Linear algebra cheat sheet (wip) by JOL

Notations (with abridged version)

scalars
$$\alpha, \beta, \gamma, \delta, \varepsilon$$
 (real values)
vectors $\boldsymbol{b}, \boldsymbol{v}, \boldsymbol{w}, \boldsymbol{x}, \boldsymbol{y}$ $\boldsymbol{x} = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix}^T = \begin{bmatrix} x_1 & \dots & x_n \end{bmatrix}^T = \begin{bmatrix} x_i \end{bmatrix}$
matrices A, C, M, L, U $A = \begin{bmatrix} a_{11} & \dots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \dots & a_{mn} \end{bmatrix} = \begin{bmatrix} a_{ij} \end{bmatrix}$
a matrix A ... with m rows and n columns is a linear

transformation from \mathbb{R}^n to \mathbb{R}^m

Vector operations

- usual(+,-,ext. product) $\alpha x + \beta y = [\alpha x_i + \beta y_i]$
- scalar product $\boldsymbol{x} \cdot \boldsymbol{y} = \sum_{i=1}^{n} x_i y_i = \boldsymbol{x}^{\mathsf{T}} \boldsymbol{y}$ 2-norme (Euclid) $\|\boldsymbol{x}\|_2 = \sqrt{x_1^2 + \dots + x_n^2} = \sqrt{\boldsymbol{x}^{\mathsf{T}} \boldsymbol{x}}$ • 1-norme $||x||_1 = |x_1| + \cdots + |x_n|$
- + ∞ -norme $\|\boldsymbol{x}\|_{\infty} = \max(|x_1|, \cdots, |x_n|)$
- norms mesure length of vectors
- norms are equivalent up to a \sqrt{n} constant
- Euclidean norm is invariant to rigid transformation (i.e. multiplication by an orthogonal matrix).

Matrix operations

- usual(+,-,ext. product) $\alpha A + \beta C = [\alpha a_{ij} + \beta c_{ij}]$
- product if $A_{m \times n}$ and $B_{n \times p}$, then C = AB is a matrix of size $m \times p$, and $c_{ij} = \sum_{i=1}^{m} a_{ik} b_{kj}$

•
$$\begin{bmatrix} a_1^{\mathsf{T}} \\ \vdots \\ a_m^{\mathsf{T}} \end{bmatrix} \begin{bmatrix} b_1 \\ \cdots \\ b_p \\ \vdots \\ a_m^{\mathsf{T}} \end{bmatrix} = \begin{bmatrix} a_1^{\mathsf{T}} b_1 & \cdots & a_1^{\mathsf{T}} b_p \\ \vdots & \ddots & \vdots \\ a_m^{\mathsf{T}} b_1 & \cdots & a_m^{\mathsf{T}} b_p \end{bmatrix} = [a_i^{\mathsf{T}} b_j^{\mathsf{T}}]$$

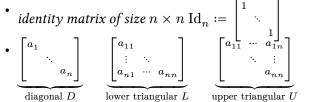
- product is associative A(BC) = (AB)C,
- product is **not** *commutative* $AB \neq BA$
- transpose $A^{\mathsf{T}}: (A+B)^{\mathsf{T}} = A^{\mathsf{T}} + B^{\mathsf{T}}, (AB)^{\mathsf{T}} = B^{\mathsf{T}}A^{\mathsf{T}}$
- conjugate transpose A^* : same as A^T if A real-valued
- norm $\| \|_{\infty}$ induced by vector norm for $* \in \{1, 2, \infty\}$ $\|Ax\|$

$$\|A\|_{*} := \sup_{x \neq 0} \frac{\|x\|_{*}}{\|x\|_{*}} \text{ or (same) } \|A\|_{*} := \sup_{x \neq 0, \|x\|_{*} = 1} \|Ax\|_{*}$$

- 1-norm: column sum $||A||_1 := \max_j \sum_i |a_{ij}|$
- ∞ -norm: row sum $||A||_{\infty} := \max_i \sum_j |a_{ij}|$
- 2-norm: spectral row $\|\widetilde{A}\|_2 := \sqrt{\lambda_{\max}(A^*A)}$
- Fröbenius norm: $\|A\|_F := \sqrt[7]{\operatorname{trace}(A^*A)}$
- $||A|| \ge 0$, $||A|| = 0 \Leftrightarrow A = 0$, $||\alpha A|| = |\alpha| ||A||$

•
$$||A + B|| \le ||A|| + ||B||,$$
 $||AB|| \le ||A|| ||B||$

Specific matrices



• symmetric matrix $A^{\mathsf{T}} = A$, antisymmetric $A^{\mathsf{T}} = -A$

• orthogonal matrix $A^{\mathsf{T}}A = AA^{\mathsf{T}} = \mathrm{Id}_n, \det(A) = \pm 1$, and rows/cols of A forms an orthonormal basis

- if A orthogonal and det(A) = 1, then A is a rotation
- DD' is diagonal, LL' is lower triangular, UU' is upper triangular

Invertibility, determinant of matrix $A_{n \times n}$

- A is invertible iff (i) $\exists B, BA = \mathrm{Id}_n$, (ii) $\det(A) \neq 0$, (iii) $\operatorname{rank}(A) = n$, or (iv) Ax = 0 has only x = 0 as solution.
- det($[a_{11}]$) = a_{11} , det(A) = $\sum_i a_{ij} \Delta_{ij}$, where cofactor $\Delta_{ij} := (-1)^{i+j} \det(A_{ij})$, if A_{ij} is the matrix A without row i and column j.

• if A is invertible,
$$A^{-1} = \frac{\lfloor \Delta_{ij} \rfloor}{\det(A)}$$
, \Rightarrow solve $Ax = b$

Cramer's rule $x_i = \det \left(\begin{bmatrix} a_{11} & \cdots & b_1 & \cdots & a_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ a_{n1} & \cdots & b_n & \cdots & a_{nn} \end{bmatrix} \right) / \det(A)$

- complexity of above is $\mathcal{O}(n!)$, used when $n \leq 4$
- · determinant of diagonal or triangular matrix is product of diagonal elements
- $$\begin{split} & \text{ matrix condition } K_p(A) = \left\|A\right\|_p \left\|A^{-1}\right\|_p, \\ & K_2(A) = \frac{|\sigma_{\max}(A)|}{|\sigma_{\min}(A)|} \\ & \bullet \ K(A) \geq K(\operatorname{Id}_n) = 1 \text{ for any } p\text{-norm} \end{split}$$

Solving linear systems Ax = b

- if A is "L", easy to solve Lx = b in n^2 flops
- if A is "U", easy to solve Ux = b in n^2 flops
- "LU" factorization: find L, U with A = LU,
- L and U found by Gauss elimination in $\frac{2}{3}n^3$ flops
- solve Ly = b then Ux = y
- "PLU" factorization: add permutation mat. P
 - PA = LU (with $P^{\mathsf{T}} = P^{-1}$)
 - look for the biggest pivot
 - A invertible \Leftrightarrow A has a PLU factorization
- Cholesky factorization
 - A SPD: $A = A^{\mathsf{T}}$ and $\forall x \neq 0, x^{\mathsf{T}}Ax > 0$
 - find L with $A = LL^{\mathsf{T}}$ in $\frac{1}{2}n^3$ flops
 - faster and more stable than PLU
 - variant as $A = LDL^{\mathsf{T}}$

Numerical stability of f wrt f

- machine precision $\mathfrak{u} \approx 1e 16$ with double)
- forward error $\|f(d) f(d)\| / \|f(d)\|$ ("aval")
- backward error $\|\tilde{d} d\| / \|d\|$, where $f(\tilde{d}) = \tilde{f}(d)$
- *forward stability*: forward error is $\mathcal{O}(u)$, e.g. fl, \otimes
- *backward stability*: backward error is $\mathcal{O}(u)$, e.g. std operations, scalar/matrix product, etc
- forward error = $K_{\rm rel}(f) \times {\rm backward}$ error
- forward stable \Rightarrow backward stable