

MapReduce–MPI Library Users Manual

<http://www.sandia.gov/~sjplimp/mapreduce.html>

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Table of Contents

MapReduce–MPI Library.....	1
Background.....	3
What is a MapReduce?.....	5
Getting Started.....	7
Writing a MapReduce program.....	8
C++ Interface to the MapReduce–MPI Library.....	9
Create a MapReduce object.....	11
Copy a MapReduce object.....	12
Destroy a MapReduce object.....	13
MapReduce add() method.....	14
MapReduce aggregate() method.....	15
MapReduce clone() method.....	16
MapReduce collapse() method.....	17
MapReduce collate() method.....	18
MapReduce compress() method.....	19
MapReduce convert() method.....	20
MapReduce gather() method.....	21
MapReduce map() method.....	22
MapReduce reduce() method.....	25
MapReduce scrunch() method.....	26
MapReduce sort_keys() method.....	27
MapReduce sort_values() method.....	28
MapReduce sort_multivalues() method.....	29
MapReduce kv_stats() method.....	30
MapReduce kmv_stats() method.....	30
KeyValue add() method.....	31
Settings and defaults.....	32
C interface to the MapReduce–MPI Library.....	35
Python interface to the MapReduce–MPI Library.....	37
Technical Details.....	44
Length and byte–alignment of keys and values.....	44
Memory requirements for KeyValue and KeyMultiValue objects.....	45
Out–of–core operation.....	46
Hash functions.....	46
Callback functions.....	47
Python overhead.....	47
Error messages.....	48
Examples.....	49
Word frequency example.....	49
R–MAT matrices example.....	49

MapReduce–MPI Library

This document describes the 13 April 2009 version of the open–source MapReduce–MPI (MR–MPI) library that implements the [MapReduce operation](#) popularized by Google on top of standard MPI message passing. The library is designed for parallel execution on distributed–memory platforms, but will also operate on a single processor. The library is written in C++, is callable from hi–level languages (C++, C, Fortran, Python, or other scripting languages), and requires no additional software except linking with an MPI library if you wish to perform MapReduces in parallel.

Similar to the original Google design, a user performs a MapReduce by writing a small program that invokes the library. The user typically provides two application–specific functions, a "map" and a "reduce", that are called by the library when a MapReduce operation is executed. "Map" and "reduce" are serial functions, meaning they are invoked independently on individual processors on portions of your data when performing a MapReduce operation in parallel.

The goal of this library is to provide a simple and portable interface for users to create their own MapReduce programs, which can then be run on any desktop or large parallel machine using MPI. See the Background section for features and limitations of this implementation.

Source codes for the library is freely available for download from the [MR–MPI web site](#) and is licensed under the modified [Berkeley Software Distribution \(BSD\) License](#). This basically means it can be used by anyone for any purpose. See the LICENSE file provided with the distribution for more details.

The distribution includes a few examples of simple programs that illustrate the use of MapReduce.

The authors of this library are [Steve Plimpton](#) at Sandia National Laboratories and [Karen Devine](#) who can be contacted via email: sjplimp@sandia.gov, kddevin@sandia.gov.

- [Background](#)
- [What is a MapReduce?](#)
- [Getting Started](#)
- [Writing a MapReduce program](#)
- [C++ Interface to the MapReduce–MPI Library](#)
 - ◆ [Create a MapReduce object](#)
 - ◆ [Copy a MapReduce object](#)
 - ◆ [Destroy a MapReduce object](#)
 - ◆ [MapReduce::add\(\)](#)
 - ◆ [MapReduce::aggregate\(\)](#)
 - ◆ [MapReduce::clone\(\)](#)
 - ◆ [MapReduce::collapse\(\)](#)
 - ◆ [MapReduce::collate\(\)](#)
 - ◆ [MapReduce::compress\(\)](#)
 - ◆ [MapReduce::convert\(\)](#)
 - ◆ [MapReduce::gather\(\)](#)
 - ◆ [MapReduce::map\(\)](#)
 - ◆ [MapReduce::reduce\(\)](#)
 - ◆ [MapReduce::scrunch\(\)](#)
 - ◆ [MapReduce::sort_keys\(\)](#)
 - ◆ [MapReduce::sort_values\(\)](#)
 - ◆ [MapReduce::sort_multivalues\(\)](#)
 - ◆ [MapReduce::kv_stats\(\)](#)
 - ◆ [MapReduce::kmv_stats\(\)](#)

- ◆ KeyValue::add()
- ◆ Settings and defaults
- C interface to the MapReduce–MPI Library
- Python interface to the MapReduce–MPI Library
- Technical Details
- Examples
 - ◆ Word frequency
 - ◆ R–MAT matrices

Background

MapReduce is the programming paradigm popularized by Google researchers [Dean and Ghemawat](#). Their motivation was to enable analysis programs to be rapidly developed and deployed within Google to operate on the massive data sets residing on their large distributed clusters. Their paper introduced a novel way of thinking about certain kinds of large-scale computations as "map" operations followed by "reduces". The power of the paradigm is that when cast in this way, a traditionally serial algorithm now becomes two highly parallel application-specific operations (requiring no communication) sandwiched around an intermediate operation that requires parallel communication, but which can be encapsulated in a library since the operation is independent of the application.

The Google implementation of MapReduce was a C++ library with communication between networked machines via remote procedure calls. They allow for fault tolerance when large numbers of machines are used, and can use disks as out-of-core memory to process huge data sets. Thousands of MapReduce programs have since been written by Google researchers and are part of the daily compute tasks run by the company.

While I had heard about MapReduce, I didn't appreciate its power for scientific computing on a monolithic distributed-memory parallel machine, until reading a SC08 paper by [Tu, et al](#) of the D.E. Shaw company. They showed how to think about tasks such as the post-processing of simulation output as MapReduce operations. In this context it can be useful for computations that would normally be thought of as serial, such as reading in a large data set and scanning it for events of a desired kind. As before, the computation can be formulated as a highly parallel "map" followed by a "reduce". The encapsulated parallel operation in the middle requires all-to-all communication to reorganize the data, a familiar MPI operation.

Tu's implementation of MapReduce was in parallel Python with communication between processors via MPI, again allowing disks to be used for out-of-core operations.

This MapReduce–MPI (MR–MPI) library is a very simple and lightweight implementation of the basic MapReduce functionality, borrowing ideas from both the [Dean and Sanjay](#) and [Tu, et al](#) papers. It has the following features:

- C++ library using MPI for inter-processor communication. This allows precise control over the memory allocated during a large-scale MapReduce.
- C++ and C and Python interfaces provided. A C++ interface means that one or more MapReduce objects can be instantiated and invoked by the user's program. A C interface means that the library can also be called from C or other hi-level languages such as Fortran. A Python interface means the library can be called from a Python script, allowing you to write serial `map()` and `reduce()` functions in Python. If your machine can run Python in parallel, you can also run a parallel MapReduce in that manner.
- Small, portable. The entire library is a few thousand lines of C++ code in a handful of C++ files which can be built on any machine with a C++ compiler. For parallel operation, you link with MPI, a standard message passing library available on all distributed memory machines. For serial operation, a dummy MPI library can be substituted, which is provided. The Python wrapper can be installed on any machine with a version of Python that includes the `ctypes` module, typically Python 2.5 or later.

Out-of-core. When a MapReduce object is created each processor allocates a chunk of memory whose size is determined by the user. When the data processed during MapReduce operations exceeds this memory, a processor writes to a disk file(s) and subsequently reads from it. This allows data sets to be processed that are larger than will fit in the aggregate memory of all the processors.

This library also has the following limitation:

No fault tolerance. Current MPI implementations do not enable easy detection of a dead processor. So like most MPI programs, a MapReduce operation will hang or crash if a processor goes away.

Finally, I call attention to [recent work](#) by Alexander Gray and colleagues at Georgia Tech. They show that various kinds of scientific computations such as N-body forces via multipole expansions, k-means clustering, and machine learning algorithms, can be formulated as MapReduce operations. Thus there is an expanding set of data-intensive or compute-intensive problems that may be amenable to solution using a MapReduce library such as this.

(Dean) J. Dean and S. Ghemawat, "MapReduce: Simplified Data Processing on Large Clusters", OSDI'04 conference (2004); J. Dean and S. Ghemawat, "MapReduce: Simplified Data Processing on Large Clusters", Communications of the ACM, 51, p 107–113 (2008).

(Tu) T. Tu, C. A. Rendleman, D. W. Borhani, R. O. Dror, J. Gullingsrud, M. O. Jensen, J. L. Kelpis, P. Maragakis, P. Miller, K. A. Stafford, D. E. Shaw, "A Scalable Parallel Framework for Analyzing Terascale Molecular Dynamics Trajectories", SC08 proceedings (2008).

(Gray) A. Gray, Georgia Tech, <http://www.cc.gatech.edu/~agray>

Alexander Gray, Georgia Tech, <http://www.cc.gatech.edu/~agray>

What is a MapReduce?

The canonical example of a MapReduce operation, described in both the [Dean and Sanjay](#) and [Tu, et al](#) papers, is counting the frequency of words in a collection of text files. Imagine a large corpus of text comprising Gbytes or Tbytes of data. To count how often each word appears, the following algorithm would work, written in Python:

```
dict = {}
for file in sys.argv[1:]:
    text = open(file, 'r').read()
    words = text.split()
    for word in words:
        if word not in dict: dict[word] = 1
        else: dict[word] += 1
unique = dict.keys()
for word in unique:
    print dict[word], word
```

Dict is a "dictionary" or associative array which is a collection of key/value pairs where the keys are unique. In this case, the key is a word and its value is the number of times it appears in any text file. The program loops over files, and splits the contents into words (separated by whitespace). For each word, it either adds it to the dictionary or increments its associated value. Finally, the resulting dictionary of unique words and their counts is printed.

The drawback of this implementation is that it is inherently serial. The files are read one by one. More importantly the dictionary data structure is updated one word at a time.

A MapReduce formulation of the same task is as follows:

```
array = []
for file in sys.argv[1:]:
    array += map(file)
newarray = collate(array)
unique = []
for entry in newarray:
    unique += reduce(entry)
for entry in unique:
    print entry[1], entry[0]
```

Array is now a linear list of key/value pairs where a key may appear many times (not a dictionary). The map() function reads a file, splits it into words, and generates a key/value pair for each word in the file. The key is the word itself and the value is the integer 1. The collate() function reorganizes the (potentially very large) list of key/value pairs into a new array of key/value pairs where each unique key appears exactly once and the associated value is a concatenated list of all the values associated with the same key in the original array. Thus, a key/value pair in the new array would be ("dog", [1,1,1,1,1]) if the word "dog" appeared 5 times in the text corpus. The reduce() function takes a single key/value entry from the new array and returns a key/value pair that has the word as its key and the count as its value, ("dog", 5) in this case. Finally, the elements of the unique array are printed.

As written, the MapReduce algorithm could be executed on a single processor. However, there is now evident parallelism. The map() function calls are independent of each other and can be executed on different processors simultaneously. Ditto for the reduce() function calls. In this scenario, each processor would accumulate its own local "array" and "unique" lists of key/value pairs.

Also note that if the map and reduce functions are viewed as black boxes that produce a list of key/value pairs (in the case of map) or convert a single key/value pair into a new key/value pair (in the case of reduce), then they are

the only part of the above algorithm that is application-specific. The remaining portions (the collate function, assignment of map or reduce tasks to processors, combining of the map/reduce output across processors) can be handled behind the scenes in an application-independent fashion. That is the portion of the code that is handled by the MR-MPI (or other) MapReduce library. The user only needs to provide a small driving program to call the library and serial functions for performing the desired map() and reduce() operations.

(Dean) J. Dean and S. Ghemawat, "MapReduce: Simplified Data Processing on Large Clusters", OSDI'04 conference (2004); J. Dean and S. Ghemawat, "MapReduce: Simplified Data Processing on Large Clusters", Communications of the ACM, 51, p 107–113 (2008).

(Tu) T. Tu, C. A. Rendleman, D. W. Borhani, R. O. Dror, J. Gullingsrud, M. O. Jensen, J. L. Kelpis, P. Maragakis, P. Miller, K. A. Stafford, D. E. Shaw, "A Scalable Parallel Framework for Analyzing Terascale Molecular Dynamics Trajectories", SC08 proceedings (2008).

Getting Started

Once you have [downloaded](#) the MapReduce MPI (MR-MPI) library, you should have the tarball `mapreduce.tar.gz` on your machine. Unpack it with the following commands:

```
gunzip mapreduce.tar.gz
tar xvf mapreduce.tar
```

which should create a `mapreduce` directory containing the following:

- README
- LICENSE
- doc
- examples
- mpistubs
- python
- src
- user

The `doc` directory contains this documentation. The `examples` directory contains a few simple MapReduce programs which call the MR-MPI library. These are documented by a README file in that directory and are discussed below. The `mpistubs` directory contains a dummy MPI library which can be used to build a MapReduce program on a serial machine. The `python` contains the Python wrapper files needed to call the MR-MPI library from Python. The `src` directory contains the files that comprise the MR-MPI library. The `user` directory contains user-contributed MapReduce programs. See the README in that directory for further details.

To build the library for use by a C++ or C program, go to the `src` directory and type

```
make -f Makefile.foo
```

where you should create and use a `Makefile.foo` appropriate for your machine, using one of the provided Makefiles as a template. Note that `Makefile.serial` builds the library for a serial machine, using the dummy MPI library in `mpistubs`. Other Makefiles build it for parallel execution using a MPI library installed on your machine. You may need to edit one of the Makefiles to be compatible with your compilers and MPI installation. If you use the dummy MPI library, you will need to build it first, by typing "make" from within `mpistubs`. Again, you may need to edit `mpistubs/Makefile` for your machine.

If you successfully build the MR-MPI library, you should produce the file `"libmrmpi.a"` which can be linked by other programs. As discussed below, both a C++ and C interface are part of the library, so the library should be usable from any hi-level language.

To use the MR-MPI library from Python, you don't need to build it from the `src` directory. Instead, you build it as a dynamic library from the `python` directory. Instructions are given below in the [Python interface](#) section.

The MapReduce programs in the `examples` directory can be built by typing

```
make -f Makefile.foo
```

from within the `examples` directory. Again, one of the provided Makefiles may need to be modified for your platform. Some of the example programs are provided as a C++ program, a C program, and as a Python script.

Writing a MapReduce program

The usual way to use the MR-MPI library is to write a small main program that calls the library. In C++, your program includes two library header files and uses the MapReduce namespace:

```
#include "mapreduce.h"
#include "keyvalue.h"
using namespace MAPREDUCE_NS
```

Follow these links for info on using the library from a [C program](#) or from a [Python program](#).

Arguments to the library's [map\(\)](#) and [reduce\(\)](#) methods include function pointers to serial "mymap" and "myreduce" functions in your code (named anything you wish), which will be "called back" from the library as it performs the parallel map and reduce operations.

A typical MapReduce program involves these steps:

```
MapReduce *mr = new MapReduce(MPI_COMM_WORLD);    // instantiate an MR object
mr->map(nfiles,                                   // parallel map
mr->collate()                                     // collate keys
mr->reduce(                                       // parallel reduce
delete mr;                                       // delete the MR object
```

The main program you write may be no more complicated than this. The API for the MR-MPI library is a handful of methods which are components of a MapReduce operation. They can be combined in more complex sequences of calls than listed above. For example, one [map\(\)](#) may be followed by several [reduce\(\)](#) operations to massage your data in a desired way. Output of final results is typically performed as part of a myreduce() function you write which executes on one or more processors and writes to a file(s) or the screen.

The MR-MPI library operates on "keys" and "values" which are generated and manipulated by your mymap() and myreduce() functions. A key and a value are simply byte strings of arbitrary length which are logically associated with each other, and can thus represent anything you wish. For example, a key can be a text string or a particle or grid cell ID. A value can be one or more numeric values or a text string or a composite data structure that you create.

C++ Interface to the MapReduce-MPI Library

This section discusses how to call the MR-MPI library from a C++ program and gives a description of all its methods and variable settings. Use of the library from a [C program](#) (or other hi-level language) or from [Python](#) is discussed in other sections of the manual.

All the library methods operate on two basic data structures stored within the MapReduce object, a KeyValue object (KV) and a KeyMultiValue object (KMV). When running in parallel, these objects are stored in a distributed fashion across multiple processors.

A KV is a collection of key/value pairs. The same key may appear many times in the collection, associated with values which may or may not be the same.

A KMV is also a collection of key/value pairs. But each key in the KMV is unique, meaning it appears exactly once (see the clone() method for a possible exception). The value associated with a KMV key is a concatenated list (a multi-value) of all the values associated with the same key in the original KV.

More details about how KV and KMV objects are stored are given in the [Technical Details](#) section.

Here is an overview of how the various library methods operate on KV and KMV objects. This is useful to understand, since this determines how the various operations can be chained together in your program:

add()	KV → KV	add pairs from one KV to another	serial
aggregate()	KV → KV	pairs are aggregated onto procs	parallel
clone()	KV → KMV	each KV pair becomes a KMV pair	serial
collapse()	KV → KMV	all KV pairs become one KMV pair	serial
collate()	KV → KMV	aggregate + convert	parallel
compress()	KV → KV	calls back to user program to compress duplicate keys	serial
convert()	KV → KMV	duplicate KV keys become one KMV key	serial
gather()	KV → KV	collect pairs on many procs to few procs	parallel
map()	create or add to a KV	calls back to user program to generate pairs	serial
reduce()	KMV → KV	calls back to user program to process KMV pairs	serial
scrunch()	KV → KMV	gather + collapse	parallel
sort_keys()	KV → KV	calls back to user program to sort pairs by key	serial

sort_values()	KV → KV	calls back to user program to sort pairs by value	serial
sort_multivalues()	KMV → KMV	calls back to user program to sort multi-values within each pair	serial

If a method creates a new KV or KMV object, the old one is deleted, if it existed. The KV object is also deleted if a KMV object is produced, and vice versa.

The methods flagged as "serial" perform their operation on the portion of a KV or KMV owned by an individual processor. They involve only local computation (performed simultaneously on all processors) and no parallel communication. The methods flagged as "parallel" involve communication between processors.

Create a MapReduce object

```
MapReduce::MapReduce(MPI_Comm comm)
MapReduce::MapReduce()
MapReduce::MapReduce(double dummy)
```

You can create a MapReduce object in any of the three ways shown, as well as via the [copy\(\)](#) method. The three creation methods differ slightly in how MPI is initialized and finalized.

In the first case, you pass an MPI communicator to the constructor. This means your program should initialize (and finalize) MPI, which creates the MPI_COMM_WORLD communicator (all the processors you are running on). Normally this is what you pass to the MapReduce constructor, but you can pass a communicator for a subset of your processors if desired. You can also instantiate multiple MapReduce objects, giving them each a communicator for all the processors or communicators for a subset of processors.

The second case can be used if your program does not use MPI at all. The library will initialize MPI if it has not already been initialized. It will not finalize MPI, but this should be fine. Worst case, your program may complain when it exits if MPI has not been finalized.

The third case is the same as the second except that the library will finalize MPI when the last instance of a MapReduce object is destructed. Note that this means your program cannot delete all its MapReduce objects in a early phase of the program and then instantiate more MapReduce objects later. This limitation is why the second case is provided. The third case is invoked by passing a double to the constructor. If this is done for any instantiated MapReduce object, then the library will finalize MPI. The value of the double doesn't matter as it isn't used. The use of a double is simply to make it different than the first case, since MPI_Comm is often implemented by MPI libraries as a type cast to an integer.

As examples, any of these lines of code will create a MapReduce object, where "mr" is either a pointer to the object or the object itself:

```
MapReduce *mr = new MapReduce(MPI_COMM_WORLD);
MapReduce *mr = new MapReduce();
MapReduce *mr = new MapReduce(0.0);
MapReduce mr(MPI_COMM_WORLD);
MapReduce mr();
MapReduce mr;
MapReduce mr(0.0);
```

Related methods: [destroy](#), [copy\(\)](#)

Copy a MapReduce object

```
MapReduce *MapReduce::copy()
```

This calls the `copy()` method of a MapReduce object, which creates a second MapReduce object which is an exact copy of the first, including all [settings](#), and returns a pointer to the new copy.

If the original MapReduce object contained a Key/Value or Key/Value object, as discussed [here](#), then the new MapReduce object will contain a copy of it. This means that all the key/value and/or key/multivalue pairs contained in the first MapReduce object are copied into the new MapReduce object. Thus the first MapReduce object could be subsequently deleted without affecting the new MapReduce object.

This is useful if you wish to retain a copy of a set of key/value pairs before processing it further. See the [add\(\)](#) method for how to merge the key/value pairs from two MapReduce objects into one. For example, this sequence of calls:

```
MapReduce *mr1 = new MapReduce(MPI_COMM_WORLD);
mr1->map(ntasks,
MapReduce *mr2 = mr1->copy();
mr2->collate();
mr2->reduce(
mr1->add(mr2);
delete mr2;
mr1->reduce(
```

would generate one set of key/value pairs from the initial [map\(\)](#) operation, then make a [copy](#) of them, which are then [collated](#) and [reduced](#) to a new set of key/value pairs. The new set of key/value pairs are [added](#) to the original set produced by the [map\(\)](#) operation to form an augmented set of key/value pairs, which could be further processed.

Related methods: [create](#), [add\(\)](#)

Destroy a MapReduce object

```
MapReduce::~~MapReduce()
```

This destroys a previously created MapReduce object, freeing all the memory it allocated internally to store keys and values.

If you created the MapReduce object in this manner:

```
MapReduce *mr = new MapReduce(MPI_COMM_WORLD);
```

then you should destroy it with

```
delete mr
```

If you created the MapReduce object in this manner:

```
MapReduce mr(MPI_COMM_WORLD);
```

then it will be destroyed automatically when the "mr" variable goes out of scope.

Related methods: [create](#)

MapReduce add() method

```
int MapReduce::add(MapReduce *mr2)
```

This calls the add() method of a MapReduce object, to add the KeyValue pairs contained in a second MapReduce object mr2, to the KeyValue object of the first MapReduce object. This is useful if multiple MapReduce objects have been created and populated with key/value pairs and you wish to combine them before performing further operations, such as a [collate\(\)](#) and [reduce\(\)](#).

For example, this sequence of calls:

```
MapReduce *mr1 = new MapReduce(MPI_COMM_WORLD);
mr1->map(ntasks,
MapReduce *mr2 = mr1->copy();
mr2->collate();
mr2->reduce(
mr1->add(mr2);
delete mr2;
mr1->reduce(
```

would generate one set of key/value pairs from the initial [map\(\)](#) operation, then make a [copy](#) of them, which are then [collated](#) and [reduced](#) to a new set of key/value pairs. The new set of key/value pairs are [added](#) to the original set produced by the [map\(\)](#) operation to form an augmented set of key/value pairs, which could be further processed.

Related methods: [copy](#), [map\(\)](#)

MapReduce aggregate() method

```
int MapReduce::aggregate(int (*myhash)(char *, int))
```

This calls the `aggregate()` method of a MapReduce object, which reorganizes a Key/Value object across processors into a new Key/Value object. In the original object, duplicates of the same key may be stored on many processors. In the new object, all duplicates of a key are stored by the same processor. The method returns the total number of key/value pairs in the new Key/Value object, which will be the same as the number in the original object.

A hashing function is used to assign keys to processors. Typically you will not care how this is done, in which case you can specify a NULL, i.e. `mr->aggregate(NULL)`, and the MR-MPI library will use its own internal hash function, which will distribute them randomly and hopefully evenly across processors.

On the other hand, if you know the best way to do this for your data, then you should provide the hashing function. For example, if your keys are integer IDs for particles or grid cells, you might want to use the ID (modulo the processor count) to choose the processor it is assigned to. Ideally, you want a hash function that will distribute keys to processors in a load-balanced fashion.

In this example the user function is called `myhash()` and it must have the following interface:

```
int iproc = myhash(char *key, int keybytes)
```

Your function will be passed a key (byte string) and its length in bytes. Typically you want to return an integer such that $0 \leq \text{iproc} < P$, where P is the number of processors. But you can return any integer, since the MR-MPI library uses the result in this manner to assign the key to a processor:

```
int iproc = myhash(key, keybytes) % P;
```

Because the `aggregate()` method will, in general, reassign all key/value pairs to new processors, it incurs a large volume of all-to-all communication. However, this is performed concurrently, taking advantage of the large bisection bandwidth most large parallel machines provide.

The `aggregate()` method should load-balance key/value pairs across processors if they are initially imbalanced.

Related methods: [collate\(\)](#)

MapReduce clone() method

```
int MapReduce::clone()
```

This calls the clone() method of a MapReduce object, which converts a KeyValue object directly into a KeyMultiValue object. It simply turns each key in KeyValue object into a key in the new KeyMultiValue object, with the same value. The method returns the total number of key/value pairs in the KeyMultiValue object, which will be the same as the number in the KeyValue object.

This method essentially enables a KeyValue object to be passed directly to a reduce operation, which requires a KeyMultiValue object as input. Typically you would only do this if the keys in the KeyValue object are already unique, to avoid the extra overhead of an [aggregate\(\)](#) or [convert\(\)](#) or [collate\(\)](#), but this is not required. If they are not, then there will also be duplicate keys in the KeyMultiValue object.

Note that one of the [map\(\)](#) methods allows an existing KeyValue object to be passed as input to a user mymap() function, generating a new Keyvalue object in the process. Thus there is typically no need to invoke clone() followed by [reduce\(\)](#).

This method is an on–processor operation, requiring no communication. When run in parallel, the key/value pairs of the new KeyMultiValue object are stored on the same processor which owns the corresponding KeyValue pairs.

Related methods: [collapse\(\)](#), [collate](#), [convert\(\)](#)

MapReduce collapse() method

```
int MapReduce::collapse(char *key, int keybytes)
```

This calls the `collapse()` method of a `MapReduce` object, which collapses a `KeyValue` object into a `KeyMultiValue` object with a single new key, given as an argument with its length in bytes. The single new value in the `KeyMultiValue` object is a concatenated list of all the keys and values in the `KeyValue` object. The method returns the total number of key/value pairs in the `KeyMultiValue` object, which will be 1 for each processor owning pairs.

For example, if the `KeyValue` object contains these key/value pairs:

```
("dog",3), ("me",45), ("parallel",1)
```

then the new `KeyMultiValue` object will contain a single key/value pair:

```
(key,["dog",3,"me",45,"parallel",1])
```

This method can be used to collect a set of key/value pairs to use in a [reduce\(\)](#) method so that it can all be passed to a single invocation of your `myreduce()` function for output. See the [Technical Details](#) section for details on how the `collapse()` method affects the alignment of keys and values that may eventually be passed to your `myreduce()` function via the [reduce\(\)](#) method.

This method is an on–processor operation, requiring no communication. When run in parallel, each processor collapses the key/value pairs it owns into a single key/value pair. Thus each processor will assign the same key to its new pair. See the [gather\(\)](#) and [scrunch\(\)](#) methods for ways to collect all key/value pairs on to one or a few processors.

Related methods: [clone\(\)](#), [collate](#), [convert\(\)](#)

MapReduce collate() method

```
int MapReduce::collate(int (*myhash)(char *, int))
```

This calls the `collate()` method of a MapReduce object, which aggregates a `KeyValue` object across processors and converts it into a `KeyMultiValue` object. This method is exactly the same as performing an [aggregate\(\)](#) followed by a [convert\(\)](#). The method returns the total number of unique key/value pairs in the `KeyMultiValue` object.

The hash argument is used by the [aggregate\(\)](#) portion of the operation and can be specified as `NULL`. See the [aggregate\(\)](#) doc page for details.

Note that if your map operation does not produce duplicate keys, you do not typically need to perform a `collate()`. Instead you can convert a `KeyValue` object into a `KeyMultiValue` object directly via the [clone\(\)](#) method, which requires no communication. Or you can pass it directly to another [map\(\)](#) operation. One exception would be if your map operation produces a `KeyValue` object which is highly imbalanced across processors. The [aggregate\(\)](#) portion of the operation should redistribute the key/value pairs more evenly.

This method is a parallel operation ([aggregate\(\)](#)), followed by an on-processor operation ([convert\(\)](#)).

Related methods: [aggregate\(\)](#), [clone\(\)](#), [collapse\(\)](#), [compress\(\)](#), [convert\(\)](#)

MapReduce compress() method

```
int MapReduce::compress(void (*mycompress)(char *, int, char *, int, int *, KeyValue *, void *), void *
```

This calls the `compress()` method of a `MapReduce` object, which compresses a `KeyValue` object with duplicate keys into a new `KeyValue` object, where each key appears once (on that processor) and has a single new value. The new value is a combination of the values associated with that key in the original `KeyValue` object. The `mycompress()` function you provide generates the new value. The method returns the total number of key/value pairs in the new `KeyValue` object.

This method is used to compress a large set of key/value pairs produced by the [map\(\)](#) method into a smaller set before proceeding with the rest of a MapReduce operation, e.g. with a [collate\(\)](#) and [reduce\(\)](#).

You can give this method a pointer (`void *ptr`) which will be returned to your `mycompress()` function. See the [Technical Details](#) section for why this can be useful. Just specify a `NULL` if you don't need this.

In this example the user function is called `mycompress()` and it must have the following interface, which is the same as that used by the [reduce\(\)](#) method:

```
void mycompress(char *key, int keybytes, char *multivalue, int nvalues, int *valuebytes, KeyValue *kv)
```

A single key/multi-value pair is passed to your function from a temporary `KeyMultiValue` object created by the library. That object creates a multi-value for each unique key in the `KeyValue` object which contains a list of the `nvalues` associated with that key. Note that this is only the values on this processor, not across all processors. The `char *multivalue` argument is a pointer to the beginning of the multi-value which contains all `nvalues`, packed one after the other. The `int *valuebytes` argument is an array which stores the length of each value in bytes. If needed, it can be used by your function to compute an offset into `char *multivalue` to where each individual value begins. Your function is also passed a `kv` pointer to a new `KeyValue` object created and stored internally by the `MapReduce` object.

Your `mycompress()` function should typically produce a single key/value pair which it registers with the `MapReduce` object by calling the [add\(\)](#) method of the `KeyValue` object. The syntax for this call is described on the doc page for the `KeyValue add()` method. For example, if the set of `nvalues` were integers, the compressed value might be the sum of those integers.

See the [Technical Details](#) section for details on the byte-alignment of keys and values that are passed to your `mycompress()` function and on how to byte-align keys and values you register with the `KeyValue add()` method.

This method is an on-processor operation, requiring no communication. When run in parallel, each processor operates only on the key/value pairs it stores. Thus you are NOT compressing all values associated with a particular key across all processors, but only those currently owned by one processor.

Related methods: [collate\(\)](#)

MapReduce convert() method

```
int MapReduce::convert()
```

This calls the `convert()` method of a `MapReduce` object, which converts a `KeyValue` object into a `KeyMultiValue` object. It does this by finding duplicate keys (stored only by this processor) and concatenating their values into a list of values which it associates with the key in the `KeyMultiValue` object. The method returns the total number of key/value pairs in the `KeyMultiValue` object, which will be the number of unique keys in the `KeyValue` object.

This operation creates a hash table to find duplicate keys efficiently. More details are given in the [Technical Details](#) section.

This method is an on–processor operation, requiring no communication. When run in parallel, each processor converts only the key/value pairs it owns into key/multi–value pairs. Thus, this operation is typically performed only after the [aggregate\(\)](#) method has collected all duplicate keys to the same processor. The [collate\(\)](#) method performs an [aggregate\(\)](#) followed by a `convert()`.

Related methods: [collate\(\)](#)

MapReduce gather() method

```
int MapReduce::gather(int nprocs)
```

This calls the `gather()` method of a `MapReduce` object, which collects the key/value pairs of a `KeyValue` object spread across all processors to form a new `KeyValue` object on a subset (`nprocs`) of processors. `Nprocs` can be 1 or any number smaller than `P`, the total number of processors. The gathering is done to the lowest ID processors, from 0 to `nprocs-1`. Processors with `ID >= nprocs` end up with an empty `KeyValue` object containing no key/value pairs. The method returns the total number of key/value pairs in the new `KeyValue` object, which will be the same as in the original `KeyValue` object.

This method can be used to collect the results of a [reduce\(\)](#) to a single processor for output. See the [collapse\(\)](#) and [scrunch\(\)](#) methods for related ways to collect key/value pairs for output. A `gather()` may also be useful before a [reduce\(\)](#) if the number of unique key/value pairs is small enough that you wish to perform the reduce tasks on fewer processors.

This method requires parallel point-to-point communication as processors send their key/value pairs to other processors.

Related methods: [scrunch\(\)](#)

MapReduce map() method

```
int MapReduce::map(int nmap, void (*mymap)(int, KeyValue *, void *), void *ptr)
int MapReduce::map(int nmap, void (*mymap)(int, KeyValue *, void *), void *ptr, int addflag)

int MapReduce::map(char *file, void (*mymap)(int, char *, KeyValue *, void *), void *ptr)
int MapReduce::map(char *file, void (*mymap)(int, char *, KeyValue *, void *), void *ptr, int addflag)

int MapReduce::map(int nmap, int nfiles, char **files, char sepchar, int delta, void (*mymap)(int, char *, KeyValue *, void *), void *ptr)
int MapReduce::map(int nmap, int nfiles, char **files, char sepchar, int delta, void (*mymap)(int, char *, KeyValue *, void *), void *ptr, int addflag)

int MapReduce::map(int nmap, int nfiles, char **files, char *sepstr, int delta, void (*mymap)(int, char *, KeyValue *, void *), void *ptr)
int MapReduce::map(int nmap, int nfiles, char **files, char *sepstr, int delta, void (*mymap)(int, char *, KeyValue *, void *), void *ptr, int addflag)

int MapReduce::map(MapReduce *mr2, void (*mymap)(int, char *, int, char *, int, KeyValue *, void *), void *ptr)
int MapReduce::map(MapReduce *mr2, void (*mymap)(int, char *, int, char *, int, KeyValue *, void *), void *ptr, int addflag)
```

This calls the `map()` method of a `MapReduce` object. A function pointer to a mapping function you write is specified as an argument. This method either creates a new `KeyValue` object to store all the key/value pairs generated by your `mymap` function, or adds them to an existing `KeyValue` object. The method returns the total number of key/value pairs in the `KeyValue` object.

For the first set of variants (with and without `addflag`) you specify a total number of map tasks *nmap* to perform across all processors. The index of a map task is passed back to your `mymap()` function.

For the second set of variants you specify a master file that contains a list of filenames. A filename is passed back to your `mymap()` function. The master file should list one file per line. Blank lines are not allowed. Leading and trailing whitespace around the filename is OK.

For the third set of variants you specify an array of one or more file names and a separation character (`sepchar`). For the fourth set of variants, you specify an array of one or more files names and a separation string (`sepstr`). The file(s) are split into *nmap* chunks with roughly equal numbers of bytes in each chunk. One chunk from one file is read and passed back to your `mymap()` function, so your code does not read the file. See details below about the splitting methodology and the `delta` input parameter.

For the fifth set of variants, you specify an existing `MapReduce` object `mr2` with key/value pairs, which can either be this `MapReduce` object or another one. The key/value pairs from `mr2` are passed back to your `mymap()` function, one key/value at a time, allowing you to generate new key/value pairs from an existing set.

You can give any of the `map()` methods a pointer (`void *ptr`) which will be returned to your `mymap()` function. See the [Technical Details](#) section for why this can be useful. Just specify a `NULL` if you don't need this.

If the last argument *addflag* is omitted or is specified as 0, then `map()` will create a new `KeyValue` object, deleting any existing `KeyValue` object. If *addflag* is non-zero, then key/value pairs generated by your `mymap()` function are added to an existing `KeyValue` object, which is created if needed.

If the fifth `map()` variant is called using the `MapReduce` object itself as an argument, and if *addflag* is 0, then the existing `KeyValue` object is effectively replaced by the newly generated key/value pairs. If *addflag* is non-zero, then the newly generated key/value pairs are added to the existing `KeyValue` object.

In this example the user function is called `mymap()` and it has one of four interfaces depending on which variant of the `map()` method is invoked:


```
void mymap(int itask, KeyValue *kv, void *ptr)
void mymap(int itask, char *file, KeyValue *kv, void *ptr)
void mymap(int itask, char *str, int size, KeyValue *kv, void *ptr)
void mymap(int itask, char *key, int keybytes, char *value, int valuebytes, KeyValue *kv, void *ptr)
```

In all cases, the final 2 arguments passed to your function are a pointer to a `KeyValue` object (kv) stored internally by the `MapReduce` object, and the original pointer you specified as an argument to the `map()` method, as `void *ptr`.

In the first case, `itask` is passed to your function with a value $0 \leq \text{itask} < \text{nmap}$, where `nmap` was specified in the `map()` call. For example, you could use `itask` to select a file from a list stored by your application. Your `mymap()` function could open and read the file or perform some other operation.

In the second case, `itask` will have a value $0 \leq \text{itask} < \text{nfiles}$, where `nfiles` is the number of filenames in the master file you specified. Your function is also passed a single filename, which it will presumably open and read.

In the third case, `itask` will have a value from $0 \leq \text{itask} < \text{nmap}$, where `nmap` was specified in the `map()` call and is the number of file segments generated. It is also passed a string of bytes (`str`) of length `size` from one of the files. `Size` includes a trailing `'\0'` that is appended to the string.

For `map()` methods that take files and a separation criterion as arguments, you must specify `nmap >= nfiles`, so that there is one or more map tasks per file. For files that are split into multiple chunks, the split is done at occurrences of the separation character or string. You specify a delta of how many extra bytes to read with each chunk that will guarantee the splitting character or string is found within that many bytes. For example if the files are lines of text, you could choose a newline character `'\n'` as the `sepchar`, and a delta of 80 (if the longest line in your files is 80 characters). If the files are snapshots of simulation data where each snapshot is 1000 lines (no more than 80 characters per line), you could choose the first line of each snapshot (e.g. "Snapshot") as the `sepstr`, and a delta of 80000. Note that if the separation character or string is not found within delta bytes, an error will be generated. Also note that there is no harm in choosing a large delta so long as it is not larger than the chunk size for a particular file.

If the separation criterion is a character (`sepchar`), the chunk of bytes passed to your `mymap()` function will start with the character after a `sepchar`, and will end with a `sepchar` (followed by a `'\0'`). If the separation criterion is a string (`sepstr`), the chunk of bytes passed to your `mymap()` function will start with `sepstr`, and will end with the character immediately preceding a `sepstr` (followed by a `'\0'`). Note that this means your `mymap()` function will be passed different byte strings if you specify `sepchar = 'A'` vs `sepstr = "A"`.

In the fourth case, `itask` will have a value from $0 \leq \text{itask} < \text{nkey}$, where `nkey` is the number of key/value pairs in the specified `MapReduce` object. Key and value are the byte strings for a single key/value pair and are of length `keybytes` and `valuebytes` respectively.

The `MapReduce` library assigns map tasks to processors. Options for how it does this can be controlled by [MapReduce settings](#). Basically, `nmap/P` tasks are assigned to each processor, where `P` is the number of processors in the MPI communicator you instantiated the `MapReduce` object with.

Typically, your `mymap()` function will produce key/value pairs which it registers with the `MapReduce` object by calling the `add()` method of the `KeyValue` object. The syntax for registration is described on the doc page of the `KeyValue add()` method.

See the [Technical Details](#) section for details on the length and byte-alignment of keys and values you register with the `KeyValue add()` method.

Aside from the assignment of tasks to processors, this method is really an on-processor operation, requiring no communication. When run in parallel, each processor generates key/value pairs and stores them, independently of other processors.

Related methods: [Keyvalue add\(\)](#), [reduce\(\)](#)

MapReduce reduce() method

```
int MapReduce::reduce(void (*myreduce)(char *, int, char *, int, int *, KeyValue *, void *), void *p
```

This calls the `reduce()` method of a `MapReduce` object, passing it a function pointer to a reduce function you write. It operates on a `KeyMultiValue` object, calling your `myreduce` function once for each unique key/multi-value pair owned by that processor. A new `KeyValue` object is created which stores all the key/value pairs generated by your `myreduce()` function. The method returns the total number of new key/value pairs stored by all processors.

You can give this method a pointer (`void *ptr`) which will be returned to your `myreduce()` function. See the [Technical Details](#) section for why this can be useful. Just specify a `NULL` if you don't need this.

In this example the user function is called `myreduce()` and it must have the following interface:

```
void myreduce(char *key, int keybytes, char *multivalue, int nvalues, int *valuebytes, KeyValue *kv,
```

A single key/multi-value pair is passed to your function from the `KeyMultiValue` object stored by the `MapReduce` object. The key is typically unique to this reduce task and the multi-value is a list of the `nvalues` associated with that key in the `KeyMultiValue` object. The `char *multivalue` argument is a pointer to the beginning of the multi-value which contains all `nvalues`, packed one after the other. The `int *valuebytes` argument is an array which stores the length of each value in bytes. If needed, it can be used by your function to compute an offset into `char *values` for where each individual value begins. Your function is also passed a `kv` pointer to a new `KeyValue` object created and stored internally by the `MapReduce` object.

Your `myreduce()` function can produce key/value pairs (though this is not required) which it registers with the `MapReduce` object by calling the [add\(\)](#) method of the `KeyValue` object. The syntax for registration is described on the doc page of the `KeyValue` [add\(\)](#) method. Alternatively, your `myreduce()` function can write information to an output file.

See the [Technical Details](#) section for details on the byte-alignment of keys and values that are passed to your `myreduce()` function and on how to byte-align keys and values you register with the `KeyValue` [add\(\)](#) method.

This method is an on-processor operation, requiring no communication. When run in parallel, each processor performs a `myreduce()` on each of the key/value pairs it owns and stores any new key/value pairs it generates.

Related methods: [Keyvalue add\(\)](#), [map\(\)](#)

MapReduce scrunch() method

```
int MapReduce::scrunch(int nprocs, char *key, int keybytes)
```

This calls the `scrunch()` method of a `MapReduce` object, which gathers a `KeyValue` object onto `nprocs` and collapses it into a `KeyMultiValue` object. This method is exactly the same as performing a [gather\(\)](#) followed by a [collapse\(\)](#). The method returns the total number of key/value pairs in the `KeyMultiValue` object which should be one for each of the `nprocs`.

The `nprocs` argument is used by the [gather\(\)](#) portion of the operation. See the [gather\(\)](#) doc page for details. The `key` and `keybytes` arguments are used by the [collapse\(\)](#) portion of the operation. See the [collapse\(\)](#) doc page for details.

Note that if `nprocs > 1`, then the same key will be assigned to the collapsed key/multi-value pairs on each processor.

This method can be used to collect a set of key/value pairs to use in a [reduce\(\)](#) method so that it can all be passed to a single invocation of your `myreduce()` function for output.

This method is a parallel operation ([gather\(\)](#)), followed by an on-processor operation ([collapse\(\)](#)).

Related methods: [collapse\(\)](#), [gather\(\)](#)

MapReduce sort_keys() method

```
int MapReduce::sort_keys(int (*mycompare)(char *, int, char *, int))
```

This calls the `sort_keys()` method of a `MapReduce` object, which sorts a `KeyValue` object by its keys to produce a new `KeyValue` object. The `mycompare()` function you provide compares pairs of keys for the sort, since the `MapReduce` object does not know how to interpret the content of your keys. The method returns the total number of key/value pairs in the new `KeyValue` object which will be the same as in the original.

This method is used to sort key/value pairs by key before a `KeyValue` object is transformed into a `KeyMultiValue` object, e.g. via the [clone\(\)](#), [collapse\(\)](#), or [convert\(\)](#) methods. Note that these operations preserve the order of pairs in the `KeyValue` object when creating a `KeyMultiValue` object, which can then be passed to your application for output, e.g. via the [reduce\(\)](#) method. Note however, that `sort_keys()` does NOT sort keys across all processors but only sorts the keys on each processor within the `KeyValue` object. Thus if you [gather\(\)](#) or [aggregate\(\)](#) after performing a `sort_keys()`, the sorted order will be lost, since those methods move key/value pairs to new processors.

In this example the user function is called `mycompare()` and it must have the following interface

```
int mycompare(char *key1, int len1, char *key2, int len2)
```

`Key1` and `key2` are pointers to the byte strings for 2 keys, each of length `len1` and `len2`. Your function should compare them and return a `-1`, `0`, or `1` if `key1` is less than, equal to, or greater than `key2`, respectively.

This method is an on-processor operation, requiring no communication. When run in parallel, each processor operates only on the key/value pairs it stores.

Related methods: [sort_values\(\)](#), [sort_multivalues\(\)](#)

MapReduce sort_values() method

```
int MapReduce::sort_values(int (*mycompare)(char *, int, char *, int))
```

This calls the `sort_values()` method of a `MapReduce` object, which sorts a `KeyValue` object by its values to produce a new `KeyValue` object. The `mycompare()` function you provide compares pairs of values for the sort, since the `MapReduce` object does not know how to interpret the content of your values. The method returns the total number of key/value pairs in the new `KeyValue` object which will be the same as in the original.

This method is used to sort key/value pairs by value before a `KeyValue` object is transformed into a `KeyMultiValue` object, e.g. via the `clone()`, `collapse()`, or `convert()` methods. Note that these operations preserve the order of pairs in the `KeyValue` object when creating a `KeyMultiValue` object, which can then be passed to your application for output, e.g. via the `reduce()` method. Note however, that `sort_values()` does NOT sort values across all processors but only sorts the values on each processor within the `KeyValue` object. Thus if you `gather()` or `aggregate()` after performing a `sort_values()`, the sorted order will be lost, since those methods move key/value pairs to new processors.

In this example the user function is called `mycompare()` and it must have the following interface

```
int mycompare(char *value1, int len1, char *value2, int len2)
```

`Value1` and `value2` are pointers to the byte strings for 2 values, each of length `len1` and `len2`. Your function should compare them and return a `-1`, `0`, or `1` if `value1` is less than, equal to, or greater than `value2`, respectively.

This method is an on-processor operation, requiring no communication. When run in parallel, each processor operates only on the key/value pairs it stores.

Related methods: [sort_keys\(\)](#), [sort_multivalues\(\)](#)

MapReduce sort_multivalues() method

```
int MapReduce::sort_multivalues(int (*mycompare)(char *, int, char *, int))
```

This calls the `sort_multivalues()` method of a `MapReduce` object, which sorts the values for each key within a `KeyMultiValue` object to produce a new `KeyMultiValue` object. The `mycompare()` function you provide compares pairs of values for the sort, since the `MapReduce` object does not know how to interpret the content of your values. The method returns the total number of key/multi-value pairs in the new `KeyMultiValue` object which will be the same as in the original.

This method can be used to sort a set of multi-values within a key before they are passed to your application, e.g. via the `reduce()` method. Note that it typically only makes sense to use `sort_multivalues()` for a `KeyMultiValue` object created by the `convert()` or `collate()` methods, not `KeyMultiValue` objects created by the `clone()` or `collapse()` or `scrunch()` methods.

In this example the user function is called `mycompare()` and it must have the following interface

```
int mycompare(char *value1, int len1, char *value2, int len2)
```

`Value1` and `value2` are pointers to the byte strings for 2 values, each of length `len1` and `len2`. Your function should compare them and return a `-1`, `0`, or `1` if `value1` is less than, equal to, or greater than `value2`, respectively.

This method is an on-processor operation, requiring no communication. When run in parallel, each processor operates only on the key/multi-value pairs it stores.

Related methods: [sort_keys\(\)](#), [sort_values\(\)](#)

MapReduce kv_stats() method

MapReduce kmv_stats() method

```
void MapReduce::kv_stats(int level)
void MapReduce::kmv_stats(int level)
```

Calling the kv_stats() method prints statistics about the KeyValue object stored within the MapReduce object. If level = 1 is specified, a one-line summary is printed for all the key/value pairs across all processors. If a level = 2 is specified, per-processor information is also printed in a one-line histogram format.

Calling the kmd_stats() method prints statistics about the KeyMultiValue object stored within the MapReduce object. If level = 1 is specified, a one-line summary is printed for all the key/multi-value pairs across all processors. If a level = 2 is specified, per-processor information is also printed in a one-line histogram format.

KeyValue add() method

```
void KeyValue::add(char *key, int keybytes, char *value, int valuebytes)
void KeyValue::add(int n, char *keys, int keybytes, char *values, int valuebytes)

void KeyValue::add(int n, char *keys, int *keybytes, char *values, int *valuebytes)
```

The methods are called by the `mymap()`, `mycompress()`, and `myreduce()` functions in your program to register key/value pairs with the `KeyValue` object stored by the `MapReduce` object whose `map()`, `compress()`, or `reduce()` method was invoked. The first version registers a single key/value pair. The second version registers *N* key/value pairs, where the keys are all the same length and the values are all the same length. The third version registers a set of *N* key/value pairs where the length of each key and of each value is specified.

As explained [here](#), from the perspective of the MR–MPI library, keys and values are variable–length byte strings. To register such strings, you must specify their length in bytes. This is done via the `keybytes` and `valuebytes` arguments, either as a single length or as a vectors of lengths. Note that if your key or value is a text string, it should typically include a trailing "0" to terminate the string. See the [Technical Details](#) section for details on the length and byte–alignment of keys and values you register with the `add()` method.

Settings and defaults

These are internal library variables that can be set by your program:

```
mapstyle = 0 (chunk) or 1 (stride) or 2 (master/slave)
verbosity = 0 (none) or 1 (summary) or 2 (histogrammed)
timer = 0 (none) or 1 (summary) or 2 (histogrammed)
memsize = N = number of Mbytes of memory
keyalign = N = byte-alignment of keys
valuealign = N = byte-alignment of values
```

They are set in the following manner from C++:

```
MapReduce *mr = new MapReduce(MPI_COMM_WORLD);
mr->verbosity = 1;
```

See the [C interface](#) and [Python interface](#) doc pages for how to set them from C and Python.

As documented below, some of these settings can be changed at any time. Others only have effect if they are changed before the MapReduce object begins to operate on Key/Value and Key/Value objects.

The *mapstyle* setting determines how the N map tasks are assigned to the P processors by the [map\(\)](#).

A value of 0 means split the tasks into "chunks" so that processor 0 is given tasks from 0 to N/P, proc 1 is given tasks from N/P to 2N/P, etc. Proc P-1 is given tasks from N - N/P to N.

A value of 1 means "strided" assignment, so proc 0 is given tasks 0,P,2P,etc and proc 1 is given tasks 1,P+1,2P+1,etc and so forth.

A value of 2 uses a "master/slave" paradigm for assigning tasks. Proc 0 becomes the "master"; the remaining processors are "slaves". Each is given an initial task by the master and reports back when it is finished. It is then assigned the next available task which continues until all tasks are completed. This is a good choice if the CPU time required by various mapping tasks varies greatly, since it will tend to load-balance the work across processors. Note however that proc 0 performs no mapping tasks.

This setting can be changed at any time.

The default value for *mapstyle* is 0.

The *verbosity* setting determines how much diagnostic output each library call prints to the screen. A value of 0 means "none". A value of 1 means a "summary" of the results across all processors is printed, typically a count of total key/value pairs and the memory required to store them. A value of 2 prints the summary results and also a "histogram" of these quantities by processor, so that you can detect memory usage imbalance.

This setting can be changed at any time.

The default value for *verbosity* is 0.

The *timer* setting prints out timing information for each call to the library. A value of 0 means "none". A value of 1 invokes an MPI_Barrier() at the beginning and end of the operation and prints the elapsed time, which will be the same on all processors. A value of 2 invokes no MPI_Barrier() calls and prints a one-line summary of timing

results across all processors and also a "histogram" of the time on each processor, so that you can detect computational imbalance.

This setting can be changed at any time.

The default value for *timer* is 0.

The *memsize* setting determines how much memory (in Mbytes) is used by the MapReduce object to perform its various operations. It is a per-processor setting. The minimum setting is 1 Mbytes; the maximum as $4096 = 4$ Gbytes. If the data owned by a processor exceeds this limit, then it writes its portion of the data to a file and reads it back in for subsequent operations. These intermediate files are created on a per-processor basis and are deleted when the MapReduce object is deleted, e.g. at the end of the user program.

The specified chunk of memory is split into 4 pieces so that one or more copies of KeyValue and KeyMultiValue objects can exist at the same time as various operations are performed. Thus if the default setting of 100 Mbytes is used, a KeyValue object will be created and written to a file in 25 Mbyte chunks, when a [map\(\)](#) method is invoked.

If you make this setting small, then processing a large data set will induce many small reads and writes to disk. If you make it large, then the reads and writes will happen in large chunks, which generally yields better I/O performance. However, past a few MBytes in size, there may be little gain in I/O performance. The intermediate files are created in the directory from which you invoke your MapReduce program. Depending on a parallel machine's disk system, this may mean many processors write/read simultaneously to the same directory.

You should ensure this setting is no larger than the physical memory available to a processor, else memory allocations may fail or occur in slow virtual memory. On a machine where many processors share the same memory, e.g. a multicore node, you should ensure the sum of the memory chunks for all processors does not exceed physical memory. Note that the *memsize* setting is a rough lower bound of the memory that will be used by various MapReduce operations. You should probably be conservative by a factor of 2x to ensure other smaller memory allocations do not exceed available memory. See the [Technical Details](#) for more discussion of this topic.

This setting can only be changed before the first KeyValue or KeyMultiValue object is created by the MapReduce object. If changed after that, it will have no effect.

The default value for *memsize* is 100, meaning 100 Mbytes.

The *keyalign* and *valuealign* settings determine the byte alignment of keys and values generated by the user program when they are stored inside the library and passed back to the user program. A setting of N means N-byte alignment. N must always be a power of two.

As explained in [this section](#), keys and values are variable-length strings of bytes. The MR-MPI library knows nothing of their contents and simply treats them as contiguous chunks of bytes. [This section](#) explains why it may be important to ensure proper alignment of numeric data such as integers and floating point values.

Because they are stored following integer lengths, keys are always at least 4-byte aligned. A larger alignment value can be specified if desired.

Because they follow keys, which may be arbitrary length (e.g. a string), values can be 1-byte aligned. Note that if all keys are integers, then values will also be 4-byte aligned. A larger alignment value can be specified if desired.

When a multi-value is returned to the user program, e.g. by the callback of a [reduce\(\)](#) method, only the first value in the multi-value is aligned to the *valuealign* setting. Subsequent values are packed one after the other. If all

values are the same data-type, e.g. integers, then they will all have the same alignment. However if the values are mixed data types (strings and integers), then you may need to insure each value is aligned properly before using it in your `myreduce()` function. See the [Technical Details](#) for more discussion of data alignment.

These settings can only be changed before the first `KeyValue` or `KeyMultiValue` object is created by the `MapReduce` object. If changed after that, they will have no effect.

The default value for *keyalign* and *valuealign* is 4, meaning 4-byte alignment of keys and values.

C interface to the MapReduce-MPI Library

The MR-MPI library can be called from a C program, using the interface defined in `src/cmapreduce.h`. This is a C file which should be included in your C program to define the API to the library:

```
#include "cmapreduce.h"
```

Note that the C interface should also be usable to call the MapReduce MPI library from Fortran or other hi-level languages, including scripting languages. See information below on how to do this from [Python](#).

The C interface consists of the following functions. Their functionality and arguments are described in the [C++ interface section](#).

```
void *MR_create(MPI_Comm comm);
void *MR_create_mpi();
void *MR_create_mpi_finalize();
void *MR_copy(void *MRptr);
void MR_destroy(void *MRptr);

int MR_add(void *MRptr);
int MR_aggregate(void *MRptr, int (*myhash)(char *, int));
int MR_clone(void *MRptr);
int MR_collapse(void *MRptr, char *key, int keybytes);
int MR_collate(void *MRptr, int (*myhash)(char *, int));
int MR_compress(void *MRptr,
                void (*mycompress)(char *, int, char *,
                                     int, int *, void *KVptr, void *APPptr),
                void *APPptr);
int MR_convert(void *MRptr);
int MR_gather(void *MRptr, int numprocs);

int MR_map(void *MRptr, int nmap,
           void (*mymap)(int, void *KVptr, void *APPptr),
           void *APPptr);
int MR_map_add(void *MRptr, int nmap,
              void (*mymap)(int, void *KVptr, void *APPptr),
              void *APPptr, int addflag);
int MR_map_file_list(void *MRptr, char *file,
                   void (*mymap)(int, char *, void *KVptr, void *APPptr),
                   void *APPptr);
int MR_map_file_list_add(void *MRptr, char *file,
                       void (*mymap)(int, char *, void *KVptr, void *APPptr),
                       void *APPptr, int addflag);
int MR_map_file_char(void *MRptr, int nmap, int files, char **files,
                   char sepchar, int delta,
                   void (*mymap)(int, char *, int, void *KVptr, void *APPptr),
                   void *APPptr);
int MR_map_file_char_add(void *MRptr, int nmap, int files, char **files,
                       char sepchar, int delta,
                       void (*mymap)(int, char *, int, void *KVptr, void *APPptr),
                       void *APPptr, int addflag);
int MR_map_file_str(void *MRptr, int nmap, int files, char **files,
                  char *sepstr, int delta,
                  void (*mymap)(int, char *, int, void *KVptr, void *APPptr),
                  void *APPptr);
int MR_map_file_str_add(void *MRptr, int nmap, int files, char **files,
                      char *sepstr, int delta,
                      void (*mymap)(int, char *, int, void *KVptr, void *APPptr),
```

```

        void *APPptr, int addflag);
int MR_map_mr(void *MRptr, void *MRptr2,
        void (*mymap)(int, char *, int, char *, int *, void *KVptr, void *APPptr),
        void *APPptr);
int MR_map_mr_add(void *MRptr, void *MRptr2,
        void (*mymap)(int, char *, int, char *, int *, void *KVptr, void *APPptr),
        void *APPptr, int addflag);

int MR_reduce(void *MRptr,
        void (*myreduce)(char *, int, char *,
                        int, int *, void *KVptr, void *APPptr),
        void *APPptr);
int MR_scrunch(void *MRptr, int numprocs, char *key, int keybytes);

int MR_sort_keys(void *MRptr,
        int (*mycompare)(char *, int, char *, int));
int MR_sort_values(void *MRptr,
        int (*mycompare)(char *, int, char *, int));
int MR_sort_multivalues(void *MRptr,
        int (*mycompare)(char *, int, char *, int));

void MR_kv_stats(void *MRptr, int level);
void MR_kmv_stats(void *MRptr, int level);

void MR_set_mapstyle(void *MRptr, int value);
void MR_set_verbosity(void *MRptr, int value);
void MR_set_timer(void *MRptr, int value);

void MR_kv_add(void *KVptr, char *key, int keybytes,
        char *value, int valuebytes);
void MR_kv_add_multi_static(void *KVptr, int n,
        char *key, int keybytes,
        char *value, int valuebytes);
void MR_kv_add_multi_dynamic(void *KVptr, int n,
        char *key, int *keybytes,
        char *value, int *valuebytes);

```

These functions correspond one-to-one with the C++ methods described [here](#), except that for C++ methods with multiple interfaces (e.g. `map()`), there are multiple C functions, with slightly different names. The `MR_set()` functions are added to the C interface to enable the corresponding library variables to be set.

Note that when you call `MR_create()` or `MR_copy()`, they return a "void *MRptr" which is a pointer to the MapReduce object created by the library. This pointer is used as the first argument of all the other MR calls. This means a C program can effectively instantiate multiple MapReduce objects by simply keeping track of the pointers returned to it.

The remaining arguments of each function call are the same as those used with the C++ methods. The only exceptions are several of the `MR_kv_add()` functions which take a `KVptr` as their first argument. This is a pointer to a Key-Value object. These calls are made from your program's `mymap()`, `myreduce()`, and `mycompress()` functions to register key/value pairs with the MR-MPI library. The `KVptr` is passed as an argument to your functions when they are called back from the MR-MPI library.

See the C programs in the examples directory for [examples](#) of how these calls are made from a C program. They are conceptually identical to the C++ programs in the same directory.

Python interface to the MapReduce-MPI Library

A Python wrapper for the MR-MPI library is included in the distribution. The advantage of using Python is how concise the language is, enabling rapid development and debugging of MapReduce programs. The disadvantage is speed, since Python is slower than a compiled language. Using the MR-MPI library from Python incurs two additional overheads, discussed in the [Technical Details](#) section.

Before using the MR-MPI library in a Python script, the Python on your machine must be "extended" to include an interface to the MR-MPI library. If your Python script will invoke MPI operations, you will also need to extend your Python with an interface to MPI itself.

Thus you should first decide how you intend to use the MR-MPI library from Python. There are 3 options:

- (1) Use the library on a single processor running Python.
- (2) Use the library in parallel, where each processor runs Python, but your application script does not use MPI.
- (3) Use the library in parallel, where each processor runs Python, and your application also makes MPI calls through a Python/MPI interface.

Note that for (2) and (3) you will not be able to interact with Python interactively by typing commands and getting a response. This is because when you have multiple instances of Python running (e.g. on a parallel machine) they cannot all read what you type.

Working in mode (1) does not require your machine to have MPI installed. You should extend your Python with a serial version of the MR-MPI library and its dummy MPI library. See instructions below on how to do this.

Working in mode (2) requires your machine to have an MPI library installed, but your Python does not need to be extended with MPI itself. The MPI library must be a shared library (e.g. a *.so file on Linux) which is not typically created when MPI is built/installed. See instruction below on how to do this. You should extend your Python with the parallel MR-MPI library which will use the shared MPI system library. See instructions below on how to do this.

Working in mode (3) requires your machine to have MPI installed (as a shared library as in (2)). You must also extend your Python with the parallel MR-MPI library (same as in (2)) and with MPI itself, via one of several available Python/MPI packages. See instructions below on how to do the latter task.

The following sub-sections cover the rest of the Python discussion:

- [Extending Python with a serial version of the MR-MPI library](#)
- [Creating a shared MPI library](#)
- [Extending Python with a parallel version of the MR-MPI library](#)
- [Extending Python with MPI itself](#)
- [Testing the MR-MPI library from Python](#)
- [Using the MR-MPI library from Python](#)

Extending Python with a serial version of the MR-MPI library

From the python directory, type

```
python setup_serial.py build
```

and then one of these commands:

```
sudo python setup_serial.py install
python setup_serial.py install --home=~ /foo
```

The "build" command should compile all the needed MR-MPI C++ files, including the dummy MPI library. The first "install" command will put the needed files in your Python's site-packages sub-directory, so that Python can load them. For example, if you installed Python yourself on a Linux machine, it would typically be somewhere like /usr/local/lib/python2.5/site-packages. Installing Python packages this way often requires you to be able to write to the Python directories, which may require root privileges, hence the "sudo" prefix. If this is not the case, you can drop the "sudo".

Alternatively, you can install the MR-MPI files (or any other Python packages) in your own user space. The second "install" command does this, where you should replace "foo" with your directory of choice.

If these commands are successful, an *mrmpi.py* and *_mrmpi_serial.so* file will be put in the appropriate directory.

Creating a shared MPI library

A shared library is one that is dynamically loadable, which is what Python requires. On Linux this is a library file that ends in ".so", not ".a". Such a shared library is normally not built if you installed MPI yourself, but it is easy to do. Here is how to do it for [MPICH](#), a popular open-source version of MPI, distributed by Argonne National Labs. From within the mpich directory, type

```
./configure --enable-sharedlib=gcc
make
make install
```

You may need to use "sudo make install" in place of the last line. The end result should be the file libmpich.so in /usr/local/lib. Note that if the file libmpich.a already existed in /usr/local/lib, you will now have both a static and shared MPICH library. This will be fine for Python MR-MPI since it only uses the shared library. But if you build other codes with libmpich.a, then those builds may fail if the linker uses libmpich.so instead, unless other dynamic libraries are also linked to.

Extending Python with a parallel version of the MR-MPI library

From the python directory, type

```
python setup.py build
```

and then one of these commands:

```
sudo python setup.py install
python setup.py install --home=~ /foo
```

The "build" command should compile all the needed MR-MPI C++ files, which will require MPI to be installed on your system. This means it must find both the header file mpi.h and a shared library file, e.g. libmpich.so if the MPICH version of MPI is installed. See the preceding section for how to create a build MPI as a shared library if it does not exist.

The first "install" command will put the needed files in your Python's site-packages sub-directory, so that Python can load them. For example, if you installed Python yourself on a Linux machine, it would typically be

somewhere like `/usr/local/lib/python2.5/site-packages`. Installing Python packages this way often requires you to be able to write to the Python directories, which may require root privileges, hence the "sudo" prefix. If this is not the case, you can drop the "sudo".

Alternatively, you can install the MR-MPI files (or any other Python packages) in your own user space. The second "install" command does this, where you should replace "foo" with your directory of choice.

If these commands are successful, an *mrmpi.py* and *_mrmpi.so* file will be put in the appropriate directory.

Extending Python with MPI itself

There are several Python packages available that purport to wrap MPI and allow its functions to be called from Python.

These include

- [pyMPI](#)
- [maroonmpi](#)
- [mpi4py](#)
- [myMPI](#)
- [Pypar](#)

All of these except pyMPI work by wrapping the MPI library (which must be available on your system as a shared library, as discussed above), and exposing (some portion of) its interface to your Python script. This means they cannot be used interactively in parallel, since they do not address the issue of interactive input to multiple instances of Python running on different processors. The one exception is pyMPI, which alters the Python interpreter to address this issue, and (I believe) creates a new alternate executable (in place of python itself) as a result.

In principle any of these Python/MPI packages should work with the MR-MPI library. However, when I downloaded and looked at a few of them, their documentation was incomplete and I had trouble with their installation. It's not clear if some of the packages are still being actively developed and supported.

The one I recommend, since I have successfully used it with the MR-MPI library, is Pypar. Pypar requires the ubiquitous [Numpy package](#) be installed in your Python. After launching python, type

```
>>> import numpy
```

to see if it is installed. If not, here is how to install it (version 1.3.0b1 as of April 2009). Unpack the numpy tarball and from its top-level directory, type

```
python setup.py build
sudo python setup.py install
```

The "sudo" is only needed if required to copy Numpy files into your Python distribution's site-packages directory.

To install PyPar (version pypar-2.1.0_66 as of April 2009), unpack it and from its "source" directory, type

```
python setup.py build
sudo python setup.py install
```

Again, the "sudo" is only needed if required to copy PyPar files into your Python distribution's site-packages directory.

If you have successfully installed Pypar, you should be able to run python serially and type

```
>>> import pypar
```

without error. You should also be able to run python in parallel on a simple test script

```
% mpirun -np 4 python test.script
```

where test.script contains the lines

```
import pypar
print "Proc %d out of %d procs" % (pypar.rank(),pypar.size())
```

and see one line of output for each processor you ran on.

Testing the MR-MPI library from Python

Before importing the MR-MPI library in a Python program, one more step is needed. The interface to the library is via Python ctypes, which loads the shared MR-MPI library via a CDLL() call, which in turn is a wrapper on the C-library dlopen(). This command is different than a normal Python "import" and needs to be able to find the MR-MPI shared library, which is either in the Python site-packages directory or in a local directory you specified in the "python setup.py install" command, as described above.

The simplest way to do this is add a line like this to your .cshrc or other shell start-up file.

```
setenv LD_LIBRARY_PATH $LD_LIBRARY_PATH:/usr/local/lib/python2.5/site-packages
```

and then execute the file to insure the path has been updated. This will extend the path that dlopen() uses to look for shared libraries.

To test if the MR-MPI library has been successfully installed, launch python in serial and type

```
>>> from mrmmpi import mrmmpi
>>> mr = mrmmpi()
```

If you get no errors, you're ready to use the library, as described below.

If you built the MR-MPI library for parallel use, launch python in parallel

```
% mpirun -np 4 python test.script
```

where test.script contains the lines

```
import pypar
from mrmmpi import mrmmpi
mr = mrmmpi()
print "Proc %d out of %d procs has" % (pypar.rank(),pypar.size()), mr
```

Again, if you get no errors, you're good to go.

Using the MR-MPI library from Python

The Python interface to the MR-MPI library consists of an "mrmmpi" class which creates a "mrmmpi" object, with a set of methods that can be invoked on that object. The sample code lines below assume you have first imported

the "mrmpi" module as follows:

```
from mrmpi import mrmpi
```

Note that when your script imports the Pypar package (same with some other Python/MPI packages), it initializes MPI for you. Pypar does not, however, make the global MPI communicator (MPI_COMM_WORLD) visible to your program, so you can't pass it to the MR-MPI library. When using Pypar, the last line of your input script should thus be `pypar.finalize()`, to insure MPI is shut down correctly.

Some of the methods defined by the `mrmpi` class take callback functions as arguments, e.g. `map()` and `reduce()`. These are Python functions you define elsewhere in your script. When you register "keys" and "values" with the library, they can be simple quantities like strings or ints or floats. Or they can be Python data structures like lists or tuples.

These are the class methods defined by the `mrmpi` module. Their functionality and arguments are described in the [C++ interface section](#).

```
mr = mrmpi()                # create an mrmpi object
mr = mrmpi(mpi_comm)        # ditto, but with a specified MPI communicator
mr = mrmpi(0.0)             # ditto, and the library will finalize MPI

mr2 = mr.copy()             # copy mr to create mr2

mr.destroy()                # destroy an mrmpi object, freeing its memory
                             # this will also occur if Python garbage collects

mr.add(mr2)
mr.aggregate()
mr.aggregate(myhash)        # if specified, myhash is a hash function
                             #   called back from the library as myhash(key)
                             # myhash() should return an integer (a proc ID)

mr.clone()
mr.collapse(key)
mr.collate()
mr.collate(myhash)          # if specified, myhash is the same function
                             #   as for aggregate()

mr.compress(mycompress)     # mycompress is a function called back from the
                             #   library as mycompress(key,mvalue,mr,ptr)
                             #   where mvalue is a list of values associated
                             #   with the key, mr is the MapReduce object,
                             #   and you (optionally) provide ptr (see below)
                             # your mycompress function should typically
                             #   make calls like mr->add(key,value)
mr.compress(mycompress,ptr) # if specified, ptr is any Python datum
                             #   and is passed back to your mycompress()
                             # if not specified, ptr = None

mr.convert()
mr.gather(nprocs)

mr.map(nmap,mymap)          # mymap is a function called back from the
                             #   library as mymap(itask,mr,ptr)
                             #   where mr is the MapReduce object,
                             #   and you (optionally) provide ptr (see below)
                             # your mymap function should typically
                             #   make calls like mr->add(key,value)
mr.map(nmap,mymap,ptr)     # if specified, ptr is any Python datum
                             #   and is passed back to your mymap()
```

```

        # if not specified, ptr = None
mr.map(nmap,mymap,ptr,addflag) # if addflag is specified as a non-zero int,
        #   new key/value pairs will be added to the
        #   existing key/value pairs

mr.map_file_list(file,mymap) # file is a file containing a list of filenames
        # mymap is a function called back from the
        #   library as mymap(itask,filename,mr,ptr)
        # as above, ptr and addflag are optional args
mr.map_file_char(nmap,files,sepchar,delta,mymap)
        # files is a list of filenames
        # mymap is a function called back from the
        #   library as mymap(itask,str,mr,ptr)
        # as above, ptr and addflag are optional args
mr.map_file_str(nmap,files,sepstr,delta,mymap)
        # files is a list of filenames
        # mymap is a function called back from the
        #   library as mymap(itask,str,mr,ptr)
        # as above, ptr and addflag are optional args
mr.map_mr(mr2,mymap)
        # pass key/values in mr2 to mymap
        # mymap is a function called back from the
        #   library as mymap(itask,key,value,mr,ptr)
        # as above, ptr and addflag are optional args

mr.reduce(myreduce)      # myreduce is a function called back from the
        #   library as myreduce(key,mvalue,mr,ptr)
        #   where mvalue is a list of values associated
        #   with the key, mr is the MapReduce object,
        #   and you (optionally) provide ptr (see below)
        # your myreduce function should typically
        #   make calls like mr->add(key,value)
mr.reduce(myreduce,ptr)  # if specified, ptr is any Python datum
        #   and is passed back to your myreduce()
        # if not specified, ptr = None

mr.scrunch(nprocs,key)

mr.sort_keys(mycompare)
mr.sort_values(mycompare)
mr.sort_multivalues(mycompare) # compare is a function called back from the
        #   library as mycompare(a,b) where
        #   a and b are two keys or two values
        # your mycompare() should compare them
        #   and return a -1, 0, or 1
        <b, or a == b, 0r a if b

mr.kv_stats(level)
mr.kmv_stats(level)

mr.mapstyle(value)      # set the mapstyle to value
mr.verbosity(value)     # set the verbosity to value
mr.timer(value)         # set the timer to value

mr.add(key,value)        # add single key and value
mr.add_multi_static(keys,values) # add list of keys and values
        # all keys are assumed to be same length
        # all values are assumed to be same length
mr.add_multi_dynamic(keys,values) # add list of keys and values
        # each key may be different length
        # each value may be different length

```

These class methods correspond one-to-one with the C++ methods described [here](#), except that for C++ methods with multiple interfaces (e.g. `map()`), there are multiple Python methods with slightly different names, similar to

the [C interface](#).

See the Python scripts in the examples directory for [examples](#) of how these calls are made from a Python program. They are conceptually identical to the C++ and C programs in the same directory.

Technical Details

This section provides additional details about using the MapReduce library and how it is implemented. These topics are covered:

- [Length and byte-alignment of keys and values](#)
 - [Memory requirements for KeyValue and KeyMultiValue objects](#)
 - [Out-of-core operation](#)
 - [Hash functions](#)
 - [Callback functions](#)
 - [Python overhead](#)
 - [Error messages](#)
-
-

Length and byte-alignment of keys and values

As explained in [this section](#), keys and values are variable-length strings of bytes. The MR-MPI library knows nothing of their contents and simply treats them as contiguous chunks of bytes.

When you register a key and value in your [mymap\(\)](#) or [mycompress\(\)](#) or [myreduce\(\)](#) function via the [KeyValue.add\(\)](#) method, you specify their lengths in bytes. Keys and values are typically returned to your program for further processing or output, e.g. as arguments passed to your [myreduce\(\)](#) function by the [reduce\(\)](#) operation, as are their lengths.

Keys and values are passed as character pointers to your functions where you may need to convert the pointer to an appropriate data type and then correctly interpret the byte string. For example, either of these lines could be used:

```
int *iptr = (int *) key;
int myvalue = *((int *) key);
```

If the key or value is a variable-length text string, you may want to terminate it with a "0", and include the trailing "0" in the byte count, so that C-library-style string functions can later be invoked on it. If a key or value is a complex data structure, your function must be able to decode it.

A related issue with keys and values is the byte-alignment of integer or floating point values they include. For example, it is usually a bad idea to store an 8-byte double such that it is mis-aligned with respect to an 8-byte boundary in memory. The reason is that using a mis-aligned double in a computation may be slow.

If your keys or values are homogeneous (e.g. all integers), you can use the *keyalign* and *valuealign* settings, discussed [here](#), to insure alignment of keys and values to desired byte boundaries. Since this may incur extra memory costs, you should typically not make these settings larger than needed.

Special care may need to be taken if your values are heterogeneous. This is because the MR-MPI library packs values one after the other into one long byte string when it is returned to your program as a multi-value, e.g. as an argument to the callback of a "reduce()" method. Only the first value in the multi-value is aligned to the *valuealign* setting. Similarly, the [collapse\(\)](#) method creates a multi-value that is sequence of key,value,key,value,etc from a KV. If the keys are variable-length text strings and the values are integers, then the values will not be aligned on 4-byte boundaries.

Here are two ideas that can be used to insure alignment of heterogeneous data:

(a) Say your "value" is a 4-byte integer followed by an 8-byte double. You might think it can be stored and registered as 12 contiguous bytes. However, this would likely mean the double is mis-aligned. One solution is to convert the integer to a double before storing both quantities in a 16-byte value string. Another solution is to create a struct to store the integer and double and use the `sizeof()` function to determine the length of the struct and use that as the length of your "value". The compiler should then guarantee proper alignment of each structure member.

(b) Your callback function can always copy the bytes of a key or value into a local data structure with the proper alignment, e.g. using the C `memcpy()` function. E.g. in the collapse example above, these lines of code:

```
int myvalue;  
memcpy(lue[offset], sizeof(int));
```

would load the 4 bytes of a particular value (at location offset) in the multi-value into the local integer "myvalue", where it can then be used for computation.

Memory requirements for KeyValue and KeyMultiValue objects

KeyValue and KeyMultiValue objects are described in [this section](#). A MapReduce object contains a single KeyValue object (KV) or a single KeyMultiValue object (KMV), depending on which methods you have invoked.

The memory cost for storing key/value pairs in a KV is as follows. The key and value each have a byte length. Two integers are also stored for the key and value length. There may also be additional bytes added to align the key and value on byte boundaries in memory; see the *keyalign* and *valuealign* settings, discussed in [this section](#). Thus the total size of a KV is the memory for the key/value datums plus 2 integers per pair plus any extra alignment bytes.

Recall that a KMV contains key/multi-value pairs where the number of pairs is typically the number of unique keys in the original KV. The memory cost for storing key/multi-value pairs in a KMV is as follows. The key and multi-value each have a byte length. For the multi-value, this is the sum of individual value lengths. Again, there may also be additional bytes added to align the key and multi-value on byte boundaries in memory; see the *keyalign* and *valuealign* settings, discussed in [this section](#). Three integers are also stored: the key and multi-value length, and the number of values N in the multi-value. An N-length integer array is also stored for the length of each value in the multi-value. Thus the total size of a KMV is the memory for the key/multi-value datums plus 3 integers per pair plus 1 integer per value in the multi-value plus any extra alignment bytes.

Note that memory for key data in a KMV is typically less than in the original KV, since the KMV only stores unique keys. The memory for multi-value data is the same as the value data in the original KV, since all the KV values are contained in the multi-values.

Note that in parallel, for a KV or KMV, each processor stores the above data only for the fraction of key/value pairs it generated during a [map\(\)](#) operation or acquired during other operations, like [collate\(\)](#). If this is imbalanced, one processor may own and process datums more than other processors.

If KV or KMV data on a processor exceeds the *memsize* setting, discussed [here](#), then data is written to temporary disk files, on a per-processor basis.

Out-of-core operation

All the MR-MPI methods can be invoked on data sets larger than fit in the aggregate memory of the processors being used. When the data on any single processor exceeds its local memory limit, as set by the *memsize* [setting](#), that processor will write data to a temporary disk file, and later read it back in.

For many data sets and MapReduce operations, the out-of-core capability of the MR-MPI library means you can effectively process arbitrarily large data sets. To first order, you can think of the *memsize* setting as a hard limit on the amount of memory a processor will use during any MR-MPI operation. However, there are 4 caveats. The first 3 may be overcome in future versions of the MR-MPI library.

(1) The [convert\(\)](#) portion of a [collate\(\)](#) operation performs an on-processor reorganization of the data in a KV to produce a KMV. For large data sets this requires breaking up a disk file of data into smaller files, so that each holds data that will contribute to one chunk of the eventual KMV file. Each smaller file requires an in-memory buffer to store data that is written/read to/from the file. Since it is hard to predict how many smaller files will be needed, the allocation of these buffers is done on-the-fly, using extra memory beyond the *memsize* allocation. If a large number of small files is needed, it's possible these extra buffers will exceed available memory, which will generate an error.

(2) The [aggregate\(\)](#) portion of a [collate\(\)](#) operation migrates data between processors. The `MPI_Send()` and `MPI_Recv()` functions from the MPI library that do this, use additional memory behind the scenes for message buffering. Since the MR-MPI library pre-posts receives for large messages, this additional memory overhead should generally be small. One exception is the case where one (or a few) processors will end up holding the majority of KV data at the end of the [aggregate\(\)](#) operation. The processor needs to pre-allocate a large buffer to receive all the incoming data. Once received, the data will be written to disk and the memory de-allocated. But if the temporary receive buffer cannot be allocated out of the *memsize* chunk, it requires an extra allocation. If this exceeds available memory, an error is generated.

Note that if the data aggregation is so imbalanced that this memory issue arises, then even if the [aggregate\(\)](#) completes, it may mean subsequent MapReduce operations, such as a [reduce\(\)](#), will likely be load-imbalanced and perform poorly in a parallel sense. So you may want to rethink how your key/value data is organized and partitioned across processors.

(3) As discussed [here](#), a *memsize* setting of N Mbytes means that KV or KMV files are written in N/4 size chunks. Currently, this requires that a single key/value or key/multi-value pair within a KV or KMV must fit in one chunk. This is typically not an issue for key/value pairs, but may be for key/multi-value pairs. For example, if *memsize* is the default 100 Mbytes, then a single key/multi-value pair cannot be larger than 25 Mbytes. This includes the unique key and all its values, as well as the integer array of value lengths. Thus, in this example, even if values were of length 0, there could be no more than about 6.25 million of them associated with a single key (6.25 million integers for the length array). If this limit is exceeded, an error is generated.

(4) There are numerous additional small allocations of memory made by the MR-MPI library. E.g. the out-of-core disk files are stored as "pages" of data. Each page requires some in-memory bookkeeping so it can be written and read. Thus if a file grows to 1000s of pages, the corresponding in-memory bookkeeping structure will also become larger. For normal *memsize* settings, e.g. the 100 Mbyte default, these additional in-memory allocations should be small compared to the *memsize* allocation.

Hash functions

The [convert\(\)](#) and [collate\(\)](#) methods use a hash function to organize keys and find duplicates. The MR-MPI library uses the `hashlittle()` function from `lookup3.c`, written by Bob Jenkins and available freely on the WWW. It

operates on arbitrary-length byte strings (a key) and produces a 32-bit integer hash value, a portion of which is used as a bucket index into a hash table.

Callback functions

Several of the library methods take a callback function as an argument, meaning that function is called back to from the library when the method is invoked. These functions are part of your MapReduce program and can perform any operation you wish on your data (or on no data), so long as they produce the appropriate information. E.g. they generate key/value pairs in the case of `map()` or `compress()` or `reduce()`, or they hash a key to a processor in the case of `aggregate()` or `collate()`, or they compare two keys or values in the case of `sort_keys()` or `sort_values()`.

The `mymap()` and `myreduce()` functions can perform simple operations or very complex, compute-intensive operations. For example, if your parallel machine supports it, they could invoke another program or script to read/parse an input file or calculate some result.

Note that in your program, a callback function CANNOT be a class method unless it is declared to be "static". It can also be a non-class method, i.e. just a stand-alone function. In either case, such a function cannot access class data.

One way to get around this restriction is to define global variables that allow your function to access information it needs.

Another way around this restriction is to use the feature provided by several of the library methods with callback function arguments which allow you to pass in a pointer to whatever data you wish. This pointer is returned as an argument when the callback is made. This pointer should be cast to `(void *)` when passed in, and your callback function can later cast it back to the appropriate data type. For example, a class could set the pointer to an array or an internal data structure or the class itself as `"(void *) this"`. Specify a NULL if your function doesn't need the pointer.

Python overhead

Using the MR-MPI library from Python incurs two not-so-obvious overheads beyond the usual slowdown due to using an interpreted language. First, Python objects used as keys and values are "pickled" and "unpickled" using the cPickle Python library when passed into and out of the C++ library. This is because the library stores them as byte strings. The pickling process serializes a Python object (e.g. an integer, a string, a tuple, or a list) into a byte stream in a way that it can be unpickled into the same Python object.

The second overhead is due to the complexity of making a double callbacks between the library and your Python script. I.e. the library calls back once to the user program which then calls back into the library. Consider what happens during a `map()` operation when the library is called from a C++ program.

- the program calls the library `map()` method
- the library `map()` calls back to the user `map()` callback function
- the user `map()` calls the library `add()` method to register a key/value pair

When doing this from Python there are 3 additional layers between the Python program and the library, the Python `mrmpi` class, an invisible C layer (created by ctypes), and the C interface on the C++ library itself. Thus the callback operation proceeds as follows:

- the program calls the `mrmpi` class `map()` method
- the `mrmpi` class `map()` calls the invisible C `map()` function
- the invisible `map()` calls the C interface `map()` function
- the C interface `map()` calls the library `map()` method
- the library `map()` calls back to the invisible C callback function
- the invisible callback calls the `mrmpi` class callback method
- the `mrmpi` callback calls the user `map()` callback function
- the user `map()` calls the `mrmpi` class `add()` method to register a key/value pair
- the `mrmpi` class `add()` calls the invisible C `add()` function
- the invisible `add()` calls the C interface `add()` function
- the C interface `add()` calls the library `add()` method

Thus 3 calls have become 11 due to the 3 additional layers data must pass through. Some of these pass throughs are very simple, but others require massaging and copying of data, like the pickling/unpickling described above, which occurs in the `mrmpi` class methods. I was somewhat surprised this double-callback sequence works as well and as transparently as it does – Python ctypes is amazing!

Error messages

The error messages printed out by the MR-MPI library are hopefully self-explanatory. At some point they will be listed in these doc pages.

Examples

This section describes the MapReduce programs provided in the examples directory of the distribution:

- [wordfreq](#)
- [rmat](#)

Each are provided in 3 formats: as a C++ program, C program, and Python script. Note that the Python scripts use the PyPar package which provides a Python/MPI interface, as discussed above in the [Python Interface](#) section, so you must have [PyPar](#) installed in your Python to run them.

The C++ and C programs can be built (assuming you have already built the MR-MPI library) by typing

```
make -f Makefile.foo
```

from within the examples directory, using one of the provided Makefiles. As with the library itself, you may need to edit one of the Makefiles to create a new version appropriate to your machine.

Word frequency example

The wordfreq programs implement the word frequency counting algorithm described above in [this section](#). The wordfreq programs are run by giving a list of text files as arguments, e.g.

```
wordfreq ~/mydir/*.cpp
mpirun -np 8 wordfreq ~/mydir/*.cpp
cwordfreq ~/mydir/*.cpp
mpirun -np 8 cwordfreq ~/mydir/*.cpp
python wordfreq.py ~/mydir/*.cpp
mpirun -np 8 python wordfreq.py ~/mydir/*.cpp
```

Total word counts and a list of the top 10 words should be printed to the screen, along with the time to perform the operation.

The 3 different versions of the wordfreq program should give the same answers, although if non-text files are used, the parsing of the contents into words can be done differently by the C library strtok() function and the Python string "split" method.

R-MAT matrices example

The rmat programs generate a particular form of randomized sparse matrix known as an [R-MAT matrix](#). Depending on the parameters chosen, the sparsity pattern in the resulting matrix can be highly non-uniform, and a good model for irregular graphs, such as ones representing a network of computers or WWW page links.

The rmat programs are run by specifying a few parameters, e.g.

```
rmat N Nz a b c d frac outfile
mpirun -np 8 rmat N Nz a b c d frac outfile
crmat N Nz a b c d frac outfile
mpirun -np 8 crmat N Nz a b c d frac outfile
python rmat.py N Nz a b c d frac outfile
```

```
mpirun -np 8 python rmat.py N Nz a b c d frac outfile
```

The meaning of the parameters is as follows. Note that only matrices with a power-of-2 number of rows can be generated, so specifying $N=20$ creates a matrix with over a million rows.

- 2^N = # of rows in matrix
- N_z = average # of non-zeroes per row
- a,b,c,d = generation params for matrix entries, must sum to 1
- $frac$ = randomization parameter between 0 and 1
- $seed$ = random # seed, positive integer
- $outfile$ = optional output file

A full description of the R-MAT generation algorithm is beyond the scope of this doc page, but here's the brief version. The a,b,c,d parameters are effectively weights on the 4 quadrants of the matrix. To generate a single new matrix element, one quadrant is chosen, with a probability proportional to its weight. This operation is repeated recursively within the chosen quadrant, applying the $frac$ parameter to randomize the weights a bit. After N iterations, a single I,J matrix location has been identified and its value is set (to 1 in this case).

The total number of matrix entries generated is $N_x * 2^N$. This procedure can generate duplicates, so those are removed, and new elements generated until the desired number is reached.

When completed, the matrix statistics are printed to the screen, along with the time to generate the matrix. If the optional *outfile* parameter is specified, then the matrix entries are written to files (one per processor). Each line of any file has the form

```
I J value
```

where I,J are the matrix row,column and value is the matrix entry (all are 1 in this case). If the files are concatenated together, the full set of matrix entries should result.

The 3 different versions of the rmat programs should give the same answers in a statistical sense. The answers will not be identical because the same random number generation scheme is not used in all 3 programs.

(RMAT) D. Chakrabarti, Y. Zhan, C. Faloutsos, R-MAT: A Recursive Model for Graph Mining", in Proceedings of the SIAM Conference on Data Mining (2004), available at <http://www.cs.cmu.edu/~deepay/mywww/papers/siam04.pdf>.