

# Dimension Reduction for Quantum Stochastic Modelling

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: Main Auditorium, CERN



National University of Singapore

# A small game



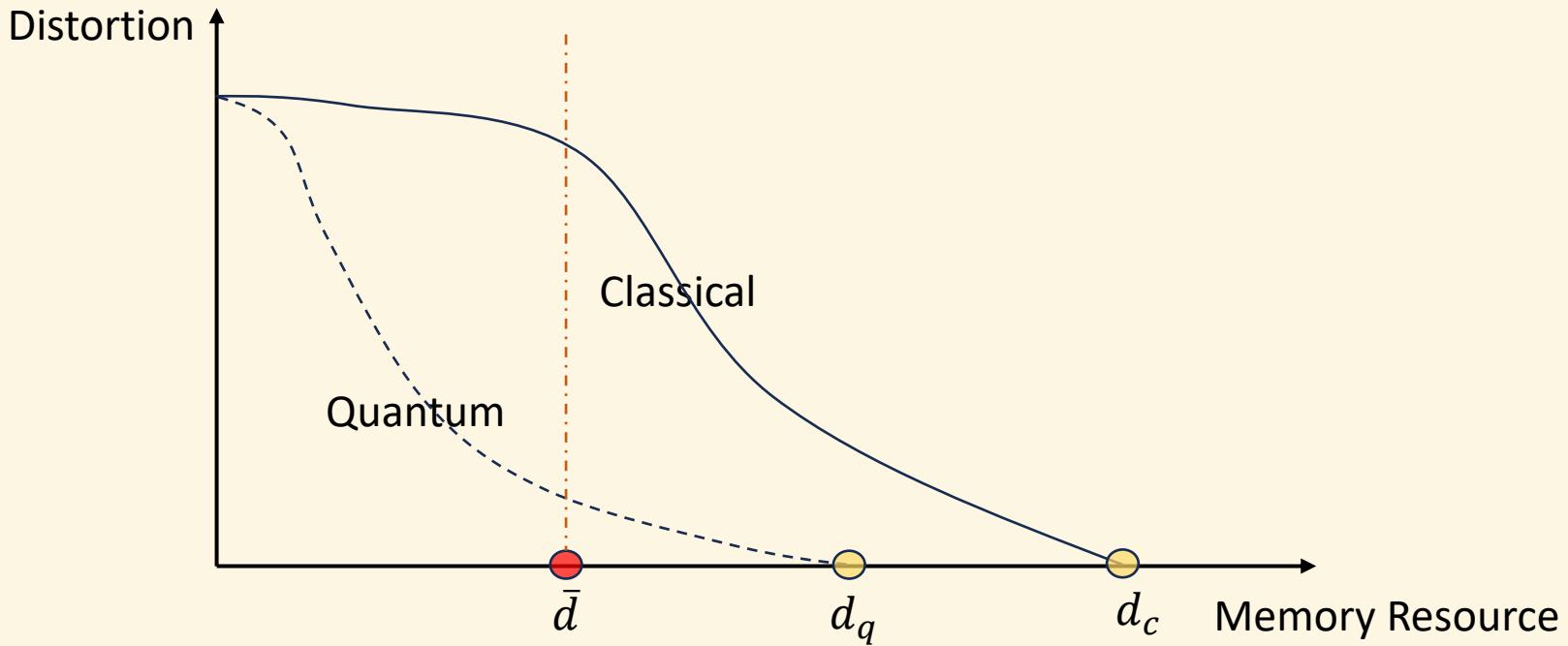
What will the main character?



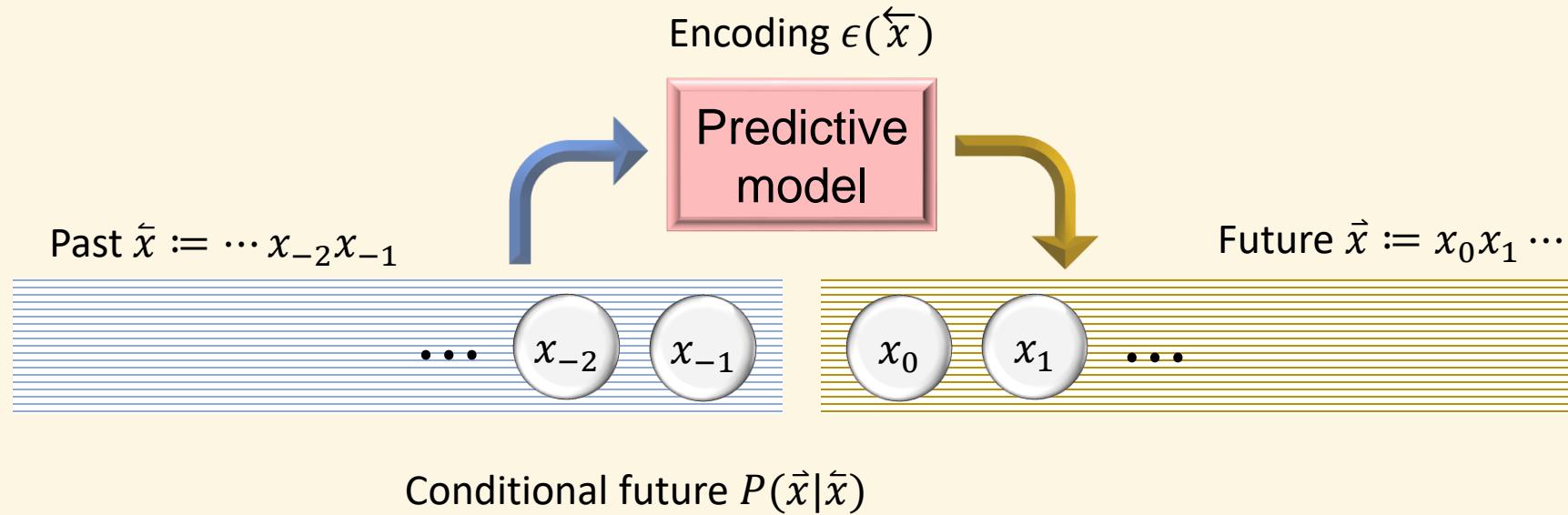
What will the main character like quantum machine learning?



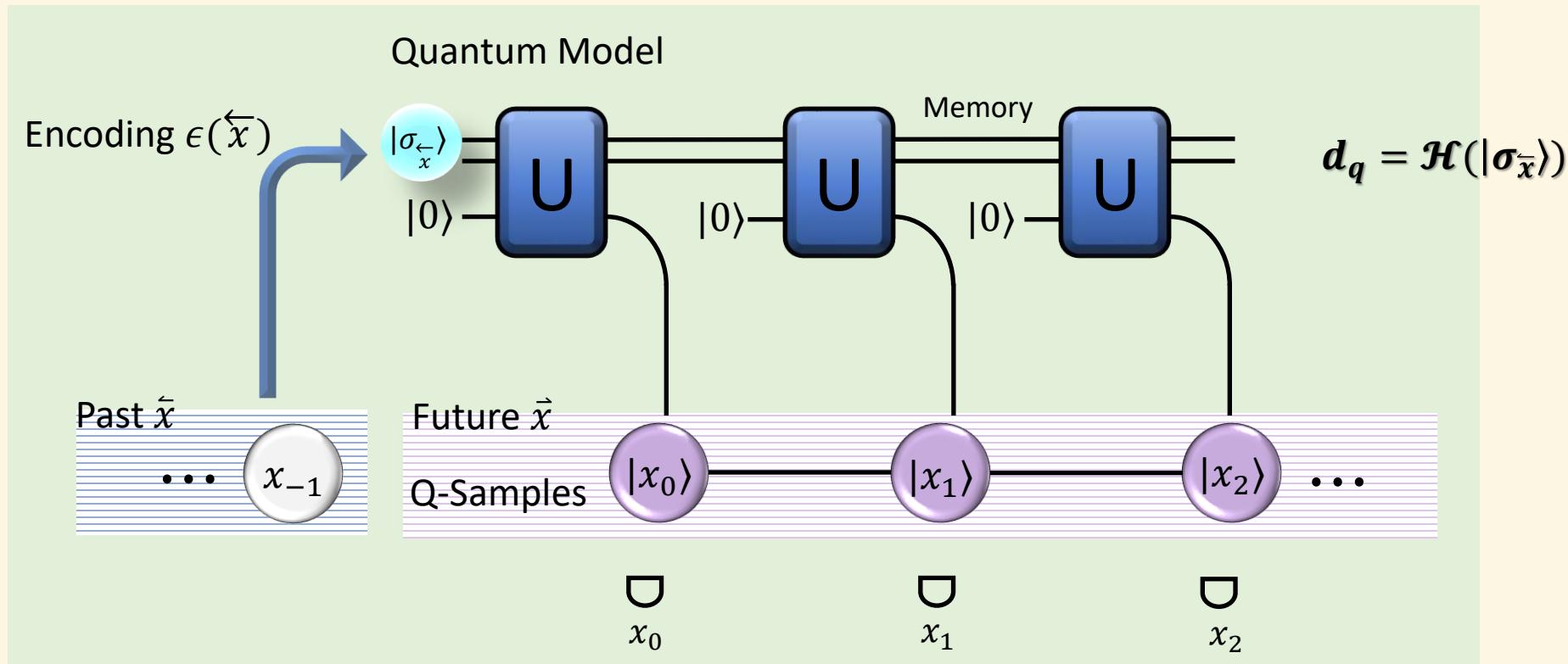
# Memory cost and distortion



# Predictive Models



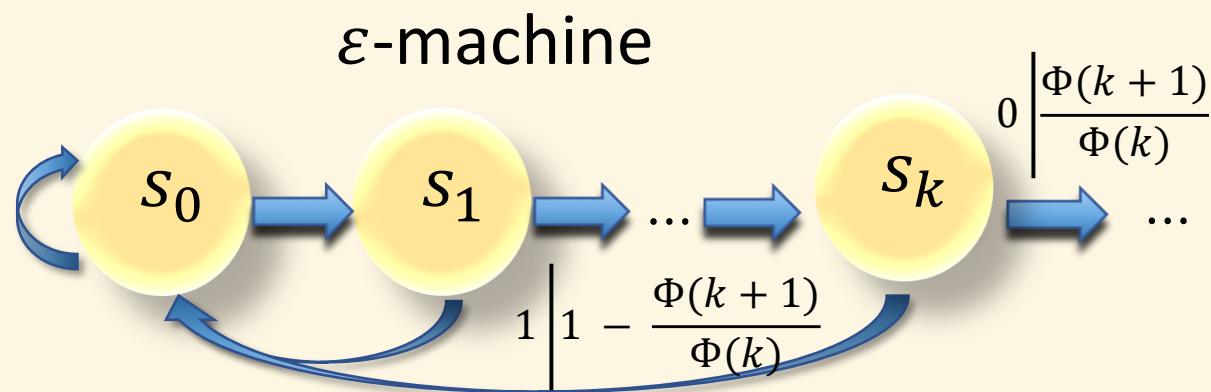
# Quantum models



# Dual Poisson processes

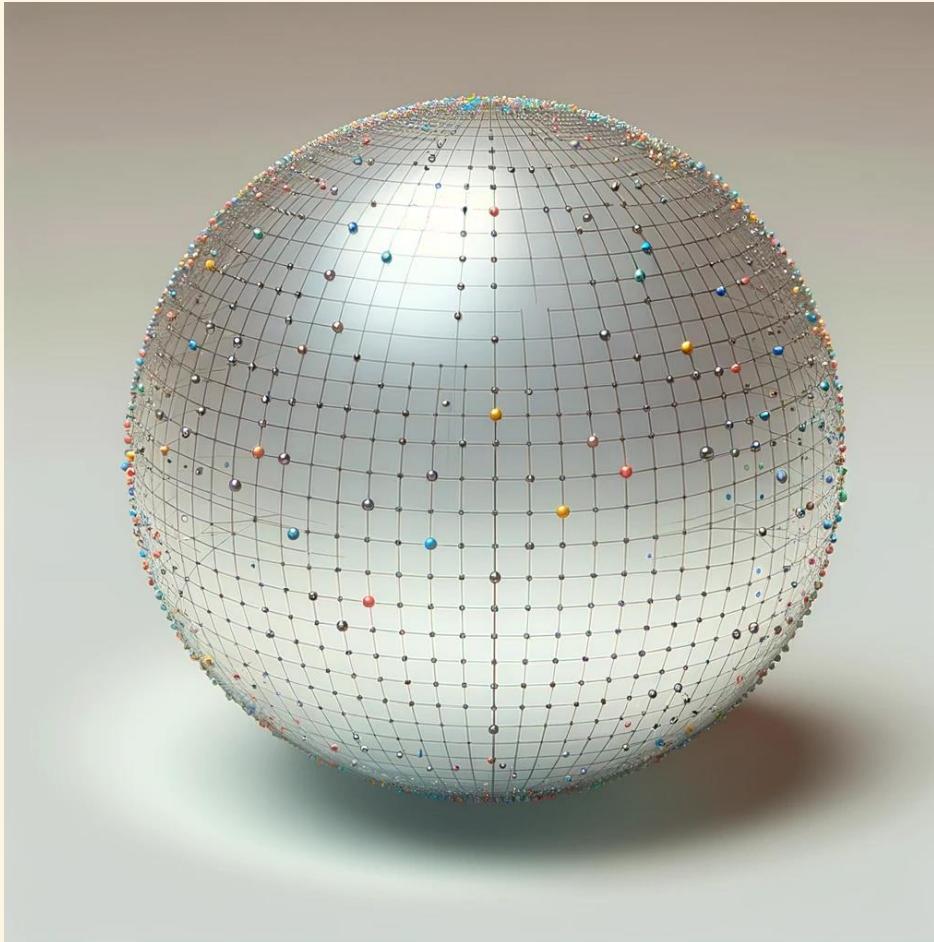
Encoding

$$\cdots \underbrace{1000 \cdots 0}_k \rightarrow s_k$$



$$\Phi(n) = p\Gamma_1^n + (1-p)\Gamma_2^n$$

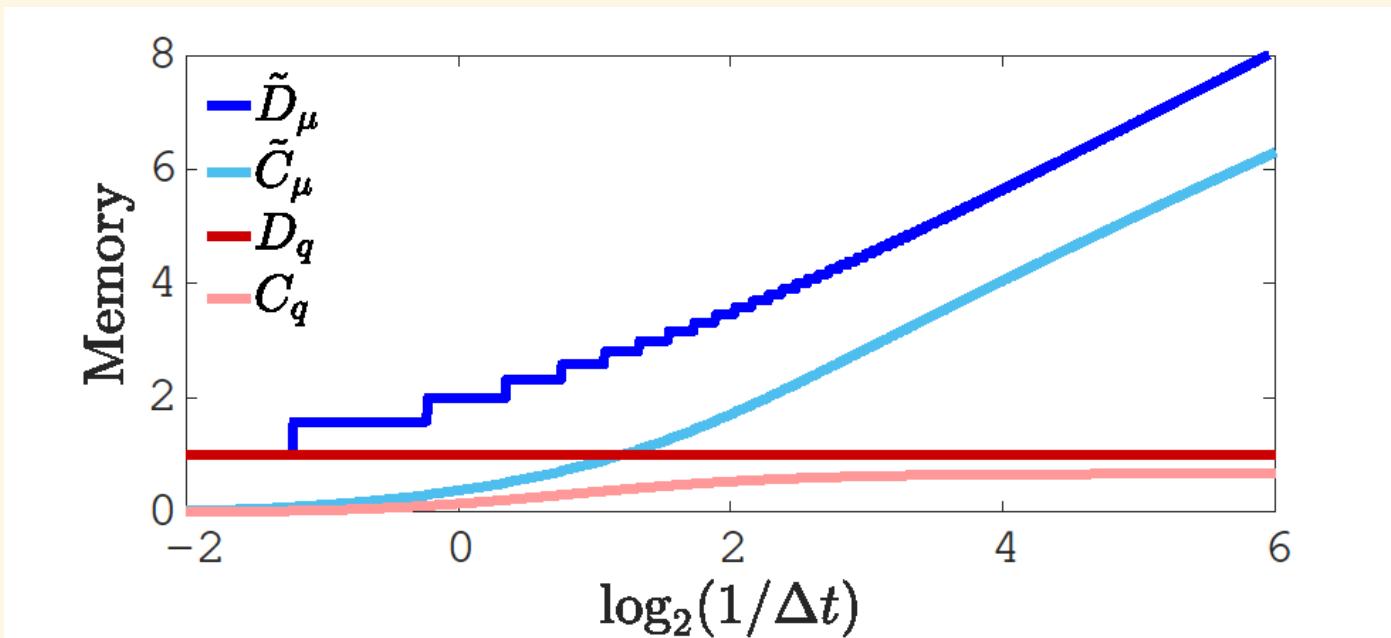
# Single Qubit Model



Unitary operator

$$U|\sigma_k\rangle = \sqrt{\frac{\Phi(k+1)}{\Phi(k)}} |\sigma_{k+1}\rangle|0\rangle + \sqrt{1 - \frac{\Phi(k+1)}{\Phi(k)}} |\sigma_0\rangle|1\rangle$$

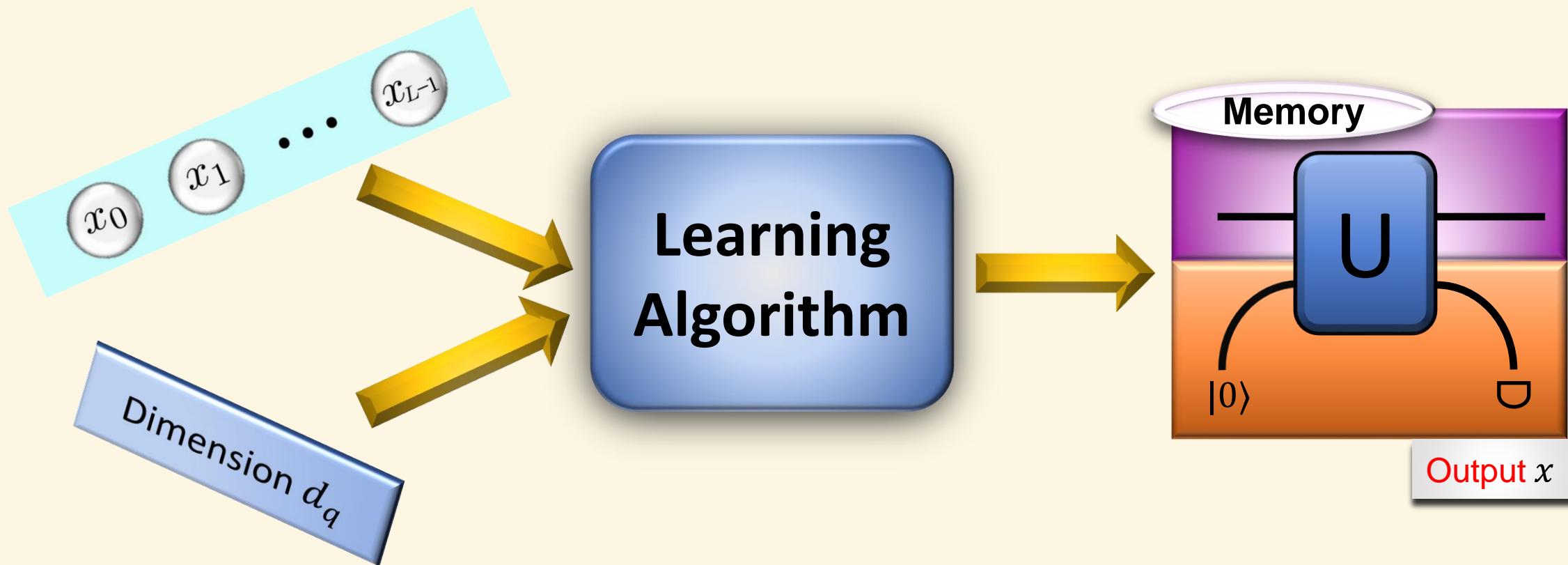
# The amount of quantum memory



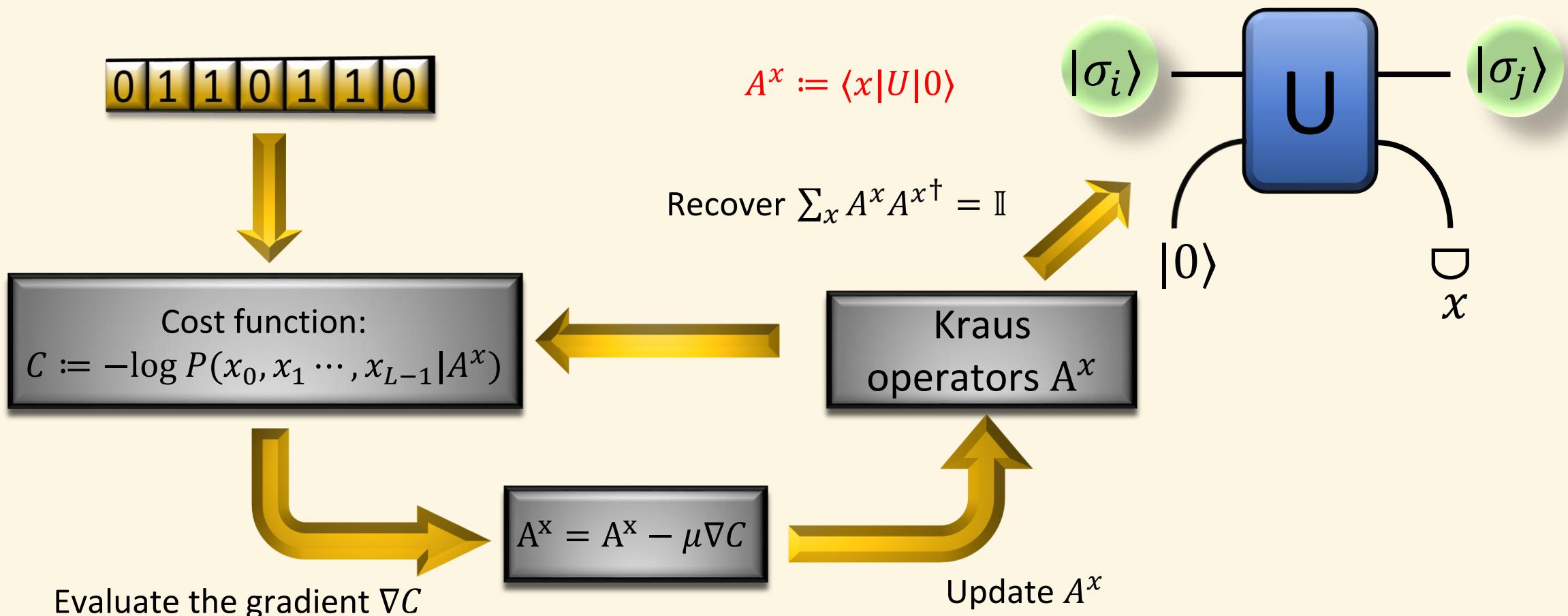
$$\Gamma_i = \exp(-\gamma_i \Delta t)$$

$$\gamma_1 = 12, \gamma_2 = 1, p = 0.9$$

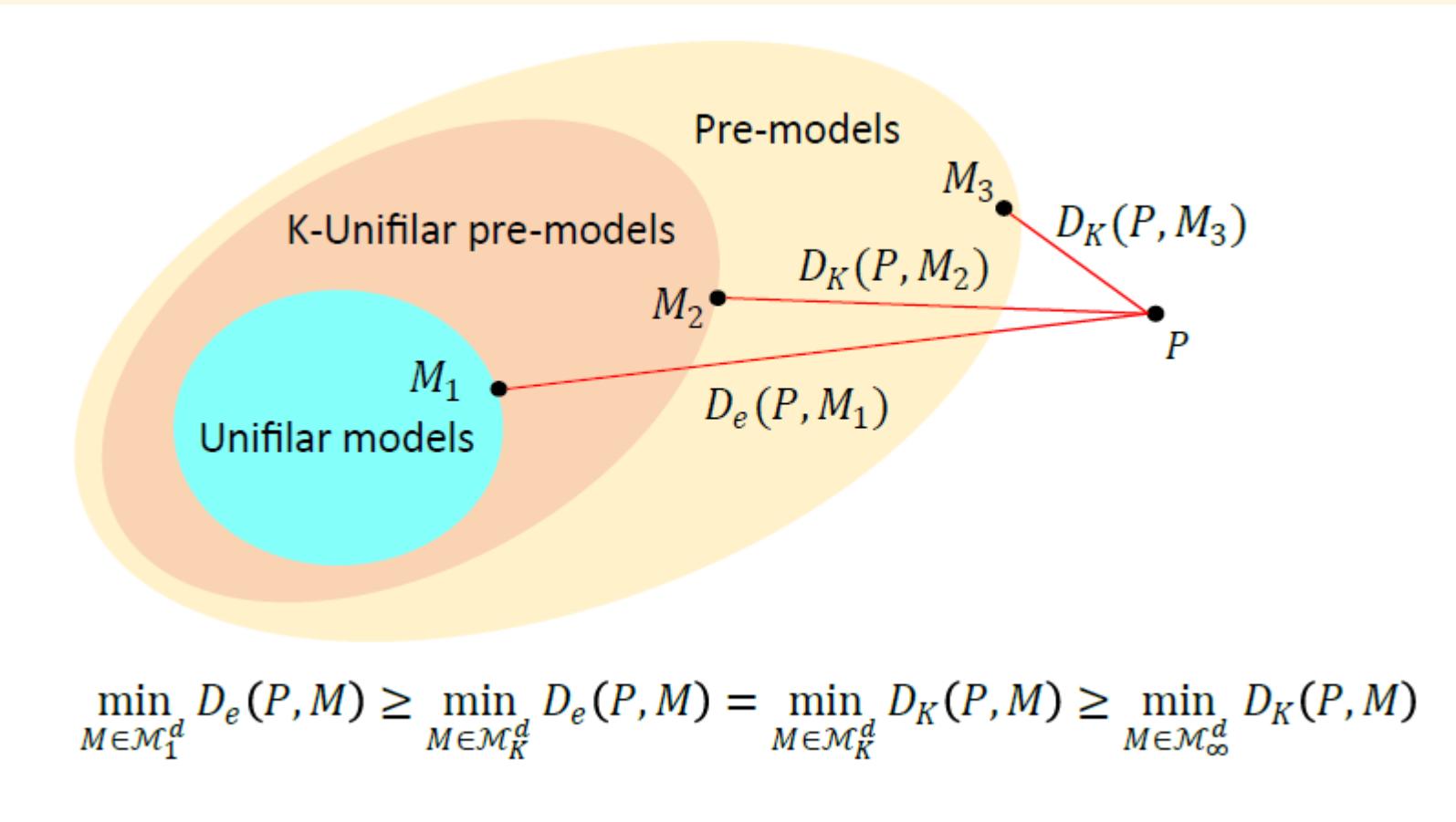
# Learn a model from data



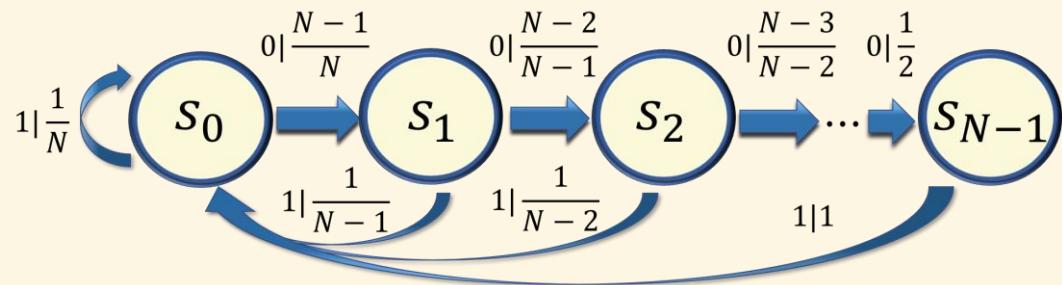
# Learning Quantum Model



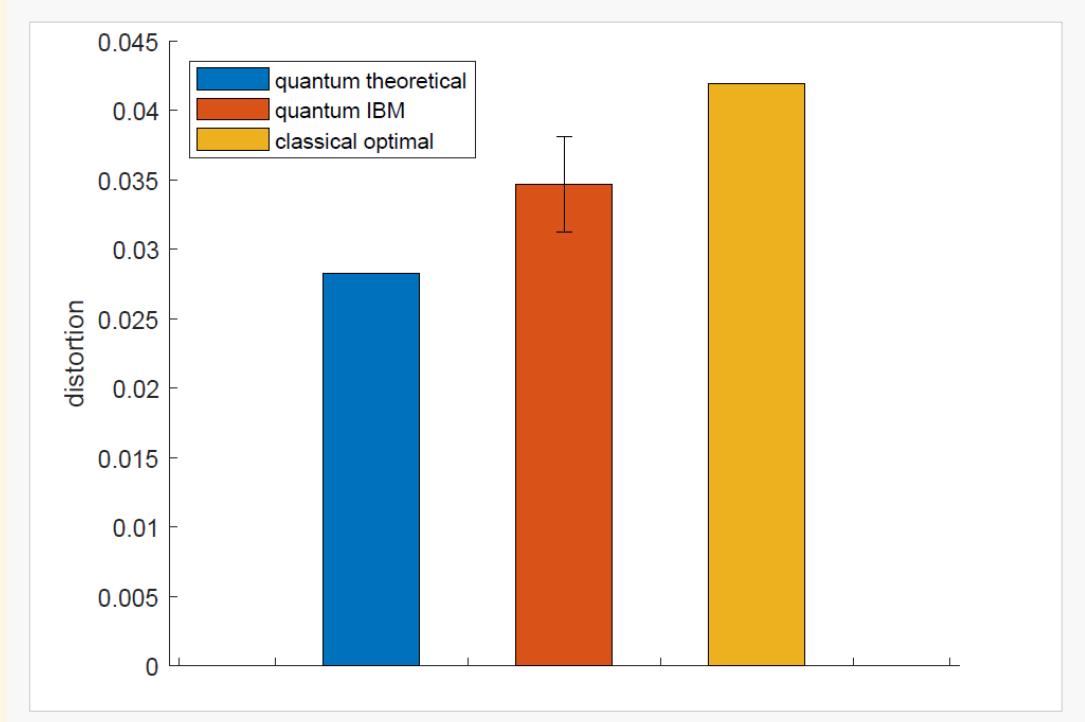
# Classical Distortion Bound



# Training result and IBM Implementation



$$d_C = d_q = 2, N = 3$$



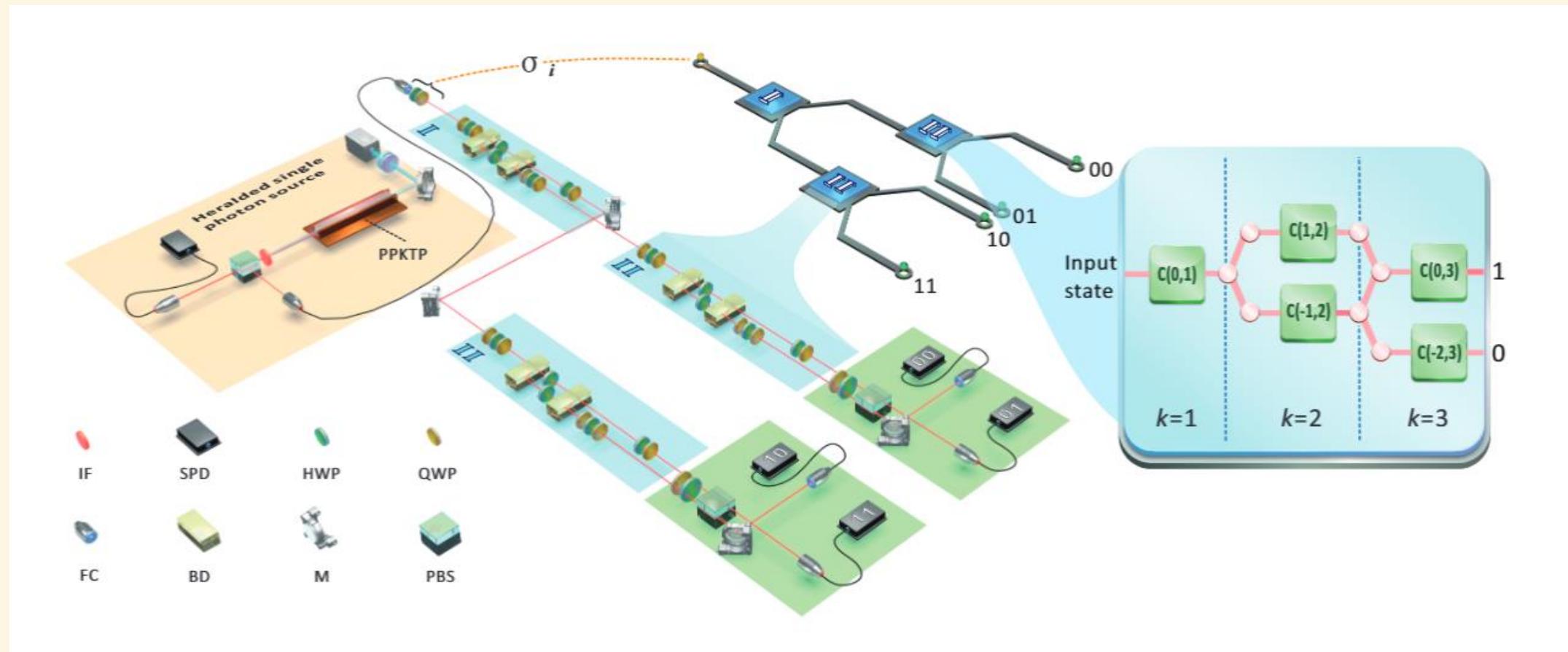
# A Clock process



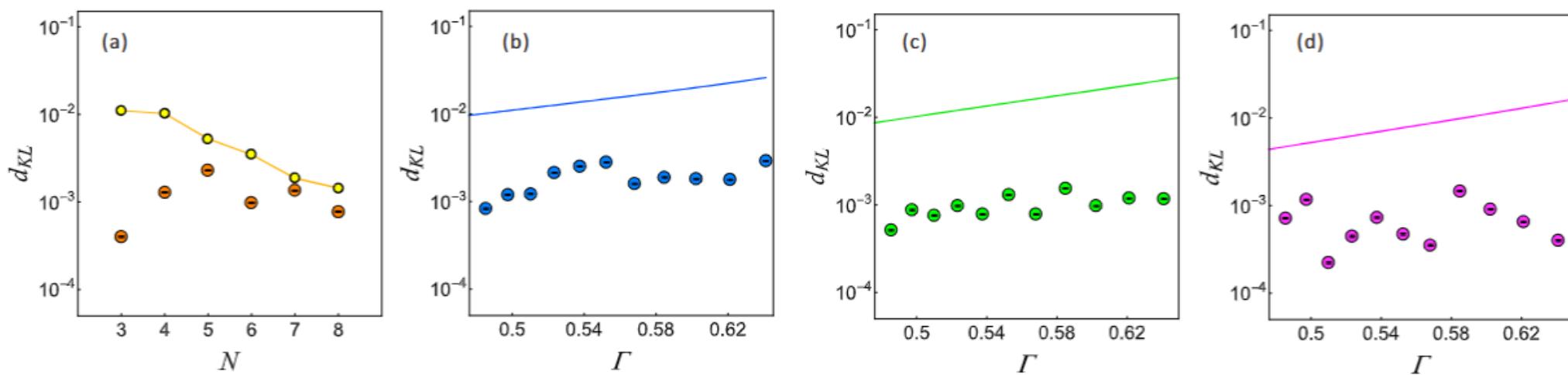
$$\Phi(n) = \Gamma^n(1 - V \sin^2 n\theta)$$

$$A_0|\sigma_n\rangle \propto |\sigma_{n+1 \bmod N}\rangle$$
$$A_1|\sigma_n\rangle \propto |\sigma_0\rangle$$

# Experimental Details



# Experimental Results



# Conclusion

1. There exists quantum models that present unbounded memory advantages over classical models
2. We develop a discovery algorithm to find accurate quantum models with reduced dimension
3. We experimentally implement quantum models that outperform the best classical model in terms of memory.