

11/19/2021

Last time

→ more properties of eigenvalues/vectors for special matrices.

summary:

- If $\underline{A} \in \mathbb{R}^{n \times n}$ has an eigenpair $(\underline{v}, \lambda)$, then $(\underline{\bar{v}}, \bar{\lambda})$ is also an eigenpair.
- If $\underline{A} = \underline{A}^*$, then its eigenvalues are real.
- Eigenvectors corresponding to distinct eigenvalues are linearly independent.
- For $\underline{A} \in \mathbb{R}^{n \times n}$, $\underline{A} = \underline{A}^T$, eigenvectors corresponding to distinct eigenvalues are orthogonal.

Thm: For $\underline{A} \in \mathbb{R}^{n \times n}$, $\underline{A} = \underline{A}^T$, there exists orthogonal $\underline{Q}$ and diagonal $\underline{\Lambda}$ so that

$$\underline{A} = \underline{Q} \underline{\Lambda} \underline{Q}^T.$$

Symmetric positive (semi) definite matrices

Def: A symmetric matrix $\underline{S} \in \mathbb{R}^{n \times n}$ is called positive definite if $\underline{v}^T \underline{S} \underline{v} > 0$ for all $\underline{v} \in \mathbb{R}^n$, $\underline{v} \neq \underline{0}$.

Def: A symmetric matrix $\underline{S} \in \mathbb{R}^{n \times n}$ is called positive semidefinite if

$$\underline{v}^T \underline{S} \underline{v} \geq 0 \quad \text{for all } \underline{v} \in \mathbb{R}^n.$$

Ex: $\begin{pmatrix} \pi & 0 \\ 0 & 5 \end{pmatrix}$ is Spd
(symmetric positive def.)

$$\begin{aligned} (v_1, v_2) \begin{pmatrix} \pi & 0 \\ 0 & 5 \end{pmatrix} \begin{pmatrix} v_1 \\ v_2 \end{pmatrix} &= (\pi v_1, 5v_2) \begin{pmatrix} v_1 \\ v_2 \end{pmatrix} \\ &= \pi v_1^2 + 5v_2^2. \end{aligned}$$

Note that $\pi v_1^2 + 5v_2^2 > 0$ if $v_1 \neq 0$ or $v_2 \neq 0$.

Ex: $\begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix}$ is symmetric positive semidefinite.

$$(v_1, v_2) \begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix} \begin{pmatrix} v_1 \\ v_2 \end{pmatrix} = v_1^2 \geq 0.$$

$$\text{Notice that } (0, \pi) \begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix} \begin{pmatrix} 0 \\ \pi \end{pmatrix} = 0.$$

Thm: A symmetric matrix $\underline{S} \in \mathbb{R}^{n \times n}$ is positive (semi) definite $\Leftrightarrow$ its eigenvalues are (nonnegative) positive.

Pf: $\underline{S} = \underline{Q} \underline{\Lambda} \underline{Q}^T$
since $\underline{S}$ is symmetric.

For $y \in \mathbb{R}^n$, look at

$$\begin{aligned} y^T \underline{S} y &= y^T \underline{Q} \underline{\Lambda} \underline{Q}^T y \\ &= \underline{z}^T \underline{\Lambda} \underline{z} \quad (\underline{z} = \underline{Q}^T y) \\ &= \sum_{i=1}^n z_i^2 \lambda_i. \end{aligned}$$

If $\lambda_i \geq 0$, then $y^T \underline{S} y \geq 0$ for any y .

If $y \neq 0$, then $\underline{z} \neq 0$ since $\underline{Q}^T$ is invertible,
so then $y^T \underline{S} y > 0 \Leftrightarrow \lambda_i > 0 \quad \forall i$.

Singular Value Decomposition (SVD)

Any matrix $\underline{A} \in \mathbb{R}^{m \times n}$ can be factored as:

$$\underline{A} = \underline{U} \underline{\Sigma} \underline{V}^T,$$

where $\underline{U} \in \mathbb{R}^{m \times m}$, $\underline{V} \in \mathbb{R}^{n \times n}$ are orthogonal matrices,
and $\underline{\Sigma} \in \mathbb{R}^{m \times n}$ is "diagonal".

Ex: $\underline{A} = \begin{pmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \end{pmatrix}$

In order to get the SVD, we are going to diagonalize $\underline{A}^T \underline{A}$ and $\underline{A} \underline{A}^T$.

$$\underline{A}^T \underline{A} = \begin{pmatrix} 1 & 1 \\ 1 & 1 \\ 1 & 1 \end{pmatrix} \begin{pmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \end{pmatrix} = \begin{pmatrix} 2 & 2 & 2 \\ 2 & 2 & 2 \\ 2 & 2 & 2 \end{pmatrix}$$

$$\underline{A} \underline{A}^T = \begin{pmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \end{pmatrix} \begin{pmatrix} 1 & 1 \\ 1 & 1 \\ 1 & 1 \end{pmatrix} = \begin{pmatrix} 3 & 3 \\ 3 & 3 \end{pmatrix}$$

Note that $\left(\begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}, 6 \right)$ is an eigenpair of $\underline{A}^T \underline{A}$.

$\left(\begin{pmatrix} 1 \\ 1 \end{pmatrix}, 6 \right)$ is an eigenpair of $\underline{A} \underline{A}^T$.

Notice that we can write

$$\underline{A} = \begin{pmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \end{pmatrix} = \sqrt{6} \underbrace{\begin{pmatrix} \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} \end{pmatrix}}_{\text{normalized eigenvector of } \underline{A} \underline{A}^T} \underbrace{\begin{pmatrix} \frac{1}{\sqrt{3}} & \frac{1}{\sqrt{3}} & \frac{1}{\sqrt{3}} \end{pmatrix}}_{\text{normalized eigenvector of } \underline{A}^T \underline{A}}.$$

We also see that

$$\left(\begin{pmatrix} -1 \\ 1 \\ 0 \end{pmatrix}, 0 \right), \left(\begin{pmatrix} 1 \\ 1 \\ -2 \end{pmatrix}, 0 \right) \text{ are the remaining eigenvectors of } \underline{A}^T \underline{A}$$

$$\text{and } \left(\begin{pmatrix} 1 \\ -1 \\ 1 \end{pmatrix}, 0 \right) \text{ is the remaining eigenvector for } \underline{A} \underline{A}^T,$$

$$\text{so } \begin{pmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \end{pmatrix} = \sqrt{6} \begin{pmatrix} \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} \end{pmatrix} \begin{pmatrix} \frac{1}{\sqrt{3}} & \frac{1}{\sqrt{3}} & \frac{1}{\sqrt{3}} \end{pmatrix}$$

$$= \underbrace{\begin{pmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} \end{pmatrix}}_{\underline{U}} \underbrace{\begin{pmatrix} \sqrt{6} & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}}_{\underline{\Sigma}} \underbrace{\begin{pmatrix} \frac{1}{\sqrt{3}} & \frac{1}{\sqrt{3}} & \frac{1}{\sqrt{3}} \\ -\frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} & 0 \\ \frac{1}{\sqrt{6}} & \frac{1}{\sqrt{6}} & -\frac{2}{\sqrt{6}} \end{pmatrix}}_{\underline{V}^T}$$

Notice: $\dim R(\underline{A}) = 1$ for

$$\underline{A} = \begin{pmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \end{pmatrix} \text{ and its SVD}$$

$$\underline{A} = \sigma_1 \underline{u}_1 \underline{v}_1^T,$$

$$\sigma_1 = \sqrt{6}, \underline{u}_1 = \begin{pmatrix} \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} \end{pmatrix}, \underline{v}_1 = \begin{pmatrix} \frac{1}{\sqrt{3}} \\ \frac{1}{\sqrt{3}} \\ \frac{1}{\sqrt{3}} \end{pmatrix}$$

contains a single "rank one" piece.

Def: The left singular vectors ($\underline{u}$) are the eigenvectors of $\underline{A} \underline{A}^T$.

Def: The right singular vectors ($\underline{v}$) are the eigenvectors of $\underline{A}^T \underline{A}$.

$$\text{So, we have } \underline{A} \underline{A}^T \underline{u}_i = \sigma_i^2 \underline{u}_i$$

$$\underline{A}^T \underline{A} \underline{v}_i = \sigma_i^2 \underline{v}_i.$$

Def: The singular values are the square roots of the nonzero eigenvalues of $\underline{A} \underline{A}^T$ or $\underline{A}^T \underline{A}$.

Question: Why are the nonzero eigenvalues of $\underline{A}\underline{A}^T$ and $\underline{A}^T\underline{A}$ the same?

Take $(\underline{x}, \lambda)$ an eigenpair of $\underline{A}\underline{A}^T$, $\lambda \neq 0$.

$$\Rightarrow \underline{A}\underline{A}^T \underline{x} = \lambda \underline{x}.$$

Notice that $\underline{A}^T \underline{x} \neq \underline{0}$ since $\lambda \neq 0$ and $\underline{x} \neq \underline{0}$. Applying $\underline{A}^T$ to both sides:

$$\underline{A}^T \underline{A} (\underline{A}^T \underline{x}) = \lambda (\underline{A}^T \underline{x}),$$

so $(\underline{A}^T \underline{x}, \lambda)$ is an eigenpair of $\underline{A}^T \underline{A}$.

Construction of the SVD.

If $(\underline{u}_i, \sigma_i^2)$, $\sigma_i \neq 0$ is an eigenpair of $\underline{A}\underline{A}^T$, then by the above argument

$\leadsto (\underline{v}_i = \sigma_i^{-1} \underline{A}^T \underline{u}_i, \sigma_i^2)$ is an eigenpair of $\underline{A}^T \underline{A}$.

This selection implies $\underline{A} \underline{v}_i = \sigma_i \underline{u}_i$.

Why is $\underline{v}_i$ scaled by σ_i^{-1} ?

$$\begin{aligned}\|\underline{v}_i\|_2^2 &= \underline{v}_i^T \underline{v}_i = \sigma_i^{-2} (\underline{A}^T \underline{u}_i)^T \underline{A}^T \underline{u}_i \\ &= \sigma_i^{-2} \underline{u}_i^T \underline{A} \underline{A}^T \underline{u}_i = \sigma_i^{-2} \sigma_i^2 = 1,\end{aligned}$$

So $\underline{v}_i$ is normalized!

Finally, $\underline{A} \underline{v}_i = \sigma_i \underline{u}_i$ can be expressed in matrix form as:

$$\underline{A} \begin{pmatrix} \underline{v}_1 & \dots & \underline{v}_r \\ | & & | \end{pmatrix} = \begin{pmatrix} \underline{u}_1 & \dots & \underline{u}_r \\ | & & | \end{pmatrix} \underline{\Sigma}.$$
