

# Parallel Singular Value Decomposition

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## Introduction

### Singular Value Decomposition

The singular value decomposition of a matrix  $A$  is the factorization of  $A$  into the product of three matrices  $A = UDV^T$  where the columns of  $U$  and  $V$  are orthonormal and the matrix  $D$  is diagonal with positive real entries. The SVD is useful in many tasks. Here we mention one example. In many applications, the data matrix  $A$  is close to a matrix of low rank and it is useful to find a low rank matrix which is a good approximation to the data matrix .

### Jacobi method

Jacobi algorithm was initially proposed by Jacobi C.G.J and is used to compute eigenvalues and eigenvectors. Based on Jacobi's algorithm, a fast and stable method was proposed by Golub-Kahan to decompose a matrix, rectangular or square, in its sub-matrices, as shown in

$$[U, S, V^T] = \text{Jacobi\_SVD}(M, \epsilon)$$

where  $M$  shows sensitivity encoding matrix,  $\epsilon$  is the tolerance level for SVD algorithm to converge.  $U$  and  $V$  are complex unitary matrices which contain left-singular and right-singular vectors of matrix  $M$ , respectively, whereas  $S$  is a diagonal matrix containing the positive singular values of  $M$ , as represented in

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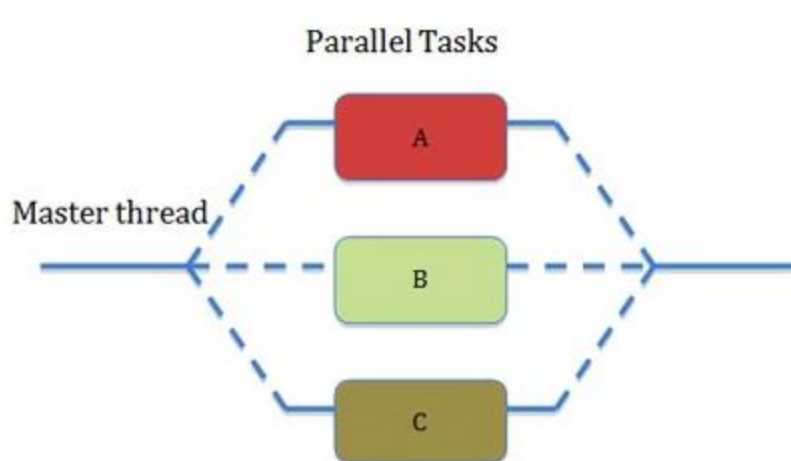
$$S = \begin{bmatrix} \sigma_x & 0 & \dots & 0 \\ 0 & \sigma_{x-1} & 0 & 0 \\ \vdots & 0 & \ddots & \vdots \\ 0 & 0 & \dots & \sigma_1 \end{bmatrix}$$

The diagonal values of  $S$  can be sorted in a descending order as:

$$\sigma_x > \sigma_{x-1} > \sigma_{x-2} > \dots > \sigma_1$$

### OpenMP

It is a directive based parallel programming model. OpenMP program is essentially a sequential program augmented with compiler directives to specify parallelism.



## Jacobi SVD Algorithm

The pseudo-code of Jacobi SVD algorithm is given below. The matrix  $U$  in the algorithm is initialized by an input matrix  $M$ , while an initial guess of the desired eigenvectors ( $V$ ) is taken as identity matrix.

```

repeat
  for all  $i < j$ 
     $\alpha = \sum_{k=1}^n U_{ki}^2$ 
     $\beta = \sum_{k=1}^n U_{kj}^2$ 
     $\gamma = \sum_{k=1}^n U_{ki} U_{kj}$ 
     $\zeta = \frac{(\beta - \alpha)}{2\gamma}$  (Compute Jacobi rotation)
     $t = \text{signum} \frac{(\zeta)}{(|\zeta| + \sqrt{1 + \zeta^2})}$ 
     $c = \frac{1}{\sqrt{1 + t^2}}$ 
     $s = ct$ 
    for all  $k < n$  (update matrix U)
       $t = U_{ki}$ 
       $U_{ki} = ct - sU_{kj}$ 
       $U_{kj} = st + cU_{ki}$ 
    endfor
    for all  $k < n$  (update matrix V)
       $t = V_{ki}$ 
       $V_{ki} = ct - sV_{kj}$ 
       $V_{kj} = st + cV_{ki}$ 
    endfor
  endfor
until all  $\frac{|c|}{\sqrt{\alpha\beta}} \leq \epsilon$ 

```

This algorithm repeatedly selects pairs of  $i < j$  from rows and columns of matrix  $MM^T$ .  $N$ -dimensional linear product space  $R_{kl}$  is given below. Jacobi rotation is applied on the 2D linear subspace of  $R_{kl}$ . The Jacobi rotation process is repeated until the

convergence criterion  $\varepsilon$  is achieved. Orthogonal updates are applied during each iteration in Jacobi algorithm to make the matrix  $M$  more diagonal than it was in the previous iteration. As a result of the diagonal update, off-diagonal elements are small enough and can be replaced by zero where  $R_{kl}$  is an identity matrix except for  $c$  placed in the diagonal and  $s$  which are symmetrically placed off the diagonal. The entries of  $c$  and  $s$  can be computed by the algorithm. The singular values ( $S$ ) are implicitly generated at convergence, and the right ( $V$ ) and left ( $U$ ) singular vectors are recovered by multiplying all the Jacobi rotations together.

The pseudo-inverse of matrix  $M$  with Jacobi SVD can be calculated using Eq. (10). The non-zero diagonal elements of  $S$  are inverted and multiplied with  $V$  and  $U^T$  to get the inverse of the rectangular matrix,  $M$ :

$$M^{-1} = V \times S^{-1} \times U^T$$

## Conclusion

Jacobi SVD algorithm is numerically stable and provides a good solution for large matrices to compute SVD. Jacobi SVD algorithm is computationally fast algorithm and is well-suited for implementation on parallel processors.

### Team Members

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