Using Quantum Computers for Machine Learning

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Conference for Undergraduate Women in Physical Sciences November 8, 2019











\$1.2 Billion

\$1.5 Billion

Over \$10 Billion





\$8 Billion...

Eventually

General Outline

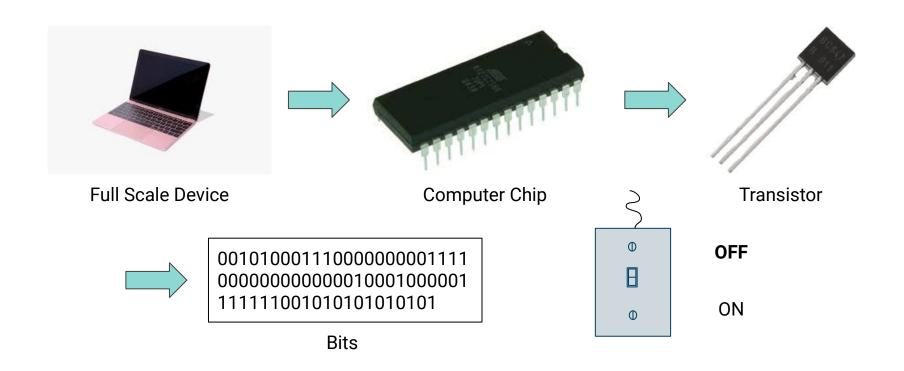
What is a quantum computer really?

How can a quantum computer improve machine learning?

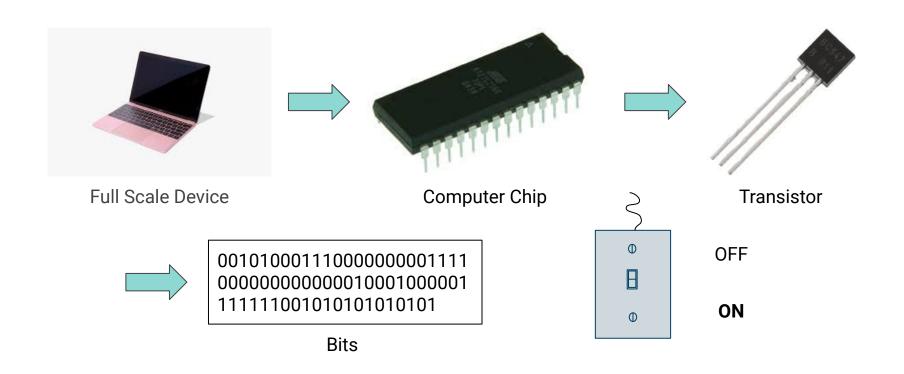
How is this going to contribute to the 2027 projection?

What is a quantum computer really?

How Does Your Computer Really Work?



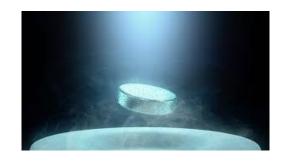
How Does Your Computer Really Work?



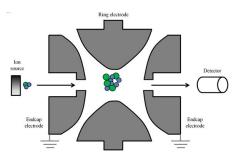
How Does A Quantum Computer Work?



Photonic



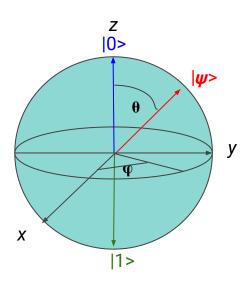
Superconducting



Trapped Ions

Qubits

What is a Qubit?



Bloch Sphere

$$|\psi\rangle = \cos(\theta/2)|0\rangle + e^{i\varphi}\sin(\theta/2)|1\rangle$$

Superposition

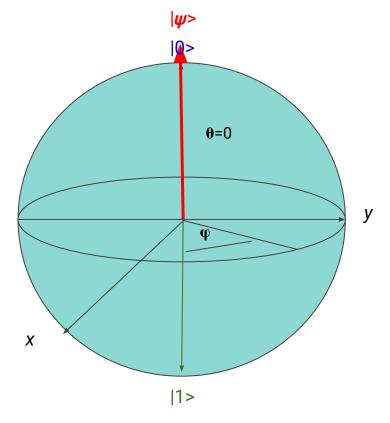
A qubit can be both be 0 and 1 at the same time, holding 2ⁿ states per qubit

Measurement

A qubit can only be measured classically as a 0 or 1, but it will have some inherent probability of being one or the other

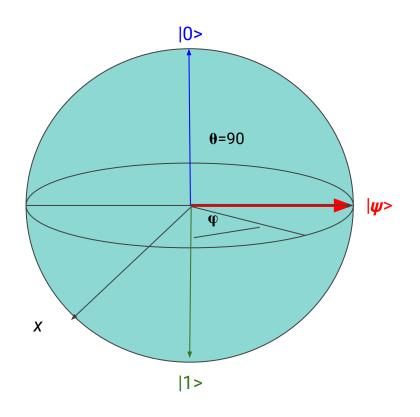
Entanglement

We can connect two qubits so that if we know information about one, then we instantly know some information about the other

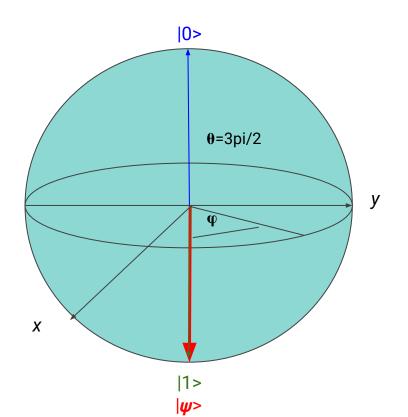


$$|\psi\rangle = \cos(\theta/2)|0\rangle + e^{i\varphi}\sin(\theta/2)|1\rangle$$

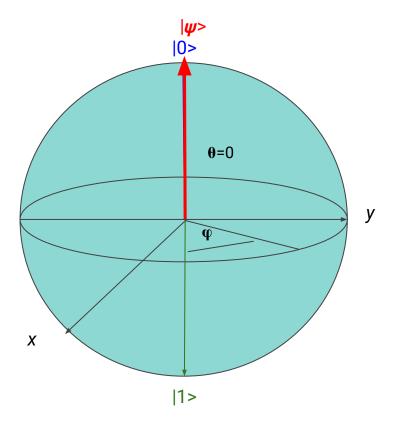
q0 _____



$$|\psi\rangle = \cos(\theta/2)|0\rangle + e^{i\varphi}\sin(\theta/2)|1\rangle$$

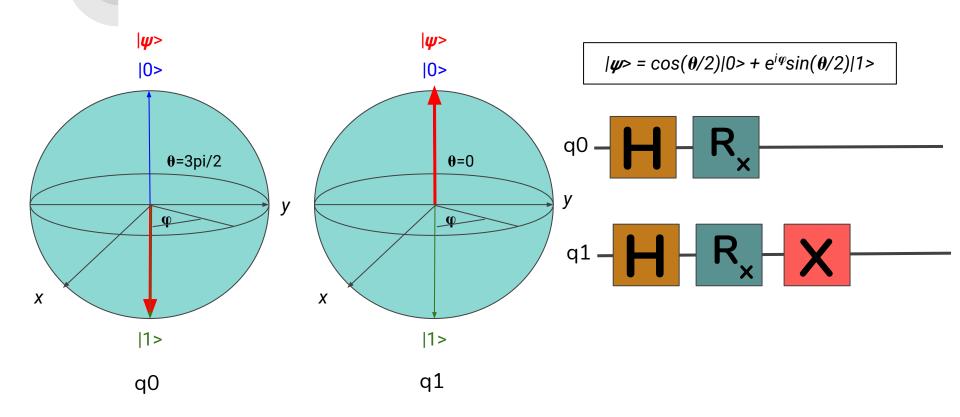


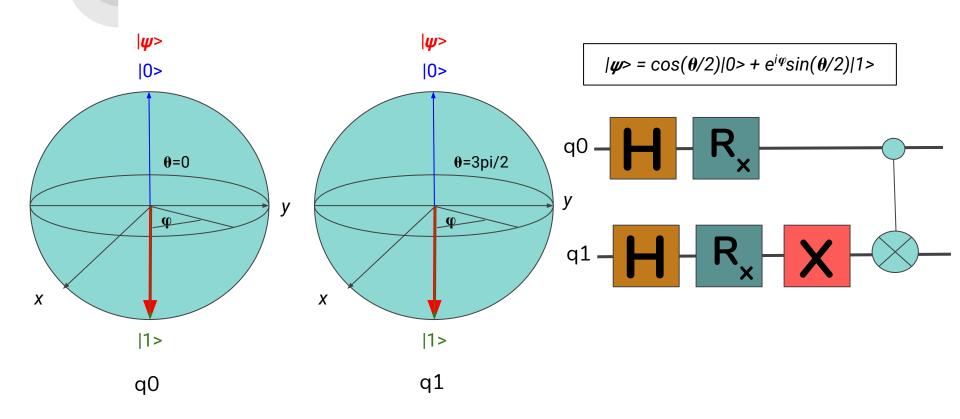
$$|\psi\rangle = \cos(\theta/2)|0\rangle + e^{i\varphi}\sin(\theta/2)|1\rangle$$

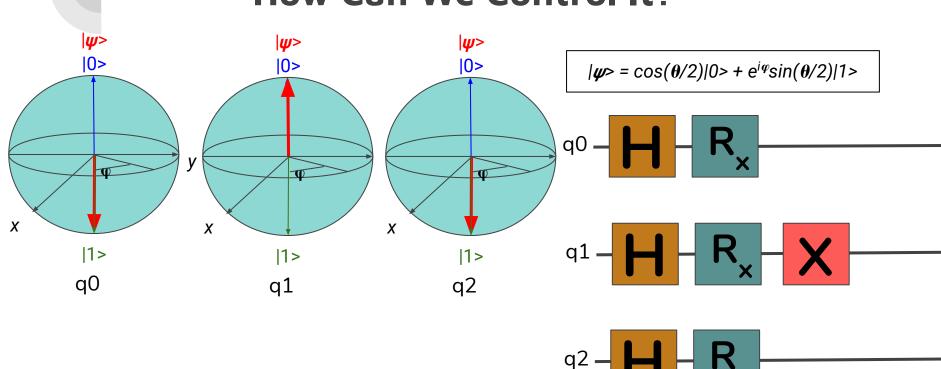


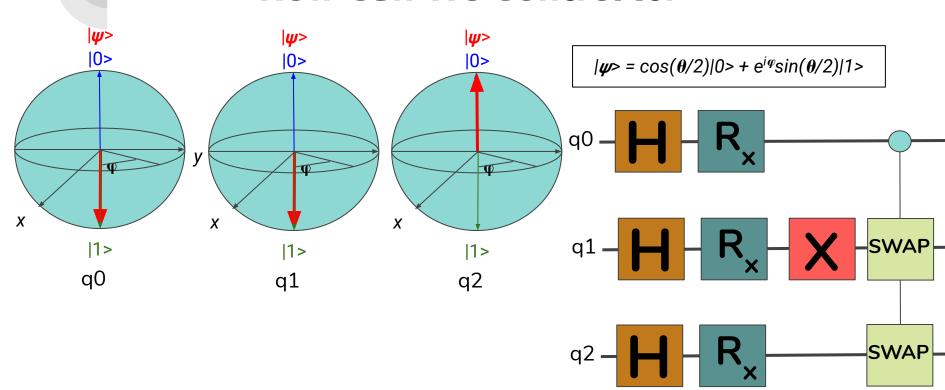
$$|\psi\rangle = \cos(\theta/2)|0\rangle + e^{i\varphi}\sin(\theta/2)|1\rangle$$











Quantum Computer Requirements

Well Defined Qubit System

- 2. Initialization
- 3. Universal set of gates
- 4. Long Coherence Times
- 5. Measurement Capability

Photonic Quantum Computer

- Two types of polarized light
 |0> = Vertically polarized
 |1> = Horizontally polarized
- 2. Polarizer on a coherent laser beam
- 3. Polarizers, half-quarter wave plates
- 4. Medium length milliseconds
- 5. Photodetectors

How can a quantum computer improve machine learning?

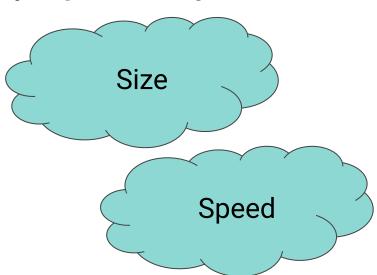
Motivation for Quantum Computing

For every n qubits there are 2ⁿ states at the same time. We can use **fewer qubits** and have **less computationally expensive** algorithms

Shor's Algorithm

- Polynomial Time
- Exponential Speed-up

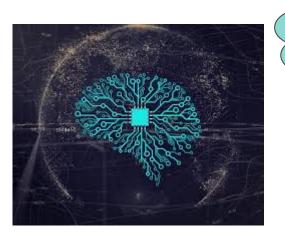
*If performed on a large scale quantum computer, it would break RSA Encryption

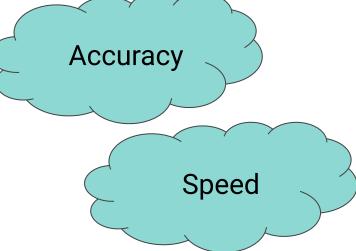


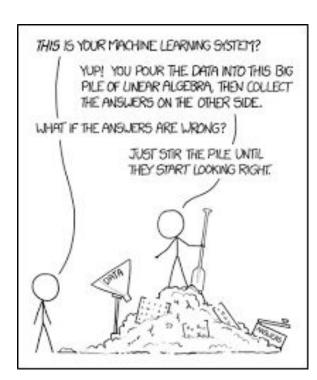


Motivation for Machine Learning

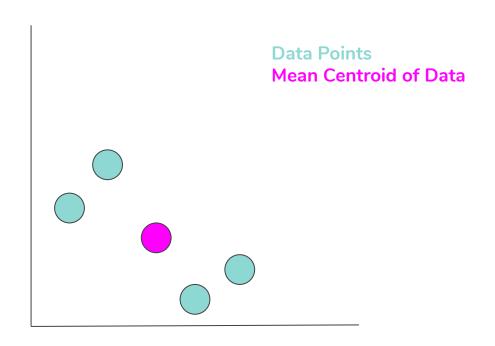
A branch of AI based on the idea that systems can **learn from data** to **update** autonomously





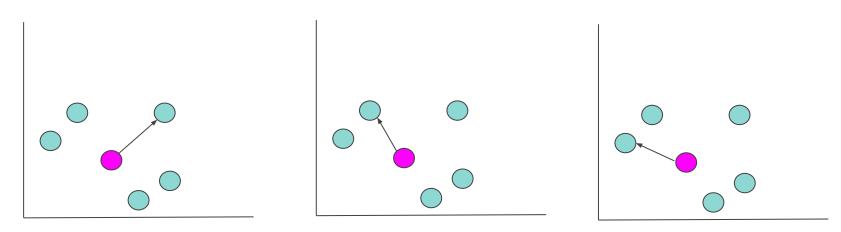


Updating the Mean Centroid of Data



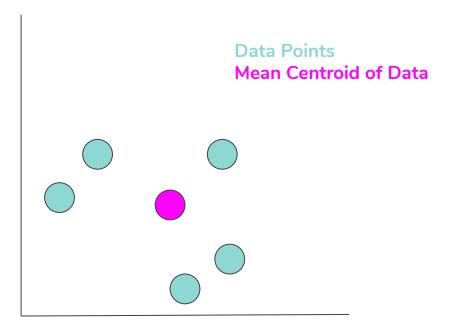
Updating the Mean Centroid of Data

Data Points
Mean Centroid of Data



Euclidean Distance Measurements

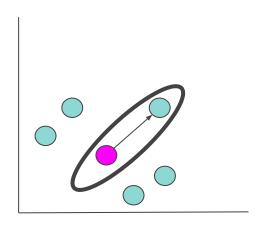
Updating the Mean Centroid of Data

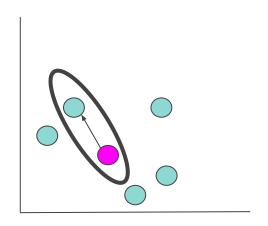


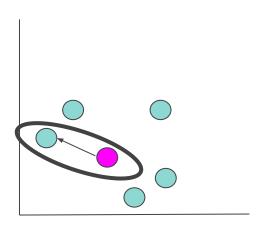
Updated Center

Slipping In the Quantum

Data Points
Mean Centroid of Data

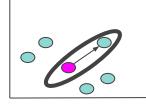


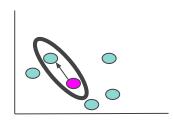


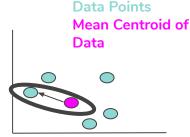


State Overlap Measurements

Slipping In the Quantum







$$|\mathbf{X}^i\rangle = \frac{1}{|\mathbf{X}^i|} \sum_{p=1}^P X_p^{(i)} |p\rangle$$

We can represent each data point of P features as a quantum state and see how well it overlaps with the state of the centroid.

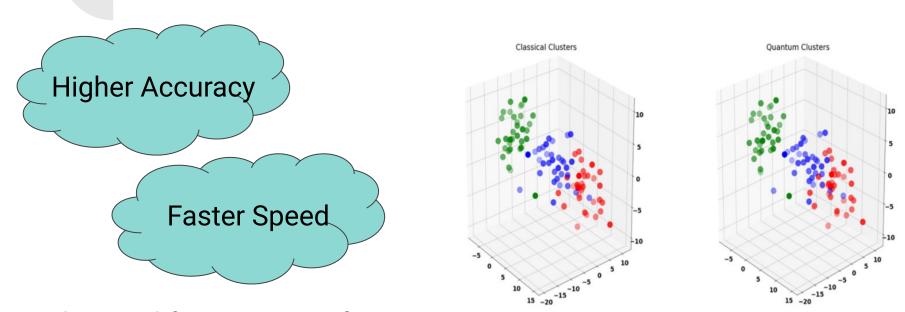
Operation Steps (P Dimensions)

- 2 Hadamard Gates
- 1 Fredkin Gate

$$\langle \mathbf{X}^i | \mathbf{X}^j
angle$$

How is this going to contribute to the 2027 projection?

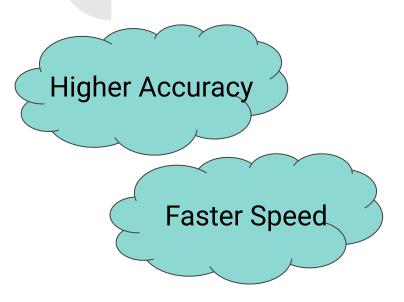
K-Means Clustering on IBM's Processor



Can be used for clustering financial datasets for P features

Sarma, A; Chatterjee, R; Gili, K; Yu, T. "Quantum Unsupervised and Supervised Learning on Superconducting Processors, arXiv 1909.04226 [Preprint]. September 10, 2019

K-Means Clustering on IBM's Processor



Algortihm	Accuracy
Classical SVM	96.7%
Quantum SVM by Havlicek et al.	63.3%
Classical K-means	88.7%
Quantum K-means	96.7%

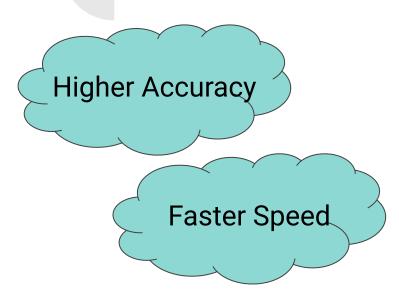
Can be used for clustering financial datasets for P features

$$O(N^2 PK) \implies O(\sqrt{\frac{N}{K}})$$

For Each Iteration

Sarma, A; Chatterjee, R; Gili, K; Yu, T. "Quantum Unsupervised and Supervised Learning on Superconducting Processors, arXiv 1909.04226 [Preprint]. September 10, 2019

Significance of Research Results



Can be used for clustering financial datasets for P features

- We can use this method for not only faster, but more accurate machine learning when clustering datasets
- Practical for industry purposes in the present time
- Can be extended to datasets of higher order dimensions when larger quantum computers become commercially available

Thank You

Supplemental Slides

K-Means Quantum Algorithm

- 1. Extract each data point and put into the state:
- 2. Set up the following states to perform the gates on
- Perform a Hadamard on the 1st qubit and a Fredkin gate on the other two:

$$|\mathbf{X}^i\rangle = \frac{1}{|\mathbf{X}^i|} \sum_{p=1}^P X_p^{(i)} |p\rangle$$

$$|0\rangle \otimes |\mathbf{X}^i\rangle \otimes |\mathbf{X}^j\rangle$$

$$\begin{aligned} |\psi\rangle &= (\mathbf{H} \otimes \mathbf{I} \otimes \mathbf{I}) \frac{1}{\sqrt{2}} [|0\rangle \otimes |\mathbf{X}^{i}\rangle \otimes |\mathbf{X}^{j}\rangle + |1\rangle \otimes |\mathbf{X}^{j}\rangle \otimes |\mathbf{X}^{i}\rangle] \\ &= \frac{1}{2} [(|0\rangle + |1\rangle) \otimes |\mathbf{X}^{i}\rangle \otimes |\mathbf{X}^{j}\rangle + (|0\rangle - |1\rangle) \otimes |\mathbf{X}^{j}\rangle \otimes |\mathbf{X}^{i}\rangle] \\ &= \frac{1}{2} |0\rangle \otimes [|\mathbf{X}^{i}\rangle \otimes |\mathbf{X}^{j}\rangle + |\mathbf{X}^{j}\rangle \otimes |\mathbf{X}^{i}\rangle] + \frac{1}{2} |1\rangle \otimes [|\mathbf{X}^{i}\rangle \otimes |\mathbf{X}^{j}\rangle - |\mathbf{X}^{j}\rangle \otimes |\mathbf{X}^{i}\rangle] \end{aligned}$$

K-Means Quantum Algorithm

- Perform another Hadamard gate on the 1st qubit
- 2. Measure the auxiliary qubit
- Use the probability of the auxiliary qubit to retrieve an equation for distance measurement

$$|\psi\rangle = (\mathbf{H} \otimes \mathbf{I} \otimes \mathbf{I}) \frac{1}{\sqrt{2}} [|0\rangle \otimes |\mathbf{X}^{i}\rangle \otimes |\mathbf{X}^{j}\rangle + |1\rangle \otimes |\mathbf{X}^{j}\rangle \otimes |\mathbf{X}^{i}\rangle]$$

$$= \frac{1}{2} [(|0\rangle + |1\rangle) \otimes |\mathbf{X}^{i}\rangle \otimes |\mathbf{X}^{j}\rangle + (|0\rangle - |1\rangle) \otimes |\mathbf{X}^{j}\rangle \otimes |\mathbf{X}^{i}\rangle]$$

$$= \frac{1}{2} |0\rangle \otimes [|\mathbf{X}^{i}\rangle \otimes |\mathbf{X}^{j}\rangle + |\mathbf{X}^{j}\rangle \otimes |\mathbf{X}^{i}\rangle] + \frac{1}{2} |1\rangle \otimes [|\mathbf{X}^{i}\rangle \otimes |\mathbf{X}^{j}\rangle - |\mathbf{X}^{j}\rangle \otimes |\mathbf{X}^{i}\rangle]$$

$$\langle \psi | \mathbf{M}_{0} | \psi \rangle = \frac{1}{4} \left\{ \langle \mathbf{X}^{i} | \otimes \langle \mathbf{X}^{j} | + \langle \mathbf{X}^{j} | \otimes \langle \mathbf{X}^{i} | \right\} \left[|\mathbf{X}^{i} \rangle \otimes |\mathbf{X}^{j} \rangle + |\mathbf{X}^{j} \rangle \otimes |\mathbf{X}^{i} \rangle \right]$$

$$= \frac{1}{2} + \frac{1}{4} \left[\left(\langle \mathbf{X}^{i} | \otimes \langle \mathbf{X}^{j} | \right) (|\mathbf{X}^{j} \rangle \otimes |\mathbf{X}^{i} \rangle) + \left(\langle \mathbf{X}^{j} | \otimes \langle \mathbf{X}^{i} | \right) (|\mathbf{X}^{i} \rangle \otimes |\mathbf{X}^{j} \rangle) \right]$$

$$= \frac{1}{2} + \frac{1}{4} \left[\langle \mathbf{X}^{i} | \mathbf{X}^{j} \rangle \langle \mathbf{X}^{j} | \mathbf{X}^{i} \rangle + \langle \mathbf{X}^{j} | \mathbf{X}^{i} \rangle \langle \mathbf{X}^{i} | \mathbf{X}^{j} \rangle \right]$$

$$P[|0\rangle] = \langle \psi | \mathbf{M}_{0} | \psi \rangle = \frac{1}{2} + \frac{1}{2} \left| \langle \varphi | \phi \rangle \right|^{2}$$

$$|\mathbf{X}^i - \mathbf{X}^j|^2 = \langle \psi | \mathbf{M}_0 | \psi \rangle = \frac{1}{2} + \frac{1}{2} |\langle \varphi | \phi \rangle|$$
$$= \frac{1}{2} + \frac{1}{4Z} |\mathbf{X}^i - \mathbf{X}^j|^2$$
$$|\mathbf{X}^i - \mathbf{X}^j|^2 = Z \left(4P[|0\rangle] - 2\right).$$