

Steady-state Solution for the Continuity Equation

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Background



Parameter Identification ¹:

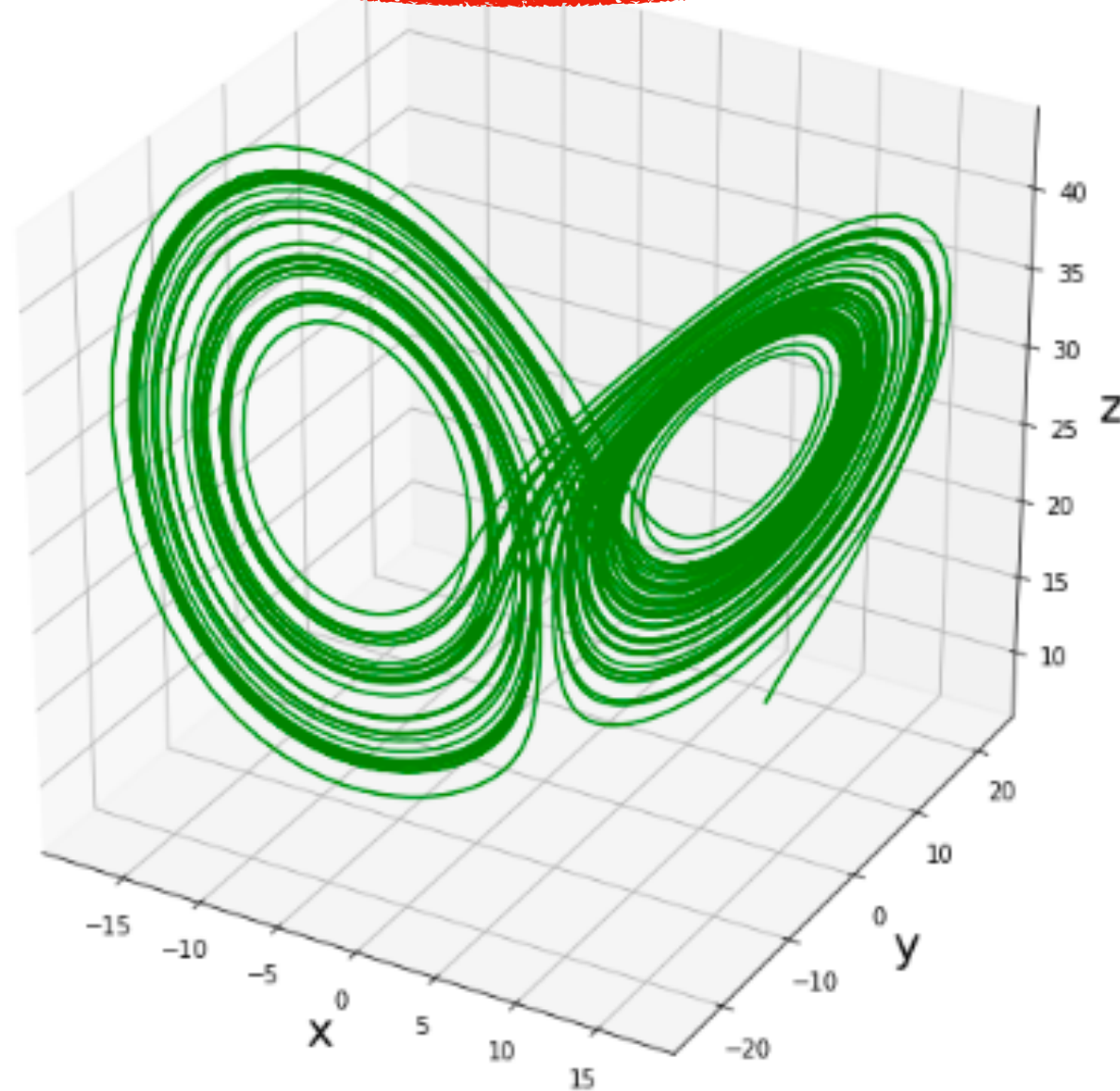
Given the **time trajectories** and
the dynamical system



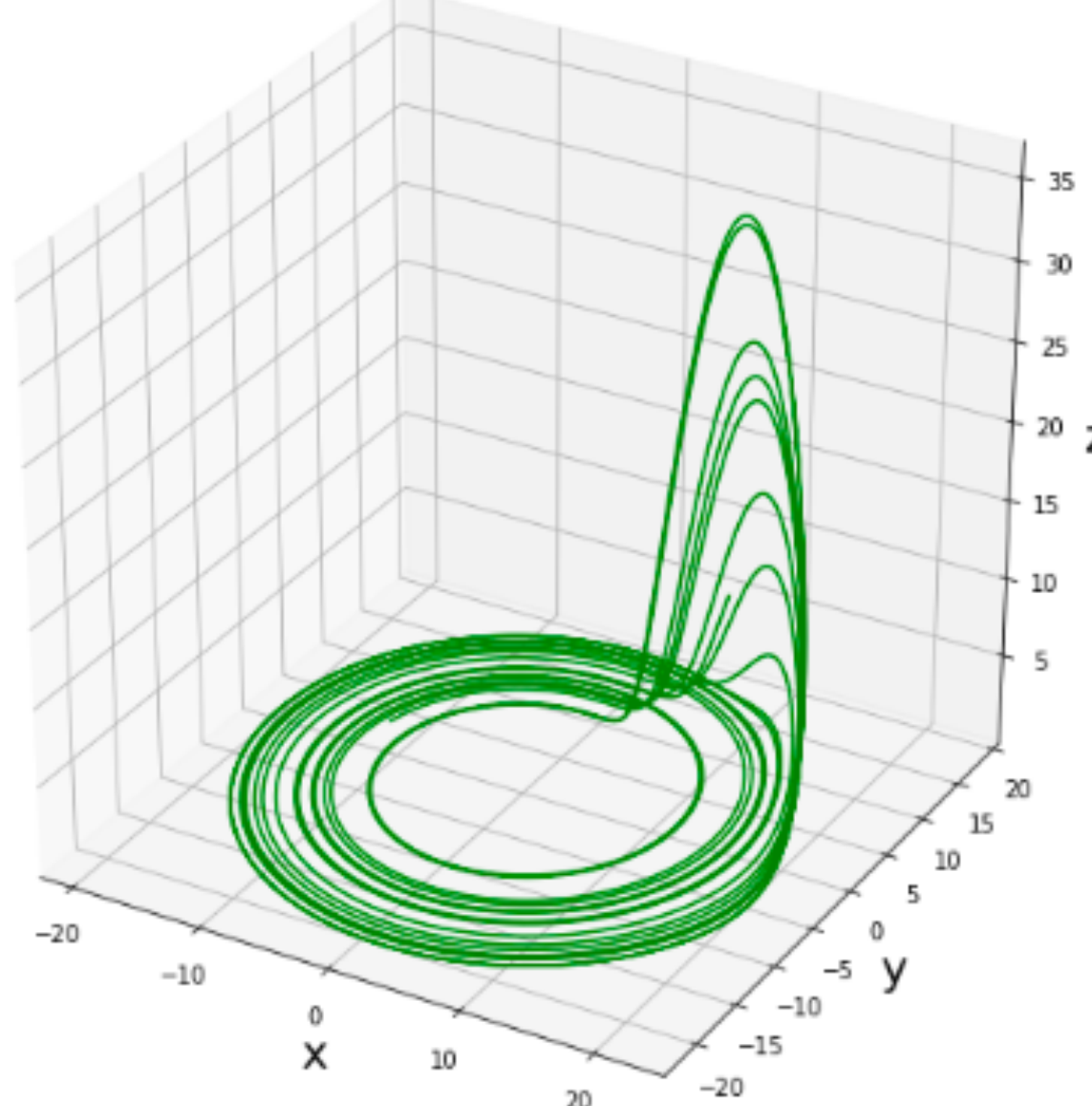
Adapt the parameters until the
model is close to **experimental data**

Chaotic Dynamical System

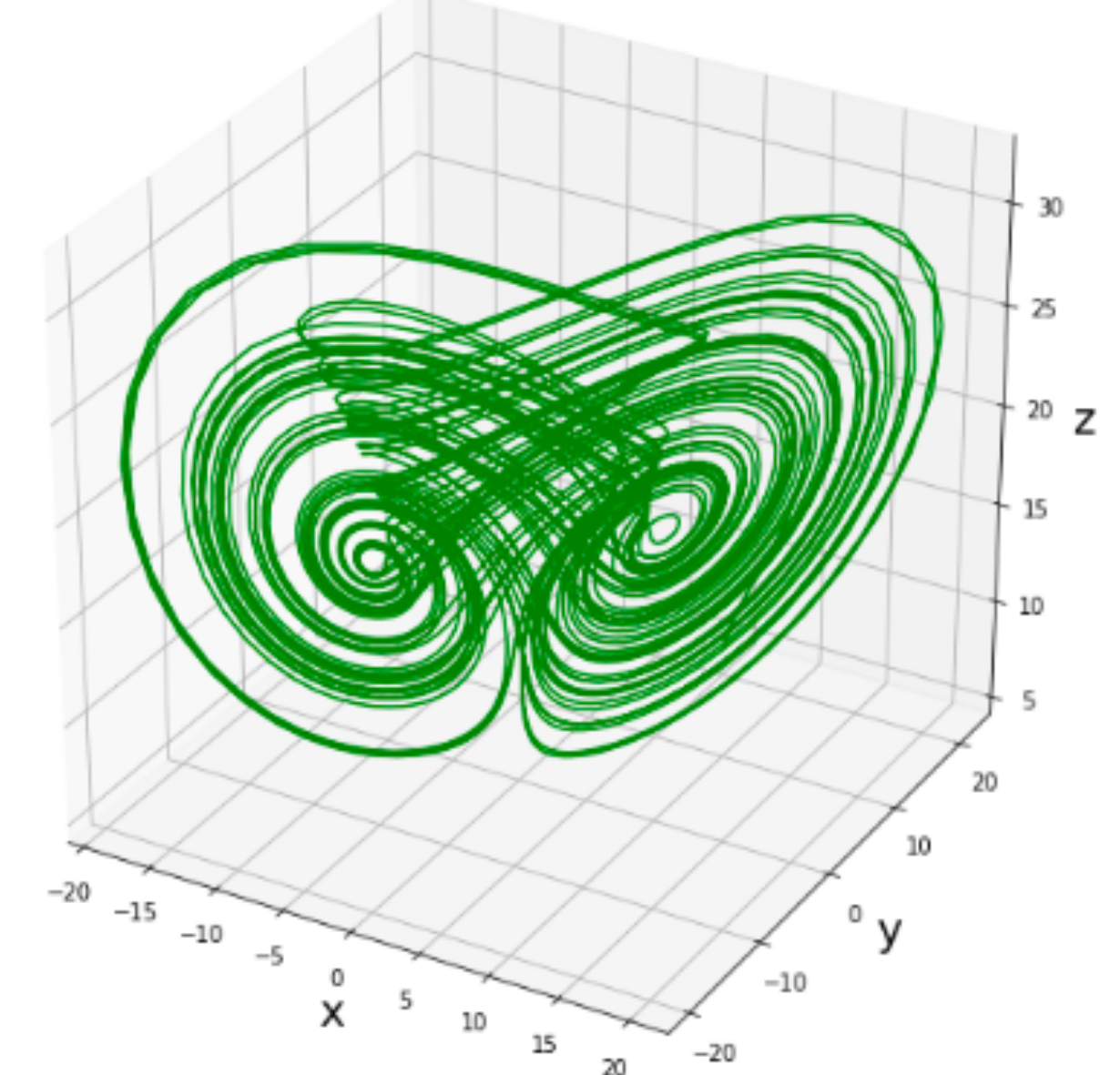
Lorenz Attractor



Rössler Attractor



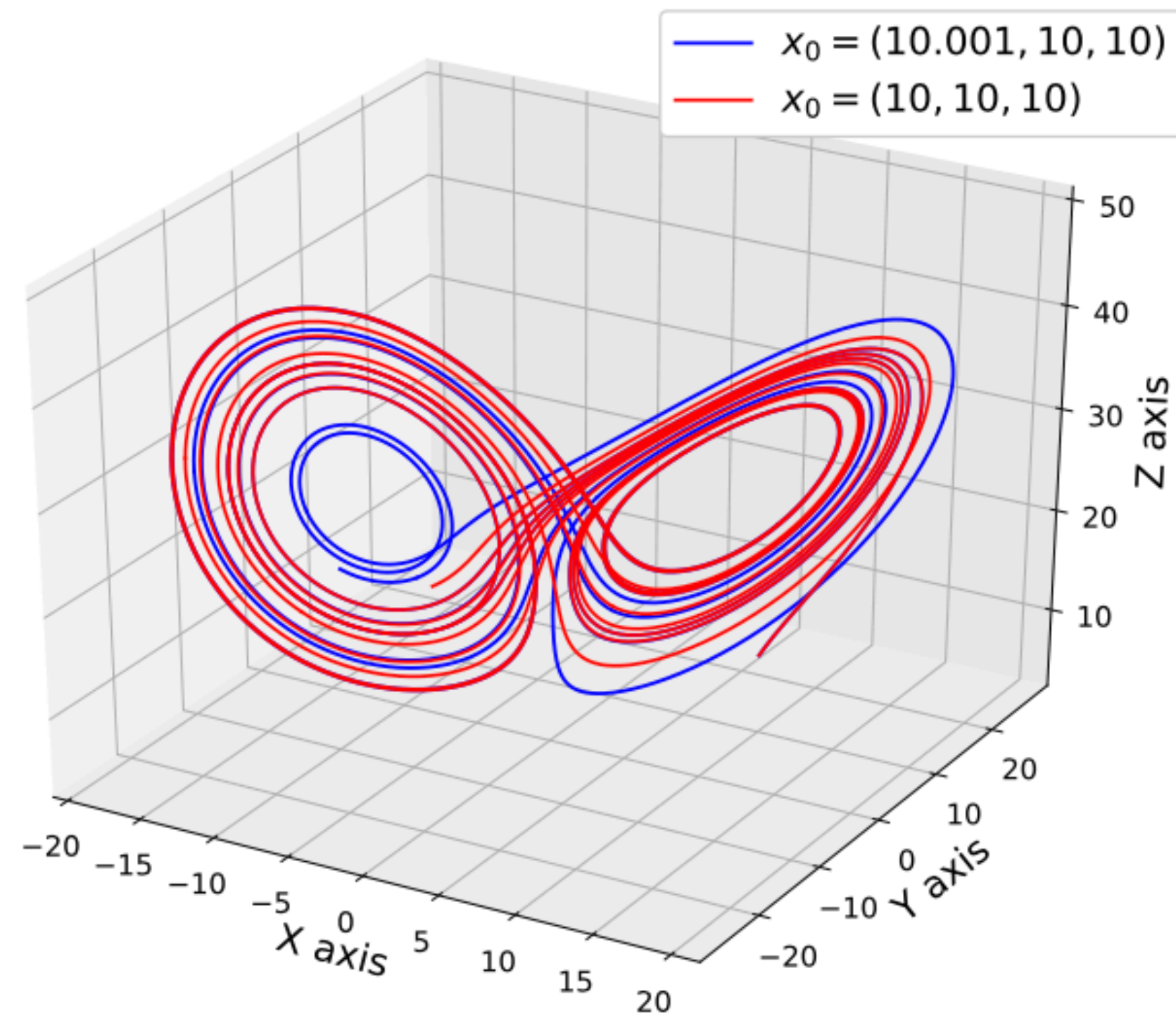
Chen Attractor



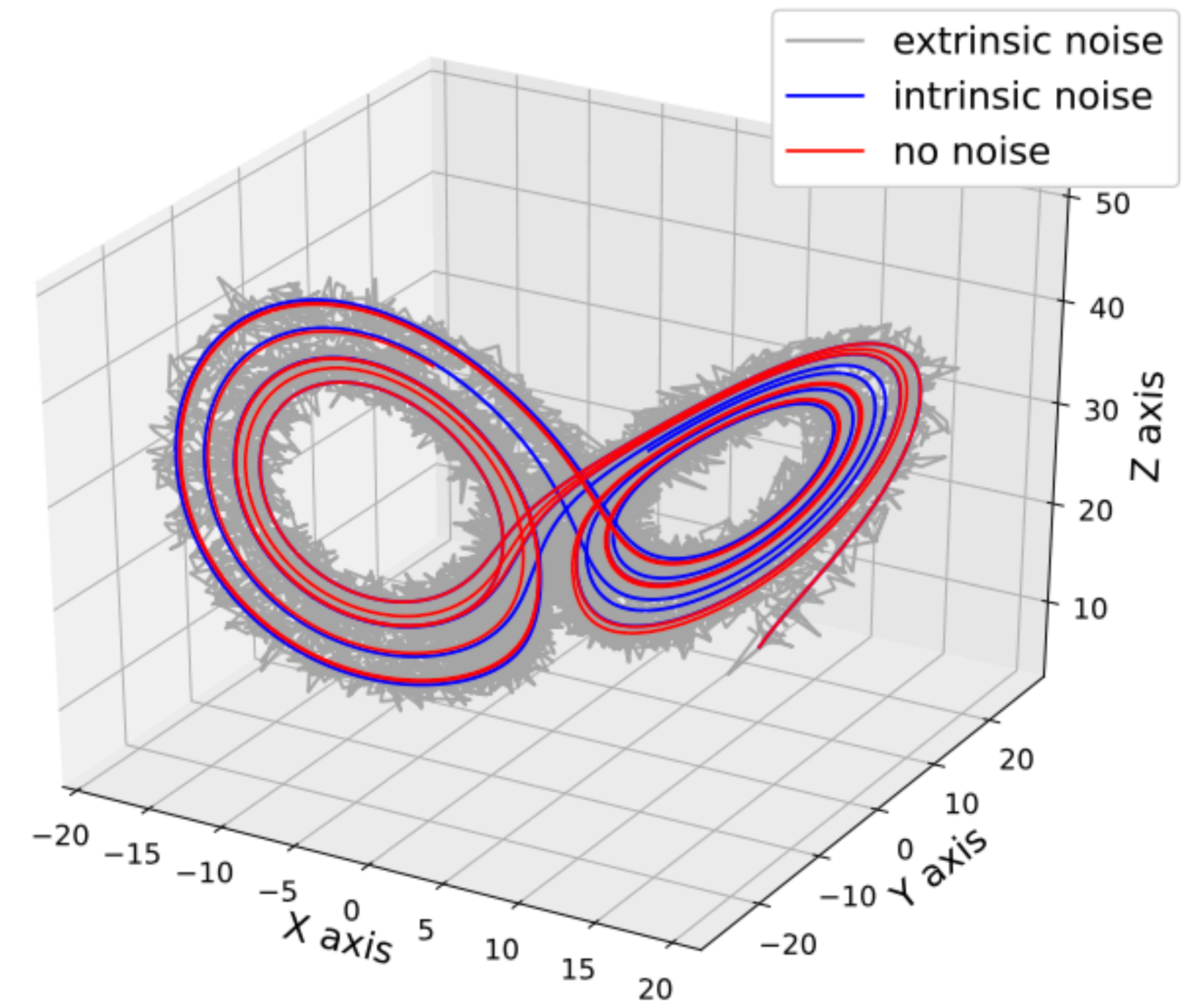
Background

- Challenges with Data-Driven Approaches:

1. Chaotic



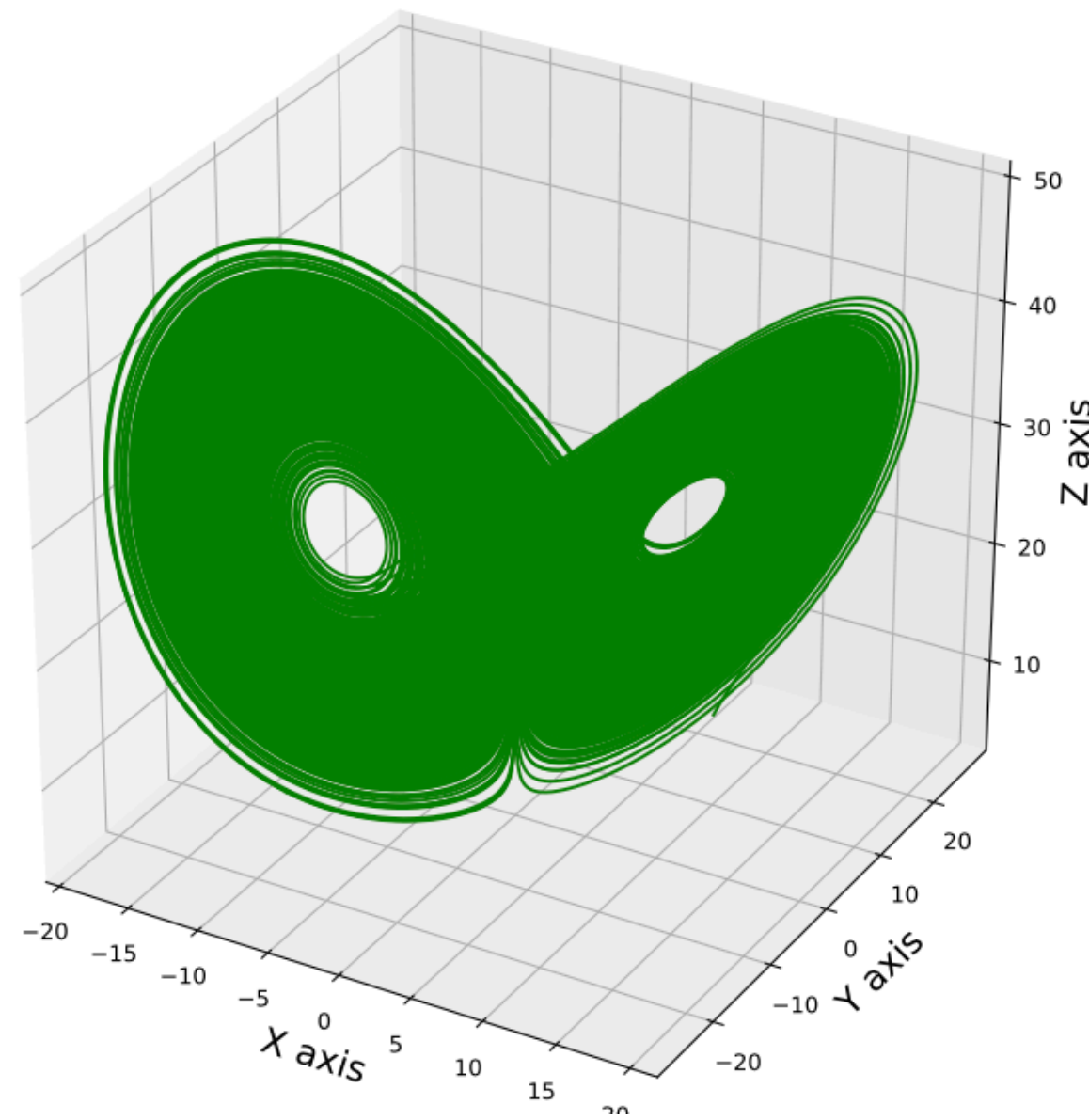
2. Noisy Measurements



How to avoid these disturbances?

Background

Lorenz system (without noise)



Solution	Past Challenges
<p>1. Occupation Measure: Time trajectory with a large T -> Histogram -> Density</p>	<p>Chaotic: invariant measure</p>
<p>2. Sinai–Ruelle–Bowen (SRB)²measure: $\frac{\partial \rho}{\partial t} = - \nabla (v(x, \theta) \rho(x, t)) = 0$ $\rho(x, t)$: probability density $v(x)$: the velocity function of variable x in t of the flux at x</p>	<p>Noisy Measurements: Computation</p>



Invariant Measure:

A measure μ is said to be invariant under the flow map f if, for every measurable set A in Σ ,

$$\mu(f^{-1}(A)) = \mu(A)$$



Steady-State:

$$\frac{\partial \rho}{\partial t} = - \nabla (v(x, \theta) \rho(x, t)) = 0$$

Background

Original Problem (ODE)

Given the **time trajectories** and the **dynamical system**, reconstruct the parameter.



Current Problem (PDE)

Given the observed **invariant measure** and the **Continuity equation**, reconstruct the parameter.

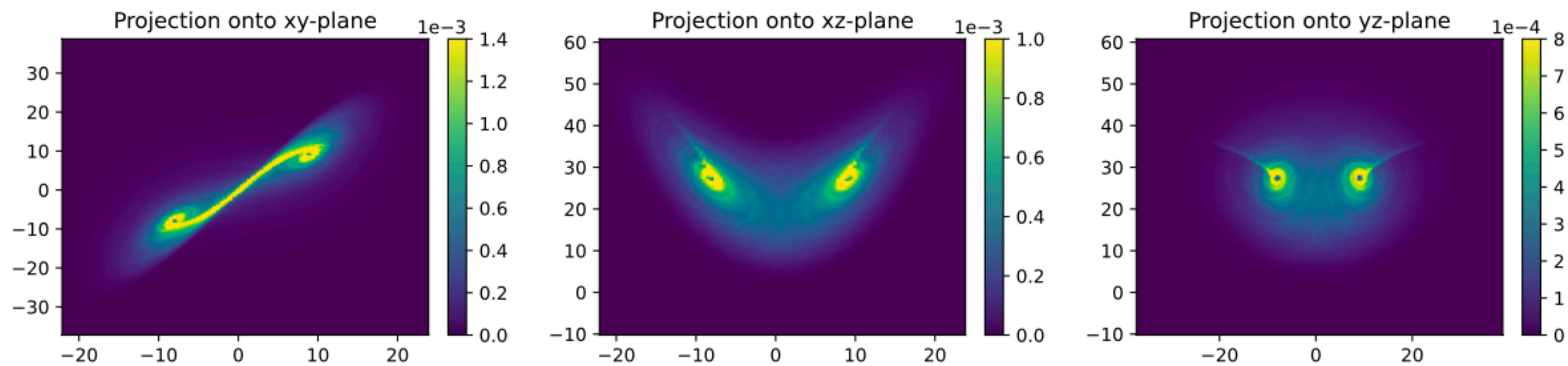
“We treat the parameter identification problem for the dynamical system as a **PDE-constrained optimization problem**¹:”

$$\theta = \underset{\theta}{\operatorname{argmin}} d(\rho^*, \rho(\theta)), \quad \text{s.t.} \quad \frac{\partial \rho}{\partial t} = -\nabla \cdot (v(x, \theta)\rho(x, t)) = 0$$

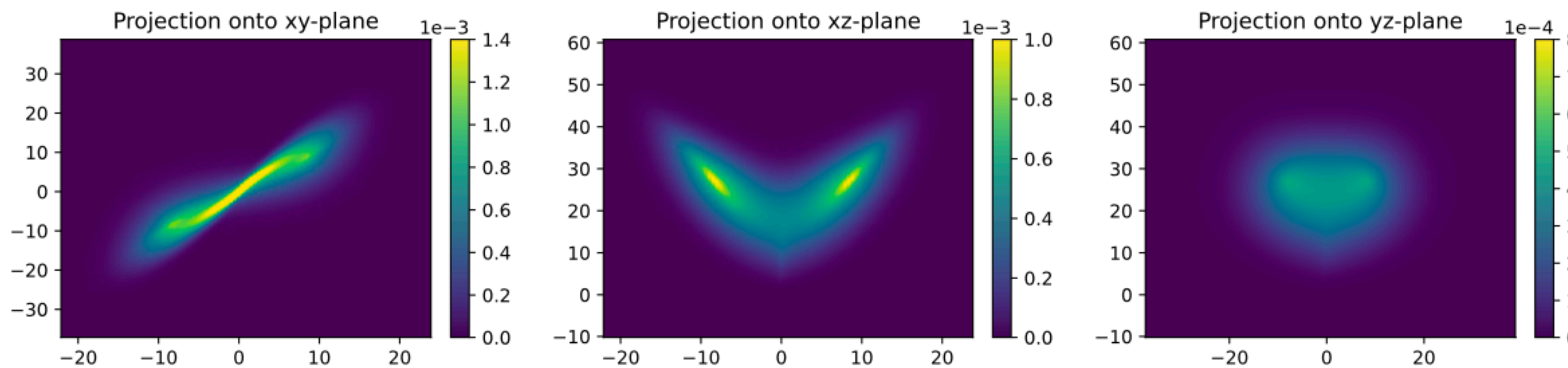
$v(x)$: the velocity function of x

$\rho(\theta)$: the steady-state solution of the continuity equation ρ^* : the observed invariant measure converted from time trajectories

Motivation



Histogram accumulated from **Lorenz system** time trajectory



Steady-state solution

Objective

Accuracy Improvement

1. Construct the solver with the **first-order finite volume split** discretization and the **Upwind Method** on a d-dimensional mesh in space and **time**.
2. **Improve the solver with corner transport.**
3. Derive the steady-state solution from the resulted matrix.

#1 First-Order Standard Upwind

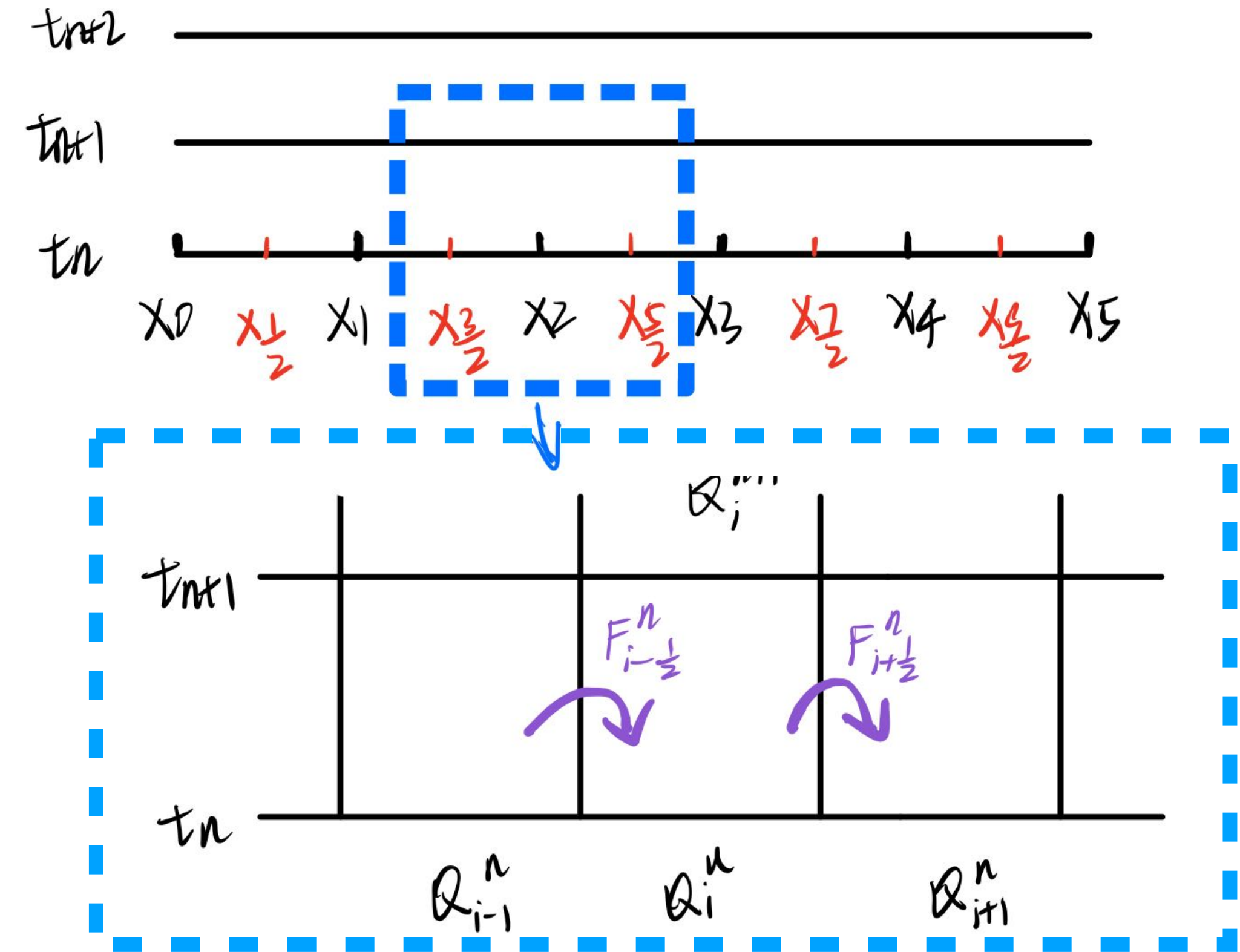
- Step 0: 1D

$$\frac{\partial \rho}{\partial t} + \frac{\partial}{\partial x}(v(x)\rho(x, t)) = 0$$

- Step 1: Spatial Domain -> Intervals⁴

$$Q_i^n \approx \frac{1}{\Delta x} \int_{x_{i-1/2}}^{x_{i+1/2}} \rho(x, t_n) dx$$

$$Q_i^{n+1} = Q_i^n - \frac{\Delta t}{\Delta x} (F_{i+1/2}^n - F_{i-1/2}^n)$$



$v(x)$: the velocity of the flux at x

$\rho(x, t)$: probability density function of variable x

Q_i^n : the average value of $\rho(x, t_n)$ over the i th interval

$F_{i-1/2}^n$: the average flux along $x = x_{i-1/2}$

#1 First-Order Standard Upwind

• Step 3:



Upwind Method:

Define $v_i = v(x_i)$, then $F_{i-1/2}^n = v_{i-1/2}^+ Q_{i-1}^n + v_{i-1/2}^- Q_i^n$

$F_{i+1/2}^n = v_{i+1/2}^+ Q_i^n + v_{i+1/2}^- Q_{i+1}^n$

$$Q_i^{n+1} = Q_i^n - \frac{\Delta t}{\Delta x} (F_{i+1/2}^n - F_{i-1/2}^n)$$

$$\Rightarrow Q_i^{n+1} = Q_i^n - \frac{\Delta t}{\Delta x} (v_{i-1/2}^+ Q_{i-1}^n + (v_{i-1/2}^- - v_{i+1/2}^+) Q_i^n - v_{i+1/2}^- Q_{i+1}^n)$$

$$\Rightarrow \begin{bmatrix} Q_0^{n+1} \\ Q_1^{n+1} \\ \vdots \\ Q_N^{n+1} \end{bmatrix} = \begin{bmatrix} Q_0^n \\ Q_1^n \\ \vdots \\ Q_N^n \end{bmatrix} - \frac{\Delta t}{\Delta x} \begin{bmatrix} -v_{1/2,0}^+ & -v_{1/2,0}^- & 0 & \dots & 0 \\ v_{1/2,0}^+ & v_{1/2,0}^- - v_{3/2,0}^+ & -v_{3/2,0}^- & \dots & 0 \\ 0 & v_{3/2,0}^+ & v_{3/2,0}^- - v_{5/2,0}^+ & -v_{5/2,0}^- & \dots \\ \dots & & & & \dots \end{bmatrix} \begin{bmatrix} Q_0^n \\ Q_1^n \\ \vdots \\ Q_N^n \end{bmatrix}$$

\downarrow
 K

$v(x)$: the velocity of the flux at x

$$v^+ = \max(v(x), 0)$$

$$v^- = \min(v(x), 0)$$

Q_i^n : the average value of $\rho(x, t_n)$ over the i th interval

$F_{i-1/2}^n$: the average flux along $x = x_{i-1/2}$

#1+#3 First-Order Standard Upwind

- 1D $Q_i^{n+1} = Q_i^n - \frac{\Delta t}{\Delta x}(F_{i+1/2}^n - F_{i-1/2}^n)$
- 2D $Q_{ij}^{n+1} = Q_{ij}^n - \frac{\Delta t}{\Delta x}(F_{i+1/2,j}^n - F_{i-1/2,j}^n) - \frac{\Delta t}{\Delta y}(G_{i,j+1/2}^n - G_{i,j-1/2}^n)$
- 3D $Q_{ijk}^{n+1} = Q_{ijk}^n - \frac{\Delta t}{\Delta x}(F_{i+1/2,j,k}^n - F_{i-1/2,j,k}^n) - \frac{\Delta t}{\Delta y}(G_{i,j+1/2,k}^n - G_{i,j-1/2,k}^n) - \frac{\Delta t}{\Delta z}(H_{i,j,k+1/2}^n - H_{i,j,k-1/2}^n)$

$$\Rightarrow \begin{bmatrix} Q_0^{n+1} \\ Q_1^{n+1} \\ \vdots \\ Q_N^{n+1} \end{bmatrix} = \begin{bmatrix} Q_0^n \\ Q_1^n \\ \vdots \\ Q_N^n \end{bmatrix} - \left(\frac{\Delta t}{\Delta x} T_1 + \frac{\Delta t}{\Delta y} T_2 + \frac{\Delta t}{\Delta z} T_3 \right) \begin{bmatrix} Q_0^n \\ Q_1^n \\ \vdots \\ Q_N^n \end{bmatrix}$$

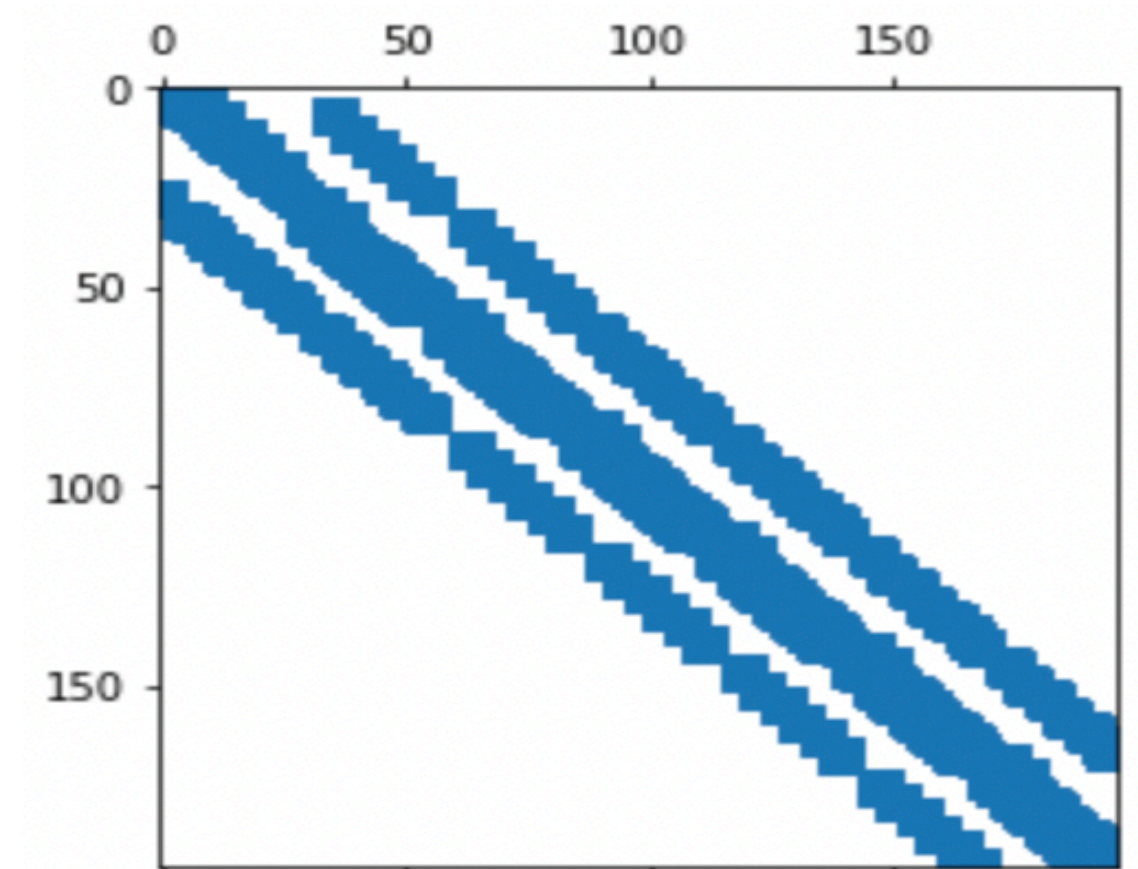
$$K = \frac{\Delta t}{\Delta x} T_1 + \frac{\Delta t}{\Delta y} T_2 + \frac{\Delta t}{\Delta z} T_3$$

Q_i^n : the average value of $\rho(x, t_n)$ over the i th interval

$F_{i-1/2}^n$: the average flux along $x = x_{i-1/2}$

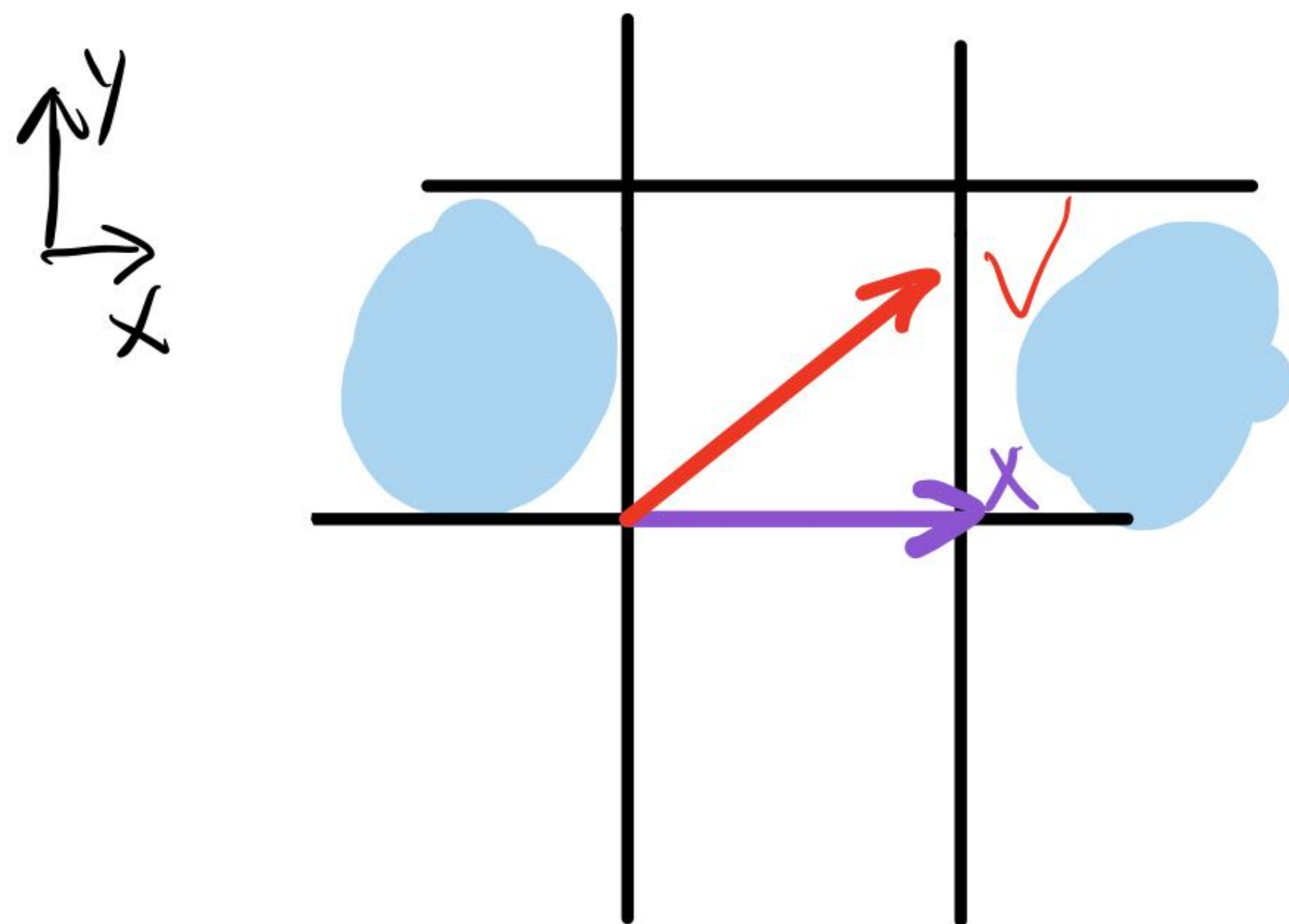
$G_{i-1/2}^n$: the average flux along $y = y_{i-1/2}$

$H_{i-1/2}^n$: the average flux along $z = z_{i-1/2}$

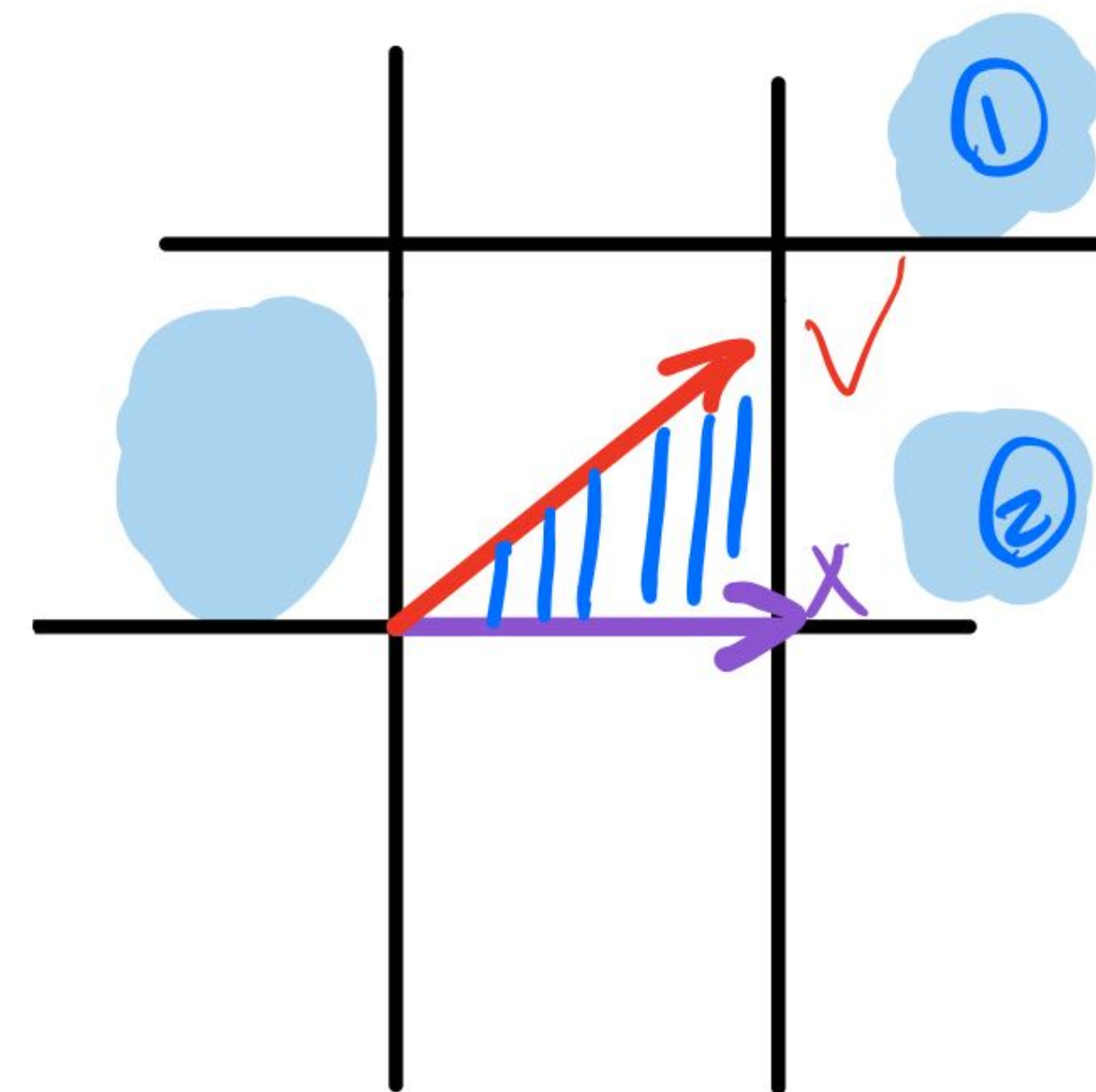


#2 Improvement

At time $t=n$,



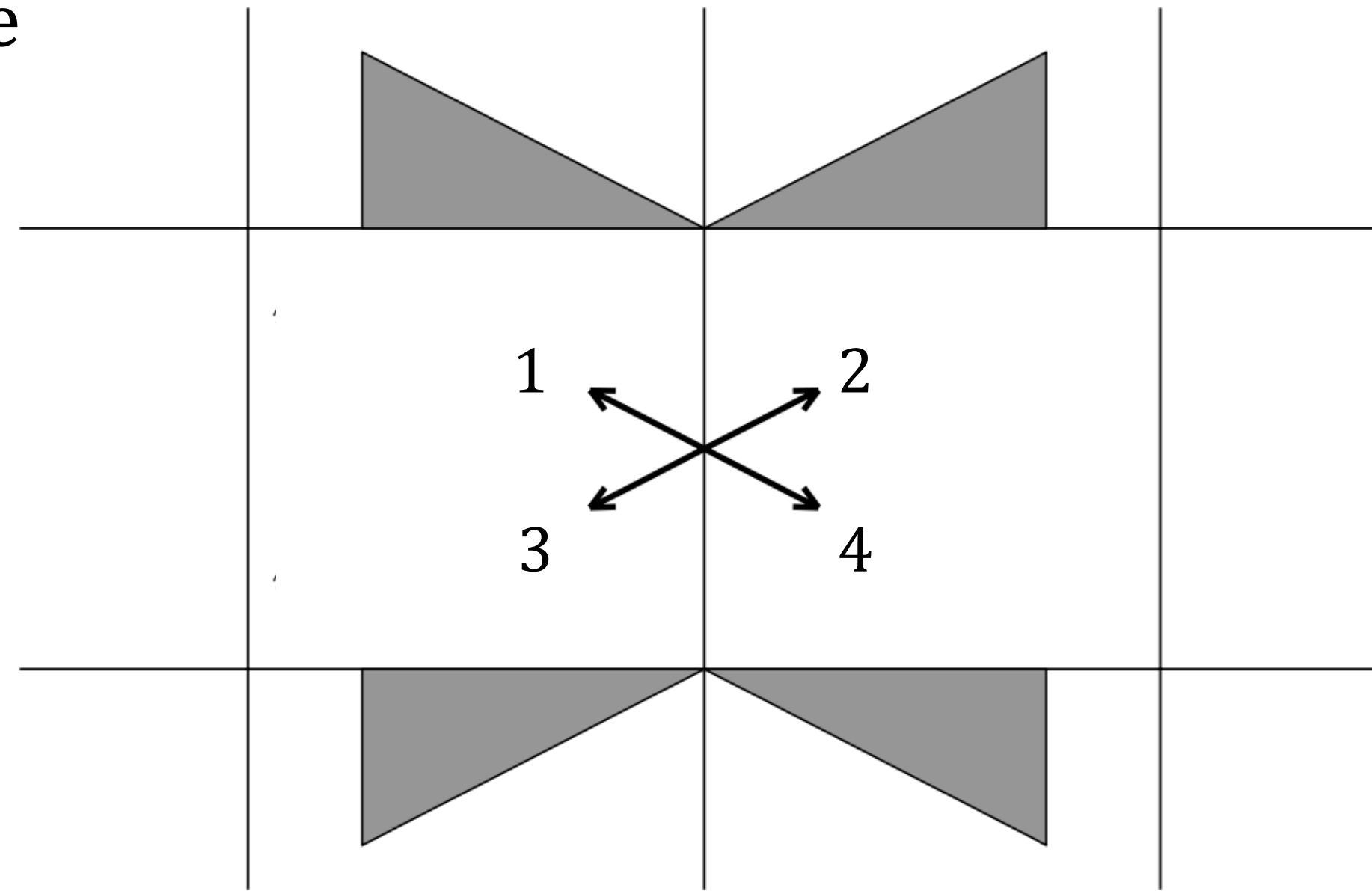
(1)



(2)

#2 Improvement—Corner transport⁴

- 2D (8): X-Y Plane



- 3D (24):

X-Y Plane
Y-Z Plane
X-Z Plane

$$\tilde{F}_{i+1/2,j-1} = -\frac{1}{2} \frac{\Delta t}{\Delta y} u_{i+1/2,j-1}^+ v_{i,j-1/2}^- (Q_{i,j} - Q_{i,j-1}) \quad \tilde{F}_{i-1/2,j-1} = -\frac{1}{2} \frac{\Delta t}{\Delta y} u_{i-1/2,j-1}^- v_{i,j-1/2}^- (Q_{i,j} - Q_{i,j-1})$$

$$\tilde{F}_{i-1/2,j} = -\frac{1}{2} \frac{\Delta t}{\Delta y} u_{i-1/2,j}^- v_{i,j-1/2}^+ (Q_{i,j} - Q_{i,j-1}) \quad \tilde{F}_{i+1/2,j} = -\frac{1}{2} \frac{\Delta t}{\Delta y} u_{i+1/2,j}^+ v_{i,j-1/2}^+ (Q_{i,j} - Q_{i,j-1})$$

#3 Steady-state solution

1. Derive the matrix K from the linear system with finite volume split discretization and the Upwind Method:

$$\begin{bmatrix} Q_0^{n+1} \\ Q_1^{n+1} \\ \vdots \\ Q_N^{n+1} \end{bmatrix} = \begin{bmatrix} Q_0^n \\ Q_1^n \\ \vdots \\ Q_N^n \end{bmatrix} - \left(\frac{\Delta t}{\Delta x} T_1 + \frac{\Delta t}{\Delta y} T_2 + \frac{\Delta t}{\Delta z} T_3 \right) \begin{bmatrix} Q_0^n \\ Q_1^n \\ \vdots \\ Q_N^n \end{bmatrix} \quad \rightarrow \quad K = \frac{\Delta t}{\Delta x} T_1 + \frac{\Delta t}{\Delta y} T_2 + \frac{\Delta t}{\Delta z} T_3$$

2. Modify the solver with corner transport, where \tilde{K} is **multi-diagonal with columns summing to 0**:

$$\begin{aligned} Q^{n+1} &= Q^n - K * Q^n + \text{CornerTransport} * Q^n \\ &= Q^n - \tilde{K} * Q^n \end{aligned} \quad \rightarrow \quad \boxed{\tilde{M} = I + s \tilde{K} \text{ with a sufficiently small } s}$$

The Markov Matrix \tilde{M} preserves the property of the probability density:

- Columns sum to 1
- Mass Conservation

#3 Steady-state solution

Markov Matrix

Imply the steady-state solution:

— ρ is the dominant eigenvector of M:

$$M\rho = \rho$$

$$\rho^{n+1} = (I + sK)\rho^n = M\rho^n$$

$$M\rho_{steady} = \rho_{steady}$$

— Tools:

- (1) Power Method
- (2) Sparse Direct Solve
- (3) Richardson Iteration

...

Questions

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Thank you for listening