Lecture 7.1: Consequences of the spectral theorem

Optimization and Computational Linear Algebra for Data Science

The Spectral theorem

Theorem

Let $A \in \mathbb{R}^{n \times n}$ be a **symmetric** matrix. Then there is a orthonormal basis of \mathbb{R}^n composed of eigenvectors of A.

That means that if A is symmetric, then there exists an orthonormal basis (v_1, \ldots, v_n) of \mathbb{R}^n and $\lambda_1, \ldots, \lambda_n \in \mathbb{R}$ such that

$$Av_i = \lambda_i v_i$$
 for all $i \in \{1, \dots, n\}$.

Theorem (Matrix formulation)

Let $A \in \mathbb{R}^{n \times n}$ be a **symmetric** matrix. Then there exists an orthogonal matrix P and a diagonal matrix D of sizes $n \times n$ such that

$$A = PDP^{\mathsf{T}}.$$

lf

$$A = P \begin{pmatrix} \lambda_1 & 0 & \cdots & 0 \\ 0 & \lambda_2 & & \vdots \\ \vdots & & \ddots & 0 \\ 0 & \cdots & 0 & \lambda_n \end{pmatrix} P^{\mathsf{T}}$$

for some orthogonal matrix *P* then:

Consequence #1: $\lambda_1, \ldots, \lambda_n$ are the only eigenvalues of A, and the number of time that an eigenvalue appear on the diagonal equals its multiplicity.

Proof sketch on an example

Consider n=3 and

$$A = P \begin{pmatrix} 3 & 0 & 0 \\ 0 & 3 & 0 \\ 0 & 0 & -1 \end{pmatrix} P^{\mathsf{T}} \quad \text{where} \quad P = \begin{pmatrix} | & | & | \\ v_1 & v_2 & | & v_3 \\ | & & | & | \end{pmatrix}$$

is an orthogonal matrix.

$$Av_1 = PDP^Tv_1 = PDe_1 = P(3e_n) = 3v_1$$

 $Av_2 = 3v_2$
 $Av_3 = -1v_3$

. dim $E_3(A) > 2$ and dim $E_1(A) > 1$

• dim
$$E_3(A)$$
 + dim $E_{-1}(A)$ ≤ 3

• therefore $| \text{clim } E_3(A) = 2$ and there is no other eigenvalues $| \text{clim } E_3(A) = 1$

lf

$$A = P \begin{pmatrix} \lambda_1 & 0 & \cdots & 0 \\ 0 & \lambda_2 & & \vdots \\ \vdots & & \ddots & 0 \\ 0 & \cdots & 0 & \lambda_n \end{pmatrix} P^{\mathsf{T}}$$

for some orthogonal matrix P then:

Consequence #2: The rank of A equals to the number of non-zero λ_i 's on the diagonal:

$$\operatorname{rank}(A) = \#\{i \mid \lambda_i \neq 0\}.$$

Proof

lf

$$A = P \begin{pmatrix} \lambda_1 & 0 & \cdots & 0 \\ 0 & \lambda_2 & & \vdots \\ \vdots & & \ddots & 0 \\ 0 & \cdots & 0 & \lambda_n \end{pmatrix} P^{\mathsf{T}}$$

for some orthogonal matrix P then:

Consequence #3: \underline{A} is invertible if and only if $\lambda_i \neq 0$ for all i. In such

case

$$A^{-1} = P \begin{pmatrix} 1/\lambda_1 & 0 & \cdots & 0 \\ 0 & 1/\lambda_2 & & \vdots \\ \vdots & & \ddots & 0 \\ 0 & \cdots & 0 & 1/\lambda_n \end{pmatrix} P^{\mathsf{T}}$$

Proof

A is invertible
$$\Rightarrow$$
 rount(A) = n (consequence 2)

Assume $\lambda_1 \neq 0$ for all i then:

A

P Diag(λ_2 --- λ_n) P^T P Diag(λ_1^2 , --- λ_n^{-1}) P^T) = A^{-1}

= P Diag($1, 1, ..., 1$) P^T

= Id.

lf

$$A = P \begin{pmatrix} \lambda_1 & 0 & \cdots & 0 \\ 0 & \lambda_2 & & \vdots \\ \vdots & & \ddots & 0 \\ 0 & \cdots & 0 & \lambda_n \end{pmatrix} P^{\mathsf{T}}$$

for some orthogonal matrix P then:

Consequence #4:
$$\operatorname{Tr}(A) = \lambda_1 + \cdots + \lambda_n$$
.

$$Tr(A) = Tr(PDP^{T}) = Tr(P^{T}PD)$$

$$= Tr(D) = \lambda_{1} + \dots + \lambda_{n}$$