Boson Sampling as a Quantum Feature Map: Hybrid Classification and Fock-Space Separability Analysis

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Abstract: We present a hybrid quantum-classical pipeline for MNIST classification using photonic boson sampling embeddings developed within the Perceval Quest. A Kullback–Leibler divergence analysis reveals that Fock-space distributions intrinsically cluster by class without training the interferometer.

Photonic quantum computing offers low decoherence and native optical interfacing, making it a leading platform for near-term quantum devices [1]. Within this framework, boson sampling, a photon-native computational primitive, can serve as a quantum feature map [2]: classical data encoded into the programmable phases of a linear-optical interferometer produces output Fock-state distributions governed by matrix permanents, with no efficient classical analogue. Yet whether such photonic embeddings yield physically meaningful class structure has remained largely unexplored.

The Perceval Quest (Quandela & Scaleway, 2024–2025), an open benchmarking initiative, provided the first standardised framework for evaluating photonic quantum machine learning [3]: we present a hybrid quantum-classical pipeline developed by our team within this initiative, and published as part of the resulting multi-team scientific paper [3], together with a quantitative demonstration that boson sampling intrinsically clusters distinct classes in Fock space, a physics result independent of any downstream classifier.

We adopt MNIST digit classification as a controlled testbed, following the protocol shared across all participating teams: each 28×28 image is reduced to 126 principal components, matching the parameter count of a 12-mode programmable photonic interferometer.

The embedding is deterministic and non-trainable: phases are set directly by the input data, so any structure in the output reflects the physics of multi-photon interference alone. A shallow classical neural network trained for 50 epochs performs the final classification: simulations use the Perceval library [4] (SLOS backend).

Consistent with this separability, the boson sampling hybrid pipeline achieves 96.5% validation accuracy, versus 93.8% for a classical model on the same reduced features: results were validated on Quandela's Ascella QPU via Scaleway QaaS. All code is publicly available at https://github.com/Quandela/HybridAIQuantum-Challenge .

Building on this analysis, we propose Quantum Contrastive Divergence (QCD): training the interferometer by minimising the KL divergence between output distributions and class-specific Fock-space targets. The photonic parameter-shift rule, recently developed for linear-optical circuits [5], enables exact gradient computation for this optimisation.

Preliminary numerical experiments confirm monotonic convergence: we thus show that multi-photon interference in a programmable interferometer produces a physically structured feature map, not merely higher accuracy on a benchmark. The QCD framework extends our approach from fixed to learned photon-native quantum kernels, charting a route toward end-to-end trainable photonic classifiers. Future work targets hardware execution on Quandela's next-generation processors and scaling to larger interferometers and datasets.

References

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