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Math Background Review

Basic Analysis:

A. Norm: A fn $f: \mathbb{R}^n \rightarrow \mathbb{R}$ is called norm if:

* (non-neg.): $f(\underline{x}) \geq 0$, $\forall \underline{x} \in \mathbb{R}^n$. $f(\underline{x}) = 0$ iff $\underline{x} = 0$.

* (homogeneity): $f(t\underline{x}) = |t|f(\underline{x})$, $\forall \underline{x} \in \mathbb{R}^n$, $t \in \mathbb{R}$.

* (triangle ineq.): $f(\underline{x} + \underline{y}) \leq f(\underline{x}) + f(\underline{y})$, $\forall \underline{x}, \underline{y} \in \mathbb{R}^n$.

If $f(\underline{x})$ is a norm, we denote it: $\|\underline{x}\|$.

2. Norm $\|\underline{x}\|$'s meaning:

* $\|\underline{x}\|$: length of \underline{x}

* $\|\underline{x} - \underline{y}\|$: dist. btwn \underline{x} & \underline{y} .

3. Unit Ball: Set of vectors with $\|\underline{x}\| \leq 1$.

$$\mathcal{B} = \{\underline{x} \in \mathbb{R}^n : \|\underline{x}\| \leq 1\}.$$

Ex:

* l_2 -norm (Euclidean norm): $\|\underline{x}\|_2 \triangleq (\underline{x}^T \underline{x})^{\frac{1}{2}} = (x_1^2 + \dots + x_n^2)^{\frac{1}{2}}$

* l_1 -norm (sum-abs.-val.): $\|\underline{x}\|_1 \triangleq |x_1| + \dots + |x_n|$.

* l_∞ -norm (Chebyshev): $\|\underline{x}\|_\infty = \max \{|x_1|, \dots, |x_n|\}$

* l_p -norm: $\|\underline{x}\|_p = (|x_1|^p + \dots + |x_n|^p)^{\frac{1}{p}}$. $\|\underline{x}\|_\infty = \lim_{p \rightarrow \infty} \|\underline{x}\|_p$ (btw).

* Quadratic norm: For any positive semidef. matrix $P \in \mathbb{R}^{n \times n}$,

$$\|\underline{x}\|_P = (\underline{x}^T P \underline{x})^{\frac{1}{2}} = \|\underline{x}^T P^{\frac{1}{2}} \underline{x}\|_2$$

$$\underline{x}^T P \underline{x} \geq 0, \forall \underline{x} \in \mathbb{R}^n$$

(2)

4. Equivalence of Norms:

Suppose $\|\cdot\|_a$ and $\|\cdot\|_b$ are norms on \mathbb{R}^n . Then $\exists \alpha, \beta > 0$ s.t. $\forall z \in \mathbb{R}^n, \alpha \|z\|_a \leq \|z\|_b \leq \beta \|z\|_a$.

$$\text{Ex: } \|z\|_2 \leq \|z\|_1 \leq \sqrt{n} \|z\|_2.$$

$$\|z\|_\infty \leq \|z\|_2 \leq \sqrt{n} \|z\|_\infty$$

$$\|z\|_\infty \leq \|z\|_1 \leq n \|z\|_\infty.$$

B. Sets and Sequences,

1. ε -neighborhood about a pt. z_0

$$N_\varepsilon(z_0) = \{z : \|z - z_0\| < \varepsilon\}.$$



2. Interior of S :

$$\text{int}(S) = \{z \in S : \exists \varepsilon > 0, \text{ s.t. } N_\varepsilon(z) \subseteq S\}.$$



3. Boundary of S :

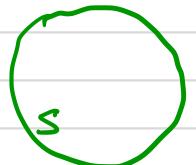
$$\partial(S) = \{z : \forall \varepsilon > 0, N_\varepsilon(z) \cap S \neq \emptyset, N_\varepsilon(z) \cap S^c \neq \emptyset\}.$$



4. Open and Closed Sets,

$$\text{Open set } S : S \cap \partial(S) = \emptyset \Leftrightarrow S = \text{int}(S).$$

$$\text{closed set } S : \partial(S) \subseteq S \Leftrightarrow \{S^c \text{ is open}\}.$$



(3)

\therefore closed b/c every pt. is bndy pt.

$S = \mathbb{R}^n$: both open and closed.

1. $S^c = \emptyset$, $\partial(S^c) = \emptyset = \partial(S)$, $S \cap \partial(S) = S \cap \emptyset = S \cap S^c = \emptyset$. Open.
2. $\partial(S) = \emptyset \subseteq S \Rightarrow S$ is closed.
(empty set is a subset of any set).

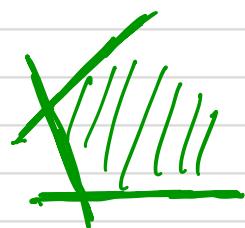


open or closed? neither.

5. Closure of S : $\text{cl}(S) = \partial(S) \cup S$. (smallest closed set that contains S).

6. S is bounded if it can be contained within a ball of finite radius.

7. S is compact if it's closed and bound.



closed but unbounded

8. Convergent Sequence and Limits.

1° Def (Convergence): A seq. of vectors $\underline{x}_1, \underline{x}_2, \dots$ are said to be convergent to a limit pt. $\bar{\underline{x}}$ if $\forall \epsilon > 0, \exists N_\epsilon \in \mathbb{N}$ s.t. $\|\underline{x}_k - \bar{\underline{x}}\| < \epsilon, \forall k \geq N_\epsilon$. ($\{\underline{x}_k\} \rightarrow \bar{\underline{x}}$ as $k \rightarrow \infty$. $\lim_{k \rightarrow \infty} \underline{x}_k = \bar{\underline{x}}$).

(4)

2. Def (Cauchy Seq.): A seq. $\{x_k\}$ is Cauchy seq. of $\forall \varepsilon > 0, \exists N \in \mathbb{N}$, s.t. $\|x_m - x_n\| < \varepsilon$, $\forall m, n \geq N$.

Thm.: A seq. in \mathbb{R}^n has a limit iff it is Cauchy.

Ex: (p-series). $a_n = \frac{1}{n^p}$. Show $\{b_n\} = \left\{ \sum_{k=1}^n a_k \right\}$ ($p=2$) has a limit.

Proof: w.l.o.g., let $m, n \in \mathbb{N}$ and $m < n$.

$$b_n - b_m = \sum_{k=1}^n \frac{1}{k^2} - \sum_{k=1}^m \frac{1}{k^2} = \sum_{k=m+1}^n \frac{1}{k^2} < \sum_{k=m+1}^n \frac{1}{k(k-1)}$$

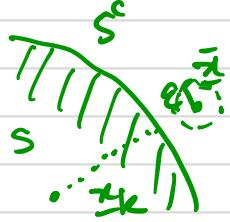
$$\begin{aligned} &= \sum_{k=m+1}^n \left(\frac{1}{k-1} - \frac{1}{k} \right) = \cancel{\frac{1}{m}} - \cancel{\frac{1}{m+1}} + \cancel{\frac{1}{m+2}} - \cancel{\frac{1}{m+3}} + \dots + \cancel{\frac{1}{n-1}} - \cancel{\frac{1}{n}} \\ &= \frac{1}{m} - \frac{1}{n} < \frac{1}{m} < \varepsilon, \end{aligned}$$

can always find suff. large m s.t. $b_n - b_m < \varepsilon$. □

9. Closedness & Compactness characterized convergent seq. & limits.

Thm.: A set S is closed iff for any seq. $\{x_k\} \rightarrow \bar{x}$, s.t. $x_k \in S$, we also have $\bar{x} \in S$.

Proof: (\Rightarrow) By contradiction: Suppose not: \exists a $\{x_k\} \rightarrow \bar{x}$, $x_k \in S, \forall k$



but $\bar{x} \notin S$.

S closed $\Rightarrow S^c$ open $\Rightarrow S^c = \text{int}(S^c)$. (*)

Since $\bar{x} \in S^c \stackrel{(*)}{\Rightarrow} \bar{x} \in \text{int}(S^c) \Rightarrow \exists N_\varepsilon(\bar{x}) \subseteq S^c$
 $\rightarrow \Leftarrow$ Convergence assumption.

(5)

(\Leftarrow) By contra: If $S \neq$ closed: $\exists \bar{x} \in \partial(S)$, but $\bar{x} \notin S$.

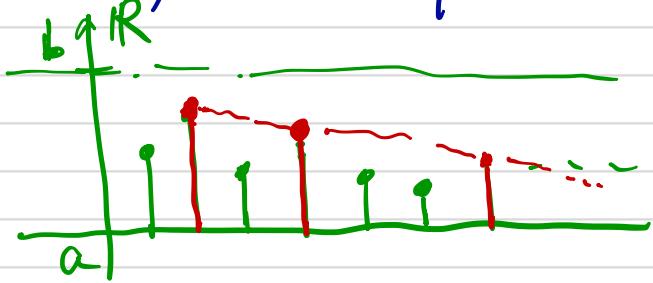


keep shrinking $\varepsilon \Rightarrow$ create a seq. $\{\underline{x}_k\} \rightarrow \bar{x}$

$$\underline{x}_k \in S, \forall k \Rightarrow \bar{x} \in S$$

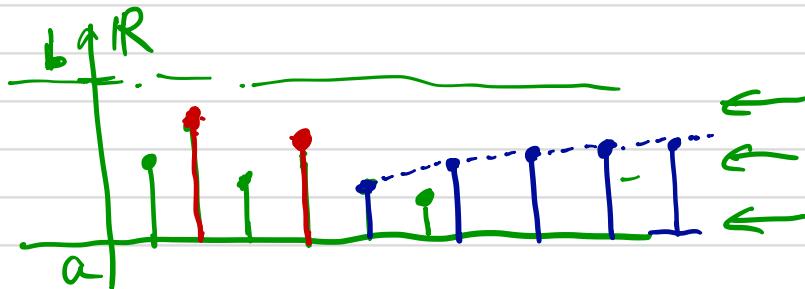
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Thm (Bolzano - Weierstrass): Every bnd seq. in \mathbb{R}^n has a convergent subseq.



1. enlightened terms are infinite

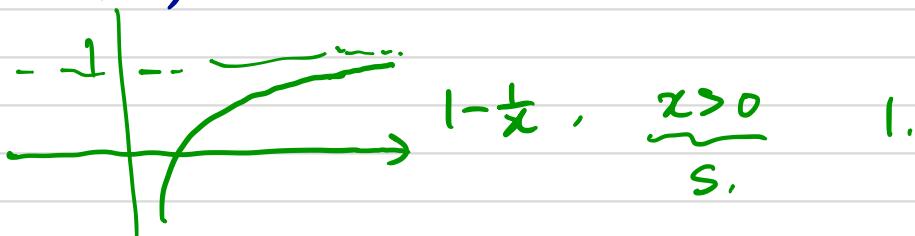
MCT: if $\{a_n\}$ is a mono seq. reals, then $\{a_n\}$ has a limit iff $\{a_n\}$ is bnded.



2. enlightened terms are finite.

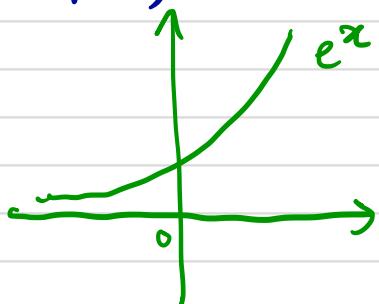
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10. Supremum of S (least UB): Smallest possible α satisfying $\alpha \geq x, \forall x \in S$.



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Infinum of S (Largest LB): Largest possible value α satisfying $\alpha \leq x, \forall x \in S$.

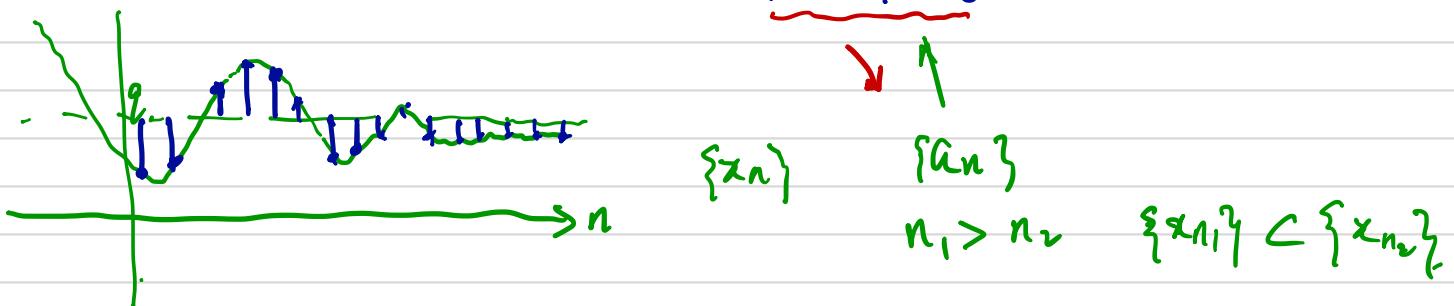


$$e^x, x \in \mathbb{R}. \text{ Infinum: } 0$$

Maximum, minimum (achievable).

* The limit superior $\limsup_{k \rightarrow \infty} x_k$ is the infimum of all $q \in \mathbb{R}$ for which all but a finite # of elements in $\{x_k\}$ exceed q .

$$\limsup_{n \rightarrow \infty} x_n = \lim_{n \rightarrow \infty} \left\{ \sup_{m \geq n} x_m \right\} \quad (\text{HW}).$$



* The limit infimum $\liminf_{k \rightarrow \infty} x_k$ is the supremum of all $q \in \mathbb{R}$ for which all but a finite # of elements in $\{x_k\}$ less than q . $\liminf_{n \rightarrow \infty} x_n = \lim_{n \rightarrow \infty} \left\{ \inf_{m \geq n} x_m \right\}$.

* \limsup and \liminf always exist.

$\{x_n\}$ converge iff $\limsup_{n \rightarrow \infty} x_n = \liminf_{n \rightarrow \infty} x_n$.

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3. Functions.

1° Cont. fn.: A fn $f: S \rightarrow \mathbb{R}$ is cont. at $\bar{x} \in S$ if $\forall \varepsilon > 0$, \exists a $\delta > 0$, s.t. $x \in S$ with $\|x - \bar{x}\| < \delta \Rightarrow |f(x) - f(\bar{x})| < \varepsilon$.
 write: $f(x) \rightarrow f(\bar{x})$, as $x \rightarrow \bar{x}$.

Fact: Cont. fn. achieves both a maximum & minimum over a non-empty compact set.
 closed & bounded.

2° Diff'ble fn:

(1) S non-empty set in \mathbb{R}^n , $x \in \text{int } S$, and $f: S \rightarrow \mathbb{R}$.
 f is diff'ble at \bar{x} if \exists a vector (called gradient).

$$\nabla f(\bar{x}) \triangleq \left[\frac{\partial f(\bar{x})}{\partial x_1}, \dots, \frac{\partial f(\bar{x})}{\partial x_n} \right]^T \text{ at } \bar{x} \text{ and fn}$$

$\beta(x, \bar{x}) \rightarrow 0$ as $x \rightarrow \bar{x}$, such that

$$f(x) = \underbrace{f(\bar{x}) + \nabla f(\bar{x})^T (x - \bar{x})}_{\text{FO-approx.}} + \underbrace{\frac{1}{2} \|x - \bar{x}\|^2 \beta(x, \bar{x})}_{O(\|x - \bar{x}\|^2)}, \quad \forall x \in S.$$

(2). f is called twice diff'ble at \bar{x} if, in addition to gradient, \exists symmetric $n \times n$ matrix $\underline{H}(\bar{x})$ (called Hessian mtrix). of f at \bar{x} , and $\beta(x, \bar{x}) \rightarrow 0$ as $x \rightarrow \bar{x}$, such that:

$$f(x) = \underbrace{f(\bar{x}) + \nabla f(\bar{x})^T (x - \bar{x}) + \frac{1}{2} (x - \bar{x})^T \underline{H}(\bar{x}) (x - \bar{x})}_{\text{SO-approx.}} + \underbrace{\frac{1}{6} \|x - \bar{x}\|^3 \beta(x, \bar{x})}_{O(\|x - \bar{x}\|^3)}.$$

$$\underline{H}(\underline{x}) \triangleq \begin{bmatrix} \frac{\partial^2 f(\underline{x})}{\partial x_1^2} & \cdots & \frac{\partial^2 f(\underline{x})}{\partial x_1 \partial x_n} \\ \vdots & & \vdots \\ \frac{\partial^2 f(\underline{x})}{\partial x_n \partial x_1} & \cdots & \frac{\partial^2 f(\underline{x})}{\partial x_n^2} \end{bmatrix} \in \mathbb{R}^{n \times n}.$$

3° A vector-valued \mathbb{R}^n function f is diffible if each component
 is diffible.
 (twice diffible).

A diffible vector-valued fn $h: \mathbb{R}^m \rightarrow \mathbb{R}^n$, the Jacobian,
 denoted by $\nabla h(\underline{x})$, is given by the $n \times m$ matrix:

$$\nabla h(\underline{x}) = \begin{bmatrix} \nabla h_1(\underline{x})^T \\ \vdots \\ \vdots \\ \nabla h_n(\underline{x})^T \end{bmatrix}_{n \times m}.$$

4° (MVT): S non-empty open convex set in \mathbb{R}^n , let
 $f: S \rightarrow \mathbb{R}$ be diffible. For every $\underline{x}_1, \underline{x}_2 \in S$, we have

$$f(\underline{x}_2) = f(\underline{x}_1) + \nabla f(\underline{x})^T (\underline{x}_2 - \underline{x}_1), \text{ where } \underline{x} = \lambda \underline{x}_1 + (1-\lambda) \underline{x}_2$$

for some $\lambda \in (0, 1)$.

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5° Taylor's Thm: S non-empty, open, convex in \mathbb{R}^n .

$f: S \rightarrow \mathbb{R}$, twice diff'ble. For every $\underline{x}_1, \underline{x}_2 \in S$, we have,

$$f(\underline{x}_2) = f(\underline{x}_1) + \nabla f(\underline{x}_1)^T (\underline{x}_2 - \underline{x}_1) + \frac{1}{2} (\underline{x}_2 - \underline{x}_1)^T H(\underline{x}) (\underline{x}_2 - \underline{x}_1), \text{ where}$$

$H(\underline{x})$ is Hessian at \underline{x} , and $\underline{x} = \lambda \underline{x}_1 + (1-\lambda) \underline{x}_2$, for some $\lambda \in (0,1)$.

Linear Algebra:

1. Linear indep: $\underline{x}_1, \dots, \underline{x}_k \in \mathbb{R}^n$ are lin. indep. if

$$\sum_{i=1}^k \lambda_i \underline{x}_i = \underline{0} \Rightarrow \lambda_i = 0, \forall i=1, \dots, k.$$

2. linear comb: $y \in \mathbb{R}^n$ is lin. comb. of $\underline{x}_1, \dots, \underline{x}_k \in \mathbb{R}^n$ if

$$y = \sum_{i=1}^k \lambda_i \underline{x}_i \text{ for some } \lambda_1, \dots, \lambda_k.$$

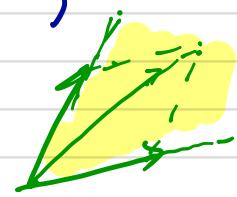
* $\sum_{i=1}^k \lambda_i = 1$: y is an affine comb. of $\underline{x}_1, \dots, \underline{x}_k$.

* $\sum_{i=1}^k \lambda_i = 1, \lambda_i \geq 0, \forall i$: y is a convex comb. of $\underline{x}_1, \dots, \underline{x}_k$.

The linear, affine, convex hull of $S \subseteq \mathbb{R}^n$ are, resp, the set of all lin., affine, convex comb. of pts in S .

3. Spanning vectors : $\underline{x}_1, \dots, \underline{x}_k \in \mathbb{R}^n$, $k \geq n$, said to be spanning \mathbb{R}^n if any vector in \mathbb{R}^n can be represented as a lin. comb. of $\underline{x}_1, \dots, \underline{x}_k$.

The cone spanned by $\underline{x}_1, \dots, \underline{x}_k$ is set of non-neg. lin. comb.



4. Basis: A set of $\underline{x}_1, \dots, \underline{x}_k \in \mathbb{R}^n$ spans \mathbb{R}^n

and if the deletion of any of $\underline{x}_1, \dots, \underline{x}_k$ prevents remaining vector from spanning \mathbb{R}^n (Basis $\underline{x}_1, \dots, \underline{x}_k$ spans \mathbb{R}^n iff $k=n$).

5. Cauchy-Schwartz Ineq: $|\langle \underline{x}, \underline{y} \rangle| = |\underline{x}^T \underline{y}| \leq \|\underline{x}\|_2 \cdot \|\underline{y}\|_2$.

(unsigned) angle btwn $\underline{x}, \underline{y} \in \mathbb{R}^n$.

$$\angle(\underline{x}, \underline{y}) \triangleq \cos^{-1} \left(\frac{\underline{x}^T \underline{y}}{\|\underline{x}\|_2 \cdot \|\underline{y}\|_2} \right) \in [0, \pi].$$

(\underline{x} & \underline{y} are orthogonal, ($\underline{x} \perp \underline{y}$), if $\langle \underline{x}, \underline{y} \rangle = 0$).

6. Orthogonal matrix : $\underline{Q} \in \mathbb{R}^{m \times n}$: $\underline{Q}^T \underline{Q} = \underline{\underline{I}}_n$ or $\underline{Q} \underline{Q}^T = \underline{\underline{I}}_m$

If \underline{Q} is square : $\underline{Q}^{-1} = \underline{Q}^T$.

7. Rank of matrix : For $\underline{A} \in \mathbb{R}^{m \times n}$, $\text{rank}(\underline{A}) = \max \# \text{ of lin. indep. rows (or equivalently, cols)} \text{ of } \underline{A}$.

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If $\text{rank } (\underline{A}) = \min \{m, n\}$, \underline{A} is full row/col rank.

8. Eigenvalues and eigenvectors : $\underline{A} \in \mathbb{R}^{n \times n}$. If λ and $\underline{x} \neq \underline{0}$ satisfy $\underline{A}\underline{x} = \lambda \underline{x}$, then λ, \underline{x} are eigenvalues & eigenvectors.

* λ can be computed by solving $\det(\underline{A} - \lambda \underline{I}) = 0$ (characteristic eqn.).

* \underline{A} is symmetric \Rightarrow n (possibly non-distinct) real eigenvalues

* Eigenvectors assoc. w/ distinct eigenvalues are orthogonal.

* Given symmetric $\underline{A} \Rightarrow$ can construct an orthogonal basis $\underline{B} \in \mathbb{R}^{n \times n}$ where each col in \underline{B} is an eigenvector of \underline{A} .

* Normalize \underline{B} to have unit l_2 norm, s.t. $\underline{B}^T \underline{B} = \underline{I}$ ($\underline{B}^T = \underline{B}^{-1}$).

Then \underline{B} is called orthonormal matrix.

* Let $\underline{\lambda}_1, \dots, \underline{\lambda}_n$ be eigenvalues of \underline{A} . Let $\underline{\Lambda} = \begin{bmatrix} \lambda_1 & & \\ & \ddots & \\ & & \lambda_n \end{bmatrix}$

Note $\underline{A} \underline{B} = \underline{B} \underline{\Lambda}$

$$\underline{A} \begin{bmatrix} \vdots & \cdots & \vdots \\ v_1 & \cdots & v_n \\ \vdots & \cdots & \vdots \end{bmatrix} = \begin{bmatrix} \vdots & \cdots & \vdots \\ v_1 & \cdots & v_n \\ \vdots & \cdots & \vdots \end{bmatrix} \begin{bmatrix} \lambda_1 & & \\ & \ddots & \\ & & \lambda_n \end{bmatrix}$$

$$\underline{B}^T = \underline{B}^{-1}$$

$$\underline{A} = \underline{B} \underline{\Lambda} \underline{B}^T = \sum_{i=1}^n \lambda_i b_i b_i^T$$

(eigenvalue decomp).

10. Singular-Value Decomposition (SVD).

Let $\underline{A} \in \mathbb{R}^{m \times n}$. Then $\underline{A} = \underline{U} \underline{\Sigma} \underline{V}^T$, where $\underline{U} \in \mathbb{R}^{m \times m}$ orthonormal,
 $\underline{V} \in \mathbb{R}^{n \times n}$ orthonormal, and $\underline{\Sigma} \in \mathbb{R}^{m \times n}$, $(\underline{\Sigma})_{ij} = 0$ for $i \neq j$.

$$\underbrace{(\underline{\Sigma})_{ij}}_{\in \mathbb{R}} \geq 0, \text{ for } i=j.$$

* Cols of \underline{U} : Normalized eigenvectors of $\underline{A} \underline{A}^T$.

* Cols of \underline{V} : - - - - - of $\underline{A}^T \underline{A}$

* $(\underline{\Sigma})_{ij}$, $i=j$: Are abs. square root of eigenvalues of
 $\underline{A}^T \underline{A}$ if $m \leq n$ or $\underline{A} \underline{A}^T$ if $m \geq n$.

12. Definite & Semidefinite Matrices: $\underline{A} \in \mathbb{R}^{n \times n}$ symmetric.

$$\text{PD} \quad \underline{x}^T \underline{A} \underline{x} > 0 \quad \forall \underline{x} \neq 0, \underline{x} \in \mathbb{R}^n$$

\underline{A} is PSD if $\underline{x}^T \underline{A} \underline{x} \geq 0$, $\forall \underline{x} \in \mathbb{R}^n$

ND $\underline{x}^T \underline{A} \underline{x} < 0$, $\forall \underline{x} \neq 0, \underline{x} \in \mathbb{R}^n$

NSD $\underline{x}^T \underline{A} \underline{x} \leq 0$, $\forall \underline{x} \in \mathbb{R}^n$.

\underline{A} is indef. if neither PSD nor NSD.

PD pos.

\underline{A} is PSD if eigenvalues are non-neg., resp.

ND neg.

NSD non-pos.

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13. If \underline{A} is PSD, then $\underline{A}^{\frac{1}{2}}$ is the matrix satisfying

$$\underline{A}^{\frac{1}{2}} \underline{A}^{\frac{1}{2}} = \underline{A}, \text{ and } \underline{A}^{\frac{1}{2}} = \underbrace{\underline{B} \underline{A}^{\frac{1}{2}} \underline{B}^T}_{\rightarrow} \begin{bmatrix} \lambda_1^{\frac{1}{2}} & & 0 \\ 0 & \ddots & 0 \\ & & \lambda_n^{\frac{1}{2}} \end{bmatrix}.$$