# Convex Optimization Note

Garrick Lin

March 13, 2019

### 1 Affine Set

## 1.1 Definition

A set A is called affine set when it satisfied:

If 
$$\mathbf{x_1} \in \mathcal{A}$$
 and  $\mathbf{x_2} \in \mathcal{A}$ , then,  $\forall \theta \in \mathcal{R}$ ,  $x = \theta \mathbf{x_1} + (1 - \theta) \mathbf{x_2}$  also belong to  $\mathcal{A}$ .

The expression  $\theta \mathbf{x_1} + (1 - \theta)\mathbf{x_2}$  represent a line that cross through  $\mathbf{x_1}$  and  $\mathbf{x_2}$ . Hence, affine set can be explained intuitively as:

Affine set is a set that contain the line which cross through any two point within this set.

#### 1.2 Properties

Assume a affine set  $\mathcal{A} \subseteq \mathcal{R}^n$ . If  $\mathcal{A}$  contain original point( $\mathbf{0}$ ), then,  $\mathcal{A}$  is a subspace. In order to prove this,  $\mathcal{A}$  must satisfied following three rules:

- 1.  $\mathcal{A}$  contain original point.
- 2. If  $\mathbf{v} \in \mathcal{A}$ , then,  $\forall \theta \in \mathcal{R}$ ,  $\theta \mathbf{v} \in \mathcal{A}$ .
- 3. If  $\mathbf{v_1}, \mathbf{v_2} \in \mathcal{A}$ , then,  $\mathbf{v_1} + \mathbf{v_2} \in \mathbf{A}$ .

The first rule is already satisfied. For the second rule,  $\forall \theta \in \mathcal{R}$ ,  $\theta \mathbf{v}$  satisfied:

$$\theta \mathbf{v} = \theta \mathbf{v} + (1 - \theta) \mathbf{0}$$

Since  $\mathcal{A}$  is affine and  $\mathbf{v}, \mathbf{0} \in \mathcal{A}$ ,  $\theta \mathbf{v} \in \mathcal{A}$  always true. For the third rule, there is:

$$\mathbf{v_1} + \mathbf{v_2} = 2(\frac{1}{2}\mathbf{v_1} + \frac{1}{2}\mathbf{v_2})$$

 $\frac{1}{2}\mathbf{v_1} + \frac{1}{2}\mathbf{v_2} \text{ is in } \mathcal{A} \text{ as } \mathcal{A} \text{ is affine and } \frac{1}{2}\mathbf{v_1}, \frac{1}{2}\mathbf{v_2} \in \mathcal{A}(\text{According to the second rule, } \mathbf{v_1}, \mathbf{v_2} \in \mathcal{A}, \text{ then, } \frac{1}{2}\mathbf{v_1}, \frac{1}{2}\mathbf{v_2} \in \mathcal{A}).$  According to the second rule,  $2(\frac{1}{2}\mathbf{v_1} + \frac{1}{2}\mathbf{v_2}) \in \mathcal{A}$ 

Therefore, any affine set  $\mathcal{A}'$  can be thought as a subspace  $\mathcal{V}$  with a transportation  $\mathbf{v}$ , which means,  $\mathcal{A}' = \mathcal{V} + \mathbf{v}$ . On the other hand, an affine set subtract some constant vector  $(\mathcal{A}' - \mathbf{v})$ , which make the new set contain original point, can form a subspace. Formally, for a affine set  $\mathcal{A} = \{\mathbf{a_1}, \mathbf{a_2}, \cdots, \mathbf{a_n}\}$  and  $\mathbf{a_i} \in \mathcal{A}$ , the set:

$$A - a_i = \{a_1 - a_i, a_2 - a_i, \cdots, a_{i-1}, 0, a_{i+1}, \cdots, a_n - a_i\}$$
(1)

form a subspace. Furthermore, any affine set A has the form:

$$\mathcal{A} = \{ \mathbf{x} | \mathcal{B}\mathbf{x} = \mathbf{c} \} \tag{2}$$

**Proof**: According to equation 1,  $\mathcal{A} - \mathbf{a_i}$  is a subspace. Denote this subspace as  $\mathcal{L} = \mathcal{A} - \mathbf{a_i}$ . Assume the space that perpendicular to  $\mathcal{L}$ , denote as  $\mathcal{L}^{\perp}$ , has basis  $\{\mathbf{b_1}, \mathbf{b_2}, \cdots, \mathbf{b_n}\}$ . Then,  $\mathcal{L}$  is the set of vectors that perpendicular to the basis of  $\mathcal{L}^{\perp}$ . As a result, if we write the basis of  $\mathcal{L}^{\perp}$  in matrix form, which is:

$$\mathcal{B} = egin{bmatrix} \mathbf{b_1}^T \\ \mathbf{b_2}^T \\ \vdots \\ \mathbf{b_n}^T \end{bmatrix}$$

We have:

$$\mathcal{L} = \{ \mathbf{y} | \mathcal{B} \mathbf{y} = 0 \} \tag{3}$$

Equation 3 always hold as all vector in  $\mathcal{L}^{\perp}$  is the linear combination of the basis, hence, if a vector  $\mathbf{v}$  satisfied  $\mathbf{b_1}^T \mathbf{v} = 0, \mathbf{b_2}^T \mathbf{v} = 0, \cdots, \mathbf{b_n}^T \mathbf{v} = 0$ , then,  $(\theta_1 \mathbf{b_1} + \theta_2 \mathbf{b_2} + \cdots \theta_n \mathbf{b_n})^T \mathbf{v} = 0$ , which means,  $\mathbf{v}$  is perpendicular to any vector in  $\mathcal{L}^{\perp}$  if  $\mathbf{v}$  is perpendicular to the basis of  $\mathcal{L}^{\perp}$ .

Since the vector in  $\mathcal{L}$  come from  $\mathcal{A}$  subtract  $\mathbf{a_i}$ , for all  $\mathbf{y} \in \mathcal{L}$ , there must exists  $\mathbf{x} \in \mathcal{A}$  such that:

$$y = x - a_i \tag{4}$$

By combining equation 4 and equation 3, we have:

$$\mathcal{A} = \{ \mathbf{x} | \mathcal{B}(\mathbf{x} - \mathbf{a_i}) = 0 \}$$

Which is equivalent to:

$$\mathcal{A} = \{\mathbf{x} | \, \mathcal{B}\mathbf{x} = \mathcal{B}\mathbf{a_i}\}$$

and has the same form as equation 2, where  $\mathbf{c} = \mathcal{B}\mathbf{a_i}$ .

## 2 Hyper-plane

#### 2.1 Definition

In a  $\mathbb{R}^n$  space, the hyperplane is defined as a n-1 dimension subspace plus a translate  $\mathbf{x_0}$ , which is perpendicular to a one dimension vector  $\mathbf{w}$ . The formal mathematical expression of hyper-plane  $\mathcal{H}$  is:

$$\mathcal{H} = \{ \mathbf{y} + \mathbf{x_0} | \mathbf{w}^T \mathbf{y} = 0 \} \tag{5}$$

We can denote  $\mathbf{x} = \mathbf{y} + \mathbf{x_0}$ , hence, equation 5 become:

$$\mathcal{H} = \{ \mathbf{x} | \mathbf{w}^T (\mathbf{x} - \mathbf{x_0}) = 0 \}$$
 (6)

It is clearly that when  $\mathbf{x} = \mathbf{x_0}$ ,  $\mathbf{w}^T(\mathbf{x_0} - \mathbf{x_0}) = 0$  always hold, hence,  $\mathbf{x_0}$  is a point within hyper-plane. As a result, equation 6 can be explained intuitively as: Hyper-plane is a set of any point  $\mathbf{x}$  which satisfied the vector  $\mathbf{x} - \mathbf{x_0}$  (start from a fixed point  $\mathbf{x_0}$  which belong to this hyper-plane, end at  $\mathbf{x}$ ) is perpendicular to a normal vector  $\mathbf{w}$ .

Equation 6 give us another way to represent hyper-plane:

$$\mathcal{H} = \{ \mathbf{x} | \mathbf{w}^T \mathbf{x} = \mathbf{b} \} \tag{7}$$

Where  $\mathbf{b} = \mathbf{w}^T \mathbf{x_0}$ .

#### 2.2 Half-space

Intuitively, a hyper-plane split the whole space into two part, each of them is called half-space. The formal mathematical expression for half-space, base on equation 6, is:

$$\{\mathbf{x} | \mathbf{w}^T (\mathbf{x} - \mathbf{x_0}) < 0\}$$

or

$$\{\mathbf{x} | \mathbf{w}^T (\mathbf{x} - \mathbf{x_0}) > 0\}$$

Which corresponding to the two split space. In geometric, two vector  $\mathbf{v_1}$  and  $\mathbf{v_2}$  satisfied:  $\mathbf{v_1}^T\mathbf{v_2} > 0$  if their angle smaller than 90 degree, otherwise,  $\mathbf{v_1}^T\mathbf{v_2} < 0$ . As a result, the half-space  $\{\mathbf{x} | \mathbf{w}^T(\mathbf{x} - \mathbf{x_0}) < 0\}$  is the set of point  $\mathbf{x}$  which satisfied the vector  $\mathbf{x} - \mathbf{x_0}$  have a angle greater than 90 degree with a normal vector  $\mathbf{w}$ . The half-space  $\{\mathbf{x} | \mathbf{w}^T(\mathbf{x} - \mathbf{x_0}) > 0\}$  can be explained in the same way except the angle is smaller than 90 degree.

Furthermore, according to 7, the expression of half-space can also be written as:

$$\{\mathbf{x} | \mathbf{w}^T \mathbf{x} < \mathbf{b}\}$$

Where  $\mathbf{b} = \mathbf{w}^T \mathbf{x_0}$ .

## 3 Cone

#### 3.1 Definition

A cone  $\mathcal{K}$  is the set of any point  $\mathbf{x}$  that satisfied: If  $\mathbf{x} \in \mathcal{K}$ , then, for any  $\theta \geq 0$ ,  $\theta \mathbf{x} \in \mathcal{K}$ . A **convex** cone, as its' name suggest, is a cone which is also a convex set.

### 3.2 Property of Convex Cone

Assume a cone K is a convex cone, then, it satisfied:

If  $\mathbf{x_1} \in \mathcal{K}$  and  $\mathbf{x_2} \in \mathcal{K}$ , then, for any  $0 \le \theta \le 1$ ,  $\theta \mathbf{x_1} + (1 - \theta) \mathbf{x_2} \in \mathcal{K}$ .

Furthermore, for any p, q > 0, the expression  $p\mathbf{x_1} + q\mathbf{x_2}$  can be written as:

$$p\mathbf{x_1} + q\mathbf{x_2} = (p+q)\left(\frac{p}{p+q}\mathbf{x_1} + \frac{q}{p+q}\mathbf{x_2}\right)$$
(8)

Following the property of convex set, the point  $(\frac{p}{p+q}\mathbf{x_1} + \frac{q}{p+q}\mathbf{x_2}) \in \mathcal{K}$ . Additionally, since  $(p+q) \in \mathcal{R}$  and p+q>0, the definition of cone indicate  $(p+q)(\frac{p}{p+q}\mathbf{x_1} + \frac{q}{p+q}\mathbf{x_2}) \in \mathcal{K}$ . As a result, it can be seen within a convex cone  $\mathcal{K}$ :

If  $\mathbf{x_1}, \mathbf{x_2} \in \mathcal{K}$ , then, for any  $\theta_1, \theta_2 > 0$ ,  $\theta_1 \mathbf{x_1} + \theta_2 \mathbf{x_2} \in \mathcal{K}$ 

#### 3.3 Dual Cone

In geometric, a point  $\mathbf{x}$  can be defined as the end point of a vector that start with the original point( $\mathbf{0}$ ) and terminate at point  $\mathbf{x}$ , which means, any point  $\mathbf{x}$  can also be thought as a vector  $\mathbf{x} - \mathbf{0}$ . Base on this, the dual cone of a cone  $\mathcal{K}$ , denote as  $\mathcal{K}^*$ , is defined as the set of any point  $\lambda$  which satisfied  $\lambda^T \mathbf{x} > 0$  for all  $\mathbf{x} \in \mathcal{K}$ , which means, the **vector**  $\lambda$  have the angle smaller than 90 degree for any **vector**  $\mathbf{x} - \mathbf{0}$  defined by the point  $\mathbf{x}$  in  $\mathcal{K}$ .

Furthermore, the expression  $\lambda^T \mathbf{x} > 0$  define a half-space according to equation 6, where the fixed point  $\mathbf{x_0}$  is the original point. As a result, the dual cone of  $\mathcal{K}$  can also be illustrated as:

A point  $\lambda$  is in  $\mathcal{K}^*$  if the half-space with the **vector**  $\lambda$  as normal vector, which expressed as  $\lambda \mathbf{x} > 0$ , contain the original cone  $\mathcal{K}$ .