Performance Comparison of a Parallel Recommender Algorithm across three Hadoop-based Frameworks

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***Abstract*—One of the challenges our society faces is the ever increasing amount of data. Among existing platforms that address the system requirements, Hadoop is a framework widely used to store and analyze "big data". On the human side, one of the aids to finding the things people really want is recommendation systems. This paper evaluates highly scalable parallel algorithms for recommendation systems with application to very large data sets. A particular goal is to evaluate an open source Java message passing library for parallel computing called MPJ Express, which has been integrated with Hadoop. As a demonstration we use MPJ Express to implement collaborative filtering on various data sets using the algorithm ALSWR (Alternating-Least-Squares with Weighted-λ-Regularization). We benchmark the performance and demonstrate parallel speedup on Movielens and Yahoo Music data sets, comparing our results with two other frameworks: Mahout and Spark. Our results indicate that MPJ Express implementation of ALSWR has very competitive performance and scalability in comparison with the two other frameworks.**

***Index Terms*—HPC, MPJ Express, Hadoop, MapReduce, YARN, Spark, Mahout**

I. Introduction

Over the last decade Apache Hadoop has established itself as a pillar in the ecosystem of software frameworks for "big data" processing. As an open source, mostly Java-based Apache project with many industrial contributors, it retains a commanding position in its field.

When first released Hadoop was a platform primarily supporting the MapReduce programming model, and other projects built on top of MapReduce. Around 2014 with the release of Hadoop 2.0 the platform was re-factored into a separate YARN (Yet Another Resource Negotiator) resource allocation manager, with MapReduce now just one of multiple possible distributed computation frameworks that could be supported on top of YARN. Several other major big data projects rapidly migrated to allow execution on the Hadoop YARN platform (for example Apache Spark [24], Apache Giraph [1], Apache Tez [15], and Microsoft Dryad [9]). Around the same time the present authors envisaged adding our existing MPJ Express framework for MPI-like computation in Java to that distinguished group, and developed a version of our software that could also run under Hadoop YARN [22].

MPJ Express is a relatively conservative port of the standard MPI 1.2 parallel programming interface to Java, and is provided with both "pure Java" implementations (based on Java sockets and

threads) and "native" implementations exploiting specific interconnect interfaces, or implementations on top of standard MPI. The vision was thus to support MPJ as one computational framework among many largely Java-based or JVM-based frameworks that could be mixed and matched for different stages of complex big data processing, with Hadoop and HDFS (the Hadoop Distributed File System) as the "glue" between stages.

The main goal of the present paper is to provide evidence that such a scenario can be realized and that it may be advantageous. We concentrate on one particular computationally intensive "big data" problem - generating product recommendations through the collaborative filtering algorithm ALSWR (Alternating Least Squares with Lambda Regularization). A version of this algorithm was developed and evaluated using MPJ running under Hadoop. We then go on to compare our implementation with two existing implementations of ALSWR that can run under Hadoop—one taken from the Apache Mahout project using MapReduce, and one using Apache Spark. Results suggest the MPJ approach can provide useful performance gains over these other established Big Data frameworks on suitable compute-intensive kernels.

The rest of the paper is organized as follows. Section I-A reviews selected related work. Background materials in Section II review Hadoop, YARN and HDFS; outline the architecture of MPJ Express and its integration in YARN; and give an overview of the collaborative filtering technique. Section III describes how we implement the collaborative filtering with ALSWR in MPJ. The Section IV evaluates and compares our results with Mahout and Spark. Section V concludes the paper and discusses future works.

A. Related Work

Recommender systems have been a subject of tremendous interest lately. However, our interested is limited to collaborative filtering applied to very large datasets with millions of records, leading to a need for parallel processing.

For the Netflix Prize [25] proposed an approach called ALSWR. In order to implement their algorithm in parallel authors used Matlab [7]. The result of the experiments showed a better performance of the ALSWR as the number of features and iterations increased. The experiments were made on the Netflix dataset consisting of 100 million ratings. The current state-of-the-art dataset comprises of billions of ratings [10] and processing this requires scalable methods. The authors in [10] explained how ALS and SGD algorithms are used with Apache Giraph to process an average of 100 billion ratings from Facebook. Yu, Hsieh, Si and Dhillon in [21] compare ALS methods to Stochastic Gradient Descent (SGD) methods and Coordinate Descent methods. A comparison of SGD with various algorithms was done in [13]. More studies have been realized in [11] with a different approach called Co-clustering Dataflow Bregman as well as another interesting research geared towards very large datasets in [16] that used ALS as algorithm on Hadoop MapReduce and JBlas as framework.

In the context of MPJ Express, previous work [22] focused on integrating the software with YARN allowing end-users to execute Java MPI programs on Hadoop clusters. As part of this effort, a new YARN-based runtime system was added to the MPJ Express library. The paper demonstrated reasonable comparative performance of YARN-based runtime against the existing runtime. This study did not compare performance of YARN-based MPJ Express library against some of the newer technologies including Apache Spark.

II. Background

A. Hadoop Overview

Hadoop is a framework that stores and processes voluminous amount of data in a reliable, fault-tolerant manner [19]. Since Hadoop 2, YARN (Yet Another Resource Negotiator) has been integrated in the infrastructure as the resource manager, enabling many other distributed frameworks besides MapReduce to process their data on Hadoop cluster. YARN depends on three main components to complete a task: a Resource Manager (RM), Node Managers (NMs), and an Application Master (AM). The RM is responsible for managing and allocating the resources across the cluster. NMs run on all nodes available in a cluster and report all the tasks to the RM such as the number of cores and memory space. Each job that is started has an AM specific to the processing framework that manages operation within containers and ensures there are sufficient containers for the task. The communication between the master nodes and slave nodes is achieved through the Heart Beat Mechanism [6].

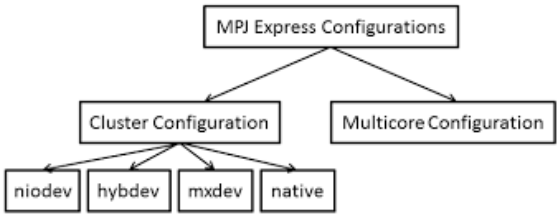


Fig. 1: MPJ Express Configuration

B. MPJ Express

MPJ Express [14] is an open source Java MPI-like library that allows application developers to write and execute parallel applications on multicore processors and compute clusters. The MPJ Express software can be configured in various ways as depicted in Figure 1. Under the cluster configuration, the MPJ Express software provides different communication devices that are suitable for the underlying interconnect. Currently, there are four communication devices available:

1) niodev - uses Java New I/O (NIO) Sockets
2) mxdev - uses Myrinet eXpress (MX) library for Myrinet networks
3) hybdev - for clusters of multicore processors
4) native - uses a native MPI library (like MPICH, MVAPICH, OpenMPI)

Since 2015, the MPJ Express software provides a YARN-based runtime that exploits the niodev communication device to execute parallel Java code on Hadoop clusters. Under this setting, HDFS is used as the distributed file system where application datasets, MPJ Express libraries, and application programs are loaded to allow all processes to access the material.

Figure 2 presents the implementation of the MPJ Express library on YARN. In this setting, the Hadoop cluster consists of a client node, where Resource Manager (RM) executes, and two compute nodes, where a Node Manager (NM) executes. The NM process operates on each compute node and is responsible for executing assigned tasks. The main phases of the implementation of YARN are explained in [22].

C. Collaborative Filtering Techniques

Recommender systems are software tools and techniques that provide suggestions to users to help them find and evaluate items likely to match their

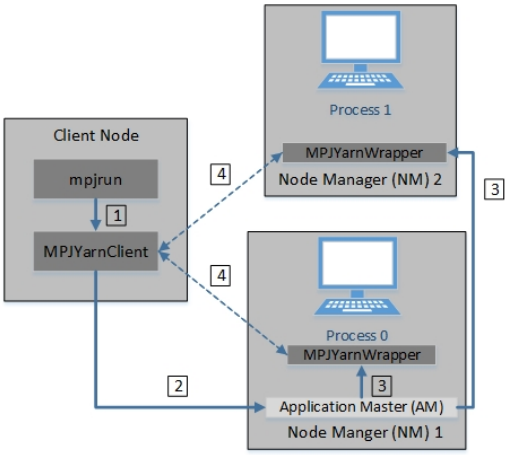


Fig. 2: MPJ Express Integrated in YARN- 1) Submit YARN application- 2) Request container allocation for AM- 3) AM generates a CLC and allocates container to each node- 4) Each mpj-yarn-wrapper send outputs and error streams of the program to the MPJYarnClient

requirements. We use the term item to describe a product or service recommended by a system. Collaborative filtering systems are based on users' purchases or decisions histories. Assuming two individuals share the same opinion on an item, they are also more likely to have similar taste on another item. In our experiments we have opted for a model based approach and we specifically use Alternating-Least-Squares with Weighted-λ-Regularization (ALSWR) algorithm.

In this section, following [25], we will often refer to items as "movies". Assume we have n_u users and n_m movies, and R is the $n_u \times n_m$ matrix of input ratings. Usually each user can rate only few movies. Therefore the matrix R will initially have many missing values or loosely speaking it will be sparse. The problem is to predict the unknown elements of R from the known elements.

We model the preferences of users by assuming they have simple numeric level of preference for each of a number n_f of features to be found in movies; thus the behaviour of user i is modelled by a vector $\mathbf{u}_i$ of length n_f. Similarly each movie is assumed to have each these features to a simple numeric degree so each movie j is modelled by a vector $\mathbf{m}_j$ of the same size. The predicted preference of user i for movie j is the dot product $\mathbf{u}_i \cdot \mathbf{m}_j$. The vectors are conveniently collected together in

matrices U and M of size $n_u \times n_f$ and $n_m \times n_f$ respectively.

To fit the model to the known elements of R we use a least squares approach, adding a regularization term parameter λ to the sum of square deviations to prevent the model from overfitting the data. The penalty function ALSWR strives to minimize is:

$$f(U, M) = \sum_{i,j} (r_{ij} - \mathbf{u}_i \cdot \mathbf{m}_j)^2 + \lambda \left(\sum_i n_{u_i} \mathbf{u}_i^2 + \sum_j n_{m_j} \mathbf{m}_j^2 \right) \quad (1)$$

where the first sum goes over i, j values where the element r_{ij} of R is known in advance, n_{u_i} is the number of items rated by a user i, and n_{m_j} is the number of users who have rated a given movie j.

ALSWR is an iterative algorithm. It shifts between fixing two different matrices. While one is fixed, the other one is updated hence solving a matrix factorization problem. The same process goes through a certain number of iterations until a convergence is reached which implies that there is little or no more change on either users and movies matrices. The ALSWR algorithm as explained by Zhou et al [25] is as follows:

- Step 1: Initialize matrix M in a pseudorandom way.
- Step 2: Fix M, Solve U by minimizing the objective function (the sum of squared errors);
- Step 3: Fix U, Solve M by minimizing the objective function similarly;

Steps 2 and 3 are repeated until a stopping criterion is satisfied. Step 2 is implemented by Equation 2 where M_{I_i} is the sub matrix of M, representing the selection of any column j in the set of movies rated by a user i, H is a unit matrix of rank equal to n_f and $R(i, I_i)$ is the row vector where columns j are chosen.

$$\mathtt{u}_i = (M_{I_i} M_{I_i}^T + \lambda n_{u_i} H)^{-1} M_{I_i} R^T(i, I_i) \quad (2)$$

Step 3 is implemented by a similar formula exchanging the roles of U and M.

III. MPJ Implementation of ALSWR

The basic strategy for distributing the ALSWR algorithm to run in parallel was already described by the original proposers in [25]. All nodes of a cluster contain a certain subset of the large, sparse, recommendations array, R. In particular it is convenient for the R array to be stored in two ways across the cluster as a whole—divided across nodes by columns and also by rows. This is illustrated in figure 3, where i is the subscript identifying users and j is the subscript identifying items, and the two different forms of decomposition of R are used in the two different steps. Step 2, as defined in equation 2, conveniently uses locally held R decomposed by i to update locally owned elements u_i of the user model. B is a block size for the locally held subset of elements, approximately constant across the cluster for good load balancing.

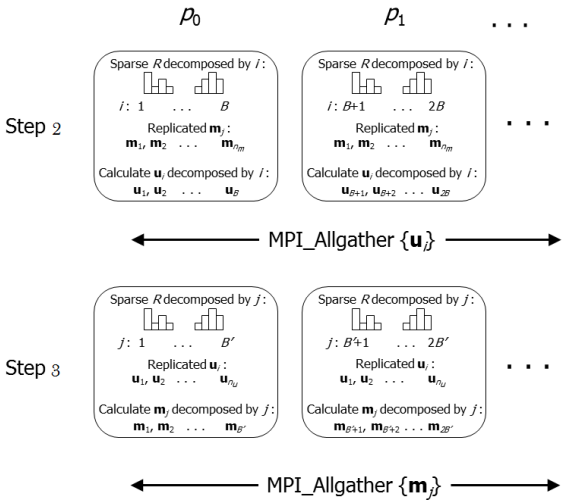


Fig. 3: Visualization of an iteration of distributed ALSWR algorithm. "Processor space" runs across the page, processes are labelled $p_0, p_1, \ldots$ and so on. Time runs down the pages with distributed computational steps labelled as on page 4. Between computational stages there are collective synchronizations in the form of "allgather" operations.

Because update of u_i potentially involves *any* element of the item model **m**, to simplify this step all elements of **m** should be stored locally, in globally replicated fashion.

Step 3 has a complementary structure, but now update of m_j may require access to any element of **u**. So between steps 1 and 2 all the locally computed elements of **u** must be gathered together and broadcast to processing nodes. Similarly between step 2 and step 3 in the *next* iteration of the algorithm, the locally computed elements of **m** must be gathered and broadcast.

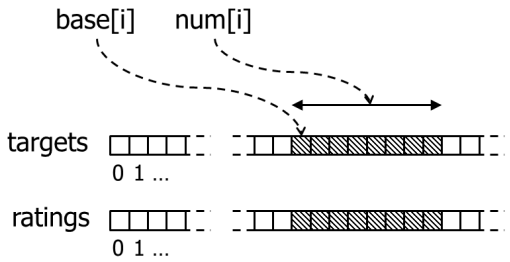


Fig. 4: Sparse data structure to represent locally held ratings. This whole structure is duplicated, once for ratings distributed by user and once for ratings distributed by items. In the "by user" case the size of the `base` and `num` arrays is the total number of locally held users, with `num[`i`]` being the number of ratings by user i; `targets` elements hold a *global* index of the rated item (index in the gathered array of item models). In the "by item" case the size of the top arrays is the number of locally held items, with `num` holding the number of ratings per item; a `target` element now holds the global index of the user who *made* the rating.

A great benefit of the MPI style of programming is the use of *collective communication*. This is embodied here in the use of MPI_Allgather, that allows data to be gathered from each process then to be distributed to all processes.

In our program the data that we used for the implementation of the ALSWR code consists of a sparse matrix of ratings, partitioned by user or by item. Figure 4 illustrates the organization of the data.

In order to solve the symmetric positive definite matrix we use Cholesky decomposition from the Intel Data Analytics Acceleration Library (DAAL) [8].

The code assumes each node holds `numLocal` elements of the distributed user model. Within a node we run `NUM_THREADS` long lived threads (they are started at the beginning of the program), where the `NUM_THREADS` parameter will be related to the number of cores on the node. The variable `me` identifies a thread within the local node (not to be confused with the MPI *rank* which identifies a node). Threads will be synchronized before MPI collective operations using barriers implemented by `java.util.concurrent.CyclicBarrier`. The MPI operations themselves are only executed by the `me` $= 0$ thread.

The ratings data for our MPJ code are read from the same HDFS text files as used by the third party implementations of ALS discussed below. We use HDFS API to determine the blocks that have replicas on nodes running MPJ processes. A heuristic is used to choose a load balanced set of local replicas to read. The locally read ratings are then partitioned to destination nodes using a variant of the CARI communication schedules introduced in [18].

IV. Performance Evaluation and Comparison of MPJ Express, Mahout, and Spark

This section details our experiments focusing on the comparative performance evaluation of MPJ Express against well-known platforms including Hadoop, Mahout and Spark. The performance evaluation compares their parallel speedup.

Apache Mahout is a distributed linear algebra framework [2], widely used for its distributed implementation on Apache Hadoop. This essentially means that datasets are stored on the HDFS and various machine learning algorithms such as collaborative filtering can be applied to the data. The ALSWR implementation with Apache Mahout is done through its machine learning library and more specifically the map-reduce implementation of ALS. This last consists of two stages: a parallel matrix factorization phase followed up by some recommendations. Both phases are detailed in [12].

Apache Spark is an open-source cluster-computing framework suitable for large scale data processing. Since Hadoop 2, Spark has been integrated with Hadoop allowing its programs to run on YARN. Spark can use memory and disk processing through its Resilient Distributed Datasets (RDD). As explained in [23], the default is to keep the RDD in memory; when there is no more space in the RAM, Spark stores the rest on disk. Shared variables and parallel operations available in Spark are detailed in [24] and [3]. We have implemented ALS on Spark through its standard machine learning library (MLlib).

For the purpose of performance evaluation, we acquired our datasets from public domains. These consist of anonymous user ratings from two different sources: MovieLens and Yahoo Music. The dataset obtained from MovieLens contains

$20,000,263$ ratings for $27,278$ movies, created by $138,493$ users [5]. The dataset from Yahoo Music—that is much larger—contains over 717 millions ratings for 136 thousands songs rated by 1.8 million users [20]. The data from Yahoo has been separated in training and test datasets. Our test environment includes a Linux cluster composed of 2 nodes having 6 cores each and 2 other nodes with 4 cores each; giving us in total 20 cores. Nevertheless in the experiments we limit ourselves to 16 cores in order to get the best results. Using too many cores could lead to a degradation of the performance. The software used for the tests consist of:

- Java 1.7
- Apache ant 1.6.2
- Hadoop-2.7.3
- MPJ Express (version 0.44), Mahout (version $0.12.2$), and Spark (version $2.2.0$)
- Intel Data Analytics Acceleration Library (DAAL) 2017

A. MovieLens 20M Ratings Experiments

Our ALSWR code is tested with 50 features, 10 iterations, 0.01 for the regularization parameter lambda λ and 0.01 for the parameter epsilon ϵ that is used in the initial guess for the item model. Figure 5a compares the performances between MPJ Express, Spark and Mahout on different number of processes. MPJ Express and Spark have both a good performance and parallel speed up: as the number of cores increases the time decreases; Mahout does not show much variances from four cores and above. Figure 5b focus on MPJ and Spark. MPJ Express has the best performance amongst the 3 frameworks. It is, on average, 13.19 times faster than Mahout and on average 1.4 faster than Spark. Figure 6 represents the parallel speedup of MPJ Express and Spark. With sixteen cores MPJ Express is almost 10 times faster than when it is run in sequence while Spark is just about 4.5 times faster than its result with one process.

B. Yahoo Webscope 700M Ratings Experiments

Mahout was unable to cope with the large Yahoo dataset. For this reason, we have evaluated only MPJ Express and Spark versions of the code for this dataset. Figure 7 shows a pattern quite similar to figure 5b although this time our dataset is about 35 times bigger. Table I displays the time measurement in minutes of the assessed frameworks. A closer look at figure 8 demonstrates a significant parallel speedup improvement of MPJ Express which now runs more than 10.5 times faster on 16 cores than its sequential time. The parallel speedup of Spark has also improved. It implements the ALS on Yahoo dataset 7.5 times faster with 16 cores than when it is run in sequence. However from 12 cores onwards, the performance of the Spark version starts decreasing.

# of Procs	MPJ Express	Spark
1	298	417
2	142	217
4	84.4	136
8	45.56	65
12	33.15	54
16	28.35	55

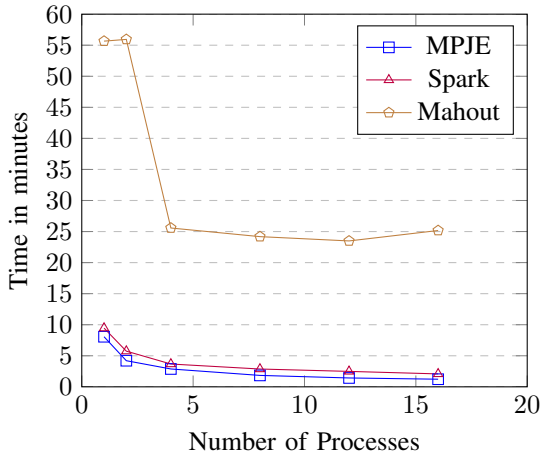
TABLE I: Performance MPJ Express vs Spark in minutes

C. Analysis of the results

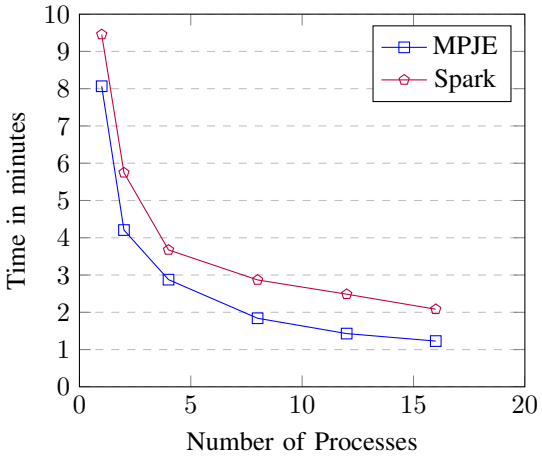
The Mahout implementation of ALS—not necessarily representative of the wider Mahout project—is based on MapReduce. The performance limitations of MapReduce on iterative algorithms are well documented, see for example [4]. According to pseudocode given in [24], the Spark implementation uses a combination of its *parallelize* and *collect* operations to reproduce the communication operation called *MPI_Allgather* here. We assume that the MPI collective algorithms can implement this pattern more efficiently. There is a discussion of efficient implementations of Allgather in [17] for example. Additionally there may be some degradation of the performance of Spark when there is not enough memory (RAM) as the storage has to be on disk when the program is running out of space.

V. Conclusion

Various computational frameworks have been adopted over the last few years for running compute-intensive kernels of recommender algorithms on Hadoop platforms. These include Apache Mahout, Apache Spark and Apache Giraph. In this paper we have added our MPJ Express framework to this list, and provided evidence that it can outperform other implementations of the central optimization algorithm. This additional performance certainly comes at some cost in terms of programming complexity. For example the MPJ programmer has



(a) MPJE vs Spark & Mahout



(b) MPJE vs Spark

Fig. 5: Frameworks Performance Comparison MPJ Express with MovieLens dataset

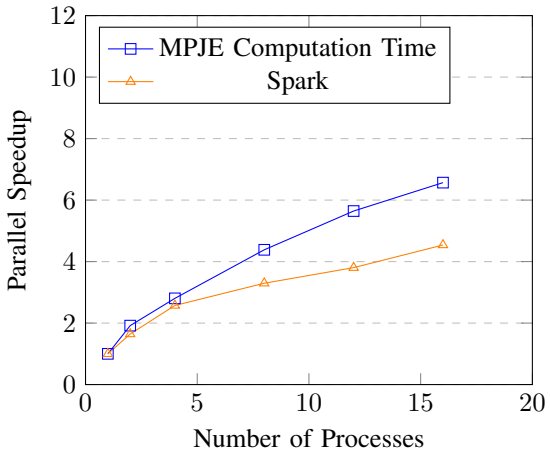


Fig. 6: Parallel Speedup MPJ Express vs Spark with MovieLens dataset

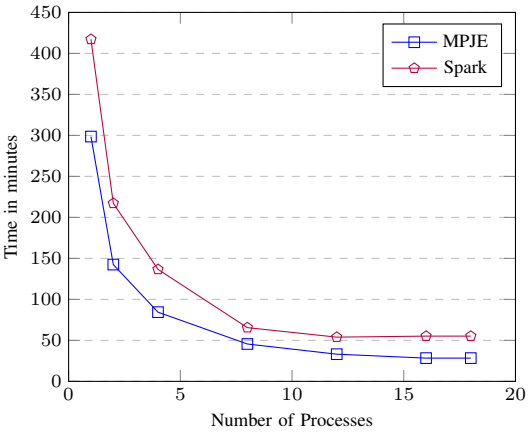


Fig. 7: Performance Comparison MPJ Express vs Spark with Yahoo dataset

to spend more time orchestrating communication between Hadoop nodes. Nevertheless we argue that for some intensive and often used kernels, the extra investment in programming may be justified by the potential performance gains. We see MPI-based processing stages as one more resource in the armoury of big data frameworks that may be used in processing pipelines run on Hadoop clusters. We also suggest that in this setting MPJ Express may be a natural choice of MPI-like platform, given that many other such processing stages will be coded in Java or JVM-based languages.

On our future work we need to evaluate alternative parallel organizations of the recommender code, like the rotational hybrid approach described in [10]. Preliminary analysis suggests that implementation of similar schemes in MPI style may benefit from extensions to the standard set of MPI collectives, currently embodied in MPJ Express. Again such an extended library could form part of a future data centric version of MPJ Express that builds on experiences of MPI processing in the Hadoop environment.

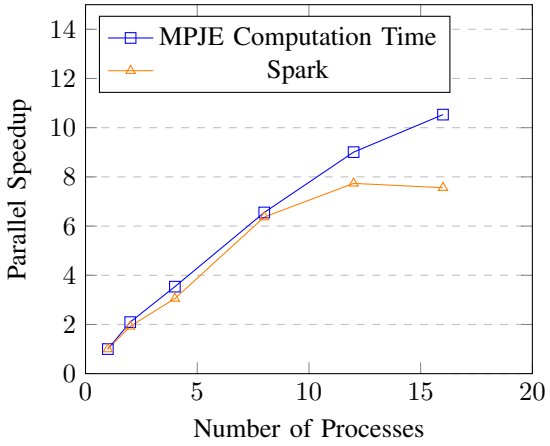


Fig. 8: Parallel Speedup MPJ Express vs Spark with Yahoo dataset

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