

# Solution of the Probabilistic Lambert Problem: Optimal Transport Approach

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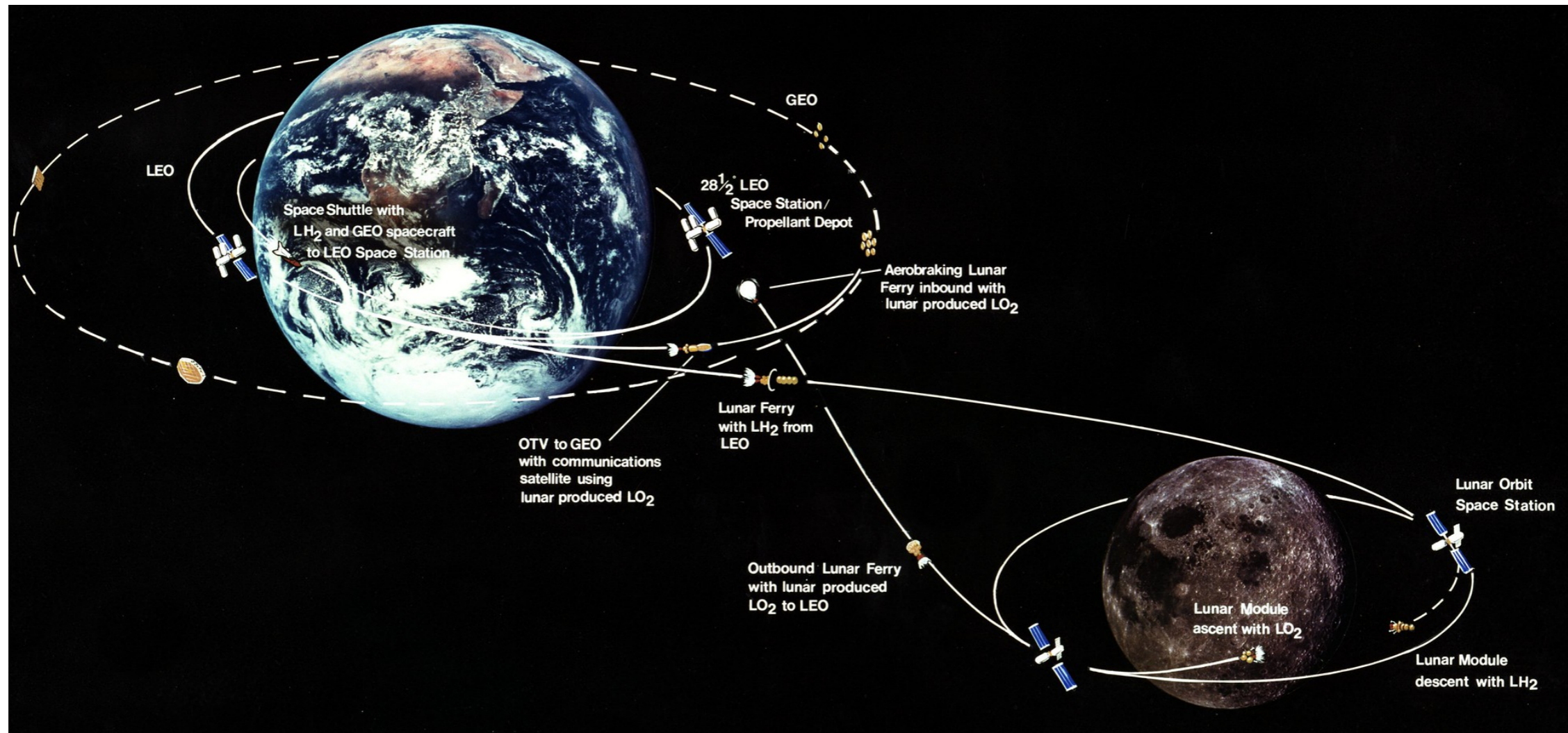
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# Lambert's Problem

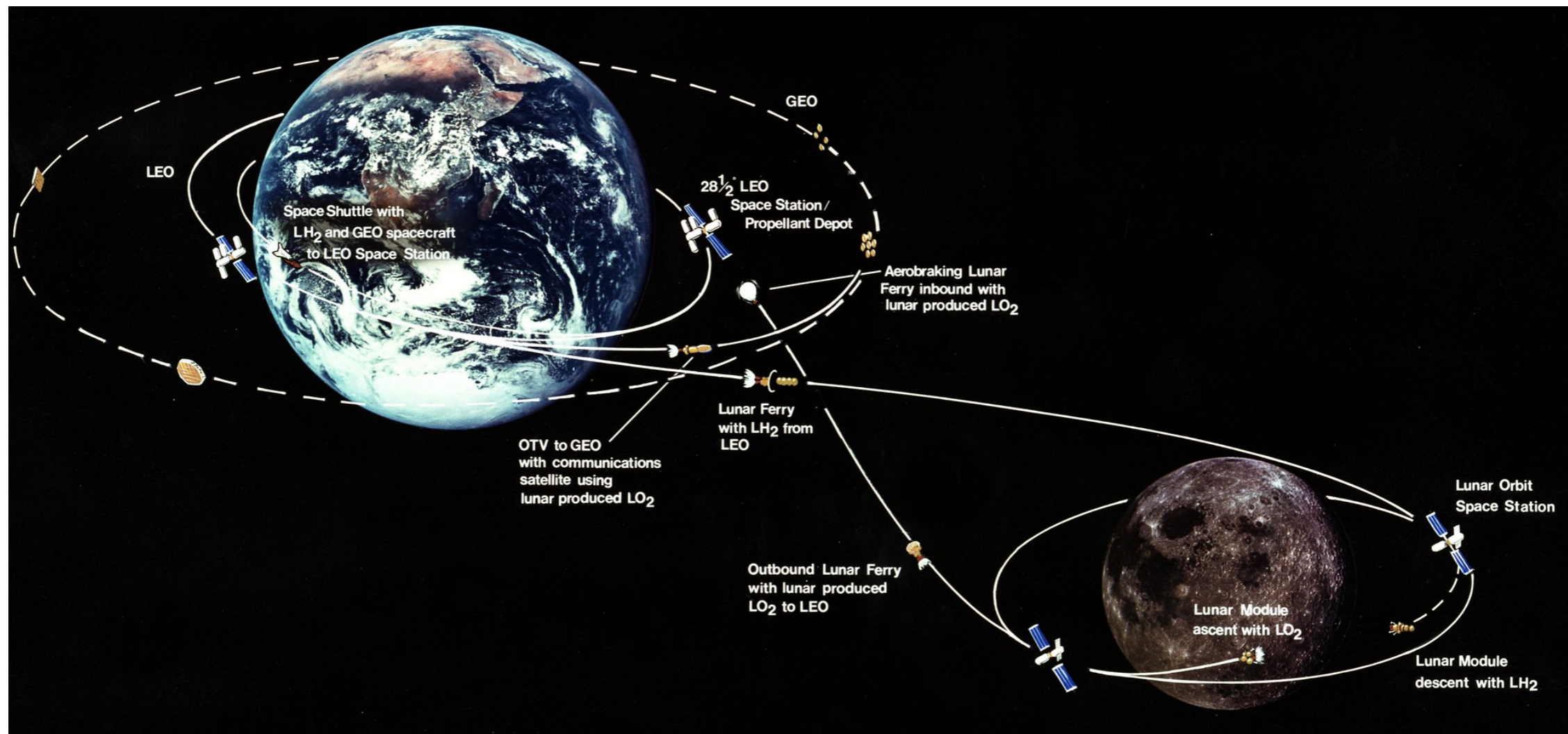


3D position coordinate  $\mathbf{r} := \begin{pmatrix} x \\ y \\ z \end{pmatrix} \in \mathbb{R}^3$

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



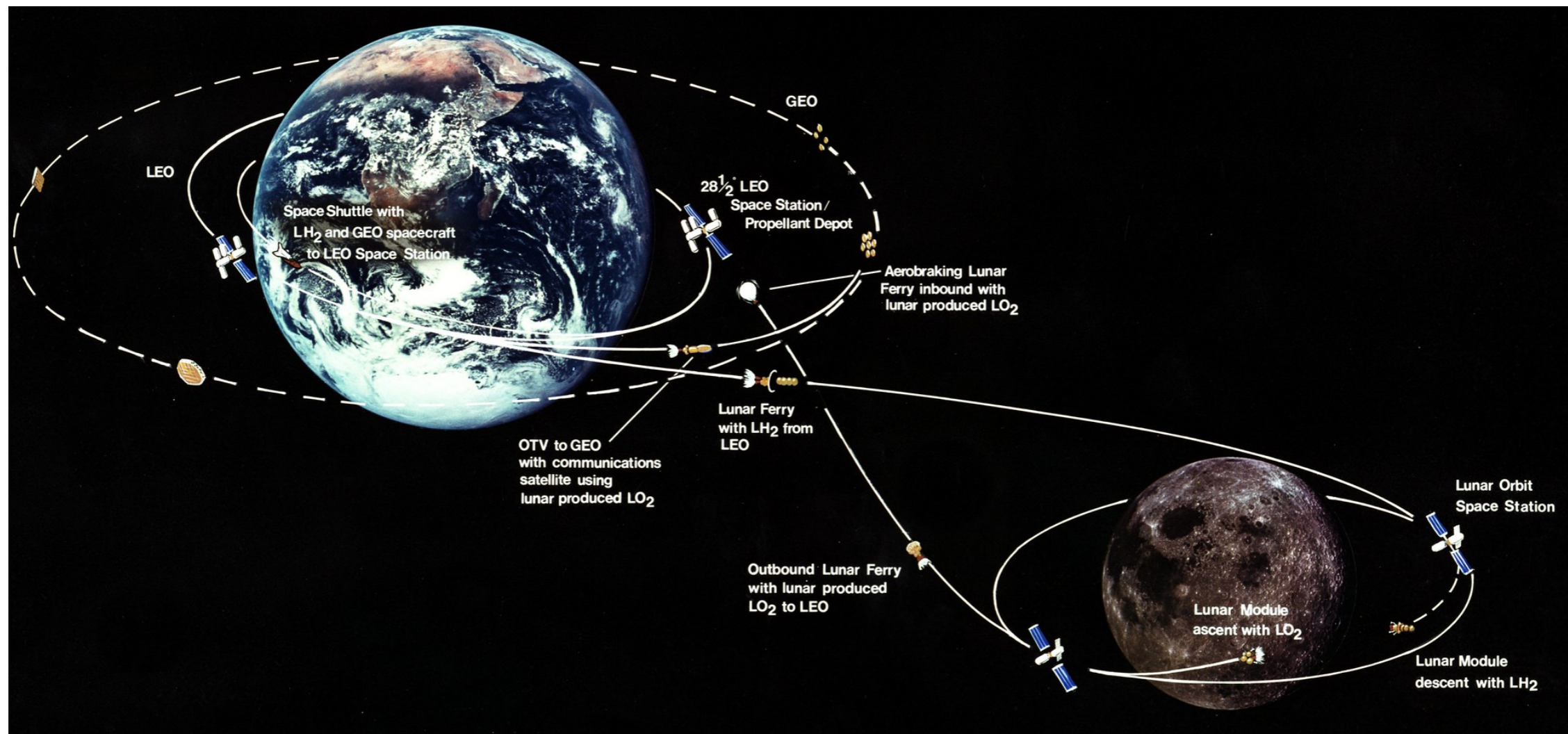
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**ODE is 2nd order but endpoint boundary conditions are first order**

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# Lambert's Problem



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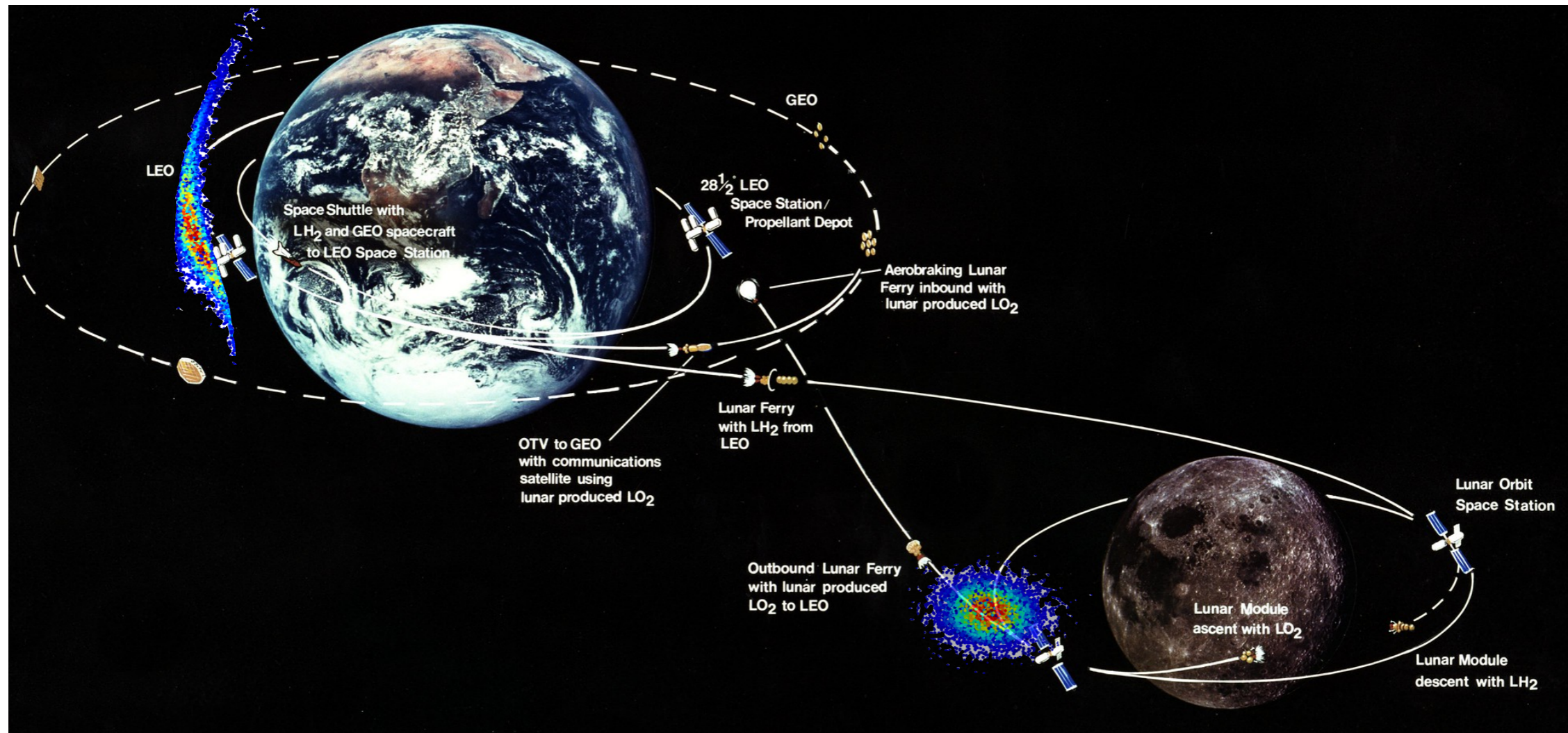
ODE is 2nd order but endpoint boundary conditions are first order

↪ 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

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

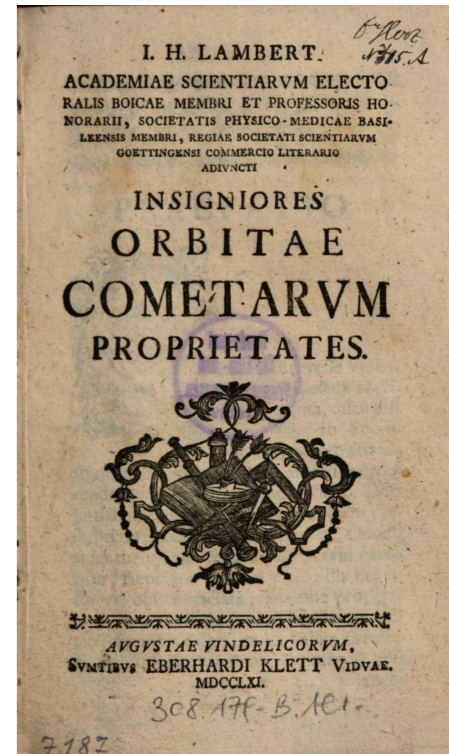
# The Beginning of Lambert's Problem



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

- known for first proof of irrationality of  $\pi$ , 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, J2 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

# 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  $\rho_0, \rho_1$  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

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

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

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

↯ **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**

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

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

# 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)

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

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

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

# 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

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

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

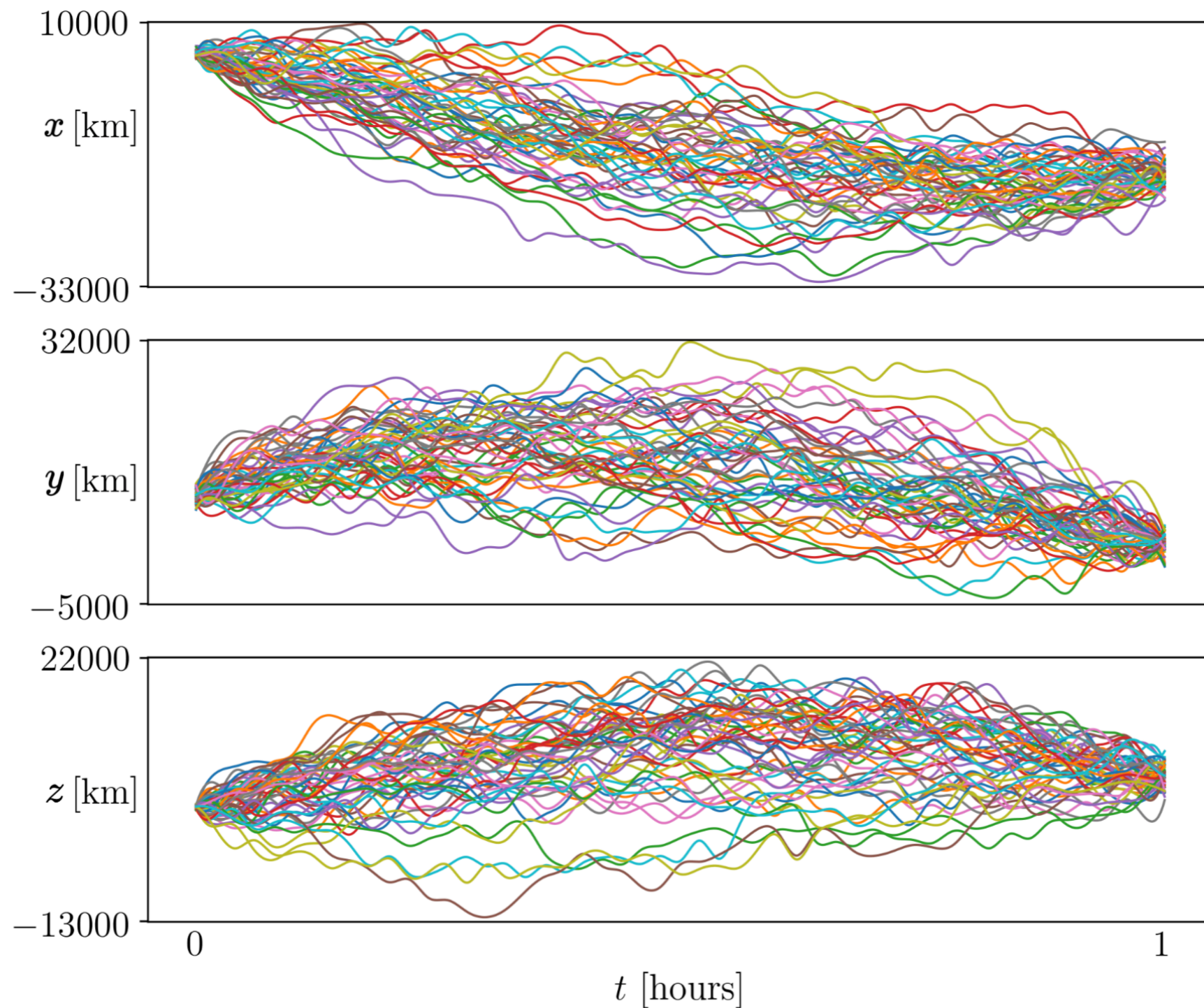
where

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

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

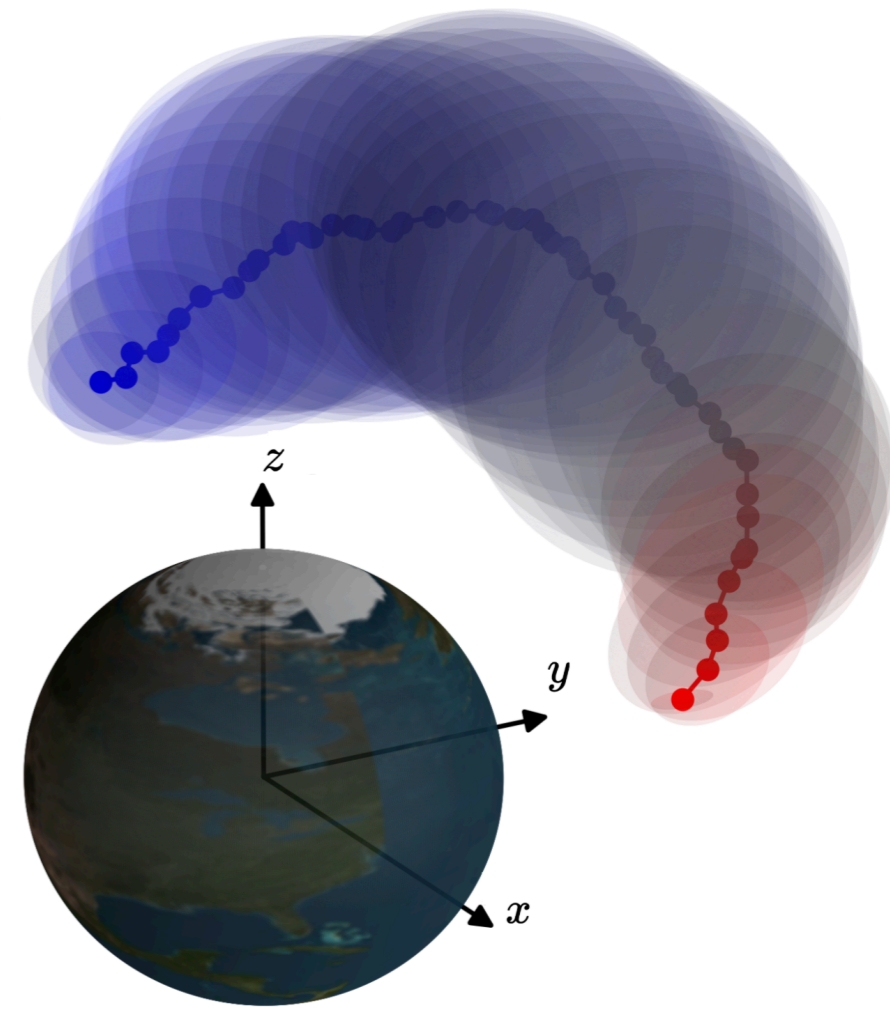
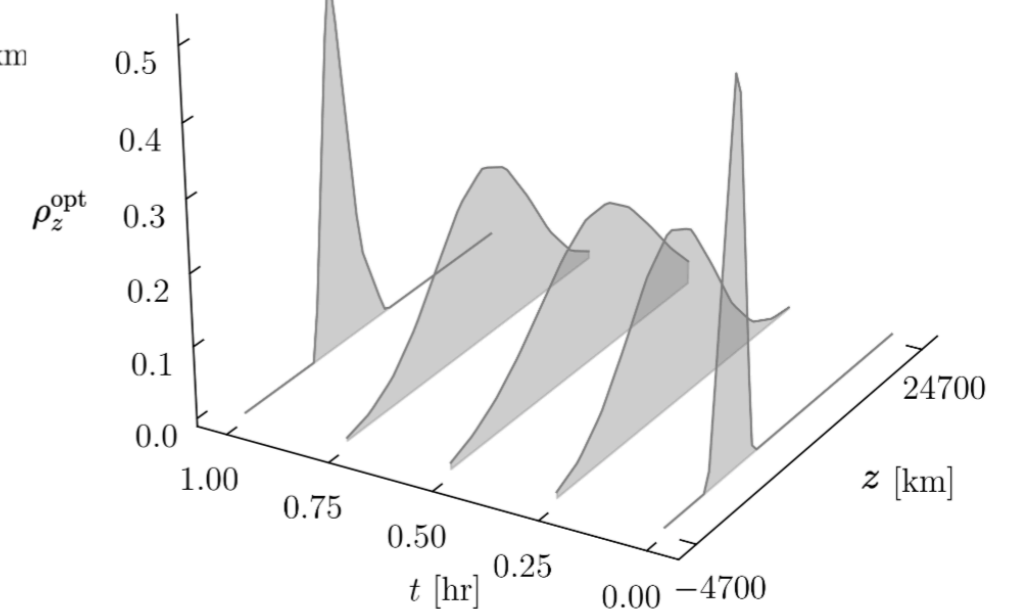
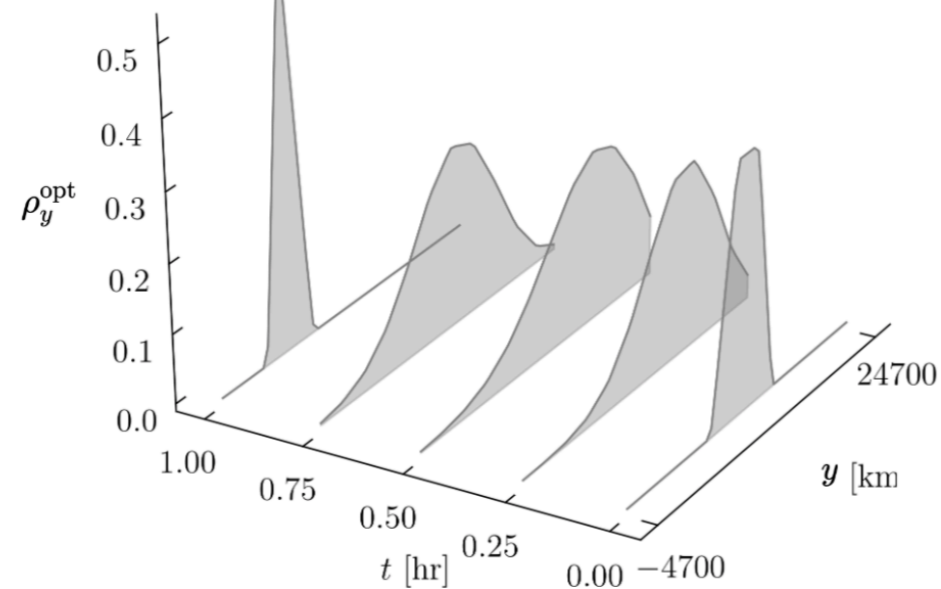
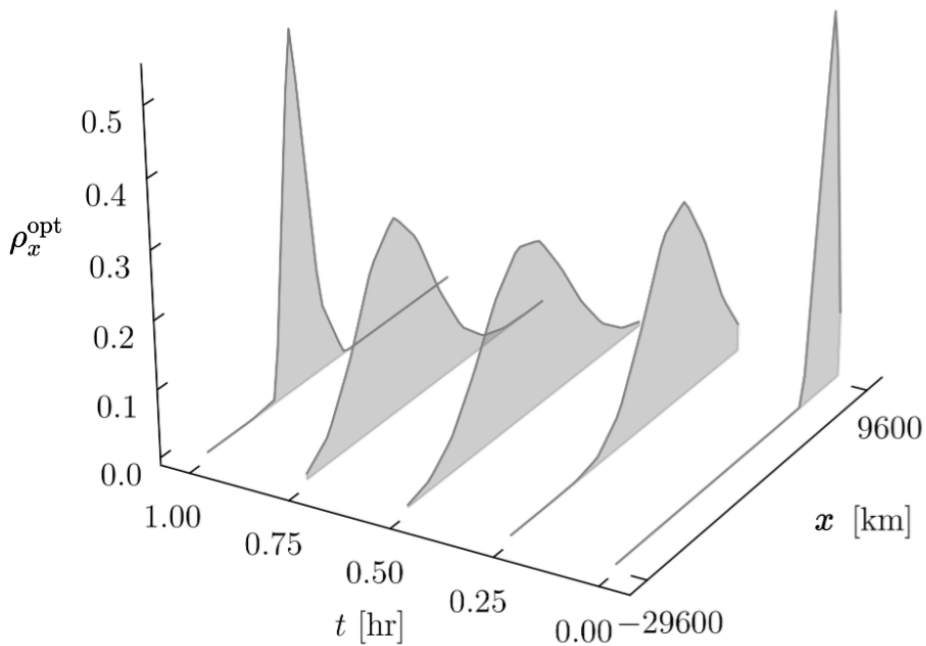
# Numerical Case Study (cont.)

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
- Preprint with L-OMT and L-SBP details: [arXiv:2401.07961](https://arxiv.org/abs/2401.07961)

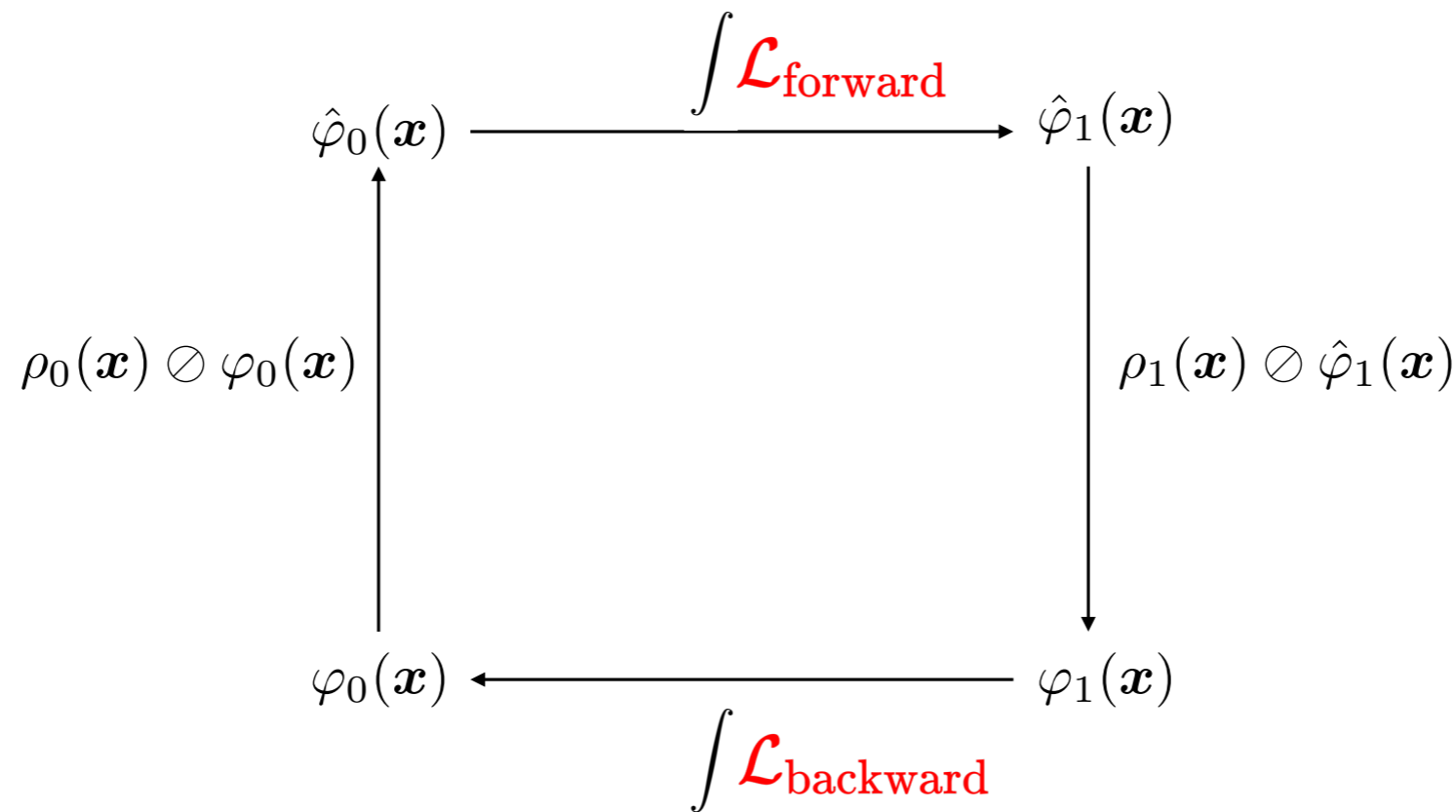


**Thank You**

# Backup Slides

# L-SBP Solution: Computation

IDEA: Fixed point recursion over pair  $(\varphi_1, \hat{\varphi}_0)$



**Thm. (Existence-uniqueness-convergence)** Proof by contraction mapping

**Thm.**  
(Fredholm Integral  
Representation)

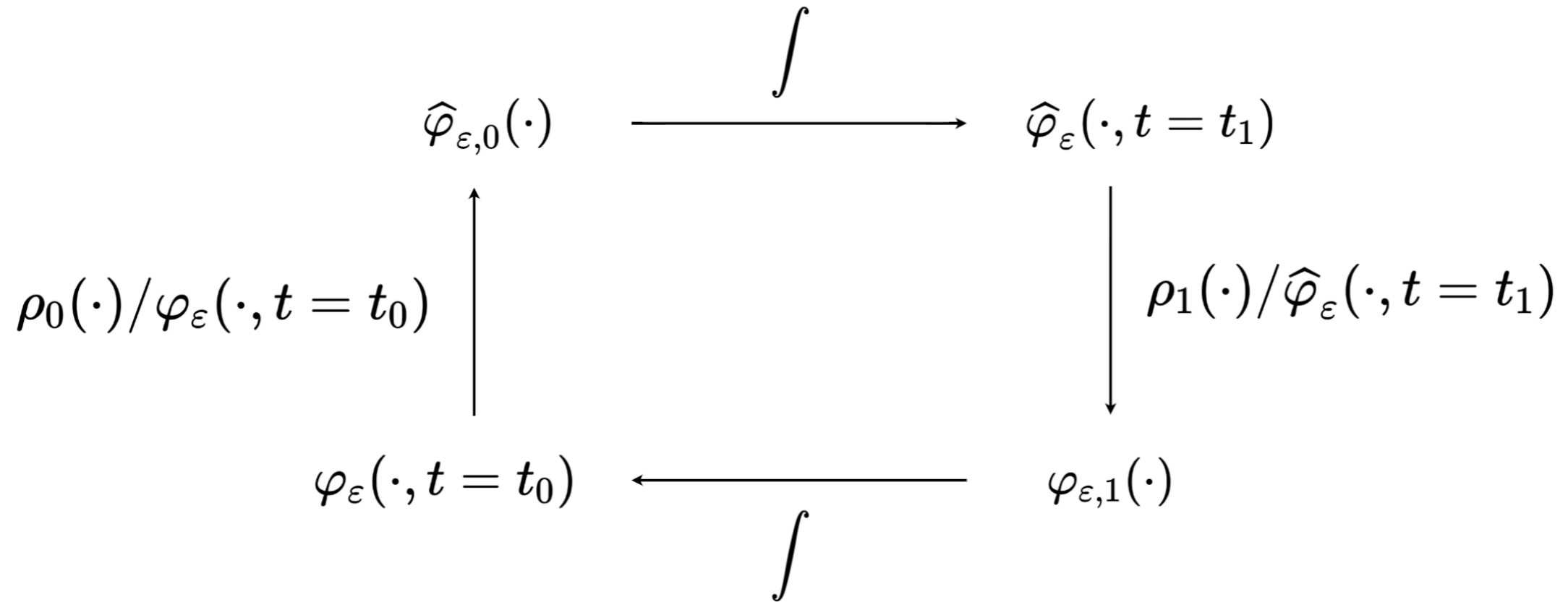
$$\hat{\varphi}(t, \mathbf{x}) = \underbrace{\frac{1}{\sqrt{(4\pi\epsilon t)^3}} \int_{\mathbb{R}^3} \exp\left(-\frac{\|\mathbf{x} - \mathbf{y}\|_2^2}{4\epsilon t}\right) \hat{\varphi}_0(\mathbf{y}) \, d\mathbf{y}}_{\text{term 1}}$$

$$+ \underbrace{\int_0^t \frac{1}{\sqrt{(4\pi\epsilon(t-\tau))^3}} \int_{\mathbb{R}^3} \exp\left(-\frac{\|\mathbf{x} - \mathbf{y}\|_2^2}{4\epsilon(t-\tau)}\right) V(\mathbf{y}) \hat{\varphi}(\tau, \mathbf{y}) \, d\mathbf{y} \, d\tau}_{\text{term 2}}$$

Likewise for  $\varphi(t, \mathbf{x})$

# Solution: Computation

IDEA: Fixed point recursion over pair  $(\varphi_1, \hat{\varphi}_0)$



**Idea:**  
**Left Riemann**  
**Approximation**  
**of Second Term**

$$\begin{aligned}
 & \int_{t_0}^{t_1} \int_{\mathbb{R}^n} f(\tilde{\mathbf{x}}, \mathbf{x}, \tau, t) d\tilde{\mathbf{x}} d\tau \\
 & \approx \sum_{q=0}^{k-1} \sum_{m=0}^{N_x} \sum_{n=0}^{N_y} \sum_{j=0}^{N_z} f(\tilde{\mathbf{x}}_{(m,n,j)}, \mathbf{x}, t_0 + k\Delta t, t) \Delta z \Delta y \Delta x \Delta t
 \end{aligned}$$

$$\text{where } \tilde{\mathbf{x}}_{(m,n,j)} = (x_0 + \Delta x, y_0 + \Delta y, z_0 + \Delta z)$$