

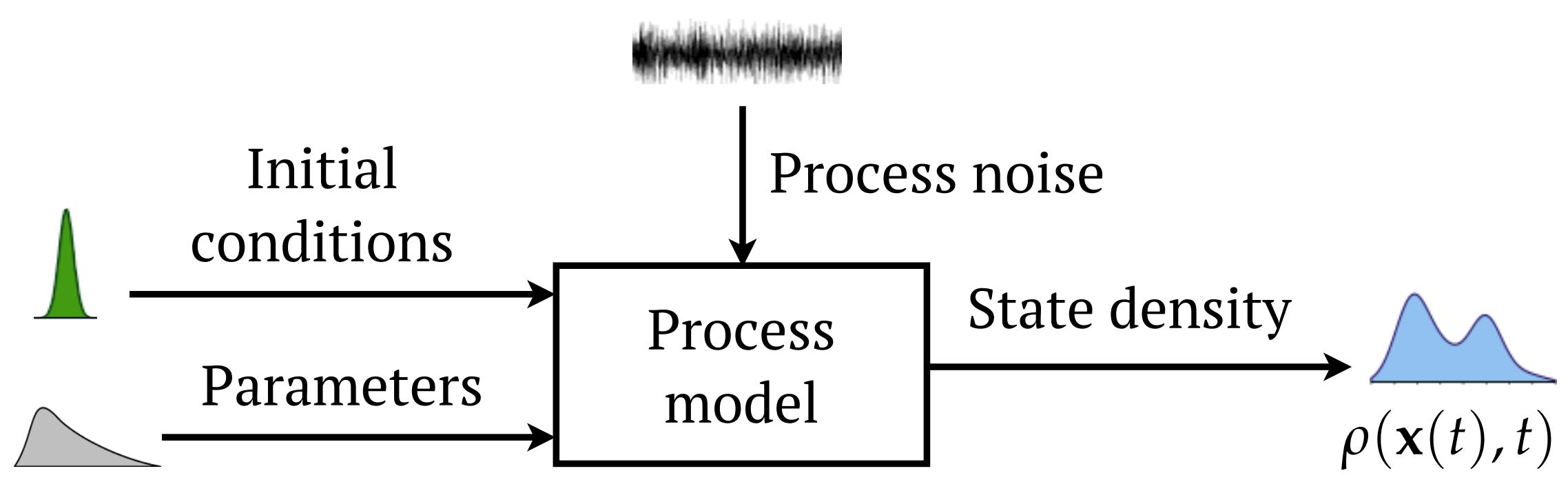
# A Proximal Algorithm for Uncertainty Propagation in Stochastic Nonlinear Systems

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## Problem: Uncertainty Propagation



### Trajectory flow (Itô SDE):

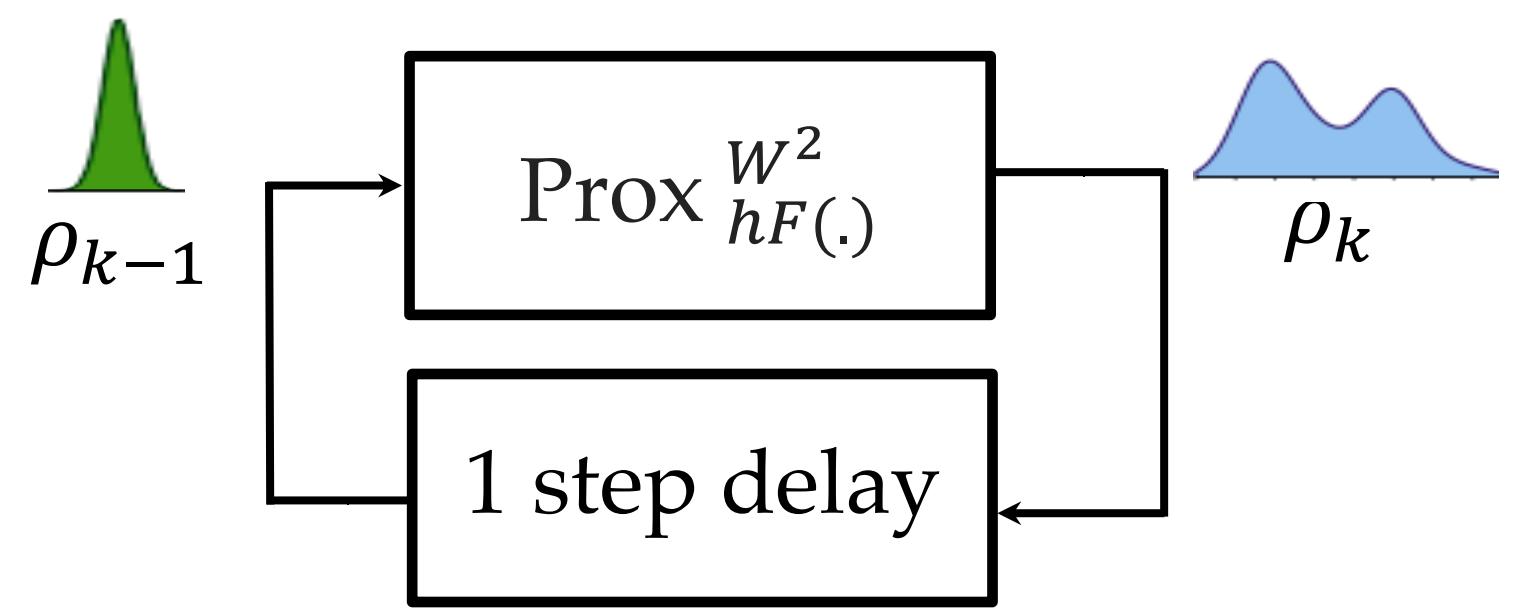
$$dx(t) = -\nabla \psi(x, t) dt + 2\beta^{-1} dw(t), \quad x \in \mathbb{R}^n,$$

$$x(0) \sim \rho_0(x), \quad dw \sim \mathcal{N}(\mathbf{0}, Idt)$$

### Joint PDF flow (Fokker-Planck-Kolmogorov PDE):

$$\frac{\partial \rho}{\partial t} = -\nabla \cdot (\rho \nabla \psi) + \beta^{-1} \Delta \rho, \quad \rho(x, t=0) = \rho_0(x)$$

## Main Idea: Variational Recursion



### Proximal recursion:

$$\rho_k = \text{Prox}_{hF(.)}^{W^2}(\rho_{k-1}) := \arg\inf_{\rho} \frac{1}{2} W^2(\rho_{k-1}, \rho) + h F(\rho)$$

### Monge-Kantorovich optimal transport cost:

$$W^2(\rho_{k-1}, \rho) := \inf_{\Phi \in \Pi(\rho_{k-1}, \rho)} \int c(x, y) d\Phi(x, y)$$

### Free energy functional:

$$F(\rho) := \int \psi \rho dx + \beta^{-1} \int \rho \log \rho dx$$

## Algorithm: Gradient Ascent on the Dual Space

$$\begin{aligned} \frac{\partial \rho}{\partial t} &= -\nabla \cdot (\rho \nabla \psi) + \beta^{-1} \Delta \rho \\ &\Downarrow \text{JKO variational scheme, 1998} \\ \rho_k = \rho(x, t = kh) &= \arg\inf_{\rho} \frac{1}{2} W^2(\rho_{k-1}, \rho) + h F(\rho), \quad h \text{ small} \\ &\Downarrow \text{Discrete primal formulation} \\ \rho_k &= \arg\min_{\rho} \left\{ \min_{\Phi \in \Pi(\rho_{k-1}, \rho)} \frac{1}{2} \langle \mathcal{C}, \Phi \rangle + h \langle \psi + \log \rho, \rho \rangle \right\} \\ &\Downarrow \text{Entropic regularization} \\ \rho_k &= \arg\min_{\rho} \left\{ \min_{\Phi \in \Pi(\rho_{k-1}, \rho)} \left\{ \frac{1}{2} \langle \mathcal{C}, \Phi \rangle + \epsilon D(\Phi) \right\} + h \langle \psi + \log \rho, \rho \rangle \right\} \\ &\Downarrow \text{Dualization} \\ \lambda_0^*, \lambda_1^* &= \arg\max_{\lambda_0, \lambda_1} \left\{ \frac{1}{2} \langle \lambda_0, \rho_{k-1} \rangle - F^*(-\lambda_1) - \epsilon \left( e^{\frac{\lambda_0}{\epsilon}} \right)^T \left( e^{\frac{-c}{\epsilon}} \right) \left( e^{\frac{\lambda_1}{\epsilon}} \right) \right\} \\ y &= e^{\frac{\lambda_0^*}{\epsilon}} \quad z = e^{\frac{\lambda_1^*}{\epsilon}} \end{aligned}$$

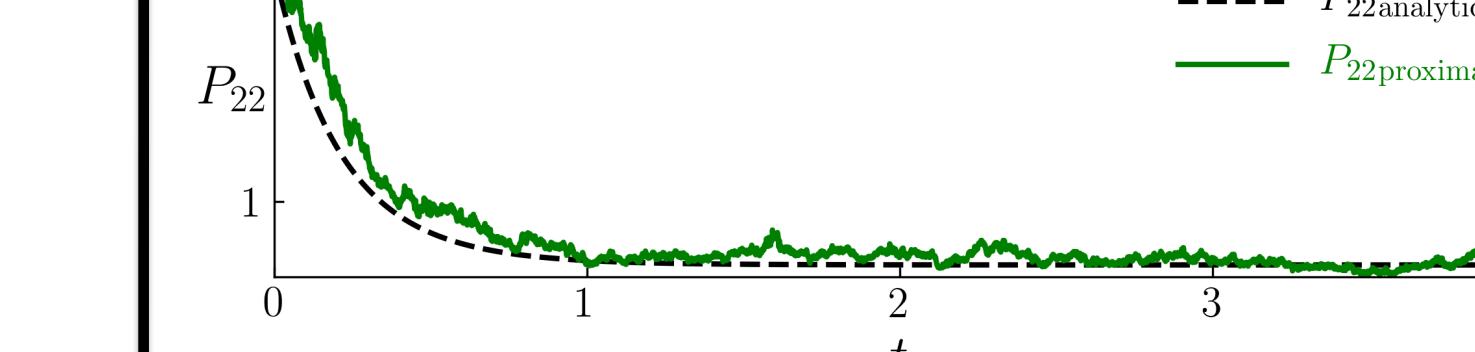
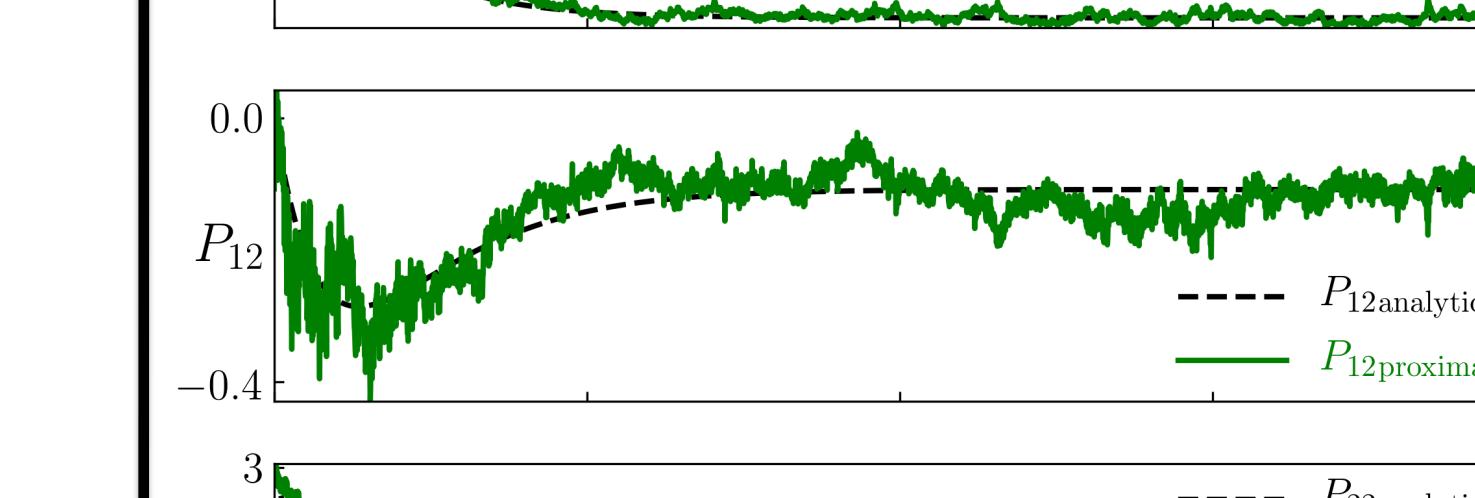
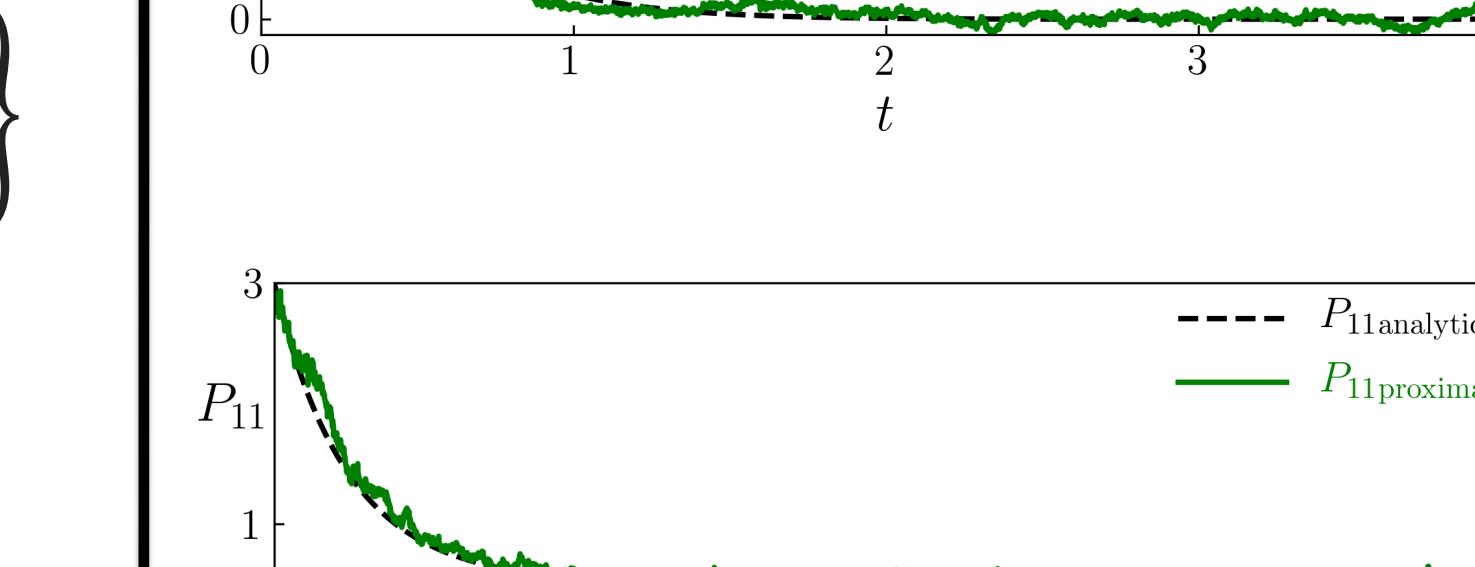
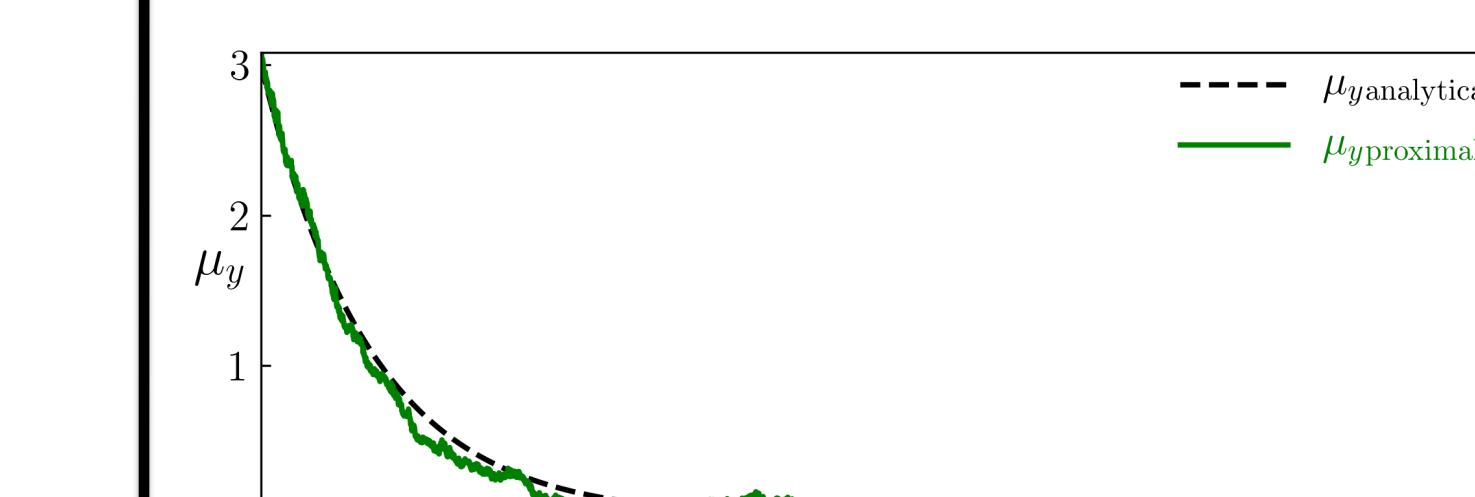
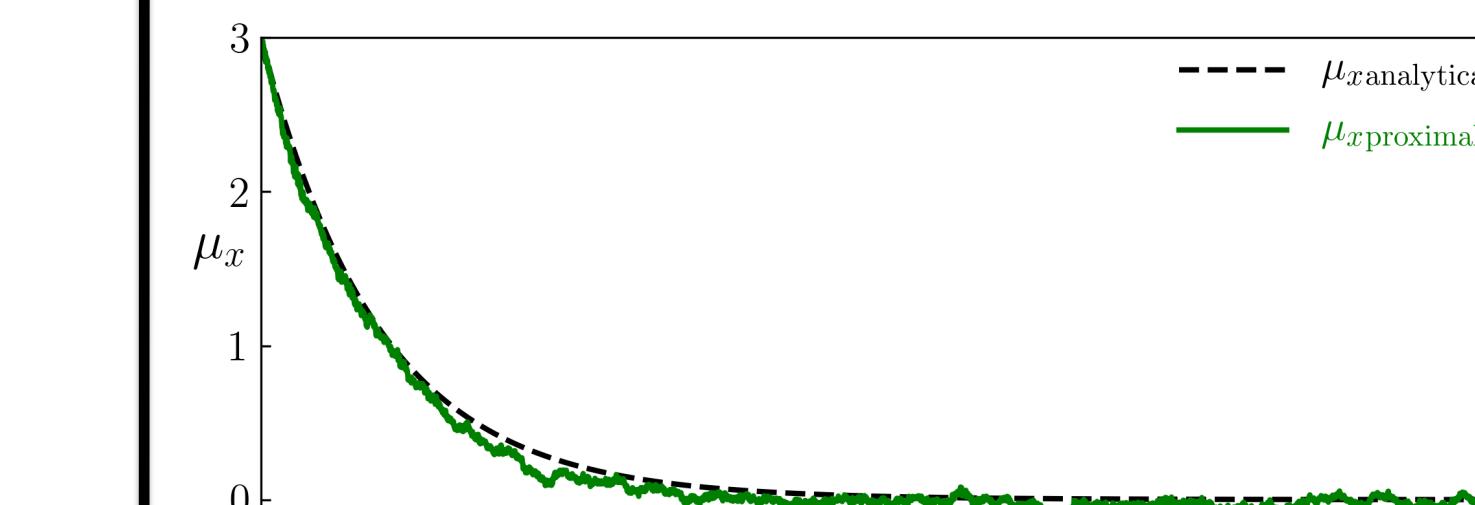
### Coupled Transcendental Equations in y and z

$$\begin{aligned} \Gamma &= e^{\frac{-c}{\epsilon}} \\ \rho_{k-1} &\rightarrow y \odot \Gamma z = \rho_{k-1} \\ \xi &= \frac{e^{-\beta \psi}}{e} \rightarrow z \odot \Gamma^T y = \xi \odot z^{\beta \epsilon / 2h} \end{aligned} \quad \rho_k = z \odot \Gamma^T y$$

### Theorem

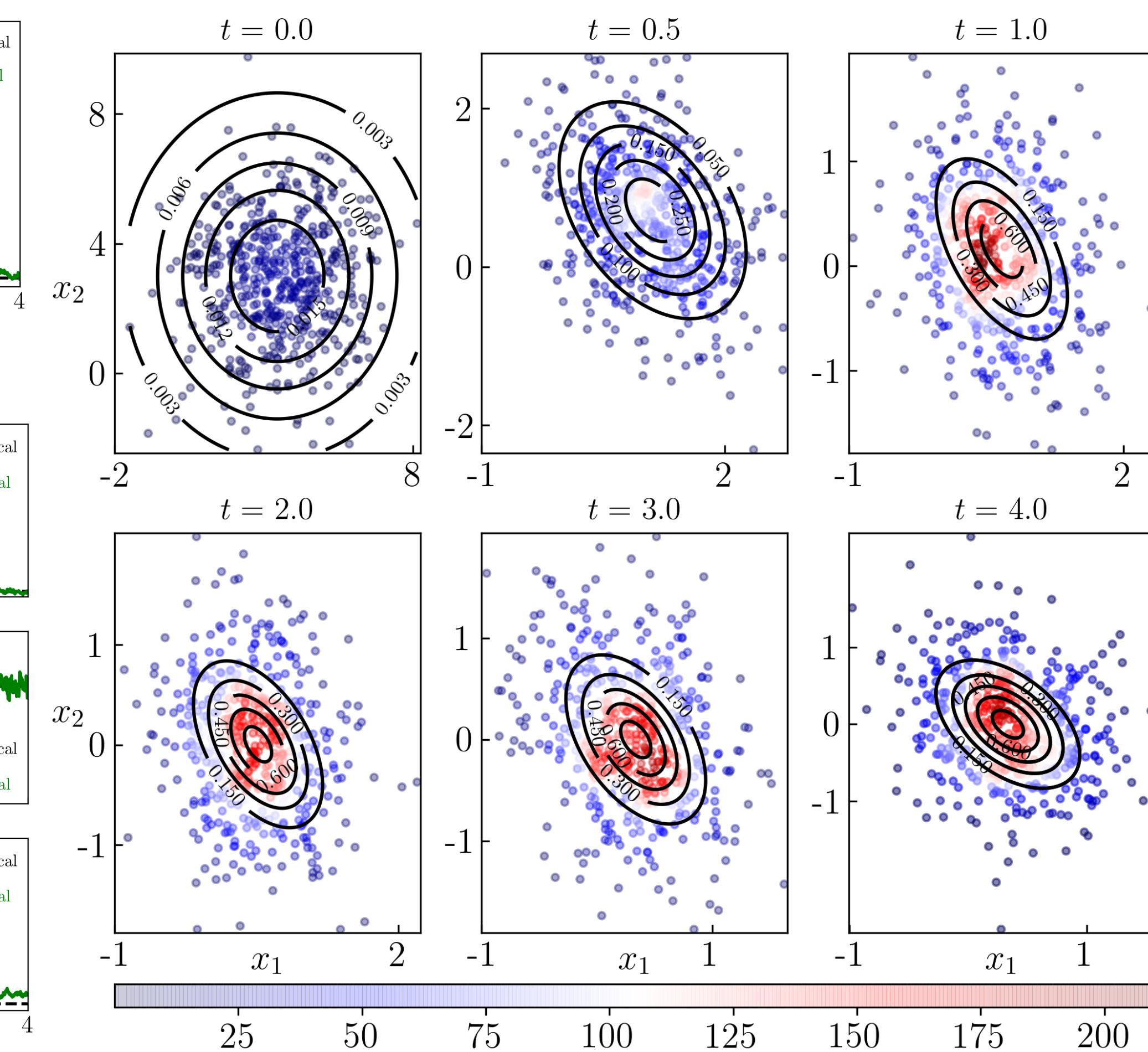
The fixed point iteration is strictly contractive with respect to the Thompson Metric. Thus it admits a unique fixed point.

## Ornstein-Uhlenbeck SDE in Two Dimensions:



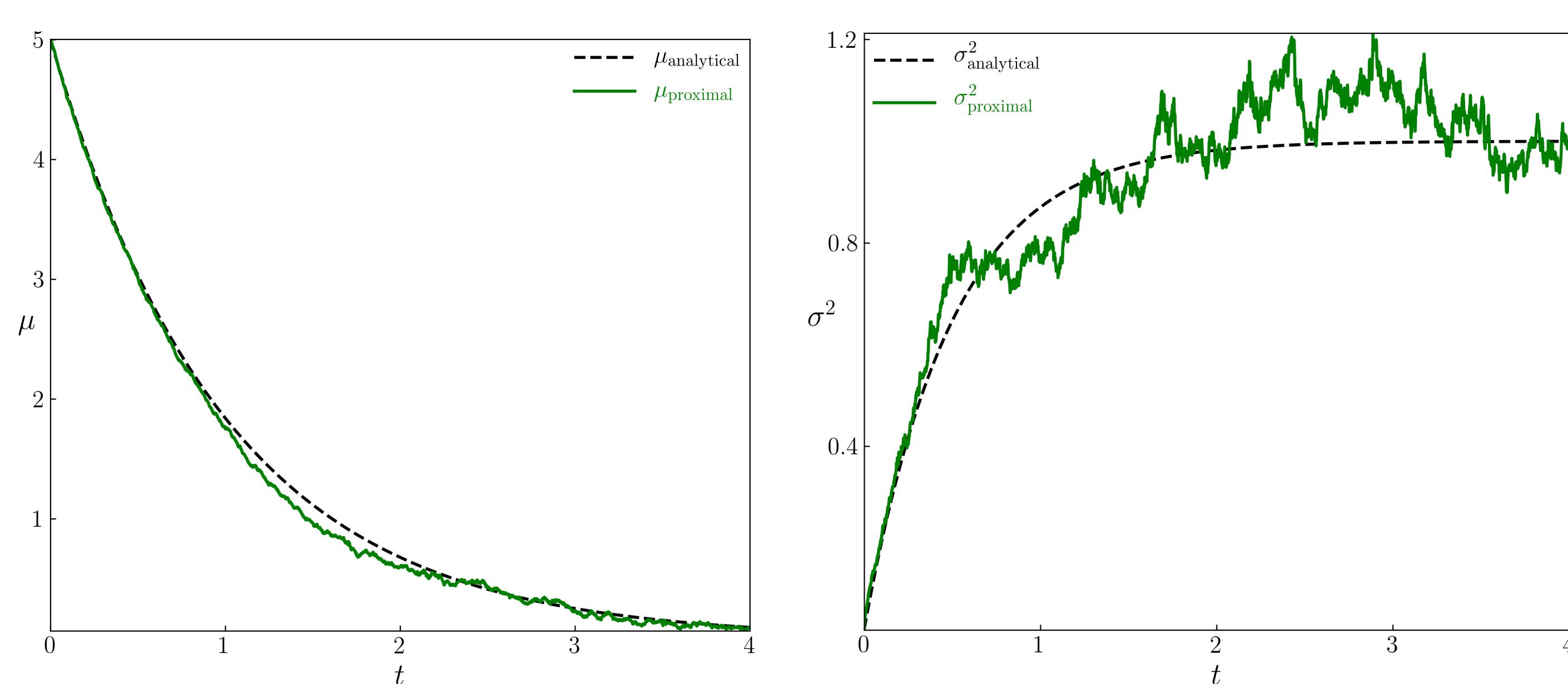
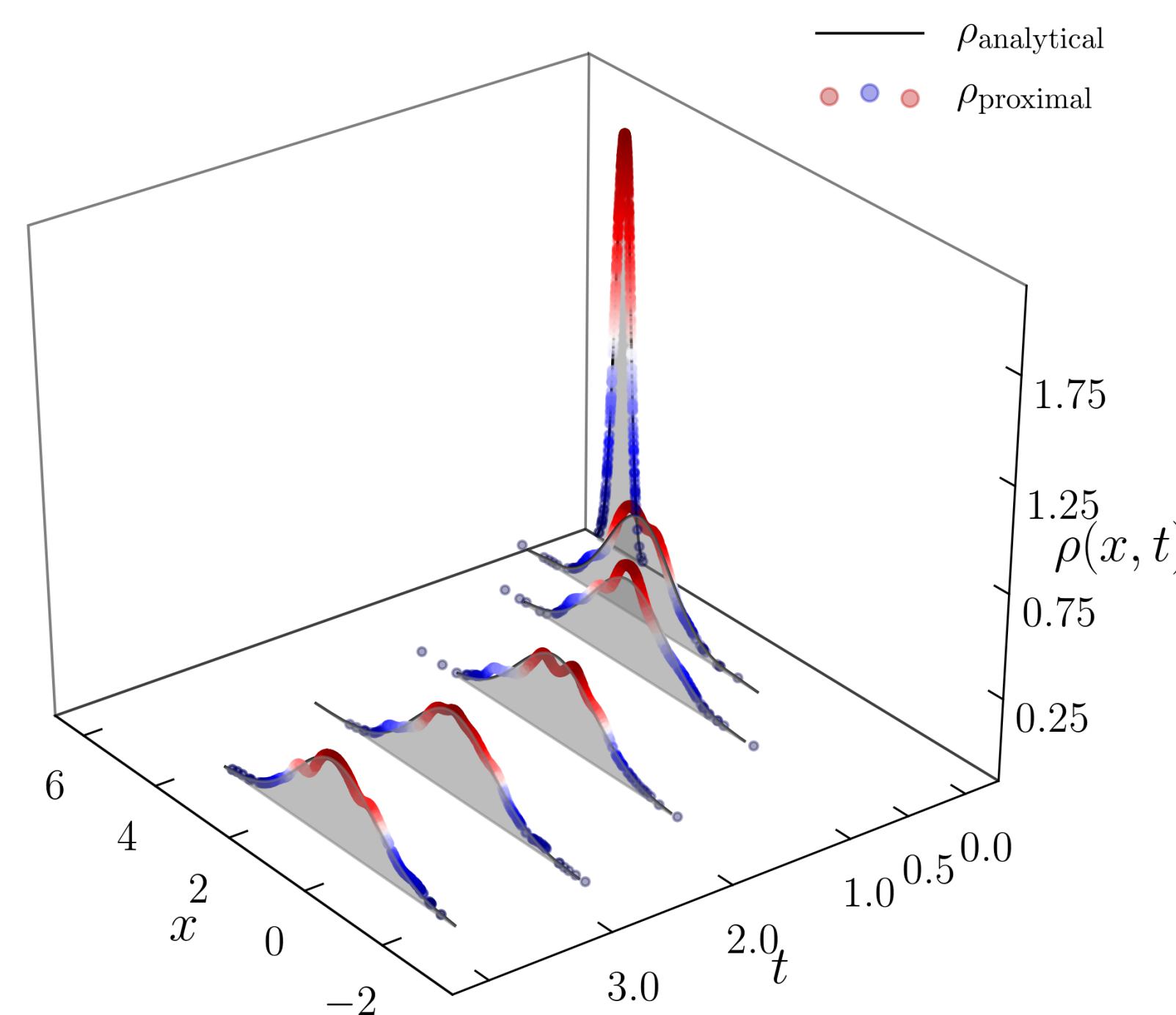
$$\psi(x) = \frac{1}{2} x^T A x, \quad A \succ 0$$

—  $\rho_{\text{analytical}}$  ●  $\rho_{\text{proximal}}$



## Numerical Simulation

$$\psi(x) = \frac{1}{2} ax^2, \quad a > 0$$



## Nonlinear SDE with Gradient Drift Field in Two Dimensions:

$$\psi(x_1, x_2) = \frac{1}{4} (1 + x_1^4) + \frac{1}{2} (x_2^2 - x_1^2)$$

—  $\rho_{\infty \text{analytical}} = \frac{1}{Z} \exp(-\beta \psi(x_1, x_2))$  ●  $\rho_{\text{proximal}}$

