



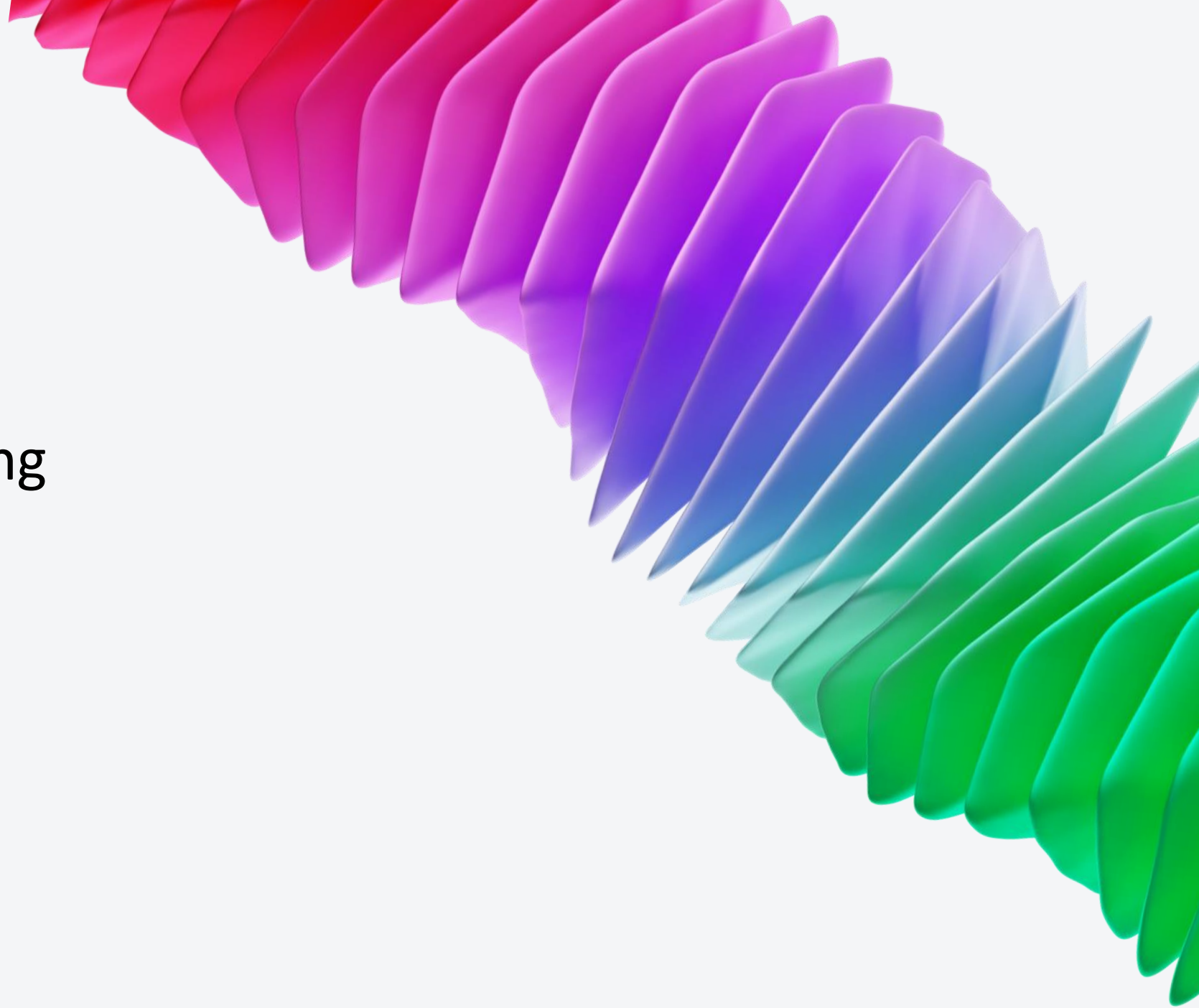
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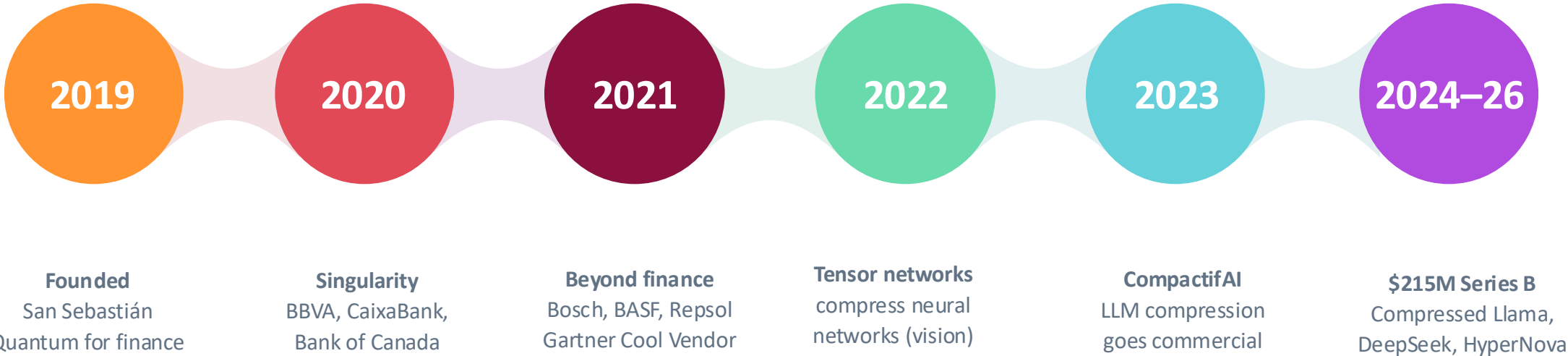
Towards Intelligent Quantum Computers

Borja Aizpurua Altuna

Multiverse Computing



Our Journey

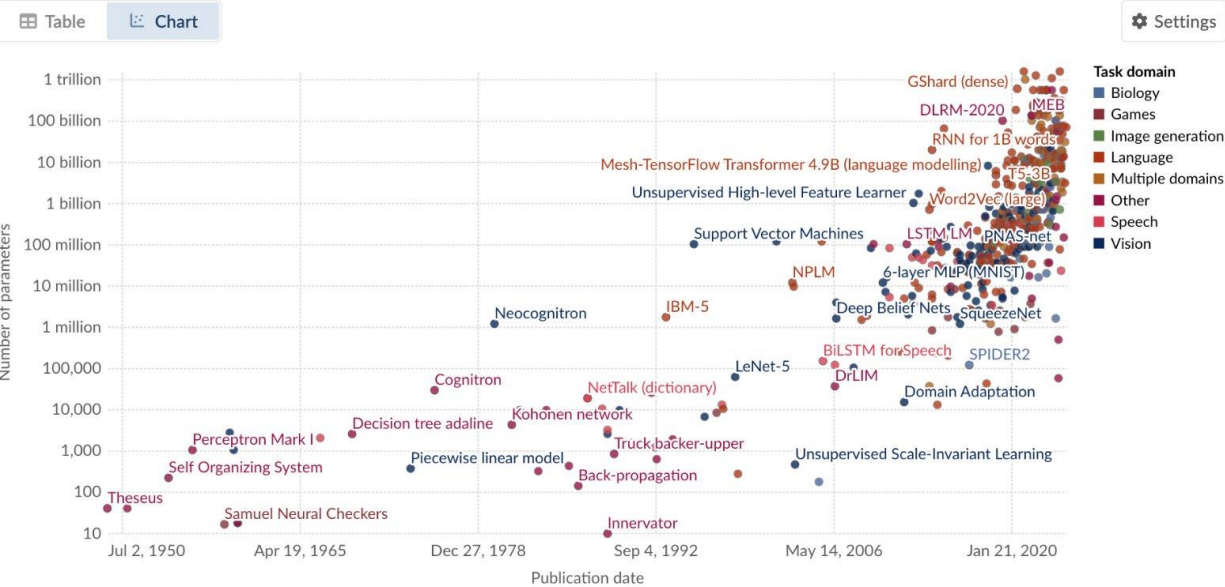


Skyrocketing AI Compute Costs

Training compute of notable AI models is doubling roughly every five months. growing at a rate of 4.6x per year. While costs are doubling every nine months for the largest AI models, growing at a rate of 2.6x per year

Parameters in notable artificial intelligence systems

Parameters are variables in an AI system whose values are adjusted during training to establish how input data gets transformed into the desired output; for example, the connection weights in an artificial neural network.



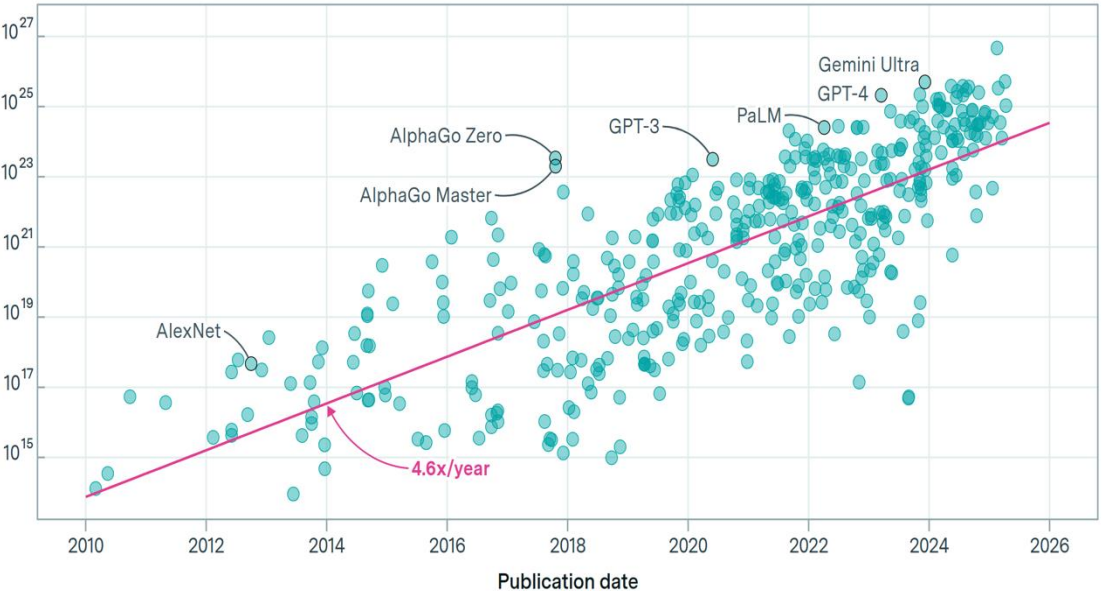
Source: Our World in Data (<https://ourworldindata.org/>)

Training compute of notable models

EPOCH AI

Training compute (FLOP)

433 models



CC-BY

epoch.ai

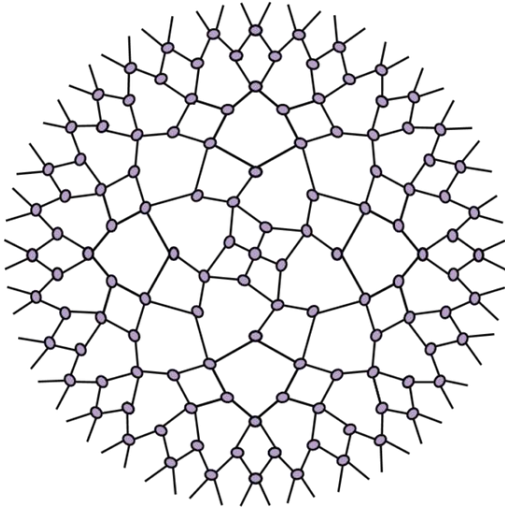
Robi Rahman and David Owen (2024), "The training compute of notable AI models is doubling roughly every five months". *Published online at epoch.ai*. Retrieved from: '<https://epoch.ai/data-insights/compute-trend-post-2010>' [online resource]. Updated on June 4th, 2025



Tensor Networks – a Quantum-Inspired Approach

A functional toolset borrowed from Quantum Physics.

Allows us to understand which parameters and layers carry knowledge and which are redundant, by examining the correlation space across model parameters to extract where the information truly lies — and where it doesn't.



Real advantages and value **TODAY**

- **Efficient** – less parameters
- **Faster** – in training and inference
- **Scalable** – over uncompressed alternatives
- **Universal** – can compress all types of NN models

Our techniques produce models **compatible** with the main libraries and plugins in the market



Singularity Machine Learning



Guides

Get started

[Introduction to Qiskit](#)[Install](#) ▾[Hello world](#)[Development workflow](#) ▾[Latest updates](#)

Qiskit Functions

[Introduction to Qiskit Functions](#)[Circuit functions](#) ▾[Application functions](#) ^

Multiverse Computing Singularity

[Q-CTRL Optimization Solver](#)[QunaSys QURI Chemistry](#)

Tools

[Circuits and operators](#) ▾

Singularity Machine Learning - Classification: A Qiskit Function by Multiverse Computing

Overview

With the "Singularity Machine Learning - Classification" function, you can solve real-world machine learning problems on quantum hardware without requiring quantum expertise. This Application function, based on ensemble methods, is a hybrid classifier. It leverages classical methods like boosting, bagging, and stacking for initial ensemble training. Subsequently, quantum algorithms such as variational quantum eigensolver (VQE) and quantum approximate optimization algorithm (QAOA) are employed to enhance the

On this page

[Overview](#)[Function description](#)[Action-based approach](#)[1. List](#)[2. Create](#)[3. Delete](#)[4. Fit](#)[5. Predict](#)[6. Fit-predict](#)[7. Create-fit-predict](#)[Download notebook](#)

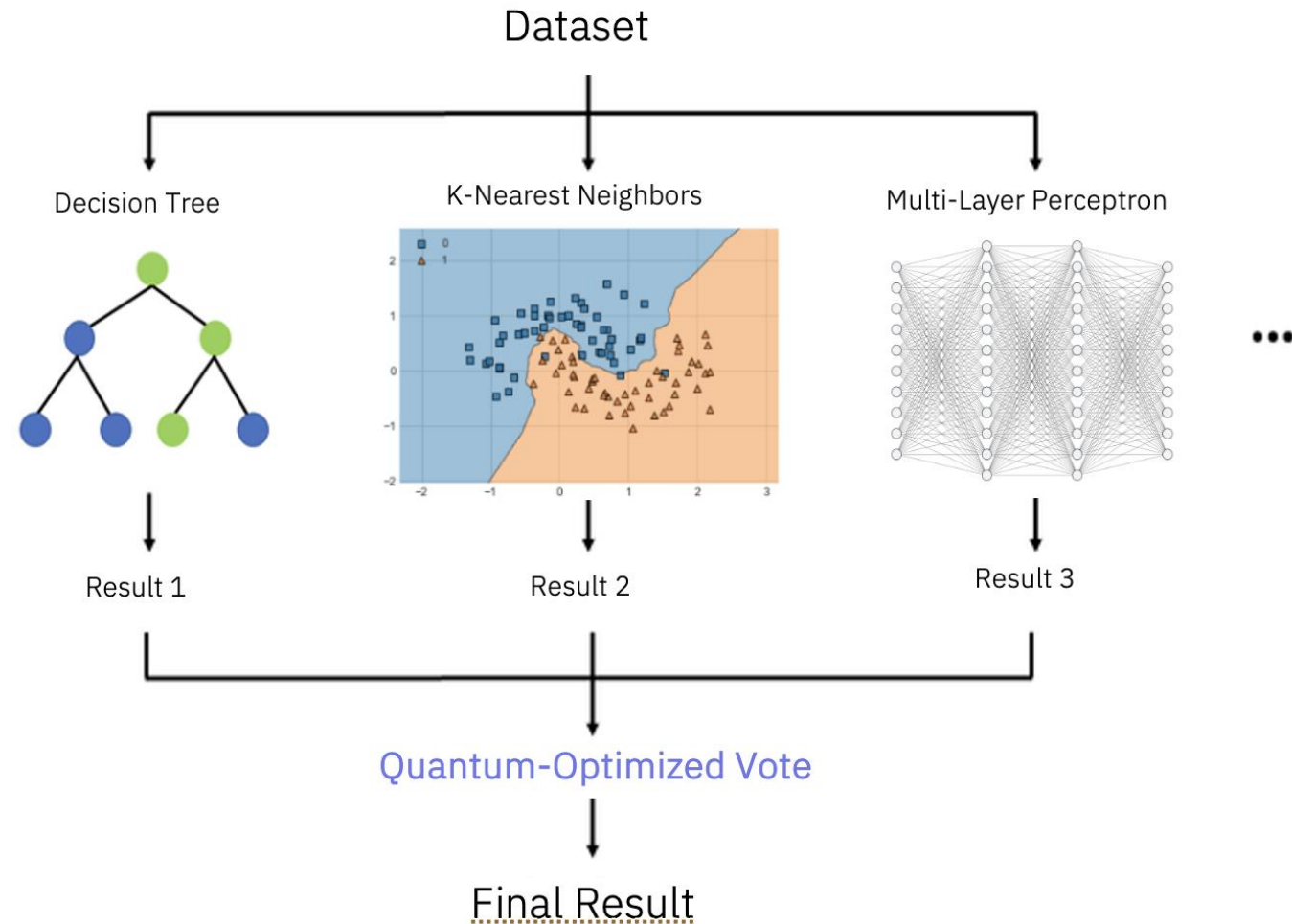
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The Classifier

- Ensemble classifier
 - Combines the predictions of various models (learners)
- Heterogeneous – can be built with different types of learners
 - Decision Trees, k-Nearest Neighbours, Multi-Layer Perceptrons + others
 - Wider perspective of the data landscape
- In *classical* ensemble models, the final result is usually obtained by *majority vote* of the learner predictions.
- Our **Quantum** approach:
 - We find the optimal subset of learners that yield the best results.
 - NP-hard binary optimization problem (need to assign 1 to learners that go to vote, 0 otherwise) → cannot be efficiently solved classically
 - Formulate as a QUBO and solve on **IBM Quantum** hardware → minimize the cost function $\mathcal{H}$.



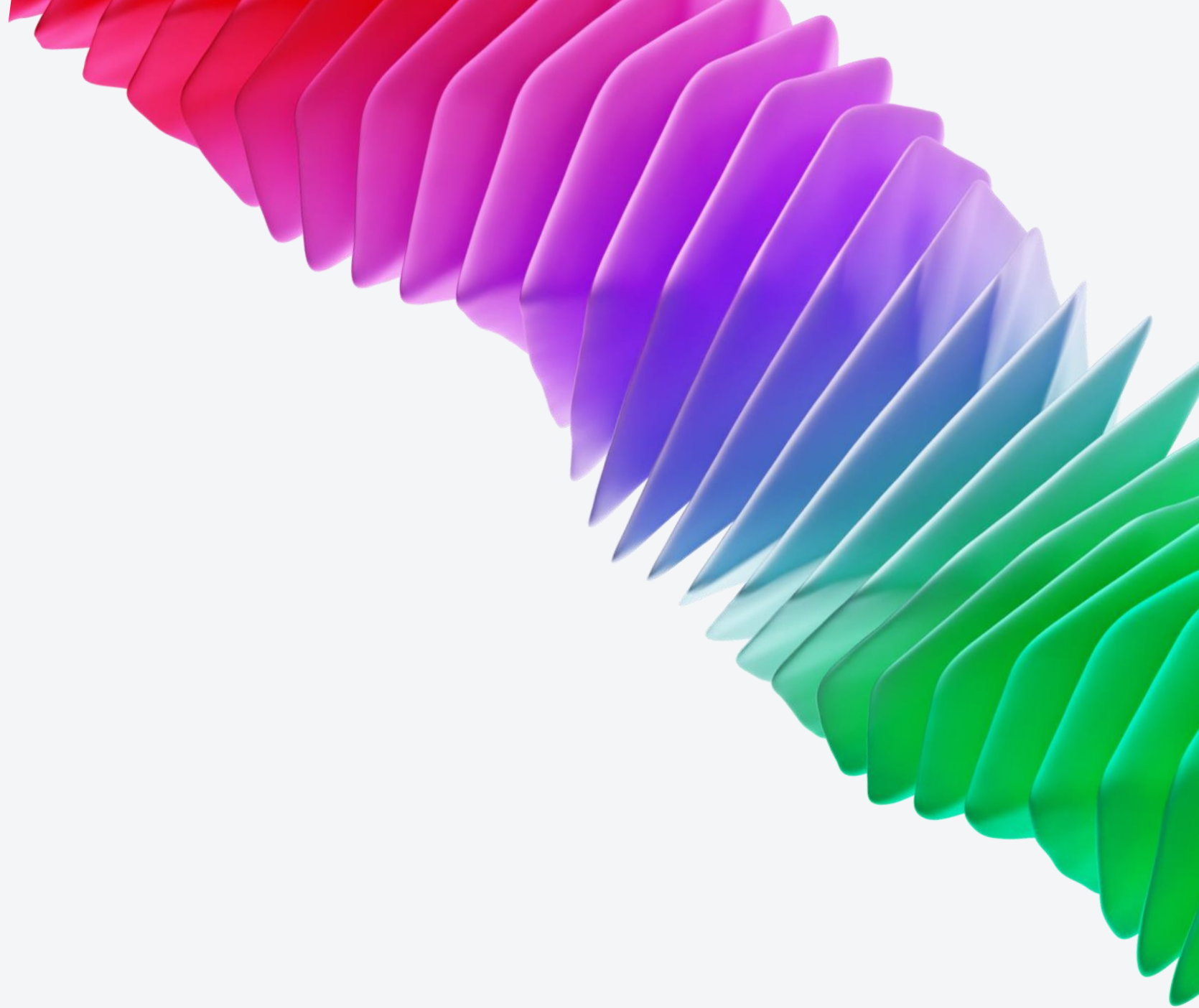
$$\mathcal{H}(w) = \sum_{i,j} w_i w_j \text{Corr}(h_i, h_j) + \sum_i w_i (\lambda - 2\text{Corr}(h_i, y))$$

w_i - the binary weight of learner i

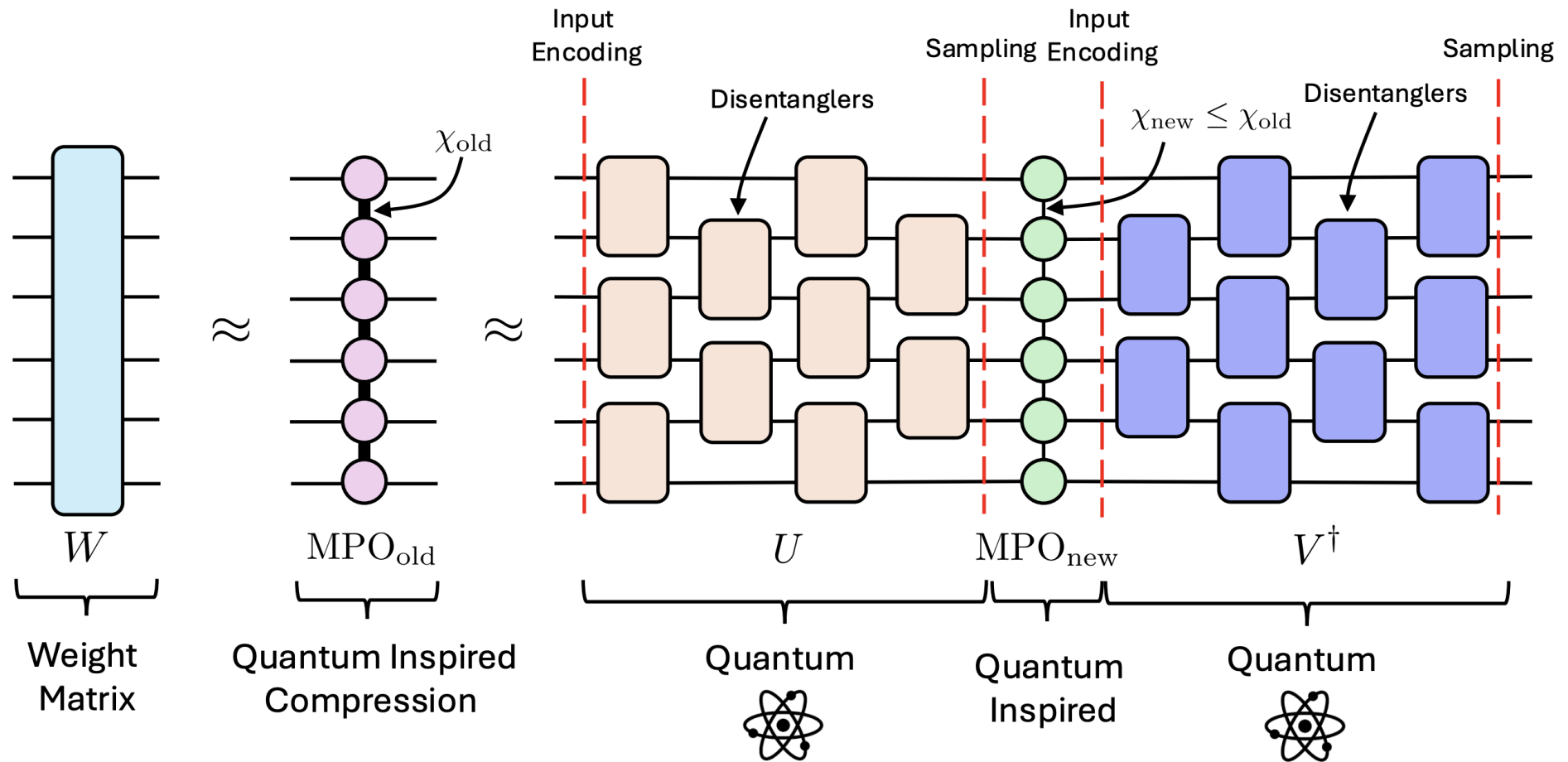
h_i - the prediction of learner i

y - the classification labels

Quantum LLM

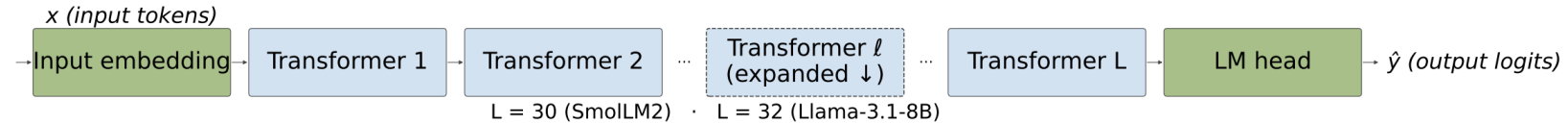


First Paper: Quantum Large Language Models via Tensor Network Disentangler

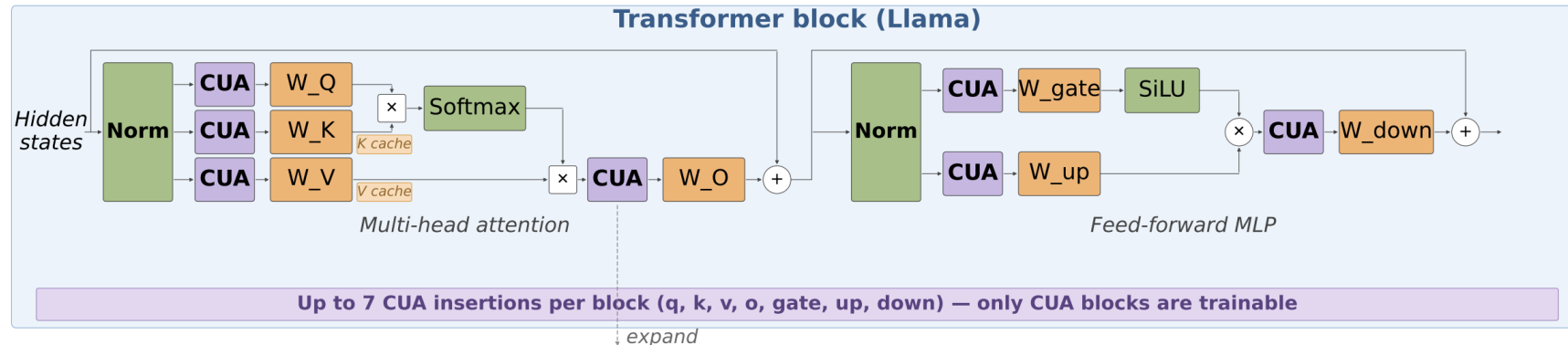


Quantum-enhanced Large Language Models on Quantum Hardware via Cayley Unitary Adapters

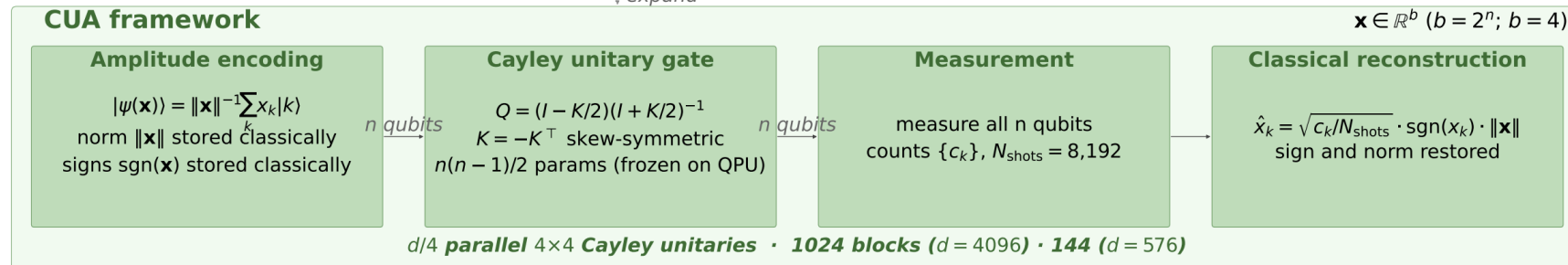
a



b



c



Legend

- CUA block (trainable, $6 \times 10^3 - 4 \times 10^7$ params)
- Projection weight matrix (frozen)
- Normalisation / activation
- Batched matrix-multiply
- Element-wise multiply
- Element-wise add



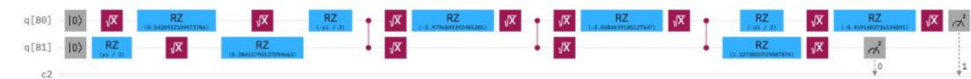
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<https://arxiv.org/abs/2605.05914>

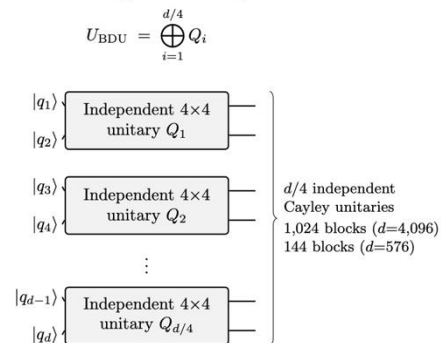
Quantum-enhanced Large Language Models on Quantum Hardware via Cayley Unitary Adapters

- We added a quantum circuit inside Llama3.1-8B and run inference on ibm_basquecountry (Donostia's IBM System Two)
- The circuit is trained classically, only inference on quantum
- Some questions that were wrong in original model are right in the quantum inference
- We did multiple scaling/noise analysis

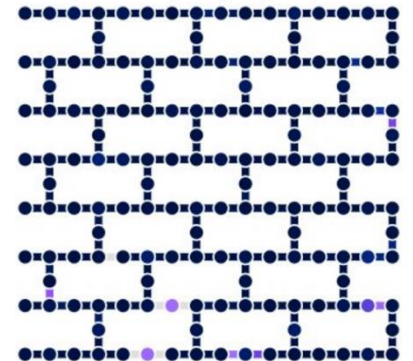
a Transpiled 2-qubit CUA circuit



b Block-diagonal unitary structure



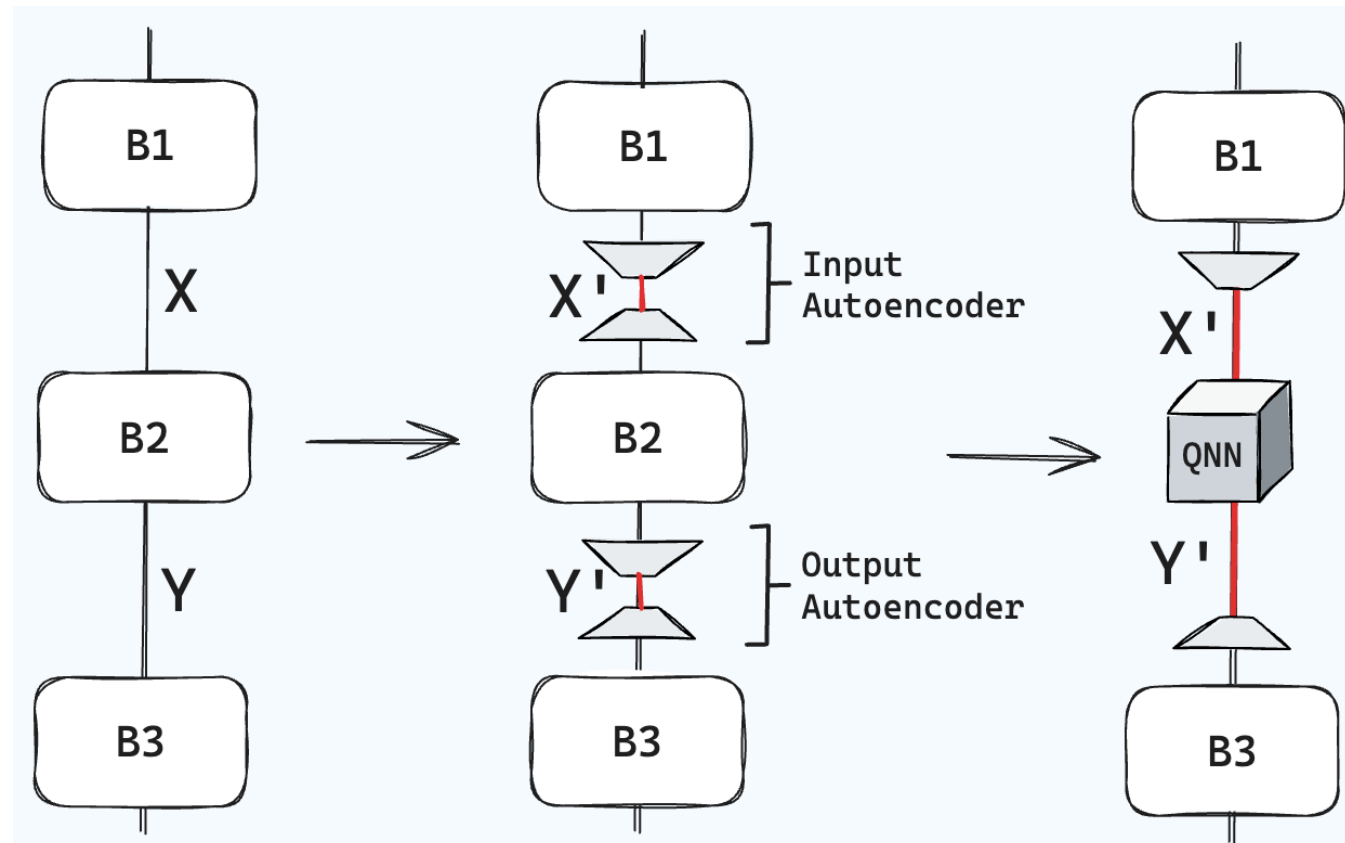
c ibm_basquecountry coupling map



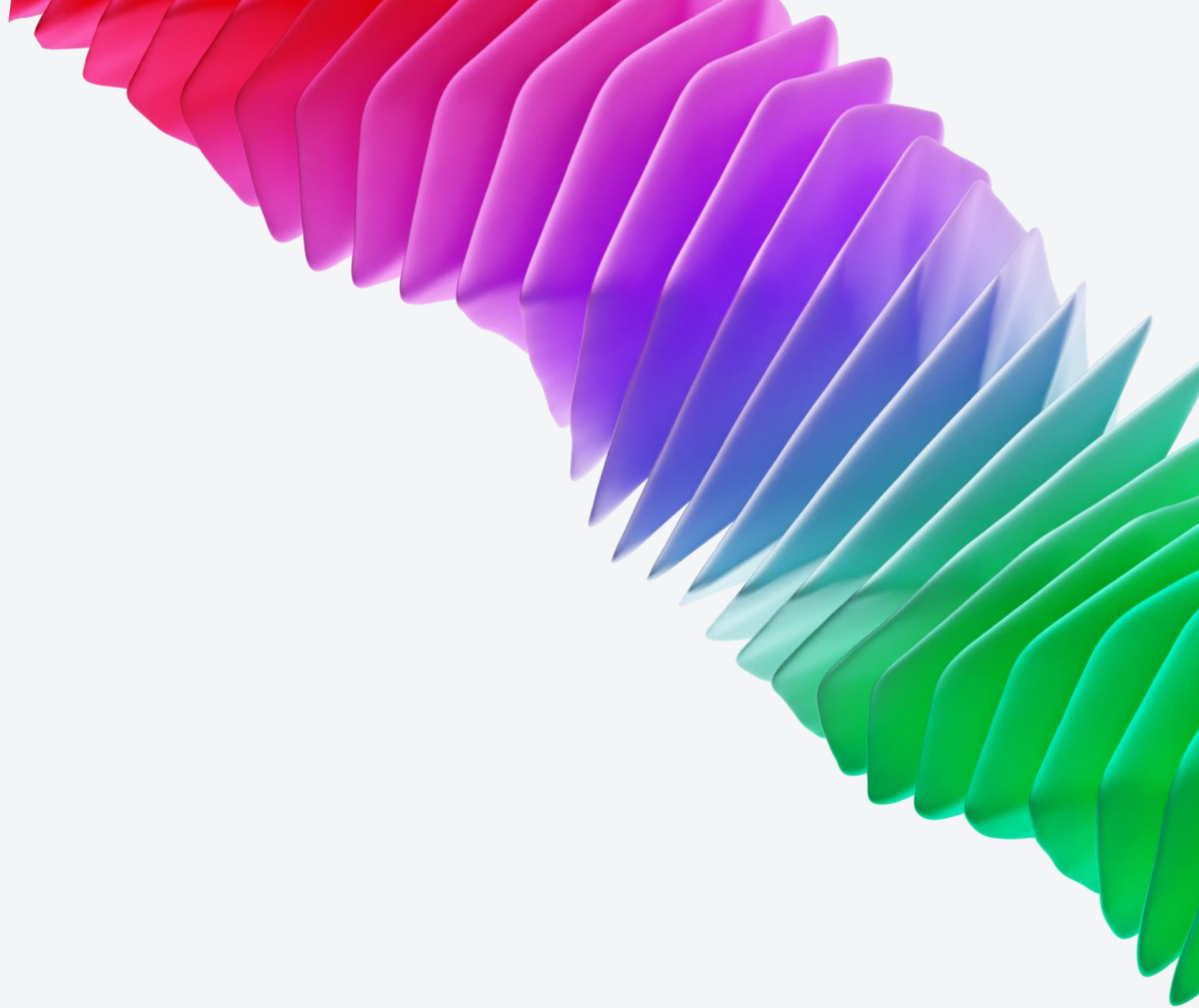
Replacing an entire Transformer block with AE + QNN

- Replace an entire block by autoencoder + QNN
- Original PPL 35.31
- Original - block PPL 41.8
- Original - block + AE + QNN

PPL 37.6 and ongoing...

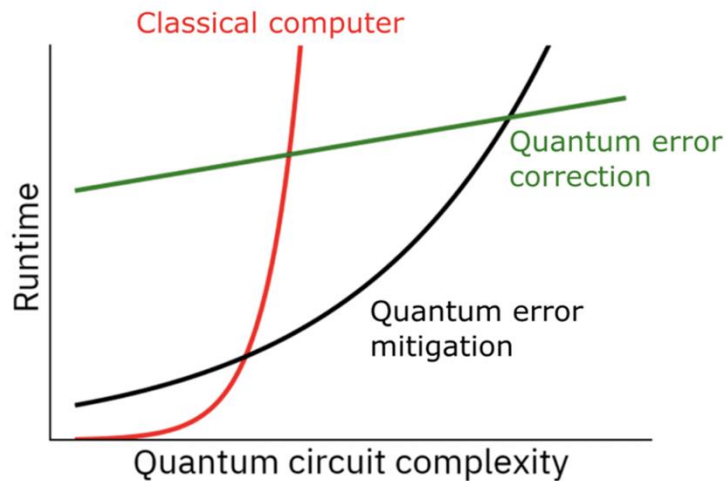


AI for Quantum



Definition of Quantum Error Mitigation

Algorithmic schemes that **reduce** the bias in expectation values caused by noise in the hardware by using **additional circuit executions** and **classical post-processing**, without requiring full quantum error correction



Qin, D., Xu, X., & Li, Y. (2022). An overview of quantum error mitigation formulas. *Chinese Physics B*, 31(9), 090306. <https://doi.org/10.1088/1674-1056/ac7b1e>

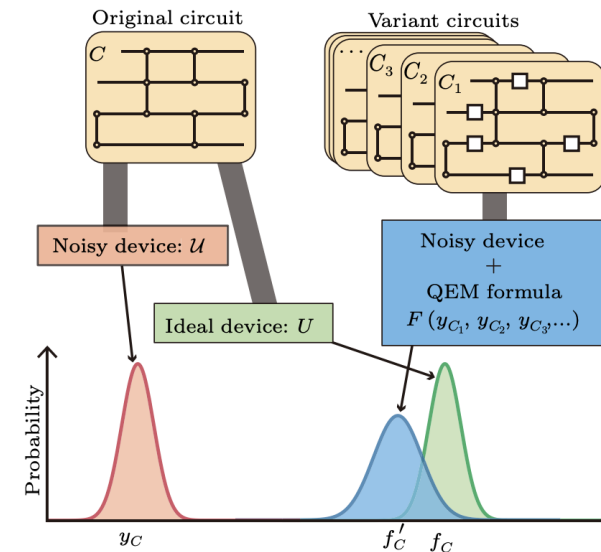
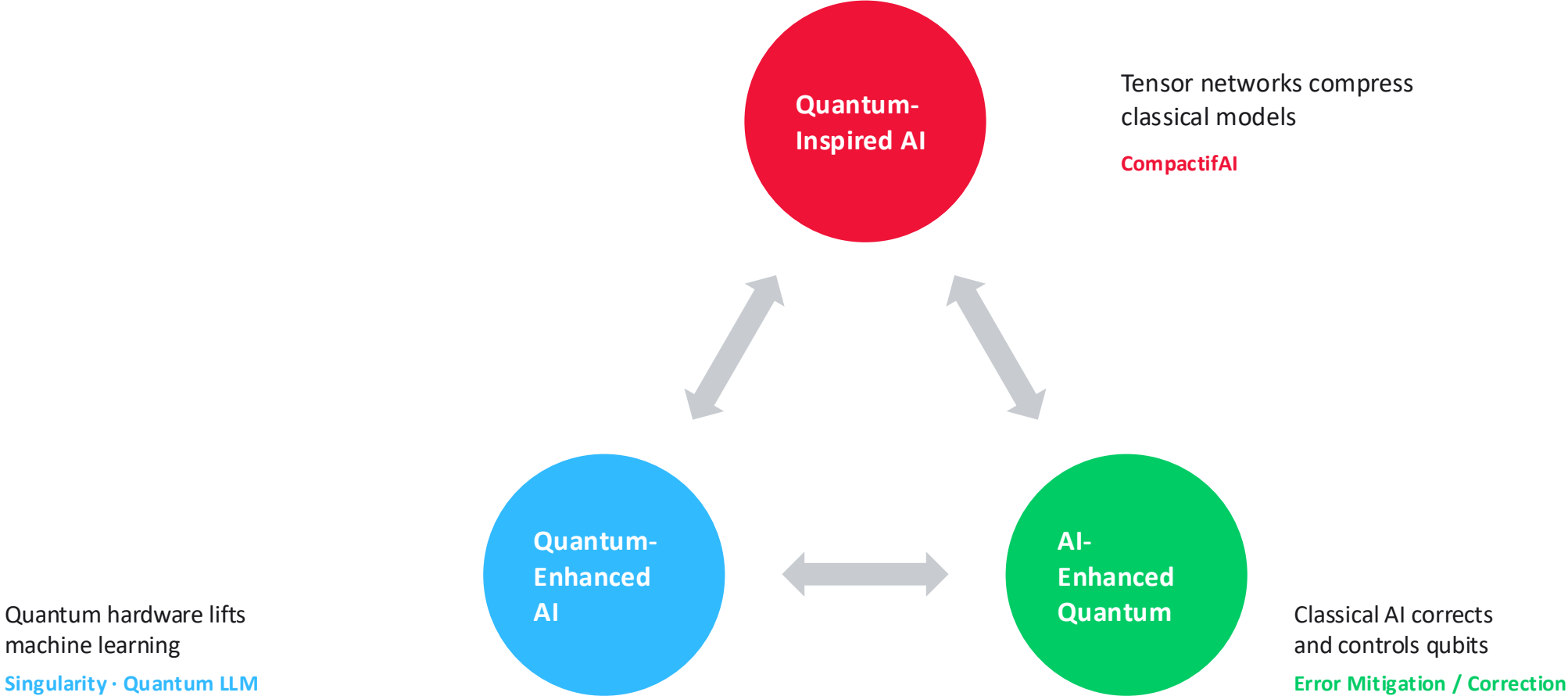


Fig. 1. Schematic diagram of quantum computing with and without QEM. The output of the original circuit is f_C on an ideal quantum device and y_C on a noisy device. Quantum error mitigation performs computations on a set of variant circuits to predict the error-free result with an increased accuracy. A general cost of quantum error mitigation is the enlarged variance.

Idea: train an AI model to learn the difference between the original circuit and the circuit + error mitigation's outputs. Given a noisy circuit, predict the output of the error mitigated circuit



Towards Intelligent Quantum Computers



The substrate is silicon. The qubits are fabricated objects. This convergence is built on the work of the people in this room.



The Real Question



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Not *when* will quantum computers become
intelligent — but *who* will build them.