readme

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Contents

Things i keep forgetting 

1 Norms

def

1. Positivity $\|x\| \geq 0$
2. Positive definiteness $\|x\| = 0 \iff x = 0$
3. Homogeneity $\|\alpha x\| = |\alpha| \|x\|$ for arbitrary scalar α
4. Triangle inequality $\|x + y\| \leq \|x\| + \|y\|$

Note: not sure if this holds for ever norm

The different matrix ones (Norms on $A \in \mathbb{R}^{m \times n}$)

$$\|A\|_1 = \max_{1 \leq j \leq n} \sum_{i=1}^{m} |a_{ij}|$$

$$\|A\|_2 = \sqrt{\lambda_{\max}\left(A^T A\right)}$$

Frobenius norm, sometimes also called the Euclidean norm

$$\|\mathrm{A}\|_F \equiv \sqrt{\sum_{i=1}^{m} \sum_{j=1}^{n} |a_{ij}|^2}$$

$$\|A\|_\infty = \max_{1 \leq i \leq m} \sum_{j=1}^{n} |a_{ij}|$$

Vector norms (Norms on $\mathbb{R}^n$)

$$|\mathbf{x}|_p \equiv \left(\sum_i |x_i|^p\right)^{1/p}$$

special case:

$$|\mathbf{x}|_\infty \equiv \max_i |x_i|$$

Tips: pretty sure think $\|\cdot\|$ usually just refers to the 2-norm.

Scalar norm (Norm on $C[a,b]$)

$$\left.\begin{array}{ll} \|f\|_p = \left(\int_a^b |f(\tau)|^p d\tau\right)^{\frac{1}{p}}, & p \in [1,\infty] \\ \|f\|_\infty = \sup\limits_{a\leq t\leq b} |f(t)| & \end{array}\right\} \mathscr{L}_p - \text{ norms} \tag{1}$$

$$C[0,\infty), \mathscr{L}_p \text{ is a Banach space}$$

$f \in \mathscr{L}_p \Leftrightarrow \|f\|_p$ is bounded, i.e. $\exists c : \|f\|_p \leq c$

2 Tensor rank

rank	object
0	scalar
1	vector
2	matrix (/Dyad)
≥ 3	tensor

Also sometimes triad, tetrad are used to refer to tensors of rank 3 and 4 respectivly. Some refer to the rank of a tensor as its order or its degree.

3 SVD

Example: $A = \begin{bmatrix} 0 & 1 & 1 \\ \sqrt{2} & 2 & 0 \\ 0 & 1 & 1 \end{bmatrix}$

The SVD is defined as

$$A = P\Sigma Q^T$$

Method

Computing:

$$AA^T = \begin{bmatrix} 2 & 2 & 2 \\ 2 & 6 & 2 \\ 2 & 2 & 2 \end{bmatrix}$$

$$\begin{aligned} -\lambda^3 + 10\lambda^2 - 16\lambda &= -\lambda\left(\lambda^2 - 10\lambda + 16\right) \\ &= -\lambda(\lambda-8)(\lambda-2) \end{aligned} \tag{2}$$

Eigenvals of AA^T are $\lambda = 8, \lambda = 2, \lambda = 0$, thus the singular values are $\sigma_1 = 2\sqrt{2}, \sigma_2 = \sqrt{2}$ (and $\sigma_3 = 0$).

Giving out the matrix

$$\Sigma = 0_{3x3} + \sigma = \begin{bmatrix} 2\sqrt{2} & 0 & 0 \\ 0 & \sqrt{2} & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

Finding the eigenvectors $(A-\lambda I)\mathbf{x}=\mathbf{0}$, we get respetivly to the egienvector who is described before: $p_1 = \left(\frac{1}{\sqrt{6}}, \frac{2}{\sqrt{6}}, \frac{1}{\sqrt{6}}\right)$, $p_2 = \left(-\frac{1}{\sqrt{3}}, \frac{1}{\sqrt{3}}, -\frac{1}{\sqrt{3}}\right)$ and $p_3 = \left(\frac{1}{\sqrt{2}}, 0, -\frac{1}{\sqrt{2}}\right)$ (note: normalised vectors).

Yeilding

$$P = \left[{p_1}^T {p_2}^T {p_3}^T\right] = \begin{bmatrix} \frac{1}{\sqrt{6}} & -\frac{1}{\sqrt{3}} & \frac{1}{\sqrt{2}} \\ \frac{2}{\sqrt{6}} & \frac{1}{\sqrt{3}} & 0 \\ \frac{1}{\sqrt{6}} & -\frac{1}{\sqrt{3}} & -\frac{1}{\sqrt{2}} \end{bmatrix}$$

$$A^T A = \begin{bmatrix} 2 & 2\sqrt{2} & 0 \\ 2\sqrt{2} & 6 & 2 \\ 0 & 2 & 2 \end{bmatrix}$$

With the eigenvals $\lambda = 8, \lambda = 2, \lambda = 0$ with eigenvectors $q_1 = \left(\frac{1}{\sqrt{6}}, \frac{3}{\sqrt{12}}, \frac{1}{\sqrt{12}}\right), q_2 = \left(\frac{1}{\sqrt{3}}, 0, -\frac{2}{\sqrt{6}}\right)$ and $q_3 = \left(\frac{1}{\sqrt{2}}, -\frac{1}{2}, \frac{1}{2}\right)$. (Acually can also use the the formula $p_i = \frac{1}{\sigma_i} A^T p_i$ to get the various q_i.

$$Q = \left[{q_1}^T {q_2}^T {q_3}^T\right] \begin{bmatrix} \frac{1}{\sqrt{6}} & \frac{1}{\sqrt{3}} & \frac{1}{\sqrt{2}} \\ \frac{3}{\sqrt{12}} & 0 & -\frac{1}{2} \\ \frac{1}{\sqrt{12}} & -\frac{2}{\sqrt{6}} & \frac{1}{2} \end{bmatrix}$$

We have then the SVD defined as

$$A = P\Sigma Q^T$$

4 Covar