# **Recitation 5**

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## **Brief Overview**

Vector norms

Matrix norms

Discussion of Homework questions

Solving exercises from book

# Norms and inequalities (15 min)

• What is a norm?

• An Lp norm is defined as  $||x||_p = (\sum_{i=1}^n |x|^p)^{1/p}$ 

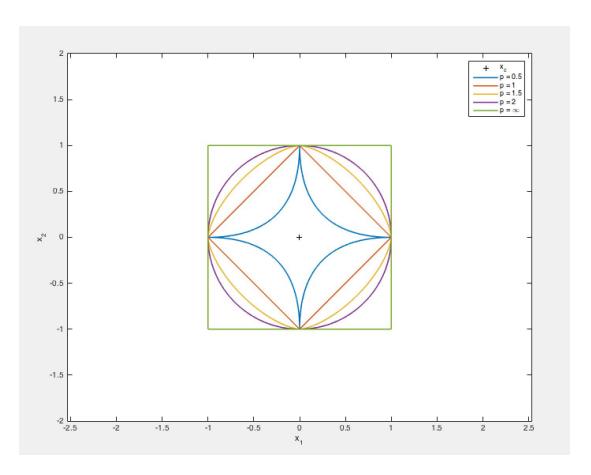
• 2-norm or Euclidean norm:  $||x||_2 = \sqrt{\sum_{i=1}^n x_i^2}$ 

• 1-norm:  $||x||_2 = \sum_{i=1}^n |x_i|$ 

•  $\infty$  - norm:  $||x||_{\infty} = max(|x_1|, |x_2|, ..., |x_n|)$ 

```
function [] = VisualizeNorms(x_c,r,p)
                                                                              %tester code
                                                                              x_c = [0,0]; %center at origin
%plots a p-norm ball with radius r, centred at x_c
  low = min(x_c);
                                                                              r = 1; %radius of ball is 1
                                                                              plot(x_c(1),x_c(2),k+') %plots the center
  high = max(x_c);
  x = linspace(low-2*r, high+2*r);
                                                                              hold on
  y = linspace(low-2*r,high+2*r);
                                                                              xlabel('x 1')
  theta = 0:pi/100:3*pi;
                                                                              ylabel('x_2')
  xp = r*sign(cos(theta)).*abs(cos(theta)).^(2/p);
                                                                              axis([-(x_c(1)+2*r) x_c(1)+2*r -(x_c(2)+2*r)
  yp = r*sign(sin(theta)).*abs(sin(theta)).^(2/p);
                                                                              x_c(2)+2*r]
  plot(xp,yp,'-','LineWidth',1.5)
                                                                              axis equal
end
                                                                              VisualizeNorms(x_c,r,0.5) %p = 0.5
                                                                              VisualizeNorms(x_c,r,1) %p = 1
                                                                              VisualizeNorms(x_c,r,1.5) %p = 1.5
                                                                              VisualizeNorms(x_c,r,2) %p = 2
                                                                              VisualizeNorms(x_c,r,inf) \%p = inf
                                                                              legend('x_c','p = 0.5','p = 1','p = 1.5','p = 2', 'p = \infty')
```

You should get a plot which looks like this:



- Think about why this happens. Read the references to know more about norms.
- Can also define matrix norms

• Subordinate norm:  $\sup_{v \in \mathbb{R}^n} \frac{||Av||}{||v||}$ 

#### **Condition number**

• Absolute condition number

$$\circ$$
  $\sup_{\delta x} (||\delta f||)/(||\delta x||)$ , where  $||\delta f|| = ||f(x + \delta x) - f(x)||$ 

Consider a mapping f from a subset D of a normed linear space  $\mathcal{V}$  with norm  $\|\cdot\|_{\mathcal{V}}$  into another normed linear space  $\mathcal{W}$  with norm  $\|\cdot\|_{\mathcal{W}}$ , depicted in Figure 2.3, where  $x \in D \subset \mathcal{V}$  is regarded as the 'input' for f and  $f(x) \in \mathcal{W}$  is the 'output'. We shall be concerned with the sensitivity of the output to perturbations in the input; therefore, as a measure of sensitivity, we define the **absolute condition number** of f by

$$\operatorname{Cond}(f) = \sup_{\substack{x,y \in D \subset \mathcal{V} \\ x \neq y}} \frac{\|f(y) - f(x)\|_{\mathcal{W}}}{\|y - x\|_{\mathcal{V}}}.$$
 (2.42)

If  $\operatorname{Cond}(f) = +\infty$  or if  $1 \ll \operatorname{Cond}(f) < +\infty$ , we say that the mapping f is **ill-conditioned**.

- Relative condition number
  - $\circ \quad sup_{\delta x}(||\delta f||/||f(x)||)/(||\delta x||/||x||)$
  - o For a matrix (image from Trefethen et al., Numerical Linear Algebra, p. 93)

$$\kappa \ = \ \sup_{\delta_{\boldsymbol{x}}} \left( \frac{\|A(x+\delta x) - Ax\|}{\|Ax\|} \left/ \frac{\|\delta x\|}{\|x\|} \right) \ = \ \sup_{\delta_{\boldsymbol{x}}} \frac{\|A\delta x\|}{\|\delta x\|} \left/ \frac{\|Ax\|}{\|x\|} \right.$$

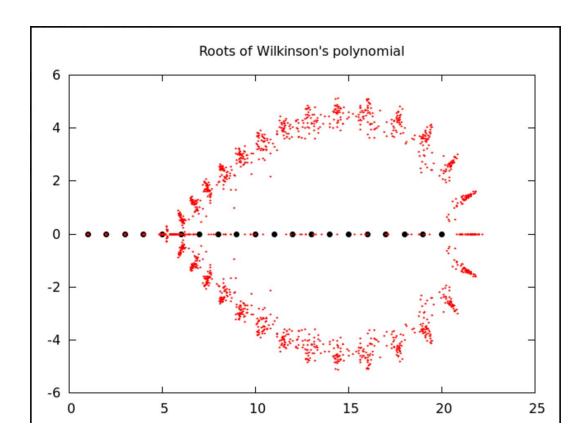
that is,

$$\kappa = \|A\| \frac{\|x\|}{\|Ax\|}$$

- Relative condition number more important in numerical analysis, as floating point system introduces relative errors
- Small condition number means well-conditioned. Large means ill-conditioned.
- Condition number of A:

$$\circ$$
  $\kappa(A) = ||A||.||A^{-1}||$ 

- Eg.
  - Finding the eigenvalues of a matrix
    - Take A = [1 1000; 0 1], eig(A) = [1 1]
    - B = [1 1000; 0.001 1], eig(B) = [0 2]
    - Problem is ill-conditioned for non-symmetric matrices, well-conditioned for symmetric matrices
  - Determining roots of a polynomial is ill-conditioned. If you. See [6] for famous example on Wilkinson's polynomial. You can also try checking this in MATLAB (see [7] for instructions).



• See [5] for more info. on examples.

### **Homework discussion and exercises**

Homework 3 problems:

- Ex. 2.3
- Ex. 2.8
- 2.12, 13

## Let's try a few exercises:

- Ex. 2.4
- Ex. 2.7
- Ex. 2.9
- Ex. 2.14

# **Helpful resources**

- 1. Notes on vector norms
- 2. Notes on matrix norms
- 3. <u>Intuition behind norms</u>
- 4. *Numerical Mathematics (Quarteroni et al)* is a very good resource for LU/norms/condition numbers/etc. It's also freely available for NYU students via Springer!
- 5. *Numerical Linear Algebra, Trefethen & Bau* also has a nice discussion on condition numbers (see Lec. 12).
- 6. <a href="https://en.wikipedia.org/wiki/Wilkinson%27s">https://en.wikipedia.org/wiki/Wilkinson%27s</a> polynomial
- 7. <a href="http://blogs.mathworks.com/cleve/2013/03/04/wilkinsons-polynomials/">http://blogs.mathworks.com/cleve/2013/03/04/wilkinsons-polynomials/</a>