

CME 345: MODEL REDUCTION

Moment Matching

David Amsallem & Charbel Farhat
Stanford University
cfarhat@stanford.edu

These slides are based on the recommended textbook: A.C. Antoulas, "Approximation of Large-Scale Dynamical Systems," Advances in Design and Control, SIAM, ISBN-0-89871-529-6

Outline

- 1 Moments of a Function
- 2 Model Reduction by Moment Matching
- 3 Moment Matching by Krylov Iterative Methods
- 4 Error Bounds

$$\begin{aligned}\frac{d}{dt}\mathbf{x}(t) &= \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{u}(t) \\ \mathbf{y}(t) &= \mathbf{C}\mathbf{x}(t) + \mathbf{D}\mathbf{u}(t) \\ \mathbf{x}(0) &= \mathbf{x}_0\end{aligned}$$

- $\mathbf{x} \in \mathbb{R}^n$: vector state variables
- $\mathbf{u} \in \mathbb{R}^p$: vector of input variables, typically $p \ll n$
- $\mathbf{y} \in \mathbb{R}^q$: vector output variables, typically $q \ll n$

- Goal: obtain a **Reduced-Order Model** (ROM)

$$\begin{aligned}\frac{d}{dt}\mathbf{x}_r(t) &= \mathbf{A}_r\mathbf{x}_r(t) + \mathbf{B}_r\mathbf{u}(t) \\ \mathbf{y}_r(t) &= \mathbf{C}_r\mathbf{x}_r(t) + \mathbf{D}_r\mathbf{u}(t)\end{aligned}$$

- $\mathbf{x}_r \in \mathbb{R}^k$: **vector of reduced state variables**
- ROM resulting from **Petrov-Galerkin** projection:

$$\begin{aligned}\mathbf{A}_r &= (\mathbf{W}^T\mathbf{V})^{-1}\mathbf{W}^T\mathbf{A}\mathbf{V} \in \mathbb{R}^{k \times k} \\ \mathbf{B}_r &= (\mathbf{W}^T\mathbf{V})^{-1}\mathbf{W}^T\mathbf{B} \in \mathbb{R}^{k \times p} \\ \mathbf{C}_r &= \mathbf{C}\mathbf{V} \in \mathbb{R}^{q \times k} \\ \mathbf{D}_r &= \mathbf{D} \in \mathbb{R}^{q \times p}\end{aligned}$$

- Let \mathbf{h} denote a general matrix valued function of time

$$\mathbf{h} : t \in \mathbb{R} \mapsto \mathbb{R}^{q \times p}$$

Example: impulse response of an LTI system

$$\mathbf{h}(t) = \mathbf{C}e^{\mathbf{A}t}\mathbf{B} + \mathbf{D}$$

- $\mathbf{H}(s)$ will denote its Laplace transform, that is

$$\mathbf{H}(s) = \int_0^\infty \mathbf{h}(t)e^{-st}dt$$

Example: impulse response of an LTI system

$$\mathbf{H}(s) = \mathbf{C}(s\mathbf{I}_n - \mathbf{A})^{-1}\mathbf{B} + \mathbf{D}$$

└ Moments of a Function

└ Moment of a Function

- Let $m \in \{0, \dots, \}$.

The m -th **moment** of $\mathbf{h} : t \in \mathbb{R} \mapsto \mathbb{R}^{q \times p}$ at $s_0 \in \mathbb{C}$ is

$$\eta_m(s_0) = \int_0^\infty t^m e^{-s_0 t} \mathbf{h}(t) dt$$

- In terms of its transfer function

$$\eta_m(s_0) = (-1)^m \left. \frac{d^m}{ds^m} \mathbf{H}(s) \right|_{s=s_0}$$

Example: impulse response of an LTI system

$$\begin{aligned} \eta_0(s_0) &= \mathbf{C}(s_0 \mathbf{I}_n - \mathbf{A})^{-1} \mathbf{B} + \mathbf{D} \\ \eta_m(s_0) &= m! \mathbf{C}(s_0 \mathbf{I}_n - \mathbf{A})^{-(m+1)} \mathbf{B}, \quad \forall m \geq 1 \end{aligned}$$

■ Development of $\mathbf{H}(s)$ in Taylor series

$$\begin{aligned}
 \mathbf{H}(s) &= \mathbf{H}(s_0) + \left. \frac{d}{ds} \mathbf{H}(s) \right|_{s=s_0} \frac{(s-s_0)}{1!} + \dots \\
 &\quad + \left. \frac{d^m}{ds^m} \mathbf{H}(s) \right|_{s=s_0} \frac{(s-s_0)^m}{m!} + \dots \\
 &= \eta_0(s_0) - \eta_1(s_0) \frac{(s-s_0)}{1!} + \dots + (-1)^m \eta_m(s_0) \frac{(s-s_0)^m}{m!} + \dots \\
 &= \eta_0(s_0) + \eta_1(s_0) \frac{(s_0-s)}{1!} + \dots + \eta_m(s_0) \frac{(s_0-s)^m}{m!} + \dots
 \end{aligned}$$

- The **Markov parameters** $\eta_m(\infty)$ of the system defined by \mathbf{h} are the coefficient in the Laurent expansion of the transfer function at infinity:

$$\mathbf{H}(s) \approx_{s \rightarrow \infty} \sum_{i=0}^{\infty} s^{-i} \eta_m(\infty)$$

Example: impulse response of an LTI system

$$\begin{aligned} \eta_0(\infty) &= \mathbf{D} \\ \eta_m(\infty) &= \mathbf{CA}^{m-1}\mathbf{B}, \quad \forall m \geq 1 \end{aligned}$$

└ Model Reduction by Moment Matching

└ General Idea

- *Goal:* Let $s_0 \in \mathbb{C}$ and a FOM $(\mathbf{A}, \mathbf{B}, \mathbf{C}, \mathbf{D})$ defined by its transfer function $\mathbf{H}(s)$.
- Compute a ROM $(\mathbf{A}_r, \mathbf{B}_r, \mathbf{C}_r, \mathbf{D}_r)$ such that the first l moments $\eta_{r,j}(s_0)$ of its transfer function \mathbf{H}_r at s_0 match their counterparts from the FOM.
- In other words

$$\eta_{r,j}(s_0) = \eta_j(s_0) \Leftrightarrow \mathbf{H}^{(j)}(s_0) = \mathbf{H}_r^{(j)}(s_0), \quad \forall j = 0, \dots, l-1$$

- a direct matching of the moment is a numerically unstable procedure
- an iterative procedure based on Krylov subspaces addresses that issue

└ Model Reduction by Moment Matching

└ Partial Realization - Moment Matching at Infinity

Theorem

Let \mathbf{V} be a right reduced-order basis such that

$$\text{span}(\mathbf{V}) = \text{span} \{ \mathbf{b}, \mathbf{A}\mathbf{b}, \dots, \mathbf{A}^{k-1}\mathbf{b} \}$$

and \mathbf{W} be a left reduced-order basis satisfying

$$\mathbf{W}^T \mathbf{V} = \mathbf{I}$$

Then, the ROM obtained by Petrov-Galerkin projection of the HFM $(\mathbf{A}, \mathbf{B}, \mathbf{C}, \mathbf{D})$ using \mathbf{W} and \mathbf{V} satisfies

$$\eta_{r,j}(\infty) = \eta_j(\infty) \Leftrightarrow \mathbf{H}_r^{(j)}(\infty) = \mathbf{H}^{(j)}(\infty), \quad \forall j = 0, \dots, k-1$$

■ $\text{span} \{ \mathbf{b}, \mathbf{A}\mathbf{b}, \dots, \mathbf{A}^{k-1}\mathbf{b} \}$ is the **Krylov subspace** $\mathcal{K}_k(\mathbf{A}, \mathbf{b})$.

└ Model Reduction by Moment Matching

└ Partial Realization - Moment Matching at Infinity

To prove the theorem, the following lemma is used

Lemma

The moments of the transfer function of a ROM only depend on the left and right subspaces considered and not the corresponding reduced-order bases.

Proof.

From the lemma, we can choose without loss of generality

$$\mathbf{V} = [\mathbf{v}_1, \dots, \mathbf{v}_k] = [\mathbf{b}, \mathbf{A}\mathbf{b}, \dots, \mathbf{A}^{k-1}\mathbf{b}]$$

Note that $\mathbf{W}^T \mathbf{V} = \mathbf{I}_k$ and $\mathbf{A}\mathbf{V}\mathbf{W}^T \mathbf{v}_i = \mathbf{A}\mathbf{v}_i = \mathbf{v}_{i+1} = \mathbf{A}^i \mathbf{b}$. Then

$$\begin{aligned} \eta_{r,0}(\infty) &= \mathbf{D} = \eta_0(\infty) \\ \eta_{r,1}(\infty) &= \mathbf{c}_r \mathbf{b}_r = \mathbf{c}\mathbf{V}\mathbf{W}^T \mathbf{b} = \mathbf{c}\mathbf{V}\mathbf{W}^T \mathbf{v}_1 = \mathbf{c}\mathbf{v}_1 = \mathbf{c}\mathbf{b} = \eta_1(\infty) \\ \eta_{r,j}(\infty) &= \mathbf{c}_r \mathbf{A}^j \mathbf{b}_r = \mathbf{c}\mathbf{V}\mathbf{W}^T (\mathbf{A}\mathbf{V}\mathbf{W}^T)^j \mathbf{b} = \mathbf{c}\mathbf{V}\mathbf{W}^T (\mathbf{A}\mathbf{V}\mathbf{W}^T)^j \mathbf{v}_1 \\ &= \mathbf{c}\mathbf{V}\mathbf{W}^T \mathbf{v}_{j+1} = \mathbf{c}\mathbf{v}_{j+1} = \mathbf{c}\mathbf{A}^j \mathbf{b} = \eta_j(\infty) \quad \blacksquare \end{aligned}$$

- Model Reduction by Moment Matching

- Rational Interpolation - Multiple Moment Matching at a Single Point

Theorem

Let $s_0 \in \mathbb{C}$ and \mathbf{V} be a right reduced-order basis such that

$$\text{span}(\mathbf{V}) = \text{span} \{ (s_0 \mathbf{I}_n - \mathbf{A})^{-1} \mathbf{b}, \dots, (s_0 \mathbf{I}_n - \mathbf{A})^{-k} \mathbf{b} \}$$

and \mathbf{W} be a left reduced-order basis satisfying

$$\mathbf{W}^T \mathbf{V} = \mathbf{I}$$

Then, the ROM obtained by Petrov-Galerkin projection of the HFM $(\mathbf{A}, \mathbf{B}, \mathbf{C}, \mathbf{D})$ using \mathbf{W} and \mathbf{V} satisfies

$$\eta_{r,j}(s_0) = \eta_j(s_0) \Leftrightarrow \mathbf{H}_r^{(j)}(s_0) = \mathbf{H}^{(j)}(s_0), \quad \forall j = 0, \dots, k-1$$

- $\{ (s_0 \mathbf{I}_n - \mathbf{A})^{-1} \mathbf{b}, \dots, (s_0 \mathbf{I}_n - \mathbf{A})^{-k} \mathbf{b} \}$ is the **Krylov subspace** $\mathcal{K}_k((s_0 \mathbf{I}_n - \mathbf{A})^{-1}, (s_0 \mathbf{I}_n - \mathbf{A})^{-1} \mathbf{b})$.
- This is a more expensive procedure as each Krylov iteration requires the solution of a large scale linear system

Theorem

Let $s_i \in \mathbb{C}$, $i = 1, \dots, k$ and \mathbf{V} be a right reduced-order basis such that

$$\text{span}(\mathbf{V}) = \text{span} \{ (s_1 \mathbf{I}_n - \mathbf{A})^{-1} \mathbf{b}, \dots, (s_k \mathbf{I}_n - \mathbf{A})^{-1} \mathbf{b} \}$$

and \mathbf{W} be a left reduced-order basis satisfying

$$\mathbf{W}^T \mathbf{V} = \mathbf{I}$$

Then, the ROM obtained by Petrov-Galerkin projection of the HFM $(\mathbf{A}, \mathbf{B}, \mathbf{C}, \mathbf{D})$ using \mathbf{W} and \mathbf{V} satisfies

$$\eta_{r,0}(s_i) = \eta_0(s_i) \Leftrightarrow \mathbf{H}_r(s_i) = \mathbf{H}(s_i), \quad \forall i = 1, \dots, k$$

└ Model Reduction by Moment Matching

└ Moment Matching at Multiple Points using Two-Sided Projections

Theorem

Let $s_i \in \mathbb{C}$, $i = 1, \dots, 2k$, \mathbf{V} be a right reduced-order basis such that

$$\text{span}(\mathbf{V}) = \text{span} \{ (s_1 \mathbf{I}_n - \mathbf{A})^{-1} \mathbf{b}, \dots, (s_k \mathbf{I}_n - \mathbf{A})^{-1} \mathbf{b} \}$$

and \mathbf{W} be a left reduced-order basis such that

$$\text{span}(\mathbf{W}) = \text{span} \{ (s_{k+1} \mathbf{I}_n - \mathbf{A}^*)^{-1} \mathbf{c}^*, \dots, (s_{2k} \mathbf{I}_n - \mathbf{A}^*)^{-1} \mathbf{c}^* \}$$

and $\mathbf{W}^T \mathbf{V}$ is nonsingular.

Then, the ROM obtained by Petrov-Galerkin projection of the HFM $(\mathbf{A}, \mathbf{B}, \mathbf{C}, \mathbf{D})$ using \mathbf{W} and \mathbf{V} satisfies

$$\eta_{r,0}(s_i) = \eta_0(s_i) \Leftrightarrow \mathbf{H}_r(s_i) = \mathbf{H}(s_i), \quad \forall i = 1, \dots, 2k$$

Definition

Let $\mathbf{A} \in \mathbb{R}^n$ and $\mathbf{b} \in \mathbb{R}^n$. The k -th Krylov subspace defined by \mathbf{A} and \mathbf{b} is

$$\mathcal{K}_k(\mathbf{A}, \mathbf{b}) = \text{span}\{\mathbf{b}, \mathbf{A}\mathbf{b}, \dots, \mathbf{A}^{k-1}\mathbf{b}\}$$

Remark: Constructing $\mathcal{K}_k(\mathbf{A}, \mathbf{b})$ only requires the ability to compute the action of the matrix \mathbf{A} onto vectors. This allows "black-box" types of approaches where the matrix \mathbf{A} is not explicitly formed.

└ Moment Matching by Krylov Iterative Methods

└ Moment Matching by Krylov Methods

- Partial realization requires the construction of $\mathcal{K}_k(\mathbf{A}, \mathbf{b})$, that is the knowledge of the action of \mathbf{A} onto vectors
- Rational interpolation requires the following Krylov space

$$\mathcal{K}_k((s_0 \mathbf{I}_n - \mathbf{A})^{-1}, (s_0 \mathbf{I}_n - \mathbf{A})^{-1} \mathbf{b}).$$

Since the knowledge of the action of $(s_0 \mathbf{I}_n - \mathbf{A})^{-1} \in \mathbb{R}^{n \times n}$ is needed, two computationally efficient approaches are possible:

- if n is small enough, an LU factorization of $s_0 \mathbf{I}_n - \mathbf{A}$ can be performed and $(s_0 \mathbf{I}_n - \mathbf{A})^{-1} \mathbf{v}$ computed by forward and backward substitution for any vector $\mathbf{v} \in \mathbb{R}^n$
- if n is too large for an LU factorization to be performed, Krylov subspace recycling techniques allowing the reuse of Krylov subspaces for multiple right-hand sides can be used

└ Moment Matching by Krylov Iterative Methods

└ The Arnoldi Method for Partial Realization

- $\mathcal{K}_k(\mathbf{A}, \mathbf{b})$ can be efficiently constructed using the Arnoldi factorization method

Input: $\mathbf{A} \in \mathbb{R}^{n \times n}$, $\mathbf{b} \in \mathbb{R}^n$

Output: Orthogonal basis $\mathbf{V}_k \in \mathbb{R}^{n \times k}$ for $\mathcal{K}_k(\mathbf{A}, \mathbf{b})$

- The following recursion is satisfied:

$$\mathbf{A}\mathbf{V}_k = \mathbf{V}_k\mathbf{H}_k + \mathbf{f}_k\mathbf{e}_k^*$$

with $\mathbf{H}_k = \mathbf{V}_k^*\mathbf{A}\mathbf{V}_k$ an upper Hessenberg matrix, $\mathbf{V}_k^*\mathbf{V}_k = \mathbf{I}_k$ and $\mathbf{V}_k^*\mathbf{f}_k = 0$.

Algorithm:

Input: $\mathbf{A} \in \mathbb{R}^{n \times n}$, $\mathbf{b} \in \mathbb{R}^n$

Output: Orthogonal basis $\mathbf{V}_k \in \mathbb{R}^{n \times k}$ for $\mathcal{K}_k(\mathbf{A}, \mathbf{b})$

- 1: $\mathbf{v}_1 = \mathbf{b} / \|\mathbf{b}\|$;
- 2: $\mathbf{w} = \mathbf{A}\mathbf{v}_1$; $\alpha_1 = \mathbf{v}_1^* \mathbf{w}$;
- 3: $\mathbf{f}_1 = \mathbf{w} - \alpha_1 \mathbf{v}_1$;
- 4: $\mathbf{V}_1 = [\mathbf{v}_1]$; $\mathbf{H} = [\alpha_1]$;
- 5: **for** $j = 1, \dots, k - 1$ **do**
- 6: $\beta_j = \|\mathbf{f}_j\|$; $\mathbf{v}_{j+1} = \mathbf{f}_j / \beta_j$;
- 7: $\mathbf{V}_{j+1} = [\mathbf{V}_j, \mathbf{v}_{j+1}]$;
- 8: $\hat{\mathbf{H}}_j = \begin{bmatrix} \mathbf{H}_j \\ \beta_j \mathbf{e}_j^* \end{bmatrix}$
- 9: $\mathbf{w} = \mathbf{A}\mathbf{v}_{j+1}$;
- 10: $\mathbf{h} = \mathbf{V}_{j+1}^* \mathbf{w}$; $\mathbf{f}_{j+1} = \mathbf{w} - \mathbf{V}_{j+1} \mathbf{h}$
- 11: $\mathbf{H}_{j+1} = [\hat{\mathbf{H}}_j, \mathbf{h}]$;
- 12: **end for**

└ Moment Matching by Krylov Iterative Methods

└ The Two-Sided Lanczos Method for Partial Realization

- $\mathcal{K}_k(\mathbf{A}, \mathbf{b})$ and $\mathcal{K}_k(\mathbf{A}^*, \mathbf{c}^*)$ can be efficiently simultaneously constructed using the Two-sided Lanczos process

Input: $\mathbf{A} \in \mathbb{R}^{n \times n}$, $\mathbf{b} \in \mathbb{R}^n$, $\mathbf{c}^* \in \mathbb{R}^n$

Output: Bi-orthogonal bases $\mathbf{V}_k \in \mathbb{R}^{n \times k}$ and $\mathbf{W}_k \in \mathbb{R}^{n \times k}$ for $\mathcal{K}_k(\mathbf{A}, \mathbf{b})$ and $\mathcal{K}_k(\mathbf{A}^*, \mathbf{c}^*)$ respectively satisfying $\mathbf{W}_k^T \mathbf{V}_k = \mathbf{I}_k$

- The following recursions are satisfied:

$$\mathbf{A} \mathbf{V}_k = \mathbf{V}_k \mathbf{T}_k + \mathbf{f}_k \mathbf{e}_k^*,$$

$$\mathbf{A}^* \mathbf{W}_k = \mathbf{W}_k \mathbf{T}_k^* + \mathbf{g}_k \mathbf{e}_k^*,$$

with $\mathbf{T}_k = \mathbf{W}_k^* \mathbf{A} \mathbf{V}_k$ a tridiagonal matrix, $\mathbf{W}_k^* \mathbf{V}_k = \mathbf{I}_k$, $\mathbf{W}_k^* \mathbf{g}_k = 0$ and $\mathbf{V}_k^* \mathbf{f}_k = 0$.

Algorithm:

Input: $\mathbf{A} \in \mathbb{R}^{n \times n}$, $\mathbf{b} \in \mathbb{R}^n$, $\mathbf{c}^* \in \mathbb{R}^n$

Output: Bi-orthogonal bases $\mathbf{V}_k \in \mathbb{R}^{n \times k}$ and $\mathbf{W}_k \in \mathbb{R}^{n \times k}$ for $\mathcal{K}_k(\mathbf{A}, \mathbf{b})$ and $\mathcal{K}_k(\mathbf{A}^*, \mathbf{c}^*)$ respectively satisfying $\mathbf{W}_k^T \mathbf{V}_k = \mathbf{I}_k$

- 1: $\beta_1 = \sqrt{|\mathbf{b}^* \mathbf{c}^*|}$, $\gamma_1 = \text{sign}(\mathbf{b}^* \mathbf{c}^*) \beta_1$
- 2: $\mathbf{v}_1 = \mathbf{b} / \beta_1$, $\mathbf{w}_1 = \mathbf{c}^* / \gamma_1$
- 3: **for** $j = 1, \dots, k - 1$ **do**
- 4: $\alpha_j = \mathbf{w}_j^* \mathbf{A} \mathbf{v}_j$;
- 5: $\mathbf{r}_j = \mathbf{A} \mathbf{v}_j - \alpha_j \mathbf{v}_j - \gamma_j \mathbf{v}_{j-1}$;
- 6: $\mathbf{q}_j = \mathbf{A}^* \mathbf{w}_j - \alpha_j \mathbf{w}_j - \beta_j \mathbf{w}_{j-1}$;
- 7: $\beta_{j+1} = \sqrt{|\mathbf{r}_j^* \mathbf{q}_j|}$, $\gamma_{j+1} = \text{sign}(\mathbf{r}_j^* \mathbf{q}_j) \beta_{j+1}$
- 8: $\mathbf{v}_{j+1} = \mathbf{r}_j / \beta_{j+1}$;
- 9: $\mathbf{w}_{j+1} = \mathbf{q}_j / \gamma_{j+1}$;
- 10: **end for**
- 11: $\mathbf{V} = [\mathbf{v}_1, \dots, \mathbf{v}_k]$, $\mathbf{W} = [\mathbf{w}_1, \dots, \mathbf{w}_k]$

- Error Bounds

- \mathcal{H}_2 Norm

Definition

The \mathcal{H}_2 norm of a continuous dynamical system $S = (\mathbf{A}, \mathbf{B}, \mathbf{C}, \mathbf{D})$ is the \mathcal{L}_2 norm of its associated impulse response $\mathbf{h}(\cdot)$.

When \mathbf{A} is stable and $\mathbf{D} = 0$, the norm is bounded and

$$\|S\|_{\mathcal{H}_2} = \int_0^\infty \text{Tr}(\mathbf{h}^*(t)\mathbf{h}(t)) dt$$

- Using Parseval's theorem, one can obtain the expression in the frequency domain using the transfer function $\mathbf{H}(\cdot)$

$$\|S\|_{\mathcal{H}_2} = \frac{1}{2\pi} \int_{-\infty}^\infty \text{Tr}(\mathbf{H}^*(-i\omega)\mathbf{H}(i\omega)) d\omega$$

- One can also derive the expression of $\|S\|_{\mathcal{H}_2}$ in terms of the reachability and observability gramians.

$$\|S\|_{\mathcal{H}_2} = \sqrt{\text{Tr}(\mathbf{B}^*\mathbf{Q}\mathbf{B})} = \sqrt{\text{Tr}(\mathbf{C}\mathbf{P}\mathbf{C}^*)}$$

Error Bounds

\mathcal{H}_2 Norm-Based Error Bounds

- In the Single Input-Single Output case, the transfer function is a rational function. Assuming for simplicity that it has distinct poles λ_i , $i = 1, \dots, n$ associated with the residues h_i , one can write it as

$$\mathbf{H}(s) = \sum_{i=1}^n \frac{h_i}{s - \lambda_i}$$

- One can then establish the following theorem:

Theorem

Let $\mathbf{H}_r(\cdot)$ be the transfer function associated with the system \mathcal{S}_r resulting from moment matching using the Lanczos procedure of the underlying system \mathcal{S} . Denoting by $h_{r,i}$ and $\lambda_{r,i}$ the respective residues and poles of $\mathbf{H}_r(\cdot)$, the following result holds:

$$\|\mathcal{S} - \mathcal{S}_r\|_{\mathcal{H}_2} = \sum_{i=1}^n h_i (\mathbf{H}(-\lambda_i^*) - \mathbf{H}_r(-\lambda_i^*)) + \sum_{i=1}^k h_{r,i} (\mathbf{H}_r(-\lambda_{r,i}) - \mathbf{H}(-\lambda_{r,i}))$$

└ Error Bounds

└ \mathcal{H}_2 Norm-Based Error Bounds

- This error equality suggests matching the transfer function at the points $-\lambda_i^*$, mirror images of the poles λ_i of the original system