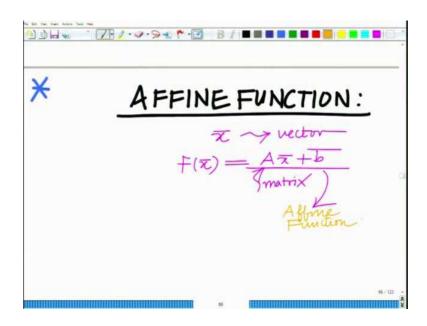
## Applied Optimization for Wireless, Machine Learning, Big Data Prof. Aditya K. Jagannatham Department of Electrical Engineering Indian Institute of Technology, Kanpur

## Lecture – 18 Introduction to Affine functions and examples: Norm cones l2, l\_P, l1, norm balls

Hello. Welcome to another module in this massive open online course. Let us discuss another important operation that preserves convexity which is known as an affine function.

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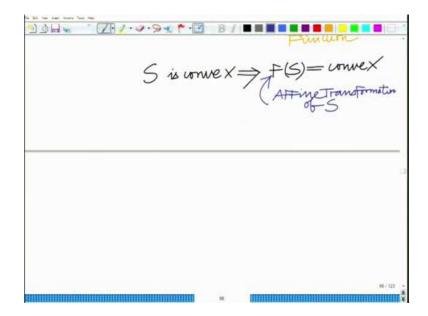


So, the next transformation that preserves convexity is known as an Affine Function. To define an affine function; take a vector  $\bar{x}$ . So an affine function is a function that is of the form given below.

$$F(\overline{x}) = A\overline{x} + \overline{b}$$

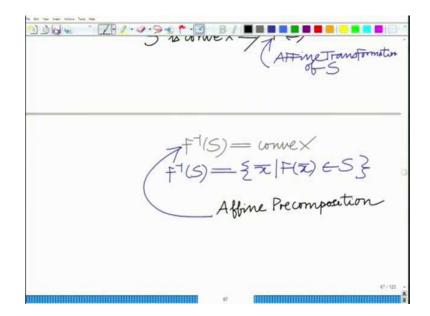
Here A is a matrix,  $\overline{b}$  is a vector.

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Therefore, according to the second property of convex set, if S is convex, then affine transformation of all elements in S that is F(S) is also convex. This property also includes that an affine pre composition that is  $F^{-1}(S)$  also results in a convex set.

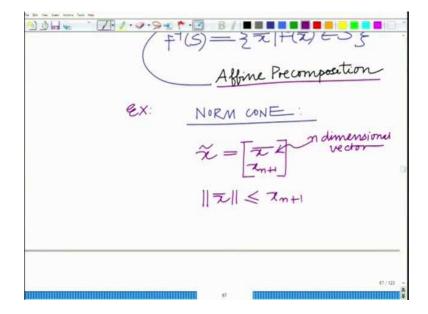
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An affined pre composition is defined as follows.

$$F^{-1}(S) = \{ \overline{x} \mid F(\overline{x}) \in S \}$$

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For instance, an application can be demonstrated as follows. Consider a Norm Cone  $\tilde{x}$  containing n-dimensional vector  $\bar{x}$  such that

$$\tilde{x} = \begin{bmatrix} \overline{x} \\ x_{n+1} \end{bmatrix}$$

As this is a norm cone, therefore

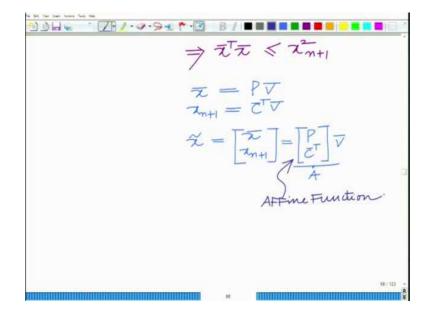
$$\|\overline{x}\| \le x_{n+1}$$

This basically implies that

$$\overline{x}^T \overline{x} \le x_{n+1}^2$$

This is an alternative representation of the Norm Core.

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Now, let us see affine pre composition of this vector  $\tilde{x}$  where  $\overline{x}$  and  $x_{n+1}$  are defined as follows.

$$\overline{x} = P\overline{V}$$
$$x_{n+1} = \overline{C}^T \overline{V}$$

Therefore,  $\tilde{x}$  would be defined as follows.

$$\tilde{x} = \begin{bmatrix} P\overline{V} \\ \overline{C}^T \overline{V} \end{bmatrix} = \begin{bmatrix} P \\ \overline{C}^T \end{bmatrix} \overline{V}$$

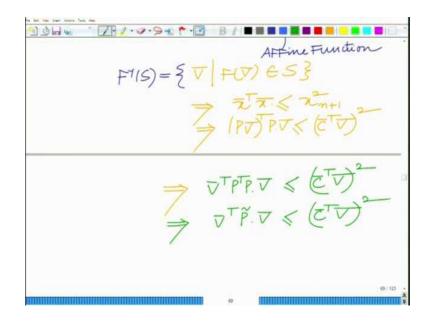
By the definition of an affine set, the vector A is

$$A = \begin{bmatrix} P \\ \overline{C}^T \end{bmatrix}$$

And vector  $\overline{b}$  is a zero vector.

So, this vector  $\tilde{x}$  is an affine Function

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Now, to find affine pre composition of this vector  $\tilde{x}$ , let us start by its definition.

$$F^{-1}(S) = \{ \overline{V} \mid F(\overline{V}) \in S \}$$

This simply implies that

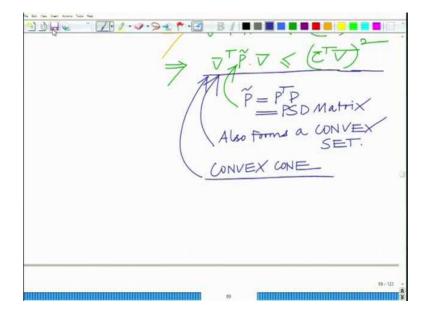
$$\overline{x}^T \overline{x} \le x_{n+1}^2$$

$$(P\overline{V})^T P \overline{V} \le (\overline{C}^T \overline{V})^2$$

$$\overline{V}^T P^T P \overline{V} \le (\overline{C}^T \overline{V})^2$$

$$\overline{V}^T \tilde{P} \overline{V} \le (\overline{C}^T \overline{V})^2$$

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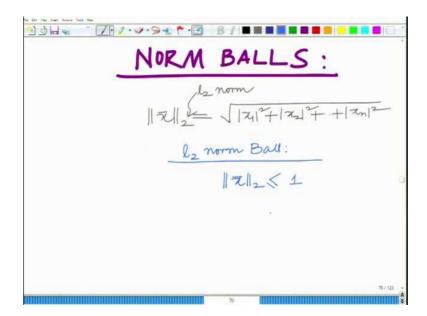


And the matrix  $\tilde{P}$  is defined as

$$\tilde{P} = P^T P$$

Which means that  $\tilde{P}$  is a positive semi definite matrix. Now, since  $F(\overline{V})$  is the norm cone therefore vector  $\overline{V}$  is the affine pre composition, and this also forms a convex set or more accurately convex cone.

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Let us move on to another interesting aspect that is the concept of Norm Ball. Remember the norm ball was defined as follows. If  $l_2$  norm is defined as

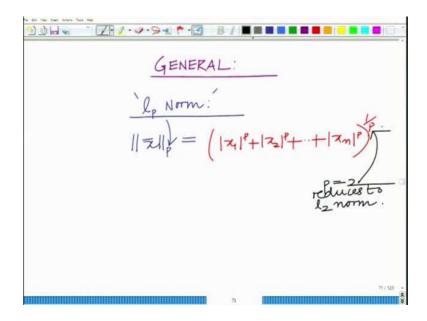
$$\|\overline{x}\|_{2} = \sqrt{|x_{1}|^{2} + |x_{2}|^{2} + \dots + |x_{n}|^{2}}$$

Then the  $l_2$  norm ball is defined as

$$\left\|\overline{x}\right\|_2 \le r$$

Where r is the radius of this norm ball. Let us say r equal to 1. Hence this norm ball is basically a circle in 2-dimensions or in n-dimensions it is a sphere.

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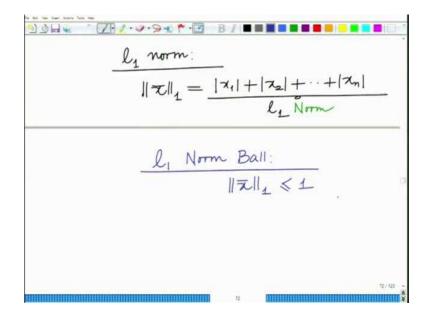


In general, one can define an  $l_p$  norm as

$$\|\overline{x}\|_{P} = \left(\sqrt{|x_{1}|^{P} + |x_{2}|^{P} + \dots + |x_{n}|^{P}}\right)^{\frac{1}{P}}$$

This is the general form of norm. If P is set as 2 then it will become  $l_2$  norm. This  $l_P$  norm can be used to construct other very interesting norm which is  $l_1$  norm.

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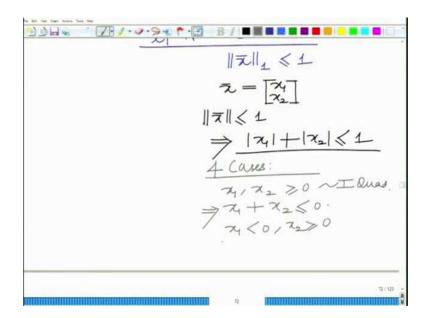
The  $l_1$  norm is one of the most fundamental and widely applied norm. For  $l_1$  norm, set P=1 in the above  $l_P$  norm expression.

$$\|\overline{x}\|_{1} = |x_{1}| + |x_{2}| + \dots + |x_{n}|$$

And similarly,  $l_1$  norm ball is given by

$$\|\overline{x}\|_1 \le 1$$

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And for instance to look at this, let us consider a 2-dimensional case.

$$\overline{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

Therefore the  $l_1$  norm ball of this  $\overline{x}$  is

$$\left\| \overline{x} \right\| \le 1$$

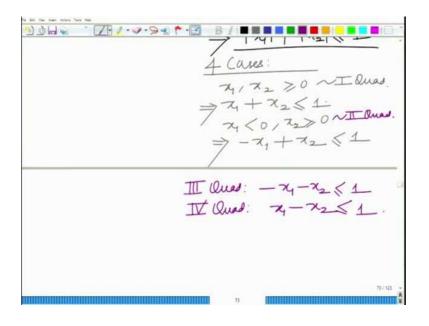
$$\left| x_1 \right| + \left| x_2 \right| \le 1$$

For this norm ball, one can consider four cases as;

1.  $x_1 \ge 0$ ,  $x_2 \ge 0$  I<sup>st</sup> Quadrant

1.  $x_1 \ge 0$ ,  $x_2 \ge 0$  II nd Quadrant 2.  $x_1 \le 0$ ,  $x_2 \ge 0$  III Quadrant 3.  $x_1 \le 0$ ,  $x_2 \le 0$  IV Quadrant 4.  $x_1 \ge 0$ ,  $x_2 \le 0$  IV Quadrant

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So for first quadrant,

$$x_1 + x_2 \le 1$$

For second quadrant,

$$-x_1 + x_2 \le 1$$

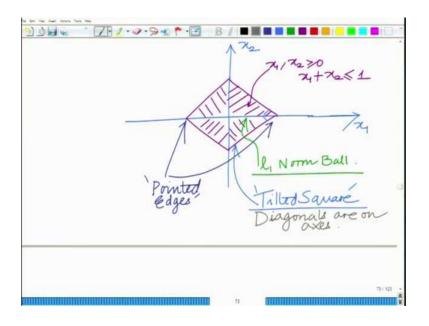
Then in the third quadrant,

$$-x_1 - x_2 \le 1$$

And in the fourth quadrant,

$$x_1 - x_2 \le 1$$

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So, these are the four cases and if all these four cases of this norm ball are plotted on a graph with  $x_1$  as x-axis and  $x_2$  as y-axis, then one will observe that this region is a tilted square with the diagonals along the axis. The  $l_2$  norm ball is a circle which means  $l_1$  norm ball is very different from the  $l_2$  norm ball in the sense that  $l_1$  norm ball has pointed edges. This simple observation leads to the profound implications that  $l_1$  norm ball is non-differentiable.

So, the  $l_2$  norm is very amenable for analysis because it can be easily differentiated.

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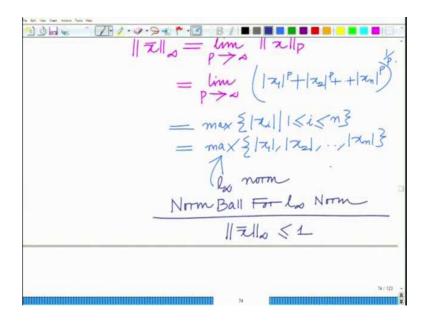
$$\frac{l_{\infty} \text{ Norm: } p \rightarrow \infty}{||\mathbf{z}||_{\infty}} = \lim_{p \rightarrow \infty} ||\mathbf{z}||_{p}$$

$$= \lim_{p \rightarrow \infty} (|\mathbf{z}||^{p} + |\mathbf{z}||^{p} + |\mathbf{z}||^{p})$$

Now, if  $P \to \infty$  in  $l_P$  norm then  $l_P$  norm becomes  $l_\infty$  norm which is another class of norm. Therefore

$$\begin{aligned} \|\overline{x}\|_{\infty} &= \lim_{P \to \infty} \|\overline{x}\|_{P} \\ &= \lim_{P \to \infty} \left( \sqrt{|x_{1}|^{P} + |x_{2}|^{P} + \dots + |x_{n}|^{P}} \right)^{\frac{1}{P}} \\ &= \max \left\{ |x_{1}|, |x_{2}|, \dots, |x_{n}| \right\} \\ &= \max \left\{ |x_{i}| \mid 1 \le i \le n \right\} \end{aligned}$$

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So,  $l_{\scriptscriptstyle \infty}$  norm is defined as the maximum of the absolute values of the components of that vector.

And corresponding to this, the  $\,l_{\scriptscriptstyle\infty}$  norm ball will be defined as

$$\|\overline{x}\|_{\infty} \le r$$

The  $l_{\infty}$  norm ball is basically the region corresponding to the  $l_{\infty}$  norm of a vector being less than or equal to any radius. In a particular case, discussed above this radius is 1 so

$$\|\overline{x}\|_{\infty} \le 1$$

Let us continue this discussion in the subsequent module.