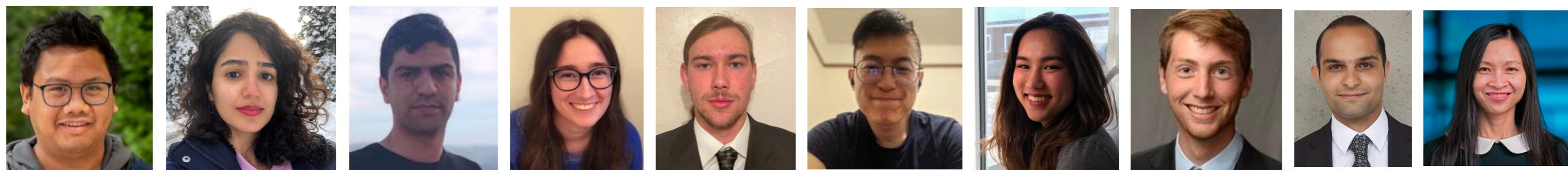


# New Developments in Schrödinger Bridge, Stochastic Control and Stochastic Learning

Abhishek Halder

Department of Aerospace Engineering  
Iowa State University

Joint work with students and collaborators



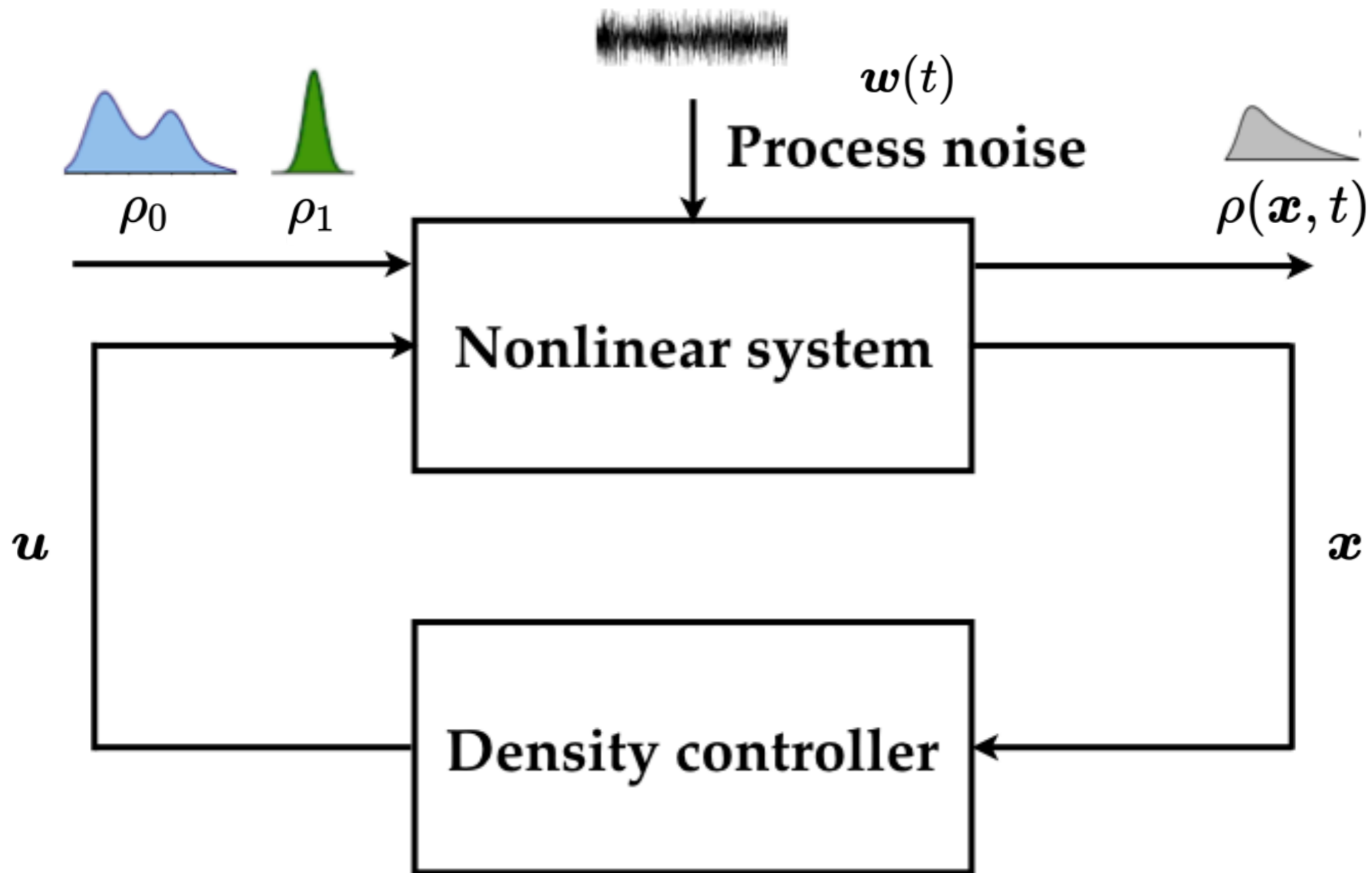
GNC Group Meeting, Department of Aerospace Engineering, Iowa State University  
April 02, 2024



# Theme of this talk

**Control and learning of  
measures/densities**

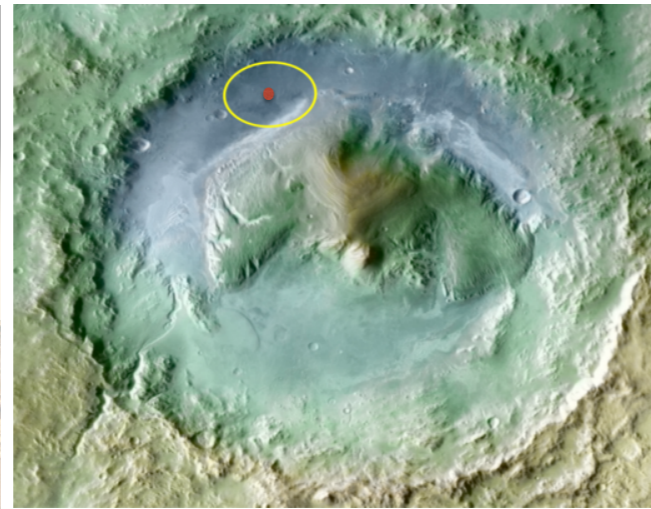
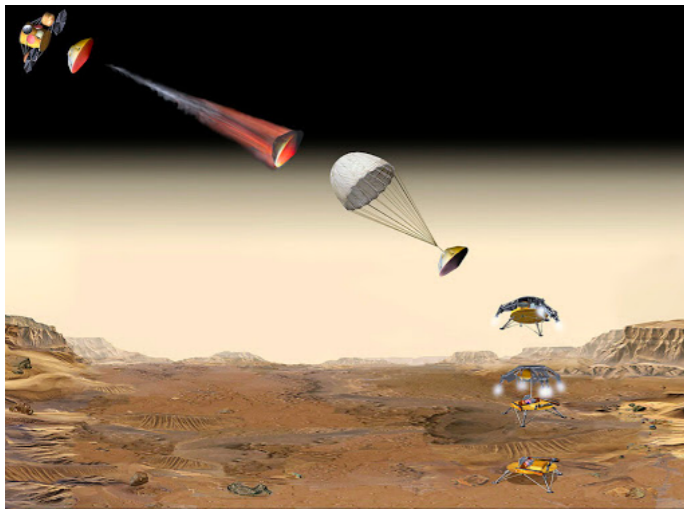
# Density Control: Generalized Schrödinger Bridge



# Motivating Applications

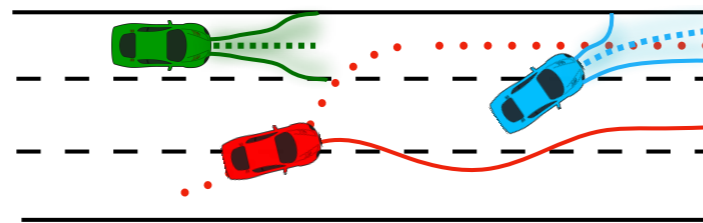
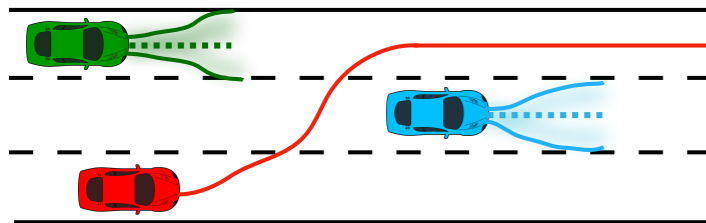
## Distribution ~ Probability

Spacecraft landing with desired statistical accuracy



Gale Crater (4.49S, 137.42E)

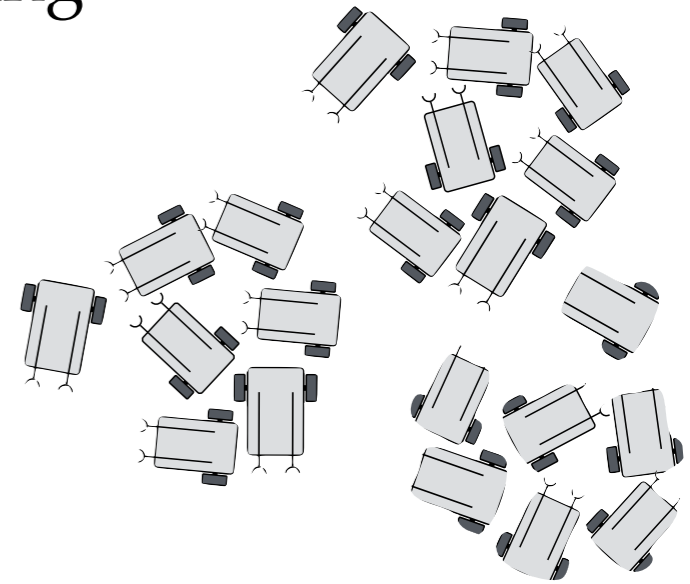
Risk management for automated driving in multi-lane highways



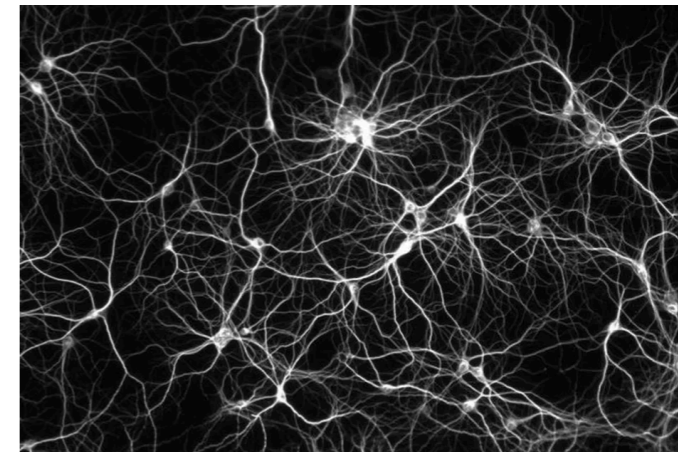
Control of uncertainties

## Distribution ~ Population

Dynamic shaping of swarms



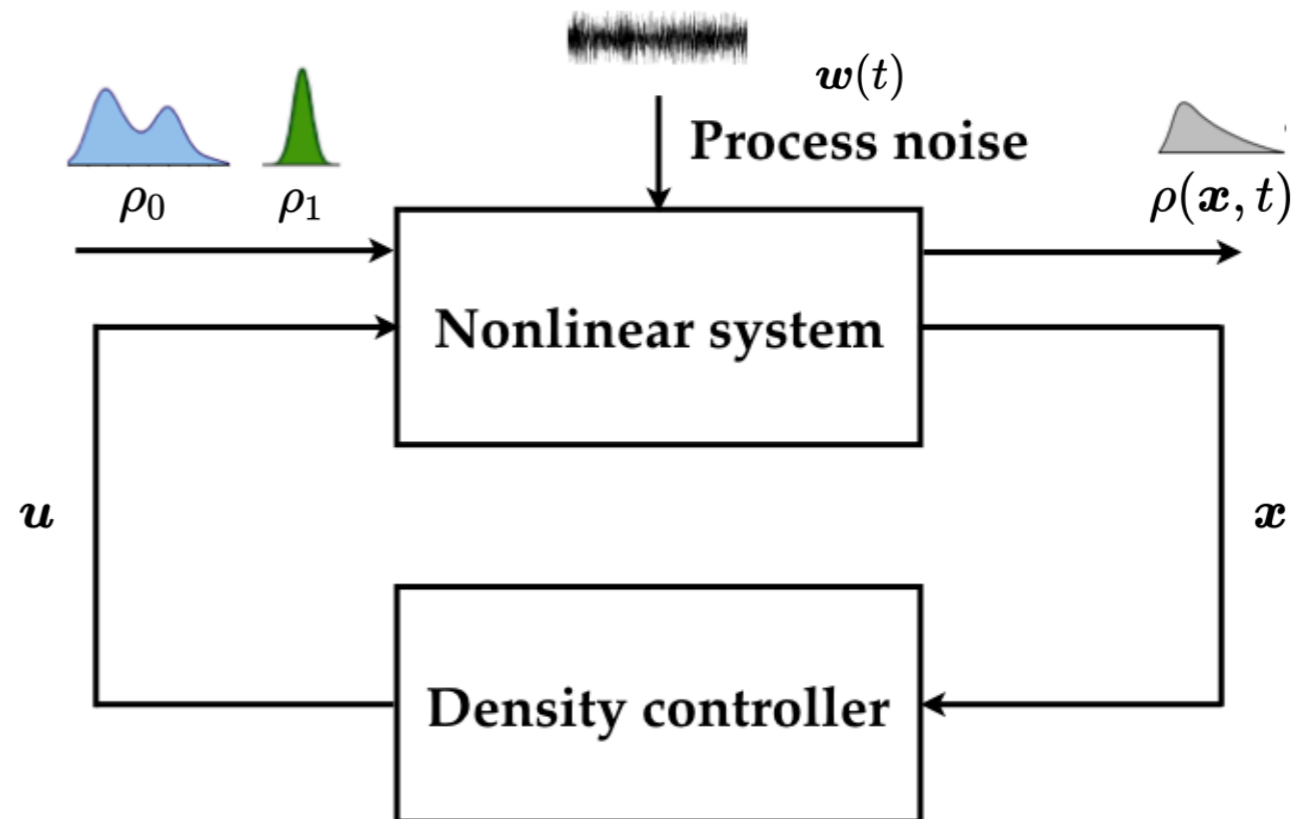
Feedback sync. and desync. of neuronal population



Control of ensemble

# State Feedback Density Steering

Steer joint state PDF via feedback control over finite time horizon



Common scenario:  $G \equiv B$

$$\text{minimize}_{u \in \mathcal{U}} \quad \mathbb{E} \left[ \int_0^1 \left( \frac{1}{2} \|u(t, x_t^u)\|_2^2 + q(t, x_t^u) \right) dt \right]$$

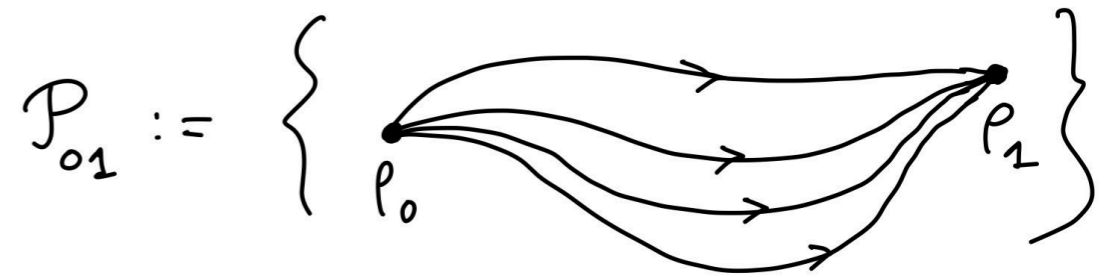
subject to

$$dx_t^u = \{f(t, x_t^u) + B(t, x_t^u)u\}dt + \sqrt{2}G(t, x_t^u)dw_t$$

$$x_0^u := x_t^u(t=0) \sim \rho_0, \quad x_1^u := x_t^u(t=1) \sim \rho_1$$

# Optimal Control Problem over PDFs

Diffusion tensor:  $D := GG^\top$



Hessian operator w.r.t. state: Hess

$$\inf_{(\rho, u) \in \mathcal{P}_{01} \times \mathcal{U}} \int_{\mathbb{R}^n} \int_0^1 \left( \frac{1}{2} \|\mathbf{u}(t, \mathbf{x}_t^u)\|_2^2 + q(t, \mathbf{x}_t^u) \right) \rho(t, \mathbf{x}_t^u) dt d\mathbf{x}_t^u$$

subject to

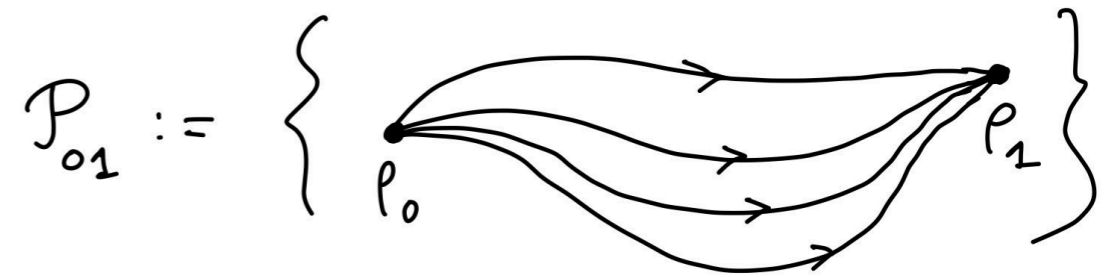
$$\frac{\partial \rho}{\partial t} + \nabla \cdot ((\mathbf{f} + \mathbf{B}u) \rho) = \langle \text{Hess}, D\rho \rangle$$

$$\rho(t = 0, \mathbf{x}_0^u) = \rho_0, \quad \rho(t = 1, \mathbf{x}_1^u) = \rho_1$$

Controlled Fokker-Planck or Kolmogorov's forward PDE

# Zero Process Noise $\rightsquigarrow$ Optimal Mass Transport

Dynamic optimal mass transport  
with prior dynamics  $f$



$$\inf_{(\rho, u) \in \mathcal{P}_{01} \times \mathcal{U}} \int_{\mathbb{R}^n} \int_0^1 \left( \frac{1}{2} \|u(t, x_t^u)\|_2^2 + q(t, x_t^u) \right) \rho(t, x_t^u) dt dx_t^u$$

subject to

$$\frac{\partial \rho}{\partial t} + \nabla \cdot ((f + Bu) \rho) = \langle \text{Hess}, D\rho \rangle$$

$$\rho(t = 0, x_0^u) = \rho_0, \quad \rho(t = 1, x_1^u) = \rho_1$$

Controlled Liouville PDE

# Necessary Conditions of Optimality (Assuming $G \equiv B$ )

**Coupled nonlinear PDEs + linear boundary conditions**

**Controlled Fokker-Planck or Kolmogorov's forward PDE**

$$\frac{\partial \rho^{\text{opt}}}{\partial t} + \nabla \cdot ((f + D\nabla\psi) \rho^{\text{opt}}) = \langle \text{Hess}, D\rho \rangle$$

**Hamilton-Jacobi-Bellman-like PDE**

$$\frac{\partial \psi}{\partial t} + \langle \nabla\psi, f \rangle + \langle D, \text{Hess}(\psi) \rangle + \frac{1}{2} \langle \nabla\psi, D\nabla\psi \rangle = q$$

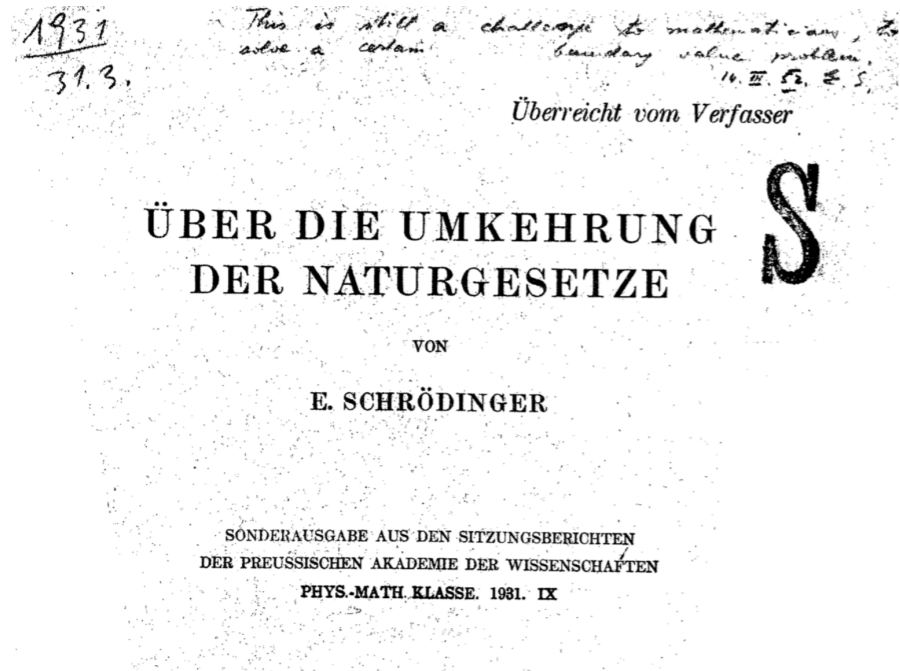
**Boundary conditions:**

$$\rho^{\text{opt}}(\cdot, t = 0) = \rho_0, \quad \rho^{\text{opt}}(\cdot, t = 1) = \rho_1$$

**Optimal control:**  $u^{\text{opt}} = B^\top \nabla\psi$



# Feedback Synthesis via the Schrödinger System



## Sur la théorie relativiste de l'électron et l'interprétation de la mécanique quantique

PAR  
E. SCHRÖDINGER

### I. — Introduction

J'ai l'intention d'exposer dans ces conférences diverses idées concernant la mécanique quantique et l'interprétation qu'on en donne généralement à l'heure actuelle ; je parlerai principalement de la théorie quantique relativiste du mouvement de l'électron. Autant que nous pouvons nous en rendre compte aujourd'hui, il semble à peu près sûr que la mécanique quantique de l'électron, sous sa forme idéale, *que nous ne possédons pas encore*, doit former un jour la base de toute la physique. A cet intérêt tout à fait général, s'ajoute, ici à Paris, un intérêt particulier : vous savez tous que les bases de la théorie moderne de l'électron ont été posées à Paris par votre célèbre compatriote Louis de BROGLIE.



## Hopf-Cole a.k.a. Fleming's logarithmic transform:

$$(\rho^{\text{opt}}, \psi) \mapsto (\hat{\varphi}, \varphi) \text{ — Schrödinger factors}$$

$$\hat{\varphi}(x, t) = \rho^{\text{opt}}(x, t) \exp(-\psi(x, t))$$

$$\varphi(x, t) = \exp(\psi(x, t)) \quad \text{for all } (x, t) \in \mathbb{R}^n \times [0, 1]$$

# Feedback Synthesis via the Schrödinger System

2 coupled nonlinear PDEs  $\rightarrow$  boundary-coupled linear PDEs!!

Uncontrolled forward-backward Kolmogorov PDEs:

$$\begin{aligned}\frac{\partial \hat{\varphi}}{\partial t} &= -\nabla \cdot (\hat{\varphi} f) + \langle \text{Hess}, D \hat{\varphi} \rangle - q \hat{\varphi}, & \hat{\varphi}_0 \varphi_0 &= \rho_0, \\ \frac{\partial \varphi}{\partial t} &= -\langle \nabla \varphi, f \rangle - \langle \text{Hess}(\varphi), D \rangle + q \varphi, & \hat{\varphi}_1 \varphi_1 &= \rho_1,\end{aligned}$$

Optimal controlled joint state PDF:  $\rho^{\text{opt}}(\mathbf{x}, t) = \hat{\varphi}(\mathbf{x}, t) \varphi(\mathbf{x}, t)$

Optimal control:  $\mathbf{u}^{\text{opt}}(\mathbf{x}, t) = 2\mathbf{B}^\top \nabla_{\mathbf{x}} \log \varphi(\mathbf{x}, t)$

# What Exactly are Schrödinger Factors?

**Classical:**  $\rho^{\text{opt}}(\mathbf{x}, t) = \varphi(\mathbf{x}, t)\hat{\varphi}(\mathbf{x}, t)$

$$\left(\frac{\partial}{\partial t} + \frac{1}{2}\Delta - q\right)\varphi = 0 \quad \text{[Backward reaction-diffusion PDE]}$$

$$\left(\frac{\partial}{\partial t} - \frac{1}{2}\Delta + q\right)\hat{\varphi} = 0 \quad \text{[Forward reaction-diffusion PDE]}$$

**Quantum:**  $\rho^{\text{opt}}(\mathbf{x}, t) = \Psi(\mathbf{x}, t)\hat{\Psi}(\mathbf{x}, t)$  [Born's relation]

wave function

$$\left(\sqrt{-1}\frac{\partial}{\partial t} + \frac{1}{2}\Delta - q\right)\Psi = 0 \quad \text{[Schrödinger PDE]}$$

$$\left(-\sqrt{-1}\frac{\partial}{\partial t} - \frac{1}{2}\Delta + q\right)\hat{\Psi} = 0 \quad \text{[Adjoint Schrödinger PDE]}$$

# Feedback Synthesis via the Schrödinger System

2 coupled nonlinear PDEs  $\rightarrow$  boundary-coupled linear PDEs!!

Uncontrolled forward-backward Kolmogorov PDEs:

$$\frac{\partial \hat{\varphi}}{\partial t} = -\nabla \cdot (\hat{\varphi} f) + \langle \text{Hess}, D \hat{\varphi} \rangle - q \hat{\varphi},$$

$$\hat{\varphi}_0 \varphi_0 = \rho_0,$$

$$\frac{\partial \varphi}{\partial t} = -\langle \nabla \varphi, f \rangle - \langle \text{Hess}(\varphi), D \rangle + q \varphi,$$

$$\hat{\varphi}_1 \varphi_1 = \rho_1,$$

$\mathcal{L}_{\text{forward}} \hat{\varphi}$   $\mathcal{L}_{\text{backward}} \varphi$

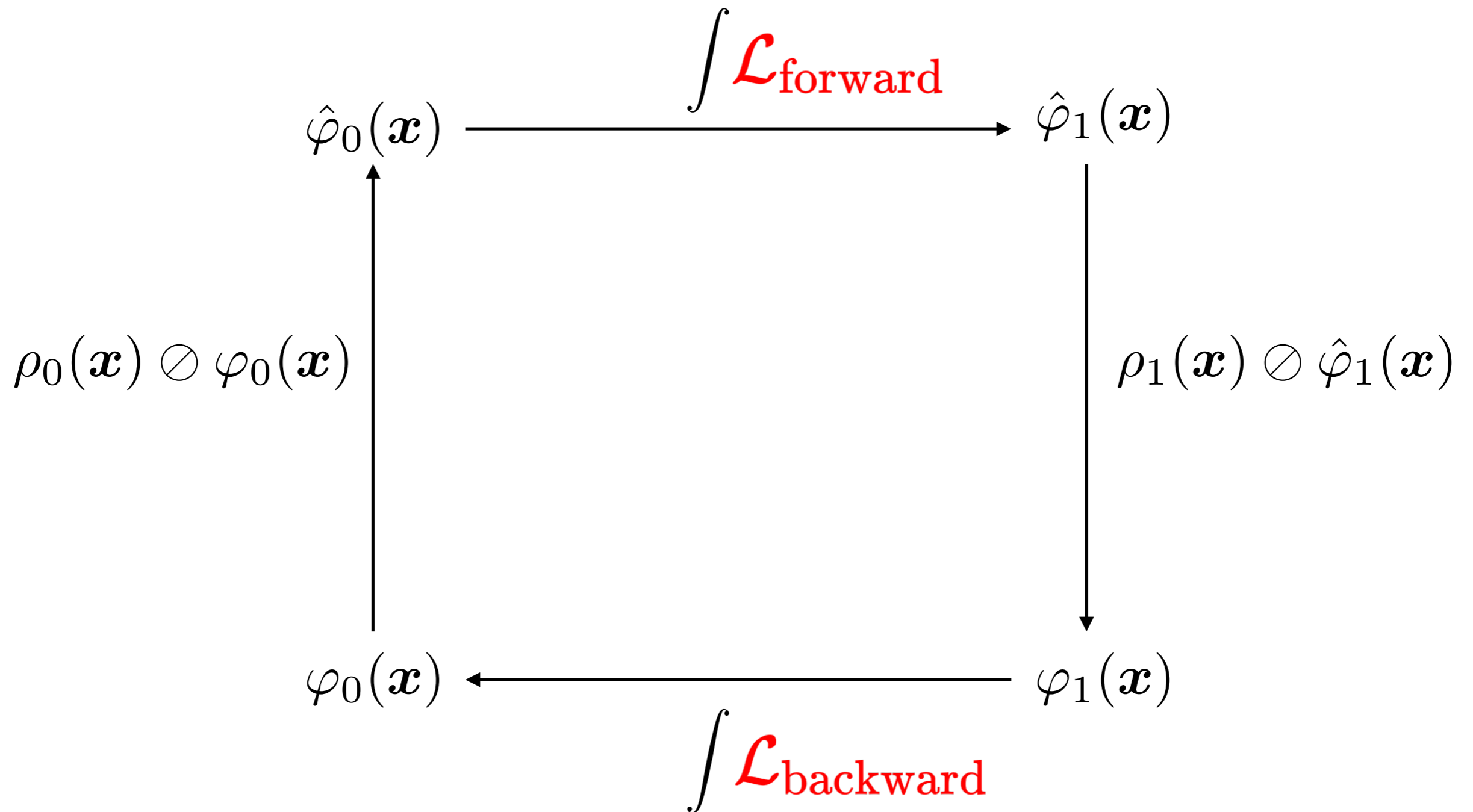
Optimal controlled joint state PDF:

$$\rho^{\text{opt}}(\mathbf{x}, t) = \hat{\varphi}(\mathbf{x}, t) \varphi(\mathbf{x}, t)$$

Optimal control:

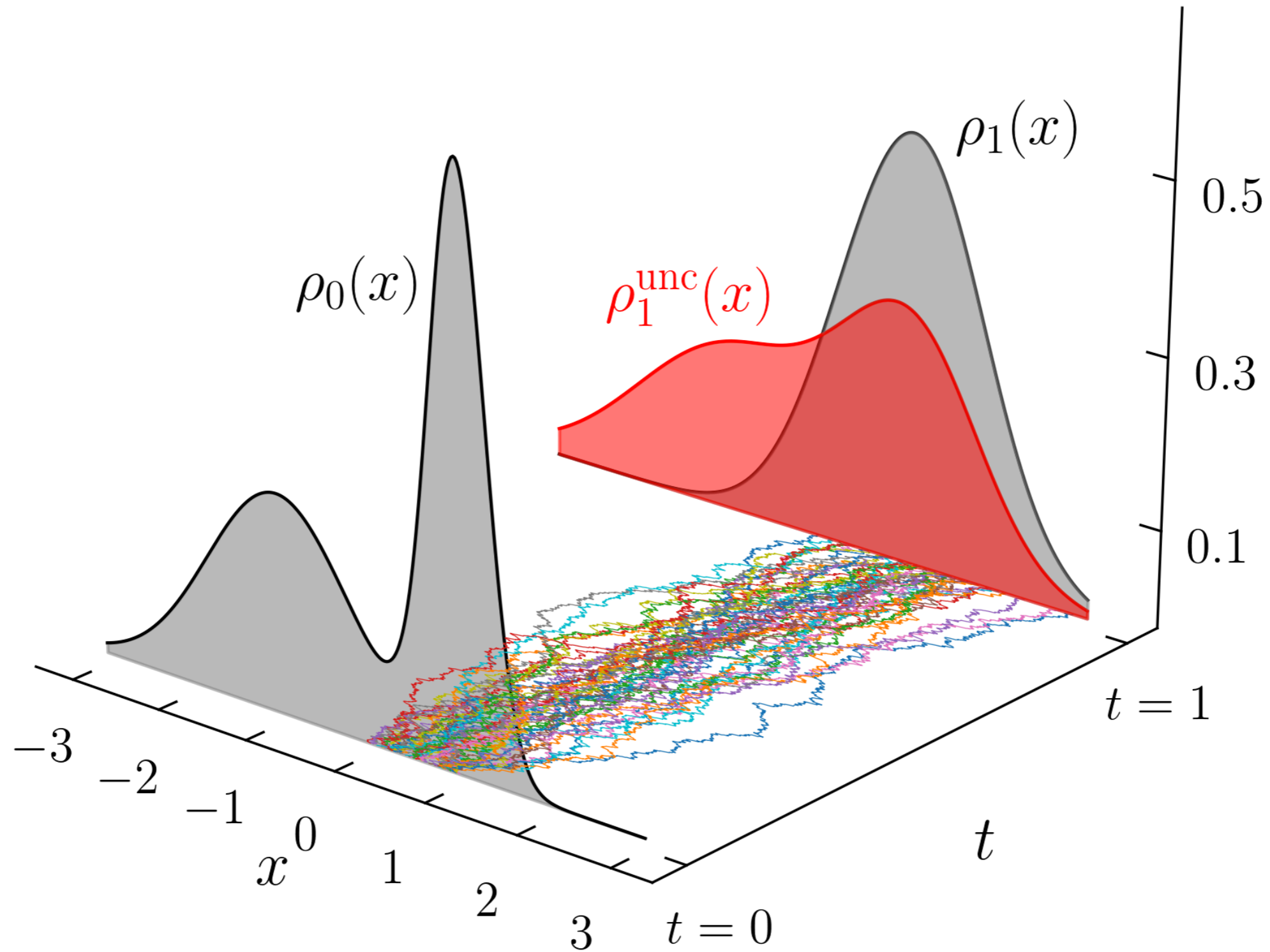
$$\mathbf{u}^{\text{opt}}(\mathbf{x}, t) = 2\mathbf{B}^\top \nabla_{\mathbf{x}} \log \varphi(\mathbf{x}, t)$$

# Fixed Point Recursion Over Pair $(\varphi_1, \hat{\varphi}_0)$



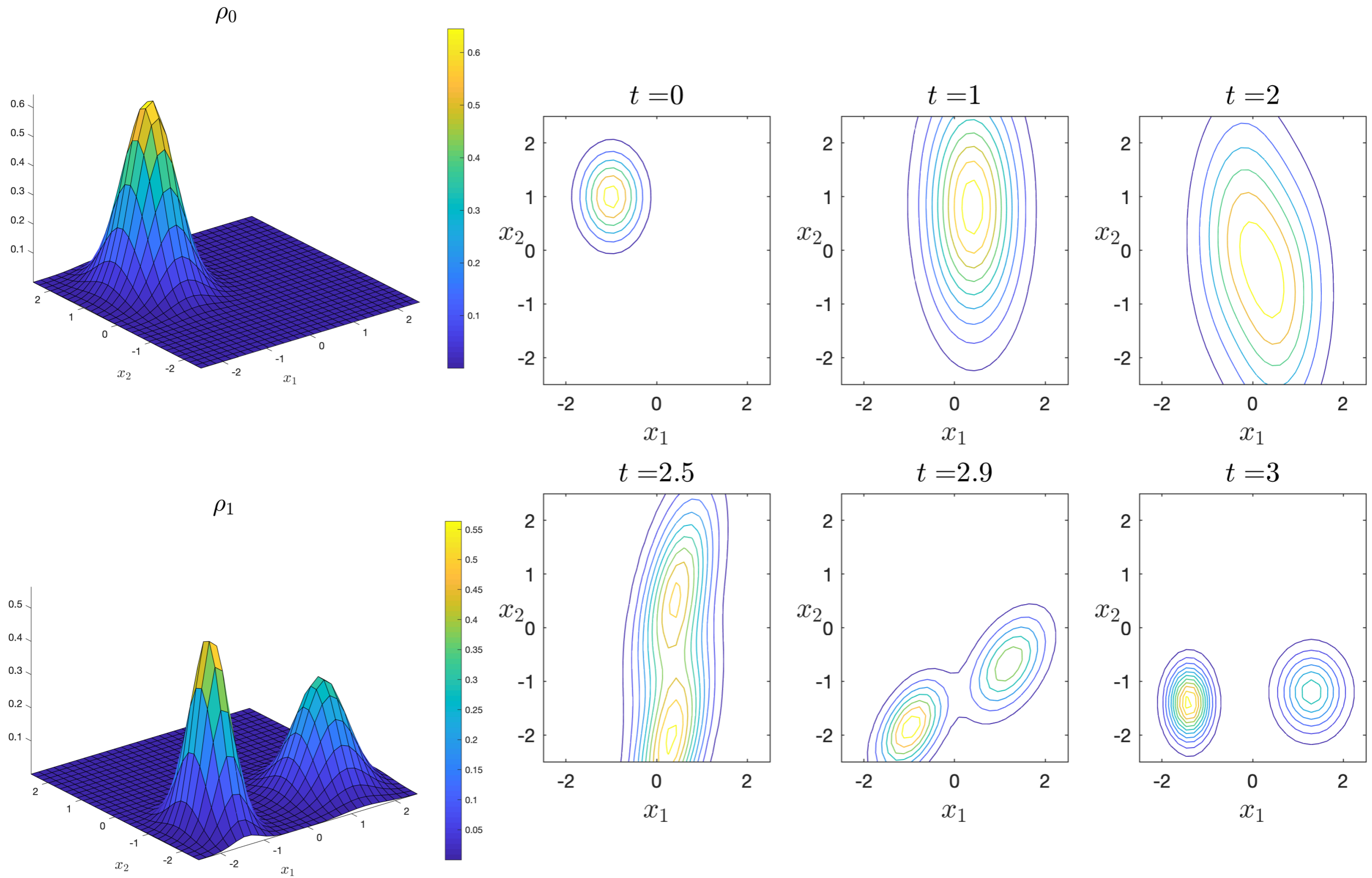
**This recursion is contractive in the Hilbert's projective metric!!**

# Feedback Density Control: $f \equiv 0, B = G \equiv I, q \equiv 0$



Zero prior dynamics

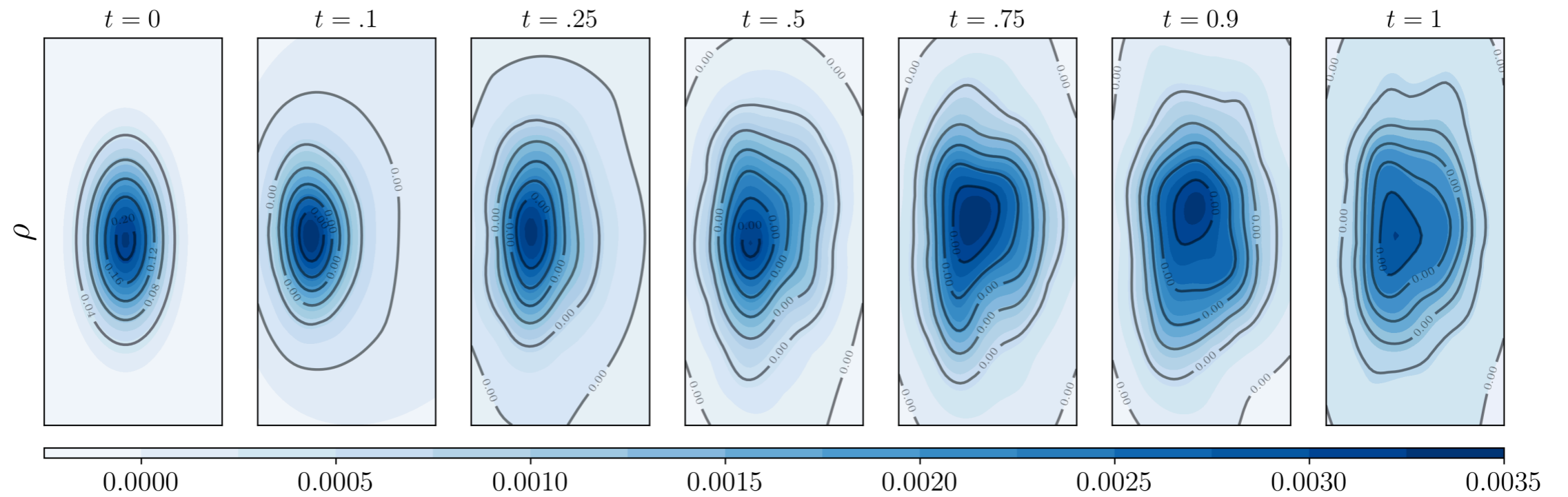
# Feedback Density Control: $f \equiv Ax, B = G, q \equiv 0$



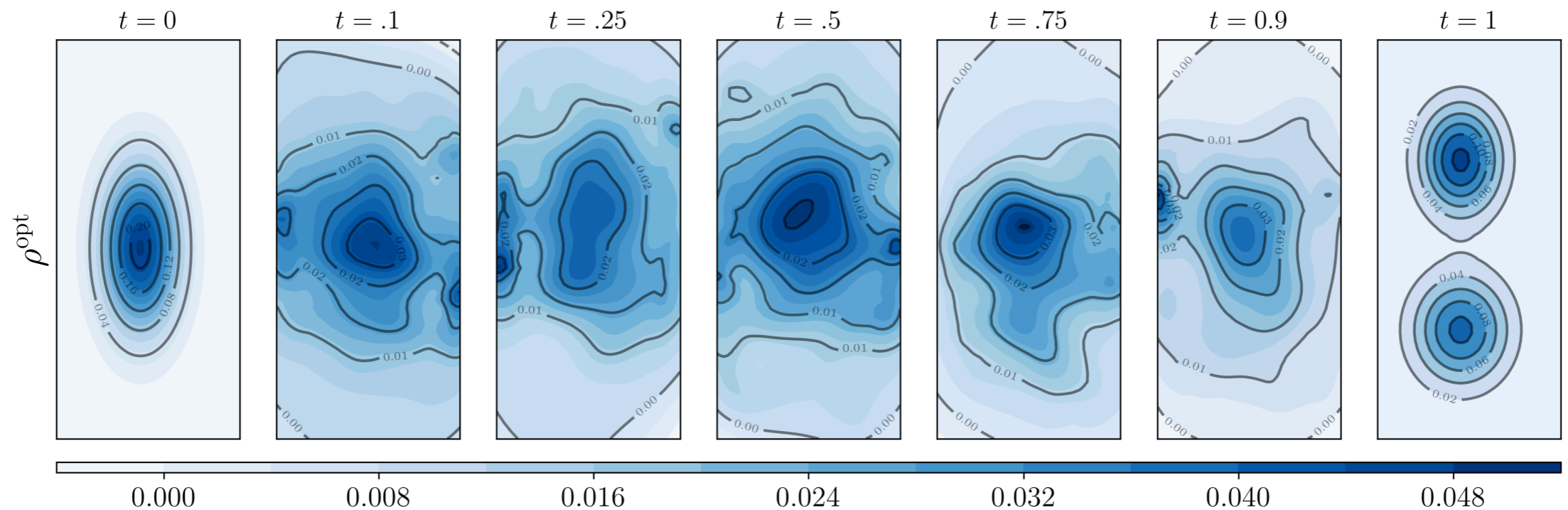
Linear prior dynamics

# Feedback Density Control: Nonlinear Grad. Drift

Uncontrolled joint PDF evolution:

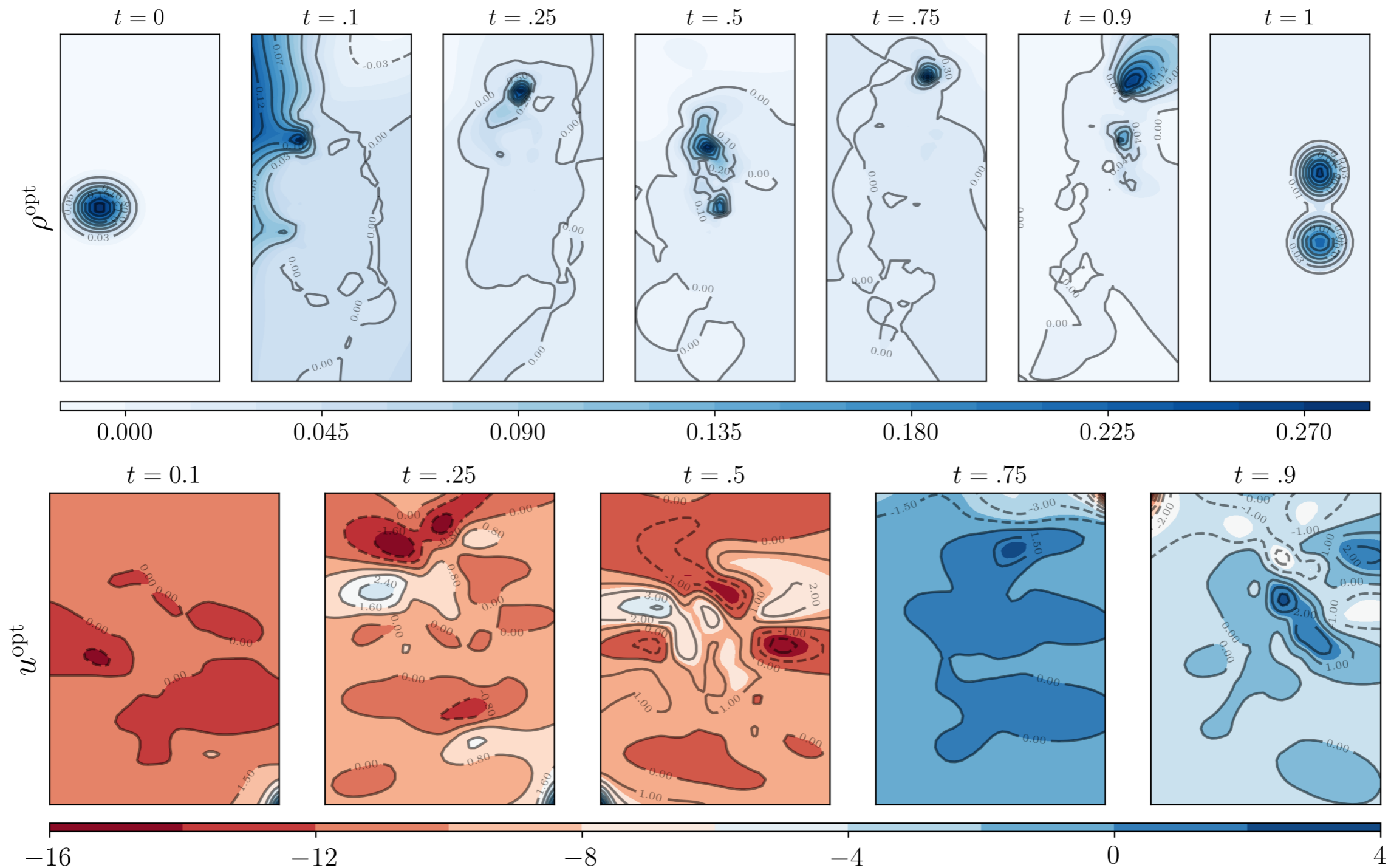


Optimal controlled joint PDF evolution:



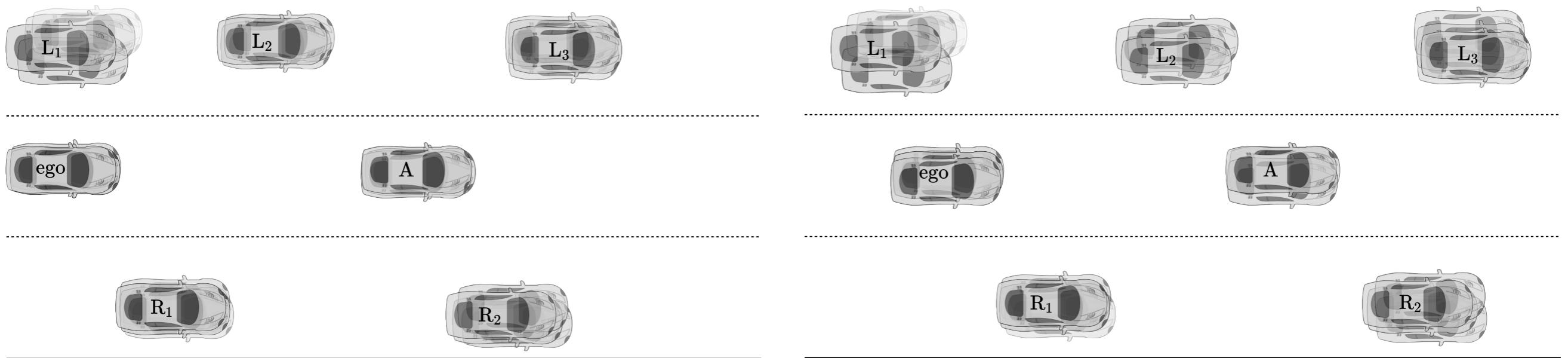


# Feedback Density Control: Mixed Conservative-Dissipative Drift



K.F. Caluya and A.H., Wasserstein proximal algorithms for the Schrödinger bridge problem: density control with nonlinear drift, *IEEE TAC* 2021.

# Application: Multi-lane Automated Driving

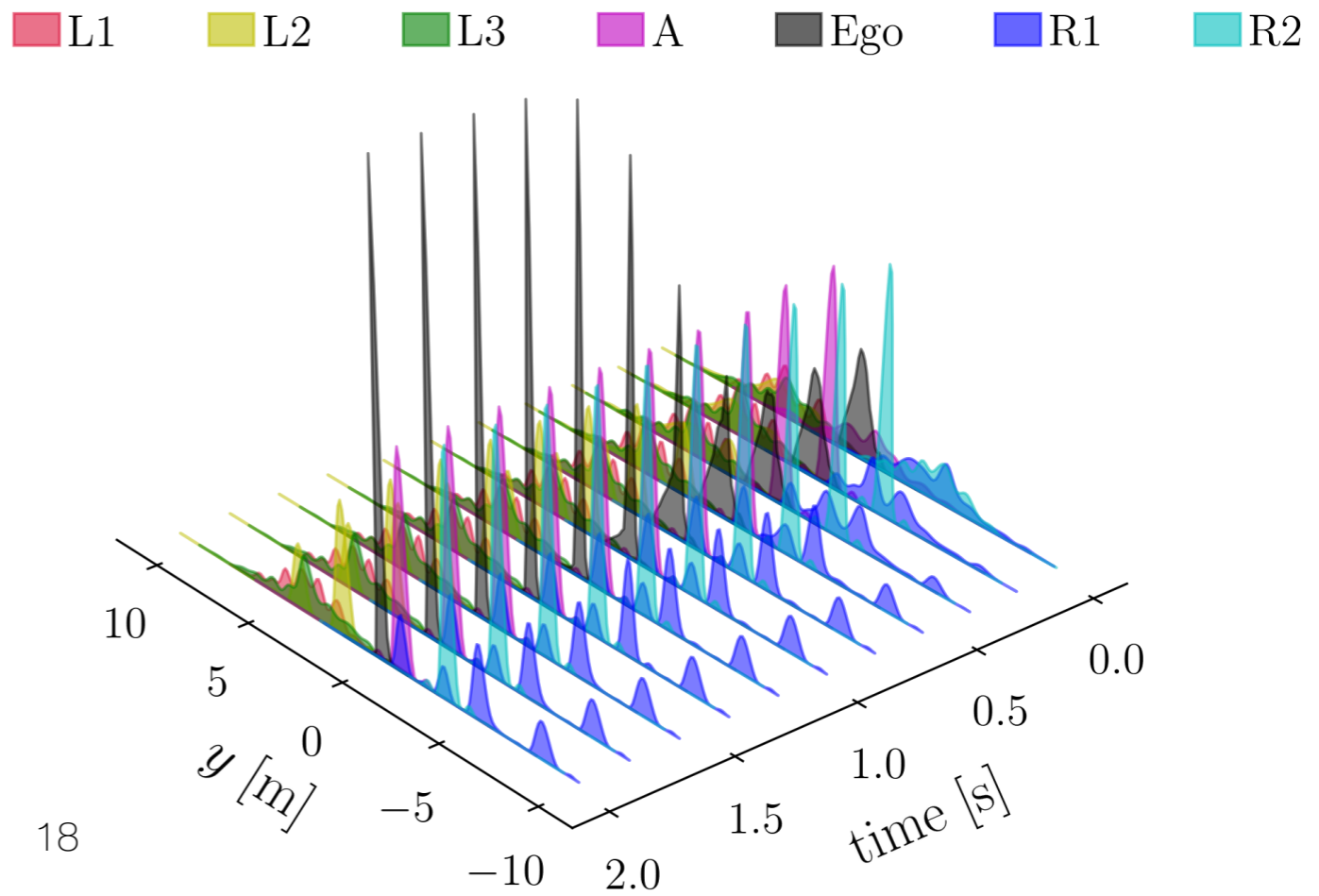
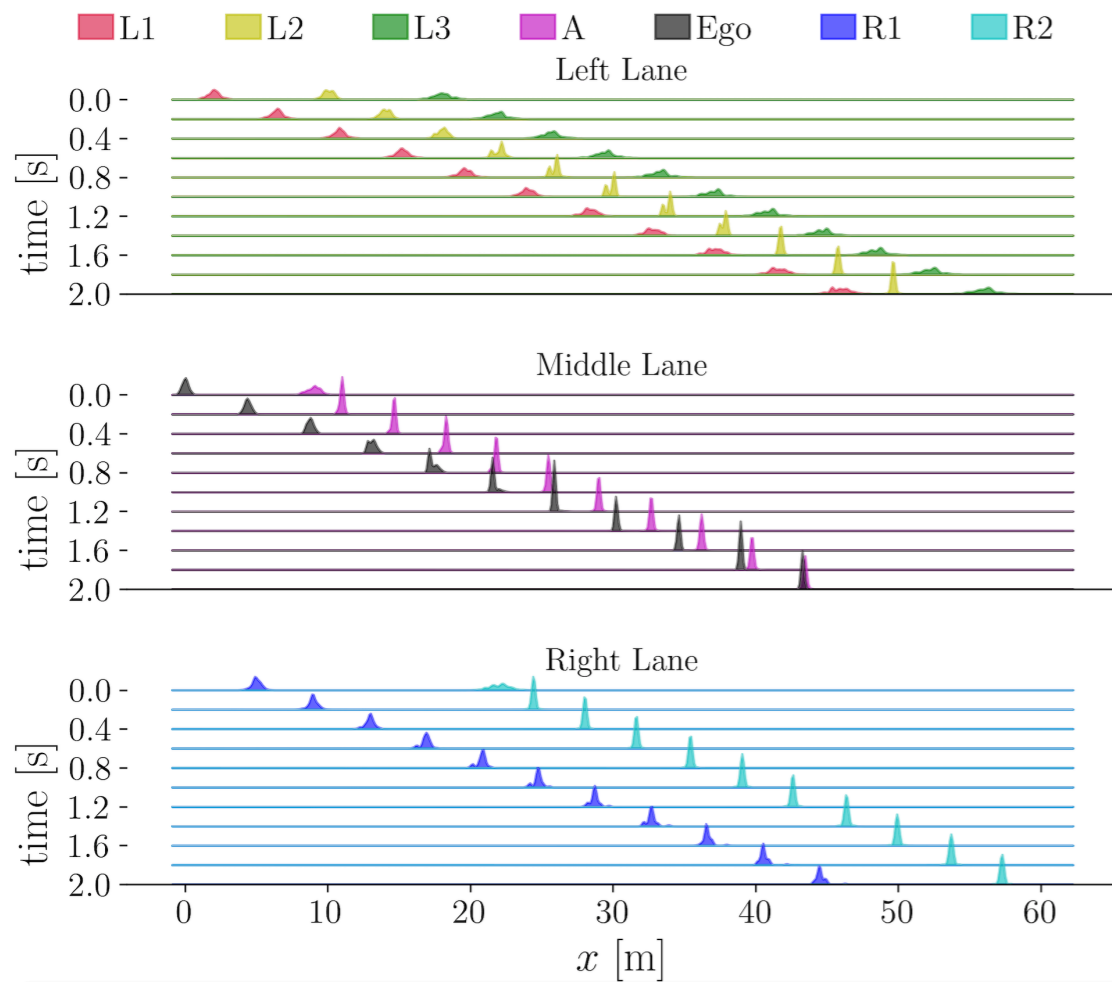


$t_0$

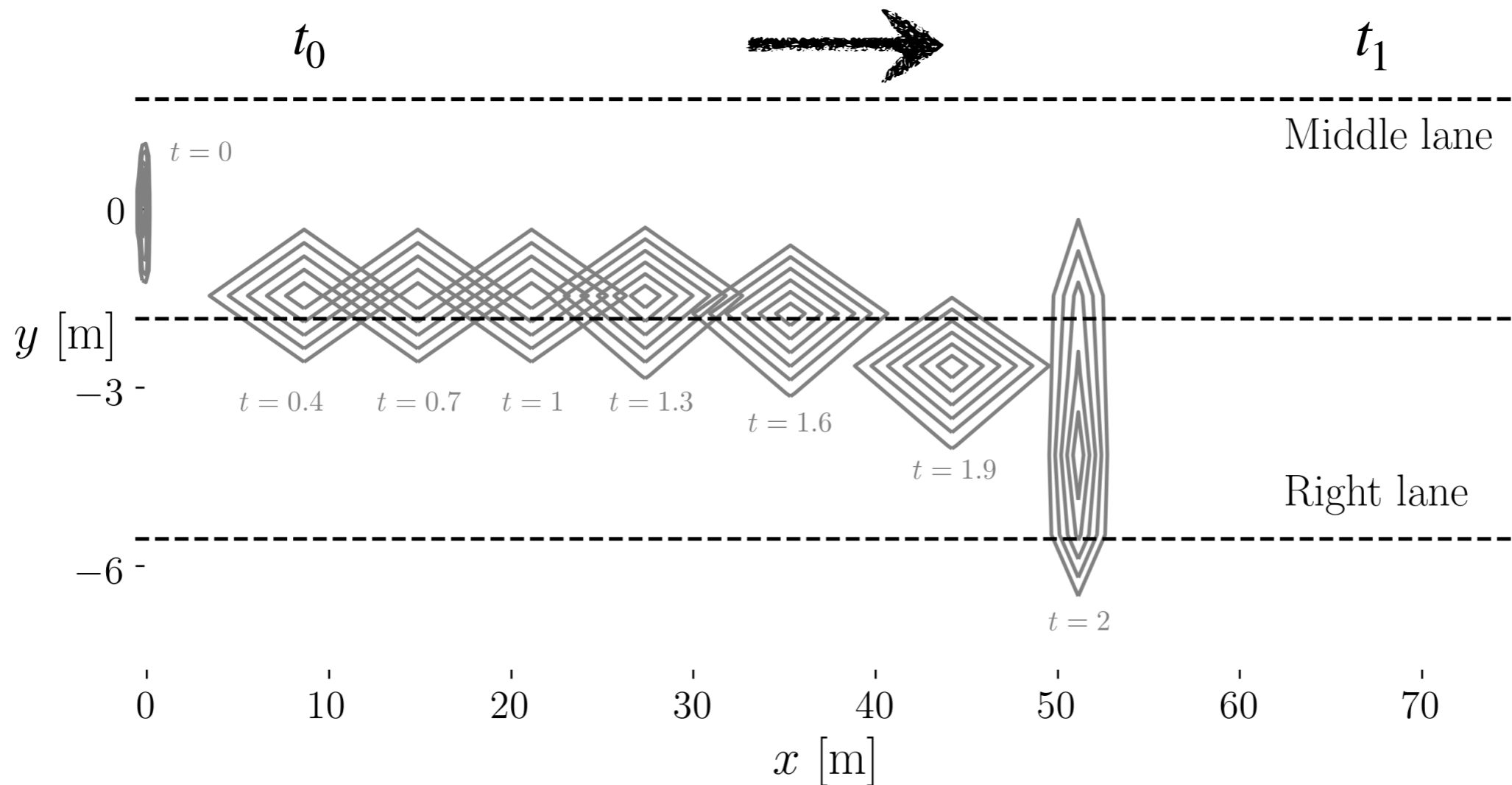
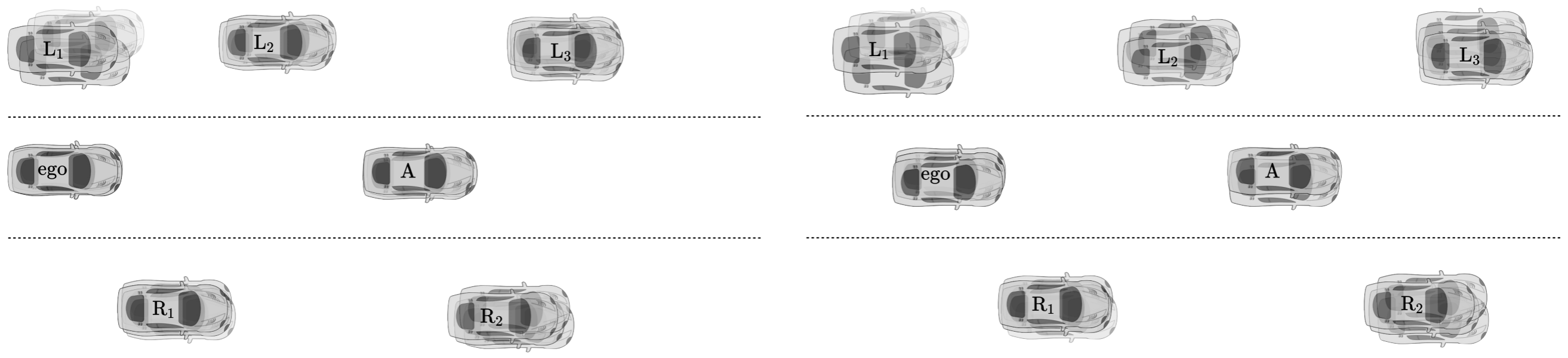
$t_1$

$x$  marginals

$y$  marginals



# Application: Multi-lane Automated Driving



# Hard Path Constraints: Reflected SBP

**Main idea: path constraints  $\sim$  reflected Itô SDEs**  
modify the controlled sample path dynamics to

$$dx_t^u = \{f(t, x_t^u) + B(t)u(t, x_t^u)\}dt + \sqrt{2\theta}G(t)dw_t + n(x_t^u)d\gamma_t$$

$x_t^u \in \bar{\mathcal{X}} := \mathcal{X} \cup \partial\mathcal{X}$ , closure of connected smooth  $\mathcal{X}$

$n$  is inward unit normal to the boundary  $\partial\mathcal{X}$

$\gamma_t$  is minimal local time stochastic process

# Reflected SBP: Schrödinger Factor Recursion

$$\int \text{with b.c. } \langle \mathbf{f}\hat{\varphi} - \theta\nabla\hat{\varphi}, \mathbf{n} \rangle|_{\partial\mathcal{X}} = 0$$

$$\hat{\varphi}_0(\mathbf{x}) \longrightarrow \hat{\varphi}_1(\mathbf{x})$$

$$\rho_0(\mathbf{x}) \oslash \varphi_0(\mathbf{x})$$

$$\rho_1(\mathbf{x}) \oslash \hat{\varphi}_1(\mathbf{x})$$

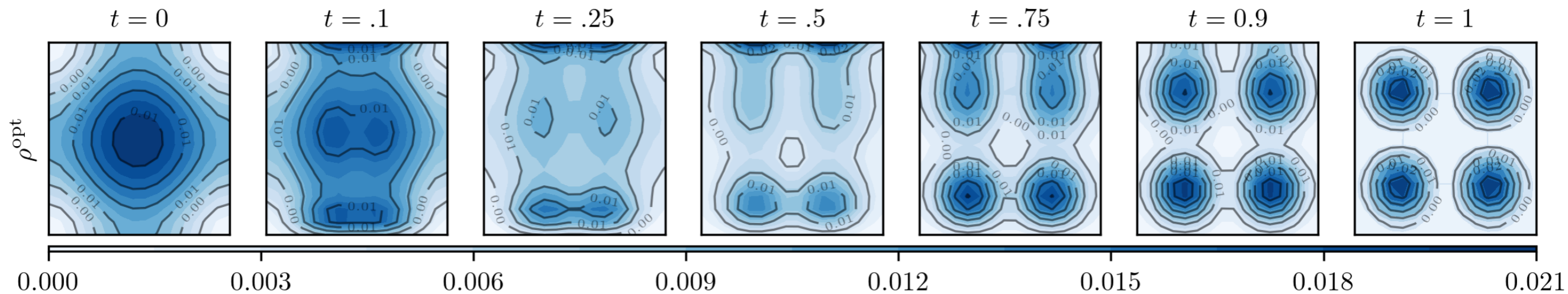
$$\varphi_0(\mathbf{x}) \longleftarrow \varphi_1(\mathbf{x})$$

$$\int \text{with b.c. } \langle \nabla\varphi, \mathbf{n} \rangle|_{\partial\mathcal{X}} = 0$$

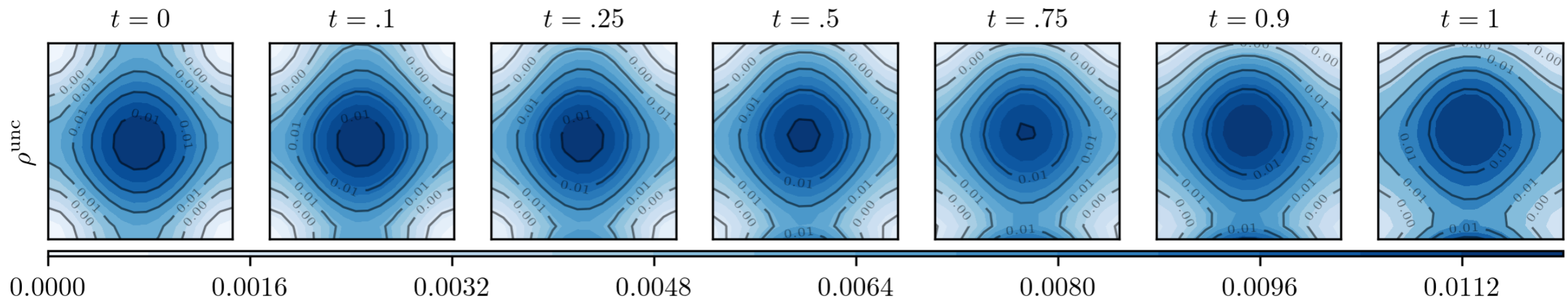
# Reflected SBP: Numerics with Gradient Drift

$$V(x_1, x_2) = (x_1^2 + x_2^3)/5, \quad \bar{\mathcal{X}} = [-4, 4]^2$$

Optimal controlled state PDFs:



Uncontrolled state PDFs:

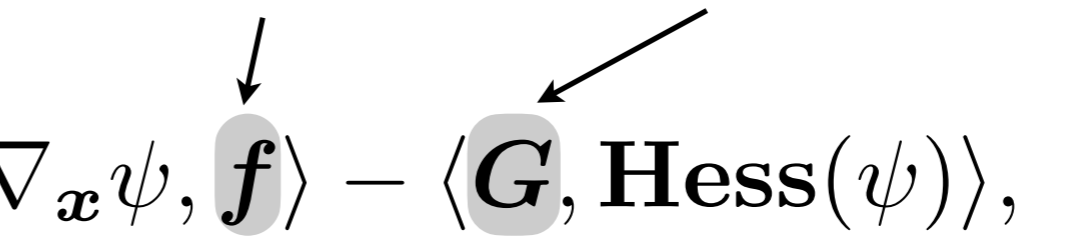


# Control Non-affine SBP: Optimality Conditions

$m + 2$  coupled PDEs with endpoint boundary conditions:

$$\begin{aligned} \frac{\partial \psi}{\partial t} &= \frac{1}{2} \|\mathbf{u}_{\text{opt}}\|_2^2 - \langle \nabla_{\mathbf{x}} \psi, \mathbf{f} \rangle - \langle \mathbf{G}, \mathbf{Hess}(\psi) \rangle, \\ \frac{\partial \rho_{\text{opt}}^{\mathbf{u}}}{\partial t} &= -\nabla \cdot (\rho_{\text{opt}}^{\mathbf{u}} \mathbf{f}) + \langle \mathbf{G}, \mathbf{Hess}(\rho_{\text{opt}}^{\mathbf{u}}) \rangle, \\ \mathbf{u}_{\text{opt}} &= \nabla_{\mathbf{u}_{\text{opt}}} (\langle \nabla_{\mathbf{x}} \psi, \mathbf{f} \rangle + \langle \mathbf{G}, \mathbf{Hess}(\psi) \rangle), \\ \rho_{\text{opt}}^{\mathbf{u}}(0, \mathbf{x}) &= \rho_0, \quad \rho_{\text{opt}}^{\mathbf{u}}(T, \mathbf{x}) = \rho_T, \end{aligned}$$

Drift coefficient      Diffusion tensor



Cf. classical SBP: two coupled PDEs + optimal policy explicit in value fn  $\psi$

# Outlook

- Density control and learning: undergoing rapid developments
- Lots of mathematics, algorithms and applications to be done
- Growing community in systems-control
- Strong intersections with many areas: probability, analysis, geometry, optimization, AI/ML, statistics, information theory, robotics, systems biology



# Thank You

Support:

