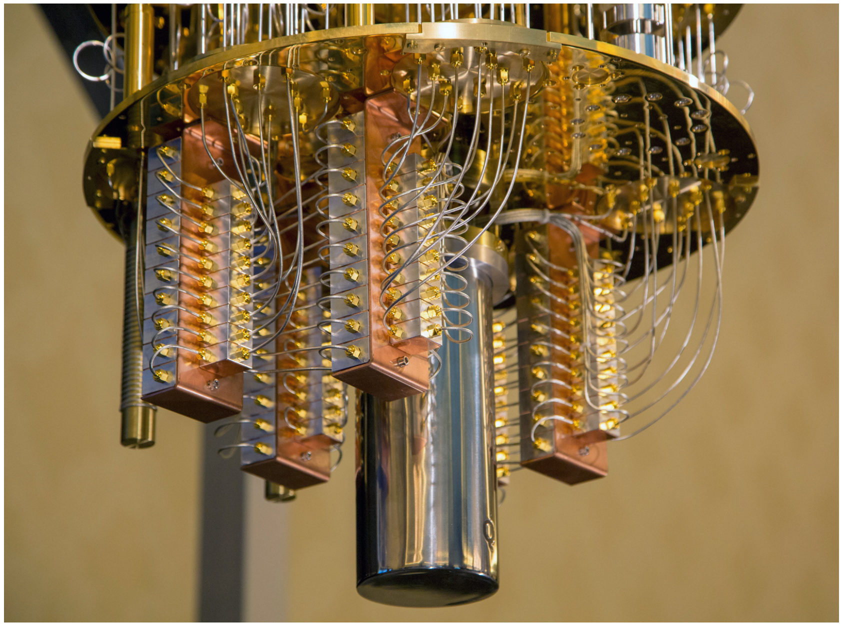
Quantum Machine Learning

Quantum Computing



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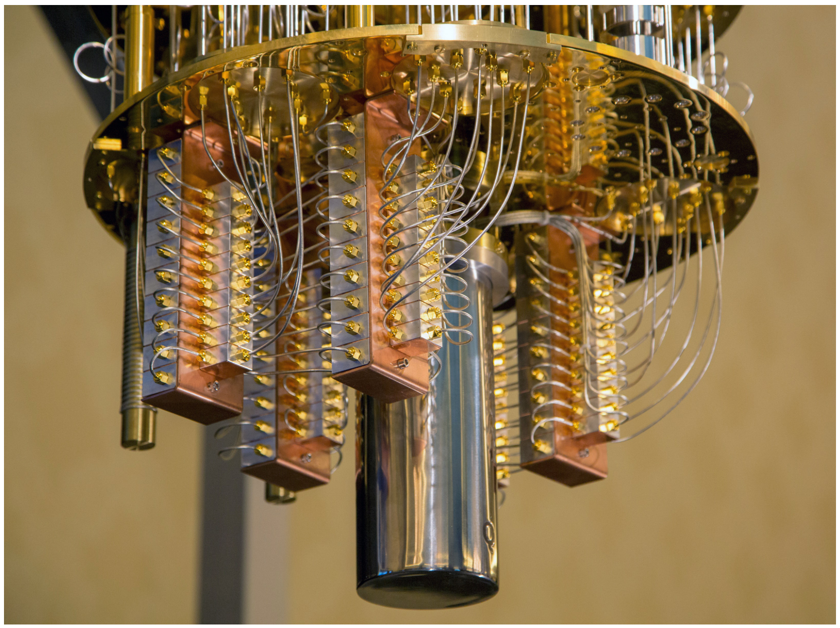

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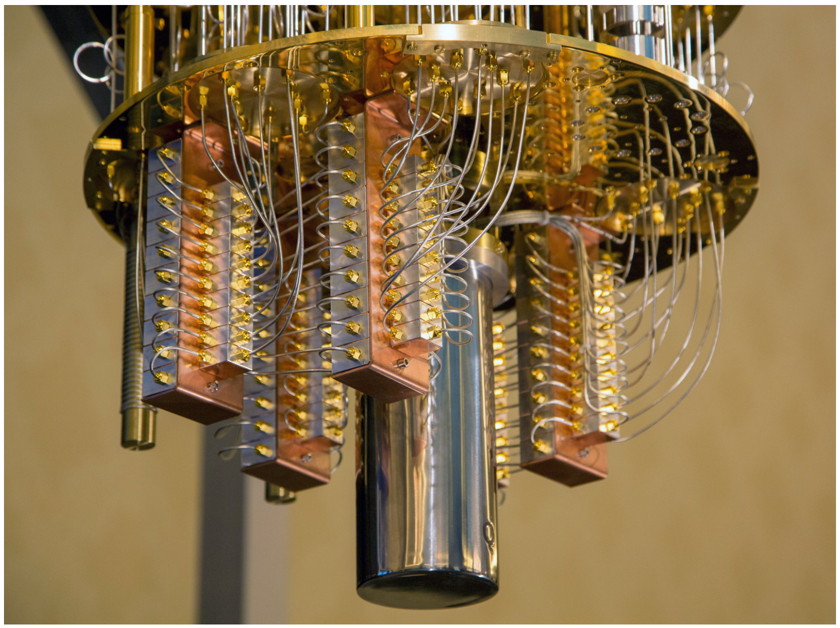

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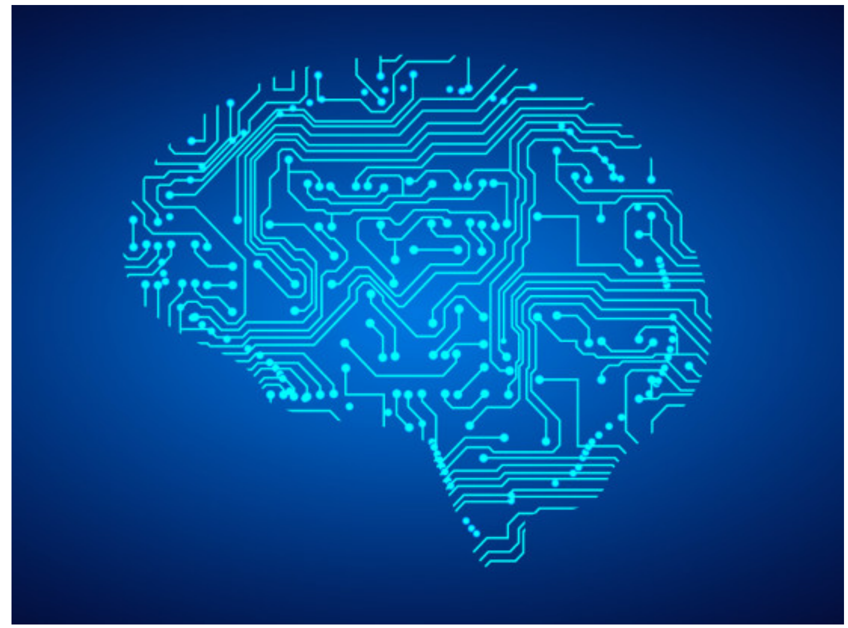

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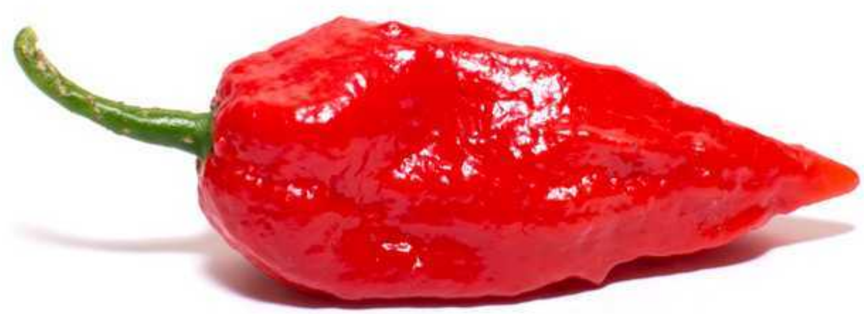
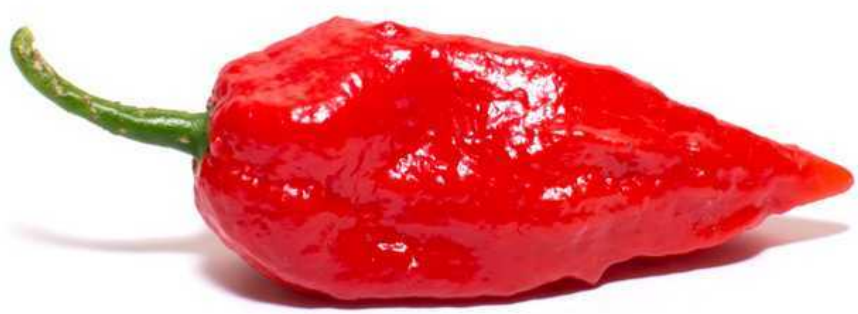


so hot

Quantum Computing



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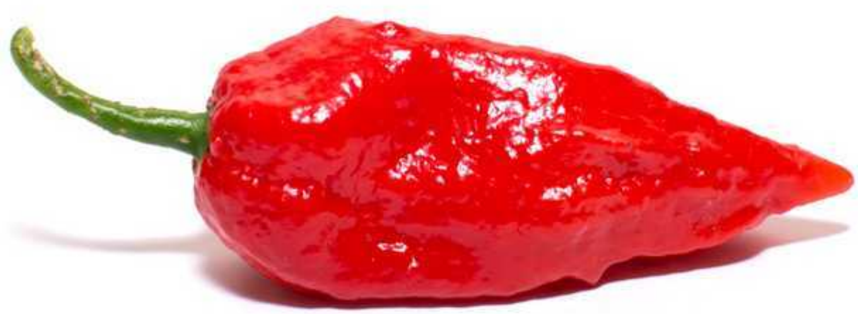

so hot

+

Machine Learning

so so hot

Quantum Machine Learning

Quantum Machine Learning

“I would predict that in 10 years there’s nothing but quantum machine learning.”
[famous QML researcher in 2015]

	Classical Dataset	Quantum Dataset
Use Classical Computer		
Use Quantum Computer		

	Classical Dataset	Quantum Dataset
Use Classical Computer	Classical Machine Learning	
Use Quantum Computer		

The Power of Quantum Computers (in theory)

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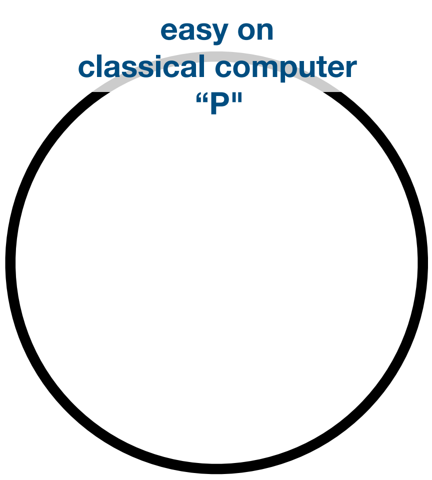

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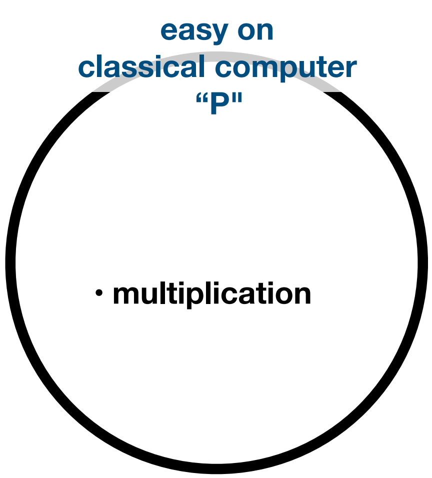

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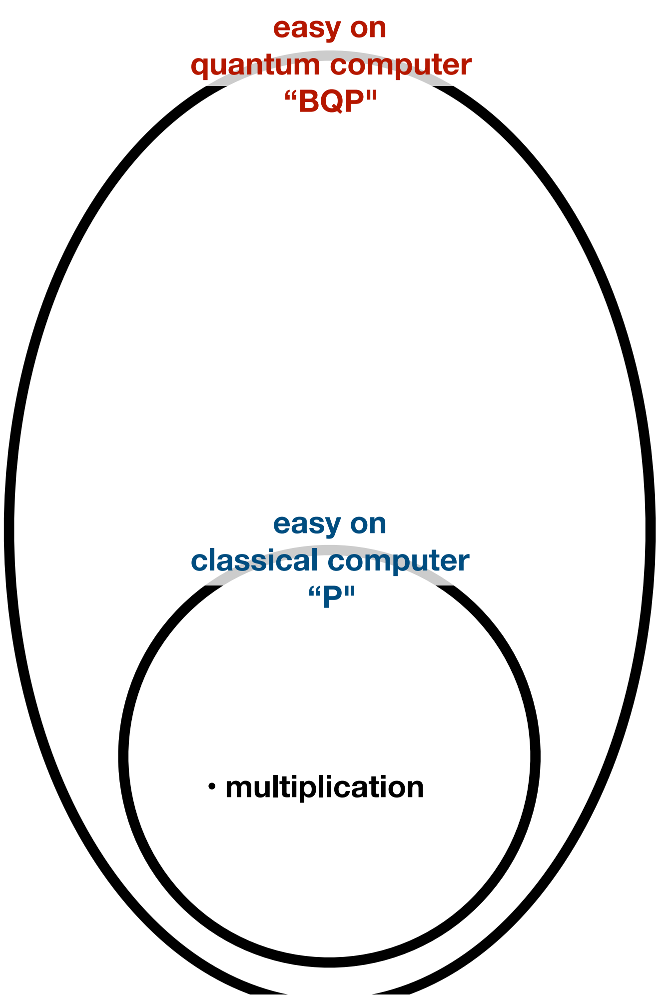

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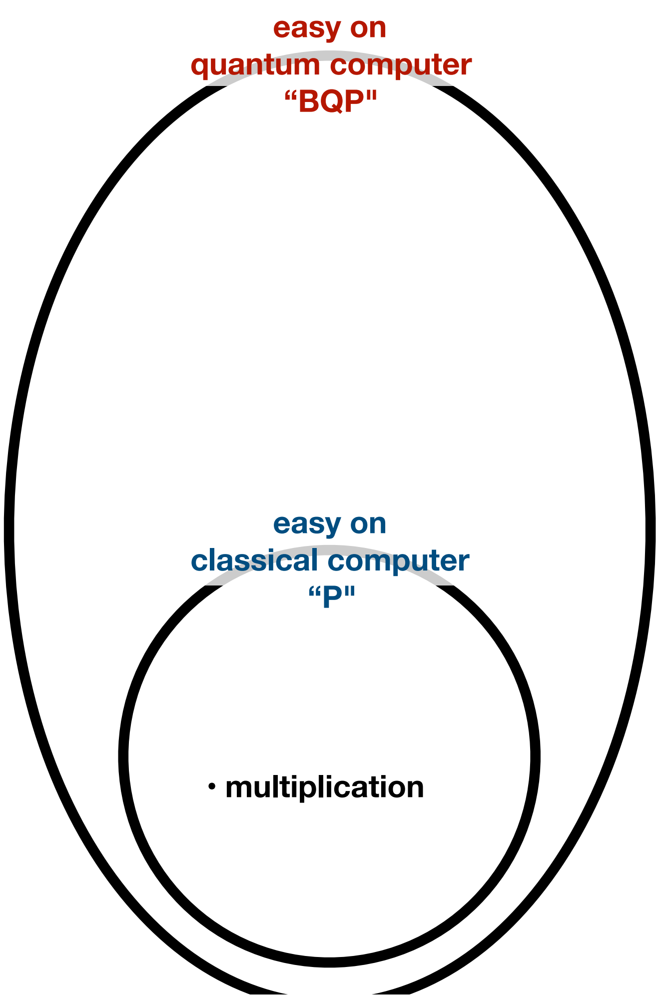

(i) BQP contains P

a quantum computer can (quickly) do
everything a classical computer can (quickly) do

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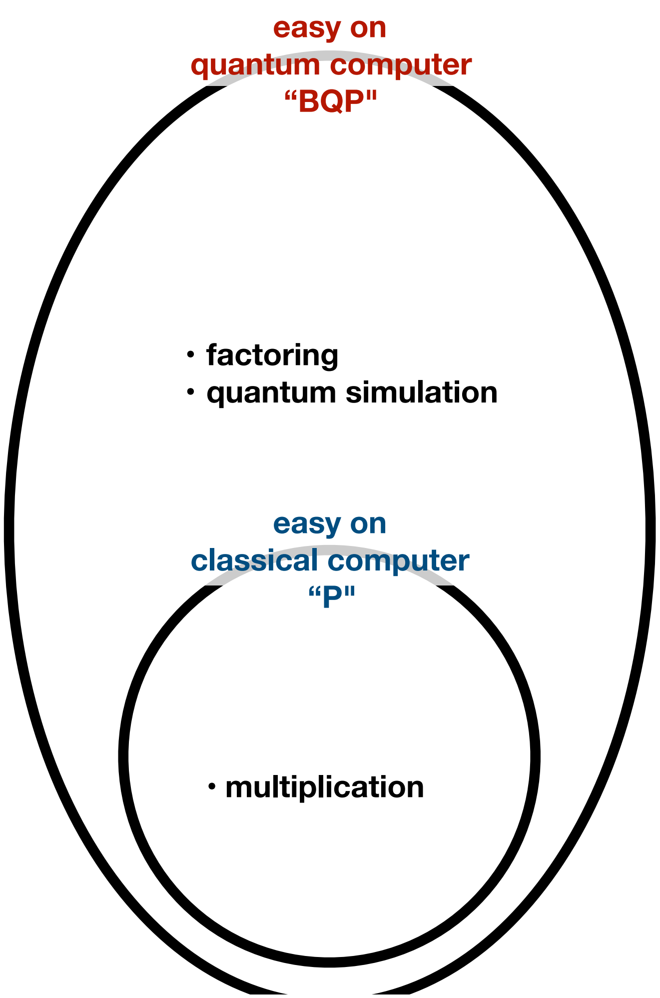

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ENCOURAGING

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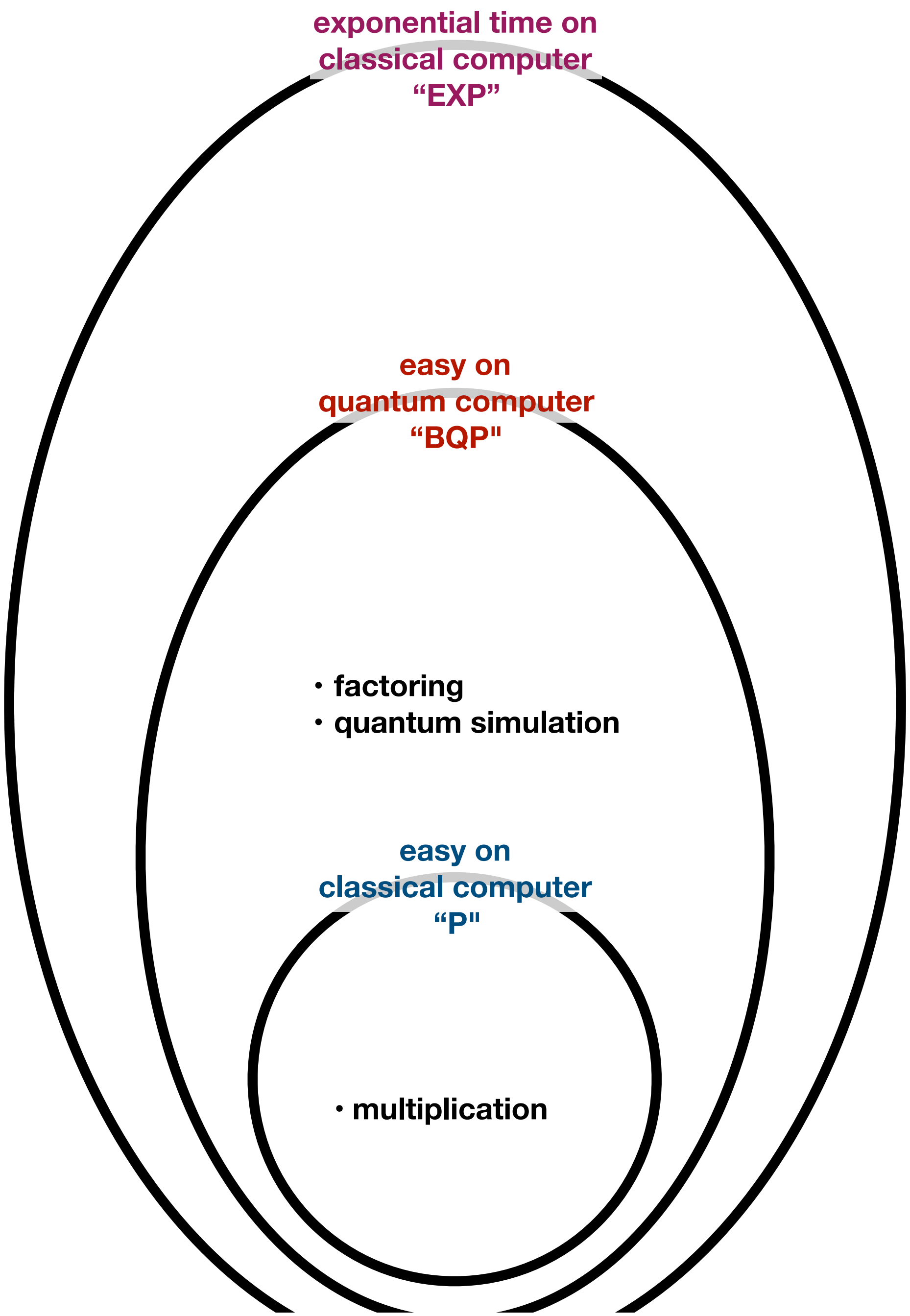

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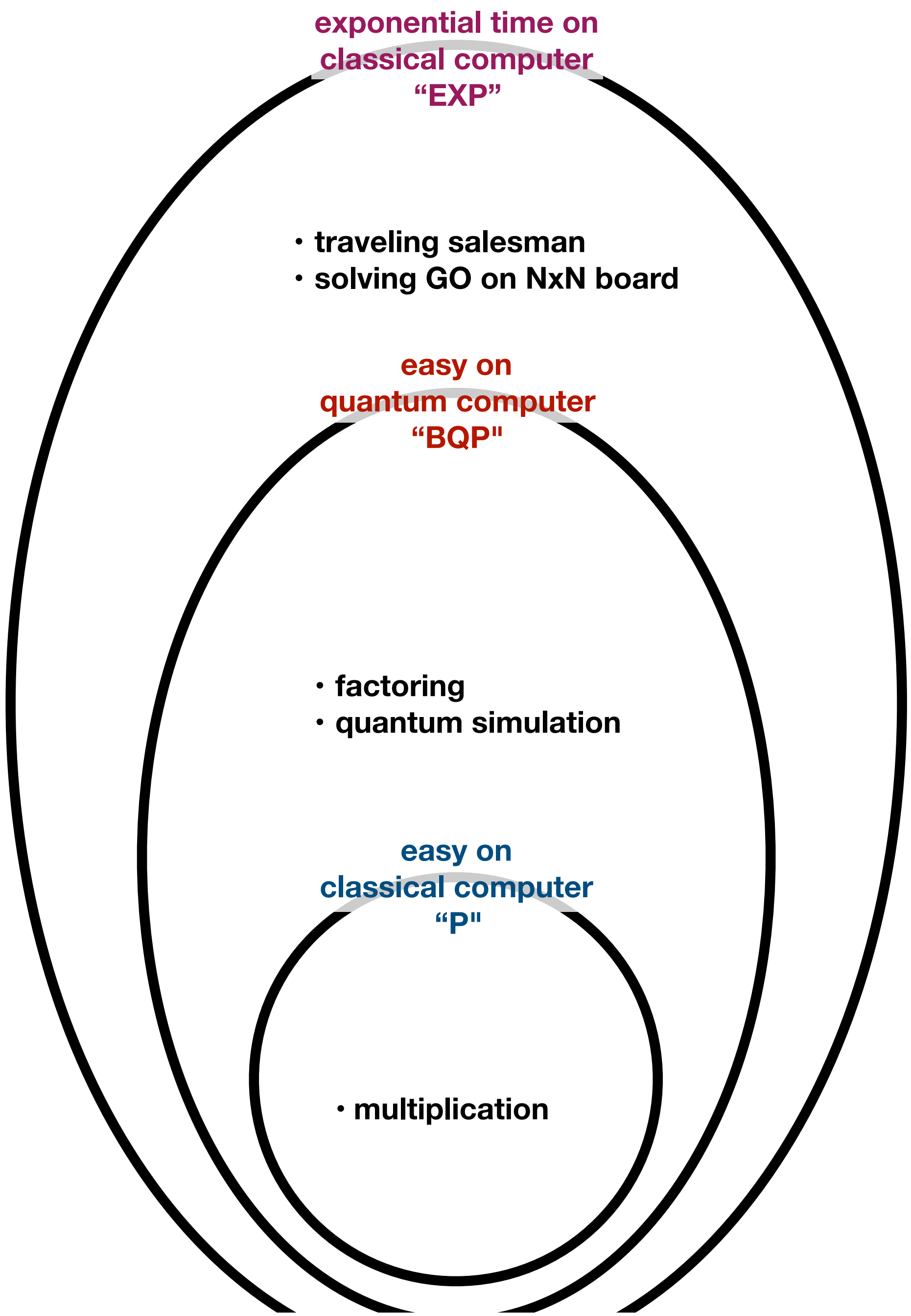

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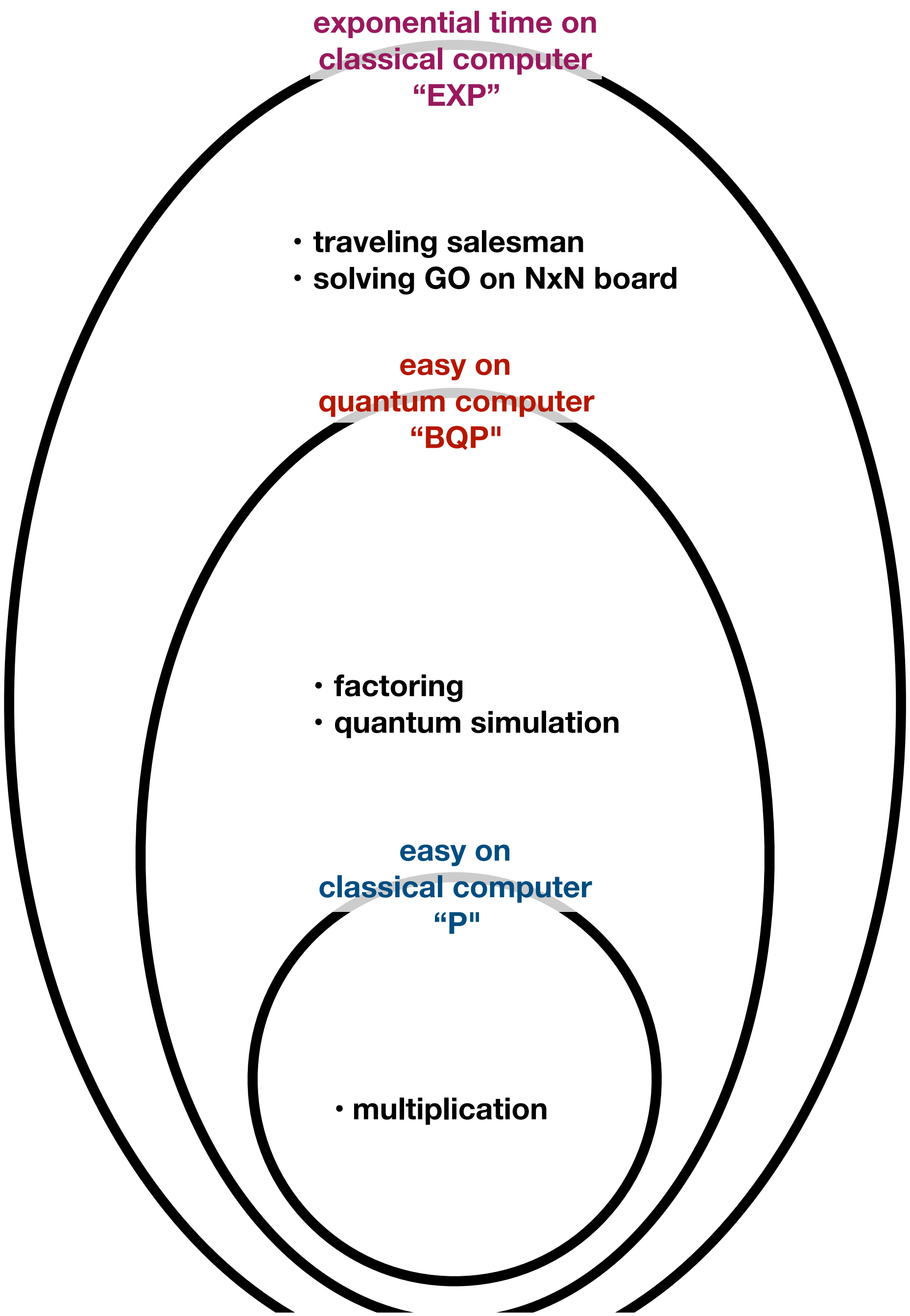

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DISCOURAGING

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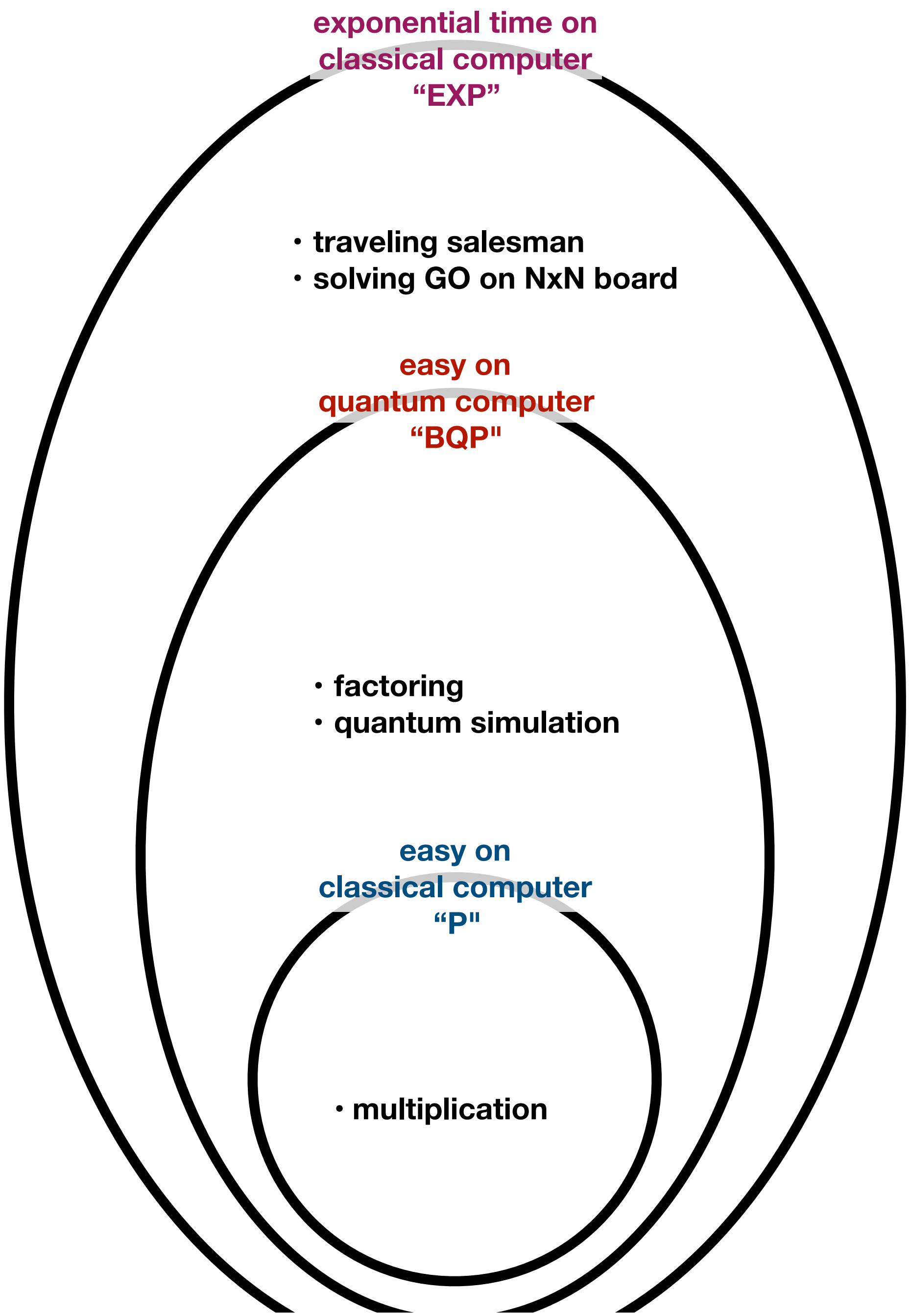

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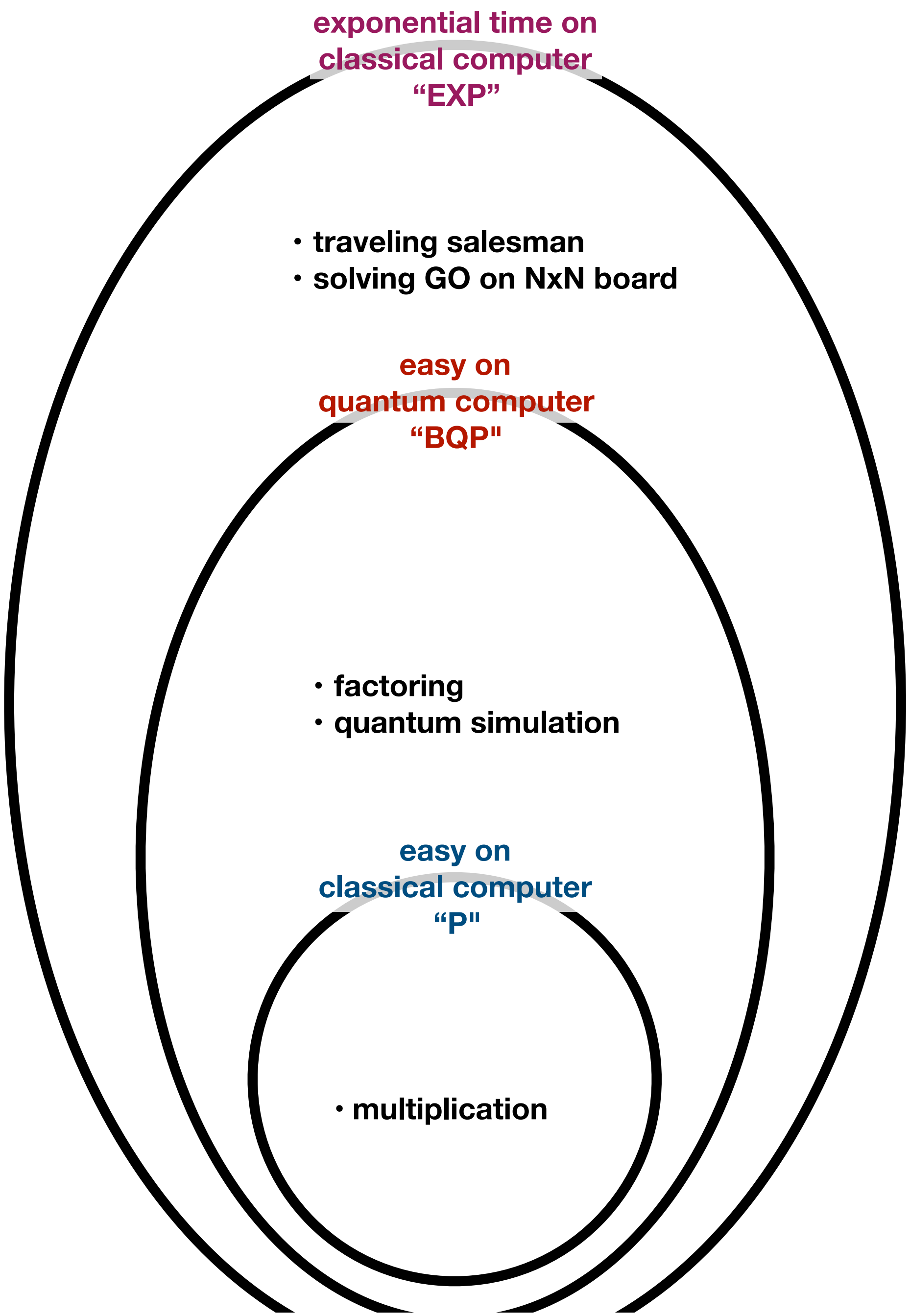

quantum superpower: EXPONENTIATION

"HILBERT SPACE IS HUGE"

to describe state of *N* qubits takes 2^N real numbers

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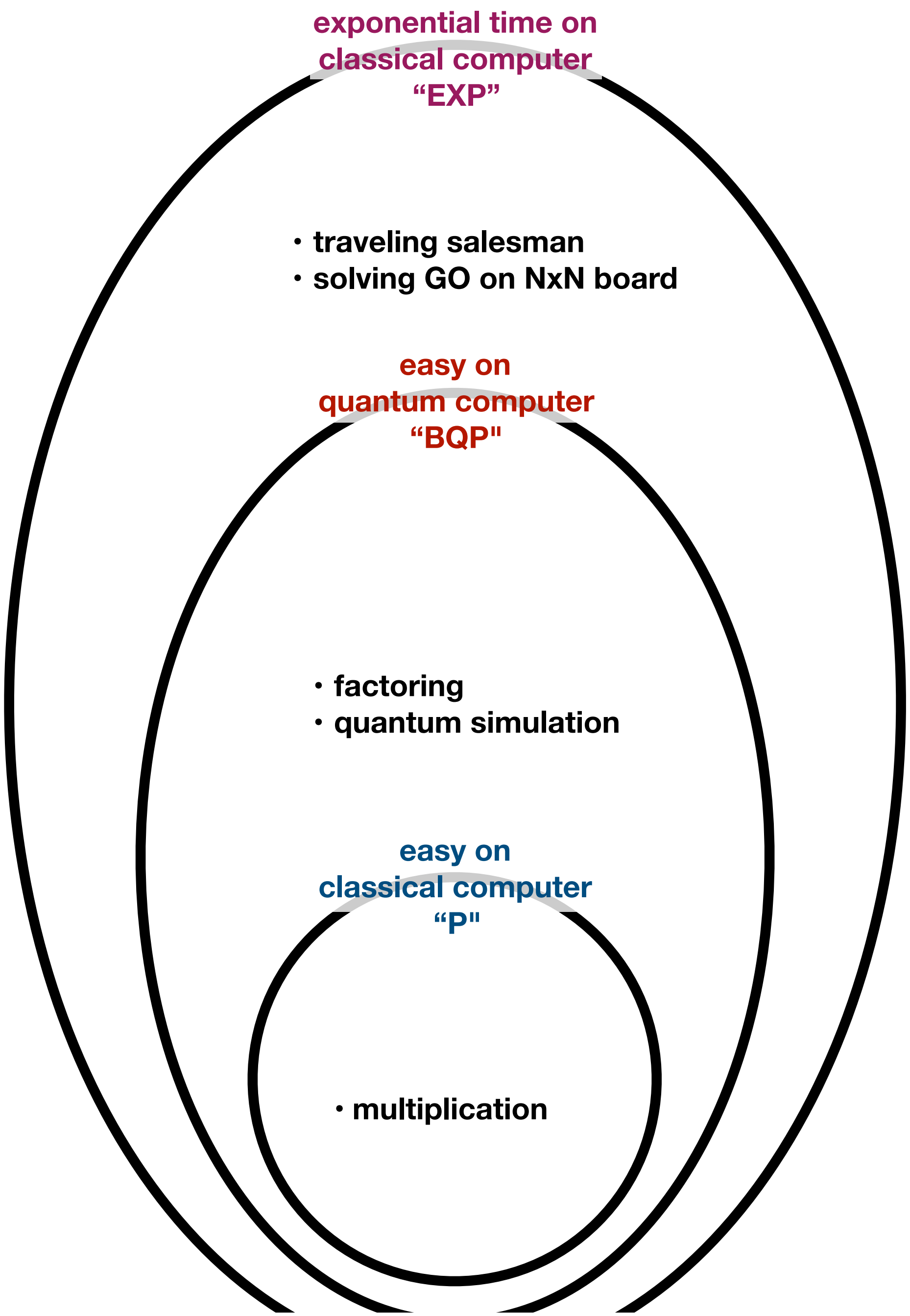

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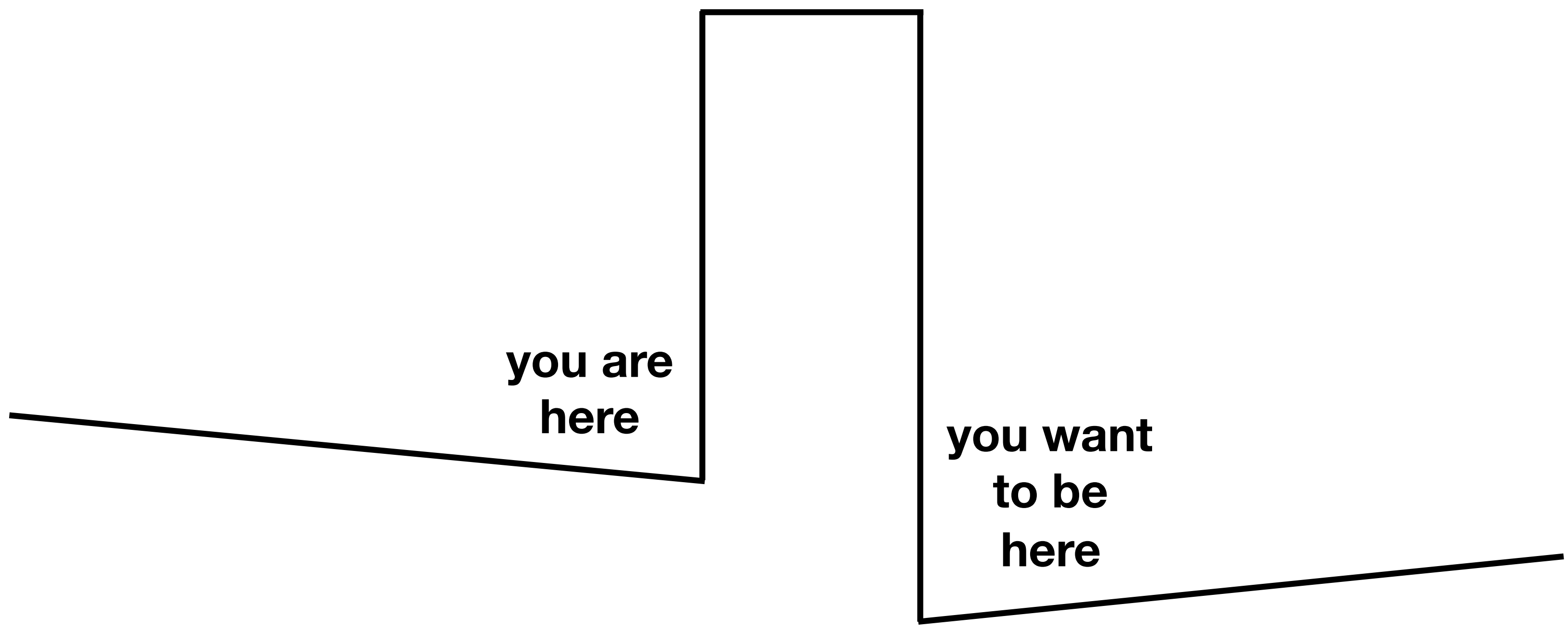
ENCOURAGING

quantum superweakness:
LINEARITY

cannot directly see wave function

“NO FREE LUNCH”

Encouraging Fact #1



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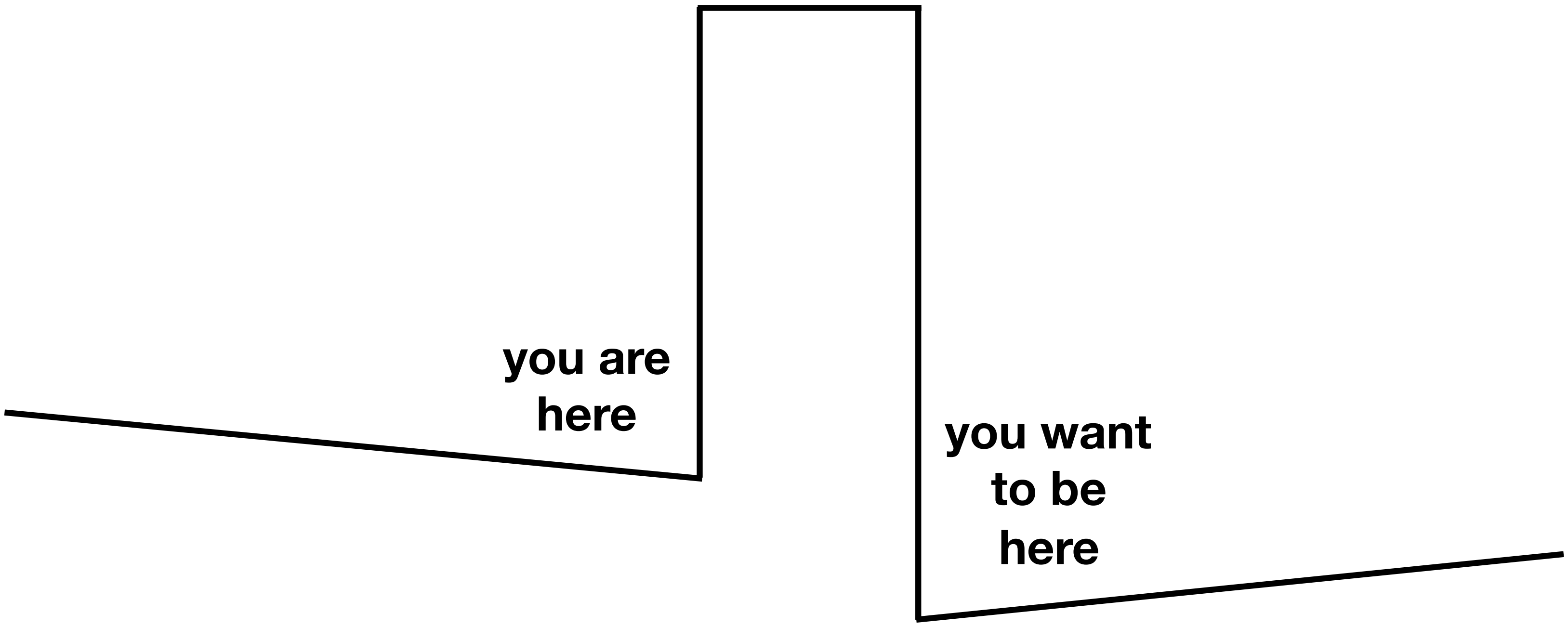

thermally fluctuate $\sim e^{-\mathrm{height}/T}$

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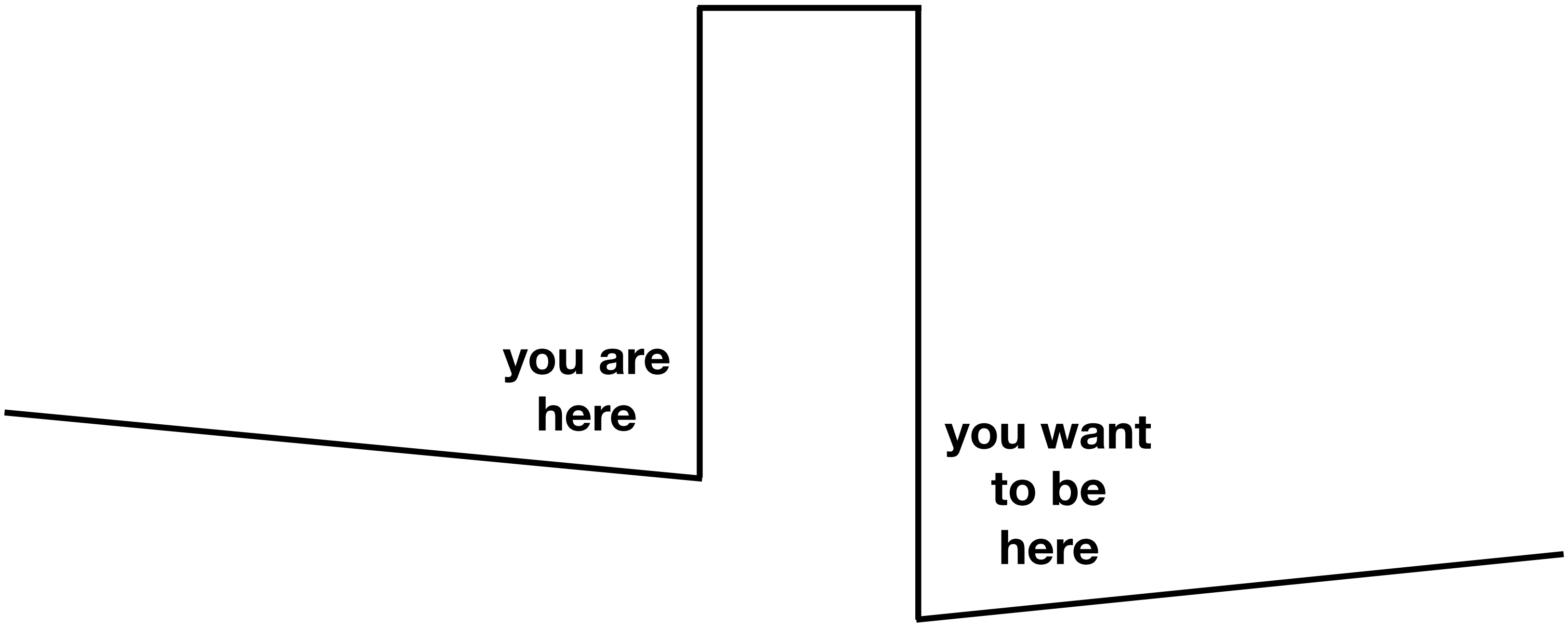

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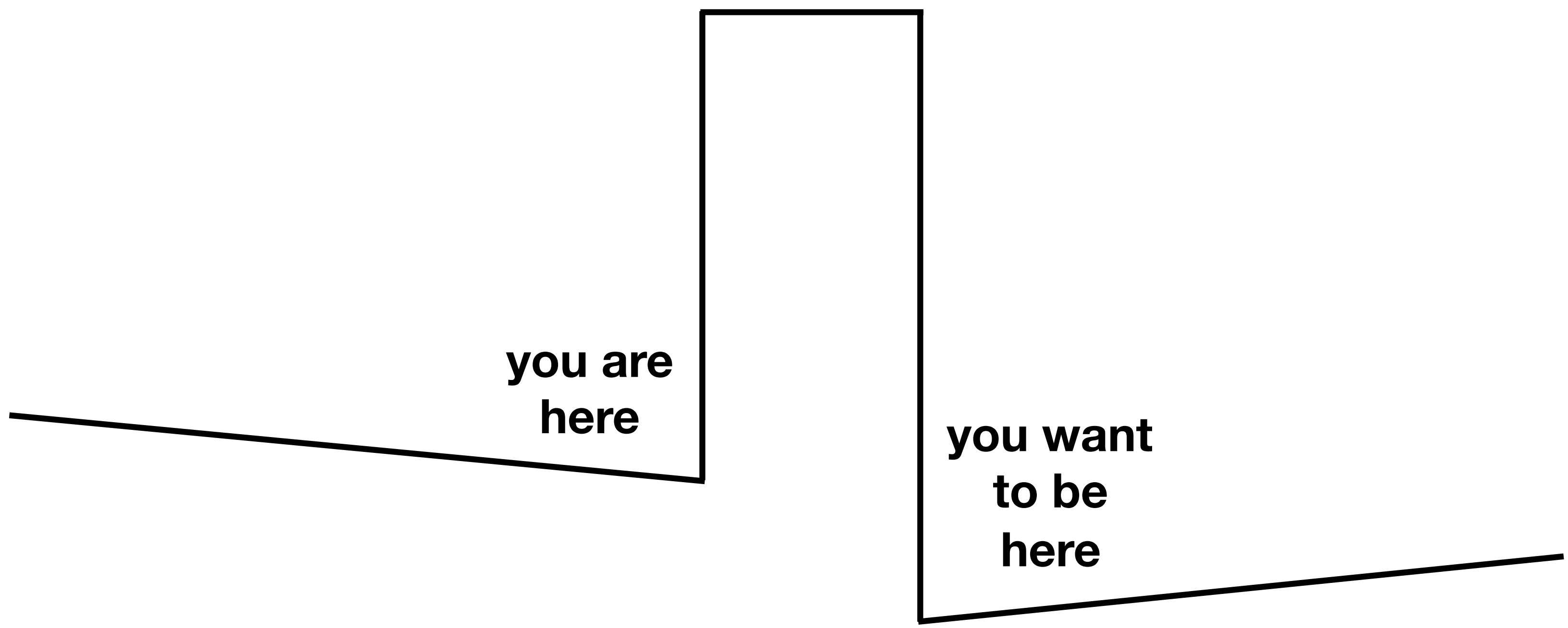

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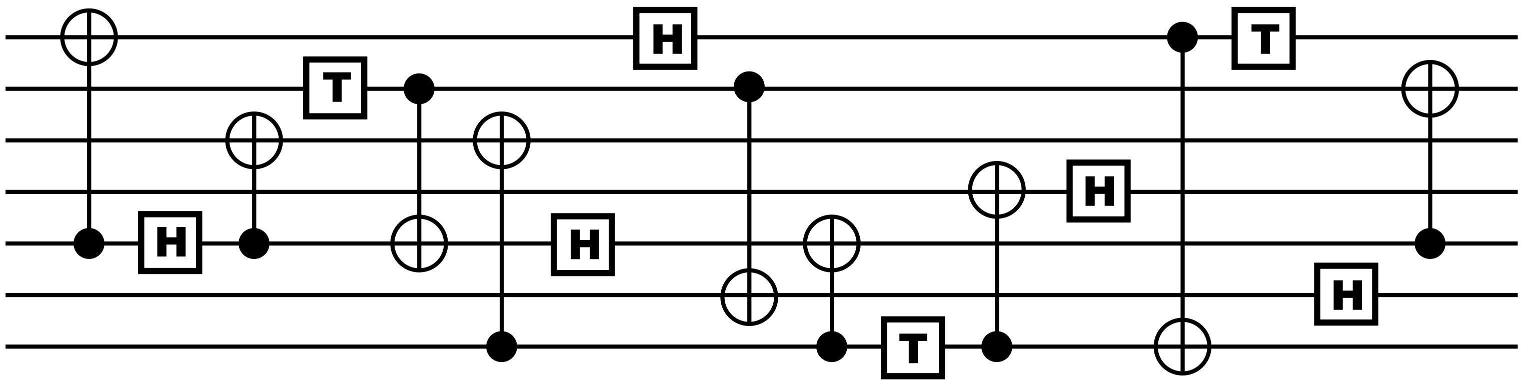
**quantum beats classical
for tall, thin barriers**

Encouraging Fact #2



there are short quantum circuits whose output is hard to classically sample (follows directly from BQP not in P)

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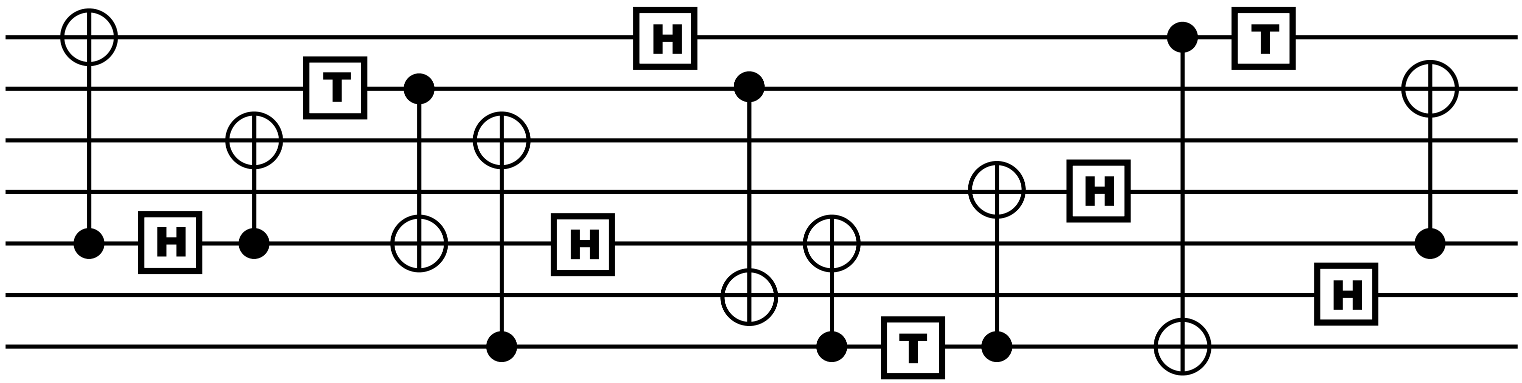

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↓

there are functions that can be expressed
with a polynomial size quantum neural network
that would require an exponentially large classical neural network

Encouraging Fact #3

Harrow, Hassidim, Lloyd algorithm (2008)

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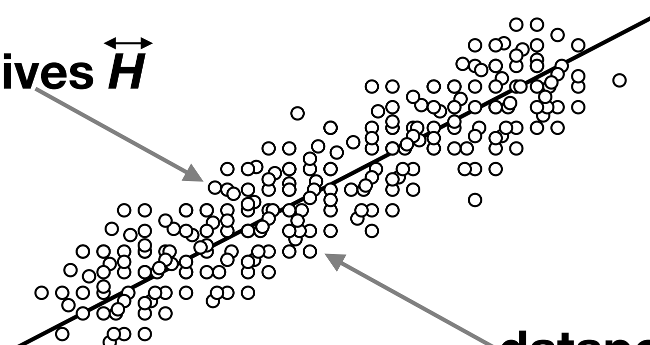
subroutine in classical supervised learning is minimize $(\overleftrightarrow{H}\,\vec{x} - \vec{b})^2$

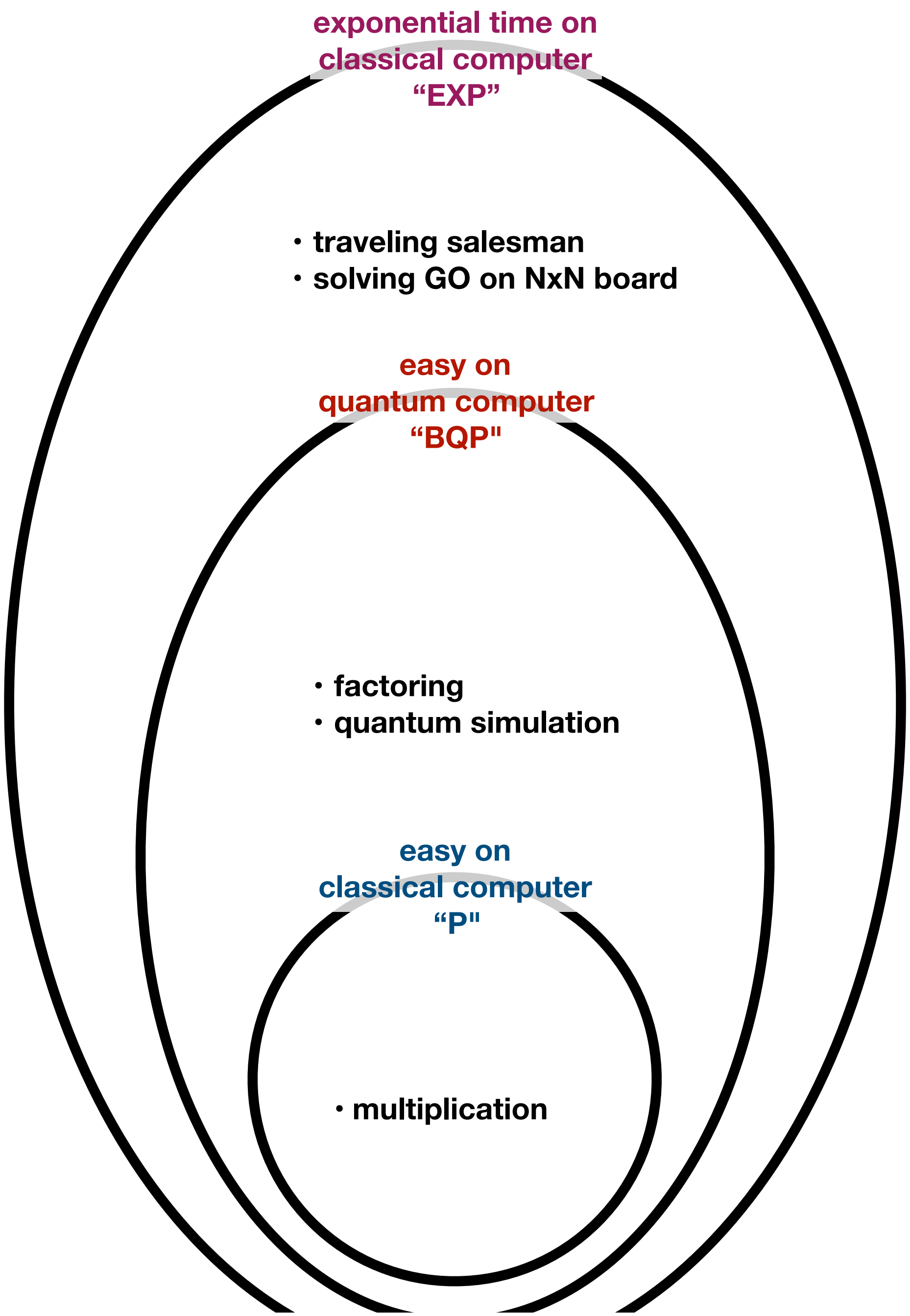
function ansatz gives $\overleftrightarrow{H}$



best fit is $\vec{x}$

datapoints are $\vec{b}$

The Power of Quantum Computers (in theory)



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- no cloning principle makes error correction hard
- classical = 10^{-24} errors per gate, quantum = 10^{-2} errors per gate

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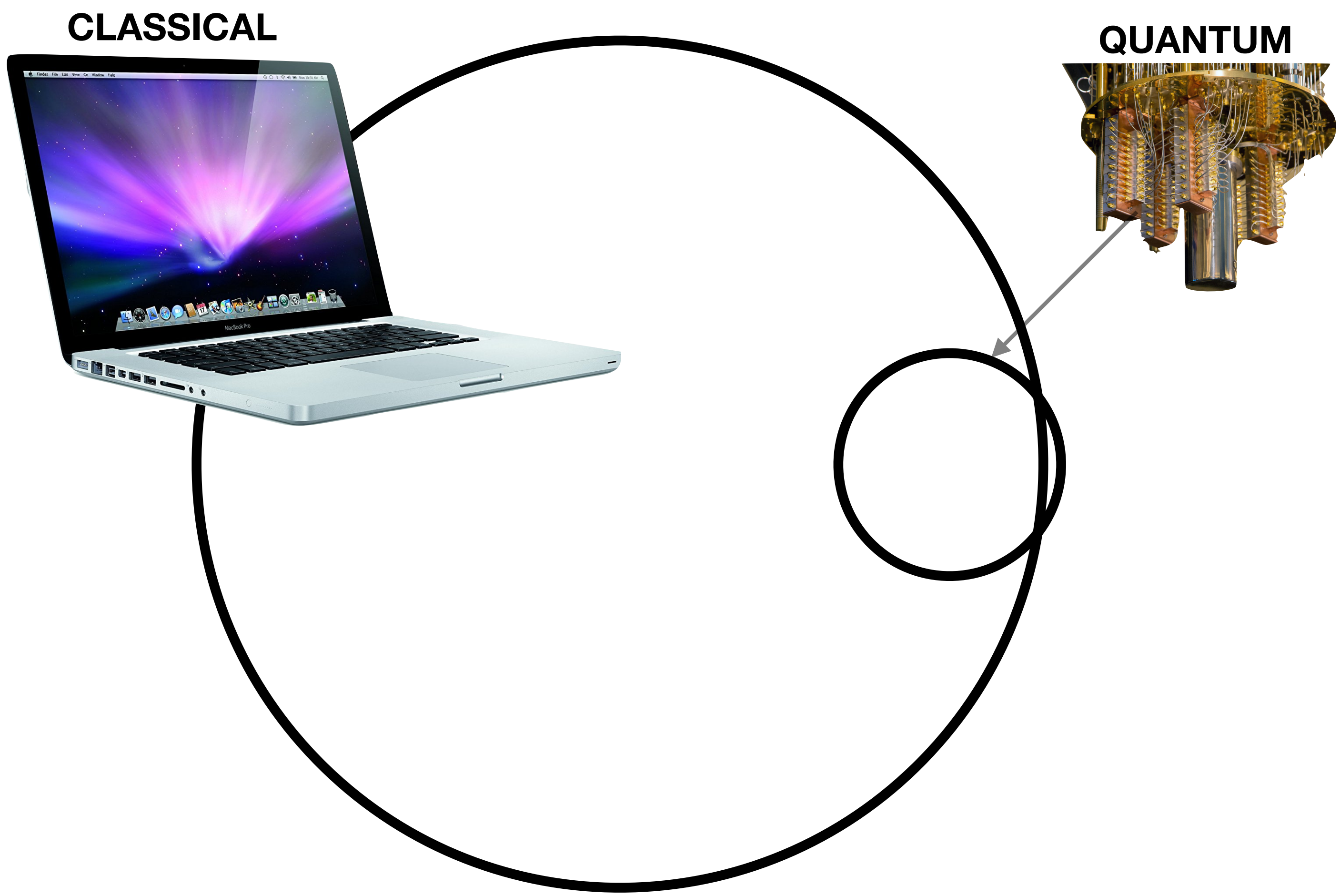

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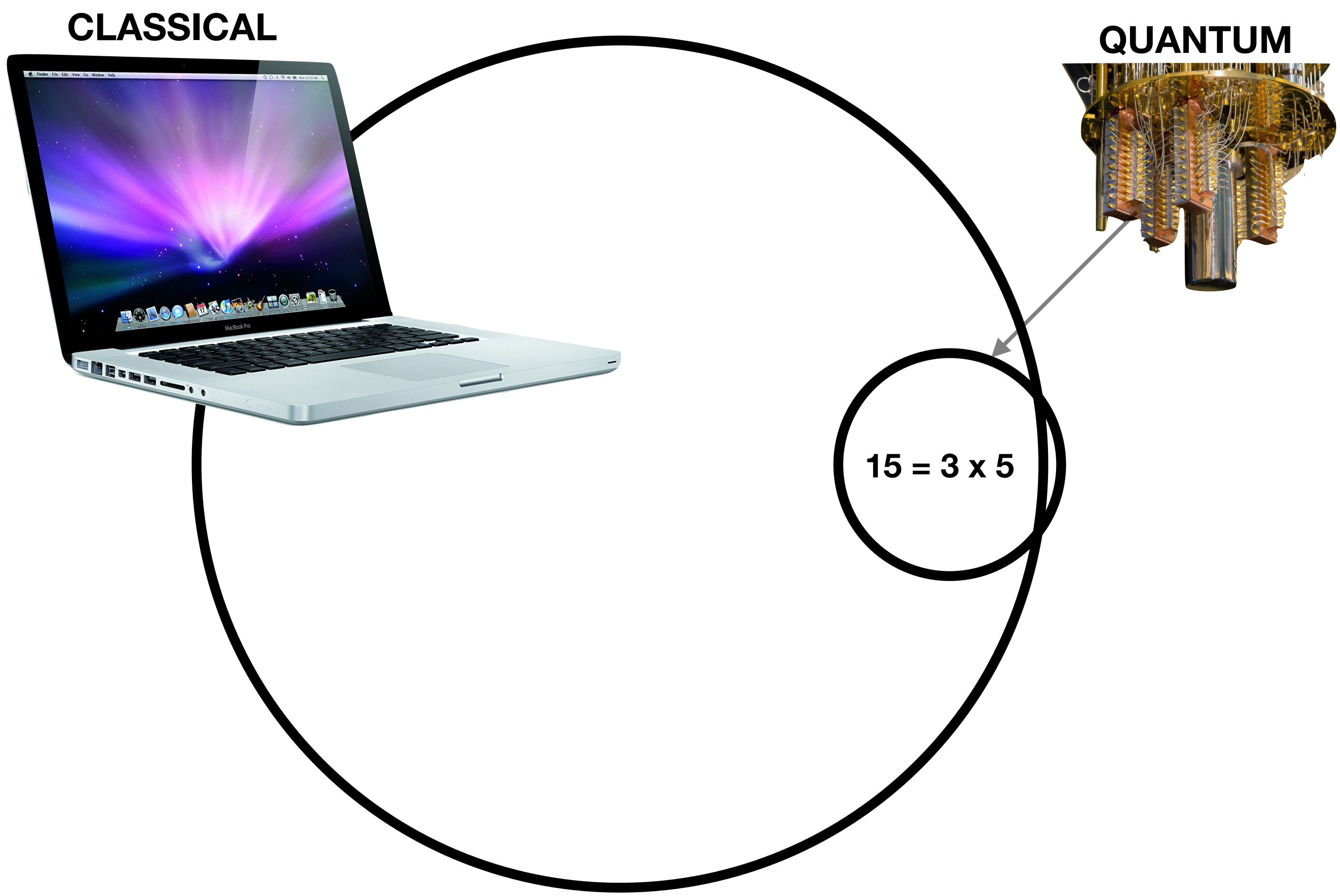

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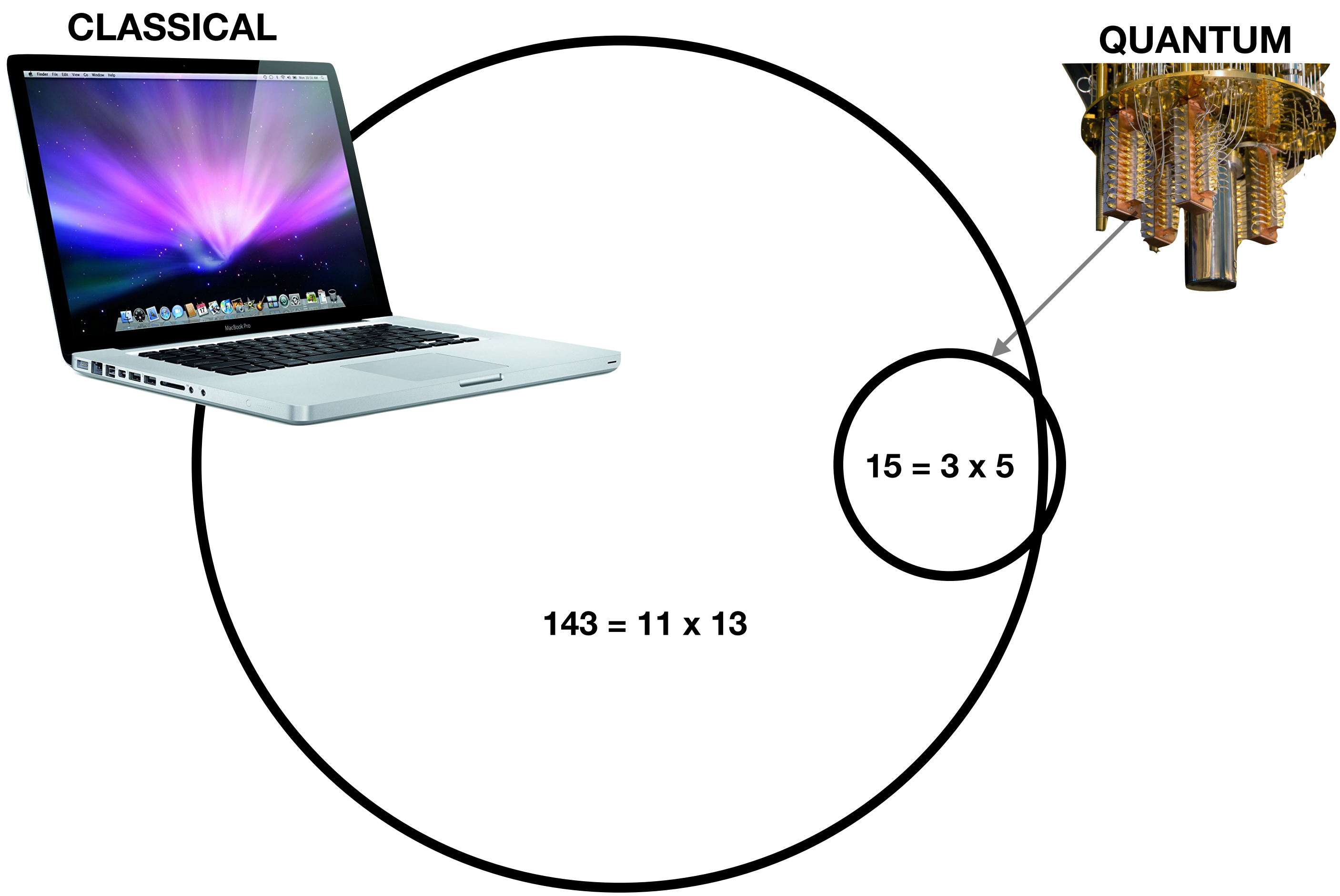

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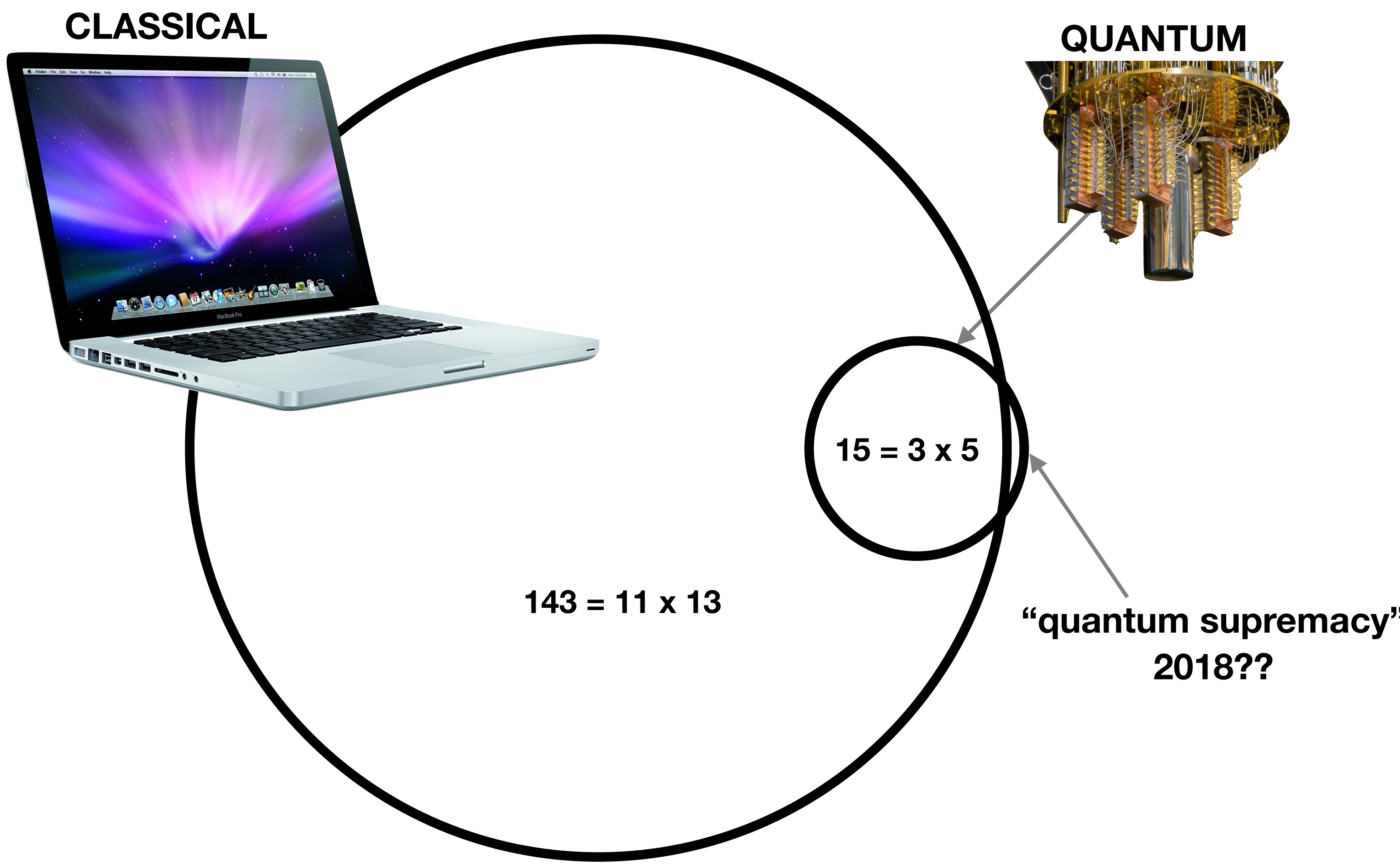
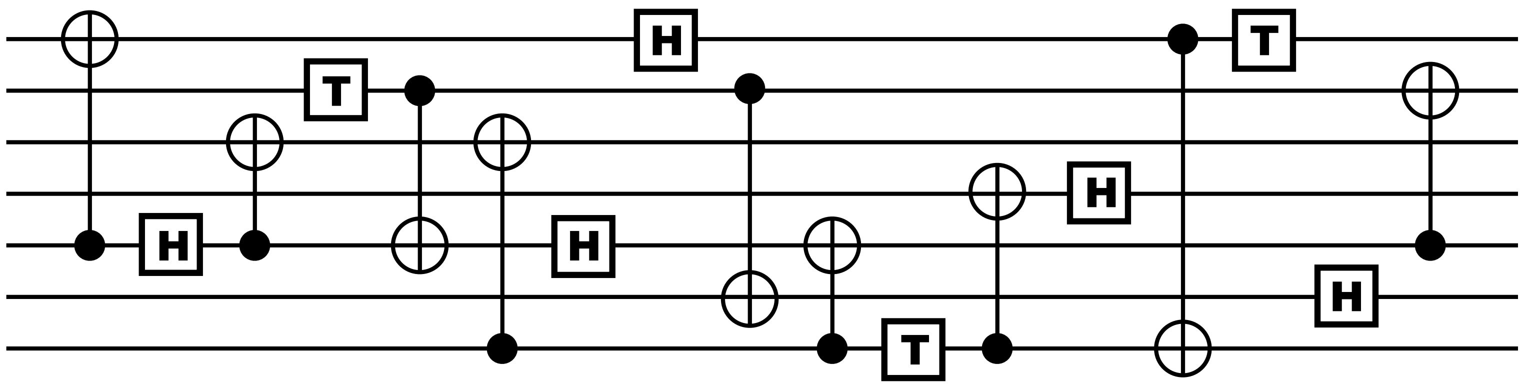


The Power of Quantum Computers (in practice)

“quantum supremacy”
2018??



input random state into ~50 qubit random quantum circuit

↓

check on classical supercomputer that you got something consistent with statistical predictions of quantum mechanics

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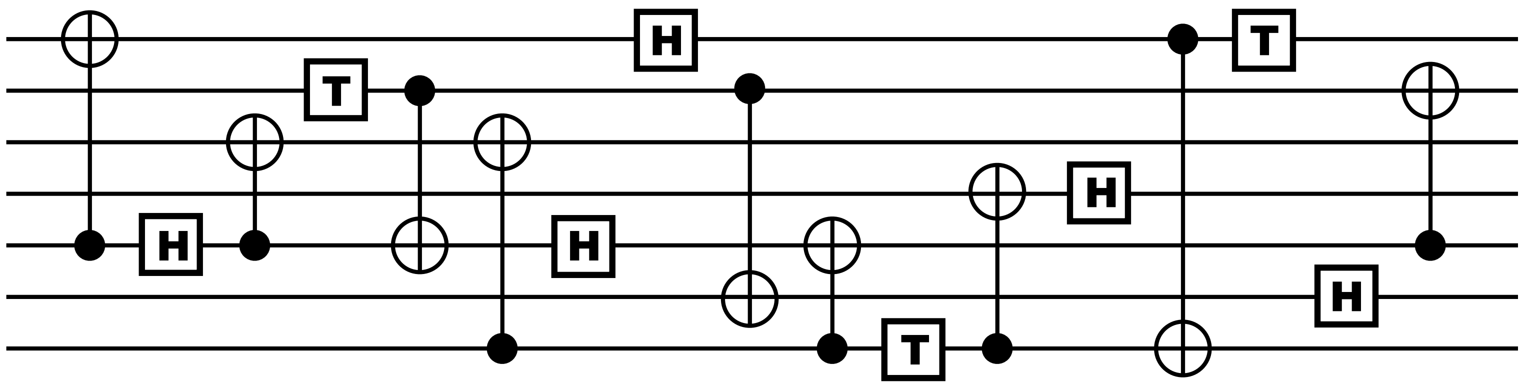

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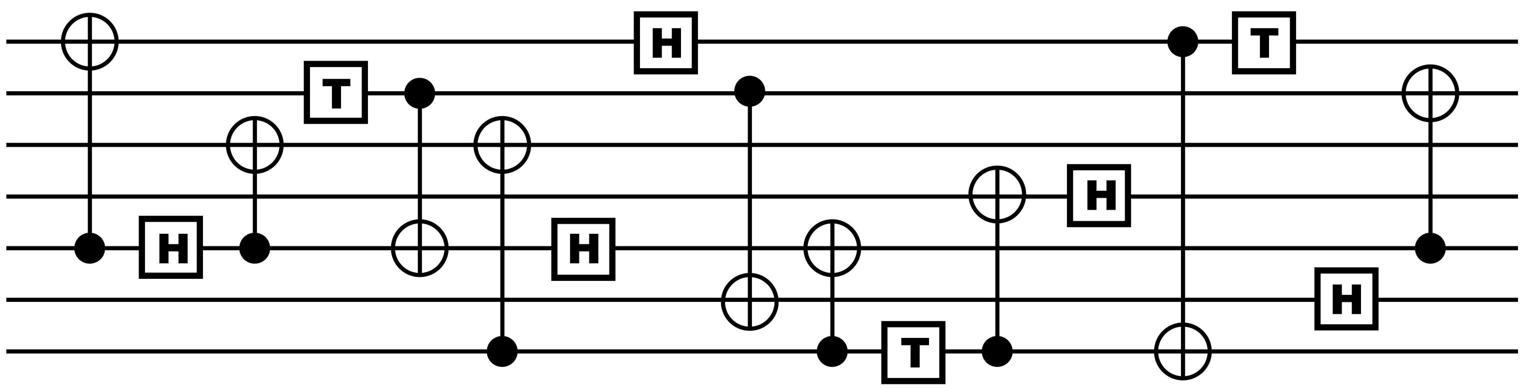

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we're a long way from cracking RSA!

Example #1: HHL algorithm

given N x N matrix $\overleftrightarrow{H}$
and given vector $\vec{b}$
"find" the vector $\vec{x}$ such that

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takes $O(N^c)$ classically

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Quantum algorithm for solving linear systems of equations
Aram W. Harrow, Avinatan Hassidim, Seth Lloyd
https://arxiv.org/abs/0811.3171

Quantum Machine Learning
Jacob Biamonte, Peter Wittek, Nicola Pancotti, Patrick Rebentrost, Nathan Wiebe, Seth Lloyd
https://arxiv.org/abs/1611.09347

Quantum Machine Learning Algorithms: Read the Fine Print
Scott Aaronson
https://scottaaronson.com/papers/qml.pdf

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$$b_i \xrightarrow[\text{“QRAM”}]{\text{store } N \text{ bits in } \log[N] \text{ qubits}} |b\rangle = \sum_i b_i |i\rangle \longrightarrow |x\rangle = \sum_i x_i |i\rangle \longrightarrow \text{use } |x\rangle$$

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returns quantum state $|x\rangle$ (**not** vector x_i) $\searrow$ use $|x\rangle$

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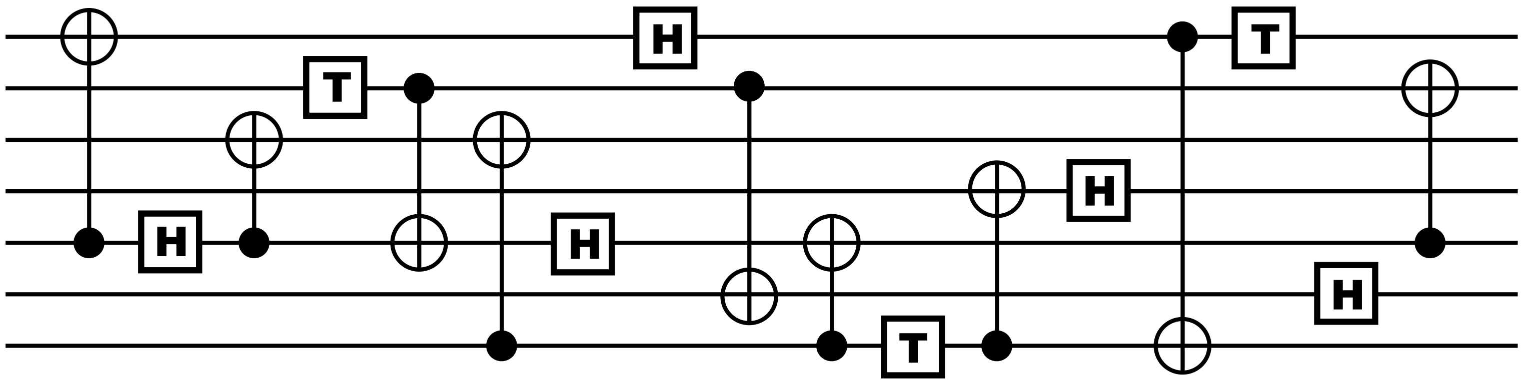

Classification with Quantum Neural Networks on Near Term Processors
Edward Farhi, Hartmut Neven
https://arxiv.org/abs/1802.06002

Barren plateaus in quantum neural network training landscapes
Jarrod R. McClean, Sergio Boixo, Vadim N. Smelyanskiy, Ryan Babbush, Hartmut Neven
https://arxiv.org/abs/1803.11173

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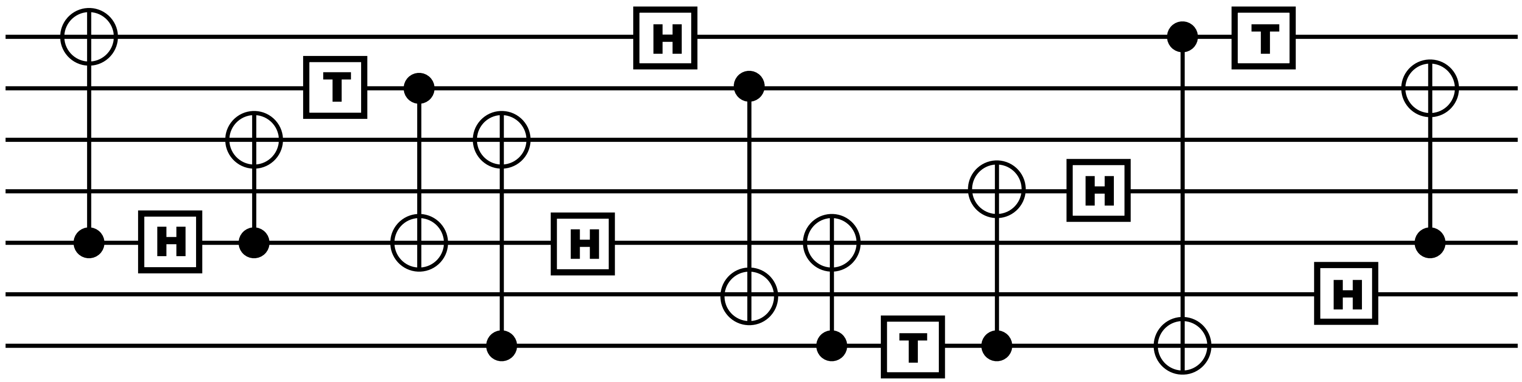

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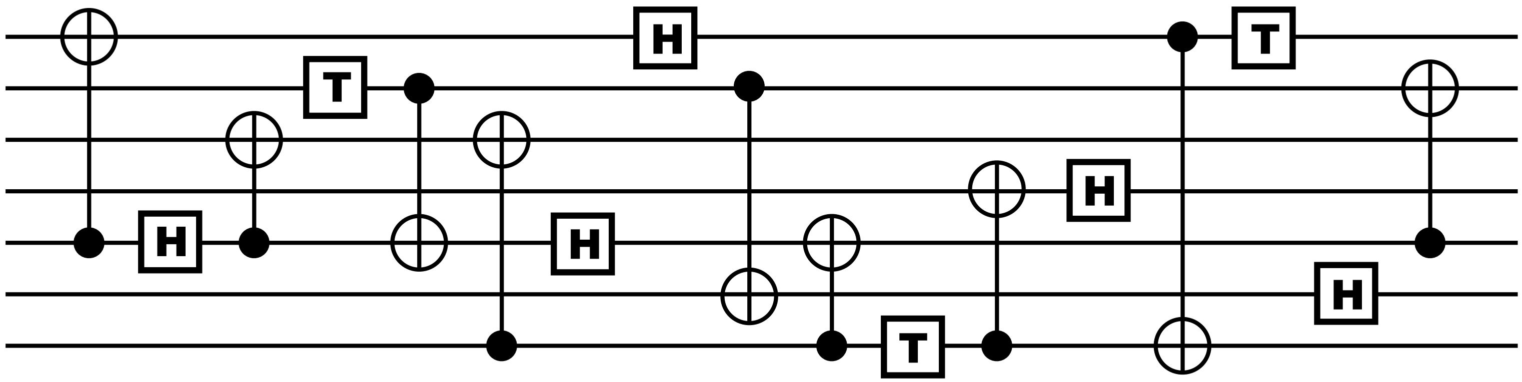

can definitely *represent* some functions
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↓

1. do we *care* about those functions?
2. can we *train* it?

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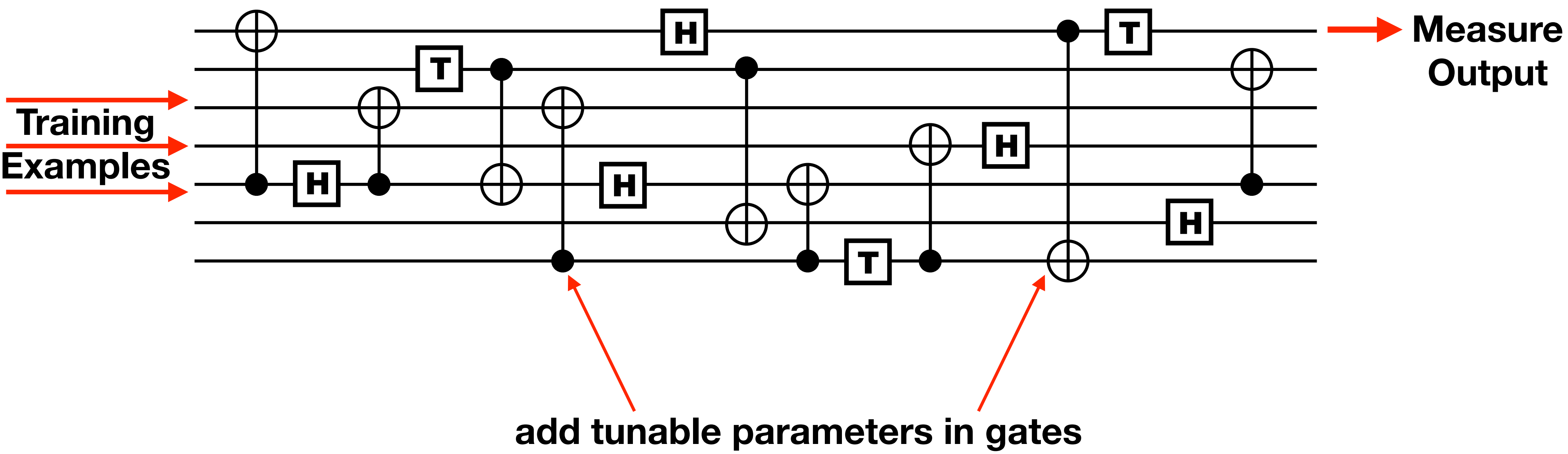

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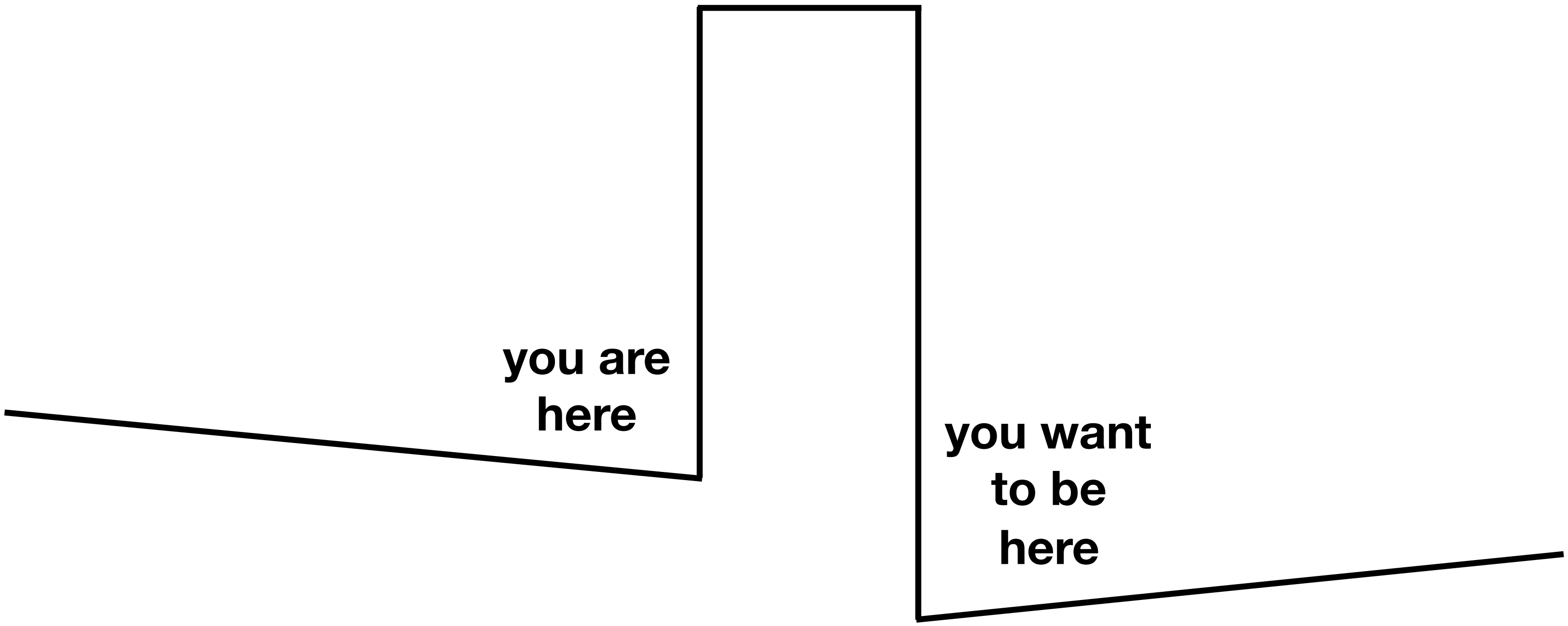

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