

Probabilistic Lambert Problem: Connections with Optimal Mass Transport, Schrödinger Bridge and Reaction-Diffusion PDEs

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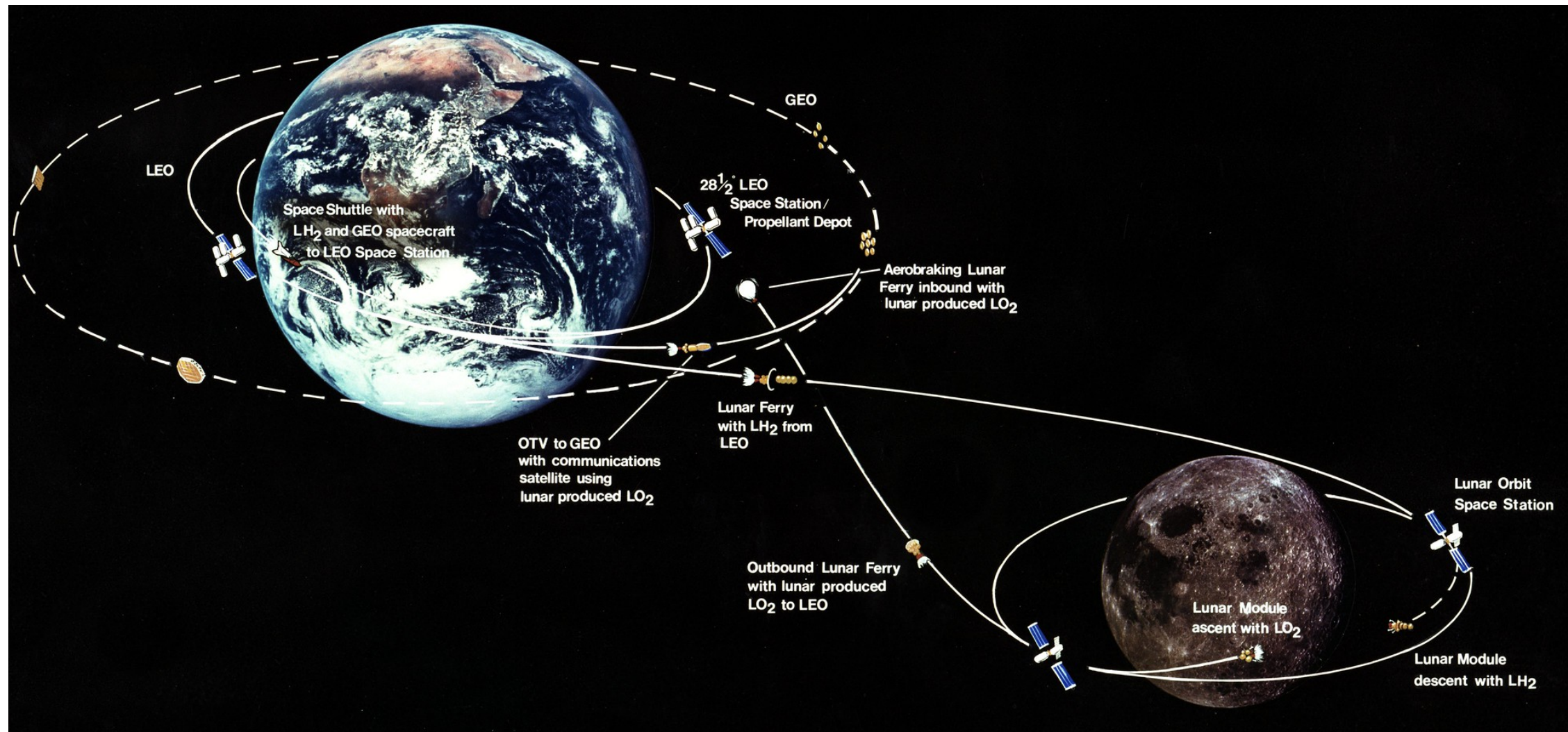
Probabilistic Lambert Problem: Connections with Optimal Mass Transport, Schrödinger Bridge, and Reaction-Diffusion PDEs*

Alexis M. H. Teter[†], Iman Nodozi[‡], and Abhishek Halder[§]



Probabilistic Lambert Problem

Lambert's Problem

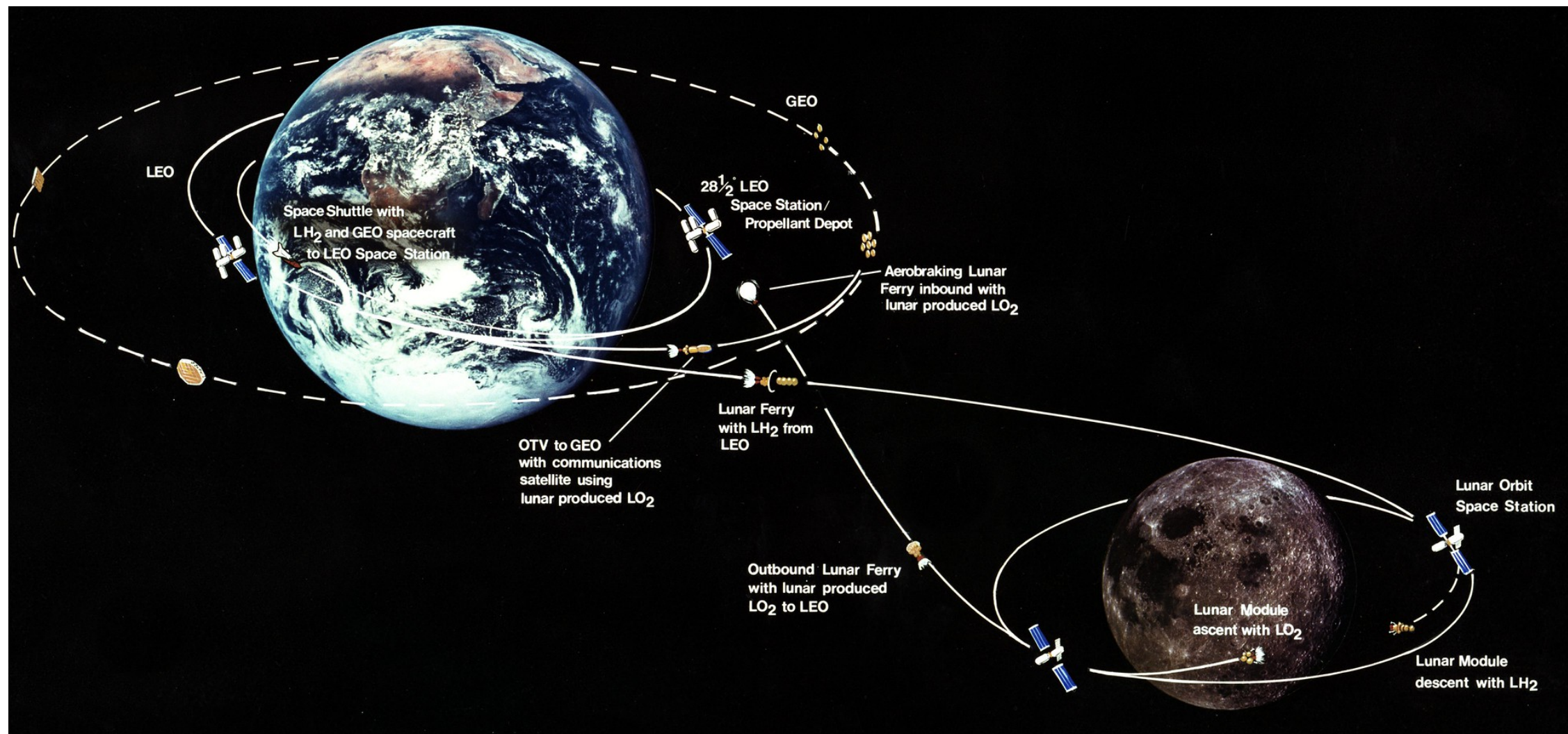


3D position coordinate $\mathbf{r} := \begin{pmatrix} x \\ y \\ z \end{pmatrix} \in \mathbb{R}^3$

Find velocity control policy $\dot{\mathbf{r}} := \mathbf{v}(t, \mathbf{r})$ such that

$$\ddot{\mathbf{r}} = -\nabla_{\mathbf{r}} V(\mathbf{r}), \quad \mathbf{r}(t = t_0) = \mathbf{r}_0(\text{ given }), \quad \mathbf{r}(t = t_1) = \mathbf{r}_1(\text{ given })$$

Lambert's Problem



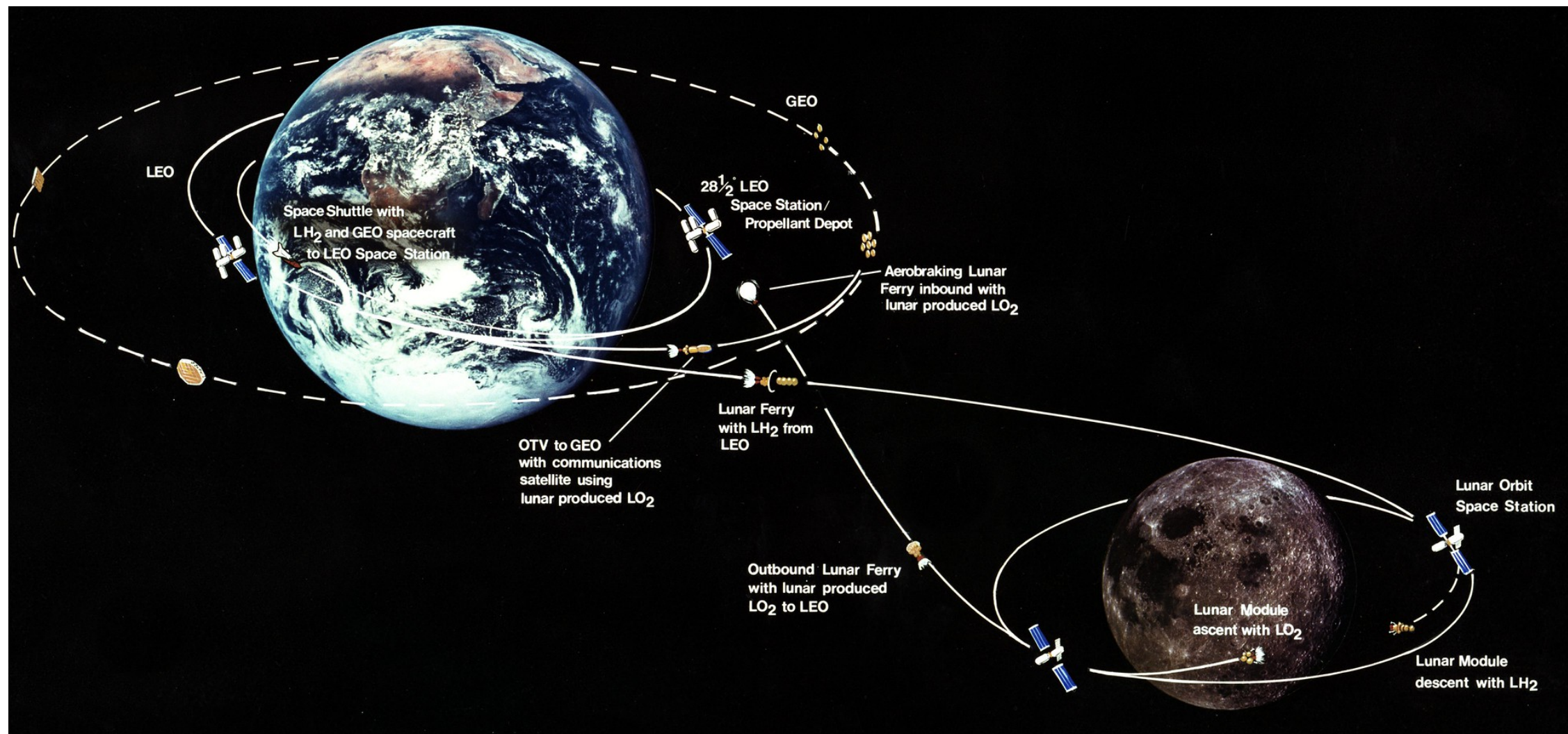
3D position coordinate $\mathbf{r} := \begin{pmatrix} x \\ y \\ z \end{pmatrix} \in \mathbb{R}^3$

ODE is 2nd order but endpoint boundary conditions are first order

Find velocity control policy $\dot{\mathbf{r}} := \mathbf{v}(t, \mathbf{r})$ such that

$$\ddot{\mathbf{r}} = -\nabla_{\mathbf{r}} V(\mathbf{r}), \quad \mathbf{r}(t = t_0) = \mathbf{r}_0(\text{ given }), \quad \mathbf{r}(t = t_1) = \mathbf{r}_1(\text{ given })$$

Lambert's Problem



3D position coordinate $\mathbf{r} := \begin{pmatrix} x \\ y \\ z \end{pmatrix} \in \mathbb{R}^3$

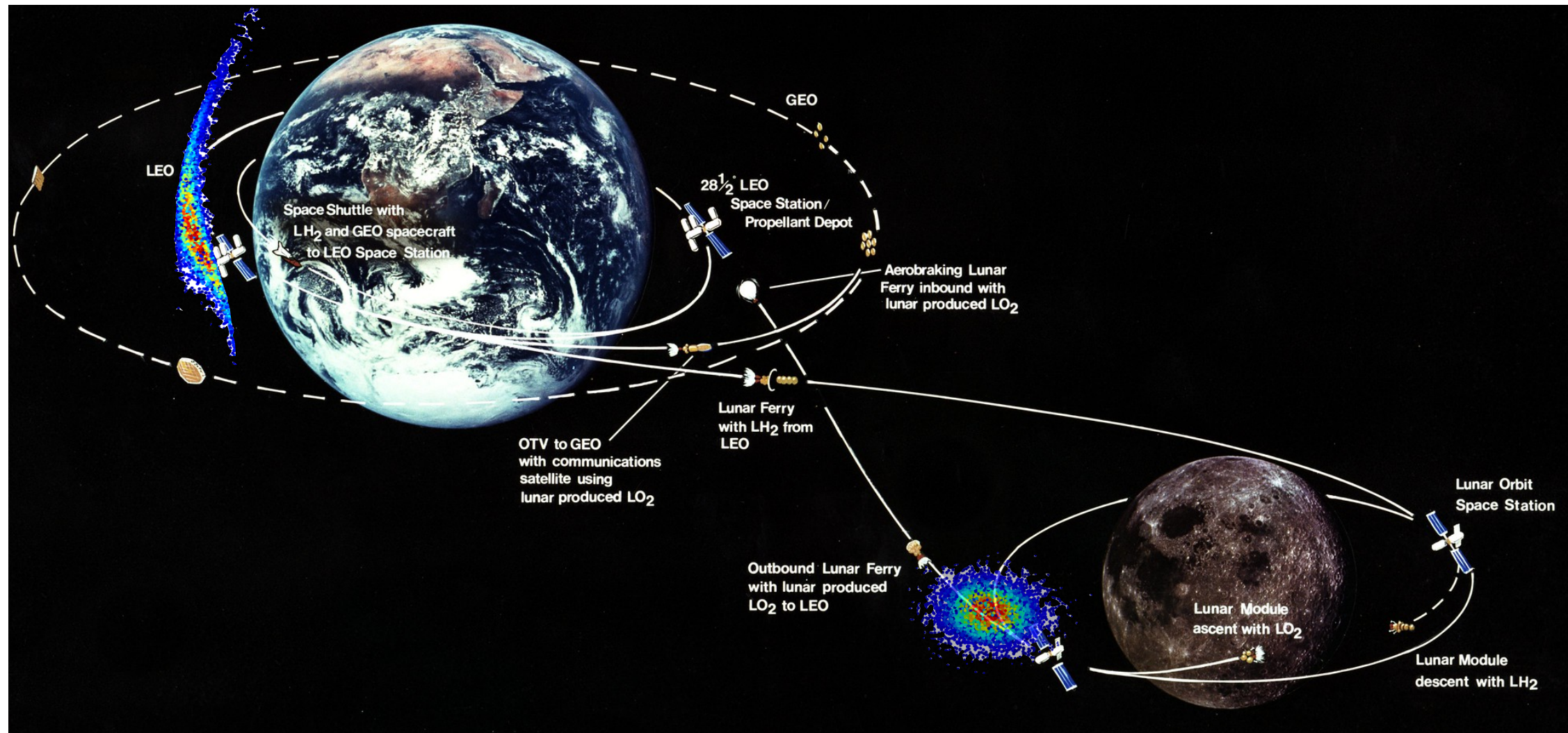
ODE is 2nd order but endpoint boundary conditions are first order

↪ partially specified TPBVP

Find velocity control policy $\dot{\mathbf{r}} := \mathbf{v}(t, \mathbf{r})$ such that

$$\ddot{\mathbf{r}} = -\nabla_{\mathbf{r}} V(\mathbf{r}), \quad \mathbf{r}(t = t_0) = \mathbf{r}_0(\text{ given }), \quad \mathbf{r}(t = t_1) = \mathbf{r}_1(\text{ given })$$

Probabilistic Lambert's Problem



3D position coordinate $\mathbf{r} := \begin{pmatrix} x \\ y \\ z \end{pmatrix} \in \mathbb{R}^3$

Find velocity control policy $\dot{\mathbf{r}} := \mathbf{v}(t, \mathbf{r})$ such that

$$\ddot{\mathbf{r}} = -\nabla_{\mathbf{r}} V(\mathbf{r}), \quad \mathbf{r}(t = t_0) \sim \rho_0 \text{ (given)}, \quad \mathbf{r}(t = t_1) \sim \rho_1 \text{ (given)}$$

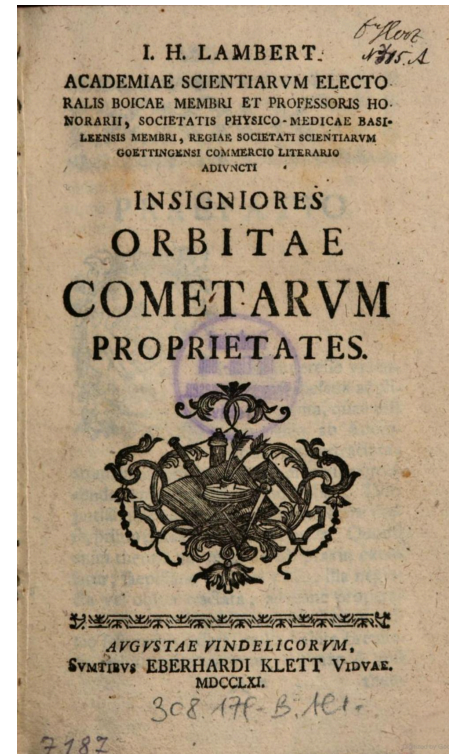
The Beginning of Lambert's Problem



Named after polymath **Johann Heinrich Lambert (1728 - 1777)**

- known for first proof of irrationality of π , W function, area of a hyperbolic triangle
- special cases solved by Euler in 1743
- Lambert mentions this problem in letter to Euler in 1761
- solves the problem for parabolic, elliptic and hyperbolic **Keplerian arcs** in 1761 book
- book receives high praise from Euler in 3 response letters
- alternative proofs by Lagrange (1780), Laplace (1798), Gauss (1809)

$$V(r) = -\frac{\mu}{|r|}$$



Modern History of Lambert's Problem

- Sustained interests for spacecraft guidance, missile interception
- 20th century astrodynamics research: fast computational algorithm, J_2 effect in V

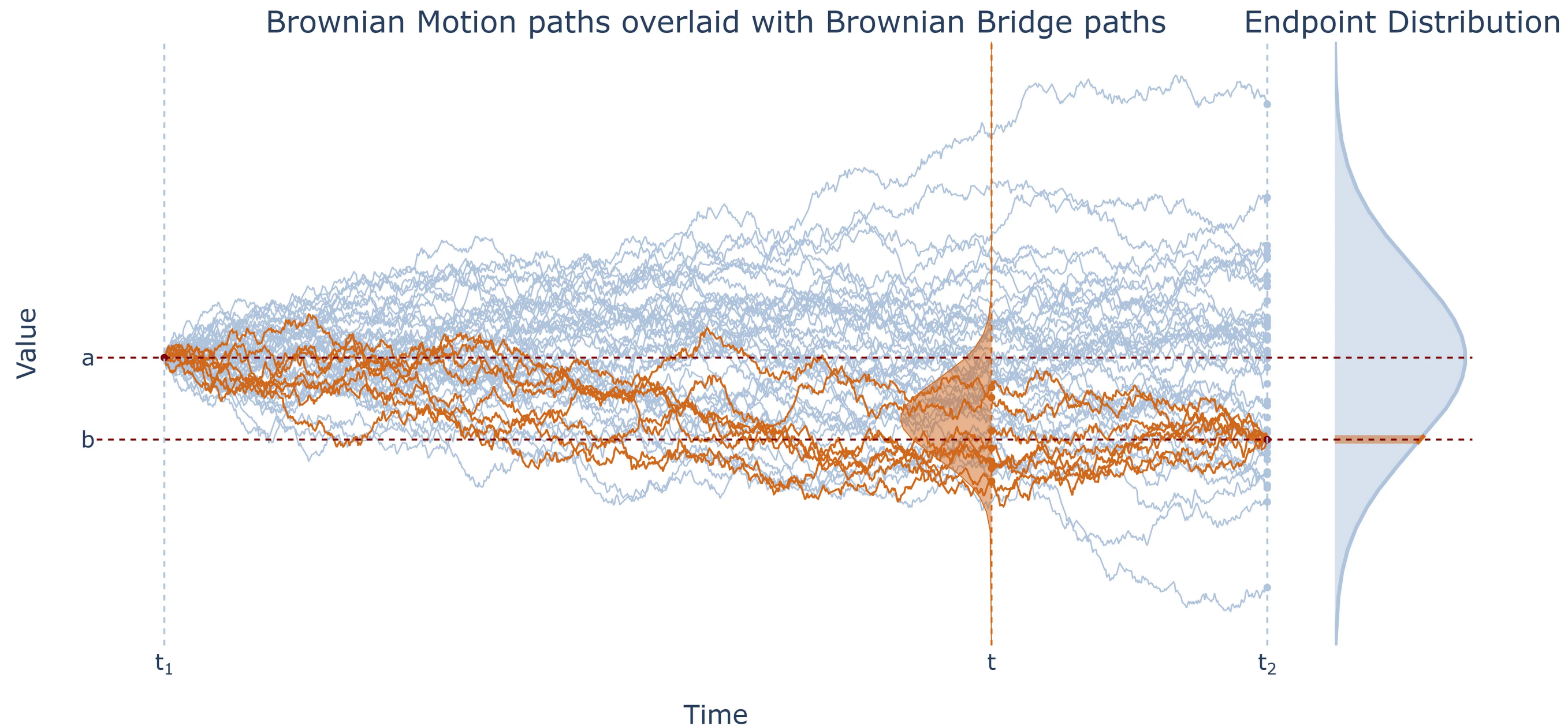
$$V(\mathbf{x}) = -\frac{\mu}{|\mathbf{x}|} \left(1 + \frac{J_2 R_{\text{Earth}}^2}{2|\mathbf{x}|^2} \left(1 - \frac{3z^2}{|\mathbf{x}|^2} \right) \right) \longrightarrow \text{Bounded and negative for } |\mathbf{x}|^2 \geq R_{\text{Earth}}^2$$

- 21st century interests in aerospace community: probabilistic Lambert's problem
- Endpoint uncertainties due to estimation errors, statistical performance
- State-of-the-art: approx. dynamics (linearization) + approx. statistics (covariance)
- Our contribution: connections with OMT and SBP
- Formulation / computation: non-parametric, well-posedness, optimality certificate

Schrödinger Bridge and Optimal Mass Transport

What is a Bridge

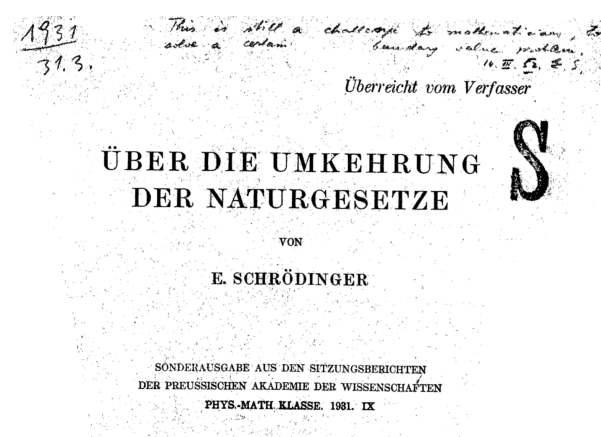
A stochastic process connecting two given states a, b in a given deadline $[t_1, t_2]$



Source: <https://medium.com/@christopher.tabori/between-certainty-and-chance-tracing-the-probability-distribution-of-paths-of-brownian-bridges-b1f97eba638d>

What is a Schrödinger Bridge

Prior physics = Brownian motion



[1931]

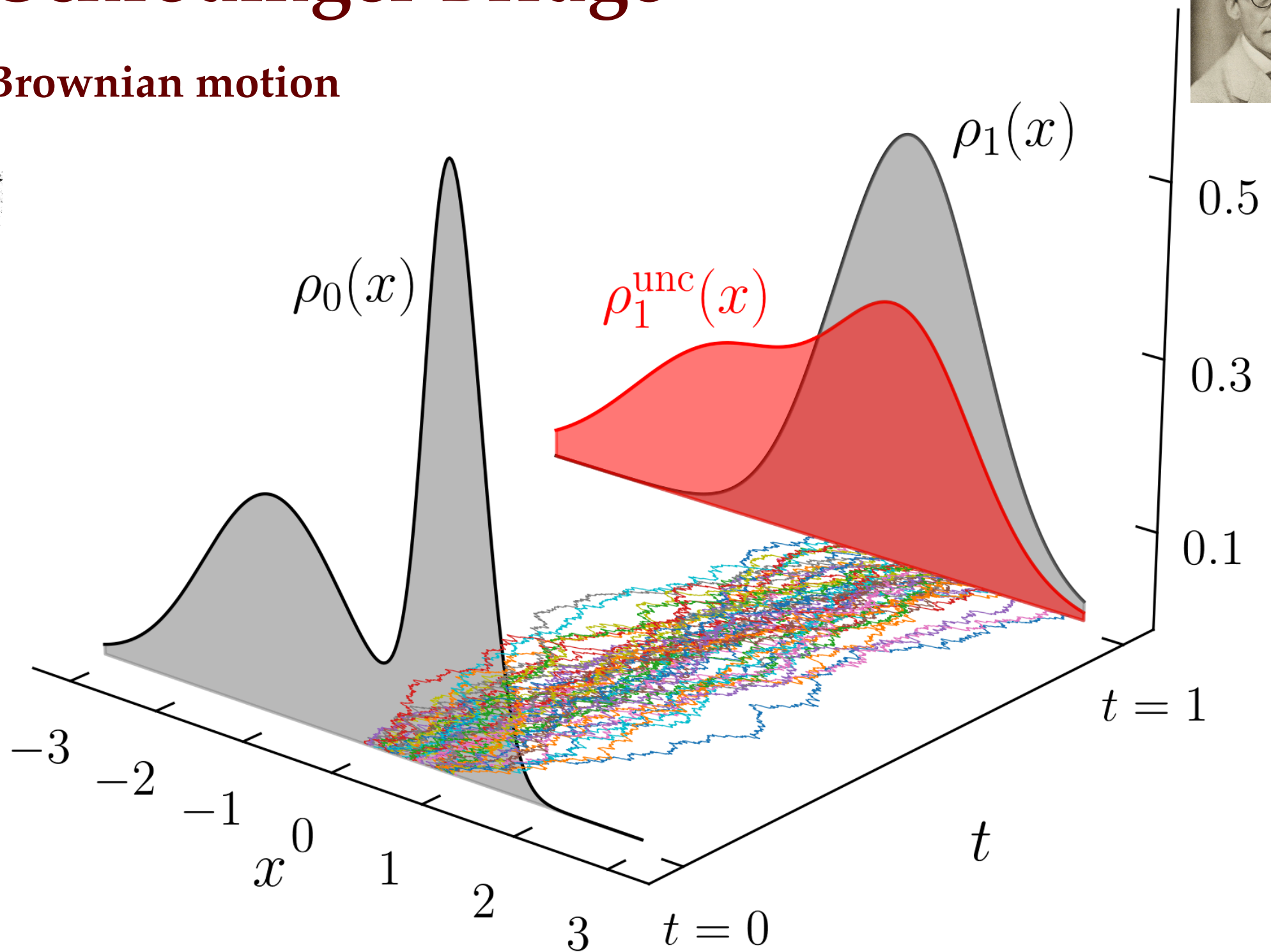
Sur la théorie relativiste de l'électron
et l'interprétation de la mécanique quantique

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.

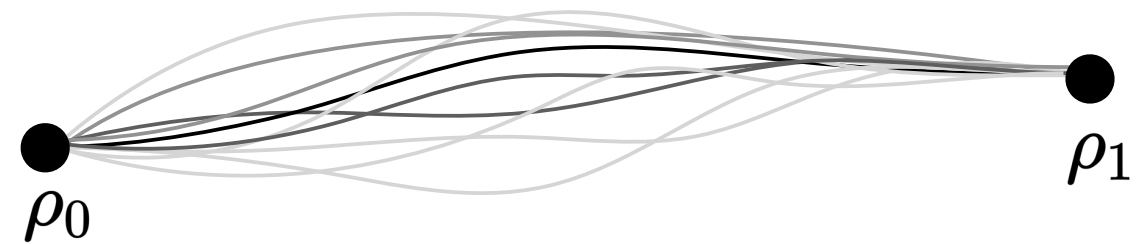
[1932]



Find the most likely explanation of observation vs prior physics mismatch

What is a Schrödinger Bridge

Path space $\Omega := C([t_0, t_1]; \mathbb{R}^n)$



Denote the collection of all probability measures on Ω as $\mathcal{M}(\Omega)$

$\Pi_{01} := \{\mathbb{M} \in \mathcal{M}(\Omega) \mid \mathbb{M} \text{ has marginal } \rho_i \text{ d}\mathbf{x} \text{ at time } t_i \forall i \in \{0, 1\}, \rho_0, \rho_1 \in \mathcal{P}_2(\mathbb{R}^n)\}$

Schrödinger bridge = $\arg \inf_{\mathbb{P} \in \Pi_{01}} D_{\text{KL}}(\mathbb{P} \parallel \mathbb{W})$

Generated by Itô diffusion

Wiener measure

$$d\mathbf{x} = \mathbf{u}(t, \mathbf{x})dt + d\mathbf{w}(t)$$

Most parsimonious correction of prior physics

Constrained maximum likelihood problem on measure-valued paths

What is a Schrödinger bridge

Schrödinger bridge as large deviation principle: **Sanov's theorem [1957]**

$$\lim_{N \uparrow \infty} \log(\text{empirical prob}_N \text{ under } \mathbb{W} \in \Pi_{01}) \asymp - \inf_{\mathbb{P} \in \Pi_{01}} \underbrace{D_{\text{KL}}(\mathbb{P} \parallel \mathbb{W})}_{\text{KL div as rate function}}$$

Schrödinger bridge as stochastic optimal control: **[1990s]**

$$\begin{aligned} & \underset{\boldsymbol{u} \in \mathcal{U}}{\text{minimize}} \mathbb{E} \left[\int_{t_0}^{t_1} \frac{1}{2} \|\boldsymbol{u}(t, \boldsymbol{x}_t^u)\|_2^2 dt \right] \\ & \text{subject to} \\ & d\boldsymbol{x}_t^u = \boldsymbol{u}(t, \boldsymbol{x}_t^u) dt + d\boldsymbol{w}_t \\ & \boldsymbol{x}_t^u(t = t_0) \sim \rho_0, \quad \boldsymbol{x}_t^u(t = t_1) \sim \rho_1 \end{aligned}$$

What is a Schrödinger bridge

Schrödinger bridge as large deviation principle: **Sanov's theorem [1957]**

$$\lim_{N \uparrow \infty} \log(\text{empirical prob}_N \text{ under } \mathbb{W} \in \Pi_{01}) \asymp - \inf_{\mathbb{P} \in \Pi_{01}} D_{\text{KL}}(\mathbb{P} \parallel \mathbb{W})$$

KL divergence as rate function

Schrödinger bridge as stochastic optimal control: **[1990s]**

$$\underset{u \in \mathcal{U}}{\text{minimize}} \mathbb{E} \left[\int_{t_0}^{t_1} \frac{1}{2} \|u(t, x_t^u)\|_2^2 dt \right]$$

subject to

$$d\mathbf{x}_t^u = u(t, \mathbf{x}_t^u) dt + d\mathbf{w}_t$$

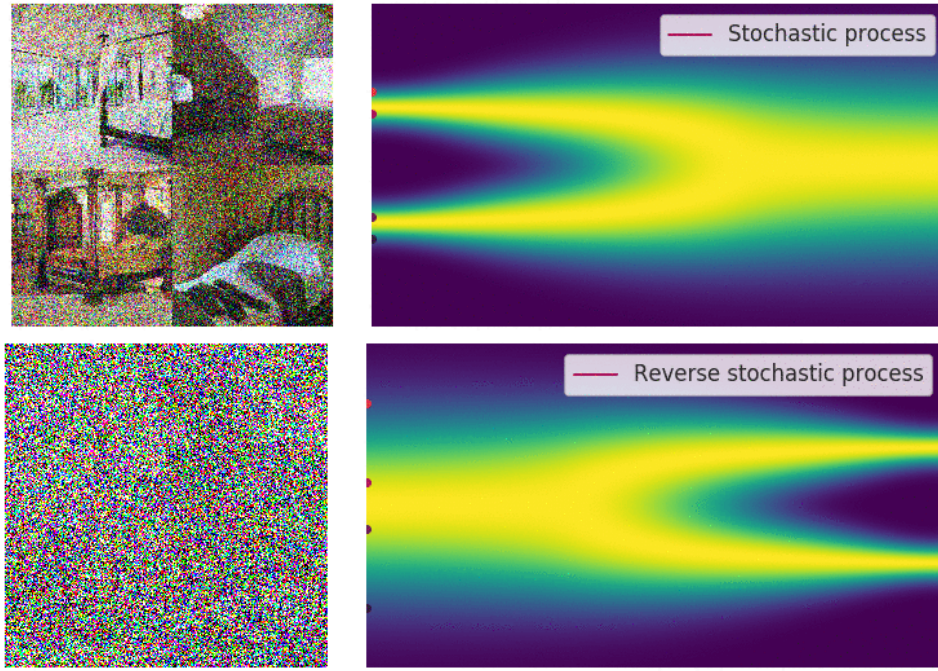
$$\mathbf{x}_t^u(t = t_0) \sim \rho_0, \quad \mathbf{x}_t^u(t = t_1) \sim \rho_1$$

0 **Benamou-Brenier OMT [1999]**

Resurgence of Schrödinger Bridge in AI

Diffusion models for generative AI

Source: <https://yang-song.net/blog/2021/score/>



UAI 2023

Aligned Diffusion Schrödinger Bridges

Vignesh Ram Somnath^{*1,2}
Maria Rodriguez Martinez²

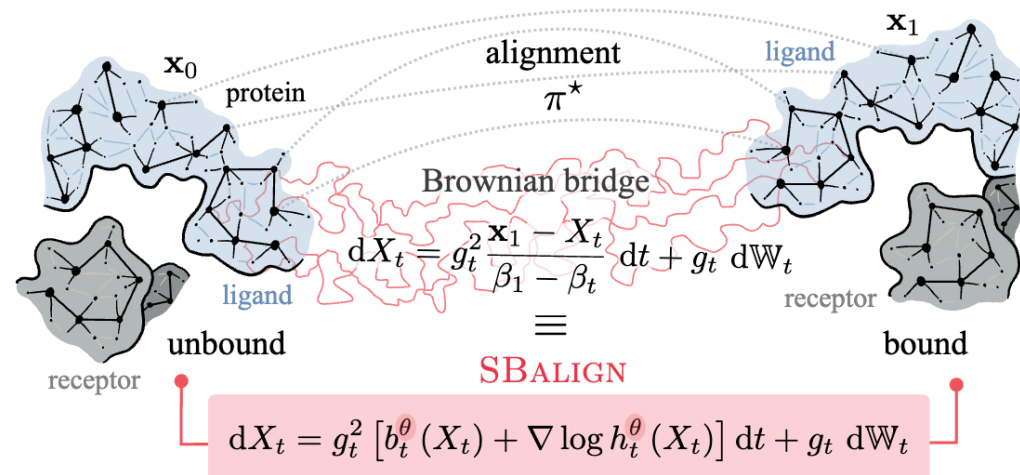
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NeurIPS 2021

Diffusion Schrödinger Bridge with Applications to Score-Based Generative Modeling

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Singapore

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Department of Statistics,
University of Oxford, UK

NeurIPS 2024

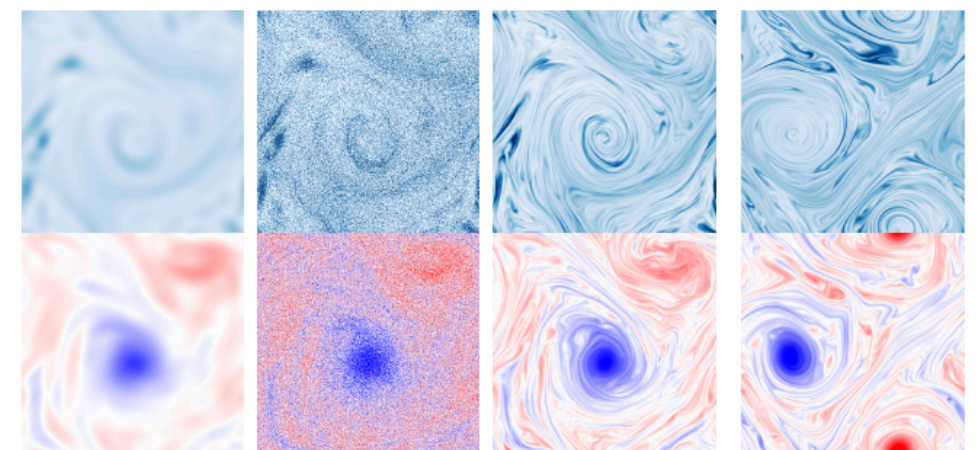
Diffusion Schrödinger Bridge Matching

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University of Oxford

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ENS ULM

Andrew Campbell
University of Oxford

Arnaud Doucet
University of Oxford



Low res

High res

Back to Probabilistic Lambert

Problem: Connecting Ideas

Connection with Optimal Control Problem (OCP)

Lambert Problem $\Leftrightarrow$ Deterministic OCP

Idea: use classical Hamiltonian mechanics to reformulate as deterministic OCP

$$\ddot{\mathbf{r}} = -\nabla_{\mathbf{r}} V(\mathbf{r}), \quad \mathbf{r}(t = t_0) = \mathbf{r}_0 \text{ (given)}, \quad \mathbf{r}(t = t_1) = \mathbf{r}_1 \text{ (given)}$$



$$\arg \inf_{\mathbf{v}} \int_{t_0}^{t_1} \left(\frac{1}{2} \|\mathbf{v}\|_2^2 - V(\mathbf{r}) \right) dt$$

Gravitational potential pushed from dynamics to Lagrangian

$$\dot{\mathbf{r}} = \mathbf{v},$$

$$\mathbf{r}(t = t_0) = \mathbf{r}_0 \text{ (given)}, \quad \mathbf{r}(t = t_1) = \mathbf{r}_1 \text{ (given)}$$

Lambertian OMT (L-OMT)

Probabilistic Lambert Problem $\Leftrightarrow$ Generalized OMT

$$\ddot{\mathbf{r}} = -\nabla_{\mathbf{r}} V(\mathbf{r}), \quad \mathbf{r}(t = t_0) \sim \rho_0 \text{ (given)}, \quad \mathbf{r}(t = t_1) \sim \rho_1 \text{ (given)}$$



$$\arg \inf_{(\rho, \mathbf{v})} \int_{t_0}^{t_1} \mathbb{E}_{\rho} \left[\frac{1}{2} \|\mathbf{v}\|_2^2 - \underbrace{V(\mathbf{r})}_{\text{Potential as state cost}} \right] dt$$

$$\dot{\mathbf{r}} = \mathbf{v},$$

Potential as state cost ($V = 0$ is OMT)

$$\mathbf{r}(t = t_0) \sim \rho_0 \text{ (given)}, \quad \mathbf{r}(t = t_1) \sim \rho_1 \text{ (given)}$$

L-OMT as Density Steering

$$\arg \inf_{(\rho, \mathbf{v})} \int_{t_0}^{t_1} \mathbb{E}_{\rho} \left[\frac{1}{2} \|\mathbf{v}\|_2^2 - V(\mathbf{r}) \right] dt$$

$$\dot{\mathbf{r}} = \mathbf{v},$$

$$\mathbf{r}(t = t_0) \sim \rho_0 \text{ (given), } \quad \mathbf{r}(t = t_1) \sim \rho_1 \text{ (given)}$$



$$\arg \inf_{(\rho, \mathbf{v})} \int_{t_0}^{t_1} \mathbb{E}_{\rho} \left[\frac{1}{2} \|\mathbf{v}\|_2^2 - V(\mathbf{r}) \right] dt$$

$$\frac{\partial \rho}{\partial t} + \nabla_{\mathbf{r}} \cdot (\rho \mathbf{v}) = 0, \quad \text{— Liouville PDE}$$

$$\rho(t = t_0, \cdot) = \rho_0, \quad \rho(t = t_1, \cdot) = \rho_1$$

Existence-Uniqueness of L-OMT Solution

Thm. (informal)

Existence-uniqueness guaranteed for V bounded C^1 ,
and ρ_0, ρ_1 with finite second moments

Proof idea.

Figalli's theory for OMT with Tonelli Lagrangians that are
induced by action integrals

Connection to SBP with state cost

$$\arg \inf_{(\rho, \mathbf{v}) \in \mathcal{P}_{01} \times \mathcal{V}} \int_{t_0}^{t_1} \int_{\mathbb{R}^n} \left(\frac{1}{2} |\mathbf{v}|^2 - V(\mathbf{x}) \right) \rho(\mathbf{x}, t) d\mathbf{x} dt$$

$$\frac{\partial \rho}{\partial t} + \nabla_r \cdot (\rho \mathbf{v}) = 0, \text{ — Liouville PDE}$$

$$\rho(t = t_0, \cdot) = \rho_0, \quad \rho(t = t_1, \cdot) = \rho_1$$

↯ **Lambertian SBP (L-SBP)**

$$\arg \inf_{(\rho, \mathbf{v}) \in \mathcal{P}_{01} \times \mathcal{V}} \int_{t_0}^{t_1} \int_{\mathbb{R}^n} \left(\frac{1}{2} |\mathbf{v}|^2 - V(\mathbf{x}) \right) \rho(\mathbf{x}, t) d\mathbf{x} dt$$

Regularization > 0

$$\frac{\partial \rho}{\partial t} + \nabla_r \cdot (\rho \mathbf{v}) = \varepsilon \Delta_r \rho, \text{ — Fokker-Planck-Kolmogorov PDE}$$

$$\rho(t = t_0, \cdot) = \rho_0, \quad \rho(t = t_1, \cdot) = \rho_1$$

L-SBP Solution

Thm. (informal) Existence and uniqueness of L-SBP is guaranteed

$$V(\mathbf{x}) = -\frac{\mu}{|\mathbf{x}|} \left(1 + \frac{J_2 R_{\text{Earth}}^2}{2|\mathbf{x}|^2} \left(1 - \frac{3z^2}{|\mathbf{x}|^2} \right) \right) \longrightarrow \text{Bounded and negative for } |\mathbf{x}|^2 \geq R_{\text{Earth}}^2$$

Thm. (Necessary conditions of optimality for L-SBP)

Dual PDE

$$\frac{\partial \psi_\varepsilon}{\partial t} + \frac{1}{2} |\nabla_{\mathbf{x}} \psi_\varepsilon|^2 + \varepsilon \Delta_{\mathbf{x}} \psi_\varepsilon = -V(\mathbf{x})$$

Primal PDE

$$\frac{\partial \rho_\varepsilon^{\text{opt}}}{\partial t} + \nabla_{\mathbf{x}} \cdot (\rho_\varepsilon^{\text{opt}} \nabla_{\mathbf{x}} \psi_\varepsilon) = \varepsilon \Delta_{\mathbf{x}} \rho_\varepsilon^{\text{opt}}$$

$$\rho_\varepsilon^{\text{opt}}(t = t_0, \cdot) = \rho_0, \quad \rho_\varepsilon^{\text{opt}}(t = t_1, \cdot) = \rho_1$$

L-SBP Solution

Thm. (Hopf-Cole a.k.a. Fleming's log transform)

Change of variable $(\rho_\varepsilon^{\text{opt}}, \psi) \mapsto (\hat{\varphi}, \varphi)$ — **Schrödinger factors**

$$\hat{\varphi}(t, \mathbf{r}) = \rho_\varepsilon^{\text{opt}}(t, \mathbf{r}) \exp\left(-\frac{\psi(t, \mathbf{r})}{2\varepsilon}\right)$$

$$\varphi(t, \mathbf{r}) = \exp\left(\frac{\psi(t, \mathbf{r})}{2\varepsilon}\right)$$

results in a boundary-coupled system of forward-backward reaction-diffusion PDEs

$$\begin{aligned}\frac{\partial \hat{\varphi}}{\partial t} &= (\varepsilon \Delta_{\mathbf{r}} + V(\mathbf{r})) \hat{\varphi} \longleftarrow \mathcal{L}_{\text{forward}} \hat{\varphi} \\ \frac{\partial \varphi}{\partial t} &= -(\varepsilon \Delta_{\mathbf{r}} + V(\mathbf{r})) \varphi \longleftarrow \mathcal{L}_{\text{backward}} \varphi\end{aligned}$$

$$\hat{\varphi}(t = t_0, \cdot) \varphi(t = t_0, \cdot) = \rho_0, \quad \hat{\varphi}(t = t_1, \cdot) \varphi(t = t_1, \cdot) = \rho_1$$

Optimally controlled joint state PDF: $\rho_\varepsilon^{\text{opt}}(t, \mathbf{r}) = \hat{\varphi}(t, \mathbf{r}) \varphi(t, \mathbf{r})$

Optimal control: $\mathbf{v}_\varepsilon^{\text{opt}}(t, \mathbf{r}) = 2\varepsilon \nabla_{\mathbf{r}} \log \varphi(t, \mathbf{r})$

L-SBP Computation via Schrödinger Factors

Recursion over pair $(\varphi_1, \hat{\varphi}_0)$

$$\begin{array}{ccc}
 \hat{\varphi}_{\varepsilon,0}(\cdot) & \xrightarrow{\int} & \hat{\varphi}_{\varepsilon}(\cdot, t = t_1) \\
 \uparrow \rho_0(\cdot)/\varphi_{\varepsilon}(\cdot, t = t_0) & & \downarrow \rho_1(\cdot)/\hat{\varphi}_{\varepsilon}(\cdot, t = t_1) \\
 \varphi_{\varepsilon}(\cdot, t = t_0) & \xleftarrow{\int} & \varphi_{\varepsilon,1}(\cdot)
 \end{array}$$

$$\begin{aligned}
 \frac{\partial \hat{\varphi}_{\varepsilon}}{\partial t} &= \left(\varepsilon \Delta_{\mathbf{r}} + \frac{1}{2\varepsilon} V(\mathbf{r}) \right) \hat{\varphi}_{\varepsilon} \\
 \frac{\partial \varphi_{\varepsilon}}{\partial t} &= - \left(\varepsilon \Delta_{\mathbf{r}} + \frac{1}{2\varepsilon} V(\mathbf{r}) \right) \varphi_{\varepsilon}
 \end{aligned}$$

$$\rho_{\varepsilon}^{\text{opt}}(t = t_0, \cdot) = \rho_0, \quad \rho_{\varepsilon}^{\text{opt}}(t = t_1, \cdot) = \rho_1$$

Numerical Case Study

Prescribed time horizon $[t_0, t_1] \equiv [0, 1]$ hours

Endpoint joint PDFs

$$\boldsymbol{x}_0 \sim \mathcal{N}(\boldsymbol{\mu}_0, \boldsymbol{\Sigma}_0)$$

$$\boldsymbol{x}_1 \sim \mathcal{N}(\boldsymbol{\mu}_1, \boldsymbol{\Sigma}_1)$$

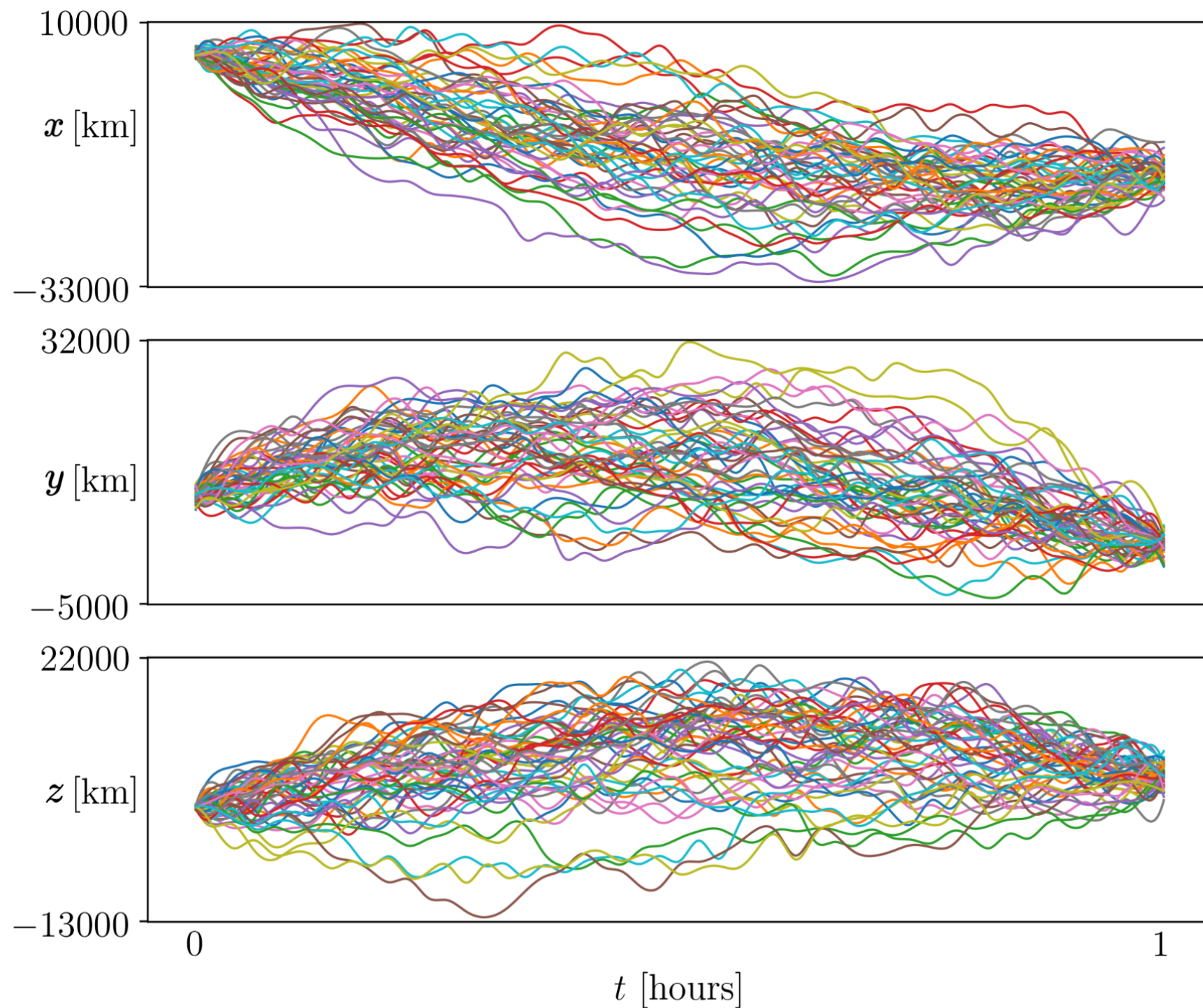
where

$$\boldsymbol{\mu}_0 = \begin{pmatrix} 5000 \\ 10000 \\ 2100 \end{pmatrix}, \quad \boldsymbol{\mu}_1 = \begin{pmatrix} -14600 \\ 2500 \\ 7000 \end{pmatrix}$$

$$\boldsymbol{\Sigma}_0 = \frac{1}{100} \text{diag}(\mu_0^2), \quad \boldsymbol{\Sigma}_1 = \frac{1}{100} \text{diag}(\mu_1^2),$$

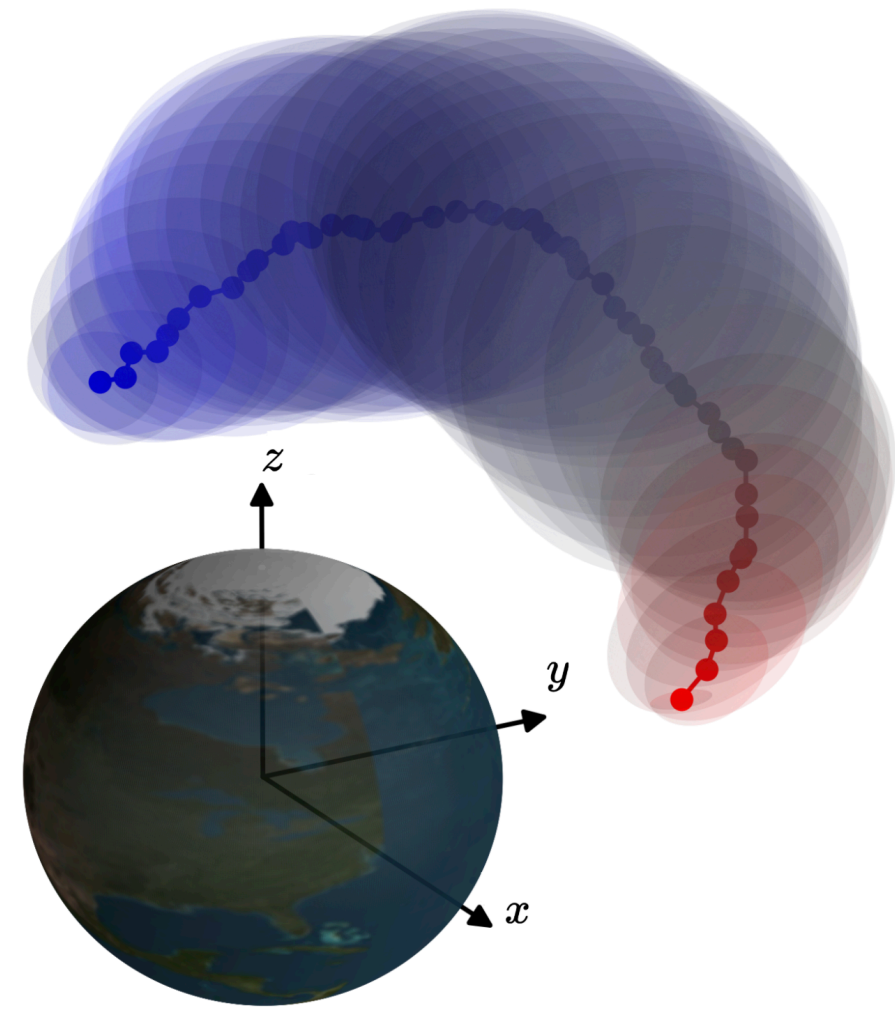
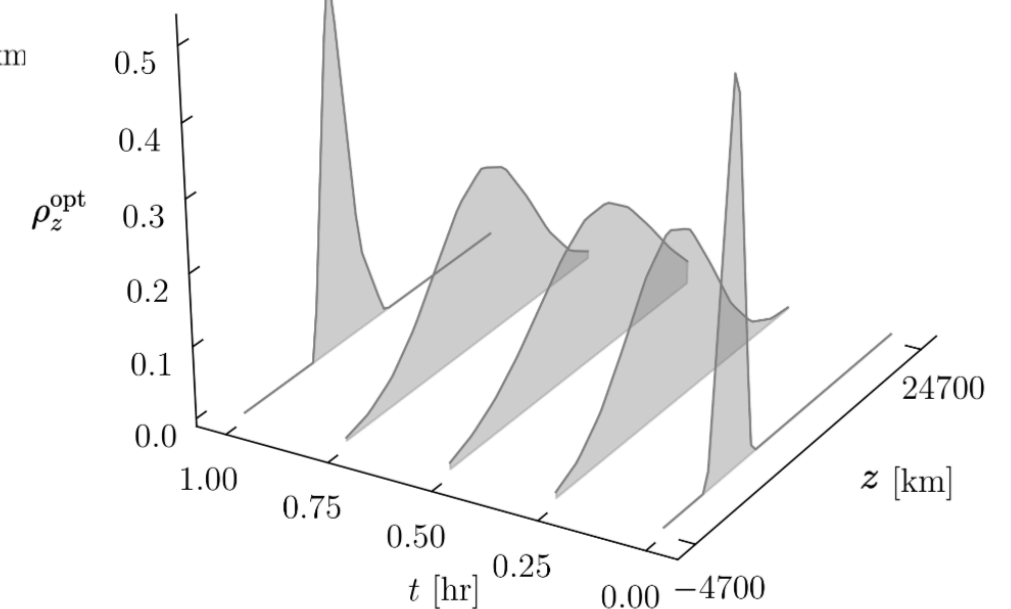
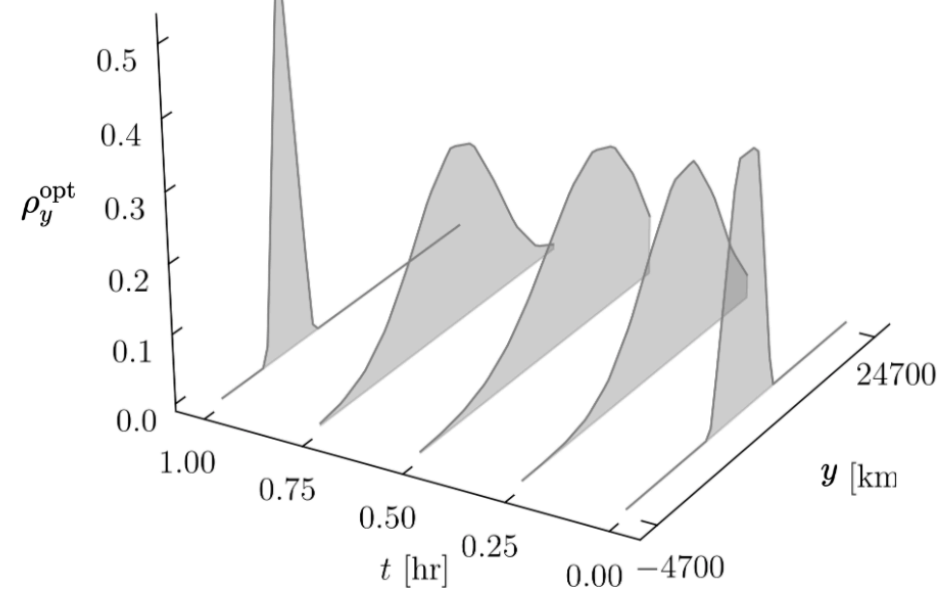
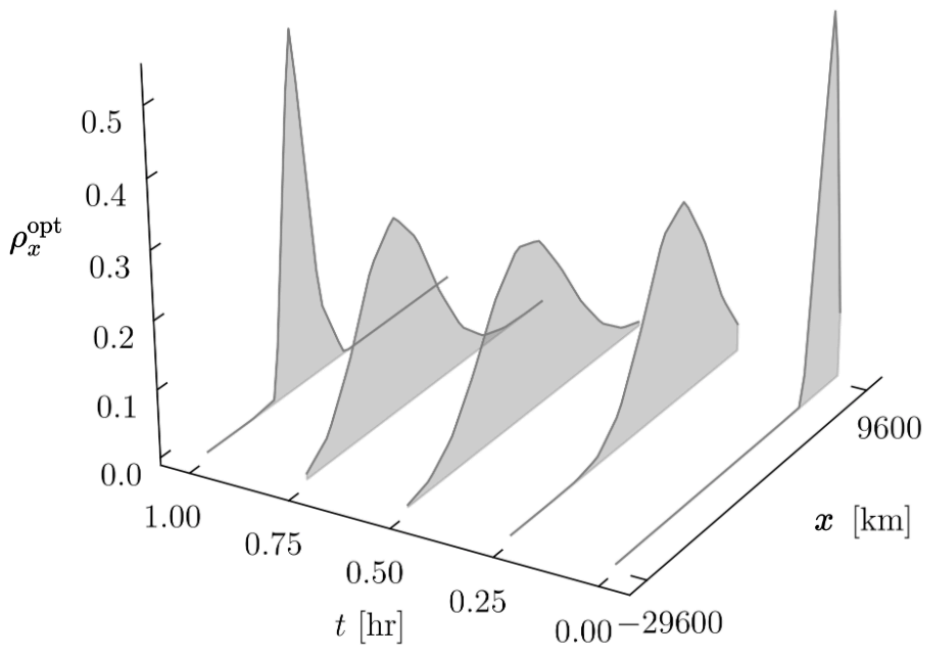
Numerical Case Study (cont.)

Optimally controlled closed loop state sample paths



Numerical Case Study (cont.)

Univariate marginals for optimally controlled joint PDFs



Ongoing Efforts

- Find explicit Green's function for reaction-diffusion PDE with reaction rate equal to gravitational potential
- Connections with solution of time-dependent Schrödinger's equation in quantum mechanics for Hydrogen atom

Thank You



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