Sublinear Quantum Algorithms for Training Linear and Kernel-based Classifiers

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Why Quantum Machine Learning?

- Quantum machine learning is becoming more and more relevant:
  - Theoretical physics has motivated many ML models (Ex. Boltzmann machine, Ising model, Langevin dynamics, etc.)
  - Classical ML techniques can be applied to quantum problems.
  - Quantum computers give speedup for training models.
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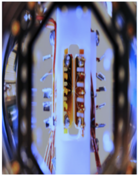
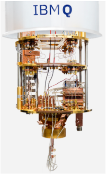
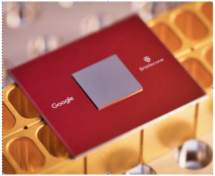
- Quantum computers are developing fast, having 50-100 qubits now:



Maryland & IonQ



IBM

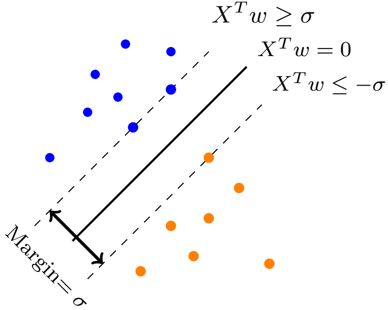


Google

Noisy, intermediate-scale quantum computers (NISQ); practical quantum computers to come in 5-10 years

Our Contribution

A promising quantum ML application: **classification**



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- *Composability:* Purely classical output, suitable for end-to-end machine learning applications.
- *Generality:* The classifier can be kernelized.

Main Results

Given n data points with dimension d, our quantum algorithms train classifiers for the following problems with complexity $\tilde{O}(\sqrt{n}+\sqrt{d})$:

- Linear classification: $X^\top w$
- Minimum enclosing ball: $\|w-X\|^2$
- ℓ_2-margin SVM: $(X^\top w)^2$
- Kernel-based classification: $\langle \Psi(X), w\rangle$, where $\Psi =$ polynomial kernel or Gaussian kernel.

The optimal classical algorithm runs in $\tilde{\Theta}(n+d)$ (Clarkson et al. '12).

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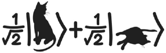
- **Standard quantum input:** *coherently* access the coordinates of data, like a Schrödinger's cat: 

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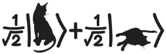
- **Standard quantum input:** *coherently* access the coordinates of data, like a Schrödinger's cat: 

- **Speed-up:** The classical $\tilde{\Theta}(n+d)$ optimal algorithm by Clarkson et al. uses a primal-dual approach:
  - Primal: $O(n)$ by multiplicative weight updates.
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  Quantum: quadratic speed-ups for both the primal and dual.

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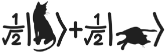
- **Standard quantum input:** *coherently* access the coordinates of data, like a Schrödinger's cat: 

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- **Optimality:** We prove quantum lower bounds $\Omega(\sqrt{n}+\sqrt{d})$, meaning that our quantum algorithms are optimal.

Thank you!

More info: #171 at poster session

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