

Density Control of Gaussian Mixtures Models: From Controlling Large Populations to Generative AI

Workshop on Stochastic Planning & Control of Dynamical Systems

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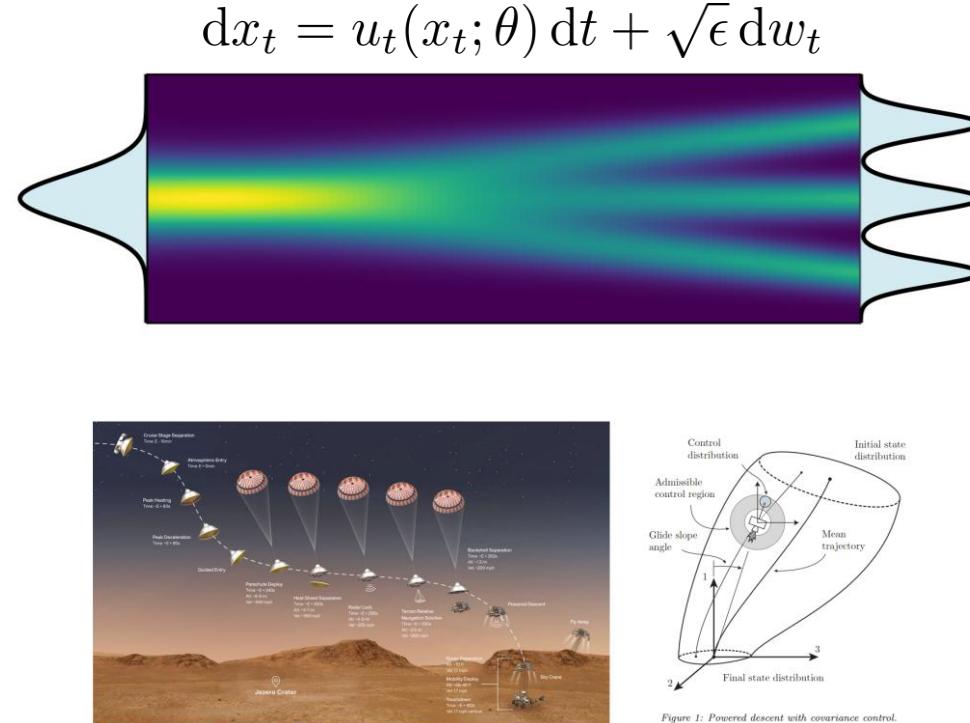
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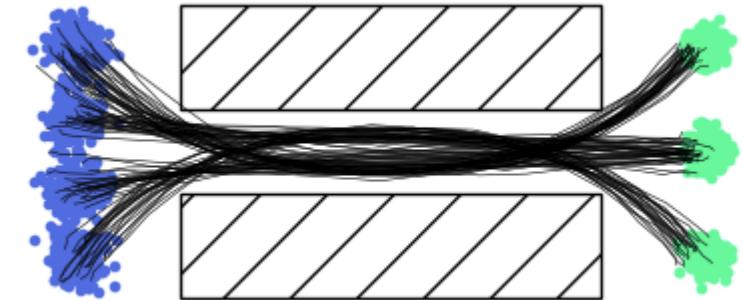
Controlling the density of dynamical systems



ChatGPT: Generate an image of a GT astronaut cat chasing a tennis ball.



Ridderhof, Jack, and Panagiotis Tsiotras. "Minimum-fuel powered descent in the presence of random disturbances." In AIAA SciTech 2019 forum, p. 0646. 2019.



George Rapakoulias, Ali Reza Pedra, Panagiotis Tsiotras. "Steering large agent populations using mean field Schrödinger Bridges and Gaussian mixture models". Control Systems letters 2025.

Schrödinger Bridge and Flow Matching

Diffusion Schrödinger Bridge Matching: “Optimal flow” = “Conditional flows” + “Transport plan” [1-4]

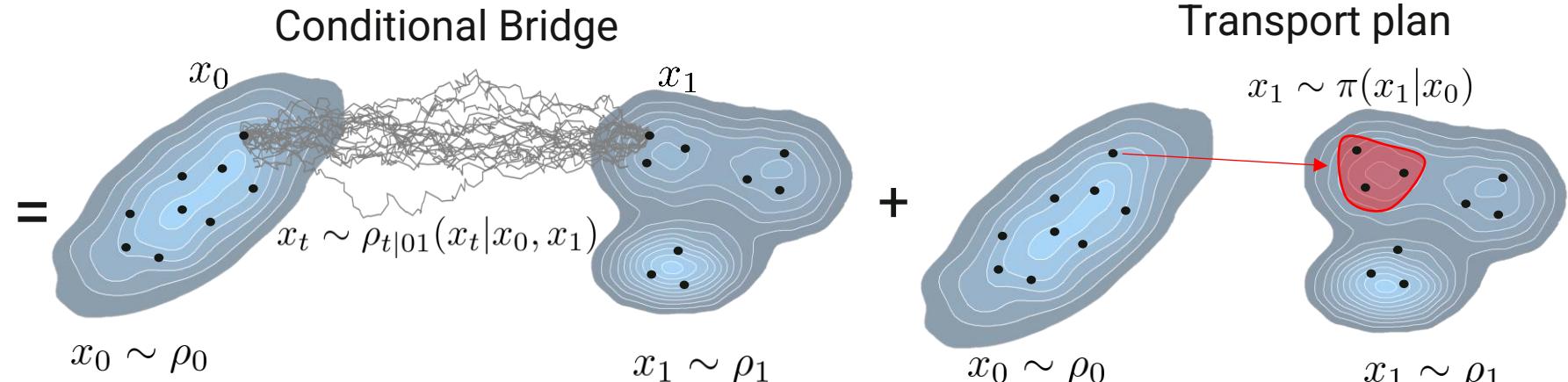
Schrödinger Bridge

$$\min_{\rho, u} \mathbb{E} \left[\int \|u_t(x_t)\|^2 dt \right],$$

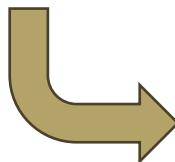
s.t. $dx_t = u_t(x_t) dt + \sqrt{\epsilon} dw$,

$x_0 \sim \rho_0$,

$x_1 \sim \rho_1$



Solution is a mixture of elementary solutions



$$x_t \sim \rho_t = \int \rho_{t|01}(x_t) d\pi, \quad u_t(x_t) = \int u_{t|01}(x_t) \frac{\rho_{t|01}(x_t)}{\rho_t(x_t)} d\pi$$

[1] Shi., et al. "Diffusion Schrödinger bridge matching." (NeurIPS 2023).

[2] Peluchetti, Stefano. "Diffusion bridge mixture transports, Schrödinger bridge problems and generative modeling." JMLR (2023).

[3] Y. Lipman, et al. "Flow Matching for Generative Modeling." (ICLR 2023).

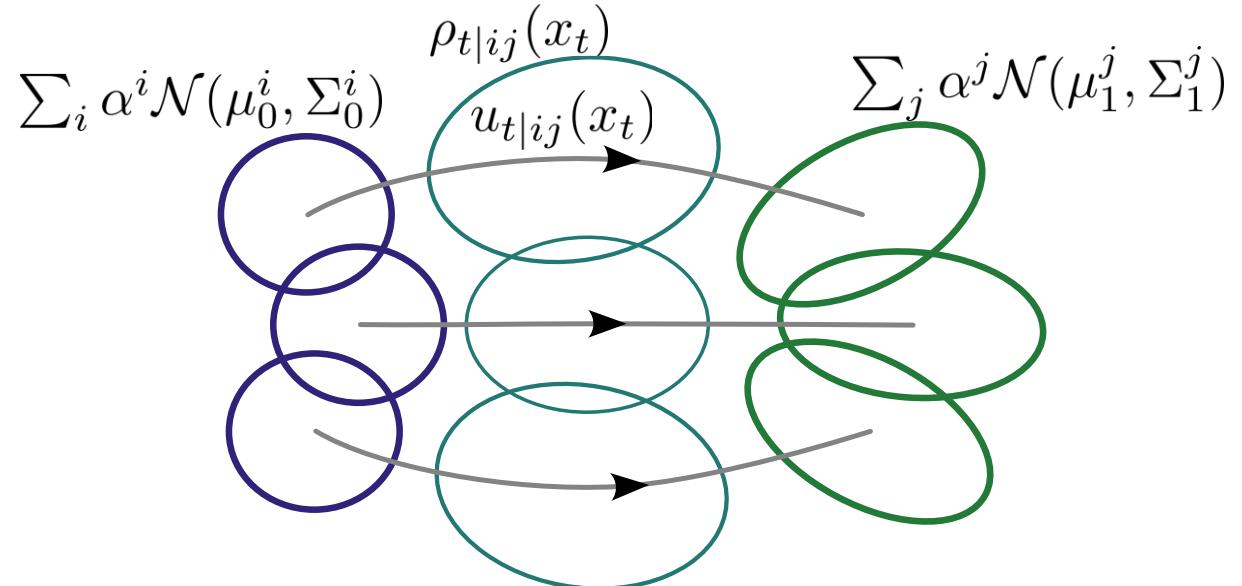
[4] Terpin, A., et al. "Dynamic programming in probability spaces via optimal transport." SIAM Journal on Control and Optimization 62.2 (2024)

Schrödinger Bridges for Gaussian Mixtures

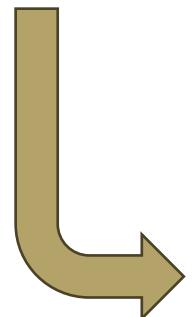
Can we find settings where this decomposition yields tractable mixtures?

GMM SB

$$\begin{aligned} \min_u \quad & J = \mathbb{E} \left[\int_0^1 \|u_t(x_t)\|^2 dt \right], \\ \text{s.t.} \quad & dx_t = u_t(x_t) dt + \sqrt{\epsilon} dt \\ & x_0 \sim \sum_{i=1}^{N_0} \alpha_0^i \mathcal{N}(\mu_0^i, \Sigma_0^i), \\ & x_1 \sim \sum_{j=1}^{N_1} \alpha_1^j \mathcal{N}(\mu_1^j, \Sigma_1^j) \end{aligned}$$



Key intuition: Define a feasible set of solutions as a **mixture of Gaussian Schrödinger Bridges**.



Family of feasible policies parametrized by λ_{ij}

$$\rho_t(x) = \sum_{i,j} \lambda_{ij} \rho_{t|ij}(x)$$

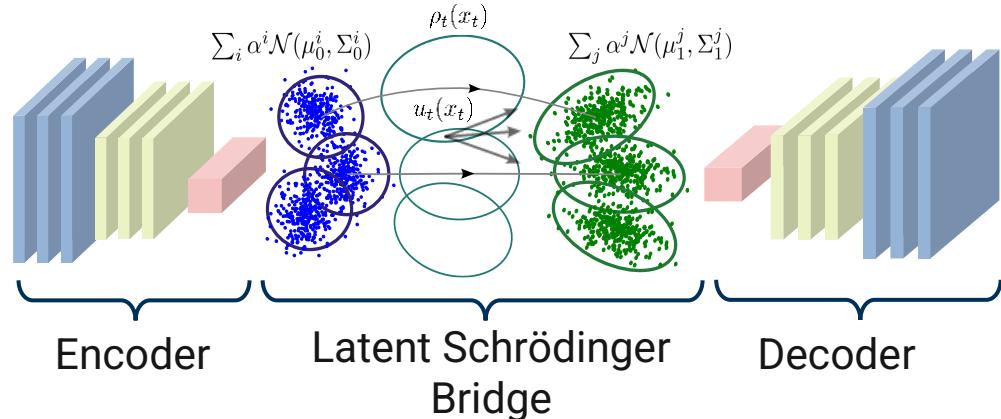
$$u_t(x) = \sum_{i,j} u_{t|ij}(x) \frac{\rho_{t|ij}(x) \lambda_{ij}}{\sum_{i,j} \rho_{t|ij}(x) \lambda_{ij}}$$

Image translation

Original



GMMflow¹ flowchart



Translated



Original



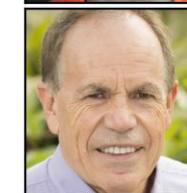
Translated



Original



Translated



Implementation details:

- ALAE² autoencoder (512-mensional latent space)
- 10-component mixture in each class.
- **Few seconds for training, sub-second inference time!**

¹Rapakoulias G. et al. "Go with the flow: Fast diffusion for Gaussian Mixture Models." NeurIPS (2025)

²Pidhorskyi et al. "Adversarial latent autoencoders." IEEE/CVF (2020).

Swarm control as a density control problem

Can we use the GMM-SB framework for swarm control?

Given the **agent-level dynamics** and the **interaction law between agents**, construct a system whose density captures the evolution of the swarm^{1,2}?

Agent dynamics $dx_t = -\nabla V(x_t)dt + dw_t$

Finite swarm $\left\{ dx_t^j = -\nabla V(x_t^j)dt - \frac{1}{N-1} \sum_{i \neq j} \nabla W(x_t^j - x_t^i) + dw_t^i, \quad j = 1, \dots, N, \right\}$

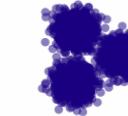
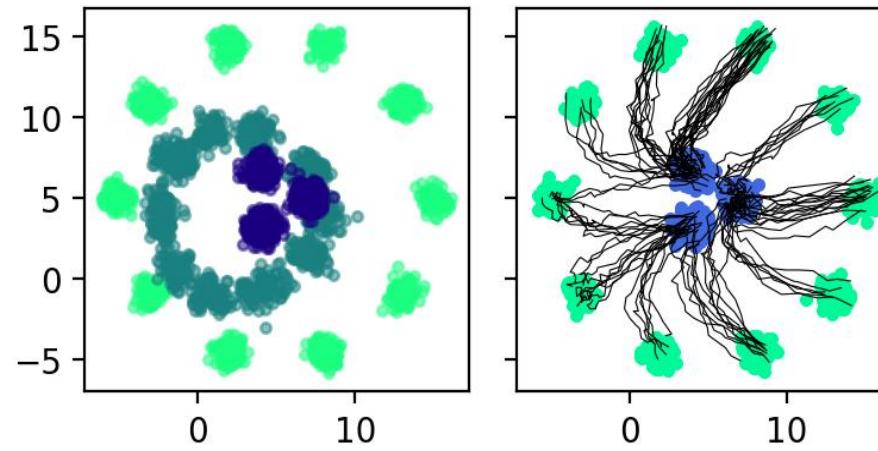
Mean-field system $dx_t = -\nabla V(x_t)dt - \int \nabla W(x_t - y) \rho_t(y) dy + dw_t$

¹Chen, Yongxin. "Density control of interacting agent systems." *IEEE Transactions on Automatic Control* 69.1 (2023): 246-260.

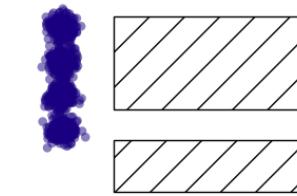
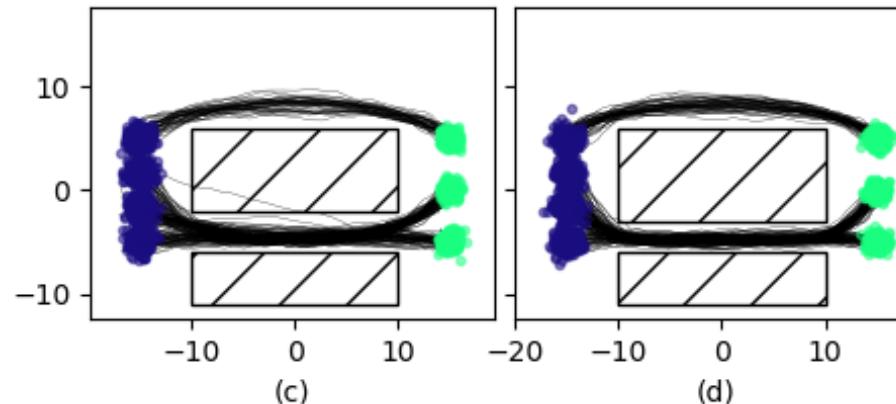
²Elamvazhuthi, Karthik, and Spring Berman. "Mean-field models in swarm robotics: A survey." *Bioinspiration & Biomimetics* 15.1 (2019): 015001.

GMM mean field examples

Unconstrained Mean-Field problem:



Constrained Mean-Field problems:



Thank you!