# Convex Optimization 

## Part 1: Preliminaries

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## Linear algebra

Vector $x \in \mathbb{R}^{n}$

- $x=\left(x_{1}, \ldots, x_{n}\right)$
- length and direction (e.g., $n=2$ )
- column vectors, row vectors


## Linear algebra

$p$-norm of vector $x \in \mathbb{R}^{n}$ where $1 \leq p \leq \infty$ :

$$
\|x\|_{p}:=\left(\sum_{i=1}^{n}\left|x_{i}\right|^{p}\right)^{\frac{1}{p}}
$$

- $p=1$
- $p=2$
- $p=\infty$
- Example of $v=(3,4)$


## Linear algebra

## Subspace

The subset $\mathcal{S} \subset \mathbb{R}^{n}$ is a subspace of $\mathbb{R}^{n}$ if the following property holds: If $x$ and $y$ are any two elements of $\mathcal{S}$, then

$$
\alpha x+\beta y \in \mathcal{S}, \quad \forall \alpha, \beta \in \mathbb{R}
$$

(i.e., set closed under addition and scaling)

## Linear algebra

## Span

$\left\{s_{1}, s_{2}, \ldots, s_{k}\right\}$ is a spanning set for $\mathcal{S}$ if any vector $s \in \mathcal{S}$ can be written as

$$
s=\alpha_{1} s_{1}+\alpha_{2} s_{2}+\ldots+\alpha_{k} s_{k},
$$

for some $\alpha_{1}, \alpha_{2}, \ldots, \alpha_{k}$.

## Linear algebra

Linear independence
A set of vectors $x_{1}, x_{2}, \ldots, x_{k} \in \mathbb{R}^{n}$ is called linearly independent if there are no $\alpha_{1}, \alpha_{2}, \ldots, \alpha_{k} \in \mathbb{R}$ such that

$$
\alpha_{1} x_{1}+\alpha_{2} x_{2}+\ldots+\alpha_{k} x_{k}=0
$$

except $\alpha_{1}=\alpha_{2}=\ldots=\alpha_{k}=0$.
(i.e., $x_{1}, x_{2}, \ldots, x_{k}$ are linearly independent if none of them can be written as a linear combination of the others.)

## Linear algebra

## Basis

If $\left\{x_{1}, \ldots, x_{k}\right\}$ are linearly independent $\&$ span $\mathcal{X}$, we call them a basis of $\mathcal{X}$

- $k$ (the number of elements in the basis) is referred to as the dimension of $\mathcal{X}$, and denoted by $\operatorname{dim}(\mathcal{X})$.
- There are many ways to choose a basis of $\mathcal{X}$ in general, but that all bases contain the same nubmer of vectors.


## Linear algebra

Inner product / dot product on $\mathbb{R}^{n}$

$$
u \cdot v=\langle u, v\rangle=u^{\top} v=\sum_{i=1}^{n} u_{i} v_{i}
$$

## Linear algebra

Angle between $u$ and $v$

$$
\cos \theta=\frac{\langle u, v\rangle}{\|u\|_{2}\|v\|_{2}}
$$

- If they are perpenicular, $\langle u, v\rangle=0$.


## Linear algebra

Projection of $v$ onto $u$

$$
v_{\mathrm{p}}=\frac{\langle v, u\rangle}{\|u\|_{2}^{2}} u
$$

## Linear algebra

Cauchy-Schwarz inequality

$$
\left|u^{\top} v\right| \leq\|u\|_{2}\|v\|_{2}
$$

- Two sides are equal iff $u$ and $v$ are linearly dependent.


## Linear algebra

Triangle inequality

$$
\|u+v\|_{2} \leq\|u\|_{2}+\|v\|_{2}
$$

## Linear algebra

Outer product

$$
u \otimes v=u v^{\top}=\left[\begin{array}{cccc}
u_{1} v_{1} & u_{1} v_{2} & \ldots & u_{1} v_{n} \\
u_{2} v_{1} & u_{2} v_{2} & \ldots & u_{2} v_{n} \\
\vdots & \vdots & \ddots & \vdots \\
u_{n} v_{1} & u_{n} v_{2} & \ldots & u_{n} v_{n}
\end{array}\right]
$$

## Linear algebra

Matrix $A \in \mathbb{R}^{m \times n}$

$$
A=\left[\begin{array}{ccc}
A_{1,1} & \ldots & A_{1, n} \\
\vdots & \ddots & \vdots \\
A_{m, 1} & \ldots & A_{m, n}
\end{array}\right]
$$

Some concepts to recall

- square matrix
- transpose of a matrix
- symmetric matrix


## Linear algebra

$\operatorname{Null}(A)=\left\{x \in \mathbb{R}^{n}: A x=0\right\}$
Range $(A)=\left\{y \in \mathbb{R}^{n}: A x=y\right.$ for some $\left.x\right\}$
Rank $(A)=$ dimension of span of columns/rows of $A$

## Linear algebra

If $A$ is $n \times n$, $\operatorname{Rank}(A)=n$ iff

- Null $(A)=\{0\}$
- Range $(A)=\mathbb{R}^{n}$
- $\operatorname{det}(A) \neq 0$


## Linear algebra

For a matrix $A \in \mathbb{R}^{n \times n}$, an eigenvalue $\lambda$ and eigenvector $v$ are those that satisfy

$$
A v=\lambda v
$$

## Linear algebra

For a symmetric matrix $A$,

- All eigenvalues are real.
- All eigenvectors are perpendicular to each other.

If $A$ is nonsingular, none of its eigenvalues are zero.

## Linear algebra

For a symmetric matrix $A$, eigen or spectral decomposition

$$
A=\sum_{i=1}^{n} \lambda_{i} v_{i} v_{i}^{\top}
$$

or

$$
A=Q \Lambda Q^{\top}
$$

using matrix forms.

## Linear algebra

Positive semidefinite matrix

- A symmetric matrix $A$ is called positive semidefinite, if all eigenvalues are greater than or equal to 0 .
- Or

$$
x^{\top} A x \geq 0, \quad \forall x \in \mathbb{R}^{n}
$$

- $A A^{\top}$ and $A^{\top} A$ are always psd.


## Analysis

Interior
An element $x \in C \subseteq \mathbb{R}^{n}$ is called an interior point of $C$ if there exists an $\epsilon>0$ for which

$$
\left\{y \mid\|y-x\|_{2} \leq \epsilon\right\} \subseteq C
$$

i.e., there exists a ball centered at $x$ that lies entirely in $C$.

Int $C$ : the set of all points interior to $C$.

## Analysis

Supremum ("least upper bound") and infimum ("greatest lower bound")
Suppose $C \subseteq \mathbb{R}$. A number $a$ is an upper bound on $C$ if $x \leq a, \forall x \in C$.
The set of upper bounds on $C$ is either

1. empty ( $C$ is unbounded above)
2. all of $\mathbb{R}(C=\emptyset)$
3. a closed infinite interval $[b, \infty)$

Then, supremum of $C($ or $\sup C)$ becomes

1. $\infty$
2. $-\infty$
3. $b$

If the set $C$ is finite, $\sup C$ is the maximum of its elements.

## Calculus

Functions and derivatives

- Continuity
- Differentiability
- Derivative
- Gradient
- Hessian
- Quadratic function example

Any questions?

