantum Networks for High Energy Physics [7]

## 1 Jet Algorithms and Jet Tagging

### 1.1 Quantum Annealing

- Quantum Algorithms for Jet Clustering [8]
- Quantum Annealing for Jet Clustering with Thrust [9]
- Adiabatic Quantum Algorithm for Multijet Clustering in High Energy Physics [10]

### 1.2 Variational Quantum Circuits

- Quantum Machine Learning for $b$-jet identification [11]

### 1.3 Algorithms Based on Amplitude Amplification

- Quantum Algorithms for Jet Clustering [8]

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

### 1.4 Quantum-Inspired Algorithms

- Quantum-inspired event reconstruction with Tensor Networks: Matrix Product States [12]
- Quantum-inspired machine learning on high-energy physics data [13]

### 1.5 Tensor Networks

- Quantum-inspired event reconstruction with Tensor Networks: Matrix Product States [12]
- Classical versus Quantum: comparing Tensor Network-based Quantum Circuits on LHC data [14]

### 1.6 Uncategorized by QIS - TEMPORARY

- A Digital Quantum Algorithm for Jet Clustering in High-Energy Physics [15]

## 2 Track Reconstruction

### 2.1 Quantum Annealing

- Charged particle tracking with quantum annealing-inspired optimization [16]
- A pattern recognition algorithm for quantum annealers [17]
- Track clustering with a quantum annealer for primary vertex reconstruction at hadron colliders [18]
- Particle track classification using quantum associative memory [19]

### 2.2 Uncategorized by QIS - TEMPORARY

- Quantum speedup for track reconstruction in particle accelerators [20]
- Hybrid Quantum Classical Graph Neural Networks for Particle Track Reconstruction [21]

## 3 Event Generation

### 3.1 Quantum Walks

- Collider Events on a Quantum Computer [22]
- A quantum walk approach to simulating parton showers [23]

### 3.2 Quantum Generative Adversarial Networks

- Style-based quantum generative adversarial networks for Monte Carlo events [24]
- Quantum integration of elementary particle processes [25]

### 3.3 Uncategorized by QIS - TEMPORARY

- Towards a quantum computing algorithm for helicity amplitudes and parton showers [26]

## 4 Detector Simulation

## 5 Signal-Background Discrimination

### 5.1 Quantum Annealing

- Solving a Higgs optimization problem with quantum annealing for machine learning [27]
- Quantum adiabatic machine learning with zooming [28]

### 5.2 Variational Quantum Circuits

- 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 [29]
- Event Classification with Quantum Machine Learning in High-Energy Physics [30]
- Quantum Machine Learning for Particle Physics using a Variational Quantum Classifier [31]
- Quantum Support Vector Machines for Continuum Suppression in B Meson Decays [32]
- Higgs analysis with quantum classifiers [33]

### 5.3 Quantum Support Vector Machines

- Application of quantum machine learning using the quantum kernel algorithm on high energy physics analysis at the LHC [34]
- Quantum Support Vector Machines for Continuum Suppression in B Meson Decays [32]

# 6 Anomaly Detection

## 6.1 Variational Quantum Circuits

- Quantum Anomaly Detection for Collider Physics [35]
- Anomaly detection in high-energy physics using a quantum autoencoder [36]

## 6.2 Continuous Variable Quantum Computing

- Unsupervised event classification with graphs on classical and photonic quantum computers [37]

## 6.3 Quantum Autoencoders

- Anomaly detection in high-energy physics using a quantum autoencoder [36]

## 6.4 Uncategorized by QIS - TEMPORARY

- A quantum algorithm for model independent searches for new physics [38]

# 7 Beyond the Standard Model

## 7.1 Quantum Annealing

- Completely Quantum Neural Networks [39]
- Quantum algorithm for the classification of supersymmetric top quark events [40]

## 7.2 Algorithms Based on Amplitude Amplification

- Implementation and analysis of quantum computing application to Higgs boson reconstruction at the large Hadron Collider [41]
- Application of a Quantum Search Algorithm to High- Energy Physics Data at the Large Hadron Collider [42]

## 7.3 Quantum Sensors

- Searching for Dark Matter with a Superconducting Qubit [43]

## 7.4 Uncategorized by QIS - TEMPORARY

- A quantum algorithm for model independent searches for new physics [38]

# 8 Quantum Field Theories

## 8.1 Quantum Simulations

- Scalar Quantum Field Theories as a Benchmark for Near-Term Quantum Computers [44]

## 8.2 Uncategorized by QIS - TEMPORARY

- Quantum Algorithms for Fermionic Quantum Field Theories [45]

# 9 Lattice Field Theories

## 9.1 Quantum Annealing

- A regression algorithm for accelerated lattice QCD that exploits sparse inference on the D-Wave quantum annealer [46]

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

## 9.2 Uncategorized by QIS - TEMPORARY

- Lattice renormalization of quantum simulations [48]

- Quantum Computation of Scattering in Scalar Quantum Field Theories [49]

- Efficient Representation for Simulating U(1) Gauge Theories on Digital Quantum Computers at All Values of the Coupling [50]

- Role of boundary conditions in quantum computations of scattering observables [51]

- Simulating lattice gauge theories on a quantum computer [52]

# 10 Neutrinos

## 10.1 Variational Quantum Circuits

- Quantum convolutional neural networks for high energy physics data analysis [53]

- Hybrid Quantum-Classical Graph Convolutional Network [54]

## 11 Cosmology

### 11.1 Quantum Annealing

- Restricted Boltzmann Machines for galaxy morphology classification with a quantum annealer [55]

## 12 Uncategorized by HEP - TEMPORARY

### 12.1 Quantum Annealing

- Leveraging Quantum Annealer to identify an Event-topology at High Energy Colliders [56]

- Degeneracy Engineering for Classical and Quantum Annealing: A Case Study of Sparse Linear Regression in Collider Physics [57]

### 12.2 Variational Quantum Circuits

- Unsupervised Quantum Circuit Learning in High Energy Physics [58]

### 12.3 Continuous Variable Quantum Computing

- Quantum Generative Adversarial Networks in a Continuous-Variable Architecture to Simulate High Energy Physics Detectors [59]

### 12.4 Quantum Generative Adversarial Networks

- Dual-Parameterized Quantum Circuit GAN Model in High Energy Physics [60]

- Running the Dual-PQC GAN on noisy simulators and real quantum hardware [61]

- Quantum Generative Adversarial Networks in a Continuous-Variable Architecture to Simulate High Energy Physics Detectors [59]

### 12.5 Quantum Circuit Born Machines

- Unsupervised Quantum Circuit Learning in High Energy Physics [58]

### 12.6 Quantum Simulations

- Simulating Collider Physics on Quantum Computers Using Effective Field Theories [62]

- SU(2) hadrons on a quantum computer via a variational approach [63]

- Quantum Algorithm for High Energy Physics Simulations [64]

### 12.7 Uncategorized by QIS - TEMPORARY

- Quantum algorithm for Feynman loop integrals [65]
- Partonic collinear structure by quantum computing [66]

## References


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

[2] A. Delgado et al., *Quantum Computing for Data Analysis in High-Energy Physics*, in *2022 Snowmass Summer Study*, 3, 2022. 2203.08805. 1

[3] C. W. Bauer et al., *Quantum Simulation for High Energy Physics*, 2204.03381. 1

[4] T. S. Humble et al., *Snowmass White Paper: Quantum Computing Systems and Software for High-energy Physics Research*, in *2022 Snowmass Summer Study*, 3, 2022. 2203.07091. 1

[5] T. Faulkner, T. Hartman, M. Headrick, M. Rangamani and B. Swingle, *Snowmass white paper: Quantum information in quantum field theory and quantum gravity*, in *2022 Snowmass Summer Study*, 3, 2022. 2203.07117. 1

[6] D. Antypas et al., *New Horizons: Scalar and Vector Ultralight Dark Matter*, 2203.14915. 1

[7] A. Derevianko et al., *Quantum Networks for High Energy Physics*, in *2022 Snowmass Summer Study*, 3, 2022. 2203.16979. 1

[8] A. Y. Wei, P. Naik, A. W. Harrow and J. Thaler, *Quantum Algorithms for Jet Clustering*, *Phys. Rev. D* **101** (2020) 094015, [1908.08949]. 1

[9] A. Delgado and J. Thaler, *Quantum Annealing for Jet Clustering with Thrust*, 2205.02814. 1

[10] D. Pires, Y. Omar and J. a. Seixas, *Adiabatic Quantum Algorithm for Multijet Clustering in High Energy Physics*, 2012.14514. 1

[11] A. Gianelle, P. Koppenburg, D. Lucchesi, D. Nicotra, E. Rodrigues, L. Sestini et al., *Quantum Machine Learning for b-jet identification*, 2202.13943. 1

[12] J. Y. Araz and M. Spannowsky, *Quantum-inspired event reconstruction with Tensor Networks: Matrix Product States*, *JHEP* **08** (2021) 112, [2106.08334]. 2

[13] T. Felser, M. Trenti, L. Sestini, A. Gianelle, D. Zuliani, D. Lucchesi et al., *Quantum-inspired machine learning on high-energy physics data*, *npj Quantum Inf.* **7** (2021) 111, [2004.13747]. 2

[14] J. Y. Araz and M. Spannowsky, *Classical versus Quantum: comparing Tensor Network-based Quantum Circuits on LHC data*, 2202.10471. 2

[15] D. Pires, P. Bargassa, J. a. Seixas and Y. Omar, *A Digital Quantum Algorithm for Jet Clustering in High-Energy Physics*, 2101.05618. 2

[16] A. Zlokapa, A. Anand, J.-R. Vlimant, J. M. Duarte, J. Job, D. Lidar et al., *Charged particle tracking with quantum annealing-inspired optimization*, *Quantum Machine Intelligence* **3** (2021) 27, [1908.04475]. 2

[17] F. Bapst, W. Bhimji, P. Calafiura, H. Gray, W. Lavrijsen, L. Linder et al., *A pattern recognition algorithm for quantum annealers*, *Comput. Softw. Big Sci.* **4** (2020) 1, [1902.08324]. 2

[18] S. Das, A. J. Wildridge, S. B. Vaidya and A. Jung, *Track clustering with a quantum annealer for primary vertex reconstruction at hadron colliders*, 1903.08879. 2

[19] G. Quiroz, L. Ice, A. Delgado and T. S. Humble, *Particle track classification using quantum associative memory*, *Nucl. Instrum. Meth. A* **1010** (2021) 165557, [2011.11848]. 2

[20] D. Magano et al., *Quantum speedup for track reconstruction in particle accelerators*, *Phys. Rev. D* **105** (2022) 076012, [2104.11583]. 2

[21] C. Tüysüz, C. Rieger, K. Novotny, B. Demirköz, D. Dobos, K. Potamianos et al., *Hybrid Quantum Classical Graph Neural Networks for Particle Track Reconstruction*, *Quantum Machine Intelligence* **3** (2021) 29, [2109.12636]. 2

[22] G. Gustafson, S. Prestel, M. Spannowsky and S. Williams, *Collider Events on a Quantum Computer*, 2207.10694. 2

[23] S. Williams, S. Malik, M. Spannowsky and K. Bepari, *A quantum walk approach to simulating parton showers*, 2109.13975. 2

[24] C. Bravo-Prieto, J. Baglio, M. Cè, A. Francis, D. M. Grabowska and S. Carrazza, *Style-based quantum generative adversarial networks for Monte Carlo events*, 2110.06933. 3

[25] G. Agliardi, M. Grossi, M. Pellen and E. Prati, *Quantum integration of elementary particle processes*, *Phys. Lett. B* **832** (2022) 137228, [2201.01547]. 3

[26] K. Bepari, S. Malik, M. Spannowsky and S. Williams, *Towards a quantum computing algorithm for helicity amplitudes and parton showers*, *Phys. Rev. D* **103** (2021) 076020, [2010.00046]. 3

[27] A. Mott, J. Job, J. R. Vlimant, D. Lidar and M. Spiropulu, *Solving a Higgs optimization problem with quantum annealing for machine learning*, *Nature* **550** (2017) 375–379. 3

[28] A. Zlokapa, A. Mott, J. Job, J.-R. Vlimant, D. Lidar and M. Spiropulu, *Quantum adiabatic machine learning with zooming*, 1908.04480. 3

[29] S. L. Wu et al., *Application of quantum machine learning using the quantum variational classifier method to high energy physics analysis at the LHC on IBM quantum computer simulator and hardware with 10 qubits*, *J. Phys. G* **48** (2021) 125003, [2012.11560]. 3

[30] K. Terashi, M. Kaneda, T. Kishimoto, M. Saito, R. Sawada and J. Tanaka, *Event Classification with Quantum Machine Learning in High-Energy Physics*, *Comput. Softw. Big Sci.* **5** (2021) 2, [2002.09935]. 3

[31] A. Blance and M. Spannowsky, *Quantum Machine Learning for Particle Physics using a Variational Quantum Classifier*, 2010.07335. 3

[32] J. Heredge, C. Hill, L. Hollenberg and M. Sevior, *Quantum Support Vector Machines for Continuum Suppression in B Meson Decays*, *Comput. Softw. Big Sci.* **5** (2021) 27, [2103.12257]. 3

[33] V. Belis, S. González-Castillo, C. Reissel, S. Vallecorsa, E. F. Combarro, G. Dissertori et al., *Higgs analysis with quantum classifiers*, *EPJ Web Conf.* **251** (2021) 03070, [2104.07692]. 3

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

[35] S. Alvi, C. Bauer and B. Nachman, *Quantum Anomaly Detection for Collider Physics*, 2206.08391. 4

[36] V. S. Ngairangbam, M. Spannowsky and M. Takeuchi, *Anomaly detection in high-energy physics using a quantum autoencoder*, *Phys. Rev. D* **105** (2022) 095004, [2112.04958]. 4

[37] A. Blance and M. Spannowsky, *Unsupervised event classification with graphs on classical and photonic quantum computers*, *JHEP* **21** (2020) 170, [2103.03897]. 4

[38] K. T. Matchev, P. Shyamsundar and J. Smolinsky, *A quantum algorithm for model independent searches for new physics*, 2003.02181. 4

[39] S. Abel, J. C. Criado and M. Spannowsky, *Completely Quantum Neural Networks*, 2202.11727. 4

[40] P. Bargassa, T. Cabos, S. Cavinato, A. Cordeiro Oudot Choi and T. Hessel, *Quantum algorithm for the classification of supersymmetric top quark events*, *Phys. Rev. D* **104** (2021) 096004, [2106.00051]. 4

[41] A. Alexiades Armenakas and O. K. Baker, *Implementation and analysis of quantum computing application to Higgs boson reconstruction at the large Hadron Collider*, *Sci. Rep.* **11** (2021) 22850. 4

[42] A. E. Armenakas and O. K. Baker, *Application of a Quantum Search Algorithm to High- Energy Physics Data at the Large Hadron Collider*, 2010.00649. 4

[43] A. V. Dixit, S. Chakram, K. He, A. Agrawal, R. K. Naik, D. I. Schuster et al., *Searching for Dark Matter with a Superconducting Qubit*, *Phys. Rev. Lett.* **126** (2021) 141302, [2008.12231]. 4

[44] K. Yeter-Aydeniz, E. F. Dumitrescu, A. J. McCaskey, R. S. Bennink, R. C. Pooser and G. Siopsis, *Scalar Quantum Field Theories as a Benchmark for Near-Term Quantum Computers*, *Phys. Rev. A* **99** (2019) 032306, [1811.12332]. 5

[45] S. P. Jordan, K. S. M. Lee and J. Preskill, *Quantum Algorithms for Fermionic Quantum Field Theories*, 1404.7115. 5

[46] N. T. T. Nguyen, G. T. Kenyon and B. Yoon, *A regression algorithm for accelerated lattice QCD that exploits sparse inference on the D-Wave quantum annealer*, *Sci. Rep.* **10** (2020) 10915, [1911.06267]. 5

[47] S. A Rahman, R. Lewis, E. Mendicelli and S. Powell, *SU(2) lattice gauge theory on a quantum annealer*, *Phys. Rev. D* **104** (2021) 034501, [2103.08661]. 5

[48] M. Carena, H. Lamm, Y.-Y. Li and W. Liu, *Lattice renormalization of quantum simulations*, *Phys. Rev. D* **104** (2021) 094519, [2107.01166]. 5

[49] S. P. Jordan, K. S. M. Lee and J. Preskill, *Quantum Computation of Scattering in Scalar Quantum Field Theories*, *Quant. Inf. Comput.* **14** (2014) 1014–1080, [1112.4833]. 5

[50] C. W. Bauer and D. M. Grabowska, *Efficient Representation for Simulating U(1) Gauge Theories on Digital Quantum Computers at All Values of the Coupling*, 2111.08015. 5

[51] R. A. Briceño, J. V. Guerrero, M. T. Hansen and A. M. Sturzu, *Role of boundary conditions in quantum computations of scattering observables*, *Phys. Rev. D* **103** (2021) 014506, [2007.01155]. 5

[52] T. Byrnes and Y. Yamamoto, *Simulating lattice gauge theories on a quantum computer*, *Phys. Rev. A* **73** (2006) 022328, [quant-ph/0510027]. 5

[53] S. Y.-C. Chen, T.-C. Wei, C. Zhang, H. Yu and S. Yoo, *Quantum convolutional neural networks for high energy physics data analysis*, *Phys. Rev. Res.* **4** (2022) 013231, [2012.12177]. 5

[54] S. Y.-C. Chen, T.-C. Wei, C. Zhang, H. Yu and S. Yoo, *Hybrid Quantum-Classical Graph Convolutional Network*, 2101.06189. 5

[55] J. a. Caldeira, J. Job, S. H. Adachi, B. Nord and G. N. Perdue, *Restricted Boltzmann Machines for galaxy morphology classification with a quantum annealer*, 1911.06259. 6

[56] M. Kim, P. Ko, J.-h. Park and M. Park, *Leveraging Quantum Annealer to identify an Event-topology at High Energy Colliders*, 2111.07806. 6

[57] E. R. Anschuetz, L. Funcke, P. T. Komiske, S. Kryhin and J. Thaler, *Degeneracy Engineering for Classical and Quantum Annealing: A Case Study of Sparse Linear Regression in Collider Physics*, 2205.10375. 6

[58] A. Delgado and K. E. Hamilton, *Unsupervised Quantum Circuit Learning in High Energy Physics*, 2203.03578. 6

[59] S. Y. Chang, S. Vallecorsa, E. F. Combarro and F. Carminati, *Quantum Generative Adversarial Networks in a Continuous-Variable Architecture to Simulate High Energy Physics Detectors*, 2101.11132. 6

[60] S. Y. Chang, S. Herbert, S. Vallecorsa, E. F. Combarro and R. Duncan, *Dual-Parameterized Quantum Circuit GAN Model in High Energy Physics*, *EPJ Web Conf.* **251** (2021) 03050, [2103.15470]. 6

[61] S. Y. Chang, E. Agnew, E. F. Combarro, M. Grossi, S. Herbert and S. Vallecorsa, *Running the Dual-PQC GAN on noisy simulators and real quantum hardware*, in *20th International Workshop on Advanced Computing and Analysis Techniques in Physics Research: AI Decoded - Towards Sustainable, Diverse, Performant and Effective Scientific Computing*, 5, 2022. 2205.15003. 6

[62] C. W. Bauer, M. Freytsis and B. Nachman, *Simulating Collider Physics on Quantum Computers Using Effective Field Theories*, *Phys. Rev. Lett.* **127** (2021) 212001, [2102.05044]. 6

[63] Y. Y. Atas, J. Zhang, R. Lewis, A. Jahanpour, J. F. Haase and C. A. Muschik, *SU(2) hadrons on a quantum computer via a variational approach*, *Nature Commun.* **12** (2021) 6499, [2102.08920]. 6

[64] C. W. Bauer, W. A. de Jong, B. Nachman and D. Provasoli, *Quantum Algorithm for High Energy Physics Simulations*, *Phys. Rev. Lett.* **126** (2021) 062001, [1904.03196]. 6

[65] S. Ramírez-Uribe, A. E. Rentería-Olivo, G. Rodrigo, G. F. R. Sborlini and L. Vale Silva, *Quantum algorithm for Feynman loop integrals*, *JHEP* **05** (2022) 100, [2105.08703]. 7

[66] QuNu collaboration, T. Li, X. Guo, W. K. Lai, X. Liu, E. Wang, H. Xing et al., *Partonic collinear structure by quantum computing*, *Phys. Rev. D* **105** (2022) L111502, [2106.03865]. 7