



## Vectorspaces

**$\mathbb{F}$ -Vectorspace**  $\langle V; +, 0, -, \cdot, 1 \rangle$

- (i) Additive abelian group  $\langle V; +, 0 \rangle$   
where  $+: V \times V \rightarrow V$ ,  $0: \rightarrow V$  and  $-: V \rightarrow V$
- (ii) Scalar algebra  $\langle V, \mathbb{F}; \cdot, 1 \rangle$  where  $\cdot: \mathbb{F} \times V \rightarrow V$  and  $1: \rightarrow \mathbb{F}$

**Subspace  $U$  of  $V$**  Must be closed under

- (i) addition ( $\forall u, v \in U \quad u + v \in U$ )
- (ii) scalar multiplication ( $\forall v \in U, c \in \mathbb{F} \quad cv \in U$ )

### Fundamental Subspaces

$C(A) = \{Ax | x \in V\} = C(AA^\top)$  span of the column vectors.

$R(A) = C(A^\top) = C(A^\top A)$  span of the row vectors.

$N(A) = \{x \in V | Ax = 0\}$  nullspace,  $N(A^\top)$  left nullspace.

**Complement Subspaces** have no vectors in common except for 0 and when combined are equivalent to the whole vectorspace.

**Orthogonal Subspaces** are subspaces where all vectors of one subspace is orthogonal to all other vectors in all other orthogonal subspaces.

$N(A)/N(A^\top)$  orthogonal complement to  $C(A^\top)/C(A)$ .

## Determinants

$\det(A) = 0 \iff A$  is singular.  $C(A) \neq \mathbb{F}^n$

$\det(A) \neq 0 \iff A$  is regular.  $C(A) = \mathbb{F}^n$

$\det(A)$  is linear in each row.

$|\det(Q)| = 1$  for any orthogonal matrix  $Q$ .

$\det(cA) = c^n \det(A)$ .

$A$  diagonal or triangular  $\implies \det(A) = \prod_{i=1}^n a_{ii}$ .

$\det(AB) = \det(A)\det(B)$

Swapping rows of  $A$  changes the sign of  $\det(A)$ .

Non swapping row ops on  $A$  do not change  $\det(A)$ .

$$\det \begin{bmatrix} A & C \\ 0 & B \end{bmatrix} = \det(A) \det(B)$$

Choose row  $j$  then  $\det(A) = \sum_{i=1}^n a_{ji} \det(C_{ji})$

where  $C_{ji}$  is  $A$  without row  $j$  and column  $i$ .

## Solving LSEs $A^{m \times n}x = b$

**Overdetermined**  $m < n$

**Underdetermined**  $m > n$

**Number of solutions**

#of sol.	$r = n$	$r < n$
$r = m$	1	$\infty$
$r < m$	0 / 1	0 / $\infty$

**$PA = LU$  Decomposition**

$P$  is the permutation of the rows during gauss.

$L$  is a lower triangular containing the gauss operations.

$U$  is a upper triangular being the gaussed matrix.

**Solving LSEs with  $PA = LU$**

solve  $Lc = Pb$  for  $c$  and then  $Ux = c$  for  $x$ .

**$A = CR$  Decomposition**

$C$  are the linear independent column of  $A$ .  $C(A) = C(C)$

$R$  is the rref form of  $A$ .

## Projections

$$\text{proj}_{\text{span}\{a\}}(b) = \frac{aa^\top}{a^\top a} b$$

$$\text{proj}_{C(A)}(b) = A\tilde{x} \text{ where } A^\top A\tilde{x} = A^\top b \text{ (normal eq)}$$

$$\text{if } A^\top A \text{ is invertible } \text{proj}_{C(A)}(b) = A(A^\top A)^{-1} A^\top b$$

### LeastSquare

fitting  $(x_{1,*}, x_{n,*}, y_*)$  to  $\alpha_1 x_1 + \dots + \alpha_n x_n = y$  for  $0 \leq * \leq m$

$$\begin{bmatrix} x_{1,1} & \dots & x_{1,n} \\ \vdots & \ddots & \vdots \\ x_{m,1} & \dots & x_{m,n} \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \vdots \\ \alpha_n \end{bmatrix} = \begin{bmatrix} y_1 \\ \vdots \\ y_m \end{bmatrix}$$

fitting  $\alpha_0 + \alpha_1 t = b$

$$\begin{bmatrix} \alpha_0 \\ \alpha_1 \end{bmatrix} = \begin{bmatrix} m & \sum_{k=1}^m t_k \\ \sum_{k=1}^m t_k & \sum_{k=1}^m t_k^2 \end{bmatrix}^{-1} \begin{bmatrix} \sum_{k=1}^m b_k \\ \sum_{k=1}^m t_k b_k \end{bmatrix} = \begin{bmatrix} \frac{1}{m} \sum_{k=1}^m b_k \\ \frac{\sum_{k=1}^m t_k b_k}{\sum_{k=1}^m t_k^2} \end{bmatrix}$$

**$A = QR$  Decomposition**

$R$  is a upper triangular matrix given by  $R = Q^\top A$ .

$Q$  is a orthogonal matrix.

### Algorithm 1 Gram-Schmidt

- 1:  $q_1 = \frac{a_1}{\|a_1\|}$
- 2: **for**  $k = 2, \dots, n$  **do**
- 3:  $q'_k = a_k - \sum_{i=1}^{k-1} (a_k^\top q_i) q_i$
- 4:  $q_k = \frac{q'_k}{\|q'_k\|}$
- 5: **end for**

**Solving LeastSquare with  $A = QR$**

$$R\hat{x} = Q^\top b$$

**Pseudoinverse  $A^\dagger$**

$\text{rank}(A) = n$  then  $A^\dagger A = I$  where  $A^\dagger = (A^\top A)^{-1} A^\top$ .

$\text{rank}(A) = m$  then  $AA^\dagger = I$  where  $A^\dagger = A(AA^\top)^{-1}$ .

$A = CR$  then  $A^\dagger = R(RR^\top)^{-1}(C^\top C)^{-1}C^\top$

# Eigenvalues and -vectors $Av = \lambda v$

**Calculating  $\lambda$ :**  $\det(A - \lambda I) = 0$   
**Calculating  $v$  of  $\lambda$ :**  $(A - \lambda I)v = 0$

**$A$  with distinct  $\lambda_1, \dots, \lambda_k$**   
 $v_1, \dots, v_k$  linearly independent.  
 $\{v_1, \dots, v_k\}$  is a basis for  $C(A)$ .  
are the same as the ones of  $A^\top$ .

**Geometric Multiplicity of  $\lambda$ :**  $\dim(N(A - \lambda I))$

**Similar Matrices**  $C = T^{-1}AT$   
 $\text{Tr}(A) = \text{Tr}(C), \det(A) = \det(C)$   
 $\text{Tr}(A) = \sum_{i=1}^n \lambda_i, \det(A) = \prod_{i=1}^n \lambda_i$

**Spectral Theorem**  
Any symmetric matrix  $A \in \mathbb{R}^{n \times n}$  has  $n$  real eigenvalues and an orthonormal basis of eigen-vectors of  $A$ .

$A = V\Lambda V^\top$   
The columns of  $V$  are the eigen-vectors of  $A$ ,  
 $\Lambda$  is a diagonal matrix with corresponding eigen-values.  
 $A^m = V\Lambda^m V^\top$

**Raylight Quotient**  $R(x) = \frac{x^\top Ax}{x^\top x}$

**Positive (Semi-) Definite**  
eigen-values  $> / \geq 0 \iff x^\top Ax > / \geq 0$

**Gram-Matrix**  $A^\top A$   
 $A^\top A$  and  $AA^\top$  have the same non-zero eigen-values.

**Cholesky Decomposition**  $M = C^\top C$   
 $M$  symmetric PSD,  $C$  upper trianular.

# SVD $A = U\Sigma V^\top$

$U \in \mathbb{R}^{m \times m}$  orthogonal ( $U^\top U = I$ ) eigenvectors of  $AA^\top$   
 $V \in \mathbb{R}^{n \times n}$  orthogonal ( $V^\top V = I$ ) eigenvectors of  $A^\top A$   
 $\Sigma \in \mathbb{R}^{m \times n}$  diagonal  $\Sigma_{ii} = \sigma_i$  singular value.  
Singular values are the square roots of the non-zero eigen-values of  $AA^\top$  /  $A^\top A$

## Calculate SVD

- (i) Caculate  $A^\top A / AA^\top$
- (ii) Find eigenvalues  $\lambda_1, \dots, \lambda_{n/r}$  of  $A^\top A / AA^\top$
- (iii)  $\Sigma_r = \begin{bmatrix} \lambda_1 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & \lambda_{n/r} \end{bmatrix}$
- (iv)  $\Sigma = \begin{bmatrix} \Sigma_r & 0 \\ 0 & 0 \end{bmatrix}$
- (v) calculate eigenvectors  $v_1, \dots, v_{n/r}$  of  $A^\top A$
- (vi) norm eigenvectors  $\frac{v_i}{\|v_i\|}$
- (vii) write  $V$  with the eigenvectors as columns
- (viii) Solve  $U_r = AV\Sigma^{-1}$
- (ix) If  $U_r$  does not have the right dimensions, we have to apply gram-schmidt
- (x)  $A = U\Sigma V^\top$