# Training a Quantum PointNet with Nesterov Accelerated Gradient Projection by Estimation

Ruoxi Shi, Hao Tang and Xian-Min Jin
Center for Integrated Quantum Information Technologies (IQIT)
Shanghai Jiao Tong University

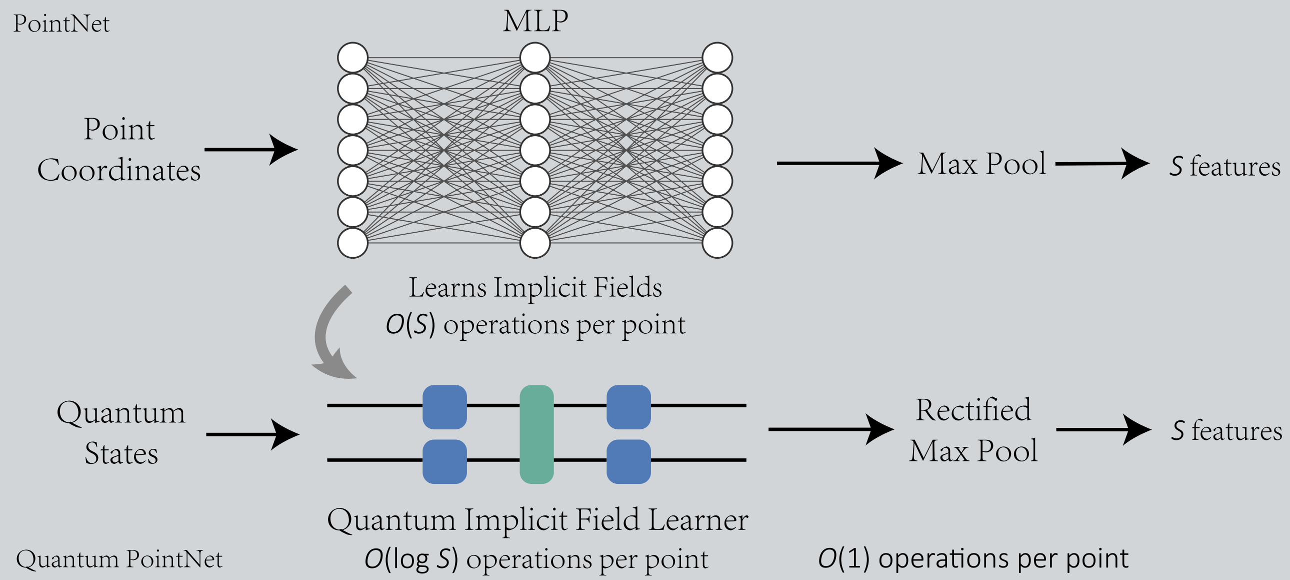
## Abstract

PointNet is a bedrock for deep learning methods on point clouds for 3D machine vision. However, the pointwise operations involved in PointNet is resource intensive, and the expressiveness of PointNet is limited by the size of its feature space. In this paper, we propose Quantum PointNet with a rectifed max pooling operation to achieve an exponential speedup performing the pointwise operations and meanwhile obtaining a quantum-enhanced feature space. We provide an implementation with quantum tensor networks and specify a circuit model that runs on near-term quantum computers. Meanwhile, we develop the NA-GEP (Nesterov Accelerated Gradient Estimation by Projection) optimization framework, together with a periodic batching scheme, to help train large-scale quantum networks more efficiently. We demonstrate that Quantum PointNet reaches competitive performance to its classical counterpart on a subset of the ModelNet40 dataset with 48x fewer operations required to process a point cloud. It is also shown that NA-GEP is robust under different kinds of noises. A mini Quantum PointNet is able to run on real quantum computers, achieving ~100% accuracy classifying three kinds of shapes with a small number of shots.

## From PointNet to Quantum PointNet

We interpret the pointwise operations in PointNet as generating implicit field values. In 3D machine vision, a field is an union of connected regions in the space, typically represented explicitly by meshes and point clouds. An implicit field is defined by a continuous function over the space, with different values inside and outside the field area. A set of disjoint implicit fields form a non-regular grid-like structure. In this sense, max pooling is invariant not only to permutations in the input point cloud, but also to the local density of points, which gives it an advantage to other symmetric operations such as averaging. Consequently, the element setting for PointNet is quite flexible, as long as the model keeps the capability of generating such fields and uses a max-out aggregation operation.

As the size of max pooling feature space is the main issue of the expressiveness of PointNet, we propose to use a quantum implicit field learner, which can provide an exponential speedup, since quantum circuits naturally have a exponentially growing feature space. Meanwhile, the generated feature space is enhanced with quantum features. A novel rectified max pooling operation together with a regularization on sparsity is applied to add more expressiveness and robustness to the architecture. A comparison between pointwise pipelines of PointNet and Quantum PointNet is shown in the figure below.




## The NA-GEP Optimization Framework

The starting point is a one-sided finite-difference estimation of the gradient, which is a direct consequence of projecting gradient onto a random vector. If we repeat the operation above on a set of random but orthogonalized vectors, we will get a more accurate estimation of the gradient. We introduceNesterov's Accelerated Gradient into the procedure. Under this setting, NAG is able to average over the past few steps of estimated gradients to reduce variance of estimation. Furthermore, we found that the Nesterov's momentum term is much better a starting direction for the projection process, and it combines effectively with NAG's lookahead property for a brake towards the direction of the momentum term. Meantime, it can contribute more in the descending rate since it is probably in a direction closer to the current gradient than a random vector. Empirical heuristics like adapting hyper-parameters on plateau and momentum clipping are also employed in the complete NA-GEP framework.

## Results

First, we trained a small scale 5-qubit Quantum PointNet that runs on a real quantum device at IBMQ Valencia. It is able to classify with high accuracy three types of shapes under a small number of (~20) shots, even under moderate noise of the quantum device. The implicit fields learned are visualized in the figure on the upper-middle.

We then trained a 8-qubit Quantum PointNet on a real-world classification problem, a subset of ModelNet dataset, ModelNet3, to further illustrate the capabilities of Quantum PointNet. We demonstrate that it is able to reach the same performance with its classical counterpart with substantially fewer operations (48x). Convergence of train and test accuracies during the training process is shown on the upper-right.

For the NA-GEP, we study its performance on a ReLU-activated classical neural network. We first compare the convergence rate under different hyper-parameter P's and with another zeroth-order optimization method SPSA (lower-left). Then we compare the performance of NA-GEP under typical Gaussian additive noise (Gauss. N.), and a stronger noise where a random value may be returned for an evaluation. It is shown that NA-GEP is robust under different types of noises (lower-middle). Convergence of the gradient projection procedure is shown in lower-right.