A Distributed Algorithm for Measure-valued Optimization with Additive Objective

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Measure-valued Optimization Problems

$$\underset{\mu \in \mathcal{P}_2(\mathbb{R}^d)}{\arg\inf} \; F(\mu)$$

Space of Borel probability measures on $\mathbb{R}^d$ with finite second moments

2-Wasserstein geodescially convex functional

In many applications, we have additive structure:

$$F(\mu) = F_1(\mu) + F_2(\mu) + \ldots + F_n(\mu)$$

where each $F_i : \mathscr{P}_2\left(\mathbb{R}^d\right) \mapsto (-\infty, +\infty]$ is proper, lsc, and 2-Wasserstein geodescially convex

Connection with Wasserstein Gradient Flows

$$\frac{\partial \mu}{\partial t} = -\nabla^{W_2} F(\mu) := \nabla \cdot \left(\mu \nabla \frac{\delta F}{\delta \mu} \right) \qquad (\star)$$

Wasserstein gradient

Minimizer of $\underset{\mu \in \mathcal{P}_2(\mathbb{R}^d)}{\arg\inf} \; F(\mu)$ $\leftsquigarrow$ Stationary solution of $(\star)$

Transient solution of $(\star)$ $\rightsquigarrow$ Discrete time-stepping realizing grad. descent of $\underset{\mu \in \mathcal{P}_2(\mathbb{R}^d)}{\arg\inf} \; F(\mu)$

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Wasserstein proximal recursion à la Jordan-Kinderlehrer-Otto (JKO) scheme

Gradient Flows

Gradient Flow in $\mathcal{X}$

$$\frac{\mathrm{d}\boldsymbol{x}}{\mathrm{d}t} = -\nabla f(\boldsymbol{x}), \quad \boldsymbol{x}(0) = \boldsymbol{x}_0$$

Recursion:

$$\begin{aligned}\boldsymbol{x}_k &= \boldsymbol{x}_{k-1} - h\nabla f(\boldsymbol{x}_k)\\ &= \underset{\boldsymbol{x}\in\mathcal{X}}{\arg\min}\left\{\frac{1}{2}\|\boldsymbol{x}-\boldsymbol{x}_{k-1}\|_2^2 + hf(\boldsymbol{x})\right\}\\ &=: \mathrm{prox}_{hf}^{\|\cdot\|_2}(\boldsymbol{x}_{k-1})\end{aligned}$$

Convergence:

$$\boldsymbol{x}_k \to \boldsymbol{x}(t=kh) \quad \text{as} \quad h\downarrow 0$$

f as Lyapunov function:

$$\frac{\mathrm{d}}{\mathrm{d}t}f = -\|\nabla f\|_2^2 \leq 0$$

Gradient Flow in $\mathcal{P}_2(\mathcal{X})$

$$\frac{\partial\mu}{\partial t} = -\nabla^W F(\mu), \quad \mu(\boldsymbol{x},0) = \mu_0$$

Recursion:

$$\begin{aligned}\mu_k &= \mu(\cdot, t=kh)\\ &= \underset{\mu\in\mathcal{P}_2(\mathcal{X})}{\arg\min}\left\{\frac{1}{2}W^2(\mu,\mu_{k-1}) + hF(\mu)\right\}\\ &=: \mathrm{prox}_{hF}^{W}(\mu_{k-1})\end{aligned}$$

Convergence:

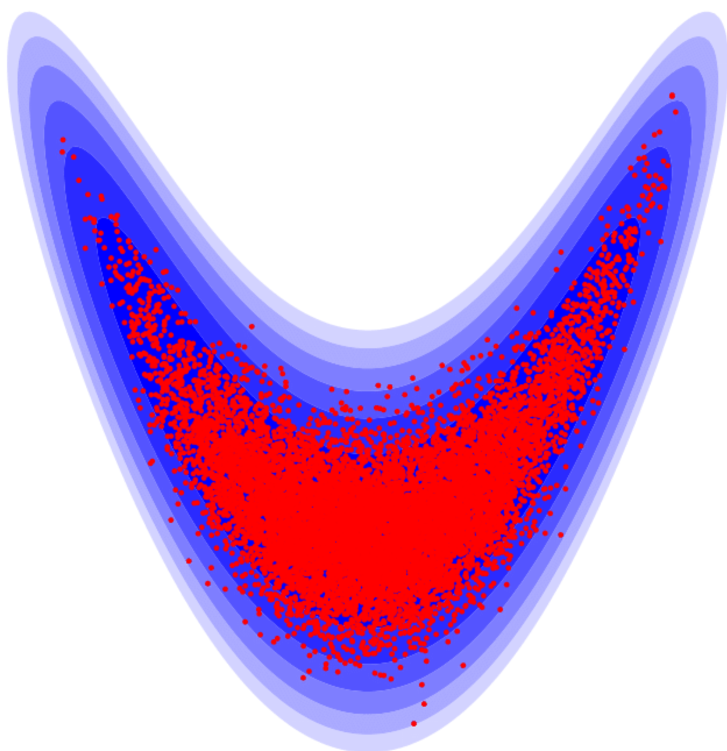
$$\mu_k \to \mu(\cdot, t=kh) \quad \text{as} \quad h\downarrow 0$$

F as Lyapunov functional:

$$\frac{\mathrm{d}}{\mathrm{d}t}F = -\mathbb{E}_\mu\left[\left\|\nabla\frac{\delta F}{\delta\mu}\right\|_2^2\right] \leq 0$$

Motivating Applications

Langevin sampling from an unnormalized prior



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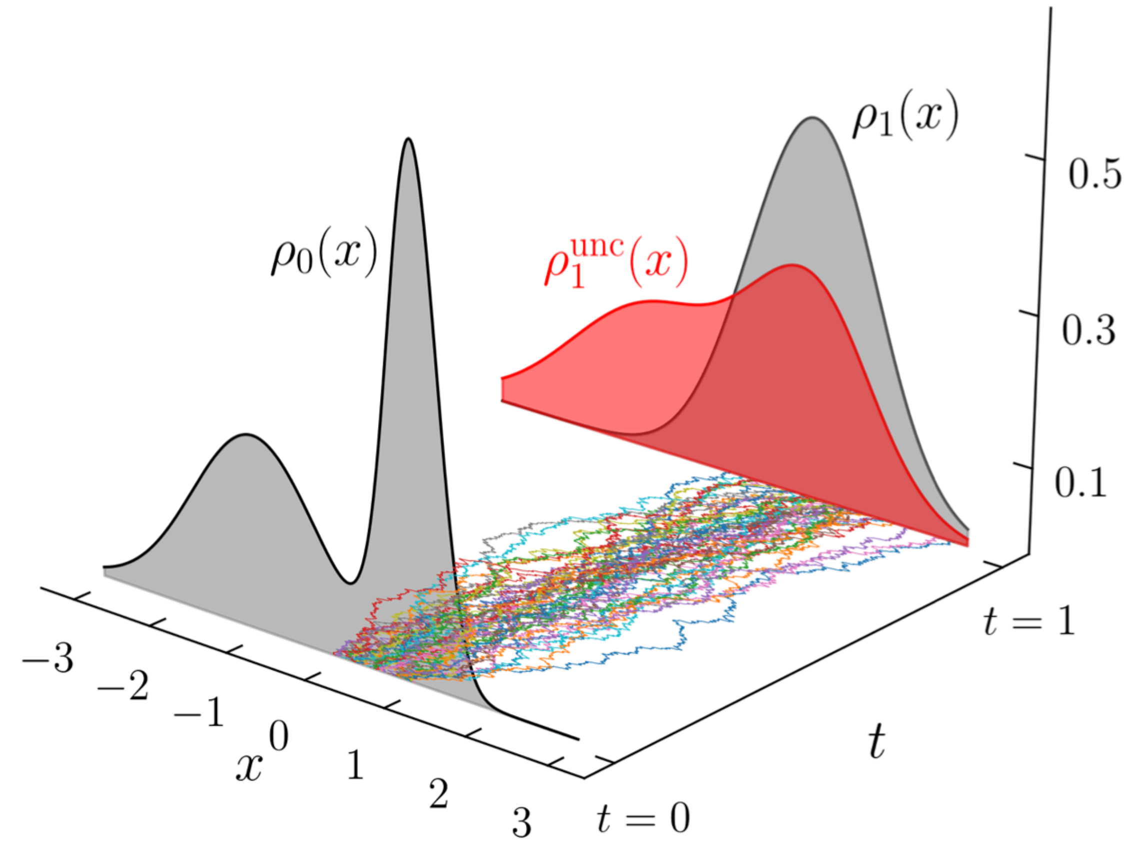
Optimal control of distributions a.k.a. Schrödinger bridge problems



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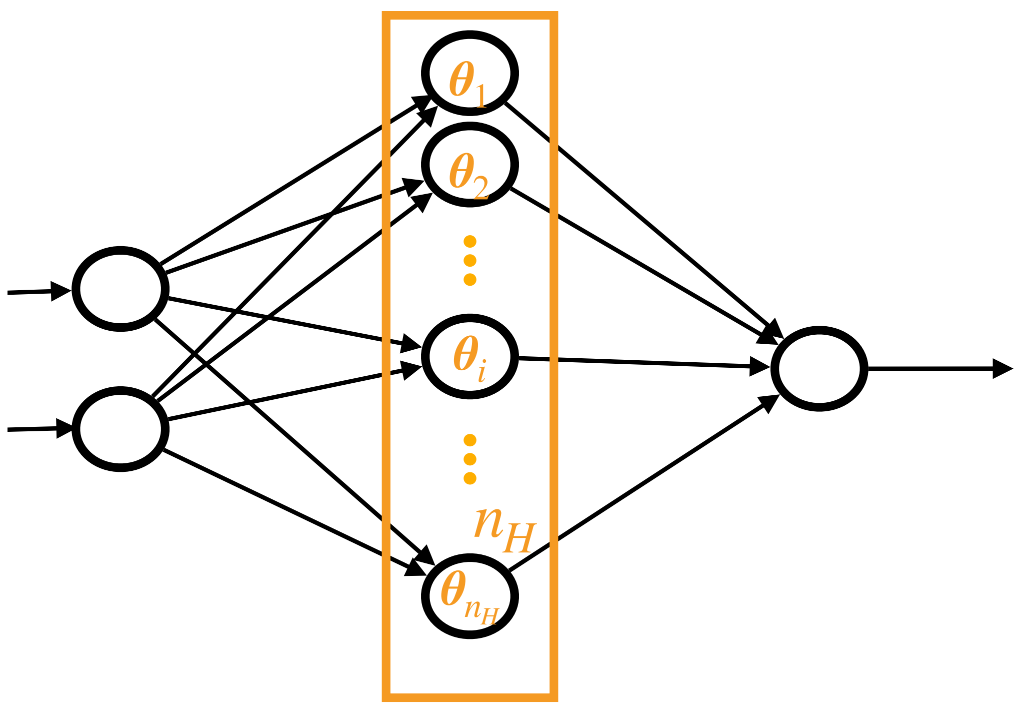
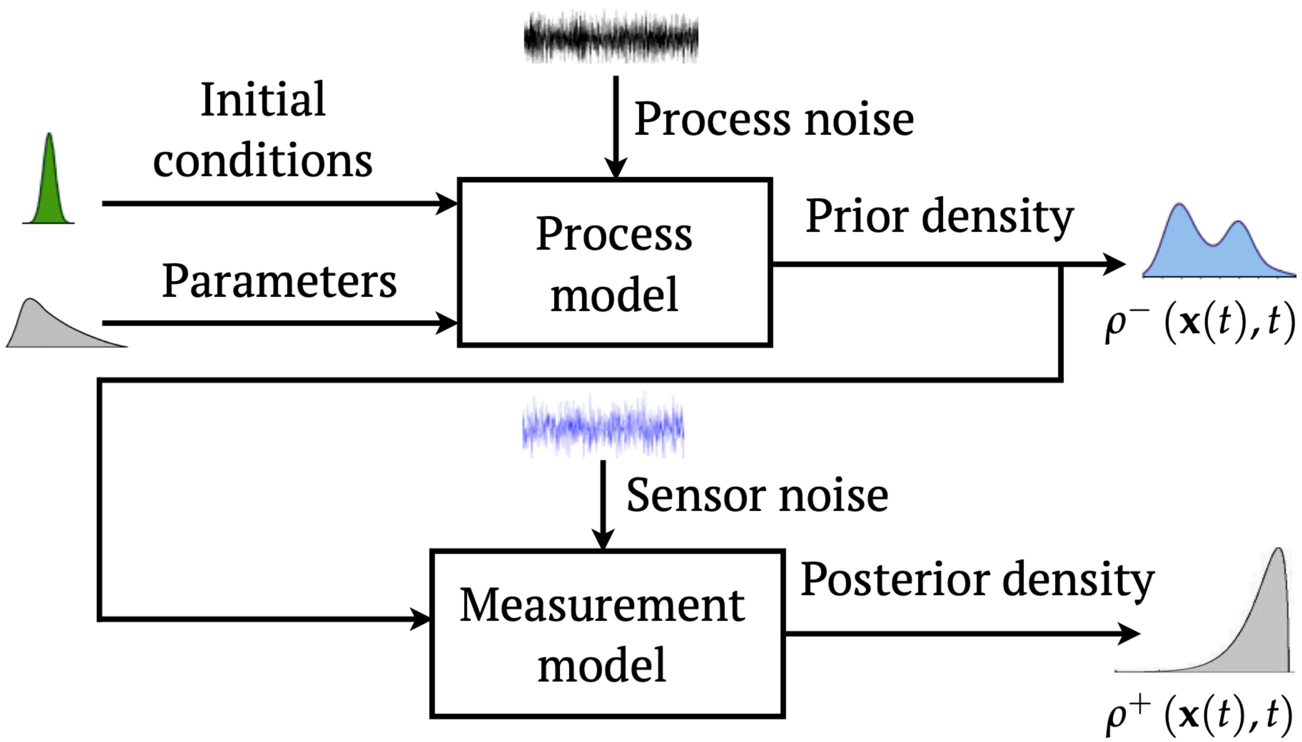
Motivating Applications (contd.)

Mean field learning dynamics in neural networks



Prediction and estimation of time-varying joint state probability densities



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Many Recently Proposed Algorithms to Solve Measure-valued Optimization Problems

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Mokrov, Korotin, Li, Gnevay, Solomon, and Burnaev, *NeurIPS*, 2021

Alvarez-Melis, Schiff, and Mroueh, *NeurIPS*, 2021

Many Recently Proposed Algorithms to Solve Measure-valued Optimization Problems

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But all require centralized computing

Present Work: Distributed Algorithm

$$\operatorname*{arg\,inf}_{\mu \in \mathcal{P}_2(\mathbb{R}^d)} \; F_1(\mu) + F_2(\mu) + \ldots + F_n(\mu)$$

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$$\operatorname*{arg\,inf}_{\mu \in \mathcal{P}_2(\mathbb{R}^d)} F_1(\mu) + F_2(\mu) + \ldots + F_n(\mu)$$

Main idea:

re-write

$$\begin{aligned} \operatorname*{arg\,inf}_{(\mu_1,\ldots,\mu_n,\zeta) \in \mathcal{P}_2^{n+1}(\mathbb{R}^d)} \quad & F_1(\mu_1) + F_2(\mu_2) + \ldots + F_n(\mu_n) \\ \text{subject to} \quad & \mu_i = \zeta \quad \text{for all } i \in [n] \end{aligned}$$

Present Work: Distributed Algorithm

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Define Wasserstein augmented Lagrangian:

$$L_\alpha(\mu_1, \ldots, \mu_n, \zeta, \nu_1, \ldots, \nu_n) := \sum_{i=1}^{n} \left\{ F_i(\mu_i) + \frac{\alpha}{2} W^2(\mu_i, \zeta) + \int_{\mathbb{R}^d} \nu_i(\boldsymbol{\theta})(\mathrm{d}\mu_i - \mathrm{d}\zeta) \right\}$$

regularization > 0

Lagrange multipliers

Proposed Consensus ADMM

$$
\begin{aligned}
\mu_i^{k+1} &= \operatorname*{arg\,inf}_{\mu_i \in \mathcal{P}_2(\mathbb{R}^d)} L_\alpha\left(\mu_1, \dots, \mu_n, \zeta^k, \nu_1^k, \dots, \nu_n^k\right) \\
\zeta^{k+1} &= \operatorname*{arg\,inf}_{\zeta \in \mathcal{P}_2(\mathbb{R}^d)} L_\alpha\left(\mu_1^{k+1}, \dots, \mu_n^{k+1}, \zeta, \nu_1^k, \dots, \nu_n^k\right) \\
\nu_i^{k+1} &= \nu_i^k + \alpha\left(\mu_i^{k+1} - \zeta^{k+1}\right)
\end{aligned}
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where $i \in [n]$, $k \in \mathbb{N}_0$

Proposed Consensus ADMM

$$\mu_i^{k+1} = \operatorname*{arg\,inf}_{\mu_i \in \mathcal{P}_2(\mathbb{R}^d)} L_\alpha\left(\mu_1, \ldots, \mu_n, \zeta^k, \nu_1^k, \ldots, \nu_n^k\right)$$
$$\zeta^{k+1} = \operatorname*{arg\,inf}_{\zeta \in \mathcal{P}_2(\mathbb{R}^d)} L_\alpha\left(\mu_1^{k+1}, \ldots, \mu_n^{k+1}, \zeta, \nu_1^k, \ldots, \nu_n^k\right)$$
$$\nu_i^{k+1} = \nu_i^k + \alpha\left(\mu_i^{k+1} - \zeta^{k+1}\right) \qquad \text{where } i \in [n],\ k \in \mathbb{N}_0$$

Define

$$\nu_{\text{sum}}^k(\boldsymbol{\theta}) := \sum_{i=1}^n \nu_i^k(\boldsymbol{\theta}), \quad k \in \mathbb{N}_0$$

and simplify the recursions to

$$\mu_i^{k+1} = \operatorname{prox}^W_{\frac{1}{\alpha}\left(F_i(\cdot) + \int \nu_i^k \,\mathrm{d}(\cdot)\right)}\left(\zeta^k\right)$$
$$\zeta^{k+1} = \operatorname*{arg\,inf}_{\zeta \in \mathcal{P}_2(\mathbb{R}^d)} \left\{ \left(\sum_{i=1}^n W^2\left(\mu_i^{k+1}, \zeta\right) \right) - \frac{2}{\alpha} \int_{\mathbb{R}^d} \nu_{\text{sum}}^k(\boldsymbol{\theta}) \mathrm{d}\zeta \right\}$$
$$\nu_i^{k+1} = \nu_i^k + \alpha\left(\mu_i^{k+1} - \zeta^{k+1}\right)$$

Proposed Consensus ADMM (contd.)

$$\boxed{\mu_i^{k+1} = \operatorname{prox}^{W}_{\frac{1}{\alpha}\left(F_i(\cdot)+\int \nu_i^k \,\mathrm{d}(\cdot)\right)}\left(\zeta^k\right)}$$

$$\zeta^{k+1} = \underset{\zeta\in\mathcal{P}_2\left(\mathbb{R}^d\right)}{\arg\inf}\left\{\left(\sum_{i=1}^{n} W^2\left(\mu_i^{k+1},\zeta\right)\right) - \frac{2}{\alpha}\int_{\mathbb{R}^d}\nu_{\text{sum}}^k(\boldsymbol{\theta})\mathrm{d}\zeta\right\}$$

$$\nu_i^{k+1} = \nu_i^k + \alpha\left(\mu_i^{k+1} - \zeta^{k+1}\right)$$

Split free energy functionals: $\Phi_i(\mu_i) := F_i(\mu_i) + \int_{\mathbb{R}^d}\nu_i^k \,\mathrm{d}\mu_i$

$\therefore$ Distributed Wasserstein prox $\approx$ time updates of $\dfrac{\partial\tilde{\mu}_i}{\partial t} = -\nabla^W\Phi_i(\tilde{\mu}_i)$

Proposed Consensus ADMM (contd.)

$$\boxed{\mu_i^{k+1} = \mathrm{prox}^{W}_{\frac{1}{\alpha}\left(F_i(\cdot)+\int \nu_i^k \,\mathrm{d}(\cdot)\right)}\left(\zeta^k\right)}$$

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$\therefore$ Distributed Wasserstein prox $\approx$ time updates of $\dfrac{\partial \tilde{\mu}_i}{\partial t} = -\nabla^W \Phi_i(\tilde{\mu}_i)$

Examples:

$\Phi_i(\cdot) = F_i(\cdot) + \int \nu_i^k \mathrm{d}(\cdot)$	PDE	Name
$\int_{\mathbb{R}^d} \left(V(\boldsymbol{\theta}) + \nu_i^k(\boldsymbol{\theta})\right) \mathrm{d}\mu_i(\boldsymbol{\theta})$	$\frac{\partial \widetilde{\mu}_i}{\partial t} = \nabla \cdot \left(\widetilde{\mu}_i \left(\nabla V + \nabla \nu_i^k\right)\right)$	Liouville equation
$\int_{\mathbb{R}^d} \left(\nu_i^k(\boldsymbol{\theta}) + \beta^{-1} \log \mu_i(\boldsymbol{\theta})\right) \mathrm{d}\mu_i(\boldsymbol{\theta})$	$\frac{\partial \widetilde{\mu}_i}{\partial t} = \nabla \cdot \left(\widetilde{\mu}_i \nabla \nu_i^k\right) + \beta^{-1} \Delta \widetilde{\mu}_i$	Fokker-Planck equation
$\int_{\mathbb{R}^d} \nu_i^k(\boldsymbol{\theta}) \mathrm{d}\mu_i(\boldsymbol{\theta}) + \int_{\mathbb{R}^{2d}} U(\boldsymbol{\theta}, \boldsymbol{\sigma}) \mathrm{d}\mu_i(\boldsymbol{\theta}) \mathrm{d}\mu_i(\boldsymbol{\sigma})$	$\frac{\partial \widetilde{\mu}_i}{\partial t} = \nabla \cdot \left(\widetilde{\mu}_i \left(\nabla \nu_i^k + \nabla \left(U \circledast \widetilde{\mu}_i\right)\right)\right)$	Propagation of chaos equation
$\int_{\mathbb{R}^d} \left(\nu_i^k(\boldsymbol{\theta}) + \frac{\beta^{-1}}{m-1} \mathbf{1}^\top \mu_i^m\right) \mathrm{d}\mu_i(\boldsymbol{\theta}), m > 1$	$\frac{\partial \widetilde{\mu}_i}{\partial t} = \nabla \cdot \left(\widetilde{\mu}_i \nabla \nu_i^k\right) + \beta^{-1} \Delta \widetilde{\mu}_i^m$	Porous medium equation

Discrete Version of the Proposed ADMM

Euclidean distance matrix

$$\begin{aligned}
\boldsymbol{\mu}_i^{k+1} &= \operatorname{prox}^W_{\frac{1}{\alpha}\left(F_i(\boldsymbol{\mu}_i)+\langle \boldsymbol{\nu}_i^k, \boldsymbol{\mu}_i\rangle\right)}\left(\boldsymbol{\zeta}^k\right) \\
&= \underset{\boldsymbol{\mu}_i \in \Delta^{N-1}}{\arg\inf} \left\{ \min_{\boldsymbol{M} \in \Pi_N(\boldsymbol{\mu}_i, \zeta^k)} \frac{1}{2}\langle \boldsymbol{C}, \boldsymbol{M}\rangle + \frac{1}{\alpha}\left(F_i(\boldsymbol{\mu}_i) + \langle \boldsymbol{\nu}_i^k, \boldsymbol{\mu}_i\rangle\right) \right\} \\
\boldsymbol{\zeta}^{k+1} &= \underset{\zeta \in \Delta^{N-1}}{\arg\inf} \left\{ \left(\sum_{i=1}^{n} \min_{\boldsymbol{M}_i \in \Pi_N(\boldsymbol{\mu}_i^{k+1}, \zeta)} \frac{1}{2}\langle \boldsymbol{C}, \boldsymbol{M}_i\rangle \right) - \frac{2}{\alpha}\langle \boldsymbol{\nu}_{\text{sum}}^k, \boldsymbol{\zeta}\rangle \right\} \\
\boldsymbol{\nu}_i^{k+1} &= \boldsymbol{\nu}_i^k + \alpha\left(\boldsymbol{\mu}_i^{k+1} - \boldsymbol{\zeta}^{k+1}\right)
\end{aligned}$$

where N is the number of samples

Discrete Version of the Proposed ADMM

$$\boldsymbol{\mu}_i^{k+1} = \operatorname{prox}^{W}_{\frac{1}{\alpha}(F_i(\boldsymbol{\mu}_i)+\langle \boldsymbol{\nu}_i^k, \boldsymbol{\mu}_i\rangle)}(\boldsymbol{\zeta}^k)$$
$$= \operatorname*{arg\,inf}_{\boldsymbol{\mu}_i \in \Delta^{N-1}} \left\{ \min_{\boldsymbol{M}\in\Pi_N(\boldsymbol{\mu}_i,\zeta^k)} \frac{1}{2}\langle \boldsymbol{C}, \boldsymbol{M}\rangle + \frac{1}{\alpha}\big(F_i(\boldsymbol{\mu}_i) + \langle \boldsymbol{\nu}_i^k, \boldsymbol{\mu}_i\rangle\big) \right\}$$
$$\boldsymbol{\zeta}^{k+1} = \operatorname*{arg\,inf}_{\boldsymbol{\zeta}\in\Delta^{N-1}} \left\{ \left(\sum_{i=1}^{n} \min_{\boldsymbol{M}_i \in \Pi_N(\boldsymbol{\mu}_i^{k+1},\boldsymbol{\zeta})} \frac{1}{2}\langle \boldsymbol{C}, \boldsymbol{M}_i\rangle \right) - \frac{2}{\alpha}\langle \boldsymbol{\nu}_{\text{sum}}^k, \boldsymbol{\zeta}\rangle \right\}$$
$$\boldsymbol{\nu}_i^{k+1} = \boldsymbol{\nu}_i^k + \alpha\big(\boldsymbol{\mu}_i^{k+1} - \boldsymbol{\zeta}^{k+1}\big)$$

With Sinkhorn regularization:

Discrete Sinkhorn divergence

$$\boldsymbol{\mu}_i^{k+1} = \operatorname{prox}^{W_\varepsilon}_{\frac{1}{\alpha}(F_i(\boldsymbol{\mu}_i)+\langle \boldsymbol{\nu}_i^k, \boldsymbol{\mu}_i\rangle)}(\boldsymbol{\zeta}^k)$$
$$= \operatorname*{arg\,inf}_{\boldsymbol{\mu}_i \in \Delta^{N-1}} \left\{ \min_{\boldsymbol{M}\in\Pi_N(\boldsymbol{\mu}_i,\zeta^k)} \left\langle \frac{1}{2}\boldsymbol{C} + \varepsilon \log \boldsymbol{M}, \boldsymbol{M} \right\rangle + \frac{1}{\alpha}\big(F_i(\boldsymbol{\mu}_i) + \langle \boldsymbol{\nu}_i^k, \boldsymbol{\mu}_i\rangle\big) \right\}$$
$$\boldsymbol{\zeta}^{k+1} = \operatorname*{arg\,inf}_{\boldsymbol{\zeta}\in\Delta^{N-1}} \left\{ \left(\sum_{i=1}^{n} \min_{\boldsymbol{M}_i \in \Pi_N(\boldsymbol{\mu}_i^{k+1},\boldsymbol{\zeta})} \left\langle \frac{1}{2}\boldsymbol{C} + \varepsilon \log \boldsymbol{M}_i, \boldsymbol{M}_i \right\rangle \right) - \frac{2}{\alpha}\langle \boldsymbol{\nu}_{\text{sum}}^k, \boldsymbol{\zeta}\rangle \right\}$$
$$\boldsymbol{\nu}_i^{k+1} = \boldsymbol{\nu}_i^k + \alpha\big(\boldsymbol{\mu}_i^{k+1} - \boldsymbol{\zeta}^{k+1}\big)$$

Discrete Version of the Proposed ADMM

$$
\begin{aligned}
\boldsymbol{\mu}_i^{k+1} &= \mathrm{prox}^{W}_{\frac{1}{\alpha}(F_i(\boldsymbol{\mu}_i)+\langle \boldsymbol{\nu}_i^k,\boldsymbol{\mu}_i\rangle)}(\boldsymbol{\zeta}^k)\\
&= \mathop{\arg\inf}_{\boldsymbol{\mu}_i\in\Delta^{N-1}}\left\{\min_{\boldsymbol{M}\in\Pi_N(\boldsymbol{\mu}_i,\zeta^k)} \frac{1}{2}\langle \boldsymbol{C},\boldsymbol{M}\rangle + \frac{1}{\alpha}\big(F_i(\boldsymbol{\mu}_i)+\langle \boldsymbol{\nu}_i^k,\boldsymbol{\mu}_i\rangle\big)\right\}\\
\boldsymbol{\zeta}^{k+1} &= \mathop{\arg\inf}_{\boldsymbol{\zeta}\in\Delta^{N-1}}\left\{\left(\sum_{i=1}^{n}\min_{\boldsymbol{M}_i\in\Pi_N(\boldsymbol{\mu}_i^{k+1},\boldsymbol{\zeta})}\frac{1}{2}\langle \boldsymbol{C},\boldsymbol{M}_i\rangle\right) - \frac{2}{\alpha}\langle \boldsymbol{\nu}_{\mathrm{sum}}^k,\boldsymbol{\zeta}\rangle\right\}\\
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\end{aligned}
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With Sinkhorn regularization:

Discrete Sinkhorn divergence

Outer layer ADMM

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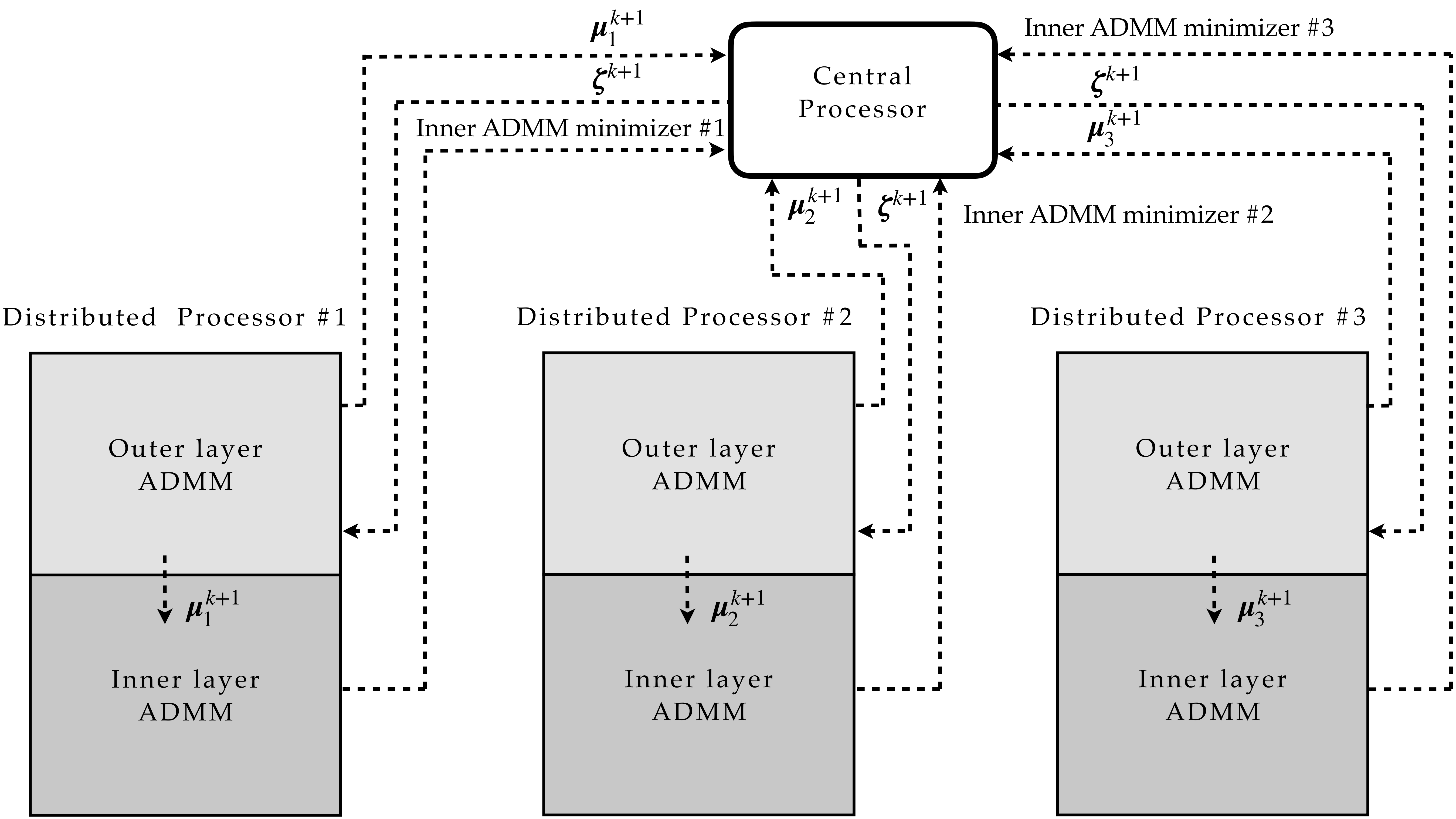
\begin{aligned}
\boldsymbol{\mu}_i^{k+1} &= \mathrm{prox}^{W_\varepsilon}_{\frac{1}{\alpha}(F_i(\boldsymbol{\mu}_i)+\langle \boldsymbol{\nu}_i^k,\boldsymbol{\mu}_i\rangle)}(\boldsymbol{\zeta}^k)\\
&= \mathop{\arg\inf}_{\boldsymbol{\mu}_i\in\Delta^{N-1}}\left\{\min_{M\in\Pi_N(\boldsymbol{\mu}_i,\zeta^k)}\left\langle \frac{1}{2}\boldsymbol{C}+\varepsilon\log\boldsymbol{M},\boldsymbol{M}\right\rangle + \frac{1}{\alpha}\big(F_i(\boldsymbol{\mu}_i)+\langle \boldsymbol{\nu}_i^k,\boldsymbol{\mu}_i\rangle\big)\right\}\\
\boldsymbol{\zeta}^{k+1} &= \mathop{\arg\inf}_{\boldsymbol{\zeta}\in\Delta^{N-1}}\left\{\left(\sum_{i=1}^{n}\min_{\boldsymbol{M}_i\in\Pi_N(\boldsymbol{\mu}_i^{k+1},\zeta)}\left\langle\frac{1}{2}\boldsymbol{C}+\varepsilon\log\boldsymbol{M}_i,\boldsymbol{M}_i\right\rangle\right) - \frac{2}{\alpha}\langle \boldsymbol{\nu}_{\mathrm{sum}}^k,\boldsymbol{\zeta}\rangle\right\}\\
\boldsymbol{\nu}_i^{k+1} &= \boldsymbol{\nu}_i^k + \alpha\big(\boldsymbol{\mu}_i^{k+1}-\boldsymbol{\zeta}^{k+1}\big)
\end{aligned}
$$

Inner layer ADMM

Overall Schematic



$\boldsymbol{\mu}_i$ update $\rightsquigarrow$ Outer Consensus (Sinkhorn) ADMM

Example. $\Phi(\boldsymbol{\mu}) := \langle \boldsymbol{a}, \boldsymbol{\mu} \rangle$, $\boldsymbol{a} \in \mathbb{R}^N \backslash \{\mathbf{0}\}$, $\boldsymbol{\mu}, \boldsymbol{\zeta} \in \Delta^{N-1}$, $\boldsymbol{\Gamma} := \exp\left(-\boldsymbol{C}/2\varepsilon\right)$, $\varepsilon > 0$

$$\operatorname{prox}^{W_\varepsilon}_{\frac{1}{\alpha}\Phi}(\boldsymbol{\zeta}) = \exp\left(-\frac{1}{\alpha\varepsilon}\boldsymbol{a}\right) \odot \left(\boldsymbol{\Gamma}^\top \left(\boldsymbol{\zeta} \oslash \left(\boldsymbol{\Gamma} \exp\left(-\frac{1}{\alpha\varepsilon}\boldsymbol{a}\right)\right)\right)\right)$$

μ_i update ⇝ Outer Consensus (Sinkhorn) ADMM

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Example. $G_i(\boldsymbol{\mu_i}) := F_i(\boldsymbol{\mu}_i) + \langle \boldsymbol{\nu}_i^k, \boldsymbol{\mu}_i \rangle, \ \boldsymbol{\zeta}^k \in \Delta^{N-1}, \ k \in \mathbb{N}_0.$

Convex

$$\boldsymbol{\mu}_i^{k+1} = \operatorname{prox}^{W_\varepsilon}_{\frac{1}{\alpha}(F_i(\boldsymbol{\mu}_i) + \langle \boldsymbol{\nu}_i^k, \boldsymbol{\mu}_i \rangle)}\left(\boldsymbol{\zeta}^k\right) = \exp\left(\frac{\boldsymbol{\lambda}_{1i}^{\text{opt}}}{\alpha\varepsilon}\right) \odot \left(\exp\left(-\frac{\boldsymbol{C}^\top}{2\varepsilon}\right) \exp\left(\frac{\boldsymbol{\lambda}_{0i}^{\text{opt}}}{\alpha\varepsilon}\right)\right)$$

where $\boldsymbol{\lambda}_{0i}^{\text{opt}}, \boldsymbol{\lambda}_{1i}^{\text{opt}} \in \mathbb{R}^N$ solve

$$\exp\left(\frac{\boldsymbol{\lambda}_{0i}^{\text{opt}}}{\alpha\varepsilon}\right) \odot \left(\exp\left(-\frac{\boldsymbol{C}}{2\varepsilon}\right) \exp\left(\frac{\boldsymbol{\lambda}_{1i}^{\text{opt}}}{\alpha\varepsilon}\right)\right) = \boldsymbol{\zeta}_k,$$

$$\mathbf{0} \in \partial_{\boldsymbol{\lambda}_{1i}^{\text{opt}}} G_i^*\left(-\boldsymbol{\lambda}_{1i}^{\text{opt}}\right) - \exp\left(\frac{\boldsymbol{\lambda}_{1i}^{\text{opt}}}{\alpha\varepsilon}\right) \odot \left(\exp\left(-\frac{\boldsymbol{C}^\top}{2\varepsilon}\right) \exp\left(\frac{\boldsymbol{\lambda}_{0i}^{\text{opt}}}{\alpha\varepsilon}\right)\right).$$

ζ update ⇝ Inner (Euclidean) ADMM

Theorem.

Consider the convex problem

$$\left(\boldsymbol{u}_1^{\text{opt}}, \ldots, \boldsymbol{u}_n^{\text{opt}}\right) = \underset{(\boldsymbol{u}_1, \ldots, \boldsymbol{u}_n) \in \mathbb{R}^{nN}}{\arg\min} \sum_{i=1}^{n} \left\langle \boldsymbol{\mu}_i^{k+1}, \log\left(\boldsymbol{\Gamma} \exp\left(\boldsymbol{u}_i/\varepsilon\right)\right) \right\rangle$$

$$\text{subject to} \quad \sum_{i=1}^{n} \boldsymbol{u}_i = \frac{2}{\alpha} \boldsymbol{\nu}_{\text{sum}}^{k}. \qquad (\heartsuit)$$

Then

$$\zeta^{k+1} = \exp\left(\boldsymbol{u}_i^{\text{opt}}/\varepsilon\right) \odot \left(\boldsymbol{\Gamma}\left(\boldsymbol{\mu}_i^{k+1} \oslash \left(\boldsymbol{\Gamma} \exp\left(\boldsymbol{u}_i^{\text{opt}}/\varepsilon\right)\right)\right)\right) \in \Delta^{N-1} \quad \forall\, i \in [n].$$

ζ update $\rightsquigarrow$ Inner (Euclidean) ADMM

Theorem.

Let $\quad f_i(\boldsymbol{u}_i) := \left\langle \boldsymbol{\mu}_i^{k+1}, \log\left(\boldsymbol{\Gamma} \exp\left(\boldsymbol{u}_i/\varepsilon\right)\right) \right\rangle, \quad \boldsymbol{u}_i \in \mathbb{R}^N, \quad$ for all $i \in [n]$,

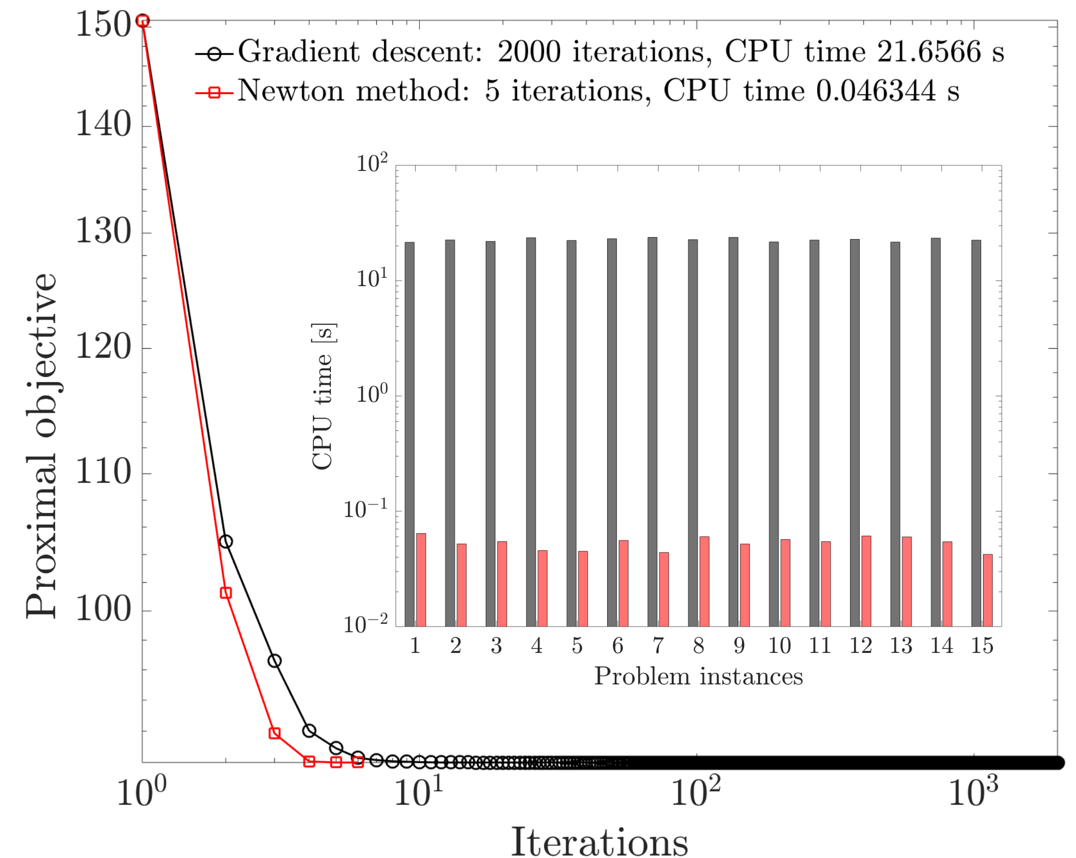
Then the following Euclidean ADMM solves (♥)

$$\boldsymbol{u}_i^{\ell+1} = \boxed{\mathrm{prox}_{\frac{1}{\tau} f_i}^{\|\cdot\|_2}\left(\boldsymbol{z}_i^{\ell} - \widetilde{\boldsymbol{\nu}}_i^{\ell}\right)}$$

No analytical solution, use e.g.,
Newton's method (has structured Hess)

$$\boldsymbol{z}_i^{\ell+1} = \left(\boldsymbol{u}_i^{\ell+1} - \frac{1}{n}\sum_{i=1}^{n} \boldsymbol{u}_i^{\ell+1}\right) + \left(\widetilde{\boldsymbol{\nu}}_i^{\ell} - \frac{1}{n}\sum_{i=1}^{n} \widetilde{\boldsymbol{\nu}}_i^{\ell}\right) + \frac{2}{n\alpha}\boldsymbol{\nu}_{\mathrm{sum}}^{k}$$

$$\widetilde{\boldsymbol{\nu}}_i^{\ell+1} = \widetilde{\boldsymbol{\nu}}_i^{\ell} + \left(\boldsymbol{u}_i^{\ell+1} - \boldsymbol{z}_i^{\ell+1}\right)$$



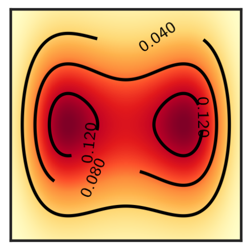
Experiment #1

Linear Fokker-Planck-Kolmogorov PDE

$$\frac{\partial \mu}{\partial t} = \nabla \cdot (\mu \nabla V) + \beta^{-1} \Delta \mu$$

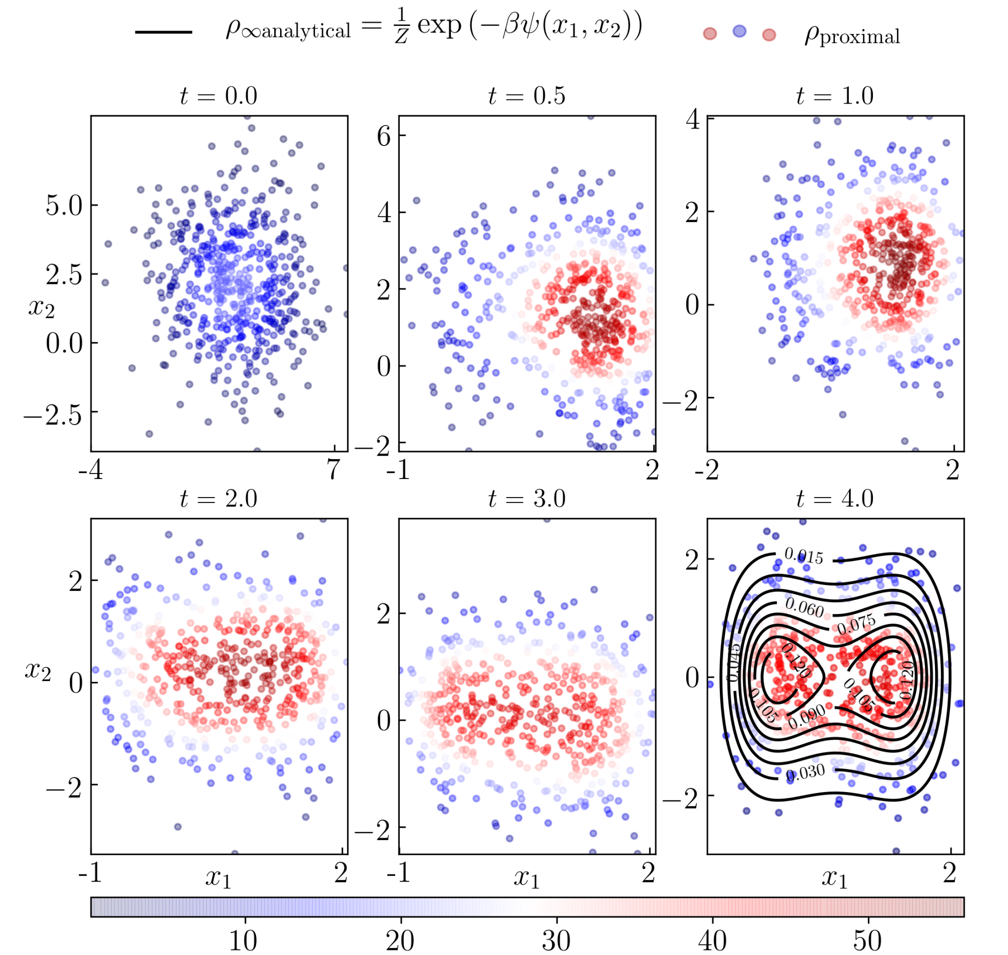
$$V(x_1, x_2) = \frac{1}{4}\left(1 + x_1^4\right) + \frac{1}{2}\left(x_2^2 - x_1^2\right)$$

$$\mu_\infty \propto \exp(-\beta V(x_1, x_2))\mathrm{d}x_1 \mathrm{d}x_2$$



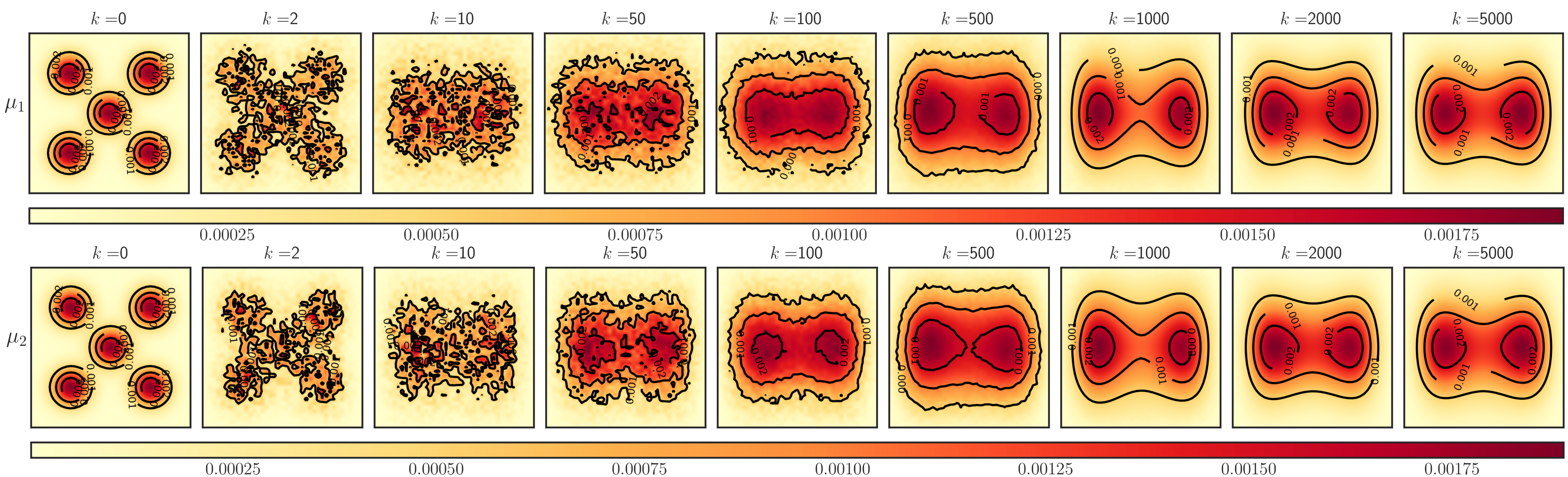
Centralized computation:

Caluya and Halder, *IEEE Trans. Automatic Control*, 2019



Distributed computation:

$$F_1(\boldsymbol{\mu}) = \langle \mathbf{V}_k, \boldsymbol{\mu} \rangle \qquad F_2(\boldsymbol{\mu}) = \left\langle \beta^{-1} \log \boldsymbol{\mu}, \boldsymbol{\mu} \right\rangle$$



Experiment #2

Aggregation-drift-diffusion nonlinear PDE

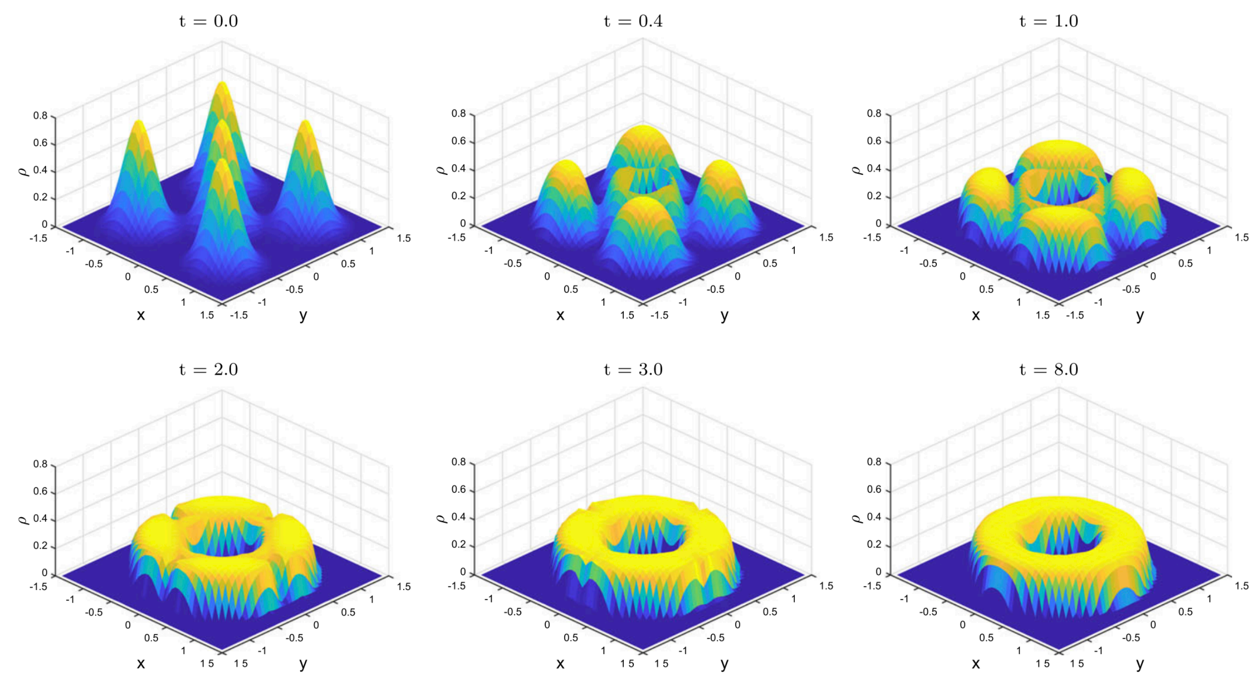
$$\frac{\partial \mu}{\partial t} = \underbrace{\nabla \cdot (\mu \nabla (U * \mu))}_{i=1} + \underbrace{\nabla \cdot (\mu \nabla V) + \beta^{-1} \Delta \mu^2}_{i=2}$$

$$U(\boldsymbol{x}) = \frac{1}{2}\|\boldsymbol{x}\|_2^2 - \ln \|\boldsymbol{x}\|_2$$

$$V(\boldsymbol{x}) = -\frac{1}{4} \ln \|\boldsymbol{x}\|_2$$

Centralized computation:

Carrillo, Craig, Wang and Wei, *FOCM*, 2021

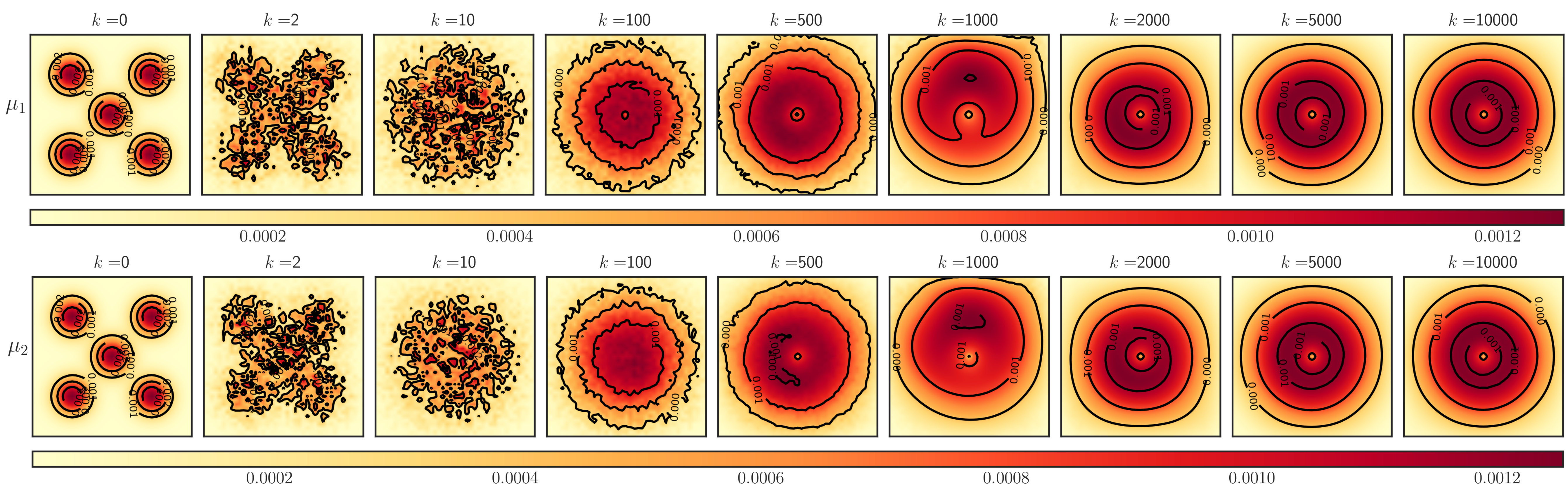


$$\lim_{\beta^{-1} \downarrow 0} \mu_\infty = \mathrm{Unif}\,(\mathscr{A})$$

Annulus with inner radius $1/2$ and outer radius $\sqrt{5}/2$

Distributed computation:

$F_1(\boldsymbol{\mu}) = \langle \boldsymbol{U}_k \boldsymbol{\mu}, \boldsymbol{\mu} \rangle \quad F_2(\boldsymbol{\mu}) = \langle \boldsymbol{V}_k + \beta^{-1} \log \boldsymbol{\mu}, \boldsymbol{\mu} \rangle$



Experiment #2 (contd.)

Aggregation-drift-diffusion nonlinear PDE

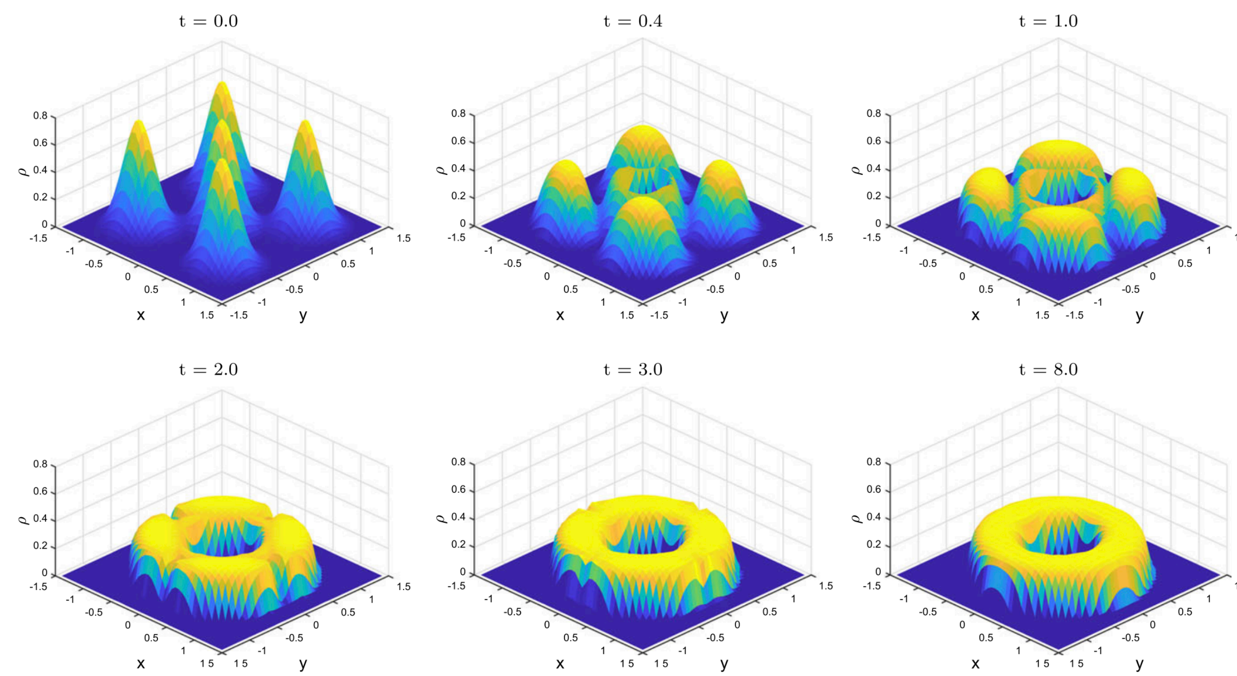
$$\frac{\partial \mu}{\partial t} = \underbrace{\nabla \cdot (\mu \nabla (U * \mu))}_{i=1} + \underbrace{\nabla \cdot (\mu \nabla V) + \beta^{-1} \Delta \mu^2}_{i=2}$$

$$U(\boldsymbol{x}) = \frac{1}{2}\|\boldsymbol{x}\|_2^2 - \ln \|\boldsymbol{x}\|_2$$

$$V(\boldsymbol{x}) = -\frac{1}{4}\ln \|\boldsymbol{x}\|_2$$

Centralized computation:

Carrillo, Craig, Wang and Wei, *FOCM*, 2021

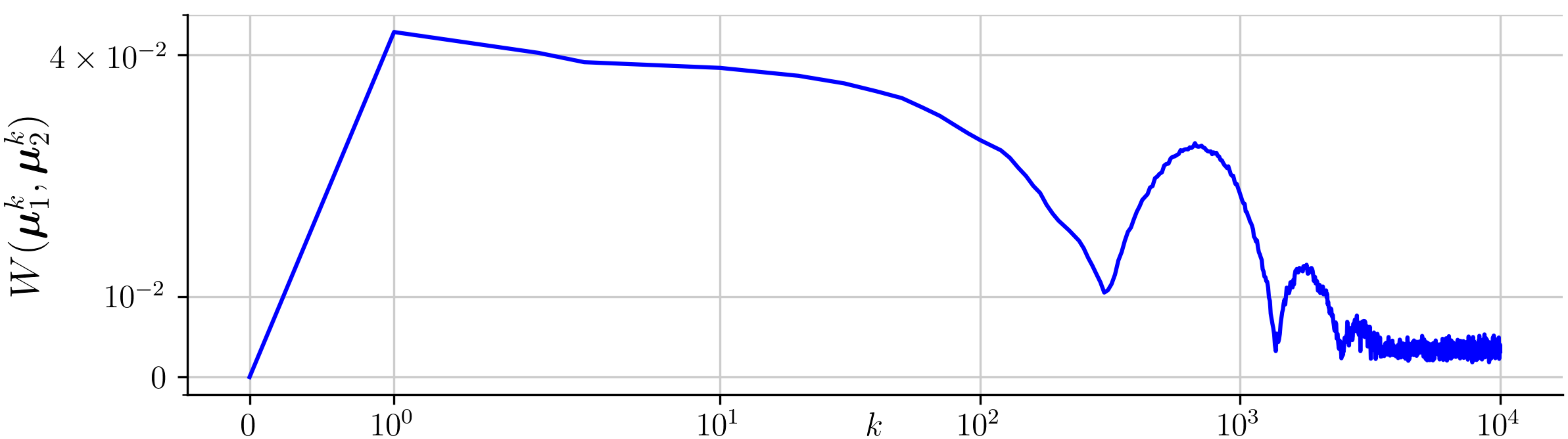


$$\lim_{\beta^{-1} \downarrow 0} \mu_\infty = \mathrm{Unif}\,(\mathscr{A})$$

Annulus with inner radius $1/2$ and outer radius $\sqrt{5}/2$

Distributed computation:

$$F_1(\boldsymbol{\mu}) = \langle \boldsymbol{U}_k \boldsymbol{\mu}, \boldsymbol{\mu} \rangle \qquad F_2(\boldsymbol{\mu}) = \langle \boldsymbol{V}_k + \beta^{-1} \log \boldsymbol{\mu}, \boldsymbol{\mu} \rangle$$

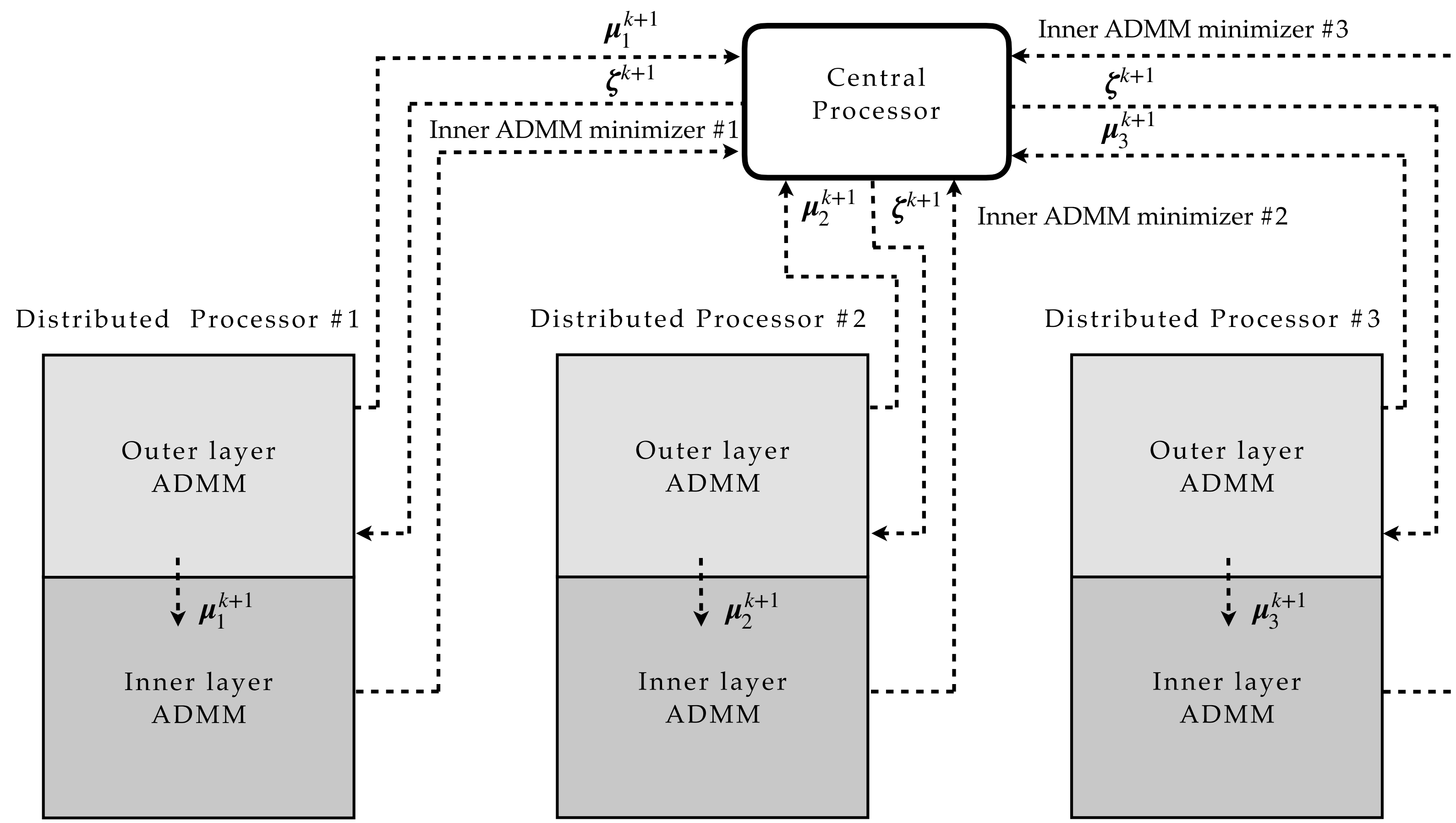


Summary

Distributed computation for measure-valued optimization

Realizes measure-valued operator splitting

Takes advantage of the existing proximal and JKO type algorithms



Ongoing

Convergence guarantees for the overall scheme

High dimensional case studies

Thank You