Lecture 3: Quantum Machine Learning and Applications of Quantum Computing to HEP

Aka: How might this be useful for us?

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Many thanks to C. Bauer, L. Linder, I. Shapoval, J.R. Vlimant, S.L. Wu and A. Yadav for slides and material

CERN Academic Training, March 2021

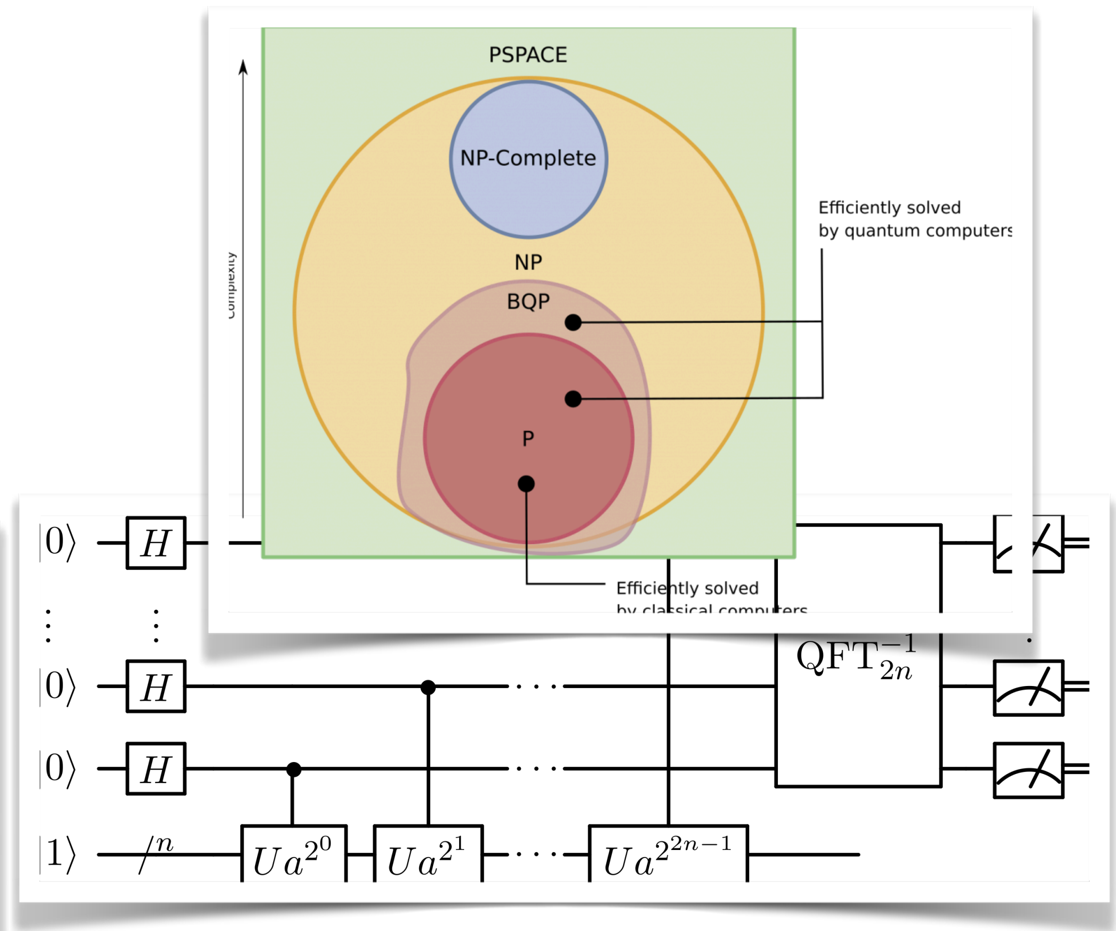
Outline for the lectures

- **Lecture 1: Fundamentals**
    - A brief history, qubits, quantum circuits, qubit technologies
- **Lecture 2: Quantum computers and quantum algorithms**
    - Quantum computers today, quantum algorithms, error correction, quantum advantage
- **Lecture 3: Applications of quantum computing in HEP**
    - Applications of quantum computing to HEP: simulation, reconstruction and physics analysis; including quantum machine learning

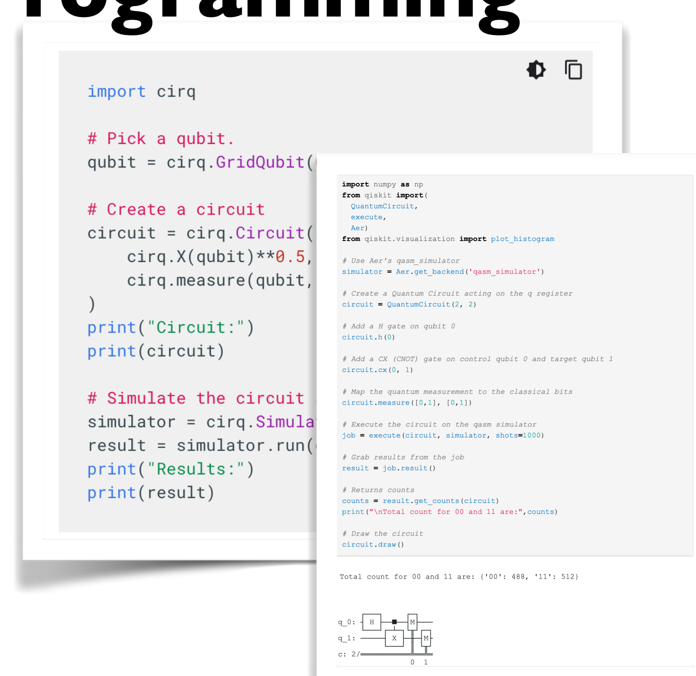
Recap from Last Time

Computers

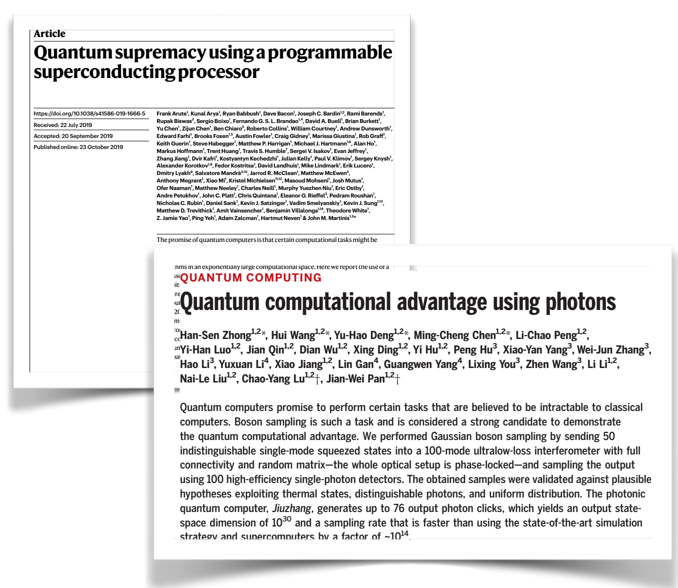
Algorithms



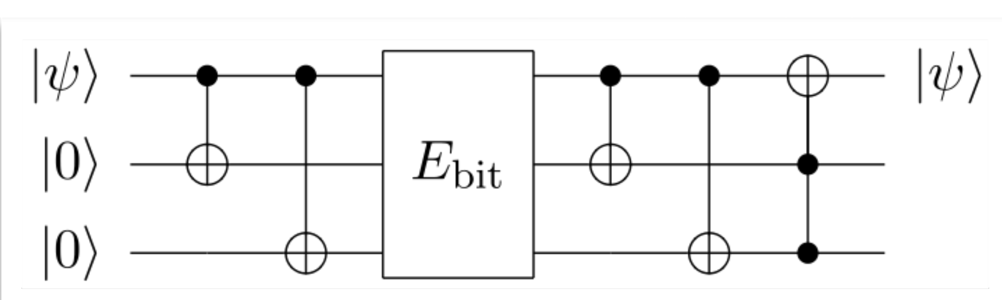
Programming



Advantage

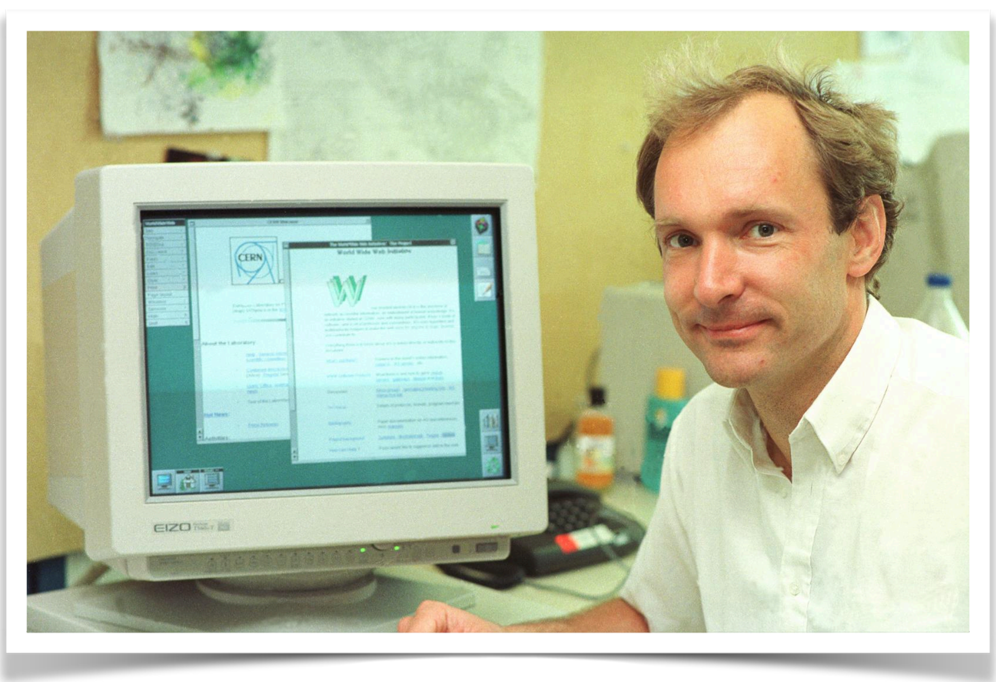


Error Correction



Computing in HEP

- Computing plays a vital role in our successful exploitation of physics results from the LHC
  - Computing is used extensively from detector control, through simulation, to data reconstruction and analysis
- HEP also has a long tradition of being at the forefront of new computing technologies (and even inventing them in certain cases)
  - e.g. the WWW and the grid
- **Can quantum computing be useful for HEP?**

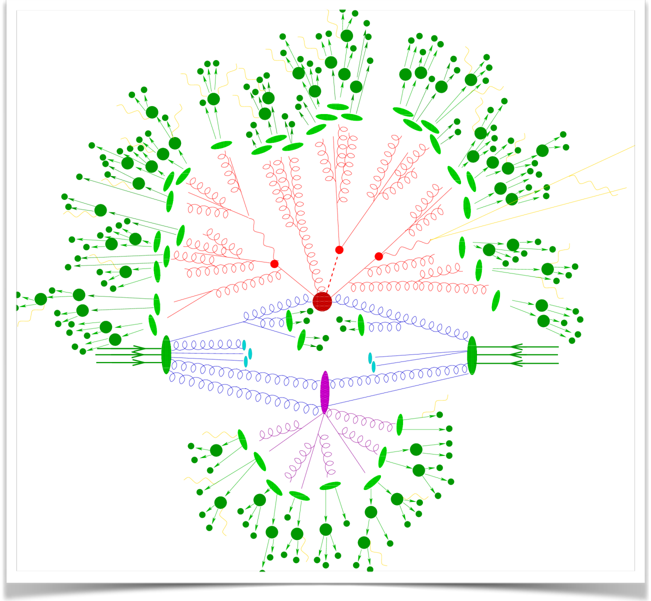


Outline for Today

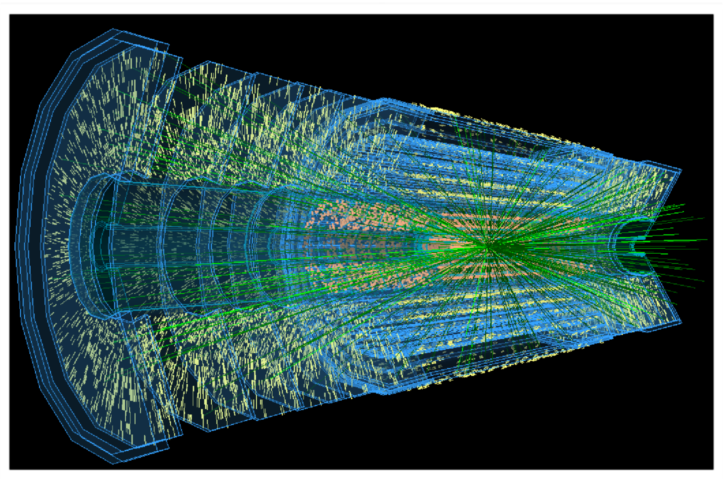
- **Applications** of quantum computing in **HEP**
  - Simulation
    - Parton shower correlations
    - Lattice QCD
  - Reconstruction
    - Particle tracking
  - Analysis
    - Higgs analyses
    - SUSY search

Progress has been very rapid here…
Relying on a mix of published and unpublished results
My apologies to anyone who's work I've left out or don't do justice to

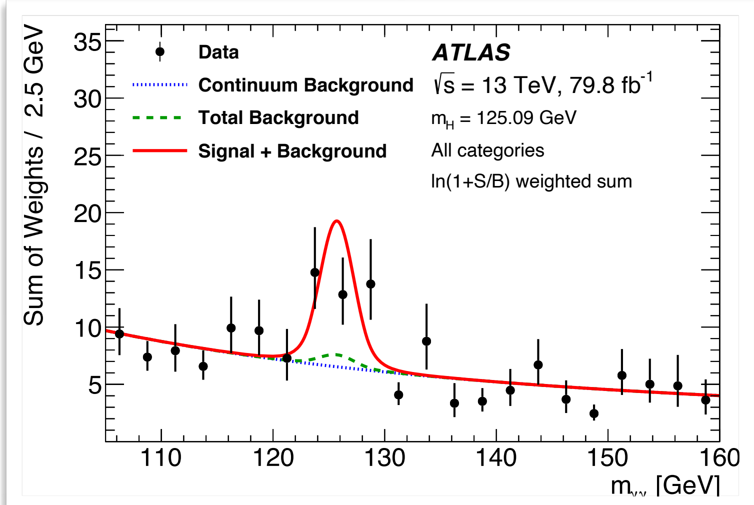
Simulation



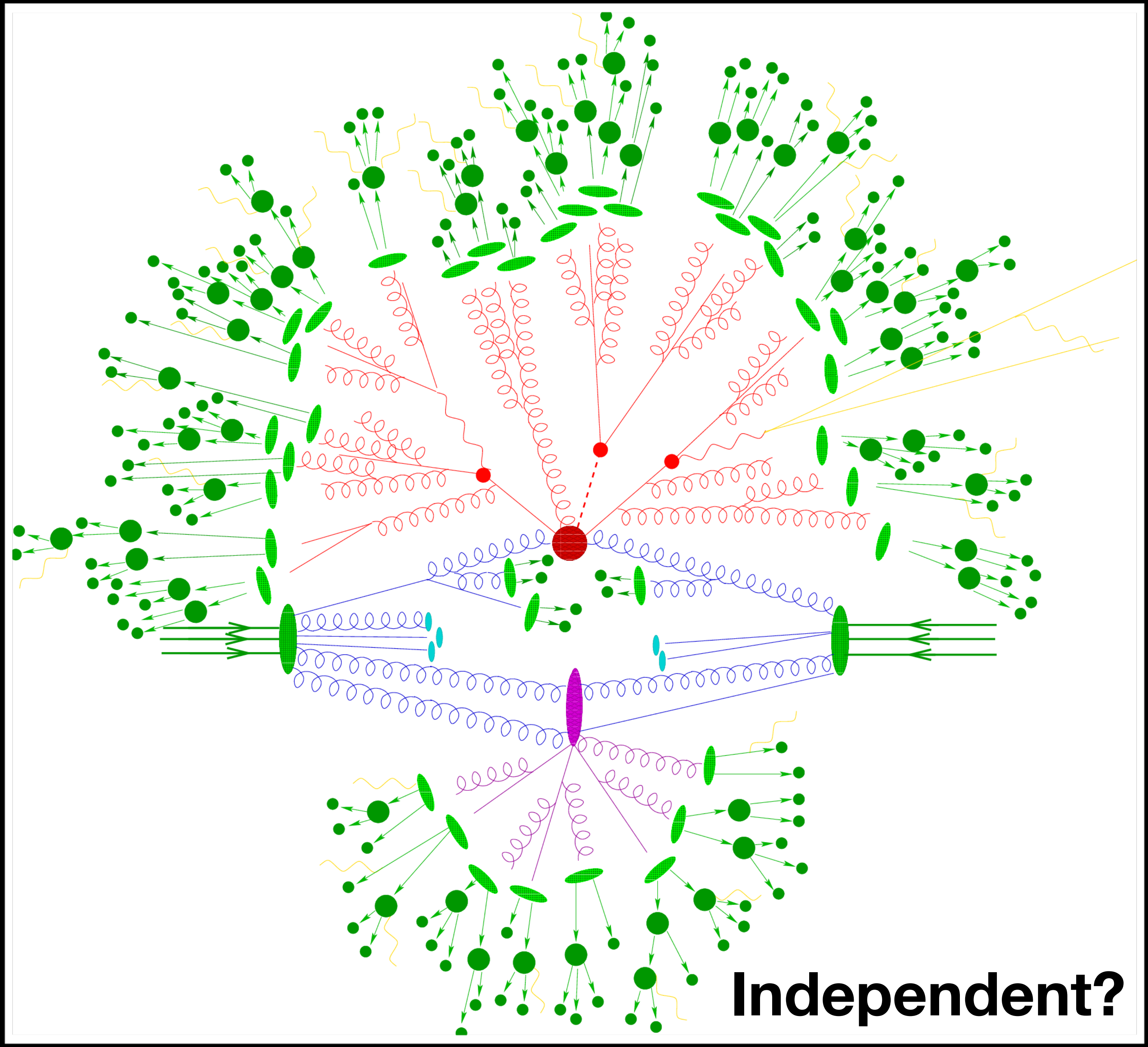
Reconstruction



Analysis



Simulation



Simulating Parton Shower Correlations

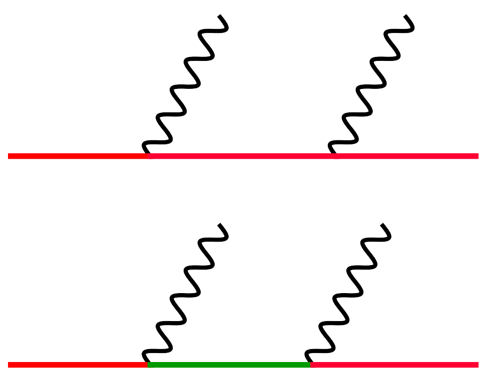
- Idea: exploit entanglement between qubits on a quantum computer to simulate correlations in the parton shower

Toy Model

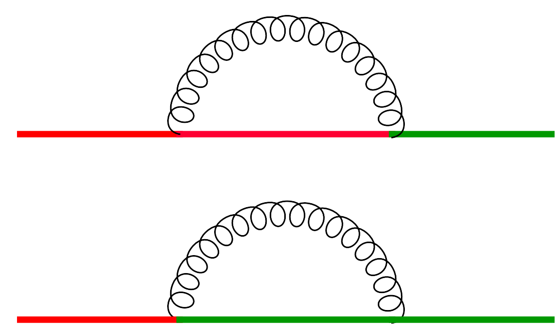
$$
\begin{aligned}
\mathcal{L} = &\bar{f}_1(i\not{\partial} + m_1)f_1 + \bar{f}_2(i\not{\partial} + m_2)f_2 + (\partial_\mu \phi)^2 \\
&+ g_1 \bar{f}_1 f_1 \phi + g_2 \bar{f}_2 f_2 \phi + g_{12}\left[\bar{f}_1 f_2 + \bar{f}_2 f_1\right]\phi
\end{aligned}
$$

The mixing g_{12} gives several interesting effects

Different real emission amplitudes give rise to interference



Virtual diagrams give rise to flavor change without radiation

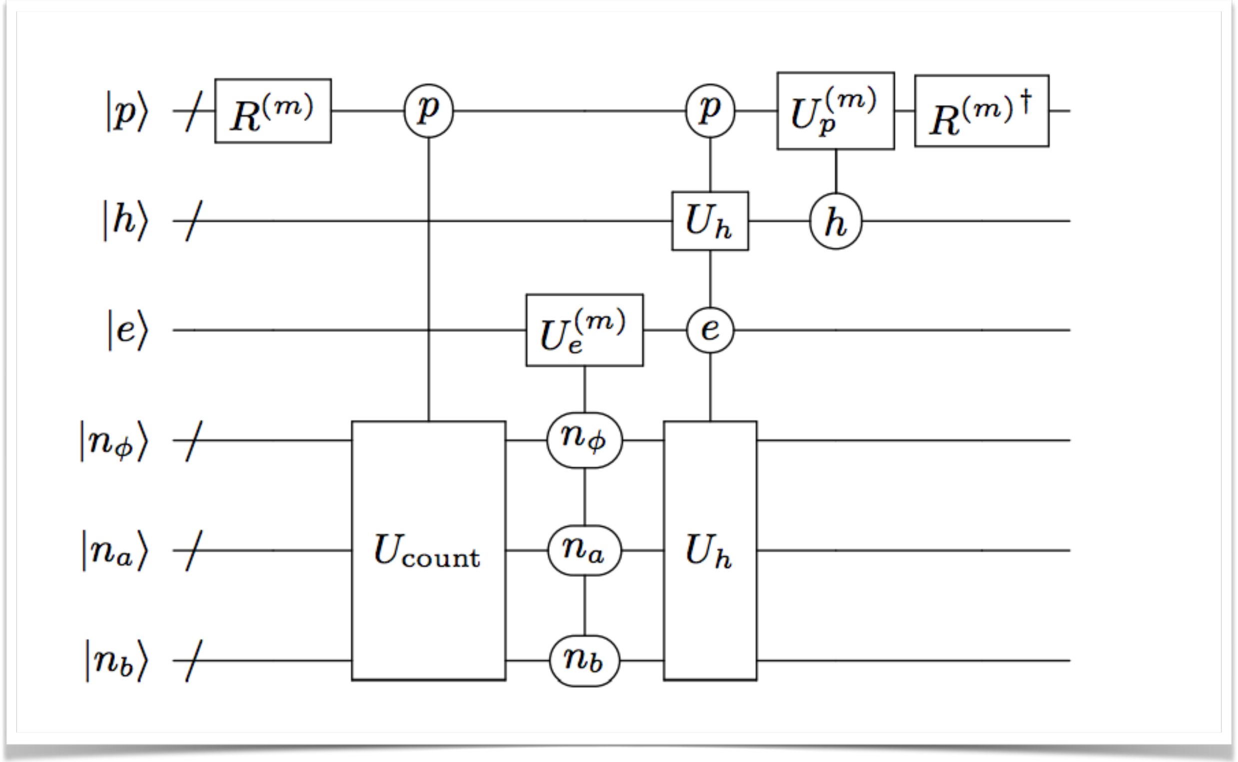


Need to correct both real and virtual effects

Similar to including subleading color

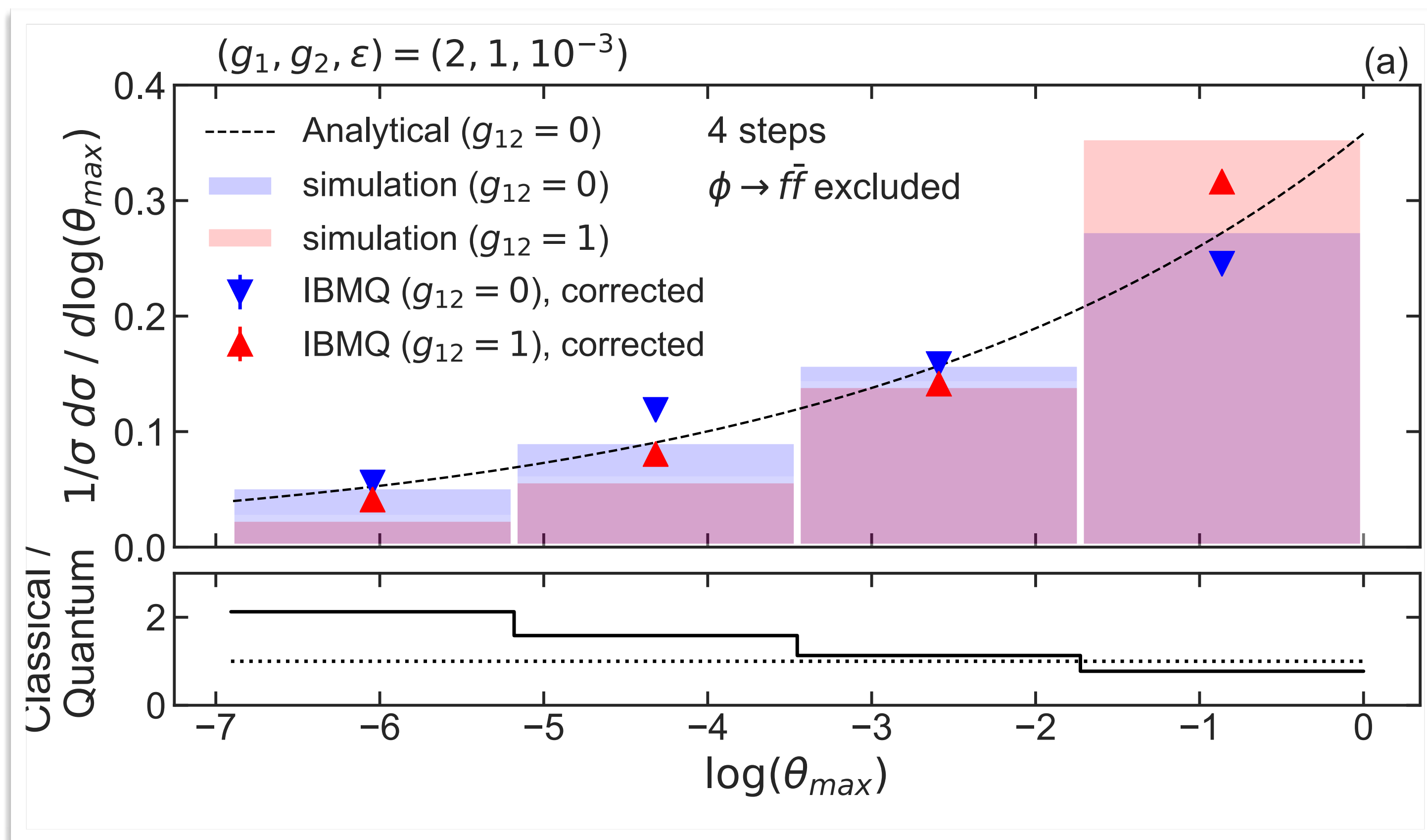
Bauer et al., arXiv:1904.03196

Toy Model Results



Quantum circuit for the final state radiation algorithm for one of the N steps

Differential cross section as a function of the largest emission angle using IBM Q
Compare interference off (blue) to interference on (red)



Bauer et al., arXiv:1904.03196

Lattice QCD

Klco et al, arXiv:1803.03326

Quantum-Classical Computation of Schwinger Model Dynamics using Quantum Computers

N. Klco,[1,*] E. F. Dumitrescu,[2] A. J. McCaskey,[3] T. D. Morris,[4]
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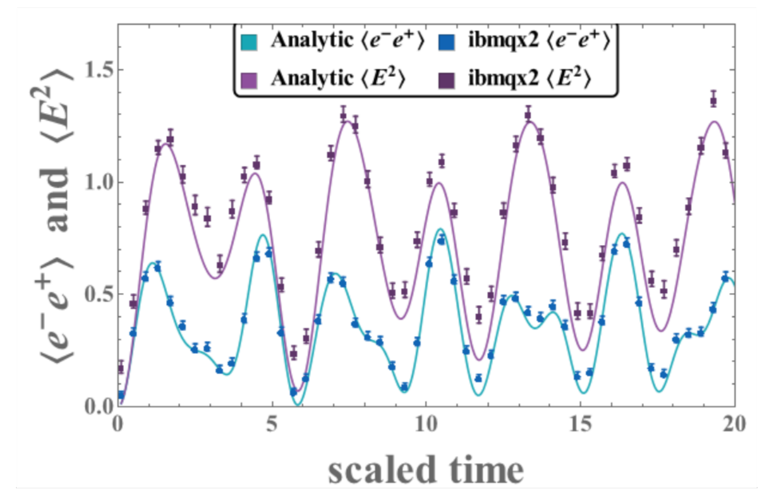
[1] *Institute for Nuclear Theory, University of Washington, Seattle, WA 98195-1550, USA*
[2] *Computational Sciences and Engineering Division, Oak Ridge National Laboratory, Oak Ridge, TN 37831, USA*
[3] *Computer Science and Mathematics Division, Oak Ridge National Laboratory, Oak Ridge, TN 37831, USA*
[4] *Physics Division, Oak Ridge National Laboratory, Oak Ridge, TN 37831, USA*
[5] *Department of Physical Chemistry, University of the Basque Country UPV/EHU, Apartado 644, E-48080 Bilbao, Spain.*
[6] *IKERBASQUE, Basque Foundation for Science, Maria Diaz de Haro 3, E-48013 Bilbao, Spain*

(Dated: October 4, 2018)

We present a quantum-classical algorithm to study the dynamics of the two-spatial-site Schwinger model on IBM's quantum computers. Using rotational symmetries, total charge, and parity, the number of qubits needed to perform computation is reduced by a factor of ~ 5, removing exponentially-large unphysical sectors from the Hilbert space. Our work opens an avenue for exploration of other lattice quantum field theories, such as quantum chromodynamics, where classical computation is used to find symmetry sectors in which the quantum computer evaluates the dynamics of quantum fluctuations.



Avkhadiev et al, arXiv:1908.04194

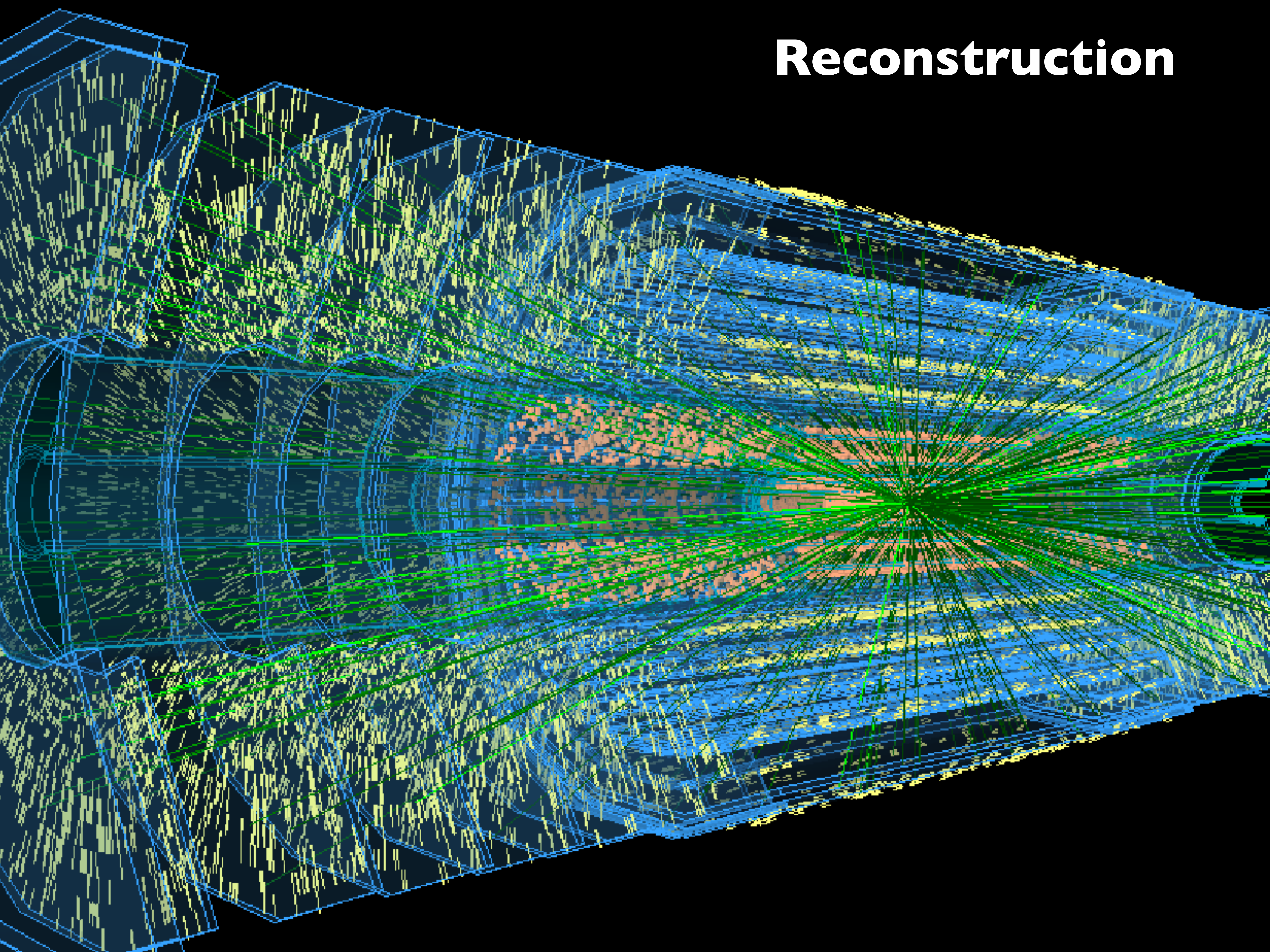
Accelerating lattice quantum field theory calculations via interpolator optimization using NISQ-era quantum computing

A. Avkhadiev,[1,2] P. E. Shanahan,[1,2] and R. D. Young[3]

[1] *Center for Theoretical Physics, Massachusetts Institute of Technology, Cambridge, MA 02139, U.S.A.*
[2] *Perimeter Institute for Theoretical Physics, Waterloo, Ontario N2L 2Y5, Canada*
[3] *CSSM, Department of Physics, University of Adelaide, Adelaide SA 5005, Australia*

The only known way to study quantum field theories in non-perturbative regimes is using numerical calculations regulated on discrete space-time lattices. Such computations, however, are often faced with exponential signal-to-noise challenges that render key physics studies untenable even with next generation classical computing. Here, a method is presented by which the output of small-scale quantum computations on Noisy Intermediate-Scale Quantum era hardware can be used to accelerate larger-scale classical field theory calculations through the construction of *optimized interpolating operators.* The method is implemented and studied in the context of the 1+1-dimensional Schwinger model, a simple field theory which shares key features with the standard model of nuclear and particle physics.

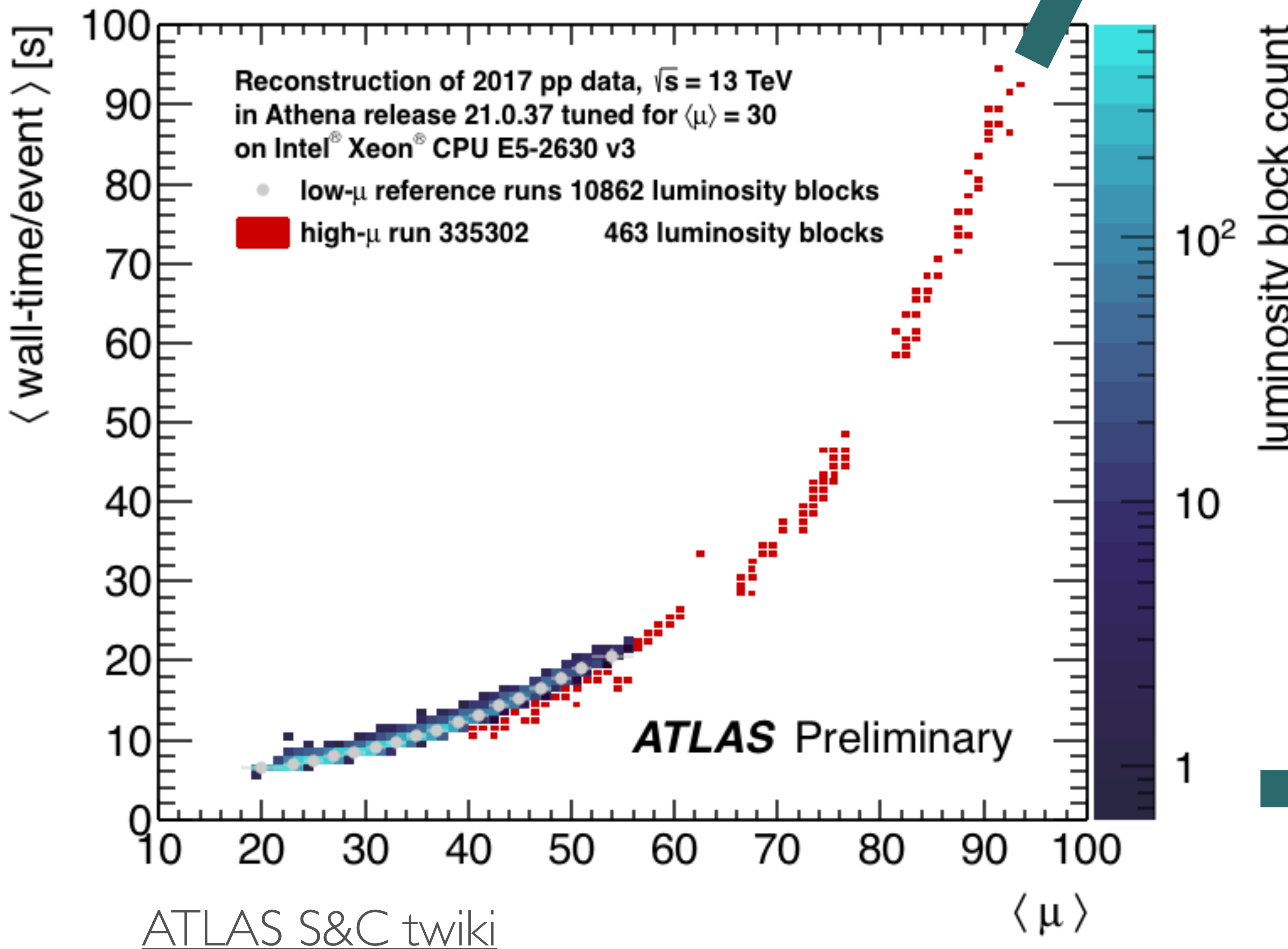
Reconstruction



Track reconstruction studies

- Quantum Annealing x 2
- Quantum Associative Memory
- Quantum Hough Transform
- Quantum Graph Neural Network

Reconstructing Tracks



ATLAS S&C twiki

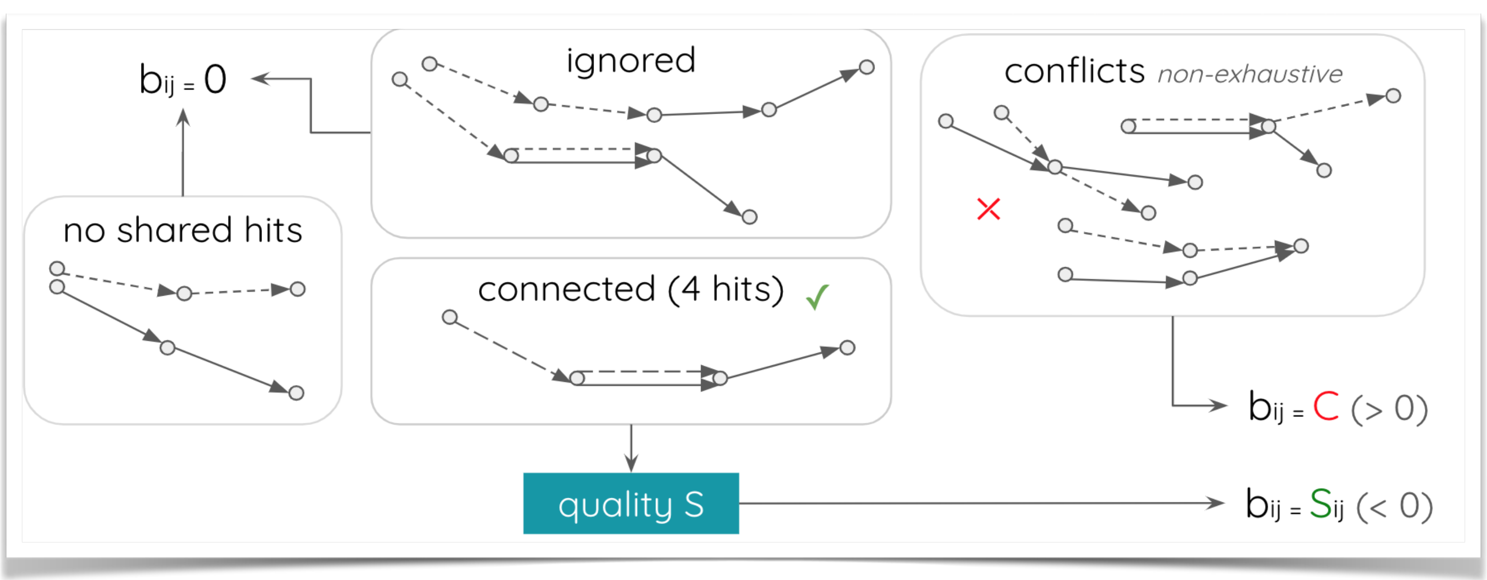
Track reconstruction is expected to have a large CPU burden at the HL-LHC … and even greater at future pp collider

HL-LHC: μ= 140-200

Almost all studies here use the trackML dataset
Many restrict the multiplicity and/or focus on the central detector region and/or high p_T

Quantum Annealing

- Reformulated track reconstruction as an energy minimisation problem
  - Solve using the D-Wave quantum annealer
    - Solution time doesn't scale with number of tracks
- Implemented QUBO minimisation on D-Wave and study scaling with track multiplicity
  - Inspired from *, but use triplets (3 hits) as the qubits
  - Encode the quality of the triplets based on physics properties. Pair-wise connections b act as constraints (>0) or incentives (<0)
  - Minimizing O means selecting the best triplets to form track candidates



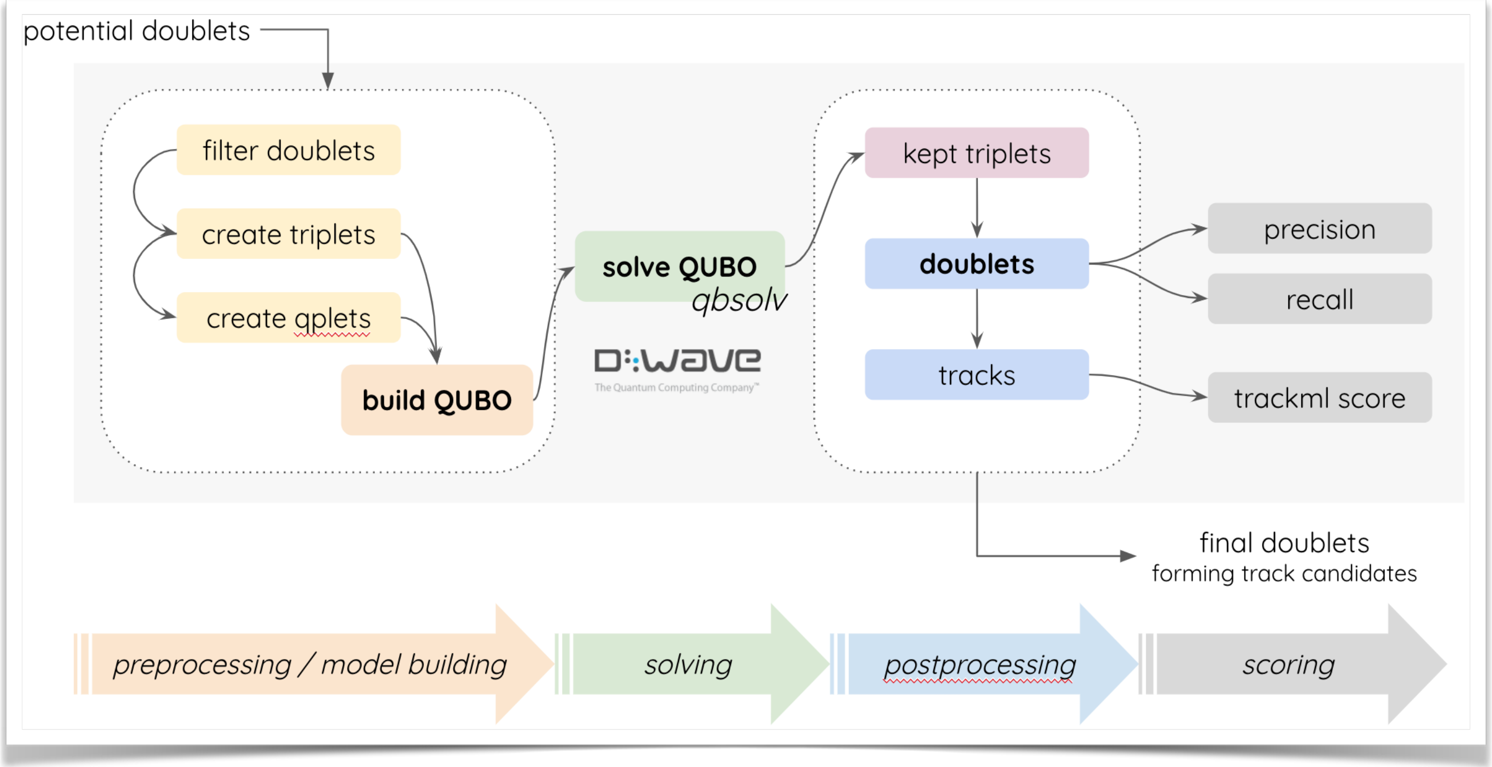
*Stimpfl-Abele & Garrido, Fast track finding with neural networks

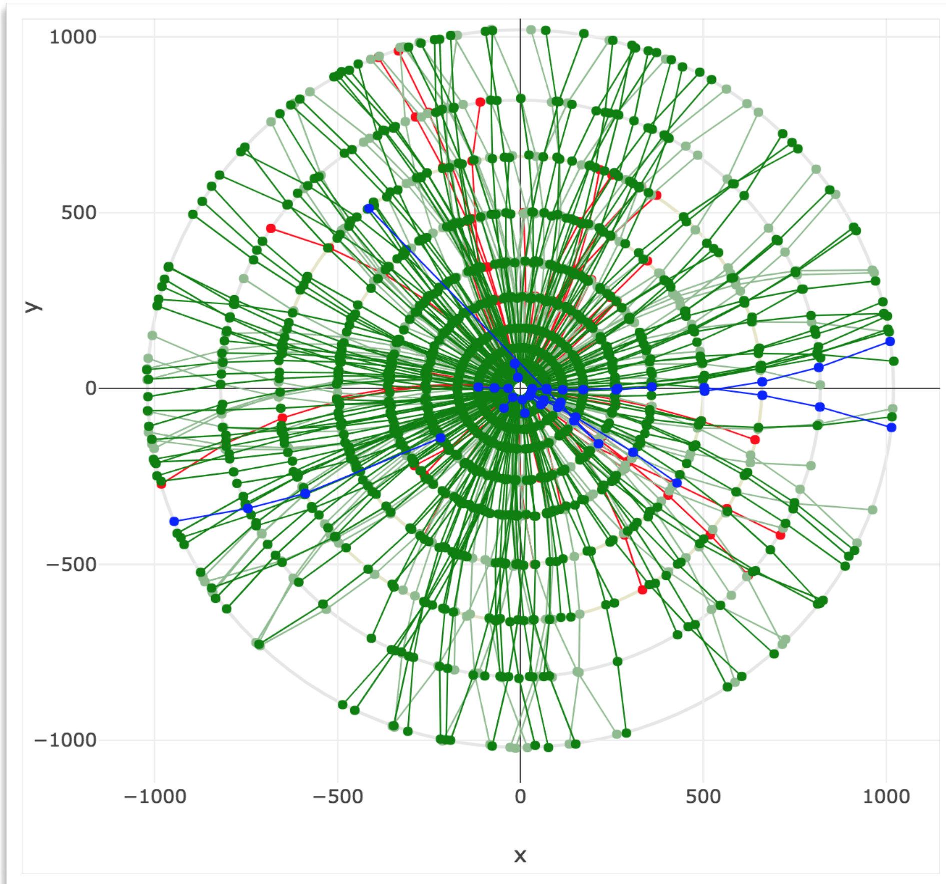
Slide credit: L. Linder

Bapst et al, arXiv:1902.08324

Implementation

- Dataset:
  - trackML dataset
  - barrel, >1 GeV, 5+ hits)
- QUBO solvers:
  - qbsolv (D-Wave + simulation)
  - neal (simulation)
- Computers
  - D-Wave 2X (1152 qubits),
  - D-Wave 2000Q (2048 qubits)
  - Fujitsu DA (1025 qubits)





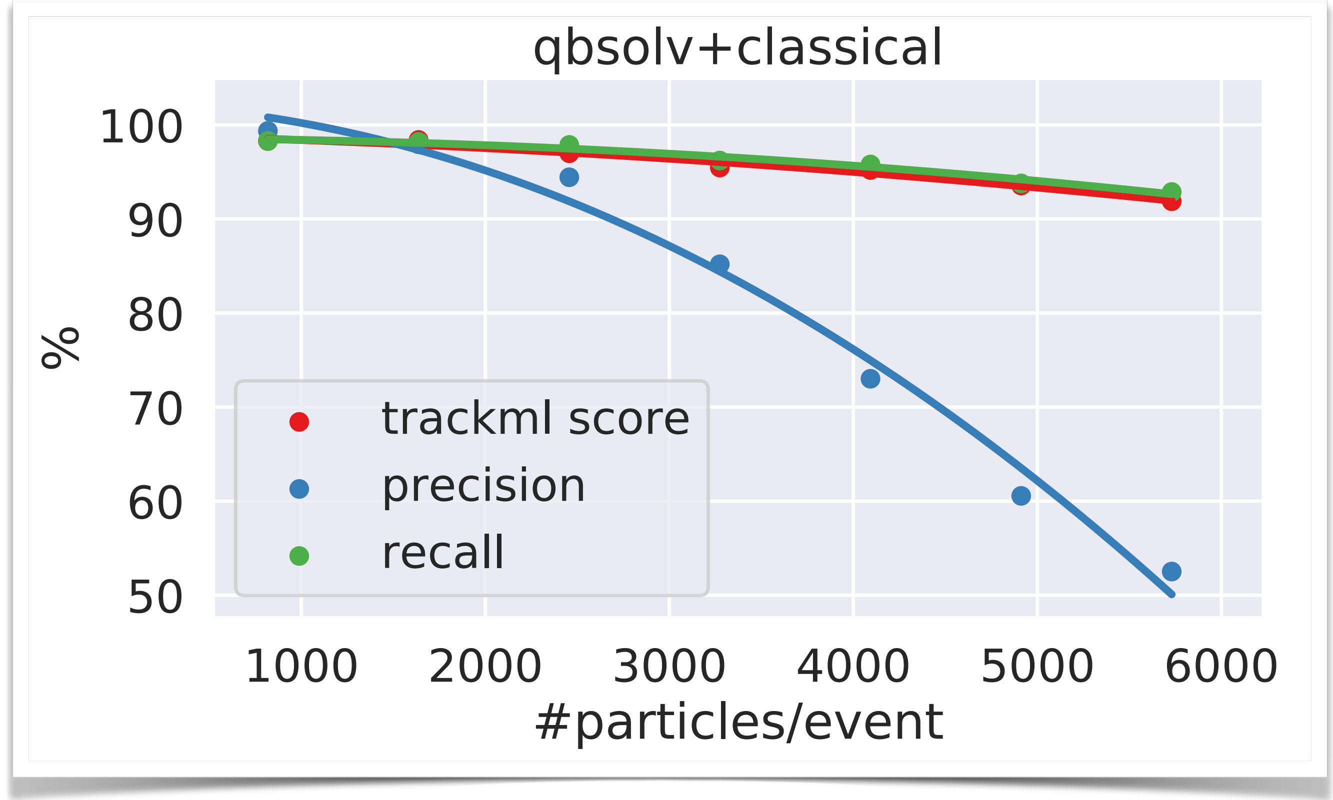
Doublets for a dataset of 2456 particles and 16855 hits

- fake
- out of acc.
- real
- missing

Slide credit: L. Linder

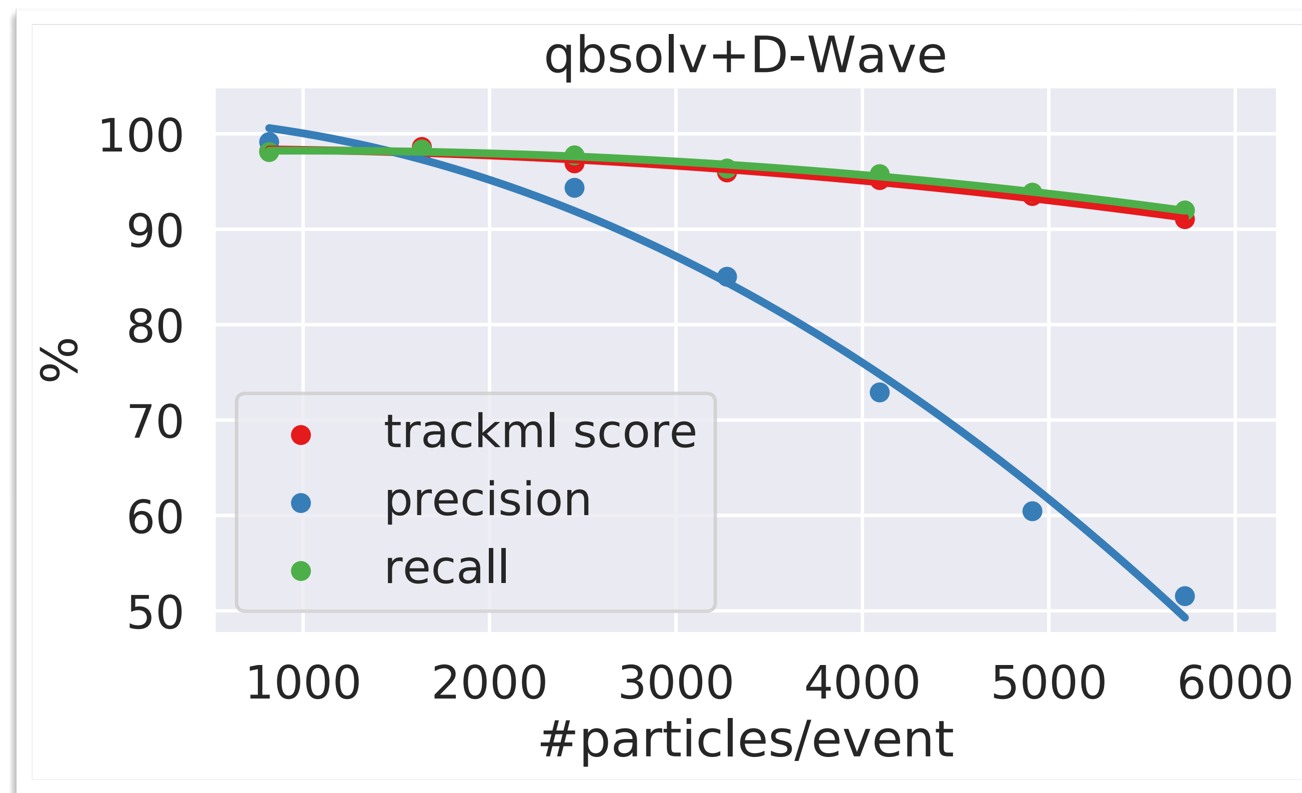
Initial Performance with DWave

Physics performance as a function of occupancy using a D-Wave 2X (qbsolv).



Timing building: 0-20 min | solving: 0-12s (sim), 0-56 min (D-Wave)

D-Wave | sim. Same physics, important time overhead with D-Wave

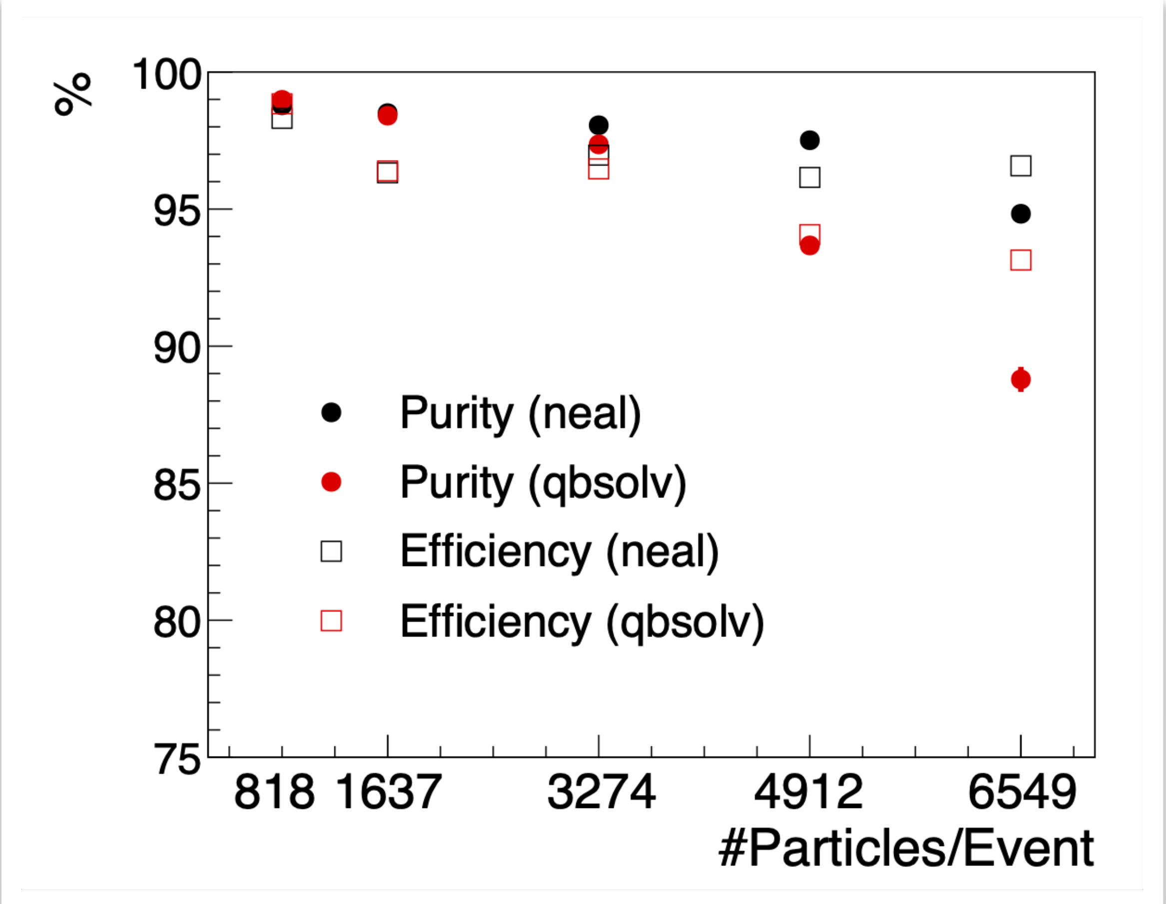


arXiv:1902.08324

Slide credit: L. Linder

Improved Performance + Digital Annealer

- Further work to improve the purity of the algorithm
  - Extend to expected HL-LHC multiplicities
- Study performance using the Fujitsu Digital Annealer
  - Annealing time is independent of the number of tracks
  - Superior performance to DWave

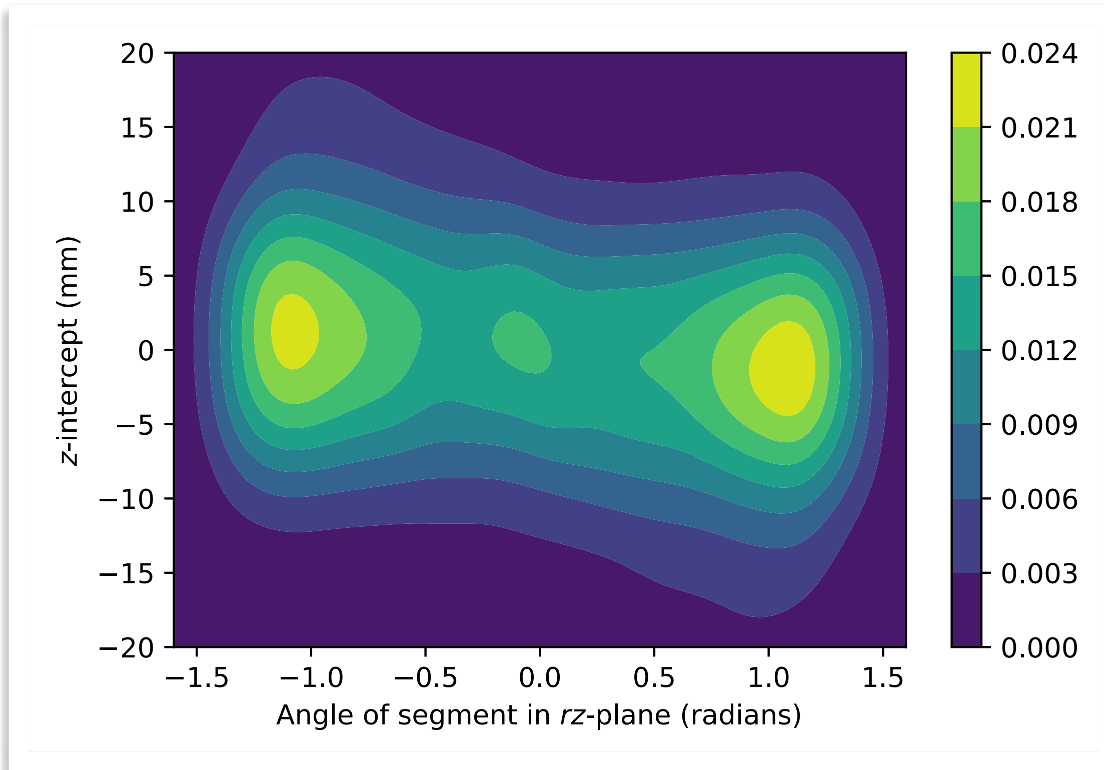


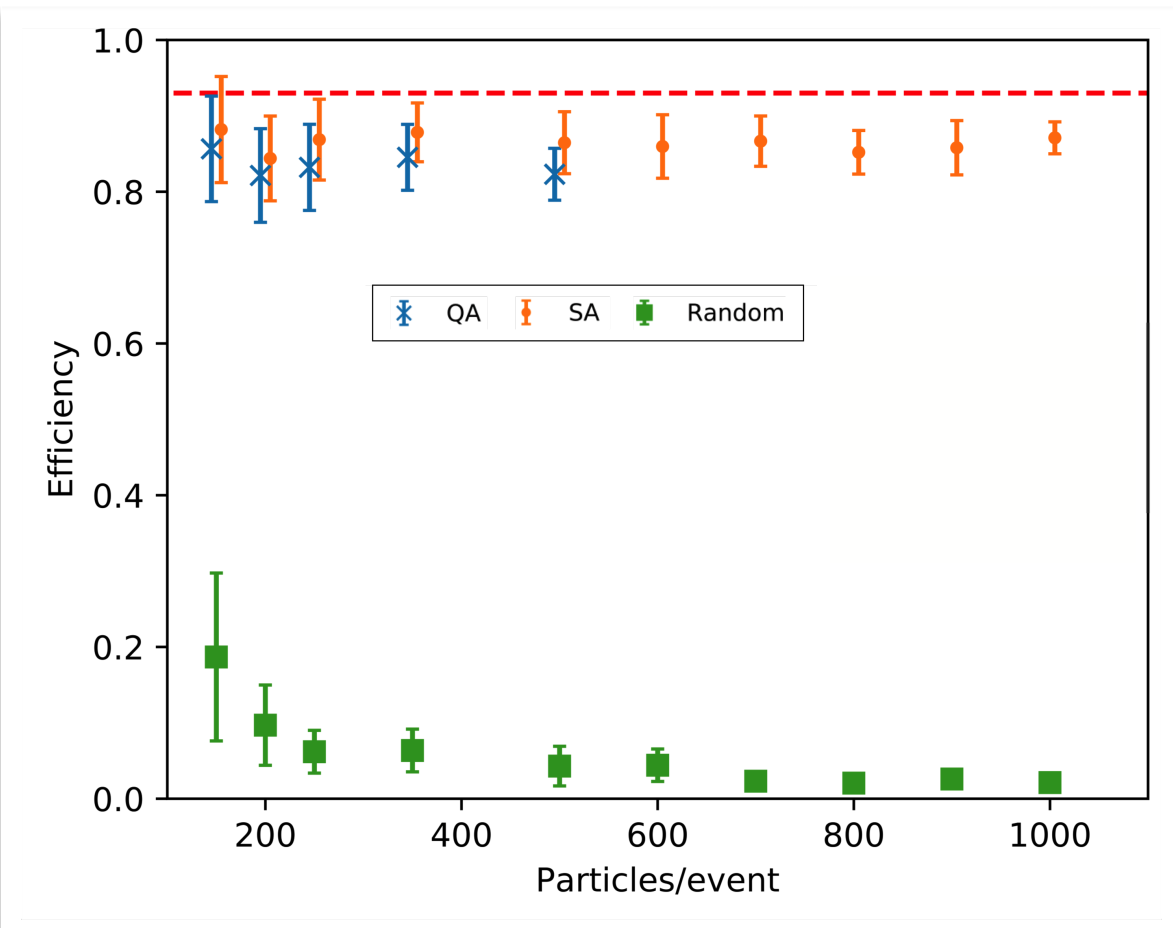
Density [%]	N_{slice}	DA [sec] CPU time	DA [sec] Anneal time	neal [sec] total time
5	46	0.09	0.29	0.27
10	68	0.15	0.42	0.66
20	71	0.22	0.44	1.29
40	74	0.52	0.45	2.46
60	73	0.94	0.45	4.29
80	74	1.79	0.46	7.49
100	74	3.73	0.45	12.87

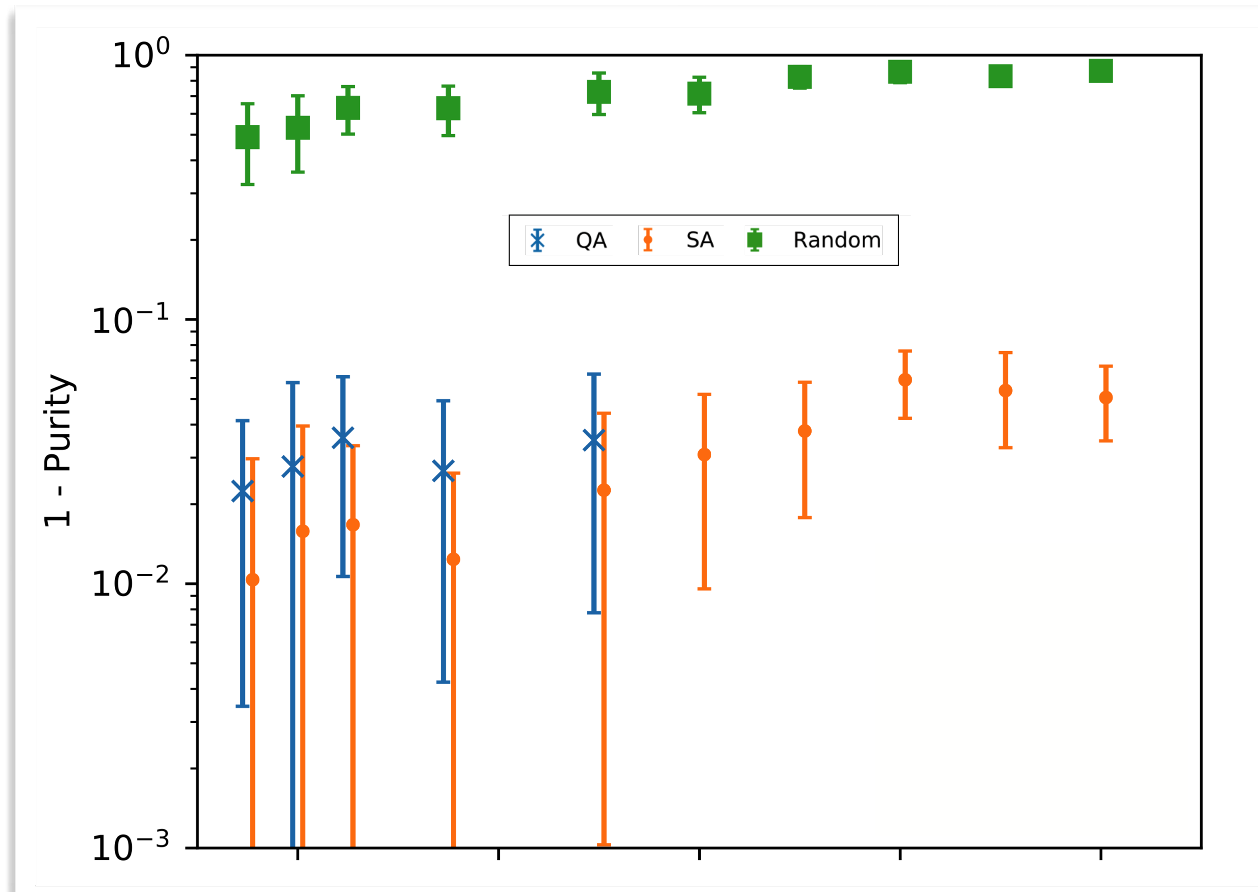
Saito et al

Quantum Annealing

- A second implementation of quantum annealing using Hopfield networks for tracking from Zlokapa et al, arXiv: 1908.04475
- KDE to estimate connection probability for a pair of hits

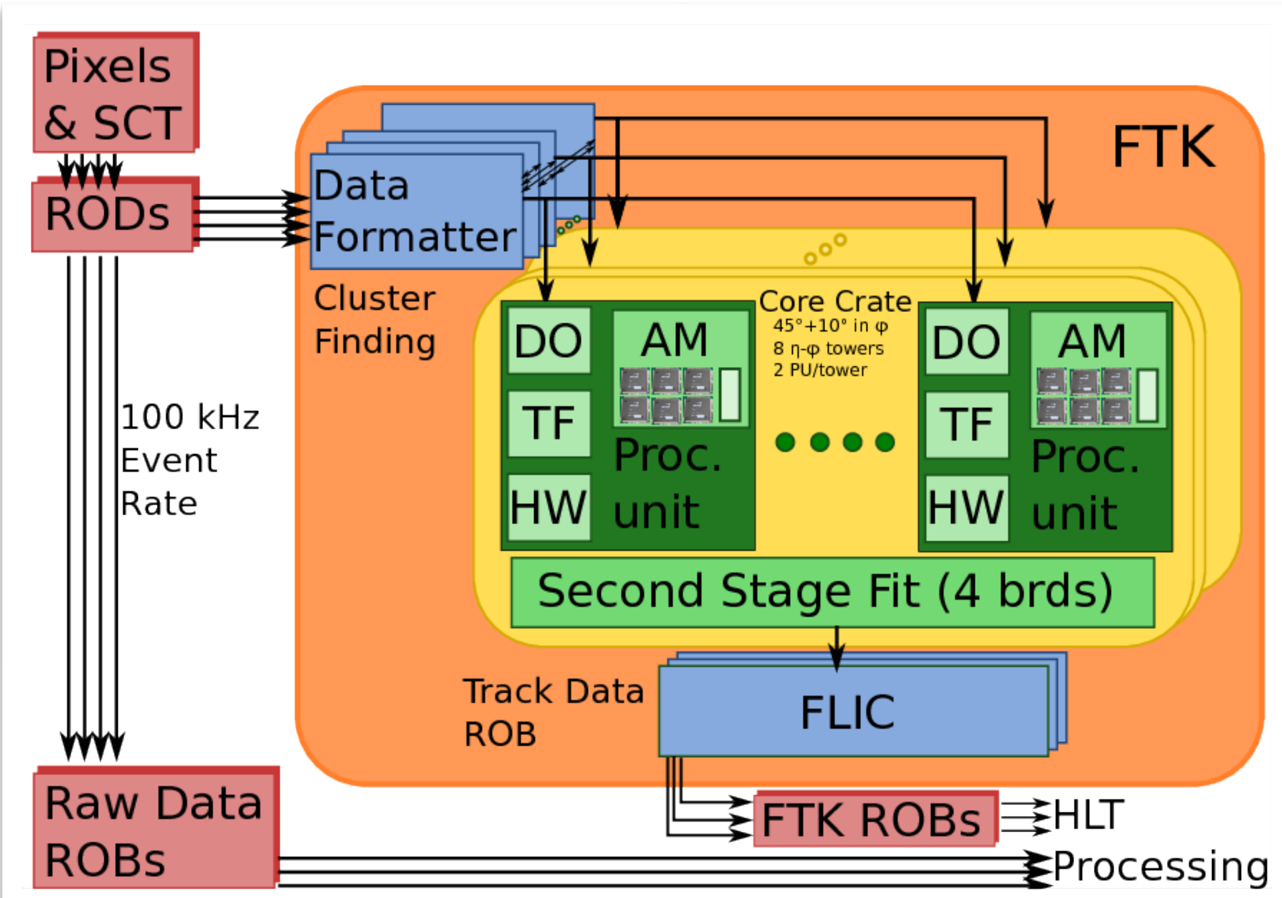






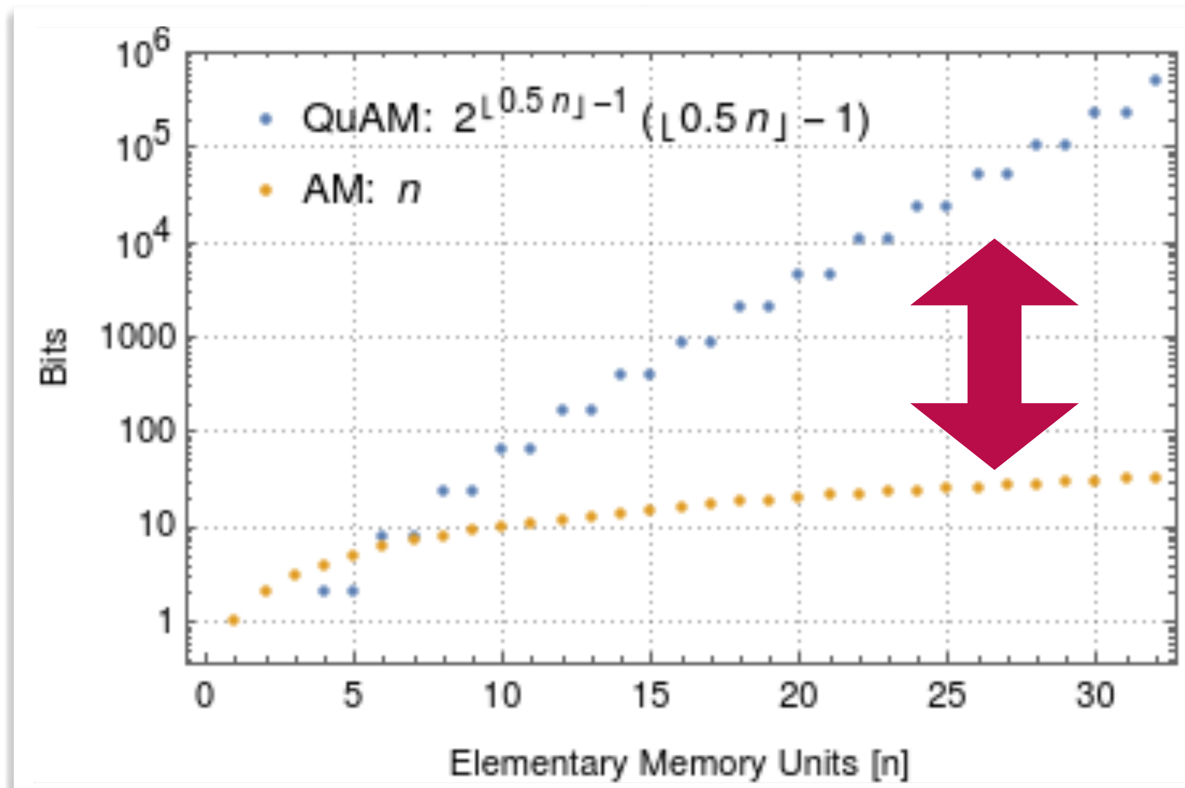
Zlokapa et al, arXiv: 1908.04475

Associative Memory



Inspired by ideas for hardware based track triggers

Memory required scales far more slowly with the number of tracks



Shapoval, arXiv:1902.00498

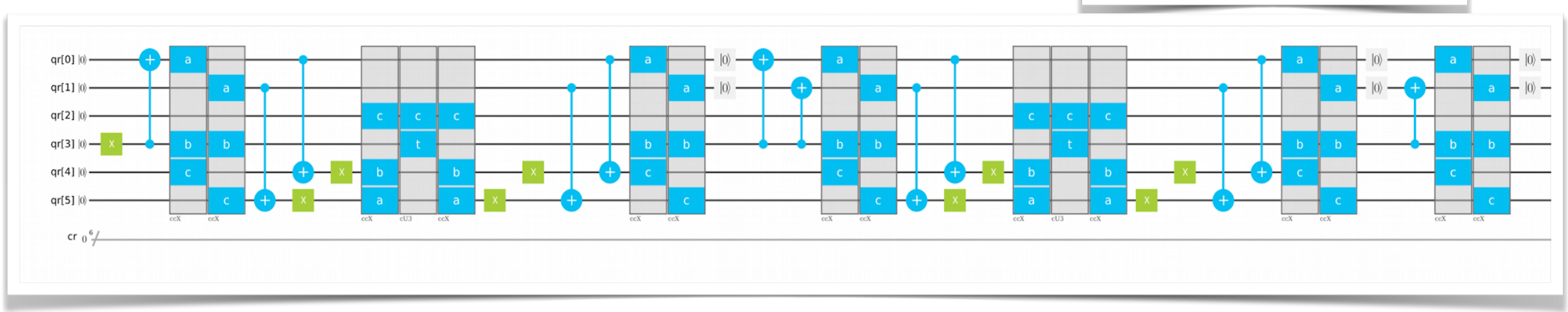
Slide credit: I. Shapoval

Implementation

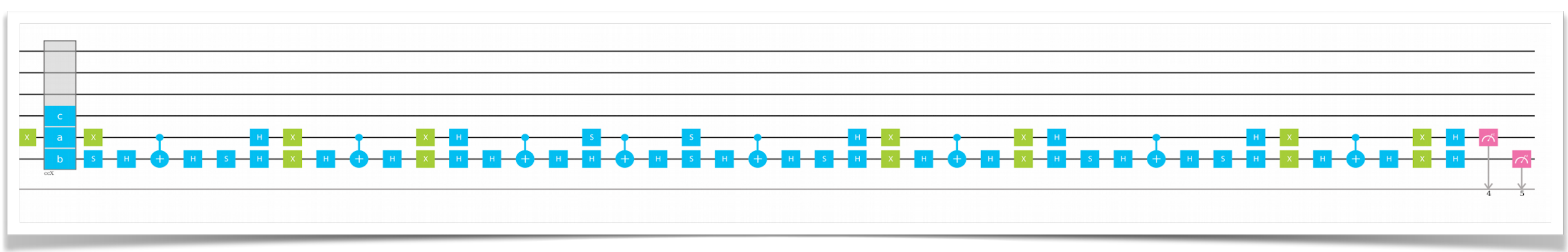
- QuAM circuit generators implementing the Trugenberger's initialization and generalized Grover's algorithms.
  - use open-source quantum computing platform, Qiskit
- Supported backends
  - IBM QE cloud-based quantum chips [5Q Yorktown/Tenerife, 14Q Melbourne, 20Q Tokyo]
  - Local/remote noisy simulators

```
OPENQASM 2.0;
include "qelib1.inc";
qreg qr[6];
creg cr[6];
x qr[3];
cx qr[3],qr[0];
ccx qr[0],qr[3],qr[4];
ccx qr[1],qr[3],qr[5];
cx qr[1],qr[5];
cx qr[0],qr[4];
x qr[5];
x qr[4];
ccx qr[5],qr[4],qr[2];
cu3(1.23095941734077,3.14159265358979,3.14159265358979) qr[2],qr[3]
ccx qr[5],qr[4],qr[2];
x qr[5];
x qr[4];
cx qr[1],qr[5];
cx qr[0],qr[4];
ccx qr[0],qr[3],qr[4];
ccx qr[1],qr[3],qr[5];
reset qr[0];
reset qr[1];
cx qr[3],qr[0];
```

Ex.: complete circuit for retrieving one 2-bit pattern



Ex.: complete circuit for retrieving one 2-bit pattern

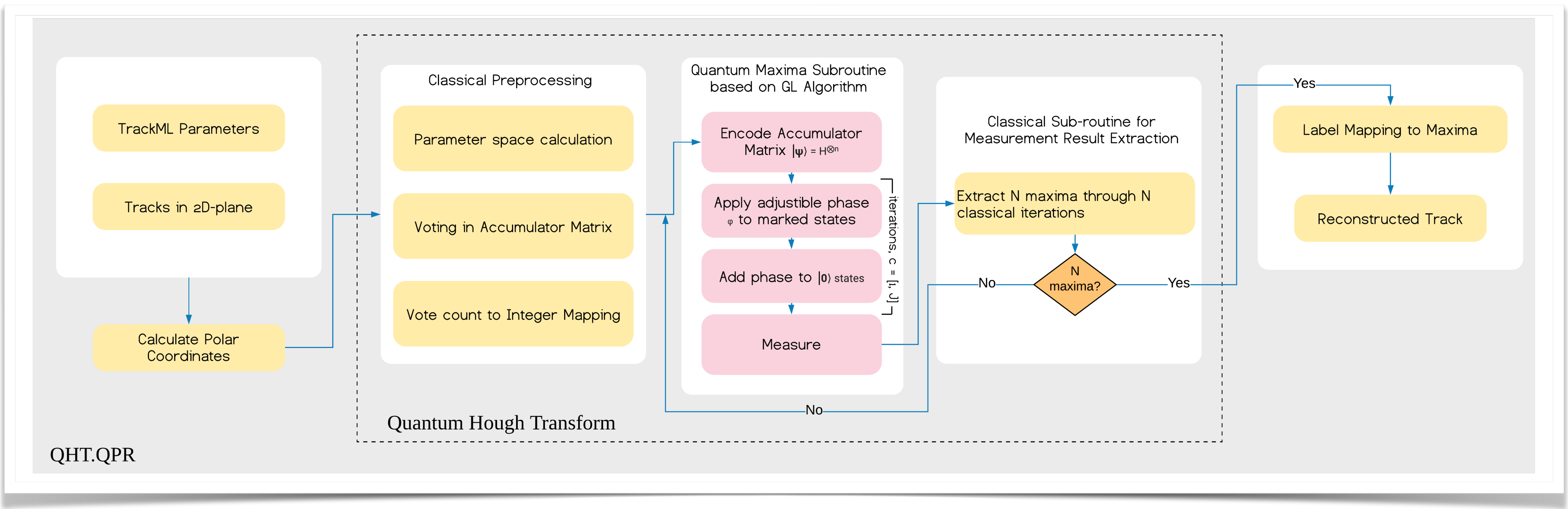


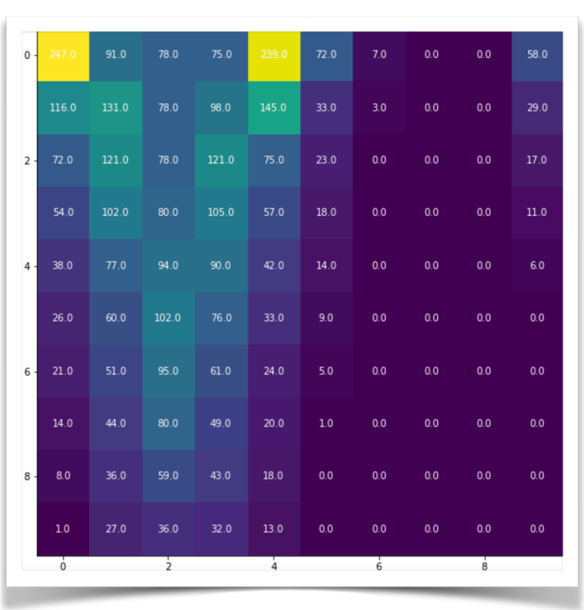
Shapoval et al, arXiv:1902.00498

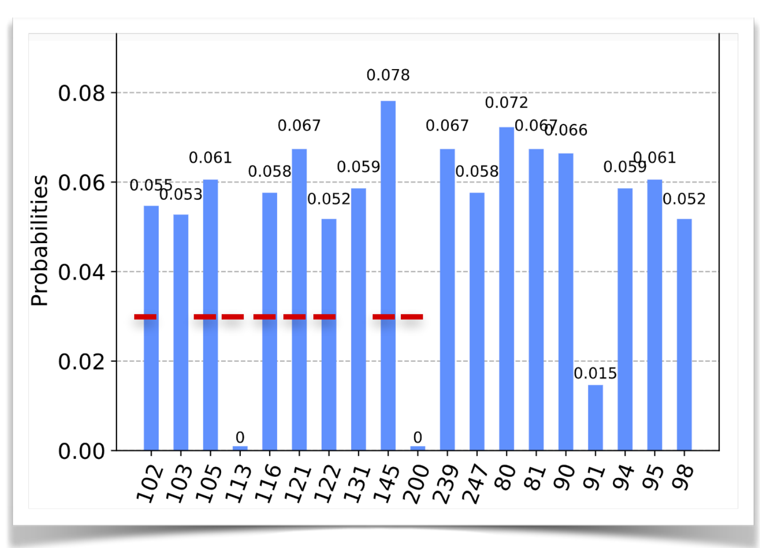
Slide credit: I. Shapoval

Quantum Hough Transform

Accumulator Space for 8 tracks







vote counts

Local Maxima Detection using Grover-Long Algorithm

```
track_index
```

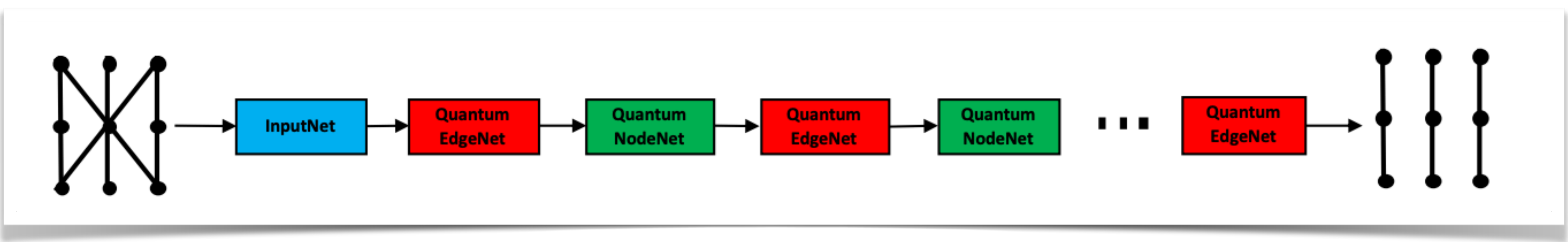
```
array([array([13, 19, 22, 28, 35, 48, 52]),
       array([ 2,  5, 16, 36, 40, 49]),
       array([23, 29, 30, 32, 43, 53, 54]),
       array([17, 18, 23, 30, 33, 39, 45, 50]),
       array([17, 18, 23, 29, 30, 33, 39, 50]),
       array([ 0,  9, 14, 34, 38, 42]), array([ 1, 11, 12, 20, 24, 27]),
       array([ 7,  8, 10, 37, 46, 57]), array([17, 23, 29, 30, 32, 54]),
       array([17, 29, 32, 43, 53, 54])], dtype=object)
```

Chen et al, arXiv:1908.07943

Slide Credit: A. Yadav

Quantum Graph Neural Networks

- GNNs for particle tracking are being developed by the Exa.TrkX collaboration
- Recent studies of the application of QGNNs to particle tracking
  - Hybrid quantum-classical algorithm
  - Encode the hit coordinates as angles
  - Iteratively apply quantum edge and node networks to propagate information to all detector layers
  - Final application of the edge network classifies the segments

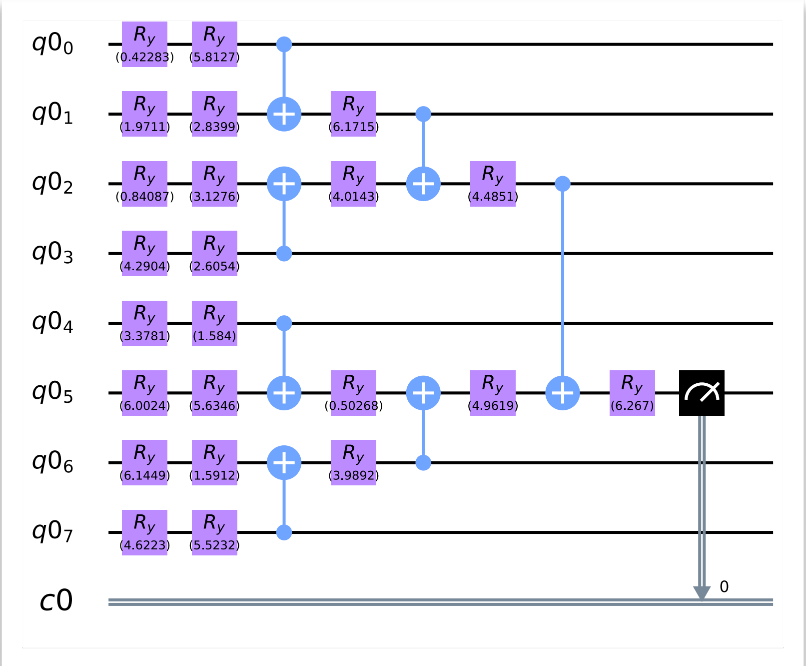


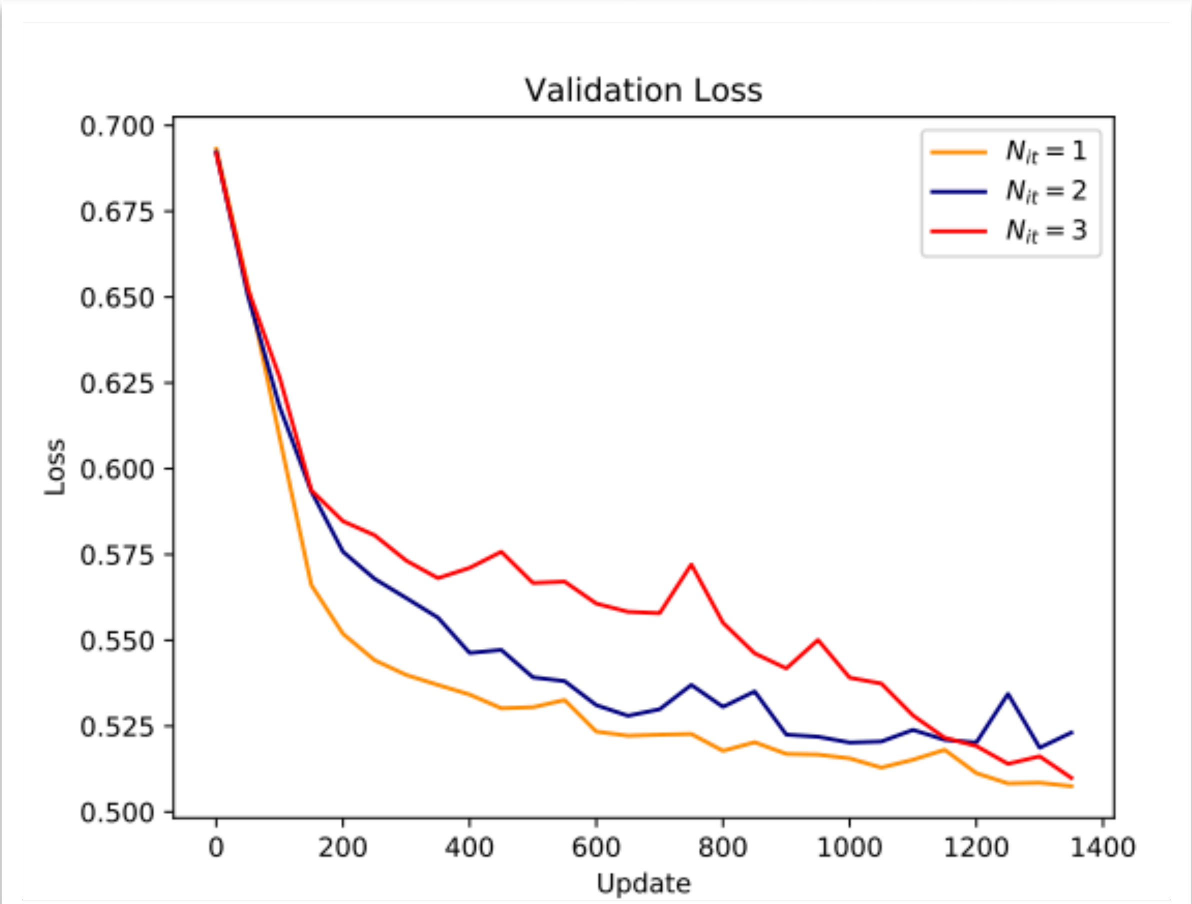
arXiv:2003.08126, arXiv:2007.06868.pdf, Talk by Tuysuz at CTD 2020

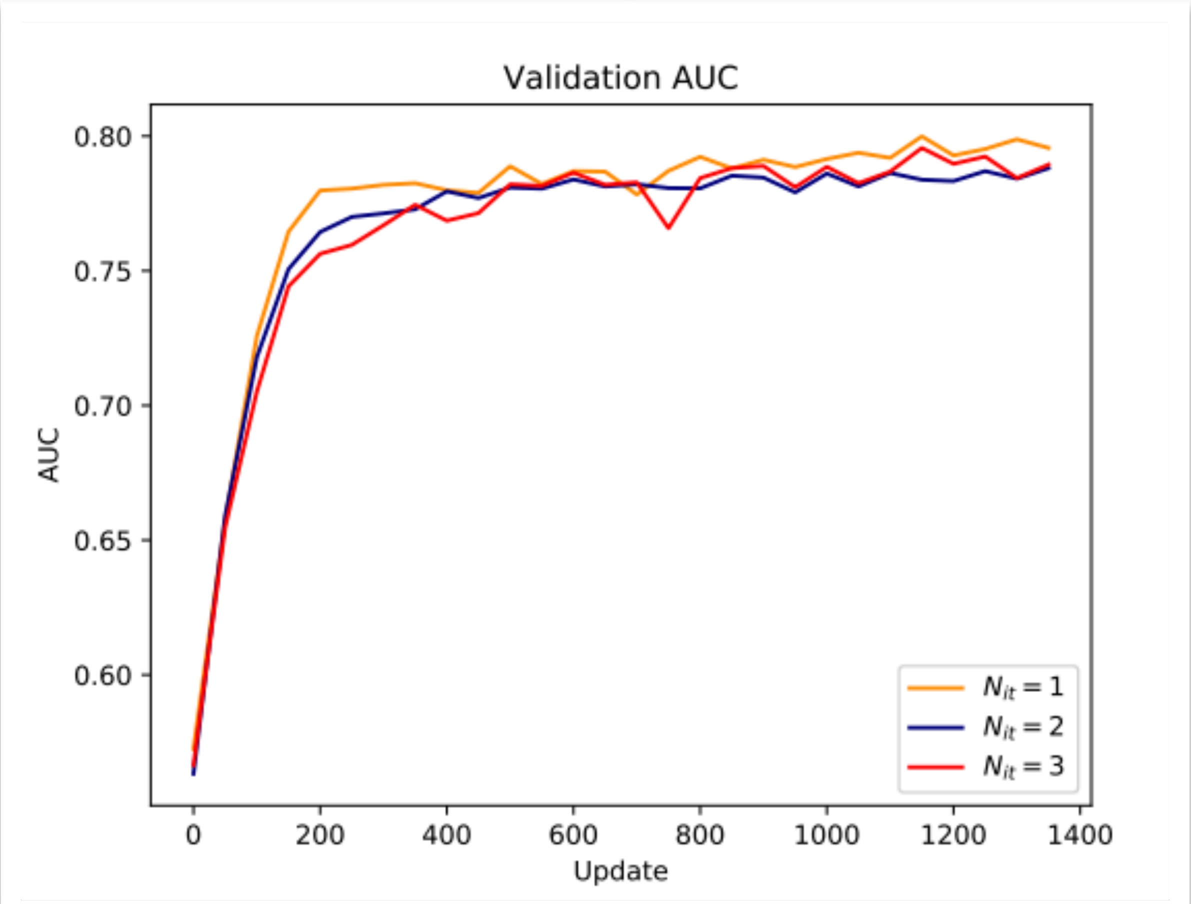
QGNN Results

Quantum edge network

- Obtains AUC on 0.8
- Performance decreases as number of iterations increases
  - Attributed to the limited statistics and network simplicity (100 events)

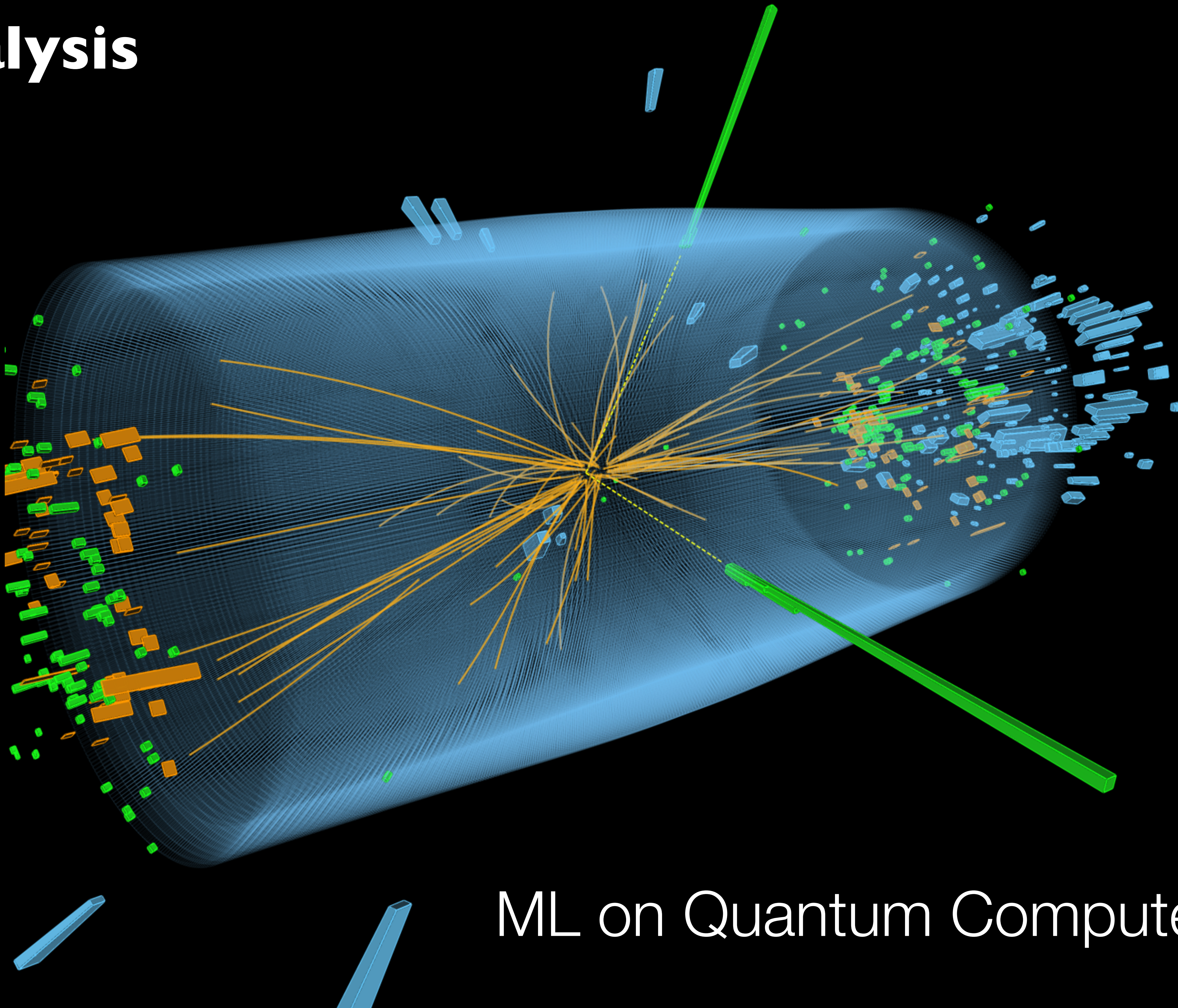






Tuysuz et al, arXiv:2007.06868

Analysis

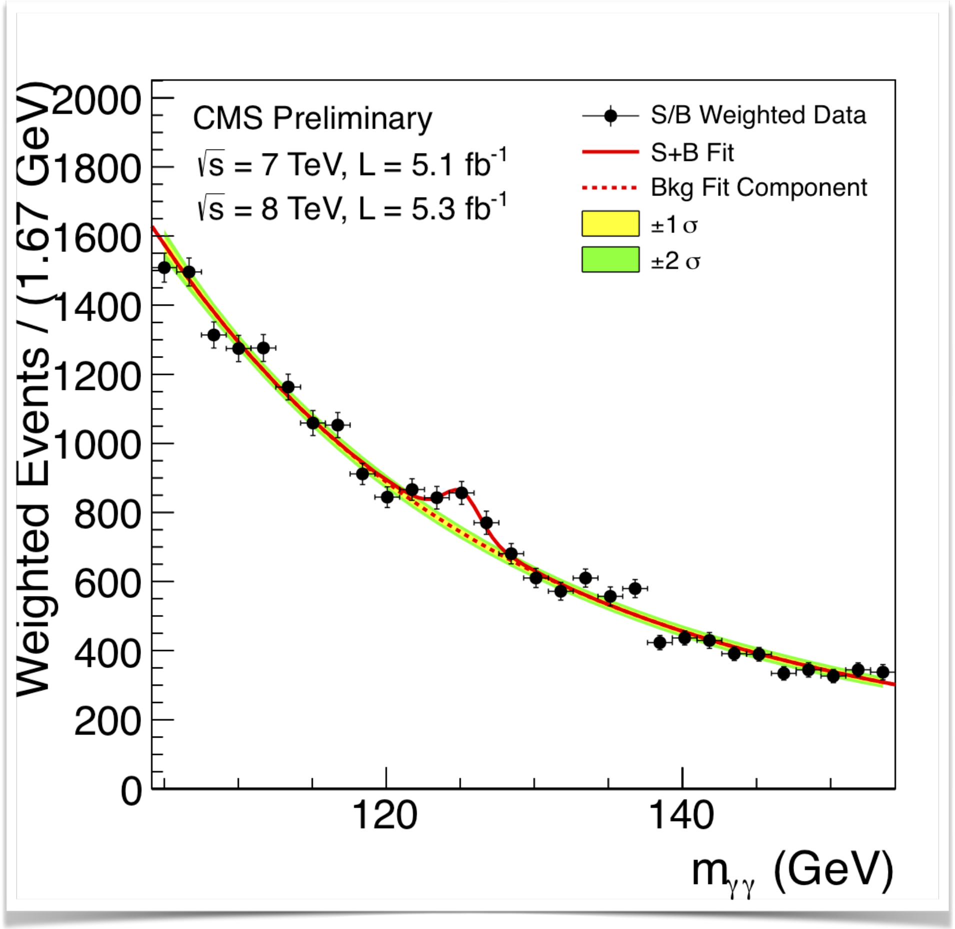


ML on Quantum Computers

Analysis

$H \to \gamma\gamma$

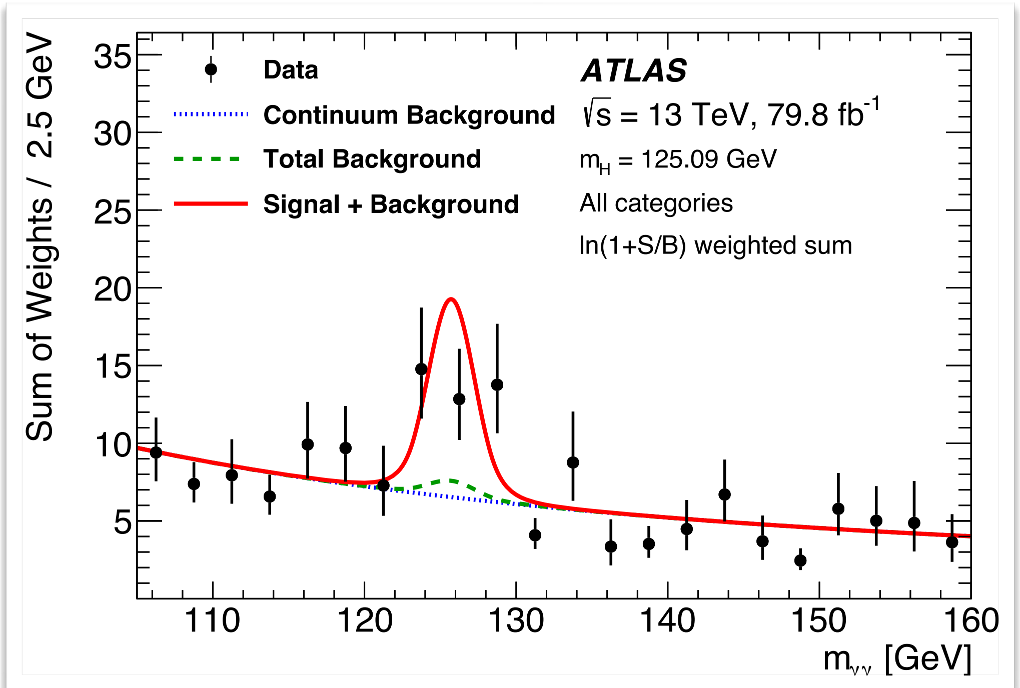
CMS, PLB 716, 30-61



Three Higgs analyses
One SUSY search

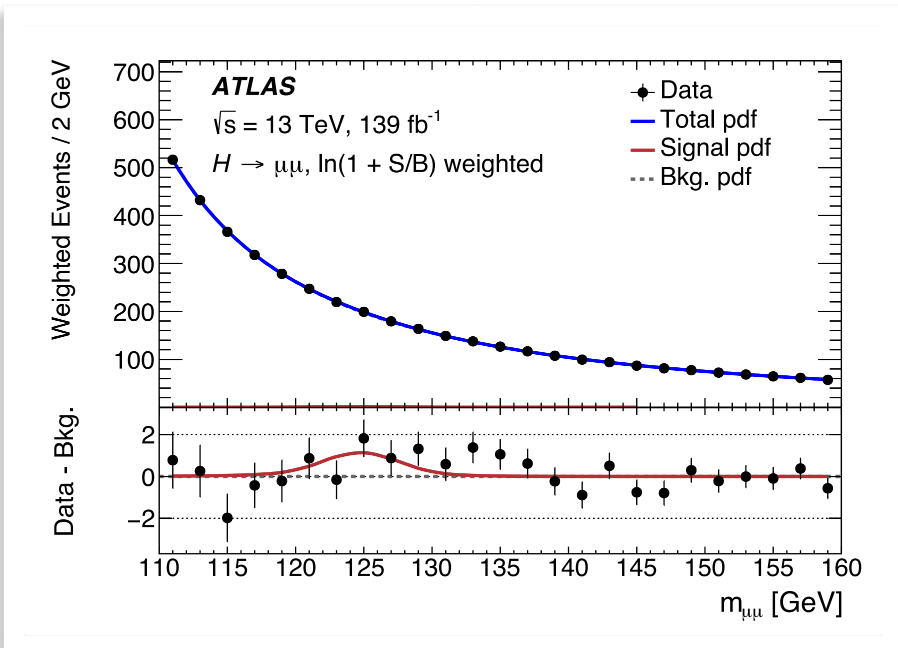
$ttH(H \to \gamma\gamma)$

ATLAS, PLB784 (2018) 173



$H \to \mu\mu$

ATLAS, PLB 812 (2021) 135980



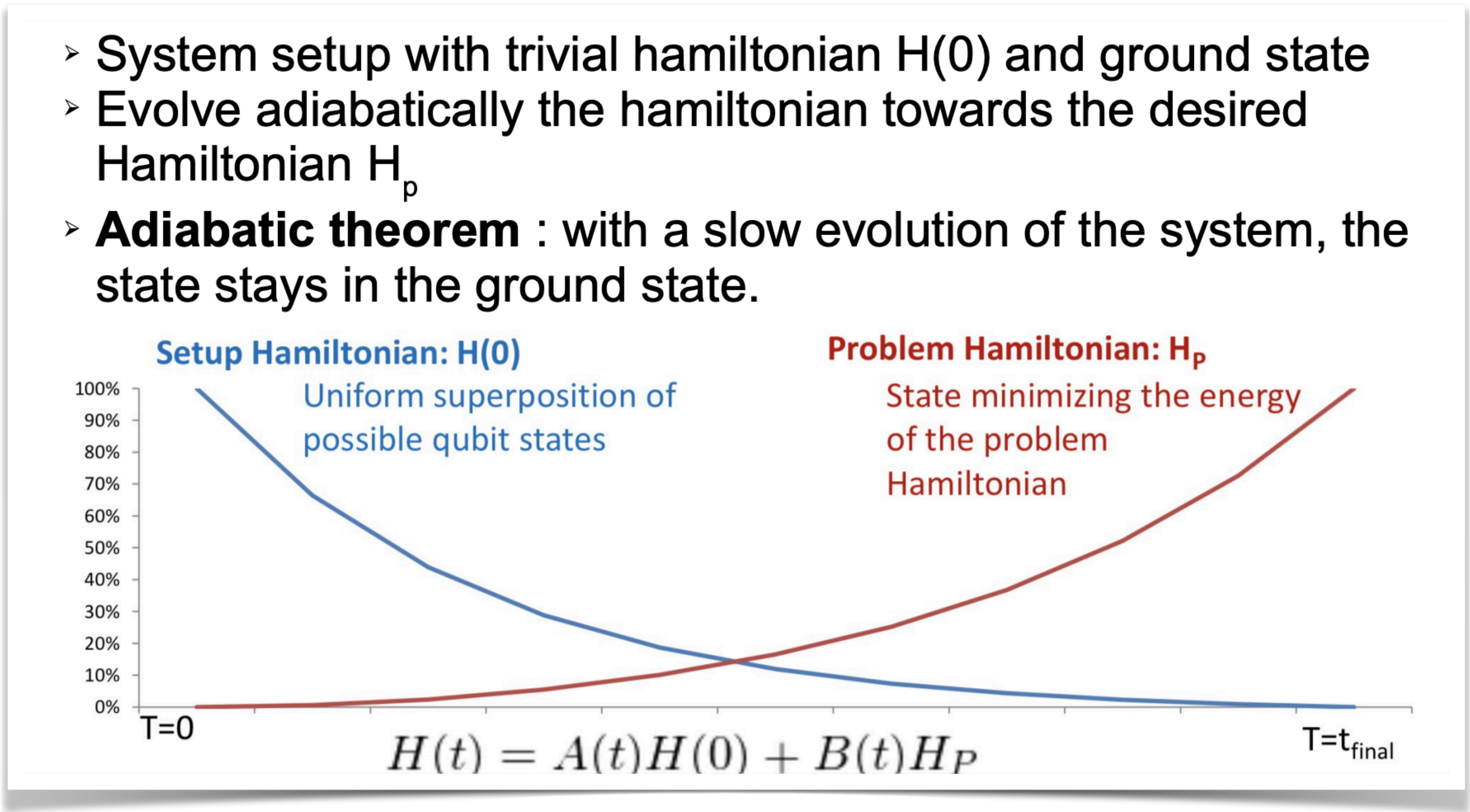
Quantum Machine Learning

- QML lies at the intersection between quantum computing and machine learning
- Usually, we're talking about using quantum computers to analyse classical data
- In many cases, the most promising methods are hybrid classical/quantum approaches
- Both quantum annealers and digital quantum computers have been explored
- Introductory QML textbook
- Recent review article about quantum machine learning in HEP
- Not trying to provide an overview here; rather trying to show examples of studies that have been performed

Don't fall for the hype! - Frank Zickert

Quantum Adiabatic Machine Learning

- CMS $H \to \gamma\gamma$ search using QAML [arXiv:0104129, arXiv:0001106] using DWave



- Pudenz et al, arXiv:1109.0325
  - Training: identify optimal set of weak classifiers to form strong classifier
  - Testing: evolve strong classifiers to identify anomalous elements

Slide Credit, J.R. Vlimant

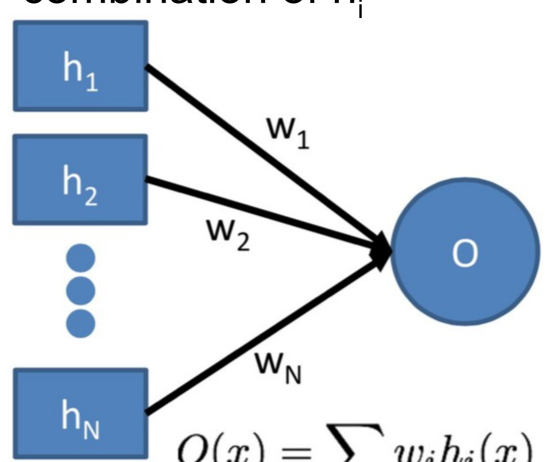
QAML for $H \rightarrow \gamma\gamma$

Classifier Definition

Define functions **h**$_i$ of the input variables into [-1,1] such that
- P(signal|h>0) > P(bkg|h>0)
- P(bkg|h<0) > P(signal|h<0)

i.e. Most signal on h>0, most bkg on h<0

Define w$_i$ as binary linear combination of h$_i$



$$O(x) = \sum_i w_i h_i(x)$$

QUBO Definition

$$\delta(\vec{w}) \propto \sum_{i,j} C_{ij} w_i w_j + \sum_i (\lambda - 2C_{iy}) w_i$$

Simple conversion of binary weights to ±1

$$H_{\text{Ising}} = \sum_i h_i \sigma_i^z + \sum_{ij} J_{ij} \sigma_i^z \sigma_j^z$$

Objective Definition

Define as a "target" function

$$y(x) = \begin{cases} +1, & \text{if } \in S, \\ -1, & \text{if } \in B \end{cases}$$

Per event error

$$E(x) = y(x) - \sum_{i=1}^{N} w_i h_i(x)$$

Full error

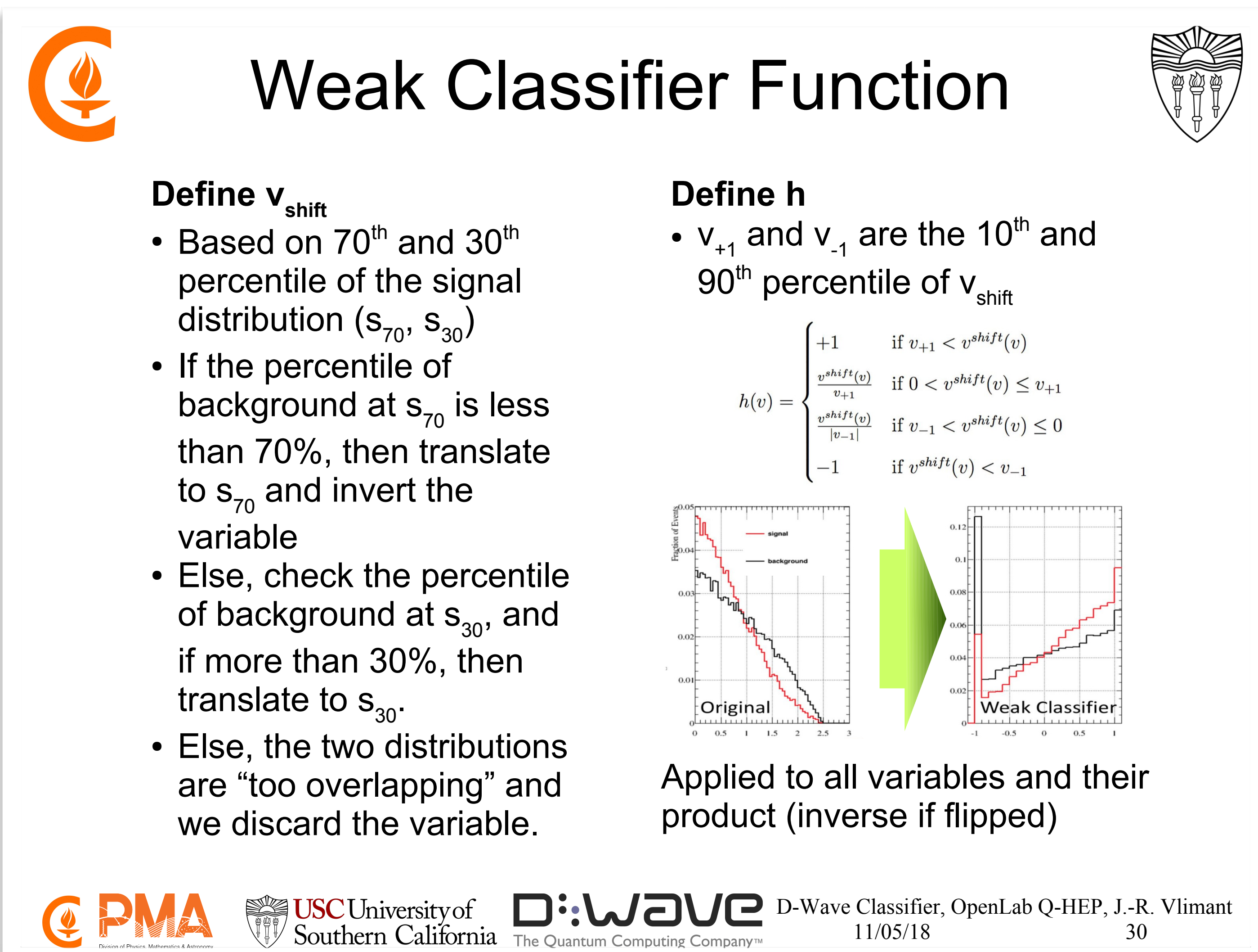
$$\delta(\vec{w}) \propto \sum_{i,j} C_{ij} w_i w_j + \sum_i (\lambda - 2C_{iy}) w_i$$

- C_{ij} and C_{iy} are summations over the values of h_i over the training set
- λ is a parameter penalizing the number of non-zero w_i

Slide Credit, J.R.Vlimant

$H \to \gamma\gamma$ Setup

- Dataset: 300k signal; 300k background events
- Training: subsets ranging from 100 to 20k events
- Testing: 100k signal; 100k background
- Key discriminating variables (photon momentum, invariant mass, etc)



- Train classical classifiers as a baseline measurement of performance.
- Evaluate the exact solution of the problem using simulating annealing of the Ising model.
- Scan for λ, penalty on number of weak classifiers.
- Classification performance depending on the size of the training set.
- Scan on the fraction of exited states included in the classifier.

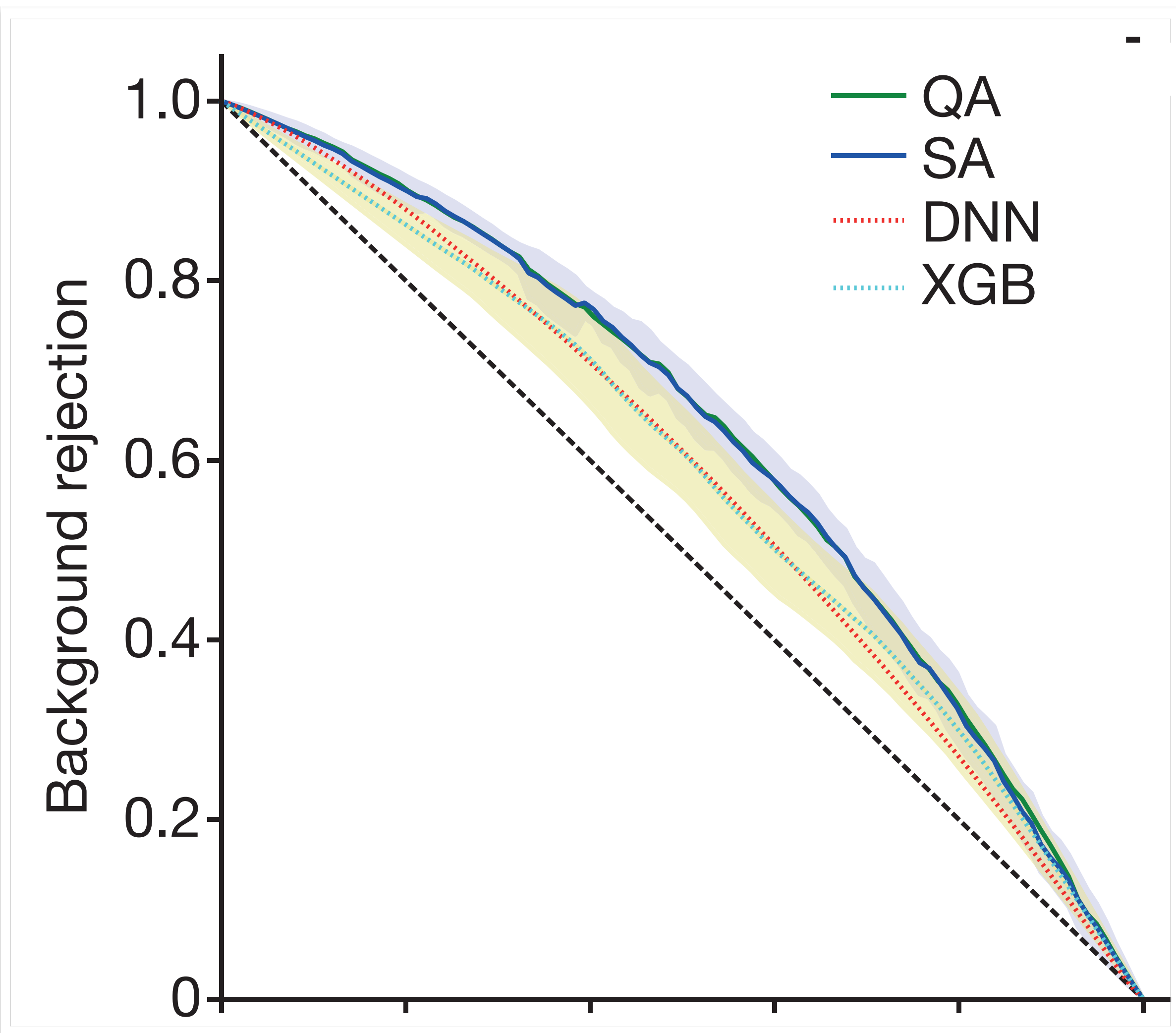
Slide Credit, J.R.Vlimant

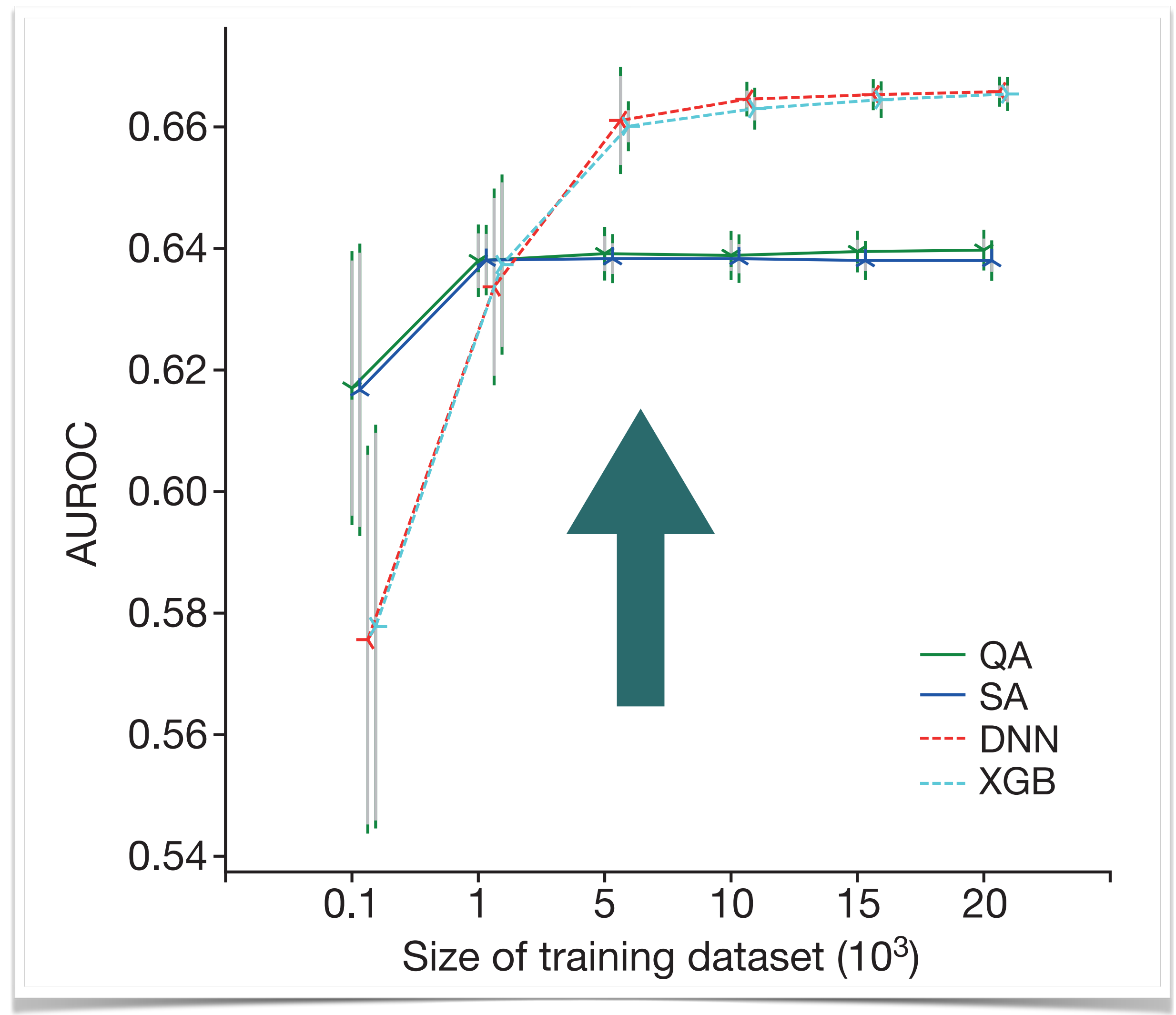
$H \to \gamma\gamma$ Results

doi:10.1038/nature24047

Solving a Higgs optimization problem with quantum annealing for machine learning

Alex Mott[1]†*, Joshua Job[2,3]*, Jean-Roch Vlimant[1], Daniel Lidar[3,4] & Maria Spiropulu[1]

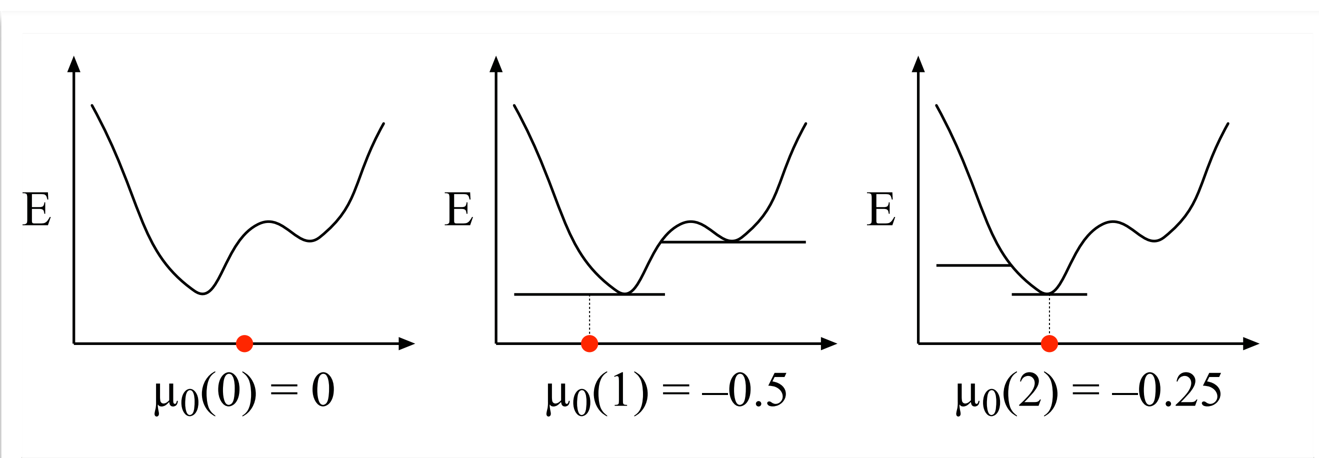




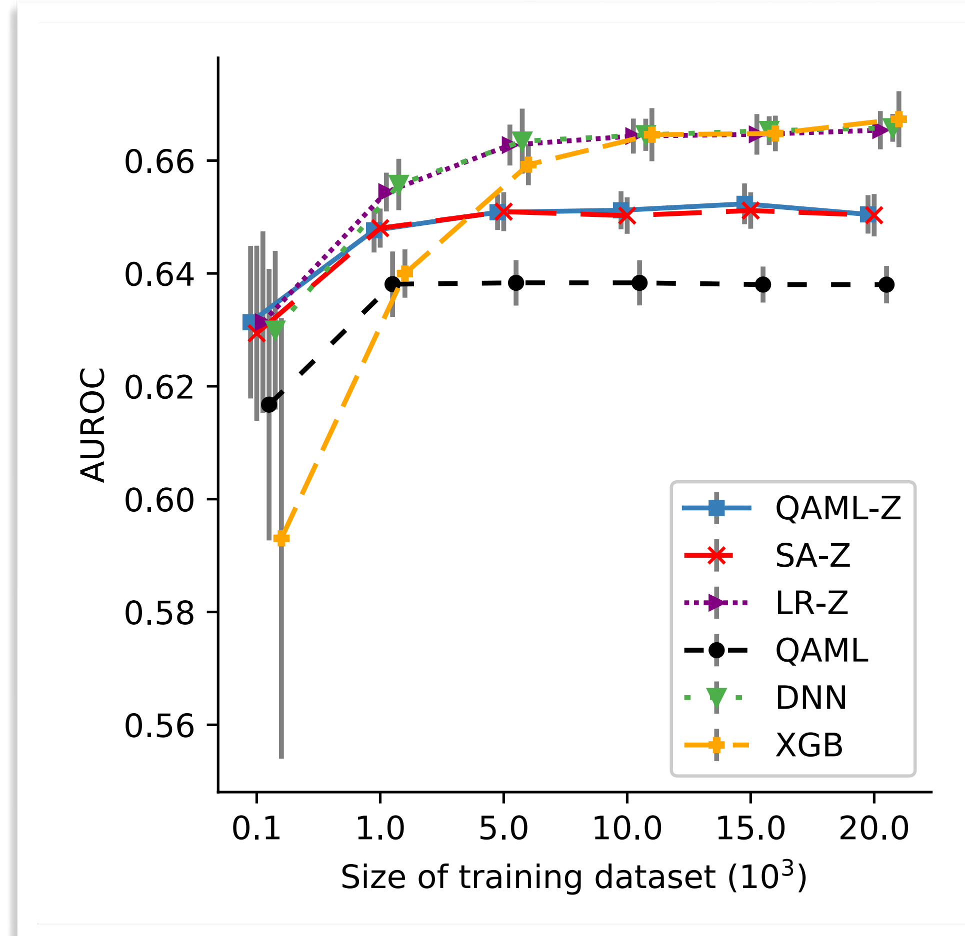
Mott, et al, doi:10.1038/nature24047

QAML with Zooming

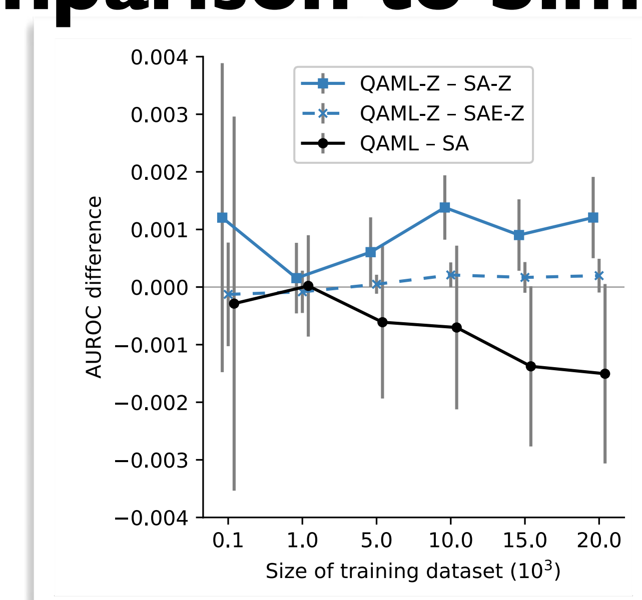
- Recent extension to these results with the introduction of QAML with zooming
- Idea: Iteratively perform QA to obtain the weights on the weak classifiers continuous
    - Binary search over energy surface using spin up/down outcomes



Results for $H \to \gamma\gamma$ on DWave 2X



Comparison to Simulation



Zlokapa et al, arXiv: 1908.04480

$ttH(H \rightarrow \gamma\gamma)$ and $H \rightarrow \mu\mu$ with ATLAS

Our program with Quantum Machine Learning

Our Goal:

To perform LHC High Energy Physics analysis with Quantum Machine Learning, to explore and to demonstrate that the potential of quantum computers can be a new computational paradigm for big data analysis in HEP, as a proof of principle

Our present program is to employ the following 3 quantum machine learning methods

1. Variational Quantum Classifier Method
2. Quantum Support Vector Machine Kernel Method
3. Quantum Neural Network Method

to LHC High Energy Physics analysis, for example ttH ($H \rightarrow \gamma\gamma$) and $H \rightarrow \mu\mu$ (two LHC flagship analyses).

Sau Lan Wu (U. Wisconsin) QuantHEP Seminar November 4, 2020 5

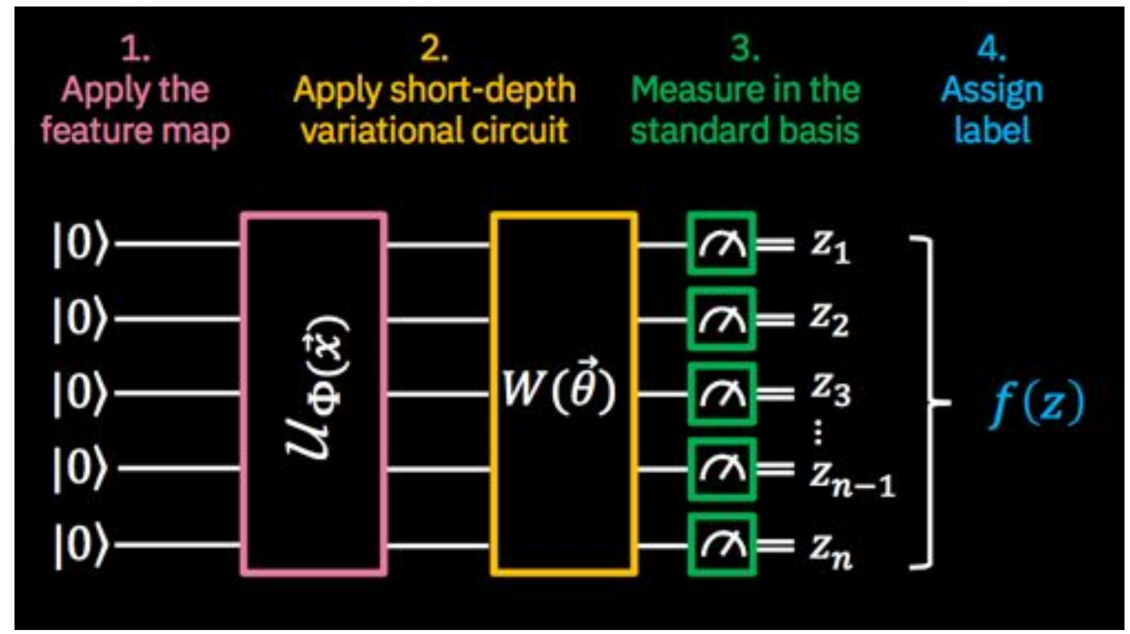
Typically used 100 events and 10 variables

Slide Credit, S.L.Wu

Variational Quantum Classifier

Method 1: Variational Quantum Classifier (VQC)

- 1. Apply feature map circuit $U_{\Phi(\vec{x})}$ to encode input data $\vec{x}$ into quantum state $|\Phi(\vec{x})\rangle$
- 2. Apply short-depth quantum variational circuit W(θ) which is parameterized by gate angles θ
- 3. Measure the qubit state in the standard basis (standard basis: $|0\rangle$, $|1\rangle$ for 1 qubit; $|00\rangle$, $|01\rangle$, $|10\rangle$, $|11\rangle$ for 2 qubits; ...)
- 4. Assign the label ("signal" or "background") to the event through the action of a diagonal operator f in the standard basis

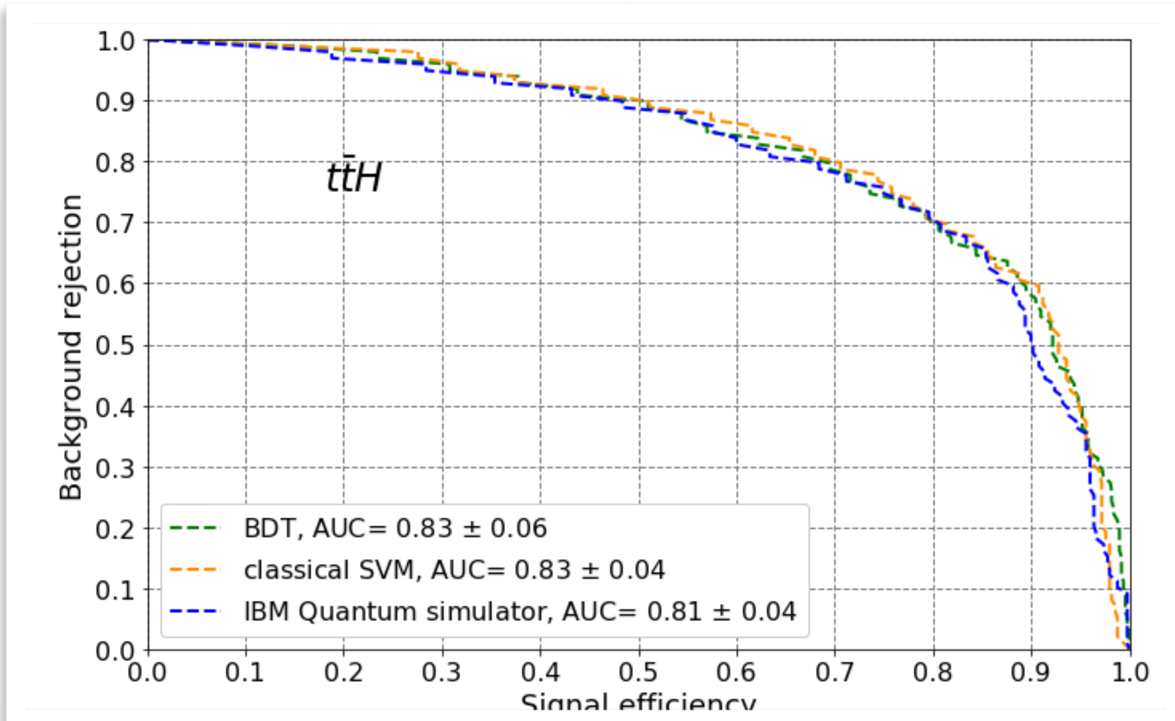


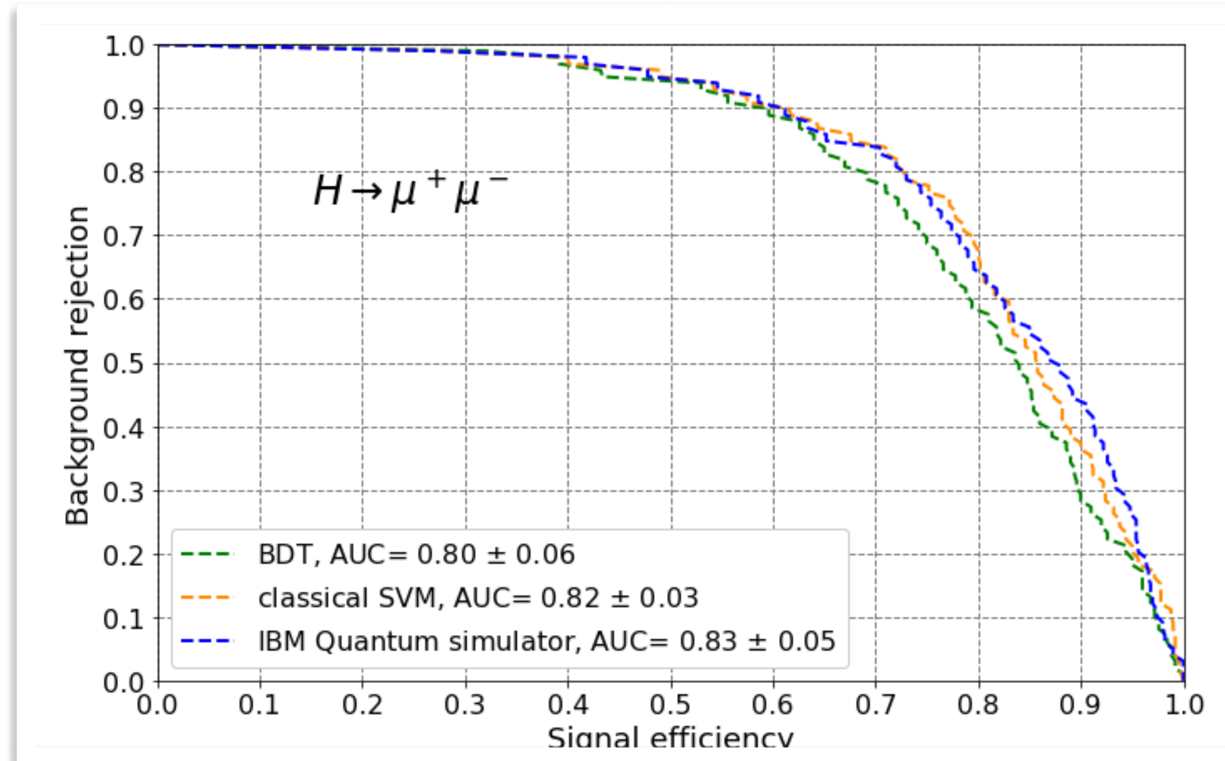
- During the training phase, a set of events are used to train the circuit W(θ) to reproduce correct classification
- Using the optimized W(θ), an independent set of events are used for evaluation and testing

Slide Credit, S.L Wu ; arXiv:2012.11560.pdf

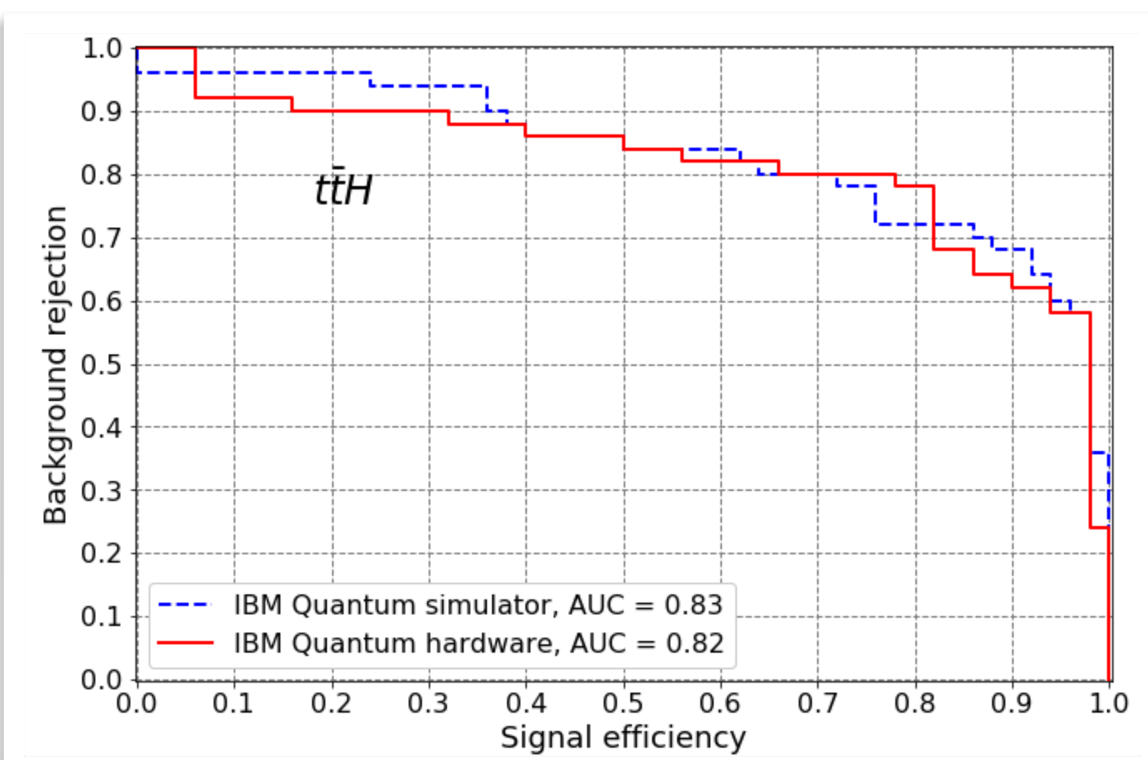
VQC Results

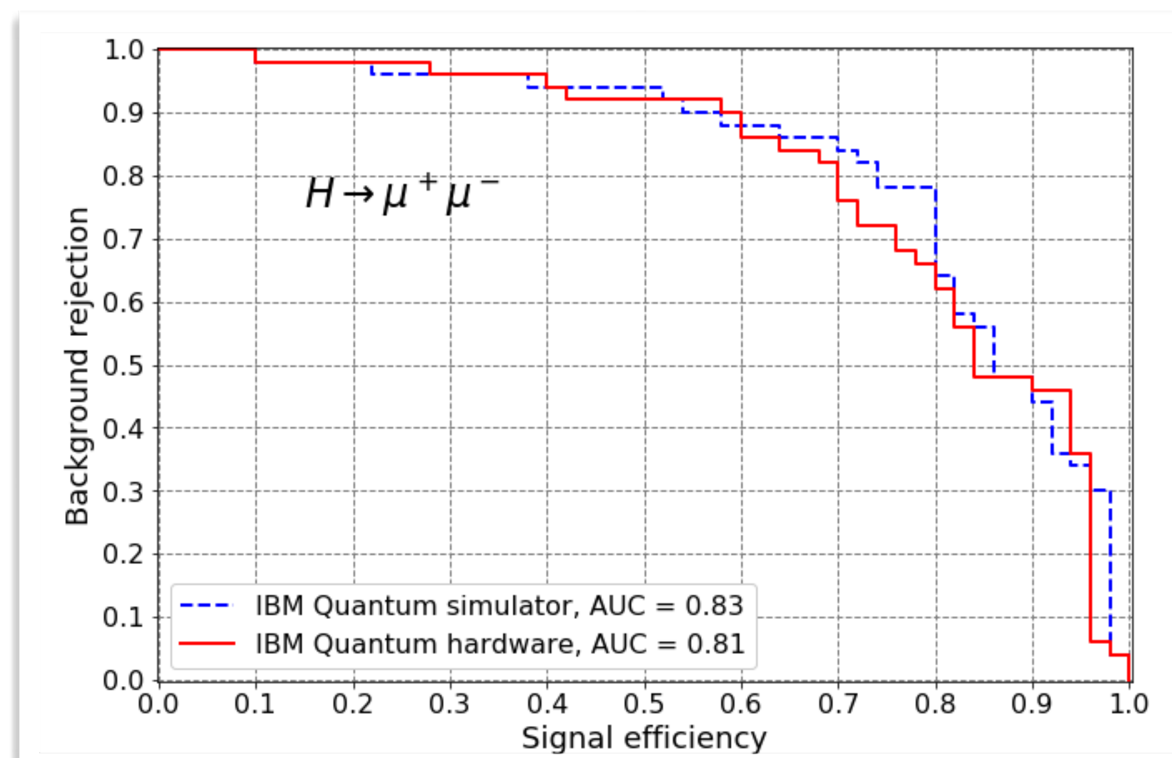
Similar performance to classical methods





Good agreement between simulation and hardware





arXiv:2012.11560.pdf

Quantum SVM Kernel Method

Method 2: Quantum SVM Kernel method

- ***Quantum SVM Kernel method*** *(introduced by IBM, published in Nature 567 (2019) 209):*
  - *map classical data $\vec{x}$ to a quantum state $|\Phi(\vec{x})\rangle$ using a Quantum Feature Map function;*
  - *calculate the similarity between any two data events ("kernel entry") as $K(\vec{x}_1,\vec{x}_2)=|\langle\Phi(\vec{x}_1)|\Phi(\vec{x}_2)\rangle|^2$ using a quantum computer;*
  - *then using the kernel entries to find a separating hyperplane that separates signal from background.*

map classical data

$\vec{x}_1 \rightarrow |\Phi(\vec{x}_1)\rangle$

$\vec{x}_2 \rightarrow |\Phi(\vec{x}_2)\rangle$

$\vec{x}_3 \rightarrow |\Phi(\vec{x}_3)\rangle$

...

calculate kernel entries

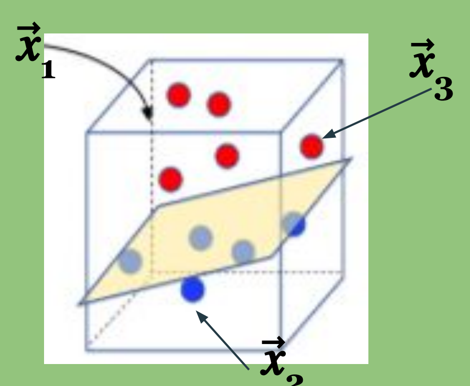
$K(\vec{x}_1,\vec{x}_2)=|\langle\Phi(\vec{x}_1)|\Phi(\vec{x}_2)\rangle|^2$

$K(\vec{x}_1,\vec{x}_3)=|\langle\Phi(\vec{x}_1)|\Phi(\vec{x}_3)\rangle|^2$

$K(\vec{x}_2,\vec{x}_3)=|\langle\Phi(\vec{x}_2)|\Phi(\vec{x}_3)\rangle|^2$

...

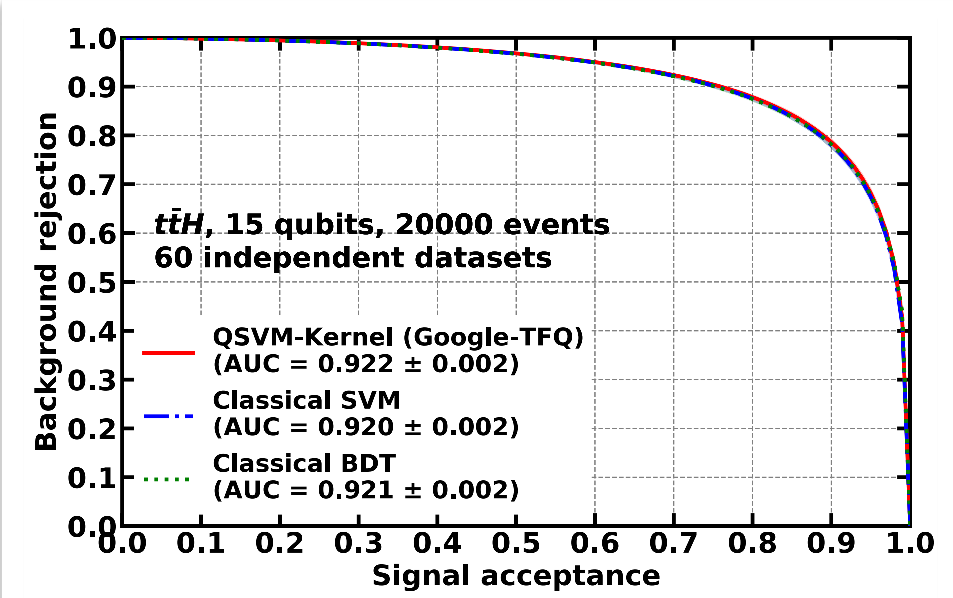
find separating hyperplane

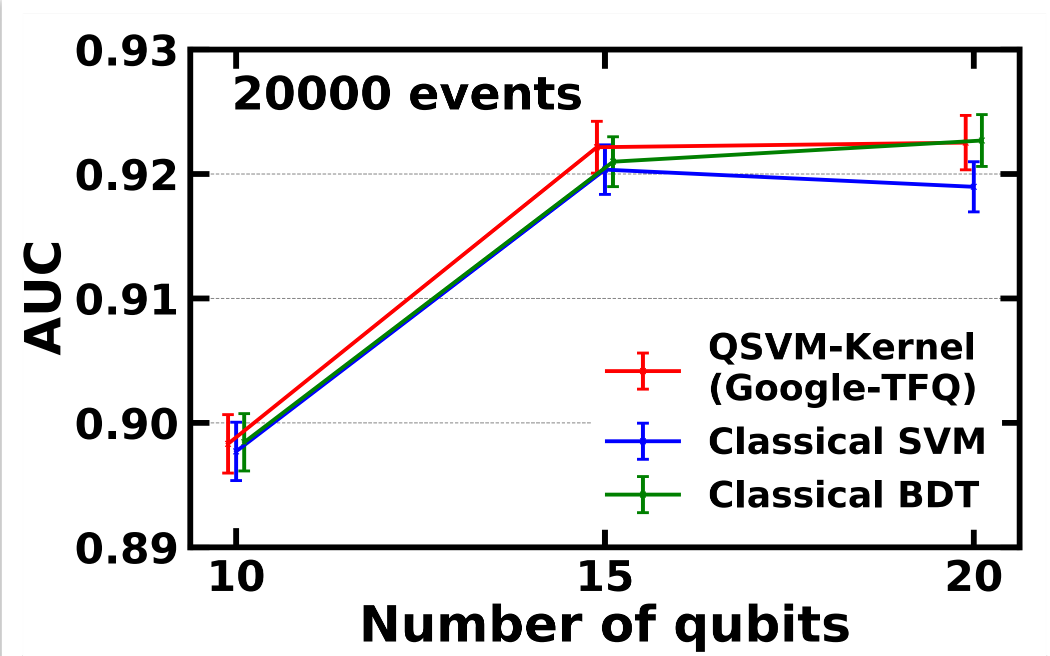


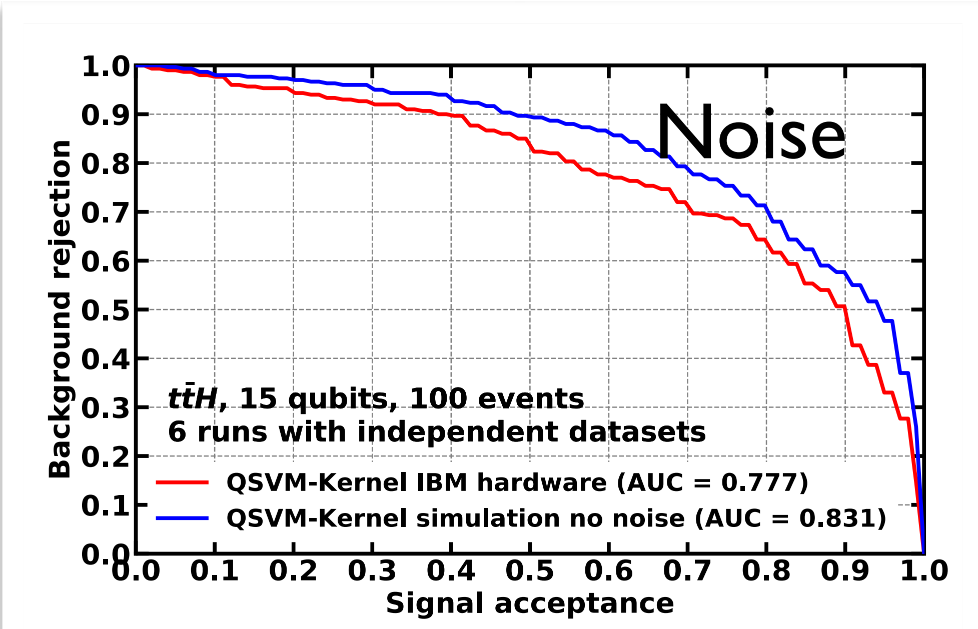
Slide Credit, S.L.Wu

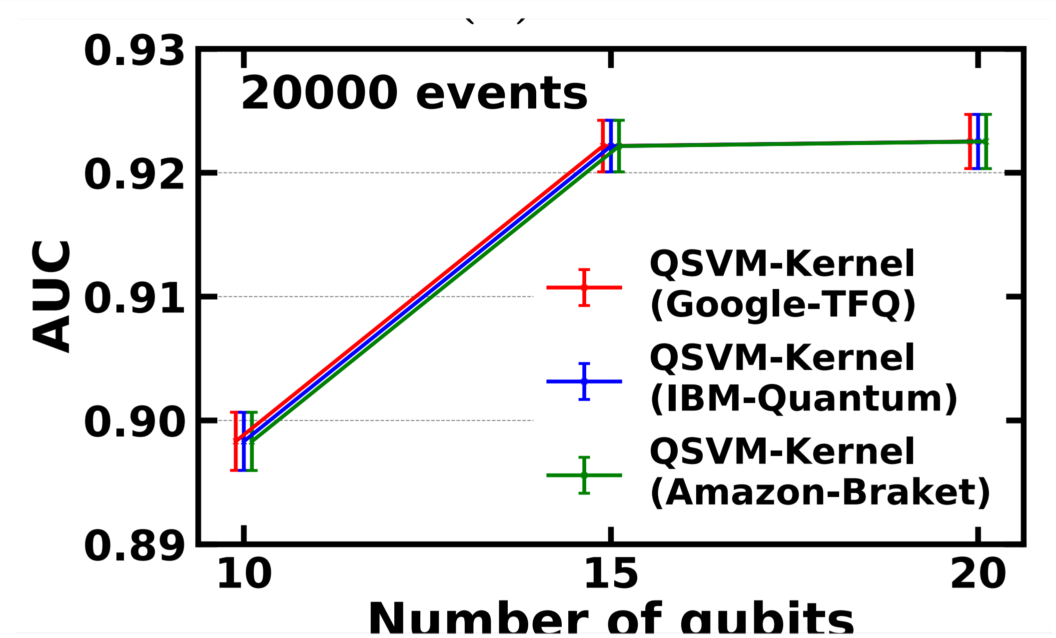
QSVM Results

- Improved performance over classical methods
- Good agreement between simulation and hardware
- Impact from noise in the hardware observed







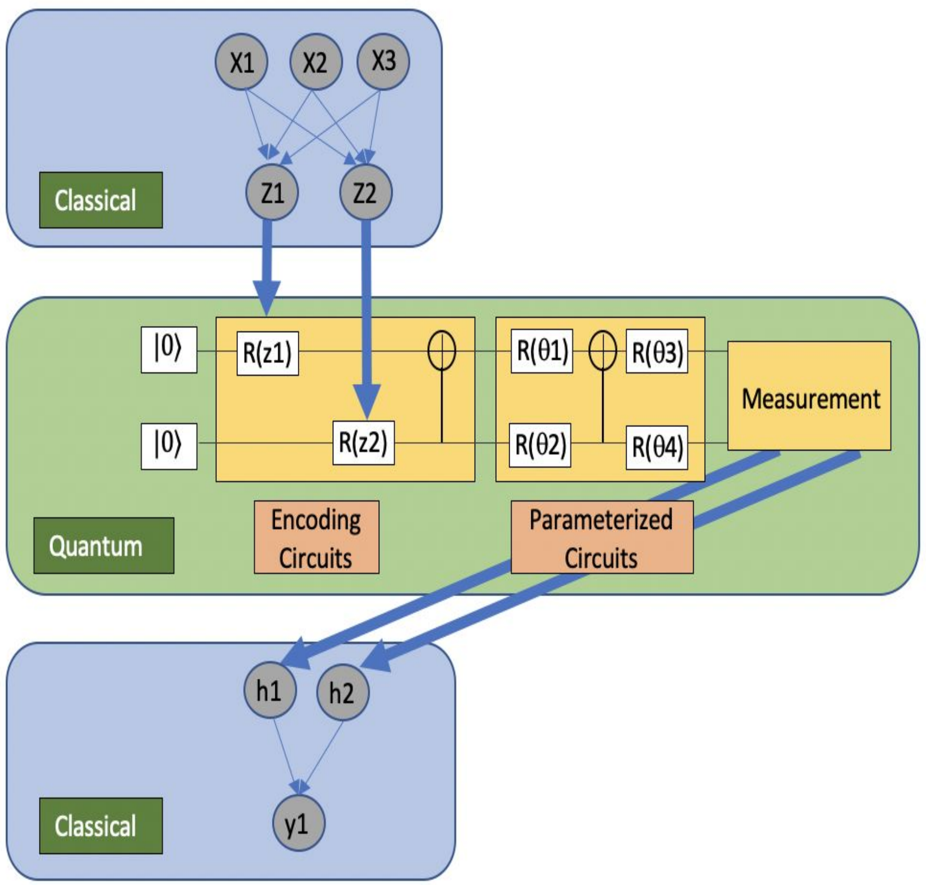


Material courtesy of S.L. Wu, publication coming soon

Hybrid Quantum Neural Network

Method 3: Hybrid Quantum Neural Network (QNN)

We have been developing a hybrid QNN of three layers:



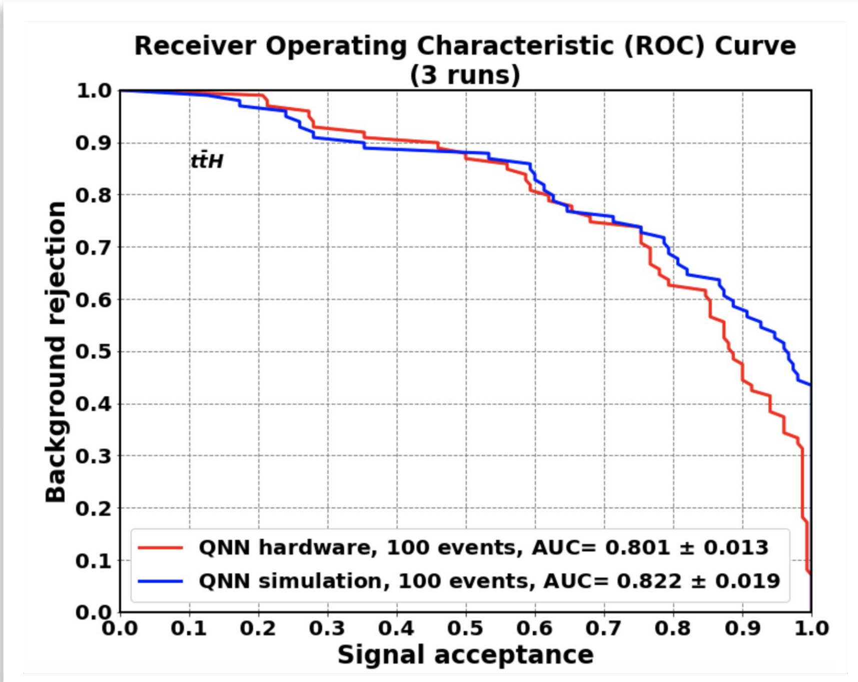
- ***Classical layer 1: transform input data so that its number of outputs matches number of qubits (PCA is no longer necessary)***
- ***Quantum layer (the core part): encode classical data into a quantum state, apply variational circuit containing trainable parameters, measure the quantum state***
- ***Classical layer 2: convert the measurement of qubits to classification labels***

Three layers are trained together to maximize the overall performance

Slide Credit, S.L. Wu

QNN Results

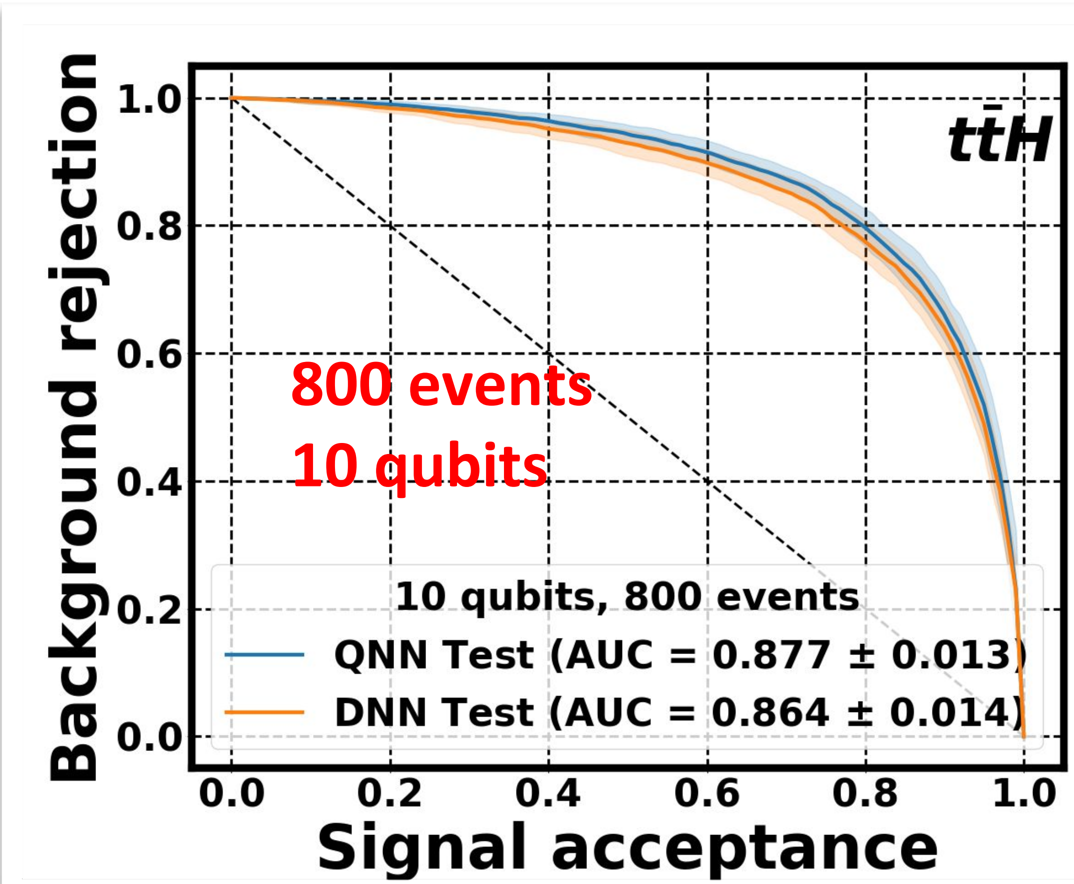
IBM hardware

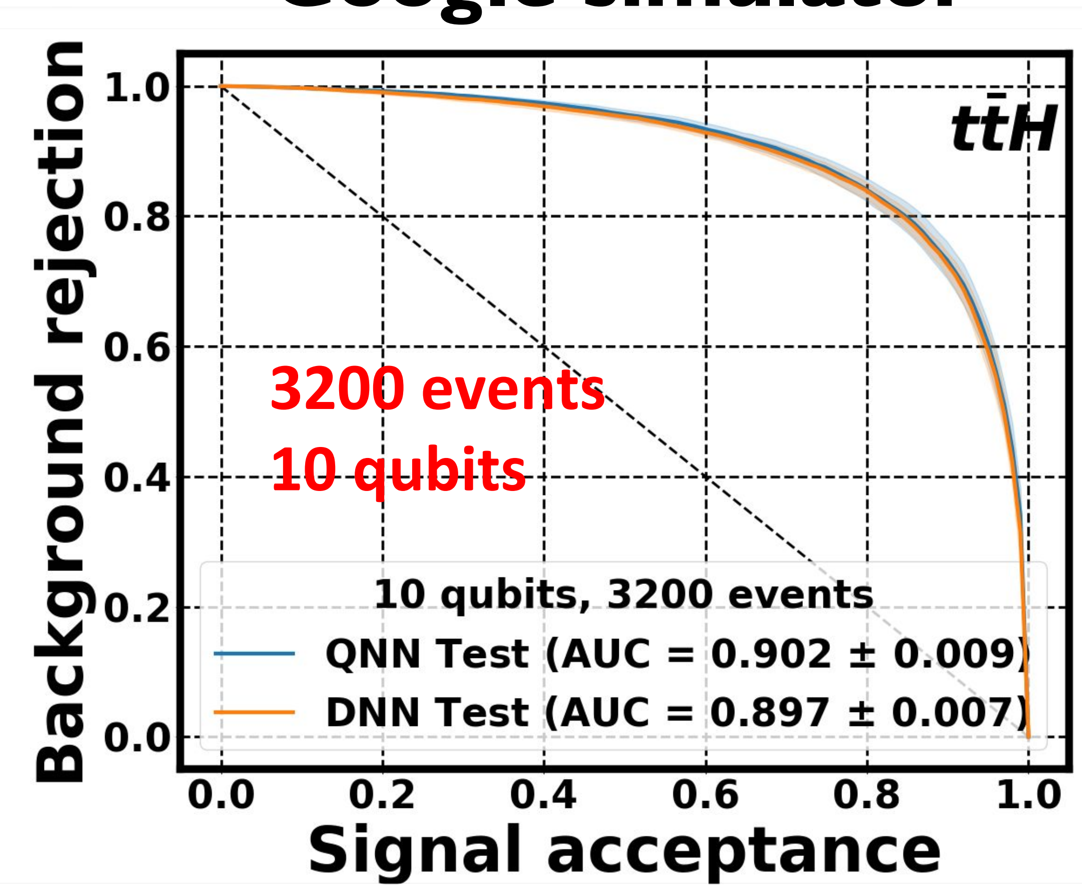


Slightly worse on IBM hardware than in simulation

In simulation, QNN has slightly better performance than DNN

Google simulator





Slide Credit, S.L. Wu

Comparison of different ML methods

ttH (H->$\gamma\gamma$)	VQC IBM simulator	QSVM Kernel IBM simulator	QSVM Kernel Amazon simulator	QNN Google simulator	QNN Google simulator
AUC	0.83 (100 events 10 qubits)	0.89 (3200 events 10 qubits)	0.89 (3200 events 10 qubit)	0.90 (3200 events 10 qubits)	0.93 (~0.5 million events 13 qubits)

~9.2 w 20k events, 20 qubits

In most cases, the performance already exceeds the reference classical algorithms

Significant variation between the different ML approaches. Best performance obtained using a QNN on a google simulator with 13 qubits

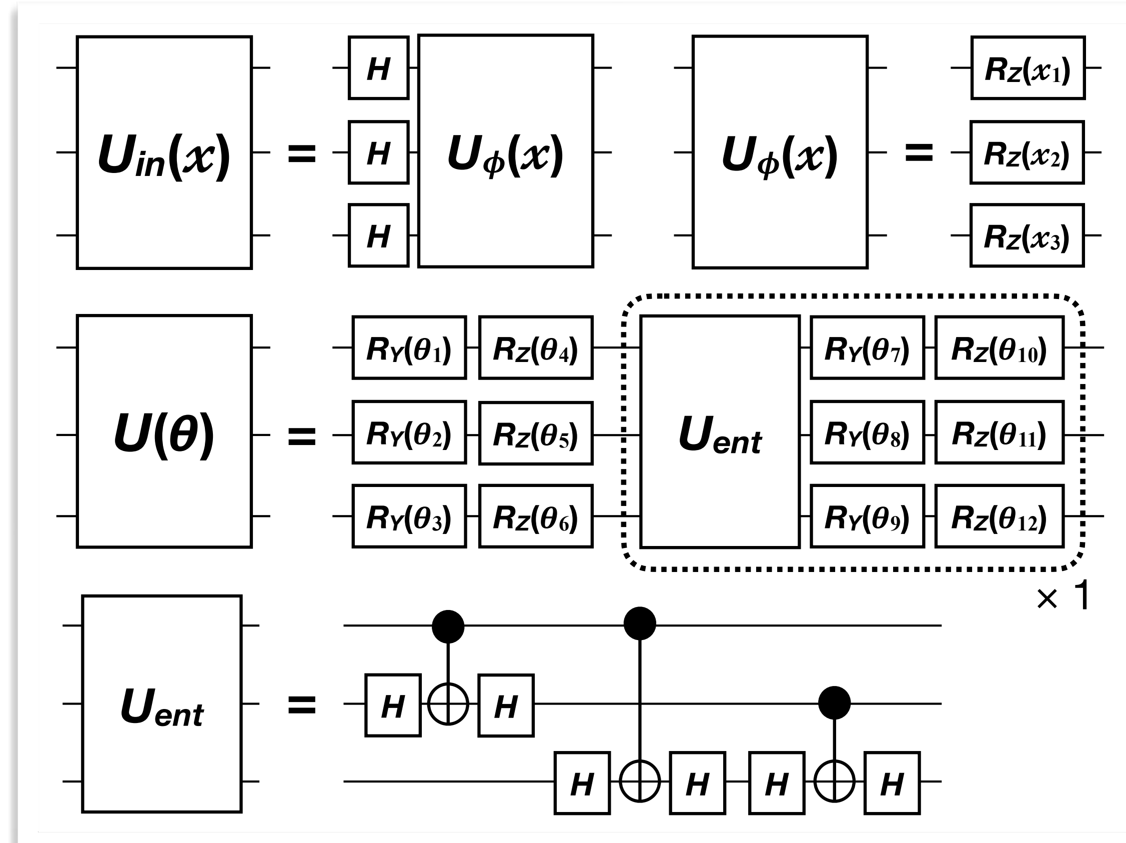
Slide Credit, S.L. Wu

QML for SUSY Studies

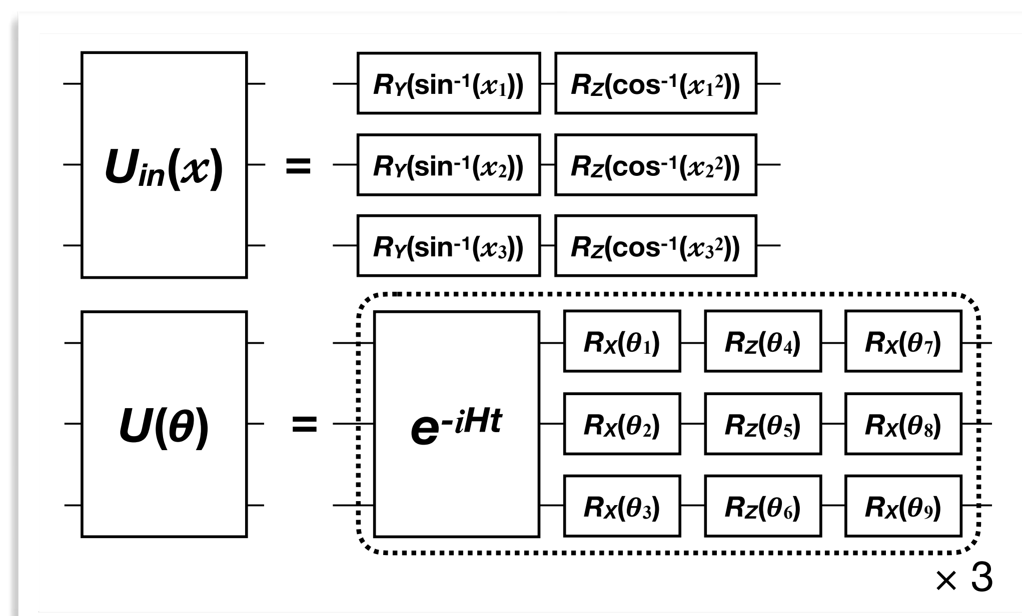
- Variational Quantum Circuit (VQC)
  - Same method as Wu et al
- Quantum Circuit Learning (QCL)
  - Classical-quantum hybrid for low-depth circuit learning
  - Input data and iteratively tune the circuit parameters to obtain the desired output
  - Output calculation on QC, parameter turning on CC
- Search for chargino pair production via a Higgs boson using SUSY dataset from UCI ML repository (2l + MET)
- 100-10k events; 3-7 variables

Terashi et al, arXiv:2002.09935.pdf

VQC Circuit



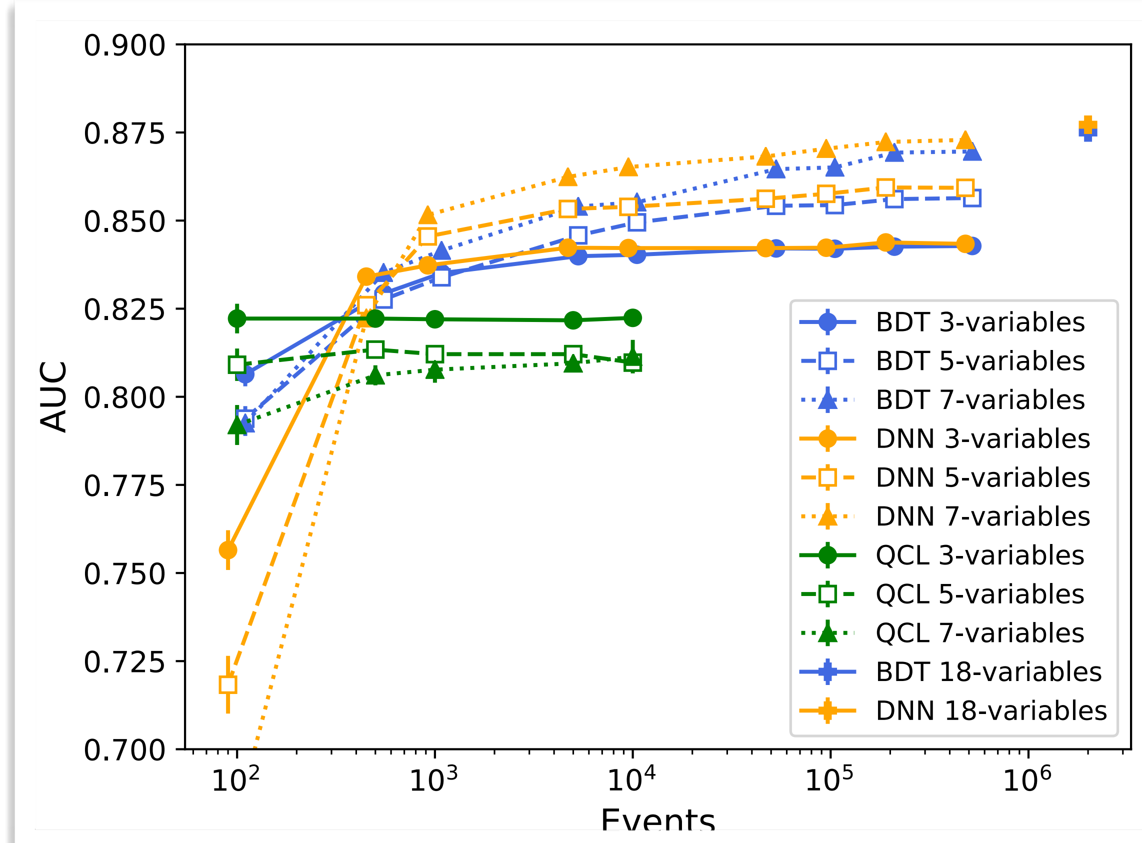
QCL Circuit



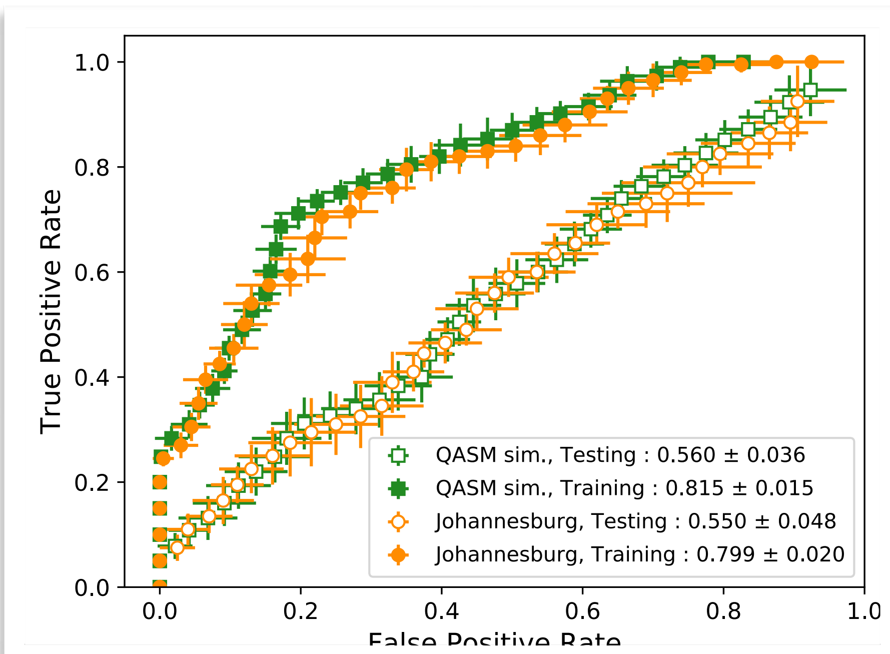
QML SUSY Results

- Use two 20 qubit IBM quantum computers and the IBM Qulacs simulator

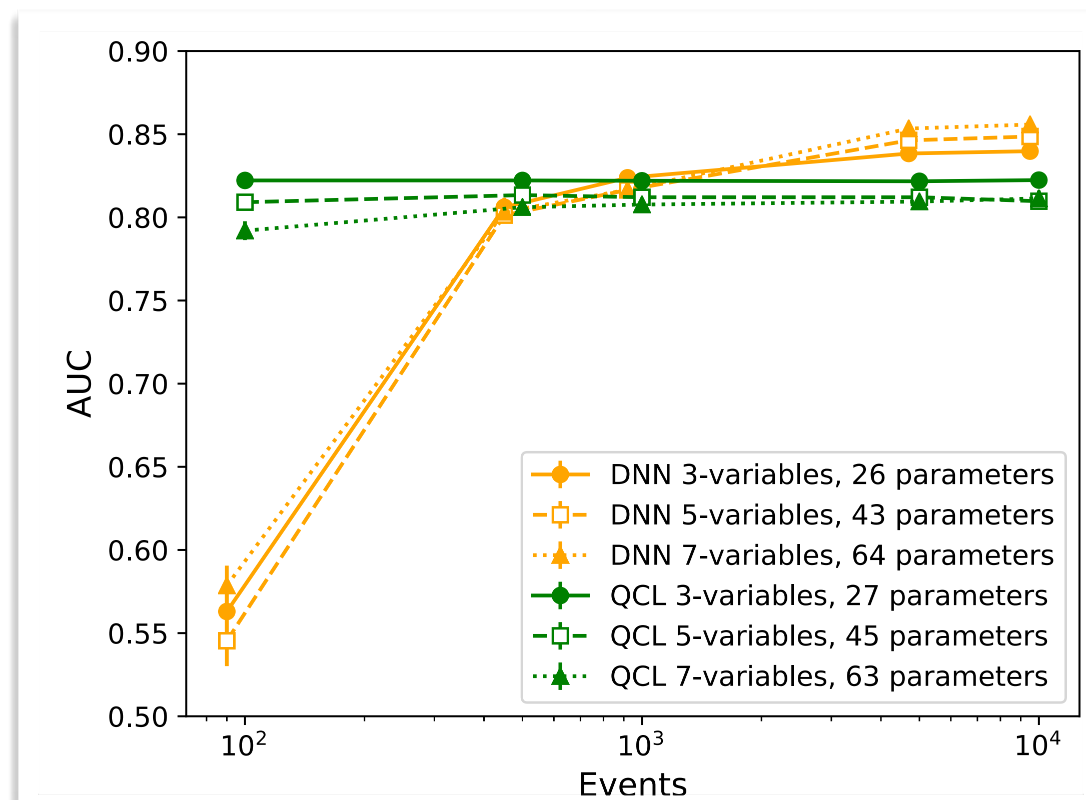
QCL Results



VQC Results



VQC Results



	Device/Condition	AUC
VQC	Johannesburg	0.799 ± 0.020
	Boeblingen	0.807 ± 0.010
	QASM simulator	0.815 ± 0.015
QCL	Qulacs simulator ($N_{\mathrm{var}}^{\mathrm{depth}} = 1$)	0.768 ± 0.082
	Qulacs simulator ($N_{\mathrm{var}}^{\mathrm{depth}} = 3$)	0.833 ± 0.063

Terashi et al, arXiv:2002.09935.pdf

Incomplete list of other studies for HEP

- Quantum gate optimization for scientific applications: https://arxiv.org/pdf/2102.10008.pdf
- Simulating collider physics on QC: https://arxiv.org/pdf/2102.05044.pdf
- Vertexing with QA: https://arxiv.org/pdf/1903.08879.pdf
- QA for jet clustering: https://journals.aps.org/prd/abstract/10.1103/PhysRevD.101.094015
- Unfolding with QA: https://link.springer.com/article/10.1007/JHEP11(2019)128
- Unfolding to mitigate readout errors: https://www.nature.com/articles/s41534-020-00309-7

And probably many more that I don't know about yet

Summary

- Quantum computing is an exciting field currently going through a rapid development cycle
  - Major players include a wide range of tech companies and governments around the world
  - A wide range of technologies are being explored including superconducting, trapped ion, photonic, silicon and topological qubits
  - People are particularly excited because
    - Quantum computers may be able to do things that classical computers cannot
    - Quantum computers may be able to solve certain problems far more quickly
  - A recent success was the demonstration of quantum advantage

Conclusion

- Currently available quantum computers have limited numbers of qubits, short coherence times and are very noisy
  - Many problems need to be solved to continue to scale the size and power of quantum computers
- Projections vary wildly about when we might expect (if ever) to have a quantum computer of the size to be more generally useful
- HEP is increasingly becoming constrained by computing resources
  - Increasing dataset sizes, increasing complexity
  - Even more true when planning future colliders
- We also have a long history of being trail blazers in many areas including computing
  - Many interesting studies have been and continue to be performed
  - Will help to determine how quantum computers can be useful for us and also can help to provide difficult problems which can impact design

Thank you!