

Parametric Transport Problems

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The “Ideal Setting”

- $A_\mu u_\mu = f$, $A_\mu : \mathcal{H} \rightarrow \mathcal{H}'$, $\mu \in \mathcal{P}$, $\rightsquigarrow \mathcal{S} := \{u_\mu : \mu \in \mathcal{P}\} \subset \mathcal{H}$
- Uniform “mapping property” $\|v\|_{\mathcal{H}} \sim \|A_\mu v\|_{\mathcal{H}'}$, $v \in \mathcal{H}$, $\mu \in \mathcal{P}$
- $S_n \subset \mathcal{H} \rightsquigarrow$ computable surrogates $R_n(u_\mu, \mu) \sim \|f - \Pi_n^\mu u_\mu\|_{\mathcal{H}'}$
 $c R_n(u_\mu) \leq \text{dist}_{\mathcal{H}}(u_\mu, S_n) = \|u_\mu - P_{S_n} u_\mu\|_{\mathcal{H}} \leq C R_n(u_\mu)$

- Greedy construction of S_n : given $u_j = u_{\mu_j}$, $j = 0, \dots, n-1$,
 $S_n = \text{span} \{u_j : j = 0, \dots, n-1\}$

$$u_n := \operatorname{argmax}_{\mu \in \mathcal{P}} R_n(u_\mu), \quad \Rightarrow \quad \|u_n - P_{S_n} u_n\|_{\mathcal{H}} \geq \frac{c}{C} \text{dist}_{\mathcal{H}}(\mathcal{S}, S_n)$$

- Convergence [Binev/Cohen/D/DeVore/Petrova/Wojtaszczyk]:

$$\inf_{\dim Y_n = n} \text{dist}_{\mathcal{H}}(\mathcal{S}, Y_n) = O(n^{-\alpha}) \quad \Longrightarrow \quad \text{dist}_{\mathcal{H}}(\mathcal{S}, S_n) = O(n^{-\alpha})$$

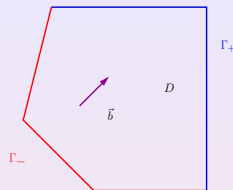
$\mu \mapsto u_\mu$ smooth $\rightsquigarrow n$ small...

- What about transport dominated problems?

A Model Problem: Transport Equation

$$\vec{b} \cdot \nabla u + cu = f_0 \quad \text{in } D$$

$$u = g \quad \text{on } \Gamma_-$$



$$\Gamma_- = \{x \in \partial D : \vec{b}(x) \cdot \vec{n}(x) < 0\} \quad \text{inflow boundary}$$

$$\Gamma_+ = \{x \in \partial D : \vec{b}(x) \cdot \vec{n}(x) > 0\} \quad \text{outflow boundary}$$

$$\Gamma_0 = \{x \in \partial D : \vec{b}(x) \cdot \vec{n}(x) = 0\} \quad \text{characteristic boundary}$$

- Parameters:
- Inflow boundary data,
 - parameter dependent velocity field $\vec{b}(\mu)$

Variational Formulation

$$\begin{aligned} \int_D f_0 v \, dx &= \int_D (\vec{b} \cdot \nabla u + cu) v \, dx = \int_D \underbrace{u(-\vec{b} \cdot \nabla v + v(c - \nabla \cdot \vec{b}))}_{=:(u, A^* v)} \, dx \\ &+ \int_{\Gamma_-} uv(\vec{b} \cdot \vec{n}) \, ds + \int_{\Gamma_+} uv(\vec{b} \cdot \vec{n}) \, ds \quad u, v \in C^1(D) \cap C(\bar{D}) \end{aligned}$$

Natural test space: $Y := \text{clos}_{\|A^* \cdot\|_{L_2(D)}} \{v \in C^1(D) \cap C(\bar{D}), v|_{\Gamma_+} = 0\}$

THEOREM:

Given $f_0 \in Y'$, $g \in L_2(\Gamma_-, \omega)$, the problem: find $u \in L_2(D)$, s.t.

$$a(u, v) := (u, A^* v) = \int_D f_0 v \, dx + \int_{\Gamma_-} |\vec{b} \cdot \vec{n}| g \gamma_-(v) \, ds =: f(v), \quad \forall v \in Y$$

has a unique solution satisfying $\|u\|_{L_2(D)} \lesssim \|f\|_{Y'}$.

If $u \in C^1(D) \cap C(\bar{D})$ then $\vec{b} \cdot \nabla u + cu = f_0$ in D , and $u|_{\Gamma_-} = g$.

A Simple Mechanism...

...how to choose the “energy space”

Mapping Properties:

Assume dense embeddings $X \subseteq L_2(D) \subseteq X'$ such that

$$A^* : D(A^*) \rightarrow X' \text{ injective}$$

- set $\|v\| := \|A^*v\|_{X'}$, $Y := \text{clos}_{\|\cdot\|} D(A^*)$, $\|v\|_Y = \|A^*v\|_{X'}$
- then $\|Av\|_{Y'} = \|v\|_X$ and $1 = \|A^*\|_{Y \rightarrow X'} = \|A\|_{X \rightarrow Y'} = \|A^{-1}\|_{Y' \rightarrow X}$

In particular: $X = X' = L_2(D)$

$$\rightsquigarrow \|v\|_Y = \|A^*v\|_{L_2(D)}, \quad \langle v, w \rangle_Y = \langle A^*v, A^*w \rangle$$

and

$$a(u, v) = (u, A^*v) = {}_{Y'}\langle Au, v \rangle_Y = {}_{Y'}\langle f, v \rangle_Y, \quad v \in Y$$

is perfectly well conditioned

PROPOSITION:

For any $X_h \subset L_2(D)$ one has

- $\|u - v_h\|_{L_2(D)} = \|A(u - v_h)\|_{Y'} = \|f - Av_h\|_{Y'}, \quad \forall v_h \in X_h$
- $u_h = \operatorname{argmin}_{v_h \in X_h} \|u - v_h\|_{L_2(D)} \Leftrightarrow u_h = \operatorname{argmin}_{v_h \in X_h} \|Av_h - f\|_{Y'}$
- $u_h = \operatorname{argmin}_{v_h \in X_h} \|u - v_h\|_{L_2(D)} \Leftrightarrow$
 $a(u_h, y_h) := (u_h, A^* y_h) = {}_{Y'} \langle f, y_h \rangle_{Y'} \quad \forall y_h \in Y_h := A^{-*} X_h$

BUT: ideal test space Y_h is not computable

... perhaps a perturbed version suffices...

A Stability Condition

δ -Proximal Subspaces

$\delta \in (0, 1)$: $Y_h^\delta \subset Y$ is called δ -proximal for $X_h \subset L_2(D)$ if

$$\forall y_h \in Y_h := A^{-*} X_h \quad \exists \tilde{y}_h \in Y_h^\delta \text{ such that } \|y_h - \tilde{y}_h\|_Y \leq \delta \|y_h\|_Y$$

THEOREM:

Let $a(v, z) := (u, A^* z)$. If Y_h^δ is δ -proximal for X_h , one has

$$\inf_{v_h \in X_h} \sup_{z_h \in Y_h^\delta} \frac{a(v_h, z_h)}{\|v_h\|_{L_2(D)} \|z_h\|_Y} \geq \frac{1 - \delta}{1 + \delta}$$

Moreover, $u_{h,\delta} \in X_h$, defined by $a(u_{h,\delta}, v_h) = \ell(v_h) \quad \forall v_h \in Y_h^\delta$, satisfies

$$\|u - u_{h,\delta}\|_{L_2(D)} \leq \frac{2}{1 - \delta} \inf_{v_h \in X_h} \|u - v_h\|_{L_2(D)}$$

How to Realize δ -Proximity? – Y -Projections

For X_h pick $Z_h \subset Y$ “somewhat larger” $\dim Z_h > \dim Y_h = \dim X_h$

$$Y_h^\delta := P_{Y,h}(A^{-*}X_h), \quad \langle P_{Y,h}y, z_h \rangle_Y = \langle y, z_h \rangle_Y \quad \forall z_h \in Z_h$$

Note: for $y_h = A^{-*}v_h \in Y_h$, $v_h \in X_h$, $\tilde{y}_h = P_h y_h$ is given by

$$(A^* \tilde{y}_h, A^* z_h) = (v_h, A^* z_h), \quad \forall z_h \in Z_h$$

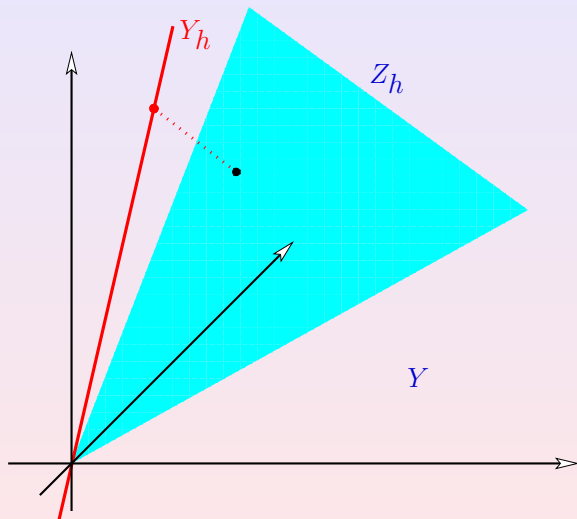
Note:

- δ -proximity relies on choice of auxiliary spaces Z_h
- In simple cases

$$X_h = \mathbb{P}_{p, \mathcal{T}_h} \subset L_2(D) \rightsquigarrow Z_h = \mathbb{P}_{p+q, \mathcal{T}_{2-r_h}} \cap C(D) \subset Y$$

Numerical experiments: $q = 1, r = 1$ or $q = 0, r = 2$ suffice

Illustration



Motivation: $u = u + A^{-1}(f - Au)$

$$\Leftrightarrow (u, v) = (u, v) + (A^{-1}(f - Au), v) \quad \text{for all } v \in L_2(D)$$

$$\Leftrightarrow (u, v) = (u, v) + {}_{Y'} \langle f - Au, A^{-*}v \rangle_Y \quad \text{for all } v \in L_2(D)$$

$$\Leftrightarrow (u, v) = (u, v) + {}_{Y'} \langle f - Au, (AA^*)^{-1}Av \rangle_Y \quad \text{for all } v \in L_2(D)$$

$$\Leftrightarrow (u, v) = (u, v) + {}_{Y'} \langle (AA^*)^{-1}(f - Au), Av \rangle_Y \quad \text{for all } v \in L_2(D)$$

$$\rightsquigarrow (u^{k+1}, v) = (u^k, v) + {}_{Y'} \langle \underbrace{(AA^*)^{-1}(f - Au^k)}_{=: \hat{r}^k}, Av \rangle_Y \quad \text{for all } v \in L_2(D)$$

$$\Leftrightarrow \left\{ \begin{array}{l} (A^* \hat{r}^k, A^* z) = {}_{Y'} \langle f - Au^k, z \rangle_Y \quad \text{for all } z \in Y \\ (u^{k+1}, v) = (u^k, v) + (A^* \hat{r}^k, v) \quad \text{for all } v \in L_2(D) \end{array} \right\}$$

\rightsquigarrow numerical scheme:

$$(A^* \hat{r}_h^k, A^* z_h) = {}_{Y'} \langle f - Au_h^k, z \rangle_Y \quad \text{for all } z_h \in Z_h \subset Y$$

$$(u_h^{k+1}, v_h) = (u_h^k, v_h) + (A^* \hat{r}_h^k, v_h) \quad \text{for all } v_h \in X_h$$

Properties of the Iterative Scheme

THEOREM:

$$a(u_{h,\delta}, \tilde{y}_h) = {}_{Y'} \langle f, \tilde{y}_h \rangle_Y, \quad \tilde{y}_h \in P_{Y,h}(A^{-*} X_h) \rightsquigarrow$$

$$\|u_{h,\delta} - u_h^{k+1}\|_{L_2} \leq \delta \|u_{h,\delta} - u_h^k\|_{L_2}, \quad k \in \mathbb{N}_0$$

\rightsquigarrow stable Petrov-Galerkin solution **without** computing test basis!

PROPOSITION:

$$(A^* \hat{r}_h, A^* z_h) = {}_{Y'} \langle \tilde{f}_h - Av_h, z_h \rangle_Y \quad \text{for all } z_h \in Z_h$$

(Stab-OSC) \rightsquigarrow

$$(1 - \delta) \|\tilde{f}_h - Av_h\|_{Y'} \leq \|\hat{r}_h\|_Y = \|A^* \hat{r}_h\|_{L_2(D)} \leq \|\tilde{f}_h - Av_h\|_{Y'}$$

Can be used to formulate an adaptive refinement scheme with optimal convergence

Radiative transfer:

$$\begin{aligned} A_{\circ} u(x, \mu) = \mu \cdot \nabla u(x, \mu) + \kappa(x) u(x, \mu) &= f_{\circ}(x), \quad x \in D \subset \mathbb{R}^d, \\ u(x, \mu) &= g(x, \mu), \quad x \in \Gamma_{-}(\mu), \end{aligned}$$

where

$$\Gamma_{\pm}(\mu) := \{x \in \partial D : \mp \mu \cdot \mathbf{n}(x) < 0\}, \quad \mu \in \mathcal{S}.$$

- For $D \subset \mathbb{R}^3$, $\mathcal{S} = \mathcal{S}^2$, the unit 2-sphere
 \rightsquigarrow high dimensional problems
- Weak formulation in $X = L_2(D \times \mathcal{S})$ or even $X = L_2(D \times \mathcal{S}) \times [0, T]$
- Reduced basis method

Exploit the Mapping Property

$$\int_D (\boldsymbol{\mu} \cdot \nabla u + \kappa u) v dx = \int_D u \underbrace{(-\boldsymbol{\mu} \cdot \nabla v + \kappa v)}_{=: A(\boldsymbol{\mu})^* v} dx + \int_{\Gamma(\boldsymbol{\mu})_-} uv (\boldsymbol{\mu} \cdot \mathbf{n}(x)) d\Gamma, \quad v|_{\Gamma(\boldsymbol{\mu})_+} = 0$$

Given $X_n = \text{span} \{ \phi_0, \dots, \phi_{n-1} \} \subset L_2(D)$, $\tilde{Y}_n(\boldsymbol{\mu}) = P_{Y(\boldsymbol{\mu}), Z_m}(A(\boldsymbol{\mu})^* X_n)$

$$\begin{aligned} \max_{\boldsymbol{\mu} \in \mathcal{S}} \|u(\cdot, \boldsymbol{\mu}) - P_{X_n} u(\cdot, \boldsymbol{\mu})\|_{L_2(D)} &\sim \|u(\cdot, \boldsymbol{\mu}) - u_{n, \delta}(\cdot, \boldsymbol{\mu})\|_{L_2(D)} \\ &= \|f - Au_{n, \delta}(\cdot, \boldsymbol{\mu})\|_{Y(\boldsymbol{\mu})'} \\ &\sim \|f - Au_n^k(\cdot, \boldsymbol{\mu})\|_{Y(\boldsymbol{\mu})'} \\ &\sim \max_{\boldsymbol{\mu} \in \mathcal{S}} \|A(\boldsymbol{\mu})^* \hat{r}_{n, \boldsymbol{\mu}}(u_n^k)\|_{L_2(D)} \end{aligned}$$

where $(A(\boldsymbol{\mu})^* \hat{r}_{n, \boldsymbol{\mu}}(v), A(\boldsymbol{\mu})^* z) = {}_{Y(\boldsymbol{\mu})'} \langle f - Av, z \rangle_{Y(\boldsymbol{\mu})}$, $z \in Z_m$

Idea: along with X_n build a somewhat larger space $Z_m \subset \bigcap_{\boldsymbol{\mu} \in \mathcal{S}} Y(\boldsymbol{\mu})$ so that $P_{Y(\boldsymbol{\mu}), Z_m}$ -projections realize δ -proximality uniformly in $\boldsymbol{\mu}$

A “Double” Greedy Scheme

X_h, Z_h “large” FE spaces, so that $P_{Y(\mu), Z_h}(A(\mu)^{-*} X_h)$ is δ -proximal for $\mu \in \mathcal{S}$

(0) Initialize: $\phi_0 = u_h(\cdot, \mu_0) \in X_h$, $\theta_0 := P_{Y(\mu_0), Z_h}(A(\mu)^{-*} \phi_0)$

(1) Given $X_n := \text{span} \{\phi_0, \dots, \phi_{n-1}\}$, $Z_m := \text{span} \{\theta_0, \dots, \theta_{m-1}\}$, compute

$$d_{n,m} := \max_{\mu \in \mathcal{S}} \max_{v \in X_n: \|v\|_{L_2}=1} \min_{z \in Z_m} \|A(\mu)^* z - v\|_{L_2}$$

if $d_{n,m} \leq \delta$, goto (2); else, extend Z_m :

$$\bar{u}_h(\cdot, \mu) = \operatorname{argmax}_{v \in X_n: \|v\|_{L_2}=1} \min_{z \in Z_m} \|A(\mu)^* z - v\|_{L_2}$$

$$\bar{\mu} = \operatorname{argmax}_{\mu \in \mathcal{S}} \left(\min_{z \in Z_m} \|A(\mu)^* z - \bar{u}_h(\cdot, \mu)\|_{L_2} \right), \quad \theta_m := P_{Y(\bar{\mu}), Z_h}(A(\bar{\mu})^{-*} \bar{u}_h(\cdot, \bar{\mu}))$$

(2) extend X_n : $\mu_n := \operatorname{argmax}_{\mu \in \mathcal{S}} \|A(\mu)^* \hat{r}_{n,\mu}(u_n^k)\|_{L_2}$, $\phi_n := u_{h,\delta}(\cdot, \mu_n) \in X_h$

Computational Tasks

$$\text{Set: } \mathbf{A}(\mu) := ((A(\mu)^* \theta_i, \phi_j))_{i,j}^{m,n}, \quad \mathbf{B}(\mu) := ((A(\mu)^* \theta_i, A(\mu)^* \theta_j))_{i,j}^m$$

$$\underline{v} = \sum_{i=0}^{n-1} v_i \phi_i, \quad z = \sum_{j=0}^{m-1} z_j \theta_j, \quad \rightsquigarrow$$

$$\max_{v \in X_n: \|v\|_{L_2}=1} \min_{z \in Z_m} \|A(\mu)^* z - v\|_{L_2}^2 = \max_{v \in \mathbb{R}^n} \frac{v^T (\mathbf{I} - \mathbf{A}(\mu)^T \mathbf{B}(\mu)^{-1} \mathbf{A}(\mu)) v}{v^T v}$$

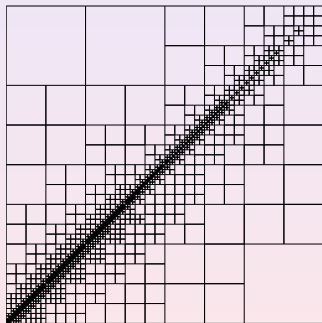
$$(A(\mu)^* \hat{r}_{n,\mu}(v), A(\mu)^* z) = \gamma(\mu) \langle f - Av, z \rangle_{\gamma(\mu)}, \quad z \in Z_m \rightsquigarrow$$

$$\mathbf{r}_{n,\mu}(v) = \mathbf{B}(\mu)^{-1} (\mathbf{f} - \mathbf{A}(\mu)v), \quad \mathbf{f} = \gamma(\mu) \langle f, \theta_j \rangle_{\gamma(\mu)}, \quad \hat{r}_{n,\mu}(v) = \sum_{j=0}^{m-1} (\mathbf{r}_{n,\mu}(v))_j \theta_j$$

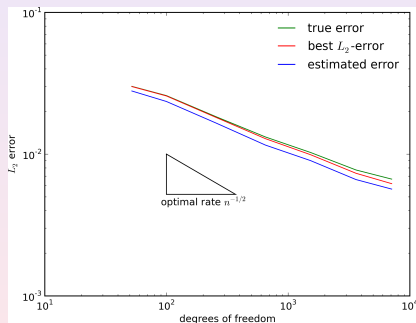
$$\mathbf{u}_n^{k+1}(\mu) = \mathbf{u}_n^k(\mu) + \mathbf{A}(\mu)^T \mathbf{r}_{n,\mu}^k, \quad \|A(\mu)^* \hat{r}_{n,s}(u_n^k)\|_{L_2}^2 = (\mathbf{r}_{n,\mu}^k)^T \mathbf{B}(\mu) \mathbf{r}_{n,\mu}^k \rightarrow \max$$

Adaptive Solution ($p = 2, r = 2$) for Fixed Velocity

$$\mu = (1, 1), \quad c = 1, \quad f = \begin{cases} 1, & x > y \\ 0.5, & x \leq y. \end{cases}$$

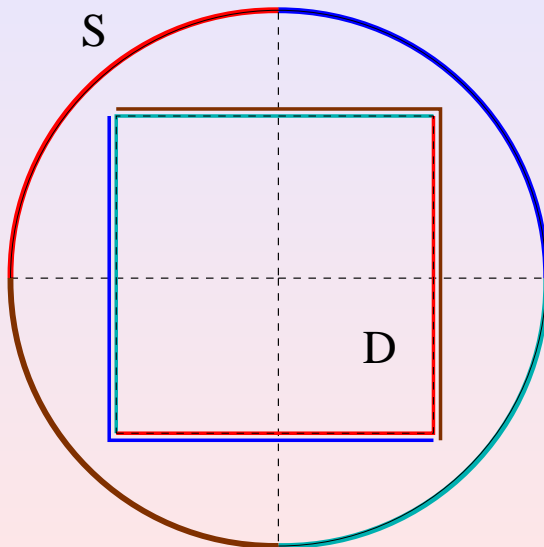


(a) Corresponding adaptive refinement grid of (b) in Figure 2.



(b) Convergence rate

First RB-Experiments



Approximations from the Reduced Space

angles/estimated errors:

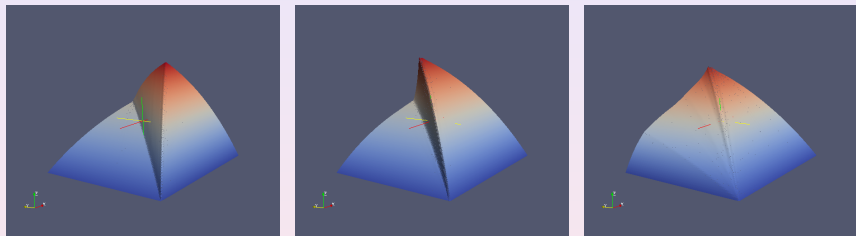


Figure: 0.567/0.000471, 0.85/0.000474, 1.255/0.00103

Error Decay: very preliminary

