

Distance to singularity for (quadratic) matrix polynomials

SPEAKER: Miryam Gnazzo

JOINT WORK WITH: Nicola Guglielmi, GSSI

14 February 2022



Distance to singularity

A **quadratic matrix polynomial** $Q(\lambda)$ is a polynomial in the form:

$$Q(\lambda) = \lambda^2 A + \lambda B + C,$$

where $A, B, C \in \mathbb{C}^{n \times n}$. The matrix polynomial $Q(\lambda)$ is called **regular** if $\det(Q(\lambda)) \not\equiv 0$. Otherwise $Q(\lambda)$ is called **singular**.

Distance to singularity

A **quadratic matrix polynomial** $Q(\lambda)$ is a polynomial in the form:

$$Q(\lambda) = \lambda^2 A + \lambda B + C,$$

where $A, B, C \in \mathbb{C}^{n \times n}$. The matrix polynomial $Q(\lambda)$ is called **regular** if $\det(Q(\lambda)) \not\equiv 0$. Otherwise $Q(\lambda)$ is called **singular**.

Distance to singularity

Given a regular quadratic matrix polynomial $\lambda^2 A + \lambda B + C$, we look for the **distance to singularity**:

$$d(A, B, C) = \min \{ \| [\Delta A, \Delta B, \Delta C] \| \text{ such that } \lambda^2 (A + \Delta A) + \lambda (B + \Delta B) + (C + \Delta C) \text{ singular} \}.$$

Motivation

Second-order control system (Nichols, Kautsky, 2001):

$$J\ddot{\mathbf{z}} - D\dot{\mathbf{z}} - C\mathbf{z} = B\mathbf{u}, \quad \mathbf{z}(0), \dot{\mathbf{z}}(0) \text{ given}$$

where $\mathbf{z}(t) \in \mathbb{R}^n$, $\mathbf{u}(t) \in \mathbb{R}^m$, $J, D, C \in \mathbb{R}^{n \times n}$ and $B \in \mathbb{R}^{n \times m}$.

Control problem: design a controller $\mathbf{u} = K_1\mathbf{z} + K_2\dot{\mathbf{z}} + \mathbf{r}$, where $K_1, K_2 \in \mathbb{R}^{m \times n}$, $\mathbf{r}(t) \in \mathbb{R}^m$ such that

$$J\ddot{\mathbf{z}} - (D + BK_2)\dot{\mathbf{z}} - (C + BK_1)\mathbf{z} = B\mathbf{r}$$

has desired properties.

Its behavior is governed by the eigenstructure of

$$Q(\lambda) = \lambda^2 J - \lambda(D + BK_2) - (C + BK_1).$$

Motivation

Motivation: Ill conditioning of eigenvalues.

Example: consider the quadratic matrix polynomial, with α, β, γ small:

$$Q(\lambda) = \lambda^2 \begin{bmatrix} 1 & \alpha \\ \beta & \gamma \end{bmatrix} + \lambda \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ \gamma & 1 \end{bmatrix}.$$

For $\alpha, \beta = 0$ and $\gamma \neq 0$, the eigenvalues are:

$$\lambda = 0, 1, -\frac{1}{2} + \frac{\sqrt{3}}{2}, -\frac{1}{2} - \frac{\sqrt{3}}{2}.$$

For $\gamma = 0$ and $\alpha, \beta \neq 0$, the eigenvalues are: $\lambda = 0, -\frac{\alpha+\beta}{\alpha\beta}$.

Motivation

Motivation: Ill conditioning of eigenvalues.

Example: consider the quadratic matrix polynomial, with α, β, γ small:

$$Q(\lambda) = \lambda^2 \begin{bmatrix} 1 & \alpha \\ \beta & \gamma \end{bmatrix} + \lambda \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ \gamma & 1 \end{bmatrix}.$$

For $\alpha, \beta = 0$ and $\gamma \neq 0$, the eigenvalues are:

$$\lambda = 0, 1, -\frac{1}{2} + \frac{\sqrt{3}}{2}, -\frac{1}{2} - \frac{\sqrt{3}}{2}.$$

For $\gamma = 0$ and $\alpha, \beta \neq 0$, the eigenvalues are: $\lambda = 0, -\frac{\alpha+\beta}{\alpha\beta}$.

$Q(\lambda)$ is in a neighborhood of the singular matrix polynomial

$$\lambda^2 \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} + \lambda \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}.$$

A few references

- R. Byers, C. He, V. Mehrmann, (1998), Where is the nearest non-regular pencil?, *Linear Algebra and its Applications*.
- C. Mehl, V. Mehrmann, M. Wojtylak. (2015). On the distance to singularity via low rank perturbations. *Operators and Matrices*.
- N. Guglielmi, C. Lubich, V. Mehrmann, (2017) On the nearest singular matrix pencil, *SIAM Journal on Matrix Analysis and Applications*.
- M. Giesbrecht, J. Haraldson, G. Labahn, (2017). Computing the nearest rank-deficient matrix polynomial. *In: Proc. International Symposium on Symbolic and Algebraic Computation (ISSAC)*. ACM Press.

Reformulation of the problem

$\lambda^2 (A + \Delta A) + \lambda (B + \Delta B) + (C + \Delta C)$ is singular \Leftrightarrow

$$\det (\mu_i^2 (A + \Delta A) + \mu_i (B + \Delta B) + (C + \Delta C)) = 0,$$

with distinct points $\mu_i \in \mathbb{C}$, for $i = 1, \dots, d$ and $d \geq 2n + 1$.

Reformulation of the problem

$\lambda^2 (A + \Delta A) + \lambda (B + \Delta B) + (C + \Delta C)$ is singular \Leftrightarrow

$$\det (\mu_i^2 (A + \Delta A) + \mu_i (B + \Delta B) + (C + \Delta C)) = 0,$$

with distinct points $\mu_i \in \mathbb{C}$, for $i = 1, \dots, d$ and $d \geq 2n + 1$.

Underlying optimization problem

$$(\Delta A_*, \Delta B_*, \Delta C_*) = \arg \min_{\Delta A, \Delta B, \Delta C \in \mathbb{C}^{n \times n}} \| [\Delta A, \Delta B, \Delta C] \|_F$$

subj to $\det (\mu_i^2 (A + \Delta A) + \mu_i (B + \Delta B) + (C + \Delta C)) = 0$
for $i = 1, \dots, d$.

Idea of the method

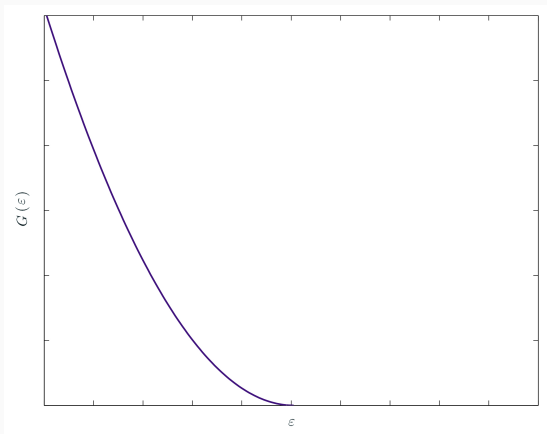
Consider $[\Delta A, \Delta B, \Delta C] = \varepsilon [\Delta, \Theta, \Gamma]$ of norm ε . Define the functional

$$G_\varepsilon (\Delta, \Theta, \Gamma) := \frac{1}{2} \sum_{i=1}^d \sigma_i^2(\Delta, \Theta, \Gamma),$$

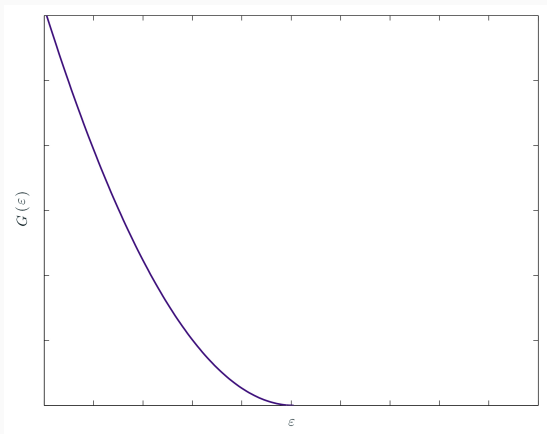
where $\sigma_i (\Delta, \Theta, \Gamma)$ is the smallest singular value of the matrix $\mu_i^2(A + \varepsilon\Delta) + \mu_i(B + \varepsilon\Theta) + (C + \varepsilon\Gamma)$.

- Compute $G(\varepsilon) = \min_{\Delta, \Theta, \Gamma} G_\varepsilon (\Delta, \Theta, \Gamma)$.
- Compute $\varepsilon^* = \min \{ \varepsilon \in \mathbb{R}^+ : G(\varepsilon) = 0 \}$.

Idea of the method

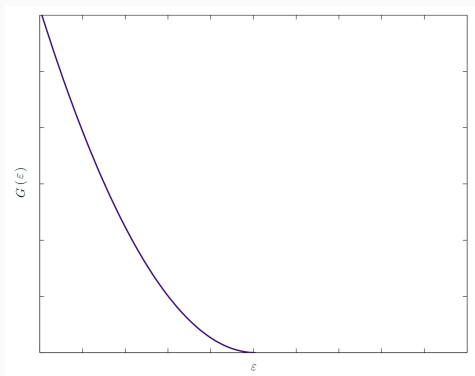


Idea of the method



- Fix the norm ε and solve $G(\varepsilon) = \min_{\Delta, \Theta, \Gamma} G_\varepsilon(\Delta, \Theta, \Gamma)$;
- Tune the value of ε in order to find the smallest zero of $G(\varepsilon)$.

Idea of the method



- Fix the norm ε and solve $G(\varepsilon) = \min_{\Delta, \Theta, \Gamma} G_\varepsilon(\Delta, \Theta, \Gamma)$;
→ **Inner iteration**
- Tune the value of ε in order to find the smallest zero of $G(\varepsilon)$. → **Outer iteration**

Inner iteration

Lemma: Let $\Delta(t), \Theta(t), \Gamma(t) \in \mathbb{C}^{n \times n}$ be a smooth path of matrices, with derivatives $\dot{\Delta}(t), \dot{\Theta}(t), \dot{\Gamma}(t)$. Then $G_\varepsilon(\Delta(t), \Theta(t), \Gamma(t))$ is differentiable with

$$\frac{d}{dt}G_\varepsilon(\Delta, \Theta, \Gamma) = \varepsilon \operatorname{Re} \left\langle [M_2, M_1, M_0], [\dot{\Delta}, \dot{\Theta}, \dot{\Gamma}] \right\rangle,$$

where $\langle X, Y \rangle = \operatorname{trace}(X^H Y)$ and

$$M_2 = \sum_{i=1}^d \sigma_i \bar{\mu}_i^2 u_i v_i^H, \quad M_1 = \sum_{i=1}^d \sigma_i \bar{\mu}_i u_i v_i^H, \quad M_0 = \sum_{i=1}^d \sigma_i u_i v_i^H$$

with u_i, v_i left and right singular vectors associated with σ_i .

Inner iteration

Along the solutions of the system of ODEs

$$\begin{cases} \dot{\Delta} = -M_2 + \eta\Delta \\ \dot{\Theta} = -M_1 + \eta\Theta \\ \dot{\Gamma} = -M_0 + \eta\Gamma \end{cases}$$

where $\eta := \operatorname{Re} \langle [M_2, M_1, M_0], [\Delta, \Theta, \Gamma] \rangle$, we have that:

1. $\|[\Delta(t), \Theta(t), \Gamma(t)]\|_F = 1$ is conserved;
2. $\frac{d}{dt} G_\varepsilon(\Delta(t), \Theta(t), \Gamma(t)) \leq 0$.

This is a constrained gradient system.

Our goal

Computing the stationary points of the gradient system.

Outer iteration

Outer iteration: update the parameter ε up to the smallest root ε^* of $G(\varepsilon) = 0$.

Newton-like method

We approach the root ε^* from the left-hand side using

$$\varepsilon_{k+1} = \varepsilon_k - \frac{G(\varepsilon_k)}{G'(\varepsilon_k)},$$

where $G'(\varepsilon) = \frac{d}{d\varepsilon}G(\varepsilon) = -\| [M_2(\varepsilon), M_1(\varepsilon), M_0(\varepsilon)] \|_F$.

Example

Consider

$$P(\lambda) = \lambda^2 \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} + \lambda \begin{bmatrix} 0 & 1 \\ 0.5 & 0 \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}.$$

Example

Consider

$$P(\lambda) = \lambda^2 \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} + \lambda \begin{bmatrix} 0 & 1 \\ 0.5 & 0 \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}.$$

The computed distance to singularity is $d \approx 0.2794$ and the nearest singular polynomial is

$$\tilde{P}(\lambda) = \lambda^2 \begin{bmatrix} 0.8645 & 0 \\ 0 & 0 \end{bmatrix} + \lambda \begin{bmatrix} 0 & 1.1058 \\ 0.6736 & 0 \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & 0.8645 \end{bmatrix}.$$

Palindromic quadratic matrix polynomials

A **palindromic** quadratic matrix polynomial is a polynomial in the form

$$P(\lambda) := \lambda^2 A + \lambda B + A^H,$$

where $B = B^H$ and $A, B \in \mathbb{C}^{n \times n}$.

We allow perturbations which respect the structure

$$\lambda^2 (A + \varepsilon \Delta) + \lambda (B + \varepsilon \Theta) + (A + \varepsilon \Delta)^H, \quad \Delta, \Theta \in \mathbb{C}^{n \times n}.$$

Given a regular quadratic matrix polynomial $\lambda^2 A + \lambda B + C$, we look for:

$$d_P(A, B, C) = \min \{ \| [\Delta A, \Delta B, \Delta C] \|_F : \lambda^2 (A + \Delta A) + \lambda (B + \Delta B) + (C + \Delta C) \text{ singular and palindromic} \}.$$

Palindromic quadratic matrix polynomials

Projection onto the manifold w.r.t. Frobenius inner product

$$\begin{aligned}\Pi_{\mathcal{M}} : \mathbb{C}^{n \times 3n} &\longmapsto \mathcal{M} := \{[\Delta, \Theta, \Gamma] \in \mathbb{C}^{n \times 3n} : \Theta = \Theta^H, \Gamma = \Delta^H\} \\ [\Delta, \Theta, \Gamma] &\longmapsto \left[\frac{\Delta + \Gamma^H}{2}, \frac{\Theta + \Theta^H}{2}, \frac{\Delta^H + \Gamma}{2} \right].\end{aligned}$$

The system of ODEs becomes

$$\begin{cases} \dot{\Delta} = -\frac{M_2 + M_0^H}{2} + \eta\Delta, \\ \dot{\Theta} = -\frac{M_1 + M_1^H}{2} + \eta\Theta, \end{cases}$$

where $\eta = \operatorname{Re} \left\langle \left[\frac{M_2 + M_0^H}{2}, \frac{M_1 + M_1^H}{2} \right], [\Delta, \Theta] \right\rangle$.

Example

Consider the palindromic polynomial

$$P(\lambda) = \lambda^2 \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix} + \lambda \begin{bmatrix} -1 & -1.5 \\ -1.5 & -1 \end{bmatrix} + \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}.$$

The nearest palindromic singular polynomial is

$$\lambda^2 \begin{bmatrix} 0.2335 & 0.1866 \\ 0.2807 & 0.2335 \end{bmatrix} + \lambda \begin{bmatrix} -1.3095 & -1.3077 \\ -1.3077 & -1.3095 \end{bmatrix} + \begin{bmatrix} 0.2335 & 0.2807 \\ 0.1866 & 0.2335 \end{bmatrix}.$$

Open issues and future work

- Choice of the set of complex points μ_i :
 - Number of points $d \geq 2n + 1$;
 - Optimal choice of μ_i ;
 - Influence on the numerical results;
 - Adding a set of test points $\tilde{\mu}_i$.
- Efficient integration of the gradient system;
- Different additional structures on the matrix polynomials;
- Computational challenges of matrix polynomials of higher degree.

Numerical experiments

$$P(\lambda) = \lambda^2 \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} + \lambda \begin{bmatrix} 0 & 1 \\ 0.5 & 0 \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}.$$

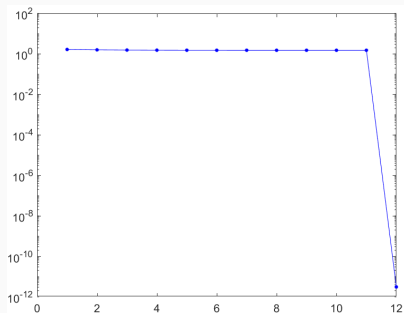


Figure 1: $|\varepsilon_{\text{up}} - \varepsilon_{\text{low}}|$

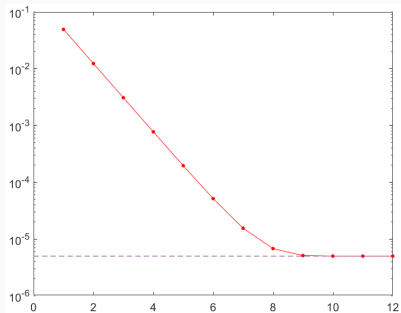


Figure 2: $G(\varepsilon)$

Iterations = 12; Tol = 5×10^{-6} ; $d = 2n + 1 = 5$.

Numerical experiments

$$P(\lambda) = \lambda^2 \begin{bmatrix} 0 & 0 \\ 0 & -2 \end{bmatrix} + \lambda \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} + \begin{bmatrix} -2 & 0 \\ -3 & 1 \end{bmatrix}.$$

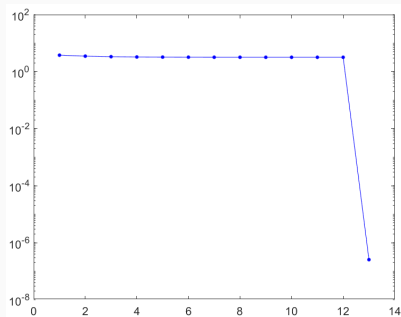


Figure 3: $|\varepsilon_{\text{up}} - \varepsilon_{\text{low}}|$

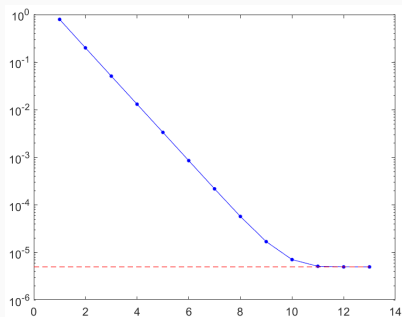


Figure 4: $G(\varepsilon)$

Iterations = 13; Tol = 5×10^{-6} ; $d = 2n + 1 = 5$.

Numerical experiments $n = 2$ randn

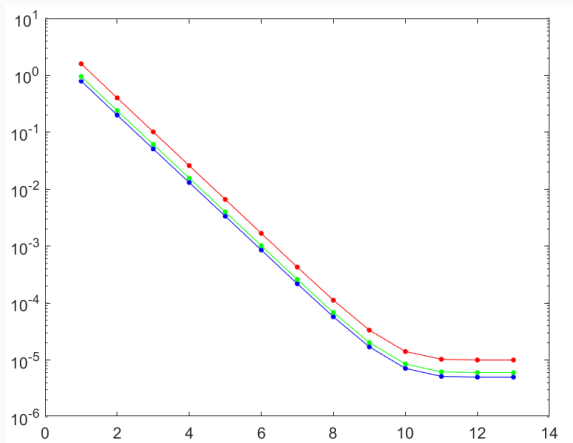


Figure 5: $G(\varepsilon)$

Three choices of d : $d = 5$ (blue), $d = 10$ (red) and $d = 3n = 6$ (green). Always 13 iterations.

Numerical experiments $n = 5$ randn

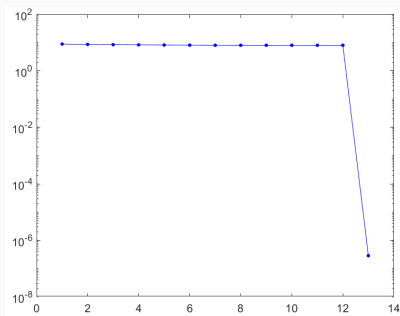


Figure 6: $|\varepsilon_{\text{up}} - \varepsilon_{\text{low}}|$, $d = 11$

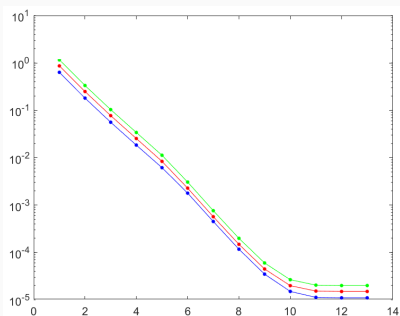


Figure 7: $G(\varepsilon)$

Iterations = 13; Tol = $d \times 10^{-6}$; $d = 11$ (blue), $d = 15$ (red) and $d = 20$ (green).

Numerical experiments $n = 10$ real

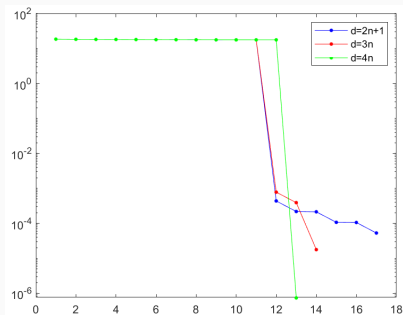


Figure 8: $|\epsilon_{\text{up}} - \epsilon_{\text{low}}|$

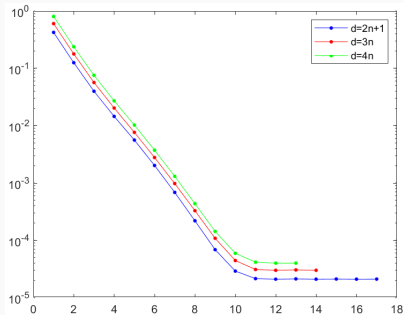


Figure 9: $G(\epsilon)$

$\text{Tol} = d \times 10^{-6}$; $d = 21$ (blue), $d = 30$ (red) and $d = 40$ (green).

Numerical experiments $n = 10$ real

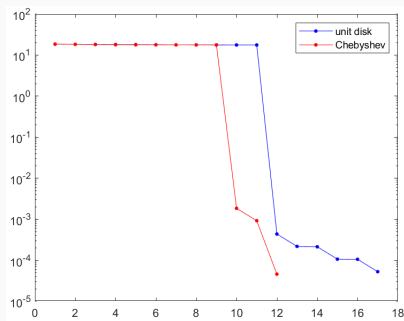


Figure 10: $|\varepsilon_{\text{up}} - \varepsilon_{\text{low}}|$

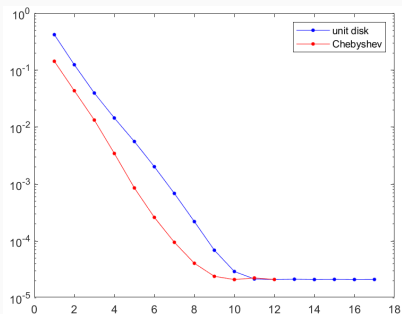


Figure 11: $G(\varepsilon)$

$\text{Tol} = d \times 10^{-6}$, $d = 21$, Points on unit disk and Chebyshev.

Numerical experiments $n = 10$ complex

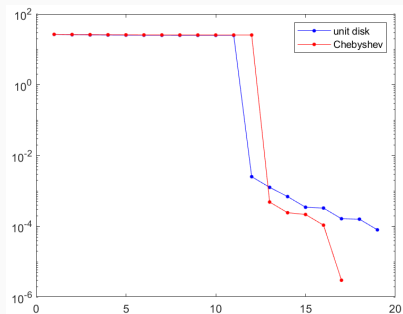


Figure 12: $|\varepsilon_{\text{up}} - \varepsilon_{\text{low}}|$

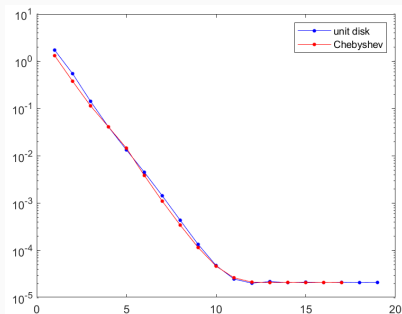


Figure 13: $G(\varepsilon)$

Tol = $d \times 10^{-6}$, $d = 21$, Points on unit disk and Chebyshev.