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“Demonstration of quantum advantage in machine learning,” Diego Ristè et al. npj Quantum Inf. 3, 16 (2017). https://doi.org/10.1038/s41534-017-0017-3

Ristè et al.'s paper investigates the application of quantum computing in machine learning, specifically aiming to demonstrate the potential advantages of quantum techniques over classical methods. The problem discussed in the paper is a learning parity with noise (LPN) problem. The goal is to identify a hidden parity function that the paper defines as $\boldsymbol{k}$ which maps a set of bits onto 0 or 1. The learner aims to decipher the hidden bit string $\boldsymbol{k}$ by making repeated queries to an oracle circuit that computes a function f involving $\boldsymbol{k}$ but without direct knowledge or control over $\boldsymbol{k}$ itself. The paper claims that a quantum algorithm can exponentially reduce the required number of oracle queries and has a super-polynomial advantage in runtime. The quantum device uses one qubit for the result and four data qubits that are coupled to the result qubit.

The paper first looks at an example where $\boldsymbol{k}$ is composed of 2 bits. The goal of the output is to find $\boldsymbol{k}$ with an error probability of $p = 0.01$. The paper finds that the quantum approach (Q) is comparable or worse than the classical approach (C) for $\boldsymbol{k} = 00$, 01 or 10, but Q reduces the number of oracle queries by more than half of C when $\boldsymbol{k} = 11$. The paper next looks at an example with a more effective strategy for C involving Bayesian estimation to greatly reduce the average error probability for all $\boldsymbol{k}$ and a more effective strategy for Q involving replacing a majority vote approach on the homodyne voltages of the data qubits with a single observation involving the digitization of the averages of the homodyne voltages of the data qubits. The paper finds that as the bit-width of the oracle $\boldsymbol{k}$ increases, the advantage given by Q also increases. It is stated that when increasing from 2 to 3 bits, C requires almost a magnitude higher amount of queries for some target error and Q is marginally affected. When adding noise to the output qubit or all of the data qubits, the paper also finds that the superiority of Q increases. The paper states that as the bit-width of $\boldsymbol{k}$ increases, C grows exponentially and Q grows linearly in a highly noisy system.

The strengths of this paper are shown in multiple areas. The use of an actual quantum computer to back the claims of the hypothesis is much stronger than relying on theory alone. The paper covers two different methods of calculating the oracle $\boldsymbol{k}$ as well as analysis of the performance of one of them with and without noise. This helps to expand the problem into more cases to help solidify the advantage of Q. The paper also introduces a novel method of calculating quantum performance compared to an equivalent classical problem that uses the same hardware. This is useful for when quantum computers grow in size, the same approach can be applied to the more complex problems that arise. The documentation that is provided by the paper is also robust enough to be replicated which helps pave the way for potential expansion on the subject matter.

The weaknesses of this paper are mostly related to the scope. The quantum circuit used is limited by size, and although the paper allows for an expansion on the quantum circuit, a stronger paper would include that expanded circuit. The paper also does not give depth on the real-world applications of its findings. This may not be necessary in the analysis of the results of the paper, but the implementation of these findings into a system that can solve a real-world problem would increase the importance of the advantage that it has over current state of the art solutions to the problem. The real-world problems that are generally associated with learning parity with noise are mostly prevalent in the field of cyber security. If this problem had more variety in its use case, then the results from the paper would be stronger.

The scientific merit of the paper is shown in a variety of ways. Its primary merit is in its ability to show a scenario where quantum computing can outperform classical computing in a machine learning application. It may not be extraordinarily groundbreaking in the field of quantum machine learning, but it is an important step in its growth. There would be superior scientific merit in the case that the paper could display a significant quantum enhancement that is applicable to a wider variety of machine learning applications. The paper also considers realistic scenarios in which noise is added to the system which helps make the findings usable in real-world implementations even though the paper may not go into depth on these potential scenarios. The experimental results of the paper also give it more merit than just a theoretical analysis would. The paper also has merit because it shows originality by highlighting a problem that has not already been considered by other researchers.