



Joint Velocity-Growth Flow Matching for Single-Cell Dynamics Modeling

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NEURAL INFORMATION PROCESSING SYSTEMS

Background & Motivation

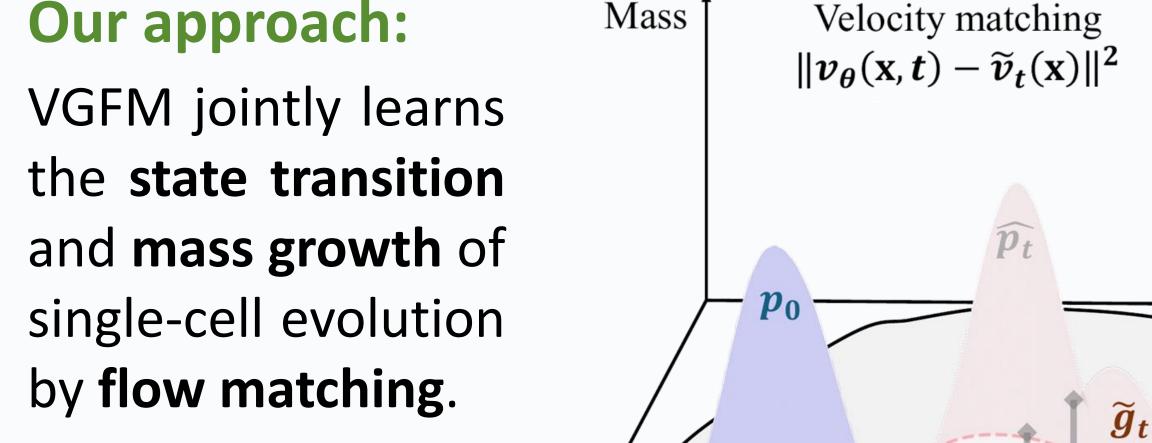
Single-cell RNA seq yields unpaired and unbalanced data.

Simulation-based models (e.g., TIGON, DeepRUOT)

- Growth rate
- Scalability

Simulation-free models (e.g., OT-CFM, SF2M)

- Growth rate
- Scalability



Trajectory and growth reconstruction

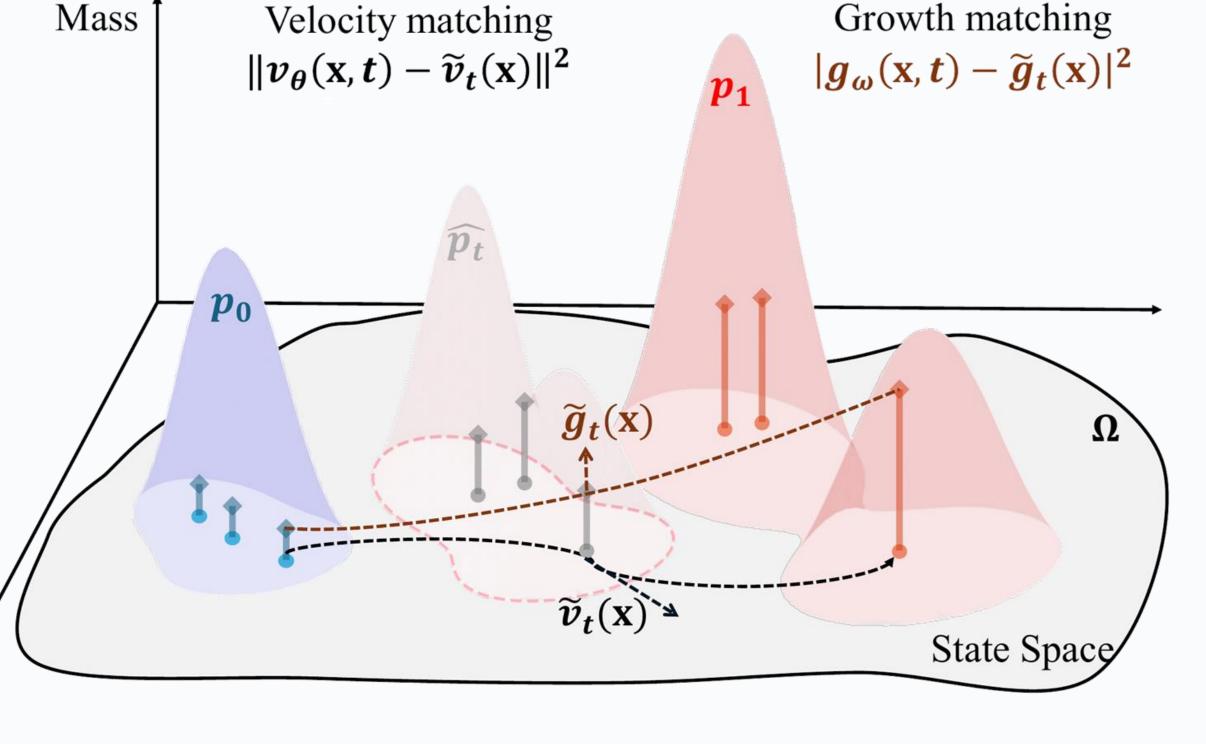
Growth rate

Simulation gene

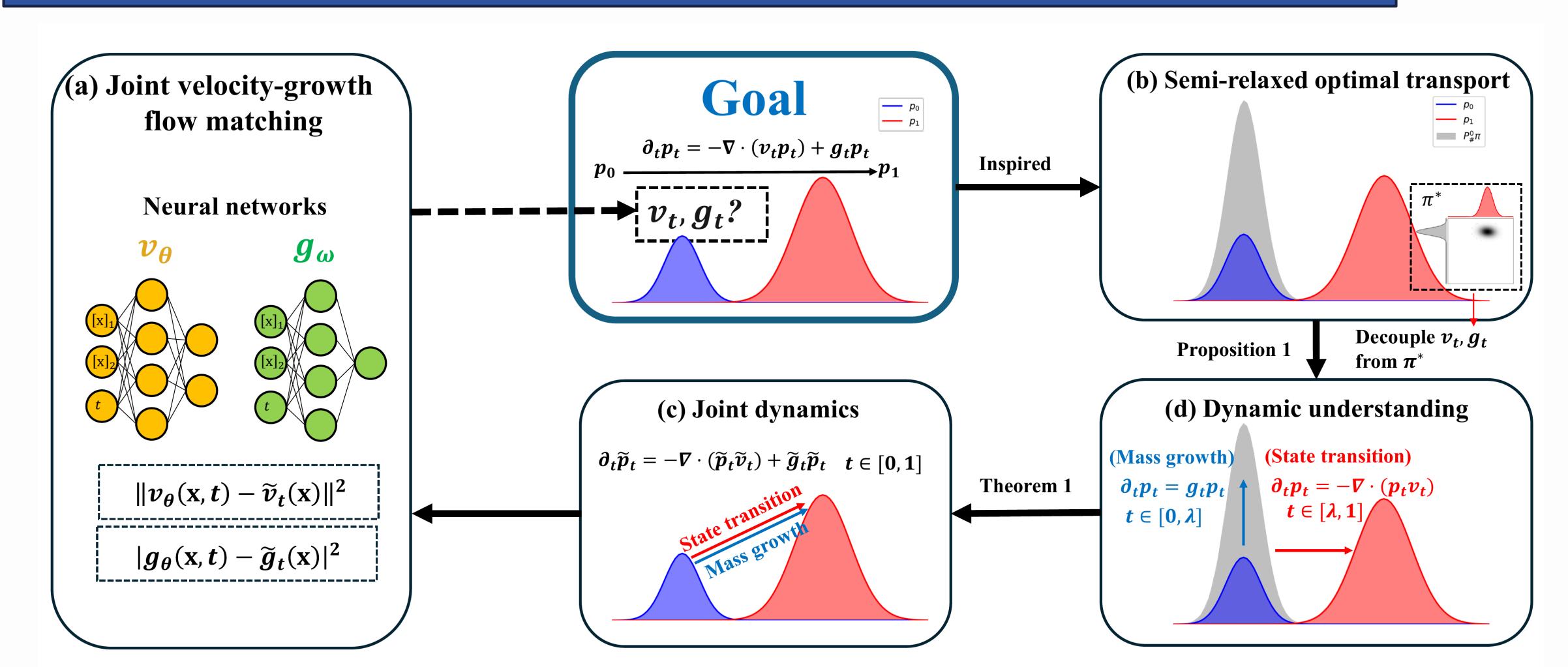
Mouse Hematopoiesis

EB

Scalability



Our Approach: Velocity-Growth Flow Matching via SROT

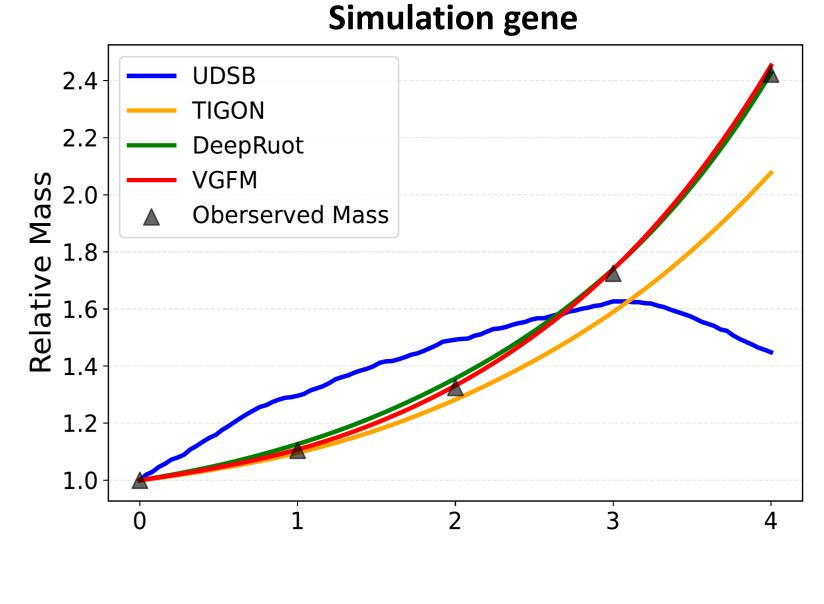


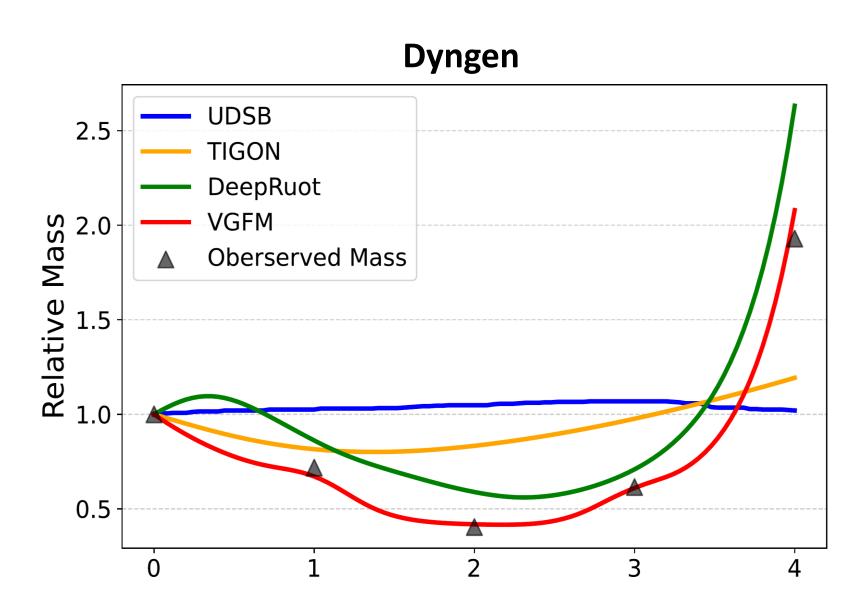
- Dynamic understanding of semi-relaxed OT (SROT) (v, g can be decoupled from SROT plan)
- Build a novel dynamic process between unbalanced distributions based on dynamic SROT
- 3. Regress $\tilde{\boldsymbol{v}}$, $\tilde{\boldsymbol{g}}$ using neural networks $\left\|v_{\theta}(\mathbf{x}_t,t)-(\mathbf{x}_1^j-\mathbf{x}_0^i)\right\|^2+\left|g_{\omega}(\mathbf{x}_t,t)-\log([\pi^{0\to1}\mathbf{1}_m]_i)\right|^2$

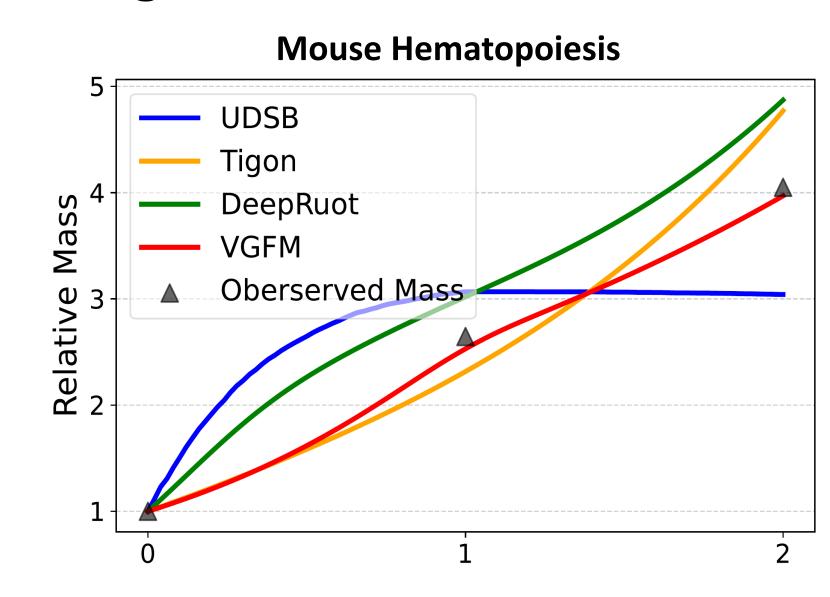
$$\mathcal{L}(\theta,\omega) = \mathcal{L}_{\text{VGFM}}(\theta,\omega) + \mathcal{L}_{\text{OT}}(\theta,\omega)$$
 Flow matching loss Distribution fitting loss

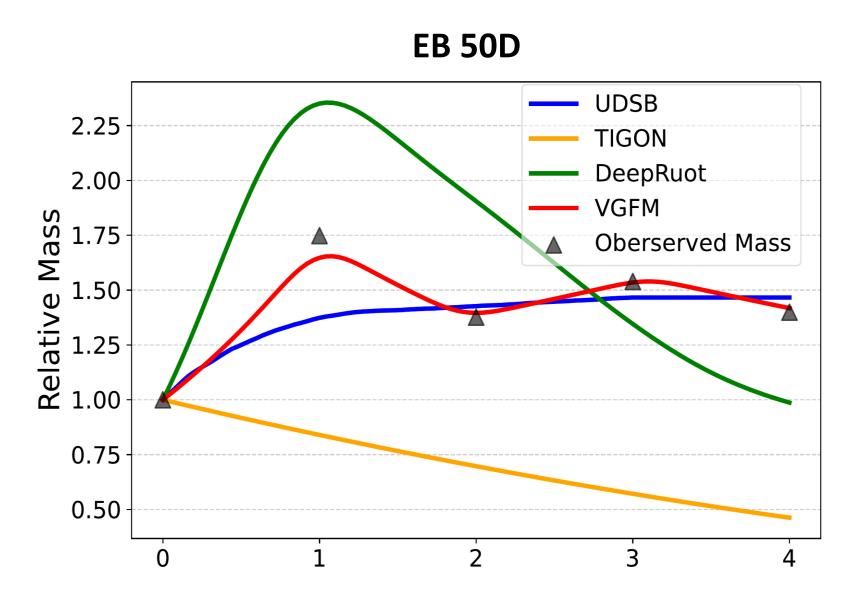
Experiments

Mass matching









Wasserstein-1 distance and Relative mass error

Method	Simulation Gene (2D)		Dyngen (5D)		Gaussian (1000D)	
	$\overline{\mathcal{W}_1}$	RME	$\overline{\mathcal{W}_1}$	RME	$\overline{\mathcal{W}_1}$	RME
OT-CFM* [22]	0.302	_	3.926	_	10.126	
OT-MFM* [38]	0.311		3.976	_	11.008	_
UDSB [57]	0.665	0.192	1.914	0.658	N/C	N/C
TIGON [23]	0.099	0.065	1.029	0.542	N/C	N/C
DeepRUOT [26]	0.068	0.016	0.474	0.199	N/C	N/C
VGFM	0.046	0.006	0.420	0.053	3.010	0.037

Training and analysis on 2k gene space

