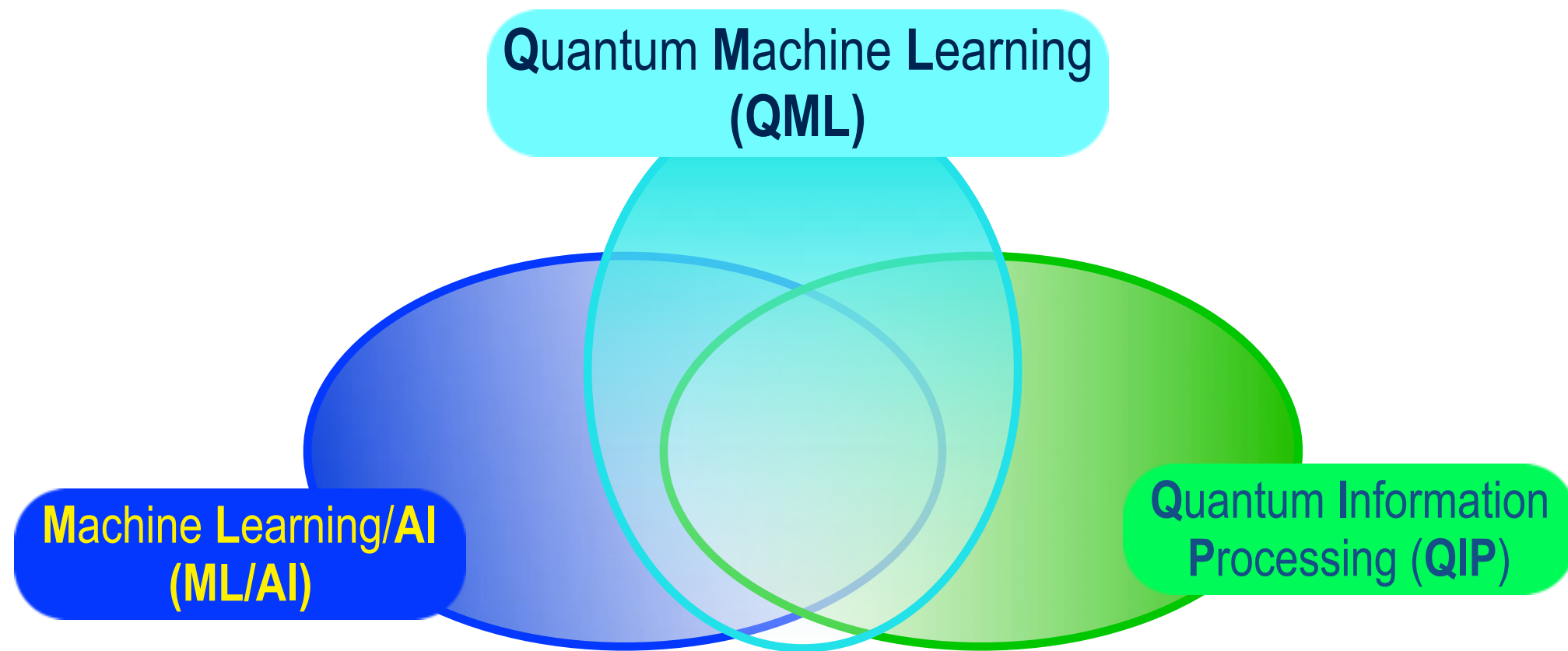


# From Quantum Machine Learning to Quantum AI

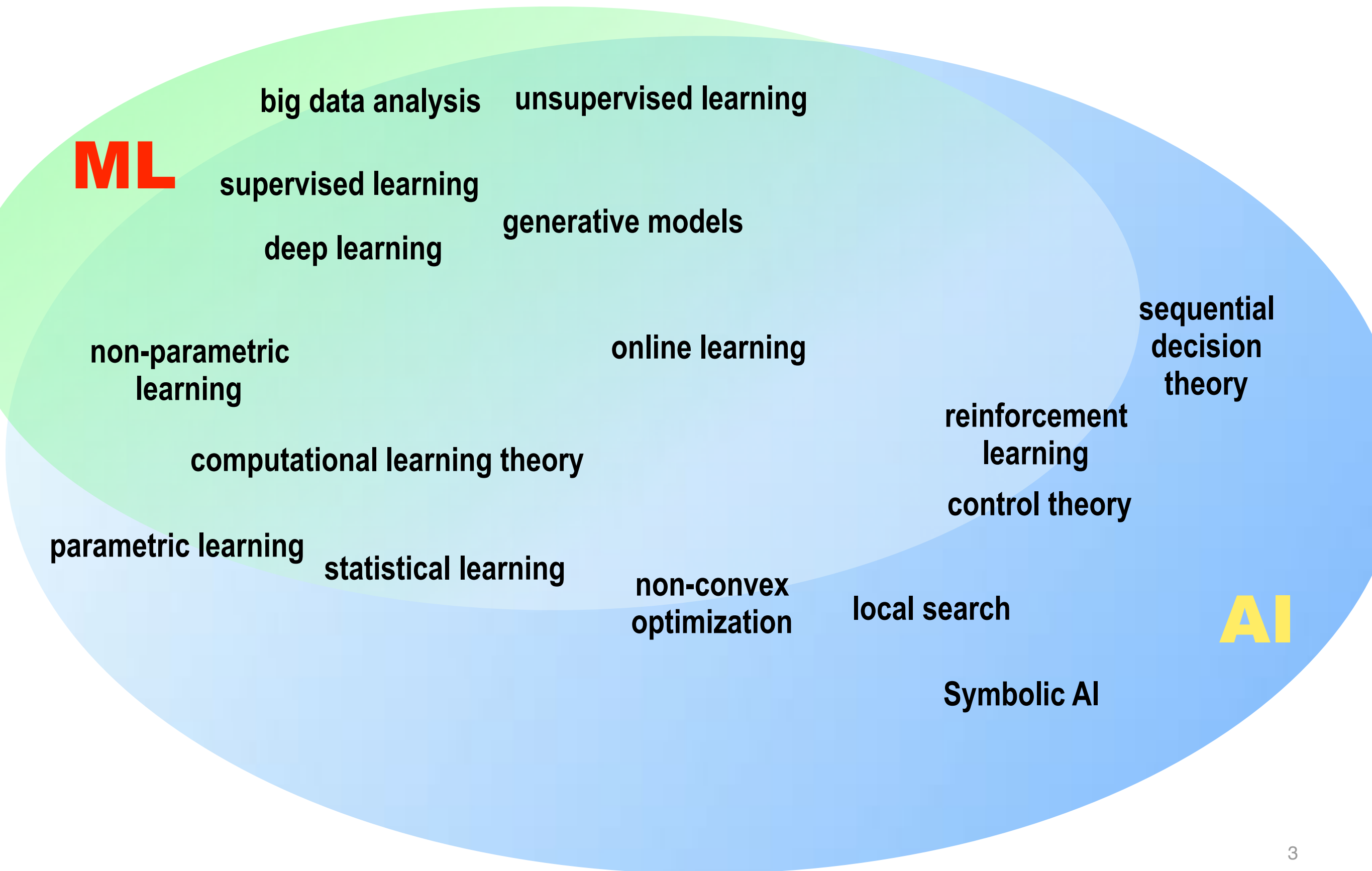
Vedran Dunjko  
[v.dunjko@liacs.leidenuniv.nl](mailto:v.dunjko@liacs.leidenuniv.nl)



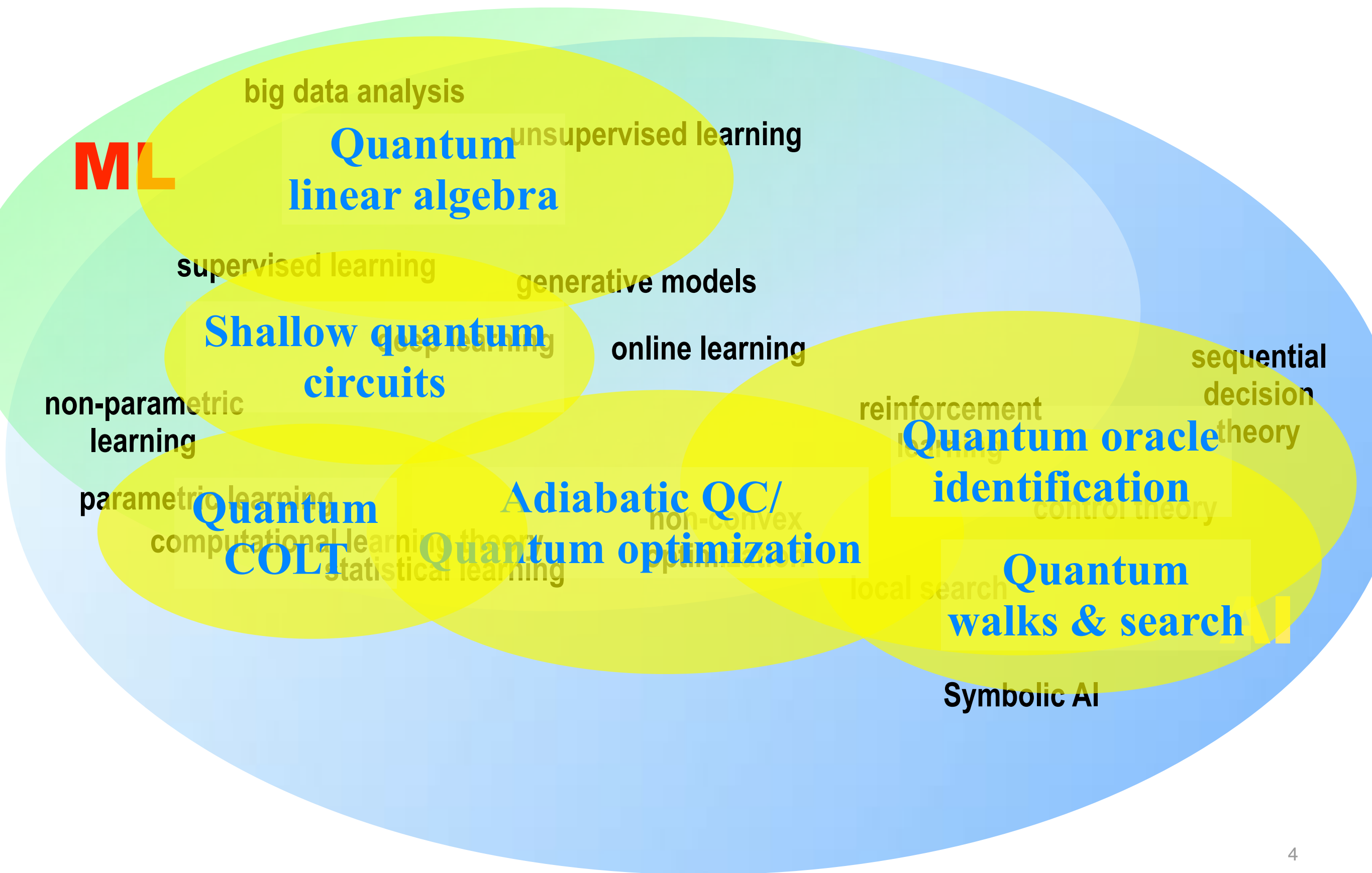


- 🔗 **ML** → **QIP** (quantum-applied ML) ['74]
- 🔗 **QIP** → **ML** (quantum-enhanced ML) ['94]
- 🔗 **QIP** ↔ **ML** (quantum-generalized learning) ['00]
- 🔗 ML-inspired QM/QIP
- 🔗 Physics inspired ML/AI

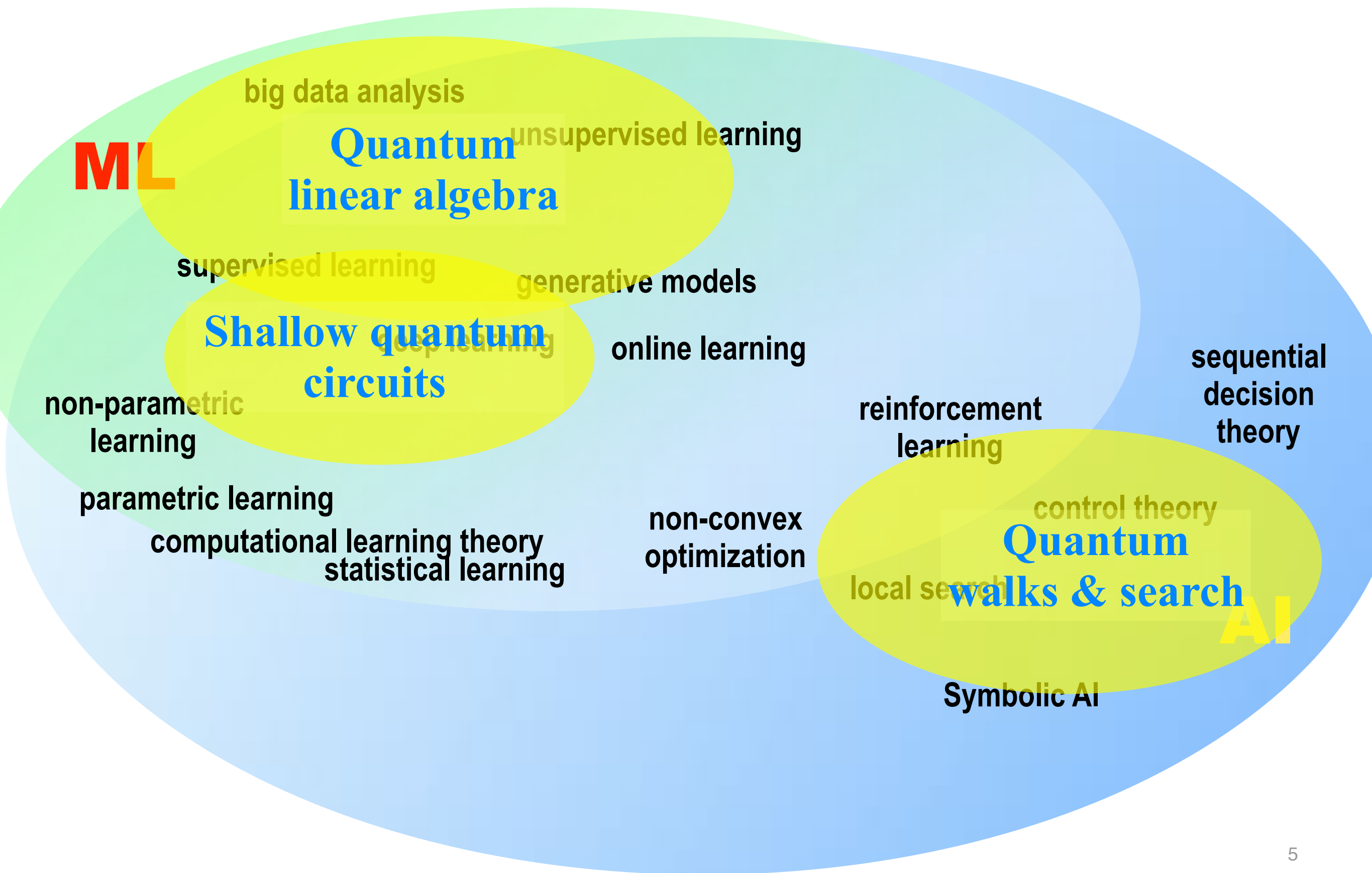
Machine learning is not one thing.  
AI is not even a few things.



# QeML is even more things

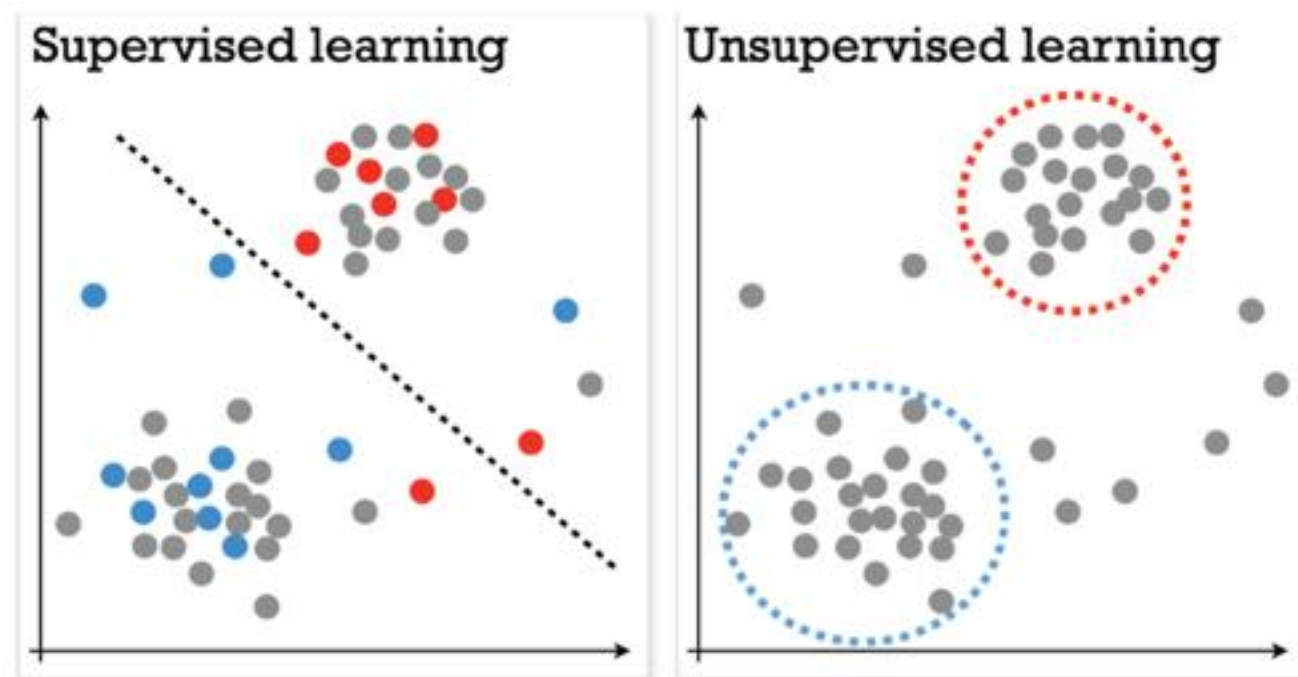


# QeML is even more things





# Machine Learning: the **WHAT**



or



*Sudo is this a cat?*

Learning  $P(\text{labels}|\text{data})$  given  
samples from  $P(\text{data}, \text{labels})$

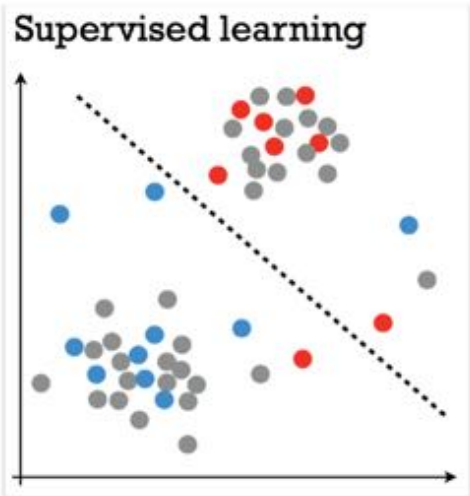
- generative models
- clustering (discriminative)
- feature extraction

*Sudo make me a cat.*

*Sudo what is a cat!?*

Learning structure in  $P(\text{data})$   
give samples from  $P(\text{data})$

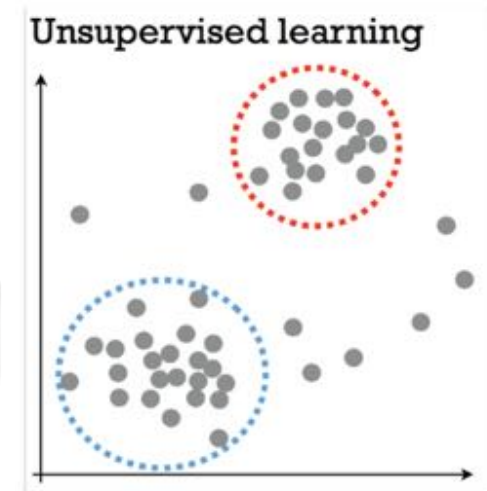
# Machine Learning: the **HOW**



output hypothesis  $h$  on  $Data \times Labels$   
*approximating*  $P(labels|data)$

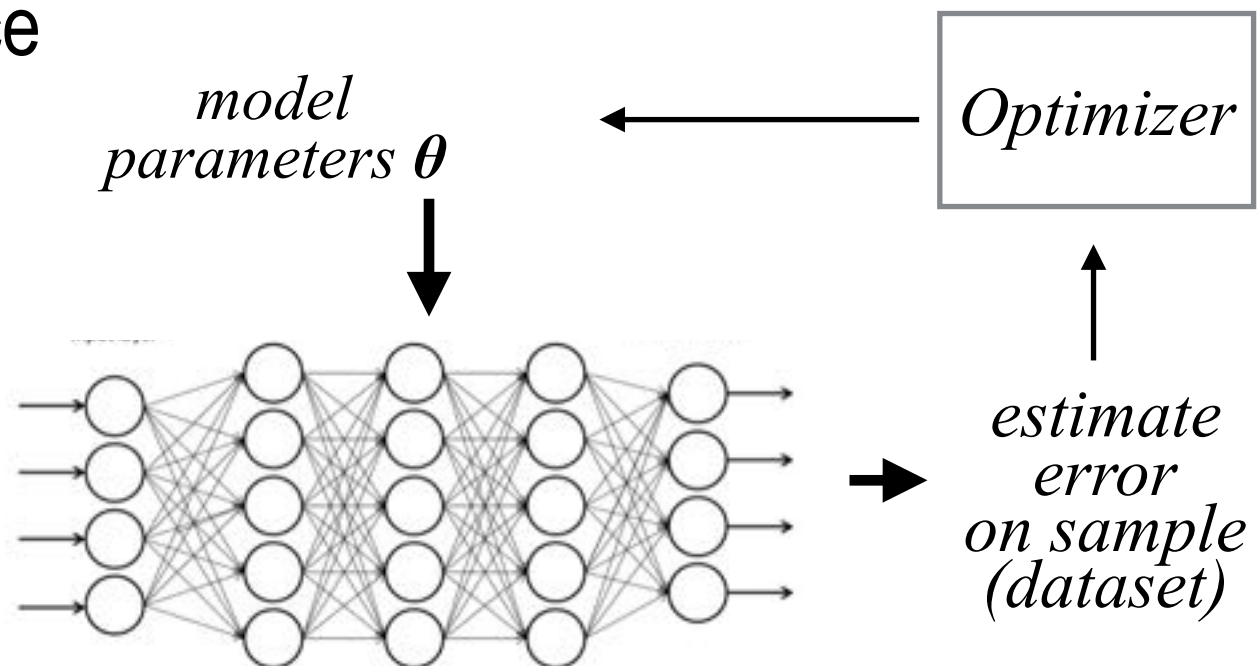
parametrized family  $\{h_{\theta}\}_{\theta}$

$\operatorname{argmin}_{\theta} \text{Err\_training\_set}(\theta) + \text{Reg}(\theta)$



output hypothesis  $h$  on  $Data$   
*"approximating"*  $P(data)$

In practice



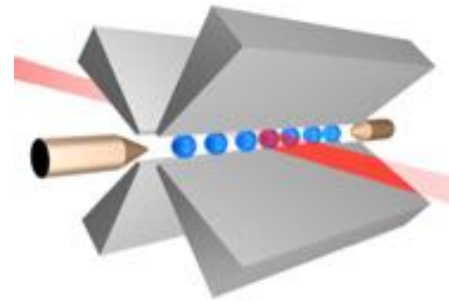
What about quantum computers?





# Quantum computers...

## ...and physics



-*manipulate* registers of 2-level systems (qubits)

-full description:



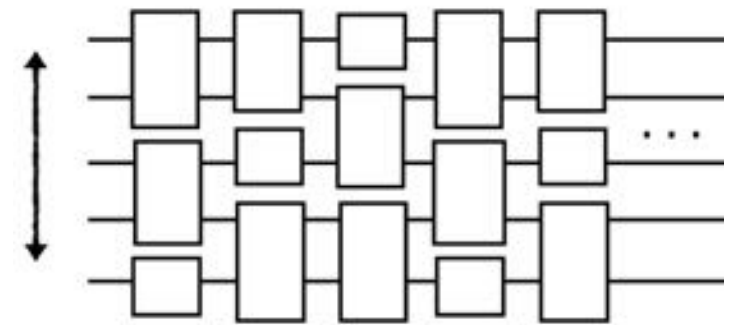
**$n$  qubits  $\rightarrow 2^n$  dimensional vector**

-manipulation: acting locally (gates)

## ...and computer science

-likely can *efficiently* compute more things than classical computers (factoring)  
e.g. factor numbers, or generate complex distributions


-even if QC is “shallow”



## ...and reality

special-purpose  
**quantum annealers**



  
Banana  
for scale

cca 50 qubit  
all-purpose  
**noisy**

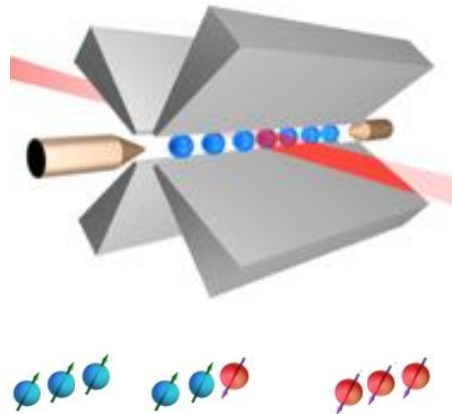
# Quantum computers...

## ...and physics

-*manipulate* registers of 2-level systems (qubits)

-full description:

***$n$  qubits  $\rightarrow 2^n$  dimensional vector***



## ...and computer science

-can compute things likely beyond **BPP** (factoring)

-can produce distributions which are hard-to-simulate for classical computers (unless **PH collapses**)

-even if QC is “**shallow**”

## ...and reality

special-purpose  
***quantum annealers***



Banana  
for scale

cca 50 qubit  
all-purpose  
**noisy**

# Bottlenecks of ML and the quantum pipeline

- a) The optimization bottleneck
- b) Big data & comp. complexity
- c) Machine learning Models

# Bottlenecks of ML and the quantum pipeline

- a) The optimization bottleneck — **quantum annealers**
- b) Big data & comp. complexity — **universal QC and Q. databases**
- c) Machine learning Models — **restricted (shallow) architectures**

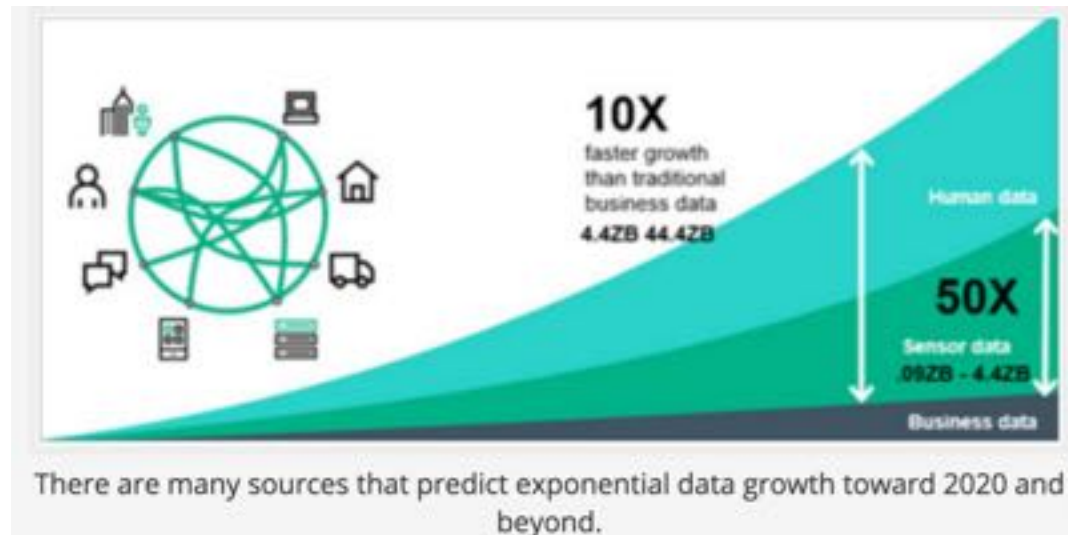
# Bottlenecks of ML and the quantum pipeline

- a) The optimization bottleneck — **quantum annealers**
- b) Big data & comp. complexity — **universal QC and Q. databases**
- c) Machine learning Models — **restricted (shallow) architectures**



# Precursors of Quantum Big Data

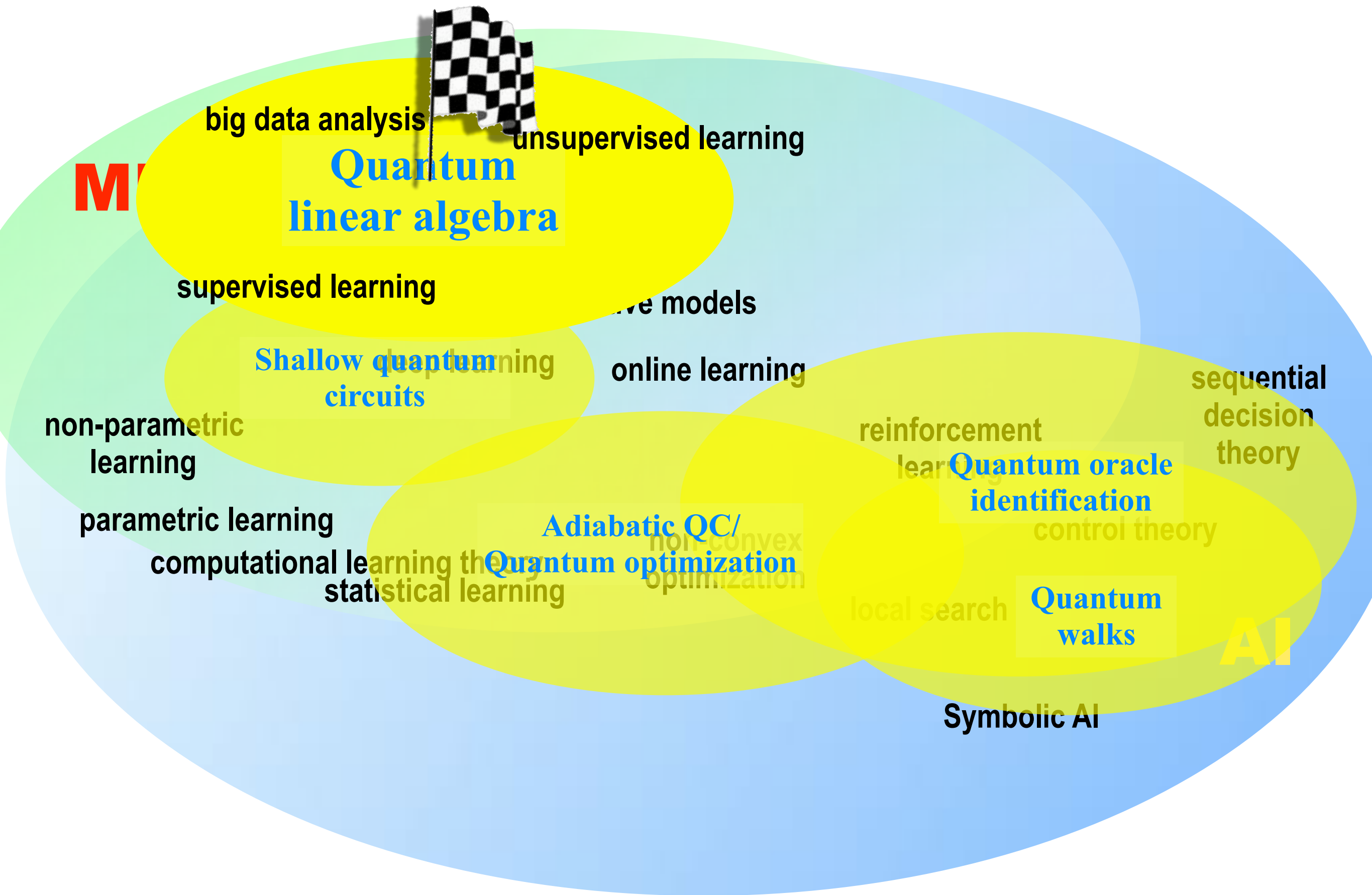
## Exponential data?



*Much of data analysis  
is linear-algebra:*

+

regression = Moore-Penrose  
PCA = SVD...



# Enter *quantum linear algebra*

**- $n$  qubits  $\leftrightarrow 2^n$  dimensional vector**

*-compute evolution = linear algebra*

*-so... evolution of quantum systems  
\*does\* linear algebra*

***-with exponentially large matrices!***

amplitude encoding

$$\mathbf{R}^N \ni \mathbf{x} = (x_i)_i$$
$$\downarrow$$
$$|\psi\rangle \propto \sum_{i=1}^N x_i |i\rangle$$

**exp(n) amplitudes  
in n qubits**

block encoding

$$U|0\rangle|\psi\rangle = \begin{bmatrix} A & B \\ C & D \end{bmatrix} \begin{bmatrix} |\psi\rangle \\ |0\rangle \end{bmatrix} = \begin{bmatrix} A\psi \\ C\psi \end{bmatrix} = |0\rangle A|\psi\rangle + |1\rangle C|\psi\rangle$$

functions of operators

$$f(A)|\psi\rangle = \alpha_0|\psi\rangle + \alpha_1 A|\psi\rangle + \alpha_2 A^2|\psi\rangle \cdots$$
$$\approx A^{-1}|\psi\rangle$$

inner products

$$P(0)_\psi = |\langle 0|\psi\rangle|^2$$

If this worked literally...this would make us *INFORMATION GODS*.

Prediction: *44 zettabytes by 2020.*

*If all data is floats, this is  $5.5 \times 10^{21}$  float values*

If this worked literally...this would make us *INFORMATION GODS*.

Prediction: *44 zettabytes by 2020.*

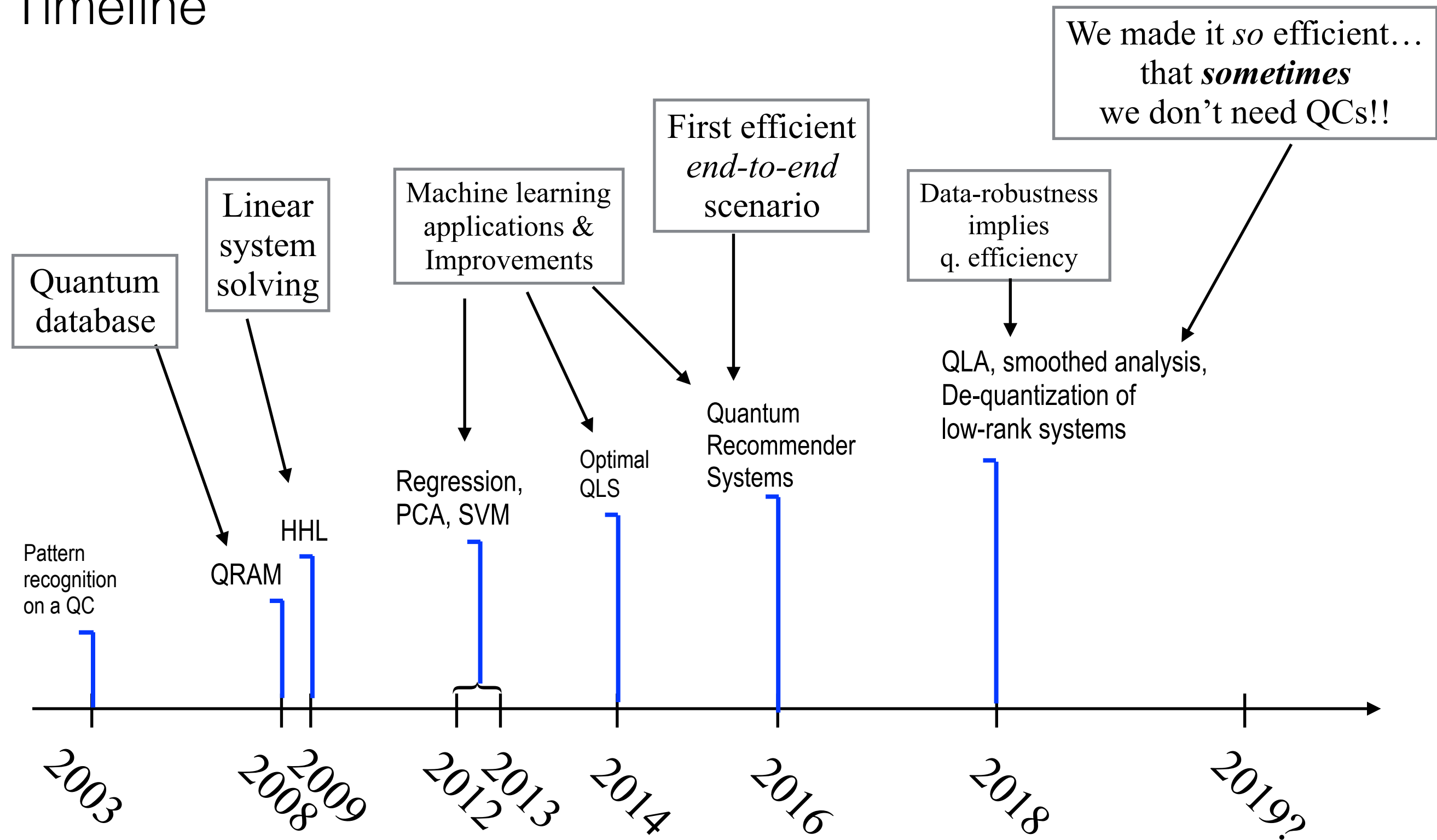
*If all data is floats, this is  $5.5 \times 10^{21}$  float values*

***... can be stored in state of 73 qubits (ions, photons....)***





# Timeline



## Summary of quantum (inspired) “big data”

### *The “bad”*

*-**not** an inexhaustible source of exponential quantum advantage*

### *Quantum and classical*

*-**exponentially efficient processing**  
given suitable databases*

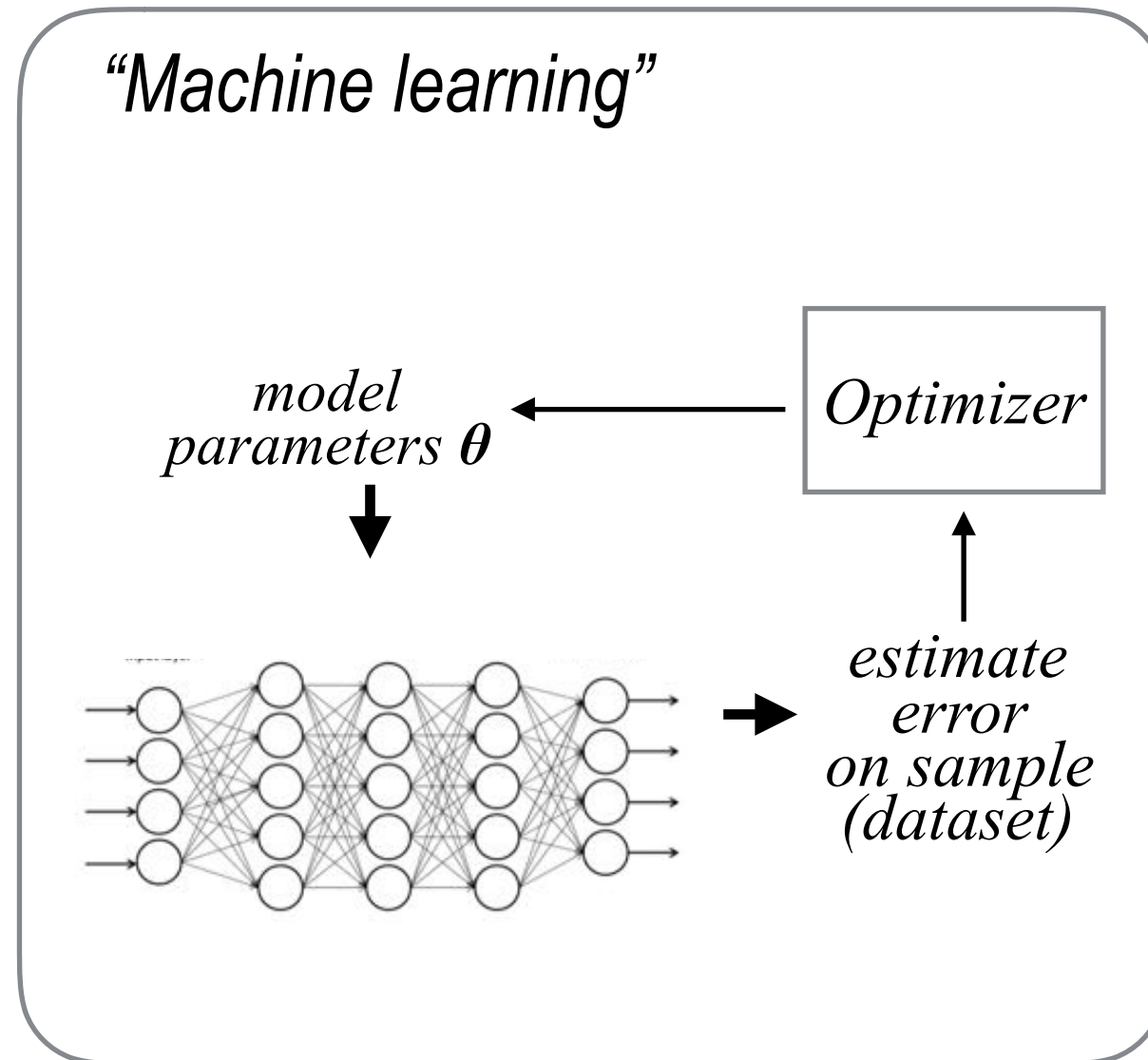
### *Quantum advantages over classical*

- Quantum works with full-rank transforms (e.g. Fourier for series)*
- polynomial advantage** (up to 16 degree difference at the moment)*
- error scaling: exponential precision v.s. poly (in-)precision*

# Bottlenecks of ML and the quantum pipeline

- a) The optimization bottleneck — **quantum annealers**
- b) Big data & comp. complexity — **universal QC and Q. databases**
- c) Machine learning Models — **restricted (shallow) architectures**

# (Quantum) Machine learning Models



Improving ML == speeding up algorithms... *or is it?*



# Machine learning Models matter!

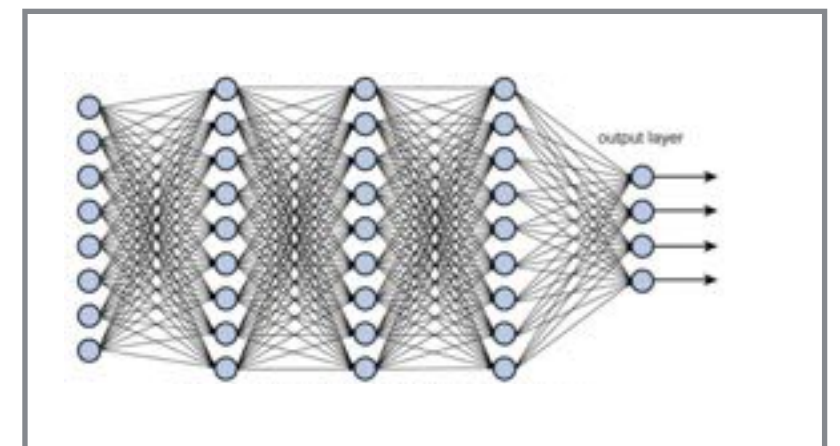
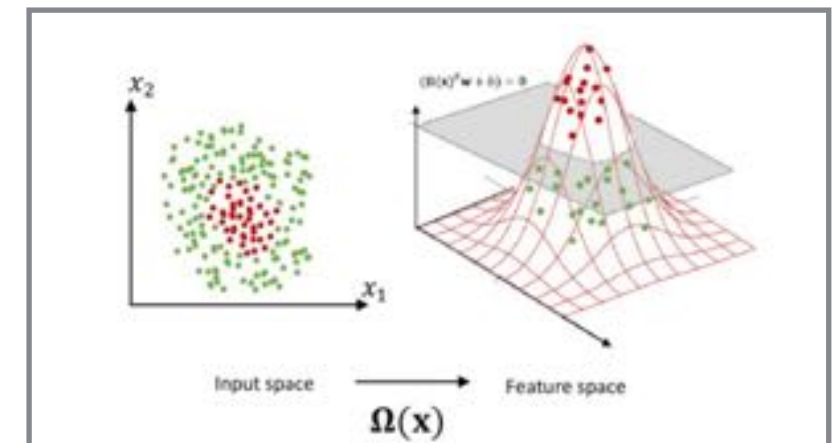
**best fit v.s. “generalization performance” or classifying well *beyond the training set***

Challenge:

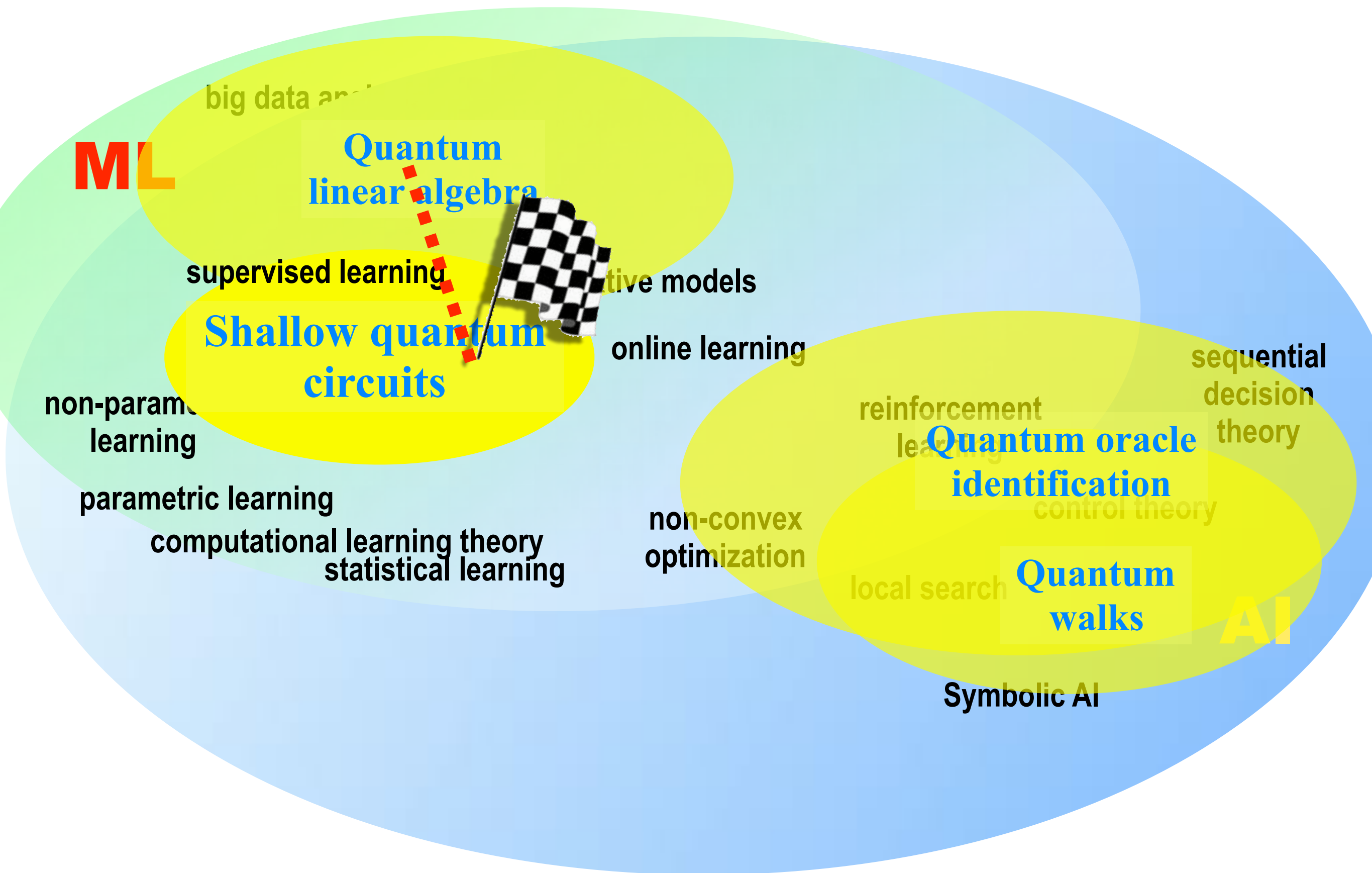
Data:



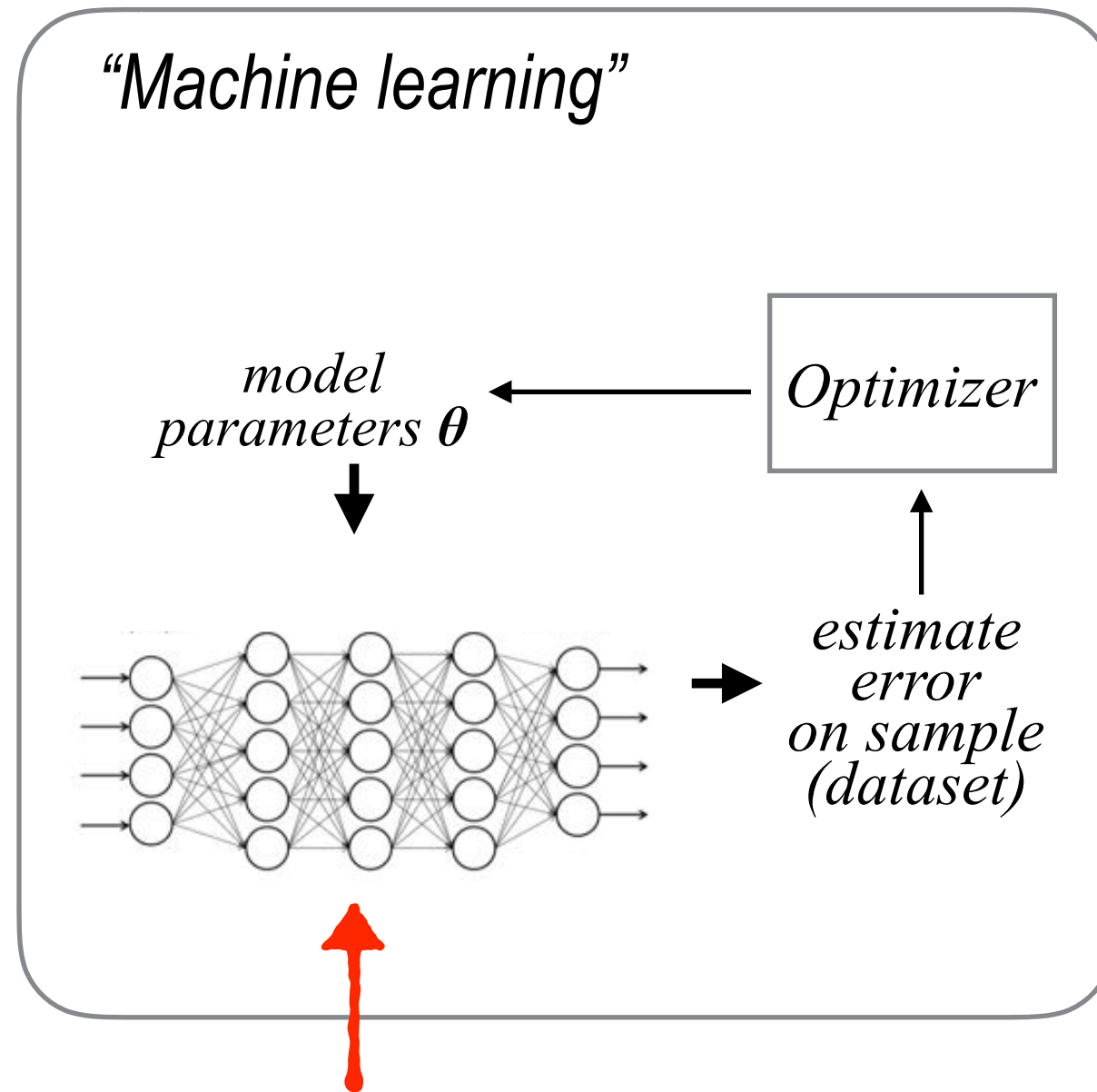
Models:



Not all models (+training algo) are born equal (for *real* datasets)...

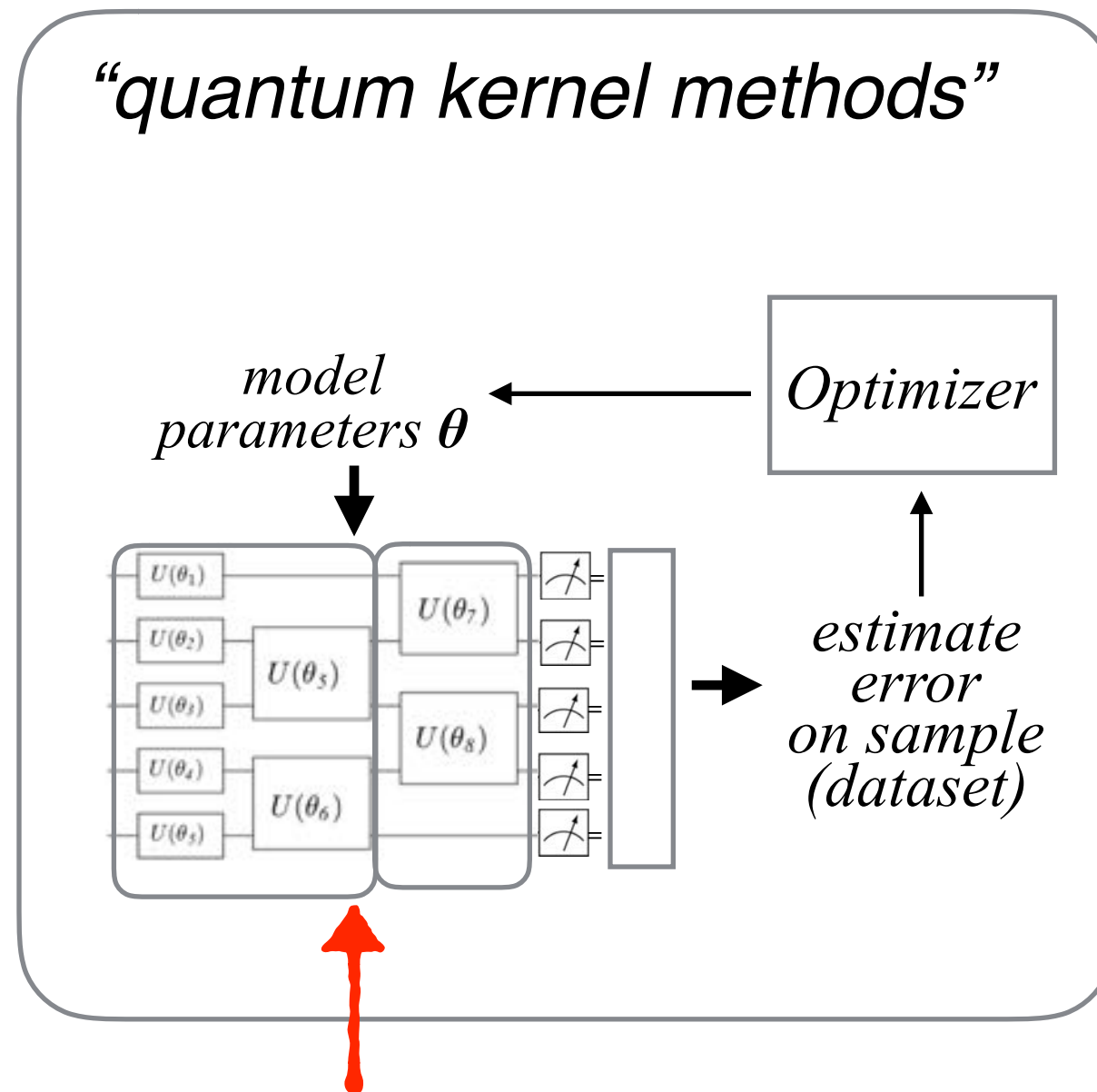


# Machine learning Models



*family of functions.*  
*if it's “good”, we can generalize well*

# Quantum Machine learning Models



*How about “shallow quantum circuits”?*  
*-instead neural network, train a QC!*  
*-related to ideas from*  
*q. condensed-matter physics (VQE)*

# Quantum Machine learning Models

## *“quantum kernel methods”*

### The good

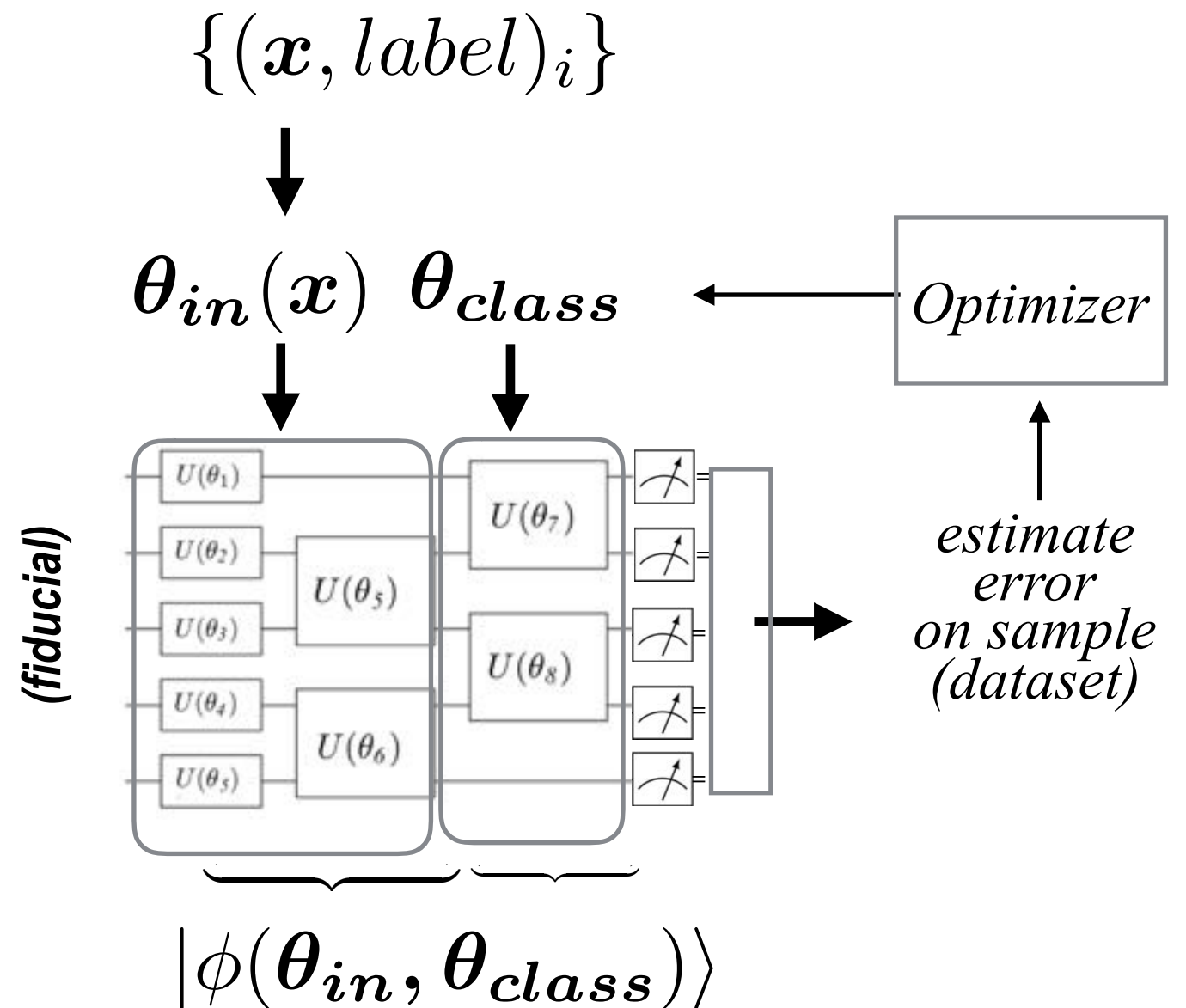
- near term architectures
- seems to be **robust**  
*(noise not inherently critical!)*
- possibly **very expressive**

### The neutral

- **many parameters**
- **model advantages** less clear  
*(contrast to variational methods!)*

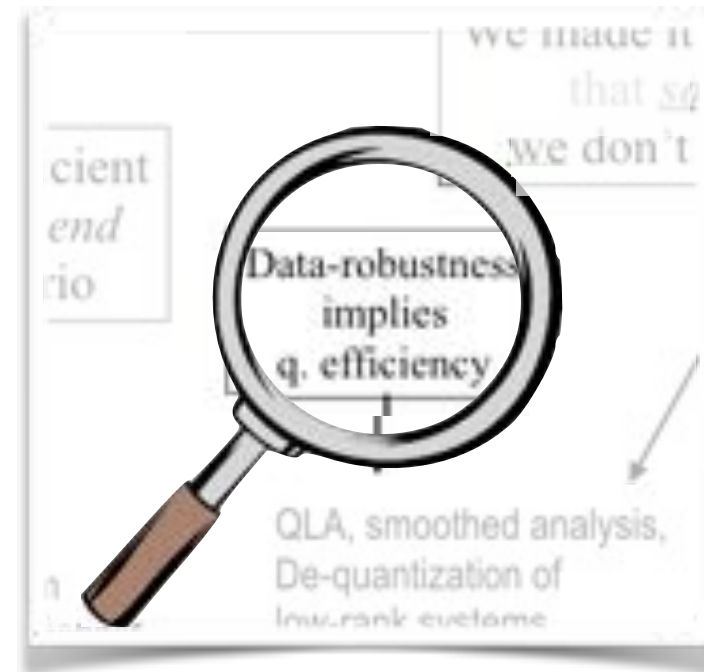
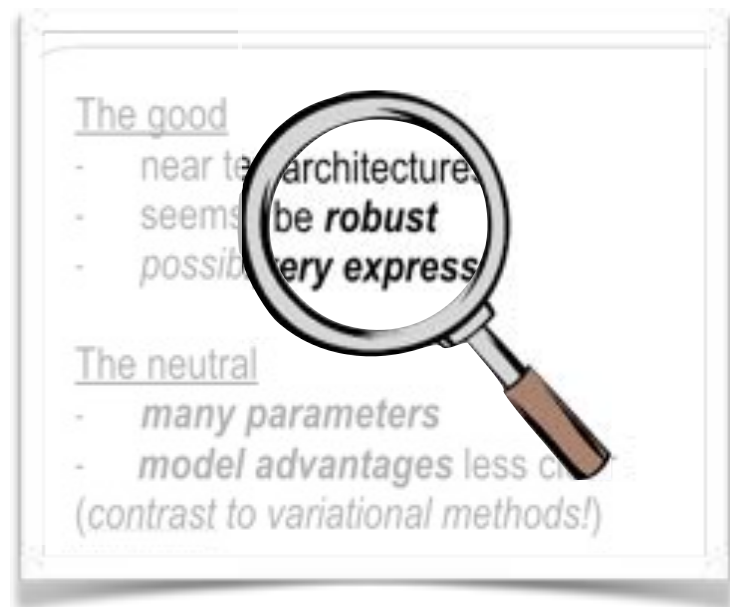
### The bad

- **barren plateaus** (also in DNN)



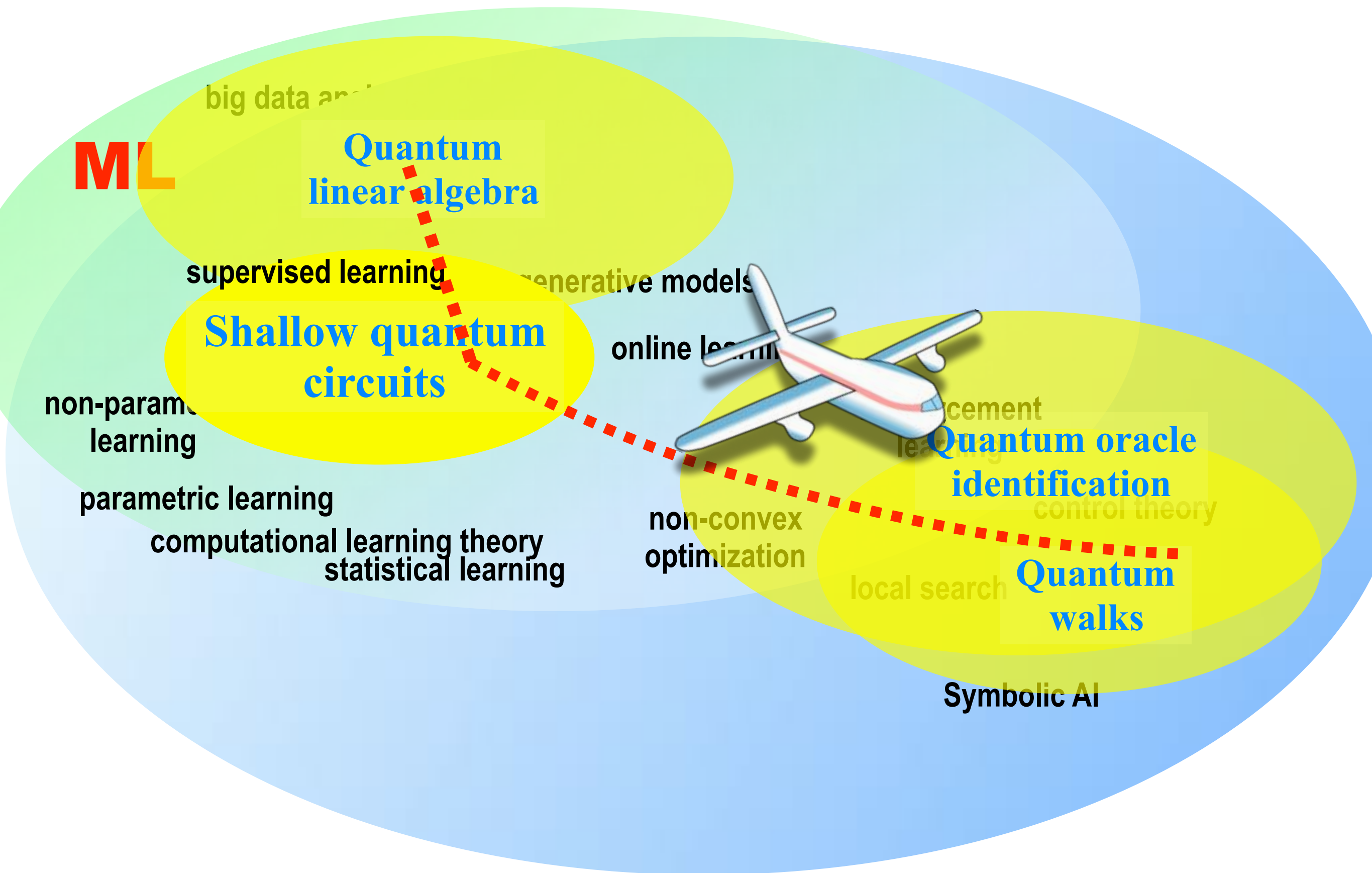


# A hope... *killer app* for noisy QCs?

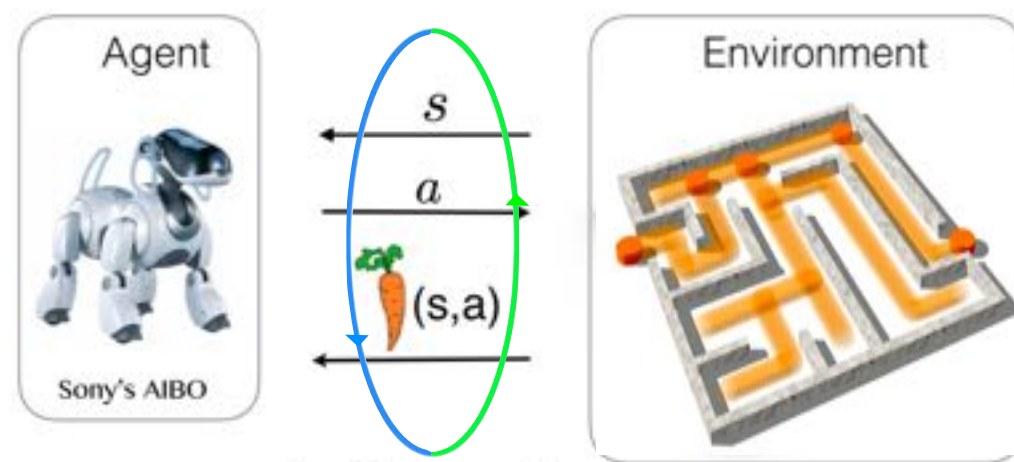


ML good for dealing with noise (in *\*data\**)...  
 Can QML deal with *its own* noise (in *\*process\**)?

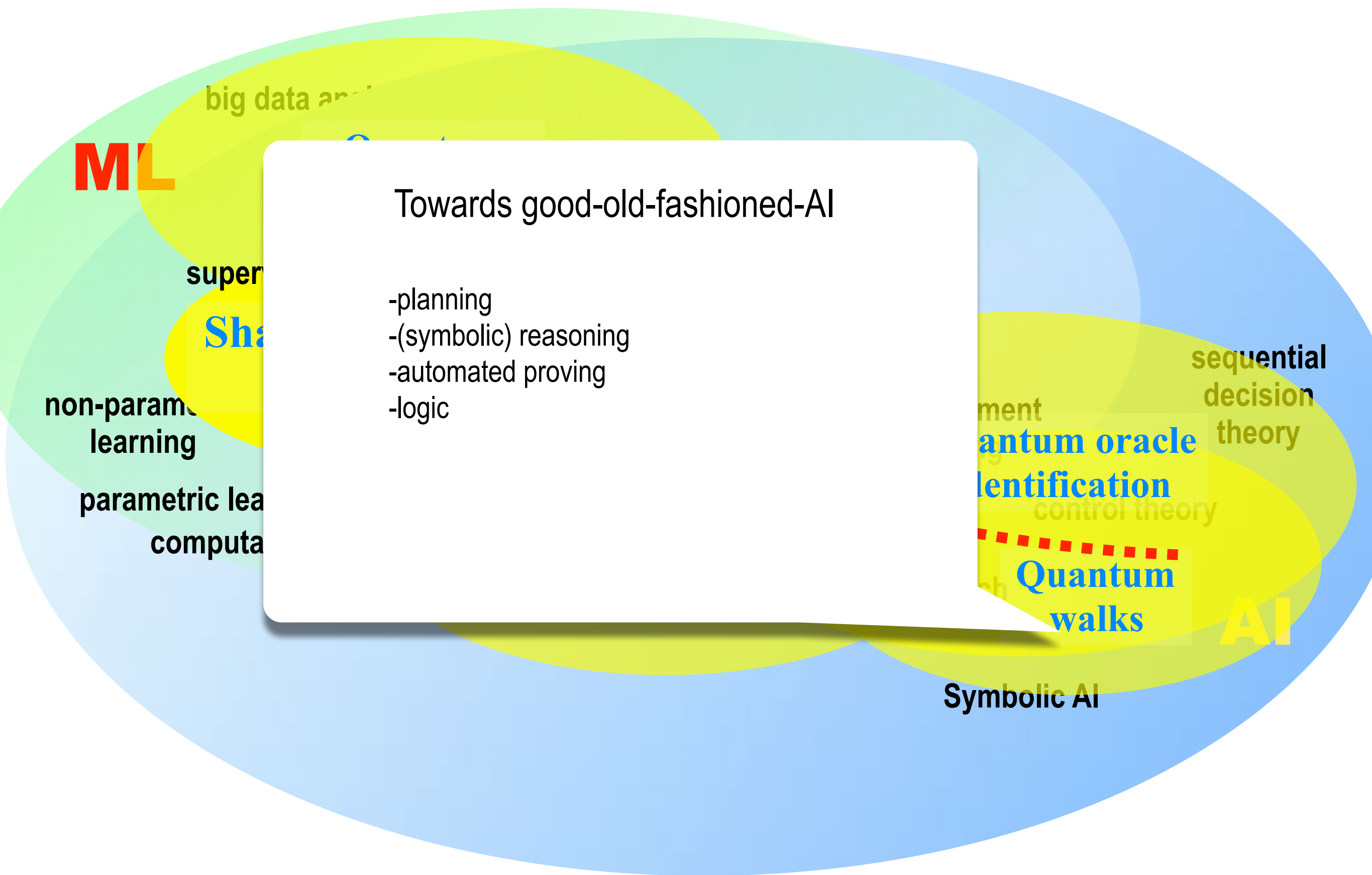
# Beyond ML?



## Quantum-enhanced reinforcement learning



c.f. Briegel



## Towards good-old-fashioned-AI

- planning
- (symbolic) reasoning
- automated proving
- logic



Optimal packing



Shortest tours

$$f(x_1, \dots, x_n) = (x_1 \vee x_{10} \vee \bar{x}_{51}) \wedge (\bar{x}_3 \vee \bar{x}_{10} \vee \bar{x}_{11}) \wedge (\bar{x}_{11} \vee \bar{x}_{44} \vee \bar{x}_{51}) \cdots$$



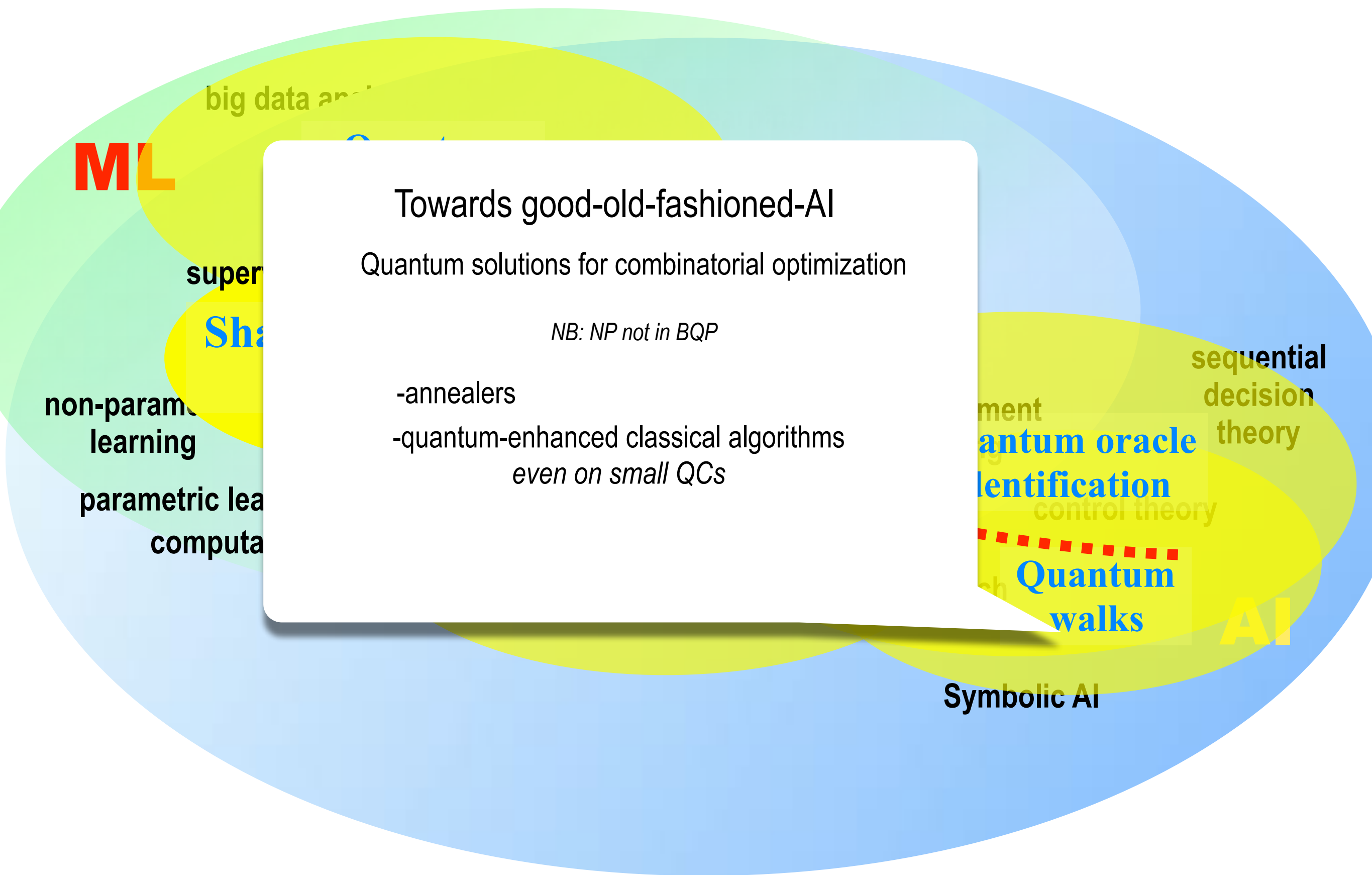
Traffic flow optimization



RL and ML

Find a proof of  
Riemann's hypothesis  
with less than a million lines  
(if it exists)?

*finding \*good\* (not worst case!) solutions to this  
is central to AI*



## Towards good-old-fashioned-AI

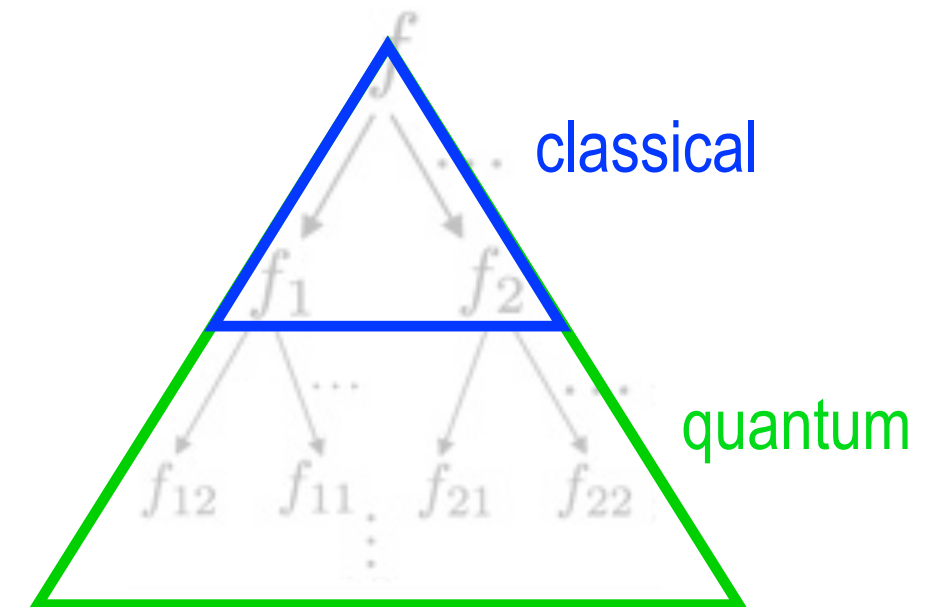
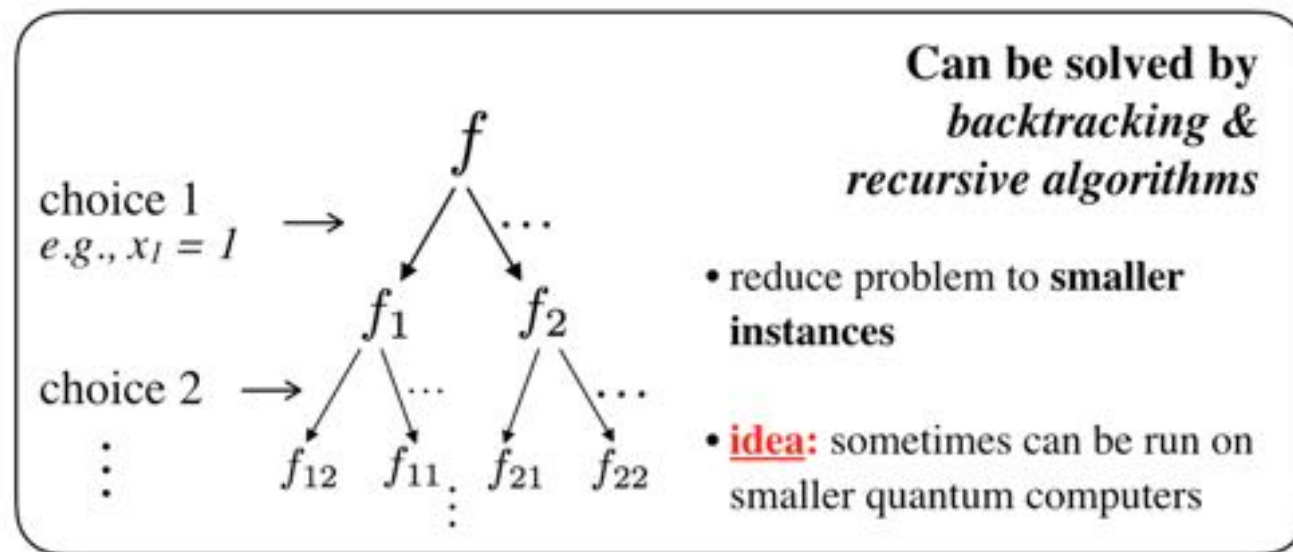
Quantum solutions for combinatorial optimization

*NB: NP not in BQP*

- annealers
- quantum-enhanced classical algorithms  
*even on small QCs*



# NP problems on smaller quantum computers

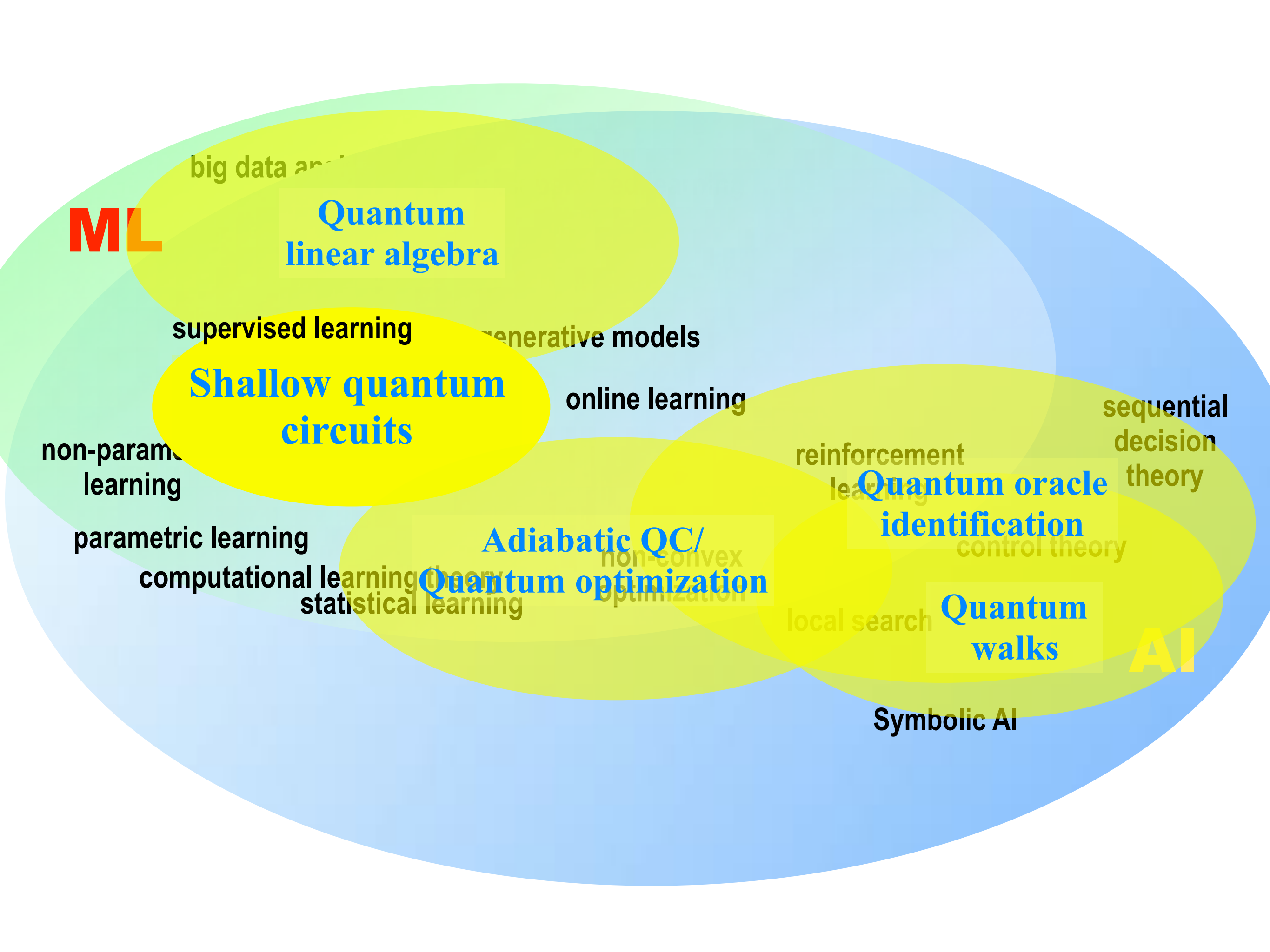


Works because structure is loose

For heuristic solutions... noise may not be a terminal problem

AI as the killer ap?







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