Blaze: Simplified High Performance Cluster Computing

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ABSTRACT
MapReduce and its variants have significantly simplified and accelerated the process of developing parallel programs. However, most MapReduce implementations focus on data-intensive tasks while many real-world tasks are compute intensive and their data can fit distributedly into the memory. For these tasks, the speed of MapReduce programs can be much slower than those hand-optimized ones. We present Blaze, a C++ library that makes it easy to develop high performance parallel programs for such compute intensive tasks. At the core of Blaze is a highly-optimized in-memory MapReduce function, which has three main improvements over conventional MapReduce implementations: eager reduction, fast serialization, and special treatment for a small fixed key range. We also offer additional conveniences that make developing parallel programs similar to developing serial programs. These improvements make Blaze an easy-to-use cluster computing library that approaches the speed of hand-optimized parallel code. We apply Blaze to some common data mining tasks, including word frequency count, PageRank, k-means, expectation maximization (Gaussian mixture model), and k-nearest neighbors. Blaze outperforms Apache Spark by more than 10 times on average for these tasks, and the speed of Blaze scales almost linearly with the number of nodes. In addition, Blaze uses only the MapReduce function and 3 utility functions in its implementation while Spark uses almost 30 different parallel primitives in its official implementation.

CCS CONCEPTS
• Computing methodologies → MapReduce algorithms; • Information systems → Data mining; Clustering; Nearest-neighbor search; Page and site ranking.

KEYWORDS
MapReduce, high performance, cluster computing, data mining, PageRank, k-means, expectation maximization, Gaussian mixture, k-nearest neighbors, serialization

1 INTRODUCTION
Cluster computing enables us to perform a huge amount of computations on big data and get insights from them at a scale that a single machine can hardly achieve. However, developing parallel programs to take advantage of a large cluster can be very difficult.

MapReduce [10, 11] greatly simplified this task by providing users a high-level abstraction for defining their computation, and taking care of the intricate low-level execution steps internally. Fig. 1 illustrates the MapReduce programming model. Logically, each MapReduce operation consists of two phases: a map phase where each input is mapped to a set of intermediate key/value pairs, and a reduce phase where the pairs with the same key are put together and reduced to a single key/value pair according to a user specified reduce function.

Many data mining algorithms are expressible with this model, such as PageRank [4, 12, 26], k-means [2, 7, 9, 13, 18, 34], Gaussian mixture model [7], and k-nearest neighbors [3, 22, 23, 29]. Although logically expressible, achieving similar efficiency as a hand-optimized parallel code is hard, especially when the data can be fit distributed into the memory. In such cases, the file system is no longer the bottleneck and the overhead from MapReduce can make the execution much slower than hand-optimized code.

Google’s MapReduce [10, 11] and most of its variants [1, 5, 6, 8, 12, 14, 16, 19, 21, 24, 28, 32] save intermediate data and result to the file system even when the data can be fit into the memory. Hence, its MapReduce performance is severely limited by the performance of the file system.

Spark [15, 30, 31, 33] offers an in-memory implementation of MapReduce, which is much faster than Google’s MapReduce. However, it uses a similar algorithm as Google’s MapReduce, which is designed for disk-based data intensive use cases and does not consider the computational overheads of MapReduce seriously. Hence, the performance of Spark is often far from the performance of hand-optimized code.
To achieve better performance while preserving the high-level MapReduce abstraction, we develop Blaze, a C++ based cluster computing library that focuses on in-memory high performance MapReduce and related operations. Blaze introduces three main improvements to the MapReduce algorithm: eager reduction, fast serialization, and special treatment for a small fixed key range. Section 2.3 provides a detailed description of these improvements.

We apply Blaze to several common data mining tasks, including word frequency count, PageRank, k-means, expectation maximization (Gaussian mixture), and k-nearest neighbors. Our results show that Blaze is on average 10 times faster than Spark on these tasks.

The main contributions of this research are listed as follows:

1. We develop Blaze, a high performance cluster computing library that allows users to write parallel programs with the high-level MapReduce abstraction while achieving similar performance as hand-optimized code for compute intensive tasks.
2. We introduce three main performance improvements to the MapReduce algorithm to make it more efficient: eager reduction, fast serialization, and special treatment for a small fixed key range.
3. We apply Blaze to 5 common data mining tasks and demonstrate that Blaze programs are easy to develop and can outperform Apache Spark programs by more than 10 times on average for these tasks.

The remaining sections are organized as follows: Section 2 describes the Blaze framework and the details of the optimization. Section 3 present the details of how we implement several key data mining and machine learning algorithms with Blaze and compare the performance with Apache Spark. Section 4 concludes the paper.

2 THE BLAZE LIBRARY

The Blaze library offers three sets of APIs: 1) a high-performance MapReduce function, 2) distributed data containers, and 3) parallel computing utility functions. These APIs are built based on the Blaze parallel computing kernel, which provides common low-level parallel computing primitives.

2.1 Distributed Containers

Blaze provides three distributed data containers: DistRange, DistVector, and DistHashMap. DistRange does not store the whole data but only the start, the end, and the step size of the data. DistVector distributedly stores an array of elements. DistHashMap distributedly stores key/value pairs.

All of the three containers support the foreach operation, where a custom function can be applied to each of its element in parallel. This function can either change the value of the element itself or use the value of the element to perform external operations.

Both the DistVector and the DistHashMap can be converted to and from C++ standard library containers with Blaze utility functions distribute and collect. DistVector can also be created from the load_file utility function, which can load text files from the file system parallelly into a distributed vector of lines.

DistVector also has a topk method, which can return the top k elements from the distributedly stored vector in O(n+k log k) time and O(k) space. Users can provide a custom comparison function to determine the priority of the elements.

2.2 MapReduce

The MapReduce function uses a functional style interface. It takes four parameters:

1. (1) Input. One of the Blaze distributed container.
2. (2) Mapper. When the input is a DistRange, the mapper should be a function that accepts two parameters: a value from the DistRange and a handler function for emitting key/value pairs. When the input is a DistVector or a DistHashMap, the mapper should be a function that accepts three parameters: a key from the input, the corresponding value, and an emit handler.
3. (3) Reducer. The function that reduce two values to one value. Blaze provides several built-in reducers, including sum, prod, min, and max, which can cover most use cases. These reducers can be used by providing the reducer name as a string, for example, "sum". Users can also provide custom reduce functions, which should take two parameters, the first one is a reference to the existing value which needs to be updated, and the second one is a constant reference to the new value.
4. (4) Target. One of the Blaze distributed container or a vector from the standard library. The target container should be mutable and it is not cleared before performing MapReduce. New results from the MapReduce operation are merged/reduced into the target container.

Blaze MapReduce also takes care of the serialization of common data types so that the map function can emit non-string key/value pairs, and the reduce function no longer requires additional logic for parsing the serialized data. Using custom data types as keys or values is also supported. For that, users only need to provide the corresponding serialize/parse methods and a hash function (for keys).

We provide two examples of using Blaze MapReduce in Appendix A.1 and A.2.
2.3 Optimization

We introduce several optimizations to make the MapReduce function faster, including eager reduction, fast serialization, and special treatment for cases where the resulting key range is small and fixed.

2.3.1 Eager Reduction. Conventional MapReduce performs the map phase first and saves all the emitted pair from the mapper function. Then, it shuffles all the emitted pairs across the networks directly, which could incur a large amount of network traffics.

In Blaze MapReduce, we perform machine-local reduce right after the mapper function emits a key/value pair. For popular keys, Blaze automatically reduces new values to a thread-local cache instead of the machine-local copy. The cross-machine shuffle operates on the locally reduced data which substantially reduces the network communication burden. During the shuffle operations, reduce functions are also operating asynchronously to maximize the throughput. Fig. 3 illustrates the difference between the conventional MapReduce and Blaze MapReduce with eager reduction.

2.3.2 Fast Serialization. During the shuffle/reduce phase, we serialize the messages into a compact binary format before casting them across the network.

Our encoding scheme and algorithm are similar to Google’s Protocol Buffers [17] but without prefixing each entry with field tags and wire types. Although these two fields allow missing fields and support serializing the fields in arbitrary order, this additional flexibility is not needed in MapReduce. On the other hand, these two fields can have a significant impact on both the performance and the serialized message size, especially when the content size of a field is small, which is common for MapReduce key/value pairs. For example, when both the key and value are small integers, the serialized message size of each pair from Protocol Buffers will be 4 bytes while the message from Blaze fast serialization will be only 2 bytes, which is 50% smaller than the one from Protocol Buffers. Removing the fields tags and wire types does not cause ambiguity as long as we always serialize the fields in the same order, which is easy to achieve in MapReduce. The smaller size in the serialized message means less network traffics, so that Blaze can scale better on large clusters when the cross-rack bandwidth becomes the bottleneck.

2.3.3 Optimization for Small Key Range. For small key range, we create a thread-local cache for each key at the beginning and set that as the reduce target during the local map/reduce phase. After the local map/reduce phase finished, we perform parallel tree based reduce operations: first locally and then across multiple machines. The resulting execution plan is essentially the same as hand-optimized parallel for loops with thread-local intermediate results.

We benchmark the performance of Blaze MapReduce against hand-optimized parallel for-loop on the Monte Carlo Pi estimation task. In this task, the mapper function first generates two random numbers \( x \) and \( y \) in the range \([0, 1]\), and then emits 1 to key 0 when \( x^2 + y^2 < 1 \). Cases like this where we reduce big data to a small number of keys are commonly seen in data mining and are not efficient with the original MapReduce algorithm. However, by using a thread-local copy as the default reduce target for each thread, Blaze MapReduce can achieve similar performance as hand-optimized code based on raw MPI and OpenMP. Table 1 reports the result and Appendix A.2 lists our implementation. The tests are performed on a local machine with Ubuntu 16.04, GCC 5.4 -O3, and an Intel i7-8550U processor.

### Table 1: Monte Carlo Pi Estimation Performance

| Samples | Blaze MapReduce | MPI+OpenMP |
|---------|-----------------|------------|
| \(10^7\) | 0.14 ± 0.01 s    | 0.14 ± 0.01 s |
| \(10^8\) | 1.44 ± 0.07 s    | 1.42 ± 0.09 s |
| \(10^9\) | 14.2 ± 1.3 s     | 14.6 ± 1.7 s  |

3 APPLICATIONS

In this section, we benchmark Blaze against a popular data mining package Spark, on common data mining tasks, including word frequency count, PageRank, k-means, expectation maximization (with the Gaussian Mixture model), and k-nearest neighbors search.

3.1 Task Description and Implementation

In this section, we describe the data mining tasks and how we implement them in Blaze and Spark. All the source code of our implementation is included in our GitHub repository [20].

3.1.1 Word Frequency Count. This task counts the number of occurrences of each unique English words in a text file. We use the Bible and Shakespeare’s works as the testing text. Since Spark has significant overhead in starting the MapReduce tasks, we repeat the Bible and the Shakespeare 200 times, so that the input file contains about 0.4 billion words.
We use MapReduce in both Blaze and Spark. The mapper function takes a single line and emits multiple (word, 1) pairs. The reducer function sums the values. Appendix A.1 contains the full Blaze implementation for this example.

### 3.1.2 PageRank.

This task calculates the PageRank score, which is defined as the stationary value of the following equation:

\[
PR(p_i) = \frac{1 - d}{N} + d \sum_{p_j \in M(p_i)} \frac{PR(p_j)}{L(p_j)}
\]  

where \(M(p_i)\) is the set of pages that link to \(p_i\), \(L(p_j)\) is the number of outbound links from page \(p_j\), \(N\) is the total number of pages, and \(d = 0.15\). When a page has no outbound links, it is called a sink and is assumed to connect to all the pages. We use the graph500 generator to generate the input graph which contains 10 million links. We set the convergence criterion to \(10^{-3}\), which results in 27 iterations for our input. The links are stored distributedly across multiple machines.

For Blaze, we use 3 MapReduce operations per iteration to implement this task. The first one calculates the total score of all the sinks. The second one calculates the new PageRank scores according to Eq. 1. The third one calculates the maximum change in the scores of all the pages. For Spark, we use the built-in PageRank module from the Spark GraphX library [27].

### 3.1.3 K-Means.

K-Means is a popular clustering algorithm. The algorithm proceeds by alternating two steps until the convergence. The first step is the assignment step where each point is assigned to the nearest clustering center. The second step is the refinement step where each clustering center is updated based on the new mean of the points assigned to the clustering center.

We generate 100 million random points around 5 clustering centers as the testing data, and use the same initial model and convergence criteria for Spark and Blaze. The points are stored distributedly across multiple machines.

For Blaze, we use a single MapReduce operation to perform the assignment step. The update step is implemented in serial. For Spark, we use the built-in implementation from the Spark MLlib library [25].

### 3.1.4 Expectation Maximization.

This task uses the expectation maximization method to train the Gaussian Mixture clustering model (GMM). Starting from an initial model, we first calculate the Gaussian probability density of each point for each Gaussian component

\[
p_k(x|\theta_k) = \frac{1}{(2\pi)^{d/2} |\Sigma_k|^{1/2}} e^{-\frac{1}{2}(x-\mu_k)^T \Sigma_k^{-1}(x-\mu_k)}
\]  

where \(\mu_1 \to \mu_K\) are the centers of these Gaussian components and \(\Sigma_1 \to \Sigma_K\) are the covariance matrices. Then we calculate the membership of each point for each Gaussian component

\[
w_{ik} = \frac{p_k(x_i|\theta_k) \cdot \alpha_k}{\sum_{m=1}^{K} p_m(x_i|\theta_m) \cdot \alpha_m}
\]  

where \(\alpha_k\) is the weights of the Gaussian component. Next, we calculate the sum of membership weights for each Gaussian component \(N_k = \sum_{i=1}^{N} w_{ik}\). After that, we update the parameters of the Gaussian mixtures

\[
\alpha_k = \frac{N_k}{N}
\]

\[
\mu_k = \frac{1}{N_k} \sum_{i=1}^{N} w_{ik} x_i
\]

\[
\Sigma_k = \frac{1}{N_k} \sum_{i=1}^{K} w_{ik} (x_i - \mu_k)(x_i - \mu_k)^T
\]

Finally, we calculate the log-likelihood of the current model for these points to determine whether the process is converged.

\[
\sum_{i=1}^{N} \log p(x_i|\Theta) = \sum_{i=1}^{N} \left( \log \sum_{k=1}^{K} \alpha_k p_k(x_i|\theta_k) \right)
\]

We generate 1 million random points around 5 clustering centers as the testing data and use the same initial model and convergence criteria for Spark and Blaze. The points are stored distributedly across multiple machines.

For Blaze, we implement this algorithm with 6 MapReduce operations per iteration. The first MapReduce calculates the probability density according to Eq. 2. The second MapReduce calculates the membership according to Eq. 3. The third MapReduce accumulates the sum of memberships for each Gaussian component \(N_k\). The next two MapReduce perform the summations in Eq. 5 and Eq. 6. The last MapReduce calculates the log-likelihood according to Eq. 7. For Spark, we use the built-in implementation from the Spark MLlib library [25].

### 3.1.5 Nearest 100 Neighbors.

In this task, we find the 100-nearest neighbors of a point from a huge set of other points. This is a common procedure in data analysis and recommendation systems. We use 200 million random points for this test.

For both Spark and Blaze, we implement this task with the top \(k\) function of the corresponding distributed containers and provide custom comparison functions to determine the relative priority of two points based on the Euclidean-distance.

### 3.2 Performance Analysis

We test the performance of both Spark and Blaze for the above tasks on Amazon Web Services (AWS). The time for loading data from the file system is not included in our measurements. Spark is explicitly set to use the \texttt{MEMORY\_ONLY} mode and we choose memory-optimized instances r5.xlarge as our testing environments which have large enough memory for Spark to complete our tasks. Each r5.xlarge has 4 logical cores, 32GB memory, and up to 10 Gbps network performance.

For Spark, we use the AWS Elastic MapReduce (EMR) service version 5.20.0, which comes with Spark 2.4.0. Since in the default setting, Spark changes the number of executors on the fly, which may obscure the results, we set the environment variable for maximizing resource allocation to true to avoid the change. We also manually specify the number of partitions to 100 to force the cross-executor shuffle on the entire cluster. For Blaze, we use GCC 7.3 with -O3 optimization and MPICH 3.2. For both Spark and Blaze, we perform warmup runs before counting the timings. Timings are converted to more meaningful results for each task.
The detailed performance comparison are shown in Fig. 4 to 8. “Spark”, “Spark (MLlib)”, “Spark (GraphX)”, “Blaze”, “Blaze TCM” denote the original Spark implementation, the MLlib library in Spark, the GraphX library in Spark, original Blaze, and Blaze linked with Thread-Caching Malloc (TCMalloc), respectively.

As shown in Fig. 4 to 8, Blaze outperforms Spark significantly on all five data mining applications. On average, Blaze is more than 10 times faster than Spark. The superior performance of Blaze shows that our highly-optimized implementation suits these data mining applications well. The performance difference between Blaze and Blaze TCM is negligible. However, without using TCMalloc, the performance has more fluctuations and can occasionally experience a significant drop of up to 30%.

3.3 Memory Consumption

We measure the memory consumption for running these tasks on a single local machine of 12 logical cores, using the same versions for all the software as the tests on AWS. As shown in Fig 9, we can see that both Blaze and Blaze TCM consumes much smaller amount of memory than Spark during the runs, especially for PageRank, K-Means, and expectation maximization (GMM), where Spark uses 10 times more memory than Blaze. The only case where the memory consumption between Spark and Blaze is close is the k-nearest neighbors search, which does not involve intermediate key/value pairs.

The memory consumption between Blaze and Blaze TCM are always on the same order of magnitude, although in one case, Blaze consumes 40% more memory when linked against TCMalloc.

3.4 Cognitive Load

Cognitive load refers to the efforts needed to develop or understand the code. Minimizing the cognitive load is the ultimate goal that MapReduce and its variants try to achieve.
There are lots of different measures for cognitive efforts. Source lines of code is not a good measure here as Spark/Scala supports chaining functions and can put several consecutive operations on a single line. Hence, a line of Spark/Scala may be much more difficult to understand than a line of C++. Here we use the number of distinct APIs used as the indicator for cognitive load. It is a legitimate indicator because people will have to do more searches and remember more APIs when a library requires more distinct API calls to accomplish a task.

Spark’s built-in implementation uses about 30 different parallel primitives for different tasks, while Blaze only uses the MapReduce function and less than 5 utility functions. We can see from Fig. 10 that the cognitive load of using Blaze is much smaller than using Spark.

4 CONCLUSION
Blaze provides a high performance implementation of MapReduce. Users can write parallel programs with Blaze’s high-level MapReduce abstraction and achieve similar performance as the hand-optimized parallel code.

We use Blaze to implement 5 common data mining algorithms. By writing only a few lines of serial code and apply the Blaze MapReduce function, we achieve over 10 times higher performance than Spark on these compute intensive tasks, even though we only use the MapReduce function and 3 utility functions in our Blaze implementation while Spark uses almost 30 different parallel primitives for different tasks in its official implementation.

The high-level abstraction and the high performance makes Blaze an appealing choice for compute intensive tasks in data mining and related fields.

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A EXAMPLES

In this section, we provide two examples to illustrate the usage of Blaze. All the source code of our implementation is included in our GitHub repository [20].

A.1 Word frequency count

In this example, we count the number of occurrences of each unique word in an input file with Blaze MapReduce. We save the results in a distributed hash map, which can be used for further processing.

To compile this example, you can clone our repository [20], go to the example folder and type `make wordcount`.

```cpp
#include <blaze/blaze.h>
#include <iostream>

int main(int argc, char** argv) {
  blaze::util::init(argc, argv);

  // Load file into distributed container.
  auto lines = blaze::util::load_file("filepath...");

  // Define mapper function.
  const auto& mapper = [&](const size_t, const std::string& line, const auto& emit) {
    std::stringstream ss(line);
    std::string word;
    while (getline(ss, word, ' ')) {
      emit(word, 1);
    }
  };

  // Define target hash map.
  blaze::DistHashMap<std::string, size_t> words;

  // Perform mapreduce.
  blaze::mapreduce<
    std::string, std::string, size_t>(
      lines, mapper, "sum", words);

  // Output number of unique words.
  std::cout << words.size() << std::endl;
}
```

A.2 Monte Carlo Pi Estimation

In this example, we present a MapReduce implementation of the Monte Carlo \( \pi \) estimation.

To compile this example, you can clone our repository [20], go to the example folder and type `make pi`.

```cpp
#include <blaze/blaze.h>
#include <iostream>

int main(int argc, char** argv) {
  blaze::util::init(argc, argv);

  const size_t N_SAMPLES = 1000000;

  // Define source.
  blaze::DistRange<size_t> samples(0, N_SAMPLES);

  // Define mapper.
  const auto& mapper = [&](const size_t, const auto& emit) {
    double x = blaze::random::uniform();
    double y = blaze::random::uniform();
    // Map points within circle to key 0.
    if (x * x + y * y < 1) emit(0, 1);
  };

  // Define target.
  std::vector<size_t> count(1); // {0}

  // Perform MapReduce.
  blaze::mapreduce<size_t, size_t>(
    samples, mapper, "sum", count);

  std::cout << 4.0 * count[0] / N_SAMPLES << std::endl;
}
```

In conventional MapReduce implementations, mapping big data onto a single key is usually slow and consumes a large amount of memory during the map phase. Hence, in practice, people usually hand-code parallel for loops in such situations. However, by using Blaze, the above code has similar memory consumption and performance as the hand-optimized parallel for loops. In short, Blaze frees users from dealing with low-level data communications while ensuring high performance.