1 Notations and Assumptions

In most cases (if without local definitions), we use

- Greek alphabets such as $\alpha$, $\beta$, and $\gamma$ to denote real numbers;
- Small letters such as $x$, $y$, and $z$ to denote vectors;
- Capital letters to denote matrices, e.g., $A$, $B$, and $C$.

Other notations:

- $\mathbb{R}$ is the one dimensional Euclidean space;
- $\mathbb{R}^n$ is the $n$ dimensional vector Euclidean space;
- $\mathbb{R}^{m \times n}$ is the $m \times n$ dimensional matrix Euclidean space;
- $\mathbb{R}_+$ denotes the range $[0, +\infty)$;
- $1_n \in \mathbb{R}^n$ denotes a vector with 1 in all entries;
- For any vector $x \in \mathbb{R}^n$, we use $|x|$ to denote the absolute vector, that is, $|x|_i = |x_i| \forall i = 1, \cdots, n$;
- $\odot$ denotes the component-wise product, that is, for any vectors $x$ and $y$, $(x \odot y)_i = x_i y_i$.

Some assumptions:

- Unless explicit (local) definition, we always assume that all vectors are column vectors.

2 Vector norms, Inner product

A function $f : x \in \mathbb{R}^n \to y \in \mathbb{R}_+$ is called a “norm”, if the following three conditions are satisfied

- $f(x) \geq 0$ and $f(x) = 0$ if and only if $x = 0$;
- For any $\alpha \in \mathbb{R}$ and $x \in \mathbb{R}^n$, $f(\alpha x) = |\alpha| f(x)$;
- (triangle inequality) Any $x, y \in \mathbb{R}^n$ satisfy $f(x) + f(y) \geq f(x + y)$. 
The $\ell_2$ norm “$\| \cdot \|_2$” (a special “$f(\cdot)$”) in $\mathbb{R}^n$ is defined as
\[
\|x\|_2 = (|x_1|^2 + |x_2|^2 + \cdots + |x_n|^2)^{1/2}.
\]
Because of $\ell_2$ is the most commonly used norm (also known as Euclidean norm), we denote it as $\| \cdot \|$ sometimes for short.

A general $\ell_p$ norm ($p \geq 1$) is defined as
\[
\|x\|_p = (|x_1|^p + |x_2|^p + \cdots + |x_n|^p)^{1/p}.
\]
Note that for $p < 1$, it is not a “norm” since the triangle inequality is violated. $\ell_\infty$ norm is defined as
\[
\|x\|_\infty = \max\{|x_1|, |x_2|, \cdots, |x_n|\}.
\]
One may notice that the $\ell_\infty$ norm is the limit of the $\ell_p$ norm, that is, for any $x \in \mathbb{R}^n$, $\|x\|_\infty = \lim_{p \to +\infty} \|x\|_p$. In addition, people use $\|x\|_0$ to denote the $\ell_0$ “norm”.

The inner product $\langle \cdot, \cdot \rangle$ in $\mathbb{R}^n$ is defined as
\[
\langle x, y \rangle = \sum_i x_i y_i.
\]
One can show that $\langle x, x \rangle = \|x\|^2$. Two vectors $x$ and $y$ are orthogonal if $\langle x, y \rangle = 0$. That is one reason why $\ell_2$ norm is so special.

If $p \geq q$, then for any $x \in \mathbb{R}^n$ we have $\|x\|_p \leq \|x\|_q$. In particular, we have $\|x\|_1 \geq \|x\|_2 \geq \|x\|_\infty$.

To bound from the order sides, we have
\[
\|x\|_1 \leq \sqrt{n} \|x\|_2 \quad \|x\|_2 \leq \sqrt{n} \|x\|_\infty.
\]

**Proof.** To see the first one, we have
\[
\|x\|_1 = \langle 1_n, |x| \rangle \leq \|1_n\|_2 \|x\|_2 = \sqrt{n} \|x\|_2
\]
where the last inequality uses the Cauchy inequality. I leave the proof of the second inequality in your homework.

Given a norm “$\| \cdot \|_A$”, its dual norm is defined as
\[
\|x\|_{A^*} = \max_{\|y\|_A \leq 1} \langle x, y \rangle = \max_{\|y\|_{A^*} = 1} \langle x, y \rangle = \max_{\|z\|_A} \langle x, z \rangle.
\]
Several important properties about the dual norm are
- The dual norm’s dual norm is itself, that is, $\|x\|_{(A^*)^*} = \|x\|_A$;
- The $\ell_2$ norm is self-dual, that is, the dual norm of the $\ell_2$ norm is still the $\ell_2$ norm;
- The dual norm of the $\ell_p$ norm ($p \geq 1$) is $\ell_q$ norm where $p$ and $q$ satisfy $1/p + 1/q = 1$. Particularly, $\ell_1$ norm and $\ell_\infty$ norm are dual to each other.
- (Holder inequality): $\langle x, y \rangle \leq \|x\|_A \|y\|_{A^*}$.
3 Linear space, subspace, linear transformation

A set $S$ is a linear space if

- $0 \in S$;
- given any two points $x, y \in S$ and any two scalars $\alpha \in \mathbb{R}$ and $\beta \in \mathbb{R}$, we have
  \[ \alpha x + \beta y \in S. \]

Note that $\emptyset$ is not a linear space. Examples: vector space $\mathbb{R}^n$, matrix space $\mathbb{R}^{m \times n}$. How about the following things:

- $0$; (no)
- $\{0\}$; (yes)
- $\{x \mid Ax = b\}$ where $A$ is a matrix and $b$ is a vector. ($b = 0$ yes; otherwise, no)

Let $S$ be a linear space. A set $S'$ is a subspace if $S'$ is a linear space and also a subset of $S$. Actually, “subspace” is equivalent to “linear space”, because any subspace is a linear space and any linear space is a subspace. They are indeed talking about the same thing.

Let $S$ be a linear space. A function $L(\cdot)$ is a linear transformation if given any two points $x, y \in S$ and two scalars $\alpha \in \mathbb{R}$ and $\beta \in \mathbb{R}$, one has

\[ L(\alpha x + \beta y) = \alpha L(x) + \beta L(y). \]

For vector space, there exists a 1-1 correspondence between a linear transformation and a matrix. Therefore, we can simply say “a matrix is a linear transformation”.

- Prove that $\{L(x) \mid x \in S\}$ is a linear space if $S$ is a linear space and $L$ is a linear transformation.
- Prove that $\{x \mid L(x) \in S\}$ a linear space assuming $S$ is a linear space, and $L$ is a linear transformation.

How to express a subspace? The most intuitive way is to use a bunch of vectors. A subspace can be expressed by

\[ \text{span}\{x_1, x_2, \ldots, x_n\} = \left\{ \sum_{i=1}^{n} \alpha_i x_i \mid \alpha_i \in \mathbb{R} \right\} = \{X\alpha \mid \alpha\}, \]

which is called the range space of matrix $X$. A subspace can be also represented by the null space of $X$ by

\[ \{\alpha \mid X\alpha = 0\}. \]
4 Eigenvalues / eigenvectors, rank, SVD, inverse

The transpose of a matrix $A \in \mathbb{R}^{m \times n}$ is defined as $A^T \in \mathbb{R}^{n \times m}$:

$$(A^T)_{ij} = A_{ji}.$$ 

One can verify that

$$(AB)^T = B^T A^T.$$ 

A matrix $B \in \mathbb{R}^{n \times n}$ is the inverse of an invertible matrix $A \in \mathbb{R}^{n \times n}$ if

$$AB = I \quad \text{and} \quad BA = I.$$ 

$B$ can be denoted as $A^{-1}$. $A$ has the inverse is equivalent to that $A$ has a full rank (the definition for “rank” will be clear very soon.) Note that the inverse of a matrix is unique. One can also verify that if both $A$ and $B$ are invertible, then

$$(AB)^{-1} = B^{-1} A^{-1}.$$ 

The “transpose” and the “inverse” are exchangeable:

$$(A^T)^{-1} = (A^{-1})^T.$$ 

When we write $A^{-1}$, we have to make sure that $A$ is invertible.

Given a square matrix $A \in \mathbb{R}^{n \times n}$, $x \in \mathbb{R}^n (x \neq 0)$ is called its eigenvector and $\lambda \in \mathbb{R}^n$ is called its eigenvalue, if the following relationship is satisfied

$$Ax = \lambda x. \quad \text{(The effect of applying the linear transformation $A$ on $x$ is nothing but scaling it.)}$$ 

Note that

• If $\{\lambda, x\}$ is a pair of eigenvalue-eigenvector, then so is $\{\lambda, \alpha x\}$ for any $\alpha \neq 0$.

• One eigenvalue may correspond to multiple different eigenvectors. “Different” means eigenvectors are different after normalization.

If the matrix $A$ is symmetric, then any two eigenvectors (corresponding to different eigenvalues) are orthogonal, that is, if $A^T = A$, $Ax_1 = \lambda_1 x_1$, $Ax_2 = \lambda_2 x_2$, and $\lambda_1 \neq \lambda_2$, then

$$x_1^T x_2 = 0.$$ 

Proof. Consider $x_1^T Ax_2$. We have

$$x_1^T Ax_2 = x_1^T (Ax_2) = x_1^T (A x_2) = x_1^T \lambda_2 x_2 = \lambda_2 x_1^T x_2,$n

and

$$x_1^T Ax_2 = (x_1^T A) x_2 = (A^T x_1)^T x_2 = (Ax_1)^T x_2 = \lambda_1 x_1^T x_2.$$ 

Therefore, we have

$$\lambda_2 x_1^T x_2 = \lambda_1 x_1^T x_2.$$ 

Since $\lambda_1 \neq \lambda_2$, we obtain $x_1^T x_2 = 0$. 

\[\square\]
A matrix $A \in \mathbb{R}^{m \times n}$ is a “rank-1” matrix, if $A$ can be expressed as

$$A = xy^T$$

where $x \in \mathbb{R}^m$ and $y \in \mathbb{R}^n$, and $x \neq 0$, $y \neq 0$. The rank of a matrix $A \in \mathbb{R}^{m \times n}$ is defined as

$$\text{rank}(A) = \min \{ r \mid A = \sum_{i=1}^{r} x_i y_i^T, \, x_i \in \mathbb{R}^m, y_i \in \mathbb{R}^n \}$$

Examples: $[1, 1; 1, 1], [1, 1; 2, 2]$, and many natural images have the low rank property. “Low rank” implies that the contained information is few.

We say “$U \in \mathbb{R}^{m \times n}$ has orthogonal columns” if $U^T U = I$, that is, any two columns $U_i$ and $U_j$ of $U$ satisfies

$$U_i^T U_j = 0 \quad \text{if} \quad i \neq j; \quad \text{otherwise} \quad U_i^T U_j = 1.$$

Swapping any two columns in $U$ to get $U'$, $U'$ still satisfies $U'^T U' = I$. If $U$ is a square matrix and has orthogonal columns, then we call it “orthogonal matrix”. It has some nice properties

- $U^{-1} = U^T$ (which means that $U U^T = U^T U = I$.)
- The effect of applying the transformation $U$ on a vector $x$ is to rotate $x$, that is, $\|Ux\| = \|x\|$.

“SVD” is short for “singular value decomposition”, which is the most important concept in linear algebra and matrix analysis. SVD almost explores all structures of a matrix. Given any matrix $A \in \mathbb{R}^{m \times n}$, it can be decomposed into

$$A = U \Sigma V^T = \sum_{i=1}^{r} \sigma_i U_i V_i^T$$

where $U \in \mathbb{R}^{m \times r}$ and $V \in \mathbb{R}^{n \times r}$ have orthogonal columns, and $\Sigma = \text{diag}\{\sigma_1, \sigma_2, \ldots, \sigma_r\}$ is a diagonal matrix with positive diagonal elements. $\sigma_i$’s are called singular values, which are positive and are arranged in the decreasing order.

- $\text{rank}(A) = r$;
- $\|Ax\| \leq \sigma_1 \|x\|$. Why?

A matrix $B \in \mathbb{R}^{n \times n}$ is positive semi-definite (PSD), if the following things are satisfied

- $B$ is symmetric;
- $\forall x \in \mathbb{R}^n$, we have $x^T B x \geq 0$.

The positive definite matrix is defined by adding one more condition

- $x^T B x = 0 \iff x = 0$. 

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We can also use an equivalent definition for PSD matrices in the following: A matrix $B \in \mathbb{R}^{n \times n}$ is positive semi-definite (PSD), if the SVD of $B$ can be written as

$$B = U\Sigma U^T$$

where $U^TU = I$ and $\Sigma$ is a diagonal matrix with nonnegative diagonal elements. Examples of PSD matrices: $I$, $A^TA$.

Assume matrices $A$ and $B$ are invertible. We have the following identity:

$$B^{-1} = A^{-1} - B^{-1}(B - A)A^{-1}.$$  

The Sherman-Morrison-Woodbury Formula is very useful to calculate the matrix inverse:

$$(A + UV^T)^{-1} = A^{-1} - A^{-1}U(I + V^TA^{-1}U)^{-1}V^TA^{-1}.$$  

This result is especially important from the perspective of computation. A special case would be that $U$ and $V$ are two vectors $u$ and $v$. Then it is in form of

$$(A + uv^T)^{-1} = A^{-1} - (1 + v^TA^{-1}u)^{-1}A^{-1}uv^TA^{-1},$$

which can be calculated with complexity $O(n^2)$ if $A^{-1}$ is known.

The Sylvester’s determinant theorem is

$$\det$$

5 Matrix norms (spectral norm, nuclear norm, Frobenius norm)

The Frobenius norm (F-norm) of a matrix $A \in \mathbb{R}^{m \times n}$ is defined as

$$\|A\|_F = \left( \sum_{1 \leq i \leq m, 1 \leq j \leq n} |A_{i,j}|^2 \right)^{\frac{1}{2}} = \left( \sum_{i=1}^m \sigma_i^2 \right)^{\frac{1}{2}}.$$  

If $A$ is a vector, one can verify that $\|A\|_F = \|A\|_2$.

The inner product $\langle \cdot, \cdot \rangle$ in $\mathbb{R}^{m \times n}$ is defined as

$$\langle X,Y \rangle = \sum_{i,j} X_{ij}Y_{ij} = \text{trace}(X^TY) = \text{trace}(Y^TX) = \text{trace}(XY^T) = \text{trace}(Y^TX).$$

An important property for $\text{trace}(AB)$:

$$\text{trace}(AB) = \text{trace}(BA) = \text{trace}(A^TB^T) = \text{trace}(B^TA^T).$$

One may notice that $\langle X, X \rangle = \|X\|_F^2$.

The spectral (trace) norm of a matrix $A \in \mathbb{R}^{m \times n}$ is defined as

$$\|A\|_{\text{spec}} = \max_{\|x\|=1} \|Ax\| = \max_{\|x\|=1,\|y\|=1} y^T Ax = \sigma_1(A).$$

The nuclear norm of a matrix $A \in \mathbb{R}^{m \times n}$ is defined as

$$\|A\|_{\text{tr}} = \sum_{i=1}^r \sigma_i(A) = \text{trace}(\Sigma)$$
where $\Sigma$ is the diagonal matrix of SVD of $A = U \Sigma V^T$.

An important relationship

$$\|A\|_{\text{spec}} \leq \|A\|_F \leq \|A\|_{\text{tr}} \quad \text{and} \quad \text{rank}(A)\|A\|_{\text{spec}} \geq \sqrt{\text{rank}(A)}\|A\|_F \geq \|A\|_{\text{tr}}.$$ 

The dual norm for a matrix norm $\|\cdot\|_A$ is defined as

$$\|Y\|_{A^*} := \max_{\|X\| \leq 1} \langle X, Y \rangle = \max_X \langle X, Y \rangle. \quad (1)$$

We have the following properties (think about why it is true):

$$\|X\|_{\text{spec}}^* = \|X\|_{\text{tr}}, \quad \|X\|_{F^*} = \|X\|_F.$$ 

### 6 Matrix and Vector Differential

Let $f(X) : \mathbb{R}^{m \times n} \rightarrow \mathbb{R}$ be a function with respect to matrix $X \in \mathbb{R}^{m \times n}$. It is differential (or gradient) is defined as

$$\frac{\partial f(X)}{\partial X} = \begin{bmatrix} \frac{\partial f(X)}{\partial X_{11}} & \cdots & \frac{\partial f(X)}{\partial X_{1j}} & \cdots & \frac{\partial f(X)}{\partial X_{1n}} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \frac{\partial f(X)}{\partial X_{i1}} & \cdots & \frac{\partial f(X)}{\partial X_{ij}} & \cdots & \frac{\partial f(X)}{\partial X_{in}} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \frac{\partial f(X)}{\partial X_{m1}} & \cdots & \frac{\partial f(X)}{\partial X_{mj}} & \cdots & \frac{\partial f(X)}{\partial X_{mn}} \end{bmatrix}.$$ 

We provide a few examples in the following

$$f(X) = \text{trace}(A^T X) = \langle A, X \rangle \quad \frac{\partial f(X)}{\partial X} = A$$

$$f(X) = \text{trace}(X^T A X) \quad \frac{\partial f(X)}{\partial X} = (A + A^T)X$$

$$f(X) = \frac{1}{2} \|A X - B\|_F^2 \quad \frac{\partial f(X)}{\partial X} = A^T (AX - B)$$

$$f(X) = \frac{1}{2} \text{trace}(B^T X^T X B) \quad \frac{\partial f(X)}{\partial X} = X B B^T$$

$$f(X) = \frac{1}{2} \text{trace}(B^T X^T A X B) \quad \frac{\partial f(X)}{\partial X} = \frac{1}{2} (A + A^T) X B B^T$$