# lecture\_13

March 2, 2017

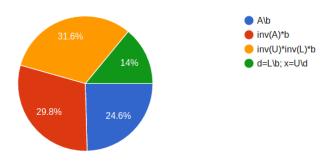
In [1]: %plot --format sug

In [2]: setdefaults

## 0.1 My question from last class

If you are solving the problem Ax=b where A=LU (the lower and upper triangular matrices of A) in matlab or octave what is the most efficient solution?

(57 responses)



q1

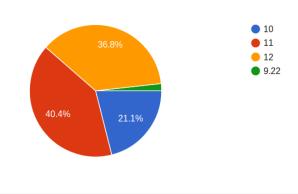
$$A = \left[ \begin{array}{rrr} 2 & -2 & 0 \\ -1 & 5 & 1 \\ 3 & 4 & 5 \end{array} \right]$$

## 0.2 Your questions from last class

- 1. Do we have to submit a link for HW #4 somewhere or is uploading to Github sufficient? -no, your submission from HW 3 is sufficient
- 2. How do I get the formulas/formatting in markdown files to show up on github? -no luck for markdown equations in github, this is an ongoing request
- 3. Confused about the p=1 norm part and  $||A||_1$

The p=1 norm is the sum of the maximum in each column, what is  $||A||_1$ ?

(57 responses)



q2

- 4. When's the exam?
  - -next week (3/9)
- 5. What do you recommend doing to get better at figuring out the homeworks? -time and experimenting (try going through the lecture examples, verify my work)
- 6. Could we have an hw or extra credit with a video lecture to learn some simple python? -Sounds great! how simple?
  - -Installing Python and Jupyter Notebook (via Anaconda) https://www.continuum.io/downloads
  - -Running Matlab kernel in Jupyter https://anneurai.net/2015/11/12/matlab-basedipython-notebooks/
  - -Running Octave kernel in Jupyter https://anaconda.org/pypi/octave\_kernel

#### 0.3 Condition of a matrix

#### 0.3.1 just checked in to see what condition my condition was in

#### 0.3.2 Matrix norms

The Euclidean norm of a vector is measure of the magnitude (in 3D this would be: |x| = $\sqrt{x_1^2 + x_2^2 + x_3^2}$  in general the equation is:

$$||x||_e = \sqrt{\sum_{i=1}^n x_i^2}$$

For a matrix, A, the same norm is called the Frobenius norm:

$$||A||_f = \sqrt{\sum_{i=1}^n \sum_{i=1}^m A_{i,j}^2}$$

In general we can calculate any *p*-norm where

$$||A||_p = \sqrt{\sum_{i=1}^n \sum_{i=1}^m A_{i,j}^p}$$
 so the p=1, 1-norm is

$$||A||_1 = \sqrt{\sum_{i=1}^n \sum_{i=1}^m A_{i,j}^1} = \sum_{i=1}^n \sum_{i=1}^m |A_{i,j}|$$

$$||A||_{\infty} = \sqrt{\sum_{i=1}^{n} \sum_{i=1}^{m} A_{i,j}^{\infty}} = \max_{1 \le i \le n} \sum_{j=1}^{m} |A_{i,j}|$$

#### 0.3.3 Condition of Matrix

```
The matrix condition is the product of
```

 $Cond(A) = ||A|| \cdot ||A^{-1}||$ 

So each norm will have a different condition number, but the limit is  $Cond(A) \ge 1$ An estimate of the rounding error is based on the condition of A:

$$\frac{||\Delta x||}{x} \le Cond(A) \frac{||\Delta A||}{||A||}$$

 $\frac{||\Delta x||}{x} \le Cond(A) \frac{||\Delta A||}{||A||}$ So if the coefficients of A have accuracy to \$10^{-t}

and the condition of A,  $Cond(A) = 10^{\circ}$ 

then the solution for x can have rounding errors up to  $10^{c-t}$ 

A =

L =

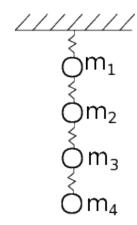
U =

Then, 
$$A^{-1} = (LU)^{-1} = U^{-1}L^{-1}$$
  
 $Ld_1 = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}$ ,  $Ux_1 = d_1 ...$ 

```
invA =
     9.0000
             -36.0000
                         30.0000
   -36.0000
            192.0000 -180.0000
    30.0000 -180.0000
                        180.0000
ans =
   1.0000e+00
               3.5527e-15 2.9976e-15
  -1.3249e-14
               1.0000e+00 -9.1038e-15
   8.5117e-15 7.1054e-15
                           1.0000e+00
   Find the condition of A, cond(A)
In [74]: % Frobenius norm
         normf_A = sqrt(sum(sum(A.^2)))
         normf_invA = sqrt(sum(sum(invA.^2)))
         cond_f_A = normf_A*normf_invA
         norm(A,'fro')
         % p=1, column sum norm
         norm1_A = max(sum(A,2))
         norm1_invA = max(sum(invA,2))
         norm(A,1)
         cond_1_A=norm1_A*norm1_invA
         % p=inf, row sum norm
         norminf_A = max(sum(A,1))
         norminf_invA = max(sum(invA,1))
         norm(A,inf)
         cond_inf_A=norminf_A*norminf_invA
normf_A = 1.4136
normf_invA = 372.21
cond_f_A = 526.16
ans = 1.4136
norm1_A = 1.8333
norm1_invA = 30.000
ans = 1.8333
cond_1_A = 55.000
norminf_A = 1.8333
norminf_invA = 30.000
```

```
ans = 1.8333
cond_inf_A = 55.000
```

Consider the problem again from the intro to Linear Algebra, 4 masses are connected in series to 4 springs with spring constants  $K_i$ . What does a high condition number mean for this problem?



Springs-masses

The masses haves the following amounts, 1, 2, 3, and 4 kg for masses 1-4. Using a FBD for each mass:

```
m_{1}g + k_{2}(x_{2} - x_{1}) - k_{1}x_{1} = 0
m_{2}g + k_{3}(x_{3} - x_{2}) - k_{2}(x_{2} - x_{1}) = 0
m_{3}g + k_{4}(x_{4} - x_{3}) - k_{3}(x_{3} - x_{2}) = 0
m_{4}g - k_{4}(x_{4} - x_{3}) = 0
in matrix form:
\begin{bmatrix} k_{1} + k_{2} & -k_{2} & 0 & 0 \\ -k_{2} & k_{2} + k_{3} & -k_{3} & 0 \\ 0 & -k_{3} & k_{3} + k_{4} & -k_{4} \\ 0 & 0 & -k_{4} & k_{4} \end{bmatrix} \begin{bmatrix} x_{1} \\ x_{2} \\ x_{3} \\ x_{4} \end{bmatrix} = \begin{bmatrix} m_{1}g \\ m_{2}g \\ m_{3}g \\ m_{4}g \end{bmatrix}
```

K =

```
0
              -10 11
        0
               0
y =
   9.8100
   19.6200
   29.4300
   39.2400
In [25]: cond(K,inf)
        cond(K,1)
         cond(K,'fro')
        cond(K,2)
ans =
        3.2004e+05
        3.2004e+05
ans =
        2.5925e+05
ans =
        2.5293e+05
ans =
In [26]: e=eig(K)
        max(e)/min(e)
e =
   7.9078e-01
   3.5881e+00
   1.7621e+01
   2.0001e+05
ans =
        2.5293e+05
```

#### **Iterative Methods** 1

#### 1.1 Gauss-Seidel method

If we have an intial guess for each value of a vector x that we are trying to solve, then it is easy enough to solve for one component given the others.

-1

1

-1

Take a  $3\times3$  matrix

$$Ax = b$$

$$\begin{bmatrix} 3 & -0.1 & -0.2 \\ 0.1 & 7 & -0.3 \\ 0.3 & -0.2 & 10 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} 7.85 \\ -19.3 \\ 71.4 \end{bmatrix}$$

$$x_1 = \frac{7.85 + 0.1x_2 + 0.3x_3}{3}$$

$$x_2 = \frac{-19.3 - 0.1x_1 + 0.3x_3}{7}$$
$$x_3 = \frac{71.4 + 0.1x_1 + 0.2x_2}{10}$$

$$x=A b$$

A =

b =

7.8500

-19.3000

71.4000

x =

3.0000

-2.5000

7.0000

#### 1.1.1 Gauss-Seidel Iterative approach

As a first guess, we can use  $x_1 = x_2 = x_3 = 0$ 

$$x_1 = \frac{7.85 + 0.1(0) + 0.3(0)}{7} = 2.6167$$

$$x_2 = \frac{-19.3 - 0.1(2.6167) + 0.3(0)}{7} = -2.7945$$

$$x_3 = \frac{71.4 + 0.1(2.6167) + 0.2(-2.7945)}{10} = 7.0056$$
Then we update the guess.

Then, we update the guess:

$$x_1 = \frac{7.85 + 0.1(-2.7945) + 0.3(7.0056)}{3} = 2.9906$$

$$x_2 = \frac{-19.3 - 0.1(2.9906) + 0.3(7.0056)}{7} = -2.4996$$

$$x_3 = \frac{71.4 + 0.1(2.9906) + 0.2(-2.4966)}{10} = 7.00029$$

The results are conveerging to the solution we found with  $\setminus$  of  $x_1 = 3$ ,  $x_2 = -2.5$ ,  $x_3 = 7$  We could also use an iterative method that solves for all of the x-components in one step:

#### 1.1.2 Jacobi method

$$x_1^i = \frac{7.85 + 0.1x_2^{i-1} + 0.3x_3^{i-1}}{3}$$

$$x_2^i = \frac{-19.3 - 0.1x_1^{i-1} + 0.3x_3^{i-1}}{7}$$

$$x_3^i = \frac{71.4 + 0.1x_1^{i-1} + 0.2x_2^{i-1}}{10}$$

Here the solution is a matrix multiplication and vector addition

$$\begin{bmatrix} x_1^i \\ x_2^i \\ x_3^i \end{bmatrix} = \begin{bmatrix} 7.85/3 \\ -19.3/7 \\ 71.4/10 \end{bmatrix} - \begin{bmatrix} 0 & -0.1 & -0.2 \\ 0.1 & 0 & -0.3 \\ 0.3 & -0.2 & 0 \end{bmatrix} \begin{bmatrix} x_1^{i-1} \\ x_2^{i-1} \\ x_3^{i-1} \end{bmatrix}$$

x_{j}	Jacobi method	vs	Gauss-Seidel
$     \begin{aligned}       x_1^i &= \\       x_2^i &=      \end{aligned} $	$ \frac{7.85+0.1x_2^{i-1}+0.3x_3^{i-1}}{3} \\ -19.3-0.1x_1^{i-1}+0.3x_3^{i-1} $		$\begin{array}{c} 7.85 + 0.1x_2^{i-1} + 0.3x_3^{i-1} \\ \hline 3 \\ -19.3 - 0.1x_1^{i} + 0.3x_3^{i-1} \end{array}$
$x_3^i =$	$\frac{71.4 + 0.1x_1^{i-1} + 0.2x_2^{i-1}}{10}$		$\frac{71.4 + 0.1x_1^7 + 0.2x_2^i}{10}$

```
In [15]: ba=b./diag(A) % or ba=b./[A(1,1);A(2,2);A(3,3)]
         sA=A-diag(diag(A)) % A with zeros on diagonal
         sA(1,:)=sA(1,:)/A(1,1);
         sA(2,:)=sA(2,:)/A(2,2);
         sA(3,:)=sA(3,:)/A(3,3)
         x0=[0;0;0];
         x1=ba-sA*x0
         x2=ba-sA*x1
         x3=ba-sA*x2
         fprintf('solution is converging to [3,-2.5,7]\n')
ba =
   2.6167
  -2.7571
   7.1400
sA =
   0.00000 -0.10000 -0.20000
   0.10000 0.00000 -0.30000
   0.30000 -0.20000
                      0.00000
sA =
   0.000000 -0.033333 -0.066667
   0.014286 0.000000 -0.042857
   0.030000 -0.020000
                       0.000000
x1 =
   2.6167
  -2.7571
   7.1400
```

x2 =

```
3.0008
  -2.4885
   7.0064
x3 =
   3.0008
  -2.4997
   7.0002
solution is converging to [3,-2.5,7]]
In [16]: diag(A)
          diag(diag(A))
ans =
    3
    7
   10
ans =
Diagonal Matrix
                0
    0
          7
                0
    0
               10
   This method works if problem is diagonally dominant,
   |a_{ii}| > \sum_{j=1, j \neq i}^{n} |a_{ij}|
If this condition is true, then Jacobi or Gauss-Seidel should converge
In [17]: A=[0.1,1,3;1,0.2,3;5,2,0.3]
          b=[12;2;4]
          A\b
A =
   0.10000
               1.00000
                           3.00000
   1.00000
               0.20000
                           3.00000
   5.00000
               2.00000
                           0.30000
```

b =

```
12
    2
    4
ans =
  -2.9393
   9.1933
   1.0336
In [20]: ba=b./diag(A) % or ba=b./[A(1,1);A(2,2);A(3,3)]
         sA=A-diag(diag(A)) % A with zeros on diagonal
         sA(1,:)=sA(1,:)/A(1,1);
         sA(2,:)=sA(2,:)/A(2,2);
         sA(3,:)=sA(3,:)/A(3,3)
         x0=[0;0;0];
         x1=ba-sA*x0
         x2=ba-sA*x1
         x3=ba-sA*x2
         fprintf('solution is not converging to [-2.93,9.19,1.03]\n')
ba =
   120.000
    10.000
    13.333
sA =
   0
       1
           3
   1
       0
           3
   5
           0
sA =
    0.00000
              10.00000
                         30.00000
    5.00000
               0.00000
                         15.00000
   16.66667
               6.66667
                          0.00000
x1 =
   120.000
    10.000
    13.333
x2 =
```

```
-380.00

-790.00

-2053.33

x3 =

6.9620e+04

3.2710e+04

1.1613e+04

solution is not converging to [-2.93,9.19,1.03]
```

#### 1.2 Gauss-Seidel with Relaxation

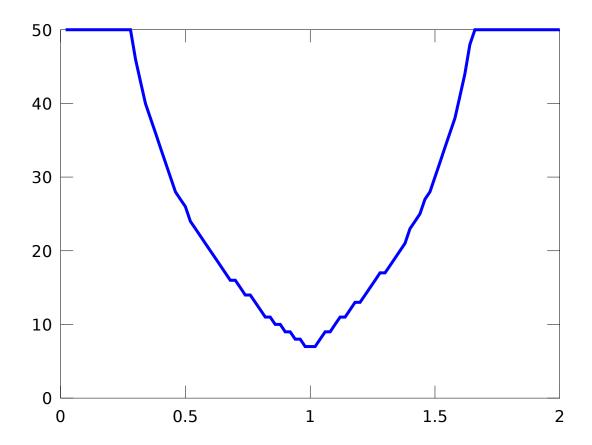
In order to force the solution to converge faster, we can introduce a relaxation term  $\lambda$ .

where the new x values are weighted between the old and new:

```
x^i = \lambda x^i + (1 - \lambda)x^{i-1}
```

after solving for x, lambda weights the current approximation with the previous approximation for the updated x

```
In [105]: % rearrange A and b
          A=[3 -0.1 -0.2;0.1 7 -0.3;0.3 -0.2 10]
          b=[7.85;-19.3;71.4]
          iters=zeros(100,1);
          for i=1:100
              lambda=2/100*i;
              [x,ea,iters(i)]=Jacobi_rel(A,b,lambda);
          plot([1:100]*2/100,iters)
A =
    3.00000
              -0.10000
                         -0.20000
               7.00000
                         -0.30000
    0.10000
    0.30000
              -0.20000
                         10.00000
b =
    7.8500
  -19.3000
   71.4000
```



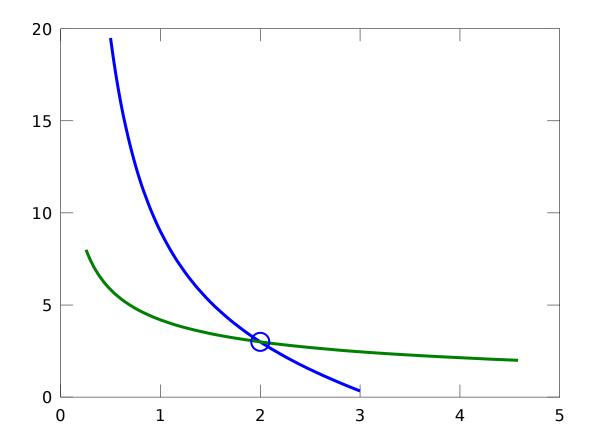
```
-2.5000
   7.0000
ea =
   1.8289e-07
   2.1984e-08
   2.3864e-08
iter = 8
x =
   3.0000
  -2.5000
   7.0000
ea =
   1.9130e-08
   7.6449e-08
   3.3378e-08
iter = 8
```

## 1.3 Nonlinear Systems

Consider two simultaneous nonlinear equations with two unknowns:

```
x_1^2 + x_1 x_2 = 10<br/>x_2 + 3x_1 x_2^2 = 57
```

Graphically, we are looking for the solution:



### 1.4 Newton-Raphson part II

Remember the first order approximation for the next point in a function is:

$$f(x_{i+1}) = f(x_i) + (x_{i+1} - x_i)f'(x_i)$$
  
then,  $f(x_{i+1}) = 0$  so we are left with:  
 $x_{i+1} = x_i - \frac{f(x_i)}{f'(x_i)}$ 

We can use the same formula, but now we have multiple dimensions so we need to determine the Jacobian

$$[J] = \begin{bmatrix} \frac{\partial f_{1,i}}{\partial x_1} & \frac{\partial f_{1,i}}{\partial x_2} & \cdots & \frac{\partial f_{1,i}}{\partial x_n} \\ \frac{\partial f_{2,i}}{\partial x_1} & \frac{\partial f_{2,i}}{\partial x_2} & \cdots & \frac{\partial f_{2,i}}{\partial x_n} \\ \vdots & \vdots & & \vdots \\ \frac{\partial f_{n,i}}{\partial x_1} & \frac{\partial f_{n,i}}{\partial x_2} & \cdots & \frac{\partial f_{n,i}}{\partial x_n} \end{bmatrix}$$

$$\begin{bmatrix} f_{1,i+1} \\ f_{2,i+1} \\ \vdots \\ f_{n,i+1} \end{bmatrix} = \begin{bmatrix} f_{1,i} \\ f_{2,i} \\ \vdots \\ f_{n,i} \end{bmatrix} + \begin{bmatrix} \frac{\partial f_{1,i}}{\partial x_1} & \frac{\partial f_{1,i}}{\partial x_2} & \cdots & \frac{\partial f_{1,i}}{\partial x_n} \\ \frac{\partial f_{2,i}}{\partial x_1} & \frac{\partial f_{2,i}}{\partial x_2} & \cdots & \frac{\partial f_{2,i}}{\partial x_n} \\ \vdots & \vdots & & \vdots \\ \frac{\partial f_{n,i}}{\partial x_1} & \frac{\partial f_{n,i}}{\partial x_2} & \cdots & \frac{\partial f_{n,i}}{\partial x_n} \end{bmatrix} \begin{pmatrix} \begin{bmatrix} x_{i+1} \\ x_{i+1} \\ \vdots \\ x_{i+1} \end{bmatrix} - \begin{bmatrix} f_{1,i} \\ f_{2,i} \\ \vdots \\ f_{n,i} \end{bmatrix} \end{pmatrix}$$

#### 1.4.1 Solution is again in the form Ax=b

$$[J]([x_{i+1}] - [x_i]) = -[f]$$
  
so  
 $[x_{i+1}] = [x_i] - [J]^{-1}[f]$ 

#### 1.5 Example of Jacobian calculation

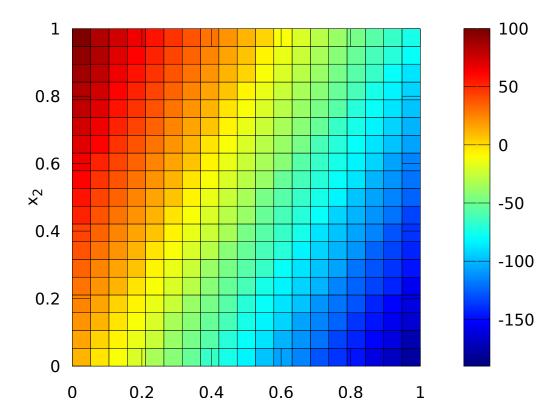
#### Nonlinear springs supporting two masses in series

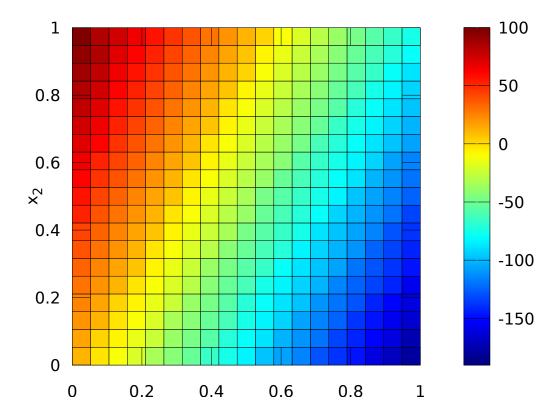
Two springs are connected to two masses, with  $m_1$ =1 kg and  $m_2$ =2 kg. The springs are identical,

but they have nonlinear spring constants, of  $k_1$ =10 N/m and  $k_2$ =-4 N/m We want to solve for the final position of the masses ( $x_1$  and  $x_2$ )  $m_1g + k_1(x_2 - x_1) + k_2(x_2 - x_1)^2 + k_1x_1 + k_2x_1^2 = 0$   $m_2g - k_1(x_2 - x_1) - k_2(x_2 - x_1)^2 = 0$  $J(1,1) = \frac{\partial f_1}{\partial x_1} = -k_1 - 2k_2(x_2 - x_1) + k_1 + 2k_2x_1$   $J(1,2) = \frac{\partial f_1}{\partial x_2} = k_1 + 2k_2(x_2 - x_1)$   $J(2,1) = \frac{\partial f_2}{\partial x_1} = k_1 + 2k_2(x_2 - x_1)$  $J(2,2) = \frac{\partial f_2}{\partial x_2} = -k_1 - 2k_2(x_2 - x_1)$ Use an initial guess of  $x_1 = x_2 = 0$ In []: m1=1; % kg m2=2; % kqk1=10; % N/mk2=-4; %  $N/m^2$ In [214]: function [f,J]=mass\_spring(x) % Function to calculate function values f1 and f2 as well as Jacobian % for 2 masses and 2 identical nonlinear springs m1=1; % kqm2=2; % kqk1=100; % N/m $k2=-10; % N/m^2$ g=9.81; % m/s^2 x1=x(1);x2=x(2);J = [-k1-2\*k2\*(x2-x1)-k1-2\*k2\*x1, k1+2\*k2\*(x2-x1);k1+2\*k2\*(x2-x1), -k1-2\*k2\*(x2-x1)]; $f=[m1*g+k1*(x2-x1)+k2*(x2-x1).^2-k1*x1-k2*x1^2;$  $m2*g-k1*(x2-x1)-k2*(x2-x1).^2$ ; end In [217]: [f,J]=mass\_spring([1,0]) f =-190.19 129.62

```
J =
  -200
         120
   120 -120
In [227]: x0=[3;2];
          [f0,J0]=mass_spring(x0);
          x1=x0-J0\f0
          ea=(x1-x0)./x1
          [f1,J1]=mass_spring(x1);
          x2=x1-J1\f1
          ea=(x2-x1)./x2
          [f2,J2]=mass_spring(x2);
          x3=x2-J2\f2
          ea=(x3-x2)./x3
          x=x3
          for i=1:3
              xold=x;
              [f,J]=mass_spring(x);
              x=x-J\backslash f;
              ea=(x-xold)./x
          end
x1 =
 -1.5142
  -1.4341
ea =
   2.9812
   2.3946
x2 =
   0.049894
   0.248638
ea =
   31.3492
    6.7678
x3 =
```

```
0.29701
  0.49722
ea =
  0.83201
  0.49995
x =
  0.29701
  0.49722
ea =
  0.021392
  0.012890
ea =
  1.4786e-05
  8.9091e-06
ea =
  7.0642e-12
  4.2565e-12
In [228]: x
         X0=fsolve(@(x) mass_spring(x),[3;5])
x =
  0.30351
  0.50372
X0 =
  0.30351
  0.50372
In [236]: [X,Y]=meshgrid(linspace(0,1,20),linspace(0,1,20));
          [N,M]=size(X);
          F=zeros(size(X));
```





In []: