

# From EIM to DEIM (and GEIM): Affinizing the Non-Affine

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# Learning goals (2h)

- Understand the motivation: offline/online splitting needs affine dependence.
- Derive and implement the Empirical Interpolation Method (EIM).
- Know how DEIM differs (POD basis + same greedy points).
- Glimpse GEIM: replace point samples with general linear functionals.
- Be able to prove: lower-triangularity/invertibility of  $B_M$ , basic error bound with Lebesgue constant, and the one-point estimator property.

# The problem

Given a parametric function  $g(x; \mu)$  (e.g. a source  $s$  or coefficient  $k$ ), we seek a separated approximation

$$I_M^x g(x; \mu) = \sum_{j=1}^M \gamma_j(\mu) \rho_j(x)$$

so that linear/bilinear forms become affine:  $\ell(v; \mu) \approx \sum_{j=1}^M \gamma_j(\mu) \int_{\Omega} \rho_j(x) v(x) dx.$

# EIM in one slide

- Build basis  $\{\rho_j\}_{j=1}^M$  and points  $\{t_j\}_{j=1}^M$  greedily.
- Interpolation:  $I_M^x g(t_i; \mu) = g(t_i; \mu)$ ,  $i = 1, \dots, M$ .
- Linear system  $B_M \gamma(\mu) = g_M(\mu)$  with  $(B_M)_{ij} = \rho_j(t_i)$ .
- $B_M$  is lower triangular with ones on the diagonal  $\Rightarrow$  fast  $\mathcal{O}(M^2)$  solve.

# Greedy EIM algorithm (offline)

- ① Choose  $\mu_1 = \arg \max_{\mu} \|g(\cdot; \mu)\|_{\infty}$ , set  $\xi_1 = g(\cdot; \mu_1)$ ;  $t_1 = \arg \max_x |\xi_1(x)|$ ;  $\rho_1 = \xi_1(t_1)$ .
- ② For  $m = 1, \dots, M - 1$ :
  - ①  $\mu_{m+1} = \arg \max_{\mu} \|g(\cdot; \mu) - I_m^x g(\cdot; \mu)\|_{\infty}$ ;  $\xi_{m+1} = g(\cdot; \mu_{m+1})$ .
  - ②  $r_{m+1} = \xi_{m+1} - I_m^x \xi_{m+1}$ .
  - ③  $t_{m+1} = \arg \max_x |r_{m+1}(x)|$ .
  - ④  $\rho_{m+1} = r_{m+1}/r_{m+1}(t_{m+1})$ .

# Properties and simple proofs

- **Triangularity & invertibility:**  $B_M$  is lower triangular with  $(B_M)_{ii} = 1$  because  $t_m$  is chosen at the maximum of  $r_m$  and  $\rho_m(r_i) = 0$  for  $i < m$ .
- **Exactness on  $X_M$ :**  $I_M^x v = v$  for any  $v \in X_M = \text{span}\{\rho_1, \dots, \rho_M\}$ .
- **Error bound:**  $\|g - I_M^x g\|_\infty \leq (1 + \Lambda_M) \inf_{z \in X_M} \|g - z\|_\infty$ ,  
 $\Lambda_M = \sup_x \sum_{i=1}^M |\ell_i^M(x)|$ .
- **One-point estimator:** if  $g(\cdot; \mu) \in X_{M+1}$  then  
 $\|g - I_M^x g\|_\infty = |g(t_{M+1}; \mu) - I_M^x g(t_{M+1}; \mu)|$ .

# Practical discretization

- Discretize  $\Omega$  by quadrature points  $\{x_k\}_{k=1}^{N_q}$ .
- Training set  $\Xi_{\text{train}} \subset \mathcal{D}$ .
- Algebraic form:  $g(\mu) \in \mathbb{R}^{N_q}$ ,  $Q = [\rho_1 | \cdots | \rho_M] \in \mathbb{R}^{N_q \times M}$ , indices  $I$  s.t.  
 $t_j = x_{I_j}$ .
- Online: solve  $Q_I \gamma(\mu) = g_I(\mu)$  then  $g_M(\mu) = Q \gamma(\mu)$ .

# DEIM in two bullets

- Build  $Q$  by POD of a snapshot matrix  $S = [g(\mu_1) | \cdots | g(\mu_{n_s})]$ .
- Select the same interpolation indices greedily; online solve  $Q_I\gamma = g_I$ .

# DEIM error intuition

If  $\sigma_{M+1}$  is the first neglected singular value of  $S$ , then

$$\|g(\mu) - g_M(\mu)\|_2 \lesssim \|Q_I^{-1}\|_2 \sigma_{M+1},$$

assuming the training set is representative.

# GEIM: beyond point samples

- Replace evaluations  $\delta_{t_i}(g) = g(t_i)$  by linear functionals  $L_i(g)$  (e.g. averages, sensor outputs).
- Interpolate:  $L_i(I_M^x g) = L_i(g)$ ,  $i = 1, \dots, M$ .
- Same greedy spirit, but maximize residuals in the dual: choose  $L_{m+1}$  where the mismatch is largest.
- Useful for inverse problems and data assimilation where only indirect measurements exist.

# Affine recovery for forms

Given  $k_M = \sum_{j=1}^{M_k} \gamma_j^k(\mu) \rho_j^k(x)$  and  $s_M = \sum_{j=1}^{M_s} \gamma_j^s(\mu) \rho_j^s(x)$ ,

$$a_M(u, v; \mu) = \sum_{j=1}^{M_k} \gamma_j^k(\mu) \int_{\Omega} \rho_j^k \nabla u \cdot \nabla v,$$

$$f_M(v; \mu) = \sum_{j=1}^{M_s} \gamma_j^s(\mu) \int_{\Omega} \rho_j^s v.$$

All parameter dependence is in scalars  $\gamma_j^{\cdot}(\mu)$ .

# What to prove in class

- ①  $B_M$  is lower triangular with ones on the diagonal.
- ② The Lebesgue-constant error bound.
- ③ The one-point lower bound and the equality when  $g(\cdot; \mu) \in X_{M+1}$ .

# Mini-exercises

- Implement EIM for  $g(x; \mu) = (1 + \mu_1) \sin((1 + \mu_2)\pi x) + \exp(-20(x - \mu_3)^2)$ .
- Compare EIM vs. Chebyshev interpolation on a fixed grid.
- Inspect  $\Lambda_M$  numerically and relate to stability.

# Takeaways

- EIM/DEIM recover separability and enable fast online queries.
- Interpolation points are data-driven “magic points”.
- GEIM broadens the game to general measurements.