

Empirical Interpolation Method (EIM)

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Outline

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- Consider *non-affine* parameter dependence function:

$$s(\cdot; \mu) \in L^\infty(\Omega),$$

where Ω = spatial domain, and $\mu \in \mathcal{D}$ = parameter domain

- Define:

$$\mathcal{M}^s \equiv \{s(\cdot; \mu) : \mu \in \mathcal{D}\}$$

- \mathcal{M}^s could be a low-dimensional space $\Rightarrow \mathcal{M}^s \simeq \text{span}\{q_1, \dots, q_m\}$ with *small* m .
- variation of \mathcal{M}^s in $\mu \in \mathcal{D}$ can be captured by a selected points $\{z_1, \dots, z_m\} \in \Omega$ with *small* m .

- Goal:** Approximate s by \hat{s} in the form:

$$\begin{aligned}\hat{s}(x; \mu) &= \sum_{\ell=1}^m q_\ell(x) \beta_\ell(\mu), & \text{with} \\ \hat{s}(z_i; \mu) &= s(z_i; \mu) & i = 1, \dots, m,\end{aligned}$$

for all $\mu \in \mathcal{D}$. Closed-form for β_1, \dots, β_m ?

Coefficient Approximation: Matrix Form

- Given

Basis: $Q(x) \equiv [q_1(x), \dots, q_m(x)]$

Interpolation Points: $\mathbf{z} \equiv [z_1, \dots, z_m]^T \in \Omega^m$

- Let Coefficient: $\beta(\mu) \equiv [\beta_1(\mu), \dots, \beta_m(\mu)]^T \in \mathbb{R}^m$
 Function at \mathbf{z} : $\mathbf{s}(\mathbf{z}; \mu) \equiv [s(z_1; \mu), \dots, s(z_m; \mu)]^T \in \mathbb{R}^m$

$$Q(\mathbf{z}) = \begin{bmatrix} q_1(z_1) & q_2(z_1) & \dots & q_m(z_1) \\ q_1(z_2) & q_2(z_2) & \dots & q_m(z_2) \\ \vdots & \vdots & \ddots & \vdots \\ q_1(z_m) & q_2(z_m) & \dots & q_m(z_m) \end{bmatrix} \in \mathbb{R}^{m \times m},$$

- $$\left\{ \begin{array}{l} \hat{\mathbf{s}}(\mathbf{x}; \mu) = Q(\mathbf{x})\beta(\mu) \\ \hat{\mathbf{s}}(\mathbf{z}; \mu) = \mathbf{s}(\mathbf{z}; \mu) \end{array} \right\} \Rightarrow \boxed{\beta(\mu) = (Q(\mathbf{z}))^{-1} \mathbf{s}(\mathbf{z}; \mu)}$$

$$\hat{\mathbf{s}}(\mathbf{x}; \mu) = Q(\mathbf{x})(Q(\mathbf{z}))^{-1} \mathbf{s}(\mathbf{z}; \mu)$$

GIVEN:

$$s(\cdot; \mu) \in L^\infty(\Omega; \mathcal{D})$$

$$\mathcal{M}^S \equiv \{s(\cdot; \mu) : \mu \in \mathcal{D}\}$$

(I) BASIS: $\{\xi_\ell\}_{\ell=1}^m$

$$\text{s.t. } \text{span}\{\xi_1, \dots, \xi_m\} \simeq \mathcal{M}^S$$

(II) INTERPOLATION

$$\text{POINTS: } \mathbf{z} = \{z_\ell\}_{\ell=1}^m$$

$$\text{s.t. } Q(\mathbf{z}) \text{ invertible}$$

EIM

$$\{q\}_{\ell=1}^m$$

$$\Downarrow$$

$$Q(x)$$

$$\{\beta_\ell(\mu)\}_{\ell=1}^m$$

$$\Downarrow$$

$$\beta(\mu) = (Q(\mathbf{z}))^{-1} s(\mathbf{z}; \mu)$$

(III) OUTPUT:

$$\hat{s}(x; \mu) = \sum_{\ell=1}^m q_\ell(x) \beta_\ell(\mu)$$

$$\Downarrow$$

$$\hat{s}(x; \mu) = Q(x)(Q(\mathbf{z}))^{-1} s(\mathbf{z}; \mu)$$

Empirical Interpolation Method (EIM)[Patera; 2004]

EIM Algorithm: Given a set of basis functions $\{\xi_i\}_{i=1}^m$, the set of m EIM interpolation points $\mathbf{z} = [z_1, \dots, z_m]^T$ is constructed as follows.

EIM steps

- Set $z_1 = \arg \operatorname{ess} \sup_{x \in \Omega} |\xi_1(x)|$.
 $q_1(x) = \frac{\xi_1(x)}{\xi_1(z_1)}$;
 $\mathbf{Q}^1(\mathbf{z}^1) = q_1(z_1) = 1$.
- For $L = 2, \dots, m$,
 - 1 Solve ρ^{L-1} from :

$$\mathbf{Q}^{L-1}(\mathbf{z}^{L-1})\rho^{L-1} = \xi_L(\mathbf{z}^{L-1}),$$
 - 2 Define

$$r_L(x) = \xi_L(x) - \mathbf{Q}^{L-1}(x)\rho^{L-1},$$
 - 3 Set

$$z_L = \arg \operatorname{ess} \sup_{x \in \Omega} |r_L(x)|$$
 - 4 Set $q_L(x) = \frac{r_L(x)}{r_L(z_L)}$

Note:

$$\begin{aligned} [(\mathbf{Q}^{L-1}(\mathbf{z}^{L-1}))_{ij}] &= [q_j(z_i)] \in \mathbb{R}^{(L-1) \times (L-1)}; \\ \xi_L(\mathbf{z}^{L-1}) &= [\xi_L(z_1), \dots, \xi_L(z_{L-1})]^T \in \mathbb{R}^{L-1}; \\ \mathbf{z}^{L-1} &= [z_1, \dots, z_{L-1}]^T \in \Omega^{L-1}; \\ \mathbf{Q}^{L-1}(x) &= [q_1(x), \dots, q_{L-1}(x)]. \end{aligned}$$

Final Output

Basis:	$\{q_1, \dots, q_m\}$
EIM points:	$\{z_1, \dots, z_m\}$

$$\begin{aligned} \text{Set } \mathbf{Q}(x) &= \mathbf{Q}^m(x) \\ \text{Set } \mathbf{Q}(\mathbf{z}) &= \mathbf{Q}^m(\mathbf{z}^m) \\ s(x; \mu) &\simeq \hat{s}_m(x; \mu) = Q(x)(Q(\mathbf{z}))^{-1}s(\mathbf{z}; \mu) \end{aligned}$$

EIM points and bases

Ex: Input $\{\xi_L\}_{L=1}^m$ are eigenvectors of discrete Laplacian (Dr. Sorensen)

EIM steps

- 1 Set $z_1 = \arg \text{ess } \sup_{x \in \Omega} |\xi_1(x)|$.

$$q_1(x) = \frac{\xi_1(x)}{\xi_1(z_1)};$$

$$\mathbf{Q}^1(\mathbf{z}^1) = q_1(z_1) = 1.$$

- For $L = 2, \dots, m$,

- 1 Solve ρ^{L-1} from :

$$\mathbf{Q}^{L-1}(\mathbf{z}^{L-1})\rho^{L-1} = \xi_L(\mathbf{z}^{L-1}),$$

- 2 Define

$$r_L(x) = \xi_L(x) - \mathbf{Q}^{L-1}(x)\rho^{L-1},$$

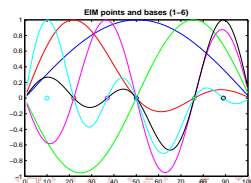
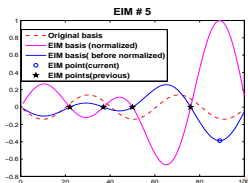
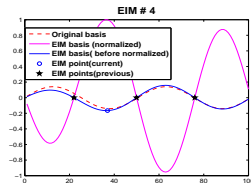
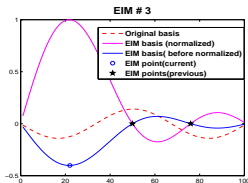
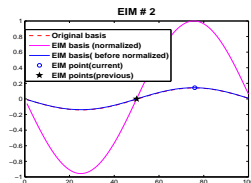
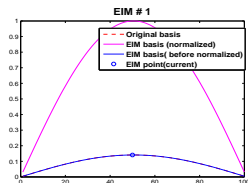
- 3 Set $z_L = \arg \text{ess } \sup_{x \in \Omega} |r_L(x)|$

- 4 Set $q_L(x) = \frac{r_L(x)}{r_L(z_L)}$

Notice: $r_L(z_i) = q_L(z_i) = 0, \forall i = 1, \dots, L-1$.

i.e., EIM points z_1, \dots, z_{L-1} are the zeros of $q_L(x)$

and $r_L(x)$



Remarks on EIM

- EIM constructs an approximation for *non-affine* parameter dependence function by using a method of greedy selection.

Given *linear independent set* $\{\xi_1, \dots, \xi_m\}$. Then, for $L = 1, \dots, m$,

- $r_L(z_L) \neq 0$, since $\{\xi_i\}_{i=1}^L$ are linearly independent.

- \exists a transformation between $\left\{ \begin{array}{ll} \text{Input basis:} & \mathbf{W} \equiv [\xi_1, \dots, \xi_m] \\ \text{EIM basis:} & \mathbf{Q} \equiv [q_1, \dots, q_m] \end{array} \right\}$

$$\mathbf{W} = \mathbf{Q}\mathbf{R},$$

where

$$\mathbf{R} := \begin{bmatrix} \xi_1(z_1) & \rho_1^1 & \rho_1^2 & \dots & \rho_1^{m-1} \\ & r_2(z_2) & \rho_2^2 & \dots & \rho_2^{m-1} \\ & & r_2(z_2) & \dots & \rho_3^{m-1} \\ & & & \ddots & \vdots \\ & & & & \rho_{m-1}^{m-1} \\ & & & & r_m(z_m) \end{bmatrix} \in \mathbb{R}^{m \times m},$$

- $\Rightarrow \text{span}\{q_1, \dots, q_L\} = \text{span}\{\xi_1, \dots, \xi_L\}$

Remarks on EIM(cont')

- $r_L(z_i) = 0$ for all $i = 1, \dots, L-1 \Rightarrow q_j(z_i) = 0$ for $0 \leq i < j \leq L$
- $\mathbf{Q}^L(\mathbf{z}^L) = [q_j(z_i)] \in \mathbb{R}^{L \times L}$ is lower triangular with:

$$\left\{ \begin{array}{ll} (\mathbf{Q}^L(\mathbf{z}^L))_{ij} = 0, & \text{if } i < j \\ (\mathbf{Q}^L(\mathbf{z}^L))_{ij} = 1, & \text{if } i = j \\ |(\mathbf{Q}^L(\mathbf{z}^L))_{ij}| \leq 1, & \text{if } i > j \end{array} \right\} \text{ for } i, j = 1, \dots, L$$

- $\mathbf{Q}^L(\mathbf{z}^L)$ is invertible, since $\det(\mathbf{Q}^L(\mathbf{z}^L)) = 1$.
- \Rightarrow The EIM steps are well-defined.
- \Rightarrow The EIM points will not repeat.
- There exists a unique EIM approx \hat{s}_m , since $\mathbf{Q}^m(\mathbf{z}^m)$ is invertible.
- The EIM is hierarchy: for $L = 1, \dots, m-1$, small

$$\begin{aligned} \{z_1, \dots, z_L\} &\subsetneq \{z_1, \dots, z_{L+1}\} \\ \{q_1, \dots, q_L\} &\subsetneq \{q_1, \dots, q_{L+1}\}. \end{aligned}$$

\Rightarrow If given $\text{span}\{\xi_{m+1}\} \not\subseteq \text{span}\{\xi_1, \dots, \xi_m\}$, we can extend EIM points:
 $\{z_L\}_{L=1}^{m+1} = \{z_L\}_{L=1}^m \cup \{z_{m+1}\}$; and bases $\{q_L\}_{L=1}^{m+1} = \{q_L\}_{L=1}^m \cup \{q_{m+1}\}$

Posteriori Error bound of EIM approx \hat{s}_m

Suppose ξ_{m+1} is not in $\text{span}\{\xi_1, \dots, \xi_m\}$, and $s(\cdot; \mu) \in W_{m+1}^s := \text{span}\{\xi_1, \dots, \xi_{m+1}\} \subset \mathcal{M}^s := \{s(\cdot; \mu) | \mu \in \mathcal{D}\}$. Define

$$\begin{aligned}\hat{\epsilon}(\mu) &:= |s(z_{m+1}; \mu) - \hat{s}_m(z_{m+1}; \mu)|, \\ \mathcal{E}(x; \mu) &:= \hat{\epsilon}(\mu) q_{m+1}(x),\end{aligned}$$

where z_{m+1} and $q_{m+1}(x)$ are the $(m+1)^{\text{th}}$ EIM point and basis. Then

1

$$s(x, \mu) - \hat{s}_m(x, \mu) = \pm \mathcal{E}(x; \mu),$$

2

$$\|s(\cdot, \mu) - \hat{s}_m(\cdot, \mu)\| \leq \hat{\epsilon}(\mu).$$

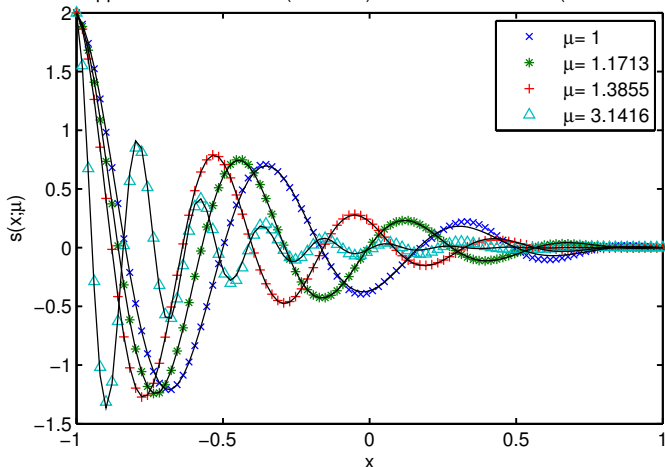
Note: in general, the assumption that $s(\cdot, \mu) \in W_{m+1}^s$ does not hold and the error bound above may not be exact (or applicable).

Ex: EIM for a nonlinear function

$$s(x; \mu) = (1 - x) \cos(3\pi\mu(x + 1)) e^{-(1+x)\mu},$$

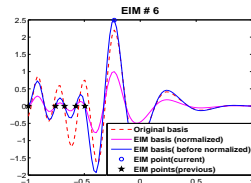
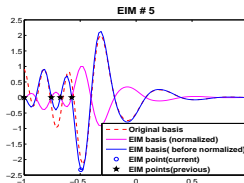
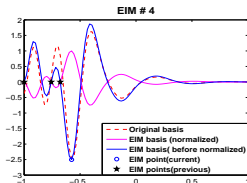
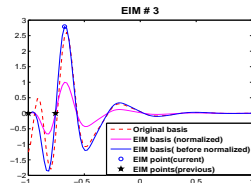
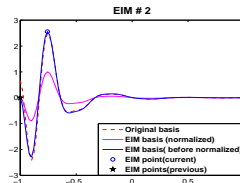
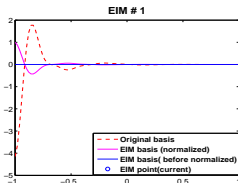
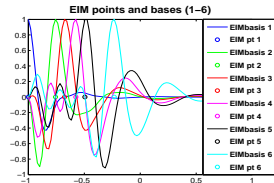
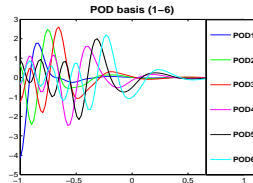
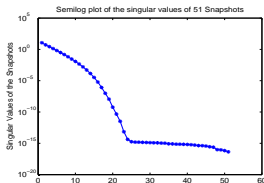
where $x \in [-1, 1]$ and $\mu \in [1, \pi]$.

Plot of Approximate Functions (dim = 10) with Exact Functions (in black solid line)



Ex: EIM for a nonlinear function(cont')

$$s(x; \mu) = (1 - x)\cos(3\pi\mu(x + 1))e^{-(1+x)\mu}$$



Ex: Application of the EIM on PDEs with nonlinearities

Ex. Unsteady 1D Burgers' Equation

$$\frac{\partial}{\partial t} y(x, t) - \nu \frac{\partial^2}{\partial x^2} y(x, t) + \frac{\partial}{\partial x} (s(y(x, t))) = 0, \quad s(y(x, t)) = \frac{y(x, t)^2}{2},$$

$$y(0, t) = y(1, t) = 0, \quad t \geq 0, \quad y(x, 0) = y_0(x), \quad x \in \Omega \equiv [0, 1],$$

Discretized system (Galerkin)

- Full-order system (dim = N): FE basis $\{\varphi_i\}_{i=1}^N$

$$\mathbf{M}_h \frac{d}{dt} \mathbf{y}(t) + \nu \mathbf{K}_h \mathbf{y}(t) - \mathbf{N}_h(\mathbf{y}(t)) = 0 \Rightarrow \boxed{y_h(x, t) = \sum_{i=1}^N \varphi_i(x) \mathbf{y}_i(t)}$$

- Reduced-order system (dim = $k < N$): reduced basis $\{\phi_i\}_{i=1}^k$

$$\tilde{\mathbf{M}} \frac{d}{dt} \tilde{\mathbf{y}}(t) + \nu \tilde{\mathbf{K}} \tilde{\mathbf{y}}(t) - \tilde{\mathbf{N}}(\tilde{\mathbf{y}}(t)) = 0 \Rightarrow \boxed{\tilde{y}_h(x, t) = \sum_{i=1}^k \phi_i(x) \tilde{\mathbf{y}}_i(t)},$$

E.g., $\{\phi_i\}_{i=1}^k$ can be constructed from POD.

Ex: Application of the EIM on PDEs with nonlinearities (cont')

Problem of reduced system from direct POD

Suppose

$$\Phi(x) = \Psi(x) \mathbf{U}_k,$$

$$\text{where } \begin{cases} \text{FE basis:} & \Psi(x) \equiv [\psi_1(x), \dots, \psi_N(x)], \\ \text{Reduced basis:} & \Phi(x) \equiv [\phi_1(x), \dots, \phi_k(x)], \\ \text{Projection:} & \mathbf{U}_k \equiv [\mathbf{u}_1, \dots, \mathbf{u}_k] \end{cases} \in \mathbb{R}^{N \times k}.$$

Note:

$$\tilde{\mathbf{N}}(\tilde{\mathbf{y}}(t)) = \underbrace{\mathbf{U}_k^T}_{k \times N} \underbrace{\mathbf{N}_h(\mathbf{U}_k \tilde{\mathbf{y}}(t))}_{N \times 1} \Leftarrow \left\{ \begin{array}{lcl} \mathbf{N}_h(\mathbf{y}(t)) & = & \int_{\Omega} \Psi'(x)^T \mathbf{s}(\Psi(x) \mathbf{y}(t)) dx \\ \tilde{\mathbf{N}}(\tilde{\mathbf{y}}(t)) & = & \mathbf{U}_k^T \int_{\Omega} \Psi'(x)^T \mathbf{s}(\Psi(x) \mathbf{U}_k \tilde{\mathbf{y}}(t)) dx \end{array} \right\}$$

\Rightarrow Computational Complexity still depends on N !!

WANT:

$$\tilde{\mathbf{N}}(\tilde{\mathbf{y}}(t)) \leftarrow \underbrace{\mathbf{C}}_{k \times m} \underbrace{\hat{\mathbf{N}}(\tilde{\mathbf{y}}(t))}_{m \times 1} \dashrightarrow \boxed{k, m \ll N} \dashrightarrow \text{Independent of } N$$

$\Rightarrow \mathbf{C}$ and $\hat{\mathbf{N}}(\tilde{\mathbf{y}}(t))$ can be constructed from the **EIM**.

Ex: Application of the EIM on PDEs with nonlinearities(cont')

How EIM works?

- Approximation from EIM:

$$s(\Psi(x)\mathbf{U}_k\tilde{\mathbf{y}}(t)) \simeq \hat{s}(x, t) = \mathbf{Q}(x)(\mathbf{Q}(\mathbf{z}))^{-1}s(\mathbf{z}, t),$$

$$\text{EIM Basis: } \mathbf{Q}(x) \equiv [q_1(x), \dots, q_m(x)]$$

$$\text{EIM Interpolation Points: } \mathbf{z} \equiv [z_1, \dots, z_m]^T \in \Omega^m$$

- Approximation for the Nonlinear term :

$$\begin{aligned} \tilde{\mathbf{N}}(\tilde{\mathbf{y}}(t)) &= \underbrace{\mathbf{U}_k^T}_{k \times N} \underbrace{\int_{\Omega} \Psi'(x)^T s(\Psi(x)\mathbf{U}_k\tilde{\mathbf{y}}(t)) dx}_{N \times 1} \\ &\simeq \underbrace{\mathbf{U}_k^T \left(\int_{\Omega} \Psi'(x)^T \mathbf{Q}(x) dx \right)}_{\substack{= \mathbf{C} \\ k \times m: \text{precomputed}}} (\mathbf{Q}(\mathbf{z}))^{-1} \underbrace{s(\mathbf{z}, t)}_{m \times 1} \\ &= \underbrace{\hat{\mathbf{N}}(\tilde{\mathbf{y}}(t))}_{m \times 1} \end{aligned}$$

Plots of Numerical Solutions from EIM with POD basis

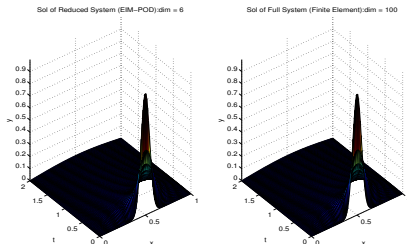
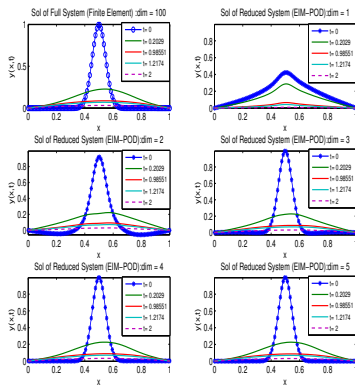
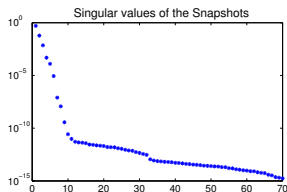


Figure: EIM-POD

ACCURACY vs. COMPLEXITY

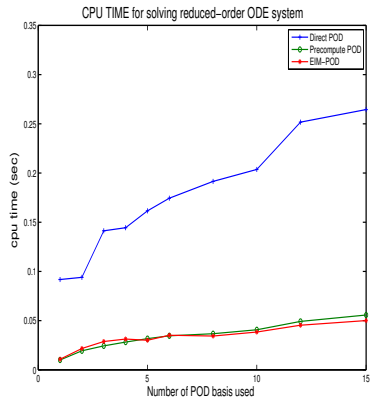
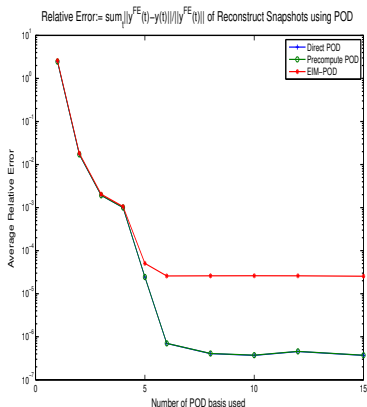


Figure: LEFT: Error $E_{avg} = \frac{1}{n_t} \sum_{i=1}^{n_t} \frac{\|\tilde{y}_h(\cdot, t_i) - y_h(\cdot, t_i)\|_X}{\|y_h(\cdot, t_i)\|_X}$.RIGHT: CPU time (sec)