Towards Quantum Advantage with Photonic State Injection

QT4HEP 2025

PRESENTED BY

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January, 23 2025

Corresponding papers:

Towards Quantum Advantage with Photonic State Injection, arXiv:2410.01572

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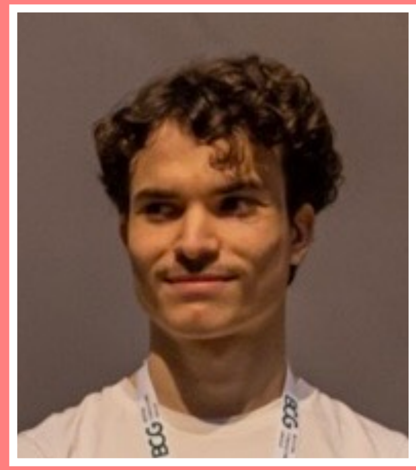
Ulysse Chabaud[3]

Eliott Mamon[1]

Léo Monbroussou[1,4]



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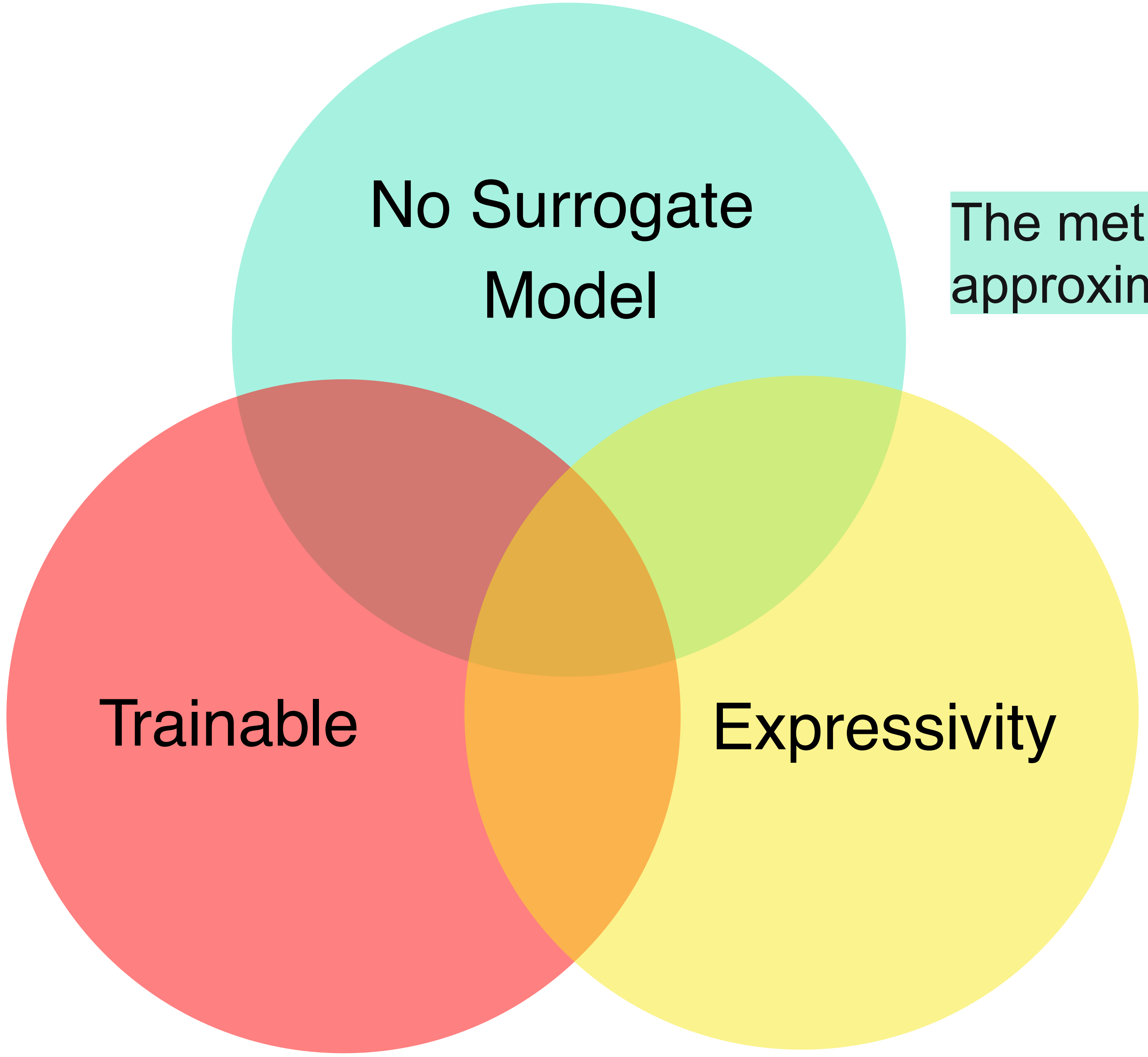
Quantum Machine Learning

Photonic Algorithm

Photonic Experimentalist

Near-term QML challenges

Near-term Quantum Machine Learning algorithms need to tackle many issues:



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

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

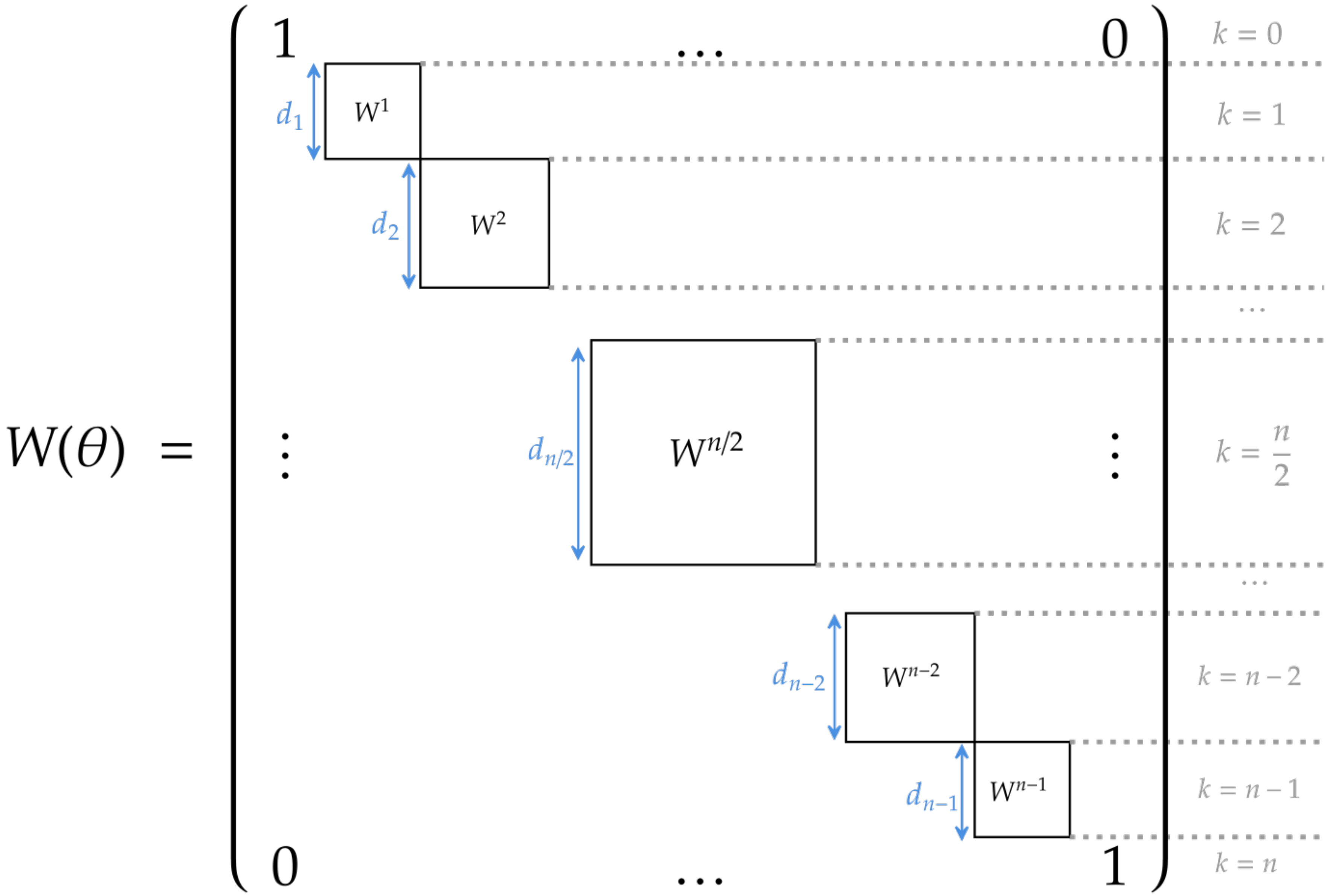
The algorithm should perform well and **not only on toy models**

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.



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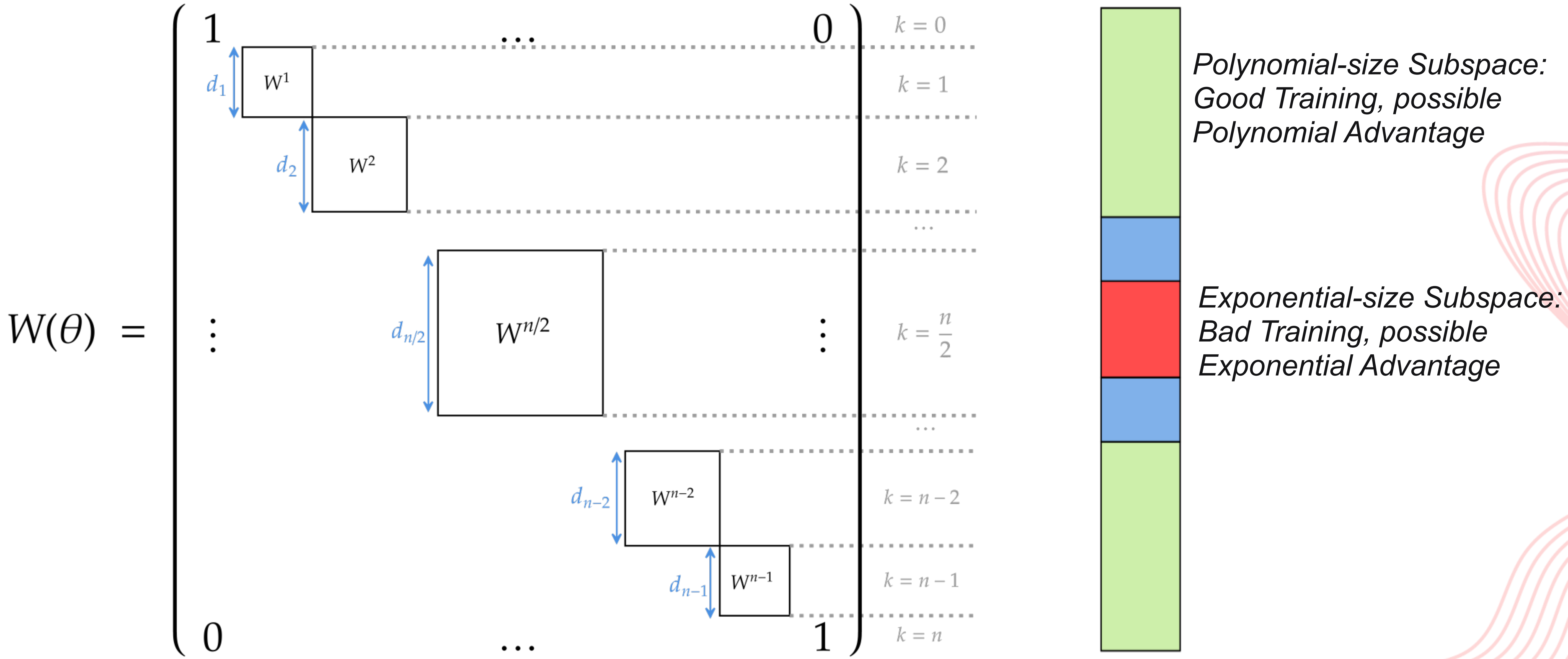
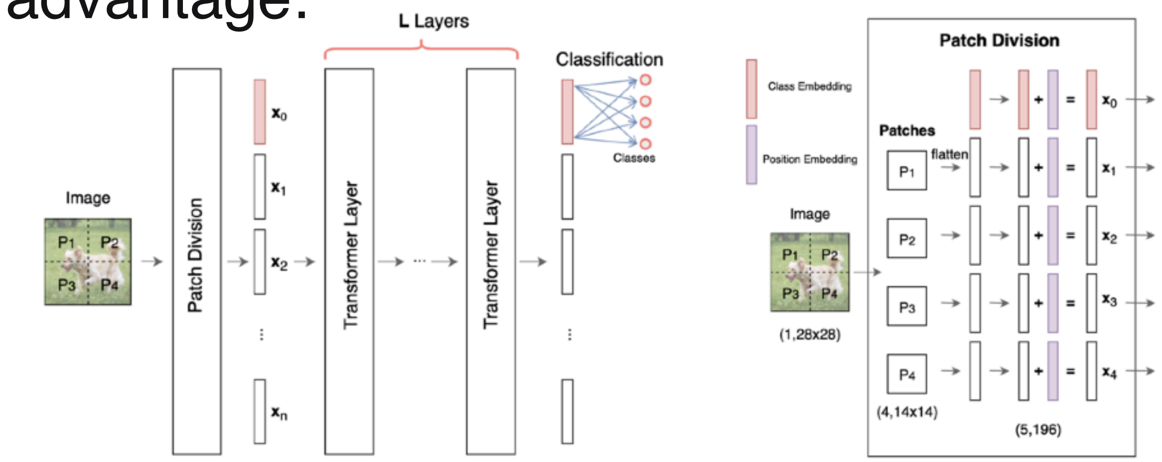


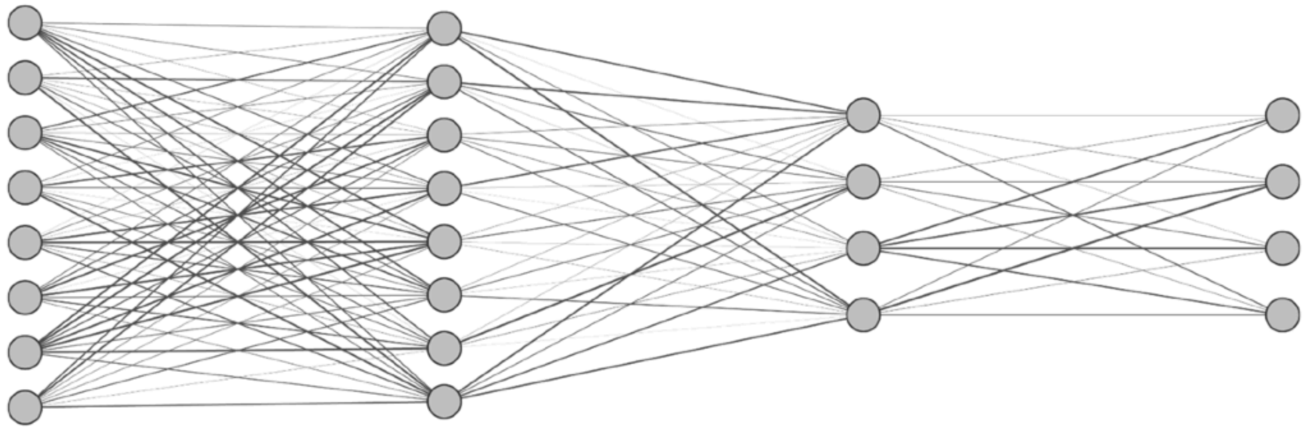
The Adjoint Is All You Need: Characterizing Barren Plateaus in Quantum Ansatze: E. Fontana, D. Herman, S. Chakrabarti, N. Kumar, R. Yalovetzky, J. Heredge, S.H. Sureshbabu, M. Pistoia. arXiv:2309.07902

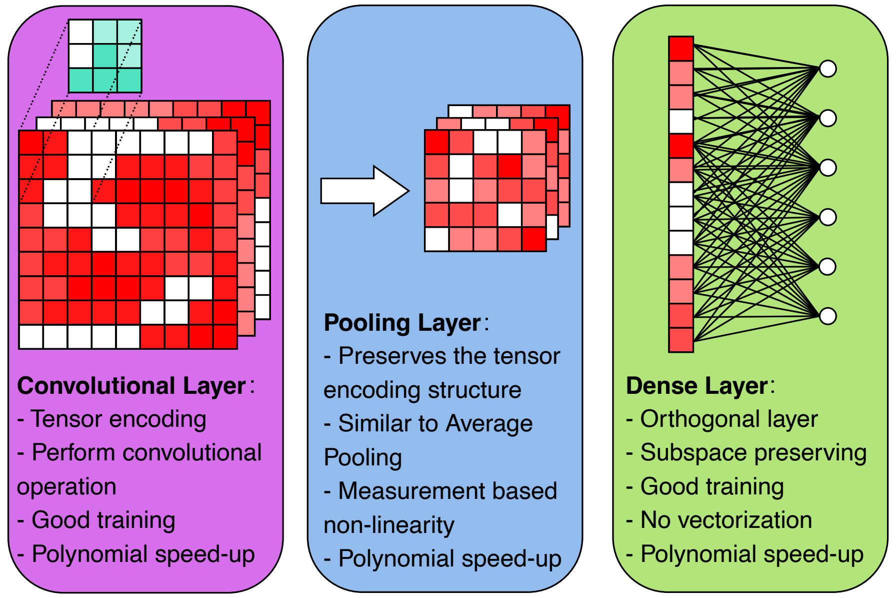
Trainability and Expressivity of Hamming-Weight Preserving Quantum Circuits for Machine Learning: **L. Monbroussou**, E.Z. Mamon, J. Landman, A.B. Grilo, R. Kukla, E. Kashefi. arXiv:2309.15547

Subspace-Preserving QML

Subspace preserving QML algorithms are very similar to classical ML architectures and offer polynomial advantage:







- *Quantum Vision Transformers*, El Amine Cherrat, et al.
  - > Transformer architectures

- *Quantum Methods for Neural Networks and Application to Medical Image Classification*, Jonas Landman, et al.
  - > Orthogonal Neural Networks

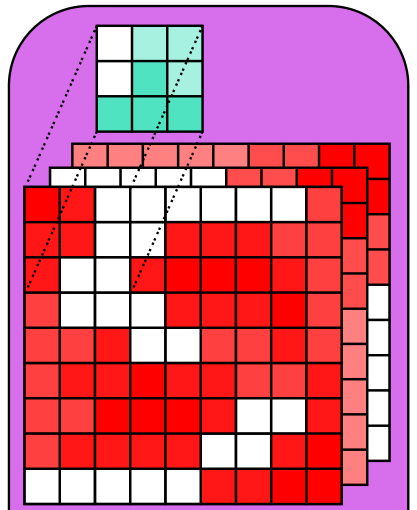
- *Subspace Preserving Quantum Convolutional Neural Network*, Léo Monbroussou, et al.
  - > building bricks for convolutional neural networks

Theoretical Guarantees

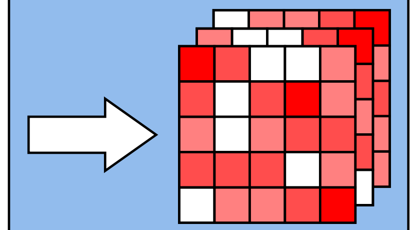
- Our method avoids dequantization results: by using tensor encoding, subspace preserving properties, and measurement based operations.

- Our method avoids vanishing gradients: by reducing the mathematical space used to one subspace of polynomial dimension, we provide theoretical guarantees on the training.

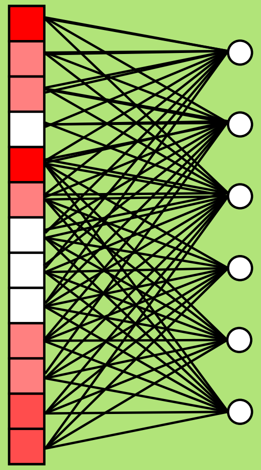
- Our method is useful for large problems: by mimicking a classical Machine Learning subroutine, we ensure that our proposal could be widely used.



Convolutional Layer:
- Tensor encoding
- Perform convolutional operation
- Good training
- Polynomial speed-up



Pooling Layer:
- Preserves the tensor encoding structure
- Similar to Average Pooling
- Measurement based non-linearity
- Polynomial speed-up



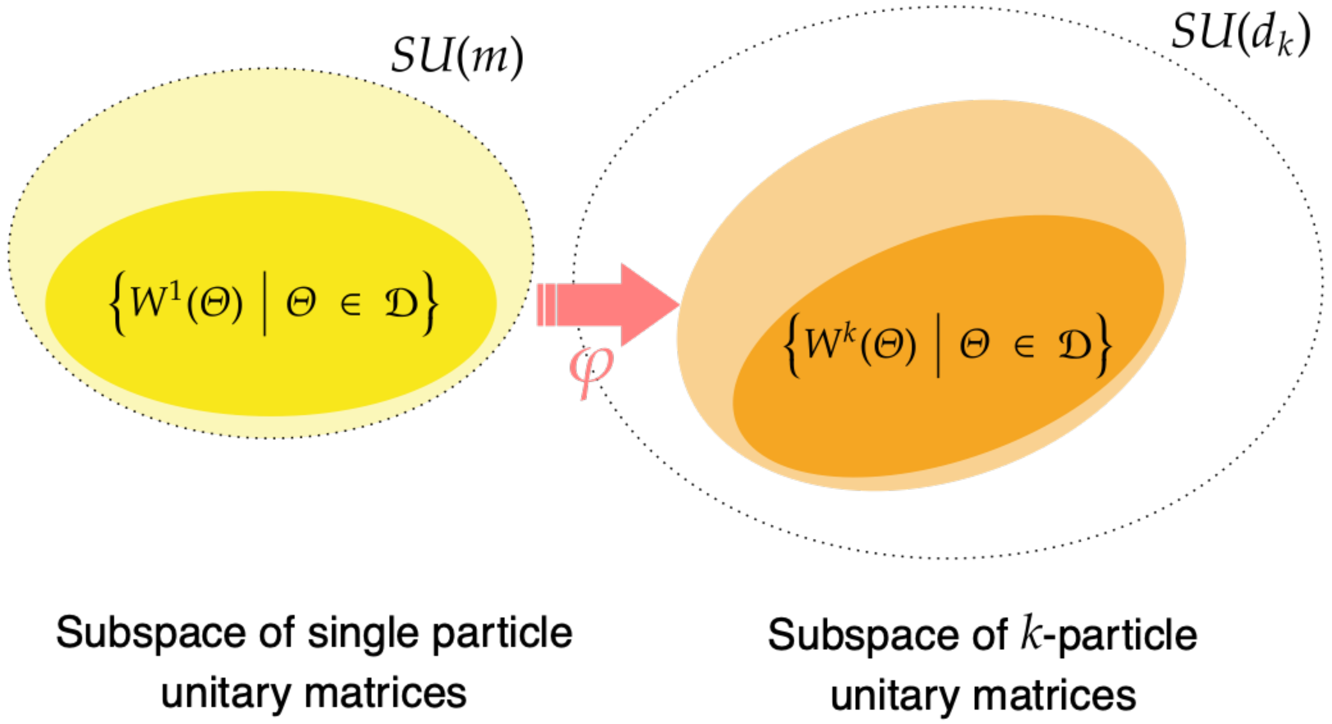
Dense Layer:
- Orthogonal layer
- Subspace preserving
- Good training
- No vectorization
- Polynomial speed-up

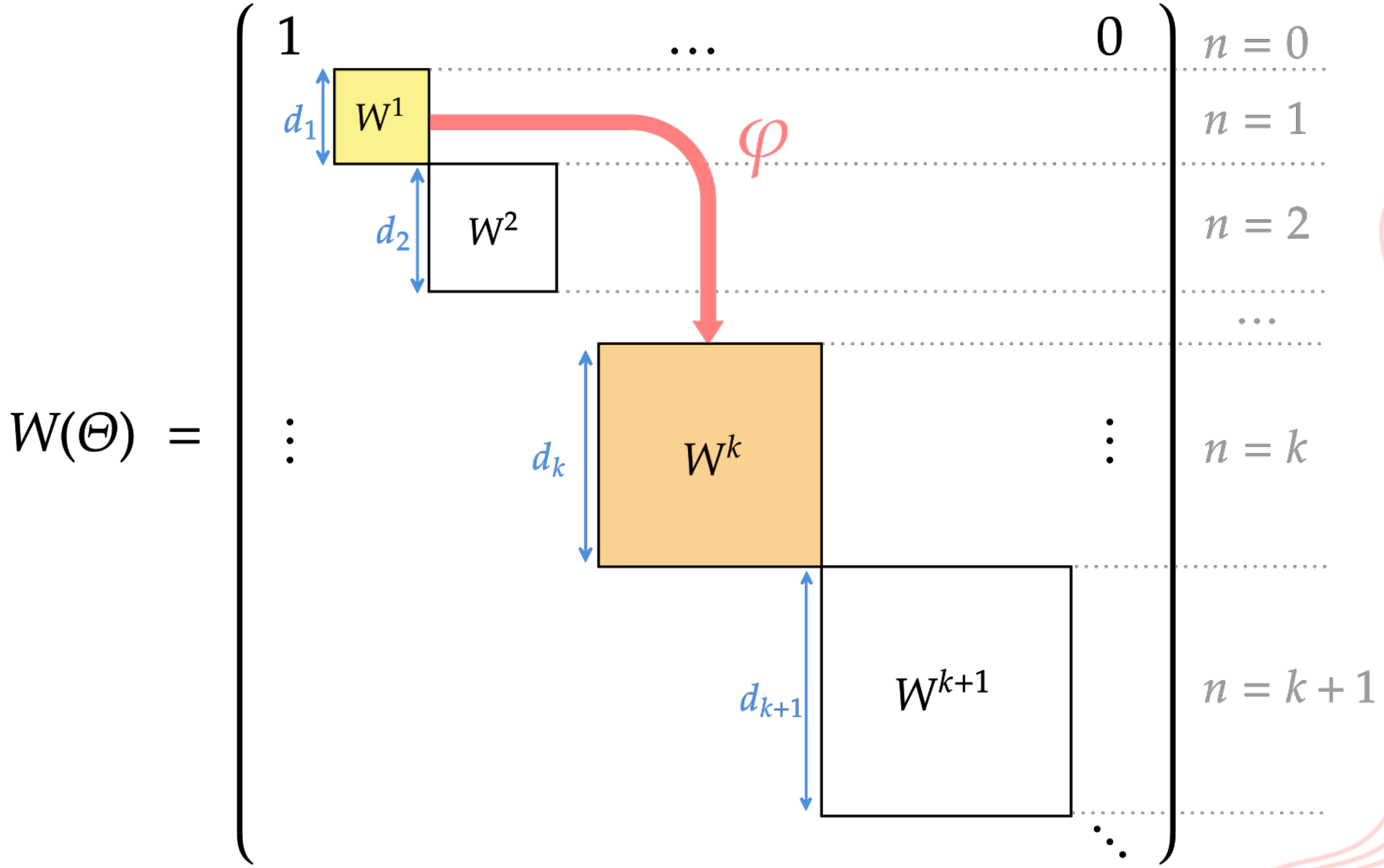
Those QPU layers could be used in large ML architectures and must be compared with GPU in term of speed, energy consumption, security, …

Subspace Preserving Circuits

Circuits that preserve the number of particles are subspace preserving.

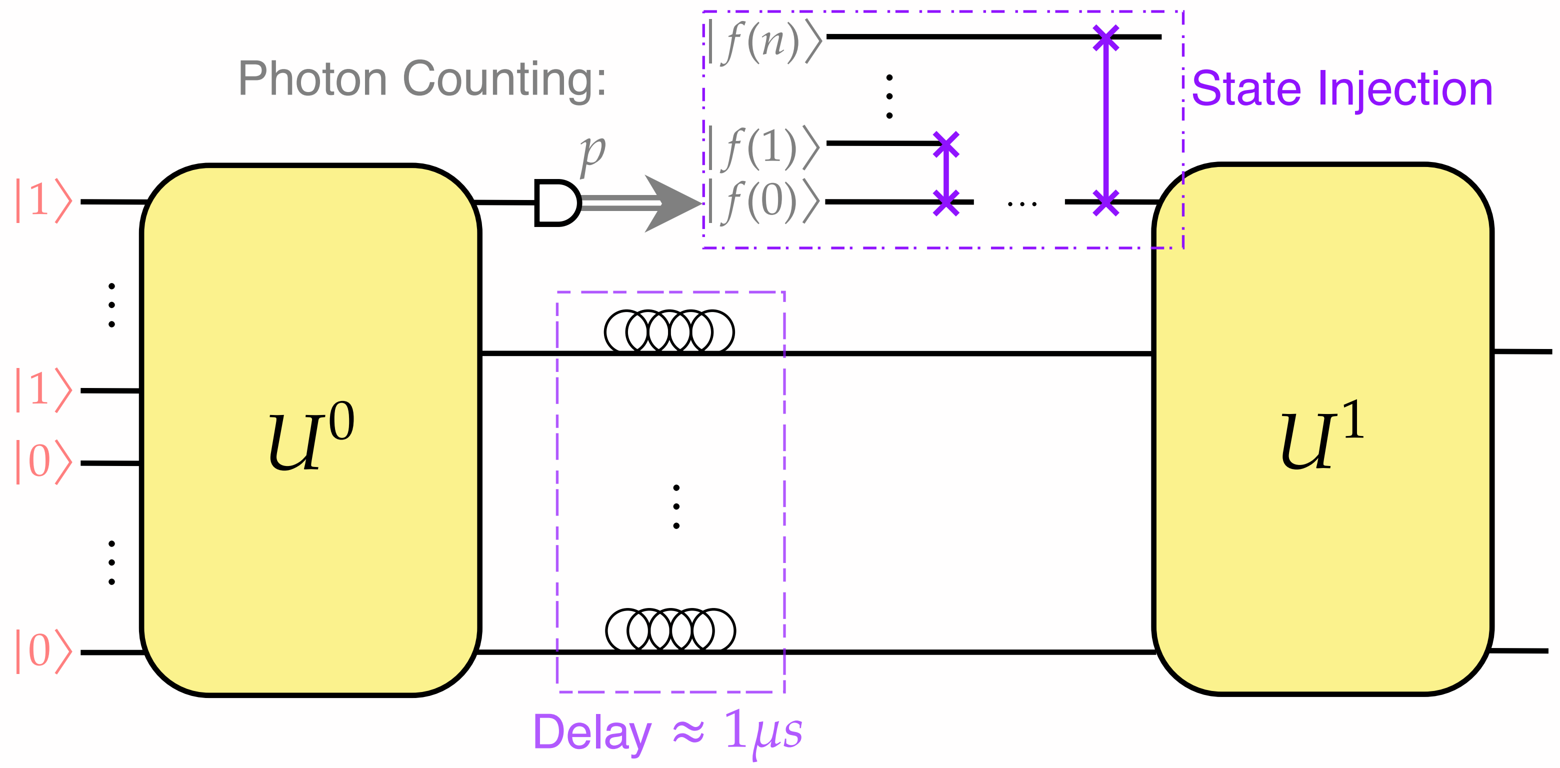
Circuits made of linear optics are limited in their controllability by the photonic homomorphism.



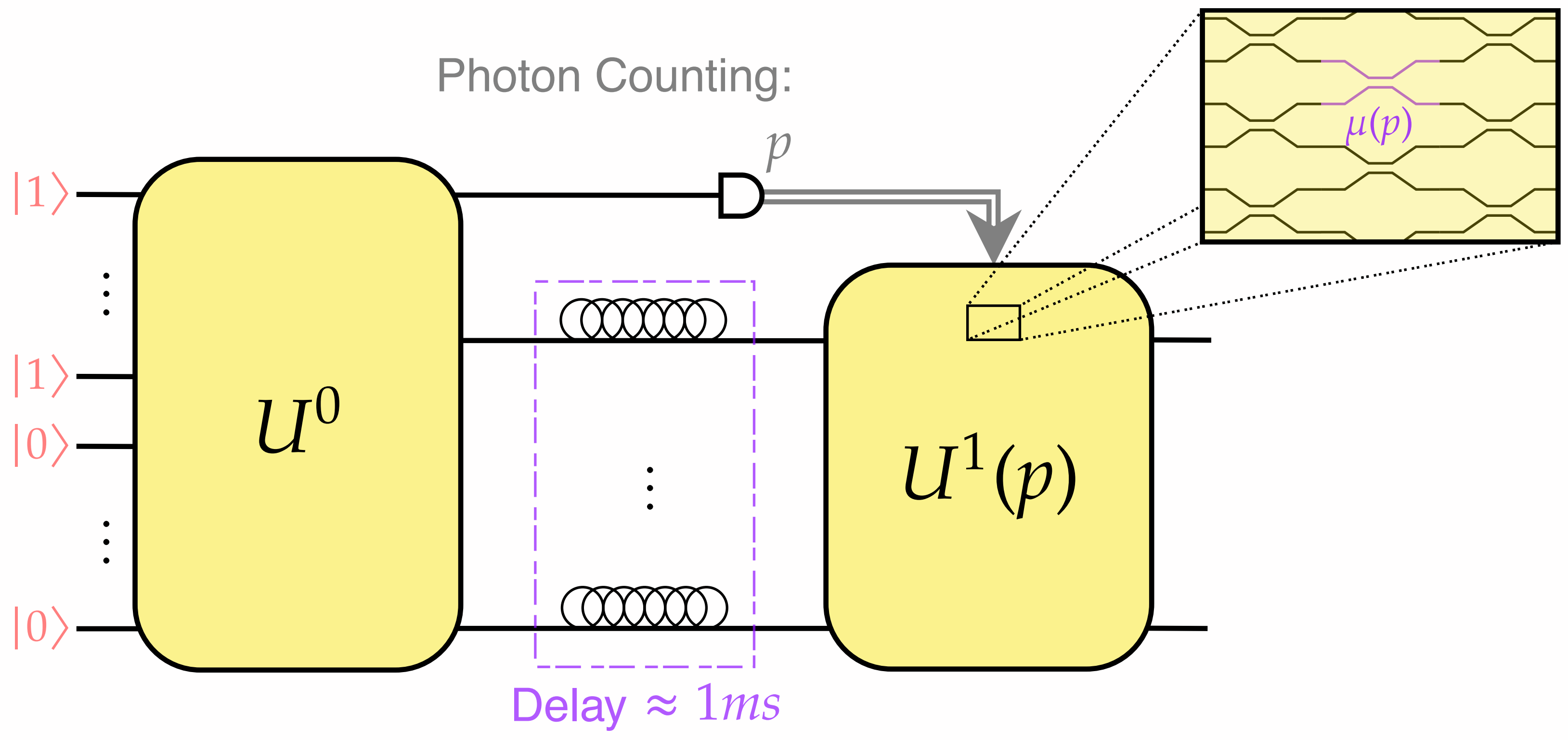


State Injection

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



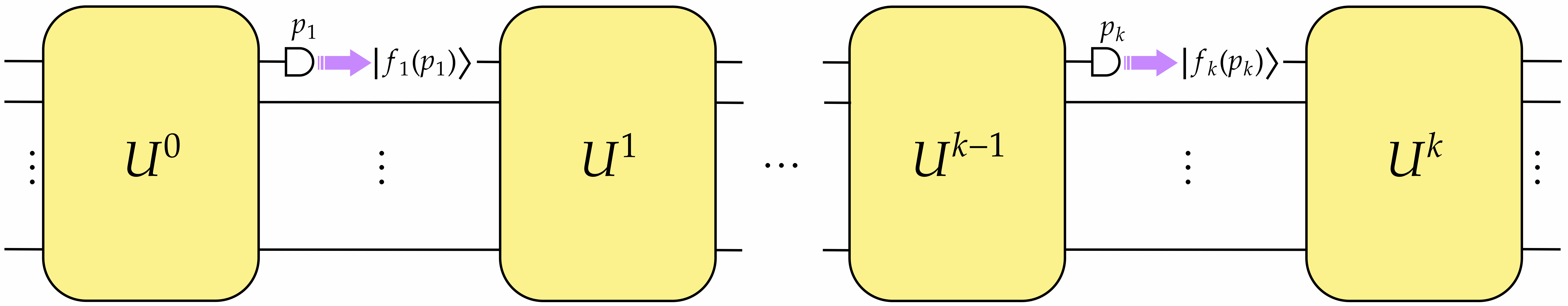
State Injection channel for a single mode measured.



Feed-Forward adaptivity for a single mode measured.

State Injection

State Injection is an non unitary operation that can preserves the number of particles:



By injecting a number of photons equal to the number of particles detected, one can ensure subspace preserving properties.

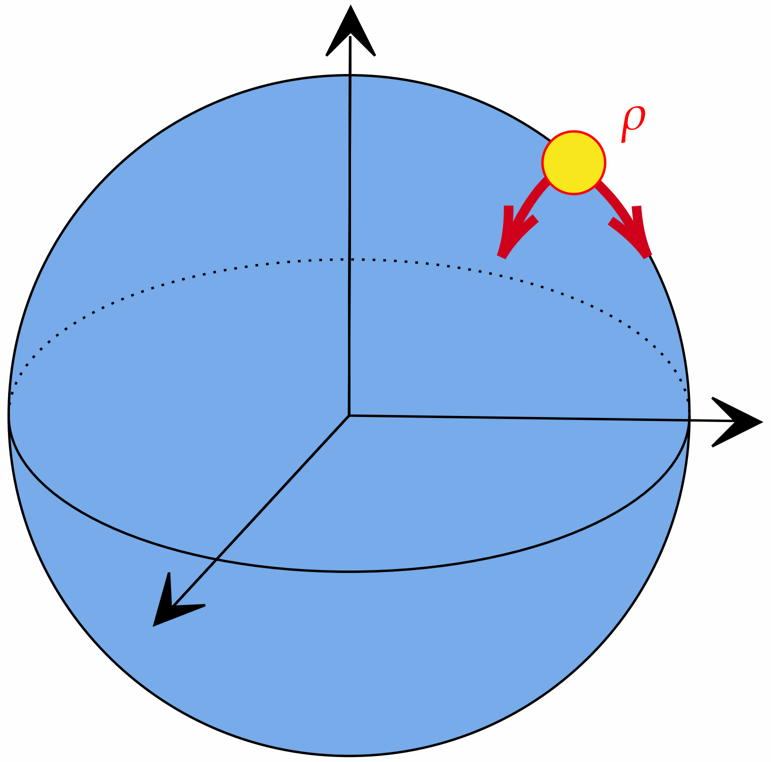
Degrees of Freedom

We define the Degrees of Freedom (DoF) of a quantum state as:

$$\mathrm{DoF}(\rho(\theta)) = \mathrm{rank}[\mathcal{J}_{\rho(\theta)}]$$

Theorem:

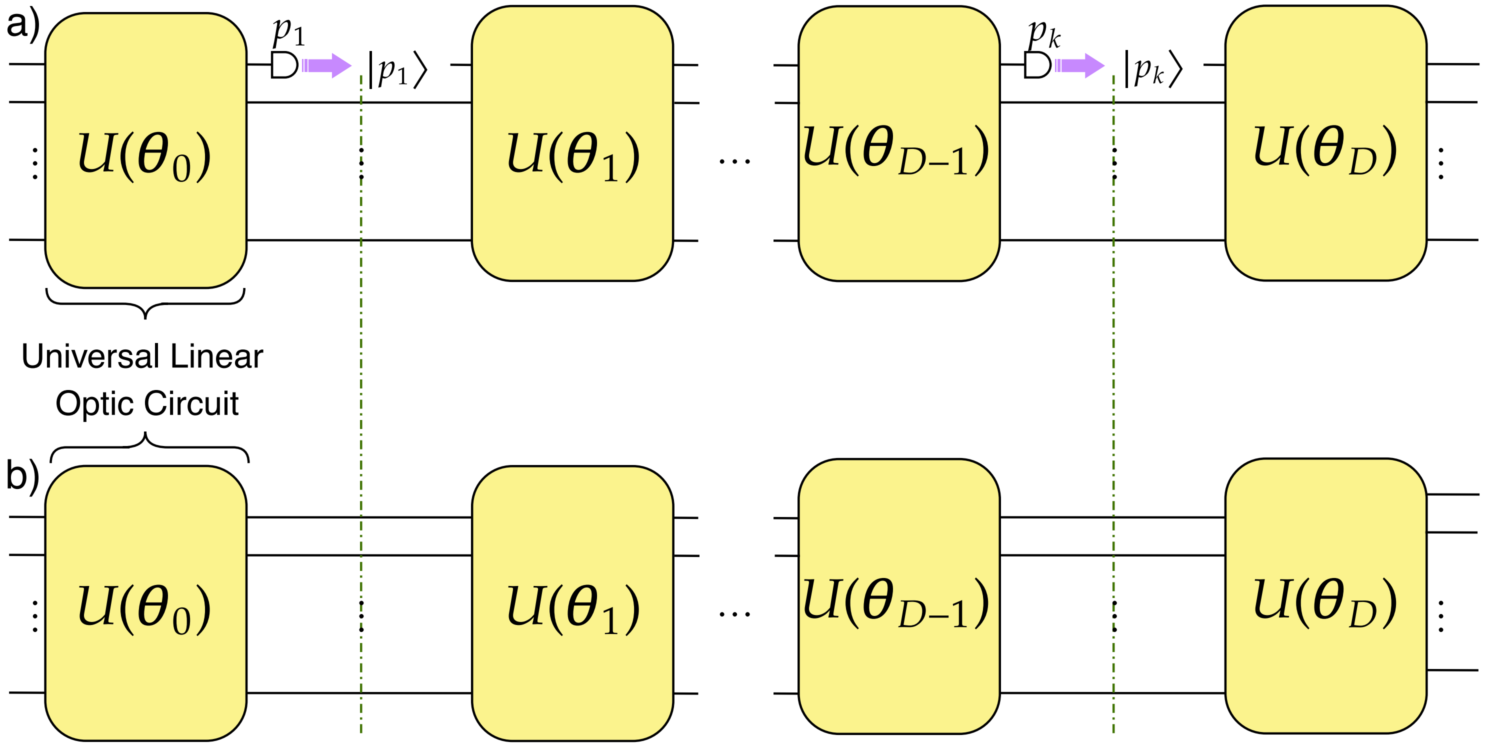
$$\mathrm{DoF}_{\max}(\rho) = \max_{\theta\in\Theta}\mathrm{DoF}(\rho)$$

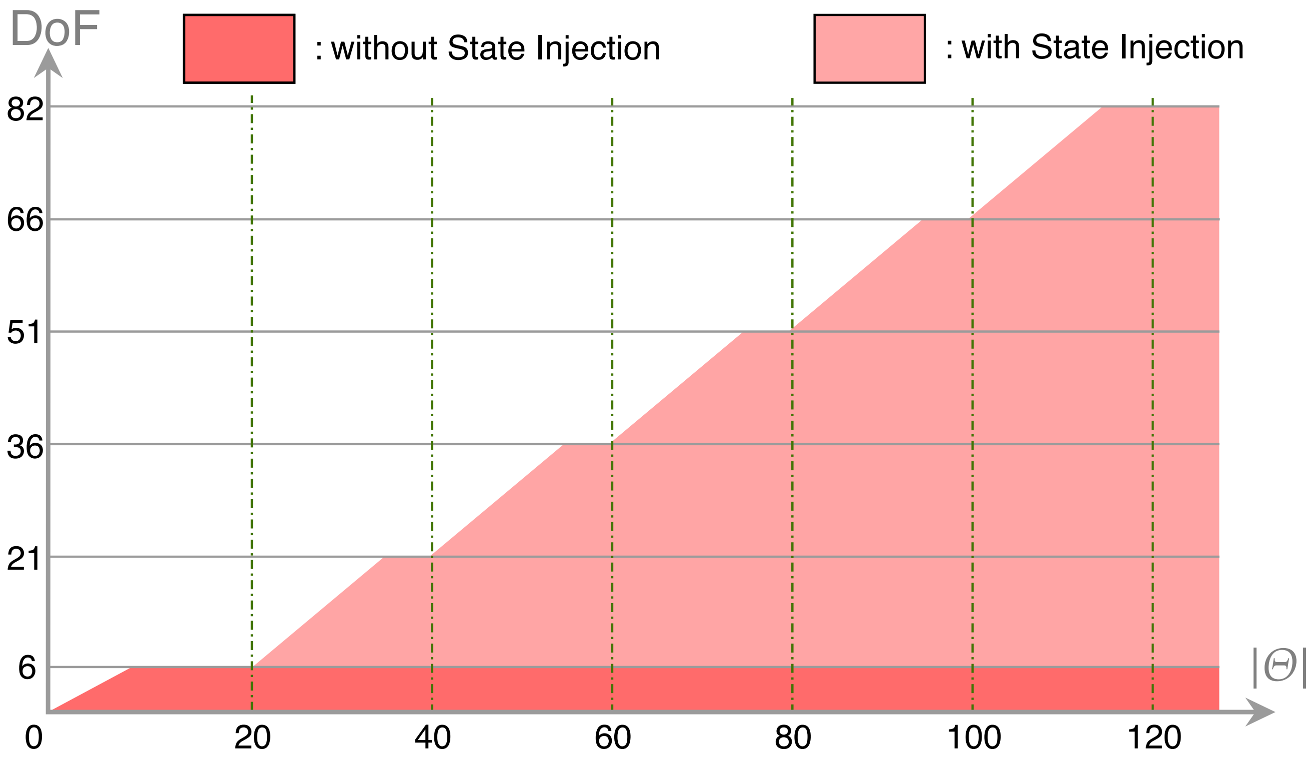


State Degrees of Freedom: Number of Independent direction it can take in the State Space

Degrees of Freedom

We compare the DoF evolution:



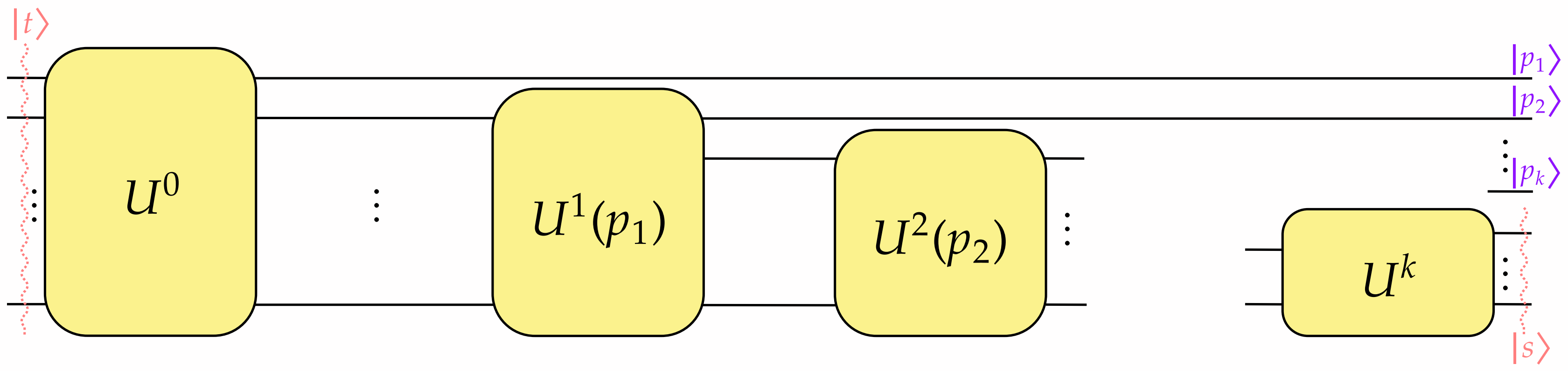


Both circuits are made of 6-mode Linear Optic block that are universal but in a) those blocks are separated with state injections, while in b) those blocks are connected.

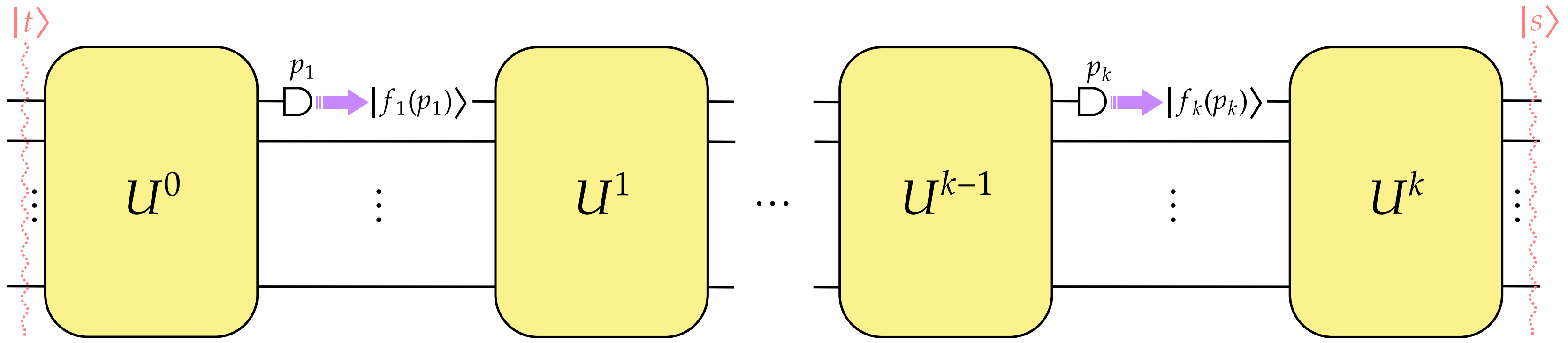
Evolution of the number of Degrees of Freedom of the state in the subspace of 3 particles according to the number of beam-splitters we consider.

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.

Probability Estimation

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

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

Classical Simulation Regime for Probability Estimation

Any questions?

Contact me!

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