

# Quantum Algorithm for Principal Component Analysis

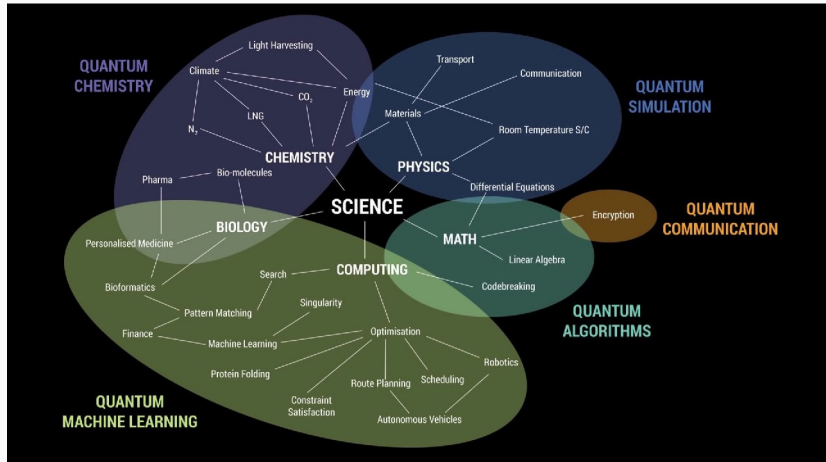
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# Introduction

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# Applications of Quantum Computing



# Quantum Machine Learning

## Quantum Clustering finding

When the data is represented in a very large dimension space, it is very difficult to perform the clustering with a classical computer. The use of quantum computers is a very good solution.



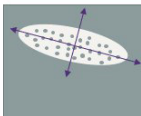
## Quantum Support Vector Machine

Finding the hyperplane that separates many data points that are represented in a high dimensional space is so difficult on a classical computer. on a quantum computer, it can be solved extremely efficiently.



## Quantum PCA

The goal of this algorithm is to find the proper axes along which to group this data. This is something that takes  $O(N^3)$  on a classical computer.



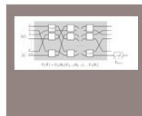
## Feature topology

This is a method for finding the topological features of data. This problem can be mapped to a problem of finding the eigenvectors and eigenvalues of some huge, high-dimensional matrix.



## Quantum Deep Learning

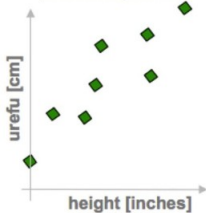
Exciting breakthroughs may soon bring real quantum neural networks, specifically deep learning neural networks, to reality. Many research papers have shown remarkable results in quantum deep learning



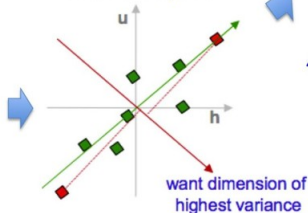
# Principal Component Analysis

## PCA in a nutshell

1. correlated hi-d data  
(“urefu” means “height” in Swahili)



2. center the points



3. compute covariance matrix

$$\begin{matrix} & h & u \\ h & \begin{pmatrix} 2.0 & 0.8 \end{pmatrix} \\ u & \begin{pmatrix} 0.8 & 0.6 \end{pmatrix} \end{matrix} \rightarrow \text{cov}(h, u) = \frac{1}{n} \sum_{i=1}^n h_i u_i$$

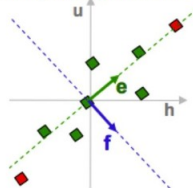
4. eigenvectors + eigenvalues

$$\begin{pmatrix} 2.0 & 0.8 \\ 0.8 & 0.6 \end{pmatrix} \begin{pmatrix} e_h \\ e_u \end{pmatrix} = \lambda_e \begin{pmatrix} e_h \\ e_u \end{pmatrix}$$

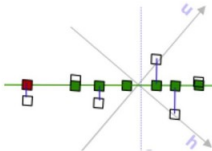
$$\begin{pmatrix} 2.0 & 0.8 \\ 0.8 & 0.6 \end{pmatrix} \begin{pmatrix} f_h \\ f_u \end{pmatrix} = \lambda_f \begin{pmatrix} f_h \\ f_u \end{pmatrix}$$

`eig(cov(data))`

5. pick  $m < d$  eigenvectors  
w. highest eigenvalues



7. uncorrelated low-d data



6. project data points to those eigenvectors

$$x'_e = x^T e = \sum_{j=1}^d x_j e_j$$

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# Complexity of Principal Component Analysis

- Must perform eigendecomposition, which is computationally intensive

## 4. eigenvectors + eigenvalues

$$\begin{pmatrix} 2.0 & 0.8 \\ 0.8 & 0.6 \end{pmatrix} \begin{pmatrix} e_h \\ e_u \end{pmatrix} = \lambda_e \begin{pmatrix} e_h \\ e_u \end{pmatrix}$$

$$\begin{pmatrix} 2.0 & 0.8 \\ 0.8 & 0.6 \end{pmatrix} \begin{pmatrix} f_h \\ f_u \end{pmatrix} = \lambda_f \begin{pmatrix} f_h \\ f_u \end{pmatrix}$$

`eig(cov(data))`

- Given this bound, standard implementations of PCA usually run in  $O(n^3)$ , where  $n$  is the number of dimensions (features)
- This is the step we will focus on

# The Quantum Algorithm

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Given a covariance matrix  $X$ , normalized w.r.t. its trace, we aim at computing its top- $k$  eigendecomposition by means of a quantum approach

The main technique we will exploit in order to do so is

- Quantum Phase Estimation
  - Phase Kickback
  - Inverse Quantum Fourier Transform



- $X$  is a matrix having eigenvector  $v$  and corresponding eigenvalue  $\lambda$   
*i.e.*  $Xv = \lambda v$
- then  $v$  is also eigenvector of  $e^X$ , with corresponding eigenvalue  $e^\lambda$   
*i.e.*  $e^X v = e^\lambda v$

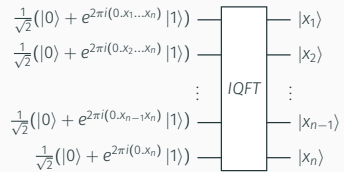
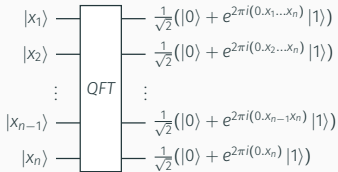
(Proven using Taylor series)

## QPE - Inverse Quantum Fourier Transform

- Consider  $U = e^{iX}$  and its eigenvalue  $e^{i\lambda} = e^{i2\pi\varphi}$
- Given a quantum state of the form  $\frac{1}{\sqrt{2^N}} \sum_{y=0}^{2^N-1} e^{2\pi i\varphi y} |y\rangle$  we can easily determine  $\varphi$  applying the inverse of the *Quantum Fourier Transform*

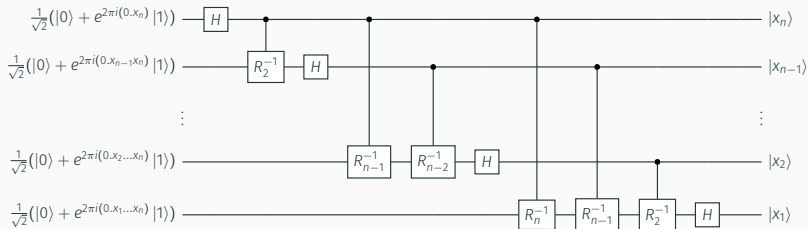
# QPE - Inverse Quantum Fourier Transform

- More specifically, we obtain the best approximation for the binary fraction expansion of  $\varphi$  over  $n$  bits
- $\varphi \approx 0.x_1x_2\dots x_{n-1}x_n$



# QPE - Inverse Quantum Fourier Transform

Circuit for the Inverse QFT



Where  $R_k^{-1} = \begin{pmatrix} 1 & 0 \\ 0 & e^{\frac{2\pi i}{2^k}} \end{pmatrix}$

- We know how to obtain  $\varphi$ , and therefore also  $\lambda$ , provided we have the quantum state  $\frac{1}{\sqrt{2^N}} \sum_{y=0}^{2^N-1} e^{2\pi i \varphi y} |y\rangle$
- But how can we build such a state?
- *Amplitude Encoding and Phase Kickback*

## QPE - Amplitude Encoding

- The eigenvector corresponding to  $e^{i\lambda}$ , for  $U$ , is  $\psi_\lambda$
- Using *Amplitude Encoding* then we could build the eigenstate (i.e. quantum state)  $|\psi_\lambda\rangle$  over  $\log_2(|\psi_\lambda|)$  qubits

$$\psi_\lambda = \begin{pmatrix} \psi_{\lambda 0} \\ \psi_{\lambda 1} \\ \vdots \\ \psi_{\lambda n} \end{pmatrix} \implies \psi_{\lambda 0} |0\dots 00\rangle + \psi_{\lambda 1} |0\dots 01\rangle + \dots + \psi_{\lambda n} |1\dots 11\rangle$$

- Then by definition  $U |\psi_\lambda\rangle = e^{i\lambda} |\psi_\lambda\rangle$

- Recall that  $|\det(e^{iX})| = |e^{\text{tr}(iX)}| = |e^i| = 1$ 
  - $X$  is normalized w.r.t. its trace!
- Since  $U$  is a unitary matrix we can implement the corresponding quantum gate, as well as its controlled version
- Let  $c-U$  be the controlled version of gate  $U$
- Then

$$\begin{aligned} |0\rangle |\psi_\lambda\rangle &\xrightarrow{c-U} |0\rangle |\psi_\lambda\rangle \\ |1\rangle |\psi_\lambda\rangle &\xrightarrow{c-U} |1\rangle e^{i\lambda} |\psi_\lambda\rangle \end{aligned}$$

- It can be proven that, from a mathematical point of view, quantum states  $|1\rangle e^{i\lambda} |\psi_\lambda\rangle$  and  $e^{i\lambda} |1\rangle |\psi_\lambda\rangle$  are **the same state**
- The phase factor is *kicked back* from the controlled register to the control register



- The state  $e^{i\lambda} |1\rangle |\psi_\lambda\rangle$  now encodes  $\lambda$  in its phase, but as a *global* phase shift, which is not measurable
- In order to introduce a *relative* phase shift that can then be measured, we must simply put the control register in a superposition prior to the application of the  $c - U$ 
  - e.g. we apply the Hadamard gate!

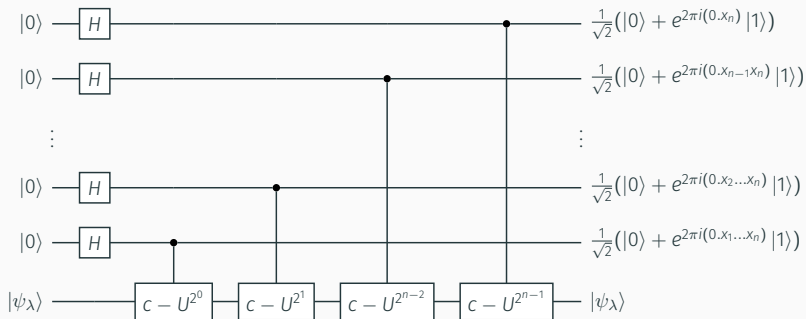
$$\frac{1}{\sqrt{2}}(|0\rangle + |1\rangle) |\psi_\lambda\rangle \xrightarrow{c-U} \frac{1}{\sqrt{2}}(|0\rangle + e^{i\lambda} |1\rangle) |\psi_\lambda\rangle$$

- As a last step, consider  $c = U$  raised to power  $k$
- Eigenvalue of  $c = U^k$  corresponding to  $|\psi_\lambda\rangle$  will be  $e^{ik\lambda}$
- Applying  $c = U^k$  using different control qubits, with  $k$  equals to **increasing powers of 2**, we obtain our goal configuration

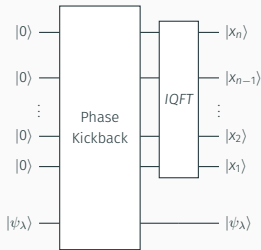
$$\frac{1}{\sqrt{2}}(|0\rangle + e^{ik\lambda} |1\rangle) |\psi_\lambda\rangle = \frac{1}{\sqrt{2}}(|0\rangle + e^{2\pi i(0.x_{(\log_2 k+1)} \dots x_n)} |1\rangle) |\psi_\lambda\rangle$$

- Note that  $|\psi_\lambda\rangle$  is left unchanged after every application, thus we can keep reusing it

## Circuit for the Phase Kickback



## Putting everything together



- This is how standard QPE works for computing an eigenvalue when the corresponding eigenvector is known
- In our case, however, **we don't know any of the eigenvectors of  $X$  a priori**, and therefore we cannot prepare the state  $|\psi_\lambda\rangle$

- How can we exploit Quantum Phase Estimation to perform eigendecomposition in our scenario?
- Quantum Algorithm Providing Exponential Speed Increase for Finding Eigenvalues and Eigenvectors (Abrams & Lloyd, 1999) [1]
- Quantum principal component analysis (Lloyd, Mohseni & Rebentrost, 2014) [2]
- Towards Pricing Financial Derivatives with an IBM Quantum Computer (Martin et al., 2019) [3]



Seth Lloyd

- As it happens, precise knowledge of  $|\psi_\lambda\rangle$  is **not** required in order to estimate  $\lambda$
- It suffices to have an estimate  $\psi_a$ , such that  $|\langle\psi_a|\psi_\lambda\rangle|^2$  is not exponentially small (w.r.t. problem size), to measure the value of  $\lambda$  in a polynomial number of trials
- Even more interestingly, when the  $n$  qubits are measured to be in state  $\lambda$ , the register that initially stored  $|\psi_a\rangle$  collapses to state  $|\psi_\lambda\rangle$  !
- How is this explained?

- The state we are using as input can be written as a **linear combination** of the true eigenvectors of  $X$ , labelled  $|\Phi_k\rangle$

$$|\psi_a\rangle = \sum_k c_k |\Phi_k\rangle$$

- QPE on this state then yields measurements of each eigenvalue  $\lambda_k$  with probability  $|c_k|^2$ , while making the initial vector collapse to the corresponding true eigenvector  $|\Phi_k\rangle$

- This is why using an estimate of a true eigenvector gives us the corresponding eigenvalue with sufficient reliability
- In this case, "unexpected" measurements are not just meaningless noise, but are in fact occurrences of different eigenvalues
- Thus, for any random initial vector  $|\psi\rangle$ , the output configuration will in general reveal **all eigenvector-eigenvalue couples**



- In addition, if we are able to obtain an approximation for an eigenvector using a random initial state, we can sequentially improve the result by using such approximation as the new initial state
- This brings us to a crucial point for the algorithm:  
**extracting information from the output state**

## Quantum PCA - *Reading the output*

- After applying QPE the eigenvectors are entangled with their eigenvalues and encoded in  $\log_2(|\psi_\lambda|)$  qubits
- Recall Amplitude Encoding:

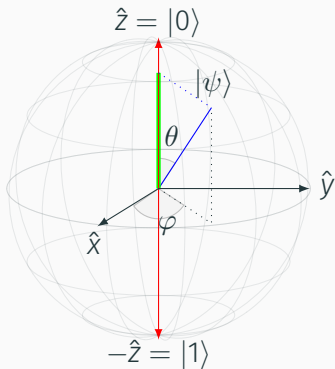
$$|\psi_\lambda\rangle = \psi_{\lambda 0} |0\dots 00\rangle + \psi_{\lambda 1} |0\dots 01\rangle + \dots + \psi_{\lambda n} |1\dots 11\rangle$$

- Using data from  $N$  shots of the circuit, we can estimate these probabilities as relative frequencies  $|\psi_{\lambda i}| = \sqrt{\frac{n_i}{N}}$
- How do we get the relative phases, *i.e.* detect signs?

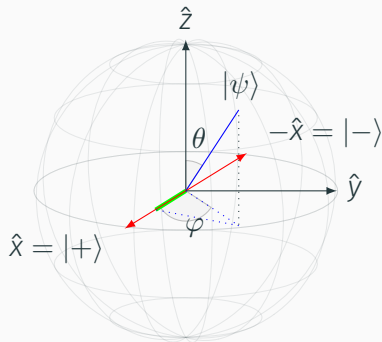
# Quantum Tomography

- The technique used to reconstruct information of a quantum state is called **Quantum State Tomography**
- Tomography is done by collecting and processing different types of measurements, or *observables*, of the system which correspond to various axes of the Bloch sphere
- Note that, still, the global phase of a state is not measurable, meaning that states  $\alpha |0\rangle - \beta |1\rangle$  and  $-\alpha |0\rangle + \beta |1\rangle$  are physically indistinguishable. This is not relevant in our scenario as we are only interested in the direction of the vector and not in its sense

# Quantum Tomography



Measurement on Z basis



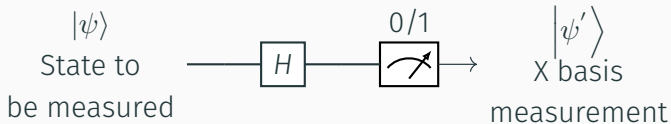
Measurement on X basis

# Quantum Tomography

- Full Quantum State Tomography of a  $b$ -qubit system is in general computationally intensive
  - $O(4^b)$  different observables must be measured
  - Data processing involves common optimization algorithms
- However, we can exploit problem structure to do better
- In particular we assume to work with *real* amplitudes (not complex as in the general case)
  - Input state has real amplitudes
  - No rotations around the  $y$  axis performed by the algorithm in the ideal execution

# Quantum Tomography

- We measure the register only in the Z basis (all qubits) and in the combinations of 1 qubit at a time in the X basis (i.e.  $b + 1$  settings)
- We obtain measurements in the X basis from ones in the *standard computational basis* (Z basis) by applying an Hadamard gate before measurement



- This operation maps the state  $|+\rangle$  to output 0 and the state  $|-\rangle$  to output 1

- Performing these measurements we can compare the probability of different outcomes in order to estimate the relative phases
- The total number of comparisons is  $2^b - 1$ , linear in the Hilbert space dimension
  - One for each amplitude!

# Implementation and Analysis

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# Implementation

- We implement the algorithm in Python using Qiskit

```
def qpca(covmat, precision, initial, backend, req_shots)
```

- *covmat*: input covariance matrix
- *precision*: number of qubits to represent the eigenvalues
- *initial*: initial vector ( $|\psi\rangle$ )
- *backend*: to run the circuit ( *qasm\_simulator* by default)
- *req\_shots*: shots of the circuit (8192 by default)

[Here](#) is a demo of the algorithm applied to the Iris dataset.

In order to analyze the algorithm and its complexity there are different points to take into account

- Implementation of gate  $e^{iX}$
- Quantum Phase Estimation
- Quantum State Tomography
- Executions of the circuit

- Exponentiation of the covariance matrix is required to implement the (controlled)  $U = e^{iX}$
- In Quantum Information, the process of finding a circuit that approximates such operator for a given Hamiltonian is called **Hamiltonian Simulation**
  - Note: also Hamiltonians are Hermitian matrices
- This was one of the original motivating problems of Quantum Computing proposed by Richard Feynman as a key part of simulating quantum mechanical systems.

### Approaches to Simulation of non-sparse $d$ -dimensional Hamiltonians

- Higher order Suzuki-Trotter expansion:  $O(d \log d)$
- Lloyd-Mohseni-Rebentrost method:  $O(\log d)$   
Assuming many copies of the Hamiltonian are available as quantum states (encoded in density matrix)
- Wang and Wossnig:  $\tilde{O}(\sqrt{d})$   
Using a more practical qRAM data structure  
[arXiv:1803.08273](https://arxiv.org/abs/1803.08273)

Gate-complexity of Quantum Phase Estimation is impacted by the precision of the eigenvalue estimation ( $m$  qubits)

- IQFT is  $O(m^2)$
- $m$  calls to powers of  $c - U$
- If  $c - U^k = k$  times  $c - U$ , gate-complexity is  $2^m$
- Then overall gate-complexity:  $O(m^2 + 2^m)$
- Note: complexity scales linearly with accuracy  $M = 2^m$

Already discussed.

Our implementation for  $d$  dimensional eigenvectors encoded in  $b = \lceil \log_2 d \rceil$  qubits

- $b + 1$  different observables to be measured
- $O(2^b) = O(d)$  comparisons on the results of such measurements

We know *what* we have to measure, but *how many* measurements should be taken?

Considering each eigenvalue/eigenvector couple

- Number of measurements in the "*all-Z basis*" scales only with precision of amplitude estimation
- Measurements in the "*one-X basis*" give clear results for strongly positive/negative amplitudes, ambiguous for values near 0



*Recall:* in principle, any random initialization reveals all eigenvalue/eigenvector couples.

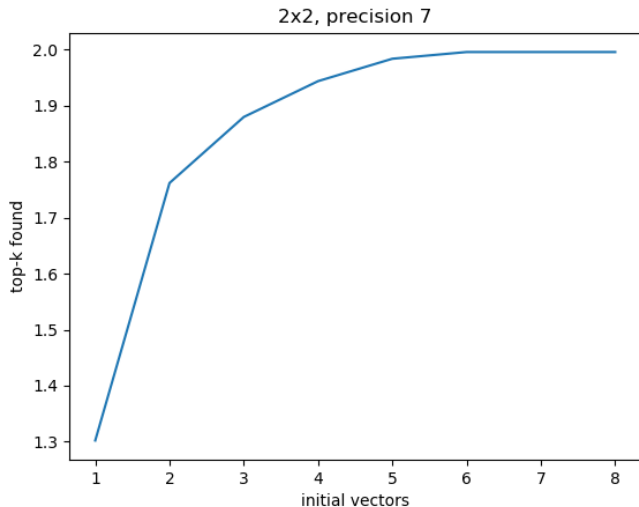
In practice, some eigenvectors may have *exponentially small* contribution to an initial vector and appear rarely in output.

Different approaches

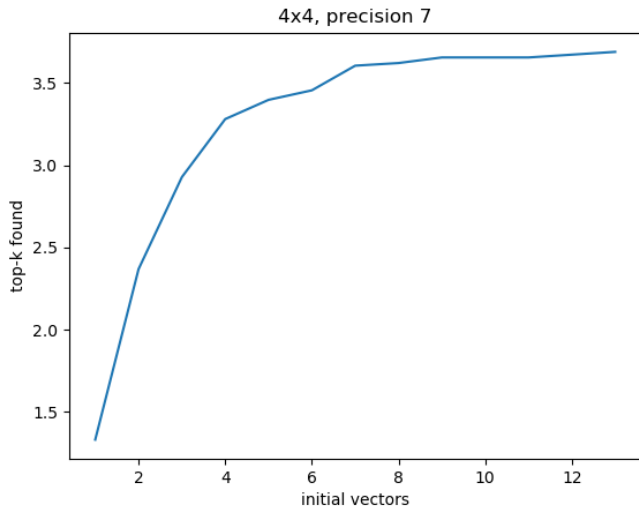
- Multiple initializations (random or by some criteria)
- Obtain rough estimate of eigenvector and iterate

## Analysis - Results

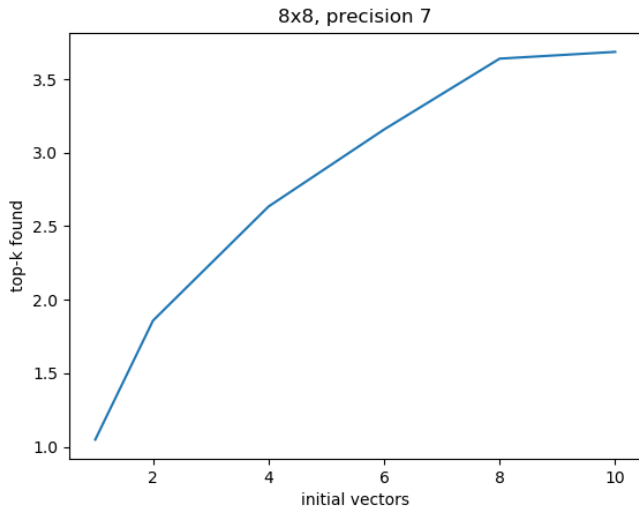
Some results for different numbers of random initializations



## Analysis - Results

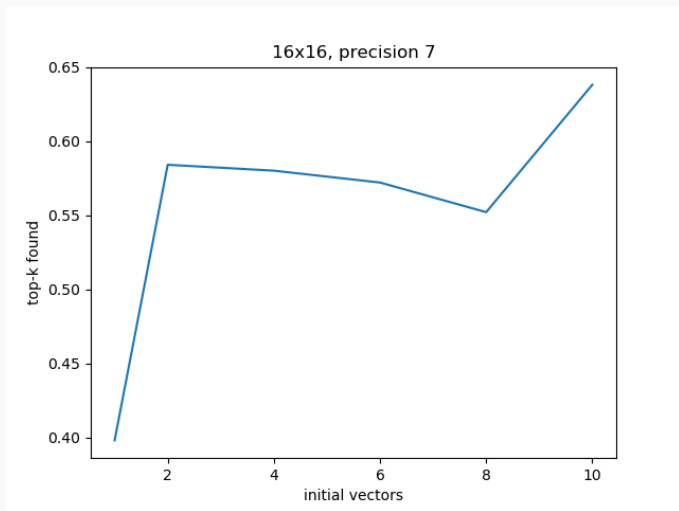


## Analysis - Results



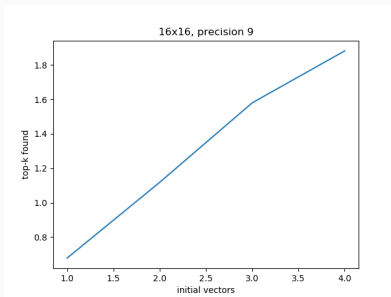
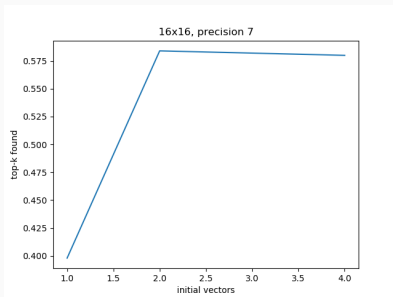
## Analysis - Results

With 7 qubits precision, results on 16x16 covariance matrices start degrading.



# Analysis - Results

Raising precision to 9 qubits makes results immediately improve



We test the algorithm on IBM's 5-qubit quantum device Vigo

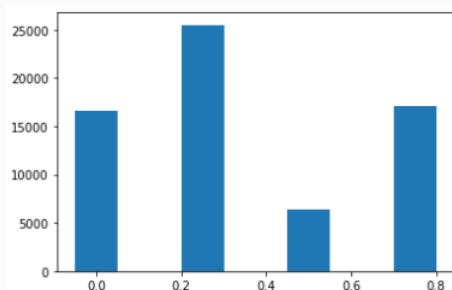
- 2x2 covariance matrix
- 2 qubits precision for the eigenvalues

Real eigendecomposition

$$\lambda_1 = 0.84212698, v_1 = \begin{bmatrix} 0.91854462 & -0.39531732 \end{bmatrix}$$
$$\lambda_2 = 0.15787302, v_2 = \begin{bmatrix} 0.39531732 & 0.91854462 \end{bmatrix}$$

## Analysis - Results on Real Device

Histogram of eigenvalues found using 4 random initial vectors

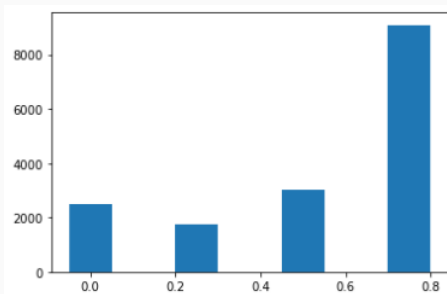


Vector corresponding to 0.75,  $v_a = \begin{bmatrix} 0.85450074 & -0.51945017 \end{bmatrix}$



## Analysis - Results on Real Device

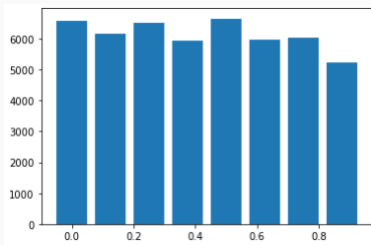
Running the algorithm using  $v_a$  as initial vector now measures






and improved vector  $v = \begin{bmatrix} 0.91533142 & -0.40270137 \end{bmatrix} \approx v_1$

## Analysis - Results on Real Device

- Iterative Approach proves effective with today's noisy quantum computers
- For 2x2 matrix we obtained decent results
- Attempts on 4x4 with 3 qubit precision are already too noisy



## References

-  Daniel S. Abrams, Seth Lloyd *A quantum algorithm providing exponential speed increase for finding eigenvalues and eigenvectors.*  
<https://arxiv.org/pdf/quant-ph/9807070v1.pdf>
-  Seth Lloyd , Masoud Mohseni and Patrick Rebentrost  
*Quantum principal component analysis.*  
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*Towards Pricing Financial Derivatives with an IBM Quantum Computer.*  
<https://arxiv.org/pdf/1904.05803.pdf>