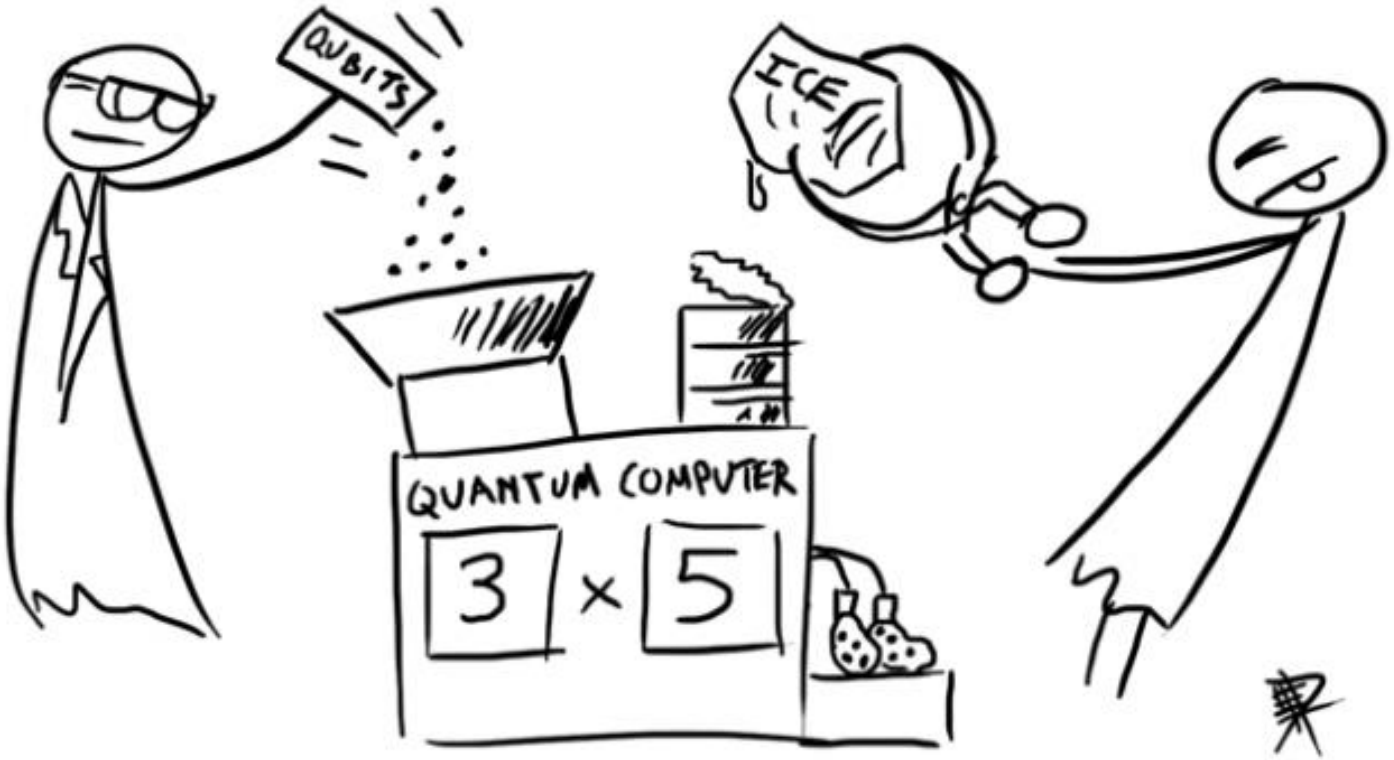
QUANTUM MACHINE LEARNING

QUANTUM SPEED UP FOR MACHINE LEARNING ALGORITHMS

GERALD JONES

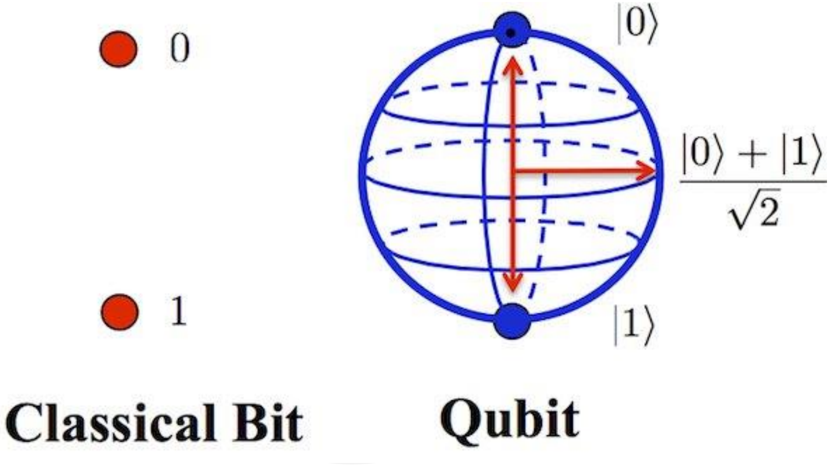
DECEMBER 2, 2019

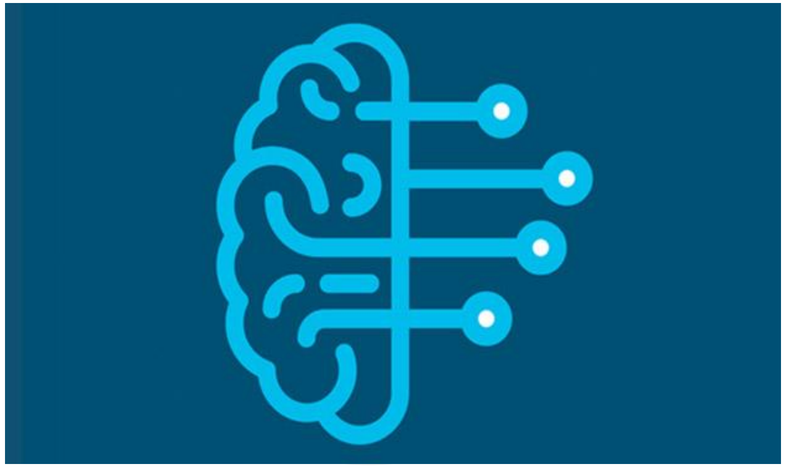


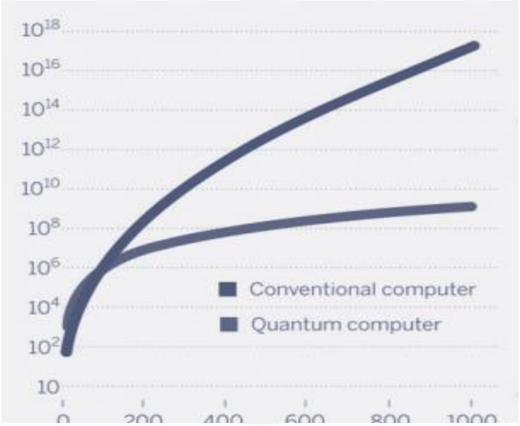
WHAT IS QUANTUM MACHINE LEARNING?

https://www.flickr.com/photos/philentropist/3116959232/sizes/o/

QUANTUM MACHINE LEARNING







QUANTUM BITS IN SUPERPOSITION
FAST LINEAR ALGEBRA

ML ALGORITHM, SUB ALGORITHM,
CLASSIFICATION TASK

PROFIT?/ QUANTUM SPEED UP

Quantum algorithms are developed to solve typical problems of machine learning using the efficiency of quantum computing

WAYS QUANTUM COMPUTING (QC) CAN HELP

- Machine Learning:
  - Data analysis to find patterns in the data (often using linear algebra)
    - Supervised, Reinforced desired outcome known
    - Unsupervised thought to be structure in the data but unknown
    - Learn how to transform inputs into correct outputs
- more data the better the model (often but not always)
  - With in limits and bound
- access to data has and is growing all the time
  - Sequential computing is time consuming on very large data sets
  - Space complexity also grows as data size grow

WAYS QUANTUM COMPUTING (QC) CAN HELP

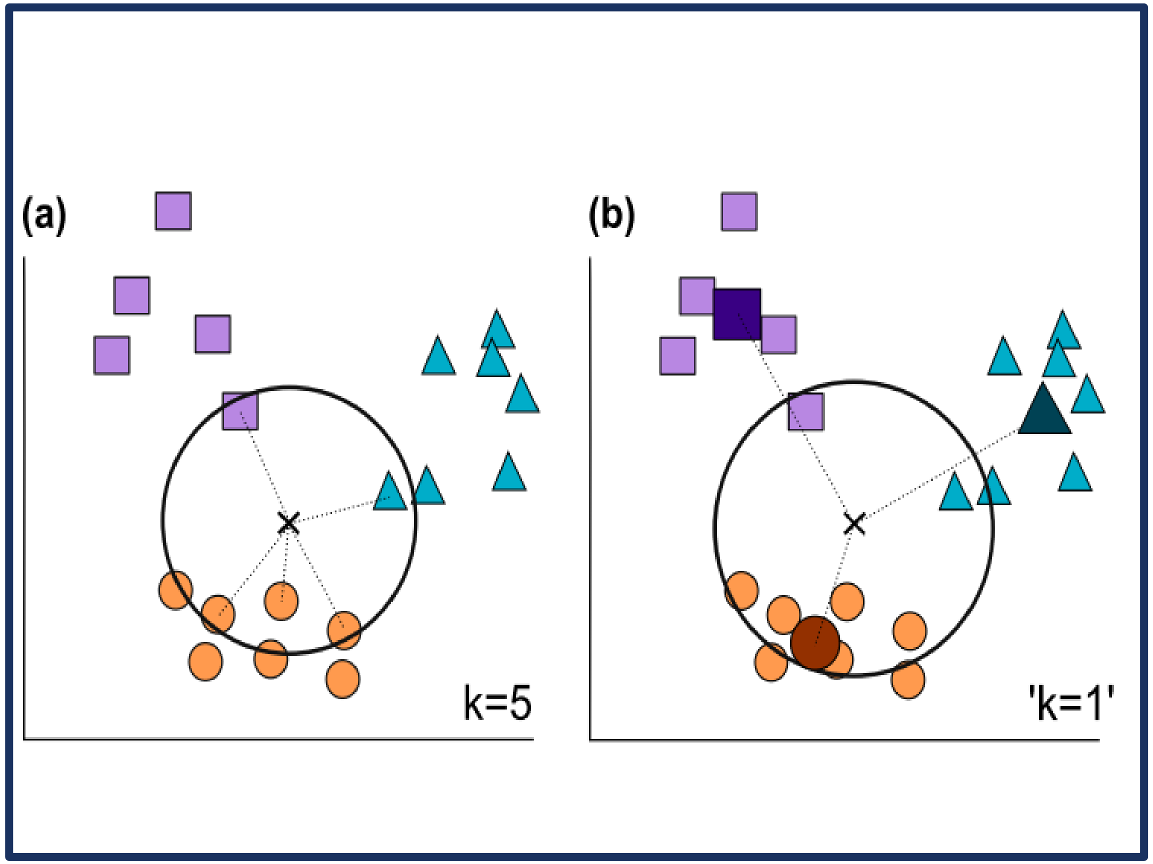
- QML can help with both
  - Fast linear algebra (quantum speed up)
    - quantum basic linear algebra subroutines (BLAS)—
    - Fourier transforms,
    - finding eigenvectors and eigenvalues,
    - solving linear equations
    - exhibit exponential quantum speedups over their best-known classical counterparts.

WAYS QUANTUM COMPUTING (QC) CAN HELP

- QML can help with both
  - use of a qubit's superposition of two quantum states in order to follow many different paths of computation at the same time (parallel computations)
  - High dimensionality with relatively small number of qubits through tensor products
  - Quantum machine learning can take time logarithmic in both the size of the training set and their dimensions
  - Classical algorithms for ML problems typically take polynomial time in the size of the training set and number of features (the dimension of the space).
    - exponential speed-up with quantum algorithms.
  - Next examples

K NEAREST NEIGHBORS (KNN)

KNN CLASSIFICATION



- Supervised
- Classification Based On measure of 'similarity'
- between a sample
  - and K nearest known samples (a)
  - K nearest centroids $^1/_{N_c} \sum_p \vec{v}^p$ (b)
- Neighbors based on Training(Known) set
- similarity some form of distance
  - Euclidean, city block, mahalanobis etc.
- Use quantum computation to perform one of the most time-consuming parts of the algorithm (distance calculation)
- O(ndk) for calculating distances for each new sample

MEASURES OF SIMILARITY

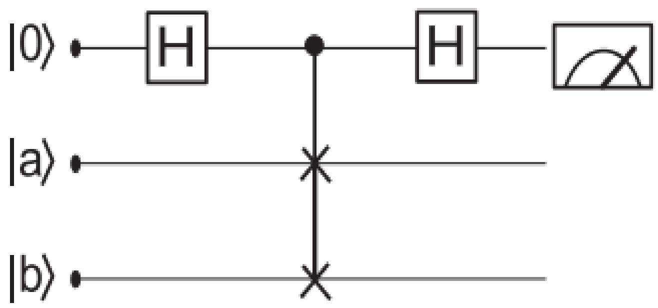
- use some form of linear calculation to measure "similarity" between samples
- use distance as a proxy for this similarity
- crafting QC algorithms that can measure "similarity" or distance similar and goals can be achieved

QUANTUM DISTANCE CALCULATION FOR KNN

- Aïmeur et al. [10] introduce the idea of overlap or fidelity of two quantum states $|a\rangle$ and $|b\rangle$
  - $|\langle a| b\rangle|$ as 'similarity measure'.
- fidelity can be obtained through quantum routine referred to as a swap test
- Given quantum state $|a, b, 0_{\text{anc}}\rangle$
  - containing the two wavefunctions a, b
  - an ancilla (control) register initially set to 0, a
- Hadamard transformation sets the ancilla into a superposition
  - $1/\sqrt{2}(|0\rangle + |1\rangle)$
- controlled swap gate on a and b swaps the two states based on the control (in superstition)
- Second Hadamard gate on the ancilla results in state

  - $|\psi_{SW}\rangle = \frac{1}{2}|0\rangle(|a, b\rangle + |b, a\rangle) + \frac{1}{2}|1\rangle(|a, b\rangle - |b, a\rangle)$

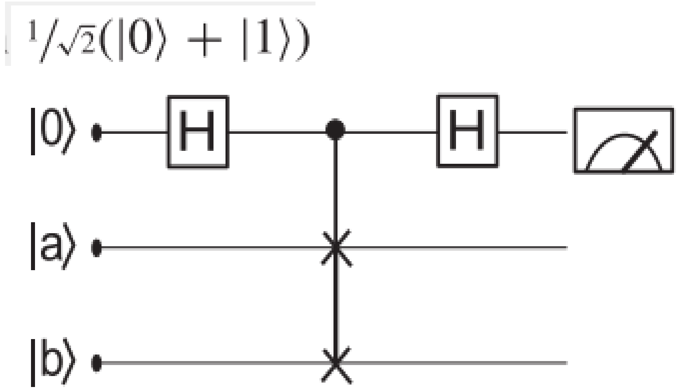
$1/\sqrt{2}(|0\rangle + |1\rangle)$



Quantum circuit representation of a swap test routine.

QUANTUM DISTANCE CALCULATION FOR KNN

- Probability of measuring ground state
  - $$P(|0_{\text{anc}}\rangle) = \frac{1}{2} + \frac{1}{2}\,|\langle a|\, b\rangle|^2$$
    $|a\rangle$ and $|b\rangle$
  - Prob = ½:
    - Two quantum states
      - Do not overlap
      - Are orthogonal
      - "very unsimilar"
  - Prob = 1 shows:
    - Have maximum overlap
    - Very "similar"



Quantum circuit representation of a swap test routine.

QUANTUM DISTANCE CALCULATION FOR KNN

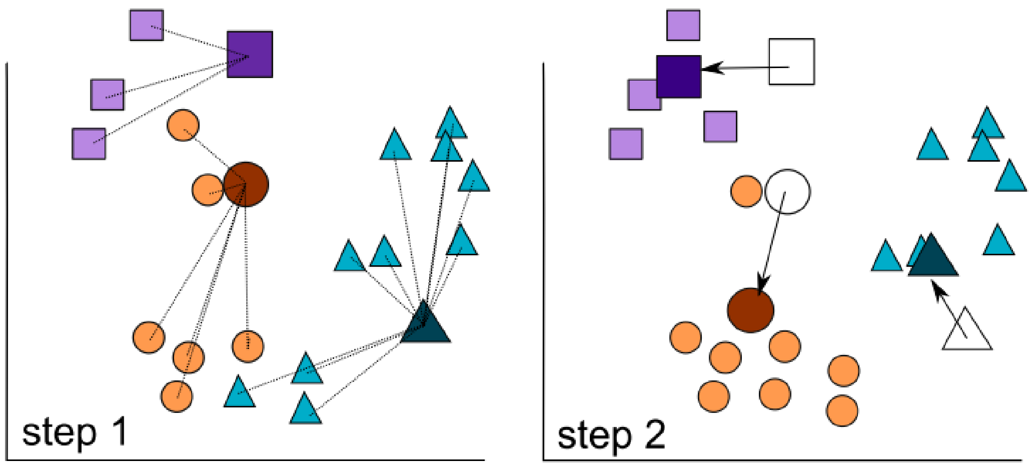
- Proposed way to retrieve distance between two real valued n-dimensional vectors a and b through quantum measurement [7]
  - Calculate inner product of:
    - Ancilla of state $|\psi\rangle = \frac{1}{\sqrt{2}}(|0, a\rangle + |1, b\rangle)$
    - State: $|\phi\rangle = \frac{1}{\sqrt{Z}}(|\vec{a}|\,|0\rangle - |\vec{b}|\,|1\rangle)$ (with $Z = |\vec{a}|^2 + |\vec{b}|^2$)
  - Evaluating $|\langle\phi|\,\psi\rangle|^2$ as part of a swap test.
    - Both states inexpensive to produce

QUANTUM DISTANCE CALCULATION FOR KNN

- The trick to making this works also comes from Lloyd and his colleges [7][9]
  - Propose to encode classical information into the norm of a quantum state:
    - $\langle x|\, x\rangle = |\vec{x}|^{-1}\vec{x}^2$
  - Leading to:
    - $|x\rangle = |\vec{x}|^{-1/2}\vec{x}$
- Using the above the identity below holds true[7][9]:
  - $|\vec{a} - \vec{b}|^2 = Z\,|\langle\phi|\, \psi\rangle|^2$
  - Thus the classical distance between two vectors can be retrieved through a simple swap test!!

K MEANS CLUSTERING

K MEANS CLUSTERING (UNSUPERVISED)



$$^{1}/_{N_c} \sum_p \vec{v}^p$$

- Unsupervised (structure unknown)
- Seeks to group given data int k groups or clusters
- Iterative process
  - Create k randomly initialized clusters
    - For each data point move into nearest cluster (mean)
    - Once all points are in nearest cluster means recalculated based on new points in the cluster
    - Repeat until no points change cluster
- Euclidean, city block, mahalanobis etc
- Use quantum computation to perform one of the most time-consuming parts of the algorithm (distance calculation)

MEASURES OF SIMILARITY

- Use linear calculation to measure "similarity"
  - Here between the centroids of the clusters and the data samples
- Again use distance as a proxy for this similarity
- Using similar idea to what we saw before the calculation of the distances to the centroids can be achieved with a swap test
- Using the input points as an input a and using the cluster centroids $1/N_c \sum_p \vec{v}^p$ as the b input
  - $\vec{a} \equiv \vec{x}$ and $\vec{b} \equiv {}_{N_c} \sum_p \vec{v}^p$
  - we can calculate:

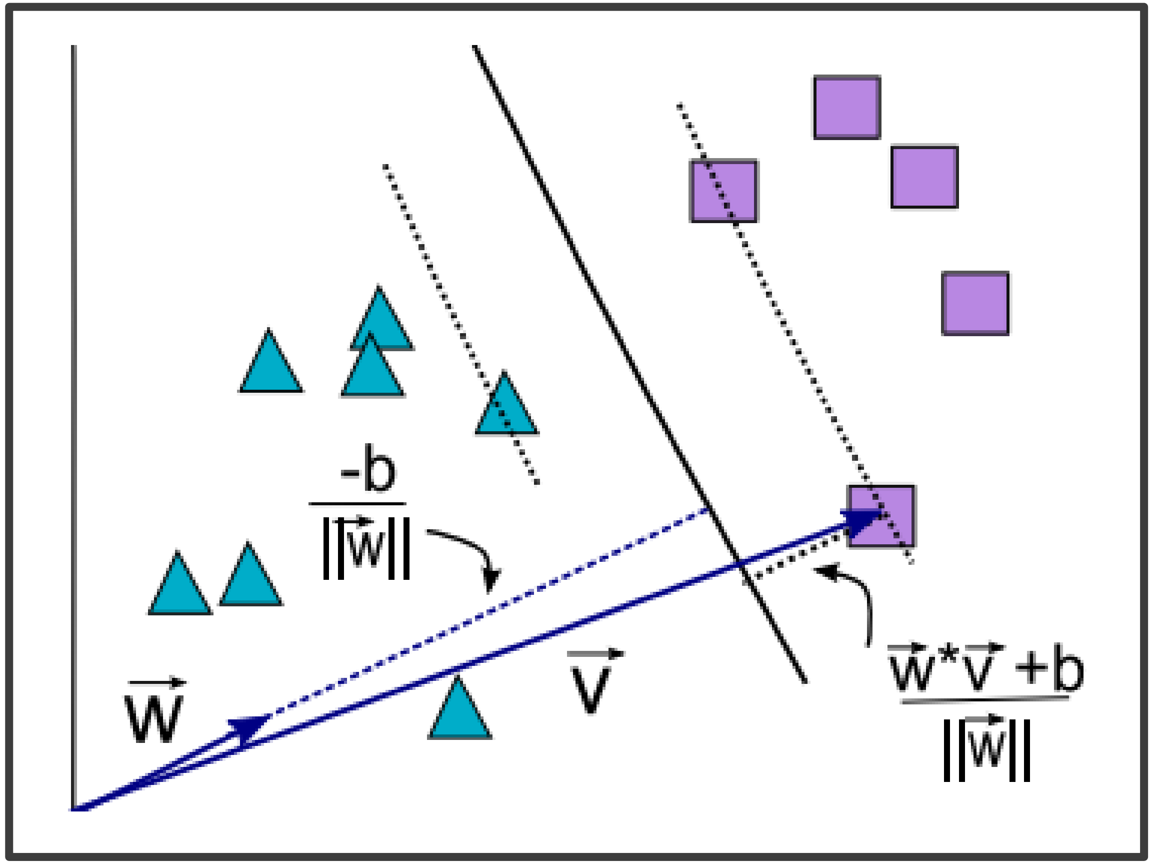
$$|\vec{x} - \frac{1}{N_c} \sum_p \vec{v}^p|^2 = Z\, |\langle\phi|\,\psi\rangle|^2$$

  - Again calculating the distance with just a swap test

QUANTUM SPEED UP IN ML OPERATIONS

- kNN O(ndk)
- k means O(nkid)
    - N number of data samples
    - K number of clusters to create
    - I Number of iterations to converge
    - D number of features

SVM



- Linear Discriminant based classifier
- Seeks to maximize generalization of classifier by creating boundary's
- The similarity is often some form of distance
  - Euclidean, city block, mahalanobis etc
- Use quantum computation to perform one of the most time-consuming parts of the algorithm (distance calculation)

$$K(\mathbf{x}, \mathbf{x}') = \exp\left(-\frac{\|\mathbf{x} - \mathbf{x}'\|^2}{2\sigma^2}\right)$$

THE FUTURE?

Current Progress and Research:

- QUANTUM NN
  - Quantum annealing
- QUANTUM DEEP LEARNING
- DIMENSION REDUCTION
  - PCA, SVD
- CLASSIFICATION OPTIMIZATION
  - Fishers Linear Discriminant, LDA

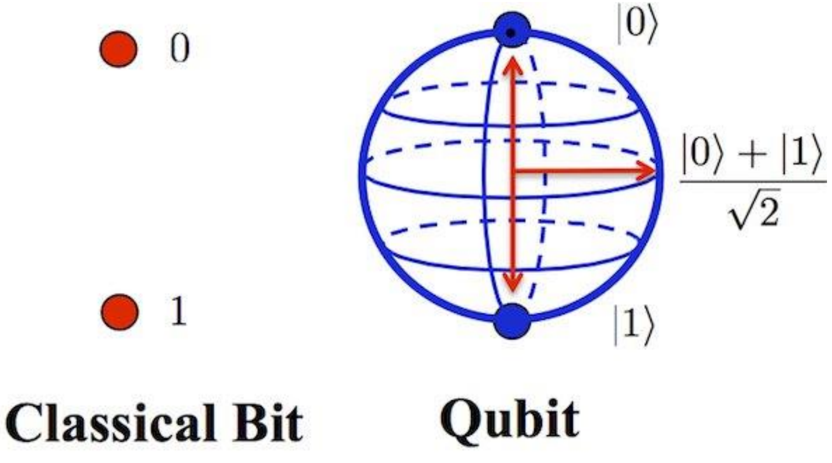
QUANTUM MACHINE LEARNING ISSUES

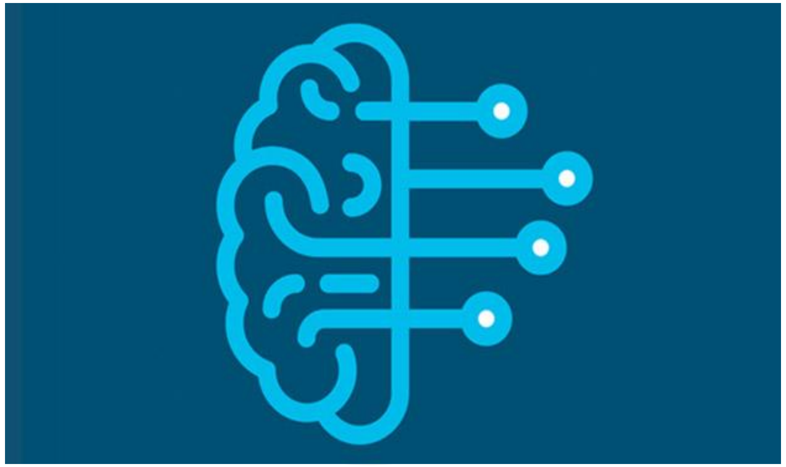
- laws of quantum mechanics restricts our access to information in Qubits
- producing quantum algorithms that outperform their classical counterparts is very difficult of artificial neural networks
- Have to be clever in how we solve these problems

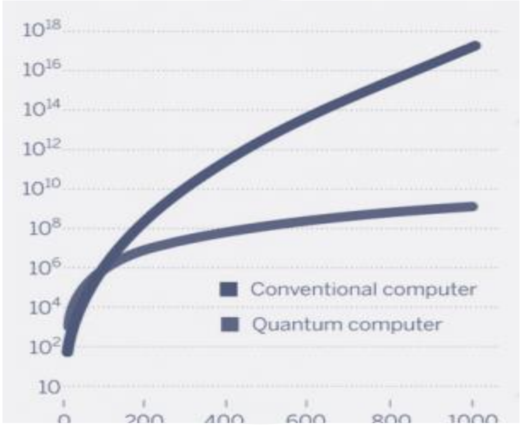
QUANTUM MACHINE LEARNING ISSUES

- quantum speedups in machine learning are currently characterized using idealized measures from complexity theory
  - Must produce theory of Quantum complexity
- Need wide access to machines to test and learn
- The technological implementation of quantum computing is emerging
- only a matter of time until the numerous theoretical proposals can be tested on real machines!!!!!

IN SUMMATION QUANTUM MACHINE LEARNING







QUANTUM BITS IN SUPERPOSITION
FAST LINEAR ALGEBRA

ML ALGORITHM, SUB ALGORITHM,
CLASSIFICATION TASK

PROFIT?/ QUANTUM SPEED UP

Quantum algorithms are developed to solve typical problems of machine learning using the efficiency of quantum computing

REFERENCES

REFERENCES

Image Sources:

- https://www.cisco.com/c/en/us/products/security/machine-learning-security.html machine learning (brain) slide 3
- https://www.allaboutcircuits.com/news/aluminum-nitride-could-replace-diamond-in-qubit-creation/ (qubit image)
- https://www.semanticscholar.org/paper/Quantum-speed-up-for-unsupervised-learning-A%C3%AFmeur-Brassard/0d49669334758a69f45f6997a4b2119fe5ab8ad1/figure/0 (speed up table)

[1] M. Schuld, I. Sinayskiy, and F. Petruccione, "An introduction to quantum machine learning," *Contemp. Phys.*, vol. 56, no. 2, pp. 172–185, 2015.

[2] P. Wittek, "Quantum Machine Learning," *Quantum Mach. Learn.*, vol. 549, no. September, pp. 11–24, 2014.

[3] X. D. Cai *et al.*, "Entanglement-based machine learning on a quantum computer," *Phys. Rev. Lett.*, vol. 114, no. 11, pp. 1–5, 2015.

[4] J. Preskill, "Quantum Computing in the NISQ era and beyond," *Quantum*, vol. 2, no. July, p. 79, 2018.

[5] S. Yoo, J. Bang, C. Lee, and J. Lee, "A quantum speedup in machine learning: Finding an N-bit Boolean function for a classification," *New J. Phys.*, vol. 16, 2014.

[6] H. Wang and H. Xiang, "Quantum algorithm for total least squares data fitting," *Phys. Lett. Sect. A Gen. At. Solid State Phys.*, vol. 383, no. 19, pp. 2235–2240, 2019.

[7] S. Lloyd, M. Mohseni, and P. Rebentrost, "Quantum algorithms for supervised and unsupervised machine learning," pp. 1–11, 2013.

[8] M. Schuld and N. Killoran, "Quantum Machine Learning in Feature Hilbert Spaces," *Phys. Rev. Lett.*, vol. 122, no. 4, p. 40504, 2019.

[9] P. Rebentrost, M. Mohseni, and S. Lloyd, Quantum support vector machine for big data classification,Phys.Rev.Let. 113 (2014), pp. 130503-1–130503-5

[10] E.Aïmeur, G. Brassard, and S. Gambs, Machine learning in a quantum world Advances in Artificial Intelligence, Lecture Notes in Computer Science Volume 4013, Springer, 2006, pp. 431–442.

QUESTIONS?

THANK YOU!

GJONES2@VOLS.UTK.EDU