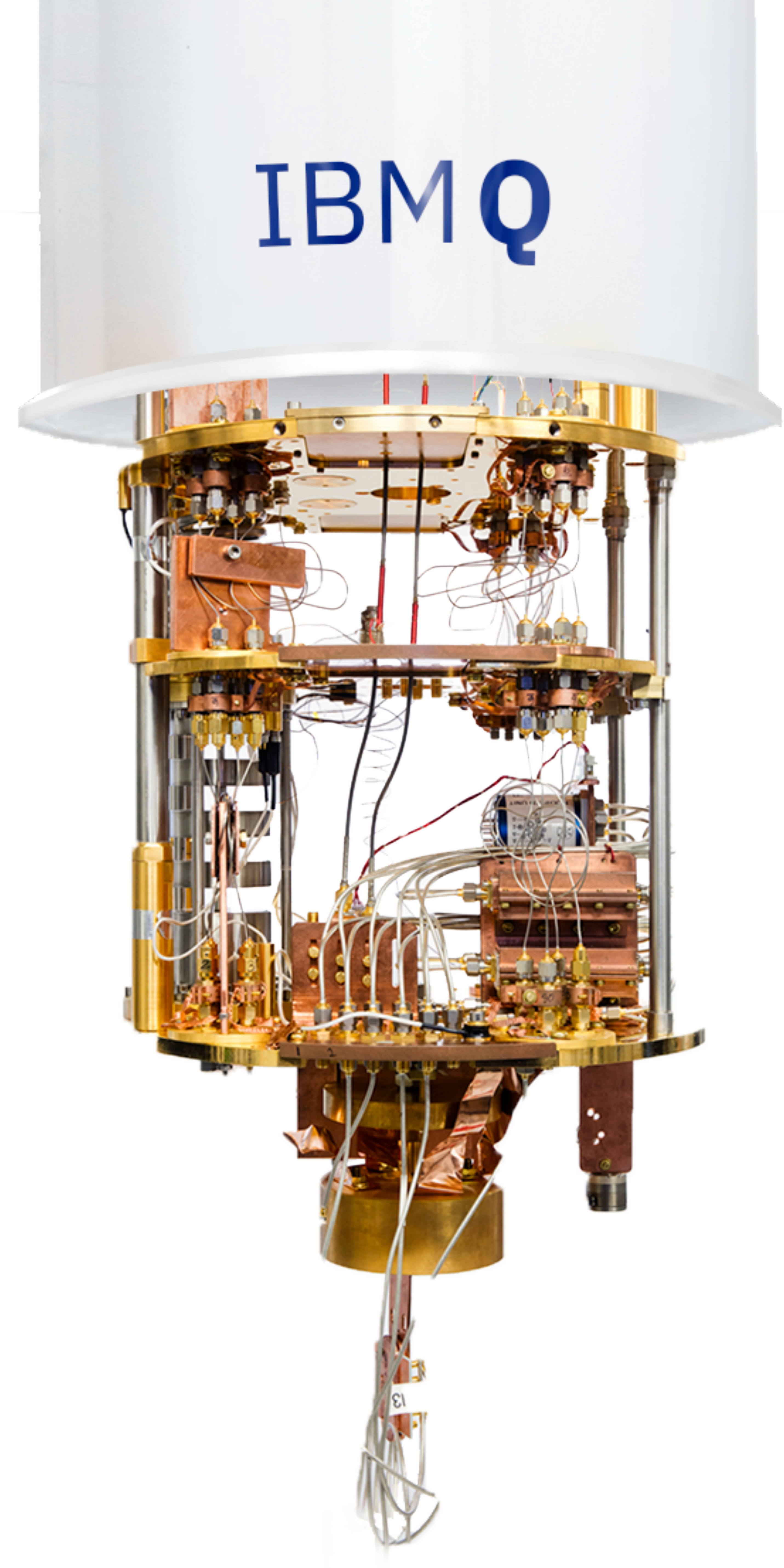


Durham University

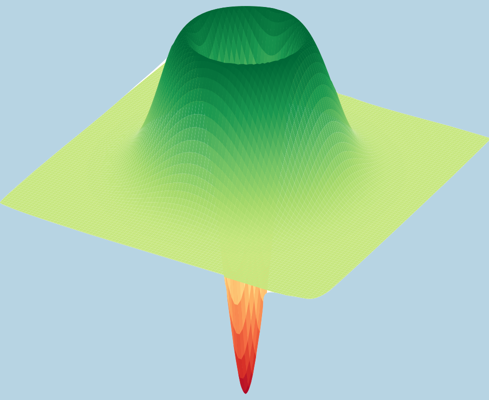
Quantum Extreme Learning Machines with Continuous-variables

Simon Williams

QC4HEP, Munich,

26th February 2026

Continuous-Variable Quantum Computing



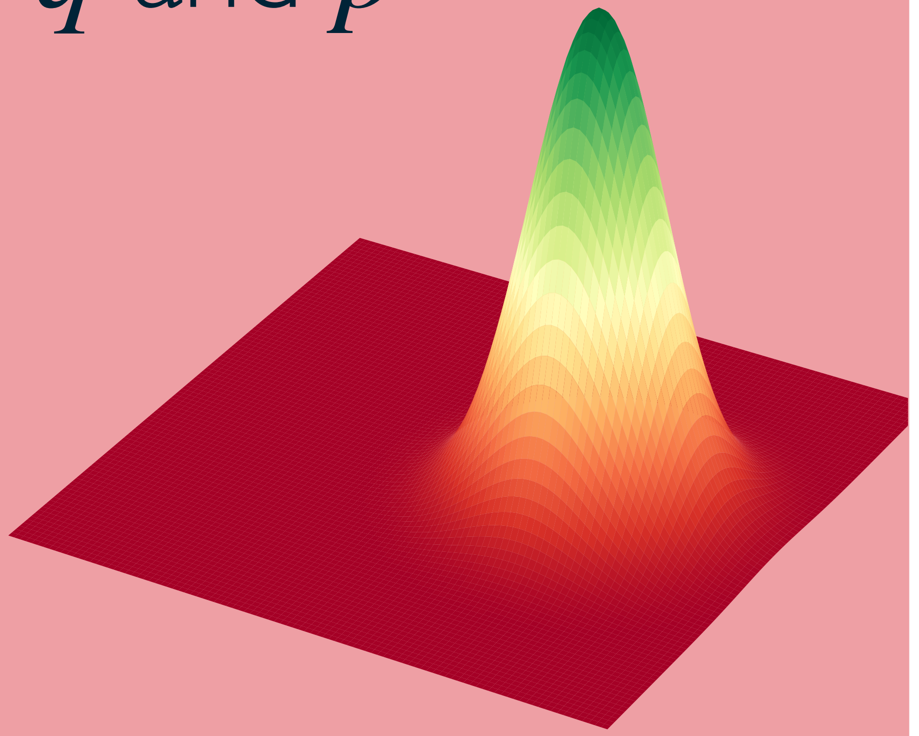
Information is encoded in observables that vary **continuously**

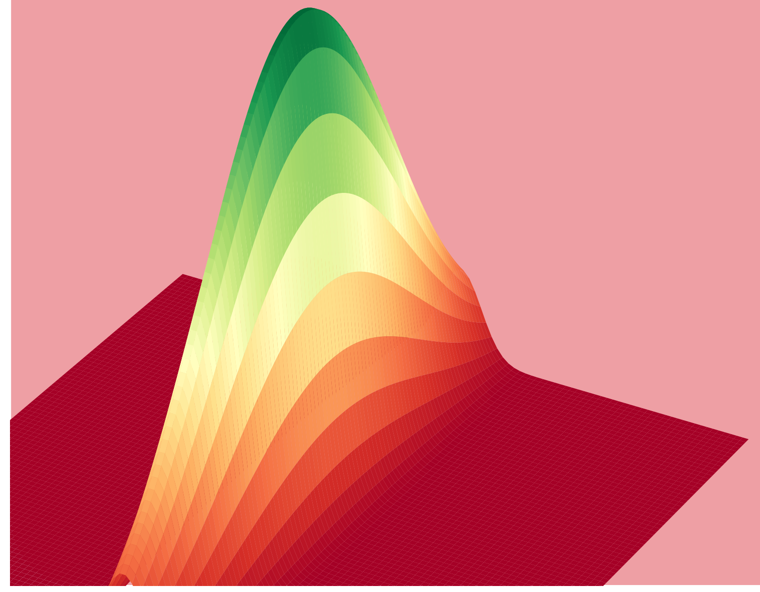
No-go theorem - universal computation impossible with only Gaussian operations

Gaussian operations:

Maps Gaussian states to Gaussian states - at most quadratic in quadrature variables $\hat{q}$ and $\hat{p}$

$$D(\alpha) = \exp\left[-i\sqrt{2}\left(\Re(\alpha)\hat{p} - \Im(\alpha)\hat{x}\right)\right]$$



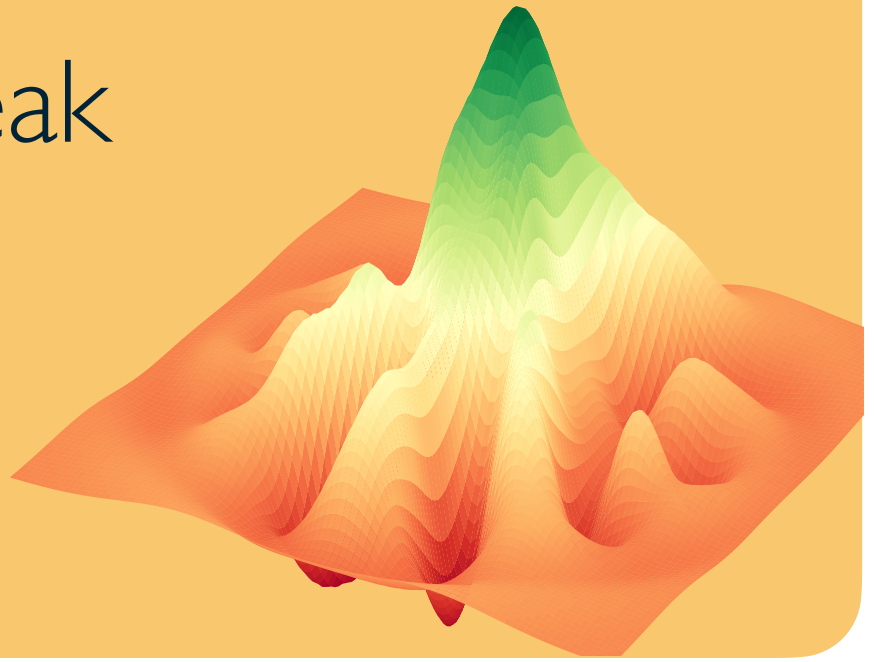


$$S(z) = \exp\left[\frac{1}{2}\left(z^* a^2 - z a^{\dagger 2}\right)\right]$$

Non-Gaussian operations:

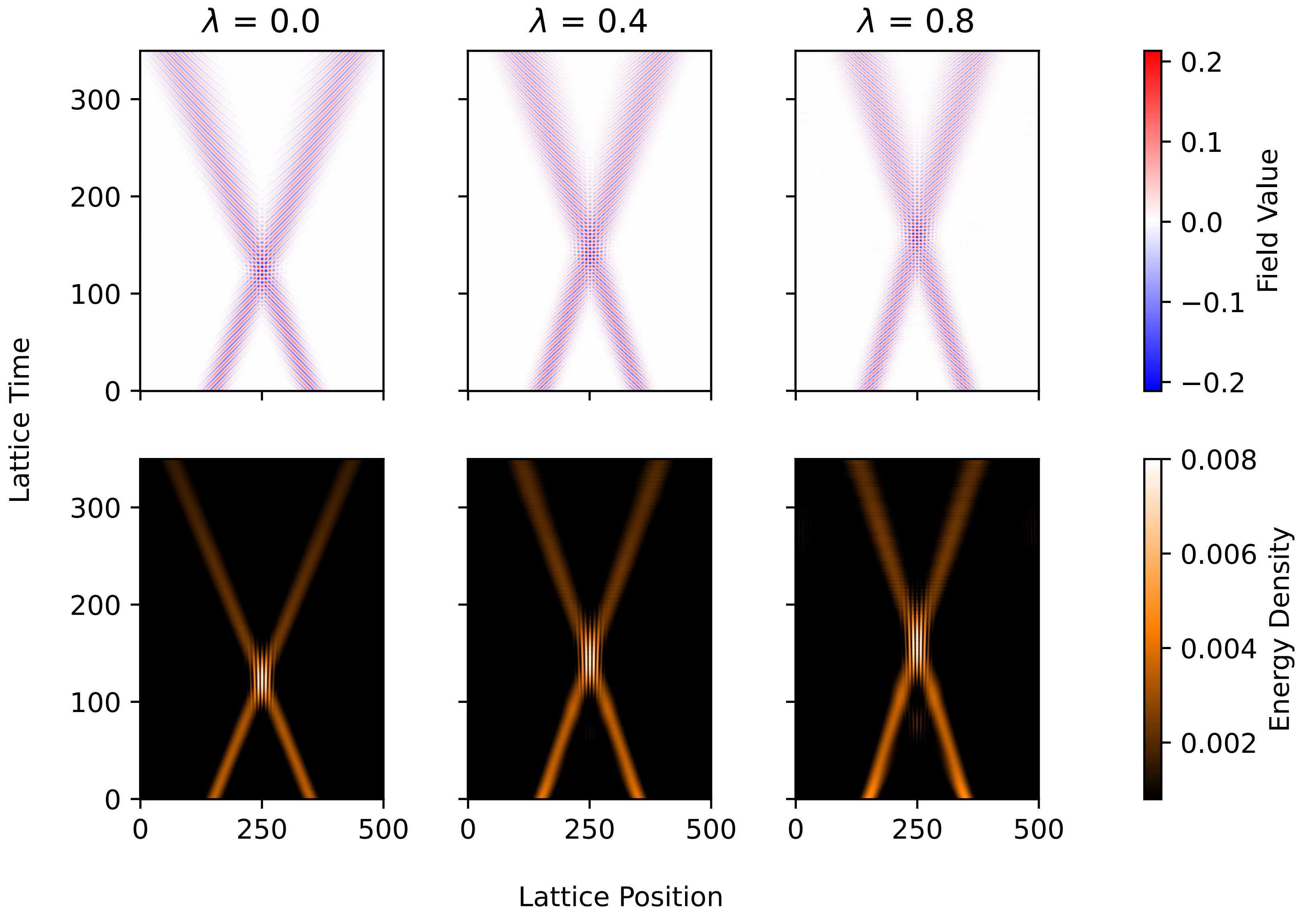
Maps Gaussian states to non-Gaussian states - greater than quadratic in quadrature variables $\hat{q}$ and $\hat{p}$

Optical non-linearities are too weak to introduce required non-Gaussianity



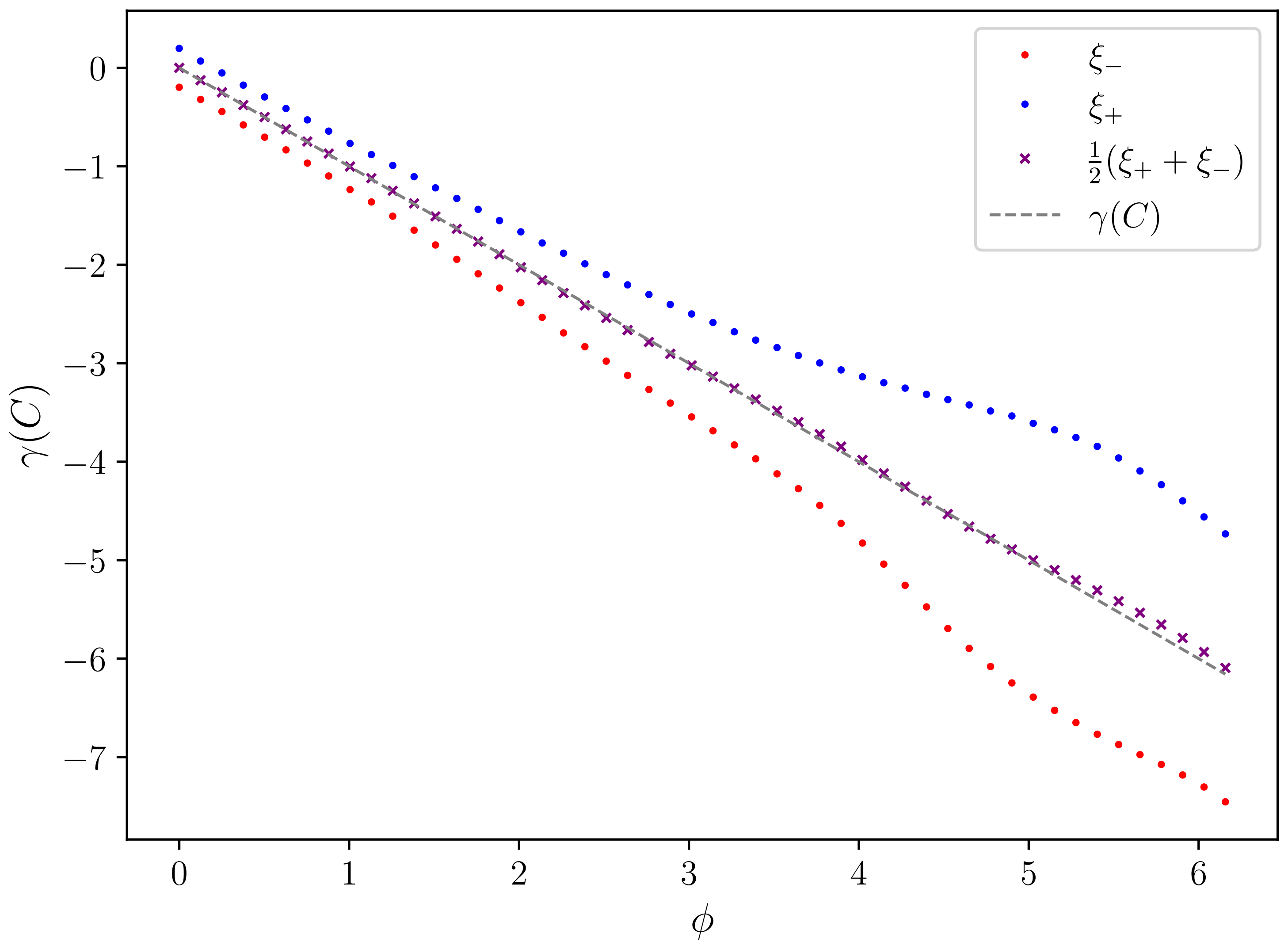
Continuous-Variable Quantum Computing

Real-time scattering processes



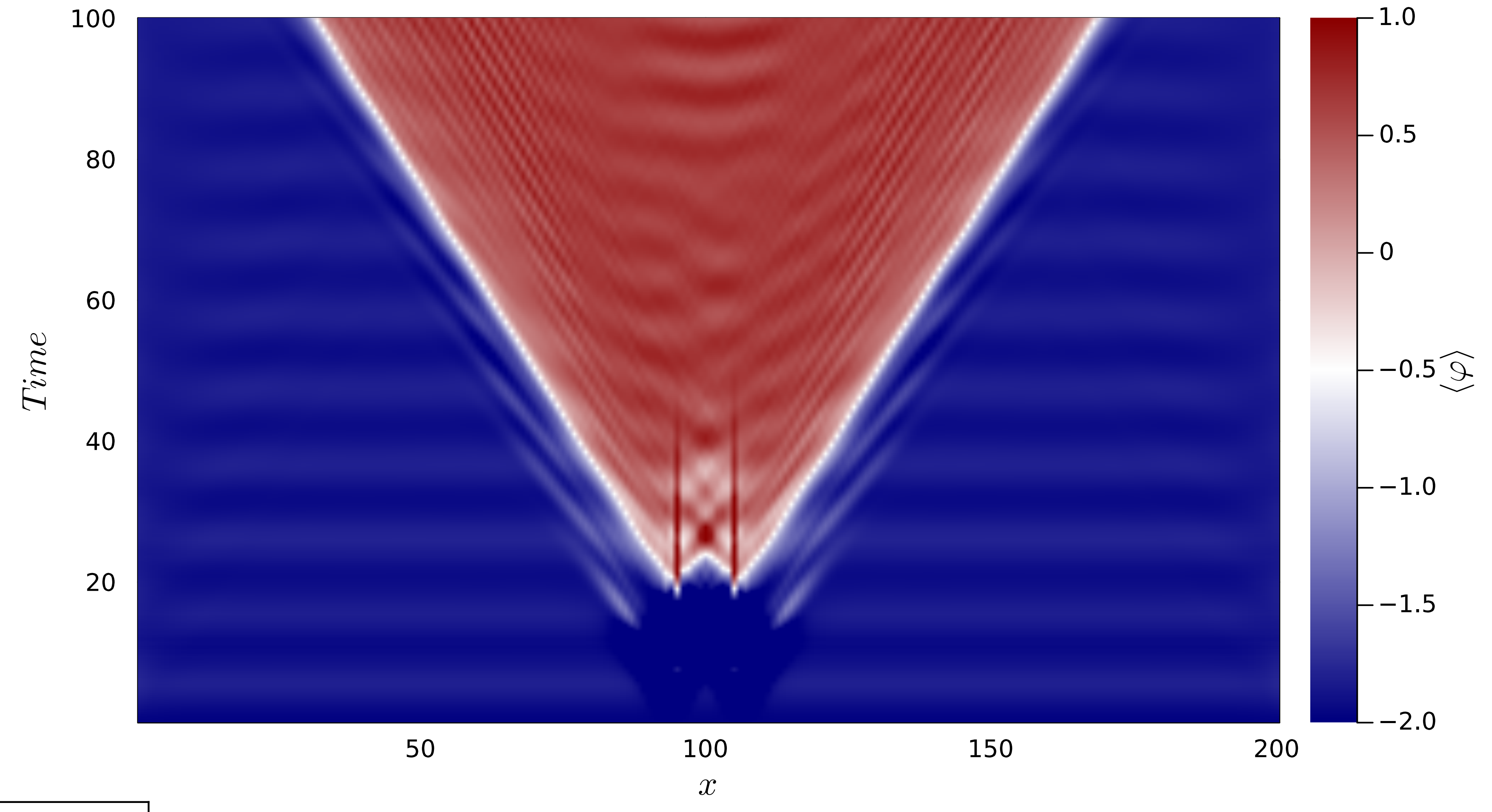
S Abel, M Spannowsky and SW,
arXiv : 2403.10619, arXiv: 2502.01767

Topological defects



S Abel, I Wasek and SW,
arXiv: 2511.19598

False-vacuum decay in scalar QFT



S Abel, M Spannowsky and SW,
arXiv: 2506.17388

Future Colliders - What's the problem?

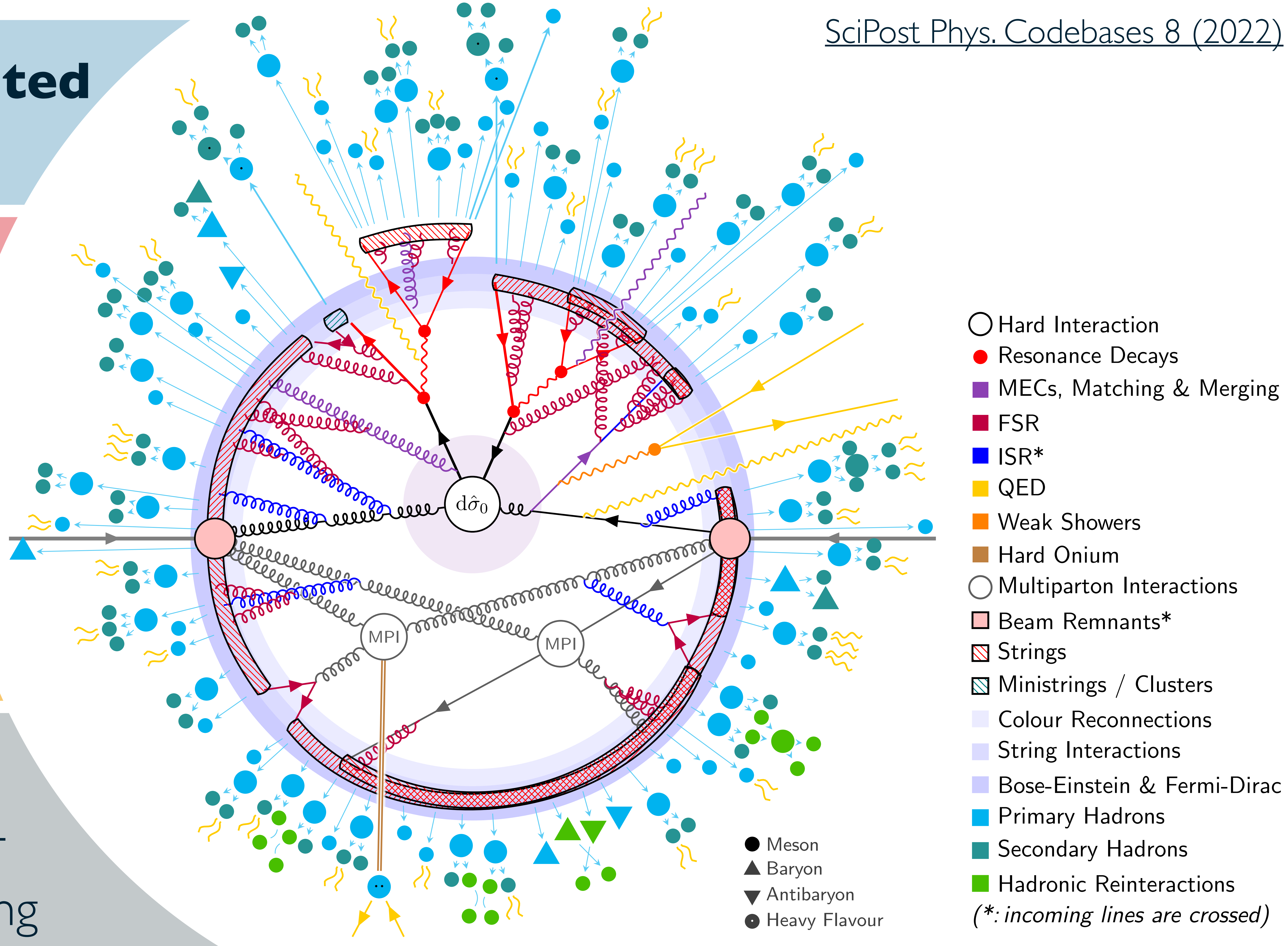
Next-gen collides demand **unprecedented** computational power and performance

Quantum algorithms are emerging for efficient, **low-latency** computation

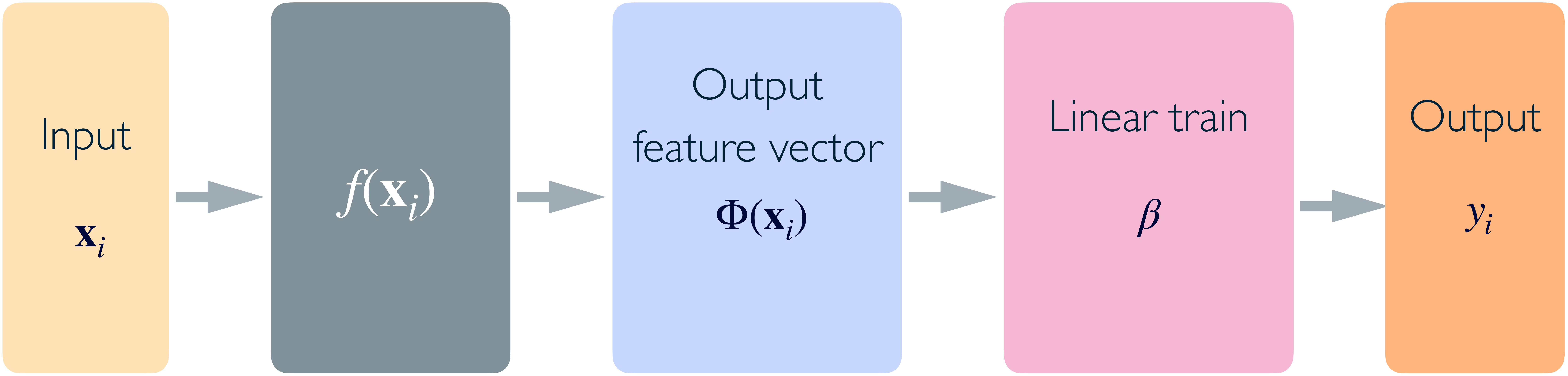
Continuous-variable quantum computing natural route to fast, highly parallel pre-processing - **photonics**

Quantum extreme learning machines attractive model class for low-latency inference and **ultra-fast** retraining

SciPost Phys. Codebases 8 (2022)



Extreme learning machines - the art of ultra fast learning



Fixed hidden-layer maps $\mathbf{x} \in \mathbb{R}^d \rightarrow \boldsymbol{\Phi}(\mathbf{x}) \in \mathbb{R}^R$

Aim is to build a matrix of mappings,

$$H_{ij} = h_j(a_j, \boldsymbol{\Phi}(\mathbf{x}_i))$$

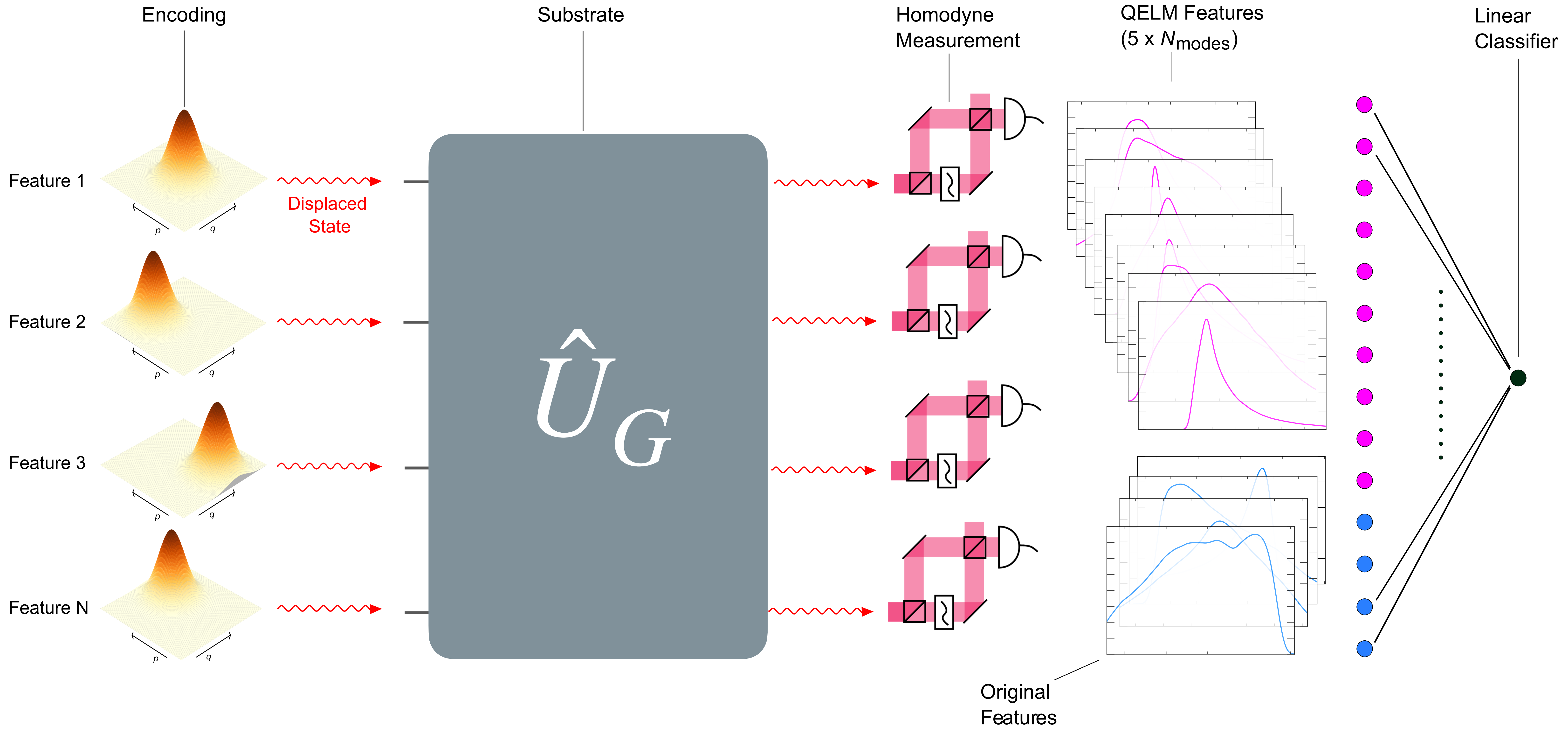
to solve $\beta H = T$

Solved by ridge regression

$$\beta = \left(H^\top H + \lambda I\right)^{-1} H^\top T$$

β learned through matrix inversion - avoids iterative **gradient descent**, backpropagation, **tuning** etc.

Continuous-Variable Quantum Extreme Learning Machine



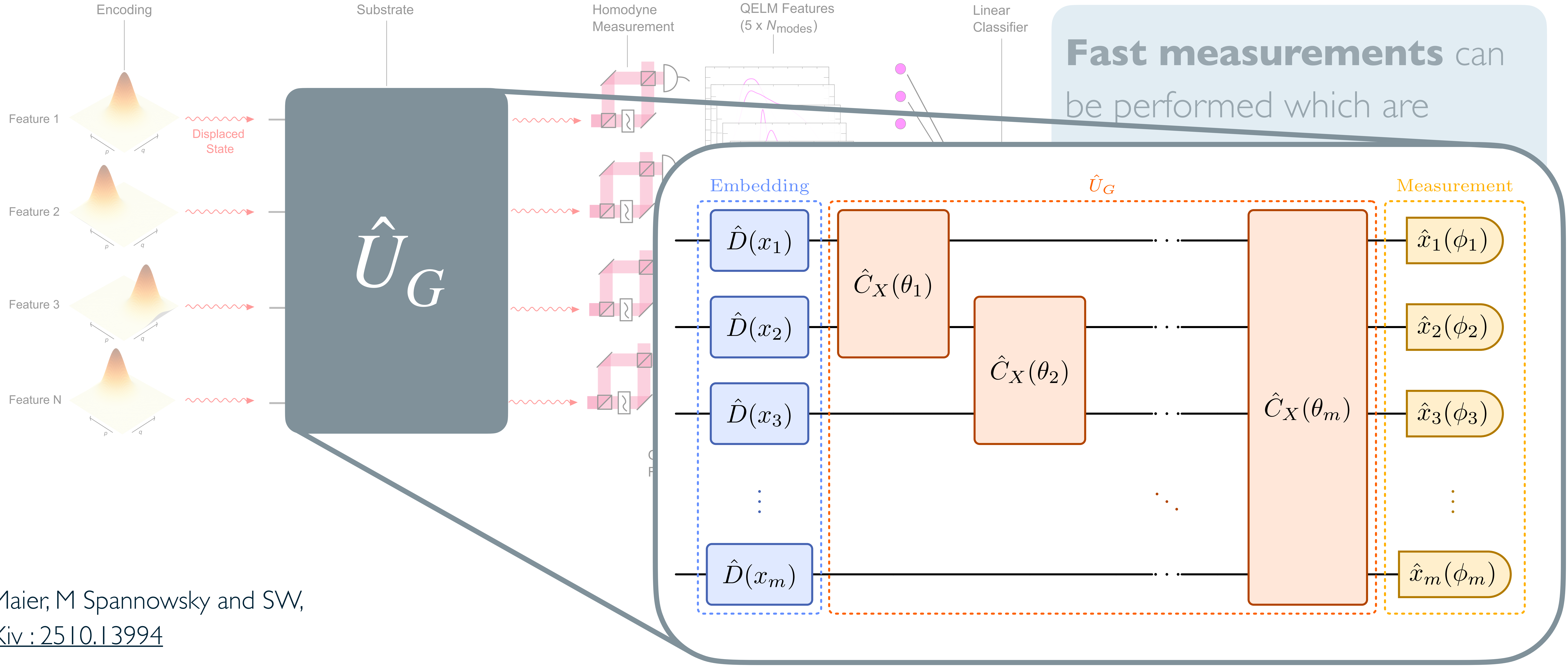
Fast measurements can be performed which are Gaussian compatible

Single trainable layer - can be trained using fast **ridge** or **logistic** regression

$$\hat{U}_G = \exp\left(-\frac{i}{2}\hat{\mathbf{r}}^\top G\hat{\mathbf{r}} + i\mathbf{d}^\top\hat{\mathbf{r}}\right)$$

B Maier, M Spannowsky and SW, arXiv : 2510.13994

Continuous-Variable Quantum Extreme Learning Machine



Fast measurements can be performed which are

B Maier, M Spannowsky and SW, arXiv : 2510.13994

CV-QELM for top jet tagging

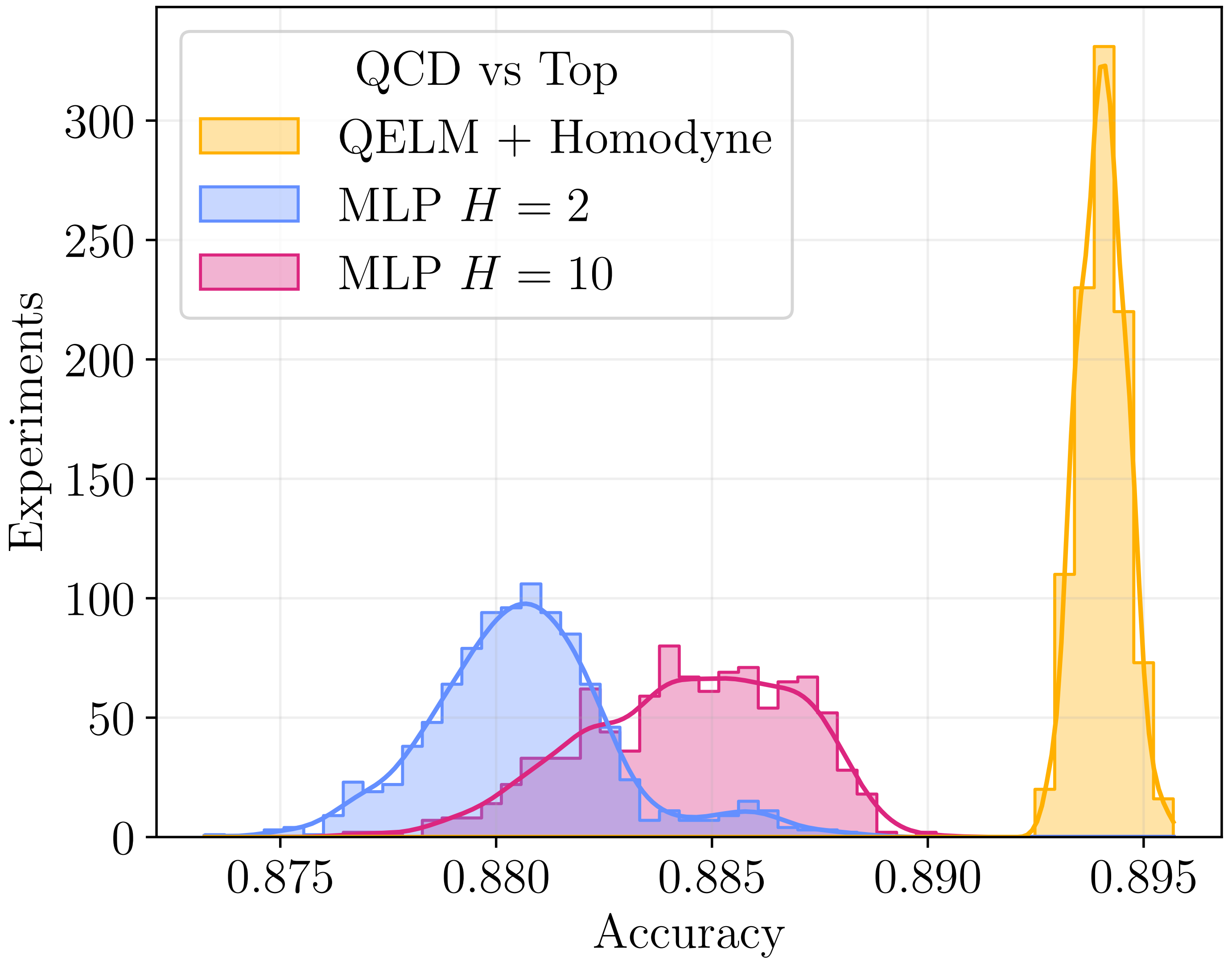
Top vs QCD classification using **HLS4ML** dataset

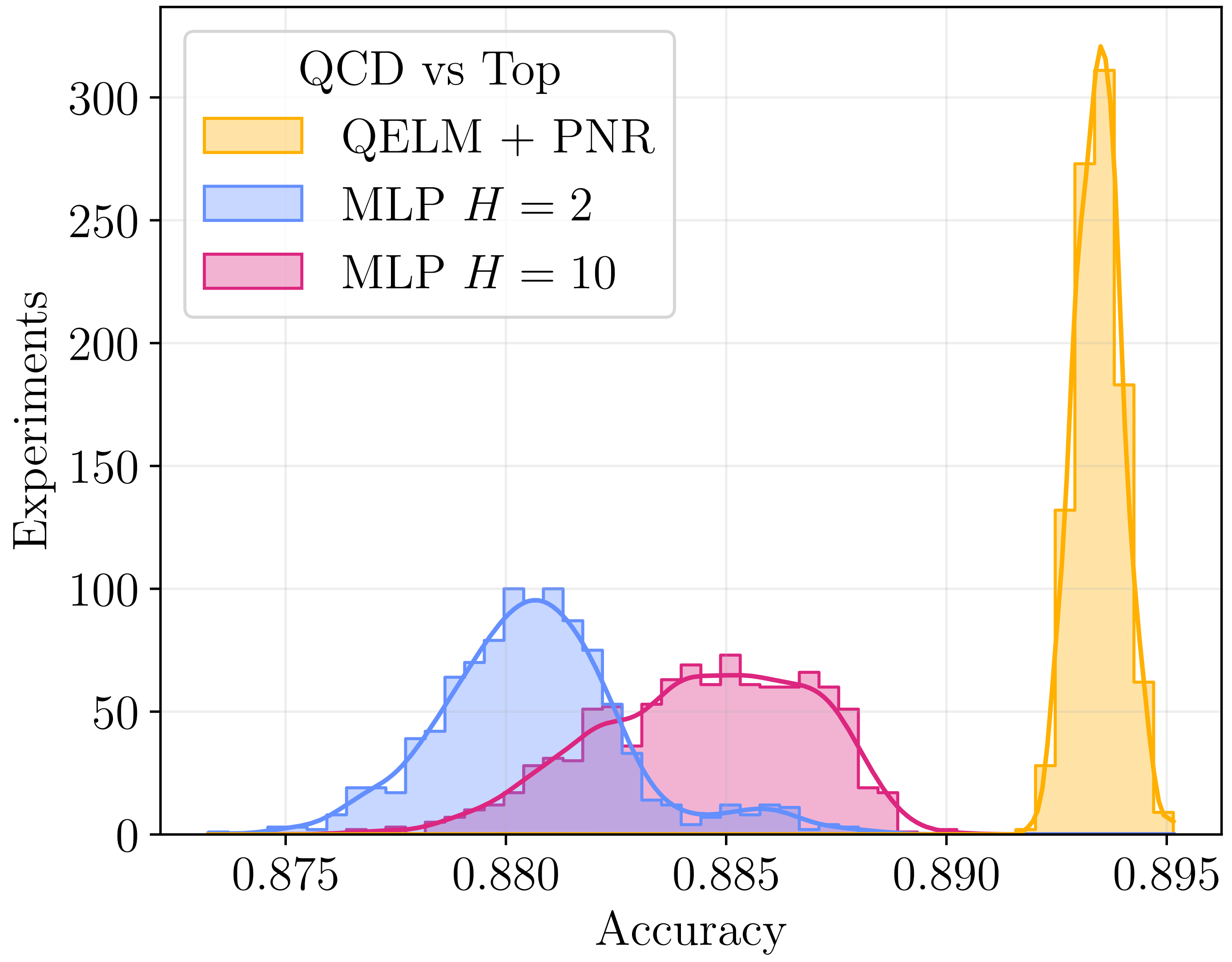
Linear classifiers used are **ridge** and **logistic regression**

Compared with MLPs with a single hidden layer of **H=2** and **H=10** - equivalent sizes to the number of feats in qELM

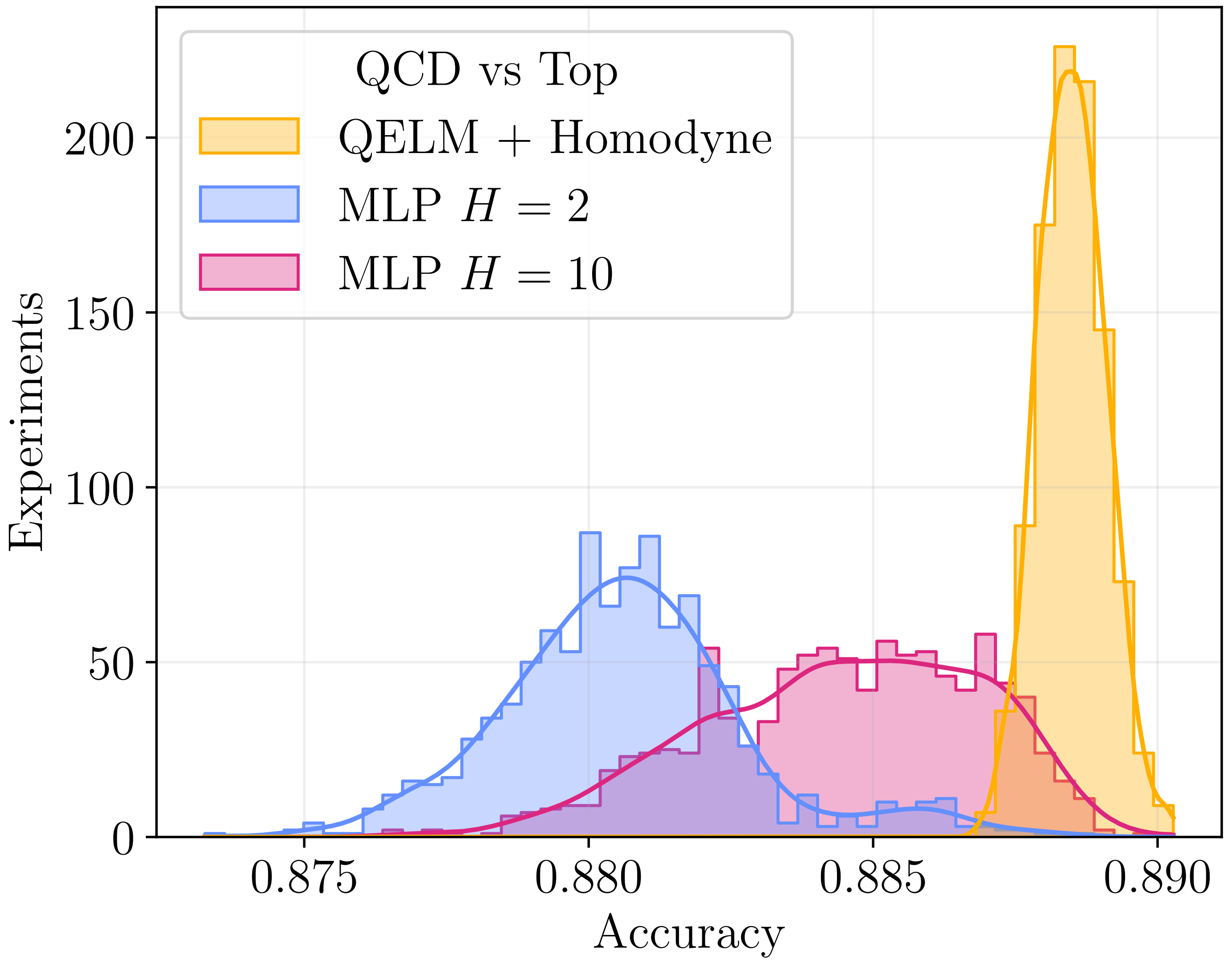
Consistent performance across the board, with the **QELM performing better than MLP**

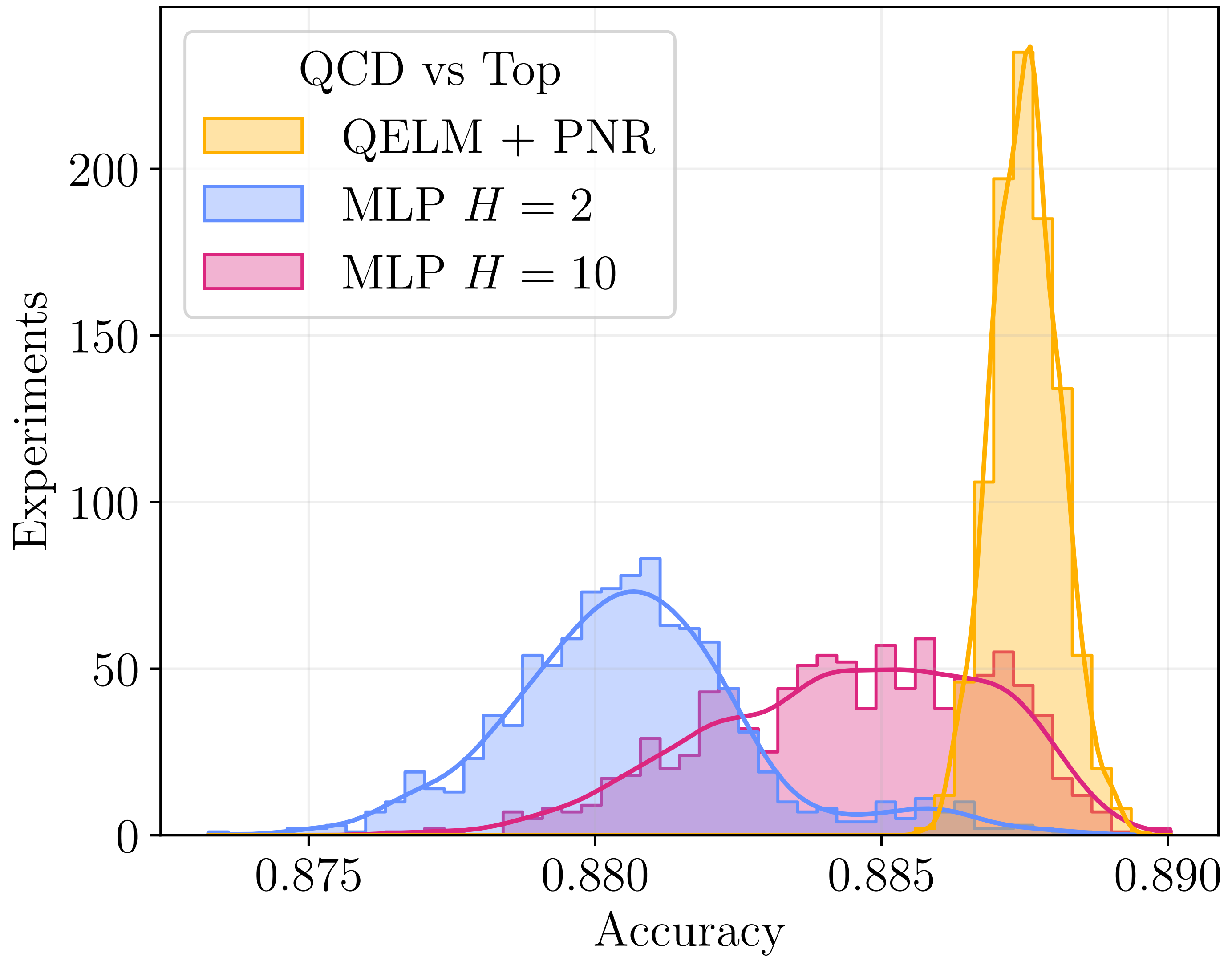
Logistic regression



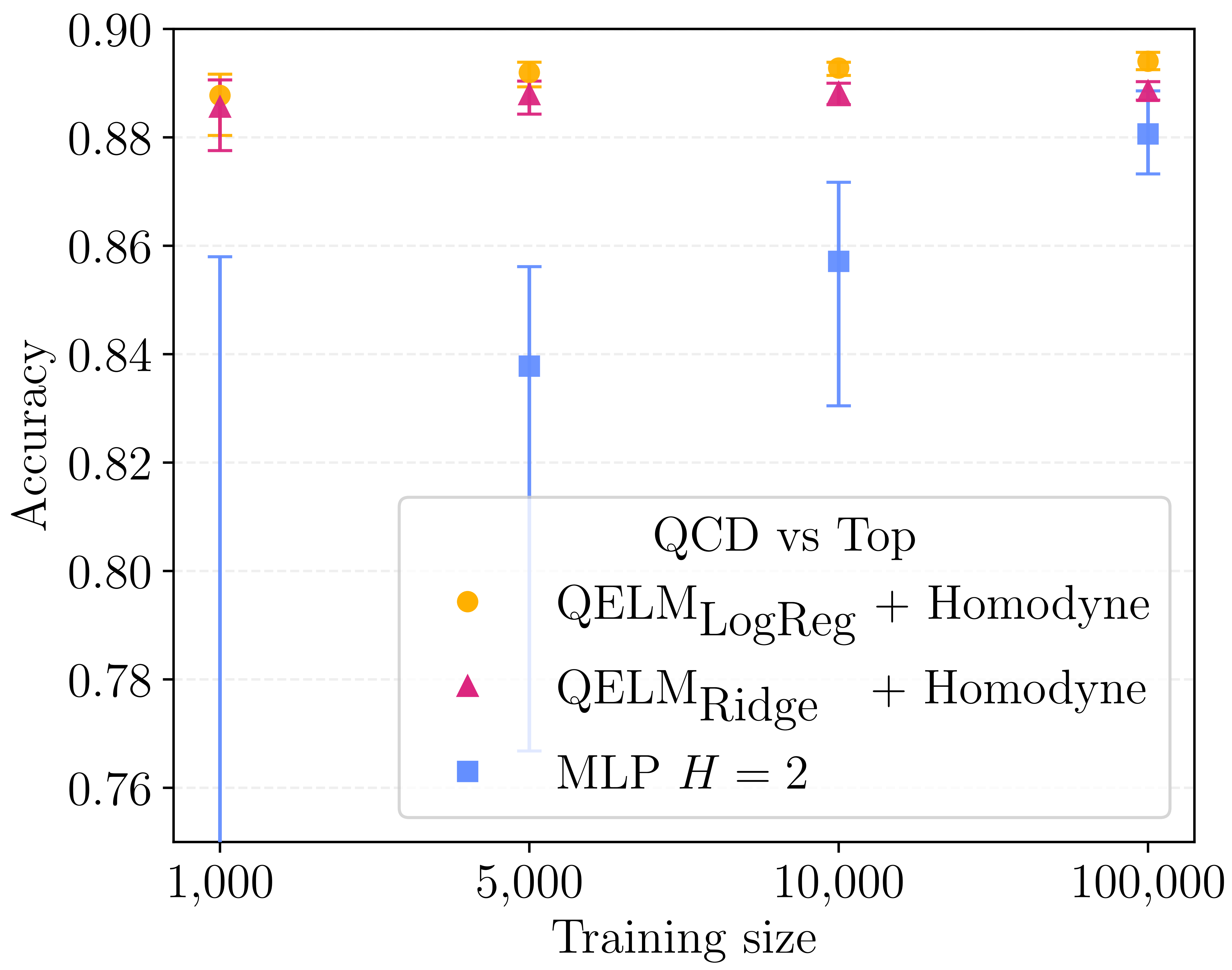


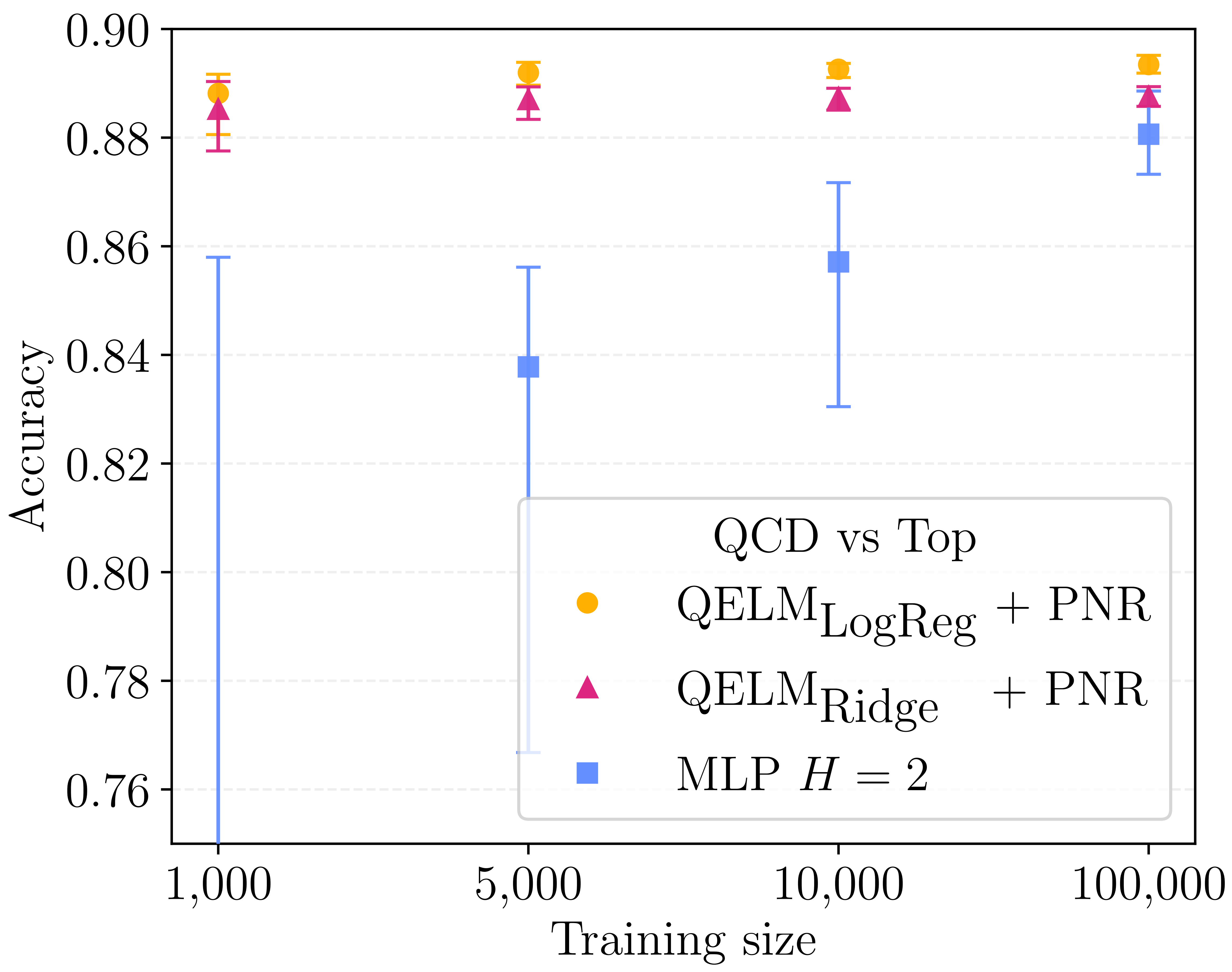
Ridge

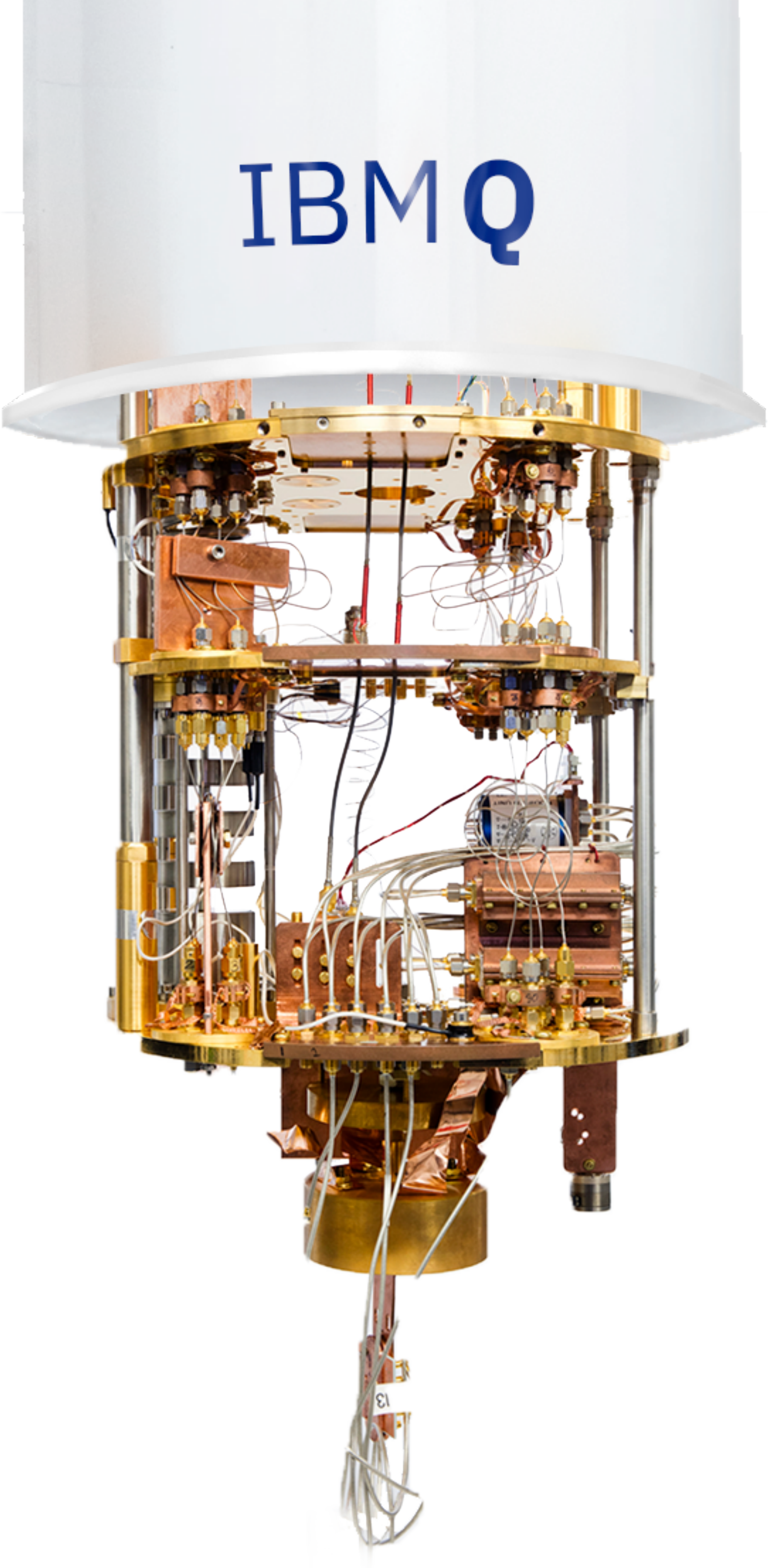




CV-QELM for top jet tagging







Extreme Learning Machines provide a random feature framework with **analytic training**

Continuous-variable photonics naturally implement **fixed-time Gaussian feature maps**. Training reduces to a single linear solve – **no variational optimisation required**

CV-QELM achieves **competitive** and **stable performance** on top vs QCD classification

A **hardware-realistic** pathway toward **low-latency collider inference**