

# Quantum Machine Learning

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# Why care now about Quantum Computing?

# The quantum revolution 2.0

The background of the slide features a subtle, abstract graphic. It consists of a network of light blue hexagonal outlines that overlap and connect to form a complex web. Interspersed among these hexagons are small, semi-transparent circular dots in various colors: light blue, teal, purple, and grey. These dots are positioned along the edges of the hexagons, suggesting a connection or interaction between the different components of the network.

# The quantum revolution 2.0

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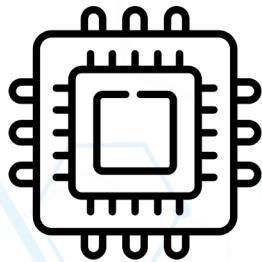
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- Quantum computing will NOT replace classical computing. It will open the way to new applications in areas like Climate, Energy, Materials, Automotive, Finance, Telecommunications, Pharmaceuticals, Healthcare, ...

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- Quantum computing will NOT replace classical computing. It will open the way to new applications in areas like Climate, Energy, Materials, Automotive, Finance, Telecommunications, Pharmaceuticals, Healthcare, ...
- We need to rethink and invent new algorithmic solutions

# Getting to quantum applications from the software side

Hardware Manufacturers



More qubits

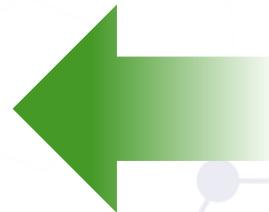


Better qubits

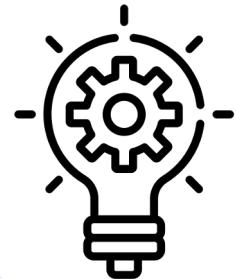
Quantum  
Applications



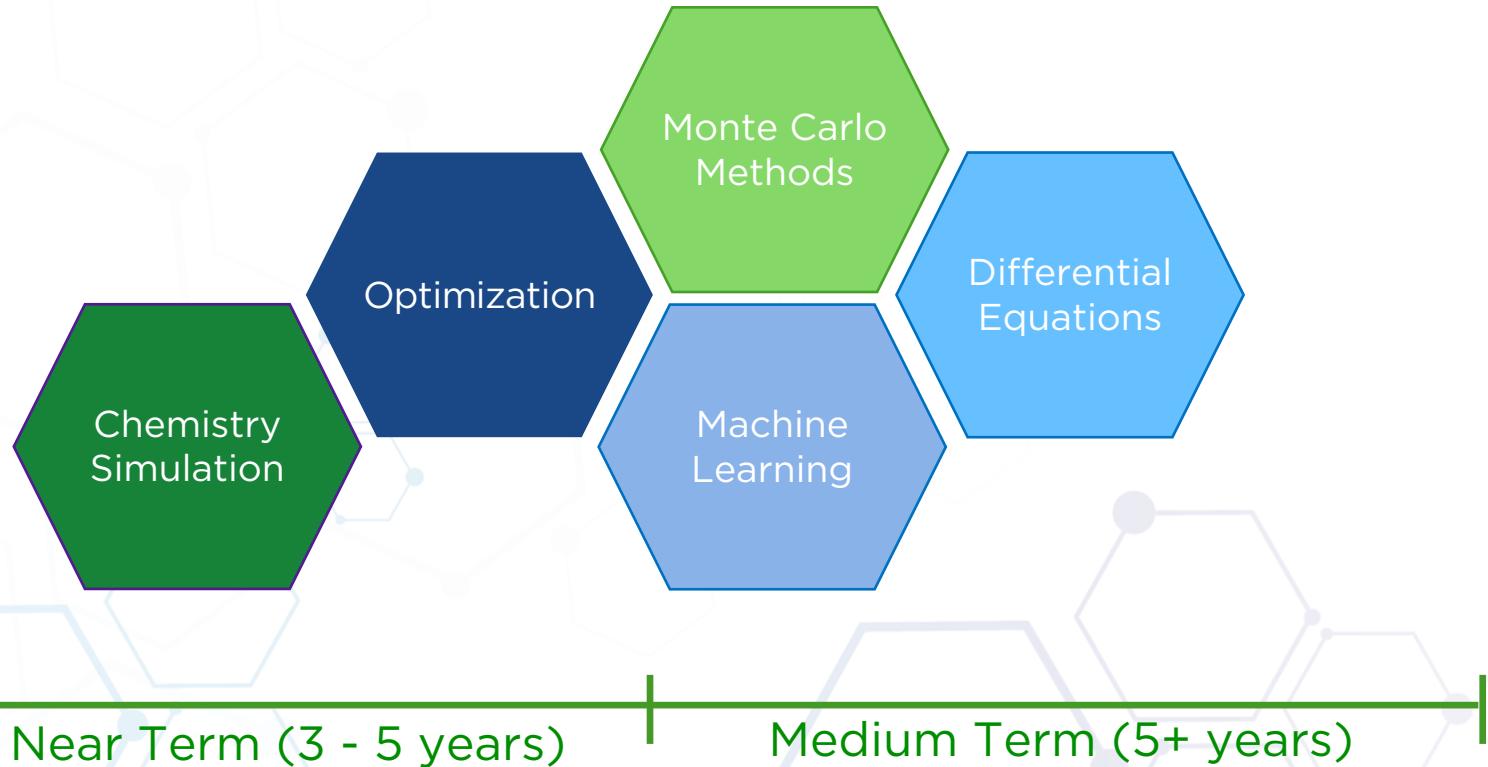
Less resources



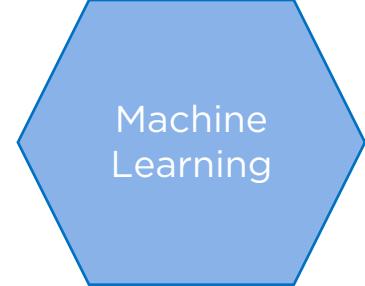
Better performance



# We focus on hard computing problems



# Quantum Machine Learning



Machine  
Learning

# Quantum Machine Learning

- Large-scale quantum computers offer big advantages

# Quantum Machine Learning

- Large-scale quantum computers offer big advantages
  - We have developed many of these algorithms – Classifiers, Recommenders, q-means, ...

Quantum Algorithms for Deep Convolutional Neural Networks – ICLR 2020  
<https://arxiv.org/abs/1911.01117>

Quantum Expectation-Maximization for Gaussian Mixture Models – ICML 2020  
<https://arxiv.org/abs/1908.06657>

q-means: A quantum algorithm for unsupervised machine learning – NeurIPS 2019  
<https://arxiv.org/abs/1812.03584>

Quantum algorithms for Second-Order Cone Programming and Support Vector Machines, Quantum 2021  
<https://arxiv.org/abs/1908.06720>

Quantum Algorithms for feedforward neural networks – ACM ToQC 2020  
<https://arxiv.org/abs/1812.03089>

Quantum classification of the MNIST dataset via Slow Feature Analysis – PRA 2020  
<https://arxiv.org/abs/1808.09266>

Quantum gradient descent for linear systems and least squares – PRA 2020  
<https://arxiv.org/abs/1704.04992>

Quantum recommendation systems (2017) – Innovations on TCS 2017  
<https://arxiv.org/abs/1603.08675>

# Quantum Machine Learning

- Large-scale quantum computers offer big advantages
  - We have developed many of these algorithms — Classifiers, Recommenders, q-means, ...
- We HAVE concrete avenues for bringing QML closer to reality
  - Data Loaders
  - Distance Estimators for Similarity Learning
  - Linear algebra for ML

# Quantum Machine Learning

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- We HAVE concrete avenues for bringing QML closer to reality
  - Data Loaders
  - Distance Estimators for Similarity Learning
  - Linear algebra for ML
- QML may offer: Efficiency, Accuracy, Interpretability, Trust, Energy savings

# A first example

# Classification

## Data

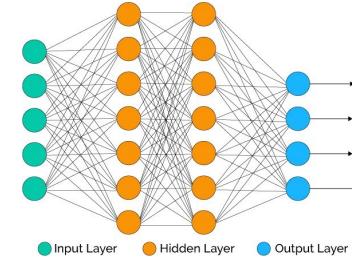
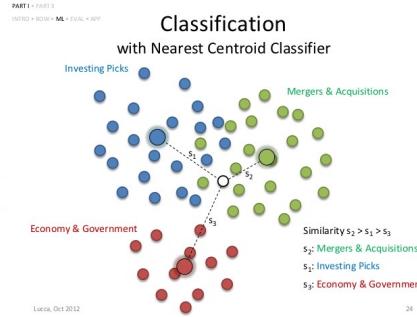


# Classification

Data



Quantum algorithms

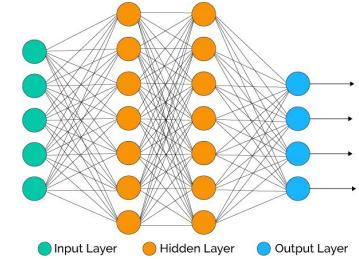
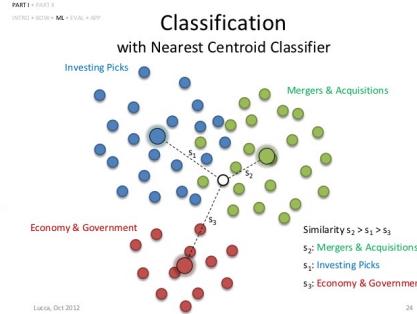


# Classification

## Data



## Quantum algorithms



## Quantum software

```
# let's create some synthetic data
X, y = generate_data_clusters()

# let's run the quantum classifier
qlabels = fit_and_predict(X,y,y,model='QNearestCentroid')

# import NearestCentroid from scikit-learn for benchmarking
clabels = sklearn.neighbors.NearestCentroid().fit(X,y).predict(X)

print('Quantum labels\n',qlabels)
print('Classical labels\n',clabels)

# let's plot the data (only for dimension=2)
plot(X,qlabels,'QNearestCentroid')
plot(X,clabels,'KNearestCentroid')

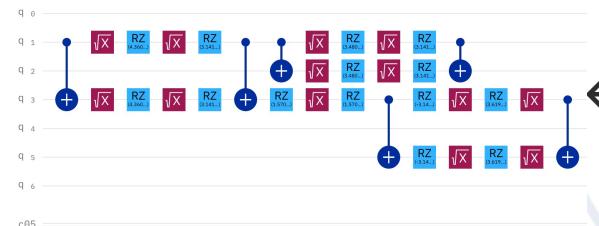
Quantum labels
[2 0 0 1 0 0 0 1 1 2 0 1 1 0 1 2 3 2 1 2 2 2 3 3 3 3 3 0 3 3 2]
Classical labels
[2 0 0 1 0 0 0 0 1 1 2 0 1 1 0 1 2 3 2 1 2 2 2 3 3 3 3 3 0 3 3 2]
```

# Classification

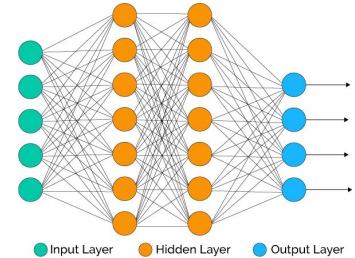
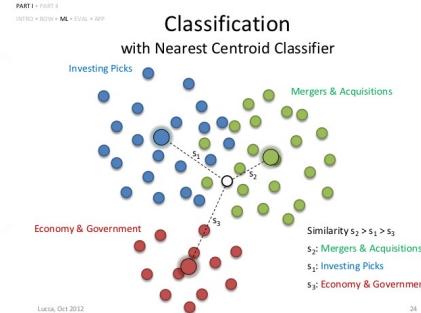
Data



Quantum circuits



Quantum algorithms



Quantum software

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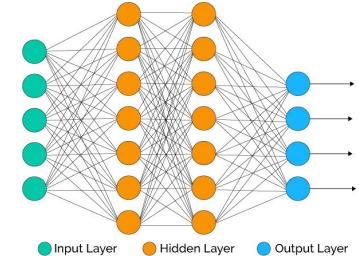
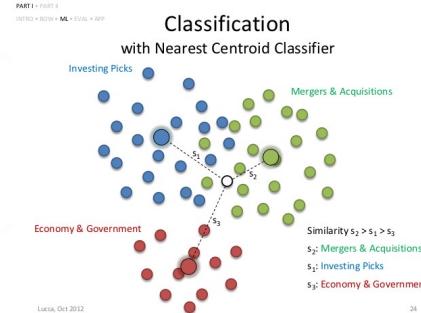
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# Classification

Data



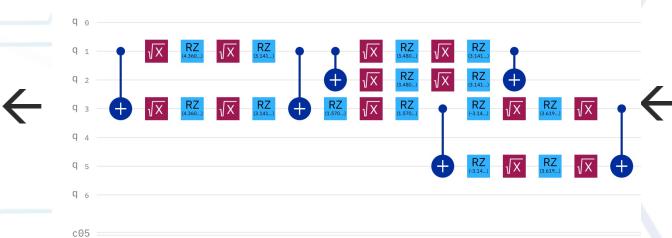
Quantum algorithms



Quantum computer



Quantum circuits



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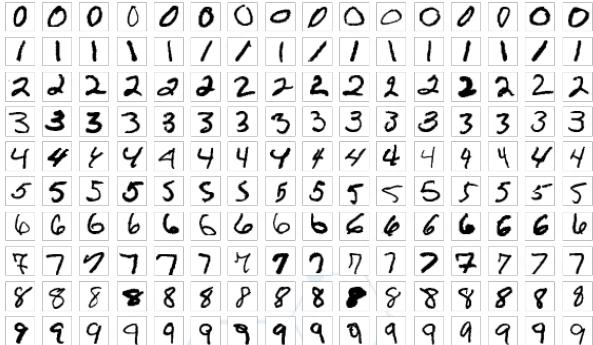
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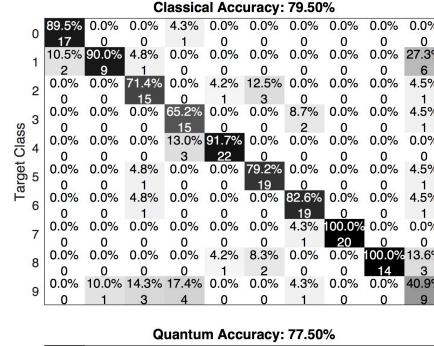
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```

# Classification

Data



Results



An 11-qubit QC  
can recognise  
8 out of 10  
handwritten digits

## Nearest Centroid Classification on a Trapped Ion Quantum Computer

Sonika Johri,<sup>1</sup> Shantanu Debnath,<sup>1</sup> Avinash Mocherla,<sup>2,3</sup> Alexandros Singh,<sup>2,4</sup> Anupam Prakash,<sup>2</sup> Jungsang Kim,<sup>1</sup> and Iordanis Kerenidis<sup>2,5</sup>

<sup>1</sup>*IonQ Inc, 4505 Campus Dr, College Park, MD 20740*

<sup>2</sup>*QC Ware, Palo Alto, USA and Paris, France*

<sup>3</sup>*UCL, Centre for Nanotechnology, London, UK*

<sup>4</sup>*Université Sorbonne Paris Nord, France*

<sup>5</sup>*CNRS, University of Paris, France*

Many more applications

# Recommendation Systems [Kerenidis, Prakash, ITCS 17]

NETFLIX

Step 1

		Products			
		Users	1	...	?
?		?	0	...	?
...		...	...	...	...
1		1	?	...	0

Step 2

Singular Value Estimation

$$W = \begin{matrix} k \\ U & S & V^T \end{matrix}$$

Step 3

Quantum computers provide competitive recommendations fast!

Efficient quantum algorithm for Singular Value Estimation

# Clustering

q-means++ [Kerenidis,Landman,Luong, Prakash NeurIPS 2019]

**Input:** N points in d-dimensions (**quantum access**)

**Output:** K clusters/centroids

1. Start with some initial centroids (e.g. ++-method)

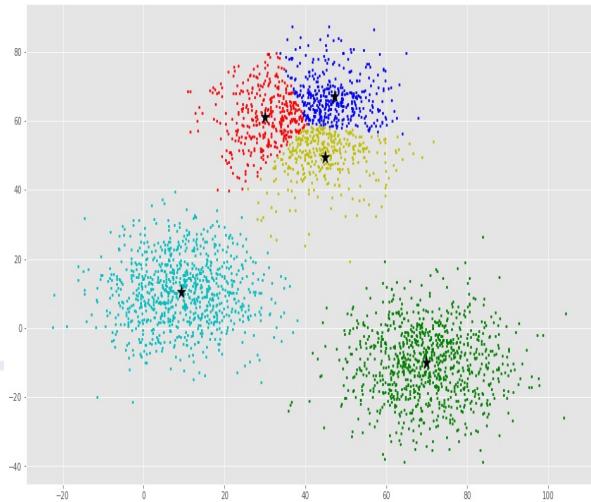
Repeat until convergence

2. For all points in superposition

estimate distances to centroids **quantumly**  
and assign to nearest centroid

3. Update the centroids

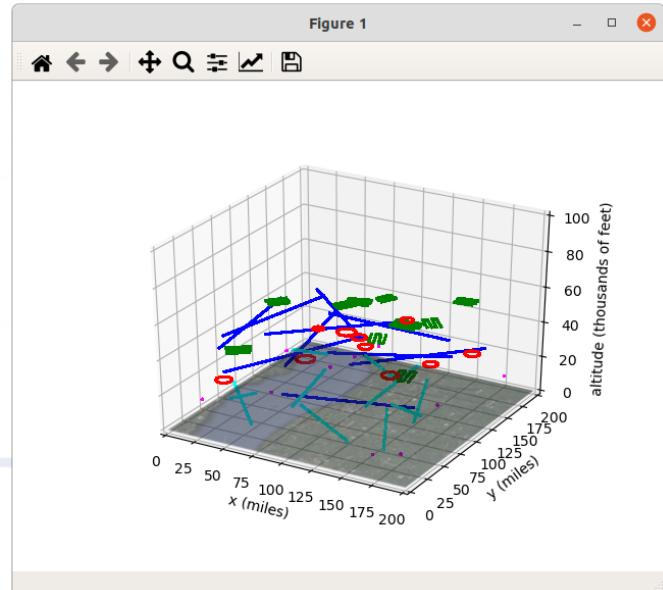
- i. Quantum linear algebra to find new centroid  
ii. Tomography to recover classical description



# Clustering: QC Ware-AFRL collaboration

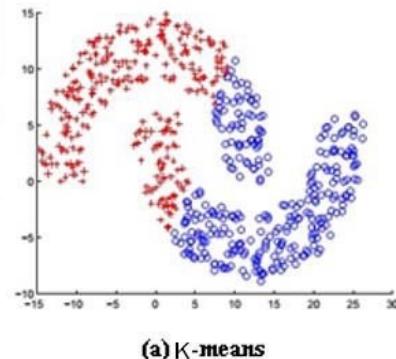
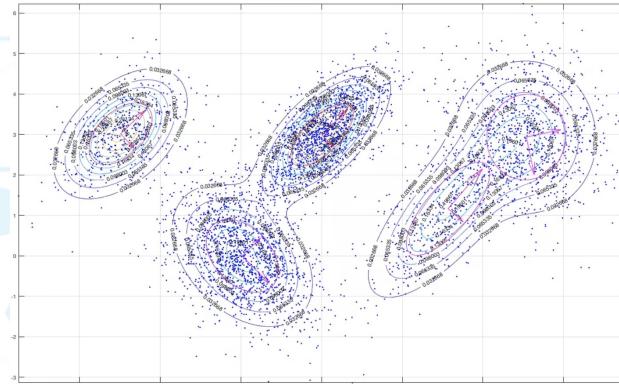
q-means++ [NeurIPS2019]

- NISQ implementation
- Simulations achieve comparable performance
- Faster quantum running times
- Preparing for hardware demonstration

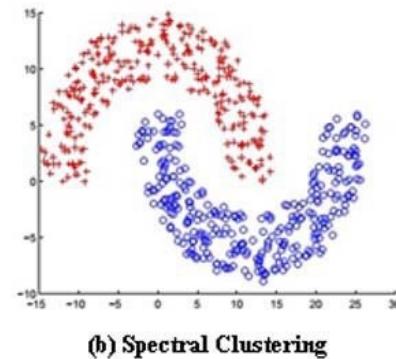


# Unsupervised learning

- Feature selection
  - Methods related to determinantal sampling/volume sampling
- Expectation Maximization for Gaussian Mixture Models [K,Luong,Prakash ICML 2020]
- Spectral Clustering [K, Landman PRA 2021]



(a) K-means



(b) Spectral Clustering

# Reinforcement Learning

## Quantum Policy Iteration [Cherrat,Kerenidis,Prakash 2021]

**Input:** states S, actions A, transitions P, Rewards R

**Output:** policy  $\pi$

1. Start with some initial  $\pi_0$

Repeat until convergence

2. solve  $(I - \gamma P^\pi)Q = R$  **quantum linear systems**
3. update  $\pi$  from  $Q$  **by measurements**

### Remarks

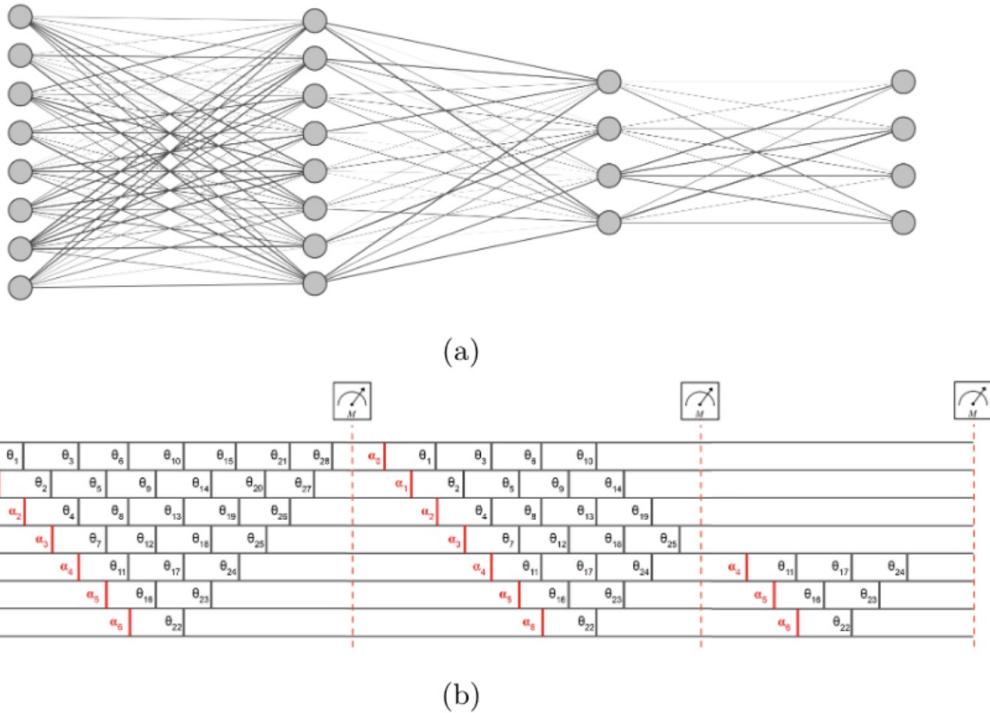
“No input” / Well-conditioned /  $\ell^\infty$  guarantees



# Quantum Neural Networks

## Quantum Orthogonal NNs

- New classical training in  $O(n^2)$
- NISQ implementations
- provable efficiency
- A new optimization landscape

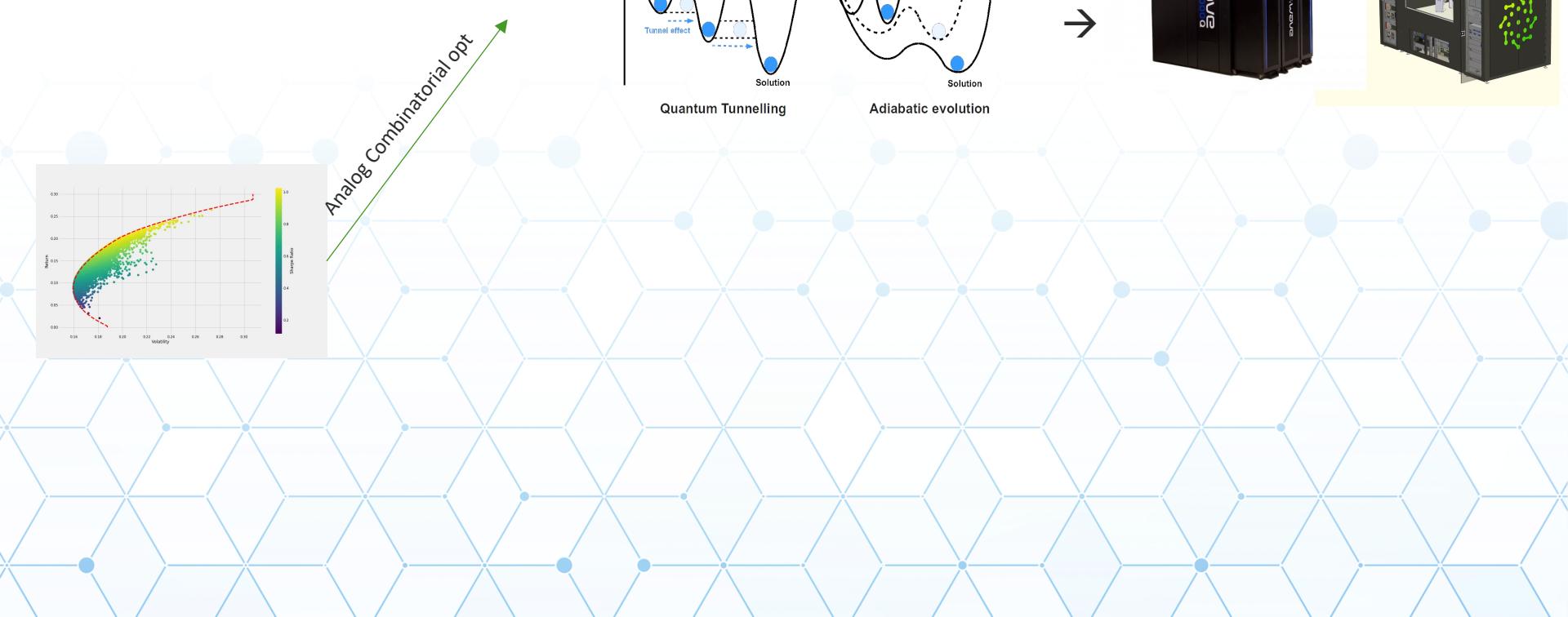


# Quantum Optimization

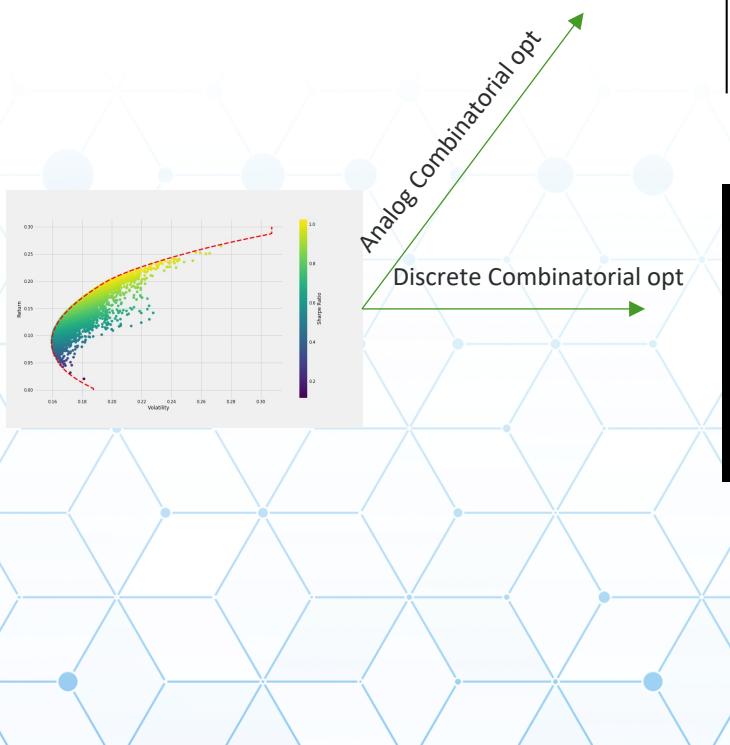
# Optimization



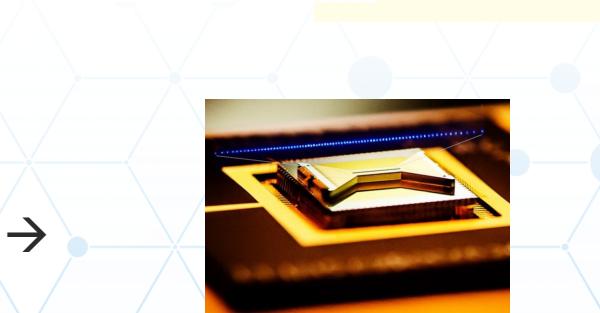
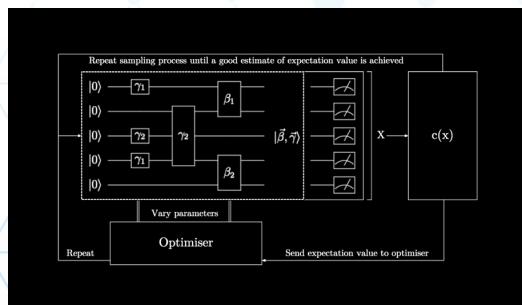
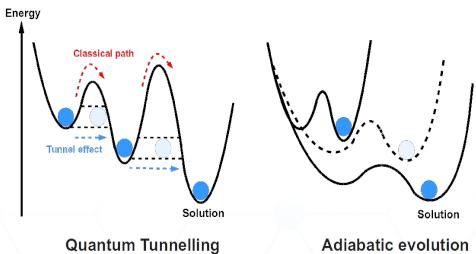
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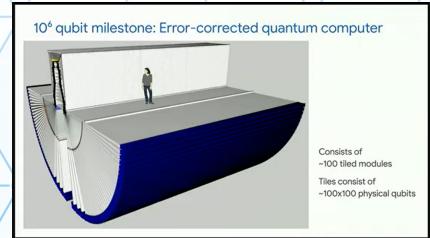
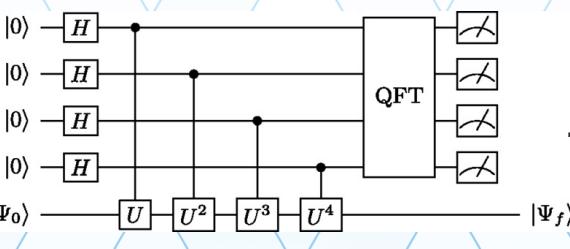
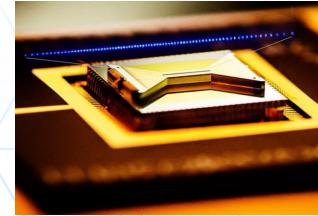
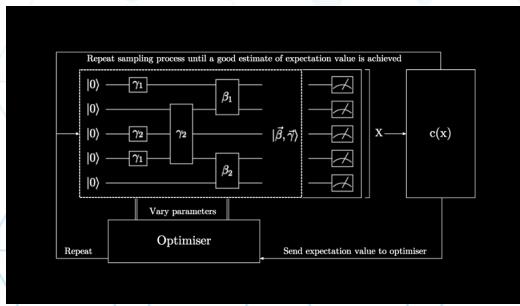
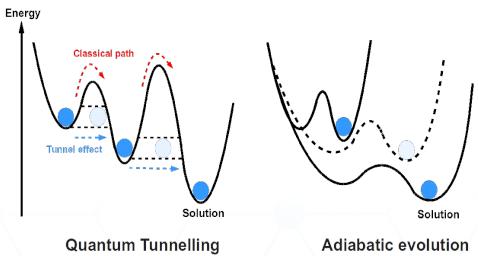
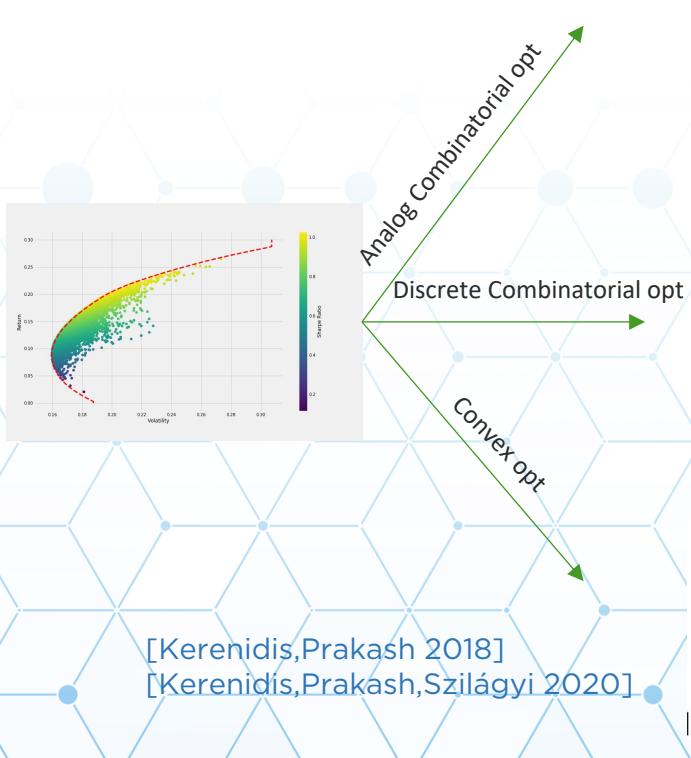
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Analog Combinatorial opt  
Discrete Combinatorial opt

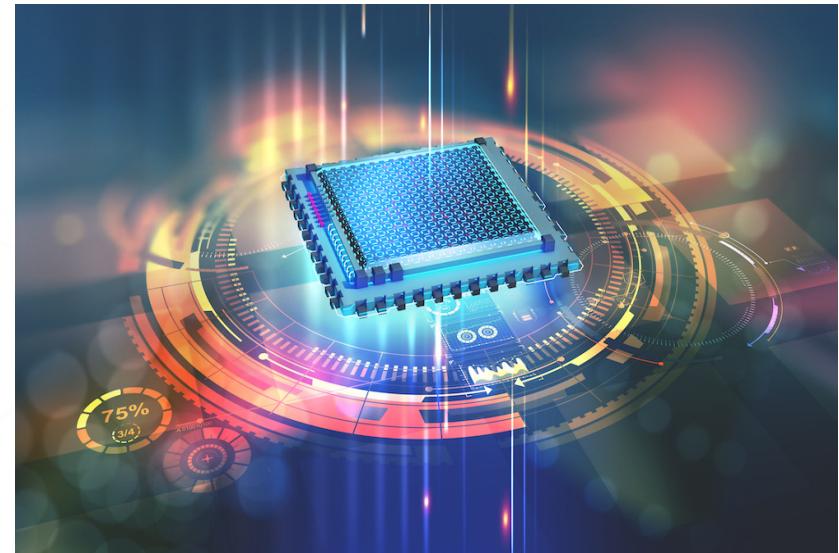


# Optimization



# Conclusions

- ✓ Quantum technologies will very soon impact most industry sectors
- ✓ Competitive advantage comes from algorithms and models
- ✓ The time to engage with quantum technologies is now





Thank you!

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