Medical Image Processing for Diagnostic Applications

Singular Value Decomposition

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Topics

Singular Value Decomposition (SVD) - Part 1 General Remarks On the Geometry of Linear Mappings Normal Form of Matrices: SVD







Singular Value Decomposition

- Powerful normal form for matrices that allows for a simple solution of most linear problems in imaging and image processing.
- SVD is a method from linear algebra ...
 - ... invented in the 19th century.
 - ... rediscovered and pushed for practical applications by Gene Golub.
 - ... established in computer vision by Carlo Tomasi's famous factorization algorithm to compute structure and camera motion from image sequences.
 - ... which is extremely robust and simple to use.







Singular Value Decomposition

SVD is a perfect tool, e.g., for

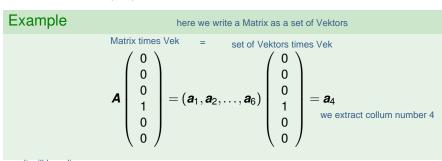
- the computation of singular values,
- the computation of the null space,
- the computation of the (pseudo-) inverse,
- the solution of overdetermined linear equations,
- the computation of condition numbers,
- enforcing a rank criterion (numerical rank),
- and other applications of matrices.







From linear algebra, we know that a matrix $\mathbf{A} \in \mathbb{R}^{m \times n}$ maps the unit vectors $e_i \in \mathbb{R}^n$ of the standard base to the corresponding column vectors $\mathbf{a}_i \in \mathbb{R}^m$ of the matrix \boldsymbol{A} , $i = 1, \dots, n$.



result will be a linear kombination of the collum vectors in the set

AR = 2 x + 2 x + ... + 2 x

Nx6 * 6x1 = Nx1result is a vektor







In the example we have made use of the following notation:

$$m{A} = egin{pmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & \ddots & & & \\ \vdots & & & & \\ a_{m1} & & & a_{mn} \end{pmatrix} = (m{a}_1, m{a}_2, \dots, m{a}_n).$$

We can write:

$$Ax = a_1x_1 + a_2x_2 + ... + a_nx_n$$

and for the first two unit vectors $\mathbf{e}_1 = (1, 0, 0, ..., 0)^T$, $\mathbf{e}_2 = (0, 1, 0, ..., 0)^T$ find:

$$Ae_1 = a_1, Ae_2 = a_2.$$







Rotate vector by multiplying with rotation matrix

Example

Compute the orthogonal matrix \mathbf{R} , i. e., $\mathbf{R}^{-1} = \mathbf{R}^{\mathsf{T}}$, that rotates points in the 2-D image plane by the angle θ .

Solution:

The base vectors are mapped as follows:

$$\left(\begin{array}{c}1\\0\end{array}\right)\mapsto \left(\begin{array}{c}\cos\theta\\\sin\theta\end{array}\right),\quad \left(\begin{array}{c}0\\1\end{array}\right)\mapsto \left(\begin{array}{c}-\sin\theta\\\cos\theta\end{array}\right),$$

and thus the 2-D rotation matrix is:

$$\mathbf{R} = \begin{pmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{pmatrix}.$$
-> eigentlich logisch, kann man sich herleiten

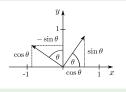


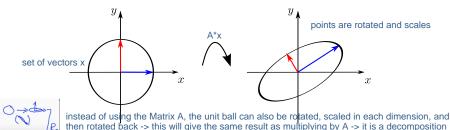
Figure 1: Rotation of 2-D unit vectors



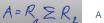




If **A** is a real $m \times n$ – matrix of rank r, then **A** maps the unit hyper-sphere in the *n*-dimensional space to an *r*-dimensional hyperellipsoid in the *m*-dimensional space.







A is rotation, skaling, rotation







Normal Form of Matrices: SVD

ortogonal -> rechtwinklige achsen -> rotationsmatrix

Theorem

If **A** is a real $m \times n$ – matrix, then there exist orthogonal matrices $\mathbf{U} \in \mathbb{R}^{m \times m}$ and $\mathbf{V} \in \mathbb{R}^{n \times n}$ such that

 $\mathbf{A} = \mathbf{U} \mathbf{\Sigma} \mathbf{V}^{\mathsf{T}}$. U and V are the rotations

where

 $oldsymbol{\Sigma} = \mathsf{diag}ig(\sigma_1, \sigma_2, \dots, \sigma_pig) \in \mathbb{R}^{m imes n}$ singular values -> usually ordered by size

with $p = \min\{m, n\}$. The diagonal elements σ_i are the singular values that fulfill

$$\sigma_1 \geq \sigma_2 \geq \cdots \geq \sigma_p \geq 0.$$







Topics

Summary Take Home Messages **Further Readings**







Take Home Messages

- SVD is a useful tool to solve a multitude of problems.
- We studied the effect of a matrix on unit vectors and the unit sphere.
- An arbitrary real matrix \boldsymbol{A} can be decomposed by $\boldsymbol{A} = \boldsymbol{U} \boldsymbol{\Sigma} \boldsymbol{V}^{\mathsf{T}}$.







Further Readings

Read the original:

Gene H. Golub and Charles F. Van Loan. *Matrix Computations*. 3rd ed. Johns Hopkins Studies in the Mathematical Sciences. Baltimore: The Johns Hopkins University Press. Oct. 1996

A very detailed and easy to follow introduction of the SVD can be found in:

Carlo Tomasi's class notes, chapter 3 (a must-read).

The theory is described in an easy to read format in:

Llovd N. Trefethen and David Bau III. Numerical Linear Algebra. Philadelphia: SIAM, 1997

For details about the numerical computation of SVD see:

William H. Press et al. Numerical Recipes - The Art of Scientific Computing. 3rd ed. Cambridge University Press, 2007. Get at http://numerical.recipes/(August 2016).

Finally, have a look at:

Kaare Brandt Petersen and Michael Syskind Pedersen. The Matrix Cookbook. Online. Accessed: 25. April 2017. Technical University of Denmark, Nov. 2012. URL: http://www2.imm.dtu.dk/pubdb/p.php?3274