

# Part I Fundamentals

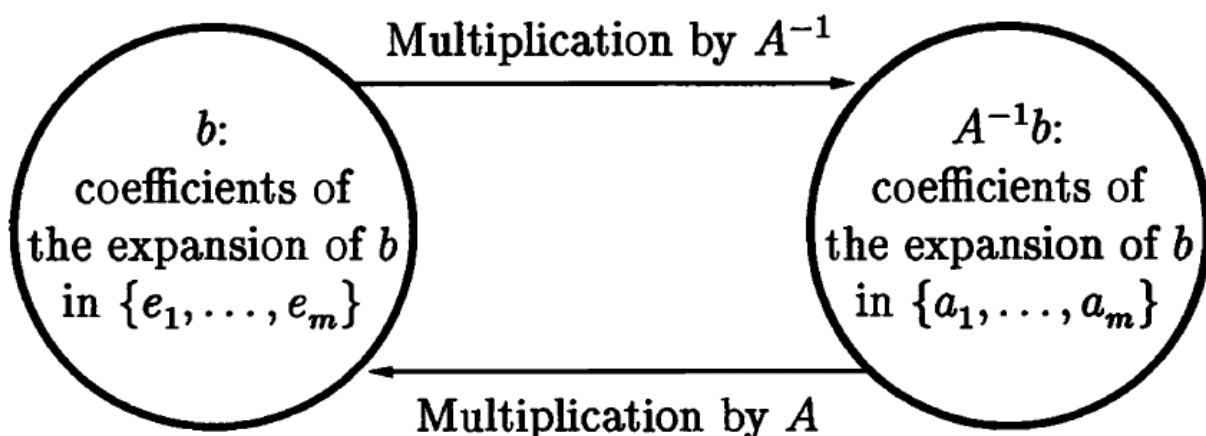
## Matrix

New terms: range (row space), adjoint/hermitian conjugate, hermitian matrix, unitary matrices,

Matrix inverse times a vector interpretation:

is the unique vector of coefficients of the expansion of in the basis of columns of .

Or in short, change of basis:



How to prove row rank and column rank are the same? SVD, both equal to the rank of .

The multiplication of a unitary matrix preserves the inner product, so it preserves the 2-norm. In the case of real matrix, it could be understood as rotation ( )/reflection operation ( ).

For the matrix norm, it also preserves the 2-norm and Frobenius norm. For the 2-norm, it is because rotation does not impact how the matrix will stretch the vector. For the Frobenius norm, it can be proved by just summing up , which is the preserved vector 2-norm.

(Theorem 3.1)

## Norms

"The Sergei plaza in Stockholm, Sweden has the shape of the unit ball in the 4-norm."

Notation difference: subscripts with parenthesis are matrix dimension notation, otherwise it is the norm notation.

There are two ways to define matrix norm:

1. Induced matrix norms. Define as the maximum factor by which  $\|x\|_p$  can "stretch" a vector  $x$ .

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These norms are named as p-Norm.

1. 1-Norm of a matrix is equal to the "maximum column sum" of  $\|A\|_1$ .
  2. The  $\infty$ -Norm of a matrix is equal to the "maximum row sum" of  $\|A\|_\infty$ .
  3. The 2-Norm of a matrix is equal to the largest singular value.
  4. General matrix norm, do not have to be induced by vector norms, just needs to satisfy the three properties of norm.
- Eg: The Frobenius norm  $\|A\|_F$  is not induced by a vector norm. Note: It is different from  $\|A\|_2$ , but in different places notations are different.

Property:

$$\sqrt{\|A\|_1 \|A\|_\infty} \geq \|A\|_2$$

Both the induced matrix norm and the Frobenius norm are sub-multiplicative. (3.14) and (3.18) below. But the induced matrix norm can not make should the equality holds.

## SVD

The idea to introduce SVD will leads to the reduced SVD:

(If  $A$  is full rank)

Together with the linear transformation idea that "**The image of the unit sphere under any matrix is a hyperellipse**", we can select a set of orthonormal vectors  $U$  to get the stretched orthonormal vectors  $V$ .

The unite sphere transformed to hyperellipse idea can be verified by the SVD itself:

First , then , ...

change of basis understanding of SVD

SVD vs eigenvalue decomposition: p33

SVD provides the low rank Approximation of a matrix that captures as much as the energy of the matrix as possible.

## Part III Conditioning and Stability

### lecture 12

absolute or relative?

difference in conditioning and stability? operational-wise?

eg 12.3?

Feynman Lucky numbers?

Polynomial root finding ill-condition?

superimposed roots?

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When are they equal?

when is multiple of the singular vector corresponding to the minimum singular value.

Fact: \_\_\_\_\_

fundamental things: theorem 12.1 and 12.2

The conclusion in the last paragraph!

### lecture 13

The 2x-1 problem?

determinant overflow?