

Hybrid Quantum Reservoir Computing

for simulating chaotic systems



presented by: Filip Wudarski

on ArXiv on Monday

Available at:

https://github.com/filutek/HQRC_paper/blob/main/main.pdf

FW, Daniel O'Connor, Shaun Geaney, Ata Akbari Asanjan, Max Wilson, Elena Strbac, Aaron Lott, Davide Venturelli

- Classical reservoir computing
- Hybrid Quantum Reservoir Computing (HQRC)
- Lorenz63 - a chaotic system
- Results
 - Simulations
 - QPU
- Conclusions

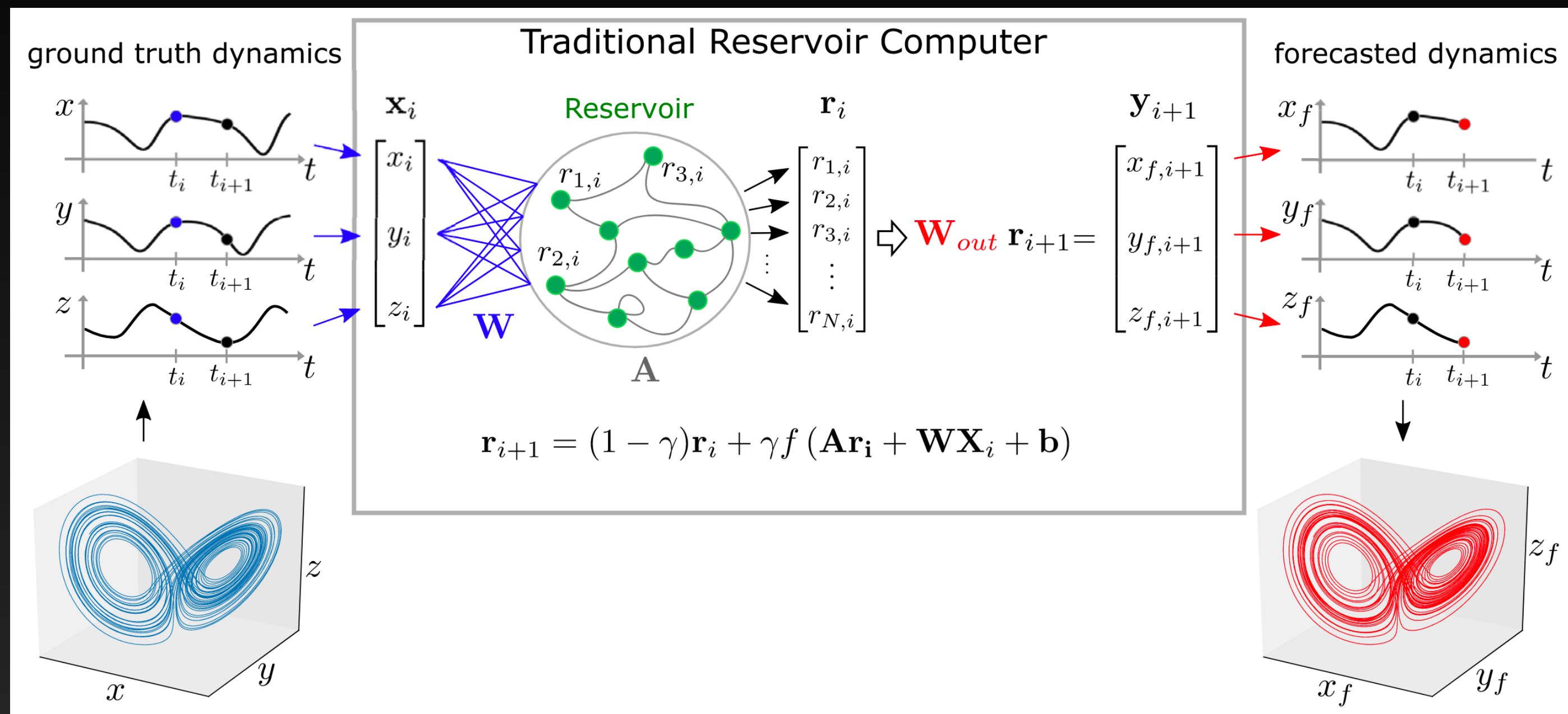
Randomized recurrent neural network

W
 A } Random matrices

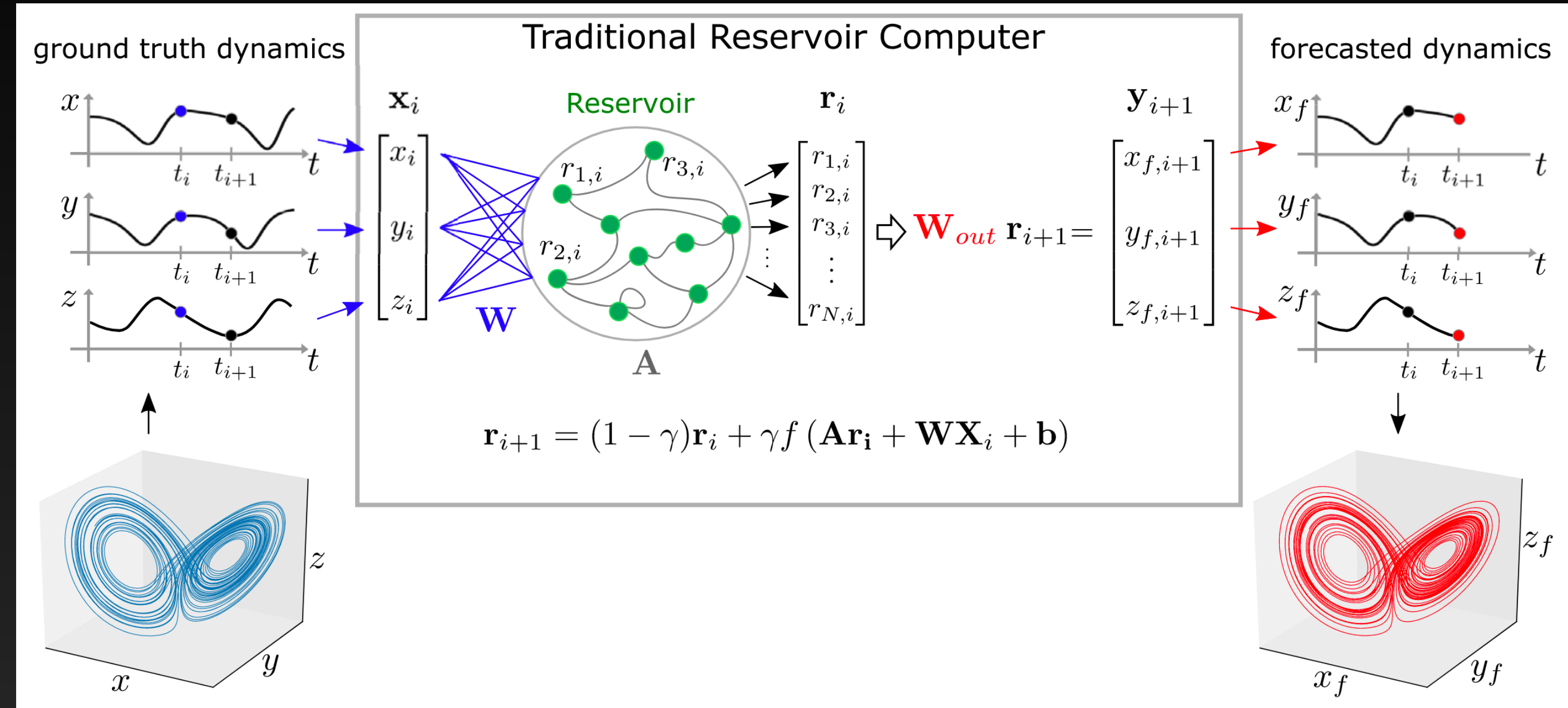
b Random vector

r_t Reservoir state

W_{out} Trainable weights



RC paradigm is particularly useful for learning dynamical systems (time series), even when the dynamics is chaotic. RC is a viable tool for weather modeling or broad ESG applications.



How to exploit the most power of quantum mechanics?

How to extend that framework for weather modeling?

Prior work on QRC

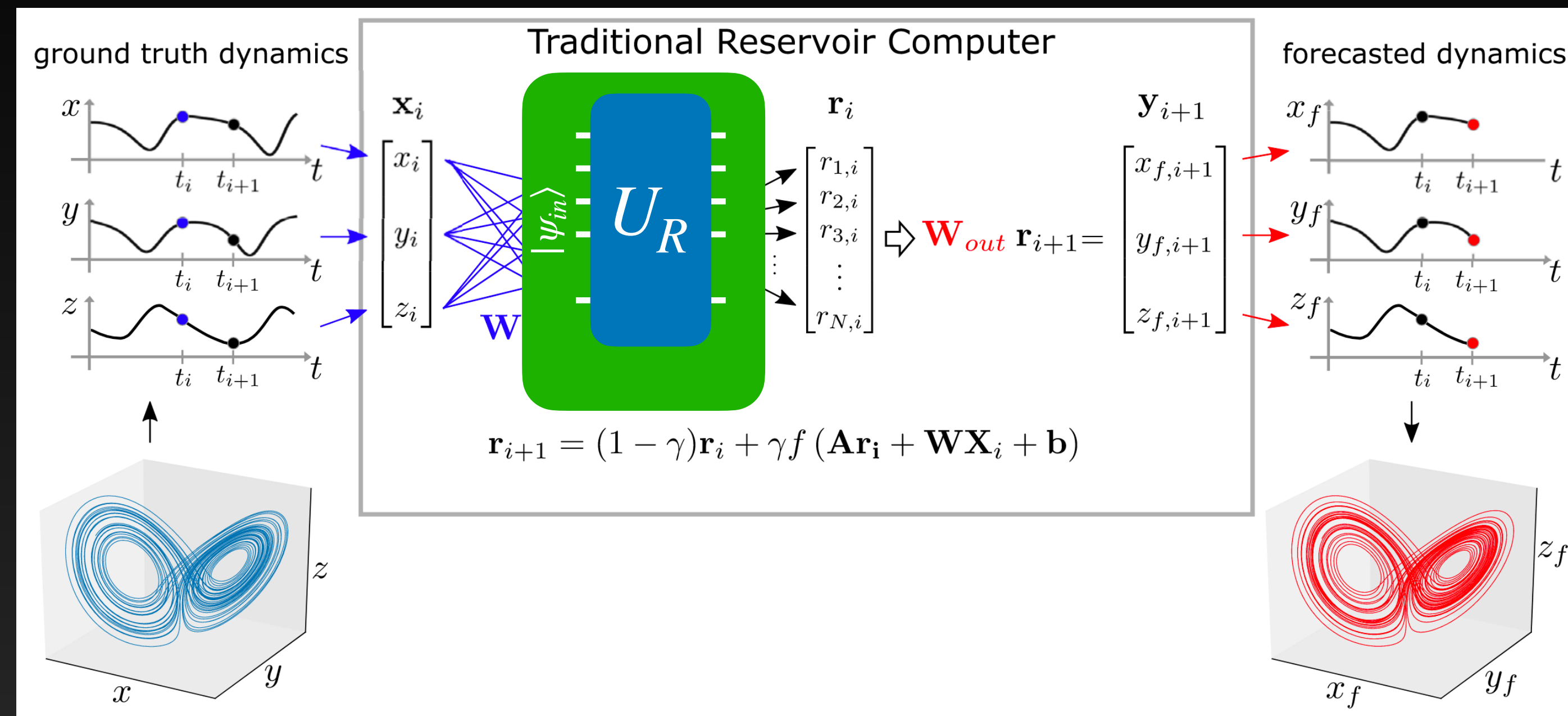
- K. Fuji, and K. Nakajima, Phys. Rev. Applied 8, 024030 (2017)*
- P. Mujal et. al, Advanced Quantum Technologies, 8, 2100027 (2021)*
- R. A. Bravo, et. al, PRX Quantum 3, 030325 (2022)*
- P. Pfeffer, F. Heyder, and J. Schumacher, arXiv: 2204.13951 (2022), 2307.03053 (2023)*
- P. Mujal et. al, npj Quantum Inf. 9, 16 (2023)*
- A. Sornsaeng, N. Dangniam, T. Chotibut, arXiv: 2308.14239 (2023) (Next talk)*

and more

$A \longrightarrow$ Quantum circuit U_R

How to exploit the most power of quantum mechanics?

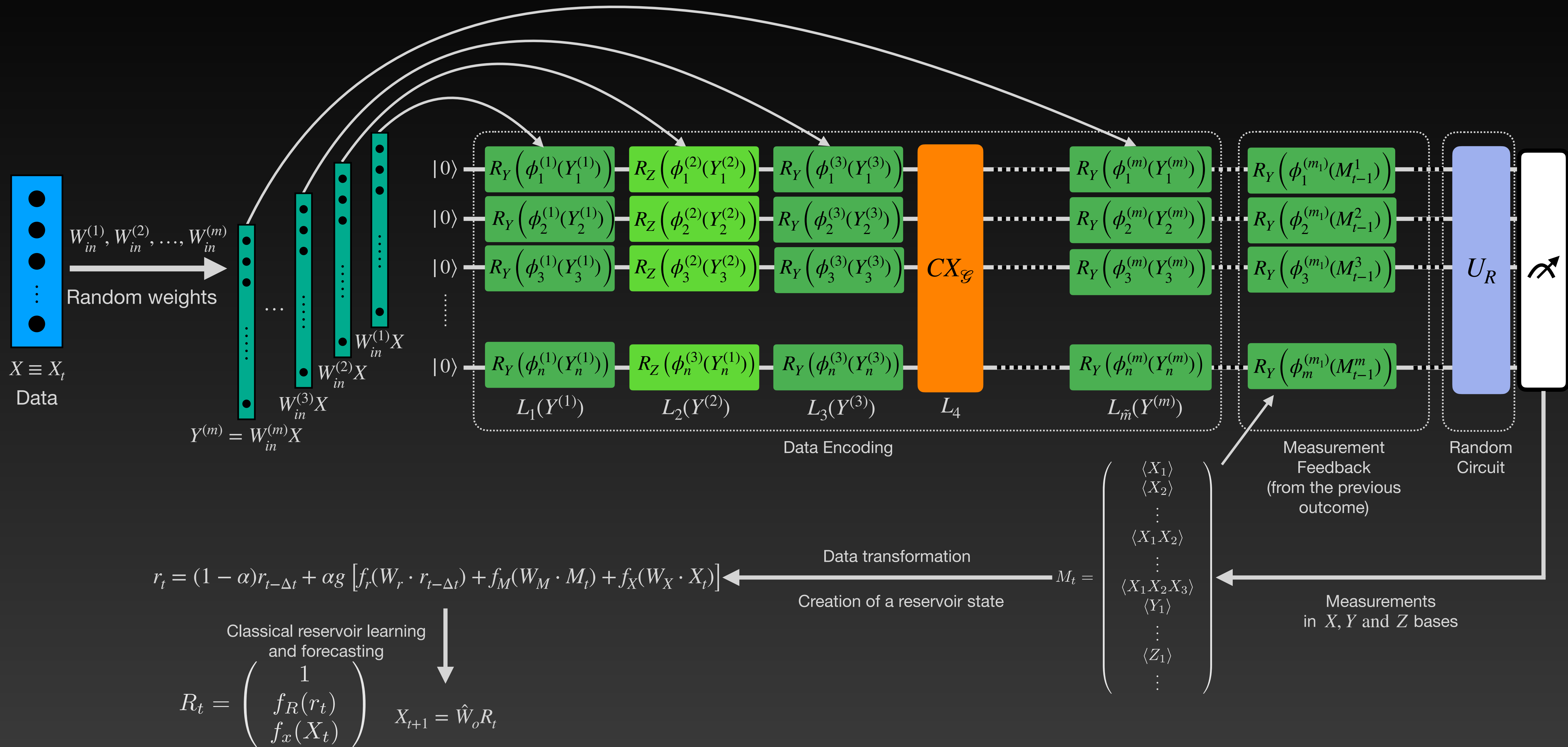
How to extend that framework for weather modeling?



Prior work on QRC

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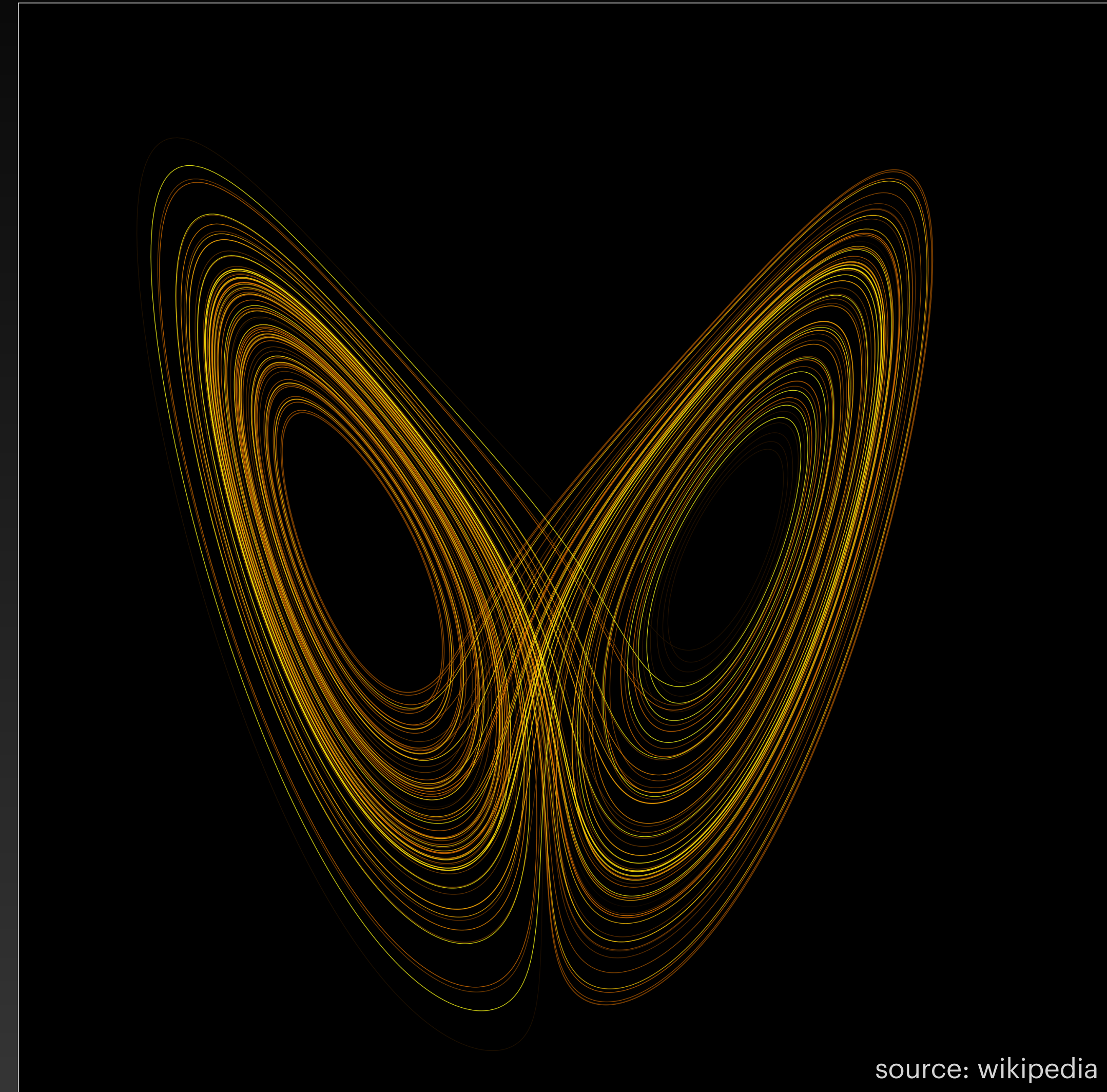


Lorenz63 a simplified model for atmospheric convection, governed by a system of ODEs:

$$\dot{x} = 10(y - x)$$

$$\dot{y} = x(28 - z) - y$$

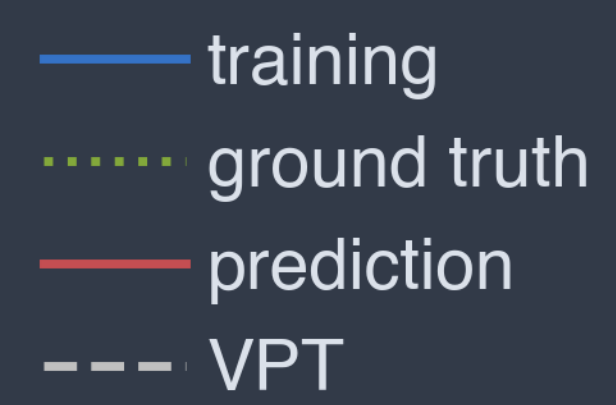
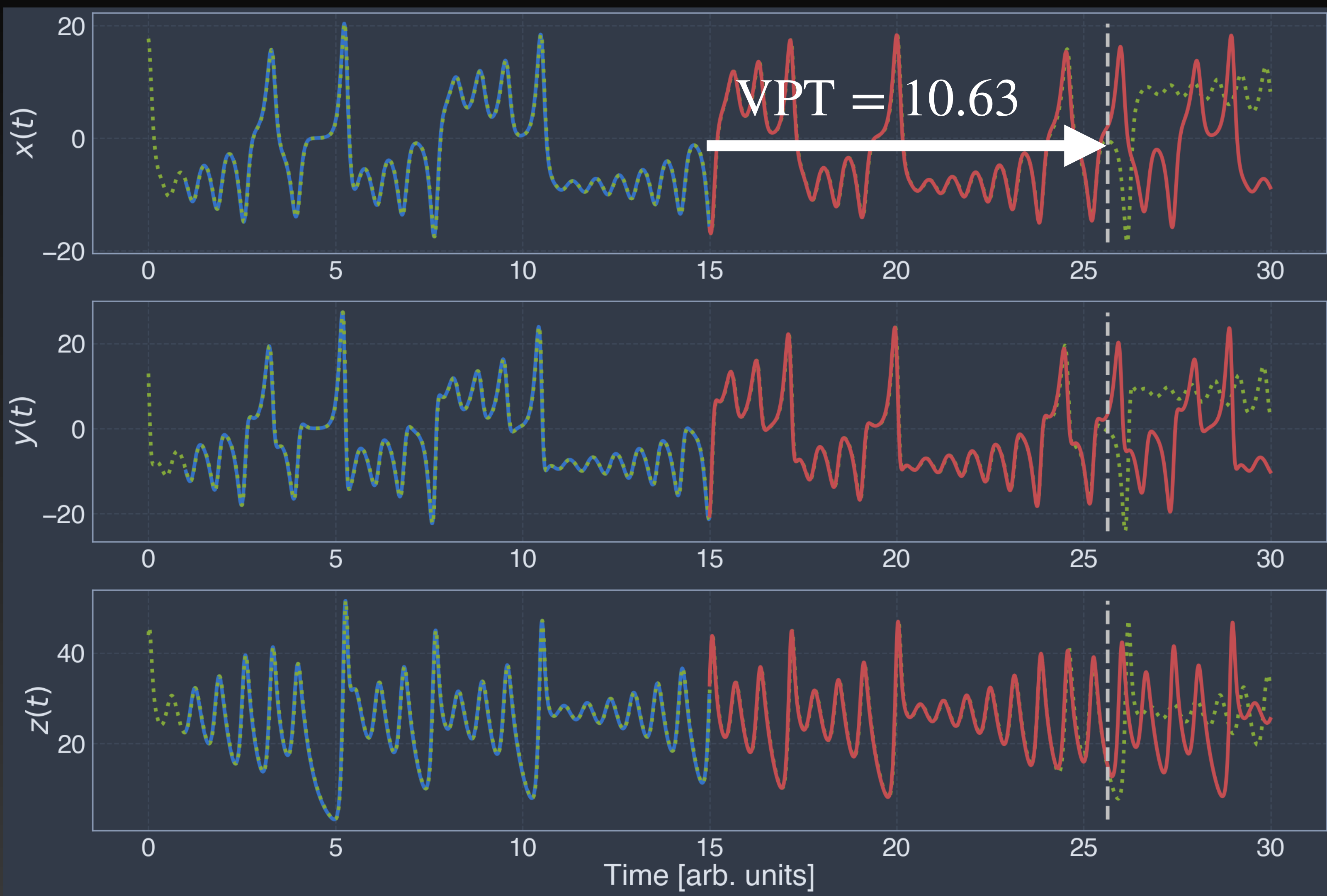
$$\dot{z} = xy - 8z/3$$



Lorenz attractor

Results

Classical simulations



Valid prediction time (VPT)

$$RMSE(t) = \sqrt{\frac{1}{D} \sum_{i=1}^D \left(\frac{\tilde{y}_i(t) - y_i(t)}{\sigma_i} \right)^2} \geq \epsilon$$

8 qubits:

Layers: R3 | CX | R3 | CX

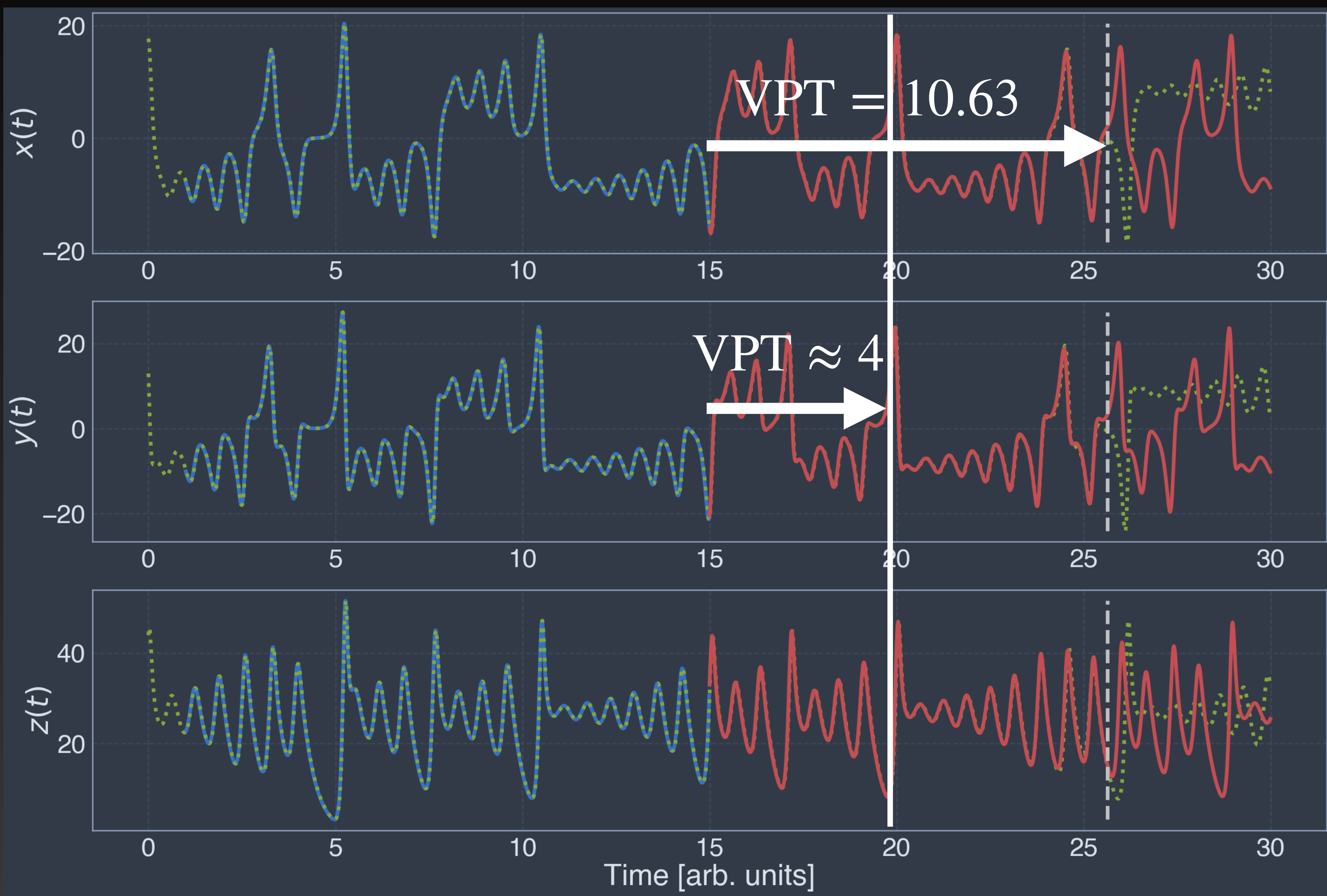
Measurements: single and two-qubit correlators

Reservoir size: 108

VPT = 10.63

Results

Classical simulations



150 reservoir size + two-step optimization

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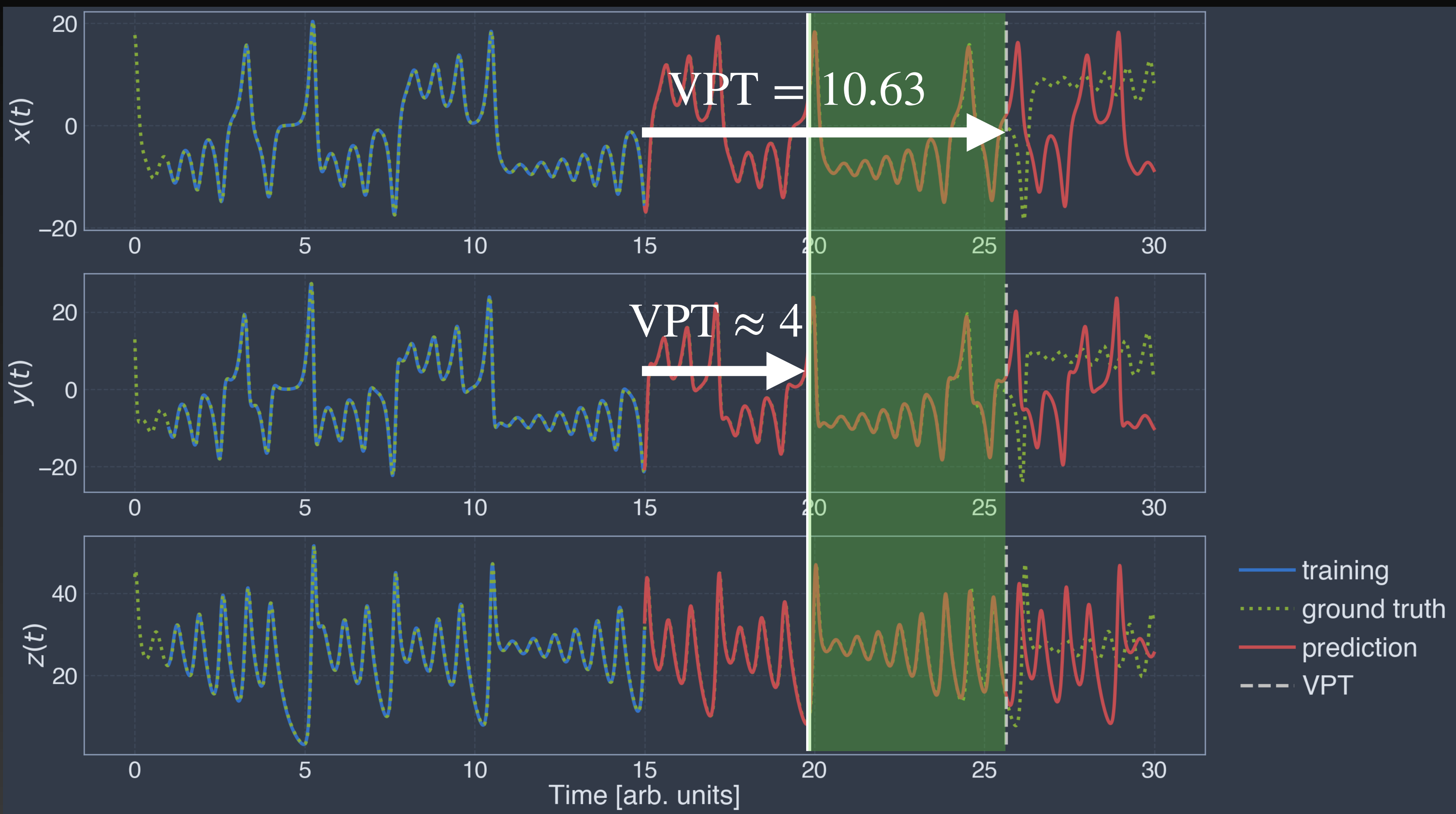
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Classical simulations

"Quantum boost"



150 reservoir size + two-step optimization

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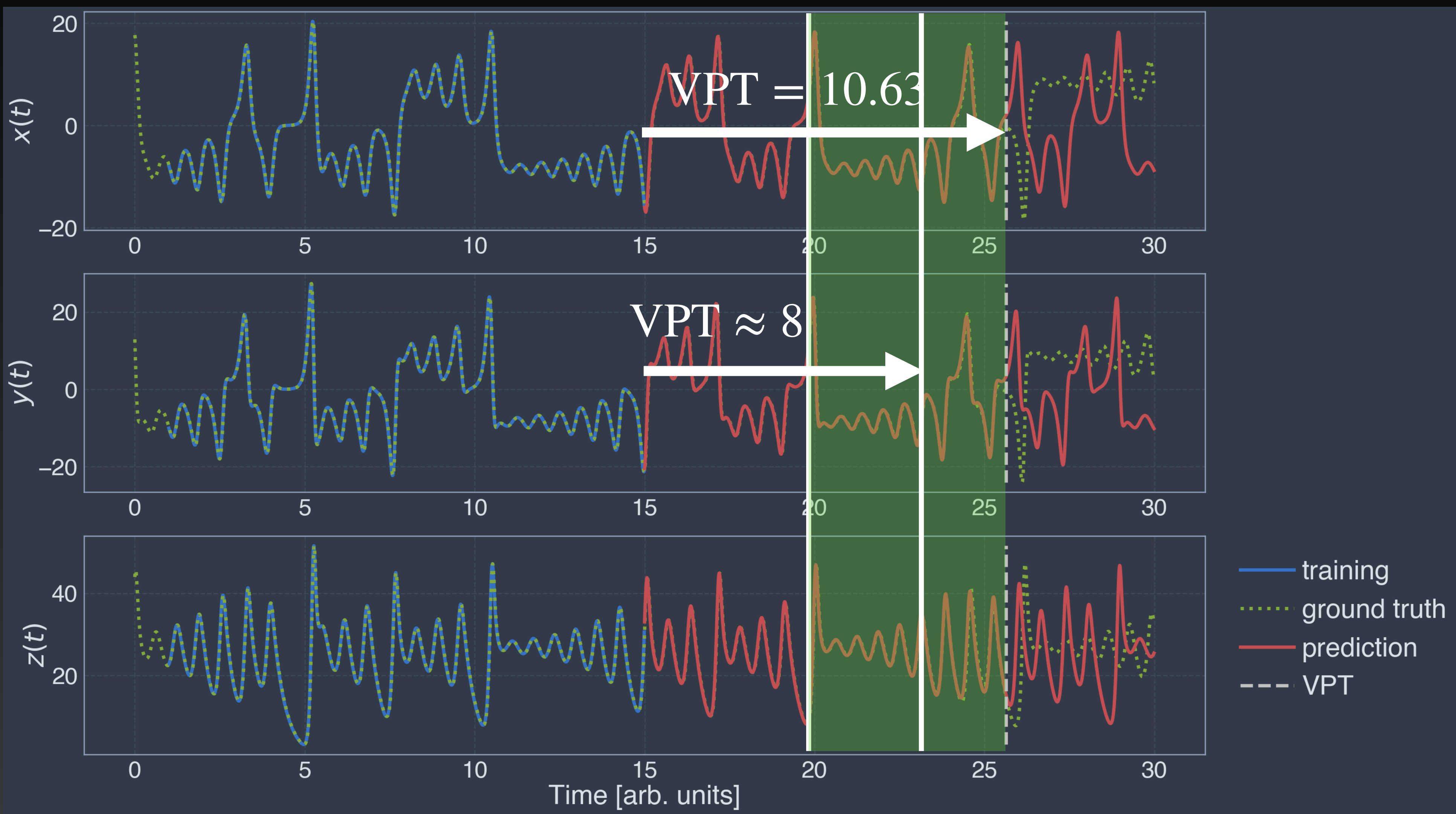
Reservoir size: 108

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Results

Classical simulations

"Quantum boost"



150 reservoir size + two-step optimization

- training
- ⋯ ground truth
- prediction
- - - VPT

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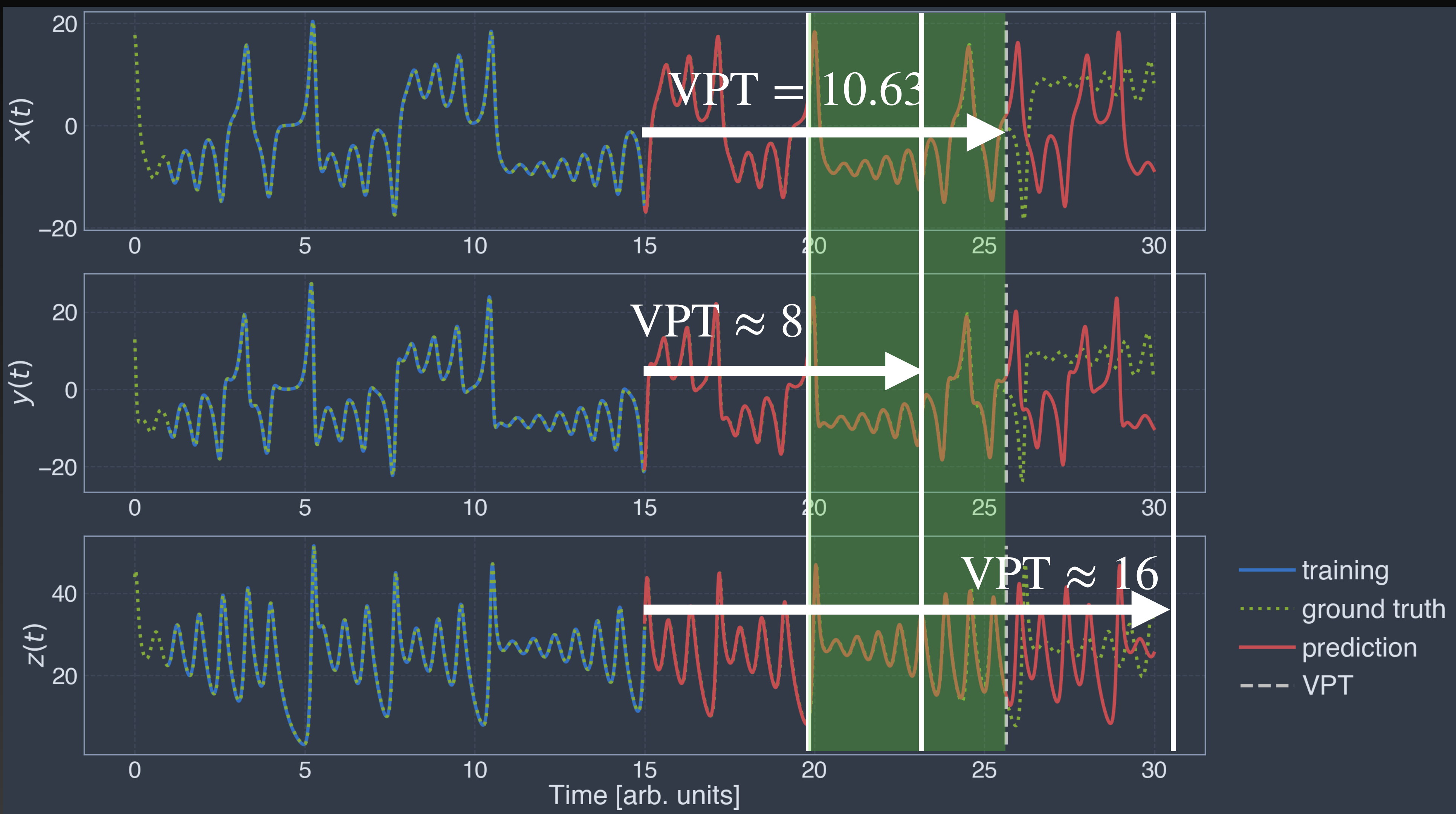
Reservoir size: 108

VPT = 10.63

Results

Classical simulations

"Quantum boost"



150 reservoir size + two-step optimization

6000 reservoir size + two-step optimization

Valid prediction time (VPT)

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8 qubits:

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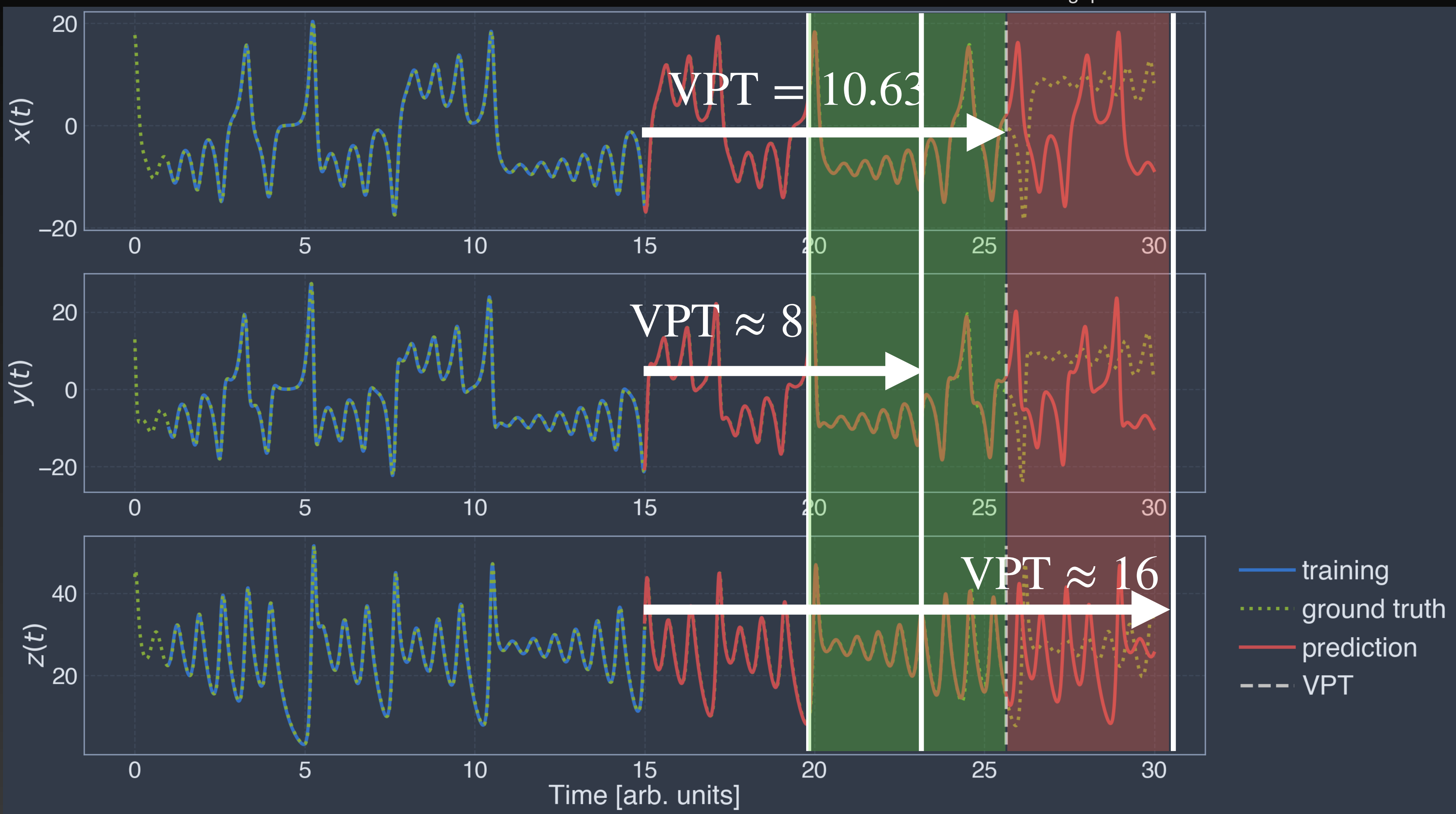
Reservoir size: 108

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Results

Classical simulations

“Quantum boost” “Quantum-classical gap”



150 reservoir size + two-step optimization

6000 reservoir size + two-step optimization

Valid prediction time (VPT)

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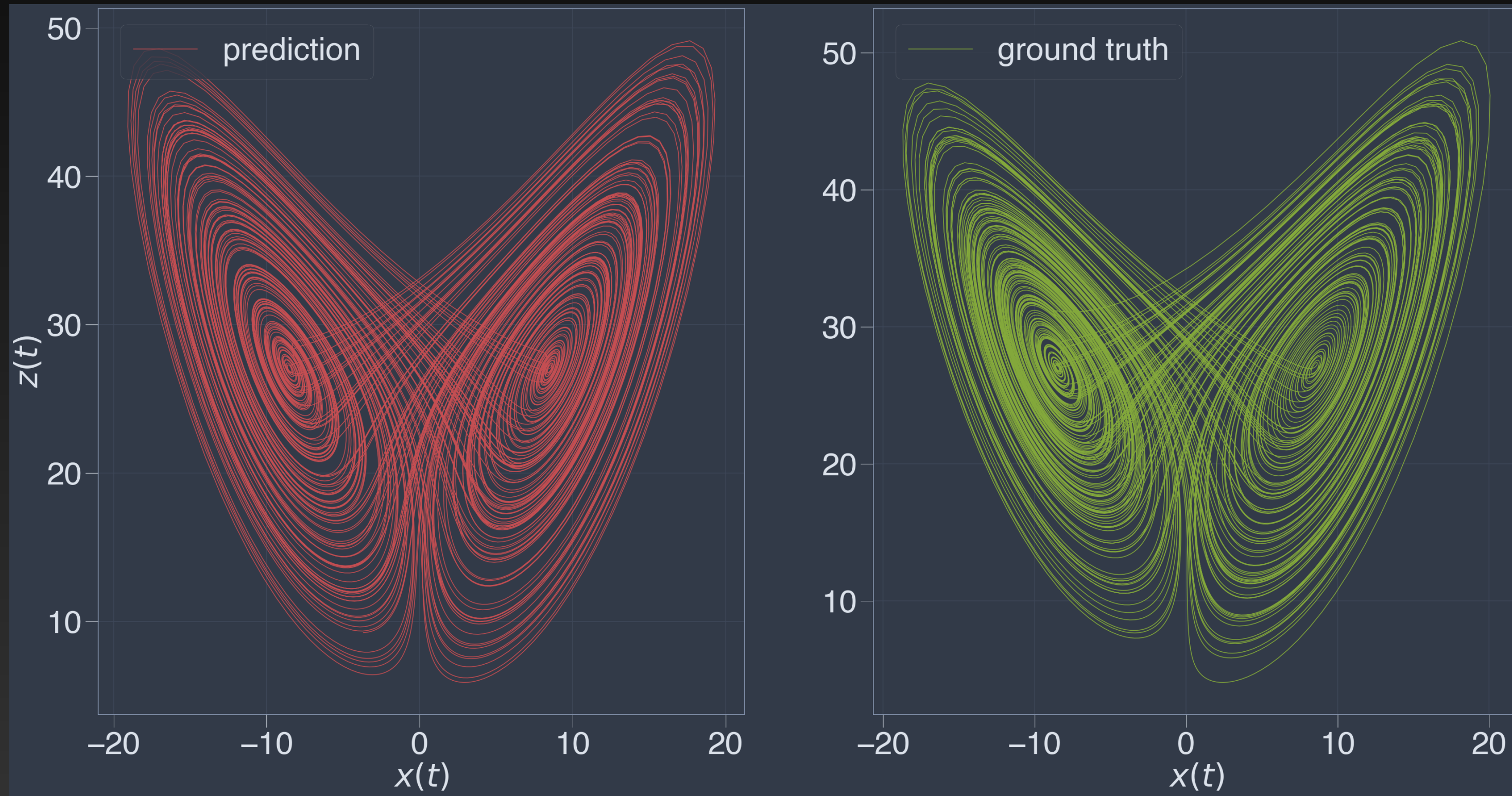
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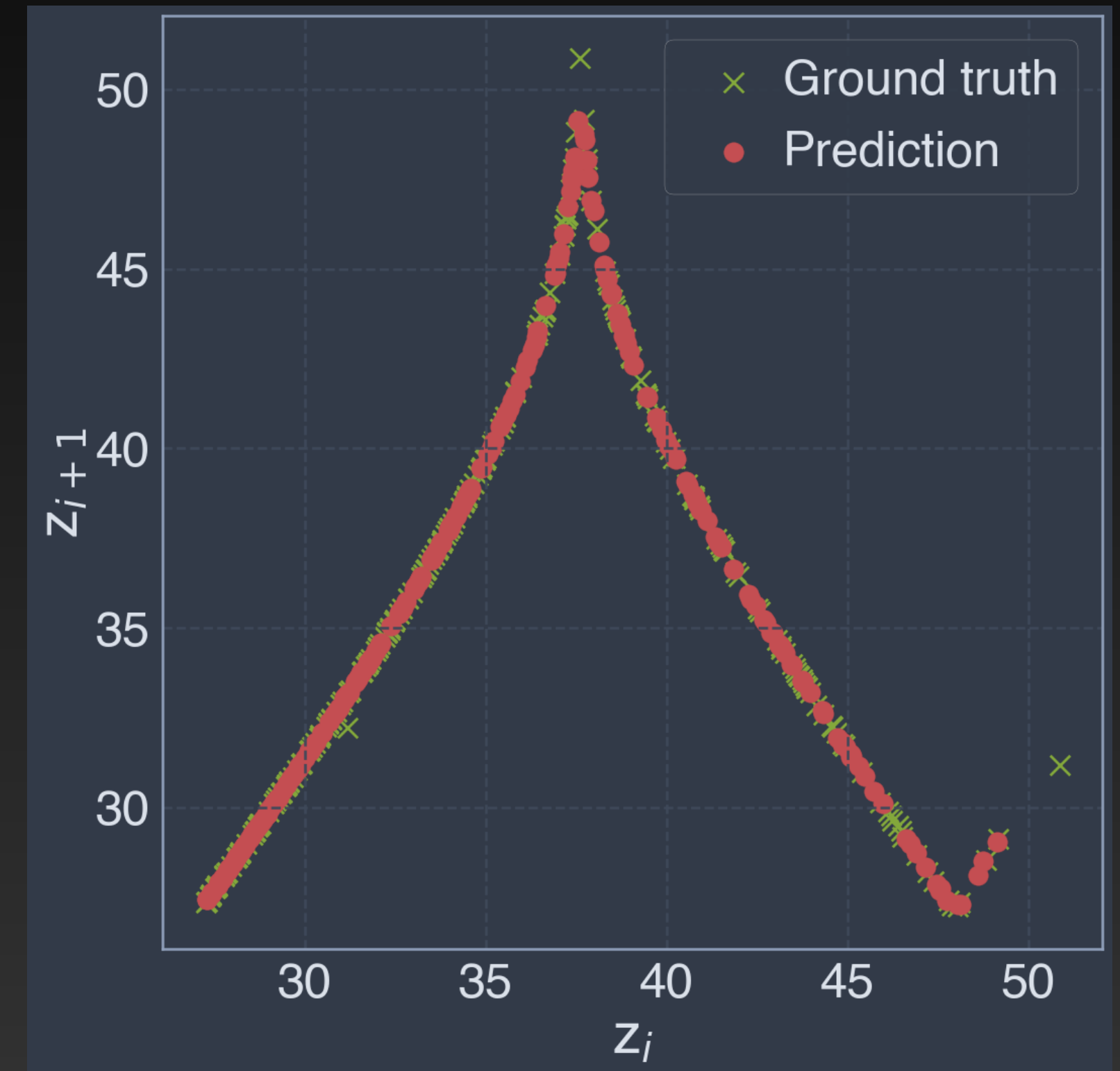
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Results

Classical simulations



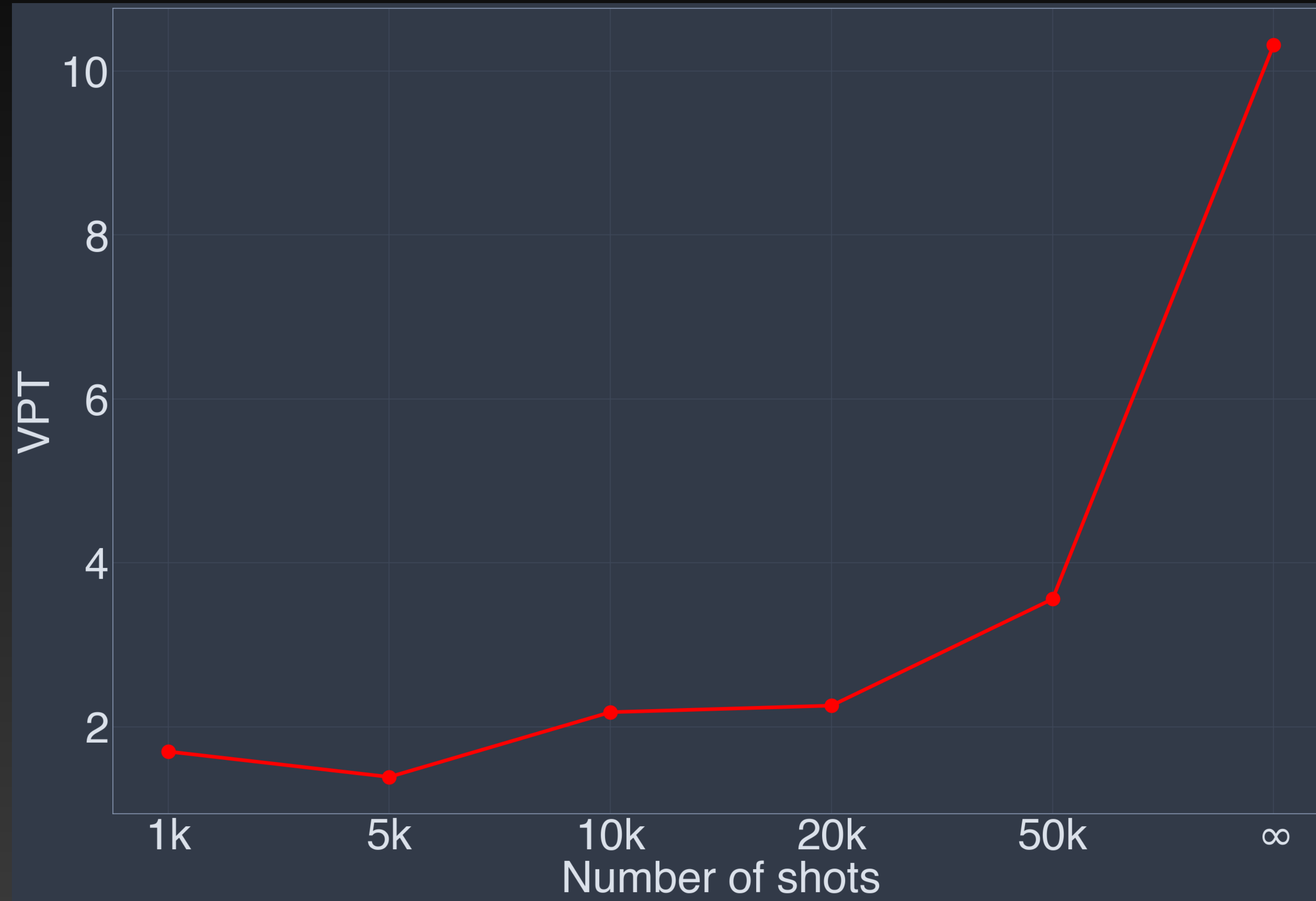
Attractor reconstruction



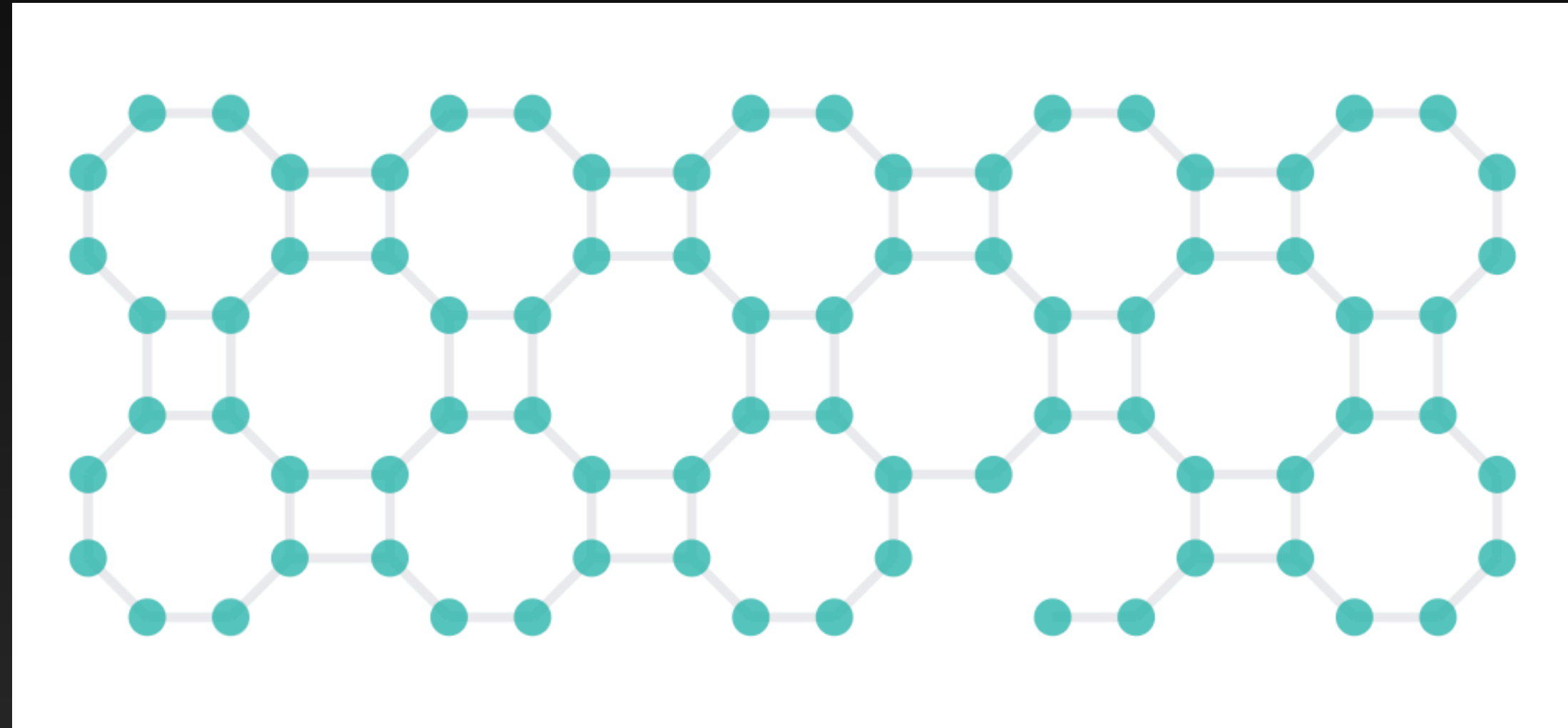
Poincaré return map

Results

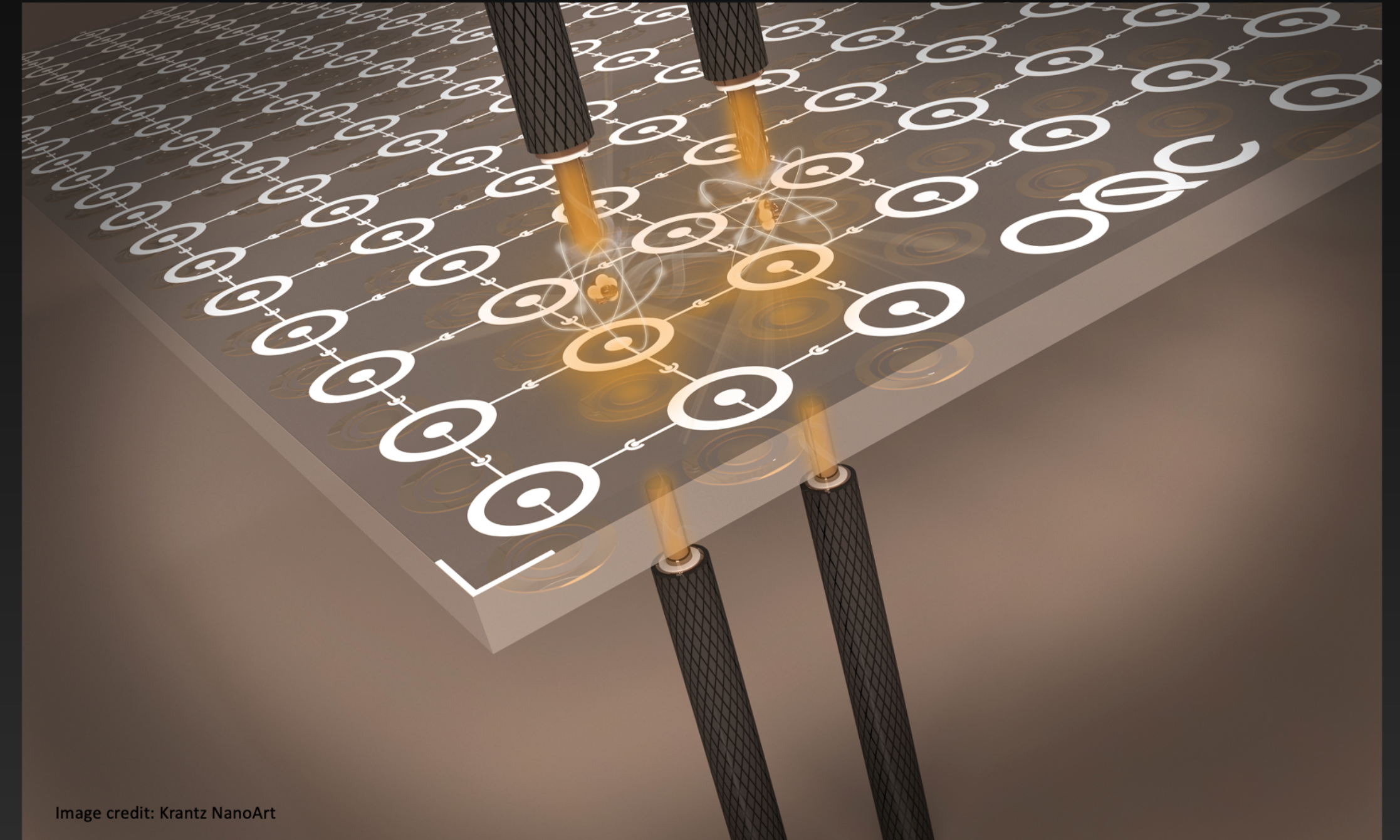
Classical simulations



Rigetti Aspen M-3 chip



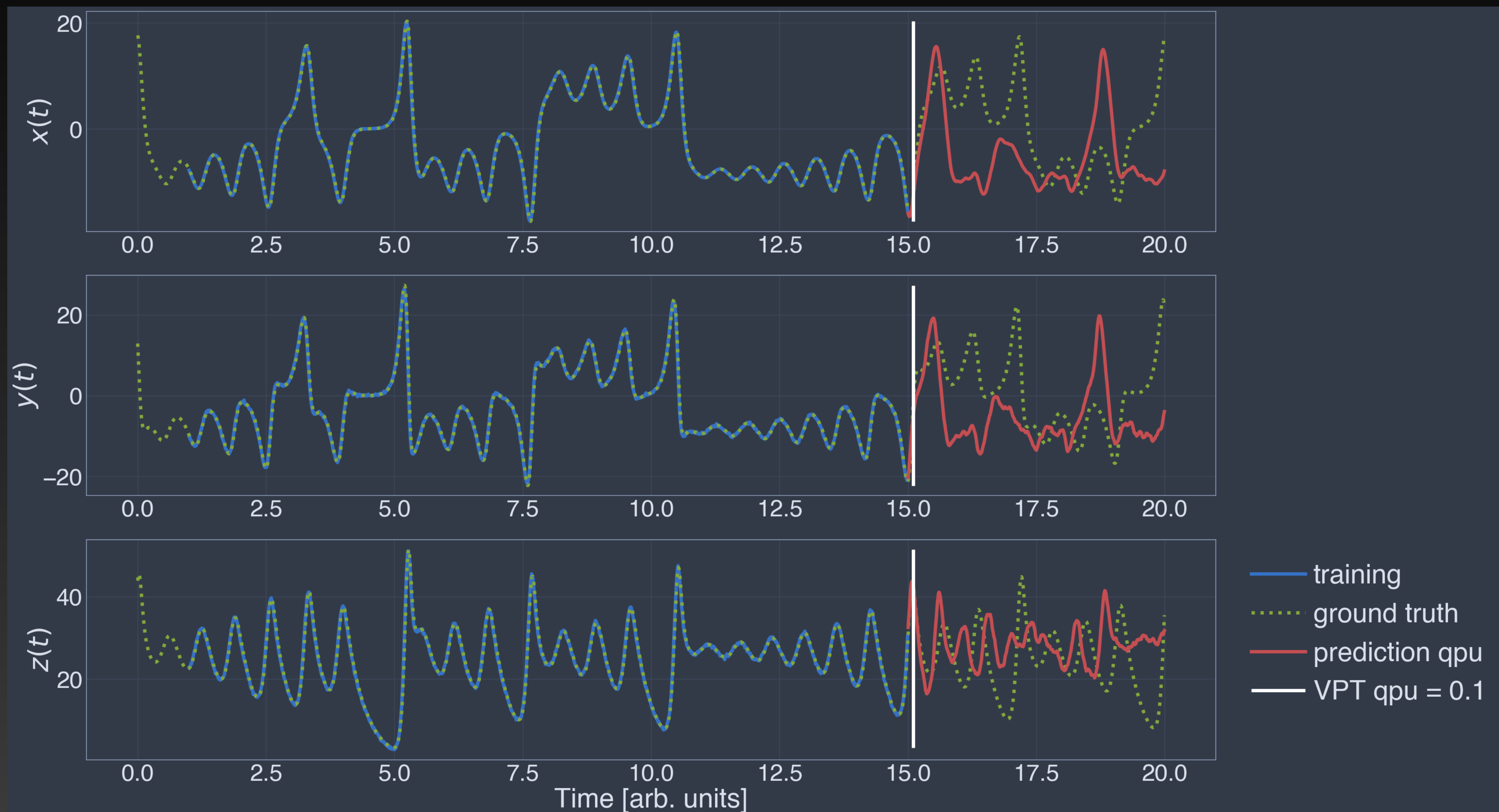
OQC Lucy



Results

QPU simulations

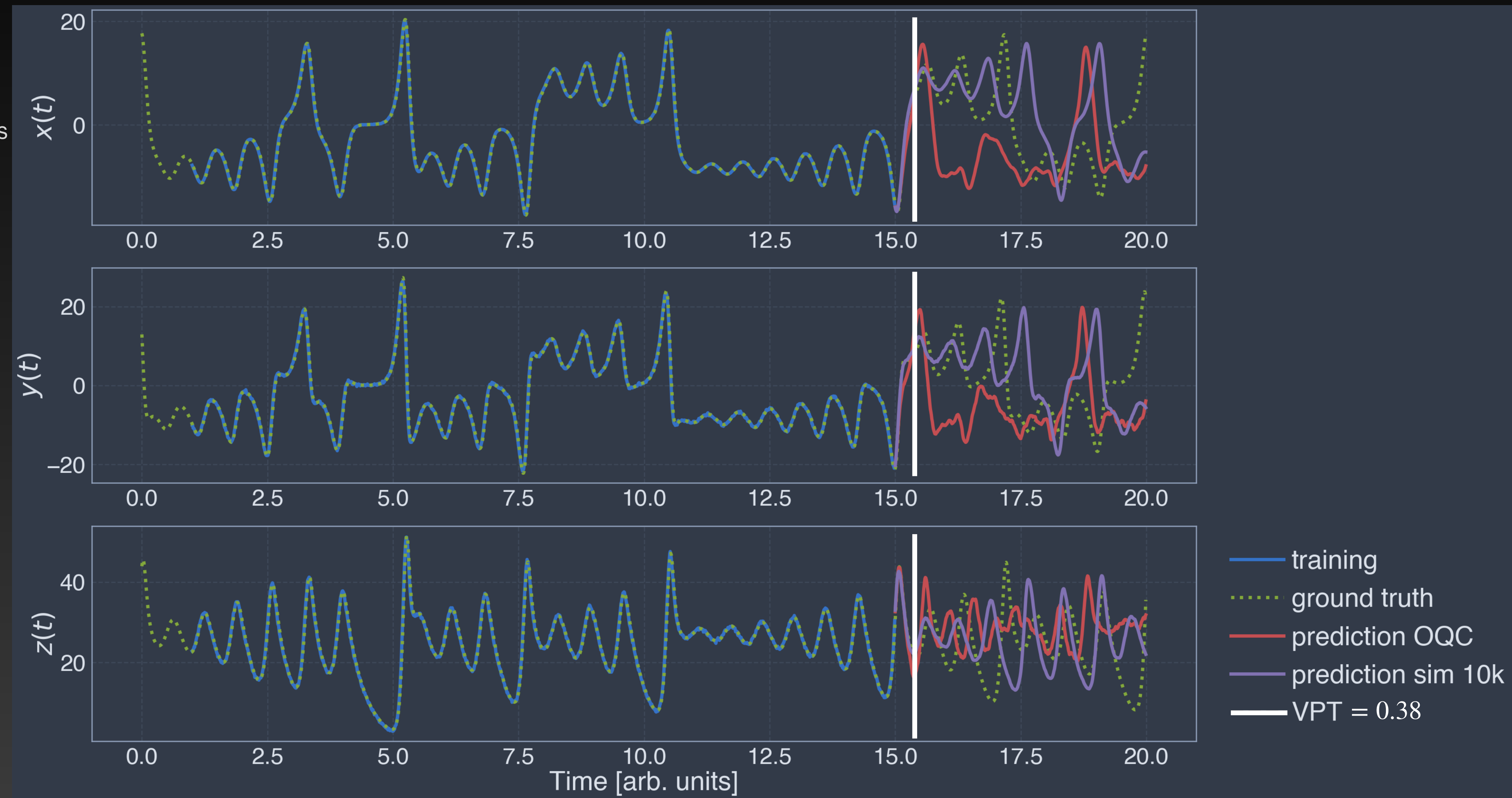
Lucy
8 qubits
2 CX layers
10k shots



Results

QPU simulations

Lucy
 8 qubits
 No CX layers
 10k shots



- The HQRC is a computational framework providing accurate short- and long-term predictions for low-dimensional chaotic systems.
- The HQRC has potential to compete with classical RC (theoretically)
- Experimentally we need more stability in processors and/or devise error mitigation strategies tailored for The HQRC
- HQRC doesn't involve optimization of circuits, so **NO** barren plateaus



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