

Welcome

Efficiency of Different Algorithms over Sparse Matrices

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Outline

- ❖ Motivation
- ❖ Objectives
- ❖ Sparse Matrix
- ❖ Representation of Sparse Matrix
- ❖ Performance of Different Algorithms

Motivation

- ❖ The large matrices that arise in real-world problems are often sparse.
- ❖ Several algorithms for solving system of equations.
- ❖ Different algorithms have different efficiencies.

Objectives

- ❖ To count the number of iteration needs to converge
- ❖ To compare the efficiency of different algorithms

Sparse Matrices

- ❖ Sparsemany elements are zero.
- ❖ Densefew elements are zero.

Structured Sparse Matrices

- ❖ Diagonal
 - ❖ Tri-diagonal
 - ❖ Lower triangular
-
- ❑ May be mapped into a 1D array
 - ❑ Mapping function can be used to locate an element

Unstructured Sparse Matrices

Airline flight matrix.

- ❖ Airports are numbered 1 through n
- ❖ $\text{flight}(i,j)$ = list of nonstop flights from airport i to airport j .

Web page matrix.

- ❖ Web pages are numbered 1 through n
- ❖ $\text{web}(i,j)$ = number of links from page i to page j

Representation of Unstructured Sparse Matrices

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❖ MATLAB provides a sparse function of the form

`matrix = sparse (i, j, s, m, n, nz_max)`

- ❖ `i` = the row indices of the nonzero elements;
- ❖ `j` = the column indices of the nonzero elements;
- ❖ `s` = the values of the nonzero elements;
- ❖ `m` = the number of rows in the matrix;
- ❖ `n` = the number of columns in the matrix;
- ❖ `nz_max` is the maximum number of nonzero elements in the matrix

Representation of Unstructured Sparse Matrices

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$$A = \begin{pmatrix} 11 & 12 & 0 & 0 & 15 \\ 0 & 22 & 23 & 0 & 0 \\ 31 & 0 & 33 & 34 & 35 \end{pmatrix} \quad m = 3, \quad n = 5, \quad nz_max = 9;$$

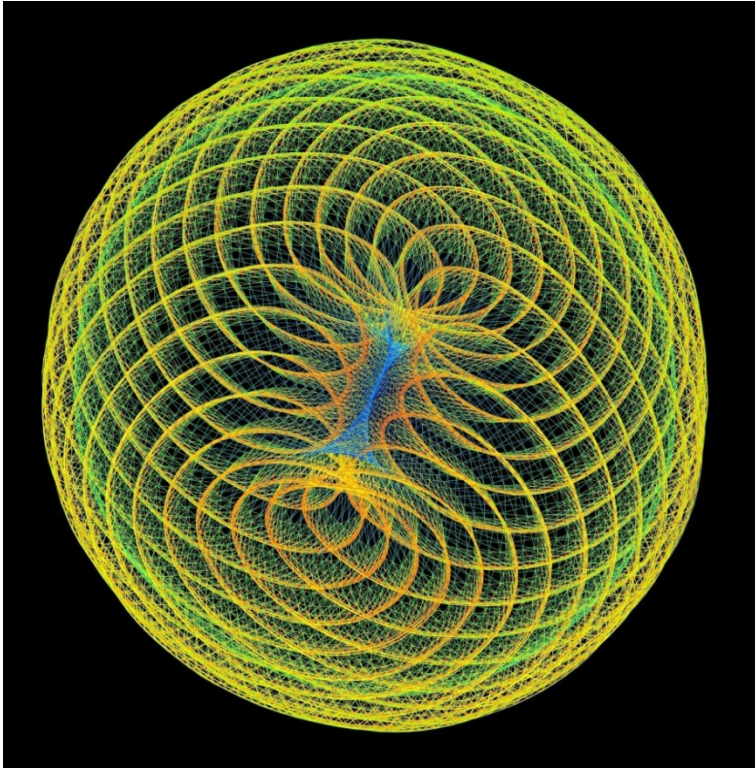
$$i = [1 \quad 1 \quad 1 \quad 2 \quad 2 \quad 3 \quad 3 \quad 3 \quad 3]$$

$$j = [1 \quad 2 \quad 5 \quad 2 \quad 3 \quad 1 \quad 3 \quad 4 \quad 5]$$

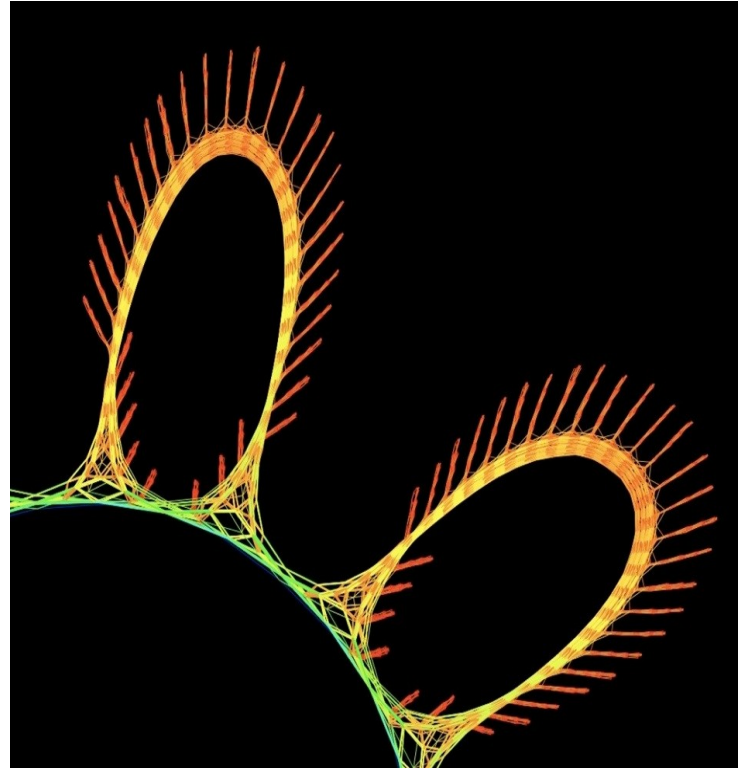
$$s = [11 \quad 12 \quad 15 \quad 22 \quad 23 \quad 31 \quad 33 \quad 34 \quad 35],$$

$$a = \text{sparse} \quad (i, j, s, m, n, nz_max)$$

Examples of Sparse Matrices

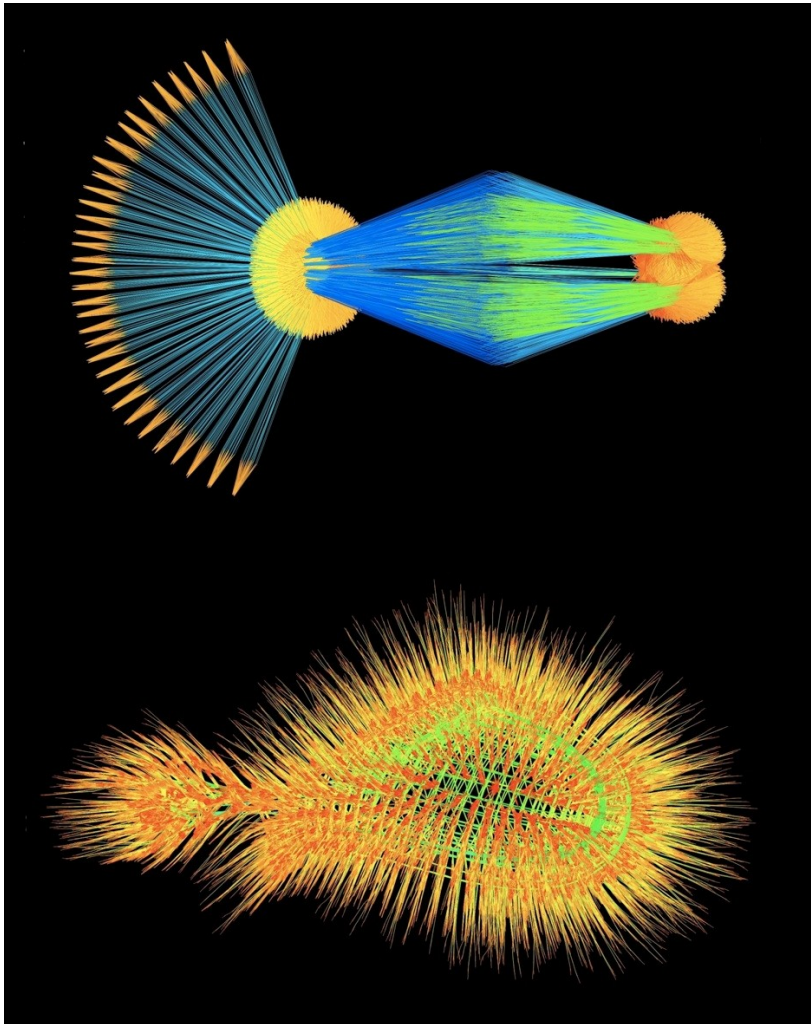


A Barrier Hessian Matrix



**A Matrix From Financial
Portfolio Optimization**

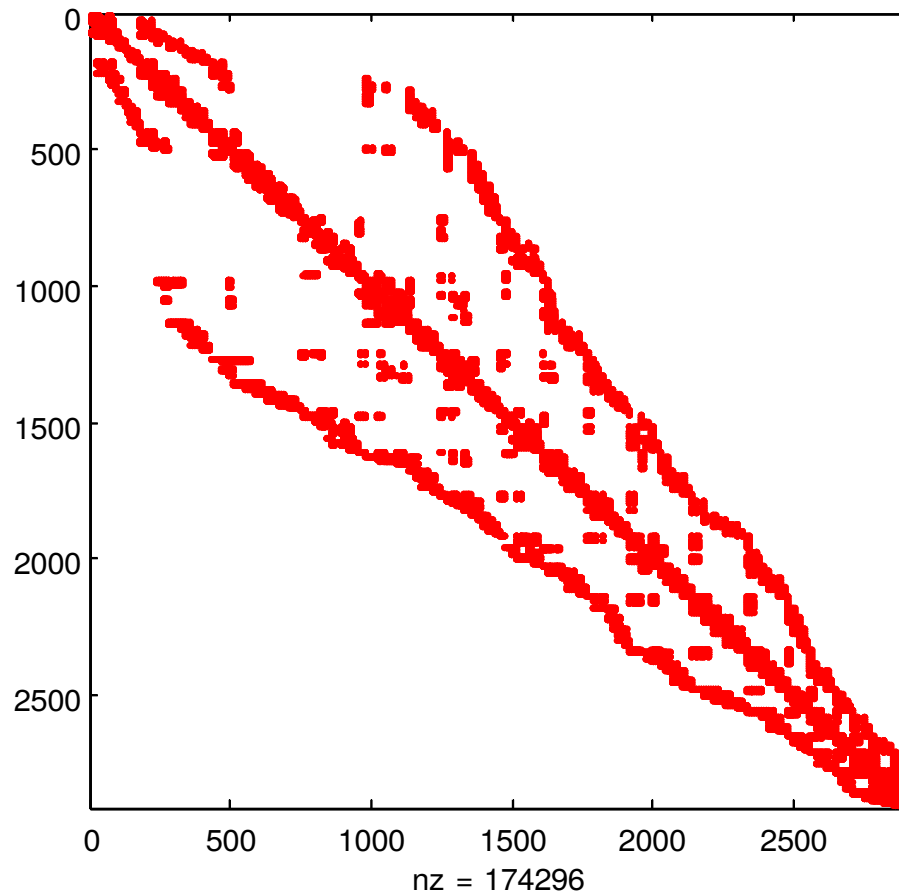
Examples of Sparse Matrices



<http://www.cise.ufl.edu/~davis/matrices.html>

The Sparse Matrix

Dimension : 2910×2910 NNZ: 174296



MATLAB Command

- ❖ `[X,FLAG, RELRES, ITER]=gmres (A, B, RESTART, TOL, MAXIT, M)`
- ❖ `[X,FLAG, RELRES, ITER]=Y(A, B, TOL, MAXIT, M)`
- ❖ Y for cgs, pcg, bicgstab.
- ❖ FLAG = 0 , convergent to the desire TOL within MAXIT.
- ❖ FLAG=1 , iterated MAXIT times, did not converge.
- ❖ FLAG=2 , preconditioner M was ill-conditioned.
- ❖ FLAG=3 , stagnated.
- ❖ FLAG=4 , one of the scalar quantities calculated during the method Y became too small or too large to continue computing.

Efficiency of Algorithms

	GMRES		CGS	
	Preconditioned	Without Preconditioned	Preconditioned	Without Preconditioned
FLAG	0	0	3	4
ITER	6510	37007	2070	2
RELRES	9.943e-07	1.000e-6	3.0126e-04	0.231

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Efficiency of Algorithms

	PCG		BICGSTAB	
	Preconditioned	Without Preconditioned	Preconditioned	Without Preconditioned
FLAG	0	0	0	0
ITER	887	3470	1266.5	8061.5
RELRES	9.8646e-07	9.7e-07	1.55e-07	8.48e-07

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Conclusion

- ❖ The Preconditioned Conjugate Gradient Method gives the better result.
- ❖ If the matrix is not in symmetric positive definite, then this method may not work.
- ❖ For unsymmetric matrix, GMRES provides the better result.

Thank You