

## Symmetric matrices and positive definiteness.

Symmetric matrices has two good properties:

- 1) Their eigenvalues are real (can be proofed)
- 2) Their eigenvectors are perpendicular:

Proof:  $A = S\Lambda S^{-1}$ ,  $A = A^T = (S\Lambda S^{-1})^T$  because  $A$  is a symmetric matrix.

$$\begin{aligned} S\Lambda S^{-1} &= (S\Lambda S^{-1})^T \\ S\Lambda S^{-1} &= S^{-1T} \Lambda^T S^T \quad (\Lambda = \Lambda^T \text{ because } \Lambda \text{ is a diagonal matrix}) \\ S\Lambda S^{-1} &= S^{-1T} \Lambda S^T \end{aligned}$$

pre-multiply both sides by  $S^{-1}$  and post-multiply both sides by  $S$

$$\begin{aligned} S^{-1}S\Lambda S^{-1}S &= S^{-1}S^{-1T} \Lambda S^TS \\ I \Lambda I &= S^{-1}S^{-1T} \Lambda S^TS \\ \Lambda &= S^{-1}S^{-1T} \Lambda S^TS \\ \Lambda &= (S^TS)^{-1} \Lambda S^TS \end{aligned}$$

This makes  $S^TS = I$  which means that  $S^T = S^{-1}$ , this makes  $S$  an orthogonal matrix (i.e. a matrix with perpendicular columns). We usually use the letter  $Q$  for such matrices. Therefore,

for a symmetric matrix  $A$ ,  $A = Q \Lambda Q^{-1}$

Definition: the spectrum of a matrix is the set of eigenvalues of and eigenvectors of this matrix.

A symmetric matrix has good properties (real eigenvalues and perpendicular eigenvectors). We can decompose a symmetric matrix:

$$\begin{aligned} A &= Q \Lambda Q^{-1} \\ &= [q_1 \ q_2 \ \dots] \text{diag}(\lambda) \begin{bmatrix} q_1^T \\ q_2^T \\ \dots \end{bmatrix} \\ &= \lambda_1 \underbrace{q_1 q_1^T}_{\text{projection matrix}} + \lambda_2 \underbrace{q_2 q_2^T}_{\text{projection matrix}} + \dots \end{aligned} \quad (\text{decomposition of symmetric matrix})$$

Every symmetric matrix is a combination of projection matrices.

For a given square matrix  $A$

Product of pivots = product of  $\lambda$ 's =  $\det(A)$

Signs of pivots same as signs of  $\lambda$ 's

Number of positive pivots = number of positive  $\lambda$ 's

Number of negative pivots = number of negative  $\lambda$ 's

### Positive definite matrix

A sub class of symmetric matrices that has an excellent properties:

1. All  $\lambda$ 's of a positive definite matrix are positive.
2. All pivots of a positive definite matrix are positive.
3. All sub-determinants of a positive definite matrix are positive.

Example:  $A = \begin{pmatrix} 5 & 2 \\ 2 & 3 \end{pmatrix}$  ( $A$  is a positive definite matrix)

Pivots are 5, 11/5

$\det(A) = 5 \cdot 11/5 = 11$

Find  $\lambda$ 's :  $\begin{bmatrix} 5-\lambda & 2 \\ 2 & 3-\lambda \end{bmatrix}$   
 $\lambda^2 - 8\lambda + 11 = 0$   
 $\lambda = 4 \pm \sqrt{5}$

Example:  $B = \begin{bmatrix} -1 & 0 \\ 0 & -3 \end{bmatrix}$

B is not a positive definite matrix as you can see one of its pivots = -1

### Pivots, determinants, eigenvalues, stability condition $x^T A x$

We have seen how can we tell if a matrix is positive definite. Why are we interested in positive definite matrices?

A 4<sup>th</sup> property of positive definite matrices is:

4. The quadratic equation  $x^T A x > 0$  (this means that if you plug any value for x in the equation  $x^T A x$ , you will always get a positive number, except for  $x = [0]$ ).

Example:  $A = \begin{bmatrix} 2 & 6 \\ 6 & 18 \end{bmatrix}$

$\det(A) = 0$  this makes A a positive semi-definite. Also, since it is a singular matrix then there must be a  $\lambda = 0$  (the other  $\lambda$  is 20 in this example). We have one pivot = 2

Now with  $x^T A x$ :

$$\begin{bmatrix} x_1 & x_2 \end{bmatrix} \begin{bmatrix} 2 & 6 \\ 6 & 18 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} x_1 & x_2 \end{bmatrix} \begin{bmatrix} 2x_1 + 6x_2 \\ 6x_1 + 18x_2 \end{bmatrix}$$

$$= \underbrace{2x_1^2 + 12x_1x_2 + 18x_2^2}_{f(x_1, x_2)}$$

(this is a quadratic form, all terms are of power 2)

now check for every  $[x_1 \ x_2]$  if this quantity  $> 0$  or there could be a non zero  $[x_1 \ x_2]$  that produces a quantity  $< 0$ . In this example, try  $(x_1 = -3, x_2 = 1)$ , the equation will  $= 0$ ) other values exist that would make the equation  $= 0$  (for example  $x_1 = 3, x_2 = -1$ ). f can never be  $< 0$  in this example, In this case, A is positive semi-definite.

Example:  $A = \begin{bmatrix} 2 & 6 \\ 6 & 7 \end{bmatrix}$

Here  $\det(A)$  is negative, pivots are 2, -11 (so it is not positive definite).

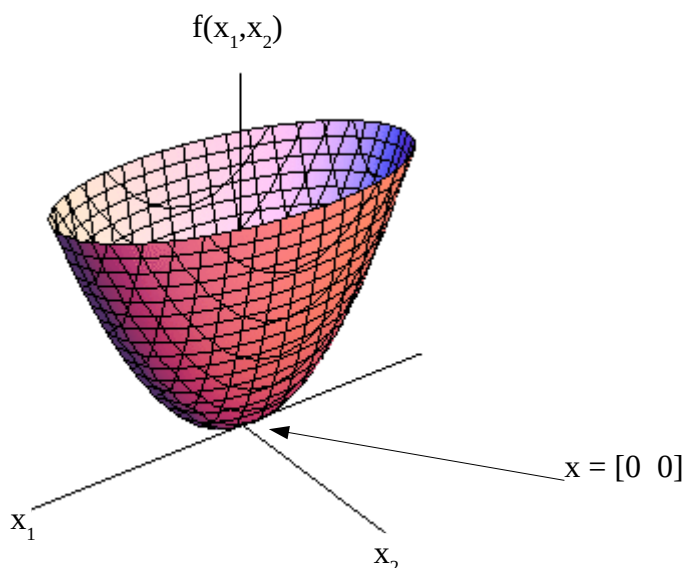
The quadratic equation:  $2x_1^2 + 12x_1x_2 + 7x_2^2$  it is easy to make it negative (take  $x_1 = 1, x_2 = -1$ ). In this case, A is not positive definite not positive semi-definite.

Example:  $A = \begin{bmatrix} 2 & 6 \\ 6 & 20 \end{bmatrix}$

You can easily find that A is positive definite here.

The quadratic equation corresponding to a symmetric matrix A:

In order to build a systematic mechanism to find if  $f(x_1, x_2)$  can be  $< 0$  for some values of  $x$  (besides  $x=[0]$ ), let's take a look at the typical shape of a quadratic equation corresponding to a positive definite  $2 \times 2$  matrix



1. Find the 1<sup>st</sup> order derivatives of  $f$  (i.e.  $\partial f / \partial x_1$  and  $\partial f / \partial x_2$ ) and equate them with 0, you will find that at  $x=[0]$  there is a minima/maxima. At  $x=[0]$  there is a minima/maxima.
2. The second order derivatives make us find out about if we increase/decrease in height as we depart the  $x=[0]$  point. Find the 2<sup>nd</sup> order derivatives and formulate the Hessian matrix:

$$H = \begin{bmatrix} \partial^2 f / \partial x_1^2 & \partial^2 f / \partial x_1 x_2 \\ \partial^2 f / \partial x_2 x_1 & \partial^2 f / \partial x_2^2 \end{bmatrix} \quad \leftarrow \text{This is the Hessian matrix for a } 2 \times 2 \text{ matrix}$$

3.  $H$  must be a positive definite in order for  $A$  to be positive semi-definite; in other words  $\det(H)$  must be  $> 0$  for  $A$  to be positive definite.

Note (and recap):

1) We resolve to using  $H$  as a check for positive definiteness (instead of the original matrix  $A$ ) because in some applications  $H$  is available while  $A$  is not.

2) If  $A$  is +def then  $A^{-1}$  is also +def. This is because eigenvalues of  $A^{-1}$  are  $1/\lambda_i$  (i.e. no change in signs of  $\lambda$ ) where  $\lambda$  is the eigenvalues of  $A$ .

3) If  $A$  is a symmetric matrix and  $\det(A) = 0$  then  $A$  is +sdef. Example,  $A = \begin{bmatrix} 1 & 3 \\ 3 & 9 \end{bmatrix}$

you still can conduct other checks (on pivot signs, on  $\lambda$  signs, and on the stability of  $x^T A x$ ) but you don't need to.

4) If  $A$  and  $B$  are +def then  $(A+B)$  is also +def. The reason is:

since  $A$  is +def then  $x^T A x > 0$  and same goes for  $B$ ;  $x^T B x > 0$

now we ask the question: is  $x^T (A+B) x > 0$  ?

$x^T A x + x^T B x > 0$  ? Yes it must be  $> 0$  because both terms are  $> 0$

5) if  $A$  is  $m \times n$  matrix (rectangular) then  $A^T A$  is square matrix, and is symmetric. But is it +def?

Let's run the test:  $x^T (A^T A) x > 0$  ?

$(x^T A^T)(A x) > 0$  ?

$(A x)^T (A x) > 0$  ? this is the length<sup>2</sup> of the vector  $A x$  so it must be  $\geq 0$

The case when  $A x = 0$  (excluding the option that  $x$  is the zero vector) could happen if  $x$  comes from the null space of  $A$  (i.e.  $\text{rank}(A) < n$ ) and the matrix  $A^T A$  is +sdef. Whereas if  $\text{rank}(A) = n$  (i.e. no null space) then the matrix  $A^T A$  is +def.

Drill exercise:

Without computing  $B = A^T A$ , is  $B$  +def or +sdef in the following cases:

$A_1 =$

$$\begin{pmatrix} 2 & 3 \\ 4 & 0 \\ -1 & 5 \end{pmatrix}$$

$A_2 =$

$$\begin{pmatrix} 3 & 4 & 0 \\ 1 & 2 & -1 \end{pmatrix}$$

6) +def matrices are computationally very safe because pivots will not be close to zero (remember we divide by pivots when we do elimination).