

Resilience enhancement using discrete a priori bounds for the detection of faulty PDE solutions

Paul Mycek^{1,2}, F. Rizzi⁴, O. Le Maître³, K. Sargsyan⁴,
K. Morris⁴, C. Safta⁴, B. Debusschere⁴, O. Knio^{2,5}.

¹CERFACS, Toulouse, France

²Duke University, Durham, NC.

³LIMSI-CNRS, Orsay, France.

⁴Sandia National Laboratories, Livermore, CA.

⁵KAUST, Thuwal, Saudi Arabia.

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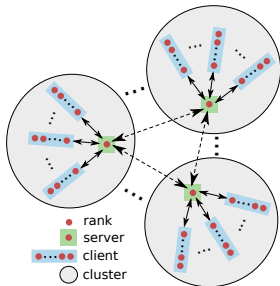
Overview — general ideas of the approach

Context: resilient solving of PDEs for problems in engineering.

- ▶ Algorithm based approach.

General overview [Sargsyan et al., 2015, SISC]

- ▶ Server-client architecture:
 - ▶ Clusters of MPI ranks (e.g. node).
 - ▶ Few **servers** (protected against faults).
 - ▶ Many **clients** (subject to faults): computing units.
 - ▶ Task-based approach: **servers** send *tasks* to **clients**.
- ▶ Domain decomposition for PDEs:
 - ▶ Global domain divided into many small subdomains.
 - ▶ Local problems (on subdomains) very cheap to solve.
- ▶ Sampling approach:
 - ▶ Sample local problems on the **clients** (unprotected).
 - ▶ Robust regression to overcome faulty or missing data.
 - ▶ Global reconstruction on the **servers** (protected).

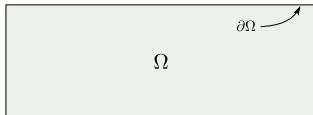


[Rizzi et al., 2015]



Overview — overlapping subdomains

Second-order elliptic PDE:
$$\begin{cases} \mathcal{L}u = f & \text{in } \Omega \\ u = g & \text{on } \partial\Omega \quad (\text{Dirichlet BCs}) \end{cases}$$

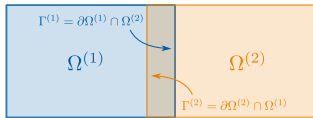




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Boundary-to-boundary mapping:
$$\begin{cases} u^{(1)}|_{\Gamma^{(2)}} = \mathcal{F}^{(1)}\left(u^{(1)}|_{\Gamma^{(1)}}\right), \end{cases}$$



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$$\begin{cases} u^{(1)}|_{\Gamma^{(2)}} = u^{(2)}|_{\Gamma^{(2)}} \\ u^{(2)}|_{\Gamma^{(1)}} = u^{(1)}|_{\Gamma^{(1)}} \end{cases}$$

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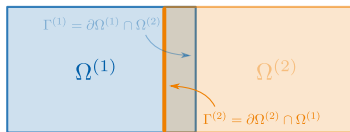
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$$\Rightarrow \boxed{\mathcal{F}(\mathbf{u}_\Gamma) = \mathbf{u}_\Gamma} \quad (\text{for linear } \mathcal{L}, \mathbf{M}\mathbf{u}_\Gamma = \mathbf{c})$$



Overview — minimization problem

Focusing on $\Omega^{(1)}$:



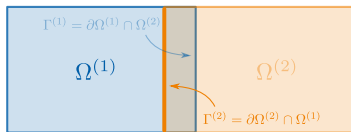
Sampling approach:

$$\underbrace{\left\{ u_i^{(1)} \Big|_{\Gamma^{(1)}} \right\}_{i=1, \dots, M}}_{\text{inputs: } \mathbf{x}} \xrightarrow{\text{PDE}} \underbrace{\left\{ u_i^{(1)} \Big|_{\Gamma^{(2)}} \right\}_{i=1, \dots, M}}_{\text{obs.: } \mathbf{y}}$$



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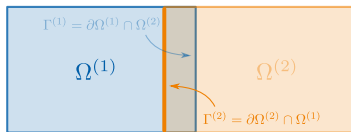
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Minimization problem: $\hat{\mathcal{F}}^{(1)} = \arg \min_{\tilde{\mathcal{F}}^{(1)}} \left\| \mathbf{y} - \tilde{\mathcal{F}}^{(1)}(\mathbf{x}) \right\|$, for some norm $\| \cdot \|$.



Outline

- 1 1d linear example
- 2 A priori bounds of (2d) PDE solutions



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1 1d linear example

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Problem description:

we want to solve the following (1d) problem

$$\begin{cases} \mathcal{L}u = g, & \text{in } \Omega = (0, 1) \\ u(0) = u^-, \\ u(1) = u^+, \end{cases}$$

where \mathcal{L} is a **linear**, elliptic operator.



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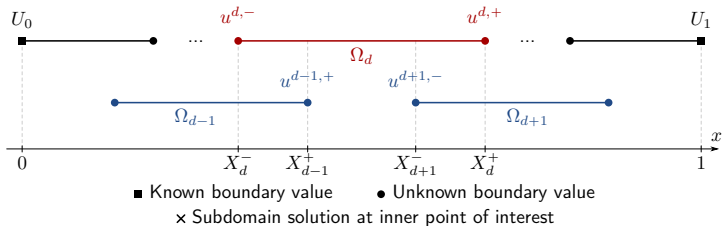
where \mathcal{L} is a **linear**, elliptic operator.

The solution at point x_0 is an **affine function** of the boundary conditions:

$$u(x_0) = f(u^-, u^+) = a + bu^- + cu^+.$$

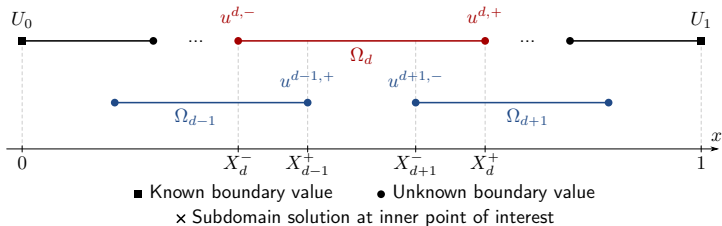


Domain decomposition overview





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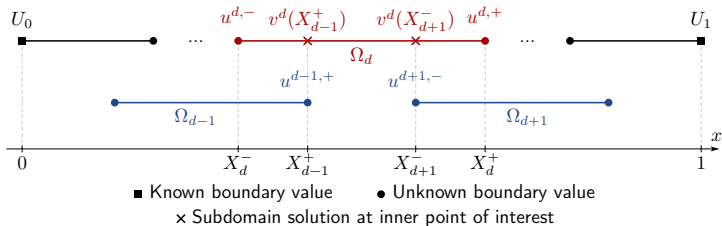


The **subproblem** is solved on each subdomain:

$$\begin{cases} \mathcal{L}v^d = g, & \text{in } \Omega_d = (X_d^-, X_d^+) \\ v^d(X_d^-) = u^{d,-}, \\ v^d(X_d^+) = u^{d,+}, \end{cases}$$



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Enforcing **compatibility conditions** ensures that v^d agrees with u :

$$\begin{cases} v^d(X_{d-1}^+) = u^{d-1,+}, \\ v^d(X_{d+1}^-) = u^{d+1,-}. \end{cases}$$



Using the affine maps yields a linear system

The compatibility conditions read:

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We recall the affine maps

$$\begin{aligned} v^d(X_{d-1}^+) &= f^{d,-}(u^{d,-}, u^{d,+}) = a^{d,-} + b^{d,-}u^{d,-} + c^{d,-}u^{d,+} \\ v^d(X_{d+1}^-) &= f^{d,+}(u^{d,-}, u^{d,+}) = a^{d,+} + b^{d,+}u^{d,-} + c^{d,+}u^{d,+} \end{aligned}$$

Using these maps, the compatibility conditions become:

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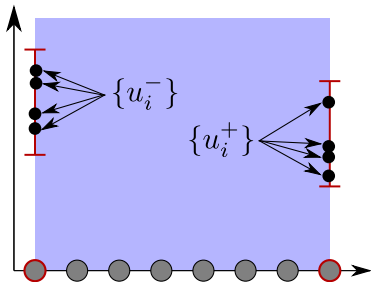
Using regression to find a , b and c

The map f has the general form:

$$f(u^-, u^+) = a + bu^- + cu^+,$$

Sampling approach:

- ▶ Sample the BCs $\Rightarrow (u_i^-, u_i^+)$





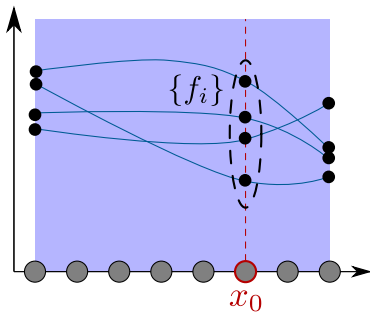
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- ▶ Distance between the **observed** and **modeled** map values:

$$r_i = f_i - (a + bu_i^- + cu_i^+).$$



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- ▶ Minimize this distance in some sense \Rightarrow **regression**.



Using (robust) regression to achieve resilience

The regression problem amounts to minimizing the residuals:

$$\mathbf{r} = \mathbf{y} - \mathbf{X}\boldsymbol{\beta}, \quad \text{with } \boldsymbol{\beta} = (a, b, c).$$

- ▶ **Goal:** determine a , b and c from limited number of observations y_i .
- ▶ Each y_i may be corrupted by a bit-flip (with small probability):

$$y_i = f_i + \epsilon_{\text{flip}}, \quad \epsilon_{\text{flip}} \text{ is **not** Gaussian!}$$



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- ▶ *Least squares* (LS) regression is not adapted:

$$J(\boldsymbol{\beta}) = \|\mathbf{y} - \mathbf{X}\boldsymbol{\beta}\|_2^2 = \sum (y_i - \mathbf{X}_i \cdot \boldsymbol{\beta})^2.$$

- ▶ Solve *least absolute deviations* (LAD) regression instead:

$$J(\boldsymbol{\beta}) = \|\mathbf{y} - \mathbf{X}\boldsymbol{\beta}\|_1 = \sum |y_i - \mathbf{X}_i \cdot \boldsymbol{\beta}|.$$



Resilient regression: LS vs. LAD

Least squares (LS) vs. Least absolute deviations (LAD):

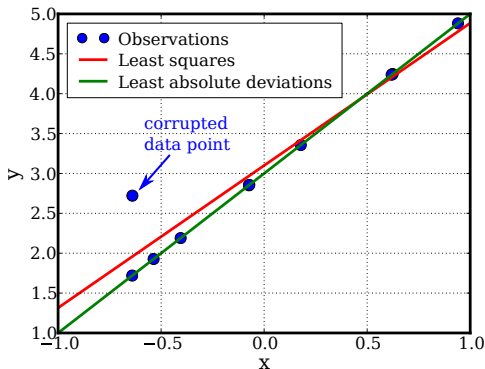


Figure: Regression with single corrupted point

ℓ_0 -“norm” of a vector = number of non-zero entries.



Algorithm overview:

1. Resilient map construction (on each subdomain):
 - Sample boundary conditions.
 - Solve PDE for each sample.
 - Build the left and right maps using resilient regression.
2. Assemble and solve the linear system \Rightarrow solution at interfaces.



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References:

- Validated in 1D [Sargayan, 2015].
- Validated in 2D with scalability measurements [Rizzi, 2015].
 - On **110,000 cores** with a **90%** parallel efficiency;
 - Small overhead caused by faults.



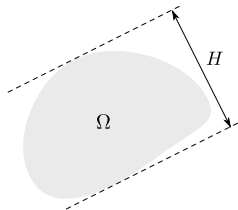
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Theorem (see, e.g. [Gilbarg & Trudinger])

- ▶ Let $\Omega \subset \mathbb{R}^D$ be an open bounded domain with boundary $\partial\Omega$ and closure $\bar{\Omega}$.
- ▶ Assume that Ω lies between two parallel planes separated by a distance H .



- ▶ Let \mathcal{L} be a second-order, elliptic operator of the form:

$$\mathcal{L}u = a_{\mathcal{L}}^{ij}(\mathbf{x}) \frac{\partial^2 u}{\partial x^i \partial x^j} + b_{\mathcal{L}}^i(\mathbf{x}) \frac{\partial u}{\partial x^i} + c_{\mathcal{L}}(\mathbf{x})u, \quad c_{\mathcal{L}} \leq 0, \quad \forall u \in C^0(\bar{\Omega}) \cap C^2(\Omega).$$

- ▶ Let $u \in C^0(\bar{\Omega}) \cap C^2(\Omega)$ be such that $\mathcal{L}u = f$ in Ω .

- ▶ **Then:**

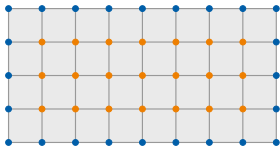
$$\sup_{\Omega} |u| \leq \sup_{\partial\Omega} |u| + C \sup_{\Omega} \frac{|f|}{\lambda}, \quad C \equiv e^{\gamma H} - 1, \quad \gamma \equiv 1 + \sup_{\Omega} \frac{\|\mathbf{b}_{\mathcal{L}}\|}{\lambda},$$

where $\lambda(\mathbf{x})$ is the minimum eigenvalue of the matrix $[a_{\mathcal{L}}^{ij}(\mathbf{x})]$.

Discrete elliptic problem — notations

Grid definition ($\mathbf{x}_k \equiv (x_k^1, \dots, x_k^D) \in \mathbb{R}^D$):

- ▶ $\bar{\Omega}_h \equiv \{\mathbf{x}_k\}_{k=1}^{n_t}$, $n_t \equiv n_i + n_b$;
- ▶ $\Omega_h \equiv \{\mathbf{x}_k\}_{k=1}^{n_i}$: **interior points**;
- ▶ $\partial\Omega_h \equiv \{\mathbf{x}_{n_i+k}\}_{k=1}^{n_b}$: **boundary points**.



Discrete elliptic Dirichlet problem of the augmented form $\bar{\mathbf{A}}\bar{\mathbf{u}} = \bar{\mathbf{b}}$:

$$\begin{array}{c}
 \text{boundary matrix} \leftarrow \text{interior solution} \quad \text{source term} \\
 \text{interior matrix} \leftarrow \text{boundary solution} \quad \text{boundary data} \\
 \left[\begin{array}{cc} \mathbf{A} & \mathbf{A}^\partial \\ \mathbf{0} & \mathbf{I} \end{array} \right] \begin{bmatrix} \mathbf{u} \\ \mathbf{u}^\partial \end{bmatrix} = \begin{bmatrix} \mathbf{b} \\ \mathbf{b}^\partial \end{bmatrix}
 \end{array}$$

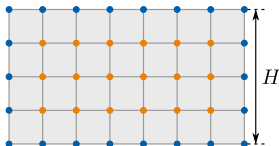
with the conditions (sufficient to ensure the *discrete maximum principle* [Ciarlet, 1970]):

- ▶ $\bar{\mathbf{A}}$ is monotone, i.e. $\bar{\mathbf{A}}^{-1} \geq 0$;
- ▶ The row sums of $\bar{\mathbf{L}} \equiv [\mathbf{A} \quad \mathbf{A}^\partial]$ are all zero: $\sum_{j=1}^{n_t} \bar{l}_{ij} = 0 \quad \forall i = 1, \dots, n_i$.



Theorem

- ▶ Let Ω_h lie between two parallel planes (say, $\perp \mathbf{e}^{\hat{d}}$) separated by a distance H .
- ▶ Let $\bar{\mathbf{u}} \in \mathbb{R}^{n_t}$ be such that $\bar{\mathbf{L}}\bar{\mathbf{u}} = \mathbf{b}$, with $\mathbf{b} \in \mathbb{R}^{n_i}$ and $\bar{\mathbf{L}}$ as defined previously.
- ▶ Let $\bar{\mathbf{w}} \equiv (w_1, \dots, w_{n_t}): \mathbb{R} \rightarrow \mathbb{R}^{n_t}$ be defined by $w_k(\alpha) = \exp(\alpha x_k^{\hat{d}})$, $\forall \alpha \in \mathbb{R}$.
- ▶ Assume there exists $\alpha \geq 0$ and $\boldsymbol{\lambda} > \mathbf{0} \in \mathbb{R}^{n_i}$ such that $\bar{\mathbf{L}}\bar{\mathbf{w}}(\alpha) \geq \boldsymbol{\lambda}$.



▶ **Then:**

$$\begin{cases} \min_{1 \leq k \leq n_i} u_k \geq \min_{1 \leq k \leq n_b} u_{n_i+k} - C \max_{1 \leq k \leq n_i} (|b_k^+|/\lambda_k), \\ \max_{1 \leq k \leq n_i} u_k \leq \max_{1 \leq k \leq n_b} u_{n_i+k} + C \max_{1 \leq k \leq n_i} (|b_k^-|/\lambda_k), \end{cases}$$

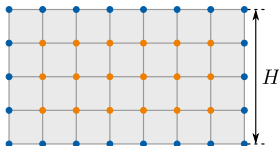
$$C \equiv e^{\alpha H} - 1.$$

Notation: for any scalar $a \in \mathbb{R}$, $a^- \equiv \min\{0, a\}$ and $a^+ \equiv \max\{0, a\}$.



Theorem

- ▶ Let Ω_h lie between two parallel planes (say, $\perp \mathbf{e}^{\hat{d}}$) separated by a distance H .
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- ▶ Assume there exists $\alpha \geq 0$ and $\lambda > 0 \in \mathbb{R}^{n_i}$ such that $\bar{\mathbf{L}}\bar{\mathbf{w}}(\alpha) \geq \lambda$.



▶ **Then:**

$$\begin{cases} \min_{1 \leq k \leq n_i} u_k \geq \min_{1 \leq k \leq n_b} u_{n_i+k} - C \max_{1 \leq k \leq n_i} (|b_k^+|/\lambda_k), \\ \max_{1 \leq k \leq n_i} u_k \leq \max_{1 \leq k \leq n_b} u_{n_i+k} + C \max_{1 \leq k \leq n_i} (|b_k^-|/\lambda_k), \end{cases}$$

$$C \equiv e^{\alpha H} - 1.$$

Notation: for any scalar $a \in \mathbb{R}$, $a^- \equiv \min\{0, a\}$ and $a^+ \equiv \max\{0, a\}$.

Diffusion equation with variable diffusion coefficient κ (assumed differentiable):

$$\mathcal{L}u \equiv \nabla \cdot [\kappa \nabla u] = \sum_{d=1}^D \mathcal{L}^d u.$$

Second-order finite difference (FD) operator defined by:

$$(\bar{\mathbf{L}}\bar{\mathbf{u}})_k \equiv \sum_{d=1}^D [\kappa_{k-}^d u_{k-}^d - 2\tilde{\kappa}_k^d u_k + \kappa_{k+}^d u_{k+}^d] / [h^d]^2.$$

In the \hat{d} -th direction:

$$\alpha = \frac{1}{h} \log \left[\frac{h\sqrt{h^2 + \beta^2 + 4} + h^2 + 2}{2 - \beta h} \right] \implies [\bar{\mathbf{L}}\bar{\mathbf{w}}(\alpha)]_k \geq \tilde{\kappa}_k^{\hat{d}} \quad \forall k = 1, \dots, n_i,$$

where $\beta \equiv \max_{1 \leq k \leq n_i} \left(\left| \tilde{\nabla}_k^{\hat{d}} \kappa \right| / \tilde{\kappa}_k^{\hat{d}} \right)$ and $h \equiv h^{\hat{d}}$.

[Reminder: $C = e^{\alpha H} - 1$].



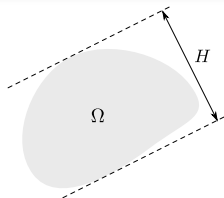
Continuous and discrete bounds

Continuous problem:

$$\begin{cases} \nabla \cdot [\kappa(\mathbf{x}) \nabla u(\mathbf{x})] = f(\mathbf{x}), & \forall \mathbf{x} \in \Omega, \\ u|_{\partial\Omega} = u_{\Gamma}. \end{cases}$$

Continuous bounds [Gilbarg & Trudinger]

$$\sup_{\Omega} |u| \leq \sup_{\partial\Omega} |u| + C \sup_{\Omega} (|f|/\kappa) \quad \text{where } C = e^{\gamma H} - 1.$$

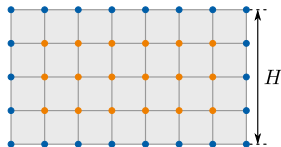




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$$\sup_{\Omega} |u| \leq \sup_{\partial\Omega} |u| + C \sup_{\Omega} (|f|/\kappa) \quad \text{where } C = e^{\gamma H} - 1.$$

Discrete problem: 2nd-order centered finite differences (conservative form)

$$\mathbf{A}\mathbf{u} = \mathbf{b} - \mathbf{A}^{\partial}\mathbf{u}^{\partial}, \quad \underbrace{\mathbf{u} = (u_1, \dots, u_{n_i})}_{\substack{n_i \text{ unknowns} \\ \text{(interior nodes)}}, \quad \underbrace{\mathbf{u}^{\partial} = (u_{n_i+1}, \dots, u_{n_i+n_b})}_{\substack{n_b \text{ Dirichlet BCs} \\ \text{(boundary nodes)}}$$

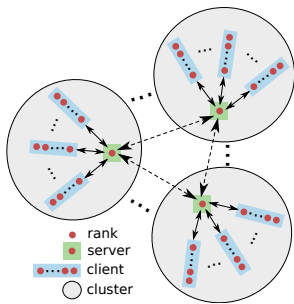
Discrete bounds [Mycek et al., 2017]

$$\begin{cases} \min_{1 \leq k \leq n_i} u_k \geq \min_{1 \leq k \leq n_b} u_{n_i+k} - C \max_{1 \leq k \leq n_i} (|b_k^+|/\tilde{\kappa}_k) \\ \max_{1 \leq k \leq n_i} u_k \leq \max_{1 \leq k \leq n_b} u_{n_i+k} + C \max_{1 \leq k \leq n_i} (|b_k^-|/\tilde{\kappa}_k) \end{cases}$$

where $C = e^{\alpha H} - 1$.




Server-client-based implementation




▶ Cluster: 1 server + n clients.

▶ Servers: 

Communicate between each other.
Safe data/state storage (sandboxed).

▶ Clients: 

One or several MPI ranks ()
Independent from one another.
Only serve as computing units.
No assumption on their reliability.

- ▶ Separates state from computation: reduces the overall vulnerability.
- ▶ Fault-tolerance supported via ULFM-MPI: support for crashing MPI processes.
- ▶ Resilient to clients crashing: even if tasks are lost, state is safe.
- ▶ Aligns with the vision of exascale architectures: heterogeneous/hierarchical hardware.
⇒ Resilience to hard faults (SC + ULFM-MPI) and soft faults (ℓ_1 -min. + bounds)



Server-client sampling mechanism

foreach *subdomain* Ω_i **do**

```
// [SERVER] Pre-processing stage  
Compute the invariant parts of the bounds for  $\Omega_i$  ;
```

```
// [SERVER] Sample boundary conditions
```

```
Sample  $s_i^*$  boundary conditions for  $\Omega_i$  ;
```

```
 $s_i \leftarrow s_i^*$  ;
```

foreach *sample* **do**

```
// [SERVER]
```

```
Add contribution of the boundary conditions to the bounds ;
```

```
Send task to a client ;
```

```
// [CLIENT]
```

```
Receive task from server ;
```

```
Solve the local PDE in  $\Omega_i$  using the received sample of boundary conditions ;
```

```
Send task (with the solution) back to server ; /* Corruption may occur
```

```
*/
```

```
// [SERVER]
```

```
Receive returning task from client ; /* Task is potentially corrupted
```

```
*/
```

```
if received solution does not lie between the bounds then
```

```
    Discard current sample ;
```

```
     $s_i \leftarrow s_i - 1$  ;
```




Server-client sampling mechanism

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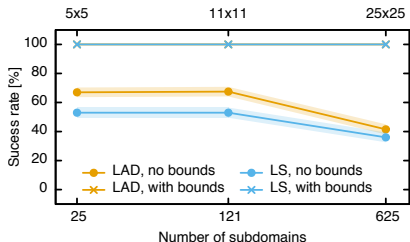


Application to our (2d) solver

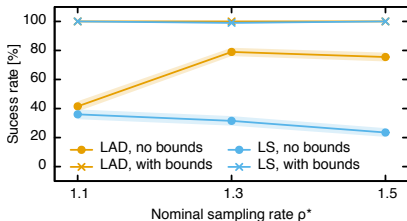
Problem:

$$\begin{cases} \nabla \cdot [\kappa(\mathbf{x}) \nabla u(\mathbf{x})] = f(\mathbf{x}), & \forall \mathbf{x} \in \Omega = (0, 1)^2, \\ u|_{\partial\Omega} = 1. \end{cases} \quad \text{with} \quad \begin{cases} \kappa(\mathbf{x}) = 1, \\ f(\mathbf{x}) = \tanh[d(\mathbf{x})/0.05] \end{cases}$$

Resilience enhancement:



$$\rho^* = 1.1$$



$$625 = 25 \times 25 \text{ subdomains}$$



Summary:

- ▶ Resilient algorithm for elliptic PDEs.
- ▶ Sampling approach + robust (resilient) minimization.
- ▶ Discrete a priori bounds to enhance overall resilience.

Outlook:

- ▶ Higher-order FD schemes → new expression for α .
- ▶ Other elliptic problems: tensor diffusion, reaction-diffusion, ...
- ▶ Non-uniform meshes (refinement).
- ▶ Apply to stochastic elliptic PDEs.
- ▶ Neumann boundary conditions?



Acknowledgments

- ▶ This material is based upon work supported by the U.S. Department of Energy, Office of Science, Office of Advanced Scientific Computing Research, under Award Numbers DE-SC0010540 and 13-016717.
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Thank you for your attention.