1. Polyhedral

$$P = \{x : Ax \le b, Cx = D\}$$

2. Euclidean Ball

$$B(x_c, x) = \{x : ||x - x_c||_2 \le r\}$$

Can use affine combination and triangular inequality of norm to prove convexity.

3. Elipse

$$E(x_c, P) = \{x : (x - x_c)^T P^{-1}(x - x_c) \le 1\}, P > 0$$

$$P = r^2 I \implies \text{Euclidean Ball}$$

$$P = Q \begin{bmatrix} \lambda_1 & \dots \\ \dots & \lambda_n \end{bmatrix} Q^T$$

$$(x - x_c)^T Q \begin{bmatrix} \lambda_1 & \dots \\ \dots & \lambda_n \end{bmatrix} Q^T (x - x_c) \le 1$$

$$\tilde{x}^T \begin{bmatrix} \lambda_1 & \dots \\ \dots & \lambda_n \end{bmatrix} \tilde{x}^T \le 1$$

$$\tilde{x}^T \begin{bmatrix} \frac{1}{\lambda_1} & \dots \\ \dots & \frac{1}{\lambda_n} \end{bmatrix} \tilde{x} = \frac{\tilde{x_1}^2}{\lambda_1} + \dots + \frac{\tilde{x_n}^2}{\lambda_n} \le 1$$
volum of elipsoid proportional to $\sqrt{\det(P)} = \sqrt{\Pi_i \lambda_i}$

4. Norm Ball

$$C = \{x : ||x|| \le 1\}$$
 for any $||*||$

Example: lp-norm

5. Cone

$$(\forall x \in C, \forall \theta \ge 0)\theta x \in C$$

6. Convex Cone Eg: S^n, S^N_+ are convex cones convexity check for S^N_+ :

$$x_1 \in S_+^n \implies v^T x_1 v \ge 0$$

$$x_2 \in S_+^n \implies v^T x_2 v \ge 0$$

$$v^T (\theta x_1 + (1 - \theta) x_2) v \ge 0$$

$$v^T \theta x_1 v + (1 - \theta) v^T x_2 v \implies x \in S_+^n$$

convexity check for cone:

$$x_1 \in S_+^n \implies \theta x_1 \in S_+^n, \theta \ge 0$$

 $(\forall v)v^T x v \ge 0 \implies v^T(\theta x)v \ge 0 \implies \text{cone}$

- 7. Proper Cone Definition:
 - convex
 - closed(contains all boundary points)
 - solid(non-empty interior)
 - pointed(contains no line): $x \in K \implies -x \in K$

Then the proper cone K fefines a generalized inequality (\leq_K) in \mathbb{R}^n

$$x \leq_K y \implies y - x \in K$$
$$x <_K y \implies y - x \in int(K)$$

Example: $K = \mathbb{R}^n_+$ (non-negative orthant):

$$n = 2$$

$$x \le_{R_+^2} y \implies y - x \in R_+^2$$

Cone provides partial ordering using difference of 2 objects Example: X $leq_{S^n_+}Y \implies Y - X \in S^n_+$ (Y-X is PSD)

- 8. Operations Preserving Convexity
 - intersection

 $S\alpha$ is affine, convex, convex cone $\forall \alpha \in A$ $\cap_{\alpha \in A} S_{\alpha}$ is affine, convex, convex cone

Example: Polyhedral is the intersection of some halfspaces and hyperplanes, so it is convex.

Any closed convex set can be represented by possibly infinitely many half spaces.

• affine functions

let
$$f(x) = Ax + b, f : \mathbb{R}^n \to \mathbb{R}^m$$

then if S is a convex set we have:

- project forward: $f(S) = \{f(X) : X \in S\}$ is convex

- project back: $f^{-1}(S) = \{X : f(X) \in S\}$ is convex

Example:

$$C = \{y : y = Ax + b, ||x|| \le 1\}$$

 $||x|| \le 1$ is convex, Ax + b is affine \implies C is convex Example:

$$C = \{x : ||Ax + b|| \le 1\}$$

 ${y: ||y|| \le 1}$

y is an affine function of $x \implies C$ is convex

9. Affine Functions $A(x) = \sum_i x_i A_i + B, A_i \in S^n, B \in S^n, x \in \mathbb{R}^n$ is $\{X : \sum_{i} x_{i} A_{i} = \tilde{A}(x) \leq B\}$ convex? let $y = B - \tilde{A}(x)$

let
$$y = R - \tilde{A}(r)$$

 $\{y: 0 \le y\}$ is convex

We know $\{y: 0 \le y\}$ is convex. Further y is an affine function of x \Longrightarrow

 $\{X: \sum_{i} x_{i} A_{i} \leq B\}$ is also convex $\{X: \sum_{i} x_{i} A_{i} \leq B\}$ is a Linear Matrix Inequality

- 10. Properties of convex sets
 - Separating Hyperplanes: if $S, T \subset \mathbb{R}^n$ are convex and disjoint, then $\exists a \neq 0, b$ such that:

$$a^T x \ge b, for all x \in S$$

 $a^T x \le b, for all x \in T$

11. Supporting Hyperplane:

if S is convex, $\forall x_0 \in \partial S$ (boundary of S), then $\exists a \neq 0$ such that $a^T x \leq a^T x_0, \in S$