

SVD Factorization for Tall-and-Fat Matrices on Map/Reduce Architectures

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Abstract

We demonstrate an implementation for an approximate rank- k SVD factorization, combining well-known randomized projection techniques with previously implemented map/reduce solutions in order to compute steps of the random projection based SVD procedure, such as QR and SVD. We structure the problem in a way that it reduces to Cholesky and SVD factorizations on $k \times k$ matrices computed on a single machine, greatly easing the computability of the problem.

1 Introduction

[1] presents many excellent techniques for utilizing map/reduce architectures to compute QR and SVD for the so-called tall-and-skinny matrices. QR factorization is turned into an $A^T A$ computation problem to be computed in parallel using map/reduce, and its key element the Cholesky decomposition, can be performed on a single machine. Since

$$A^T A = (QR)^T (QR) = R^T Q^T QR = R^T R$$

and because Cholesky factorization of an $n \times n$ symmetric positive definite matrix is

$$A = LL^T$$

where L is an $n \times n$ lower triangular matrix, and R is upper triangular, we can conclude if we factorize A into L and L^T , this implies $LL^T = RR^T$, we have a method of calculating R of QR using Cholesky factorization on $A^T A$. The key observation here is $A^T A$ computation results in an $n \times n$ matrix and if A is “skinny” then n is relatively small (in the thousands), then Cholesky

decomposition can be executed on a small $n \times n$ matrix on a single computer utilizing an already available function in a scientific computing library. Q is computed simply as $Q = AR^{-1}$. This again is relatively cheap because R is $n \times n$, the inverse is computed locally, matrix multiplication with A can be performed through map/reduce.

SVD is an additional step. SVD decomposition is

$$A = U\Sigma V^T$$

If we expand it with $A = QR$

$$QR = U\Sigma V^T$$

$$R = Q^T U \Sigma V^T$$

Let's call $\tilde{U} = Q^T U$

$$R = \tilde{U} \Sigma V^T$$

This means if we run a local SVD on R (we just calculated above with Cholesky) which is an $n \times n$ matrix, we will have calculated \tilde{U} , the real Σ , and real V^T .

Now we have a map/reduce way of calculating QR and SVD on $m \times n$ matrices where n is small.

1.1 Approximate rank-k SVD

Switching gears, we look at another method for calculating SVD. The motivation is computing SVD if n is large, creating a “fat” matrix which might have columns in the billions would require reducing the dimensionality of the problem. According to [2], one way to achieve is through random projection. First we draw an $n \times k$ Gaussian random matrix Ω . Then we calculate

$$Y = A\Omega$$

We perform QR decomposition on Y

$$Y = QR$$

Then form $k \times n$ matrix

$$B = Q^T A$$

Then we can calculate SVD on this small matrix

$$B = \hat{U}\Sigma V^T$$

Then form the matrix

$$U = Q\hat{U}$$

The main idea is based on

$$A = QQ^T A$$

if replace Q which comes from random projection Y ,

$$A \approx \tilde{Q}\tilde{Q}^T A$$

Q and R of the projection are close to that of A . In the multiplication above R is called B where $B = \tilde{Q}^T A$, and,

$$A \approx \tilde{Q}B$$

then, as in [1], we can take SVD of B and apply the same transition rules to obtain an approximate U of A .

This approximation works because of the fact that projecting points to a random subspace preserves distances between points, or in detail, projecting the n -point subset onto a random subspace of $O(\log n/\epsilon^2)$ dimensions only changes the interpoint distances by $(1 \pm \epsilon)$ with positive probability [3]. It is also said that Y is a good representation of the span of A .

1.2 Combining Both Methods

Our idea was using approximate k -rank SVD calculation steps where $k \ll n$, and using map/reduce based QR and SVD methods to implement those steps. By utilizing random projection, we would be able to work in a smaller dimension which would translate to local Cholesky, and SVD calls on $k \times k$ matrices that can be performed in a speedy manner. Below we outline each map/reduce job.

Algorithm 1: Random Projection Job

```
input : A
output: Y
function MAP(key, value)
    Tokenize value and pick out id value pairs
    result  $\leftarrow$  zeros(1,k)
    for each  $j^{th}$  token  $\in$  value do
        Initialize seed with j
        r  $\leftarrow$  generate k random numbers
        result  $\leftarrow$  result + r  $\cdot$  token[j]
    end
    emit key, result
function REDUCE(key, value)
    noop
```

Each value of A will arrive to the algorithm as a key and value pair. Key is line number or other identifier per row of A . Value is a collection of id value pairs where id is column id this time, and value is the value for that column. Sparsity is handled through this format, if an id for a column does not appear in a row of A , it is assumed to be zero. The resulting Y matrix has dimensions $m \times k$.

Algorithm 2: $A^T A$ Cholesky Job

```
input : Y
output: R
function MAP(key k, val a)
    for i, row in enumerate( $a^T a$ ) do
        | emit i, row
    end
function REDUCE(key, value)
    | emit (k, sum( $\langle v_j^k \rangle$ ))
function FINAL LOCAL REDUCE (key, value)
    | result  $\leftarrow$  Cholesky( $A_{sum}$ )
    | emit (result)
```

The FINAL_LOCAL_REDUCE step is a function provided in most map/reduce frameworks, it is a central point that collects the output of all reducers, naturally a single machine which makes it ideal to execute the final Cholesky call on by now a very small ($k \times k$) matrix. The output is R .

Algorithm 3: Q Job

```
input  : Y,R
output: Q
function INIT()
|  $R_{inv} = R^{-1}$ 
function MAP(key, value)
| for row in Y do
| | emit (key, row ·  $R_{inv}$ )
end
```

There is no reducer in the Q Job, it is a very simple procedure, it merely computes multiplication between row of Y and a local matrix R . Matrix R is very small, $k \times k$, hence it can be kept locally in every node. The *INIT* function is used to store the inverse of R locally, once the mapper is initialized, it will always use the same R^{-1} for every multiplication.

Algorithm 4: $A^T Q$ Job

```
input  : A,Q
output:  $B^T$ 
function REDUCE (key, value)
| for row in value do
| | if row is from A then
| | | left = row
| | end
| | if row is from Q then
| | | right = row
| | end
| end
| for nonzero  $j^{th}$  cell in left do
| | emit j, left[j] · right
| end
function REDUCESUM (key, value)
| result ← zeros(1,k)
| for row in value do
| | result ← result + row
| end
emit key, result
```

The job above takes A and Q matrices at the same time. Both of these

matrices are based on the same key (line number, or other pre-existing id) and we need to join them first. If a mapper is a pass-through mapper, in other words if it does not exist, it is assumed to simply re-emit the key and value, which will, indirectly force matching rows with the same id from A and Q to be sent to the first reducer. Then for each unique id, the first reducer gets exactly two rows. This is an indirect way of performing a join in map/reduce environment.

Once we have these two rows we need to deduce if the row is a Q row or an A row. We need this information because which row we iterate depends on it. We prefer to iterate cells of A one by one, which is assumed to be sparse, and multiply the entire row of Q . Then for each j^{th} non-zero cell of A , we multiply this value with the row from Q and emit the multiplication result with key j .

This job's formula in 1.1 is described $Q^T A$. For implementation purposes we changed this formula into

$$B^T = A^T Q$$

because as output we needed to have a $n \times k$ matrix instead of a $k \times n$ one, which would allow us to use map/reduce SVD that translates into a local Cholesky and SVD on $k \times k$ matrices. Since we take SVD of B^T instead of B , that changes the output as well,

$$B = U \Sigma V^T$$

becomes

$$B^T = V \Sigma U^T$$

In other words, in order to obtain U of B , we need to take $(U_{BT}^T)^T$ from the SVD of B^T . This is how $A^T A$ Cholesky Job is called, this time with B^T as its input data.

Algorithm 5: $Q\tilde{U}$ Job

```
input : Q,R
output: U
function INIT()
|  $\tilde{U}$  = svd of  $R$ 
function MAP(key, value)
| for row in  $Q$  do
| | emit (key, row ·  $\tilde{U}$ )
| end
```

The order of execution for everything is as follows:

Algorithm 6: Map/Reduce SVD

```
 $Y$  = Random Projection Job ( $A$ )
 $R_Y = A^T A$  Cholesky Job( $Y$ )
 $Q_Y = Q$  Job
 $B^T = A^T Q$  Job
 $R_{BT} = A^T A$  Cholesky Job( $B^T$ )
 $U = Q\tilde{U}$  Job( $R_{BT}, Q$ )
```

1.3 Discussion

We performed few experiments on the Movielens 1M dataset which has 1 million ratings from 6000 users on 4000 movies. The implementation was programmed on Hadoop through mrjob framework, and SVD calculation on the full dataset with $k = 7$ on a single notebook computer took 6 minutes. Sparse SVD from Scipy numeric library on the same dataset is much faster, however map/reduce environment incurs certain costs during its start-up and preparation phases for its jobs, plus writing, reading to and from disks due to the record-by-record processing nature of Hadoop can cause a slower performance. However, exactly for the same reasons a map/reduce algorithm can scale horizontally, processing records in the billions, proportional to the number of nodes in a cluster. All code relevant for this paper can be here https://github.com/burakbayramli/classnotes/tree/master/stat/stat_hadoop_rnd_svd

There are only two passes necessary on the full dataset, and three passes on m rows but with reduced k dimensions this time. Perhaps predictably, the procedure spends most of its time at $A^T Q$ Job. This step performs not

only a join between A and Q , it also emits k cells per non-zero value of A 's rows, then creates partial sums these k vectors creating $n \times k$ result. If for simplicity we assume k non-zero cells in each A row, the complexity of this step would be $O(mk)$ indicating that system, disk level improvements can greatly decrease the performance number shared above.

References

- [1] Gleich, Benson, Demmel, *Direct QR factorizations for tall-and-skinny matrices in MapReduce architectures*, [arXiv:1301.1071](#) [cs.DC], 2013
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- [4] M. Kurucz, A. A. Benczúr, K. Csalogány, *Methods for large scale SVD with missing values*, ACM, 2007