## Linear algebra reminders



A matrix  $A \in \mathbb{R}^{n \times p}$  has n rows and p columns

It can be seen as:

A table of numbers

A linear application:  $A: \mathbb{R}^p \to \mathbb{R}^n$ 

For  $x \in \mathbb{R}^p$ ,  $Ax \in \mathbb{R}^n$ 

## Eigenvalues

When A is square (n = p), an eigenvalue of A is a scalar  $\lambda \in \mathbb{R}$  such that for some  $x \neq 0$ :

$$Ax = \lambda x$$

 $\boldsymbol{x}$  is called an eigenvector of A

## Spectral theorem

When A is symmetric  $A^{\top} = A$  there is an orthonormal basis of eigenvectors  $x_1, \ldots, x_p$  associated to eigenvalues  $\lambda_1 \leq \cdots \leq \lambda_p$  such that :

Orthogonality: For all 
$$i \neq j$$
,  $\langle x_i, x_j \rangle = 0$   
Unit norm: For all i,  $||x_i|| = 1$   
Eigenvalues: For all i,  $Ax_i = \lambda_i x_i$ 

#### Spectral theorem, matrix formulation

**Orthogonality:** For all  $i \neq j$ ,  $\langle x_i, x_j \rangle = 0$ 

Unit norm: For all i,  $||x_i|| = 1$ 

**Eigenvalues:** For all i,  $Ax_i = \lambda_i x_i$ 

**Q:** define the p x p matrix  $U = [x_1, \ldots, x_p]$ What can we say about U?

#### Spectral theorem, matrix formulation

Define the p x p matrix  $U = [x_1, \ldots, x_p]$ 

**Orthogonality + unit norm:** U is *orthogonal* :

$$UU^{\top} = U^{\top}U = I_p$$

**Eigenvalues:**  $AU = U \operatorname{diag}(\lambda_i)$ 

$$A = U\Lambda U^{\top}$$

## Singular value decomposition (SVD)

Now, A is no longer square :  $A \in \mathbb{R}^{n \times p}$ ,  $n \ge p$ 

There exist  $U \in \mathbb{R}^{n \times p}$ ,  $V \in \mathbb{R}^{p \times p}$ , and  $0 \le \sigma_1 \le \cdots \le \sigma_p$  such that

**Orthogonality:** 
$$U^{\top}U = V^{\top}V = I_p$$
  $!!UU^{\top} \neq I_n$ 

**Decomposition:**  $A = U\Sigma V^{\top}, \ \Sigma = \operatorname{diag}(\sigma_i)$ 

The  $\sigma_i$  are called the singular values of A

# Link between spectral theorem and SVD

**Question :** how can we recover the SVD of A using the spectral theorem ?

Hint: you can use an analysis-synthesis reasoning. If  $A = U\Sigma V^{\top}$  is the SVD of A, does V correspond to the eigenvalue decomposition of some matrix?

#### Matrix norms

There are many ways to define norms on matrices. Two important:

Frobenius: 
$$||A||_F = \sqrt{\sum_{i,j=1}^n A_{ij}^2}$$

**Spectral:** 
$$||A||_2 = \max_{||x||=1} ||Ax||$$

**Q**: can you relate these quantities to the singular values of A?