Solving sparse systems of linear equations (with symbolic entries)

ERICH KALTOFEN

Rensselaer Polytechnic Institute Department of Computer Science

Joint work with: B. David Saunders

University of Delaware

Department of Computer & Inform. Sciences

Austin Lobo (graduate student, RPI)

Outline

• The non-singular case

- what is a sparse matrix?
- Wiedemann's method

• The singular case

- making principal sub-matrices non-singular
 - by Toeplitz matrix perturbation
 - by Beneš permutation networks
- computing the rank
- picking a random solution

• Implementation efforts

• on Sparc 2 workstations

• Open problems

What is a sparse matrix?

• matrices with "few" non-zero entries

- a band matrix from a finite element method
- a matrix over GF(2) from integer factoring by the NFS: 52250×50001 with 1095532 entries $\neq 0$ ($\approx 21/\text{row}$)

• matrices with special structure

• the Sylvester matrix corresponding to a polynomial resultant

$$R = \begin{pmatrix} a_n & a_{n-1} & \dots & a_0 \\ a_n & \dots & a_1 & a_0 & 0 \\ 0 & \ddots & \ddots & \ddots \\ & & a_n & \dots & a_0 \\ b_n & b_{n-1} & \dots & b_0 \\ & b_n & \dots & b_1 & b_0 & 0 \\ & & & \ddots & \ddots & \\ & & & b_n & \dots & b_0 \end{pmatrix}$$

• a "black box" matrix an efficient program with the specifications



e.g., for the Sylvester matrix R, $R \times y$ costs

$$O(n \log(n) \log\log(n))$$

arithmetic operations using fast polynomial multiplication

Symbolic objects given by black box representation are known for many problems:

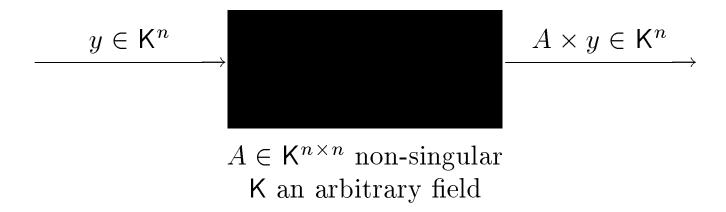
- symbolic determinants using Gaussian elimination
- the polynomial remainder sequence of $f_0(x)$ and $f_1(x)$ using continued fraction approximations

$$\{q_i(x)\}_{i\geq 2}$$
 such that $f_i(x) = f_{i-2}(x) - q_i(x)f_{i-1}(x)$

- $A^{-1} = P^{-1}U^{-1}L^{-1}$, the LUP factorization of $A \in K^{n \times n}$.
- streams for infinite objects, such as a program for the *i*-th order coefficient of a power series

Linear system solution with a black box matrix

Given a black box



compute $A^{-1}b$ "efficiently."

D. Wiedemann (1986) constructs a Las Vegas randomized algorithm that computes $A^{-1}b$ in at most

$$3n$$
 " $A \times y$ steps"

and

 $O(n^2)$ additional arithmetic operations in K.

The algorithm needs O(n) space.

The KRYLOV subspace

Consider the minimum linear dependency of the sequence of vectors $\{A^ib\}_{i>0}$,

$$\underbrace{f_0^{(b)}b + f_1^{(b)}Ab + f_2^{(b)}A^2b + f_3^{(b)}A^3b + \dots + f_k^{(b)}A^kb}_{f^{(b)}(\lambda) = f_0^{(b)} + f_1^{(b)}\lambda + \dots + f_k^{(b)}\lambda^k \in \mathsf{K}[\lambda]} = 0, \quad f_k^{(b)} \neq 0.$$

As a consequence of the Cayley/Hamilton Theorem,

$$f^{(b)}(\lambda)$$
 divides $\operatorname{Det}(\lambda I - A)$, thus $k \leq n$.

Hence: If
$$f_0^{(b)} = 0$$
, then $\text{Det}(A) = 0$;
otherwise $A^{-1}b = x \leftarrow -\frac{1}{f_0^{(b)}} \Big(f_1^{(b)}b + f_2^{(b)}Ab + \dots + f_k^{(b)}A^{k-1}b \Big)$.

Idea for finding $f^{(b)}(\lambda)$ given A and b

Let $u \in \mathsf{K}^n$ and consider the sequence of field elements

$$a_0 = u^{\mathrm{T}}b, \ a_1 = u^{\mathrm{T}}Ab, \ a_2 = u^{\mathrm{T}}A^2b, \ a_3 = u^{\mathrm{T}}A^3b, \dots$$

Since $u^{\mathrm{T}} A^{j} f^{(b)}(A) b = 0$, we have

$$\forall j \ge 0: f_0^{(b)} a_{0+j} + f_1^{(b)} a_{1+j} + \dots + f_k^{(b)} a_{k+j} = 0$$

that is $\{a_i\}_{i=0,1,...}$ satisfies a linear recurrence.

By the Berlekamp/Massey (1969) or the extended Euclidean algorithm we can compute in O(n l) steps a minimal recurrence polynomial

$$f^{(b,u)}(\lambda) = f_0^{(b,u)} + f_1^{(b,u)} \lambda + \dots + f_{l-1}^{(b,u)} \lambda^{l-1} - \lambda^l$$

that generates $\{a_i\}_{i=0,1,...}$

$$\forall j \ge 0 : a_{l+j} = f_{l-1}^{(b,u)} a_{l-1+j} + f_{l-2}^{(b,u)} a_{l-2+j} + \dots + f_0^{(b,u)} a_{0+j}.$$

Important fact: For "random" u with high probability

$$f^{(b,u)}(\lambda) = f^{(b)}(\lambda).$$

Making leading principal sub-matrices non-singular a) our method using Toeplitz multipliers

Let $A \in \mathsf{K}^{n \times n}$,

$$\widetilde{A} = \begin{pmatrix} 1 & t_2 & t_3 & \dots & t_n \\ & 1 & t_2 & \dots & t_{n-1} \\ & & 1 & \ddots & \vdots \\ & & & \ddots & \vdots \\ & & & & 1 \end{pmatrix} A \begin{pmatrix} 1 & & & & & \\ l_2 & 1 & & & & \\ l_3 & l_2 & 1 & & & \\ \vdots & & \ddots & \ddots & & \\ l_n & l_{n-1} & \dots & l_2 & 1 \end{pmatrix}$$

If $t_i, l_i \in S \subset K$ are randomly and uniformly selected, the probability

$$\operatorname{Prob}(\underbrace{\operatorname{Det}(\widetilde{A}_{1...s,1...s})}_{s'\text{th leading principal minor}} \neq 0) \geq 1 - \frac{2s}{\operatorname{card}(S)}, \quad \text{for } s \leq \operatorname{rank}(A).$$

After an idea by Borodin, von zur Gathen, Hopcroft (1982).

b) Wiedemann's method using Beneš networks

The generic row/column exchange matrix

$$E(t) = \begin{pmatrix} 1 & 0 \\ 1 & 1 \end{pmatrix} \begin{pmatrix} 1 & t \\ 0 & 1 \end{pmatrix} \begin{pmatrix} 1 & 0 \\ -1 - 2t & 1 \end{pmatrix}$$
$$= \begin{pmatrix} 1 - t - 2t^2 & t \\ -3t - 2t^2 & 1 + t \end{pmatrix} = \begin{cases} \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} & \text{for } t = 0 \\ \begin{pmatrix} 0 & -1 \\ 1 & 0 \end{pmatrix} & \text{for } t = -1 \end{cases}$$

Use randomized network exchanges

$$\widetilde{A} = \underbrace{\prod_{i=1}^{2\log_2(n)-1} E_i(t_{i,1}, \dots, t_{i,n/2})}_{V} \quad A \quad \underbrace{\prod_{j=1}^{2\log_2(n)-1} E_j(l_{j,1}, \dots, l_{j,n/2})}_{W}$$

Note that V and W are black box matrices with

 $V \times y$ and $W \times y$ costing $O(n \log(n))$ field operations.

Computing the rank (without binary search)

Suppose perturbed \widetilde{A} has rank < n; then for random d_i , the minimum polynomial of

$$\widetilde{A} \begin{pmatrix} d_1 & & & 0 \\ & d_2 & & 0 \\ 0 & & \ddots & \\ & & & d_n \end{pmatrix}$$

has with high probability degree = $\operatorname{rank}(\widetilde{A}) + 1$

Also, with high probability, for random vectors u and v,

$$f^{(u,v)}(\lambda) = \text{minimum polynomial}$$

Picking a random solution of a singular system

Let $\widetilde{A} \in \mathsf{K}^{n \times n}$ be of rank r with the leading principal $r \times r$ submatrix non-singular;

suppose $\widetilde{A}x = b$ is solvable; then for

$$\widetilde{A} \underbrace{\begin{pmatrix} y' \\ 0 \\ \vdots \\ 0 \end{pmatrix}}_{y} \right\}_{n-r} = b + \widetilde{A}v, \quad v \text{ random in } \mathbb{K}^{n},$$

y-v uniformly samples the solution manifold of $\widetilde{A}x=b$.

Our current implementation efforts

Ausin Lobo has implemented in C

- the general case using Beneš networks for $\mathsf{K} = \mathsf{GF}(2^m)$ on $\mathsf{Sun}4/\mathsf{Sparc}2$'s
- a special method for finding a non-zero solution of homogenous problems

Comparison with

- LaMacchia and Odlyzko's conjugate gradient method
- Coppersmith's blocked Wiedemann method

Odlyzko's example over GF(2)

16309 25417 28976 29051 33269 35446 37117

We found one non-zero linear dependence in 113.5 hours on a Sun4, namely the rows

1 6 7 9 12 14 16 17 19 20 21 22 24 ... 49995 49996 49997 49999 50000 (23587 rows are chosen).

Open problems

- Compute the characteristic polynomial
 - multi-polynomial resultant computation
- Reduce cardinality of field in probability estimates
- Compute entire right null space
- Numerical error analysis
 - → general sparse linear system solver
- Implement in distribute fashion
 - \longrightarrow Coppersmith's blocked Wiedemann method on our DSC system