

# MAS 5145 Matrix Theory

## Final and Comp Prep

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# 1 Definitions

## 1.1 Eigenvalues and Eigenvectors

Let  $A$  be  $n \times n$ .

The scalar  $\lambda$  is said to be an eigenvalue of  $A$  if there is a non-zero vector  $\underline{x}$  such that  $A\underline{x} = \lambda\underline{x}$ .

Such a vector  $\underline{x}$  is called an eigenvector of  $A$  belonging to the eigenvalue  $\lambda$ .

## 1.2 Characteristic Polynomial

Let  $A$  be  $n \times n$ .

The polynomial calculated by  $\det(A - \lambda I)$  is called the characteristic polynomial.

Its roots are the eigenvalues of  $A$ .

## 1.3 Algebraic Multiplicity

Let  $A$  be  $n \times n$  and  $\lambda$  be an eigenvalue of  $A$ .

The algebraic multiplicity of  $\lambda$  is the number of times  $\lambda$  appears as a root of the char. poly. of  $A$ .

## 1.4 Geometric Multiplicity

Let  $A$  be  $n \times n$  and  $\lambda$  be an eigenvalue of  $A$ .

The geometric multiplicity of  $\lambda$  is the dimension of the eigenspace of  $\lambda$ .

This is the same as the number of linearly independent eigenvectors belonging to  $\lambda$ .

## 1.5 Similar and Unitarily Similar

Let  $A$  and  $B$  be  $n \times n$ .

$B$  is said to be similar to  $A$  if there exists an invertible matrix  $S$  so that  $S^{-1}AS = B$ .

$A$  and  $B$  are unitarily similar if  $P$  is a unitary matrix (i.e.  $PP^* = P^*P = I$ ).

## 1.6 Diagonalizable Matrix

Let  $A$  be  $n \times n$ .

$A$  is said to be diagonalizable if  $A$  is similar to a diagonal matrix.

There is an invertible matrix  $S$  such that  $S^{-1}AS = D$  is diagonal.

## 1.7 Orthogonal and Unitary

A real matrix  $Q$  is an orthogonal matrix if  $QQ^T = Q^TQ = I$ .

A complex matrix  $U$  is a unitary matrix if  $UU^* = U^*U = I$ .

## 1.8 Minimal Polynomial

Let  $A$  be  $n \times n$ .

The minimal polynomial of  $A$  is the monic (i.e. coefficient of highest powered  $x$  in  $p(x)$  is 1) polynomial of least degree that annihilates the matrix  $A$ .

## 1.9 Symmetric/Hermitian/Skew-symmetric/Skew-hermitian/Normal

symmetric	$\Leftrightarrow$	$A = A^T$
hermitian	$\Leftrightarrow$	$A = A^*$
skew-symmetric	$\Leftrightarrow$	$A = -A^T$
skew-hermitian	$\Leftrightarrow$	$A = -A^*$
normal	$\Leftrightarrow$	$AA^* = A^*A \Leftrightarrow$ exists unitary $U$ s.t. $UAU^{-1}$ is diagonal

## 1.10 Positive Definite and Semi-Definite

Let  $A$  be hermitian.

If  $\underline{x}^* A \underline{x} > 0$  for all  $\underline{x} \neq 0$  then  $A$  is positive definite.

If  $\underline{x}^* A \underline{x} \geq 0$  for all  $\underline{x} \neq 0$  then  $A$  is positive semi-definite.

## 1.11 Singular Values

Let  $A$  be  $n \times n$ .

The singular values of  $A$  are the square roots of the eigenvalues of  $A^* A$ .

The singular value decomposition of  $A$  is given as  $A = U D V^*$ , where  $U, V$  are unitary and  $D$  is a diagonal matrix whose elements are the singular values.

## 1.12 Trace

The trace of a matrix is the sum of its diagonal elements and the sum of its eigenvalues.

## 2 Proofs of Key Results

### 2.1 Hermitian/Skew-hermitian matrix eigenvalues are real/purely imaginary

If  $A$  is a hermitian matrix, then every eigenvalue of  $A$  is real.

Let  $A$  be a hermitian matrix (i.e.  $A = A^*$ ),  $\underline{x}$  be an eigenvector belonging to  $\lambda$ , and  $\underline{x} \neq 0$ .

$$\begin{aligned} \text{Then } A\underline{x} &= \lambda\underline{x} \\ \underline{x}^* A\underline{x} &= \underline{x}^* (\lambda\underline{x}) \\ (\underline{x}^* A)\underline{x} &= \lambda(\underline{x}^* \underline{x}) \\ (\underline{x}^* A)\underline{x} &= \lambda(\underline{x}^* \underline{x}) \\ (A^* \underline{x})^* \underline{x} &= \lambda(\underline{x}^* \underline{x}) \\ (A\underline{x})^* \underline{x} &= \lambda(\underline{x}^* \underline{x}) \quad \text{because } A = A^* \\ (\lambda\underline{x})^* \underline{x} &= \lambda(\underline{x}^* \underline{x}) \\ \overline{\lambda}(\underline{x}^* \underline{x}) &= \lambda(\underline{x}^* \underline{x}) \\ (\overline{\lambda} - \lambda)\underline{x}^* \underline{x} &= 0 \end{aligned}$$

We can see that  $\underline{x}^* \underline{x} = \|\underline{x}\|^2 > 0$  since  $\underline{x} \neq 0$ . Hence  $(\overline{\lambda} - \lambda) = 0$ .

Let  $\lambda = a + ib$  and  $\overline{\lambda} = a - ib$  for  $a, b \in \mathbb{R}$ . So  $(\overline{\lambda} - \lambda) = a - ib - (a + ib) = -2ib = 0$ . This implies that  $b = 0$  and therefore  $\lambda$  is a real number.

If  $A$  is a skew-hermitian matrix, then every eigenvalue of  $A$  is purely imaginary.

Let  $A$  be a skew-hermitian matrix (i.e.  $A = -A^*$ ),  $\underline{x}$  be an eigenvector belonging to  $\lambda$ , and  $\underline{x} \neq 0$ .

$$\begin{aligned} \text{Then } A\underline{x} &= \lambda\underline{x} \\ \underline{x}^* A\underline{x} &= \underline{x}^* (\lambda\underline{x}) \\ (\underline{x}^* A)\underline{x} &= \lambda(\underline{x}^* \underline{x}) \\ (\underline{x}^* A)\underline{x} &= \lambda(\underline{x}^* \underline{x}) \\ (A^* \underline{x})^* \underline{x} &= \lambda(\underline{x}^* \underline{x}) \\ (-A\underline{x})^* \underline{x} &= \lambda(\underline{x}^* \underline{x}) \quad \text{because } A = -A^* \\ (-\lambda\underline{x})^* \underline{x} &= \lambda(\underline{x}^* \underline{x}) \\ -\overline{\lambda}(\underline{x}^* \underline{x}) &= \lambda(\underline{x}^* \underline{x}) \\ (\overline{\lambda} + \lambda)\underline{x}^* \underline{x} &= 0 \end{aligned}$$

We can see that  $\underline{x}^* \underline{x} = \|\underline{x}\|^2 > 0$  since  $\underline{x} \neq 0$ . Hence  $(\overline{\lambda} + \lambda) = 0$ .

Let  $\lambda = a + ib$  and  $\overline{\lambda} = a - ib$  for  $a, b \in \mathbb{R}$ . So  $(\overline{\lambda} + \lambda) = a - ib + (a + ib) = 2a = 0$ . This implies that  $a = 0$  and therefore  $\lambda$  is purely imaginary.

## 2.2 Unitary matrix eigenvalues have absolute value 1

Let  $A$  be a unitary matrix (so  $AA^* = A^*A = I$ ) with eigenvalue  $\lambda$ .

Then for any vector  $\underline{x} \neq 0$ , we have

$$\begin{aligned} A\underline{x} &= \lambda\underline{x} \text{ and} \\ \underline{x}^* A^* &= \lambda^* \underline{x}^* \Rightarrow \end{aligned}$$

$$\begin{aligned} \underline{x}^* A^* A \underline{x} &= \lambda^* \underline{x}^* \lambda \underline{x} \Rightarrow \\ \underline{x}^* \underline{x} &= \lambda^* \lambda \underline{x}^* \underline{x} \Rightarrow \\ \|\underline{x}\|^2 &= |\lambda|^2 \|\underline{x}\|^2 \Rightarrow \\ |\lambda| &= 1 \quad \square \end{aligned}$$

## 2.3 Eigenvectors belonging to distinct eigenvalues are linearly independent

Suppose  $c_1 \underline{x}_1 + c_2 \underline{x}_2 = 0$ , where one of the coefficients (say  $c_1$ ) is not zero. Then  $\underline{x}_1 = \alpha \underline{x}_2$  for some  $\alpha \neq 0$ . Left multiplying both sides by  $A$  gives

$$A\underline{x}_1 = \lambda_1 \underline{x}_1 = \alpha A\underline{x}_2 = \alpha \lambda_2 \underline{x}_2$$

But multiplying  $\underline{x}_1 = \alpha \underline{x}_2$  by  $\lambda_1$  also gives

$$A\underline{x}_1 = \lambda_1 \underline{x}_1 = \alpha \lambda_1 \underline{x}_2$$

Subtracting these equations gives

$$\alpha \lambda_2 \underline{x}_2 - \alpha \lambda_1 \underline{x}_2 = \alpha (\lambda_2 - \lambda_1) \underline{x}_2 = 0$$

But we know that  $\alpha \neq 0$  and  $\lambda_2 - \lambda_1 \neq 0$  and  $\underline{x}_2 \neq 0$ .

Thus our assumption that the coefficients  $c_1$  and  $c_2$  are not zero is incorrect and  $\underline{x}_1$  and  $\underline{x}_2$  are linearly independent.

The can easily be extended for the  $\underline{x}_n$  case. □

## 2.4 Eigenvectors for distinct eigenvalues of a hermitian matrix are orthogonal

Let  $A$  be an  $n \times n$  Hermitian matrix,  $\lambda_1, \lambda_2$  distinct eigenvalues of  $A$ , and  $\underline{x}_1, \underline{x}_2$  eigenvectors belonging to respectively  $\lambda_1, \lambda_2$ . We will show that  $\underline{x}_1$  and  $\underline{x}_2$  are orthogonal.

Since  $A$  is hermitian, we know these eigenvalues are real.

We can calculate  $\langle \underline{x}_1, A\underline{x}_2 \rangle$  in two ways:

$$\langle \underline{x}_1, A\underline{x}_2 \rangle = \underline{x}_1^* A \underline{x}_2 = (\underline{x}_1^* A) \underline{x}_2 = (A^* \underline{x}_1)^* \underline{x}_2 = (A \underline{x}_1)^* \underline{x}_2 = (\lambda_1 \underline{x}_1)^* \underline{x}_2 = \overline{\lambda_1} \underline{x}_1^* \underline{x}_2 = \overline{\lambda_1} \langle \underline{x}_1, \underline{x}_2 \rangle$$

$$\langle \underline{x}_1, A\underline{x}_2 \rangle = \underline{x}_1^* A \underline{x}_2 = \underline{x}_1^* \lambda_2 \underline{x}_2 = \lambda_2 \underline{x}_1^* \underline{x}_2 = \lambda_2 \langle \underline{x}_1, \underline{x}_2 \rangle$$

We then set these two results equal.

$$\overline{\lambda_1} \langle \underline{x}_1, \underline{x}_2 \rangle = \lambda_2 \langle \underline{x}_1, \underline{x}_2 \rangle \Rightarrow (\overline{\lambda_1} - \lambda_2) \langle \underline{x}_1, \underline{x}_2 \rangle = 0$$

Since  $\lambda_1$  and  $\lambda_2$  are real we know that  $\overline{\lambda_1} = \lambda_1 \neq \lambda_2$ , so  $\langle \underline{x}_1, \underline{x}_2 \rangle$  must be zero. Therefore  $\underline{x}_1$  and  $\underline{x}_2$  are orthogonal.

This can easily be extended to the  $\underline{x}_n$  case. □

## 2.5 Trace of a matrix = Sum of its eigenvalues

For every square matrix  $A$  there is a nonsingular  $P$  such that  $A = PJP^{-1}$  where  $J$  is upper triangular with its eigenvalues on the diagonals.

We know that  $\text{trace}(A) = \text{trace}(PJP^{-1}) = \text{trace}(PP^{-1}J) = \text{trace}(J)$ . □

## 2.6 Gershgorin disc theorem part (a)

Let  $A$  is an  $n \times n$  matrix.

Define the Gershgorin Radii as  $R'_i = \sum_{\substack{j=1 \\ j \neq i}}^n |a_{ij}|$ .

and the Gershgorin Disc as  $D_i = \{z | z \in \mathbb{C}, |z - a_{ii}| \leq R'_i\}$

and the Gershgorin Region as  $G = \bigcup_{i=1}^n D_i$ .

(a) Every eigenvalue of  $A$  is in the Gershgorin disc

(b) If the union of  $k$  of the discs is disjoint from the remaining  $n - k$  discs, then there are exactly  $k$  eigenvalues (counting multiplicity) in the union of the  $k$  discs.

Proof of (a): Let  $\lambda$  be an eigenvalue of  $A$  and  $\underline{x} \neq \underline{0}$  be an eigenvector belonging to  $\lambda$ .

So  $A\underline{x} = \lambda\underline{x}$  for  $\underline{x} \in \mathbb{C}^n$ . Let  $|x_p| = \max(|x_1|, \dots, |x_n|)$  and we look at the  $p$ -th entries of  $A\underline{x}$  and  $\lambda\underline{x}$ .

$$\begin{aligned}
 (A\underline{x})_p &= \lambda x_p \Rightarrow \\
 \sum_{j=1}^n a_{pj} x_j &= \lambda x_p \Rightarrow \\
 a_{pp} x_p + \sum_{\substack{j=1 \\ j \neq p}}^n a_{pj} x_j &= \lambda x_p \Rightarrow \\
 (\lambda - a_{pp}) x_p &= \sum_{\substack{j=1 \\ j \neq p}}^n a_{pj} x_j \Rightarrow \\
 |(\lambda - a_{pp}) x_p| &= \left| \sum_{\substack{j=1 \\ j \neq p}}^n a_{pj} x_j \right| \Rightarrow \\
 |(\lambda - a_{pp})| |x_p| &= \left| \sum_{\substack{j=1 \\ j \neq p}}^n a_{pj} x_j \right| \Rightarrow \\
 |(\lambda - a_{pp})| |x_p| &\leq \sum_{\substack{j=1 \\ j \neq p}}^n |a_{pj}| |x_j| \Rightarrow \\
 |(\lambda - a_{pp})| |x_p| &\leq \sum_{\substack{j=1 \\ j \neq p}}^n |a_{pj}| |x_p| \quad \text{since } |x_i| \leq |x_p| \forall i \\
 |(\lambda - a_{pp})| &\leq \sum_{\substack{j=1 \\ j \neq p}}^n |a_{pj}| = R'_p \quad \text{since } |x_p| > 0 \\
 \therefore \lambda &\text{ lies in } D_p \leq G \quad \square
 \end{aligned}$$

## 2.7 Results pertaining to positive definite matrices

### 2.8 Min poly divides every annihilating polynomial

Let  $A$  be  $n \times n$  and let  $p(x)$  annihilate  $A$ . Then the minimal polynomial,  $m(x)$  is a factor of  $p(x)$ .

From the Euclidean algorithm we know that  $p(x) = q(x)m(x) + r(x)$ .

Substituting  $x = A$  gives us

$$\begin{aligned} p(A) &= q(A)m(A) + r(A) \\ 0 &= q(A)0 + r(A) \end{aligned}$$

Therefore  $r(A) = 0$  and we conclude that  $m(x)$  divides  $p(x)$ .

### 2.9 Roots of the min poly are precisely the eigenvalues of the matrix

We know that  $C_A(x)$  annihilates  $A$  and therefore  $m_A(x)$  is a factor of  $C_A(x)$ .

We also know that the only roots of  $C_A(x)$  are the eigenvalues of  $A$ . Therefore, every root of  $m_A(x)$  is also an eigenvalue of  $A$ .

### 2.10 Hermitian matrix is Positive Definite if and only if all its eigenvalues are positive

( $\Rightarrow$ ) Let  $A$  be positive definite and  $\lambda$  be an eigenvalue of  $A$ .

$$\begin{aligned} A\underline{x} &= \lambda\underline{x} \Rightarrow \\ \underline{x}^* A \underline{x} &= \lambda \underline{x}^* \underline{x} = \lambda \|\underline{x}\|^2 \Rightarrow \\ \lambda &= \frac{\underline{x}^* A \underline{x}}{\|\underline{x}\|^2} > 0 \quad \square \end{aligned}$$

( $\Leftarrow$ ) Let  $A$  be hermitian and let all its eigenvalues be positive.

Since  $A$  is hermitian there exists unitary  $U$  such that  $U^*AU = D$  where  $D$  is a diagonal matrix composed of the eigenvalues of  $A$ .

We want to show that  $\underline{x}^* A \underline{x} = \underline{x}^* U D U^* \underline{x}$  for all  $\underline{x} \neq \underline{0}$ .

Let  $U^* \underline{x} = \underline{y} = [y_1 \dots y_n]^T$ . Since  $\underline{x} \neq \underline{0}$ , we know  $U^* \underline{x} \neq \underline{0}$ .

$$\text{So } \underline{x}^* U D U^* \underline{x} = \underline{y}^* D \underline{y} = [\bar{y}_1 \dots \bar{y}_n] \begin{bmatrix} \lambda_1 y_1 \\ \vdots \\ \lambda_n y_n \end{bmatrix} = \lambda_1 |y_1|^2 + \dots + \lambda_n |y_n|^2 > 0 \text{ because } \lambda_i > 0 \text{ and at least one } y_i \neq 0.$$

Thus  $\underline{x}^* A \underline{x} > 0$  and  $A$  is positive definite. □

### 2.11 Trace( $A^*A$ ) = sum of square of moduli of eigenvalues of $A$ when $A$ is normal

Since  $A$  is normal, there exists unitary diagonalizable matrix  $U$  such that  $U^*AU = D$  is diagonal with the eigenvalues of  $A$ .

We can write  $A^*A = UAU^*UA^*U^* = UD^*DU^*$ .

So  $\text{trace}(A^*A) = \text{trace}(UD^*DU^*) = \text{trace}(UU^*D^*D) = \text{trace}(ID^*D) = \text{trace}(D^*D)$ .

$D^*D = \text{diag}(\lambda_1 \bar{\lambda}_1, \dots, \lambda_n \bar{\lambda}_n)$  which means the trace is the sum of square moduli of the eigenvalues of  $A$ .

### 3 Statements of Theorems

#### 3.1 Schur's Upper Triangularization Theorem

Let  $A$  be  $n \times n$  over  $\mathbb{F}$ . Then there exists a unitary matrix  $U$  such that  $U^*AU = T$  is upper triangular.

The eigenvalues of  $A$  are the diagonal entries of  $T$ .

If  $A$  is real and all eigenvalues of  $A$  are real, then  $U$  can be chosen to be real orthogonal.

#### 3.2 Cayley-Hamilton Theorem

The characteristic polynomial of an  $n \times n$  matrix  $A$  annihilates  $A$ .

#### 3.3 Gershgorin Disc Theorem (include radii, discs, and region)

Let  $A$  is an  $n \times n$  matrix.

Define the Gershgorin Radii as  $R'_i = \sum_{\substack{j=1 \\ j \neq i}}^n |a_{ij}|$ .

and the Gershgorin Disc as  $D_i = \{z | z \in \mathbb{C}, |z - a_{ii}| \leq R'_i\}$

and the Gershgorin Region as  $G = \bigcup_{i=1}^n D_i$ .

(a) Every eigenvalue of  $A$  is in the Gershgorin disc

(b) If the union of  $k$  of the discs is disjoint from the remaining  $n - k$  discs, then there are exactly  $k$  eigenvalues (counting multiplicity) in the union of the  $k$  discs.

#### 3.4 Necessary and sufficient conditions for the diagonalizability of a matrix

#### 3.5 Significant of a matrix being normal ( $A$ is normal iff $A$ is unitarily diagonalizable)

### 4 Problems - LOOK AT CLASS NOTES TOO

#### 4.1 Proof Type Problems

Similar to those on problem sets, homework assignments, class tests, and those done in class.

#### 4.2 Computational Problems

1. Finding eigenvalues/bases for eigenspaces
2. Illustrating Schur's Theorem
3. Applying the Cayley-Hamilton Theorem
4. Eigenvalues of polynomials of a matrix
5. Computing singular values and related computations
6. Jordan Canonical Form and related problems (e.g. J form of the power of a J-block)
7. Gershgorin discs
8. Computing singular values and related matters
9. Eigenvalues of a polynomials of a matrix