Subspace Preserving Quantum Machine Learning Algorithms

Quantum Utility through Sub-Optimal Models

PRESENTED BY

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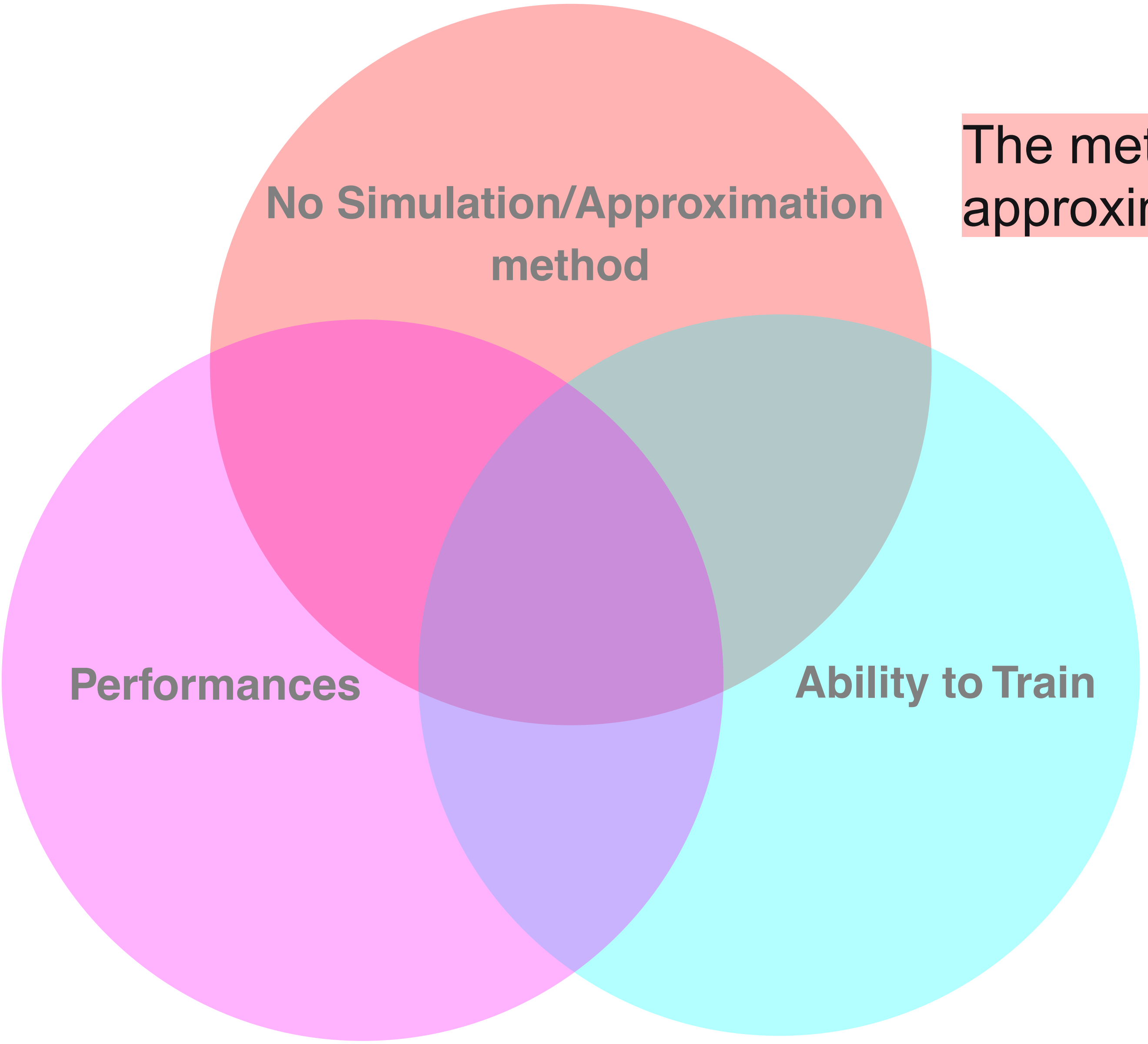
Summary

- Challenges in Near-term QML and Motivation
- Subspace Preserving Variational Quantum Algorithms
- Subspace Preserving QCNN
- State Injection Scheme

I.1 Challenges for near-term QML

To design a QML algorithm, one should investigate:



The method should **not be dequantized** using approximation or simulation method

The algorithm should perform well and **not only on toy models**

The neural network should **avoid vanishing gradient phenomena**

I.2 Motivation and Use Case

Our proposal is not use case oriented but it offer a **speed-up Machine Learning subroutines**.

We give theoretical guarantees on:

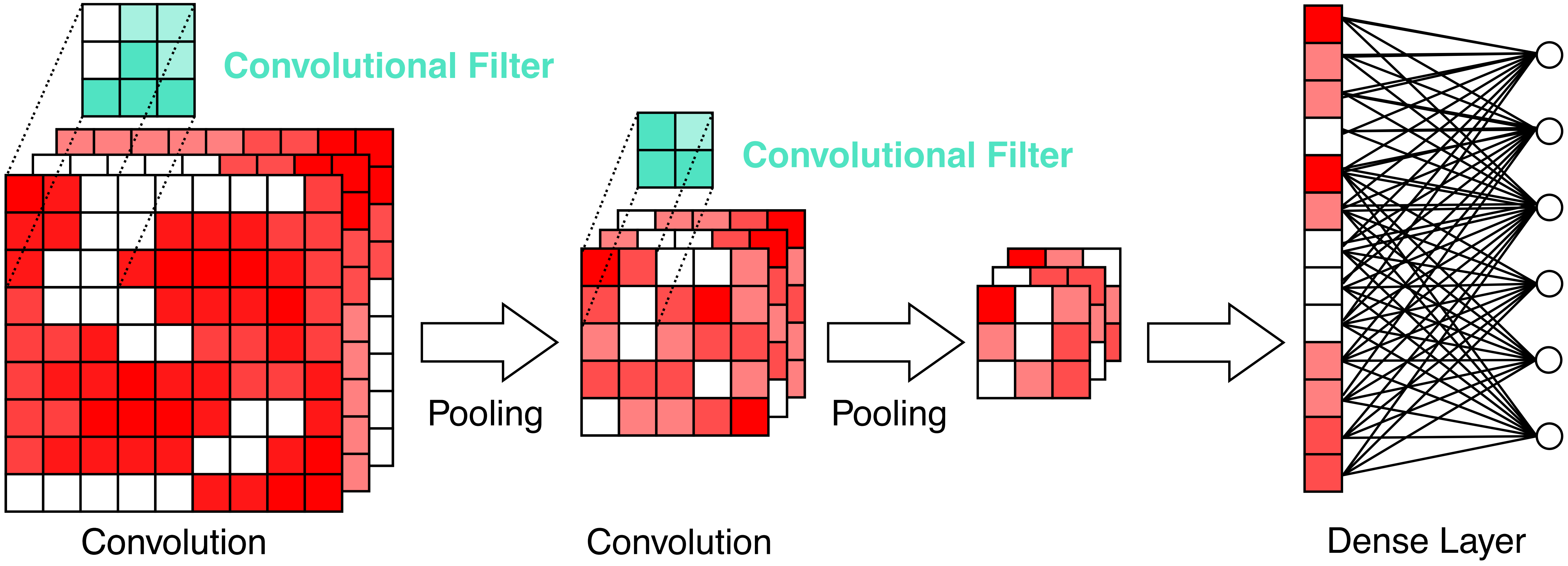
- The dequantization of our method: by using amplitude encoding and subspace preserving properties.

- The training of the neural network: **no vanishing gradient** while using subspace preserving circuits and polynomial size subspace.

- The scaling: we **mimics classical method** to ensure the well behavior of our method **even for large scale implementation**. We also prove theoretically **important polynomial speed-ups**.

I.3 Motivation and Architectures

We present a **Subspace Preserving Quantum Convolutional Neural Network** with all those guarantees:



Corresponding papers:

Subspace Preserving Quantum Convolutional Neural Network, arXiv:2409.18918

L. Monbroussou, J. Landman, L. Wang, A.B. Grilo, E. Kashefi

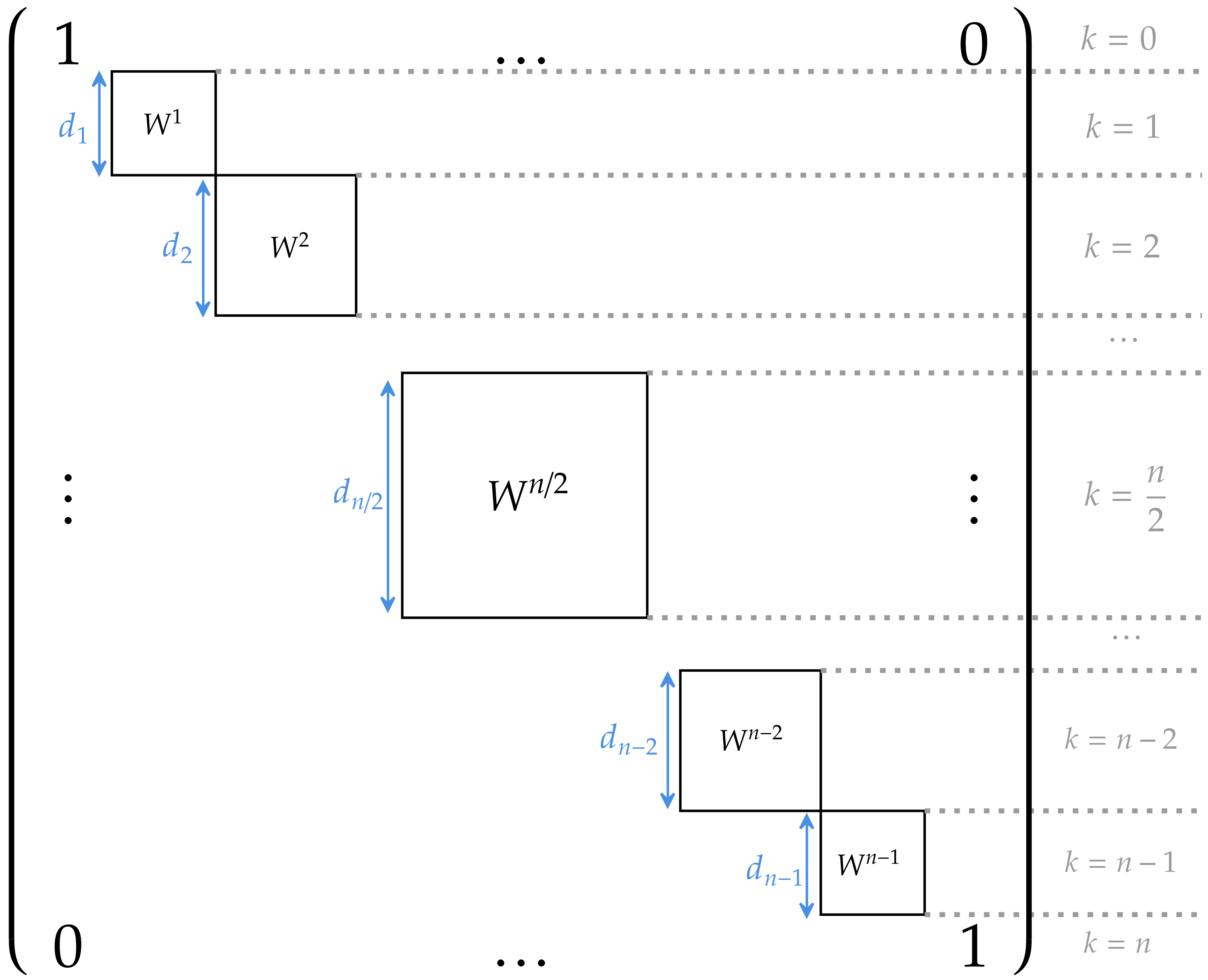
II.1 Subspace Preserving Circuits

Subspace preserving operations present some symmetries that allow to preserve sub-basis of the Hilbert space.

$$RBS(\theta) = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & \cos(\theta) & \sin(\theta) & 0 \\ 0 & -\sin(\theta) & \cos(\theta) & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}$$

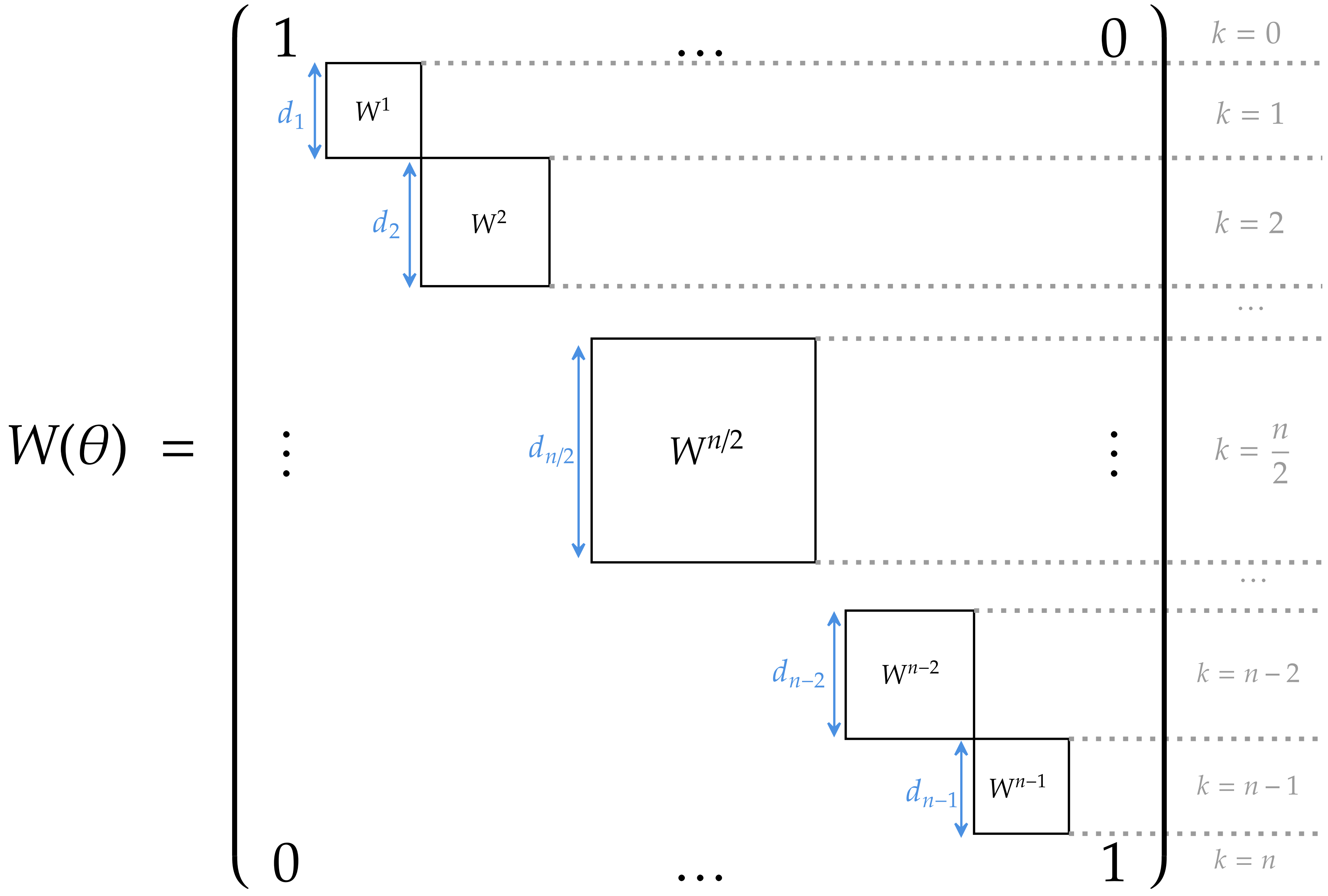
For example the Reconfigurable BeamSplitter Gate is Hamming Weight Preserving.

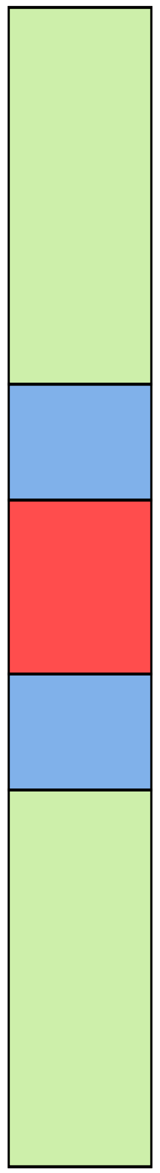
$W(\theta) =$



II.2 Training Theoretical Guarantees

Subspace preserving operations present some symmetries that allow to preserve sub-basis of the Hilbert space.





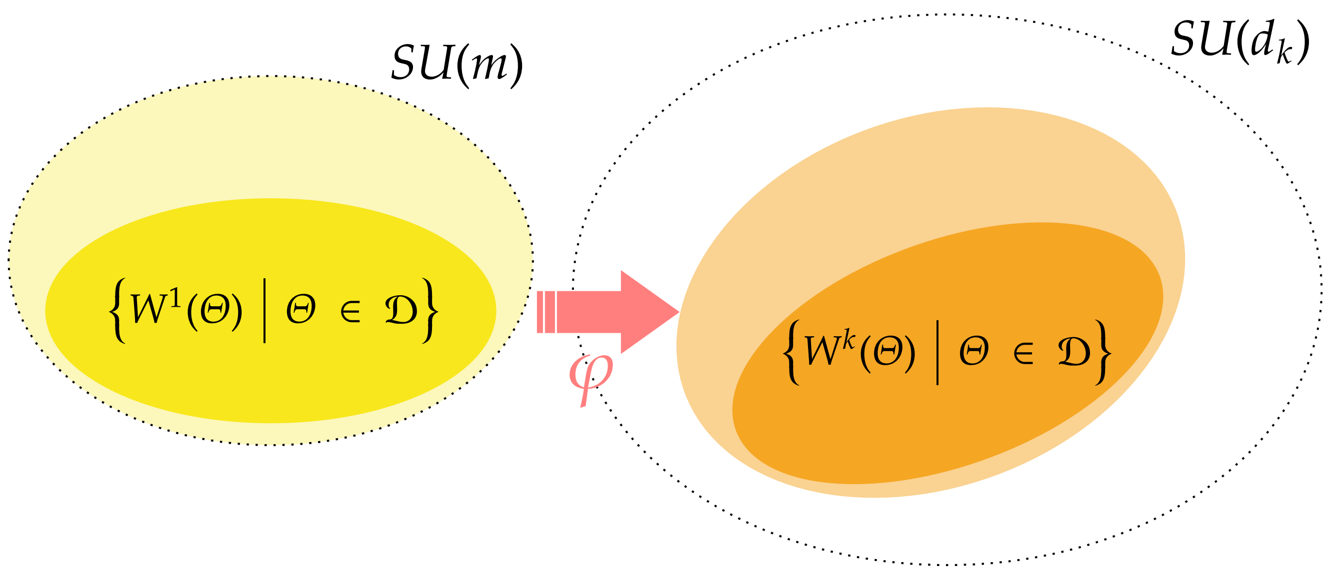
The Adjoint Is All You Need: Characterizing Barren Plateaus in Quantum Ansatze: E. Fontana, D. Herman, S. Chakrabarti, N. Kumar, R. Yalovetzky, J. Heredge, S.H. Sureshbabu, M. Pistoia. **arXiv:2309.07902**

Trainability and Expressivity of Hamming-Weight Preserving Quantum Circuits for Machine Learning: **L. Monbroussou**, E.Z. Mamon, J. Landman, A.B. Grilo, R. Kukla, E. Kashefi. **arXiv:2309.15547**

II.3 Linear Optical Circuits

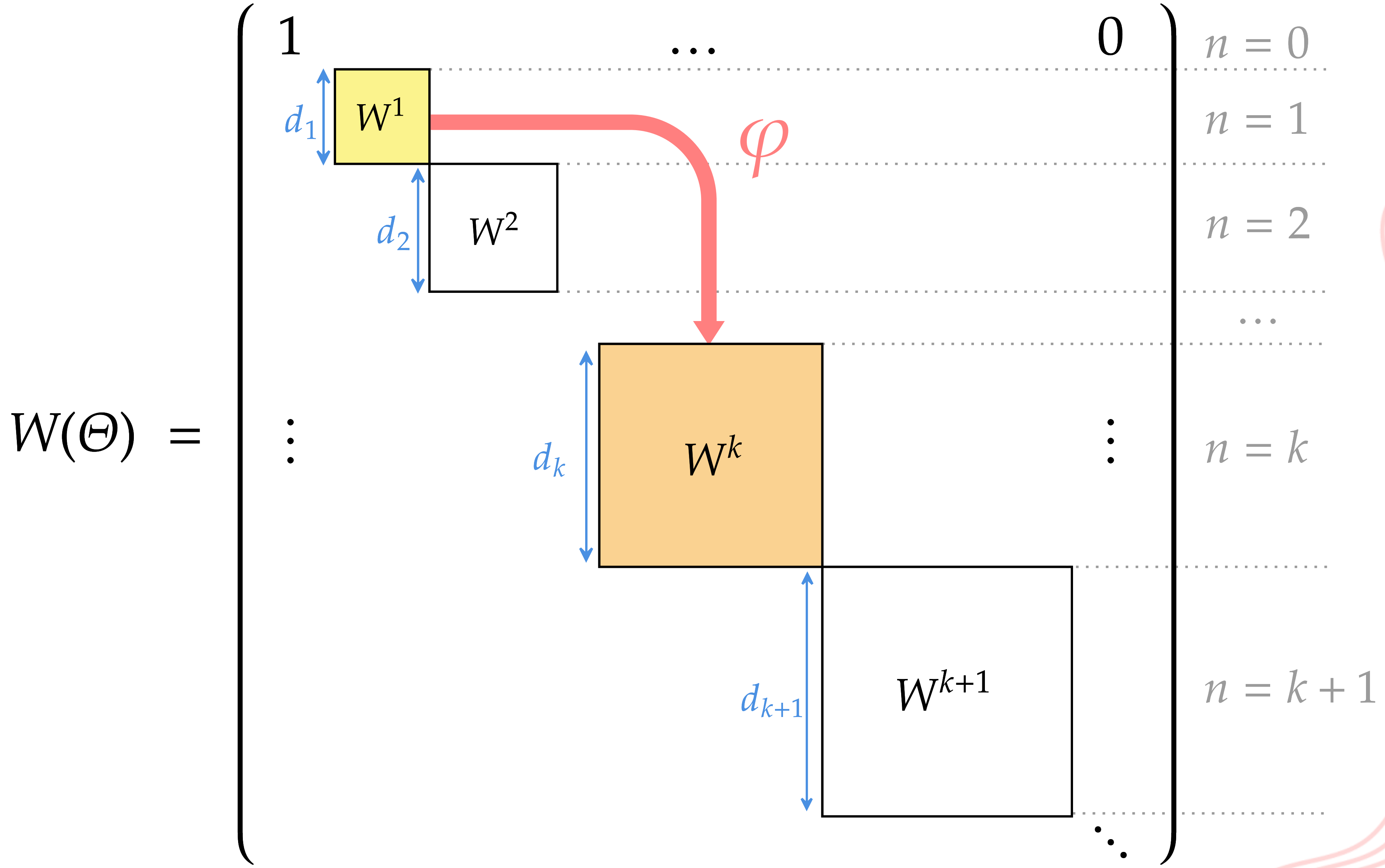
Circuits that preserve the number of particles are subspace preserving.

Circuits made of linear optics are limited in their controllability by the photonic homomorphism.



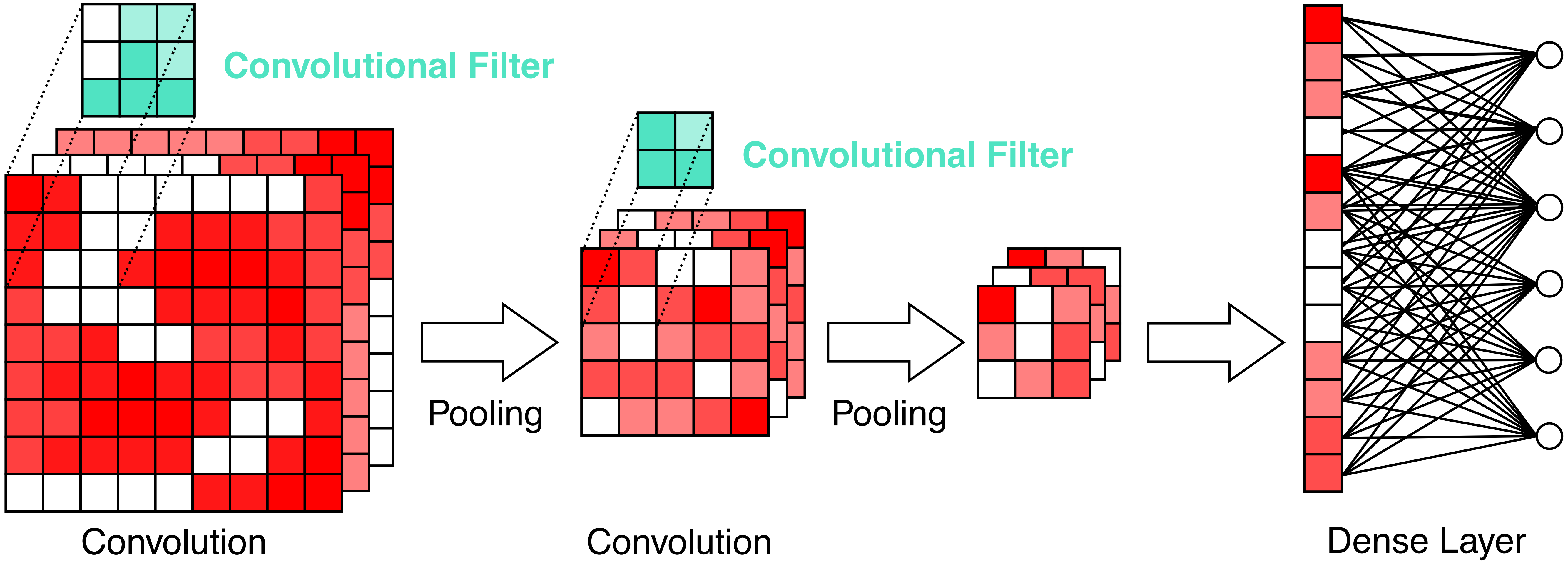
Subspace of single particle unitary matrices

Subspace of k-particle unitary matrices



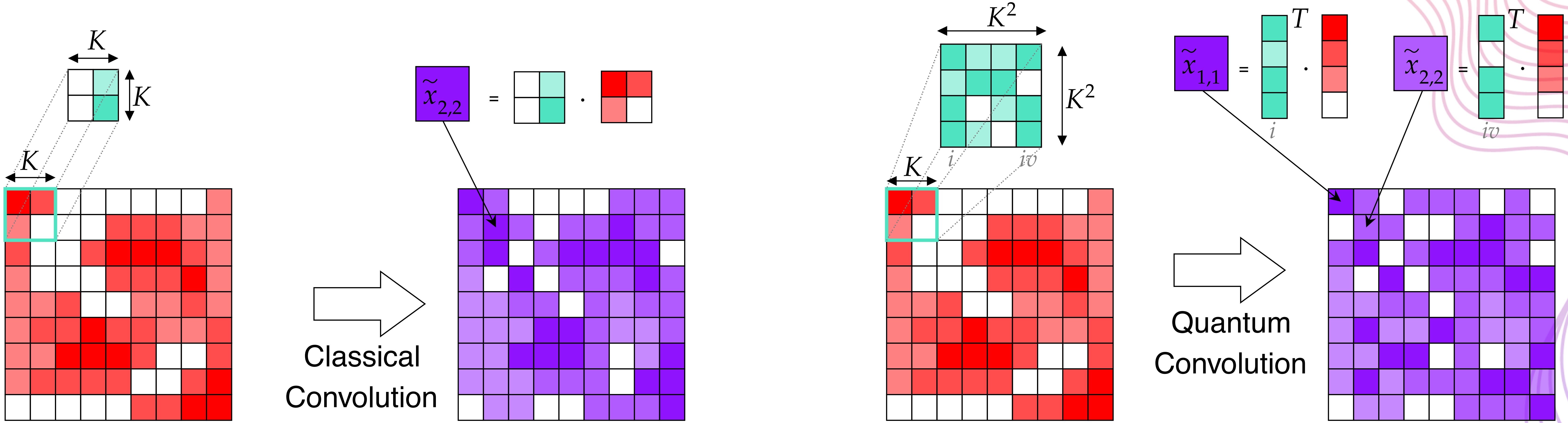
II. QCNN Architecture

We present a **Subspace Preserving Quantum Convolutional Neural Network**:



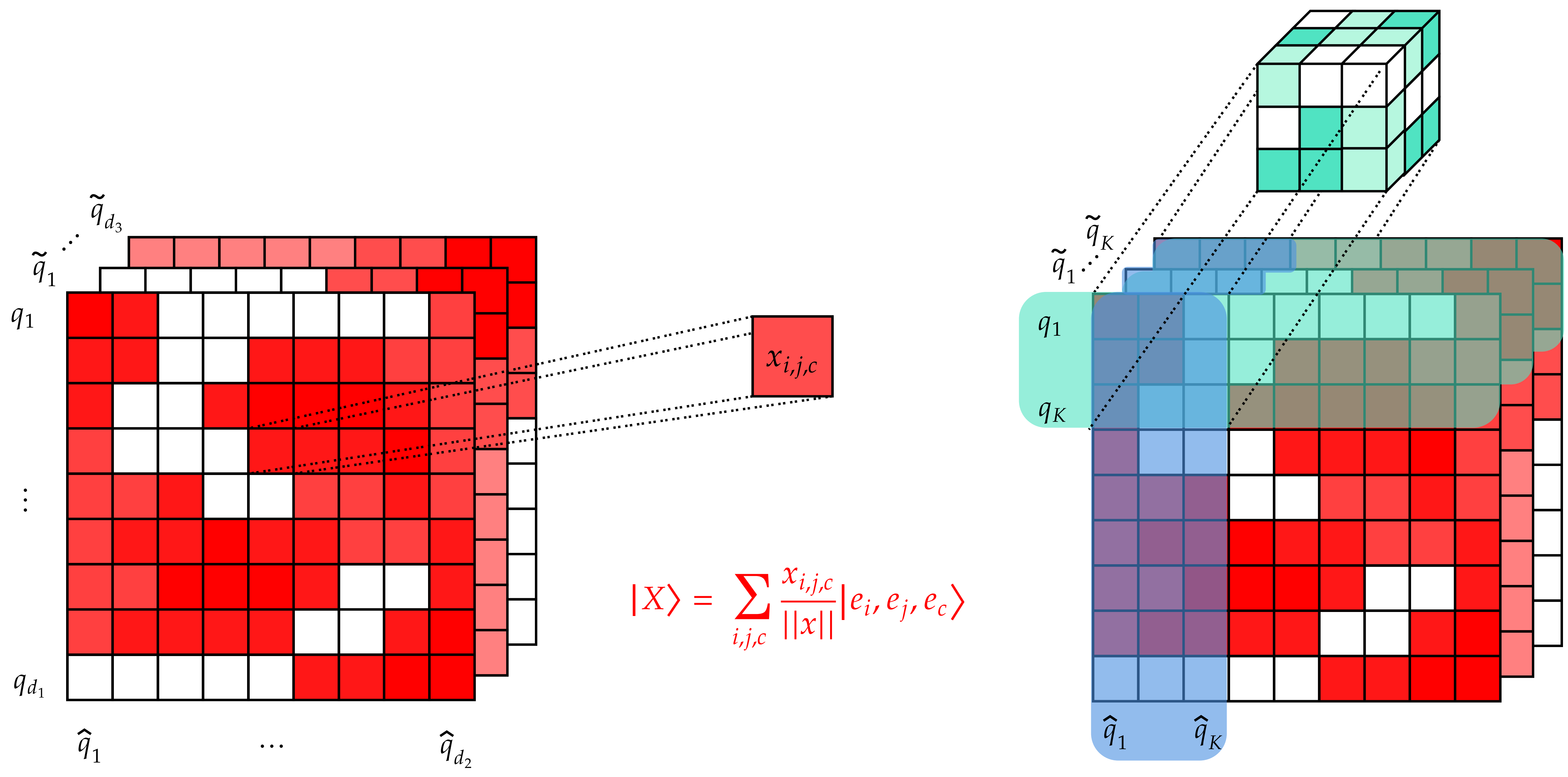
II.1 Convolutional Architectures

A convolutional layer applies a parametrized filter to the input data. The filter is optimized through the training process.



III.2 Tensor Encoding

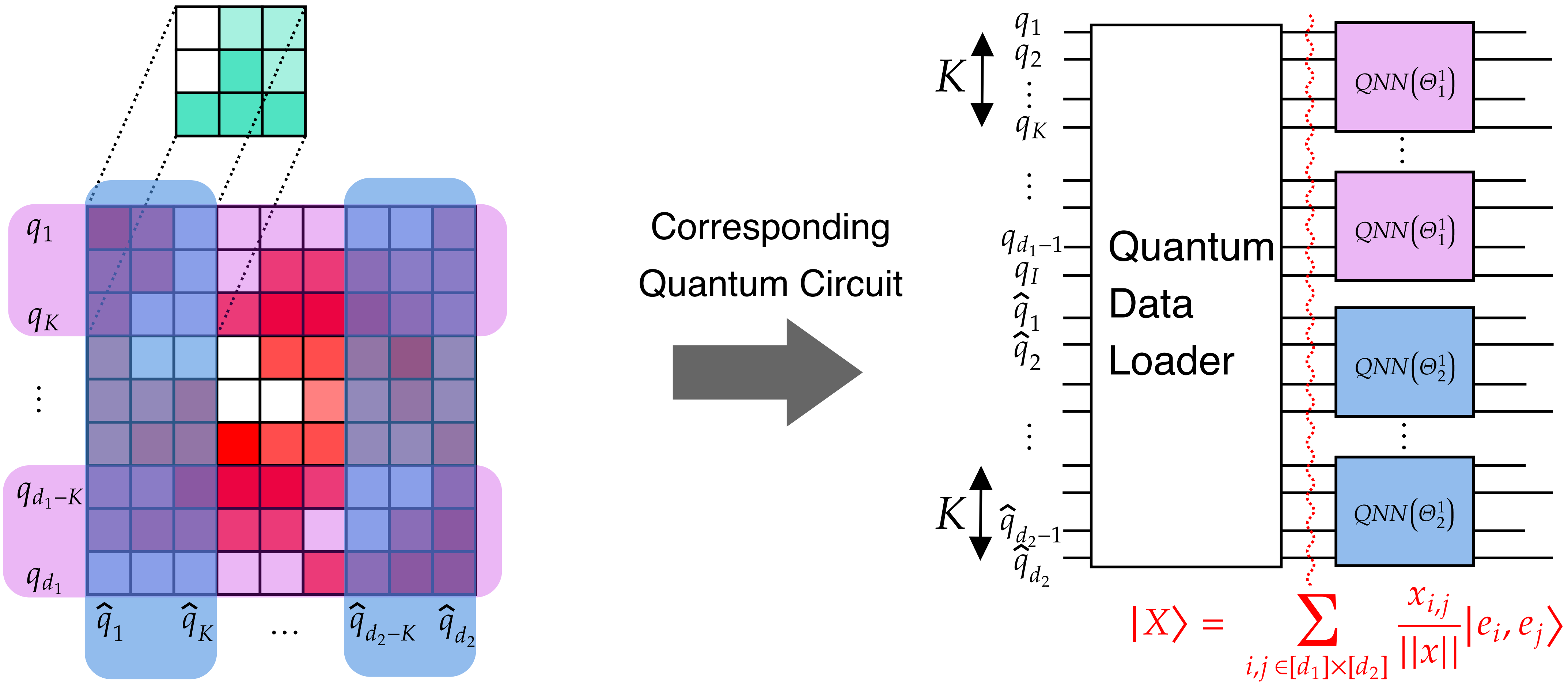
The subspace preserving convolutional layer is based on the *tensor encoding*, that allows to preserve the image structure.



$$|X\rangle = \sum_{i,j,c} \frac{x_{i,j,c}}{||x||} |e_i, e_j, e_c\rangle$$

III.3 Convolutional Layers

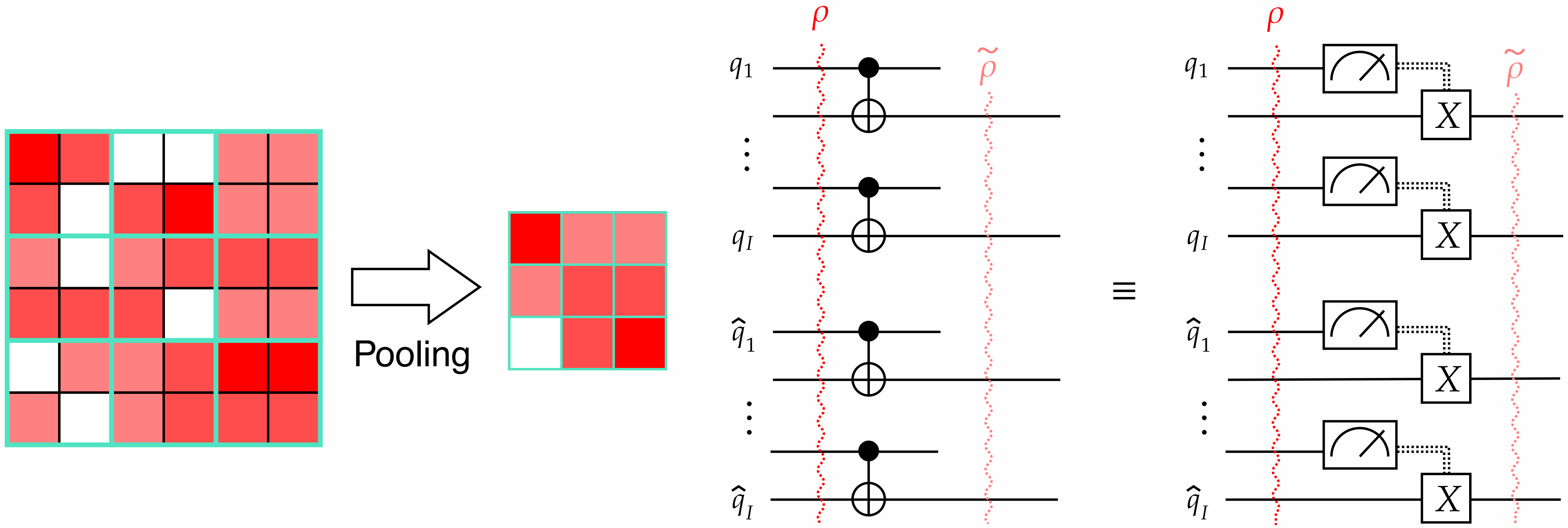
Considering the tensor encoding, Reconfigurable BeamSplitters and Photonic BeamSplitters act the same:



$|X\rangle = \sum_{i,j \in [d_1]\times[d_2]} \frac{x_{i,j}}{||x||} |e_i, e_j\rangle$

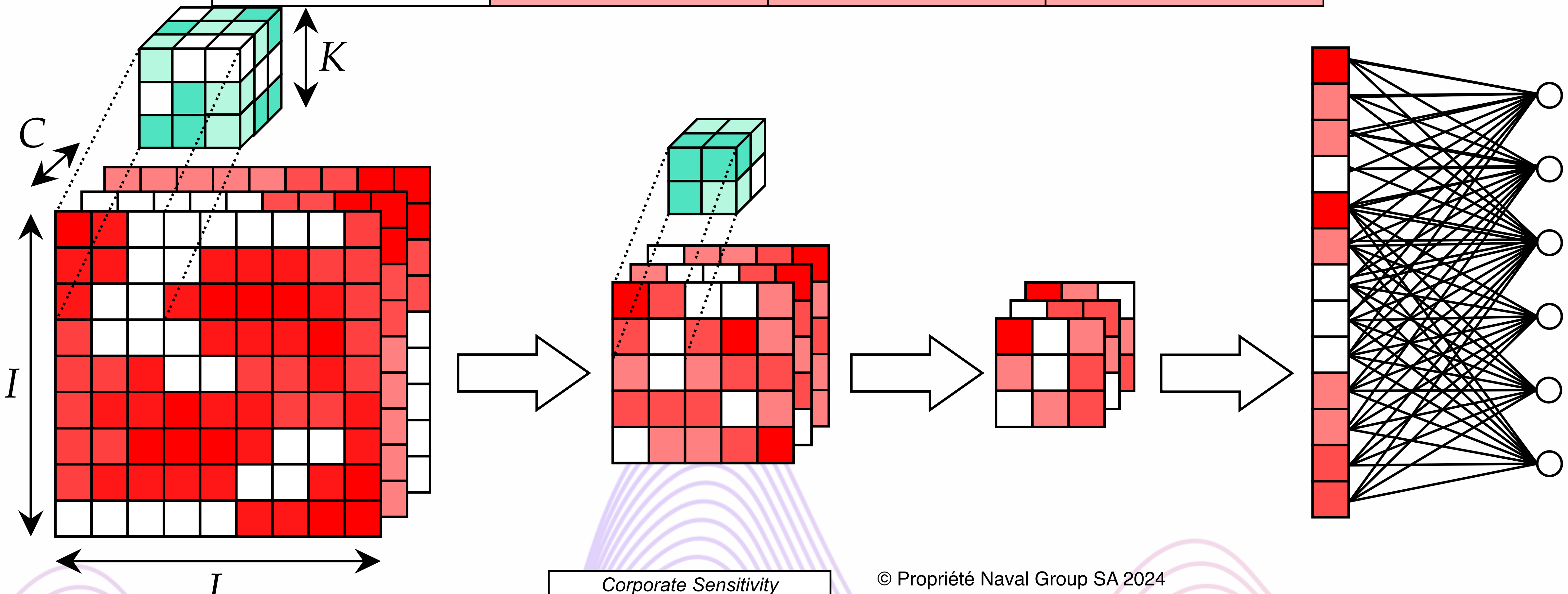
III.4 Pooling Layers

The pooling layers is subspace preserving and measurement-based:



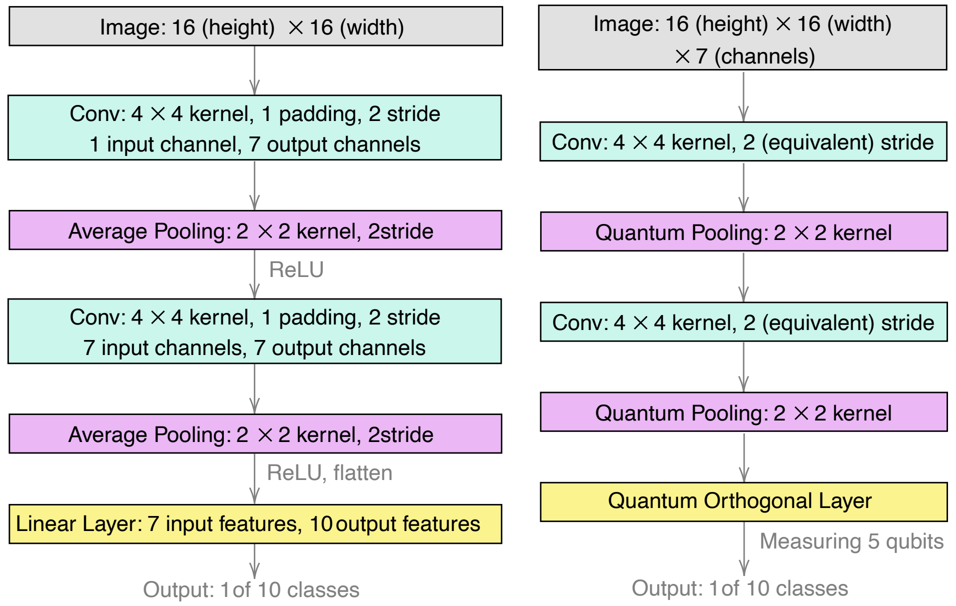
III.5 Complexity Speed-up

	Convolution	Pooling	Orthogonal Dense
Quantum	$O\left(\log K\right)$	$O\left(1\right)$	$O\left(\frac{p}{n}\right)$
Classical	$O\left(I^2 C\, K\right)$	$O\left(I^2\, C\right)$	$O\left(p\binom{n}{3}\right)$

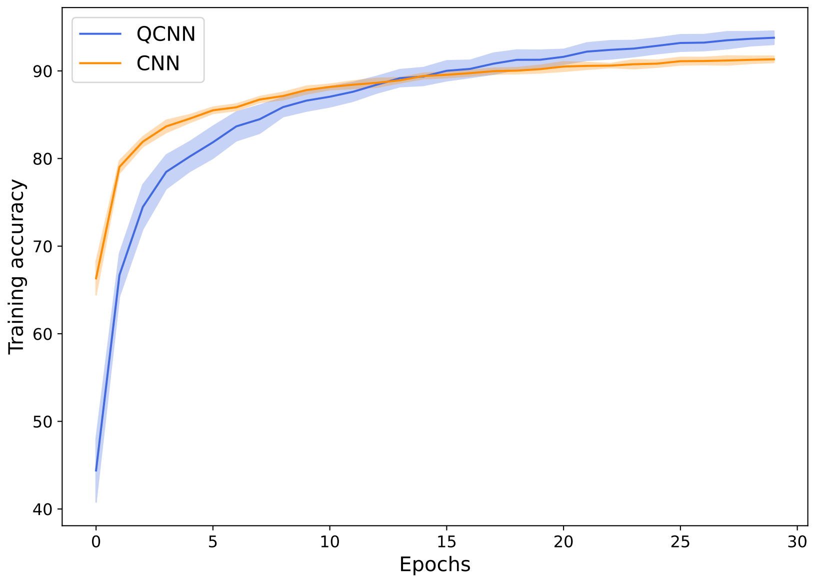


III.6 GPU based simulations

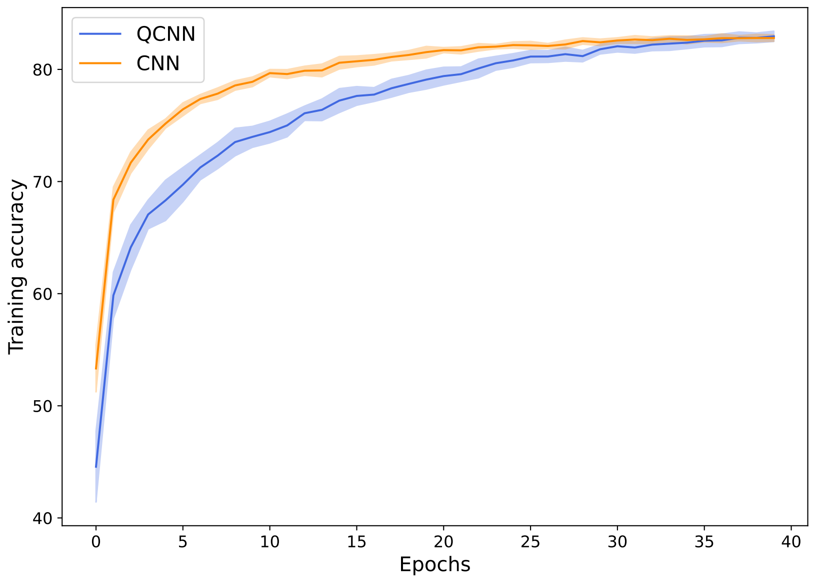
We developed a GPU oriented library to simulate subspace-preserving quantum circuits. Here are some comparisons:



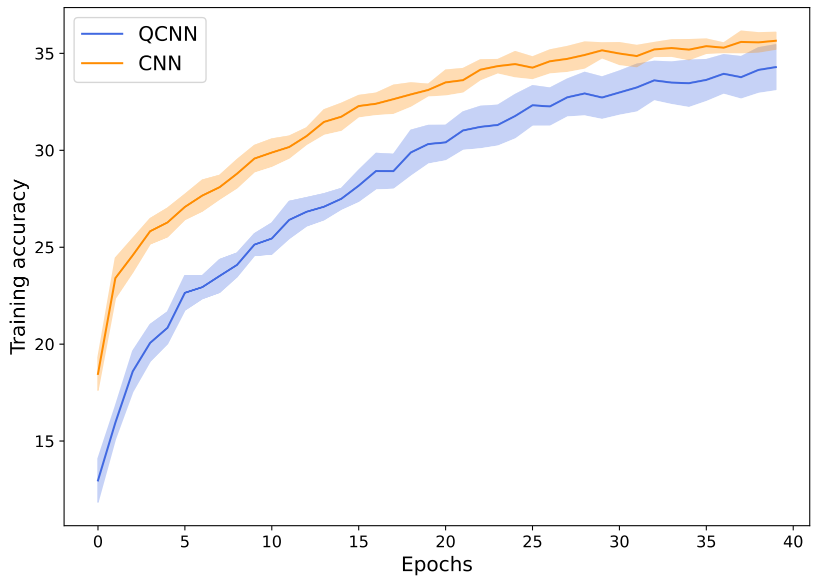
Classical and Quantum Architectures



10-classe MNIST dataset



10-classe FashionMNIST dataset



10-classe CIFAR dataset

The QCNN has similar performances with less parameters (755 versus 990) and offers a polynomial speed-up.

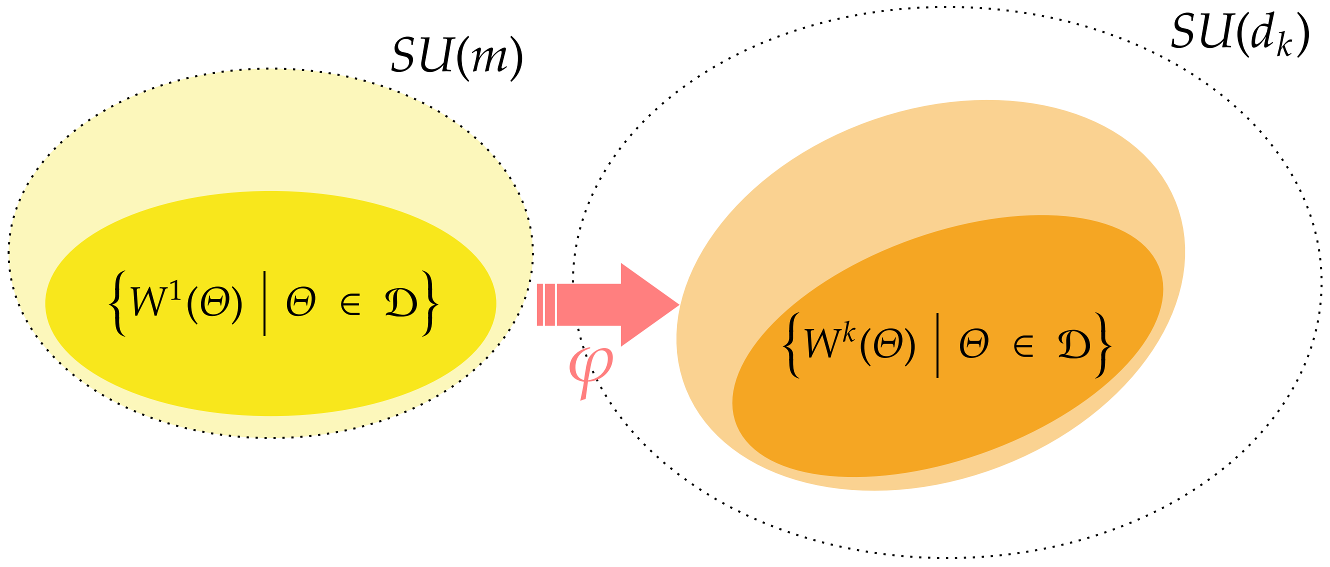
Simulation Software:

Hamming Weight Preserving Quantum Convolutional Neural Network Simulation Software: GPU oriented (PyTorch).

IV.1 State Injection Motivation

Circuits that preserve the number of particles are subspace preserving.

Circuits made of linear optics are limited in their controllability by the photonic homomorphism.



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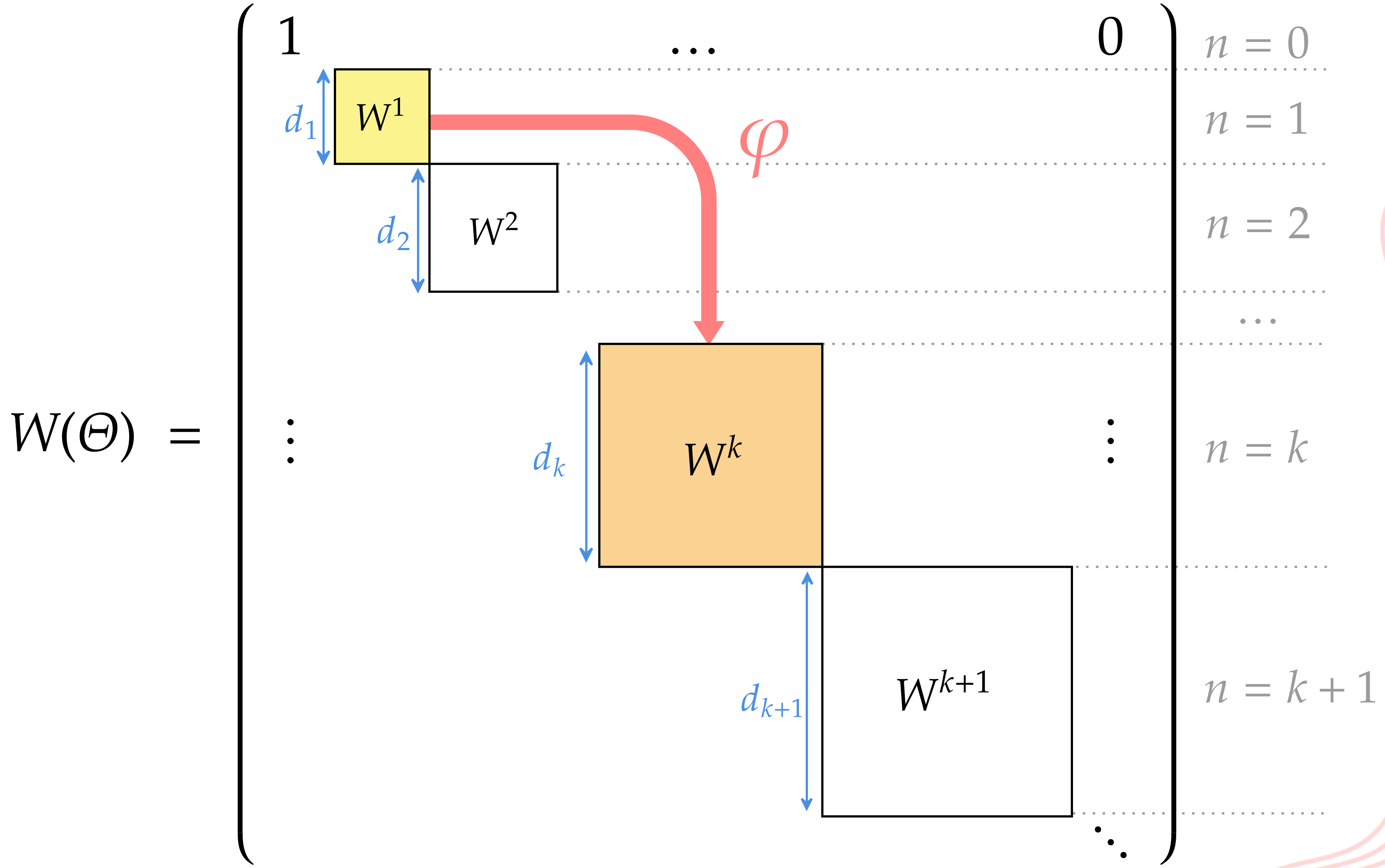
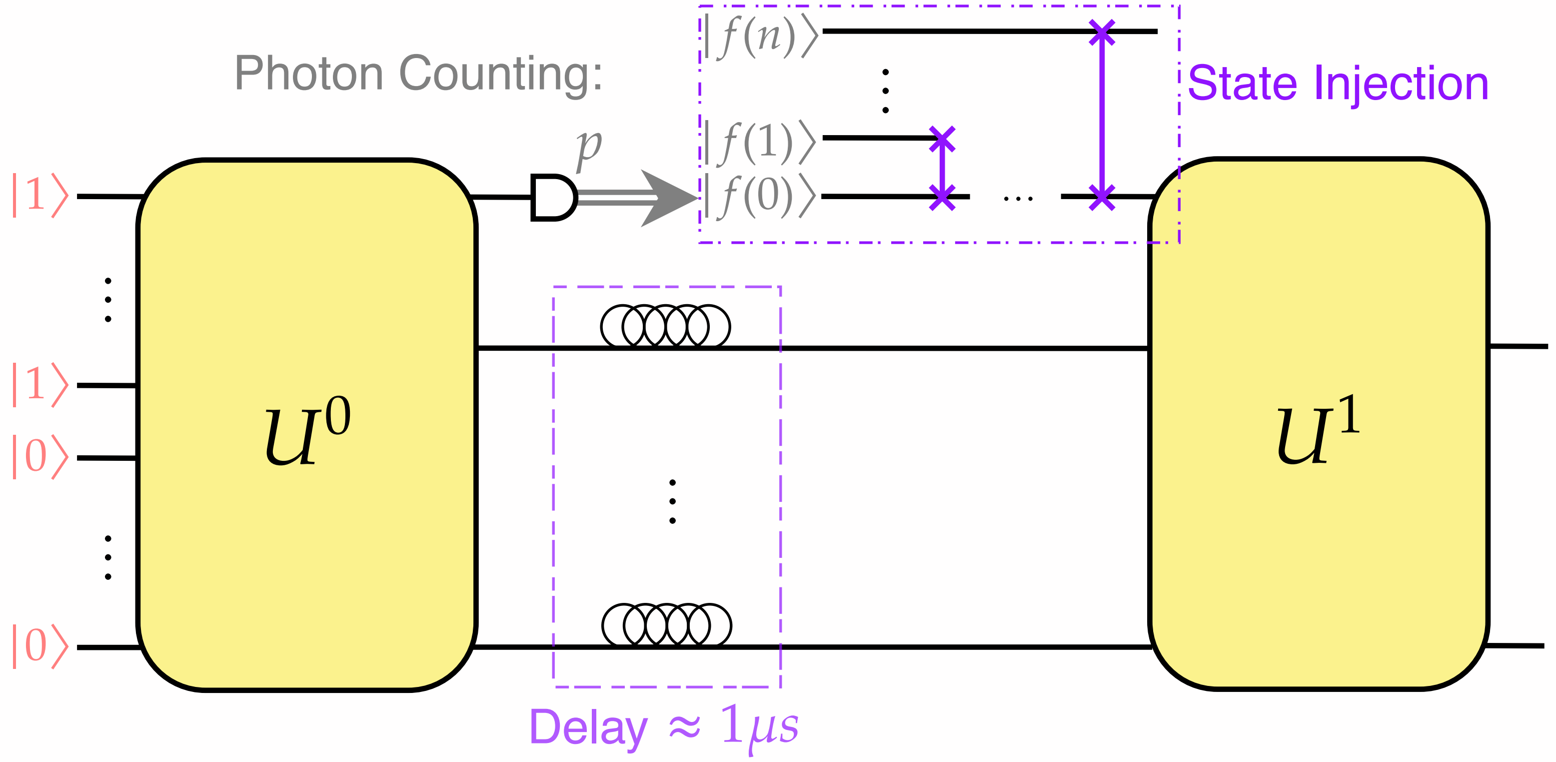
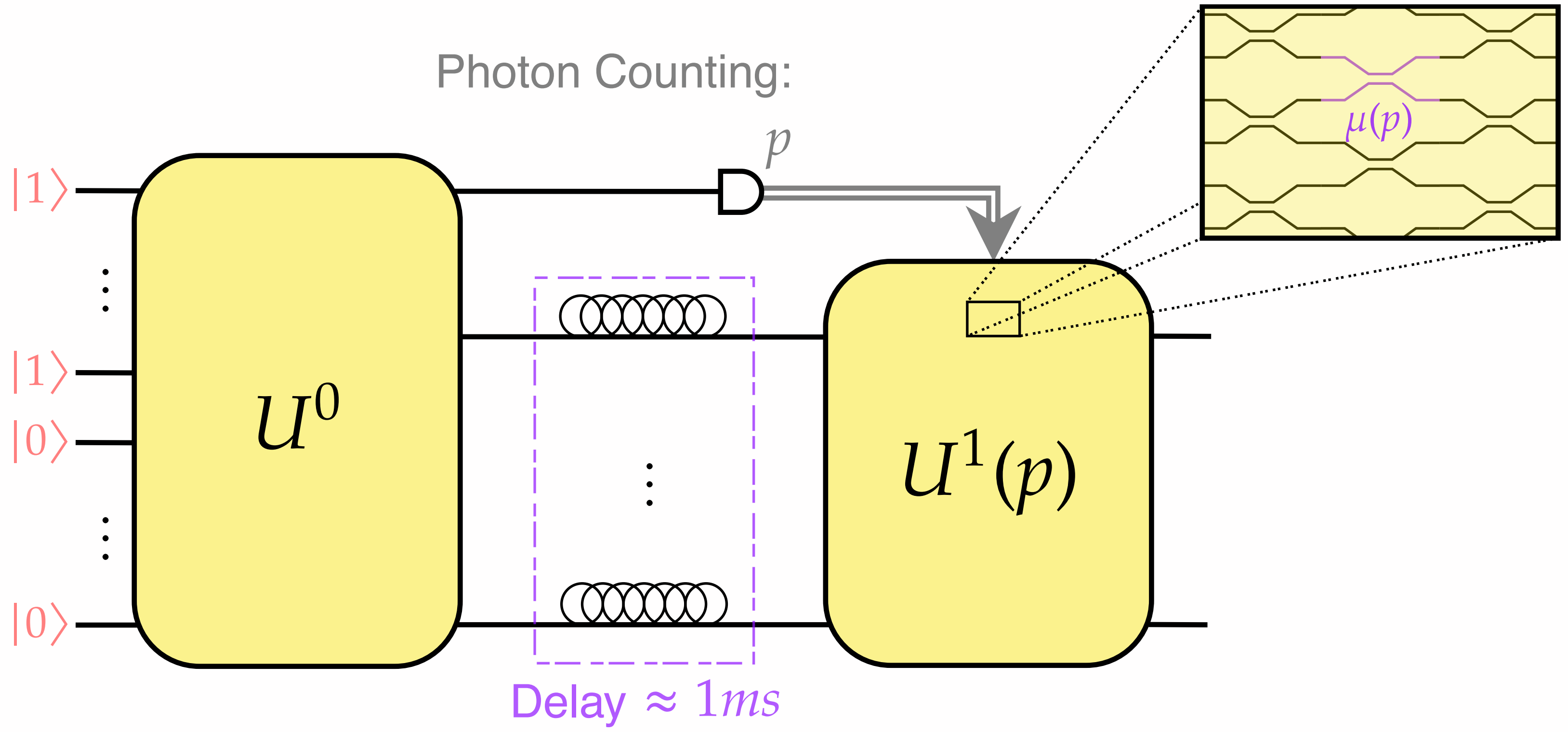


IV.2 State Injection

State Injection is an adaptive scheme that increases the controllability of the photonic circuits.



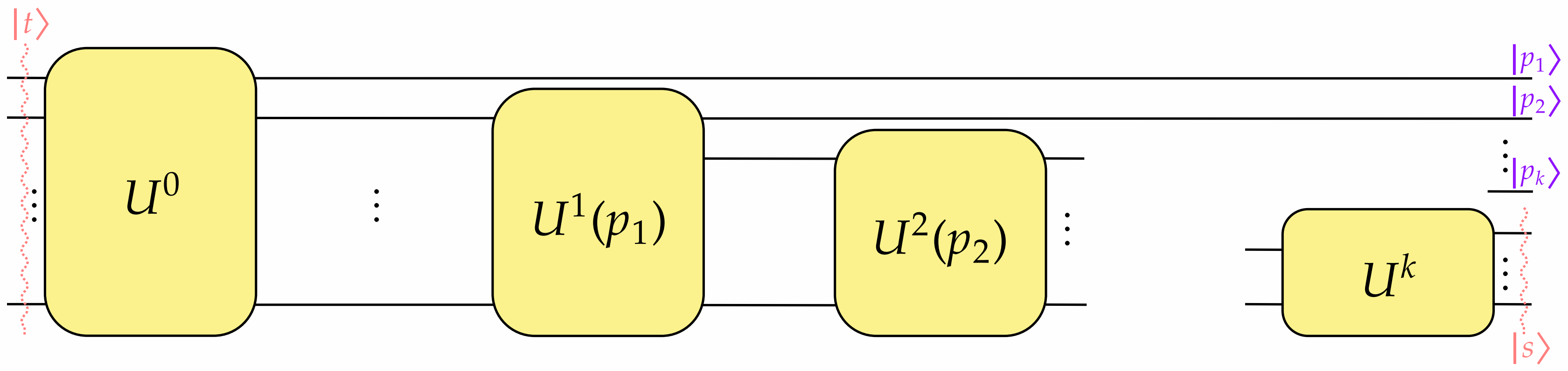
State Injection channel for a single mode measured.



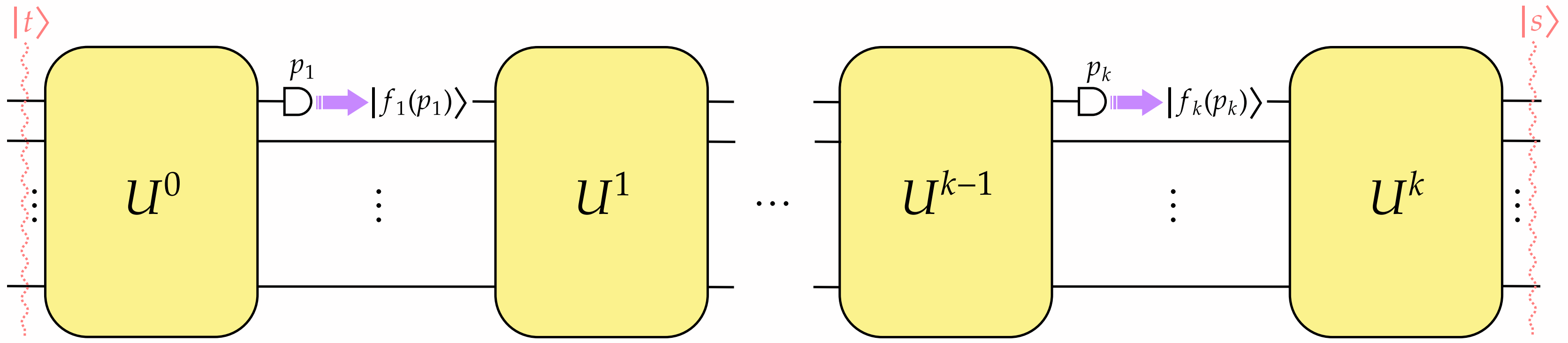
Feed-Forward adaptivity for a single mode measured.

IV.3 Probability Estimation

We can use Linear Optical circuits with Adaptivity schemes to perform a learning subroutine that is believed to be **exponentially hard classically** called probability estimation.



Feed-Forward adaptivity for a single mode measured.



State Injection channel for a single mode measured.

IV.3 Probability Estimation

State Injection is **easier to do experimentally**, and can achieve **hard simulation regime with less ressources**.

r \ k	$O(1)$	$O(\log m)$	$O(m)$
$O(1)$			
$O(\log m)$			
$O(m)$			

Classical Simulation Regime for Probability Estimation

Corresponding papers:

Towards Quantum Advantage with Photonic State Injection, arXiv:2410.01572

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Any questions?

Contact me!

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