On Speeding-up Parallel Jacobi Iterations for SVDs

Soumitra Pal Sudipta Pathak Sanguthevar Rajasekaran
Computer Science and Engineering, University of Connecticut
371 Fairfield Road, Storrs, CT 06269, USA
{mitra@,sudipta.pathak@,rajasek@engr.}uconn.edu

***Abstract*—We live in an era of big data and the analysis of these data is becoming a bottleneck in many domains including biology and the internet. To make these analyses feasible in practice, we need efficient data reduction algorithms. The Singular Value Decomposition (SVD) is a data reduction technique that has been used in many different applications. For example, SVDs have been extensively used in text analysis. Several sequential algorithms have been developed for the computation of SVDs. The best known sequential algorithms take cubic time which may not be acceptable in practice. As a result, many parallel algorithms have been proposed in the literature. There are two kinds of algorithms for SVD, namely, QR decomposition and Jacobi iterations. Researchers have found out that even though QR is sequentially faster than Jacobi iterations, QR is difficult to parallelize. As a result, most of the parallel algorithms in the literature are based on Jacobi iterations. JRS is an algorithm that has been shown to be very effective in parallel. JRS is a relaxation of the classical Jacobi algorithm. In this paper we propose a novel variant of the classical Jacobi algorithm that is more efficient than the JRS algorithm. Our experimental results confirm this assertion. We also provide a convergence proof for our new algorithm. We show how to efficiently implement our algorithm on such parallel models as the PRAM and the mesh.**

***Keywords*-SVD; Jacobi iterations; JRS; parallel algorithms**

I. Introduction

Singular Value Decomposition (SVD) is a fundamental computational problem in linear algebra and it has application in various computational science and engineering areas. For example, it is widely used in areas such as statistics where it is directly related to principal component analysis, in signal processing and pattern recognition as an essential filtering tool, and in control systems. Recently, it is used as one of the fundamental steps in many machine learning applications such as least square regressions, information retrieval and so on. With the advent of BigData, it has become essential to process data matrices with thousands of rows and columns in real time. The SVD is one of the data reduction techniques. Hence, there is a strong need for efficient sequential and parallel algorithms for the SVD.

SVD takes as input a matrix $A \in \mathbb{F}^{m\times n}$ where $\mathbb{F}$ could be the field of real ($\mathbb{R}$) or complex ($\mathbb{C}$) numbers and outputs three matrices U, S, V such that $A = USV^T$, where $U \in \mathbb{F}^{m\times m}$, $V \in \mathbb{F}^{n\times n}$ are orthogonal matrices (i.e. $U^TU = I_m$, $V^TV = I_n$) and $S \in \mathbb{R}^{m\times n}$ is a diagonal matrix. If $S = diag(\sigma_1, \sigma_2, ...\sigma_{\min\{m,n\}})$, then the diagonal elements σ_is are called the singular values of A. The columns of U and V are referred to as the left and right singular vectors respectively. Without loss of generality, we assume that $m \geq n$. We also assume that the input matrices are real, the algorithms in this paper can be easily extended to complex matrices.

There are various methods of computing the SVD [1]. The most commonly used algorithms for dense matrices, which we consider in this paper, can be classified as *QR-based* and *Jacobi-based*. The QR-based algorithms work in two stages. In the first stage the input matrix is converted to a band matrix (bidiagonal, tridiagonal and so on) using factorizations such as Cholesky, LU and QR. In the final stage the band matrix is converted to a diagonal form to obtain the singular values and the singular vectors are also computed accordingly. In the sequential setting, the QR based methods are more frequently used as they are faster than the sequential Jacobi based methods. However, Jacobi-based methods are known to be more accurate [2] and also have a higher degree of potential parallelism. Though there have been efforts to implement QR based algorithms in out-of-core setting [3], [4] as well as in homogeneous multi-core setting [5], our focus is on designing faster parallel implementations of Jacobi based algorithms.

There are two different variations of the Jacobi based algorithms, *one-sided* and *two-sided*. The two sided Jacobi algorithms are applicable only when the input matrix is symmetric and are also computationally more intensive. The one-sided Jacobi algorithms are used more frequently. The one-sided Jacobi algorithm proposed by Hestenes [6] is as follows. Using a series of plane rotation matrices $V_1, V_2, \ldots, V_k$ the input matrix A is first converted to a matrix $B = AV_1V_2 \ldots V_k$ such that the columns of B are orthogonal. Suppose $\bar{B}$ be the matrix having only the non-zero columns of B. The decomposition $\bar{B} = US$ gives us the required left singular vectors and the singular values respectively, where U is obtained by normalizing the columns of $\bar{B}$ and for the diagonal matrix S, S_{ii} is the norm of ith column of $\bar{B}$. The right singular vectors V can be obtained by using the same set of plane rotations on the identity matrix I_n.

A more general and more widely used algorithm is One-Sided Jacobi SVD algorithm that deals with any matrix. One-Side Jacobi SVD algorithm finds an orthogonal matrix

$V \in \mathbb{R}^{n\times n}$, such that $B = (b_1, b_2, ..., b_n) = AV$ where $B \in \mathbb{R}^{m\times n}$ is an orthogonal matrix. The above statement implies that:

$$b_i^T b_j = \sigma_i^2 \delta_{ij}$$

where

$$\delta_{ij} = \begin{cases} 0, & \text{for } i \neq j \\ 1, & \text{for } i = j \end{cases}$$

The quantities σ_i are called *Singular Values* of matrix A. B can be written as $B = US$ where $U = (u_1, u_2, ..., u_k)$such that $u_j = \frac{b_j}{\sigma_j}$ for $\sigma_j \neq 0$ and $U^T U = I \in \mathbb{R}^{n\times n}$. Hence we can now write $B = AV$ as $US = AV$ or using properties of orthogonality $A = USV^T$. If some of the σ_js are zeros singular values, the corresponding columns of U are set to null vectors. The first k singular values are always chosen to be non-zero causing the matrix $U^T U$ to be unit matrix of order k augmented to order n with zeros. This is written as follows :

$$S = \begin{pmatrix} \mathbf{1}_k & \\ & \mathbf{0}_{n-k} \end{pmatrix} \tag{1}$$

The matrix V used for orthogonalization of A is a product of matrices indexed by $V^{(k)}$.

$$V = \prod_{k=1}^{z} V^{(k)}$$

V is constructed in such a way that

$$(a_i, a_j) \begin{bmatrix} c & -s \\ s & c \end{bmatrix} = (a_i^{k+1}, a_j^{k+1}) \tag{2}$$

, $i < j$ and $||a_i^{k+1}||_2 > ||a_j^{k+1}||_2$, here a_i is the $i-$th column of A. This is achieved by choosing

$c = [\frac{\beta+\gamma}{2\gamma}]^{\frac{1}{2}}$ and $s = [\frac{\alpha}{2\gamma c}]$, $s = [\frac{\gamma-\beta}{2\gamma}]^{\frac{1}{2}}$ and $c = [\frac{\alpha}{2\gamma s}]$

where $\alpha = 2a_i^T a_j$, $\beta = ||a_j||_2^2$ and $\gamma = (\alpha^2 + \beta^2)^{\frac{1}{2}}$

The matrices given by $V^{(k)}$ are called rotation matrices and z is not dependent of dimension of A.

Describe one sided Jacobi with math notations from Dr Rajs paper:

A. Block Householder Jacobi

For $A \in \mathbb{R}^{m\times n}$ where $m >> n$, a common practice is to reduce the problem complexity by applying initial orthogonal factorization on A followed by one-sided Jacobi method. Given A we apply the following orthogonal facotirzation given by $A = QR$, where $Q \in \mathbb{R}^{m\times n}$ is an orthogonal matrix and $R \in \mathbb{R}^{n\times n}$ is an upper triangular matrix. Next, One-sided Jacobi SVD algorithm is applied on R. The Block Householder- Jacobi SVD algorithm is presented below: Step 1: Factorize A by $A = QR$ where $Q \in \mathbb{R}^{m\times n}$ with orthonormal columns and $R \in \mathbb{R}^{n\times n}$ is upper triangular.

Step 2: Determine SVD of the upper triangular matrix using One-sided Jacobi algorithm.

$$R = \hat{U} \begin{bmatrix} \hat{S} \\ 0 \end{bmatrix} V^T \tag{3}$$

where $\hat{U} \in \mathbb{R}n \times p$ and $V \in \mathbb{R}n \times p$ orthogonal matrices and $\hat{S} = \text{diag}(\sigma_i)$ is a diagonal matrix containing p non-zero singular values of A.

Step 3: Compute $U = Q\hat{U}$. Left singular vectors of A are given by u_i where u_i are columns of U.

[7]–[9] introduced and implemented the idea of parallel one-sided block jacobi algorithm with dynamic ordering and variable blocking. Their approach, known as OSBJ method, accomplishes the parallel SVD in three stages namely, pre-processing, iteration and post processing. There are two types of pre-processing depending on the dimension of the matrix, namely QR-pre-processing and LQ pre-processing. During QR-pre-processing OSBJ decomposes input matrix $A = Q_1 R$ where $A \in \mathbb{R}^{m\times n}$, orthonormal matrix $Q_1 \in \mathbb{R}^{m\times m}$ and upper triangular matrix $R \in \mathbb{R}^{n\times n}$. On the contrary, LQ-pre-processing decomposes input matrix $A = LQ_2$ where $L \in \mathbb{R}^{n\times n}$ is a lower triangular matrix and $Q_2 \in \mathbb{R}^{\ltimes\times\ltimes}$ is an orthogonal matrix. The L or R matrix in pre-processing stage is considered as input A^0 for the iteration stage. A^0 is partitioned into column blocks. Let, $A_i^{(r)}$ and $A_j^{(r)}$ are one such column block pair where $1 \leq i < j \leq l$ assuming we have l such column blocks. Weight $\hat{w}_{ij}^r = \frac{||A_i^{(r)^T} A_j^{(r)} \mathbf{e}||_2}{||\mathbf{e}||_2}$, where $\mathbf{e} = (1, 1, ...1)^T \in \mathbb{R}^{\frac{n}{l}}$. $\hat{w}_{ij}^r$ serves as an approximate measure of inclination between $Im(A_i^r)$ and $Im(A_j^r)$. The column block pairs are ordered based on their mutual inclination and the most mutually inclined pair is chosen to be orthogonalized and those columns are excluded from the set for next iteration. The process is repeated until all the column blocks are used up. For each column block pair a 2×2 Gram matrix $G_s \in \mathbb{R}^{\frac{2n}{l}\times\frac{2n}{l}}$ is constructed as is given by $G_s = [A_{i_{r,s}}^{(r)}, A_{j_{r,s}}^{(r)}]^T [A_{i_{r,s}}^{(r)}, A_{j_{r,s}}^{(r)}]$ where $1 \leq s \leq \frac{l}{2}$. This gram matrix is them diagonalized as $G_s = V_s D_s V_s^T$ where V_s is an orthogonal matrix and D_s is a diagonal matrix. The column blocks for next iteration $A^{(r+1)}$ is computed by $[A_{i_{r,s}}^{(r+1)}, A_{j_{r,s}}^{(r+1)}] = [A_{i_{r,s}}^{(r)}, A_{j_{r,s}}^{(r)}] V_s$. Iteration process continues until all the columns are mutually orthogonal.

The Jacobi Relaxation Scheme (JRS) algorithm by Rajasekaran and Song introduced the idea of improving parallelism in SVD computation by multiplying the off-diagonal element in each iteration by a very small number ϵ such that $0 < \epsilon < 1$ instead of setting the off-diagonal element to zero. [10] compares number of iterations taken by JRS algorithm to converge with that of Strumpen's Independent Jacobi algorithm **[?]** and shows that JRS takes much less number of iterations to converge than Independent Jacobi.

This paper has done same parallel implementation: [11].

This paper seems to do some kind of sorting for [12].

B. Contributions

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II. Quick Pivoting

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III. Parallel Implementation

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IV. Experimental Results

V. Conclusion

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