Optimal Transport Augmented Weak Collocation Regression Parameter Identification For Chaotic Dynamics Via Invariant Mesure

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1 Dynamic System Setting

Noisy observations are denoted as

$$\mathbf{X}^* = (\mathbf{x}^*(t_0) + \eta_0, \mathbf{x}^*(t_1) + \eta_1, \dots, \mathbf{x}^*(t_n) + \eta_n)$$
(1)

where x^* is the solution of the autonomous dynamical system of $\dot{x} = v(x, \theta^*)$, and $\{\eta_0, \eta_1, \dots, \eta_n\}$ are the measurement errors or uncertainties.

We suppress the time variable and consider the state-space distribution of data

$$\rho^* = \frac{\sum_{i=0}^n \delta_{x^*(t_i)}}{n+1} \tag{2}$$

The dynamic system admits a physical measure $\rho(\theta)$ if for a Lebesgue positive set of initial condition x(0) = x, one has that

$$\rho(\theta) = \lim_{T \to \infty} \frac{1}{T} \int_0^T \delta_{x(t)} dt \tag{3}$$

Mathematically, statistical properties of can be characterized by the occupation measure $\rho_{x,T}$ defined as

$$\rho_{x,T}(B) = \frac{1}{T} \int_0^T \mathbf{1}_B(\mathbf{x}(s)) \, ds = \frac{\int_0^T \mathbf{1}_B(\mathbf{x}(s)) \, ds}{\int_0^T \mathbf{1}_{\mathbb{R}^d}(\mathbf{x}(s)) \, ds} \tag{4}$$

where B is any Borel Measurable set. If there exist an invariant measure ρ such that aull $\rho_{x,T}$ weakly converges to ρ for all initial condition, then ρ is an physical measure.

By definition of physical measures μ^* , we have

$$\lim_{T \to \infty} \frac{1}{T} \int_0^T f(x(t)) dt = \int_{\mathbb{R}^d} f(x) d\mu^*(x), \quad f \in C_c^{\infty}(\mathbb{R}^d)$$
 (5)

By taking $f(x) = \nabla \phi(x) \cdot v(x)$ for some $\phi \in C_c^{\infty}(\mathbb{R}^d)$

$$\begin{split} \int_{\mathbb{R}^d} & \nabla \; \phi(x) \cdot v(x) \, d \, \mu^*(x) = \lim_{T \to \infty} \frac{1}{T} \int_0^T \! \nabla \; \phi(x(t)) \cdot v(x(t)) \, d \, t = \lim_{T \to \infty} \frac{1}{T} \int_0^T \! \nabla \; \phi(x(t)) \cdot \dot{x}(t) \, d \, t \\ &= \lim_{T \to \infty} \frac{1}{T} \left(\phi(x(T)) - \phi(x(0)) \right) = 0 \end{split}$$

This shows that μ^* is the stationary distributional solution

$$\nabla \cdot (v(x,\theta)\rho(x,\theta)) = 0. \tag{7}$$

2 Weak Collocation Regression

- 3 Regularization Method
- 3.1 Polynomial regularization
- 3.2 Diffusion regularization

4 Optimal Transport Model Refinement

Obtaining the sparse identification of parameters in library, we use a forward based parameter identification method to refine the estimation. Indeed, we perform the following steps:

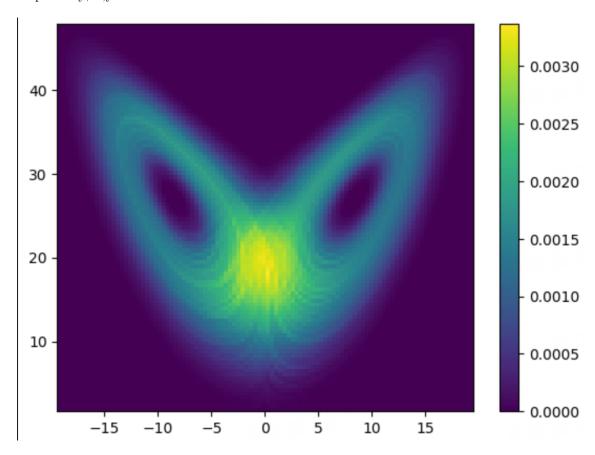
- 1. Sample batch data from noisy observation $\{x_i\}_{i=1}^{\text{batch}} \sim \mathbf{X}$ to construct emperical density estimation $\rho_{\text{batch},0} = \sum_{i=1}^{\text{batch}} \frac{\delta_{x_i}}{\text{batch}}$ for initial time
- 2. Compute $\rho_{\text{batch},T} = \text{ODESolve}(f(x,\theta), \rho_{\text{batch},0}, T)$ by odesolver like RK4
- 3. Compute Sliced Wasserstein Loss Loss = $SWD(\rho_{batch,T}, \rho_{batch,0})$ and obtain gradient
- 4. Normalized the source term $f(x, \theta)$

5 Experiment

- 5.1 ODE System
- 5.2 Lorentz System

$$\begin{cases} \dot{x} = \sigma(y-x) \\ \dot{y} = x(\rho-z) - y \\ \dot{z} = xy - \beta z \end{cases}$$

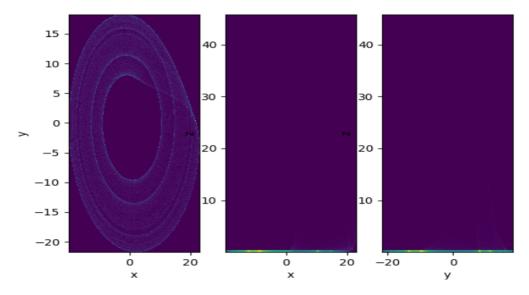
Here $\sigma = 10$, $\rho = 28$, $\sigma = 8/3$, initial condition is [1,1,5], T = 20000, dt = 0.01. the projection of density map wrt xy,xz,yz direction is below.



5.3 Rossler System

$$\begin{cases} \dot{x} &= -y-z \\ \dot{y} &= x+\mathrm{ay} \\ \dot{z} &= b+z(x-c) \end{cases},$$

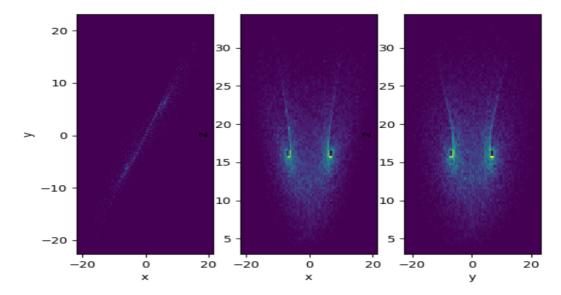
Here a=0.1, b=0.1, c=14. initial condition is [2,2,5], T=20000, dt=0.01..the projection of density map wrt xy,xz,yz direction is below.



5.4 Chen System

$$\begin{cases} \dot{x} &= a(y-x) \\ \dot{y} &= (c-a)x - \mathbf{xz} + \mathbf{cy} \\ \dot{z} &= \mathbf{xy} - \mathbf{bz} \end{cases}$$

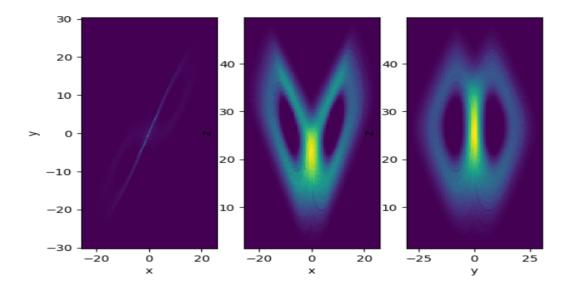
Here a=40, b=3, c=28. initial condition is [2,2,5], T=20000, dt=0.01.the projection of density map wrt xy,xz,yz direction is below.



5.5 Arctan Lorentz System

$$\begin{cases} \dot{x} &= 50 \mathrm{arctan} \left(\frac{\sigma(y-x)}{50} \right) \\ \dot{y} &= 50 \mathrm{arctan} \left(\frac{x(\rho-z)-y}{50} \right), \\ \dot{z} &= 50 \mathrm{arctan} \left(\frac{(\mathrm{xy}-\beta z)}{50} \right) \end{cases}$$

Here $\sigma = 10$, $\rho = 28$, $\sigma = 8/3$, initial condition is [1,1,5], T = 20000, dt = 0.01. the projection of density map wrt xy,xz,yz direction is below.



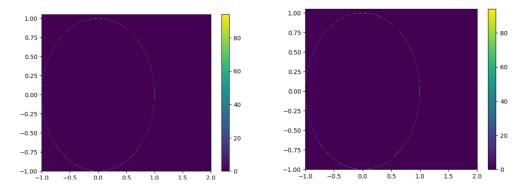
5.6 2D Periodic Attractor

$$\left\{ \begin{array}{ll} \dot{x} & = & x - y - (x^2 + y^2)x \\ \dot{y} & = & x + y - (x^2 + y^2)y \end{array} \right. ,$$

This is a planar system which has a unique closed orbit γ and is a periodic attractor.

Note that the phase chart of such equation is almost the same as

$$\left\{ \begin{array}{ll} \dot{x} & = & x - 0.3 \ y - (x^2 + y^2) x \\ \dot{y} & = & 0.3 x + y - (x^2 + y^2) y \end{array} \right. ,$$



we parametrize the equation as follow

$$\left\{ \begin{array}{ll} \dot{x} &=& x-y-\mathrm{ax}^3-\mathrm{bxy}^2\\ \dot{y} &=& x+y-\mathrm{cx}^2y-y^3 \end{array} \right.,$$

The reference result is [1,1,1,1]

5.7 Parameter Identification by WCR

Lorenz:

表格 1. Lorenz

Gauss Sigma sample Threshold Result Error $200 \quad 4 \quad lhs \quad 0.2 \quad (10.058,28.029,2.666) \quad 0.217\%$

https://wandb.ai/zhijunzeng/attractor_collect/runs/lorenz_parameter_inference_200?workspace=user-zhijunzeng

Rossler:

表格 2. Rossler

Gauss Sigma sample Threshold Result Error 200 4 lhs 0.01 (0.1039,0.0798,13.93)) 0.66%

https://wandb.ai/zhijunzeng/attractor_collect/runs/rossler_parameter_inference_200_0?workspace=user-zhijunzeng

Chen:

表格 3. Chen

Gauss Sigma sample Threshold Result Error 200 4 lhs 0.01 39.99,3.0,27.99 3.8e-5

Arctan lorenz:

表格 4. Arctan Lorenz

Gauss Sigma sample Threshold Result Error $2000 \ 1$ lhs $0.2 \ (9.995,28.001,2.663)$ 2e-4

https://wandb.ai/zhijunzeng/attractor_collect/runs/elb4mxmn?workspace=userzhijunzeng

Limit cycle:

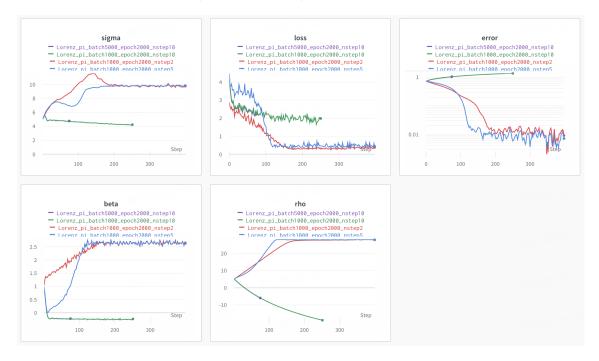
表格 5. Limit cycle

5.8 Parameter Identification by OT

https://wandb.ai/zhijunzeng/attractor_pi_contrastive?workspace=user-zhijunzeng

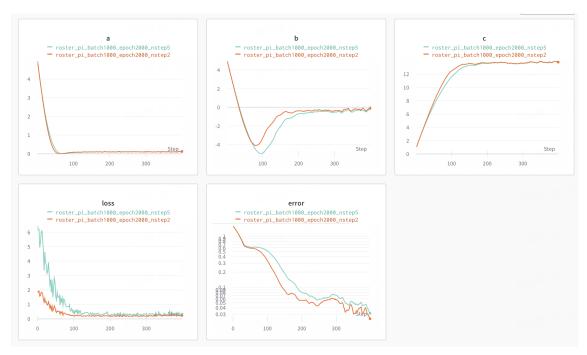
Lorenz:

表格 6. Lorenz

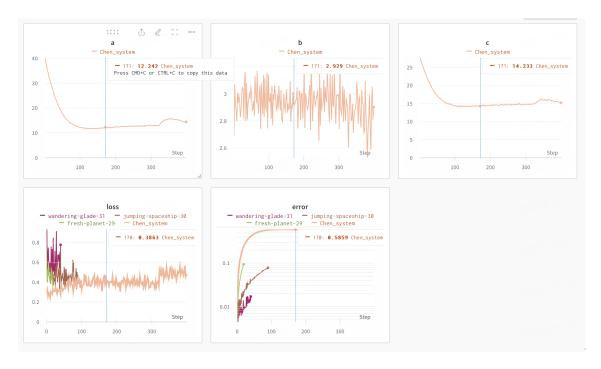


Rossler:

表格 7. Rossler

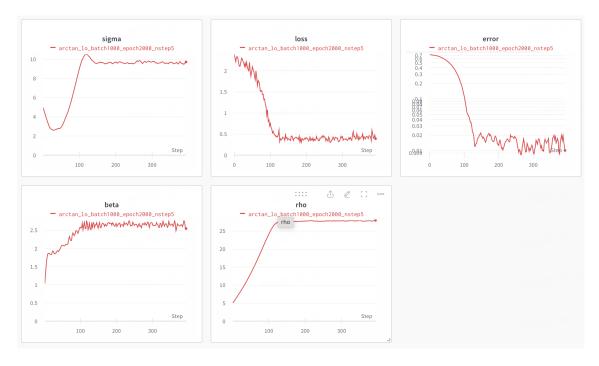


Chen:



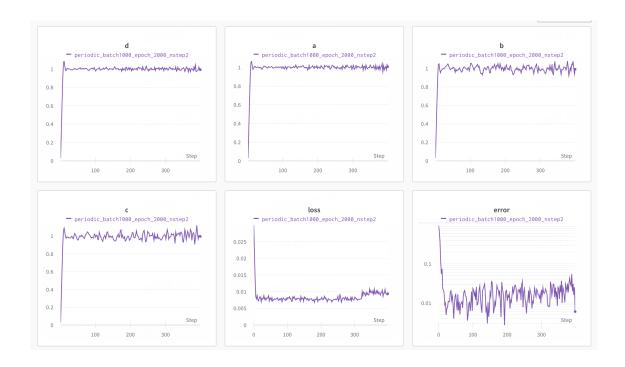
Arctan_lo:

表格 8. Arctan_lo



Periodic:

表格 9. Periodic



5.9 WCR polynomial regularization

Lorenz:

表格 10. Lorenz

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Gauss Sigma sample Threshold epsilon Error 300 \quad 4 \quad \text{lhs} \quad 0.1 \quad 0.1 \quad 0.213\%
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Rossler:

表格 11. Rossler

Gauss Sigma sample Threshold epsilon Error 300 4 lhs 0.05 0.1 1.04%

Chen:

表格 12. Chen

Gauss Sigma sample Threshold epsilon Error $300 ext{ 4}$ lhs $0.2 ext{ 0.1} ext{ 3.2}\%$

5.10 WCR diffusion regularization

Lorenz:

表格 13. Lorenz

Gauss Sigma sample Threshold epsilon Error 300 4 lhs 0.2 0.1 4.2%

Rossler:

表格 14. Rossler

Gauss Sigma sample Threshold epsilon Error 300 6 lhs 0.04 2 6.95%

Chen:

表格 **15.** Chen

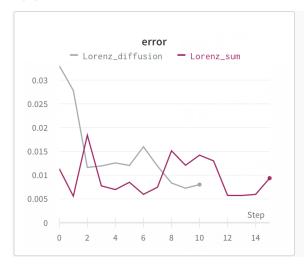
Gauss Sigma sample Threshold epsilon Error 300 5 lhs 0.5 2 6.83%

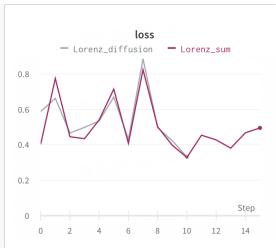
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https://wandb.ai/zhijunzeng/attractor_wcr_poly?workspace=user-zhijunzeng

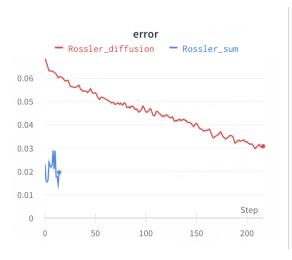
5.11 WCR+OT refinement

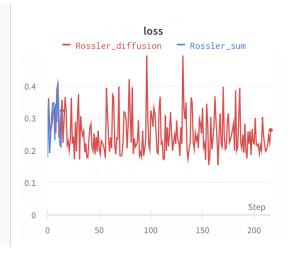
Lorenz





Rossler





Chen



