

Density estimation via adiabatic quantum computing

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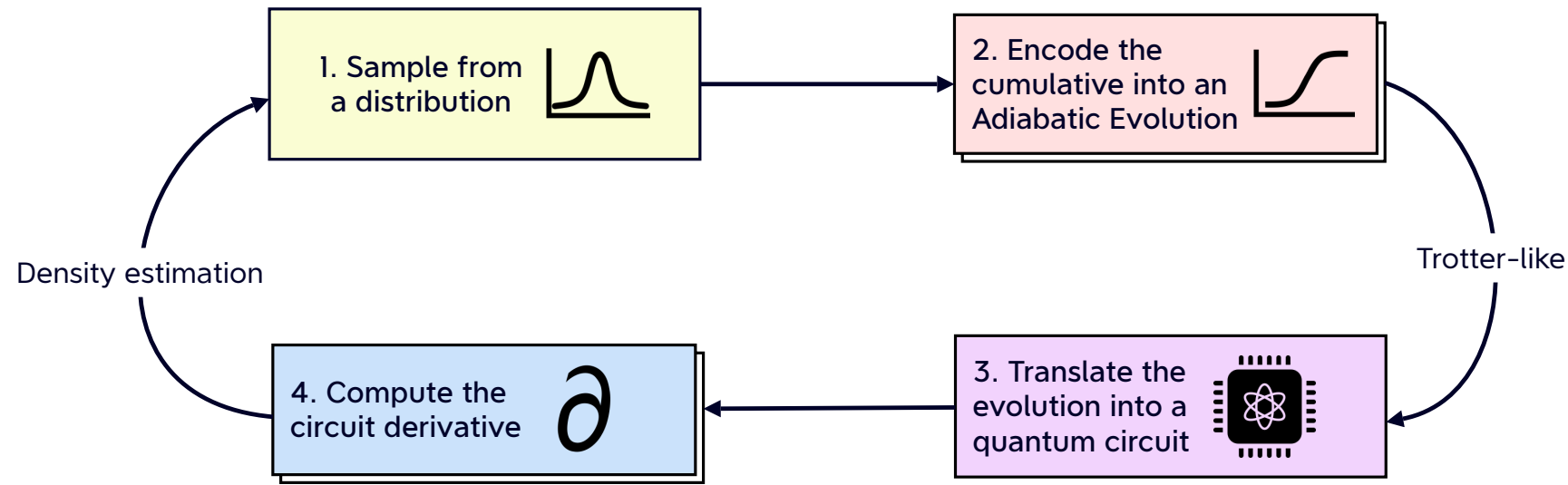
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Aim of the project

We propose a novel strategy to perform density estimation: given a variable x sampled from an unknown distribution $\rho(x)$, we aim to estimate the puntual Probability Density Function (PDF) value $\hat{\rho}(x)$.

We focus on one-dimensional distributions, and then extend the study to the case of joint PDFs of independent variables.

Schematic pipeline of the algorithm



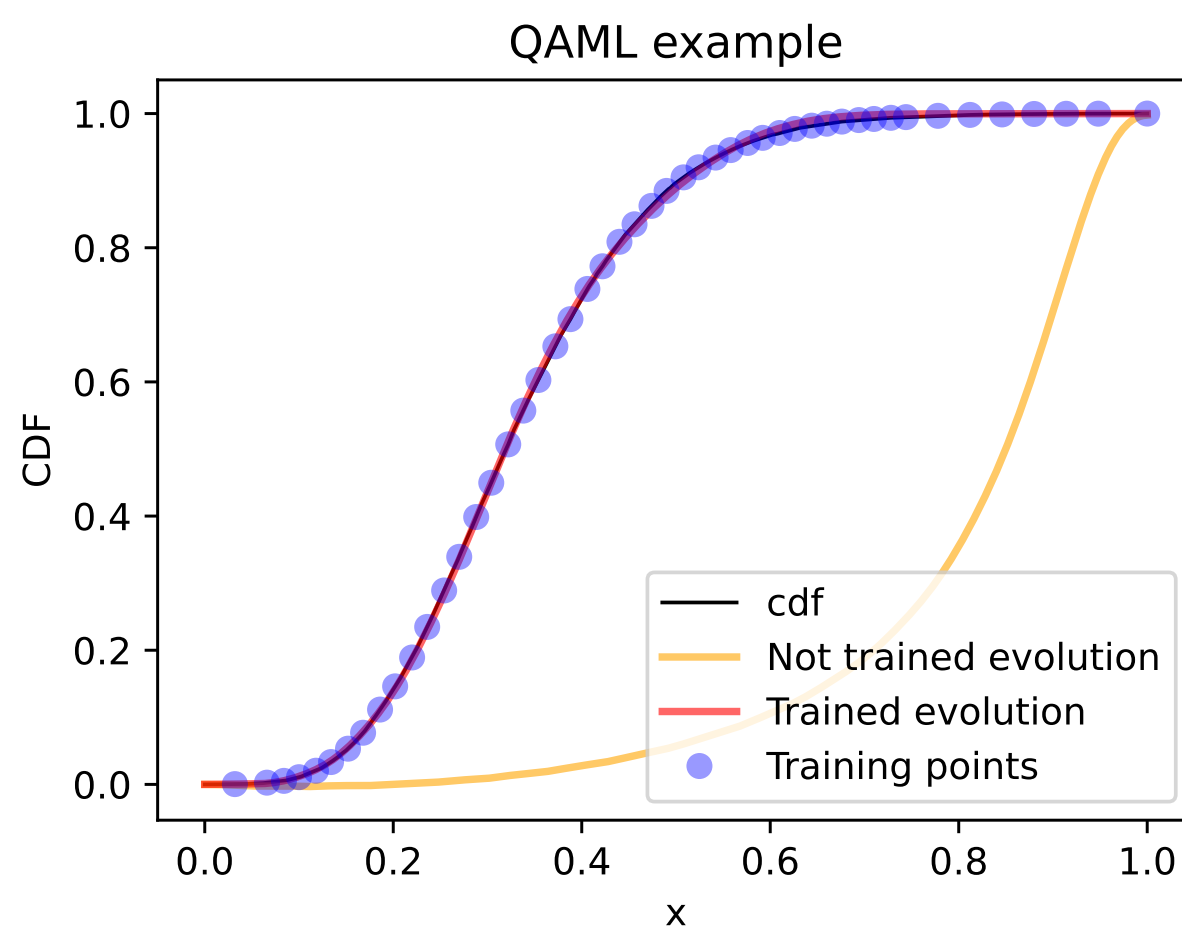
Encoding a CDF into an adiabatic evolution

We use Qibo [1] to simulate an adiabatic evolution on time τ

$$H_{\text{ad}}(\tau|\theta) = [1 - s(\tau|\theta)]H_0 + s(\tau|\theta)H_1, \quad (1)$$

Where $s(\tau|\theta)$ is a parametric scheduling function.

We map $\{x, F(x)\}$ into $\{\tau, -E(\tau)\}$, where $E(\tau)$ energy of a non-interacting Pauli Z over the evolved ground state of H_{ad} at τ .

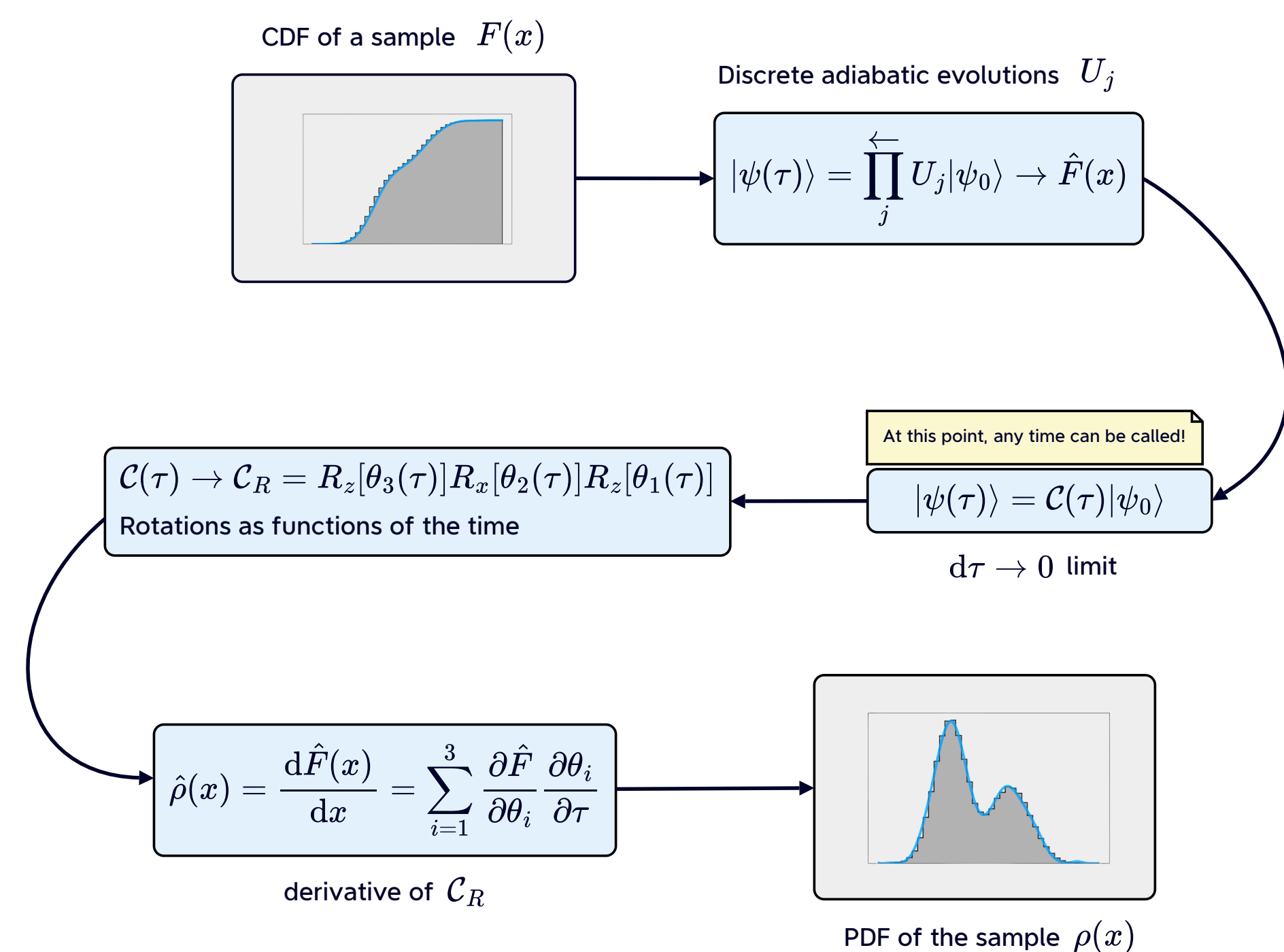


Optimizing the adiabatic evolution

1. perform the evolution with initial guess θ_0 in the scheduling;
2. estimate a loss function $J_{\text{mse}}[F, -E(\theta)]$;
3. update θ using a chosen optimizer until convergence.

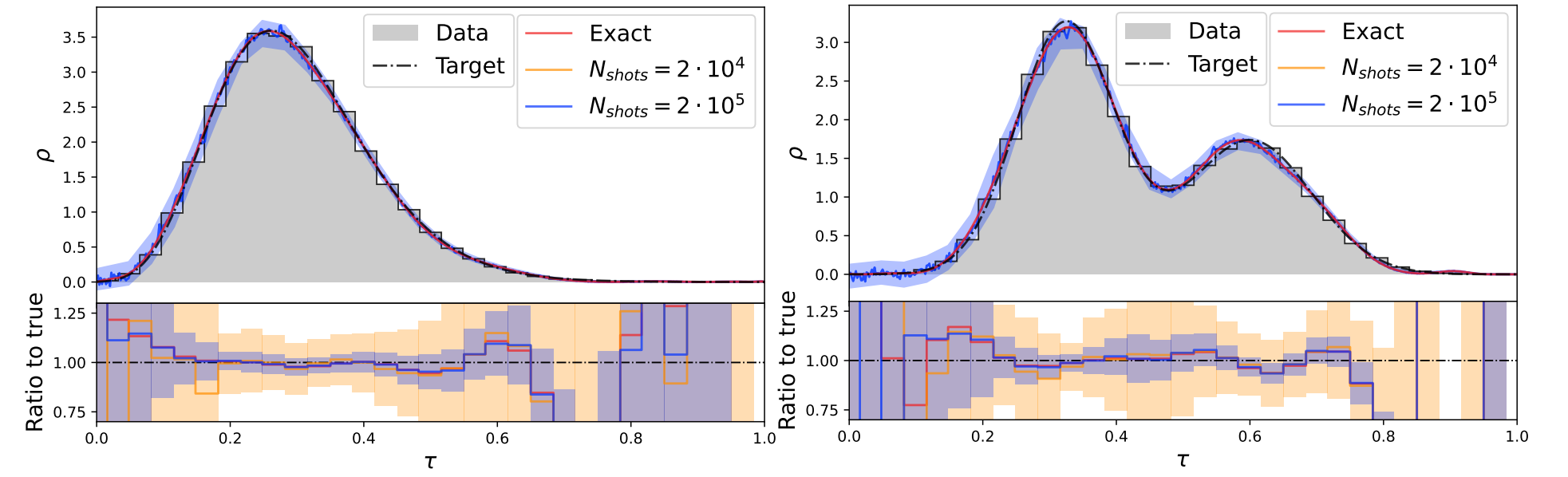
Building a derivable circuit

After encoding the CDF into the evolution, we translate H_{ad} into a circuit derivable via shift rules [2]:



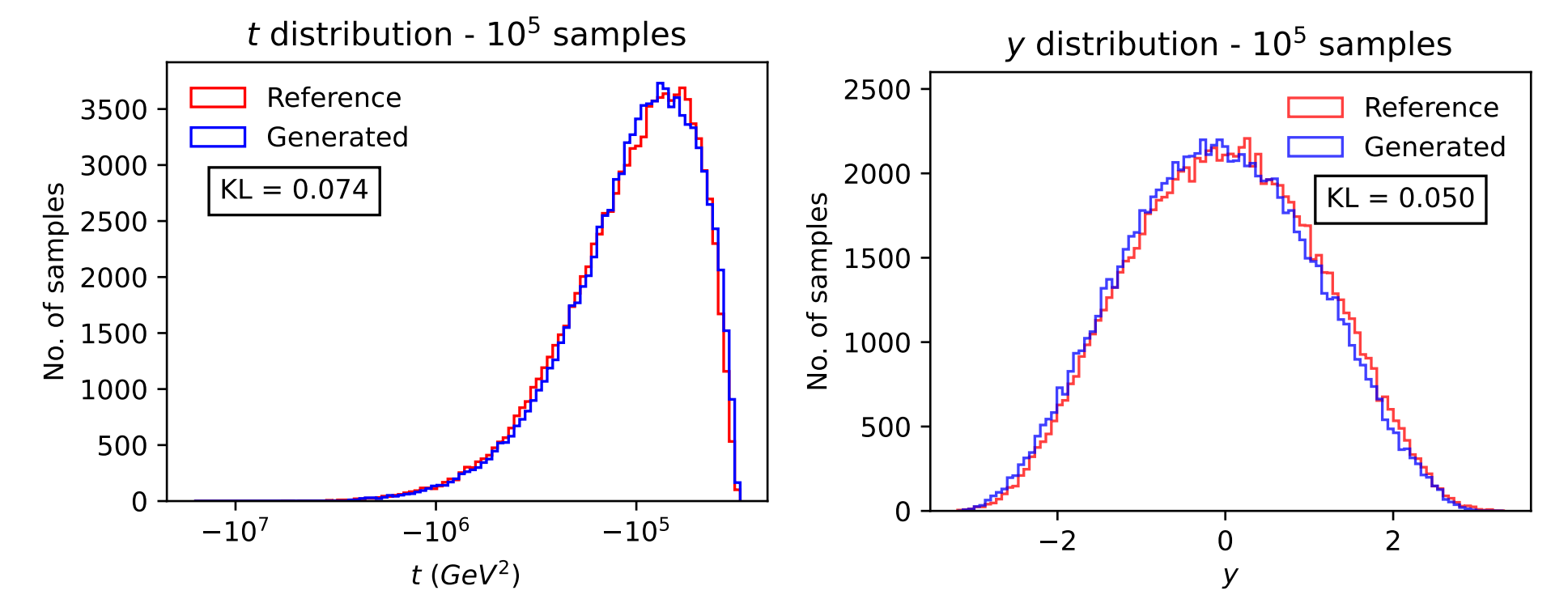
Validation cases

We firstly test the QAML procedure on a Gamma distribution and on a Gaussian mixture.

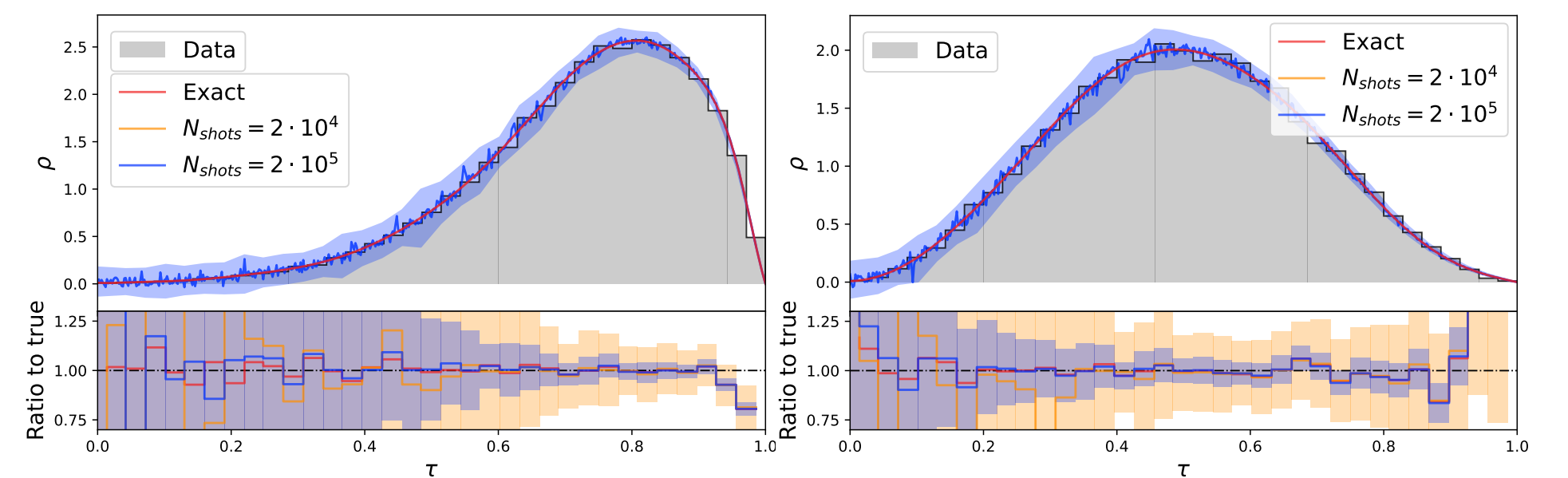


Quantum density estimation of quantum generated data

LHC events of a $pp \rightarrow t\bar{t}$ decay generated with a quantum GAN [3].



On which we apply the QAML algorithm:



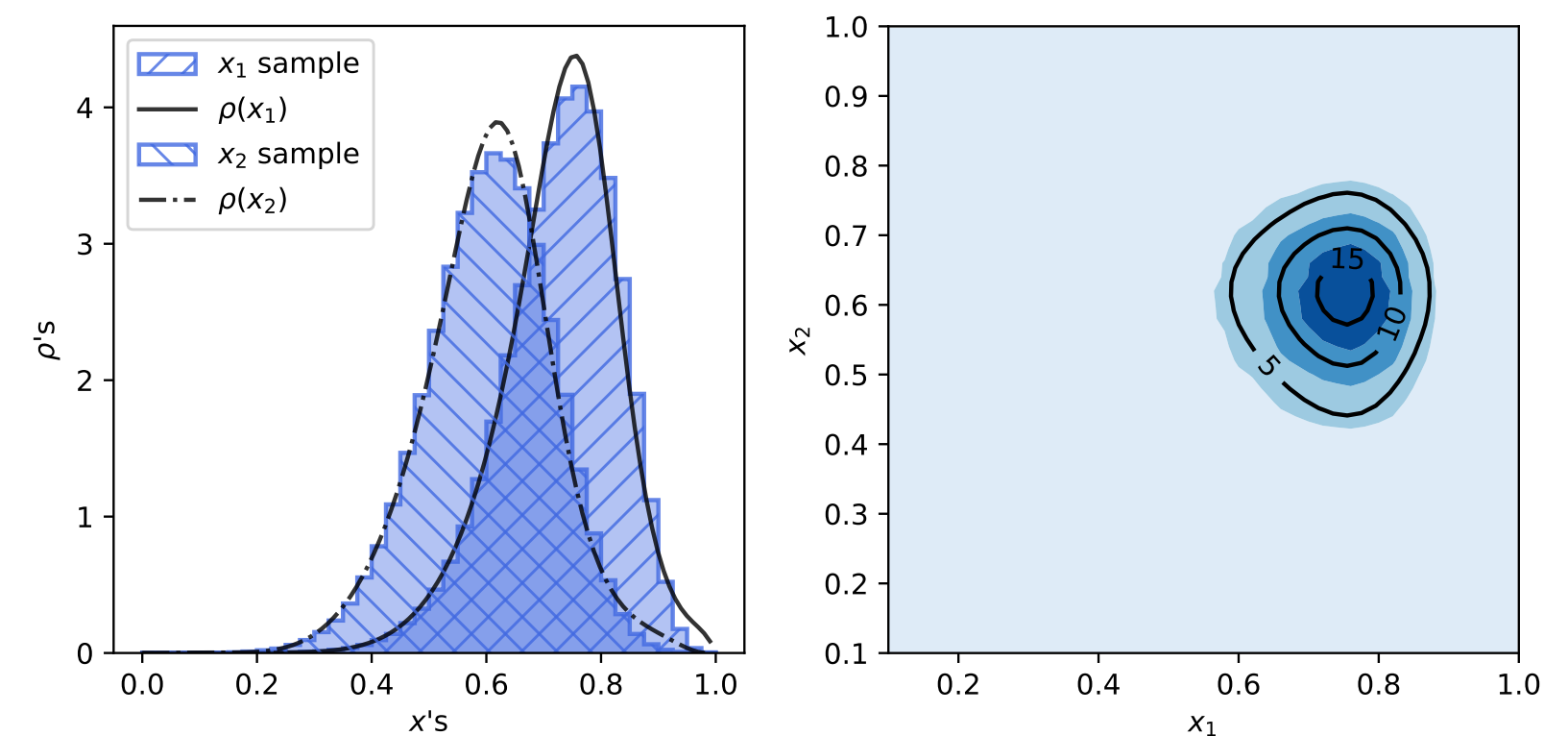
Results

Simulation with $N_{\text{nshots}} = 5 \cdot 10^4$.

Fit function	N_{sample}	p	J_f	N_{ratio}	χ^2
Gamma	$5 \cdot 10^4$	25	$2.9 \cdot 10^{-6}$	31	$2.2 \cdot 10^{-4}$
Gaussian mix	$2 \cdot 10^5$	30	$2.75 \cdot 10^{-5}$	31	$4.39 \cdot 10^{-3}$
t	$5 \cdot 10^4$	20	$2.1 \cdot 10^{-6}$	34	$3.4 \cdot 10^{-4}$
s	$5 \cdot 10^4$	20	$7.9 \cdot 10^{-6}$	34	$1.20 \cdot 10^{-3}$
y	$5 \cdot 10^4$	8	$3.7 \cdot 10^{-6}$	34	$1.45 \cdot 10^{-3}$

Scale up with dimensionality

We can extend this framework to d -dim joint PDFs $\rho_j(x)$ composing a d -qubits circuit which encodes the rotations corresponding to d adiabatic evolutions. We then execute this circuit six times (shift rules) and we reconstruct the joint PDF. In the following we estimate $\rho_j(x_1, x_2) = \Gamma_1(x_1|k=10, \lambda=0.2) \cdot \Gamma_2(x_2|k=50, \lambda=0.5)$.



References

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- [2] M. Schuld, V. Bergholm, C. Gogolin, J. Izaac, and N. Killoran, "Evaluating analytic gradients on quantum hardware," *Physical Review A*, vol. 99, mar 2019.
- [3] C. Bravo-Prieto, J. Baglio, M. Cè, A. Francis, D. M. Grabowska, and S. Carrazza, "Style-based quantum generative adversarial networks for monte carlo events," *Quantum*, vol. 6, p. 777, aug 2022.