

Mirror and Preconditioned Gradient Descent in Wasserstein Space

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Contributions

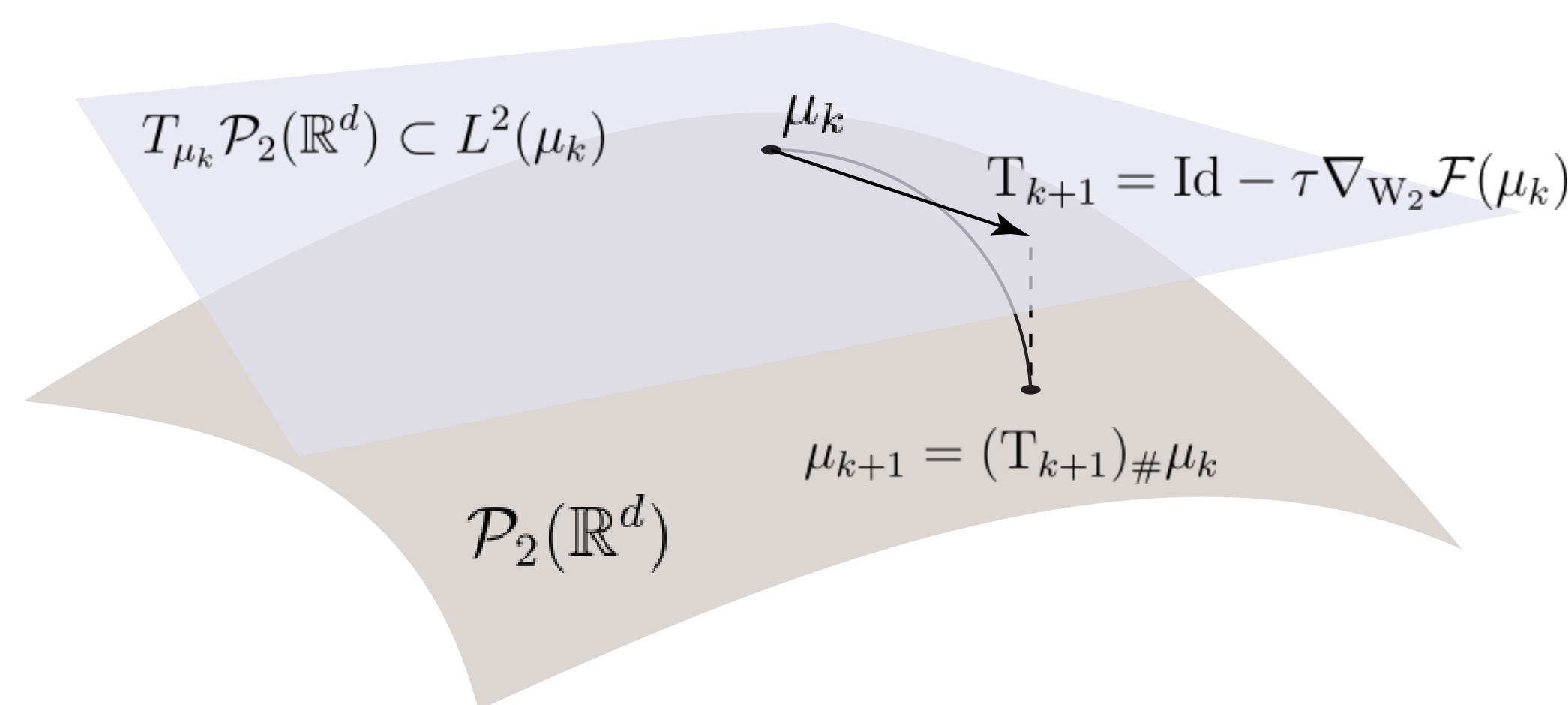
Goal: $\min_{\mu \in \mathcal{P}_2(\mathbb{R}^d)} \mathcal{F}(\mu)$ for $\mathcal{F} : \mathcal{P}_2(\mathbb{R}^d) \rightarrow \mathbb{R}$

• Study two optimization schemes of the form

$$\begin{cases} T_{k+1} = \operatorname{argmin}_{T \in L^2(\mu_k)} d(T, \operatorname{Id}) + \langle \nabla_{W_2} \mathcal{F}(\mu_k), T - \operatorname{Id} \rangle_{L^2(\mu_k)} \\ \mu_{k+1} = (T_{k+1})_{\#} \mu_k \end{cases}$$

• Provide descent and convergence conditions

• Verification of the benefit on experiments



Wasserstein Space

Wasserstein gradient: For $\mathcal{F} : \mathcal{P}_2(\mathbb{R}^d) \rightarrow \mathbb{R}$, $\gamma \in \Pi_o(\mu, \nu)$,

$$\mathcal{F}(\nu) = \mathcal{F}(\mu) + \int \langle \nabla_{W_2} \mathcal{F}(\mu)(x), y - x \rangle d\gamma(x, y) + o(W_2(\mu, \nu))$$

For $\mathcal{F} : \mathcal{P}_2(\mathbb{R}^d) \rightarrow \mathbb{R}$, define $\tilde{\mathcal{F}}_{\mu}(T) := \mathcal{F}(T_{\#} \mu)$.

If \mathcal{F} W_2 -differentiable, $\nabla \tilde{\mathcal{F}}_{\mu}(T) = \nabla_{W_2} \mathcal{F}(T_{\#} \mu) \circ T$.

Examples: potentials $\mathcal{V}_V(\mu) = \int V d\mu$, interactions $\mathcal{W}_W(\mu) = \iint W(x-y) d\mu(x) d\mu(y)$, entropy $\mathcal{H}(\mu) = \int \log(\mu(x)) d\mu(x)$.
 $\nabla_{W_2} \mathcal{V}_V(\mu) = \nabla V$, $\nabla_{W_2} \mathcal{W}_W(\mu) = \nabla W \star \mu$, $\nabla_{W_2} \mathcal{H}(\mu) = \nabla \log \mu$

Bregman Divergence and Convexity

Bregman divergence: Let $\phi_{\mu} : L^2(\mu) \rightarrow \mathbb{R}$, $T, S \in L^2(\mu)$,

$$d_{\phi_{\mu}}(T, S) = \phi_{\mu}(T) - \phi_{\mu}(S) - \langle \nabla \phi_{\mu}(S), T - S \rangle_{L^2(\mu)}$$

Relative smoothness/convexity along $t \mapsto \mu_t$ with $\mu_t = (T_t)_{\#} \mu$, $T_t = (1-t)S + tT$ for $S, T \in L^2(\mu)$. \mathcal{F} is β -smooth (resp. α -convex) relative to \mathcal{G} along $t \mapsto \mu_t$ if for all $s, t \in [0, 1]$, $d_{\tilde{\mathcal{F}}_{\mu}}(T_s, T_t) \leq \beta d_{\tilde{\mathcal{G}}_{\mu}}(T_s, T_t)$ (resp. $d_{\tilde{\mathcal{F}}_{\mu}}(T_s, T_t) \geq \alpha d_{\tilde{\mathcal{G}}_{\mu}}(T_s, T_t)$).

• For $\mathcal{F} = \mathcal{V}_V$, $\mathcal{G} = \mathcal{V}_U$: holds provided V β -smooth (resp. α -convex) relative to U

• For $\mathcal{F} = \mathcal{W}_W$, $\mathcal{G} = \mathcal{W}_K$: holds provided W β -smooth (resp. α -convex) relative to K

• $\mathcal{F} = \mathcal{V}_V + \mathcal{H}$ 1-convex relative to \mathcal{V}_V and \mathcal{H}

Implementation of the Schemes

Mirror descent: $d = \frac{1}{\tau} d_{\phi_{\mu}}$, by FOC: $\nabla \phi_{\mu}(T_{k+1}) = \nabla \phi_{\mu}(\operatorname{Id}) - \tau \nabla_{W_2} \mathcal{F}(\mu_k)$

For $\phi_{\mu}(T) = \int V \circ T d\mu = \mathcal{V}_V(T_{\#} \mu)$, $T_{k+1} = \nabla V^* \circ (\nabla V - \tau \nabla_{W_2} \mathcal{F}(\mu_k))$

In general: Newton method

Preconditioned gradient descent:

$$d(T, S) = \phi_{\mu}^h((S - T)/\tau)\tau = \int h((S(x) - T(x))/\tau)\tau d\mu(x)$$

FOC: $T_{k+1} = \operatorname{Id} - \tau \nabla h^* \circ \nabla_{W_2} \mathcal{F}(\mu_k)$

For $\mu_k = \frac{1}{n} \sum_{i=1}^n \delta_{x_i^k}$, for all $k \geq 0$, $i \in \{1, \dots, n\}$, $x_i^{k+1} = T_{k+1}(x_i^k)$.

Theory of Mirror Descent in Wasserstein Space

Let $\beta > 0$, $\tau \leq \frac{1}{\beta}$. For any $\mu \in \mathcal{P}_2(\mathbb{R}^d)$, let $\phi_{\mu} : L^2(\mu) \rightarrow \mathbb{R}$ be strictly convex, proper and differentiable. Assume $\phi_{\mu}(T) = \phi(T_{\#} \mu)$ for $\phi : \mathcal{P}_2(\mathbb{R}^d) \rightarrow \mathbb{R}$.

Define $W_{\phi}(\mu, \nu) = \inf_{\gamma \in \Pi(\mu, \nu)} \phi(\nu) - \phi(\mu) - \int \langle \nabla_{W_2} \phi(\mu)(y), x - y \rangle d\gamma(x, y)$.

Assumptions: Let $T_{\phi_{\mu_k}^{\mu^*}}^{\mu_k, \mu^*} = \operatorname{argmin}_{T, T_{\#} \mu_k = \mu^*} d_{\phi_{\mu_k}}(T, \operatorname{Id})$. For all $k \geq 0$,

- \mathcal{F} is β -smooth relative to ϕ along $t \mapsto ((1-t)\operatorname{Id} + tT_{k+1})_{\#} \mu_k$
- \mathcal{F} is α -convex relative to ϕ along the curves $t \mapsto ((1-t)\operatorname{Id} + tT_{\phi_{\mu_k}^{\mu^*}}^{\mu_k, \mu^*})_{\#} \mu_k$
- $d_{\phi_{\mu_k}}(T_{\phi_{\mu_k}^{\mu^*}}^{\mu_k, \mu^*}, \operatorname{Id}) = W_{\phi}(\mu^*, \mu_k)$ and $d_{\phi_{\mu_k}}(T_{\phi_{\mu_k}^{\mu^*}}^{\mu_k, \mu^*}, T_{k+1}) \geq W_{\phi}(\mu^*, \mu_{k+1})$ (True e.g. if $\mu_k, \mu_{k+1} \in \mathcal{P}_{2,ac}(\mathbb{R}^d)$ and $\nabla_{W_2} \phi(\mu_k), \nabla_{W_2} \phi(\mu_{k+1})$ invertibles)

Convergence Results

- Under 1), for all $k \geq 0$ $\mathcal{F}(\mu_{k+1}) \leq \mathcal{F}(\mu_k) - \frac{1}{\tau} d_{\phi_{\mu_k}}(\operatorname{Id}, T_{k+1})$
- Under 1), 2), 3), for all $k \geq 1$, $\mathcal{F}(\mu_k) - \mathcal{F}(\mu^*) \leq \frac{1-\alpha\tau}{k\tau} W_{\phi}(\mu^*, \mu_0)$

Theory of Preconditioned GD in Wasserstein Space

Let $\beta > 0$, $\tau \leq \frac{1}{\beta}$ and $\bar{T} = \operatorname{argmin}_{T, T_{\#} \mu_k = \mu^*} d_{\tilde{\mathcal{F}}_{\mu_k}}(\operatorname{Id}, \bar{T})$.

Assumptions: For all $k \geq 0$,

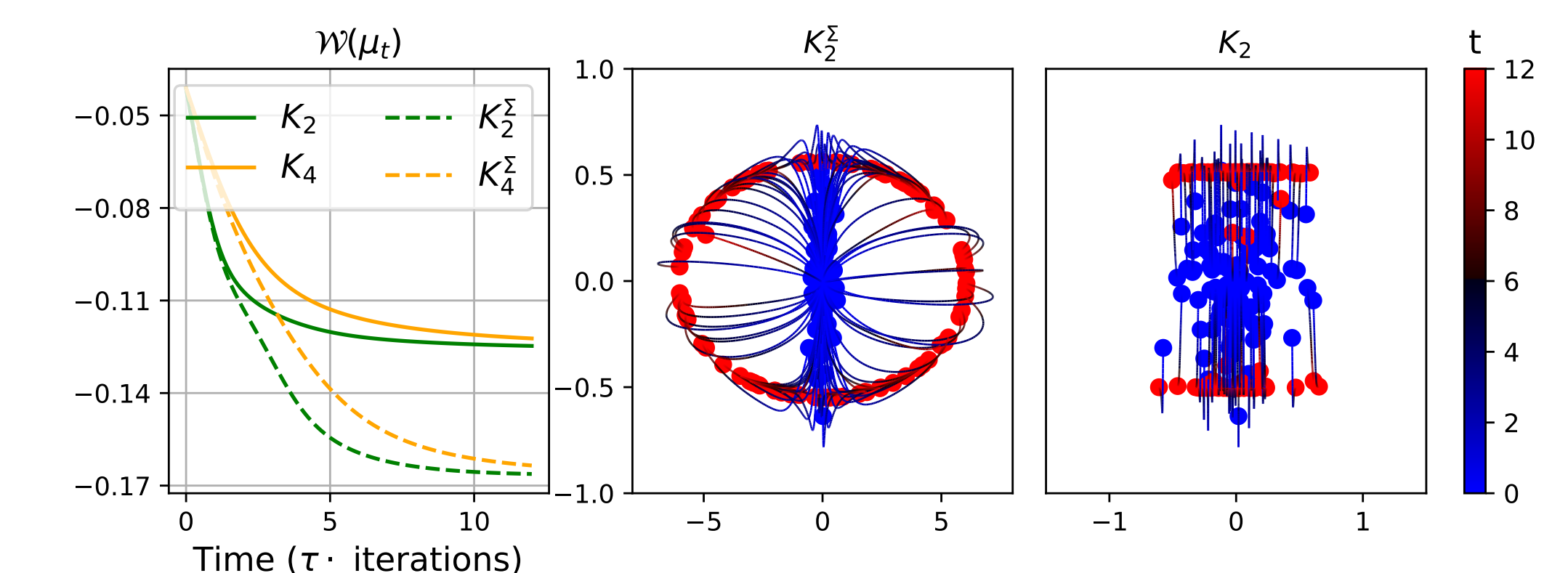
- \mathcal{F} convex along $t \mapsto ((1-t)\operatorname{Id} + tT_{k+1})_{\#} \mu_k$
- $d_{\phi_{\mu_k}^*}(\nabla_{W_2} \mathcal{F}(\mu_{k+1}) \circ T_{k+1}, \nabla_{W_2} \mathcal{F}(\mu_k)) \leq \beta d_{\tilde{\mathcal{F}}_{\mu_k}}(\operatorname{Id}, T_{k+1})$
- $\alpha d_{\tilde{\mathcal{F}}_{\mu_k}}(\operatorname{Id}, \bar{T}) \leq d_{\phi_{\mu_k}^*}(\nabla_{W_2} \mathcal{F}(\bar{T}_{\#} \mu_k) \circ \bar{T}, \nabla_{W_2} \mathcal{F}(\mu_k))$

Convergence Results

- Under 1), 2), $\phi_{\mu_{k+1}}^h(\nabla_{W_2} \mathcal{F}(\mu_{k+1})) \leq \phi_{\mu_k}^h(\nabla_{W_2} \mathcal{F}(\mu_k)) - \frac{1}{\tau} d_{\tilde{\mathcal{F}}_{\mu_k}}(T_{k+1}, \operatorname{Id})$
- Under 1), 2), 3), $\phi_{\mu_k}^h(\nabla_{W_2} \mathcal{F}(\mu_k)) - h^*(0) \leq \frac{1-\tau\alpha}{\tau k} (\mathcal{F}(\mu_0) - \mathcal{F}(\mu^*))$

Mirror Descent Experiments

Minimization of an interaction energy $\mathcal{F}(\mu) = \mathcal{W}_W(\mu)$ with $W(z) = \frac{1}{4} \|z\|_{\Sigma^{-1}}^4 - \frac{1}{2} \|z\|_{\Sigma^{-1}}^2$ and $\phi(\mu) = \mathcal{W}_K(\mu)$ with $K_2^{\Sigma}(z) = \frac{1}{2} \|z\|_{\Sigma^{-1}}^2$, $K_2 = K_2^I$, $K_4^{\Sigma}(z) = \frac{1}{4} \|z\|_{\Sigma^{-1}}^4 + \frac{1}{2} \|z\|_{\Sigma^{-1}}^2$, $K_4 = K_4^I$.

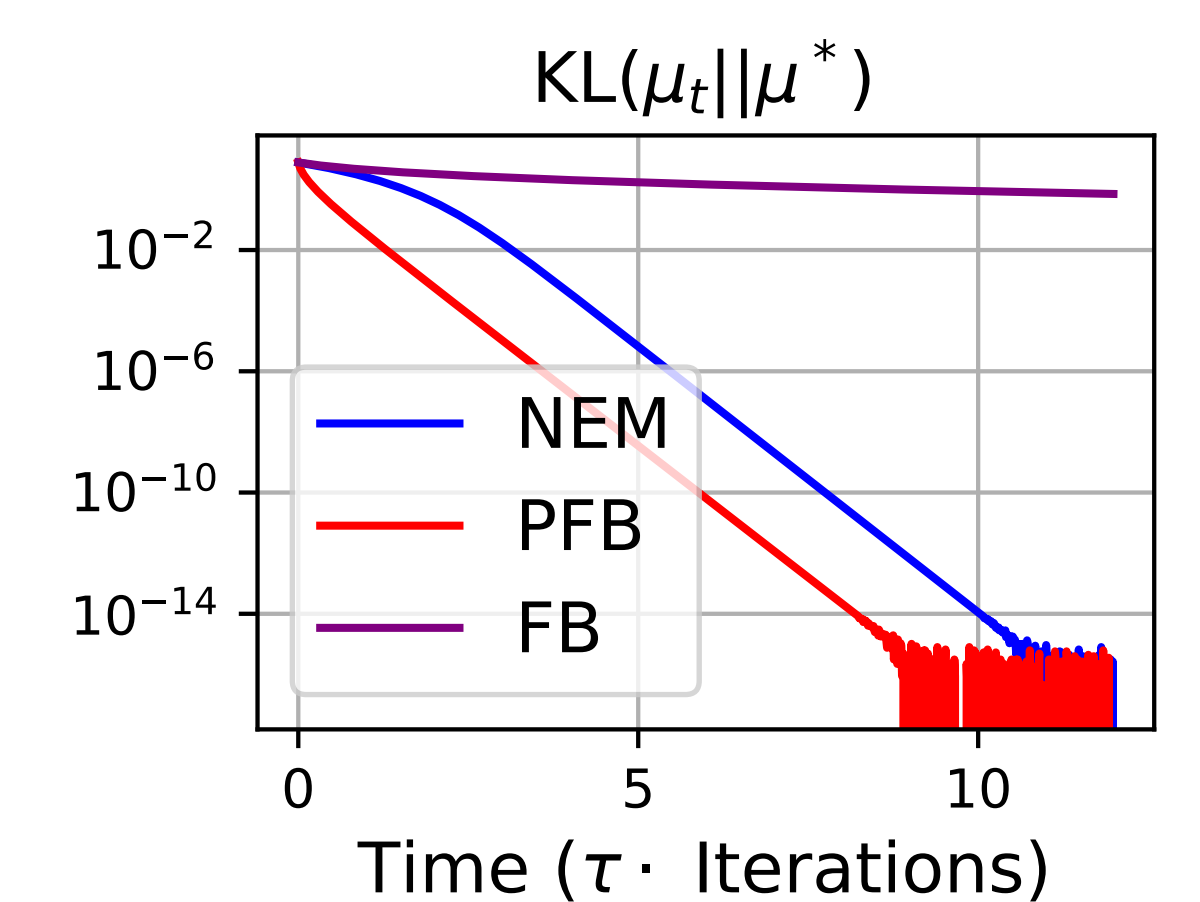


Minimization of

$$\mathcal{F}(\mu) = \mathcal{V}_V(\mu) + \mathcal{H}(\mu),$$

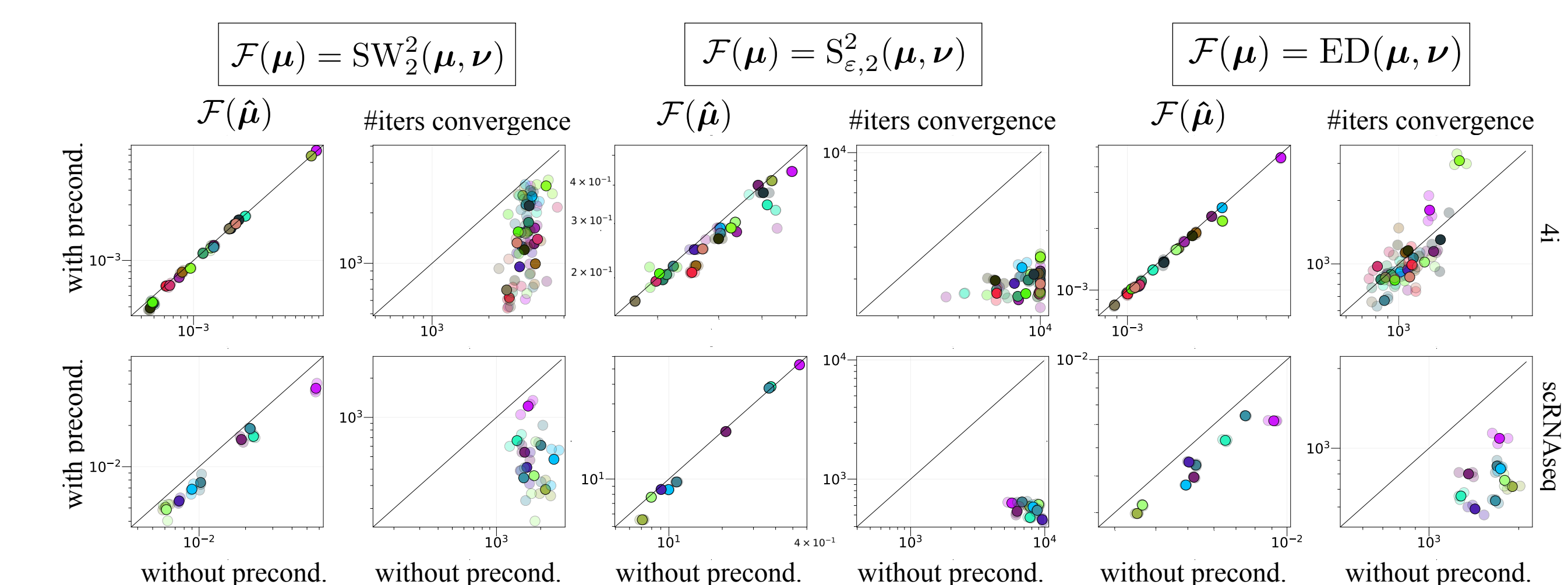
for $V(x) = \frac{1}{2} x^T \Sigma^{-1} x$ with

$$\begin{aligned} \phi(\mu) &= \int \frac{1}{2} \|x\|_2^2 d\mu(x) && \text{(FB)}, \\ \phi(\mu) &= \mathcal{V}_V(\mu) && \text{(PFB)}, \\ \phi(\mu) &= \mathcal{H}(\mu) && \text{(NEM)}. \end{aligned}$$



Preconditioned GD for Single Cells

Minimize $\mathcal{F}(\mu) = D(\mu, \nu)$ with μ_0 untreated cells and ν perturbed cells. Use $h^*(x) = (\|x\|_2^a + 1)^{1/a} - 1$ with $a \in \{1.25, 1.5, 1.75\}$ which is well suited to minimize functions growing in $\|x - x^*\|^{a/(a-1)}$.



• Rows: 2 profiling technologies

• Points: For treatment i , $z_i = (x_i, y_i)$ with x_i value of $\mathcal{F}(\hat{\mu}) = D(\hat{\mu}, \nu)$ (1st subcolumn) or number of iterations to converge (2nd subcolumn) without preconditioning and y_i with preconditioning

→ Points below the diagonal: **Preconditioned GD provides a better minimum or converges faster**