

# Introduction to Linear Algebra

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# Chapter 1

## Introduction to Vectors

### 1.1 Vectors and Linear Combinations

linear combination = vector addition + scalar multiplication  
col / row vector  
three vector representations

### 1.2 Lengths and Dot products

dot / inner prod.  
length / norm of a vector  
unit vector  
angle between two vectors, cosine formula, perp.  
Schwarz Inequality, Triangle Inequality; Geometric mean, Arithmetic mean

### 1.3 Matrices<sup>1</sup>

Matrix times vector  $Ax$  = comb. of cols of  $A$  or multiplication a row at a time  
 $Ax = b, x = A^{-1}b$ , if  $A$  is inv.  
indep. / dep.

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<sup>1</sup>This sec is looking ahead the key ideas, not fully explained yet.

## Chapter 2

# Solving Linear Equations

### 2.1 Vectors and linear equations

a system of equs	vector equ	mat equ
row pic	col pic	matrix pic
dot prod. with rows	comb. of cols	matrix-vector multiplication

### 2.2 The idea of elimination

Gauss elimination  $\rightarrow$  Upper triangular  $U$   
pivot, multiplier  
forward elimination, back substitution, exchange rows  
#pivots, singular

### 2.3 Elimination using matrices

elementary (elimination) matrix, permutation matrix  
augmented matrix  
matrix multiplication by rows / cols

### 2.4 Rules for matrix operations

inner (dot) / outer prod.  
 $mnp$  multiplications  
four ways to matrix multi., the fourth way!  
The laws of matrix operations  
powers of  $A$   
block matrices and block multi., block elimination  $\rightarrow$  Schur complement

## 2.5 Inverse Matrices

inv. def

#pivots and invty; if  $Ax = 0$  has a nonzero sol'n, then  $A$  is not inv.

inverse of a prod. of mats

Gauss-Jordan elim.  $\rightarrow$  rref.

diagonally dominant mats are inv.

## 2.6 Elimination = Factorization: $A = LU$

Gauss elim. without row exchanges  $\rightarrow A = LU$

triangular factorization:  $A = LU$  or  $A = LDU$ , for better symmetry. Here  $D$  is the pivot matrix

predict zeros in  $L$  and  $U$  according to the first entry of rows and cols of  $A$

$L$  stores the multiplier  $l_{ij}$

factor and solve

## 2.7 Transposes and Permutations

tranpose of sum, prod. and inverses

inner prod. and outer prod. with the introduction of tranpose  $T$

symmetric mats  $S$ ,  $A^T A$  and  $AA^T$

$A = LDU \rightarrow$  symmetric factorization  $S = LDL^T$  (with no row exchanges,  $U$  is exactly  $L^T$ )

$P^{-1}$  is also permutation mat if  $P$  is a permutation mat;  $P^T = P^{-1}$  because both come from the prod. of row exchanges *in reverse order*

## Chapter 3

# Vector Spaces and Subspaces

### 3.1 Spaces of Vectors

vector spaces  $\mathbb{R}^2$ ,  $\mathbb{C}^2$ ,  $\mathbb{Z}$ , all real 2 by 2 matrices, all real functions, ...  
eight rules for vector addition and scalar multiplication a vector space must obey  
subspace, linear comb. requirement, every subspace contains the zero “vector”  
cols of  $A$  span the col space  $C(A)$ , attainable right side  $\mathbf{b}$

### 3.2 The Nullspace of $A$ : Solving $Ax = 0$ and $Rx = 0$

nullspace  $N(A)$   
pivot / free cols  $\rightarrow$  pivot / free vars  $\rightarrow$  special sol'ns  $s$   
adding extra eqs (giving extra rows), imposing more conditions,  $N(A)$  certainly cannot go larger; adding extra unknowns (giving extra cols), more dofs.,  $N(A)$  goes larger (more #components of vector  $\mathbf{v}$  in  $N(A)$ )  
rref.  $R$  reveals pivot cols and free cols, pivot rows and cols contain  $I$   
with  $n > m$  there's at least one free var, then  $Ax = 0$  has nonzero sol'ns  
every “free col” is a comb. of earlier pivot cols. It's the special sol'ns  $s$  that tell us those combinations (with signs reversed)  
dimension of a vector space, #components of a vector  
rank  $r$ , rank one matrix  $A = uv^T$ , geometry of rank 1 matrices

### 3.3 The Complete Solution to $Ax = b$

particular sol'n  $x_p$  (free vars = 0)  $\rightarrow Ax_p = b$

special sol'ns  $x_n$  (free vars = 1, 0, 0, ...)  $\rightarrow Ax_n = 0$

complete sol'n  $\rightarrow x = x_p + x_n$  = one particular sol'n + all special sol'ns

$x_p$  comes directly from  $d$  on the right side,  $x_n$  comes from the free cols of  $R$

full col rank  $r = n \leq m$ ,  $R = \begin{bmatrix} I \\ \mathbf{0} \end{bmatrix} = \begin{bmatrix} \text{maxidentitymatrix} \\ m - \text{nrows of zeros} \end{bmatrix}$ ,  $A$  is overdetermined,  $Ax = b$  has at most one sol'n

full row rank  $r = m \leq n$ ,  $R = [I \ F]$ ,  $F$  is the free part of  $R$ ,  $A$  is underdetermined,  $Ax = b$  has one or  $\infty$  sol'ns

inv mat  $r = m = n$ , it always has one sol'n

### 3.4 Independence, Basics and Dimension

linear indep / dep: put a sequence of vecs into a mat and consider its shape and rank

row space  $C(A^\top)$  in  $\mathbb{R}^n$ , col space  $C(A)$  in  $\mathbb{R}^m$

span = fill, no need to be indep; basis = span + indep

basis of a space is not unique; every vector of the space is a unique comb. of the basis

find basis from a set of vecs: put them into the rows (cols) of a mat, and eliminate to find the pivot rows of  $A$  or  $R$  (pivot cols of  $A$ , not  $R$ )

standard basis for  $\mathbb{R}^n$ :  $n \times n$   $I$

$C(A) \neq C(R)$ , their bases are different, their dims are the same

dimension = #vectors in any and every basis of the space = "dofs" of the space

basis and dim for matrix spaces

### 3.5 Dimensions of the Four Subspaces

The Big Picture, four fundamental subspaces:

	dim	basis
row space $C(A^\top)$ in $\mathbb{R}^n$	$r$	pivot rows
col space $C(A)$ in $\mathbb{R}^m$	$r$	pivot cols
nullspace $N(A)$ in $\mathbb{R}^n$	$n - r$	special sol'ns
left nullspace $N(A^\top)$ in $\mathbb{R}^m$	$m - r$	special sol'ns for $A^\top y = \mathbf{0}$ or $y^\top A = \mathbf{0}^\top$

Fundamental Theorem of Linear Algebra, Part I:

- Rank Theorem:  $\dim(C(A)) = \dim(C(A^\top)) = \text{rank} \quad r$

- Counting Theorem:  $\dim(C(A)) + \dim(N(A)) = \dim(\mathbb{R}^n) \rightarrow r + (n - r) = n$ ,  
or replace  $A$  for  $A^\top$ ,  $\dim(C(A^\top)) + \dim(N(A^\top)) = \dim(\mathbb{R}^m) \rightarrow m + (m - r) = m$

$A \xrightarrow{\text{elim.}} R$ :

- $C(A) \neq C(R)$ , the cols of  $A$  don't often end in zero rows while  $R$  does
- $C(A^\top) = C(R^\top)$ , every row of  $A$  is a comb. of the rows of  $R$ , and vice versa
- $N(A) = N(R)$ , elim. doesn't change sol'ns

incidence matrix, nodes and edges (ideas in Graph Theory), loops  $\rightarrow$  dependence, trees  $\rightarrow$  independence, Kirchhoff's Voltage Law, Kirchhoff's Current Law  
rank one mats  $A = \mathbf{uv}^\top$  = a basis for  $C(A) \times$  a basis for  $C(A^\top)$ . (they are both single vector)

rank two mats = rank one mat + rank one mat

every rank  $r$  mat is a sum of  $r$  rank one mats. (The original mat  $A$  is separated into  $E^{-1}$  and  $R$ , and the cols of  $E^{-1} \times$  rows of  $R$  get rank one mats, and then sum these mats to recover  $A$ )



## Chapter 4

# Orthogonality

### 4.1 Orthogonality of the Four Subspaces

orthogonal subspaces  $\mathbf{V}$  and  $\mathbf{W}$ ,  $\mathbf{v}^\top \mathbf{w} = 0$  for all  $\mathbf{v}$  in  $\mathbf{V}$  and all  $\mathbf{w}$  in  $\mathbf{W}$

when a vector is in two subspaces, it must be the zero vector

$C(A^\top) \perp N(A)$ , proved using  $Ax = 0$ , rows of  $A \times x \rightarrow 0$

$C(A) \perp N(A^\top)$ , proved using  $A^\top y = 0$ , rows of  $A^\top \times y \rightarrow 0$

orthogonal complements  $V^\perp$  contains every vector that is perp. to  $V$

Fundamental Theorem of Linear Algebra, Part II:

- $C(A^\top)^\perp = N(A)$
- $C(A)^\perp = N(A^\top)$

every  $\mathbf{x}$  can be split into a row space component  $\mathbf{x}_r$  (which goes to the col space,  $Ax_r = Ax$ ), and a nullspace component  $\mathbf{x}_n$  (which goes to zero,  $Ax_n = 0$ )

a basis has two properties, when the #vectors is right, one property implies the other

when a matrix has the right #vectors, it's inv.

### 4.2 Projections

To find projection  $p = \hat{x}_1 a_1 + \dots + \hat{x}_n a_n$ :

1. certain multiple  $\hat{x}$ :  $A^\top(b - A\hat{x}) = 0$  or  $A^\top A\hat{x} = A^\top b \Rightarrow \hat{x} = A(A^\top A)^{-1}A^\top b$ ,  
 $A$  is comb. of  $a$ 's. We're projecting onto the  $C(A)$ . When  $n = 1$ ,  $A = a$ ,  
we're projecting onto a line.  
This normal equation can be derived by geometry (perp.) or by linear algebra (nullspace).
2. projection  $p$ :  $p = A\hat{x}$
3. projection matrix  $P = A(A^\top A)^{-1}A^\top$

Projecting  $b$  onto a subspace leaves the error vector  $e = b - p$  perp. to the subspace.  $b$  can be split into two components:  $p$  in  $C(A)$  and  $e$  in  $N(A^\top)$ .  
 $(I - P)b = b - p = e \Rightarrow I - P$  projects  $b$  onto the  $C(A)^\perp$ .  
 Note that  $A^\top A$  generally cannot be split into  $A^{-1} \times (A^\top)^{-1}$ , because there's no  $A^{-1}$  if  $A$  is rectangular.  
 $A^\top A$  is inv. iff  $A$  has indep. cols (no need for  $A$  to be inv.)  
 $A^\top A$  has the same nullspace as  $A$   
 $P^\top = P$ ;  $P^2 = P$ , projecting a second time doesn't change anything.

### 4.3 Least Squares Approximations

### 4.4 Orthogonal Bases and Gram-Schmidt

## Chapter 5

# Determinants

5.1 The Properties of Determinants

5.2 Permutations and Cofactors

5.3 Cramer's Rule, Inverses, and Volumes