

# Linear algebra VI

## Spectral decomposition

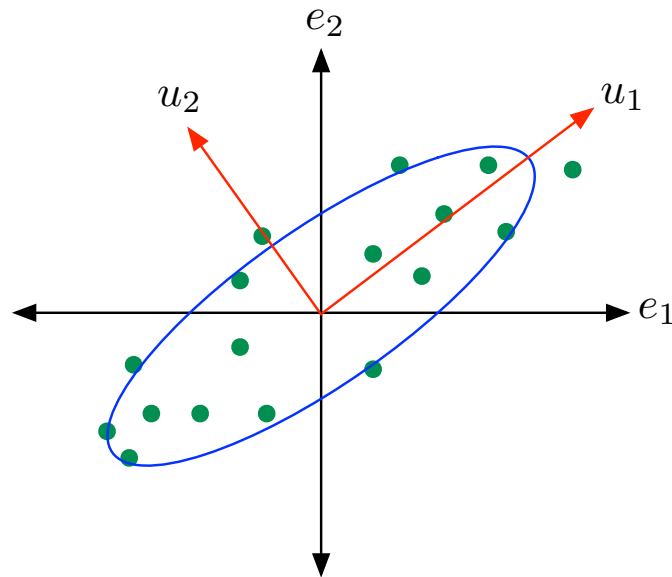
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### Topics we'll cover

- ① The eigenbasis as a natural coordinate system for a matrix
- ② Spectral decomposition of a symmetric matrix
- ③ Principal component analysis revisited

## Moving between coordinate systems



## Eigenvectors and eigenvalues

Let  $M$  be a  $d \times d$  matrix. We say  $u \in \mathbb{R}^d$  is an **eigenvector** of  $M$  if

$$Mu = \lambda u$$

for some scaling constant  $\lambda$ . This  $\lambda$  is the **eigenvalue** associated with  $u$ .

Key point:  $M$  **maps eigenvector  $u$  onto the same direction.**

**Fact:** Let  $M$  be any real symmetric  $d \times d$  matrix. Then  $M$  has

- $d$  eigenvalues  $\lambda_1, \dots, \lambda_d$
- corresponding eigenvectors  $u_1, \dots, u_d \in \mathbb{R}^d$  that are orthonormal

**Eigenvectors: axes of a natural coordinate system for  $M$ .**

## Spectral decomposition

**Fact:** Let  $M$  be any real symmetric  $d \times d$  matrix. Then  $M$  has orthonormal eigenvectors  $u_1, \dots, u_d \in \mathbb{R}^d$  and corresponding eigenvalues  $\lambda_1, \dots, \lambda_d$ .

**Spectral decomposition:** Another way to write  $M$ :

$$M = \underbrace{\begin{pmatrix} \uparrow & \uparrow & & \uparrow \\ u_1 & u_2 & \cdots & u_d \\ \downarrow & \downarrow & & \downarrow \end{pmatrix}}_{U: \text{ columns are eigenvectors}} \underbrace{\begin{pmatrix} \lambda_1 & 0 & \cdots & 0 \\ 0 & \lambda_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \lambda_d \end{pmatrix}}_{\Lambda: \text{ eigenvalues on diagonal}} \underbrace{\begin{pmatrix} \leftarrow u_1 \rightarrow \\ \leftarrow u_2 \rightarrow \\ \vdots \\ \leftarrow u_d \rightarrow \end{pmatrix}}_{U^T}$$

Thus  $Mx = U\Lambda U^T x$ :

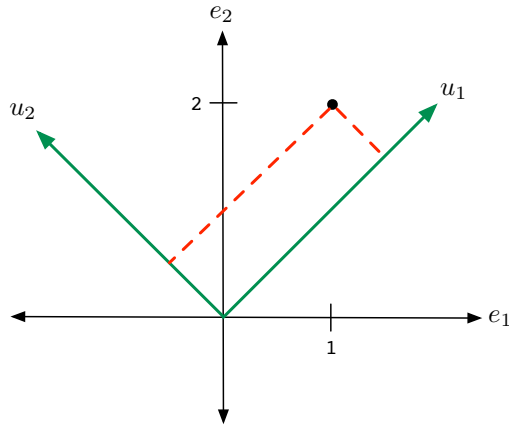
- $U^T$  rewrites  $x$  in the  $\{u_i\}$  coordinate system
- $\Lambda$  is a simple coordinate scaling in that basis
- $U$  sends the scaled vector back into the usual coordinate basis

Apply spectral decomposition to the matrix we saw earlier:  $M = \begin{pmatrix} 1 & -2 \\ -2 & 1 \end{pmatrix}$

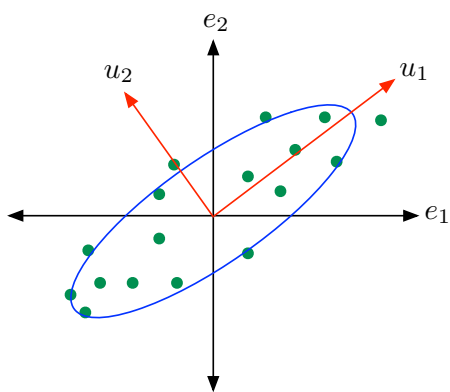
- Eigenvectors  $u_1 = \frac{1}{\sqrt{2}} \begin{pmatrix} 1 \\ 1 \end{pmatrix}$ ,  $u_2 = \frac{1}{\sqrt{2}} \begin{pmatrix} -1 \\ 1 \end{pmatrix}$
- Eigenvalues  $\lambda_1 = -1$ ,  $\lambda_2 = 3$ .

$$M = \begin{pmatrix} 1 & -2 \\ -2 & 1 \end{pmatrix} = \underbrace{\frac{1}{\sqrt{2}} \begin{pmatrix} 1 & -1 \\ 1 & 1 \end{pmatrix}}_U \underbrace{\begin{pmatrix} -1 & 0 \\ 0 & 3 \end{pmatrix}}_\Lambda \underbrace{\frac{1}{\sqrt{2}} \begin{pmatrix} 1 & 1 \\ -1 & 1 \end{pmatrix}}_{U^T}$$

$$M \begin{pmatrix} 1 \\ 2 \end{pmatrix} = U \Lambda U^T \begin{pmatrix} 1 \\ 2 \end{pmatrix}$$



## Principal component analysis revisited



Data vectors  $X \in \mathbb{R}^d$

- Covariance matrix  $\Sigma$  is a  $d \times d$  symmetric matrix.
- Eigenvalues  $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_d$   
Eigenvectors  $u_1, \dots, u_d$ .
- $u_1, \dots, u_d$ : another basis in which to represent data.
- Variance of  $X$  in direction  $u_i$  is  $\lambda_i$ .
- Projection to  $k$  dimensions:  $x \mapsto (x \cdot u_1, \dots, x \cdot u_k)$ .

What is the covariance of the projected data?