

# Lecture 5: Introduction

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# Outline

- 1 The Singular Value Decomposition
  - Defining the SVD,  $2 \times 2$  case
  - Derivation

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# SVD

$A$  is any matrix  $2 \times 2$ .

## Definition

The **SVD** of  $A$  is a decomposition

$$A = U\Sigma V',$$

where

- $U$  and  $V$  are orthogonal  $2 \times 2$ .
- $\Sigma$  is diagonal with non-negative diagonal entries.
- The columns of  $U$  are **left singular vectors** of  $A$ .
- The columns of  $V$  are **right singular vectors** of  $A$ .
- The diagonal entries of  $\Sigma$  are **singular values** of  $A$ .

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# SVD

**Comment:** Let  $R$  be a diagonal matrix with unit diagonal entries. Then, if  $A = U\Sigma V'$ , then also  $A = (UR)\Sigma(RV')$ . Since  $UR$  and  $RV'$  are still orthogonal, this is another SVD of  $A$ . Up to this triviality (i.e., the multiplication of the singular vectors by  $-1$ ), the SVD is unique whenever  $\Sigma(1, 1) > \Sigma(2, 2)$ .

# 'Reverse engineering' on the SVD

Assume that  $A = U\Sigma V'$  as before.

## First fundamental computation

$$AA' = (U\Sigma V')(U\Sigma V')' = (U\Sigma V')(V\Sigma U') = U\Sigma(V'V)\Sigma U' = U\Sigma^2 U',$$

and

$$A'A = V\Sigma^2 V'.$$



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## Conclusion

- The left singular vectors are the eigenvectors of  $AA'$ .
- The right singular vectors are the eigenvectors of  $A'A$ .
- The squares of the singular values are the eigenvalues of  $A'A$  and of  $AA'$ .

# 'Reverse engineering' on the SVD

Assume that  $A = U\Sigma V'$  as before.

## Second fundamental computation

$$A' = (U\Sigma V')' = V\Sigma U'.$$

So,

- The left singular vectors of  $A$  are the right singular vectors of  $A'$ .
- The left singular vectors of  $A'$  are the right singular vectors of  $A$ .
- The singular values of  $A$  and  $A'$  are the same.

# 'Reverse engineering' on the SVD

Assume that  $A = U\Sigma V'$  as before.

## Third fundamental computation

$$AV = U\Sigma(V'V) = U\Sigma,$$

i.e.,  $Av_1 = \Sigma(1, 1)u_1$ ,  $Av_2 = \Sigma(2, 2)u_2$ .

Similarly,

$$A'U = V\Sigma.$$

# What are we really looking for?

The SVD reads as

$$AV = U\Sigma.$$

It therefore find two vector  $v_1, v_2$  (The columns of  $V$ ) such that

- $v_1, v_2$  is an orthonormal basis for  $\mathbb{R}^2$ .
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Indeed, if you find such  $v_1, v_2$ , you may define

$$u_i := \frac{Av_i}{\|Av_i\|_2}.$$

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We get then

$$AV = U\Sigma,$$

with  $V, U$  as above (orthonormal then), and  $\Sigma$  diagonal, with diagonal entries  $\|Av_i\|_2$ .

# Derivation

We take  $v_1, v_2$  the orthonormal eigenbasis of  $A'A$ .

We then prove that  $Av_1, Av_2$  are eigenvectors of  $AA'$ . If their eigenvalues are different, they must be perpendicular (since  $AA'$  is symmetric).

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So,  $(\lambda_i, v_i)$ , is an eigenpair of  $A'A$ , and we want  $Av_i$  to be an eigenpair of  $AA'$ :

$$(AA')(Av_i) = A(A'A)v_i = A(\lambda_i v_i) = \lambda_i Av_i.$$



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The above works if  $A$  is non-singular, and  $\lambda_1 \neq \lambda_2$

# Demo #3