

# Quantum annealing applications in high-energy physics

**ACAT 2022**

S.A. Abel, JCC, M. Spannowsky, [2202.11727](#)

JCC, M. Spannowsky, [2204.03657](#)

JCC, R. Kogler, M. Spannowsky, [2207.10088](#)

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# Classical and quantum optimisation

**Classical**

Minimize the loss function  $\mathcal{L}(x)$

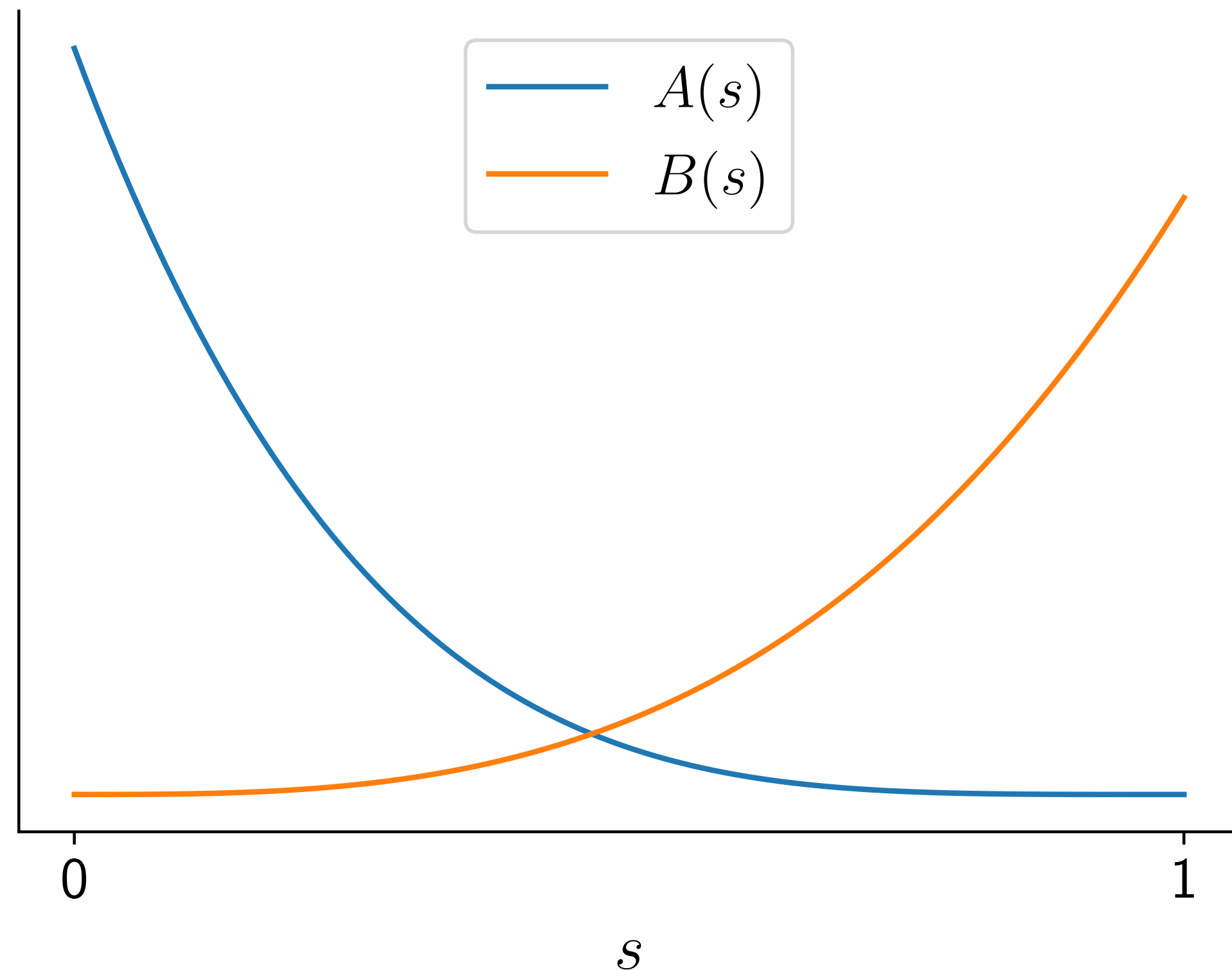
**Quantum**

Find the ground state of the Hamiltonian  $H$

Machine learning, fits, ...

# Quantum annealing

$$H(s) = A(s)H_0 + B(s)H_1$$

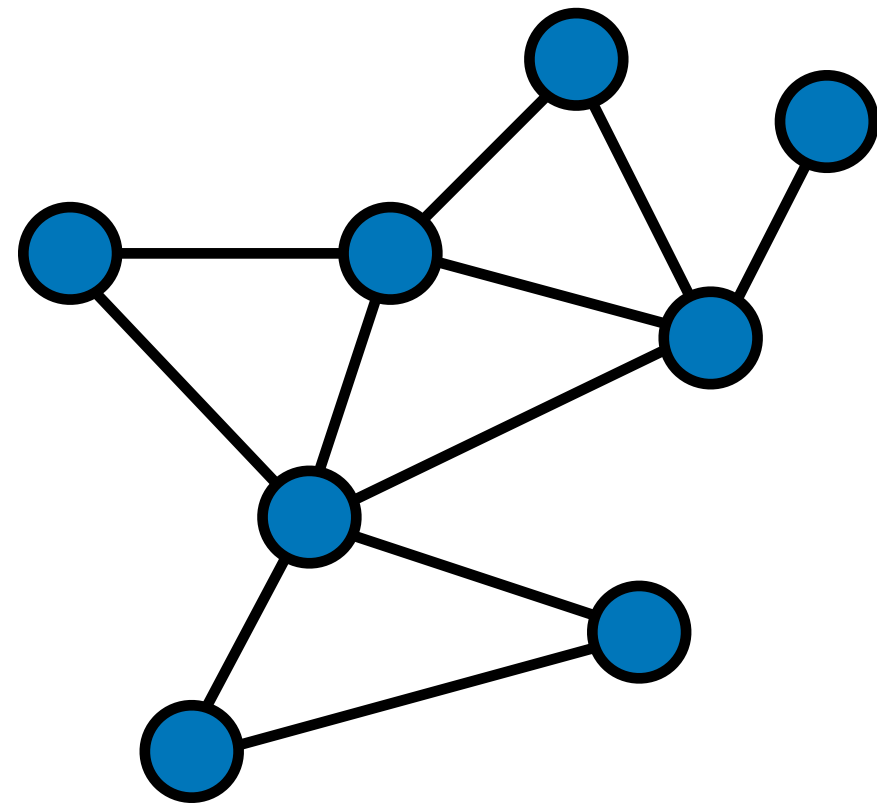


1. Prepare the system in the ground state of  $H_0$
2. Change  $s$  slowly from 0 to 1
3. Measure: **obtain the ground state of  $H_1$**



By the **adiabatic theorem**

# Transverse-field Ising model QA



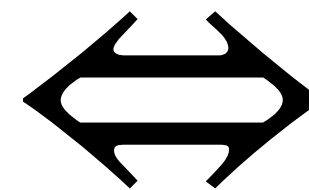
$$H(s) = A(s)H_0 + B(s)H_1$$

$$H_0 = \sum_i \sigma_i^x \quad H_1 = \sum_{ij} J_{ij} \sigma_i^z \sigma_j^z + \sum_i h_i \sigma_i^z$$

Measuring the eigenvalue  $(s_1, s_2, \dots)$  of  $(\sigma_1^z, \sigma_2^z, \dots)$  solves the problem

**Ising**

$$\min_{s_i = \pm 1} \sum_{ij} J_{ij} s_i s_j + \sum_i h_i s_i$$

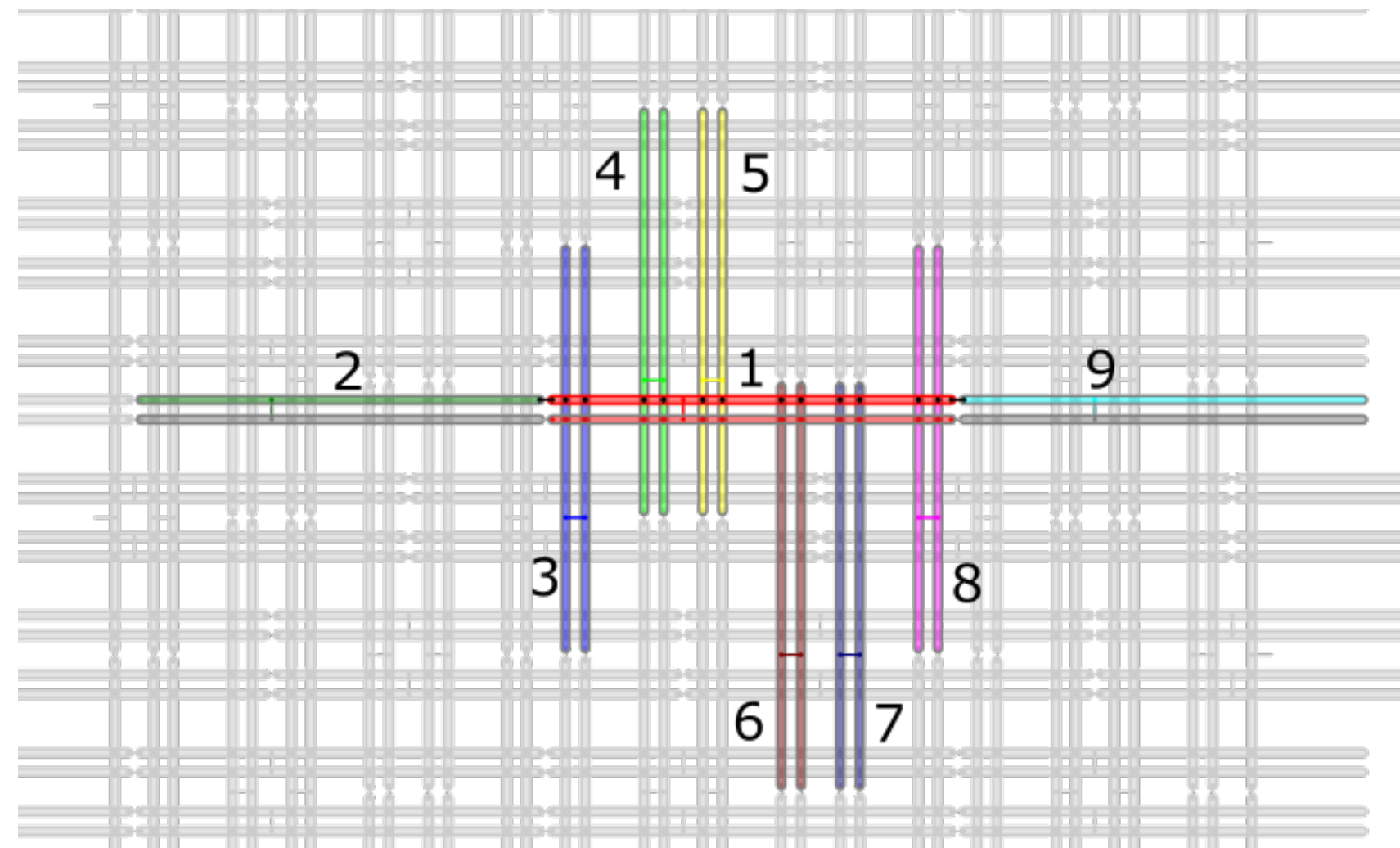


**QUBO**

$$\min_{q_i \in \{0,1\}} \sum_{ij} Q_{ij} q_i q_j$$

# D-Wave quantum annealers

## Pegasus architecture



## Advantage\_system6.1

5616 qubits

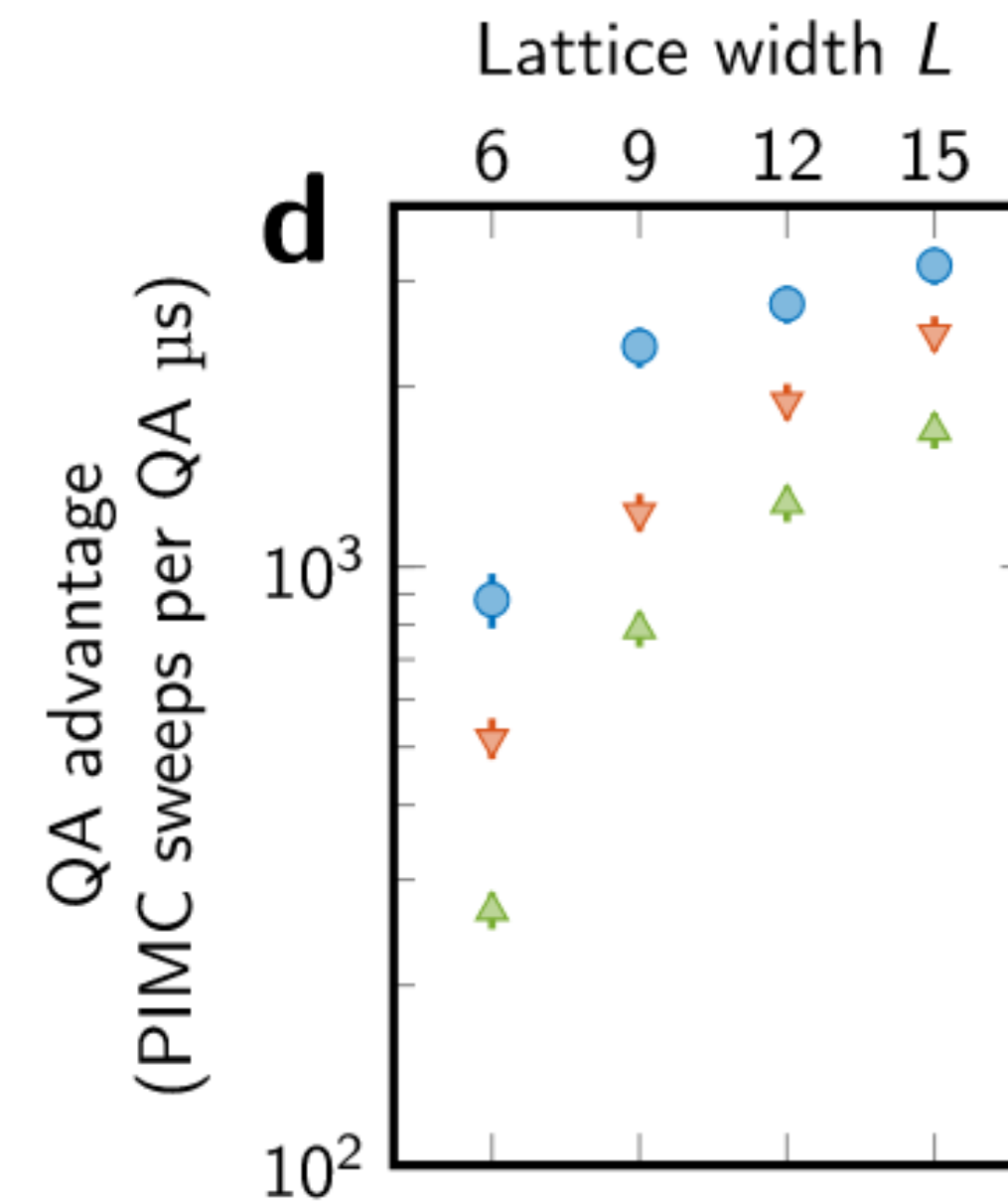
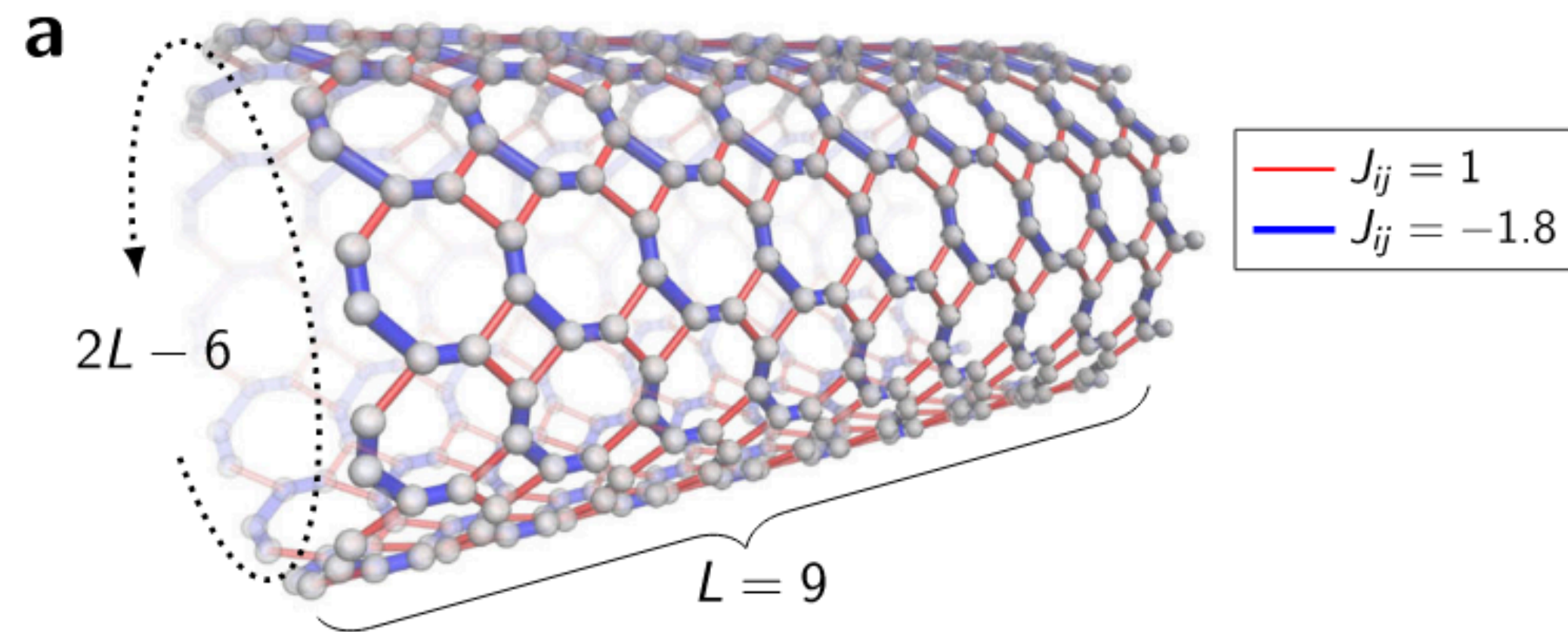
40135 couplings

Max. 16 couplings per qubit

If the Ising model is more densely connected  $\implies$  **chain** several qubits together

# Quantum annealing advantage

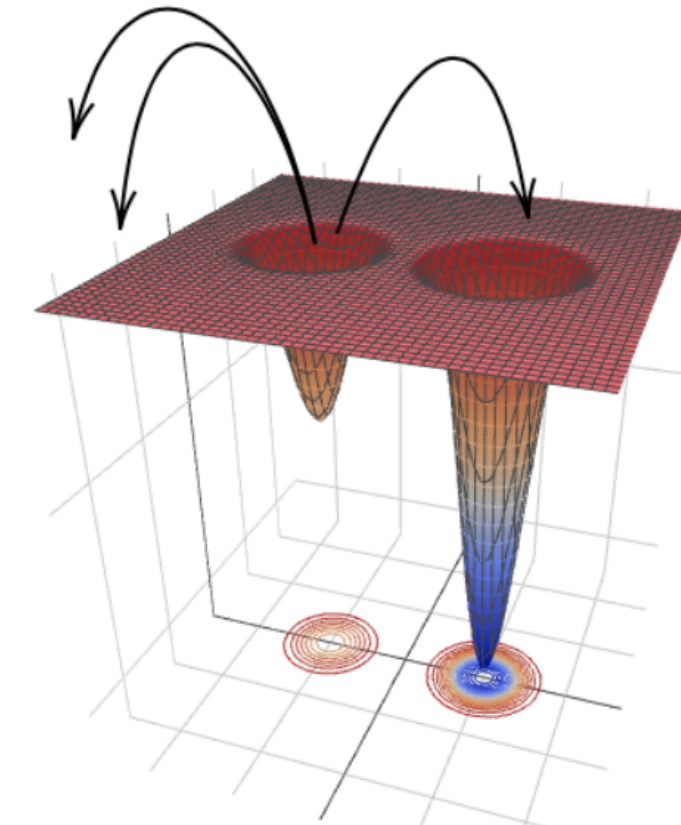
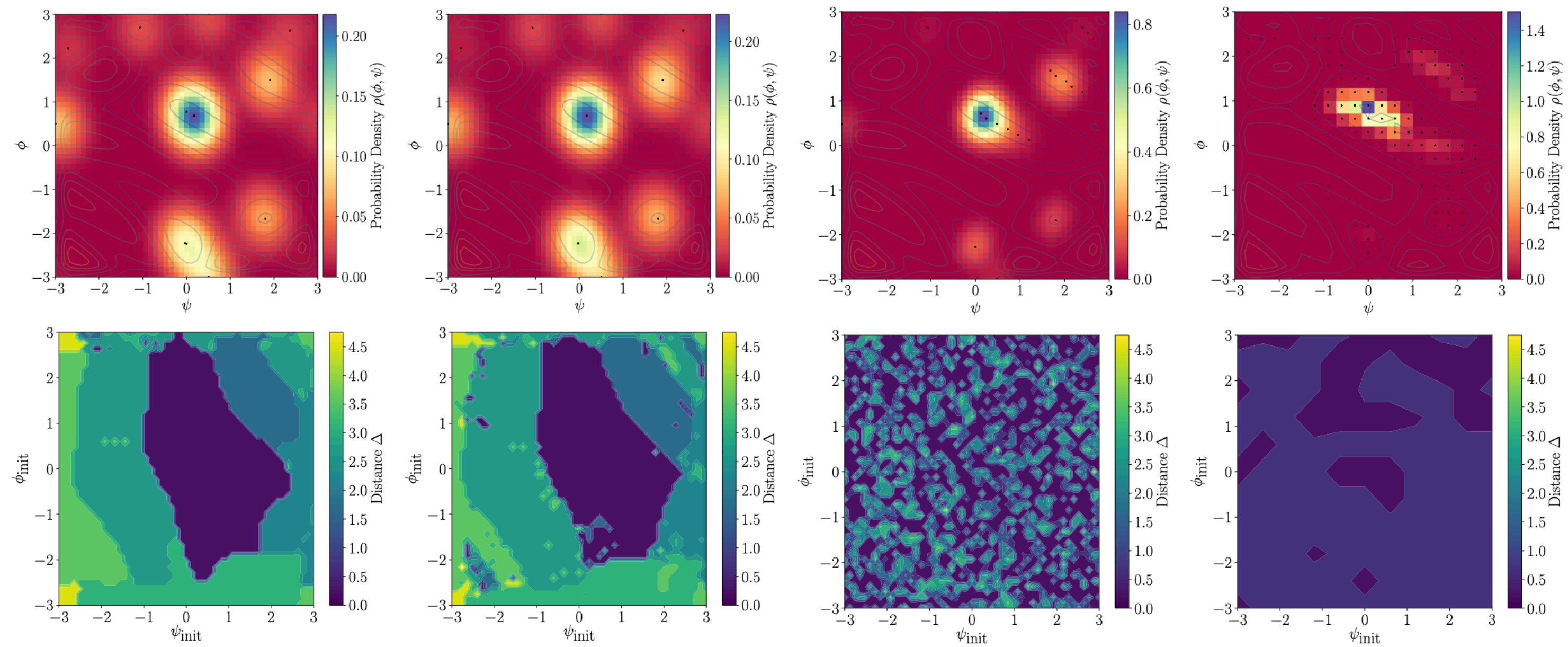
A.D. King, Nature Communications (2021)12:1113



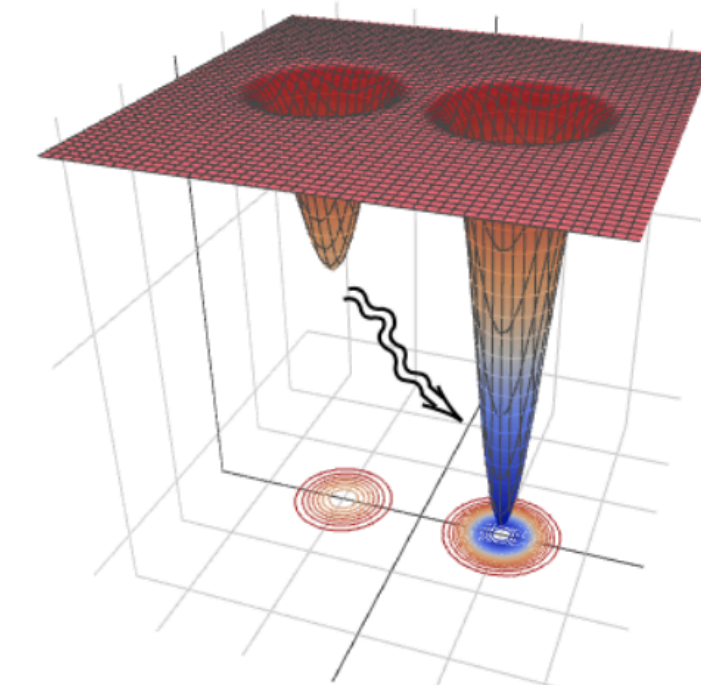


# Tunneling

S.A. Abel, A. Blance, M. Spannowsky, [2105.13945](#)



*Thermal excitations over top of barrier at large  $T$*



*Quantum excitations through barrier at small  $s$*

# Encoding



# Binary encoding

Minimize a loss function  $\mathcal{L}(x_1, x_2, \dots)$

in a box  $[L_1, U_1] \times [L_2, U_2] \times \dots$

up to a finite precision  $1/2^p$

$$x_i = L_i + \frac{U_i - L_i}{1 - 2^{-n-1}} \sum_{\alpha=1}^p \frac{q_{i\alpha}}{2^\alpha} \quad (q_{i\alpha} \in \{0,1\})$$

# Reduction to quadratic

What if  $\mathcal{L}(x)$  has higher-degree terms in  $x$ ?

It becomes a higher-degree polynomial in the qubits  $q_a$

1. Introduce **auxiliary** qubits  $p_{ab}$ , representing the products  $p_{ab} = q_a q_b$

2. New **loss function**:  $\mathcal{L}'(q, p) = \mathcal{L}(q, p) + \lambda \sum_{ab} C(q_a, q_b, p_{ab})$

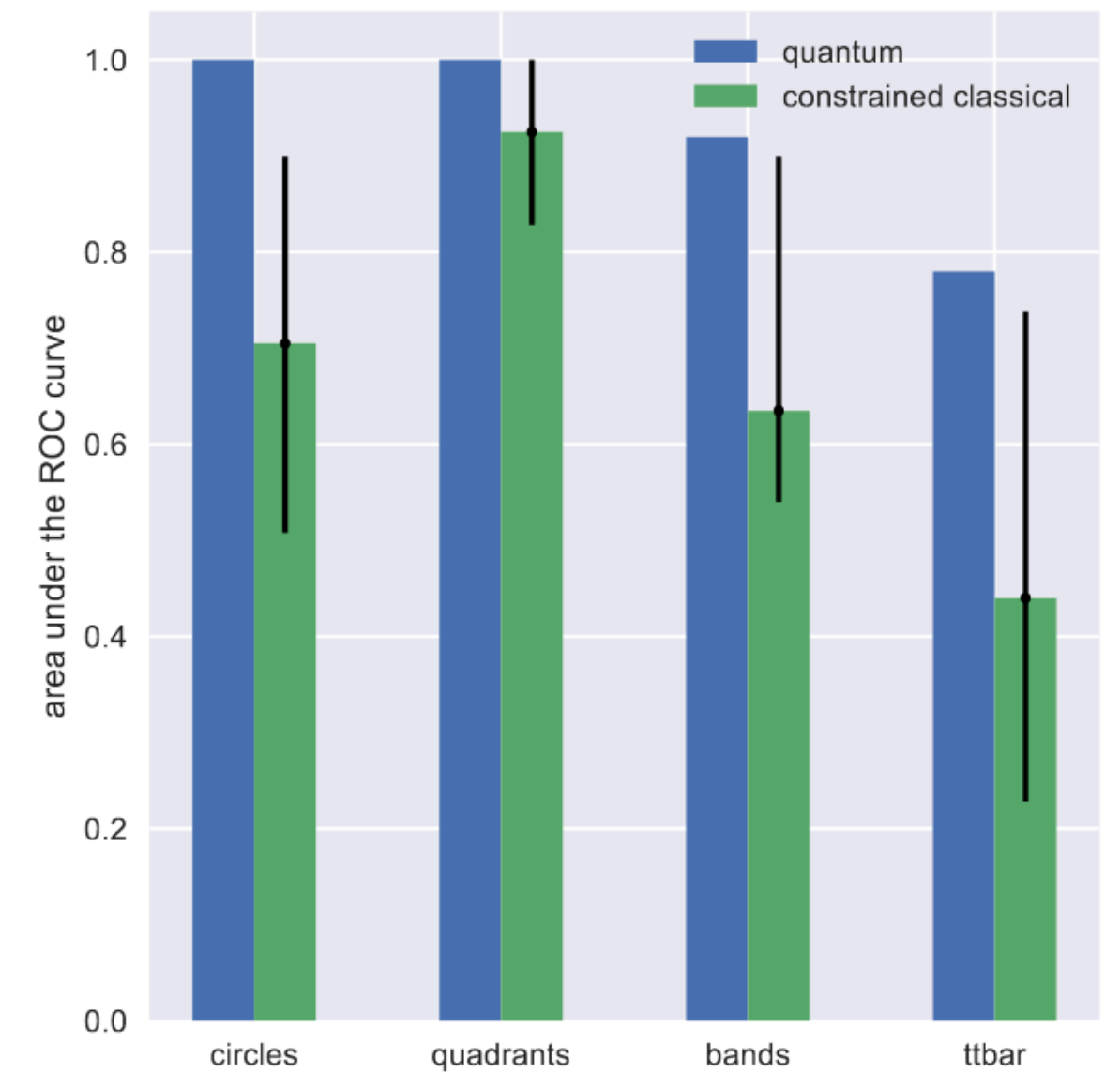
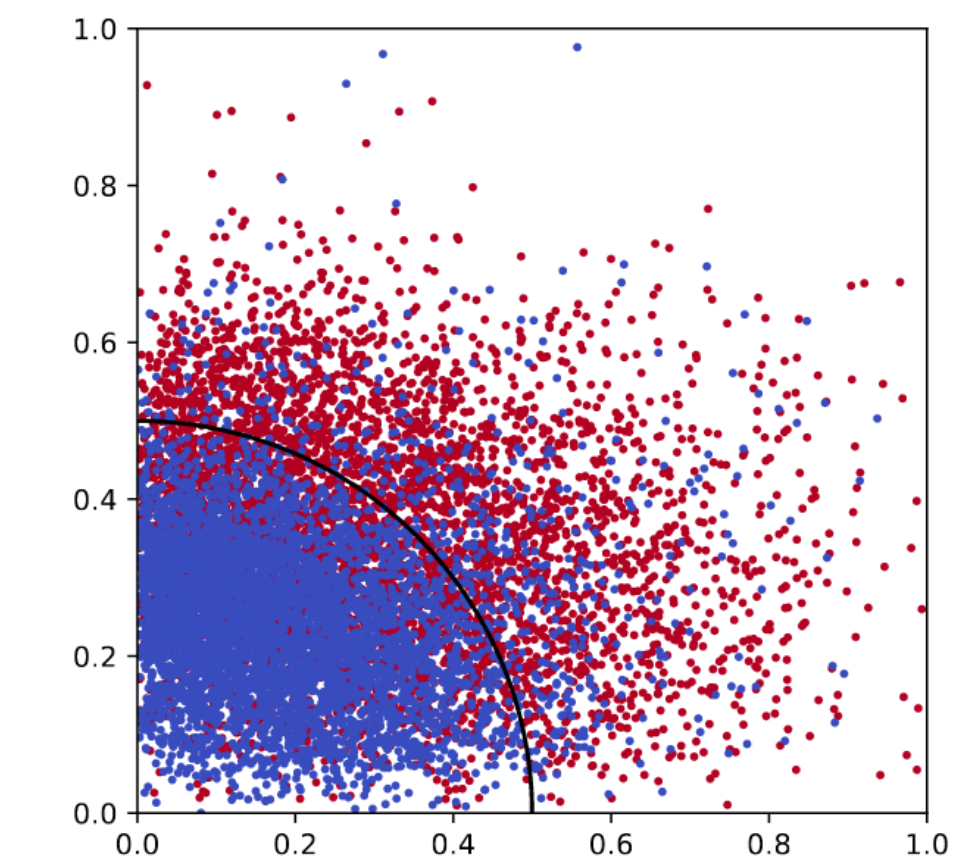
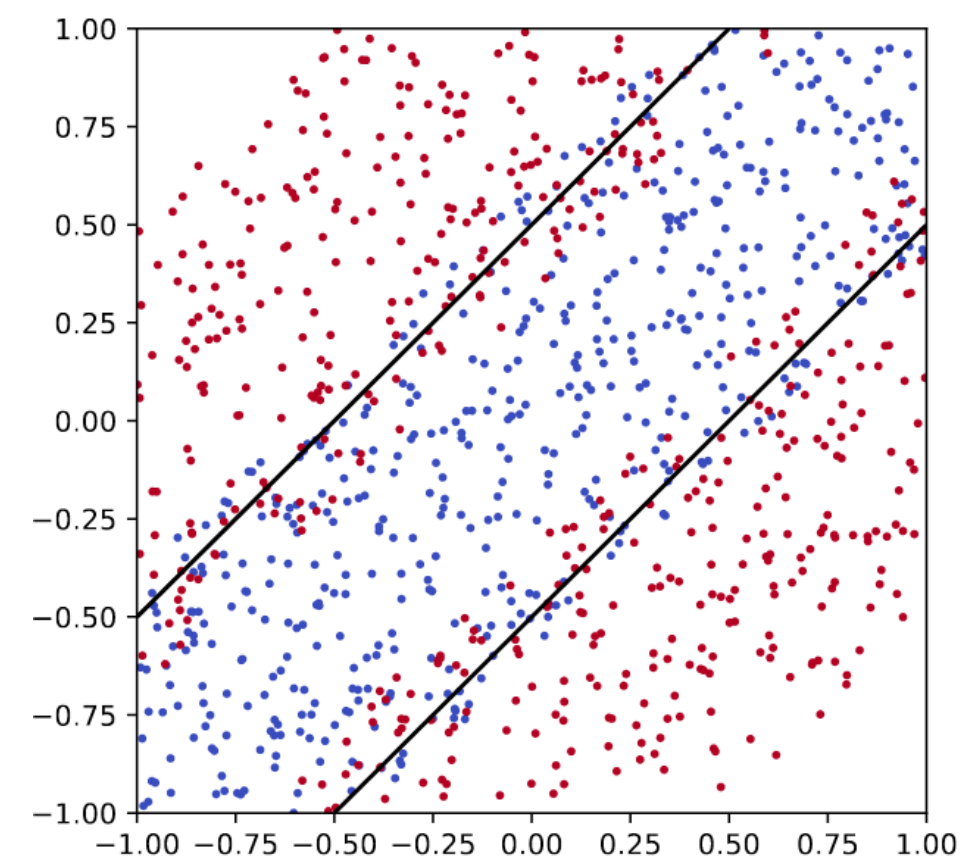
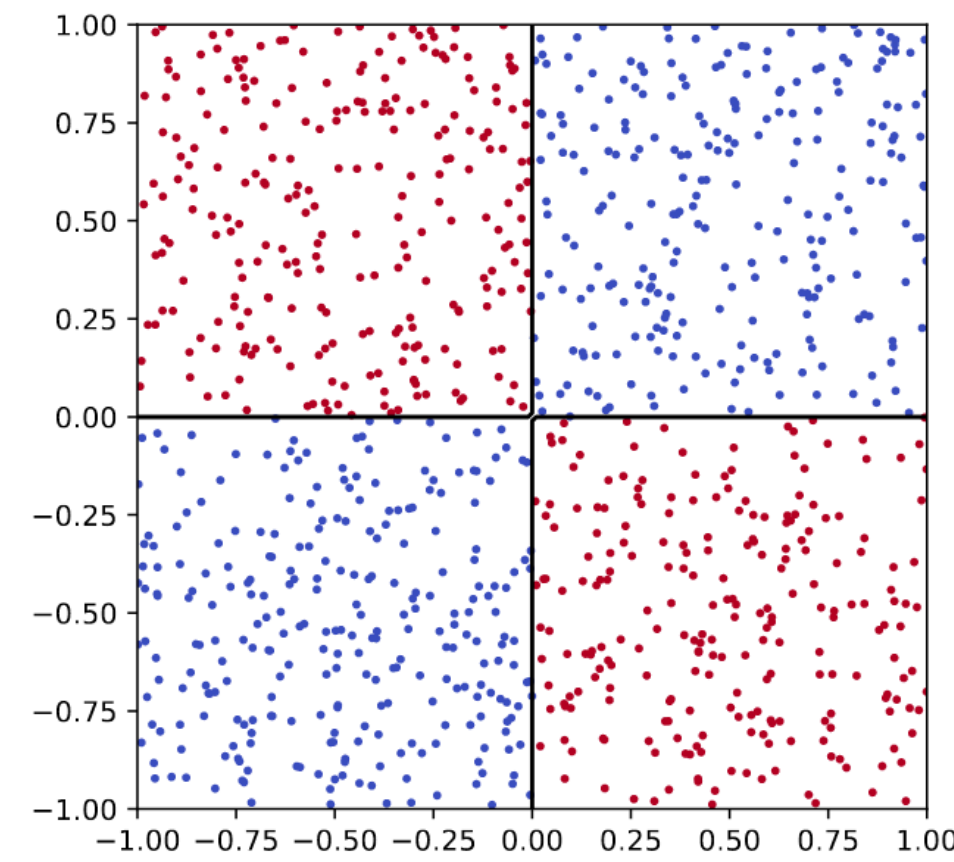
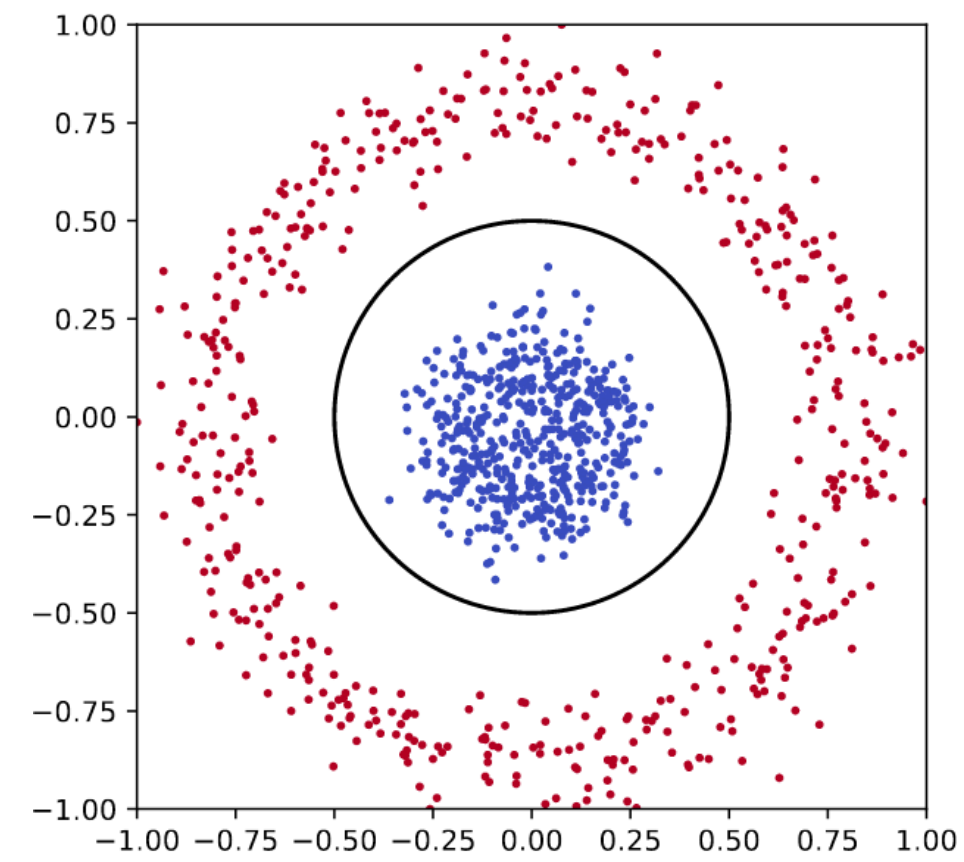
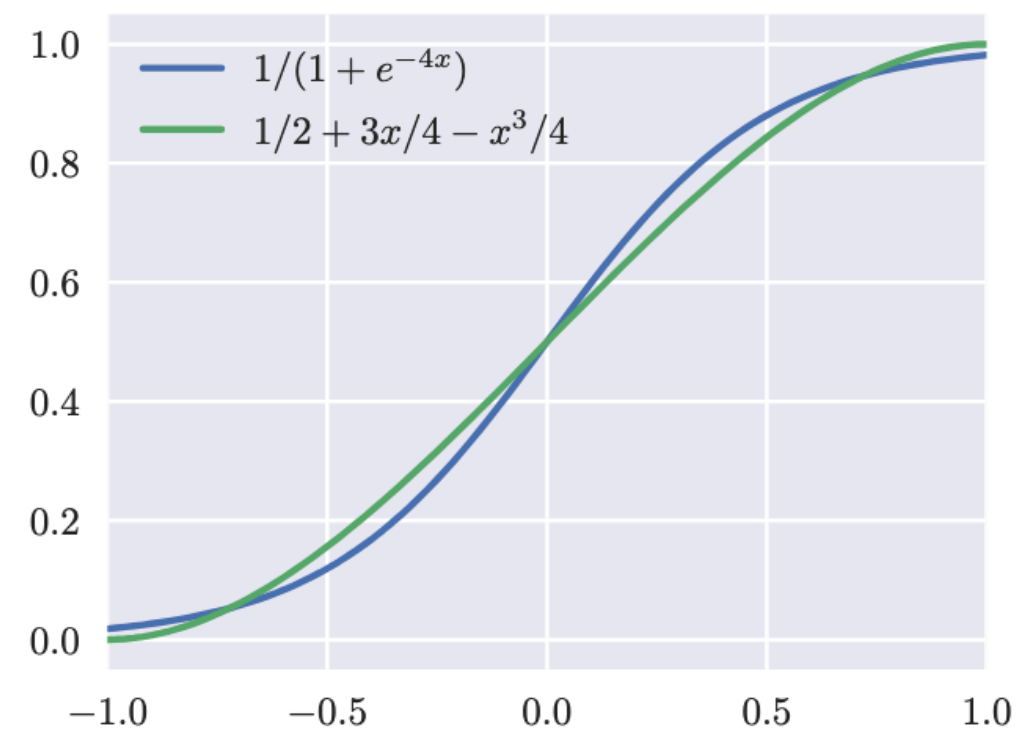
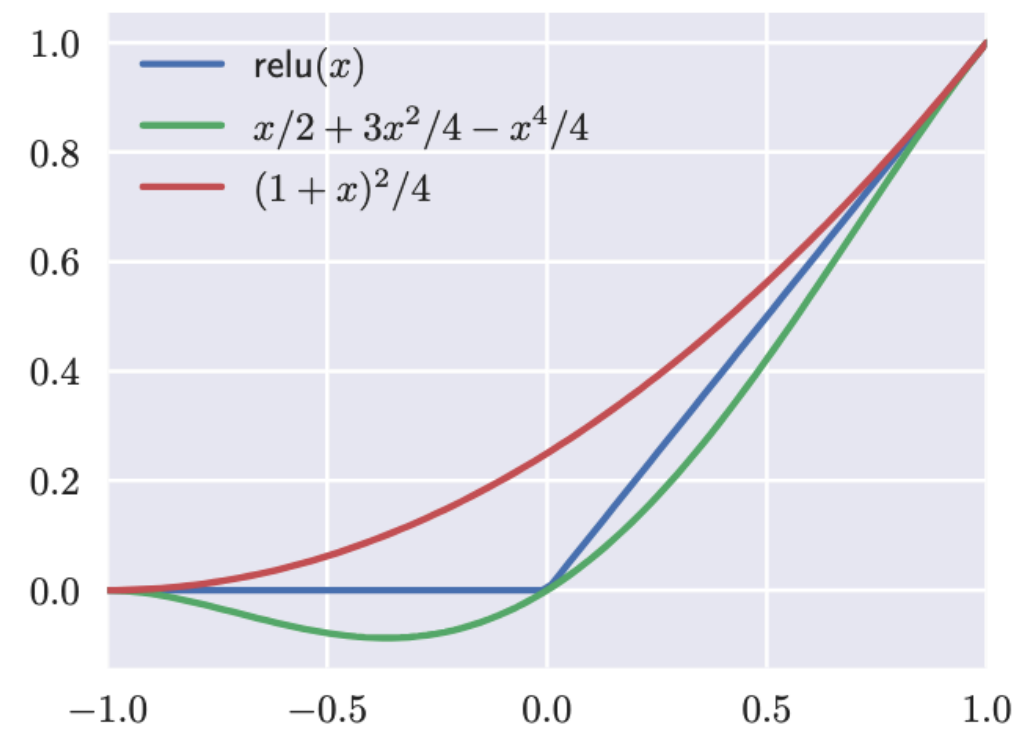
$$C(x, y, z) = xy - 2z(x + y) + 3z \text{ minimised } \iff xy = z$$

# Applications

# Training neural networks

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## Approximate activation functions with polynomials

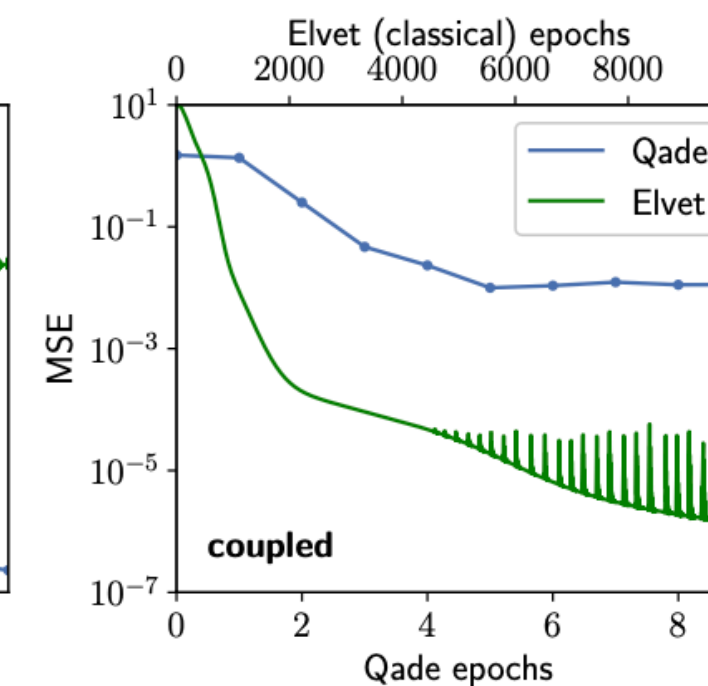
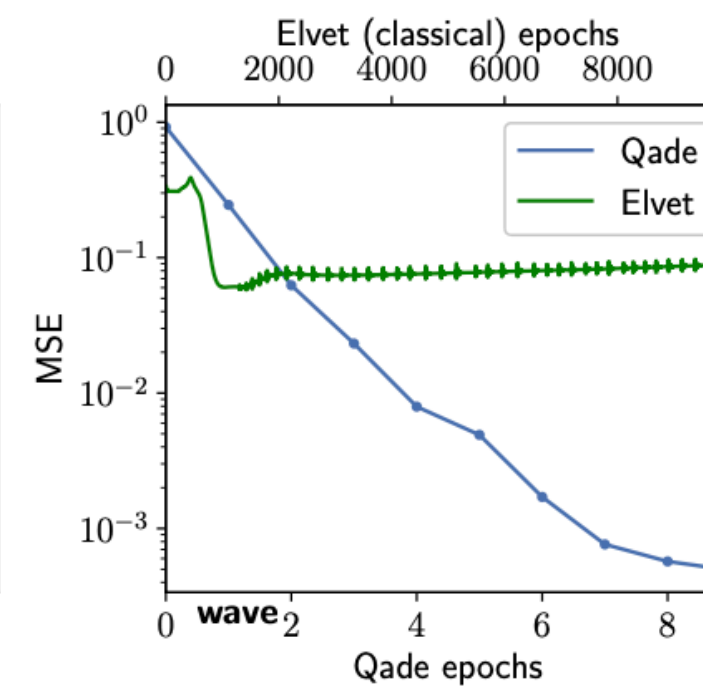
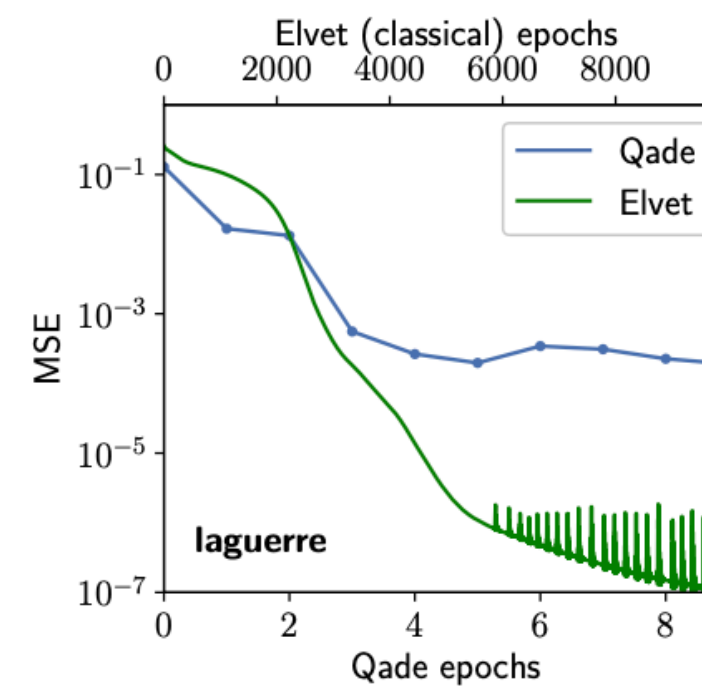
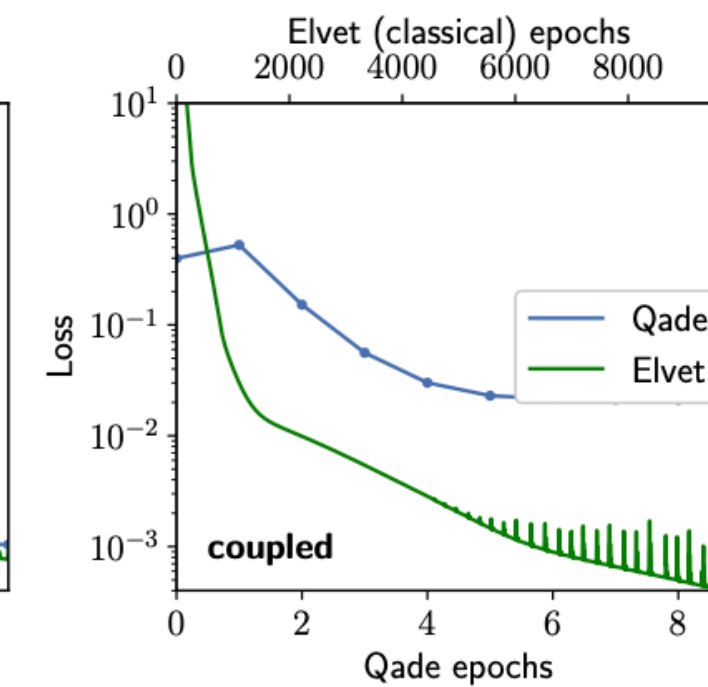
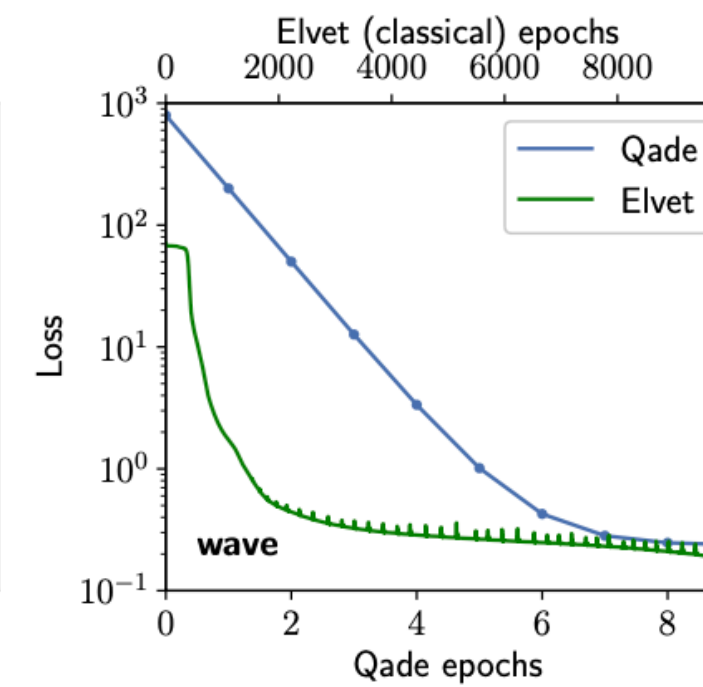
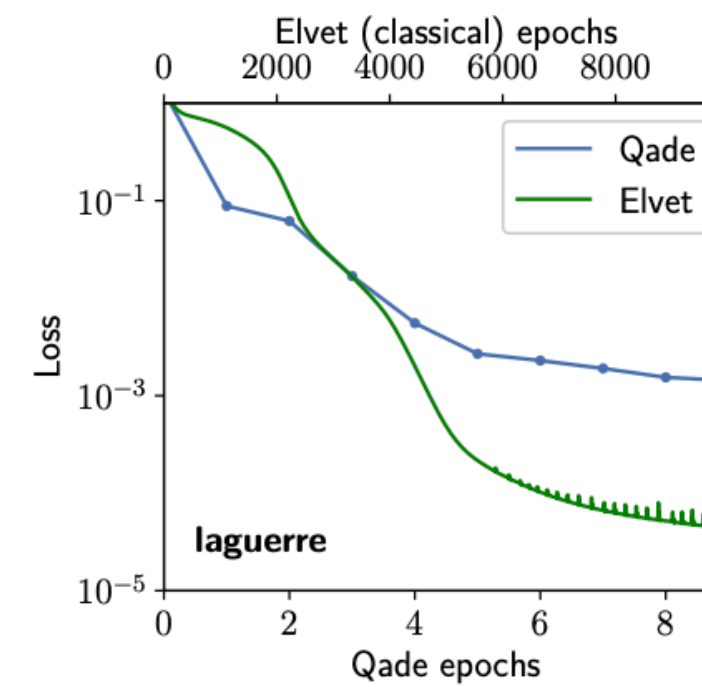
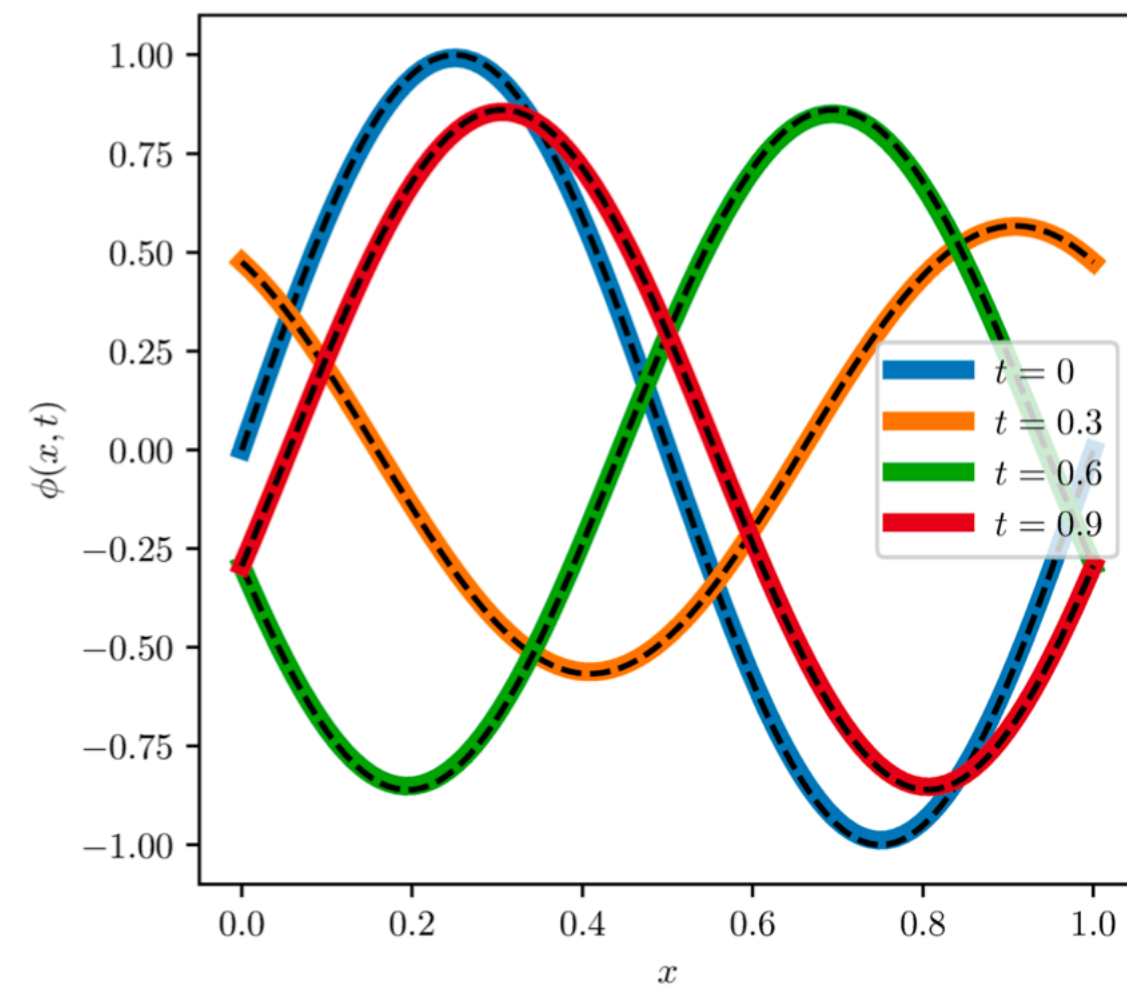
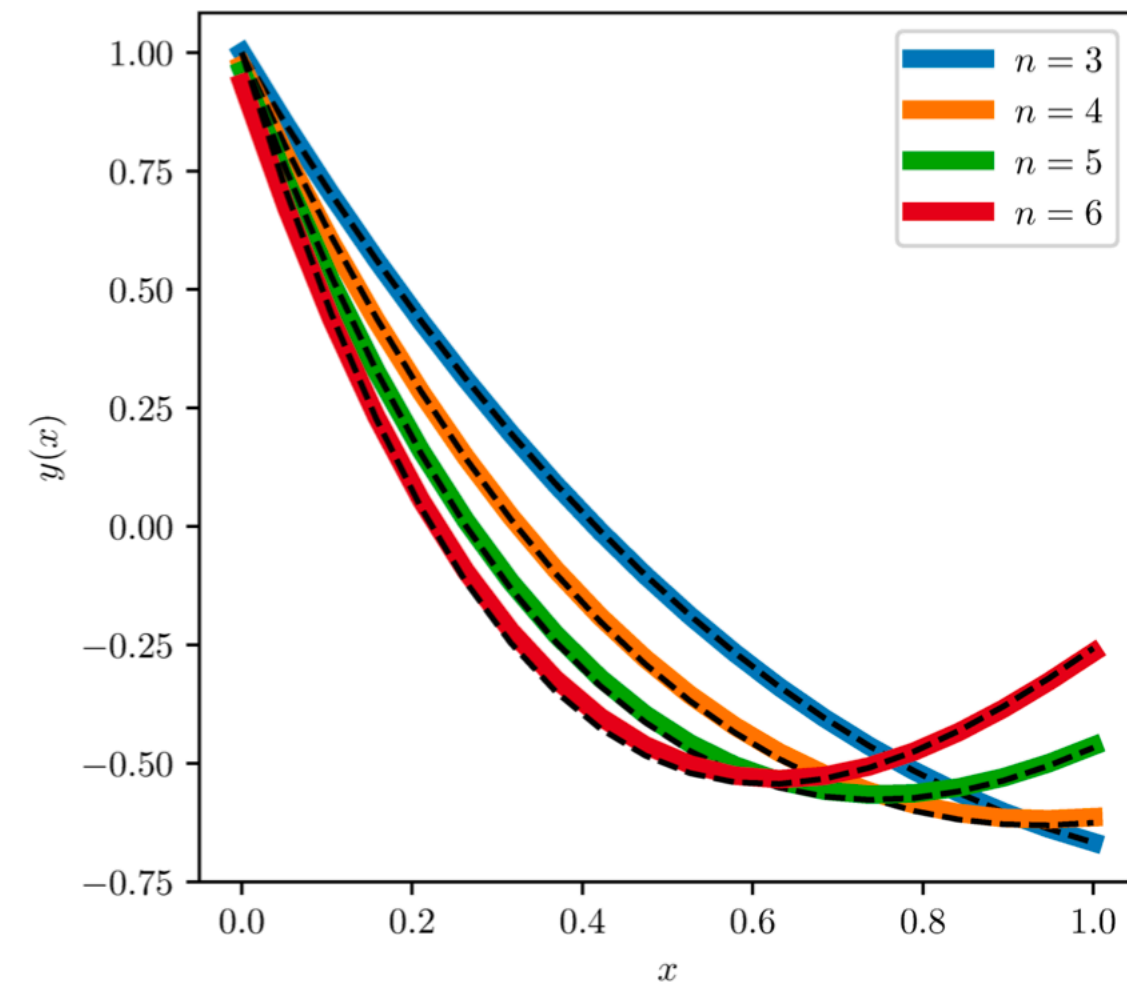


# Qade: solving differential equations

2204.03657

[gitlab.com/jccriado/qade](https://gitlab.com/jccriado/qade)

$$\mathcal{L} = \sum_i E_i(f, \partial f, \dots)^2 + \sum_j BC_j(f, \dots)^2$$





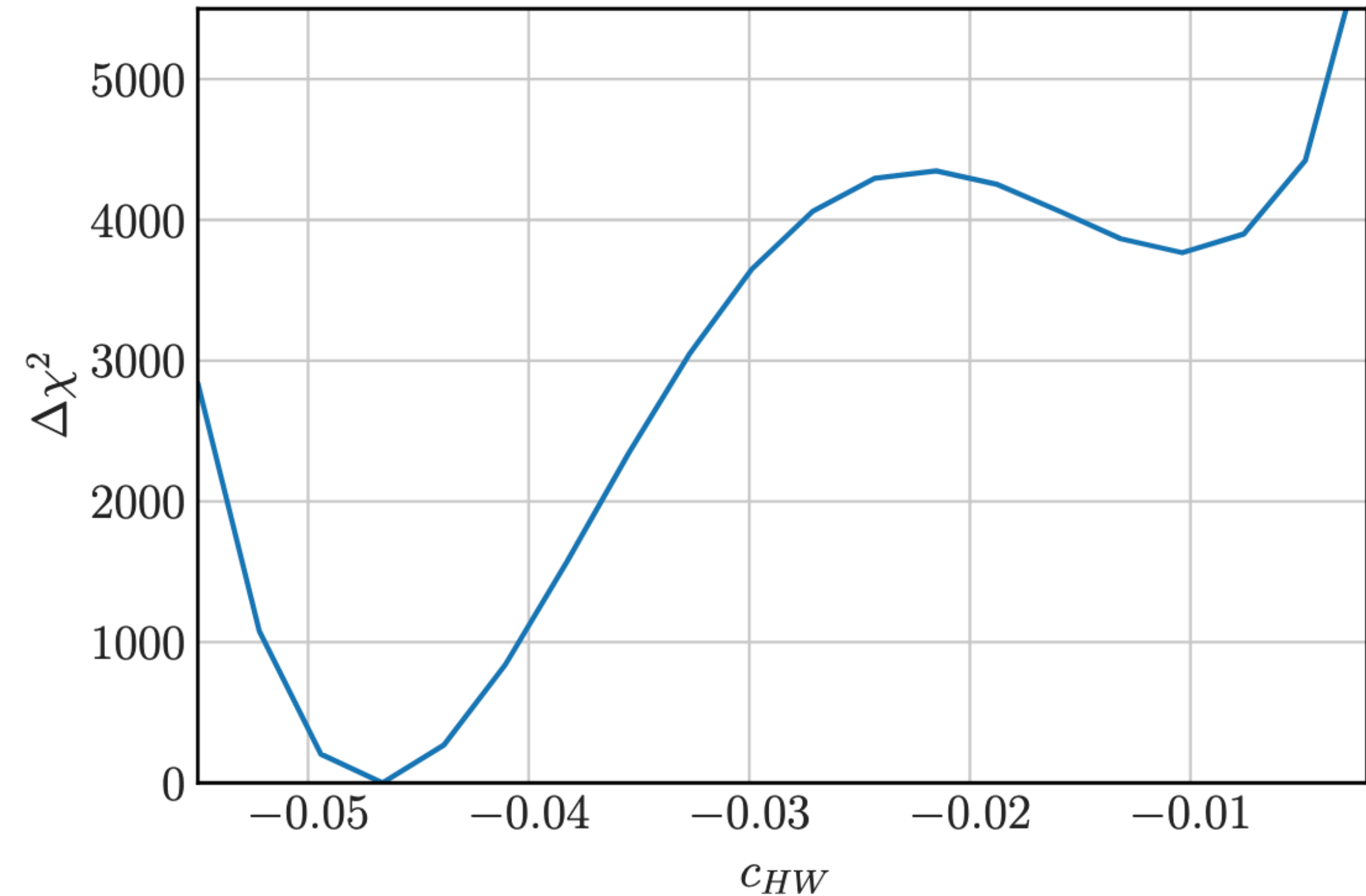
# QFitter: EFT Wilson coefficient fits

2207.10088

$$\chi^2 = \sum_{ij} V_a C_{ab}^{-1} V_b, \quad V_a = O_a^{(\text{exp})} - O_a^{(\text{th})}(c)$$

$$O_a^{(\text{th})}(c) = A_a + \sum_i B_{ai} c_i + \sum_{ij} C_{aij} c_i c_j$$

$$\begin{aligned} \mathcal{L} = & \frac{c_u 3y_t}{v^2} (\phi^\dagger \phi) (\bar{q}_L \tilde{\phi} u_R) + \frac{c_d 3y_b}{v^2} (\phi^\dagger \phi) (\bar{q}_L \phi d_R) \\ & + \frac{ic_W g}{2m_W^2} (\phi^\dagger \sigma^a D^\mu \phi) D^\nu W_{\mu\nu}^a + \frac{c_H}{4v^2} (\partial_\mu (\phi^\dagger \phi))^2 \\ & + \frac{c_\gamma (g')^2}{2m_W^2} (\phi^\dagger \phi) B_{\mu\nu} B^{\mu\nu} + \frac{c_g g_S^2}{2m_W^2} (\phi^\dagger \phi) G_{\mu\nu}^a G^{a\mu\nu} \\ & + \frac{ic_{HW} g}{4m_W^2} (\phi^\dagger \sigma^a D^\mu \phi) D^\nu W_{\mu\nu}^a \\ & + \frac{ic_{HB} g'}{4m_W^2} (\phi^\dagger D^\mu \phi) D^\nu B_{\mu\nu} + \text{h.c.} \end{aligned}$$



# Conclusions

- **Quantum annealing** paradigm: find the ground state of the Ising model
  - Scaling advantage in performance over classical methods
  - Robust global-minimum finding in non-convex loss functions
- Minimisation of general functions of continuous variables:
  - **Binary encoding**
  - **Reduction** to quadratic
- Applications:
  - Purely **quantum-trained neural networks**
  - Solving **partial differential equations**
  - **Fitting** EFT coefficients