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Assignments

present

About assignments

1. You should submit your homework through Github pull request. Xuanzhao Gao will comment on your PR, then you should resolve the issues to get your PR merged. You should submit different PRs for different assignments. [Open repo](#)
2. We will grade based on your merged PRs. You will not be failed if your submission is complete.
3. You may check the answers of other students, but you must credit him in your PR description, e.g.

Reference:
* PR #3
* PR #4

System of Linear Equations

Solving : $\mathbf{Ax} = \mathbf{b}$

Quiz: In a cage, chickens and rabbits add up to 35 heads and 94 feet. Please count the number of chickens and rabbits.

Table of contents

- Gaussian elimination algorithm
- Pivoting technique
- Sensitivity analysis and condition number
- Getting matrix inverse with Gauss-Jordan elimination
- Solving linear equations for special matrices (optional)

Schetch of solving the linear equation

$$A = LU$$
$$x = A^{-1}b = U^{-1}L^{-1}b$$

Solving tridiagonal linear equation

$$Lx = b$$

$$L = \begin{pmatrix} l_{11} & 0 & 0 \\ l_{21} & l_{22} & 0 \\ l_{31} & l_{32} & l_{33} \end{pmatrix}$$

Algorithm 2.1: Forward-Substitution for Lower Triangular System

$$x_1 = b_1/l_{11}, \quad x_i = \left(b_i - \sum_{j=1}^{i-1} l_{ij}x_j \right) / l_{ii}, \quad i = 2, \dots, n$$

back_substitution! (generic function with 1 method)

```
1 function back_substitution!(l::AbstractMatrix, b::AbstractVector)
2     n = length(b)
3     @assert size(l) == (n, n) "size mismatch"
4     x = zero(b)
5     # loop over columns
6     for j = 1:n
7         # stop if matrix is singular
8         if iszero(l[j, j])
9             error("The lower triangular matrix is singular!")
10        end
11        # compute solution component
12        x[j] = b[j] / l[j, j]
13        for i = j+1:n
14            # update right hand side
15            b[i] = b[i] - l[i, j] * x[j]
16        end
17    end
18    return x
19 end
```

```
l = 4x4 Matrix{Float64}:
 0.547284  0.0      0.0      0.0
 -1.068    0.759989  0.0      0.0
 -0.197166 -0.345128 -0.81142  0.0
 0.735737 -0.971137 -0.300388 -0.0411604
```

```
1 l = tril(randn(4, 4))
```

```
b = [-0.930708, -0.623271, -0.471425, -0.917524]
```

```
1 b = randn(4)
```

```
[-1.7006, -3.20992, 2.35952, 50.4085]
```

```
1 back_substitution!(l, copy(b))
```

The Julia's version

```
1 using LinearAlgebra
```

```
[-1.7006, -3.20992, 2.35952, 50.4085]
```

```
1 LowerTriangular(l) \ b
```

LU Factorization

$$A = LU$$

The Gaussian elimination process

$$A = \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix}$$

The elementary elimination matrix

$$M_1 A = \begin{pmatrix} a_{11} & a_{12} & \dots \\ 0 & a'_{22} & \dots \\ \vdots & \vdots & \ddots \end{pmatrix}$$

$$M_k = \begin{pmatrix} 1 & \dots & 0 & 0 & 0 & \dots & 0 \\ \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & 1 & 0 & 0 & \dots & 0 \\ 0 & \dots & 0 & 1 & 0 & \dots & 0 \\ 0 & \dots & 0 & -m_{k+1} & 1 & \dots & 0 \\ \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & 0 & -m_n & 0 & \dots & 1 \end{pmatrix}$$

where $m_i = a_i/a_k$.

Then

$$L = M_1^{-1} M_2^{-1} \dots M_{n-1}^{-1}$$

Properties of elimination matrices

$$M_k^{-1} = 2I - M_k$$

$$M_k M_{k' > k} = M_k + M_{k'} - I$$

Coding: Properties of elimination matrices

```
A3 = 3x3 Matrix{Int64}:
```

```
 1  2  2
 4  4  2
 4  6  4
```

```
1 A3 = [1 2 2; 4 4 2; 4 6 4]
```

elementary_elimination_matrix (generic function with 1 method)

```
1 function elementary_elimination_matrix(A::AbstractMatrix{T}, k::Int) where T
2     n = size(A, 1)
3     @assert size(A, 2) == n
4     # create Elementary Elimination Matrices
5     M = Matrix{Float64}(I, n, n)
6     for i=k+1:n
7         M[i, k] = -A[i, k] ./ A[k, k]
8     end
9     return M
10 end
```

The elimination

```
3x3 Matrix{Float64}:
```

```
1.0  0.0  0.0
-4.0  1.0  0.0
-4.0  0.0  1.0
```

```
1 elementary_elimination_matrix(A3, 1)
```

```
3x3 Matrix{Float64}:
```

```
1.0  2.0  2.0
0.0 -4.0 -6.0
0.0 -2.0 -4.0
```

```
1 elementary_elimination_matrix(A3, 1) * A3
```

The inverse

```
3x3 Matrix{Float64}:
```

```
1.0  0.0  0.0
4.0  1.0  0.0
4.0  0.0  1.0
```

```
1 inv(elementary_elimination_matrix(A3, 1))
```

The multiplication

```
3x3 Matrix{Float64}:
```

```
1.0  0.0  0.0
0.0  1.0  0.0
0.0 -1.5  1.0
```

```
1 elementary_elimination_matrix(A3, 2)
```

```
3x3 Matrix{Float64}:
```

```
1.0  0.0  0.0  
4.0  1.0  0.0  
4.0  1.5  1.0
```

```
1 inv(elementary_elimination_matrix(A3, 1)) * inv(elementary_elimination_matrix(A3, 2))
```

Algorithm 2.3: LU Factorization by Gaussian Elimination

lufact_naive! (generic function with 1 method)

```
1 function lufact_naive!(A::AbstractMatrix{T}) where T  
2     n = size(A, 1)  
3     @assert size(A, 2) == n  
4     M = Matrix{T}(I, n, n)  
5     for k=1:n-1  
6         m = elementary_elimination_matrix(A, k)  
7         M = M * inv(m)  
8         A .= m * A  
9     end  
10    return M, A  
11 end
```

```
(3x3 Matrix{Float64}::, 3x3 Matrix{Int64}::)  
1.0  0.0  0.0      1  2  2  
4.0  1.0  0.0  
4.0  1.5  1.0
```

```
1 lufact_naive!(copy(A3))
```

```
1 using Test
```

Test Passed

```
1 let  
2     A = [1 2 2; 4 4 2; 4 6 4]  
3     L, U = lufact_naive!(copy(A))  
4     @test L * U ≈ A  
5 end
```

Better implementation

lufact! (generic function with 1 method)

```
1 function lufact!(a::AbstractMatrix)
2     n = size(a, 1)
3     @assert size(a, 2) == n "size mismatch"
4     m = zero(a)
5     m[1:n+1:end] .+= 1
6     # loop over columns
7     for k=1:n-1
8         # stop if pivot is zero
9         if iszero(a[k, k])
10             error("Gaussian elimination fails!")
11         end
12         # compute multipliers for current column
13         for i=k+1:n
14             m[i, k] = a[i, k] / a[k, k]
15         end
16         # apply transformation to remaining sub-matrix
17         for j=k+1:n
18             for i=k+1:n
19                 a[i, j] -= m[i, k] * a[k, j]
20             end
21         end
22     end
23     return m, triu!(a)
24 end
```

lufact (generic function with 1 method)

```
1 lufact(a::AbstractMatrix) = lufact!(copy(a))
```

DefaultTestSet("LU", [], 3, false, false, true, 1.677652817066939e9, 1.677652817066971e9)

```
1 @testset "LU" begin
2     a = randn(4, 4)
3     L, U = lufact(a)
4     @test istril(L)
5     @test istriu(U)
6     @test L * U ≈ a
7 end
```

Test Summary: | Pass Total Time
LU | 3 3 0.0s

A4 = 4×4 Matrix{Float64}:
-1.13722 0.32243 1.17589 0.309568
-0.499461 0.502538 -0.212333 0.325516
0.291973 0.860287 -1.58332 0.191323
0.79411 -0.58919 0.293682 0.449737

```
1 A4 = randn(4, 4)
```

(4×4 Matrix{Float64}:
1.0 0.0 0.0 0.0, 4×4 Matrix{Float64}:
-1.13722 0.32243 1.17589 0.309568)

```
1 lufact(A4)
```


The Julia's version

```
julia_lures = LU{Float64, Matrix{Float64}, Vector{Int64}}  
  L factor:  
  4×4 Matrix{Float64}:  
    1.0      0.0      0.0      0.0  
    0.439196 1.0      0.0      0.0  
   -0.256744 2.6129   1.0      0.0  
   -0.698293 -1.00862 0.609723 1.0  
  U factor:  
  4×4 Matrix{Float64}:  
   -1.13722 0.32243 1.17589 0.309568  
    0.0     0.360928 -0.728778 0.189556  
    0.0     0.0      0.622801 -0.224488  
    0.0     0.0      0.0      0.993971
```

```
1 julia_lures = lu(A4, NoPivot()) # the version we implemented above has no pivot
```

```
4×4 Matrix{Float64}:  
-1.13722 0.32243 1.17589 0.309568  
 0.0     0.360928 -0.728778 0.189556  
 0.0     0.0      0.622801 -0.224488  
 0.0     0.0      0.0      0.993971
```

```
1 julia_lures.U
```

```
LU{Float64, Matrix{Float64}, Vector{Int64}}
```

```
1 typeof(julia_lures)
```

```
(:factors, :ipiv, :info)
```

```
1 fieldnames(julia_lures) |> typeof
```

Complexity Analysis

$$O(n^3)$$

Issue: how to handle small diagonal entries?

 -2.0

```
1 @bind ε Slider(-20:0.01:0.0; default=-2, show_value=true)
```

```
small_diagonal_matrix = 2×2 Matrix{Float64}:  
 1.0e-20 1.0  
 1.0     1.0
```

```
1 small_diagonal_matrix = [10^(ε) 1; 1 1]
```

```
lures = (2×2 Matrix{Float64}:, 2×2 Matrix{Float64}:)  
 1.0      0.0      1.0e-20 1.0
```

```
1 lures = lufact(small_diagonal_matrix)
```

A better approach

```
(2×2 Matrix{Float64}::, 2×2 Matrix{Float64}::)
 1.0      0.0      1.0  1.0
1 lufact(small_diagonal_matrix[end:-1:1, :])
```

Pivoting technique

$$PA = LU$$

```
2×2 Matrix{Float64}::
 1.0      1.0
1.0e-20   1.0
1 [10^(ϵ) 1; 1 1][end:-1:1, :]
```

Gaussian Elimination process with Partial Pivoting

$$A = \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix}$$

$$\dots M_2 P_2 M_1 P_1 A = U$$

NOTE: P_{k+1} and M_k commute

Algorithm 2.4 LU Factorization by Gaussian Elimination with Partial Pivoting

lufact_pivot! (generic function with 1 method)

```
1 function lufact_pivot!(a::AbstractMatrix)
2     n = size(a, 1)
3     @assert size(a, 2) == n "size mismatch"
4     m = zero(a)
5     P = collect(1:n)
6     # loop over columns
7     @inbounds for k=1:n-1
8         # search for pivot in current column
9         val, p = findmax(x->abs(a[x, k]), k:n)
10        p += k-1
11        # find index p such that  $|a_{pk}| \geq |a_{ik}|$  for  $k \leq i \leq n$ 
12        if p != k
13            # swap rows k and p of matrix A
14            for col = 1:n
15                a[k, col], a[p, col] = a[p, col], a[k, col]
16            end
17            # swap rows k and p of matrix M
18            for col = 1:k-1
19                m[k, col], m[p, col] = m[p, col], m[k, col]
20            end
21            P[k], P[p] = P[p], P[k]
22        end
23        if iszero(a[k, k])
24            # skip current column if it's already zero
25            continue
26        end
27        # compute multipliers for current column
28        m[k, k] = 1
29        for i=k+1:n
30            m[i, k] = a[i, k] / a[k, k]
31        end
32        # apply transformation to remaining sub-matrix
33        for j=k+1:n
34            akj = a[k, j]
35            for i=k+1:n
36                a[i, j] -= m[i, k] * akj
37            end
38        end
39    end
40    m[n, n] = 1
41    return m, triu!(a), P
42 end
```

Test Passed

```
1 let
2   n = 5
3   A = randn(n, n)
4   L, U, P = lufact_pivot!(copy(A))
5   pmat = zeros{Int, n, n}
6   setindex!.(Ref(pmat), 1, 1:n, P)
7   @test L ≈ lu(A).L
8   @test U ≈ lu(A).U
9   @test pmat * A ≈ L * U
10 end
```

```
1 using BenchmarkTools
```



```
1 @bind benchmark_lu CheckBox()
```

```
1 if benchmark_lu let
2   n = 200
3   A = randn(n, n)
4   @benchmark lufact_pivot!($A)
5 end end
```

```
1 if benchmark_lu let
2   n = 200
3   A = randn(n, n)
4   @benchmark lu($A)
5 end end
```

Complete pivoting

$$PAQ = LU$$

Sensitivity Analysis

Issue: An Ill Conditioned Matrix

$$A = \begin{pmatrix} 0.913 & 0.659 \\ 0.457 & 0.330 \end{pmatrix}$$

```
ill_conditioned_matrix = 2×2 Matrix{Float64}:
  0.913  0.659
  0.457  0.33
```

```
1 ill_conditioned_matrix = [0.913 0.659; 0.457 0.330]
```

```
lures2 = (2×2 Matrix{Float64}::, 2×2 Matrix{Float64}::)
  1.0      0.0      0.913  0.659
```

```
1 lures2 = lufact(ill_conditioned_matrix)
```

```
(2×2 Matrix{Float64}::, 2×2 Matrix{Float64}::)
  1.0      0.0      0.913  0.659
```

```
1 lures2
```

```
12485.031415973668
```

```
1 cond(ill_conditioned_matrix)
```

Forward Error and Backward Error

Forward error:

$$\text{dist}(f(x), \hat{f}(x))$$

Backward error

$$\text{dist}(x, f^{-1}(\hat{f}(x)))$$

Absolute Error and Relative Error

Absolute error: $\|x - \hat{x}\|$

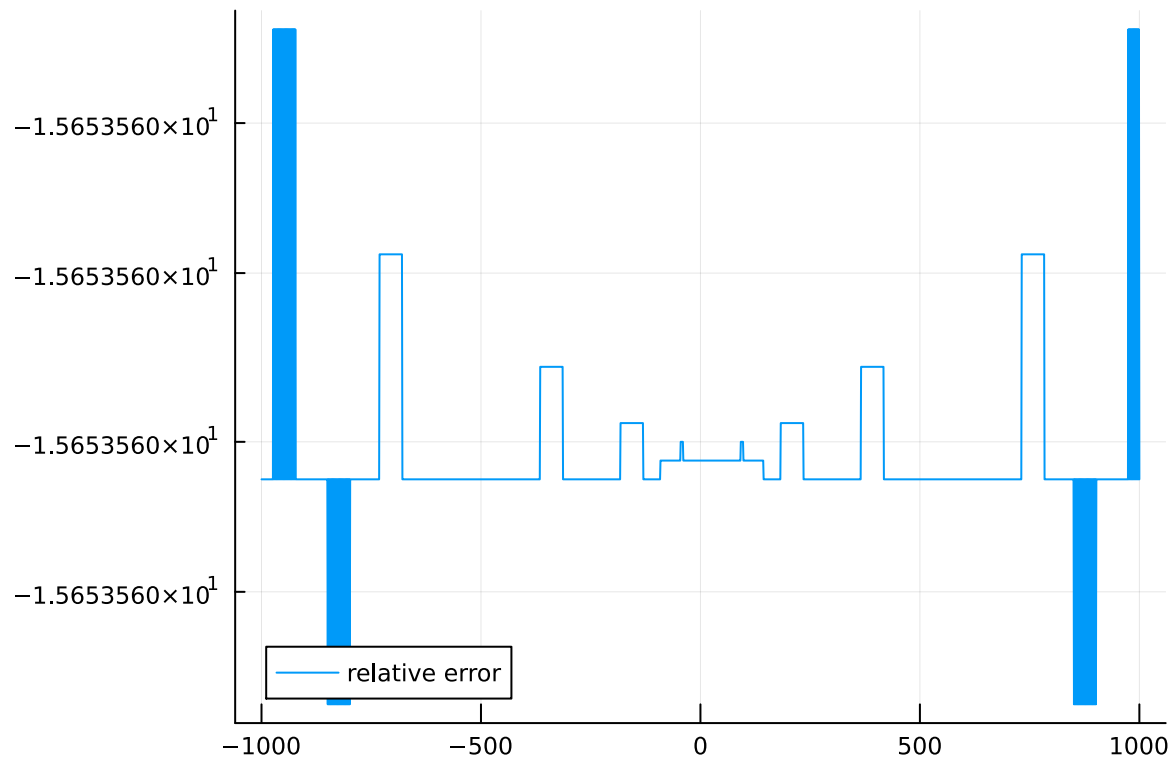
Relative error: $\frac{\|x - \hat{x}\|}{\|x\|}$

where $\|\cdot\|$ is a measure of size.

Coding: Floating point numbers have "constant" relative error

```
2.220446049250313e-16
```

```
1 eps(Float64)
```



```

1 let
2     n = 1000
3     reltol = zeros(2n+1)
4     for i=-n:n
5         f = 2.0^i
6         reltol[i+n+1] = log10(eps(f)) - log10(f)
7     end
8     plot(-n:n, reltol; label="relative error")
9 end

```

GKS: Possible loss of precision in routine SET_WINDOW

2.220446049250313e-16

```
1 eps(1.0)/1.0
```

2.220446049250313e-16

```
1 eps(2.0)/2.0
```

1.570092458683775e-16

```
1 eps(sqrt(2))/sqrt(2)
```

(Relative) Condition Number

$$\lim_{\epsilon \rightarrow 0^+} \sup_{\|\delta x\| \leq \epsilon} \frac{\|\delta f(x)\| / \|f(x)\|}{\|\delta x\| / \|x\|}$$

Quantify Error of a Scalar Operator

$$y = \exp(x)$$

Why we should avoid using floating point numbers being too big/small?

$$a + b$$

Measuring the size of a vector: Norms

$$\|v\|_p = \left(\sum_i |v_i|^p \right)^{1/p}$$

Measure the size of a matrix

$$\|A\| = \max_{x \neq 0} \frac{\|Ax\|}{\|x\|}$$

Coding: Vector and Matrix Norms

5.0

```
1 norm([3, 4], 2)
```

7.0

```
1 norm([3, 4], 1)
```

4.0

```
1 norm([3, 4], Inf)
```

2.0

```
1 # l0 norm is not a true norm
2 norm([3, 4], 0)
```

1.0

```
1 norm([3, 0], 0)
```

```
mat = 2x2 Matrix{Float64}:
  -0.284666  -1.24104
  -0.0321259  2.3657
```

```
1 mat = randn(2, 2)
```

3.6067408469604665

```
1 opnorm(mat, 1)
```

2.3978261092617075

```
1 opnorm(mat, Inf)
```

2.673499761890822

```
1 opnorm(mat, 2)
```

ArgumentError: invalid p-norm p=0. Valid: 1, 2, Inf

```
1. opnorm(::Matrix{Float64}, ::Int64) @ generic.jl:740
2. top-level scope @ [Local: 1 [inlined]
```

```
1 opnorm(mat, 0)
```

10.020429724445629

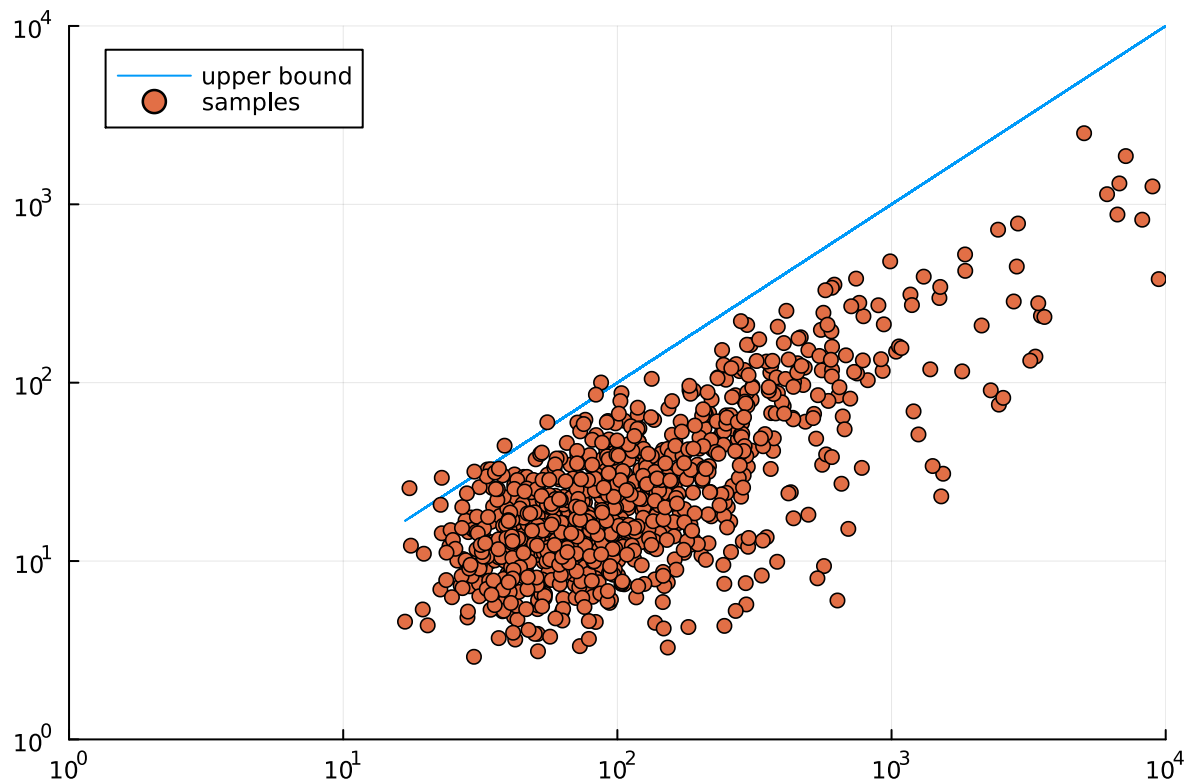
```
1 cond(mat)
```

Condition Number of a Linear Operator

$$\text{cond}(A) = \|A\| \|A^{-1}\|$$

Coding: Numeric experiment on condition number

1 using Plots



```
1 let
2     n = 1000
3     p = 2
4     errors = zeros(n)
5     conds = zeros(n)
6     for k = 1:n
7         A = rand(10, 10)
8         b = rand(10)
9         dx = A \ b
10        sx = Float32.(A) \ Float32.(b)
11        errors[k] = (norm(sx - dx, p)/norm(dx, p)) / (norm(b-Float32.(b), p)/norm(b,
12        p))
13        conds[k] = cond(A, p)
14    end
15    plt = plot(conds, conds; label="upper bound", xlim=(1, 10000), ylim=(1, 10000),
16    xscale=:log10, yscale=:log10)
17    scatter!(plt, conds, errors; label="samples")
18 end
```

Computing Matrix Inverse

Gauss Jordan Elimination Matrix

$$N_k = \begin{pmatrix} 1 & \dots & 0 & -m_1 & 0 & \dots & 0 \\ \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & 1 & -m_{k-1} & 0 & \dots & 0 \\ 0 & \dots & 0 & 1 & 0 & \dots & 0 \\ 0 & \dots & 0 & -m_{k+1} & 1 & \dots & 0 \\ \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & 0 & -m_n & 0 & \dots & 1 \end{pmatrix}$$

where $m_i = a_i/a_k$.

Computing the inverse

$$SN_n N_{n-1} \dots N_1 A = I$$

Then

$$A^{-1} = SN_n N_{n-1} \dots N_1$$

Special Matrices

Positive definite symmetric matrix

- (Real) Symmetric: $A = A^T$,
- Positive definite: $x^T A x > 0$ for all $x \neq 0$.

Cholesky decomposition

$$A = LL^T$$

Algorithm 2.7 Cholesky Factorization

chol! (generic function with 1 method)

```
1 function chol!(a::AbstractMatrix)
2     n = size(a, 1)
3     @assert size(a, 2) == n
4     for k=1:n
5         a[k, k] = sqrt(a[k, k])
6         for i=k+1:n
7             a[i, k] = a[i, k] / a[k, k]
8         end
9         for j=k+1:n
10            for i=k+1:n
11                a[i,j] = a[i,j] - a[i, k] * a[j, k]
12            end
13        end
14    end
15    return a
16 end
```

10×10 Matrix{Float64}:

```
-5.55112e-17 -2.77556e-17 -2.77556e-16 ... 1.38778e-17 -2.77556e-17
 0.0        -1.11022e-16  2.77556e-17  5.89806e-17 -1.11022e-16
 0.0         0.0         0.0         -1.11022e-16 -6.93889e-17
 0.0         0.0         2.77556e-17  5.55112e-17 -6.93889e-18
 0.0         0.0         0.0         -1.63389e-16  4.16334e-17
 0.0         1.6263e-19  0.0         ... -2.08167e-17  1.71738e-16
 0.0        -2.77556e-17  1.38778e-17 -5.55112e-17  1.249e-16
 0.0         0.0        -6.93889e-18  0.0        -8.32667e-17
 0.0         0.0         2.77556e-17  5.55112e-17  2.77556e-17
-1.38778e-17  0.0         0.0         0.0         0.0
```

```
1 let
2     n = 10
3     Q, R = qr(randn(10, 10))
4     a = Q * Diagonal(rand(10)) * Q'
5     L = chol!(copy(a))
6     tril(L) * tril(L)' - a
7     # cholesky(a) in Julia
8 end
```

Banded matrices

Sparse matrices and linear operators

Accessing every element is not allowed, but matrix-vector multiplication is defined.

You need iterative solvers like GMRES (Package: [IterativeSolvers](#)).

Rank 1 update: Sherman-Morrison formula

$$(A - uv^T)^{-1} = A^{-1} + A^{-1}u(1 - v^T A^{-1}u)^{-1}v^T A^{-1}$$

which requires only $O(n^2)$ extra work.

Assignments

1. Get the relative condition number of division operation a/b .
2. Classify each of the following matrices as well-conditioned or ill-conditioned:

$$(a). \begin{pmatrix} 10^{10} & 0 \\ 0 & 10^{-10} \end{pmatrix}$$

$$(b). \begin{pmatrix} 10^{10} & 0 \\ 0 & 10^{10} \end{pmatrix}$$

$$(c). \begin{pmatrix} 10^{-10} & 0 \\ 0 & 10^{-10} \end{pmatrix}$$

$$(d). \begin{pmatrix} 1 & 2 \\ 2 & 4 \end{pmatrix}$$

3. Implement the Gauss-Jordan elimination algorithm to compute matrix inverse. In the following example, we first create an augmented matrix $(A|I)$. Then we apply the Gauss-Jordan elimination matrices on the left. The final result is stored in the augmented matrix as (I, A^{-1}) .

$$\begin{bmatrix} 1 & 0 & 0 \\ -4 & 1 & 0 \\ -4 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 2 & 2 & | & 1 & 0 & 0 \\ 4 & 4 & 2 & | & 0 & 1 & 0 \\ 4 & 6 & 4 & | & 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 2 & 2 & | & 1 & 0 & 0 \\ 0 & -4 & -6 & | & -4 & 1 & 0 \\ 0 & -2 & -4 & | & -4 & 0 & 1 \end{bmatrix},$$

$$\begin{bmatrix} 1 & 0.5 & 0 \\ 0 & 1 & 0 \\ 0 & -0.5 & 1 \end{bmatrix} \begin{bmatrix} 1 & 2 & 2 & | & 1 & 0 & 0 \\ 0 & -4 & -6 & | & -4 & 1 & 0 \\ 0 & -2 & -4 & | & -4 & 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & -1 & | & -1 & 0.5 & 0 \\ 0 & -4 & -6 & | & -4 & 1 & 0 \\ 0 & 0 & -1 & | & -2 & -0.5 & 1 \end{bmatrix},$$

$$\begin{bmatrix} 1 & 0 & -1 \\ 0 & 1 & -6 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & -1 & | & -1 & 0.5 & 0 \\ 0 & -4 & -6 & | & -4 & 1 & 0 \\ 0 & 0 & -1 & | & -2 & -0.5 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & | & 1 & 1 & -1 \\ 0 & -4 & 0 & | & 8 & 4 & -6 \\ 0 & 0 & -1 & | & -2 & -0.5 & 1 \end{bmatrix},$$

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & -0.25 & 0 \\ 0 & 0 & -1 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 & | & 1 & 1 & -1 \\ 0 & -4 & 0 & | & 8 & 4 & -6 \\ 0 & 0 & -1 & | & -2 & -0.5 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & | & 1 & 1 & -1 \\ 0 & 1 & 0 & | & -2 & -1 & 1.5 \\ 0 & 0 & 1 & | & 2 & 0.5 & -1 \end{bmatrix},$$

Task: Please implement a function `gauss_jordan` that computes the inverse for a matrix at any size. Please also include the following test in your submission.

```
@testset "Gauss Jordan" begin
    n = 10
    A = randn(n, n)
```

```
@test gauss_jordan(A) * A ≈ Matrix{Float64}(I, n, n)
end
```