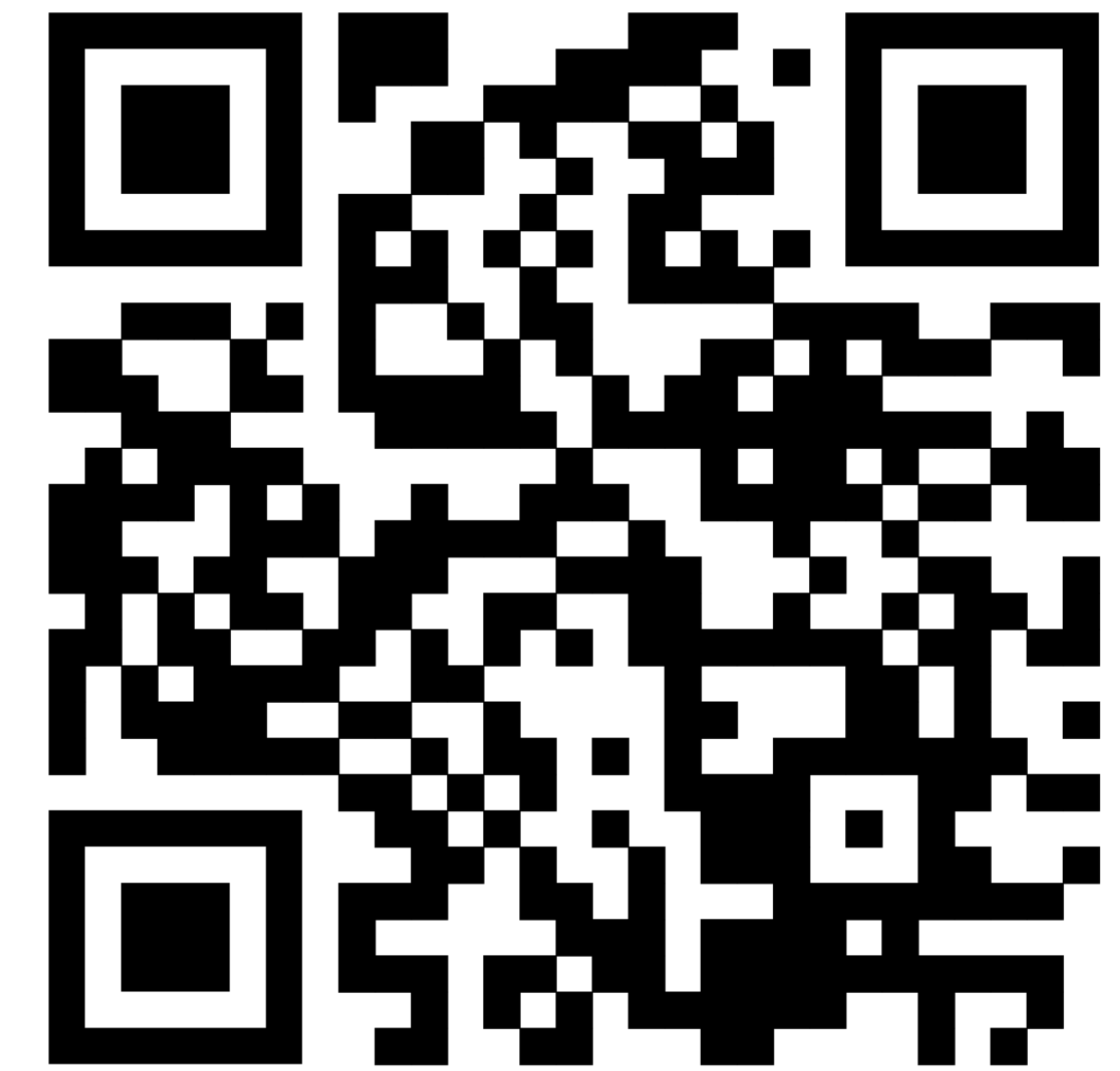


Reconstructing charged particle track segments with a quantum-enhanced support vector machine

P. Duckett, G. Facini, M. Jastrzebski, S. Malik, S. Rettie, T. Scanlon



<https://arxiv.org/abs/2212.07279>



Marcin Jastrzebski

**river
Lane**

Cambridge, UK



London, UK

UCL-HEP-Q



**Callum
Duffy**



**Dr Mohammad
Hassanshahi**

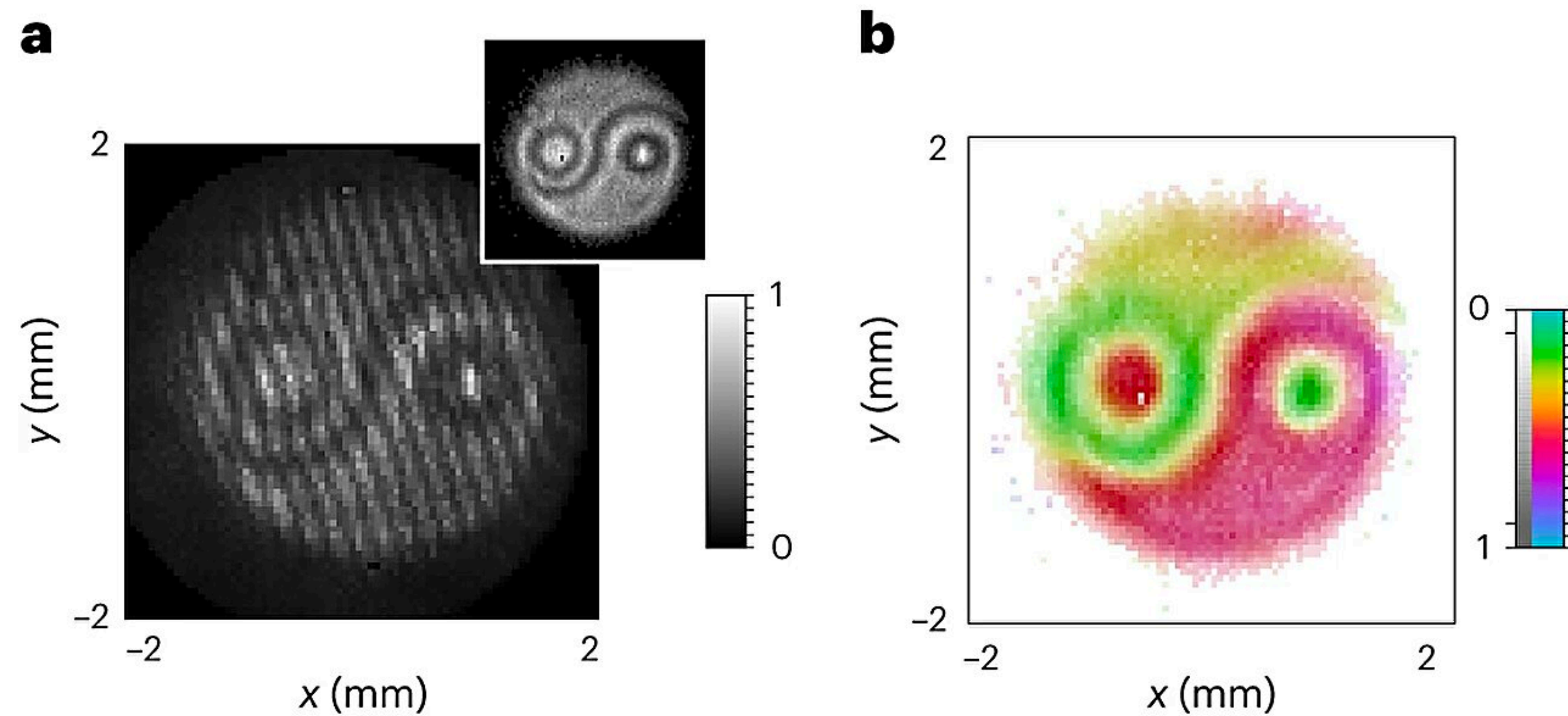
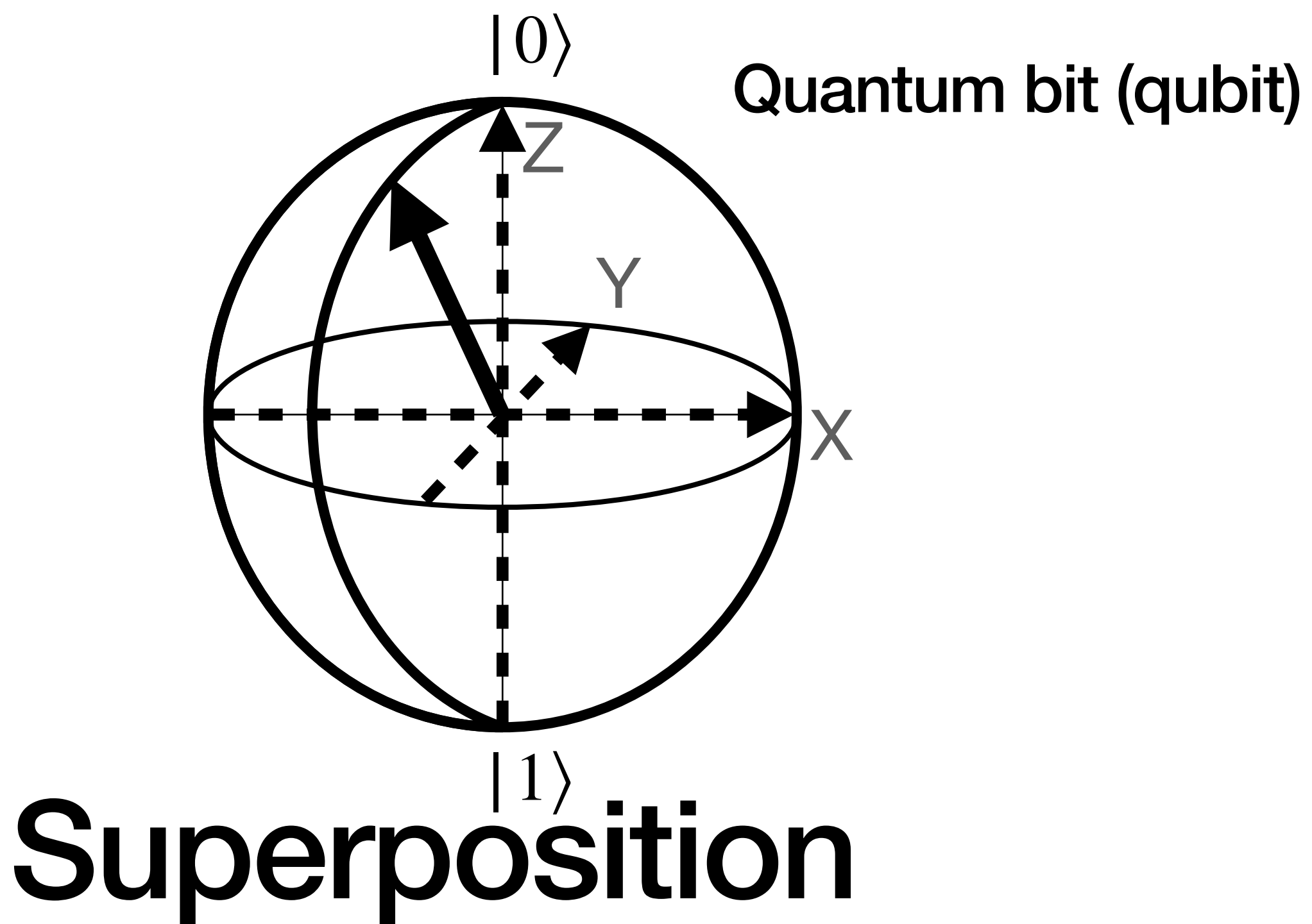


**Marcin
Jastrzębski**

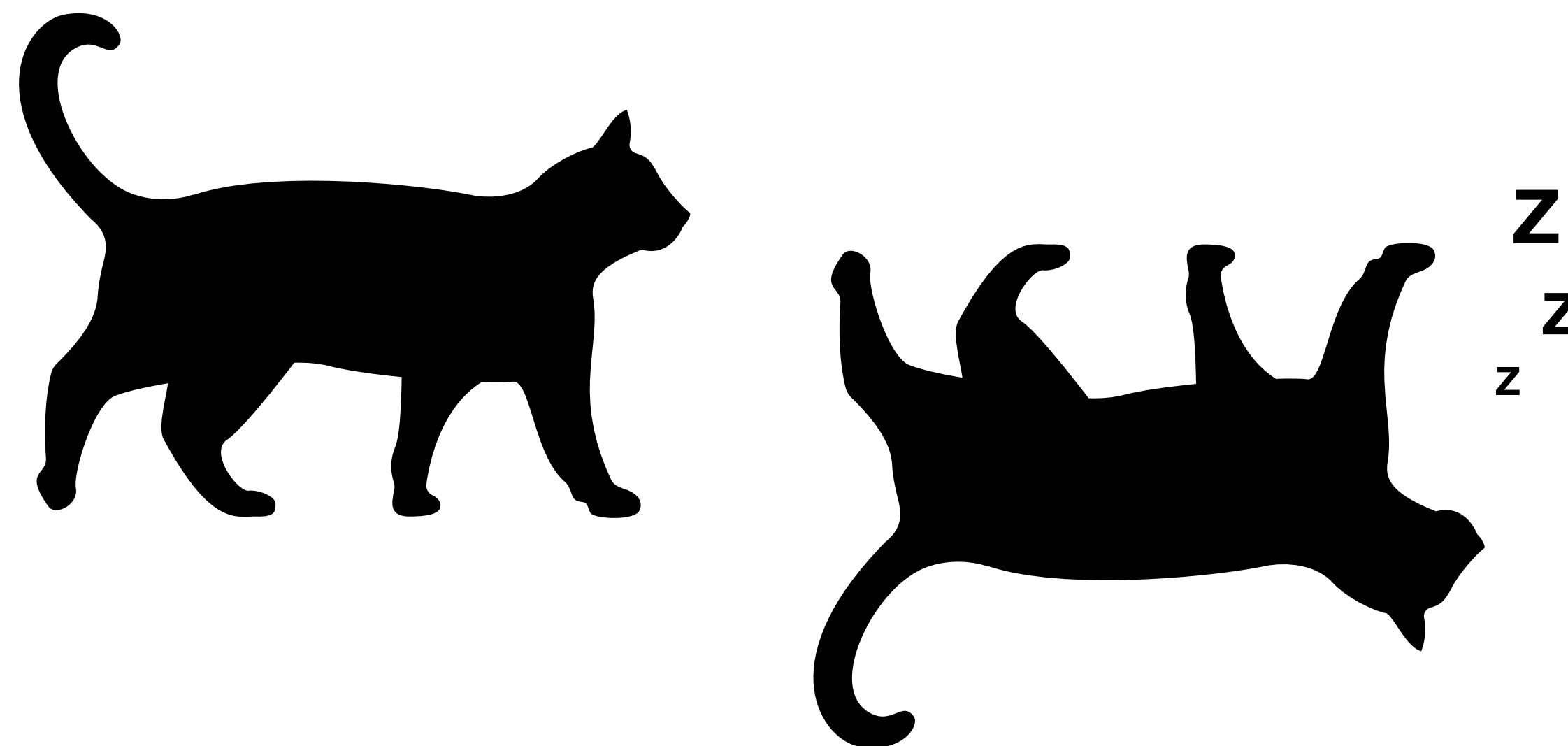


**Dr Sarah
Malik**

Quantum computation



Entanglement



Randomness

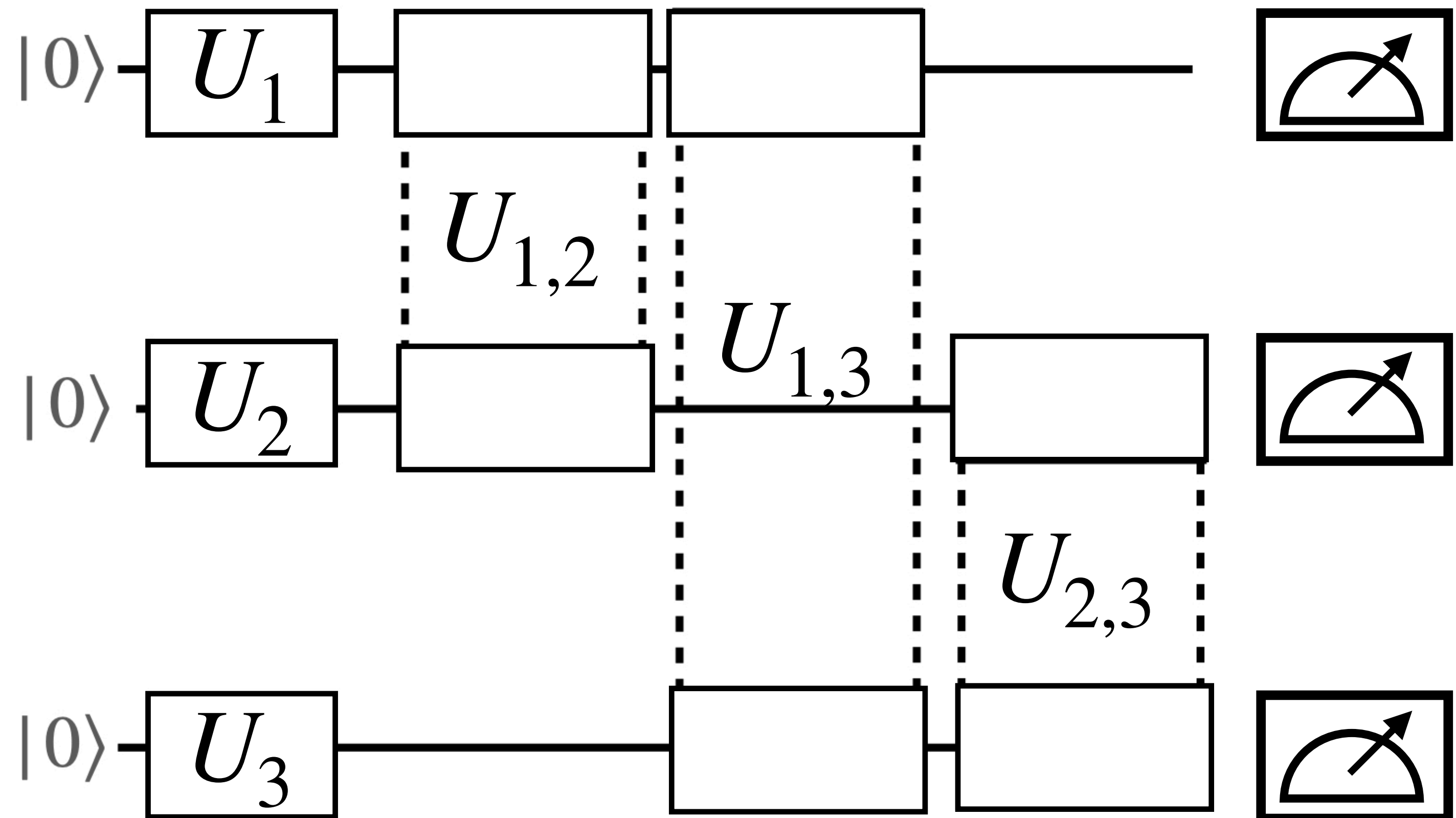
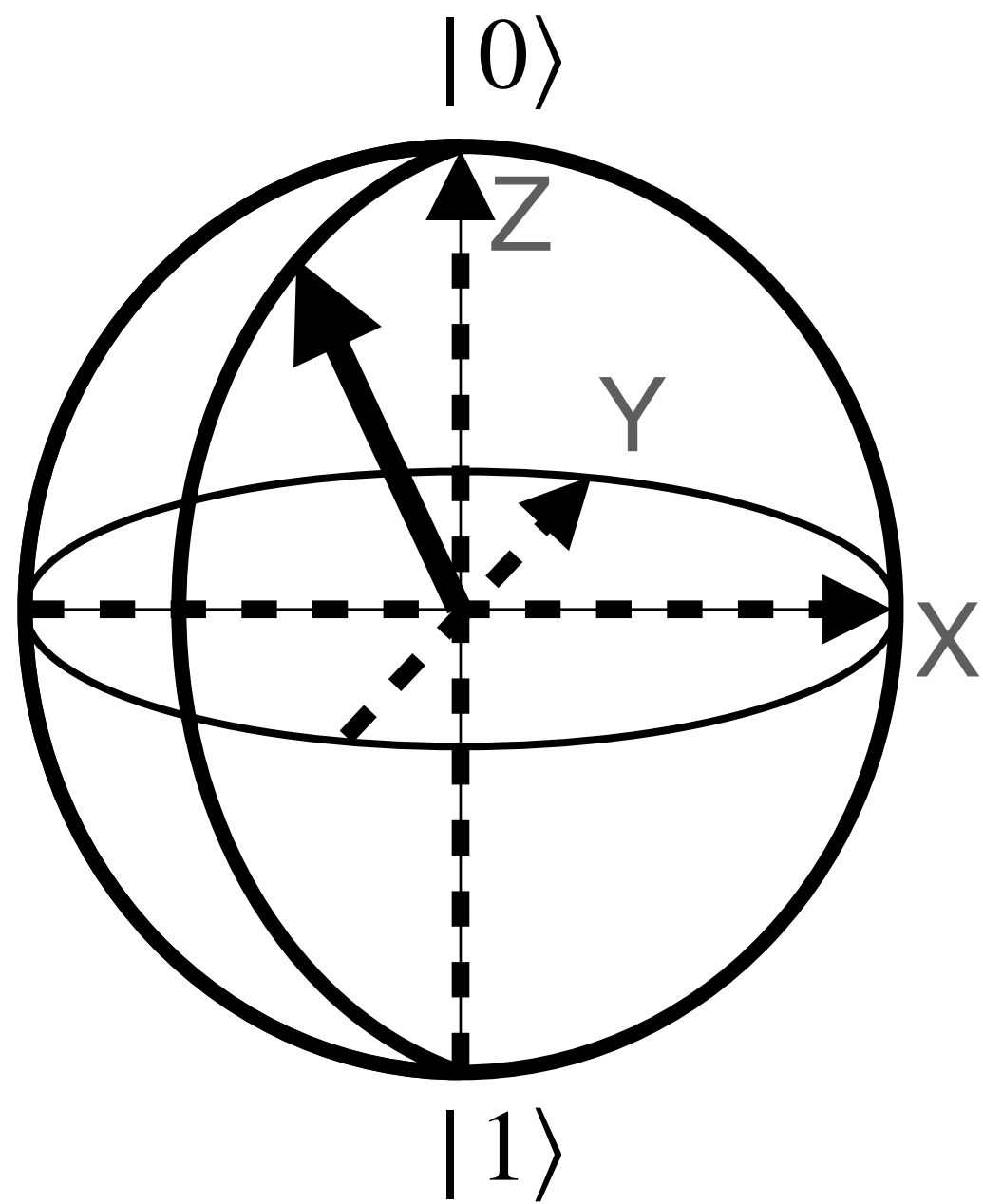
Quantum computation - circuit

$$|0\rangle^{\otimes N} \rightarrow (\alpha|0\rangle + \beta|1\rangle)^{\otimes N} \rightarrow \alpha|00\dots 0\rangle + \beta|00\dots 1\rangle + \dots \rightarrow (011\dots 1)$$

Superposition

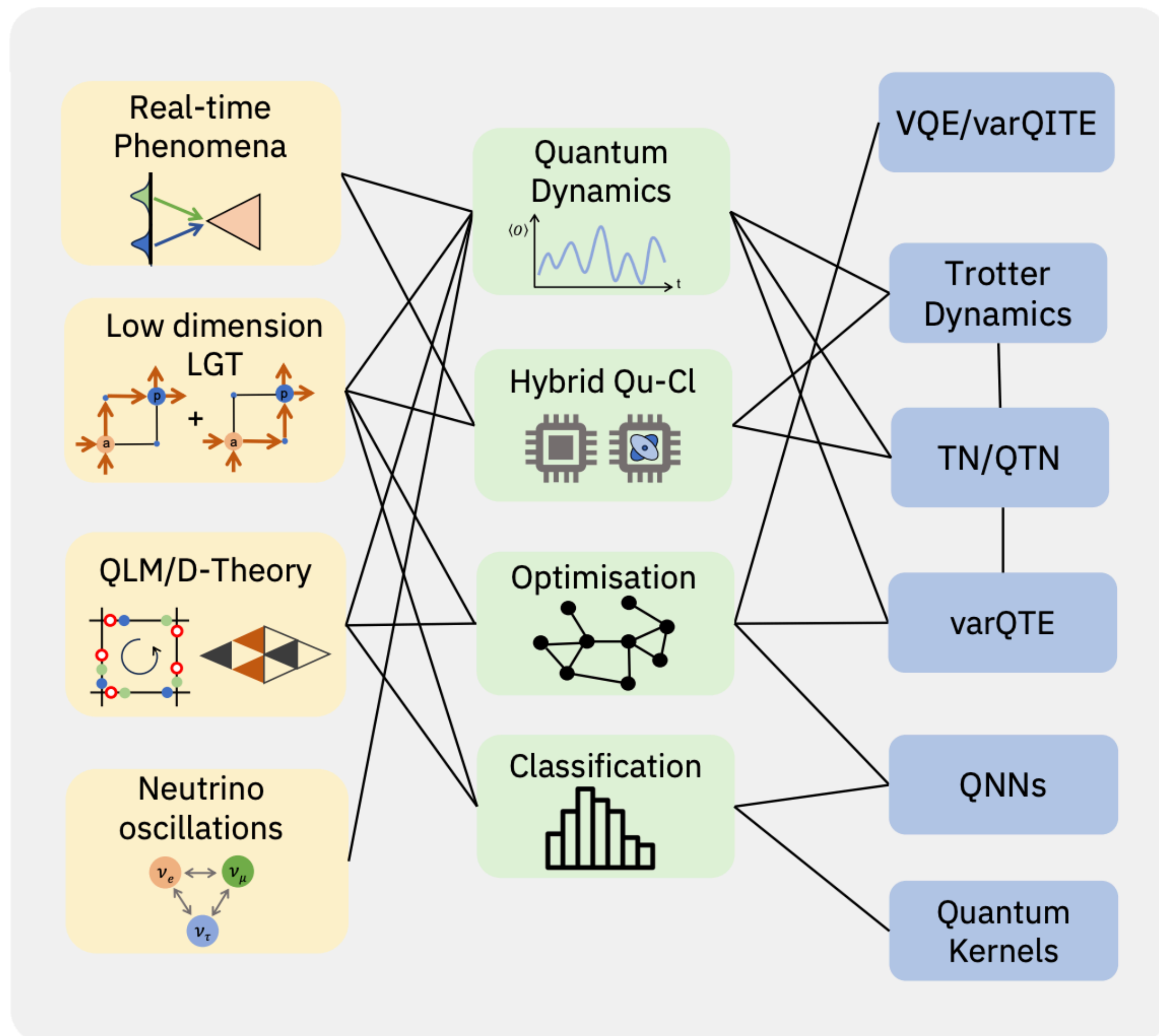
Entanglement

Randomness

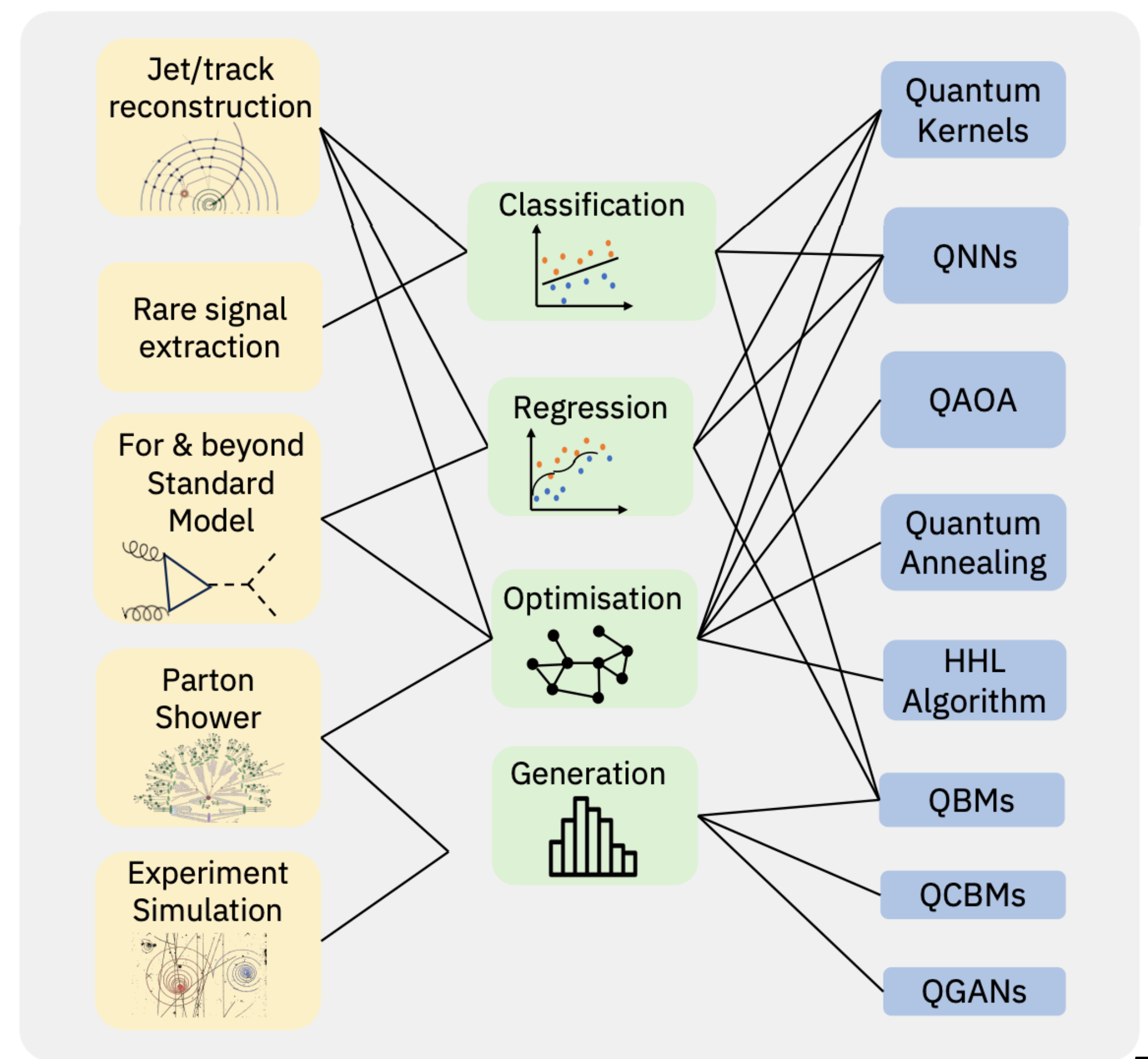


QC for HEP landscape

Theory

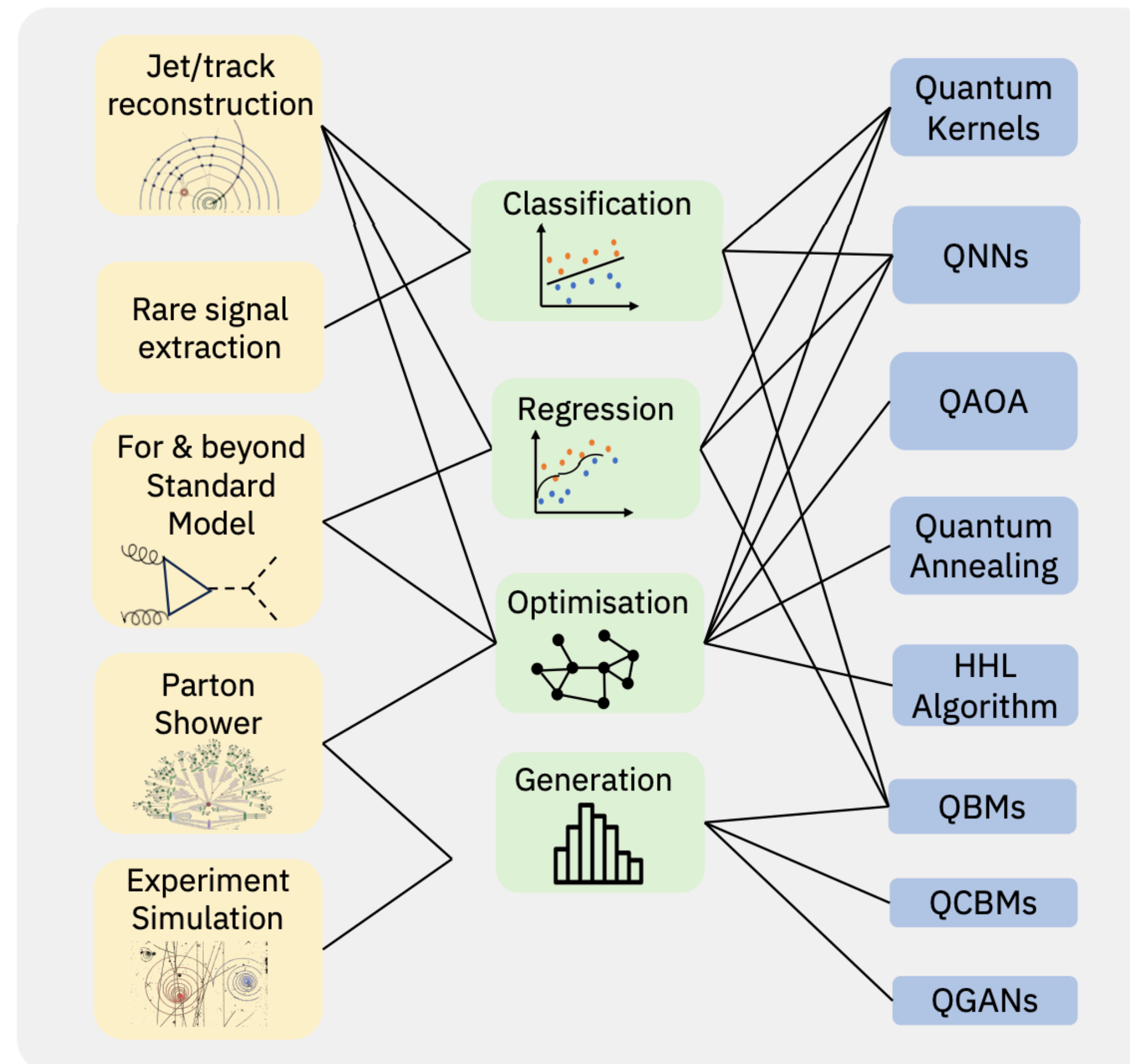


Experiment



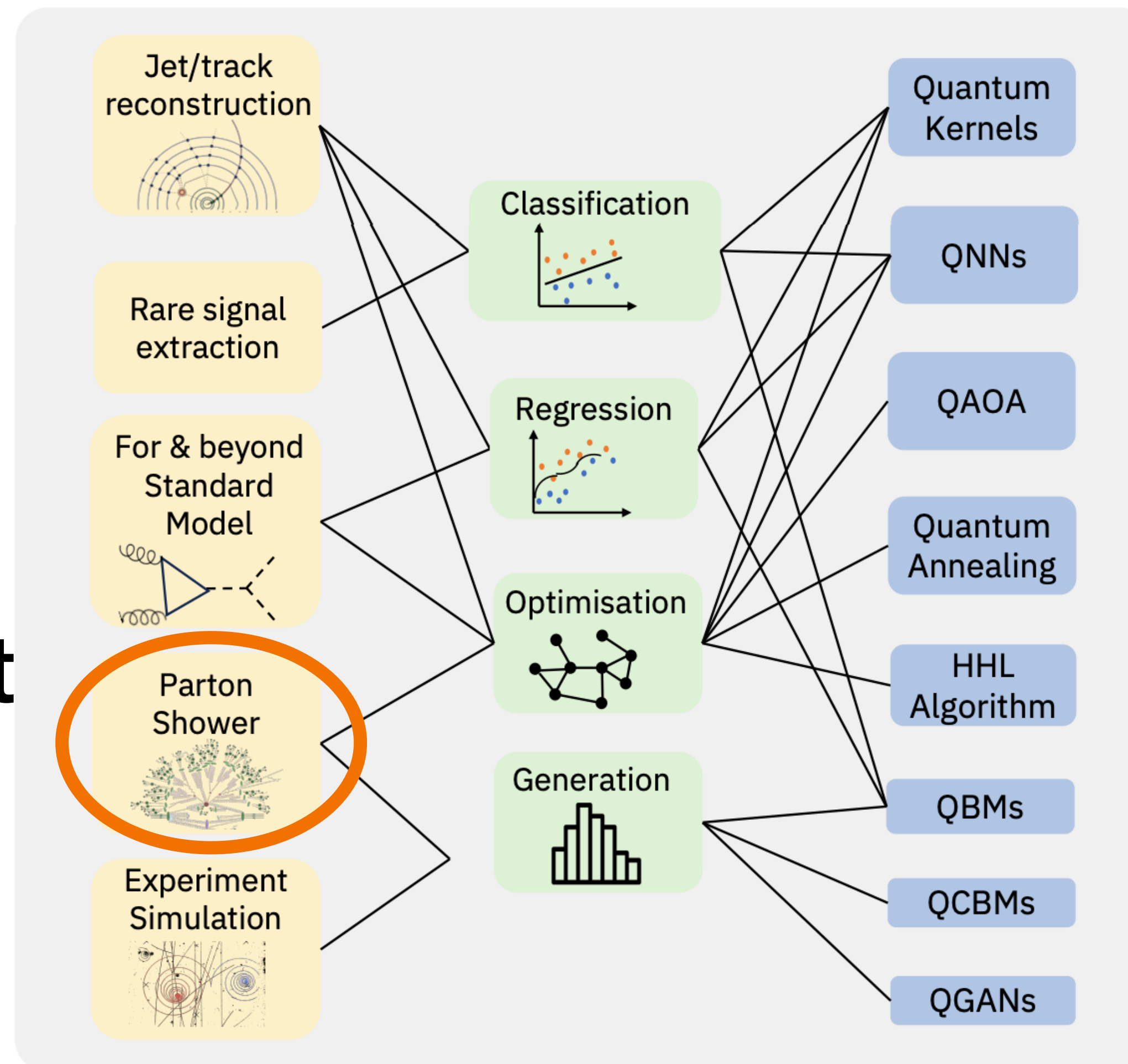
QC for HEP landscape

Experiment



QC for HEP landscape

Experiment



Check out



<https://www.nature.com/articles/s42254-022-00528-1>

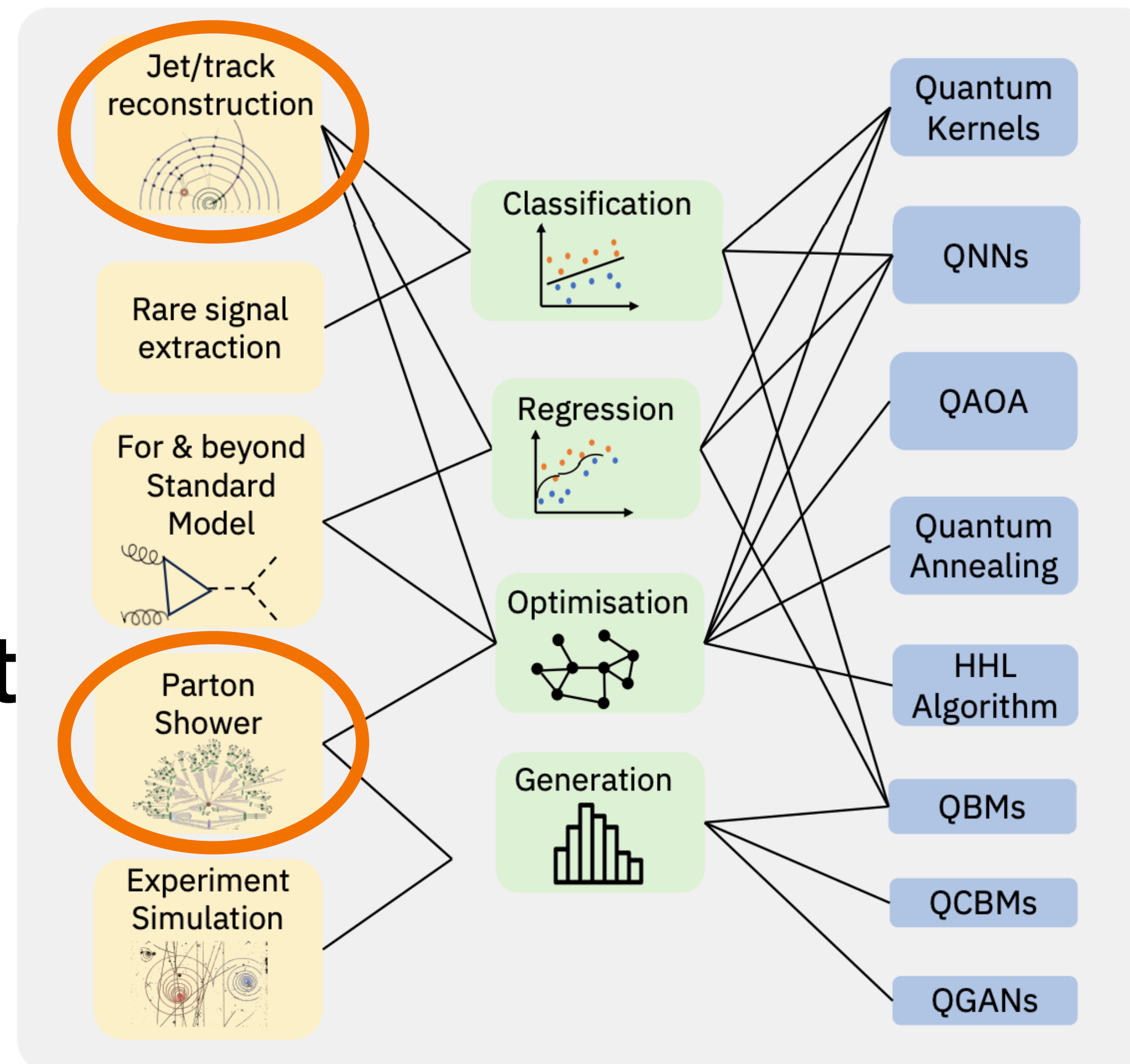
QC for HEP landscape

Experiment

This workshop

Check out

<https://www.nature.com/articles/s42254-022-00528-1>



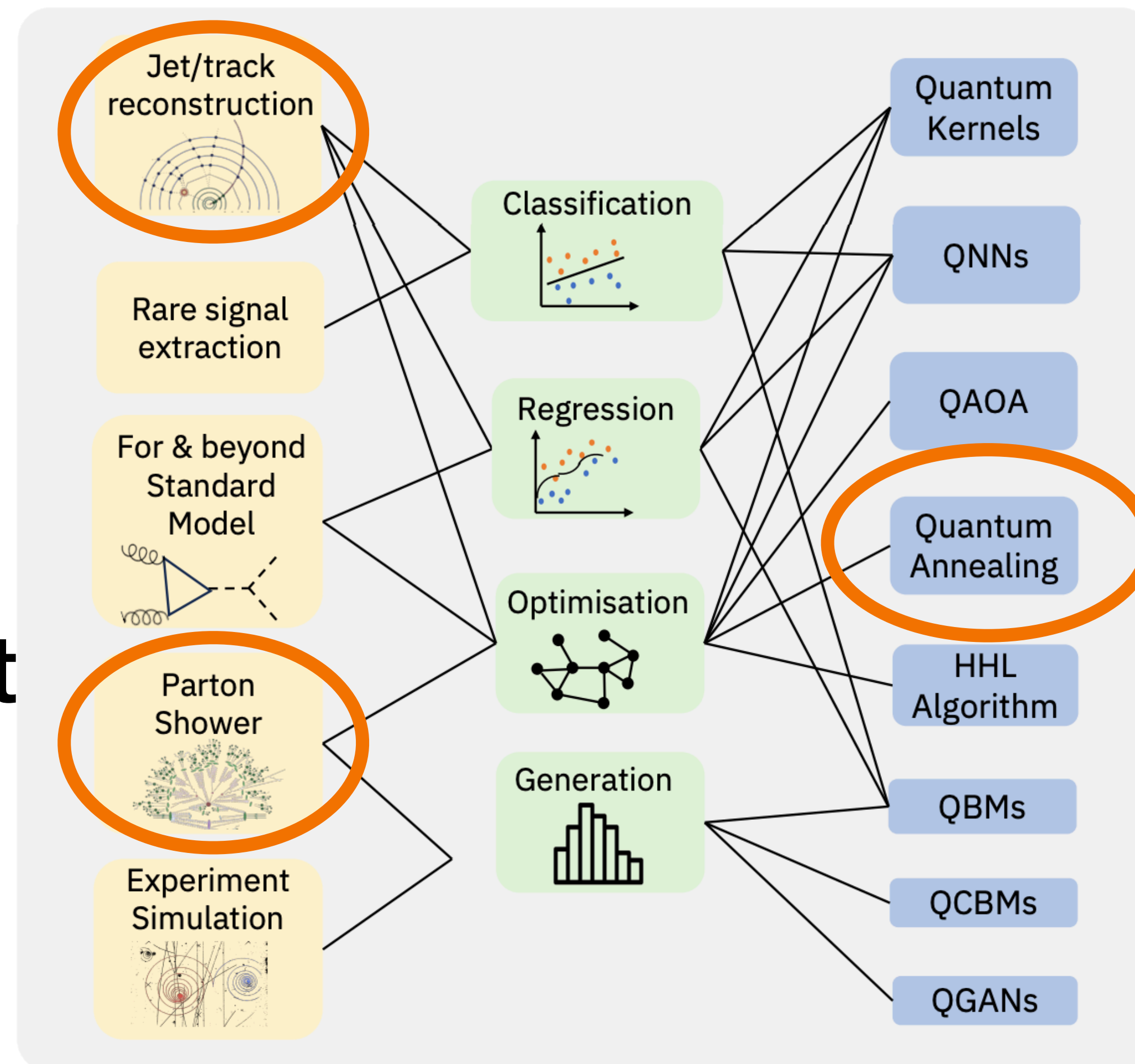
QC for HEP landscape

Experiment

This workshop

Check out

<https://www.nature.com/articles/s42254-022-00528-1>



Later today

QC for HEP landscape

Experiment

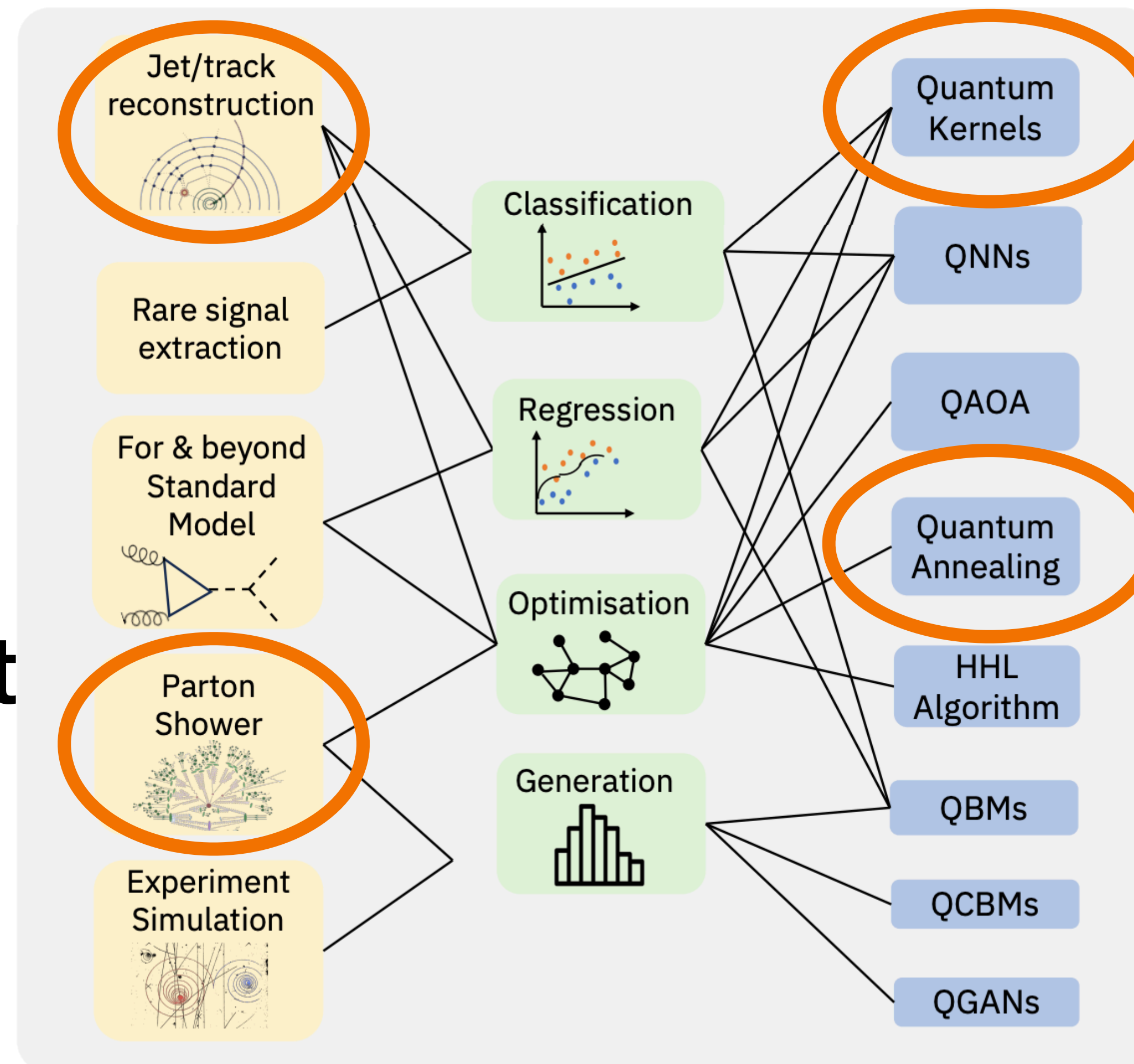
This workshop

Right now!

Later today

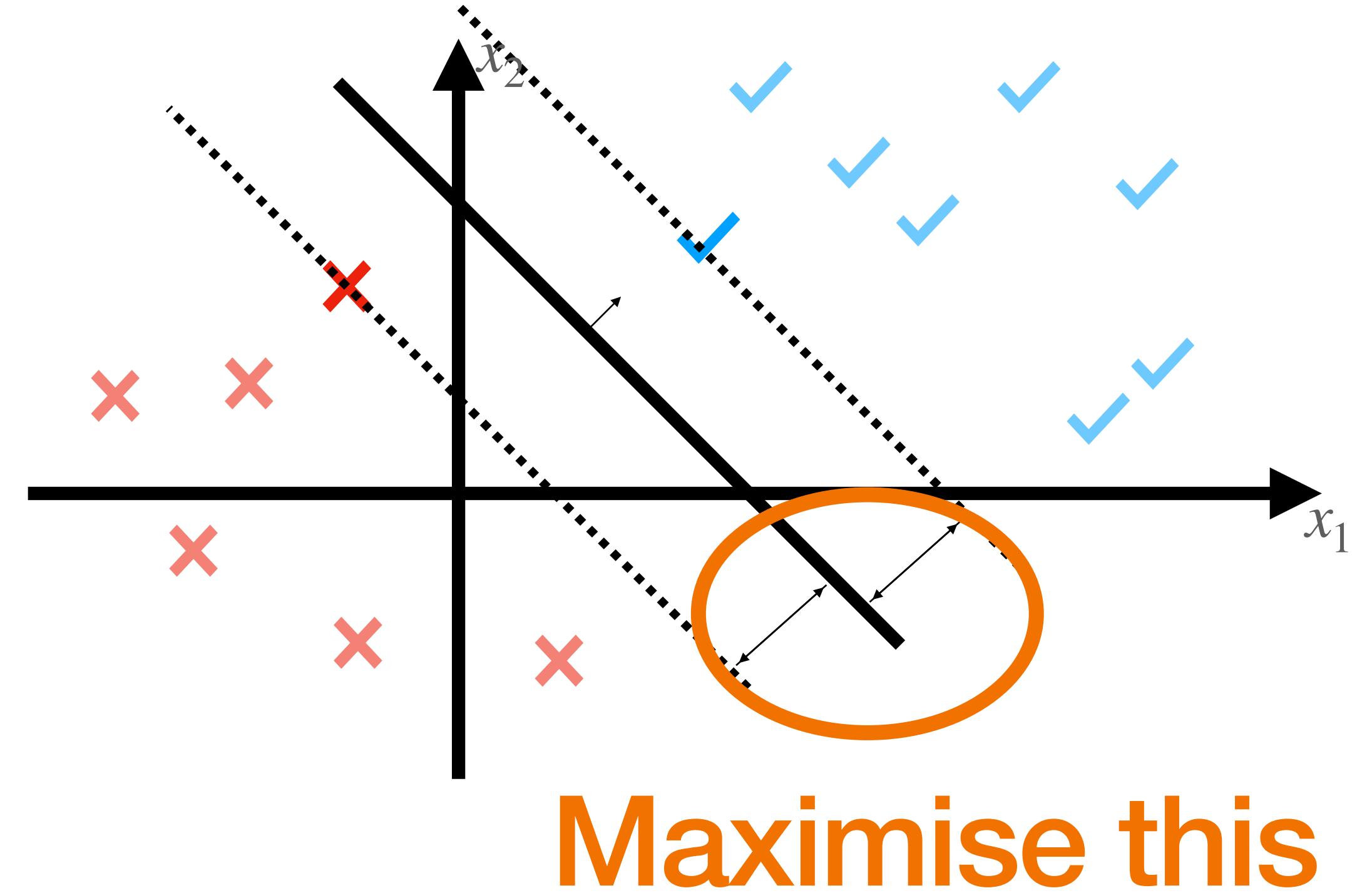
Check out

<https://www.nature.com/articles/s42254-022-00528-1>



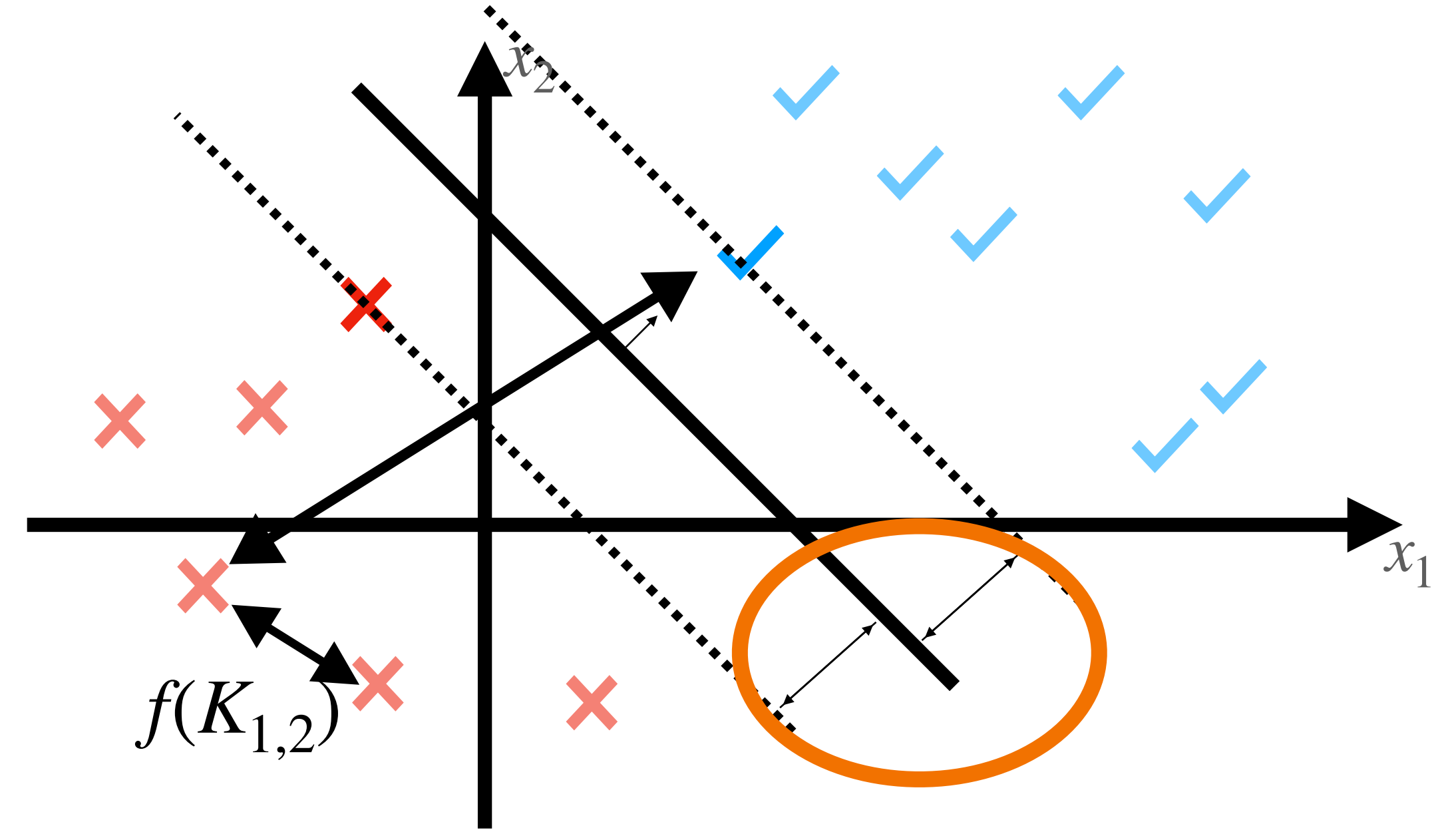
Intro to SVM

Usually done using the dual (think Lagrangian multipliers)



Intro to SVM

Usually done using the dual (think Lagrangian multipliers)



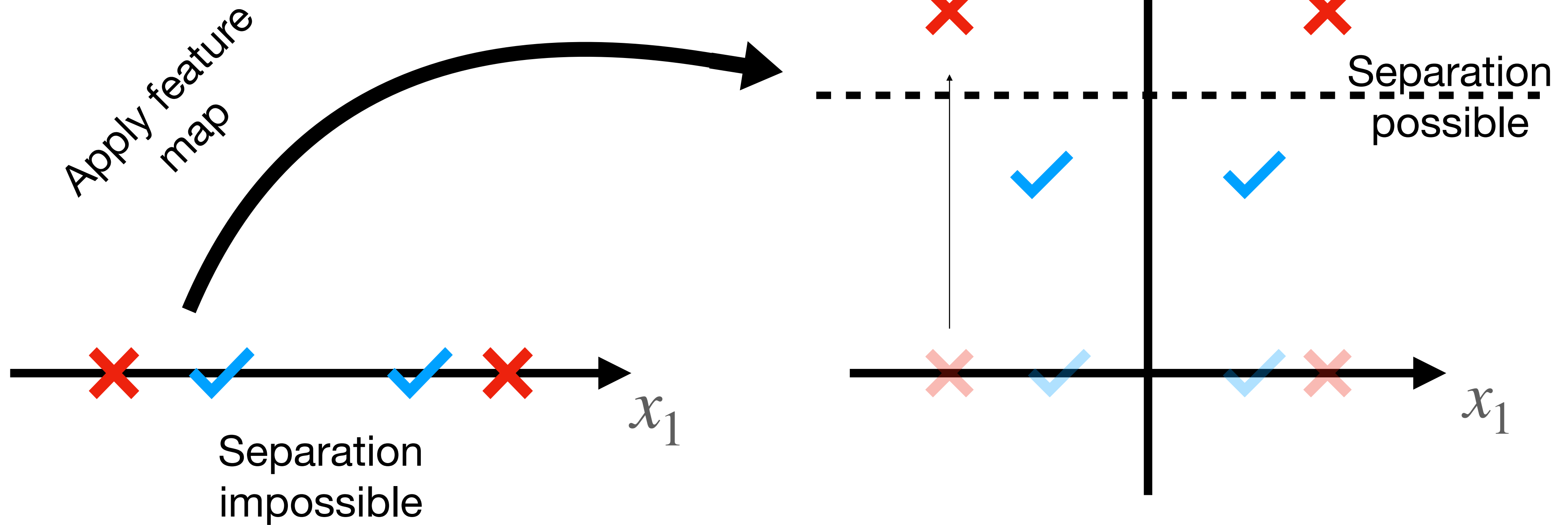
Maximise this

Results in building a kernel matrix

$K_{1,1}$	$K_{1,2}$	$K_{1,3}$
$K_{2,1}$	\cdot	\cdot
		\cdot

Intro to SVM - feature map

$$\mathbf{x} = (x_1)^T \rightarrow \phi(\mathbf{x}) = (x_1, x_1^2)^T$$

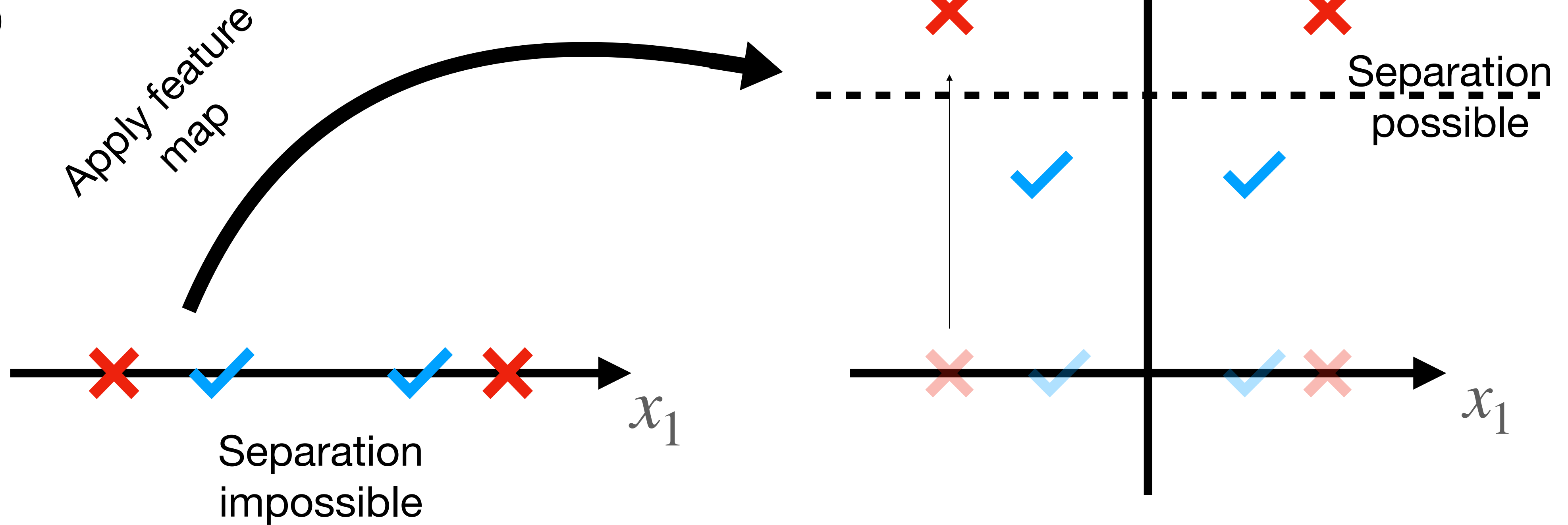


Intro to SVM - feature map

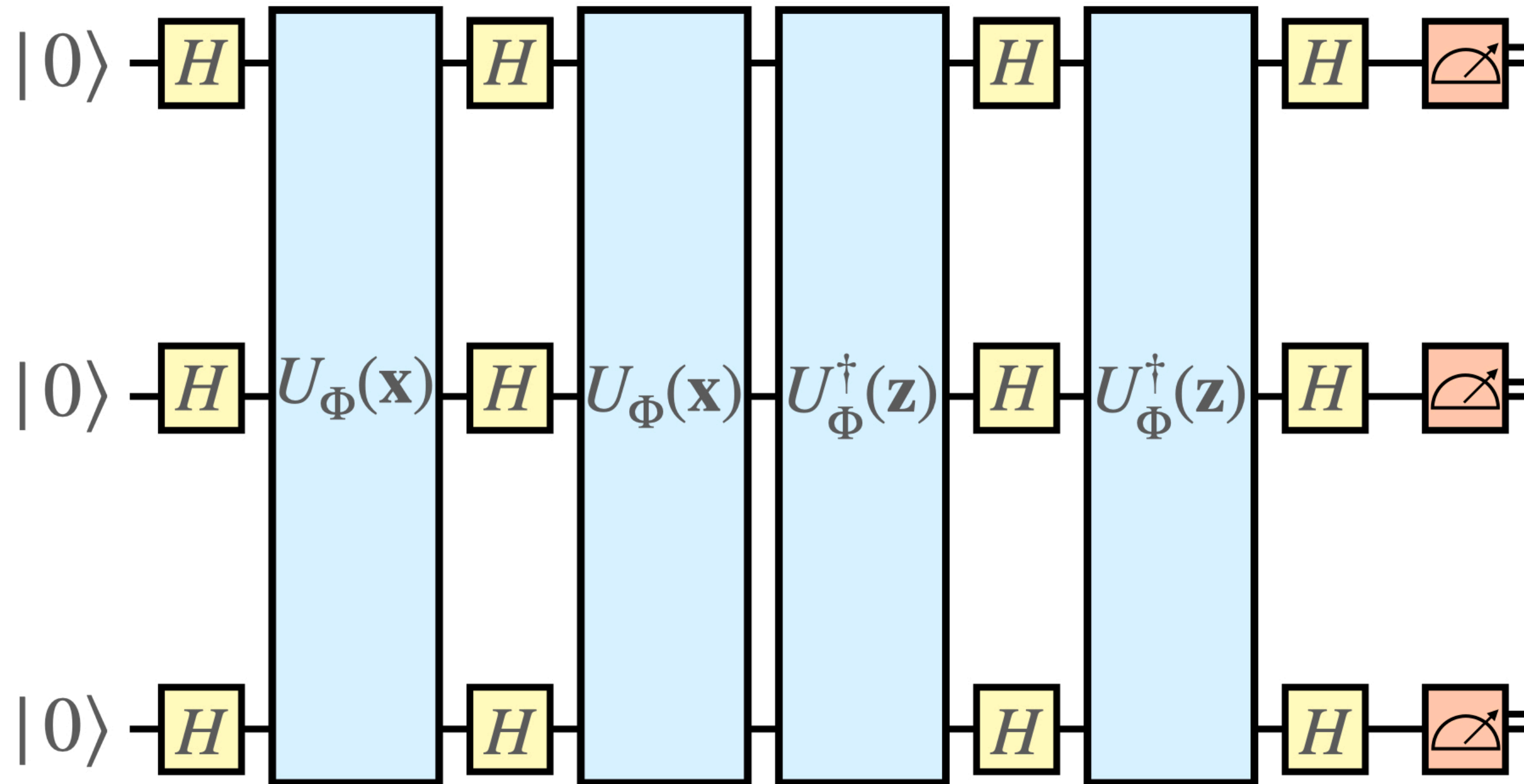
Feature map
hidden in

$K_{1,1}$	$K_{1,2}$	$K_{1,3}$
$K_{2,1}$	\dots	
		\dots

$$\mathbf{x} = (x_1)^T \rightarrow \phi(\mathbf{x}) = (x_1, x_1^2)^T$$

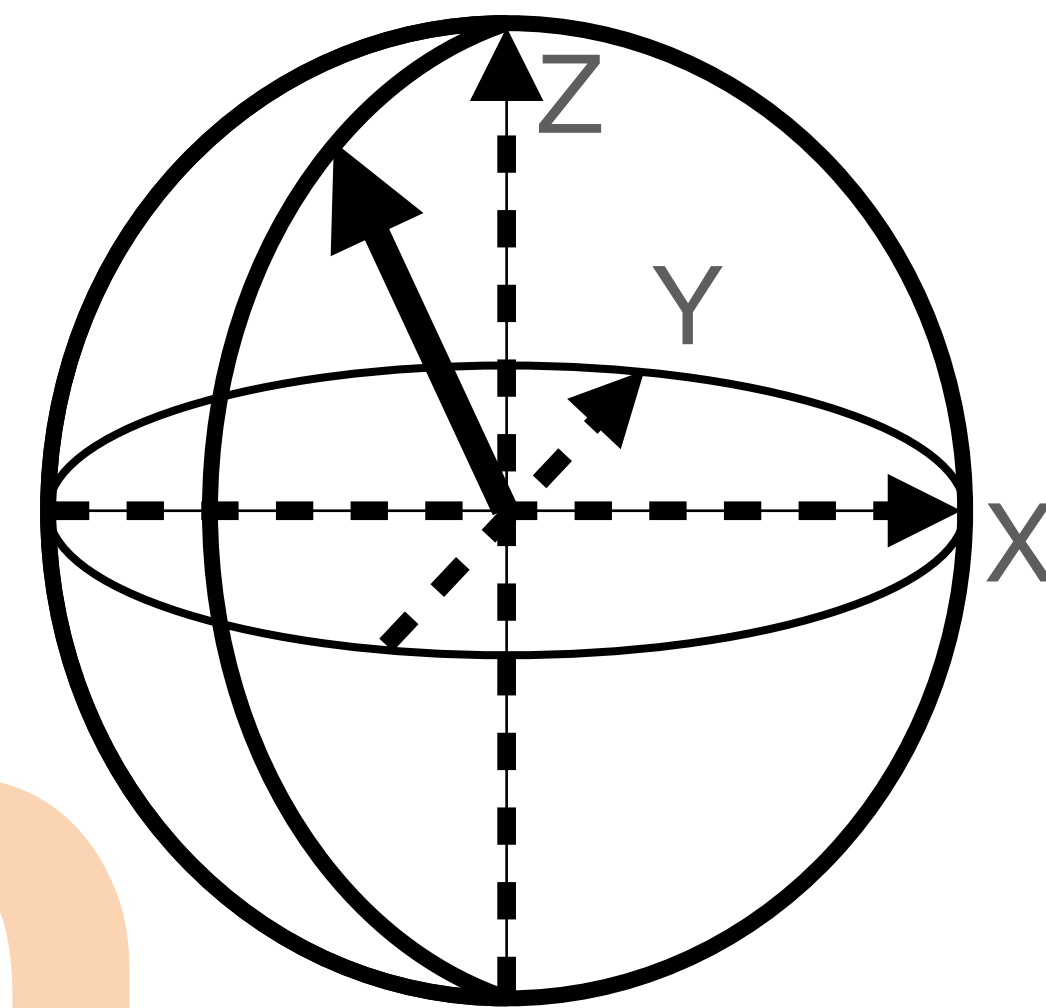


Quantum circuit as feature map and kernel



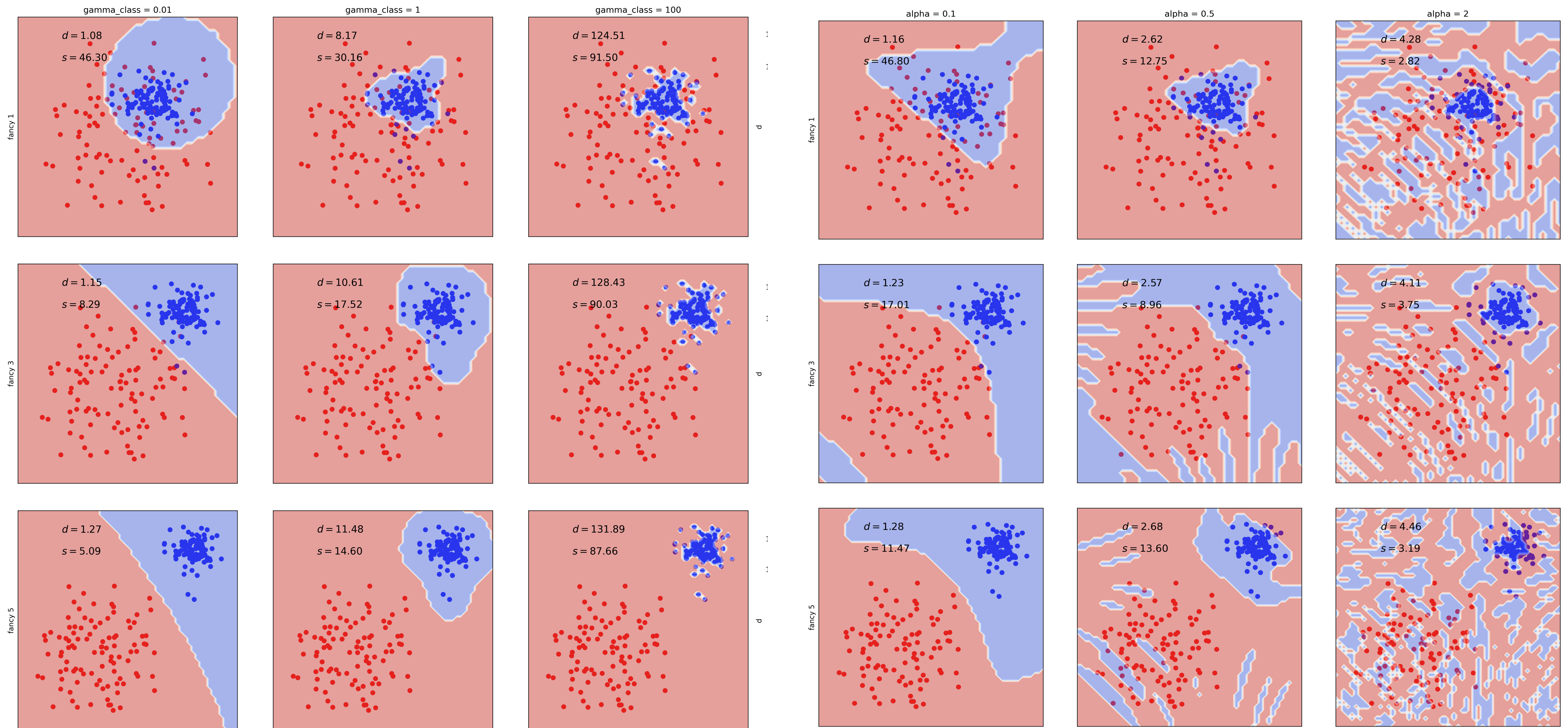
Encode data point \mathbf{x} in the circuit

Encode data point \mathbf{z} in the circuit (backwards)



$K_{1,1}$	$K_{1,2}$	$K_{1,3}$
$K_{\mathbf{x},\mathbf{z}}$		

The only quantum part of the SVM!



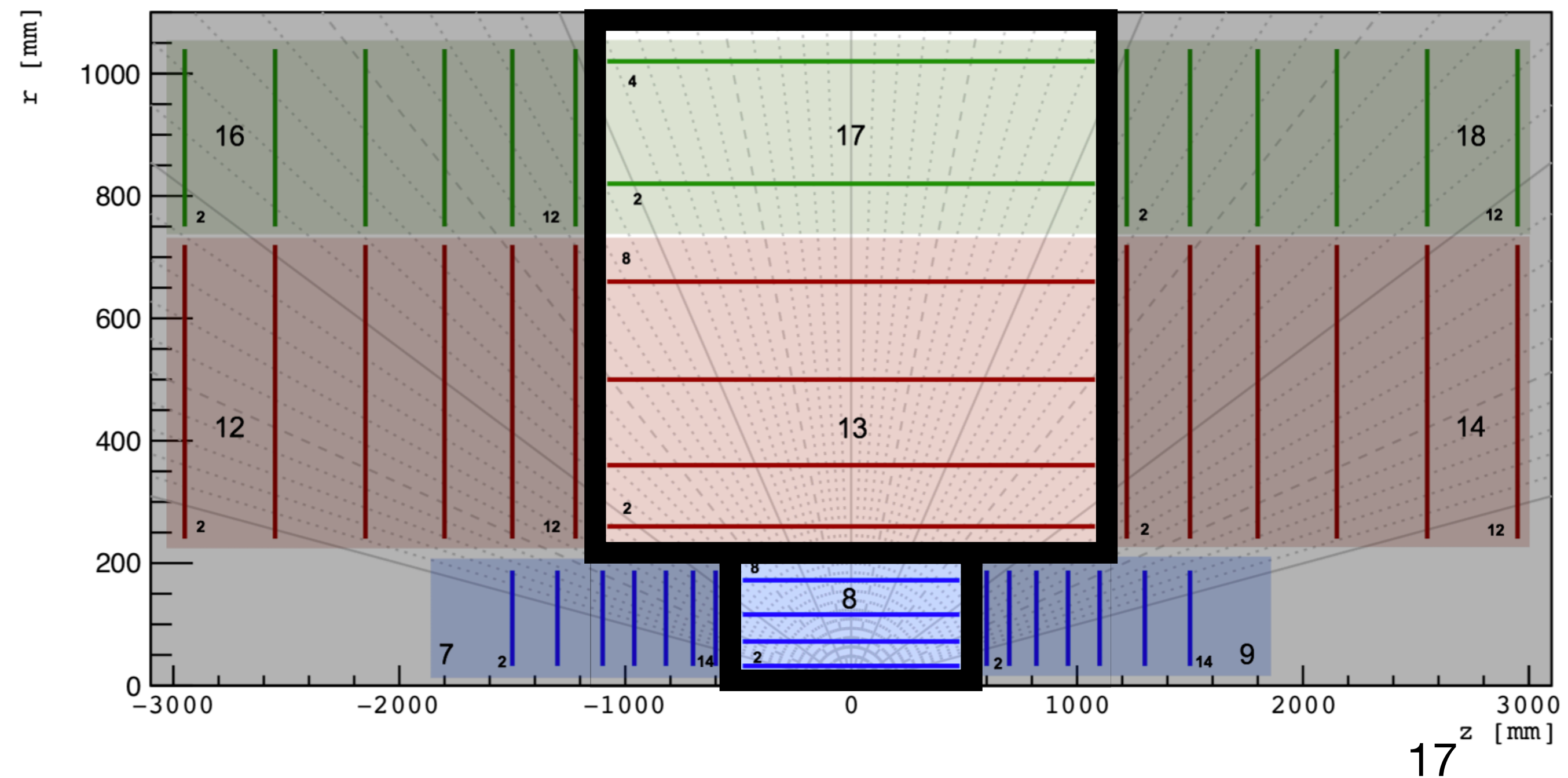
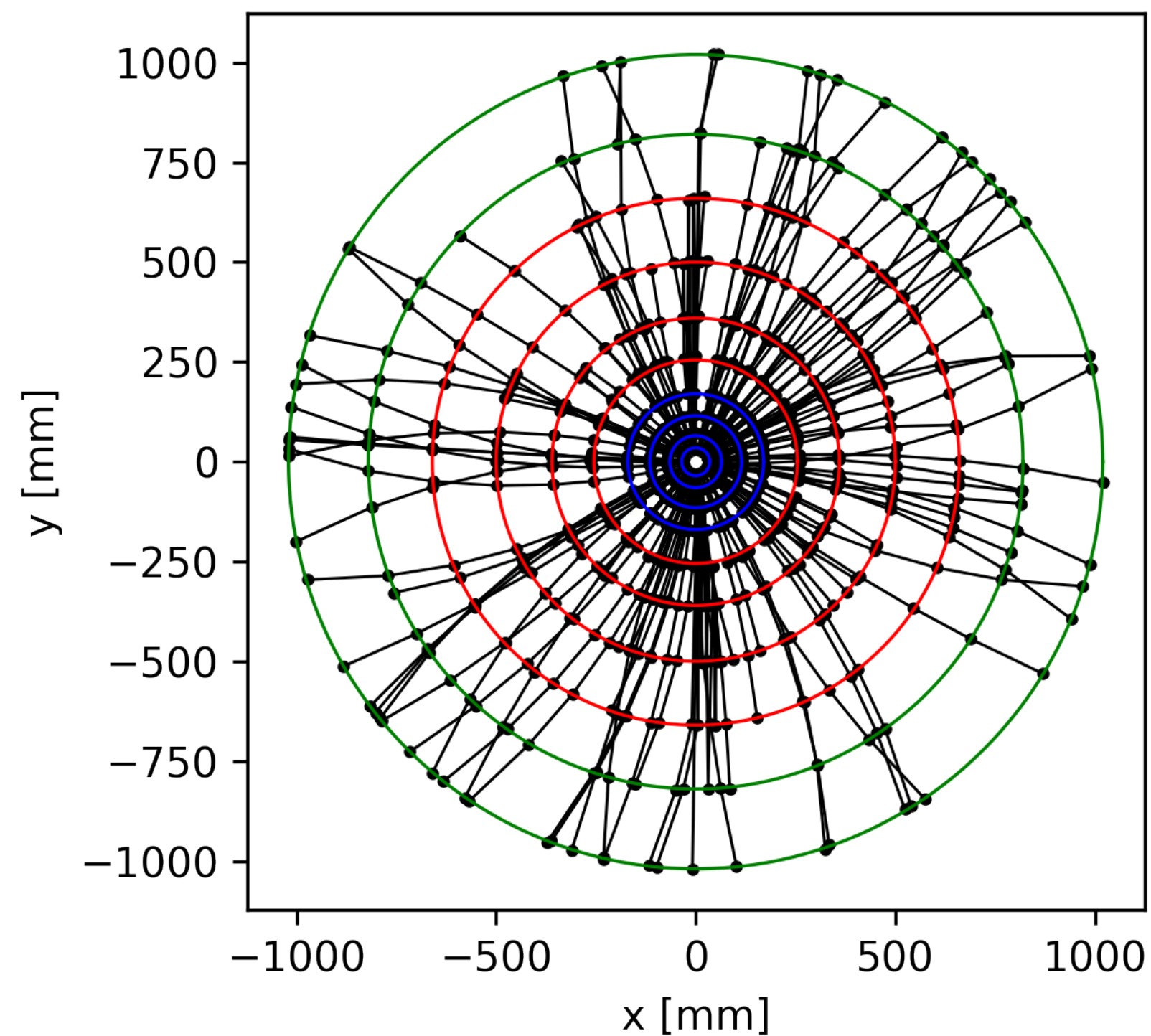
Classical

Quantum

Dataset + Simplifications

kaggle™

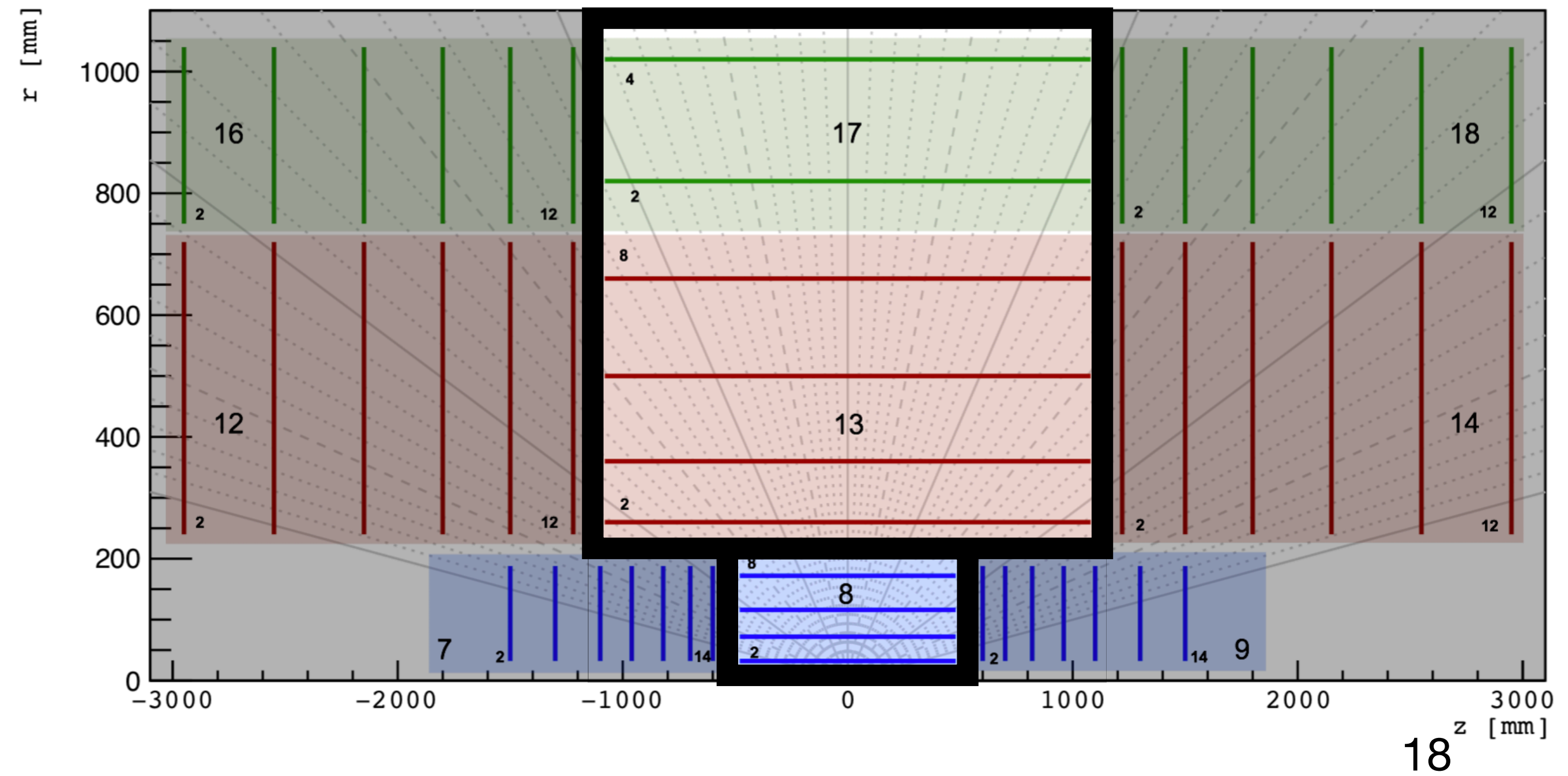
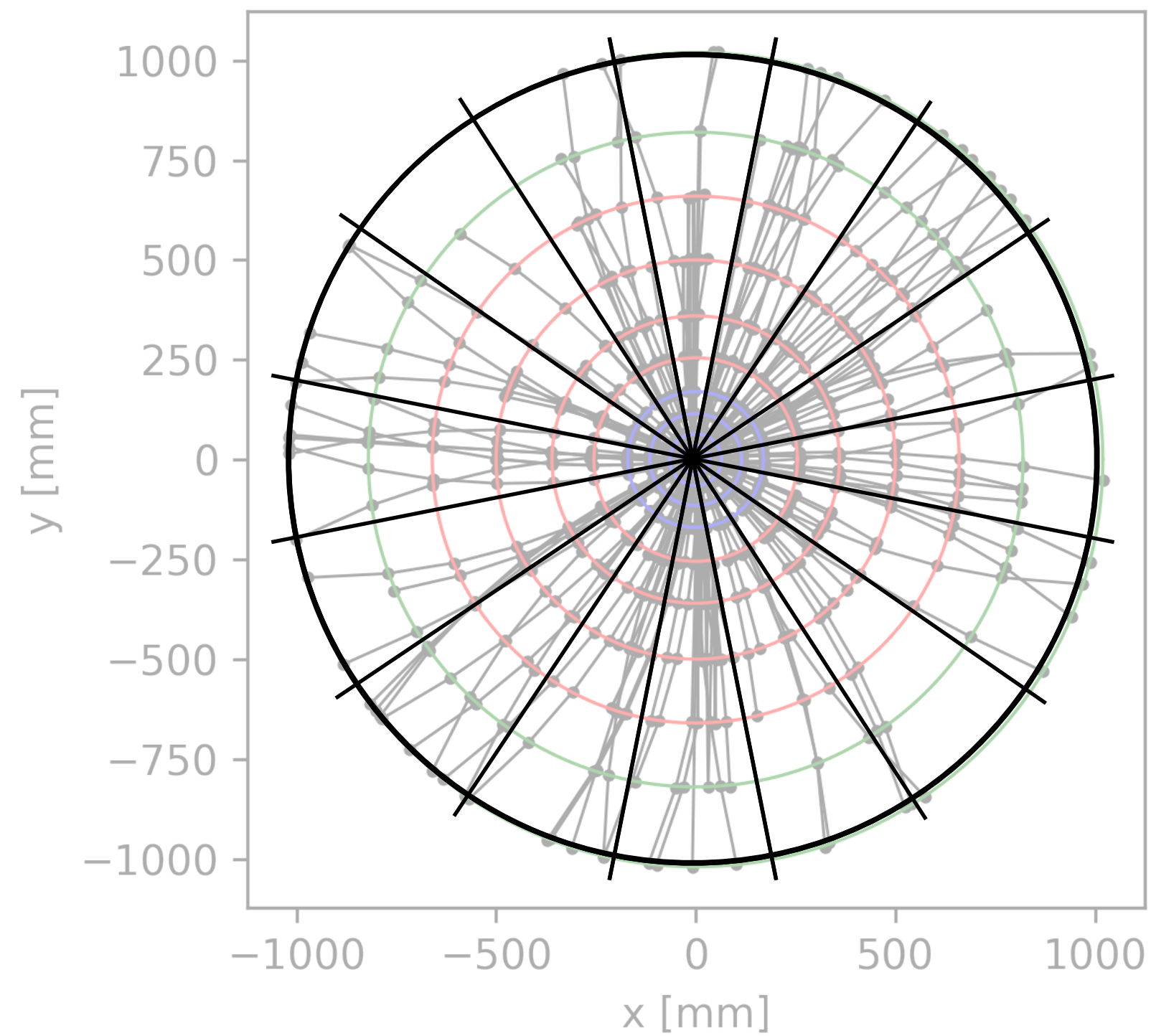
- Barrel only
- Remove noise
- One hit per track per layer
- Look at $>0.75\text{GeV}$ only



Dataset + Simplifications

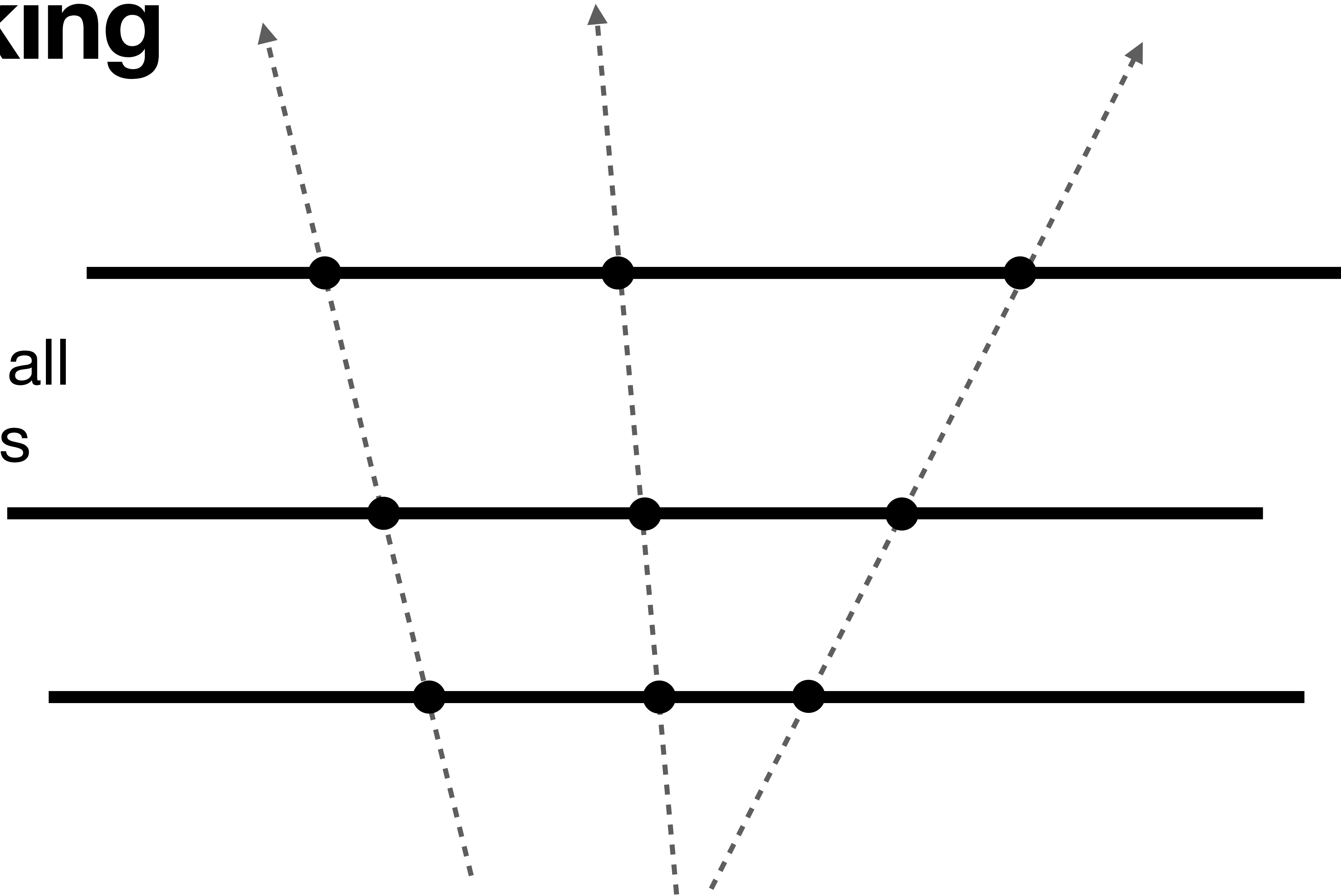


- Slice-up the detector



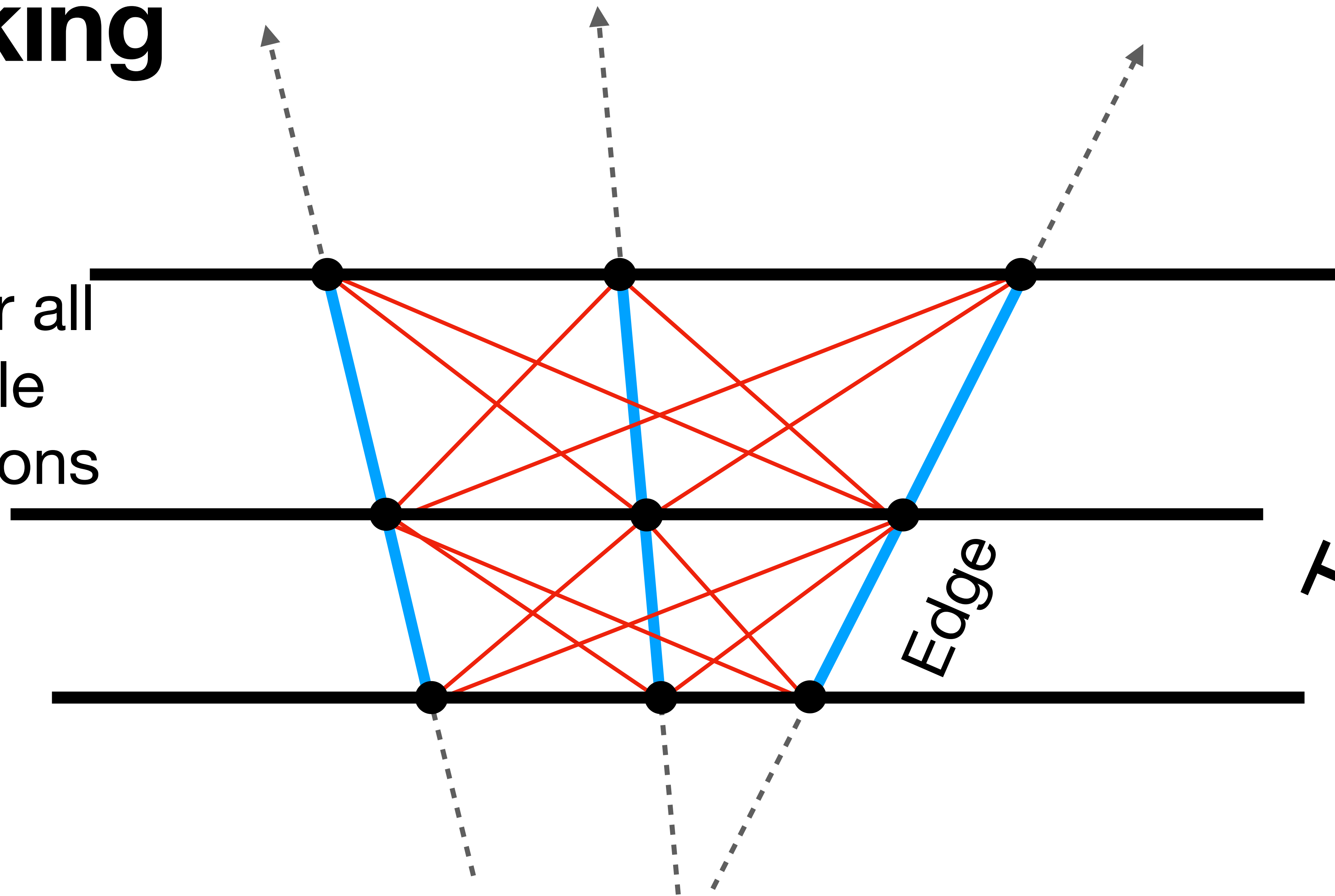
Recap of tracking

Record all the hits

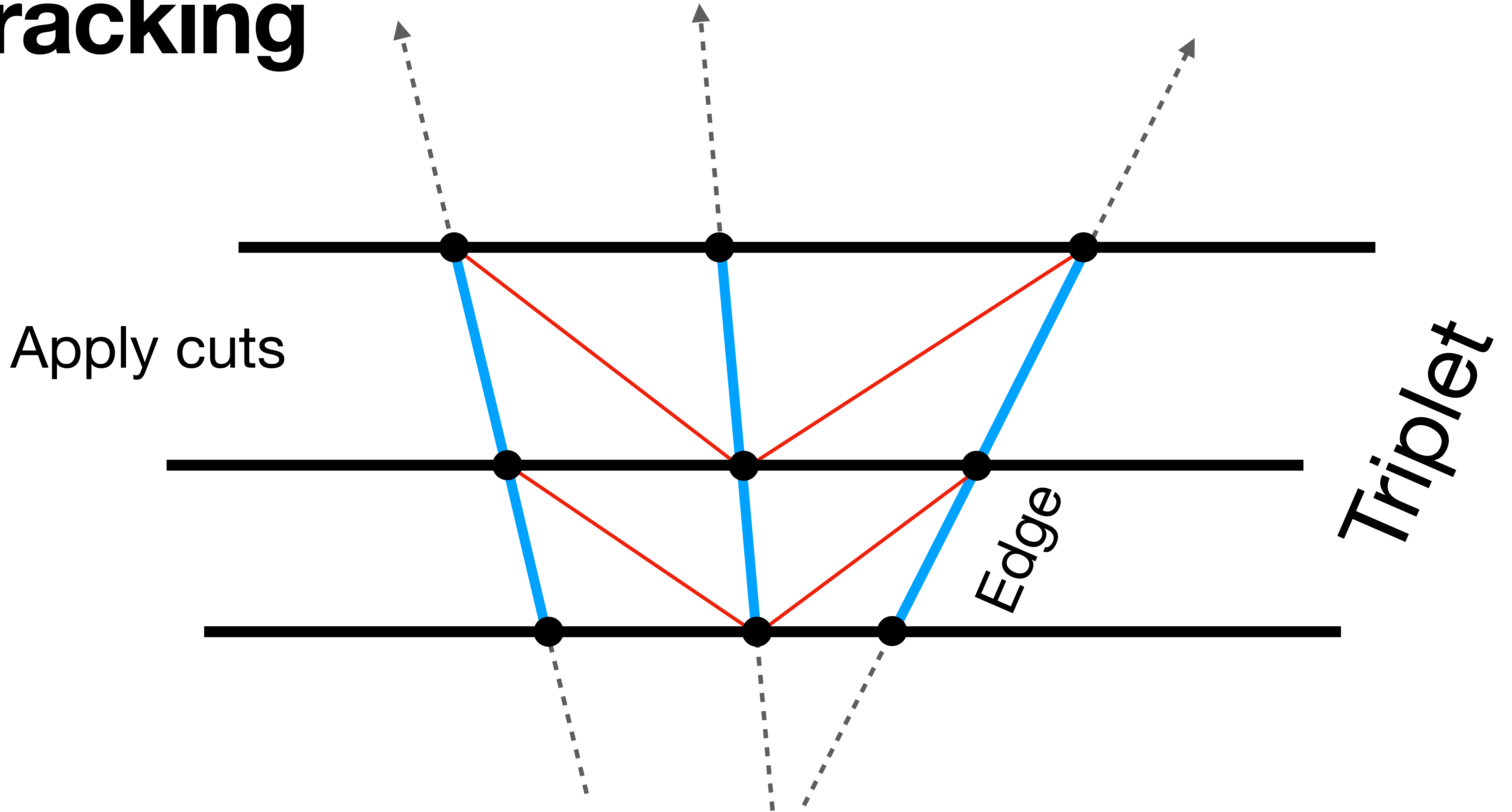


Recap of tracking

Consider all possible connections

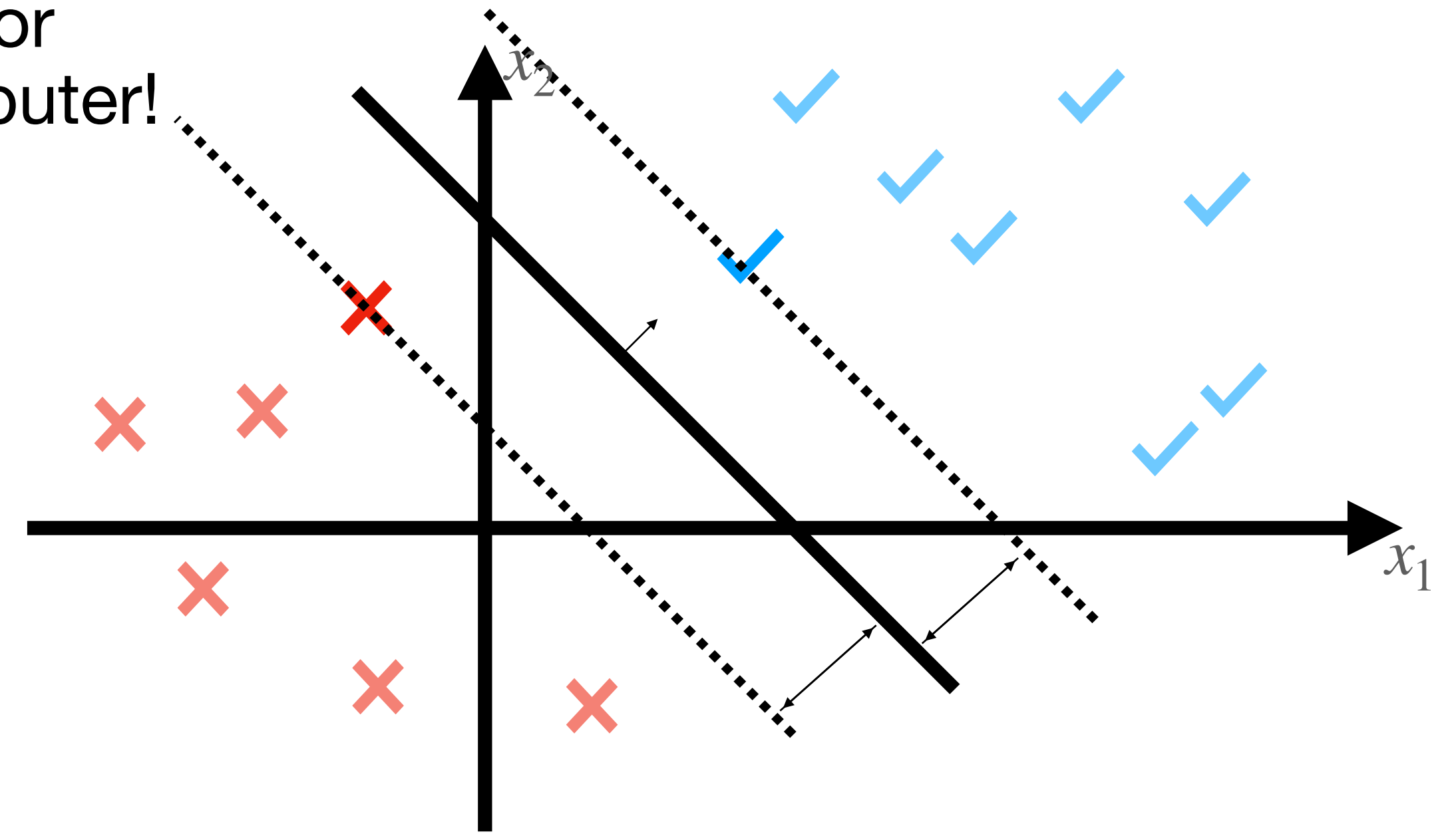
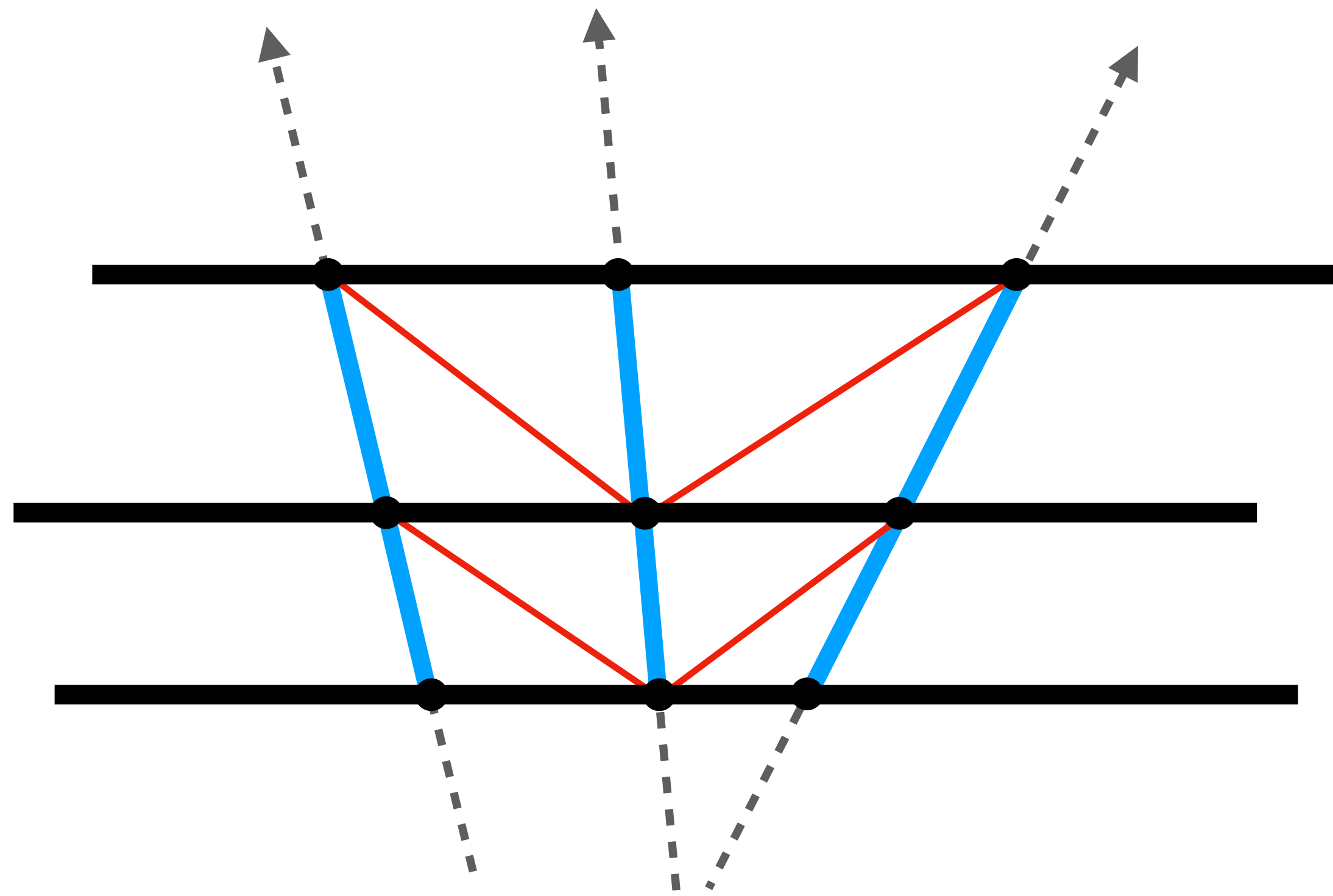


Recap of tracking



Intro to SVM

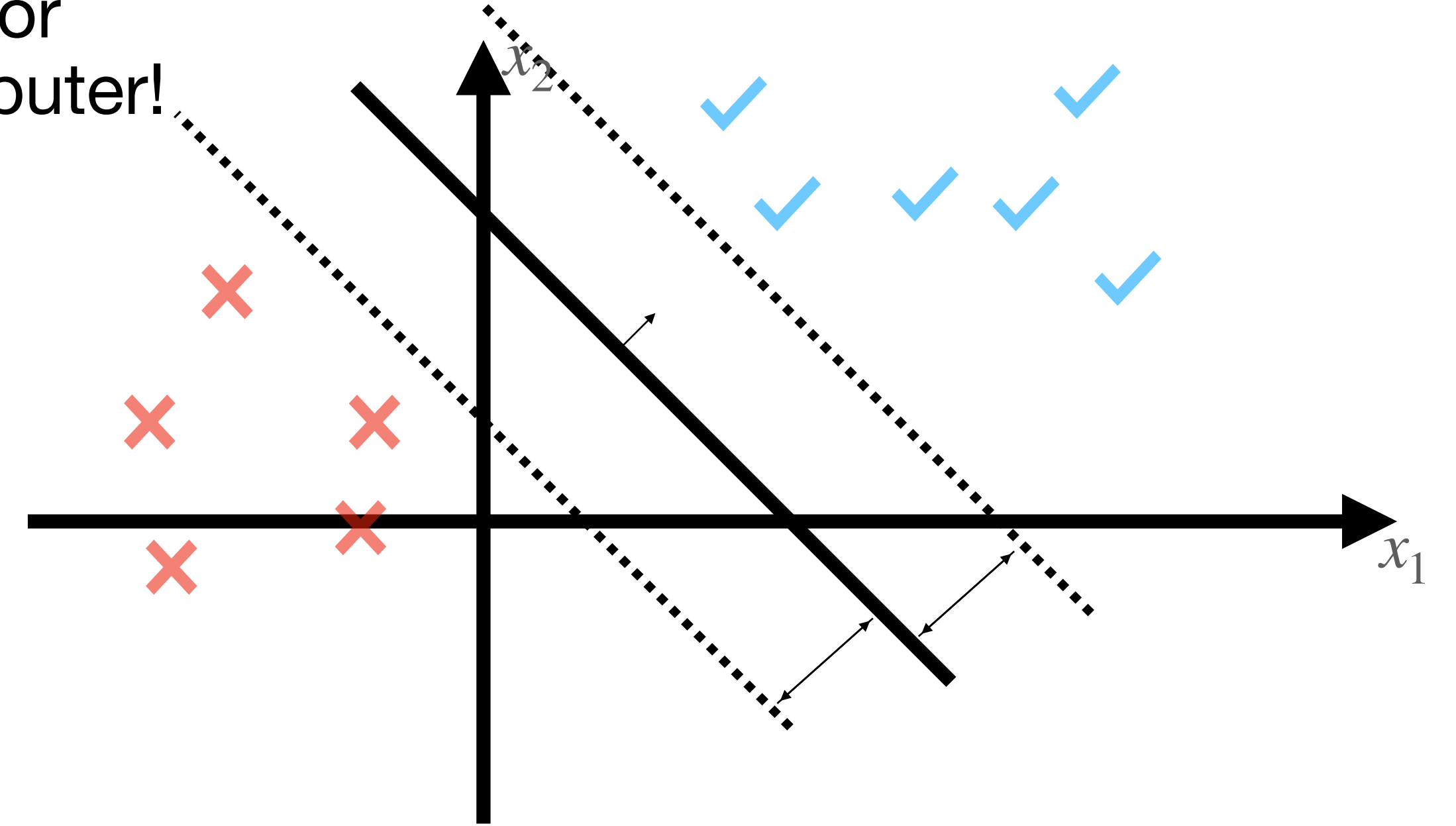
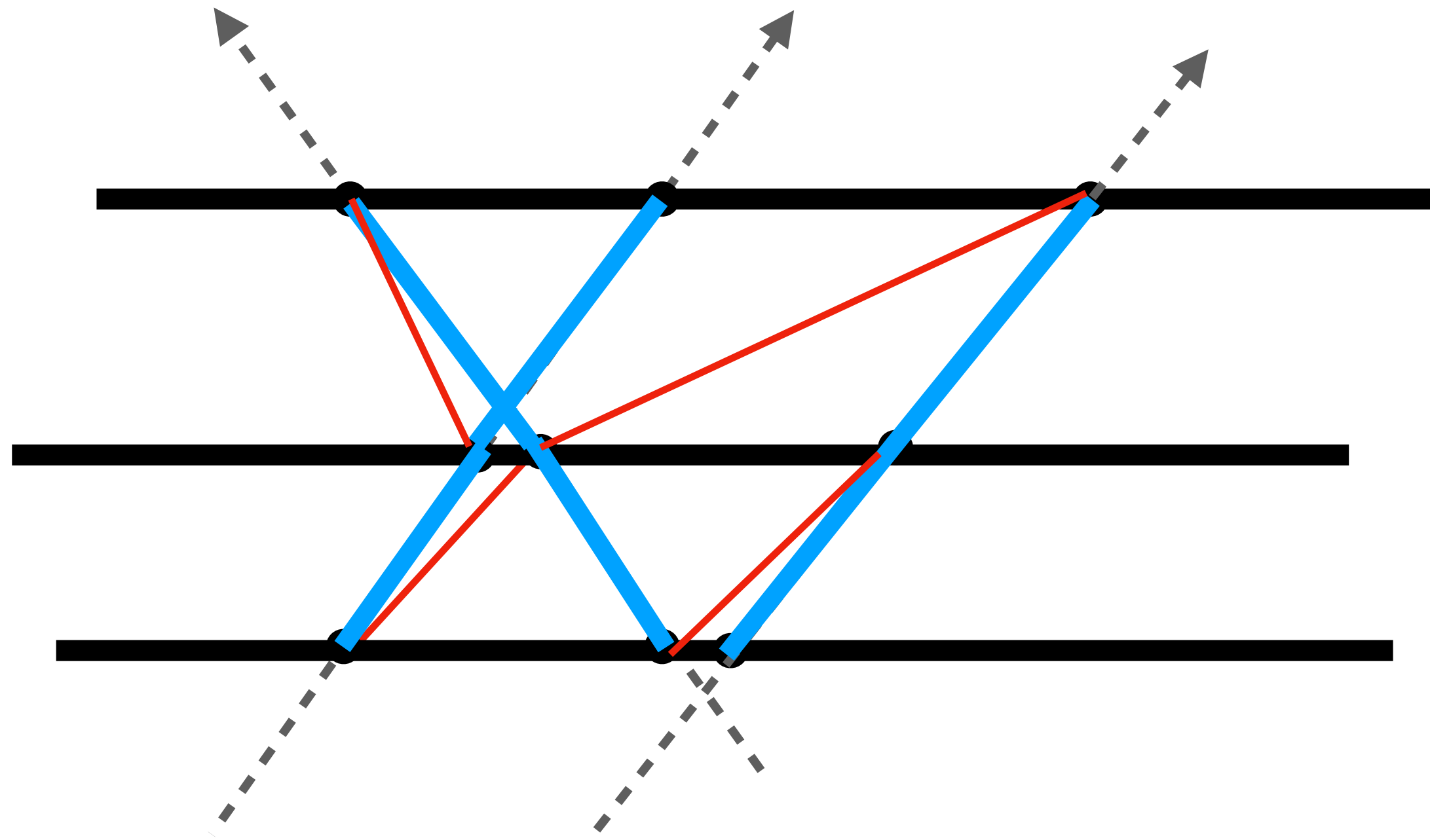
Kernel for this with
a classical or
quantum computer!



Supervised learning -
**show examples to train
on, test on unseen data**

Intro to SVM

Kernel for this with
a classical or
quantum computer!



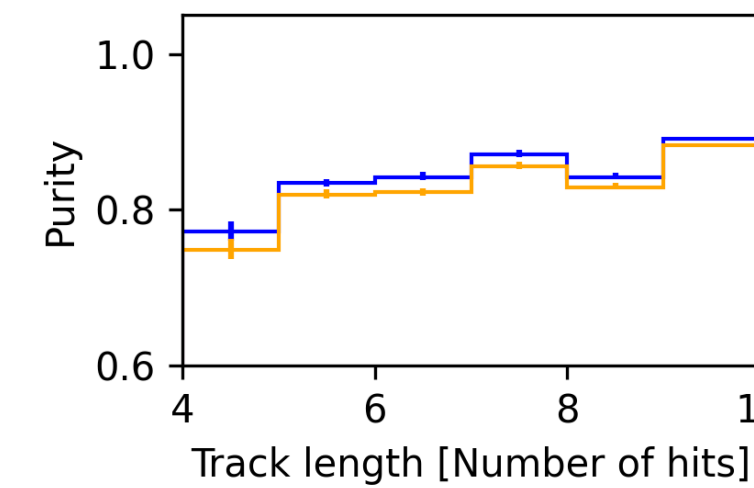
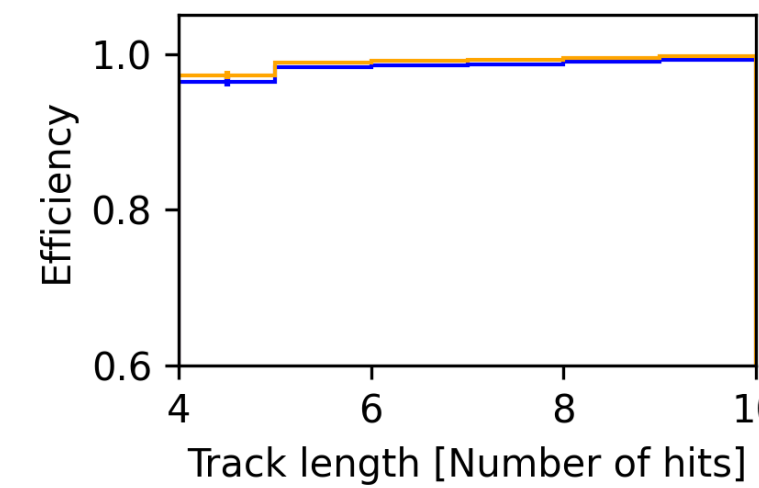
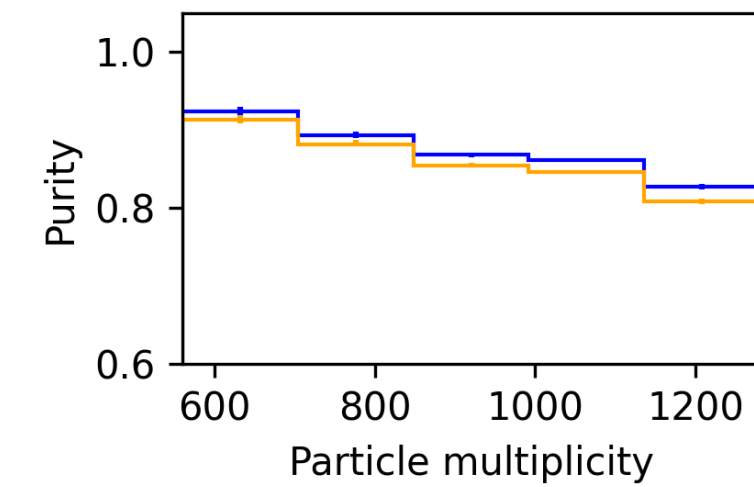
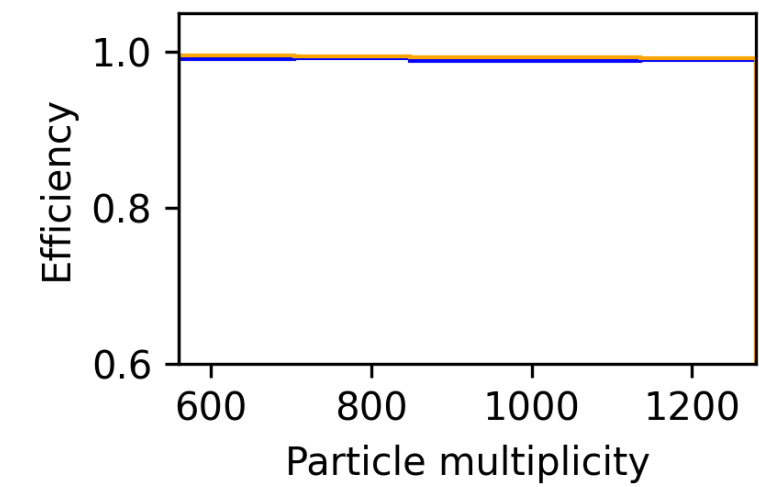
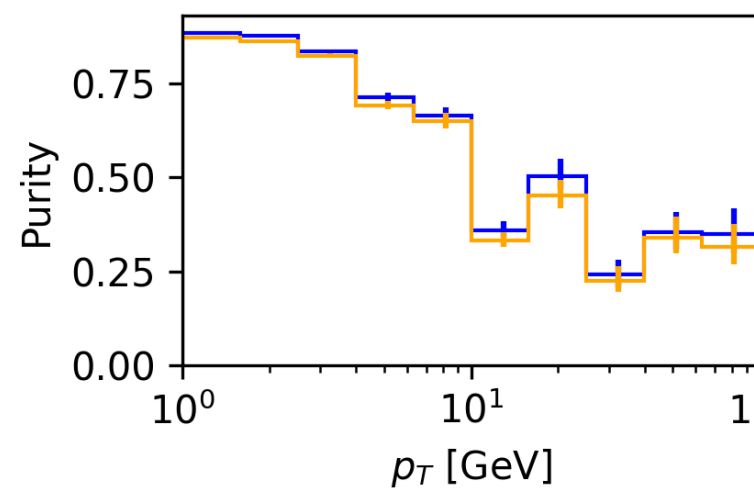
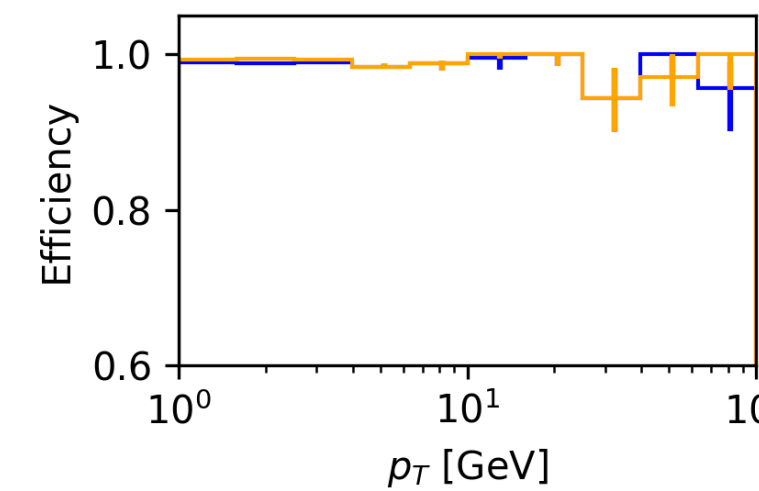
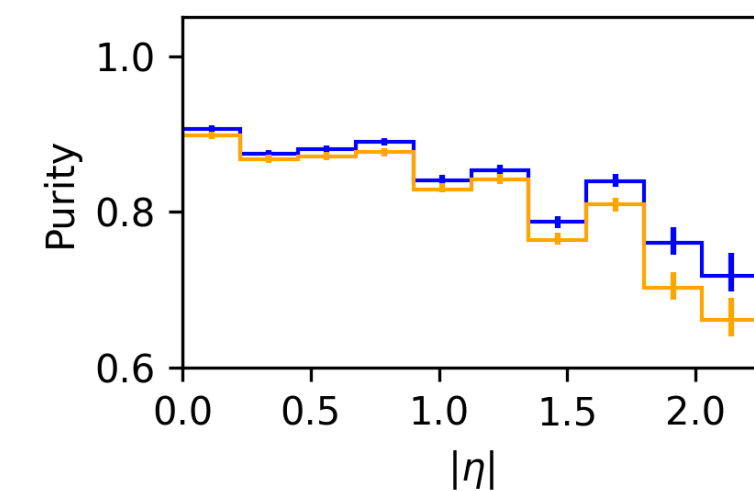
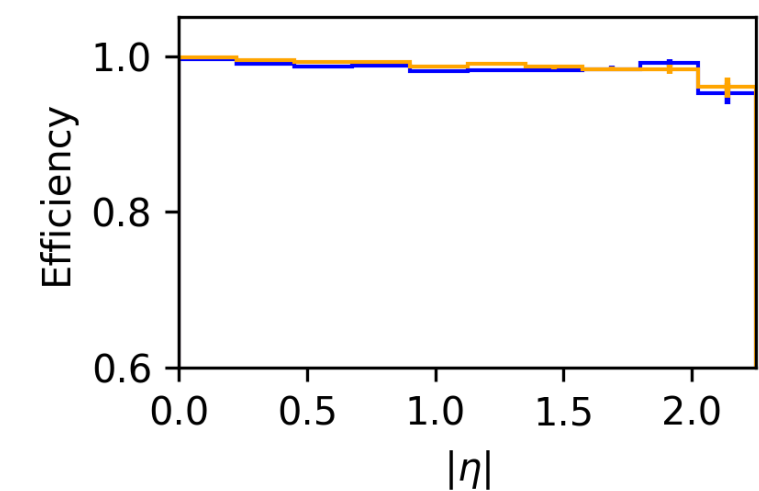
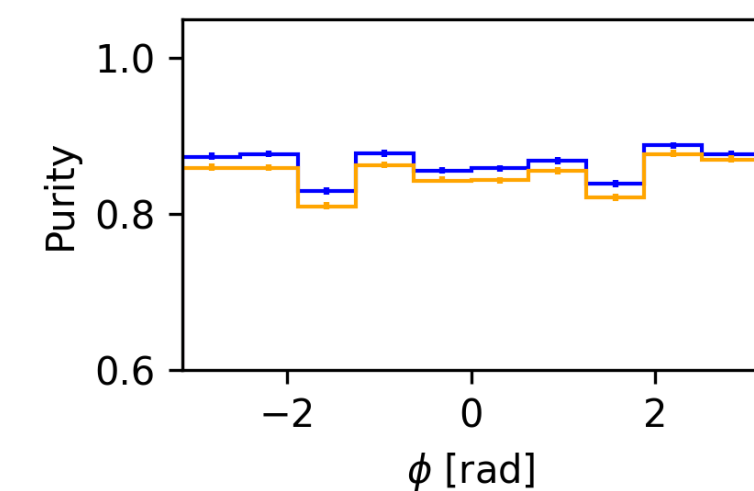
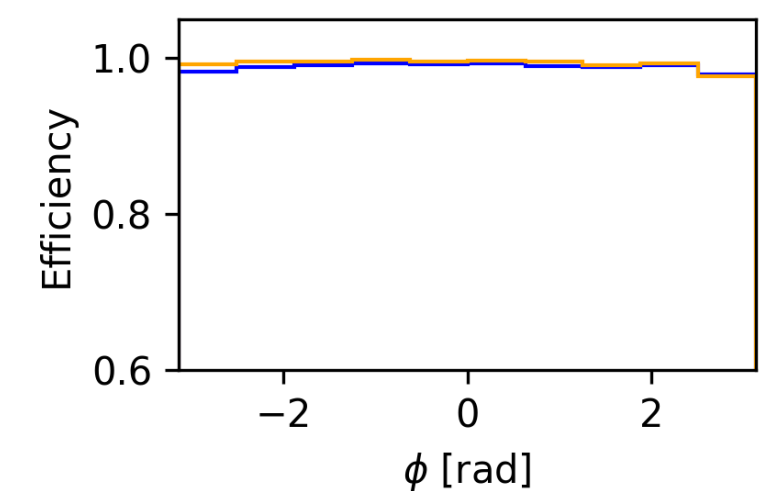
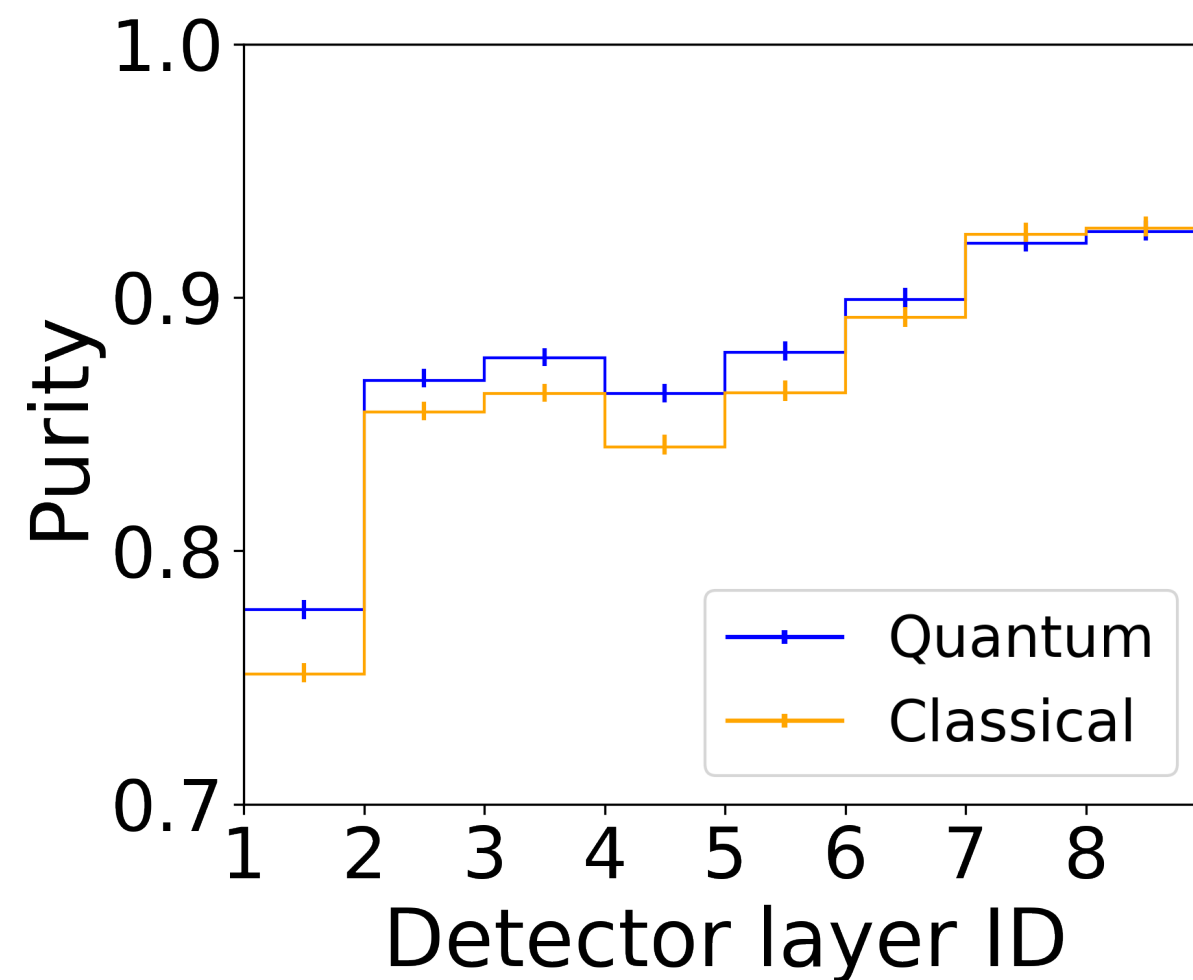
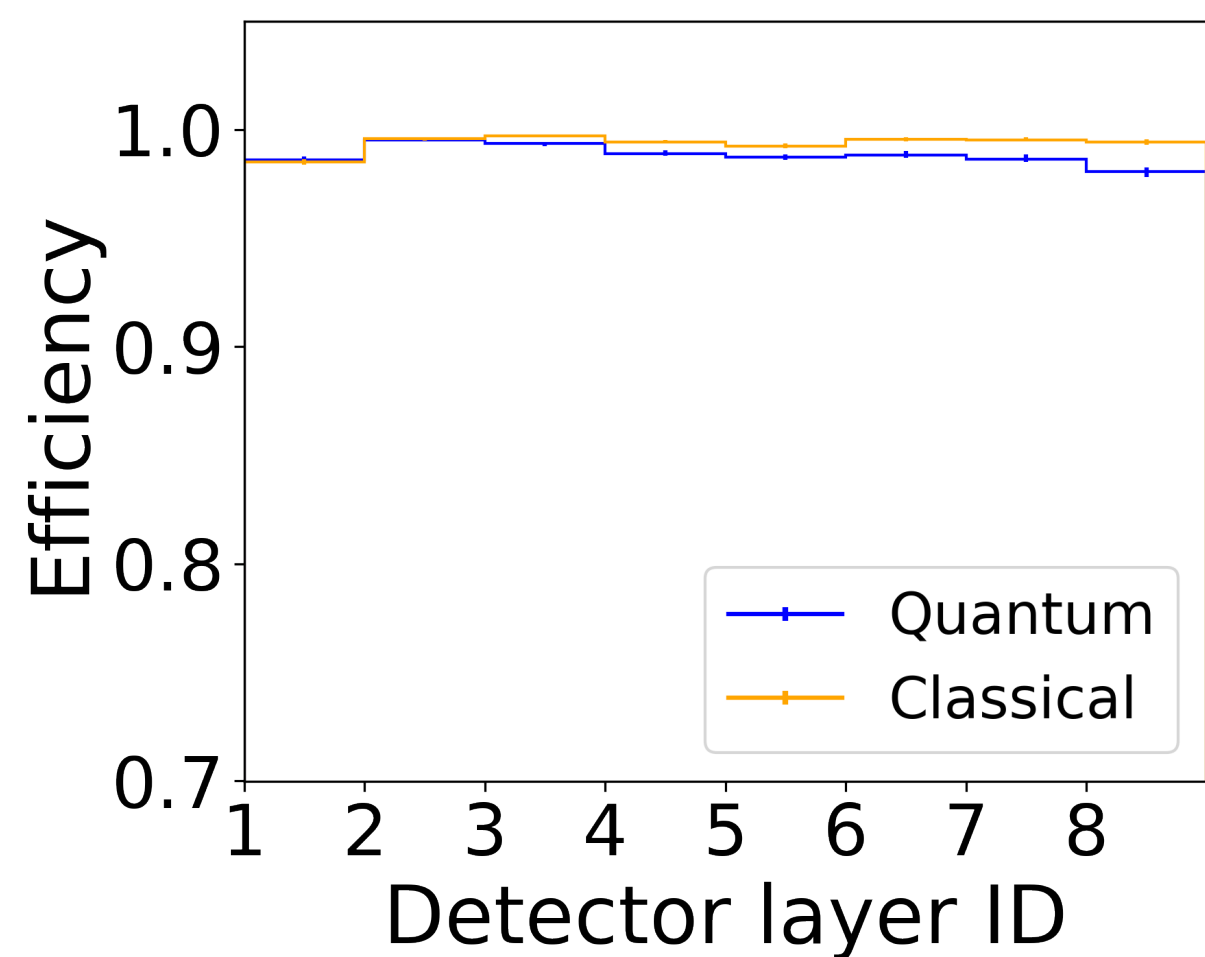
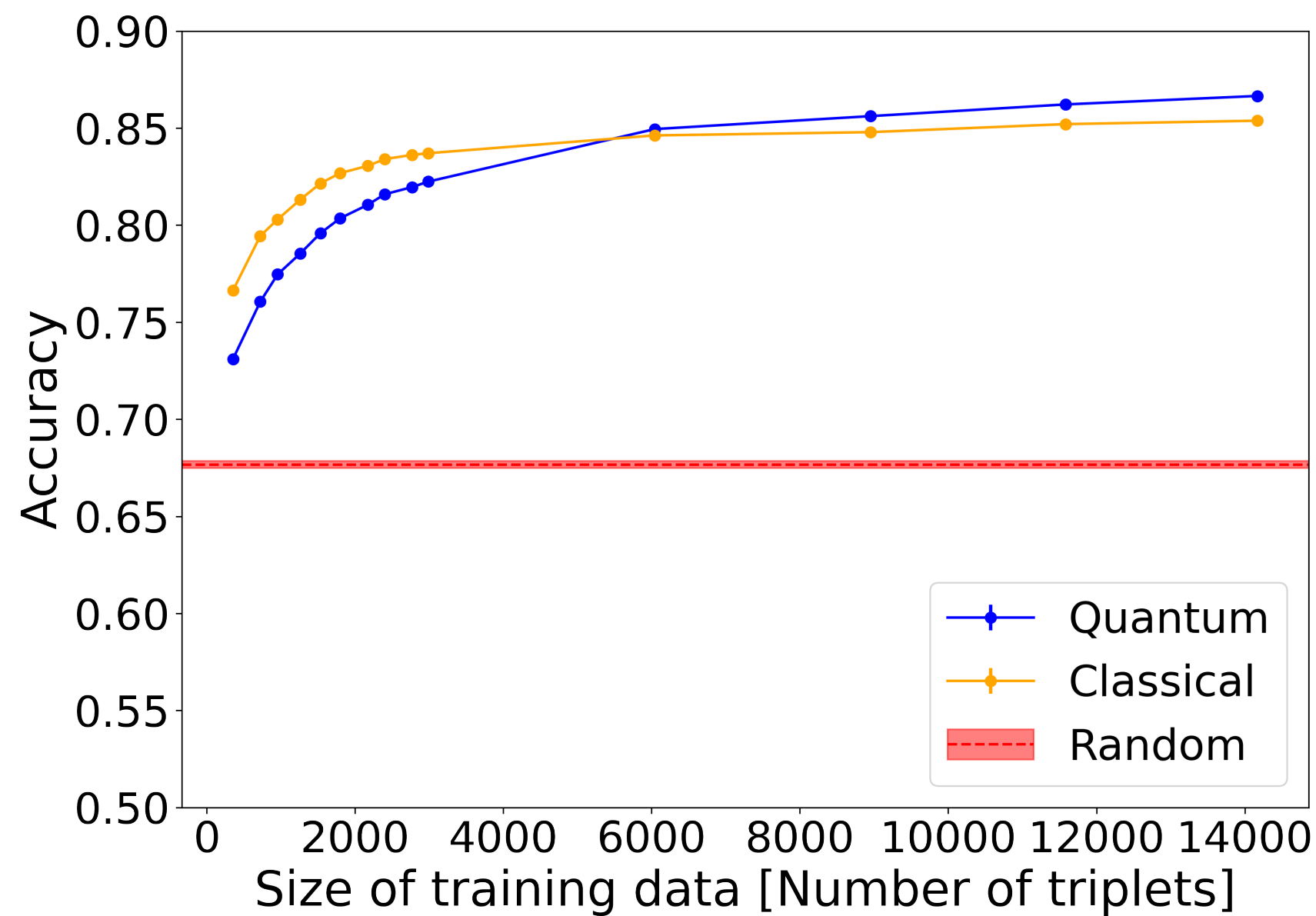
Supervised learning -
show examples to train
on, **test on unseen data**

NOTE: All results
shown here are
obtained on a
*classical computer
pretending to be a
quantum computer*

(We are running on hardware but no worthy results yet)

Results

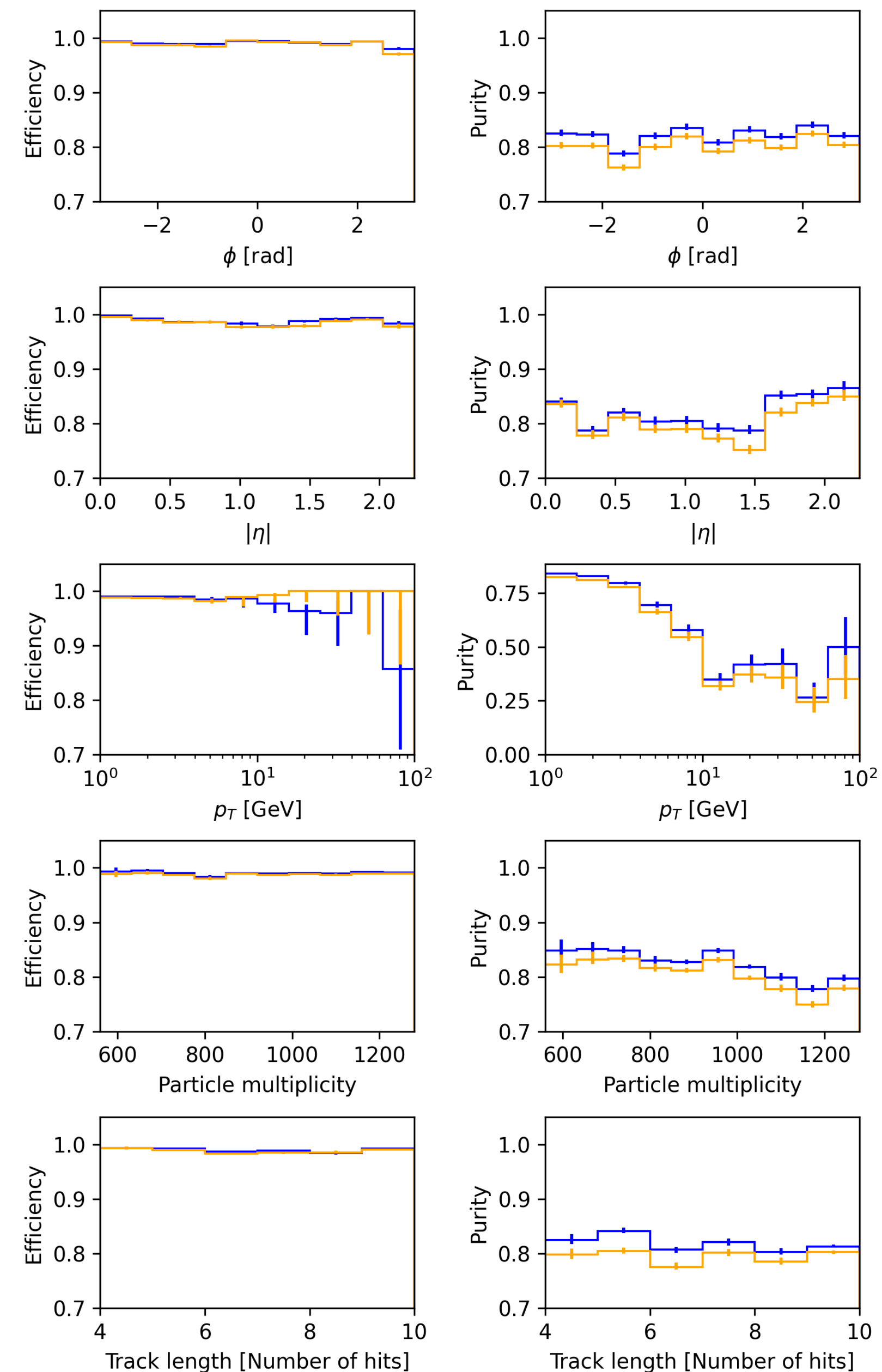
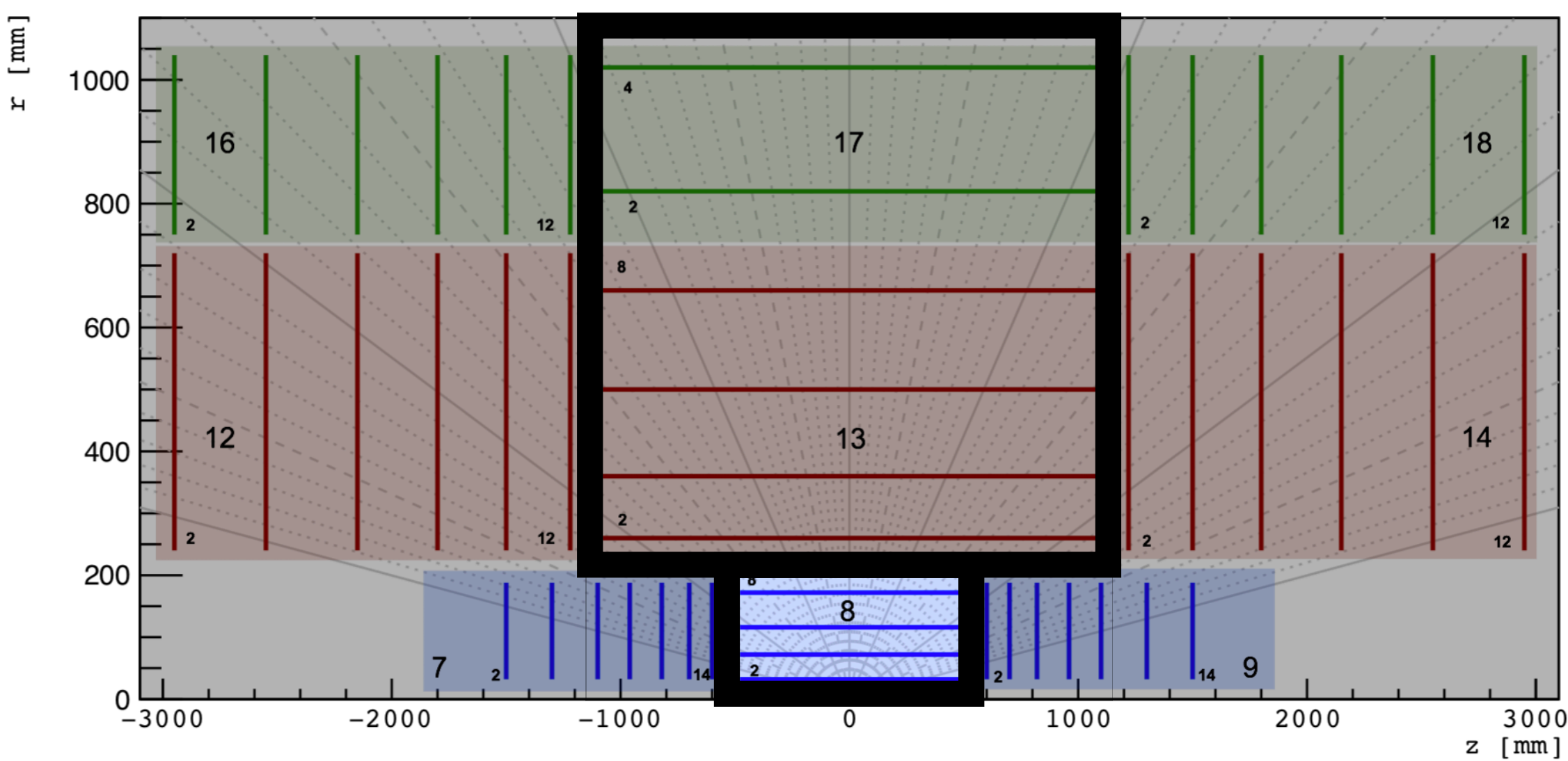
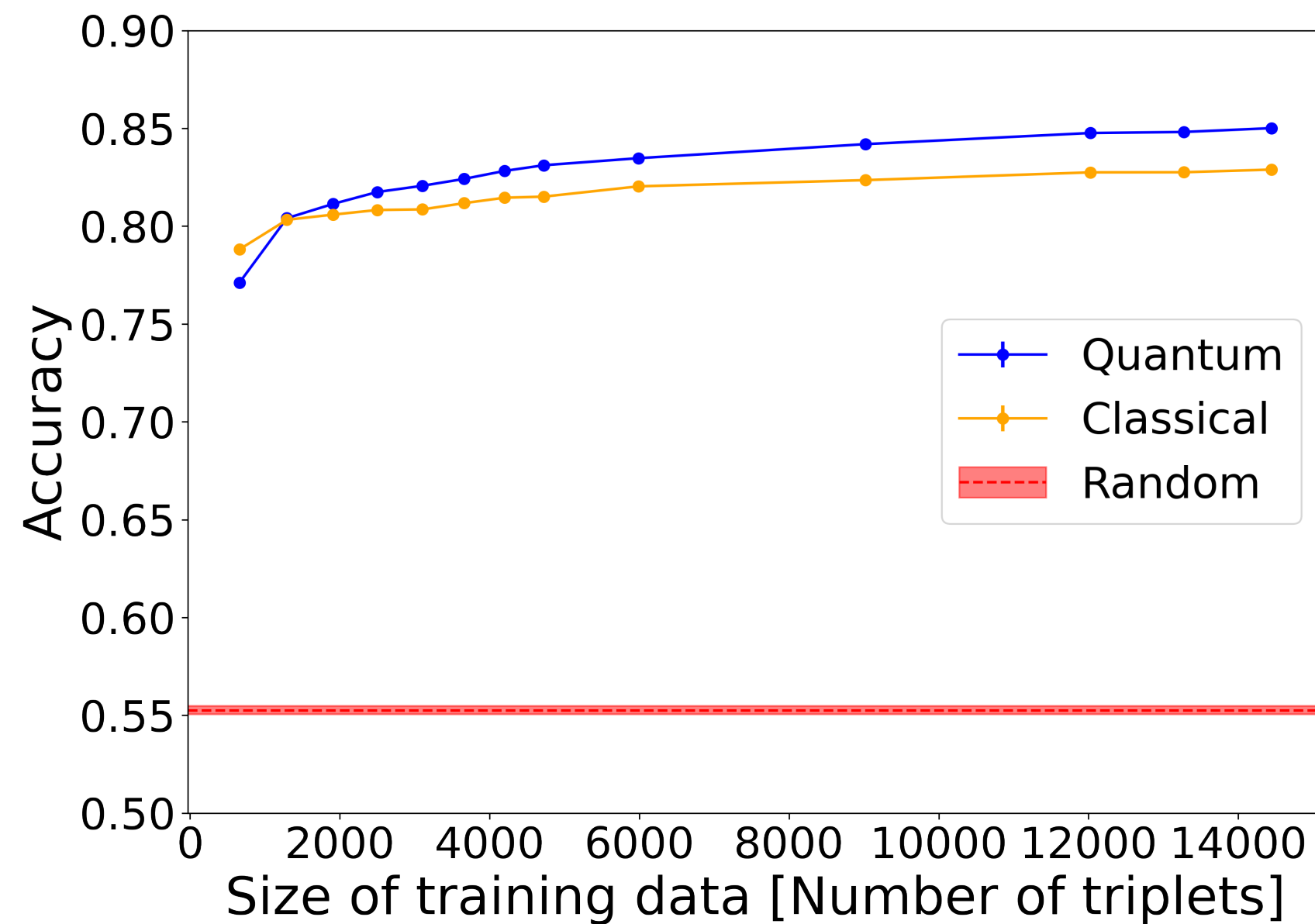
Train on up to 50 events



Quantum Classical

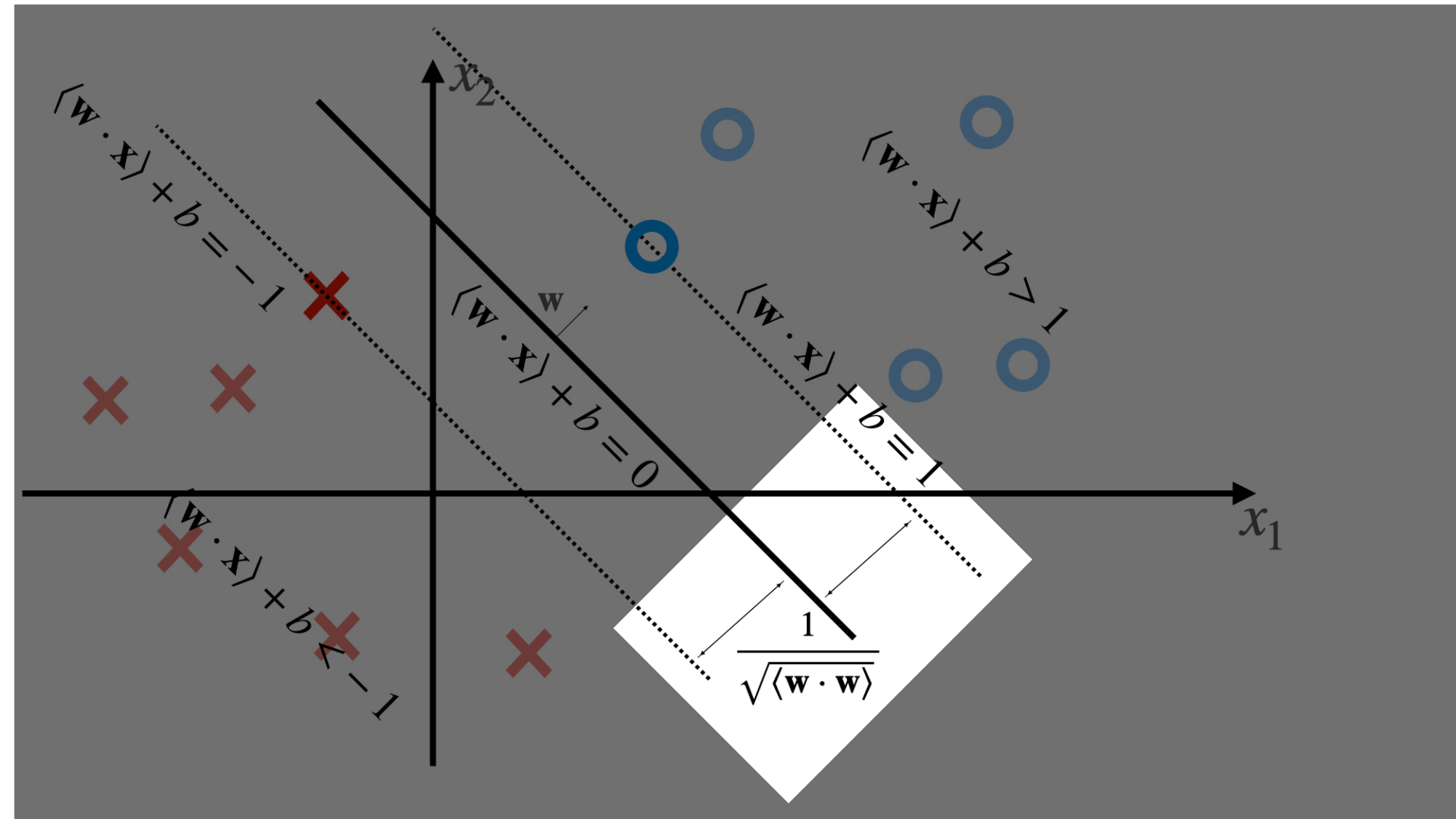
Results

Train on up to 240 events

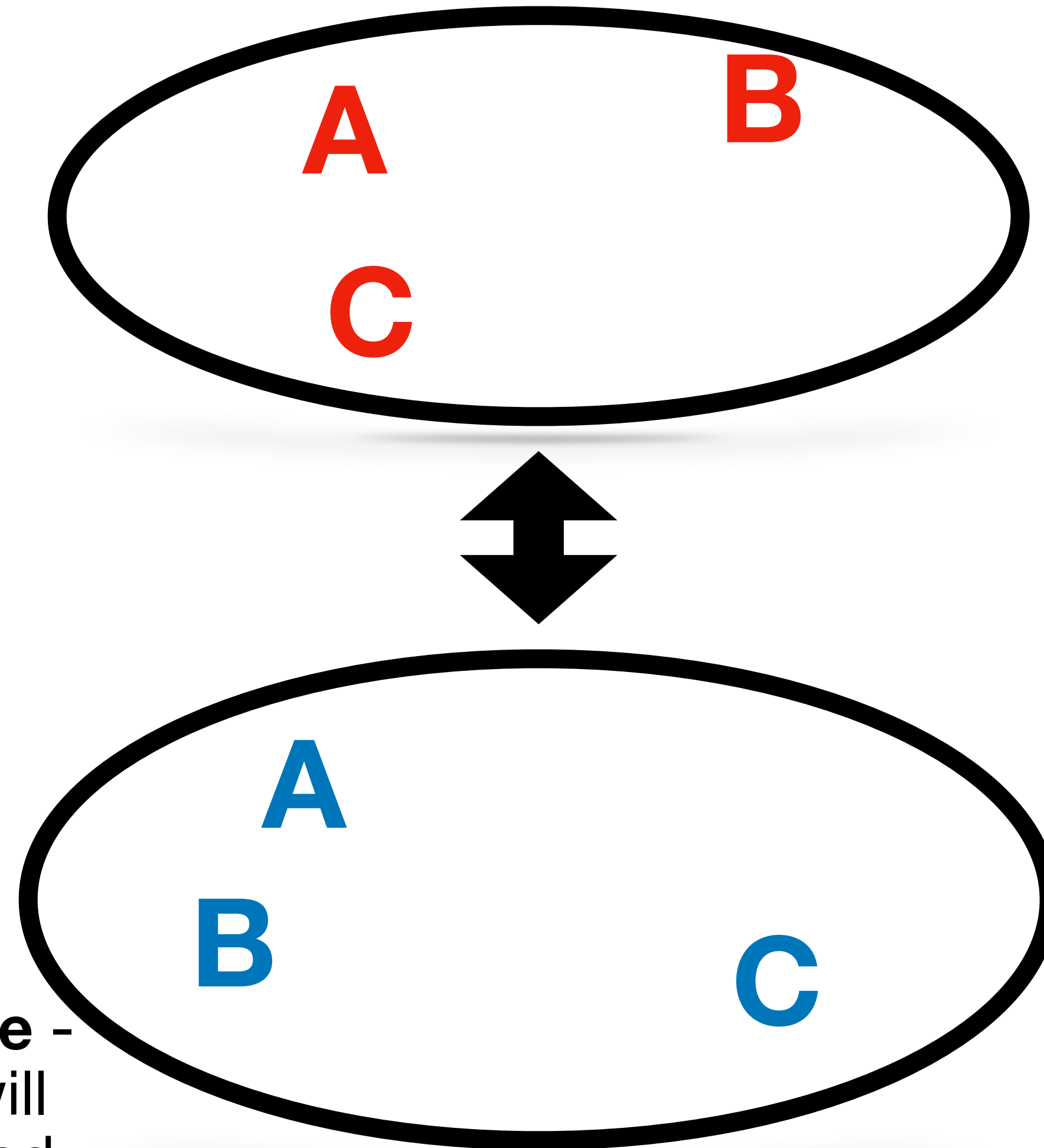
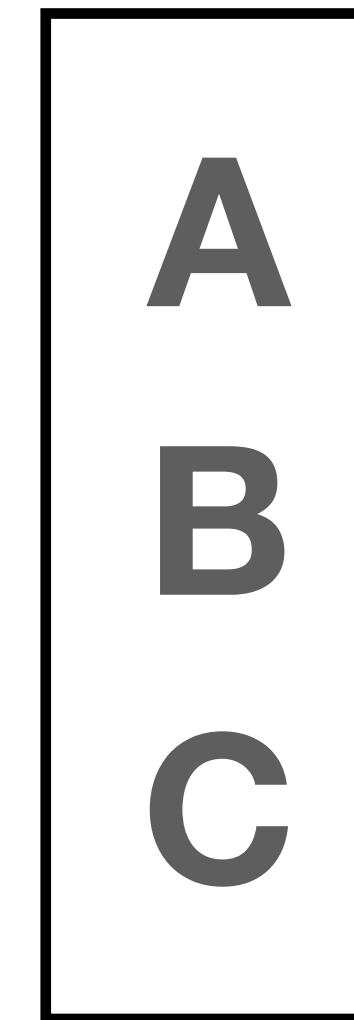


Quantum Classical

BONUS: Complexity



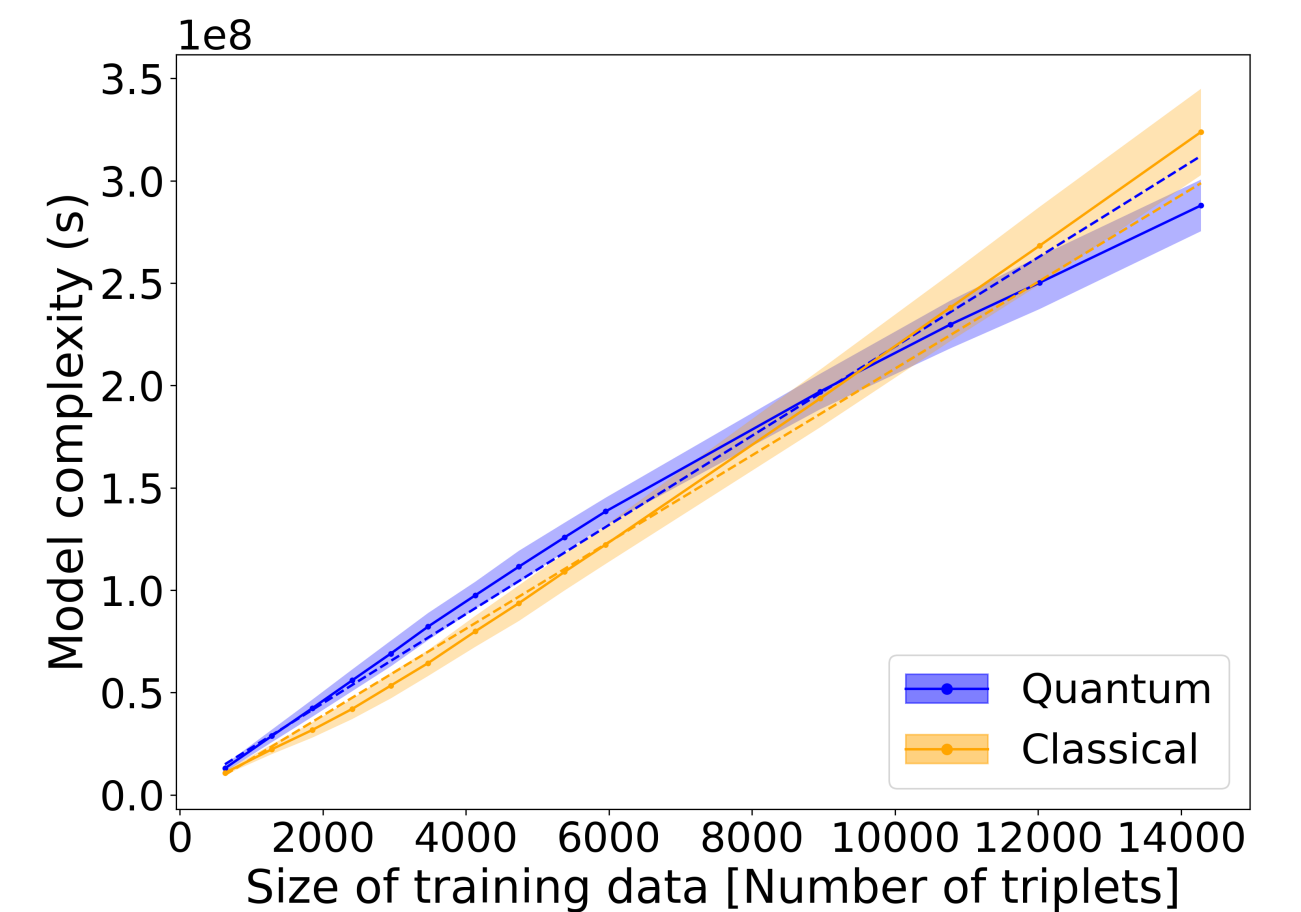
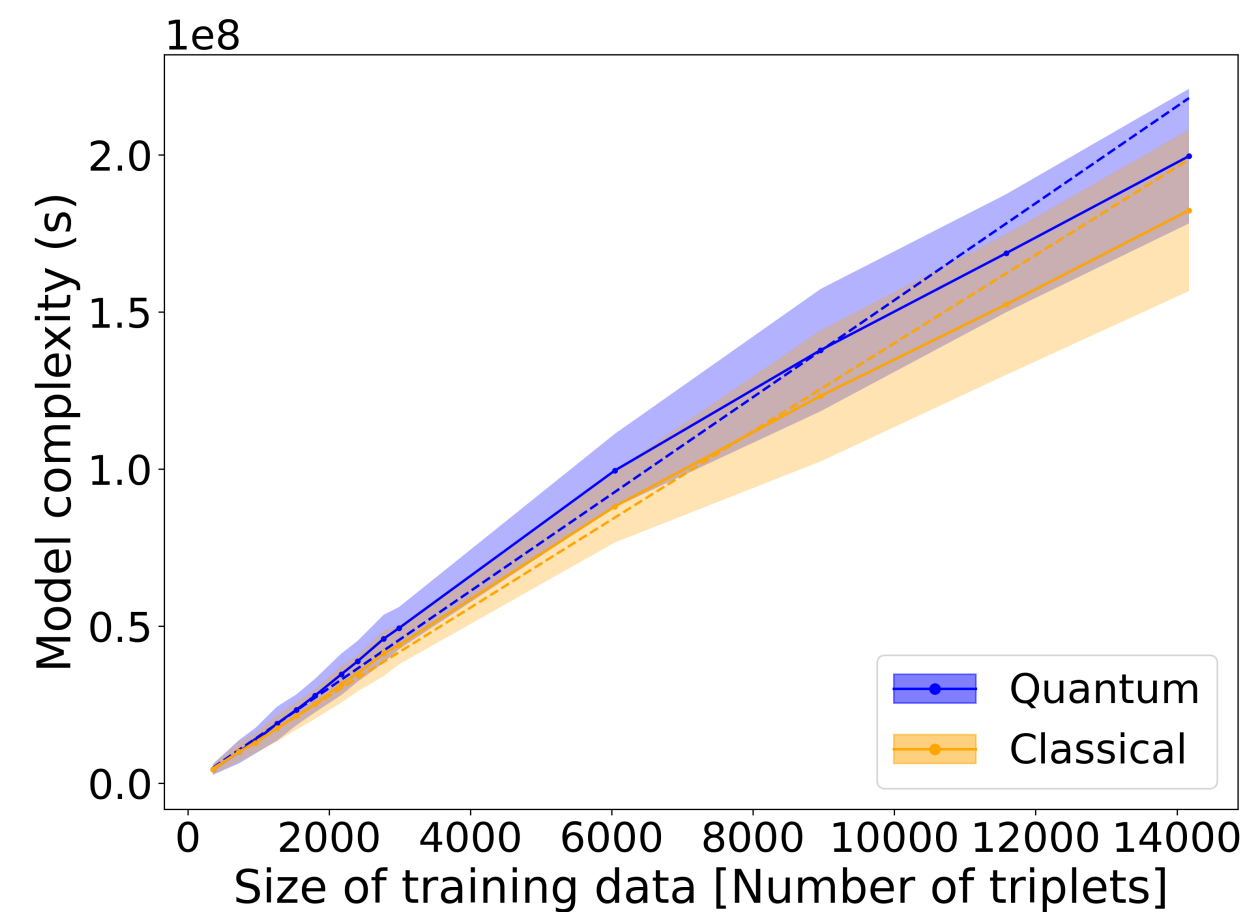
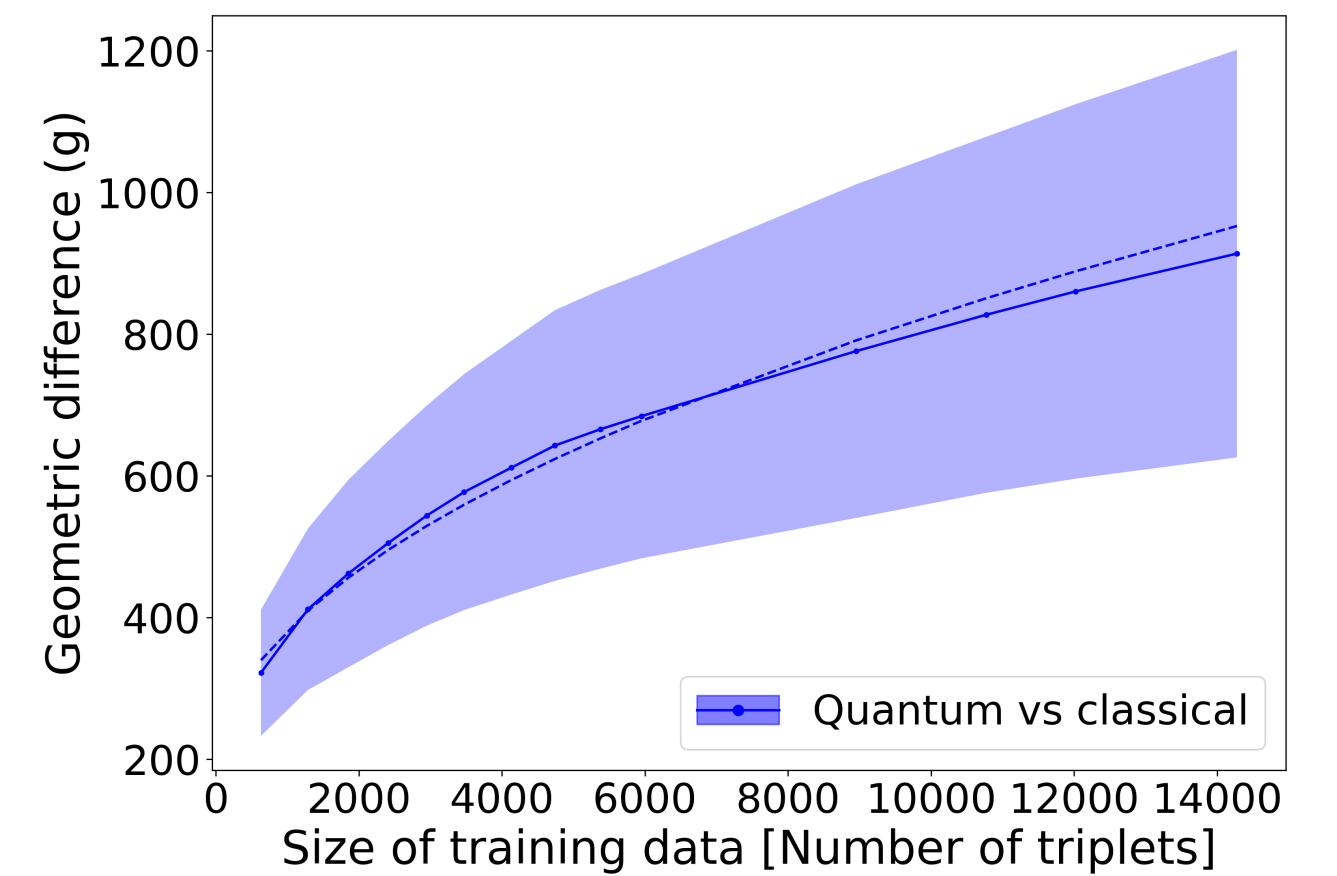
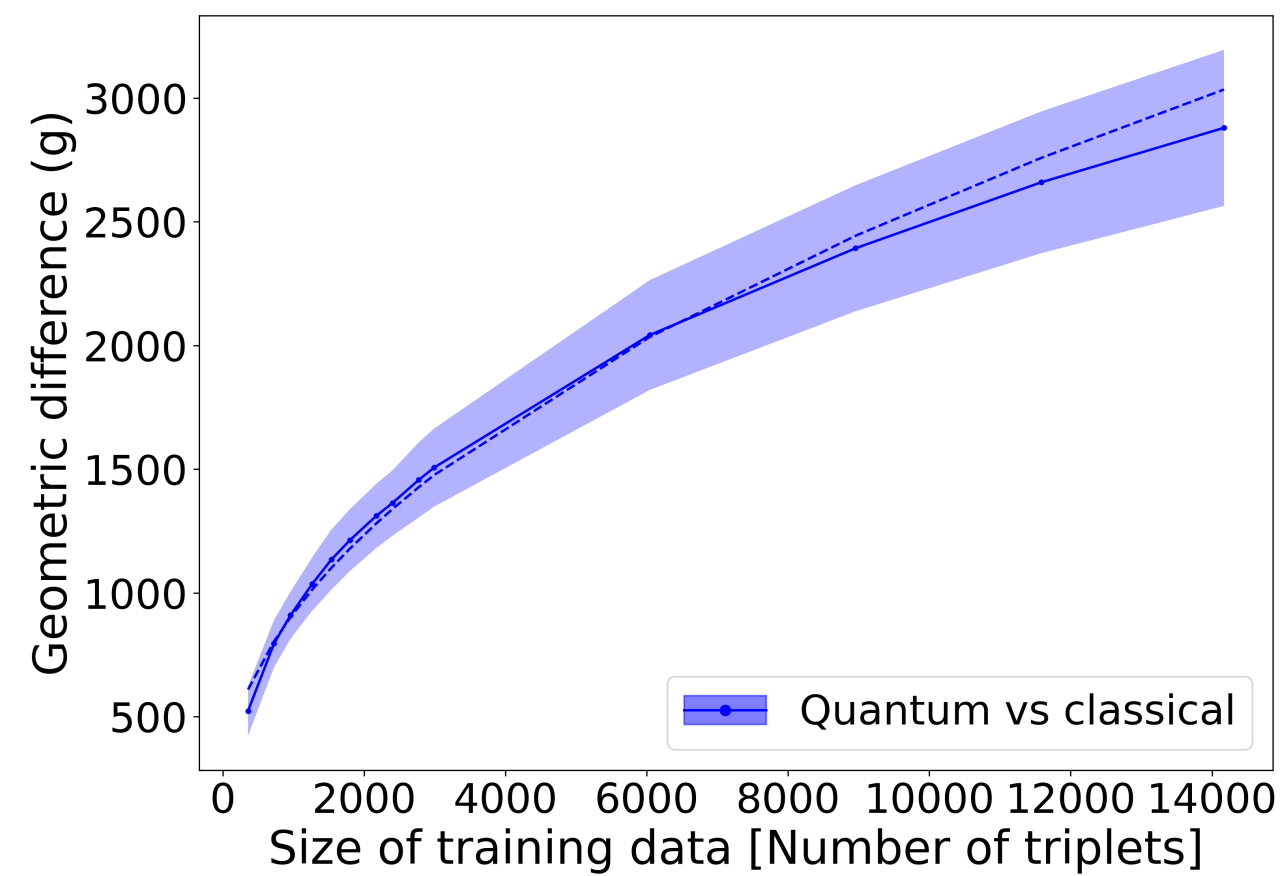
Complexity - how narrow is the margin?



Geometric difference - given two models, will same data be mapped similarly?

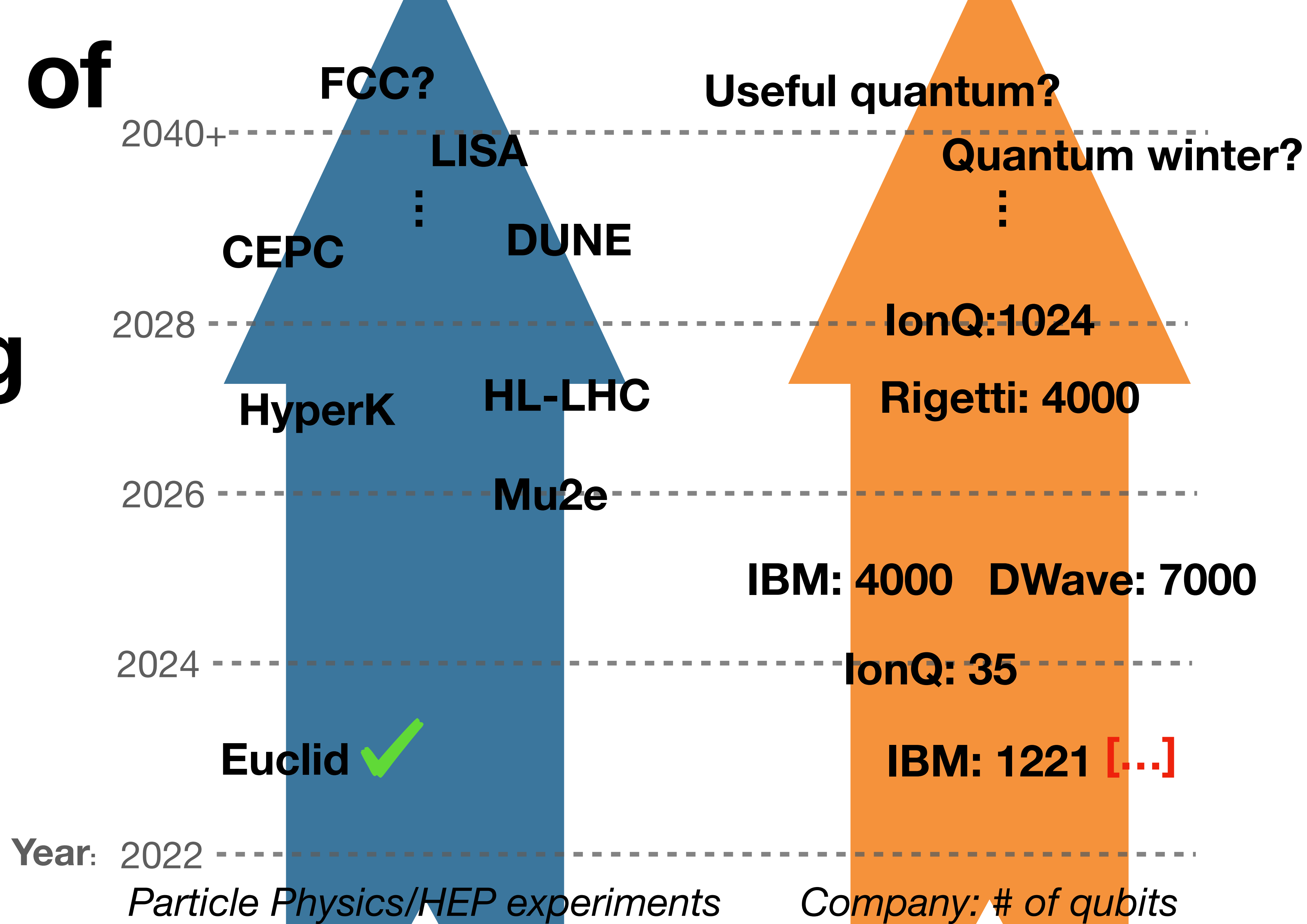
BONUS: Complexity results

Quantum
kernel
sufficiently
different and
less complex!



The future of HEP and quantum computing

But error mitigation and error correction will be necessary



Thank you



- Slide 3 top right pic: <https://www.nature.com/articles/s41566-023-01272-3>
- Slides 5-10: <https://arxiv.org/abs/2307.03236>
- Slides 17/18: trackml logo <https://www.kaggle.com/competitions/trackml-particle-identification/overview>
- Slide 35: <https://arxiv.org/abs/1804.11326>
- Slide 37: <https://quantumtech.blog/2022/10/20/quantum-computing-modalities-a-qubit-primer-revisited/>

BONUS: Main cons/ pros

**Algorithmic complexity
(M^2)**

**The shots with data scaling
means most likely need a
more sophisticated
implementation**

**No chance of advantage
until larger number of
features**

**Most tangible possibility for
proven advantage**

**Feature mapping (thus
kernels) very natural for
quantum computers**

**IBM takes kernel methods
seriously (paper estimating
runtimes). They suggest
collaboration with kernel
methods experts**

BONUS: Areas of current/future focus

Collaboration

Running on hardware

Quantum autoencoders

Generative models

BONUS: What's needed for advantage?

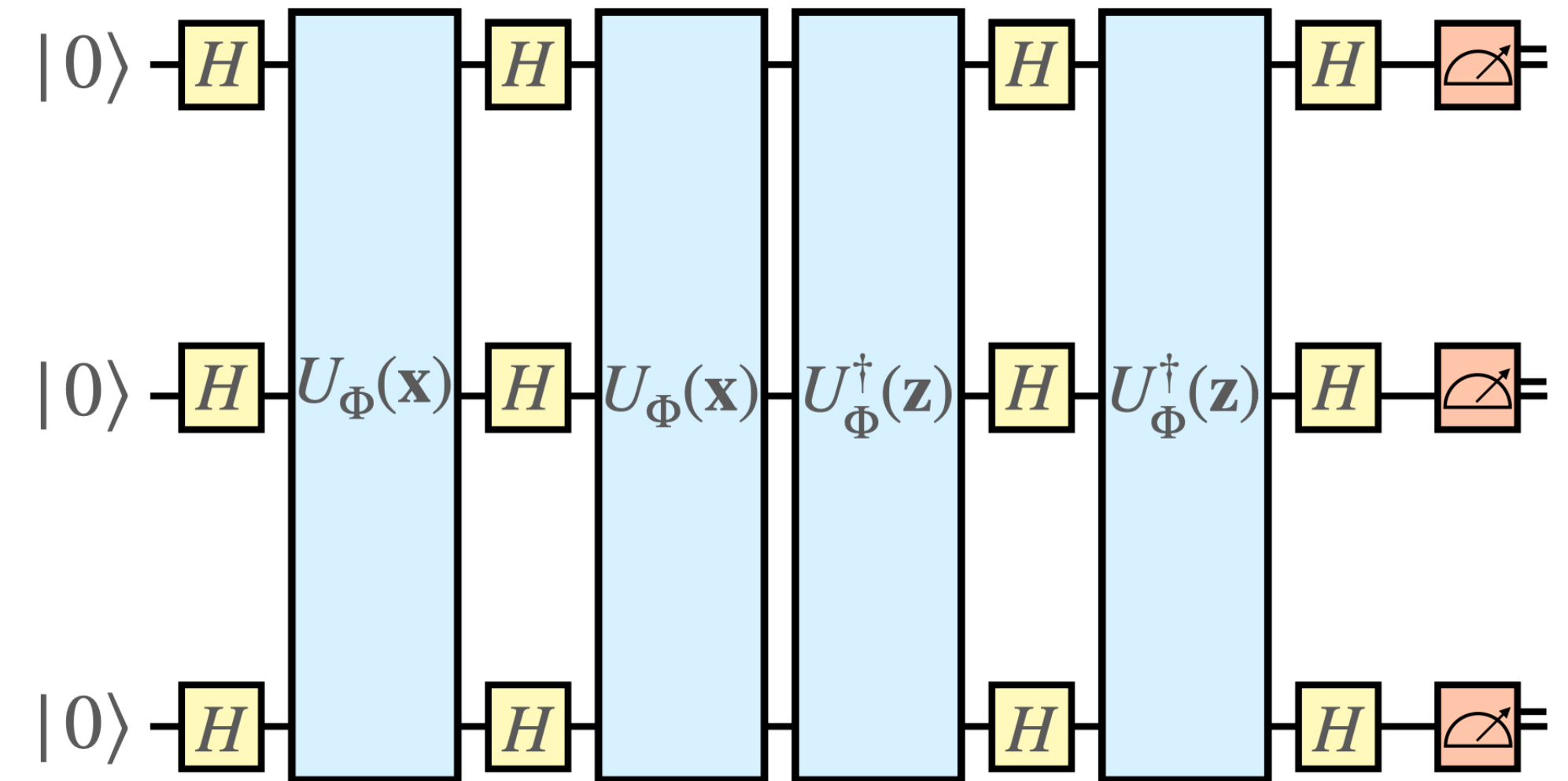
Algorithm

Use case

[probably] Error correction

[maybe] error mitigation

BONUS: Advantage from kernels - forrelation



ent-function and it's dual. It can be shown that with respect to this oracle there is an exponential separation in query complexity over classical query algorithms.

The final circuit we implement to estimate the overlap $|\langle \Phi(\mathbf{x}) | \Phi(\mathbf{y}) \rangle|^2$, c.f. Fig 5 b) is still larger. This circuit has four layers of Hadamard gates and 3 diagonal layers. A circuit that has this kind of structure is related to a problem introduced by Aaronson and Ambainis [8]. The problem is referred to k -fold Forrelation, c.f. [8], section 1.1.3. where given k total Boolean functions $f_i : \{0, 1\} \rightarrow \{+1, -1\}$, $i = 1 \dots k$ one has to decide, whether the sum

$$F_{f_1, f_2, \dots, f_k} = \frac{1}{2^{(k+1)n/2}} \sum_{x_1, \dots, x_k \in \{0, 1\}^n} f_1(x_1)(-1)^{x_1 \circ x_2} f_2(x_2)(-1)^{x_2 \circ x_3} \dots (-1)^{x_{k-1} \circ x_k} f_k(x_k), \quad (35)$$

satisfies $|F_{f_1, f_2, \dots, f_k}| \leq 100^{-1}$ or whether $F_{f_1, f_2, \dots, f_k} \geq 3/5$, promised that one of these holds. The authors show, that any classical, randomized algorithm that has only black box access to the Boolean functions must make $\mathcal{O}(2^{n/2} n^{-1})$ queries to these black box functions to solve the problem. However, a quantum computer is able to solve this problem with k queries (in fact only $\lceil k/2 \rceil$ queries) to a phase oracle that encodes the Boolean function through

phase gates $U_{\Phi(\mathbf{x})}$, $U_{\Phi(\mathbf{y})}^\dagger U_{\Phi(\mathbf{x})}$ and $U_{\Phi(\mathbf{y})}^\dagger$ assume the roles of the oracles U_{f_1} , U_{f_2} and U_{f_3} queried in 3-fold Forrelation respectively. Hence, the kernel estimation we perform here is directly related to the Forrelation problem by Aaronson and Ambainis.

BONUS:Cluster computers

DELL PowerEdge servers, 15 with two six-core Intel Xeon E5-2430 2.7 GHz CPUs and 48GB of RAM, 11 with two eight-core Intel Xeon E5-2620 3.0 GHz CPUs and 64GB of RAM or better.

BONUS: qubit modalities

Qubit Type	Pros/Cons	Select Players
Superconducting	<p>Pros: High gate speeds and fidelities. Can leverage standard lithographic processes. Among first qubit modalities so has a head start.</p>	
	<p>Cons: Requires cryogenic cooling; short coherence times; microwave interconnect frequencies still not well understood.</p>	
Trapped Ions	<p>Pros: Extremely high gate fidelities and long coherence times. Extreme cryogenic cooling not required. Ions are perfect and consistent.</p>	
	<p>Cons: Slow gate times/operations and low connectivity between qubits. Lasers hard to align and scale. Ultra-high vacuum required. Ion charges may restrict scalability.</p>	
Photonics	<p>Pros: Extremely fast gate speeds and promising fidelities. No cryogenics or vacuums required. Small overall footprint. Can leverage existing CMOS fabs.</p>	
	<p>Cons: Noise from photon loss; each program requires its own chip. Photons don't naturally interact so 2Q gate challenges.</p>	
Neutral Atoms	<p>Pros: Long coherence times. Atoms are perfect and consistent. Strong connectivity, including more than 2Q. External cryogenics not required.</p>	
	<p>Cons: Requires ultra-high vacuums. Laser scaling challenging.</p>	
Silicon Spin/Quantum Dots	<p>Pros: Leverages existing semiconductor technology. Strong gate fidelities and speeds.</p>	
	<p>Cons: Requires cryogenics. Only a few entangled gates to-date with low coherence times. Interference/cross-talk challenges.</p>	