

Hermitian Matrices and Location of Polynomials Zeroes using Schur-Cohn Theorem

PRANSHU GABA

Indian Institute of Science, Bangalore
gabapranshu@ug.iisc.in

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Abstract

We looked at various concepts in linear algebra such as norms, unitary matrices, and Hermitian matrices, and studied their applications. In particular, we examined the generalized Schur-Cohn theorem, which relates the number of roots of a polynomial lying within and without the unit circle with the parity of eigenvalues of a matrix formed by coefficients of the polynomial.

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1 Introduction

There are many different ways to locate the roots of polynomials, such as the Jenkins-Traub algorithm, the Durand-Kerner method, and Dandelin-Lobachesky-Graeffe method. The Schur-Cohn theorem is one such method.

The Schur-Cohn theorem shows a surprising relation between linear algebra and the roots of a polynomial. Using this theorem, it is possible to find out how many roots of a polynomial lie inside the unit circle and how many lie outside. This theorem has a wide range of applications in control theory, optimization and digital systems processing, where it must be determined if all the roots lie in a stability radius of a given point.

2 Key Concepts in Linear Algebra

First we will look at some key concepts in linear algebra that will be used to prove the Schur-Cohn theorem.

2.1 Norm of a matrix

2.1.1 Operator norm

Given $A \in \mathbb{M}_n$ (the set of $n \times n$ square matrices with complex elements), the operator norm of A , denoted by $\|A\|$, is defined as

$$\|A\| = \sup_{x \neq 0} \frac{\|Ax\|}{\|x\|} = \sup_{\|x\|=1} \|Ax\|$$

Theorem 1. *The operator norm satisfies the triangle inequality $\|A + B\| \leq \|A\| + \|B\|$.*

Proof.

$$\begin{aligned} \|A + B\| &= \sup_{x \neq 0} \frac{\|(A + B)x\|}{\|x\|} \leq \sup_{x \neq 0} \frac{\|Ax\| + \|Bx\|}{\|x\|} \\ &\leq \sup_{x \neq 0} \frac{\|Ax\|}{\|x\|} + \sup_{x \neq 0} \frac{\|Bx\|}{\|x\|} = \|A\| + \|B\| \end{aligned}$$

□

Theorem 2. *The operator norm is submultiplicative, $\|AB\| \leq \|A\| \|B\|$ for all square matrices $A, B \in \mathbb{M}_n$.*

Proof.

$$\begin{aligned} \|AB\| &= \sup_{x \neq 0} \frac{\|ABx\|}{\|x\|} \\ &= \sup_{Bx \neq 0} \frac{\|ABx\|}{\|x\|} \\ &= \sup_{Bx \neq 0} \frac{\|ABx\|}{\|Bx\|} \frac{\|Bx\|}{\|x\|} \\ &\leq \sup_{y \neq 0} \frac{\|Ay\|}{\|y\|} \sup_{x \neq 0} \frac{\|Bx\|}{\|x\|} = \|A\| \|B\| \end{aligned}$$

□

2.1.2 Hilbert-Schmidt norm

The Hilbert-Schmidt norm of matrix A , denoted by $\|A\|_2$, is defined as the square root of sum of squares of all entries in A .

$$\|A\|_2 = \left(\sum_{i,j} |a_{ij}|^2 \right)^{1/2}$$

Theorem 3. *The operator norm is always less than or equal to the Hilbert-Schmidt norm.*

Proof.

$$\begin{aligned} \|Ax\|^2 &= \sum_{i=1}^n \left| \sum_{j=1}^n a_{ij} x_j \right|^2 \\ &\leq \sum_{i=1}^n \left(\sum_{j=1}^n |a_{ij}| |x_j| \right)^2 \\ &\leq \left(\sum_{i=1}^n \sum_{j=1}^n |a_{ij}|^2 \right) \left(\sum_{j=1}^n |x_j|^2 \right) = \left(\sum_{i,j} |a_{ij}|^2 \right) \|x\|^2 \end{aligned}$$

Therefore $\frac{\|Ax\|}{\|x\|} \leq \left(\sum_{i,j} |a_{ij}|^2 \right)^{1/2}$, which is equivalent to $\|A\| \leq \|A\|_2$.

□

2.2 Inner product

The inner product is a binary operator on two vectors $\langle \cdot, \cdot \rangle: V \times V \rightarrow \mathbb{C}$. It satisfies the following conditions for all $x, y, z \in V$ and $a \in \mathbb{C}$:

- It is linear in the first term.

$$\langle ax, y \rangle = a \langle x, y \rangle$$

$$\langle x + y, z \rangle = \langle x, z \rangle + \langle y, z \rangle$$

- It becomes its complex conjugate when the arguments are reversed.

$$\langle x, y \rangle = \overline{\langle y, x \rangle}$$

- Inner product of a vector with itself is non-negative.

$$\langle x, x \rangle \geq 0. \text{ Here equality is achieved if and only if } x = 0.$$

For vectors on \mathbb{C}^n , the inner product $\langle x, y \rangle$ is defined as $x^T \bar{y}$, the vector multiplication of the transpose of the first term with the complex conjugate of the second term. This definition satisfies all the above mentioned conditions.

2.3 Positive Definite Matrix

A matrix $A \in \mathbb{M}_n$ that satisfies $\langle Ax, x \rangle \geq 0$ for all $x \in \mathbb{C}^n$ is called a *positive semidefinite matrix* and is denoted as $A \geq 0$. If the inequality is strict, $\langle Ax, x \rangle > 0$, then A is called a *positive definite matrix*, and it is denoted as $A > 0$.

For two matrices $A, B \in \mathbb{M}_n$, $A \leq B$ denotes $B - A$ is positive semidefinite. As a result, $\langle (B - A)x, x \rangle \geq 0$, or $\langle Ax, x \rangle \leq \langle Bx, x \rangle$ for all x .

Theorem 4. *Let $A \in \mathbb{M}_n$ be a positive semidefinite matrix. Then all eigenvalues of A are non-negative.*

Proof. Let $\lambda_1, \lambda_2, \dots, \lambda_n$ be the eigenvalues of A , and let x_1, x_2, \dots, x_n be the corresponding eigenvectors, that is: $Ax_i = \lambda_i x_i$.

For any eigenvector x_i , the inner product $\langle Ax_i, x_i \rangle = \langle \lambda_i x_i, x_i \rangle$. Since λ_i is a scalar, it can come out of the inner product, so $\langle \lambda_i x_i, x_i \rangle = \lambda_i \langle x_i, x_i \rangle$. We get

$$\lambda_i = \frac{\langle Ax_i, x_i \rangle}{\langle x_i, x_i \rangle}$$

Here $\langle Ax_i, x_i \rangle$ is non-negative because A is positive semidefinite, and $\langle x_i, x_i \rangle$ is positive by definition of inner product. Hence $\lambda_i \geq 0$; all eigenvalues of A are non-negative. \square

2.4 Adjoint

Let $A \in \mathbb{M}_n$. The adjoint of matrix A , denoted by A^* , is the matrix that satisfies $\langle A^*x, y \rangle = \langle x, Ay \rangle$. The adjoint of a matrix, A^* , like A , represents a linear transformation on \mathbb{C}^n .

Theorem 5. *The adjoint of a matrix is obtained by taking the complex conjugate of every element, followed by transposing the matrix.*

Proof. Using properties of inner product on \mathbb{C}^n ,

$$\begin{aligned}\langle A^*x, y \rangle &= (A^*x)^T \bar{y} \\ &= x^T (A^*)^T \bar{y} \\ &= \langle x, Ay \rangle = x^T \overline{Ay}\end{aligned}$$

Therefore $(A^*)^T = \overline{A}$, or $A^* = (\overline{A})^T$. □

Remark. The adjoint of the adjoint of a matrix is the original matrix itself, $(A^*)^* = A$.

Theorem 6. The norm of a matrix is equal to the norm of its adjoint. $\|A\| = \|A^*\|$

Proof.

$$\begin{aligned}\|A\|^2 &= \sup_{\|x\|=1} \|Ax\|^2 = \sup_{\|x\|=1} \langle Ax, Ax \rangle = \sup_{\|x\|=1} \langle A^*Ax, x \rangle = \|A^*A\| \\ \|A^*\|^2 &= \sup_{\|x\|=1} \|A^*x\|^2 = \sup_{\|x\|=1} \langle A^*x, A^*x \rangle = \sup_{\|x\|=1} \langle AA^*x, x \rangle = \|AA^*\| \leq \|A\| \|A^*\|\end{aligned}$$

However, using Theorem 2, we get $\|A^*A\| \leq \|A^*\| \|A\|$ in the first equation. Hence, $\|A\|^2 \leq \|A^*\| \|A\|$, which implies $\|A\| \leq \|A^*\|$. Similarly, in the second equation we get $\|A^*\| \leq \|A\|$.

Since both these inequalities are true, it necessarily means that $\|A\| = \|A^*\|$. □

Theorem 7. A^*A and AA^* are positive semidefinite for all $A \in \mathbb{M}_n$.

Proof. $\langle A^*Ax, x \rangle = \langle Ax, Ax \rangle = \|Ax\|^2 \geq 0$ □

2.5 Unitary Matrix

A square matrix U that satisfies $U^*U = I$ is called a unitary matrix.

Theorem 8. The columns of a unitary matrix U form an orthonormal basis.

Proof. Let u_i be the i^{th} column of U . Then $U = [u_1 \ u_2 \ u_3 \ \cdots \ u_n]$ and $U^* = \begin{bmatrix} u_1^* \\ u_2^* \\ u_3^* \\ \vdots \\ u_n^* \end{bmatrix}$.

Using the fact that U is a unitary matrix, $U^*U = I$:

$$\begin{bmatrix} u_1^* \\ u_2^* \\ u_3^* \\ \vdots \\ u_n^* \end{bmatrix} [u_1 \ u_2 \ u_3 \ \cdots \ u_n] = \begin{bmatrix} 1 & 0 & 0 & \cdots & 0 \\ 0 & 1 & 0 & \cdots & 0 \\ 0 & 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 1 \end{bmatrix}$$

We see that $u_i^*u_j = \langle u_i, u_j \rangle = \delta_{ij}$. Here δ_{ij} is the Kronecker Delta function which is defined as

$$\delta_{ij} = \begin{cases} 0 & \text{if } i \neq j \\ 1 & \text{if } i = j \end{cases}$$

Each column has norm 1 since $\langle u_i, u_i \rangle = \|u_i\|^2 = 1$, and any two columns are orthogonal $\langle u_i, u_j \rangle = 0$. Hence the column vectors u_1, u_2, \dots, u_n of a unitary matrix form an orthonormal basis. □

Theorem 9. *A unitary matrix preserves inner product: $\langle Ux, Uy \rangle = \langle x, y \rangle$ for all $x, y \in \mathbb{C}_n$.*

Proof. $\langle x, y \rangle = \langle Ix, y \rangle = \langle U^*Ux, y \rangle = \langle Ux, Uy \rangle$ □

2.6 Trace

The trace of matrix A is the sum of the diagonal elements of the matrix.

$$\text{Tr}(A) = \sum_{i=1}^n a_{ii} = \sum_{i=1}^n \langle Ae_i, e_i \rangle$$

Remark. Here a_{ij} denotes the element in the i^{th} row and j^{th} column. e_i denotes the i^{th} standard basis vector. Note that $a_{ij} = \langle e_i, e_j \rangle$.

Theorem 10. *The trace of A^*A is equal to the square of the Hilbert-Schmidt norm of A .*

$$\text{Tr}(A^*A) = \|A\|_2^2$$

Proof. The sum of diagonal elements of A^*A is

$$\begin{aligned} \text{Tr}(A^*A) &= \sum_{i=1}^n \langle A^*Ae_i, e_i \rangle \\ &= \sum_{i=1}^n \langle Ae_i, Ae_i \rangle \\ &= \sum_{i=1}^n \|Ae_i\|^2 \\ &= \sum_{i=1}^n \sum_{j=1}^n |a_{ji}|^2 = \|A\|_2^2 \end{aligned}$$

□

2.7 Hermitian Matrix

A matrix that satisfies $A = A^*$ is called a Hermitian matrix (or a self-adjoint matrix).

Theorem 11. *Let $A \in \mathbb{M}_n$ be a Hermitian matrix. Then all eigenvalues of A are real.*

Proof. Let v be an eigenvector of a matrix A , and let λ be the corresponding eigenvalue. Then $Av = \lambda v$.

$$\lambda \langle v, v \rangle = \langle \lambda v, v \rangle = \langle Av, v \rangle = \langle v, A^*v \rangle = \langle v, Av \rangle = \langle v, \lambda v \rangle = \bar{\lambda} \langle v, v \rangle$$

This implies $\lambda = \bar{\lambda}$ for all v . Hence, λ is real. All eigenvalues of a Hermitian matrix are real. □

Theorem 12. *Eigenvectors corresponding to distinct eigenvalues are orthogonal.*

Proof. Suppose λ and μ are distinct eigenvalues of A . Suppose the corresponding eigenvectors are u and v respectively. We have $Au = \lambda u$ and $Av = \mu v$. Since A is Hermitian,

$$\lambda \langle u, v \rangle = \langle \lambda u, v \rangle = \langle Au, v \rangle = \langle u, Av \rangle = \langle u, \mu v \rangle = \mu \langle u, v \rangle$$

Since $\lambda \neq \mu$, $\langle u, v \rangle$ must be zero. Eigenvectors u and v are orthogonal. □

Theorem 13 (Spectral theorem). *For every Hermitian matrix A , there exists a unitary matrix*

U such that $A = U\Lambda U^$, where Λ is the diagonal matrix*

$$\begin{bmatrix} \lambda_1 & 0 & 0 & \cdots & 0 \\ 0 & \lambda_2 & 0 & \cdots & 0 \\ 0 & 0 & \lambda_3 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & \lambda_n \end{bmatrix}$$
containing

eigenvalues of A .

Proof. Since U is unitary, we have $U^*U = I$, or $U^{-1} = U^*$. Thus $A = U\Lambda U^*$ is equivalent to $\Lambda = U^*AU$.

The matrix A is a linear transformation T with respect to the standard basis I . The matrix U is a unitary matrix, so its columns u_1, u_2, \dots, u_n form an orthonormal basis for Λ . Since $U^* = U^{-1}$, it means $U^*AU = U^{-1}AU$. This means Λ is the matrix of the same transformation T with respect to a different basis U , and that A and Λ have the same eigenvalues.

Start with any eigenvalue λ_1 of A . Let u_1 be the corresponding unit eigenvector. Let W be the subspace of \mathbb{C}^n spanned by u_1 .

If we choose an orthonormal basis u_2, u_3, \dots, u_n of W^\perp , then $u_1, u_2, u_3, \dots, u_n$ will be an orthonormal basis for \mathbb{C}^n . Then the block matrix of T in this basis will be

$$\Lambda = \left[\begin{array}{c|c} \lambda_1 & \alpha \\ \hline 0 & A_1 \end{array} \right]$$

Here α and 0 are row and column vectors, and A_1 is an $(n-1) \times (n-1)$ matrix. Since Λ is Hermitian, $\alpha = 0$ and A_1 is a Hermitian matrix with basis $u_2, u_3, u_4, \dots, u_n$ for transformation T restricted to W^\perp . We can repeat this process until we get Λ as a diagonal matrix. \square

Theorem 14 (Rayleigh). *If A is Hermitian, with eigenvalues $\lambda_1 \leq \lambda_2 \leq \dots \leq \lambda_n$, then*

$$\lambda_1 = \inf_{x \neq 0} \frac{\langle Ax, x \rangle}{\langle x, x \rangle}, \quad \text{and} \quad \lambda_n = \sup_{x \neq 0} \frac{\langle Ax, x \rangle}{\langle x, x \rangle}$$

Proof. Using Spectral theorem, A is equal to $U\Lambda U^*$. Let $y = U^*x$. Then

$$\frac{\langle Ax, x \rangle}{\langle x, x \rangle} = \frac{\langle U\Lambda U^*x, x \rangle}{\langle x, x \rangle} = \frac{\langle \Lambda y, y \rangle}{\langle y, y \rangle} = \frac{\sum \lambda_i |y_i|^2}{\sum |y_i|^2}$$

We get the following inequality.

$$\lambda_1 = \lambda_1 \frac{\sum |y_i|^2}{\sum |y_i|^2} \leq \frac{\sum \lambda_i |y_i|^2}{\sum |y_i|^2} \leq \lambda_n \frac{\sum |y_i|^2}{\sum |y_i|^2} = \lambda_n$$

Therefore

$$\lambda_1 = \inf_{x \neq 0} \frac{\langle Ax, x \rangle}{\langle x, x \rangle} \leq \frac{\langle Ax, x \rangle}{\langle x, x \rangle} \leq \sup_{x \neq 0} \frac{\langle Ax, x \rangle}{\langle x, x \rangle} = \lambda_n$$

\square

Theorem 15 (Courant-Fischer). *Let $A \in \mathbb{M}_n$ be Hermitian with eigenvalues $\lambda_1 \leq \lambda_2 \leq \lambda_3 \leq \dots \leq \lambda_n$. Then*

$$\begin{aligned} \lambda_k &= \min_{\dim(V)=k} \max_{\substack{x \neq 0 \\ x \in V}} \frac{\langle Ax, x \rangle}{\langle x, x \rangle} \\ &= \max_{\dim(V)=n-k+1} \min_{\substack{x \neq 0 \\ x \in V}} \frac{\langle Ax, x \rangle}{\langle x, x \rangle} \end{aligned}$$

Proof. (Adapted from Horn Johnson [?]) Let $x_1, x_2, \dots, x_n \in \mathbb{C}^n$ be orthonormal vectors such that $Ax_i = \lambda_i x_i$ for $i = 1, 2, 3, \dots, n$. Let V be any k dimensional subspace of \mathbb{C}^n and let $V' = \text{span}\{x_k, x_{k+1}, \dots, x_n\}$. Then note that

$$\dim(V \cap V') = \dim(V) + \dim(V') - \dim(V \cup V') = k + (n - k + 1) - n = 1$$

This ensures that $\{x : x \in V \cap V', x \neq 0\}$ is non-empty. Using Rayleigh's theorem,

$$\begin{aligned} \sup_{\substack{x \neq 0 \\ x \in V}} \frac{\langle Ax, x \rangle}{\langle x, x \rangle} &\geq \sup_{\substack{x \neq 0 \\ x \in V \cap V'}} \frac{\langle Ax, x \rangle}{\langle x, x \rangle} \\ &\geq \inf_{\substack{x \neq 0 \\ x \in V \cap V'}} \frac{\langle Ax, x \rangle}{\langle x, x \rangle} \\ &\geq \inf_{\substack{x \neq 0 \\ x \in V}} \frac{\langle Ax, x \rangle}{\langle x, x \rangle} \\ &= \min_{\substack{x \neq 0 \\ x \in V}} \frac{\langle Ax, x \rangle}{\langle x, x \rangle} = \lambda_k \end{aligned}$$

Since this is true for any V , we have

$$\inf_{\dim(V)=k} \sup_{\substack{x \neq 0 \\ x \in V}} \frac{\langle Ax, x \rangle}{\langle x, x \rangle} \geq \lambda_k$$

One of the valid choices of V is $\text{span}(x_1, x_2, \dots, x_k)$. When this particular V is chosen, $\frac{\langle Ax_k, x_k \rangle}{\langle x_k, x_k \rangle} = \lambda_k$, so the above inequality is actually an equality, and the infimum and the supremum are attained. Hence we get

$$\lambda_k = \min_{\dim(V)=k} \max_{\substack{x \neq 0 \\ x \in V}} \frac{\langle Ax, x \rangle}{\langle x, x \rangle}$$

Since $\lambda_k(-A) = -\lambda_{n-k+1}(A)$, the second equality in the theorem follows from the first one by replacing A with $-A$. \square

Theorem 16. *If $A \in \mathbb{M}_n$ is Hermitian, then $\langle Ax, x \rangle$ is real for all x .*

Proof. $\langle Ax, x \rangle = \langle x, A^*x \rangle = \langle x, Ax \rangle = \overline{\langle Ax, x \rangle}$. \square

The converse of this theorem is also true.

Theorem 17 (Converse of Theorem 16). *If $A \in \mathbb{M}_n$ and $\langle Ax, x \rangle \in \mathbb{R}$ for every $x \in \mathbb{C}_n$, then A is a Hermitian matrix.*

Proof. Let $\alpha \in \mathbb{C}$ and $h, g \in \mathbb{C}^n$. Then

$$\langle A(h + \alpha g), h + \alpha g \rangle = \langle Ah, h \rangle + \alpha \langle Ag, h \rangle + \bar{\alpha} \langle Ah, g \rangle + |\alpha|^2 \langle Ag, g \rangle$$

The first and the last terms $\langle Ah, h \rangle$ and $|\alpha|^2 \langle Ag, g \rangle$ are both real. We now look at the sum of second and third terms:

$$\alpha \langle Ag, h \rangle + \bar{\alpha} \langle Ah, g \rangle = \bar{\alpha} \langle h, Ag \rangle + \alpha \langle g, Ah \rangle$$

We can substitute values of $\alpha = 1$ and $\alpha = i$ in this equation to get a system of linear equations.

$$\begin{aligned} \langle Ag, h \rangle + \langle Ah, g \rangle &= \langle h, Ag \rangle + \langle g, Ah \rangle \\ i \langle Ag, h \rangle - i \langle Ah, g \rangle &= -i \langle h, Ag \rangle + i \langle g, Ah \rangle \end{aligned}$$

Solving this system gives us $\langle Ag, h \rangle = \langle g, Ah \rangle$, which is equal to $\langle A^*g, h \rangle$. Hence $Ag = A^*g$ for all g , and $A = A^*$. We see that A is a Hermitian matrix. \square

Corollary. *Every positive semidefinite matrix $A \in \mathbb{M}_n$ is Hermitian.*

Proof. A is a positive semidefinite matrix, so $\langle Ax, x \rangle \geq 0$, so $\langle Ax, x \rangle \in \mathbb{R}$ for all x . By Theorem 17, A is Hermitian. \square

Theorem 18. *If A is Hermitian, then $\|A\| = \sup\{|\langle Ah, h \rangle| : \|h\| = 1\}$.*

Proof. By Cauchy Schwarz, $\|Ah\| \|h\| \geq |\langle Ah, h \rangle|$. For $\|h\| = 1$, we have $\|A\| \geq |\langle Ah, h \rangle|$. Now we will prove the reverse inequality.

Let $M = \sup\{|\langle Ah, h \rangle| : \|h\| = 1\}$. If $h, g \in \mathbb{C}^n$ with $\|h\| = \|g\| = 1$, then

$$\begin{aligned} \langle A(h \pm g), h \pm g \rangle &= \langle Ah, h \rangle \pm \langle Ah, g \rangle \pm \langle Ag, h \rangle + \langle Ag, g \rangle \\ &= \langle Ah, h \rangle \pm \langle Ah, g \rangle \pm \langle g, Ah \rangle + \langle Ag, g \rangle \\ &= \langle Ah, h \rangle \pm 2\operatorname{Re}\langle Ah, g \rangle + \langle Ag, g \rangle \end{aligned}$$

From this, we get a bound on $\operatorname{Re}\langle Ah, g \rangle$:

$$\begin{aligned} 4\operatorname{Re}\langle Ah, g \rangle &= \langle A(h + g), h + g \rangle - \langle A(h - g), h - g \rangle \\ &\leq |\langle A(h + g), h + g \rangle| + |\langle A(h - g), h - g \rangle| \\ &\leq \left| \left\langle A \frac{h + g}{\|h + g\|}, \frac{h + g}{\|h + g\|} \right\rangle \right| \|h + g\|^2 + \left| \left\langle A \frac{h - g}{\|h - g\|}, \frac{h - g}{\|h - g\|} \right\rangle \right| \|h - g\|^2 \\ &\leq M(\|h + g\|^2 + \|h - g\|^2) \\ &= M(2\|h\|^2 + 2\|g\|^2) = 4M \end{aligned}$$

We get $\operatorname{Re}\langle Ah, g \rangle \leq M$ for any $h, g \in \mathbb{C}^n$ with $\|h\| = \|g\| = 1$.

If $\langle Ah, g \rangle$ is not real, then we can write it as $\langle Ah, g \rangle = e^{i\theta} |\langle Ah, g \rangle|$. We get $|\langle Ah, g \rangle| = e^{-i\theta} \langle Ah, g \rangle$ is real, and is equal to $\langle Ae^{-i\theta}h, g \rangle$. Since $\|e^{-i\theta}h\| = 1$, the above inequality still holds:

$$|\langle Ah, g \rangle| = \langle Ae^{-i\theta}h, g \rangle = \operatorname{Re}\langle Ae^{-i\theta}h, g \rangle \leq M$$

We also have the following relation

$$\|A\| = \sup_{\|h\|=1} \|Ah\| = \sup_{\|h\|=1} \sup_{\|g\|=1} |\langle Ah, g \rangle|$$

Therefore $|\langle Ah, g \rangle| \leq M$ implies $\|A\| \leq M$. Since $\|A\| \geq M$ and $\|A\| \leq M$ both hold true, it means that $\|A\| = M = \sup\{|\langle Ah, h \rangle| : \|h\| = 1\}$. \square

Corollary. If $\langle Ax, x \rangle = 0$ for all x , then $A = 0$.

Proof. Since $\langle Ax, x \rangle = 0$ for all x , we have $\sup |\langle Ax, x \rangle| = 0$. By Theorem 18, $\|A\| = 0$. This is true only when $A = 0$. \square

Corollary. If $A \geq 0$, then $\|A\| = \sup_{\|x\|=1} \langle Ax, x \rangle$

Proof. By the Corollary in Theorem 17, every positive semidefinite matrix is Hermitian, and for a positive semidefinite matrix, $|\langle Ax, x \rangle| = \langle Ax, x \rangle$. Hence, $\|A\| = \sup_{\|x\|=1} \langle Ax, x \rangle$ \square

2.8 Projectors

A matrix P is a projector if $P^2 = P$ and $P^* = P$

Theorem 19. There exists a subspace M of \mathbb{C}^n such that

$$\begin{cases} Pm = m & \forall m \in M \\ Px = 0 & \forall x \in M^\perp \end{cases}$$

Proof. $\text{range}(P) = M$ and $\text{range}(I - P) = M^\perp$ satisfy the above properties. These subspaces are orthogonal. Let $Pv \in M$, $w - Pw \in M^\perp$.

$$\langle w - Pw, Pv \rangle = \langle w, Pv \rangle - \langle Pw, Pv \rangle = \langle w, Pv \rangle - \langle w, P^*Pv \rangle = \langle w, Pv \rangle - \langle w, P^2v \rangle = \langle w, Pv \rangle - \langle w, Pv \rangle = 0$$

Let $m \in \text{range}(P)$, that is, $m = Pv$ for some $v \in \mathbb{C}^n$. Then $Pm = P^2v = Pv = m$.

Now let $x \in \text{range}(I - P)$, that is, $x = (I - P)v = v - Pv$ for some $v \in \mathbb{C}^n$. $Px = Pv - P^2v = Pv - Pv = 0$. \square

2.9 Shift Matrix

Let S , the *shift matrix*, be the $n \times n$ square matrix

$$\begin{bmatrix} 0 & 1 & 0 & \cdots & 0 \\ 0 & 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 1 \\ 0 & 0 & 0 & \cdots & 0 \end{bmatrix}.$$

Remark. S is a nilpotent matrix of order n , i.e. S^n is a zero matrix.

The following matrices will be useful in proving the Schur-Cohn theorem. Note that $I - S^*S = e_1e_1^*$ is a projector matrix.

$$S^* = \begin{bmatrix} 0 & 0 & \cdots & 0 & 0 \\ 1 & 0 & \cdots & 0 & 0 \\ 0 & 1 & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & 1 & 0 \end{bmatrix}, \quad S^*S = \begin{bmatrix} 0 & 0 & 0 & \cdots & 0 \\ 0 & 1 & 0 & \cdots & 0 \\ 0 & 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 1 \end{bmatrix}, \quad I - S^*S = \begin{bmatrix} 1 & 0 & \cdots & 0 & 0 \\ 0 & 0 & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & 0 & 0 \\ 0 & 0 & \cdots & 0 & 0 \end{bmatrix}$$

3 Schur-Cohn Theorem

3.1 Theorem

For any polynomial

$$p(z) = a_0 z^n + a_1 z^{n-1} + a_2 z^{n-2} + \cdots + a_{n-1} z + a_n, \quad a_i \in \mathbb{C}$$

such that none of the roots lie on the unit circle $|z| = 1$, and $p(0) \neq 0$, we want to find out how many of its roots lie inside the unit circle ($|z| < 1$) and how many roots lie outside ($|z| > 1$).

Without loss of generality, let $a_0 = 1$ as it does not change the roots of the polynomial. Suppose p has roots α_i . Then $p(z) = (z - \alpha_1)(z - \alpha_2) \cdots (z - \alpha_n)$.

Note that $p(S)$ is
$$\begin{bmatrix} a_n & a_{n-1} & a_{n-2} & \cdots & a_1 \\ 0 & a_n & a_{n-1} & \cdots & a_2 \\ 0 & 0 & a_n & \cdots & a_3 \\ \vdots & \vdots & \ddots & \ddots & \vdots \\ 0 & 0 & \cdots & 0 & a_n \end{bmatrix},$$
 where S is the shift matrix.

The matrix $p(S)$ can be factorized as

$$p(S) = (S - \alpha_1 I)(S - \alpha_2 I) \cdots (S - \alpha_n I)$$

Denote $S - \alpha_j I$ by B_j . Then $p(S) = \prod_{j=1}^n B_j = B_1 B_2 B_3 \cdots B_n$

Next, define q to be the polynomial

$$q(z) = \overline{a_n} z^n + \overline{a_{n-1}} z^{n-1} + \cdots + \overline{a_0}$$

The roots of $q(S)$ are $\frac{1}{\overline{\alpha_i}}$.

$$\begin{aligned} q\left(\frac{1}{\overline{\alpha_i}}\right) &= \frac{\overline{a_n}}{\overline{\alpha_i}^n} + \frac{\overline{a_{n-1}}}{\overline{\alpha_i}^{n-1}} + \cdots + \overline{a_0} \\ &= \frac{1}{\overline{\alpha_i}^n} (\overline{a_n} + \overline{a_{n-1}} \overline{\alpha_i} + \cdots + \overline{a_0} \overline{\alpha_i}^n) \\ &= \frac{\overline{p(\alpha_i)}}{\overline{\alpha_i}^n} = 0 \end{aligned}$$

$q(z)$ can be factorized as $q(z) = (1 - \overline{\alpha_1} z)(1 - \overline{\alpha_2} z) \cdots (1 - \overline{\alpha_n} z)$.

The matrix $q(S)$ can be factorized as

$$q(S) = (I - \overline{\alpha_1} S)(I - \overline{\alpha_2} S) \cdots (I - \overline{\alpha_n} S)$$

Denote $I - \overline{\alpha_j} S$ by C_j . Then $q(S) = \prod_{j=1}^n C_j = C_1 C_2 C_3 \cdots C_n$.

We now state the Schur-Cohn theorem:

Theorem 20 (Schur). *Consider the matrix*

$$H = q^*(S)q(S) - p^*(S)p(S)$$

The polynomial p will have all its roots inside the unit circle $|z| = 1$ if and only if H is positive definite. It will have all the roots outside the unit circle if and only if H is negative definite.

Theorem 21 (Cohn Generalization). *The polynomial p , it will have k roots inside the circle $|z| = 1$, and $n - k$ roots outside the circle if and only if k eigenvalues of H are positive and $n - k$ are negative.*

3.2 Proof

We will first prove the Schur-Cohn theorem for $n = 1$, that is for linear polynomials. It will then be extended to polynomials of higher degrees.

Let's write $q(S)$ and $p(S)$ as a product of the linear terms.

$$q(S)^*q(S) - p(S)^*p(S) = (C_1C_2C_3 \dots C_n)^*(C_1C_2C_3 \dots C_n) - (B_1B_2B_3 \dots B_n)^*(B_1B_2B_3 \dots B_n)$$

For $n = 1$, this is equal to $C_1^*C_1 - B_1^*B_1$.

$$\begin{aligned} C_1^*C_1 - B_1^*B_1 &= (I - \overline{\alpha_1}S)^*(I - \overline{\alpha_1}S) - (S - \alpha_1I)^*(S - \alpha_1I) \\ &= (I - \alpha_1S^*)(I - \overline{\alpha_1}S) - (S^* - \overline{\alpha_1}I)(S - \alpha_1I) \\ &= (I - \alpha_1S^* - \overline{\alpha_1}S + |\alpha_1|^2 S^*S) - (S^*S - \alpha_1S^* - \overline{\alpha_1}S + |\alpha_1|^2 I) \\ &= I - |\alpha_1|^2 I - S^*S + |\alpha_1|^2 S^*S \\ &= (1 - |\alpha_1|^2)(I - S^*S) \\ &= (1 - |\alpha_1|^2)e_1e_1^* \end{aligned}$$

For $n = 1$, $I - S^*S$ is a 1×1 matrix, so $H = [1 - |\alpha_1|^2]$.

Note that $I - S^*S$ is a positive definite matrix of rank 1.

- If $|\alpha_1| < 1$, then the root of the linear polynomial lies within the unit circle. Matrix H has one positive eigenvalue.
- Similarly, if $|\alpha_1| > 1$, then the root of the linear polynomial lies outside the unit circle, and the eigenvalue of H is negative.

This shows that the Schur-Cohn theorem is true for $n = 1$. We will now extend the proof for all n .

$$\begin{aligned} H &= q^*(S)q(S) - p^*(S)p(S) \\ &= (C_1C_2C_3 \dots C_n)^*(C_1C_2C_3 \dots C_n) - (B_1B_2B_3 \dots B_n)^*(B_1B_2B_3 \dots B_n) \\ &= (C_n^* \dots C_1^*)(C_1 \dots C_n) - (B_n^* \dots B_1^*)(B_1 \dots B_n) \end{aligned}$$

B_i commutes with C_j , so we can rearrange their order in each term according to our convenience. We can add and subtract terms to get a telescoping series:

$$\begin{aligned} H &= \begin{aligned} &(C_n^* \dots C_2^*)C_1^*C_1(C_2 \dots C_n) &-& (C_n^* \dots C_2^*)B_1^*B_1(C_2 \dots C_n) \\ + &B_1^*(C_n^* \dots C_3^*)C_2^*C_2(C_2 \dots C_n)B_1 &-& B_1^*(C_n^* \dots C_3^*)B_2^*B_2(C_3 \dots C_n)B_1 \\ + &B_1^*B_2^*(C_n^* \dots C_4^*)C_3^*C_3(C_4 \dots C_n)B_2B_1 &-& B_1^*B_2^*(C_n^* \dots C_4^*)B_3^*B_3(C_4 \dots C_n)B_2B_1 \\ + &\vdots &-& \vdots \\ + &\vdots &-& \vdots \\ + &(B_1^*B_2^* \dots B_{n-1}^*)C_n^*C_n(B_{n-1} \dots B_2B_1) &-& (B_1^* \dots B_{n-1}^*)B_n^*B_n(B_{n-1} \dots B_1) \end{aligned} \\ &= \sum_{j=1}^n (B_1^*B_2^* \dots B_{j-1}^*)(C_n^* \dots C_{j+1}^*)(C_j^*C_j - B_j^*B_j)(C_{j+1} \dots C_n)(B_{j-1} \dots B_2B_1) \end{aligned}$$

In the case of p being a linear polynomial, we saw that $C_j^* C_j - B_j^* B_j = (1 - |\alpha_j|^2)(I - S^* S) = (1 - |\alpha_j|^2)e_1 e_1^*$. Hence,

$$\begin{aligned} H &= \sum_{j=1}^n (B_1^* B_2^* \cdots B_{j-1}^*) (C_n^* \cdots C_{j+1}^*) ((1 - |\alpha_j|^2) e_1 e_1^*) (C_{j+1} \cdots C_n) (B_{j-1} \cdots B_2 B_1) \\ &= \sum_{j=1}^n (1 - |\alpha_j|^2) v_j v_j^*, \quad \text{where } v_j = B_1^* \cdots B_{j-1}^* C_{j+1}^* \cdots C_n^* e_1. \end{aligned}$$

Let V be the matrix with columns v_i , let D be the diagonal matrix with $d_{ii} = 1 - |\alpha_i|^2$,

$$V = [v_1 \quad v_2 \quad v_3 \quad \cdots \quad v_n]$$

$$D = \begin{bmatrix} 1 - |\alpha_1|^2 & 0 & 0 & \cdots & 0 \\ 0 & 1 - |\alpha_2|^2 & 0 & \cdots & 0 \\ 0 & 0 & 1 - |\alpha_3|^2 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 1 - |\alpha_n|^2 \end{bmatrix}$$

then

$$H = V D V^*$$

If matrix H is invertible, then matrix V is also invertible.

Lemma. H is invertible if and only if D is invertible

Proof. Let H be positive definite (\Rightarrow). Then

$$\begin{aligned} \langle D x, x \rangle &= \langle V^{-1} H (V^*)^{-1} x, x \rangle \\ &= \langle (V^{-1}) H (V^{-1})^*, x \rangle \\ &= \langle H (V^{-1})^*, (V^{-1})^* x \rangle \\ &= \langle H y, y \rangle \\ &= \sum_{j=1}^n (1 - |\alpha_j|^2) |y_j|^2 > 0 \end{aligned}$$

Let D be positive definite (\Leftarrow). Then

$$\begin{aligned} \langle H x, x \rangle &= \langle V D V^* x, x \rangle \\ &= \langle D V^* x, V^* x \rangle \\ &= \langle D y, y \rangle \\ &= \sum_{j=1}^n (1 - |\alpha_j|^2) |y_j|^2 > 0 \end{aligned}$$

□

Hence if all the roots of $p(z)$ lie within the unit circle, then every eigenvalue of D is positive, so every eigenvalue of H is also positive. Similarly if all the roots of $p(z)$ lie outside the unit circle, then every eigenvalue of H is negative.

We will now look at the generalized version by Cohn, where some roots are inside the circle and some roots are outside.

Let the eigenvalues of H be $\lambda_1 \leq \lambda_2 \leq \dots \leq \lambda_k \leq \dots \leq \lambda_n$. From the Spectral theorem, we get the values of the lowest and the highest eigenvalues.

$$\lambda_1 = \inf_{x \neq 0} \frac{\langle Hx, x \rangle}{\langle x, x \rangle}, \quad \lambda_n = \sup_{x \neq 0} \frac{\langle Hx, x \rangle}{\langle x, x \rangle}$$

To find the intermediate eigenvalues, the Courant-Fischer theorem will be required.

Let λ_k be the smallest positive eigenvalue. Then given any $w_1, w_2, \dots, w_{n-k} \in \mathbb{C}^n$, we have some $x \neq 0$ such that x is orthogonal to w_1, w_2, \dots, w_{n-k} and $\langle Dx, x \rangle > 0$.

$$\langle Hx, x \rangle = \langle VDV^*x, x \rangle = \langle DV^*x, V^*x \rangle$$

Let W be the subspace spanned by w_1, w_2, \dots, w_{n-k} . Now let $y \in W^\perp$ so $\langle y, w_j \rangle = 0$ for all j . Let $x = V^*y$. Then $\langle (V^*)^{-1}x, w_i \rangle = 0$, which implies $\langle x, V^{-1}w_i \rangle = 0$. This implies x is orthogonal to all of $V^{-1}w_1, V^{-1}w_2, \dots, V^{-1}w_{n-k}$.

Hence,

$$\langle Dx, x \rangle > 0 \implies \langle V^{-1}H(V^*)^{-1}x, x \rangle > 0 \implies \langle Hy, y \rangle > 0$$

This means for every positive eigenvalue of D , there is a positive eigenvalue of H . Similarly, for every negative eigenvalue of D , there is a negative eigenvalue of H .

- Thus, the number of roots inside the unit circle is equal to the number of positive eigenvalues of D , which is equal to the number of positive eigenvalue of H .
- Analogously, the number of roots outside the unit circle is equal to the number of negative eigenvalues of D , which is equal to the number of negative eigenvalues of H .

This concludes the proof of the generalized Schur-Cohn theorem. \square

3.3 Example

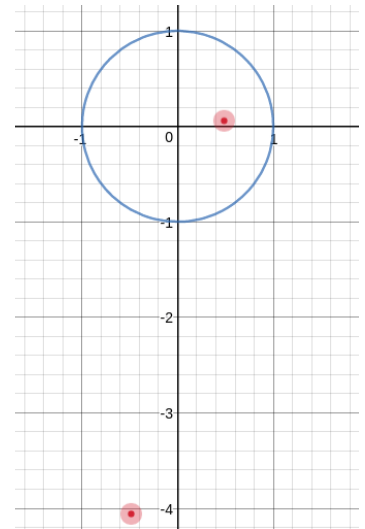
We will apply the Schur-Cohn theorem on the polynomial $p(z) = z^2 + 4iz - 2i$.

$$\begin{aligned} p(S) &= \begin{bmatrix} -2i & 4i \\ 0 & -2i \end{bmatrix}, & p^*(S) &= \begin{bmatrix} 2i & 0 \\ -4i & 2i \end{bmatrix}, & p^*(S)p(S) &= \begin{bmatrix} 20 & -8 \\ -8 & 4 \end{bmatrix} \\ q(S) &= \begin{bmatrix} 1 & 4 \\ 0 & 1 \end{bmatrix}, & q^*(S) &= \begin{bmatrix} 1 & 0 \\ 4 & 1 \end{bmatrix}, & q^*(S)q(S) &= \begin{bmatrix} 17 & 4 \\ 4 & 1 \end{bmatrix} \end{aligned}$$

We get matrix H as

$$H = q^*(S)q(S) - p^*(S)p(S) = \begin{bmatrix} -3 & 12 \\ 12 & -3 \end{bmatrix} = 3 \begin{bmatrix} -1 & 4 \\ 4 & -1 \end{bmatrix}$$

The eigenvalues of this matrix are -5 and 3 . Since one eigenvalue is positive and one is negative, by Schur-Cohn theorem, it means that the polynomial has one root inside the unit circle and one root outside the unit circle. Indeed when the roots are plotted, this result is verified:



4 Conclusion

The algorithm described above was to determine the location of roots with respect to the unit circle. It can be modified to find the location of roots with respect to a circle of any radius about the origin. To find the number of roots of $p(z)$ inside a circle of radius r , repeat the above Schur Cohn theorem but with the polynomial $p(\frac{z}{r})$ instead. Combining this with bisection method with varying radii, it is possible to find the location of roots up to very thin disks.

This algorithm can be also be modified to find the number of roots of a polynomial in one half plane of \mathbb{C} . Modified versions of the Schur-Cohn algorithm exist, which are faster but only state if all the roots are within the unit circle or not.

This algorithm fails when $\bar{\alpha}$ and $\frac{1}{\alpha}$ are both roots of the polynomial for some $\alpha \in \mathbb{C}$. All the points on the unit circle will satisfy this condition $p(\bar{\alpha}) = p(\frac{1}{\alpha}) = 0$. In such a case, H becomes singular and the algorithm fails. To avoid this, one workaround is to compute the eigenvalues at a circle of a different radius. If the polynomial does not have repeated zeros, then another way is to fix this is to apply the Schur-Cohn test on the derivative of p .

More different ways to fix this are presented in these papers:

References