View of Camerino

Quantum enhanced optimization and machine learning

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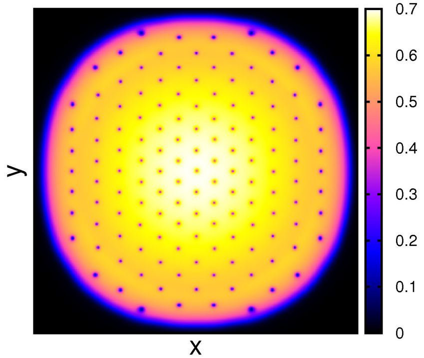
Ph.D. program in Quantum Technologies
Inauguration
Naples, February 8th 2019

ultracold gases

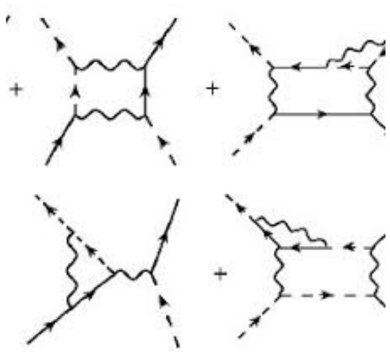
BEC-BCS crossover, quantum magnetism, Anderson localization

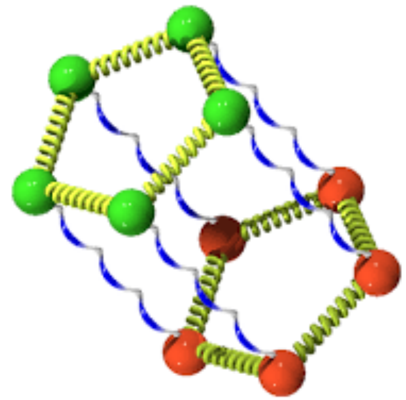


Simonucci, Pieri, Strinati, Nature Physics (2015)

Computational quantum many-body physics

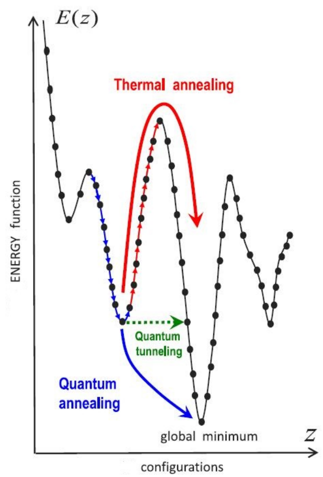
Feynman diagrams, quantum Monte Carlo simulations, Bogoliubov-de Gennes eq.





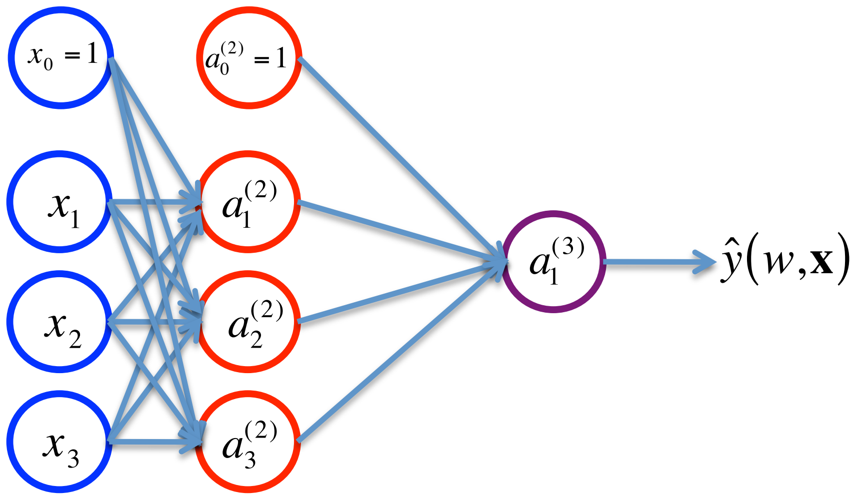
quantum enhanced optimization

quantum annealing, stochastic optimization, etc..



machine learning

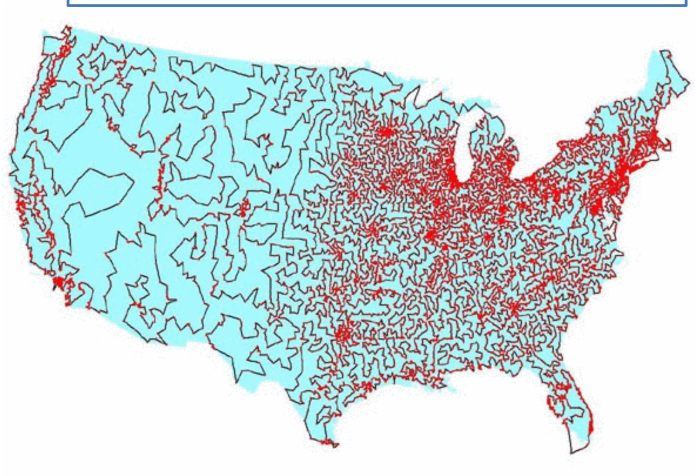
ML for quantum systems, protein-molecule binding, booking engines (6tour.com)



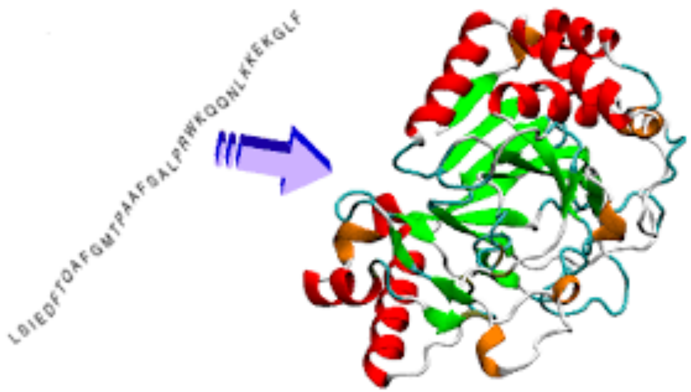
Can quantum effects help us in solving complex optimization problems?

Optimization Problems

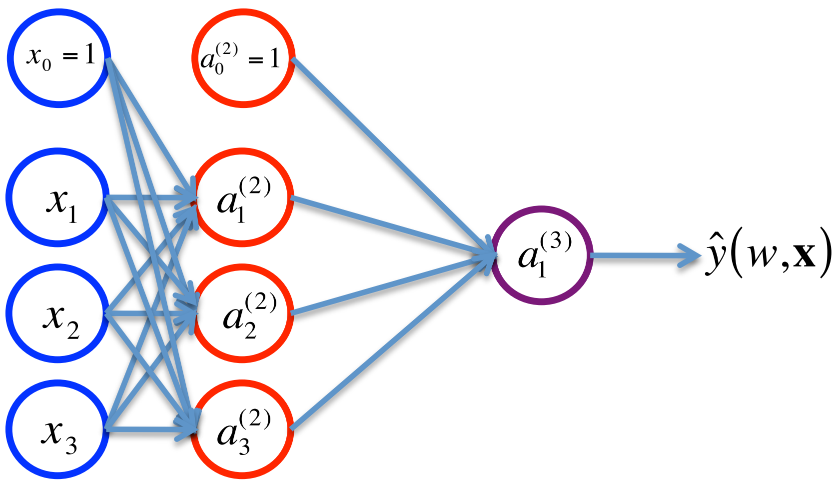
Traveling salesman problem



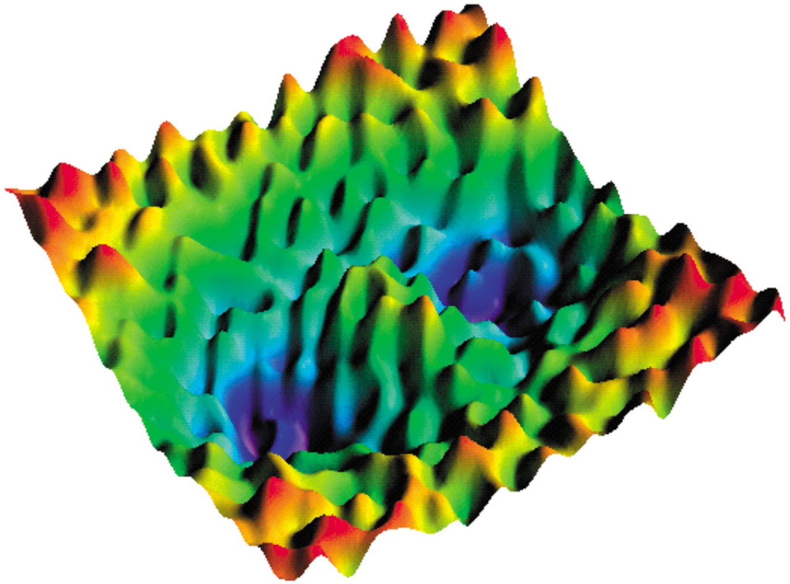
Protein Folding

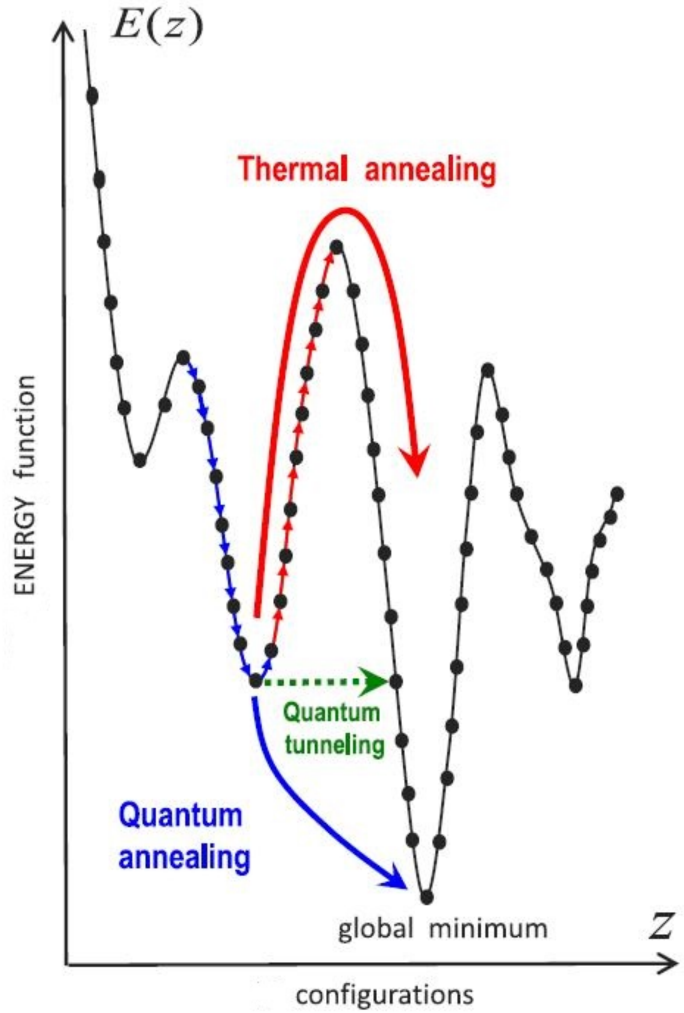


Training neural networks



Simulated (Classical) Annealing vs Quantum Annealing





Adiabatic quantum computing: Quadratic Unconstrained Binary Optimization

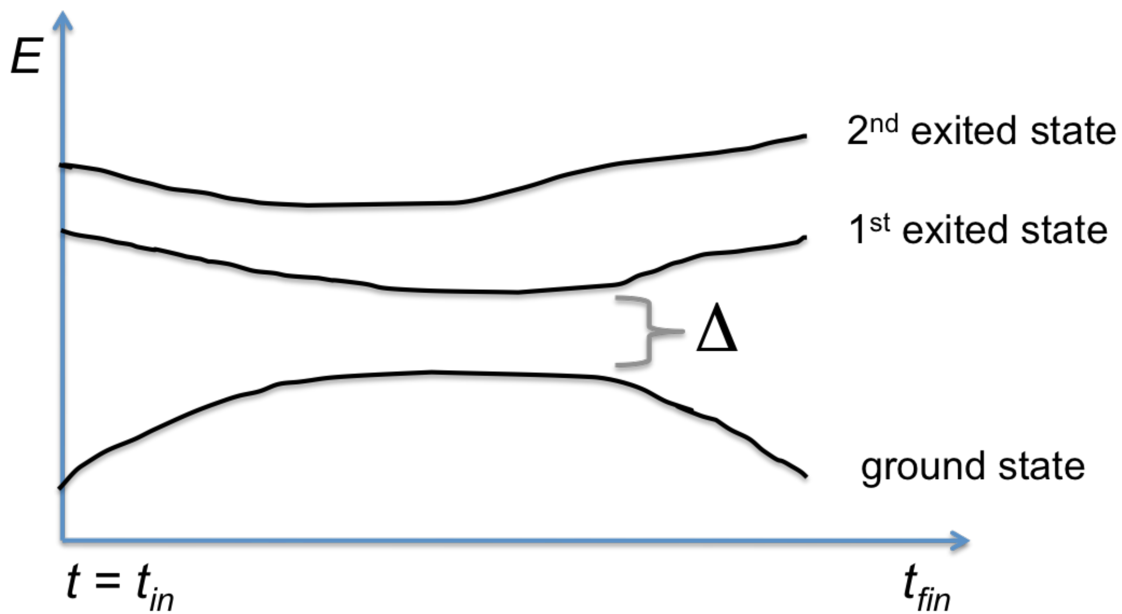
$$H_{\rm cl} = -\sum_{ij} J_{ij}\sigma_i^z\sigma_j^z - \sum_i h_i\sigma_i^z \qquad \sigma_i^z = \pm 1$$

Ising glass: finding the ground state is a hard problem

$$H_{\rm tot} = H_{\rm cl} + H_{\rm kin}$$

$$H_{\rm kin} = -\Gamma(t)\sum_i \sigma_i^x$$

introduce quantum fluctuations



How slow?

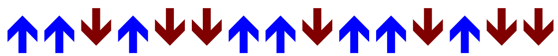
Adiabatic theorem:

$$t_{fin} >> \frac{\alpha}{\Delta^2}$$

$\Delta \equiv$ smallest gap

$$\Gamma(t = t_{\rm in}) >> J_{ij}, h_i$$

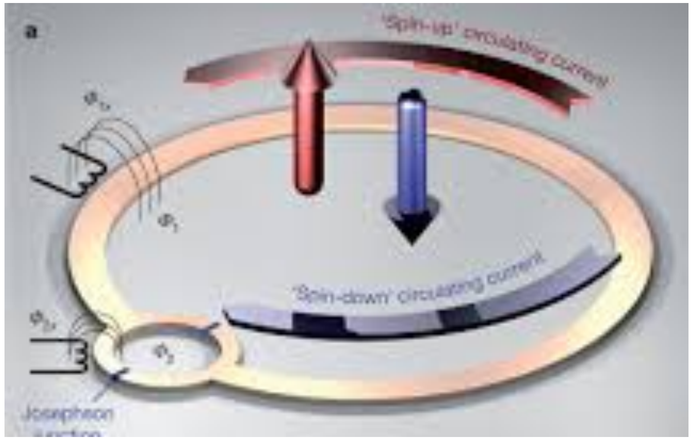
$$\Gamma(t = t_{fin}) = 0$$

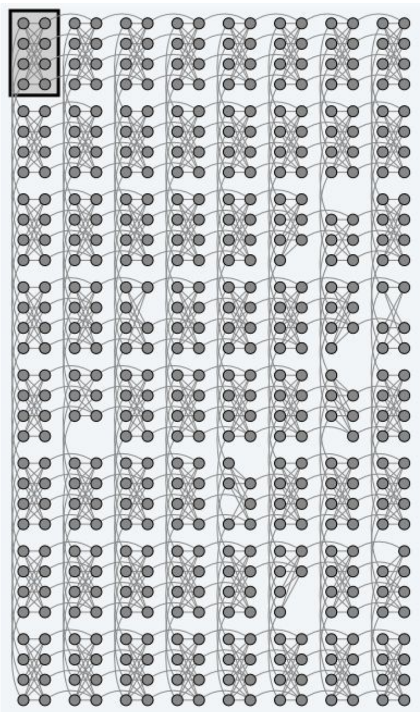


Quantum Annealing with an adiabatic quantum computer

$$H_{\text{cl}} = -\sum_{ij} J_{ij}\sigma_i^z\sigma_j^z - \sum_i h_i\sigma_i^z \qquad H_{\text{kin}} = -\Gamma(t)\sum_{ij}\sigma_i^x$$

E.g., linear schedule: $\Gamma(t) = \Gamma_0\left(1 - \frac{t}{t_{fin}}\right)$





Can a quantum annealer like D-Wave outperform (any) classical optimization method?

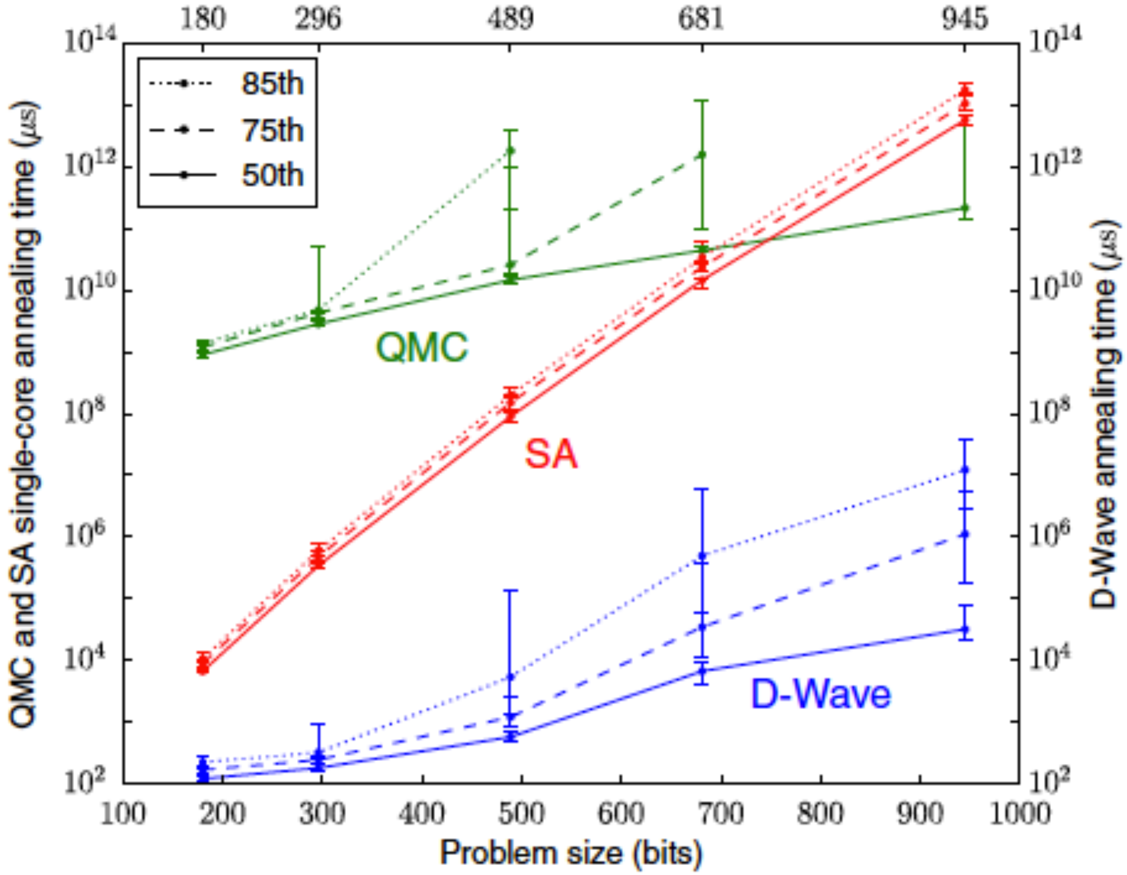
Difficult to answer: one cannot simulate the (unitary) dynamics using classical computers (computational times scales exponentially)

QUESTIONS:

Can quantum Monte Carlo algorithms simulate quantum annealers?

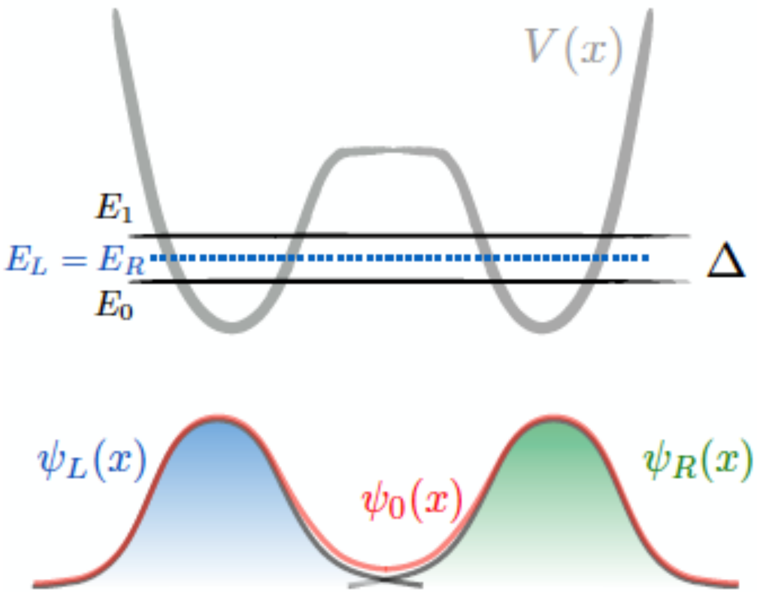
Can we use quantum Monte Carlo simulations to solve complex optimization problems?

D-Wave versus Classical Simulated Annealing (SA) and Simulated Quantum Annealing (QMC)



Denchev, Boixo, Isakov, Ding, Babbush, Smelyanskiy, Martinis, Neven, PRX 2016

Tunneling in a double-well problem



$$\psi_0 \equiv \text{ ground state w.f.}$$

$$\psi_1 \equiv 1^{\text{st}} \text{ excited state}$$

$$\psi_L \equiv \frac{\psi_0 - \psi_1}{\sqrt{2}} \qquad \psi_R \equiv \frac{\psi_0 + \psi_1}{\sqrt{2}}$$

$$\Delta \equiv \mathrm{E}_1 - \mathrm{E}_0$$

Isolated system

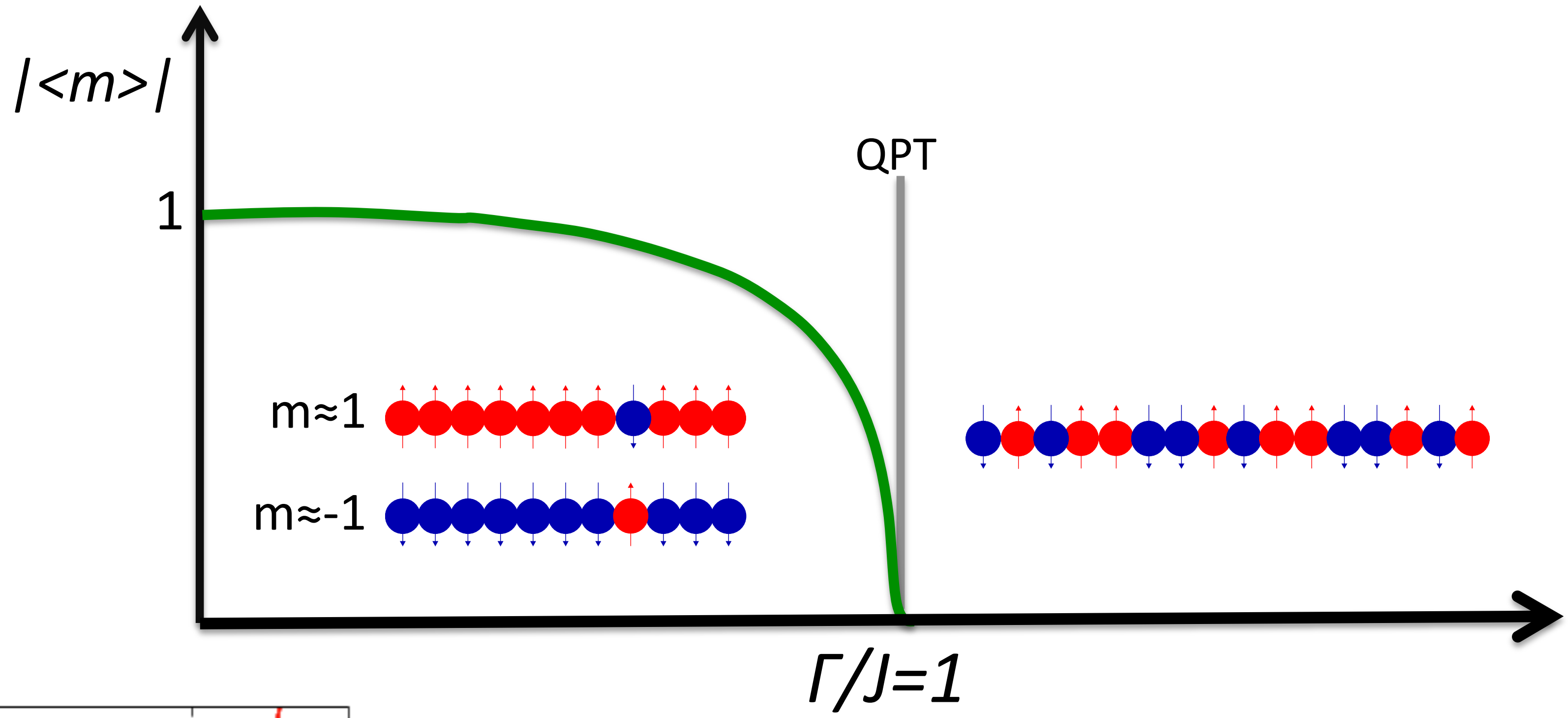
period of coherent oscillations = $\xi_{\text{coh}} \propto \dfrac{1}{\Delta}$

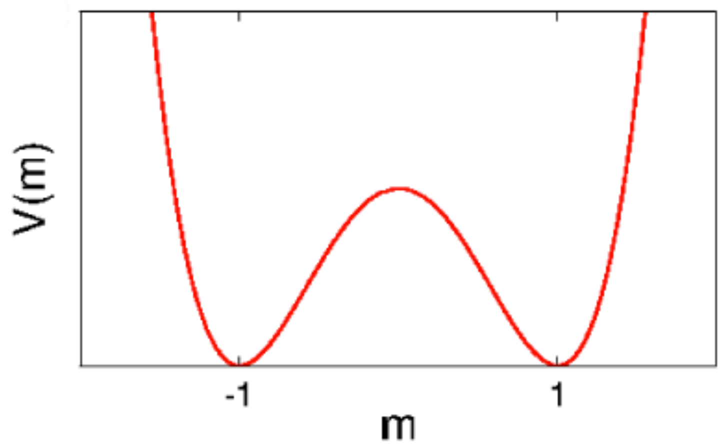
Coupling to environment:

incoherent quantum tunneling time = $\xi_{\text{incoh}} \propto \dfrac{1}{\Delta^2}$

Adiabatic theorem - > annealing time to avoid diabatic transitions $\xi_{\text{anneal}} = \dfrac{\alpha}{\Delta^2}$

1D ferromagnetic quantum Ising model: $H_{\mathrm{cl}} = -J\sum_{\langle ij\rangle}\sigma_i^z\sigma_j^z - \Gamma\sum_i \sigma_i^x$

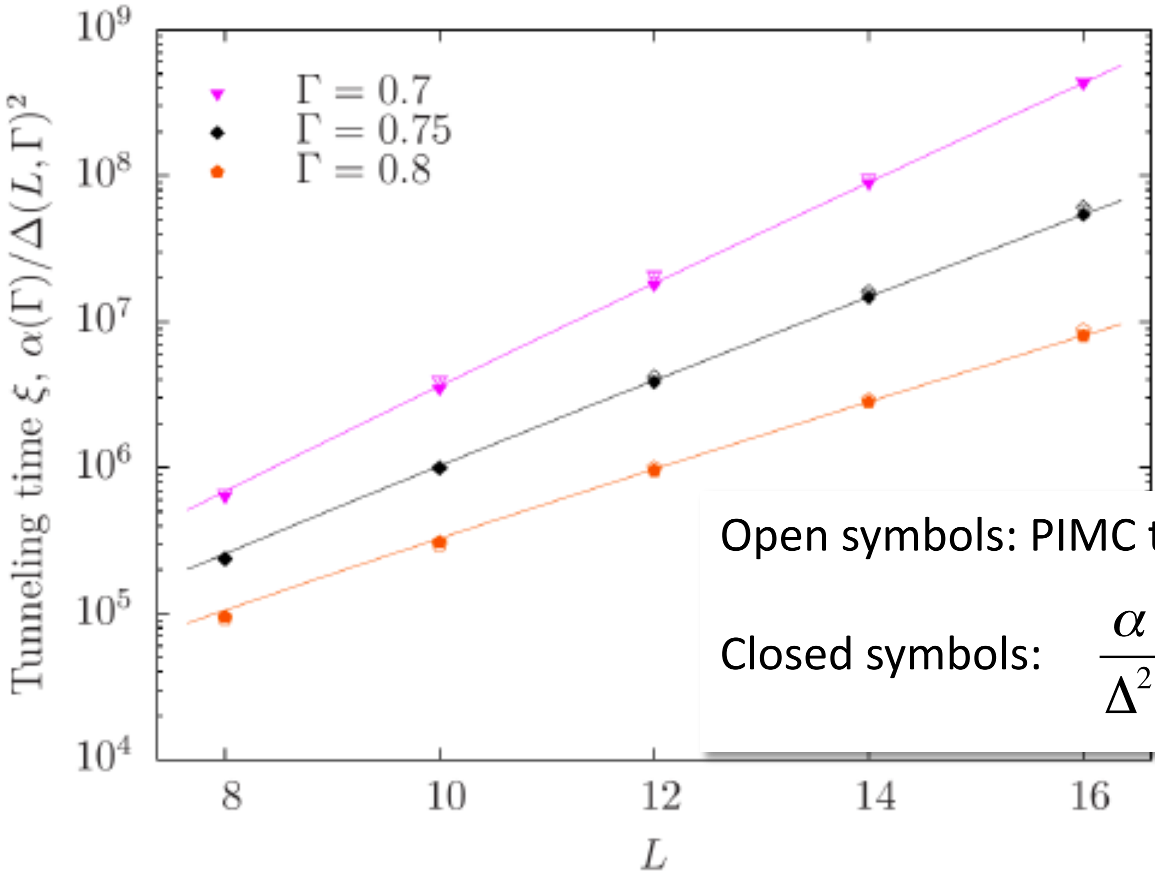




exponentially small energy gap: $\Delta \propto \exp(-\alpha L)$

Quantum Monte Carlo tunneling time: Path Integral MC

Isakov, Mazzola, Smelyanskiy, Jiang, Boixo, Neven, Troyer, PRL (2016)



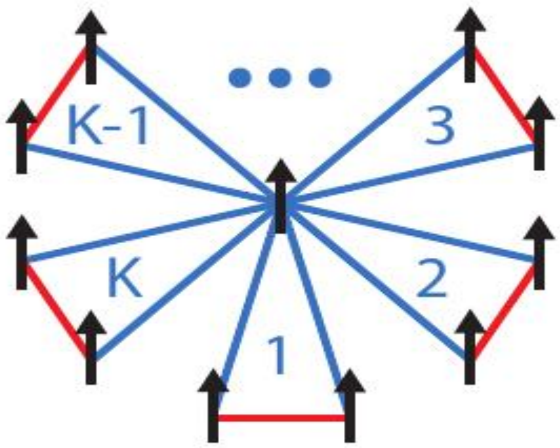
Open symbols: PIMC tunneling time

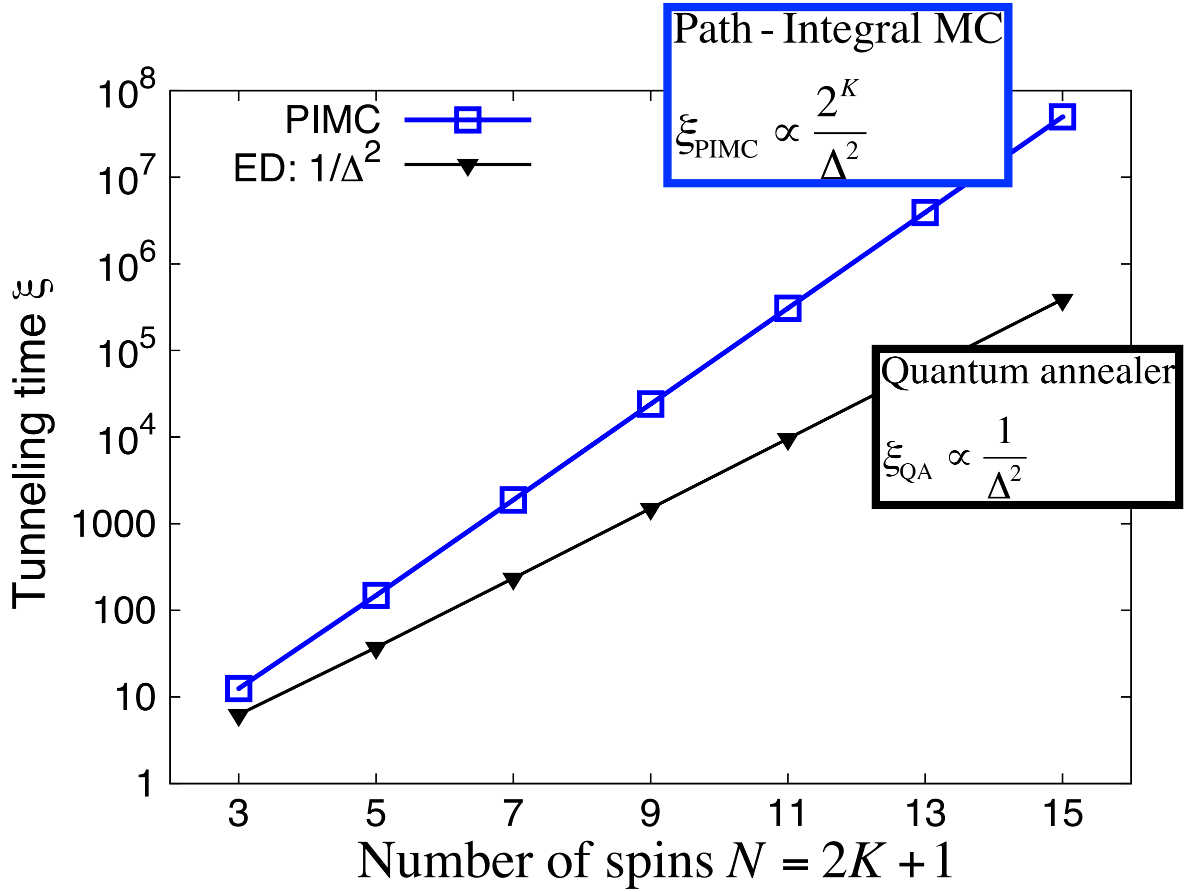
Closed symbols: $\frac{\alpha}{\Delta^2}$

The PIMC algorithm efficiently simulates incoherent quantum tunneling (in this model).
Is this general?

Shamrock: a model of frustrated rings

E. Andriyash and M. H. Amin (D-Wave Systems Inc.), *"Can quantum Monte Carlo simulate quantum annealing?"*, arXiv:1703.09277, 2017





Recently realized @Google
Kafri, D., Quintana, C., Chen, Y., Martinis, J., & Neven, H. Progress Towards Quantum Annealer v2. 0, Bulletin of the American Physical Society (2018).

- Path-integral slows down due to "topological" obstruction, **slower than Quantum annealer!**

Shamrock: a model of frustrated rings

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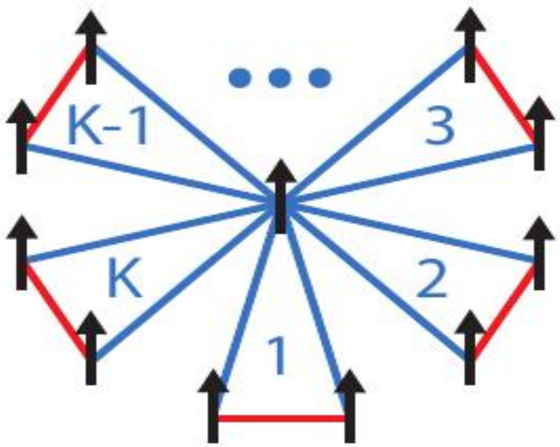

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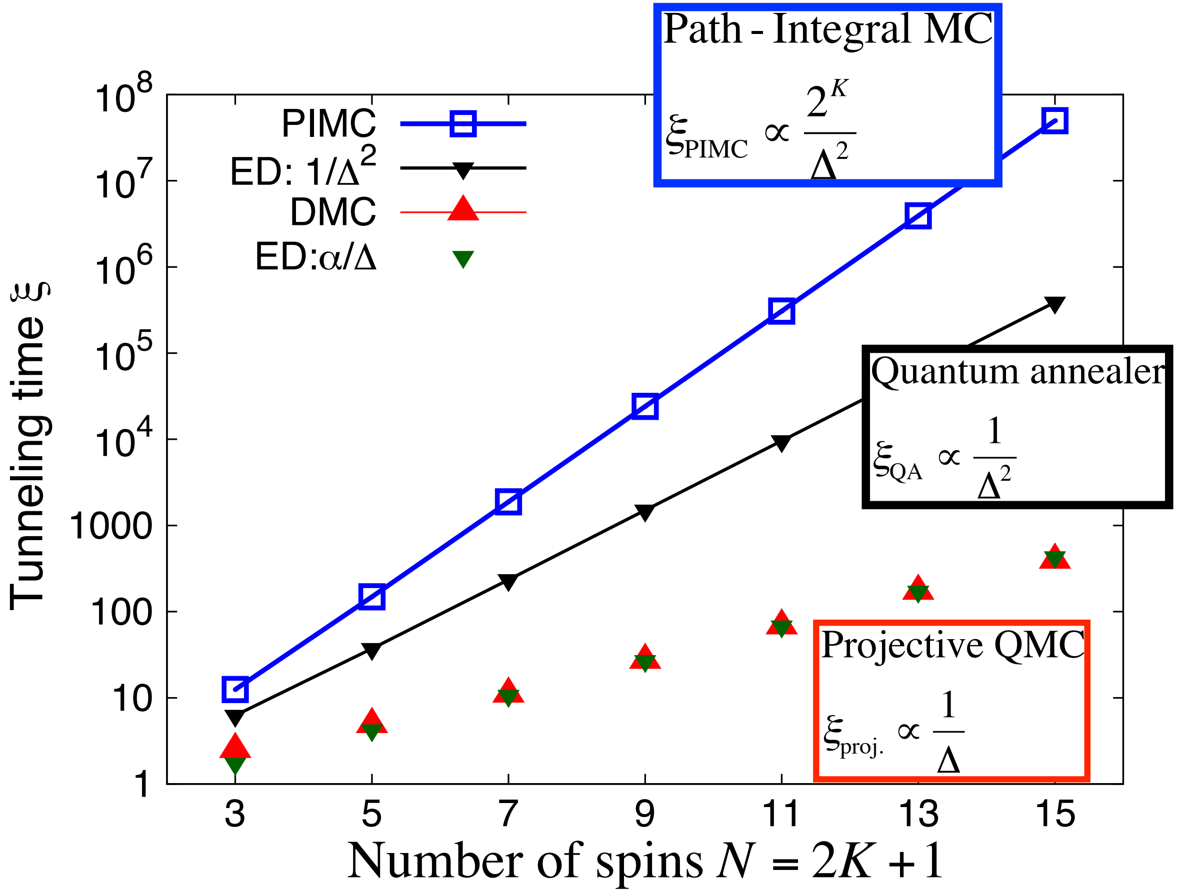


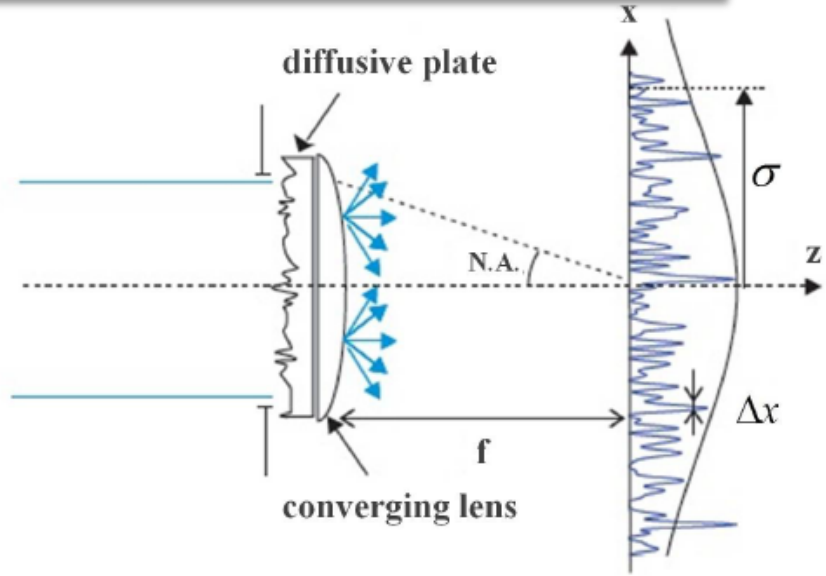
- Path-integral slows down due to "topological" obstruction, **slower than Quantum annealer!**
- Projective QMC like $1/\Delta$ (i.e., "faster" than QA)

E. M. Inack, G. Giudici,T. Parolini, G.E. Santoro, SP, PRA (2018)

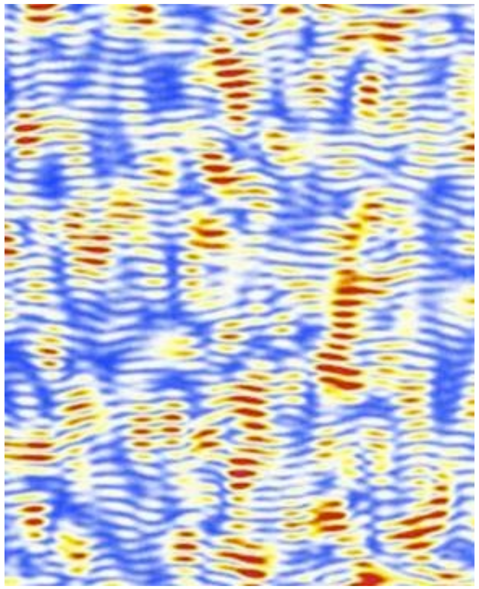
Q1: Can a machine learn to solve quantum mechanics problems from data?

Q2: Can we use experimental data to train a machine to solve quantum problems that cannot be solved using classical computers?

Disorder: optical speckle patterns

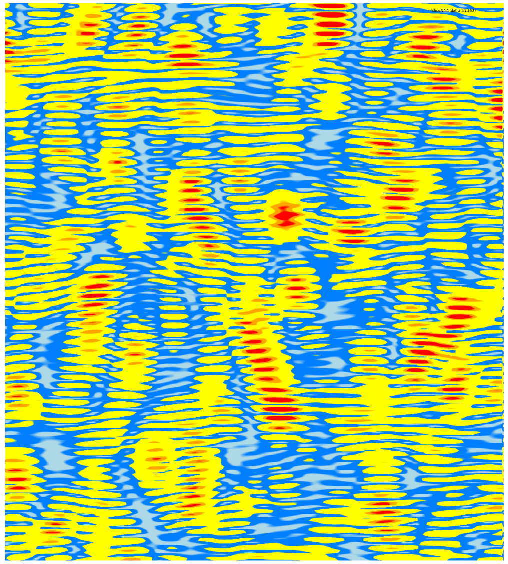


Exp. @ LENS



Semeghini, Landini, Castilho, Roy, Spagnolli, Trenkwalder, Fattori, Inguscio, Modugno Nature Phys. 2015

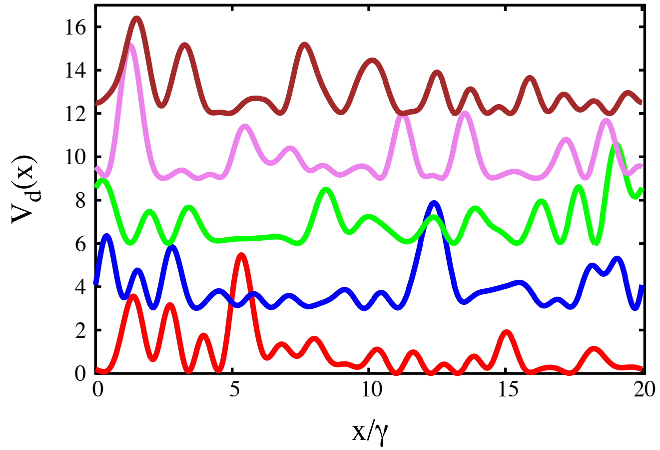
Computer Simulation

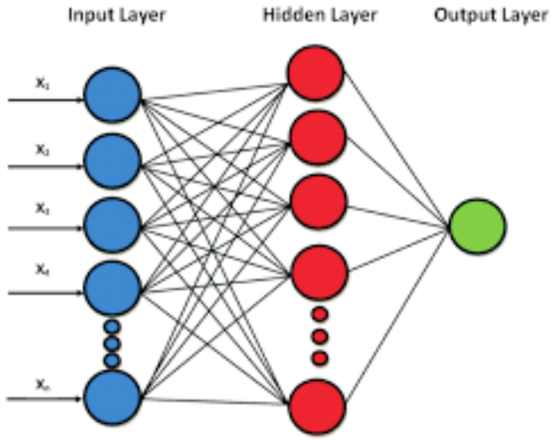


Fratini, SP PRA (R) 2015

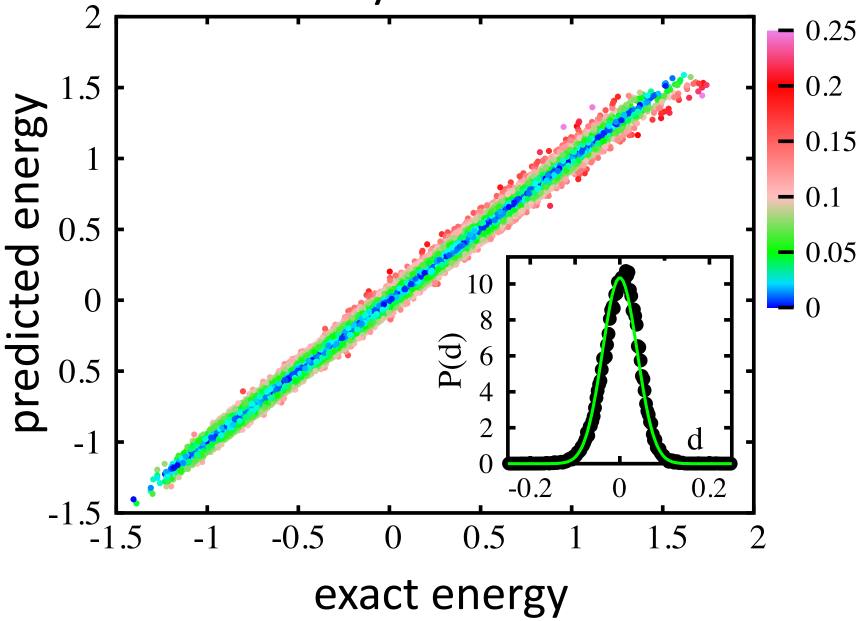
CAN WE TRAIN ARTIFICIAL NEURAL NETWORKS USING EXPERIMENTAL DATA?

quantum particle in speckle field

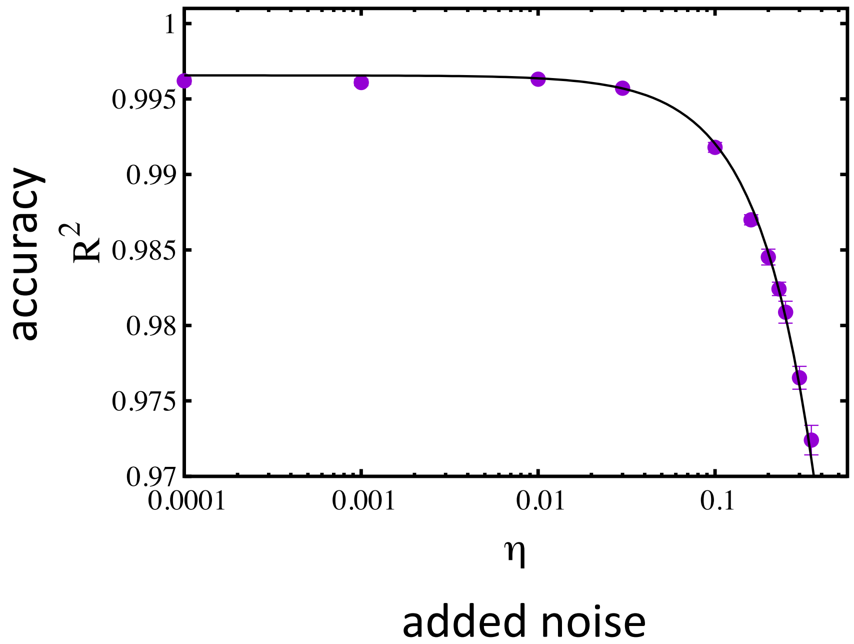




Test on synthetic data



Synthetic data with added noise



(Near) Future perspective:

using cold-atom quantum simulators to train artificial neural networks to solve models that cannot be solved using classical computers