



# **Incremental Learning of Quantum Generative Adversarial Network**

**Czech Technical University in Prague, Faculty of Information Technology,  
Department of Computer Science**

**Bc. Artem Kandaurov  
Supervisor: Ing. Ivo Petr, Ph.D.**

# Preparing generic quantum state problem and existing solutions

- Superposition and entanglement
- Quantum computer operates with quantum registers
- Loading classical data into quantum registers

$$|\Psi\rangle = \sum_{j=0}^{2^n-1} \sqrt{P(b_j)} |b_j\rangle$$

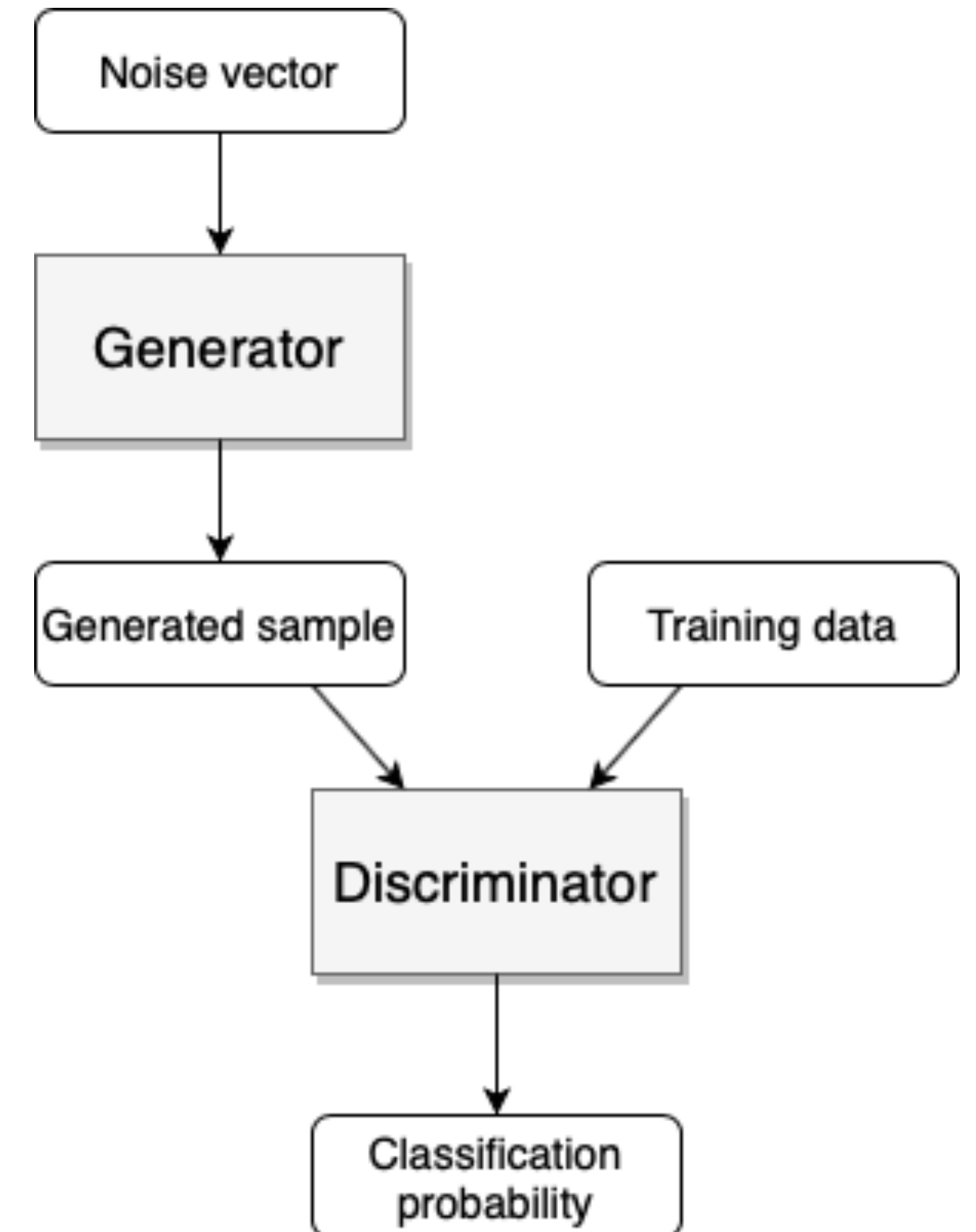
- Loading particular generic state in  $n$  qubits requires  $O(2^n)$  gates
- Approximation

# Generative Adversarial Network

## Principles

- Introduced by Ian J. Goodfellow et al.
- Generator creates fake examples
- Discriminator labels real and fake samples
- Generator and discriminator are neural networks
- Adversarial learning as a minimax game

$$\min_{\theta_g} (\max_{\theta_d} (\mathbb{E}_{x \sim p_{real}} [\log D_{\theta_d}(x)] + \mathbb{E}_{z \sim p_{prior}} [\log(1 - D_{\theta_d}(G_{\theta_g}(z)))]))$$



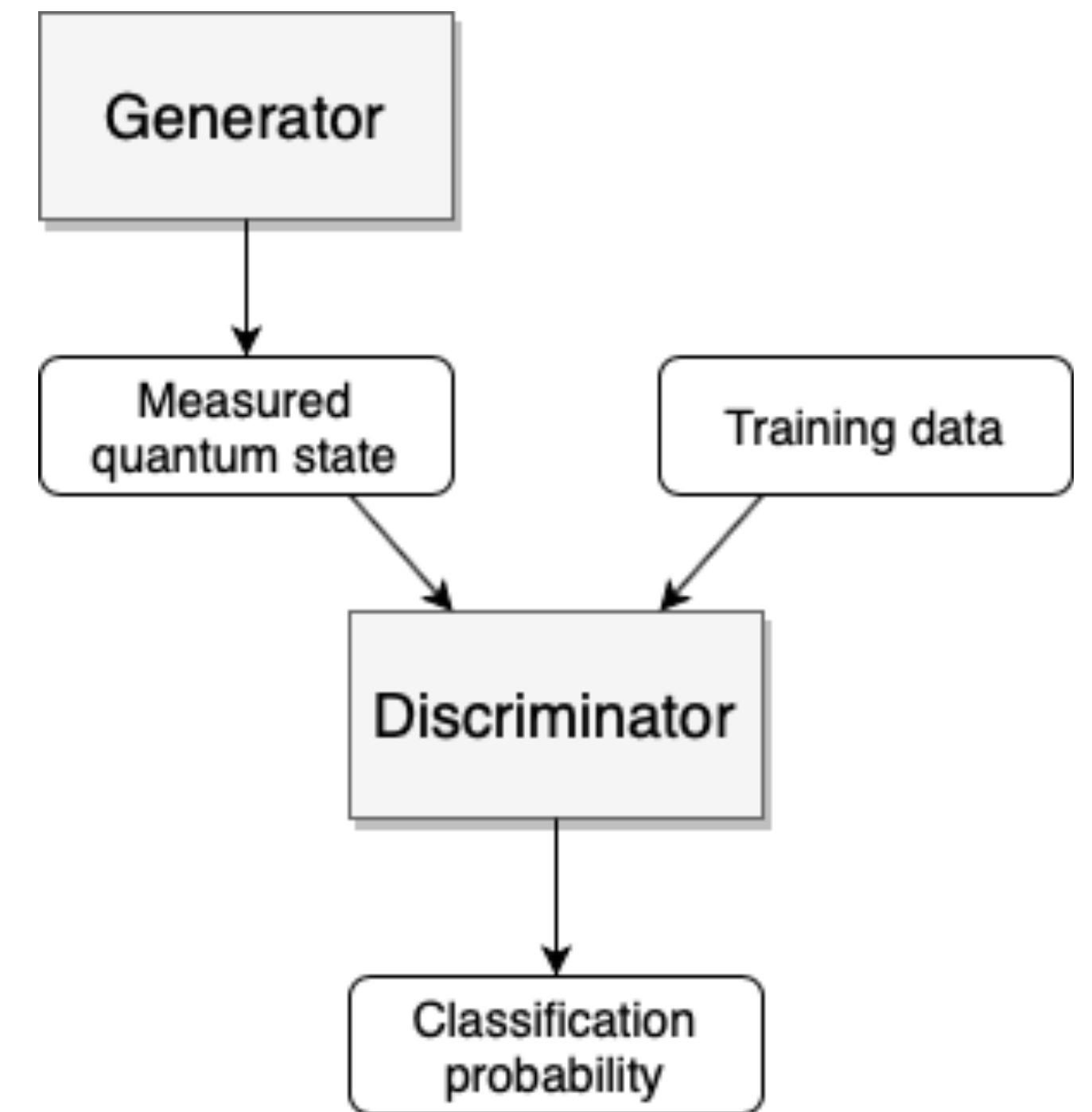
# Quantum Generative Adversarial Network

## Principles

- Introduced by Seth Lloyd et al.
- Quantum generator and classical discriminator
- More natural than classical GAN
- Loss functions

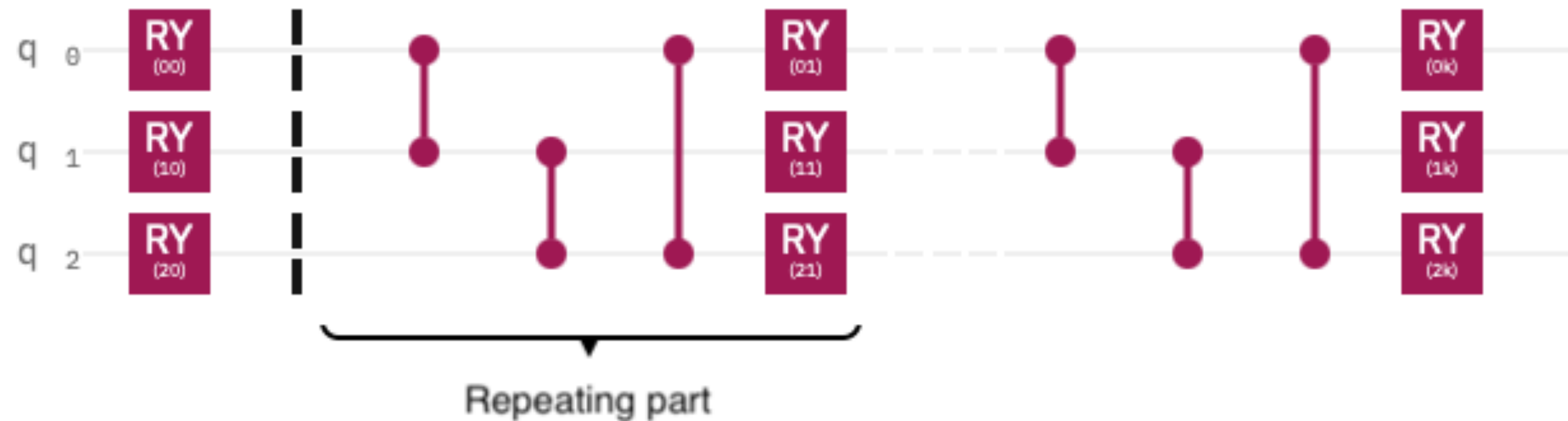
$$L_G(\theta_g, \theta_d) = - \mathbb{E}_{g \sim G_{\theta_g}} [\log(D_{\theta_d}(g))]$$

$$L_D(\theta_g, \theta_d) = \mathbb{E}_{x \sim p_{real}} [\log D_{\theta_d}(x)] + \mathbb{E}_{g \sim G_{\theta_g}} [\log(1 - D_{\theta_d}(g))]$$



# Quantum Variational Circuit

- Parametrizing schemes: **RX, RY, RZ**
- Entanglement schemes: **CZ, CNOT**



# Quantum Generative Adversarial Networks for learning and loading random distributions

- Introduced by Christa Zoufal et al.
- Quantum variational circuit should represent a probability distribution
- Underlying process is defined implicitly with a training dataset
- Loading requires  $O(\text{poly}(n))$  gates
- Implementation is a part of Qiskit
- Training time is still the issue

# Incremental learning of Quantum Generative Adversarial Network

- Complete dataset availability assumption and data streams
- Extension of the original algorithm
- Stationary underlying processes learning
- Non-stationary underlying processes learning
- Possible application in quantum finances
- Code availability

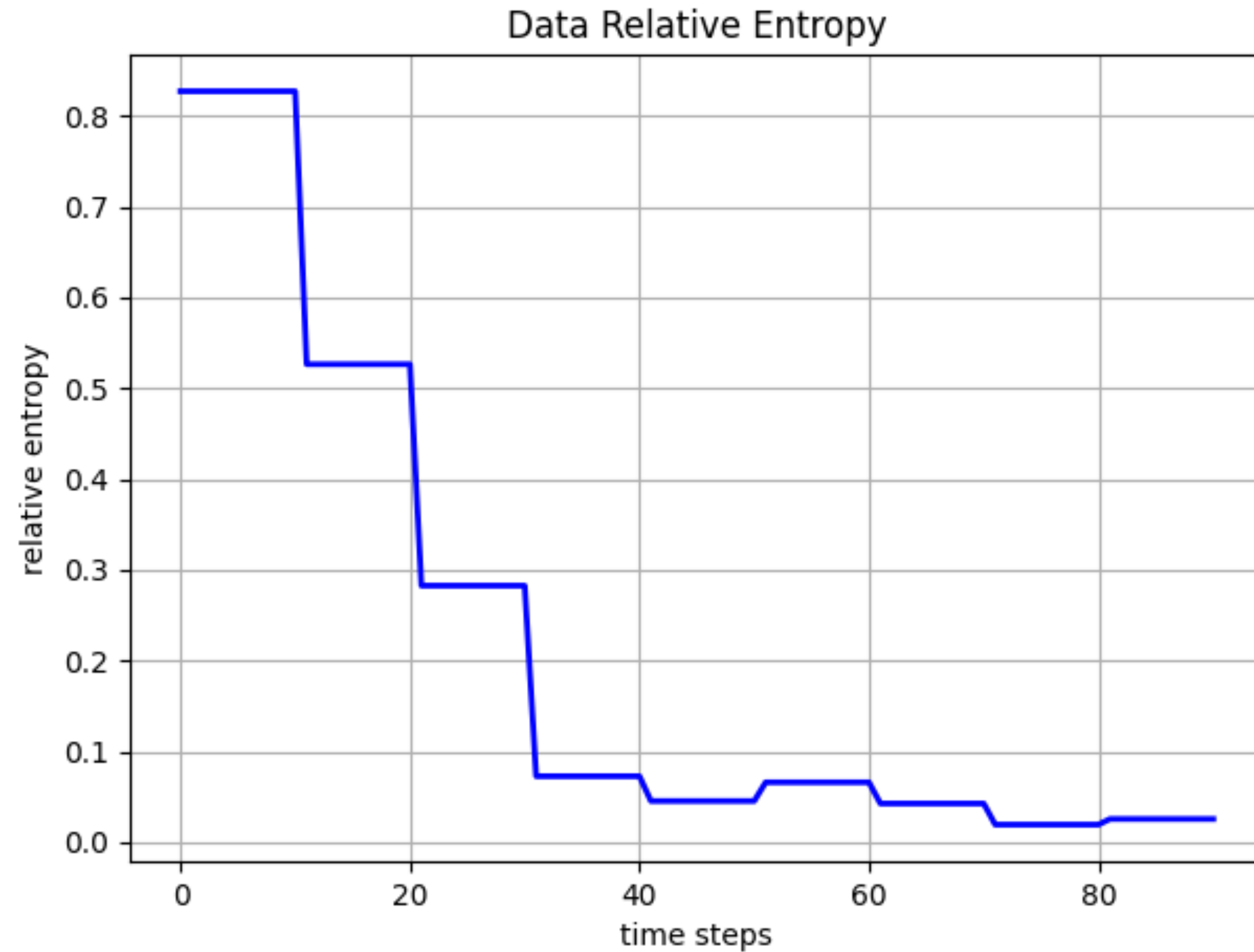
# Stationary process learning test case definition

- Number of qubits: 2
- Generator's distribution: Uniform
- Target distribution: Log-normal with  $\mu = 1$ ,  $\sigma = 1$
- Data stack limit: Unlimited
- Data source: Batch per 10 time steps



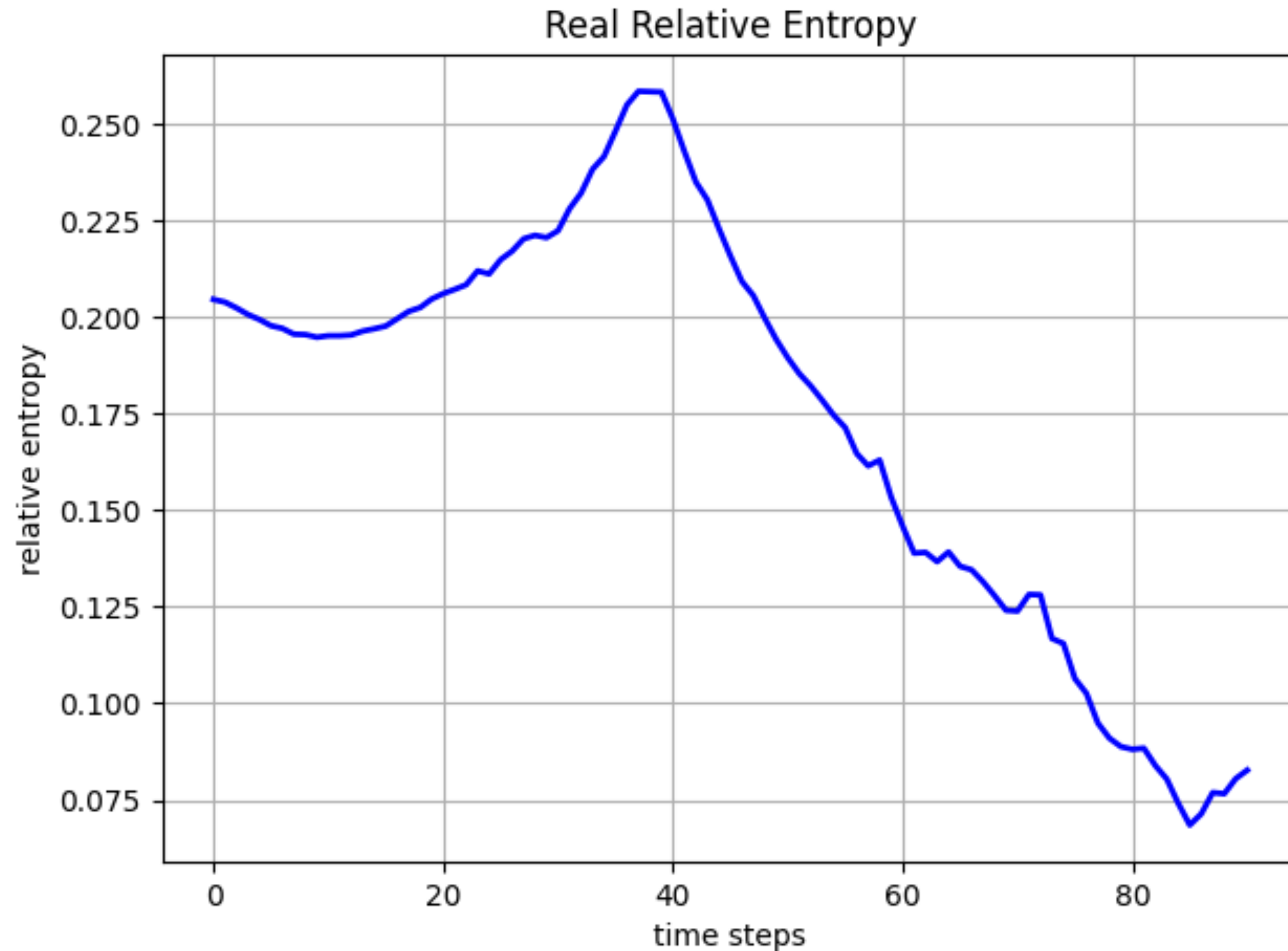
# Stationary process learning

Relative entropy between *available* and *unknown* dataset



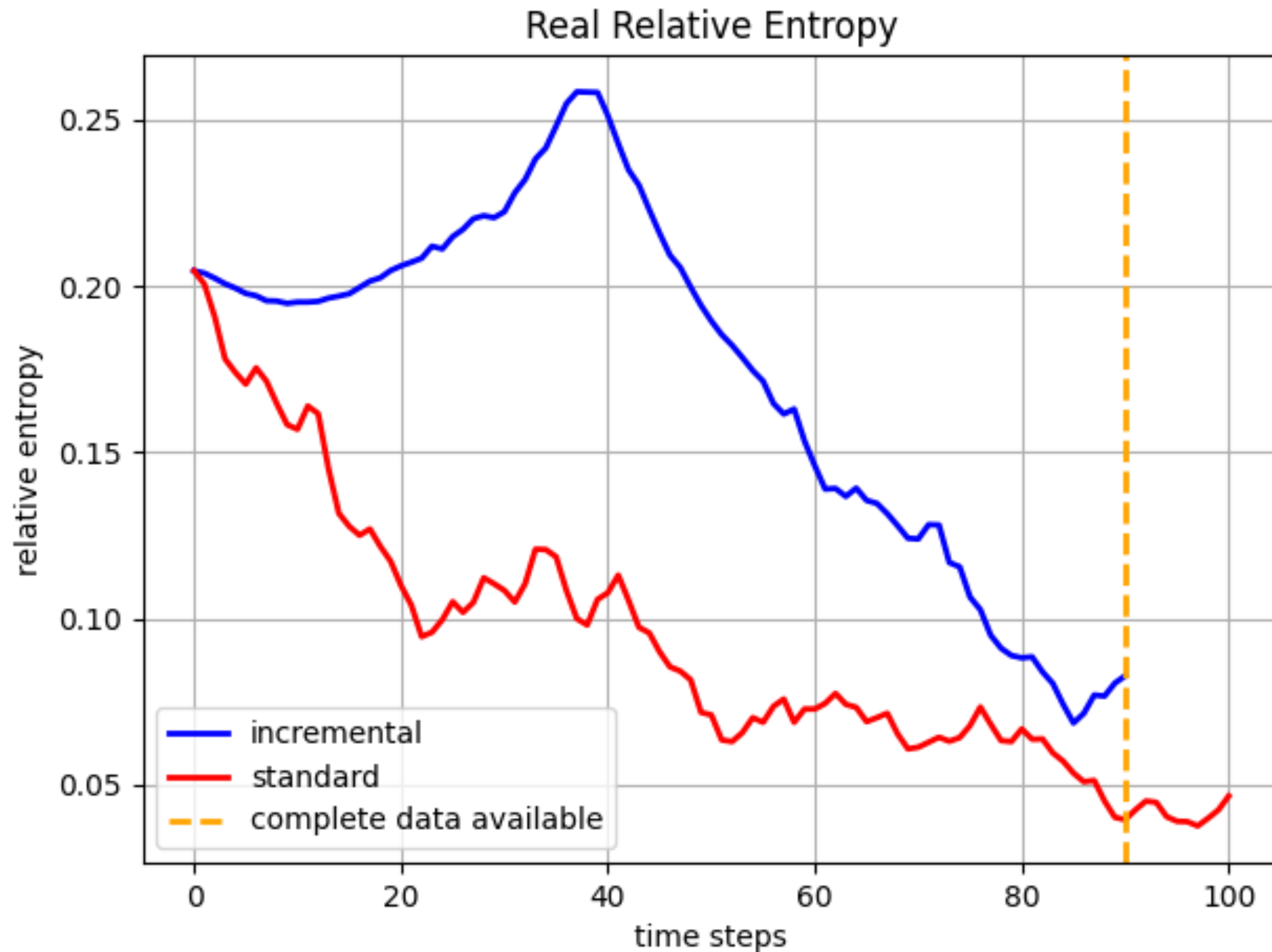
# Stationary process learning

Relative entropy between *trained* and *unknown wanted* state



# Stationary process learning

## Real relative entropy comparison

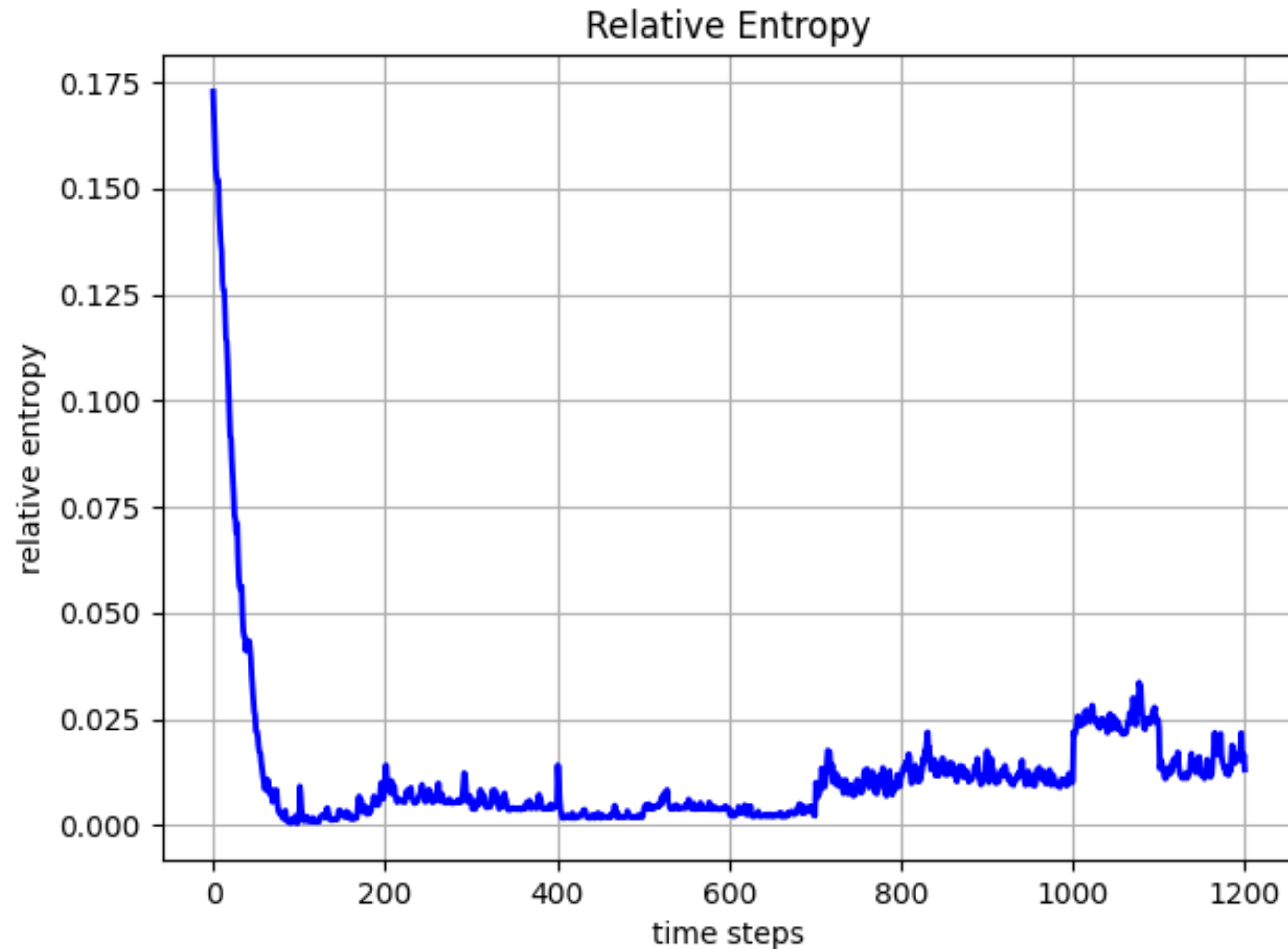


# Non-stationary process learning test case definition

- Number of qubits: 2
- Generator's distribution: Uniform
- Initial distribution: Log-normal with  $\mu = 1, \sigma = 1$
- Target distribution: Log-normal with  $\mu = 2, \sigma = 1$
- Data stack limit: 10 batches
- Data source: Batch per 100 time steps

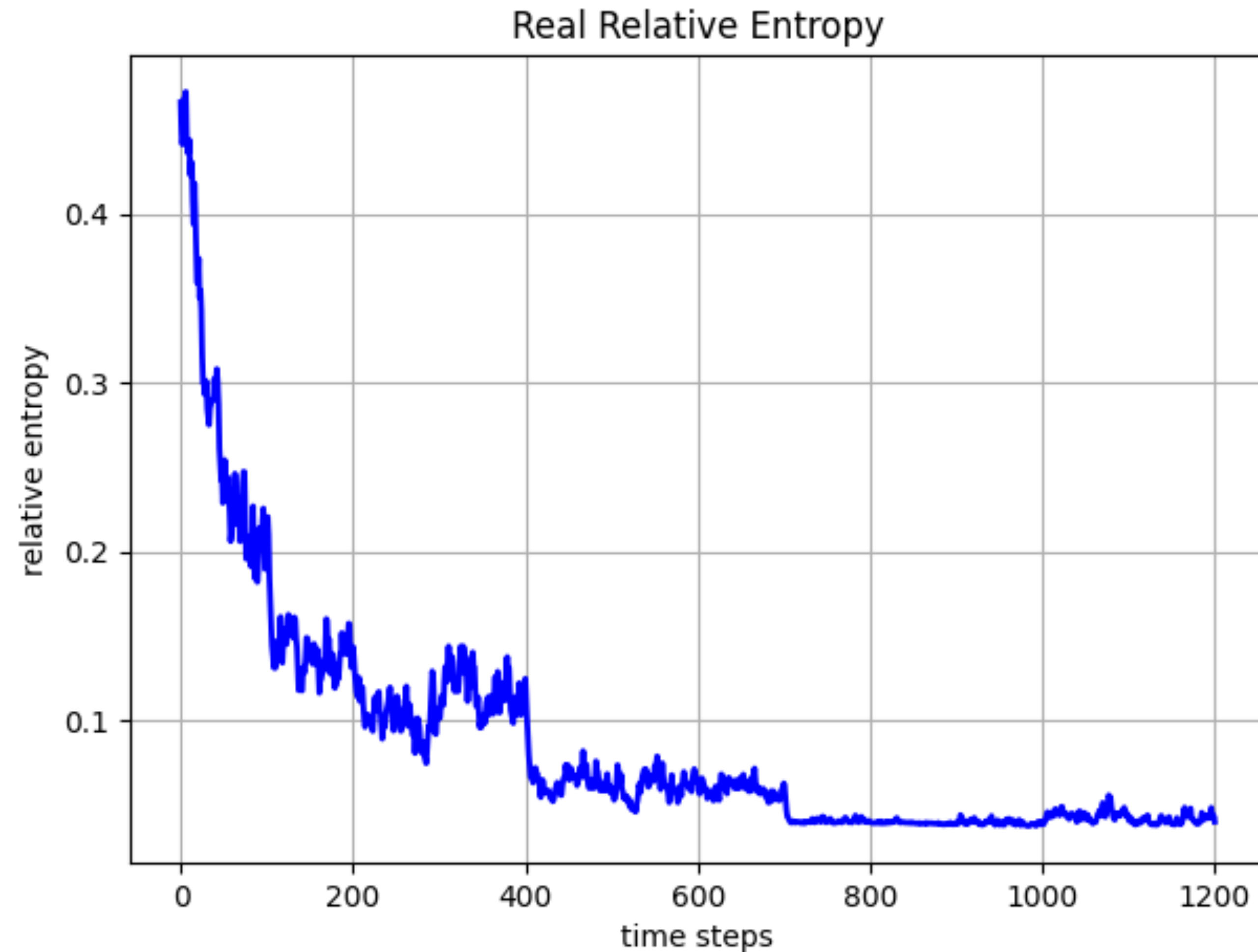
# Non-stationary process learning

Relative entropy between *trained* and *wanted* state



# Non-stationary process learning

Relative entropy between *trained* and *unknown wanted end state*

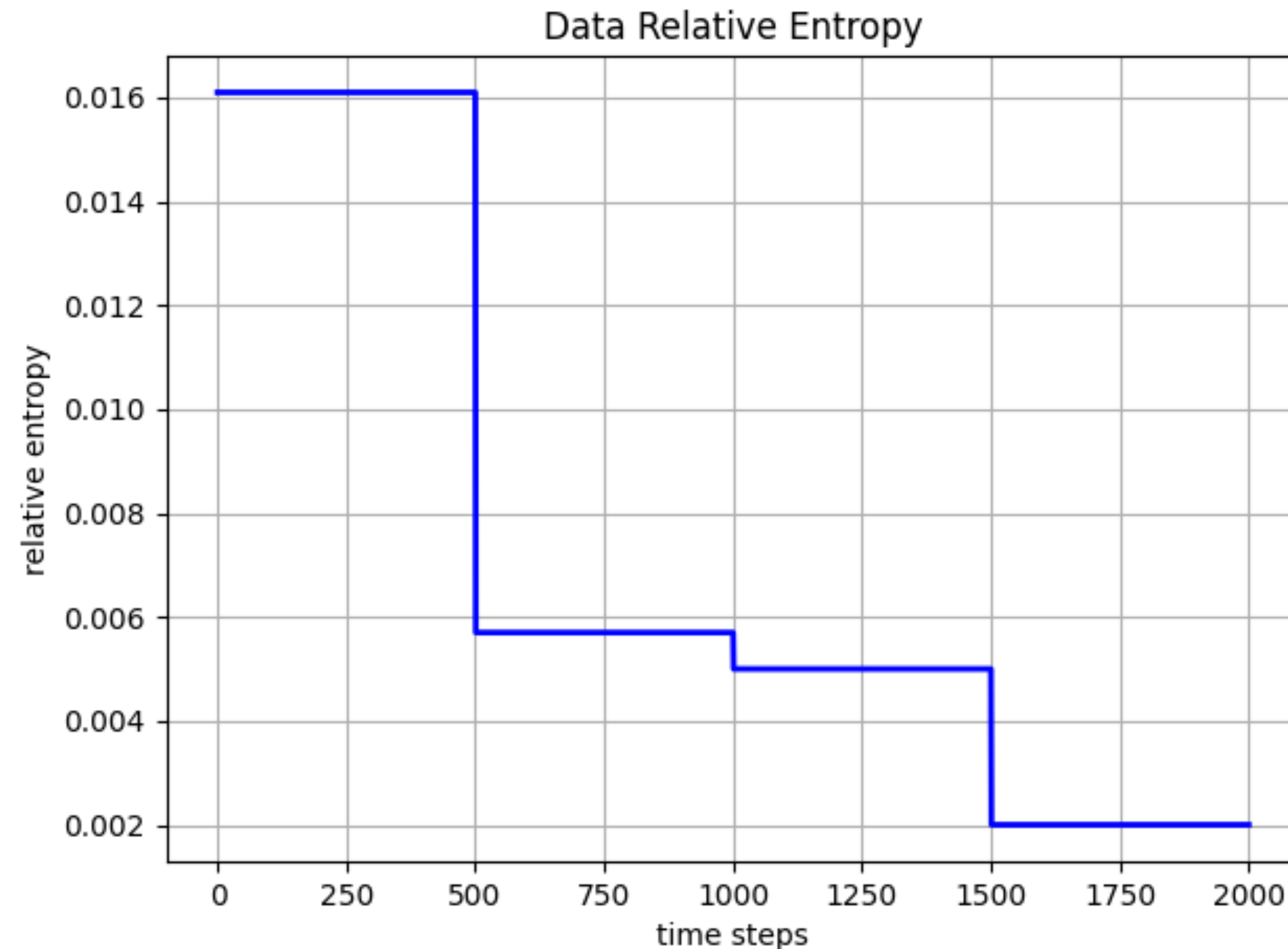


# Stationary process learning with noisy simulator test case definition

- Number of qubits: 2
- Generator's distribution: Uniform
- Target distribution: Log-normal with  $\mu = 1, \sigma = 1$
- Data stack limit: Unlimited
- Data source: Batch per 500 time steps

# Stationary process learning with noisy simulator

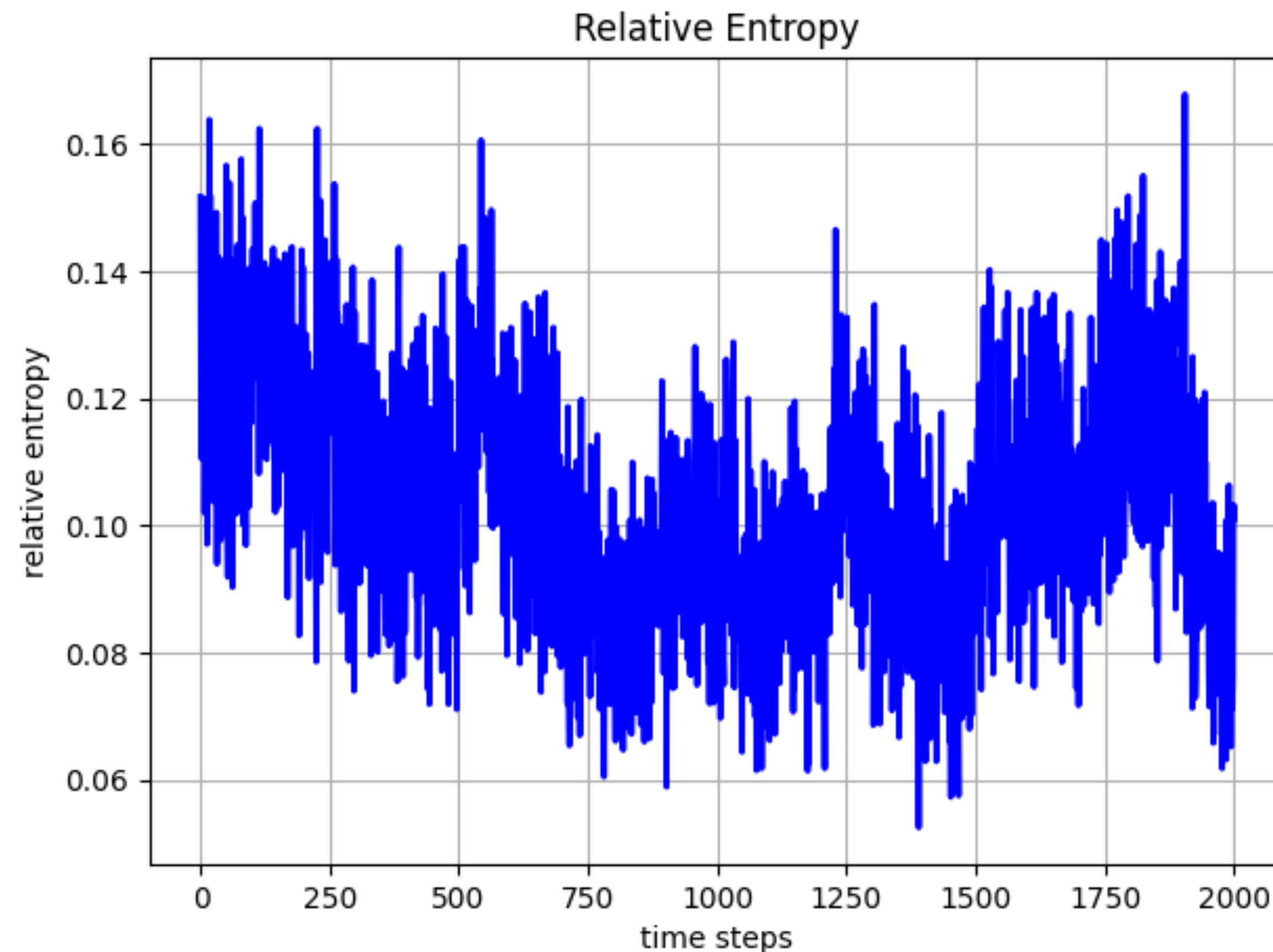
Relative entropy between *available* and *unknown* dataset





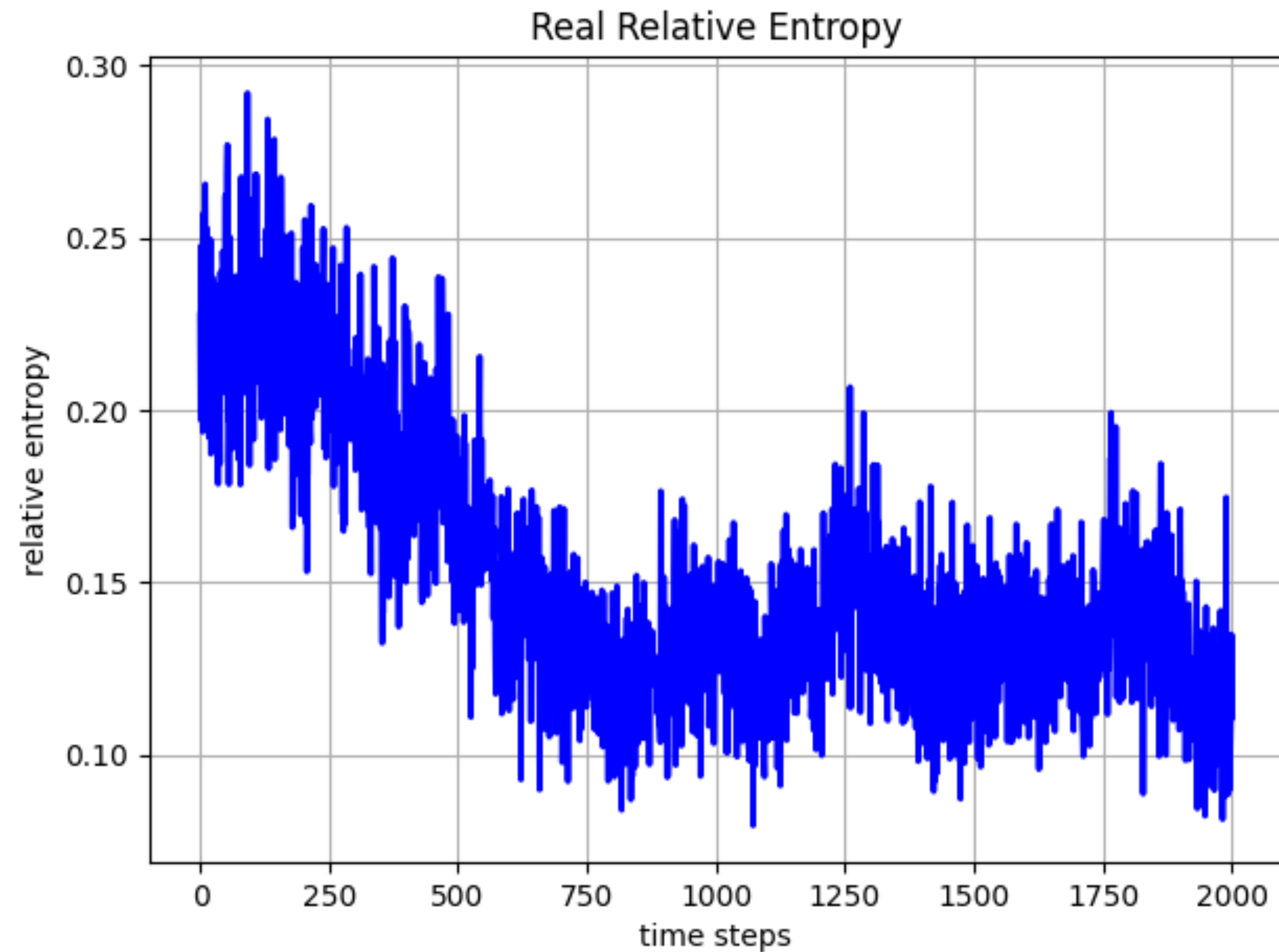
# Stationary process learning with noisy simulator

Relative entropy between *trained* and *wanted* state



# Stationary process learning with noisy simulator

Relative entropy between *trained* and *unknown wanted* state



# References

- Goodfellow, I. J.; Pouget-Abadie, J.; et al. Generative adversarial networks. *arXiv preprint arXiv:1406.2661*, 2014.
- Lloyd, S.; Weedbrook, C. Quantum generative adversarial learning. *Physical review letters*, volume 121, no. 4, 2018: p. 040502.
- Zoufal, C.; Lucchi, A.; et al. Quantum generative adversarial networks for learning and loading random distributions. *npj Quantum Information*, volume 5, no. 1, 2019: pp. 1–9.