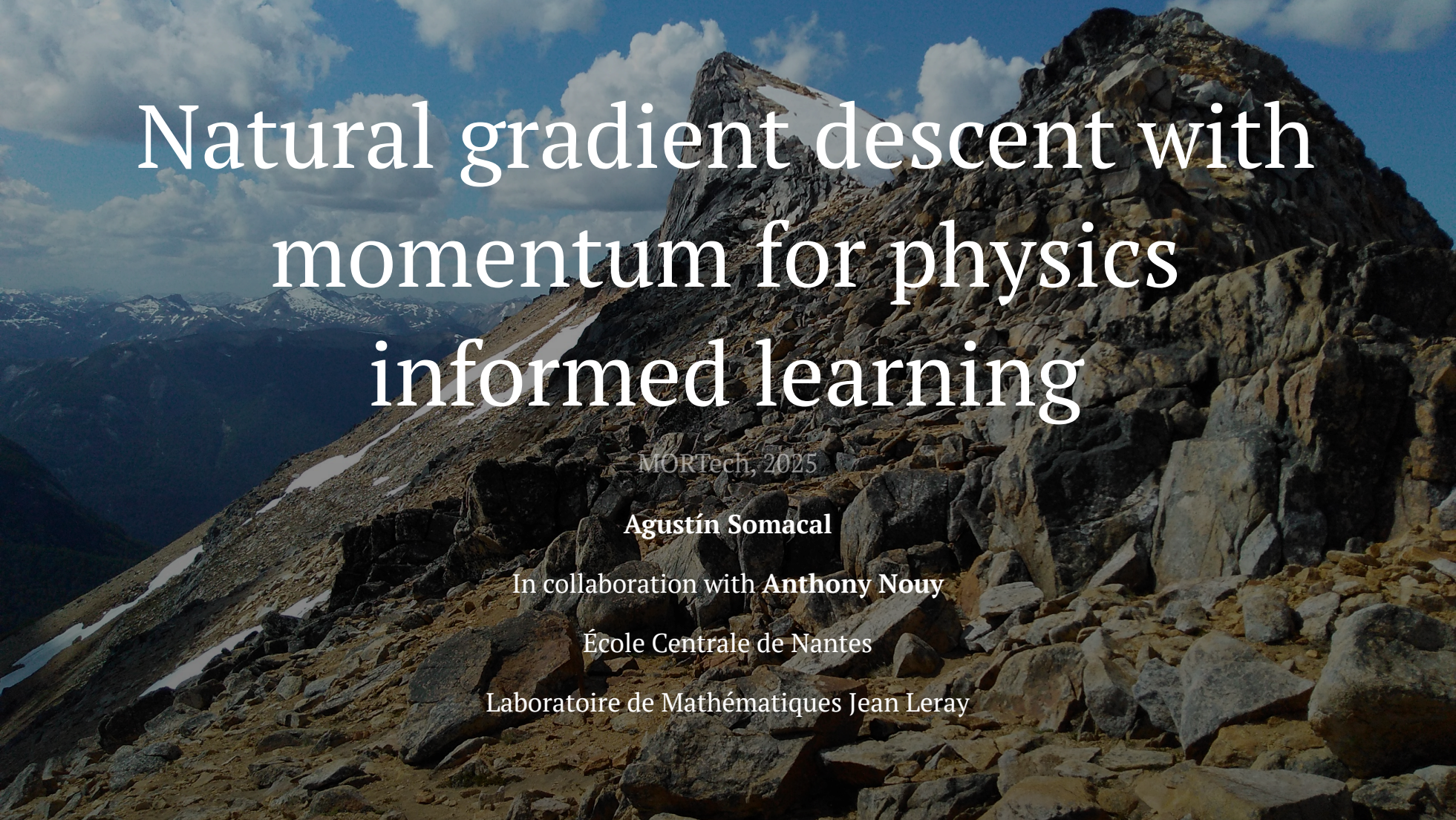

Natural gradient descent with momentum for physics informed learning

— MORTech, 2025

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Outline

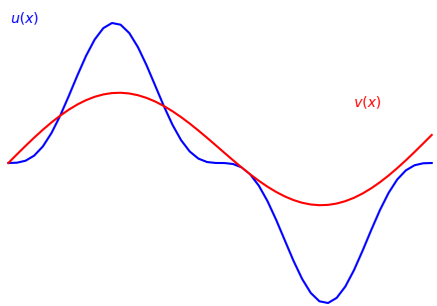
1. **What is natural gradient and why we may need it?**
   - Problem setting
   - From gradient descent to Newton's method.
   - From Newton's method to natural gradient.
   - Toy examples to gain intuition.
2. **What is momentum and when we may need it?**
3. **How to combine momentum and natural gradient.**
   - Some toy examples
   - Some less toy examples

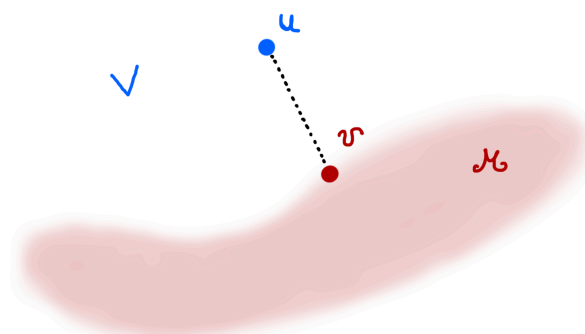
Problem formulation

Objective: approximate target function $u \in V$ by $v \in \mathcal{M} \subset V$

Target function $\quad u : \mathbb{R}^d \to \mathbb{R} \in V$

Hilbert space
$L^2(\Omega), H^1(\Omega), \ldots$





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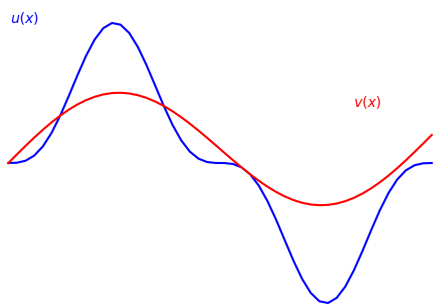
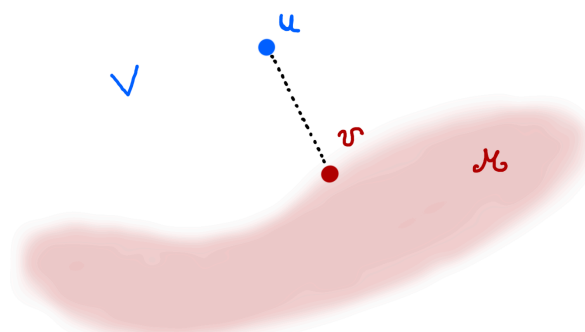
Hilbert space $L^2(\Omega), H^1(\Omega), \ldots$

Approximation manifold $\quad \mathcal{M} := \{v_\theta(x) = A(\theta)(x);\ \theta \in \mathbb{R}^p\}$

Linear model

$$A(\theta)(x) = \theta_1 \phi_1(x) + \cdots + \theta_p \phi_p(x)$$
$$= \theta^T \mathbf{\Phi}(x)$$





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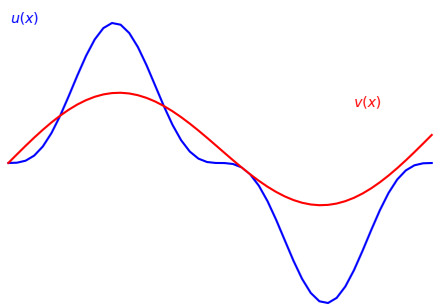

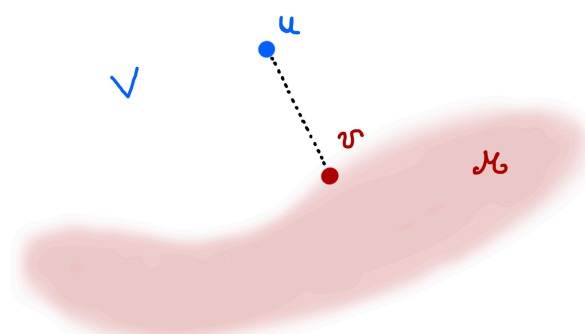

Minimization problem

Objective: approximate $u \in V$ by $v \in \mathcal{M}$.

Continuous problem

$$
\begin{aligned}
\mathcal{L}_u(v) &= \frac{1}{2}\|u - v\|_V^2 \\
&= \frac{1}{2}\langle u - v, u - v\rangle_V \\
&= \frac{1}{2}\int (u(x) - v(x))^2 \mathrm{d}\mu(x)
\end{aligned}
$$

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Discrete problem

$$\begin{aligned}\mathcal{L}_u(v) &= \frac{1}{2}\|u - v\|_m^2 \\ &= \frac{1}{2}\langle u - v, u - v\rangle_m \\ &= \frac{1}{2m}\sum_{i=1}^{m}(u(x_i) - v(x_i))^2\end{aligned}$$

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Functional perspective

$$v^* = \arg\min_{v \in \mathcal{M}} \mathcal{L}_u(v)$$

Parameter perspective

$$\theta^* = \arg\min_{\theta \in \mathbb{R}^p} \mathcal{L}_u(A(\theta))$$

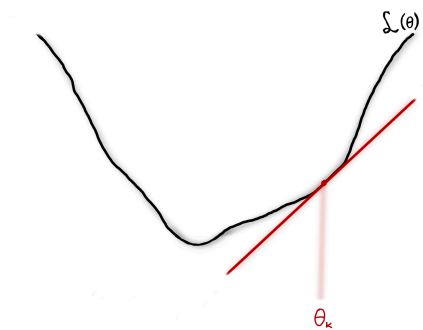
$$\mathcal{L}_u(A(\theta)) = (\mathcal{L}_u \circ A)(\theta) =: L(\theta)$$

Gradient descent

Iteratively improve approximation by minimizing $L(\theta_k)$.

Taylor expansion around current iterate θ_k.

$$L(\theta) \approx L(\theta_k) + \langle \nabla_\theta L(\theta_k), \theta - \theta_k \rangle_{\mathbb{R}^p}$$

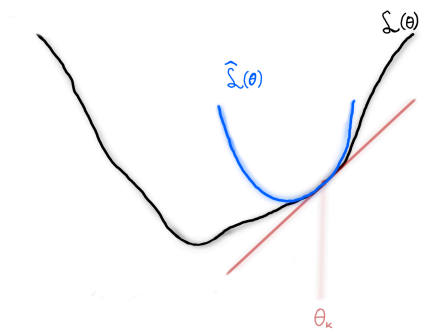


Gradient descent

Iteratively improve approximation by minimizing $L(\theta_k)$.

Taylor expansion around current iterate θ_k plus penalization on the distance traveled on each step.

$$L(\theta) \approx L(\theta_k) + \langle \nabla_\theta L(\theta_k), \theta - \theta_k \rangle_{\mathbb{R}^p} + \frac{1}{2s}\rho(\theta, \theta_k)$$



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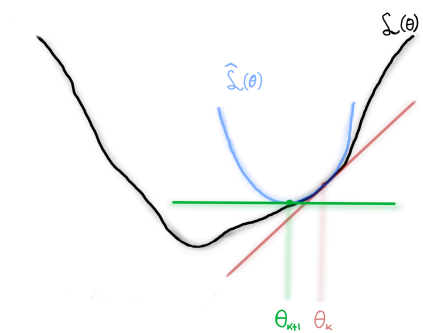
Taylor expansion around current iterate θ_k plus penalization on the distance traveled on each step.

$$0 = \nabla_\theta \left[L(\theta_k) + \langle \nabla_\theta L(\theta_k), \theta - \theta_k \rangle_{\mathbb{R}^p} + \frac{1}{2s} \rho(\theta, \theta_k) \right]$$



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Gradient descent

$$\rho(\theta, \theta_k) = \|\theta - \theta_k\|^2_{\mathbb{R}^p}$$

$$\nabla_\theta \rho(\theta, \theta_k) = 2(\theta - \theta_k)$$

$$\theta = \theta_k - s\nabla_\theta L(\theta_k)$$

Preconditioned gradient

Iteratively improve approximation by minimizing $L(\theta_k)$.

Taylor expansion around current iterate θ_k plus penalization on the distance traveled on each step.

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Gradient descent	Preconditioned gradient
$\rho(\theta, \theta_k) = \|\theta - \theta_k\|^2_{\mathbb{R}^p}$	$\rho(\theta, \theta_k) = \|\theta - \theta_k\|^2_M$
$\nabla_\theta \rho(\theta, \theta_k) = 2(\theta - \theta_k)$	$\nabla_\theta \rho(\theta, \theta_k) = 2M(\theta - \theta_k)$
$\theta = \theta_k - s\nabla_\theta L(\theta_k)$	$\theta = \theta_k - sM^{-1}\nabla_\theta L(\theta_k)$

Newton's method

Iteratively improve approximation by minimizing $L(\theta_k)$.

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Gradient descent	Newton's method
$\rho(\theta, \theta_k) = \|\theta - \theta_k\|^2_{\mathbb{R}^p}$	$\rho(\theta, \theta_k) = \|\theta - \theta_k\|^2_H$
$\nabla_\theta \rho(\theta, \theta_k) = 2(\theta - \theta_k)$	$\nabla_\theta \rho(\theta, \theta_k) = 2H(\theta - \theta_k)$
$\theta = \theta_k - s\nabla_\theta L(\theta_k)$	$\theta = \theta_k - sH^{-1}\nabla_\theta L(\theta_k)$

Functional gradient and geometric intuition

Some properties [Gruhlke, Robert, Anthony Nouy, and Philipp Trunschke. 2024].

$$H_{ij} = \frac{\partial^2 L}{\partial\theta_i \partial\theta_j} = \frac{\partial}{\partial\theta_i}\left[\frac{\partial L}{\partial\theta_j}\right] = \frac{\partial}{\partial\theta_i}\left[\frac{\partial}{\partial\theta_j}(\mathcal{L}_u \circ A)\right] = \frac{\partial}{\partial\theta_i}\left[\int_\Omega \nabla\mathcal{L}_u(v_\theta)(x)\frac{\partial A}{\partial\theta_j}(x)\mathrm{d}\mu(x)\right]$$

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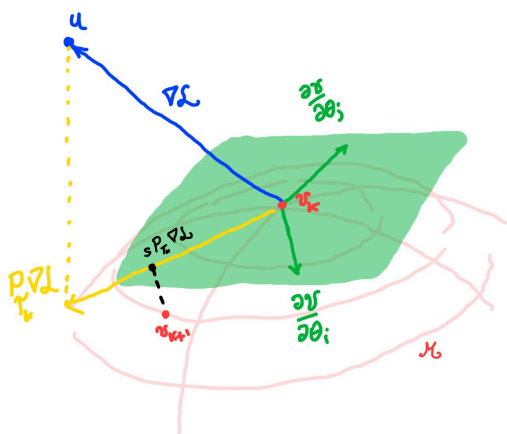

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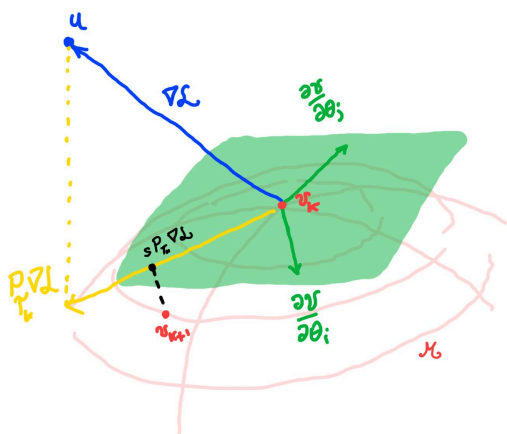

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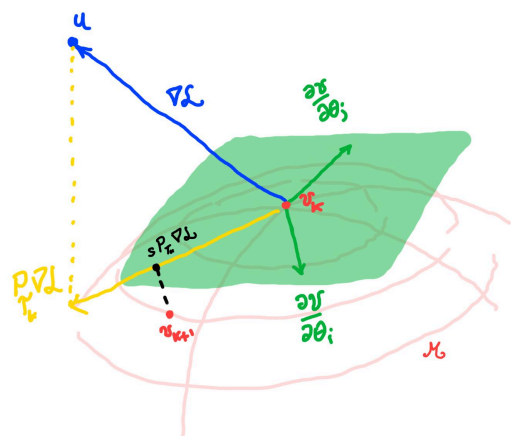

$$\mathcal{L}_u(v) = \frac{1}{2}\|u - v\|^2_{L^2(\Omega)}$$

$$V \ni \nabla\mathcal{L}_u = u - v$$

Natural gradient from Newton's method

[Amari, Shun-ichi. 1998] [Martens, James 2020].

$$
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&= \left\langle H_V\mathcal{L}\frac{\partial A}{\partial\theta_i}, \frac{\partial A}{\partial\theta_j}\right\rangle_V + \left\langle \nabla\mathcal{L}_u, \frac{\partial^2 A}{\partial\theta_i\partial\theta_j}\right\rangle_V \\
&= G^{H_\mathcal{L}} + \langle \nabla\mathcal{L}_u, H_A\rangle_V
\end{aligned}
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$$
G_{ij}^{H_\mathcal{L}} = \int \frac{\partial A}{\partial\theta_i}(x)[H_V\mathcal{L}(v)](x)\frac{\partial A}{\partial\theta_j}(x)\mathrm{d}\mu(x).
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\mathcal{L}_u(v) = \frac{1}{2}\|u - v\|^2_{L^2(\Omega)} \qquad \longrightarrow \qquad H_V\mathcal{L}(v)(x) = 1
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$$= G^{H_\mathcal{L}} \cancel{+ \langle \nabla\mathcal{L}_u, H_A\rangle_V}$$

Model linearization

$$G^{H_\mathcal{L}}_{ij} = \int \frac{\partial A}{\partial\theta_i}(x)[H_V\mathcal{L}(v)](x)\frac{\partial A}{\partial\theta_j}(x)\mathrm{d}\mu(x).$$

$$\mathcal{L}_u(v) = \frac{1}{2}\|u - v\|^2_{L^2(\Omega)} \qquad \longrightarrow \qquad H_V\mathcal{L}(v)(x) = 1$$

$$G_{ij} = \int \left[\frac{\partial A}{\partial\theta_i}\frac{\partial A}{\partial\theta_j}\right](x)\mathrm{d}x$$

Natural gradient flow dynamics

$$\rho(\theta, \theta_k) = \|\theta - \theta_k\|_G^2 \qquad \longrightarrow \qquad \theta = \theta_k - sG^{-1}\nabla_\theta L(\theta_k)$$

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Preconditioned gradient flow
in **parameter space**

$$\frac{\partial \theta}{\partial s} = -M^{-1}\nabla_\theta L$$

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in **parameter space**

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$$\begin{aligned}
\frac{\partial v_\theta}{\partial s} = \frac{\partial v_\theta}{\partial \theta}\frac{\partial \theta}{\partial s} = \frac{\partial A}{\partial \theta}^T M^{-1}\nabla_\theta L &= -\frac{\partial A}{\partial \theta}^T M^{-1}\left\langle \nabla\mathcal{L}, \frac{\partial A}{\partial \theta}\right\rangle_V \\
&= -\left(G^{-\frac{1}{2}}\frac{\partial A}{\partial \theta}\right)^T G^{\frac{1}{2}} M^{-1} G^{\frac{1}{2}} \left\langle \nabla\mathcal{L}, G^{-\frac{1}{2}}\frac{\partial A}{\partial \theta}\right\rangle_V \\
&= -E^T G^{\frac{1}{2}} M^{-1} G^{\frac{1}{2}} \left\langle \nabla\mathcal{L}, E\right\rangle_V
\end{aligned}$$

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\frac{\partial v_\theta}{\partial s} = \frac{\partial v_\theta}{\partial \theta}\frac{\partial \theta}{\partial s} = \frac{\partial A}{\partial \theta}^T M^{-1}\nabla_\theta L &= -\frac{\partial A}{\partial \theta}^T M^{-1}\left\langle \nabla\mathcal{L}, \frac{\partial A}{\partial \theta}\right\rangle_V \\
&= -\left(G^{-\frac{1}{2}}\frac{\partial A}{\partial \theta}\right)^T G^{\frac{1}{2}} M^{-1} G^{\frac{1}{2}}\left\langle \nabla\mathcal{L}, G^{-\frac{1}{2}}\frac{\partial A}{\partial \theta}\right\rangle_V \\
&= -E^T G^{\frac{1}{2}} M^{-1} G^{\frac{1}{2}} \langle \nabla\mathcal{L}, E\rangle_V
\end{aligned}$$

$$\langle E, E\rangle_V = \int_\Omega \left(G^{-\frac{1}{2}}\frac{\partial A}{\partial \theta}\right)^T \left(G^{-\frac{1}{2}}\frac{\partial A}{\partial \theta}\right) \mathrm{d}\mu(x) \quad = \int_\Omega \frac{\partial A}{\partial \theta}^T G^{-1}\frac{\partial A}{\partial \theta}\mathrm{d}\mu(x) = I$$

Natural gradient flow dynamics

$$\rho(\theta, \theta_k) = \|\theta - \theta_k\|_G^2 \qquad \longrightarrow \qquad \theta = \theta_k - sG^{-1}\nabla L(\theta_k)$$

Preconditioned gradient flow in **parameter space**

$$\frac{\partial \theta}{\partial s} = -M^{-1}\nabla_\theta L$$

Preconditioned gradient flow in **functional space**

$$\frac{\partial v_\theta}{\partial s} = -E^T G^{\frac{1}{2}} M^{-1} G^{\frac{1}{2}} \langle \nabla \mathcal{L}, E \rangle_V$$

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$$\frac{\partial v_\theta}{\partial s} = -E^T G^{\frac{1}{2}} M^{-1} G^{\frac{1}{2}} \langle \nabla \mathcal{L}, E \rangle_V$$

Gradient descent $M = I$
in **functional space**

$$\frac{\partial v_\theta}{\partial s} = -E^T G^{\frac{1}{2}} I^{-1} G^{\frac{1}{2}} \langle \nabla \mathcal{L}, E \rangle_V$$

Natural gradient flow dynamics

$$\rho(\theta, \theta_k) = \|\theta - \theta_k\|_G^2 \qquad \longrightarrow \qquad \theta = \theta_k - sG^{-1}\nabla L(\theta_k)$$

Preconditioned gradient flow
in **parameter space**

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Preconditioned gradient flow
in **functional space**

$$\frac{\partial v_\theta}{\partial s} = -E^T G^{\frac{1}{2}} M^{-1} G^{\frac{1}{2}} \langle \nabla \mathcal{L}, E \rangle_V$$

Gradient descent $M = I$
in **functional space**

$$\frac{\partial v_\theta}{\partial s} = -E^T G \langle \nabla \mathcal{L}, E \rangle_V$$

Natural gradient flow dynamics

$$\rho(\theta, \theta_k) = \|\theta - \theta_k\|_G^2 \qquad \longrightarrow \qquad \theta = \theta_k - sG^{-1}\nabla L(\theta_k)$$

Preconditioned gradient flow
in **parameter space**

$$\frac{\partial \theta}{\partial s} = -M^{-1}\nabla_\theta L$$

Preconditioned gradient flow
in **functional space**

$$\frac{\partial v_\theta}{\partial s} = -E^T G^{\frac{1}{2}} M^{-1} G^{\frac{1}{2}} \langle \nabla \mathcal{L}, E \rangle_V$$

Gradient descent $M = I$
in **functional space**

$$\frac{\partial v_\theta}{\partial s} = -E^T G \langle \nabla \mathcal{L}, E \rangle_V$$

Natural gradient $M = G$
in **functional space**

$$\frac{\partial v_\theta}{\partial s} = -E^T G^{\frac{1}{2}} G^{-1} G^{\frac{1}{2}} \langle \nabla \mathcal{L}, E \rangle_V$$

Natural gradient flow dynamics

$$\rho(\theta, \theta_k) = \|\theta - \theta_k\|_G^2 \qquad \longrightarrow \qquad \theta = \theta_k - sG^{-1}\nabla L(\theta_k)$$

Preconditioned gradient flow
in **parameter space**

$$\frac{\partial \theta}{\partial s} = -M^{-1}\nabla_\theta L$$

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$$\frac{\partial v_\theta}{\partial s} = -E^T G^{\frac{1}{2}} M^{-1} G^{\frac{1}{2}} \langle \nabla \mathcal{L}, E \rangle_V$$

Gradient descent $M = I$
in **functional space**

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in **functional space**

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Gradient descent $M = I$
in **functional space**

$$\frac{\partial v_\theta}{\partial s} = -E^T G \langle \nabla \mathcal{L}, E \rangle_V$$

Natural gradient $M = G$
in **functional space**

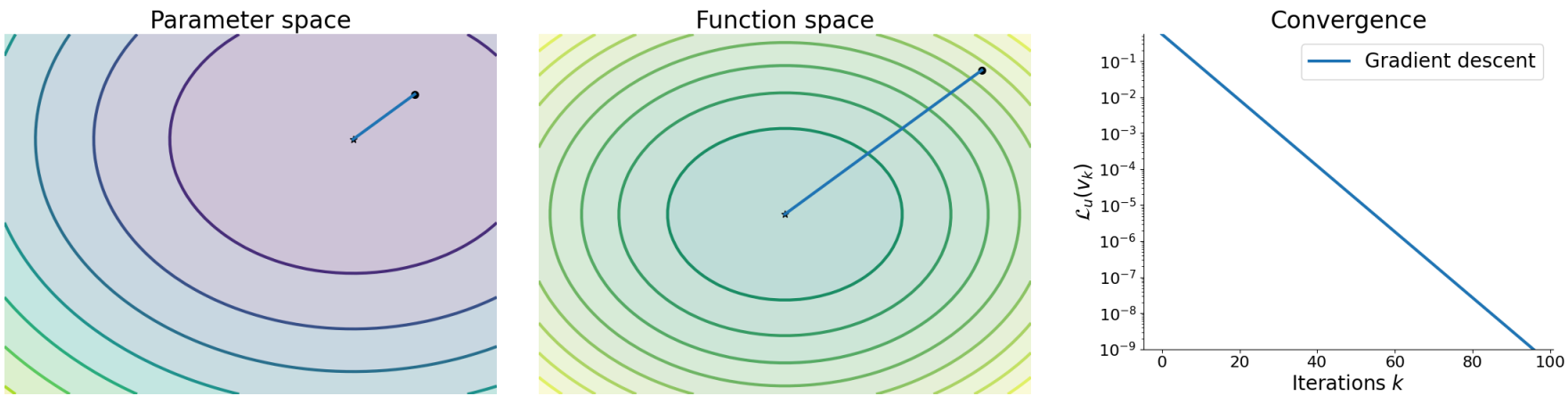
$$\frac{\partial v_\theta}{\partial s} = -P_{\mathcal{T}_k} \nabla \mathcal{L}$$

Toy example

Gradient descent trajectory.

$$u \in L^2([-1,1])$$
$$\mathcal{L}_u(v) = \frac{1}{2}\|u - v\|^2$$
$$v_\theta(x) = A(\theta)(x) = \theta^T \Phi(x)$$
$$= \theta^T \begin{bmatrix} \sin(2\pi x) \\ \cos(2\pi x) \end{bmatrix}$$

$$\frac{\partial A}{\partial \theta_i}(\theta)(x) = \Phi_i(x)$$
$$G_{ij} = \int [\Phi_i \Phi_j](x)\mathrm{d}x = \delta_{ij}$$



Toy example

Gradient descent is biased in functional space.

$$u \in L^2([-1,1])$$

$$\mathcal{L}_u(v) = \frac{1}{2}\|u - v\|^2$$

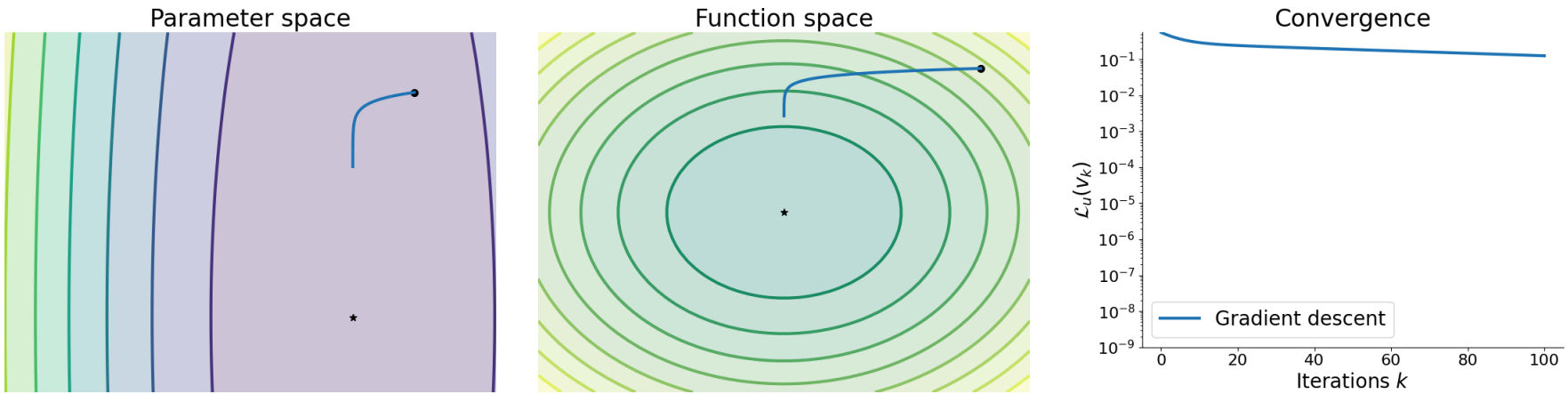
$$v_\theta(x) = A(\theta)(x) = \theta^T B \Phi(x)$$

$$= \theta^T B \begin{bmatrix} \sin(2\pi x) \\ \cos(2\pi x) \end{bmatrix}$$

$$\mathbb{R}^{p\times p} \ni B = \begin{bmatrix} 1 & 0 \\ 0 & 0.2 \end{bmatrix}$$

$$\frac{\partial A}{\partial \theta_i}(\theta)(x) = B_i \Phi(x)$$

$$G_{ij} = \int \left[\Phi^T B_i^T B_j \Phi\right](x)\mathrm{d}x = B_i^T B_j$$



Toy example

Natural gradient descent.

$$u \in L^2([-1,1])$$
$$\mathcal{L}_u(v) = \frac{1}{2}\|u - v\|^2$$
$$v_\theta(x) = A(\theta)(x) = \theta^T B \Phi(x)$$
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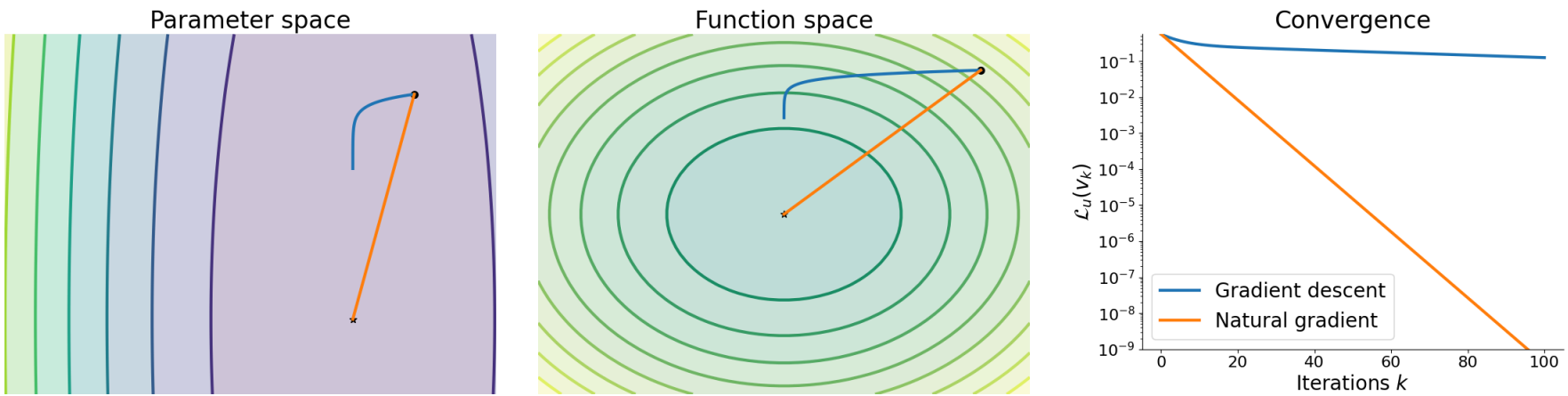
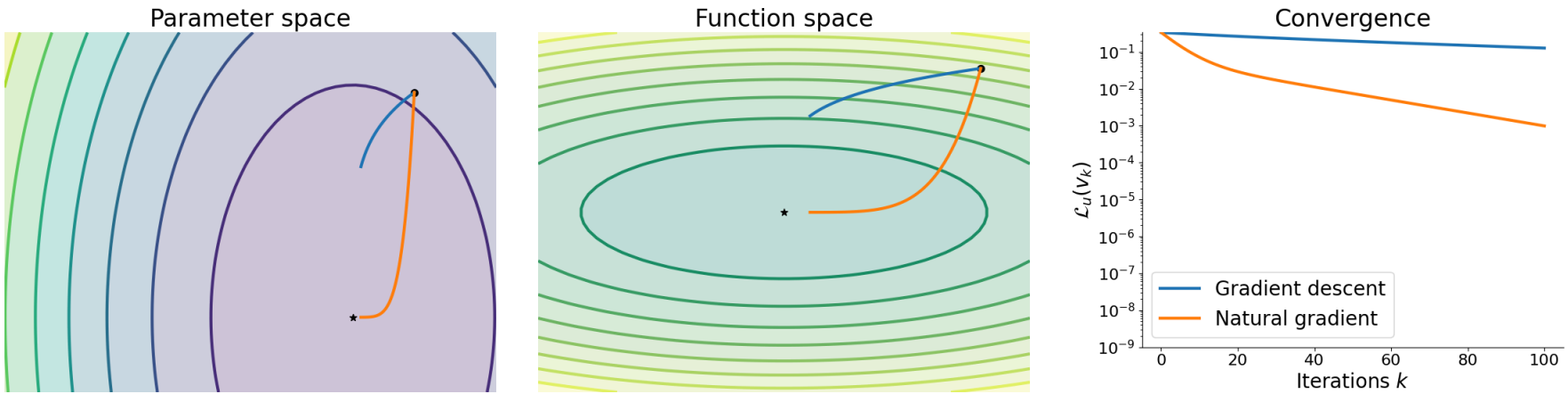


Toy example

Non isotropic loss.

$$u \in L^2([-1,1])$$
$$\mathcal{L}_u(v) = \frac{1}{2}\|u - v\|_K^2$$
$$v_\theta(x) = A(\theta)(x) = \theta^T B \Phi(x)$$
$$= \theta^T B \begin{bmatrix} \sin(2\pi x) \\ \cos(2\pi x) \end{bmatrix}$$

$$\mathbb{R}^{p\times p} \ni B = \begin{bmatrix} 1 & 0 \\ 0 & 0.2 \end{bmatrix}$$
$$\frac{\partial A}{\partial \theta_i}(\theta)(x) = B_i \Phi(x)$$
$$G_{ij} = \int \left[\Phi^T B_i^T K B_j \Phi\right](x)\mathrm{d}x = B_i^T K B_j$$



Toy example

Natural gradient descent with loss hessian.

$$u \in L^2([-1,1])$$

$$\mathcal{L}_u(v) = \frac{1}{2}\|u - v\|_K^2$$

$$v_\theta(x) = A(\theta)(x) = \theta^T B \Phi(x)$$

$$= \theta^T B \begin{bmatrix} \sin(2\pi x) \\ \cos(2\pi x) \end{bmatrix}$$

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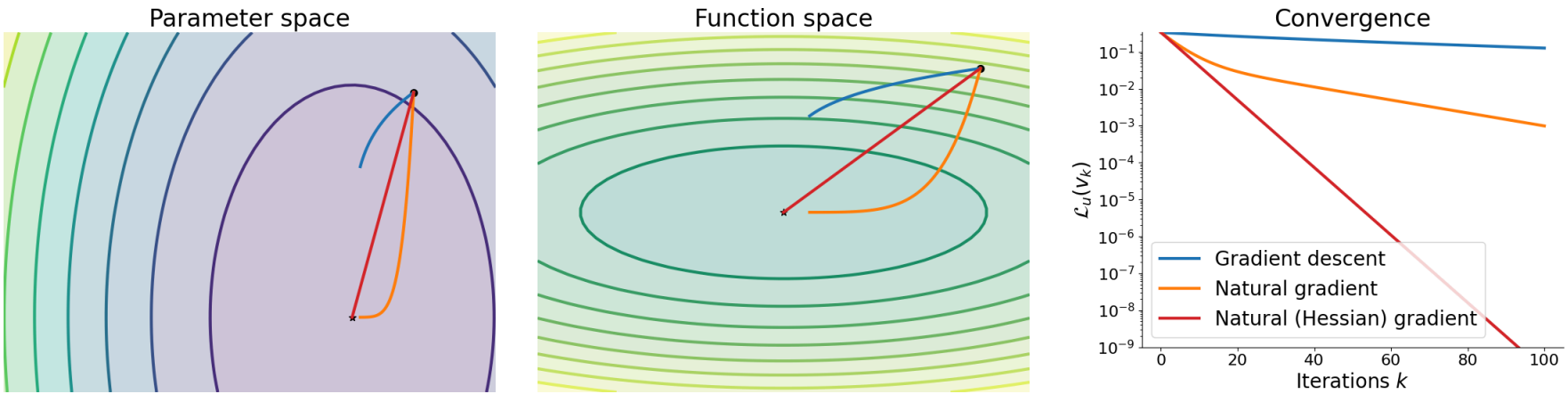

Toy example

Natural gradient and Newton method are equivalent for linear models.

$$u \in L^2([-1,1])$$

$$\mathcal{L}_u(v) = \frac{1}{2}\|u - v\|_K^2$$

$$v_\theta(x) = A(\theta)(x) = \theta^T B \Phi(x)$$

$$= \theta^T B \begin{bmatrix} \sin(2\pi x) \\ \cos(2\pi x) \end{bmatrix}$$

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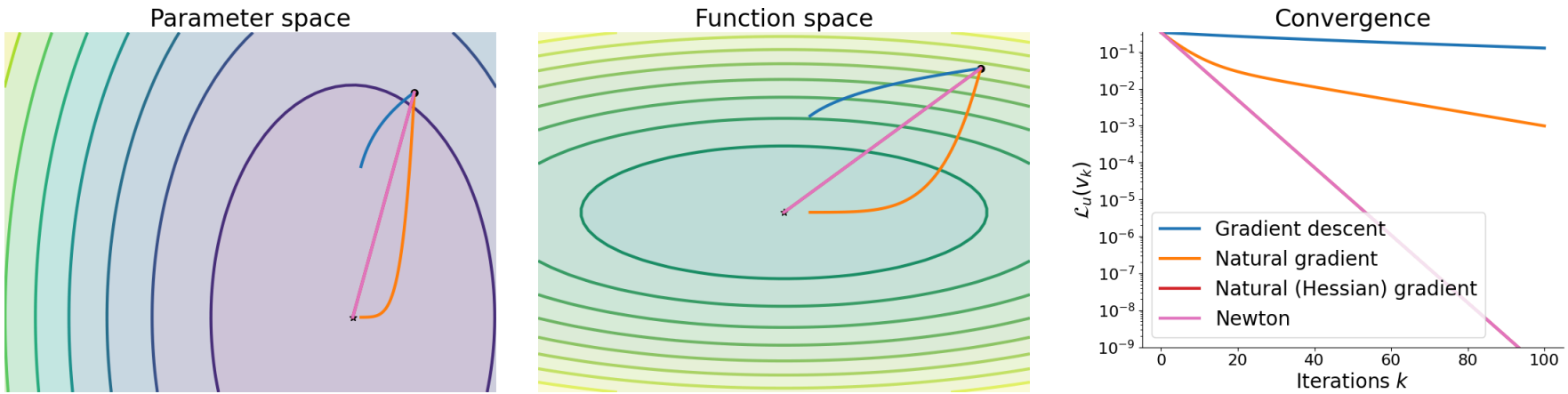
$$G_{ij} = \int \left[\Phi^T B_i^T K B_j \Phi\right](x)\mathrm{d}x = B_i^T K B_j$$

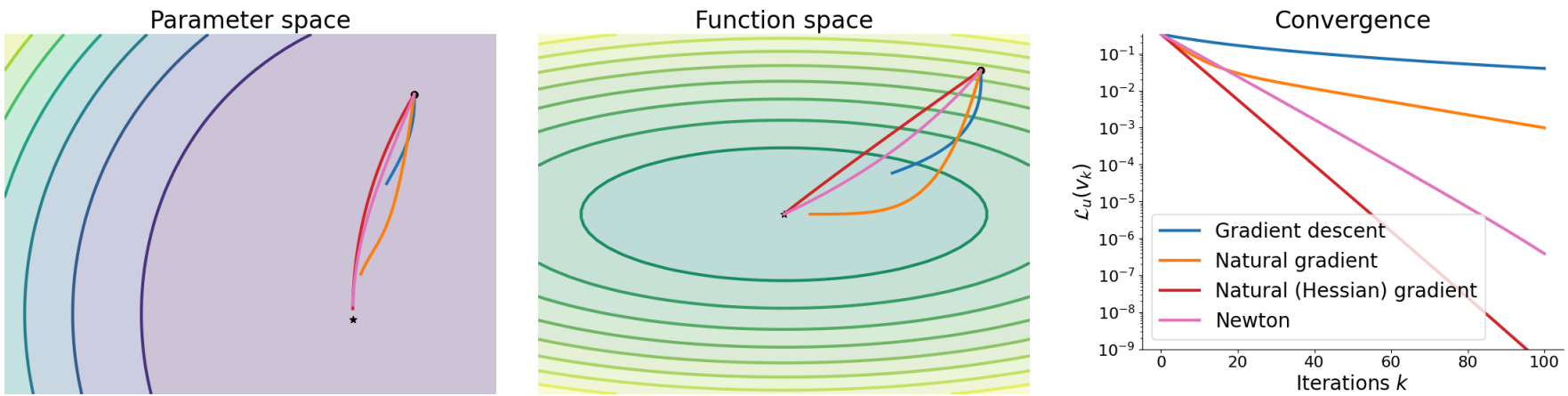


Toy example

Nonlinear manifold.

$$u \in L^2([-1,1])$$
$$\mathcal{L}_u(v) = \frac{1}{2}\|u - v\|_K^2$$
$$v_\theta(x) = A(\theta)(x) = \theta^T(B + Q\theta)\Phi(x)$$

$$\mathbb{R}^{p\times p} \ni B = \begin{bmatrix} 1 & 0 \\ 0 & 0.2 \end{bmatrix}, Q \in \mathbb{R}^{p\times p\times p}$$
$$\frac{\partial A}{\partial \theta_i}(\theta)(x) = (B_i + Q_i\theta)\Phi_i(x)$$
$$G_{ij}(\theta) = [(B + Q_i\theta)^T K (B + Q_i\theta)]_{ij}$$



Why we need momentum

Using momentum to **scape local minima** and **correct the biased step** of NGD.

Beyond L^2 loss

Classification
KL-div

$$\int \left[v \log \frac{v}{u} \right](x)\mathrm{d}x$$

PDE residual

$$\begin{aligned}\mathcal{L}(v) &= \|R(v)\|^2 \\ &= \| -\epsilon \partial_{xx} v + \partial_x v - 1\|^2\end{aligned}$$

Non-linear model

$$\theta_{k+1} = \theta_k - s G_k^{-1} \nabla_\theta L(\theta_k)$$

$$\theta_s = \theta_k - \int_0^s G_k^{-1}(\theta_\ell) \nabla_\theta L(\theta_\ell) \mathrm{d}\ell$$

Inacurate estimation of update

Stochastic setting
empirical loss

$$\mathcal{L}_u(v_k) = \|u - v_k\|_m^2$$

Solving NGD system

$$G^{-1} \begin{cases} \xrightarrow{Penrose} V(\Sigma_{\sigma > \varepsilon})^{-1} V^T \\ \xrightarrow{Tikhonov} (G + \varepsilon I)^{-1} \end{cases}$$

Escape local minima

$$\frac{\partial v_\theta}{\partial s} = -P_{\mathcal{T}_k} \nabla \mathcal{L}$$

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Momentum dynamics

From gradient flow to momentum [Polyak, B.T. 1964] [Nesterov, Yurii. 1983].

$$\frac{\partial \theta}{\partial s} = -\nabla_\theta L \quad \longrightarrow \quad \frac{\partial^2 \theta}{\partial s^2} = -\gamma \frac{\partial \theta}{\partial s} - \nabla_\theta L$$

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Heavy-ball

$$\begin{aligned} \theta_{k+1} &= \theta_k + p_k \\ p_k &= \beta p_{k-1} - \alpha \nabla_\theta L(\theta_k) \end{aligned}$$

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Nesterov

$$\begin{aligned} y_k &= \theta_k + \beta(\theta_k - \theta_{k-1}) \\ \theta_{k+1} &= y_k - \alpha \nabla_\theta L(y_k) \end{aligned}$$

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$$\theta_{k+1} = \theta_k + \beta(\theta_k - \theta_{k-1}) - \alpha \nabla_\theta L(y_k)$$

Momentum dynamics in functional space

From momentum in parameter space to functional space.

Heavy-ball: "momentum variable"

$$\theta_{k+1} - \theta_k = \beta p_{k-1} - \alpha \nabla_\theta L(\theta_k)$$

Heavy-ball: iterates difference

$$\theta_{k+1} - \theta_k = \beta(\theta_k - \theta_{k-1}) - \alpha \nabla_\theta L(\theta_k)$$

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$$\theta_{k+1} - \theta_k = \beta p_{k-1} - \alpha \nabla_\theta L(\theta_k)$$

$$\mathcal{T}_k \ni \mathrm{d}v_k = P_{\mathcal{T}_k}[\beta p_{k-1} - \alpha \nabla \mathcal{L}(v_k)]$$

Heavy-ball: iterates difference

$$\theta_{k+1} - \theta_k = \beta(\theta_k - \theta_{k-1}) - \alpha \nabla_\theta L(\theta_k)$$

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$$P_{\mathcal{T}_k} \nabla \mathcal{L}(v_k)$$

$$P_{\mathcal{T}_k} p_{k-1}$$

Heavy-ball: iterates difference

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$$P_{\mathcal{T}_k}(v_k - v_{k-1})$$

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$$P_{\mathcal{T}_k} \nabla \mathcal{L}(v_k)$$

$$G_k^{-1} \nabla_\theta \mathcal{L}(\theta_k)$$

$$P_{\mathcal{T}_k} p_{k-1}$$

$$G_k^{-1} G_{k,k-1} p_{k-1}$$

$$G_{k,k-1} = \int \left[\left.\frac{\partial A}{\partial \theta}\right|_{\theta_k} \left.\frac{\partial A}{\partial \theta}\right|_{\theta_{k-1}} \right](x)\mathrm{d}x$$

Heavy-ball: iterates difference

$$\theta_{k+1} - \theta_k = \beta(\theta_k - \theta_{k-1}) - \alpha \nabla_\theta L(\theta_k)$$

$$\mathcal{T}_k \ni \mathrm{d}v_k = P_{\mathcal{T}_k}[\beta(v_k - v_{k-1}) - \alpha \nabla \mathcal{L}(v_k)]$$

$$P_{\mathcal{T}_k}(v_k - v_{k-1})$$

$$G_k^{-1} \int \left[\left.\frac{\partial A}{\partial \theta}\right|_{\theta_k} (v_k - v_{k-1}) \right](x)\mathrm{d}x$$

Toy example

Escaping local minima.

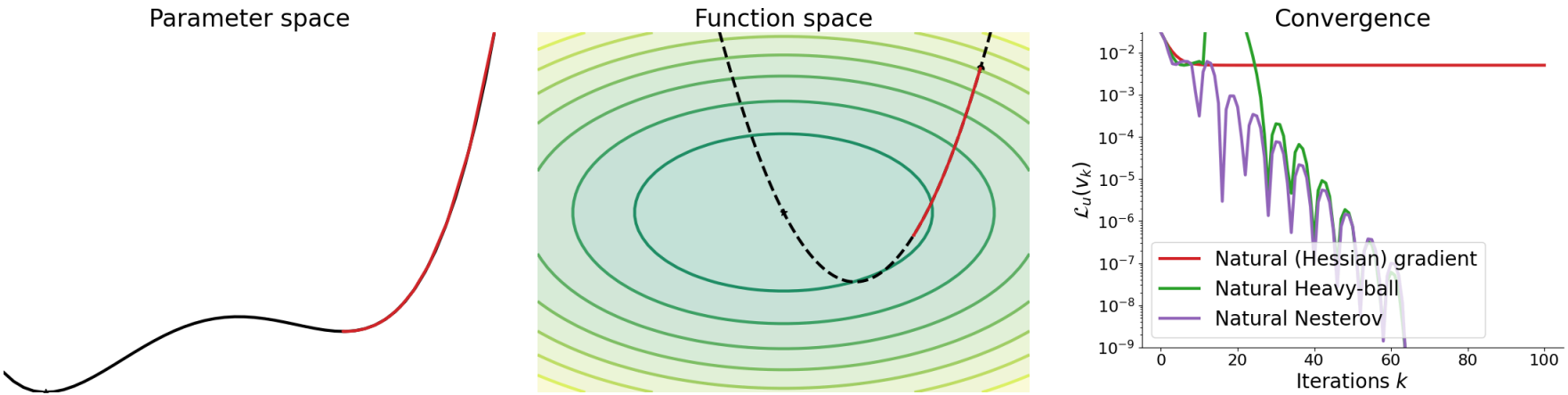
$$u \in L^2([0,1])$$

$$\mathcal{L}_u(v) = \frac{1}{2}\|u - v\|_K^2$$

$$v_\theta(x) = \theta_1 b^T \Phi(x) + \theta_1^2 b^{\perp T} \Phi(x)$$

$$\mathrm{d}v_k^{HB} = P_{\mathcal{T}_k}[\beta p_{k-1} - \alpha \nabla \mathcal{L}(v_k)]$$

$$\mathrm{d}v_k^{N} = P_{\mathcal{T}_k}[\beta(v_k - v_{k-1}) - \alpha \nabla \mathcal{L}(y_k)]$$



Physics informed learning.

Reaction diffusion (PINNs)
[Müller J., Zeinhofer M. (2023)]
[Schwencke N., Furtlehner C. (2024)].

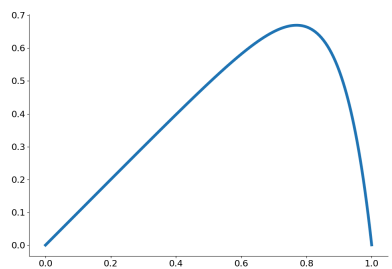
$$v(x) = x(1-x)\,\mathcal{NN}_\theta(x)$$

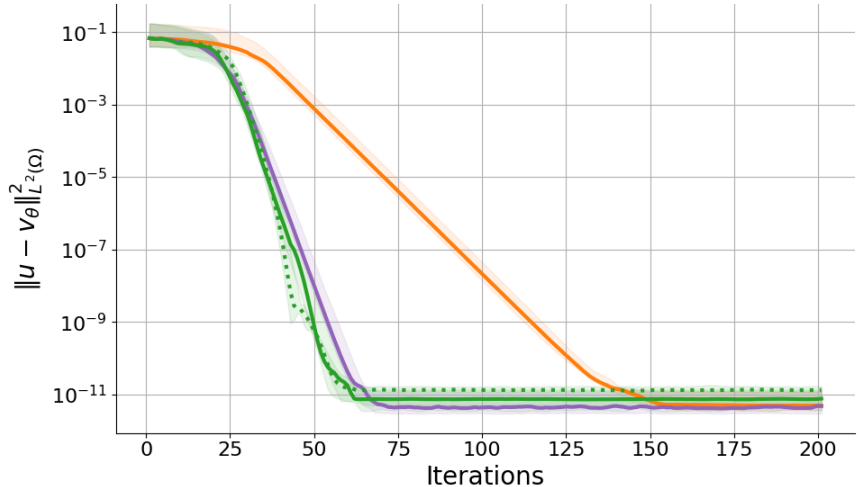
$$\mathcal{L}(v) = \| -\epsilon\partial_{xx}v + \partial_x v - 1\|^2_{L^2([0,1])}$$

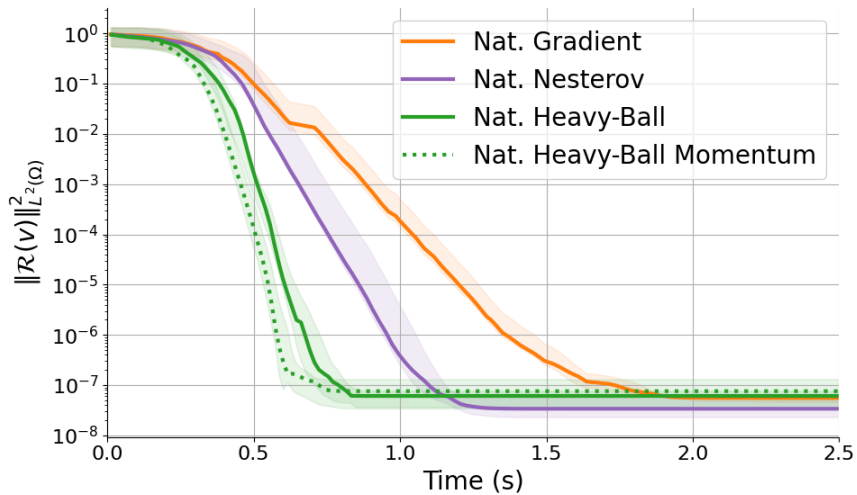
$$\mathcal{L}(v) = \|\mathcal{R}(v)\|^2_{L^2([0,1])}$$

$$\mathcal{L}(v') = \|v'\|^2_{L^2([0,1])}$$

$$v' \in \mathcal{M}' := \{v' = \mathcal{R}(v)\}$$







Physics informed learning.

Non-linear PDE (PINNs)
[Müller J., Zeinhofer M. (2023)]
[Schwencke N., Furtlehner C. (2024)].

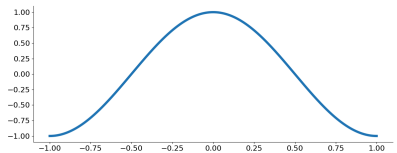
$$v(x) = (1-x)^2(x-1)^2\,\mathcal{NN}_\theta(x) + c + a\left(\frac{x^3}{3} - x\right)$$

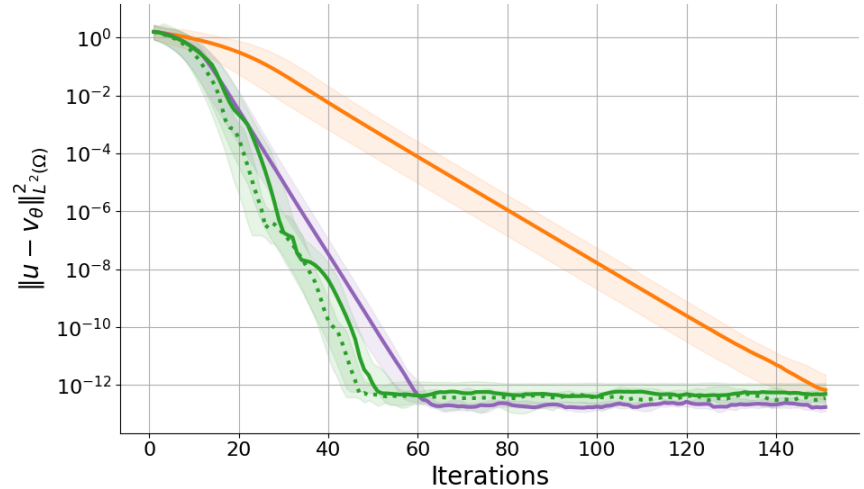
$$\mathcal{L}(v) = \| -\partial_{xx} v + v^3 - \pi^2\cos(\pi x) + \cos^3(\pi x)\|^2$$

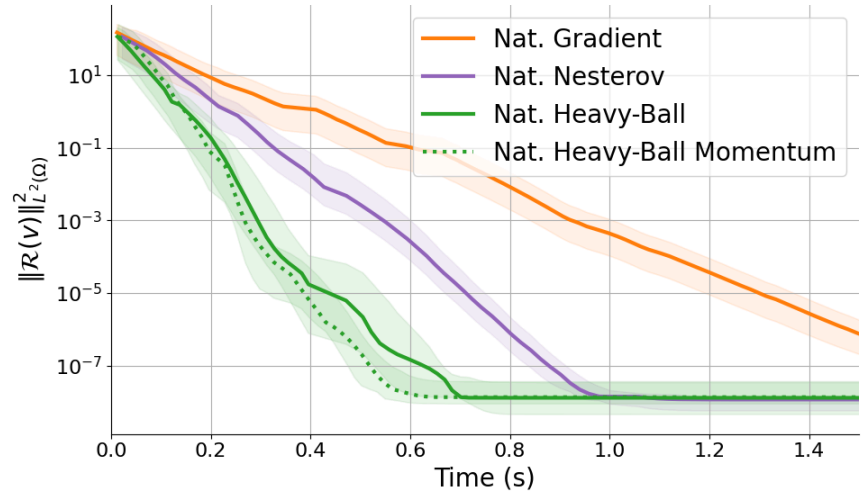
$$\mathcal{L}(v) = \|\mathcal{R}(v)\|^2_{L^2([-1,1])}$$

$$\mathcal{L}(v') = \|v'\|^2_{L^2([-1,1])}$$

$$v' \in \mathcal{M}' := \{v' = \mathcal{R}(v)\}$$







Classification task

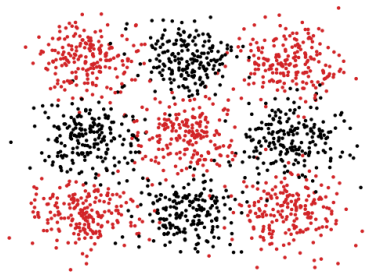
Another less toy example from [Park, H, S.-I Amari, and K Fukumizu (2000)].

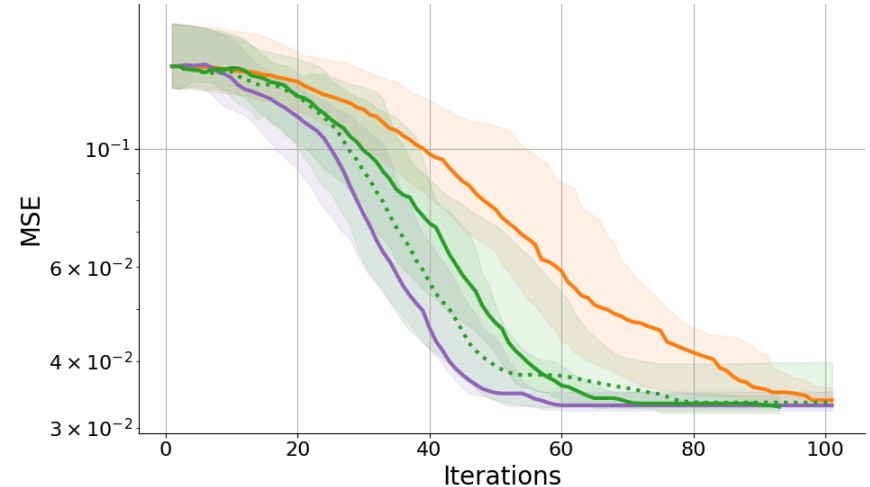
Mackey Glass caotic time series:

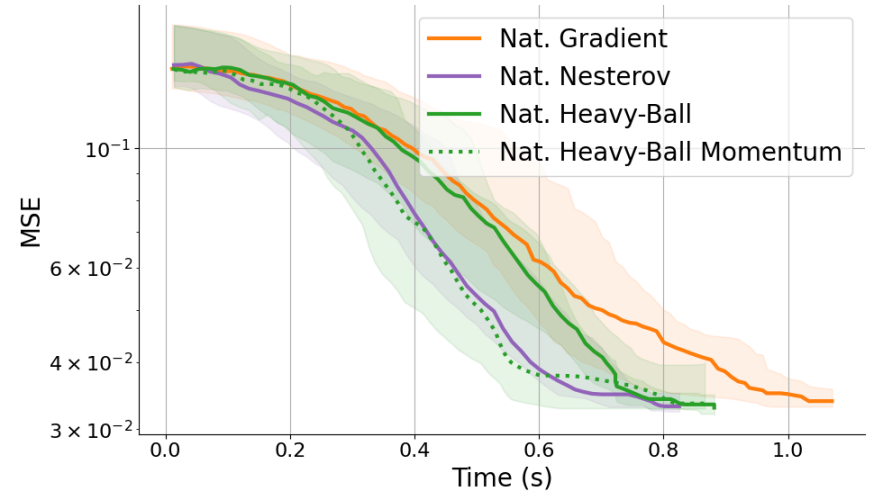
- Input: $z \in \mathbb{R}^2$
- Output: $c \in \{0, 1\}$

$$\mathcal{L}_u(v) = \int -u \log(v) - (1-u)\log(1-v)$$

Model (Shallow NN): $v_\theta : \mathbb{R}^2 \to [0, 1]$







Conclusion

What is done, what is still to be done.

We saw how to build a **Natural inertial dynamics** for gradient optimization on non linear approximation manifolds.

Some directions

- Step-size adaptivity
- Theoretical questions: convergence? optimality?

Thank you!

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