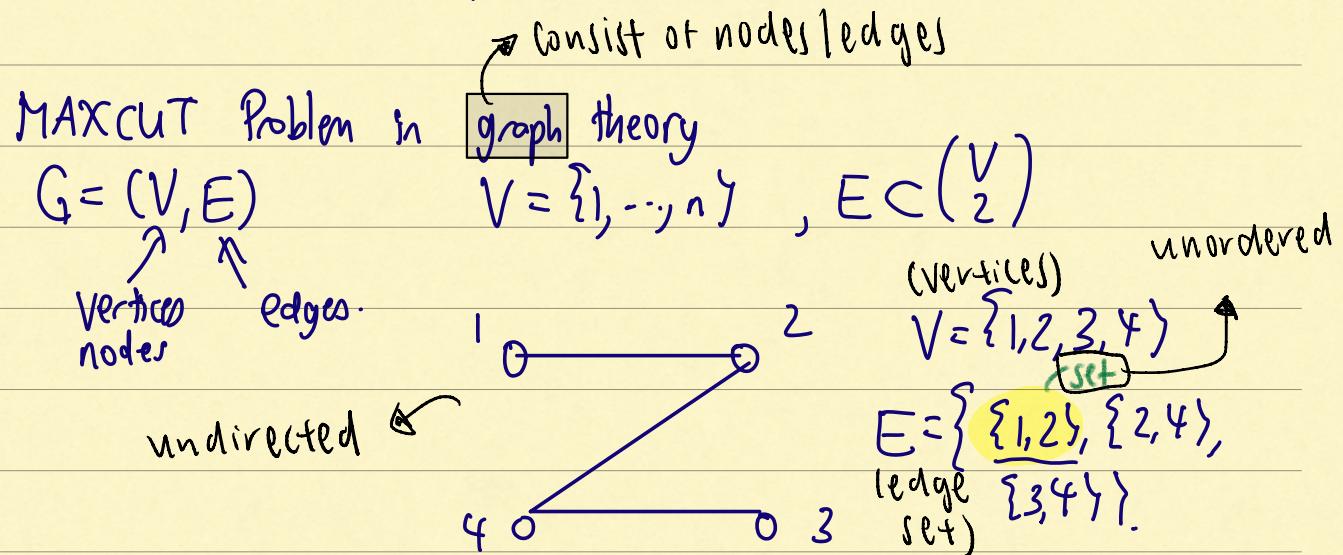
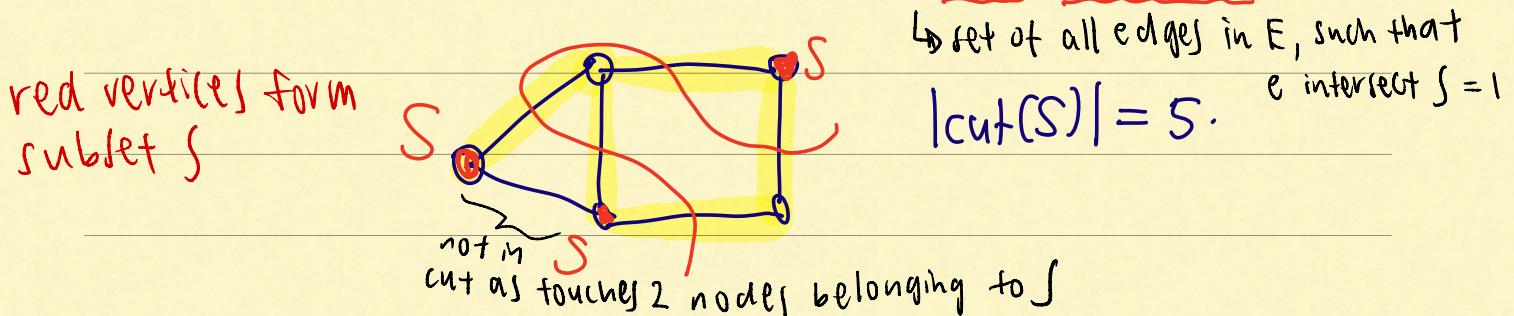


DSA3102: Convex Optimization (Lecture 1)

Motivation for convex optimization.



Cut: Given a subset $S \subset V$, $\text{cut}(S) = \{e \in E : |e \cap S| = 1\}$.



Given a graph G , find $S \subset V$ st. $|\text{cut}(S)|$ is maximized.

$$\text{eg. } 2^{|E|}$$

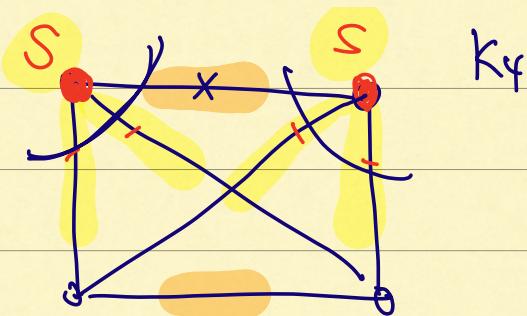
Ex: Complete graph $G = K_n$ (n even)

complete graph with n nodes

(edges) that have intersection | with S)
exactly |

$$|S|=1$$

$$|\text{cut}(S)| = n - 1 \\ = 1(n-1)$$



$$|S|=2, |\text{cut}(S)| = (n-2) + (n-2) = \underline{2(n-2)}$$

$$\text{In general, if } |S|=k, \quad |\text{cut}(S)| = k(n-k)$$

To maximize $k(n-k)$ over all $k \in \{0, 1, \dots, n\}$,
by symmetry the optimal $\frac{k=n/2}{\downarrow \downarrow}$, e.g. $S = \{1, \dots, n/2\}$

$$\text{MAXCUT}(k_n) = \frac{n}{2} \left(n - \frac{n}{2} \right) = \left(\frac{n}{2} \right)^2.$$

n even

only activated when on diff sides
of the cut

optimization prob

Write the MAXCUT problem $\forall G = (V, E)$ as.

(IOP Integer Quadratic Program) $\text{OPT}(G) = \max_{x_1, \dots, x_n} \sum_{\{i,j\} \subseteq E} \frac{1 - x_i x_j}{2}, \quad x_i \in \{-1, +1\}$

binary

$x_i = +1 \Leftrightarrow i \in S, \quad x_i = -1 \Leftrightarrow i \in S^c = V \setminus S.$ of the cut

$$\frac{1 - x_i x_j}{2} = \begin{cases} 0 & \text{if } i \& j \text{ are on the same side} \\ 1 & \text{if } i \& j \text{ are on diff sides of the cut} \end{cases}$$

restricted to boolean values

NP-hard

(very difficult)

binary \Rightarrow continuous?

optimising over n vectors in \mathbb{R}^n

$$\text{Reformulate this to approximated opt problem. } L_2 \text{ norm}$$

$$\max_{v_1, \dots, v_n} \sum_{\{i,j\} \in E} \frac{1 - \langle v_i, v_j \rangle}{2} \quad \underbrace{\|v_i\| = 1}_{i=1, \dots, n}, \quad v_i \in \mathbb{R}^n.$$

If $n=1$, this problem reduces to the above IQP

This problem can be written as a convex opt problem.

semi definite programme

SDP

$$\max_{X \in \mathbb{R}^{n \times n}, X \succeq 0} \frac{1}{2} \sum_{\{i,j\} \in E} \frac{1 - X_{ij}}{2}, \quad X_{ii} = 1 \quad i=1, \dots, n$$

over a matrix that is positive semi-definite eigenvalues are all non-negative

$$X_{ij} = \langle v_i, v_j \rangle, \quad V = \begin{bmatrix} | & \dots & | \\ v_1 & \dots & v_n \\ | & \dots & | \end{bmatrix} \quad \rightarrow \text{matrix of inner products}$$

$$V^T V = \begin{bmatrix} -v_1^T & - \\ \vdots & \ddots \\ -v_n^T & - \end{bmatrix} \begin{bmatrix} | & \dots & | \\ v_1 & \dots & v_n \\ | & \dots & | \end{bmatrix} = \begin{bmatrix} \langle v_1, v_1 \rangle & \dots & \langle v_1, v_n \rangle \\ \vdots & \ddots & \vdots \\ \langle v_n, v_1 \rangle & \dots & \langle v_n, v_n \rangle \end{bmatrix}$$

diagonal elements all have to be norm 1

Suppose we can solve the SDP for $v_1, v_2, \dots, v_n \in \mathbb{R}^n$.

Goemans-Williamson alg.

let $r \in \mathbb{R}^n$, $\|r\| = 1$ be a random vector drawn from $\{y \in \mathbb{R}^n : \|y\| = 1\}$.

non-negative inner product with random vector

random rounding

generate cut

$$S = \left\{ i \in \{1, \dots, n\} : \langle v_i, r \rangle \geq 0 \right\}$$

Thm: $\underbrace{\text{OPT}^*(G)}_{\text{efficient}} \geq \underbrace{0.87856}_{\alpha} \underbrace{\text{OPT}(G)}_{\text{cannot attain}}$

solved using SDP.

(with convex programme)

acute angle \Rightarrow include in S

one is inside the cut,
one is outside the cut

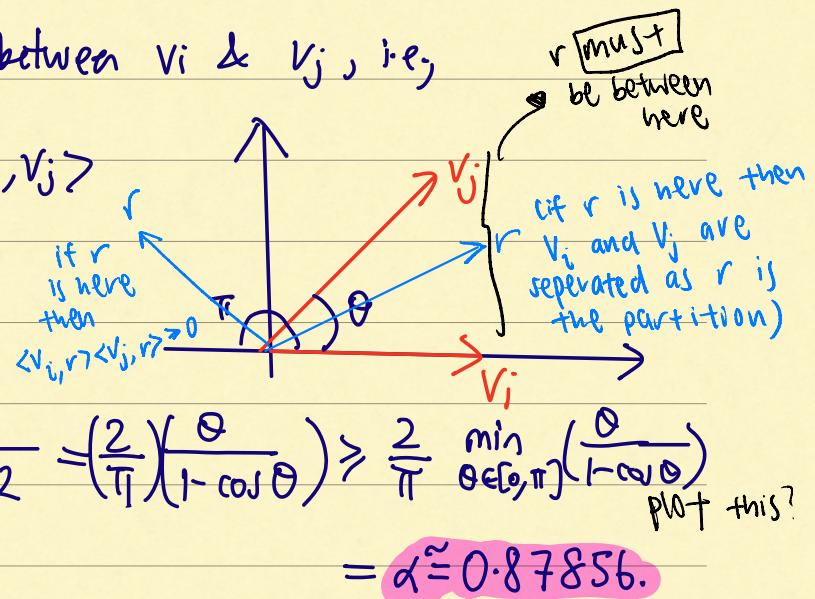
Def: $i, j \in V = \{1, \dots, n\}$ are separated if $\langle v_i, r \rangle \langle v_j, r \rangle \leq 0$
 $|\{i, j\} \cap S| = 1$

probability
Lem: $\Pr(i, j \text{ are separated}) \geq \alpha \left(\frac{1 - \langle v_i, v_j \rangle}{2} \right)$

Pf: Suppose θ is the angle between v_i & v_j , i.e.,

$$\cos \theta = \langle v_i, v_j \rangle$$

$$\Pr(i, j \text{ separated}) = \frac{\theta}{\pi}$$



$$\frac{\Pr(i, j \text{ sep})}{(1 - \langle v_i, v_j \rangle / 2)} = \frac{\theta/\pi}{(1 - \cos \theta)/2} = \frac{(2/\pi) \left(\frac{\theta}{1 - \cos \theta} \right)}{2} \geq \frac{2}{\pi} \min_{\theta \in [0, \pi]} \left(\frac{\theta}{1 - \cos \theta} \right)$$

plot this?
 $= \alpha \approx 0.87856.$

$A(G)$: our cut obtained by SDP and random rounding.

$$\mathbb{E}[A(G)] = \sum_{\substack{i, j \in E \\ \text{our cut}}} \mathbb{E}\left[\mathbb{1}_{\{|\{i, j\} \cap S| = 1\}} \right]$$

$$= \sum_{\substack{i, j \in E}} \Pr(i, j \text{ sep})$$

Count the number of edges where one is inside S and 1 is outside S

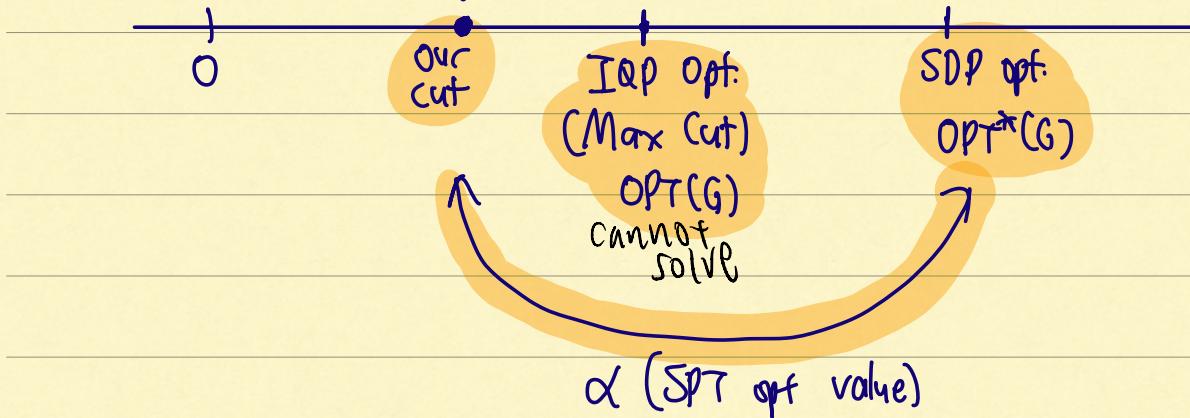
Lem.

$$> \alpha \sum_{\substack{i, j \in E}} \left(\frac{1 - \langle v_i, v_j \rangle}{2} \right)$$

$$= \alpha (\text{SDP opt. value})$$

this number is the best
that you can achieve
(given restriction to
convex programs)

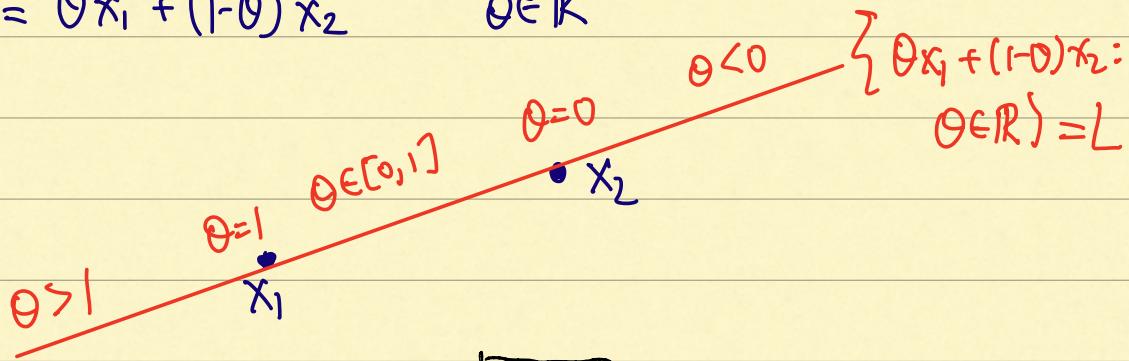
≥ 0.87856 of $\text{OPT}(G)$.



Section 2.1 & 2.2 of BV.

$x_1, x_2 \in \mathbb{R}^n$ two distinct points in n -dim Euclidean space.

$$y = \theta x_1 + (1-\theta) x_2 \quad \theta \in \mathbb{R}$$



Def: A set $C \subset \mathbb{R}^n$ is affine if the line through
any two distinct points of C belongs to C

$$\forall x_1, x_2 \in C, \quad \theta x_1 + (1-\theta)x_2 \in C \quad \forall \theta \in \mathbb{R}.$$

generalisation
of the
above

Ex: If C is an affine set, then $\forall x_1, \dots, x_k \in C$, then
the point $\sum_{i=1}^k \theta_i x_i \in C$ if $\sum_{i=1}^k \theta_i = 1$
When $k=2$, it reduces to def. above.

Ex: If C is an affine set and $x_0 \in C$, then the set

$$V = C - x_0 = \{x - x_0 : x \in C\}$$

is a subspace, i.e., closed under sum & scalar multiplication.

Pf: Take $v_1, v_2 \in V$ & $\alpha, \beta \in \mathbb{R}$.

\Downarrow

$$v_1 + x_0, v_2 + x_0 \in C$$

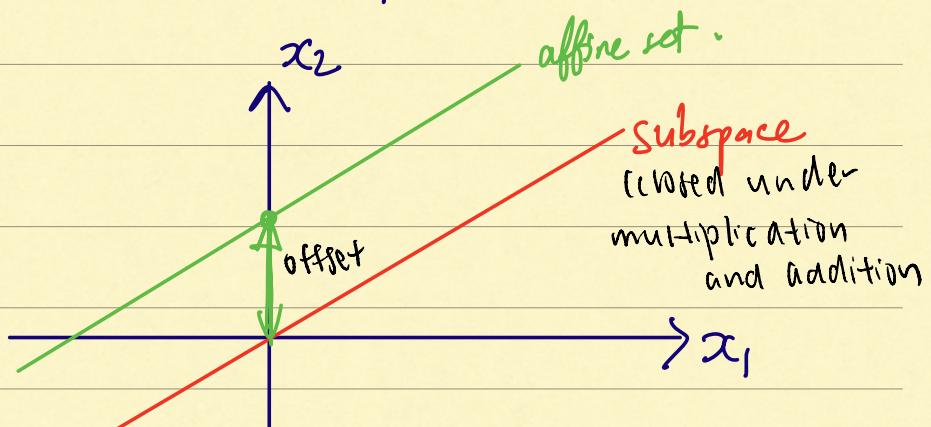
$$\underline{\alpha v_1 + \beta v_2 + x_0} = \underline{\alpha(v_1 + x_0)} + \underline{\beta(v_2 + x_0)} + \underline{(1-\alpha-\beta)x_0} \in C.$$

scalar sum to one

$$\because \alpha + \beta + (1-\alpha-\beta) = 1$$

Thus $\alpha v_1 + \beta v_2 \in V$ since $\alpha v_1 + \beta v_2 + x_0 \in C$. \square

Rmk: Any affine set C can be expressed as a subspace plus an offset



Ex: Solution of linear equation.

$$C = \{x \in \mathbb{R}^n : Ax = b\}$$

Take $x_1, x_2 \in C$. Then $Ax_1 = b, Ax_2 = b$. Take arb. $\theta \in \mathbb{R}$.

Consider $A(\theta x_1 + (1-\theta)x_2) = \theta Ax_1 + (1-\theta)Ax_2$
 $\qquad\qquad\qquad \text{in } C$
 $\qquad\qquad\qquad = \theta b + (1-\theta)b = b.$

\Rightarrow Set C is affine. by linearity
of matrix operations

Def: Set of all affine combinations of pts in a set $C \subset \mathbb{R}^n$
 is called the affine hull of C

$$\text{aff}(C) = \left\{ \theta x_1 + \dots + \theta_k x_k : x_1, \dots, x_k \in C, \sum_{i=1}^k \theta_i = 1 \right\}$$

no need to be non-negative

Rmk: Affine hull of any set C is the smallest affine
set that contains C .

Relative interior of C :

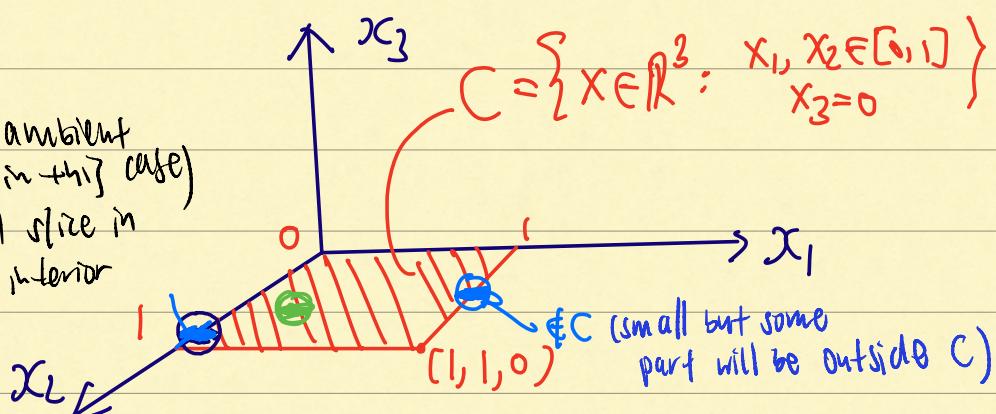
$$\text{relint}(C) = \{x \in C \mid B(x, r) \cap \text{aff}(C) \subseteq C \text{ for some } r > 0\}.$$

ball centered at x with radius r .

$$\text{int}(C) = \emptyset$$

interior \Rightarrow relative to ambient space (\mathbb{R}^3 in this case)

\hookrightarrow red portion only 1 slice in 3 dimension thus interior is empty



If you choose a small enough r , you will be strictly contained inside C , after done intersection with affine hull

take any 2 points in red square and take all possible affine combinations \rightarrow affine hull

$$\text{aff}(C) = x_1, x_2 \text{ plane} = \{x \in \mathbb{R}^3 : x_3 = 0\}$$

$$\text{relint}(C) = \left\{ x \in \mathbb{R}^3 : x_1, x_2 \in (0, 1), x_3 = 0 \right\}$$

\hookrightarrow open interval (do not contain sides)

Recall: Norm. Fix $x \in \mathbb{R}^n$.

$$\|x\|_2 = \sqrt{x_1^2 + \dots + x_n^2}$$

$$\|x\|_1 = |x_1| + \dots + |x_n|$$

$$\|x\|_\infty = \max_{1 \leq i \leq n} |x_i|.$$

$$\|x\|_p = \left(\sum (x_i)^p \right)^{\frac{1}{p}}$$

$p \geq 1$

Ex: $0 \leq p < 1$,

Is $\|x\|_p$ a norm?

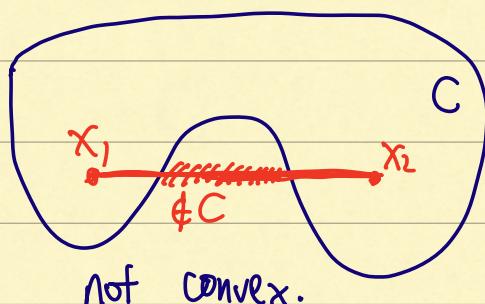
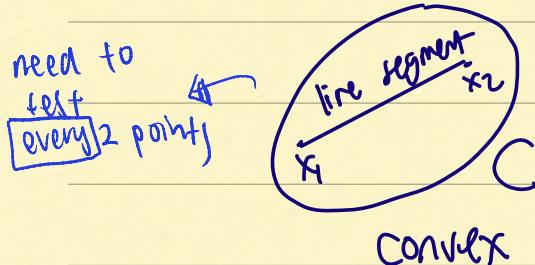
Homogeneity triangle inequality

$$\|x\|_p = 0 \Rightarrow x = 0$$

Convex Sets.

Def: A set $C \subseteq \mathbb{R}^n$ is convex if the line segment between any 2 points in C lies in C .

$\forall x_1, x_2 \in C$ and any $\theta \in [0, 1]$, $\theta x_1 + (1-\theta)x_2 \in C$.



Def: Convex combination of points $x_1, \dots, x_k \in C$ is
 a point of the form $\theta_1 x_1 + \dots + \theta_k x_k$, $\theta_i \geq 0, \sum_{i=1}^k \theta_i = 1$

\uparrow \rightarrow
 coefficients (probability mass
function)
 (must all be non-negative
and add up to 1)

Def: A set C is a cone if $\forall x \in C, \theta \geq 0, \theta x \in C$
 C is a convex cone if it is convex & a cone.
 $\Rightarrow \forall x_1, x_2 \in C, \theta_1, \theta_2 \geq 0, \theta_1 x_1 + \theta_2 x_2 \in C$.

A point $\sum_{i=1}^k \theta_i x_i$ with $\theta_i \geq 0, i \in \{1, \dots, k\}$, is called
 a conic combination of x_1, \dots, x_k

$\theta_i \geq 0$ \curvearrowleft \curvearrowright adding up

$$\text{Conichull}(C) = \left\{ \underbrace{\theta_1 x_1 + \dots + \theta_k x_k}_{\substack{\text{take any } k \text{ points in } C \text{ and} \\ \text{look at the conic combination}}} : \begin{array}{l} x_i \in C \\ \theta_i \geq 0 \quad \forall i = 1, \dots, k \end{array} \right\}$$

Examples:

1) \emptyset : empty set is convex, affine (no two points to take)

2) $\{x_0\}$: singleton is convex, affine (same point)

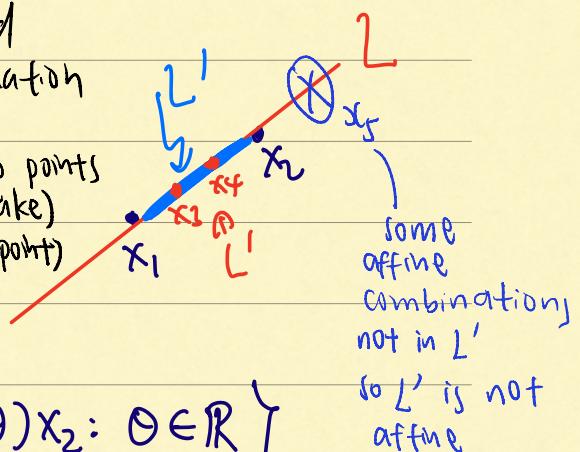
3) \mathbb{R}^n : convex, affine (very big space)

4) Fix $x_1, x_2 \in \mathbb{R}^n$. $L = \{\theta x_1 + (1-\theta)x_2 : \theta \in \mathbb{R}\}$.

convex, affine

5) Line segment $L' = \{\theta x_1 + (1-\theta)x_2 : \theta \in [0, 1]\}$

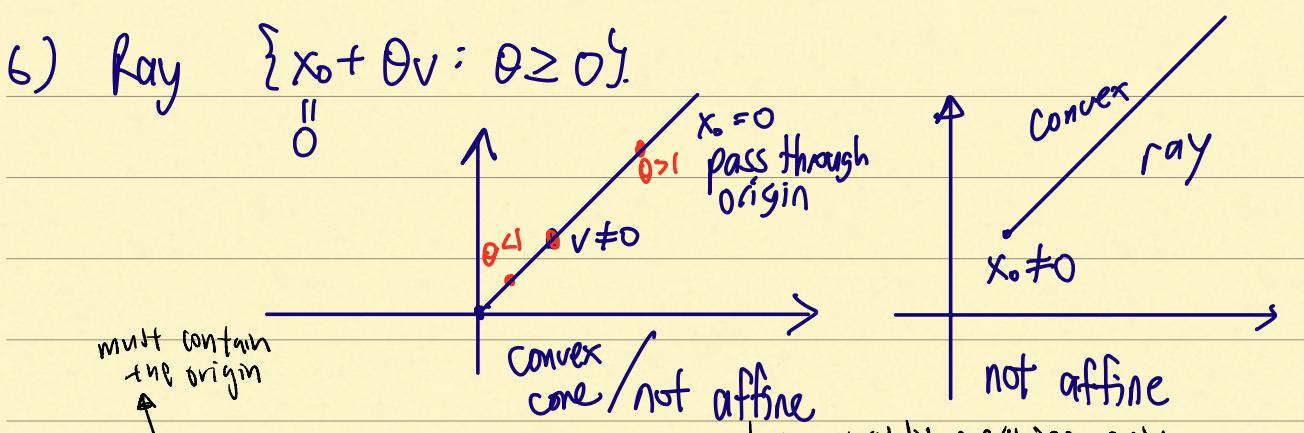
convex, **not** affine.



some
affine
combinations
not in L'

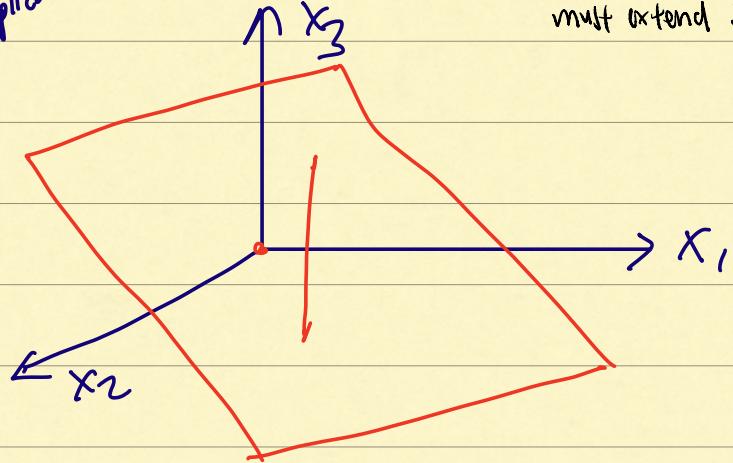
so L' is not
affine

6) Ray $\{x_0 + \theta v : \theta \geq 0\}$



7) A subspace is affine & a convex cone. roughly speaking, only extends in 1 direction (for something to be affine, must extend in all directions)

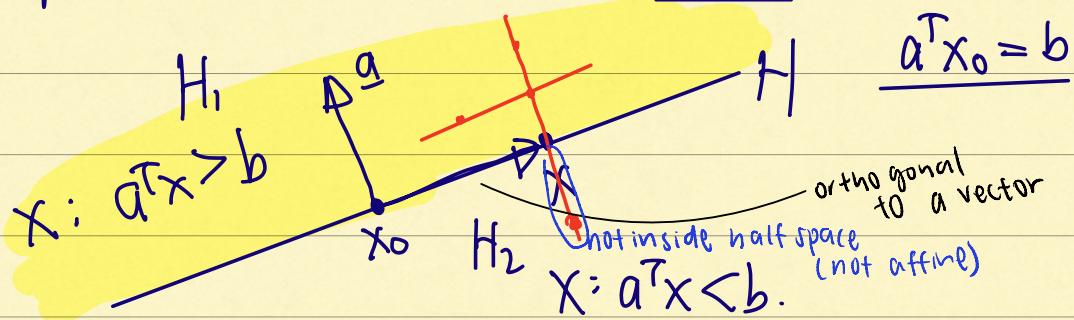
closed under addition & scalar multiplication



Hyperplanes & Halfspaces.

Hyperplane

$$H = \{x \in \mathbb{R}^n : a^T x = b\} = \{x : a^T(x - x_0) = 0\}$$



If H is a hyperplane, it divides \mathbb{R}^n into two halfspaces

$$H_1 = \{x : a^T x > b\} \quad \text{open halfspace.}$$

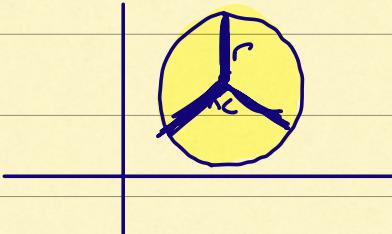
$$H_1 = \{x : a^T x \geq b\} \quad \text{closed halfspace}$$

$$H_2 = \{x : a^T x < b\} \quad \text{open}$$

H_1 halfspace: convex, not affine.

Euclidean balls. $\|x\|_2 = \sqrt{x_1^2 + \dots + x_n^2}$, $\|x\|_2^2 = x^T x$

$$\begin{aligned} B(x_c, r) &= \{x : \|x - x_c\| \leq r\} \\ &\stackrel{\uparrow}{\text{center}} \stackrel{\nearrow}{\text{radius}} \\ &= \{x : (x - x_c)^T (x - x_c) \leq r^2\} \end{aligned}$$



$B(x_c, r) = \{x_c + ru : \|u\| \leq 1\}$ all balls with radius $r \Rightarrow$ translating it into location x_c and scaling it

Fact: $B(x_c, r)$ is convex

Pf: Take $x_1, x_2 \in B(x_c, r)$. $\|x_i - x_c\| \leq r \quad \forall i = 1, 2$.

Fix $\theta \in [0, 1]$. Consider $\theta x_1 + (1-\theta)x_2$ convex combination

$$\begin{aligned} &\|\theta x_1 + (1-\theta)x_2 - x_c\| \\ &= \|\theta x_1 + (1-\theta)x_2 - \theta x_c - (1-\theta)x_c\| \\ &= \|\theta(x_1 - x_c) + (1-\theta)(x_2 - x_c)\| \\ &\leq \|\theta(x_1 - x_c)\| + \|(1-\theta)(x_2 - x_c)\| \quad (\text{w.p. } \triangle \text{ equality}) \\ &= \theta \|x_1 - x_c\| + (1-\theta) \|x_2 - x_c\| \quad (\text{homogeneity property}) \\ &\leq \theta r + (1-\theta)r = r \end{aligned}$$

$\Rightarrow \theta x_1 + (1-\theta)x_2 \in B(x_c, r) \Rightarrow B(x_c, r)$ convex.

Ellipsoid: $E = \{x \in \mathbb{R}^n : (x - x_c)^T P^{-1} (x - x_c) \leq 1\}$.

$P = P^T > 0$: P is a symmetric positive definite matrix.

x_c : center

↳ invertible (eigenvalues all bigger than 0)

lengths of the semi-axes of E are given by $\sqrt{\lambda_i}$

λ_i : eigenvalues of P .

proportional
to identity matrix
identity

Euclidean ball = Ellipsoid $P = r^2 I$

$$(x - x_c)^T (r^2 I)^{-1} (x - x_c) \leq 1$$

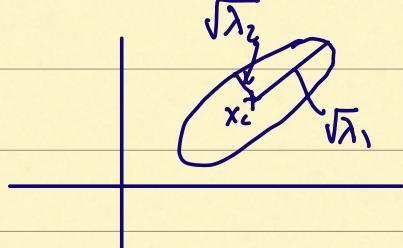
$$\Leftrightarrow \|x - x_c\|^2 \leq r^2 \quad (\text{equation of a sphere})$$

P : PD, $\exists A = P^{1/2}$. The ellipsoid is the set of all x s.t.

$$(x - x_c)^T (A^T A)^{-1} (x - x_c) \leq 1$$

$$\Leftrightarrow (x - x_c)^T A^{-1} (A^T)^{-1} (x - x_c) \leq 1$$

$$\| \underbrace{(A^{-1})^T (x - x_c)}_u \| \leq 1$$



Any point in the ellipsoid can be written as

$$x = x_c + Au \quad \text{where } \|u\| \leq 1$$

Norm:
(ball) $\{x : \|x - x_c\| \leq r\}$ is convex.

Norm cone: $\{(x, t) \in \mathbb{R}^{n+1} : \|x\| \leq t\}$ is a convex cone.
 {
 t is a scalar
 n-dim

Pf convex: $(x_1, t_1), (x_2, t_2) \in C$ Column vector of length $n+1$

$$\|x_1\| \leq t_1, \|x_2\| \leq t_2$$

Consider $\theta(x_1, t_1) + (1-\theta)(x_2, t_2) \in C \quad \theta \in [0, 1]$

$$\|\theta x_1 + (1-\theta)x_2\| \leq \theta \|x_1\| + (1-\theta)\|x_2\|$$

$$\leq \theta t_1 + (1-\theta)t_2.$$

show that it's convex

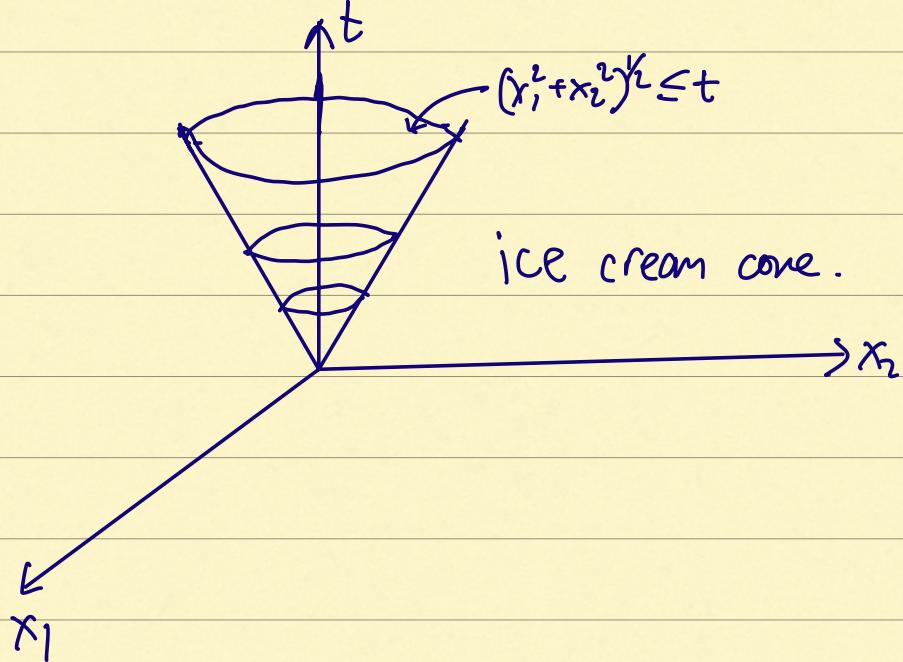
norm of the first
n coordinates less
than last
coordinate

Pf conc: Take any point $(x, t) \in C$. Fix $\theta \geq 0$.

WTS: $\underbrace{\theta(x, t)}_{\in \mathbb{R}^{n+1}} \in C \quad \frac{\theta[x]}{t} \in C$ homogeneity

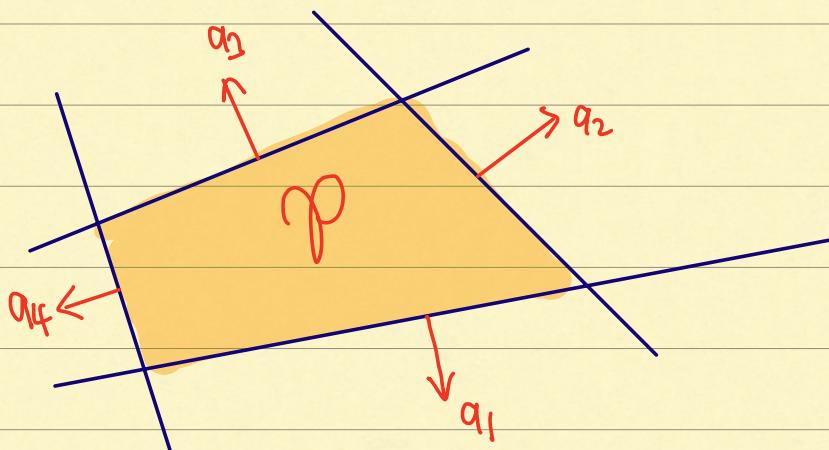
$$\|\theta x\| \leq \theta \|x\| \leq \theta t \quad //$$

$$\{(x_1, x_2, t) \in \mathbb{R}^3 : \sqrt{x_1^2 + x_2^2} \leq t\}$$



Polyhedra (Plural of polyhedron)

$$\mathcal{P} = \left\{ x \in \mathbb{R}^n : \begin{array}{l} a_j^T x \leq b_j, \quad j=1, \dots, m \\ c_j^T x = d_j, \quad j=1, \dots, p \end{array} \right\}$$



Can be written more concisely as.

$$\mathcal{P} = \{x : Ax \leq b, Cx = d\}.$$

vector inequality *vector componentwise.*

$$A = \begin{bmatrix} -a_1^T & - \\ \vdots & \vdots \\ -a_m^T & - \end{bmatrix} \quad b = \begin{bmatrix} b_1 \\ \vdots \\ b_m \end{bmatrix} \quad C = \begin{bmatrix} -c_1^T & - \\ \vdots & \vdots \\ -c_p^T & - \end{bmatrix}$$

$$d = \begin{bmatrix} d_1 \\ \vdots \\ d_p \end{bmatrix}$$

Simplexes (plural of simplex)

$v_0, \dots, v_k \in \mathbb{R}^n$ affinely independent

$\Leftrightarrow v_1 - v_0, v_2 - v_0, \dots, v_k - v_0$ are linearly independent

if θ is a vector component wise bigger than 0

$$C = \text{conv}\{v_0, \dots, v_k\} = \left\{ \theta_0 v_0 + \dots + \theta_k v_k \mid \begin{array}{l} \theta \geq 0, \quad \underline{\theta^T \theta = 1} \\ \theta \in \mathbb{R}^{k+1} \quad \sum_{i=0}^k \theta_i = 1 \end{array} \right\}$$

adding up components

Ex: $v_0 = 0, v_1 = e_1, v_2 = e_2, \dots, v_k = e_k$

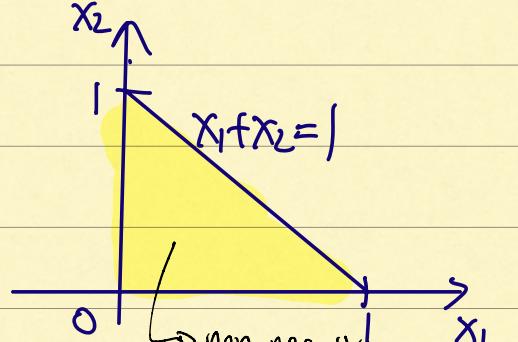
$$e_i = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ i \\ 0 \end{bmatrix} \leftarrow i^{\text{th}} \text{ location. } (\text{i}^{\text{th}} \text{ unit vector})$$

\sum of all comp. of x .

$C = \text{set of all } x \text{ st. } x \geq 0, \quad \underline{1^T x \leq 1}$

Why? $x = \theta_0 \underbrace{v_0}_{e_0} + \theta_1 \underbrace{v_1}_{e_1} + \dots + \theta_k \underbrace{v_k}_{e_k} = \begin{bmatrix} \theta_0 \\ \vdots \\ \theta_k \end{bmatrix} \geq 0$

$$\sum_{i=0}^k \theta_i = 1 \Leftrightarrow \underbrace{\theta_0 + \theta_1 + \dots + \theta_k}_{\geq 0} = 1 \leq 1$$



non negative,
sum up to not more
than 1

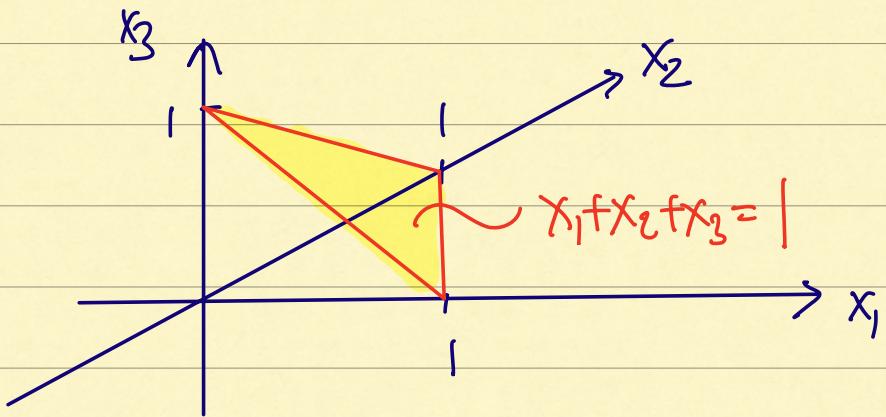
Ex: Probability simplex. $v_0 = e_1, v_1 = e_2, \dots, v_{n-1} = e_n$

C contains all x st.

$$x = \theta_0 e_1 + \theta_1 e_2 + \dots + \theta_{n-1} e_n = \begin{bmatrix} \theta_0 \\ \theta_1 \\ \vdots \\ \theta_{n-1} \end{bmatrix} \geq 0$$

$$\theta_i \geq 0, \quad \sum_{i=0}^{n-1} \theta_i = 1$$

X is s.t. $x \geq 0, \sum x_i = 1$



Q: Affine? No!

Q: Cone No!

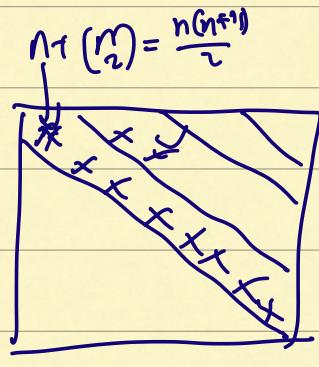
Q: Convex? Yes!

Positive Semidefinite Cone

S^n : set of $n \times n$ symmetric matrices

$$X \in S^n \text{ iff } X = X^T$$

Vector space with dim $\frac{n(n+1)}{2}$,



$M(n) = \frac{n(n+1)}{2}$
↳ need to describe diagonal entries and off diagonals

S_f^n : set of PSD symmetric matrices

$$X \in S_f^n \text{ iff } \forall z \in \mathbb{R}^n \quad z^T X z \geq 0$$

S_{ff}^n : set of positive definite matrices

$$X \in S_{ff}^n \text{ iff } \forall z \in \mathbb{R}^n \setminus \{0\}, \quad z^T X z > 0$$

S_f^n is a (convex cone)

Pf: $A, B \in S_f^n$. $\theta_1, \theta_2 \geq 0$. Fix $z \in \mathbb{R}^n$.

Consider $z^T (\theta_1 A + \theta_2 B) z$

$$= \theta_1 \underbrace{z^T A z}_{\geq 0} + \theta_2 \underbrace{z^T B z}_{\geq 0} \geq 0$$

|||

Fix $\theta \in [0, 1]$. Consider $\theta A + (1-\theta)B$