## Wasserstein Consensus ADMM

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Main Idea
$\underset{\mu \in \mathcal{P}_{2}\left(\mathbb{R}^{d}\right)}{\arg \inf } F_{1}(\mu)+F_{2}(\mu)+\ldots+F_{n}(\mu)$

$\vdots$ re-write
$\underset{\left(\mu_{1}, \mu^{()}\right) \in \mathcal{P}^{n+1}\left(\mathbb{R}^{d}\right)}{\arg \inf } F_{1}\left(\mu_{1}\right)+F_{2}\left(\mu_{2}\right)+\ldots+F_{n}\left(\mu_{n}\right)$
subject to $\quad \mu_{i}=\zeta$ for all $i \in[n]$
Define Wasserstein augmented Lagrangian:
$L_{\alpha}\left(\mu_{1}, \ldots, \mu_{n}, \zeta, \nu_{1}, \ldots, \nu_{n}\right):=\sum_{i=1}^{n}\left\{F_{i}\left(\mu_{i}\right)+\frac{\alpha}{2} W^{2}\left(\mu_{i}, \zeta\right)+\int_{\mathbb{R}^{d}} \nu_{i}(\boldsymbol{\theta})\left(\mathrm{d} \mu_{i}-\mathrm{d} \zeta\right)\right\}$ regularization $>0 \quad$ Lagrange multipliers
$\mu_{i}^{k+1}=\arg \inf L_{\alpha}\left(\mu_{1}, \ldots, \mu_{n}, \zeta^{k}, \nu_{1}^{k}, \ldots, \nu_{n}^{k}\right)$ $\mu_{i} \in \mathcal{P}_{2}\left(\mathbb{R}^{d}\right)$
$\zeta^{k+1}=\underset{\zeta \subset \mathcal{P}^{2}\left(\mathbb{R}^{d}\right)}{\arg \inf } L_{\alpha}\left(\mu_{1}^{k+1}, \ldots, \mu_{n}^{k+1}, \zeta, \nu_{1}^{k}, \ldots, \nu_{n}^{k}\right)$ $\zeta \in \mathcal{P}_{2}\left(\mathbb{R}^{d}\right)$
$\nu_{i}^{k+1}=\nu_{i}^{k}+\alpha\left(\mu_{i}^{k+1}-\zeta^{k+1}\right)$
and simplify the recursions to

$$
\begin{aligned}
\mu_{i}^{k+1} & =\operatorname{prox}_{\frac{1}{\alpha}\left(F_{i}(\cdot)+\int \nu_{i}^{k} \mathrm{~d}(\cdot)\right)}^{W}\left(\zeta^{k}\right) \\
\zeta^{k+1} & =\underset{\zeta \in \mathcal{P}_{2}\left(\mathbb{R}^{d}\right)}{\arg \inf }\left\{\left(\sum_{i=1}^{n} W^{2}\left(\mu_{i}^{k+1}, \zeta\right)\right)-\frac{2}{\alpha} \int_{\mathbb{R}^{d}} \nu_{\text {sum }}^{k}(\boldsymbol{\theta}) \mathrm{d} \zeta\right\} \\
\nu_{i}^{k+1} & =\nu_{i}^{k}+\alpha\left(\mu_{i}^{k+1}-\zeta^{k+1}\right)
\end{aligned}
$$



Schematic

| Outer layer <br> ADMM |
| :---: |
|  |
| Inner layer <br> ADMM |


$\begin{array}{c:c}\hat{1} \mu_{2}^{k+1} & \zeta^{k+1} \\ \text { inner ADMM minimizer \#2 }\end{array}$


Centralized computation:


Distributed computation:
$F_{1}(\boldsymbol{\mu})=\left\langle\boldsymbol{V}_{k}, \boldsymbol{\mu}\right\rangle \quad F_{2}(\boldsymbol{\mu})=\left\langle\beta^{-1} \log \boldsymbol{\mu}, \boldsymbol{\mu}\right\rangle$


| Examples: |  |  |
| :---: | :---: | :---: |
| $\Phi_{i}(\cdot)=F_{i}(\cdot)+\int \nu_{i}^{k} \mathrm{~d}(\cdot)$ | PDE | Name |
| $\int_{\mathbb{R}^{d}}\left(V(\boldsymbol{\theta})+\nu_{i}^{k}(\boldsymbol{\theta}) \mathrm{d} \mu_{i}(\boldsymbol{\theta})\right.$ | $\frac{\partial \widetilde{\mu}_{i}}{\partial t}=\nabla \cdot\left(\widetilde{\mu}_{i}\left(\nabla V+\nabla \nu_{i}^{k}\right)\right)$ | 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 |
| $\int_{\mathbb{R}^{d}} \nu_{i}^{k}(\boldsymbol{\theta}) \mathrm{d} \mu_{i}(\boldsymbol{\theta})+\int_{\mathbb{R}^{2 d}} U(\boldsymbol{\theta}, \boldsymbol{\sigma}) \mathrm{d} \mu_{i}(\boldsymbol{\theta}) \mathrm{d} \mu_{i}(\boldsymbol{\sigma})$ | $\frac{\partial \widetilde{\mu}_{i}}{\partial t}=\nabla \cdot\left(\widetilde{\mu}_{i}\left(\nabla \nu_{i}^{k}+\nabla\left(U \circledast \widetilde{\mu}_{i}\right)\right)\right)$ | 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 |

## Wasserstein distance



Centralized computation:
$\left\{\begin{array}{l}\text { Aggregation-drift-diffusion nonlinear PDE } \\ \frac{\partial \mu}{\partial t}=\underbrace{\nabla \cdot(\mu \nabla(U * \mu))}_{i=1}+\underbrace{\nabla \cdot(\mu \nabla V)+\beta^{-1} \Delta \mu^{2}}_{i=2} \\ U(\boldsymbol{x})=\frac{1}{2}\|\boldsymbol{x}\|_{2}^{2}-\ln \|\boldsymbol{x}\|_{2} \\ V(\boldsymbol{x})=-\frac{1}{4} \ln \|\boldsymbol{x}\|_{2}\end{array}\right.$

Distributed computation:

Wasserstein distance
100 run for statistics each of the 4 ways of splitting: ( $2^{n}-n-1$ ways in general)

| Splititing case | Functionals | Wasserstein distance |
| :---: | :---: | :---: |
| \#1 | $\begin{aligned} & F_{1}(\boldsymbol{\mu})=\left\langle V_{k}+\beta^{-1} \boldsymbol{\mu}_{\boldsymbol{\prime}} \boldsymbol{\mu},\right. \\ & F_{2}(\boldsymbol{\mu})=\left\langle\boldsymbol{U}_{k} \boldsymbol{\mu}^{k}, \boldsymbol{\mu}\right\rangle \end{aligned}$ |  |
| \#2 |  |  |
| \#3 | $\begin{aligned} & F_{1}(\boldsymbol{\mu})=\left\langle U_{\boldsymbol{k}} \mu^{k}+V_{k}, \boldsymbol{\mu},\right. \\ & F_{2}(\boldsymbol{\mu})=\left\langle\beta^{-1} \mu, \mu\right\rangle \end{aligned},$ |  |
| \#4 | $\begin{aligned} F_{1}(\boldsymbol{\mu}) & =\left\langle V_{k, ~}, \boldsymbol{\mu}\right\rangle, \\ F_{2}(\mu) & =\left\langle U_{k}{ }^{k}\right\rangle \\ F_{3}(\mu) & =\left\langle\beta^{-1} \mu, \boldsymbol{\mu}\right\rangle \end{aligned}$ |  |

