The BNL QuantISED Program

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Advances in modern quantum sensing and quantum computing are expected to provide excellent opportunities for high energy physics. We describe below BNL QuantISED program, which started in 2019 and has been renewed in 2021. The topics are listed below along with their BNL POCs.

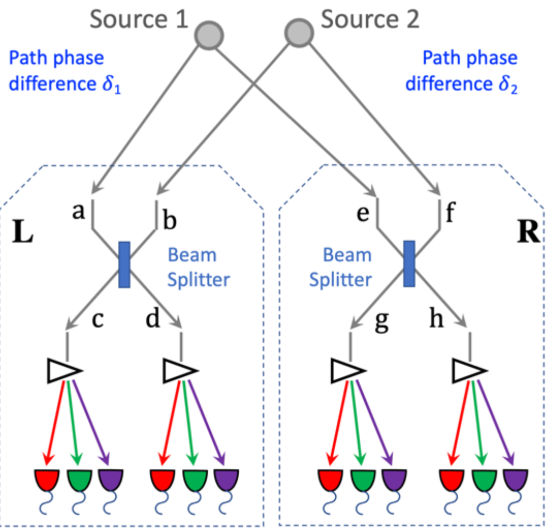
Quantum-assisted optical interferometers: *PI Andrei Nomerotski (BNL), co-PIs: Paul Stankus (BNL), Ning Bao (BNL)*

This QuantISED project is expected to provide major improvements in astrometric precision of optical telescopes. Photon phase difference in two locations is measured employing sources of entangled photons and teleportation techniques. This enables long baselines and improves astrometric precision by few orders of magnitude with major impact on several Cosmic Frontier research areas. The approach can be generalized from the entanglement of photon pairs to multipartite entanglement in multiple stations to explore different configurations and to guide future experimental developments. In addition to the capability to generate and distribute entangled photons over long distances, practical schemes under investigation require photon detectors with excellent temporal and spectral resolutions. Our goal is to develop a small-scale on-sky experiment with HEP scope by 2024. This project leverages BNL efforts in quantum networking research and would be one of its first science applications. The project web site with first results and publications can be accessed at https://www.quantastro.bnl.gov .

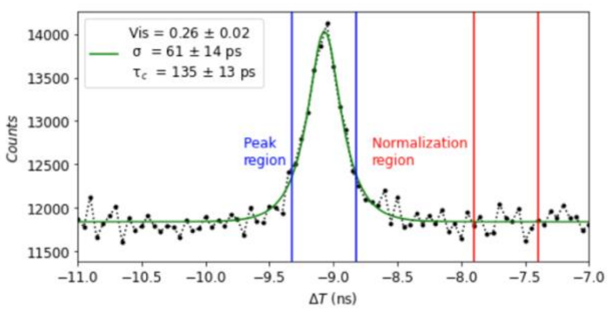
Quantum-accelerated artificial intelligence: *PI Shinjae Yoo (BNL), co-PIs Chao Zhang (BNL), Yen-Chi (Sam) Chen (BNL), Tzu-Chieh Wei (Stony Brook University), Sau Lan Wu (University of Wisconsin)*

This QuantISED project is investigating the advantages of using Quantum Machine Learning for data-intensive HEP applications, where we are developing new quantum-enhanced deep learning methods. The project is targeting the future long baseline neutrino oscillation experiment DUNE data and also the LHC data for the quantum-accelerated event classification and particles trajectories fitting. Early results, which employ the quantum convolutional neural network (QCNN), quantum graph convolutional neural network (QGCNN), and quantum long short-term memory (QLSTM), have shown a similar performance or quantum advantage in terms of convergence speed and accuracy for key tasks, in comparison to current solutions using classical computing methods. Specifically, we plan to apply hybrid quantum-classical approach to demonstrate quantum generative adversarial network and quantum autoencoder on both DUNE and LHC applications. To further improve our representation, we plan to investigate quantum tensor network and quantum metric learning. Our metaQuantum software framework for quantum machine learning significantly improved our productivities in simulation and real quantum computer experiment and we plan to improve further by enabling AutoML capabilities (automatic hyperparameter tuning and automated quantum architecture search).

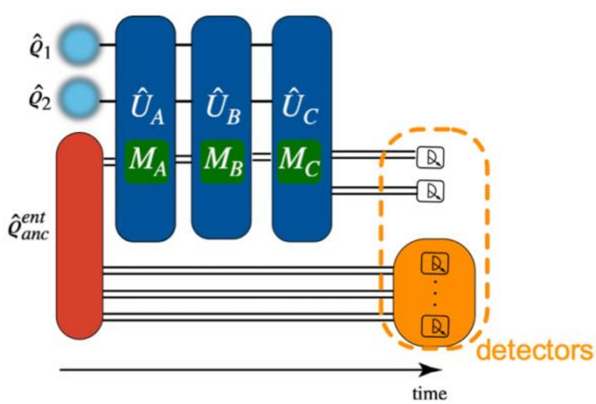
Supporting materials for **<u>Quantum-assisted optical interferometers</u>**



Basic arrangement of the novel interferometer is the following: the photon modes a and b at station L are brought to the inputs of a symmetric beam splitter, with output modes labelled c and d; and the same for input modes e and f split onto output modes g and h at station R. The four outputs are then each viewed by a fast, single-photon sensitive detector. If the two photons are close enough together in both time and frequency, then due to quantum mechanical interference the pattern of coincidences between measurements at "c" and "d" in L and "g" and "h" in R will be sensitive to the difference in phase differences $(\delta_1 - \delta_2)$; and this in turn will be sensitive to the opening angle between the two sources.



We started bench-top experiments of two-photon interferometry employing thermal 794 nm photons emitted by a narrow spectral line of argon vapor. The photons are registered with superconducting nanowire single-photon detectors and single-photon avalanche detectors. See example of the Henry Brown – Twiss peak fit with a Lorentzian function with decay time of 135 ps convoluted with experimental resolution of 61 ps.

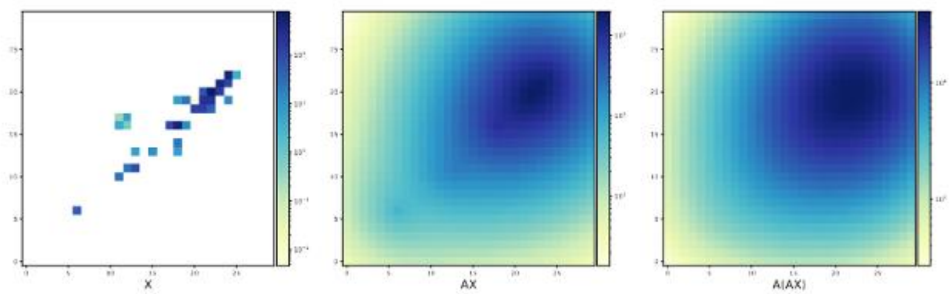


We are developing new theoretical schemes for the proposed interferometer which use multi-partite entanglement (ex W or GHZ states) distributed between multiple stations, and quantum protocols to process information in noisy environment for evaluation of experimental observables. The shown quantum circuit illustrates density operators ρ with multi-partite entanglement distributed over three stations (A, B, C) and states registered by single-photon detectors.

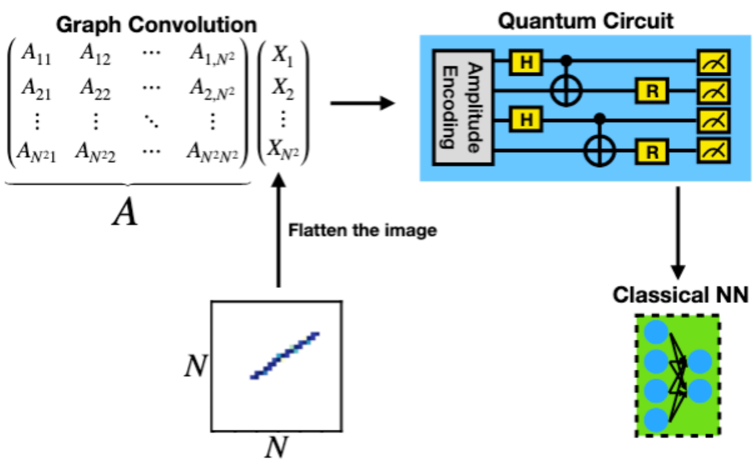
Publications:

1. P.Stankus et al, arxiv:2010.09100, in review.
2. A.Nomerotski et al, arxiv:2012.02812, SPIE Proceedings.
3. Y Zhang et al, Phys Rev A 101 (5), 053808 (2020).
4. P Svihra et al, Appl. Phys. Lett. 117, 044001 (2020).
5. A.Nomerotski et al, arxiv: 2107.09229, TIPP Proceedings.

Supporting materials for **Quantum-accelerated artificial intelligence**

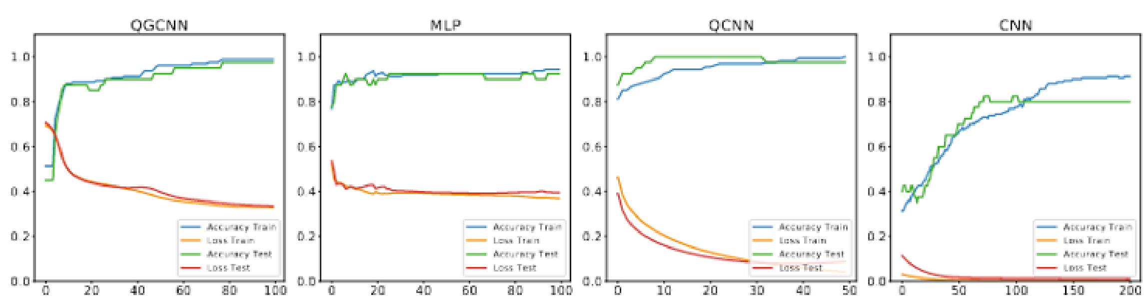


The original DUNE input data, **X**, is rather sparse, making it difficult for QML models to classify. The situation worsens when encoding the image with amplitude encoding (AE) as the vector normalization procedure causes significant information loss. The input X is multiplied by the adjacency matrix **A**. The results of AX and A^2X shows much more smooth results for better AE.



We developed hybrid quantum-classical graph convolution (shown left). The proposed hybrid quantum-classical graph CNN contains three major components: 1) graph convolution 2) VQC, and 3) classical post-processing.

We compared the performance between different architectures in the task of muon versus proton binary classification. QGCNN and QCNN demonstrates superior performance (higher accuracy and converge faster) than classical MLP and CNN models (shown below). QGCNN is much faster than GCNN on the quantum simulation.



Publications:

1. QCNN: Chen, S.Y.C.; Wei, T.C.; Zhang, C.; Yu, H.; Yoo, S. Quantum Convolutional Neural Networks for High Energy Physics Data Analysis. arXiv 2020, arXiv:2012.12177.
2. QGCNN: Chen, S.Y.C.; Wei, T.C.; Zhang, C.; Yu, H.; Yoo, S. Hybrid Quantum-Classical Graph Convolutional Network. arXiv 2021, arXiv:2101.06189
3. QLSTM: Chen, S.Y.C.; Yoo, S.; Fang, Y.L.L. Quantum Long Short-Term Memory. arXiv 2020, arXiv:2009.01783.