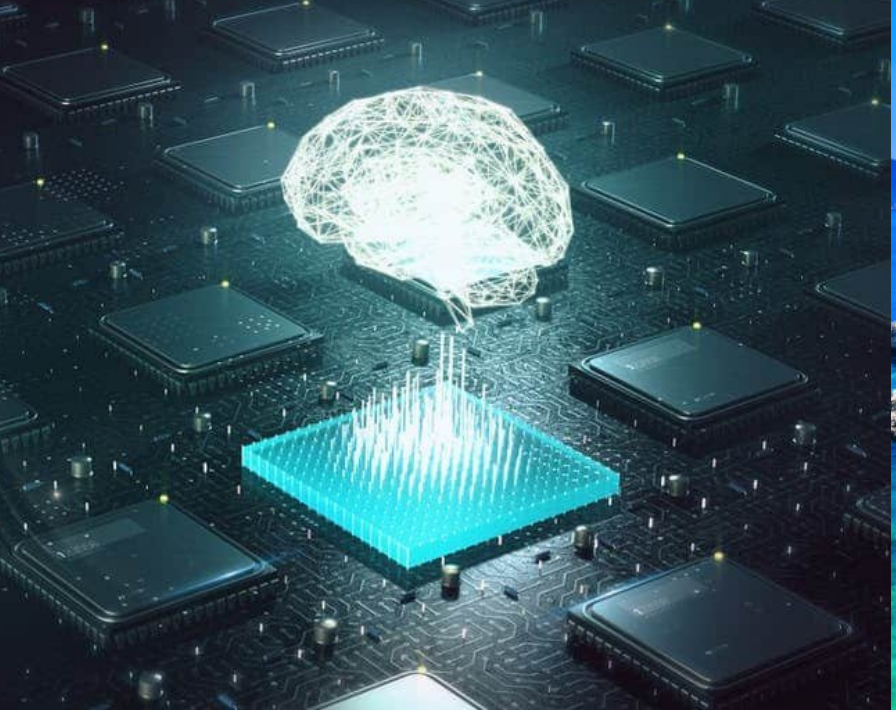
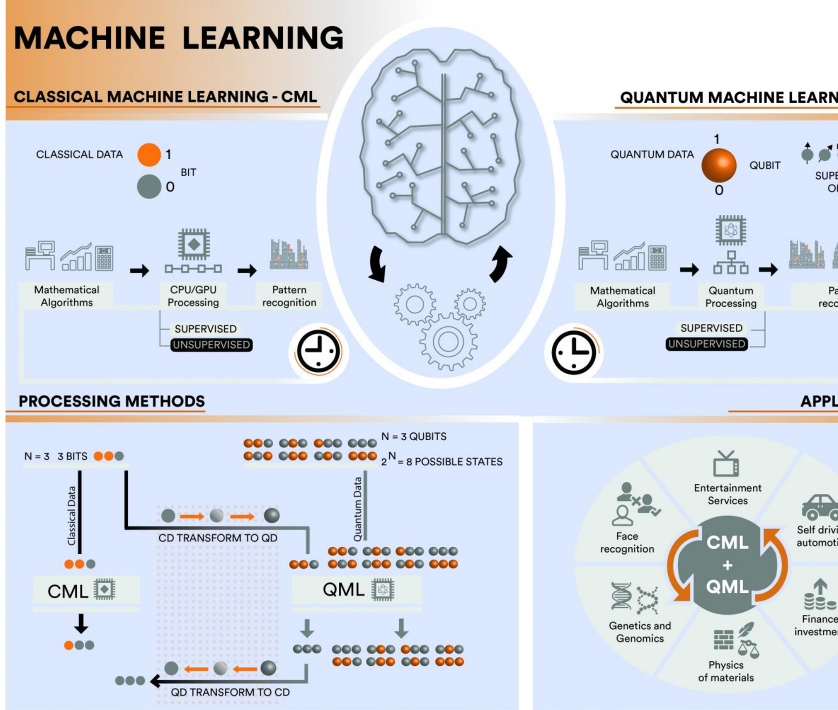


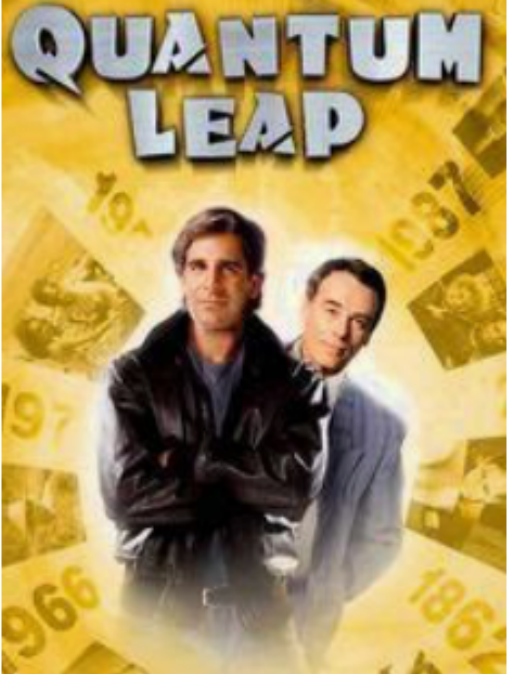


Quantum Computing for High-Energy Physics

Michael Spannowsky

with **Steve Abel** and **Simon Williams**

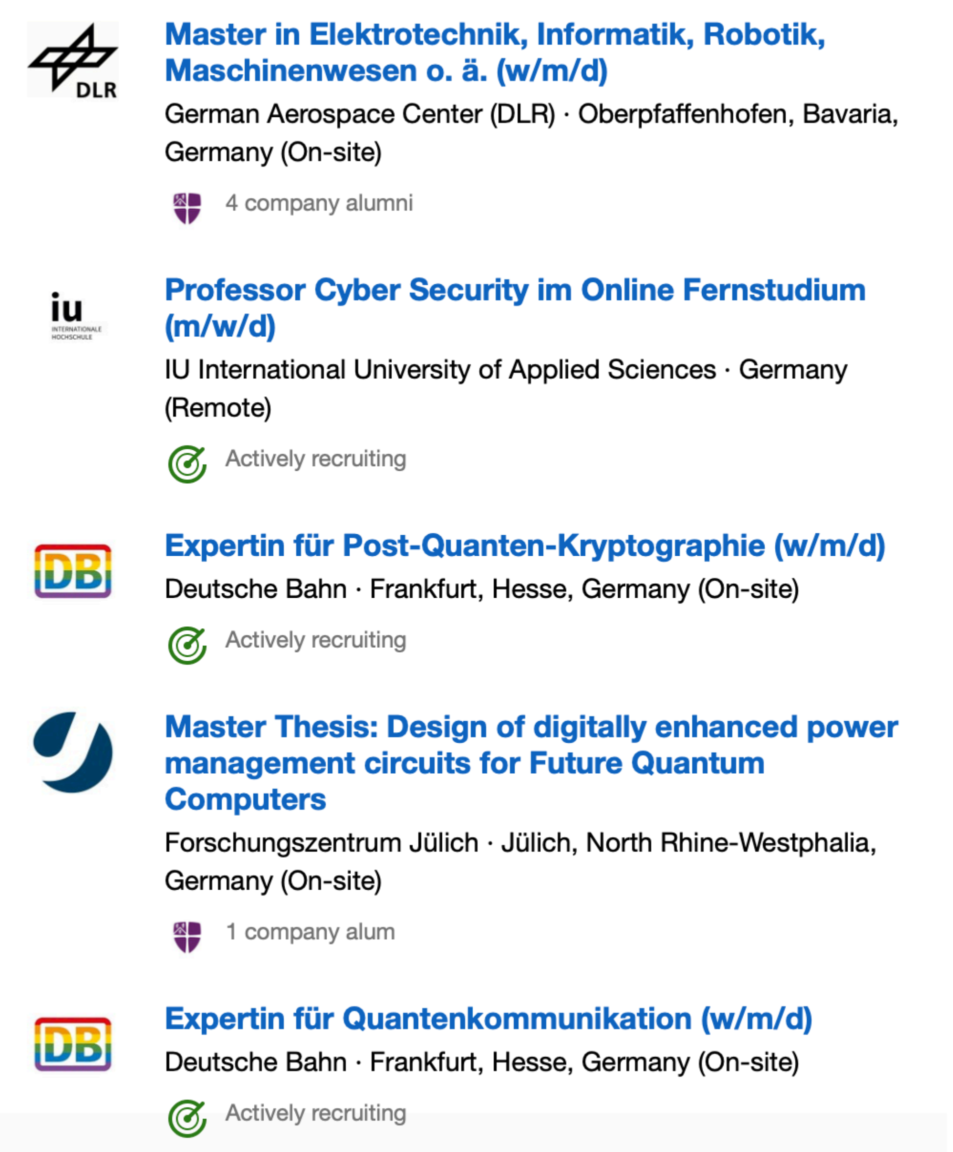
IPPP, Durham University



The Morning After: Google claims 'quantum supremacy'

And a controversial 'Ghost in the Shell' trailer.

R. Lawler
@Rjcc
October 24th, 2019



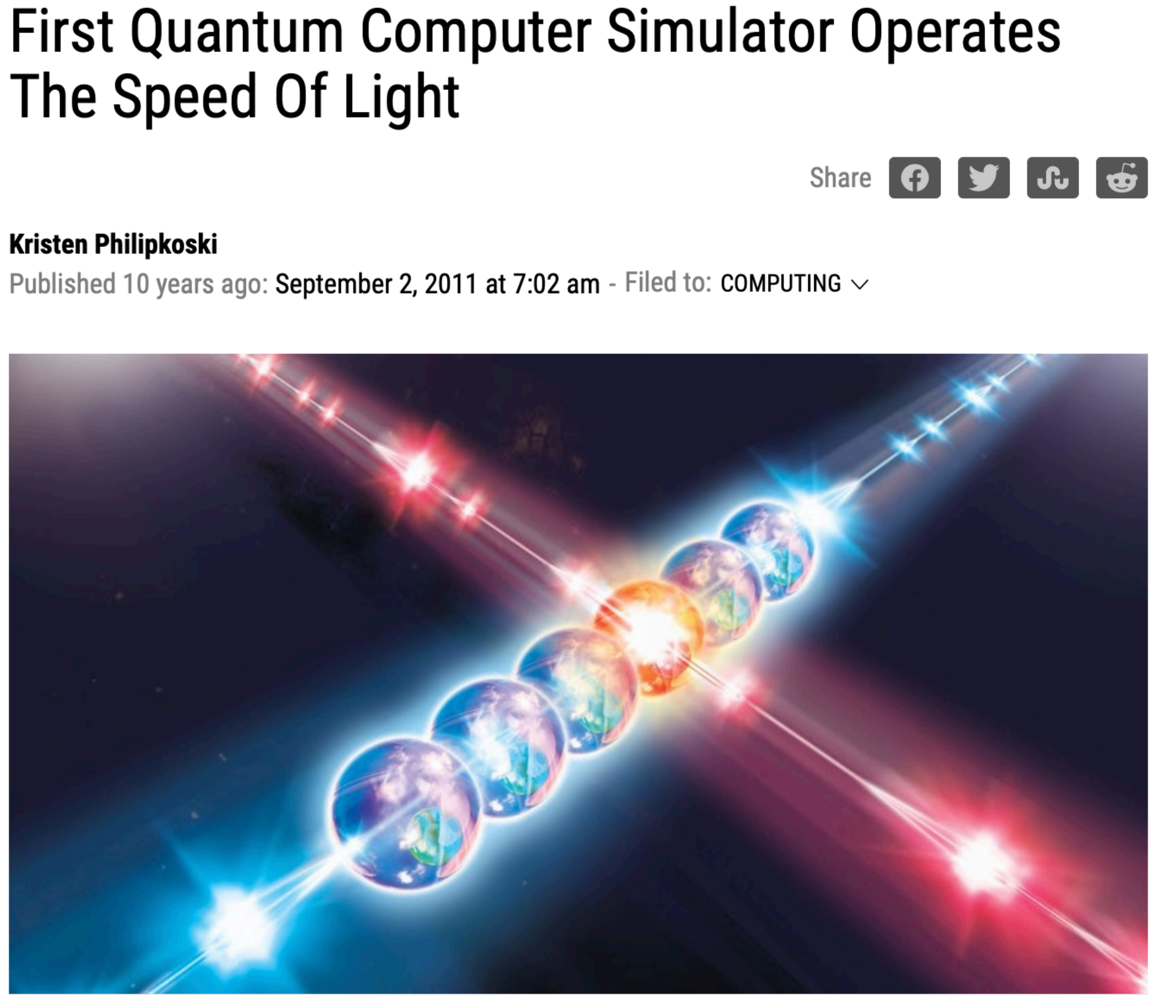
Master in Elektrotechnik, Informatik, Robotik, Maschinenwesen o. ä. (w/m/d)
German Aerospace Center (DLR) · Oberpfaffenhofen, Bavaria, Germany (On-site)
4 company alumni

Professor Cyber Security im Online Fernstudium (m/w/d)
IU International University of Applied Sciences · Germany (Remote)
Actively recruiting

Expertin für Post-Quanten-Kryptographie (w/m/d)
Deutsche Bahn · Frankfurt, Hesse, Germany (On-site)
Actively recruiting

Master Thesis: Design of digitally enhanced power management circuits for Future Quantum Computers
Forschungszentrum Jülich · Jülich, North Rhine-Westphalia, Germany (On-site)
1 company alum

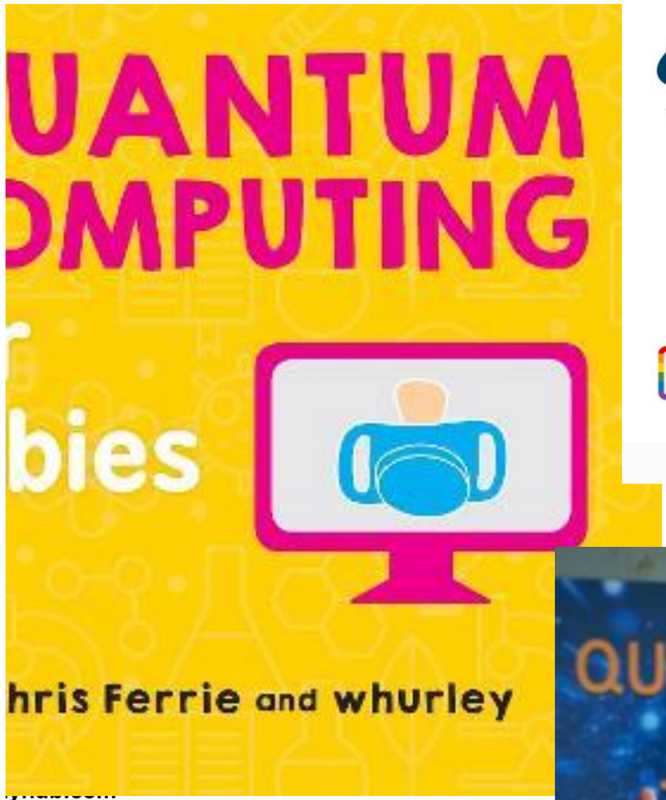
Expertin für Quantenkommunikation (w/m/d)
Deutsche Bahn · Frankfurt, Hesse, Germany (On-site)
Actively recruiting

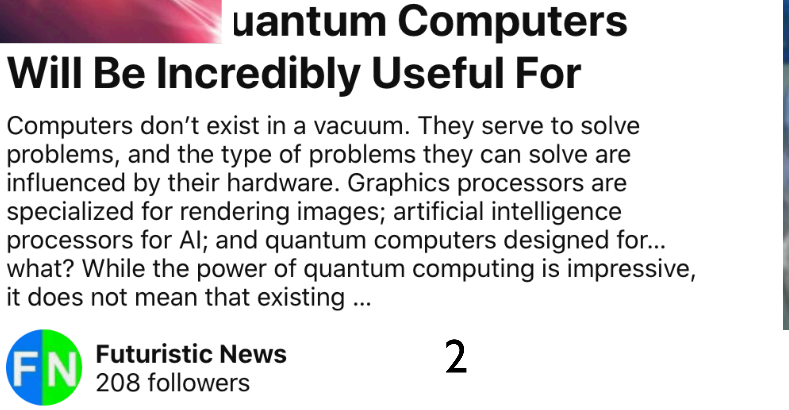


First Quantum Computer Simulator Operates The Speed Of Light

Share

Kristen Philipkoski
Published 10 years ago: September 2, 2011 at 7:02 am - Filed to: COMPUTING





uantum Computers Will Be Incredibly Useful For

Computers don't exist in a vacuum. They serve to solve problems, and the type of problems they can solve are influenced by their hardware. Graphics processors are specialized for rendering images; artificial intelligence processors for AI; and quantum computers designed for... what? While the power of quantum computing is impressive, it does not mean that existing ...

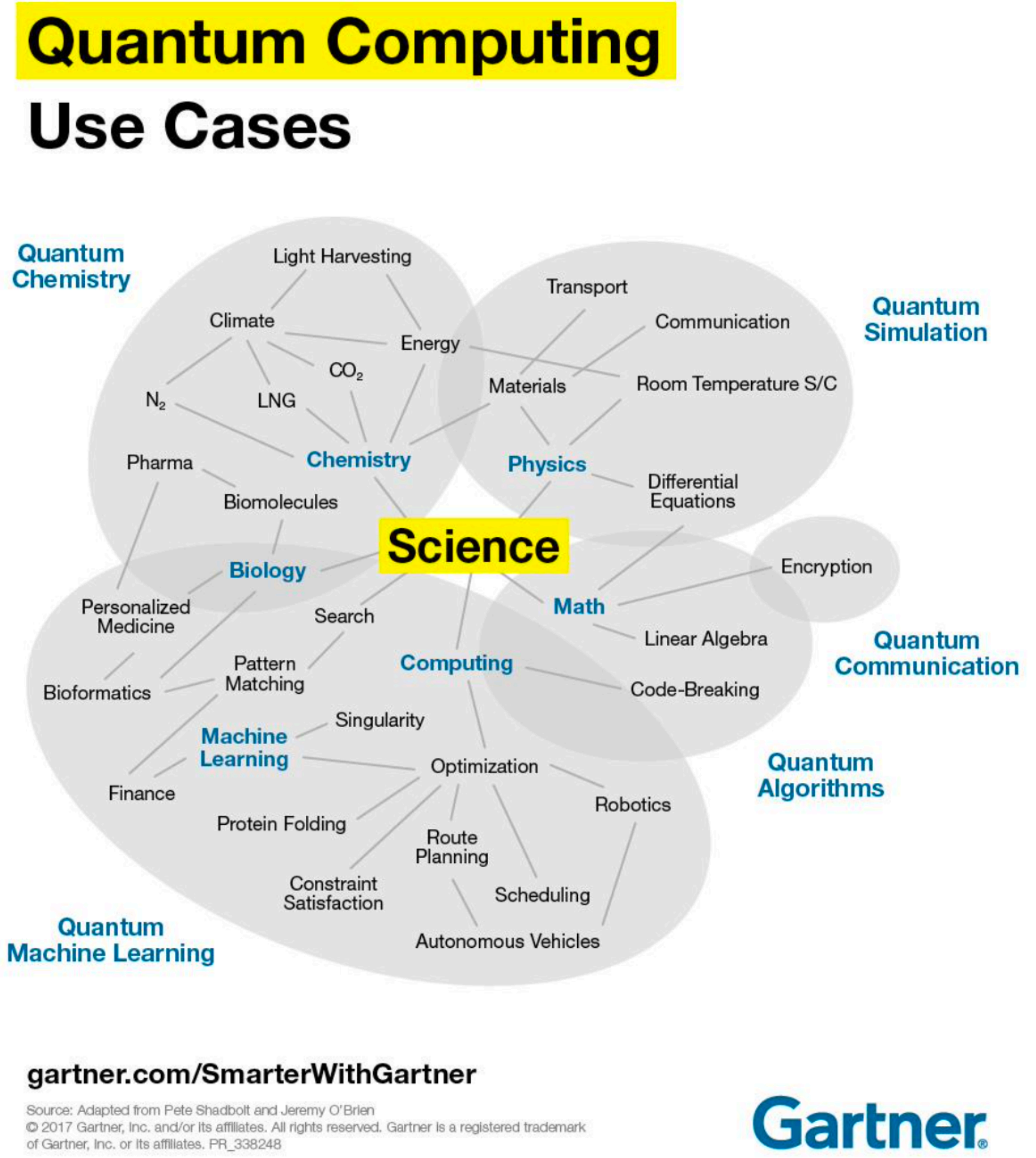
Futuristic News
208 followers

“Nature is quantum […]
so if you want to
simulate it, you need a
quantum computer”
- Richard Feynman
(1982)

Easily said … so how do we do that?

Beginning of a scientific journey that accelerated in recent years tremendously….

Private and Public Sector is placing big bets on Quantum Computing



Quantum Computing

Use Cases

gartner.com/SmarterWithGartner

Source: Adapted from Pete Shadbolt and Jeremy O'Brien
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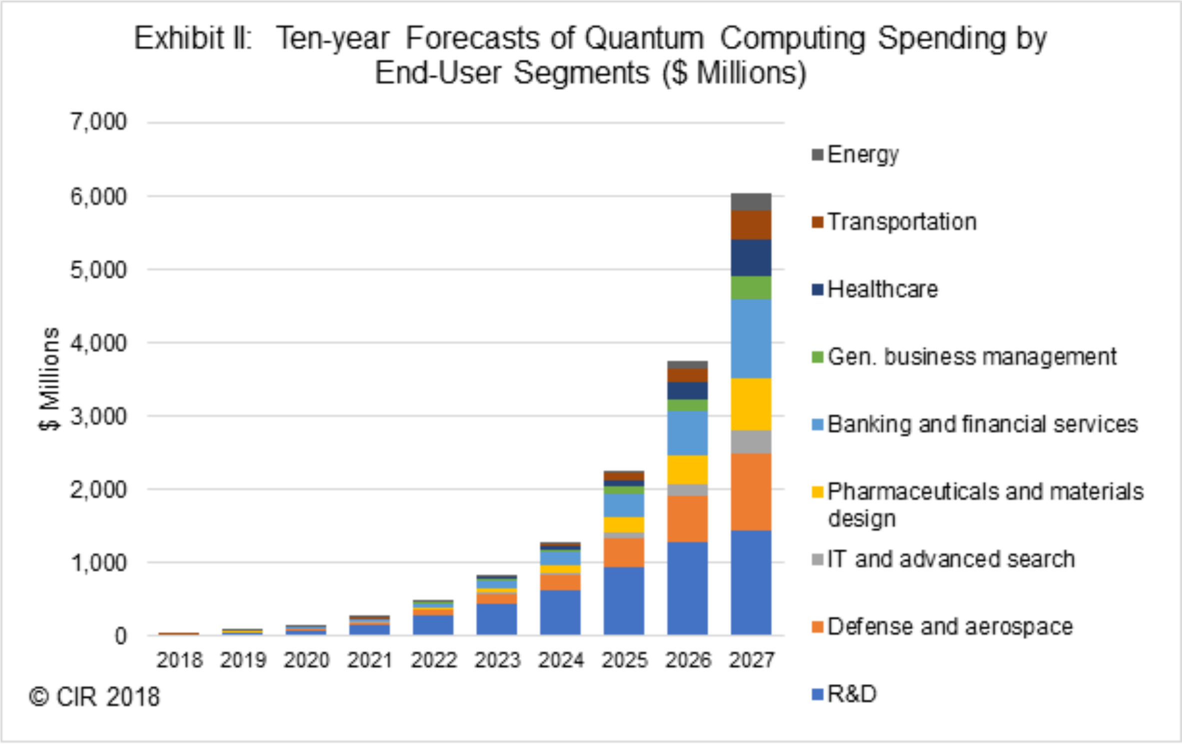


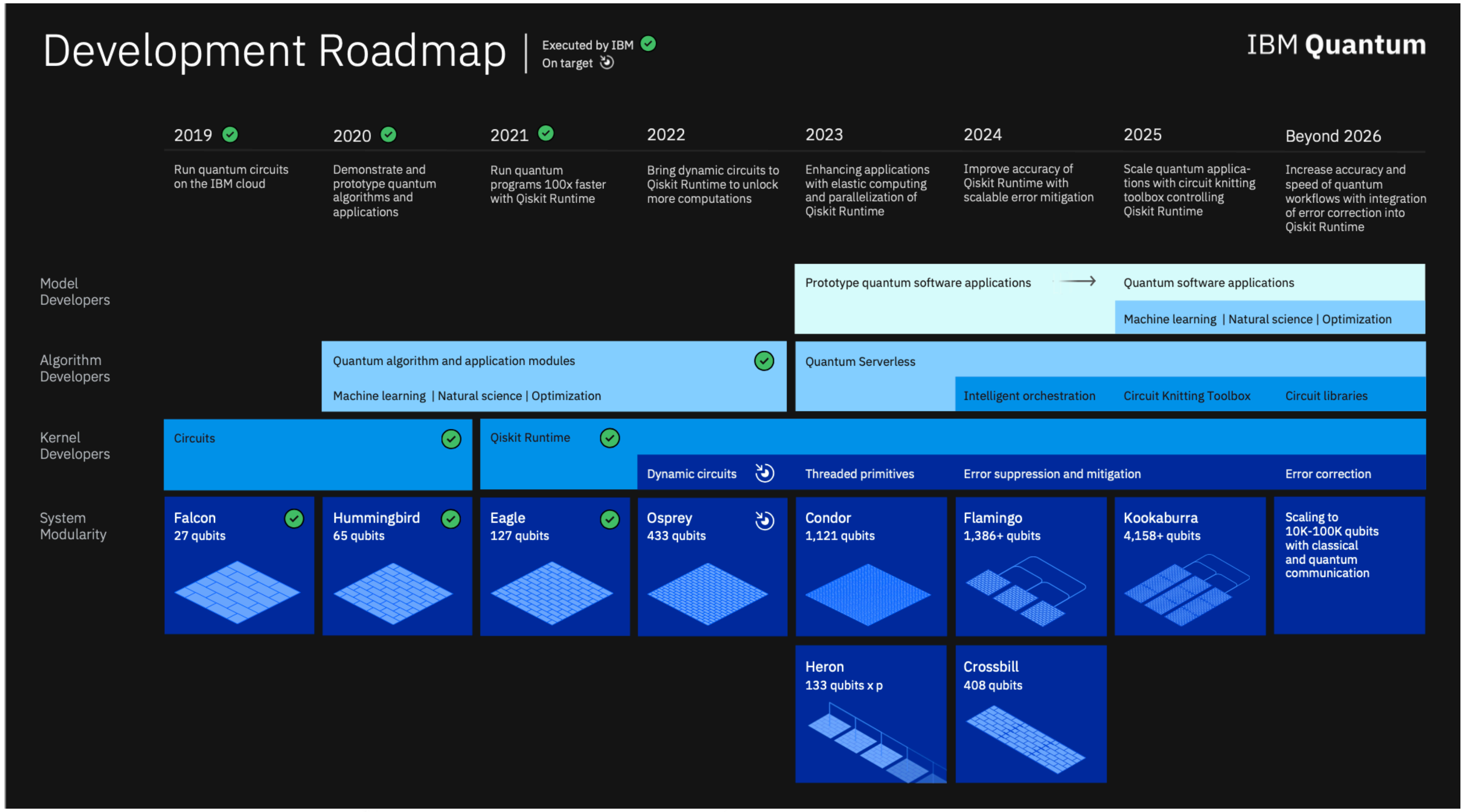
Exhibit II: Ten-year Forecasts of Quantum Computing Spending by End-User Segments ($ Millions)

© CIR 2018

Significant financial investment expected across many sectors

In US, already now higher financial investment from private than public sector

All national and international labs have QC programmes (Fermilab, BNL, LBNL, DESY, CERN, Singapur, Abu Dhabi, …)



Development Roadmap | Executed by IBM ✓ On target

IBM **Quantum**

	2019 ✓	2020 ✓	2021 ✓	2022	2023	2024	2025	Beyond 2026
	Run quantum circuits on the IBM cloud	Demonstrate and prototype quantum algorithms and applications	Run quantum programs 100x faster with Qiskit Runtime	Bring dynamic circuits to Qiskit Runtime to unlock more computations	Enhancing applications with elastic computing and parallelization of Qiskit Runtime	Improve accuracy of Qiskit Runtime with scalable error mitigation	Scale quantum applications with circuit knitting toolbox controlling Qiskit Runtime	Increase accuracy and speed of quantum workflows with integration of error correction into Qiskit Runtime
Model Developers					Prototype quantum software applications →		Quantum software applications Machine learning | Natural science | Optimization	
Algorithm Developers		Quantum algorithm and application modules ✓ Machine learning | Natural science | Optimization			Quantum Serverless	Intelligent orchestration	Circuit Knitting Toolbox	Circuit libraries
Kernel Developers	Circuits ✓		Qiskit Runtime ✓	Dynamic circuits	Threaded primitives	Error suppression and mitigation		Error correction
System Modularity	Falcon ✓ 27 qubits	Hummingbird ✓ 65 qubits	Eagle ✓ 127 qubits	Osprey 433 qubits	Condor 1,121 qubits	Flamingo 1,386+ qubits	Kookaburra 4,158+ qubits	Scaling to 10K-100K qubits with classical and quantum communication
					Heron 133 qubits x p	Crossbill 408 qubits		

→ FCC

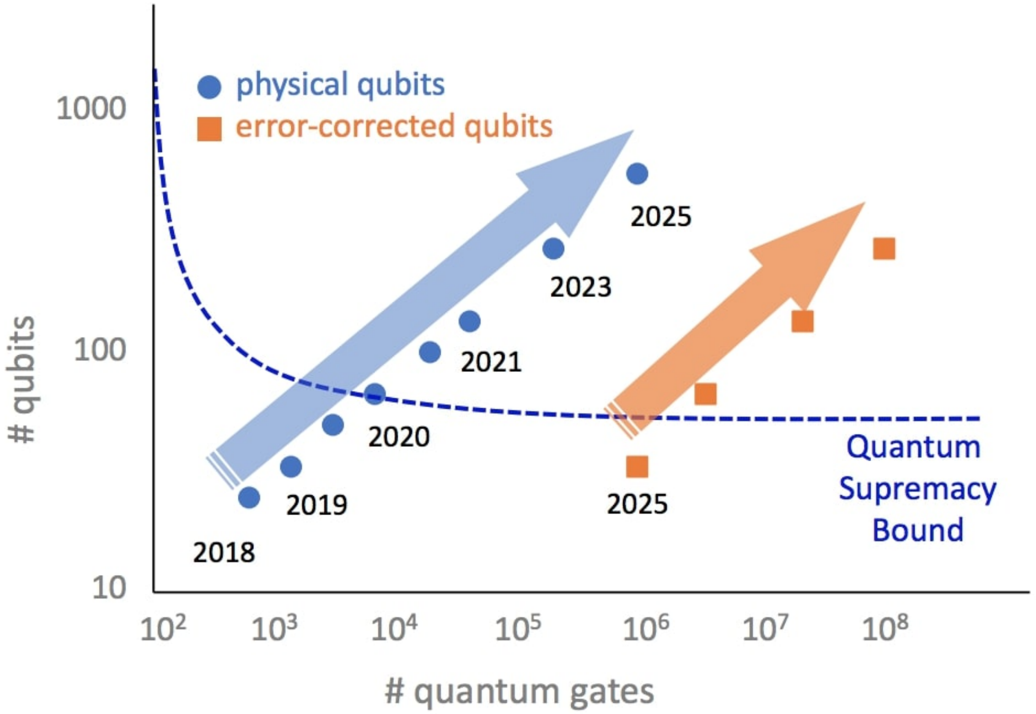
1 mio physical qubits

->

1k logical qubits

by 2029

IonQ Roadmap into the Future

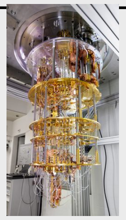
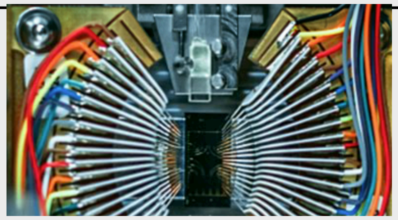
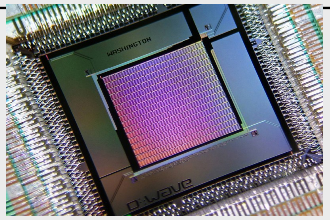
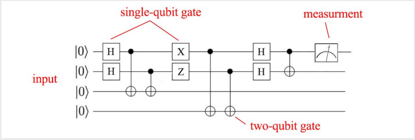
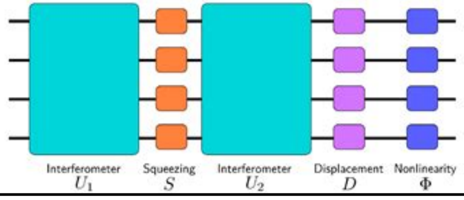
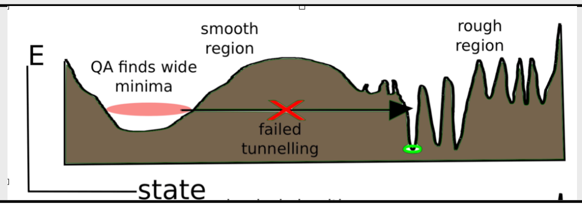


Design Principle

$$Qubits = \sqrt{Gates}$$

timescales much smaller than FCC's

Popular Quantum Computing paradigms

Type	Discrete Gate (DG)	Continuous Variable (CV)	Quantum Annealer (QA)
Computing	Digital	Digital/Analog	Analog
Property	Universal (any quantum algorithm can be expressed)	Universal - GBS non-Universal	Not universal — certain quantum systems
Advantage	most algorithms and tech support	uncountable Hilbert (configuration) space	continuous time quantum process
How?	IBM - Qiskit ~500 Qubits	Xanadu	DWave - LEAP ~7000 Qubits
What?			
			

See S. Abel

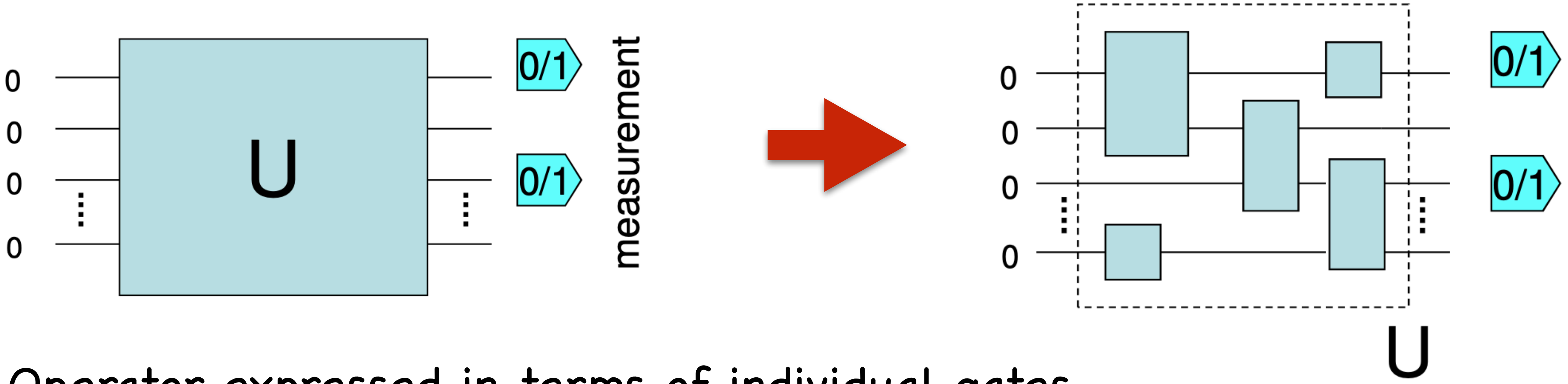
How most quantum algorithms work

operator acts on Hilbert space states $U\,|x\rangle = |\Psi_1\rangle$

measurement of observable $\hat{U}$ corresponds to exp. value of operator U $\left\langle \hat{U} \right\rangle_\Psi = \frac{\langle\Psi|U|\Psi\rangle}{\langle\Psi|\Psi\rangle}$

statistical statement need to evaluate often

Need to encode Hilbert space and operator suitable for quantum system

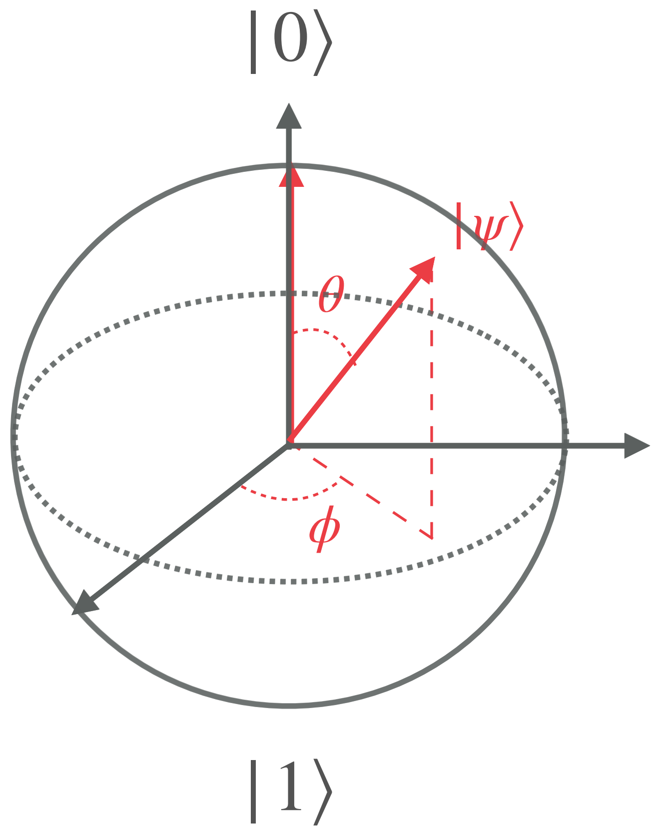


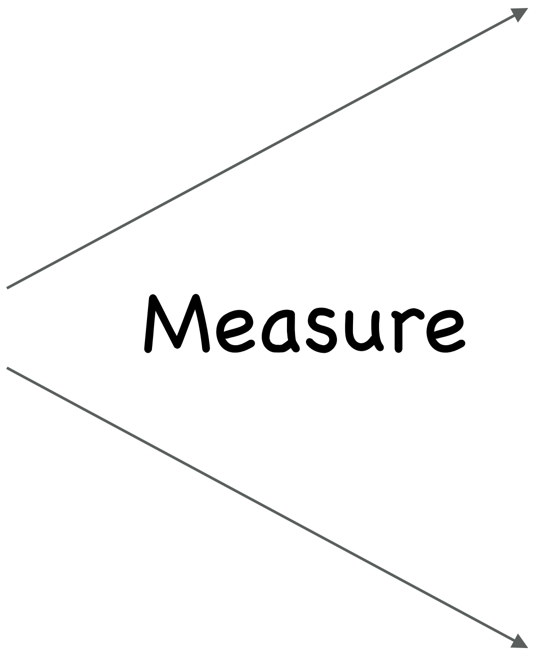
- Operator expressed in terms of individual gates
- Often ‘Trotterization’ (Suzuki-Trotter decomposition) needed:

For $H = \sum_{j=1}^{m} H_j \longrightarrow e^{iHt} = \left(\prod_{j=1}^{m} e^{-iH_j t/r} \right)^r + \mathcal{O}(m^2 t^2 / r)$

Rotation about the Bloch Sphere and state parametrisation

$$|\psi\rangle = \cos\frac{\theta}{2}|0\rangle + e^{i\phi}\sin\frac{\theta}{2}|1\rangle = \begin{pmatrix} \cos\frac{\theta}{2} \\ \sin\frac{\theta}{2}e^{i\phi} \end{pmatrix}$$





Measure

$|0\rangle$

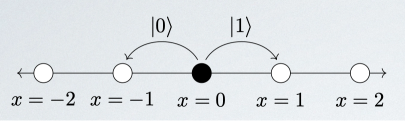
$|1\rangle$ $\text{Prob}\big(|1\rangle\big) = \left(e^{i\phi}\sin\frac{\theta}{2}\right)^2$

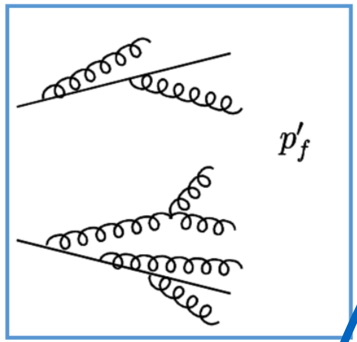
$|0\rangle$ $\text{Prob}\big(|0\rangle\big) = \left(\cos\frac{\theta}{2}\right)^2$

$|1\rangle$

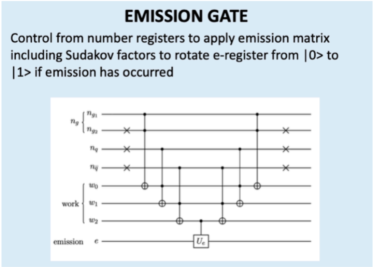
Apply Unitary rotation $U_3|0\rangle$: $U_3(\theta,\phi,\lambda) = \begin{pmatrix} \cos\left(\frac{\theta}{2}\right) & -e^{i\lambda}\sin\left(\frac{\theta}{2}\right) \\ e^{i\phi}\sin\left(\frac{\theta}{2}\right) & e^{i(\phi+\lambda)}\cos\left(\frac{\theta}{2}\right) \end{pmatrix}$

Extending this to a system of N qubits forms a 2^N-dimensional Hilbert Space





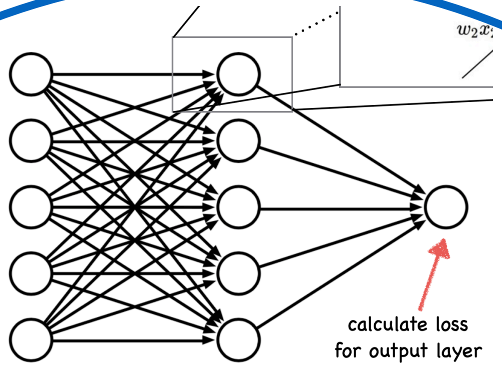
Particle Collision Calculations



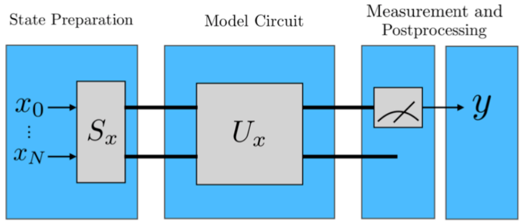
EMISSION GATE

Control from number registers to apply emission matrix including Sudakov factors to rotate e-register from |0> to |1> if emission has occurred

New physics searches



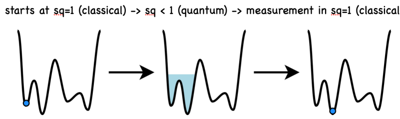
Data analysis



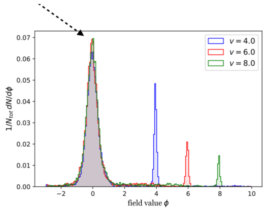
HEP

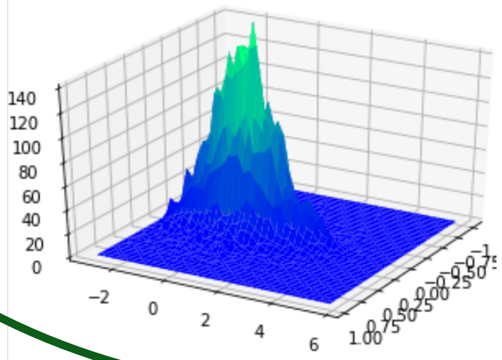
Multi particle dynamics

Matter antimatter asymmetry



Quantum Field Theory





See talk by S. Williams

See also talk by S. Abel

HEP application focused quantum simulation

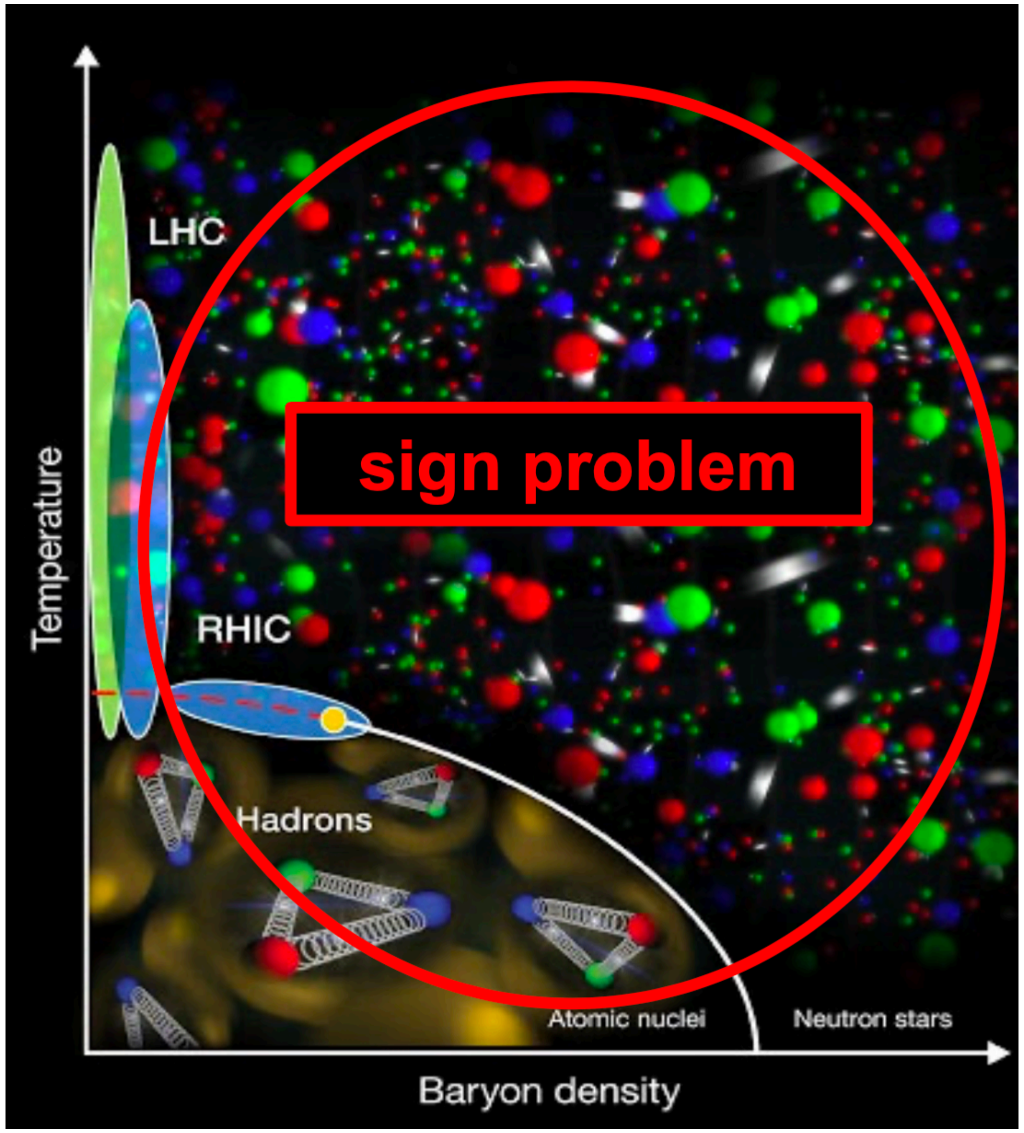
- Sign problem - profound challenge for simulation of field theories
  - Can arise in presence of chemical potential, topological terms, multi-particle dynamics, …
- Example chemical potential $\mu\bar{\psi}\gamma^0\psi$

$$Z = \int \mathscr{D}\bar{\psi}\mathscr{D}\psi\mathscr{D}A \; e^{-S[\bar{\psi},\psi,A]} \quad \text{(partition function)}$$

$$S = \int_0^{1/T} d\tau \int d^3x \left[\bar{\psi}(\gamma^\mu D_\mu + m)\psi + \frac{1}{4}F^a_{\mu\nu}F^{a\mu\nu} + \mu\bar{\psi}\gamma^0\psi\right]$$

and integration over fermion fields and Wick rotation

$$Z = \int \mathscr{D}A e^{-S_{\text{gauge}}[A]} \cdot \det(\gamma^\mu D_\mu + m + \mu\gamma^4) \longrightarrow \text{For } \mu \neq 0 \text{ complex phases don't cancel}$$



HEP application focused quantum simulations

- Importance sampling

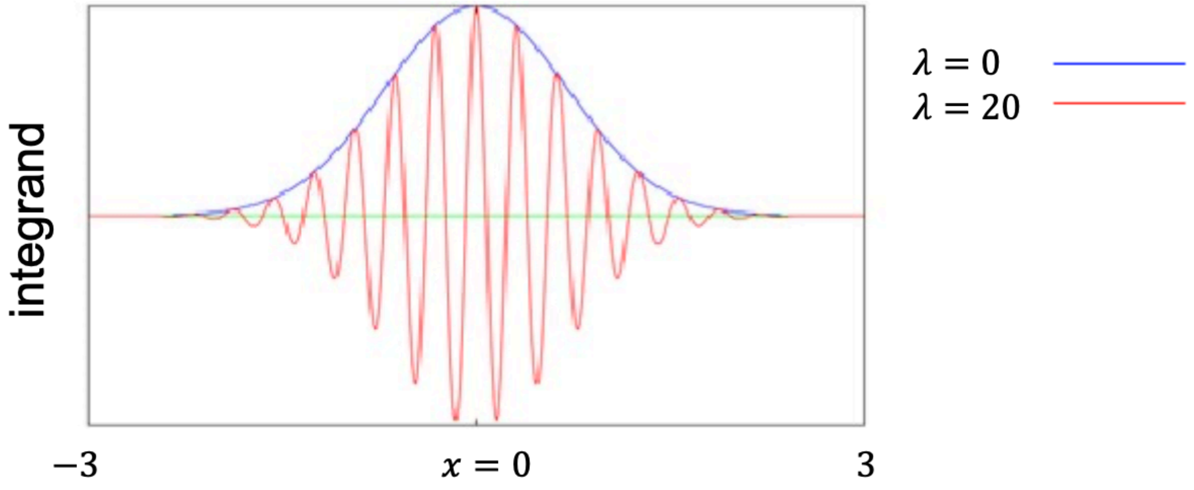
  Interpretation of $e^{-S_{\text{gauge}}} \det(M)$

  as probability weight

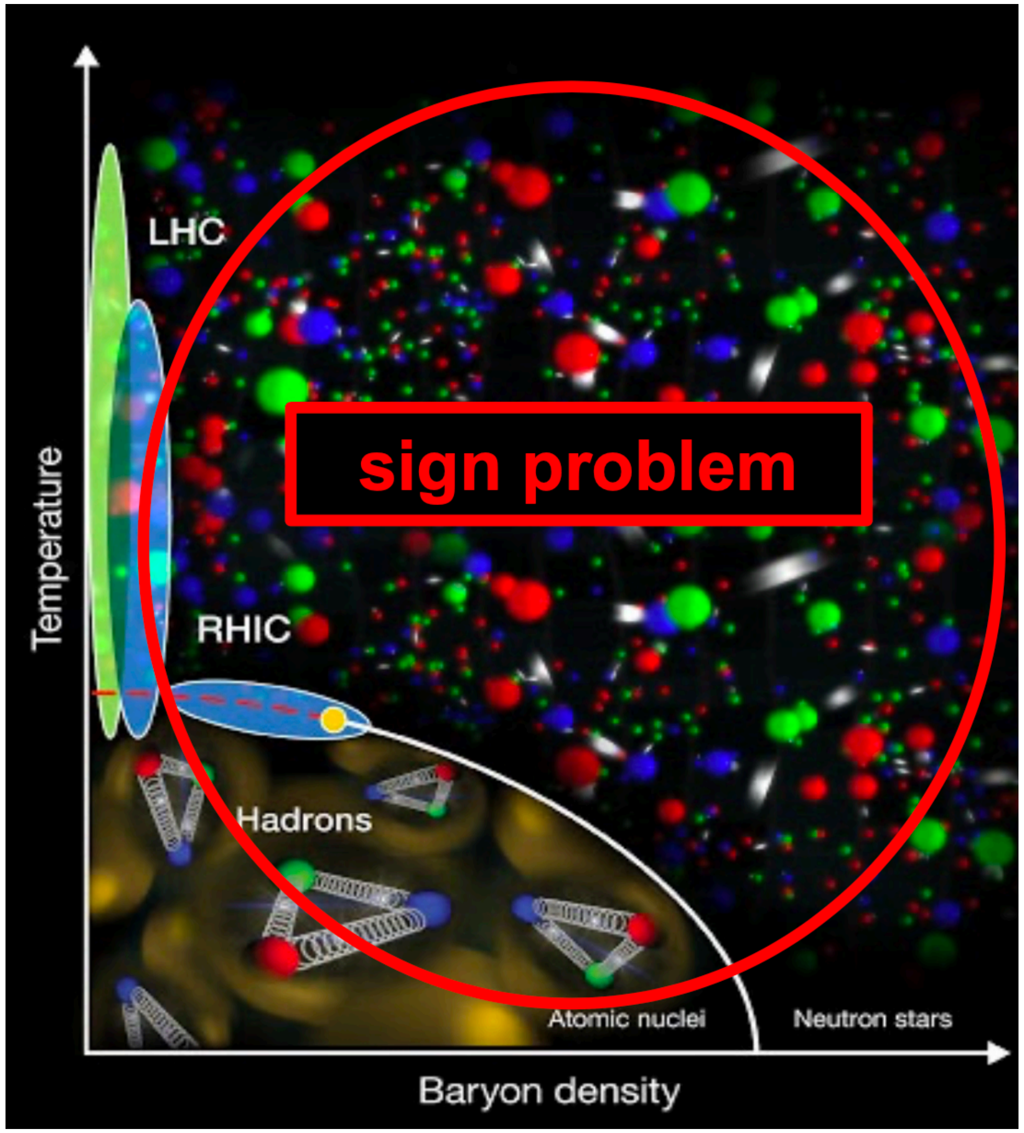
- Highly oscillatory integrands

$$\langle O \rangle = \frac{\int \mathscr{D}A e^{-S_{\text{gauge}}} \, O \, |\det(M)| e^{i\phi}}{\int \mathscr{D}A e^{-S_{\text{gauge}}} |\det(M)| e^{i\phi}}$$

near cancellation of pos and neg contribs



$$\int dx \exp(-x^2 + i\lambda x) \to \int dx \exp(-x^2) \cos(\lambda x)$$

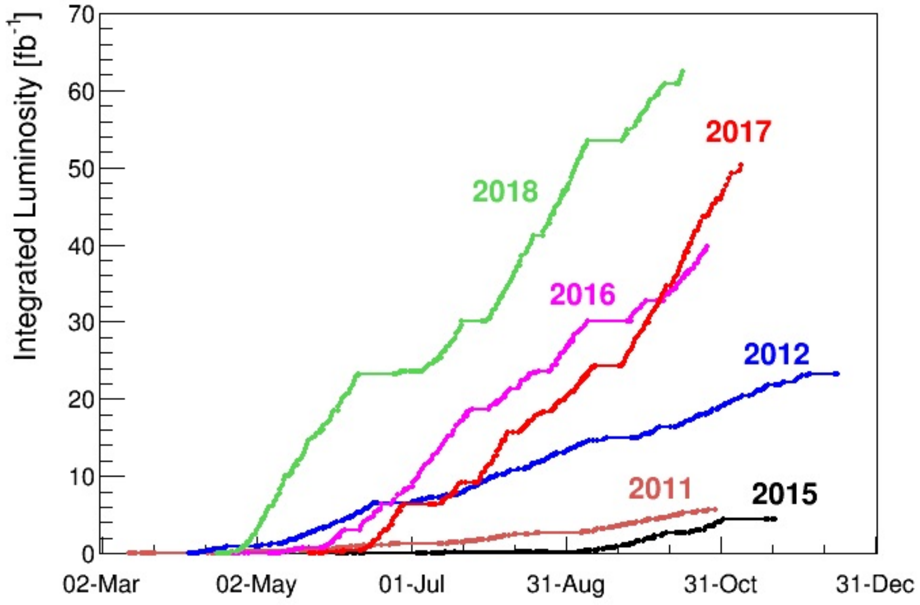


[de Forcrand '10]

Big Data in HEP @ the LHC

→ ATLAS/CMS 200 events/s passing triggers

→ ATLAS/CMS 2 PB/year of data



High-Energy Physics

Tremendous amount of highly complex data

However, theoretically very precise description of data

Machine Learning

Highly performant data analysis techniques

Often used for classification in HEP:

- Supervised learning
- Anomaly detection

⟷

Ideal interplay

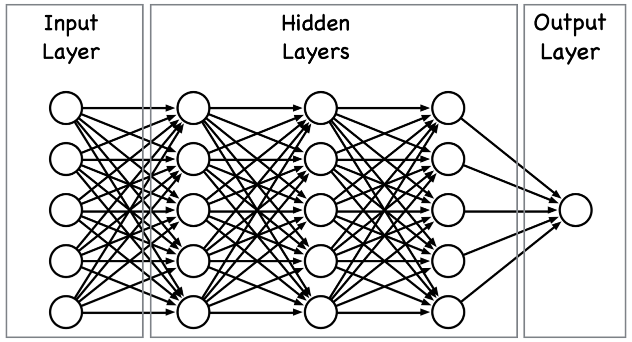
See talk by T. Golling

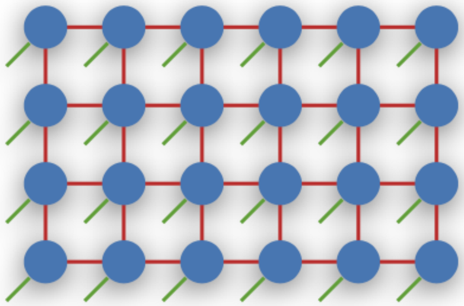
Classical ML Algorithms

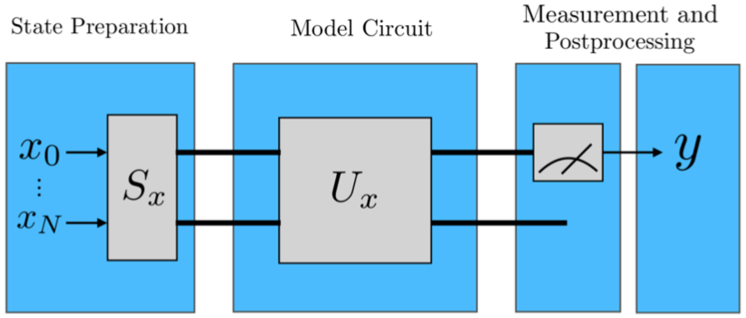
Tensor Networks

Quantum Computing

1. an adaptable complex system that allows approximating a complicated function







2. the calculation of a loss function used to define the task the method

$$E(y,y') = \frac{1}{2}|y-y'|^2$$

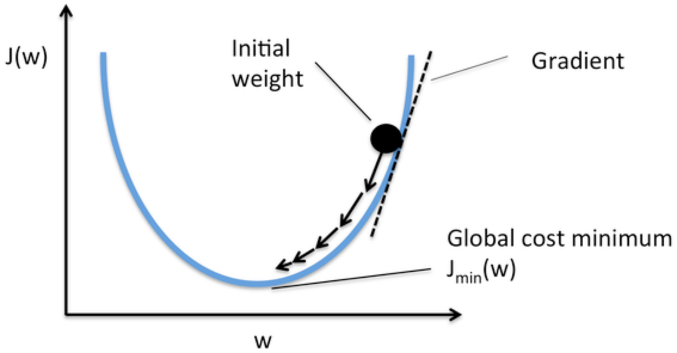
$$B^{s_2}{}_{p_1 p_2}\Gamma^{l p_1 p_2}{}_{s_2} = f^l(\mathbf{x}^{(\mathbf{n})})$$

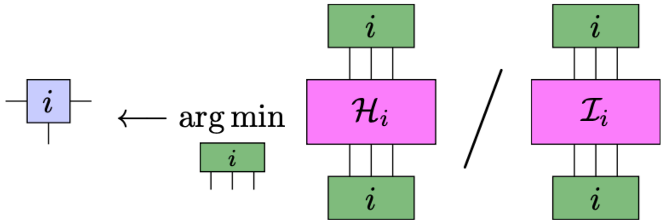
$$\mathcal{L} = L\left(p(l,\mathbf{x}),\ l^{truth}\right)$$

ground state

$$|\Gamma\rangle := \arg\min_{|\psi\rangle\in\mathcal{D}} \frac{\langle\psi|H|\psi\rangle}{\langle\psi|\psi\rangle}$$

3. a way to update 1. while minimising the loss function





quantum: annealing

hybrid: classical opti.

optimisation → Data Analysis (Classification, anomaly, regression, fitting, ...)
→ Simulation of field theories (Groundstate, tunnelling, Real-time...)
→ Calculation of differential equations, etc etc

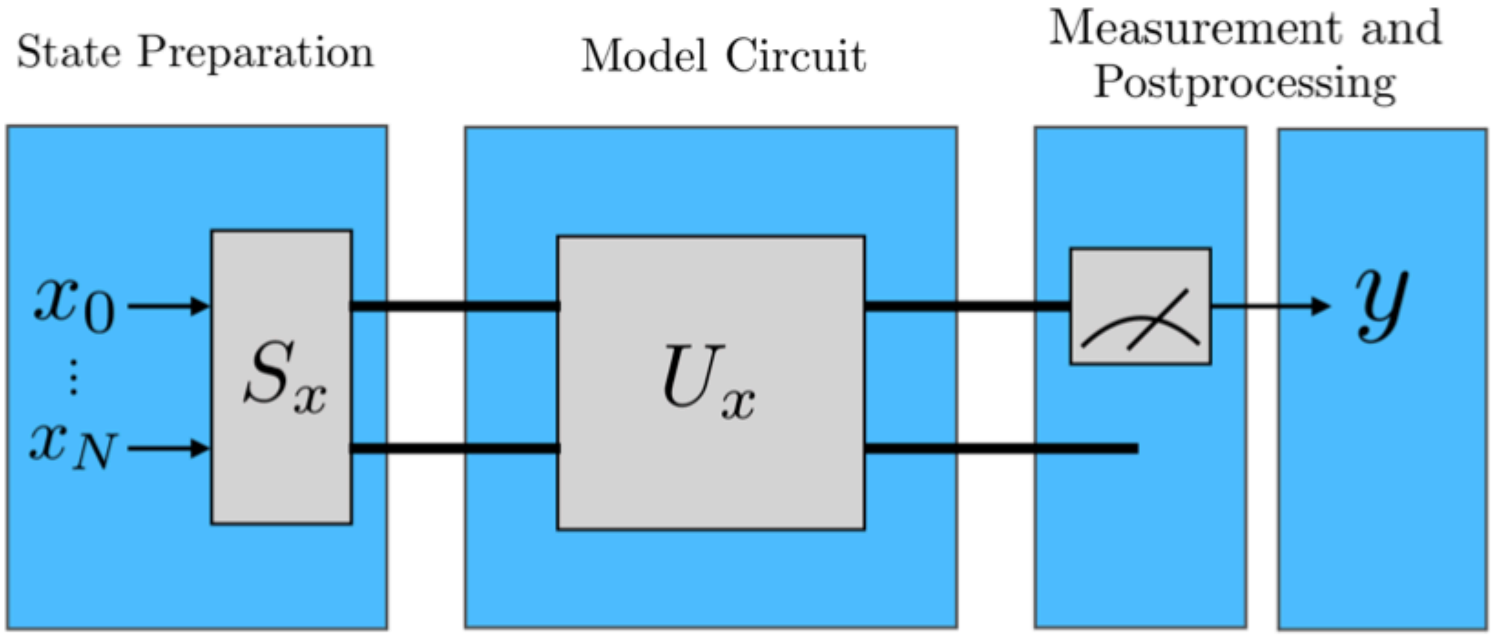
Quantum Machine Learning with a Variational Quantum Circuit

[McClean et al '16]

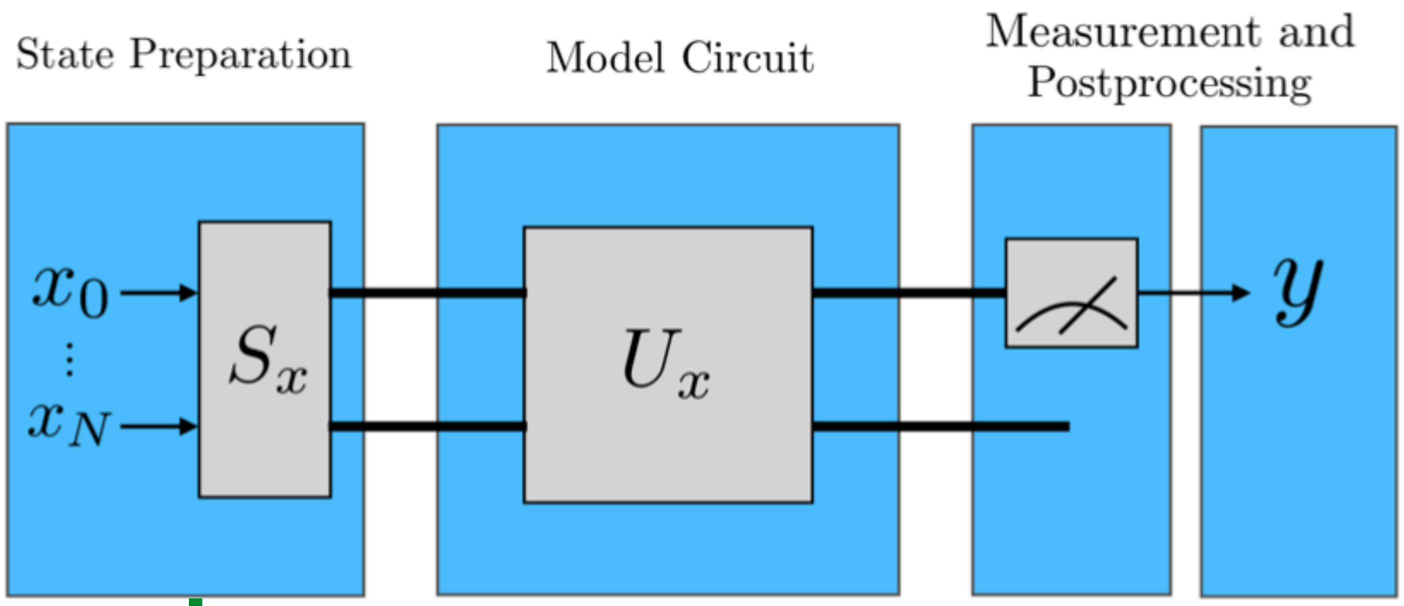
[Farhi, Neven '18]

[Schuld et al '20]

[Blance, MS '20]



Quantum Machine Learning
with a Variational Quantum Circuit



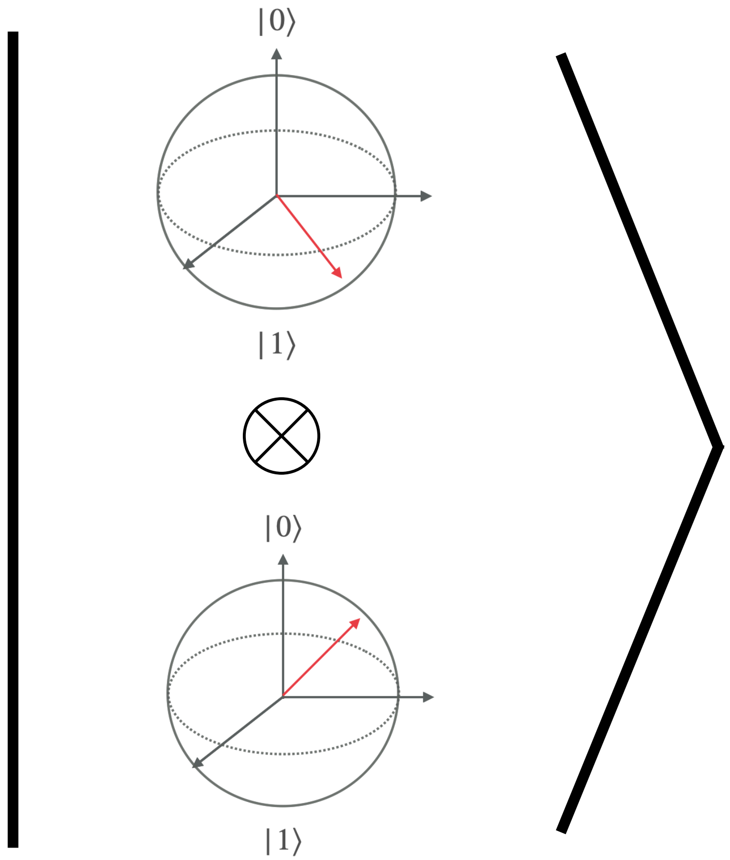
state preparation

n corresponds to # features

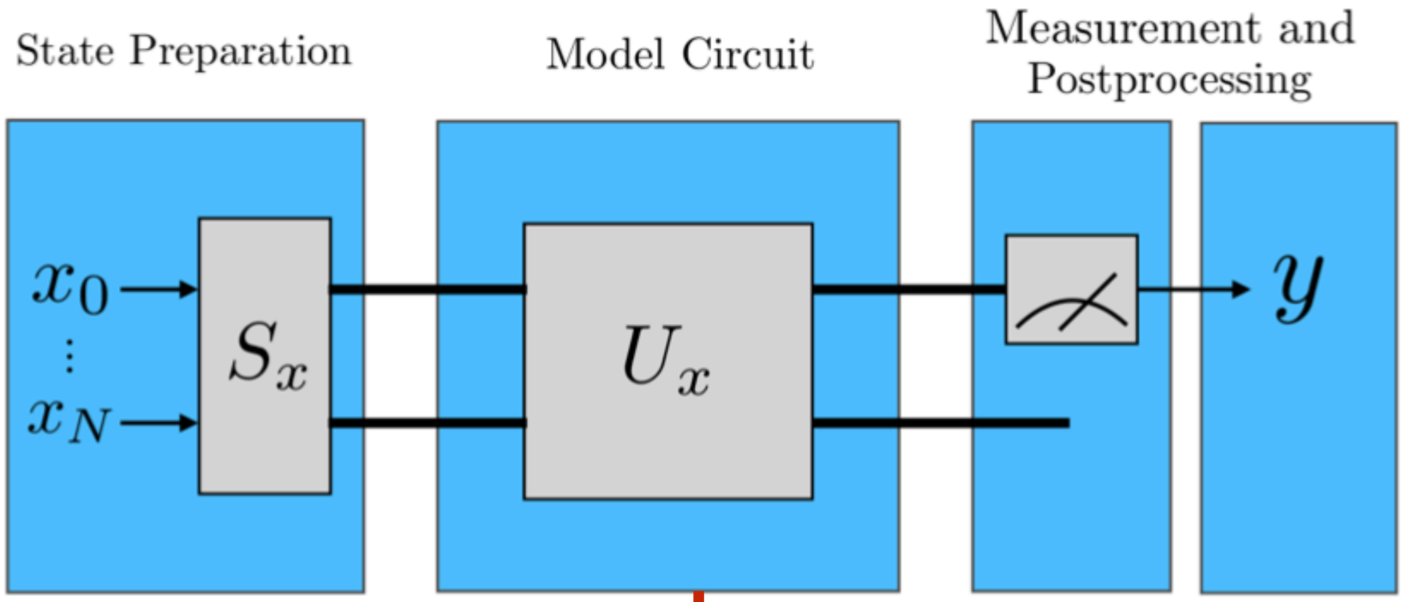
$$x \mapsto S_x|\phi\rangle = S_x|0\rangle^{\otimes n} = |x\rangle$$

e.g. angle encoding

$$|x\rangle = \bigotimes_{i=1}^{n} \cos(x_i)|0\rangle + \sin(x_i)|1\rangle$$



Quantum Machine Learning
with a Variational Quantum Circuit



$$|\psi\rangle = U(w)|x\rangle$$

with

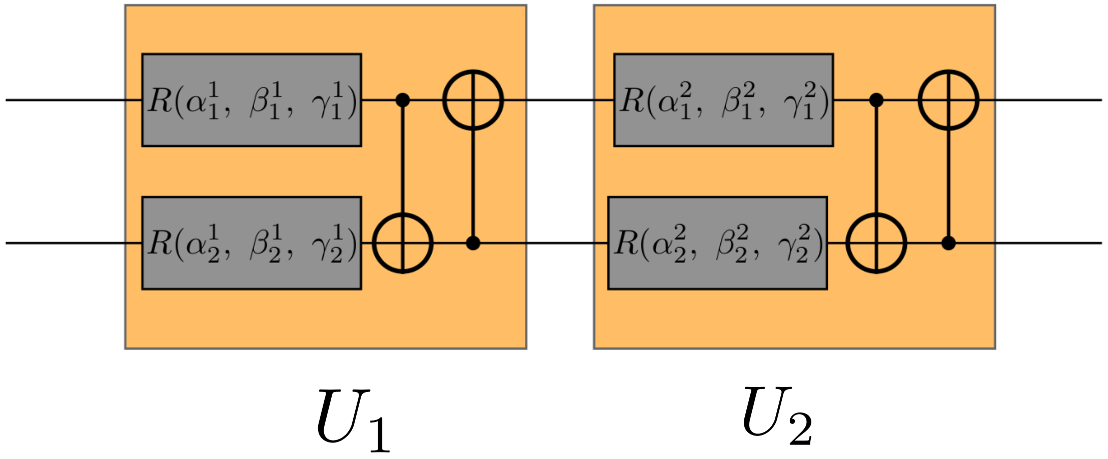
$$U(w) = U_{l_{\max}}(w_{l_{\max}})...U_l(w_l)...U_1(w_1)$$

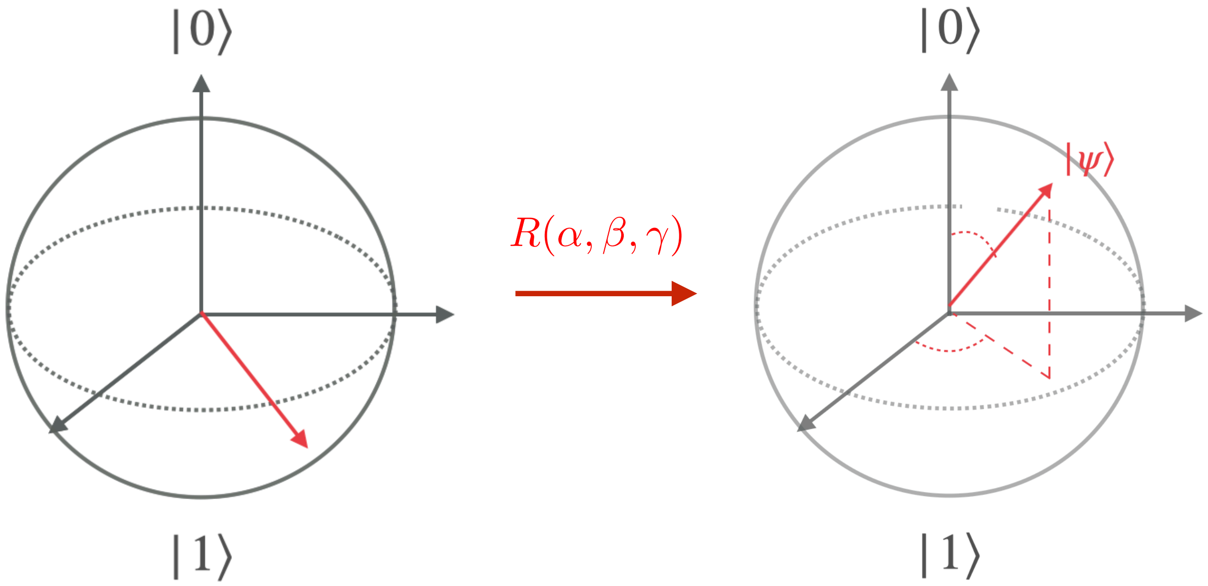
model circuit

trainable parameters

prepared state

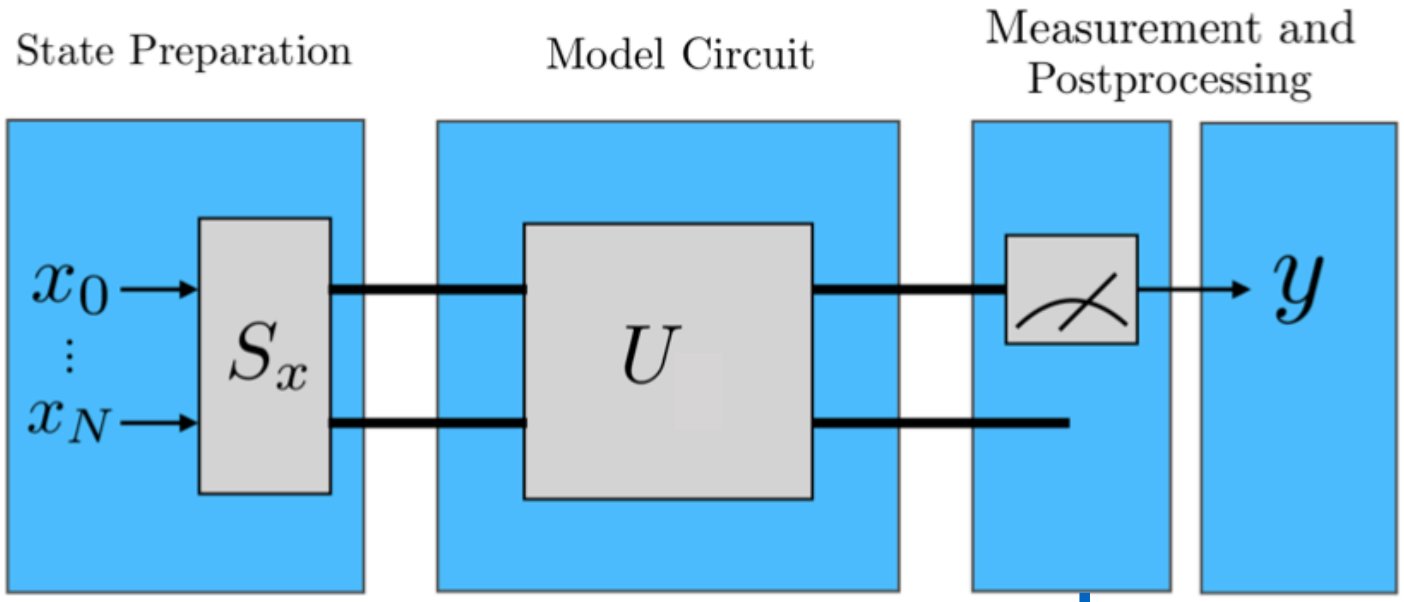
2-layer Variational Quantum Circuit





→ Rotation + CNOT -> Entanglement

Quantum Machine Learning with a Variational Quantum Circuit



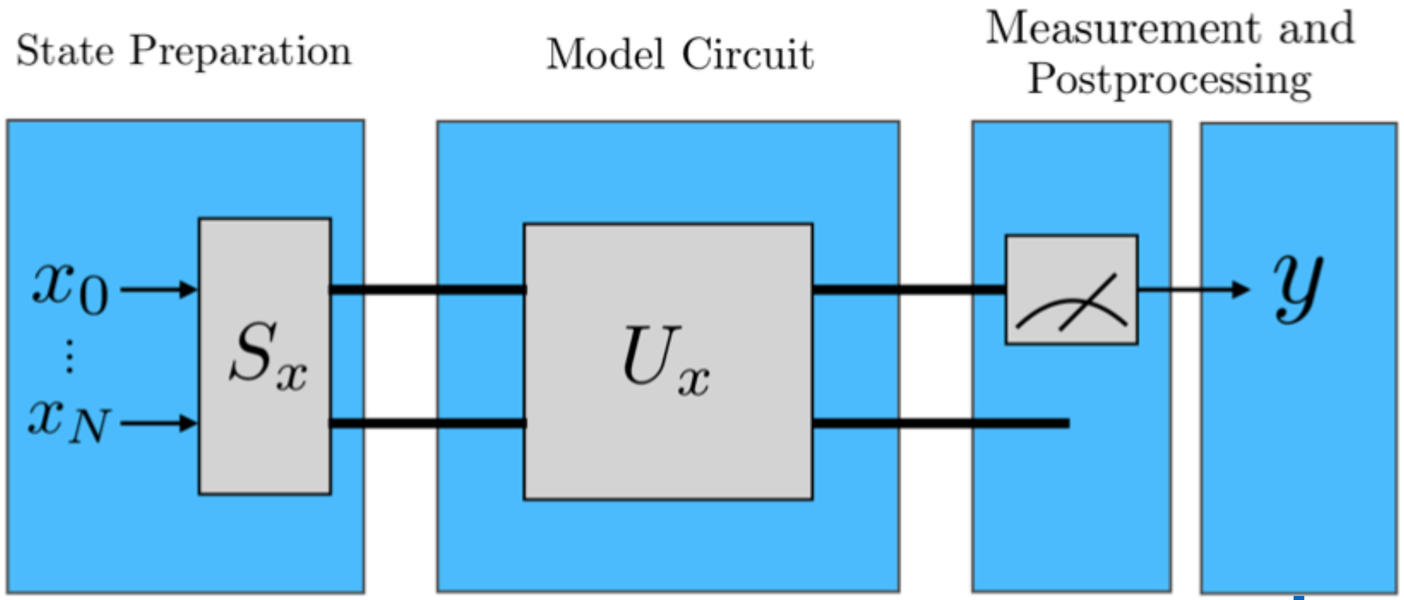
- Entangled state shares information across qubits
- Evaluate expectation value of qubits to construct loss

for supervised S vs B classification one qubit sufficient

$$\mathbb{E}(\sigma_z) = \langle 0|S_x(x)^\dagger U(w)^\dagger \hat{O} U(w) S_x(x)|0\rangle = \pi(w,x) \quad \text{for} \quad \hat{O} = \sigma_z \otimes \mathbb{I}^{\otimes(n-1)}$$

- Quantum network output: $f(w,b,x) = \pi(w,x) + b$
- Changing operator and loss => VQE, VQT, ... (simulate QFT)

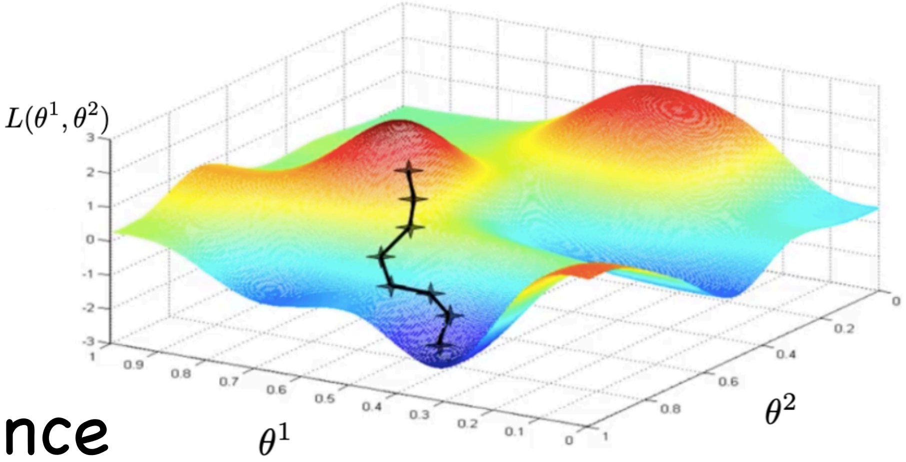
Quantum Machine Learning with a Variational Quantum Circuit



- Hybrid approach (QC to calculate exp. value, CC to optimise U operator)

- Loss function $L = \frac{1}{n}\sum_{i=1}^{n}\left[y_i^{\text{truth}} - f(w,b,x_i)\right]^2$

label (signal, bkg), supervised learning



- Quantum gradient descent - for fast convergence

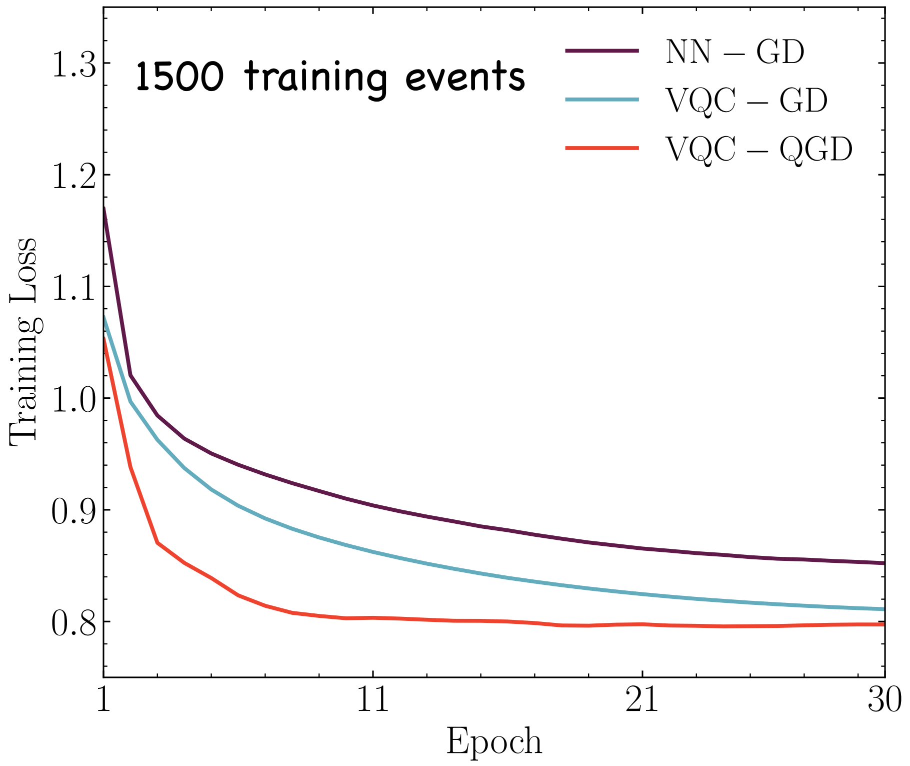
Fubiny-Study metric underlies geometric structure of VQC parameter space: $\theta_{t+1} = \theta_t - \eta g^{+}\nabla L(\theta)$

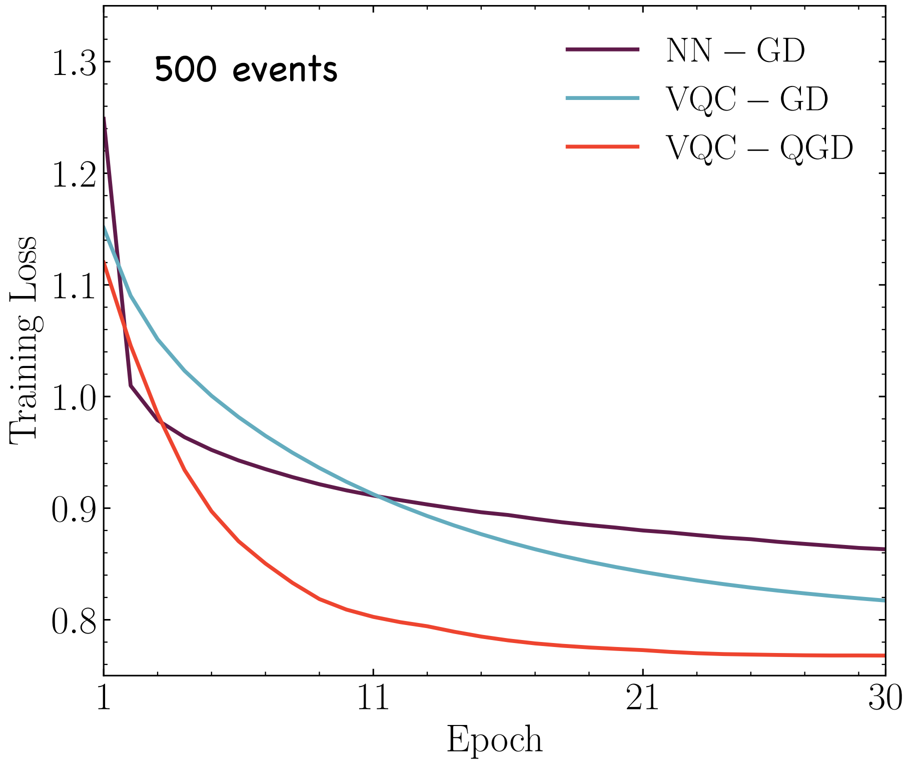
[Cheng '10]

[Blance, MS '20]

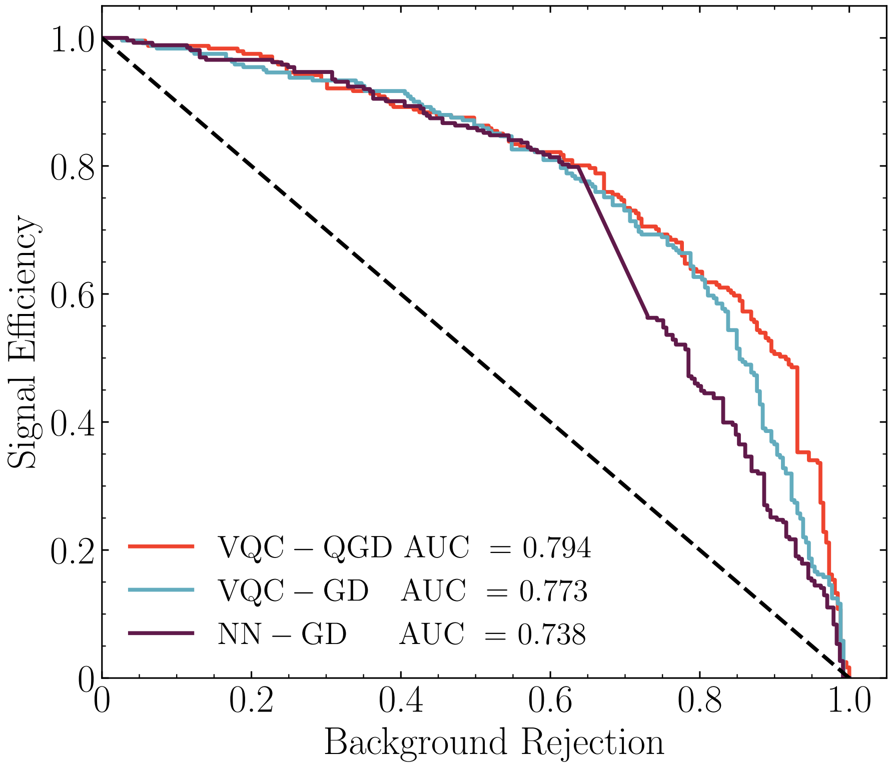
[Abbas et al '20]

Gate quantum machine learning in action





[Blance, MS '20]



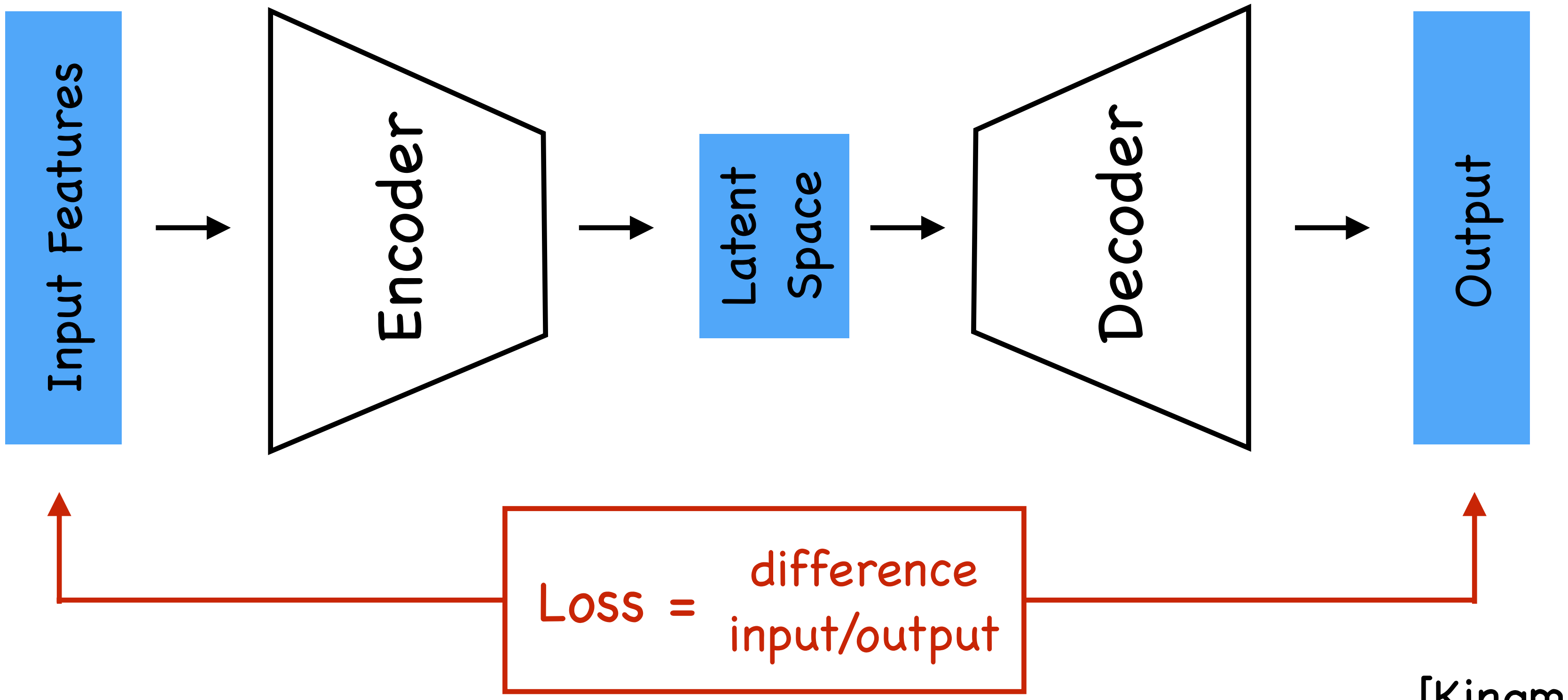
QC device vs simulator

Device	**Accuracy (%)**
PennyLane default.qubit	72.6
ibmq_qasm_simulator	72.6
ibmqx2	71.4

- Applied to $pp \to t\bar{t}$ vs $pp \to Z' \to t\bar{t}$ lept. top dec for 2d feature space only p_{T,b_1} and $\not{E}_T$

Autoencoder for unsupervised learning

Most popular NN-based anomaly detection method



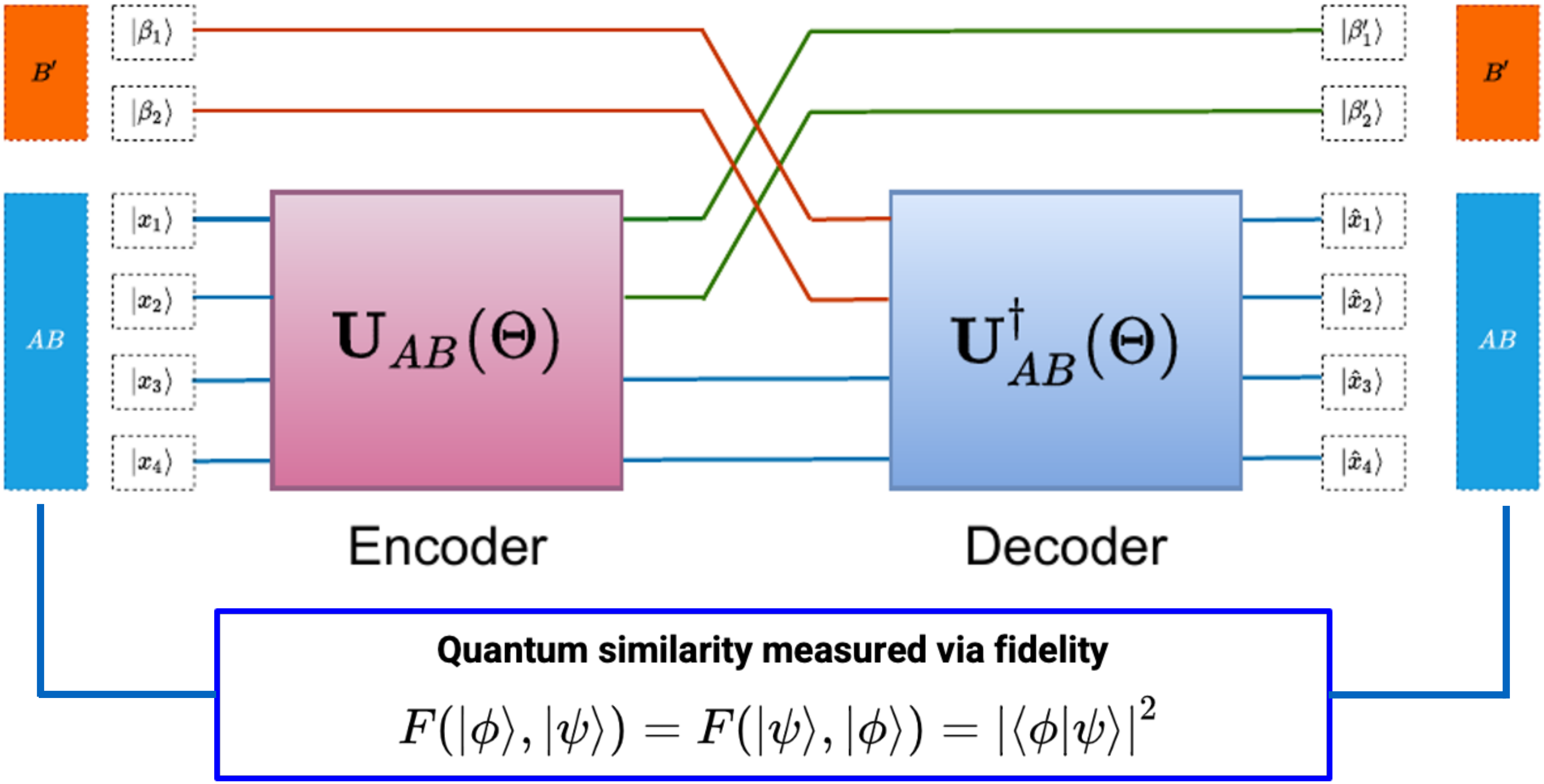
Don't see T. Golling

[Kingma, Welling '13]

- in first step input is encoded into information bottleneck
- between input/output layer and bottleneck can be several hidden layers (conv./deep NNs) -> highly non-linear
- after bottleneck decoding step
- Reconstructed output is then compared with input via loss-function (often MSE)
- NN is trained such that input and output high degree of similarity

Unsupervised learning with quantum-gate Autoencoder

[Ngairangbam, MS, Takeuchi '21]



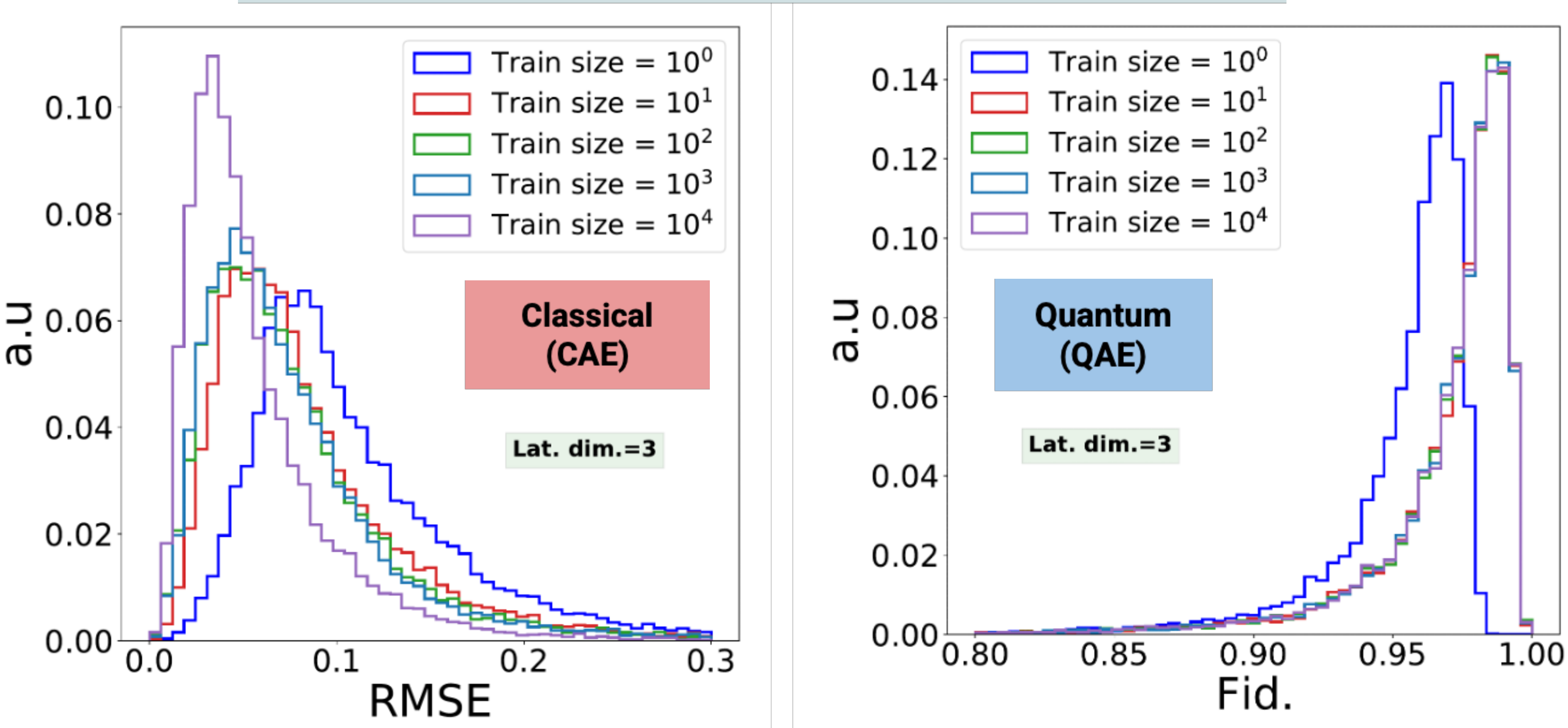
Quantum similarity measured via fidelity

$$F(|\phi\rangle, |\psi\rangle) = F(|\psi\rangle, |\phi\rangle) = |\langle\phi|\psi\rangle|^2$$

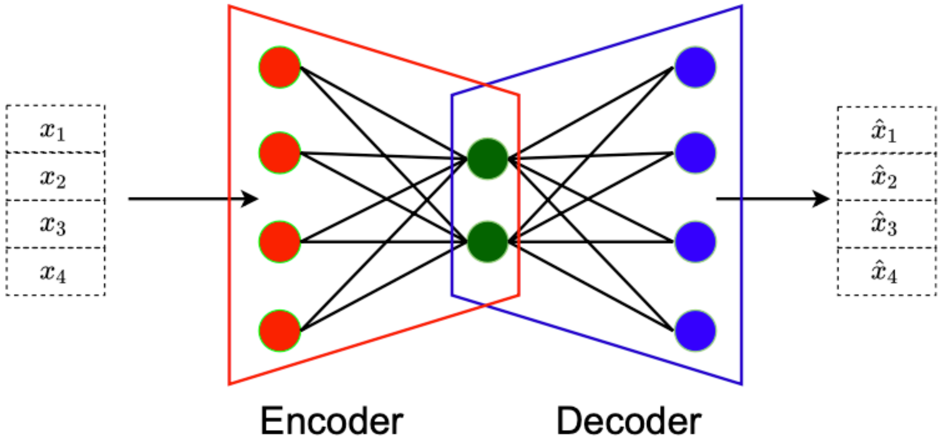
Induce ***information bottleneck*** by **discarding states of B system** after encoding, and **replacing with reference states B'** with no connection with the encoder.

Results: Training size dependence

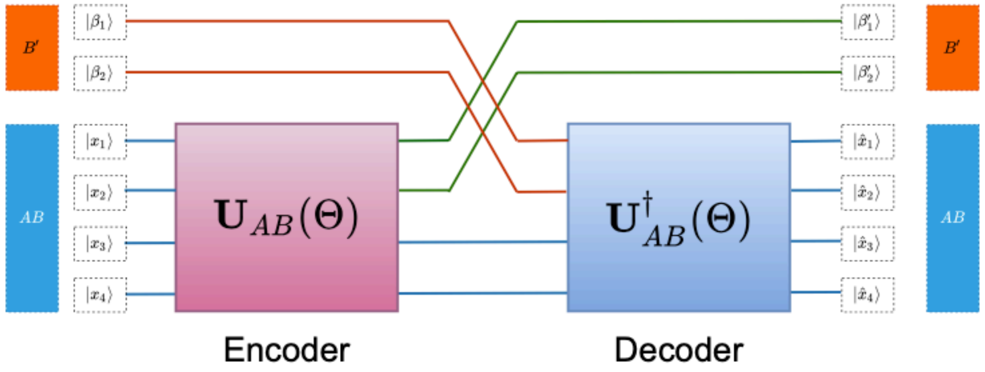
Dependence of (BG) test loss on training size

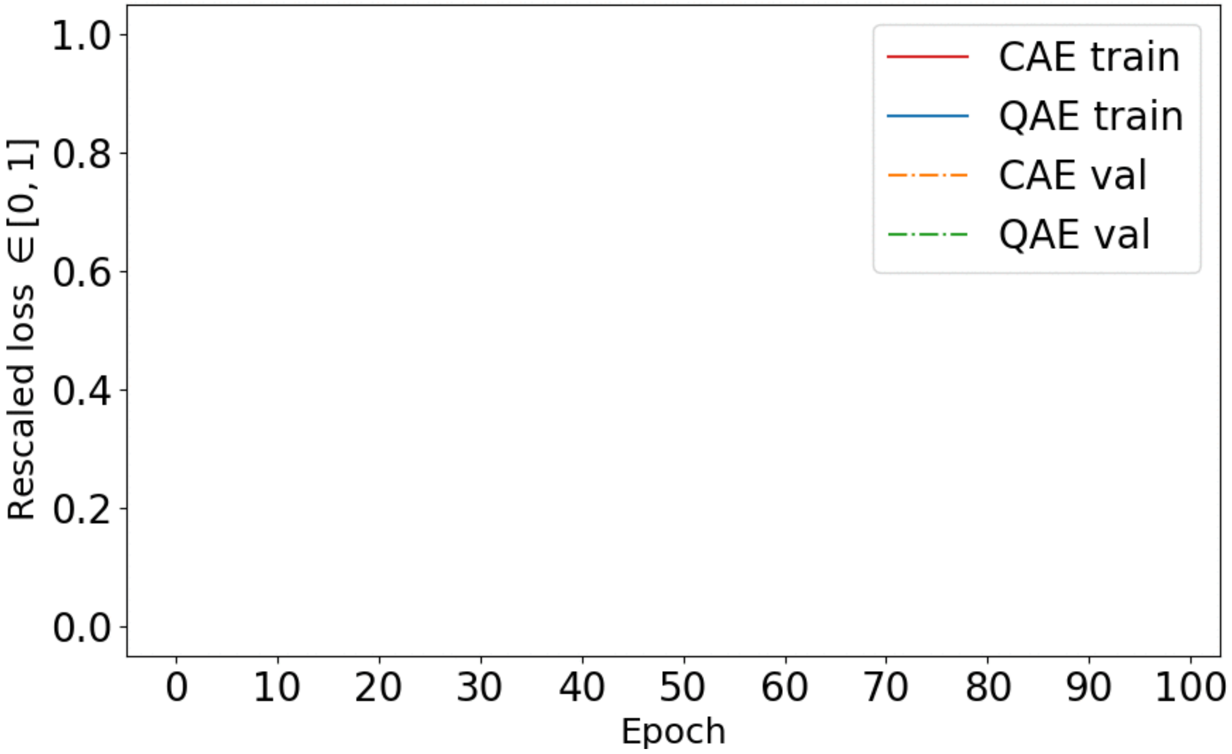


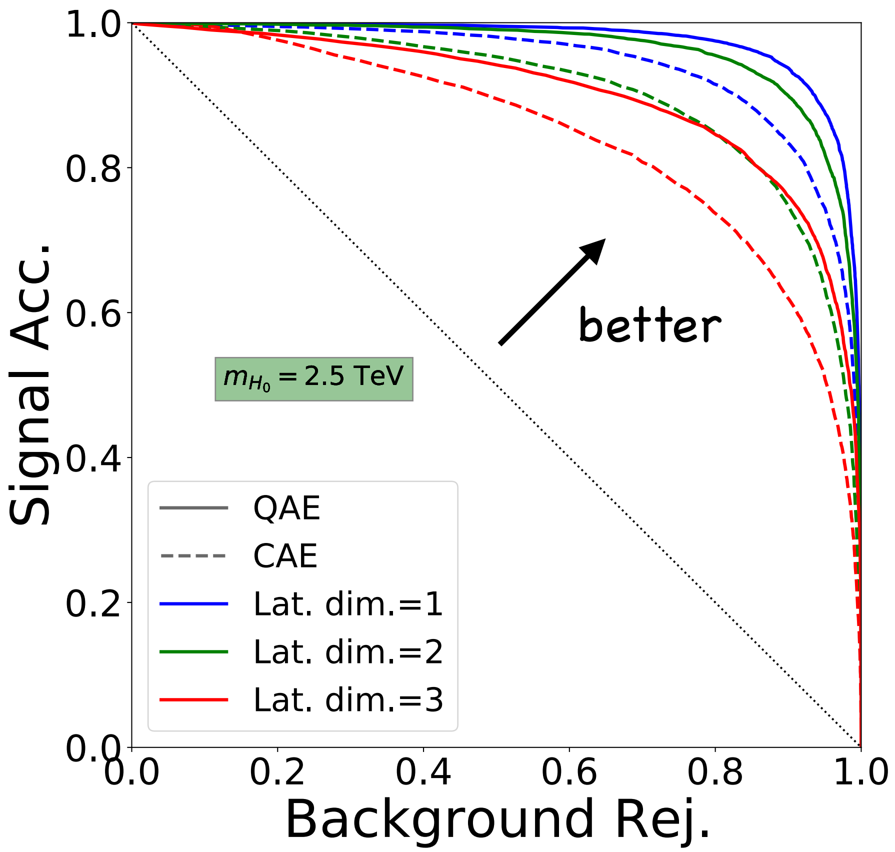
Classical autoencoder



Quantum autoencoder







→ Much faster training and better performance for Quantum autoencoder

→ In our test case, outcome prevails for much larger classical networks

Adiabatic quantum computing

- Adiabatic quantum computing (AQC) proposed as application of quantum adiabatic theorem to solve optimisation problems [Farhi, Goldstone, Gutmann '00]

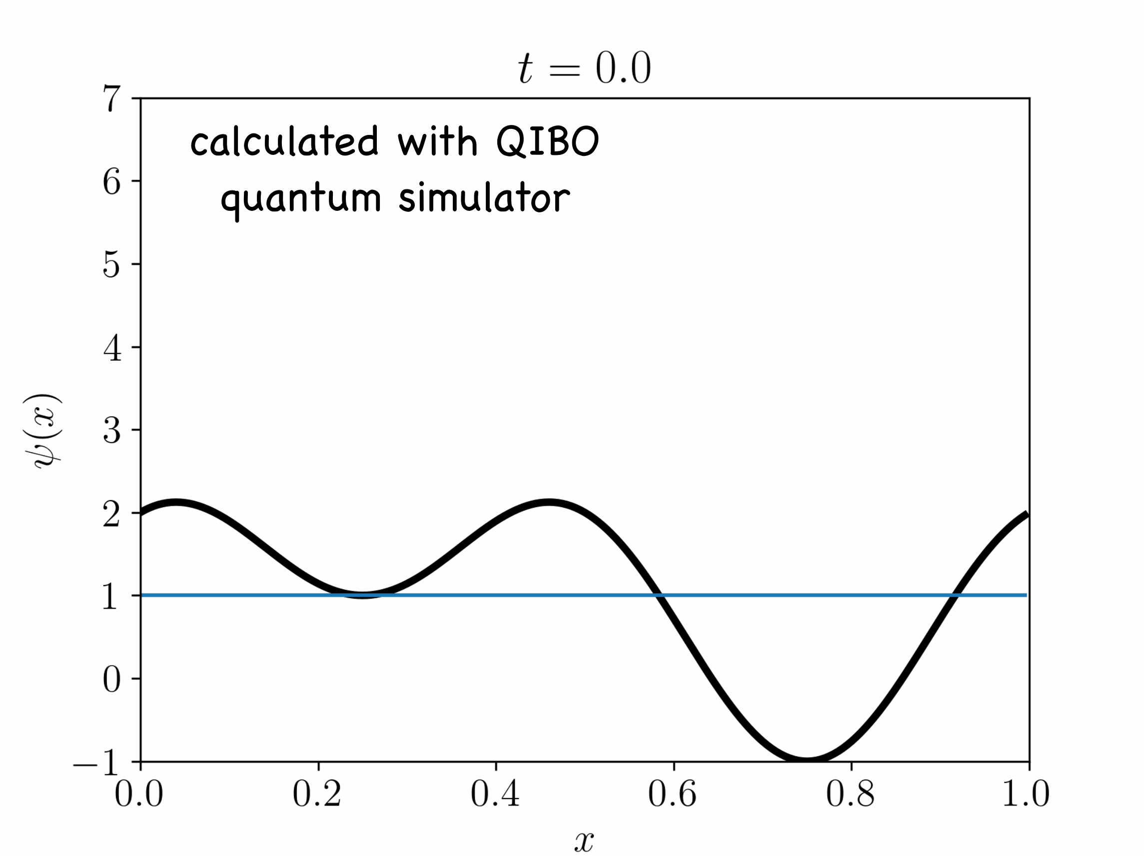
- Turns out to equivalent to quantum circuit model, i.e. it is universal [Aharonov, et al '07]

- States that if system prepared in ground state $|\psi_0\rangle$ of Hamiltonian $\mathcal{H}$

  If Hamiltonian changed smoothly and slowly enough system remains in ground state

  ➡ A time variation of the Hamiltonian from $\mathcal{H}_I$ to $\mathcal{H}_P$ is implemented according to:

$$\mathcal{H}(t) = (1 - s(t))\mathcal{H}_I + s(t)\mathcal{H}_P \quad t \in [0, T] \quad s : [0, \tau] \to [0, 1]$$



$$H = (1 - t)\,\frac{p^2}{2m^2} + t\;V(x)$$

$$\uparrow$$

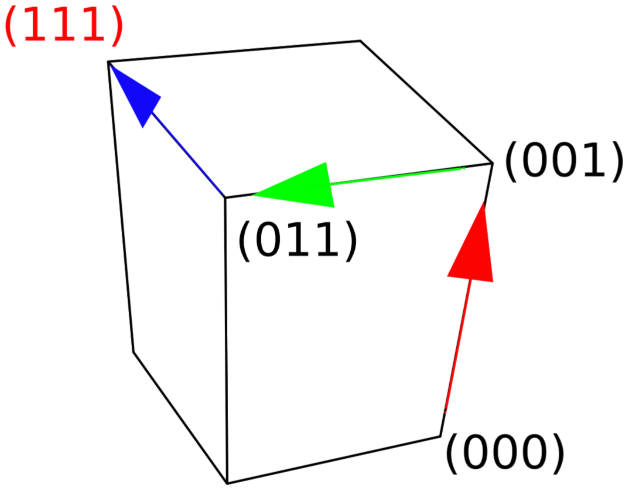
encode problem/optimisation task here

Quantum annealing:
Non-universal but powerful?

- Specific Hamiltonian. What does the "anneal" mean?

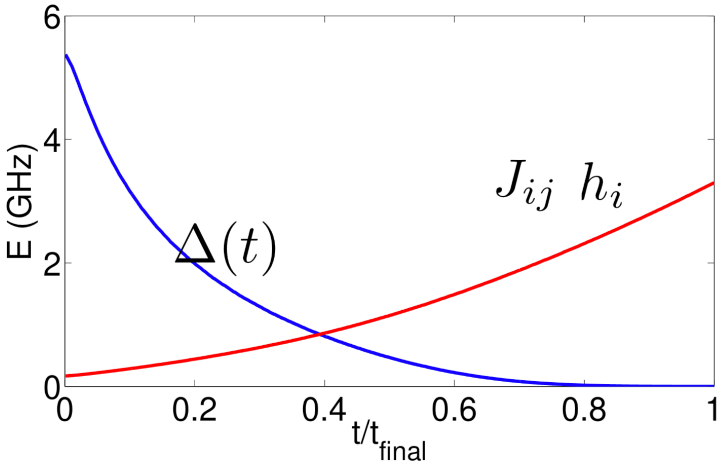
$$\mathcal{H}_{\mathrm{QA}}(t) = \underbrace{\sum_i \sum_j J_{ij}\sigma_i^Z \sigma_j^Z + \sum_i h_i \sigma_i^Z}_{\text{final Hamiltonian (encodes actual problem)}} + \underbrace{\Delta(t) \sum_i \sigma_i^X}_{\text{initial Hamiltonian (ground state = superposition of qubits with 0 and 1)}}$$

$\Delta(t)$ induces bit-hopping in the Hamming/Hilbert space



- Anneal idea: transition from ground state of initial Hamiltonian into ground state of problem Hamiltonian

- The idea is to dial this parameter to land in the global minimum (i.e. the solution) of some "problem space" described by J, h:

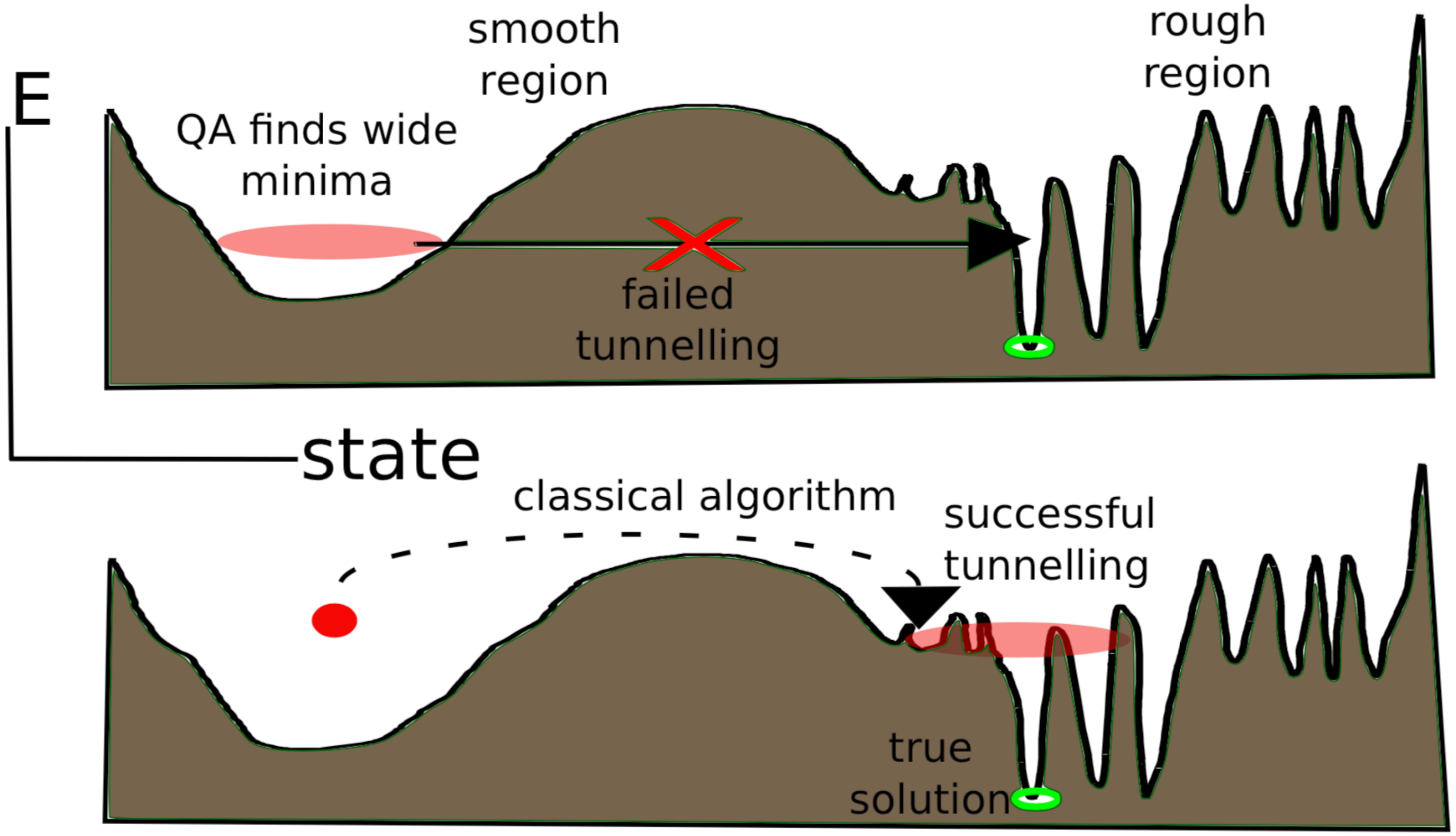


Thermal (classical) and Quantum Annealing are complementary:

- Thermal tunnelling is fast over broad shallow potentials $\sim e^{-\mathrm{height}/T}$ (Quantum "tunnelling" is exponentially slow)

- Quantum tunnelling is fast through tall thin potentials $\sim e^{-\sqrt{\mathrm{height}}\times\mathrm{width}/\hbar}$ (Thermal "tunnelling" is exponentially slow - Boltzmann suppression)

- Hybrid approach can be useful depending on solution landscape



A quantum laboratory for QFT and QML

- going beyond the reach of classical computers -

- Using the spin-chain approach for field theories discussed before, we can encode a QFT on a quantum annealer and study its dynamics directly.

[Abel, MS '20]

- To show that the system is a true and genuine quantum system we investigate if the state can tunnel from a meta-stable vacuum into a the true vacuum.

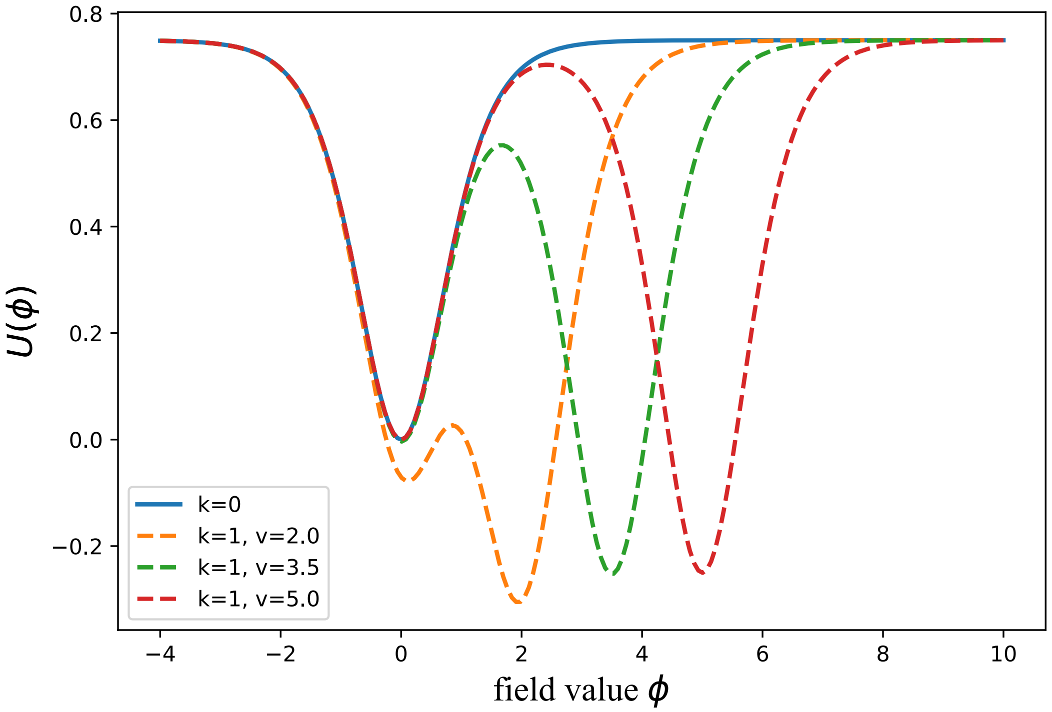
- Choose a potential of interest:

$$U(\phi) = \frac{3}{4}\tanh^2\phi - k(t)\,\mathrm{sech}^2\left(c(\phi - v)\right)$$

time dependent

where $\phi = \eta/\eta_0$

$\phi(t)$ is the field and c, v are dimless constants



- For real-time evolution of field theory on QA see [Fromm, Philipsen, Winterowd '22]

The tunnelling probability in a QFT is calculated by evaluating the path-integral in Euclidean space around the action's critical points using the steepest gradient-descent method

$$\langle \eta_i | \eta_f \rangle_E = \int \mathcal{D}\delta\eta \, e^{-\hbar^{-1} \int dt \left(\frac{m(\dot{\eta}_{cl}+\delta\dot{\eta})^2}{2} + U(\eta_{cl}+\delta\eta) - E_0 \right)} = A e^{-\hbar^{-1} S_{E,cl}}$$

↖ quantum annealer

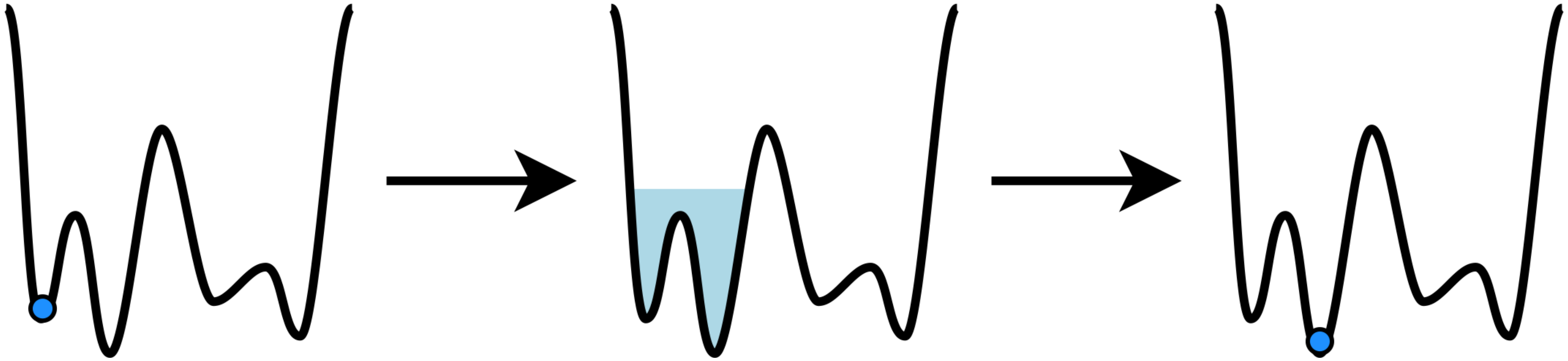
For the tunnelling rate $\Gamma = |\langle \eta_i | \eta_f \rangle_E|^2 \approx e^{-2\hbar^{-1} S_{E,cl}}$ with $S_{E,cl} = \int_{\eta_+}^{\eta_e} d\eta \sqrt{2m(U - E_0)}$

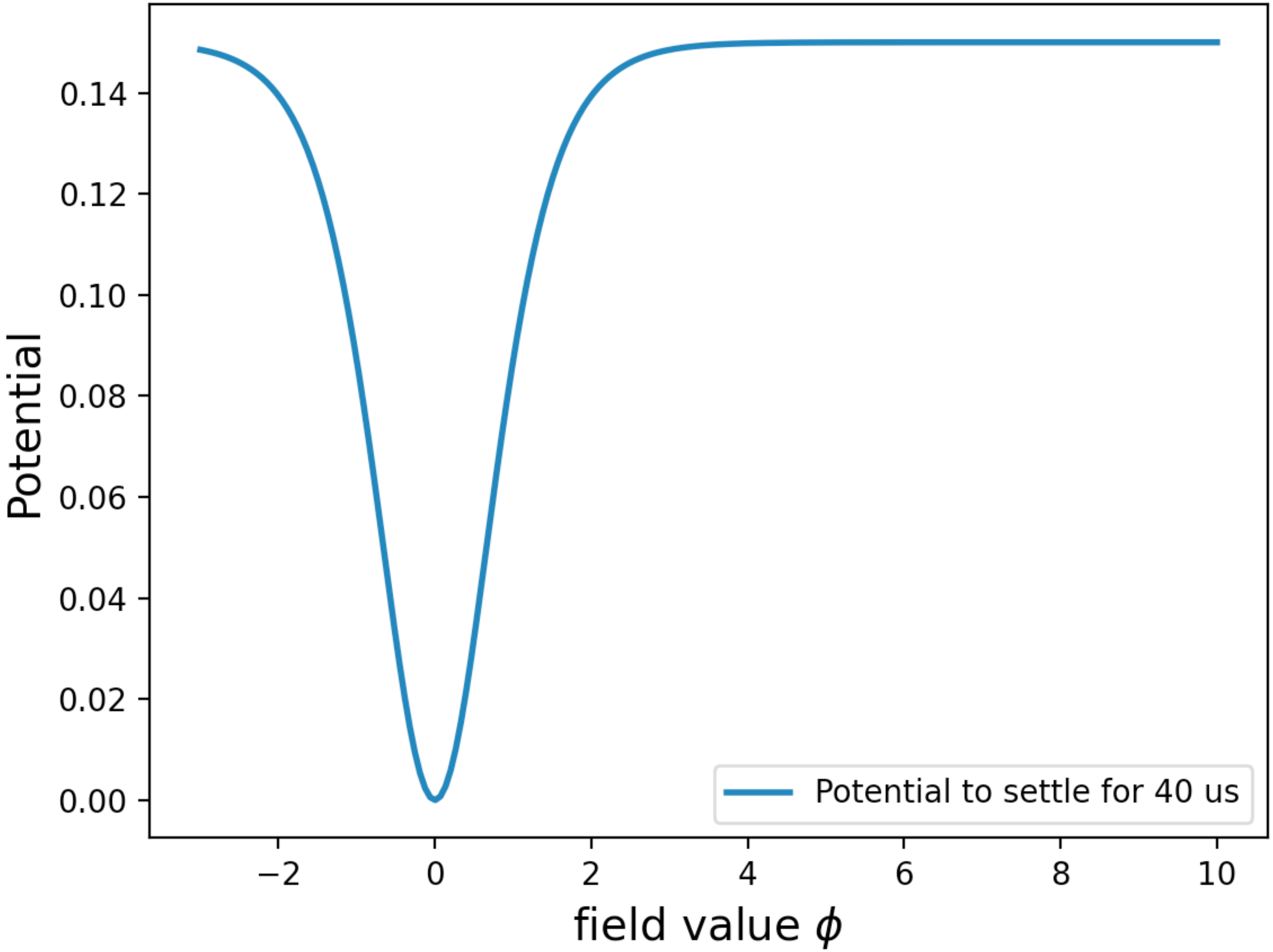
Exponent is object of interest: $\hbar^{-1} S_E \approx \gamma^{-\frac{1}{2}} \int_{\phi_+}^{\phi_e} \sqrt{\frac{3}{4} \tanh^2 \phi - \operatorname{sech}^2(\phi - v)} \, d\phi$ with $\gamma \overset{\text{def}}{=} \hbar^2 / 2m\eta_0^2$

$$\boxed{\log \Gamma \approx -2\hbar^{-1} S_E \approx \sqrt{\frac{3}{\gamma}} \left(\frac{5}{3} - v \right)}$$

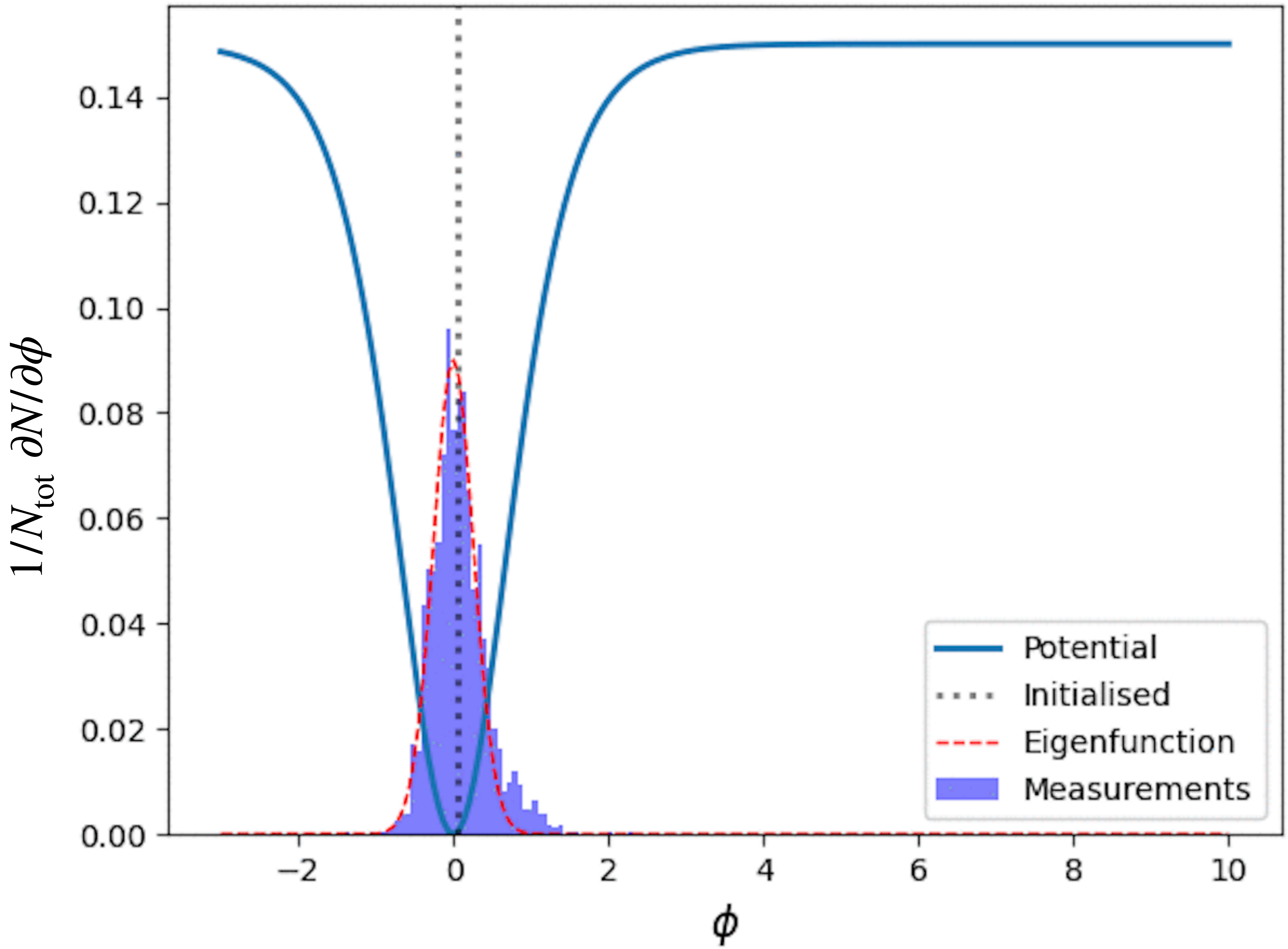
D-Wave reverse annealing

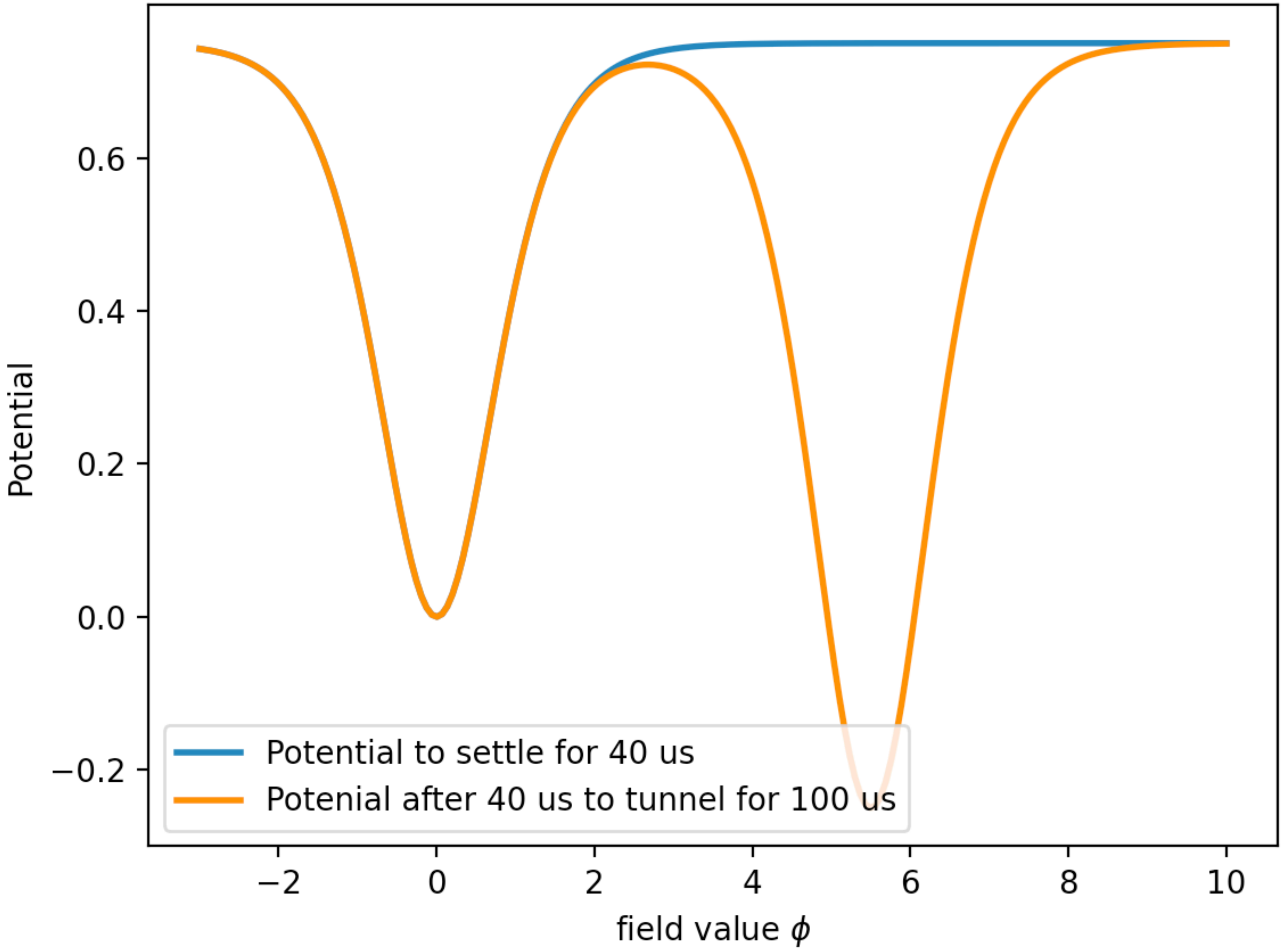
starts at sq=1 (classical) -> sq < 1 (quantum) -> measurement in sq=1 (classical)



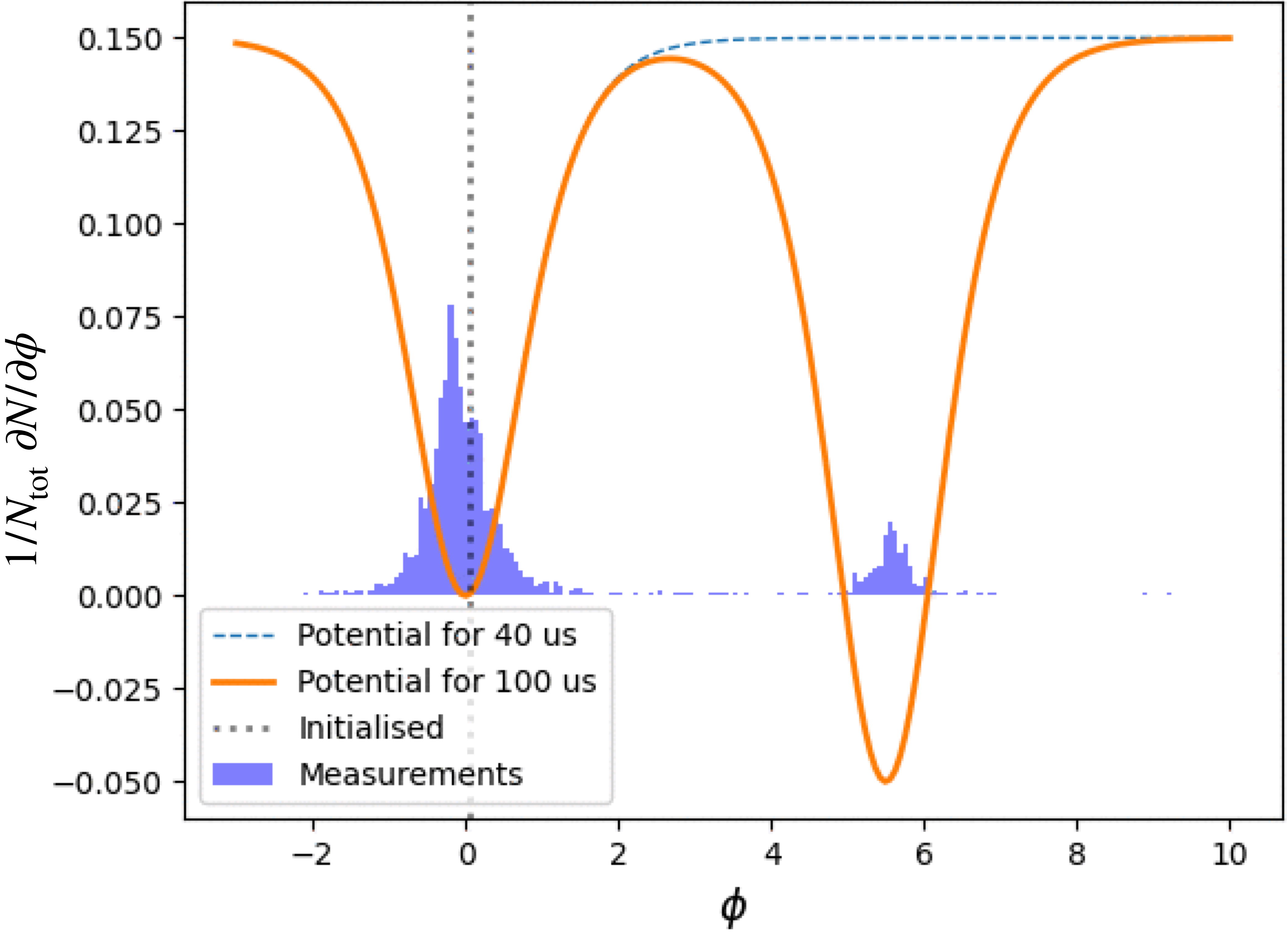

Potential
0.14
0.12
0.10
0.08
0.06
0.04
0.02
0.00
−2
0
2
4
6
8
10
field value ϕ
Potential to settle for 40 us

Implemented and executed on D-Wave Q2000 machine

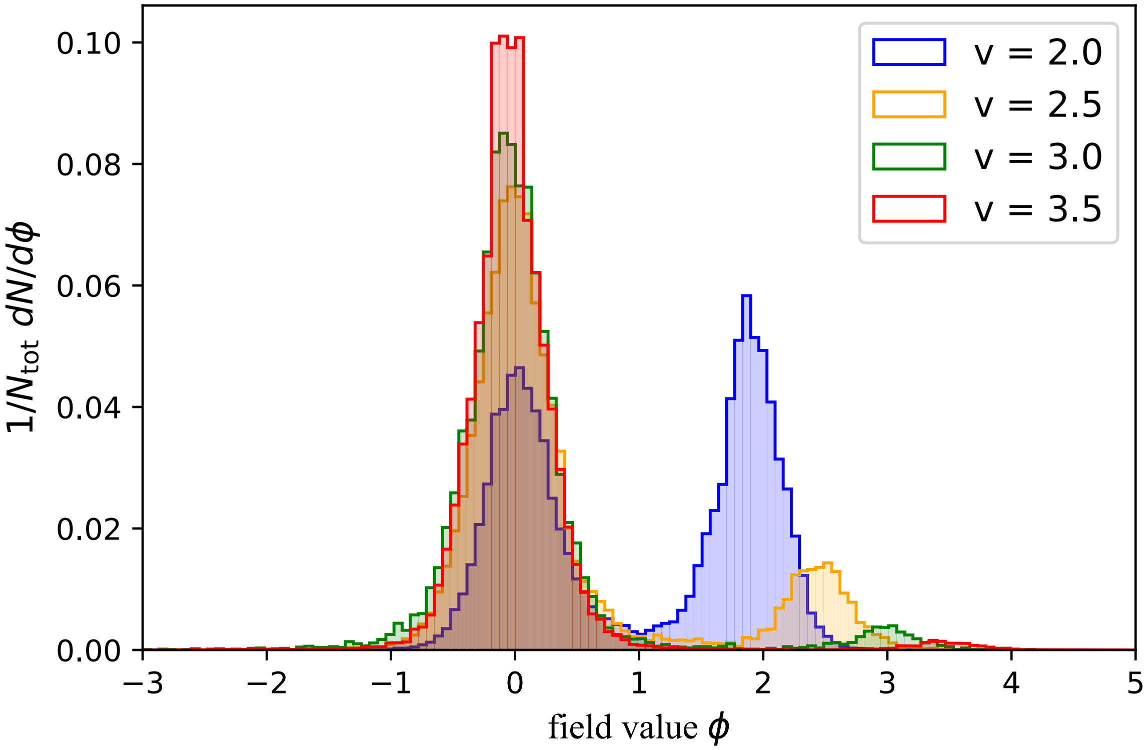



Potential
0.6
0.4
0.2
0.0
−0.2
−2
0
2
4
6
8
10
field value ϕ
Potential to settle for 40 us
Potenial after 40 us to tunnel for 100 us

Implemented and executed on D-Wave Q2000 machine



Results: it decays with v as expected

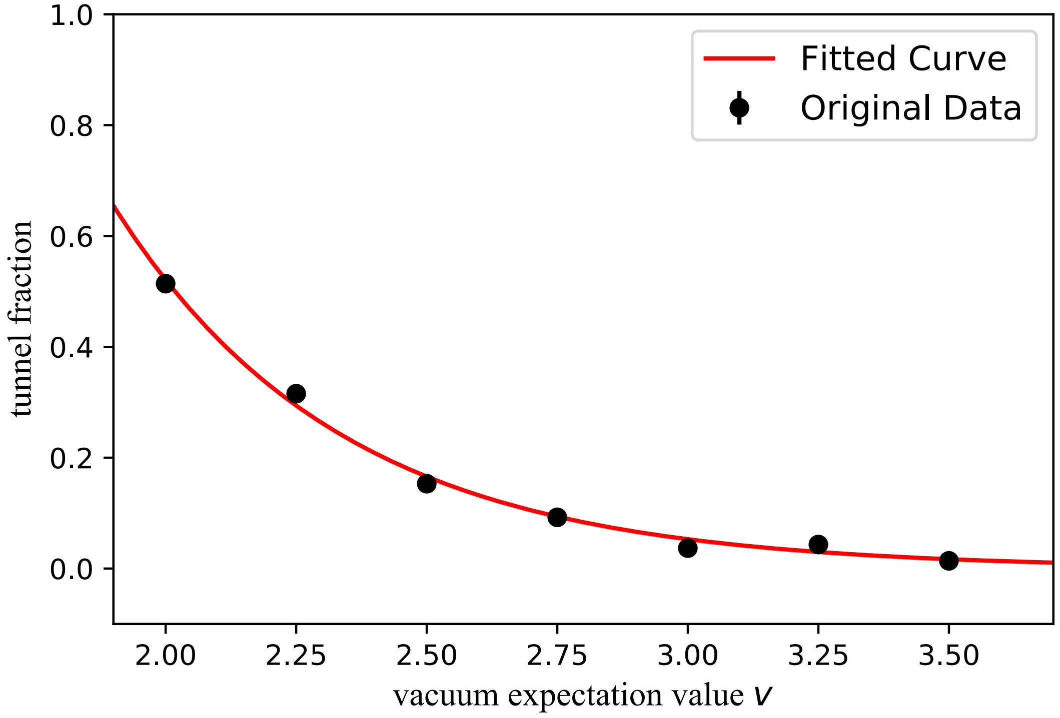


Perform tunnelling for

$t_{\rm tunnel} = 100\mu s$ at $s_q = 0.7$

Theory: $\log\Gamma \;=\; 3.0 \times (1.66 - v)$

Exp: $\log\Gamma = 2.29 \times (1.71 - v)$

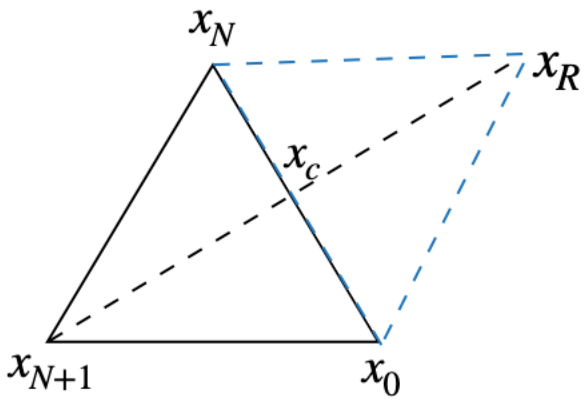


Optimisation comparison quantum vs classical

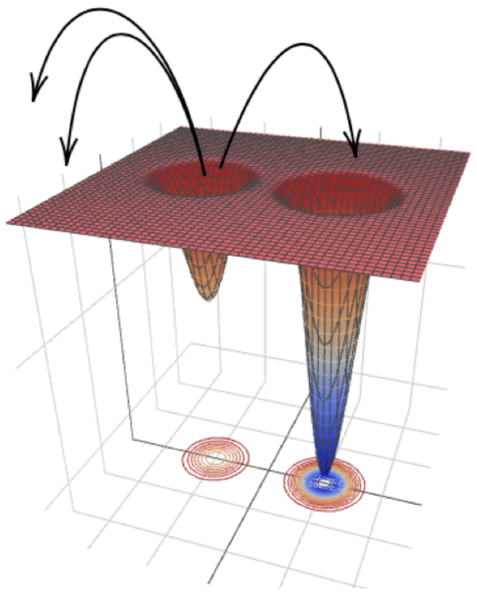
gradient descent

$$x_{i+1} = x_i - \nabla f(x_i)$$

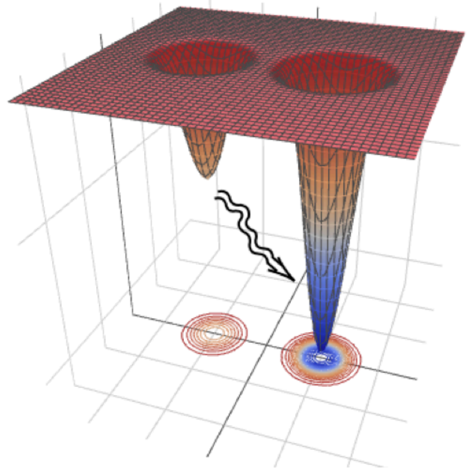
Nelder-Mead



Thermal Annealing

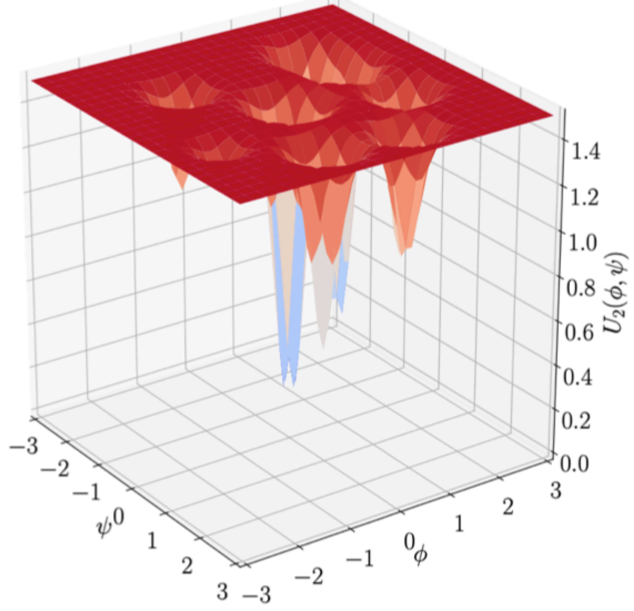


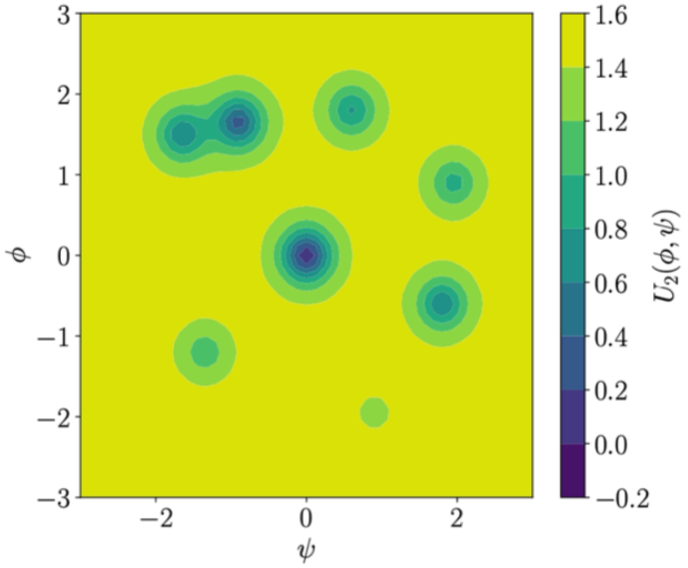
Quantum Annealing



Applied to several examples in [Abel, Blance, MS '21], let's show one here:

Multi-well potential



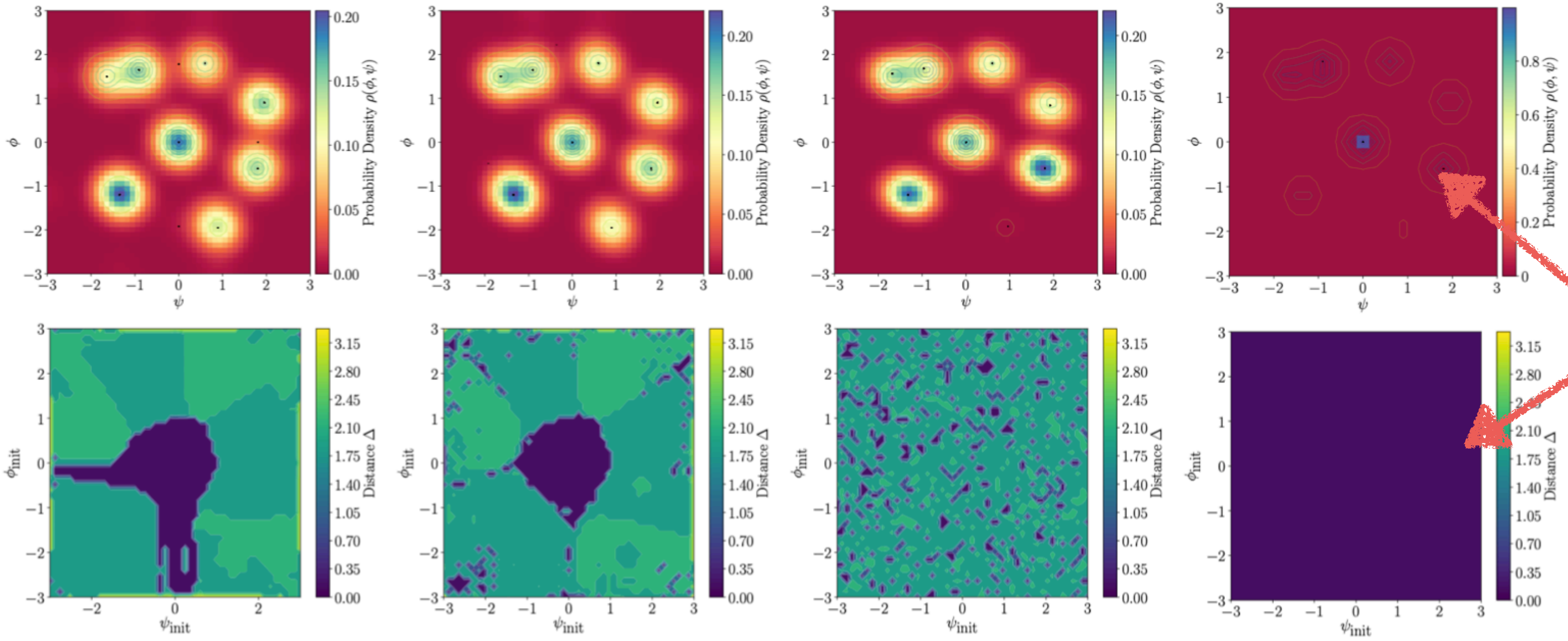


Results for Multi-well potential

- Quantum algorithms finds global minimum of potential reliably and fast!

Method	Time/run (μs)
Nelder-Mead	4900
Gradient Descent	2900
Thermal Annealing	5×10^5
Quantum Annealing	115

[Abel, Blance, MS '21]



(a) Nelder-Mead (b) Gradient descent (c) Thermal annealing (d) Quantum annealing

Quantum annealer almost never gets stuck in wrong minimum

QA is depth savvy, i.e. works qualitatively different

Clear advantage

Completely Quantum Neural Networks

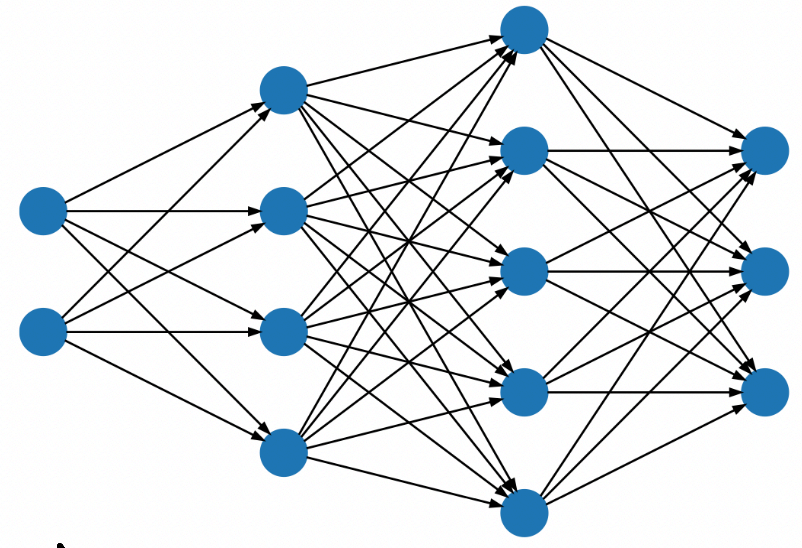
Structure of node i, in layer L $$L_i(x) = g\left(\sum_i w_{ij} x_i + b_i\right)$$

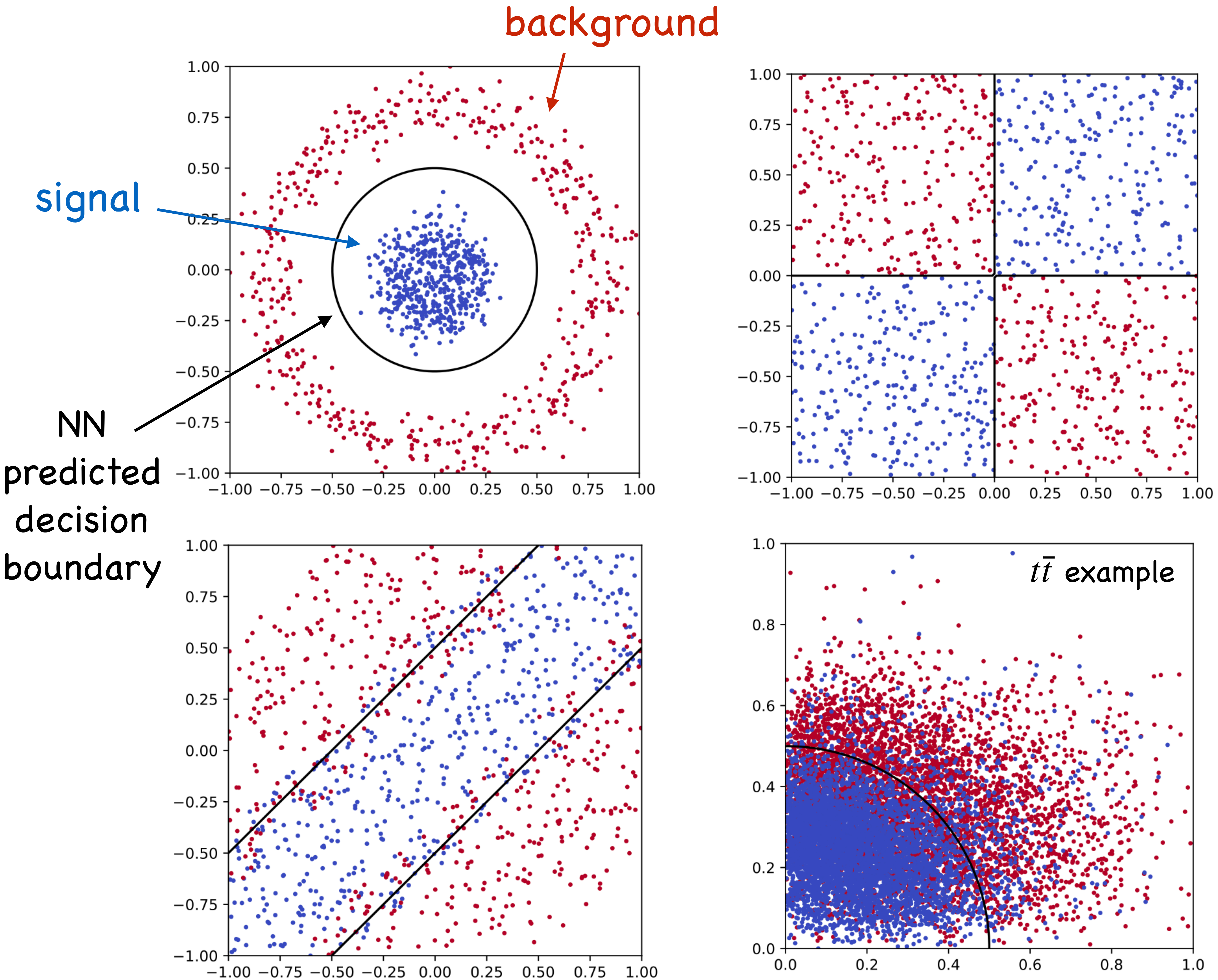
Network output in final layer $$Y = L^{(n)} \circ \ldots \circ L^{(0)}$$

Loss function $$\mathcal{L}(Y) = \frac{1}{N_d}\sum_a |y_a - Y(x_a)|^2$$

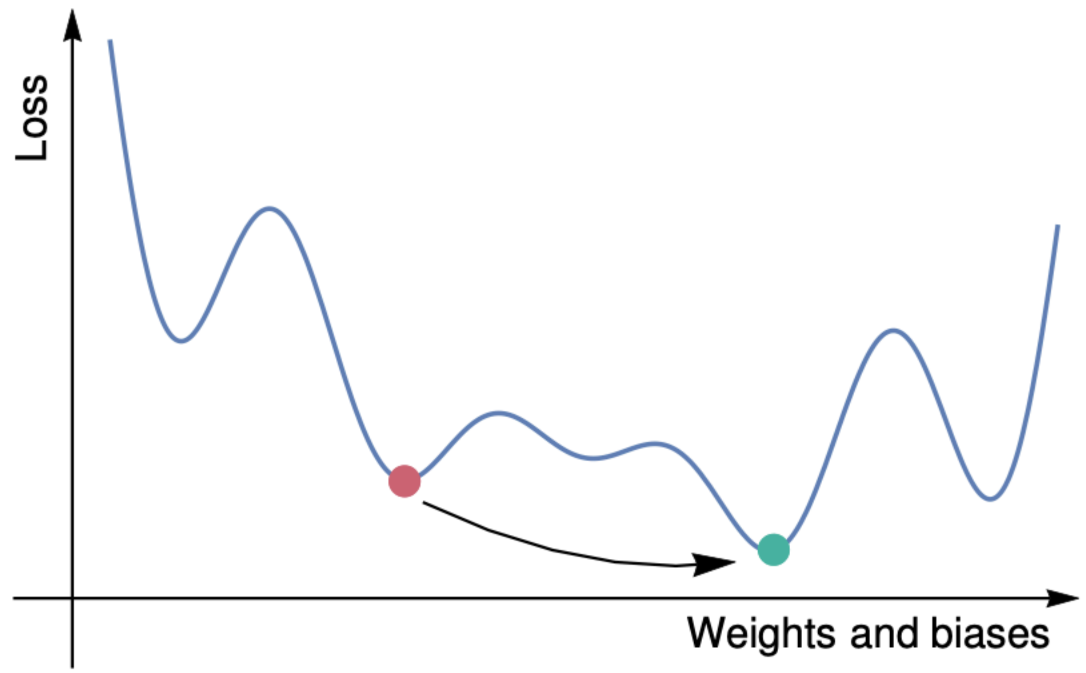
[Abel, Criado, MS '22]

- Developed binary encoding of weights (discretised)
- Polynomial approximation of activation function
- Reduction of binary higher-order polynomials into quadratic ones (Ising model)

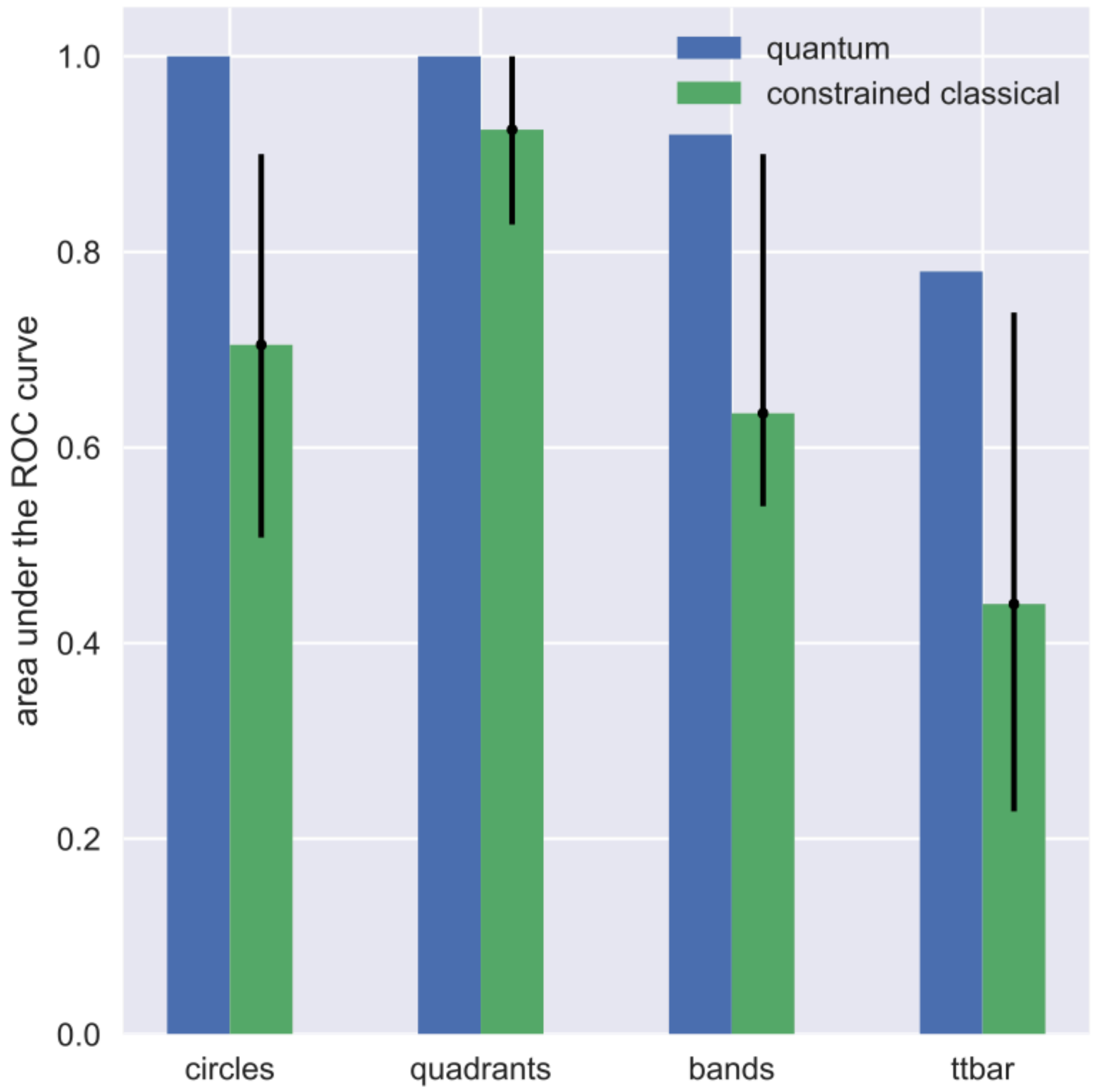



background
signal
NN
predicted
decision
boundary
$t\bar{t}$ example
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0.0
0.2
0.4
0.6
0.8
1.0

Completely Quantum Neural Networks



Reliable and very fast ground-state finder of loss function



Optimal network training

Application to differential equations and variational methods

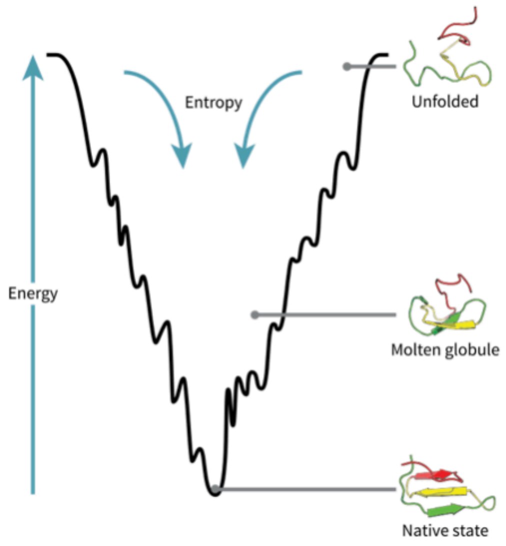
Define your mathematical task as an **optimisation problem**

$$\mathcal{F}_m(\vec{x}, \phi_m(\vec{x}), \nabla\phi_m(\vec{x}), \cdots, \nabla^j\phi_m(\vec{x})) = 0$$

Build the full function, here a DE into the loss function, incl boundary conditions

$$\mathcal{L}(\{w, \vec{b}\}) = \frac{1}{i_{\max}} \sum_{i,m} \hat{\mathcal{F}}_m(\vec{x}^i, \hat{\phi}_m(\vec{x}^i), \cdots, \nabla^j\hat{\phi}_m(\vec{x}^i))^2 + \sum_{\text{B.C.}} (\nabla^p\hat{\phi}_m(\vec{x}_b) - K(\vec{x}_b))^2 \ ,$$

[Piscopo, MS, Waite '19]



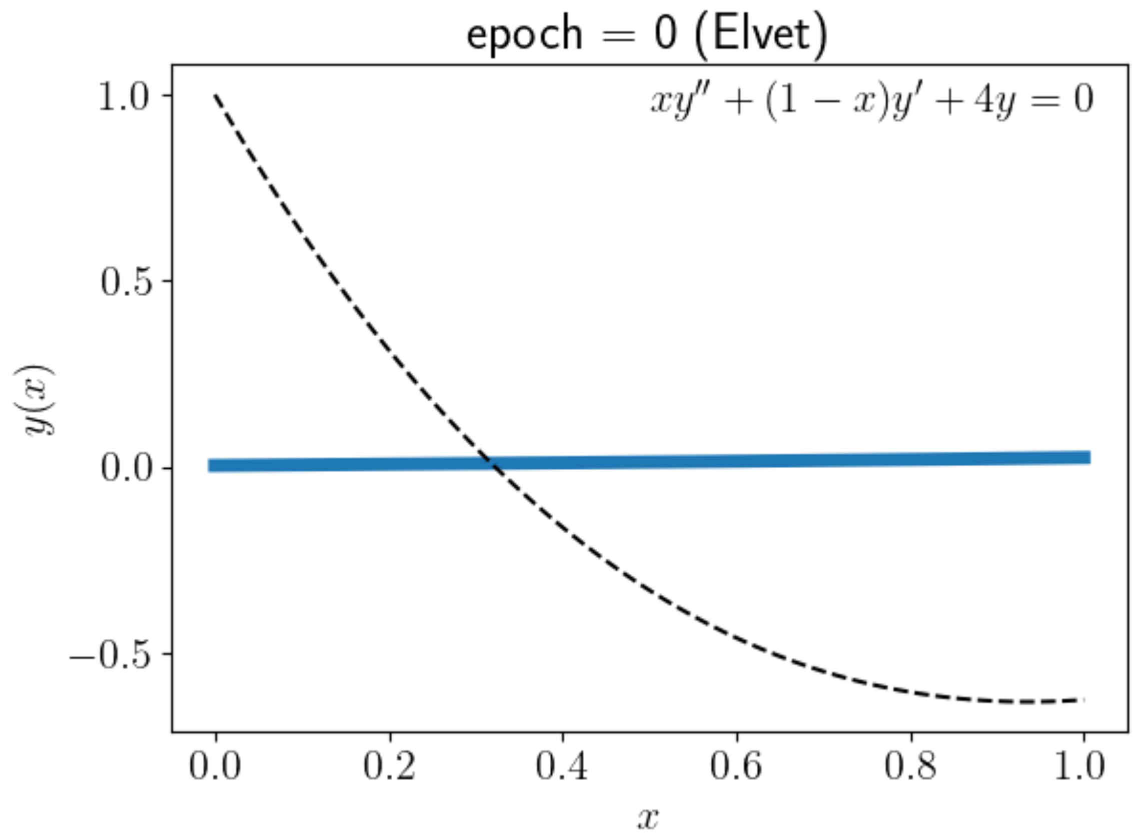
identify trial solution with network output $\hat{\phi}_m(\vec{x}) \equiv \breve{N}_m(\vec{x}, \{w, \vec{b}\})$

QADE: Solving differential equations with a quantum annealer

[Criado, MS '22]

Example Laguerre differential equation:

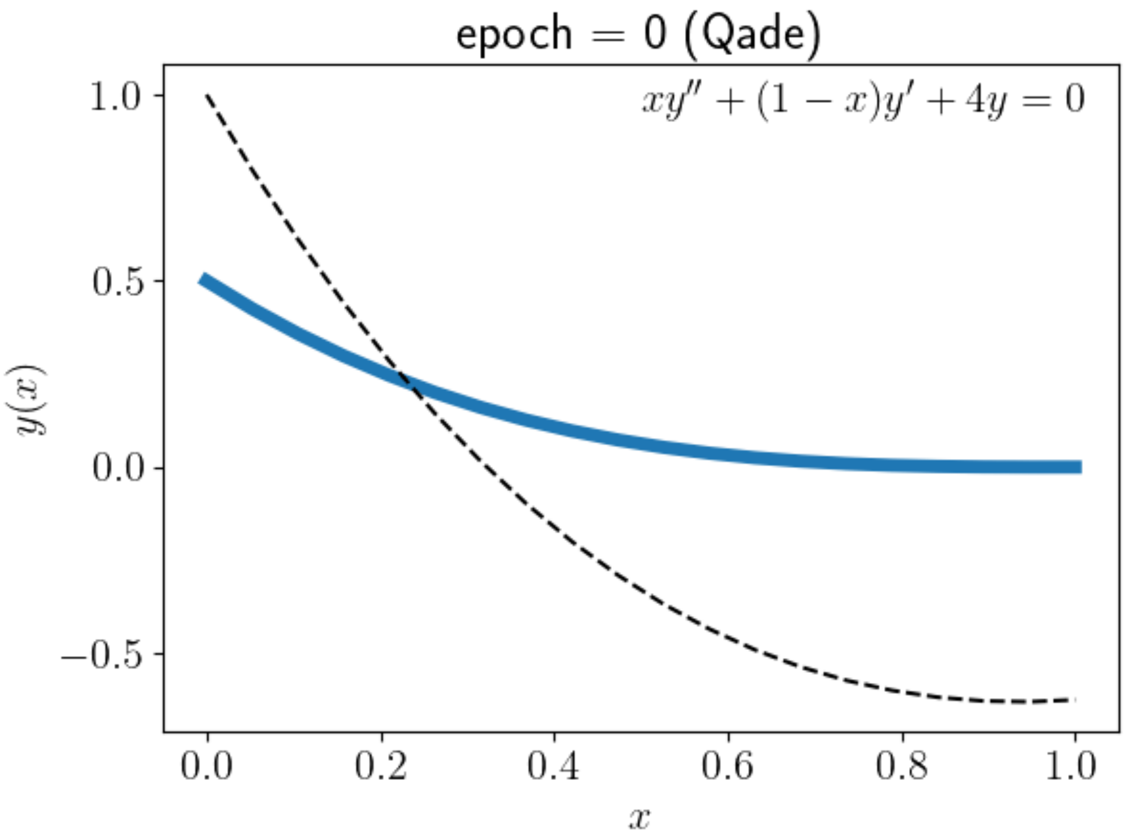
$$xy'' + (1-x)y' + 4y = 0 \text{ with } y(0) = 1 \text{ and } y(1) = L_4(1)$$



Classical Neural Network

https://gitlab.com/elvet/elvet

[Piscopo, MS, Waite '19] [Araz, Criado, MS '21]



Quantum algorithm

http://gitlab.com/jccriado/qade

QFitter

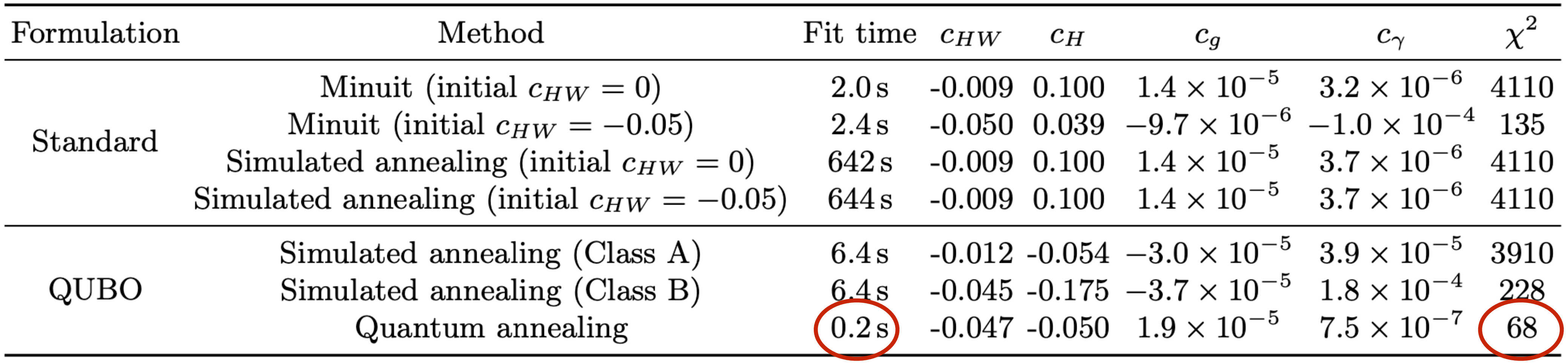
Example Higgs EFT fit:

[Criado, Kogler, MS '22]

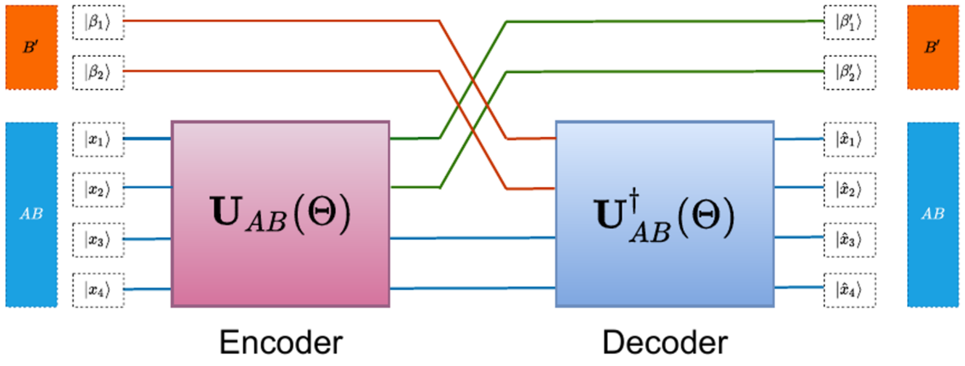
$$\begin{aligned}\mathcal{L} = {} & \frac{c_{u3} y_t}{v^2}(\phi^\dagger\phi)(\bar{q}_L\tilde{\phi}u_R) + \frac{c_{d3} y_b}{v^2}(\phi^\dagger\phi)(\bar{q}_L\phi d_R) \\ & + \frac{i c_W g}{2m_W^2}(\phi^\dagger\sigma^a D^\mu\phi)D^\nu W^a_{\mu\nu} + \frac{c_H}{4v^2}\left(\partial_\mu(\phi^\dagger\phi)\right)^2 \\ & + \frac{c_\gamma (g')^2}{2m_W^2}(\phi^\dagger\phi)B_{\mu\nu}B^{\mu\nu} + \frac{c_g g_S^2}{2m_W^2}(\phi^\dagger\phi)G^a_{\mu\nu}G^{a\mu\nu} \\ & + \frac{i c_{HW} g}{4m_W^2}(\phi^\dagger\sigma^a D^\mu\phi)D^\nu W^a_{\mu\nu} \\ & + \frac{i c_{HB} g'}{4m_W^2}(\phi^\dagger D^\mu\phi)D^\nu B_{\mu\nu} + \text{h.c.}\end{aligned}$$

$$\chi^2 = \sum_{ij} V_a C^{-1}_{ab} V_b \qquad V_a = O_a^{(\text{exp})} - O_a^{(\text{th})}(c)$$

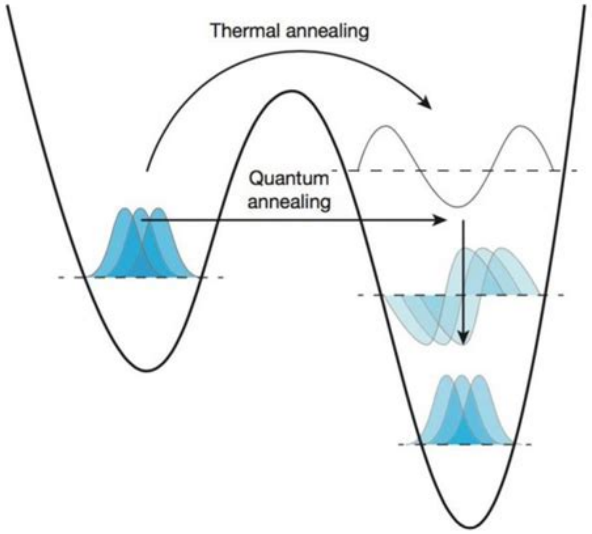
- Fast and reliable state-of-the-art Higgs, ELW, … fits
- Convergence no problem for non-convex $\Delta\chi^2 = \chi^2 - \chi^2_{\text{min}}$ functions



Formulation	Method	Fit time	c_{HW}	c_H	c_g	c_γ	χ^2
Standard	Minuit (initial $c_{HW} = 0$)	2.0 s	-0.009	0.100	1.4×10^{-5}	3.2×10^{-6}	4110
	Minuit (initial $c_{HW} = -0.05$)	2.4 s	-0.050	0.039	-9.7×10^{-6}	-1.0×10^{-4}	135
	Simulated annealing (initial $c_{HW} = 0$)	642 s	-0.009	0.100	1.4×10^{-5}	3.7×10^{-6}	4110
	Simulated annealing (initial $c_{HW} = -0.05$)	644 s	-0.009	0.100	1.4×10^{-5}	3.7×10^{-6}	4110
QUBO	Simulated annealing (Class A)	6.4 s	-0.012	-0.054	-3.0×10^{-5}	3.9×10^{-5}	3910
	Simulated annealing (Class B)	6.4 s	-0.045	-0.175	-3.7×10^{-5}	1.8×10^{-4}	228
	Quantum annealing	0.2 s	-0.047	-0.050	1.9×10^{-5}	7.5×10^{-7}	68



Summary



- Quantum Computing is exciting research area that rapidly expands, supported through private and public sector. Many methods to be invented.
  - ➡ Can exploit QM prop: entanglement, superposition principle and tunnelling
- HEP is inherently quantum mechanical, thus description in terms of quantum computing should be advantageous
  - ➡ Suitable theory description needed for QC devices
  - ➡ Path to an application yielding quantum advantage

- For quantum advantage in real-world applications need development of technical realisation of quantum computers (size, fault tolerance, type of operations,…)