# Sparse Matrices in Numerical Mathematics 

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## Sparse vectors and matrices in a computer

## Sparse vector in a computer

## Example

Consider the sparse row vector $v \in \mathbb{R}^{8}$

$$
v=\left(\begin{array}{llllllll}
1 . & -2 . & 0 . & -3 . & 0 . & 5 . & 3 . & 0 . \tag{1}
\end{array}\right)
$$

The real array valv that stores the nonzero values and corresponding integer array of their indices indV are of length $|\mathcal{S}\{v\}|=5$ and are as follows:

| Subscripts | 1 | 2 | 3 | 4 | 5 |
| :--- | :---: | :---: | :---: | :---: | :---: |
| valv | 1. | -2. | -3. | 5. | 3. |
| indV | 1 | 2 | 4 | 6 | 7 |

## Sparse vectors and matrices in a computer

## Sparse vector in a computer

- Alternatively, a linked list can be used.
- linked list - based format: stores matrix rows/columns as items connected by pointers
- linked lists can be cyclic, one-way, two-way
- A figure for demonstration, only values (not their indices) are shown

- rows/columns embedded into a larger array: emulated dynamic behavior


## Sparsity

## Sparse vector in a computer

- Linked list can be embedded into a large array.


## Example

Two possible ways of storing the sparse vector using linked lists.

| Subscripts | 1 | 2 | 3 | 4 | 5 |
| :--- | :---: | :---: | :---: | :---: | :---: |
| Values | 1. | -2. | -3. | 5. | 3. |
| Indices | 1 | 2 | 4 | 6 | 7 |
| Links | 2 | 3 | 4 | 5 | 0 |
| Header | 1 |  |  |  |  |
| Subscripts | 1 | 2 | 3 | 4 | 5 |
| Values | 5. | 3. | 1. | -2. | -3. |
| Indices | 6 | 7 | 1 | 2 | 4 |
| Links | 2 | 0 | 4 | 5 | 1 |
| Header | 3 |  |  |  |  |

## Sparse vectors and matrices in a computer

- Reasons for using linked lists: straightforward adds and removes.


## Example

On the left, an entry -4 has been added in position 5 . On the right, an entry -2 in position 2 has been removed. $*$ indicates the entry is not accessed. The links that have changed are in bold.

| Subscripts | 1 | 2 | 3 | 4 | 5 | 6 |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
| Values | 1. | -2. | -3. | 5. | 3. | -4. |
| Indices | 1 | 2 | 4 | 6 | 7 | 5 |
| Links | 2 | 3 | 4 | 5 | 6 | 0 |
| Header | 1 |  |  |  |  |  |


| Subscripts | 1 | 2 | 3 | 4 | 5 |
| :--- | :---: | :---: | :---: | :---: | :---: |
| Values | 1. | $*$ | -3. | 5. | 3. |
| Indices | 1 | $*$ | 4 | 6 | 7 |
| Links | 3 | $*$ | 4 | 5 | 0 |
| Header | 1 |  |  |  |  |

## Sparse vectors and matrices in a computer

## Sparse matrix storage

- coordinate (or triplet format: the individual entries of $A$ are held as triplets $\left(i, j, a_{i j}\right)$, where $i$ is the row index and $j$ is the column index of the entry $a_{i j} \neq 0$. (dynamic storage format)
- CSR (Compressed Sparse Row) format. The column indices of the entries of $A$ held by rows in an integer array (which we will call colindA) of length $n z(A)$, with those in row 1 followed by those in row 2 , and so on (with no space between rows). Sorted or unsorted. (static storage format)
- CSC (Compressed Sparse Columns): analogously by columns instead of rows.
- If $A$ is symmetric, only the lower (or upper) triangular part is generally stored.
- Possible to store only $\mathcal{S}\{A\}$.


## Sparse vectors and matrices in a computer

Sparse matrix in the coordinate format

- Example matrix $A \in \mathbb{R}^{5 \times 5}$

$$
\begin{align*}
&  \tag{2}\\
& 1 \\
& 2 \\
& 3 \\
& 4 \\
& 5
\end{align*}\left(\begin{array}{ccccc}
1 & 2 & 3 & 4 & 5 \\
3 . & & & -2 . & \\
& 1 . & & & 4 . \\
-1 . & & 3 . & & 1 . \\
& & & 1 . & \\
& 7 . & & & 6 .
\end{array}\right)
$$

## Example

| Subscripts | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| rowindA | 3 | 2 | 3 | 4 | 1 | 1 | 2 | 5 | 3 | 5 |
| colindA | 3 | 2 | 1 | 4 | 4 | 1 | 5 | 5 | 5 | 2 |
| valA | 3. | 1. | -1. | 1. | -2. | 3. | 4. | 6. | 1. | 7. |

## Sparse vectors and matrices in a computer

## Sparse matrix stored using linked lists

- Easy adding and deleting entries is possible if t linked lists are used: the matrix held as a collection of columns, each in a linked list. colA_head holds header pointers.


## Example

| Subscripts | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| rowindA | 3 | 2 | 3 | 4 | 1 | 1 | 2 | 5 | 3 | 5 |
| valA | 3. | 1. | -1. | 1. | -2. | 3. | 4. | 6. | 1. | 7. |
| link | 0 | 10 | 0 | 0 | 4 | 3 | 9 | 0 | 8 | 0 |
| colA_head | 6 | 2 | 1 | 5 | 7 |  |  |  |  |  |

If we consider column 4 , then colA_head(4) $=5$, rowindA(5) $=1$ and $\operatorname{valA}(5)=-2$., so the first entry in column 4 is $a_{1,4}=-2$.. Next, $\operatorname{link}(5)=4$, rowindA $(4)=4$ and valA $(4)=1$., so the next entry in column 4 is $a_{4,4}=1$..

## Sparse vectors and matrices in a computer

## Sparse matrix in the CSR format

- CSR format represents $A$ as follows. Here the entries within each row are in order of increasing column index.

Example

| Subscripts | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| rowptrA | 1 | 3 | 5 | 8 | 9 | 11 |  |  |  |  |
| colindA | 1 | 4 | 2 | 5 | 1 | 3 | 5 | 4 | 2 | 5 |
| valA | 3. | -2. | 1. | 4. | -1. | 3. | 1. | 1. | 7. | 6. |

- In our codes we often use: ia: rowptrA, ja: colindA, aa: valindA


## Sparse vectors and matrices in a computer

Sparse matrix: static versuis dynamic formats

- dynamic data structures:
-     - more flexible but this flexibility might not be needed
-     - difficult to vectorize
-     - difficult to keep spatial locality
-     - used preferably for storing vectors
- static data structures:
-     - ad-hoc insertions/deletions should be avoided (better algorithms)
-     - much simpler to vectorize
-     - efficient access to rows/columns


## Sparse vectors and matrices in a computer

## Simulating dynamic storage format

- A disadvantage of linked list storage: prohibits the fast access to rows (or columns) of the matrix. And this is needed!
- Simulated dynamism of storage schemes: storage format with some additional elbow space for new non zero entries of $A$ is needed.
- Often the case in approximate factorizations where new non zero entries can be added and/or removed and it is hard to predict the necessary space in advance.
- In this case, the elbow space can embed new non zeros.
- The format is called the DS format.


## Sparse vectors and matrices in a computer

## Sparse matrix: DS formats

- Consider again the sparse matrix $A \in \mathbb{R}^{5 \times 5}$ (2). The DS format represents $A$ as follows.

| Example |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Subscripts | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
| rowptrA | 1 | 5 | 8 | 12 | 14 |  |  |  |  |  |  |  |  |  |
| colindA | 1 | 4 |  |  | 2 | 5 |  | 1 | 3 | 5 |  | 4 |  | 2 |
| valAR | 3. | -2. |  |  | 1. | 4. |  | -1. | 3. |  | 1. |  | 1. | 7. |
| rowlength | 2 | 2 | 3 | 1 | 2 |  |  |  |  |  |  |  |  |  |
| colptrA | 1 | 4 | 6 | 9 | 12 |  |  |  |  |  |  |  |  |  |
| rowindA | 1 | 3 |  | 2 | 5 | 3 |  |  | 1 | 4 |  | 2 | 3 | 5 |
| valAC | 3. | -1. |  | 1. | 7. | 3. |  |  | -2. | 1. |  | 4. | 1. | 6. |
| collength | 2 | 2 | 1 | 2 | 3 |  |  |  |  |  |  |  |  |  |

## Sparse vectors and matrices in a computer

## Sparse matrix: DS formats

- It can happen that the free space between row and/or column segments disappears throughout a computational algorithm. Then the DS format must be reorganized.
- In particular, a row segment can be moved to the end of the arrays valAR and colindA implying also a corresponding update in rowptrA. The space where the row $i$ originally resided is then denoted as free.
- If there is no free space at the end of the arrays valAR and colindA, a compression of the row segments or full reallocation should be done.
- While the DS format seems to be complicated, it can be extremely useful in some cases. Surprisingly efficient if the amount of changes is limited as it often is in approximate factorizations.


## Sparse matrices and data structures

## Block formats

- Blocked formats may be used to accelerate multiplication between a sparse matrix and a dense vector.
- The Variable Block Row (VBR) format groups together similar adjacent rows and columns.
- The data structure of the VBR format uses six arrays. Integer arrays rptr and cptr hold the index of the first row in each block row and the index of the first column in each block column, respectively. In many cases, the block row and column partitionings are conformal and only one of these arrays is needed. The real array valA contains the entries of the matrix block-by-block in column-major order. The integer array indx holds pointers to the beginning of each block entry within valA. The index array bindx holds the block column indices of the block entries of the matrix and, finally, the integer array bptr holds pointers to the start of each row block in bindx.


## Sparse matrices and data structures

## Sparse matrix: DS formats

## Example

Consider the sparse matrix $A \in \mathbb{R}^{8 \times 8}$

|  | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | ( 1. | 2. |  |  |  | 3. |  | ) |
| 2 | 4. | 5. |  |  |  | 6. |  |  |
| 3 |  |  | 7. | 8. | 9. | 10. |  |  |
| 4 | 11. | 12. |  |  |  |  | 15. | 16. |
| 5 |  | 13. |  |  |  |  | 17. |  |
| 6 | 14. |  |  |  |  |  |  | 18. |
| 7 |  |  | 19. |  | 20. |  |  |  |
| 8 | ( |  | 21. | 22. |  |  |  | ) |

Here the row blocks comprise rows $1: 2,3,4: 6$ and $7: 8$. The column blocks comprise columns 1:2, 3:5, 6, 7:8. The VBR format stores $A$ as follows.

## Sparse matrices and data structures

## Sparse matrix: DS formats

| Example |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| Subscripts | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 |
| rptr | 1 | 3 | 4 | 7 | 9 |  |  |  |  |  |  |  |  |  |  |  |  |
| cptr | 1 | 3 | 6 | 7 | 9 |  |  |  |  |  |  |  |  |  |  |  |  |
| valA | 1 | 4 | 2. | 5 | 3. | 6 | 7. | 8 | 9. | 10 | 11 | 14 | 12 | 13. | 15 | 17. | 16. |
| indx | 1 | 5 | 7 | 10 | 11 | 15 | 19 |  |  |  |  |  |  |  |  |  |  |
| bindx | 1 | 3 | 2 | 3 | 1 | 4 | 2 |  |  |  |  |  |  |  |  |  |  |
| bptr | 1 | 3 | 5 | 7 |  |  |  |  |  |  |  |  |  |  |  |  |  |

## Sparse matrices and data structures

## Matmats in CSR/CSC

1) $C S R$ - CSC

$$
C=A B, A=\left(\begin{array}{c}
a_{1}  \tag{3}\\
\vdots \\
a_{m}
\end{array}\right), B=\left(b_{1}, \ldots, b_{n}\right), C=\left(c_{i j}\right)
$$

- Each entry $c_{i j}$ computed as a product of a compressed row of $A$ and compressed column of $B$
- Not clear whether the result $c_{i j}$ is nonzero
- Consequently: $O\left(n^{3}\right)$ operations, not useful for sparse matrices.


## Sparse matrices and data structures

Matmats in CSR/CSC
2) CSR - CSR

$$
C=A B, A=\left(\begin{array}{c}
a_{1}  \tag{4}\\
\vdots \\
a_{m}
\end{array}\right), B=\left(\begin{array}{c}
b_{1} \\
\vdots \\
b_{n}
\end{array}\right), C=\left(c_{i j}\right)
$$



## Sparse matrices and data structures

Matmats in CSR/CSC
2) CSR - CSR

$$
C=A B, A=\left(\begin{array}{c}
a_{1}  \tag{5}\\
\vdots \\
a_{m}
\end{array}\right), B=\left(\begin{array}{c}
b_{1} \\
\vdots \\
b_{n}
\end{array}\right), C=\left(c_{i j}\right)
$$



## Sparse matrices and data structures

## Matmats in CSR/CSC

> 3) CSC - CSR

$$
C=A B, A=\left(a_{1}, \ldots, a_{m}\right), B=\left(\begin{array}{c}
b_{1}  \tag{6}\\
\vdots \\
b_{n}
\end{array}\right), C=\left(c_{i j}\right)
$$

- How one can store $A$ by CSC and pass it by rows?
- Pointers to first entries in columns: (array first)
- First test: nonzero in the first row $\rightarrow$ move one step down, add next nonzero into the list value(next)
- Complexity: $O$ (nonzeros) $+O(n)$


## Sparse matrices and data structures

## Matmats in CSR/CSC

## 3) CSC - CSR



Based on forming virtual rows in $A$

