Presto: Distributed Machine Learning and Graph Processing with Sparse Matrices

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Abstract

It is cumbersome to write machine learning and graph algorithms in data-parallel models such as MapReduce and Dryad. We observe that these algorithms are based on matrix computations and, hence, are inefficient to implement with the restrictive programming and communication interface of such frameworks.

In this paper we show that array-based languages such as R [3] are suitable for implementing complex algorithms and can outperform current data parallel solutions. Since R is single-threaded and does not scale to large datasets, we have built Presto, a distributed system that extends R and addresses many of its limitations. Presto efficiently shares sparse structured data, can leverage multi-cores, and dynamically partitions data to mitigate load imbalance. Our results show the promise of this approach: many important machine learning and graph algorithms can be expressed in a single framework and are substantially faster than those in Hadoop and Spark.

1. A matrix-based approach

Many real-world applications require sophisticated analysis on massive datasets. Most of these applications use machine learning, graph algorithms, and statistical analyses that are easily expressed as matrix operations.

For example, PageRank corresponds to the dominant eigenvector of a matrix `G` that represents the Web graph. It can be calculated by starting with an initial vector `x` and repeatedly performing `x=G*x` until convergence [8]. Similarly, recommendation systems in companies like Netflix are implemented using matrix decomposition [37]. Even graph algorithms, such as shortest path, centrality measures, strongly connected components, etc., can be expressed using operations on the matrix representation of a graph [19].

Array-based languages such as R and MATLAB provide an appropriate programming model to express such machine learning and graph algorithms. The core construct of arrays makes these languages suitable to represent vectors and matrices, and perform matrix computations. R has thousands of freely available packages and is widely used by data miners and statisticians, albeit for problems with relatively small amounts of data. It has serious limitations when applied to very large datasets: limited support for distributed processing, no strategy for load balancing, no fault tolerance, and is constrained by a server's DRAM capacity.

1.1 Towards an efficient distributed R

We validate our hypothesis that R can be used to efficiently execute machine learning and graph algorithms on large scale datasets. Specifically, we tackle the following challenges:

Effective use of multi-cores. R is single-threaded. The easiest way to incorporate parallelism is to execute programs across multiple R processes. Existing solutions for parallelizing R use message passing techniques, including network communication, to communicate among processes [25] . This multi-process approach, also used in commercial parallel MATLAB, has two limitations. First, it makes local copies of many data objects, boosting memory requirements. Figure 1 shows that two R instances on a single physical server would have two copies of the same data, hindering scalability to larger datasets. Second, the network communication overhead becomes proportional to the number of cores utilized instead of the number of distinct servers, again limiting scalability.

Existing efforts for parallelizing R have another limitation. They do not support point-to-point communication. Instead data has to be moved from worker processes to a designated master process after each phase. Thus, it is inefficient to execute anything that is not embarrassingly parallel [25]. Even simple iterative algorithms are costly due to the communication overhead via the master.

Imbalance in sparse computations. Most real-world datasets are *sparse*. For example, the Netflix prize dataset is a matrix with 480K users (rows) and 17K movies (cols) but only 100 million of the total possible 8 billion ratings are available. Similarly, very few of the possible edges are

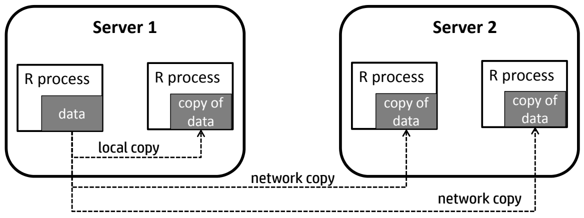


Figure 1. R's poor multi-core support: multiple copies of data on the same server and high communication overhead across servers.

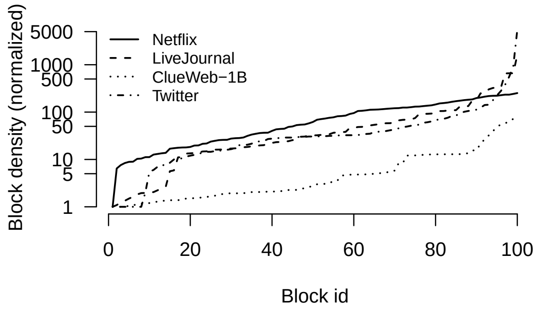


Figure 2. Variance in block density. Y-axis shows density of a block normalized by that of the sparsest block. Lower is better.

present in Web graphs. It is important to store and manipulate such data as sparse matrices and retain only non-zero entries. These datasets also exhibit skew due to the power-law distribution [14], resulting in severe computation and communication imbalance when data is partitioned for parallel execution. Figure 2 illustrates the result of naïve partitioning of various sparse data sets: LiveJournal (68M edges) [4], Twitter (2B edges), pre-processed ClueWeb sample[1] (1.2B edges), and the ratings from Netflix prize (100M ratings). The y-axis represents the block density relative to the sparsest block, when each matrix is partitioned into 100 blocks having the same number of rows/columns. The plot shows that a dense block may have 1000× more elements than a sparse block. Depending upon the algorithm, variance in block density can have a substantial impact on performance (Section 7).

1.2 Limitations of current data-parallel approaches

Existing distributed data processing frameworks, such as MapReduce and DryadLINQ, simplify large-scale data processing [12, 17]. Unfortunately, the simplicity of the programming model (as in MapReduce) or reliance on relational algebra (as in DryadLINQ) makes these systems unsuitable for implementing complex algorithms based on matrix operations. Current systems either do not support stateful computations, or do not retain the structure of global shared data (e.g., mapping of data to matrices), or do not allow point to point communication (e.g., restrictive MapReduce communication pattern). Such shortcomings in the programming model have led to inefficient implementations of algorithms or the development of domain specific systems. For example, Pregel was created for graph algorithms because MapReduce passes the entire state of the graph between steps [24].

There have been recent efforts to better support large-scale matrix operations. Ricardo [11] and HAMA [30] convert matrix operations to MapReduce functions but end up inheriting the inefficiencies of the MapReduce interface. PowerGraph [14] uses a vertex-centric programming model (non matrix approach) to implement data mining and graph algorithms. MadLINQ provides a linear algebra platform on Dryad but does not efficiently handle sparse matrix computations [29]. Unlike MadLINQ and PowerGraph, our aim is to address the issues in scaling R, a system which already has a large user community. Additionally, our techniques for handling load imbalance in sparse matrices can be applicable to existing systems like MadLINQ.

1.3 Our Contribution

We present Presto, an R prototype to efficiently process large, sparse datasets. Presto introduces the distributed array, `darray`, as the abstraction to process both dense and sparse datasets in parallel. Distributed arrays store data across multiple machines. Programmers can execute parallel functions that communicate with each other and share state using arrays, thus making it efficient to express complex algorithms.

Presto programs are executed by a set of worker processes which are controlled by a master. For efficient multi-core support each worker on a server encapsulates multiple R instances that read shared data. To achieve zero copying overhead, we modify R's memory allocator to directly map data from the worker into the R objects. This mapping preserves the metadata in the object headers and ensures that the allocation is garbage collection safe.

To mitigate load imbalance, the runtime tracks the execution time and the number of elements in each array partition. In case of imbalance, the runtime dynamically merges or sub-divides array partitions between iterations and assigns them to a new task, thus varying the parallelism and load in the system. Dynamic repartitioning is especially helpful for iterative algorithms where computations are repeated across iterations.

We have implemented seven different applications in Presto, ranging from a recommendation system to a graph centrality measure. Our experience shows that Presto programs are easy to write and can be used to express a wide variety of complex algorithms. Compared to published results of Hadoop and Spark [36], Presto achieves equally good execution times with only a handful of multi-core servers. For the PageRank algorithm, Presto is more than 40× faster than Hadoop and 15× faster than Spark. We also show how Presto's multi-core support reduces communication overhead and finally measure the impact of dynamic repartitioning using two real-world applications.

[1] http://lemurproject.org/clueweb09.php

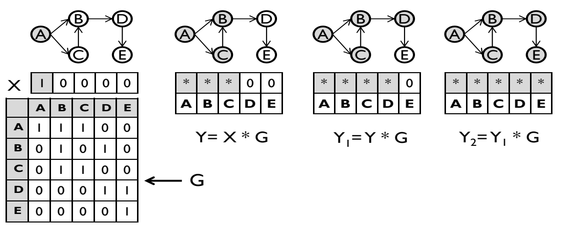


Figure 3. Breadth-first search using matrix operations. The k^{th} multiplication uncovers vertices up to k hop distance away.

2. Background

Matrix computation is heavily used in data mining, image processing, graph analysis, and elsewhere [32]. Our focus is to analyze sparse datasets that are found as web graphs, social networks, product ratings in Amazon, and so on. Many of these analyses can be expressed using matrix formulations that are difficult to write in data-parallel models such as MapReduce.

Example: graph algorithms. Many common graph algorithms can be implemented by operating on the adjacency matrix [19]. To perform breadth-first search (BFS) from a vertex i we start with a $1 \times N$ vector `x` which has all zeroes except the i^{th} element. Using the multiplication `y=x*G` we extract the i^{th} row in `G`, and hence the neighbors of vertex i. Multiplying `y` with `G` gives vertices two steps away and so on. Figure 3 illustrates BFS from source vertex `A` in a five vertex graph. After each multiplication step the non-zero entries in $\mathtt{Y}_i$ (starred) correspond to visited vertices. If we use a sparse matrix representation for `G` and `x`, then the performance of this algorithm is similar to traditional BFS implementations on sparse graphs.

The Bellman-Ford single-source shortest path algorithm (SSSP) finds the shortest distance to all vertices from a source vertex. SSSP can be implemented by starting with a distance vector `d` and repeatedly performing a modified matrix multiplication, $\mathtt{d}=\mathtt{d}\otimes\mathtt{G}$. In the modified multiplication $\mathtt{d(j)}=min_k\{\mathtt{d(k)+G(k,j)}\}$ instead of the usual $\mathtt{d(j)}=\sum_k\{\mathtt{d(k)*G(k,j)}\}$. In essence, each multiplication step updates the vertex distances by choosing the minimum of the current distance, and that of reaching the vertex using one more edge.

2.1 R: An array-based environment

R provides an interactive environment to analyze data. It has interpreted conditional execution (`if`), loops (`for, while, repeat`), and uses array operators written in C, C++ and FORTRAN for better performance. Line 1 in Figure 4 shows how a 3×3 matrix can be created. The argument `dim` specifies the shape of the matrix and the sequence $10:18$ is used to fill the matrix. One can refer to entire subarrays by omitting an index along a dimension. For example, in line 3 the first row of the matrix is obtained by $A[1,]$, where the column index is left blank to fetch the entire first row. Subsections of a matrix can be easily extracted using *index vectors*. Index vectors are an ordered vector of integers. To extract the diagonal of `A` we create an index matrix `idx` in line 4 whose elements are $(1,1)$,$(2,2)$ and $(3,3)$. In line 6, `A[idx]` returns the diagonal elements of `A`. In a single machine environment, R has native support for matrix multiplication, linear equation solvers, matrix decomposition and other operations. For example, $\%*\%$ is an R operator for matrix multiplication (line 7).

```
1: > A<-array(10:18,dim=c(3,3))      #3x3 matrix
2: > A
        [,1] [,2] [,3]
   [1,]   10   13   16
   [2,]   11   14   17
   [3,]   12   15   18
3: > A[1,]                           #First row
   [1] 10 13 16
4: > idx<-array(1:3,dim=c(3,2))      #Index vector
5: > idx
        [,1] [,2]
   [1,]    1    1
   [2,]    2    2
   [3,]    3    3
6: > A[idx]                          #Diagonal of A
   [1] 10 14 18
7: > A%*%idx                         #Matrix multiply
        [,1] [,2]
   [1,]   84   84
   [2,]   90   90
   [3,]   96   96
```

Figure 4. Example array use in R.

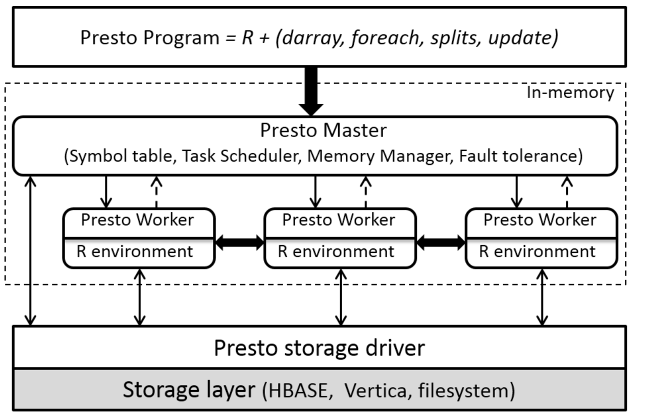
3. Programming model

Presto is R with new language extensions and a runtime to manage distributed execution. The extensions add data distribution and parallel execution. The runtime takes care of memory management, scheduling, dynamic data partitioning, and fault tolerance. As shown in Figure 5, programmers write a Presto program and submit it to a *master* process. The runtime at the master is in charge of the overall execution. It executes the program as distributed tasks across multiple *worker* processes. Table 1 depicts the Presto language constructs which we discuss in this section.

3.1 Distributed arrays

Presto solves the problem of structure and scalability by introducing distributed arrays. Distributed array (`darray`) provides a shared, in-memory view of multi-dimensional data stored across multiple servers. Distributed arrays have the following characteristics:

Partitioned. Distributed arrays can be partitioned into contiguous ranges of rows, columns or blocks. Users specify the size of the initial partitions. Presto workers store partitions of the distributed array in the compressed sparse column format unless the array is defined as dense. Programmers use partitions to specify coarse-grained parallelism by writing functions that execute in parallel and operate on par-



Presto Program = R + (darray, foreach, splits, update)
In-memory
Presto Master
(Symbol table, Task Scheduler, Memory Manager, Fault tolerance)
Presto Worker
R environment
Presto Worker
R environment
Presto Worker
R environment
Presto storage driver
Storage layer (HBASE, Vertica, filesystem)

Figure 5. Presto architecture

titions. Partitions can be referred to by the `splits` function. The `splits` function automatically fetches remote partitions and combines them to form a local array. For example, if `splits(A)` is an argument to a function executing on a worker then the whole array `A` would be reconstructed by the runtime, from local and remote partitions, and passed to that worker. The i^{th} partition can be referenced by `splits(A,i)`.

Shared. Distributed arrays can be read-shared by multiple concurrent tasks. The user simply passes the array partitions as arguments to many concurrent tasks. Arrays can be modified inside tasks and the changes are visible globally when `update` is called. Presto supports only a single writer per partition.

Dynamic. Partitions of a distributed array can be loaded in parallel from data stores such as HBase, Vertica, or from files. Once loaded, arrays can be dynamically re-partitioned to reduce load imbalance and prevent straggling.

3.2 Distributed parallelism

Presto provides programmers with a `foreach` construct to execute deterministic functions in parallel. The functions do not return data. Instead, programmers call `update` inside the function to publish changes. The Presto runtime starts tasks on worker nodes for parallel execution of the loop body. By default, there is a barrier at the end of the loop to ensure all tasks finish before statements after the loop are executed.

3.3 Repartition and invariants

At runtime, programmers can use the `repartition` command to trigger Presto's dynamic repartitioning method. Repartitioning can be used to subdivide an array into a specified number of parts. Repartitioning is an optional performance optimization which helps when there is load imbalance in the system.

One needs be careful while repartitioning structured data, otherwise program correctness may be affected. For example, when multiplying two matrices, the number of rows and columns in partitions of both the matrices should conform. If we repartition only one of the matrices then this invariant may be violated. Therefore, Presto allows programmers to optionally specify the array invariants in the program. We show in Section 5.3 how the runtime can use the `invariant` and `repartition` functions to automatically detect and reduce imbalance without any user assistance.

Note that for programs with general data structures (e.g., trees) writing invariants is difficult. However, for matrix computation, arrays are the only data structure and the relevant invariant is the compatibility in array sizes. The `invariant` in Presto is similar in spirit to the alignment directives used in High Performance Fortran (HPF [22]). The HPF directives align elements of multiple arrays to ensure the arrays are distributed in the same manner. Unlike HPF, in Presto the invariants are used to maintain correctness during repartitioning.

Functionality	Description
`darray(dim=, blocks=, sparse=)`	Create a distributed array with dimensions specified by `dim`, and partitioned by blocks of size `blocks`.
`splits(A,i)`	Return i^{th} partition of the distributed array `A` or the whole array if *i* is not specified.
`foreach(v, A, f())`	Execute function `f` as distributed tasks for each element `v` of `A`. Implicit barrier at the end of the loop.
`update(A)`	Publish the changes to A.
`repartition(A, n=, merge=)`	Repartition `A` into `n` parts.
`invariant(A, B, type=)`	Declare compatibility between arrays `A` and `B` by rows or columns or both. Used by the runtime to maintain invariants while re-partitioning.

Table 1. Main programming language constructs in Presto

4. Applications

We illustrate Presto's programming model by discussing the implementation of two algorithms: PageRank and Alternating Least Squares.

PageRank. Figure 6 shows the Presto code for PageRank. `M` is the modified adjacency matrix of the Web graph. PageRank is calculated in parallel (lines 7–13) using the power method [8]. In line 1, `M` is declared as an NxN array. `M` is loaded in parallel from the underlying filesystem using the Presto driver, and is partitioned by rows. In line 3 the number of columns of `M` is used to define the size of a dense vector `pgr` which acts as the initial PageRank vector. This vector is partitioned such that each partition of `pgr` has the same number of rows as the corresponding partition of `M`. The accompanying illustration points out that each partition of the vector `pgr` requires the corresponding (shaded) partitions of `M`, `Z`, and the whole array `xold`. The Presto runtime passes these partitions and reconstructs `xold` from its partitions before executing `prFunc` at each worker. In line 12

```
#Load data in parallel into adjacency matrix
1 : M<- darray(dim=c(N,N),blocks=c(s,N), sparse=T)
2 : load(M, file="...")
3 : pgr<- darray(dim=c(ncol(M),1),blocks=c(s,1),sparse=F)
4 : xold<- darray(dim=c(ncol(M),1),blocks=c(s,1),sparse=F)
5 : ...
6 : invariant(pgr,M,xold,Z, type=ROW)
#Calculate PageRank (pgr)
7 :  repeat{
      #Distributed matrix operations
8 :    foreach(i, 1:numsplits(M),
             prFunc(p=splits(pgr,i), m=splits(M,i),
                    x=splits(xold), z=splits(Z,i)) {
9 :          p<-(m%*%x)+ z
10 :         update(p)
11:     })
12:     if(norm(pgr-xold)<1e-9) break
13:     xold<-pgr
14:  }
```

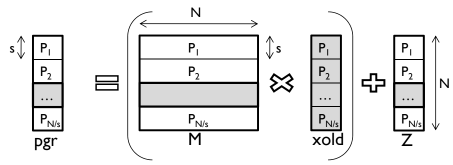


Figure 6. PageRank on a Web graph.

the norm of the two distributed arrays, `pgr` and `xold`, are calculated in parallel. Internally, `norm` is implemented using `foreach`.

Line 6 is an example invariant for the PageRank code. Each of `pgr`, `M`, `xold`, and `Z` should have the same number of rows in each partition. By specifying this invariant, the programmer constrains the runtime to adhere to this compatibility between arrays even during automatic repartitioning.

Alternating Least Squares. The Alternating Least Squares (ALS) algorithm with weighted regularization is known to perform well for matrix problems that arise in recommendation systems, as exemplified by the Netflix Prize competition [2]. Figure 7 shows the implementation of a parallel version of the algorithm in Presto [37]. In Line 1 we declare `R`, a sparse distributed array partitioned by columns. `R` is a `nu`$\times$`nm` array where `nu` and `nm` are the number of users and number of movies respectively. The ratings are loaded from the filesystem in line 2. In line 3 and 4, we create distributed arrays to hold the feature matrices for users and movies, and partition the arrays by columns. Each iteration of the ALS algorithm consists of two steps: the first step updates the movie feature matrix (`M`) based on the existing user feature matrix (`U`), while the second step uses `M` to compute updates for `U`. Lines 9–29 show how the first step of the algorithm is expressed in Presto.

The `foreach` loop updates each partition of `M` in parallel. To update a particular partition, we pass the corresponding partition of the ratings matrix `R` and the entire user feature matrix `U` (lines 9 – 12). One of the advantages of Presto is that existing R functions can be used directly. For example, in line 23 R's linear solver minimizes the sum of the squares of the differences between the known and the predicted ratings and computes the new values of `M`. Similarly,

```
#Load ratings into a sparse matrix
1  : R <- darray(dim=c(nu,nm), blocks=c(nu,ms), sparse=T)
2  : load(R, file="...")
# Create feature matrices for users and movies
3  : M <- darray(dim=c(nf,nm), blocks=c(nf,ms), sparse=F)
4  : U <- darray(dim=c(nf,nu), blocks=c(nf,us), sparse=F)
5  : ...
6  : # Initialize the features
7  : ...
8  : repeat {
      # Update movie features based on user ratings
9  :   foreach(i, 1:numsplits(M),
10 :         function(ms = splits(M, i),
11 :                  us = splits(U),
12 :                  rs = splits(R, i)) {
13 :    lamI <- diag(lambda, nrow=nf, ncol=nf)
        # Function to update single movie's features
15 :    update_movie <- function(movieRatings) {
16 :      # Get users who have rated this movie
17 :      users <- which(movieRatings != 0)
18 :      Um <- matrix(nrow=nf, data=us[, users])
19 :
20 :      # Update by minimizing least squares
21 :      vec <- Um %*% movieRatings[users]
22 :      mat <- Um %*% t(Um) + (length(users)*lamI)
23 :      m_new <- solve(mat, vec)
24 :      return(m_new)
25 :    }
26 :    # Calculate updates for movies in this split
27 :    ms <- apply(rs, 2, update_movie)
28 :   update(ms)
29 :  })
30 :  # Similarly update user features using movies
31 :  ...
32 :  # Check for convergence by computing RMSE
33 :  rmse <- compute_rmse(U, M)
34 :  if (rmse < threshold) { break }
35 : }
```

Figure 7. ALS algorithm on a Netflix ratings dataset

in line 27 the familiar R construct *apply* is used to invoke the function `update_movie` on all the movies present in the partition. Finally, in line 28 the new values of movie features are made globally visible by invoking `update`.

5. System design

The Presto master acts as the control thread. The workers execute the loop body in parallel whenever `foreach` loops are encountered. The master keeps a symbol table which maps variables to their physical location. This map is used by workers to exchange information using pairwise communication. In this paper we describe only the main mechanisms related to multi-core support, and optimizations for sparsity and caching.

5.1 Versioning arrays

Presto uses versioning to ensure correctness when arrays are shared across different machines. Each partition of a distributed array has a version. The version of a distributed array is a concatenation of the versions of its partitions, similar in spirit to vector clocks. Updates to array partitions create a new version of the partition. By updating the version, concurrent readers of previous versions will not be affected by the update. For example, the PageRank vector `pgr` in Figure 6 starts with version $\langle 0,0,..,0\rangle$. In the first iteration, every task reads in one partition `pgr` with version 0. At the

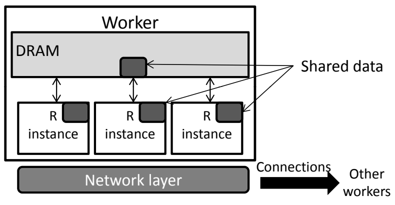


Figure 8. Multiple R instances share data hosted in a worker.

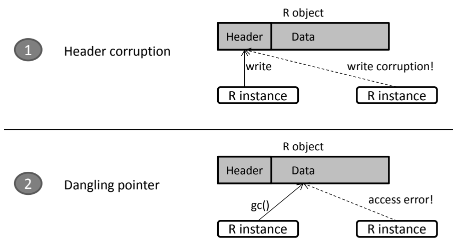


Figure 9. Simply sharing R objects can lead to errors.

end of the task when `update` is called, a new partition with version 1 is created. Hence, after the first iteration the distributed array's new version becomes $\langle 1, 1, .., 1 \rangle$. Presto uses reference counting to garbage collect older versions of arrays not used by any task.

5.2 Efficient multi-core support

Since R is not thread safe, a simple approach to utilize multi-cores is to start multiple worker processes on the same server. There are three major drawbacks: (1) on the server multiple copies of the same array will be created, thus inhibiting scalability, (2) copying the data across processes, using pipes or network, takes time, and (3) the network communication increases as we increase the number of cores being utilized.

Instead, Presto allows a worker to encapsulate multiple R processes that can communicate through shared memory with zero copying overhead (Figure 8). The key idea in Presto is to efficiently initialize R objects by mapping data using mmap or shared memory constructs. However, there are some important safety challenges that need to be addressed.

Issues with data sharing. Each R object consists of a fixed-size header, and an array of data immediately following the header. The header (among other things) has information about the type and size of the corresponding data part. Simply pointing an R variable to an external data source leads to data corruption. As shown in Figure 9, if we were to share an R object across different R instances two problems can arise. First, both the instances may try to write instance specific values to the object header. This conflict will lead to header corruption. Second, R is a garbage-collected language. If one of the instances garbage collects the object then the other instance will be left with a dangling pointer.

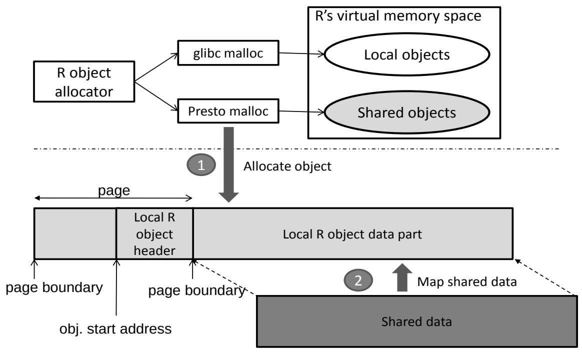


Figure 10. Shared object allocation in an R instance.

Safe data sharing. We solve the data sharing challenge by entrusting each worker with management of data shared by multiple R processes. We only share read-only data since only one process may write to a partition during a loop iteration and writes always create a new version of a partition. Presto first allocates process local objects in each R instance and then maps the shared data on the data part of the object. Since the headers are local to each R instance, write conflicts do not occur on the header.

There is another issue that has to be solved: the mmap call locates data only to an address at a page boundary. However, R's internal allocator does not guarantee that the data part of an object will start at a page boundary. To solve this issue, Presto overrides the behavior of the internal allocator of R. We use `malloc_hook` to intercept R's malloc() calls. Whenever we want to allocate a shared R object we use our custom malloc to return a set of pages rounded to the nearest multiple of the page size. Once the object has been allocated the shared data can be mapped using mmap.

Figure 10 shows that R objects are allocated through the default malloc for local objects and through Presto's malloc function for shared objects. The shared objects consist of a set of pages with the data part aligned to the page boundary. The first page starts with an unused region because the header is smaller than a full page.

When the objects are no longer needed, these specially allocated regions need to be unmapped. Presto uses `free_hook` to intercept the calls to the glibc free() function. Presto also maintains a list of objects that were specially allocated. The list contains the starting address and allocation size of the shared objects. Whenever free is called, the runtime checks if the object to be freed is present in the list. If it is then munmap is called. Otherwise, the glibc free function is called. Note that while the malloc hook is used only when allocating shared R objects, the free hook is active throughout the lifetime of the program, because we do not know when R may garbage collect objects.

5.3 Dynamic partitioning for sparse data

While shared memory constructs help in reducing the network overhead, the overall time taken for a distributed computation also depends on the execution time. Partitioning a sparse matrix into contiguous ranges of rows or columns may lead to uneven distribution of nonzero elements and cause a skew in task execution times. Moreover, the number of tasks in the system is tied to the number of partitions which makes it difficult to effectively use additional workers at runtime. Presto uses dynamic partitioning to mitigate load imbalance, and to increase or decrease the amount of parallelism in the program at runtime. One can determine optimal partitions statically to solve load imbalance but it is an expensive solution. Such partitions may not remain optimal as data is updated and static partitioning does not adjust to changes in the number of workers.

Presto uses two observations to dynamically adjust partitions. First, since our target algorithms are iterative, we refine the partitions based on the execution of the first few iterations. Second, by knowing the invariants for the program we can re-partition data without affecting correctness.

The Presto runtime tracks both the number of elements in a partition (e_i) and the execution time of the tasks (t_i). It uses these metrics to decide when to repartition data to reduce load imbalance. The runtime starts with an initial partitioning (generally user-specified), and in subsequent iterations may either merge or sub-divide partitions to create new ones. The aim of dynamic partitioning is to keep the partition sizes and the execution time of each task close to the median [5]. The runtime tracks the median partition size (e_m) and task execution time (t_m). After each iteration, the runtime checks if a partition has more (fewer) elements than the median by a given constant (partition threshold e.g. $e_i/e_m \geq \delta$) and sub-divides (merges) them. In the PageRank program (Figure 6), after repartitioning the runtime simply invokes the loop function (`pgFunc`) for a different number of partitions and passes the corresponding data. No other changes are required. While our current implementation only uses partition sizes for repartitioning, we plan to explore other metrics which combine partition sizes and execution times.

For dynamic partitioning, the programmer needs to specify the invariants and annotate functions as *safe* under repartitioning. For example, a function that assigns the first element of each partition is unsafe. Such a function is closely tied to each partition, and if we sub-divide an existing partition then two cells will be updated instead of one. In our applications, the only unsafe functions are related to initialization such as setting `A[i]=1` in breadth-first search.

5.4 Co-location, scheduling, and caching

Presto workers execute functions which generally require multiple array partitions, including remote ones. Presto uses three mechanisms to reduce communication: locality based scheduling, partition co-location, and caching.

The Presto master schedules tasks on workers. The master uses the symbol table to calculate the amount of remote data copy required when assigning a task to a worker. It then schedules tasks to minimize data movement. Partitions that are accessed and modified in the same function can be co-located on the same worker. As matrix computations are structured, in most cases co-locating different array partitions simply requires placing the i^{th} partition of the corresponding arrays together. For example, in PageRank, the i^{th} partition of vectors `pgr`, `M`, and `Z` should be co-located. Instead of another explicit placement directive, Presto reuses information provided by the programmer in the `invariant` function to determine which arrays are related and attempts to put the corresponding partitions on same workers. This strategy of co-location works well for our applications. In the future, we plan to consider work-stealing schedulers [6, 28].

Presto automatically caches and reuses arrays whose versions have not changed. For example, in the PageRank code `Z` is never modified. After the first iteration, workers always reuse `Z` as its version never changes. The runtime simply keeps the reference to partitions of `Z` alive and is informed by the master when a new version is available. Due to automatic caching, Presto does not need to provide explicit directives such as broadcast variables [36].

5.5 Fault tolerance

Presto uses primary-backup replication to withstand failures of the master node. Only the meta-data information like the symbol table, program execution state, and worker information is replicated at the backup. The state of the master is reliably updated at the backup before a statement of the program is considered complete. R programs are generally a couple of hundred lines of code, but most lines perform a compute intensive task. The overhead of check-pointing the master state after each statement is low compared to the time spent to execute the statement.

We use existing techniques in literature for worker fault tolerance. The master sends periodic heartbeat messages to determine the progress of worker nodes. When workers fail they are restarted and the corresponding functions are reexecuted. Like MapReduce and Dryad we assume that tasks are deterministic, which removes checkpointing as data can be recreated using task re-execution. The matrix computation focus of Presto simplifies worker fault-tolerance. Arrays undergo coarse-grained transformations and hence it is sufficient to just store the transformations reliably instead of the actual content of the arrays. Therefore, Presto recursively recreates the corresponding versions of the data after a failure. The information on how to recreate the input is stored in a table which keeps track of what input data versions and functions result in specific output versions. In practice, arrays should periodically be made durable for faster recovery.

6. Implementation

Presto is implemented as an R add-on package and provides support for the new language features described in Section 3. Dense and sparse matrices are stored using R's Matrix li-

Application	Algorithm Characteristic	R LOC	Presto LOC
PageRank	Eigenvector calculation	20	41
Vertex centrality	Graph Algorithm	40	128
Edge centrality	Graph Algorithm	48	132
SSSP	Graph Algorithm	30	62
Netflix recommender [37]	Matrix decomposition	78	130
Triangle count [18]	Top-k eigenvalues	65	121
k-Means clustering	Dense linear algebra	35	71

Input data	Size	Application
Twitter	V=54M, E=2B	Triangle counting
Twitter-S	V=41M, E=1.4B	PageRank, Centrality, SSSP
ClueWeb-S	V=100M, E=1.2B	PageRank
ClueWeb	V=2B, E=6B	PageRank
Netflix	V=480K, E=100M	Collaborative Filtering

Table 2. Presto applications and their input data.

brary. Our current prototype has native support for a limited set of distributed array operators such as load, save, matrix multiplication, addition, and so on. Other operators and algorithms can be written by programmers using functions inside `foreach`. The implementation of both Presto master and workers use ZeroMQ servers [16]. Control messages, like starting the loop body in a worker or calls to garbage collect arrays, are serialized and sent using Google's protocol buffers. Transfers of arrays between workers are implemented directly using BSD sockets. The Presto package contains 800 lines of R code and $10,000$ lines of C++ code.

7. Evaluation

Programmers can express various algorithms in Presto that are difficult or inefficient to implement in current systems. Table 2 lists seven applications that we implement in Presto. These applications span graph algorithms, matrix decomposition, and dense linear algebra. The sequential version of each of these algorithms can be written in fewer than 80 lines in R. In Presto, the distributed versions of the same applications take at most 135 lines. Therefore, only a modest effort is required to convert these sequential algorithms to run in Presto.

In this paper we focus on PageRank, vertex centrality, single-source shortest path (SSSP), triangle counting, and collaborative filtering. We compare the performance of Presto to Spark [36], which is a recent in-memory system for cluster computing, and Hadoop-mem, which is Hadoop-0.20 but run entirely on ramfs to avoid disk latencies. Spark performs in-memory computations, caches data, and is known to be $20\times$ faster than Hadoop on certain applications. In all the experiments we disregard the initial time spent in loading data from disk. Subsequent references to Hadoop in our experiments refer to Hadoop-mem.

Our evaluation shows that:

- Presto is the first R extension to efficiently leverage multi-cores by reducing memory and network overheads.
- Presto can handle load imbalance due to sparsity by dynamic partitioning.
- Presto is much faster than current systems. On PageRank Presto is $40\times$ faster than Hadoop, $15\times$ faster than Spark, and comparable to MPI implementations.

Our experiments use a cluster of 50 HP SL390 servers with Ubuntu 11.04. Each server has two 2.67GHz (12-core) Intel Xeon X5650 processors, 96GB of RAM, 120GB SSD, and the servers are connected with full bisection bandwidth on a 10Gbps network. Presto, Hadoop, and Spark are run with the same number of workers or mappers. Hadoop algorithms are part of Apache Mahout [1].

7.1 Application description

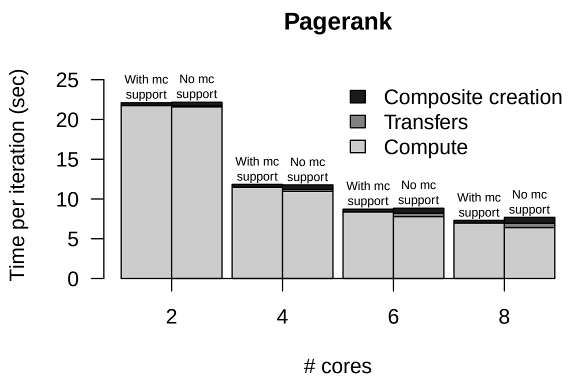
Since we have discussed PageRank and SSSP in Section 2, we briefly describe centrality measure and triangle counting algorithms.

Centrality. Vertex or edge betweenness centrality determines the importance of a vertex or edge in a network (e.g., social graph) based on the number of shortest paths that include the vertex or edge. We implement Brandes' algorithm for unweighted graphs [7]. Each betweenness algorithm consists of two phases: first the shortest paths from each vertex to all other vertices are determined (using BFS) and then these paths are used to update the centrality measure using scalar transformations. In our experiments we show the results of starting from a vertex whose BFS has 13 levels.

Triangle counting. In large social network graphs, anomalous behavior can be detected by counting the number of triangles that every vertex belongs to [18]. Since a direct count is expensive for large graphs, the number of triangles is approximated using the top eigenvalues [33]. We implement the iterative Lanczos algorithm with selective reorthogonalization to find the top-k eigenvalues of a matrix. In each iteration of the algorithm, the sparse input matrix is multiplied by a dense vector representing the Lanczos vector from the previous iteration. The result is then orthogonalized to form a new basis vector and the eigenvalues for the input matrix can be computed using the last k orthogonalized Lanczos vectors. To handle numerical inaccuracies, the algorithm uses selective-reorthogonalization, where basis vectors are selectively chosen for reorthogonalization. Not every step in this algorithm needs to be distributed across the cluster, and using Presto, we can effectively mix parallel computation with computation on the master. For example, the matrix-vector multiplication is distributed across machines, but finding the eigenvalues from the basis vectors is performed on the master using existing R functions.

7.2 Advantages of multi-core support

With Presto's multi-core support, the memory footprint and communication overhead are lesser than when using a single R-instance per core. In this section we vary the number of cores and show the time spent during computation, composite creation (constructing a distributed array from its partitions), and data transfer. We use Presto-NoMC to denote



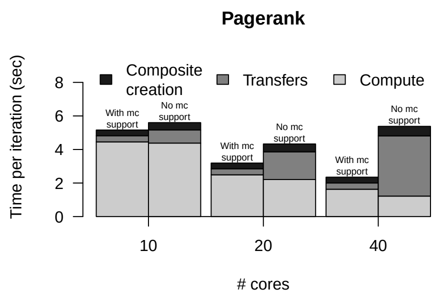
Input data	Vertices	#Cores	Additional memory used (no MC)
Twitter-S	41M	8	2.1G
ClueWeb-S	100M	8	5.3G

Figure 11. Multi-core (MC) support lowers total execution time and memory usage on a single server. Lower is better.

the system which does not have multi-core support and has single core workers.

Single server: low memory overhead. The first advantage of multi-core support is that there is no need to copy data between two R instances that are running on the same server. Unlike other R packages, Presto can safely share data across processes through shared memory. Figure 11 shows the average iteration time of PageRank on the 1.5B edge Twitter graph when executed on a single server. The data transferred in this algorithm is the PageRank vector. In Presto there is no transfer overhead as all the R instances are on the same server and can share data. At 8 cores Presto-NoMC spends 7% of the time in data transfers and takes 5% longer to complete than Presto. The difference in execution time is not much as communication over `localhost` is very efficient even with multiple workers per server. However, the real win for multi-core support in a single server is the reduction in memory footprint. The table in Figure 11 shows that at 8 cores the redundant copies of the PageRank vector in Presto-NoMC increase the memory footprint by 2 GB, which is 10% of the total memory usage. For the Clueweb-S dataset Presto-NoMC uses up to 5.3 GB of extra memory.

Multiple servers: low communication overhead. The second advantage of Presto is that in algorithms with all-to-all communication (broadcast), the amount of data transferred is proportional only to the number of servers, not the number of R instances. Figure 12 shows the significance of this improvement for experiments on the Twitter-S graph. In these experiments we fix the number of servers to 5 and vary the total number of cores. Figure 12(a) shows that the network transfer overhead for Presto-NoMC is 2.1× to 9.7× higher than Presto as we vary the total cores from 10 to 40. Worse still, at 40 cores the PageRank code on Presto-NoMC not only stops scaling rather it takes more time to complete than



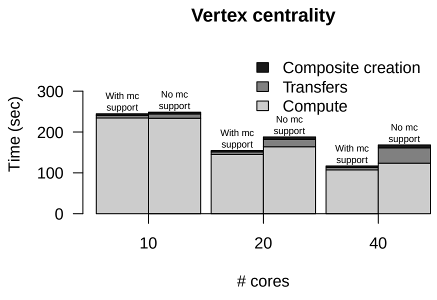


Figure 12. Multi-core support reduces communication overhead in (a) PageRank (b) Centrality. Lower is better.

with 20 cores due to higher transfer overhead. In comparison, Presto can complete an iteration of PageRank in about 3 seconds, though there is only marginal benefit of adding more than 20 cores for this dataset. Figure 12(b) shows similar behavior for the centrality measure algorithm. Using Presto the execution time for a single vertex decreases from 244 seconds at 10 cores to 116 seconds at 40 cores. In comparison, with no multi-core support Presto-NoMC incurs very high transfer overhead at 40 cores and the execution time is worse by 43% and takes 168 seconds.

7.3 Advantages of dynamic partitioning

While multi-core support lowers the memory and communication overhead, dynamic repartitioning of matrices reduces imbalance due to data sparsity. We evaluate the effectiveness of dynamic partitioning using two algorithms: first by running PageRank on the ClueWeb graph with 2B vertices and 6B edges and secondly by using the Lanczos method to find top-*k* eigenvalues on the Twitter graph with 54M vertices and 2B edges.

7.3.1 PageRank

We first look at the PageRank experiments which were run using 25 servers each with 8 R instances. Even though we use 200 cores in this experiment, we initially partition the graph into 1000 parts. This allows the scheduler to intelligently overlap computations and attempts to improve the balance. In this section we show that dynamic repartitioning improves performance even in such a case.

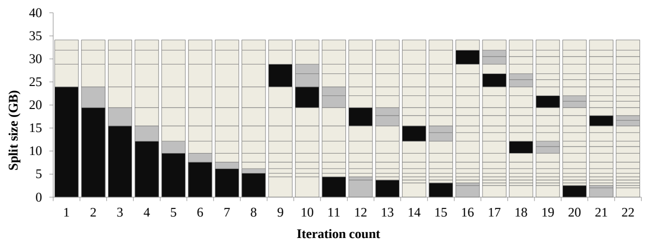


Figure 13. We trace the repartitioning seen in the initial four matrix blocks. Black boxes represents *heavy* blocks chosen for repartitioning and gray boxes indicate newly created blocks.

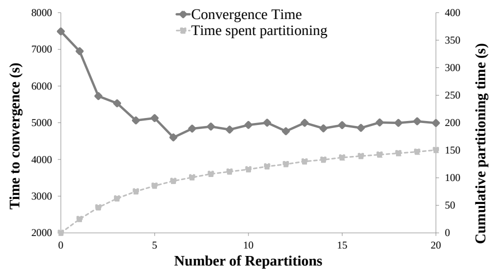


Figure 14. Convergence time decreases with repartitioning. The cumulative partitioning time is the time spent in repartitioning.

Effects of repeated partitioning. Figure 13 shows how the repartitioning algorithm proceeds on the ClueWeb dataset. A black colored partition indicates that the particular block was *heavy* and chosen for repartitioning. The newly created array partitions are shown in gray. In Figure 13 the first block (also the densest) is continuously repartitioned from iteration 1 to iteration 7 and then again at iterations 11, 13, 15, and 20. Overall, repartitioning reduces the size of this partition from 23GB to 2.2GB.

However there is a cost associated with repartitioning. In our current implementation, PageRank iterations are paused while the graph is being repartitioned. To quantify the cost-benefit trade-off, we estimate the total running time of PageRank as we increase the number of repartitions. Assuming that we need to perform 50 iterations for convergence, Figure 14 shows the estimated time to converge as we vary the number of repartitions. We calculate the total execution time after a certain number of re-partitions by assuming no more repartitions will occur. For example, at x-axis value of 5, Presto has performed five repartitions and the convergence time is 5,126 seconds if no further repartitions occur. The convergence time reduces by 32% (40 minutes) after the first four repartitions, but the benefits diminish beyond that. Note that the cumulative time spent in partitioning is a small fraction of the total execution time (between 0.3% and 3%).

Benefits of reducing imbalance. Reducing the imbalance among partitions helps decrease the PageRank iteration time. Figure 15 shows the time taken by each worker during one iteration of PageRank. The horizontal bars depict what part of the total time was spent in transferring data versus the time taken to perform the computation. Since there is a barrier at the end of an iteration, the iteration time is determined by the maximum execution time among the workers. Figure 15(a) shows that the slowest worker takes 147 seconds initially but after four repartitions (Figure 15(b)) it finishes in 95 seconds thus reducing the per-iteration time.

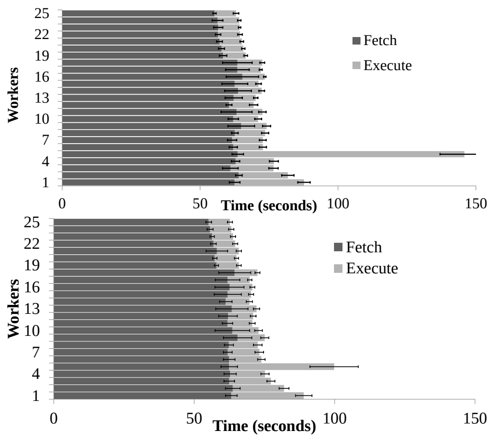


Figure 15. Per worker execution time for PageRank (a) before repartitioning (b) after four repartitions. Shorter bar is better.

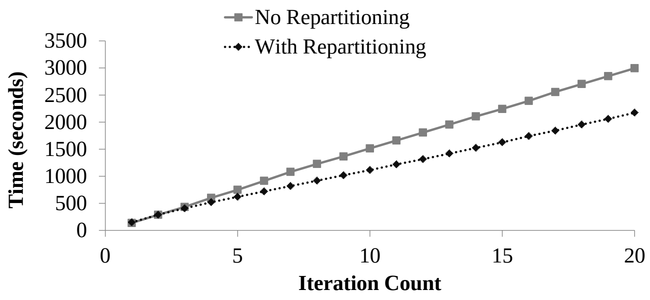


Figure 16. Comparison of overall execution time with and without repartitioning. Lower is better.

Reducing imbalance is especially important for iterative algorithms as the overall execution time can be significantly high due to the skew among workers. As seen in Figure 16, re-partitioning reduces the completion time by around 822 seconds (13.7 minutes) when the PageRank algorithm is run for 20 iterations.

7.3.2 Lanczos calculation

We ran the Lanczos algorithm on the Twitter graph using 20 servers. As the dataset was relatively smaller (2B edges), we divide the graph into 20 partitions. Each server uses as many R instances as the number of partitions present on the server. Similar to the PageRank experiments, we study the benefits of dynamic partitioning by looking at the imbalance among different workers while executing a single iteration of

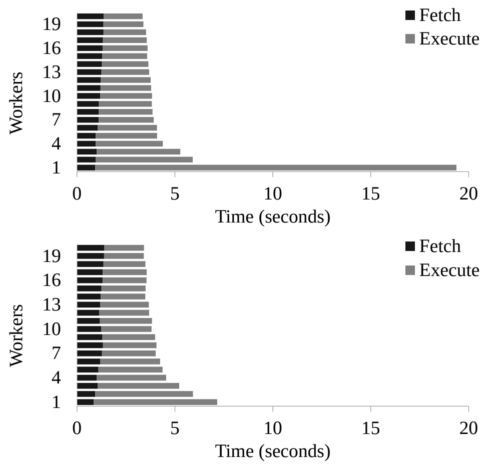


Figure 17. Per worker execution time for Lanczos algorithm on Twitter dataset (a) before repartitioning (b) after eight repartitions. Shorter bar is better.

the Lanczos algorithm. The time taken in a single iteration of the Lanczos algorithm is dominated by the sparse matrix-dense vector multiplication. The execution time for this step grows linearly as the number of non-zero entries in the matrix increase. Figure 17 shows the time taken by each worker during one iteration with and without repartitioning. We observe that the Twitter dataset contains one partition which is much larger than the others, and that repartitioning reduces the per iteration execution time from 19s to 7s.

7.4 Scalability

We evaluate the scalability of Presto using two algorithms: collaborative filtering [29] (CF) and single-source shortest path (SSSP). In the following set of experiments we use 8 cores per server and measure the time taken as we increase the number of cores. In our first experiment, we load the Netflix ratings dataset [2] as a matrix (R) and run two steps of a collaborative filtering algorithm. The first step computes $R^t \times R$, and the second step multiplies R with the output of the first step computing $(R \times R^t) \times R$. Figure 18 shows the time taken by each step of the algorithm as we increase the number of cores. Presto scales quite well in this case with a speedup of 4.89$\times$ (755s to 154s) while using 6$\times$ more cores (8 to 48). These numbers also indicate that Presto's performance is competitive to published results for MadLINQ [29] which takes 840s on 48 machines for the same algorithm. As the performance numbers for MadLINQ are from a different hardware configuration, instead of direct comparison, our results only indicate that Presto can match the performance of existing matrix-based systems. We also tried to compare Presto's performance to a vanilla-R implementation of collaborative filtering. While vanilla-R took 385s to perform $R^t \times R$, the second multiplication ($R \times R^t \times R$) failed to complete as the intermediate data did not fit in the server's 96GB

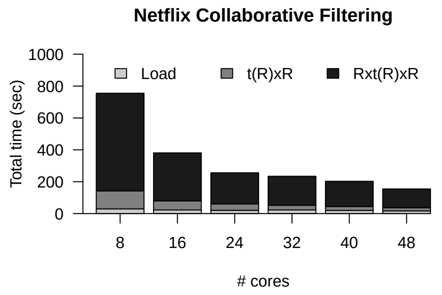


Figure 18. Running time for collaborative filtering on the Netflix dataset as we increase the number of cores.

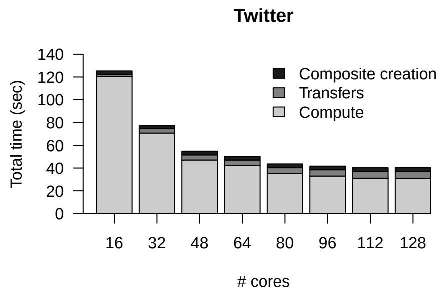


Figure 19. SSSP scalability on the Twitter-S dataset.

memory. This example highlights the need for distributing the computation across more servers.

Figure 19 uses SSSP on the 1.5B edge Twitter-S dataset to show the performance scaling of Presto. While Presto can scale to hundreds of cores, and the execution time continues to decrease, in this case the scaling factor is less than the ideal. For example, when increasing the cores from 16 to 128 (8$\times$), the execution time drops from 125 seconds to 41 seconds (3$\times$). The less than ideal scaling is a result of the communication overhead involved in SSSP, which is proportional to the number of vertices in the graph. In future we plan to rewrite the SSSP algorithm to use block partitions of the matrix (instead of row partitions) so that no single R instance requires the full shortest path vector.

7.5 Comparison with MPI, Spark, and Hadoop

PageRank experiments on the 1.2B edge ClueWeb-S graph shows that Presto is more than 40$\times$ faster than Hadoop, more than 15$\times$ faster than Spark, and can outperform simple MPI implementations.

MPI. We implemented PageRank using sparse matrix and vector multiplication in MPI. The communication phase in the code uses `MPI_Allgather` to gather the partitions of the PageRank vector from processes and distribute it to all. Figure 20(a) shows that Presto outperforms the MPI code

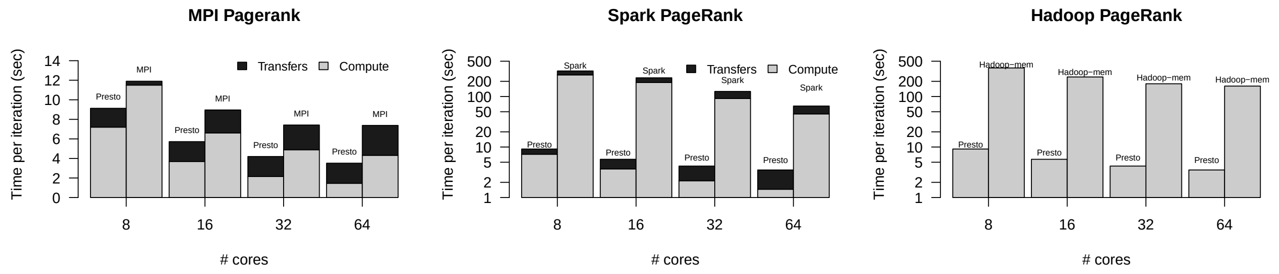


Figure 20. Performance advantage over (a) MPI (b) Spark and (c) Hadoop. Lower is better.

sometimes by 2×. There are two reasons for this performance difference. First, the MPI code does not handle compute imbalance. For example, at 64 cores one MPI process finishes in just 0.6 seconds while another process takes 4.4 seconds. Since processes wait for each other before the next iteration, the compute time is determined by the slowest process. Second, while MPI's network overhead is very low at 8 processes, it increases with the increase in the number of cores. However, for Presto the network overhead is proportional to the number of multi-core servers used, and hence does not increase at the same rate. With more effort one can implement multi-threaded programs executing at each MPI process. Such an implementation will reduce the network overhead but not the compute imbalance.

Spark. We use Spark's PageRank implementation [36] to compare its performance with Presto. Spark takes about 64.185 seconds per-iteration with 64 cores. The per-iteration time includes a map phase which computes the rank of vertices and then propagates them to reducers that sum the values. We found that the first phase was mostly compute intensive and took around 44.3 seconds while the second phase involved shuffling data across the network and took 19.77 seconds. At fewer cores, the compute time is as high as 267.26 seconds with 8 cores. The main reason why Spark is at least 15× slower than Presto is because it generates a large amount of intermediate data and hence spends more time than Presto during execution and network transfers. Note that the Y-axis in the plot is log scale.

Hadoop. Figure 20(c) compares the performance of Mahout's PageRank implementation to that of Presto. Since mappers and reducers overlap during the Hadoop computation, we depict only the overall execution time. Each iteration of Mahout's PageRank takes 161 seconds with 64 mappers. In comparison each iteration of PageRank in Presto takes less than 4 seconds. A portion of the 40× performance difference is due to the use of Java. However unlike Presto, MapReduce has the additional overhead of the sort phase and the time spent in deserialization. Presto preserves the matrix structure in between operations, and also eliminates the need to sort data between iterations.

Existing R packages. To obtain a baseline for R-implementations, we measured the time taken for a single PageRank iteration using vanilla-R. R takes 30 seconds per iteration in our setup and was faster than Presto which takes 58 seconds when using a single-core. We found that Presto was slower due to the overheads associated with mapping and processing 128 partitions. When the dataset was merged to form a single partition (similar to vanilla-R case) Presto's performance matches that of vanilla-R. However, partitioning the dataset is helpful when using multiple cores. Presto running on 8 cores takes less than 10 seconds for each PageRank iteration.

Unfortunately, existing parallel R packages only allow side-effect free functions to be executed in parallel. It means that R objects in workers are deleted across iterations. Thus, to run more than one iteration of parallel PageRank the whole graph needs to be reloaded in the next iteration making the measurements flawed. Instead, we ran a microbenchmark with 8 cores where the sparse matrices were not exchanged and only a dense vector of 100M entries was exchanged after each round (similar to the PageRank vector). By efficiently using multi-cores and worker-worker communication Presto is more than 4× faster than `doMC`, a parallel-R package.

8. Discussion

Presto makes it easy for users to algorithmically explore large datasets. It is a step towards a platform on which high level libraries can be implemented. We believe that Presto packages that implement scalable machine learning and graph algorithms will help the large R user base reap the benefits of distributed computing.

However, certain challenges remain both in the current prototype and in the applicability of R to all problems. First, the current prototype is limited by main memory: datasets need to fit the aggregate memory of the cluster. While most pre-processed graphs are in the low terabyte size range, for larger datasets it may be economical to use an out-of-core system. We are working on adding out-of-core support for distributed arrays in future versions of Presto.

Second, Presto assumes that there is one writer per partition during a single foreach execution. Instead of using locks to synchronize concurrent accesses, in Presto multiple tasks explicitly write to their partitions and then combine or reduce the data in another `foreach` loop. For example, in k-means the centers are calculated and stored in separate arrays by each task and then summed up in another loop. This programming model retains the simplicity of R and we have found it sufficient for all the algorithms implemented so far. This model may not be appropriate for implementing irregular applications like Delaunay mesh refinement that require fine grained synchronization [20].

When applied to different datasets, array-based programming may require additional pre-processing. For example, Presto is based on R and is very efficient at processing arrays. However, graphs may have attributes attached to each vertex. An algorithm which uses these attributes (e.g., search shortest path with attribute pattern) may incur the additional overhead of referencing attributes stored in R vectors separate from the adjacency matrix. In general, real world data is semi-structured and pre-processing may be required to extract relevant fields and convert them into arrays. Unlike the Hadoop ecosystem which has both storage (HDFS) and computation (MapReduce), Presto only has a efficient computation layer. In our experience, it's easier to load data into Presto if the underlying store has tables (databases, HBase, etc.) and supports extraction mechanisms (e.g., SQL).

9. Related Work

Dataflow models. MapReduce and Dryad are popular dataflow systems for parallel data processing [12, 17]. To increase programmer productivity high-level programming models–DryadLINQ [35] and Pig [27]—are used on top of MapReduce and Dryad. These systems scale to hundreds of machines. However, they are best suited for batch processing, and because of their restrictive programming and communication interface make it difficult to implement matrix operations. Recent improvements, such as HaLoop [9], Twister [13], and Spark [36], do not change the programming model but improve iterative performance by caching data or using lineage for efficient fault tolerance. CIEL increases the expressibility of programs by allowing new data-dependent tasks during job execution [26]. However, none of these systems can efficiently express matrix operations.

Piccolo runs parallel applications that can share state using distributed, in-memory, key-value tables [28]. Compared to MapReduce, Piccolo is better suited for expressing matrix operations. However, Piccolo's key-value interface optimizes for low level reads and writes to keys instead of structured vector processing. Unlike Presto, Piccolo does not handle sparse datasets and the resulting load imbalance.

Pregel and GraphLab support bulk synchronous processing (BSP [34]) to execute parallel programs [23, 24]. With BSP, each vertex processes its local data and communicates with other vertices using messages. Both systems require an application to be (re)written in the BSP model. Presto shows that the widely used R system can be extended to give similar performance without requiring any programming model changes. Presto's execution time of PageRank on the Twitter graph (Figure 11, 8 cores, 7.3s) compares favorably to published results of PowerGraph (512 cores, 3.6s) [14].

Matrix computations. Ricardo [11] and HAMA [30] use MapReduce to implement matrix operations. While they solve the problem of scaling to large datasets, the implementation is inefficient due to the restrictive MapReduce interface. In light of this observation, MadLINQ provides a platform on Dryad specifically for matrix computations [29]. Similar to Presto, MadLINQ reuses existing matrix libraries on local partitions, is fault tolerant and distributed. While MadLINQ's techniques are efficient for dense matrices, their system does not efficiently handle sparse datasets, or support dynamic partitioning to overcome load imbalance.

Popular high-performance computing (HPC) systems like ScaLAPACK do not support general sparse matrices. The few systems that do support sparse matrices (SLEPc [15], ARPACK [21]) typically provide only eigensolvers. To write a new algorithm, such as the betweenness centrality, one would have to implement it with their low level interfaces including FORTRAN code. None of these systems have load balancing techniques or fault tolerance. MATLAB's parallel computing toolbox and existing efforts in parallelizing R can run single programs on multiple data. Unlike these systems, Presto can safely share data across multiple processes, has fewer redundant copies of data, and can mitigate load imbalance due to sparse datasets.

Parallel languages. HPC applications use explicit message passing models like MPI. MPI programmers have the flexibility to optimize the messaging layer but are difficult to write and maintain. New parallel programming languages like X10 [10] and Fortress [31] use the partitioned global address space model (PGAS). These languages are not optimized for matrix operations and the programmer has to deal with low level primitives like synchronization and explicit locations. For example, in X10 programmers specify on what processors computations should occur using *Place*. None of these languages are as popular as R, and users will have to rewrite hundreds of statistical algorithms that are already present in R.

10. Conclusion

Presto advocates the use of sparse matrix operations to simplify the implementation of machine learning and graph algorithms in a cluster. Presto uses distributed arrays for structured processing, efficiently uses multi-cores, and dynamically partitions data to reduce load imbalance. Our experience shows that Presto is a flexible computation model that can be used to implement a variety of complex algorithms.

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References

[1] Apache mahout. `http://mahout.apache.org`.

[2] Netflix prize. `http://www.netflixprize.com/`.

[3] The R project for statistical computing. `http://www.r-project.org`.

[4] Stanford network analysis package. `http://snap.stanford.edu/snap`.

[5] G. Ananthanarayanan, S. Kandula, A. Greenberg, I. Stoica, Y. Lu, B. Saha, and E. Harris. Reining in the outliers in map-reduce clusters using Mantri. In *In OSDI'10*, Vancouver, BC, Canada, 2010.

[6] R. D. Blumofe and C. E. Leiserson. Scheduling multithreaded computations by work stealing. In *SFCS '94*, pages 356–368, Washington, DC, USA, 1994.

[7] U. Brandes. A faster algorithm for betweenness centrality. *Journal of Mathematical Sociology*, 25:163–177, 2001.

[8] S. Brin and L. Page. The anatomy of a large-scale hypertextual Web search engine. In *WWW7*, pages 107–117, 1998.

[9] Y. Bu, B. Howe, M. Balazinska, and M. D. Ernst. HaLoop: Efficient iterative data processing on large clusters. *Proc. VLDB Endow.*, 3:285–296, September 2010.

[10] P. Charles, C. Grothoff, V. Saraswat, C. Donawa, A. Kielstra, K. Ebcioglu, C. von Praun, and V. Sarkar. X10: An object-oriented approach to non-uniform cluster computing. In *OOPSLA'05*, pages 519–538, 2005.

[11] S. Das, Y. Sismanis, K. S. Beyer, R. Gemulla, P. J. Haas, and J. McPherson. Ricardo: Integrating R and Hadoop. In *SIGMOD Conference'10*, pages 987–998, 2010.

[12] J. Dean and S. Ghemawat. MapReduce: Simplified data processing on large clusters. *Commun. ACM*, 51(1), 2008.

[13] J. Ekanayake, H. Li, B. Zhang, T. Gunarathne, S.-H. Bae, J. Qiu, and G. Fox. Twister: A runtime for iterative MapReduce. In *HPDC '10*, pages 810–818, 2010.

[14] J. E. Gonzalez, Y. Low, H. Gu, D. Bickson, and C. Guestrin. PowerGraph: Distributed Graph-Parallel Computation on Natural Graphs. In *OSDI'12*, Hollywood, CA, October 2012.

[15] V. Hernandez, J. E. Roman, and V. Vidal. Slepc: A scalable and flexible toolkit for the solution of eigenvalue problems. *ACM Trans. Math. Softw.*, 31(3):351–362, Sept. 2005.

[16] P. Hintjens. ZeroMQ: The Guide, 2010.

[17] M. Isard, M. Budiu, Y. Yu, A. Birrell, and D. Fetterly. Dryad: Distributed data-parallel programs from sequential building blocks. In *EuroSys '07*, pages 59–72, 2007.

[18] U. Kang, B. Meeder, and C. Faloutsos. Spectral Analysis for Billion-Scale Graphs: Discoveries and Implementation. In *PAKDD (2)*, pages 13–25, 2011.

[19] J. Kepner and J. Gilbert. *Graph Algorithms in the Language of Linear Algebra*. Fundamentals of Algorithms. SIAM, 2011.

[20] M. Kulkarni, K. Pingali, B. Walter, G. Ramanarayanan, K. Bala, and L. P. Chew. Optimistic parallelism requires abstractions. In *PLDI '07*, pages 211–222.

[21] R. B. Lehoucq, D. C. Sorensen, and C. Yang. *ARPACK users' guide - solution of large-scale eigenvalue problems with implicitly restarted Arnoldi methods.* Software, environments, tools. SIAM, 1998.

[22] D. Loveman. High performance Fortran. *IEEE Parallel & Distributed Technology: Systems & Applications*, 1(1):25–42, 1993.

[23] Y. Low, J. Gonzalez, A. Kyrola, D. Bickson, C. Guestrin, and J. M. Hellerstein. GraphLab: A New Framework for Parallel Machine Learning. *CoRR*, pages 1–1, 2010.

[24] G. Malewicz, M. H. Austern, A. J. Bik, J. C. Dehnert, I. Horn, N. Leiser, and G. Czajkowski. Pregel: A system for large-scale graph processing. In *SIGMOD '10*, pages 135–146, 2010.

[25] Q. E. McCallum and S. Weston. *Parallel R*. O'Reilly Media, Oct. 2011.

[26] D. G. Murray and S. Hand. CIEL: A universal execution engine for distributed data-flow computing. In *NSDI '11*, Boston, MA, USA, 2011.

[27] C. Olston, B. Reed, U. Srivastava, R. Kumar, and A. Tomkins. Pig latin: A not-so-foreign language for data processing. In *SIGMOD'08*, pages 1099–1110, 2008.

[28] R. Power and J. Li. Piccolo: Building fast, distributed programs with partitioned tables. In *OSDI '10*, Vancouver, BC, Canada, 2010. USENIX Association.

[29] Z. Qian, X. Chen, N. Kang, M. Chen, Y. Yu, T. Moscibroda, and Z. Zhang. MadLINQ: large-scale distributed matrix computation for the cloud. In *EuroSys '12*, pages 197–210, 2012.

[30] S. Seo, E. J. Yoon, J. Kim, S. Jin, J.-S. Kim, and S. Maeng. Hama: An efficient matrix computation with the mapreduce framework. In *In CLOUDCOM'10*, pages 721–726.

[31] G. L. Steele, Jr. Parallel programming and code selection in fortress. In *PPoPP '06*, pages 1–1, 2006.

[32] G. Strang. *Introduction to Linear Algebra, Third Edition*. Wellesley Cambridge Pr, Mar. 2003.

[33] C. E. Tsourakakis. Fast counting of triangles in large real networks without counting: Algorithms and laws. In *ICDM'08*, pages 608–617. IEEE, 2008.

[34] L. G. Valiant. A bridging model for parallel computation. *Commun. ACM*, 33:103–111, August 1990.

[35] Y. Yu, M. Isard, D. Fetterly, M. Budiu, U. Erlingsson, P. K. Gunda, and J. Currey. DryadLINQ: A system for general-purpose distributed data-parallel computing using a high-level language. In *OSDI '08*, pages 1–14, 2008.

[36] M. Zaharia, M. Chowdhury, T. Das, A. Dave, J. Ma, M. McCauley, M. J. Franklin, S. Shenker, and I. Stoica. Resilient distributed datasets: a fault-tolerant abstraction for in-memory cluster computing. In *NSDI'12*, San Jose, CA, 2012.

[37] Y. Zhou, D. Wilkinson, R. Schreiber, and R. Pan. Large-Scale Parallel Collaborative Filtering for the Netflix Prize. In *AAIM '08*, pages 337–348, Shanghai, China, 2008.