

Linear Algebra (Review)

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Vectors

- k, M, N are scalars
- A one-dimensional array \mathbf{c} is a column vector. Thus in two dimensions,

$$\mathbf{c} = \begin{pmatrix} c_1 \\ c_2 \end{pmatrix}$$

- c_i is the i -th component of \mathbf{c}
- $\mathbf{c}^T = (c_1, c_2)$ is a row vector, the transposed of \mathbf{c}

Matrices

- A two-dimensional array \mathbf{A} is a matrix, e.g.,

$$\mathbf{A} = \begin{bmatrix} a_{1,1} & a_{1,2} & a_{1,3} \\ a_{2,1} & a_{2,2} & a_{2,3} \end{bmatrix}$$

- If \mathbf{A} is an $N \times M$ -dimensional matrix,
 - then the transposed \mathbf{A}^T is an $M \times N$ -dimensional matrix
 - the columns (rows) of \mathbf{A} are the rows (columns) of \mathbf{A}^T and vice versa

$$\mathbf{A}^T = \begin{bmatrix} a_{1,1} & a_{2,1} \\ a_{1,2} & a_{2,2} \\ a_{1,3} & a_{2,3} \end{bmatrix}$$

Addition of Two Vectors

- Let $\mathbf{c} = \mathbf{a} + \mathbf{d}$
- Then $c_j = a_j + d_j$

Multiplication of a Vector with a Scalar

- $\mathbf{c} = k\mathbf{a}$ is a vector with $c_j = ka_j$
- $\mathbf{C} = k\mathbf{A}$ is a matrix of the dimensionality of \mathbf{A} , with $c_{i,j} = ka_{i,j}$

Scalar Product of Two Vectors

- The **scalar product** (also called dot product) is defines as

$$\mathbf{a} \cdot \mathbf{c} = \mathbf{a}^T \mathbf{c} = \sum_{j=1}^M a_j c_j$$

and is a scalar

- Special case:

$$\mathbf{a}^T \mathbf{a} = \sum_{j=1}^M a_j^2$$

Matrix-Vector Product

- A matrix consists of many row vectors. So a product of a matrix with a column vector consists of many scalar products of vectors
- If \mathbf{A} is an $N \times M$ -dimensional matrix and \mathbf{c} is an M -dimensional column vector
- Then $\mathbf{d} = \mathbf{A}\mathbf{c}$ is an N -dimensional column vector \mathbf{d} with

$$d_i = \sum_{j=1}^M a_{i,j}c_j$$

Matrix-Matrix Product

- A matrix also consists of many column vectors. So a product of matrix with a matrix consists of many matrix-vector products
- If \mathbf{A} is an $N \times M$ -dimensional matrix and \mathbf{C} an $M \times K$ -dimensional matrix
- Then $\mathbf{D} = \mathbf{AC}$ is an $N \times K$ -dimensional matrix with

$$d_{i,k} = \sum_{j=1}^M a_{i,j}c_{j,k}$$

Multiplication of a Row-Vector with a Matrix

- **Multiplication of a row vector with a matrix is a row vector.** If A is a $N \times M$ -dimensional matrix and \mathbf{d} a N -dimensional vector and if

$$\mathbf{c}^T = \mathbf{d}^T A$$

Then \mathbf{c} is a M -dimensional vector with $c_j = \sum_{i=1}^N d_i a_{i,j}$

Outer Product

- Special case: **Multiplication of a column vector with a row vector is a matrix.**

Let \mathbf{d} be a N -dimensional vector and \mathbf{c} be a M -dimensional vector, then

$$\mathbf{A} = \mathbf{d}\mathbf{c}^T$$

is an $N \times M$ matrix with $a_{i,j} = d_i c_j$

Example:

$$\begin{bmatrix} d_1 c_1 & d_1 c_2 & d_1 c_3 \\ d_2 c_1 & d_2 c_2 & d_2 c_3 \end{bmatrix} = \begin{bmatrix} d_1 \\ d_2 \end{bmatrix} \begin{bmatrix} c_1 & c_2 & c_3 \end{bmatrix}$$

Matrix Transposed

- The transposed \mathbf{A}^T changes rows and columns
- We have

$$\left(\mathbf{A}^T\right)^T = \mathbf{A}$$

$$(\mathbf{AC})^T = \mathbf{C}^T \mathbf{A}^T$$

Unit Matrix

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$$\mathbf{I} = \begin{pmatrix} 1 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 \\ & & \dots & \\ 0 & \dots & 0 & 1 \end{pmatrix}$$

Diagonal Matrix

- $N \times N$ diagonal matrix:

$$\mathbf{A} = \begin{pmatrix} a_{1,1} & 0 & \dots & 0 \\ 0 & a_{2,2} & \dots & 0 \\ & & \dots & \\ 0 & \dots & 0 & a_{N,N} \end{pmatrix}$$

Matrix Inverse

- Let \mathbf{A} be an $N \times N$ square matrix
- If there is a unique inverse matrix \mathbf{A}^{-1} , then we have

$$\mathbf{A}^{-1}\mathbf{A} = \mathbf{I} \quad \mathbf{A}\mathbf{A}^{-1} = \mathbf{I}$$

- If the corresponding inverse exist, $(\mathbf{AC})^{-1} = \mathbf{C}^{-1}\mathbf{A}^{-1}$

Orthogonal Matrices

- **Orthogonal Matrix** (more precisely: Orthonormal Matrix): \mathbf{R} is a (quadratic) orthogonal matrix, if all columns are orthonormal. It follows (non-trivially) that all rows are orthonormal as well and

$$\mathbf{R}^T \mathbf{R} = \mathbf{I} \quad \mathbf{R} \mathbf{R}^T = \mathbf{I} \quad \mathbf{R}^{-1} = \mathbf{R}^T \quad (1)$$

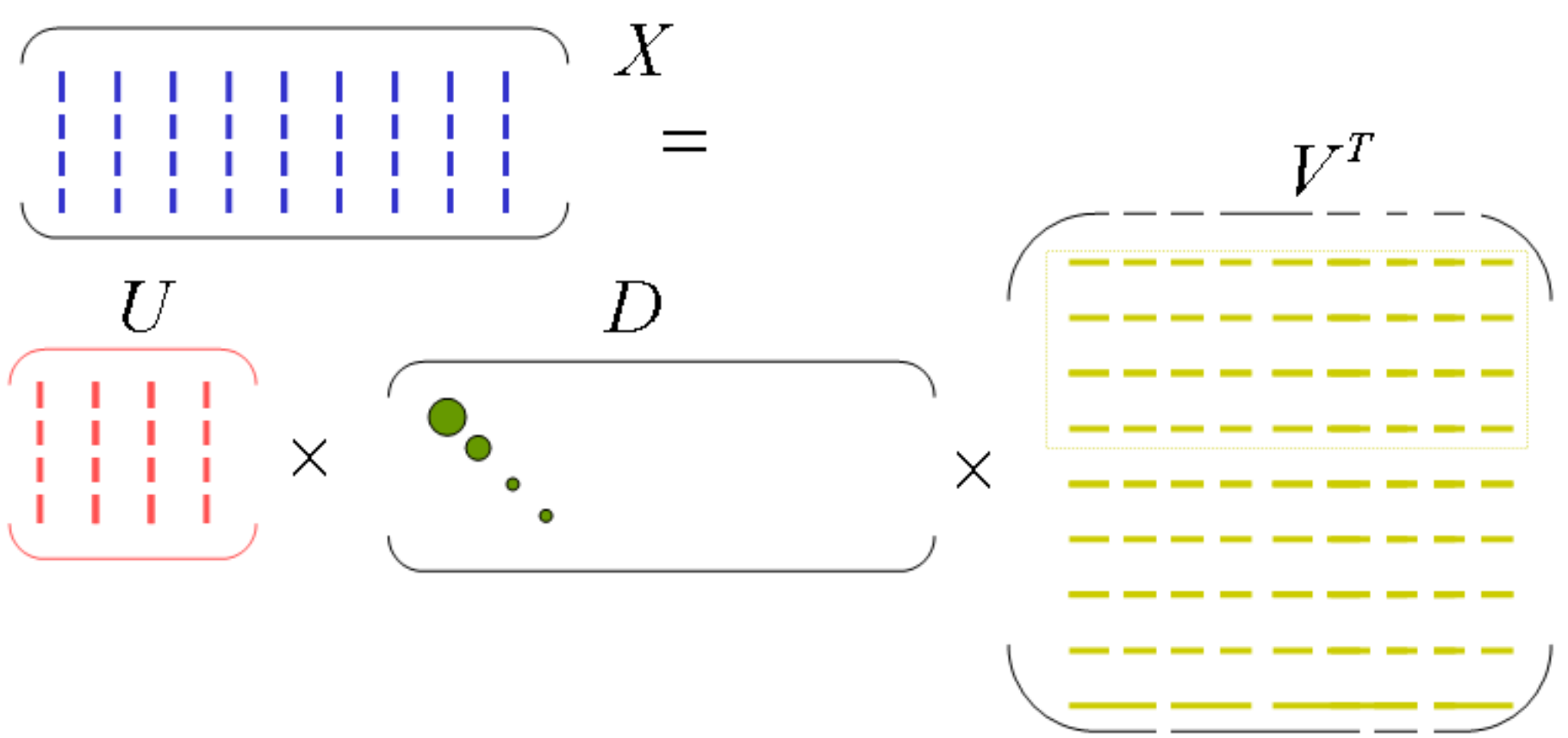
Singular Value Decomposition (SVD)

- Any $N \times M$ matrix \mathbf{X} can be factored as

$$\mathbf{X} = \mathbf{U}\mathbf{D}\mathbf{V}^T$$

where \mathbf{U} and \mathbf{V} are both **orthonormal** matrices. \mathbf{U} is an $N \times N$ Matrix and \mathbf{V} is an $M \times M$ Matrix.

- \mathbf{D} is an $N \times M$ **diagonal matrix** with diagonal entries (singular values) $d_i \geq 0, i = 1, \dots, \tilde{r}$, with $\tilde{r} = \min(M, N)$
- The \mathbf{u}_j (columns of \mathbf{U}) are the left singular vectors
- The \mathbf{v}_j (columns of \mathbf{V}) are the right singular vectors
- The d_j (diagonal entries of \mathbf{D}) are the singular values



Appendix*

- A vector is defined in a vector space. Example: $\mathbf{c} \in \mathbb{R}^2$ and $\mathbf{c} = c_1\mathbf{e}_1 + c_2\mathbf{e}_2$ with an orthogonal basis $\mathbf{e}_1, \mathbf{e}_2$. We denote with \mathbf{c} both the vector and its component representation
- A matrix is a 2-D array that is defined with respect to a vector space
- The dot product is identical to the **inner product** $\langle \mathbf{a}, \mathbf{c} \rangle$ for Euclidean vector spaces with orthonormal basis vectors \mathbf{e}_i

$$\langle \mathbf{a}, \mathbf{c} \rangle = \left(\sum_i a_i \mathbf{e}_i \right) \cdot \left(\sum_{i'} c_{i'} \mathbf{e}_{i'} \right) = \sum_i a_i c_i = \mathbf{a} \cdot \mathbf{c} = \mathbf{a}^T \mathbf{c}$$

- An outer product is also called a dyadic product or an **outer product** (when related to vector spaces) and is written as $\mathbf{d} \otimes \mathbf{c}$. Note that a matrix is generated from two vectors
- An outer product is a special case of a **tensor product**

- $\mathbf{C} = \mathbf{A}\mathbf{B}^T$, can be written as a sum of outer products $\mathbf{C} = \sum_j \mathbf{a}_j \mathbf{b}_j^T$, where \mathbf{a}_j is a columns vector of \mathbf{A} and \mathbf{b}_j is a columns vector of \mathbf{B}